Research Article

Urban Heat Island Disparities: A Geospatial Analysis of Household Income and Land Surface Temperatures in Lafayette, Louisiana

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Abstract: The urban heat island (UHI) effect increases heat exposure in cities and disproportionately affects vulnerable groups. This study investigates the relationship between household income, vegetation cover, and land surface temperature (LST) in Lafayette, Louisiana. We used Landsat 8 thermal infrared imagery from July 30, 2023, to measure LST at a 30-m resolution. We then compared these results with 2018 U.S. Census block group income data. We classified land cover into vegetation and non-vegetation classes using 2023 NAIP aerial images, and we validated our classification with an accuracy assessment based on 200 random points. Our results show a negative relationship ($r = -0.38$, $R^2 = 0.14$, $p < 0.05$) between income and surface temperature and a positive relationship ($r = 0.41$, $R^2 = 0.17$, $p < 0.05$) between income and vegetation. Block groups with lower incomes also had less vegetation cover. This suggests that the lack of vegetation contributes to higher LST. We did not find a significant relationship between parcel size and income, which means that land ownership density alone does not explain differences in heat. These findings highlight how socioeconomic and environmental factors work together to create uneven heat burdens. Policymakers may consider targeted tree planting and green infrastructure projects in vulnerable communities to mitigate heat-related risks and reduce energy costs.

Keywords: urban heat island, heat disparities, remote sensing, vegetation cover, land surface temperature

1. Introduction

Urban heat islands (UHIs) are urban areas that experience higher temperatures than nearby suburban and rural areas. UHIs can be classified into surface, canopy, and boundary types, with surface UHIs commonly derived from satellite imagery (Xian & Crane, 2006). In contrast, canopy and boundary UHIs are more difficult to measure because they require complex models based on interpolating weather station data. The UHI effect mainly comes from the heat-retaining qualities of impervious surfaces like asphalt and concrete, reduced vegetation cover, and building designs that restrict airflow. In contrast, areas with vegetation help cool cities by providing shade and releasing moisture through evapotranspiration (Knipling, 1970; Bowler *et al.*, 2010).

UHI effects do not appear evenly throughout cities. Dense development reduces the space available for green infrastructure, such as parks and community gardens. This leads to uneven exposure to heat, which is often called heat disparity or heat inequity. Socioeconomic factors are closely linked to these disparities. Several studies show that low-income and minority groups often live in hotter neighborhoods with less vegetation and more impervious surfaces (Hsu *et al.*, 2021; Jesdale *et al.*, 2013; Nesbitt *et al.*, 2019). These inequities pose a risk to public health, as heat exposure increases the risk of heat exhaustion, heat stroke, and heart problems, particularly for the elderly, young children, and individuals with existing health issues (Anderson & Bell, 2011). Beyond health impacts, UHIs may lead to higher household energy use for cooling,

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with some estimates suggesting that urban heat can raise electricity use by nearly 20% in certain U.S. cities (Li *et al.*, 2019). These effects add to the financial burdens faced by low-income households.

While research has clearly shown UHI disparities in large cities, there are fewer studies focused on medium-sized cities in the southern U.S., where poverty rates may be high and local planning resources may be limited. Lafayette, Louisiana, presents a useful case study because of its hot, humid climate, high poverty rate, and lack of previous UHI research. Understanding local heat disparities is important for guiding future planning and informing mitigation strategies for current conditions.

The purpose of this study is to investigate the presence and causes of UHI disparities in Lafayette, Louisiana. Specifically, this study will aim to answer the following research questions: (1) Do lower-income block groups have higher land surface temperatures than higher-income groups?, (2) How does vegetation cover change with household income, and how much does it influence the relationship between income and heat exposure?, and (3) Does parcel size, which indicates land ownership patterns and development density, relate to household income and surface temperature? By addressing these questions, this study will add to the existing literature on UHI and environmental disparities, filling in the knowledge gaps for this area. It will also provide relevant insights to support equitable climate adaptation and urban planning in Lafayette and similar areas.

2. Study Area and Methods

2.1. Study Area and Data

Lafayette, Louisiana, was chosen as the study area because it is a mid-sized city in the southern United States (U.S.; Figure 1). It has hot, humid summers and socioeconomic differences across the city. These factors make Lafayette a good case study for examining how urban heat island affects vulnerable communities. The city's poverty rates, expanding impervious surfaces, and the lack of previous UHI research emphasize its importance for studying urban heat inequalities.

