Health and social inequalities in Urban Heat Exposure Areas in New Orleans

Introduction

Background

The Urban Heat Island (UHI) effect is a serious environmental issue that increases heat in urban areas and creates significant challenges for the social, economic, health, and environmental systems of the cities. (Nguyen, 2024) In recent years, attention has focused on the social and health disparities caused by the uneven distribution of heat, as exposure has been linked to serious health risks, including heat stress (Arifwidodo and Chandrasiri, 2020) and increased mortality rates (Heaviside et al., 2016) among vulnerable population groups. Numerous studies have highlighted how urban heat disproportionately impacts marginalized communities, highlighting the need to better understand this critical issue. (Dialesandro et al., 2021; Hsu et al., 2021; Mitchell and Chakraborty, 2015).

Although extreme heat affects all urban residents, its impacts vary widely based on factors like age, race, income, and housing conditions (Benz & Burney, 2021; Karner et al., 2015; Renteria et al., 2022; Stillman, 2019). Health-related factors, particularly among vulnerable groups like older adults, children, people with disabilities, people of color and low-income population further worsen these disparities. Education also plays a critical role, as lower levels of education often lead to reduced awareness of heat risks and limited capacity to adapt (Shortridge et al., 2022). Considering social disparities, Renteria et al. (2022) found that neighborhoods with higher concentrations of racial minorities and lower socioeconomic status experience greater heat exposure. Similarly, Karner et al. (2015) observed that in the San Francisco Bay Area, low-income households face disproportionate exposure to heat due to factors like limited access to transportation.

In the context of New Orleans, studies have emphasized the connection between social factors and urban heat (de Jesús Crespo and Rogers, 2022). Nearly 80% of New Orleans residents live in areas that act as urban heat islands and make it feel at least 8°F hotter, according to Climate Central's analysis. (Brasted, Beheraj. 2024). The majority of population living in those areas of higher heat exposure, tend to be communities with lower-income residents and people of color with lower educational attainment. The studies found that areas with fewer trees, higher land surface temperatures (LST), more impervious surfaces, and a larger percentage of vulnerable residents are primarily concentrated in the southern part of New Orleans. Additionally, according to research by Lief (2014) there is a noticeable shift in the intensity and distribution of urban heat, highlighting the lasting impact of social inequalities in the face of climate-related disasters.

In this paper, our overall objective is to assess social and health inequalities in urban heat exposure in New Orleans. Using remote sensing data alongside socioeconomic variables provides valuable insights into the intricate relationship between environmental conditions and vulnerable populations. This approach has been widely recognized for its effectiveness in highlighting social inequalities (Mills et al., 2016; Sathyakumar et al., 2019). We pair mean land surface temperature data for summer month (August

2024) from the United States Geological Survey (USGS) with sociodemographic data from the American Community Survey at the block group level. We answer research questions on how social disparities and health status in New Orleans influence vulnerability to urban heat. We examine factors such as race, income, health conditions, and educational attainment to explore how social disparities influence vulnerability to urban heat. Specifically, our study assesses social disparities through an Urban Heat Risk Index (UHRI) and identifies hot spots of vulnerability across the city. We hypothesize that block groups with high UHRI will correlate with low-income population, minority populations, and lower socioeconomic status as well as people with health issues.

Study Area

The city of New Orleans, Louisiana, is a vibrant and historically rich city located in the southeastern United States along the Gulf Coast. With a total estimated population of 364,136 as of 2023, New Orleans has experienced a decline of approximately 5% over the past decade, according to the U.S. Census Bureau. This population change is linked to a complex set of factors, among them is ongoing impacts of climate change. New Orleans frequently experiences extreme heat events that are exacerbated by its low-lying coastal topography and urban heat island effect.

According to studies, New Orleans experienced one of the nation's largest increases in the number of heat waves and the length of heat wave seasons. (Abugov, 2024) These extreme heat conditions contribute to heightened social and health inequalities, disproportionately impacting marginalized and low-income communities.

The present study analyses the intersection of heat exposure, demographic patterns, and socioeconomic as well as health factors in New Orleans. Since the city has very diverse social and economic characteristics as well as experiencing one the worst urban heat in the country, ranked first out of 20 cities, this study presents an excellent example of mapping and monitoring risk factors to make future development more sustainable and livable.(Fritz, 2021)

