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Green Urban Planning Using Computer Vision and Machine Learning

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Abstract **- Urban areas worldwide face the dual challenge of managing rising temperatures due to the urban heat island (UHI) effect and creating sustainable urban spaces. This paper introduces an integrated tool that combines UHI simulation with plant species optimization for green roofs and walls. The tool employs machine learning (ML), computer vision (CV), and geographic information systems (GIS) to aid architects and urban planners in designing climate-resilient cities. By leveraging local climate data, vegetation indices, and building characteristics, the tool predicts the impact of increased vegetation on UHI mitigation and provides optimal plant recommendations. The comprehensive workflow includes data collection, predictive modelling, and user-friendly visualization, enabling informed decision-making for sustainable urban planning.**

Keywords: Machine Learning, Computer Vision, Urban planning, UHI (Urban Heat Island).

I. INTRODUCTION

Urban greenery plays a crucial role in enhancing the sustainability and livability of cities by providing environmental benefits such as air purification, temperature regulation, and ecological balance. However, rapid urbanization has led to the depletion of green spaces, resulting in several challenges such as the intensification of the urban heat island (UHI) effect. The UHI effect occurs due to factors like high infrastructure density, reduced vegetation cover, and heat-retaining surfaces such as concrete and asphalt, which lead to elevated temperatures in urban areas compared to surrounding rural regions. This phenomenon contributes to increased energy consumption, deteriorating air quality, public health risks such as heat-related illnesses, and significant ecological imbalances. Addressing these challenges requires a strategic approach that integrates urban planning with innovative technologies to optimize green infrastructure solutions effectively.

Machine learning (ML) and computer vision (CV) have emerged as powerful tools to tackle these challenges by offering data-driven solutions for sustainable urban development. ML algorithms can analyse vast amounts of climate and urban data to predict temperature changes associated with different levels of vegetation, while CV enables automated plant species identification and monitoring through image analysis. By leveraging these technologies, our proposed tool aims to support urban planners and architects in making informed decisions for implementing green roofs and walls to mitigate the effects of UHI.

In this paper, we utilize specific ML algorithms that have been carefully selected to enhance the accuracy and efficiency of our system. For UHI simulation, we employ Random Forest Regression, an ensemble learning method that builds multiple decision trees and averages their predictions to provide accurate temperature forecasts. This algorithm is particularly effective in capturing complex, non linear relationships between variables such as vegetation index (NDVI), albedo, urban density, and land surface temperature. Random Forest Regression also provides feature importance scores, allowing planners to identify the most influential factors in temperature regulation and prioritize them accordingly. Additionally, for plant species recommendation, we implement Support Vector Machines (SVM), a robust classification algorithm that excels at handling high-dimensional datasets and identifying the optimal plant species based on environmental parameters such as sunlight exposure, soil moisture, and climate compatibility. SVM constructs hyperplanes to classify data points effectively, making it well-suited for our use case, where plant selection requires precision and accuracy.

Furthermore, to enable automated plant identification, our system incorporates Convolutional Neural Networks (CNNs), specifically leveraging the MobileNetV2 architecture. MobileNetV2 is a lightweight and efficient deep learning model that is optimized for mobile and edge applications, making it ideal for real-time plant recognition from user-uploaded images. This model analyses plant features such as leaf shape, colour, and texture, providing accurate species identification that aligns with the environmental conditions required for sustainable urban greening initiatives.

The proposed integrated approach follows a systematic workflow that begins with data collection from various sources, including satellite imagery, climate databases, and urban GIS datasets. This raw data undergoes preprocessing

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and feature extraction, where key parameters such as NDVI, albedo, and building density are derived to serve as inputs for the ML models. The trained UHI simulation model then predicts temperature variations under different greening scenarios, while the plant recommendation model suggests species that are best suited to the local conditions. Finally, the outputs are visualized through an interactive GIS-based platform that allows users to assess the potential impact of green infrastructure and adjust parameters to refine their strategies. This iterative approach empowers stakeholders to explore multiple scenarios, optimizing urban greenery interventions for maximum effectiveness.

