Modeling the Future Challenge
Team Model Magic 20077
Hot to Go: An Analysis of the Urban Heat Island Effect in Newark, New Jersey

March 2, 2025

Executive Summary

Cities are creating dangerously hot climates for the people living inside of them through the urban heat island effect (UHI). In Newark, this effect is particularly evident, with residents in Newark facing temperatures up to 8.4°F higher than their rural neighbors. Low-income communities are particularly vulnerable, as many residents lack access to air conditioning or other cooling options. This paper is aimed at city policymakers and urban planners, providing data-driven insights to help mitigate the issue.

We identified several key contributors to the UHI effect - albedo, transpiration, anthropogenic black carbon emissions, population, humidity, and road miles, being our dependent variables, and the near surface air temperature being our independent variable. Using satellite data, census records, and state transportation data, we first applied a multivariate regression to predict the magnitude of the effect on the urban temperature that each of these factors have using historical data. We used SARIMA to project each factor to 2034, and we used these projections and our multivariate regression to predict Newark's average summer temperature in 2034. Without intervention, Newark's July temperatures are expected to rise by $4.37°F$ by 2034.

To reduce the UHI effect, we recommend increasing the reflectivity of urban surfaces by implementing cool roofs, reflective pavements, and green roofs. Expanding tree-planting initiatives and improving green infrastructure would also help lower temperatures.

To test the implementation of our recommendation, we analyzed satellite imagery of Newark by using RGB values to determine a material, and then associating that value with its albedo. We found that if enough concrete is painted white so that the average albedo value for concrete in the city increases from 0.3 to 0.7, the temperature is predicted to decrease by up to $10.70°F$.

Additionally, the city should establish more cooling centers to launch public awareness campaigns to protect residents during heatwaves. Insurance companies can play a role by offering incentives for heat-resistant infrastructure, while policymakers should integrate climate resilience into urban planning and zoning laws.

By taking these steps, Newark can reduce the impact of extreme heat, protect vulnerable communities, and create a more sustainable and livable city.

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1 Introduction & Background

1.1 Background

According to the World Health Organization, heat is the leading cause of weather-related deaths [1]. Higher temperatures can cause heat injury and heat stroke and exacerbate underlying health conditions because the heat places a high demand on the body's processes, and prevents recovery during sleep. Excessive heat also disrupts essential services with power outages and transportation issues. Heat waves are also associated with an increase in air pollution. The Centers for Disease Control and Prevention estimates 600 to 700 preventable deaths per year are caused by extreme heat [2]. However, this is likely an underestimate, as heat stress exacerbates existing conditions.

In cities, the urban heat island (UHI) effect describes how urban areas have higher temperatures than neighboring rural areas due to heat re-emitting infrastructure such as roads or buildings and minimal vegetation. City characteristics such as street width and building height also play a role by creating urban canyons that stifle airflow.

We chose Newark to be the subject of our analysis because it has the second highest area-weighted urban heat index of 8.4°F, second only to New York City with 8.6°F. The urban heat index value describes how much the urban built environment increases the environmental temperature. Newark is characterized as having a sprawling heat intensity zone, indicating that the UHI effect is high and widespread throughout the city [3]. Newark, situated in Essex County in northern New Jersey, is the largest city in the state with a population of approximately 310,000 and serves as the state's industrial hub. It is also a transportation center, with a major airport, a seaport, and many highways.

The UHI effect is an issue of environmental justice. Approximately one in four Newark residents live in poverty, which is almost double the national average [4]. This large vulnerable population is disproportionately affected by the UHI effect, as they lack access to or cannot afford air conditioning [5]. Many times, people are forced to prioritize other expenses, such as rent or food, over additional energy costs for air conditioning. Heat vulnerable neighborhoods are denser and hotter with less green space, shade, or public facilities with cooling [6].

The prevalence of conventional man-made materials, such as asphalt, concrete, and dark-colored roofs and roads in industrial Newark, contributes to the UHI effect. Due to nearby highways and transportation, anthropogenic carbon and heat emissions exacerbate the effect. The UHI effect in Newark is surface rather than atmospheric, meaning it is more intense during the day when the sun is shining, due to man-made factors.

1.2 Problem Statement

The purpose of this paper is to investigate the causes and risks of the UHI effect in Newark, New Jersey. The UHI effect causes higher temperatures in urban areas compared to nearby rural areas due to factors such as lack of vegetation and heat-absorbing infrastructure. This can lead to risks that include worsening rates of heat injury, air pollution, mortality, energy consumption costs, and productivity.

Populations that are especially at risk include people with existing health conditions and those who are excessively exposed to heat with minimal refuge, due to lack of access to air conditioning or other similar circumstances. Our recommendations are targeted at city officials and urban planners of future cities. We also aim to educate Newark residents on heat safety and urge them to take their own health precautions.

2 Data Methodology

According to the United States Environmental Protective Agency (EPA), the UHI effect is caused by reduced natural landscape, urban materials, urban geometry, anthropogenic activities, and weather [7]. Data was collected for five of the six causes, with historical information about Newark's urban geometry of buildings unavailable. This data helps characterize and refine categories of potential outcomes, as we are analyzing the factors that cause the UHI effect. The temperature, which we also collected, helps define the severity of the UHI effect outcome.

Data was collected exclusively from U.S. government websites. Historical data for temperature, albedo, transpiration, anthropogenic black carbon, and humidity was found using NASA Giovanni software to access satellite data. Population data for Essex County was found from the United States Census, and road mileage data was available through New Jersey's official website.

2.1 Collecting Data

Our data is from the NASA Geo-spatial Interactive Online Visualization and Analysis Infrastructure (Giovanni), United States Census, and the New Jersey Department of Transportation.

The datasets from NASA Giovanni are monthly area-averaged time series within the rough coordinates of Newark (-74.2579,40.6307, -74.1041,40.7625) from 2002 to 2025. The application houses many satellite datasets and allows for visualization and analysis of over 2,000 variables.

We chose to mostly use data from NASA Giovanni because there is less risk of a major discrepancy in the data than if we used multiple data sources for the natural factors of the UHI effect. Additionally, the software allowed us to select data for only Newark, eliminating the need to extrapolate from data of New Jersey or Essex County.

