Lecture 10:
Intro to Spatial Data

Big Data and Machine Learning for Applied Economics
Econ 4676

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Announcement

- **Problem Set 1 is due next Tuesday September 15 at 11:00**
- At some point over the weekend I'll send what points everyone should present
- Assignment would be based on the groups created on `Github`
- You should consider class presentations as mini-seminars, just 2-5 minutes using one or two transparencies
- Attempt to make a concise interpretation of the relevant material, making effective use of supporting numerical and graphical evidence.

Agenda

Motivation

- In Big Data volume was only a part of the story
- Big Data are data of high complexity: anarchic and spontaneous
- They are the by product of an action: pay with credit card, tweet, move from point A to point B, buy a house, etc.
- Now we are going to center on spatial data

Motivation

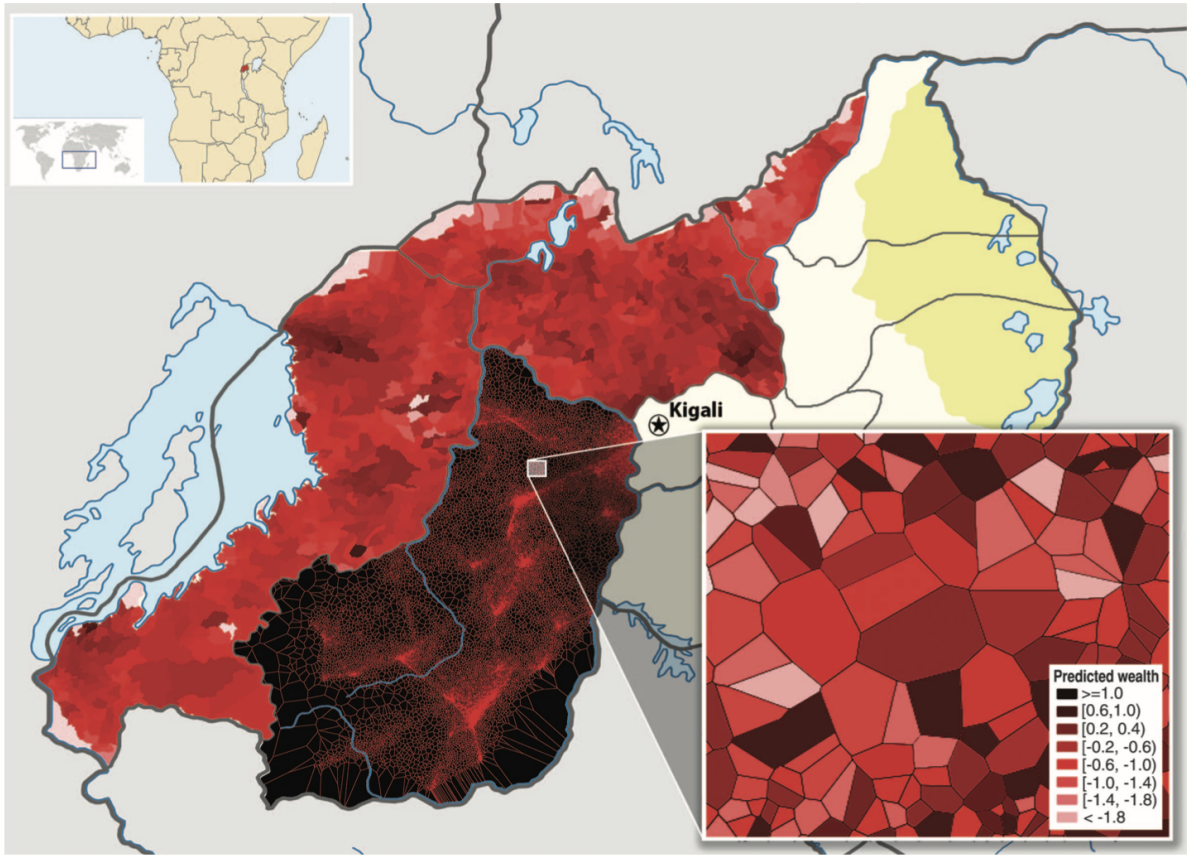
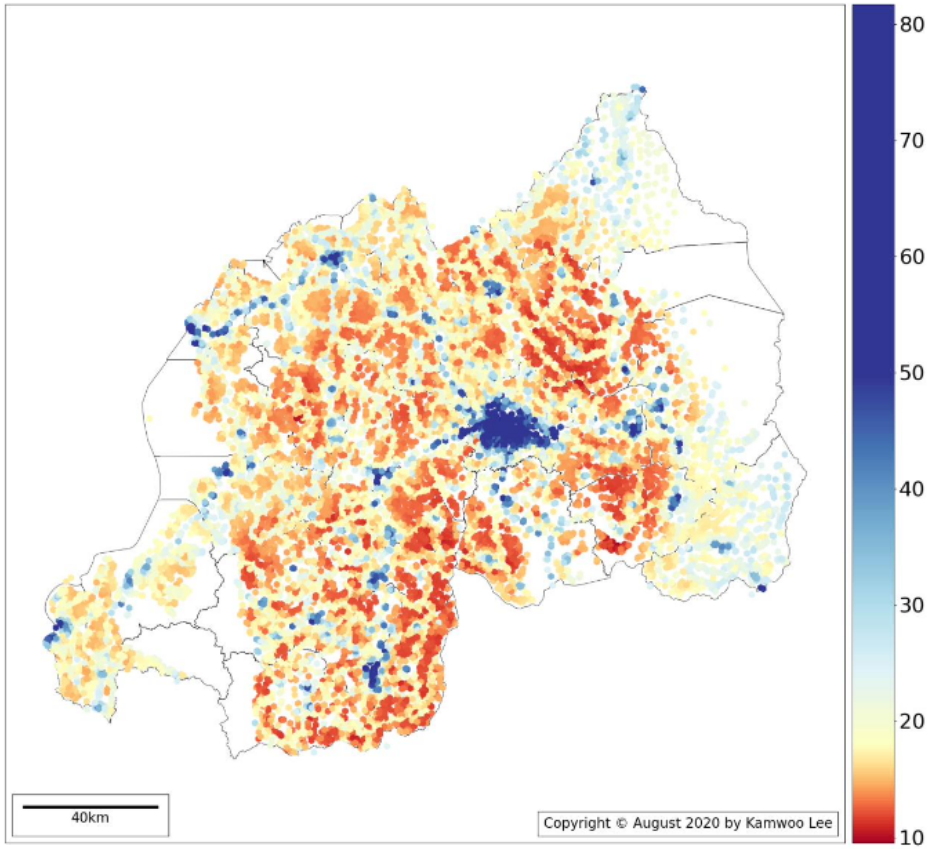


Fig. 2. Construction of high-resolution maps of poverty and wealth from call records. Information derived from the call records of 1.5 million subscribers is overlaid on a map of Rwanda. The northern and western provinces are divided into cells (the smallest administrative unit of the country), and the cell is shaded according to the average (predicted) wealth of all mobile subscribers in that cell. The southern province is overlaid with a Voronoi division that uses geographic identifiers in the call data to segment the region into several hundred thousand small partitions. (**Bottom right inset**) Enlargement of a 1-km^2 region near Kiyonza, with Voronoi cells shaded by the predicted wealth of small groups (5 to 15 subscribers) who live in each region.

