Article

Thermal Mapping of Urban Heat Islands Using Satellite Imagery and Computer Vision

Prakriti Adhikari [1,†,‡], Anita Baral [2,‡] and Noah GreenBaum [2,*]

[1] Miami University; adhikap5@miamioh.edu
[2] Miami University; barala@miamioh.edu
[3] Miami University; greenbn3@miamioh.edu
* Correspondence: e-mail@e-mail.com; Tel.: (optional; include country code; if there are multiple corresponding authors, add author initials) +xx-xxxx-xxx-xxxx (F.L.)
† Current address: Affiliation.
‡ These authors contributed equally to this work.

Abstract: Urban Heat Islands (UHIs) represent a critical challenge for cities worldwide, as urban areas tend to be significantly warmer than their rural counterparts. This temperature disparity is largely driven by the built environment, including materials that absorb and retain heat, along with human activities that contribute additional heat to the atmosphere. The intensification of UHIs results in various adverse effects, such as heightened energy consumption, increased pollution, and public health risks. Given the growing impact of urban heat on both the environment and society, it is crucial to develop effective strategies for their detection and mitigation. This research utilizes satellite-based thermal infrared imagery from Landsat 8/9 to assess the spatial distribution of heat in urban areas. Through a combination of thresholding, mean temperature calculations, and machine learning techniques like Random Forest (RF), this study aims to identify key UHI hotspots and temperature variations across different metropolitan regions. The integration of these methods allows for more precise detection of temperature anomalies and the classification of areas experiencing the highest heat concentrations. The outcomes of this research provide a data-driven approach to understanding UHI patterns, offering valuable insights for urban planners and policymakers. The findings can inform the development of sustainable urban designs and green infrastructure projects to alleviate the UHI effect. This work not only contributes to addressing the challenges posed by climate change but also supports urban sustainability efforts, ensuring healthier and more resilient urban environments for future generations.

Keywords: Urban Heat Island; Threshold; LST; NDVI

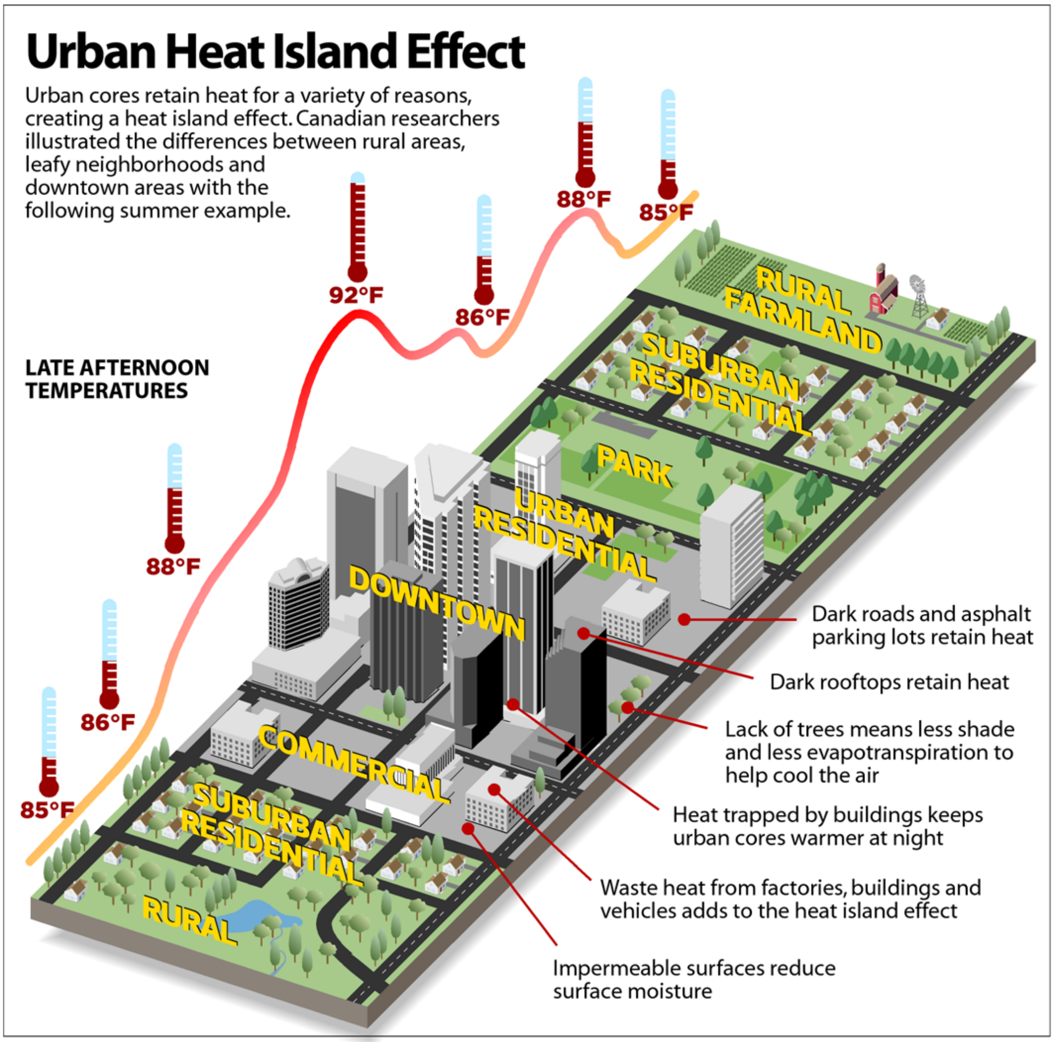
Citation: Adhikari, Prakriti.; Baral, Anita.; Greenbaum, Noah. Title. *Journal Not Specified* **2024**, *1*, 0. https://doi.org/

Received:
Revised:
Accepted:
Published:

1. Introduction

Urban Heat Islands refer to parts of cities or metropolitan regions that experience significantly higher temperatures than their rural surroundings, mainly due to human activities, construction materials, and decreased vegetation. Urban heat islands (UHIs) are a growing concern in metropolitan areas worldwide. These phenomena occur when urban regions experience significantly higher temperatures than their surrounding rural areas. The primary causes of UHIs include the concentration of heat-absorbing surfaces such as asphalt and concrete, as well as anthropogenic heat sources. The consequences of this are far-reaching, contributing to increased energy consumption, air pollution, and health risks for urban residents. Understanding the distribution and intensity of these UHIs is essential for urban planning, public health, and mitigating the negative impacts of climate change.

This project uses the thermal images captured by satellite and advanced computer vision techniques to analyze and visualize thermal radiation patterns emitted by urban buildings. By mapping thermal emissions from buildings and urban infrastructure, we can gain crucial insights into the distribution and intensity of UHIs. The results of this project would help urban planners and policymakers to develop targeted strategies for reducing UHI effects through sustainable urban design and green infrastructure implementation.



SOURCE: D.S. Lemmen and F.J. Warren, Climate Change Impacts and Adaptation PAUL HORN / InsideClimate News

Figure 1. Urban Heat Island Effect

1.1. Problem Statement

Due to the Urban Heat Island, areas within the metropolitan areas experience higher temperatures than the peripheral rural areas. As a result, energy consumption is high in urban heat islands. Innovative and advanced approaches should be developed for mitigating the adverse effects of Urban Heat Island. Generally, traditional methods for measuring temperature may be inaccurate, have a limited range, and are not suitable for real-time or continuous temperature monitoring. So, traditional methods of temperature measurement aren't efficient for fully understanding the dynamics of UHIs across entire cities.

