Addressing UHI Effects in Arizona through the Strategic Urban Greening using AI-Driven Semantic Segmentation of Satellite Imagery

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Abstract

This paper explores the application of deep learning techniques, specifically U-Net-based semantic segmentation models, to identify the most optimal sites in urban areas for afforestation to mitigate Urban Heat Island effects. The study focuses on urban areas of Arizona, USA, leveraging high-resolution NAIP satellite imagery. The approach combines advanced image processing techniques with environmental science to select optimal sites for urban mini forests to enhance urban sustainability and improve environmental quality.

Keywords: Urban Heat Island, Semantic Segmentation, Deep Learning, Afforestation, Satellite Imagery.

1 Introduction

The Urban Heat Island (UHI) [1] effect is a significant environmental phenomenon where urban areas experience higher temperatures than their rural counterparts. This discrepancy arises from the extensive replacement of vegetation with surfaces such as asphalt and concrete, which absorb and retain heat. This not only exacerbates energy consumption due to increased demands for air conditioning but also contributes to elevated emissions of air pollutants and greenhouse gases, thus degrading urban quality of life and overall environmental health.

Arizona exemplifies the challenges associated with UHI due to its rapid urban expansion and arid climate [2]. The city's growth patterns significantly intensify the UHI effect, making it a pertinent area for studying and implementing UHI mitigation strategies. Urban mini forests, known for their ability to cool the local climate through shade and evapotranspiration, emerge as effective solutions. These green spaces also enhance biodiversity, reduce air pollution, and manage stormwater. However, implementing these green spaces within urban settings is challenged by high land costs and limited availability of suitable locations. Additionally, traditional methods for identifying potential vacant lands for afforestation are time-consuming and fraught with inaccuracies, highlighting the necessity for an innovative, technology-driven approach to urban environmental management.

In response to these challenges, this research harnesses the potential of machine learning, specifically deep learning, to provide automated, precise, and scalable solutions. Semantic segmentation, a deep learning technique proficient at analyzing high-resolution satellite imagery, is employed to effectively detect vacant lands [3]. This study utilizes U-Net [4] based architectures, renowned for their efficiency in image segmentation tasks, to develop models capable of identifying lands suitable for afforestation. The innovation of this approach lies in its application of advanced machine learning techniques to directly address critical environmental science issues, thereby enhancing urban sustainability [5] and planning.

The overarching goal of this research is to identify the most optimal locations for developing urban mini forests that mitigate the UHI effect. This involves deploying semantic segmentation models to accurately detect vacant urban lands and subsequently developing an algorithm to assess and select the most suitable sites for afforestation based on their potential impact on UHI mitigation. This dual approach not only addresses the critical need for effective land use in urban planning but also leverages cutting-edge technology to enhance sustainability practices within metropolitan areas.

This study significantly contributes to the fields of urban planning and environmental science by providing a dynamic tool that assists in strategic urban greening initiatives. The findings not only promise to enhance the ecological and aesthetic value of urban areas but also offer a scalable model that can be adapted by other cities facing similar UHI challenges. By automating the detection of potential sites for urban forests, this research aligns with broader sustainability goals, particularly those outlined in the United Nations Sustainable Development Goals related to sustainable cities and communities, climate action, and life on land.

2 Literature Review

The Urban Heat Island (UHI) effect is a well-documented phenomenon where urban areas exhibit significantly higher temperatures than their rural counterparts. This section reviews the underlying causes of UHI, effective mitigation strategies through urban greenery, and the role of advanced technological approaches in urban environmental management.

UHI Dynamics: Oke (1982) [6] established the foundational understanding of UHI, attributing the temperature disparities primarily to the heat absorption and emission properties of urban materials compared to natural environments. This early work elucidates the physical mechanisms of UHI and emphasizes the role of urban planning in modifying surface albedo, thermal properties, and heat capacities to mitigate these effects.

Mitigation Strategies: Subsequent research has focused on the mitigation of UHI effects through the integration of urban greenery. Studies by Gill et al. (2007) [7] and Akbari (2009) [8] demonstrate that urban vegetation can significantly reduce temperatures through mechanisms such as shading and evapotranspiration. These findings support the strategic use of urban forests and green roofs as effective tools in reducing urban temperatures and improving environmental quality.