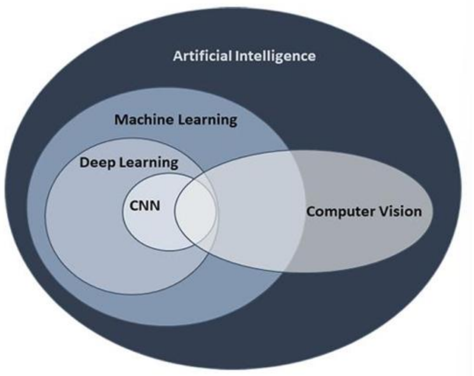

Figure 1: Relationship between ML and CV

By combining ML and CV technologies, our tool provides a comprehensive and data-driven approach to addressing the challenges posed by the urban heat island effect and inadequate greenery. The insights generated by the system facilitate evidence based decision-making, enabling cities to create sustainable, climate-resilient urban environments that benefit both the ecosystem and the community. Moving forward, the integration of real-time IoT data from sensors embedded in urban landscapes could further enhance the accuracy and responsiveness of the system, paving the way for smarter and greener cities of the future.

II. LITERATURE SURVEY

Raveena Marasinghe et.al proposed several computer vision (CV) techniques used in urban greenery and planning, such as image segmentation (semantic and instance) for analyzing vegetation and urban compositions, object detection and tracking for monitoring greenery and infrastructure, and scene classification for evaluating urban landscapes. Advanced methods like 3D modeling, multi-view geometry reconstruction, and VR-based visualization support spatial analysis and design. These techniques rely on data from satellite imagery, street view images, aerial photography, and social media, utilizing machine learning models like CNNs and FCNs to extract insights, enhance decision-making, and promote sustainable urban development.

Jan Niedzielko et.al utilizes several machine learning models for urban greenery classification, with a particular focus on CatBoost, a gradient boosting algorithm. CatBoost was chosen for its ability to handle extensive and unbalanced datasets and demonstrated superior performance compared to other classifiers like Random Forest, LightGBM, and XGBoost. The study highlights CatBoost's unique features, such as symmetric trees and efficient gradient estimation techniques, which make it well-suited for processing high-dimensional remote sensing datasets. Additionally, the study references other commonly used models like Support Vector Machines (SVM) and Random Forest (RF), emphasizing their historical use in similar environmental studies.

CatBoost was chosen for urban greenery classification due to its ability to handle extensive, high-dimensional, and unbalanced datasets effectively. It demonstrated superior performance, achieving a higher Kappa score (0.803) compared to classifiers like Random Forest, LightGBM, and XGBoost. Key features such as symmetric trees with uniform leaf depths mitigate overfitting, while biased pairwise gradient estimation optimizes gradient calculations for efficient classification. Its suitability for remote sensing applications, particularly in processing spatial raster inputs and managing feature importance, made it ideal for creating accurate tree species maps. These strengths, combined with its high classification accuracy across diverse taxonomic classes, ensured practical applicability for urban greenery management.

Jianfei Li et.al suggested a combined stated choice experiment (SCE) and land-use modeling approach for urban greenery planning. It uses mixed logit models to estimate homeowners' preferences for neighborhood and accessibility attributes, based on a national sample. These utility parameters are then integrated into a housing land-use model (HLM) to optimize spatial allocation of urban green space (UGS) and housing. The model balances trade-offs between accessibility, neighborhood characteristics, and housing types (apartments, row houses, and detached houses). This approach allows urban planners to simulate and optimize land-use scenarios based on both market value and residents' utility.