Blumenstock et al (2015)

Motivation



Lee, K., & Braithwaite, J. (2020)

Datos de luces
- Datos de Encuestas
-

Types of Spatial Data

Spatial data comes in many "shapes" and "sizes", the most common types of spatial data are:

- Points are the most basic form of spatial data. Denotes a single point location, such as cities, a GPS reading or any other discrete object defined in space.
- Lines are a set of ordered points, connected by straight line segments
- Polygons denote an area, and can be thought as a sequence of connected points, where the first point is the same as the last
- Grid (Raster) are a collection of points or rectangular cells, organized in a regular lattice → data satelitales
  - altitud
  - terreno
  - Pollution
  - Comen

Types of Spatial Data: Points

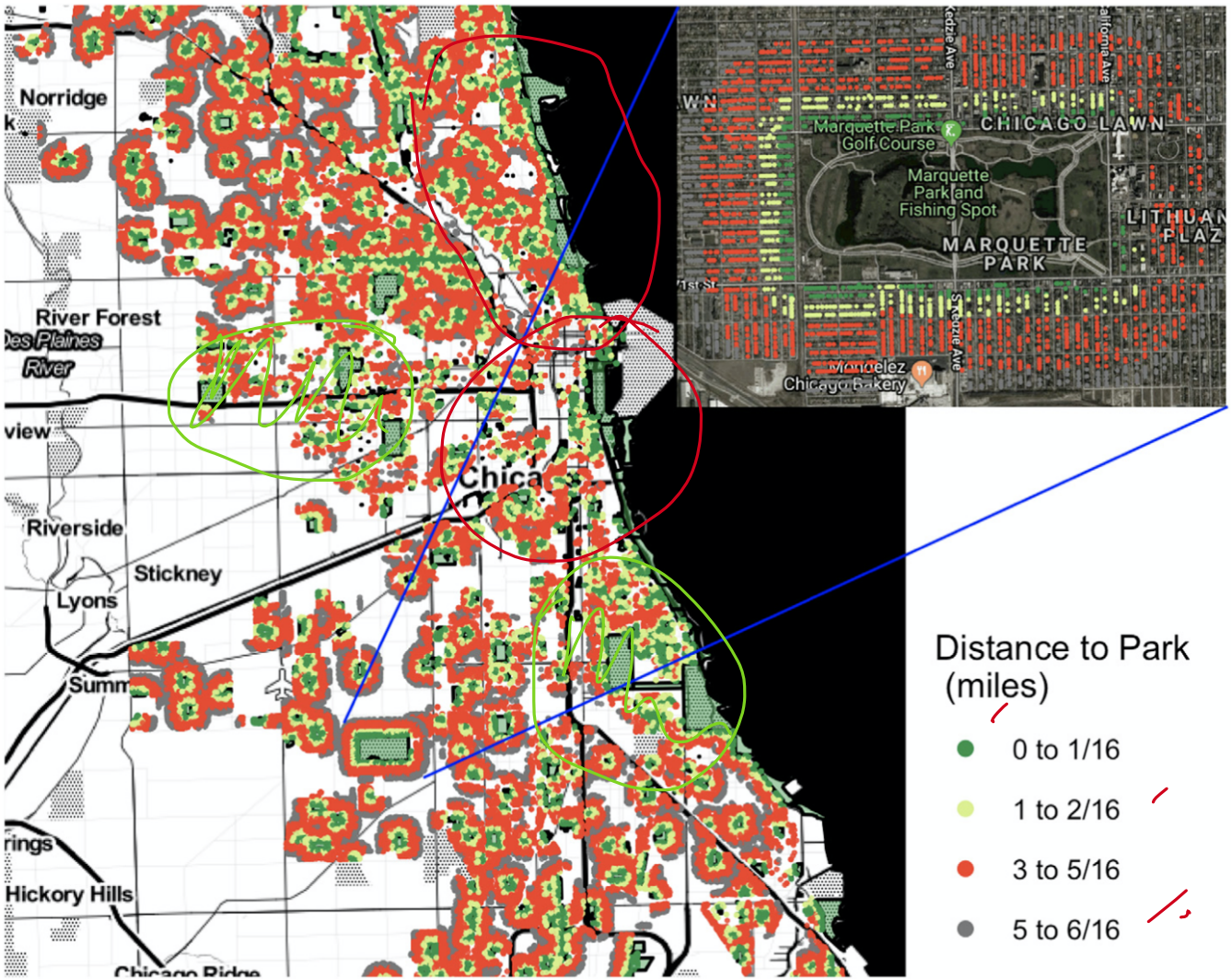


Fig. 1. Housing transactions around parks: neighborhood distance intervals. Notes: The following figure shows transactions within 3/8 miles of the nearest park in Chicago. The zoom in figure represents the 'neighborhood' around Marquette Park. It contains all of the transactions (4623) within three-eights of a mile that are not closer to another a park. Colors correspond to different distance intervals or 'bands' around the park. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Types of Spatial Data: Lines

