Bridget Atchison-Nevel 5/13/2025

Remote Sensing Final Project: **Assessing the Impact of Urban Tree Canopy on Urban Heat Islands Using Remote Sensing: Climate Justice and Urban Heat Island Mitigation in Miami, Florida**

CSCI-E-158: Remote Sensing Data And Applications, Spring 2025
Professor Magaly Koch

Background:

The distribution of urban green space in Miami is closely tied to both heat exposure and socioeconomic inequality. Neighborhoods with limited vegetation, often lower-income communities and those with higher proportions of minority residents, experience elevated temperatures due to reduced tree canopy and increased impervious surface coverage. This disparity not only contributes to the Urban Heat Island (UHI) effect but also exacerbates public health risks for the city's most vulnerable populations.

Despite growing recognition of these issues, Miami faces ongoing challenges in expanding its urban tree canopy. According to a 2016 Urban Tree Canopy Assessment, Miami's canopy coverage stood at just 19.9%, far below the current national urban average of 39% (Nowak et al., 2022). Although Miami-Dade County set a goal of increasing canopy cover to 30% by 2030, a follow-up assessment in 2021 showed no significant progress, with coverage remaining virtually unchanged at 20%.(Hartwig et al. 2021)

The inequitable distribution of green space is well-documented in the 2016 Tree Canopy Assessment. Identified was a strong positive correlation between income and tree canopy coverage, and a negative correlation with the proportion of minority residents. These findings underscore the structural barriers to greening in underserved areas.

In March 2025, Miami-Dade County released a comprehensive Urban Forestry Plan aimed at reinvigorating efforts to expand tree cover. The plan outlines strategies for environmental education, climate resilience, and five-year monitoring using LIDAR remote sensing technologies.(Miami-Dade Office of Environmental Risk and Resilience, 2025)

This renewed urgency is driven by the intensifying impact of the UHI effect, especially in densely built areas with minimal vegetation. Urban tree cover plays a critical role in mitigating heat through shading, surface cooling, and enhanced evapotranspiration. Yet, as of 2019, only 5.3% of downtown Miami's 1,100 acres were shaded by trees.(Miami Downtown Development Authority, 2019)

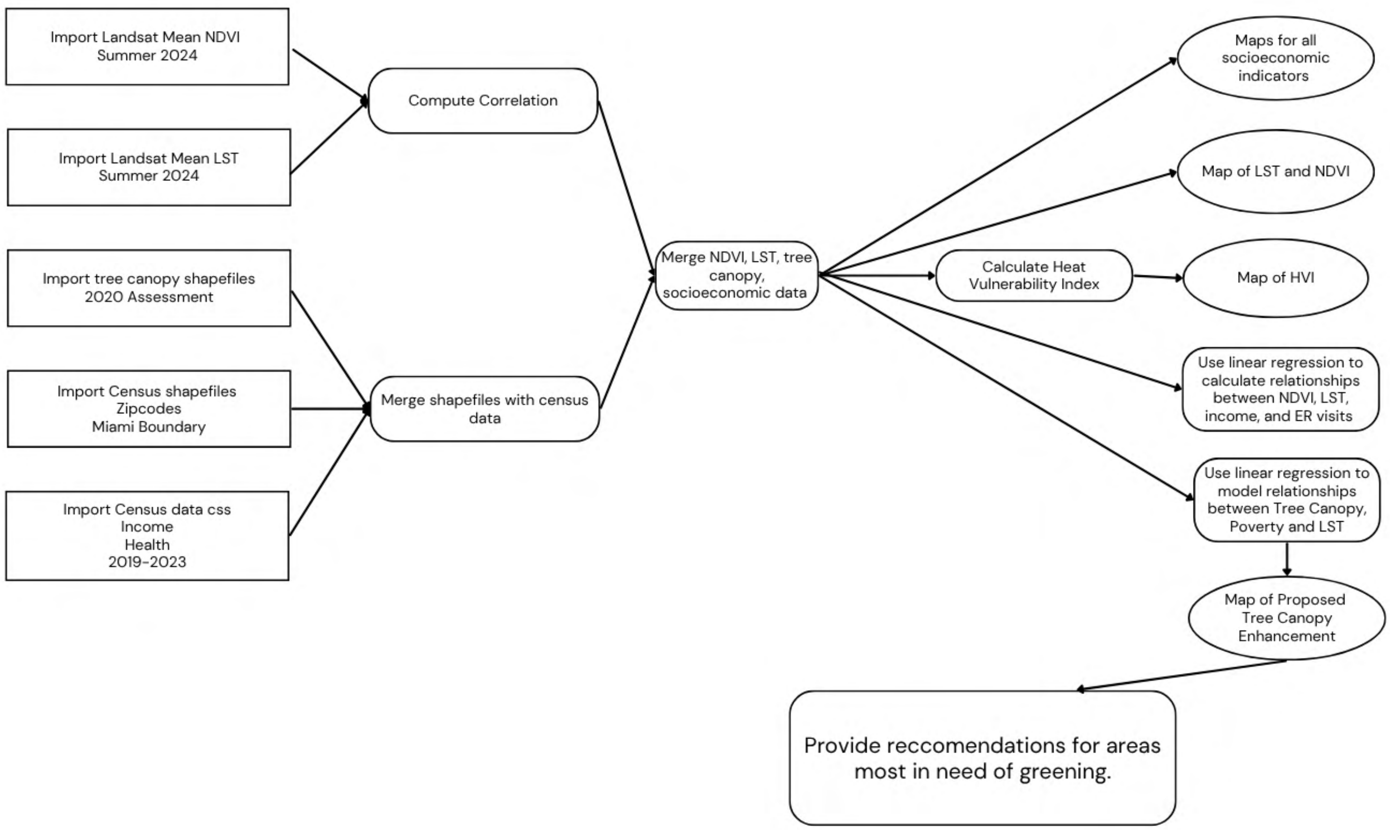
Florida currently leads the nation in heat-related illnesses (Tsoukalas, 2024), and Miami's combination of high temperatures and humidity places outdoor workers, the uninsured, and other vulnerable populations at heightened risk.

Research Goals:

This project aims to deliver an analysis of Miami's current heat landscape and its relationship to urban green space. By integrating satellite imagery, census data, public health and survey records, I will examine the correlations between vegetation cover, income levels, health outcomes, and surface temperature patterns across the city.

A key objective is the development of a Heat Vulnerability Index to identify communities most at risk from extreme heat and most in need of targeted greening interventions. Additionally, the project will generate data-driven estimates of the scale of vegetation increase required in these vulnerable neighborhoods to meaningfully mitigate the effects of the Urban Heat Island (UHI) phenomenon.

Remote Sensing Workflow:



Data:

Data Sets	Source	Type	Dates
Landsat 8/9 level 2 mean LST	Climate Engine	Raster	(May 23rd to September 23rd) 2024
Landsat 8/9 level 2 mean NDVI	Climate Engine	Raster	(May 23rd to September 23rd) 2024
American Family Survey	census.Gov	csv	2019-2023
2020 Urban Tree Canopy	FIU Research Data Portal	Shapefile	2020
2021 Landcover Classification	FIU Research Data Portal	Raster	2021
Miami Health Equity Index	Miami Matters Data Portal	Csv	2025

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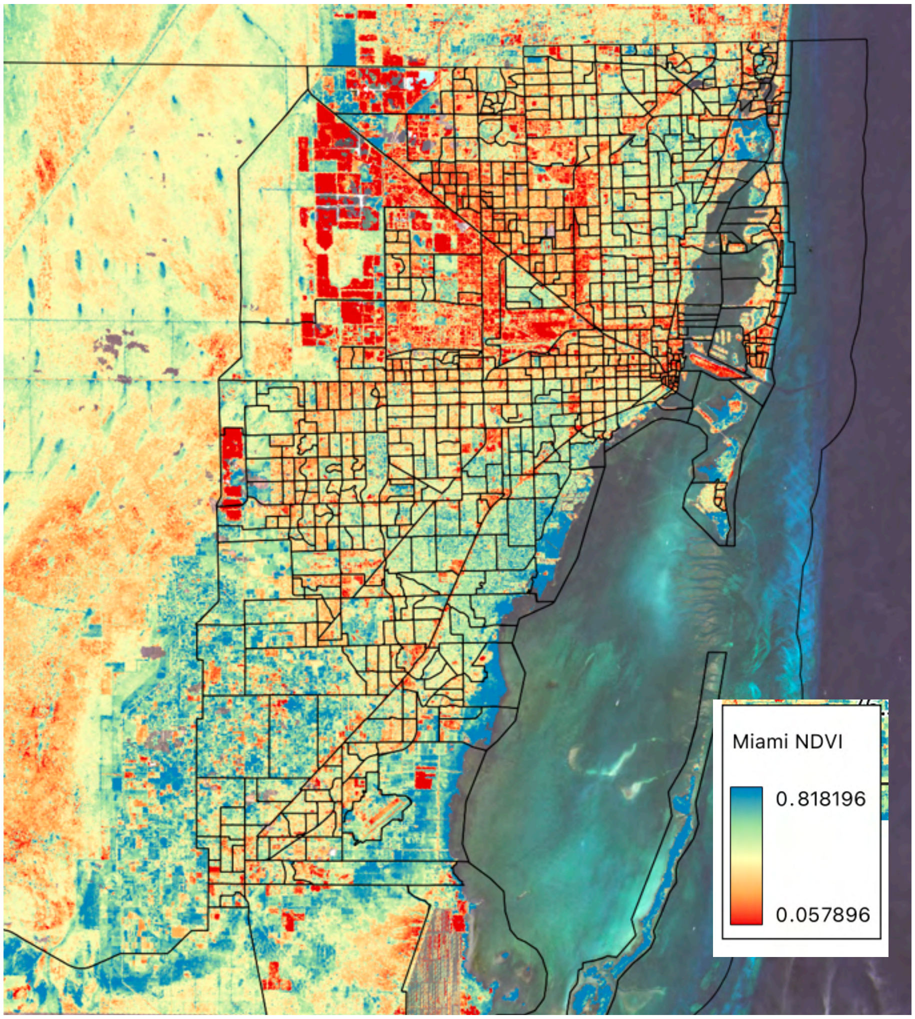
Vegetation (NDVI) Analysis:

