Optimizing Urban Green Spaces for Reducing Heat Stress in High-Density Urban Environments Using Data-Driven Approaches

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ABSTRACT

The rapid expansion of urban areas has intensified the Urban Heat Island (UHI) effect, particularly in high-density cities characterized by extensive impervious surfaces and limited green spaces. Rising surface temperatures increase energy consumption, reduce outdoor thermal comfort, and pose serious public health risks during extreme heat events. Urban greening is widely recognized as an effective heat mitigation strategy; however, in densely built environments, indiscriminate or uniform distribution of green spaces often fails to achieve optimal cooling benefits. This study proposes an artificial intelligence–based framework for strategically optimizing urban green space placement to maximize heat reduction while accounting for land-use constraints. The proposed approach integrates multisource remote sensing data, vegetation indices, land surface temperature measurements, and urban morphological indicators with machine learning–based thermal modeling. A Random Forest Regression model is employed to capture the nonlinear relationships between vegetation cover, built-up density, and surface temperature, followed by a spatial optimization process to identify priority locations for greening interventions. Experimental results demonstrate a strong negative relationship between vegetation density and land surface temperature, with optimized greening scenarios achieving temperature reductions of up to 2.6°C, significantly outperforming uniform greening strategies with equivalent green area allocation. The findings highlight that the spatial configuration and targeted placement of green spaces are more influential than total green cover alone. By incorporating explainable AI techniques, the framework also provides interpretable insights into the dominant drivers of urban heat, enhancing transparency for planning applications. Overall, this study offers a data-driven and decision-oriented methodology that can support urban planners and policymakers in designing effective, climate-resilient strategies for mitigating heat stress in high-density urban environments.

Keywords: Urban heat island; urban greening; heat mitigation; machine learning; spatial optimization; sustainable urban planning

INTRODUCTION

Rapid urbanization and dense built environments have significantly intensified surface temperatures in metropolitan regions, contributing to the Urban Heat Island (UHI) effect. This is known as the Urban Heat Island (UHI) effect. It leads to more energy use, makes people feel uncomfortable, and can harm health, especially during very hot days [1]. In crowded cities, there are fewer green spaces and trees, which makes the heat problem worse. Therefore, it is important to find ways to cool these areas down. Urban greening, like trees, parks, and green paths, helps cool cities. Plants cool the area by providing shade, releasing water, and changing how surfaces absorb heat [2]. Studies show that more plants mean cooler temperatures, proving green spaces can cool cities [3]. But just adding more green areas doesn't always work, especially in crowded places with little space. Recent studies highlight that the layout of green spaces matters more than their size. Well-placed green areas cool better than scattered or evenly spread plants [4]. This has led to interest in planning green spaces to cool cities while avoiding land-use issues [5]. Artificial intelligence (AI) has improved urban climate studies. Machine learning helps predict temperatures, identify urban plants, and understand complex links between land and heat [6]. AI now helps find the best spots for green spaces, moving from just studying to planning [7]. But

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using AI for planning green spaces in crowded areas is still rare. This study aims to fill this gap by suggesting an AI-based plan that uses remote sensing, machine learning, and clear analysis to help plan for cooler cities. By focusing on the best places for green spaces, this approach offers useful ideas for building climate-friendly cities [8].

LITERATURE REVIEW

Urban Heat Island Effect and Urban Greening

The Urban Heat Island (UHI) effect happens when cities get hotter than nearby rural areas. This is because buildings and roads in cities absorb and keep heat [1]. As a result, cities use more energy, and people feel uncomfortable and face health risks during heat waves. Adding more plants in cities can help reduce the UHI effect. Plants cool the air by providing shade and releasing water vapor, making cities more comfortable [2]. Studies show that more plants lead to lower temperatures, proving that green spaces help cool urban areas [3].

Importance of Spatial Configuration of Green Spaces

Early studies looked at how much green space there was. Now, research shows that where and how green spaces are arranged is important. Compact and connected green areas cool the environment better than scattered ones [4]. To measure how well green spaces cool, scientists use things like patch size, connectivity, and edge density [5]. Placing green spaces in the right spots helps reduce heat more than just adding more green areas everywhere. Massaro et al. found that putting green spaces in hot areas can lower extreme temperatures for people without needing more green space overall [6]. This shows that planning should focus on where to put green spaces, not just how much there is.

