Received: September 19, 2025. Revised: November 12, 2025.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Bridging Prediction and Immersion: A GTB–FSM Framework for Urban Heat Island Simulation in 3D Virtual Cities

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Abstract: The Urban Heat Island (UHI) effect intensifies thermal stress in cities, requiring tools that combine predictive accuracy with effective visualization. This study introduces a framework that integrates Gradient Tree Boosting (GTB) for Land Surface Temperature (LST) prediction with a Finite State Machines (FSM) for dynamic simulation in a 3D virtual city. Using multisource satellite and urban form data, the GTB model achieved high predictive accuracy ($R^2 = 0.88$). The outputs were embedded into a virtual environment where FSM logic classified thermal states and enabled real-time transitions across Cool, Transition, and Hot Zones. Usability testing involving 30 participants produced an average System Usability Scale (SUS) score of 88.92, indicating excellent user acceptance. The results show that the proposed platform not only strengthens UHI prediction but also provides an interactive and immersive medium for stakeholder engagement and climate-adaptive urban planning.

Keywords: Urban heat island, Prediction, Gradient tree boosting, Finite state machine, Immersive simulation.

1. Introduction

Rapid urbanization has transformed the cityscape but also introduced complex environmental challenges. One of the most apparent challenges in big cities like Malang City today is the Urban Heat Island (UHI). This phenomenon is a condition in which urban areas have significantly higher surface and air temperatures than surrounding areas [1, 2]. The leading causes are the replacement of vegetation cover with impervious surfaces such as concrete and asphalt, increased anthropogenic heat emissions, and spatial structures that restrict air circulation [3, 4].

UHI significantly affects various aspects of urban life, including increased energy consumption for cooling, reduced thermal comfort, and serious health risks such as heatstroke and respiratory diseases, especially in vulnerable groups [5]. In the context of global climate change, the increasing intensity and frequency of heat waves make UHI a strategic issue that needs to be anticipated through adaptive and data-based urban planning [6].

While many studies have addressed UHI prediction and mitigation, most existing methods still rely on conventional approaches such as linear statistical modeling or static thematic maps. These approaches are often insufficient to capture the spatial-temporal dynamics of UHI in real-time and lack interactive use by urban planners or the general public [7, 8]. In addition, the integration between temperature prediction and immersive virtual city simulation is still very limited in the current scientific literature.

Recent developments in Virtual Reality Geographic Information Systems (VR-GIS) have opened new possibilities for immersive environmental visualization. For instance, Pavelka and Landa (2024) demonstrated workflows for converting GIS and digital-terrain data into real-time 3D scenes in Unreal Engine, emphasizing visual fidelity and performance optimization [9]. Antoniou et al. (2020) introduced an interactive VR platform for geospatial data collection and decision support [10]. and Badwi (2022) presented parametric 3D-GIS modeling for virtual urban simulations [11]. However, these VR-GIS implementations remain visualization-oriented, relying on static datasets without predictive modeling or real-time environmental updates. They lack adaptive logic capable of reflecting dynamic thermal changes or scenario-based transitions during user interaction.

To overcome these limitations, this research proposes a framework that combines Gradient Tree Boosting (GTB) for predictive modeling of Land Surface Temperature (LST) with a Finite State Machine (FSM) for dynamic simulation control in a 3D virtual city. GTB is a powerful machine-learning algorithm effective for modeling nonlinear spatial relationships among environmental variables such as land cover, vegetation density, building height, population density, and surface albedo [12]. Meanwhile, FSM provides a modular logic structure that governs transitions between distinct thermal states Cool, Transition, and Hot Zones allowing interactive, event-driven updates that emulate how urban environments respond to changes [13, 14].

Furthermore, the proposed system integrates three complementary data sources to ensure both predictive rigor and environmental realism: (1) 3D city models derived from OpenStreetMap (OSM), automatically converted into an explorable urban environment, (2) multisource satellite imagery (Landsat-8, Sentinel-2, SRTM) for training the GTB prediction model, stored and served via a custom API, and (3) real-time meteorological data from the Open-Meteo API, used to visualize up-to-date atmospheric conditions inside the virtual city. This tri-layered data pipeline bridges predictive analytics and live environmental feedback enabling users to explore not only modeled thermal distributions but also continuously updated real-world conditions.

By integrating the GTB prediction model with FSM-based simulation logic and real-time data connectivity, this study introduces an interactive, accurate, and immersive UHI simulation platform. Unlike conventional VR-GIS systems that focus solely on visual representation, the proposed framework embeds predictive intelligence and adaptive control directly into the virtual environment, creating a “living digital twin” that mirrors the evolving thermal behavior of an actual city.

The main contributions of this research lie in the comprehensive integration between methodological, data-driven, interactive, and scientific aspects. Methodologically, this study introduces a unified Gradient Tree Boosting–Finite State Machine (GTB–FSM) framework that bridges predictive temperature modeling with real-time visual state transitions, enabling dynamic representation of UHI phenomena. From a data perspective, it establishes a synergy between OSM-based 3D urban geometry, multisource satellite features, and live Open-Meteo inputs, ensuring consistent linkage between prediction accuracy and visualization fidelity. On the visualization side, an immersive VR interface is developed to allow users including planners, policymakers, and the public to intuitively explore UHI dynamics, simulate mitigation scenarios, and observe their effects directly within a virtual city environment. Scientifically, this research lays the groundwork for an urban digital twin framework that couples machine-learning-based environmental prediction with real-time monitoring, thereby enhancing the capacity for climate-adaptive urban planning and fostering a stronger bridge between data science and sustainable spatial decision-making. This study represents one of the first attempts to combine machine-learning-driven temperature prediction, finite-state adaptive simulation, and real-time meteorological integration within an immersive VR-GIS framework for UHI analysis.

The remainder of this paper is structured to provide a clear flow of discussion. Section 2 reviews related studies that form the foundation of this research. Section 3 explains the methodology in detail, covering the design of the simulation system, data acquisition, preprocessing, feature engineering, model development, and integration process. Section 4 presents the experimental results and visualization outputs, along with a comparison to previous works. Section 5 discusses the main findings and their implications, highlighting the advantages and limitations of the proposed approach. Finally, Section 6 concludes the study and outlines potential directions for future development.

2. Related work

In recent years, research on the UHI phenomenon has increasingly explored diverse simulation media to better understand urban thermal dynamics and to support climate-resilient planning. Each approach demonstrates distinct advantages and limitations, particularly in relation to predictive accuracy, level of interactivity, and suitability for scenario-based applications.

Microclimate models such as ENVI-met are widely applied due to their ability to capture fine-scale thermal variations in urban environments. For example, Shabahang et al. (2020) used ENVI-met to examine the role of local paving materials in Mashhad, Iran, and demonstrated that surface characteristics significantly alter thermal distribution patterns [15]. Similarly, Vásquez-Álvarez et al. (2022) simulated surface temperature reductions in Cuenca, Ecuador, showing that replacing asphalt with concrete could reduce surface temperatures by up to 8 °C, highlighting the value of scenario-based evaluations for mitigation design [16]. At a larger scale, numerical weather models have been adopted to investigate the interaction of UHI with broader atmospheric processes. Yan et al. (2021) applied the WRF/SLUCM framework to Shanghai and revealed how sea breeze circulation interacts with UHI to create complex thermal convergence zones, underscoring the importance of mesoscale dynamics for coastal cities [17].