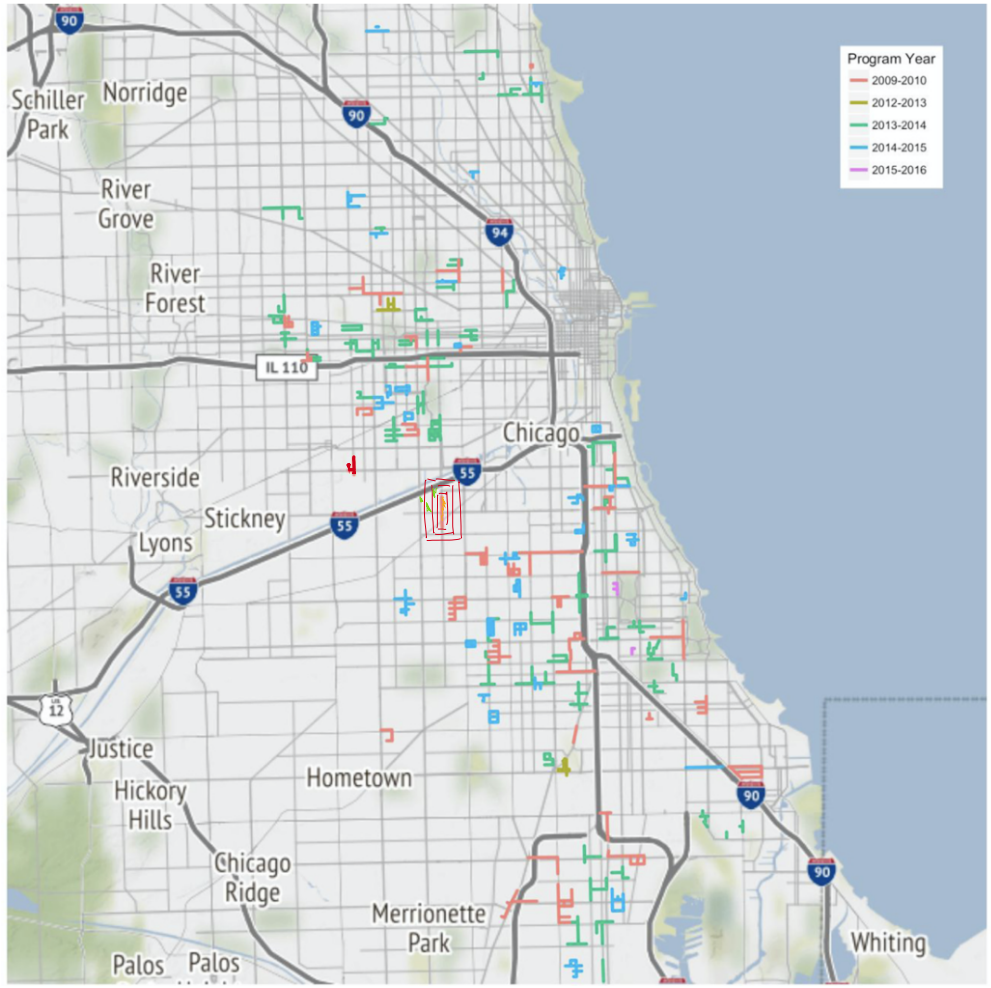
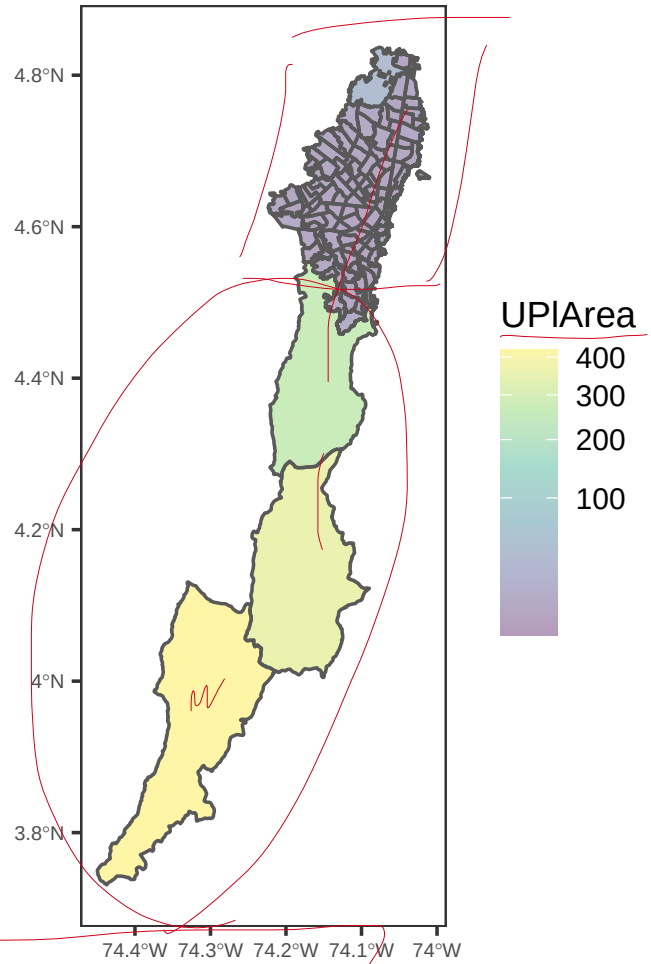


Fig. 1. Safe Passage Routes, by year of program adoption.
Note: Shapefiles with Safe Passage shape and location where obtained from the Chicago Data Portal and year that the program was launched at each location through a FOIA request.

