Exploring Patterns of Environmental Justice: Redlining and Biodiversity

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EDS-223 Homework Assignment #2

Objective

In this project, I investigated the Homeowner's Owners' Loan Corporation (HOLC) or *redlining* in Los Angeles County. I am tasked with producing a map of HOLC grades in LA county as well as looking at the relationship between redlining and environmental justice. In addition, I investigated biodiversity observations by HOLC grade to see the relationship between community science and redlined regions.

Environment Set-up

```
# Load relevant libraries
library(sf) # For vector data
library(stars) # For raster data
library(tmap) # For static and interactive maps
library(here) # For importing data
library(tidyverse) # For data cleaning
library(dplyr) # For filtering data
library(paletteer) # For pretty colors
library(testthat) # For efficient workflows
```

Load in Data

```r
#|output: false

# Load in EJSCREEN data for data on census blocks
ejscreen <- sf::st_read(here::here("data", "ejscreen","EJSCREEN_2023_BG_StatePct_with_AS_CNMI
```

```
Reading layer `EJSCREEN_StatePctiles_with_AS_CNMI_GU_VI' from data source
  `/Users/isabellasegarra/Documents/MEDS/EDS-223/HW-assignments/eds-223-hw-2/data/ejscreen/E
  using driver `OpenFileGDB'
Simple feature collection with 243021 features and 223 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -19951910 ymin: -1617130 xmax: 16259830 ymax: 11554350
Projected CRS: WGS 84 / Pseudo-Mercator
```

```r
# Load in HOLC Redlining data
redlining <- sf::st_read(here::here("data", "mapping-inequality", "mapping-inequality-los-ang
```

```
Reading layer `mapping-inequality-los-angeles' from data source
  `/Users/isabellasegarra/Documents/MEDS/EDS-223/HW-assignments/eds-223-hw-2/data/mapping-ine
  using driver `GeoJSON'
Simple feature collection with 417 features and 14 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -118.6104 ymin: 33.70563 xmax: -117.7028 ymax: 34.30388
Geodetic CRS:  WGS 84
```

```r
# Load in Bird Observations data
bird_obs <- sf::st_read(here::here("data", "gbif-birds-LA", "gbif-birds-LA.shp"))
```

```
Reading layer `gbif-birds-LA' from data source
  `/Users/isabellasegarra/Documents/MEDS/EDS-223/HW-assignments/eds-223-hw-2/data/gbif-birds-
  using driver `ESRI Shapefile'
Simple feature collection with 1288865 features and 1 field
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: -118.6099 ymin: 33.70563 xmax: -117.7028 ymax: 34.30385
Geodetic CRS:  WGS 84
```

Part 1: Legacy of redlining in current environmental (in)justice

Objective:

Explore historical redlining in Los Angeles and its legacy on present-day environmental justice.

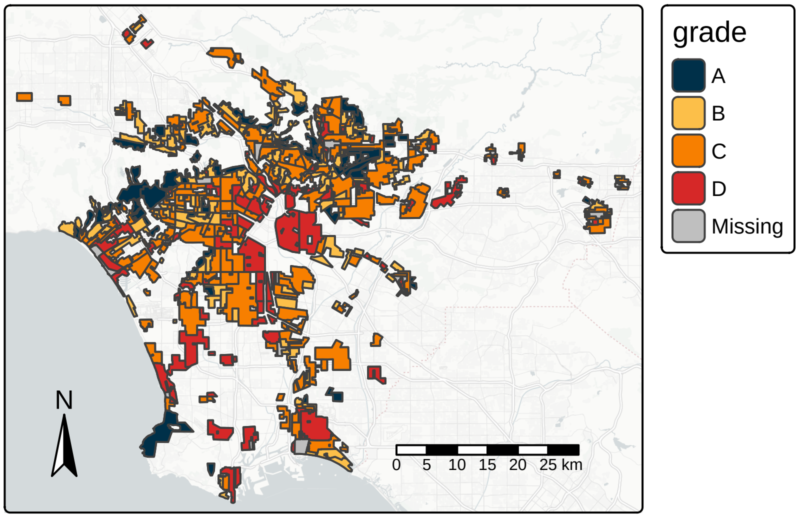
Map 1: Historical Redlining of Neighborhoods in Los Angeles, CA

```
#......Create a map of historical redlining neighborhoods......

redlining_map <- tm_shape(redlining) + # Map layer of redlined neighborhoods
  tm_borders() +
  tm_polygons(fill = "grade",
              palette = c("#003049", "#fcbf49", "#f77f00", "#d62828")) + # Fill in polygons l
  tm_legend(title = "HOLC Grade", size = 0.5) + # Add map legend
  tm_title(
    "Historical Redlining of Neighborhoods in Los Angeles, CA",
    size = 1,
    fontface = "bold"
  ) + # Add title and subtitle
  tm_title("Data source: Digital Scholarship Lab (University of Richmond)") +
  #tm_graticules() +
  tm_scalebar() + # Add scalebar
  tm_compass(position = c("left", "bottom")) + # Add compass
  tm_basemap("CartoDB.PositronNoLabels") # Add basemap

redlining_map # View map
```

```
|---------|---------|---------|---------|
=========================================
```