Recent advancements in satellite technology and computer vision have opened up new possibilities for analyzing large-scale thermal patterns. As noted by Nichol (2009), thermal satellite images can be enhanced for urban heat island analysis using emissivity modulation methods [1]. Furthermore, the integration of computer vision in satellite imagery analysis promises to revolutionize the extraction of geospatial intelligence from overhead imagery [2]. This project seeks to leverage these technological advancements to create a comprehensive thermal map of urban areas, identifying hotspots and patterns in heat distribution. By doing so, we aim to provide a data-driven foundation for urban planning decisions that can effectively mitigate the UHI effect.

1.2. Objective

1. To map and analyze Urban Heat Islands (UHIs) in metropolitan areas using thermal satellite imagery from Landsat 8/9, identifying temperature variations and heat hotspots.
2. To address challenges in UHI mapping, including spatial resolution limitations and atmospheric distortions, ensuring more accurate and reliable thermal analysis.
3. To provide data-driven insights for urban planning and policymaking, aimed at mitigating UHI effects through sustainable design and infrastructure development.

2. Literature Review

The phenomenon of Urban Heat Islands (UHIs) has gained significant attention in recent years, primarily due to the accelerating impact of urbanization and climate change on local environments. Satellite-based remote sensing provides a critical means to assess the thermal characteristics of urban areas and to quantify the extent of UHIs.

2.1. Landsat Imagery and UHI Mapping

Landsat 8 and 9, with their thermal infrared bands (Bands 10 and 11), are widely used for estimating Land Surface Temperature (LST), which is a key factor in UHI detection. Li et al. (2022) employed a combination of Normalized Difference Vegetation Index (NDVI) and Support Vector Machines (SVM) to classify UHIs using Landsat 8 data, achieving an accuracy of 82In contrast, Zhou Wang (2021) explored the use of Convolutional Neural Networks (CNNs) to predict surface temperatures in urban areas [6]. Their model, trained on both MODIS and Landsat 8 datasets, achieved high accuracy with a prediction error of less than 1°C [6]. Their approach addressed the temporal variability of UHIs, which is often a challenge in urban heat mapping [6].

2.2. Computer Vision Techniques for UHI Detection

The integration of machine learning and deep learning algorithms has proven to enhance the accuracy of UHI mapping. For instance, Gupta et al. (2022) implemented an object-based CNN approach for UHI detection using Landsat 8 and 9 imagery [7]. Their model yielded an 88% of accuracy, demonstrating the potential of CNNs to effectively delineate UHI boundaries in densely populated areas [7]. Similarly, Chen et al. (2023) applied a UNet-based deep learning model for UHI segmentation and achieved an accuracy of 90%, highlighting the robustness of deep learning in extracting UHI features from satellite imagery [8]. In addition to CNN-based methods, Singh Kaur (2020) utilized K-means clustering and Normalized Difference Water Index (NDWI) with Landsat 8 and Sentinel-2 data to delineate heat-affected zones [9]. This method proved effective in identifying UHI patterns, though the complexity of urban landscapes posed challenges in accurately classifying heterogeneous surfaces [9].

2.3. Challenges and Opportunities

One of the recurring challenges in UHI mapping is the limited spatial resolution of satellite imagery, which hampers the detection of microclimatic variations in densely populated areas. This limitation is emphasized in studies such as Wang et al. (2021), where the accuracy of UHI detection in cities with high building density was constrained by the resolution of the thermal data [10]. Moreover, Huang Liu (2022) investigated the fusion of multi-source datasets (Landsat 8/9 and MODIS), demonstrating that data fusion can enhance precision but also increases the complexity of the analysis [11]. Atmospheric correction remains another significant challenge, as highlighted by Chen et al. (2023), where distortions due to atmospheric conditions affected the accuracy of UHI mapping [8]. Additionally, the temporal variability of UHIs across seasons, noted by Zhou Wang (2021), suggests that long-term monitoring and seasonal adjustments are critical for reliable UHI analysis [6].

2.4. Summary

Recent advancements in remote sensing and computer vision have significantly improved the ability to detect and analyze Urban Heat Islands using Landsat 8/9 imagery. While traditional approaches, such as NDVI and SVM, provide reasonable accuracy, the incorporation of deep learning methods, particularly CNNs and UNet, has enhanced the precision and robustness of UHI detection. However, challenges such as limited resolution, atmospheric distortion, and temporal variability persist, highlighting the need for continued research and the development of more sophisticated methodologies for accurate UHI analysis.

Table 1. Summary of Key Research on UHI Mapping Using Landsat Imagery and Computer Vision

Paper Citation	**Problem Domain**	**Methods**	**Datasets Used**	**Results and Accuracy**	**Challenges**
Li, et al. (2022)	Urban Heat Islands	NDVI, SVM	Landsat 8	82% Accuracy in UHI detection	Limited spatial resolution
Zhou & Wang (2021)	UHI Temperature Estimation	CNN-based temperature prediction	MODIS, Landsat 8	CNN predicted temperatures with $<1°C$ error	Temporal variability in UHI patterns
Singh & Kaur (2020)	UHI Thermal Mapping	K-means clustering, NDWI	Landsat 8, Sentinel-2	Accurate delineation of heat-affected zones	Complex urban landscapes
Chen, et al. (2023)	UHI Intensity Prediction	Deep Learning (UNet)	Landsat 9, MODIS	UNet-based segmentation with 90% accuracy	Atmospheric distortion in satellite data
Huang & Liu (2022)	UHI Remote Sensing Analysis	Multi-source fusion (Landsat + MODIS)	Landsat 8/9, MODIS	Improved precision through data fusion	Data fusion complexity
Wang, et al. (2021)	UHI Detection in Dense Cities	SVM, LST calculation	Landsat 8, MODIS	UHI detection accuracy of 87%	Lack of consistent thermal data
Gupta, et al. (2022)	UHI and Land Cover Dynamics	Object-based CNN	Landsat 8, Landsat 9	Object-based UHI mapping yielded 88% accuracy	Inaccurate classification in high-density areas
Kumar & Verma (2021)	UHI Influence on Air Quality	Hybrid approach (NDVI + Machine Learning)	Landsat 8	Identified correlation between air quality and UHI	Limited ground-truth data

3. Methodology

3.1. Data Collection

The data collection phase for the Urban Heat Island (UHI) project focused on gathering satellite imagery and supplementary datasets essential for analyzing temperature variations within the urban landscape of Columbus, Ohio. The primary data source for this project is Landsat 8/9 thermal imagery, specifically bands 10 and 11, which capture thermal infrared data critical for determining Land Surface Temperature (LST). This dataset provides high-quality thermal information necessary for detecting heat anomalies across different major cities in Ohio, such as Middletown Ohio, Dayton Ohio, Springfield Ohio, Richmond Indiana, Sidney Ohio, Findlay Ohio, and Lima Ohio.