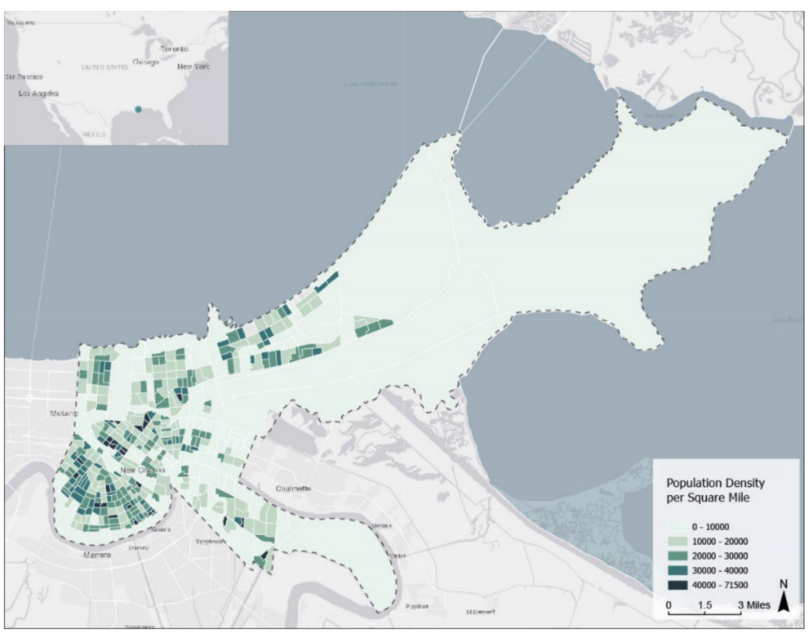

Figure 1 City of New Orleans map overlaid with population density

Data and Methodology

Data Collection

The data for this research was collected through several different means. The primary datasets included Landsat 8 level 1 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) 15- to 30- meter multispectral data has been selected for the month of August 2024, with less than 10% could cover from the USGS Earth Explorer, demographic and socioeconomic data from the United States Census Bureau's American Community Survey (ACS) 5-year estimates (2018 to 2022) for Orleans Parish at the block group level, and health data from the CDC's PLACES. Once these datasets were gathered, they were processed and prepared for analysis using ArcGIS Pro and R.

The diagram below illustrates the overall methodology employed in this research.

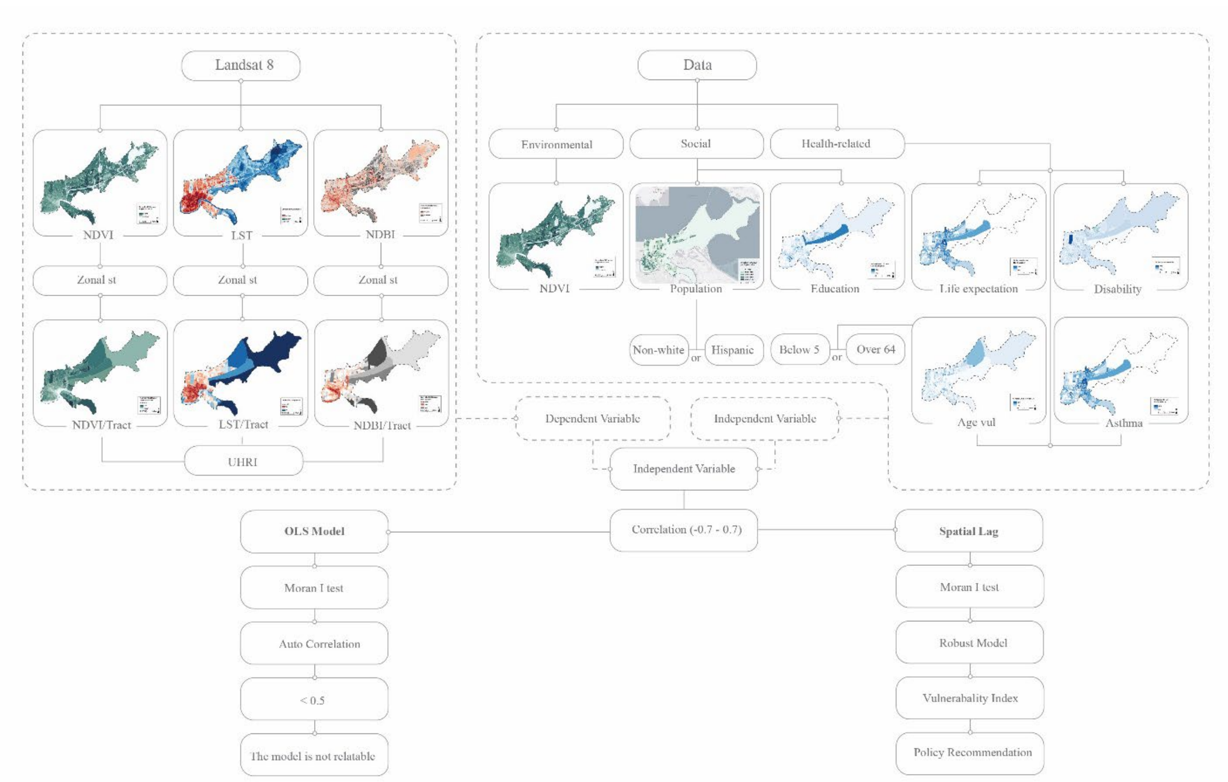

Figure 2 Flow chart of research design

Data Analysis

Land Surface Temperature (LST) Calculation: Landsat 8 imagery was preprocessed to calculate the Land surface temperature (LST)using Band 4 (Red), 5 (Near Infrared), and 10 (Thermal Infrared). The method described by Pal and Ziaul (2017) was employed to calculate the LST in Celsius for the Orleans Parish boundary. This process involved:

- Band 4 and Band 5: Used for calculating emissivity based on the NDVI.
- Band 10: Utilized for deriving the thermal radiance and brightness temperature.

