Redlining's lasting mark:

Persisting disparities in climate change-driven health risks in New Haven, CT

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April 12, 2024

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Acknowledgements

This thesis is only possible because of everyone who supported me. I am extremely grateful for all who offered encouragement and guidance throughout every stage of my Yale education, and in particular, during this thesis. Thank you to Dr. Xuhui Lee for being a wonderful thesis advisor. Thank you to Tarek Kandakji for your dedication to the Yale Center for Earth Observation and answering all my ARCGIS questions. Thank you to Professor Park for your mentorship throughout this daunting process. Thank you to my thesis advising group for your comradery, suggestions, and kindness. Thank you to the faculty and staff that make the EVST community so special. Thank you to my family and friends for their encouragement and love. Thank you to my team at RMI for introducing me to redlining as an environmental justice issue. Thank you to New Haven for being the best home for the past 4 years. Thank you, thank you, thank you!

Abstract

This research looks to explore the relationship in New Haven, CT between "redlining", a discriminatory housing practice enacted in 1934 by the Home Owners' Loan Corporation (HOLC) and current exposure to climate-related health risks, defined as extreme heat, lower prevalence of green space, and increased air pollution concentrations. Exposure to these risks will grow as climate change worsens and will not be evenly distributed across communities. Through a spatial analysis of Landsat satellite imagery, datasets of urban trees and air pollution, and demographic data, this research looks to understand the following question: *To what extent do unfavorable HOLC designations predict higher present-day exposure to climate-related health risks in New Haven neighborhoods?* Results of this investigation reveal that unfavorable HOLC designations generally correlate to higher exposure to climate-related health risks. Land surface temperature values are higher by an average of 1.8ºC in redlined neighborhoods than in surrounding non-redlined areas, and the Normalized Difference Vegetation Index (NDVI), a quantitative measure of green space, is lower by 0.108. Pollution levels are not clearly correlated. It is necessary to understand the historical forces driving modern climate risk disparities to bolster environmental justice, direct urban planning, and enact policies to mitigate such adverse effects.

Introduction

Climate change continues to accelerate as the world fails to curb the use of fossil fuels.[i] The 2015 Paris Agreement established an imperative to limit global temperature increase to well below 2ºC above pre-industrial values, and to pursue efforts to limit the temperature increase to 1.5ºC.[ii] Current greenhouse gas emissions trends are set to bypass this target significantly, which will change the world as we know it. Climate changes is expected to spur various adverse impacts, including, but not limited to increased global surface temperatures, rising mean sea level, shifts in hydrological cycles, biodiversity loss, greater frequency and intensity of severe weather events, and greater spread of infectious disease.[i] These risks will not be evenly distributed; marginalized communities will face the most adverse impacts.[i] Effective future mitigation requires an understanding of current disparities in climate-driven health risk factors, as well as the social forces that have shaped them.

Redlining is one such force. This discriminatory mortgage lending practice shaped economic and social conditions for the past century in cities across the United States, including New Haven. This thesis examines the extent to which redlining also shaped the natural environment, specifically the distribution of exposure to climate-driven health risks in New Haven, CT. I define these risks to include extreme heat, lower prevalence of green space, and higher levels of air pollution. To investigate this, I analyze a variety of materials including Landsat 8 satellite imagery, a database of urban trees on public land, a dataset of air pollution concentrations, and responses to the 2019 American Community Survey. Remote sensing satellite data is particularly suitable for this investigation as it allows for uniform collection of geospatial data over a wide span of time and large areas.[iii] Additionally, the data is publicly available and easily accessible.[iii] I measure extreme heat via land surface temperature quantified by Band 10 of Landsat 8's thermal infrared sensor. Green space is measured via NDVI using Landsat 8's Bands 4 and 5, as well as the TreeKeeper database. These two measures are complimentary as NDVI encompasses all forms of vegetation, while TreeKeeper only captures trees on public land. Finally, air pollution is measured in a dataset of fine particular matter ($PM_{2.5}$) concentrations. Data from the American Community Survey is used to contextualize these environmental factors in their social contexts.

Research Question

This thesis looks to answer the following question:

> *To what extent do unfavorable HOLC designations predict higher present-day exposure to climate-related health risks in New Haven neighborhoods?*

Hypothesis

The working hypothesis for this thesis is:

> *Unfavorable HOLC designations are significantly correlated with increased land surface temperatures, decreased access to green space, and higher air pollution concentrations.*

Literature Review

This literature review aggregates demonstrations of satellite-based remote sensing data to quantify the impacts of redlining on climate-driven health risks. Key search terms included “redlining,” “urban heat,” “green space,” “air pollution,” and “remote sensing.” This survey was primarily aggregated from the Yale Library Quicksearch repository.

Previous research on the relationship between redlining and climate-driven health risks

While there is a large pool of research examining the correlation between exposure to climate-driven health risks and socioeconomic factors, redlining has not entered the climate literature until quite recently. Many of the landmark studies have been published in the last several years. This emerging research suggests a national pattern of positive correlation between redlining and increased exposure to climate-driven health risks. In 2020, Jeremy Hoffman et al. published a survey of 108 cities across the United States examining exposure to intra-urban heat in correlation to redlining.[iv] This study found that 94% of urban areas display city-scale patterns of elevated land surface temperatures in formerly redlined areas compared to non-redlined surrounding areas by as much as 7ºC.[iv] The primary materials were Landsat 8 raster images and HOLC shape files.[iv] This trend was reinforced by Bev Wilson et al. 2020, who used Landsat 8 data to observe higher land surface temperatures in neighborhoods that received worse HOLC ratings in Baltimore, Dallas, and Kansas City.[v]

A 2021 study by Anthony Nardone et al. established a positive correlation between worse HOLC grades and reduced green space across 102 U.S. cities.[vi] The materials included satellite imagery from the NASA MODerate-resolution Imaging Spectroradiometer (MODIS) mission and calculated green space based on NDVI.[vii] Average NDVI decreased from 0.47, to 0.43, to 0.39, to 0.36 across HOLC grades “A”, to “B”, to “C”, to “D”.[vi]

There is also literature demonstrating a relationship between redlining and increased air pollution exposure. In 2022, Haley Lane et al. found a pattern of higher concentrations of nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$) in historically redlined neighborhoods in a survey of 202 U.S. cities.[viii] Intraurban disparities for NO_2 and $PM_{2.5}$ were significantly larger by HOLC grade than by current race or ethnicity.[viii] Associations between redlining and increased pollutant concentration were strong for NO_2, and weak, but present, for $PM_{2.5}$. [viii]

This existing literature establishes relationships between unfavorable HOLC designations and increased extreme heat, reduced green space, and higher concentrations of $PM_{2.5}$ in cities across the United States. This thesis will examine to what extent these trends are observable in New Haven.

Background

Before examining potential causality between redlining and current exposure to climate-driven health risks, it is critical to understand redlining's historical context, how HOLC assessments were generated, and observed relationships between redlining and current social inequities. Additionally, this section details the mechanisms by which extreme heat, low prevalence of green space, and increased air pollution concentrations negatively impact human health.

A history of redlining

In 1933, New Deal legislation sought to fix the rapid foreclosure rates of the Great Depression.[ix] Across the United States, banks were foreclosing on 13.3 per 1,000 mortgages, resulting in economic and social turmoil.[ix] The Home Owners' Loan Corporation (HOLC) was created to remedy this chaos by reforming the mortgage lending process.[x] This federal agency was charged with aiding banks in streamlining the process of vetting properties and homeowners for mortgage lending, with the intention of reducing loan default and foreclosure rates.[x] As a part of this initiative, the HOLC created a grading system to capture the degree of perceived risk of lending in a certain neighborhood.[x] Over the 1930s, HOLC representatives traveled across the United States, assessing mortgage lending risk in over 200 cities, including New Haven, CT.[xi]

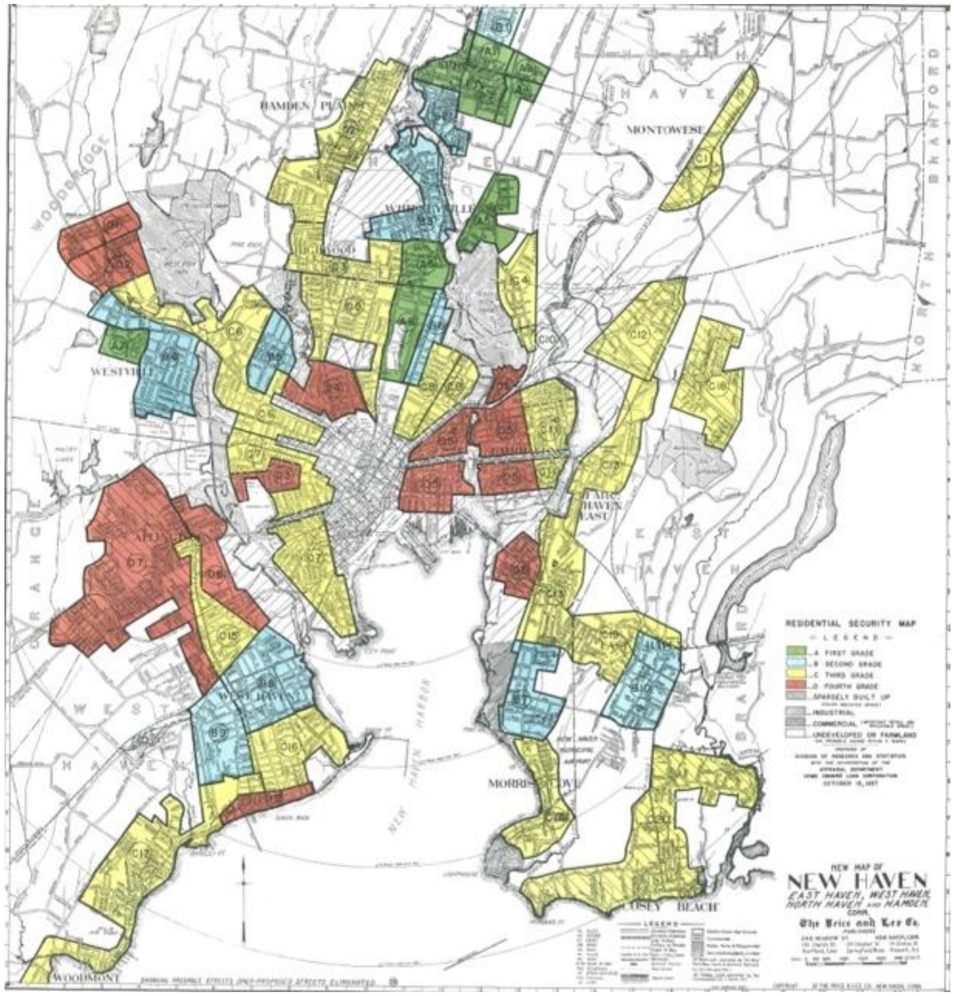
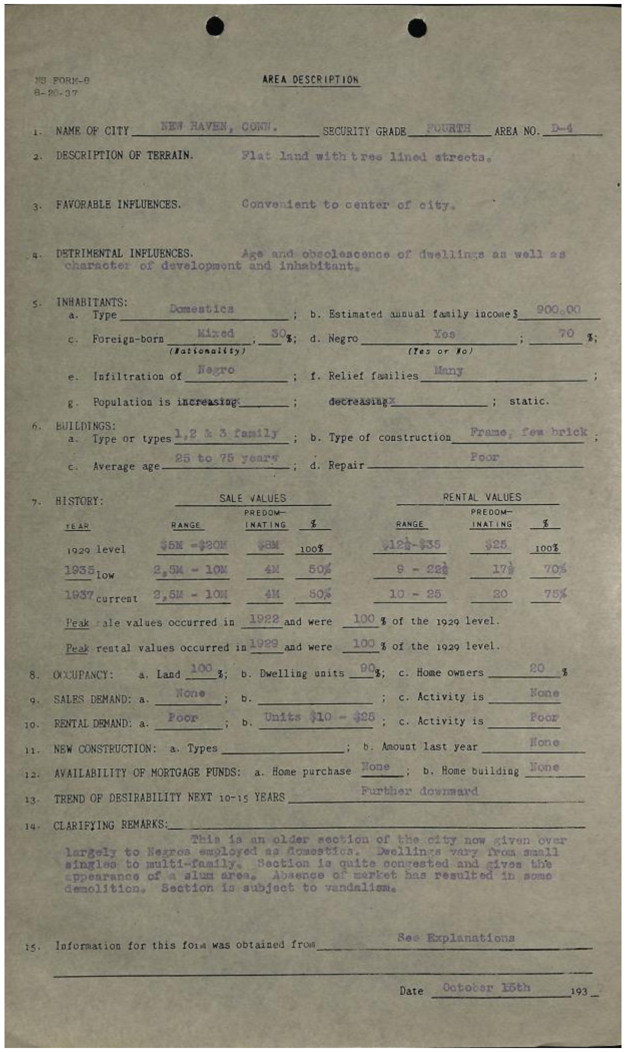


Figure 1: HOLC map of New Haven, CT (Source: Mapping Inequality project)[xi]

To easily visualize these different tiers of risk, the HOLC created maps for banks to use in making lending decisions.[Error! Bookmark not defined.] These maps delineated areas that were d eemed safer for investment, and therefore more deserving of easy access to credit.[ix] Conversely, they defined areas that carried greater risk, thereby restricting flow of capital to these neighborhoods.[Error! Bookmark not defined.] Grades ranged from “A”, “B”, “C”, and “D”, which r espectively correlated to “Best,” “Still Desirable,” “Definitely Declining,” and “Hazardous.”[Error! Bookmark not defined.] Neighborhoods receiving an “A” grade were colored in green, “B” in blue, “C” in yellow, and “D” in red, leading to the term redlining.[Error! Bookmark not defined.]