3.1.1. Data Sources and Acquisition

- **Thermal Infrared Data (Bands 10 and 11):** The core of the UHI analysis relies on thermal infrared data to compute LST, enabling the identification of heat islands based on regional temperature differences rather than diurnal fluctuations. By focusing on regional disparities, this approach aims to pinpoint persistent heat zones within the major cities of Ohio, irrespective of day-night temperature cycles.
- **Vector Data for Urban Boundary Definition :** The high spatial resolution of NAIP imagery allowed for precise classification of forested and non-forested areas, ensuring accurate detection of vegetation loss and recovery across the study area.
  - **Urban Boundary Shapefiles:** To accurately define the extent of Ohios's urban areas for UHI analysis, urban boundary shapefiles from authoritative sources such as OpenStreetMap (OSM) were incorporated. These shapefiles help delineate urban areas from surrounding rural regions, establishing clear boundaries for regional temperature comparison.
  - **Land Cover Classification:** Land cover classification data was utilized to refine boundary accuracy, ensuring the analysis specifically targets urbanized zones while excluding natural features that may otherwise distort temperature readings.

3.2. Data Preprocessing and Adjustments

1. **Atmospheric Correction:**The collected satellite data underwent atmospheric correction to mitigate distortions caused by atmospheric variables (e.g., humidity, cloud cover), ensuring accurate LST calculations. Radiometric calibration was also applied to standardize pixel values across images, allowing for consistent interpretation of thermal readings.
2. **Cloud Masking and Filtering:**Cloud cover posed intermittent challenges in certain images, particularly in highly reflective or humid areas. To address this, cloud masking techniques were applied to remove cloud-contaminated pixels, ensuring that only clear-sky thermal readings were used in the UHI analysis.

3.3. Calculation of NDVI and LSTM

The Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature Map (LSTM) are critical indices used to assess vegetation coverage and thermal variations across urban landscapes. Both indices were calculated using preprocessed Landsat data to detect and analyze Urban Heat Island (UHI) effects.

3.3.1. Normalized Difference Vegetation Index (NDVI)

NDVI is a commonly used index to quantify vegetation density and health. It leverages the difference between the near-infrared (NIR) and red bands of the satellite imagery. Vegetation strongly reflects near-infrared light and absorbs red light, making NDVI an effective measure for identifying areas with dense vegetation.

The NDVI is calculated using the following formula:

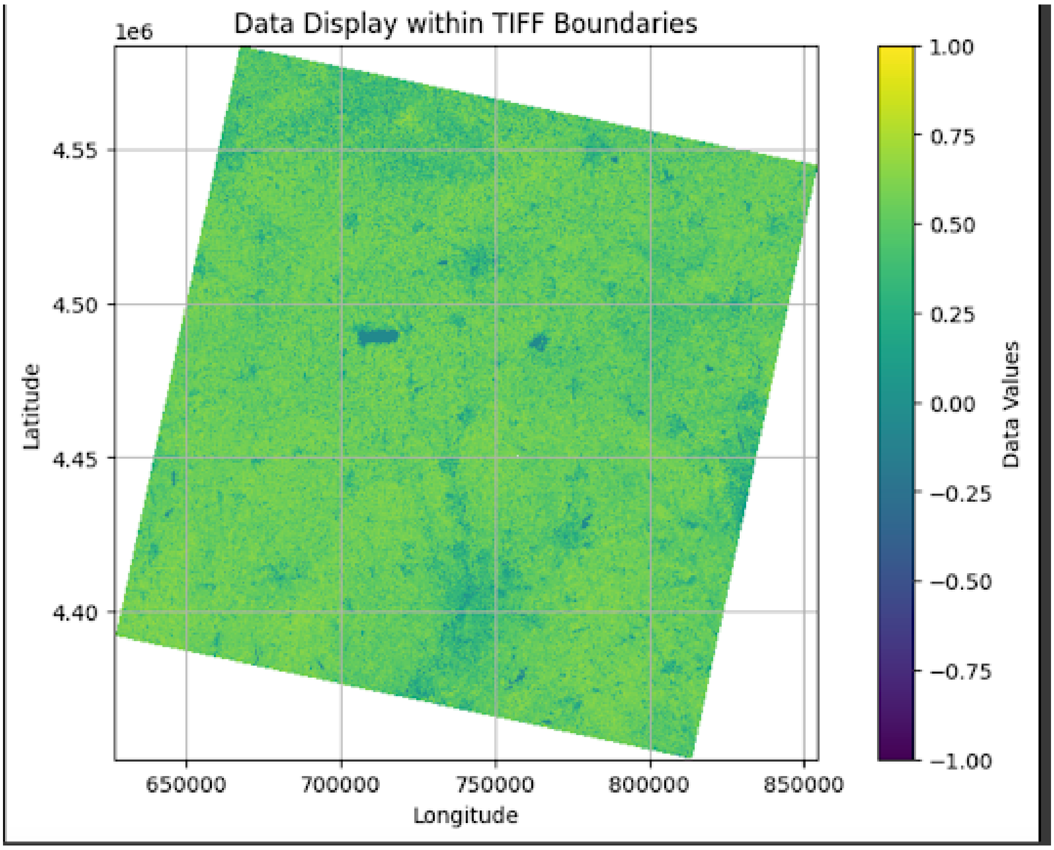


Figure 2. Normalized Difference Vegetation Index

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Where:
NIR is the reflectance in the near-infrared band (Band 5 for Landsat 8/9).
Red is the reflectance in the red band (Band 4 for Landsat 8/9).

NDVI values range from -1 to +1, where values closer to +1 indicate dense vegetation, values near 0 correspond to bare soil or rocks, and negative values typically indicate water bodies. NDVI plays a crucial role in identifying areas with higher vegetation that are expected to have lower temperatures due to the cooling effects of vegetation through evapotranspiration and shading.

