

Computing & Climate Justice

What's in this module?

Description

This module provides a curriculum that integrates climate justice (CJ) and machine learning (ML) for practical real-world applications. Part 1 explores why ML is useful to advance CJ, ethical considerations, and sociotechnical frameworks. Part 2 discusses how to move from data to impact. Part 3 explores urban heat disparities as a case study for interpretable ML applications. Parts 4 and 5 explore climate health equity in heat-related illness.

Activities

4 parts
10 readings
2 optional projects

Key Resources

- [The Future of Conservation Lies in Justice-led Technology](#) (Longdon, 2024)
- [Indigenous agents fight deforestation with drones and AI in Brazilian Amazon](#) (Ennes and Chaves, 2021)

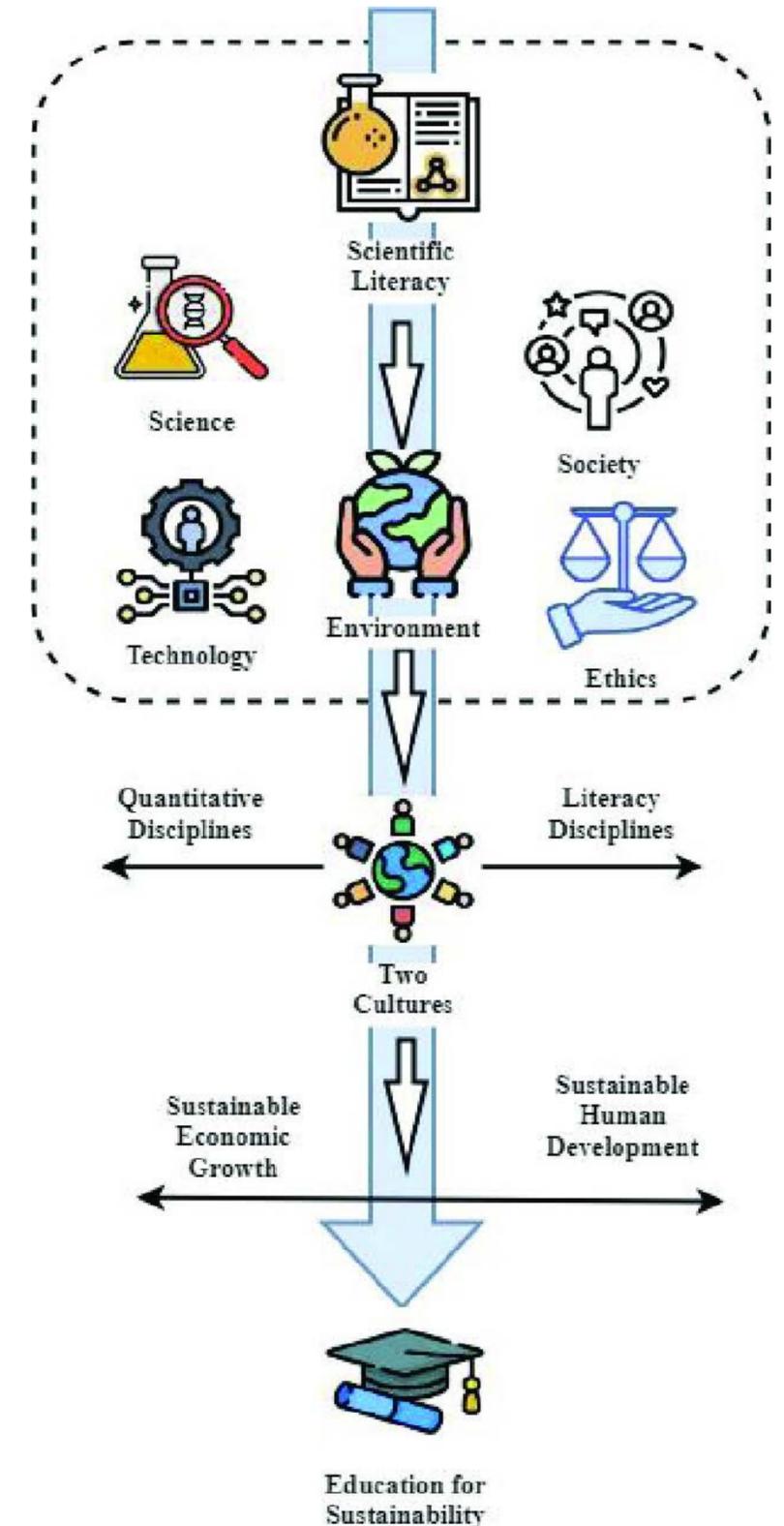


Figure from Tan, Huang, & Xian, 2024. License: CC BY.

Learning Objectives

01

Understand why ML is useful to study climate justice, social justice frameworks for applied ML, and the ethical implications.

02

Learn how to leverage machine learning to quantify and address societal disparities in climate change related outcomes.

03

Gain deeper insights into climate justice patterns through machine learning interpretability techniques.

04

Construct a project with an external climate justice related dataset that considers context.

Introduction

PART 1

Why ML for CJ?

Advanced Modeling

ML models go beyond parametric assumptions, providing capabilities for highly non-linear and non-parametric modeling that can capture more complex patterns in the data.