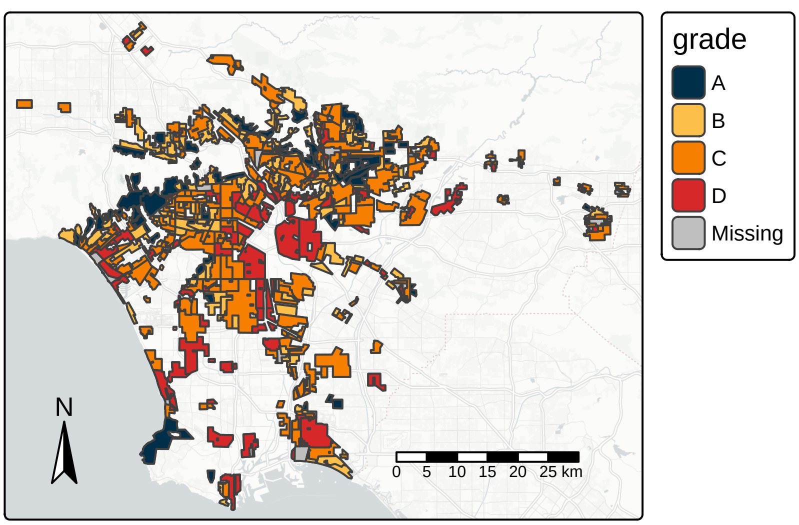
```
|---------|---------|---------|---------|
=========================================
```

Historical Redlining of Neighborhoods in Los Angeles, CA
Data source: Digital Scholarship Lab (University of Richmond)




```r
# Save map
tmap_save(redlining_map, here("redlining_map.png"))
```

Historical Redlining of Neighborhoods in Los Angeles, CA
Data source: Digital Scholarship Lab (University of Richmond)



Data Wrangling

CRS Matching

In order to work with the EJ Screen and Redlining/HOLC dataset as one dataset, I need to first check if the coordinate refrence system (CRS) match.

```
# Check that the CRS for 'ejscreen' and 'redlining' match
st_crs(ejscreen) # EPSG 3857
st_crs(redlining) # EPSG 4326

# Another way to check CRS
st_crs(ejscreen) == st_crs(redlining) # FALSE

# Transform the CRS of ejscreen to match redlining
ejscreen_transform <- st_transform(ejscreen, crs = st_crs(redlining))

# Check CRS of ejscreen
st_crs(ejscreen_transform) == st_crs(redlining) # TRUE

# Check is CRS of `bird_obs` match
st_crs(bird_obs)
```

```
[1] "CRS Match!"
```

```
[1] "CRS Match!"
```

Filtering

For the purposes of this assignment, the EJ Screen data only needs to show Los Angeles County.

```
#......Filter EJ Screen data......

# Filter to all data from Los Angeles County

la_ejscreen <- ejscreen_transform %>%
  dplyr::filter(CNTY_NAME == "Los Angeles County") %>%
  janitor::clean_names()
```

CRS Matching

In order to combine the EJ Screen and the Redlining data, I need to make sure there are no invalid geometries that can prevent the joining of the data.

```
#......Checking for invalid geometries in 'la_ejscreen'......

# Check for 'la_ejscreen' invalid geometries
st_is_valid(la_ejscreen)
which(!st_is_valid(la_ejscreen))

# Make geometries valid
la_ejscreen <- st_make_valid(la_ejscreen)

# Check if it worked
test_that("All geometries in la_ejscreen are valid", {
  expect_equal(which(!st_is_valid(la_ejscreen)), integer(0))
})
```

```
#......Checking for invalid geometries in 'redlining'......

# Check for 'redlining' invalid geometries
st_is_valid(redlining)
which(!st_is_valid(redlining))

# Make geometries valid
redlining <- st_make_valid(redlining)

# Check if it worked
test_that("All geometries in redlining are valid", {
  expect_equal(which(!st_is_valid(redlining)), integer(0))
})
```

```
#......Checking for invalid geometries in 'redlining'......

# Check for invalid geometries in 'bird_obs'

st_is_valid(bird_obs)
which(!st_is_valid(bird_obs))
bird_obs <- st_make_valid(bird_obs)

# Check if it worked
test_that("All geometries in bird_obs are valid", {
```

```
  expect_equal(which(!st_is_valid(bird_obs)), integer(0))
})
```