Technological Approaches: Advancements in remote sensing and Geographic Information Systems (GIS) have greatly enhanced the ability to study and manage UHI. Weng (2009) [9] and Tran et al. (2017) [10] utilized thermal infrared satellite imagery to map urban temperature distributions, providing invaluable data for analyzing heat fluxes and identifying hot spots within cities. This capability allows for targeted interventions and facilitates the monitoring of mitigation strategy effectiveness over time.

Semantic Segmentation and Machine Learning: The development of machine learning techniques, especially in semantic segmentation, has provided new avenues for urban classification. The introduction of the U-Net architecture by Ronneberger et al. (2015) marked a significant advance in this field, offering a robust method for accurately segmenting urban land cover from satellite imagery. The precision and efficiency of this model make it particularly suited for identifying vacant lands within urban settings, which are potential sites for creating mini forests to combat UHI.

Conclusion: The integration of insights from urban climatology with cutting-edge technologies like remote sensing and machine learning sets the stage for innovative urban planning solutions. This study leverages these advancements to identify and utilize vacant urban lands for afforestation, aiming to mitigate the impacts of UHI effectively.

3 Data Collection

High-resolution Imagery Data: The study utilized RGB imagery from the National Agriculture Imagery Program (NAIP) [11], accessed via Google Earth Engine [12], which contains 1m resolution satellite imagery over the whole US territory. The model was trained from data downloaded for Gilbert city. The images were manually annotated using Label Studio [13], classifying each pixel as either 'vacant' (1) or 'occupied' (0), as shown in Figure 1. Patches of 256*256*3 and corresponding masks of 256*256 were derived from the annotated image for model training as shown in Figure 2. Patches were de-

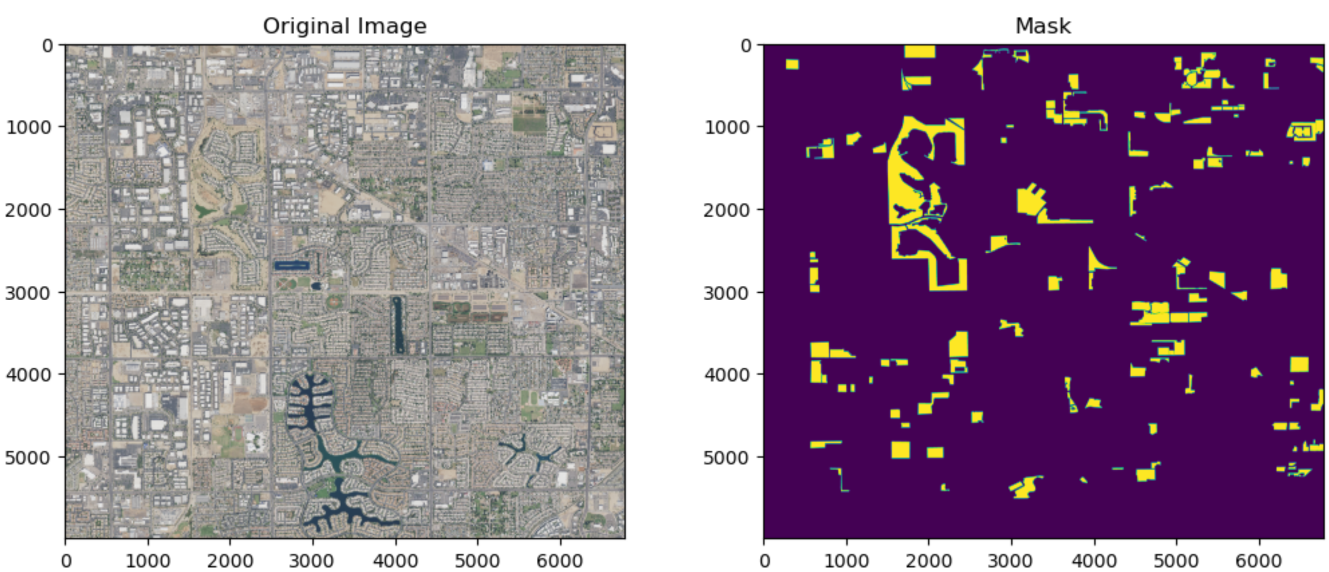

Figure 1: Combined figure showing original high-resolution RGB image from Gilbert city (left) and annotated image showing vacant and occupied areas (right).

