Correlates and Policy Recommendations of DC's Urban Heat Island Effect

Evan Bowman

December 07, 2022

Introduction

A major discussion in today's politics are the consequences of climate change and shifting environmental trends if no meaningful attempt at mitigating atmospheric greenhouse gasses occurs. These consequences, on a meta level, range from higher mean temperatures, sea level rise, and changes in the ability to grow sustainable food. This poses large public health risks such as increases in heat related deaths and illness. This is cause for concern as about 25 percent of natural hazard mortality in the country is caused by heat exposure (Benz and Burney 2021). Furthermore, heat-related mortality in the USA causes roughly 1,500 more deaths annually than other severe weather events, and causes other health outcomes such as heat strokes, dehydration, loss of labor productivity, and decreased learning (Hsu et al. 2021). The potential increase in heat related health incidents requires a substantial need for policy to combat increases in mean temperatures.

Little discussion looks at the discrepancies these effects might have on urban populations. On the topic of increased global temperature averages, there is a need to look at the intersectionality of an already occurring phenomenon: urban heat island effects. This concept revolves around the key fact that urbanized city centers already create higher mean temperatures compared to their rural counterparts. Not only are these urban centers more likely to have higher mean temperatures than rural areas, there are clear sociodemographic discrepancies between populations within these cities. Few studies have been published analyzing these demographic discrepancies. However, in one report, research has found that roughly 77 percent of counties studied show that there are large differences in change of daytime temperature between census tracts with the highest and lowest Black population proportions. Furthermore, 81 percent of counties studied with lower difference in daytime temperature are majority non-Hispanic White. (Benz and Burney 2021). There is also empirical evidence that shows discrepancies in urban heat island effects targeting communities that are more impoverished. For example, a 2020 study found that there is a negative correlation of .88 between cities' urban heat island effects and income (Chakraborty et al. 2020). This is further cause for concern when looking at potential correlations between poverty and race in city census tracts.

These findings are consistent with research that shows majority minority populations in urban centers have less tree cover and larger proportions of impervious surfaces than majority non-Hispanic White populations. This shows a clear need for social policy that protects majority minority census tracts from being disproportionately affected by increased heat island effects. Research regarding the effects of urban heat island effects must be on a local level to adequately identify meaningful social demographic trends for areas within urban centers. These could be specific neighborhoods, districts, census tracts, etc. In the context of racial inequities in Washington DC, most research is done at the ward level. For this study, census tracts are chosen as sample observations to be able to identify which specific areas of DC's eight wards are most at risk of the urban heat island effect, and the demographic patterns that coincide with these risks.

Research Questions

What are reoccurring sociodemographic trends that are associated with higher heat sensitivity indexes? Who are the communities at a larger risk of heat-induced health events due to higher heat sensitivity index (HSI)? HSI is a metric that describes an individuals ability to adapt, cope, or recover from extreme heat and is explained by specific demographic and health variables of DC's census tracts. Identifying socioeconomic and health trends can assist policy makers in identifying the communities who would best benefit from policy implementation.

What are the environmental metrics that are correlated with the census tracts with the highest HSI? What environmental characteristics of certain census tracts create larger heat exposure indexes (HEI)? In the data, HEI is a metric that takes a census tract's mean ambient air temperature as the exposure variable (50 percent) and two physical variables (impervious surfaces: 25 percent, lack of tree cover: 25 percent) that describe a tract's heat retention. Understanding the environmental factors would help in identifying policy approaches that would mitigate the consequences of the urban heat island effect by assisting at risk census tracts with solutions to heat retention.

Do these findings highlight environmental justice issues that exist within Washington DC? Do the findings of this study concur with previous research regarding race inequities for heat exposure and sensitivity in urban centers? The ultimate goal in answering these two research questions is to find the intersectionality of environmental factors that exacerbate the urban heat island effect and the populations of urban centers most at risk.