1. Albedo
Rationale: The amount of energy reflected by a surface is called albedo. Surfaces such as dark-colored concrete, asphalt, turf, buildings, roads, highways, have low albedo, which means that instead of reflecting sunlight, it absorbs the energy and emits it like a radiator, increasing the surface temperature [8].
Source: Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2), accessed through NASA Giovanni [9]

2. Transpiration
Rationale: The amount of transpiration, the release of water vapor from plant leaves, reflects the amount of vegetation in an area. Vegetation can work to cool the surface temperature, since the water vapor takes heat with it as it evaporates [10].
Source: North American Land Assimilation System (NLDAS), accessed through NASA Giovanni [11]

3. Anthropogenic black carbon emissions
Rationale: Black carbon particles are released by burning fossil fuels, wood, and other biomass fuels, as well as waste. In Newark, the main source of emissions is from the diesel engines of trucks. The emissions create a greenhouse effect-like layer, trapping heat and raising the temperature in the city [12].
Source: MERRA-2 Reanalysis, accessed through NASA Giovanni [13]

4. Yearly Population
Rationale: A greater population indicates more human activities, such as running air conditioning, using vehicles, creating waste, and working in industrial facilities.
Cleaning: We had to use linear regression to fill in the years in between the decennial censuses. There is also a major jump during COVID-19, which we assume to be

accurate and not a mistake, since it is probable that people migrated during such a disruption.
Source: U.S. Census Bureau [14]

5. Humidity
Rationale: Humans undergo increased thermal stress under the combination of humidity and excessive heat. Humidity prevents perspiration, leaving people feeling like it is hotter outside than it actually is. This leads to increased anthropogenic heat waste from excessive energy demanded from cooling buildings and air conditioners [15].
Source: Atmospheric Infrared Sounder (AIRS), accessed through NASA Giovanni [16]

6. Yearly Road Length
Rationale: Newark is a major transportation hub. Vehicles release emissions when they are driven on roads. The amount of road in the city changes albedo, since roads are often dark-colored and absorb heat from the sun. These factors contribute to the UHI effect.
Reliability: While the government website is reliable, we are cautious when interpreting results with this variable because of the significant spike around 2003.
Source: New Jersey Department of Transportation [17]

7. Surface Temperature
Rationale: The 2-meter near surface air temperature is representative of the temperature that Newark residents are experiencing with the UHI effect. In Figure 5, the average annual temperature of New Jersey is shown [18]. There is an upward trend, which aligns with the trend of global warming and increasing UHI effect.
Source: Famine Early Warning Systems Network (FLDAS), accessed through NASA Giovanni [19]

2.2 Data Cleaning

We excluded data from the non-summer months. Specifically, we used data from June, July, and August as the UHI effect is most prevalent during the summer. Only data for the months of June, July, and August were used, because the UHI effect generally exists during the summer. However, to account for the different temperatures between June, July, and August, the differences per month were used for our model (e.g. the change in temperature from June 2024 to June 2025).

3 Mathematics Methodology

3.1 Purpose

The goal of our project is to find the best risk mitigation strategy for the overall effect of urban heat island effect in Newark, New Jersey, by modeling how a variety of factors affect the temperature.

3.2 Assumptions

- **Assumption:** The population for a year is consistent throughout its months. A linear trend describes the population of Newark from 2001-2009. A linear regression was chosen over ARIMA because of the lack of seasonality and data points.
- **Justification:** The U.S. Census is only every 10 years, so we cannot obtain a time series of the exact population of Newark.
- **Assumption:** The amount of road in Essex County is the same for June, July, and August.
- **Justification:** We only have yearly data of the road miles in Essex County. It is likely that there are no significant changes to the amount of road miles on a month-to-month basis.
- **Assumption:** Any effects that COVID-19 had on the datasets are meaningful and therefore not excluded.
- **Justification:** While it is too soon to tell if COVID-19's effects cause outliers in the datasets, we will assume that the data in that time period is meaningful because COVID is unlikely to have affected existing infrastructure or weather-related factors.

3.3 Variables

Variable	Definition (percent change in)	Units
T_r	Transpiration	Wm^{-2}
C_r	Anthropogenic black carbon emission rate	$kgm^{-2}s^{-1}$
H	Humidity	(unit-less)
A	Albedo	(unit-less)
R	Road	$miles$
P	Population	$people$
T_s	Surface temperature	K

Variables for multivariate regression

4 Factor Analysis: Multivariate Regression

4.1 Reasoning

We determined that a multivariate regression would be the best approach because of how many factors directly contribute to increasing and decreasing the temperature within the city. Humans have a lot of control over many of these factors as cities are man-made, so the results of this regression can help Newark city officials determine how to effectively mitigate the UHI effect.

4.2 Correlation Analysis

We conducted a Pairwise Correlational Analysis (PCA) to confirm that no two factors were excessively correlated. This metric helps identify redundancy in our data and highlight factors contributing to col-linearity. When multivariate regression includes highly correlated factors, it can distort the model's representation of the relationship between the dependent variable, temperature, and the affected independent variable(s).

Because no two variables are highly correlated ($r > 0.6$) in Figure 1, the effects of col-linearity are unlikely to manifest in our model. This means that any correlation that our model predicts is likely to be true correlation.

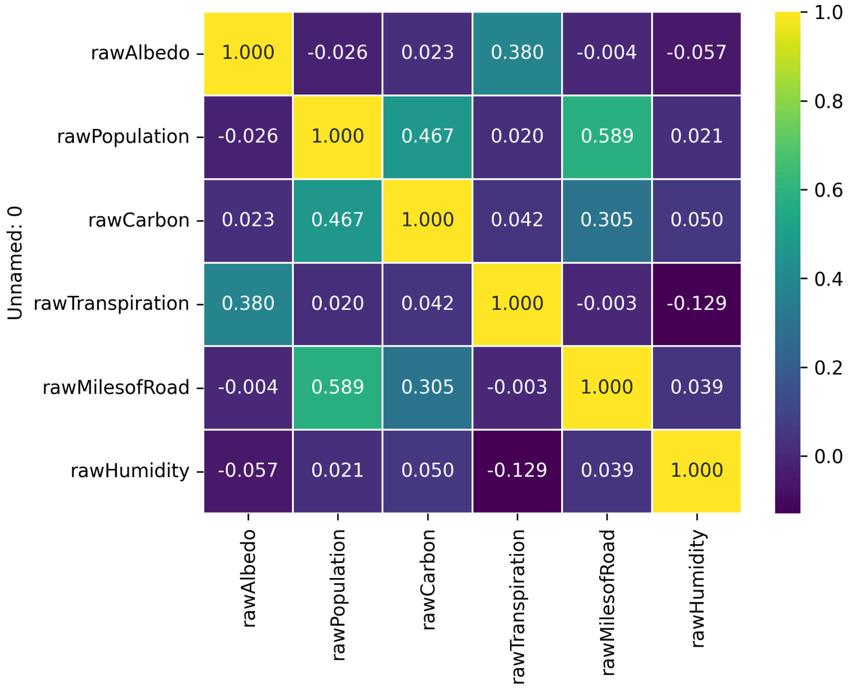

Figure 1: Pairwise Correlation Analysis

4.3 Description

To predict the magnitude of effects that each of the listed factors above have on the urban temperature in Newark, we performed a multivariate regression. Although we either had or were able to predict historical data for all seven data sets for every month, we chose to only include the summer months of June, July, and August.

To account for seasonality between June, July, and August, we converted all independent and dependent factors into a percent change since 12 months ago. For example, the average temperature in Newark in July 2022 was 298.74K and in July 2021 was 297.34K. So, the July 2022 percent change since 12 months ago would be $\frac{298.74-297.34}{297.34}$ or +4.68%. This ensures that seasonal factors that we did not account for, such as general weather conditions and many human behaviors, do not negatively affect the results of our model.

4.4 Results

Our multivariate regression model estimates the following relationship between the variables.

$$\hat{T}_s = -0.000899856966T_r + 0.106610538C_r - 0.000471124716H$$
$$-0.37755155A - 0.217952923R + 0.00178079902P$$

This means that we predict that the temperature will increase as black carbon emissions and population increases, and that the temperature will decrease as transpiration, humidity, albedo, and road length increase.

