Urban Heat Island Distribution: A Spatial Analysis

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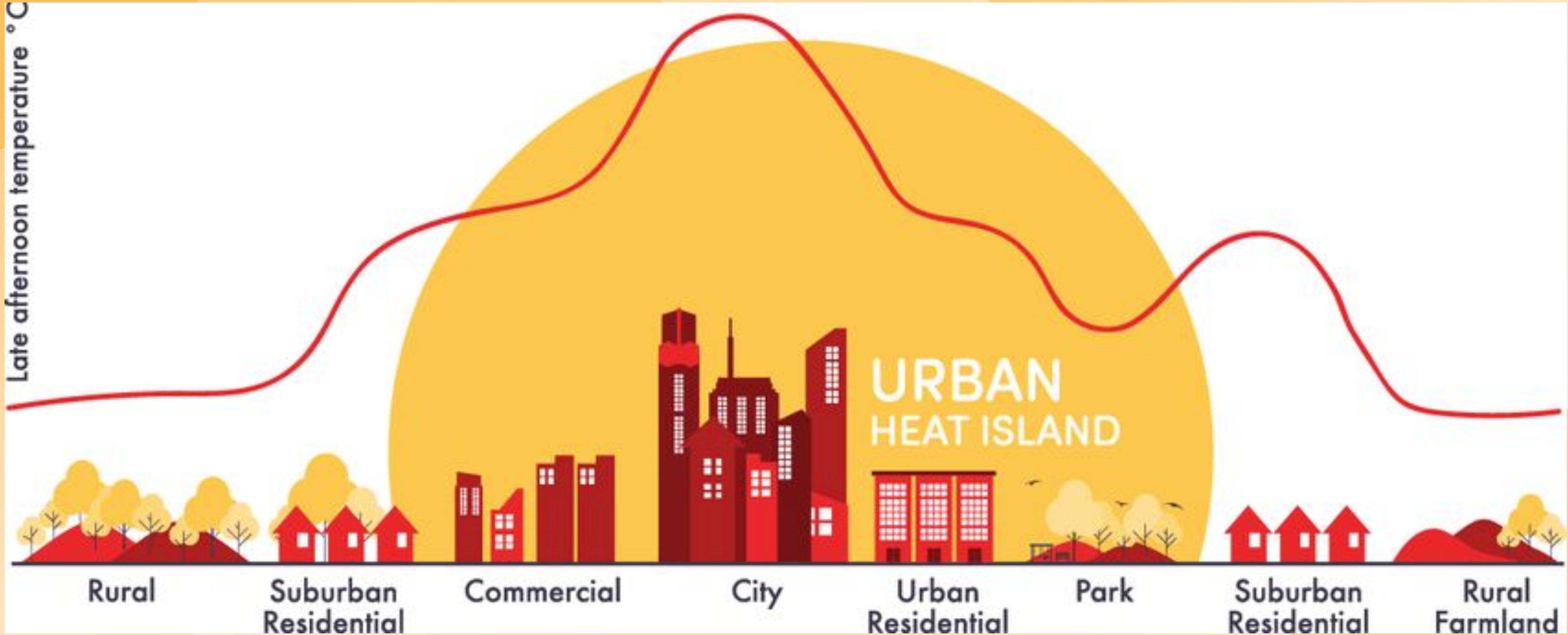
What is an Urban Heat Island?

”Heat islands are urbanized areas that experience **higher temperatures than outlying areas**. Structures such as buildings, roads, and other infrastructure absorb and re-emit the sun’s heat more than natural landscapes such as forests and water bodies. Urban areas, where these structures are highly concentrated and greenery is limited, become ‘islands’ of higher temperatures relative to outlying areas.”

–EPA



Fuladlu, Kamyar & Riza, Müge & Ilkan, Mustafa. (2018). THE EFFECT OF RAPID URBANIZATION ON THE PHYSICAL MODIFICATION OF URBAN AREA.