Predictive Power

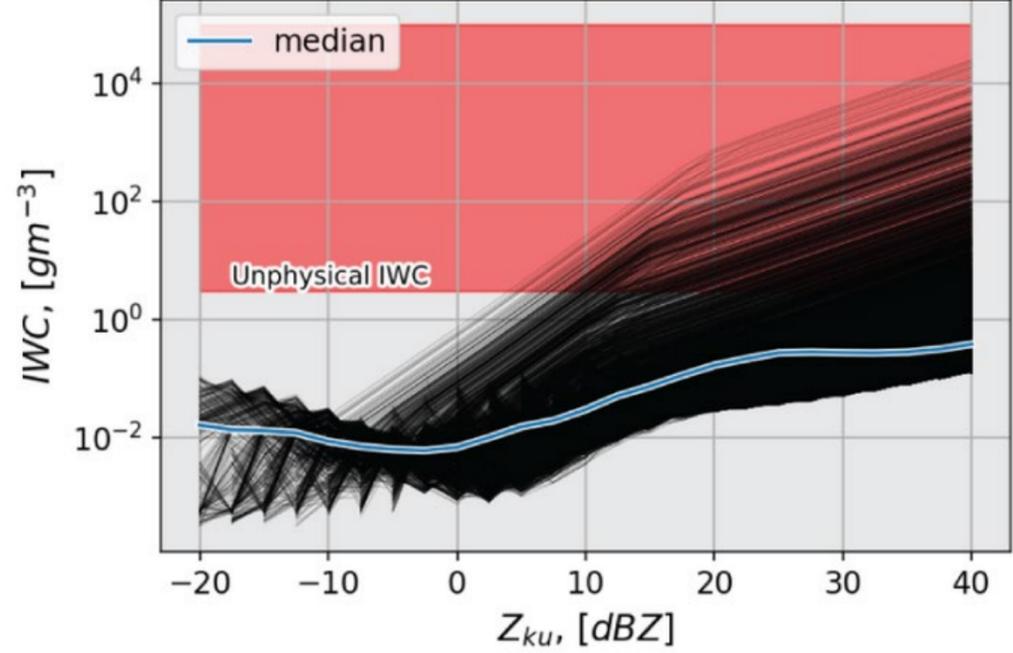
ML enables us to answer the question: “What factors are most predictive of our outcomes of interest?” This is a prominent question in quantitative social science and policy development.

Pattern Recognition

Advances in interpretability methods for black-box ML models help us gain deeper insight into models to advance our understanding of complex societal patterns concerning climate issues.

Ethical Considerations

<p>Technical Solutionism</p>	<p>ML is not a cure all; it is only one tool to approach climate justice issues. A simpler model might perform the same as a deep learning model and permit interpretability for stakeholders. Qualitative data is also informative (e.g., interviews, testimonials, etc.).</p>
<p>Fairness, Accountability, Transparency, and Ethics</p>	<p>Models could exacerbate existing social disparities. Aim for participatory ML (i.e., nothing about us without us) and transparency in models (e.g., explaining the model's decisions to stakeholders).</p>
<p>High Carbon Output</p>	<p>Some approaches to ML for climate currently use very high dimensional data (e.g., satellite images) and large neural networks which can lead to high carbon output. Aim for transparency on the emissions for deep learning models. Provide critical discussion on why you feel the benefits outweighed the cost.</p>



(b) Example of a partial dependency plot (Molnar, 2018) which shows how an AI model could produce unphysical results when given unexpected inputs (Section 2.2.4). From (Chase et al., 2021). ©Molnar. Reproduced under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License (CC-BY-NC-SA 4.0).

Graph originally from A dual-frequency radar retrieval of two parameters of the snowfall particle size distribution using a neural network.
 Above from: Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science

Roles for Computing in Climate Justice

01

Diagnostic

Computing research can help us to understand and measure social problems related to climate change with precision and clarity.

02

Formalizer

The process of formalizing a problem can serve as a site of contestation for frontline communities and discussion of equitable climate policy.

03

Rebuttal

Computing can clarify the limits of technical interventions, and of policies premised on them, helping to justify the non-computational changes that are necessary for effective reform.

04

Synecdoche

Media outlets can bring broad attention to applications of machine learning to climate justice research, making climate justice issues further salient in the public eye.

Examples: Roles for Computing in Climate Justice

01

Diagnostic

Machine learning can highlight the factors that make certain urban areas hotter than others, providing further information to policymakers.

02

Formalizer

An algorithm to allocate green infrastructure that prioritizes trees can be contested in hurricane-prone areas where fallen trees may destroy housing.

03

Rebuttal

While models often formalize the environmental factors of urban heat, they often do not formalize historical and contextual factors such urban planning, housing policy, and transportation policy.

04

Synecdoche

Media outlets can bring broad attention to applications of machine learning to climate justice research, making climate justice issues further salient in the public eye.

Contextualizing Our Work

“The Data Don’t Speak for Themselves” - Data Feminism

It is important to consider a) the context of the setting we are considering (e.g., sea level rise in Louisiana) and b) the context of the data (e.g., the origin, collection, limitations, etc.).

Historical Factors

Current circumstances are mediated by historical factors. It is important to both acknowledge and consider these in our work.

Community Input

Communities often have their own perspectives and they may differ from academia/industry. Frontline communities know better what information they need than academics.

CONSIDER THE CONTEXT

Data feminism asserts that data are not neutral or objective. They are the products of unequal social relations, and this context is essential for conducting accurate, ethical analysis.

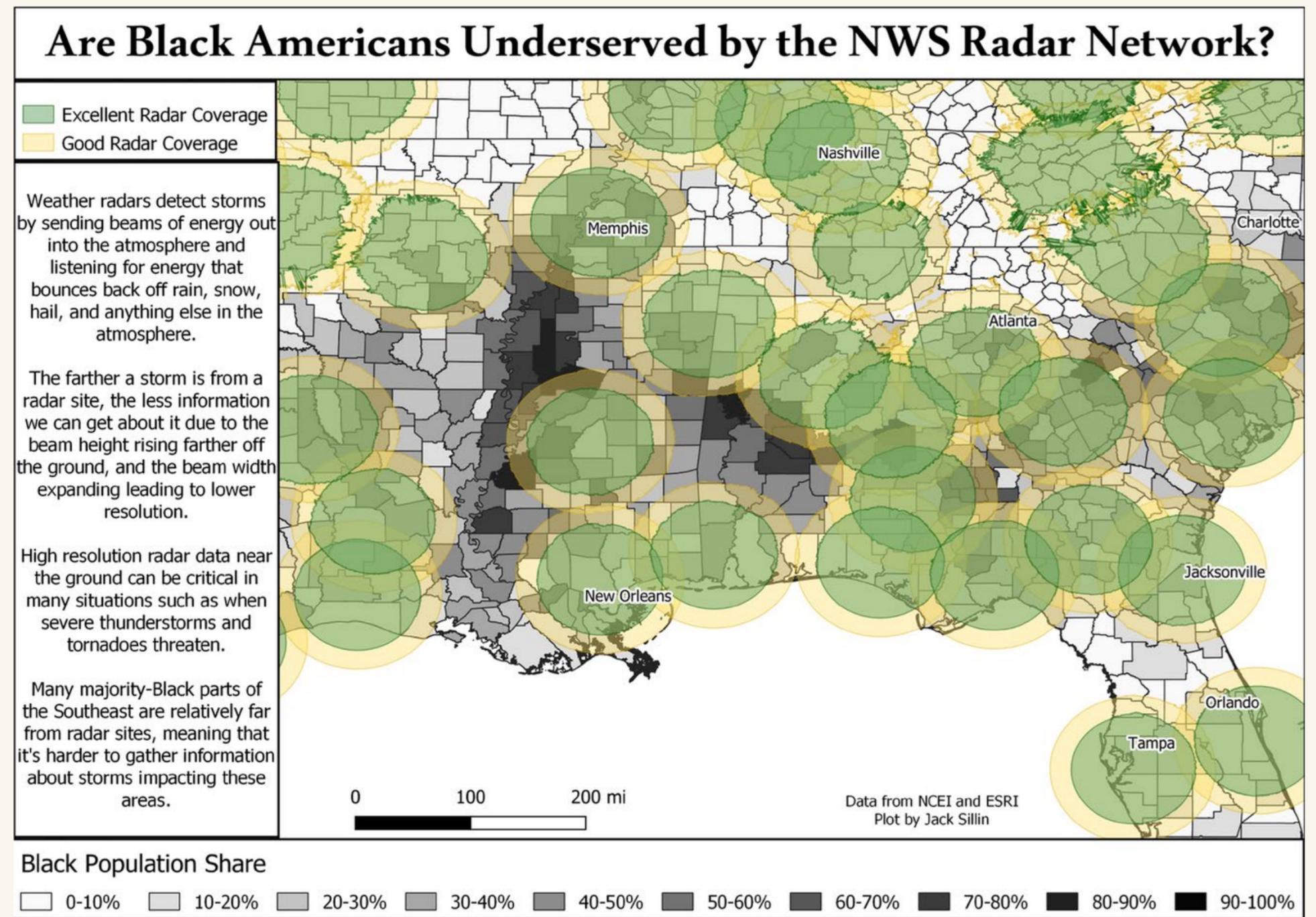
Source: [Data Feminism by D’Ignazio and Klein](#)

