DEVELOP Technical Report

Chatham County Health & Air Quality

Mapping Urban Heat to Identify Priority Mitigation Areas in Chatham County, Georgia

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Abstract: Recent development within Chatham County, Georgia have replaced natural tree canopy, raising concerns about increased urban heat island (UHI) impacts. To combat urban heat, the Chatham County Government has sponsored tree canopy evaluations and set up cooling stations during peak summer months. In an effort to help the local government better characterize county-wide UHI impacts, we used optical and infrared imagery from the NASA/USGS Landsat 8 Operational Land Imager (OLI) and, Thermal Infrared Sensor (TIRS), Landsat 9 OLI-2 and TIRS-2, ISS ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station, and National Land Cover Database imagery to map changes in urban heat and vegetation during growing season months between 2014 and 2024. Additionally, we combined the U.S. Census Bureau's community resilience index for heat with environmental risk factors to develop a heat vulnerability index between 2020 and 2022. We also used the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Urban Cooling Model from the Natural Capital Project to create a heat mitigation index for 2021. We found that changes in urban heat and vegetation were both concentrated towards the northwestern part of the county and associated with development activities. We additionally found that the county lost nearly 17% of its existing canopy between 2014 and 2024. Lastly, our analyses of both heat vulnerability and heat mitigation indicate that urbanized areas have high susceptibility to heat stress. The results suggest that Earth observations can be used to map heat-related environmental factors that contribute to the UHI effect in Chatham County and support new policy initiatives and community outreach efforts around urban heat in the county.

Key Terms: urban heat island, land surface temperature, canopy cover, InVEST, NDVI, remote sensing, Landsat, heat mitigation

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1. Introduction

1.1 Background Information

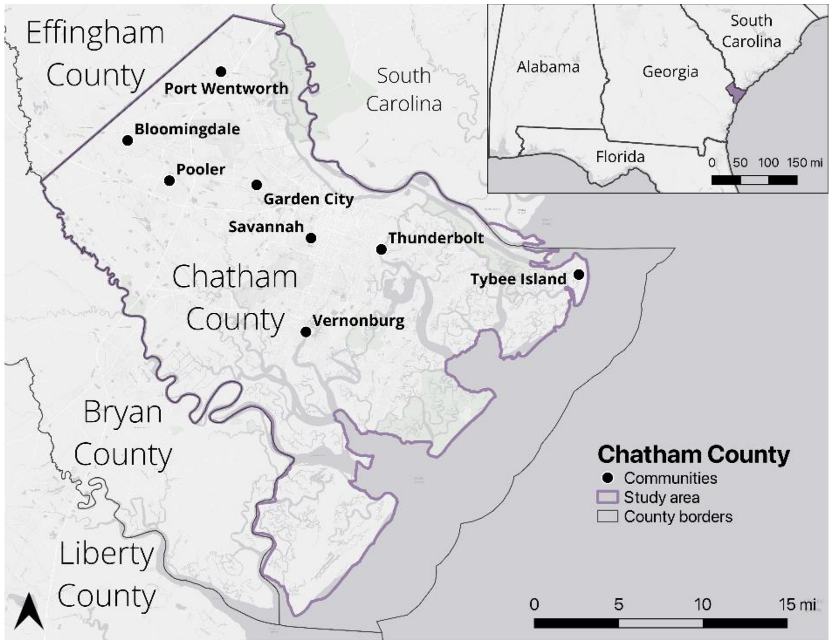
The urban heat island (UHI) effect is a phenomenon where urban areas experience higher temperatures relative to nearby non-urban areas, posing threats to human health and safety (Straub et al., 2019; Tamaskani Esfehankalateh et al., 2021). Researchers have identified several root causes for the UHI effect, including high concentrations of impervious surfaces, restricted airflow between buildings, and heat domes created by greenhouse gases (Leal Filho et al., 2018; Tamaskani Esfehankalateh et al., 2021). The UHI effect is a concern from both a public health and climate perspective, having been linked to higher rates of heat-related morbidity and mortality (Heidari et al., 2020; Wong, Paddon, & Jimenez, 2013) and changes to local weather patterns (Akbari et al., 2016; Leal Filho et al., 2018). It is anticipated that the UHI effect will become more frequent and prolonged in urbanized areas in the future due to climate change (Leal Filho et al., 2018).

The UHI effect can be mitigated by introducing vegetation, which prevents solar radiation from being absorbed and converted to heat by urban surfaces (Bowler et al., 2010; Rogan et al., 2013) by providing shade, absorbing solar radiation as fuel for evapotranspiration, and reflecting solar radiation (Balany et al., 2020). Specifically, trees have been shown to reduce peak ambient temperatures by 0.36 – 9.41 °F, and up to 57.2 °F when assessing physiological equivalent temperature (Balany et al., 2020; Tamaskani Esfehankalateh et al, 2021). Thus, green infrastructure remains a focus for policy makers when facing temperature increases in urban areas (Balany et al., 2020).

Earth observations can be leveraged to determine the magnitude of the UHI effect and identify factors that are contributing to urban heat. Land Surface Temperature (LST), derived from Landsat 8 and 9 Thermal Infrared Sensors (TIRS), has been used to detect UHI — establishing a remotely sensed alternative to measuring ambient air temperatures (Sagris & Sepp, 2017). Satellite imagery can also be used to detect canopy cover, which plays a role in mitigating urban heat (McDonald et al., 2021). Further, remotely sensed data can be used to estimate variables, such as evapotranspiration and albedo, which can be input into the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Urban Cooling Model (Natural Capital Project, 2025) to assess the heat mitigation ability of vegetation (Zawadzka et al., 2011). Heat mitigation represents the ability of an area to cool itself, and when used in tandem with social vulnerability data, provides an understanding of areas in which heat mitigation strategies should be implemented.

1.2 Study Area

Located on the Atlantic coast, Chatham County is the easternmost county in Georgia (Figure 1). Chatham is well known for the historic city of Savannah, and a combination of tourism and ports contribute to 6% of the total Gross Domestic Product of Georgia (Kraeger, 2020). With a population of 307,336 and a land area of 433.12 mi^2 (US Census Bureau, 2024b), Chatham County continues to grow in terms of population, industrialization, and development. Specifically, county officials attribute the influx of large companies, such as Hyundai, to the region as being a principal driver of their recent demographic trends. These changes have likely contributed to an increase in urban heat and a resulting increase in heat-related morbidity and mortality. Thus, this project focuses on Chatham County due to concerns of rising temperatures in association with loss of canopy cover within the county and a desire to pinpoint hotspot areas of immediate concern.



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure 1. Study area of Chatham County, Georgia

1.3 Project Partners and Objectives

Our team collaborated with the local government of Chatham County to determine the feasibility of utilizing NASA Earth observations to identify areas with high heat risk and inform heat mitigation measures to protect county residents. Chatham County has previously taken steps to understand UHI impacts, contracting the Savannah Tree Foundation (STF) in 2015 to evaluate tree canopy loss in the county and determine associated heat trends (Savannah Tree Foundation, 2015). STF found that Chatham lost over 20,000 acres of canopy between 1999 and 2014, with a projected 40,000 additional acres to be lost by 2050 (Savannah Tree Foundation, 2015). In 2022, STF, in collaboration with the Savannah College of Art and Design, found that 97% of the existing tree canopy within Savannah was nearing the end of its life cycle (Savannah Tree Foundation, 2022). They also found a 35 °F temperature difference between impervious surfaces and vegetation, highlighting the importance of vegetation in mitigating urban heat. To support Chatham County in their search for data to inform UHI mitigation efforts, our team chose to analyze trends within the county for May–October of 2014–2024. We selected this study period to align with the STF studies and to coincide with peaks in annual temperature and regional vegetative growth.

Our team established three main objectives for this project, leveraging NASA Earth observations collected during 2014–2024. Our first objective was to explore how remotely sensed environmental factors, such as urban heat, vegetation heath, and canopy cover, changed during the study period, see where the greatest changes occurred, and try to identify the causes. After pinpointing these changes, we were able to work towards our second objective of identifying areas most at risk of urban heat impacts, as indicated by high environmental risk, high social vulnerability, as well as low heat mitigation ability. Lastly, after identifying these areas, our final objective was to help Chatham County reassess their heat mitigation strategy considering our new data. By showing county officials where urban heat effects are most severe, the county may be able to create effective vegetation and heat station implementation projects, as well as development and resilience policies.

