



ThermoShield: AI-Powered Urban Heat Prediction and Automated Mitigation System

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ABSTRACT

Urban areas are experiencing rising temperatures due to rapid urbanization, reduced vegetation, dense infrastructure, and changing climatic conditions, a phenomenon commonly described as the urban heat island effect. Prolonged exposure to excessive heat affects public health, increases energy consumption, degrades environmental conditions, and undermines urban sustainability. This paper proposes ThermoShield, an AI-powered system that predicts urban heat conditions and proactively triggers mitigation measures. The system analyses weather and environmental parameters, including temperature, humidity, solar radiation, and wind conditions, along with urban factors such as vegetation cover and built-up density, to identify heat patterns and forecast high-risk conditions. Machine learning models estimate future temperature levels and classify locations and time periods into heat-risk categories. Based on the predicted risk level, the system automatically initiates suitable mitigation measures, such as smart misting, adaptive shading control, or other cooling interventions, with the option of operator review for high-impact actions. By integrating heat prediction with automated mitigation, ThermoShield aims to shift urban heat management from a reactive to a proactive approach. The framework can support smart-city planning, improve urban resilience, reduce heat-related risks, and contribute to more sustainable, climate-responsive cities.

Keywords: Urban Heat Island, Heat Prediction, Machine Learning, Automated Mitigation, Smart City, Climate Resilience

1. INTRODUCTION

Urbanization and rapid population growth have significantly altered the physical structure of cities. The growing number of buildings, roads, and vehicles, combined with the loss of vegetation, has contributed to rising temperatures in urban areas. This phenomenon is widely known as the **Urban Heat Island (UHI) effect**, in which urban regions become considerably warmer than their surrounding areas. Elevated temperatures and prolonged heat exposure pose risks to human health, increase energy consumption for cooling, and undermine the overall sustainability and comfort of urban environments.

Traditional approaches to urban heat management are often reactive, with mitigation measures implemented only after extreme heat conditions have already occurred. This reactive approach leaves insufficient time for preventive action. Moreover, many existing heat-monitoring systems focus primarily on measuring or predicting temperature without directly linking the prediction process to suitable mitigation actions. There is therefore a need for an intelligent system that can identify potential heat risks in advance and support timely mitigation.

1.1 Aim of the Study

The main aim of this study is to develop **ThermoShield, an AI-Powered Urban Heat Prediction and Automated Mitigation System** that supports proactive responses to potential heat risks. The system analyzes relevant environmental and urban factors, including temperature, humidity, solar radiation, wind speed, vegetation cover, and built-up density. Based on these factors, the AI-based prediction model identifies heat patterns and classifies the expected heat-risk level for a given area or time period. When a high-risk condition is predicted, the system recommends or activates appropriate mitigation measures, such as smart misting and dynamic shading.

1.2 Importance of the Study

The importance of this study lies in combining **heat prediction with automated mitigation** rather than treating them as separate processes. Early identification of heat-risk conditions provides valuable lead time for preventive action before conditions become severe. Smart misting can offer temporary, localized cooling, while dynamic shading can reduce direct solar exposure in targeted areas. By linking AI-based prediction with these mitigation mechanisms, the proposed system supports more proactive and efficient urban heat management.

The proposed approach can also provide useful information for city planners, environmental management teams, and smart-city applications. It can help identify locations and time periods that are more vulnerable to excessive heat, supporting data-driven planning of mitigation strategies. In this way, ThermoShield aims to contribute to safer urban environments, improved climate resilience, and more sustainable heat-management practices.

Overall, ThermoShield follows a **predictive-to-action approach**: environmental and urban data are collected and analyzed → the AI model predicts future heat conditions → the system determines the heat-risk level → suitable mitigation measures are recommended or activated → the response is monitored to inform further decision-making. This integration of prediction and mitigation forms the central concept of the proposed system.

2. LITERATURE REVIEW

Recent studies have explored Artificial Intelligence (AI) and Machine Learning (ML) techniques for predicting and analysing the Urban Heat Island (UHI) effect. Syeda, Castillo-Villar, and Alaeddini (2025) compared Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machine (GBM) models to predict land surface temperature (LST) across five functional zones in San Antonio, Texas, incorporating both environmental variables — imperviousness, NDVI, building area, solar influx — and socio-demographic factors such as income and population density; SVM achieved the highest R^2 (0.870), while RF produced the lowest prediction error (RMSE = 0.488°C). Their study further found that urban imperviousness was the most consistent predictor of elevated LST across all zones and all three models, reinforcing the well-established link between surface sealing and urban heat.