The formula used in created these grades was far from objective; this is particularly relevant in research that looks at the current environmental impacts of these assessment grades. The area description cards filled out by HOLC members include descriptions of the terrain, favorable influences, detrimental influences, inhabitants, buildings, history, occupancy, demand, trend of desirability over the next 10-15 years, and any clarifying remarks.[xi] Further investigation reveals that the inhabitants section specified the following characteristics: types, foreign-born, infiltration, estimated annual family income, Negro, and relief families.[Error! Bookmark not defined.] T he formula penalized areas for populations of Black and Hispanic people, as well as other people of color.[Error! Bookmark not defined.] Additionally, the assessment considered immigrants and low-income people unfavorably.[Error! Bookmark not defined.] HOLC ratings were overtly discriminatory; racial and economic discrimination were clearly codified into the HOLC's assessment formula.



HS FORM-8
8-20-37

AREA DESCRIPTION

1. NAME OF CITY NEW HAVEN, CONN. SECURITY GRADE FOURTH AREA NO. D-4
2. DESCRIPTION OF TERRAIN. Flat land with tree lined streets.
3. FAVORABLE INFLUENCES. Convenient to center of city.
4. DETRIMENTAL INFLUENCES. Age and obsolescence of dwellings as well as character of development and inhabitant.
5. INHABITANTS:
   a. Type Domestics ; b. Estimated annual family income $ 900.00
   c. Foreign-born Mixed (Nationality) ; 30 %; d. Negro Yes (Yes or No) ; 70 %;
   e. Infiltration of Negro ; f. Relief families Many ;
   g. Population is increasing ; decreasing x ; static.
6. BUILDINGS:
   a. Type or types 1,2 & 3 family ; b. Type of construction Frame, few brick ;
   c. Average age 25 to 75 years ; d. Repair Poor
7. HISTORY:

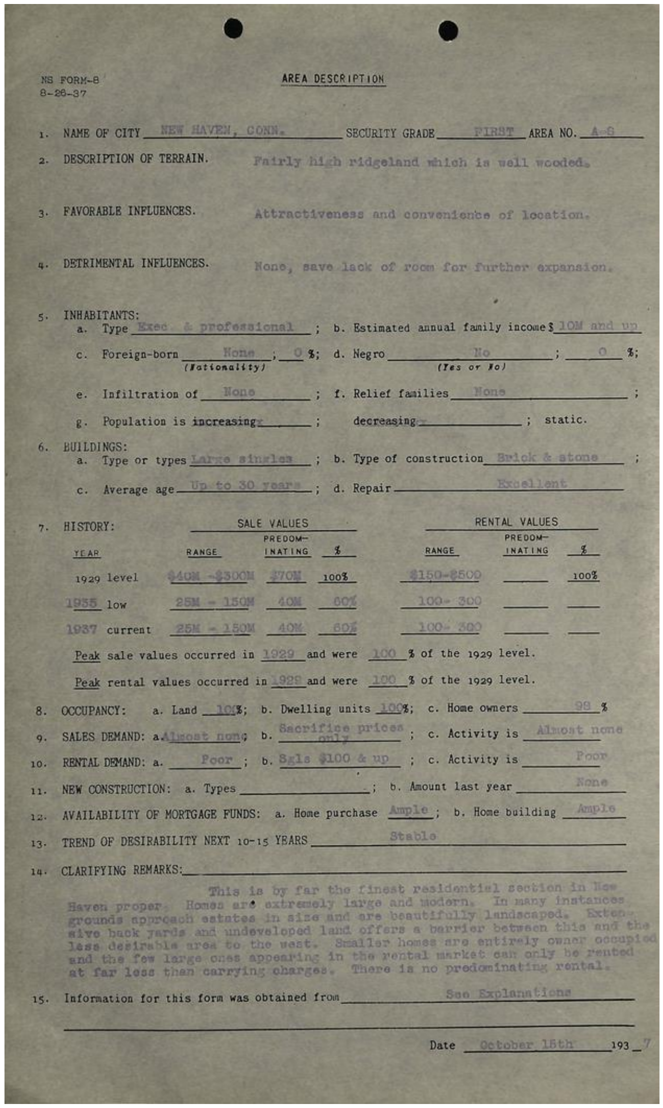
YEAR	SALE VALUES RANGE	PREDOMINATING	%	RENTAL VALUES RANGE	PREDOMINATING	%
1929 level	$5M -$20M	$8M	100%	$12½-$35	$25	100%
1935 low	2,5M - 10M	4M	50%	9 - 22½	17½	70%
1937 current	2,5M - 10M	4M	50%	10 - 25	20	75%

Peak sale values occurred in 1922 and were 100 % of the 1929 level.
Peak rental values occurred in 1929 and were 100 % of the 1929 level.

8. OCCUPANCY: a. Land 100 %; b. Dwelling units 90 %; c. Home owners 20 %
9. SALES DEMAND: a. None ; b. ; c. Activity is None
10. RENTAL DEMAND: a. Poor ; b. Units $10 - $25 ; c. Activity is Poor
11. NEW CONSTRUCTION: a. Types ; b. Amount last year None
12. AVAILABILITY OF MORTGAGE FUNDS: a. Home purchase None ; b. Home building None
13. TREND OF DESIRABILITY NEXT 10-15 YEARS Further downward
14. CLARIFYING REMARKS: This is an older section of the city now given over largely to Negros employed as domestics. Dwellings vary from small singles to multi-family. Section is quite congested and gives the appearance of a slum area. Absence of market has resulted in some demolition. Section is subject to vandalism.
15. Information for this form was obtained from See Explanations

Date October 15th 193_

Figure 2: HOLC assessment sheet for Dixwell neighborhood in New Haven, CT (Source: Mapping Inequality project)[xi]



NS FORM-8
8-26-37

AREA DESCRIPTION

1. NAME OF CITY NEW HAVEN, CONN. SECURITY GRADE FIRST AREA NO. A-6
2. DESCRIPTION OF TERRAIN. Fairly high ridgeland which is well wooded.
3. FAVORABLE INFLUENCES. Attractiveness and convenience of location.
4. DETRIMENTAL INFLUENCES. None, save lack of room for further expansion.
5. INHABITANTS:
   a. Type Exec. & professional ; b. Estimated annual family income $ 10M and up
   c. Foreign-born None (Nationality) ; 0 %; d. Negro No (Yes or No) ; 0 %;
   e. Infiltration of None ; f. Relief families None ;
   g. Population is increasing ; decreasing ; static.
6. BUILDINGS:
   a. Type or types Large singles ; b. Type of construction Brick & stone ;
   c. Average age Up to 30 years ; d. Repair Excellent
7. HISTORY:

YEAR	SALE VALUES RANGE	PREDOMINATING	%	RENTAL VALUES RANGE	PREDOMINATING	%
1929 level	$40M - $300M	$70M	100%	$150-$500		100%
1935 low	25M - 150M	40M	60%	100- 300		
1937 current	25M - 150M	40M	60%	100- 300		

   Peak sale values occurred in 1929 and were 100 % of the 1929 level.
   Peak rental values occurred in 1929 and were 100 % of the 1929 level.
8. OCCUPANCY: a. Land 100%; b. Dwelling units 100%; c. Home owners 98 %
9. SALES DEMAND: a. Almost none; b. Sacrifice prices only ; c. Activity is Almost none
10. RENTAL DEMAND: a. Poor ; b. Sgls $100 & up ; c. Activity is Poor
11. NEW CONSTRUCTION: a. Types ; b. Amount last year None
12. AVAILABILITY OF MORTGAGE FUNDS: a. Home purchase Ample ; b. Home building Ample
13. TREND OF DESIRABILITY NEXT 10-15 YEARS Stable
14. CLARIFYING REMARKS:
   This is by far the finest residential section in New Haven proper. Homes are extremely large and modern. In many instances grounds approach estates in size and are beautifully landscaped. Extensive back yards and undeveloped land offers a barrier between this and the less desirable area to the west. Smaller homes are entirely owner occupied and the few large ones appearing in the rental market can only be rented at far less than carrying charges. There is no predominating rental.
15. Information for this form was obtained from See Explanations

Date October 15th 1937

Figure 3: HOLC assessment sheet for East Rock neighborhood in New Haven, CT (Source: Mapping Inequality project)[xi]

These assessment sheets provide qualitative insight into bias implicit in the formulation of HOLC grades in New Haven. The area descriptions for the Dixwell and East Rock neighborhoods contrast quite intensely. In the above image, the HOLC states that the Dixwell neighborhood had a “infiltration” of “Negro” residents.[xi] The type of inhabitants is described as “Domestics,” and detrimental influences include the “character of development and inhabitants.”[xi] The East Rock neighborhood is portrayed quite differently. The type of inhabitant is described as "Exec. & professional", infiltration is "none", and there are no foreign-born or Black people.[xi] Perhaps unsurprisingly, the Dixwell neighborhood received a "D" grade, and the East Rock neighborhood received an "A" grade.[xi]

These maps were built on bias, and they propagated further systemic inequity for decades. The Fair Housing Act was passed in 1968 and ended banks' use of these HOLC maps, but their influence persists into the prescence.[xii] Historically redlined neighborhoods today experience reduced access to capital, lower homeownership rates, worse credit scores, higher poverty and vacancy rates, increased risk of loan denials, subprime lending, and worse property values, and lower economic mobility.[xiv,xii,xiii]

It is important to consider how green space was treated in HOLC assessments. In both the Dixwell and East Rock assessment sheets, the natural environment was mentioned. In the Dixwell street, the terrain was described as "flat land with tree lined streets."[xi] East Rock was described as "well wooded", "attractively located", and having "extensive back yards." [xi] The environment in 1937 was considered in the HOLC assessments, meaning that one would expect to see perhaps more abundant green space in these same areas. However, modern environmental discrepancies must be explained by a multitude of socioeconomic and policy factors, and not just the state of the land prior to HOLC intervention.

It is important to understand the exact mechanisms by which redlining codified inequity; their initial assessment captured racial and economic prejudice, but the HOLC designations then skewed access to economic opportunity based on this initial bias. Banks made decades of lending decisions based on the lines on the HOLC maps, severely biasing the flow of financial capital into neighborhoods for generations.[xiv] Neighborhoods with better HOLC grades had greater accessibility to lending, while redlined neighborhoods were significantly restricted.[xiv] This inequitable access to capital perpetuated low homeownership rates in neighborhoods with unfavorable HOLC grades.[xii] Homeownership helps to build generational wealth[xv] and drives civic engagement,[xvi] meaning that those with favorable HOLC designations, and therefore greater access to lending capital, slowly accrued greater influence over local place building. This includes decision-making about the location of major development projects, such as highways and industrial facilities. [xvii] These types of development can exacerbate environmental risk, through direct emissions of heat and pollution, or reduction of green space.[xiii] Such projects are susceptible to NIMBY-ism, defined by individuals opposing development projects near their own neighborhoods, due to perceived threats to their homes and health.[xviii] In addition to personal risk, perceived risk to property values is also a facet of NIMBY-ism.[xviii] Relatedly, homeowners are likely to support increased green space due to related property value increases.[xix] Redlining created a feedback loop between access to mortgage capital, homeownership, and environmental engagement.