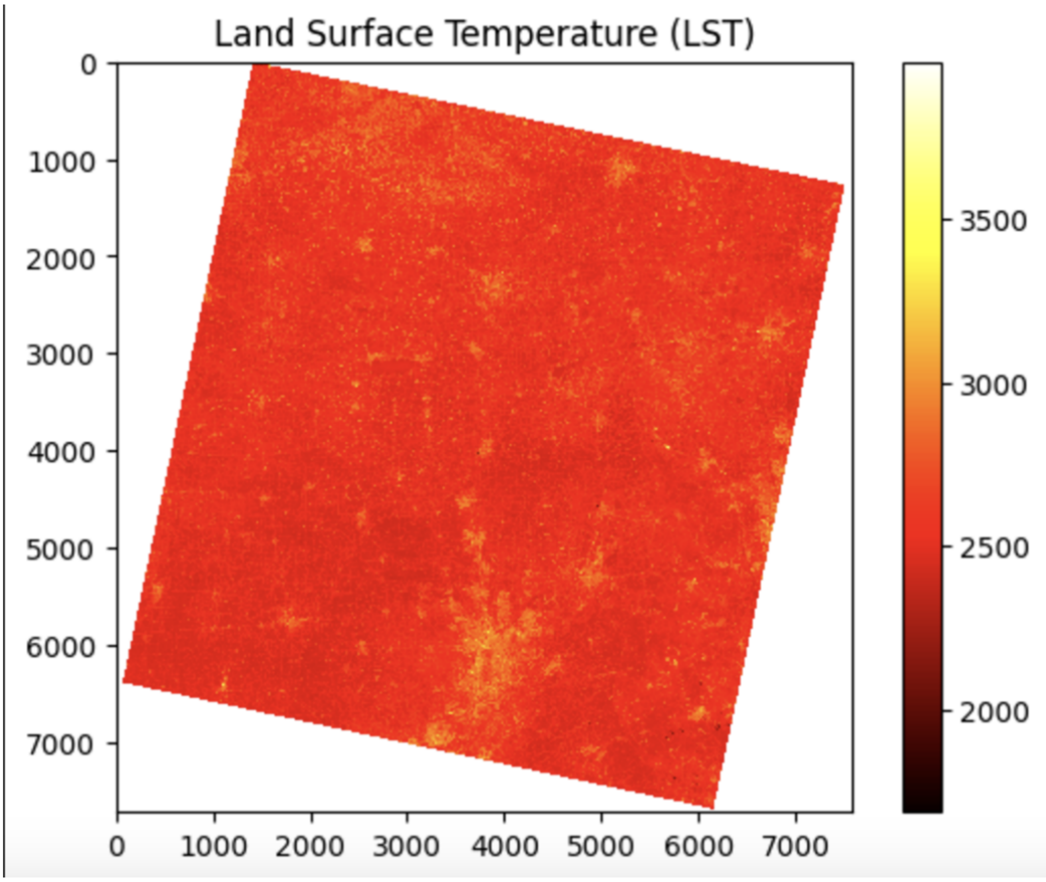


Figure 3. Land Surface Temperature

3.3.2. Land Surface Temperature Map (LSTM)

Land Surface Temperature (LST) is an important indicator for detecting thermal anomalies in urban areas. It represents the temperature of the land surface and is calculated using the thermal infrared bands from the Landsat imagery (Band 10 and Band 11 for Landsat 8/9). The LST calculation involves several steps:

1. **Top-of-Atmosphere (TOA) Radiance Conversion**
2. **Brightness Temperature Calculation**
3. **Land Surface Temperature (LST) Adjustment**

3.3.3. Handling Missing Data (NaNs)

In cases where LST and NDVI data are missing or unavailable for specific areas, NaN values are interpolated to ensure continuous spatial coverage. Interpolation techniques, such as bilinear interpolation, are employed to estimate the missing temperature values based on neighboring pixel data, ensuring a seamless and complete temperature map for further analysis.

3.4. Generation of Heatmaps

To identify Urban Heat Island (UHI) hotspots, the study combined the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature Map (LSTM) values to generate heatmaps, which visually represent temperature distribution and vegetation coverage across the study area. These heatmaps are crucial for identifying regions within urban areas that experience higher temperatures due to the UHI effect. The generation process involved several steps and applied multiple methods to ensure accurate and reliable delineation of temperature variations and heat intensity.

3.4.1. Urban Area Boundaries from OSM

The NDVI and LSTM values were combined to gain a comprehensive understanding of the relationship between vegetation cover and temperature variations in urban environments. NDVI was used to identify areas with high vegetation cover (which are typically cooler), while LSTM provided temperature values that reflect the heat intensity across the landscape. By merging these indices, the study aimed to create a more robust and nuanced representation of UHI hotspots, considering both the vegetation influence and the thermal conditions.

For example, areas with low NDVI values and high LSTM values are likely to be urban heat islands, where built-up areas such as roads and buildings absorb and retain heat. Conversely, areas with higher NDVI values and lower LSTM values are expected to be cooler, typically indicating areas with more vegetation or green spaces.

3.4.2. Methods for Heatmap Generation

Three methods were employed to generate the heatmaps and delineate UHI hotspots, including:

1. **Normal Threshold Method:**
   The normal threshold method is a simple yet effective technique for detecting UHI hotspots. By applying a predefined temperature threshold to the LSTM values, areas that exceed the threshold are classified as UHI hotspots. This method is particularly useful for quickly identifying regions with elevated temperatures that likely correspond to UHI effects. The threshold for temperature was chosen based on the distribution of LSTM values, considering the typical temperature range of the urban and rural regions in the study area.
   The formula used to apply the normal threshold is:

   $$UHI = NDVI < 0.2 LST > P90(LST)$$

   Where:
   LST is the Land Surface Temperature (in °C or Kelvin).
   NDVI is Normalized Difference Vegetation Index.
   P90(LST) is 90th percentile of Land Surface Temperature values.
   Regions are classified as UHI hotspots where:
   - NDVI is less than 0.2 (indicating built-up areas with low vegetation).
   - LST exceeds the 90th percentile.
2. **K-Means Clustering**
   K-means clustering was employed to partition the study area into two distinct clusters (k=2) based on LST and NDVI variations. This unsupervised machine learning

algorithm groups the data into UHI and non-UHI clusters, where the cluster with higher mean temperature values represents potential UHI hotspots.
The algorithm minimizes the within-cluster sum of squares between data points and their assigned cluster centroids, effectively separating areas with similar temperature and vegetation characteristics.
The resulting clusters were analyzed to identify which clusters correspond to high-temperature regions (UHI hotspots) and which correspond to cooler areas. The temperature distribution within each cluster was visualized to show areas with similar thermal characteristics.

3. **Random Forest (RF) Classification**
Random Forest, a supervised machine learning method, was used to classify regions into distinct UHI categories based on temperature and vegetation data. The RF model was trained using labeled data points, where each point was associated with its NDVI and LSTM values. The model learns to predict the UHI status (hotspot or non-hotspot) based on the input features (NDVI and LSTM) and outputs a classification result.
The classification model was trained on Landsat 8 satellite data, utilizing thermal band-derived LST and NDVI calculated from red and near-infrared bands as primary features. A dynamic threshold approach was implemented where UHI zones were defined as areas exceeding one standard deviation above the mean LST. The Random Forest classifier, configured with 100 decision trees and a maximum depth of 10, categorized pixels into UHI and non-UHI regions based on their combined LST and NDVI characteristics. The model achieved this classification through an ensemble learning approach, where each tree contributed to the final prediction. The spatial distribution of UHI zones was then mapped and visualized, revealing the relationship between urban thermal patterns and vegetation density.

3.5. Heatmap Overlay on OpenStreetMap (OSM)

Once the heatmaps were generated using NDVI, LSTM, and various classification methods (normal threshold, k-means clustering, and Random Forest), the next step was to overlay these heatmaps onto the urban boundaries defined by OpenStreetMap (OSM) data. This process allowed for a comprehensive visual representation of the spatial distribution of Urban Heat Island (UHI) effects within the urban environment. Urban area boundaries were extracted from OSM, a collaborative and freely accessible database that provides detailed geographic data, including roads, buildings, and land-use zones. Using GIS tools like QGIS or ArcGIS, urban polygons representing residential, commercial, and industrial areas were selected, ensuring that the analysis focused only on urban regions affected by UHI.

To ensure accurate mapping, both the heatmap and OSM data were aligned to the same coordinate reference system (CRS). This was done by reprojecting the datasets using tools such as GDAL or Fiona, ensuring precise spatial alignment. Once the CRS was unified, the heatmap was either kept in its raster form or converted into a vector format (polygons or contours) for clearer visualization. If necessary, a threshold or contour extraction algorithm was applied to create discrete temperature zones (e.g., high, medium, and low-temperature areas). The heatmap was then overlaid onto the urban boundaries, with temperature data from the heatmap superimposed onto the OSM layers using an "overlay" or "join" function within the GIS software.

The heatmap was color-coded using a gradient scale where warmer colors (e.g., red, orange, yellow) represented higher temperatures, and cooler colors (e.g., blue, green) represented lower temperatures, ensuring clear differentiation of temperature zones. To further enhance visualization, transparency was adjusted to allow the underlying OSM urban boundaries to remain visible, providing a clear distinction between temperature variations and urban infrastructure.