Tanoori, Soltani, and Modiri (2024) applied ensemble ML methods, including SVM and gradient boosting, to predict LST, identifying impervious surfaces, vegetation indices, and building areas as primary UHI drivers, and confirmed that urban morphology remains a central factor in heat formation. Building on this direction, Hoang, Tran, and Huynh (2025) compared LightGBM, SVM, RF, and Deep Neural Networks for LST modelling in Da Nang, Vietnam, using Shapley Additive Explanations (SHAP) to interpret model predictions; LightGBM achieved the strongest performance (R^2 up to 0.92), and built-up density and greenspace density consistently emerged as the two most influential predictors across 2014, 2019, and 2024.

Separately, a body of work has examined automated heat mitigation technologies. Ulpiani and Zinzi (2023) experimentally tested an urban cooling shelter combining water misting with solar shading and wind shielding near Rome, finding that misting alone achieved a median air temperature reduction of 3.5°C, and that adding a wind shield increased cooling to a median of 7.5°C. Critically, their comfort-driven smart control system matched this cooling performance while cutting pump activation by 80%, demonstrating that automated, sensor-responsive control substantially improves resource efficiency over continuous misting — though their system still reacted to real-time comfort thresholds rather than acting on forward-looking predictions.

Although existing studies provide robust methods for both UHI prediction and heat mitigation individually, few approaches directly connect the two. Prediction-focused studies (Syeda et al., 2025; Tanoori et al., 2024; Hoang et al., 2025) stop at risk classification or variable-importance analysis, without extending their outputs into an automated response mechanism. Mitigation studies, even where "smart control" is used (Ulpiani & Zinzi, 2023), generally react to real-time sensor thresholds rather than acting on predictions from a trained AI model. This distinction matters: a threshold-triggered system responds only once conditions are already uncomfortable, whereas a prediction-driven system could act pre-emptively, before a heat-risk threshold is even crossed. This gap creates a clear opportunity for an integrated system that moves from AI-based prediction to automated, anticipatory mitigation.

The proposed ThermoShield addresses this gap by combining AI-based heat prediction, heat-risk classification, and automated or recommended mitigation measures such as smart misting and dynamic shading within a single pipeline. In doing so, the system adopts a predictive-to-action approach for proactive urban heat management, distinguishing it from prior work that treats prediction and reactive mitigation as separate, disconnected processes.

3. METHODOLOGY

The proposed ThermoShield system follows a predictive-to-action approach for urban heat management. The methodology consists of data collection, preprocessing, feature selection, machine learning model development, heat-risk prediction, and automated mitigation.

3.1 Data Collection

The system collects relevant environmental and urban parameters such as temperature, humidity, solar radiation, wind speed, vegetation cover, and built-up (impervious surface) density. Historical data is used to identify heat patterns and train the prediction model.

3.2 Data Pre-processing

The collected data is cleaned and prepared for model development. Missing or inconsistent values are handled, and the dataset is normalized where required. The processed dataset is then divided into training and testing sets for model development and evaluation.

3.3 Feature Selection

Relevant features influencing heat conditions — such as vegetation cover, built-up density, and solar radiation — are identified and selected to improve model accuracy and reduce computational complexity.

3.4 Heat Prediction Model

Machine learning techniques are applied to analyse the relationship between environmental/urban parameters and heat conditions. The trained model predicts the expected temperature or heat condition for a specific location and time period.

3.5 Heat-Risk Classification

Based on the predicted heat conditions, the system classifies the risk level into categories such as Low, Moderate, and High. This classification determines the appropriate mitigation response.

3.6 Automated Mitigation

When a high heat-risk condition is identified, the system recommends or activates suitable mitigation measures, such as smart misting for localized cooling and dynamic shading to reduce direct solar exposure. In a software-based prototype, these actions are simulated through the system interface.

3.7 Monitoring and Visualization

The predicted heat level, risk category, and mitigation status are displayed through a user-friendly interface, allowing users or responsible authorities to monitor heat conditions and make timely decisions.