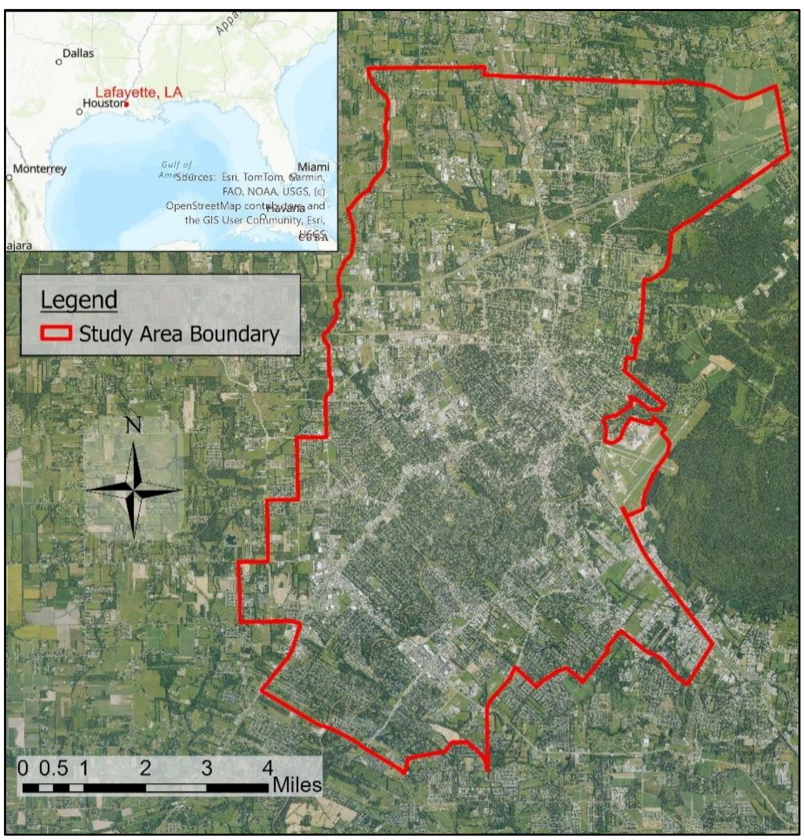

Figure 1. Natural color NAIP image of Lafayette, LA, with its relative location to the Southeast United States.

Census block groups mainly within the city limits were used as the unit of analysis to combine environmental and socioeconomic data. This study used four main datasets: (1) Landsat 8 thermal infrared imagery to calculate land surface temperature (LST), (2) National Agriculture Imagery Program (NAIP) aerial imagery for land cover classification, (3) U.S. Census Bureau block group data for household income and poverty statistics, and (4) local parcel boundaries from the Lafayette Consolidated Government (LCG) to evaluate land ownership density. Table 1 summarizes all datasets, including their sources, formats, and uses.

Table 1. Summary of datasets used in this study.

Dataset	Source	Year/ Date	Format	Resolution/ Scale	Purpose
Landsat 8 Collection 2 Level 2 Surface Temperature (Band 10)	USGS EarthExplorer	July 30, 2023	Raster (TIFF)	30 m	Derivation of land surface temperature
National Agriculture Imagery Program Aerial Mosaic	USDA NRCS Geospatial Data Gateway	2023	Raster (TIFF)	0.3 m (30 cm)	Supervised classification of vegetation vs. non-vegetation
Census Block Groups with Demographics	Esri Demographics Team (ACS 5-year estimates)	2018	Vector (Shapefile/Feature Layer)	Block group	Median household income, poverty statistics
Parcel Boundaries	Lafayette Consolidated Government	2023	Vector (Shapefile)	Parcel	Proxy for land ownership density (average parcel size)
Lafayette City Limits	LCG / ArcGIS Online	2023	Vector (Shapefile)	Municipal boundary	Define the study area extent

2.2. Workflow Overview

We conducted all geospatial analysis in ArcGIS Pro 3.4. The geospatial workflow included four sequential steps: (1) obtain land surface temperature data, (2) perform land cover classification, (3) integrate socioeconomic data, and (4) perform statistical analysis. First, we processed Landsat 8 thermal infrared imagery (Band 10) from July 30, 2023, to derive LST using scaling factors from the USGS, then converted it from Kelvin to degrees Fahrenheit. We then projected the LST raster to NAD 1983 UTM Zone 15N and clipped it to the Lafayette city limits. Figure 2a presents the resulting LST raster where red symbolizes hotter temperatures and blue symbolizes cooler temperatures. Next, we classified land cover from 2023 NAIP color-infrared imagery into vegetation and non-vegetation categories using a supervised maximum likelihood method, with training samples gathered from representative areas such as tree canopies, lawns, impervious surfaces, and rooftops. We evaluated classification accuracy using 200 random points, compared against reference NAIP imagery, and summarized the results in a confusion matrix. We used block group boundaries as the unit of analysis. The block groups used for this study can be viewed in Figure 2b, displayed in a red-to-yellow color scheme based on their 2023 median household income. Red block groups have the lowest median values, while yellow ones have the highest. We applied zonal statistics to calculate average LST and percent vegetation for each block group, while parcel boundaries from the Lafayette Consolidated Government were used to determine mean parcel size. We joined all outputs to socioeconomic attributes using 2018 American Community Survey (ACS) block group income data for statistical comparison in Microsoft Excel. Lastly, we performed Pearson correlation and linear regression to quantify relationships among income, vegetation, parcel size, and LST. This workflow provided a reproducible, multi-scalar method for linking socioeconomic disparities with patterns of heat exposure in Lafayette.