An overview of climate-driven risks to human health

This section provides an overview of the ways that various climate-driven health risks influence human health. This is particularly relevant as climate change continues to worsen.

Extreme heat

Extreme heat has caused more fatalities in the United States than any other form of hazardous weather.[xx] Climate chance will increase both the frequency and severity of extreme heat events.[xxi] The risk from heat stress depends on heat, humidity, and direct exposure to sunlight, measured by a wet bulb global temperature.[xxii] This metric captures the human body's ability and thresholds to regulate our temperature via physiological processes. [xxii] High wet bulb temperatures conditions cause direct health effects, such as heat exhaustion and heat stroke.[xxiii]

Additionally, extreme heat exacerbates chronic conditions, such as cardiovascular disease, respiratory disease, cerebrovascular disease, and diabetic conditions.[xxiv] High temperatures also create a financial burden, driven by an increased use of air conditioners, fans, or other cooling technologies.[xxv] Certain demographics are most vulnerable to the effects of extreme heat. This includes demographics such as unhoused persons and those with physical, outdoor jobs.[xxvi] Many New Haven residents lack air conditioning, making extreme heat especially dangerous.[xxvii]

The urban heat island effect is particularly relevant to understanding the state of extreme heat in cities such as New Haven. Heat islands are urban areas that experience higher temperatures than surrounding, non-urban areas.[xxviii]

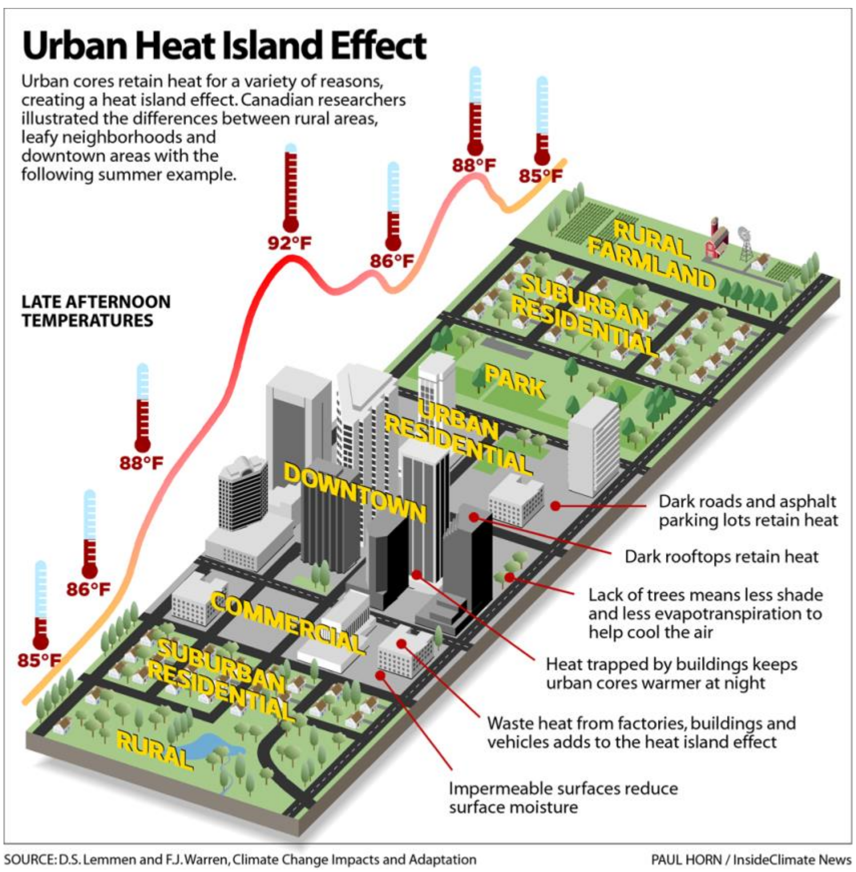


Figure 4: Urban heat island effect diagram (Source: D.S. Lemmen and F.J. Warren, Climate Change Impacts and Adaptation)[xxix]

On average, urban areas are 1-7ºC warmer than surrounding non-urban areas during the daytime.[xxx] Built structures in cities, such as buildings, roads, and other infrastructure made from impervious materials, absorb, retain, and re-emit solar energy more so than naturally occurring materials.[xxviii] These materials also provide less moisture and shade than natural landscape features, which contribute to cooling.[xxviii] The albedo, or the fraction of light that a surface reflects, also influences the amount of solar heat that is retained; darker surfaces retain more heat, while lighter colors reflect more solar radiation.[xxx] Additionally, the layout and geometry of buildings can trap heat by reducing wind flow.[xxviii] Cities also have a higher density of heat-producing anthropogenic sources, such as vehicles, air-conditioning units, and industrial facilities.[xxviii] These factor coalesce and result in hotter living temperatures for urban citizens.

Urban green space

Green space includes various forms of outdoor environments, including nature reserves and urban parks.[xxxi] However, not all types of plant cover are created equal. Research has shown that trees in particular boast a myriad of physical health benefits for humans.[xxxii,xxxiii] Urban trees reduce the harmful health effects of air pollution, including fine particular matter ($PM_{2.5}$),[xxxiv] coarse particular matter (PM_{10}),[xxxv] nitrogen dioxide (NO_2),[xxxvi] ozone (O_3),[xxxvii] and sulfur dioxide (SO_2).[xxxi] Trees remove these pollutants via the following mechanisms: temperature reduction and other microclimatic effects, removal of air pollution through leaf stomata, adsorption onto the leaf surface, and emission of volatile organic compounds, which can reduce ozone concentrations via atmospheric reaction pathways.[xxxviii] Shade from trees also can lessen the energy needed to regulate buildings, thereby lowering energy consumption and mitigating associated emissions.[xxxviii] Areas with higher densities of urban trees are associated with a lower prevalence of asthma[xxxix] and lung cancer[xl] and reduced asthma hospitalization rates when ambient pollutant concentrations are high.[xli] Shade from trees, particularly those with wide and dense canopies, reduce exposure to ultraviolet radiation,[xlii] which is a major risk factor for most skin cancers.

Urban trees also reduce air and surface temperatures, and thereby reduce the negative health effects of extreme heat.[xliii] This occurs through several mechanisms, including canopy shading and transpiration, which influence the balance of surface energy and the water vapor cycle of the hydrosphere-atmosphere-biosphere. [xliv] Through this, trees can adjust the outdoor radiant heat and change microclimates.[xlv,xlvi] Additionally, trees can reduce wind speed, enhance airflow turbulence, and reduce convective heat.[xlvii] The physical properties of trees, such as diameter at breast height, crown width, and leaf area all greatly influence the extent to which the tree influences its local microclimate.[xlviii] Because of differences in these aforementioned variables, in addition to root depth, tree morphology, and leaf reflectance, the cooling properties of a tree also depends greatly on species. [xlix]

Research also suggests that higher urban tree cover is correlated with mental health benefits.[l] Increased urban tree cover is linked with lower rates of both property and violent crime in New Haven, CT.[l] Furthermore, there is a wealth of evidence that trees boost cognitive function[li] and mental health, including lower rates of anxiety, depression, anger, confusion, stress, and fatigue.[lii] Finally, urban trees are correlated with higher measures of active living, including commuted-related walking among children,[liii] recreational walking,[liv] and total physical activity,[lv] as well as reduced rates of obesity.[lvi] Trees provide diverse human health benefits, and their absence in various communities directly harms those who inhabit those neighborhoods.

$PM_{2.5}$ air pollution

Air pollution is directly linked to many health issues.[lvii] Particulate matter less than 2.5 microns ($PM_{2.5}$) is one of the key pollutants measured as a part of the National Ambient Air Quality Standards and monitored in the Clean Air Act.[lviii] $PM_{2.5}$ is produced through both primary and secondary mechanisms, including combustion emissions of oil or gasoline, or atmospheric reaction pathways resulting from the interactions of SO_2, NO_x and organic compounds.[lix] Exposure to $PM_{2.5}$ is harmful to human health as their small size allows them to penetrate deep into the lungs and bloodstream.[lx] This can lead to a variety of health issues including impaired lung function, respiratory tract diseases, and raised morbidity and mortality of cardiopulmonary disease.[lxi] The EPA recommends that $PM_{2.5}$ concentrations remain below an annual standard of 12 $\mu g/m^3$ and a 24-hour standard of 35 $\mu g/m^3$.[lxii]

Primary emission sources of $PM_{2.5}$ include power plants, industrial facilities, and motor vehicles.[lxiii] These emission sources, including power plants, industrial facilities, and highways, are more likely to be in low-income neighborhoods and communities of color than in wealthy, white neighborhoods.[lxiv]

Materials

This research analyzes a variety of materials, including a GEOJSON shapefile and primary HOLC area descriptions from the University of Richmond's "Mapping Inequality" Lab,[xi] Landsat 8 raster images, Tree Keeper data, $PM_{2.5}$ data, and 2019 American Community Survey demographic data.

"Mapping Inequality" resources

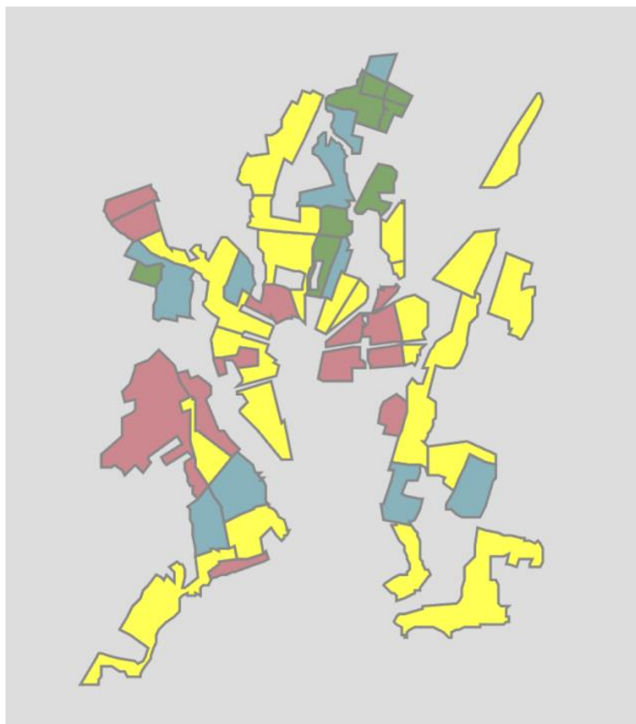


Figure 5: Shapefile of HOLC neighborhoods in New Haven (Source: Mapping Inequality project)[xi]

I downloaded a GEOJSON shapefile of the HOLC map of New Haven from the University of Richmond's Digital Scholarship Lab's *Mapping Inequality* project. As downloaded, the shapefile is geo-referenced by the HOLC delineations and includes the neighborhood grades (A-D). The shapefile can be overlaid over various data layers to calculate statistics based on the spatial boundaries. In addition to the shapefile, I examined *Mapping Inequality's* area description images, which are written records of the assessment process HOLC representatives used to assign each neighborhood a classification. These area descriptions include information on the terrain, favorable and detrimental influences, inhabitants, buildings, and history, as well as other factors. Examining the area description records provides qualitative context for the bias present in the HOLC assessment process. Additionally, these records can be compared with current demographic data to understand how these neighborhoods have changed since the HOLC assessments of New Haven in 1937.