Variable	Rank (% change)
Albedo	1
Road Mileage	2
Black Carbon	3
Population	4
Humidity	5
Transpiration	6

Table 1: Ranking of UHI factors' impact on temperature

4.5 Sensitivity Analysis

To ensure that our predictions are not heavily affected by possible errors in our data, we performed a sensitivity analysis. We first changed every input value into our model by a random percentage between -5% and 5%. We ran another multivariate regression on the randomized data and generated new predictions. We compared these new predictions to what our actual model generated for August 2024, the latest data point. Then, we repeated this process 50 times. The results of this process is summarized below.

Percent Change from Original Prediction Statistic	**Value**
Mean	0.075%
Median	0.075%
Standard Deviation	0.015%

Table 2: Summary statistics from August 2024 sensitivity analysis

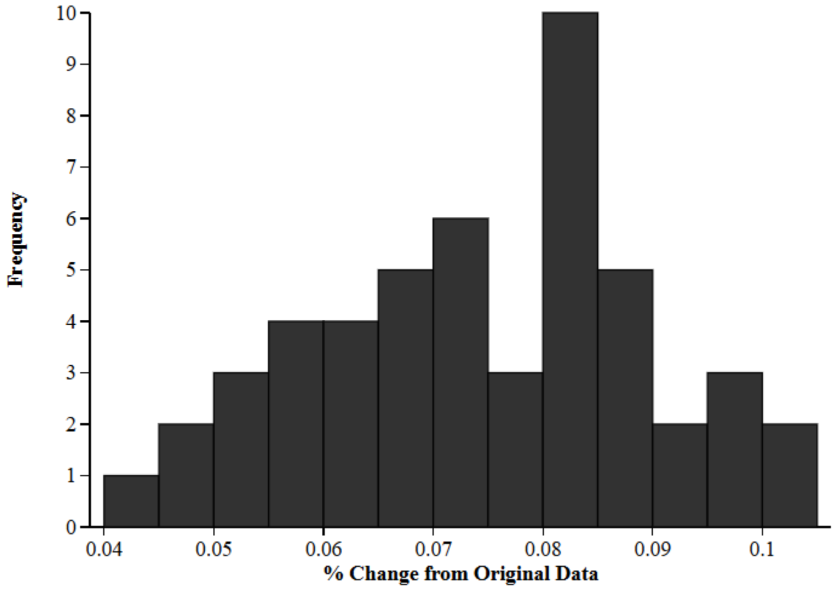

Figure 2: Histogram of August 2024 sensitivity analysis

Based off the low mean change from the original prediction, we concluded that our model is relatively stable and is not overly sensitive to errors in the data.

4.6 Strengths and Weaknesses

A strength of our model is that it helps measure and compare how different factors affect the UHI effect. Using multivariate regression, we can see how each variable influences temperature while accounting for other factors. This helps us identify the biggest contributors to urban heat, which can guide solutions like adding more vegetation or using reflective surfaces to reduce heat.

Due to the nature of the multivariate regression, we acknowledge that the relationship only shows correlation and cannot prove causation. While there have been many studies on the UHI effect using these variables, we do not have definitive proof that these factors cause an increase in urban temperature.

5 Temperature Prediction: SARIMA

5.1 Reasoning

To determine the severity of the UHI effect in Newark, we decided to predict the future temperature in Newark based off of the six factors used in the multivariate analysis. To achieve this, we projected each of the six factors up until 2034 using SARIMA, and then we plugged in the forecast values in our Multivariate Analysis model.

Given the high seasonality of our data, we considered the auto-regressive models Facebook Prophet and ARIMA (Auto-Regressive Integrated Moving Average), due to their ability to forecast seasonal data accurately. Although these models succeed with more simplistic data, they struggle to model complex data that displays high seasonality. Ultimately, we chose to use SARIMA, an extension of ARIMA that can better account for seasonality because it specifically incorporates seasonality patterns as an additional parameter s, along with ARIMA's constants p, d, and q.

To determine whether each factor's data is appropriate for SARIMA by being seasonal, we graphed an Autocorrelation Function (ACF) plot and a Partial Autocorrelation Function (PACF) plot for it. The ACF showed us its seasonality in the data. This means that as the lag, or change in time between two related variables in a time series analysis increases, the autocorrelation values decrease gradually rather than suddenly. This graph also tells us if the data has a strong correlation over time and could indicate a non-stationary trend (such as a long-term increase or decrease). The PACF shows significant lags, which indicate potential auto-regressive components and a potential need for removing trends or seasonal patterns to transform a non-stationary series into a stationary one using differencing. Based on these plots, we determined whether there would likely be high order auto-regressive terms and differencing.The plots for albedo are shown below in Figure 3.

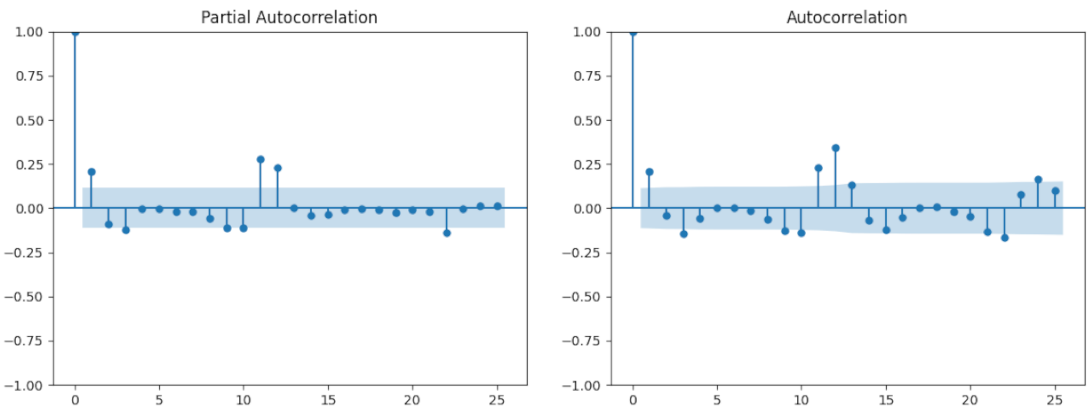

Figure 3: ACF and PACF Chart for Albedo

To create our SARIMA model for each factor:

1. We created a time series for each of the factors we are forecasting.

2. We fit the model with 67% of our past data and tuned it with the last 33% for each of the factors individually.

3. We analyzed if the forecast was properly fitting our historical data using mean squared error and mean absolute error, and tuned our constants to ensure that it maximizes fit while avoiding over-fitting.

Then, we performed Augmented Dickey-Fuller tests, which test the null hypothesis of whether a unit root is present in a time series sample, which yields a statistic and a p-value. When the p-value is greater than 0.05, the null hypothesis of non-stationary data cannot be rejected, and there would be a need for a differencing value in the SARIMA model.

5.2 Description

We predicted future temperatures in Newark using our multivariate regression and our SARIMA predictions. For every year in each of the six factors that we used, we determined the percent change since 12 months ago for up to 2034 with the SARIMA predictions. This conversion allowed us to plug our projections into the following equation produced by our multivariate to predict the temperature in Newark up until 2034:

$$\begin{aligned} \hat{T}_s = -0.0008998569 66T_r + 0.106610538C_r - 0.000471124716H \\ -0.37755155A - 0.217952923R + 0.00178079902P \end{aligned}$$

5.3 Results

We predicted that the average temperature in Newark in July of 2034 will be around $81.30°F$, which is about $4.37°F$ higher than the average temperature in July of 2023 of $76.93°F$. Our model forecasts an upward trend for all 3 months.