To assess vegetation across the Miami-Dade metropolitan area, I utilized Normalized Difference Vegetation Index (NDVI) data derived from LANDSAT 9 OLI, averaged over the summer months of 2024 (May 23 to September 23). This data was accessed through the Climate Engine platform and offers a 30-meter spatial resolution, enabling a detailed view of vegetative patterns throughout the region. NDVI calculations are as follows:

$$NDVI = \frac{NIR - red}{NIR + red}$$

The NDVI map visualizes vegetative density, with blue tones indicating high vegetation and red areas denoting minimal or no vegetation. Averaging over the summer period helped mitigate issues caused by frequent cloud cover in Miami's satellite imagery during that season.



2024 Mean Summer NDVI (LandSat 8/9)
Climate Engine. (2025). Desert Research Institute and University of California, Merced. Accessed on (4/17/2025). http://climateengine.org, version 2.1.

Land Surface Temperature (LST) Analysis:

To model Miami-Dade County's temperature distribution, I utilized Land Surface Temperature (LST) data obtained from the LANDSAT 9 TIRS (Thermal Infrared Sensor). The raw LST data, presented in digital number (DN) pixel values, was converted to Kelvin using the following calibration equation:

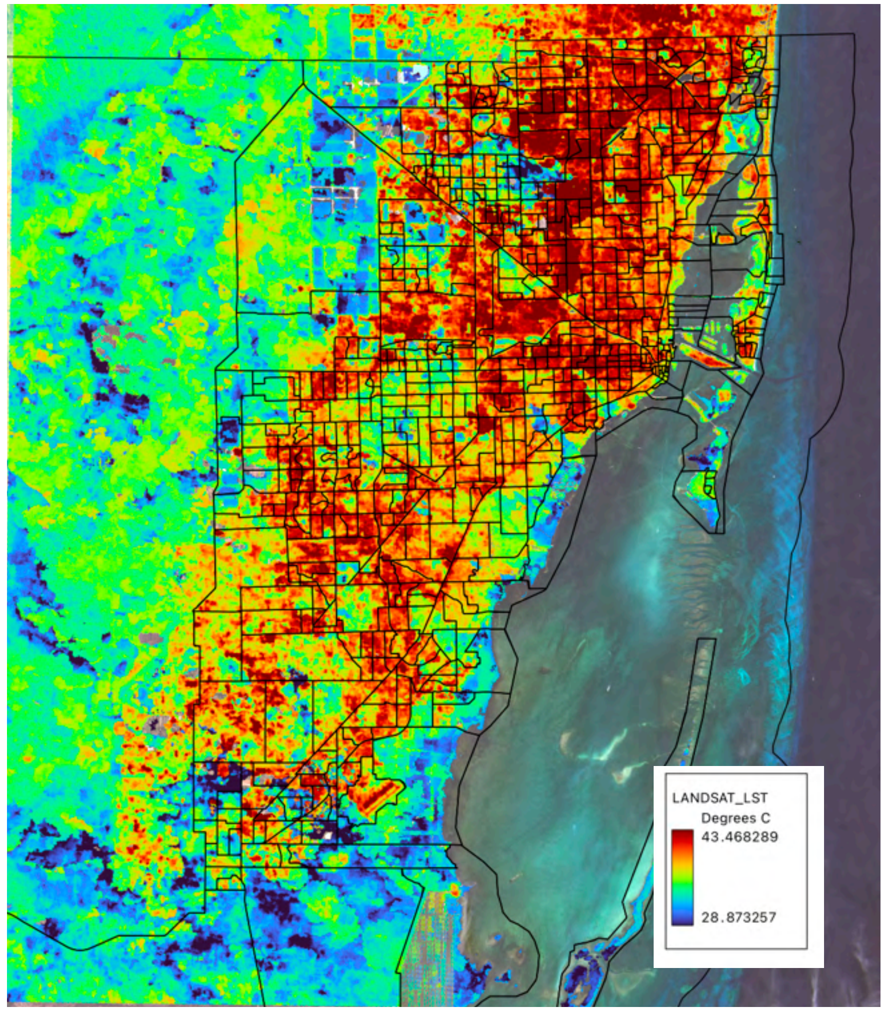
$$\text{LST (K)} = (\text{DN} \times 0.00341802) + 149.0$$

Subsequently, temperatures were converted to Celsius for interpretability:

$$\text{LST (°C)} = \text{LST (K)} - 273.15$$

For this study, I analyzed summer-averaged LST data from May 23 to September 23, 2024, accessed through the Climate Engine platform. The resulting heat map visualizes temperature distribution, with red regions indicating higher surface temperatures and blue regions indicating cooler areas.

By comparing this LST data with NDVI maps from the same time period, spatial variations in vegetation and surface temperature become apparent. This side-by-side analysis enables the exploration of correlations between vegetative cover and urban heat, providing key insights into the localized impacts of the Urban Heat Island (UHI) effect.



2024 Mean Summer LST (LandSat 8/9)
Climate Engine. (2025). Desert Research Institute and University of California, Merced. Accessed on (4/17/2025). http://climateengine.org, version 2.1.

Correlation analysis:

To explore the relationship between heat distribution and vegetation across Miami-Dade County, I analyzed the correlation between Land Surface Temperature (LST) and the Normalized Difference Vegetation Index (NDVI) at two spatial scales: pixel-level and census tract-level.

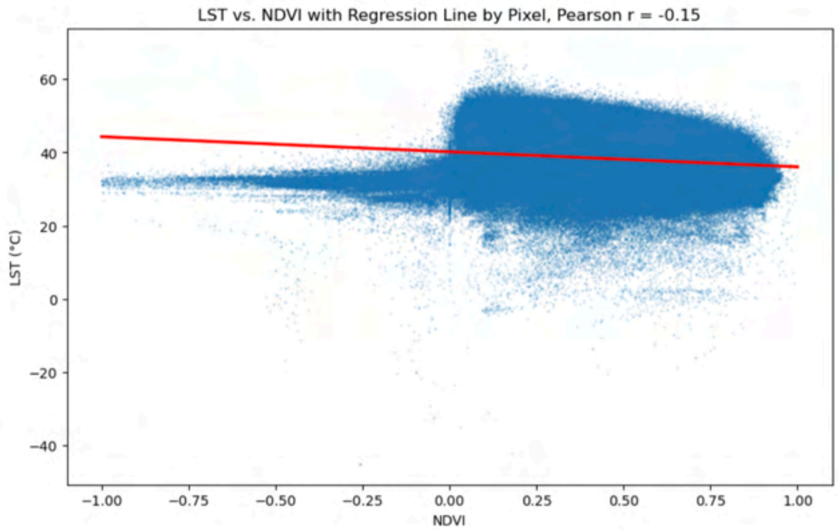
Initial pixel-by-pixel analysis revealed a modest negative correlation of -0.15 between LST and NDVI—significantly lower than expected based on my prior research. Several factors may explain this low correlation:

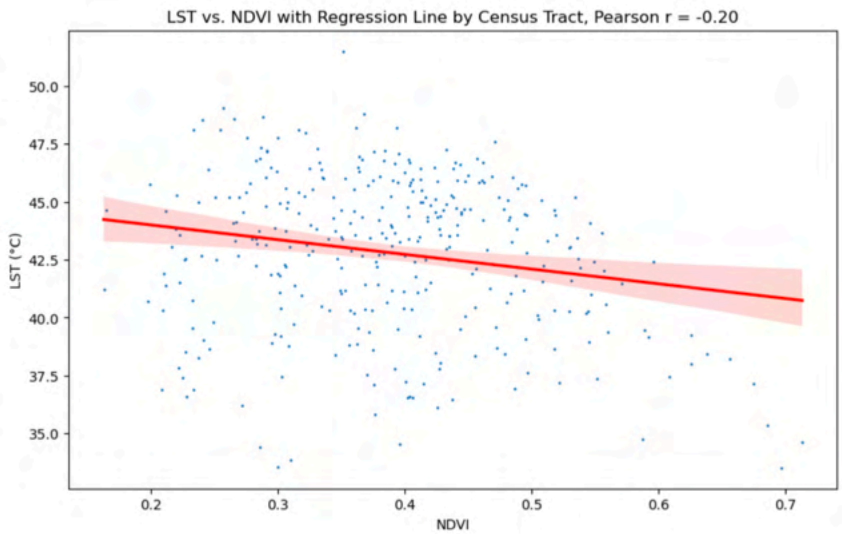
- Coastal Cooling: Shoreline areas may experience naturally lower temperatures due to proximity to large bodies of water, independent of vegetative cover.
- Water-Dominated Tracts: Some tracts contain large expanses of water, which yield low mean NDVI values while also exhibiting low surface temperatures, thereby skewing the overall correlation.

