Week 9 Lab

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Set up Libraries

Are the households that receive SNAP clustered within Baltimore, MD?

```
library(tidycensus)
library(tidyverse)
library(tigris)
library(sf)
library(dplyr)
library(ggplot2)
library(spdep)
library(tmap)
library(RColorBrewer)

options(tigris_class = "sf") # Make sure we're using sf for tigris
options(tigris_use_cache = TRUE) # Make sure we cache
```

Baltimore Data

```
# This gets the 2014-2018 population, race+eth, household SNAP data
balt_tract_snap_20 <- get_acs(geography = "tract",
                           variables = c("pop" = "B03002_001", # Total
                                         "pop_nhwhite" = "B03002_003", # NH White
                                         "pop_nhblack" = "B03002_004", # NH Black
                                         "pop_nhamind" = "B03002_005", # NH Am Ind
                                         "pop_nhasian" = "B03002_006", # NH Asian
                                         "pop_nhhwnpi" = "B03002_007", # NH Hawaiin/PI
                                         "pop_nhother" = "B03002_008", # One Other
                                         "pop_nhtwomr" = "B03002_009", # Two+
                                         "pop_hispltx" = "B03002_012", # Hispanic/Latinx
                                         "house_total"  = "B22003_001", # Total Households
                                         "received_snap" = "B22003_002", #Households that receiv
ed food stamps/snap in the past 12 months,
                                         "not_snap" = "B22003_005" # Households that did not rec
eive snap in the past 12 months
                                         ),

                           year = 2020,
                           survey = "acs5",
                           state = c(24),
                           county = c(510),
                           geometry = TRUE,
                           output = "wide")

balt_tract_snap_20 <- st_transform(balt_tract_snap_20, 3857)
```

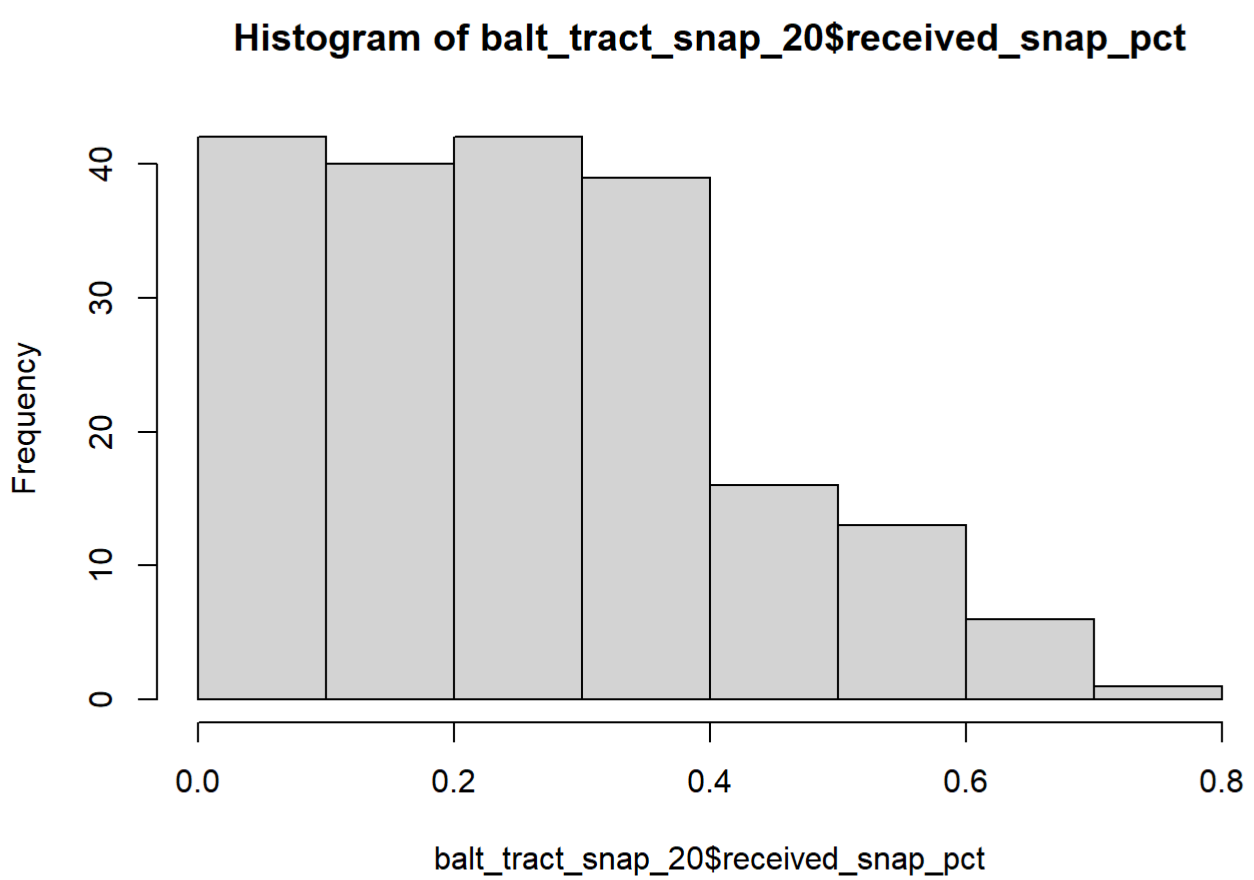
Problematically Reducing Race and Ethnicity into 5 Categories