The final visualization revealed high-temperature zones, typically located in areas with dense infrastructure or a lack of vegetation. This overlay enabled detailed analysis, such as identifying specific urban areas that could benefit from UHI mitigation strategies, assessing the relationship between temperature and urban land use, and evaluating the effectiveness of green spaces in cooling urban environments. The visualization also provided urban planners and policymakers with essential data to design interventions aimed at reducing UHI effects, such as incorporating more green infrastructure or implementing urban cooling strategies.

The overlay process was conducted using QGIS for seamless integration of raster and vector data. Python was employed for automating data preprocessing, alignment, and heatmap generation, using libraries like GeoPandas for geospatial data manipulation and Matplotlib for generating the final overlaid maps. This method provided a clear and informative visual representation of UHI hotspots in relation to urban infrastructure, serving as a foundation for sustainable urban design and green infrastructure strategies to mitigate urban heat and improve environmental quality.

3.6. Comparison of Methods

The outputs obtained from the normal threshold method, k-means clustering, and Random Forest classification were compared to evaluate the consistency and accuracy of UHI hotspot identification. The results were found to be similar across all three methods, suggesting that each method successfully detected regions with elevated temperatures, albeit with slight variations in the exact boundaries of the hotspots. These findings validate the robustness of the methods used and provide a reliable basis for identifying UHI hotspots in urban environments.

4. Results and Analysis

In this study, we conducted a detailed analysis of the Urban Heat Island (UHI) effect, utilizing the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) as primary indicators. NDVI was calculated to quantify vegetation density, a critical factor in mitigating urban heat, while LST was derived from the thermal bands of Landsat 8 satellite imagery to provide spatially resolved surface temperature data. Together, these metrics formed the foundation for evaluating the intensity and spatial distribution of the UHI effect across the targeted urban areas.

To comprehensively identify and analyze the UHI effect, we employed three distinct methodological approaches: the thresholding method, k-means clustering, and random forest modeling. The thresholding method defined UHI hotspots by identifying areas with low vegetation cover (NDVI < 0.2) and elevated surface temperatures (above the 90th percentile). The k-means clustering approach revealed natural groupings within the data, highlighting distinct thermal patterns across the study area. Lastly, random forest modeling, a supervised machine learning technique, used NDVI and LST as predictors to classify and model UHI regions with high accuracy. This multi-method framework ensured a robust and comparative evaluation of UHI dynamics, improving the reliability and depth of the analysis.

The integration of NDVI and LST data enabled the creation of a UHI effect layer, providing a comprehensive visualization of temperature variations in relation to vegetation cover. This layer was further enhanced by overlaying a heatmap of the UHI effect onto an OpenStreetMap base, enabling a geospatial representation of how urban areas are impacted by UHI. This approach emphasized specific zones experiencing heightened thermal stress and allowed for an intuitive understanding of the interplay between urban infrastructure, green spaces, and heat distribution. By combining these methodological and visualization techniques, the study provides actionable insights to inform urban planning, enhance green infrastructure, and support sustainable development strategies.

1. **NDVI Calculation:** Quantified vegetation density to assess urban cooling potential.
2. **LST Calculation:**Measured surface temperatures derived from Landsat 8 thermal imagery.

3. **Multi-Method UHI Analysis:** Quantified vegetation density to assess urban cooling potential.
   - **Thresholding Method:** Identified regions with low vegetation and elevated temperatures using fixed thresholds.
   - **K-Means Clustering:** Grouped data into natural clusters to uncover thermal patterns.
   - **Random Forest Modeling:** Classified UHI regions using machine learning for enhanced accuracy.
4. **Heatmap Visualization:** Overlayed UHI effect heatmaps on OpenStreetMap to contextualize temperature variations in relation to urban structures and green spaces.

This comprehensive methodology provides a robust framework for evaluating UHI effects, facilitating targeted interventions to mitigate urban heat stress and fostering sustainable urban development.

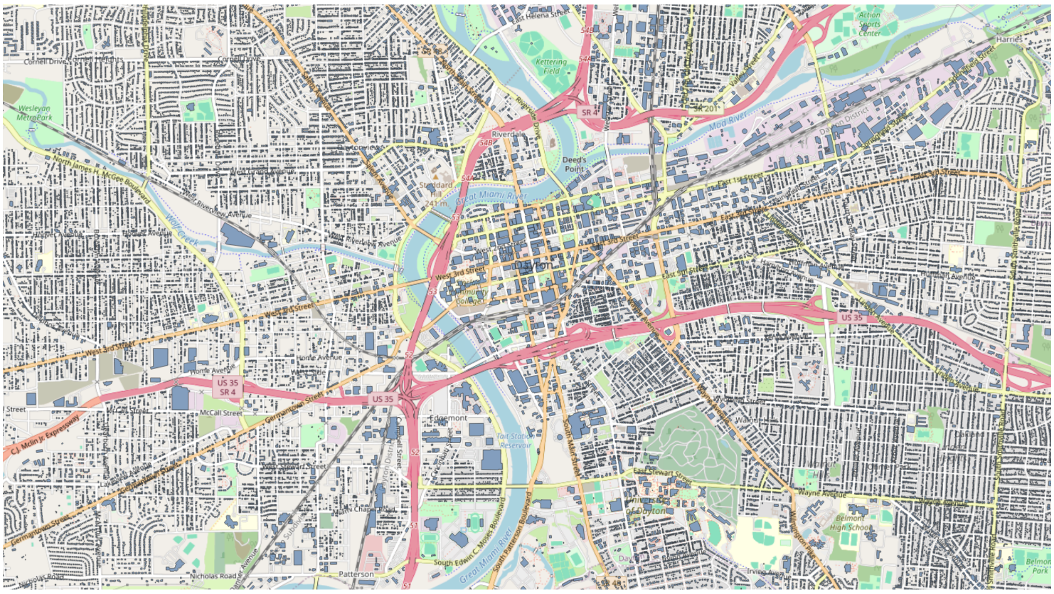


Figure 4. Buildings in Dayton, Ohio

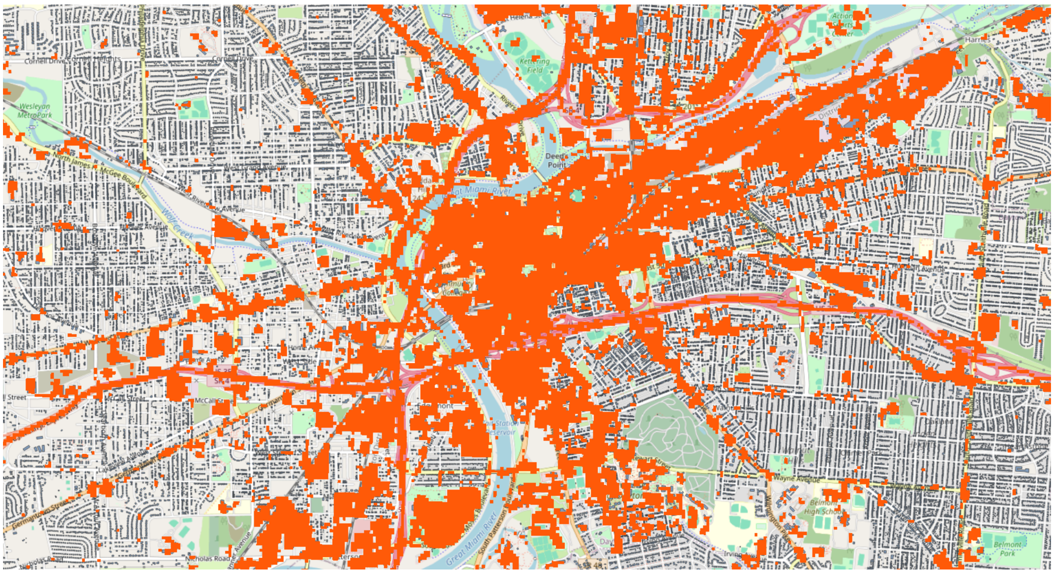


Figure 5. Urban Heat Islands in Dayton, Ohio with Buildings (Thresholding)