2. Methodology

To address Chatham County's concerns, we used Earth observations from NASA Landsat 8 Thermal Infrared Sensor (TIRS), Landsat 9 TIRS-2, and ISS ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) to generate various maps displaying urban heat trends across the county. We mapped the current state of urban heat, vegetation, and canopy cover, as well as changes in these variables from 2014–2024. We additionally focused on two northwestern Chatham County communities, Pooler and Port Wentworth, to evaluate how changes in urban heat and vegetation health correlate with one another. To assess the county's vulnerability to heat, we developed an environmental risk index (ERI), created using satellite imagery, in tandem with our social vulnerability index (SVI), adapted from the U.S. Census' Bureau's Community Resilience Estimates (CRE) for Heat. We also used the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Urban Cooling Model, inputting data provided by satellite imagery to generate a map of heat mitigation across Chatham County.

2.1 Data Acquisition

2.1.1 Urban Heat, Vegetation, and Canopy Cover

To assess urban heat and vegetation health in Chatham County, we acquired Collection 2 Level 2 imagery from NASA's Landsat 8 Operational Land Imager (OLI)/TIRS and Landsat 9 OLI-2/TIRS-2 (Table A1; Earth Resources Observation and Science, 2020). We accessed these data through the PySTAC Planetary Computer Collection via the Python (3.10.16) application programming interface, written in the Visual Studio Code (1.98.2) integrated development environment. Our Python script accessed this collection and selected images that covered the study area during May–October from 2014–2024. To limit cloud contamination, we selected images with less than 30% cloud cover and composited valid images for further processing. To look specifically at tree canopy, we used the EarthExplorer data portal to acquire Landsat 8 OLI Level 2 imagery from the United States Geological Survey (USGS) for our study period (Table A1).

2.1.2 Heat Vulnerability

The data acquisition process for heat vulnerability involved acquiring environmental risk and social vulnerability data. For the environmental component, we used 2021 LST, vegetation, and canopy cover data acquired using the methods described above. For the social component, we obtained the U.S. Census Bureau's 2022 CRE for Heat, an index created in collaboration with Arizona State University's Knowledge Exchange for Resilience using survey data collected during 2020–2022 (U.S. Census Bureau, 2024a). The CRE for Heat captures 11 possible indicators of social vulnerability to heat exposure, including factors such as "no health insurance coverage" and "households that potentially lack air conditioning" (Table C1). For use in our analyses, we downloaded the 2022 Census Tract-level data comma-separated values (CSV) file from the Census Bureau website and uploaded it into QGIS (3.40 LTR) for processing.

2.1.3 Heat Mitigation

To run the InVEST Urban Cooling Model, which calculates an index of heat mitigation (Natural Capital Project, 2025), we acquired data for albedo, evapotranspiration, landcover, and canopy cover inputs. The InVEST heat mitigation index (HMI) represents an area's ability to reduce heat on its own via vegetation. We used InVEST to map heat mitigation across Chatham County, using data from 2021, the most recent year with all required inputs. To find albedo, we first acquired surface reflectance data from Landsat 8 OLI and Landsat 9 OLI-2 (Earth Resources Observation and Science, 2020) using Python in Visual Studio Code via the PySTAC Planetary Computer (Table A1). We developed a script to select images during May–October 2021 with less than 5% null values and 30% cloud cover. To obtain evapotranspiration data, we used the AppEEARS interface to extract daily evapotranspiration data from ECOSTRESS (Hook & Fisher, 2019) and the corresponding quality control data (L3_L4_QA_ECOSTRESS_L2_QC) for May–October 2021. These data were downloaded as tagged image files (TIFF) along with a CSV file (ECO3ETPTJPL-001-Statistics), which provided statistics of the downloaded evapotranspiration data. Lastly, to obtain land cover data (Dewitz, 2023) for InVEST, we used the Multi-Resolution Land Characteristics Consortium's National Land Cover Database Viewer (MRLC NLCD Viewer). We used the Data Download tool, chose the Rectangle method to select an area encompassing Chatham County, and downloaded 2021 landcover data as TIFFs. Canopy cover data was acquired for 2021 from Landsat 8 using the methods described in section 2.1.1.

2.2 Data Processing

2.2.1 Urban Heat and Vegetation

From the Landsat 8 and 9 infrared images collected, we calculated LST by selecting both the long-wave infrared band (lwir11) band and the Pixel Quality Assessment Band (QA_pixel), a band that denotes factors affecting image clarity, such as cloud cover and snow cover. We signed the URL of both bands using the odc.stac package to assure accurate image retrieval. Once retrieved, we used the QA_pixel band to apply a cloud mask that filtered out pixels with excessive clouds and cloud shadows. We then rescaled the raw temperature data to floating points using a scale factor and an offset, then converted the raw temperature data from Kelvin to Fahrenheit to get an LST composite image. To determine the extent of the UHI effect using our LST image, we subtracted a reference temperature taken from a rural reference area (Figure A1). The reference area was chosen as it was found to have a consistent land cover type of evergreen forest and woody wetlands throughout the study period. We aggregated the selected urban heat bands to create median composite rasters for the time ranges of 2014–2016 and 2022–2024. We used three-year aggregates to achieve a statistically significant composite with 30-plus images (Kwak & Kim, 2017) given the sparsity of viable images available. Using the Rasterio Python package, we exported the median urban heat composite images as TIFF files and imported them into ArcGIS Pro (3.1.1) for further processing.

Using an adaptation of our LST script, we calculated the Normalized Difference Vegetation Index (NDVI), a widely used metric which assesses health and density of vegetation, by selecting the red and near-infrared bands for processing and QA_pixel for quality control and cloud masking. We calculated NDVI with using red (Red) and near-infrared (NIR) bands (Equation 1; Kriegler et.al., 1969) and took the 90th quantile of the result to assess peak growth, eliminating erroneous values that may result from taking the maximum. Next, we added a cloud mask to remove any remaining clouds and created composite NDVI images for May through October of 2014–2015, 2014–2016, 2022–2024, and 2024. We selected these aggregates to align with LST aggregates and achieve statistical significance by compiling 30+ images (Table A3). The resulting raster images had a range of -1 to 1 with negative values representing water, 0 representing barren land, and 1 representing dense, healthy vegetation. We imported our 90th quantile NDVI TIFF files into QGIS for analysis.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}$$

2.2.2 Canopy Cover

To make Landsat 8 imagery usable for canopy cover analysis, we utilized ArcGIS Pro to combine bands 2–5 (Blue, Green, Red, Near-Infrared) of Landsat 8 imagery, then used the composite tool with the bands to create natural color imagery. We clipped the imagery to the study area and performed pixel classification, splitting surface features into three categories: impervious surfaces, non-tree vegetation, and trees. Pixels classified as trees were used to find canopy cover for the years of 2014, 2021 and 2024.

2.2.3 Heat Vulnerability

To assess heat vulnerability, we created our ERI and SVI, which we used in tandem to calculate our heat vulnerability index (HVI). To calculate our ERI, we processed LST, NDVI, and canopy cover as explained in 2.2.1, then used the Extract by Mask tool in QGIS to clip the rasters to the tract boundaries. Next, we used the Zonal Statistics tool to find the median value of each environmental risk factor per census tract, then used quantiles to score each environmental risk factor from 1–3 and summed these scores to create our ERI, which ranges from 3–9. To calculate our SVI**,** we imported the CRE for Heat and census tract boundaries into QGIS, filtered the data to Chatham County, and selected the variable PRED3_PE, the rate of individuals with three or more components of social vulnerability, which has a range of 0-49.