Join Data

Now, finally join the data!

```
#......Join Los Angeles ejscreen with redlining data......

# Use 'st_join()' because you want to utilize the geometries of redlining while keeping the 

la_redlining <- st_join(x = redlining, y = la_ejscreen, join = st_intersects) %>%
  st_drop_geometry()

# View the new dataframe
head(la_redlining)
```

```
    area_id city_id grade    fill label name category_id sheets         area
1      7761      16     A #76a865    A1                  1      1 0.0003359915
1.1    7761      16     A #76a865    A1                  1      1 0.0003359915
1.2    7761      16     A #76a865    A1                  1      1 0.0003359915
1.3    7761      16     A #76a865    A1                  1      1 0.0003359915
1.4    7761      16     A #76a865    A1                  1      1 0.0003359915
1.5    7761      16     A #76a865    A1                  1      1 0.0003359915
                                                                      bounds
1   [ [ 34.136969999999998, -118.46807 ], [ 34.153350000000003, -118.42031 ] ]
1.1 [ [ 34.136969999999998, -118.46807 ], [ 34.153350000000003, -118.42031 ] ]
1.2 [ [ 34.136969999999998, -118.46807 ], [ 34.153350000000003, -118.42031 ] ]
1.3 [ [ 34.136969999999998, -118.46807 ], [ 34.153350000000003, -118.42031 ] ]
1.4 [ [ 34.136969999999998, -118.46807 ], [ 34.153350000000003, -118.42031 ] ]
1.5 [ [ 34.136969999999998, -118.46807 ], [ 34.153350000000003, -118.42031 ] ]
    residential commercial industrial     label_coords           id state_name
1          TRUE      FALSE      FALSE 34.147, -118.452 060371411022 California
1.1        TRUE      FALSE      FALSE 34.147, -118.452 060371412021 California
1.2        TRUE      FALSE      FALSE 34.147, -118.452 060371412022 California
1.3        TRUE      FALSE      FALSE 34.147, -118.452 060371412023 California
1.4        TRUE      FALSE      FALSE 34.147, -118.452 060371413041 California
1.5        TRUE      FALSE      FALSE 34.147, -118.452 060371413061 California
    st_abbrev          cnty_name region acstotpop acsipovbas acseducbas
1          CA Los Angeles County      9      1976       1976       1369
1.1        CA Los Angeles County      9       598        598        492
```

```
1.2        CA Los Angeles County      9      1483       1483       1260
1.3        CA Los Angeles County      9       843        843        641
1.4        CA Los Angeles County      9      2056       2056       1635
1.5        CA Los Angeles County      9      1202       1158        853
    acstothh acstothu acsunempbas demogidx_2 demogidx_5 peopcolor peopcolorpct
1        892      939        1231  0.3135121 0.11476109       687    0.3476721
1.1      244      282         269  0.1956522 0.06644609       138    0.2307692
1.2      765      793         960  0.2316251 0.10137074       374    0.2521915
1.3      426      471         570  0.2046263 0.07105258       259    0.3072361
1.4     1034     1061        1381  0.1383755 0.07730342       242    0.1177043
1.5      471      471         791  0.2701162 0.14303515       421    0.3502496
    lowincome lowincpct unemployed   unemppct lingiso lingisopct lesshs
1         552 0.2793522        112 0.09098294       8 0.00896861     36
1.1        96 0.1605351         12 0.04460966       0 0.00000000      5
1.2       313 0.2110587         27 0.02812500     105 0.13725490     17
1.3        86 0.1020166         67 0.11754386       8 0.01877934      0
1.4       327 0.1590467         64 0.04634323      26 0.02514507     32
1.5       220 0.1899827        284 0.35903919       0 0.00000000      0
     lesshspct under5  under5pct over64  over64pct lifeexppct     pm25    ozone
1   0.02629657    160 0.08097166    205 0.10374494  0.1682051 9.609375 68.69327
1.1 0.01016260      9 0.01505017    138 0.23076923  0.1169231 9.576977 68.39775
1.2 0.01349206     52 0.03506406    204 0.13755900  0.1169231 9.576977 68.39775
1.3 0.00000000     83 0.09845789     90 0.10676157  0.1169231 9.576977 68.39775
1.4 0.01957187     90 0.04377432    396 0.19260700  0.1364103 9.508976 68.62157
1.5 0.00000000     54 0.04492513     76 0.06322795  0.1661538 9.436807 68.77954
        dslpm cancer resp rsei_air    ptraf pre1960 pre1960pct       pnpl
1   0.3023720     30  0.4 613.7916 133.0188     377  0.4014909 0.11357558
1.1 0.2978447     30  0.4 606.2344 184.4731     174  0.6170213 0.10324907
1.2 0.2978447     30  0.4 596.1628 414.2293      89  0.1122320 0.10161938
1.3 0.2978447     30  0.4 603.5170 186.7753      81  0.1719745 0.10572021
1.4 0.3205067     30  0.4 589.6666 241.9766     326  0.3072573 0.09634827
1.5 0.3474764     30  0.4 586.4985 115.2426     183  0.3885350 0.09183156
         prmp    ptsdf       ust    pwdis   d2_pm25  d5_pm25  d2_ozone d5_ozone
1   0.2639333 3.172618  5.756172 6.554039 20.691802 7.574232 20.691802 7.574232
1.1 0.3178154 3.142294  9.509666 3.736989 12.717391 4.318996 12.717391 4.318996
1.2 0.3024260 3.812831 13.401645 4.916065 15.055630 6.589098 15.055630 6.589098
1.3 0.2889005 3.540514 11.801294 5.368539 13.300712 4.618418 13.300712 4.618418
1.4 0.3086742 5.368964  9.622310 4.256178  8.856031 4.947419  9.132782 5.102026
1.5 0.4981627 4.153295  3.966843 4.290219 17.017318 9.011215 17.827666 9.440320
     d2_dslpm  d5_dslpm d2_cancer d5_cancer   d2_resp  d5_resp d2_rsei_air
1   19.751265  7.229949 13.167510  4.819966 18.183704 6.656143   20.064777
1.1 12.130435  4.119658  8.217391  2.790736 11.347826 3.853873   12.521739
1.2 14.360755  6.284986  9.728254  4.257571 13.434255 5.879503   14.824005
```

```
1.3 12.686833  4.405260  8.594306  2.984208 11.868327 4.121049   13.096085
1.4  9.132782  5.102026  5.811770  3.246744  8.025778 4.483598    8.717656
1.5 19.178247 10.155496 11.344879  6.007476 15.666737 8.296039   17.017318
    d5_rsei_air  d2_ptraf d5_ptraf  d2_ldpnt d5_ldpnt   d2_pnpl  d5_pnpl
1      7.344710 12.226974 4.475683 20.064777 7.344710 19.437753 7.115188
1.1    4.252550  9.391304 3.189412 15.652174 5.315687 11.347826 3.853873
1.2    6.487727 16.445381 7.197323  8.570128 3.750717 13.202630 5.778132
1.3    4.547365  9.822064 3.410524  9.003559 3.126313 12.072954 4.192102
1.4    4.870116  7.749027 4.328992  7.749027 4.328992  7.610652 4.251688
1.5    9.011215  9.454065 5.006230 17.017318 9.011215 14.586272 7.723898
      d2_prmp   d5_prmp  d2_ptsdf d5_ptsdf   d2_ust    d5_ust d2_pwdis
1   17.870192  6.541382 11.913462 4.360922 28.84312 10.558021 29.15663
1.1 11.934783  4.053212  7.434783 2.524951 18.78261  6.378825 17.80435
1.2 13.897505  6.082244 10.423129 4.561683 22.46763  9.832962 21.30951
1.3 12.072954  4.192102  8.594306 2.984208 19.84875  6.892100 19.03025
1.4  8.440905  4.715509  7.887403 4.406295 13.28405  7.421129 12.73054
1.5 18.908131 10.012461 12.965575 6.865687 23.50011 12.444058 24.85069
     d5_pwdis p_demogidx_2 p_demogidx_5 p_peopcolorpct p_lowincpct p_unemppct
1   10.672782           30           41             21          57         74
1.1  6.046594           11           13             10          34         44
1.2  9.326108           17           34             12          45         30
1.3  6.607890           13           16             17          21         84
1.4  7.111915            5           20              3          34         46
1.5 13.159234           23           54             21          40         99
    p_lingisopct p_lesshspct p_under5pct p_over64pct p_lifeexppct p_pm25
1             29          19          76          35           42     66
1.1            0          11          16          81            4     65
1.2           77          13          34          51            4     65
1.3           34           0          85          36            4     65
1.4           38          16          43          71           12     64
1.5            0           0          44          15           39     63
    p_ozone p_dslpm p_cancer p_resp p_rsei_air p_ptraf p_ldpnt p_pnpl p_prmp
1        66      63       42     58         64      39      64     62     57
1.1      65      62       42     58         64      48      80     58     61
1.2      65      62       42     58         64      71      37     57     60
1.3      65      62       42     58         64      48      44     59     59
1.4      66      66       42     58         63      56      56     55     61
1.5      66      71       42     58         63      35      63     54     70
    p_ptsdf p_ust p_pwdis p_d2_pm25 p_d5_pm25 p_d2_ozone p_d5_ozone p_d2_dslpm
1        38    92      93        54        60         53         58         51
1.1      38    96      91        38        41         37         39         35
1.2      45    97      92        44        55         43         53         40
1.3      42    97      93        40        43         39         41         37
```