I found that a stronger correlation was exhibited when data was aggregated at the census tract level, where the LST-NDVI correlation increased to -0.2.

This pattern suggests that while individual trees or small patches of greenery may have minimal impact, larger vegetative areas exert a more measurable cooling influence. The improved correlation at a broader spatial scale supports the notion that collective vegetation density—rather than isolated greenery—is more effective in mitigating surface heat.

Despite this improvement, the relatively weak correlation highlights that NDVI alone may not fully explain LST variation across Miami. This raises important questions about additional factors—such as





building materials, environmental characteristics, impervious surface area, and air circulation patterns—that may also shape urban heat distribution.

Socioeconomic indicators:

Socioeconomic indicators offer valuable insights into local variations in urban temperature across Miami-Dade County. To investigate these patterns, I mapped census tract-level socioeconomic data alongside mean NDVI and Land Surface Temperature (LST) values. The majority of this data is drawn from the American Community Survey (ACS) five-year estimates (2019–2023), a dataset offering detailed demographic information.
Census tracts provide an ideal spatial unit for this analysis, as they are smaller and more socially homogeneous than zip code zones. This granularity enables more precise comparisons between neighborhoods with similar demographic and economic profiles.

Several socioeconomic indicators from the ACS were used in this analysis, including:

- Per capita income
- Percentage of residents below the poverty line
- Percentage of uninsured individuals
- Self-reported health status (percentage of individuals reporting poor to fair health)

Additionally, I incorporated the Miami Health Equity Index, developed by the Conduent Healthy Communities Institute, which quantifies socioeconomic need and its correlation with health disparities. The index ranges from 0 to 100, with 100 indicating the highest level of vulnerability.

The results show a strong negative correlation between income and LST, indicating that wealthier areas tend to be cooler. In contrast, indicators of economic and health vulnerability—such as poverty rate, uninsured rate, poor health status, and the Health Equity Index—are all positively correlated with higher surface temperatures.

These correlations underscore the intersection of environmental and social inequity, revealing that the most heat-vulnerable communities are also those with the fewest resources to adapt or recover. This

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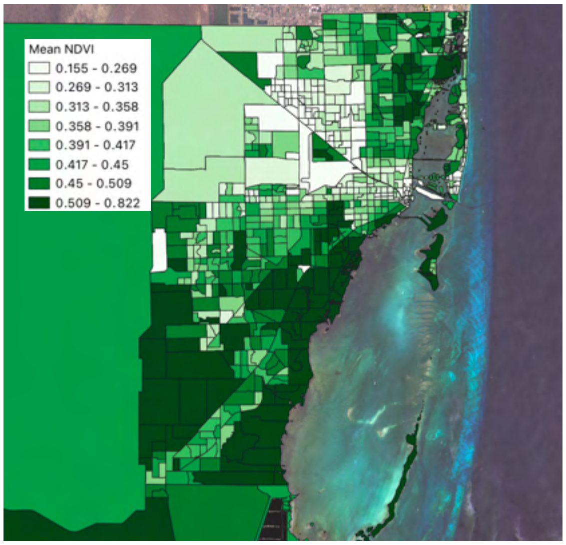
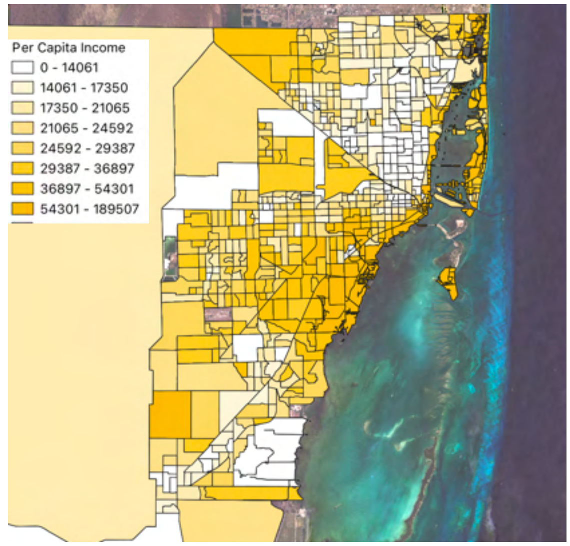
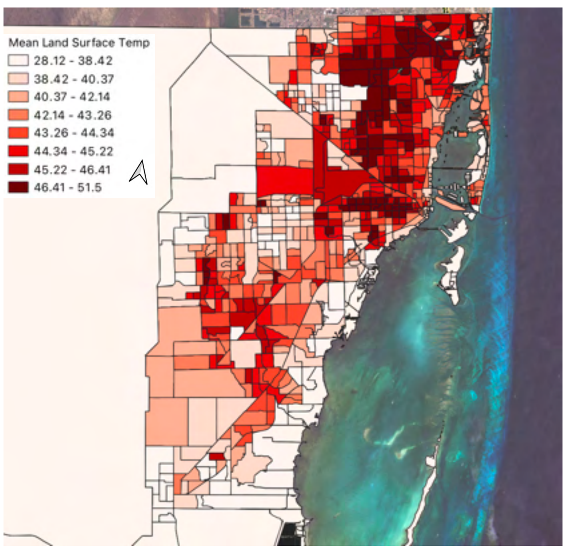


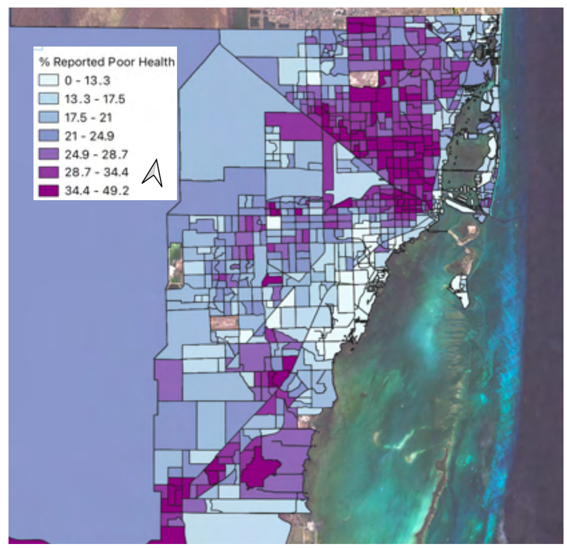
2024 Summer Mean NVDI



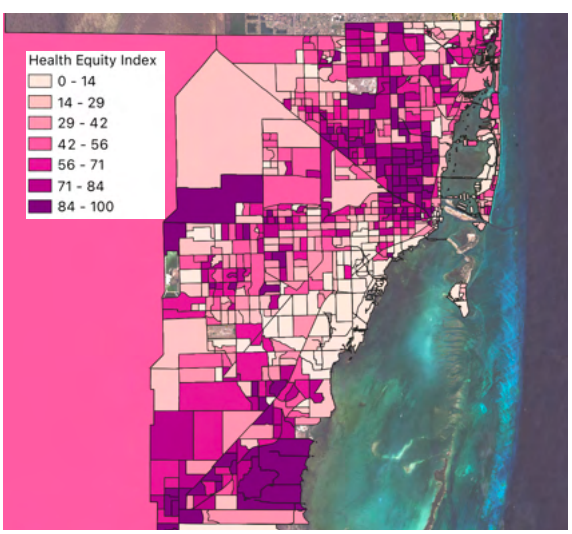
Per Capita Income (2022)



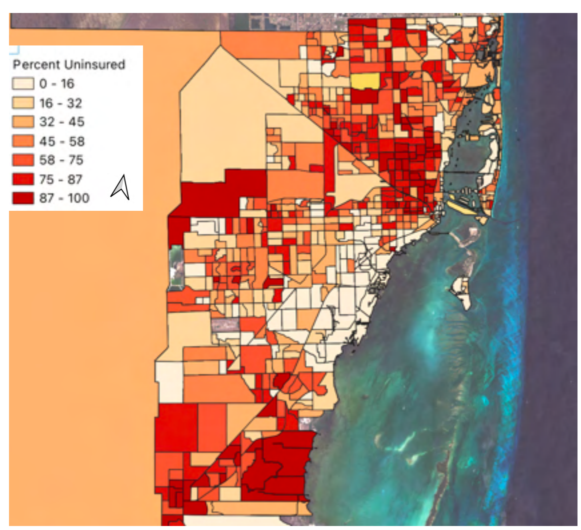
2024 Summer Mean LST



Percentage Self Reporting Poor Health (2022)



Miami Health Equity Index, 2025 (100 is Highest Needs)



