

Homework 1

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Homework 1 Assignment

Assignment here: <https://eds-223-geospatial.github.io/assignments/HW1.html>

Github Repo here: <https://github.com/cnordheim-maestas/eds-223-hw1.git>

Setup

```
library(stars) # for raster data
library(tmap) # for static and interactive maps
library(tidyverse) # wrangling
library(sf) # vectors
library(here) # File pathing
library(viridisLite) # colors
```

Read in data

```
## read in data
# read in geodatabase of EJScreen data at the Census Block Group level
ejscreen <- sf::st_read(here("data", "ejscreen",
                           "EJSCREEN_2023_BG_StatePct_with_AS_CNMI_GU_VI.gdb"),
                      quiet = TRUE)

# California
# filter to state of CA
california <- ejscreen %>%
  dplyr::filter(ST_ABBREV == "CA")
```

```

# find the average values for all variables within the county
ca_counties <- aggregate(california,
                        by = list(california$CNTY_NAME),
                        FUN = mean)

# New Mexico
# filter to state of NM
nm<- ejsscreen %>%
  dplyr::filter(ST_ABBREV == "NM")

# find the average values for all variables within the county
nm_counties <- aggregate(nm, by = list(nm$CNTY_NAME),
                        FUN = mean)

```

Map 1

Plot Percent of people of color and the diesel particulate matter pollution relationship across counties in CA

```

# base map: california counties outlined

ca_map <- tm_shape(ca_counties) + # vector data, use tmshape.
  tm_graticules() + # add graticules at this layer

# next layer: fill by percent people of color
tm_polygons(fill = "PEOPCOLORPCT", # column name with the values
# specify the color scale, using viridis because it is colorblind friendly
  fill.scale = tm_scale(values = viridis(2)),
  fill.legend = tm_legend(title = "Proportion of People of Color",
    position = tm_pos_out("right"))) +

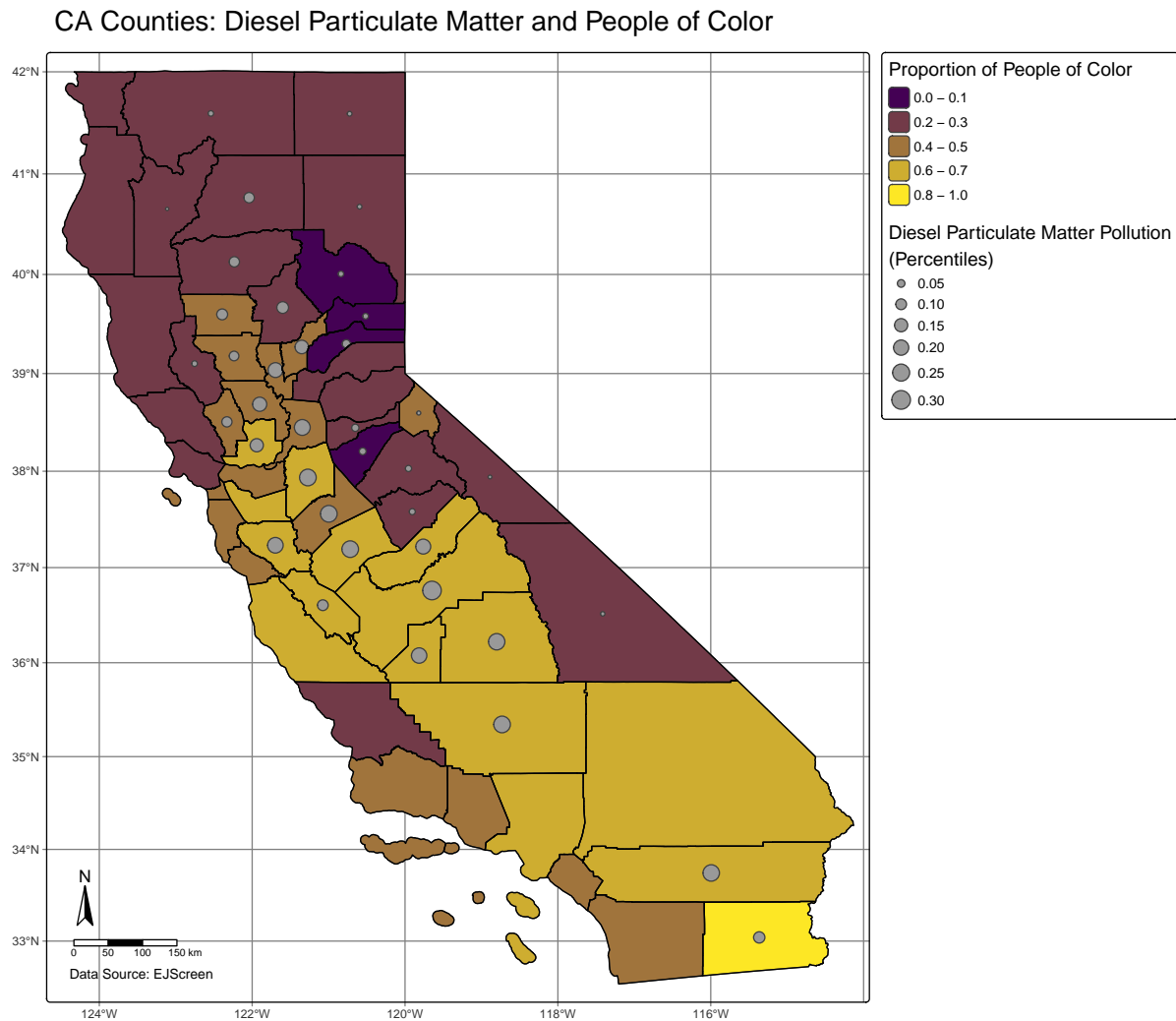
# next layer: point with diesel pollution by size
tm_symbols(size = "DSLPM",
  size.legend = tm_legend(
    title = "Diesel Particulate Matter Pollution\n(Percentiles)",
    orientation = "portrait",
    position =tm_pos_out("right"))) +

# next layer: label the counties
tm_borders(col = "black") + # borders of the counties