Longlong Zhang et.al outlines several computer vision techniques used to enhance green rooftop landscape designs in urban environments. Image processing algorithms play a crucial role in tasks such as segmentation, feature extraction, and object recognition, allowing for detailed analysis of plant distribution and spatial arrangements. Tools like 3D modeling software, such as 3DMax2020, are utilized to create realistic

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visualizations and simulate various design elements, enabling precise layout planning and interactive exploration. Virtual reality (VR) immerses users in a simulated environment, providing an engaging platform to experience and refine rooftop garden designs. Additionally, machine learning algorithms are employed to quantify greening levels through metrics like the green view index (GVI), facilitating the evaluation of biodiversity and ecological balance. Simulation techniques are also used to predict plant growth and seasonal changes, ensuring sustainable and optimized rooftop landscapes. These technologies collectively enable designers to create more informed, interactive, and efficient designs for green urban spaces.

Wenya Liu et.al discusses an advanced automatic extraction architecture for urban green spaces using remote sensing imagery. The core of this architecture is the DeepLabv3plus semantic segmentation model, which enables pixel-level classification for high-resolution satellite images. The process begins with data preprocessing, including orthophoto correction, image fusion, and enhancement, followed by creating labeled samples for training. The architecture applies Atrous Spatial Pyramid Pooling (ASPP) and encoder-decoder structures within the DeepLabv3plus framework to capture rich contextual information and recover object boundaries accurately. This approach effectively differentiates urban green spaces from similar features, such as farmland, and achieves superior accuracy compared to traditional methods like Maximum Likelihood (ML), Support Vector Machines (SVM), Object-Oriented classification, and other deep learning models such as U-Net and Fully Convolutional Networks (FCN). The proposed system demonstrates a significant improvement in precision, recall, and overall accuracy, making it a robust tool for urban green space monitoring and management.

III. PROPOSED METHODOLOGY

The integrated tool performs two primary functions:

Urban Heat Island Simulation

The tool predicts temperature variations under different greening scenarios, enabling planners to evaluate the impact of increased vegetation on urban microclimates. The simulation uses historical temperature data, vegetation indices (NDVI), and urban infrastructure attributes to model heat distribution.

Plant Species Optimization

Using ML and CV, the tool recommends optimal plant species for green roofs and walls based on parameters like climate compatibility, sunlight exposure, water requirements, and structural load tolerance. The recommendations ensure efficient use of resources while maximizing UHI mitigation.

Workflow

1. Data Collection: The data collection process involves gathering diverse datasets from reliable sources to build a comprehensive model. Specifically, historical climate data is sourced from NASA's MODIS Land Surface Temperature datasets and NOAA's climate archives, providing crucial temperature trends. Satellite imagery, such as Sentinel-2 and Landsat 8, is utilized to obtain vegetation indices like NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index), which indicate vegetation health and density. GIS layers containing urban layout information, such as building footprints, green space distribution, and land use data, are obtained from OpenStreetMap and local urban planning departments. Additionally, plant species data, including growth characteristics, water requirements, and sunlight needs, is collected from botanical databases such as the Global Biodiversity Information Facility (GBIF) and local horticultural sources.

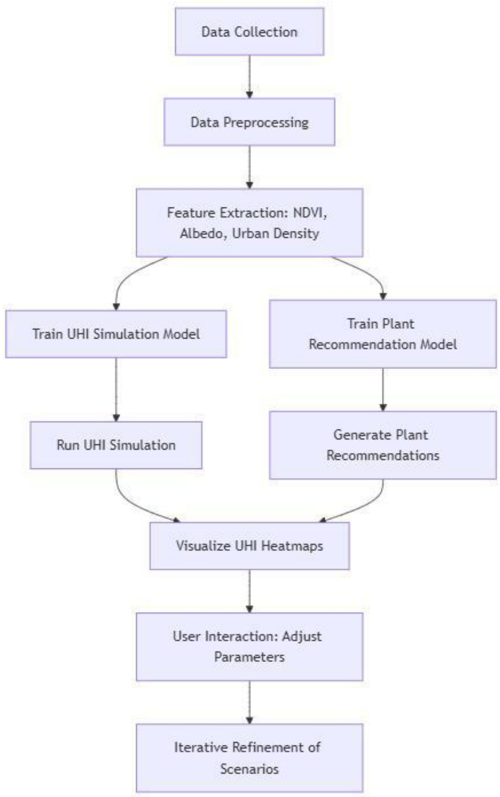

Figure 1: Workflow of the proposed methodology

2. Preprocessing: Data preprocessing involves cleaning raw datasets, normalizing temperature and vegetation indices, and generating training and testing datasets for ML

