Working with Geographic Data

Greg Ridgeway

2026-08-05

Table of contents

1 Introduction

Geographic data include

- point - crime locations, intersections, schools, transit stops
- lines - roads, paths, routes
- polygons - area within city boundaries, gang injunction safety zones, areas within 1000 ft of a school, census tracts

Geographic data also include the data that go along with each of these shapes such as the area or length of the geographic object, the name of the object (e.g. City of Los Angeles), and other characteristics of the geography (e.g. population, date established).

Many questions about crime and the justice system involve the use of geographic data. In this section we will work toward answering questions about the race distribution of residents inside Los Angeles gang injunction zones, the number of crimes within 100 feet of Wilshire Blvd, and examine crimes near Metrorail stations.

We will be learning how to use the `sf` package for managing spatial data, the `tigris` package for obtaining TIGER files storing boundaries and roads, and `jsonlite` and `tidycensus` for pulling population data about residents in an area, like number of residents or race distribution.

2 Exploring Los Angeles gang injunction maps

To start, along with our familiar data organizing packages, load the `sf` (simple features) package to get access to all the essential spatial tools. Also load the `lubridate` package since we will need to work with dates along the way.

```
library(dplyr)
library(purrr) # for set_names() and pluck()
library(tidyr) # for pivot_wider/pivot_longer
library(sf)
library(lubridate)
```

All of the spatial functions in the `sf` package have a prefix `st_` (spatial type). We will first read in `allinjunction.shp`, a shapefile containing the geographic definition of Los Angeles gang injunctions. You should have a collection of four files related to `allinjunctions`, a .dbf file, a .prj file, a .shx file, and a .shp file. Even though the `st_read()` function appears to just ask for the .shp file, you need to have all four files in the same folder.

```
mapSZ <- st_read("09_shapefiles_and_data/allinjunctions.shp")
```

```
Reading layer `allinjunctions' from data source
  `C:\gitdev\R4crim\09_shapefiles_and_data\allinjunctions.shp'
  using driver `ESRI Shapefile'
Simple feature collection with 65 features and 13 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 6378443 ymin: 1715015 xmax: 6511590 ymax: 1940541
Projected CRS: Lambert_Conformal_Conic
```

Let's take a look at what we have. `mapSZ` has a lot of data packed into it that we will explore. To make the plot we need to ask R to just extract the geometry.

```
mapSZ |>
   st_geometry() |>
   plot()
axis(1); axis(2); box()
```

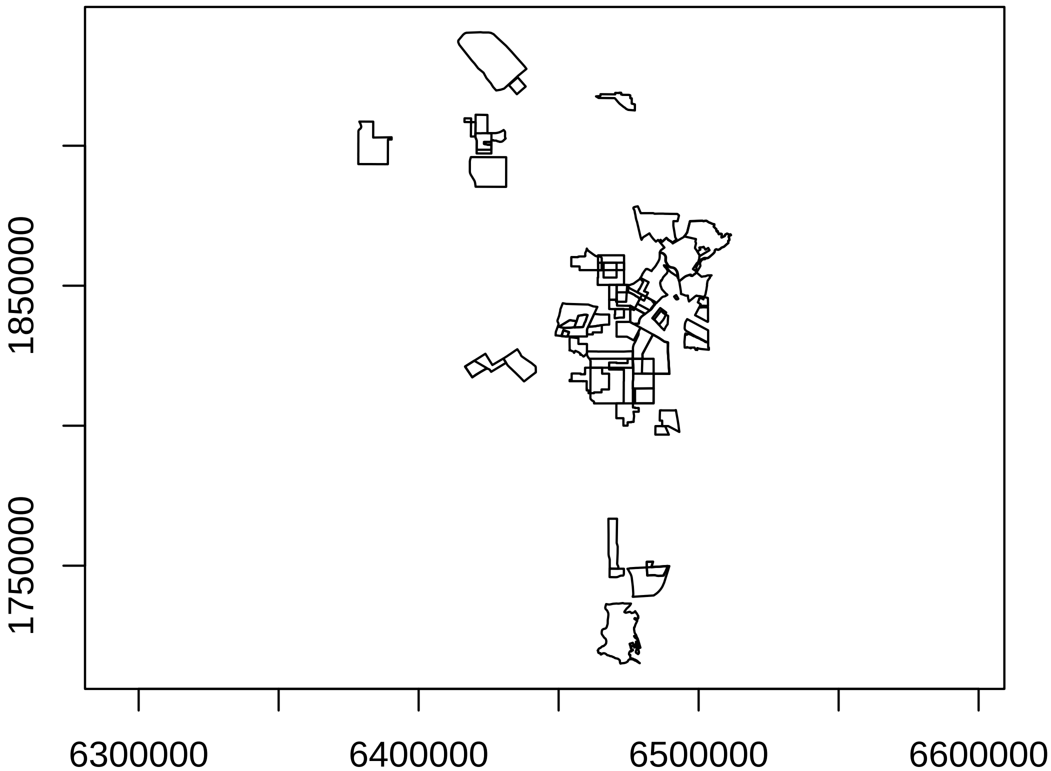


Figure 1: Map of Los Angeles gang injunctions

I have added the x and y axis so that you note the scale. We can check the coordinate system for these data.

```r
st_crs(mapSZ)
```

```
Coordinate Reference System:
  User input: Lambert_Conformal_Conic
  wkt:
PROJCRS["Lambert_Conformal_Conic",
    BASEGEOGCRS["NAD83",
```

```
        DATUM["North American Datum 1983",
            ELLIPSOID["GRS 1980",6378137,298.257222101,
                LENGTHUNIT["metre",1]],
            ID["EPSG",6269]],
        PRIMEM["Greenwich",0,
            ANGLEUNIT["Degree",0.0174532925199433]]],
    CONVERSION["unnamed",
        METHOD["Lambert Conic Conformal (2SP)",
            ID["EPSG",9802]],
        PARAMETER["Latitude of false origin",33.5,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8821]],
        PARAMETER["Longitude of false origin",-118,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8822]],
        PARAMETER["Latitude of 1st standard parallel",34.0333333333333,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8823]],
        PARAMETER["Latitude of 2nd standard parallel",35.4666666666667,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8824]],
        PARAMETER["Easting at false origin",6561666.66666667,
            LENGTHUNIT["US survey foot",0.304800609601219],
            ID["EPSG",8826]],
        PARAMETER["Northing at false origin",1640416.66666667,
            LENGTHUNIT["US survey foot",0.304800609601219],
            ID["EPSG",8827]]],
    CS[Cartesian,2],
        AXIS["(E)",east,
            ORDER[1],
            LENGTHUNIT["US survey foot",0.304800609601219,
                ID["EPSG",9003]]],
        AXIS["(N)",north,
            ORDER[2],
            LENGTHUNIT["US survey foot",0.304800609601219,
                ID["EPSG",9003]]]]
```

Of greatest importance is to notice that the projection is not latitude and longitude, although this is clearly the case from the previous plot. The coordinate system is the Lambert Conic Conformal (LCC) tuned specifically for the Los Angeles area. This coordinate system is oriented for the North American continental plate (NAD83), so precise that this coordinate system moves as the North America tectonic plate moves (2cm per year!). Also note that the unit of measurement is in feet. Whenever we compute a distance or area with these data, the units will be in feet or square feet. This projection is EPSG 2229, commonly called "California StatePlane Zone 5 (Los Angeles area), NAD83, US survey feet." Curiously, the term "EPSG 2229" does not show up in this CRS. Whoever created the polygons in "allinjunctions.shp" included the mathematical description of the LCC projection, but not the EPSG tag. Very fixable:

```
# only do this if you *know* for sure this is the right EPSG
#    it does *not* transform one coordinate system to another
st_crs(mapSZ) <- 2229
```

Let's examine the data attached to each polygon. Here are the first three rows.

```
mapSZ |> head(3)
```

```
Simple feature collection with 3 features and 13 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 6378443 ymin: 1893403 xmax: 6438243 ymax: 1924413
Projected CRS: NAD83 / California zone 5 (ftUS)
       AREA PERIMETER GANG_INJ11 GANG_INJ_1 SHADESYM           NAME Inj_
1  18152790  17048.67          2          9        8       Foothill   09
2  11423653  20863.36          3          1      760 Langdon Street   04
3 129459650  54419.87          4         11      140    Canoga Park   11
   case_no      Safety_Zn    LAPD_Div      Pre_Date       Perm_Date
1 PC027254       Foothill    Foothill          <NA>  Aug. 22, 2001
2 LC048292 Langdon Street  Devonshire  May 20, 1999  Feb. 17, 2000
3 BC267153    Canoga Park West Valley Feb. 25, 2002 April 24, 2002
             gang_name                       geometry
1 Pacoima Project Boys POLYGON ((6435396 1924413, ...
2       Langdon Street POLYGON ((6418722 1908442, ...
3  Canoga Park Alabama POLYGON ((6379791 1908614, ...
```

An `sf` object is really just a data frame with a special `geometry` column containing a description of the geographic object associated with that row. In this case we can see that each row is associated with a polygon. Each polygon in the map is associated with a specific gang injunction. The data attached to each polygon gives details about the associated injunction, such as the name of the injunction, in which LAPD division it is located, dates of the preliminary and permanent injunction, and the name of the gang that the injunction targets.

We can extract the coordinates of an injunction. Let's grab the coordinates of the polygon for the first injunction.

```r
mapSZ |>
   head(1) |>
   st_coordinates()
```

```
             X       Y L1 L2
 [1,] 6435396 1924413  1  1
 [2,] 6435607 1924174  1  1
 [3,] 6435792 1923960  1  1
 [4,] 6435872 1923867  1  1
 [5,] 6436158 1923545  1  1
 [6,] 6436349 1923325  1  1
 [7,] 6437295 1922239  1  1
 [8,] 6438231 1921163  1  1
 [9,] 6438243 1921150  1  1
[10,] 6437992 1920931  1  1
[11,] 6437743 1920714  1  1
[12,] 6437495 1920498  1  1
[13,] 6437246 1920282  1  1
[14,] 6436874 1919958  1  1
[15,] 6436472 1919608  1  1
[16,] 6435940 1919144  1  1
[17,] 6435771 1918998  1  1
[18,] 6435633 1918878  1  1
[19,] 6435311 1918597  1  1
[20,] 6435143 1918451  1  1
[21,] 6435086 1918401  1  1
[22,] 6434689 1918857  1  1
[23,] 6434139 1919485  1  1
[24,] 6433857 1919808  1  1
[25,] 6433742 1919938  1  1
[26,] 6433189 1920572  1  1
[27,] 6433040 1920743  1  1
[28,] 6432908 1920894  1  1
[29,] 6432706 1921120  1  1
[30,] 6432500 1921348  1  1
[31,] 6432467 1921385  1  1
[32,] 6432279 1921596  1  1
[33,] 6432227 1921658  1  1
[34,] 6432296 1921718  1  1
[35,] 6432466 1921866  1  1
[36,] 6433399 1922679  1  1
[37,] 6433404 1922683  1  1
[38,] 6433857 1923073  1  1
```

```
[39,] 6434399 1923545  1  1
[40,] 6434790 1923885  1  1
[41,] 6434822 1923914  1  1
[42,] 6435396 1924413  1  1
```

Let's highlight the first injunction in our map. We can use `filter()` to select rows in `mapSZ` using any feature listed in `names(mapSZ)`. We will select it using its case number. Use `add=TRUE` to add the second plot to the first.

```r
mapSZ |>
   st_geometry() |>
   plot()
mapSZ |>
   filter(case_no=="PC027254") |>
   st_geometry() |>
   plot(col="red", border=NA, add=TRUE)
```

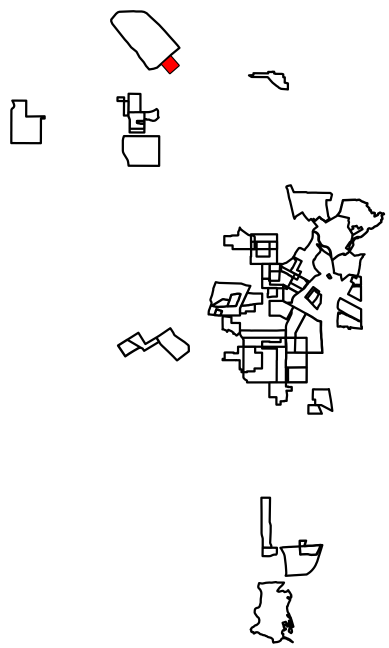


Figure 2: Map of Los Angeles gang injunctions, PC027254 highlighted in red

Now we can see this tiny injunction shaded in red at the top of the map.

Turning back to the data attached to the map, we need to do some clean up on the dates. They are not in standard form and include a typo. We will fix the spelling error and use `lubridate` to standardize those dates. We will also add a `startDate` feature as the smaller of the preliminary injunction date and the permanent injunction date using the pairwise minimum function `pmin()`.

```
mapSZ <- mapSZ |>
  mutate(Pre_Date = gsub("Jne", "June", x=Pre_Date) |>
```

```
            mdy(),
         Perm_Date = mdy(Perm_Date),
         startDate = pmin(Pre_Date, Perm_Date, na.rm=TRUE)) |>
  # some start dates I looked up in court records
  #   https://www.lacourt.ca.gov/pages/lp/access-a-case/tp/find-case-information/cp/os-civil
  mutate(startDate=recode_values(case_no,
           "BC415694" ~ ymd("2009-06-12"),
           "BC435316" ~ ymd("2011-04-19"),
           "BC175684" ~ ymd("1998-11-10"), # dismissed 2001/12/14
           "BC190334" ~ ymd("1998-05-01"), # dismissed 2001/03/02
           "VC024170" ~ as.Date(NA), # never granted/enforced
           "BC399741" ~ ymd("2008-10-10"),
           "BC187039" ~ as.Date(NA), # never granted
           default=startDate))
```

Now let's highlight the injunctions before 2000 in red, those between 2000 and 2010 in green, and those after 2010 in blue. Since many of the polygons overlap, we are going to make the colors a little transparent so that we can see the overlap.

```
mapSZ |>
  mutate(period = cut(year(startDate),
                      breaks = c(0, 1999, 2009, Inf),
                      labels = c("pre-2000","2000s","2010+"))) |>
  select(period) |>
  plot(pal = adjustcolor(c("red","green","blue"),
                         alpha.f=0.5), # make a little transparent
       border = "black",
       main="")
```

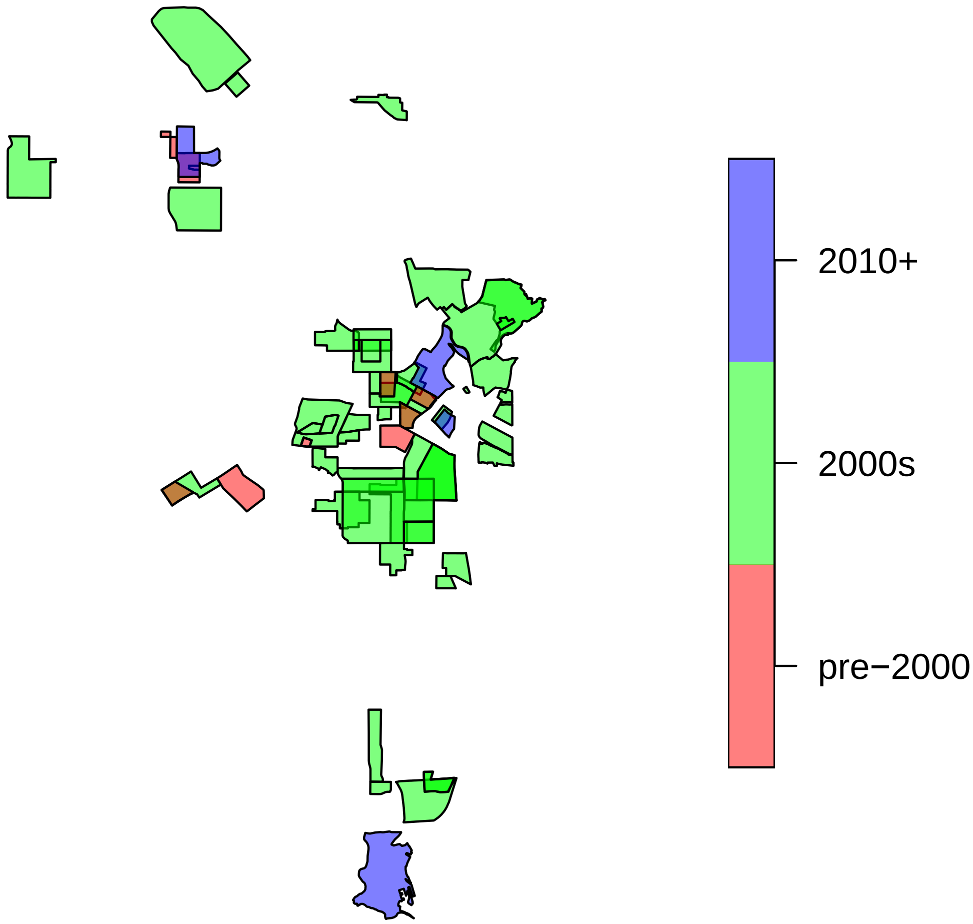


Figure 3: Map of Los Angeles gang injunctions. Those initiated prior to 2000 are in red, those initiated between 2000 and 2010 are in green, and those initiated after 2010 are in blue

When we loaded up the **sf** package, we also gained access to the GEOS library of geographic operations. For example, we can union (combine) all of the polygons together into one shape.

```
mapSZunion <- st_union(mapSZ)
mapSZunion |>
   st_geometry() |>
   plot()
```

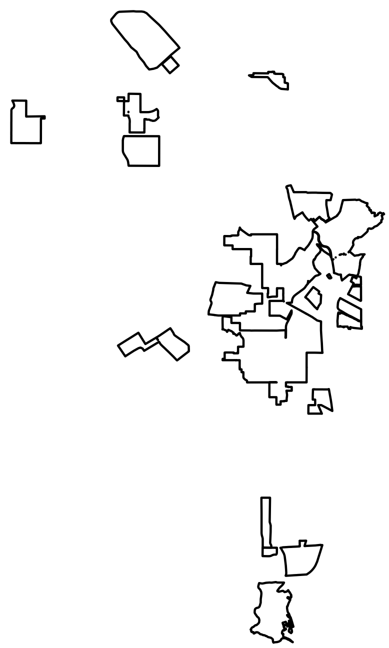


Figure 4: Map of Los Angeles gang injunctions after applying `st_union()`

Any overlapping injunctions have been combined into one polygon. `mapSZunion` now contains this unioned collection of polygons. Note that `mapSZunion` no longer has any data attached to it. Once we union polygons together, it is no longer obvious how to combine their associated data.

```
mapSZunion
```

```
Geometry set for 1 feature
Geometry type: MULTIPOLYGON
Dimension:     XY
```

```
Bounding box:  xmin: 6378443 ymin: 1715015 xmax: 6511590 ymax: 1940541
Projected CRS: NAD83 / California zone 5 (ftUS)
```

```
MULTIPOLYGON (((6457867 1818625, 6457867 181847...
```

Let's draw a polygon defining the area of Los Angeles that is within 1000 feet of an injunction. First, we will double check the units this map uses.

```
# check units
st_crs(mapSZunion)$units
```

```
[1] "us-ft"
```

```
# create a buffer 1000 feet around the injunctions
mapSZ1000ft <- mapSZunion |> st_buffer(dist=1000)
mapSZ1000ft |>
   st_geometry() |>
   plot()
mapSZunion |>
   st_geometry() |>
   plot(col="red", border=NA, add=TRUE)
```

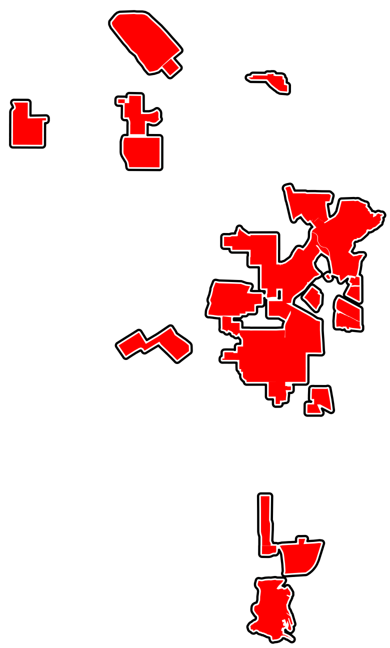


Figure 5: A 1000-foot buffer around the Los Angeles gang injunctions

Every injunction area is shaded red. The white bands between the red shapes and the black outlines is the 1000-foot buffer.