Calculation of NDVI (Normalized Difference Vegetation Index): NDVI was calculated to identify and quantify vegetative cover within Orleans Parish using Bands 4 (Red) and 5 (Near Infrared). The formula for NDVI is:

$$NDVI = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$

NDVI values range from -1 to 1, where higher values indicate dense vegetation, and lower or negative values represent sparse or non-vegetated surfaces.

Calculation of NDBI (Normalized Difference Built-up Index): NDBI was derived to map built-up areas and assess urban infrastructure using Bands 5 (Near Infrared) and 6 (Shortwave Infrared 1). The formula for NDBI is:

$$NDBI = \frac{\text{SWIR1} - \text{NIR}}{\text{SWIR1} + \text{NIR}}$$

NDBI values are used to identify built-up and impervious surfaces, aiding in the assessment of urbanization and infrastructure.

Urban Heat Risk Index (UHRI) Development: The final UHRI map was created by standardizing and combining the following variables:

- **LST**: Higher values indicate higher heat exposure.
- **NDVI**: Lower values contribute to higher risk due to lack of vegetation.
- **NDBI**: Higher values are indicative of denser built-up areas contributing to heat.

First, each dataset (LST, NDVI, and NDBI) was aggregated to the block group level using the Zonal Statistics tool in ArcGIS Pro. This step calculated the "Mean" and "Standard Deviation" for each block group. Then, each metric was standardized to a common scale using Z-score method to ensure comparability. And last, the standardized metrics were combined to calculate the UHRI using the approach described by Mitchell and Chakraborty (2018) as shown below:

$$UHRI = (LST + NDBI) - NDVI$$

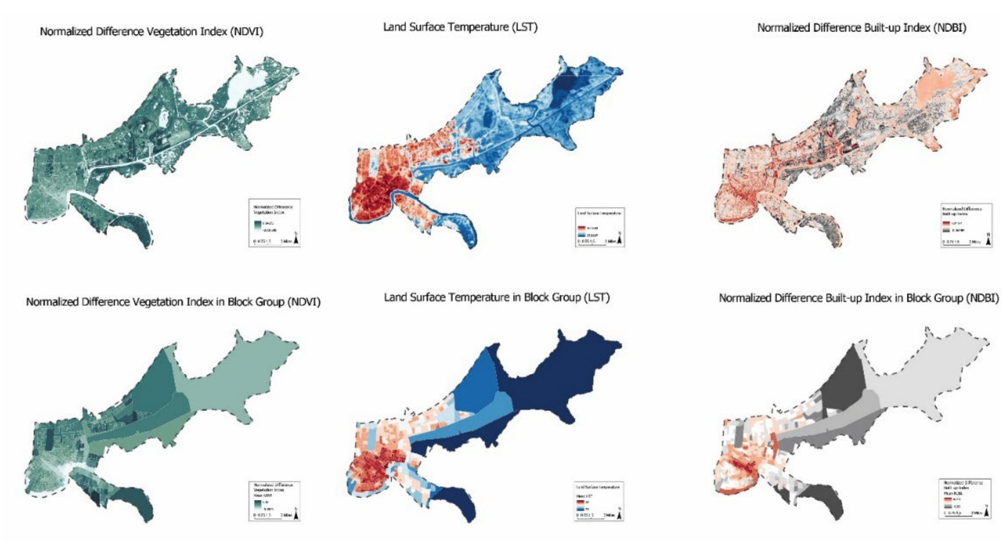

Figure 3 Series of maps illustrating NDVI, LST and NDBI (left to right)

Urban Heat Hot Spot Analysis

Urban Heat Hot Spot Analysis is used to identify statistically significant spatial clusters of high and low temperatures within the New Orleans boundary. This analysis helps specify areas where extreme heat is concentrated (hot spots) and cooler areas (cold spots). Spatial analysis tools, including Global Moran's I was used to measure spatial autocorrelation across the entire study area. Global Moran's I (0.27) for New Orleans suggests heat risk values are not randomly distributed; clusters exist and we can use this result to run Hot Spot Analysis (Getis–Ord Gi*) to locate specific areas of intense heat or cool zones in the urban heat risk index within New Orleans. The Getis–Ord Gi* statistic was calculated in ArcGIS Pro using the equations given below.