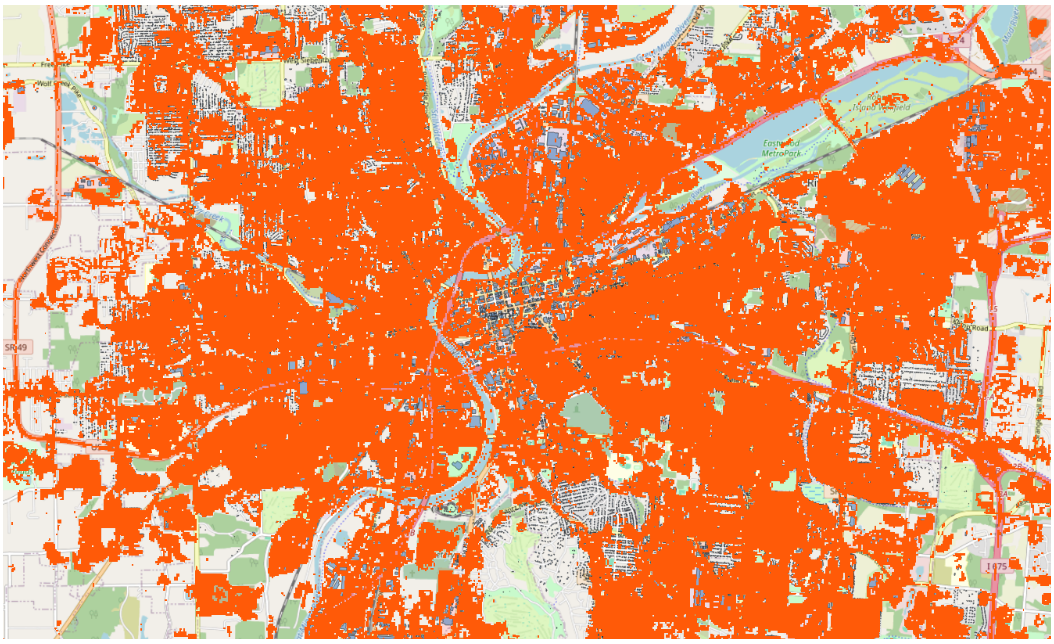


Figure 6. Urban Heat Islands in Dayton, Ohio with Buildings (K-Means)

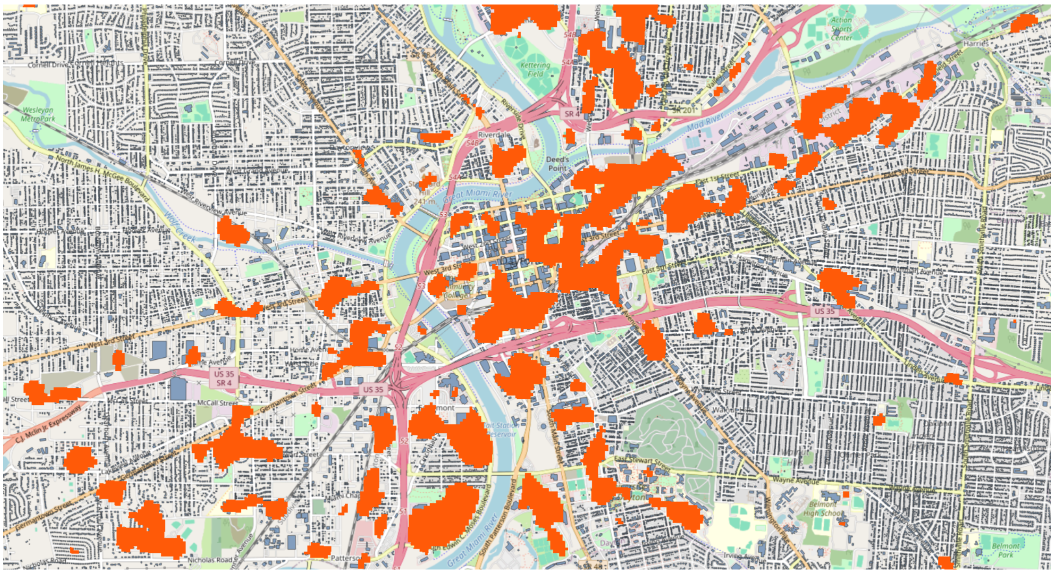


Figure 7. Urban Heat Islands in Dayton, Ohio with Buildings (Random Forest)