Impacts of Urban Heat Islands

- Increased incidence of **heat-related illnesses** (Kovats & Hajat, 2007)
- Increase length and severity of **heat waves** (Broadbent, Scott, Georgescu, 2020)
- Increased **air pollution** levels (US Department of Energy, 2013)
- Myriad other effects on water bodies, flora and fauna, and energy costs

Research Question

Which demographic factors affect the spatial distribution of urban heat islands within American cities and how do these factors vary city by city?

Objective

01 Create individual spatial models of UHI distribution for two cities from different regions of the United States

02 Compare model similarity and performance across selected cities

Literature Review

- Age, socioeconomic status, race, ethnicity, and income covary with natural vegetation, greenspace, and higher surface temperatures (Casey et al., 2017)

- Formerly redlined neighborhoods in the United States exhibit a higher average land surface temperature of 2.6 ºC (4.68 ºF) (Hoffman et al., 2020)

City Selection

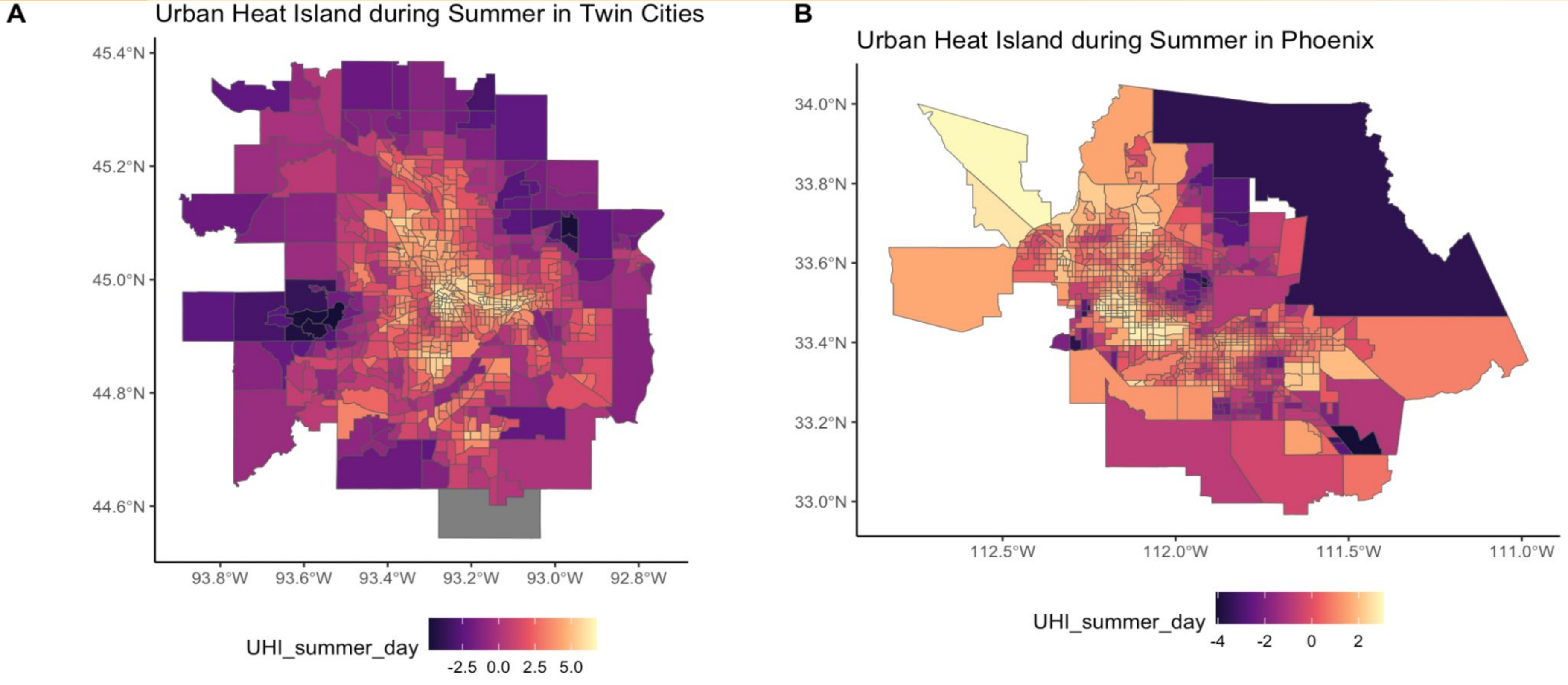
- Southwestern cities studied most, exhibit highest UHI effect; Midwestern cities exhibit lowest UHI effect (Hoffman et al., 2020)