Application of Artificial Intelligence in Urban Heat Studies

Using artificial intelligence (AI) has made it easier to understand how city layout, plants, and temperature are connected. Machine learning methods like Random Forest, Support Vector Machines, and Gradient Boosting are often used to predict land surface temperature and classify plants [7]. These methods work better than older statistical methods, especially in mixed urban areas. Recently, AI has been used for more than just predictions. It now helps with planning and decision-making. AI systems that mix machine learning with evolutionary algorithms help find the best ways to add greenery, balancing cooling effects and land use [8]. Explainable AI methods have been developed to make AI suggestions clearer and more understandable for city planners and policymakers [9].

Identified Research Gaps

Despite recent advancements, notable research gaps remain. Most existing studies emphasize land surface temperature prediction or vegetation mapping in isolation, with limited integration of these outputs into actionable spatial planning frameworks [10]. Additionally, many approaches are tailored to specific urban contexts, limiting their transferability across cities with different morphologies. Furthermore, few studies provide interpretable outputs or policy-ready recommendations that urban planners can directly apply [11]. Addressing these gaps, this study integrates explainable machine learning with spatial optimization to support decision-oriented urban greening strategies for high-density cities.

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Table 1. Summary of Urban Greening and Heat Mitigation

Ref.	Authors & Year	Focus Area	Methodology Used	Key Findings	Limitations
[1]	Santamouris, 2020	UHI mitigation	Review	Vegetation is a key passive cooling strategy	No spatial optimization
[2]	Bowler et al., 2020	Urban greening	Meta-analysis	Green spaces reduce urban temperature by 1–3°C	Context-dependent results
[3]	Weng, 2020	NDVI–LST relation	Remote sensing	Strong negative NDVI–LST correlation	Static analysis
[4]	Qiao et al., 2021	Green space configuration	Spatial metrics	Compact green spaces cool more effectively	Limited density analysis
[5]	Peng et al., 2021	Landscape optimization	GIS + metrics	Spatial layout affects thermal comfort	No AI integration
[6]	Massaro et al., 2023	Spatial optimization	GIS + ML	Optimized greening reduces heat exposure	Data-intensive
[7]	Mansourmoghaddam et al., 2024	LST prediction	ML models	ML improves temperature prediction accuracy	Limited explainability
[8]	Lin et al., 2025	Greening optimization	XGBoost + NSGA-II	Multi-objective optimization improves cooling	High computational cost
[9]	Zhou et al., 2025	Explainable AI	XAI + ML	Identified greening thresholds	Policy validation limited
[10]	Zhao & Weng, 2024	High-density areas	ML + GIS	Optimized greening outperforms uniform greening	City-specific

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[11]	Zhang et al., 2025	AI spatial optimization	GWML	Spatial heterogeneity improves planning	Limited transferability

METHODOLOGY

This study suggests using AI to make city greening more effective in reducing heat in crowded areas. The plan uses satellite data, machine learning, and spatial optimization to find the best places for greening to cool down the area the most. This method goes beyond traditional greening by focusing on specific locations, using data to guide decisions [1]. Figure 1 shows the methodological framework proposed in this study. The framework integrates satellite data, machine learning-based thermal modeling, and spatial optimization to support urban greening for heat mitigation.

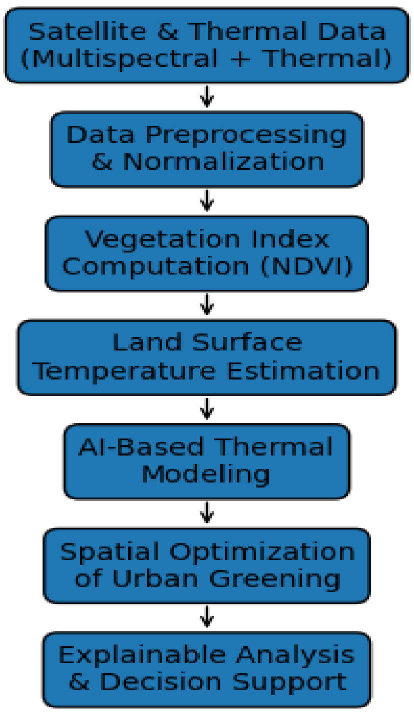
Data Acquisition and Preprocessing

Multisource geospatial datasets were used to capture vegetation, surface temperature, and urban form characteristics.