2.2.4 Heat Mitigation

To run the InVEST model and assess heat mitigation, we processed model inputs by calculating albedo from satellite imagery and cleaning evapotranspiration data. To calculate albedo from surface reflectance, we first used the rescaling coefficient and offset as instructed by USGS (2023). We then used the V03 Method (Equation 2; Andres-Anaya et al., 2023), to solve for a direct estimate of surface albedo (α) using ρ_λ, the monochromatic reflectance of the spectral band (λ) provided by Landsat 8. To process ECOSTRESS evapotranspiration data, we followed the framework provided in the tutorials section of the ECOSTRESS website and used Python in Visual Studio Code to remove granules with no data in more than half of the pixels. We imported the TIFF files into QGIS and used the Cell Statistics algorithm from the Processing Toolbox to calculate median evapotranspiration values. We then clipped the median evapotranspiration and albedo rasters to the study area.

$$\alpha = 0.043 + 0.082 \cdot \rho_1 + 0.173 \cdot \rho_2 + 0.114 \cdot \rho_4 + 0.237 \cdot \rho_5 + 0.252 \cdot \rho_6 + 0.034 \cdot \rho_7 \quad (2)$$

2.3 Data Analysis

2.3.1 Vegetation and Urban Heat

To understand how urban heat has changed throughout the county over time, we created a difference map by subtracting the 2014–2016 urban heat TIFF from the 2022–2024 urban heat TIFF using the Raster Calculator tool. We binned the results using increments of 5 °F for display purposes and created a pie chart to look at the distribution of these bins throughout the county. Similarly, we created two difference maps for NDVI by subtracting the 2014–2016 composite from the 2022–2024 composite, for comparison with LST, as well as the 2014–2015 composite from the 2024 composite to assess change NDVI alone. Rather than binning our results for vegetation, we used a continuous color ramp to display our results. As a visual check, we also compared the urban heat and vegetation maps to historic aerial photography to examine if land use changes influenced the patterns we were seeing.

To get a better understanding of the temperature outliers, we used z-scores to determine statistically significant temperature thresholds for our urban heat difference maps, using a Python script. We defined statistical significance as 2 standard deviations outside of our mean, which is equivalent to being within the 95th percentile or a z-score of 2.58. After determining the threshold, we used the script to count how many pixels experienced statistically significant changes and converted the number of pixels to total area in acres. Zooming in, we clipped our urban heat and vegetation results to Pooler and Port Wentworth, our municipalities of interest, and continued analysis in Python. Specifically, we conducted a Pearson's correlation between NDVI and LST to show how these two variables are associated.

2.3.2 Canopy Cover

To analyze canopy cover, we calculated the percentage of Chatham County covered by trees for 2014 and 2024. This was done by taking our classified tree canopy cover layers for 2014 and 2024 respectively and comparing them to the total Chatham County area to determine percentage of canopy cover for each year. We overlaid the 2014 and 2024 canopy cover results to create a map showcasing the loss of canopy over the study period. Next, we utilized the Apportion Polygon tool in ArcGIS Pro to determine the percentage of tree canopy per census tract for both 2014 and 2024. We then calculated the difference between these values to show the change in canopy cover per census tract over the study period. To ensure accuracy of our canopy classification, we cross referenced our results with the true color imagery. With this, we are able to compare the 2014 and 2024 classifications to highlight areas where changes in canopy cover levels occurred.

2.3.3 Heat Vulnerability

After calculating our ERI and SVI, our final step in assessing heat vulnerability was to calculate and display our HVI. To do this, we calculated the sum of our ERI and SVI, which resulted in an HVI with ranges from

4–12. To display the HVI as a bivariate plot, we overlayed our scored ERI and SVI layers using the blending by multiplication method in QGIS.

2.3.4 Heat Mitigation
To analyze heat mitigation, we ran the InVEST urban cooling model using InVEST workbench (3.14.3) software to calculate HMI. We inputted the landcover raster, evapotranspiration raster, county shapefile, and our user-defined biophysical table (Table D1) into InVEST. The landcover raster that contained data of areas outside of the county border, such that the cooling effects of these areas were captured in our model. The biophysical table provides InVEST with the shade, albedo, and crop coefficient of each landcover class and if the given class is considered a green area. We gave all landcover classes a crop coefficient of 1 because we input evapotranspiration instead of potential evapotranspiration. We classified all forest classes, both wetland classes, shrub/scrub, herbaceous, and hay/pasture as green areas. To find the shade and albedo for each landcover class, we imported the canopy cover, albedo, and landcover rasters into QGIS and clipped all rasters to the county boundary. Next we used the raster layer zonal statistics algorithm, selecting the "Zones layer" (the landcover raster) as the reference layer, and calculating the mean canopy cover (shade) and albedo in each landcover class.

To finalize our model inputs, we chose the "factors" cooling capacity calculation method and input the remaining parameters: reference air temperature, UHI effect, air blending distance, and maximum cooling distance. We calculated the reference air temperature by using the zonal statistics tool in QGIS to find the 2021 median land surface temperature of a rural reference area just outside of Chatham County (Figure A1). Next, to find UHI effect, we used the raster calculator in QGIS to subtract the reference temperature from the 2021 land surface temperature raster for Chatham County. We then clipped this raster to only show data within an urban reference area within the county. Using Python, we found the 90th percentile of these land surface temperature difference values and used this to represent UHI effect. We used the 90th percentile temperature difference value instead of the instructed maximum value because we used land surface temperature instead of air temperature, likely resulting in irregularly high values due to the presence of urban surfaces. We chose an air blending distance of 600m as recommended by Shatz & Kucharik (2014) and a value of 450m, as recommended by InVEST documentation (Natural Captial Project, 2025). After preparing all inputs and parameters, we ran the model, outputting an HMI TIFF. We imported this TIFF into QGIS for visualization. For more details on the InVEST model and our inputs, refer to Appendix D: *InVEST Urban Cooling Model.*

3. Results

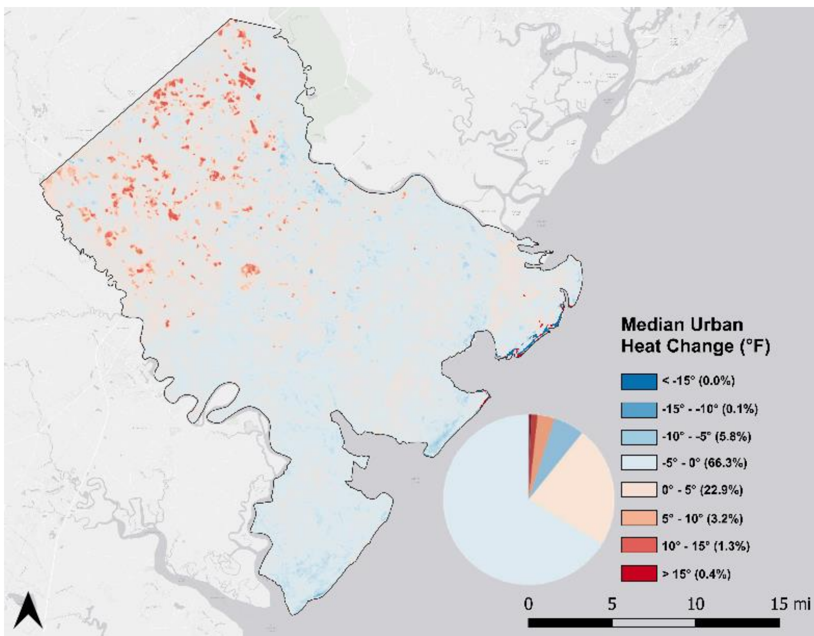
3.1 Analysis of Results

3.1.1 Urban Heat and Vegetation Health
Our urban heat map shows the difference between 2014–2016 and 2022–2024 urban heat composite images (Figure 2). Upon initial inspection, we found that the mean temperature change for the county was -1.14 °F. Nearly 2/3 of the county showed minor temperature decreases on the order of 0–5 °F, while another 23% of the county showed minor increases between 0–5 °F. From our z-score threshold, we found that the 95th percentile temperature change threshold for our data were 7.56 °F on the high end, and that approximately 7,332 acres of the county exceeded this high threshold. These areas are concentrated in the northwest of the county and tend to correspond to areas that were developed during the study period (Figure 2). In addition, we mapped the UHI effect in Chatham County for 2022–2024 (Figure B1). Values shown are normalized to a reference area temperature (Figure A1) of 87.5 °F. Based on these results, we found that UHI is high in urbanized areas and low in non-urban areas.