- NH White
- NH Black
- Hisp/Latx
- NH Asian
- NH Multi/Other

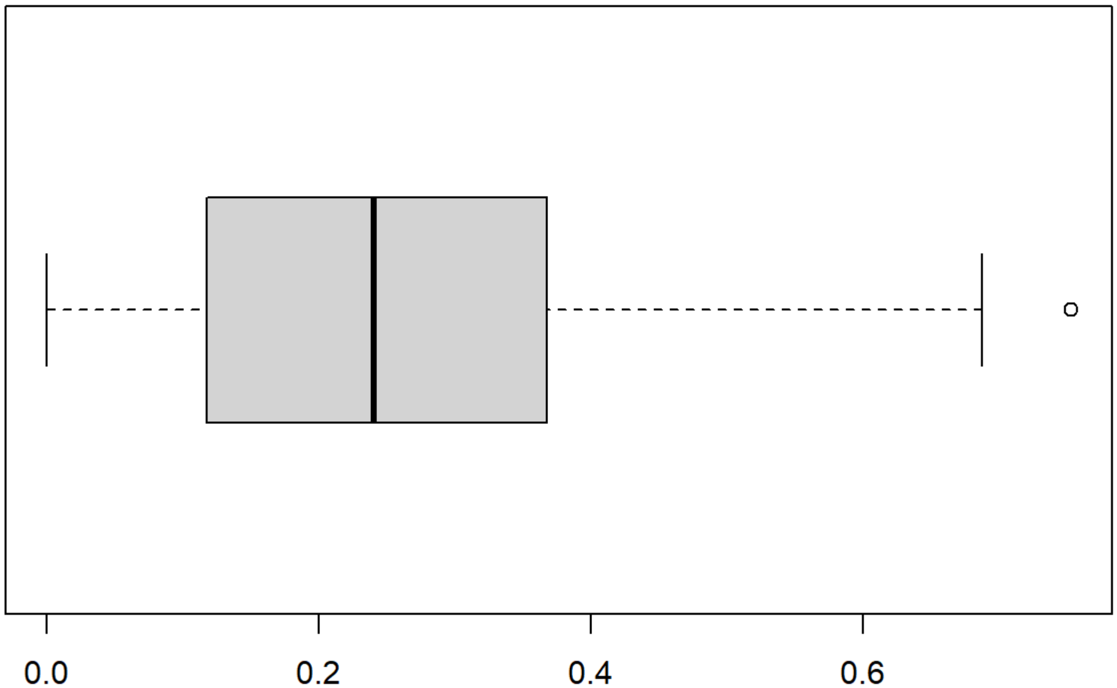
```
# Computes the NH Asian Population
balt_tract_snap_20$pop_nhasianXE <-
  balt_tract_snap_20$pop_nhasianE + balt_tract_snap_20$pop_nhhwnpiE
# Computes the NH "Other" Population
balt_tract_snap_20$pop_nhotherXE <-
  balt_tract_snap_20$pop_nhamindE + balt_tract_snap_20$pop_nhotherE + balt_tract_snap_20$pop_nht
womrE

# Computes percent of total households receiving food stamps
balt_tract_snap_20$received_snap_pct <- balt_tract_snap_20$received_snapE/balt_tract_snap_20$hou
se_totalE

# Replace NaNs with 0
balt_tract_snap_20$received_snap_pct[is.nan(balt_tract_snap_20$received_snap_pct)] <- 0
balt_tract_snap_20$received_snap_pct <- as.numeric(balt_tract_snap_20$received_snap_pct)
```