Previously we had to clean up some typos on the injunction dates data. The data can also have errors in the geography that require fixing. Have a look at the MS13 gang injunction.

```
mapSZms13 <- mapSZ |>
   filter(case_no=="BC311766")
mapSZms13 |>
   st_geometry() |>
```

```r
  plot()
```

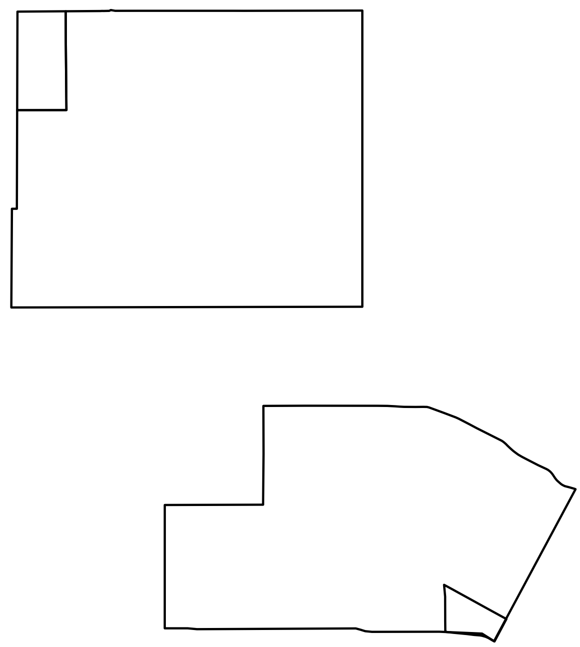


Figure 6: Map of MS13 gang injunction, Case BC311766

The injunction has two mutually exclusive polygons that define the injunction. Both have strange artifacts. Examining the `mapSZms13` object, we can see that it has four polygons. Let's color them so we can see which one is which. The ones with the smallest areas must be the artifacts.

```r
mapSZms13
```

```
Simple feature collection with 4 features and 14 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 6463941 ymin: 1841325 xmax: 6479076 ymax: 1858250
Projected CRS: NAD83 / California zone 5 (ftUS)
      AREA PERIMETER GANG_INJ11 GANG_INJ_1 SHADESYM                   NAME
      ↪ Inj_
1 70459367 34712.862         13          1        0 Rampart/East Hollywood
 ↪  18
2  3452577  7902.383         14          1        0 Rampart/East Hollywood
 ↪  18
3 49977447 32248.724         18          2        0 Rampart/East Hollywood
 ↪  18
4  1403021  5211.601         22          2        0 Rampart/East Hollywood
 ↪  18
   case_no                  Safety_Zn    LAPD_Div   Pre_Date  Perm_Date
1 BC311766 Rampart/East Hollywood (MS) Hwd/Wil/Rmp 2004-04-08 2004-05-10
2 BC311766 Rampart/East Hollywood (MS) Hwd/Wil/Rmp 2004-04-08 2004-05-10
3 BC311766 Rampart/East Hollywood (MS) Hwd/Wil/Rmp 2004-04-08 2004-05-10
4 BC311766 Rampart/East Hollywood (MS) Hwd/Wil/Rmp 2004-04-08 2004-05-10
         gang_name                       geometry  startDate
1 Mara Salvatrucha POLYGON ((6470191 1858229, ... 2004-04-08
2 Mara Salvatrucha POLYGON ((6465399 1858217, ... 2004-04-08
3 Mara Salvatrucha POLYGON ((6468057 1844983, ... 2004-04-08
4 Mara Salvatrucha POLYGON ((6477222 1841927, ... 2004-04-08
```

```r
# rows 1 & 3 seem to have the largest AREA
plot(st_geometry(mapSZms13),
     border = c("green","red","green","blue"),
     lwd    = c(3,1,3,1))
```

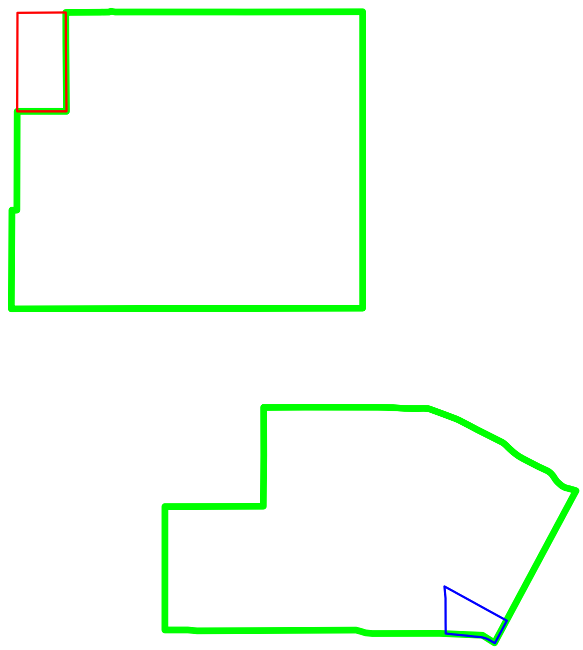


Figure 7: Map of MS13 gang injunction with artifacts highlighted

The Los Angeles City Attorney's Office had an injunction map posted on its website that I have archived so we can see what the correct shape is supposed to be. Let's clear out the weird artifacts to repair the gang injunction geometry. We can use **st_union()** to combine all the polygons together.

```
a <- st_union(mapSZms13)
a
```

```
Geometry set for 1 feature
Geometry type: MULTIPOLYGON
```

```
Dimension:     XY
Bounding box:  xmin: 6463941 ymin: 1841325 xmax: 6479076 ymax: 1858250
Projected CRS: NAD83 / California zone 5 (ftUS)

MULTIPOLYGON (((6476845 1841356, 6476741 184141...
```

Remember that `st_union()` will eliminate the associated data elements. Let's borrow all the data from the first polygon, combine it with our unioned polygons, and use `st_sf()` to make a new simple features object.

```
mapSZms13 <- mapSZms13 |>
   head(1) |>
   select(NAME, case_no, Safety_Zn, gang_name, startDate) |>
   st_sf(geometry=a)
```

Now let's plot the final MS13 gang injunction safety zone and color in a 500-foot buffer around it. `st_difference()` computes the "difference" between two geometric objects. Here we take the polygon defined by being 500 feet out from the MS13 injunction area and "subtract" the injunction area leaving a sort of donut around the injunction area. You can safely ignore warnings about "attribute variables are assumed to be spatially constant throughout all geometries." `st_difference()` assumes its result can inherit the data associated from the original objects used in the difference.

```
mapSZms13 |>
   st_geometry() |>
   plot()
mapSZms13 |>
   st_buffer(dist=500) |>
   st_geometry() |>
   plot(add=TRUE)
mapSZmapBuf <- mapSZms13 |>
   st_buffer(dist=500) |>
   st_difference(mapSZms13)
mapSZmapBuf |>
   st_geometry() |>
   plot(col="green", add=TRUE)
```

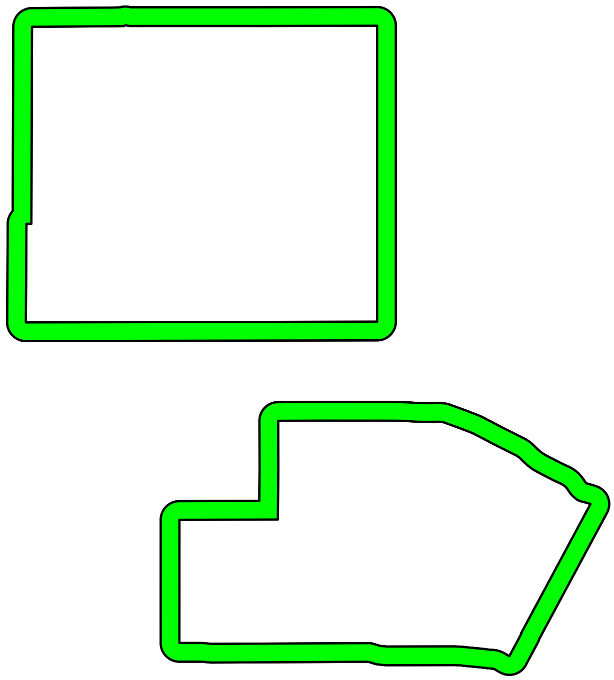


Figure 8: Map of MS13 gang injunction with a 500-foot buffer

2.1 Exercises

1. Find the largest and smallest safety zones (use `st_area(mapSZ)`)
2. Plot all the safety zones. Color the largest in one color and the smallest in another color
3. Use `st_overlaps(mapSZ, mapSZ, sparse=FALSE)` or `print(st_overlaps(mapSZ, mapSZ, sparse=TRUE), n=Inf, max_nb=Inf)` to find two safety zones that overlap (not just touch at the edges)

4. With the two safety zones that you found in the previous question, plot using three different colors the first safety zone, second safety zone, and their intersection (hint: use `st_intersection()`)

3 Using TIGER files from the US Census to merge in other geographic data

The US Census Bureau provides numerous useful geographic data files. We will use their TIGER files to get a map of the City of Los Angeles and we will get the census tracts that intersect with the city. Once you know an area's census tract, you can obtain data on the population of the area. All of the TIGER files are available at https://www.census.gov/cgi-bin/geo/shapefiles/index.php.

First, we will extract an outline of the city. The file `tl_2010_06_place.shp` file is a TIGER line file, created in 2010, for state number 06 (California is 6th in alphabetical order), and contains all of the places (cities and towns). Here is the entire state.

```
mapCAplaces <- st_read("09_shapefiles_and_data/tl_2010_06_place10.shp")
```

```
Reading layer `tl_2010_06_place10' from data source
  `C:\gitdev\R4crim\09_shapefiles_and_data\tl_2010_06_place10.shp'
  using driver `ESRI Shapefile'
Simple feature collection with 1523 features and 16 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -124.2695 ymin: 32.53417 xmax: -114.229 ymax: 41.99323
Geodetic CRS:  NAD83
```

```
mapCAplaces |>
   st_geometry() |>
   plot()
```

Figure 9: Map of all cities and towns in California

The `tigris` package simplifies the process of navigating the Census website, locating the right shape files, and storing them in the right local folder. It will do all of those steps and load it into R as an `sf` object.

```
library(tigris)
```

```
Warning: package 'tigris' was built under R version 4.6.1
```

```r
options(tigris_use_cache = TRUE) # avoids repeated downloads of same file
# tigris does not have places before 2011
mapCAplaces <- places(state="CA", year=2011, class="sf")
```

And here is just the part of that shapefile containing Los Angeles.

```r
mapLA <- mapCAplaces |>
   filter(NAMELSAD=="Los Angeles city")
mapLA |>
   st_geometry() |>
   plot()
```

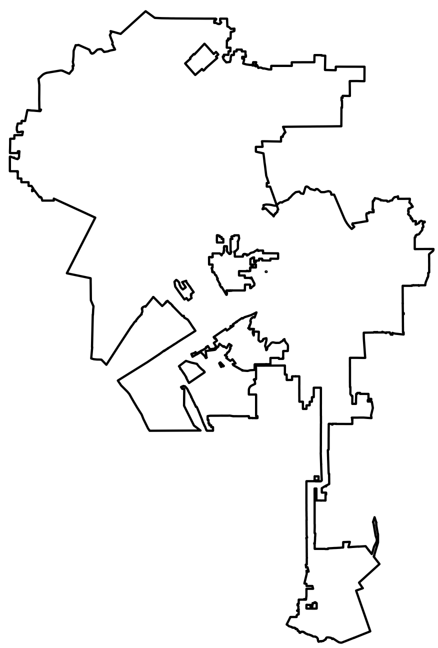


Figure 10: Map of of the border of Los Angeles, California

Now let's load in the census tracts for all of California.

```
# approach using tigris
mapCens <- tracts(state="CA", year=2010, class="sf")
# or if you have it local
# mapCens <- st_read("09_shapefiles_and_data/tl_2010_06037_tract10.shp")
```

`mapCens` contains polygons for all census tracts in California. That is a lot more than we need. We just need the ones that overlap with Los Angeles. `st_intersects()` can help us determine which census tracts are in Los Angeles.

```r
mapCens |>
   slice(6300:6309) |> # pick out some near LA
   st_intersects(mapLA)
```

```
Sparse geometry binary predicate list of length 10, where the predicate
was `intersects'
 1: 1
 2: 1
 3: 1
 4: 1
 5: 1
 6: 1
 7: 1
 8: (empty)
 9: (empty)
 10: (empty)
```

The resulting object has the same length as the number of census tracts in `mapCens`. The value of each component is the index of `st_intersects()` second argument that it intersects. In this example, `mapLA` is a single object so `st_intersects()` is either going to be a 1 or empty.

3.1 Transform to a shared coordinate system

Both `mapLA` and `mapCens` use the latitude/longitude coordinate system, which is not the same as the coordinate system we are using for the gang injunctions.

```r
st_crs(mapLA)
```

```
Coordinate Reference System:
  User input: NAD83
  wkt:
GEOGCRS["NAD83",
    DATUM["North American Datum 1983",
        ELLIPSOID["GRS 1980",6378137,298.257222101,
            LENGTHUNIT["metre",1]]],
    PRIMEM["Greenwich",0,
        ANGLEUNIT["degree",0.0174532925199433]],
    CS[ellipsoidal,2],
        AXIS["latitude",north,
            ORDER[1],
            ANGLEUNIT["degree",0.0174532925199433]],
        AXIS["longitude",east,
```

```
            ORDER[2],
            ANGLEUNIT["degree",0.0174532925199433]],
    ID["EPSG",4269]]
```

```r
st_crs(mapCens)
```

```
Coordinate Reference System:
  User input: NAD83
  wkt:
GEOGCRS["NAD83",
    DATUM["North American Datum 1983",
        ELLIPSOID["GRS 1980",6378137,298.257222101,
            LENGTHUNIT["metre",1]]],
    PRIMEM["Greenwich",0,
        ANGLEUNIT["degree",0.0174532925199433]],
    CS[ellipsoidal,2],
        AXIS["latitude",north,
            ORDER[1],
            ANGLEUNIT["degree",0.0174532925199433]],
        AXIS["longitude",east,
            ORDER[2],
            ANGLEUNIT["degree",0.0174532925199433]],
    ID["EPSG",4269]]
```

```r
st_crs(mapSZ)
```

```
Coordinate Reference System:
  User input: EPSG:2229
  wkt:
PROJCRS["NAD83 / California zone 5 (ftUS)",
    BASEGEOGCRS["NAD83",
        DATUM["North American Datum 1983",
            ELLIPSOID["GRS 1980",6378137,298.257222101,
                LENGTHUNIT["metre",1]]],
        PRIMEM["Greenwich",0,
            ANGLEUNIT["degree",0.0174532925199433]],
        ID["EPSG",4269]],
    CONVERSION["SPCS83 California zone 5 (US survey foot)",
        METHOD["Lambert Conic Conformal (2SP)",
            ID["EPSG",9802]],
        PARAMETER["Latitude of false origin",33.5,
            ANGLEUNIT["degree",0.0174532925199433],
            ID["EPSG",8821]],
```

```
        PARAMETER["Longitude of false origin",-118,
            ANGLEUNIT["degree",0.0174532925199433],
            ID["EPSG",8822]],
        PARAMETER["Latitude of 1st standard parallel",35.4666666666667,
            ANGLEUNIT["degree",0.0174532925199433],
            ID["EPSG",8823]],
        PARAMETER["Latitude of 2nd standard parallel",34.0333333333333,
            ANGLEUNIT["degree",0.0174532925199433],
            ID["EPSG",8824]],
        PARAMETER["Easting at false origin",6561666.667,
            LENGTHUNIT["US survey foot",0.304800609601219],
            ID["EPSG",8826]],
        PARAMETER["Northing at false origin",1640416.667,
            LENGTHUNIT["US survey foot",0.304800609601219],
            ID["EPSG",8827]]],
    CS[Cartesian,2],
        AXIS["easting (X)",east,
            ORDER[1],
            LENGTHUNIT["US survey foot",0.304800609601219]],
        AXIS["northing (Y)",north,
            ORDER[2],
            LENGTHUNIT["US survey foot",0.304800609601219]],
    USAGE[
        SCOPE["Engineering survey, topographic mapping."],
        AREA["United States (USA) - California - counties Kern; Los Angeles;
         ↪  San Bernardino; San Luis Obispo; Santa Barbara; Ventura."],
        BBOX[32.76,-121.42,35.81,-114.12]],
    ID["EPSG",2229]]
```

Furthermore, `st_intersects()` and most other geographic functions do not work well, with latitude and longitude. We should really work with all of our spatial objects having the same projection. We can transform `mapLA` and `mapCens` to have the same coordinate system as our injunction area map, `mapSZ`, which uses a projection (LCC) different from latitude/longitude.

```r
mapCens <- mapCens |> st_transform(crs=st_crs(mapSZ))
mapLA   <- mapLA   |> st_transform(crs=st_crs(mapSZ))
```

Now we can ask R to tell us for each census tract whether or not it intersects with the Los Angeles map. The result of `st_intersects()` is a list where `a[[1]]` will tell us which of the polygons in `mapLA` intersects with the first polygon in `mapCens`. Again, since `mapLA` only has one polygon, `a[[1]]` will either be empty or 1. Therefore, to create an indicator of intersecting Los Angeles we just need to know whether the length of each element of `a` exceeds 0 (is not empty). We will create a new column in the `mapCens` data containing a `TRUE`/`FALSE` indicator of whether that census tract is in Los Angeles or not.

```
a <- mapCens |> st_intersects(mapLA)
# length equals the number of census tracts
length(a) == nrow(mapCens)
```

```
[1] TRUE
```

```
# lengths() asks every component of a how many elements they contain
mapCens$inLA <- lengths(a) > 0
```

Equivalently, we could have asked `st_intersects()` to create a list of census tracts that intersect with `mapLA`, by reversing `mapLA` and `mapCens` in `st_intersects()`.

```
a <- mapLA |> st_intersects(mapCens)
# should equal 1, there's only one shape in mapLA
length(a)
```

```
[1] 1
```

```
# save the indices of census tracts that intersect with mapLA
iLAtracts <- a |>
   unlist()
iLAtracts |> head(10) # print out the first 10 to check
```

```
 [1] 4677 4713 4714 5724 5726 5727 5728 5729 5730 5731
```

```
mapCens <- mapCens |>
   mutate(inLA = (row_number() %in% iLAtracts))
```

Let's check that the census tracts with `TRUE` for `inLA` actually intersect Los Angeles.

```
mapCens <- mapCens |>
   filter(inLA)
mapCens |>
   st_geometry() |>
   plot()
mapLA |>
   st_geometry() |>
   plot(add=TRUE, border="red", lwd=3)
```

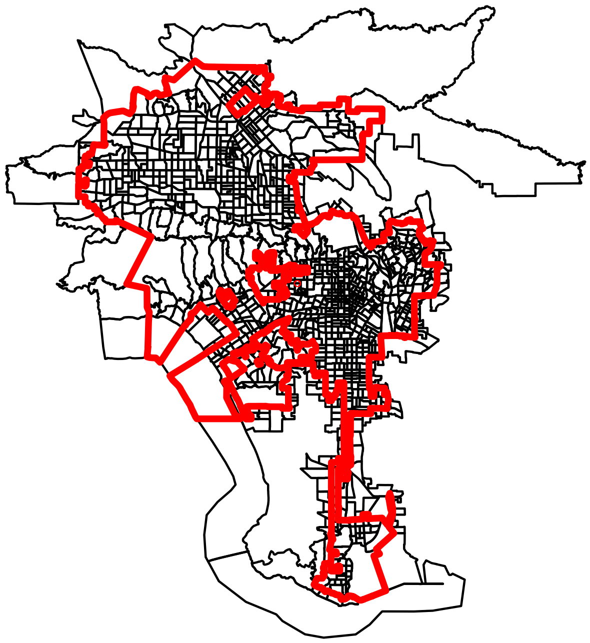


Figure 11: Map of all census tracts that overlap Los Angeles

Which census tracts cover the MS13 safety zone?

```
mapSZms13 |> st_intersects(mapCens)
```

```
Sparse geometry binary predicate list of length 1, where the predicate
was `intersects'
 1: 88, 89, 90, 91, 108, 162, 178, 179, 180, 281, ...
```

```
a <- mapSZms13 |>
   st_intersects(mapCens) |>
   unlist()
mapCens <- mapCens |>
   mutate(inMS13 = (row_number() %in% a))
mapCens |>
   filter(inMS13) |>
   st_geometry() |>
   plot()
mapSZms13 |>
   st_geometry() |>
   plot(border="red", lwd=3, add=TRUE)
```

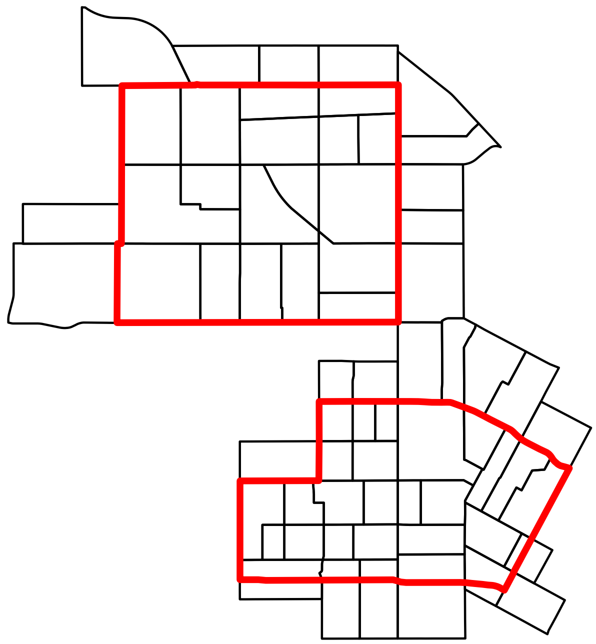


Figure 12: Map of all census tracts that overlap the MS13 injunction

3.2 Exercise

5. Census tracts that just touch the boundary of the safety zone are included. To eliminate, rather than use `st_intersects()` with `mapSZms13`, use `st_intersects()` with `st_buffer()` with a negative `dist` to select census tracts

4 Merge in demographic data from the American Community Survey

The full census of the United States occurs every ten years, but in between those surveys the Census Bureau collects data through the American Community Survey (ACS) by selecting a sample of households. These surveys have a lot of information about people and neighborhoods. We are going to use the ACS to gather race data on the residents within census tracts.