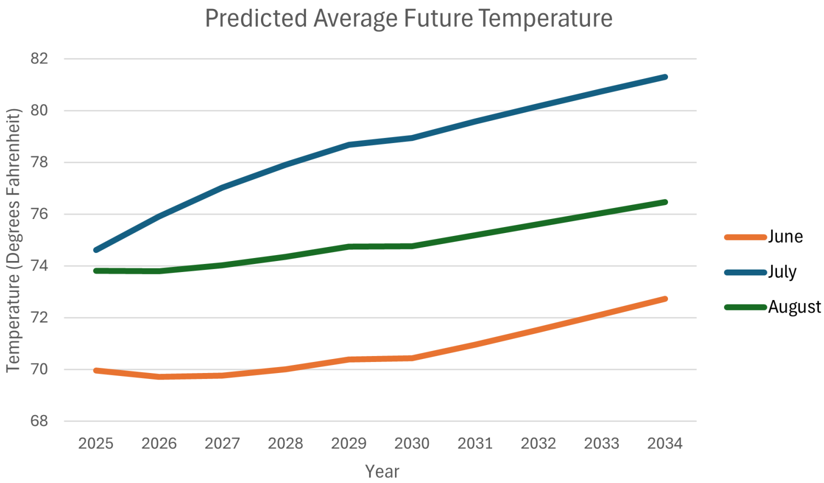

Figure 4: Predicted Future Average Temperatures in Newark

Year	Month	Predicted Average Temperature $^{\circ}F$
2028	June	70.01
	July	77.91
	August	74.35
2031	June	70.96
	July	79.57
	August	75.18
2034	June	72.72
	July	81.30
	August	76.46

Table 3: Predicted Future Average Temperature in Newark

5.4 Strengths and Weaknesses

A strength of our SARIMA model is that since it is auto-regressive, it can capture patterns within complex datasets that other models such as logarithmic or linear struggle with. The use of SARIMA over ARIMA accounts for the high seasonality of our data. By training our model with three months of data per year, rather than just one month, variance in our model is reduced and accuracy is improved.

One limitation of the SARIMA model is its reliance on historical data patterns, which assumes that past trends will continue in the future. However, climate change and rapid urban development can introduce unpredictable changes that SARIMA cannot fully account for. External factors such as new infrastructure projects, policy interventions, or unexpected climate shifts may cause actual temperature trends to deviate from the model's predictions.

6 Recommendations

Our investigation into the causes of the UHI effect leads us to recommend the city to focus on one area: increasing albedo. Albedo's coefficient in our multivariate analysis was -0.378, which was the highest magnitude out of the 6 factors that we considered.

6.1 Reducing Albedo (Modifying Outcomes)

While many buildings are privately-owned, the city of Newark can reach out to property owners and educate them about the UHI effect so that they can integrate the following practices to reduce their effect on it. Additionally, the warehouses can benefit from decreased cooling and air conditioning demands, since their building will be absorbing less heat from the sun. In non-air-conditioned residential buildings, cool roofs can lower maximum indoor temperatures by 1.2–3.3°C (2.2 to 5.9°F) [20]. To mitigate the effects of a city made with mostly low albedo materials, we recommend the following strategies:

Cool Roofs and Pavements Implementing cool roof and cool pavement technologies, such as reflective coatings or light-colored materials, can significantly reduce surface temperatures and lower indoor cooling demands.

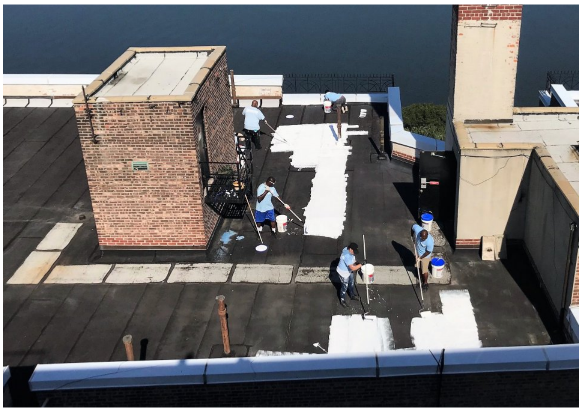

Figure 5: Workers paint a roof white

A pilot study in Arizona found that conventional paving materials such as asphalt can reach surface temperatures up to 152°F at mid-day, while the surface temperature of cool pavements remained 10 to 16°F cooler [21].

Parking lots have major potential to be improved to absorb less sunlight. They are especially important because people use them directly every day and they can heat to dangerous levels. While it is difficult to change existing parking lots and streets, the city can implement green infrastructure such as above-ground planters, grassy medians, and trees.

The city should provide grants and tax incentives for property owners to paint their roofs white, since it would be an extra expense that does not help a business or property owner directly. Communities that want to use cool pavements as part of a heat island mitigation program may find it hard to estimate the net costs or benefits based on temperature reduction alone. The greatest overall value may result when multiple benefits, such as improved storm water management and water quality, are factored into the evaluation of a paving approach.

Zoning laws and building codes should be updated to require or incentivize the use of high-albedo materials in new developments and renovations. Cool roof requirements have been integrated into building and energy standards or ordinances in at least 13 cities and counties, seven states, and the District of Columbia.

Green Roofs The installation of green roofs, vegetative coverings on building rooftops, can further mitigate the effects of UHI by providing insulation, reducing heat absorption, and improving air quality. However, this option is less viable than simply increasing albedo with paint or a reflective material because green roofs require consistent upkeep.

Urban Tree Planting Increasing urban greenery, particularly in hot zones, can provide significant cooling effects through shading and transpiration. Expanding tree-planting initiatives in Newark's most affected areas can reduce surface temperatures and improve public health outcomes. Maintenance of existing trees, gardens, and parks is also crucial.

6.2 Satellite Image Analysis

Our findings indicate that albedo, or the reflectivity of surfaces, is the most significant risk factor contributing to the UHI effect in Newark. The prominence of dark-colored rooftops, roads, and general surfaces leads to excessive heat absorption. For example, 60 Lister Avenue and the nearby 69 Blanchard Street warehouses in Figure 5 both have major surface area and their roofs are dark-colored.

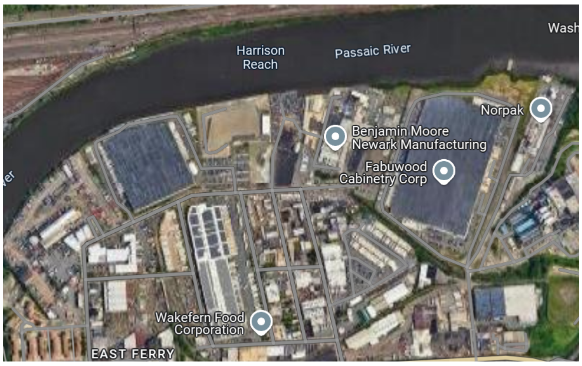

Figure 6: Satellite image of two warehouses with dark roofs in Newark

We acquired high-resolution satellite imagery using Google Earth Pro [22] and removed sections of the image outside of the city borders of Newark. The four surfaces most prominent in the Newark area are trees, dirt, concrete, and asphalt. We estimated the RGB, or red green blue value color value, of each surface by color-picking off the satellite image, and we sourced approximate albedo values [23] [24] [25] [26] [27] for each of these surfaces.