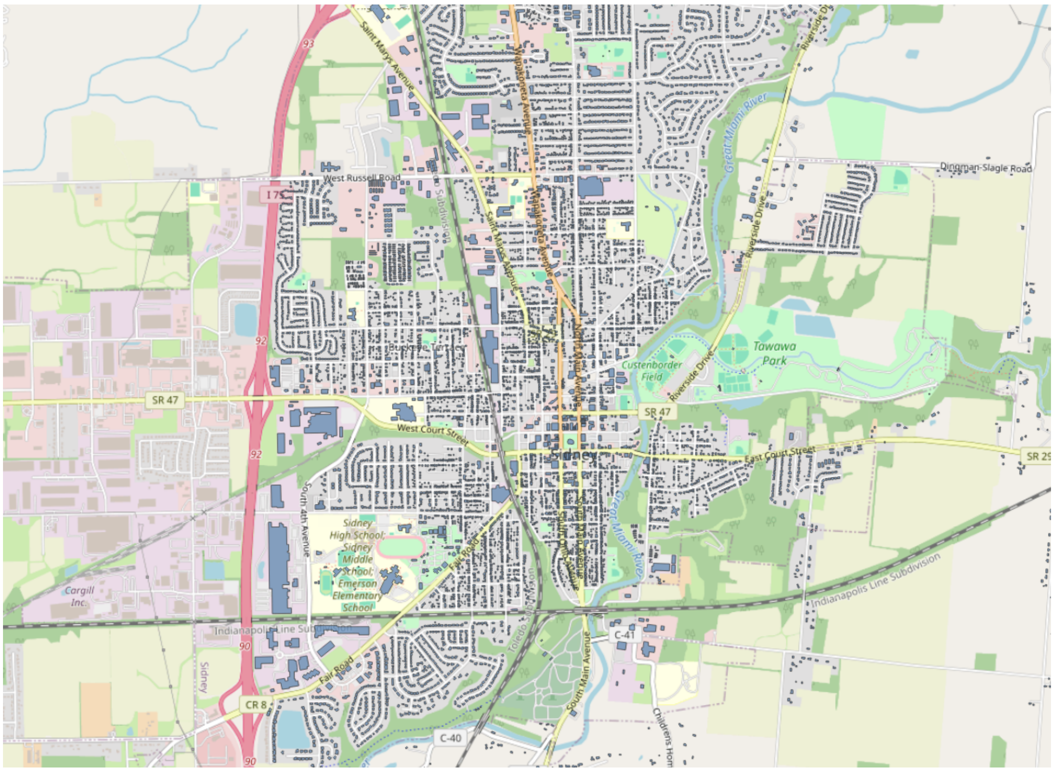


Figure 8. Buildings in Springfield, Ohio

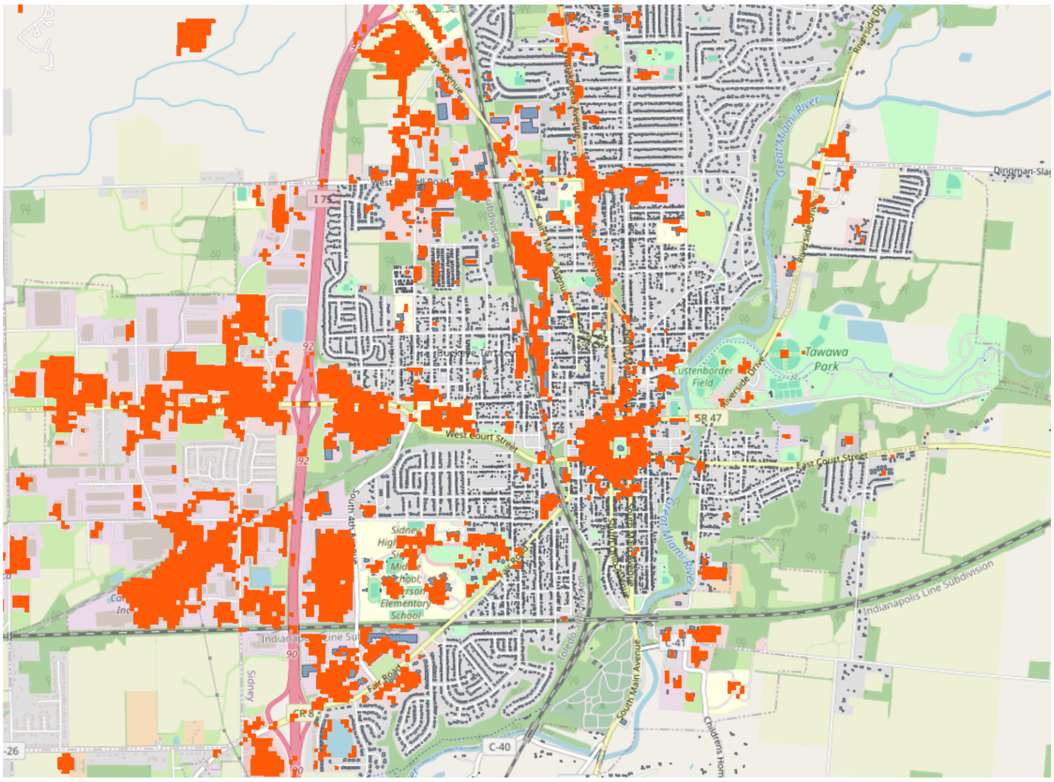


Figure 9. Urban Heat Islands in Springfield, Ohio with Buildings (Thresholding)

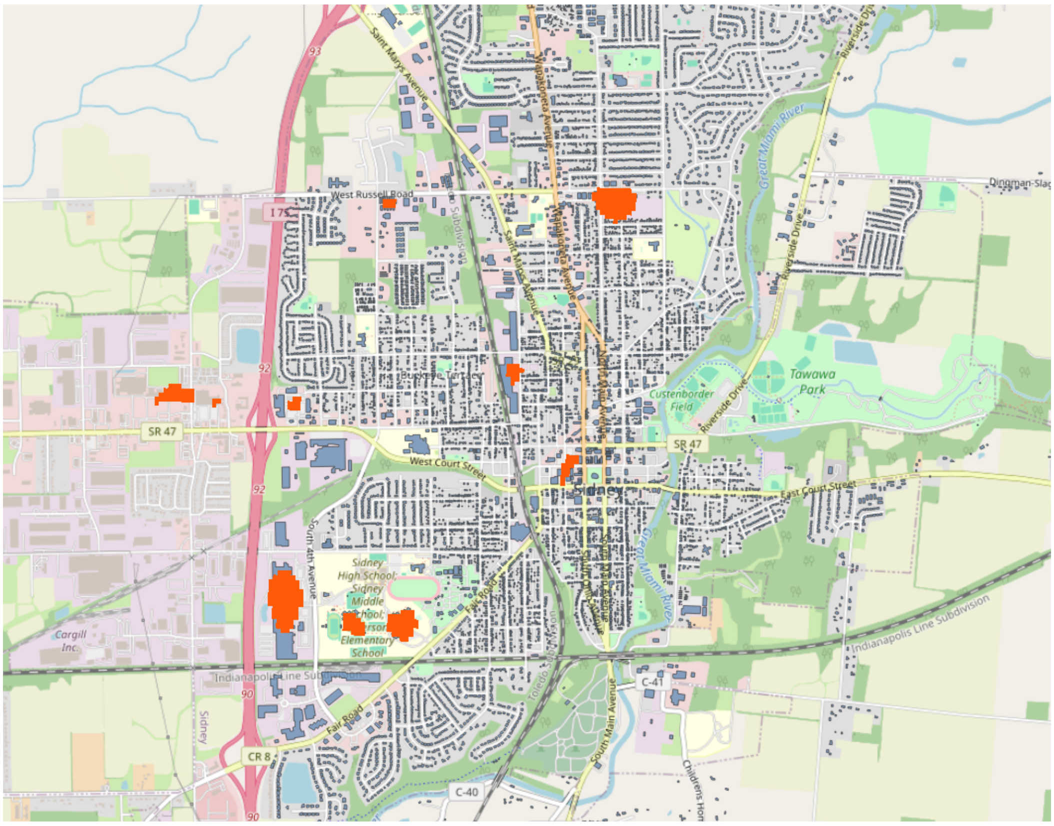


Figure 10. Urban Heat Islands in Springfield, Ohio with Buildings (Random Forest)

5. Analysis Of the Results Obtained

The analysis of Urban Heat Island (UHI) effects, based on the NDVI, Land Surface Temperature (LST), and the UHI effect map, provides significant insights into the spatial distribution of heat across urban and vegetated areas. The NDVI map reveals clear patterns of vegetation density, with higher NDVI values representing densely vegetated regions and lower values indicating urbanized or barren areas. The cooling influence of vegetation is evident, as regions with dense vegetation correspond to lower surface temperatures, emphasizing the role of green spaces in mitigating urban heat.

The LST map highlights the distribution of surface temperatures across the study area, with elevated temperatures predominantly observed in urbanized zones, as indicated by red and yellow tones. These regions align with built-up areas characterized by higher concentrations of impervious surfaces, which are known to retain and radiate heat. Conversely, cooler temperatures, represented by darker tones, are concentrated in areas with significant vegetation cover, corroborating the inverse relationship between vegetation and surface temperatures.

The UHI effect map integrates NDVI and LST data to provide a comprehensive visualization of heat-affected zones. The overlay of the heatmap on OpenStreetMap further validates the spatial alignment of UHI hotspots with urban structures. The results indicate that areas with dense building concentrations, such as commercial or residential zones, experience significantly higher UHI intensity, while vegetated areas demonstrate a notable cooling effect. This relationship underscores the critical impact of urbanization on thermal patterns and highlights the mitigating potential of vegetation in reducing localized heat stress.