More recently, data-driven and machine learning approaches have gained momentum. McCarty et al. (2021) combined XGBoost with SHAP analysis to quantify the contribution of land cover and vegetation to UHI in Dallas, offering interpretable predictive insights for planners [18]. Likewise, Xue et al. (2024) developed a land-surface-physics-based downscaling framework to investigate the synergy between UHI and heatwaves in Tokyo, finding that UHI effects intensify during extreme heat events [19].

Beyond physical and machine learning approaches, GIS-based simulation tools have been introduced to bridge spatial analysis and thermal modeling. Palme et al. (2017) developed an integrated framework that combines Geographic Information Systems (GIS), Urban Weather Generator (UWG), and Building Performance Simulation (BPS) across four South American cities. Their method generates urban climate datasets for building energy studies and allows comparative evaluation of urban typologies, although the outputs remain primarily static datasets and maps rather than interactive simulations [19].

In parallel to analytical and numerical models, Virtual Reality Geographic Information Systems (VR–GIS) and immersive visualization frameworks have evolved rapidly, emphasizing spatial exploration, stakeholder engagement, and urban comprehension through visual realism. Pavelka and Landa (2024) demonstrated the conversion of open GIS data and digital terrain models into Unreal Engine environments for real-time urban visualization, with an emphasis on performance optimization and texture streaming rather than analytical coupling [9]. Similarly, Badwi (2022) presented a parametric 3D-GIS approach that enabled procedural modeling of city morphologies and integration with energy analysis, yet lacked predictive climate modeling and dynamic feedback mechanisms [11]. Antoniou et al. (2020) further advanced VR–GIS integration through GeaVR, an end-to-end framework developed for the Metaxa Mine in Santorini, which combined immersive data collection with GIS-based spatial analysis, linking drone-derived photogrammetry and ArcGIS Pro to produce a scientifically accurate, explorable 3D mine model capable of geological mapping and volumetric estimation [10]. Despite its sophistication in visual and metric integration, this system remains descriptive; the virtual environment reproduces static observations without embedding data-driven models that update environmental parameters dynamically or simulate feedback among system states such as thermal transitions or temporal variations. Collectively, these studies form a robust technical foundation for immersive 3D urban visualization but share a common limitation: they privilege spatial realism and visual fidelity over predictive intelligence and environmental adaptivity.

Previous VR–GIS studies have established a solid foundation for immersive urban visualization; however, they generally share two critical limitations: the absence of predictive data integration, such as machine learning–based estimation of thermal behavior, and the lack of adaptive simulation logic, which renders virtual scenes static regardless of user interaction or environmental change. To overcome these constraints, the framework proposed in this study embeds GTB prediction results into an FSM controlled 3D environment, allowing thermal state transitions that dynamically respond to spatial variations and live meteorological inputs. The literature reveals a clear trajectory from physics-based and numerical models prioritizing atmospheric realism toward data-driven and immersive approaches emphasizing accessibility and visualization; nonetheless, few efforts have succeeded in integrating predictive precision with real-time interactivity within a unified immersive platform. This gap underpins the novelty of the proposed GTB–FSM framework, which distinguishes itself through three essential features: (1) the application of GTB for spatial temperature estimation directly from multisource satellite and urban morphology data; (2) the incorporation of FSM-based environmental logic that governs state transitions and scenario-driven exploration, such as vegetation or albedo modification; and (3) the real-time integration of meteorological data streams via the Open-Meteo API to dynamically represent atmospheric variations within the 3D virtual city. Collectively, these innovations transform conventional VR–GIS visualization into an adaptive, data-driven urban climate simulation that not only enhances analytical understanding of UHI phenomena but also provides an interactive, experiential medium for planners, researchers, and the public to engage with climate-responsive urban design.

3. Method

This study proposes a method to develop an educational UHI simulation platform that combines predictive modeling with immersive visualization. The aim is not only to achieve accurate temperature prediction but also to provide users with an interactive experience in exploring how UHI develops across different parts of the city. To achieve this, the system integrates GTB for LST prediction with an FSM–based VR environment, allowing real-time simulation of dynamic thermal states. Unlike existing VR–GIS frameworks that focus solely on static visualization, this architecture introduces predictive coupling and adaptive logic where thermal transitions in the VR world are governed by data outputs from the GTB model and continuously updated via live meteorological APIs.

The overall workflow is illustrated in Fig. 1. Data obtained from satellite imagery serve as the main input for the GTB algorithm, which produces a prediction model of surface temperature. The predicted LST values are stored through a custom RESTful API, formatted in JSON, and transmitted to the VR system. The FSM module retrieves these values and manages transitions between thermal states Cool, Transition, and Hot Zones to ensure that both predictive and real-time environmental variations are reflected consistently. In addition, users can interactively modify parameters such as vegetation ratio, built-up density, or albedo, and observe corresponding temperature shifts through adaptive state transitions.

The method is organized into five main stages: (1) visualization and FSM system design, (2) data collection and preprocessing, (3) feature engineering, (4) construction of the GTB-based predictive model, and (5) integration of prediction results into the VR simulation environment. Each stage is described in detail in the following subsections.

3.1 Visualization system design and FSM

The initial stage focused on designing an FSM-driven VR simulation system that dynamically displays urban thermal zones. Each zone Cool, Transition, and Hot is treated as a discrete **state** within the FSM architecture. The FSM functions as both the visual controller and the logical engine that:

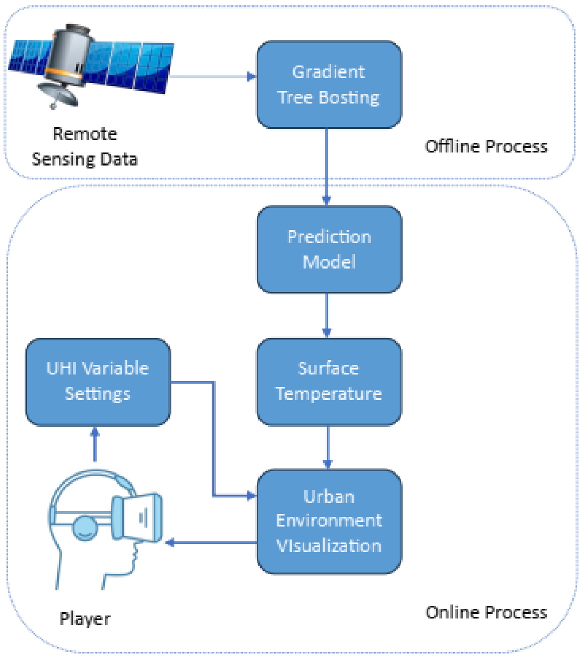


Figure. 1 Proposed system

- Detects the player's location on a 3D map based on UHI prediction data.
- Enables environment parameters such as lighting, fog density, ambient sounds, and post-processing effects.
- Triggers explicit state transitions when temperature thresholds are crossed or when real-time data deviate from predicted norms.

