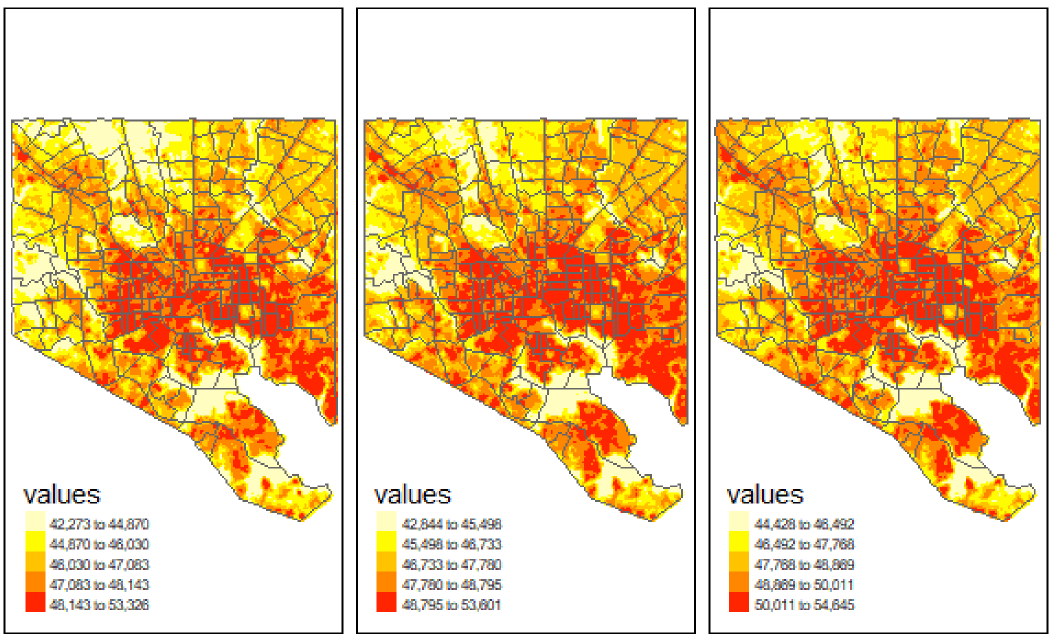
The Urban Heat Island Effect and its Correlates in Baltimore

The urban heat island effect is a phenomenon where inner cities tend to be hotter than areas further out because of man-made materials absorbing heat better than natural ground and activities that generate or trap heat. In this project, I mapped surface temperature in Baltimore City with several other factors to see what patterns correlated with the heat island effect.

I obtained surface temperature from EarthExplorer using LandSat Surface Temperature data. I searched for images taken between June and August and chose the images that had no cloud cover in Baltimore. I downloaded the large data tile containing Baltimore for each year and cropped it using the Baltimore census tract geometry. I used tmap to plot the three Surface Temperature maps side by side. The pattern of warmer and cooler areas is constant between the years, so for further analysis I chose to use only 2020.