Our NDVI change detection map (Figure 3) depicts changes in vegetation health from 2014/2015 to 2024. The most dramatic changes occurred in the northwest part of the county, shown in red. These changes are associated with approximately 9,435 acres, or about 3% of the county area, which have seen statistically significant decreases in vegetation health. This statistical significance, the 95th percentile NDVI change found using with our z-score threshold, is associated with a NDVI decrease of 0.16. We additionally produced an

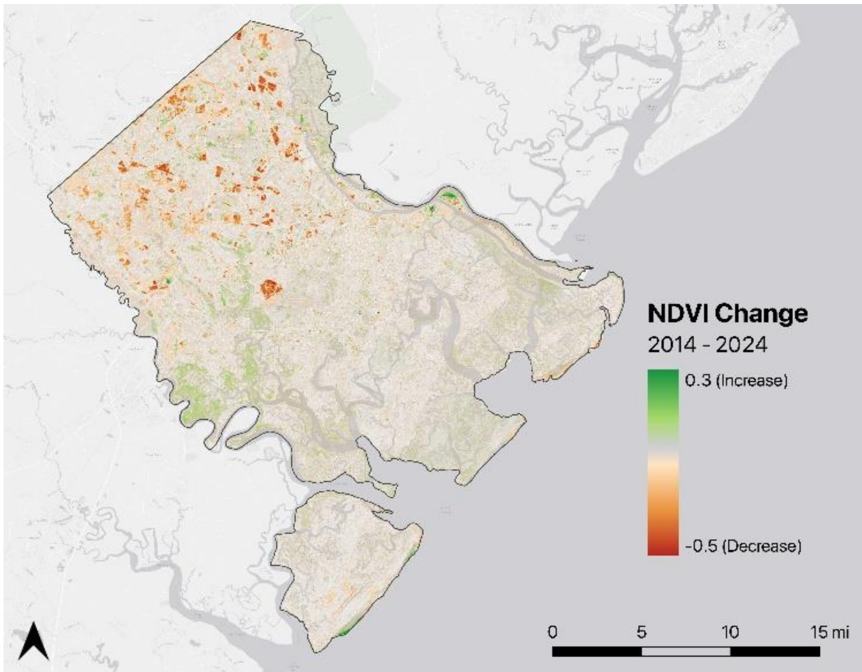
NDVI composite map from 2022 to 2024 to depict the recent state of vegetation health across the county (Figure B2). The maximum NDVI value for Chatham County was 0.53, corresponding to forested areas in the northern part of the county. Conversely, the urban area surrounding Savannah along with suburban areas in the northwest of the county and marsh areas are shown to have the lowest vegetation health. Yet, the marsh area results were likely skewed by high levels of water amongst vegetation in the marsh.

Given that urban heat and NDVI results visually indicated that urban heat has increased and vegetation health has decreased in the northwestern part of the county, our team performed a Pearson correlation analysis between urban heat and NDVI for two communities located in this area: Pooler and Port Wentworth. The Pearson correlation analysis measures the linear relationship between two variables. The analysis produces an r value, ranging from -1 to 1, in which -1 indicates a perfect negative linear correlation, 1 indicates a perfect positive linear correlation, and 0 indicates no linear correlation. The Pearson correlations for Pooler (Figure 4) and Port Wentworth (Figure B3) were found to produce Pearson r values of -0.618 and -0.561, respectfully. These results indicate that urban heat and NDVI are moderately negatively correlated within these communities, meaning that there is a significant linkage between decreasing vegetation and increasing urban heat, but that they are not completely dependent on one another.

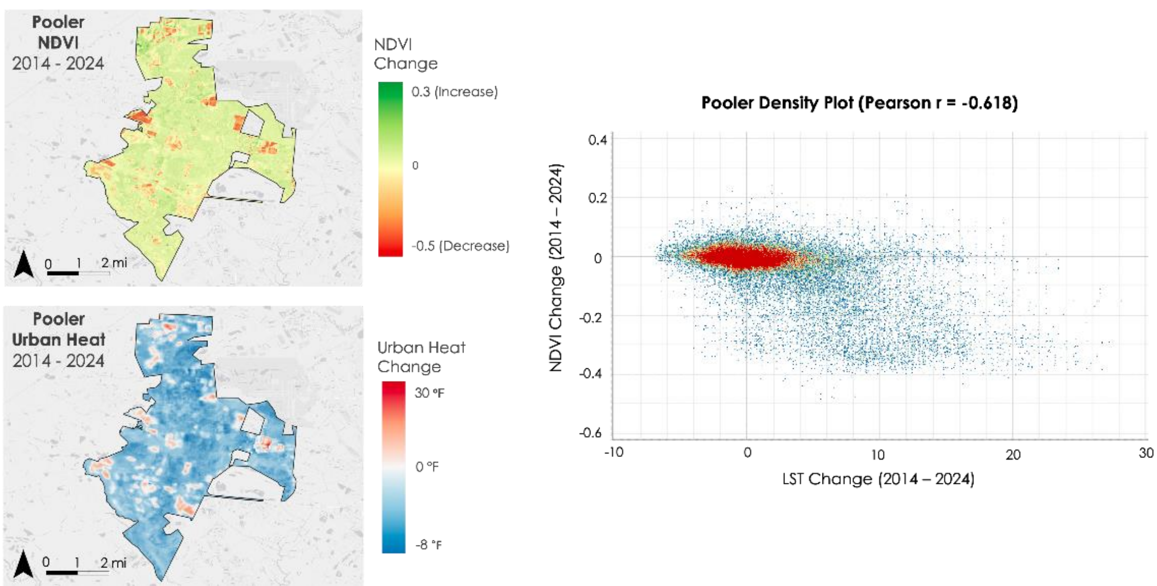


ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure 2. Change in urban heat between 2014-2016 and 2022-2024



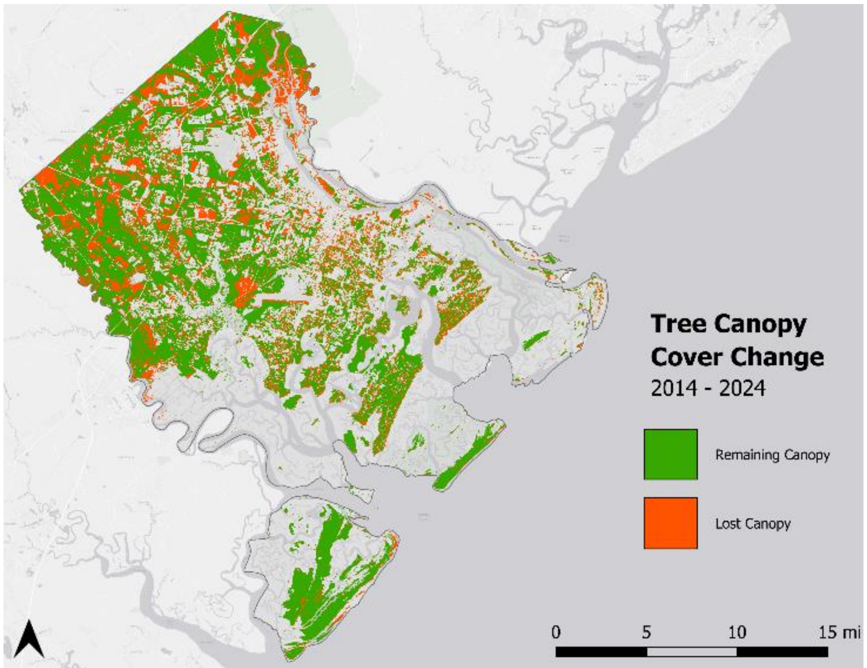
ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)
Figure 3. Vegetation change



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)
Figure 4. Urban heat-vegetation correlation at Pooler community.

3.1.2 Canopy Cover
We found that the percentage of area covered by tree canopy decreased within all census tracts across the county within the study period (Figure B4). Canopy cover within Chatham County decreased around 17% between 2014 and 2024, decreasing from 31.80% to 26.49% of the county's total area (Figure 5). Some urban

areas within Savannah experienced higher canopy cover loss than other areas, but the majority of canopy cover loss is located in the north and northwest of the county.