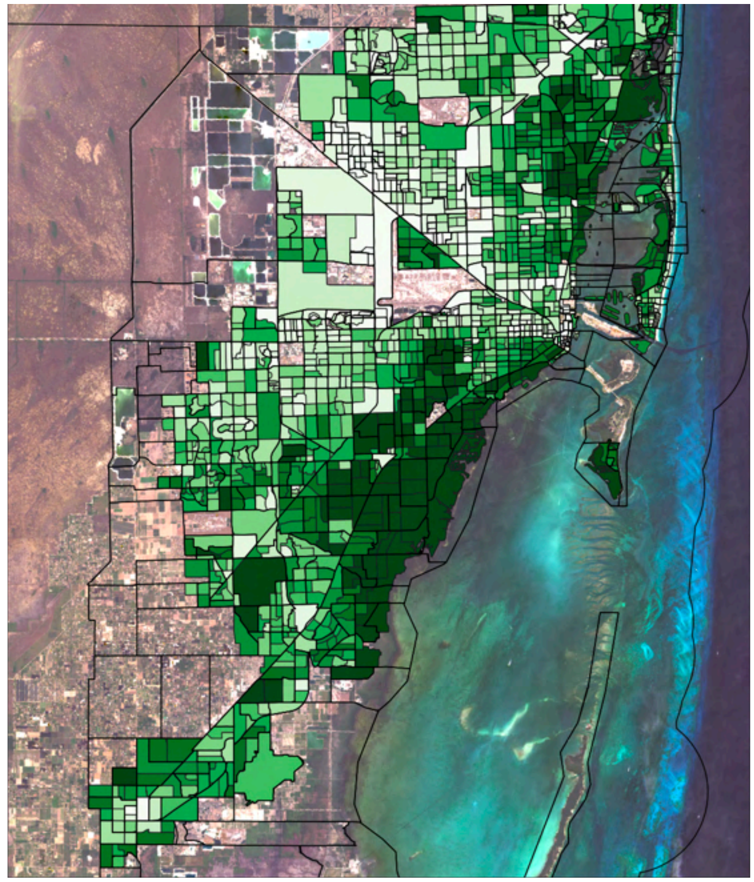
Percentage Uninsured People (2019-2023) evidence further supports the need for targeted greening interventions in underserved neighborhoods.

Tree Canopy as a More Accurate Indicator of Urban Cooling:

Given the relatively low correlation between the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), a more reliable indicator of vegetative cooling is needed. Tree canopy coverage offers a more accurate reflection of long-term, cooling vegetation than NDVI, which may be influenced by short-term ground cover or grasses.

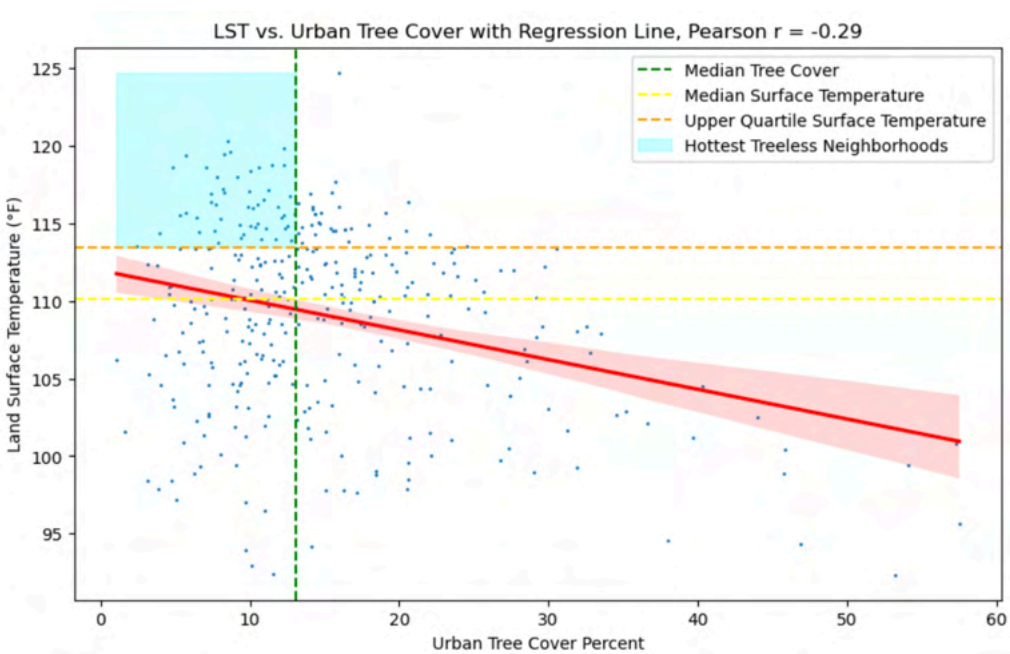
To assess this, I used tree canopy statistics published in Miami-Dade County's 2021 Urban Tree Canopy Assessment. While the data precedes the 2024 LST data by four years, tree canopy growth tends to be gradual, making it reasonable to assume that the canopy distribution has remained somewhat consistent over this period.

The analysis revealed a strong negative correlation (-0.29) between LST and tree canopy percentage. This correlation is notably stronger than that of NDVI with LST, affirming the tree canopy as a better indicator of vegetative cooling in urban contexts.



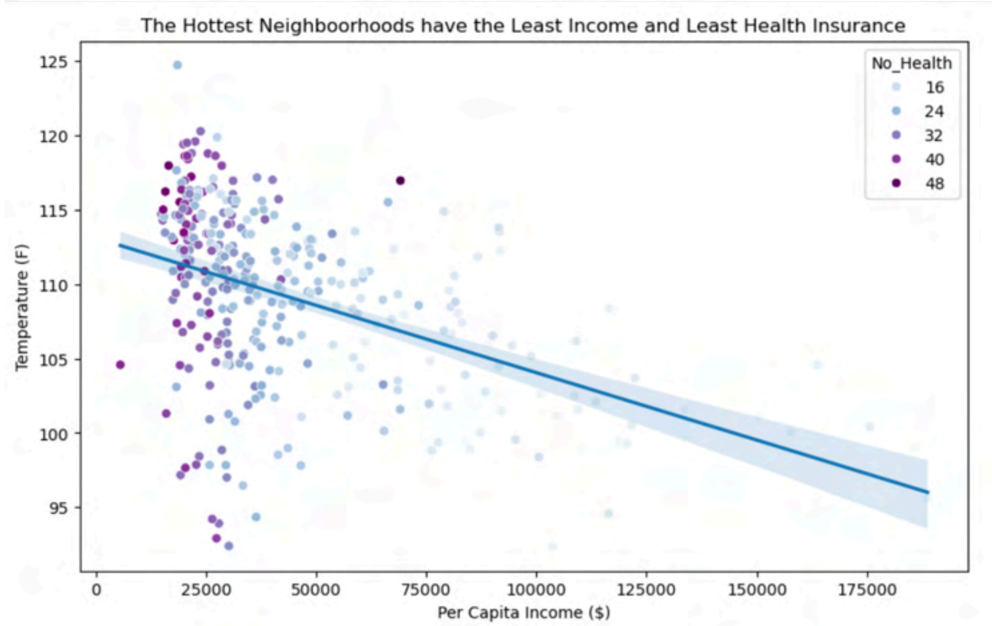
2020 Urban Tree Canopy
"Areal Statistics of Urban Tree Canopy for the Miami-Dade Urban Area 2020", https://doi.org/10.34703/gzx1-9v95/1WWUEM, FIU Research Data Portal, V1

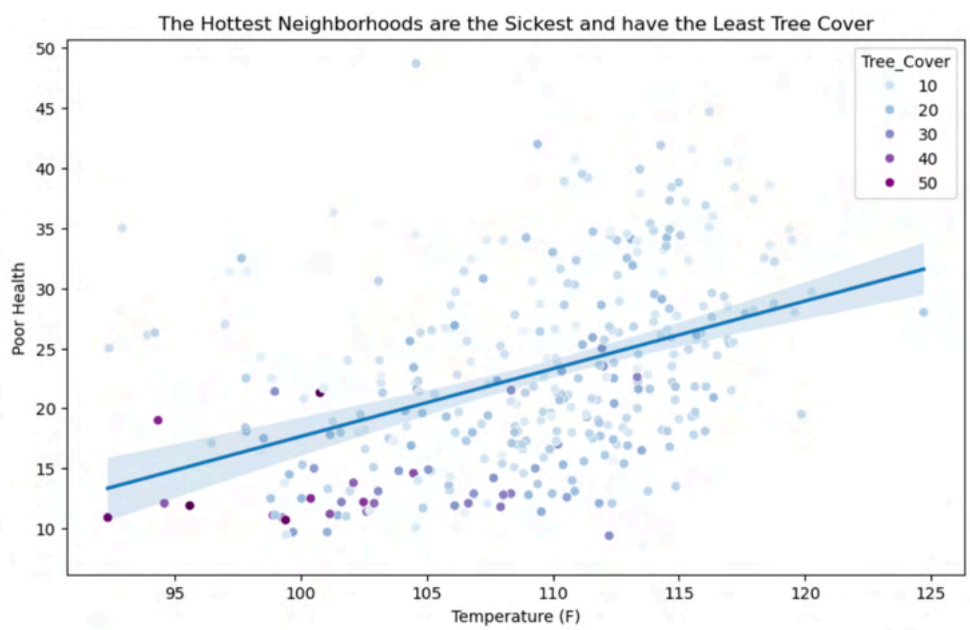
As observed with other socio-economic indicators, neighborhoods with dense tree coverage tend to be wealthier and cooler, while areas with low canopy cover are hotter and home to residents with lower income, lower are of health insurance , and poorer health reporting.



The plot to the left visualizes this

correlation, highlighting in blue the communities with both high temperatures and minimal tree coverage. These neighborhoods emerge as clear priorities for greening interventions based on their physical and environmental vulnerabilities.