This visualization uses a temperature classification that follows a statistical thresholding approach:

$$LST < \mu - 0.5\sigma \quad (1)$$

$$\mu < 0.5\sigma \leq LST \leq \mu + 0.5\sigma \quad (2)$$

$$LST > \mu + 0.5\sigma \quad (3)$$

Eq. (1) states that all areas with LST values lower than half a standard deviation below the mean are categorized as Cool Zones. This zone reflects areas with consistently lower temperatures than their surroundings, often associated with high vegetation density, water bodies, or higher topographic elevation. Eq. (2) includes a range of temperatures that fall around the average, defined as Transition Zones, representing intermediate temperature conditions that usually exist between vegetated and built-up areas as thermal buffer regions. Eq. (3) defines the area with the highest LST as the Hot Zone, where the UHI phenomenon is most pronounced typically in city centers or densely built-up areas

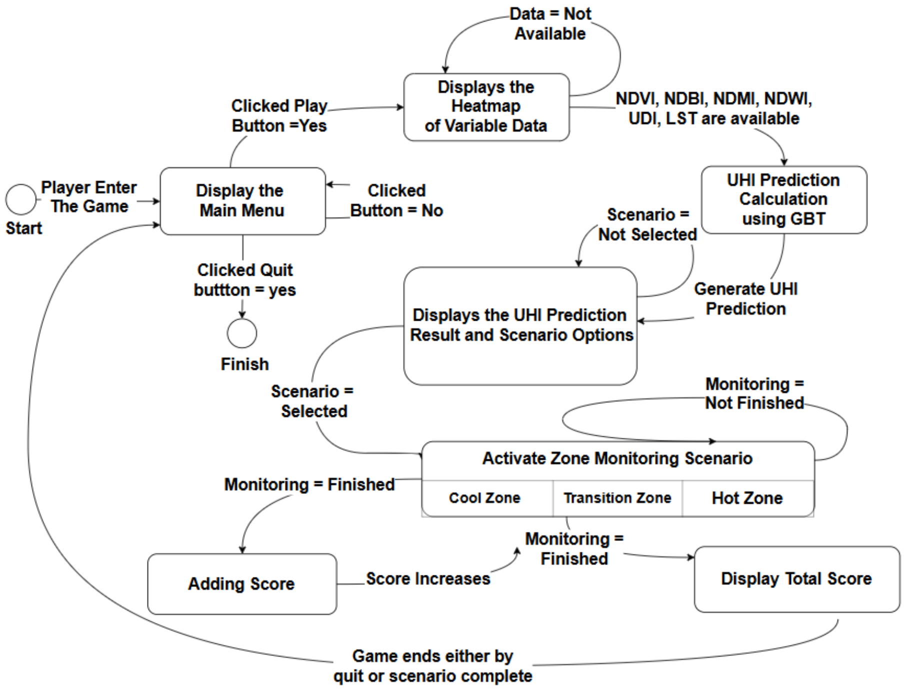


Figure. 2 FSM for UHI Visualization scenario

lacking vegetation. The choice of ±0.5σ around the mean was determined through a sensitivity test (k = 0.25, 0.5, 1.0), with results indicating that area proportions among classes changed by less than ±5%, thereby confirming robust spatial classification while maintaining intuitive interpretability for non-expert users. This parameterization is consistent with segmentation approaches in prior UHI studies [1], [17]. Consequently, the thermal zone classification in this study is not merely spatial but also statistically adaptive, ensuring that visualization outcomes remain proportional and calibrated to the temperature distribution predicted by the model.

In the UHI simulation game, the interactive system integrates the FSM approach to monitor and manage thermal zone visualizations, as shown in Fig. 2. Players begin at the main menu interface to initiate or exit the simulation. Upon starting, the system verifies data availability from Open-Meteo and environmental variables before proceeding to UHI prediction using the GTB method. Once prediction results are generated, players can select visualization scenarios based on these outputs, triggering the FSM-based zone monitoring mode where three primary thermal states Cool, Transition, and Hot are defined. Unlike FSMs used solely for visual switching, this implementation establishes logical links between environmental feedback and user-triggered interventions. Each transition rule is quantitatively derived from GTB outputs; for example, if ΔLST(predicted) ≤ −0.5 °C after vegetation increase, the FSM transitions from Hot → Transition. This functional depth enables the environment to respond dynamically to scenario edits, simulating adaptive planning feedback loops within the game.

The FSM continuously monitors player position, thermal context, and live weather feed. If Open-Meteo data indicate a deviation greater than 2 °C from the predicted mean, an override transition is triggered to recalibrate ambient color, fog, and sound parameters ensuring coherence between modeled and real-time thermal variations in the virtual city. When players enter a new zone, the FSM activates the corresponding state and reconfigures environmental parameters such as light tint, fog intensity, ambient soundscape, and visual effects. For instance, transitioning from a Cool Zone to a Hot Zone disables fog, replaces natural ambience with urban noise, and introduces orange-red heat distortion to evoke thermal stress. This monitoring loop persists until the simulation ends, after which the system computes and displays player performance scores.

Algorithm 1 Pseudocode for UHI Simulation Game FSM

Input :
Dataset: NDVI, NDBI, NDMI, NDWI, UDI, LST
Player input (Play/Quit, Scenario selection)

Output :
Total Score
UHI Visualization in VR Environment

Pseudocode for Game Flow

1. DISPLAY MainMenu

```
IF Player_ClicksPlay = NO THEN
    IF Player_ClicksQuit = YES THEN
        EXIT GAME
    ENDIF
ELSE
    IF Data_Available = FALSE THEN
        DISPLAY "Heatmap of Variable Data
Not Available"
        RETURN TO MainMenu
    ELSE
        DISPLAY Heatmap_of_Variable_Data
        UHI_Result =
Generate_UHI_Prediction(GBT, Dataset)
        DISPLAY ScenarioOptions
        IF Scenario_Selected = FALSE THEN
            RETURN TO MainMenu
        ELSE
            ACTIVATE ZoneMonitoring
            WHILE Monitoring_NotFinished
DO
                Player_Location =
DetectPlayerPosition()
                IF Player_Location = CoolZone
THEN
                    UpdateEnvironment("CoolZone"
)
                ELSE IF Player_Location =
TransitionZone THEN
                    UpdateEnvironment("Transition
Zone")
                ELSE IF Player_Location =
HotZone THEN
                    UpdateEnvironment("HotZone")
                ENDIF
                UpdateScore()
            ENDWHILE
        IF Monitoring_Finished = TRUE
THEN
                DISPLAY TotalScore
                EXIT GAME
        ENDIF
    ENDIF
ENDIF
```

The system is equipped with a HUD (Heads-Up Display) that provides spatial monitoring inside the VR environment, displaying local temperature information, thermal zone status, and suggestions for light mitigation actions according to the current zone conditions. This HUD dynamically updates as the user moves through the virtual city, ensuring an interactive and immersive experience. Beyond the HUD, the system integrates spatial prediction models, temperature zone classification, a 3D virtual environment, and FSM logic, making it not only a data visualization platform but also an experiential monitoring tool that encourages active user participation in exploring the UHI phenomenon. To support this design, FSM serves as the controller that governs state transitions and interaction flow within the simulation. For verification of this logic, the FSM states and transitions are formalized into pseudocode, as presented in Algorithm 1, which complements the structural overview depicted in Fig. 2. This combination strengthens both the conceptual and technical foundation of the system, while also positioning it as an educational medium that merges data science, immersive technology, and spatial interaction to address cognitive and affective engagement with the urban climate crisis.