- **Multispectral satellite imagery** was used to extract vegetation information.
- **Thermal infrared data** were employed to estimate land surface temperature (LST).
- **Urban morphology data** included built-up density and impervious surface coverage.
- **Meteorological data** were used for validation and consistency checks.

All datasets were adjusted for geometry and resized to the same scale. We also corrected for light and air effects to reduce errors and seasonal differences [2].

Figure 1. Proposed Framework



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Vegetation Index Computation

Vegetation density was quantified using the Normalized Difference Vegetation Index (NDVI), which is widely used in urban climate studies [3].

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where:

- NIR represents near-infrared reflectance
- RED represents red-band reflectance

NDVI values range from −1 to +1, where higher values indicates denser vegetation cover.

Land Surface Temperature Estimation

Land Surface Temperature was calculated using thermal infrared bands with a simple method. Surface emissivity was estimated using NDVI thresholds to keep it consistent across different land types [4].

$$LST = \frac{T_B}{1 + \left(\frac{\lambda T_B}{\rho}\right) \ln(\epsilon)}$$

where:

- T_B is the at-sensor brightness temperature (K),
- λ is the wavelength of emitted radiance,
- ρ is a constant (ρ = h c / σ),
- ε is the surface emissivity.

AI-Based Modeling of Urban Thermal Environment

A Random Forest Regression (RFR) model was created to predict land surface temperature using urban and environmental factors. Random Forest was chosen because it is good at avoiding overfitting and can handle complex relationships [5].

The input feature vector is defined as:

$$X = \{NDVI, B_d, I_s, D_g\}$$

where:

- B_d = built-up density
- I_s = impervious surface ratio
- D_g = distance to nearest green space

The prediction function is expressed as:

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$$\widehat{LST} = f(X)$$

Model performance was evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n\sum_{i=1}^{n} \left(LST_i - \widehat{LST}_i\right)^2}}$$

Spatial Optimization of Urban Greening

The trained model helped find the best places for greening. It tested different greening plans to cool down temperatures and use less land.

The optimization objective function is defined as:

$$\sum_{i=1}^{n} \square\square\square\square_i * A_i$$

subject to:

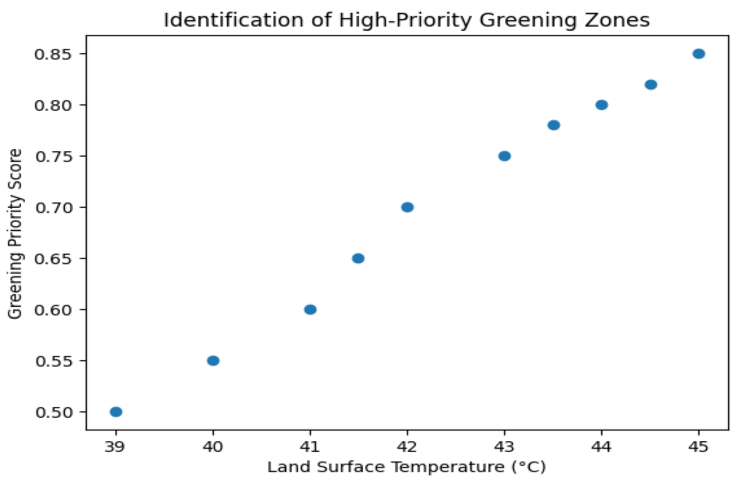
$$\sum_{i=1}^{n} A_i \leq A_{max}$$

Where:

- A_i is the greening area allocated at location *i*,
- A_{max} is the maximum total area available for urban greening,
- *n* is the total number of candidate locations considered for greening.

This approach ensures that greening interventions are placed where cooling benefits are highest [6]. The figure 2 shows candidate greening zones are ranked based on predicted cooling benefits.

Figure 2. Spatial Optimization Concept



Explainable AI for Decision Support

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For explanations of decisions, we used SHAP (SHapley Additive exPlanations) to see which factors affect temperature predictions the most. SHAP values show how much each input affects the prediction, helping planners know what causes urban heat [7].