Surface	Baseline Color (RGB)	Approximate Albedo
Tree	(65, 87, 64)	0.18
Dirt	(177, 156, 134)	0.50
Concrete	(197, 194, 179)	0.47
Asphalt	(111, 108, 107)	0.10
White Paint	N/A	0.6

Table 4: Color and Albedo Values for Each of Our Surfaces

We coded a program to iterate through every single pixel in the image, calculate the distance of its RGB to that of each baseline by treating all values as 3-dimensional vectors, assigning the least distant RGB as the associated material and thus albedo, and finally saving this map of the image as a .csv file. This results in a 2-D matrix of the surface materials across the entirety of Newark. Then, we found the average albedo of the city.

To test our actionable recommendation, we replaced the albedo for concrete in the code with that of white paint, and multiplied the albedo with the ratio of homes and buildings to sidewalk/other concrete surfaces to get an appropriate representation of the surfaces that could be painted white.

Our calculated albedo value after the actionable recommendation is 0.247, which is 5.314% higher than without the white roofs. Through the use of our multivariate regression, we determined that this change in This leads to a temperature decrease of $10.698°F$ during an average summer day.

6.3 Protecting Citizens (Behavior Changes)

To address the immediate effects of increasing urban temperatures and the risks posed to vulnerable populations, we recommend that the city of Newark expand its network of Code Red or cooling shelters in accessible locations, especially within regions classified as hot zones. These shelters should be well-advertised and equipped with air conditioning, water, and medical support for those affected by extreme heat events.

Using existing action plans, Newark should focus on engaging marginalized communities that bear a disproportionate burden of UHI risks. Public awareness campaigns should be launched to educate residents on recognizing heat-related illnesses, staying hydrated, and accessing cooling resources.

To tackle this public health crisis, we urge city official to create an Excessive Heat Task Force, such as the one in Jacksonville, Florida [?]. Their actions have included creating social media accounts under the name @JaxReady to inform residents and providing 6 staffed cooling centers that are available from 12PM-6PM, or peak temperatures. The Jacksonville Transportation Authority provides free transportation to anyone seeking a cooling center, which helps overcome a major barrier.

Like Jacksonville, we recommend that the city of Memphis use our findings and heat vulnerability index to place cooling centers close to where the most vulnerable neighborhoods are. It should be easily accessible with public transportation. Ideally, these cooling centers would already be community centers that can serve as resilience hubs that people are aware of and can spread knowledge of through word-of-mouth. The cooling centers should be staffed and open as often as possible, but especially while Heat Advisories or Excessive Heat Warnings are in effect. As resilience hubs, they can be a place to coordinate resources or for community members to gather and create or revitalize community connections, which help communities unite to overcome hardships.

6.4 Insurance

Organizations like the World Health Organization (WHO) stress the need for better planning and response to extreme heat. Insurance companies can help by offering lower premiums for properties with cool roofs, green spaces, or energy-efficient designs. Cities can also use insurance policies to fund emergency responses to heatwaves and invest in climate resilience.

Insurance can support broader efforts by helping identify high-risk areas and guiding urban planning. Parametric insurance, which pays out when temperatures reach a certain level, can fund cooling centers, public health measures, and infrastructure improvements.

Additionally, insurers can encourage businesses and homeowners to adopt heat-resistant practices by offering discounts for reflective surfaces, tree coverage, and better ventilation. Partnerships between insurers, governments, and researchers can also help fund projects like reflective pavements and urban tree planting. By aligning financial incentives with climate protection, insurance can play a key role in reducing the risks of the UHI effect.

7 Climate Resilience Award Addendum

Prompt 1: Community Scope We chose Newark to be the subject of our analysis because it has the second highest area-weighted urban heat index of 8.4°F, second only to New York City with 8.6°F. Newark is characterized as having a sprawling heat intensity zone, indicating that the UHI effect is high and widespread throughout the city. Approximately one in four Newark residents live in poverty, which is almost double the national average. This large vulnerable population is disproportionately affected by the UHI effect, as they lack access to or cannot afford air conditioning.

Prompt 2: Climate Hazard The urban heat island effect intensifies the impacts of heat waves, which are becoming more frequent, prolonged, and severe due to climate change. Using FEMA's National Risk Index, the rating is Relatively Moderate compared to the rest of the U.S., with Expected Annual Loss being Relatively Moderate. The most concerning metrics are that Community Resilience is rated Relatively Low and Social Vulnerability is Very High. Compared to the rest of New Jersey, Newark, in Essex County, is a low outlier in Community Resilience. Additionally, the combination of extreme heat and high humidity can create dangerous conditions that increase the likelihood of heat exhaustion, heatstroke, and even death. Addressing this hazard is crucial, as failure to mitigate the UHI effect will result in greater energy demands, increased healthcare costs, and declining public health outcomes in the long term.

Prompt 3: Risk Mitigation Strategy As defined by FEMA, community resilience is the ability of a community to prepare for anticipated natural hazards, adapt to changing conditions, and withstand and recover rapidly from disruptions. The UHI effect falls under the "stressors" category, since it is a long-term strain on urban communities. The component of our risk mitigation strategy that aims to protect citizens and the community includes creating emergency shelters and increasing public awareness of the dangers of heat. With this goal, we aim to create a resilient community where residents and community members are informed and united in their knowledge of their changing environment, addressing both interventative and preventative components of a solution.

Prompt 4: Stakeholder The Newark Office of Planning and Zoning oversees regulations regarding land use, zoning, and urban development. This office plays a crucial role in implementing heat mitigation strategies by integrating cool roofs, reflective pavements, and green infrastructure requirements into city policies. By partnering with this office, we can push for zoning incentives that encourage developers to adopt UHI-reducing strategies, such as green spaces and high-albedo materials.
Additionally, Mayor Ras J. Baraka and the Newark City Council have the authority to establish new policies and task forces dedicated to addressing the UHI effect. They can lead public outreach campaigns, allocate funding for resilience initiatives, and coordinate city-wide efforts to reduce extreme heat risks. The mayor's office is particularly well-positioned to launch an Excessive Heat Task Force, similar to initiatives in other cities, which would focus on providing real-time resources and emergency responses for vulnerable populations during heat waves. By engaging these stakeholders, we can ensure that UHI mitigation becomes a priority in Newark's climate resilience strategy.

Newark Office of Planning and Zoning Room 112 City Hall 920 Broad Street Newark, NJ 07102 (973) 733-6333

Newark City Council Ras J. Baraka City Hall 920 Mayor Kenneth A. Gibson Blvd Newark, NJ 07102 (973) 733-4311

Prompt 5: Identify FEMA Community Lifelines The community lifelines that our recommended risk mitigation strategy are Health and Medical and Food, Hydration, Shelter.
Health and Medical: Excessive heat is a significant public health concern, leading to increased hospitalizations and mortality, especially among vulnerable populations such as the elderly, low-income residents, and those with pre-existing health conditions. Our proposal to expand cooling centers and increase public awareness of heat-related illnesses directly supports public health and emergency medical response efforts. By implementing an early warning system and public outreach campaigns, Newark can reduce heat-related hospital visits and improve overall health resilience.