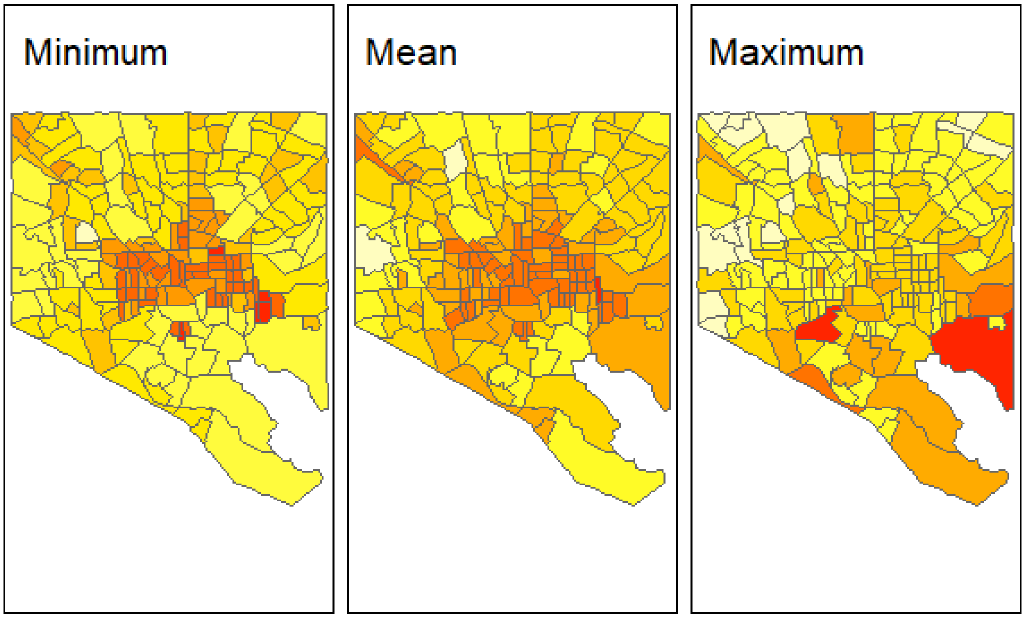



```{r}

# for reference area

year_built <-get_acs(

 geography = "tract",

 variables = "B25034_001",

 state = "MD",

 year=2015,

 county = "Baltimore City",

 geometry = TRUE)
```

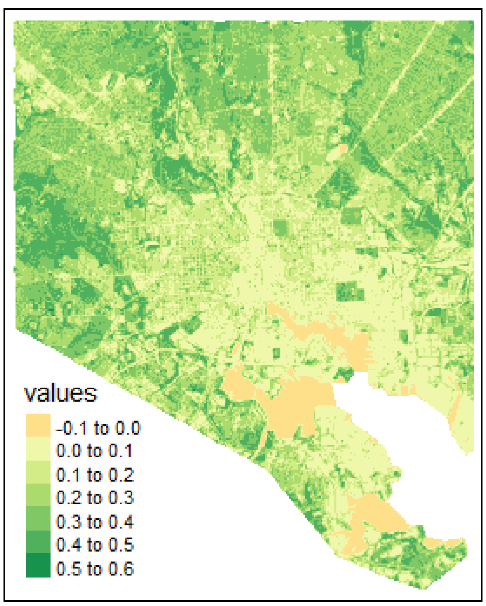
```
baltcity<-year_built$geometry

heat <- colorRampPalette(c('#FFFDBF','#FFFB01','#FFC300', '#FF8700', '#FF2500'))

#2015

heat2015<-rast("C:/Users/rache/OneDrive/Documents/Advanced GIS
Mahmoudi/A.final/2015heat/LC08_CU_028008_20150716_20210502_02_ST_B10.TIF")

heat15proj<-terra::project(heat2015, 'epsg:4269')
heat15crop<-terra::crop(heat15proj, vect(baltcity))
heat15<-terra::mask(heat15crop, vect(baltcity))

heatmap15<-tm_shape(heat15)+
  tm_raster(legend.show = TRUE, palette = heat(5), style="fisher")+
  tm_shape(baltcity)+
  tm_borders()+
  tm_layout(legend.position = c('left','bottom'))



#2018

heat2018<-rast("C:/Users/rache/OneDrive/Documents/Advanced GIS
Mahmoudi/A.final/2018heat/LC08_CU_028008_20180708_20210503_02_ST_B10.TIF")

heat18proj<-terra::project(heat2018, 'epsg:4269')
heat18crop<-terra::crop(heat18proj, vect(baltcity))
heat18<-terra::mask(heat18crop, vect(baltcity))
```

```
heatmap18<-tm_shape(heat18)+
  tm_raster(legend.show = TRUE, palette = heat(5), style="fisher")+
  tm_shape(baltcity)+
  tm_borders()+
  tm_layout(legend.position = c('left','bottom'))


#2020
heat2020<-rast("C:/Users/rache/OneDrive/Documents/Advanced GIS Mahmoudi/A.final/2020heat/LC08_CU_028008_20200729_20210504_02_ST_B10.TIF")

heat20proj<-terra::project(heat2020, 'epsg:4269')
heat20crop<-terra::crop(heat20proj, vect(baltcity))
heat20<-terra::mask(heat20crop, vect(baltcity))

heatmap20<-tm_shape(heat20)+
  tm_raster(legend.show = TRUE, palette = heat(5), style="fisher")+
  tm_shape(baltcity)+
  tm_borders()+
  tm_layout(legend.position = c('left','bottom'))



tmap_arrange(heatmap15,heatmap18,heatmap20, ncol=3, nrow=1)
```