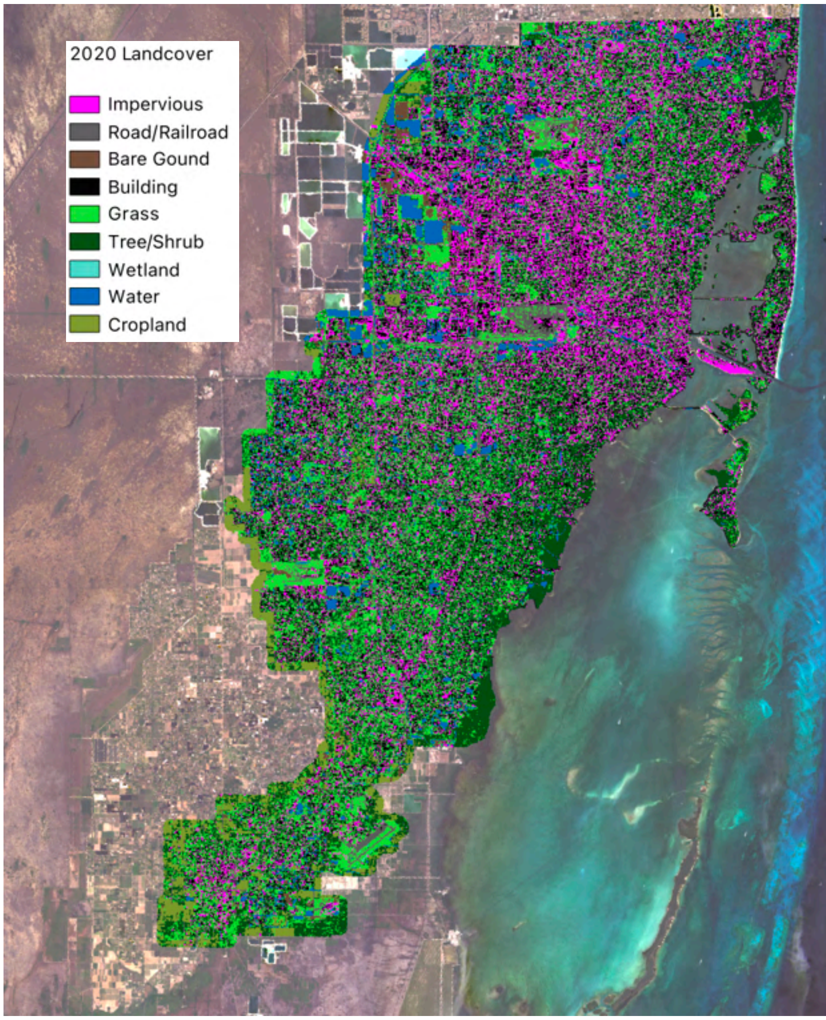
To integrate these findings with demographic data, I developed a Heat Vulnerability Index, which combines LST, tree canopy percentage, and socio-economic indicators. This index helps identify communities most in need of targeted investment in urban forestry and climate resilience.

Classification of Land Cover and Tree Canopy Change:

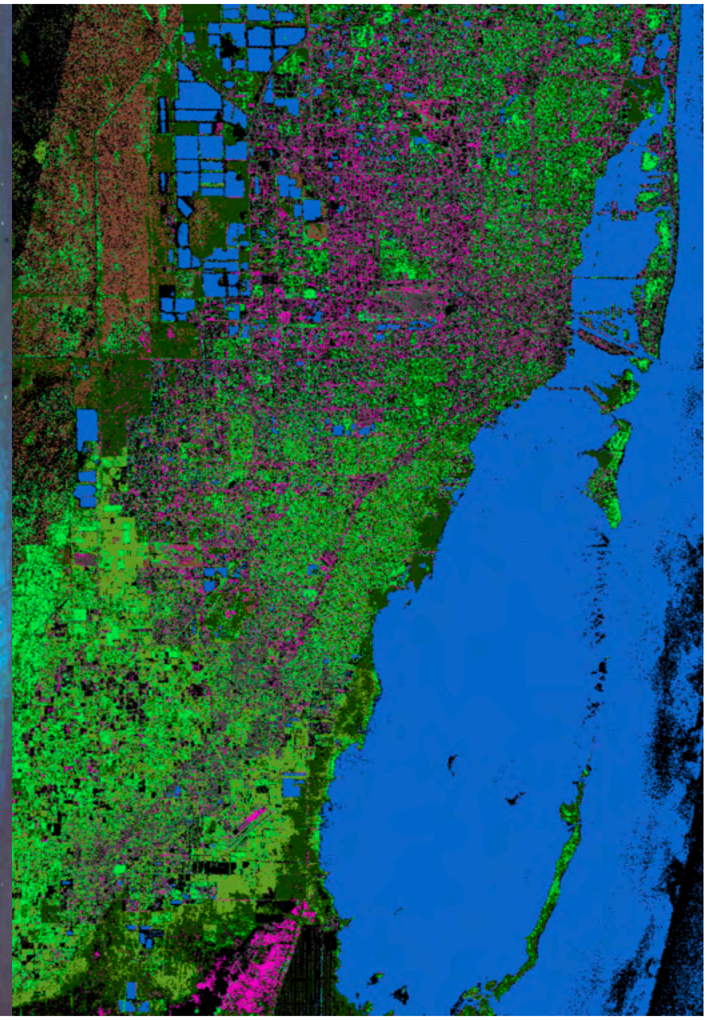
In an effort to replicate Miami-Dade County's 2021 Tree Canopy Assessment using updated 2025 data, I conducted a land cover classification using Planet Labs' PlanetScope imagery (8-band, 1-meter resolution). Despite training the model with nearly 20 regions of interest (ROIs) per class, I was unable to match the classification quality of the original 2020 map, which had been generated from WorldView-2 data (8-band spectral, 2-meter spatial resolution).

The original classification process involved a sophisticated pipeline: an initial Random Forest classifier, followed by reclassification using vector data, expert post-processing, and a morphological filter—steps that exceed the scope of my current project capabilities.

While my classification results were not robust enough to produce accurate 2025 tree canopy statistics, they do serve to highlight discrete land cover changes. One example is the redevelopment of a large



2021 Landcover Classification
"Miami-Dade County Land Cover Map (2021)", https://doi.org/10.34703/gzx1-9v95/HK3EJK, FIU Research Data Portal, V2)



My 2025 (5/18) Landcover Classification
Planet Scope Scene Image © 2025 Planet Labs PBC, https://www.planet.com/

golf course into the Miami Freedom Park, a 131-acre complex anchored by a 25,000-seat soccer stadium.

Below, I display a comparative analysis showing changes in the classified land cover, corresponding NDVI, and photographic imagery from Google Earth, which together document this transformation.

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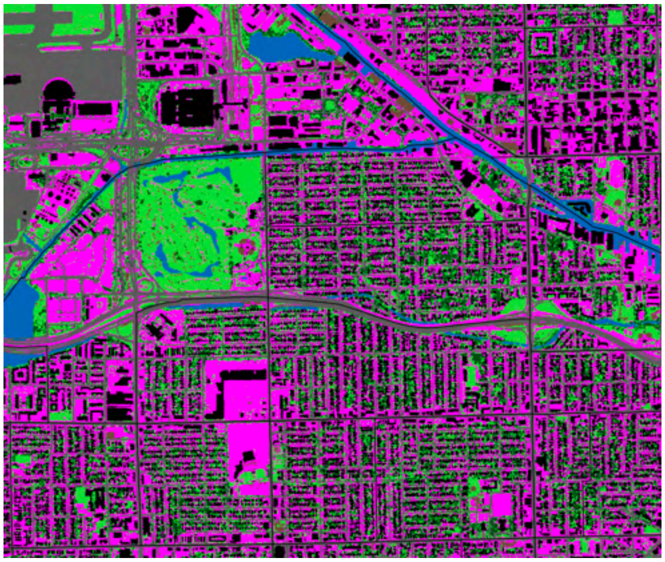
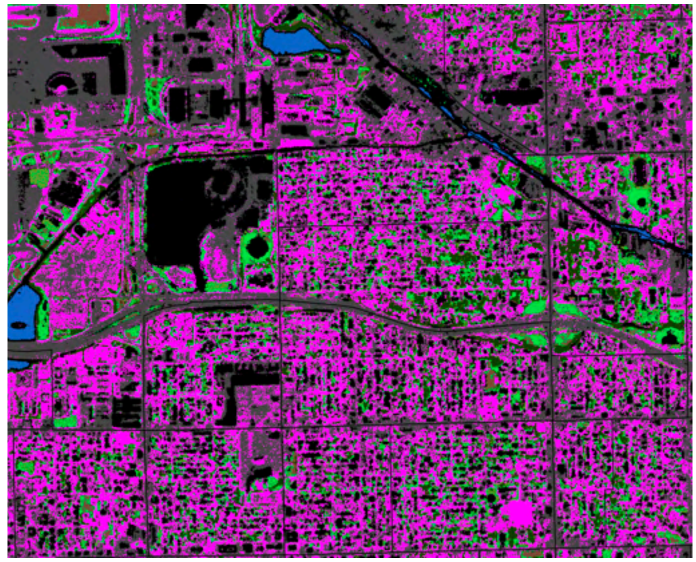
Landcover Change, 2023-2025 Development of Miami Freedom Park