The Getis-Ord Gi* statistics are calculated using the following formula:

$$Gi* = [\,(Sum\ of\ (wij\ *\ xj)) - (X^{-}\ *\ Sum\ of\ wij)\,]\ /\ [S\ *\ sqrt(\,(Sum\ of\ wij^{\wedge}2 - (Sum\ of\ wij)^{\wedge}2\ /\ n)\ /\ (n\ -\ 1)\,)]$$

Where, xj = attribute value for feature j, n = total number of features, $w_{i,\,j}$ = spatial weight feature between i and j. X̄= the mean of the attribute values across all features and S= the standard deviation of the attribute values, representing the dispersion of data points from the mean.

Based on the optimal distance generated from the autocorrelation method, a fixed distance of 510 meters has been selected for the hotspot analysis. This distance, determined by the highest z-score in the Incremental Spatial Autocorrelation results, ensures that the analysis captures the most significant clustering patterns within the data.

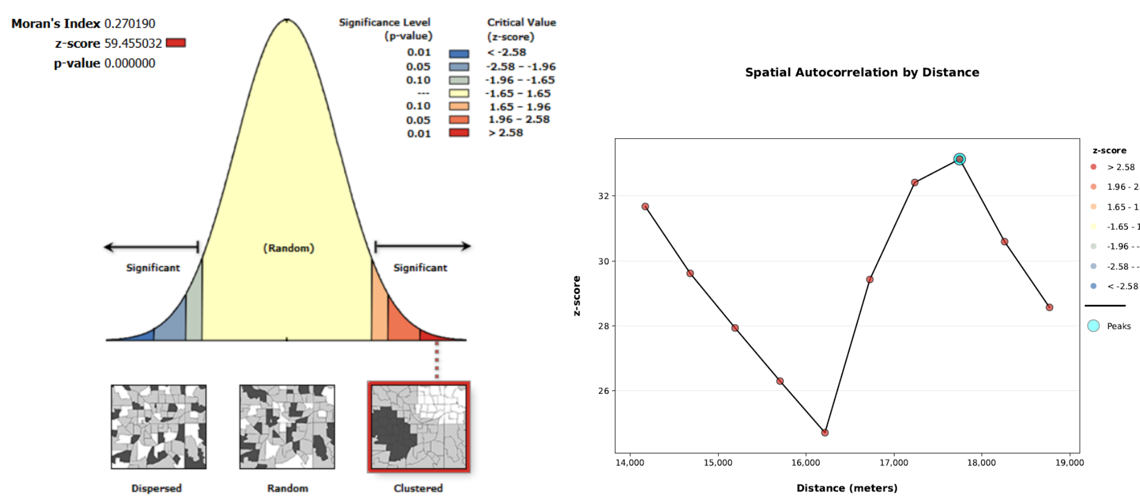

Figure 4 Optimal distance as result of Autocorrelation on UHRI

Dependent Variable

Urban heat risk calculated from LST, NDVI and NDBI was selected as the dependent variable for this explanatory analysis due to its comprehensive representation of urban heat exposure and associated impacts. This variable allows for a focused exploration of the relationships between urban heat risk and contributing factors, facilitating targeted strategies for resilience and mitigation planning. This approach also enables the identification of key explanatory variables that contribute to higher heat risk levels, such as socioeconomic characteristics, health status and level of greenness.

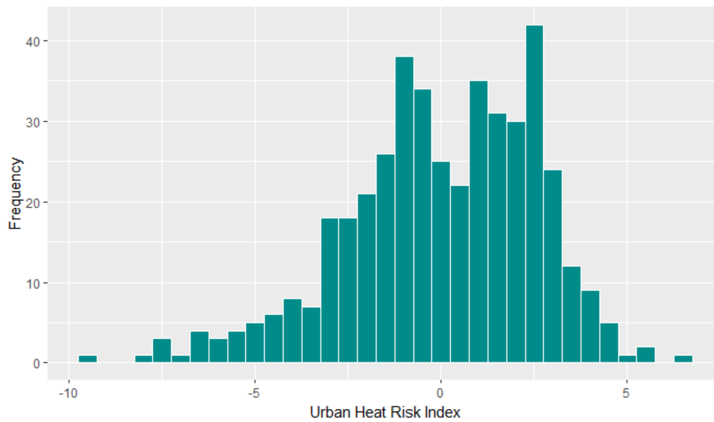

Figure 5 Distribution of UHRI

Explanatory Variable

Considering the social disparities and health inequalities in urban heat risk areas, we studied a range of variables. Key health indicators include rates of cancer, asthma prevalence, disability rates and percentage of people with lower life expectancy show how certain populations are more vulnerable to environmental stress. Vulnerable age groups, specifically children under five and adults over 64, are also examined due to their increased sensitivity to heat exposure and related health risks.

Socioeconomic and demographic factors, including the percentage of low-income populations, people of color, and renter-occupied households, provide insight into social and economic conditions that may increase heat-related health risks. These datasets were prepared for regression analysis by standardizing each variable, and removing any missing values, and ensuring spatial alignment across geographic units. This setup allows us to accurately analyze how each factor influences urban heat risk and related health disparities.