Consider Context

One common task in weather modeling is using discrete station measurements to estimate continuous weather patterns in places without stations.

This graph highlights gaps in coverage in rural, Black areas.

What could happen if we developed a machine learning model to interpolate the NWS radar network data?



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From Data to Impact

PART 2

From Research to Engagement

Data Science Helped Propel the Environmental Justice Movement

The field of environmental justice studies helps inform EPA policy. Many quantitative studies of air pollution have led the EPA to apply regulations that have led to overall reductions. Little research exists to inform CJ with ML, and you can be a pioneer in the field.

Broader Impact (e.g., policy, grassroots activism)

ML4CJ can provide important insights to inform policy (e.g., the Justice40 initiative and urban/regional planning) as well as grassroots activists who rely on research to advocate for their communities and fight for change.



Photo by [Hannah Busing](#) on [Unsplash](#)

From Data to Impact

Resources for Communities

Data science can provide information for communities to advocate for themselves, e.g., dashboards. Data science can also support allocation of funding to frontline communities.

Education

Data science can educate people on the issues facing their community. A climate justice oriented data science education can encourage students to be civically engaged.

Policy

Data science can provide background and justifications for policy proposals.

Your research can provide justification for a community grant proposal to the EPA and philanthropic organizations.

US EPA Environmental Justice Thriving Communities Program



Retrieved from EPA

This map is in the public domain.

CASE STUDY #1

Urban Heat in Richmond, VA

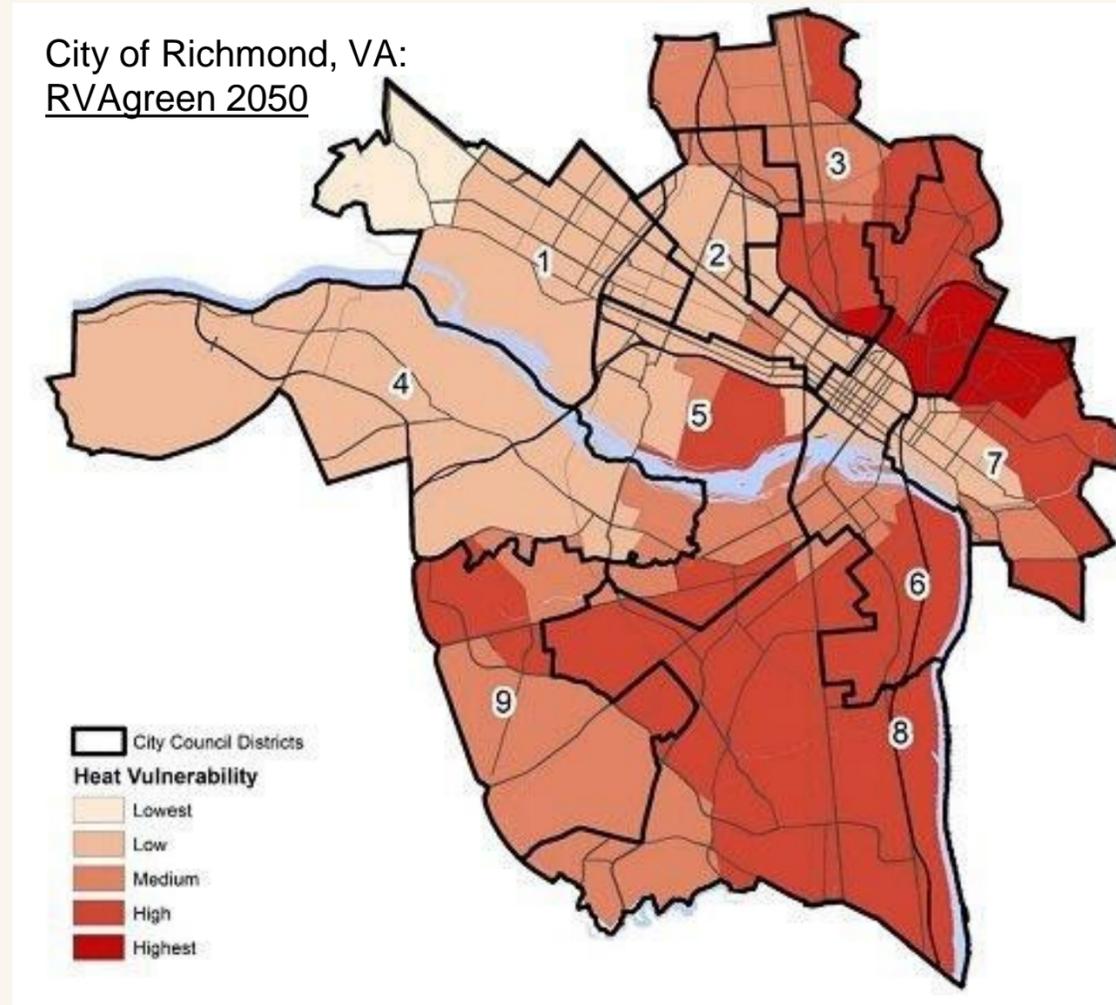
Collaborative Data Science

In partnership with the Science Museum of Virginia, Virginia Commonwealth University, University of Richmond, and Groundwork RVA, the City of Richmond mapped its urban heat islands, land cover, and vulnerable demographics.