Heat Sensitivity Index and Socioeconomic Patterns

Visualizing Patterns

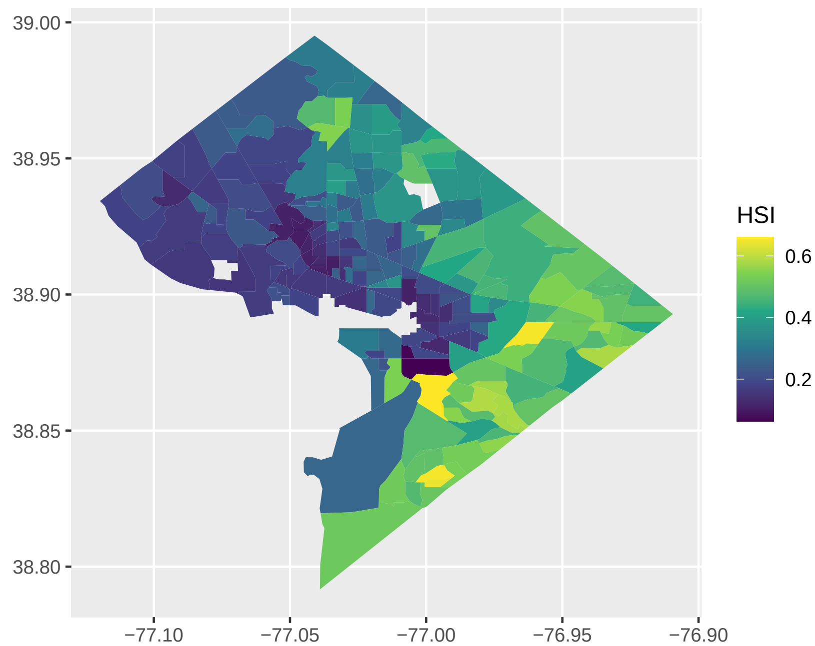


Fig. 1

As seen from the Figure 1, the census tracts with the highest HSI levels fall within areas along the Anacostia River, also found within Wards 7 and 8. These census tracts are a vast contrast when compared to census tracts with low HSI levels found in the Northwest portion of the city. Areas along the Anacostia River are typically known for being predominately majority minority as well as lower income compared to census tracts in the Northwest. This further contributes to the hypothesis of racial inequity in DC's Urban Heat Island Effect as the intersectionality of poverty and race exacerbates individuals ability to cope with extreme heat (Fig. 2). Analysis conducted in this section will look to define what specific patterns exist within tracts with high HSI levels.

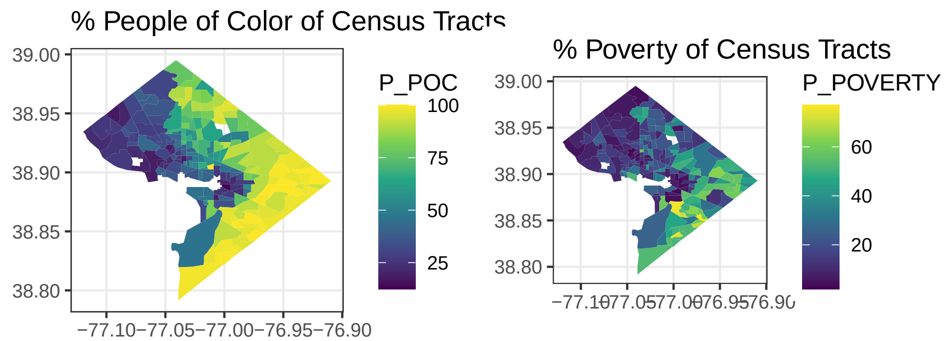


Fig. 2

Other interesting patterns found within the data are health trends and specific discrepancies between predominately non-Hispanic White census tracts and predominately Black census tracts. For all four health variables found within the data set, asthma, obesity, coronary heart disease (CHD), and disability, majority minority census tracts exhibit higher prevalence than predominately White tracts (Fig. 3). This highlights the increased risk of health related events that are exacerbated by a higher sensitivity to heat and the inability to cope or adapt to it.