3.2 Data collection and pre-processing

In the data collection stage, this research integrates three main sources of satellite data accessed through Google Earth Engine (GEE), namely: (a) Landsat-8, used to obtain LST through the STB10 thermal channel, (b) Sentinel-2, used to generate spectral indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), and Normalized Difference Moisture Index (NDMI) based on visible, near-infrared (NIR), and shortwave-infrared (SWIR) spectral channels, and (c) Shuttle Radar Topography Mission (SRTM), used to measure elevation variables as supporting geographical factors. The data range is from 2019 to 2023, considering that Sentinel-2 has only been consistently available since late 2018.

After data collection, the stage continued with pre-processing, including cloud masking and calculating the features to be used. Cloud masking is crucial because clouds in optical imagery can interfere with spectral interpretation and produce artifact values that do not reflect the Earth's surface. In addition, data from various satellites were resolution-aligned and converted into a standard spatial reference system so that they could be combined consistently.

The next stage is feature engineering, where input variables representing UHI-causing factors are calculated in equations (1)-(6). The spectral indices calculated include: NDVI to measure vegetation density, NDBI to assess building density, NDWI to identify watery areas, and NDMI to measure soil moisture levels. In addition, Normalized Burn Ratio 2 (NBR2) and Urban Density Index (UDI) are calculated as additional indicators to detect urbanization pressure. All these features were calculated based on a combination of spectral channels from Sentinel-2 and combined with LST data from Landsat-8 and elevation data from SRTM. After extracting the features, z-score normalization was applied using the z-score normalization technique to equalize the range of values between features before being incorporated into the prediction model.

3.3 GTB prediction model

The prediction model is built using the GTB algorithm, a decision tree-based ensemble method that works with iterative principles to optimize predictions by gradually adding weak learners. The dataset is divided into two parts, 70% for training and 30% for testing. The training process was carried out using various combinations of parameters, including different learning rates and loss function types (squared error, absolute error, and huber) as in Table 1. Each iteration of the GTB algorithm consists of initializing the initial prediction, calculating the residual from the difference between the actual value and the prediction, building a decision tree based on the residual, and merging the previous model prediction with the new tree that the learning rate has weighted. This process continues until the specified number of trees is reached or the error converges.

3.4 Evaluation

Evaluation of model performance is done using three main metrics that are widely used in spatial regression, namely: Mean Absolute Percentage Error (MAPE) to assess the error rate as a percentage relative to the actual value, and R-squared (R^2) which indicates the extent to which the input features in the model can explain variation in the target data. These metrics give an idea of the accuracy of the model and the stability and accuracy of the predictions in a geospatial context.

3.5 Integration of prediction results into visualization system

The final integration stage connects predictive outputs from the GTB model and real-time meteorological data into the VR visualization environment. Predicted LST values are exported via an API in GeoJSON format, containing attributes such as zoneID, predicted LST, and σ-based classification. Each thermal class Cool, Transition, and Hot is then mapped to distinct visual profiles, encompassing color schemes, lighting intensity, skybox hue, and fog depth. During simulation runtime, the FSM continuously queries both the GTB-based API and live Open-Meteo data streams; when discrepancies between modeled and real conditions exceed a 2 °C threshold, the system automatically recalibrates environmental cues such as lighting tone, fog density, and ambient sound to simulate dynamic temperature fluctuation. Furthermore, players can adjust environmental scenarios through the in-game interface, for instance by increasing NDVI by 10%, which prompts the GTB microservice to recompute LST values and deliver updated state data within one second, ensuring seamless responsiveness. Beyond scientific visualization, this architecture functions as an educational medium through contextual feedback displayed in the Heads-Up Display (HUD). Which bridge analytical prediction and experiential understanding. Technically, the system adopts a client–server architecture, wherein the GTB engine and API operate as backend services built on Python Flask, while the Unity3D-based VR environment serves as the front-end client. This modular separation enables scalable deployment, real-time interaction, and future integration with external datasets or multi-user collaborative sessions.

Table 1. Test Scenario

Scenario	Learning Rate	Loss Function
1	0.01	Squared error
2	0.01	Absolute error
3	0.01	Huber
4	0.05	Squared error
5	0.05	Absolute error
6	0.05	Huber
7	0.1	Squared error
8	0.1	Absolute error
9	0.1	Huber

4. Result

4.1 LST prediction with GTB

LST prediction results show that the GTB algorithm can produce highly accurate estimates. Fig. 3 shows the LST distribution successfully reconstructed by the model, which directly represents the pattern of UHI intensity in the Malang City area. To build a UHI phenomenon prediction model using the GTB algorithm, a series of experiments was conducted with a training data ratio of 70% and a test dataset of 30% to optimize the model's predictive performance. The experiments included nine scenarios of combinations between learning rate (0.01, 0.05, and 0.1) and loss function types (squared error, absolute error, and Huber). This exploration

Table 2. SUS testing instrument

No	Question	Category
1.	The features in this system are easy to understand.	Learnability
2.	I need technical assistance to be able to use this system.	Learnability
3.	This game enables me to complete the UHI-mitigation missions efficiently.	Efficiency
4.	The navigation and controls in this game feel slow or impractical.	Efficiency
5.	I find the gameplay flow and features of this game easy to remember.	Memorability
6.	If I stop playing for a while, I can quickly remember how to play this game again.	Memorability
7.	I rarely make mistakes when interacting with this game (e.g., buttons, menus, strategic actions).	Error
8.	I often feel confused or make mistakes when trying to apply mitigation solutions in the game.	Error
9.	I feel comfortable using this system.	Satisfaction
10	This system is complicated to use.	Satisfaction