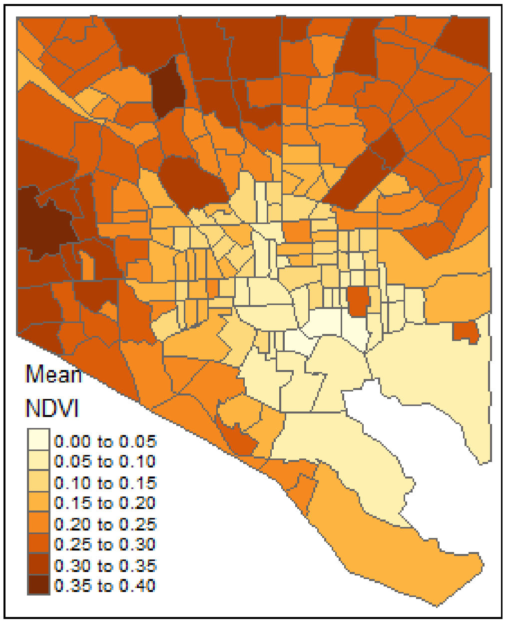
Next I extracted the values from the raster into each tract polygon. Because the temperature is so variable, I included maps of extracted values representing minimum and maximum in addition to mean.

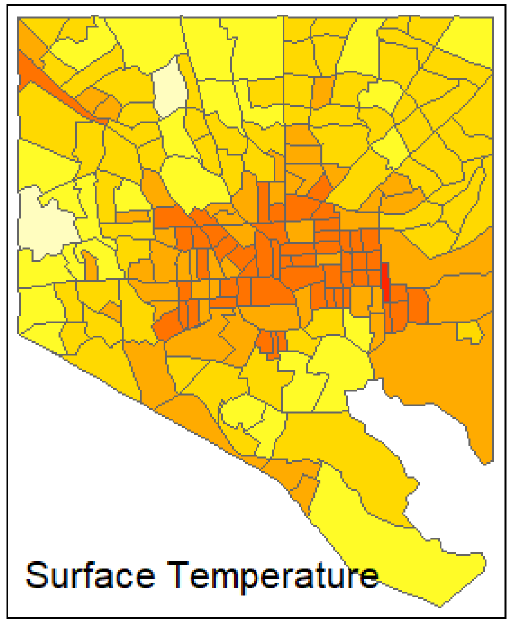


The most likely factor in determining severity of the heat island effect is surface material. Plants are known to regulate heat, so I wanted to compare level of vegetation to surface temperature. In order to include both tree canopy and smaller areas of vegetation like grass, I chose to use the Normalized Difference Vegetation Index (NDVI). I downloaded the individual bands 4 and 5 from EarthExplorer for the 2020 image and did raster calculations in R.



In order to use a Pearson's product-moment correlation test, I extracted the NDVI to the same census tracts as the surface temperature data.