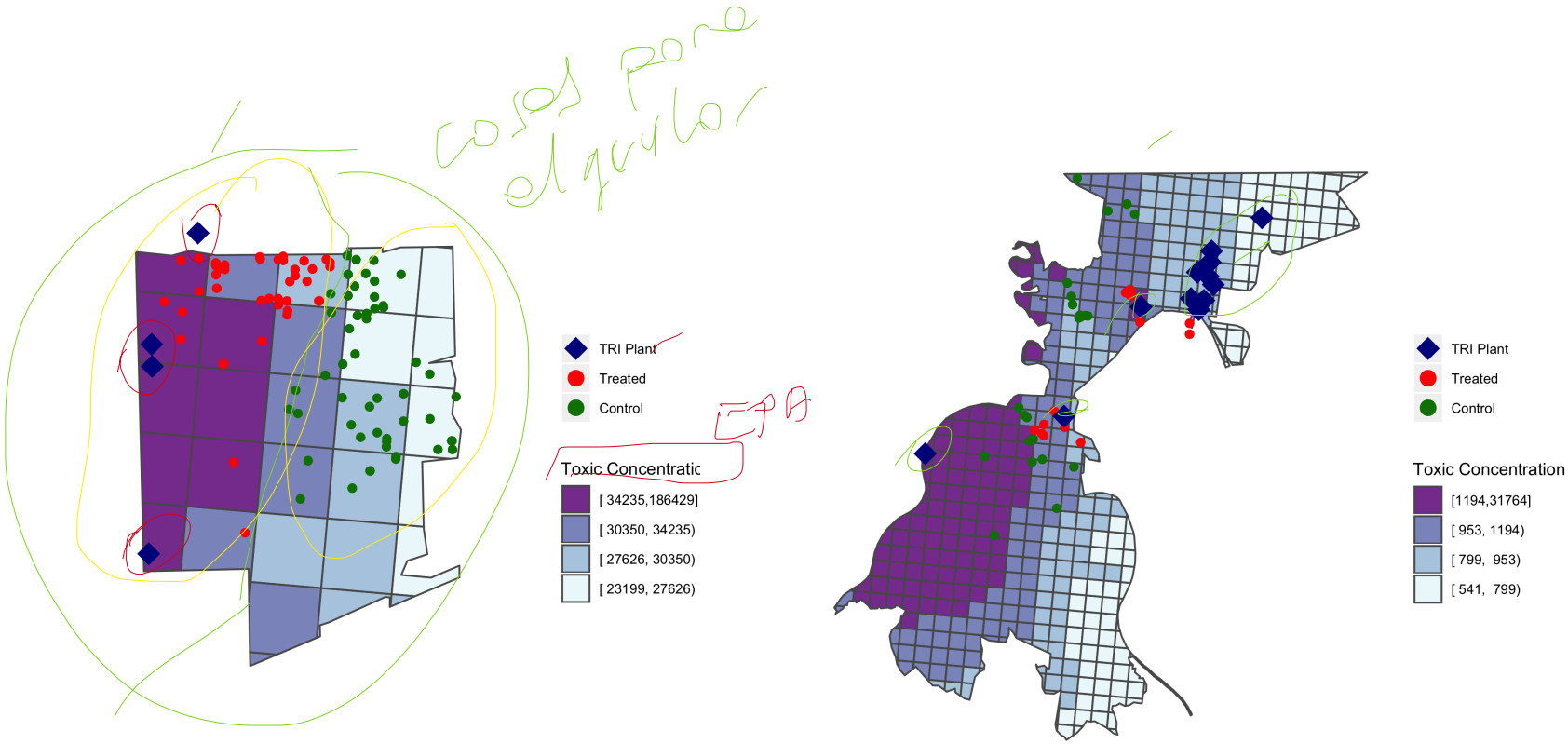
McMillen, Sarmiento-Barbieri & Singh, 2019

Types of Spatial Data: Polygons



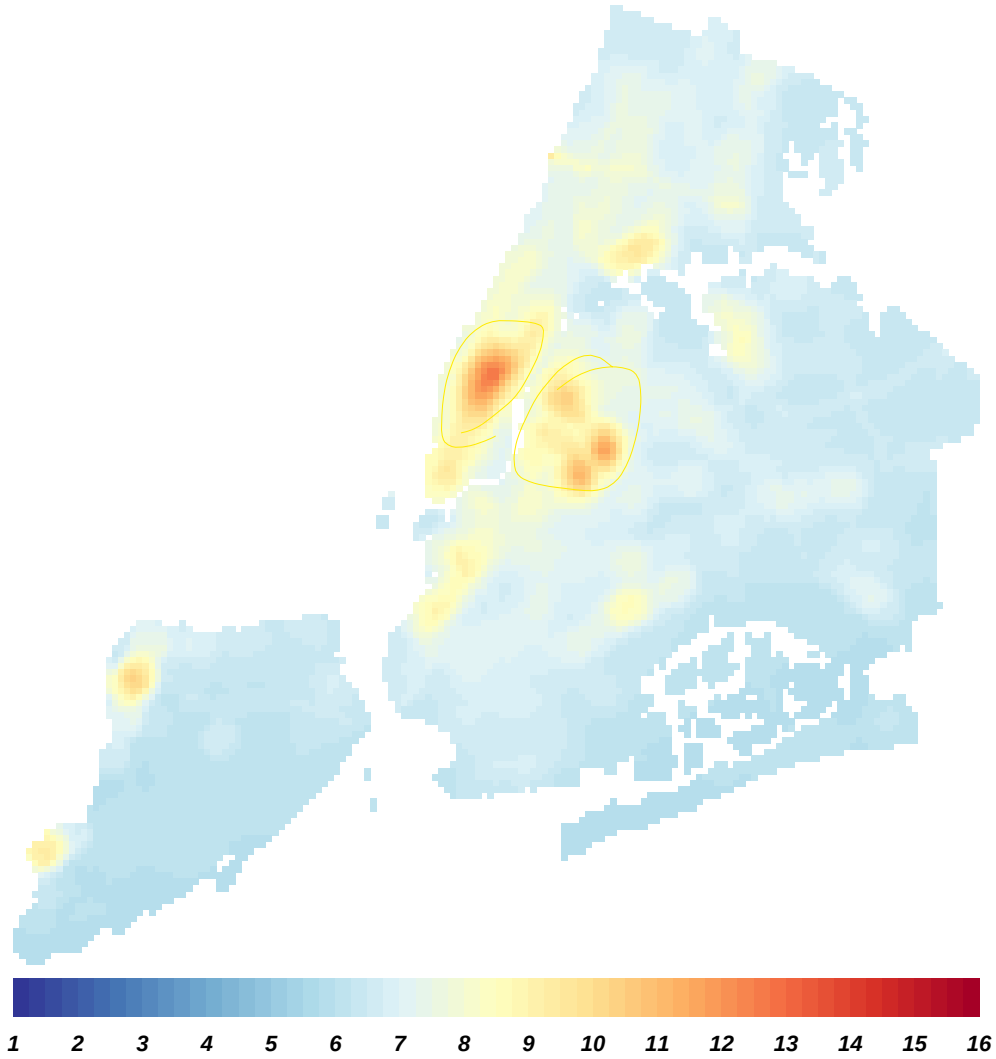
Source: https://datosabiertos.bogota.gov.co/dataset/unidad-de-planeamiento-bogota-d-c

Types of Spatial Data: Combination



Christensen,Sarmiento-Barbieri & Timmins (2020)

Types of Spatial Data: Rasters



2018-2020
PM 2.5

Source:https://data.cityofnewyork.us/Environment/NYCCAS-Air-Pollution-Rasters/q68s-8qxv