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models. NDVI values are extracted using satellite images, while urban attributes are derived from GIS layers. Once the data is collected, preprocessing is essential to clean, normalize, and prepare it for analysis. This involves handling missing values, scaling numerical features, and encoding categorical attributes to ensure consistency. Feature extraction is performed to derive important parameters such as NDVI, land surface temperature, soil moisture content, albedo, and urban density. Data augmentation techniques, such as interpolation and smoothing, are applied to fill gaps in satellite imagery. The preprocessing pipeline is implemented using machine learning techniques such as Principal Component Analysis (PCA) for dimensionality reduction, which helps remove redundant features while preserving critical information. Additionally, normalization techniques like Min-Max Scaling are applied to standardize values across different data sources, ensuring uniformity for model training.

3. Modeling: The modeling phase focuses on building predictive models for both UHI simulation and plant species selection. The UHI simulation model employs Random Forest Regression, an ensemble-based approach that constructs multiple decision trees to capture complex interactions between variables such as vegetation density, urban layout, and land surface temperature. This model provides feature importance metrics, highlighting the key factors influencing temperature variations. For plant species selection, a Support Vector Machine (SVM) classifier is trained using environmental parameters such as climate zone, sunlight exposure, and water availability to recommend optimal plant species for green roofs and walls. The training process involves hyperparameter tuning using grid search to achieve the best performance.
4. Simulation: Once the models are trained, the simulation component enables the user to test various greening scenarios by adjusting vegetation coverage levels and evaluating their impact on urban temperatures. The system generates predictive heatmaps that visualize how different plant species and coverage percentages influence heat distribution in the urban environment. Scenario-based simulations allow planners to optimize green infrastructure interventions by analyzing trade-offs between cooling effects, maintenance costs, and structural feasibility. The simulation engine runs multiple iterations to provide confidence intervals, ensuring robust decision-making. Visualization: Provides interactive heatmaps and plant recommendations.
5. Visualization: The visualization component provides an intuitive interface to help stakeholders understand and interact with the model outputs. Interactive heatmaps display temperature variations across different city zones, highlighting areas that would benefit most from increased greenery. Plant recommendation dashboards provide a list of suitable species with key attributes such as drought tolerance and growth patterns. The GIS-based visualization platform allows users to overlay vegetation scenarios on city maps and explore the impact of their decisions in real time. The visualization module is built using web technologies such as React.js for the frontend and Mapbox for interactive mapping, ensuring a seamless user experience.

IV. MODLES AND DATASETS

For analyzing urban and geographical data, generating simulations, and designing plant recommendations for different weather conditions,the following machine learning models and computer vision techniques can be used:

4.1 ML Models:

Random Forest Regression (RF):

Random Forest (RF) is an ensemble machine learning model that combines the predictions of multiple decision trees to provide accurate and reliable results. It can be highly effective for predicting the impact of vegetation in Urban Heat Island (UHI) areas and identifying suitable plants for specific weather conditions due to its ability to handle non-linear relationships and complex datasets. RF uses historical data to learn the relationships between environmental factors (e.g., temperature, humidity, vegetation density) and their impact on UHI or plant health. It identifies the key features contributing to temperature regulation, such as vegetation indices (e.g., NDVI), urban density, and soil conditions. RF captures complex, non-linear interactions between variables, such as how soil moisture and sunlight exposure together affect vegetation growth. It works well with high-dimensional datasets, making it suitable for analyzing a variety of factors in urban and geographical regions. RF is highly accurate for tasks with structured data and numerous interacting features. RF's accuracy can exceed 85-90% when predicting vegetation effects on temperature or urban heat islands.