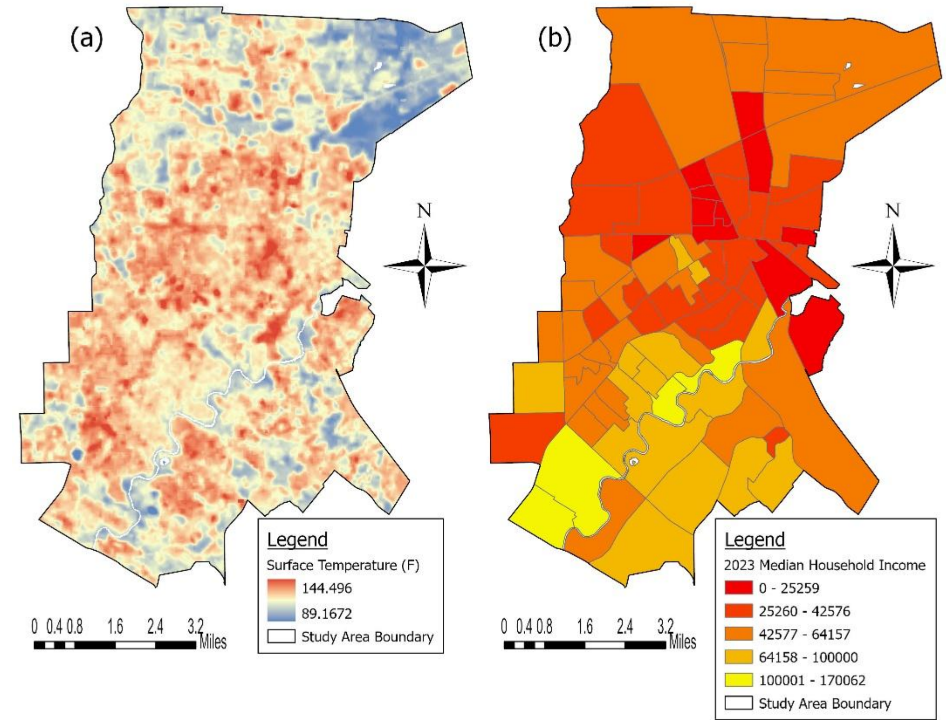

Figure 2. The city of Lafayette study area with (a) land surface temperature and (b) 2023 median income for each block group, where red is the lowest and yellow is the highest.

2.3. Land Surface Temperature Retrieval

This study focused solely on surface temperature disparities due to the complexity of modeling the surface, canopy, and boundary UHIs together. Deriving surface temperatures from raw satellite images can be a complicated process as well. Conveniently, the Landsat U.S. Collection 2 (C2) Analysis Ready Data (ARD) dataset in the USGS EarthExplorer database offers reliable surface temperature products. These products include pre-calculated land surface temperature values generated using numerous factors, including the Level 1 Top of Atmosphere (TOA) reflectance from Band 10 and normalized difference vegetation index (NDVI) values. Therefore, a Landsat Collection 2 Level 2 surface temperature image tile from this dataset was used to create a surface temperature map of Lafayette, LA.

The surface temperature raster layer used for statistical analysis was created from a preprocessed Band 10 (thermal infrared) image tile captured by Landsat 8's Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS). Landsat 8 Collection 2 Level 2 data (Path 23, Row 39) acquired on July 30, 2023, were chosen because of low cloud cover of less than 5% and because they matched peak summer conditions, when UHI intensity is highest.

Thermal band data (Band 10) were changed from digital numbers to at-sensor brightness temperature using the radiometric rescaling coefficients in the metadata (Sayler, 2024). We then calculated surface temperature using the emissivity correction method and converted it from Kelvin to degrees Fahrenheit for easier understanding (Ahmed *et al.*, 2024). The resulting LST raster was reprojected to NAD 1983 UTM Zone 15N and clipped to the Lafayette municipal boundary to define the area for the analysis.

2.4. Land Use/Land Cover Classification

Land use classifications are valuable for quantifying the types of land use within a designated study area (Poirier Chicola, 2021). This method was particularly useful for generating land use statistics that were subsequently compared with income statistics provided by the U.S. Census Bureau. An aerial image of Lafayette, collected by the National Agriculture Imagery Program (NAIP) in 2023, was used for land use classification due to its high spatial resolution of 30 cm. A color-infrared county mosaic for Lafayette Parish was obtained from the Natural Resource Conservation Service (NRCS) Geospatial Data Gateway.

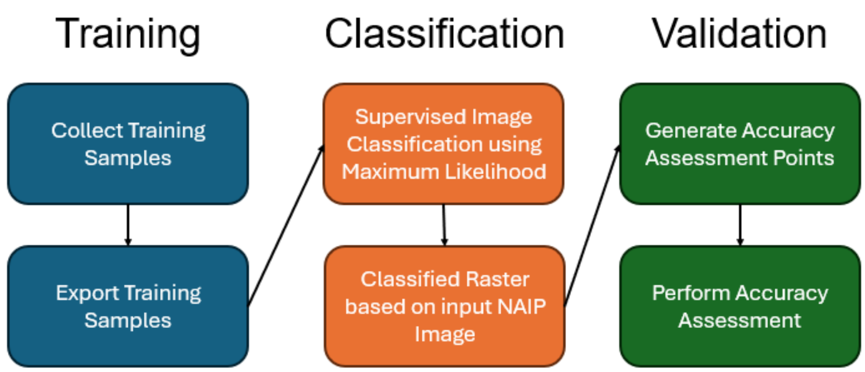

Figure 3. The general land use classification workflow used in this study. Training data was used to classify the NAIP aerial imagery of the city of Lafayette. An accuracy assessment was used to determine the effectiveness of the classification method (Congalton & Green, 1999).