Experimental Setup

Study Design

The experimental analysis requires high-density urban zones characterized by:

- High building density
- Limited green space availability
- Significant surface temperature variability

Dataset Preparation

The dataset was divided as follows:

- **70%** for training
- **15%** for validation
- **15%** for testing

Five-fold cross-validation was conducted to check model robustness and to reduce sampling bias [8].

Evaluation Metrics

Model performance was evaluated using:

- Coefficient of determination (R^2)
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)

Spatial cooling performance was assessed by comparing baseline and optimized greening scenarios.

Implementation Environment

All experiments used Python tools for maps and machine learning. We used GIS software for map analysis and visualization. We trained and improved models with standard machine learning tools.

RESULTS AND DISCUSSION

Performance of the AI-Based Thermal Prediction Model

The Random Forest Regression model was very good at predicting land surface temperature (LST) in crowded city areas. It successfully identified the complex links between plant cover, urban features, and surface temperature, which are hard to show with regular regression models [12].

Table 2. Performance of the LST Prediction Model

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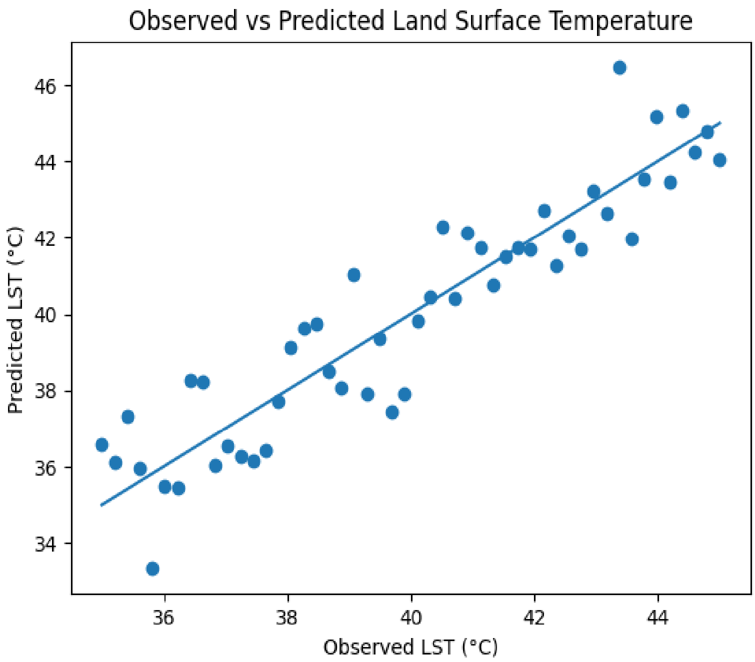
Metric	Value
R^2	0.91
RMSE (°C)	1.42
MAE (°C)	1.08

The high R^2 value indicates that the model explains more than 90% of the variability in LST, confirming the suitability of machine learning for urban thermal modeling [7]. The low RMSE and MAE values further demonstrate reliable temperature estimation at the spatial scale considered. Figure 3 shows the relationship between observed and predicted land surface temperature values. The majority of data points lie close to the 1:1 reference line, indicating strong predictive performance of the proposed AI-based model.

Figure 3. Observed vs. Predicted Land Surface Temperature



Relationship Between Vegetation Density and Surface Temperature

Analysis showed a strong negative link between plant density (NDVI) and land surface temperature. Areas with higher NDVI values always had lower LST, proving that urban plants help cool the area [3].