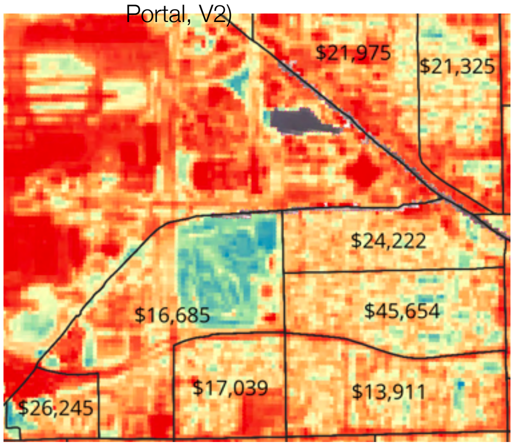
2021 Landcover Classification

"Miami-Dade County Land Cover Map (2021)", https://doi.org/10.34703/gzx1-9v95/HK3EJK, FIU Research Data Portal, V2)



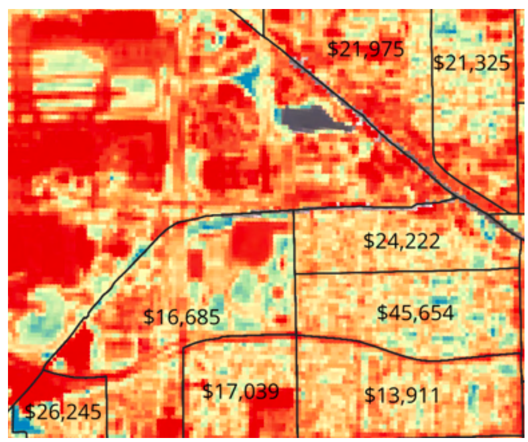
My 2025 (5/18) Landcover Classification

Planet Scope Scene Image © 2025 Planet Labs PBC, https://www.planet.com/



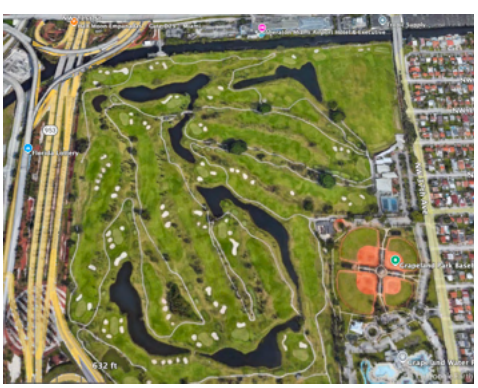
March 2021 NDVI (LandSat 8/9)

Earth Resources Observation and Science (EROS) Center. (2020). Landsat 8-9 Operational Land Imager / Thermal Infrared Sensor Level-2, Collection 2 [dataset]. U.S. Geological Survey.



2024 Mean Summer NDVI (LandSat 8/9)

Climate Engine. (2025). Desert Research Institute and University of California, Merced. Accessed on (4/17/2025). http://climateengine.org, version 2.1.



Google earth V 7.3.6.10201 (2021 left , 2025 right). Miami, Florida. 25° 47’25.03”N, 80° 15’36.87”W, elev. -1 feet.

Heat Vulnerability Index (HVI):

Many cities have developed their own versions of a Heat Vulnerability Index (HVI)—a metric widely used in academic research and public policy to identify populations at greatest risk during extreme heat events. Some HVIs, such as Yale's 2022 index (Manware et al., 2022), are highly comprehensive, incorporating indicators like the Environmental Vulnerability Index (EVI), summertime air temperature, and demographic variables including income, race, disability, and age.
Other cities have adopted simpler frameworks. For example, New York City's HVI includes temperature, vegetation, income, and access to air conditioning.

To assess heat vulnerability in Miami-Dade County, I developed a custom HVI that incorporates both physical and socioeconomic metrics, including:

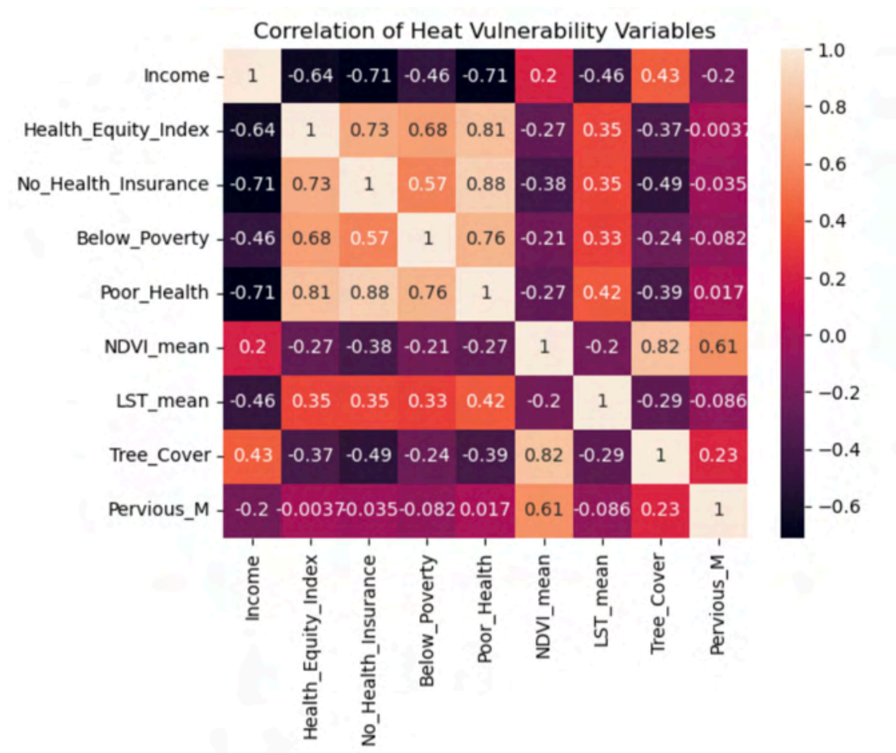
- Negative Per Capita Income
- Percent of People Without Health Insurance
- Negative Mean Normalized Difference Vegetation Index (NDVI)
- Land Surface Temperature (LST)
- Negative Percent Tree Canopy Coverage
- Percent Impervious Surface Coverage

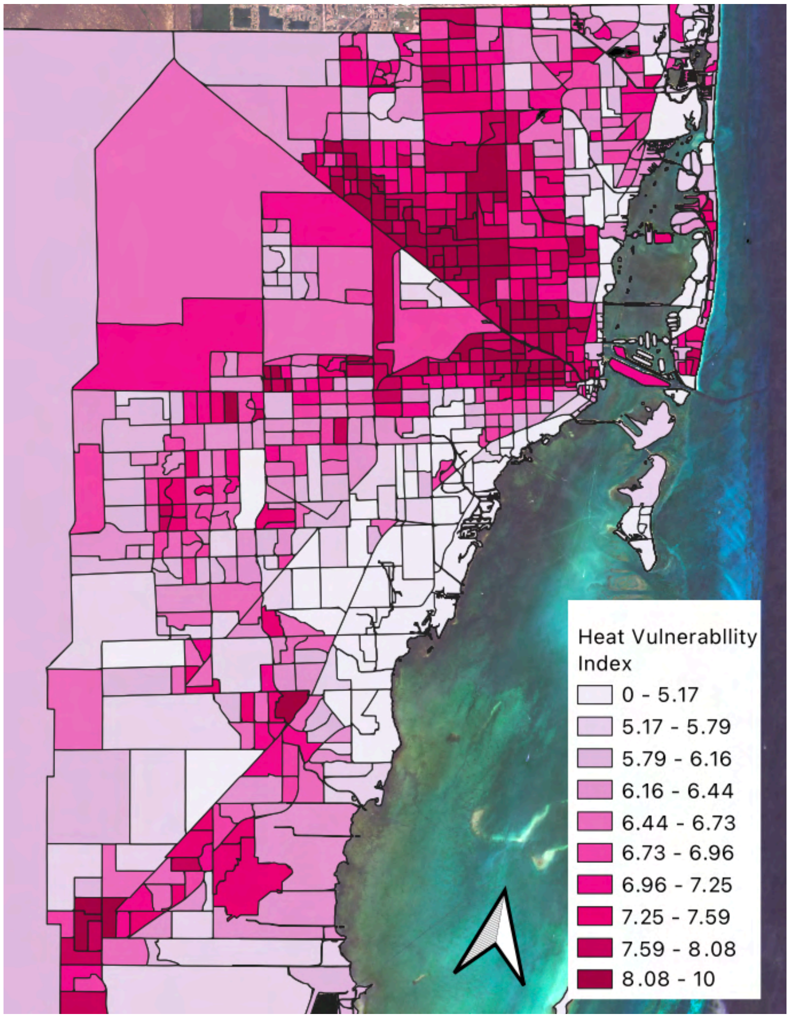
To compute the HVI, these indicators were weighted using Principal Component Analysis (PCA), which allowed the combined metric to explain 54% of the variance across all indicators. The final composite scores were then normalized using Min-Max Scaling, producing index values ranging from 0 to 10. A score of 10 represents the highest level of heat vulnerability.

The top 10% most heat-vulnerable communities are concentrated primarily in central Miami, especially around the Hialeah area. These neighborhoods exhibit a combination of high surface temperatures, low vegetative cover, poor health outcomes, and limited socioeconomic resources.