The color-infrared NAIP imagery was classified into two categories: vegetation (tree canopy, grass, lawns) and non-vegetation (impervious surfaces, rooftops, bare soil). This classification used a supervised maximum likelihood classification (MLC) approach. MLC was chosen for its strong performance in binary vegetation classification tasks and its fit with NAIP's spectral characteristics (Aziz & Alwan, 2021).

Color-infrared imagery consists of near-infrared, red, and green spectral bands in that order. This color-infrared band combination was selected instead of natural color to better distinguish between vegetation and developed land. Plant leaves reflect high amounts of near-infrared light (Knipling, 1970), allowing color-infrared imagery to effectively highlight the presence of vegetation and facilitate identification during image classification. Training data included 37 manually digitized polygons (17 for vegetation and 20 for non-vegetation) spread across the study area to capture spectral variability among different land cover types. We assessed classification accuracy with 200 stratified random points validated against unclassified NAIP imagery. A confusion matrix was created to calculate overall accuracy, user's accuracy, producer's accuracy, and the kappa coefficient. Although the kappa statistics have limitations as a reliability metric (Foody, 2020), it was included for consistency with earlier UHI classification studies.

2.5. Socioeconomic and Parcel Data

Socioeconomic data, such as median household income and the number of households living in poverty, came from the 2018 American Community Survey 5-year estimates. This data is the latest demographic information available at the block group level. Although the ACS data is older than the 2023 satellite imagery, we recognize this timing issue as a limitation, but it does not significantly impact the spatial patterns of income distribution.

We obtained parcel boundary data from the Lafayette Consolidated Government to calculate the average parcel size for each block group. We included parcel size as a way to measure land ownership density and development intensity. This allows us to explore whether patterns of parcelization affect heat exposure.

2.6. Statistical Analysis

All spatial analyses were done in ArcGIS Pro 3.4. Zonal statistics calculated block group averages for land surface temperature and vegetation cover. We determined percent vegetation cover as the ratio of classified vegetation pixels within each block group polygon. The average parcel size was found by dividing the total parcel area by the number of parcels in each block group.

We calculated Pearson correlation coefficients to examine relationships among variables, reporting significance testing (p-values). Linear regression models estimated the strength of associations, and R^2 values described explanatory power.

3. Results

3.1. Land Cover Classification Accuracy

The supervised classification of 2023 NAIP imagery reached an overall accuracy of 85% and a kappa coefficient of 0.79. This shows a strong agreement between classified and reference data. User accuracy was 89% for vegetation and 82% for non-vegetation. Producer accuracy was 87% and 84%, respectively. Full results of this accuracy assessment are listed in the confusion matrix generated during the assessment, which is displayed as Table 2. Misclassifications occurred most often in shaded vegetation and senescent grass areas, where spectral signatures overlapped with non-vegetated surfaces. The kappa coefficient value from the 200-point assessment was lower, yet a kappa coefficient of 0.79 still suggests substantial agreement between user and producer values, as noted by Geymen (2016), thus validating the classification method. A kappa coefficient of 0.79 indicates substantial agreement between classified and ground-truth values, as defined by Landis & Koch (1977).

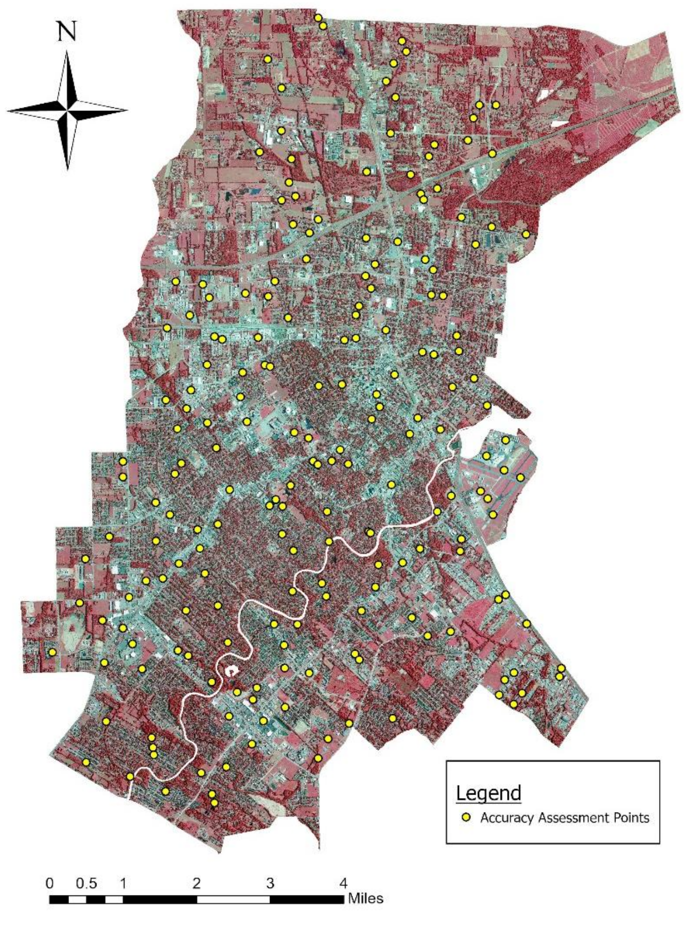

Figure 4. Distribution of 200 points generated for accuracy assessment overlayed on 2023 Color Infrared NAIP imagery used for supervised image classification. Accuracy assessment points are displayed in yellow.