```

```
# add map elements
tm_title(text = "CA Counties: Diesel Particulate Matter and People of Color") +
tm_compass(show.labels = 1, position = c("left","bottom")) +
tm_scalebar(position = c("left", "bottom")) +
tm_credits("Data Source: EJScreen", position = c("left", "bottom"))
```

ca_map



Paragraph 1

This map depicts the state of California, and data is averaged by each county. Here, we can see that the proportion of People of Color (denoted by increasingly more yellow color) has a distinct geographical pattern, with values being higher in the Central Valley and Southern California. This map also shows the amount of Diesel Particulate Matter Pollution, where larger circles denote higher pollution levels, where the values are also higher in the Central Valley, though we are missing this data from the coastal counties of California. Interestingly, there seems to be a correlation with higher Diesel Particulate Matter in counties with more People of Color, which is a huge environmental justice issue. From this map, I would suggest to lawmakers to focus on reducing the adverse effects of pollution levels in the counties where the Diesel Pollution is highest. Moreover, they need to ensure that there is equal access to healthcare across racial groups, especially in areas with a high proportion of people of color, as more pollution exposure leads to a higher health risk. I would even recommend targeted research into how accessible and affordable healthcare is for people of color in these counties, to pinpoint barriers and improve access.

Map 2

Now let's look at the same comparison but in another state to see if the trend holds, and make some different stylistic choices to play with tmap

```
# base map: california counties outlined
nm_map <- tm_shape(nm_counties) + # vector data, use tmsshape.
  tm_graticules() + # add graticules at this layer

# next layer: fill by percent people of color
tm_polygons(fill = "PEOPCOLORPCT", # column name with the values
  # specify the color scale, using viridis because it is colorblind friendly.
  # same color scale as other map for easy comparisons
  fill.scale = tm_scale(values = viridis(2)),
  # title of legend
  fill.legend = tm_legend(title = "Proportion of People of Color",
    # make this one up and down
    orientation = "portrait",
    # put it on the right
    position = tm_pos_out("right")))) +

# next layer: point with diesel pollution by size
tm_symbols(size = "DSLPM", # bigger dots = more diesel particulate matter pollution
```

```

# title of legend
size.legend = tm_legend(title = "Diesel Particulate Matter Pollution\n(Percentiles)",
# landscape
orientation = "landscape",
position =tm_pos_out("right"))) +
# ^ put on the right, the bottom looked weird

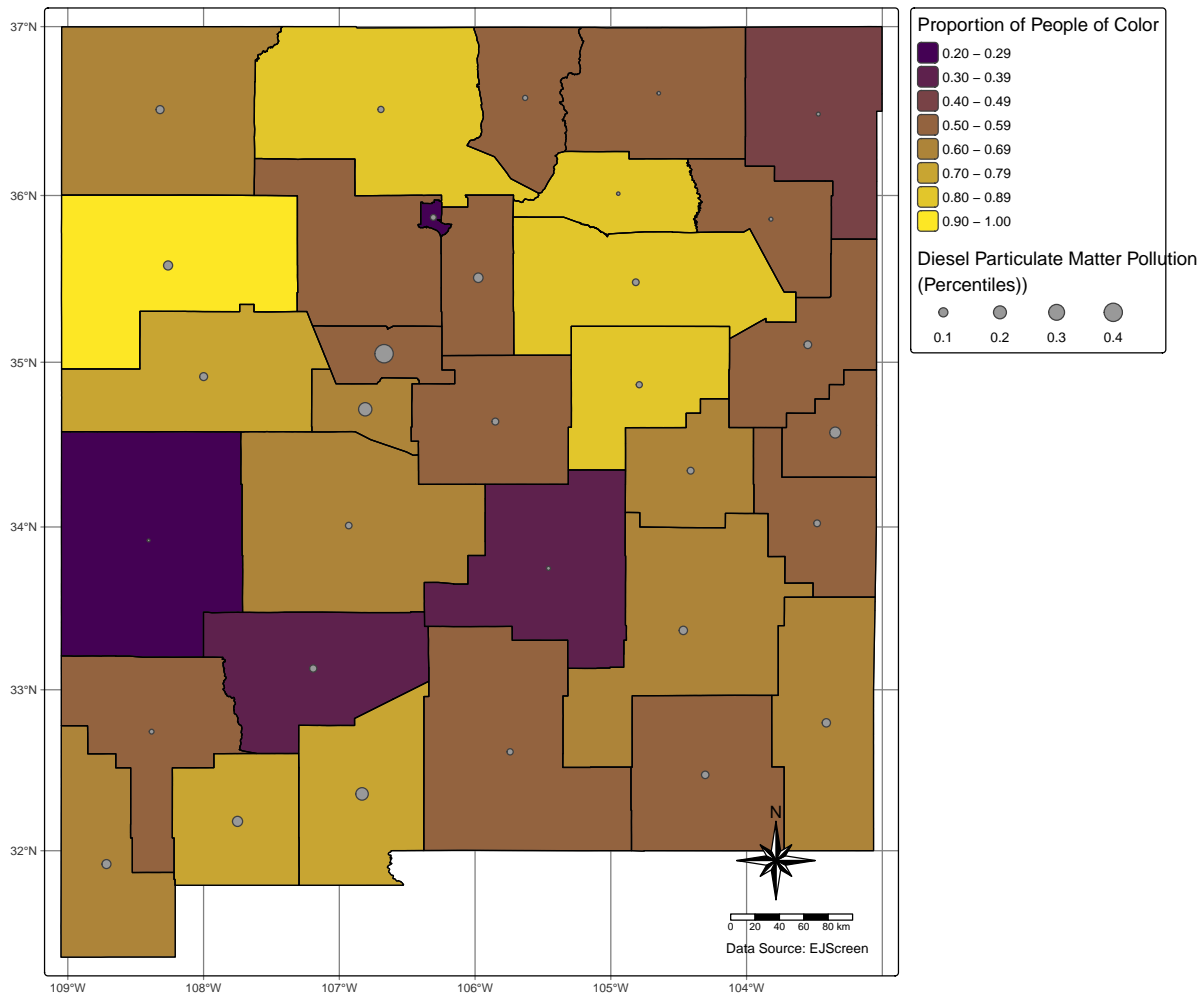
# next layer: label the counties
tm_borders(col = "black") + # borders of the counties

# add map elements
tm_title(text = "NM Diesel Pollution & People of Color") +
# add a compass, let's go with the 8star one in bottom roiht
tm_compass(show.labels = 1,
type = "8star",
position = c("right","bottom")) +
# scale bar in bottom right
tm_scalebar(position = c("right", "bottom")) +
# add data source
tm_credits("Data Source: EJScreen",
position = c("right", "bottom"))

nm_map