JSON (JavaScript Object Notation) is a very common protocol for moving data. The ACS provides JSON access to its data. There are other ways of accessing ACS data, like downloading the entire ACS dataset, but we are going to use JSON so that you become familiar with how JSON works. Also, when we only need a small amount of information (just race data from particular census tracts) it can save a lot of effort when compared with downloading and processing the full ACS dataset.

First, let's load the `jsonlite` library.

```
library(jsonlite)
```

The Census Data API requires a free API key. You can request one from the Census API key signup page. Do not put the key directly in your script. One option is to run `tidycensus::census_api_key("YOUR KEY", install=TRUE)` once and then restart R. This stores the key in an environment variable named `CENSUS_API_KEY`, where both `tidycensus` and the examples below can retrieve it. If you do not want to restart R right now you can run `Sys.setenv(CENSUS_API_KEY="YOUR_KEY")` to set the environment variable for this session.

Here is how you can access the ACS data on the total population of the United States in 2010

```
censusKey <- Sys.getenv("CENSUS_API_KEY")
if(!nzchar(censusKey))
{
   stop("Set CENSUS_API_KEY before running the Census API examples")
}

fromJSON(paste0(
   "https://api.census.gov/data/2010/acs/acs5?get=NAME,B01001_001E&for=us:*",
   "&key=", censusKey))
```

```
     [,1]            [,2]          [,3]
[1,] "NAME"          "B01001_001E" "us"
[2,] "United States" "303965272"   "1"
```

Let's deconstruct this URL. First, we are accessing data from the 2010 ACS data using `https://api.census.gov/data/2010/acs/`. Second, we are using the data from the ACS sample collected over the last five years to estimate the total population... that is the `acs5` part.

Third, we are accessing variable `B01001_001E`, which contains an estimate (the E at the end is for estimate) of the number of people in the United States. This we needed to track down, but the Social Explorer website makes this easier. Navigate to Social Explorer through the Penn Library to gain full access. Lastly, we asked `for=us:*`, meaning for the entire United States.

If we want the total number of people in specific census tracts, then we can make this request.

```
fromJSON(paste0(
   "https://api.census.gov/data/2010/acs/acs5?get=B01001_001E&for=tract:204920,205110&in=sta
   "&key=", censusKey))
```

```
     [,1]          [,2]    [,3]     [,4]
[1,] "B01001_001E" "state" "county" "tract"
[2,] "2483"        "06"    "037"    "204920"
[3,] "3865"        "06"    "037"    "205110"
```

Here we have requested population data (variable `B01001_001E`) for two specific census tracts (204920 and 205110) from California (state 06) in Los Angeles County (county 037).

If we want the total population in each tract in Los Angeles County, just change the tract list to an *.

```
fromJSON(paste0(
   "https://api.census.gov/data/2010/acs/acs5?get=B01001_001E&for=tract:*&in=state:06+county
   "&key=", censusKey)) |>
   # over 2000 census tracts in LA County... show  first 10
   head()
```

```
     [,1]          [,2]    [,3]     [,4]
[1,] "B01001_001E" "state" "county" "tract"
[2,] "4493"        "06"    "037"    "141400"
[3,] "2715"        "06"    "037"    "141500"
[4,] "3693"        "06"    "037"    "141600"
[5,] "3002"        "06"    "037"    "141700"
[6,] "3900"        "06"    "037"    "143100"
```

Many more examples are posted at the Census API website.

Now let's get something more complete that we can merge into our geographic data. For each census tract in Los Angeles County, we will extract the total population (`B03002_001`), the number of non-Hispanic white residents (`B03002_003`), non-Hispanic black residents (`B03002_004`), and Hispanic residents (`B03002_012`).

We could craft a JSON query to pull these data. However, the `tidycensus` package provides a handy set of tools that wrap around these JSON API calls. Since we stored the Census API key in CENSUS_API_KEY, get_acs() can use it without displaying the key in our code. Here we get ACS data on race using get_acs().

```
library(tidycensus)
```

```
Warning: package 'tidycensus' was built under R version 4.6.1
```

```
dataRace <-
   get_acs(geography = "tract",
           variables = c("B03002_001","B03002_003",
                         "B03002_004","B03002_012"),
           state     = "CA",
           county    = "Los Angeles",
           year      = 2010,
           survey    = "acs5",
           cache_table = TRUE,
           show_call = TRUE)
```

```
Getting data from the 2006-2010 5-year ACS

Census API call:
↪ https://api.census.gov/data/2010/acs/acs5?get=B03002_001E%2CB03002_001M%
↪ 2CB03002_003E%2CB03002_003M%2CB03002_004E%2CB03002_004M%2CB03002_012E%2C
↪ B03002_012M%2CNAME&for=tract%3A%2A&in=state%3A06%2Bcounty%3A037
```

```
dataRace
```

```
# A tibble: 9,384 x 5
   GEOID       NAME                                       variable estimate
    ↪ moe
   <chr>       <chr>                                      <chr>       <dbl>
    ↪ <dbl>
 1 06037101110 Census Tract 1011.10, Los Angeles County~ B03002_~     5017
  ↪ 362
 2 06037101110 Census Tract 1011.10, Los Angeles County~ B03002_~     3248
  ↪ 466
 3 06037101110 Census Tract 1011.10, Los Angeles County~ B03002_~       38
  ↪ 41
 4 06037101110 Census Tract 1011.10, Los Angeles County~ B03002_~     1085
  ↪ 390
 5 06037101122 Census Tract 1011.22, Los Angeles County~ B03002_~     3663
  ↪ 287
 6 06037101122 Census Tract 1011.22, Los Angeles County~ B03002_~     2426
  ↪ 286
```

```
 7 06037101122 Census Tract 1011.22, Los Angeles County~ B03002_~        0
  ↪   132
 8 06037101122 Census Tract 1011.22, Los Angeles County~ B03002_~      451
  ↪   167
 9 06037101210 Census Tract 1012.10, Los Angeles County~ B03002_~     6799
  ↪   575
10 06037101210 Census Tract 1012.10, Los Angeles County~ B03002_~     3235
 ↪   529
# i 9,374 more rows
```

With `show_call = TRUE` I have asked `get_acs()` to reveal the JSON query it used to fetch the data. For each census tract/variable combination we have an estimate and its margin of error. Let's clean this up, give clearer race labels, and pivot to create one row per census tract.

```r
dataRace <- dataRace |>
   select(GEOID, variable, estimate) |>
   mutate(race = recode_values(variable,
                               "B03002_001" ~ "total",
                               "B03002_003" ~ "white",
                               "B03002_004" ~ "black",
                               "B03002_012" ~ "hisp")) |>
   select(-variable) |>
   pivot_wider(names_from = race,
               values_from = estimate,
               values_fill = 0) |>
   mutate(other = total-white-black-hisp)
dataRace
```

```
# A tibble: 2,346 x 6
   GEOID       total white black  hisp other
   <chr>       <dbl> <dbl> <dbl> <dbl> <dbl>
 1 06037101110  5017  3248    38  1085   646
 2 06037101122  3663  2426     0   451   786
 3 06037101210  6799  3235   252  2790   522
 4 06037101220  3189  1768    23  1148   250
 5 06037101300  3808  3121    12   423   252
 6 06037101400  3733  2868   132   406   327
 7 06037102103  1841  1264    39   298   240
 8 06037102104  3695  2763    32   550   350
 9 06037102105  1525   166     0  1193   166
10 06037102107  3503  2332    40   826   305
# i 2,336 more rows
```

Now we have a data frame that links the census tract numbers to populations and race data.

Let's add race information to the MS13 injunction data. And since we have been using a lot of base R's plotting functions, to change things up let's create a `ggplot`.

```
library(ggplot2)
# match tract IDs and merge in % hispanic
mapCens |>
   # merge in race data
   left_join(dataRace, join_by(GEOID10==GEOID)) |>
   mutate(pctHisp = if_else(total>0 & !is.na(hisp), hisp/total, 0),
          # choose a shade of gray
          colGray = gray(pctHisp),
          # nicely formatted percentages
          pctHispLabel = scales::percent(pctHisp, accuracy = 1)) |>
   filter(inMS13) |>
   ggplot() +
   geom_sf(aes(fill = colGray), color = NA) +
   geom_sf(data=mapSZms13, col="red", fill=NA) +
   # tells ggplot fill has actual color values
   scale_fill_identity() +
   geom_sf_text(aes(label = pctHispLabel),
                # function giving where to place label
                fun.geometry = st_point_on_surface,
                size = 3,
                color = "black",
                # text that overlaps previous text not plotted
                check_overlap = TRUE) +
   labs(x = NULL, y = NULL) +
   theme_minimal()
```

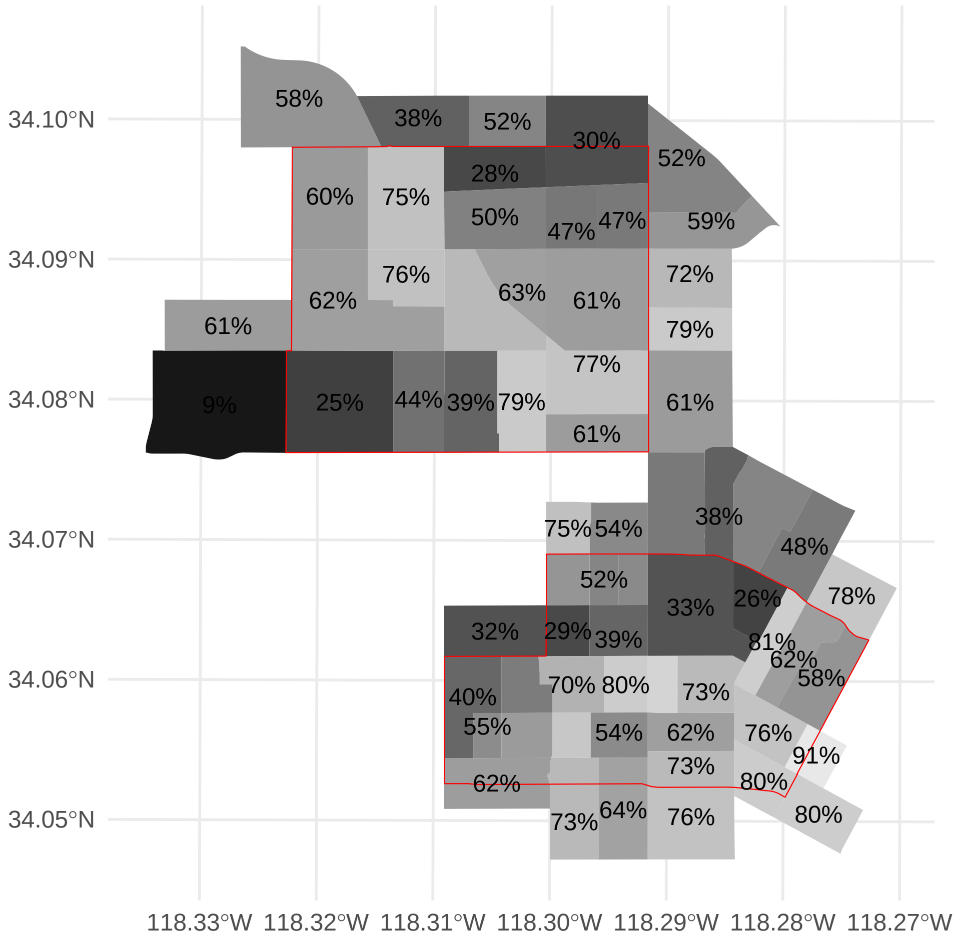


Figure 13: Percentage of Hispanic residents in census tracts overlapping the MS13 gang injunction safety zones

4.1 Exercise

6. Create a map of all census tracts in the City of Los Angeles within 1 mile of one of the safety zones (you choose which safety zone)
7. Color each area based on a census feature (e.g. % non-white, or some other feature from the ACS data)
8. Add the polygon with your injunction zone
9. Add other injunction zones that intersect with your map

5 Working with point data using Los Angeles crime data

The Los Angeles Police Department (LAPD) posts all of its crime data at Los Angeles' open data portal. We are interested in the 2010-2019 crime data held in the 2010-2019 crime data file. We are also interested in the crime data for 2020 to 2024, which LAPD posts separately.

There are several ways we could go about retrieving the data. One method is to ask R to download the data to our computer and then use `read.csv()` to import it. Conveniently, the Los Angeles open data portal allows "SoQL" queries, meaning that we can use SQL-like where clauses. By default, SoQL will limit the result to 1,000 rows, so I have modified the limit to 5 million, more than enough to get all the 2019 crime data. Here I demonstrate retrieving just the 2019 crime incidents.

```
# Method #1
if(!file.exists("09_shapefiles_and_data/LAPD crime data 2019.csv.gz"))
{
   download.file("https://data.lacity.org/resource/63jg-8b9z.csv?$where=date_extract_y(date_c
                 destfile = "09_shapefiles_and_data/LAPD crime data 2019.csv")

   R.utils::gzip("09_shapefiles_and_data/LAPD crime data 2019.csv",
                 remove = TRUE, overwrite = TRUE)
}
dataCrime <- read.csv("09_shapefiles_and_data/LAPD crime data 2019.csv.gz",
                      as.is=TRUE)

# check data range
range(dataCrime$date_occ)
```

```
[1] "2019-01-01T00:00:00.000" "2019-12-31T00:00:00.000"
```

```
# check number of rows and columns
dim(dataCrime)
```

```
[1] 218918     28
```

```
# check first few rows
head(dataCrime, 3)
```

```
      dr_no               date_rptd                date_occ time_occ area
1 191907191 2019-03-11T00:00:00.000 2019-03-08T00:00:00.000     1500   19
2 191911786 2019-06-13T00:00:00.000 2019-06-13T00:00:00.000      100   19
3 190518997 2019-12-05T00:00:00.000 2019-12-04T00:00:00.000     1800    5
  area_name rpt_dist_no part_1_2 crm_cd      crm_cd_desc mocodes vict_age
```

```
1   Mission        1918        1     510 VEHICLE - STOLEN                 0
2   Mission        1987        1     510 VEHICLE - STOLEN                 0
3    Harbor         525        1     510 VEHICLE - STOLEN                 0
  vict_sex vict_descent premis_cd premis_desc weapon_used_cd weapon_desc
   ↪  status
1                            101      STREET             NA
 ↪  IC
2                            101      STREET             NA
 ↪  IC
3                            101      STREET             NA
 ↪  IC
  status_desc crm_cd_1 crm_cd_2 crm_cd_3 crm_cd_4
1 Invest Cont      510       NA       NA       NA
2 Invest Cont      510       NA       NA       NA
3 Invest Cont      510       NA       NA       NA
                                  location cross_street     lat       lon
1 13200    FOOTHILL                     BL              34.2991 -118.4211
2 14300    PARTHENIA                    ST              34.2297 -118.4436
3   500 N  AVALON                       BL              33.7739 -118.2678
```

Alternatively, we can just skip the download and ask R to directly read in the data from the Los Angeles data portal. The only downside to this is if you mess up your data, then you will need to download it all over again, which can be slow.

```r
# Method #2
dataCrime <- read.csv("https://data.lacity.org/resource/63jg-8b9z.csv?$where=date_extract_y(d
                      as.is=TRUE) # don't convert strings to other types (e.g. logical)
# check data range
range(dataCrime$date_occ)
```

```
[1] "2019-01-01T00:00:00.000" "2019-12-31T00:00:00.000"
```

```r
# check number of rows and columns
dim(dataCrime)
```

```
[1] 218918     28
```

```r
# check first few rows
head(dataCrime, 3)
```

```
      dr_no               date_rptd                date_occ time_occ area
1 191907191 2019-03-11T00:00:00.000 2019-03-08T00:00:00.000     1500   19
2 191911786 2019-06-13T00:00:00.000 2019-06-13T00:00:00.000      100   19
3 190518997 2019-12-05T00:00:00.000 2019-12-04T00:00:00.000     1800    5
```

```
  area_name rpt_dist_no part_1_2 crm_cd      crm_cd_desc mocodes vict_age
1   Mission        1918        1    510 VEHICLE - STOLEN                0
2   Mission        1987        1    510 VEHICLE - STOLEN                0
3    Harbor         525        1    510 VEHICLE - STOLEN                0
  vict_sex vict_descent premis_cd premis_desc weapon_used_cd weapon_desc
   ↪  status
1                             101      STREET             NA
 ↪  IC
2                             101      STREET             NA
 ↪  IC
3                             101      STREET             NA
 ↪  IC
  status_desc crm_cd_1 crm_cd_2 crm_cd_3 crm_cd_4
1 Invest Cont      510       NA       NA       NA
2 Invest Cont      510       NA       NA       NA
3 Invest Cont      510       NA       NA       NA
                                 location cross_street     lat       lon
1 13200    FOOTHILL                    BL              34.2991 -118.4211
2 14300    PARTHENIA                   ST              34.2297 -118.4436
3   500 N  AVALON                      BL              33.7739 -118.2678
```