Table 2. Accuracy assessment of the classified image using 200 random points.

		Reference Image		User Accuracy
		Non-Vegetation	**Vegetation**	
Classified Image	**Non-Vegetation**	**95**	5	0.95
	Vegetation	16	**84**	0.84
Producer's Accuracy		0.86	0.94	**0.90**
Kappa		**0.79**		

Certain surfaces and their features led to more significant errors in classification than others. For instance, shaded vegetation was frequently misidentified as non-vegetation. Thick layers of hay also resulted in incorrect classifications. Large grass fields that should have appeared as solid areas were often marked by random spots or splotches of non-vegetation, which were indicated by lighter shades of pink on the color-infrared NAIP image. After visiting some of these sites, it was confirmed that these lighter colors were indeed caused by the presence of hay. This issue mainly occurred due to the decomposition of chlorophyll in the grass, which hindered the reflection of near-infrared light.

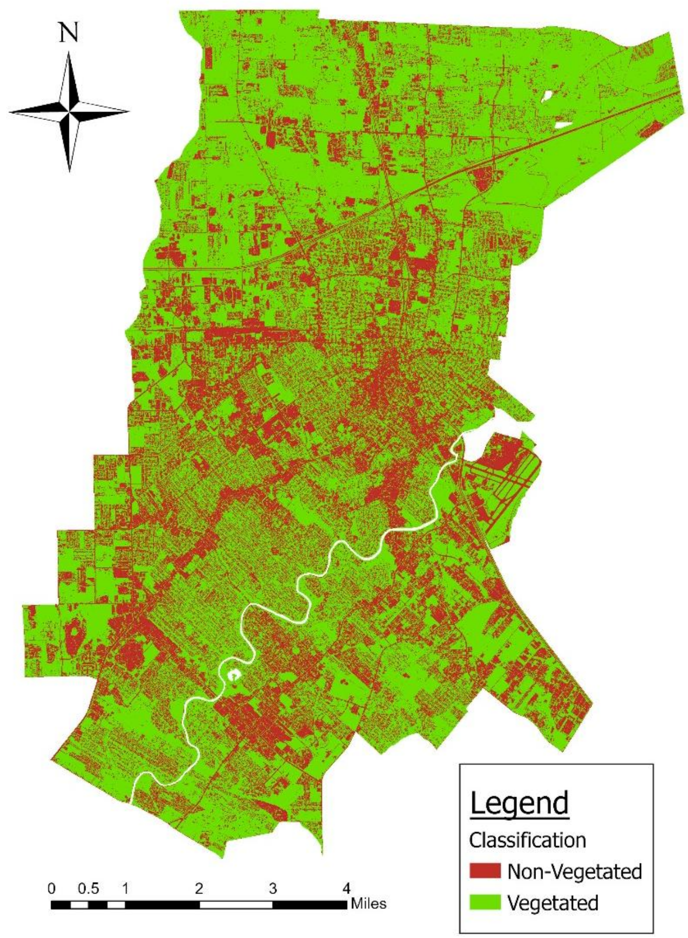

Figure 5. Classified image produced by the maximum likelihood image classification method using the 2023 Color Infrared NAIP image. Green represents areas classified as vegetation, whereas red/brown represents non-vegetated areas.

3.2. Mean Income Relationships

3.2.1. Income and Surface Temperature

Average land surface temperatures in block groups ranged from 110°F to 129°F, with standard deviations between 1.6°F and 8.5°F. Regression analysis showed a significant negative relationship between median household income and average land surface temperature ($r = -0.38$, $R^2 = 0.14$, $p < 0.05$), meaning that lower-income block groups generally had higher surface temperatures than higher-income areas (Figure 6).

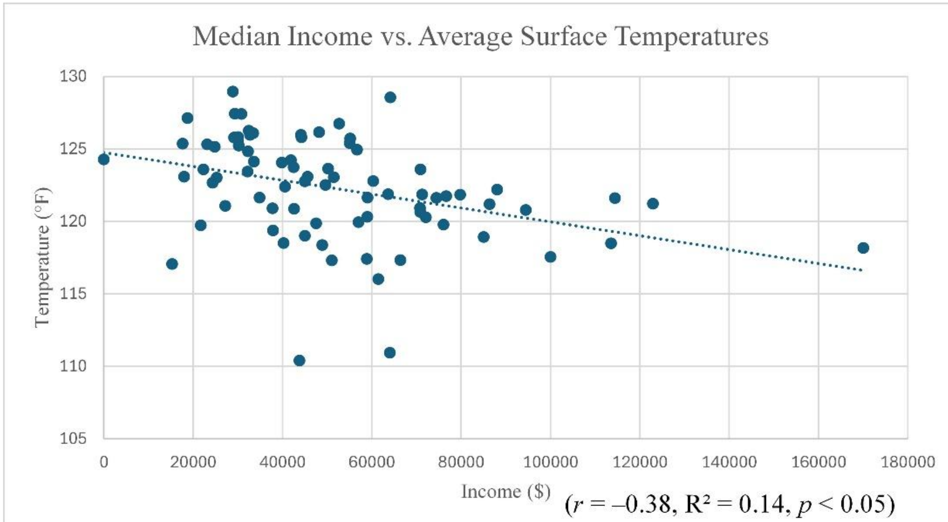

Figure 6. 2023 block group median household income relationship with average surface temperatures.