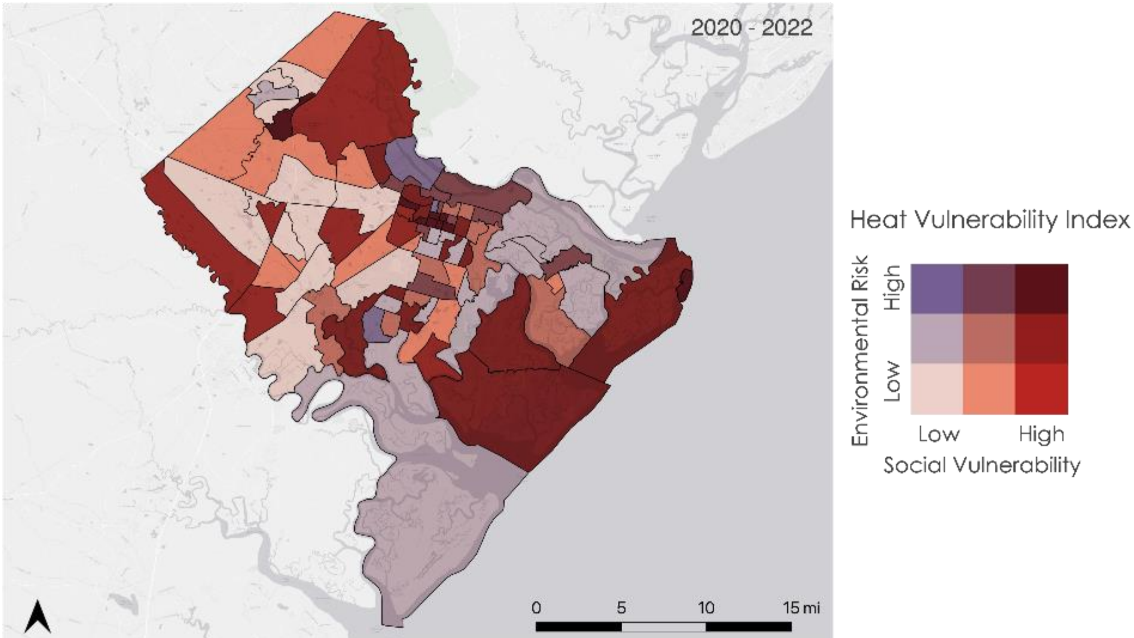


ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure 5. Canopy cover loss between 2014–2024

3.1.3 Heat Vulnerability and Heat Mitigation

Our heat vulnerability index bivariate map (Figure 6) considers both environmental risk and social vulnerability, as they relate to heat. It depicts the relationships between the Environmental Risk Index (Figure C1) and the Social Vulnerability Index (Figure C2), by census tract. Tracts near the center of Savannah, as well as northern Pooler and Tybee Island, display the greatest vulnerability to heat events.



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure 6. Heat Vulnerability Index

3.1.4 Heat Mitigation

As expected, the HMI map (Figure 7) shows that the areas with the lowest heat mitigation are in Savannah, where the UHI effect is most pronounced, the concentration of urban surfaces are high, and the concentration of vegetation and greenery are low. Low heat mitigation can also be found in other urban areas, including Garden City, Pooler, Port Wentworth, and Thunderbolt. Areas of high heat mitigation are found on the borders of the county, where large green areas are found in abundance.

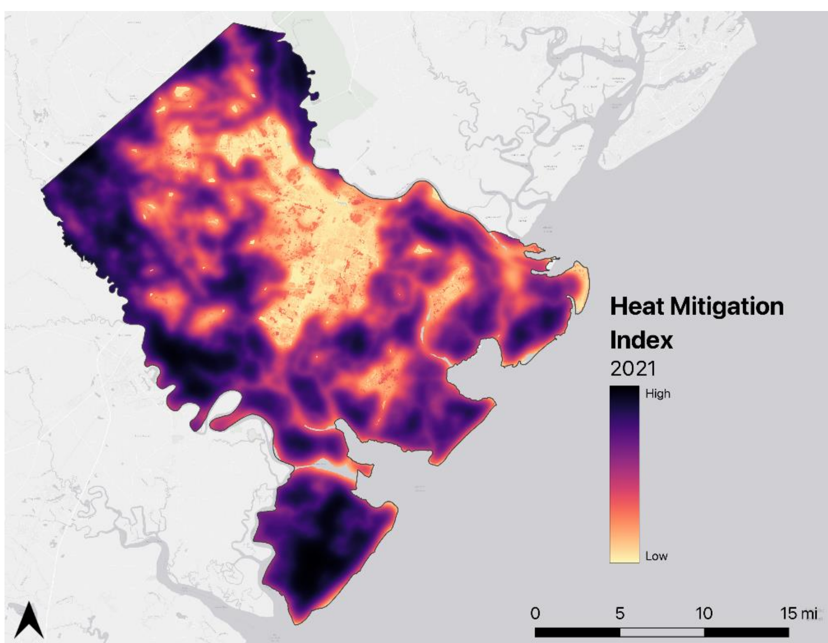


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Figure 7. InVEST's Heat Mitigation Index

3.2 Errors & Uncertainties

When generating our results, we ran into some inherent errors and uncertainties with our data. Specifically, there were an inconsistent number of images that were available across months and years due to cloud contamination and null data. Further, our datasets had inconsistent spatial and temporal resolutions. This specifically impacted our LST and NDVI results, as LST had been resampled from 100m resolution to 30m resolution whereas NDVI is collected at 30m resolution initially. Additionally, due to inconsistent temporal resolutions in the CRE for heat data, our HVI map consists of data between 2020–2022 (Table A2). Similarly, when analyzing the change of urban heat and NDVI over time, we had to compile images across multiple years in order to achieve statistical significance. When detecting canopy cover over time, we did not have enough images to achieve statistical significance. Moreover, since our analyses only used data from the first three and last four years of our study period, we did not account for any changes that may have occurred in 2017, 2018, or 2019. Finally, cloud masking resulted in some areas having null data, preventing them from being incorporated into analyses.

Additionally, remotely sensed data has inherent uncertainty and does not provide a perfectly accurate depiction of the measured variable. For example, when measuring NDVI the presence of water among vegetation in marsh areas resulted in a negative skew. Additionally, the heat mitigation index provided by InVEST has inherent uncertainty because it uses equations with empirical weights. Also, the InVEST heat mitigation index does not take into account any dynamic meteorological effects, such as wind or sea breeze, when quantifying heat mitigation.

4. Conclusions

4.1 Interpretation of Results

From our analysis of urban heat, vegetation health, and canopy cover, we found that the urban heat island effect is at play in Chatham County, particularly within urbanized areas. The effect is particularly strong in downtown Savannah, as well as in the northwestern part of the county in communities like Garden City, Pooler, and Port Wentworth, where vegetation has recently given way to urban development. Looking at how urban heat trends have changed within the county over the study period, we found that new pockets of urban heat have appeared in the northwestern part of the county. These new urban heat pockets coincide with new development projects, where natural vegetation is being replaced with urbanized land uses. Our team found that urban heat stayed relatively unchanged within the southeastern part of the county. In total, our team found that the county has lost approximately 17% of its canopy cover since 2014, resulting in the expansion of urban heat.

Our team also looked at how able the county is to mitigate against urban heat on its own. Results from InVEST show that the urban core of Savannah, as well as parts of Garden City and Port Wentworth, have low heat index scores. These areas are the least able to naturally mitigate against adverse urban heat effects due to the prevalence of urbanized surfaces relative to vegetation. The model also found that less urbanized areas with unbroken expanses of greenspace tend to have stronger natural heat mitigation. Moreover, by overlaying the U.S. Census CRE with our environmental risk factors, we found that in addition to the core of Savannah, northern Pooler and Tybee Island exhibit high vulnerability to heat events due to high combined environmental risk and social vulnerability. The compounding effects of low heat mitigation and environmental and social vulnerability make Savannah an area for concern regarding heat and a key area for policy.

4.2 Feasibility & Partner Implementation

Despite some errors and uncertainties, our team found that it is feasible to use Earth observations to map heat-related environmental factors that contribute to the UHI effect in Chatham County. We were able to use Earth observations to gather information on parameters, such as urban heat, vegetation health, and canopy cover. Using this data, we were able to examine both spatial and temporal trends in these environmental parameters to understand how the urban heat island effect has evolved within the county. We were also able to successfully pair our environmental parameters with social vulnerability data to identify communities most vulnerable to heat impacts. Beyond looking at spatial and temporal trends, we were able to model Chatham County's natural ability to mitigate against heat to further contextualize where mitigation efforts can be focused. Finally, though our results indicate that the urban heat effect is both present in Chatham County and expanding with each new development, this also means that there are many opportunities to implement heat mitigation strategies and see significant improvement. Using the information provided from this project, we hope that Chatham County is better able to prioritize their heat mitigation efforts. Current mitigation efforts that Chatham County implements, such as installing mobile cooling stations and implementing tree planting initiatives, can leverage Earth observations to better target their efforts on higher risk areas. Moreover, the results presented herein can help Chatham County by supporting new policy initiatives and community outreach efforts around urban heat.