Let's download all 2010-2019 data as well as the 2020-2024 data so that we can explore changes in crime over time.

```r
options(timeout = 600) # ten minutes

# get the 2010-2019 data
if(!file.exists("09_shapefiles_and_data/LAPD crime data 2010-2019.csv.gz"))
{
   download.file("https://data.lacity.org/resource/63jg-8b9z.csv?$limit=5000000",
                 destfile = "09_shapefiles_and_data/LAPD crime data 2010-2019.csv",
                 quiet=TRUE)

   R.utils::gzip("09_shapefiles_and_data/LAPD crime data 2010-2019.csv",
              remove = TRUE, overwrite = TRUE)
}

# get the 2020-2024 data
if(!file.exists("09_shapefiles_and_data/LAPD crime data 2020-2024.csv.gz"))
{
   download.file("https://data.lacity.org/resource/2nrs-mtv8.csv?$limit=5000000",
                 destfile = "09_shapefiles_and_data/LAPD crime data 2020-2024.csv",
                 quiet=TRUE)
```

```
  R.utils::gzip("09_shapefiles_and_data/LAPD crime data 2020-2024.csv",
             remove = TRUE, overwrite = TRUE)
}

# combine 2010-2019 data and 2020-2024 data
dataCrime <-
  read.csv("09_shapefiles_and_data/LAPD crime data 2010-2019.csv.gz",
           as.is=TRUE) |>
  bind_rows(
    read.csv("09_shapefiles_and_data/LAPD crime data 2020-2024.csv.gz",
             as.is=TRUE))
```

Like always, let's check the size and peek at the first three rows to see what we have.

```
nrow(dataCrime)
```

```
[1] 3138031
```

```
dataCrime |> head(3)
```

```
     dr_no               date_rptd                date_occ time_occ area
1  1307355 2010-02-20T00:00:00.000 2010-02-20T00:00:00.000     1350   13
2 11401303 2010-09-13T00:00:00.000 2010-09-12T00:00:00.000       45   14
3 70309629 2010-08-09T00:00:00.000 2010-08-09T00:00:00.000     1515   13
  area_name rpt_dist_no part_1_2 crm_cd
1    Newton        1385        2    900
2   Pacific        1485        2    740
3    Newton        1324        2    946
                                              crm_cd_desc        mocodes
1                                VIOLATION OF COURT ORDER 0913 1814 2000
2 VANDALISM - FELONY ($400 & OVER, ALL CHURCH VANDALISMS)           0329
3                               OTHER MISCELLANEOUS CRIME           0344
  vict_age vict_sex vict_descent premis_cd           premis_desc
1       48        M            H       501 SINGLE FAMILY DWELLING
2        0        M            W       101                 STREET
3        0        M            H       103                  ALLEY
  weapon_used_cd weapon_desc status  status_desc crm_cd_1 crm_cd_2 crm_cd_3
1             NA                 AA Adult Arrest      900       NA       NA
2             NA                 IC  Invest Cont      740       NA       NA
3             NA                 IC  Invest Cont      946       NA       NA
  crm_cd_4                                location
1       NA  300 E  GAGE                         AV
```

```
2       NA          SEPULVEDA                    BL
3       NA 1300 E   21ST                         ST
                      cross_street      lat        lon
1                                  33.9825 -118.2695
2 MANCHESTER                    AV 33.9599 -118.3962
3                                  34.0224 -118.2524
```

It is also a good idea to check counts over time and over places. Note that there are some strange anomalies, like areas 18, 19, 20, 21 in 2015 followed by very large jumps in 2016. Looks like 2015 and 2016 data were miscoded for these areas in these years.

```
dataCrime |>
   count(year=year(ymd_hms(date_occ)),area) |>
   pivot_wider(names_from=year,values_from=n) |>
   print(n=Inf, width=Inf)
```

```
# A tibble: 21 x 16
    area `2010` `2011` `2012` `2013` `2014` `2015` `2016` `2017` `2018`
    ↪  `2019`
   <int>  <int>  <int>  <int>  <int>  <int>  <int>  <int>  <int>  <int>
    ↪  <int>
 1     1   7146   7175   8084   7598   8407  10070  11240  11947  13224
  ↪  13606
 2     2   8707   8444   8626   8148   8557   9004   9531   9662   9689
  ↪  9567
 3     3  13659  12934  13126  12738  13014  13390  14699  14324  14396
  ↪  13549
 4     4   7406   6542   7085   6712   6916   7771   9547   9078   8829
  ↪  8384
 5     5   9598   9841   9443   8431   8306   9231   9874   9703   9127
  ↪  8727
 6     6   9211   9246   9332   8550   8585   9418  11019  11322  11446
  ↪  11201
 7     7   8186   8285   8051   7842   7932   8002   9493   9896  10775
  ↪  10460
 8     8   8200   8612   8592   8178   8195   9221   9809   9057  10113
  ↪  9260
 9     9  10089   9544   9659   9387   9479  10049  10982  10826  10489
  ↪  9623
10    10   9270   8844   9037   8419   7955   8246  10156   9800   9528
  ↪  8729
11    11  10629   9837   9868   9288   9705   9852  10807  10548  10333
  ↪  9682
```

```
12    12  14447  14267  14318  13756  14075  14172  15935  15559  15014
 ↪  14267
13    13   9999   9354   8901   8638   9231   9399  11368  11777  10923
 ↪  10772
14    14  11093  10384  10322  10116  10763  11247  12303  12097  12203
 ↪  12278
15    15  11365  10700  11293  10963  10414  11246  12636  12448  12090
 ↪  11147
16    16   9350   8545   7956   7504   7164   7331   8398   8218   8122
 ↪  7654
17    17  10641   9644   9443   8694   8667   9552  17507  10696   9605
 ↪  9058
18    18  11080  11060  10612  10197  10574    871  23054  11888  12012
 ↪  11764
19    19  10566  10553  10605  10301   9977      1  22172  10891  10210
 ↪  9199
20    20   8764   7988   8544   8305   9164      3  21202  11173  11038
 ↪  10282
21    21   9919   9113   8938   9110   8799     NA  22066  10841  10602
 ↪  9709
   `2020` `2021` `2022` `2023` `2024`
    <int>  <int>  <int>  <int>  <int>
 1  11604  13171  17715  16966  10212
 2   9025   9465  11204  11529   5601
 3  11180  11419  13416  13112   8307
 4   7807   8029   8522   8410   4313
 5   8875   8875   9200   9135   5307
 6  10174  12109  12546  11448   6152
 7   9292   9752  11176  11713   6304
 8   9311   9900  10515  10587   5412
 9   8764   8700   9716   9942   5759
10   8095   8543  10288   9938   5282
11   8452   9351  10184   9716   5248
12  13353  13102  14573  13953   6775
13   9995   9926  11933  11933   5386
14  11576  12935  13048  13792   8162
15  10169  10932  11200  11557   7248
16   7107   7048   7867   7160   3947
17   7984   8507   9597   9776   5879
18  10849  10434  11748  11294   5604
19   8482   8238   9281   8981   5360
20   9640  10836  12068  11756   5770
21   8113   8604   9462   9647   5539
```

Now keep incidents that are not missing the latitude or longitude, are not on the equator (0,0), and convert the data frame into a simple features spatial object.

```
dataCrime <- dataCrime |>
   filter(!is.na(lat) & lat > 0 &
          !is.na(lon) & lon < 0 ) |>
   st_as_sf(coords=c("lon","lat"),
            crs=4326)
```

Setting `crs=4326` tells R that this spatial object has coordinates in latitude and longitude. Remember that EPSG 4326 refers to latitude and longitude.

Now we need to reproject the data into the coordinate system to match the injunction safety zone map.

```
dataCrime <- dataCrime |>
   st_transform(st_crs(mapSZms13))
```

Let's now identify which crimes occurred within one mile of the MS13 injunction. I did some checking and noted that LAPD areas 1, 2, 3, 6, 7, 11, and 20 intersected with the MS13 safety zone, so I picked out just those crimes and plotted them each in different colors.

```
mapMS13mileBuffer <- mapSZms13 |> st_buffer(5280)
bboxMS13          <- st_bbox(mapMS13mileBuffer)

ggplot() +
   geom_point(data = dataCrime |>
                 filter(area %in% c(1,2,3,6,7,11,20)) |>
                 mutate(X = st_coordinates(geometry)[,"X"],
                        Y = st_coordinates(geometry)[,"Y"]) |>
                 st_drop_geometry() |>
                 select(X, Y, area) |>
                 filter(X>bboxMS13["xmin"] & X<bboxMS13["xmax"] &
                        Y>bboxMS13["ymin"] & Y<bboxMS13["ymax"]) |>
                 distinct(),
              aes(X, Y, color = factor(area)),
              shape = 16,
              size = 1) +
   geom_sf(data  = mapMS13mileBuffer,
           fill  = NA,
           color = "black") +
   geom_sf(data      = mapSZms13,
           fill      = NA,
```

```
        color     = "red",
        linewidth = 1) +
  scale_color_viridis_d(option = "D", name = "Area") +
  # crop to area near MS13 safety zone
  coord_sf(xlim = c(bboxMS13$xmin, bboxMS13$xmax),
           ylim = c(bboxMS13$ymin, bboxMS13$ymax),
           expand = FALSE) +
  # larger points in the legend
  guides(color = guide_legend(override.aes = list(size = 4))) +
  theme_minimal() +
  labs(x = NULL, y = NULL)
```

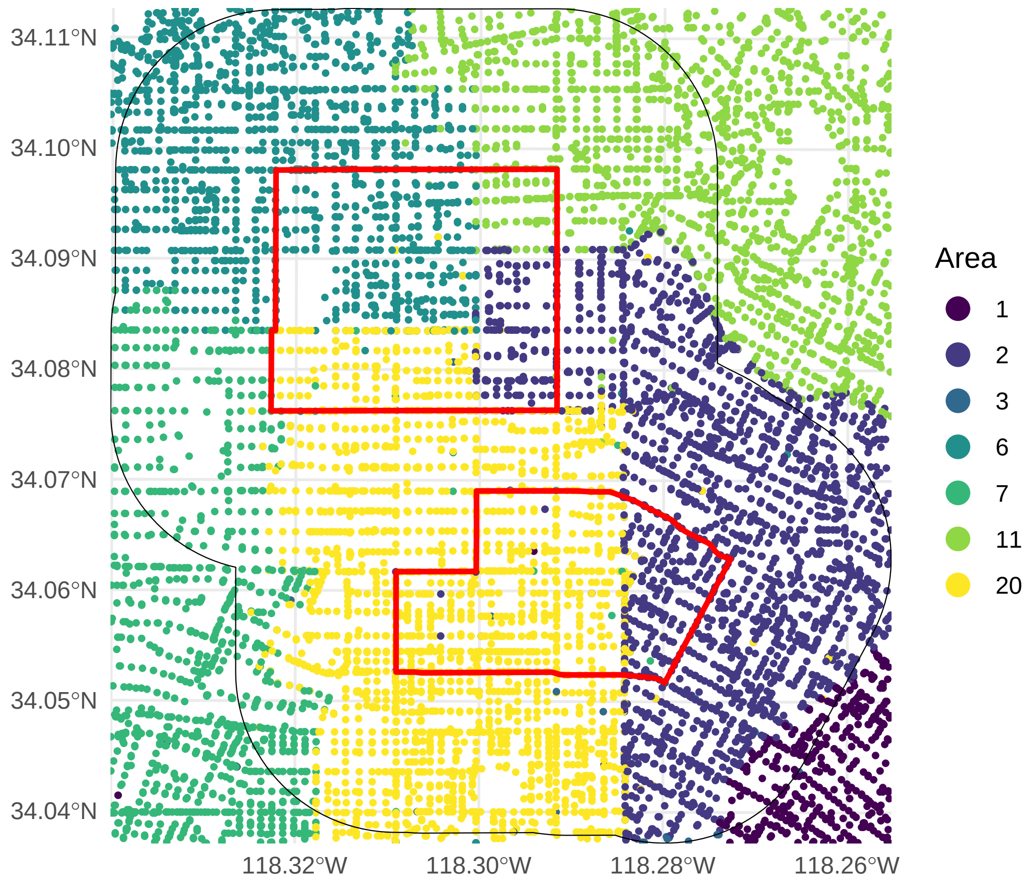


Figure 14: Plot of Los Angeles crime locations near the MS13 gang injunction safety zones

A very useful operation is to find out which crimes occurred inside, near, or farther outside an area. We will figure out which crimes occurred inside the safety zone, in a one-mile buffer around the safety zone, or more than a mile away from the safety zone. We will filter to just those crimes that occurred in areas near the MS13 safety zone. This step is not essential, but it can save some computer time. There is no need for R to try to figure out if crimes in LAPD Area 4 fell inside the MS13 safety zone. All of those crimes are much more than a mile from the safety zone.

```
# just get those crimes in areas near the MS13 safety zone
dataCrimeMS13 <- dataCrime |>
   filter(area %in% c(1,2,3,6,7,11,20))
```

We are going to use two different methods so you learn about different ways of solving these problems. The first method will use the now familiar `st_intersects()` function. In our `dataCrimeMS13` data frame we are going to make a new column that labels whether a crime is inside the injunction safety zone (SZ), within a one-mile buffer around the safety zone (buffer), or beyond the buffer (outside).

```
# create a variable to label the crime's location
iSZ <- mapSZms13 |> st_intersects(dataCrimeMS13) |> unlist()
iBuff <- mapSZms13 |>
   st_buffer(dist=5280) |>
   st_difference(mapSZms13) |>
   st_intersects(dataCrimeMS13) |>
   unlist()

dataCrimeMS13 <- dataCrimeMS13 |>
   mutate(place1 = case_when(
      row_number() %in% iSZ   ~ "SZ",
      row_number() %in% iBuff ~ "buffer",
      .default = "outside"))
```

Now `dataCrimeMS13` has a new column `place1` categorizing the location of the incident relative to the MS13 gang injunction safety zone.

```
head(dataCrimeMS13, 3)
```

```
Simple feature collection with 3 features and 27 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 6461916 ymin: 1836559 xmax: 6486290 ymax: 1859520
Projected CRS: NAD83 / California zone 5 (ftUS)
```

```
      dr_no              date_rptd                date_occ time_occ area
1  90631215 2010-01-05T00:00:00.000 2010-01-05T00:00:00.000      150    6
2 100100501 2010-01-03T00:00:00.000 2010-01-02T00:00:00.000     2100    1
3 100100506 2010-01-05T00:00:00.000 2010-01-04T00:00:00.000     1650    1
  area_name rpt_dist_no part_1_2 crm_cd
1 Hollywood         646        2    900
2   Central         176        1    122
3   Central         162        1    442
                              crm_cd_desc       mocodes vict_age vict_sex
1                 VIOLATION OF COURT ORDER 1100 0400 1402       47        F
2                          RAPE, ATTEMPTED           0400       47        F
3 SHOPLIFTING - PETTY THEFT ($950 & UNDER)      0344 1402       23        M
  vict_descent premis_cd      premis_desc weapon_used_cd
1            W       101           STREET            102
2            H       103            ALLEY            400
3            B       404 DEPARTMENT STORE             NA
                                    weapon_desc status  status_desc crm_cd_1
1                                      HAND GUN     IC  Invest Cont      900
2 STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)     IC  Invest Cont      122
3                                                  AA Adult Arrest      442
  crm_cd_2 crm_cd_3 crm_cd_4                              location
1      998       NA       NA        CAHUENGA                    BL
2       NA       NA       NA        8TH                         ST
3       NA       NA       NA 700 W  7TH                         ST
                   cross_street                geometry  place1
1 HOLLYWOOD                  BL POINT (6461916 1859520)  buffer
2 SAN PEDRO                  ST POINT (6486290 1836559) outside
3                               POINT (6483602 1839950) outside
```

Let's check that all the crimes are correctly labeled with a map.

```
ggplot() +
   geom_sf(data = mapSZms13 |>
              st_buffer(dist=5280),
           fill = NA,
           color = "black") +
   geom_sf(data = mapSZms13,
           fill = NA,
           color = "red",
           linewidth = 3) +
   geom_sf(data = dataCrimeMS13 |>
              # filter to points in bounding box
              st_filter(st_as_sfc(bboxMS13)),
           aes(color = place1),
```

```
          shape = 16,
          size = 0.3,
          alpha = 0.7) +
  scale_color_manual(values = c(SZ="red", buffer="blue", outside= "green"),
                     name    = "Location") +
  coord_sf(xlim = c(bboxMS13$xmin, bboxMS13$xmax),
           ylim = c(bboxMS13$ymin, bboxMS13$ymax),
           expand = FALSE) +
  theme_minimal() +
  guides(color = guide_legend(override.aes = list(size = 4))) +
  labs(x = NULL, y = NULL)
```

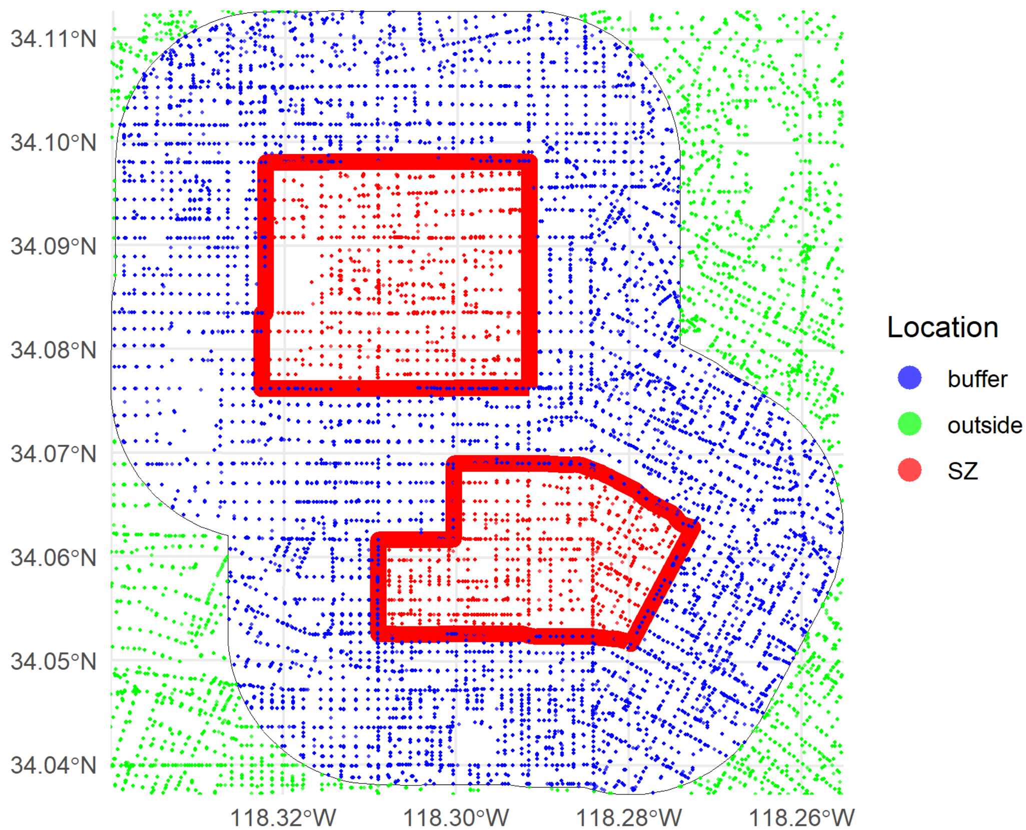
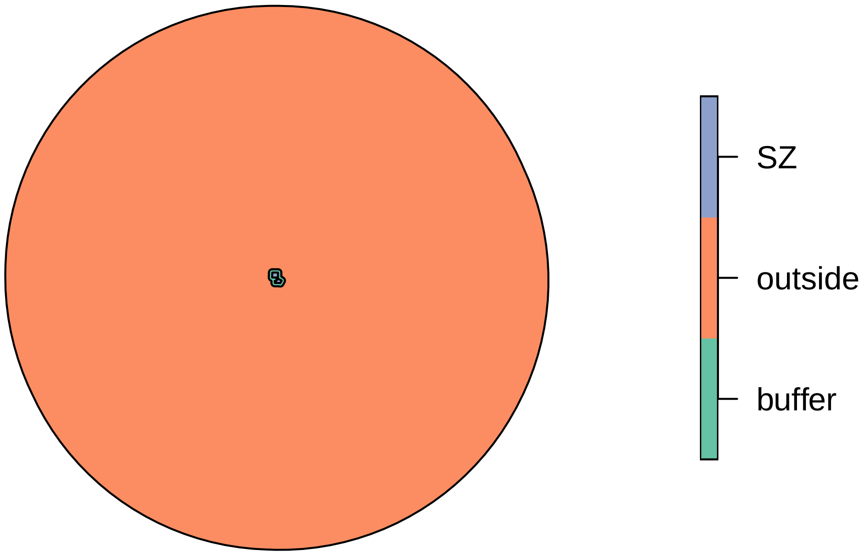


Figure 15: Plot of MS13 safety zone with a one-mile buffer and Los Angeles crime locations

So using `st_intersects()` can correctly label the locations of different crimes.