Food, Hydration, Shelter: Our proposal includes the development of accessible cooling centers that provide hydration and shelter during extreme heat events. These facilities will serve as temporary relief locations during heat waves, ensuring that vulnerable residents have access to safe indoor environments with air conditioning and clean water. Additionally, policies that promote tree-planting and green infrastructure indirectly contribute to improved community resilience by creating shaded areas and lowering overall urban temperatures.

Prompt 6: Implementation **Budget:** We estimate that implementing our recommendations will require funding in the range of **several million dollars**. The primary costs will be associated with infrastructure upgrades, such as cool roofs, reflective pavements, and tree-planting initiatives. Cooling centers and public outreach campaigns will also require operational funding. However, these costs can be offset by federal and state grants, as well as partnerships with private stakeholders and nonprofits focused on climate resilience.
Timeline: The initial implementation phase will take approximately **1-3 years**, with short-term efforts focused on expanding cooling centers and launching public awareness campaigns. Mid-term efforts, such as tree-planting initiatives and infrastructure improvements, will take **3-5 years** to see measurable impact. Long-term goals, including policy changes and widespread urban development modifications, will require ongoing monitoring over the next **10+ years**. Immediate benefits, such as increased cooling center availability and public education, can be achieved within a few months, while long-term UHI reduction efforts will gradually improve Newark's resilience over time.

Prompt 7: Impact Goals Below is a list of possible metrics that could be used to track the implementation of our risk mitigation strategy.

1. Reduction in heat-related hospital visits: Track emergency room admissions due to heatstroke and dehydration before and after implementation.
2. Urban temperature changes: Conduct satellite and ground-based monitoring of surface and ambient temperature reductions in targeted areas.
3. Energy consumption data: Measure electricity usage reductions in buildings with cool roofs, green roofs, and energy-efficient adaptations.
4. Increase in green space coverage: Use remote sensing and city records to track tree canopy expansion and green infrastructure growth.

5. Infrastructure maintenance costs: Assess changes in road and building maintenance costs due to heat-resistant materials.

6. Community engagement metrics: Analyze participation in sustainability programs, such as tree-planting initiatives and public awareness campaigns.

7. Policy implementation success: Evaluate the number of newly enacted UHI mitigation policies and their enforcement rates.

8 Discussion

In summary, we selected Newark, New Jersey to be the subject of our analysis for its severe and widespread display of the UHI effect. We identified 6 factors that cause the UHI effect: albedo, transpiration (vegetation), anthropogenic black carbon emission rate, population, humidity, and road miles in the county.

We conducted a multivariate regression on these factors with the near surface air temperature, and we found that albedo is the most significant contributing factor, followed by road miles and black carbon emission rate. A sensitivity analysis was performed, and after changing each value by 5% randomly, the mean, median, and standard deviation changed by less than 1% each, indicating that our model is relatively stable and robust to variations.

Using SARIMA predictions on the same factors to 2034 and plugging these predictions into our multivariate regression, we concluded, assuming no unpredictable world event takes place and no action plan is put into place, that the average temperature in Newark will only continue to rise, with average July temperatures reaching $81.30°F$ in 2034.

One of our recommendations was to paint roofs within the city white. To determine how effective this strategy would be, we utilized satellite imagery and analyzed the albedo values of surfaces before and after painting city roofs white. We determined that widespread use of this paint could decrease the average temperature in Newark by up to $10.70°F$.

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A Code Appendix

A.1 SARIMA Code in Python

```
# code for SARIMA


import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from sklearn.metrics import mean_absolute_error, mean_squared_error
import statsmodels.api as sm
from statsmodels.stats.diagnostic import acorr_ljungbox
```

```
# turns any raw data pasted from excel into a list with float values
def excelToList(inp):
    temp = inp.splitlines()
    temp2 = []
    for val in temp:
        temp2.append(float(val))
    return temp2


# reverses a column in excel that is not going in order of dates (need a
    timeseries for SARIMA)
def reverseColumn(inp):
    ret = []
    for v in inp:
        ret.insert(0,v)
    return ret


# Checks if the timeseries is stationary, determines whether differencing
    will be necessary in the model
def check_stationarity(timeseries):
    # Performs the Dickey-Fuller test
    result = adfuller(timeseries, autolag='AIC')
    # p value to determine whether the reject the null hypothesis (is
        stationary)
    p_value = result[1]
    print(f'ADF Statistic: {result[0]}')
    print(f'p-value: {p_value}')
    print('Stationary (passes the dickley test)' if p_value < 0.05 else
        'Non-Stationary (fails the dickley test)')




# fits a SARIMA model and then plots it
def
    SARIMA(independent,dependent,constants,order,seasonalOrder,timeseries,forecastPeriods,
```

```
    # defines the model's parameters
    model =
        SARIMAX(endog=timeseries.indep.astype(float),order=order,seasonalOrder=seasonalOrde
    # trains the model
    results = model.fit()
    residuals = results.resid


#
    ----------------------------------------------------------------------------
    # forecast number of steps indicated in parameter
    forecast = results.get_forecast(steps=forecastPeriods)
    # mean is the expected value in the future
    forecast_mean = forecast.predicted_mean
    # generates a 95% confidence interval of the future values
    forecast_ci = forecast.conf_int()

    observed = timeseries.indep[-forecastPeriods:]
    # determines the forecasts mean absolute error and mean squared error
    mae = mean_absolute_error(observed, forecast_mean)
    mse = mean_squared_error(observed, forecast_mean)
    print(f'MAE: {mae}')
    print(f'MSE: {mse}')


    # plots the forecast (if indicated in the parameter)
    if plotting:
        plt.figure(figsize=(12, 6))
        # historical data
        plt.plot(timeseries.indep,label='Observed')
        # forecast data
        plt.plot(forecast_mean, label='Forecast', color='red')
        # confidence interval of the forecast
        plt.fill_between(forecast_ci.index, forecast_ci.iloc[:, 0],
            forecast_ci.iloc[:, 1], color='pink')
        plt.title(f"{exportFilename}")
        plt.xlabel("Date")
        plt.ylabel(f"{exportFilename}")
        plt.legend()
        plt.show()
```

```
    # exports the forecast as a csv (mean values and confidence intervals)
    file_name = exportFilename
    forecast_mean.to_csv(f'{file_name}.csv' )
    forecast_ci.to_csv(f'{file_name}CI.csv' )


# plots lists for visualization
def plot_data(indep,indeplbl,dep,deplbl,title):
    plt.figure()
    plt.plot(np.array(indep),np.array(dep), linewidth=3,c='cyan')
    plt.title(title)
    plt.xlabel(indeplbl)
    plt.ylabel(deplbl)
    plt.show()


# plots the acf and pacf graph to determine seasonality, differencing
    requirements, AR components
def plotACFPACF(timeseries):
    plot_acf(timeseries.indep)
    plot_pacf(timeseries.indep)
    plt.show()


# for inputting raw data from excel
#-----------------------------------------------------------------------------
rawIndep = """"""
rawDep = """"""
#-----------------------------------------------------------------------------
rawIndep = excelToList(rawIndep)
rawDep = excelToList(rawDep)


# starting date for timeseries (if only using raw independent values)
begin_date = '2010-01-01'


# p d q
ArimaOrder = (29,2,34)
# p d q s
ArimaSeasonalOrder = (34,0,29,12)
```

```
# plot labels
indepLbl = 'date'
depLbl = 'output'


# creates a dataframe of datetime values for the timeseries that goes into
    the model
data_df =
    pd.DataFrame({'date':pd.date_range(begin_date,periods=len(rawIndep),freq='M'),'indep':



#plotACFPACF(data_df)
#check_stationarity(data_df.indep)
#plot_data(rawIndep,"date",rawDep,"output","title")
#SARIMA(rawIndep,rawDep,[0,0,0],ArimaOrder,ArimaSeasonalOrder,data_df,168,"SARIMA
    for Memphis Monthly Electrical Consumption",True)


# for quickly checking a range of arima constants, allows you to set a
    change pattern and then compare the MSE and MAE after each run to
    determine where the best fit lies
def AutoArima():
    count = 0
    # starting constants
    AO = [15,2,7]
    SO = [7,0,15,12]
    # total full runs for change pattern
    for i in range(5):
        # total runs of pattern p1 changes
        for j in range(3):
            SO[2] += 1
            AO[0] += 1
            # total runs of pattern p2 changes
            for k in range(2):
                AO[2] += 1
                SO[0] += 1
                # runs SARIMA with the changing parameters, and saves all
                    the forecasted data throughout
```

```
        SARIMA(rawIndep,rawDep,[0,0,0],AO,SO,data_df,350,f"{count}Memphis_Energy_Co

#AutoArima()
```