Analyzing the Household SNAP Reciepents

```
hist(balt_tract_snap_20$received_snap_pct)
```

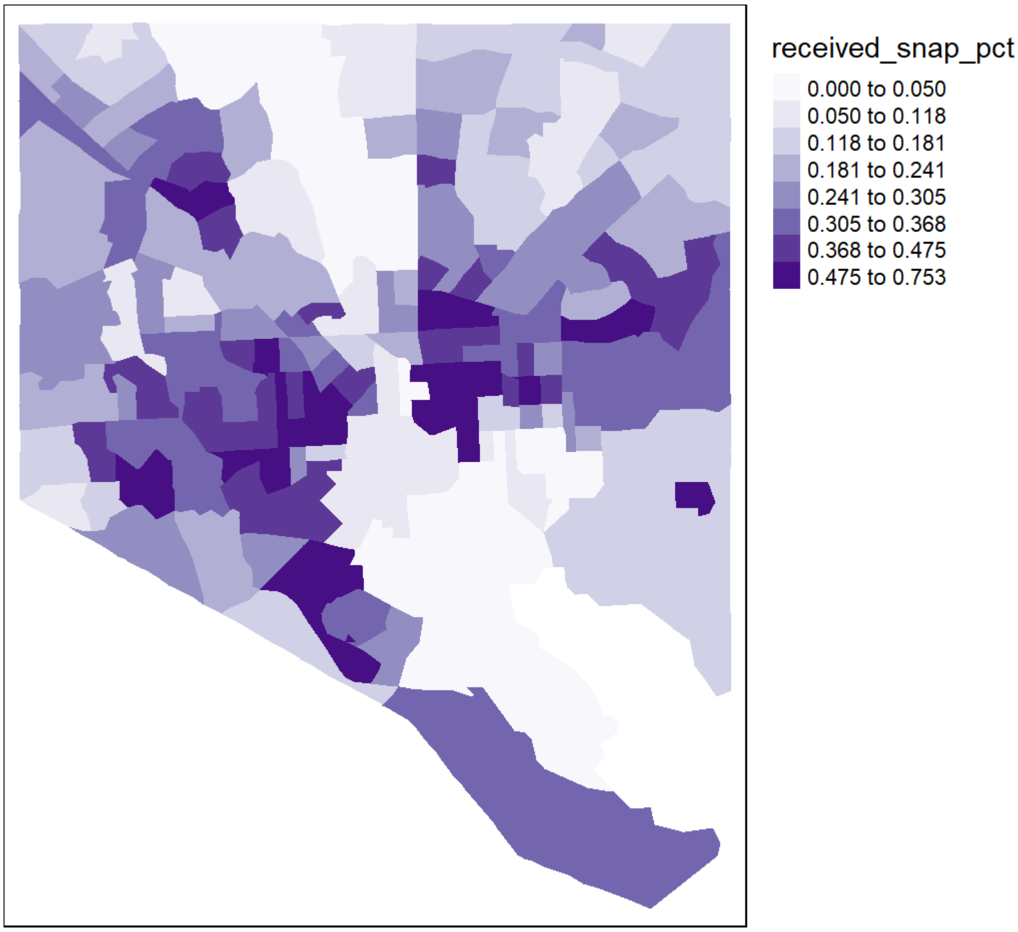



```
boxplot(balt_tract_snap_20$received_snap_pct, horizontal = TRUE)
```



Map of the percent of households receiving SNAP

```
tm_shape(balt_tract_snap_20) + tm_fill(col="received_snap_pct", style="quantile", n=8, palette=
"Purples") +
              tm_legend(outside=TRUE)
```



Creating a matrix of neighboring polygons for each tract.

Queen's Neighbor

```
balt_tract_snap_nb  <- poly2nb(balt_tract_snap_20, queen=TRUE)
balt_tract_snap_lw  <- nb2listw(balt_tract_snap_nb, style="W", zero.policy=TRUE)
```

Compute Moran's I

```
balt_tract_snap_moran <- moran.test(balt_tract_snap_20$received_snap_pct, balt_tract_snap_lw)
balt_tract_snap_moran
```

```
##
##  Moran I test under randomisation
##
## data:  balt_tract_snap_20$received_snap_pct
## weights: balt_tract_snap_lw
##
## Moran I statistic standard deviate = 11.533, p-value < 2.2e-16
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##       0.468594935      -0.005050505       0.001686689
```

Moran’s I interpretation SNAP Receiptants

With a Moran’s I of 0.47 there is a less than 1 % chance that this clustered pattern is a result of random chance.