Table 1 Description of the dependent and independent variables used in the regression analysis

Variable Name	Data Source	Year
Normalized Difference Vegetation Index (NDVI)	Landsat 8 level 1 OLI and TIRS	2024
Land Surface Temperature (LST)	Landsat 8 level 1 OLI and TIRS	2024
Normalized Difference Built-in Index (NDBI)	Landsat 8 level 1 OLI and TIRS	2024
Urban Heat Risk Index (UHRI)	Landsat 8 level 1 OLI and TIRS	2024
%People of Color	United States Census Bureau's (ACS) 5-year	2022
%People with less than Diploma Education	United States Census Bureau's (ACS) 5-year	2022
%People Over 64 years old	United States Census Bureau's (ACS) 5-year	2022
%People less than 5 years old	United States Census Bureau's (ACS) 5-year	2022
%People with Disability	United States Census Bureau's (ACS) 5-year	2022
%People with Low Life Expectancy	PLACES - Centers for Disease Control and Prevention	2021

Explanatory Analysis

To explore the relationship between the dependent and explanatory variables, we first assessed correlations among the explanatory variables, confirming none had a correlation coefficient exceeding 0.7 to avoid multicollinearity. We then applied a classical linear regression model using the ordinary least squares (OLS) method. The Model helps us to explore the relationship between urban heat Risk as our dependent variable and the socioeconomic and health related variables and to what extent the change in each unit of these variable makes an impact on Urban Heat Risk.

Table 2 Summary of Correlation among independent variables

Variable 1	Variable 2	Correlation
%People with less than Diploma Education	%People of Color	0.5048
NDVI	%People of Color	0.3423
%People with Disability	%People of Color	0.3251
%People with less than Diploma Education	%People with Disability	0.2681
%People with Low Life Expectancy	%People of Color	0.2468
%People with Low Life Expectancy	%People with less than Diploma Education	0.2429
%People with Low Life Expectancy	%People with Disability	0.1752
%People less than 5 years old	NDVI	0.1347
%People Over 64 years old	%People with Disability	0.1252
%People less than 5 years old	%People of Color	0.09847
%People with Disability	NDVI	0.06389
%People with less than Diploma Education	NDVI	0.05781
%People with Low Life Expectancy	%People less than 5 years old	0.03481
%People with less than Diploma Education	%People less than 5 years old	0.0172
%People with less than Diploma Education	%People Over 64 years old	0.01078
%People with less than Diploma Education	%People Over 64 years old	0.01078
%People with Low Life Expectancy	%People Over 64 years old	-0.003468
%People Over 64 years old	NDVI	-0.005265
%People with Disability	%People less than 5 years old	-0.08557
%People Over 64 years old	%People of Color	-0.1463
%People less than 5 years old	%People Over 64 years old	-0.2412

However, the regression result was not reliable due to the significant autocorrelation of residual based on Moran's I test. The Moran's I statistic for the OLS model's residuals is 0.508, ($p < 0.0001$), which is relatively high and positive. The extremely small p-value (essentially zero) indicates significant positive spatial autocorrelation in the OLS residuals. This means that the OLS model is inadequate due to unaddressed spatial dependencies which violates the assumptions of the OLS model.

Therefore, a spatial lag model was chosen over an Ordinary Least Squares (OLS) model due to the presence of spatial autocorrelation in the data (Anselin, 2003). The spatial lag model includes a term for the dependent variable that accounts for the influence of neighboring observations. This allows the model to account for spatial dependencies, resulting in more reliable and interpretable estimates. Anselin (2005) suggests that when both the Lagrange Multiplier (LM) lag and LM error statistics are significant ($p < 0.001$), the next step is to evaluate the robust test statistics. In this analysis, the robust LM statistic for the spatial lag model was significant ($p < 0.001$), whereas the robust LM statistic for the spatial error model was not significant, indicating that a spatial lag model is the appropriate choice for this analysis.

Table 3 Summary of Lagrange Multiplier (LM) and Robust LM Tests for Spatial Dependence

test	Value	Interpretation
LM (Spatial Lag)	370.59	Significant
LM (Spatial Error)	333.47	Significant
Robust (Spatial Lag)	68.826	Not significant
Robust (Spatial Error)	31.704	**Robust test Strongly support spatial lag model**

According to the result of Moran I test as 0.0726, the spatial lag model's residuals show no significant spatial autocorrelation, which indicates it is a suitable model for capturing spatial dependencies in our variables. The maximum likelihood (ML) estimation method was applied for Spatial lag model estimation in this study using the formula as:

$$y=\rho Wy+X\beta+\epsilon$$

where:

- *y: Dependent variable (response).*
- *ρ: Spatial autoregressive coefficient (captures spatial dependence).*
- *W: Spatial weights matrix (defines spatial relationships).*
- *X: Matrix of independent variables (predictors).*
- *β: Vector of regression coefficients.*
- *ϵ: Random error term*

Result

Urban Heat Risk Index

According to urban Heat Risk Index map below, the urban heat index of the city of New Orleans ranges from -9.7 to 6.3. High UHRI values, indicating greater heat risk, are concentrated in densely built areas, including the Central Business District, Tulane Gravier, Mid city, Gert Town, B.W. Cooper, French Quarter, Central City, Freret, Marigny and Bayou St. John. In contrast, areas with significant vegetation—such as City Park, New Aurora, Viavant venetian Isles and Bayou Sauvage National Wildlife Refuge—exhibit lower UHRI values, reflecting a mitigated heat risk due to natural cooling effects.