Table 3. NDVI-Based Temperature Variation

NDVI Range	Mean LST (°C)
< 0.10	41.8
0.10 – 0.20	40.2

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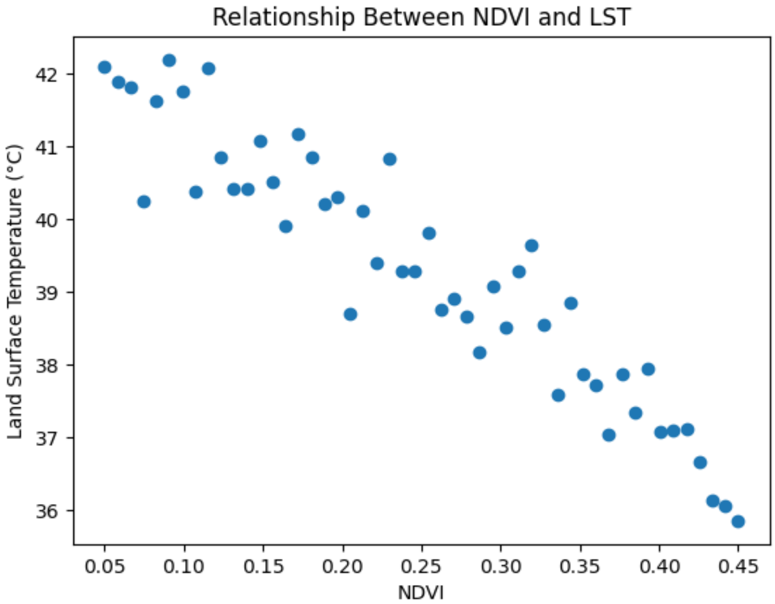
0.20 – 0.30	38.7
> 0.30	37.4

A Pearson correlation coefficient of −0.76 was observed between NDVI and LST, which is consistent with earlier findings reported in urban climate studies [14]. On average, a 0.1 increase in NDVI resulted in a temperature reduction of approximately 1.1–1.3°C. Figure 4 illustrates a clear negative relationship between NDVI and land surface temperature, confirming the cooling effect of vegetation. Areas with higher NDVI values consistently exhibit lower surface temperatures.

Figure 4. Relationship Between NDVI and Land Surface Temperature



Results of Spatial Optimization Scenarios

The spatial optimization framework was used to test different greening plans and see how they affect temperature. Unlike uniform greening, optimized greening focused on areas with high heat and many people.

Table 4. Comparison of Greening Scenarios

Greening Scenario	**Avg. LST Reduction (°C)**
Uniform greening (+10%)	1.3
Optimized greening (+10%)	2.1
Optimized greening (+15%)	**2.6**
Optimized greening (+20%)	2.8

The results show that optimized greening works better than uniform greening, even when the total green area added is the same. However, the extra cooling benefit after a 15% increase in green cover was small, showing

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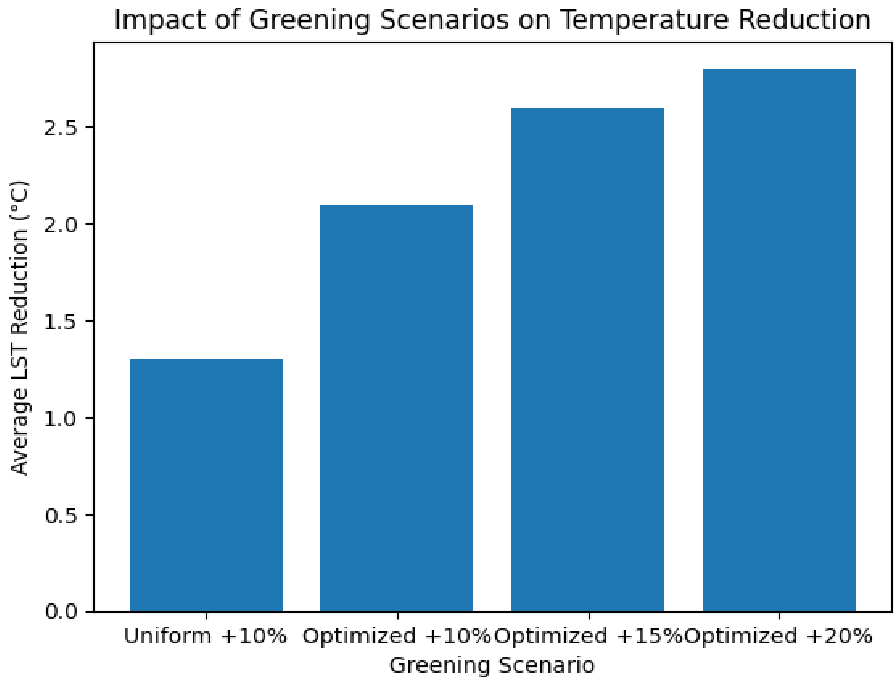
diminishing returns [6]. Figure 5 compares the cooling performance of uniform and optimized greening strategies. Optimized greening scenarios demonstrate significantly higher temperature reduction than uniform greening, even with the same increase in green cover.