Landsat8 images

I used Landsat 8 images to assess land surface temperature (LST) and green space. Launched in 2013, the Landsat 8 mission is a collaboration between NASA and the U.S. Geological Survey.[lxv] The satellite payload has two scientific instruments, the Operation Land Imager and the Thermal Infrared Sensor.[lxv] These sensors provide global coverage with a polar Sun-synchronous orbit[lxv] and an altitude of 705 kilometers.[lxv] The mission completes a revolution once every 16 days.[lxv] The images were extracted from the Universal Traverse Mercator (UTM) Zone 18N, which contains New Haven, CT. I selected images (n = 16) between 2015 and 2022 during the summertime (June-September) in the northern hemisphere, because extreme heat exposure risk is highest during these months. Maps were only generated from images that satisfied a threshold of less than 10 percent cloud cover, as clouds prevent proper data collection from satellites.[lxvi] The following days were selected based on this criteria: August 3, 2015; June 18, 2016; July 4, 2016; July 20, 2016; August 5, 2016; September 22, 2016; September 25, 2017; July 10, 2018; July 29, 2019; August 3, 2019; September 15, 2015; June 13, 2020; June 16, 2021; July 13, 2022; September 15, 2022; and September 23, 2022. I used spectral bands 4, 5, and 10, which correlate respectively to red (0.64 – 0.67 μm), near infrared (0.85-0.88 μm), and thermal infrared sensor 1 (10.6 – 11.19 μm).[lxv] Bands 4 and 5 have a spatial resolution of 30 m, and band 10 has a spatial resolution of 100 m.[lxv] For LANSAT 8, Band 10 is Level-2 product, meaning that the data is presented as a scaled integer.[lxvii] Band 10 is represented by an integer value that can be converted to Kelvin via a conversion factor of $0.00341802*x + 149.0$.[lxvii]

Figure 6: UTM18 Landsat 8 true color image from July 29, 2019 (Source: Landsat 8 in ArcGIS Pro)

It is important to note that the Band 10 thermal infrared resolution is coarser, which complicates analysis for dense urban areas.[lxviii] Additionally, Band 10 measures LST, which is not quite equivalent to air temperature.[v] Despite this, thermal infrared data is a widely accepted method of investigating large-scale patterns regarding heat-related public health outcomes.[lxix]

These Landsat 8 raster images will be used to calculate LST (Band 10) and NDVI (Bands 4 and 5). NDVI captures all forms of vegetation, including trees, shrubs, and grasses, which provides a holistic measure of green space, compared with the TreeKeeper data which just includes trees.

TreeKeeper database

New Haven's Urban Resources Initiative (URI) maintains an inventory map of every street tree in New Haven in the TreeKeeper database.[lxx] This data is a particularly robust measure of environment quality, as trees provide the most significant ecosystem service benefits to humans, when compared with other forms of green space.[xxxii] There are over 29,000 street trees associated with the New Haven area.[lxx] Each tree is catalogued with its latitude coordinate, longitude coordinate, species, neighborhood, and diameter at breast height (DBH) in inches.[lxx] The database is updated regularly as trees are planted.

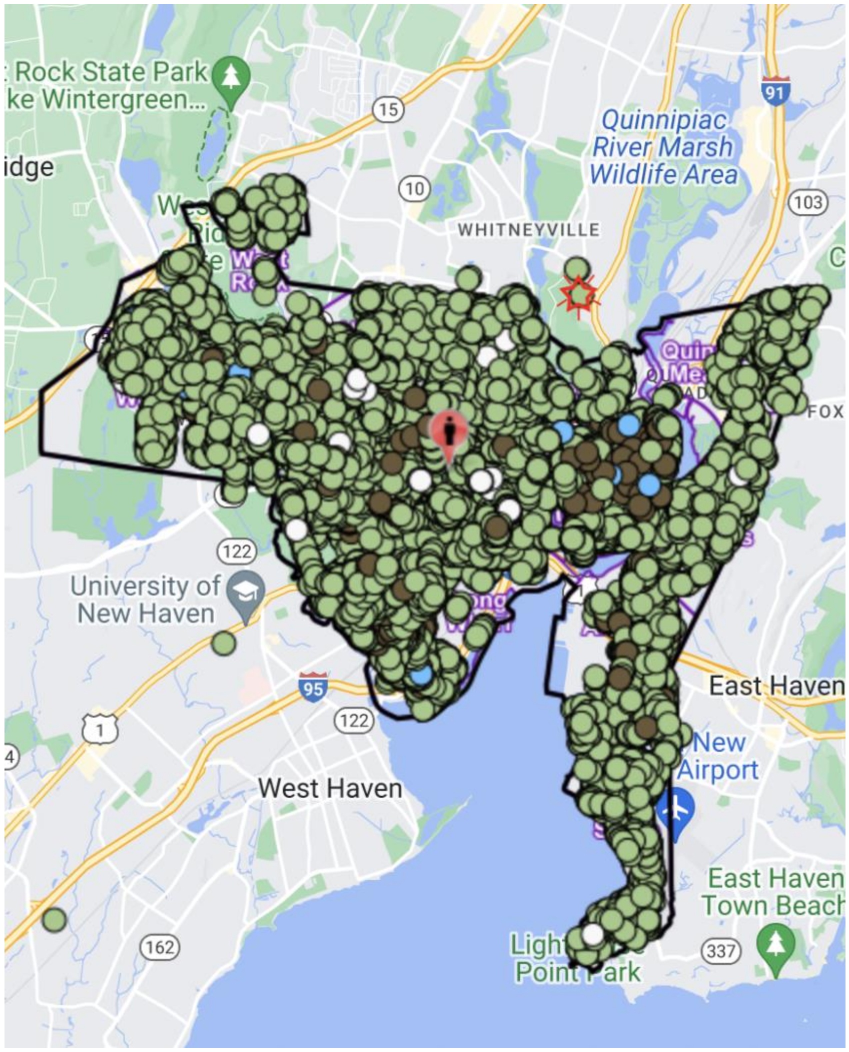


Figure 7: TreeKeeper dataset (Source: TreeKeeper points in ArcGIS Pro)

The database also includes a summary of ecosystem services provided by the urban trees, including CO_2 uptake, storm water mitigation, and air pollution removal.[lxx] One limitation of this database is that it only contains street trees and does not capture trees on private property. I mitigate this by considering other measures of green space in conjunction with this database.

American Community Survey

I used the American Community Survey from 2019 to capture current demographic data on New Haven. The 2019 survey is based on data collected from 2015 – 2019 and is the most recent iteration of the survey.[lxxi] Responses are collected across the U.S. population via a sample survey delivered as an internet questionnaire, with additional options to respond via mail, phone call or a personal visit.[lxxii] Annually, approximately 3.4 million housing addresses across the United States are selected for participate in the American Community Survey.[lxxii] The dataset is segmented by census tracts and includes granularity down to the block-group level.[lxxii] For each census tract, I used the following metrics: total population count, population by race (White / Black / Asian / Native American / Pacific Islander / Other / Two or more races), population for whom poverty status is determined in the past 12 months, number of households, medium household income, number of housing units, occupied units, vacant units, renter occupied units, and owner-occupied units. To geospatially reference the survey results, I used a shapefile of the New Haven census tract boundaries from the New Haven GIS Gallery. This data helps us understand how redlining has shaped current socioeconomic conditions across New Haven, as well as how those factors are correlated with higher climate risk exposure.

Air pollution dataset

Yichen Yang at the Yale School of the Environment collected a dataset of ensemble means of $PM_{2.5}$ concentrations in New Haven averaged across 90 replicate transects. The data set contains data on $PM_{2.5}$ concentration measurements in parts per million (ppm); each data point is associated with a latitudinal and longitudinal coordinate. The measurements were obtained between October 2022 and August 2023 by biking around the city along a set route with a $PM_{2.5}$ sensor. The data includes 84 replicates of the transects during the day and 77 replicates at night. Satellites do not directly measure $PM_{2.5}$, although the aerosol optical depth measurement can be used as a proxy.[lxxiii] I opted to use the sensor data instead of satellite data for greater measurement precision and because the dataset was easily accessible.

Figure 8: $PM_{2.5}$ concentration collection route (Source: $PM_{2.5}$ points in ArcGIS Pro)

Methodology

I used ArcGIS Pro and R Studio to complete my analysis. I began by downloading New Haven's GEOJSON shapefile from the University of Richmond's Digital Scholarship Lab's "Mapping Inequality" database. The shapefile is already geo-referenced in the WGS84 coordinate plane in UTM, meaning that it aligns with the ArcGIS Pro map without needing adjustment. Additionally, I uploaded the Landsat 8 raster layers, TreeKeeper data points, and the air pollution data points into ArcGIS Pro.

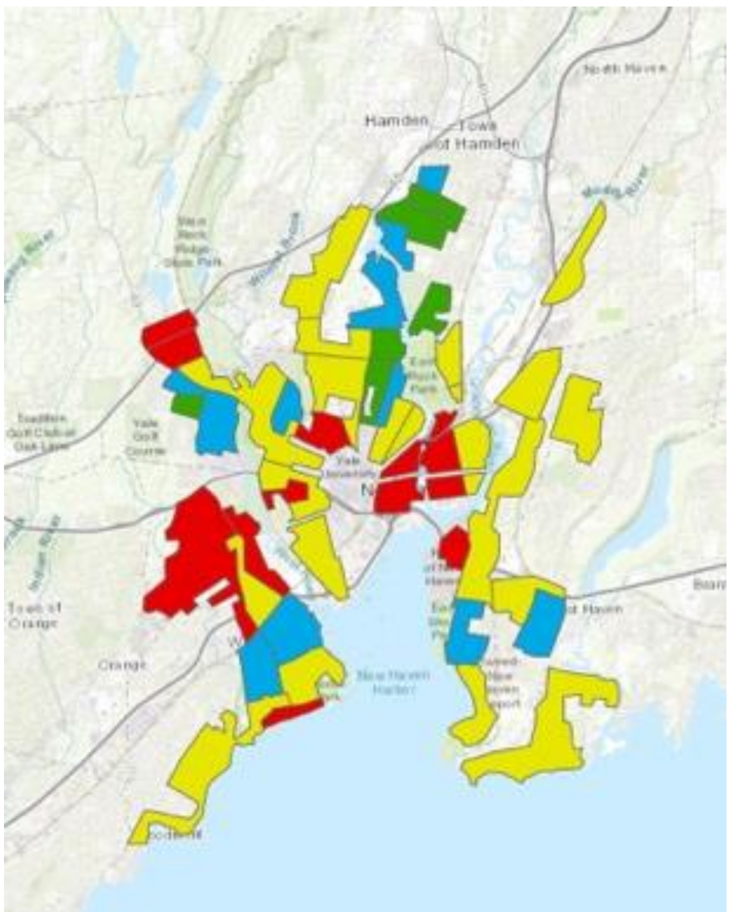


Figure 9: HOLC neighborhood shapefile layer in ArcGIS Pro (Source: Image created in ArcGIS Pro)

First, I corrected the shapefile boundaries to be able to accurately process all datasets. Because the shapefile is highly precise, some of the TreeKeeper data points appeared just barely outside of the neighborhood boundaries. For example, in many cases, the shapefile boundary would trace along the sidewalk, meaning that it would exclude trees planted on the grassy strip of curb between the sidewalk and road. To remedy this, I slightly expanded (< 5 m) some exterior edges of the shapefile polygons, so that trees that were just outside of the original shapefile boundary would be accounted for in analysis.

Once I had this updated shapefile, I began analyzing the Landsat raster images from northern hemisphere summertime (June-September). Because I only downloaded images that met the < 10% low cloud cover criteria, there was no need to mask out clouds.

I first calculated statistics for intra-urban LST based on the United States Geological Survey calculation protocol, using the Landsat 8 Band 10 raster image.[lxxiv] I used Zonal Statistics in the ArcGIS Pro Spatial Analyst toolbox to calculate the mean and standard deviation of the Landsat 8-dervied LST for each day (n = 16) for each individual HOLC neighborhood polygon (n = 47).