Block groups with more varied land cover had larger standard deviations in surface temperature. This indicates that local climate differences are affected by the uneven distribution of vegetation. Poverty metrics showed a similar trend: areas with more households living below the poverty line had significantly higher average surface temperatures (Figure 7).

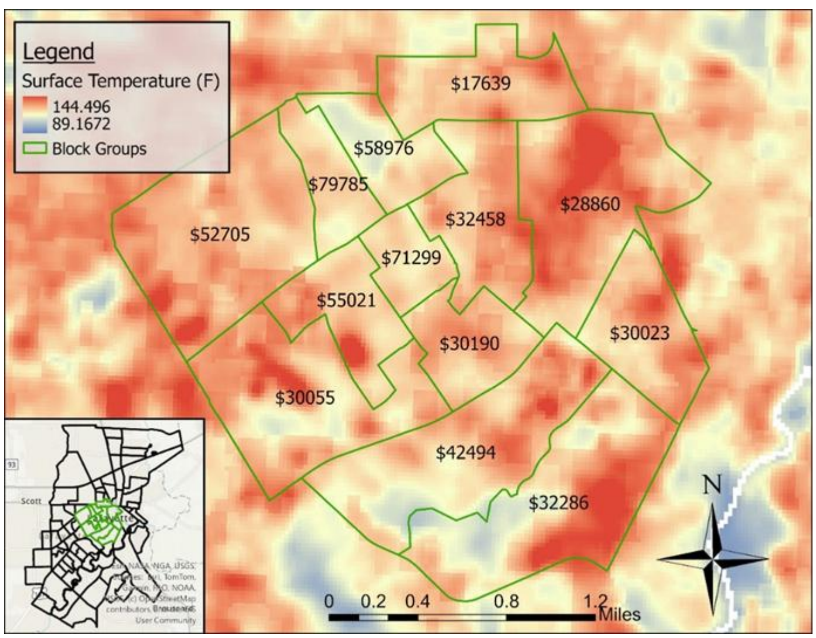

Figure 7. Block groups located in the center of the study area, with the corresponding 2023 median income superimposed on the surface temperature map. Red shades represent hotter temperatures, where yellows and blues are cooler.

3.2.2. Income and Vegetation Cover

Vegetation cover had a positive relationship with median household income ($r = 0.41$, $R^2 = 0.17$, $p < 0.05$). This means that higher-income neighborhoods had significantly more vegetation than lower-income ones (Figure 8). This connection implies that vegetation is important in creating heat differences. Wealthier neighborhoods benefit from more tree cover and green spaces, which help lower surface temperatures through shading and evapotranspiration.

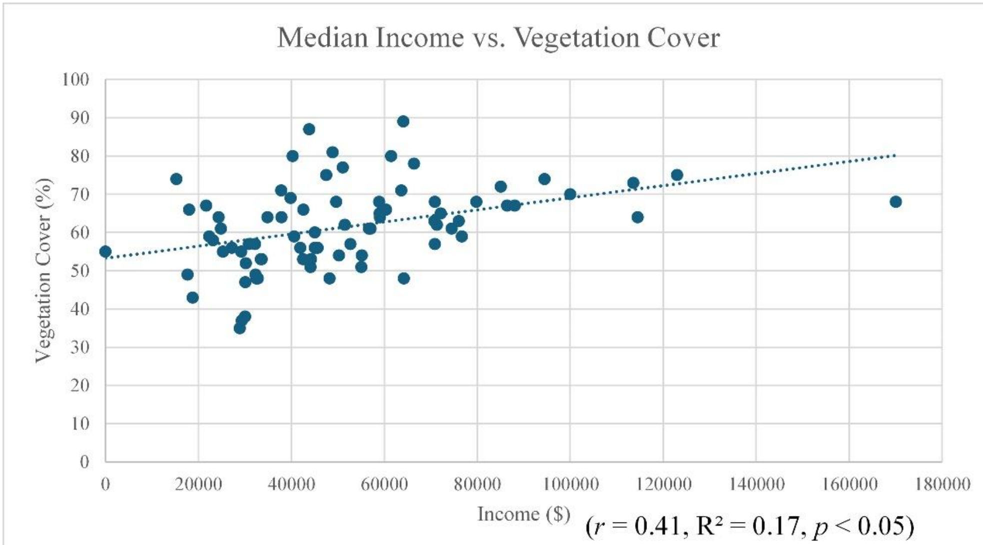

Figure 8. 2023 block group median household income relationship with vegetation cover.