XGBoost (Extreme Gradient Boosting) and LightGBM (Light Gradient Boosting Machine):

XGBoost is an optimized gradient boosting framework designed for speed and performance. It is widely used for structured/tabular datasets and is highly effective in predicting outcomes where feature interactions are non-linear and complex. LightGBM is another gradient boosting framework optimized for faster training and lower memory usage. It is particularly effective with large datasets and high-dimensional

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features, making it an excellent choice for vegetation and environmental modeling. XGBoost and LightGBM are powerful gradient boosting algorithms suitable for predicting vegetation impact and plant suitability in various weather conditions. XGBoost builds decision trees sequentially, correcting errors at each step, and incorporates regularization (L1/L2) to prevent overfitting, making it robust for complex, high-dimensional environmental data. It handles missing values efficiently and provides feature importance rankings to identify critical factors like temperature, soil quality, and vegetation type. LightGBM, on the other hand, grows trees leaf-wise, capturing intricate feature interactions faster and more efficiently than XGBoost. Its histogram-based binning reduces memory usage, making it ideal for large datasets such as NDVI maps and climate data. Both models excel in scalability and prediction accuracy, allowing for scenario-based simulations and data-driven vegetation recommendations with precise visualizations.

Table 1: Comparison: XGBoost vs. LightGBM for Vegetation Prediction

Feature	XGBoost	LightGBM
Tree Growth	Level-wise (slower, prevents overfitting)	Leaf-wise (faster, captures feature splits better)
Speed	Slightly slower	Faster, especially on large datasets
Handling Large Data	Handles moderately large datasets	Optimized for very large datasets
Memory Usage	Higher memory usage	Lower memory usage
Accuracy	Excellent	Comparable or slightly better in some cases

Support Vector Machines (SVMs):

Support Vector Machines (SVMs) are highly effective for plant species classification because they excel at handling structured, high-dimensional data. They work by finding an optimal hyperplane that separates data points into distinct classes, making them particularly useful for determining which plant species are best suited to specific environmental conditions. Environmental features like soil type, rainfall, sunlight, and climate zones often interact in non-linear ways. SVMs use kernel functions (e.g., radial basis function or polynomial) to transform the data into a higher-dimensional space, allowing them to capture these complex relationships effectively. SVMs are known for their robustness in cases where data points are close to the decision boundary. This ensures that even small differences in environmental parameters lead to accurate classification of plant species. Unlike deep learning models that require large datasets, SVMs perform well with limited labeled data, which is common in niche applications like plant suitability analysis. SVMs can efficiently process datasets with many features, such as a combination of NDVI values, soil moisture, temperature ranges, and other plant-specific attributes. SVMs offer a precise, flexible, and computationally efficient method for classifying plant species based on their environmental suitability. This makes them invaluable in urban planning projects focused on sustainable vegetation and mitigating the Urban Heat Island effect.

Clustering Algorithms:

K-Means: K-Means groups data points into a specified number of clusters (k) based on their similarity, as measured by a distance metric (e.g., Euclidean distance). Each cluster is represented by its centroid, which reflects the average values of the cluster's features. Urban areas can be divided into clusters based on vegetation density, soil type, NDVI (Normalized Difference Vegetation Index), temperature, and rainfall. It identifies patterns in environmental variables such as sunlight exposure, soil pH, and urban density, grouping similar areas to recommend plants suited to their conditions. Once clusters are identified, specific plant species can be assigned to each group based on their compatibility with the cluster's environmental parameters.