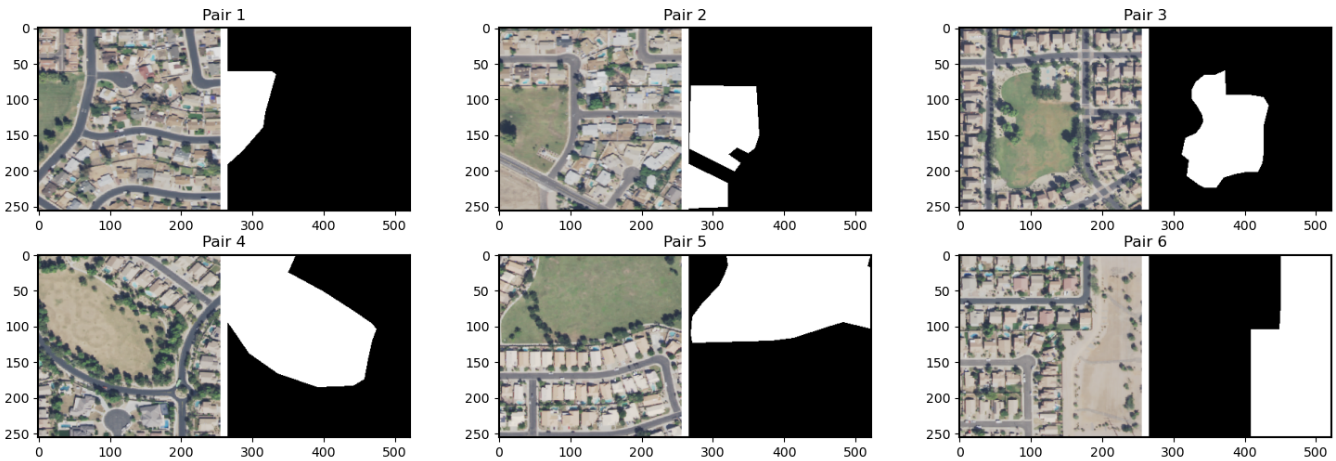

Figure 2: Patches of 256×256×3 and corresponding masks of 256×256 were derived from the manually annotated image for model training

rived ensuring a balanced representation between classed to prevent dataset bias. Large tiles from the cities of Mesa, Phoenix and Paradise Valley were used for practical application of the model testing its robustness.

Land Surface Temperature Data: Temperature data were obtained from the thermal band (ST_B10) of the Landsat 9 [14] satellite, which provides data with a resolution of 10 meters per pixel. The raw digital numbers (DN) from the thermal band were converted into surface temperature in Celsius using the formula:

$$\text{Temperature} = (\text{DN} \times 0.00341802 - 149) - 273.15$$

This method aligns the thermal data with typical temperature measurements, which is essential for analyzing land surface temperatures. Figure 3 shows the overlay of temperature data on the satellite imagery for a clearer understanding of the data.

Population Density Data: WorldPop Global Project Population Data [15] which is 100m resolution, downloaded from google earth engine, was used in the algorithm for optimal site selection.

Temporal Aspects: Data for all the datasets is from January 2021 to December 2022.

4 Model Development for Vacant Land Identification

This section details the development of deep learning models employed to identify vacant lands from satellite