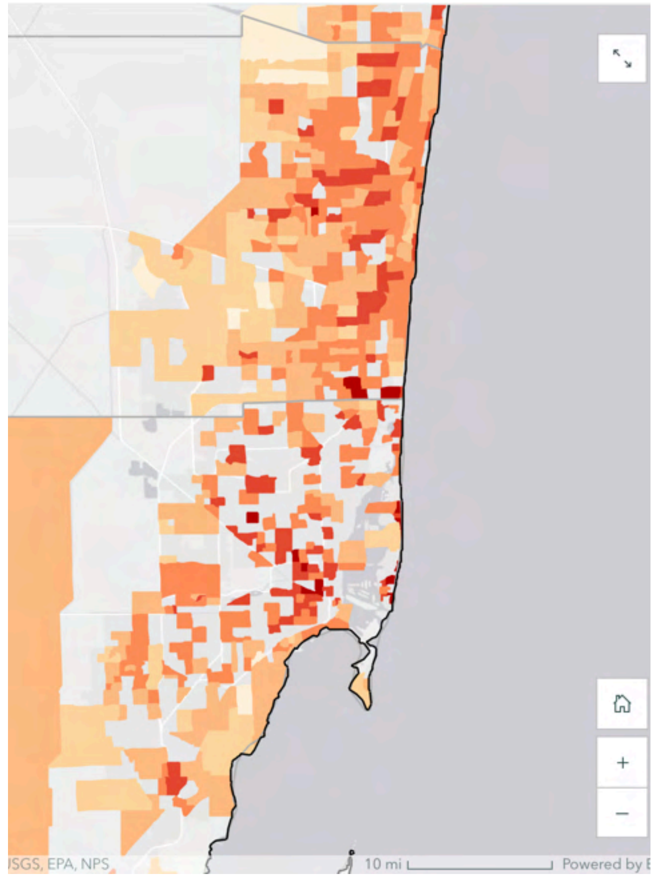
	PC1
Income	0.360002
No_Health_Insurance	0.417549
Poor_Health	0.387472
NDVI_mean	0.385834
LST_mean	0.271810
Tree_Cover	0.427311
Impervious	0.374932

First Primary Component of Each Indicator Used as Weights for HVI





Miami HVI, 10 Being at Most Heat Risk



Yale created HVI, Miami, 2022, https://storymaps.arcgis.com/stories/887792e05ea744d3b085856ca061ef53

Predictive Model Development and Results:

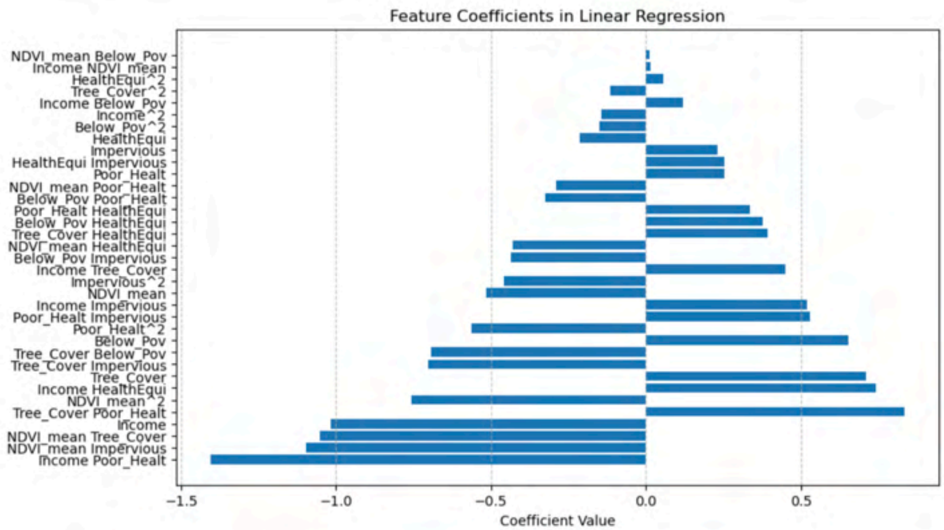
To explore the relationship between Land Surface Temperature (LST) and various physical and socioeconomic indicators, I tested five different regression models including, Linear, Ridge, GradientBoosting, Support Vector, and Random Forest varying their feature scaling and hyperparameters. Of these, a Linear Regression model with degree 2 polynomial features yielded the most accurate predictions.

All features were normalized, and degree 2 polynomial transformations were applied to capture potential nonlinear interactions. The final model achieved:

- Root Mean Squared Error (RMSE): 2.37°C
- R-squared (R^2): 0.4828

While the model does not fully capture the complexity of LST variations, it demonstrates the potential for integrating demographic as well a physical indicators into predictive models for urban temperature analysis. Below, the indicators and their corresponding coefficients are presented.

	Feature	Coefficient
11	Income Poor_Healt	-1.403851
19	NDVI_mean Impervious	-1.097044
15	NDVI_mean Tree_Cover	-1.051598
0	Income	-1.015681
22	Tree_Cover Poor_Healt	0.833414
14	NDVI_mean^2	-0.755220
12	Income HealthEqui	0.741504
2	Tree_Cover	0.711926
24	Tree_Cover Impervious	-0.702603
21	Tree_Cover Below_Pov	-0.691658
3	Below_Pov	0.652703
29	Poor_Healt^2	-0.561405
31	Poor_Healt Impervious	0.530296
13	Income Impervious	0.521143
1	NDVI_mean	-0.516334
34	Impervious^2	-0.458325
9	Income Tree_Cover	0.449007
28	Below_Pov Impervious	-0.436544
18	NDVI_mean HealthEqui	-0.430858
23	Tree_Cover HealthEqui	0.392507
27	Below_Pov HealthEqui	0.377930
30	Poor_Healt HealthEqui	0.337142
26	Below_Pov Poor_Healt	-0.325763
17	NDVI_mean Poor_Healt	-0.291123
4	Poor_Healt	0.254015
33	HealthEqui Impervious	0.251793
6	Impervious	0.231402
5	HealthEqui	-0.212557
25	Below_Pov^2	-0.148896
7	Income^2	-0.143889
10	Income Below_Pov	0.120669
20	Tree_Cover^2	-0.115201
32	HealthEqui^2	0.056496
8	Income NDVI_mean	0.016109
16	NDVI_mean Below_Pov	0.011319



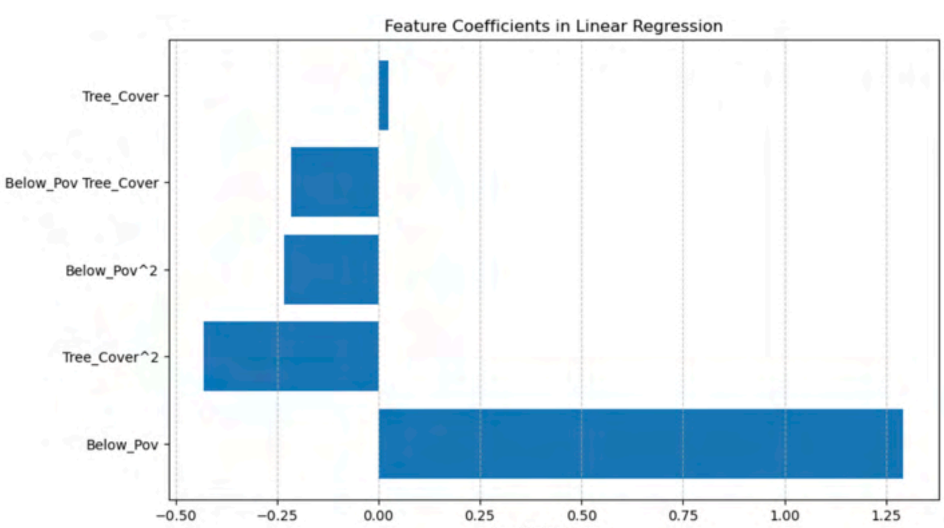
RMSE: 2.3767
R2 Score: 0.4828

Achieved dropping NAN's, scaling all indicators with degree 2 polynomial and using linear regression.

Modeling Tree Canopy, Poverty, and LST with Regression

To estimate local temperature changes resulting from increases in tree canopy, I refined the set of predictors to focus specifically on the negative correlation between tree cover and surface temperature. The most effective model utilized just two indicators—Percent Tree Canopy Cover and Percent Population Below Poverty Level—with both variables transformed using degree-two polynomial scaling in a linear regression framework. This model achieved the following performance metrics:

- Root Mean Squared Error (RMSE): 2.89°C
- R-squared (R^2): 0.2324



	Feature	Coefficient
0	Below_Pov	1.292936
4	Tree_Cover^2	-0.430935
2	Below_Pov^2	-0.233340
3	Below_Pov Tree_Cover	-0.216018
1	Tree_Cover	0.024183

RMSE: 2.8937
R2 Score: 0.2324

Dropped Nan values, 2nd degree polynomial scaling with linear regression over Tree Cover and % Below Poverty Level Indicators

I then applied this model to generate temperature predictions for all census tracts identified as highly heat-vulnerable in my Heat Vulnerability Index (HVI). The chart below presents estimated reductions in surface temperature (in degrees Celsius) associated with 5%, 10%, and 20% increases in tree canopy coverage within these tracts.

Although not a comprehensive predictor of LST, the model highlights that variables such as tree canopy and poverty are meaningful contributors to urban heat distribution. These findings support the potential of urban greening—particularly in socioeconomically disadvantaged neighborhoods—as a targeted strategy to alleviate the urban heat burden in Miami-Dade County.