K-Means is efficient for large datasets, making it suitable for city-wide vegetation analysis. Results are straightforward, with clear groupings of urban areas for vegetation planning. The number of clusters (k) can be tailored to the scale and granularity of the urban area being analyzed. Outliers in the data can skew cluster centroids, potentially reducing accuracy.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise): DBSCAN groups data based on the density of points in a region, defining clusters as areas of high point density separated by areas of low density. Unlike K-Means, it does not require predefining the number of clusters and is more robust to outliers. DBSCAN can locate areas with high vegetation density based on NDVI values, separating these from regions with sparse vegetation or barren land. Since DBSCAN works well with spatial datasets, it can analyze satellite imagery or GIS data to cluster regions based on environmental factors like soil moisture, land use, and proximity to urban infrastructure. Urban areas with unique conditions (e.g., highly polluted or arid zones) may be flagged as outliers, helping planners allocate special resources for these regions. It automatically determines the number of clusters based on data density. Effectively handles noise, which is common in environmental datasets. Designed to work well with irregularly distributed data, such as urban

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environmental datasets. Requires careful tuning of parameters like epsilon (maximum distance between points in a cluster) and min_samples (minimum points in a cluster).

4.2 Computer Vision Techniques for Visual Analysis

EfficientNet: The Balanced Solution for Accuracy and Efficiency

EfficientNet is a family of deep learning architectures designed to achieve state-of-the-art performance in image classification tasks while optimizing computational efficiency. Developed by Google, it scales the network in a systematic and balanced way, making it highly suitable for applications requiring both high accuracy and resource efficiency, such as vegetation classification and environmental simulations. EfficientNet uses a unique compound scaling method to systematically scale three critical dimensions of a neural network:

- Depth (number of layers): Improves the network's ability to capture complex features.
- Width (number of neurons per layer): Enhances the capacity to process more information at each layer.
- Resolution (input image size): Allows the model to handle higher-detail images for better feature extraction.

This ensures that the network achieves better accuracy without wasting computational resources. EfficientNet models (e.g., EfficientNet-B0 to B7) achieve higher accuracy than traditional architectures like ResNet, using significantly fewer parameters.

EfficientNet can classify plant species or vegetation types using input features like leaf texture, color, and shape. Its ability to handle high-resolution images ensures accurate identification of subtle differences between species. By analyzing high-resolution satellite or drone imagery, EfficientNet can detect vegetation health issues like pest infestations, drought stress, or nutrient deficiencies. EfficientNet can be used to analyze NDVI (Normalized Difference Vegetation Index) maps and predict the impact of vegetation on urban microclimates, such as temperature reduction or carbon sequestration. EfficientNet's efficiency enables large-scale simulations over urban and rural landscapes, accounting for seasonal variations in vegetation growth or health.

Table 2: Comparison of EfficientNet with other architectures

Feature	EfficientNet	ResNet	MobileNet
Accuracy	High	High, but requires deeper models	Moderate
Efficiency	Highly optimized for resource efficiency	Computationally intensive	Lightweight and fast
Scalability	Flexible scaling (B0 to B7)	Fixed-depth models	Limited scalability
Best Use Case	Balanced accuracy and efficiency	High-accuracy tasks with sufficient resources	Real-time or low-resource environments

4.3 Graphical Simulation Techniques

Geospatial Data Visualization:

Geospatial Data Visualization plays a critical role in urban vegetation analysis and planning by providing interactive, visually intuitive platforms for displaying predictions, simulations, and recommendations derived from machine learning (ML) models. Integrating geospatial visualization tools like Mapbox or Google Earth Engine with ML models allows planners to make data-driven decisions by visually analyzing vegetation patterns, environmental conditions, and their potential impact on urban microclimates. ML models, such as Random Forest, XGBoost, or CNNs, generate predictions about vegetation health, species suitability, or the cooling effect of greenery on urban areas. These predictions are converted into geospatial data layers (e.g., shapefiles, GeoJSON) that can be visualized on platforms like Mapbox or Google Earth Engine. Users can interact with maps to zoom in on specific regions, filter by environmental factors (e.g., soil moisture or temperature), and adjust vegetation coverage scenarios to see real-time effects.

Matplotlib

Matplotlib is a powerful Python library for creating static, interactive, and animated visualizations. While it is not a geospatial library like Mapbox or Google Earth Engine, it can be effectively used to create 2D plots and simulations for analyzing vegetation patterns, temperature variations, and the impact of urban greenery. We can use Matplotlib to create heatmaps or overlays, overlay additional data like urban boundaries or regions. Matplotlib can also be used to simulate different greening scenarios. Thus Matplotlib can be used for the efficient visualization of recommendations and current vegetation status in UHIs.