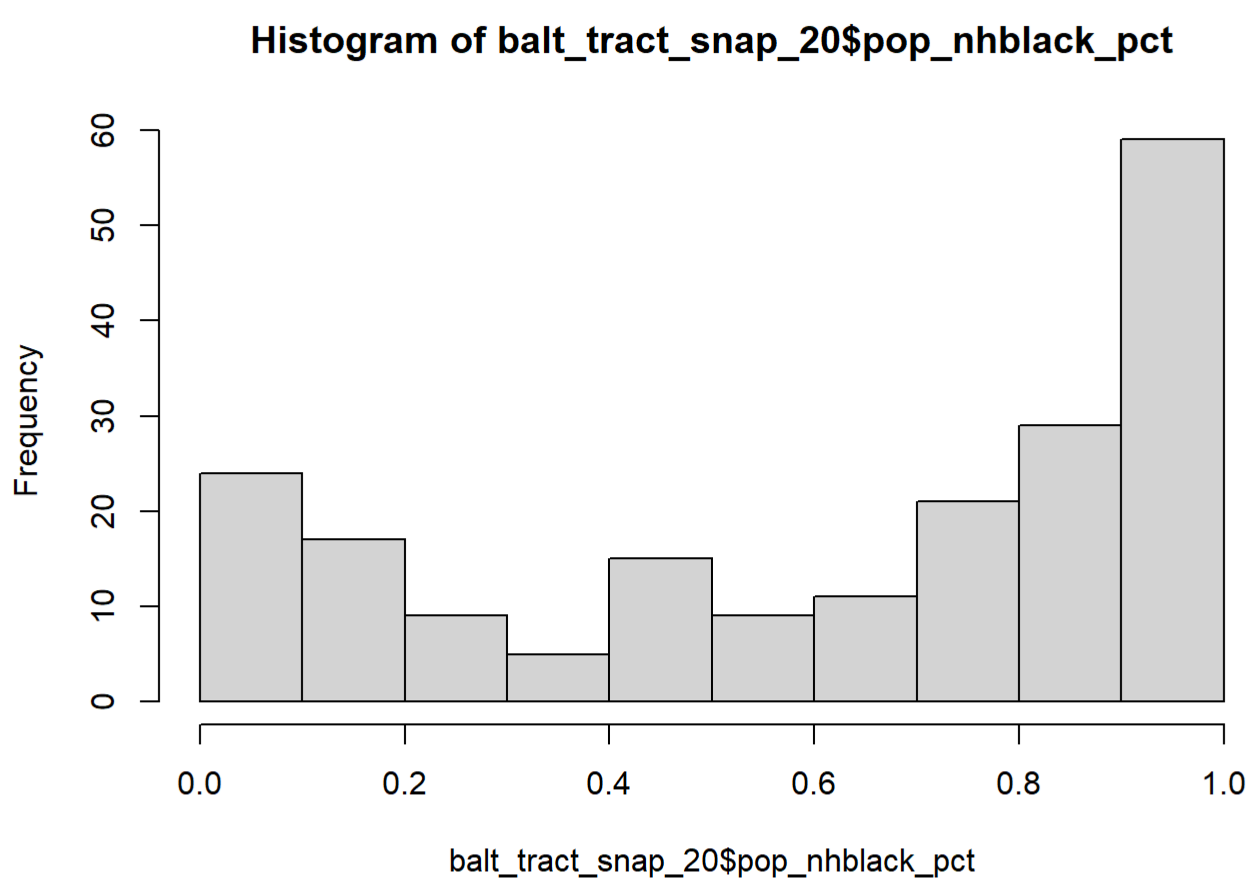
Moran’s I for Non-Hispanic Black

Data Prep

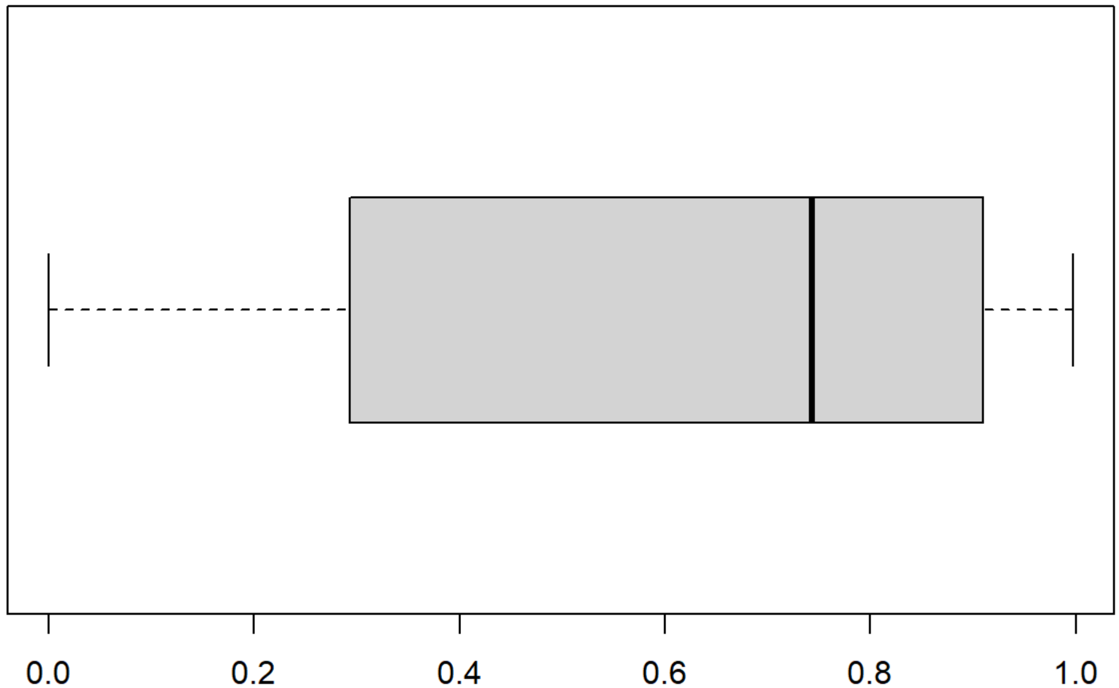
```
# Computes percent of non-hispanic black population
balt_tract_snap_20$pop_nhblack_pct <- balt_tract_snap_20$pop_nhblackE/balt_tract_snap_20$popE

# Replace NaNs with 0
balt_tract_snap_20$pop_nhblack_pct[is.nan(balt_tract_snap_20$pop_nhblack_pct)] <- 0