I then calculated the Normal Difference Vegetation Index (NDVI) for each day (n =16), which is derived from bands 4 (red) and 5 (near infrared). NDVI is calculated by:

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

NIR – reflection in the near-infrared spectrum
RED – reflection in the red range of the spectrum

Figure 10: NDVI formula (Source: OneSoil)[lxxv]

NDVI is used to quantify vegetation greenness to understand vegetation density and health.[vii] Values range from -1 to 1, with greater, positive values associated with more abundant healthy vegetation.[vii] The formula is derived from the understanding that healthy vegetation is highly reflective of near-infrared vegetation, and much less reflective of red spectral frequencies. NDVI values are therefore associated with certain land surface cover types. NDVI values of 0.500 correlate to dense vegetation, 0.140 to intermediate green vegetation, 0.090 to sparse vegetation, 0.0235 to bare soil, 0.002 to clouds, -0.046 to snow and ice, and -0.257 to water.[lxxvi]

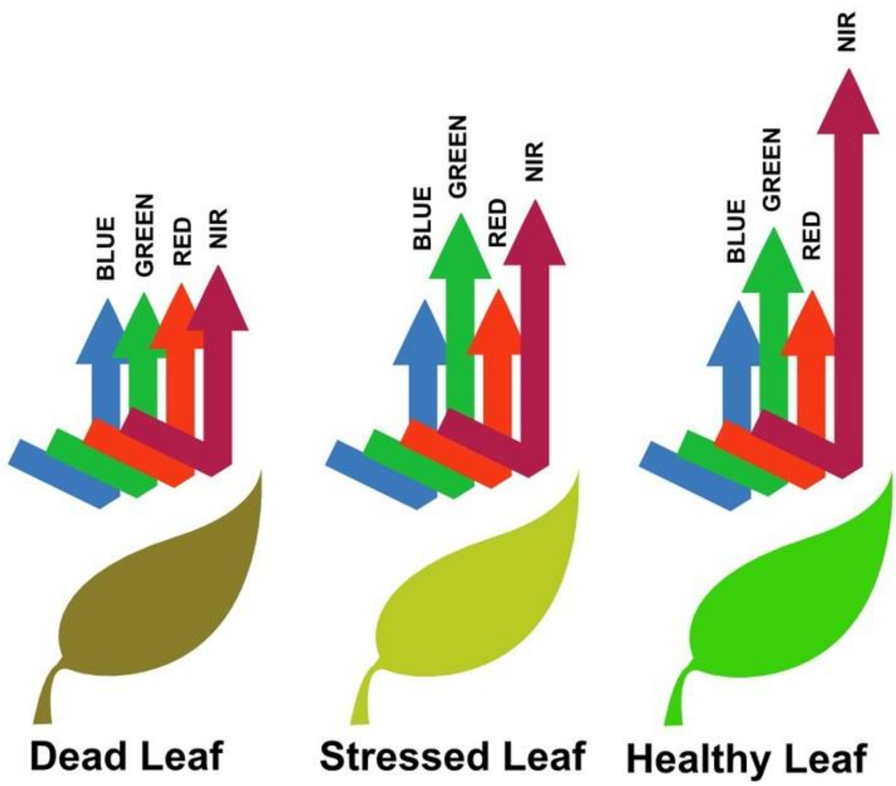


Figure 11: Reflectivity of spectral frequencies dependent on vegetation health (Source: PhysicsOpenLab)[lxxvii]

I produced the NDVI layer for each day by using the ArcGIS Pro Band Math feature to calculate NDVI via Landsat 8 Band and 4 and 5 in accordance with the aforementioned NDVI formula. I ensured that I use the *Float()* function for each calculation to produce non-integer output values. Then using this NDVI layer, I used Zonal Statistics again to calculate the mean and standard deviation of NDVI for each HOLC neighborhood polygon.

I then used ArcGIS Pro's Zonal Statistics again in conjunction with the TreeKeeper data points to calculate the number of trees per HOLC neighborhood polygon, tagged with species and DBH.

I repeat this process once more to get the $PM_{2.5}$ measurements tagged by HOLC neighborhood polygon.

Finally, I calculated current demographic statistics for each HOLC polygon based on the 2019 American Community Survey. The results from this survey were reported by census tract block, which did not always align with the HOLC neighborhood boundaries. To account for this, I used area-weighted resampling to adjust the data for analysis. By overlaying a shapefile of New Haven's census tracts over the HOLC neighborhood polygons, I estimated the resampling coefficients for each area. I then took a weighted average of the American Community Survey results and multiplied them by the census tract to HOLC neighborhood conversation rate to get the statistics segmented by HOLC neighborhood.

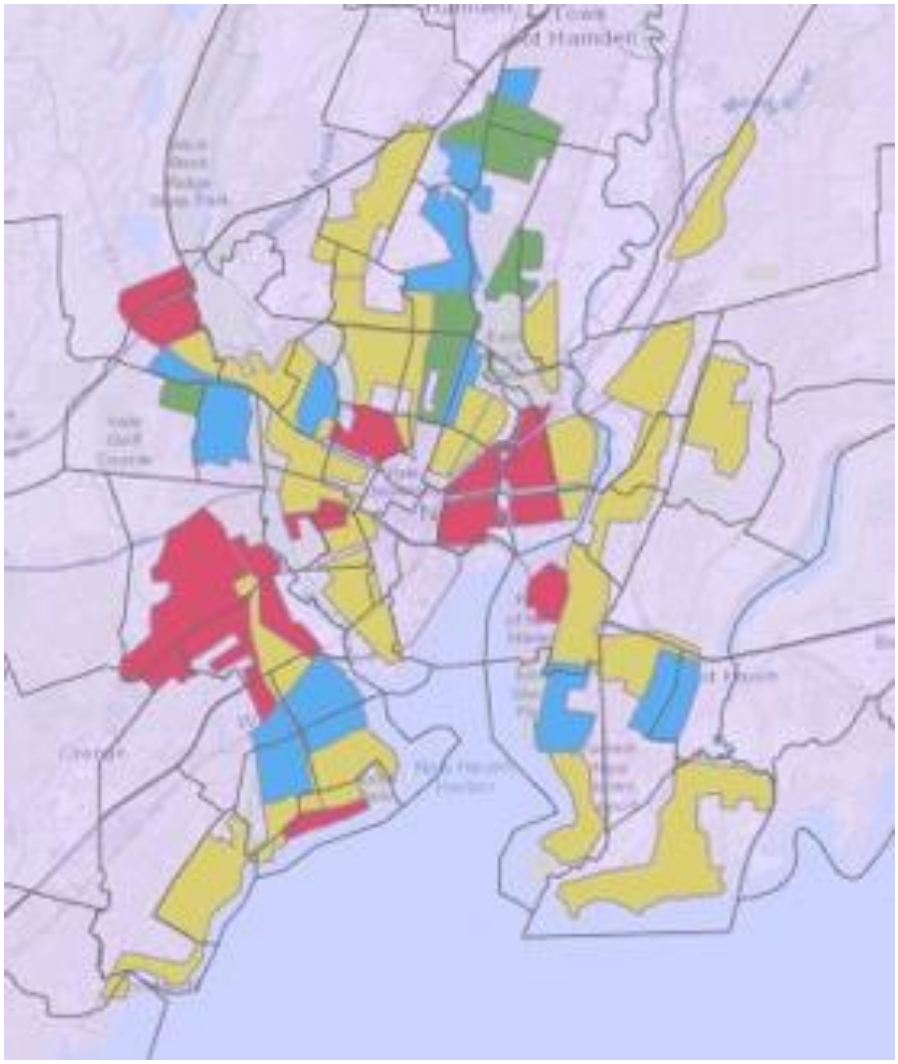


Figure 12: HOLC neighborhood polygons overlaid with New Haven census tracts (Source: Image created in ArcGIS Pro)

Once I had these statistics, I used R to understand the correlation between HOLC neighborhood grade, LST, NDVI, tree count, $PM_{2.5}$ readings, and 2019 New Haven American Community Survey results, including race, homeownership rates, poverty rates, and median income. In R, I averaged the measurements across temporal replicates so that each HOLC neighborhood (n = 47) had one associated mean value for LST and NDVI. This accounted for the natural variation associated with day-to-day temperature differences. Using temporal means for statistical analysis isolated the spatial variation, which is the focus of this research. I used several R packages including: ggplot2, tidyr, dplyr, lattice, and corrplot.

To estimate the significance of mean LST and NDVI differences, I used ANOVA comparisons, including Tukey's Honest Significant Differences Test. This test estimates the differences among group sample means for statistical significance. The ANOVA test determines the statistical significance of differences between the mean across groups using a studentized range distribution. I used ANOVA because I am testing the influence of a categorical independent variable (HOLC grade) on a continuous dependent variable (NDVI, or LST, or number of trees, or $PM_{2.5}$ concentration).

Results

My Landsat data was collected from Landsat8 days that satisfied <10% cloud coverage between June 1, 2015, and September 30, 2023. Regression tests conclude that there is an insignificant relationship between the day and the data patterns observed.

My data reveals multiple significant trends that help answer the original research question. First, there is a statistically significant distribution of differences for urban heat, suggesting that redlining manifests in urban heat disparities. Mean LST ranges from 31.12ºC for "A" grade areas, to 33.93ºC for "B" grade areas, to 35.43ºC for "C" grade areas, to 36.28ºC for "D" grade areas. This trend held true across almost all days, with only one day observing LST values that did not uniformly increase from "A" to "B", to "C", to "D". The standard deviations for each grade were 1.21ºC for "A" grade areas, to 1.75ºC for "B" grade areas, to 1.48ºC for "C" grade areas, to 1.30ºC to "D" grade areas. ANOVA tests between the HOLC grade and LST means yielded a p-value of 1.1e-8, demonstrating that there is a highly statistically significant correlation between HOLC grade and LST. This enforces my original hypothesis that worse HOLC designations would result in higher extreme heat exposure. Figure 13 displays the boxplot distribution of LST means, where the LST mean value for each HOLC neighborhood (n = 47) was averaged temporally. Error bars represent +/- 1 standard deviation of spatial replicates.

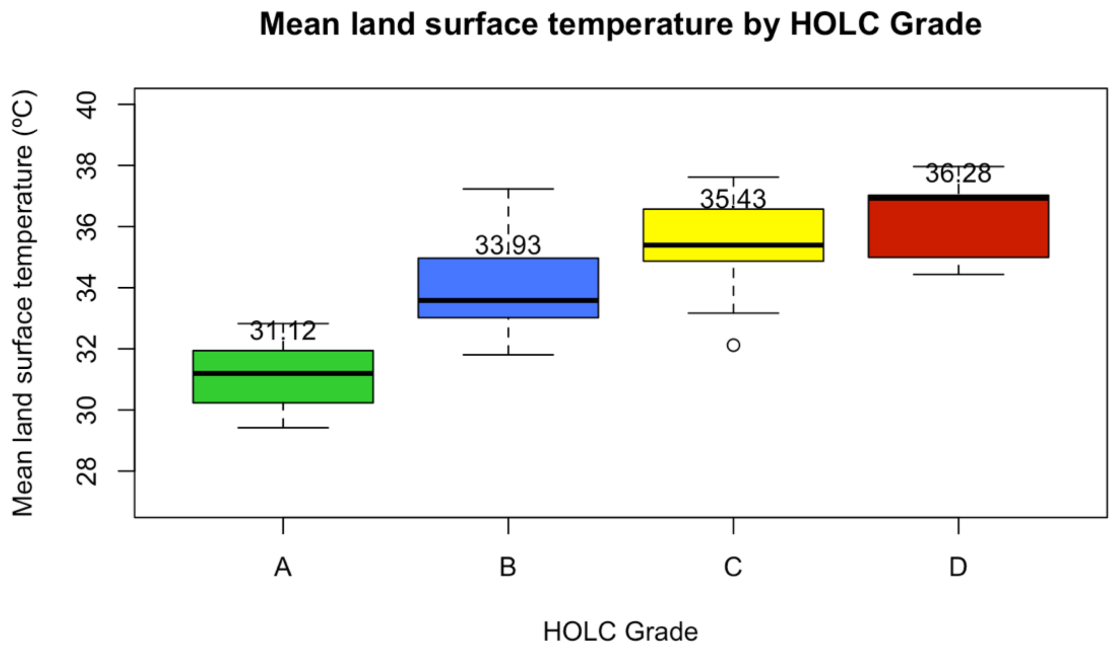


Figure 13: Mean land surface temperatures by HOLC grade

Additionally, viewing the distribution of LST values within individual neighborhoods yields a close view into the degree of bias based on HOLC grade. For example, in Figure 14, the mean LST value for each HOLC neighborhood is displayed for one day's worth of data (July 29, 2019). While there is some slight variation with grades "A" and "D", the maximum value for grade "A" is still less than the minimum value for grade "D." This view demonstrates that LST trends are relatively consistent within grades; the bias of HOLC grades is notable, even defined on smaller geographic areas.