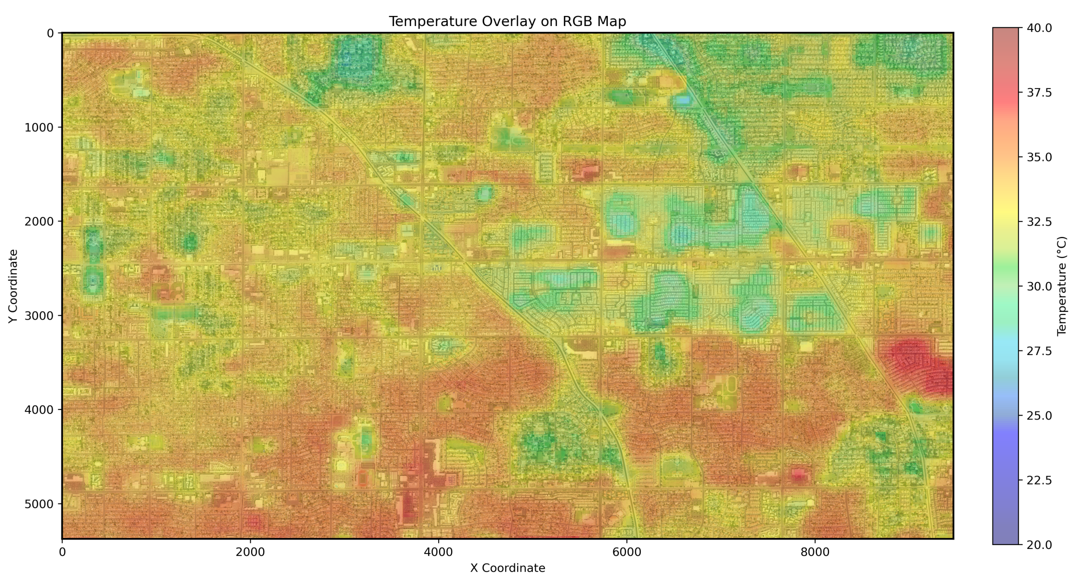

Figure 3: Overlay of temperature data on the satellite imagery.

imagery. We utilized two variations of the U-Net architecture. The variants included a U-Net with approximately 58,000 parameters,and a larger U-Net with 4 million parameters. The architecture has been displayed in Figure 4.

4.1 Data Augmentation

To improve the models' robustness and their ability to generalize across different urban environments, we applied data augmentation techniques. These included rotations, width and height shifts, and both horizontal and vertical flips. Such transformations help simulate varying orientations and configurations, providing the models with a diverse training experience.

4.2 Model Training and Validation

The models were trained on a dataset derived from manually annotated high-resolution images, categorized into vacant and occupied urban spaces. We employed a standard train-test-validation split to ensure a comprehensive evaluation, with 10% of the data reserved for validation and another 10% used for independent testing.

4.3 Model Architecture

Each U-Net variant was specifically designed to handle the intricate features of urban landscape images provided by the NAIP dataset. The architectures included multiple layers of convolution and pooling, with dropout layers interspersed to mitigate overfitting (Figure 4).

4.4 Performance Evaluation

The criteria for model performance evaluation is IoU. Intersection over Union (IoU), also known as the Jaccard Index, is a statistic used to quantify the percentage overlap between the target mask and the prediction output by a model. It is particularly used in the evaluation of object detection and segmentation algorithms. The IoU is calculated using the following formula:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

where:

- **Area of Overlap** is the area covered by both the predicted and the true regions.

- **Area of Union** is the area covered by either the predicted or the true regions.

This metric provides a simple, clear measure of how well the predicted boundaries of the object match the actual reported boundaries. The Intersection over Union