Let's try a second approach using `st_join()`, a spatial version of the joins that we did when studying SQL. First, we will make a new spatial object with three polygons, the MS13 safety zone, the buffer, and the region outside the buffer. We will label those three polygons and use `st_join()` to ask each crime in which polygon they fall.

```
# combine the geometries of the three polygons
mapA <- c(# inside safety zone
          mapSZms13 |> st_geometry(),
          # ring buffer around safety zone
          mapSZms13 |>
             st_buffer(dist=5280) |>
             st_difference(mapSZms13) |>
             st_geometry(),
          # outside ring buffer
          mapSZms13 |>
             st_buffer(dist=80*5280) |>
             st_difference(mapSZms13 |>
                                st_buffer(dist=5280)) |>
             st_geometry())
# create an sf object
mapA <- st_sf(place2=c("SZ","buffer","outside"),
              geom=mapA)
plot(mapA, main="")
```




```
dataCrimeMS13 <- dataCrimeMS13 |> st_join(mapA)
```

`st_join()` will add a new column `place2` to the `dataCrimeMS13` data frame containing the label of the polygon in which it landed. Indeed, `dataCrimeMS13` now has a `place2` column categorizing the incident location.

```
dataCrimeMS13 |> head(3)
```

```
Simple feature collection with 3 features and 28 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 6461916 ymin: 1836559 xmax: 6486290 ymax: 1859520
Projected CRS: NAD83 / California zone 5 (ftUS)
      dr_no              date_rptd                date_occ time_occ area
1  90631215 2010-01-05T00:00:00.000 2010-01-05T00:00:00.000      150    6
2 100100501 2010-01-03T00:00:00.000 2010-01-02T00:00:00.000     2100    1
3 100100506 2010-01-05T00:00:00.000 2010-01-04T00:00:00.000     1650    1
  area_name rpt_dist_no part_1_2 crm_cd
1 Hollywood         646        2    900
2   Central         176        1    122
3   Central         162        1    442
                           crm_cd_desc        mocodes vict_age vict_sex
1                  VIOLATION OF COURT ORDER 1100 0400 1402       47        F
```

```
2                          RAPE, ATTEMPTED           0400       47         F
3 SHOPLIFTING - PETTY THEFT ($950 & UNDER)      0344 1402       23         M
  vict_descent premis_cd      premis_desc weapon_used_cd
1            W       101           STREET            102
2            H       103            ALLEY            400
3            B       404 DEPARTMENT STORE             NA
                                         weapon_desc status  status_desc crm_cd_1
1                                           HAND GUN     IC  Invest Cont      900
2 STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)     IC  Invest Cont      122
3                                                    AA Adult Arrest      442
  crm_cd_2 crm_cd_3 crm_cd_4                                 location
1      998       NA       NA         CAHUENGA                      BL
2       NA       NA       NA         8TH                           ST
3       NA       NA       NA 700 W   7TH                           ST
                     cross_street  place1  place2                geometry
1 HOLLYWOOD                    BL  buffer  buffer POINT (6461916 1859520)
2 SAN PEDRO                    ST outside outside POINT (6486290 1836559)
3                                 outside outside POINT (6483602 1839950)
```

And we can confirm that both methods produce the same results.

```r
dataCrimeMS13 |>
   count(place1, place2) |>
   st_drop_geometry()
```

```
   place1  place2      n
1      SZ      SZ 119113
2  buffer  buffer 312969
3 outside outside 643778
```

Does crime behave differently inside the safety zone compared with the areas beyond the safety zone? Let's break down the crime counts by year and plot them. We are going to divide the crime count by their average so that they are on the same scale. The area beyond the buffer is very large and it does not make sense to compare their counts directly.

```r
dataCrimeMS13 <- dataCrimeMS13 |>
   mutate(date_occ = date_occ |> ymd_hms())

# count the number of crimes by year and area
a <- dataCrimeMS13 |>
   st_drop_geometry() |>
   count(place1, year=year(date_occ)) |>
   group_by(place1) |>
   # normalize to the average crime count over the period
```

```
  mutate(relativeN = n/mean(n)) |>
  ungroup()

a |>
  select(-n) |>
  pivot_wider(names_from=place1, values_from=relativeN)
```

```
# A tibble: 15 x 4
    year    SZ buffer outside
   <dbl> <dbl>  <dbl>   <dbl>
 1  2010 0.916  0.926   0.925
 2  2011 0.862  0.905   0.889
 3  2012 0.924  0.906   0.914
 4  2013 0.867  0.861   0.876
 5  2014 0.951  0.902   0.907
 6  2015 0.493  0.703   0.959
 7  2016 1.63   1.36    1.09
 8  2017 1.11   1.10    1.10
 9  2018 1.11   1.10    1.14
10  2019 1.05   1.06    1.12
11  2020 0.975  0.964   0.960
12  2021 1.10   1.07    1.04
13  2022 1.22   1.26    1.22
14  2023 1.22   1.23    1.19
15  2024 0.576  0.650   0.686
```

```
ggplot(a, aes(x=year, y=relativeN, color=place1)) +
  geom_line(linewidth = 2) +
  scale_color_manual(values = c(SZ="red", buffer="blue", outside="green")) +
  labs(y = "Number of crimes relative to the average", color = "Location") +
  theme_minimal()
```

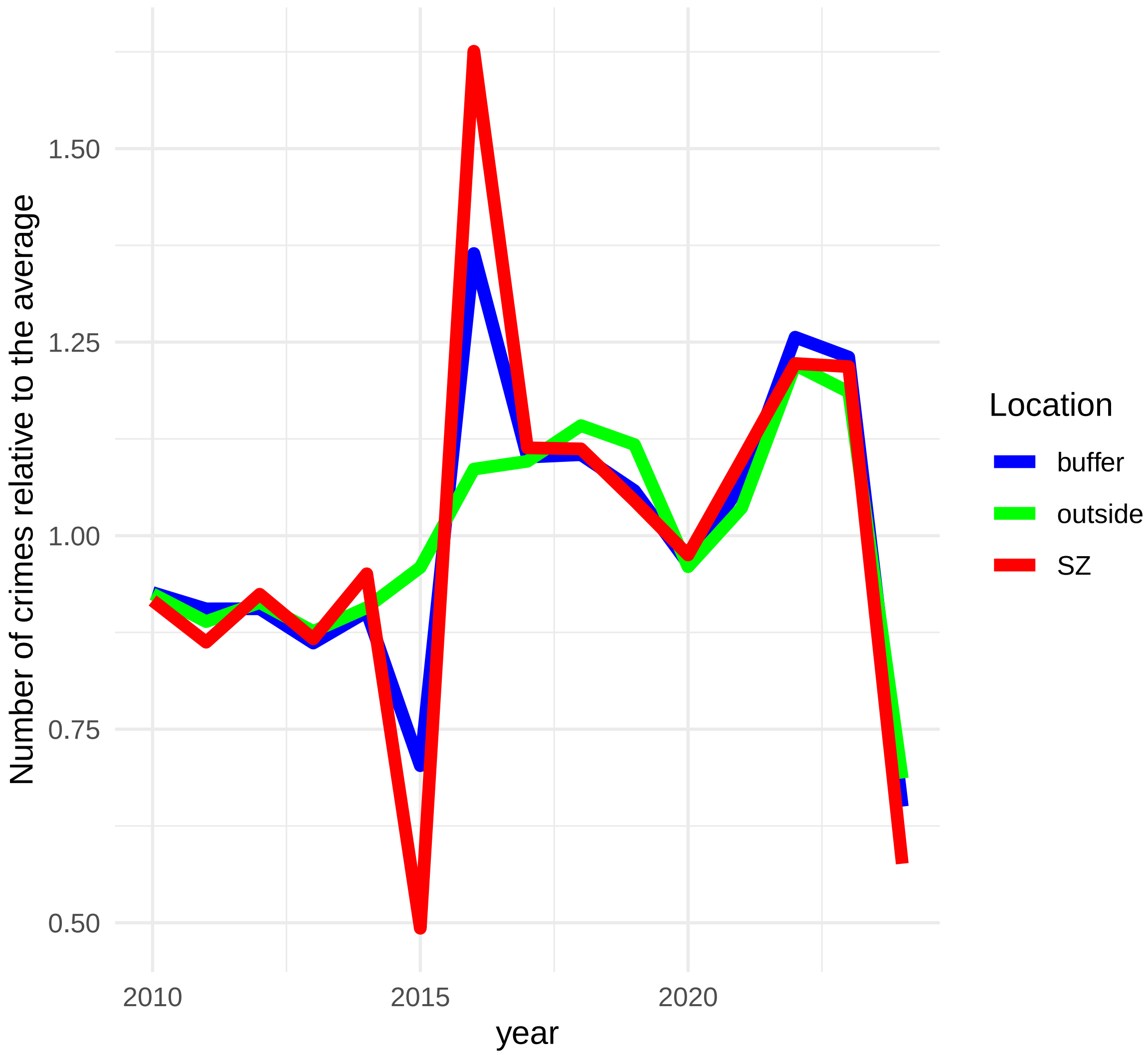


Figure 16: Trends in crime relative to their average

For the most part the crime trends look the same. However, in which years do we see some large differences? The large dip and spike are in 2015 and 2016. Remember when loading the crime data we noticed that 2015 and 2016 data looked miscoded in areas 18, 19, 20, and 21.

```
a <- dataCrimeMS13 |>
   filter(area %notin% c(18,19,20,21)) |>
   st_drop_geometry() |>
   count(place1, year=year(date_occ)) |>
   group_by(place1) |>
```

```
    mutate(relativeN = n/mean(n)) |>
    ungroup()

ggplot(a, aes(x=year, y=relativeN, color=place1)) +
  geom_line(linewidth = 2) +
  scale_color_manual(values = c(SZ="red", buffer="blue", outside="green")) +
  labs(y = "Number of crimes relative to the average", color = "Location") +
  theme_minimal()
```

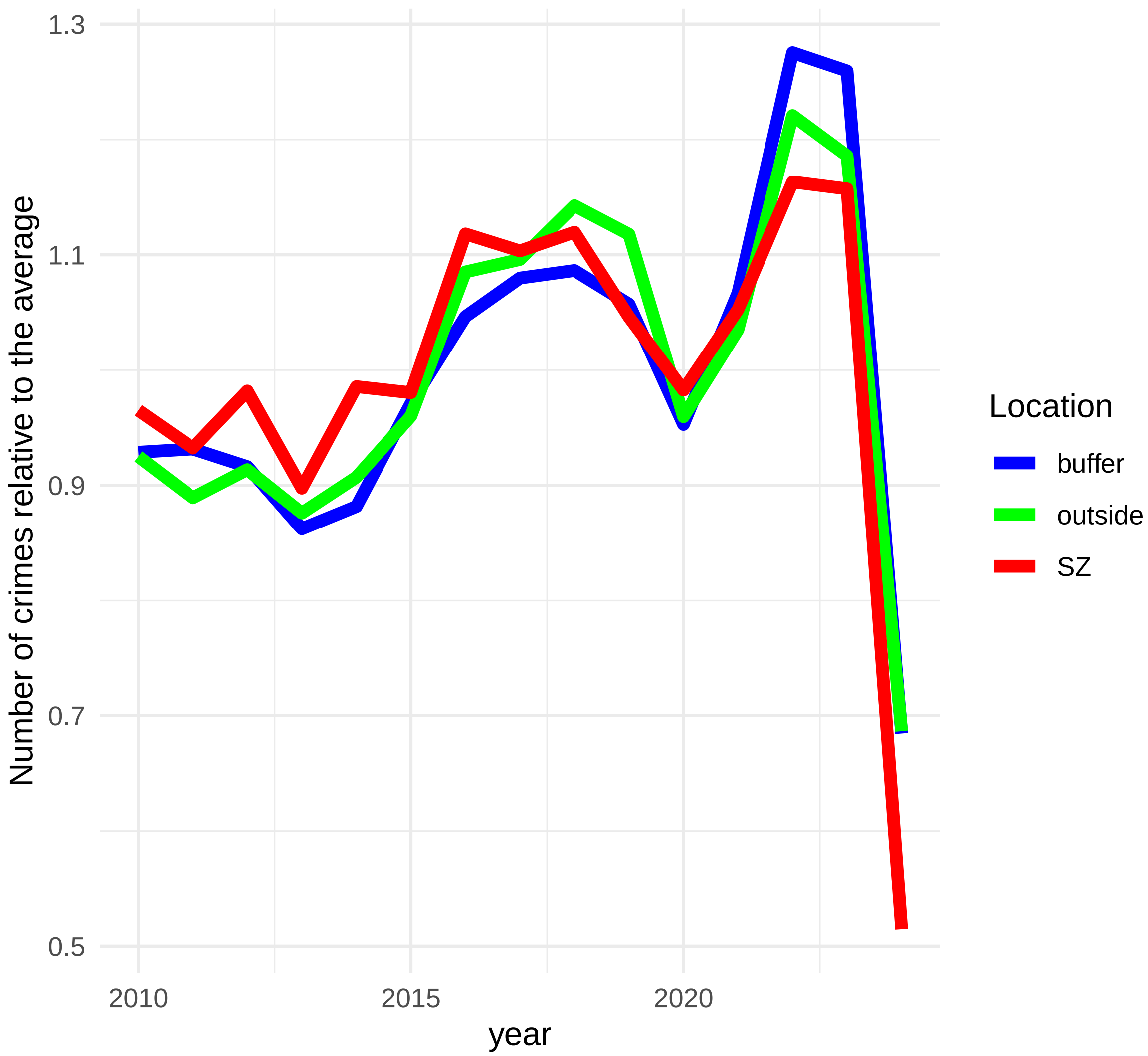


Figure 17: Trends in crime relative to their average (dropping areas 18, 19, 20, 21)

5.1 Exercises

10. How many 2019 crimes occurred inside safety zones?
11. How many crimes per square mile inside safety zones? (Hint 1: use `st_area()` for area)
12. How many crimes per square mile outside the safety zone, but within 1 mile of a safety zone

6 Creating new geographic objects

Remember that the MS13 safety zone had a northern and southern component. We are going to work with just the southern component, but first we need to separate it from its northern component. We will work through a several ways to accomplish this. The first will work directly with the `sf` objects and the second is an interactive method.

Right now, the MS13 map is stored as `MULTIPOLYGON` object.

```
is(st_geometry(mapSZms13))
```

```
[1] "sfc_MULTIPOLYGON" "sfc"              "oldClass"
```

A `MULTIPOLYGON` object is useful for managing a spatial object that involves several non-overlapping polygons, like this MS13 injunction, or the Hawaiian Islands, or the city of San Diego. We now want to break it apart into separate `POLYGON` objects using `st_cast()`.

```
a <- st_cast(mapSZms13, "POLYGON")
a
```

```
Simple feature collection with 2 features and 5 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 6463941 ymin: 1841325 xmax: 6479076 ymax: 1858250
Projected CRS: NAD83 / California zone 5 (ftUS)
                       NAME  case_no                     Safety_Zn
1   Rampart/East Hollywood BC311766 Rampart/East Hollywood (MS)
1.1 Rampart/East Hollywood BC311766 Rampart/East Hollywood (MS)
           gang_name  startDate                       geometry
1   Mara Salvatrucha 2004-04-08 POLYGON ((6476845 1841356, ...
1.1 Mara Salvatrucha 2004-04-08 POLYGON ((6473357 1850297, ...
```

Now we can see that `a` has two distinct polygons. The second row corresponds to the southern polygon. Let's store that one separately.

```
# which one is further south?
mapSZms13s <- a |>
   mutate(minLat =
             # coordinates applies to entire column
             st_coordinates(geometry) |>
             data.frame() |>
             # split by polygon
             group_by(L2) |>
             summarize(minLat=min(Y)) |>
             pull(minLat)) |>
   slice_min(minLat)

mapSZms13s |>
   st_geometry() |>
   plot()
```

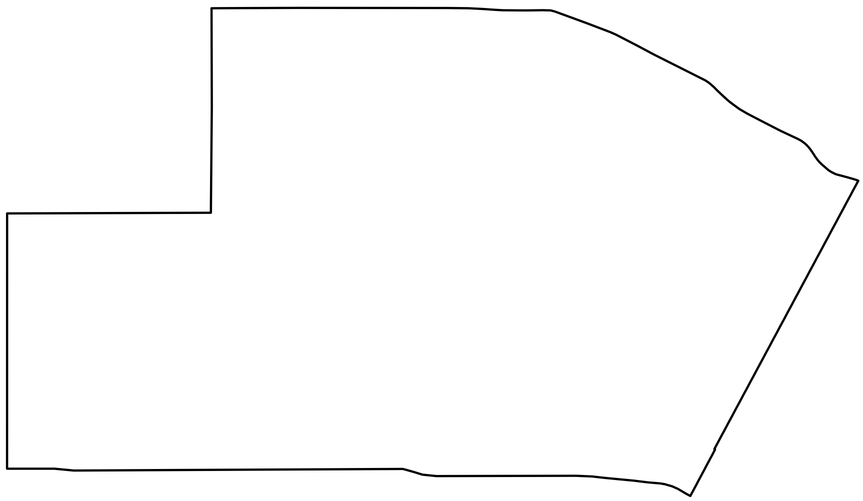


Figure 18: Southern polygon from the MS13 safety zone

Using `st_cast()` is the most direct method. However, sometimes the shapes are more complicated and we might want to select the shape interactively. To interactively select the southern component, use the R function `locator()`. It allows you to click on an R plot and will return the coordinates of the points you have selected. Let's first get the plot of the full MS13 safety zone in the plot window.

```
mapSZms13 |>
   st_geometry() |>
   plot()
```

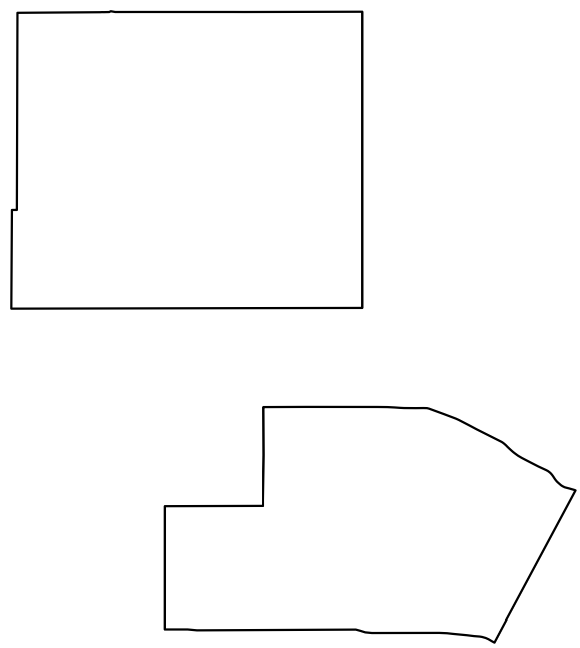


Figure 19: Both polygons marking the MS13 safety zone

Next, run `boxXY <- locator()`. In the top left of the plot window you will see "Locator active (Esc to finish)". Then click several points around the southern MS13 polygon as if you are cutting out just the southern polygon. When you have finished clicking the points, press the Esc key on your keyboard. Here are the places that I clicked.