1.4	57	96	92	27	45	28	45	28
1.5	48	87	92	48	66	48	67	50

	p_d5_dslpm	p_d2_cancer	p_d5_cancer	p_d2_resp	p_d5_resp	p_d2_rsei_air
1	58	53	59	64	67	52
1.1	38	45	46	54	53	36
1.2	52	47	56	59	64	41
1.3	41	45	47	56	55	37
1.4	45	43	48	42	57	27
1.5	70	50	66	62	73	46

	p_d5_rsei_air	p_d2_ptraf	p_d5_ptraf	p_d2_ldpnt	p_d5_ldpnt	p_d2_pnpl
1	59	35	40	53	56	51
1.1	39	28	30	44	45	35
1.2	54	44	57	27	35	39
1.3	42	29	32	29	30	37
1.4	44	24	39	26	39	25
1.5	67	28	44	47	64	42

	p_d5_pnpl	p_d2_prmp	p_d5_prmp	p_d2_ptsdf	p_d5_ptsdf	p_d2_ust	p_d5_ust
1	58	47	53	34	40	81	83
1.1	38	35	38	24	25	77	77
1.2	51	39	50	31	41	78	82
1.3	40	35	39	27	29	77	78
1.4	41	27	42	25	40	75	79
1.5	61	48	68	37	56	78	86

	p_d2_pwdis	p_d5_pwdis	b_demogidx_2	b_demogidx_5	b_peopcolorpct	b_lowincpct
1	69	75	4	5	3	6
1.1	49	53	2	2	2	4
1.2	56	70	2	4	2	5
1.3	52	56	2	2	2	3
1.4	38	59	1	3	1	4
1.5	62	82	3	6	3	5

	b_unemppct	b_lingisopct	b_lesshspct	b_under5pct	b_over64pct	b_lifeexppct
1	8	3	2	8	4	5
1.1	5	1	2	2	9	1
1.2	4	8	2	4	6	1
1.3	9	4	1	9	4	1
1.4	5	4	2	5	8	2
1.5	11	1	1	5	2	4

	b_pm25	b_ozone	b_dslpm	b_cancer	b_resp	b_rsei_air	b_ptraf	b_ldpnt	b_pnpl
1	7	7	7	5	6	7	4	7	7
1.1	7	7	7	5	6	7	5	9	6
1.2	7	7	7	5	6	7	8	4	6
1.3	7	7	7	5	6	7	5	5	6
1.4	7	7	7	5	6	7	6	6	6

1.5	7	7	8	5	6	7	4	7	6

	b_prmp	b_ptsdf	b_ust	b_pwdis	b_d2_pm25	b_d5_pm25	b_d2_ozone	b_d5_ozone
1	6	4	10	10	6	7	6	6
1.1	7	4	11	10	4	5	4	4
1.2	7	5	11	10	5	6	5	6
1.3	6	5	11	10	5	5	4	5
1.4	7	6	11	10	3	5	3	5
1.5	8	5	9	10	5	7	5	7

	b_d2_dslpm	b_d5_dslpm	b_d2_cancer	b_d5_cancer	b_d2_resp	b_d5_resp
1	6	6	6	6	7	7
1.1	4	4	5	5	6	6
1.2	5	6	5	6	6	7
1.3	4	5	5	5	6	6
1.4	3	5	5	5	5	6
1.5	6	8	6	7	7	8