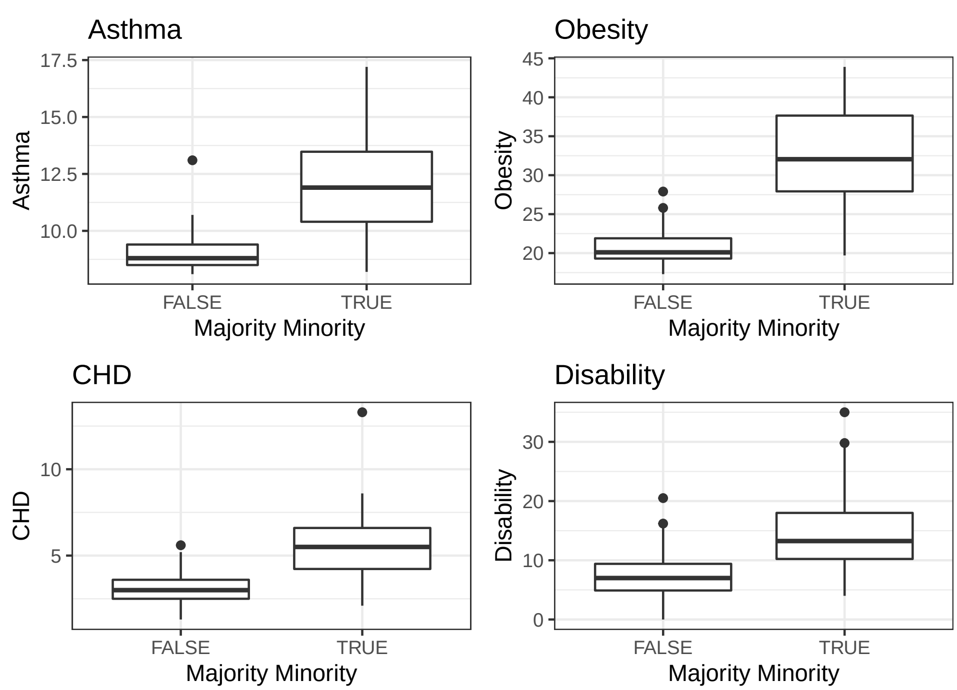


Fig. 3

With preliminary patterns relating to a census tract's Heat Sensitivity Index established, this paper will shift to creating a preliminary model that best exemplifies which variables contribute most to HSI metrics for a given census tract.

Regression Definition

Preliminary Regression Identification

To best understand to what magnitude socioeconomic factors affect HSI levels, preliminary regression models will be created to identify variables of statistical significance. To achieve the best possible model, best subsets regression, forward stepwise, and backward stepwise will be conducted and the best model will be taken following the analysis of adjusted r-squared, Mallows CP, and BIC.

The first model will be utilizing the best subsets regression strategy through the leaps package. The model was fitted and the best eight models are shown below. Summary statistics of each model will be analyzed to figure which model will be chosen (Table 1).

Table 1: Best Subsets Regression

model	adjr2	cp	bic
1	0.8979830	4521756.42	-453.7521
2	0.9350345	2865107.80	-541.0617
3	0.9555091	1952266.17	-613.6160
4	0.9727876	1188009.46	-709.1226
5	0.9859260	611231.14	-838.6844
6	0.9911926	380491.58	-929.5581
7	0.9960067	171535.88	-1085.8489
8	0.9979555	87284.43	-1217.4780

Model 6 returned the third highest adjusted r-squared value, lowest Mallow's Cp value, and third lowest BIC value. This shows that the model captures one of the the highest variations in HSI, the best predicting power for all possible models, and the third lowest bias for all possible models using the Best Subsets method. Forward and Backwards Stepwise regression returned the similar results (Table 3). However, for the data, no model is shown to be the clear best.