Broader Impact

The city leveraged this data to center equity in its RVAgreen 2050 plan for climate action and resilience. For example, the city partnered with community organizations to enhance green infrastructure and reduce the urban heat island effect.

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Heat vulnerability corresponds to places that are both hotter and have demographic/health vulnerability to heat. More vulnerable places tend to have less greenspace and closer proximity to roads.

Climate Injustice in the Brazilian Amazon

Deforestation

Amazonian Indigenous communities face deforestation of their lands (e.g., for mining, agriculture).

Mining/Forest Fires

Fires are used to clear the forest for mining against the will of Indigenous people. These forest fires present serious human health threats due to air pollution.

Preservation

Indigenous communities are fighting to preserve the Amazon rainforest even amidst threats of violence.



Photo courtesy of Neil Palmer/CIAT. License: CC BY-NC-ND. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>.

Data to Preserve the Brazilian Amazon

Remote Sensing

Indigenous people in the Amazon use satellite images and drones to monitor and respond to deforestation.

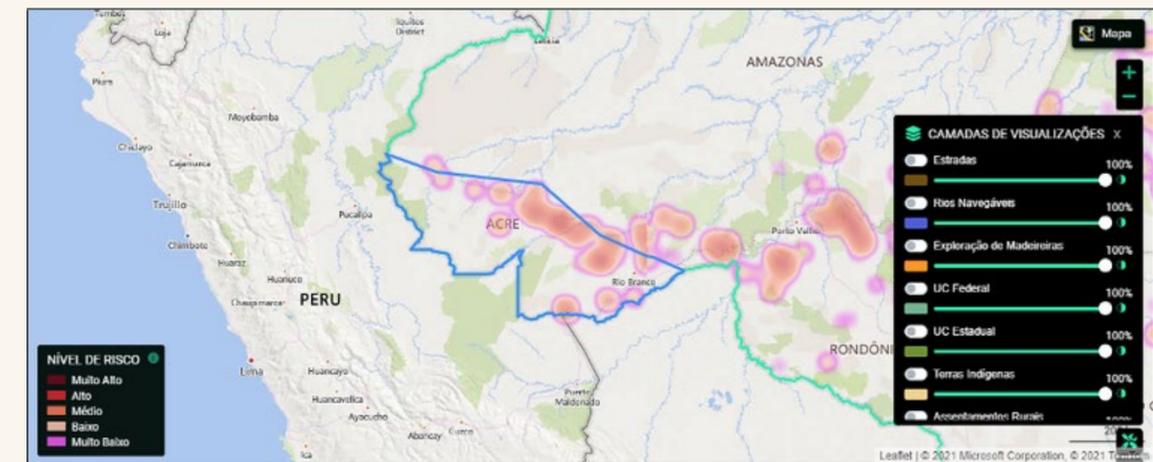
Air Pollution Sensors

They also use PM2.5 sensors to measure air pollution resulting from forest fires, highlighting the unjust distribution of pollution in Indigenous communities.

PrevisIA

In collaboration with local Indigenous groups, PrevisIA provides an open sources platform that integrates AI to monitor deforestation risk.

Public domain image by Jesse Allen, courtesy of NASA EO-1 team.



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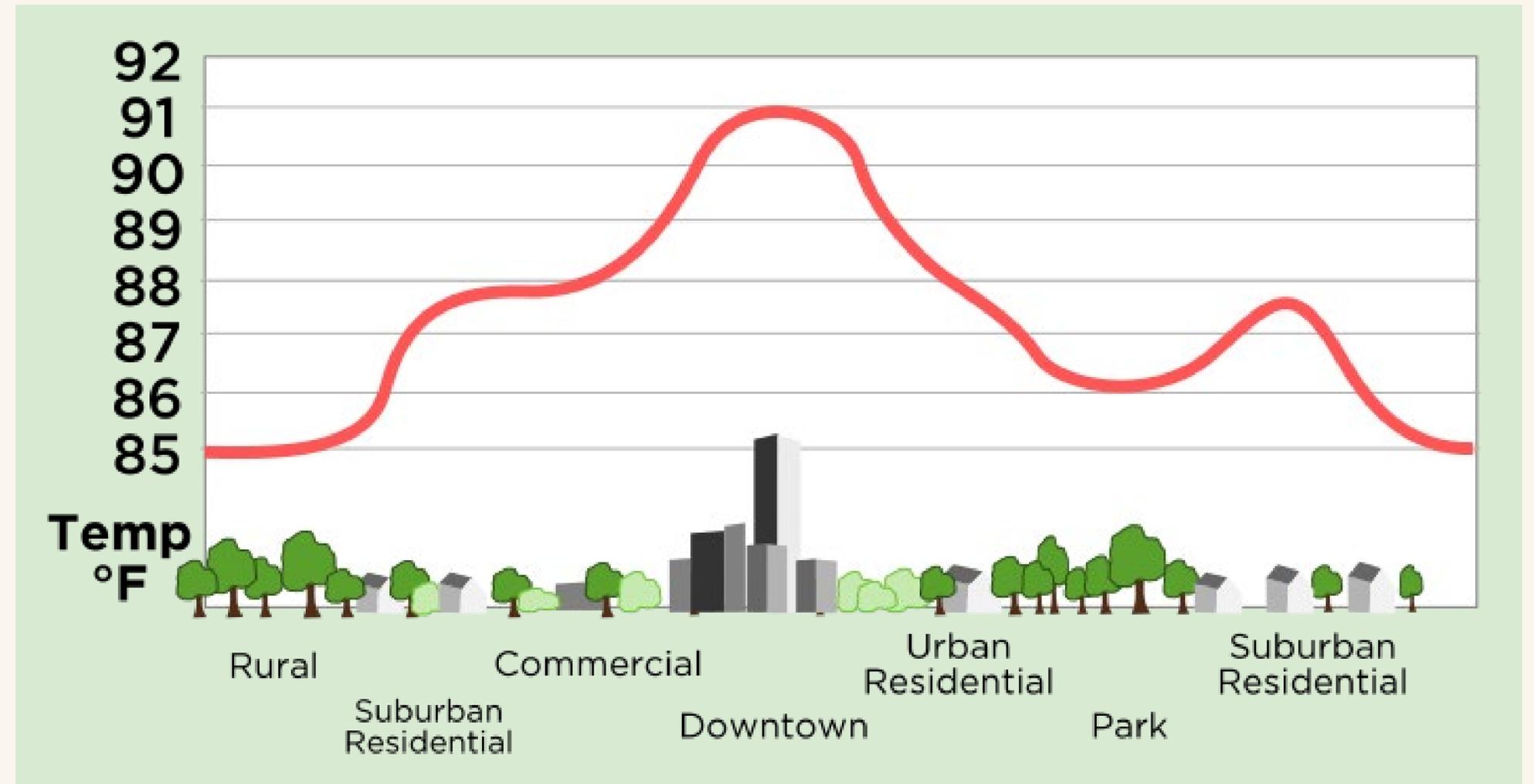
Urban Heat Islands