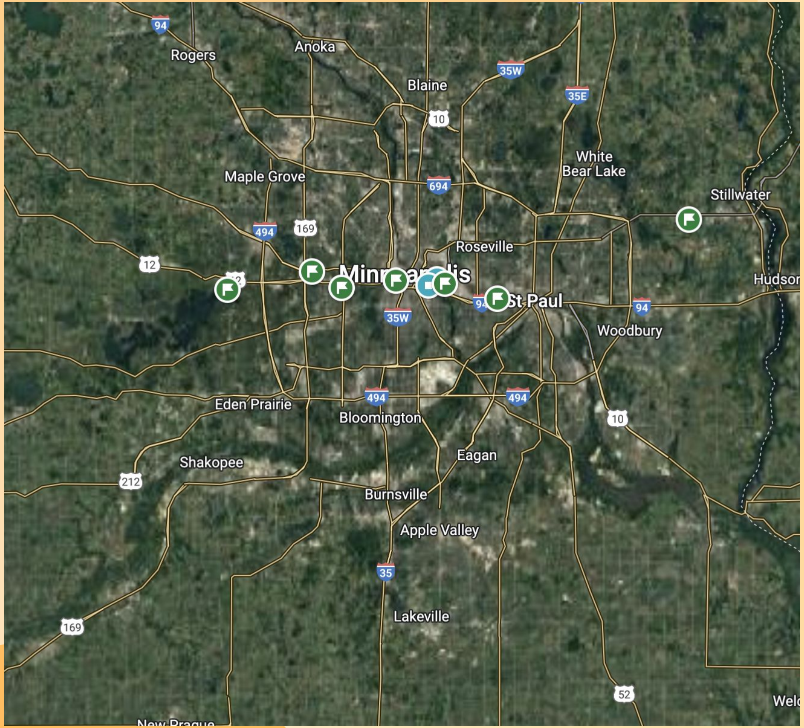
- We choose **Minneapolis-St.Paul** & **Phoenix** to yield a unique comparative analysis and due to data availability

Data Source

- **2019 American Community Survey** (US Census Bureau)
  - via TidyCensus

- **UHI composite effect** (Chakraborty et al., 2020)
  - Remote sensing of surface temperature
  - Surface reflectance
  - Elevation & land cover data
  - Tree canopy


A
Urban Heat Island during Summer in Twin Cities
45.4°N
45.2°N
45.0°N
44.8°N
44.6°N
93.8°W
93.6°W
93.4°W
93.2°W
93.0°W
92.8°W
UHI_summer_day
-2.5 0.0 2.5 5.0
B
Urban Heat Island during Summer in Phoenix
34.0°N
33.8°N
33.6°N
33.4°N
33.2°N
33.0°N
112.5°W
112.0°W
111.5°W
111.0°W
UHI_summer_day
-4 -2 0 2



Twin Cities

Phoenix

Data Cleaning Process

- Joining UHI & census dataset

Challenges:
- Missing values complicating join process
- One dataset with geometry, one without
- Incorporation of physical geography

Variable Selection

- Guided by literature, we consider age, birthplace, race, ethnicity, income, home value, and predominant industry by census tract in model building process

- Individual random forests for Phoenix and Minneapolis-St. Paul and include highest-performing variables

Spatial Autocorrelation

$$Y_i = x_i^T \beta + \epsilon_i$$

- Account for spatial trends and spatial autocorrelation
  - Trend: Fit a regression model
  - Test the residuals after detrending with Moran's I
- **Simultaneous Autoregressive (SAR) model**
  - Includes a spatial lag term (ρWY_i), which incorporates the weighted average of neighboring observations for each spatial unit