Table 2: Forward and Backward Stepwise

model	adjr2	cp	bic	model	adjr2	cp	bic
1	0.8979830	4521756.42	-453.7521	1	0.8141234	8238877.04	-331.9635
2	0.9350345	2865107.80	-541.0617	2	0.9095647	3988449.75	-473.9139
3	0.9555091	1952266.17	-613.6160	3	0.9351507	2845681.30	-537.1296
4	0.9719987	1222453.67	-703.3216	4	0.9539562	2010260.43	-602.3611
5	0.9859260	611231.14	-838.6844	5	0.9800948	864557.15	-768.3144
6	0.9911926	380491.58	-929.5581	6	0.9896876	445543.48	-897.5332
7	0.9960067	171535.88	-1085.8489	7	0.9950826	211270.99	-1043.5956
8	0.9977593	95677.64	-1198.8777	8	0.9979555	87284.43	-1217.4780

Due to the relative similarities in adjusted r-squared, Mallows Cp, and BIC, the top model from each regression method was trained and validated to understand which is the best to proceed with. Best Subsets and forward stepwise returned a model that included the variables P_POC, P_CHILD, P_ELDERLY, P_POVERTY, P_LIMENG, and OBESITY. Backwards stepwise returned a model that inlcuded all varialbes with the exception of OBESITY.

```
## # A tibble: 3 x 4
##   .metric .estimator   best backward
##   <chr>   <chr>       <dbl>    <dbl>
```

```
## 1 rmse    standard   0.0143  0.00644
## 2 rsq     standard   0.992   0.998
## 3 mae     standard   0.0112  0.00484
```

The results of further analyzing the two models shows that the model chosen by backwards stepwise has better predicting power based on the root mean square error (rmse) and mean absolute error (mae). The fitted model is shown below:

```
## # A tibble: 9 x 5
##   term          estimate std.error statistic   p.value
##   <chr>            <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)  -0.192   0.00513       -37.4 1.21e- 90
## 2 P_POC         0.00161 0.0000421      38.3 2.19e- 92
## 3 P_CHILD       0.00608 0.000131       46.3 7.56e-107
## 4 P_ELDERLY     0.00242 0.0000954      25.4 1.56e- 63
## 5 P_POVERTY     0.00101 0.0000608      16.6 4.84e- 39
## 6 P_DISABILITY  0.00370 0.000122       30.4 8.87e- 76
## 7 P_LIMENG      0.00305 0.000111       27.5 6.01e- 69
## 8 ASTHMA        0.0189  0.000687       27.6 4.39e- 69
## 9 CHD           0.0127  0.000538       23.6 6.37e- 59
```