My `boxXY` looks like this.

```
boxXY
```

```
$x
```

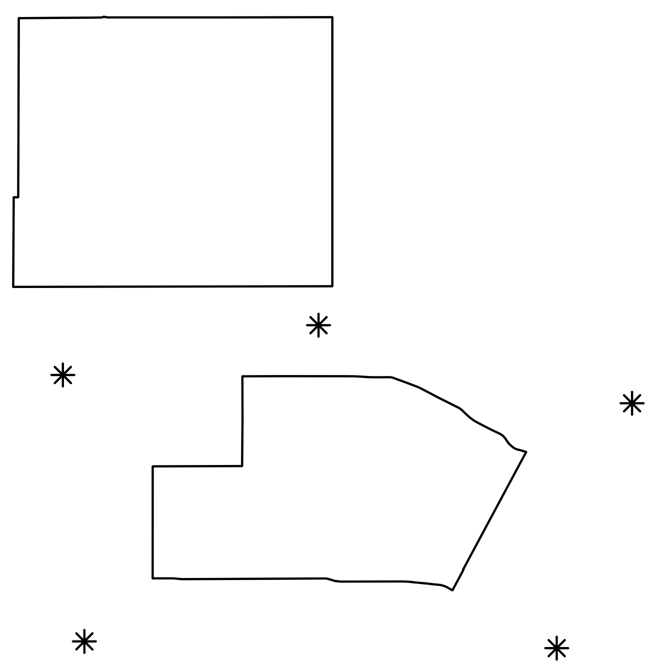


Figure 20: Points selected with `locator()` to extract southern polygon

```
[1] 6465406 6472950 6482201 6479978 6466041

$y
[1] 1847679 1849148 1846845 1839619 1839818
```

Yours will almost certainly look different and may even have more elements. Check to make sure your box completely surrounds the southern safety zone.

```r
# Make the end of the box reconnect back to the beginning
boxXY$x <- c(boxXY$x, boxXY$x[1])
boxXY$y <- c(boxXY$y, boxXY$y[1])
plot(st_geometry(mapSZms13),
     ylim=range(st_coordinates(st_geometry(mapSZms13))[,"Y"],
                boxXY$y))
lines(boxXY, col="red")
```

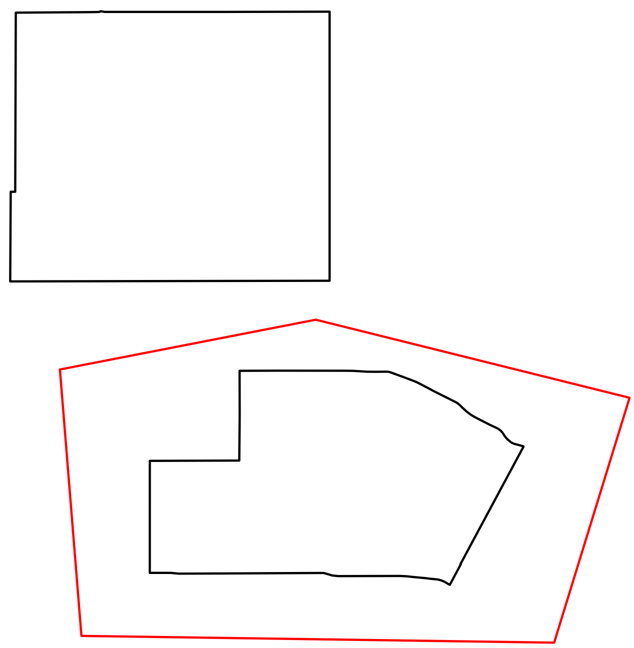


Figure 21: Polygon formed from `locator()`

If you are not satisfied with your outline, just rerun `boxXY <- locator()` and rerun this plot to check your revised box.

We need to turn this collection of points defining our box into an `sf` object. We will explore the several ways you can accomplish this. The first version we will use WKT (well known text), a way of using plain text to describe a geometric shape. This is a particularly useful method if you are able to type out the specific shape that you want or need to copy a shape from another application that also uses the WKT format. You have probably already noticed a `geometry` variable in the `dataCrime` data frame that has elements that look like

```r
dataCrime |>
   head(1) |>
   st_geometry() |>
   st_as_text()
```

```
[1] "POINT (6479964 1816123)"
```

You can also make polygons using a `POLYGON` tag instead of a `POINT` tag. Here is what the first safety zone looks like in WKT format.

```r
st_geometry(mapSZ) |> pluck(1)
```

```
POLYGON ((6435396 1924413, 6435607 1924174, 6435792 1923960, 6435872 1923867,
↪  6436158 1923545, 6436349 1923325, 6437295 1922239, 6438231 1921163,
↪  6438243 1921150, 6437992 1920931, 6437743 1920714, 6437495 1920498,
↪  6437246 1920282, 6436874 1919958, 6436472 1919608, 6435940 1919144,
↪  6435771 1918998, 6435633 1918878, 6435311 1918597, 6435143 1918451,
↪  6435086 1918401, 6434689 1918857, 6434139 1919485, 6433857 1919808,
↪  6433742 1919938, 6433189 1920572, 6433040 1920743, 6432908 1920894,
↪  6432706 1921120, 6432500 1921348, 6432467 1921385, 6432279 1921596,
↪  6432227 1921658, 6432296 1921718, 6432466 1921866, 6433399 1922679,
↪  6433404 1922683, 6433857 1923073, 6434399 1923545, 6434790 1923885,
↪  6434822 1923914, 6435396 1924413))
```

We can paste together the coordinates in `boxXY` to match this format.

```r
boxTemp <- paste0("POLYGON((",
                  paste(paste(boxXY$x, boxXY$y), collapse=","),
                  "))")
boxTemp
```

```
[1] "POLYGON((6465406 1847679,6472950 1849148,6482201 1846845,6479978
↪  1839619,6466041 1839818,6465406 1847679))"
```

The text looks correct, so now we convert it to a simple features object, making sure to also tell R the coordinate system that we are using.

```r
boxTemp <- st_as_sfc(boxTemp,
                     crs=st_crs(mapSZms13))
mapSZms13 |>
   st_geometry() |>
   plot(ylim=c(1839619,1858250))
boxTemp |>
```

```
  st_geometry() |>
  plot(border="red", add=TRUE)
```

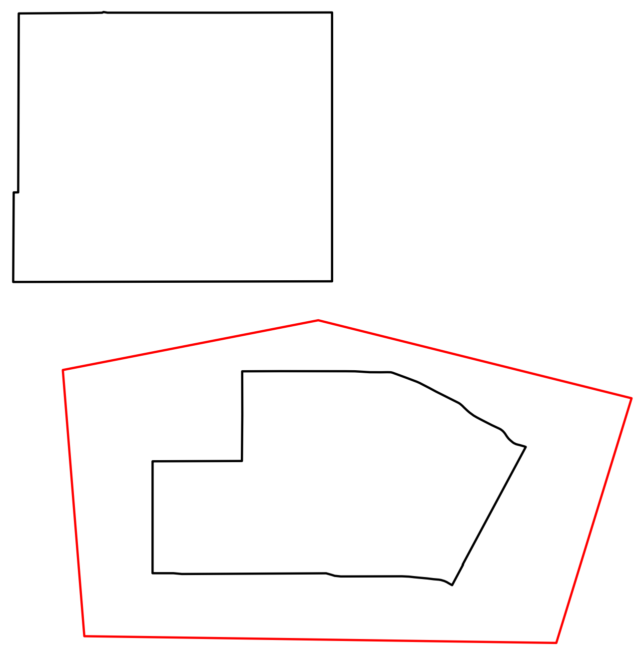


Figure 22: Polygon from `locator()` constructed from WKT

That was the WKT method. Let's try the `st_polygon()` method. `st_polygon()` takes in a matrix of coordinates and creates a simple features spatial object. Actually, it takes in a list of matrices. That way you can make objects like the northern and southern MS13 safety zones where the coordinates of each of the separate components are collected in one list.

```r
boxTemp <- cbind(boxXY$x, boxXY$y) |>
   list() |>
   st_polygon() |>
   st_sfc(crs=st_crs(mapSZms13))

mapSZms13 |>
   st_geometry() |>
   plot(ylim=c(1839619,1858250))
boxTemp |>
   st_geometry() |>
   plot(border="red", add=TRUE)
```

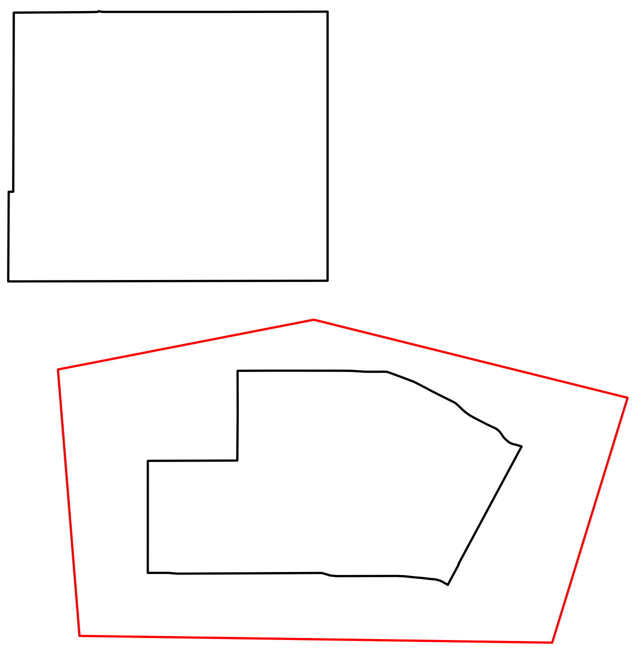


Figure 23: Polygon from `locator()` constructed using `st_polygon()`

Now the only reason we did this process of creating `boxTemp` is so that we could select just the southern polygon, which is the intersection of our `boxTemp` and the original `mapSZms13`.

```
mapSZms13s <- mapSZms13 |>
  st_intersection(boxTemp)
```

```
Warning: attribute variables are assumed to be spatially constant throughout
all geometries
```

```
mapSZms13s |>
  st_geometry() |>
  plot()
```

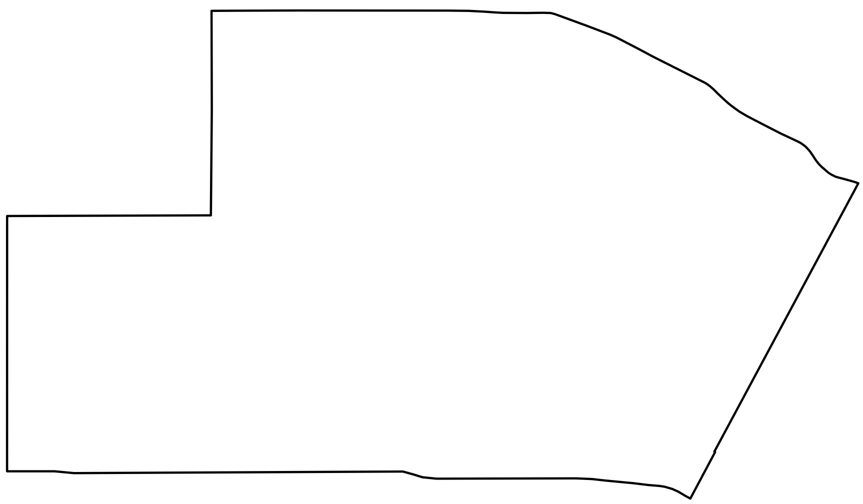


Figure 24: Final selection of southern MS13 safety zone

With the southern MS13 safety zone extracted, let's explore the streets in this neighborhood.

7 Overlaying a street map

Let's load the street map for Los Angeles County, the county that contains the city of Los Angeles.

```
# using tigris
mapLAstreet <- roads(state="CA",
                     county="Los Angeles",
                     year=2019,
                     class="sf")
```

If you would rather work from a shapefile stored locally on your computer, the file to use is `tl_2019_06037_roads.shp`. The naming convention says that this is a TIGER line file, from 2019, for state 06 (California), for county 037 (Los Angeles County), containing roads. Los Angeles County is large and this file has over 135,000 street segments. It can take a little while to load and project.

```
mapLAstreet <- st_read("09_shapefiles_and_data/tl_2019_06037_roads.shp")
```

Regardless of the method, we then need to make sure we use the same projection for the streets as the injunction map.

```
mapLAstreet <- mapLAstreet |>
   st_transform(st_crs(mapSZms13s))
mapLAstreet |> head(3)
```

```
Simple feature collection with 3 features and 4 fields
Geometry type: LINESTRING
Dimension:     XY
Bounding box:  xmin: 6487582 ymin: 1835878 xmax: 6510389 ymax: 1857279
Projected CRS: NAD83 / California zone 5 (ftUS)
       LINEARID             FULLNAME RTTYP MTFCC
        ↪  geometry
1 1101576755652 Golden State Fwy Rmp     M S1400 LINESTRING (6487884
 ↪  1856781...
2 1101576692583       Pomona Fwy Rmp     M S1400 LINESTRING (6510389
 ↪  1835878...
3 1101576663753         Soto St Rmp      M S1400 LINESTRING (6501699
 ↪  1845173...
```

The file contains the geometry of each road (`geometry`), the name of the road (`FULLNAME`), and the type of road (`RTTYP` and `MTFCC`). `RTTYP` stands for "route type code" where

- M: Common (municipal) street
- C: County road
- S: State road (e.g. Highway 1, Route 66)
- I: Interstate highway (e.g. I-5, I-405, I-10)
- U: U.S. highway (U.S. 101)
- O: Other (e.g. forest roads, utility service roads)

`MTFCC` stands for "MAF/TIGER Feature Class Code". There are numerous MTFCCs, one for just about every geographical feature you can think of (e.g shorelines, water towers, campgrounds), but some of the common ones for our purposes here are

- s1100: Primary road (limited access highway)
- s1200: Secondary road (main arteries and smaller highways)
- s1400: Local neighborhood road
- s1730: Alley
- s1780: Parking lot

We do not need all the streets of Los Angeles County, so let's just get the ones that intersect with the southern MS13 safety zone. `st_filter()` by default uses `st_intersect()` to decide whether to keep a street or not. You can alter this default behavior by choosing a different function for `.predicate` like `st_crosses()` or `st_within()`.

```
mapMS13street <- mapLAstreet |>
  st_filter(mapSZms13s)
```

Let's take a look at the streets.

```
mapMS13street |>
  st_geometry() |>
  plot()
mapSZms13s |>
  st_geometry() |>
  plot(border="red", lwd=3, add=TRUE)
```

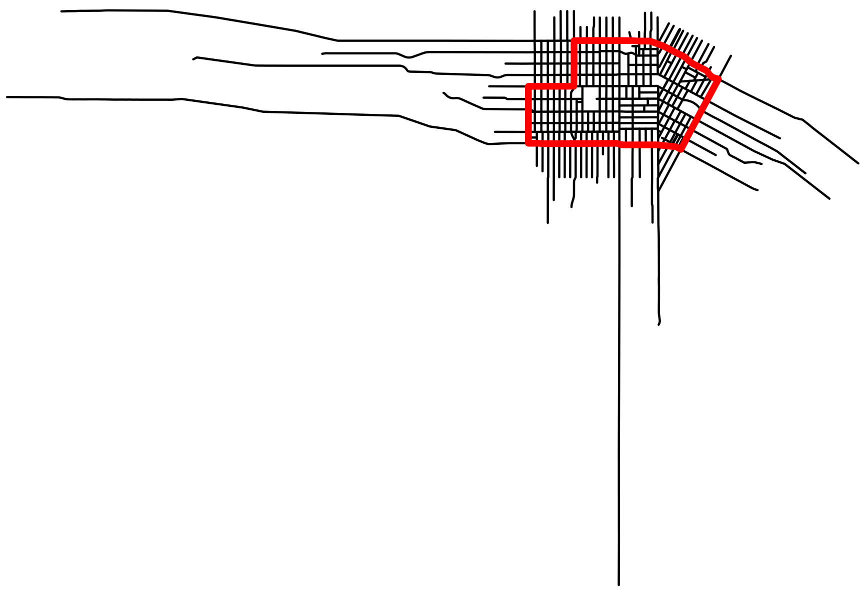


Figure 25: Streets that intersect the southern MS13 safety zone

```
mapMS13street |>
   # crop to mapSZms13s bounding box
   st_crop(mapSZms13s) |>
   st_geometry() |>
   plot()
mapSZms13s |>
   st_geometry() |>
   plot(border="red", lwd=3, add=TRUE)

mapMS13street <- mapMS13street |>
```

```r
st_crop(mapSZms13s)
```

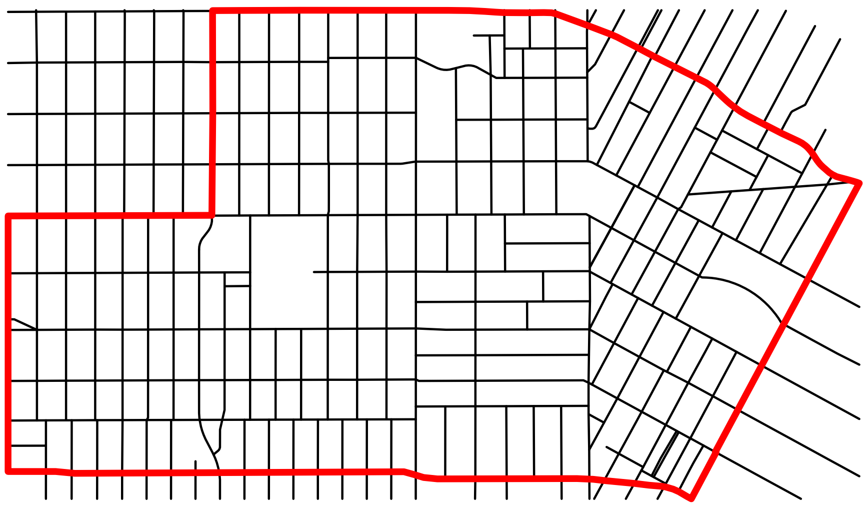


Figure 26: Streets that intersect the southern MS13 safety zone, cropped to safety zone bounding box

Now we have our safety zone and the streets that run through the safety zone. Let's put some street names over the map so we can read it more like a street map. It is hard to do this perfectly, but the following steps will work for our purposes. For each street segment we want to select a point on the street, near or inside the safety zone where we will put the label. We will use `st_line_sample()` with `sample=0.5` to select a point in the middle of the line (`mid_X`, `mid_Y`). Some streets run north/south, others east/west, and others diagonally. So, we need to figure out an angle for the label too. I will also find another point (`p_lo_X`, `p_lo_Y`) a little before the point where we will place the label. The slope of the line connecting the two points `p_lo` and `mid` can give us the angle of the street at that point (has it been a while since you have used the inverse tangent function?)

```
# save geometry column
g <- mapMS13street |>
   filter(!is.na(FULLNAME)) |>
   st_geometry()

delta <- 0.001
mapMS13street <- mapMS13street |>
   filter(!is.na(FULLNAME)) |>
   mutate(mid = geometry |>
             st_cast("LINESTRING") |>
             st_line_sample(sample = 0.5) |>
             st_cast("POINT") |>
             st_coordinates() |>
             data.frame(),
          p_lo =  geometry |>
             st_cast("LINESTRING") |>
             st_line_sample(sample = 0.5-delta) |>
             st_cast("POINT") |>
             st_coordinates() |>
             data.frame()) |>
   unnest_wider(mid,  names_sep="_") |> # separate into X & Y columns
   unnest_wider(p_lo, names_sep="_") |>
   # convert the slope of the street to the angle
   mutate(ang = atan2(mid_Y - p_lo_Y, mid_X - p_lo_X) * 180 / pi,
          # want -90 to 90 only, flip any upside down angles
          ang = if_else(abs(ang) > 90,
                        ang - sign(ang)*180,
                        ang)) |>
   st_as_sf(crs = st_crs(mapMS13street)) |>
   mutate(geometry = g)

mapMS13street |>
   st_geometry() |>
   plot()
mapSZms13s |>
   st_geometry() |>
   plot(border = "red", lwd = 3, add = TRUE)
for(i in 1:nrow(mapMS13street))
```

```
{
   text(mapMS13street$mid_X[i],
        mapMS13street$mid_Y[i],
        labels = mapMS13street$FULLNAME[i],
        srt = mapMS13street$ang[i],
        cex = 0.6)
}
```