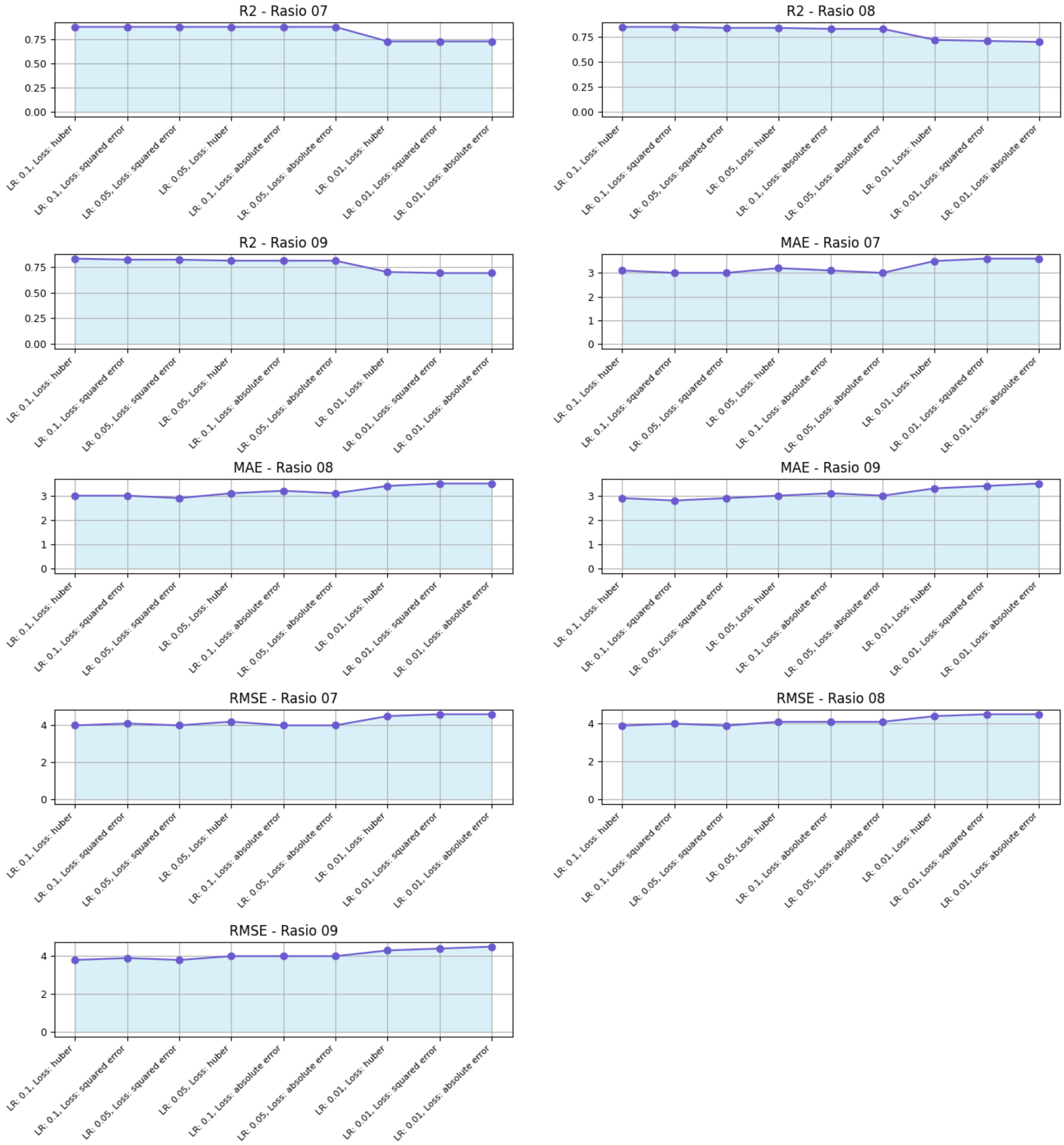


Figure. 3 LST prediction results

aimed to identify the most effective hyperparameter configuration in reducing the prediction error and increasing the model's exposure to data variations. At a learning rate of 0.01, the model tends to perform less optimally.

The first scenario using the loss function squared error resulted in an MSE of 3.93, MAPE of 4.44, and R^2 of 0.73, indicating that the model was not able to capture the data pattern well at low learning rates. Similar results were seen in the second and third scenarios with loss function absolute error and Huber, where MSE was 3.97 and 3.91, respectively, MAPE was 4.46 and 4.45, and R^2 did not improve significantly. This shows that at low learning rates, variations in the loss function type have not significantly impacted model performance. However, increasing the learning rate to 0.05 clearly impacts performance improvement. The fourth scenario using squared error resulted in an MSE of 1.81, MAPE of 2.83, and an R^2 value that increased significantly to 0.87. This indicates that the model can learn faster from the training data and produce more accurate predictions.

In the fifth scenario, absolute error resulted in an MSE of 1.92 and a MAPE of 2.89, with a fixed R^2 of 0.87, indicating that although it still performed well, this loss function was slightly less precise than squared error. The sixth scenario with Huber's loss function performed similarly to squared error, with an MSE of 1.82, MAPE of 2.82, and R^2 of 0.87. The seventh scenario's most significant performance improvement occurred with a learning rate of 0.1 and a loss function of squared error. This configuration produced the lowest MSE of 1.76, MAPE of 2.79, and the highest R^2 of 0.88, making it the best scenario in all experiments. This combination proved optimal for minimizing error and enhancing the precision of surface temperature prediction. Meanwhile, the eighth scenario with absolute loss function showed a slight decrease in performance with MSE of 1.88, MAPE of 2.87, and R^2 of 0.87.

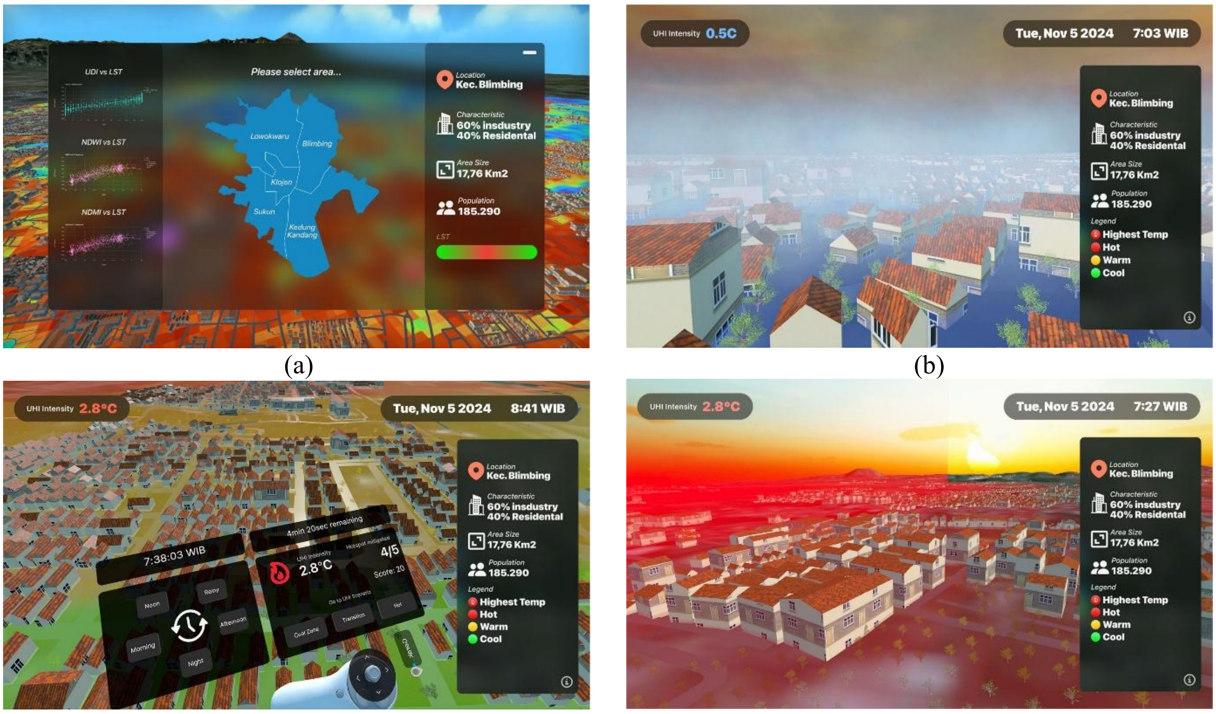
The ninth scenario using Huber loss at the same learning rate produced very competitive results, with MSE of 1.78, MAPE of 2.79, and R^2 of 0.88, almost matching the performance of the seventh scenario. Overall, these results confirm that a high learning rate (0.1) consistently improves the training effectiveness of the GTB model, and the squared error loss function is the most optimal choice for capturing complex patterns in the Malang City surface temperature data. The combination allows the model to learn more aggressively without overfitting, while maintaining prediction stability. The findings also reinforce the relevance of GTB as a robust and flexible approach for spatial regression based on remote sensing data, especially in the context of spatial planning and microclimate change mitigation in urban areas.