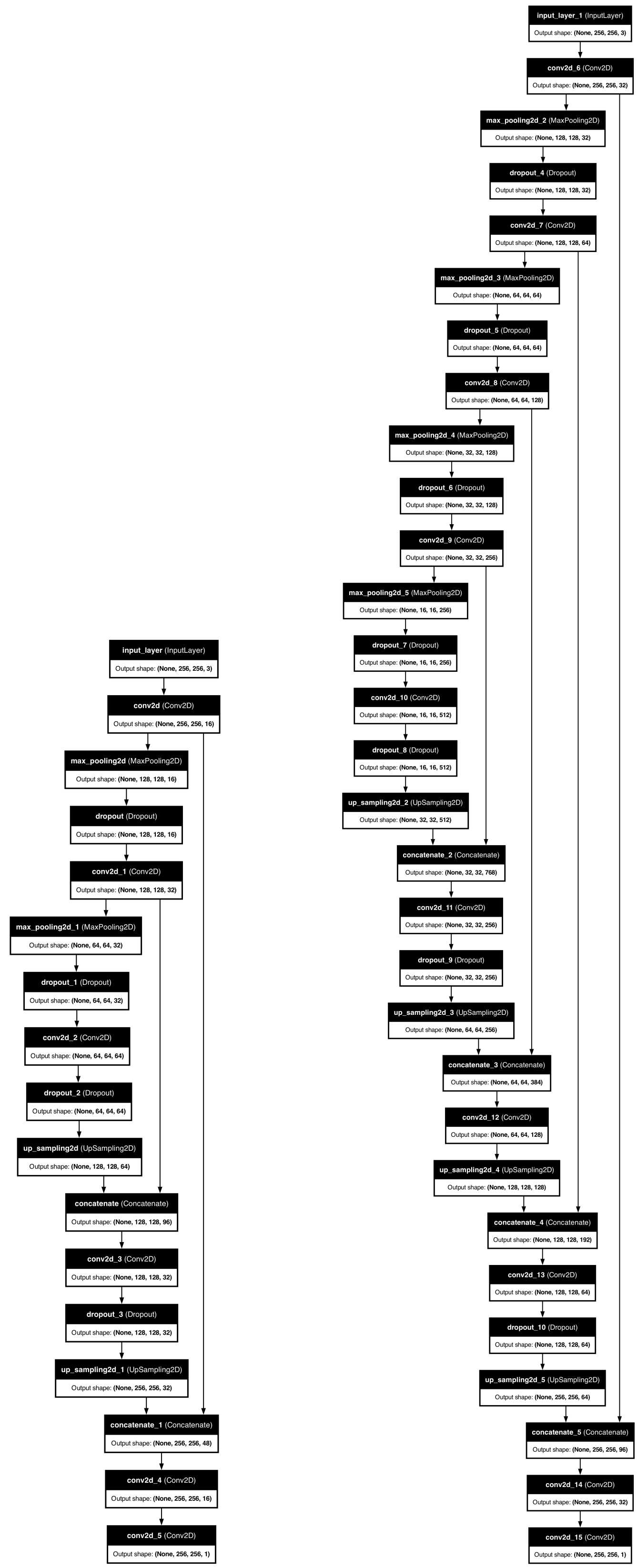

Figure 4: Comparison of Simple (left) and Complex (right) U-Net Architectures.

(IoU) obtained for the vacant class (1) for Simple Unet is 79.7% and for Complex Unet is 84.6%. Figure 5 shows an example.

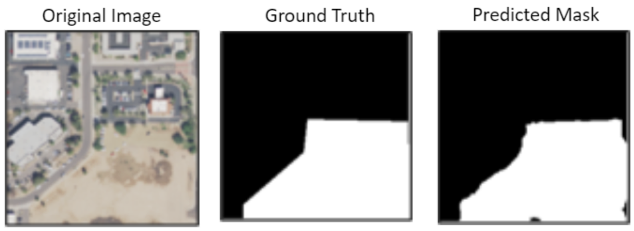

Figure 5: Performance of U-Net2

5 Practical Application

The trained semantic segmentation models were applied to high-resolution satellite imagery from Mesa, Phoenix, and Paradise Valley to assess their effectiveness in detecting vacant lands suitable for afforestation. This practical application was crucial to validate the models' adaptability and accuracy across diverse urban settings. To ensure a thorough evaluation, the detected vacant lands were compared against known ground truth data. This involved documenting the number of suitable vacant lands actually present in the analyzed tiles, based on manual verifications and existing urban planning records.

5.1 Post-Processing

Following the initial segmentation by the U-Net models, a post-processing step was necessary to refine the segmentation results and ensure their practical applicability. This step involved applying morphological operations to the segmented images to reduce noise and eliminate small, fragmented regions that are not viable for urban forestry.

Specifically, the segmented output was first converted to a binary format, where pixels representing vacant lands were set to one. Morphological erosion was then applied to eliminate smaller patches, followed by dilation to smooth the segmentation boundaries. A size threshold of 10,000 square meters was imposed to filter out any regions below this threshold. This criterion was based on research indicating that urban forests smaller than 10,000 square meters are less effective in mitigating Urban Heat Island effects. The aim was to retain only those segments large enough to function as effective green spaces. The final processed image represents areas deemed suitable for the development of urban mini forests, aligning with the goals of effective UHI mitigation. The effect of post-processing can be seen in Figure 6.

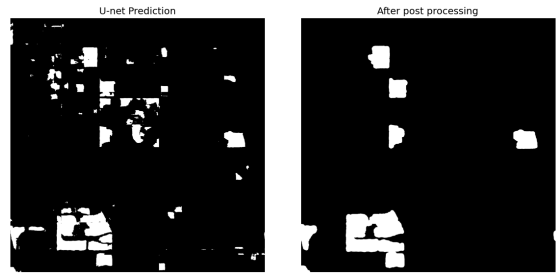

Figure 6: U-Net Prediction and Post-Processed Images.