```

NM Diesel Pollution & People of Color



Paragraph 2

Here, I am depicting the state of New Mexico to compare and contrast the trends of demographics and pollution rate to that of California, and the data is also averaged by county. There is a less clear geographic trend of areas with more or less People of Color, compared to California, that has a clear North-South and Coastal-Inland trend. Additionally, the Diesel Particulate Matter Pollution does not have a clear geographic trend either. There does seem to be a clear pattern that the areas with a very low proportion of people of color (more purple areas) have lower levels of pollution, but it is not a linear increase with more people of color like it was in California. As the pollution levels get higher (larger dots) the counties are not necessarily more yellow, in fact, the moderate values of people of color (the oranges) seem to have the highest pollution. From this map, I would still use the counties with the largest

dots as areas to target to minimize the adverse effects of pollution by investing in healthcare and screening. In New Mexico, there is not a clear racial pattern in the pollution exposure disparities like in California, however it is always important to ensure all people have access to healthcare regardless of their race.

Appendix

Statistical exploration to select my demographic parameter and environmental parameter

Uncomment code and run if you like, but the plot is too large to knit so it is commented out here

```
# library (psych) # for correlation plot
#
# explore_counties_ca <-
#   ca_counties %>%
#   st_drop_geometry() %>%
#   dplyr::select(
#     c("PEOPCOLORPCT",
#       "LOWINCPCT",
#       "UNEMPPCT",
#       "OVER64PCT",
#       "PM25",
#       "OZONE",
#       "DSLPM",
#       "CANCER",
#       "RESP",
#       "RSEI_AIR",
#       "PRE1960PCT")) %>%
#   drop_na()
#
# cor.plot(explore_counties_ca)
#
# # There is a positive correlation with the percent of people of color
# # and the diesel particulate matter pollution in these counties in CA
#
# explore_counties_nm <-
#   nm_counties %>%
#   st_drop_geometry() %>%
#   dplyr::select(
#     c("PEOPCOLORPCT",
```

```

# "LOWINCPCT",
# "UNEMPPCT",
# "OVER64PCT",
# "PM25",
# "OZONE",
# "DSLPM",
# "CANCER",
# "RESP",
# "RSEI_AIR",
# "PRE1960PCT")) %>%
#   drop_na()
#
# cor.plot(explore_counties_nm)
#
# # that correlation disappears in New Mexico, interesting!

```