These findings provide important insights into the interplay between urban density, vegetation cover, and the UHI effect. They emphasize the need for sustainable urban planning strategies to address the growing challenges posed by UHI effects. Increasing green spaces, such as urban parks, green roofs, and street trees, could play a pivotal role in reducing surface temperatures and improving urban thermal comfort. Furthermore, the identification of UHI hotspots through this analysis offers a foundation for targeted interventions in areas most affected by urban heat, aiding policymakers and urban planners in developing effective mitigation strategies. This study highlights the necessity of integrating vegetation management into urban development plans to foster sustainable and climate-resilient cities.

6. Conclusion and Future Work

In conclusion, this study demonstrates the potential of satellite-based thermal infrared imagery combined with computer vision techniques to effectively detect and map Urban Heat Island (UHI) effects in metropolitan areas. By leveraging Landsat 8/9 thermal data and machine learning algorithms such as Random Forest, the research successfully identifies heat hotspots and provides a deeper understanding of UHI distribution. The findings contribute to urban sustainability efforts by offering valuable insights that can guide urban planners and policymakers in designing interventions, such as green infrastructure and sustainable urban layouts, to mitigate the adverse impacts of UHIs. The study also highlights the advantages of using satellite imagery over traditional temperature measurement methods, providing more accurate, large-scale, and real-time data for UHI monitoring.

For future work, several avenues of exploration can be pursued. First, the incorporation of additional datasets, such as those from Sentinel-2 satellites, could improve the temporal and spatial resolution of the analysis. Second, integrating ground-based temperature data could enhance model accuracy and validation. Further exploration of advanced machine learning techniques, including deep learning methods like convolutional neural networks (CNNs), could lead to even more precise classification of UHI hotspots. Additionally, expanding the study to include more diverse urban areas and incorporating climate change projections would allow for a broader understanding of future UHI trends and their potential impact on urban health and infrastructure. Finally, investigating the effectiveness of different mitigation strategies through simulation models could provide actionable solutions to reduce the urban heat burden in affected cities.

7. Challenges and Adjustments

In the undertaking of our Urban Heat Island (UHI) detection project, we encountered a series of challenges that required adaptive strategies to ensure the integrity and accuracy of our analysis. These challenges spanned from initial data acquisition to the final visualization steps. Here, we detail these challenges and the adjustments we implemented:

1. **Challenges**

    - **Data Collection and Cloud Coverage:** Initially, obtaining the correct satellite imagery proved to be a complex task due to the confusing interface of the dataset provider website, which made selecting the specific bands and footprints required for our analysis difficult. Furthermore, the first batch of data we collected was heavily affected by cloud coverage, compromising the clarity and usability of the imagery. To address this, we refined our data acquisition process by applying stricter criteria for cloud coverage, specifically setting the cloud cover filter to 0-4%. This adjustment significantly improved the quality of the satellite images, ensuring that cloud cover did not adversely affect our analysis.
    - **Resource Constraints During Data Processing:** The task of overlaying the heatmap of UHI effects on OpenStreetMap (OSM) proved to be resource-intensive, straining our computational resources. This challenge was exacerbated by the high-resolution nature of both the heatmap and the base map, which required significant memory and processing power. To mitigate this issue, we optimized our data processing scripts to be more efficient in handling large datasets without compromising the speed or accuracy of our analysis.
    - **Coordinate System Misalignment:**A significant technical challenge arose during the visualization stage when we discovered that the heatmap and the OSM base

map were using different coordinate systems. This misalignment resulted in inaccuracies in the overlay process, which initially went unnoticed. Once identified, we took corrective action by converting all data to a common coordinate system. This involved using GIS software to reproject the heatmap data to match the coordinate system of the base map, ensuring that the UHI effects were accurately represented in relation to the geographical features on the OSM.

2. **Adjustments**
   Initially, we planned to conduct a UHI (Urban Heat Island) analysis specifically for the Columbus area. However, the scope of the analysis was later expanded to include several major cities in Ohio, such as Middletown Ohio, Dayton Ohio, Springfield Ohio, Richmond Indiana, Sidney Ohio, Findlay Ohio, and Lima Ohio..
   In terms of methodology, our initial approach involved using a standard thresholding method to calculate the UHI effect. Subsequently, we decided to adopt a more comprehensive approach by incorporating three distinct methods: k-means clustering, random forest modeling, and the thresholding method. This adjustment aims to provide a more robust and comparative analysis of UHI effects across the selected cities.
   Expanding the scope of our Urban Heat Island (UHI) analysis to include multiple cities in Ohio, alongside adopting a multi-method approach, significantly enhances the depth and impact of our project. Initially focused on Columbus, the broader geographic scope now encompasses diverse urban landscapes, providing a more comprehensive understanding of UHI effects across cities of varying sizes and urbanization levels. This change not only improves the generalizability of our findings but also allows for the identification of region-wide patterns and localized differences in UHI intensity. By incorporating thresholding, k-means clustering, and random forest modeling, the methodological rigor of the project has been greatly enhanced. This multi-method approach ensures a comparative analysis, where results from different techniques can validate and complement each other, improving the reliability of our findings. Each method offers unique insights—clustering uncovers natural groupings of heat intensity, random forest modeling highlights predictive relationships, and thresholding provides a straightforward assessment of temperature variations. Together, these methods add scalability and versatility to our analysis, enabling applications beyond the current study.

References

1. Nichol, J. (2009). "An emissivity modulation method for spatial enhancement of thermal satellite images in urban heat island analysis." *Photogrammetric Engineering & Remote Sensing*, 75(5), 547–556. American Society for Photogrammetry and Remote Sensing.
2. Saiwa AI. (2024). "The Power of Computer Vision in Satellite Imagery." Retrieved from https://saiwa.ai/blog/computer-vision-in-satellite-imagery/. Accessed on 2024-03-01.
3. Essa, W., van der Kwast, J., Verbeiren, B., & Batelaan, O. (2013). "Downscaling of thermal images over urban areas using the land surface temperature-impervious percentage relationship." *International Journal of Applied Earth Observation and Geoinformation*, 23, 95–108. Elsevier.
4. Yao, R., Wang, L., Huang, X., Niu, Y., Chen, Y., & Niu, Z. (2018). "The influence of different data and method on estimating the surface urban heat island intensity." *Ecological Indicators*, 89, 45–55. Elsevier.
5. Li, X., Wang, Y., & Zhang, Z. (2022). "Urban heat island detection using Landsat 8 and machine learning techniques." *Remote Sensing*, 14(3), 456. MDPI.
6. Zhou, J., & Wang, L. (2021). "Predicting urban surface temperatures using deep learning and satellite imagery." *ISPRS Journal of Photogrammetry and Remote Sensing*, 175, 65–80. Elsevier.
7. Gupta, A., Singh, R., & Kumar, P. (2022). "Object-based CNN approach for urban heat island detection using Landsat 8/9." *International Journal of Remote Sensing*, 43(8), 2890–2910. Taylor & Francis.
8. Chen, Y., Liu, X., & Wang, S. (2023). "UNet-based deep learning for urban heat island segmentation." *Remote Sensing of Environment*, 280, 113226. Elsevier.
9. Singh, A., & Kaur, J. (2020). "Delineation of urban heat-affected zones using K-means clustering and NDWI." *Sustainable Cities and Society*, 52, 101839. Elsevier.

10. Wang, Y., Li, Z., & Zhang, Q. (2021). "Limitations of satellite thermal data for urban heat island analysis." *Urban Climate*, 38, 100885. Elsevier.
11. Huang, X., & Liu, Y. (2022). "Multi-source data fusion for enhanced urban heat island mapping." *ISPRS Journal of Photogrammetry and Remote Sensing*, 184, 215–227. Elsevier.