Reading and Mapping spatial data in R

- Spatial data in various formats.
- One of the most used format are `shapefiles`
- This type of files stores non topological geometry and attribute information for the spatial features in a data set
  - Main file: file.shp
  - Index file: file.shx
  - dBASE table: file.dbf
- Today I'm going to use data from `https://datosabiertos.bogota.gov.co`

Reading shapefiles in R

- Basic Packages
  - Read and handle spatial data

```
require("sf")
```

  - Plotting and data wrangling

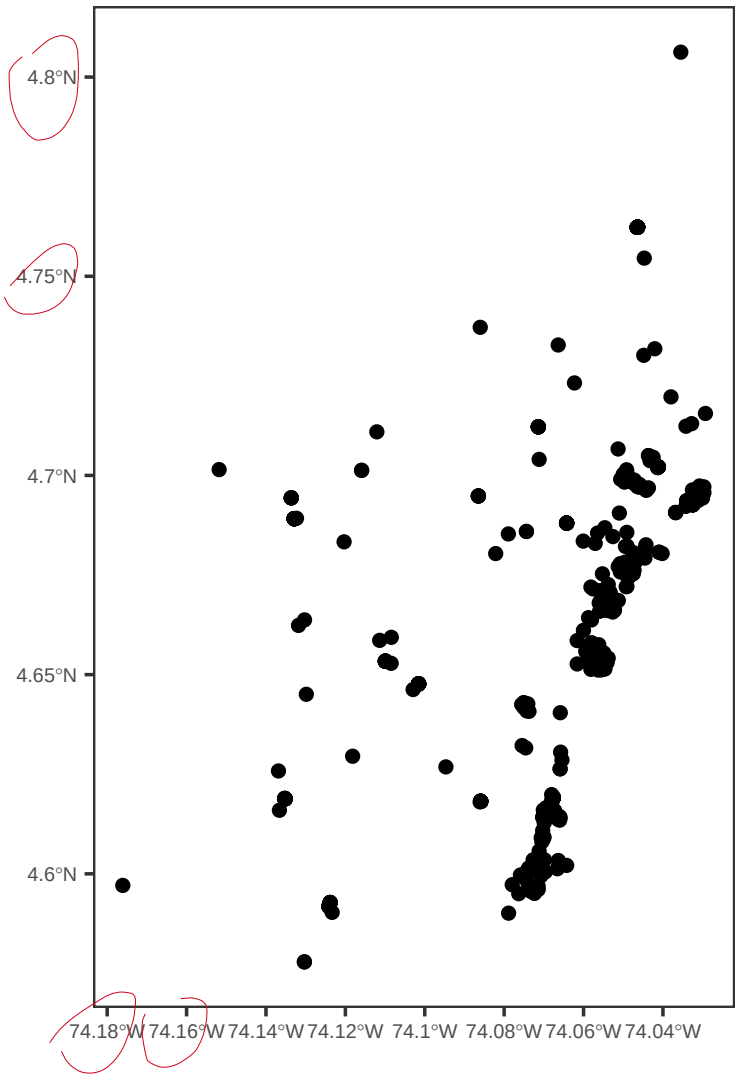
```
require("ggplot2")
require("dplyr")
```

```
bars<-st_read("egba/EGBa.shp")
```

```
## Reading layer 'EGBa' from data source 'egba/EGBa.shp' using driver
## 'ESRI Shapefile'
## Simple feature collection with 515 features and 7 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: -74.17607 ymin: 4.577897 xmax: -74.02929 ymax: 4.806253
## CRS:            4686
```

Visualizing Points

```
ggplot()+
  geom_sf(data=bars) +
  theme_bw() +
  theme(axis.title =element_blank(),
panel.grid.major = element_blank(),
panel.grid.minor = element_blank(),
axis.text = element_text(size=6))
```



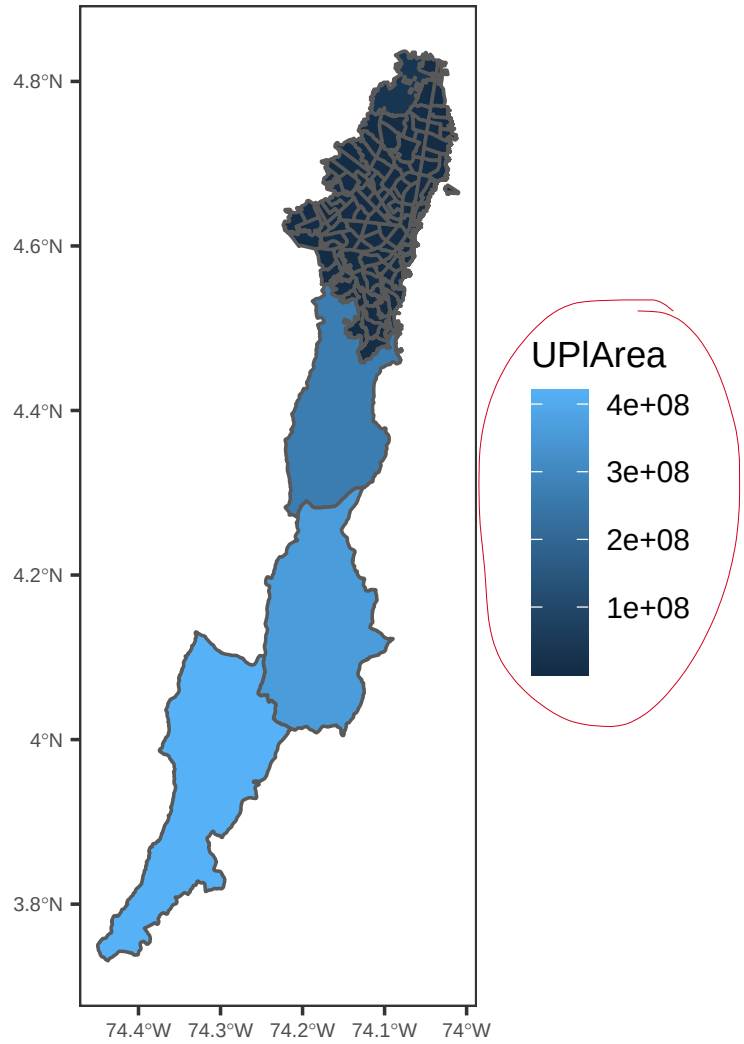
Visualizing Lines

```
ciclovias<-read_sf("Ciclovia/Ciclovia.shp")
ggplot()+
  geom_sf(data=ciclovias) +
  theme_bw() +
  theme(axis.title =element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.text = element_text(size=6))
```