5.2 Evaluation

The performance of the models was quantitatively assessed by calculating several key metrics: the number of correctly identified vacant lands, and the number of false positives where non-vacant lands were incorrectly classified as vacant. These metrics provided a quantitative measure of the models' accuracy and reliability. The results obtained are present in Table 1.

The findings from these practical applications are crucial for the ongoing development and scaling of this project, aiming to provide robust tools for urban planners and environmental scientists. The results indicate a high level of accuracy in identifying vacant lands suitable for the development of urban mini forests, with some variability across different urban environments. This variability underscores the necessity for continuous model training and updating as new data becomes available, ensuring that the models remain effective and relevant to current urban conditions.

6 Cooling Intensity Model for Urban Forests

To quantify and optimize the cooling impacts of urban forests effectively, we have developed a comprehensive model that considers environmental and spatial factors.

Our model describes the cooling intensity, CI, as a function of the local surface temperature (x), the size of the urban forest (S) (here, $S = 1$ corresponds to an area of $100m^2$), and the distance from the forest (d). The

Metric	**Simple U-Net**			**Complex U-Net**		
	Mesa	**Phoenix**	**Paradise Valley**	**Mesa**	**Phoenix**	**Paradise Valley**
Ground Truth Vacant Lands	61	50	28	61	50	28
Correctly Identified Vacant Lands	38	41	24	52	47	27
Incorrectly Identified Areas	7	31	4	9	28	4

Table 1: Model performance metrics in practical application across different cities.

formula employed is:

$$CI(x,S,d) = \left(\frac{6}{1+e^{-k\cdot(x-x_0+\alpha\cdot\ln(S))}}\right)(5.76 - 0.847\ln(d))$$

[16]

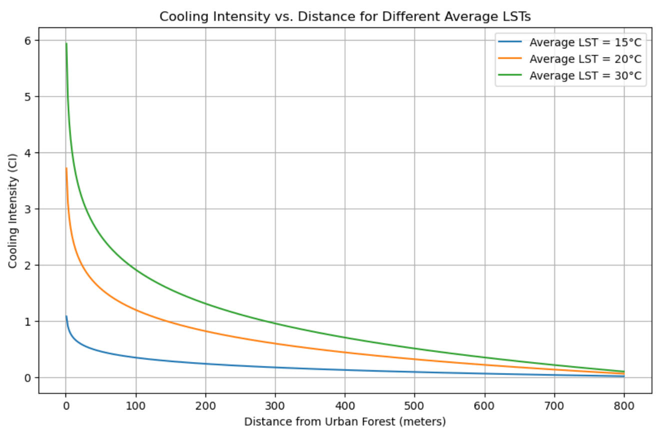

Figure 7: Cooling intensity vs. distance for different average LSTs for $S = 500$

In this model, the first component utilizes a logistic function adjusted by the natural logarithm of the size of the urban forest (S), illustrating how forest size influences the cooling effect. This term alone calculates the cooling effect within the urban forest itself. The parameters α, k and x_0, are derived from empirical data.

The second component introduces a decay function that quantifies how the cooling effect reduces with increasing distance from the forest's edge as seen in the Figure 7. This decay is modelled logarithmically, with the empirical constants 5.76 and -0.847 effectively portraying how temperature reduction tapers off as one moves away from the forest. The entire model is applicable for distances from 0 to 900 meters from the urban forest, beyond which the cooling effect significantly decreases.

This equation is an approximation based on from environmental science studies and is adapted from empirical research that measured temperature variations around different sizes and types of urban forests. The inclusion of both a logistic growth component and a decay function allows our model to provide a nuanced prediction of cooling effects [17] [18] based on both forest size and proximity.

By implementing this model in our analysis, we evaluate and simulate the potential cooling benefits of urban forest placements effectively. This model not only aids in strategic urban planning but also serves as a valuable tool in assessing urban sustainability, allowing city planners to prioritize afforestation projects that offer the most substantial cooling benefits.