A.2 Pairwise Correlation Analysis in Python

```
# Pairwise Correlation Analysis


import pandas as pd


# turns any raw data pasted from excel into a list with float values
def excelToList(inp):
    temp = inp.splitlines()
    temp2 = []
    for val in temp:
        temp2.append(float(val))
    return temp2




# turns data of a specific interval into a larger one (month to year, day
    to week)
def repeatColumnBy(num,inp):
    ret = []
    for val in inp:
        for i in range(num):
            ret.append(val)
    return ret
```

```
# creates a dataframe from a csv
df = pd.read_csv('Memphis Zip Codes Only(All Data).csv')
data = pd.DataFrame(df)
# print(data.head())


# calculates the pairwise correlation
print(data.corr(), '\n')
# calculates the Pearson correlation coefficient
print("Pearson", data.corr(method='pearson'), '\n')
# calculates the Kendall rank correlation
print("Kendall", data.corr(method='kendall') , '\n')


file_name = "PairwiseCorrelationAnalysis"
# saves the correlations as csvs
data.corr(method='pearson').to_csv(f'{file_name}Pearson.csv' )
data.corr(method='kendall').to_csv(f'{file_name}Kendall.csv' )
data.corr().to_csv(f'{file_name}default.csv')
```

A.3 Heatmap Generation Code in Python

```
# Heatmap Code


import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt


# function to create a heatmap of a pairwise correlation analysis (PCA)
def createHeatmap(path_to_file):
    # creates a dataframe from the csv of the PCA
    df = pd.read_csv(f"{path_to_file}")
    df_corr = df.set_index("Unnamed: 0")
    # gets the correct datatype of the correlation values (large decimals
        from 0-1)
    df_corr = df_corr.astype(float)
```

```
    # creates a plot, 12 inches by 8 inches
    plt.figure(figsize=(12, 8))
    # creates a heatmap that represents correlation using a color gradient
        (warm colors are positive correlation (darker is more), cool are
        vice versa)
    sns.heatmap(df_corr, annot=True, cmap="coolwarm", fmt=".2f",
        linewidths=0.5)
    # titles the heatmap
    plt.title("Pairwise Correlation Heatmap")
    # renders the heatmap
    plt.show()
    #sns.heatmap(df_corr, annot=True, cmap="viridis", fmt=".3f",
        linewidths=0.5)
    # saves the heatmap (PNG)
    plt.savefig(f"m3{path_to_file}Heatmap.png", dpi=300,
        bbox_inches='tight')


createHeatmap(r"PairwiseCorrelationAnalysisdefault.csv")
createHeatmap(r"PairwiseCorrelationAnalysisKendall.csv")
createHeatmap(r"PairwiseCorrelationAnalysisPearson.csv")




import numpy as np
import pandas as pd
```

A.4 Multivariate Analysis Code in Python

```
# code for multivariate analysis

import os
import numpy as np
from sklearn import linear_model
import math
from sklearn.model_selection import train_test_split
import dataio
```

```
# Perform linear regression
def _Run_multivariate(data_mod_const):

    # Get data
    i = 1
    independents = []
    # load independent variable data
    while os.path.exists(f"independent{i}.txt"):
        print(dataio.getDataFromFile(f"independent{i}.txt"))
        independents.append(dataio.getDataFromFile(f"independent{i}.txt"))
        i += 1
    # load dependent variable data
    dependent = dataio.getDataFromFile("dependent.txt")

    # Check if input data is valid
    if len(independents) == 0:
        print("No data files found")
        return False
    # error catching for data lengths
    for independent in independents:
        if len(independent) != len(dependent):
            print("Data length does not match")
            return False

    # Format input data
    independents = np.array(independents)
    independents = np.transpose(independents)
    dependent = np.array(dependent)

    # Perform regression
    model = linear_model.LinearRegression(fit_intercept=False)
    # fit the model
    model.fit(independents, dependent)

    # Get fit
    X_b = np.c_[np.ones((independents.shape[0], 1)), independents] # get
        bias term
    # get predictions with model coefficients
    y_pred = X_b @ np.append(model.intercept_, model.coef_)
    #c compute total sum of squares
    ss_total = np.sum((dependent - np.mean(dependent))**2)
    # compute residual sum of squares
```

```
    ss_residual = np.sum((dependent - y_pred)**2)
    # get r^2, coefficient of determination
    r2 = 1 - (ss_residual / ss_total)
    # calculate correlation coefficient - r
    r = np.sqrt(r2)

    print("DONE MULTIVARIATE")
    # print model coefficients
    print(model.coef_)
    # print correlation
    print(r)

    # Export coefficients and model performance
    dataio.exportData([], [], "output/multivariate.csv",
       notes=["Coefficients"]+[model.coef_] + [f"r^2: {r2}", f"r: {r}"])
```