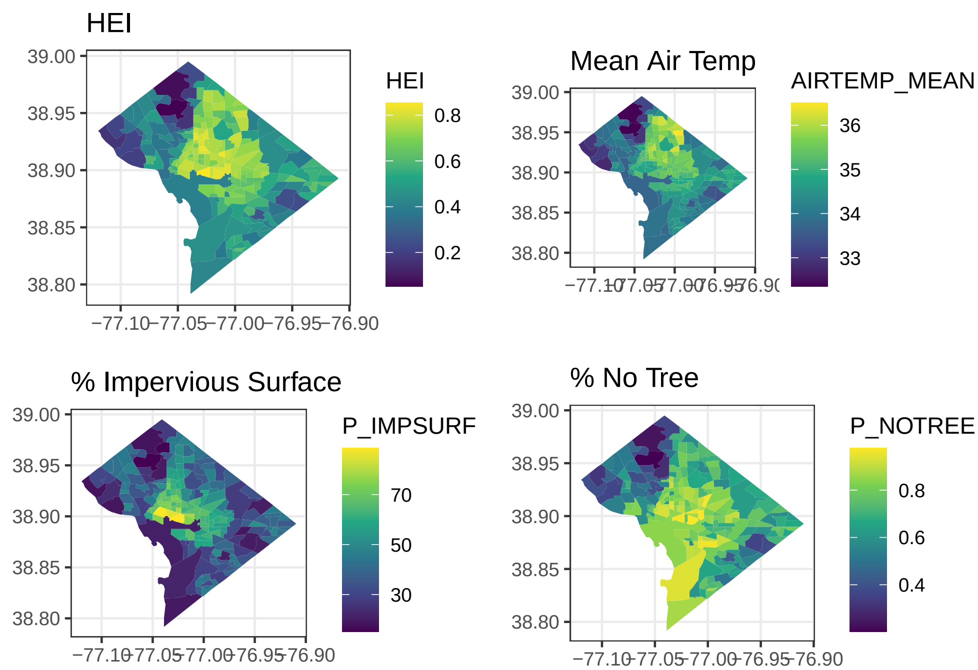
Shrinkage Regression

While backward stepwise regression identified the best model as including eight variables, there is clear covariation that affects the magnitude of the coefficients (Appendix Tab. 3). As a result, a LASSO regression model will be fitted and compared to the original regression model. LASSO takes into account the covariation of the predictors, and adjusts the coefficients accordingly.

```
## # A tibble: 9 x 5
##   term           estimate std.error statistic  p.value
##   <chr>             <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  -0.190    0.00546       -34.7 2.01e-74
## 2 P_POC         0.00164  0.0000472      34.6 2.78e-74
## 3 P_CHILD       0.00595  0.000145       41.2 1.11e-84
## 4 P_ELDERLY     0.00237  0.000106       22.3 5.72e-50
## 5 P_POVERTY     0.000994 0.0000677      14.7 5.04e-31
## 6 P_DISABILITY  0.00375  0.000142       26.4 7.19e-59
## 7 P_LIMENG      0.00299  0.000129       23.1 7.63e-52
## 8 ASTHMA        0.0187   0.000727       25.8 1.67e-57
## 9 CHD           0.0126   0.000574       22.0 3.00e-49
```

Environmental Factors of Heat Exposure Indexes

It is important to understand not only socioeconomic factors that contribute to a census tract's HSI statistic, but also the environmental factors that contribute to their Heat Exposure Index. However, unlike HSI, HEI is defined for each census tract as 50 percent mean air temperature, 25 percent lack of tree canopy, and 25 percent impervious surface. As a result, analysis will be centered around patterns of the three variables as opposed to any model building to predict HEI values.



As shown by the maps above, there are fewer patterns in discrepancies between environmental factors and census tracts compared to that of the HSI data. Predominately Black census tracts are not disproportionately affected by any of the environmental variables (Fig. 7). These maps highlight areas such as downtown being at the highest risk of heat exposure. This makes intuitive sense as this is the city center of DC which includes high amounts of impervious surface and lacks cooling characteristics such as large parks or trees. When compared to areas of interest in the HSI section, census tracts that were poorer and majority minority are relatively similar to more White Census tracts. However, given the urban nature of the city, proportions of census tracts that are impervious surfaces and the lack of tree cover is a cause for concern given the socioeconomic patterns discussed previously. This creates the need for both environmental and social policy to adequately mitigate the risk of heat induced health incidents.