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6. Glossary
CRE – Community Resilience Estimate; we used the CRE for Heat created by the U.S. census bureau, an index created using survey data that represents social vulnerability to heat events
LST – Land Surface Temperature; the temperature of the surface of the Earth
ERI – Environmental Risk Index; an index representing environmental risk pertaining to heat, which we created using LST, NDVI, and canopy cover data
HMI – Heat Mitigation Index; the output of the InVEST Urban Cooling Model, which represents an area's ability to cool itself
HVI – Heat Vulnerability Index; an index representing areas most susceptible to heat risk, which we created using environmental and social data.
InVEST – Integrated Valuation of Ecosystem Services and Tradeoffs; a series of models created by Natural Capital Project including the Urban Cooling Model, which we used to find heat mitigation
NDVI – Normalized Difference Vegetation Index; an index representing vegetation density and health

OLI – Operational Land Imager; sensors on Landsat 8 and 9 which measure the visible, near infrared, and shortwave infrared wavelengths
STF – Savannah Tree Foundation; a nonprofit that protects and grows Chatham County's urban forests
SVI – Social Vulnerability Index; an index representing areas where residents are most vulnerable to heat, which we created using the CRE for Heat
TIRS – Thermal Infrared Sensors; sensors on the Landsat 8 and 9 which measure land surface temperature in two thermal infrared bands
UHI – Urban Heat Island; a phenomenon where urban areas have higher temperatures than nearby non-urban areas. This results from the trapping of heat by urban surfaces, buildings, and greenhouse gas emissions

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8. Appendices

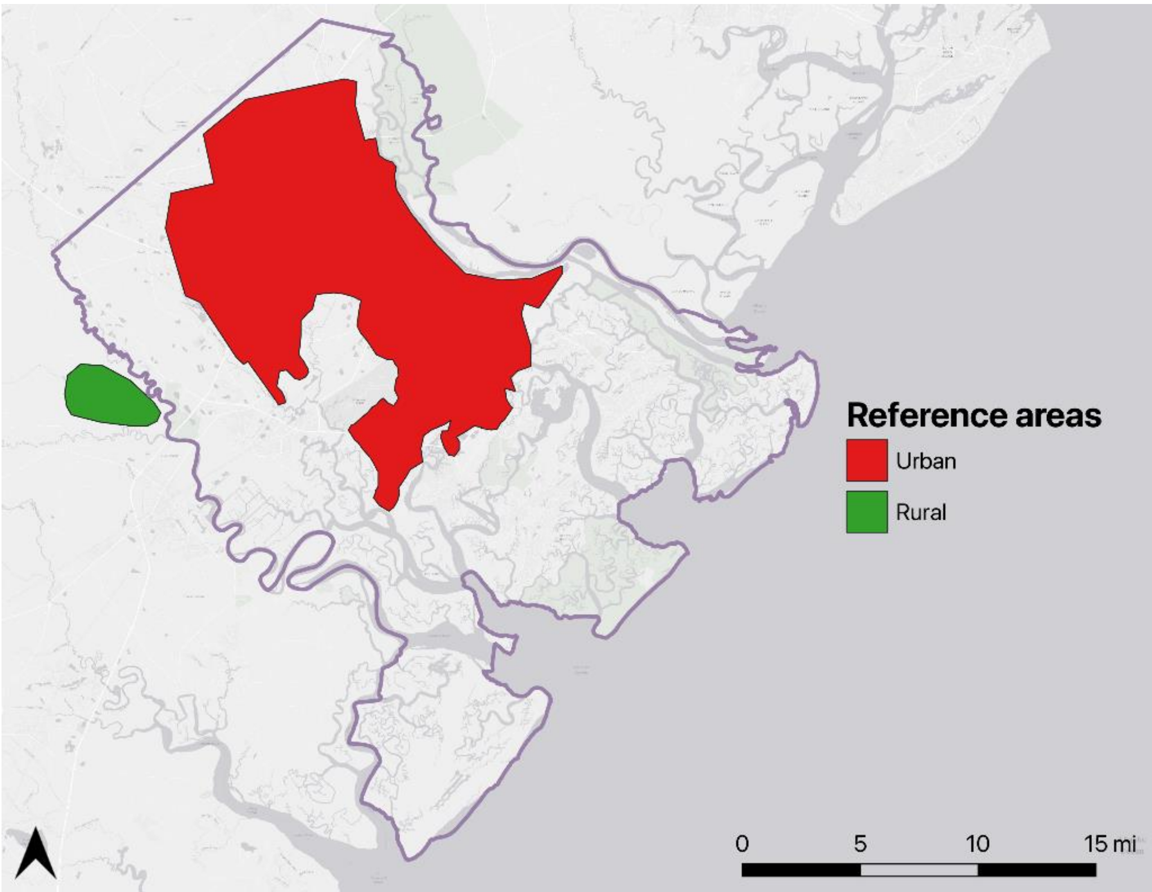
Appendix A: *Data Information*

Table A1
Datasets used in this study

Dataset	Spatial Resolution	Time Period	Description	Source
Landsat 8 OLI	30m	2014–2024	Red and near infrared bands: used to calculate NDVI	PySTAC Planetary Computer
		2021	Surface reflectance: used to calculate Albedo	
Landsat 8 TIRS	100m	2014–2024	Long-wave infrared band: used to calculate LST	PySTAC Planetary Computer
Landsat 9 OLI-2	30m	2022–2024	Red and near infrared bands: used to calculate NDVI	PySTAC Planetary Computer
		2021	Surface reflectance: used to calculate Albedo	
Landsat 9 TIRS-2	100m	2022–2024	Long-wave infrared band: used to calculate LST	PySTAC Planetary Computer
CRE for Heat	N/A	2020–2022	Community Resilience Index for Heat: used to create Heat Vulnerability Index	U.S. Census Bureau
ECOSTRESS	70m	2021	Daily evapotranspiration	AppEEARS
NLCD	30m	2021	Land cover classification	MRLC NLCD Viewer

Table A2
Years of data used for analyses

Analysis	Years of data used
Urban Heat change	2014–2016 & 2022–2024 (statistical significance achieved)
NDVI change	2014–2015 & 2024 (statistical significance achieved)
Canopy Cover change	2014 & 2024 (statistical significance *not* achieved)
Community Resilience Estimate for Heat	2020–2022
Environmental Risk Index	2021
InVEST	2021



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

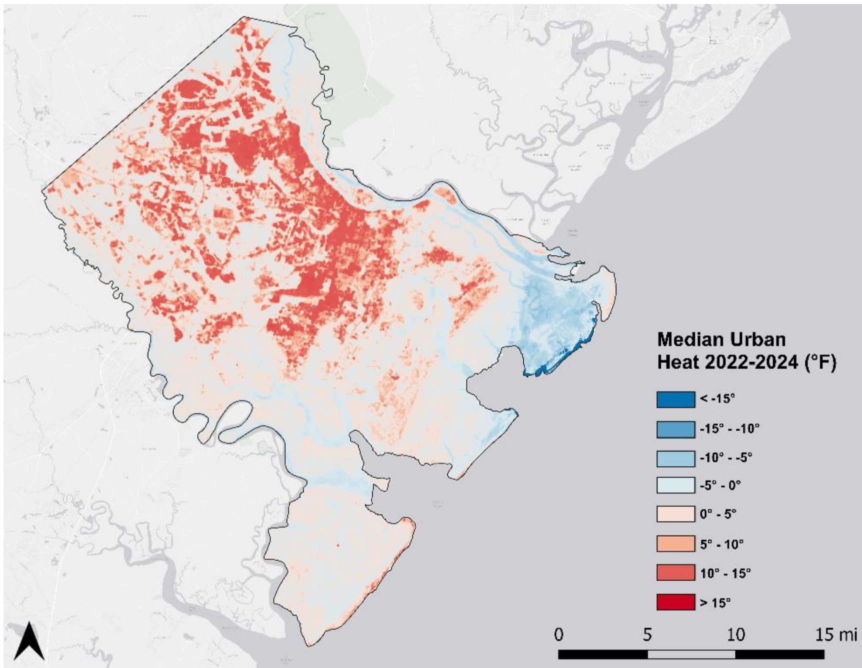
Figure A1. Urban and rural reference areas