Visualizing Polygons

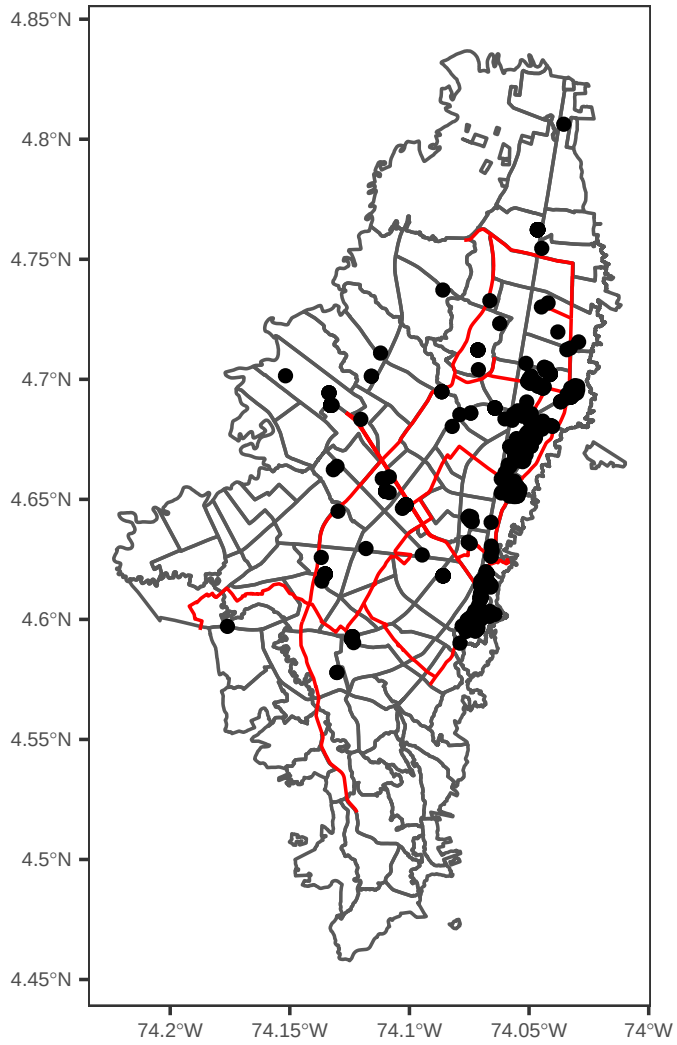
```
upla<-read_sf("upla/UPla.shp")

ggplot()+
  geom_sf(data=upla, aes(fill = UPlArea)) +
  theme_bw() +
  theme(axis.title =element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.text = element_text(size=6))
```



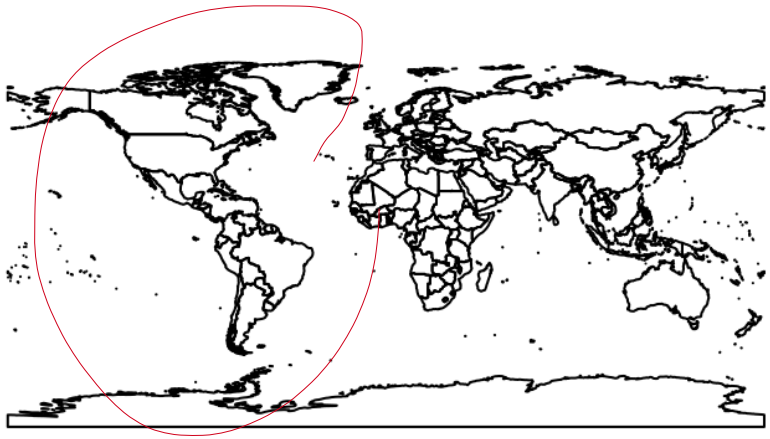
Visualizing Points, Lines, and Polygons

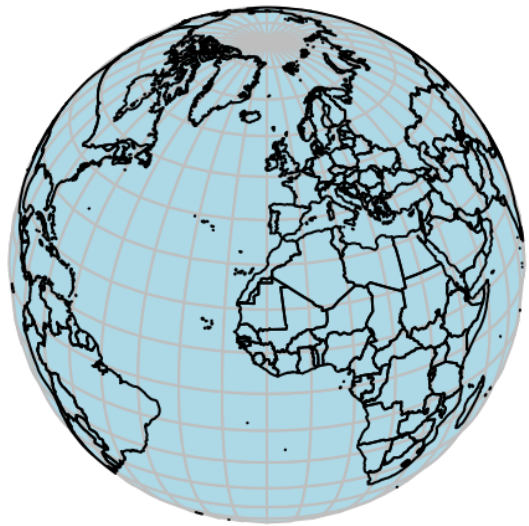
```
ggplot()+
  geom_sf(data=upla
%>% filter(grepl("RIO",UPlNombre)==FALSE),
fill = NA) +
  geom_sf(data=ciclovias, col="red") +
  geom_sf(data=bars) +
  theme_bw() +
  theme(axis.title =element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.text = element_text(size=6))
```



The earth ain't flat

- The world is an irregularly shaped ellipsoid, but plotting devices are flat
- But if you want to show it on a flat map you need a map projection,
- This will determine how to transform and distort latitudes and longitudes to preserve some of the map properties: area, shape, distance, direction or bearing





The earth ain't flat

- For example, sailors use Mercator projection where meridians and parallels cross each other always at the same 90 degrees angle.
- It allows to easy locate your self on the line showing direction in which you sail
- But the projection do not preserve distances

Source: https://www.geoawesomeness.com/all-map-projections-in-compared-and-visualized/

Which projection should I choose?

- "There exist no all-purpose projections, all involve distortion when far from the center of the specified frame" (Bivand, Pebesma, and Gómez-Rubio 2013)

- Geographic coordinate systems: coordinate systems that span the entire globe (e.g. latitude / longitude).
  - For geographic CRSs, the answer is often WGS84
  - WGS84 is the most common CRS in the world, EPSG code: 4326.