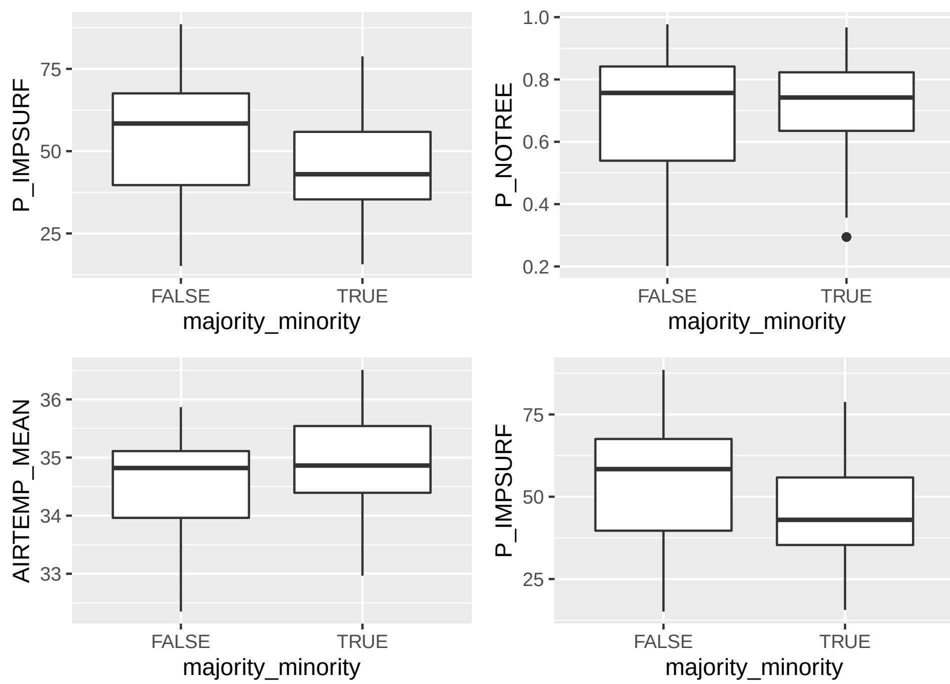


Fig. 8

Potential Policy Recommendations

Environmental Policy Recomendations

Policy recommendations revolving around mitigating mean air temperature of census tracts is centered around both impervious surfaces and tree canopy cover. Both of these factors are main contributors of heat retention due to the inability to deflect solar rays. Advancing infrastructure improvements such as cool roofs or cool pavements is key in reducing mean air temperature. Infrastructure projects such as these would need to prioritize census tracts that are majority minority or poor. These areas are at most need of infrastructure improvements already and would benefit far more than other tracts due to their increased sensitivity to heat.

Social Policy Recomendations

Policy recommendations relating to socioeconomic factors must center around enabling individuals in census tracts with high HSI metrics to be able to adapt and cope to instances of extreme heat. One clear avenue is to strengthen DC's Heat Emergency Plan (HEP) which opens resources when temperature exceed 95 degrees Fahrenheit. These resources are deemed cooling centers and range from pools, libraries, shelters, etc. located across the city (Appendix 2). However, the city must be able to give clear and concise information regarding where these centers are located and the hours they are open. Furthermore, the city must be able to offer more cooling centers that are accessible during non-business hours. As of right now, the city only advertises four options that are open 24/7 in cases of extreme heat. While temperatures do decrease during the night hours, individuals with low heat tolerance are still at adverse risk of heat induced illness Opening more accessible cooling centers in census tracts with high HSI will drastically reduce the possibility of heat induced health incidents.

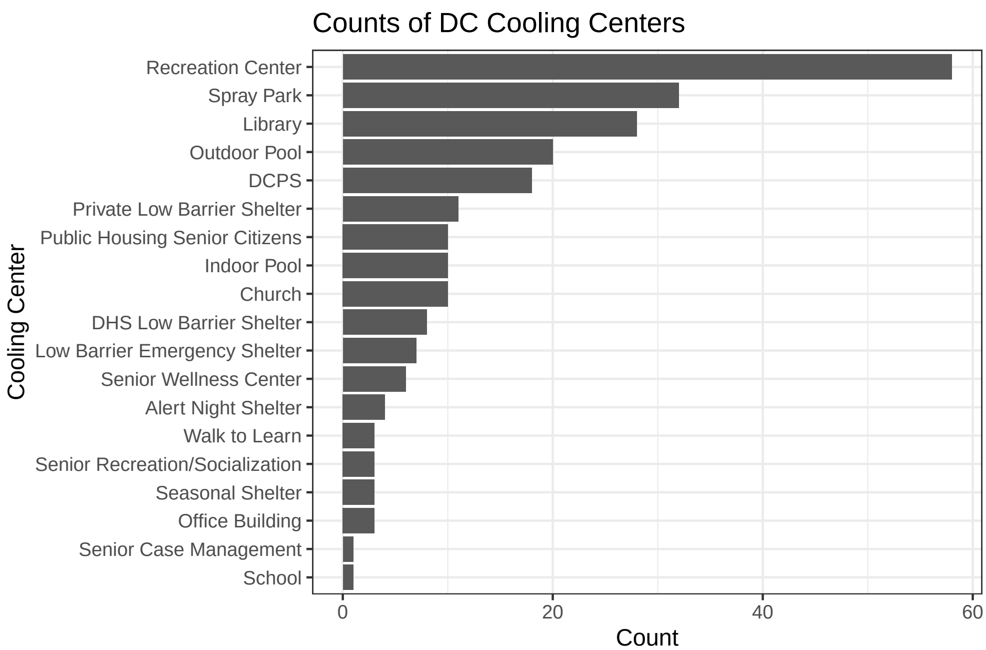
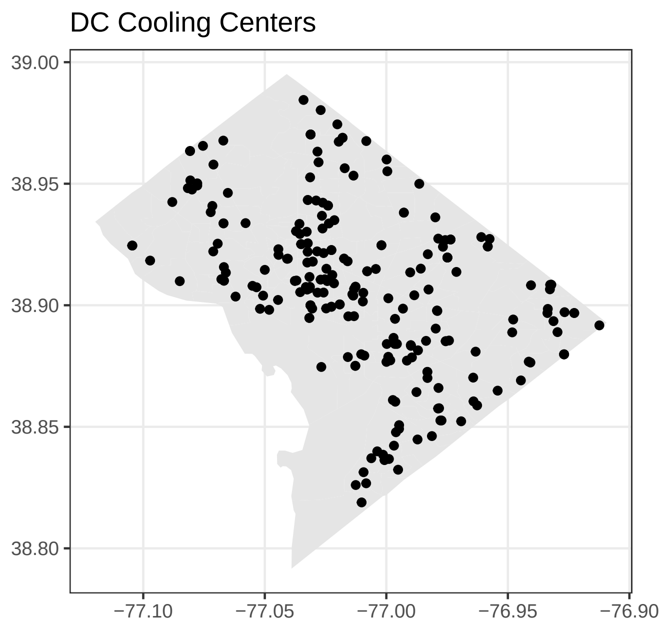