Table A3

Number of images in composites

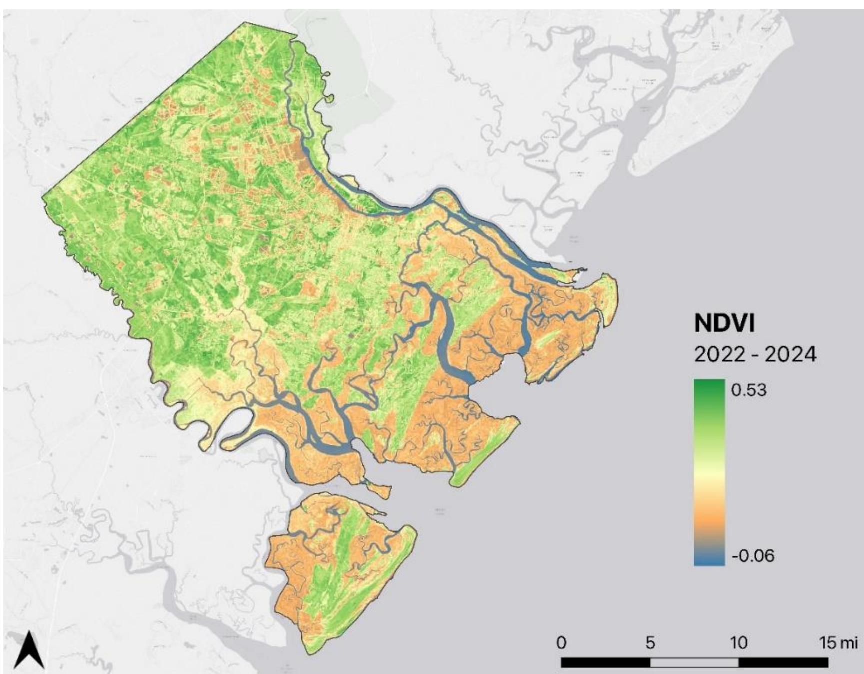
Parameter	Time Period	Number of Selected Images
LST	2014–2016	34
	2022–2024	63
NDVI	2014–2015	33
	2014–2016	49
	2022–2024	94
	2024	42

Appendix B: *Urban Heat, Vegetation Health, & Canopy Cover*



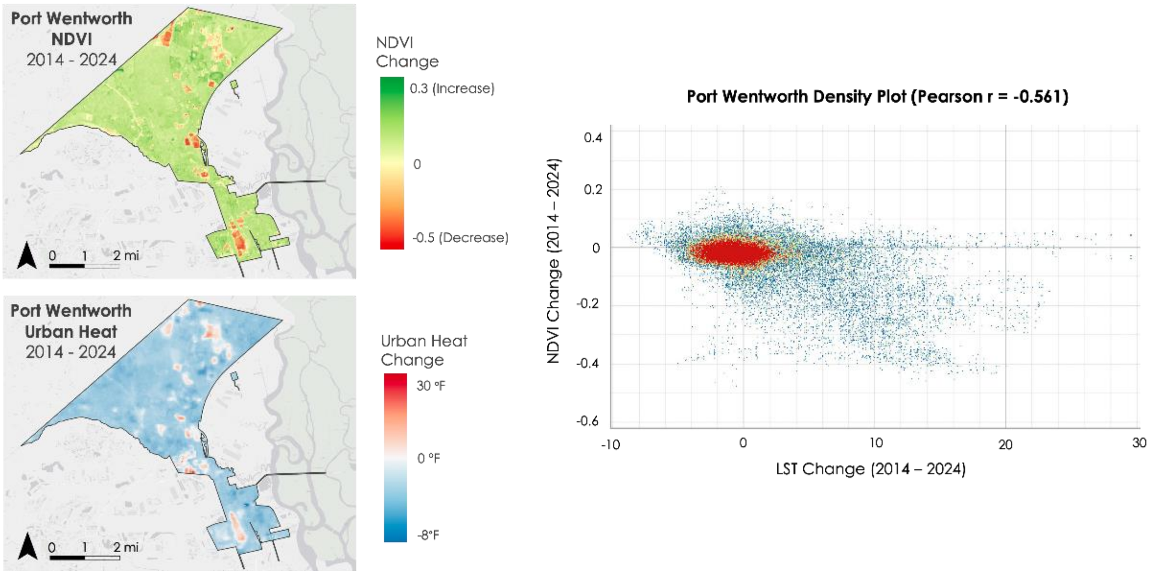
ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure B1. Median Urban Heat: 2022–2024



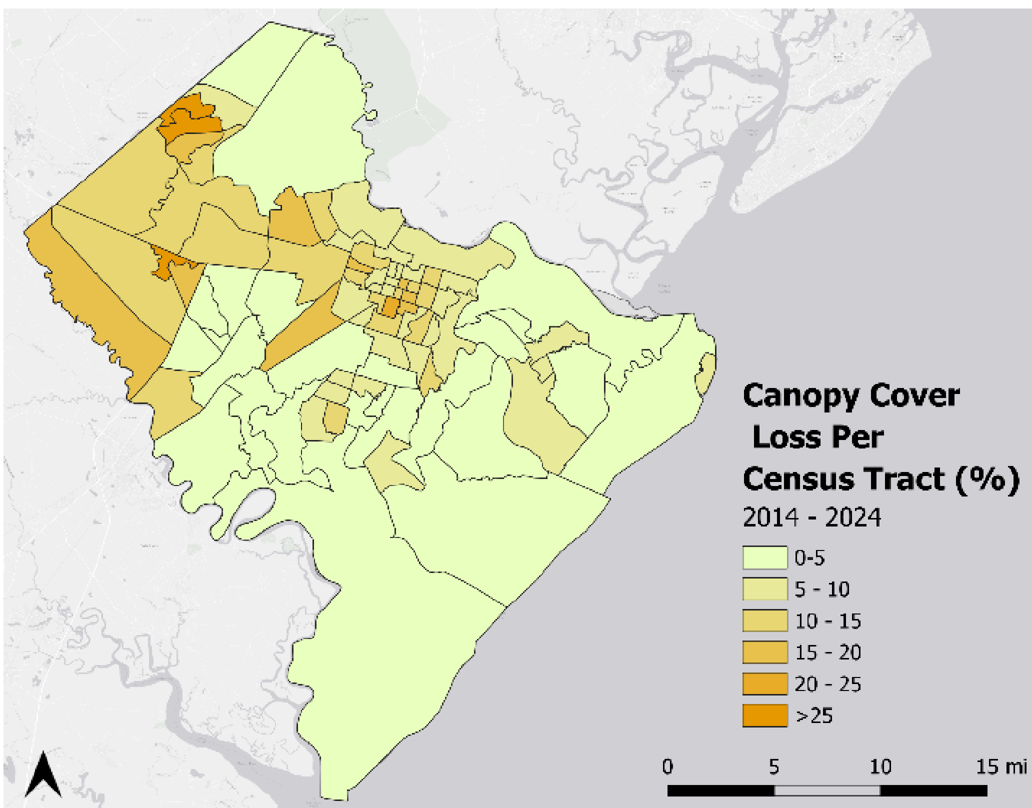
ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure B2. NDVI: 2022–2024



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure B3: Urban Heat-Vegetation Correlation – Port Wentworth