A comparison shows this gap clearly: a high-income block group with 68% vegetation cover had an average land surface temperature of 106.3°F, while a low-income block group with 43% vegetation cover had an average land surface temperature of 127.1°F (Figure 9).

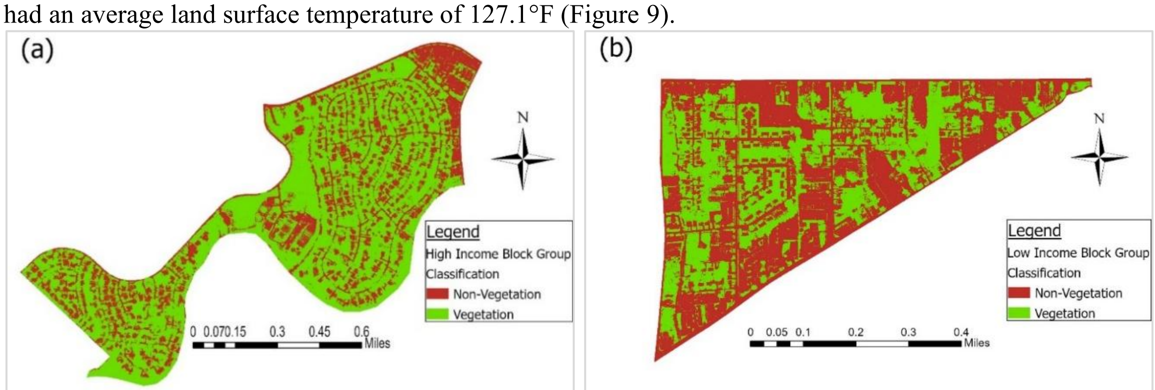

Figure 9. Comparison of vegetation cover in high- and low-income block groups using a classified NAIP image of Lafayette. (a) A higher income block group with a median income of $170,062, 68% vegetation coverage, and 106.3 °F average surface temperature compared to (b) a lower income block group with a median income of $18,747, 43% vegetation coverage, and 127.1 °F average surface temperature.

3.2.3. Income and Parcel Size

There was no significant relationship between parcel size and median household income ($r \approx 0.0$). This suggests that the patterns of land ownership and parcel size do not explain the heat differences seen (Figure 10). These findings indicate that vegetation cover is the key factor affecting spatial differences in heat exposure across Lafayette, not parcel size.

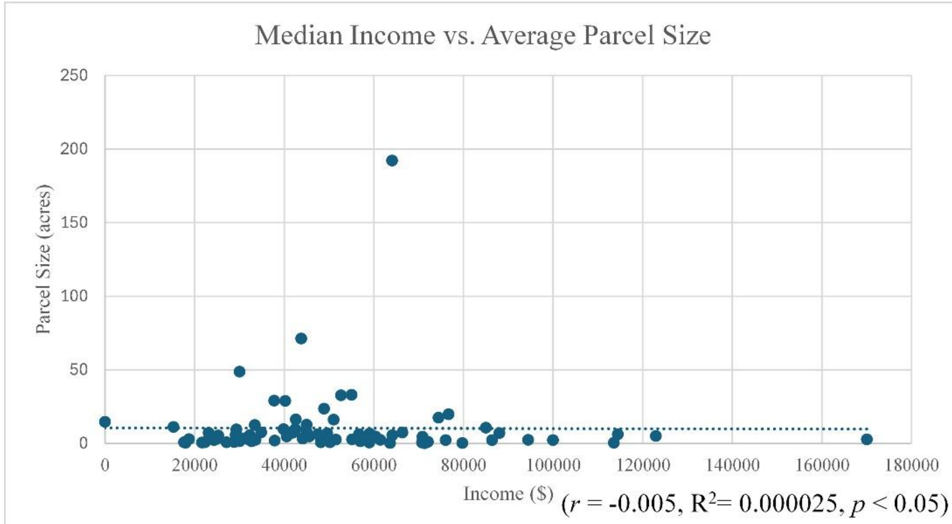

Figure 10. The 2023 block group median household income relationship with the average parcel size.

4. Discussion

This study shows that heat disparities exist across Lafayette, Louisiana. Lower-income neighborhoods face higher land surface temperatures and have less vegetation. These findings are aligned with nationwide studies that have found greater exposure to UHIs in low-income and minority areas (Hsu *et al.*, 2021; Jesdale *et al.*, 2013). By focusing on Lafayette, a medium-sized city in the southern U.S., this study expands environmental justice studies beyond the larger cities that often dominate the UHI literature.

4.1. Vegetation as a Mediating Factor

The negative correlation observed between income and temperature, along with the positive correlation between income and vegetation cover, highlights the role of vegetation in mitigating UHI. Vegetation lowers surface temperatures through shading and evapotranspiration (Bowler *et al.*, 2010). In Lafayette, lower-income areas have fewer trees and less green space, with limited changes for large-scale greening due to denser buildings and smaller lots. Similar issues with vegetation distribution have been found in other U.S. cities, where people in wealthier neighborhoods have more access to trees and parks (Nesbitt *et al.*, 2019).