PART 3

Urban Heat Island Profile

Based on this graph, which places are hottest? Which places are cooler?

Looking at the pictures, what differences do you notice between different areas? Relate the differences to temperature.



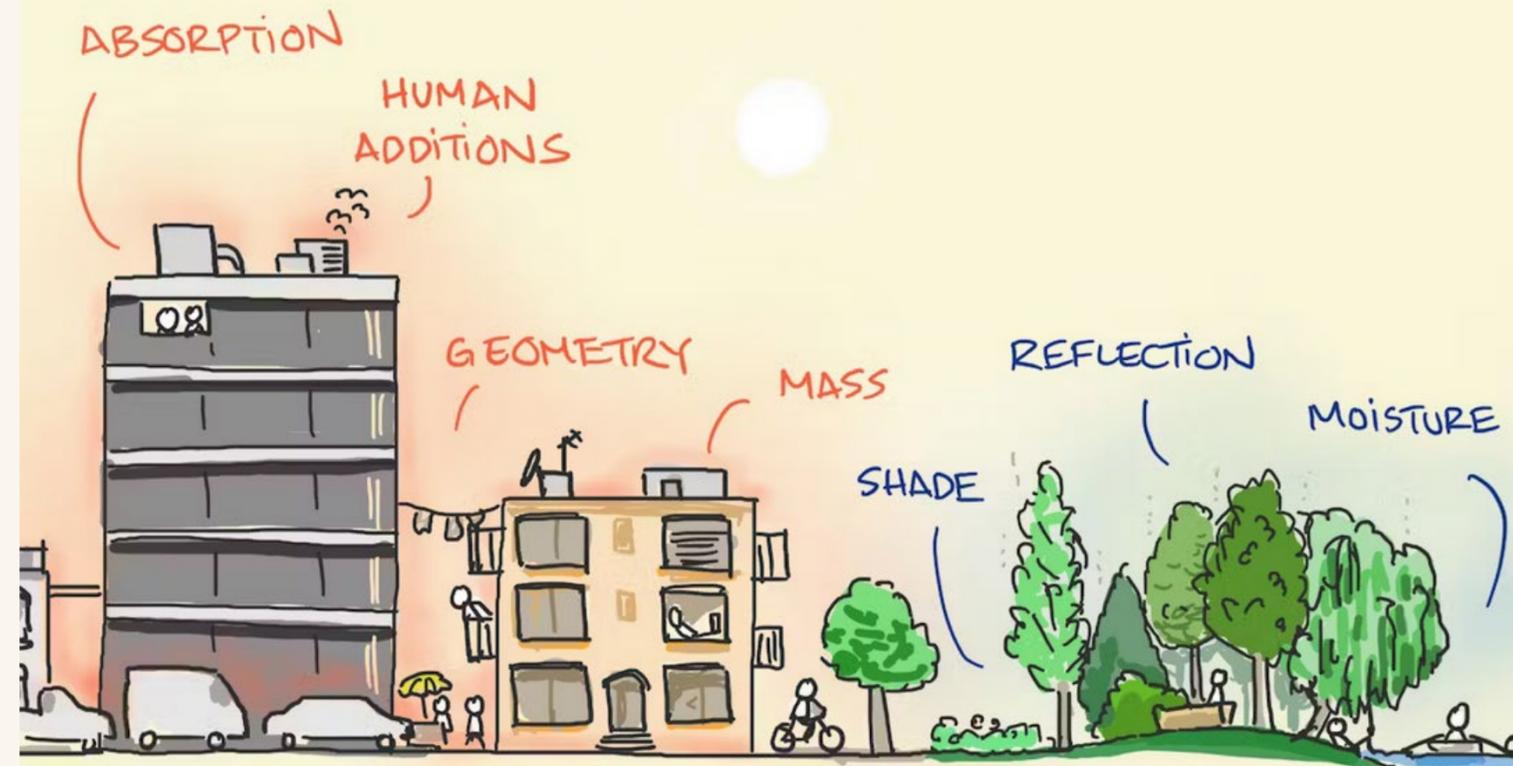
Public domain image courtesy of TheNewPhobia on Wikimedia. Originally created by NOAA.

Why are cities hotter?