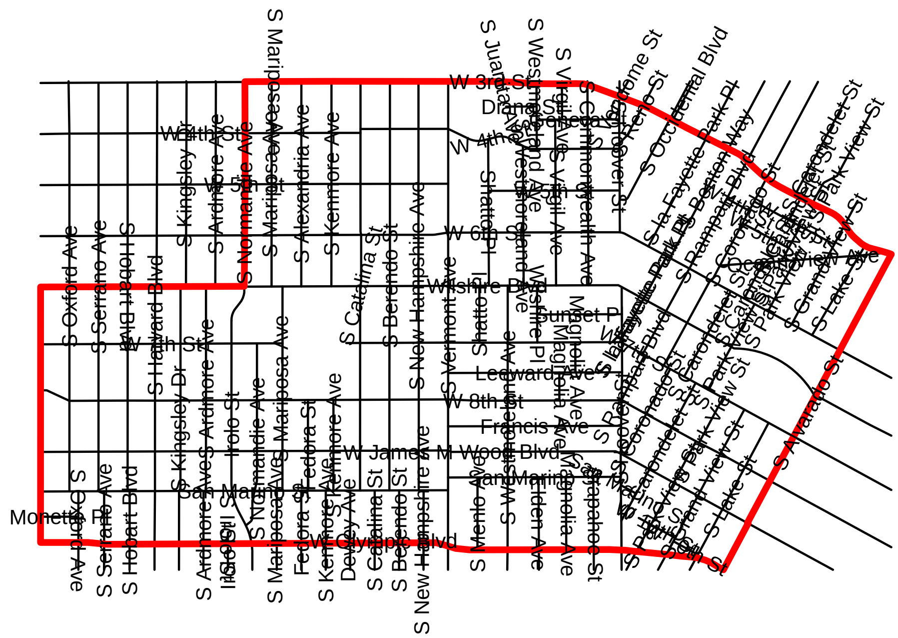


Figure 27: Street map through the southern MS13 safety zone

Wilshire Blvd is a major street that runs from the Pacific Ocean to downtown Los Angeles running through the MS13 safety zone along the way. You can see it highlighted in green here.

```
mapMS13street |> st_geometry() |> plot()
mapSZms13s |> st_geometry() |> plot(border = "red", lwd = 3, add = TRUE)
for(i in 1:nrow(mapMS13street))
{
   text(mapMS13street$mid_X[i], mapMS13street$mid_Y[i],
        labels = mapMS13street$FULLNAME[i],
        srt = mapMS13street$ang[i], cex = 0.6)
}
mapWilshire <- mapMS13street |>
   filter(FULLNAME=="Wilshire Blvd")
mapWilshire |> st_geometry() |> plot(col="green", lwd=3, add=TRUE)
```

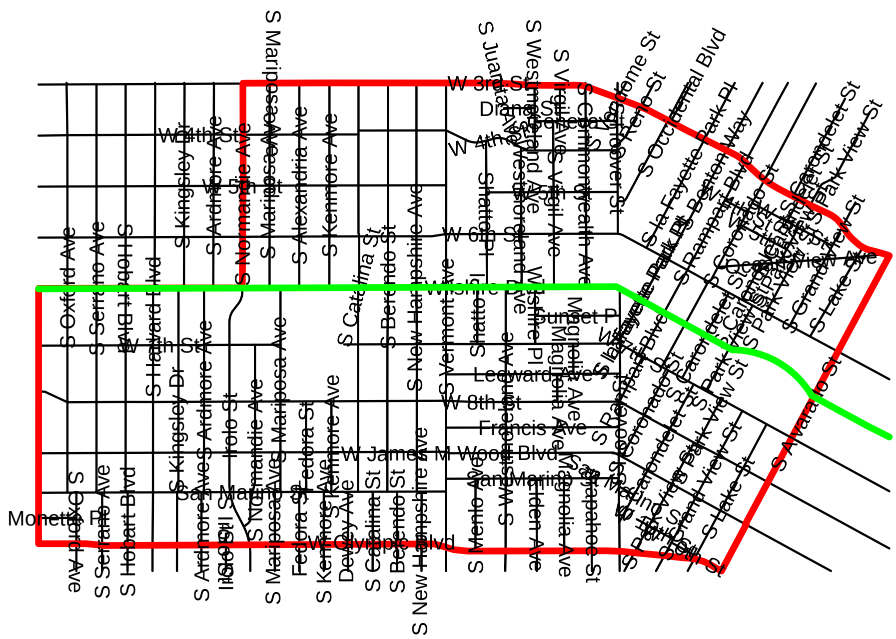


Figure 28: Street map in southern MS13 safety zone, Wilshire Blvd highlighted in green

We are going to count how many crimes occurred within 100 feet of Wilshire Blvd. Note that it is unlikely that any crimes will have occurred exactly on top of the line that is representing Wilshire Blvd in the map. We will work through two different methods. The first method will use a 100-foot buffer and count the crimes that land in it. The second method will compute the distance each crime is to Wilshire Blvd.

```
# create a 100-foot buffer, but only the part that is in the ms13 safety zone
mapWilbuffer <- mapWilshire |>
   st_buffer(dist=100) |>
   st_intersection(mapSZms13s)
```

```r
dataCrimeMS13 <- dataCrimeMS13 |>
   mutate(inWilbuf = lengths(st_intersects(geometry, mapWilbuffer)) > 0)

mapMS13street |> st_geometry() |> plot()
mapSZms13s |> st_geometry() |> plot(border = "red", lwd = 3, add = TRUE)
for(i in 1:nrow(mapMS13street))
{
   text(mapMS13street$mid_X[i], mapMS13street$mid_Y[i],
        labels = mapMS13street$FULLNAME[i],
        srt = mapMS13street$ang[i], cex = 0.6)
}
mapWilbuffer |> st_geometry() |> plot(col="green", lwd=3, add=TRUE)

# add crime locations
dataCrimeMS13 |>
   filter(inWilbuf) |>
   st_geometry() |>
   plot(col="blue", add=TRUE, pch=16, cex=0.5)
```

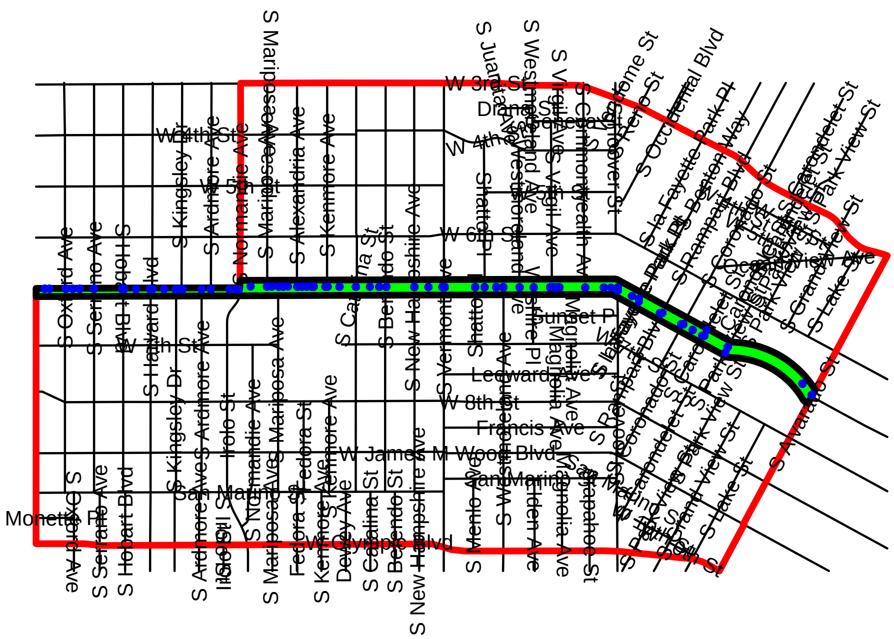


Figure 29: Crime locations on Wilshire Blvd

And what are the most common crime types along Wilshire Blvd?

```
dataCrimeMS13 |>
  st_drop_geometry() |>
  filter(inWilbuf) |>
  count(crm_cd_desc) |>
  slice_max(n, n=5)
```

```
                          crm_cd_desc    n
1                BATTERY - SIMPLE ASSAULT 1136
```

```
2            THEFT PLAIN - PETTY ($950 & UNDER) 1020
3                          BURGLARY FROM VEHICLE  677
4                                        ROBBERY  571
5 ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT  537
```

In the previous method we created a 100-foot buffer and then asked which crimes landed inside the buffer. Alternatively, we can compute the distance between each crime point location and Wilshire Blvd. This second method takes a lot more computational effort and will be much slower, but you should be familiar with the functions that compute distances.

```
# explore st_distance() with first 10 incidents
dataCrimeMS13 |>
   head(10) |>
   st_distance(mapWilshire)
```

```
Units: [US_survey_foot]
           [,1]
 [1,] 15785.502
 [2,]  9710.824
 [3,]  5491.395
 [4,]  6892.608
 [5,] 10238.992
 [6,]  4944.466
 [7,]  7296.952
 [8,] 10995.036
 [9,] 12953.951
[10,]  6707.485
```

```
mapMS13street |>
   st_geometry() |>
   plot()
mapWilbuffer |>
   st_geometry() |>
   plot(add=TRUE, border="green")
mapSZms13s |>
   st_geometry() |>
   plot(border="red", lwd=3, add=TRUE)

dataCrimeMS13 |>
   # include only those within 100 feet of Wilshire Blvd
   filter(as.numeric(st_distance(geometry, mapWilshire)) < 100) |>
   st_geometry() |>
   plot(col="purple", add=TRUE, pch=16, cex=0.5)
```

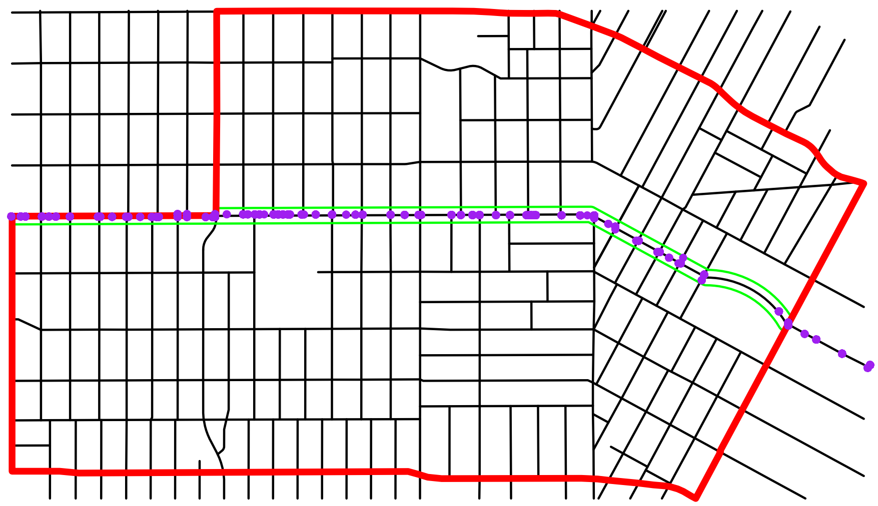


Figure 30: Crime locations on Wilshire Blvd, computed using `st_distance()`

7.1 Exercise

13. Are there more crimes along Wilshire Blvd or S Vermont Ave?

8 Find which line is closest to a point

We are going to find out which street is closest to each point. Yes, the crimes already have an address associated with them, but we will use that to check our work.

First, let's subset our crime data so we just have crimes that fall into the MS13 southern safety zone.

```
dataCrimeMS13s <- dataCrimeMS13 |>
   st_filter(mapSZms13s)

mapMS13street |>
   st_geometry() |>
   plot()
mapSZms13s |>
   st_geometry() |>
   plot(border="red", lwd=3, add=TRUE)
dataCrimeMS13s |>
   st_geometry() |>
   plot(add=TRUE, col="blue",pch=16, cex=0.5)
```

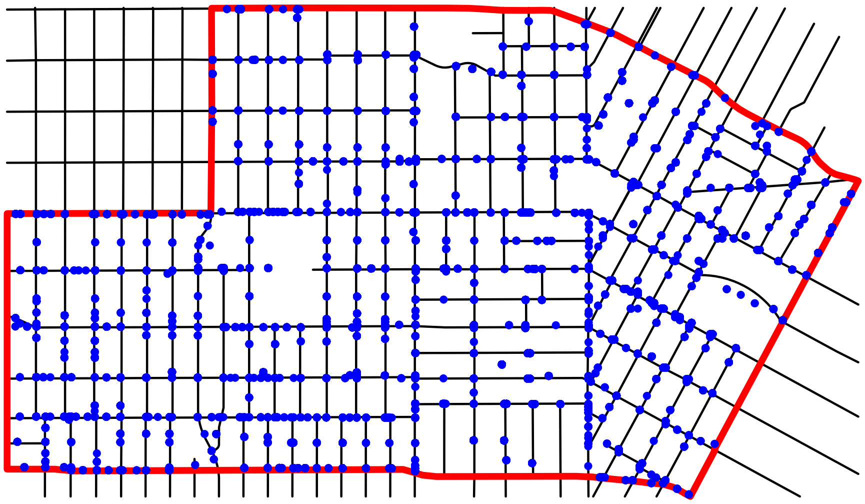


Figure 31: Crime locations in southern MS13 safety zone

Now let's compute the distance for each point to the closest street in `mapMS13street`.

```
d <- st_distance(dataCrimeMS13s, mapMS13street)
dim(d) # row for each crime, column for each street
```

```
[1] 68558   107
```

`d` is a matrix of distances with 68,558 rows and 107 columns, a distance from every crime point to every street. Now let's figure out which street is closest.

```r
# for each row (crime) find out which column (street)
iClose <- apply(d, 1, which.min)

# for the first crime check that the original address is similar to closest street
dataCrimeMS13s |>
   st_drop_geometry() |>
   head(1) |>
   select(location, cross_street)
```

```
  location cross_street
1      7TH     WILSHIRE
```

```r
mapMS13street |>
   st_drop_geometry() |>
   slice(iClose[1]) |>
   select(FULLNAME)
```

```
# A tibble: 1 x 1
  FULLNAME
  <chr>
1 W 7th St
```

```r
mapMS13street |> st_geometry() |> plot()
mapSZms13s |> st_geometry() |> plot(border = "red", lwd = 3, add = TRUE)
for(i in 1:nrow(mapMS13street))
{
   text(mapMS13street$mid_X[i], mapMS13street$mid_Y[i],
        labels = mapMS13street$FULLNAME[i],
        srt = mapMS13street$ang[i], cex = 0.6)
}

dataCrimeMS13s |>
   head(1) |>
   st_geometry() |>
   plot(add=TRUE, col="red", pch=16, cex=2)
```

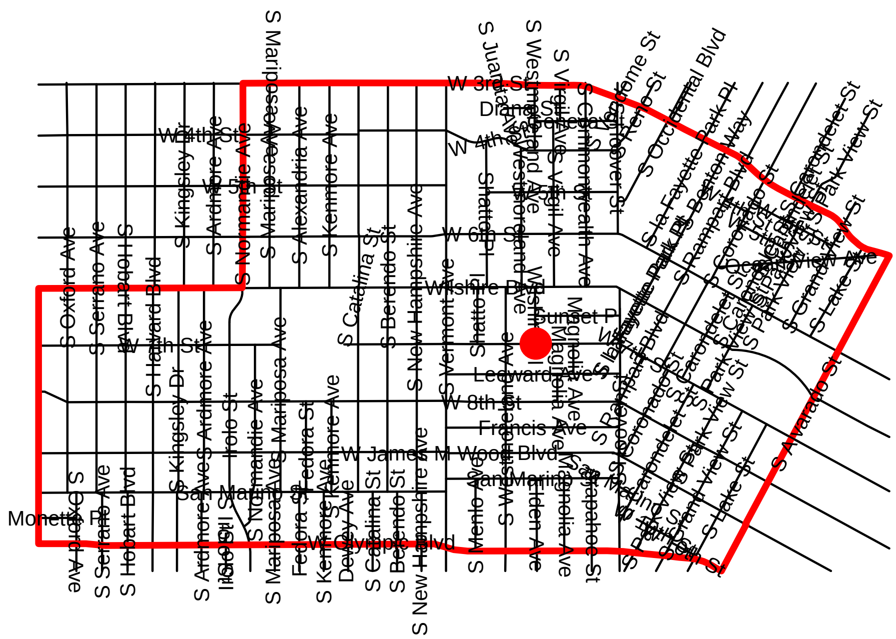


Figure 32: Example crime location checking its nearest street

Which streets have the most incidents?

```
# using distance calculation
table(mapMS13street$FULLNAME[iClose]) |>
   sort() |>
   tail(10)
```

```
    S Berendo St       S Catalina St          S Hoover St W James M Wood
  ↪   Blvd
```

```
              2118                 2201                 2280
                ↪  2353
          W 8th St             W 4th St             W 5th St             W 7th
            ↪  St
              2868                 3100                 3275
                ↪  4636
     Wilshire Blvd             W 6th St
              6318                 9923
```

```
# or, just using the addresses
dataCrimeMS13s$location |>
   gsub("^[0-9]+ ", "", x=_) |>
   gsub(" * ", " ", x=_) |>
   table() |>
   sort() |>
   tail(10)
```

```
      6TH ST   S RAMPART BL   S VERMONT AV  S ALVARADO ST   S KENMORE AV
        1347           1349           1552           1554           1639
 S BERENDO ST  S CATALINA ST        W 8TH ST        W 6TH ST    WILSHIRE BL
        1783           1824           2561           3159           7185
```

8.1 Exercise

14. There are LA Metrorail stations along Wilshire at S Western Ave (farthest west), S Normandie Ave, S Vermont Ave, and S Alvarado St (farthest east). How many crimes occurred within 500 feet of a Metrorail station?

Hint: Consider finding the stations using `st_intersection()`.

```
mapMetro <- mapLAstreet |>
   filter(FULLNAME %in%
            c("S Western Ave","S Normandie Ave",
              "S Vermont Ave","S Alvarado St")) |>
   st_intersection(mapLAstreet |>
                     filter(FULLNAME=="Wilshire Blvd"))
```

15. RFK Community Schools occupy the site between S Mariposa Ave and S Catalina St and W 8th St and Wilshire Blvd. How many crimes occurred within 500 feet of the RFK School? The RFK Schools occupies the site of the Ambassador Hotel where Robert F. Kennedy was assassinated on June 5, 1968. Trump Wilshire Associates bought it in 1989,

followed by a decade long fight with the Los Angeles School District who wished to take the site by eminent domain. The schools opened in 2011.)

Hints:

```
a <- mapLAstreet |>
   filter(FULLNAME %in% c("S Mariposa Ave","S Catalina St")) |>
   st_intersection(mapLAstreet |>
                      filter(FULLNAME %in% c("W 8th St","Wilshire Blvd")))
```

```
Warning: attribute variables are assumed to be spatially constant throughout
all geometries
```

```
mapMS13street |> st_geometry() |> plot()
mapSZms13s |> st_geometry() |> plot(border = "red", lwd = 3, add = TRUE)

# plot the intersection points (why are there five?)
a |>
   st_geometry() |>
   plot(col="orange", add=TRUE, pch=16, cex=1)
# keep only the four most eastern points
#   dropping the west Mariposa/Wilshire intersection
a <- a |>
   slice_max(st_coordinates(geometry)[,"X"],
             n=4)
a |> st_geometry() |>
   plot(pch=21, bg ="orange", col="red", cex=1.5, add=TRUE)

# compute the convex hull of the remaining four points
mapRFKschool <- a |>
   st_union() |>
   st_convex_hull()
mapRFKschool |>
   st_geometry() |>
   plot(border="purple", add=TRUE, lwd=3)
```

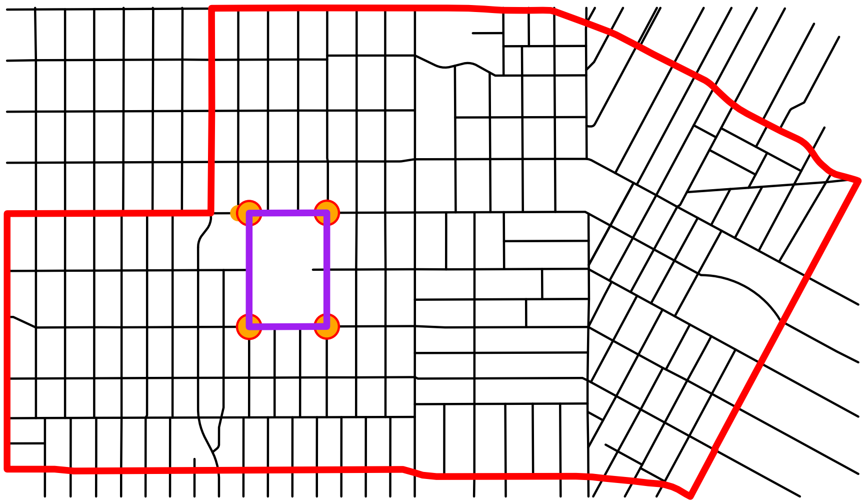


Figure 33: Boundaries of the RFK school

9 Make a KML file to post to Google Maps

KML (keyhole markup language) is a standard way that Google Maps stores geographic information (Keyhole was a company that Google acquired, renaming their product Google Earth). You can convert any of the maps you make in R to KML format and post them to Google Maps.

```
mapSZms13 |>
   st_transform(crs=4326) |>
   st_write(dsn="ms13.kml",
            layer= "ms13",
            driver="KML",
            delete_dsn = TRUE)
```

```
Deleting source `ms13.kml' using driver `KML'
Writing layer `ms13' to data source `ms13.kml' using driver `KML'
Writing 1 features with 5 fields and geometry type Multi Polygon.
```

Now you can navigate to https://www.google.com/mymaps, click import, select your `ms13.kml` file, and then it will be visible as an overlay on top of the usual Google map of Los Angeles.