balt_tract_snap_20$pop_nhblack_pct <- as.numeric(balt_tract_snap_20$pop_nhblack_pct)
```

Analyzing the Percent Non-Hispanic Black Population

```
hist(balt_tract_snap_20$pop_nhblack_pct)
```

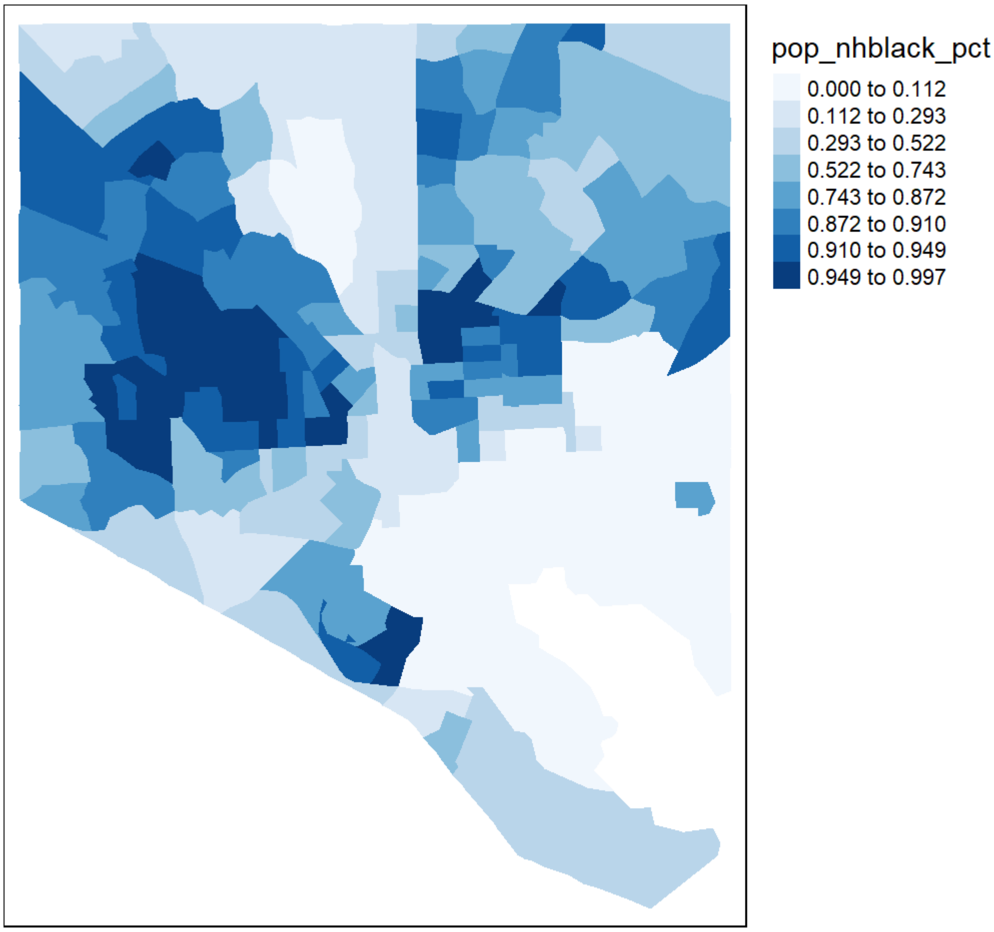



```
boxplot(balt_tract_snap_20$pop_nhblack_pct, horizontal = TRUE)
```