Jono Hey, Sketchplanations

HEAT ISLANDS

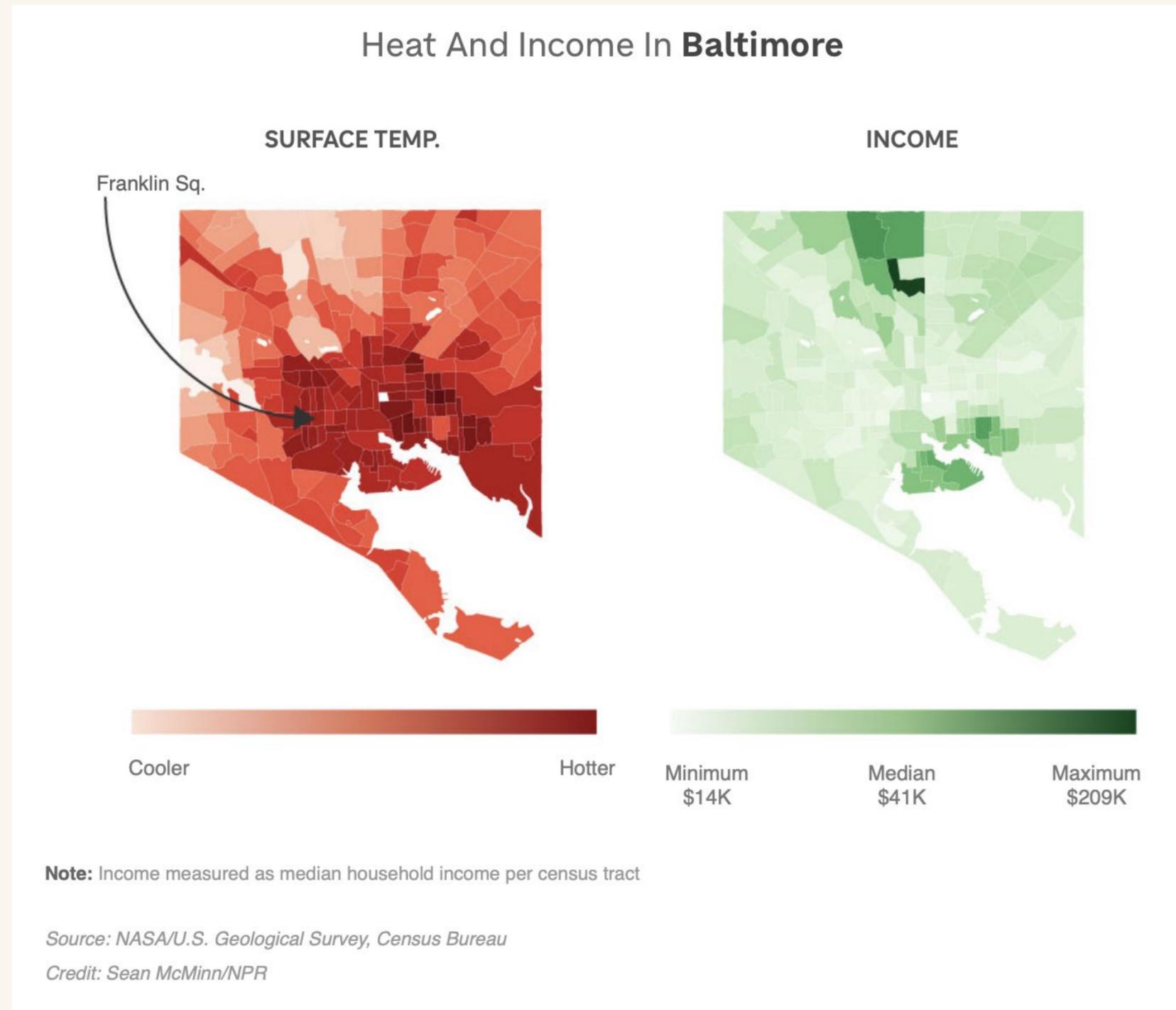
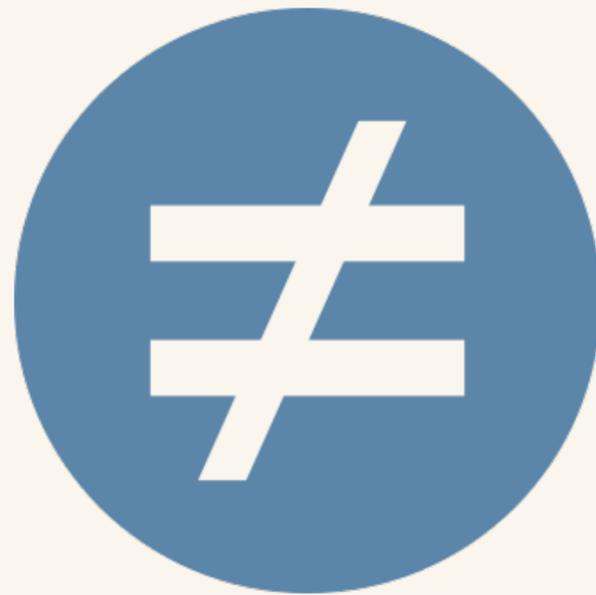


URBAN AREAS AND STRUCTURES ABSORB AND RETAIN HEAT

MAKING THEM HOTTER THAN SURROUNDING NATURAL AREAS

sketchplanations

Urban heat is not distributed equally.