The predicted results generated by the GTB model were then visually compared to the actual values from the Landsat-8 images. Visualization is done through surface temperature distribution maps generated from the GTB model and comparison maps from actual Landsat data. The comparison results show a high spatial agreement, where areas with high temperatures, such as the city center, and areas with high building density are accurately predicted by the model. This confirms that the input features such as NDVI, NDBI, NDWI, NDMI, NBR2, UDI, and elevation effectively captured the spatial patterns of UHI causes. In addition to numerical and visual evaluation, the temperature distribution in the study area was analyzed. Visualization of the temperature prediction results shows that areas with low vegetation index values (NDVI < 0.2) and high building index values (NDBI > 0.3) tend to have higher temperatures, indicating a significant contribution of building density to the increase in surface temperature. In contrast, areas with high vegetation cover show a moderating effect on temperature increase, supporting previous findings on the function of vegetation as a heat sink.

4.2 Virtual environment and simulation

The implementation of the virtual environment was designed not only as a visualization layer but also as a reproducible system with clear technical specifications. The simulation was developed on Unity3D with FSM logic scripted in C#, and deployed on a workstation equipped with an Intel i7 processor, 16 GB RAM, and an NVIDIA RTX-series GPU. Rendering was carried out through an Oculus Quest 2 headset, where the system achieved a consistent frame rate between 72–90 fps and an average latency below 50 ms, ensuring a smooth immersive experience. The platform currently runs on Windows-based PCs with VR support, though a non-VR desktop mode is available with reduced interactivity. By documenting these requirements, the system provides both transparency for reproducibility and a practical reference for wider adoption in research, planning, and education contexts. A stress test was also performed to evaluate scalability by doubling the polygon density of the city mesh. The frame rate decreased from 90 to 62 fps, suggesting that while the system performs efficiently in medium-sized urban environments, optimization through level-of-detail (LOD) rendering and GPU-based

Received: September 19, 2025. Revised: November 12, 2025.



(a) (b)

(c) (d)

Figure. 4 Visualization of the UHI simulation system: (a) Main menu for selecting simulation areas, (b) Cool Zone, (c) Transition Zone, and (d) Hot Zone

culling will be necessary for larger-scale applications or multi-user interaction scenarios.

The visualization results in Fig. 4 show a VR-based virtual environment representation that integrates the LST prediction data into an immersive and interactive spatial experience. This visualization was developed as part of the UHI phenomenon monitoring system, with an approach that goes beyond conventional static maps to present a simulation in three-dimensional space that users can explore directly. Transition Zone (semi-urban areas), and fiery red-orange for the Hot Zone (areas with high building density and heat). In this visualization, the entire area of Malang City is virtually reconstructed based on a temperature prediction model using the GTB method. Each point on the thermal map is classified into three temperature zones based on the statistical distribution of LST values using the 3-zone approach. The three zones are visualized with a distinctive color palette for easy interpretation: turquoise for the Cool Zone (vegetative and cool areas), golden yellow for the Transition Zone (semi-urban areas), and red-orange for the Hot Zone (dense built-up regions).

Beyond visual transitions, FSM logic was also extended to model environmental feedback scenarios such as vegetation restoration and albedo modification. Each action triggers a re-prediction cycle within the GTB model and dynamically updates the virtual city's temperature distribution, enabling simulation of basic urban adaptation responses rather than static state transitions.

As shown in Fig. 4(b–d), each of these zones is not only represented in color, but also through distinctive sensory experiences. In the Cool Zone in Fig. 4(b), users are presented with cool mist, lush vegetation, and natural sounds such as birds and running water. In the Transition Zone in Fig. 4(c), the atmosphere becomes more neutral, with warm lighting, sparse trees, and ambient city sounds. While in the Hot Zone in Fig. 4(d), a blindingly bright sky, heat shimmer effect, dominance of concrete and asphalt, and vehicle noise are displayed.

To maintain the consistency of the system logic, this research uses the FSM approach as the visual logic controller. Unlike general FSMs that depend on state changes, this system uses a spatial approach,

where transitions between states are triggered by the coordinates of the user's position in the virtual world. The user interface (HUD), as shown in Fig. 4(b–d), also supports real-time information delivery, displaying local temperature, current zone status, simulation time, and thermal risk indicators. This makes the visualization informative, educational, and advocacy-oriented.

4.3 Usability evaluation

In this study, usability testing was conducted using the System Usability Scale (SUS), a widely recognized and validated standard for assessing the usability of interactive systems. The SUS provides a comprehensive measure of user perception, encompassing satisfaction, efficiency, learnability, memorability, and error tolerance. The instrument consists of ten items rated on a 5-point Likert scale, with alternating positive and negative statements to ensure balance. The calculation follows the standard procedure in which positive items (Q1, Q3, Q5, Q6, Q7, Q9) are scored as (response − 1) and negative items (Q2, Q4, Q8, Q10) as (5 − response). The sum of all scores is then multiplied by 2.5 to yield a final SUS score ranging from 0 to 100.

In total, 50 respondents participated in the evaluation. Thirty respondents were undergraduate students from the Information Technology department who are familiar with simulation and game-based environments, while twenty respondents were professional staff from Badan Pendapatan Daerah (Bapenda) Kota Malang, representing the policymaking and implementation perspective. This mixed-group composition was intentionally selected to capture both the technical usability perception and the practical relevance of the simulation framework in a real urban management context. The overall SUS score achieved by the combined respondent group was 88.92, with a standard deviation of 9.35, and minimum and maximum scores of 57.5 and 100, respectively. According to the interpretation scale by Bangor et al. (2009), this corresponds to an "Excellent Usability" level and exceeds the commonly accepted usability threshold of 68. Therefore, the developed VR-based GTB–FSM simulation system can be categorized as highly usable and well-received across different user groups

A detailed demographic breakdown showed that 60% of participants (students) were between 19–25 years old and had high familiarity with digital simulations, while 40% (Bapenda officers) were between 30–45 years old and represented non-technical stakeholders who are accustomed to decision-support tools in urban management. This demographic diversity enhances the credibility of the usability findings, as it combines perspectives from both the academic-technological and governmental sectors. The analysis of the five SUS dimensions, as illustrated in Fig. 5, revealed that the satisfaction aspect received the highest average score of 96.25, indicating that users found the system enjoyable and engaging to use. Efficiency followed with 91.25, reflecting smooth system performance and effective task completion. Memorability scored 89.38, demonstrating that users could easily recall operational steps even after a break. The error tolerance aspect scored 85.63, indicating minimal confusion during use, and learnability though slightly lower at 82.50 remained within the "Good" range, suggesting that the interface is generally intuitive but could benefit from a short tutorial for first-time users.