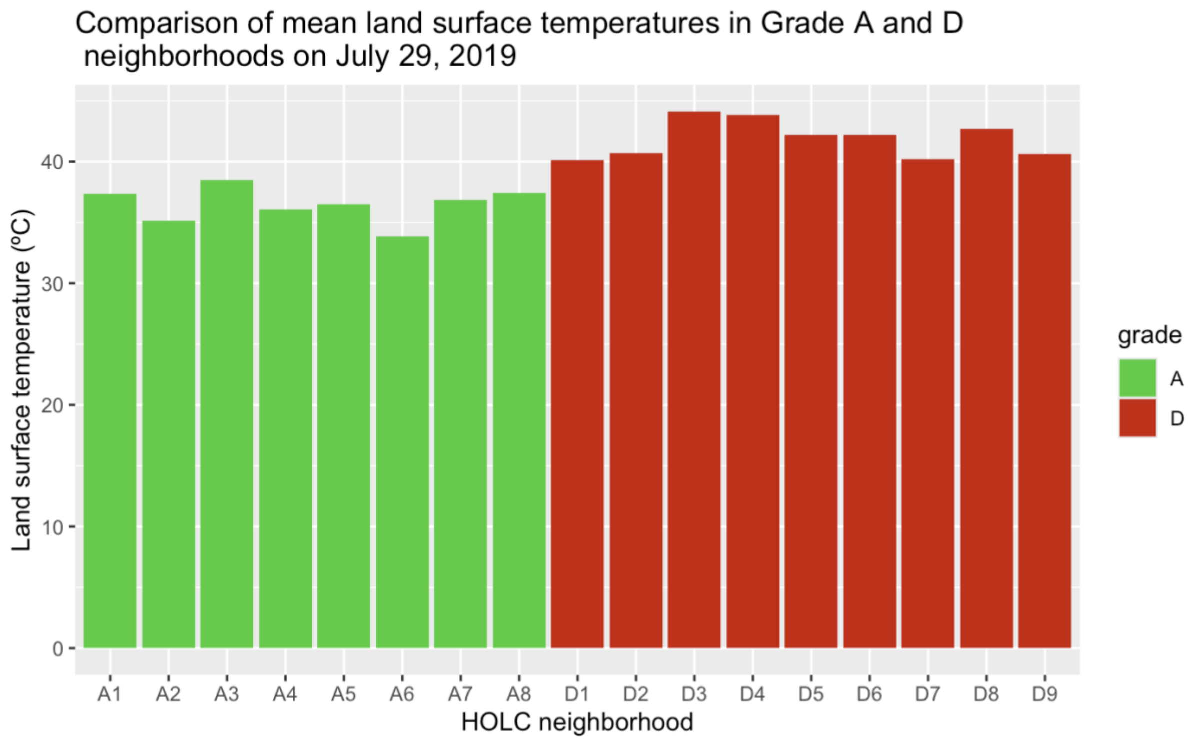


Figure 14: July 29, 20219 land surface temperature by individual HOLC neighborhoods for grades "A" and "D"

Likewise, there is a statically significant distribution of differences for NDVI, suggesting that redlining manifests in ununiform access to green space. Mean NDVI values range from 0.318 for "A" grade areas, to 0.265 for "B" grade areas, to 0.235 for "C" grade areas, to 0.210 for "D" grade areas. Higher NDVI values are indicative of more abundant, healthy plant life. Like the temperatures, this trend held true for nearly 100% of days, with only one day observing NDVI that did not uniformly decrease from "A" to "B", to "C", to "D". Standard deviations were 0.0223 for "A" grade areas, 0.0340 for "B" grade areas, 0.0320 for "C" grade areas, and 0.0511 for "D" grade areas. ANOVA tests between the HOLC grade and NDVI means yielded a p-value of 5.7e-7, demonstrating that there is a highly statistically significant correlation between grade and NDVI. This aligns with my original hypothesis that NDVI would increase as HOLC grade increases. Figure 15 displays the boxplot distribution of NDVI means, where the NDVI mean value for each HOLC neighborhood (*n* = 47) was averaged temporally. Error bars represent +/- 1 standard deviation of spatial replicates.

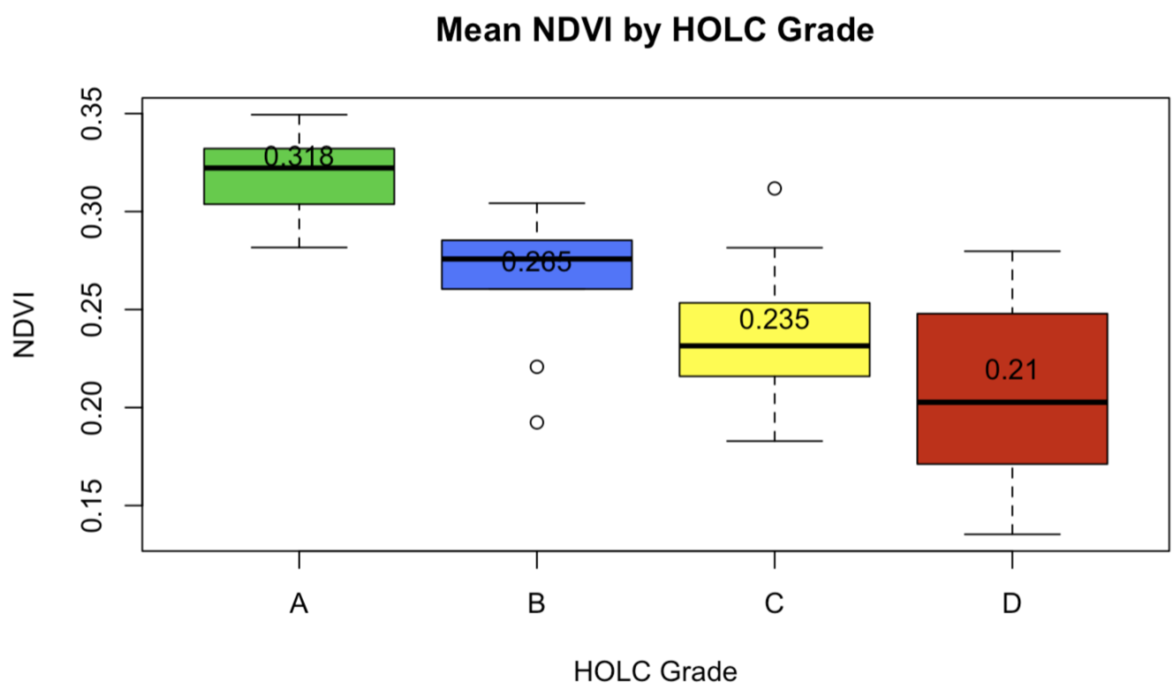


Figure 15: Mean NDVI by HOLC grade

In considering the trends for LST and NDVI, it is important to note the correlation between the two. Plotting NDVI means per day per HOLC neighborhood against the mean land surface yields a clear gradual negative relationship between the two. The linear model has an intercept value of 44.79, and a coefficient of -40.85. The Pearson statistical correlation between NDVI means as a predictor of LST means is -0.898, which is a strong negative relationship. This is expected given current understandings of vegetation's influence on temperature via shading and transpiration. In the graph below, the points represent the temporal average of NDVI and LST for each HOLC neighborhood (*n* = 47) over the 16 days, where colors denote their respective grade.

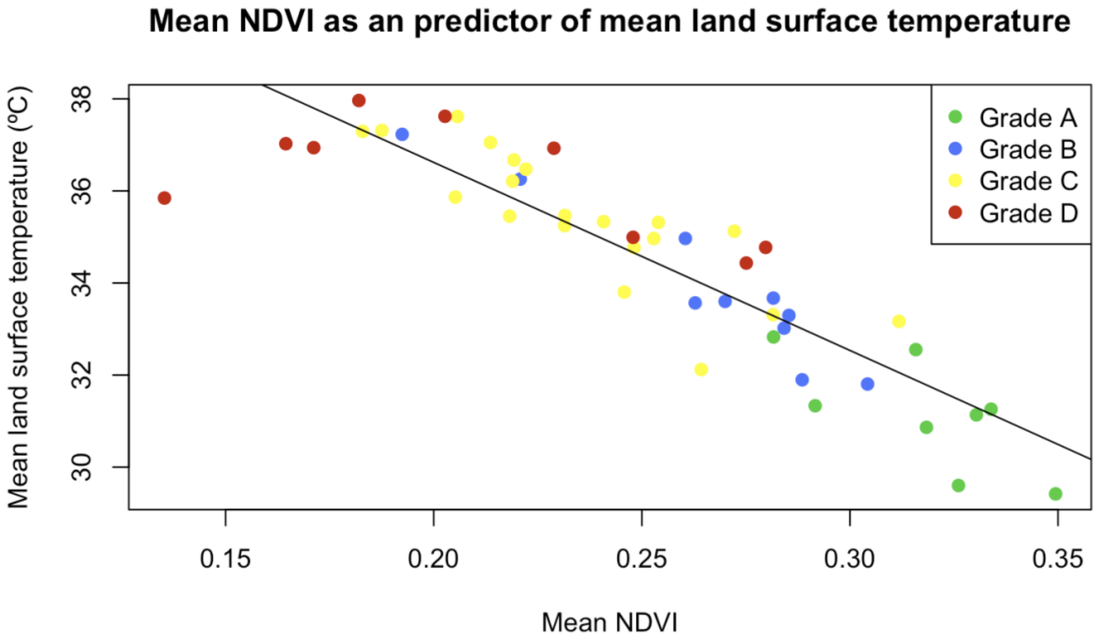


Figure 16: Correlation between NDVI and land surface temperature

In contrast to LST and NDVI, the relationship between $PM_{2.5}$ concentrations and HOLC grade was not significant. $PM_{2.5}$ concentrations were only available for 12 of the 47 HOLC neighborhoods. Figure 17 displays the $PM_{2.5}$ concentrations means for each of these 12 neighborhoods; there is no clear trend based on grade. We see however that “A” and “C” have the higher concentrations, while “B” and “D” have relatively lower concentrations. Correspondingly, the ANOVA test between $PM_{2.5}$ concentration and HOLC grade produces an unsignificant p-value of 0.73. This is contrary to my hypothesis that higher concentrations would be associated with worse HOLC designations. It is important to note that the Lane study referenced in the Literature Review section found $PM_{2.5}$ concentrations differences across HOLC grades to be significant but not large.[viii] Additionally, this study analyzed aggregated pollution data across a greater area, while these data points only represented a bike route through 12 of the 47 HOLC neighborhoods in New Haven.[viii] Perhaps the relationship between $PM_{2.5}$ concentration and HOLC grade would appear more pronounced if the $PM_{2.5}$ concentrations were aggregated from across a greater area.

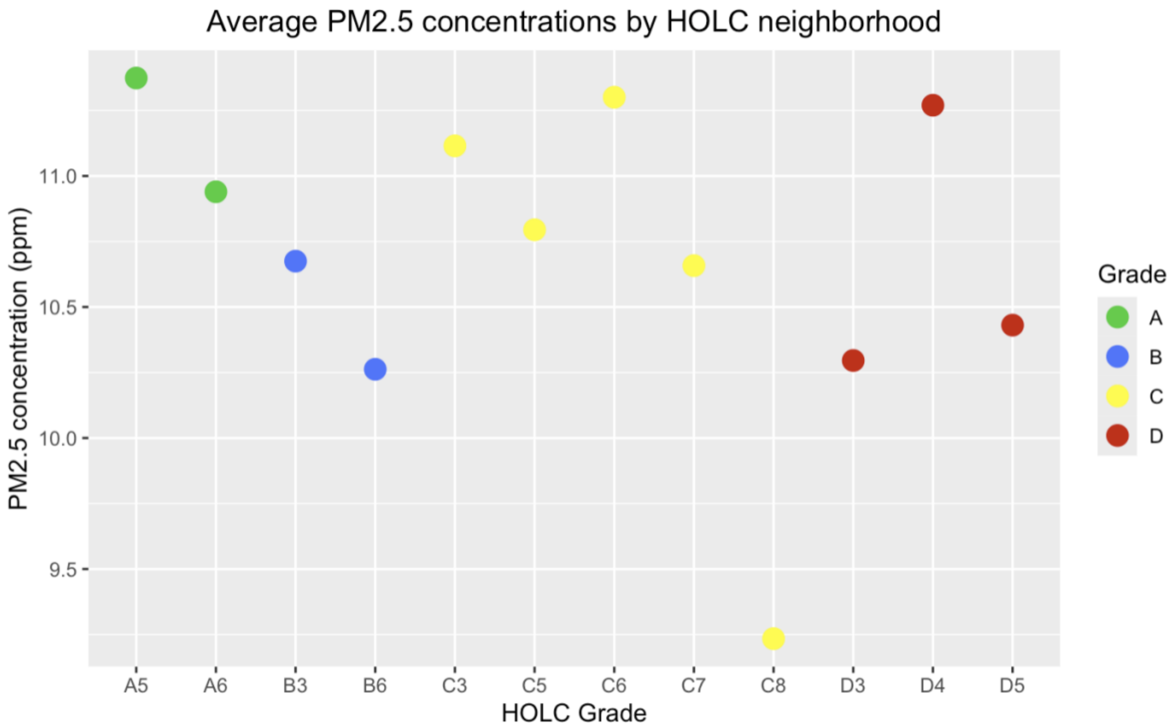


Figure 17: $PM_{2.5}$ concentrations by HOLC grade

In addition to measuring green space by NDVI, the TreeKeeper database provides another robust measure of green space distribution, especially since trees are regarded as having more health-promoting effects compared with other types of green space.[xxxii] NDVI and tree density were not entirely correlated. TreeKeeper density was highest in HOLC grade “B”, then “C”, then “A”, then “D”. This trend contrasts with NDVI which observed a continuous downward trend as HOLC grade decreased. This difference could potentially be explained by the exclusion of private trees from TreeKeeper’s database; properties in the “A” neighborhood likely have a higher proportion of trees on private land, as opposed to the street.