Minneapolis-St. Paul

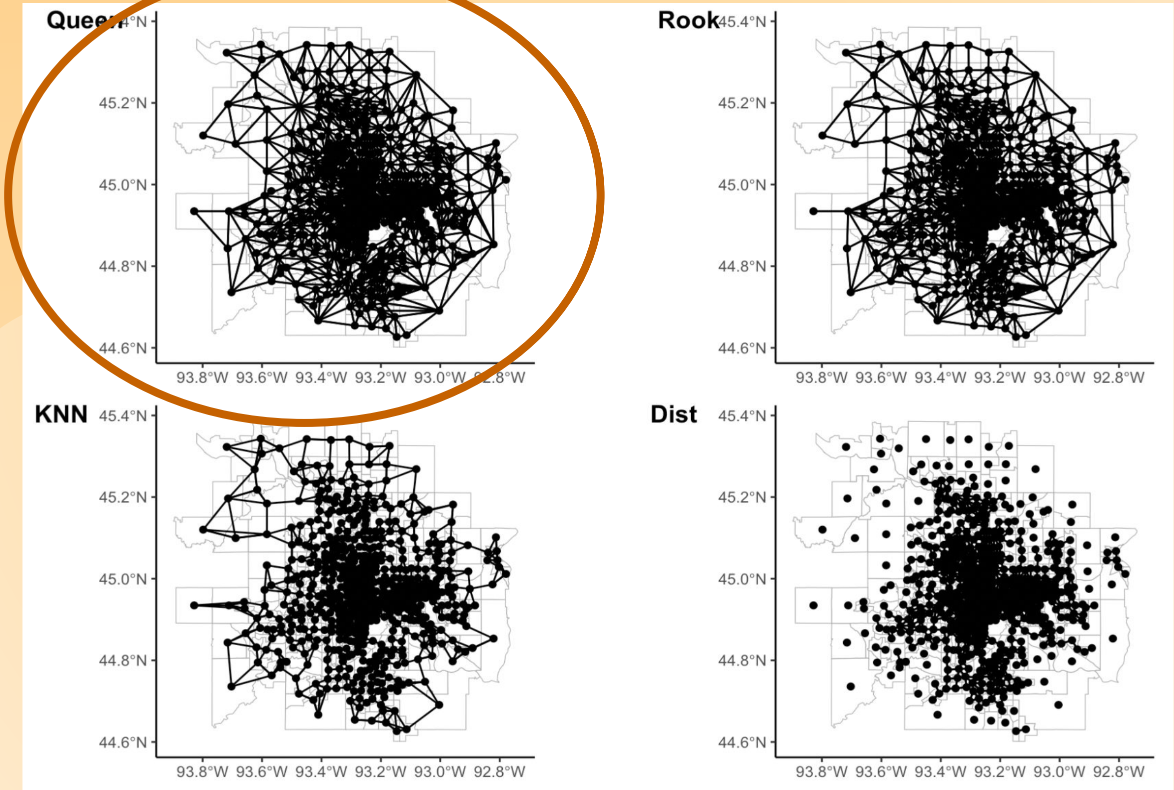
Variable Selection

- Guided by literature, we consider **age**, **birthplace**, **race**, **ethnicity**, **income**, **home value**, and **predominant industry** by census tract in model building process

- Random forest shows that **proportion of black residents**, **proportion of white residents**, and **proportion of residents born in-state** of census tracts are most highly predictive variables