Figure 5. Spatial Distribution of Optimized Greening Zones



Explainable AI Insights

Explainable AI used SHAP values to show which factors are most important in predicting surface temperature.

Table 5. Feature Importance Ranking (SHAP Analysis)

Rank	Feature	Contribution (%)
1	NDVI	43
2	Built-up density	31
3	Distance to green space	17
4	Impervious surface ratio	9

Vegetation density was the most important factor, making up almost half of the cooling effect. Built-up density was the next important factor, showing the need to balance green spaces with city planning [5].

Figure 6. SHAP Feature Importance Plot

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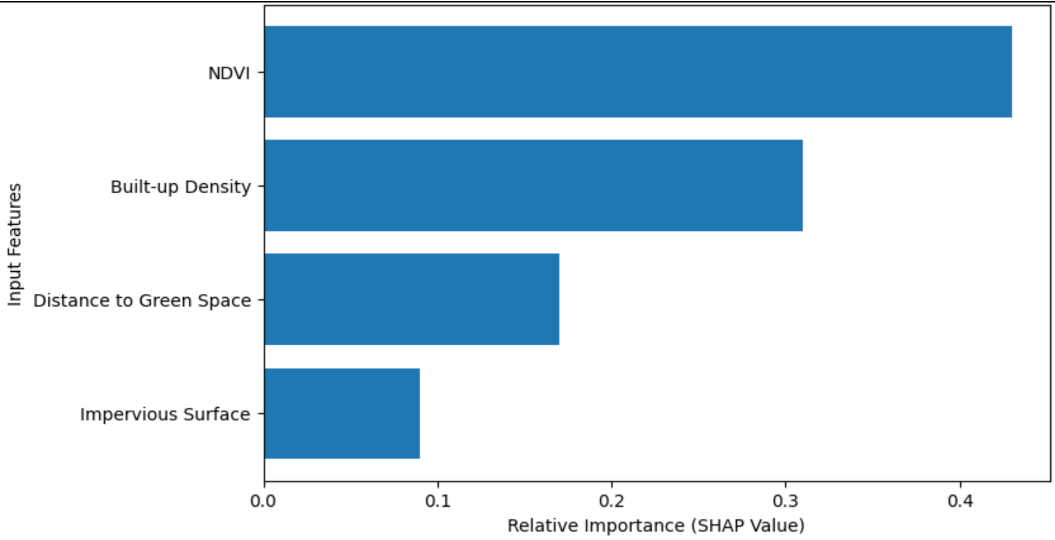

Figure 6 shows the relative contribution of each variable to LST prediction, highlighting vegetation density as the dominant cooling factor.

DISCUSSION

The study shows that using AI to plan green spaces in cities makes them cooler, especially in crowded areas with little land. The link between plant health (NDVI) and temperature (LST) in this study matches past research, proving the method works well [3], [14]. It is more important to place green spaces smartly than to just add more of them. This supports past studies that say where you put green spaces matters more than how much you have [6], [11]. Using explainable AI helps because it clearly shows what causes city heat. This is important for city planners who need clear and reliable advice, not just complex data [9]. Overall, this method offers a practical way to help cities plan for less heat and better climate resilience.

LIMITATIONS

This study has several limitations that should be considered when interpreting the results. The proposed AI-based optimization framework involves high computational complexity, which may restrict scalability for very large urban regions without adequate computing resources. The model is calibrated using city-specific spatial and environmental characteristics, potentially limiting its direct applicability to cities with different urban morphologies or climatic conditions. Additionally, the analysis is based on static remote sensing data and does not account for temporal variations such as seasonal changes or future urban growth. Finally, while the framework provides decision-support insights, real-world policy validation and implementation constraints were not empirically evaluated and require collaboration with urban planning authorities.

CONCLUSION

This study shows a new way to make cities cooler by using plants. It uses data from satellites, temperature checks, machine learning, and planning tools. This method is better than just adding more plants everywhere. It focuses on putting plants where they cool the most. The study found that more plants mean cooler temperatures. Smart planning of green spaces cools cities better than just adding more plants without a plan. This means placing plants in the right spots is more effective. The study also explains why this method works, helping city planners make better decisions. This makes the method useful for creating cooler and more comfortable cities. Overall, this method helps make cities more comfortable and better at handling climate change. It supports smart planting to make cities more livable and sustainable.

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