High HVI Neighborhood Temperature(C) Change Predictions Based on %Tree Canopy Increase

	GEOCODE	HVI_rescaled	Neighborhood	temp change if tree + 20%	temp change if tree + 10%	temp change if tree + 5%
0	12086005409	10.000000	Citrus Grove	-4.000880	-2.873328	-2.700319
1	12086000710	9.764493	Hialeah	-2.803026	-2.105117	-2.146929
2	12086000705	9.602636	Hialeah	-0.569569	-0.063028	-0.200525
3	12086005410	9.542944	Citrus Grove	-4.168251	-2.739802	-2.416345
4	12086000712	9.460116	Hialeah	-0.105374	0.465225	0.359758
5	12086005304	9.417645	Latin Quarter	-4.037419	-2.986958	-2.852495
6	12086001605	9.405318	Hialeah	-0.507699	0.161073	0.104692
7	12086000903	9.267888	Unincorporated Miami Dade	-4.745420	-3.422485	-3.151784
8	12086002900	9.266954	Allapatth Industrial District	-3.166236	-2.036096	-1.861793
9	12086005406	9.222846	Citrus Grove	-3.805175	-2.705452	-2.546358
10	12086005303	9.181482	Latin Quarter	-3.465129	-2.492126	-2.396391
11	12086000807	9.121966	Hialeah	-1.775405	-0.974039	-0.964123
12	12086002404	9.078507	Melrose	-3.796469	-2.455127	-2.175222
13	12086001603	9.049794	Hialeah	-6.013890	-5.438022	-5.540856
14	12086002800	9.044810	Fashion District, Wynwood ...	-1.517625	-0.460501	-0.322705
15	12086005201	9.031041	Orange Bowl	-2.740174	-2.024158	-2.056916
16	12086005202	9.023384	East Little Havana	-2.279793	-1.320032	-1.230918
17	12086013700	9.019480	Hialeah Gardens	2.850620	3.257753	3.070552
18	12086000806	9.017489	Hialeah	-1.977295	-1.065917	-1.000996

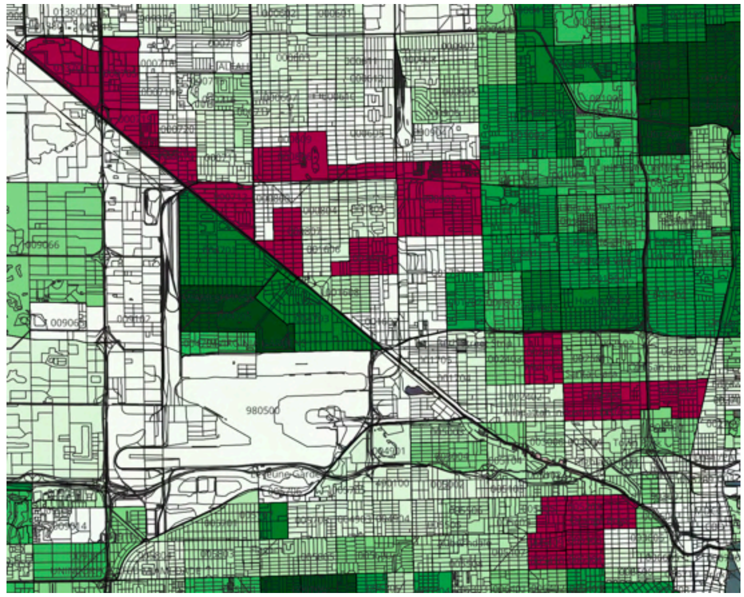
Results and Discussion:

This analysis underscores the urgent need to expand vegetative cover—particularly tree canopy—in Miami-Dade County. Throughout this study, I investigated the relationship between Land Surface Temperature (LST), vegetation indices, and socioeconomic indicators, finding that vegetation alone is insufficient to fully explain variations in urban temperature. Instead, indicators such as income, perceived health, and insurance coverage help capture deeper structural and environmental factors, such as differences in building materials, surface reflectivity, and neighborhood infrastructure.

The results reveal that hotter neighborhoods are often poorer, have less tree cover, and experience higher rates of illness and lower health insurance coverage. These intersecting factors indicate that certain communities are disproportionately vulnerable to the intensifying effects of climate change.

To quantify and spatially identify this vulnerability, I developed a Heat Vulnerability Index (HVI). This index categorized all census tracts in Miami-Dade County by vulnerability level and highlighted the most at-risk communities for targeted intervention.

To inform adaptation strategies, I also developed a linear regression model that estimates local temperature change as a function of changes in tree canopy coverage. In many of the highest-HVI neighborhoods, the model suggests that a 5% increase in tree canopy could lead to a 2–3°C reduction in surface temperature—highlighting a tangible path toward climate resilience.



Neighborhoods with Highest HVI in Red, NDVI in Green

Limitations:

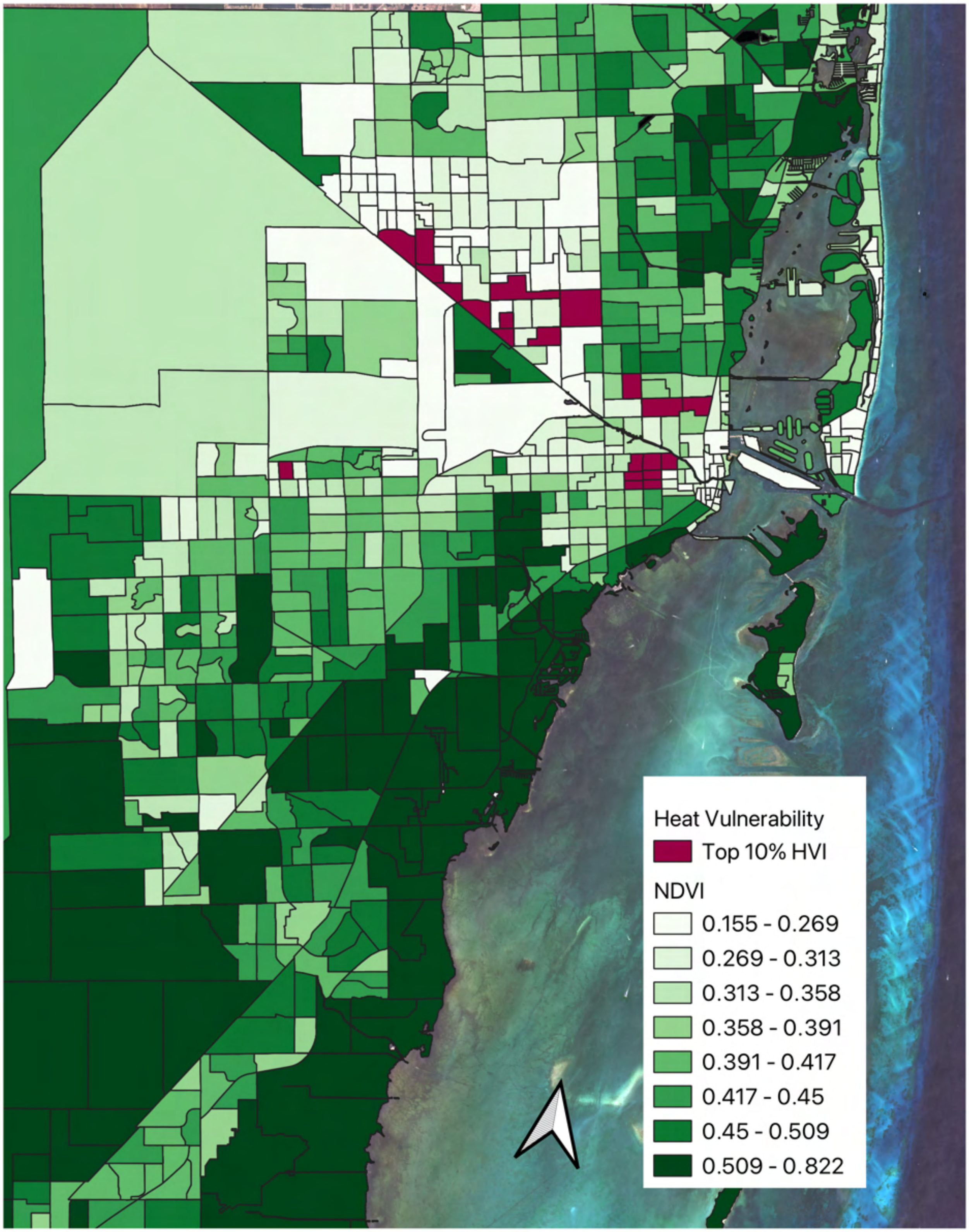
While this study provides valuable insights, several limitations should be acknowledged:

- Data Temporal Mismatch: The analysis used publicly available data collected between 1990 and 2024. A more accurate model would benefit from fully synchronized datasets—including socioeconomic, land cover, and vegetation data—all from 2025.
- Omitted Physical Variables: Local temperature dynamics are influenced by complex physical interactions. This study does not account for water surface area, proximity to coastlines or canals, or building height/material composition, which are likely important in a city like Miami. Incorporating these variables would require additional physical science and urban planning expertise.
- Static Modeling Approach: The regression model assumes static conditions and does not account for dynamic changes over time, such as seasonal shifts, future urban development, or climate variability.
-

Despite these limitations, the findings demonstrate the potential for targeted greening strategies—especially tree planting in vulnerable areas—to substantially mitigate urban heat and promote health equity in Miami-Dade County.

Bridget Atchison-Nevel 5/13/2025

Most Heat Vulnerable Communities Miami, Florida 2025



Resources

Maps

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