7 Algorithm for Optimal Urban Forest Placement

The central component of this research involves an algorithm designed to identify the most optimal locations for urban mini forests within a cityscape. Here, optimal is defined as the location which is worst hit by the effects of UHI and has a significant population. To quantify this the algorithm looks for the vacant land with the highest score iteratively. Score is defined as-

$$\text{score} = \text{M} \times \text{P}$$

where M and P refer to the mean temperature and population density of the area within 900 meters from the boundary of the vacant land.This algorithm integrates machine learning outputs with geographic and demographic data to prioritize afforestation in areas that will maximize environmental and social benefits.

7.1 Algorithm Overview

The algorithm takes as input:

- A land cover map indicating vacant lands, derived from semantic segmentation of satellite imagery.
- A heat map of the area, indicating surface temperatures.
- A population density map, which influences the prioritization of areas for afforestation based on potential human impact.
- The total area designated by urban planners for developing urban forests.

The output of the algorithm includes:

- Updated heat map reflecting potential temperature reductions after forestation.
- A list of selected vacant lands where urban forests should be established.

7.2 Workflow

Figure 7 shows the implementation workflow. The workflow of the algorithm is as follows:

1. **Initialization**: Load the land cover, heat, and population density maps. Initialize an array to track the cumulative cooling effect across the cityscape, ensuring it does not exceed 6 degrees Celsius in any area as per empirical constraints.
2. **Land Selection Loop**: While there is area left in the allocated afforestation budget:
    (a) Identify vacant lands that fit within the remaining area budget.

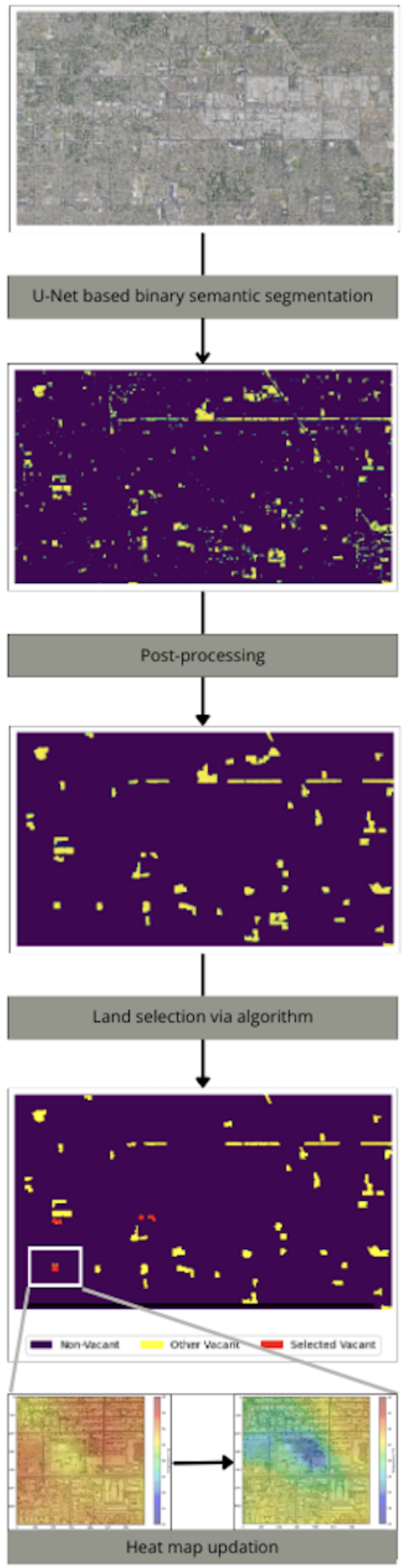

Figure 8: Flowchart of the Project Implementation on Mesa city.

(b) For each potential land, calculate a score based on its average heat map value and the local population density to determine its potential impact on mitigating UHI and benefiting residents.

(c) Select the land with the highest score.

3. **Cooling Effect Simulation**: Apply the derived cooling intensity model to simulate the reduction in temperature due to the new forest. Update the cumulative cooling effect array to reflect this change.

4. **Termination Checks**: If no more lands can fit within the remaining area or if all potential lands have been considered, terminate the loop.

5. **Final Updates**: Output the updated heat map and the list of selected lands for forest development.

7.3 Stopping Conditions

The algorithm stops when:

- The total allocated area for afforestation is used up.
- No more vacant lands are available or suitable based on the size and impact criteria.

This algorithm is designed to be dynamic and adaptable, capable of incorporating updated data on land use and temperature changes, ensuring its long-term applicability and effectiveness in urban planning strategies.