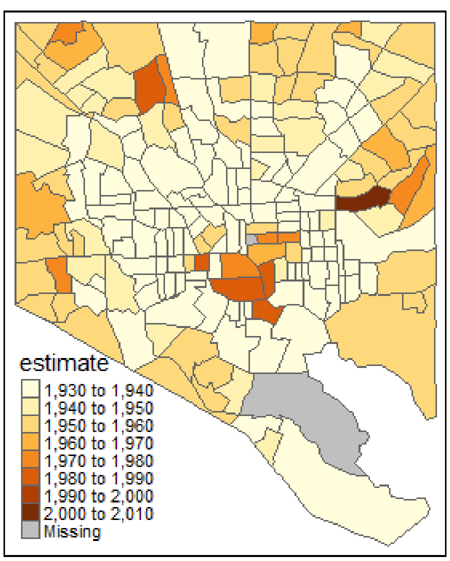


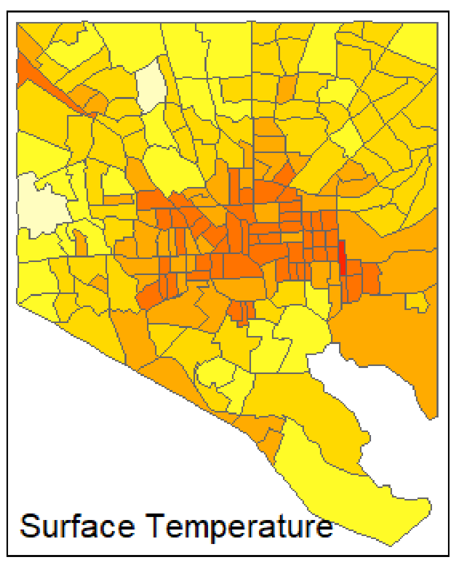


The correlation was -0.790 with a p-value less than 2.2 x 10^-16 (included in summary table below).

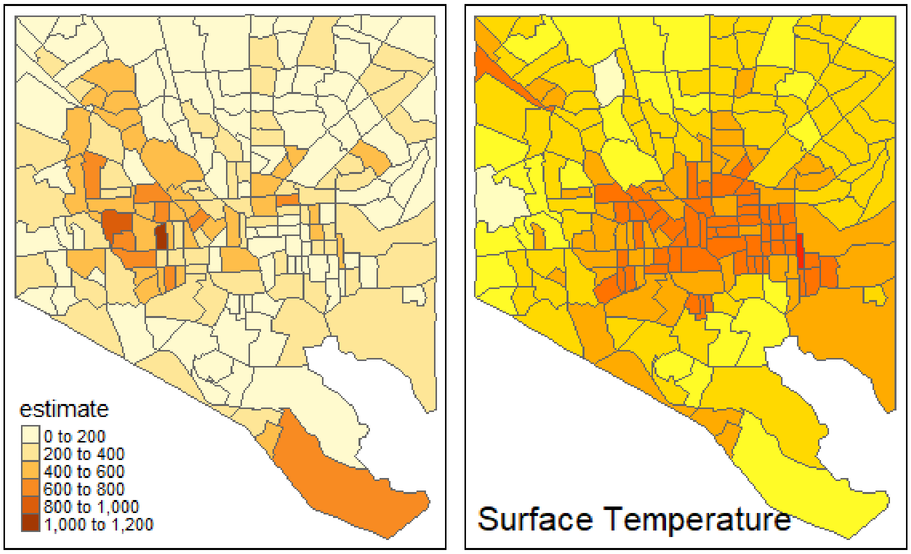
I also got data from the census bureau via the tidycensus package in R. Variables were vacancies, median year structures built, median value of homes, average yearly income, and percent of residents that have no vehicle available to them. I compared each of these to surface temperature by mapping them side by side and performing the Pearson's correlation test on each.