10 Solutions to the exercises

1. Find the largest and smallest safety zones (use `st_area(mapSZ)`)

```
mapSZ |>
   mutate(area = st_area(geometry)) |>
   st_drop_geometry() |>
   summarize(iMin = which.min(area),
             iMax = which.max(area))
```

```
  iMin iMax
1   17   51
```

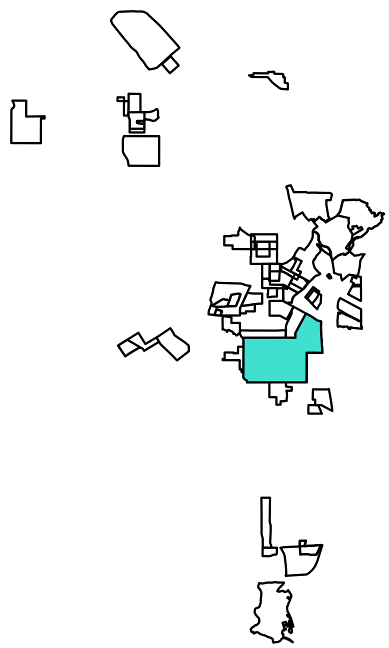
```
# or a more complete solution that combines areas by case number
mapSZ |>
   group_by(case_no) |>
   summarize(area = st_area(st_union(geometry))) |>
   ungroup() |>
   arrange(area) |>
   slice(1,n())
```

```
Simple feature collection with 2 features and 2 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 6451005 ymin: 1807966 xmax: 6489595 ymax: 1834100
Projected CRS: NAD83 / California zone 5 (ftUS)
# A tibble: 2 x 3
```

```
  case_no                area
   ↪  geometry
  <chr>    [US_survey_foot^2]                         <POLYGON
   ↪  [US_survey_foot]>
1 VC024170           4116319. ((6453176 1831871, 6452515 1831860, 6451005
 ↪  18320~
2 BC397522         445331479. ((6461015 1823912, 6476533 1823933, 6479929
 ↪  18239~
```

2. Plot all the safety zones. Color the largest in one color and the smallest in another color

```r
mapSZ |>
   st_geometry() |>
   plot()
mapSZ |>
   mutate(area = st_area(geometry)) |>
   slice_min(area) |>
   st_geometry() |>
   plot(add=TRUE, col="salmon")
mapSZ |>
   mutate(area = st_area(geometry)) |>
   slice_max(area) |>
   st_geometry() |>
   plot(add=TRUE, col="turquoise")
```



The smallest one is very tiny, just to the northeast of the biggest one.

3. Use `st_overlaps(mapSZ, mapSZ, sparse=FALSE)` or `print(st_overlaps(mapSZ, mapSZ, sparse=TRUE), n=Inf, max_nb=Inf)` to find two safety zones that overlap (not just touch at the edges)

```
mapSZ |>
  st_overlaps(mapSZ, sparse = TRUE) |>
  print(n=Inf, max_nb=Inf)
```

```
Sparse geometry binary predicate list of length 65, where the predicate
was `overlaps'
```

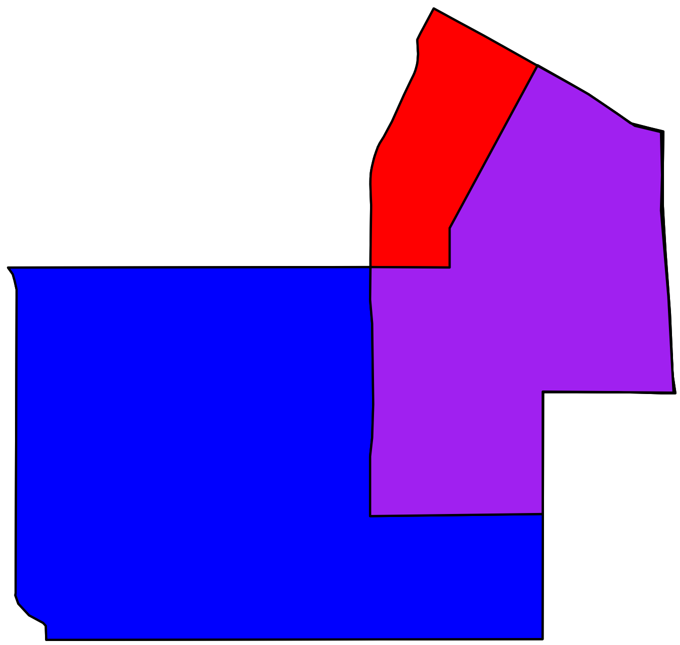
```
1: (empty)
2: 57
3: (empty)
4: 57
5: 57
6: 7, 8
7: 6, 13, 49
8: 6
9: 10, 12
10: 9, 11, 12, 65
11: 10, 65
12: 9, 10
13: 7
14: 15, 16, 20, 22, 52, 59, 60, 61, 62
15: 14, 61
16: 14, 20, 22, 52, 60, 61, 62
17: (empty)
18: (empty)
19: 63
20: 14, 16, 22, 60
21: (empty)
22: 14, 16, 20, 60
23: (empty)
24: (empty)
25: (empty)
26: (empty)
27: (empty)
28: 60
29: (empty)
30: 33, 37, 38, 51, 53
31: 63
32: (empty)
33: 30, 37, 51
34: 46
35: 36
36: 35, 39
37: 30, 33
38: 30, 46, 51, 53
39: 36
40: 46, 51
41: (empty)
42: (empty)
43: 54, 64
```

```
44: (empty)
45: (empty)
46: 34, 38, 40, 51
47: 56
48: (empty)
49: 7
50: (empty)
51: 30, 33, 38, 40, 46, 53
52: 14, 16, 59, 62
53: 30, 38, 51
54: 43, 64
55: (empty)
56: 47
57: 2, 4, 5
58: (empty)
59: 14, 52, 62
60: 14, 16, 20, 22, 28
61: 14, 15, 16
62: 14, 16, 52, 59
63: 19, 31
64: 43, 54
65: 10, 11
```

4. With the two safety zones that you found in the previous question, plot using three different colors the first safety zone, second safety zone, and their intersection (hint: use `st_intersection()`)

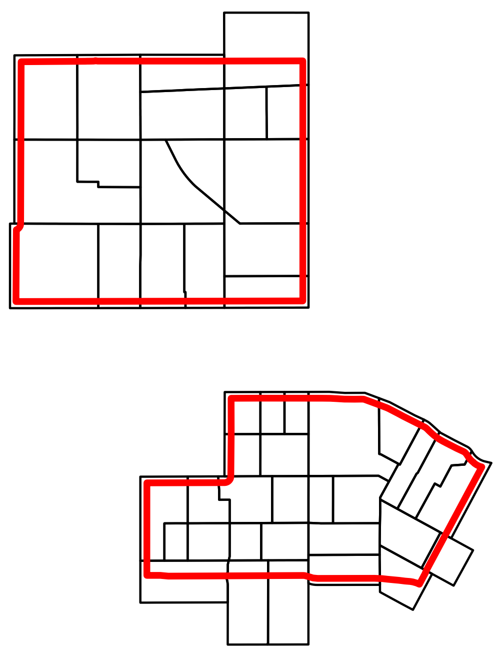
```
mapSZ |>
   slice(c(30,51)) |>
   st_geometry() |>
   plot()
mapSZ |>
   slice(30) |>
   st_difference(mapSZ |>
                  slice(51)) |>
   st_geometry() |>
   plot(col="red", add=TRUE)
mapSZ |>
   slice(51) |>
   st_difference(mapSZ |>
                  slice(30)) |>
   st_geometry() |>
   plot(col="blue", add=TRUE)
```

```r
mapSZ |>
   slice(51) |>
   st_intersection(mapSZ |>
                     slice(30)) |>
   st_geometry() |>
   plot(col="purple",
        add=TRUE)
```



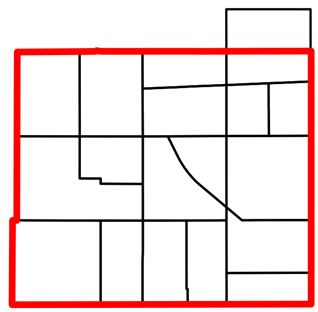
5. Census tracts that just touch the boundary of the safety zone are included. To eliminate, rather than use `st_intersects()` with `mapSZms13`, use `st_intersects()` with `st_buffer()` with a negative `dist` to select census tracts

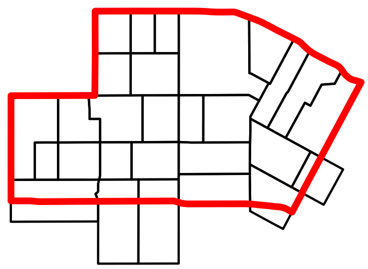
```
mapCens |>
   st_filter(mapSZms13 |>
                st_buffer(dist=-200)) |>
   st_geometry() |>
   plot()
mapSZms13 |>
   st_buffer(dist = -200) |>
   st_geometry() |>
   plot(border="red",
        lwd=3,
        add=TRUE)
```



```r
# or
i <- mapSZms13 |>
  st_buffer(dist=-200) |>
  st_intersects(mapCens) |>
  unlist()
mapCens <- mapCens |>
   mutate(inMS13 = (row_number() %in% i))
```

```r
mapCens |>
   st_filter(mapSZms13 |> st_buffer(dist=-50)) |>
   st_geometry() |>
   plot()
mapSZms13 |>
   st_geometry() |>
   plot(border="red", lwd=3, add=TRUE)
```





6. Create a map of all census tracts in the City of Los Angeles within 1 mile of one of the safety zones (you choose which safety zone)
7. Color each area based on a census feature (e.g. % non-white, or some other feature from the ACS data)
8. Add the polygon with your injunction zone
9. Add other injunction zones that intersect with your map

```
# get total population for each census tract
dataRes <- get_acs(geography = "tract",
                   variables = "B01001_001E",
                   state     = "CA",
                   county    = "Los Angeles",
```

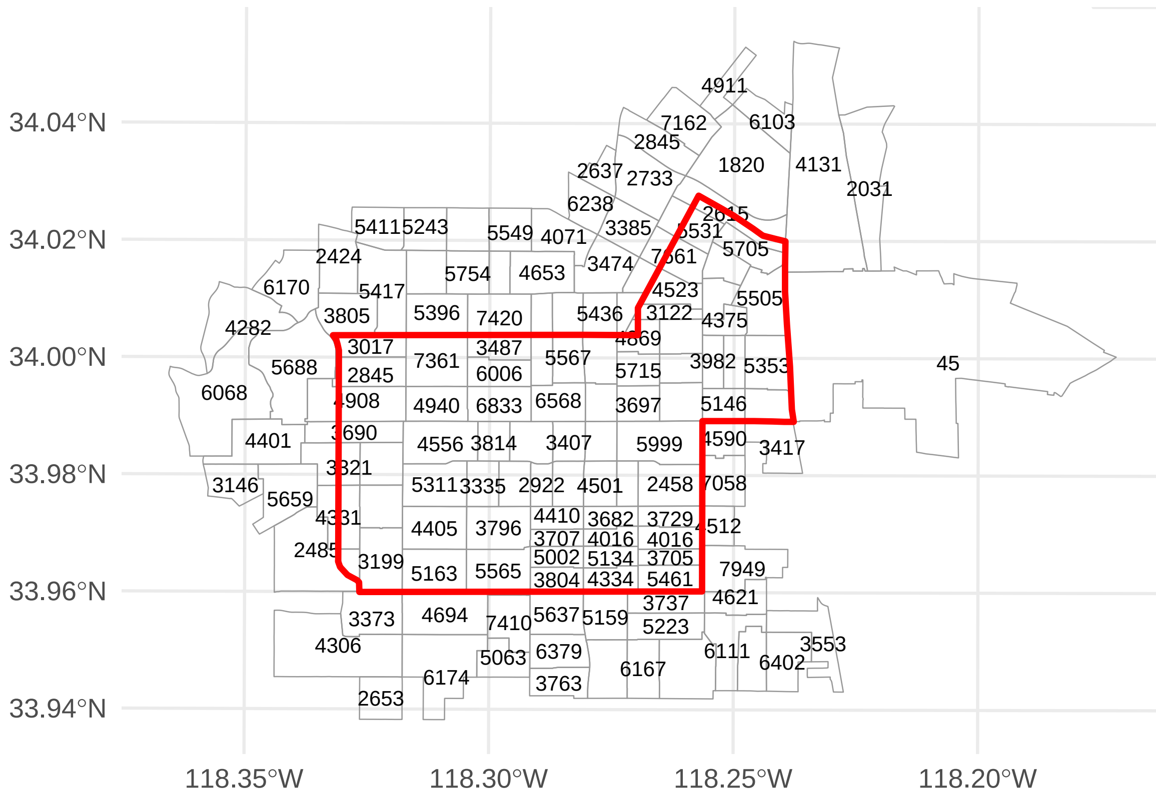
```
                   year       = 2019,
                   survey     = "acs5",
                   cache_table = TRUE) |>
   select(GEOID, estimate) |>
   rename(pop = estimate)
```

```
Getting data from the 2015-2019 5-year ACS
```

```
# merge total population into census map
mapCens <- mapCens |>
   left_join(dataRes, join_by(GEOID10==GEOID))

# census tracts within 1 mile of safety zone #51
mapCensMS13 <- mapCens |>
   st_filter(mapSZ |>
                slice(51) |>
                st_buffer(dist=5280))

ggplot() +
  geom_sf(data = mapCensMS13,
          fill = NA,
          color = "grey60",
          linewidth = 0.2) +
  geom_sf_text(data = mapCensMS13,
               aes(label = pop),
               # function for selecting label points
               fun.geometry = st_point_on_surface,
               size = 2.5,
               color = "black",
               check_overlap = TRUE) +
  geom_sf(data = mapSZ |> slice(51),
          fill = NA,
          color = "red",
          linewidth = 1) +
  labs(x = NULL, y = NULL) +
  theme_minimal()
```



10. How many 2019 crimes occurred inside safety zones?

```
nSZcrimes <- dataCrime |>
   filter(year(date_occ)==2019) |>
   st_filter(mapSZ |>
               st_union()) |>
   nrow()
nSZcrimes
```

```
[1] 100879
```

11. How many crimes per square mile inside safety zones? (Hint 1: use `st_area()` for area)

```
# use set_units() to convert to square miles
#   equivalent to multiplying by 5280^2
units::set_units(nSZcrimes / st_area(st_union(mapSZ)), value="1/mile^2")
```

```
913.4101 [1/mile^2]
```

12. How many crimes per square mile outside the safety zone, but within 1 mile of a safety zone

```
mapBuf <- mapSZ |>
   st_union() |>
   st_buffer(dist=5280) |>
   st_difference(st_union(mapSZ)) |>
   st_intersection(mapLA)

nBufCrimes <- dataCrime |>
   filter(year(date_occ)==2019) |>
   st_filter(mapBuf) |>
   nrow()
nBufCrimes
```

```
[1] 63936
```

```
units::set_units(nBufCrimes / st_area(mapBuf), value="1/mile^2")
```

```
476.4311 [1/mile^2]
```

13. Are there more crimes along Wilshire Blvd or S Vermont Ave?

```
mapMS13street |>
   filter(FULLNAME=="S Vermont Ave") |>
   st_buffer(dist=100) |>
   st_intersection(mapSZms13s) |>
   st_intersects(dataCrime) |>
   lengths()
```

```
[1] 4405
```

```
mapMS13street |>
   filter(FULLNAME=="Wilshire Blvd") |>
   st_buffer(dist=100) |>
   st_intersection(mapSZms13s) |>
   st_intersects(dataCrime) |>
   lengths()
```

```
[1] 8953
```

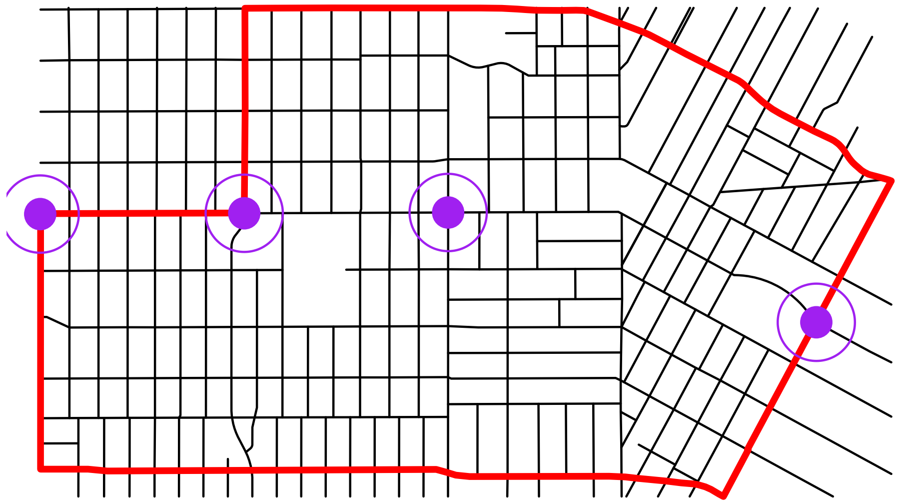
14. There are LA Metrorail stations along Wilshire at S Western Ave (farthest west), S Normandie Ave, S Vermont Ave, and S Alvarado St (farthest east). How many crimes occurred within 500 feet of a Metrorail station?

```
mapMetro <- mapLAstreet |>
   filter(FULLNAME %in% c("S Western Ave","S Normandie Ave",
                          "S Vermont Ave","S Alvarado St")) |>
   st_intersection(mapLAstreet |>
                     filter(FULLNAME=="Wilshire Blvd"))
```

```
Warning: attribute variables are assumed to be spatially constant throughout
all geometries
```

```
mapMS13street |>
   st_geometry() |>
   plot()
mapSZms13s |>
   st_geometry() |>
   plot(border="red", lwd=3, add=TRUE)
mapMetro |>
   st_geometry() |>
   plot(col="purple", add=TRUE, pch=16, cex=2)

mapMetro |>
   st_buffer(dist=500) |>
   st_geometry() |>
   plot(add=TRUE, border="purple")
```



```r
# how many crimes near each station?
mapMetro |>
   st_buffer(dist=500) |>
   st_intersects(dataCrime) |>
   lengths()
```

```
[1] 1367  900 1303 1531
```

```r
# how many crimes overall?
mapMetro |>
   st_buffer(dist=500) |>
   st_union() |>  # combine them into one shape
```

```
    st_intersects(dataCrime) |>
    lengths()
```

```
[1] 5101
```

```
# or
mapMetro |>
    st_buffer(dist=500) |>
    st_intersects(dataCrime) |>
    lengths() |>
    sum()
```

```
[1] 5101
```

15. RFK Community Schools occupy the site between S Mariposa Ave and S Catalina St and W 8th St and Wilshire Blvd. How many crimes occurred within 500 feet of the RFK School?

```
mapRFKschool |>
    st_buffer(dist=500) |>
    st_intersects(dataCrime) |>
    lengths()
```

```
[1] 6488
```