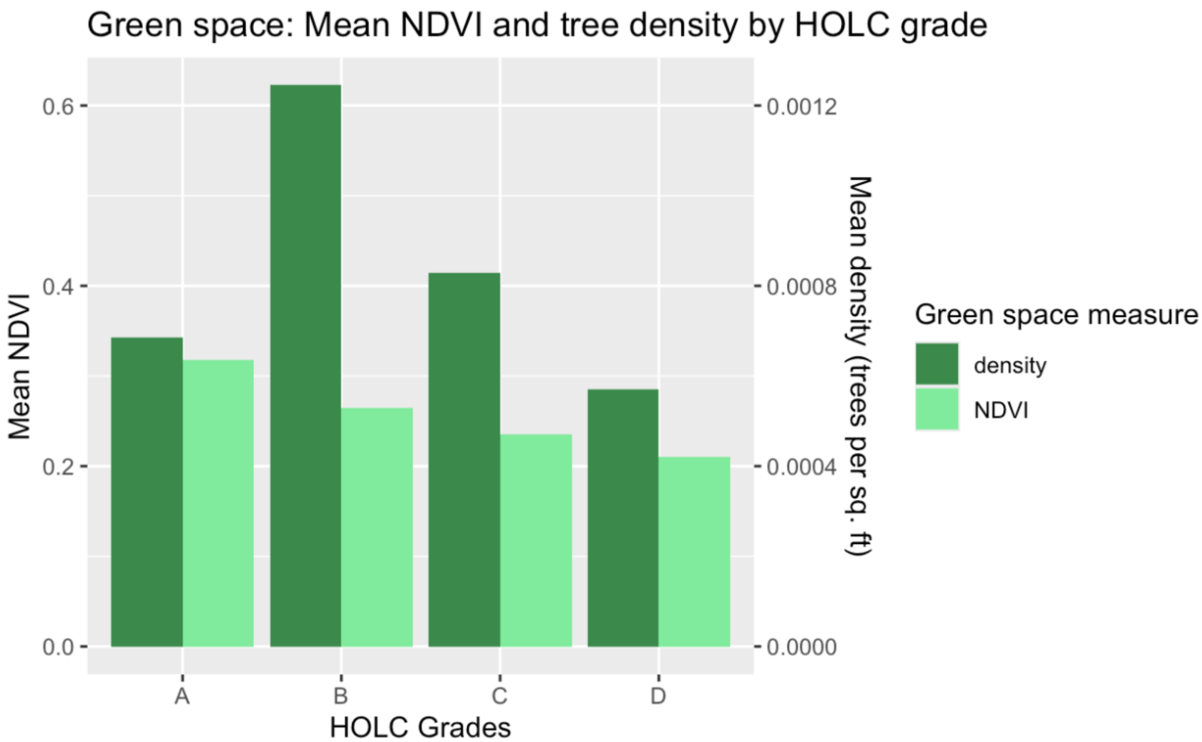


Figure 18: NDVI and tree density by HOLC grade

In addition to the density of trees per square foot, I examined the difference in means of tree size (DBH) between neighborhoods. Larger, more mature trees provide more ecosystem services, including air pollution removal and temperature regulation.[lxxviii] The relationship between tree DBH and HOLC neighborhood yielded inconclusive results; there is no clear difference in means, suggesting that average street tree size does is not influenced by HOLC grade. The log transformation allowed for a better view of the data. Error bars represent +/- 1 standard deviation of log of DBH.

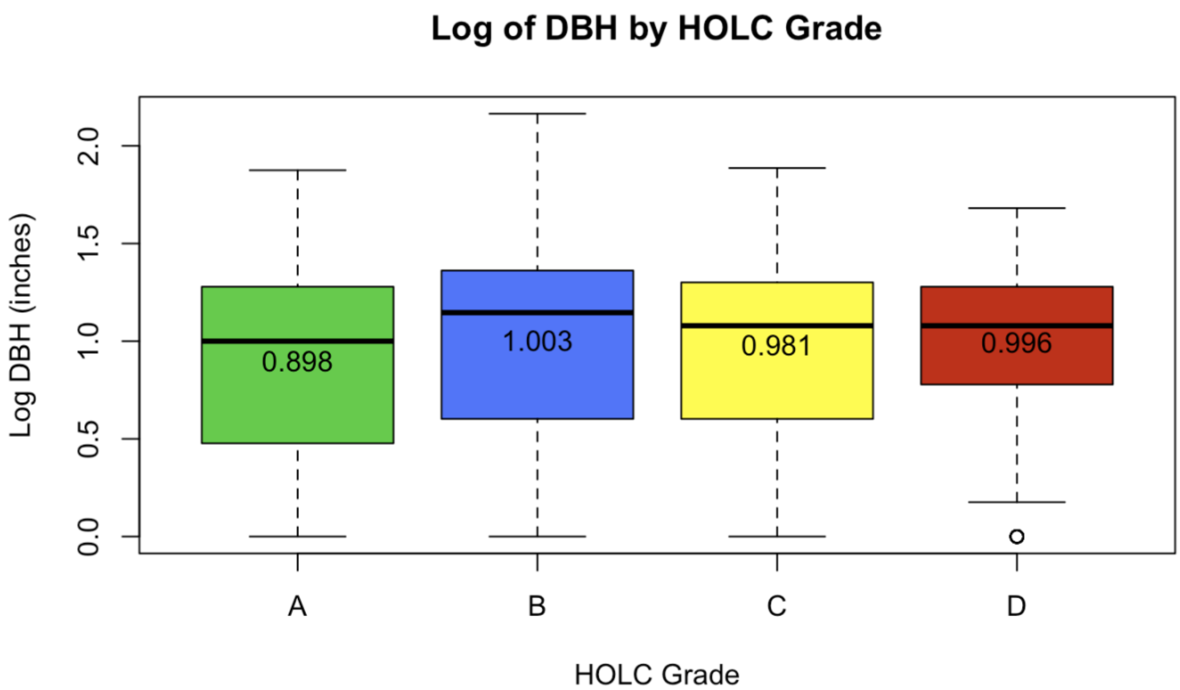


Figure 19: DBH by HOLC grade

Besides size, a tree's species also substantially influences its impact on the ecosystem, including temperature, humidity, and air pollution regulation.[lxxix] Additionally, the species of tree also influences its climate change resilience, as certain species are better poised to thrive with rising global mean temperatures.[lxxx] Finally, certain species promote greater biodiversity and supports wildlife more than others.[lxxix] Examining the species composition of each HOLC neighborhood provides another measure of green space quality in New Haven neighborhoods.

Figure 20 captures the most abundant species of trees on public land in each HOLC grade. Overall, the most abundant species were Pin Oak (3,158 trees), Norway Maple (2,511 trees), and London Planetree (2,258 trees). Significantly the London Planetree was concentrated heavily in grades "C" and "D" and did not appear in "A" or "B." Pin Oaks were the most abundant species in all HOLC grades, except D, where London Planetrees was the most prevalent. URI is the organization that maintains the TreeKeeper database and coordinates many street tree planting initiatives; they also produce a tree catalogue detailing the characteristics of each species in New Haven. URI states that Pin Oaks have a long lifespan, are native to Connecticut, and support wildlife of all kinds.[lxxxi] This is due to their tree structure and acorn production.[lxxxii] Additionally, Pin Oaks are most tolerant of urban conditions of the oak species, and they transplant well.[lxxxiii] Pin Oaks are intolerant of shade and grow best in full sunlight.[lxxxi] URI describes London Planetrees as popular in New Haven and fast-growing.[lxxxi] It is widely used as a street tree, as it is highly tolerant of urban microclimate conditions and resistant to air pollution, particularly $PM_{2.5}$.[lxxxiv] Additionally, it supports biodiversity, transplants well, and is tolerant to full or partial sun conditions[lxxxv]. However, there are several negative impacts of London Planetrees, such as production of organic debris from annual foliage regrowth[lxxxvi] and high emissions of Biogenic Volatile Organic Compounds and pollen grains.[lxxxvii] While London Planetrees certainly provide net positive ecosystem service benefits, there seem to be a greater proportion of associated negative impacts than Pin Oaks.

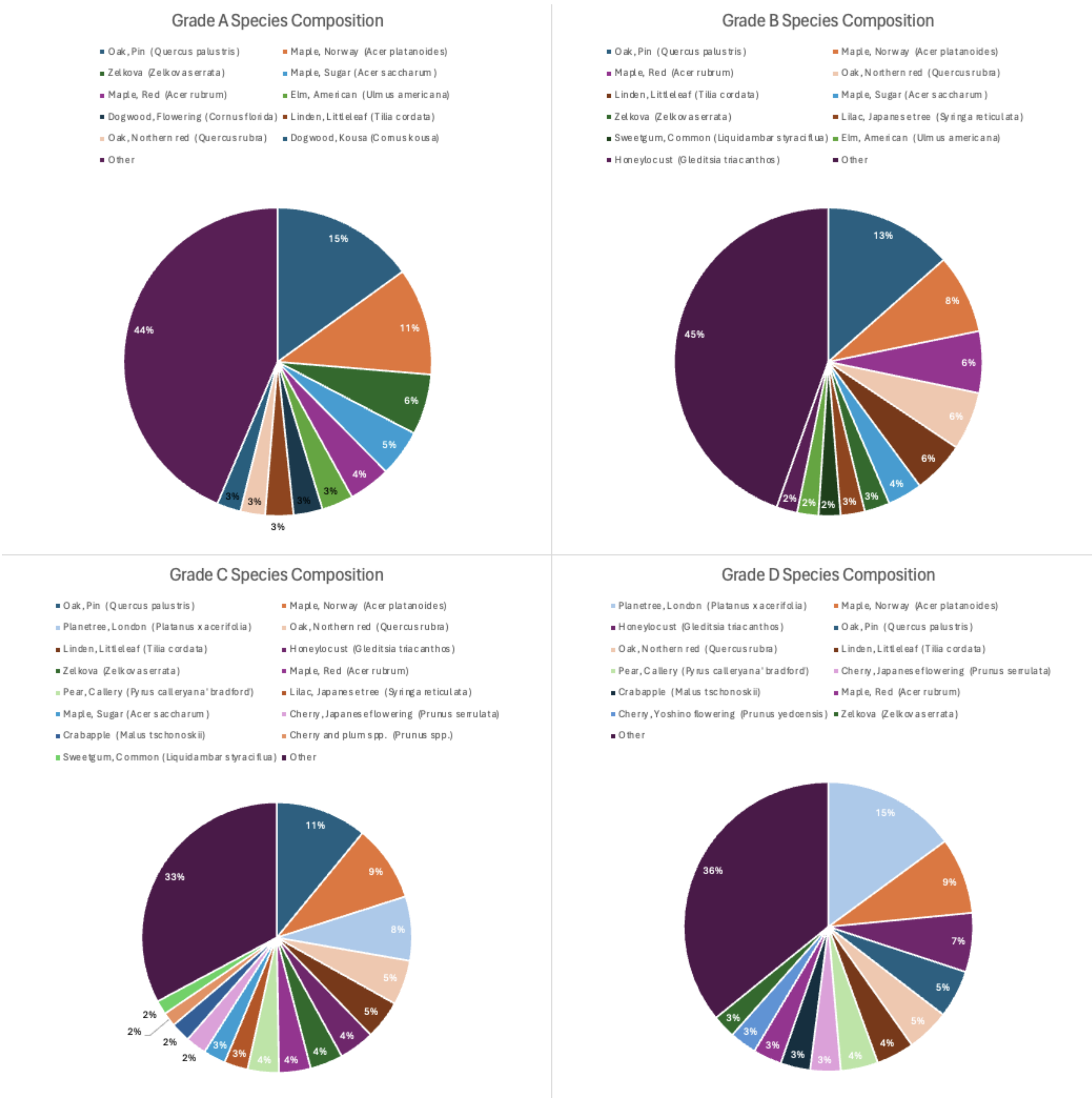


Figure 20: Species composition by HOLC grade

Finally, examining current socioeconomic data helps to contextualize these environmental disparities. Using the ACS, I analyzed the current state of HOLC neighborhoods, including the racial composition of each area, homeownership areas, poverty rates, and median household income. Today, areas that were historically redlined have more people of color and lower median household incomes.