A.5 Getting Albedo Values in Python

```
import csv
from PIL import Image
import numpy as np
import pandas as pd
import math

# Minimum and Maximum albedo values of each material we are observing
TREE_ALBEDO_MIN = 0.15
TREE_ALBEDO_MAX = 0.18
WATER_ALBEDO_MAX = 0.1
CONCRETE_ALBEDO_MAX = 0.47
ASPHALT_ALBEDO_MAX = 0.1
DIRT_ALBEDO_MAX = 0.5
CONCRETE_ALBEDO_MIN = 0.32
ASPHALT_ALBEDO_MIN = 0.05
# water helps UHI so this is not contributing to albedo
WATER_ALBEDO_MIN = 0
DIRT_ALBEDO_MIN = 0.05
WHITE_PAINT_ALBEDO_MIN = 0.32
WHITE_PAINT_ALBEDO_MAX = 0.6
WHITE_ALBEDO_ALL = 1
```

```
#actionable reccomendation
CONCRETE_ALBEDO_MAX = WHITE_PAINT_ALBEDO_MAX
CONCRETE_ALBEDO_MIN = WHITE_PAINT_ALBEDO_MIN
#-------------------------------------------

# representative rgb's for our materials
BASELINE_RGB_TREE = (65,87,64)
BASELINE_RGB_CONCRETE = (197,194,179)
BASELINE_RGB_DIRT = (177,156,134)
BASELINE_RGB_ASPHALT = (111,108,107)
BASELINE_RGB_WATER = (50,65,69)
RGB_EXCLUDE = (255,255,255)

MinAlbedoList =
    [TREE_ALBEDO_MIN,CONCRETE_ALBEDO_MIN,ASPHALT_ALBEDO_MIN,DIRT_ALBEDO_MIN,WATER_ALBEDO_MI
MaxAlbedoList =
    [TREE_ALBEDO_MAX,CONCRETE_ALBEDO_MAX,ASPHALT_ALBEDO_MAX,DIRT_ALBEDO_MAX,WATER_ALBEDO_MA


# function to calculate the distance of each material and then return the
    closest material
def returnClosestAlbedo(rgb):

    if (rgb[0] + rgb[1] + rgb[2]) == 765:
        return "white"

    distTree = -1
    distDirt = -1
    distConcrete = -1
    distAsphalt = -1
    distWater = -1

    listDistances = []
    identifiedMaterial = ""

    # calculating each distance
    distTree = math.sqrt(math.pow(BASELINE_RGB_TREE[0] - rgb[0],2) +
        math.pow(BASELINE_RGB_TREE[1] - rgb[1],2) +
        math.pow(BASELINE_RGB_TREE[2] - rgb[2],2))
    listDistances.append(distTree)
```

```
    distDirt = math.sqrt(math.pow(BASELINE_RGB_DIRT[0] - rgb[0],2) +
        math.pow(BASELINE_RGB_DIRT[1] - rgb[1],2) +
        math.pow(BASELINE_RGB_DIRT[2] - rgb[2],2))
    listDistances.append(distDirt)

    distConcrete = math.sqrt(math.pow(BASELINE_RGB_CONCRETE[0] - rgb[0],2)
        + math.pow(BASELINE_RGB_CONCRETE[1] - rgb[1],2) +
        math.pow(BASELINE_RGB_CONCRETE[2] - rgb[2],2))
    listDistances.append(distConcrete)

    distWater = math.sqrt(math.pow(BASELINE_RGB_WATER[0] - rgb[0],2) +
        math.pow(BASELINE_RGB_WATER[1] - rgb[1],2) +
        math.pow(BASELINE_RGB_WATER[2] - rgb[2],2))
    listDistances.append(distWater)

    distAsphalt = math.sqrt(math.pow(BASELINE_RGB_ASPHALT[0] - rgb[0],2) +
        math.pow(BASELINE_RGB_ASPHALT[1] - rgb[1],2) +
        math.pow(BASELINE_RGB_ASPHALT[2] - rgb[2],2))
    listDistances.append(distAsphalt)

    # finding the minimum distance
    min = 999999
    indexMin = -1
    for i in range(len(listDistances)):
        if listDistances[i] < min:
            min = listDistances[i]
            indexMin = i
    # returning the closest material
    if indexMin == 0:
        identifiedMaterial = "tree"
    elif indexMin == 1:
        identifiedMaterial = "dirt"
    elif indexMin == 2:
        identifiedMaterial = "concrete"
    elif indexMin == 3:
        identifiedMaterial = "water"
    else:
        identifiedMaterial = "asphalt"

    return identifiedMaterial

# returning the correct albedo value based on the material determined
```

```
def calculateAlbedo(material,type):
    if type == "min":
        if material == "white":
            return WHITE_ALBEDO_ALL
        elif material == "tree":
            return TREE_ALBEDO_MIN
        elif material == "dirt":
            return DIRT_ALBEDO_MIN
        elif material == "concrete":
            return CONCRETE_ALBEDO_MIN
        elif material == "water":
            return WATER_ALBEDO_MIN
        else:
            return ASPHALT_ALBEDO_MIN
    else:
        if material == "white":
            return WHITE_ALBEDO_ALL
        elif material == "tree":
            return TREE_ALBEDO_MAX
        elif material == "dirt":
            return DIRT_ALBEDO_MAX
        elif material == "concrete":
            return CONCRETE_ALBEDO_MAX
        elif material == "water":
            return WATER_ALBEDO_MAX
        else:
            return ASPHALT_ALBEDO_MAX
    return -1

# satellite image of Newark
img = Image.open("newark_cropped.jpg")
npImg = np.asarray(img)

AlbedoValueListMax = []
AlbedoValueListMin = []

# iterating through every pixel and mapping it as an elbedo value
for i in range(len(npImg)):
    AlbedoValueListMax.append([])
    AlbedoValueListMin.append([])
    print(f"finished {i-1}th row")
    for j in range(len(npImg[i])):
```

```
        AlbedoValueListMin[i].append(calculateAlbedo(returnClosestAlbedo([int(npImg[i][j][0
        AlbedoValueListMax[i].append(calculateAlbedo(returnClosestAlbedo([int(npImg[i][j][0


dfAlbedoMax = pd.DataFrame(AlbedoValueListMax)
dfAlbedoMin = pd.DataFrame(AlbedoValueListMin)
# saving the albedo values as a csv
dfAlbedoMax.to_csv('AlbedoValuesMaxActionableReccomendation.csv')#,
    index=False)
dfAlbedoMin.to_csv('AlbedoValuesMinActionableReccomendation.csv')#,
    index=False)
```

A.6 Calculating Newark's Albedo Value in Python

```
import csv
from PIL import Image
import numpy as np
import pandas as pd
import math

# loading the albedo values
albedosNewarkMax =
    np.loadtxt('AlbedoValuesMaxActionableReccomendation.csv',
    delimiter=',')
albedosNewarkMin =
    np.loadtxt('AlbedoValuesMinActionableReccomendation.csv',
    delimiter=',')


totalAlbedoMax = 0
totalAlbedoMin = 0
count = 0
# calculating the total albedo value and the count
for i in range(len(albedosNewarkMax)):
    for j in range(len(albedosNewarkMax[i])):
        if not (albedosNewarkMax[i][j] >= 1) and not
            (albedosNewarkMax[i][j] <= 0):
            totalAlbedoMax += albedosNewarkMax[i][j]
            totalAlbedoMin += albedosNewarkMin[i][j]
            count += 1
```

```
# outputting the average value
print(float(totalAlbedoMax)/count)
print(float(totalAlbedoMin)/count)

# real albedo value: 0.234691605
# our albedo value: 0.2151735536069454
# change in temperature after actionable reccomendation: 10.6979853696 F

# conversion factor to normalize our findings with the real values
conversion_factor = 0.234691605/0.2151735536069454
print("Our calculated albedo value after the actionable recommendation is
    " ,(conversion_factor * float(totalAlbedoMax)/count))
```