	b_d2_rsei_air	b_d5_rsei_air	b_d2_ptraf	b_d5_ptraf	b_d2_ldpnt	b_d5_ldpnt
1	6	6	4	5	6	6
1.1	4	4	3	4	5	5
1.2	5	6	5	6	3	4
1.3	4	5	3	4	3	4
1.4	3	5	3	4	3	4
1.5	5	7	3	5	5	7

	b_d2_pnpl	b_d5_pnpl	b_d2_prmp	b_d5_prmp	b_d2_ptsdf	b_d5_ptsdf	b_d2_ust
1	6	6	5	6	4	5	9
1.1	4	4	4	4	3	3	8
1.2	4	6	4	6	4	5	8
1.3	4	5	4	4	3	3	8
1.4	3	5	3	5	3	5	8
1.5	5	7	5	7	4	6	8

	b_d5_ust	b_d2_pwdis	b_d5_pwdis	t_demogidx_2	t_demogidx_5	t_peopcolorpct
1	9	7	8	30 %ile	41 %ile	21 %ile
1.1	8	5	6	11 %ile	13 %ile	10 %ile
1.2	9	6	8	17 %ile	34 %ile	12 %ile
1.3	8	6	6	13 %ile	16 %ile	17 %ile
1.4	8	4	6	5 %ile	20 %ile	3 %ile
1.5	9	7	9	23 %ile	54 %ile	21 %ile

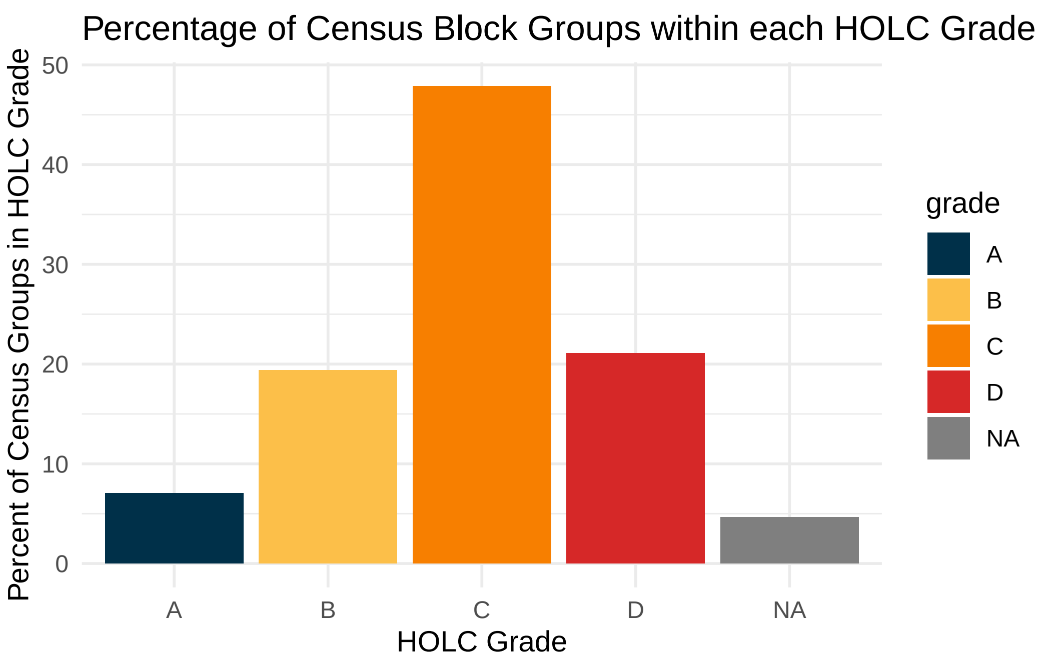
	t_lowincpct	t_unemppct	t_lingisopct	t_lesshspct	t_under5pct	t_over64pct
1	57 %ile	74 %ile	29 %ile	19 %ile	76 %ile	35 %ile
1.1	34 %ile	44 %ile	0 %ile	11 %ile	16 %ile	81 %ile
1.2	45 %ile	30 %ile	77 %ile	13 %ile	34 %ile	51 %ile
1.3	21 %ile	84 %ile	34 %ile	0 %ile	85 %ile	36 %ile
1.4	34 %ile	46 %ile	38 %ile	16 %ile	43 %ile	71 %ile
1.5	40 %ile	99 %ile	0 %ile	0 %ile	44 %ile	15 %ile

```
    t_lifeexppct  t_pm25 t_ozone t_dslpm t_cancer  t_resp t_rsei_air t_ptraf
1        42 %ile 66 %ile 66 %ile 63 %ile  42 %ile 58 %ile    64 %ile 39 %ile
1.1       4 %ile 65 %ile 65 %ile 62 %ile  42 %ile 58 %ile    64 %ile 48 %ile
1.2       4 %ile 65 %ile 65 %ile 62 %ile  42 %ile 58 %ile    64 %ile 71 %ile
1.3       4 %ile 65 %ile 65 %ile 62 %ile  42 %ile 58 %ile    64 %ile 48 %ile
1.4      12 %ile 64 %ile 66 %ile 66 %ile  42 %ile 58 %ile    63 %ile 56 %ile
1.5      39 %ile 63 %ile 66 %ile 71 %ile  42 %ile 58 %ile    63 %ile 35 %ile
    t_ldpnt  t_pnpl  t_prmp t_ptsdf   t_ust t_pwdis t_d2_pm25 t_d5_pm25
1   64 %ile 62 %ile 57 %ile 38 %ile 92 %ile 93 %ile   54 %ile   60 %ile
1.1 80 %ile 58 %ile 61 %ile 38 %ile 96 %ile 91 %ile   38 %ile   41 %ile
1.2 37 %ile 57 %ile 60 %ile 45 %ile 97 %ile 92 %ile   44 %ile   55 %ile
1.3 44 %ile 59 %ile 59 %ile 42 %ile 97 %ile 93 %ile   40 %ile   43 %ile
1.4 56 %ile 55 %ile 61 %ile 57 %ile 96 %ile 92 %ile   27 %ile   45 %ile
1.5 63 %ile 54 %ile 70 %ile 48 %ile 87 %ile 92 %ile   48 %ile   66 %ile
    t_d2_ozone t_d5_ozone t_d2_dslpm t_d5_dslpm t_d2_cancer t_d5_cancer
1      53 %ile    58 %ile    51 %ile    58 %ile     53 %ile     59 %ile
1.1    37 %ile    39 %ile    35 %ile    38 %ile     45 %ile     46 %ile
1.2    43 %ile    53 %ile    40 %ile    52 %ile     47 %ile     56 %ile