The distribution of UHRI values highlights a pattern of high-risk clusters in urbanized areas, while lower risk values are observed in greener, less developed regions. This spatial clustering suggests that built environment characteristics play a critical role in shaping urban heat risk and further spatial analysis is necessary since clustering is visually evident.

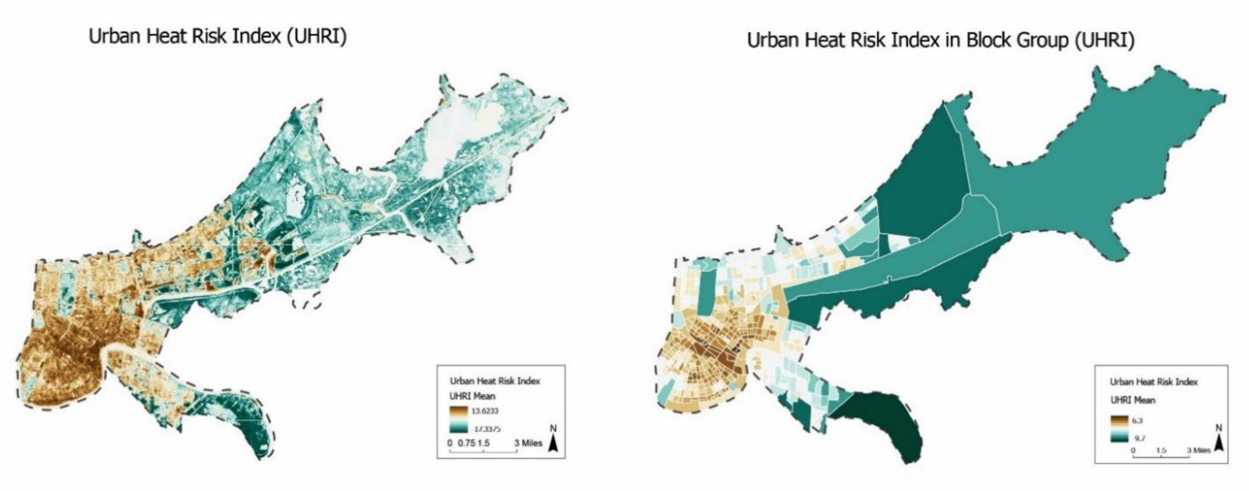

Figure 6 Urban Heat Risk Map

Hot Spot Analysis

The hot spot analysis reveals specific high-temperature areas in New Orleans, primarily concentrated in densely developed areas. The areas in red experience significantly elevated land surface temperatures, which increases potential health risks for residents.

We used the Getis–Ord Gi* statistic to identify clusters of high and low Urban Heat Risk Index (UHRI) values across New Orleans, providing insight into spatial patterns of heat risk. As shown in Figure 4, red areas represent hot spots, blue areas indicate cold spots, and white areas are non-significant. High-confidence hot spots are concentrated in regions with elevated UHRI, such as the Central Business District and French Quarter, while cold spots with similar confidence levels appear in greener areas where vegetation mitigates heat risk. This analysis highlights the spatial clustering of UHRI, guiding cooling strategies in high-risk areas.

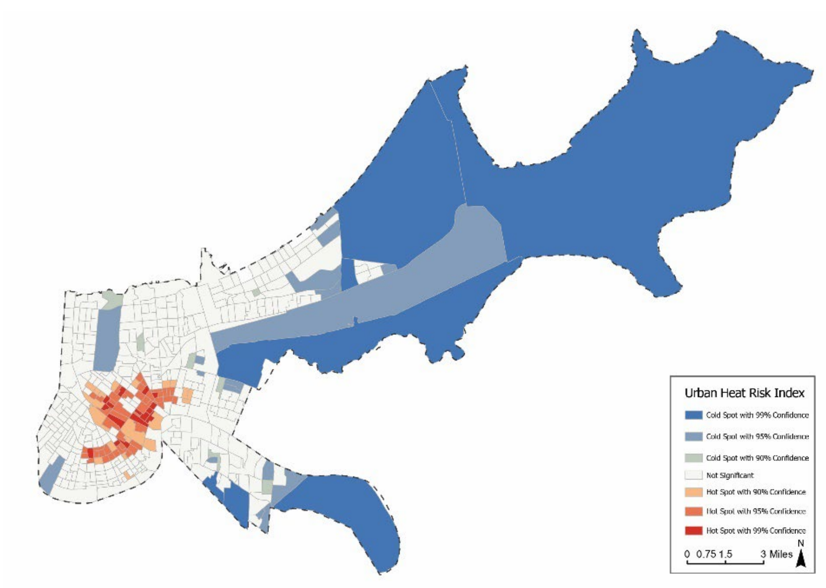

Figure 7 Urban Hot Spot Map

Regression Analysis

In the following, there is a series of maps showing the distribution of each variable used within this study. According to our analysis, the highest vulnerability of each variable is mostly concentrated in the areas identified as urban heat islands.