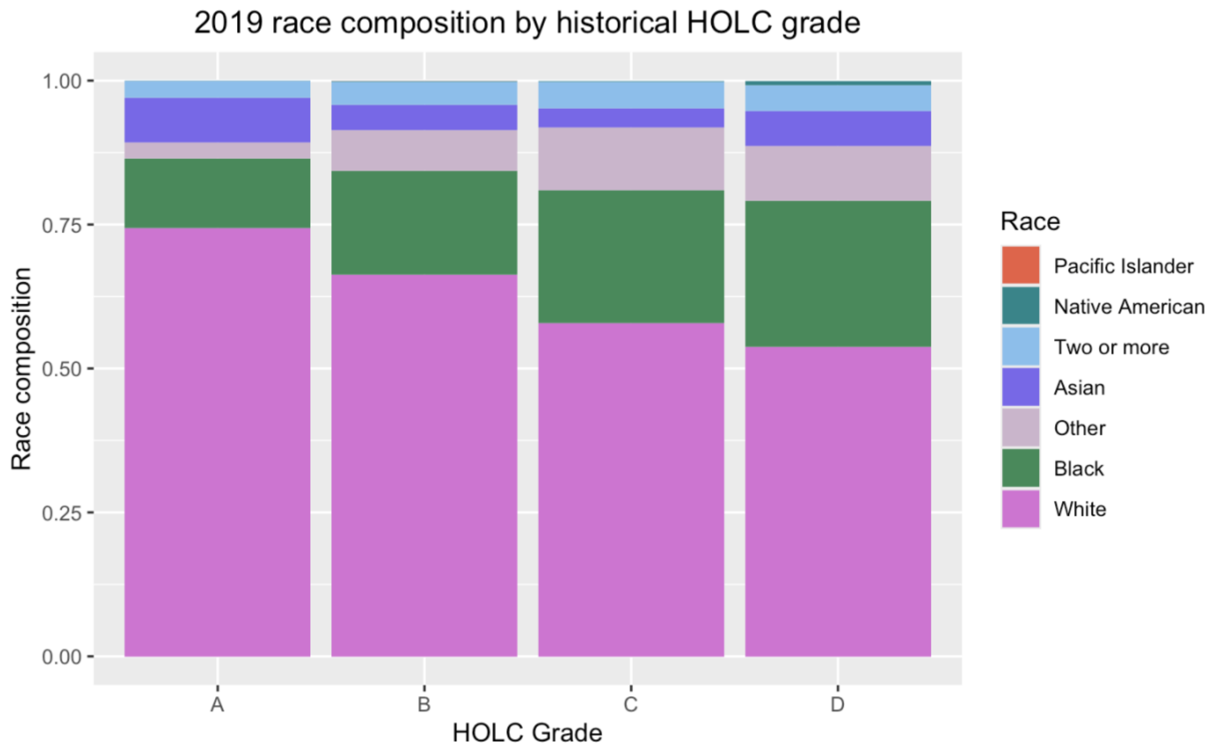


Figure 21: Current race demographics by historic HOLC boundaries

Additionally, viewing these demographic statistics in conjunction with the climate-driven health risk distribution helps to display the populations most at risk. Viewing LST and NDVI plotted against median household income shows that low-income residents are highest risk. This correlates with redlining grades, which follow a similar pattern; median household income decreases as HOLC grade decreases, and while LST increases, and NDVI decreases. In Figures 22 and 23, each plot represents the mean income and LST or NDVI value for each of the HOLC neighborhood areas ($n = 47$). The color is associated with the HOLC-assigned grade.

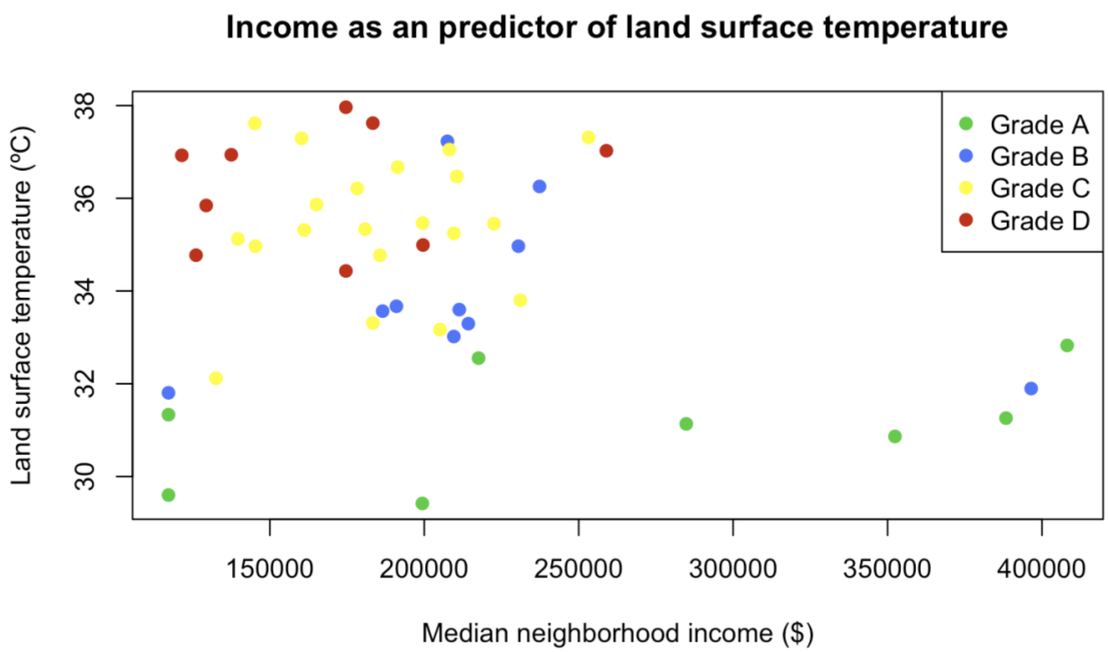


Figure 22: Land surface temperature predicted by median household income and HOLC grade

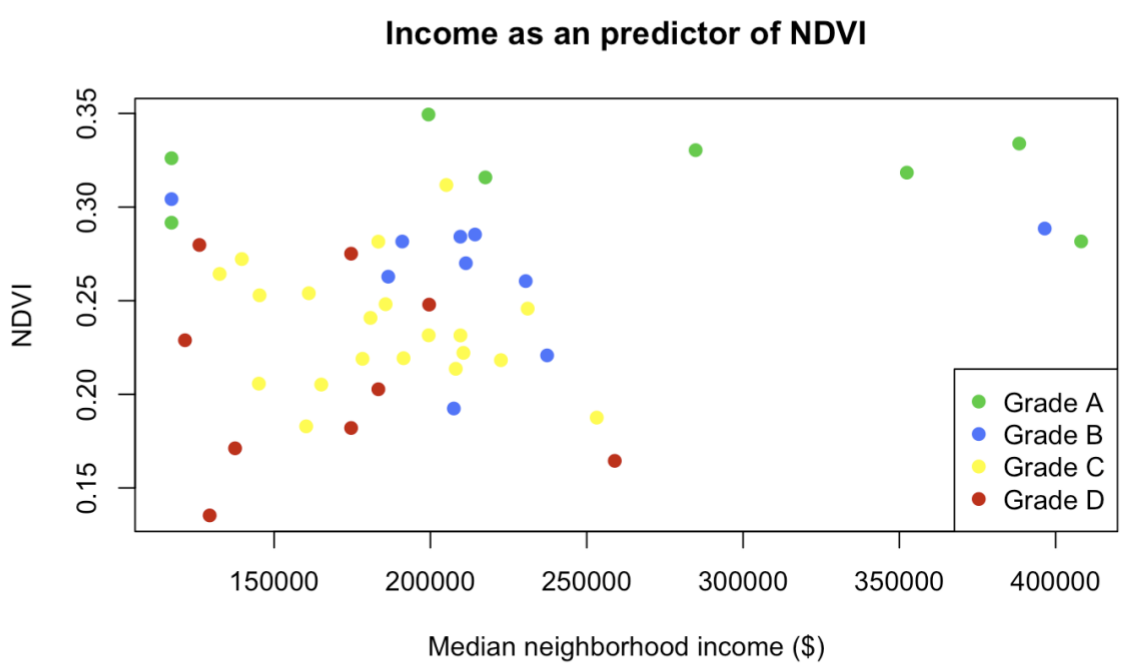


Figure 23: NDVI predicted by median household income and HOLC grade

Conclusion

This study sought to understand the extent to which redlining has resulted in differences in climate-related health risks. Understanding the extent to which racist and discriminatory housing policies impact our current environment is extremely important, especially as climate change continues to accelerate and economic inequality in the United States persists.

The result of this study leads us to accept the initial hypothesis and suggests that the racially biased HOLC maps created environmental health disparities that persist into the current day. In New Haven, CT, neighborhoods that were assigned worst HOLC designations experience more intense urban heat than neighborhoods that received more favorable HOLC ratings. Redlined areas experience mean LST values higher by 5.2ºC and NDVI lower by 0.108 than the neighborhoods that received "A" designation by the HOLC. These disparities are congruent with earlier studies which found elevated mean temperatures and reduced green space in formerly redlined areas relative to non-redlined neighboring areas.[iv,vi] Additionally, LST and NDVI proved to be statistically coorelated. Species composition of trees on public land also depends on HOLC grade; Pin Oaks are most prevalent in grades "A", "B", and "C", while London Planetrees are most abundant in grade "D." $PM_{2.5}$ data yielded inconclusive results regarding the influence of HOLC grade. Furthermore, these risks are found in communities with lower median annual incomes, higher poverty rates, reduced homeownership rates, and communities of color. These findings join a growing body of research arguing for understanding how climate change will further exacerbate current, and historically based inequities in the United States.

Why do these disparities exist? It is difficult to distill singular causations that connect lines and colors on a map to current environmental disparities, but there are several prominent factors. For one, green space is paramount. Given that vegetation, especially trees, provides innumerous ecosystem services, such as temperature regulation[xxxiv,] and air pollution removal, [xliii] the co-occurrence of low vegetation likely exacerbates disparities in LST and air pollution levels. Additionally, green space is often replaced with impervious surfaces.[lxxxviii] One such material that is particularly heat-producing is roadway. Historic federal programs provided incentives for highway building. Since the time the HOLC drew up these maps, the I-95 highway was constructed in New Haven.[lxxxix] Major highways bring heat and exhaust emissions, which result in greater health risk exposure.[lxxxvii] The I-95 highway crosses through Long Wharf and Annex, neighborhoods that received poor HOLC ratings. However, beyond specific development projects, it is critical to consider the decades of reduced capital access, lower homeownership rates, and resulting diminished local influence over the build environment. It is probable that this feedback loop was a key driver in driving disparities in climate-driven health risks in New Haven.

While understanding the links between discriminatory housing policy and current climate-related health risks is certainly a step in the right direction, it begs the question: how do we correct this? There are several strategies that may be implemented to promote environmental equity. One such strategy could involve reducing the abundance of impervious surfaces and increasing the albedo in redlined neighborhoods.[xc] Various green infrastructure techniques, such as bioswales,[xci] may be well poised to expand in New Haven. In a similar vein, increasing the tree canopy cover in historically redlined neighborhoods could provide innumerous benefits. Increased tree canopy provides shade, reduces air pollution, and provides greater temperature regulation from plant respiration.[v] New Haven is positioned well to execute on this strategy; URI currently works to plant street trees in New Haven.[xcii] Beyond just planting trees, it could be beneficial to examine more closely the species that are being prioritized. Different tree types can provide greater cooling benefits[xciii] and are more resilient to climate change-related disruptions.[xciv] Additionally, by understanding that LST is higher in historically redlined neighborhoods, we expect an increased need for summertime energy use for cooling technologies. By understanding that these communities face higher financial burdens due to historic environmental racism, New Haven policy may perhaps offer aid in shouldering these costs. From a public health perspective, areas of higher LST correlates with increased morbidity and mortality from heat-related health effects.[xx] Prioritizing these neighborhoods for cooling centers in times of high heat could help to remedy some of the undue burden.

As climate change continues to worsen and economic inequity in the United States persists, addressing systemic environmental disparities grows even more imperative. These environmental adaptations and policy implementations should be prioritized in New Haven to provide a safe and livable environment for all citizens.

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