4.2. Implications for Public Health

Heat disparities lead to health inequities. Higher surface temperatures increase the risk of heat exhaustion, heat stroke, and cardiovascular stress, especially for vulnerable groups like the elderly, children, and individuals with pre-existing conditions (Anderson & Bell, 2011). In Lafayette, where poverty rates are higher than the national averages, the energy and health burdens of UHI disproportionately impact those with fewer resources to cope, raising risks during extreme heat events.

4.3. Energy Use and Economic Burden

Higher surface temperatures boost household energy needs for cooling, driving up utility bills. Previous studies have shown that UHIs can lead to a nearly 20% rise in urban energy use (Li *et al.*, 2019). In Lafayette's low-income areas, the increased demand for cooling adds financial strain to already tight household budgets. This "energy-poverty-heat" connection highlights the need for policies that tackle environmental justice, climate resilience, and affordable housing.

4.4. Adaptation and Policy Relevance

Several strategies emerge from these findings. Increasing tree canopy cover through targeted planting in heat-vulnerable neighborhoods could greatly lower surface temperatures and improve comfort. Low-cost actions, like planting shade trees along residential streets or turning vacant lots into community green spaces, have successfully reduced local UHI intensity (Fadhil *et al.*, 2023). These strategies also contribute to goals of lowering peak electricity use and reducing health risks associated with heat exposure. For Lafayette, including equity-focused heat mitigation in city planning and zoning could ensure that investments in green infrastructure benefit underserved neighborhoods and future neighborhood development.

4.5. Contributions and Limitations

This study provides the first spatial analysis of UHI disparities in Lafayette, Louisiana. What started off as an undergraduate semester research project for a class turned into a study that can add to the limited research on UHI in smaller U.S. cities. It shows how open-source Earth observation data can be used with socioeconomic information to uncover heat exposure inequalities. However, there are some limitations to note. First, the income data from 2018 and LST imagery from 2023 do not match in time, due to data availability; this does not invalidate the correlations found, but does lower temporal accuracy. Second, only surface temperature was examined; canopy and boundary-layer UHIs, which might impact human thermal comfort more directly, were not considered. Also, while NAIP imagery provided finer resolution for small-scale land use-land cover classification, the use of the National Land Cover Dataset (NLCD) may improve standardization and reproducibility across larger study areas. This research study was part of an undergraduate semester course project where students were required to download their own imagery and perform their own land use-land cover classification based on training samples they created. Future studies should use multi-seasonal and multi-year imagery, include health outcome data, and explore different classification methods beyond maximum likelihood, which was the required classification method for the class research project, to strengthen vegetation analysis.

4.6. Broader Significance

Urban heat inequities are not limited to large cities but are also evident in smaller cities such as Lafayette, Louisiana. By documenting these differences, this study provides local policymakers and community members with information to support climate resilience projects. More broadly, it emphasizes the importance of including environmental justice factors in UHI research and resilience planning, ensuring that climate adaptation strategies protect the most vulnerable groups and help inform future infrastructure development.

5. Conclusions

The results of this study suggest that lower-income neighborhoods in Lafayette, Louisiana, have higher land surface temperatures and less vegetation cover. The negative correlation between household income and land surface temperature, along with the positive connection between income and vegetation cover, highlights how green spaces can impact urban heat differences. While parcel size did not relate significantly to income or temperature, the results point to vegetation loss as a main component contributing to unequal heat exposure.

The study adds to the understanding of UHI and environmental justice by looking at a medium-sized city in the southern U.S., which has not been explored in previous studies. The findings make it clear that heat inequity is not just a problem in large metropolitan areas, but it also affects smaller cities, especially those with high poverty levels.

From a policy perspective, the results stress the need for focused interventions that promote better public health. Programs that incorporate tree planting, turn vacant lots into green spaces, and prioritize greening efforts in low-income neighborhoods can help lower local temperatures, ease energy costs, and improve public health. Including these strategies in urban planning will be essential for building future infrastructure and helping combat rising temperatures in Lafayette and similar communities.

Future research is needed to address data and methodological limitations by incorporating multi-season analyses, studying canopy and boundary-layer UHIs, and adding health outcomes data. These efforts will increase understanding of the connections between socioeconomic factors, land cover, and urban heat, and support evidence-based adaptation strategies.

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Data Availability Statement: Data are available at their respective open-source locations: High-resolution aerial imagery for Lafayette Parish was sourced from the USDA's 2023 NAIP mosaic, available via https://nrcs.app.box.com/v/naip/file/1442308681697. Demographic data, including population and socioeconomic variables from 2018, were accessed through Esri's ArcGIS REST service (https://services.arcgis.com/P3ePLMYs2RVChkJx/arcgis/rest/services/AGOL_Base_2018_Final/FeatureServer). U.S. Census Bureau Block Groups with Demographic Attributes (ACS 5-Year Estimates) were obtained from ArcGIS Online. Local administrative boundaries, including parish and city delineations, were obtained from the Lafayette Consolidated Government's BaseLayers dataset (https://www.arcgis.com/home/item.html?id=4744e86e1607481aab7b42e03941ddeb). To assess land surface temperature, we utilized the Landsat Collection 2 ARD Tile Surface Temperature Bundle, downloadable through the USGS EarthExplorer platform (earthexplorer.usgs.gov). These combined resources enabled a multi-scalar analysis of urban heat island effects across geospatial, demographic, and thermal dimensions.

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