Year built

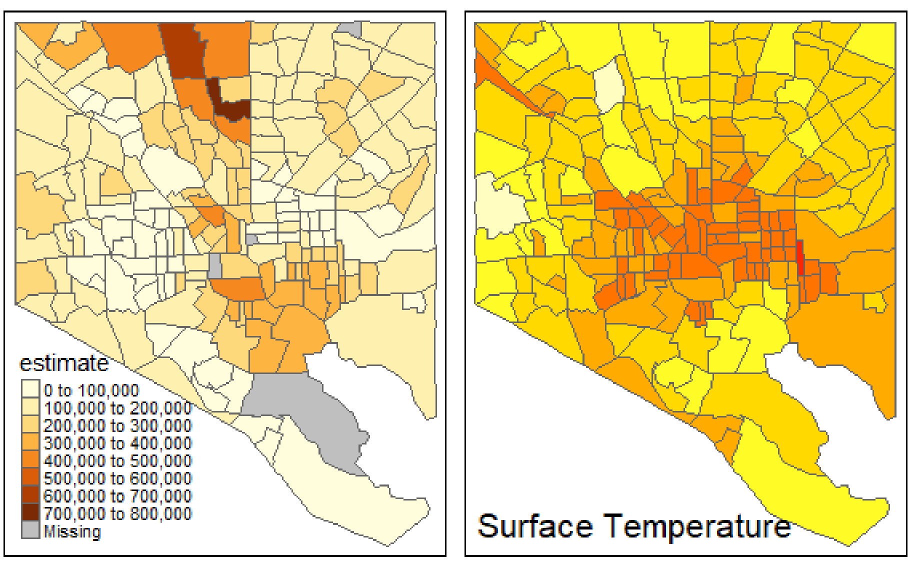




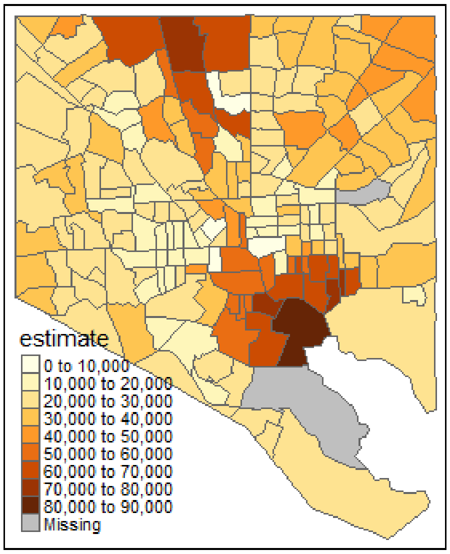
Vacancy

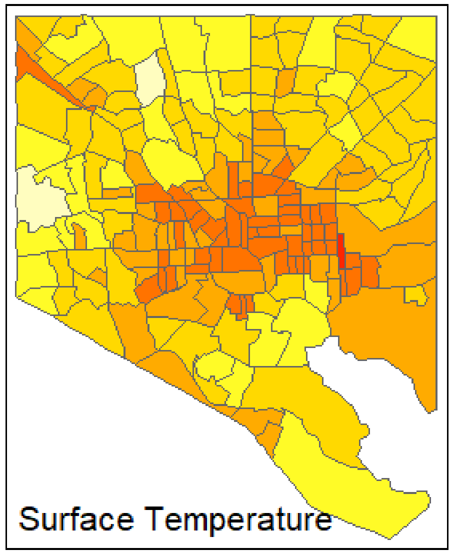


Median Value

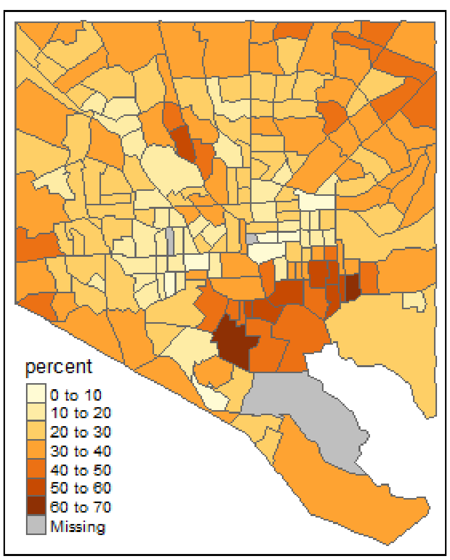


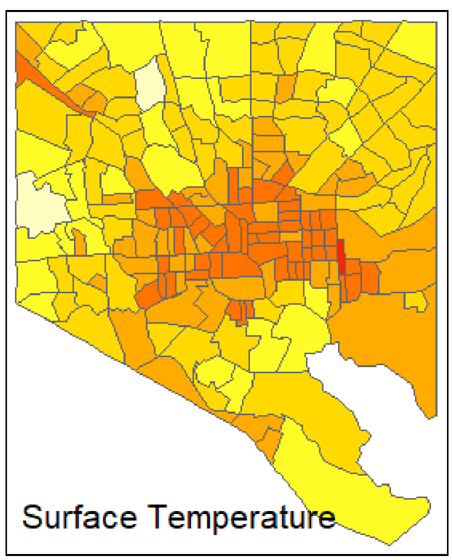
Yearly Income





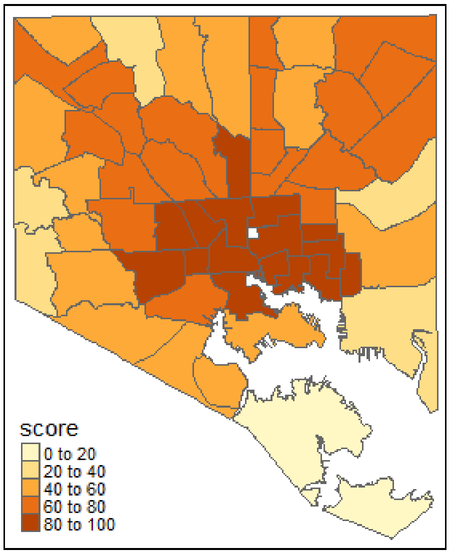
Percent with No Vehicle

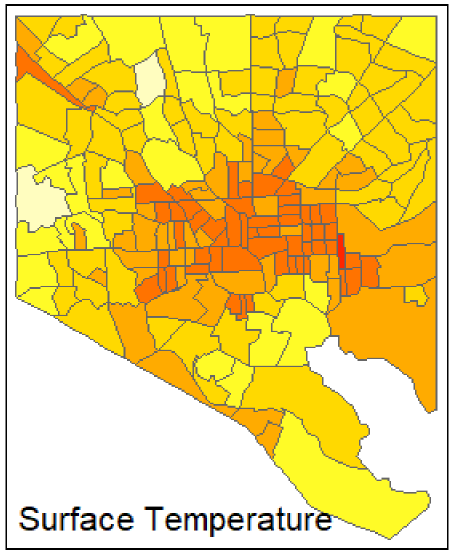




There is a measure called a walkability score which measures how easy it is to walk to things like grocery stores, banks, schools and other essential places. Baltimore was assessed most recently in 2017, and data is available via the openbaltimore site. Values range from 0-100, with 100 being the best score for a given area. I mapped this next to surface temperature.

Walkability Score





Because the scores were calculated by Community Statistical Area, I had to extract the values to census tracts to compare them using a Pearson's test. The results from this and the other tests is below. Red indicates a p-value less than 0.05, and therefore not a likely correlation. Green indicates a p-value below 0.05.

variable	correlation	p-value
NDVI	-0.79	0.00000000000000022
vacancy	0.228	0.00000000000000022
year built	-0.02	0.76100000000000000
median value	-0.1	0.00021800000000000
yearly income	-0.129	0.00000293100000000
no vehicles	-0.211375	0.00000000000001070
walkability	0.688	0.00000000000000022

NDVI has a very small p-value, indicating a high likelihood of correlation. It also has the strongest correlation, which is negative. This means as surface temperature increases, NDVI decreases. Vacancy has a very small p-value and a correlation of positive .2. This indicates that it there are more vacancies where it is hotter in the city. Year built was the only variable I tested that turned out to have a p-value indicating correlation. Median value has a small p-value and a correlation of -0.1, meaning there is a loss of median value as census tracts get hotter. Likewise, yearly income of residents appears to decrease as surface temperature increases.

On the bright side, some variables showed that those in hotter areas of the city were better off. The percent of people without a vehicle had a p-value almost as small as NDVI and vacancy, with a correlation of -0.2, meaning there are more people with available cars in hotter areas. Also, walkability had a p-value just as small as NDVI with a correlation of 0.688, showing that those in hotter areas have better access to essential places.