Neighborhood Structure

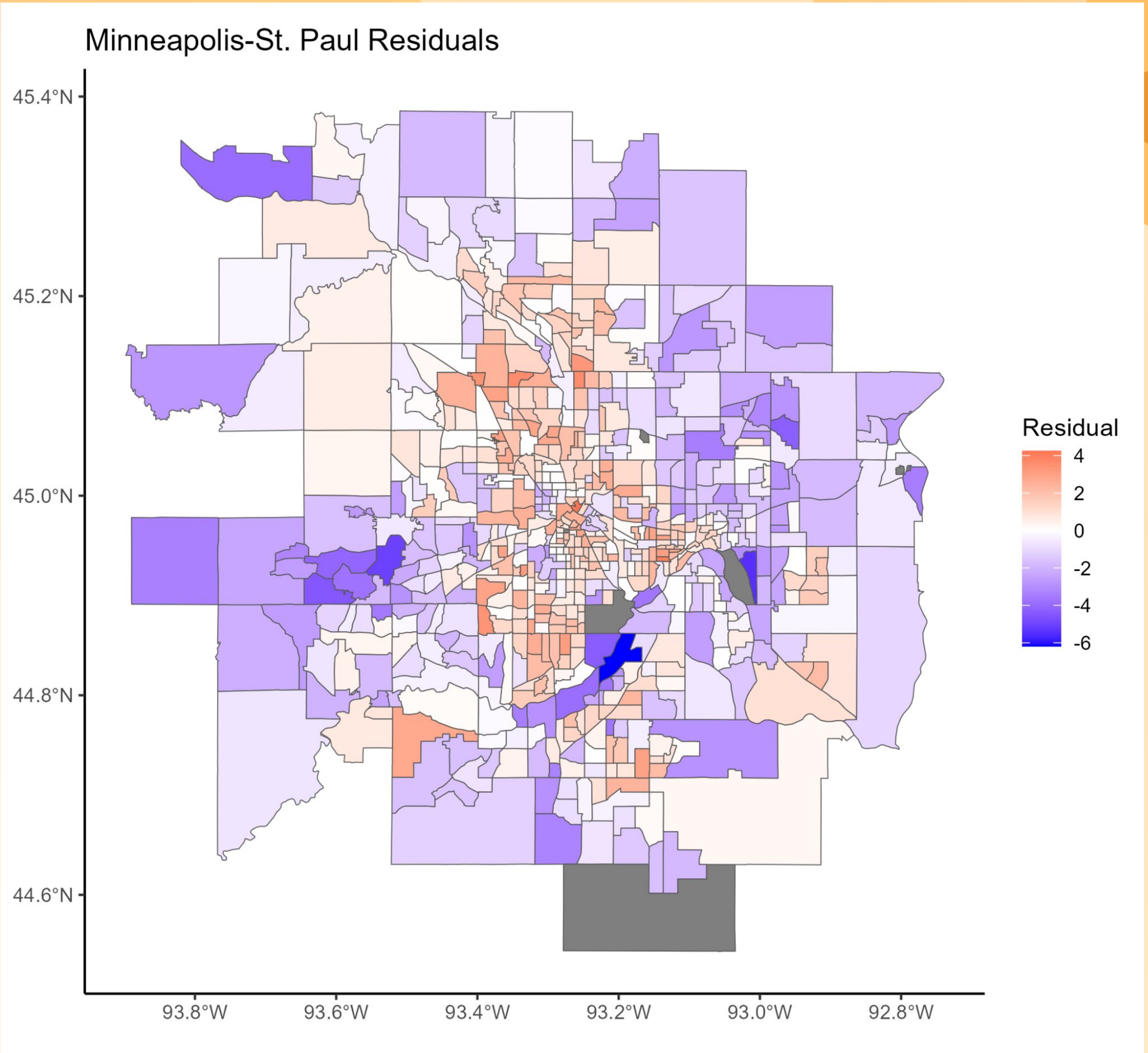
Smallest BIC →



Final Model: SAR Model (Queen)

	Coefficient	SE	P-value
Intercept	3.417	0.782	0.000
% Race White (Below 0.75)	0.196	0.093	0.035
House Value (Below 250k)	0.088	0.083	0.288
House Value (Above 500k)	-0.377	0.173	0.030
% Owner Occupied	-0.472	0.226	0.037
Age	-0.018	0.007	0.013

- Lambda = 0.93174 (SE = 0.013)
- P-value (Moran I) = 0.002735 → Dependent residual
    - Moran I statistic = 0.064 → Spatial randomness


Minneapolis-St. Paul Residuals
45.4°N
45.2°N
45.0°N
44.8°N
44.6°N
93.8°W
93.6°W
93.4°W
93.2°W
93.0°W
92.8°W
Residual
4
2
0
-2
-4
-6