UHI Disparities

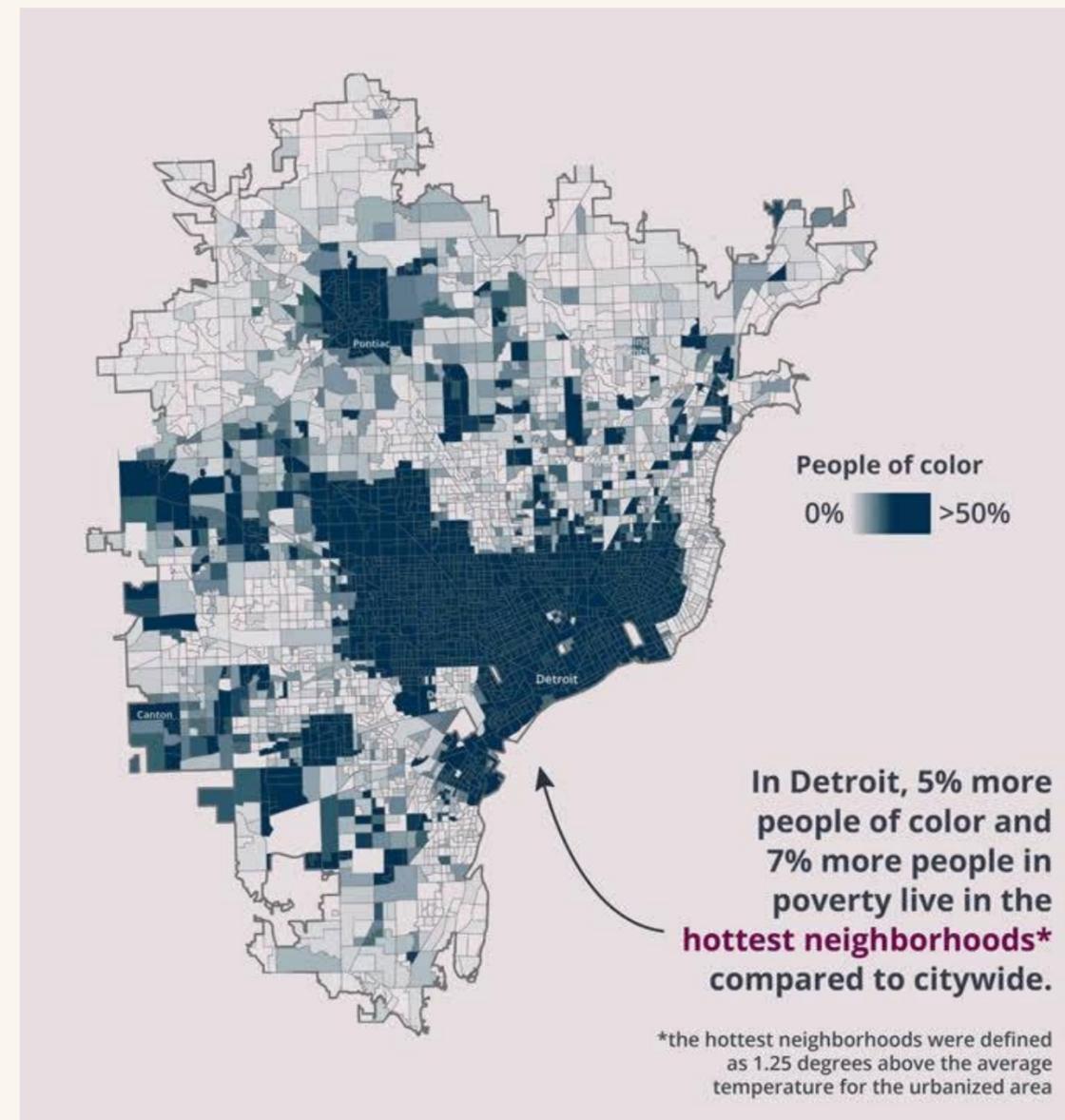
Ample Evidence

Many research studies have found disparities in exposure to urban heat. Marginalized communities often have more impervious surfaces and less greenspace, making their neighborhoods hotter than average.

Redlining

Redlined neighborhoods tend to be hotter than their counterparts, partially due to less tree coverage and more impervious surface.

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Urban Heat Equity - An American Forests Data Short

Photo by Susana © Union of Concerned Scientists. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/>.

Historic Context of UHIs

Historic Underinvestment

Marginalized communities have historically experienced under- and disinvestment (e.g., redlining, refusal to provide African American WWII veterans VA loans). Greenspace requires investment.

Environmental Injustice/ Urban Planning Disparities

Marginalized communities tend to be zoned for higher density and industrial use, resulting in increased impervious surfaces and anthropogenous sources of heat. Urban planners have historically placed roads, which have higher albedo, near marginalized communities.

Source: [Boston Area Communities Work Together to Beat the Heat](#)



“On the left is the view of Chestnut Street standing at Beacon Street. The lack of trees and vegetation is notable, particularly given the proximity to the loud and dirty Tobin Bridge. On the right is Boatswain Way, a block away. This street, and the rest of Admiral’s Hill, has an abundance of trees and vegetation that offer protection from the heat as well as the air and noise pollution of the Tobin Bridge. I am hopeful that when city officials see these photos, they’ll see how much inequity is present throughout the city.” - Susana

Heat Vulnerability Index

PART 4

Heat Vulnerability Index

What is it?

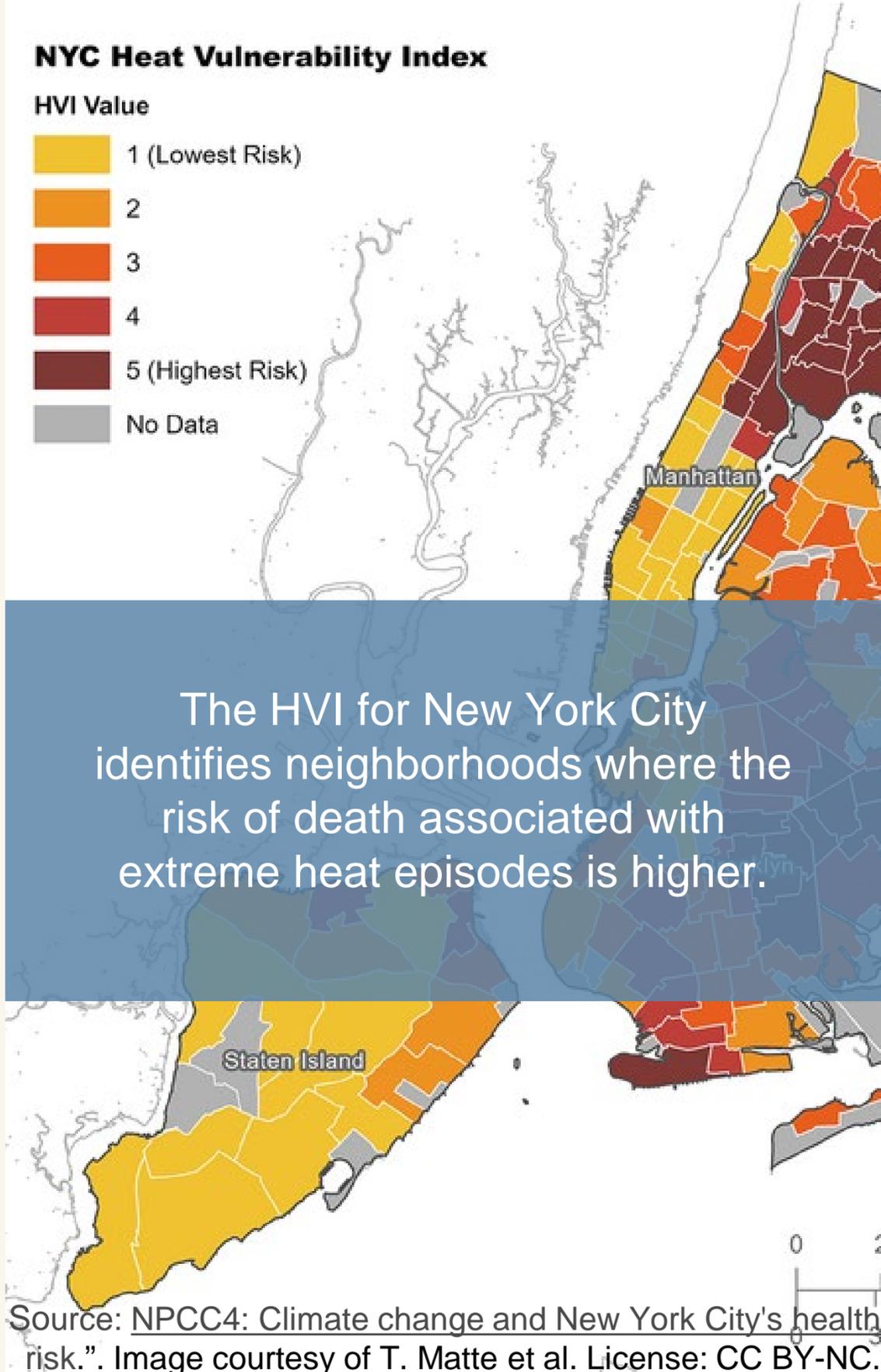
A heat vulnerability index (HVI) is a metric that combines data related to heat, demographics, and sometimes health and the environment. Ideally, the HVI will be correlated to heat-related health outcomes.