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4.4 Datasets

Temperature Data: NASA MODIS Land Surface Temperature datasets and NOAA climate archives.

Vegetation Data: NDVI maps from Landsat or Sentinel-2 satellites.

Urban Layout Data: GIS layers from OpenStreetMap, including building footprints, heights, and land use.

Plant Database: Botanical datasets with attributes like drought tolerance, sunlight needs, and root depth.

V. RESULTS AND DISCUSSIONS

The tool was tested in a case study for a metropolitan city:

UHI simulation predicted a temperature reduction of 1.5°C with a 20% increase in urban vegetation. The plant optimization module recommended drought-tolerant species like Sedum and Agave for green roofs in arid zones and moisture-loving plants like Ferns for humid regions. The visualization platform enabled city planners to assess multiple scenarios interactively, aiding decision-making.

VI. CONCLUSION

This integrated tool demonstrates the potential of combining UHI simulation with green roof optimization to promote sustainable urban planning. By leveraging advanced technologies like ML, CV, and GIS, the system provides actionable insights for mitigating UHI and enhancing urban greenery. The project underscores the importance of data-driven approaches in addressing climate resilience and urban sustainability.

REFERENCES

[1] NASA MODIS Land Surface Temperature Data: https://modis.gsfc.nasa.gov/
[2] NOAA National Centers for Environmental Information: https://www.noaa.gov/
[3] OpenStreetMap: https://www.openstreetmap.org/
[4] Landsat Satellite Program: https://landsat.gsfc.nasa.gov/
[5] Urban Climate Resilience Studies, Journal of Environmental Management, 2021.
[6] Jianfei Li, Ioulia Ossokina and Theo Arentze, "The spatial planning of housing and urban green space: A combined stated choice experiment and land-use modeling approach" June 2024.
[7] Longlong Zhang and ChulsooKim , "Computer Vision Interaction Design in Sustainable Urban Development: A Case Study of Roof Garden Landscape Plants in Marine Cities" September 2023.
[8] Wenya Liu, Anzhi Yue, Weihua Shi, Jue Ji and Ruru Deng, "An Automatic Extraction Architecture of Urban Green Space Based on DeepLabv3plus Semantic Segmentation Model" 2019 IEEE.
[9] Jan Niedzielko, Dominik Kope, Anna Halladin-Dąbrowska, Justyna Wylazłowska, Maria Niedzielko, Adam Kania, Karol Berłowski and Jacob Charyton, "Airborne data and machine learning for urban tree species mapping: Enhancing the legend design to improve the map applicability for city greenery management" March 2024.
[10] Raveena Marasinghe, Tan Yigitcanlar, Severine Mayere, Tracy Washington and Mark Limb, "Computer vision applications for urban planning: A systematic review of opportunities and constraints" November 2023.
[11] Fellipe Silva Martins, Henrique César de Lima Araújo, Tatiana Tucunduva Philippi Cortese and Giuliano Maselli Locosselli, "Artificial intelligence in urban forestry — A systematic review".
[12] Junghyeon Ahn, Jaekyoung Kim, Junsuk Kang, "Development of an artificial intelligence model for CFD data augmentation and improvement of thermal environment in urban areas using nature-based solutions".
[13] Nadine J. Galle, Cecil Konijnendijk Van Den Bosch, James W.N. Steenberg, "Smarter ecosystems for smarter cities? A review of trends, technologies, and turning points for smart urban forestry".
[14] Abdulrazzaq Shaamala, Tan Yigitcanlar, Alireza Nili, Dan Nyandega, "Algorithmic green infrastructure optimisation: Review of artificial intelligence driven approaches for tackling climate change".
[15] Doo Hong Lee, Hye Yeon Park, Joonwhoan, "A Review on Recent Deep Learning-Based Semantic Segmentation for Urban Greenness Measurement".

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