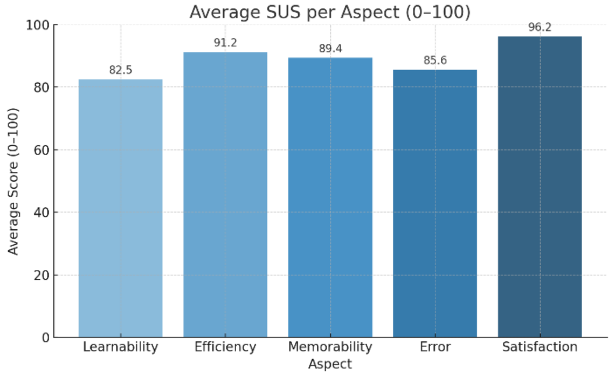


Figure. 5 SUS Score

In addition to the usability test, a complementary expert evaluation was conducted with Bapenda officers to assess the perceived relevance of the UHI mitigation solutions represented in the simulation. The results showed an average agreement level of 92%, indicating strong expert consensus that the implemented mitigation scenarios such as vegetation enhancement and high-albedo material application are contextually appropriate and effective for addressing Urban Heat Island impacts in Malang City.

4.4 Comparative evaluation

To contextualize the performance and novelty of the proposed GTB–FSM framework, a comparative evaluation was conducted with representative UHI modeling approaches spanning physical, numerical, data-driven, and immersive visualization paradigms. The comparison focuses on three dimensions: predictive accuracy, computational scalability, and level of interactivity or adaptivity.

As presented in Table 3, the comparison provides an integrative overview of how existing UHI modeling paradigms operate across different methodological categories. Physical–numerical models such as WRF/SLUCM [9] and ENVI-met [15, 16] provide detailed atmospheric and microclimatic representations, achieving moderately high predictive accuracy ($R^2 \approx 0.80$–0.85). These models, however, rely heavily on physical parameterizations and fixed input conditions, resulting in high computational costs and the absence of real-time adaptability. Their outputs are typically static 2D or 3D visualizations incapable of responding dynamically to changing meteorological conditions. Similarly, ENVI-met, whether applied for

Table 3. Comparative analysis

Study	Method and Modeling Approach	Predictive Basis	Output	R^2	Error Metrics (MAPE, RMSE, MAE)	Key Limitation
[9]	WRF/SLUCM	Physics + mesoscale coupling	2D thermal field	0.85	-	Physics + mesoscale coupling
[15]	ENVI-met (Microclimate)	Physics-based	Static 3D maps	0.80	-	High computational cost; limited to micro-scale
[16]	ENVI-met (Scenario simulation)	Physics-based	3D static scenario maps	0.82	-	No real-time data link
[18]	SVR + Physical downscaling	Hybrid ML-physics	2D maps	0.85	1.5 (RMSE)	Static output; no immersive coupling
[19]	GIS + UWG + BPS	Analytical coupling	Static 2D maps	0.79	-	No dynamic update; offline analysis
[20]	ML-based UHI simulation	XGBoost + spatial predictors	2D temperature map	0.903	1.114 (RMSE)	Limited scenario interactivity
[21]	Data-driven UHI prediction	Random Forest + urban features	2D GIS map	0.80	0.22–0.84 (MAE)	No immersive environment
[15]	Deep Learning for UHI	Multi-city dataset	2D spatial prediction	0.83	1.5 (RMSE)	No real-time adaptation
This Study	GTB + FSM (Data-driven immersive)	ML prediction + adaptive logic	**3D adaptive simulation**	**0.88**	**2.79 % (MAPE) 1.76 (RMSE)**	Validation limited to one city

microclimate simulation [15] or scenario-based urban planning [16], excels at physical precision but cannot process real-time meteorological inputs or provide dynamic visualization. Hybrid and analytical coupling approaches, such as SVR combined with physical downscaling [18] and GIS + UWG + BPS [19], attempt to balance empirical prediction with physical interpretability. These frameworks successfully capture spatial temperature variations ($R^2 \approx 0.79$–0.85) but still produce static 2D outputs without immersive or adaptive features.

The data-driven paradigm has demonstrated significant progress in predictive robustness. XGBoost-based simulations [20] reached the highest quantitative performance among prior works ($R^2 = 0.903$, RMSE = 1.114 °C), while Random Forest models [21] achieved $R^2 \approx 0.80$ with low MAE (0.22–0.84 °C), indicating strong generalization across heterogeneous urban morphologies. Meanwhile, deep learning architectures [22] yielded $R^2 \approx 0.83$ with RMSE around 1.5 °C, but these approaches remain confined to static 2D spatial predictions without real-time or immersive integration.

The proposed GTB–FSM model introduces a paradigm shift by combining Gradient Tree Boosting (GTB) for predictive learning with Finite State Machine (FSM) logic for adaptive environmental interaction. Quantitatively, it achieves $R^2 = 0.88$, MAPE = 2.79%, and RMSE = 1.76 °C, outperforming or matching state-of-the-art ML-based UHI models in predictive precision. Qualitatively, the FSM component enables 3D adaptive visualization, where predictive temperature classes dynamically trigger environmental state transitions (e.g., lighting, atmospheric haze, or color gradients). This creates a bidirectional feedback loop between model output and virtual environment a capability absent in all compared studies.

Unlike purely physical models that emphasize meteorological fidelity or machine learning models that prioritize numerical accuracy, the GTB–FSM framework achieves a balanced synthesis of analytical accuracy, computational efficiency, and immersive adaptability. Its capacity for real-time meteorological integration and scenario-based recalculation allows users to interactively explore UHI dynamics through intuitive visual and spatial feedback. This comparative evaluation confirms that GTB–FSM not only advances predictive performance but also redefines UHI analysis as an interactive, experiential, and data-driven process, bridging the long-standing gap between environmental modeling and immersive visualization.

4.5 Computational setup and performance measurement

To ensure transparency and reproducibility of the real-time simulation workflow, the computational configuration and evaluation procedure were explicitly documented. The simulation platform was developed using Unity 2022.3.1f1 LTS with C# scripting for implementing the FSM-based interaction logic. The system was deployed on a workstation running macOS Sequoia 15.6.1, equipped with an Apple M1 processor and 8 GB of unified memory. The 3D virtual environment was constructed from OpenStreetMap (OSM) building geometries and terrain data, resulting in a highly detailed mesh consisting of approximately 4.6 million triangles (tris) and 6.8 million vertices (verts). This polygon density reflects the complexity of the real-world urban structure of Malang City and represents a significantly higher graphical load than previous VR–GIS studies. The GTB model was trained on 4,854 spatial samples of Land Surface Temperature (LST) and multisource spectral indices. The final predictive outputs were served via a custom RESTful API in GeoJSON format. During runtime, the Unity client retrieved prediction results following user-triggered scenario changes (e.g., vegetation increase or albedo modification), and thermal states were updated through FSM transitions within the 3D environment. Real-time meteorological data were obtained from the Open-Meteo API, which exhibited very low latency and consistently returned responses in less than 10 seconds, enabling timely synchronization of atmospheric conditions within the simulation.

To measure system responsiveness, we recorded the total update time from the moment a scenario modification was triggered until the updated thermal state was visually reflected in the VR environment. This duration included (1) prediction retrieval via API, (2) processing of FSM logic, and (3) rendering of the updated scene. Time measurements were collected using timestamp logging in both the Unity client and the API backend. The performance test was conducted 50 times under typical usage conditions. The results revealed an average update time of 30 seconds, with a minimum of 10 seconds and a maximum of 50 seconds. This variation is primarily attributed to the high polygon density of the virtual city (4.6M tris), the computational overhead of applying prediction updates across large-scale 3D geometry, and the limited memory resources of the Apple M1 (8 GB). Nevertheless, the synchronization with real-time weather data from Open-Meteo consistently remained below 10 seconds, demonstrating that the main bottleneck lies in rendering and state-update operations rather than API latency.