1.3    39 %ile    41 %ile    37 %ile    41 %ile     45 %ile     47 %ile
1.4    28 %ile    45 %ile    28 %ile    45 %ile     43 %ile     48 %ile
1.5    48 %ile    67 %ile    50 %ile    70 %ile     50 %ile     66 %ile
    t_d2_resp t_d5_resp t_d2_rsei_air t_d5_rsei_air t_d2_ptraf t_d5_ptraf
1     64 %ile   67 %ile       52 %ile       59 %ile    35 %ile    40 %ile
1.1   54 %ile   53 %ile       36 %ile       39 %ile    28 %ile    30 %ile
1.2   59 %ile   64 %ile       41 %ile       54 %ile    44 %ile    57 %ile
1.3   56 %ile   55 %ile       37 %ile       42 %ile    29 %ile    32 %ile
1.4   42 %ile   57 %ile       27 %ile       44 %ile    24 %ile    39 %ile
1.5   62 %ile   73 %ile       46 %ile       67 %ile    28 %ile    44 %ile
    t_d2_ldpnt t_d5_ldpnt t_d2_pnpl t_d5_pnpl t_d2_prmp t_d5_prmp t_d2_ptsdf
1      53 %ile    56 %ile   51 %ile   58 %ile   47 %ile   53 %ile    34 %ile
1.1    44 %ile    45 %ile   35 %ile   38 %ile   35 %ile   38 %ile    24 %ile
1.2    27 %ile    35 %ile   39 %ile   51 %ile   39 %ile   50 %ile    31 %ile
1.3    29 %ile    30 %ile   37 %ile   40 %ile   35 %ile   39 %ile    27 %ile
1.4    26 %ile    39 %ile   25 %ile   41 %ile   27 %ile   42 %ile    25 %ile
1.5    47 %ile    64 %ile   42 %ile   61 %ile   48 %ile   68 %ile    37 %ile
    t_d5_ptsdf t_d2_ust t_d5_ust t_d2_pwdis t_d5_pwdis arealand areawater
1      40 %ile  81 %ile  83 %ile    69 %ile    75 %ile   494282         0
1.1    25 %ile  77 %ile  77 %ile    49 %ile    53 %ile   344702         0
1.2    41 %ile  78 %ile  82 %ile    56 %ile    70 %ile   159206         0
1.3    29 %ile  77 %ile  78 %ile    52 %ile    56 %ile   196267         0
1.4    40 %ile  75 %ile  79 %ile    38 %ile    59 %ile   441310         0
1.5    56 %ile  78 %ile  86 %ile    62 %ile    82 %ile   268213         0
    npl_cnt tsdf_cnt exceed_count_80 exceed_count_80_sup shape_length
```

```
1          0        0               1                   0     4219.665
1.1        0        0               0                   0     4170.983
1.2        0        0               0                   0     2506.184
1.3        0        0               0                   0     3096.982
1.4        0        1               0                   0     3619.952
1.5        0        0               0                   5     2851.479
    shape_area
1     723466.8
1.1   504513.6
1.2   233033.8
1.3   287278.3
1.4   645960.2
1.5   392602.9
```