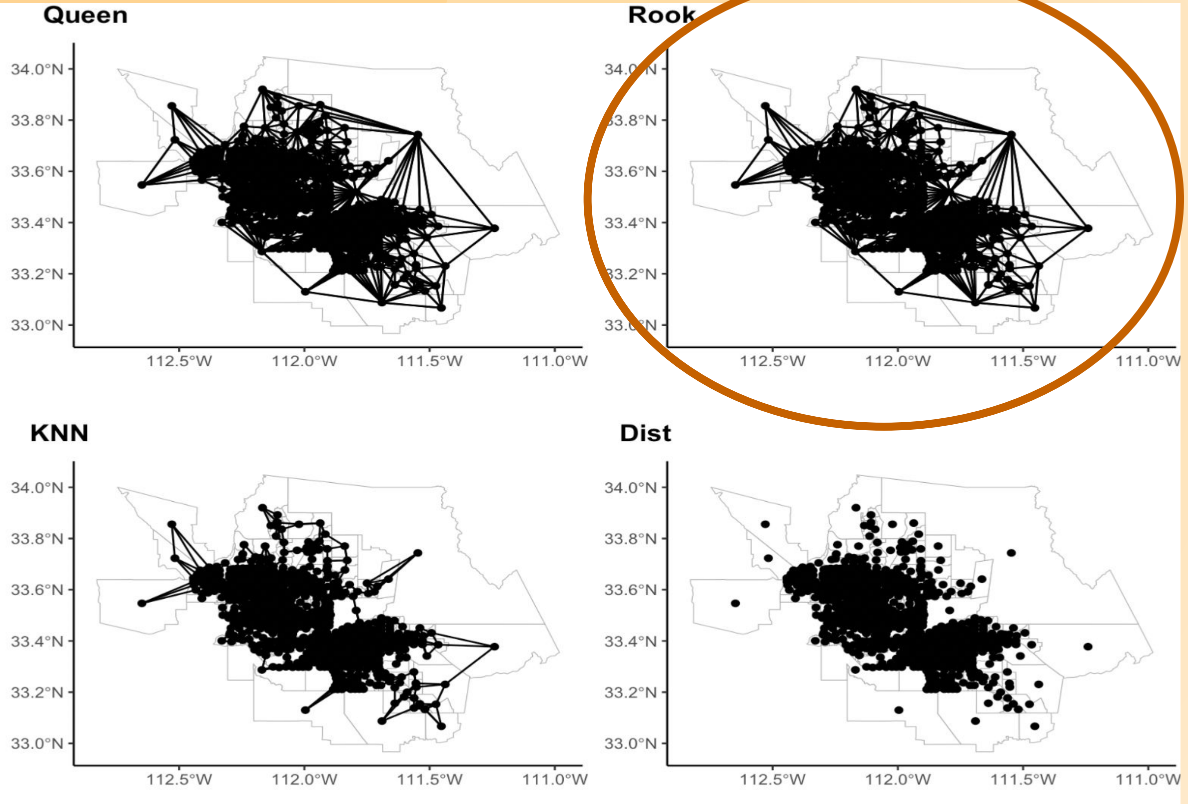
Phoenix

Variable Selection

- Random forest shows that **proportion of black residents**, **proportion of white residents**, and **average income** of census tracts are most highly predictive variables