Map of the percent NH Black Population

```
tm_shape(balt_tract_snap_20) + tm_fill(col="pop_nhblack_pct", style="quantile", n=8, palette="Bl
ues") +
            tm_legend(outside=TRUE)
```



Even with a change in variable, the queen’s neighbors and the neighbors weight do not change because the geometry and the number of attributes are the same.

Compute Moran’s I

```
balt_tract_black_moran <- moran.test(balt_tract_snap_20$pop_nhblack_pct, balt_tract_snap_lw)
balt_tract_black_moran
```

```
##
##  Moran I test under randomisation
##
## data:  balt_tract_snap_20$pop_nhblack_pct
## weights: balt_tract_snap_lw
##
## Moran I statistic standard deviate = 15.778, p-value < 2.2e-16
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##       0.644329446      -0.005050505       0.001693820
```

Moran’s I Interpretation for Percent NH Black Population

With a Moran’s I of 0.64, there is less than 1 % chance that this pattern is clustered by random chance.

Data Source: U.S. Census Bureau American Community Survey 5 Year Estimate

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A Critical Physical Geography of Urban Soil Contamination
Review and Comments

There is a delicate balance to consider all concepts and stakeholders affected by a research topic. The understanding that lead (Pb) contaminated soil is not just an ecological or human health error, that is this is a social justice issue is critical. The disciple Critical Physical Geography (CPG) is one approach for handling the previous limitations of soil contamination research. This report focuses on the groundwork for CPG of urban soil contamination, attempting to answer the question, "how might a CPG approach provide new insights into the socio-spatial origins and impacts of urban soil Pb (McClintock, 2015)?" Throughout history, many forms of anthropogenic Pb have been found in soils, from mining and factories to standard house paint. When the devastating health problems were identified, there was a slow movement to reduce Pb exposure and increase Pb poisoning prevention initiatives. These contaminated Pb soils fall into the categories of urban soils or soils that are human-altered. Urban soils have previously been analyzed at various small scales, but McClintock (2015) and CPG focus on city-scale for examining Pb soil patterns in relation to the history of fluctuation social metabolism. McClintock (2015) starts by creating a thematic series, which displays the white population distribution, living in poverty distribution, soil Pb concentration, and blood Pb concentrations. These maps show that the flatland areas of Oakland have the most soil Pb concentration, a higher percentage of living in poverty, and lower percentages of the white population. A spatial regression of log was also calculated, showing that old housing stock is the only significant explanatory variable. Some strengths in this research are the research extent; as the author stated, research of soils is often small scale and does not consider any outside factors. Another strength is assessing multiple factors and looking into the history of the area. The redlining map that is examined gives a better understanding of the relationship between the change in the Pb concentration through time and how that concentration could have driven social injustice. One of the weaknesses is the limited discussion on any remediation done in the area. Similarly, he doesn't display a soil Pb concentration change over time. These are not direct connections to the human well-being aspect of this research, but it is vital to consider when looking for and pushing for improvement.

Reference

McClintock, N. (2015). A critical physical geography of urban soil contamination. *Geoforum*, *65*, 69-85.