Summary tables

```
#........Summary tables........

# The percentage of census block groups that fall within each HOLC grade

tot_grade <- nrow(la_redlining["grade"])

census_block_grade <- la_redlining %>%
  group_by(grade) %>%
  summarize(percent_grade_HOLC = n()/tot_grade * 100)

# Add visualization

percent_grade_census <- ggplot(census_block_grade, aes(x = grade, y = percent_grade_HOLC, fil
  geom_col() +
  scale_fill_manual(values = c( "A" = "#003049", "B" = "#fcbf49", "C" = "#f77f00",
                               "D" = "#d62828")) +
  labs( x = "HOLC Grade",
       y = "Percent of Census Groups in HOLC Grade",
       title = "Percentage of Census Block Groups within each HOLC Grade in LA County") +
  theme_minimal()

# View figure
percent_grade_census
```




```
# Save figure
ggsave(here::here("figs", "percent_grade_census.png"))
```

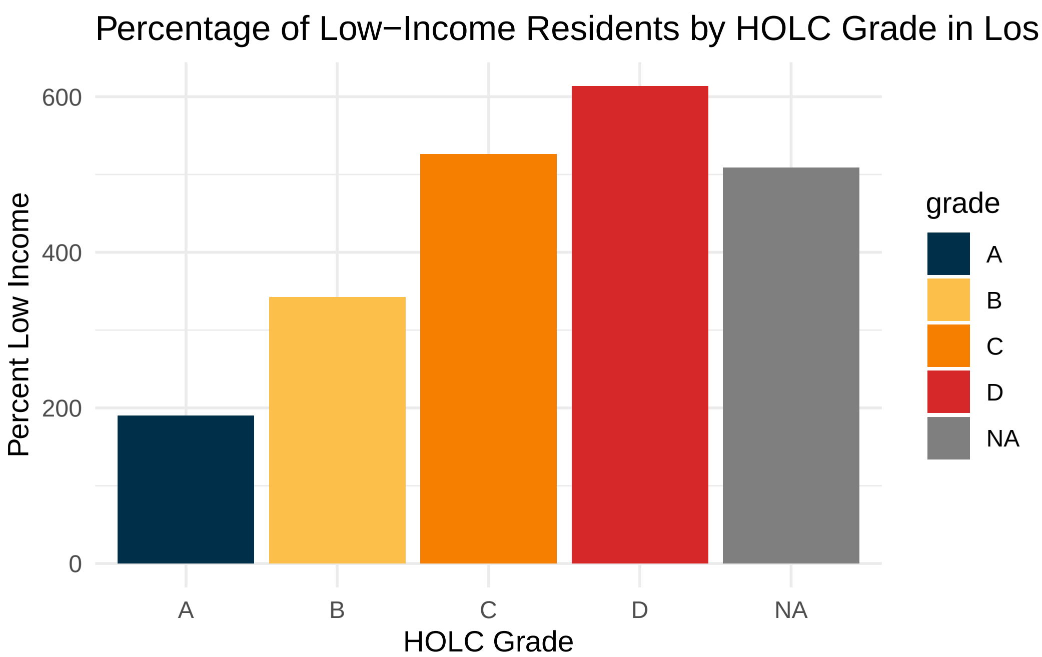
```
#........Summary tables........

# The percent of census block groups that don't fall within a HOLC grade

# Use 'st_joint()' in the 'st_join() argument to return features in 'la_ejscreen' that don't

la_redlining_disjoin <- st_join(la_ejscreen, redlining, join = st_disjoint) %>%
  st_drop_geometry()

tot_no_grade <- nrow(la_redlining_disjoin["grade"])

census_block_no_grade <- la_redlining_disjoin %>%
  group_by(grade) %>%
  summarize(percent_not_HOLC = n()/tot_no_grade * 100)

# Combine the 'census_block_grade' and 'census_block_no_grade'
sum_holc<- full_join(census_block_grade,census_block_no_grade, by = "grade")

# View table
sum_holc
```

```
# A tibble: 5 x 3
  grade percent_grade_HOLC percent_not_HOLC
  <chr>              <dbl>            <dbl>
1 A                   7.03           13.7
2 B                  19.4            29.0
3 C                  47.9            40.0
4 D                  21.1            17.0
5 <NA>                4.63            0.230
```

Visualizations

% Low Income

```r
# Group the 'la_redlining' data by HOLC grade and get the mean of the 'lowincome' variable.

low_income <- la_redlining %>% group_by(grade) %>%
  summarize(low_income_mean = mean(lowincome, na.rm = TRUE))

# Plot 'low_income' data

low_income_grade_plot <- ggplot(low_income, aes(x = grade, y = low_income_mean, fill = grade)
  geom_col() +
  scale_fill_manual(values = c( "A" = "#003049", "B" = "#fcbf49", "C" = "#f77f00",
                              "D" = "#d62828")) +
  labs( x = "HOLC Grade",
       y = "Percent Low Income",
       title = "Percentage of Low-Income Residents by HOLC Grade in Los Angeles County") +
  theme_minimal()

# View plot
low_income_grade_plot
```

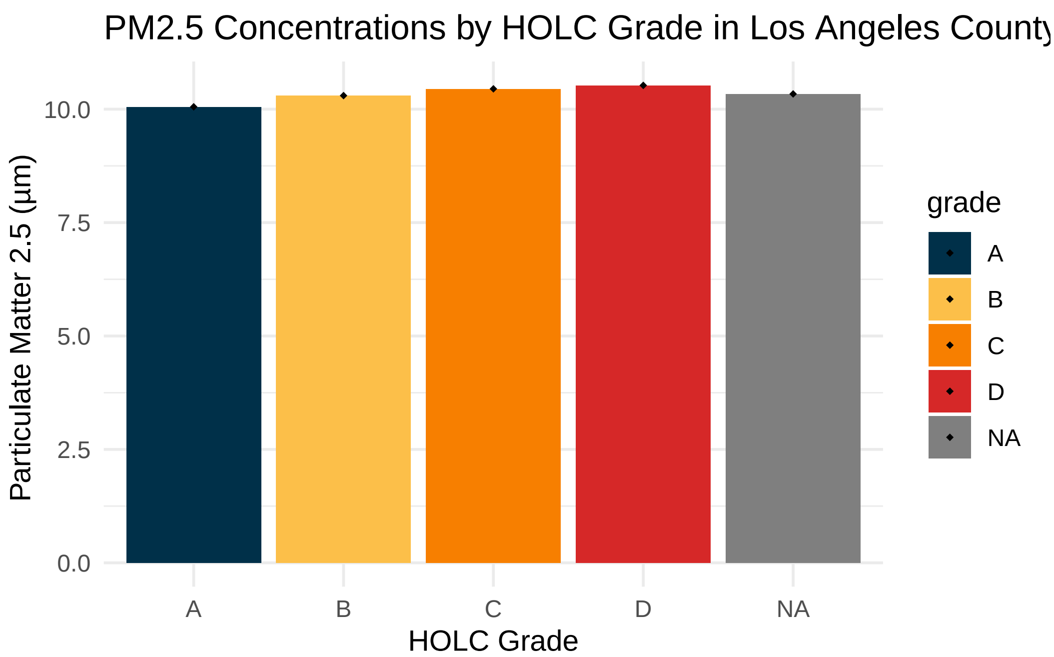



```
# Save figure
ggsave(here::here("figs", "low_income_grade_plot.png"))
```