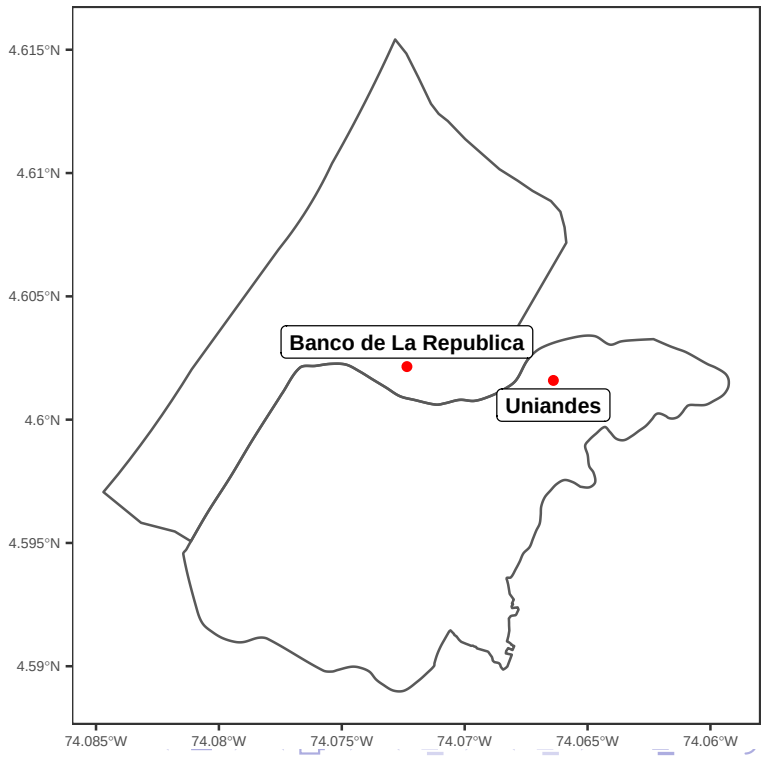
understood.

- Projected coordinate systems: coordinate systems that are localized to minimize visual distortion in a particular region (e.g. Robinson, UTM, State Plane)
  - In some cases, it is not something that we are free to decide: "often the choice of projection is made by a public mapping agency" (Bivand, Pebesma, and Gómez-Rubio 2013).
  - This means that when working with local data sources, it is likely preferable to work with the CRS in which the data was provided.
  - For Bogotá the IGAC promotes the adoption of MAGNA-SIRGAS. EPSG code: 4626

Creating Spatial Objects

```
db<-data.frame(place=c("Uniandes","Banco de La Republica"),
               lat=c(4.601590,4.602151),
               long=c(-74.066391,-74.072350),
               nudge_y=c(-0.001,0.001))
db<-db %>% mutate(latp=lat,longp=long)
db<-st_as_sf(db,coords=c('longp','latp'),crs=4326)
```

```
ggplot()+
  geom_sf(data=upla
        %>% filter(UPlNombre
        %in%c("LA CANDELARIA","LAS NIEVES")), fill = NA) +
  geom_sf(data=db, col="red") +
  geom_label(data = db, aes(x = long, y = lat,
                            label = place),
        size = 3, col = "black", fontface = "bold",
        nudge_y =db$nudge_y) +
  theme_bw() +
  theme(axis.title =element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.text = element_text(size=6))
```

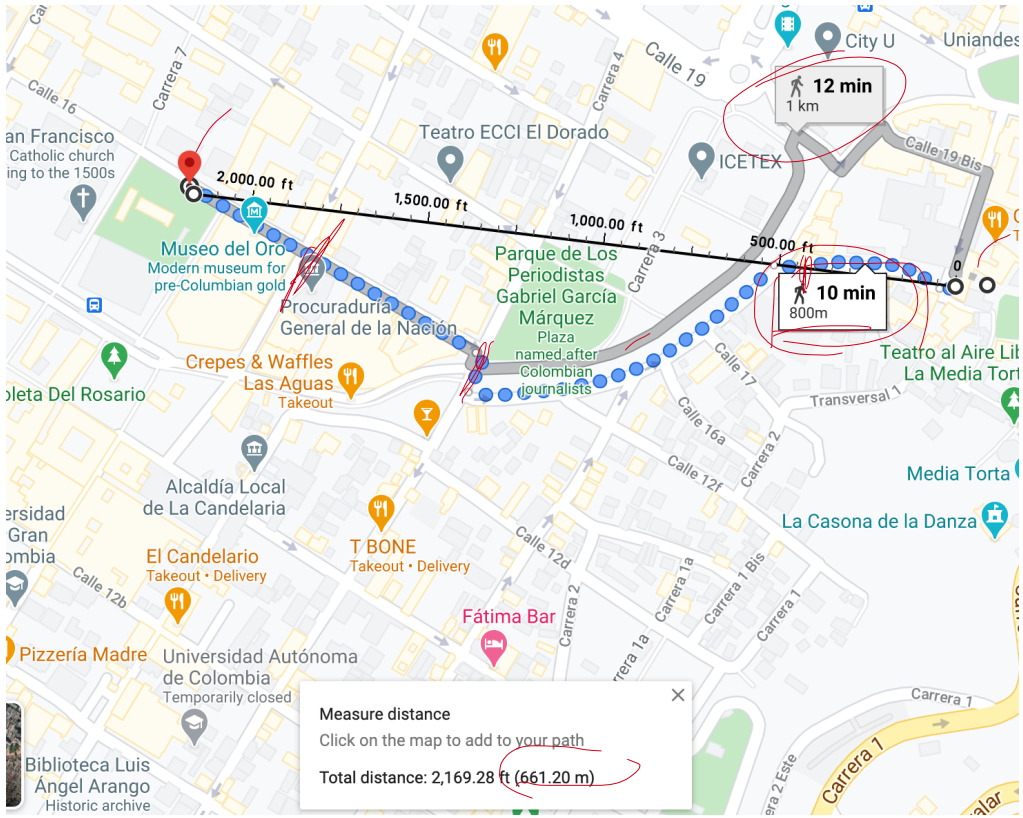


Measuring Distances

```
st_distance(db)
```

```
## Units: [m]
##           [,1]     [,2]
## [1,]   0.0000 664.1323
## [2,] 664.1323   0.0000
```