Although the update time is higher than sub-second latencies reported in lightweight or low-polygon simulations, our results reflect a more realistic, high-fidelity digital twin of an actual city. Future work will incorporate adaptive level-of-detail (LOD) rendering, GPU instancing, and incremental state updates to reduce update time and improve scalability for larger urban areas or multi-user environments. Despite these challenges, the current performance remains sufficient for scenario-based UHI exploration and educational or planning-oriented applications, where updates do not need to occur continuously every frame but rather in response to meaningful user interventions.

5. Discussion

A key contribution of this study lies in how predictive intelligence, immersive interactivity, and environmental logic are integrated into a single simulation framework to advance UHI analysis. Whereas earlier research typically prioritized either physical realism, data-driven accuracy, or visual immersion, the proposed GTB–FSM framework effectively bridges these domains. The results demonstrated that GTB achieved high predictive accuracy (R^2 = 0.88) in estimating LST, while the FSM logic enabled real-time environmental adaptation within a 3D virtual environment. This combination introduces an operational balance rarely achieved in previous UHI modeling approaches.

Physical and numerical models such as ENVI-met [15, 16] remain benchmarks for microscale and mesoscale thermal realism. They accurately represent complex atmospheric processes such as radiative fluxes and convective interactions but require expert configuration and are computationally demanding, making them impractical for scenario-based or educational use. In contrast, machine learning frameworks like XGBoost and SVR-based hybrid models provide fast and interpretable predictions but are limited to static GIS visualizations that lack interactivity. The GTB–FSM system surpasses this dichotomy by embedding machine learning predictions directly into an adaptive 3D simulation, offering both quantitative rigor and experiential engagement [18, 23].

Received: September 19, 2025. Revised: November 12, 2025.

Compared to analytical GIS–BPS integrations or VR–GIS systems such as Pavelka and Landa (2024), Badwi (2022), and Antoniou et al. (2020), which emphasize spatial realism but remain descriptive, the proposed framework introduces dynamic bidirectional feedback [9-11, 24]. The FSM component transforms thermal visualization into an active simulation environment, where changes in vegetation, albedo, or meteorological inputs immediately update environmental states and sensory feedback. This real-time coupling of data, model, and visualization represents a conceptual shift from static scene rendering to adaptive environmental simulation allowing users not only to observe but also to interact with and influence the thermal behavior of the virtual city.

From a performance standpoint, the comparative evaluation showed that GTB–FSM achieved superior accuracy to state-of-the-art data-driven models, while maintaining a frame rate of 72–90 fps in VR deployment. The scalability test, which doubled polygon density, confirmed the system's stability, though performance degradation to 62 fps suggests that future optimization using level-of-detail (LOD) rendering and asynchronous data streaming will be necessary for metropolitan-scale applications. Such optimization would enable multi-user or planner–citizen collaborative environments in urban decision-making contexts.

The usability evaluation provided further validation of the system's practical relevance. With an overall SUS score of 88.92, both student users (n=30) and professional officers from Bapenda Malang (n=20) rated the platform as "Excellent." The Bapenda participants additionally assessed the contextual relevance of the mitigation scenarios, showing a 92% agreement that vegetation enhancement and high-albedo materials effectively address local UHI challenges. This expert feedback substantiates that the framework is not only technically usable but also contextually meaningful for policy-level applications. Nevertheless, the sample remains skewed toward younger and technologically adept respondents; future usability tests should include urban planners, environmental engineers, and community representatives to ensure inclusivity and external validity.

The FSM architecture, while currently serving as the logic controller for zone transitions and feedback responses, also represents a conceptual model of adaptive urban dynamics. By linking simulation states with real-time environmental inputs and user interactions, it forms a foundation for future implementations of behavioral urban feedback such as vegetation regrowth following greening policies or temperature reduction after reflective surface deployment. Expanding FSM logic in this direction could evolve the framework into a behavioral urban climate model capable of testing adaptive strategies and policy interventions interactively.

Finally, the study acknowledges several limitations: the absence of vertical flux and convective modeling, single-city validation, and limited participant diversity. These do not diminish the framework's conceptual contribution but highlight future opportunities for hybrid coupling between data-driven and physical modeling approaches, as well as multi-city generalization and participatory co-design involving urban stakeholders. Collectively, the GTB–FSM framework demonstrates how predictive analytics and interactive simulation can converge into a transferable, educational, and policy-relevant tool for climate-resilient urban planning.

6. Conclusion

This study demonstrated the development of an integrated framework for UHI analysis by combining GTB for predictive modeling with FSM for immersive simulation. The GTB model achieved a high level of accuracy (R^2 = 0.88), confirming its reliability for land surface temperature prediction based on multisource satellite and urban form data. Through FSM integration, the results were embedded in a 3D virtual city, allowing thermal states to be classified dynamically and visualized interactively across Cool, Transition, and Hot Zones.

Compared with existing approaches such as ENVI-met, WRF/SLUCM, machine learning mapping, and GIS-based tools, the proposed framework offers a unique contribution by bridging predictive accuracy with real-time, user-driven interactivity. Usability testing further reinforced this contribution, with participants giving an average SUS score of 88.92, placing the system in the "excellent" category. These findings highlight the value of the platform not only as a scientific tool but also as a participatory medium for planners and stakeholders.

Overall, this study advances UHI research by demonstrating how predictive analytics can be coupled with immersive visualization to support climate-adaptive planning. Future work could extend this framework by integrating higher-resolution datasets, expanding environmental variables, and testing applications in participatory urban design contexts.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Y.M. Arif and S.A. Rohma; methodology, Y.M. Arif, S.A. Rohma, and T. Kusumadewi; software, S.A. Rohma, M. Daniyal, M.H. Arkan, and A.F. Karami; validation, Y.M. Arif, H. Nurhayati, S.A. Rohma, and F. Nugroho; formal analysis, Y.M. Arif and S.A. Rohma; investigation, T. Kusumadewi, H. Nurhayati, and F. Nugroho; resources, Y.M. Arif and S.A. Rohma; data curation, Y.M. Arif, S.A. Rohma, M.H. Arkan, and A.F. Karami; writing original draft preparation, Y.M. Arif and S.A. Rohma; writing review and editing, Y.M. Arif and S.A. Rohma; visualization, Y.M. Arif, S.A. Rohma, and M. Daniyal; supervision, Y.M. Arif, T. Kusumadewi, H. Nurhayati, A.F. Karami, and F. Nugroho; project administration, Y.M. Arif, T. Kusumadewi, and H. Nurhayati; funding acquisition, Y.M. Arif, T. Kusumadewi, and H. Nurhayati,.

Acknowledgments

This research was supported by the RIIM LPDP Grant and BRIN, grant number 165/IV/KS/11/2023 and 3291/LP2M/TL.00/11/2023. We also thank to Universitas Islam Negeri Maulana Malik Ibrahim Malang and Geomedia Sinergi.

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