7.4 Integration with Population Density Data

A unique feature of this algorithm is the integration of population density data, which allows the prioritization of afforestation efforts in densely populated areas where the cooling effects of urban forests would benefit the most residents. This integration ensures that the algorithm not only addresses environmental concerns but also enhances urban living conditions, making it a holistic tool for sustainable urban development.

8 Results

Model Performance:

Our U-Net models were tasked with identifying vacant lands suitable for urban forestation from high-resolution satellite imagery. The models showed high effectiveness, with the complex U-Net variant achieving an Intersection over Union (IoU) of 84.6% and the simpler version achieving 79.7%. This demonstrates a robust ability to distinguish between vacant and occupied lands with considerable accuracy.

Accuracy Across Cities:

- **Mesa:** The complex U-Net correctly identified 52 out of 61 vacant lands, showing a success rate significantly higher than the simpler model.
- **Phoenix:** Despite the complex urban structure, the complex model identified 47 out of 50 vacant plots, surpassing the simpler model which struggled particularly in this densely built environment.
- **Paradise Valley:** Both models performed comparably well, with the complex model slightly outperforming in accurately identifying smaller and fragmented vacant lands.

Effectiveness of the Algorithm:

Using our algorithm, which integrates temperature and population density data, we targeted areas that would benefit most from urban forests. The algorithm prioritized lands based on their potential to reduce temperature and affect a significant number of urban residents. Table 2 shows the results obtained on the application of the algorithm on urban areas in three cities in Arizona, Mesa, Phoenix and Paradise Valley. The table shows the cooling effect created, the area affected and the population effected per hectare forestation if based on our algorithm.

Algorithmic Impact:

- **Cooling Effect:** We observed an average temperature decrease ranging from 1.69°C in Mesa to 3.19°C in Phoenix, reflecting substantial local climate moderation.
- **Area and Population Affected:** The algorithm effectively identified and utilized urban spaces that maximized cooling effects and social benefits. For instance, in Phoenix, forestation affected approximately 21.6 hectares, impacting over 1,500 residents.

Comparison with Random Allocation:

To underscore the benefits of our strategic approach, we compared the outcomes with those derived from a random selection of the same amount of vacant land. The results were telling:

- **Increased Efficiency:** Our method resulted in a 53% higher cooling effect compared to random allocation.
- **Broader Impact:** There was a 43% increase in the number of people benefiting from the cooling effects, indicating not just more extensive but also more effective coverage.

9 Discussion

This study substantiates the strategic placement of urban mini forests to maximize cooling effects and benefit the community significantly. By specifically targeting areas that benefit most from urban forestry, the research demonstrates how effectively such green spaces can mitigate the Urban Heat Island (UHI) effect while enhancing community health and well-being.

The utilization of deep learning models for the identification of suitable locations for urban forestry exemplifies an efficient approach to resource management and space optimization in urban planning. This method ensures that urban green spaces are established where they can have the greatest impact, enhancing urban sustainability. However, the variation in model performance, especially the higher incorrect identification rate observed in densely built environments like Phoenix, underscores the need for city-specific adaptations of the models. This points to potential scalability limitations of the current model setups and highlights the importance of adapting the models to reflect local urban structures and conditions to improve their accuracy.

Looking forward, integrating real-time data related to environmental and urban conditions could significantly enhance the adaptive capabilities of urban forest planning tools. Such integration would allow for more dynamic and responsive planning strategies that can adjust to changing urban and environmental conditions, thereby optimizing the ecological and social benefits of urban forests.

Moreover, there is significant potential for algorithm enhancement by including more comprehensive environmental variables such as air quality, water availability, and biodiversity indices. This would allow for a more holistic assessment of potential urban forest sites, ensuring that multiple environmental and ecological objectives are addressed. The potential for broadening the application of this research to include various cities and climates around the world is immense. Extending and testing the models in diverse urban settings globally would help in refining the models further and validating their effectiveness across different urban landscapes, promoting global urban sustainability.

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Places	**Mean Cooling Effect (°C)**	**Area Affected (ha)**	**Population Affected**
Mesa	1.69	44.3	1343
Phoenix	3.19	21.6	1524
Paradise Valley	2	33.7	494

Table 2: Impact per hectare algorithm based forestation

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