- Many linear models perform very similarly to one another

Neighborhood Structure

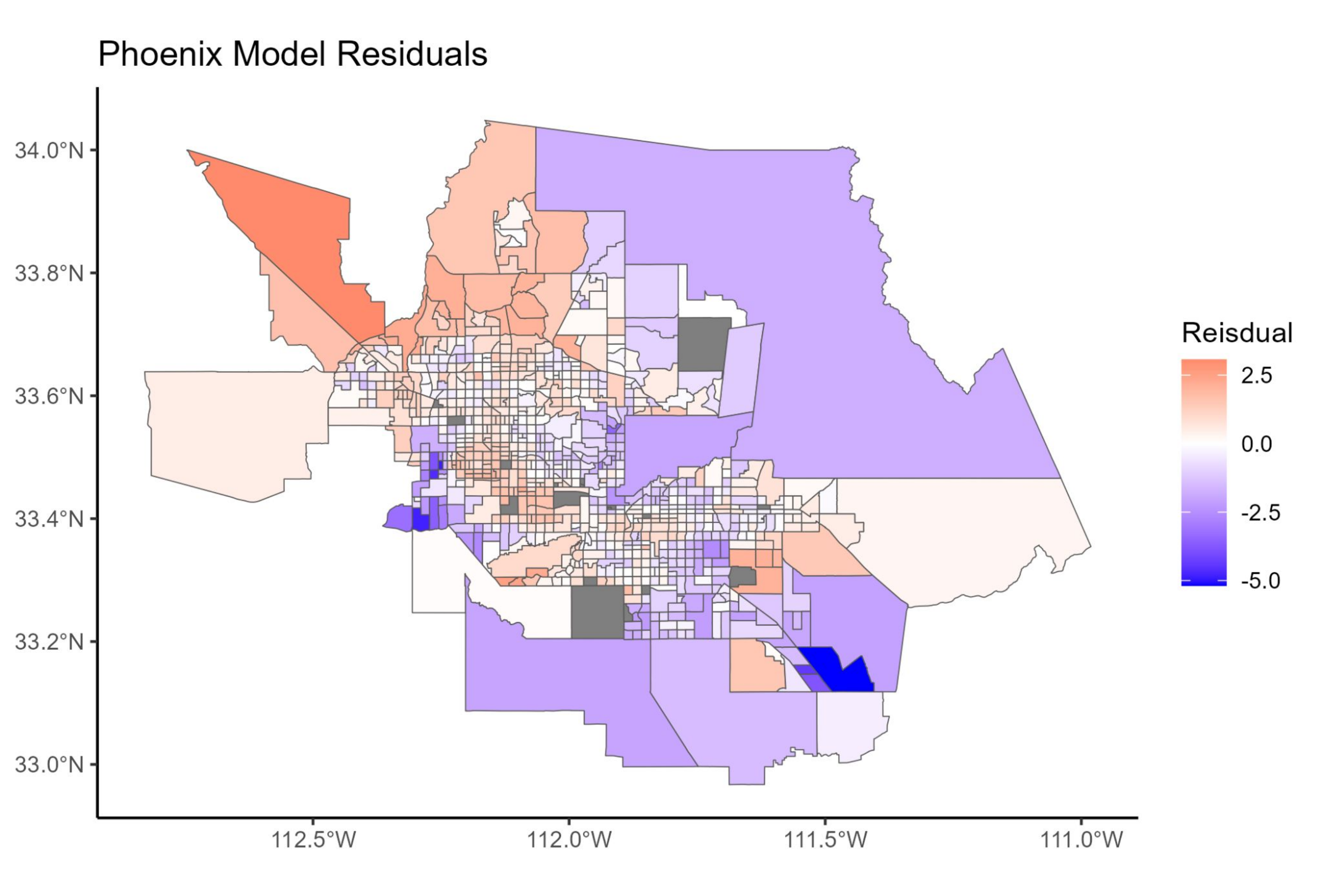


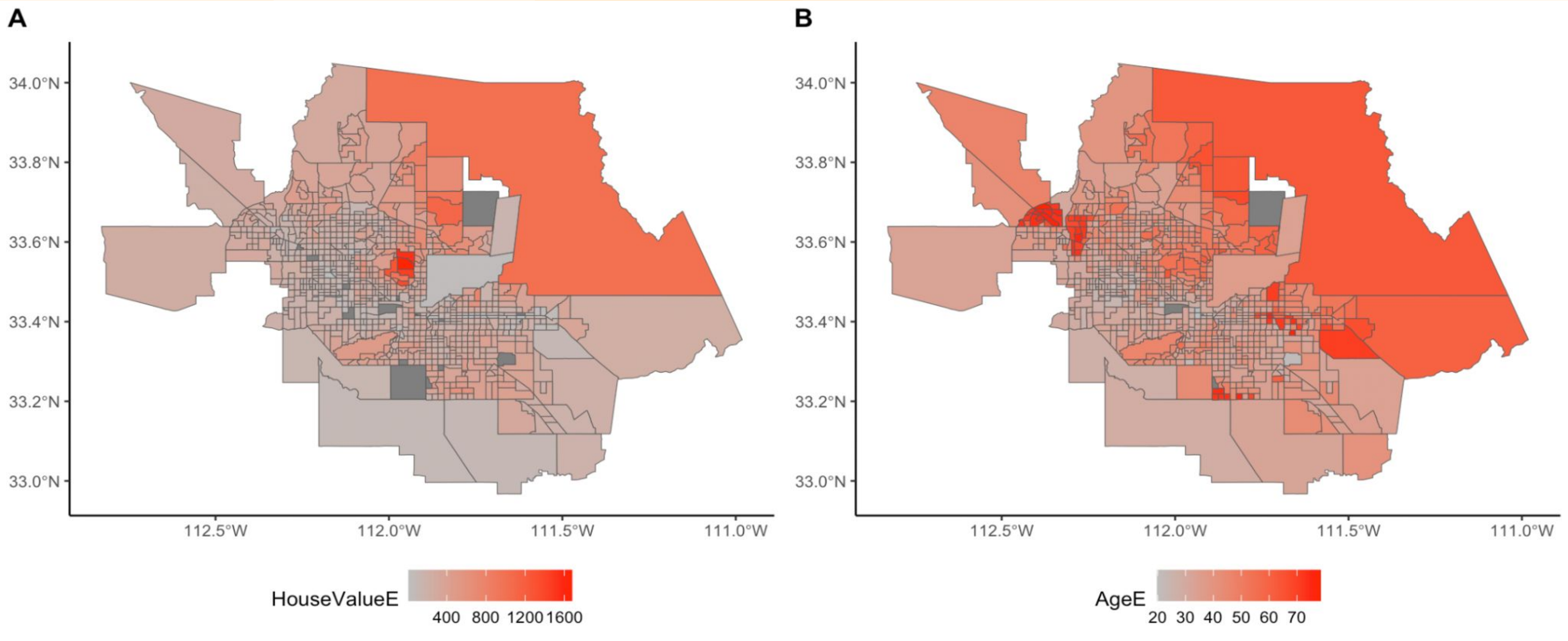
← Smallest BIC

Final Model: SAR Model (Rook)

	Coefficient	SE	P-value
Intercept	0.996	0.254	0.000
House Value (250k to 500k)	-0.223	0.054	0.000
House Value (Above 500k)	-0.632	0.112	0.000
Age	-0.008	0.002	0.001

- Lambda = 0.95856 (SE = 0.011)
- P-value (Moran I) = 0.1821 → Independent residual :)


Phoenix Model Residuals
34.0°N
33.8°N
33.6°N
33.4°N
33.2°N
33.0°N
112.5°W
112.0°W
111.5°W
111.0°W
Reisdual
2.5
0.0
-2.5
-5.0


A
34.0°N
33.8°N
33.6°N
33.4°N
33.2°N
33.0°N
112.5°W
112.0°W
111.5°W
111.0°W
HouseValueE
400
800
1200
1600
B
34.0°N
33.8°N
33.6°N
33.4°N
33.2°N
33.0°N
112.5°W
112.0°W
111.5°W
111.0°W
AgeE
20
30
40
50
60
70

Model Comparison

- **Phoenix**: Simple model, less spatial autocorrelation after SAR
- **Minneapolis–St. Paul**: Complex model, more spatial correlation remaining

- Proportion of black residents & income highly predictive of UHI, but not significant in model and lead to higher BIC

Conclusion

- UHI is associated with race and income in both cities
- Spatial distribution of UHI varies by strength and type of demographic predictors between Minneapolis–St. Paul and Phoenix
- Can inform policy interventions to mitigate UHI and increase urban greenspace in underserved areas
    - Demographic factors & Income

Thank you :)