Counts of DC Cooling Centers
Recreation Center
Spray Park
Library
Outdoor Pool
DCPS
Private Low Barrier Shelter
Public Housing Senior Citizens
Indoor Pool
Church
DHS Low Barrier Shelter
Low Barrier Emergency Shelter
Senior Wellness Center
Alert Night Shelter
Walk to Learn
Senior Recreation/Socialization
Seasonal Shelter
Office Building
Senior Case Management
School
Cooling Center
0
20
40
60
Count

Fig. ?

Appendix

Table 3: Correlation table of HSI variables

	P_POC	P_CHILD	P_ELDERLY	P_POVERTY	P_DISABILITY	P_LIMENG	ASTHM
P_POC	1.000	0.353	-0.032	0.761	0.681	0.165	0.85
P_CHILD	0.353	1.000	-0.062	0.322	0.123	-0.019	0.37
P_ELDERLY	-0.032	-0.062	1.000	-0.131	0.244	-0.037	-0.10
P_POVERTY	0.761	0.322	-0.131	1.000	0.632	0.100	0.89
P_DISABILITY	0.681	0.123	0.244	0.632	1.000	0.000	0.65
P_LIMENG	0.165	-0.019	-0.037	0.100	0.000	1.000	-0.02
ASTHMA	0.857	0.378	-0.109	0.891	0.651	-0.020	1.00
CHD	0.748	0.287	0.396	0.609	0.650	0.011	0.68
OBESITY	0.928	0.403	-0.048	0.823	0.710	0.030	0.93
HSI	0.929	0.470	0.147	0.842	0.771	0.152	0.90



Appendix Fig. 1

References

Benz, Susanne Amelie, and Jennifer Anne Burney. 2021. "Widespread Race and Class Disparities in Surface Urban Heat Extremes Across the United States." *Earth's Future* 9 (7): e2021EF002016.

Chakraborty, T, A Hsu, D Manya, and G Sheriff. 2020. "A Spatially Explicit Surface Urban Heat Island Database for the United States: Characterization, Uncertainties, and Possible Applications." *ISPRS Journal of Photogrammetry and Remote Sensing* 168: 74–88.

Hsu, Angel, Glenn Sheriff, Tirthankar Chakraborty, and Diego Manya. 2021. "Disproportionate Exposure to Urban Heat Island Intensity Across Major US Cities." *Nature Communications* 12 (1): 1–11.