3.8 Overall Methodology Flow

Data Collection → Data Preprocessing → Feature Selection → ML Model Training → Heat Prediction → Risk Classification → Mitigation Decision → Smart Misting / Dynamic Shading → Monitoring

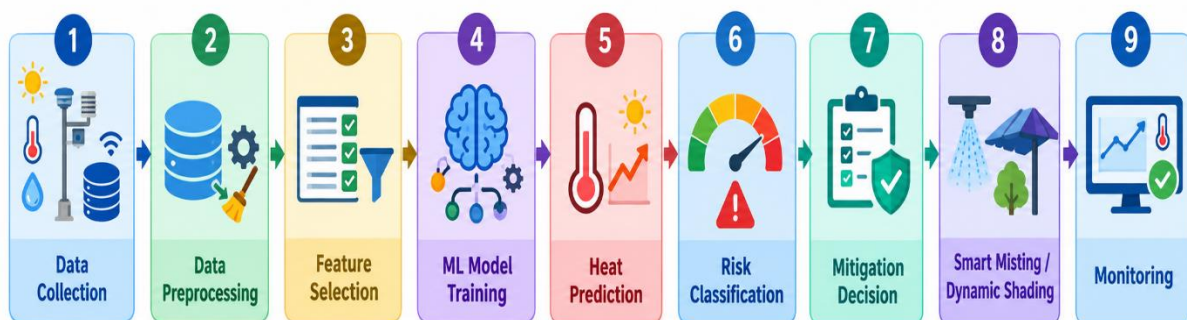


Fig 1 **Methodology** of ThermoShield

This methodology enables ThermoShield to move beyond conventional heat prediction by linking predicted heat risks with appropriate mitigation responses, supporting proactive, climate-responsive urban heat management.

4. RESULTS AND DISCUSSION

The proposed ThermoShield framework is designed to predict urban heat conditions and identify areas that may experience increased heat risk. The system analyses environmental and urban parameters — temperature, humidity, solar radiation, wind speed, vegetation cover, and built-up (impervious surface) density — to identify patterns associated with urban heat conditions.

The prediction model produces an estimated heat condition for a given location and time period. Based on the predicted condition, the system categorizes the heat risk into Low, Moderate, and High levels. This classification offers a simple way to interpret the severity of the predicted heat condition and supports timely decision-making.

When the predicted heat risk reaches a high level, the system identifies an appropriate mitigation response. For example, smart misting is recommended for localized cooling, while dynamic shading is used to reduce direct exposure to solar radiation. In the software-based implementation, these mitigation actions are represented through the system interface to demonstrate the decision-making process.

The results also highlight the importance of considering multiple environmental and urban factors rather than relying on temperature alone. Humidity, solar radiation, vegetation cover, and built-up density each influence local heat conditions; combining these parameters therefore provides a more informative representation of urban heat risk than any single variable would.

The proposed predictive-to-action approach offers a key advantage over systems that only display or predict heat conditions: by linking the predicted risk level with a suitable mitigation response, ThermoShield supports proactive heat management rather than passive monitoring. However, the effectiveness of the system depends on the quality and availability of input data, model performance, and the availability of suitable mitigation infrastructure.

Overall, the proposed framework demonstrates the potential of integrating AI-based heat prediction with mitigation decision support to improve urban heat management. Further evaluation using larger real-world datasets and real-time sensor data would help assess the system's performance under diverse environmental and urban conditions.

5.CONCLUSION

This paper presented ThermoShield, an AI-Powered Urban Heat Prediction and Automated Mitigation System, designed to support proactive management of urban heat conditions. The proposed framework analyses environmental and urban parameters to predict heat conditions and classify them into different risk levels. Based on the predicted risk, suitable mitigation measures such as smart misting and dynamic shading are recommended or activated to reduce localized heat exposure.

The main contribution of ThermoShield lies in the integration of AI-based heat prediction with mitigation decision-making, enabling a transition from reactive heat management to a predictive, proactive approach. The framework offers useful support for urban monitoring, smart-city planning, and climate-resilient infrastructure development.

However, practical deployment requires reliable real-time data, suitable infrastructure, and further validation under diverse environmental and urban conditions. Future work should focus on integrating IoT-based sensors, real-time weather and satellite data, advanced deep learning models, and physical mitigation devices to improve the system's scalability and effectiveness.

Overall, ThermoShield provides a practical framework for combining intelligent prediction with timely mitigation, contributing to the development of safer, more sustainable, and climate-responsive urban environments.

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