Methodology

PCA and average percentiles is common. A statistical model may be used to estimate the variance between heat mortality and dependent variables.

Drawbacks

For unsupervised methods, the heat vulnerability index may not be predictive of health outcomes. Due to its sensitivity, fine-grained heat-related health data is not publicly accessible, making some HVIs difficult to validate.



Heat EMS Risk Scores

PART 5

Heat EMS Activations

Heat Emergency Medical Services Activations

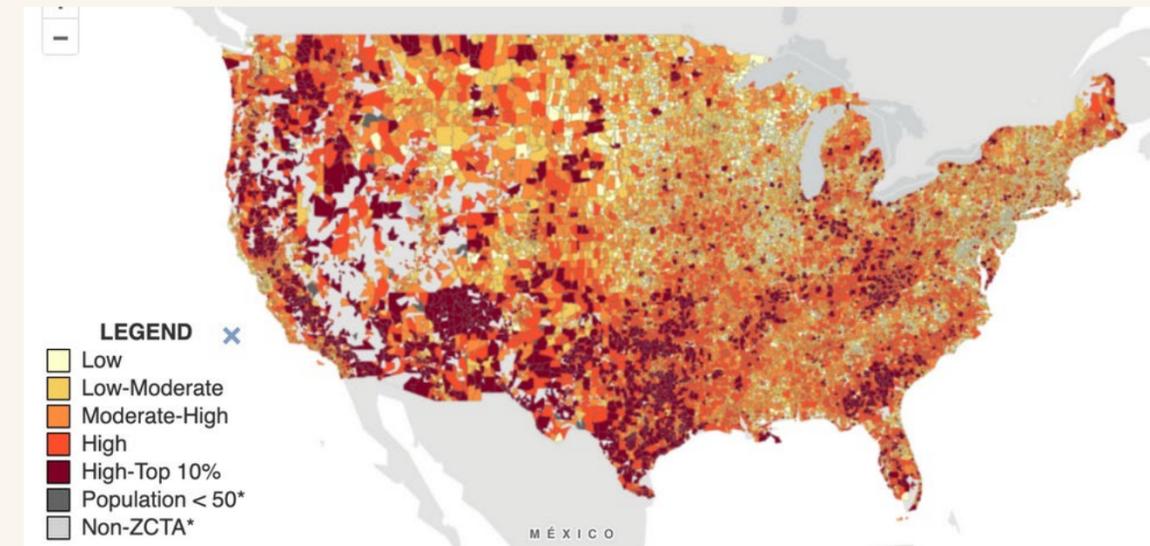
Summer months see a spike in heat-related emergency service (EMS) activations (i.e., emergency calls that lead to EMS arriving).

Heat EMS and Social Vulnerability

Heat EMS activations have been shown to be correlated with social vulnerability (e.g., poverty), existing health conditions, and impervious surfaces.

What is a risk score?

A risk score represents the level of vulnerability toward some health outcome. In clinical machine learning, logistic regression provides the probability of an event occurring.



The CDC Heat and Health Index (HHI) combines data related to heat EMS activations, heat waves, trees/impervious surfaces, and socioeconomic vulnerability. Public domain map courtesy of US CDC.

Beyond the Module

PART 6

ML for Green Infrastructure

Help plant trees!

Use satellite imagery and orthography to estimate where an urban area could plant trees or place parks to respond to heat. Estimate the benefits to vulnerable groups.

Example Datasets

1. [GEE Tree Cover Data](#)
2. [National Agriculture Imagery Program](#)
3. [Reforestation Hub](#)

Further Reading

- [The tree cover and temperature disparity in US urbanized areas](#)
- [How Upstream Tech's Lens Platform and Planet Imagery Help One Tree Planted Visualize The Future of Global Reforestation](#)



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Deforestation

Monitoring Driving Factors of Deforestation in the Global South

Forests serve many purposes (economic, food source, carbon sinks) to local communities in the Global South. Yet they are at risk of deforestation for private gain. Use satellite imagery to monitor the effects of mining, agriculture, conflict, etc. on deforestation.

Example Datasets

1. Forest Data

Further Reading

- [A pantropical assessment of deforestation caused by industrial mining](#)
- [Disentangling the numbers behind agriculture-driven tropical deforestation](#)
- [What peace means for deforestation: An analysis of local deforestation dynamics in times of conflict and peace in Colombia](#)



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More Resources

[Climate and Economic Justice Screening Tool](#)

[U.S. Climate Resilience Toolkit](#)

[NASA Applied Sciences](#)
[NASA SEDAC](#)

[Climate Central](#)

[Google Earth Engine](#)

[Thriving Earth Exchange](#)

[Environmental Data and Governance Initiative](#)

[Climate Change AI](#)

For more resources on climate and environmental justice: **Please explore other modules in the Climate Justice Instructional Toolkit.**



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