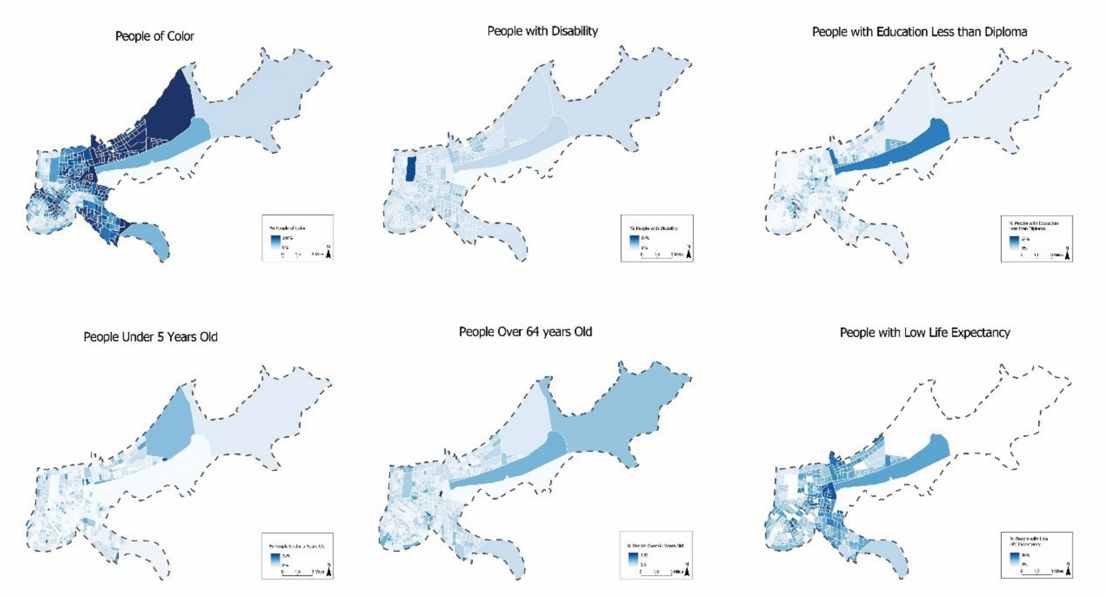

Figure 8 Series of maps illustrating the independent variables

The summary table of the variables shows the descriptive statistics of all the variables used in this study. The mean value for dependent variable, UHRI, was 0.001, which was calculated from the z-score of LST, NDVI and NDBI. The range of UHRI between -9.66 and 6.33 shows variation across block groups. The rage of percentage of the six different social variables shows a considerable variation across block groups. Moreover, the Variance Inflation Factor (VIF) is used to address the multicollinearity of the independent variables, and a VIF value less than 5 is usually considered acceptable.

Table 4 shows the VIF values for independent variables, where VIF values were less than 5 for all variables.

Table 4 Descriptive statistics of the variables used in the study

Variable Name	Mean	SD	Minimum	Maximum	VIF
LST	35.69	1.86	28.48	39.205	N/A
NDVI	0.22	0.06	-0.0043	0.401	1.17
NDBI	-0.0803	0.035	-0.02003	0.014	N/A
UHRI	0.001	2.58	-9.66	6.32	N/A
%People of Color	65.1	31.2	0	100	1.74
%People with Disability	14.25	6.43	0	63.28	1.19
%People with Low Life Expectancy	22.63	5.002	0	36.1	1.09
%People less than 5 years old	5.077	5.16	0	31.81	1.07
%People Over 64 years old	16.66	10.63	0	83.44	1.11
%People with less than Diploma Education	11.3	11.3	0	62.31	1.42

In Table 5, we compare the results from a traditional linear regression model and a spatial lag model, estimated using OLS and ML methods, respectively. For the spatial lag model, the constant term (Estimate=5.958,$p<0.001$) is positive and highly significant. Consistent with expectations, the percentage of people of color does not exhibit a significant relationship with UHRI after accounting for spatial dependence ($p>0.05$). A significant negative relationship is observed between UHRI and the percentage of people with disabilities ($p<0.01$), indicating that areas with higher disability populations tend to experience lower UHRI. Additionally, areas with lower life expectancy are significantly associated with higher UHRI ($p<0.001$), suggesting a potential link between environmental stressors such as heat and health outcomes.