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

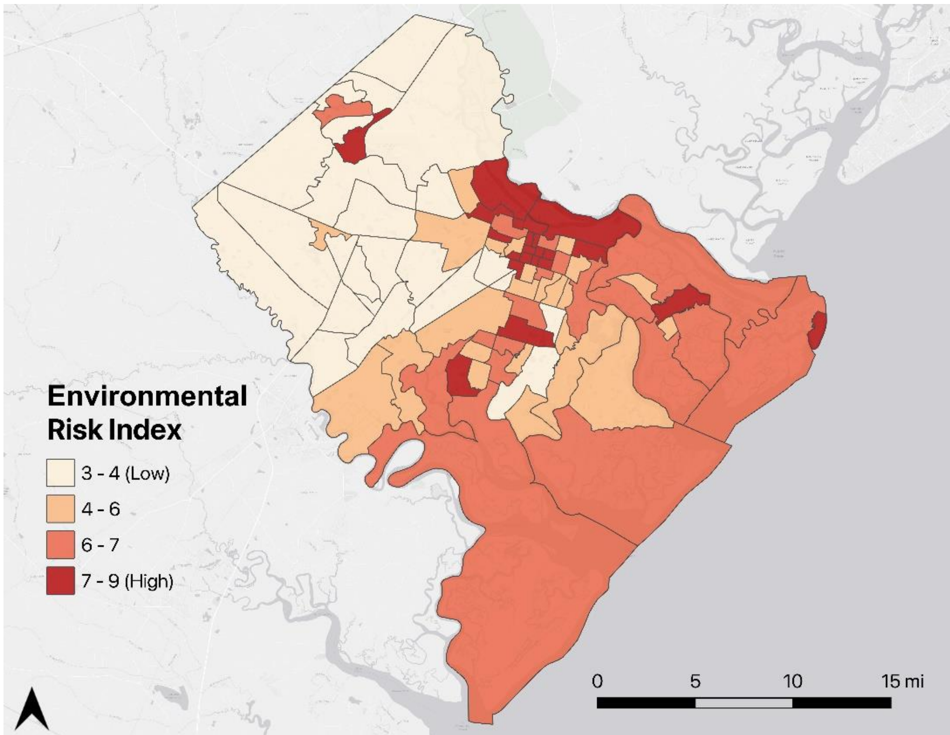
Figure B4: Canopy Cover Change per Census Tract: 2014–2024

Appendix C: *Social vulnerability & Environmental Risk*

Table C1

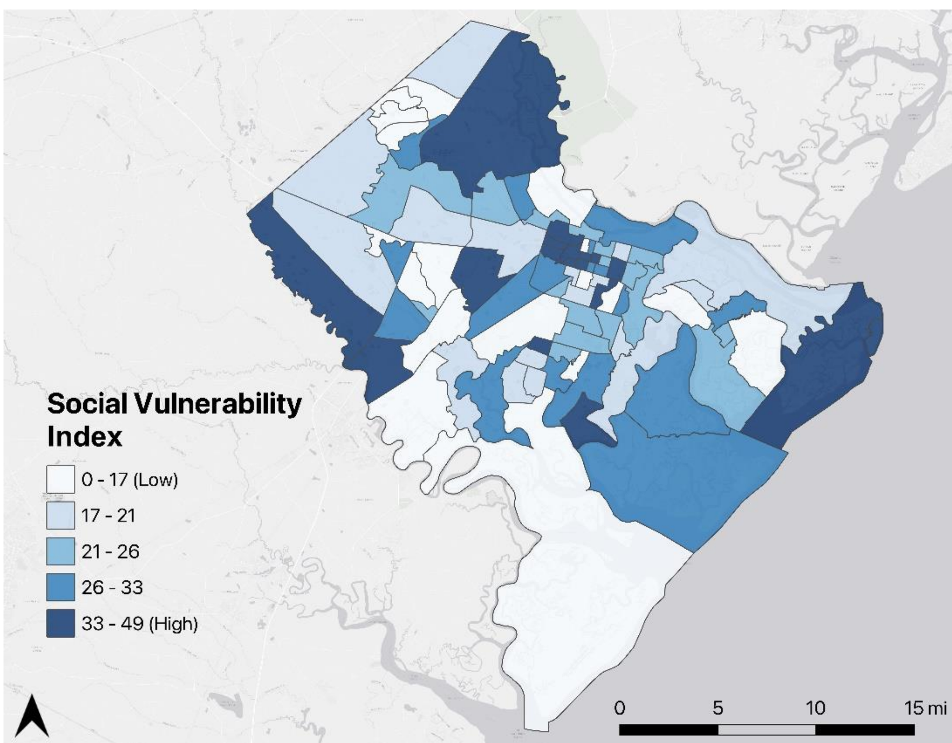
CRE Components of Social Vulnerability for Household (HH) and Individuals (I)

Component Name	**Vulnerability Qualification**	**HH or I**
Financial hardship	Income-To-Poverty Ratio < 130 percent or 50% < for housing/rental costs	HH
Single or zero caregiver household	Only one or no individuals living in the household who are 18-64	HH
Housing quality	Unit-level crowding with >0.75 persons per room or live in a mobile home, boat, RV, van, or other	HH
Communication barrier	Limited English-speaking households or no one in the household has a high school diploma	HH
No one in the household is employed full-time (not applicable if all residents are 65+)	As stated in component name	HH
Disability posing constraint to significant life activity	As stated in component name	I
No health insurance coverage	As stated in component name	I
65 years or older	As stated in component name	I
Transportation exposure	No vehicle access (HH) or work commuting methods with increased exposure to heat (I)	HH/I
No broadband internet access	As stated in component name	HH
Potentially lacking air conditioning	As stated in component name	HH



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure C1. Environmental Risk Index



ArcGIS. (Basemap Credits: Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS User Community)

Figure C2. Social Vulnerability Index

Appendix D: *InVEST Urban Cooling Model*

InVEST Model Description

The InVEST Urban Cooling Model incorporates the cooling effect of large green spaces (>2ha) and the cooling capacity of land cover across the county. If a pixel is within the Maximum Cooling Distance (d_{cool}) of a large green space, the heat mitigation index is calculated as a distance-weighted average of cooling capacity from the large green spaces and the given pixel. We chose the "factors" Cooling Capacity Calculation Method, which finds the cooling capacity for each land cover type (CC_i) using the weighted sums of the evapotranspiration index (ETI), shade, and albedo (Equation D1).

Shade and albedo are provided by the user for each of the land cover classes in the biophysical table (Table D1). ETI is a normalized value for evapotranspiration found by dividing the product of the crop coefficient (K_c) and reference evapotranspiration (ET_o) by the maximum ET_o value (ET_{max}) within the area of interest (Equation D2). Since we had high-resolution evapotranspiration values, we replaced $K_c \bullet ET_o$ with evapotranspiration (ET) by setting K_c to 1 in the biophysical table for all landcover classes and inputting ET into InVEST in place of ET_o.

$$CC_i = 0.6 \cdot shade + 0.2 \cdot albedo + 0.2 \cdot ETI \ (D1)$$

The "factors" method of calculating Cooling Capacity in InVEST (Natural Capital Project, 2025).

$$ETI = \frac{K_c \cdot ET_o}{ET_{max}} \ (D2)$$

Evapotranspiration index in InVEST (Natural Capital Project, 2025).

Biophysical Table Description

The Lucode column in the biophysical table (Table D1) is the land use/land cover code from the landcover raster, with the description of each landcover class found in the Description column. The Green_area column is a boolean value that states if the given landcover class is a green area or not. We classified all forest classes, both wetland classes, shrub/scrub, herbaceous, and hay/pasture as green areas. Shade represents the proportion of pixels for each landcover class with at least 2m of canopy cover. We estimated this using canopy cover, assuming that all canopy cover is at least 2m in height. To find the shade and albedo for each landcover class, we imported the canopy cover, albedo, and landcover rasters into QGIS and used the Raster Layer Zonal Statistics algorithm, selecting the "Zones layer" (the landcover raster) as the Reference layer, to find the mean canopy cover (shade) and albedo in each land cover class.

Table D1
Biophysical Table

Lucode	Description	Shade	Kc	Albedo	Green_area
0	Unclassified	0	0	0	0
11	Open Water	0.00930668	1	0.03558867	0
21	Developed, Open Space	0.21158548	1	0.13902962	0
22	Developed, Low Intensity	0.09245063	1	0.1396577	0
23	Developed, Medium Intensity	0.03266511	1	0.15450701	0
24	Developed, High Intensity	0.00950386	1	0.19655787	0
31	Barren Land	0.11909935	1	0.1649514	0
41	Deciduous Forest	0.46666667	1	0.14160579	1
42	Evergreen Forest	0.46077527	1	0.11732823	1
43	Mixed Forest	0.49559105	1	0.13204845	1
52	Shrub/Scrub	0.20152609	1	0.13261597	1
71	Herbaceuous	0.08008577	1	0.13571433	1
81	Hay/Pasture	0.11792525	1	0.1474621	1
82	Cultivated Crops	0.12666965	1	0.13660696	0
90	Woody Wetlands	0.37859294	1	0.11813085	1
95	Emergent Herbaceuous Wetlands	0.00924471	1	0.0713674	1