Open street - API Google



Measuring Distances

```
st_distance(db,ciclovias)
Error in st_distance(db, ciclovias) : st_crs(x) == st_crs(y) is not TRUE
st_crs(ciclovias)
```

```
## Coordinate Reference System:
##   User input: 3857
##   wkt:
## PROJCS["WGS 84 / Pseudo-Mercator",
##     GEOGCS["WGS 84",
##         DATUM["WGS_1984",
##             SPHEROID["WGS 84",6378137,298.257223563,
##                 AUTHORITY["EPSG","7030"]],
##             AUTHORITY["EPSG","6326"]],
##         PRIMEM["Greenwich",0,
##             AUTHORITY["EPSG","8901"]],
##         UNIT["degree",0.0174532925199433,
##             AUTHORITY["EPSG","9122"]],
##         AUTHORITY["EPSG","4326"]],
##     PROJECTION["Mercator_1SP"],
##     PARAMETER["central_meridian",0],
##     PARAMETER["scale_factor",1],
##     PARAMETER["false_easting",0],
##     PARAMETER["false_northing",0],
##     UNIT["metre",1,
##         AUTHORITY["EPSG","9001"]],
##     AXIS["X",EAST],
##     AXIS["Y",NORTH],
##     EXTENSION["PROJ4","+proj=merc +a=6378137 +b=6378137 +lat_ts=0.0 +lon_0=0.0 +x_0=0.0 +y_0=0 +k=1.0 +units
##     AUTHORITY["EPSG","3857"]]
```

Measuring Distances

```
ciclovias<-st_transform(ciclovias, 4686)
st_crs(ciclovias)
```

```
## Coordinate Reference System:
##   User input: EPSG:4686
##   wkt:
## GEOGCS["MAGNA-SIRGAS",
##     DATUM["Marco_Geocentrico_Nacional_de_Referencia",
##         SPHEROID["GRS 1980",6378137,298.257222101,
##             AUTHORITY["EPSG","7019"]],
##         TOWGS84[0,0,0,0,0,0,0],
##         AUTHORITY["EPSG","6686"]],
##     PRIMEM["Greenwich",0,
##         AUTHORITY["EPSG","8901"]],
##     UNIT["degree",0.0174532925199433,
##         AUTHORITY["EPSG","9122"]],
##     AUTHORITY["EPSG","4686"]]
```

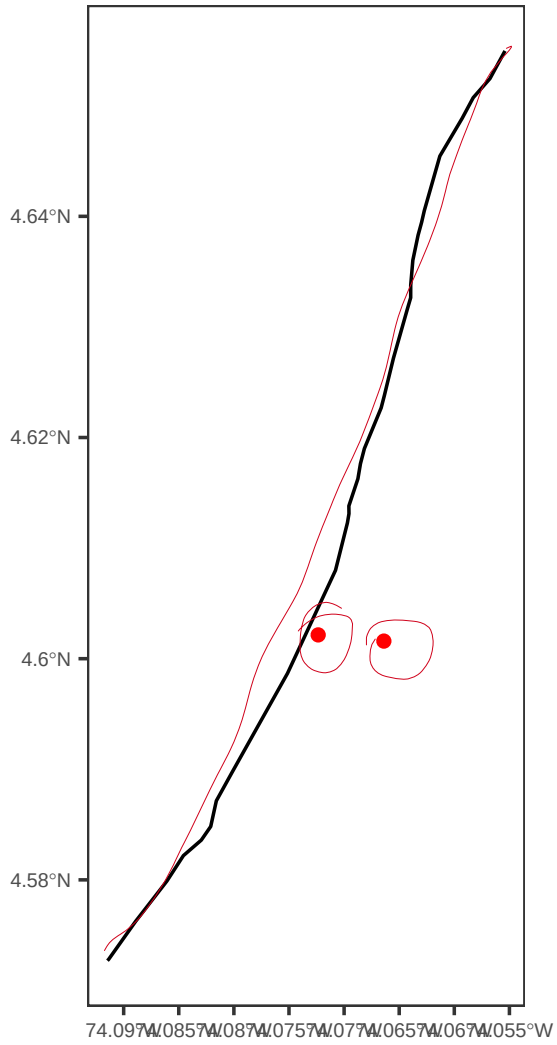
```
db<-st_transform(db, 4326)
st_distance(db,ciclovias)
```

```
## Units: [m]
##           [,1]     [,2]     [,3]     [,4]     [,5]     [,6]     [,7]     [,8]
## [1,] 9514.617 10789.90 6035.283 12855.90 6025.017 8311.922 4579.450 741.6047
## [2,] 9221.998 10686.39 6143.960 13004.84 5871.073 7656.183 4014.993 116.5939
##           [,9]    [,10]    [,11]    [,12]    [,13]    [,14]
## [1,] 1002.8751 6255.692 2385.125 8402.580 8669.030 3788.265
## [2,]  981.1991 5839.565 2425.508 7738.774 8048.108 3436.819
```

Measuring Distances

```
ciclovias_sp<-ciclovias[8,]

ggplot()+
  geom_sf(data=ciclovias[8,], fill = NA) +
  geom_sf(data=db, col="red") +
  theme_bw() +
  theme(axis.title =element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.text = element_text(size=6))
```



Review & Next Steps

- Intro to Shapes
- Basics in R
- Projections
- Next class: Problem Set Presentations
- Questions? Questions about software?

Further Readings

- Arbia, G. (2014). A primer for spatial econometrics with applications in R. Palgrave Macmillan.
- Albouy, D., Christensen, P., & Sarmiento-Barbieri, I. (2020). Unlocking amenities: Estimating public good complementarity. Journal of Public Economics, 182, 104110.
- Bivand, R. S., & Pebesma, E. J. (2020). Spatial Data Science https://keen-swartz-3146c4.netlify.app/ (Chapter 8)
- Bivand, R. S., Gómez-Rubio, V., & Pebesma, E. J. (2008). Applied spatial data analysis with R (Vol. 747248717, pp. 237-268). New York: Springer.
- Blumenstock, J., Cadamuro, G., & On, R. (2015). Predicting poverty and wealth from mobile phone metadata. Science, 350(6264), 1073-1076.
- Christensen, P., Sarmiento-Barbieri, I., Timmins C. (2020). Housing Discrimination and the Pollution Exposure Gap in the United States. NBER WP No. 26805
- Lee, K., & Braithwaite, J. (2020). High-Resolution Poverty Maps in Sub-Saharan Africa. arXiv preprint arXiv:2009.00544.
- Lovelace, R., Nowosad, J., & Muenchow, J. (2019). Geocomputation with R. CRC Press. (Chapters 2 & 6)
- McMillen, D., Sarmiento-Barbieri, I., & Singh, R. (2019). Do more eyes on the street reduce Crime? Evidence from Chicago's safe passage program. Journal of urban economics, 110, 1-25.
- Wasser, L. GIS With R: Projected vs Geographic Coordinate Reference Systems https://www.earthdatascience.org/courses/earth-analytics/spatial-data-r/