The percentage of children under 5 years old does not have a statistically significant relationship with UHRI in this model ($p>0.05$). However, a significant negative relationship is observed between UHRI and the percentage of older adults ($p<0.001$). This finding may reflect spatial patterns where older populations are more likely to reside in cooler areas. Furthermore, a significant positive association is found between UHRI and the percentage of individuals without a high school diploma ($p<0.05$), highlighting potential disparities in environmental exposure across educational attainment levels.

The spatial lag model provides a robust framework for analyzing UHRI and its socio-environmental predictors by accounting for spatial dependence. Key predictors such as NDVI ($p<0.001$), percentage of people with low life expectancy ($p<0.001$), and percentage of individuals with less than a diploma ($p<0.05p$) demonstrate strong and significant relationships with UHRI. The strong spatial lag parameter ($\rho=0.71319$) and the lower AIC (1463.559) further confirm the spatial lag model's suitability for capturing spatial dynamics. These results underscore the importance of employing spatial models to ensure accurate and unbiased estimates in geospatial analyses.

The estimated autoregressive coefficient (ρ) was 0.713 ($p < 0.001$), indicating strong spatial dependence, where higher UHRI values in one block group correlate with neighboring areas. Model fit improved significantly, with the AIC decreasing from 1778.8 in the OLS model to 1463.6 in the spatial lag model, highlighting the spatial lag model's superior ability to account for spatial dependence.

Table 5 The result of the classical linear regression and spatial lag model analysis

Variable Name	*OLS*		*Spatial Model*	
	Estimate	SE	Estimate	SE
Intercept	5.958***	0.418	2.8223***	0.307
NDVI	-25.764***	1.441	-12.084***	1.137
%People of Color	-0.884**	0.371	0.217	0.242
%People with Disability	2.346	1.487	-2.311**	0.977
%People with Low Life Expectancy	2.126**	1.016	2.213***	0.663
%People less than 5 years old	-0.278	1.763	-0.847	1.149
%People Over 64 years old	-3.716***	0.87	-2.034***	0.569
%People with less than Diploma Education	3.502***	0.92	1.159*	0.605
Observation	437		437	
R2	0.507			
ρ (spatial lag parameter)			0.71319	
AIC	1778.803		1463.559	
Observed Moran's I for residuals	0.50871		0.0726**	

*Note: Level of significance: *p<0.05; **p<0.01; ***p<0.001*

Discussion

This study highlights key implications for public health, urban planning, and environmental justice. The strong negative relationship between NDVI and UHRI underscores the importance of green infrastructure in mitigating heat stress. Expanding vegetation cover in high-risk areas is crucial for improving health outcomes, especially for disadvantaged communities. Health-related social factors, such as low life expectancy and low educational attainment, are positively associated with UHRI, indicating that vulnerable populations face disproportionate heat exposure. Targeted interventions like urban greening and improved cooling infrastructure are essential to address these disparities. Conversely, older populations and individuals with disabilities are associated with lower UHRI, possibly due to spatial patterns where cooler, vegetated areas provide greater protection.

While the spatial lag model effectively accounts for spatial dependence, the significant Moran's I for residuals ($p<0.01$) suggests some spatial autocorrelation persists. Future research should refine these findings by using alternative spatial models and incorporating finer-scale and longitudinal data to better capture interactions between social factors and heat exposure.

Despite limitations such as the use of aggregated spatial data and the absence of information on air conditioning access, this study advances understanding of urban heat exposure and its links to health-related social inequalities. The findings emphasize the urgent need for strategies such as green infrastructure expansion and targeted adaptation measures to reduce heat disparities. As urban heat risk intensifies with climate change, cities like New Orleans must prioritize mitigation and resilience planning to protect vulnerable populations. By addressing social inequalities, this research provides actionable insights for creating healthier, more inclusive, and climate-resilient cities.

Conclusion

It is crucial to understand the health risks associated with heat exposure and identify populations most vulnerable to heat-related impacts from both public health and environmental justice perspective. Using spatial modeling and socioenvironmental data, this study explores the relationship between urban heat exposure and various health-related social factors in the context of New Orleans. Urban heat exposure remains a persistent challenge, disproportionately affecting vulnerable populations.

Our findings indicate that areas with lower vegetation cover like Downtown New Orleans, areas with higher percentages of individuals with lower life expectancy, and more residents without a high school diploma tend to experience elevated heat exposure. Conversely, areas with a higher proportion of older adults or people with disabilities were associated with lower heat exposure. The significant spatial lag parameter ($\rho=0.713$) demonstrates that urban heat exposure is not confined to individual locations but is heavily influenced by surrounding areas, underscoring the interconnected nature of urban heat dynamics.

By addressing these health-related disparities and environmental justice concerns, this research provides valuable insights into the unequal distribution of urban heat risks. These findings can guide the implementation of mitigation strategies, such as increasing vegetation cover, enhancing urban planning measures, and targeting at-risk populations to create more equitable and resilient urban environments in the face of climate change.

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