Percentile Particle Matter 2.5

```
# Group the 'la_redlining' data by HOLC grade and get the mean of the 'pm25' variable.

pm_25_grade <- la_redlining %>% group_by(grade) %>%
  summarize(pm_25_mean = mean(pm25, na.rm = TRUE))

# Plot 'pm_25_grade' data

pm_25_grade_plot <- ggplot(pm_25_grade, aes(x = grade, y = pm_25_mean, fill = grade)) +
  geom_col() +
 stat_summary(fun = mean, geom = "point",
              color = "black", shape = 18, size = 1) +
  scale_fill_manual(values = c( "A" = "#003049", "B" = "#fcbf49", "C" = "#f77f00",
                                "D" = "#d62828")) +
  labs( x = "HOLC Grade",
       y = "Particulate Matter 2.5 (µm) ",
       title = "PM2.5 Concentrations by HOLC Grade in Los Angeles County") +
  theme_minimal()
```

```r
# View plot
pm_25_grade_plot
```




```r
# Save figure
ggsave(here::here("figs", "pm_25_grade_plot.png"))
```

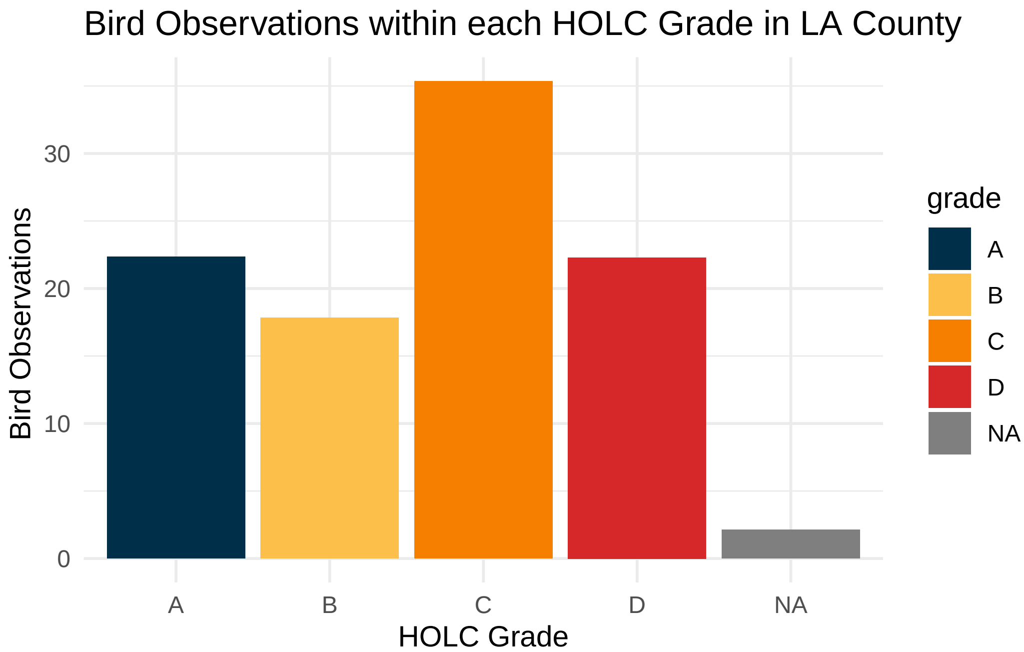
My results

In the graph "Percentage of Low-Income Residents by HOLC Grade in Los Angeles County", we see that HOLC grades C-D have more low-income residents. This coincides with the Home Owners'Loan Corporation zoning that led to reduced investments in grades C and D (University of Richmond, 2023). This reducing in investments and subsequent "redlining" led to a reduced income for residents in those regions of Los Angeles county. In addition to reduced income and limited community resources, these communities also face environmental injusticies. In the graph "PM2.5 Concentrations by HOLC Grade in Los Angeles County", we see that all Los Angeles counties had an average of 10 μm of particulate matter 2.5 (PM 2.5) pollution. This reflects the present-day pollution issue within Los Angeles county. In the context of the HOLC grade, those in grades C and D show a slightly higher average of PM 2.5, displaying once again, the relationship between environmental justice and limited resources in communities that are within the redlining districts.

Part 2: Legacy of redlining in biodiversity observations

```
#........Join redlining with birds.........

# Filter 'bird_obs' to 'redlining' extent
bird_obs <- bird_obs[redlining, ]

# 'st_join()' the redlining and 'bird_obs'
bird_redlining <- st_join(bird_obs, redlining, st_intersects) %>%
   st_drop_geometry() # Drop geometry
```

```
#........Find the percentage of bird observations within each HOLC grade.........


grade_bird <- bird_redlining %>%
  mutate(total_rows = n()) %>%
  group_by(grade) %>%
  summarise(perc_grade = n()/first(total_rows) * 100)

# Plot 'grade_bird' data
bird_grade_plot <- ggplot(grade_bird, aes(x = grade, y = perc_grade, fill = grade)) +
  geom_col() +
  scale_fill_manual(values = c( "A" = "#003049", "B" = "#fcbf49", "C" = "#f77f00",
                              "D" = "#d62828")) +
  labs( x = "HOLC Grade",
       y = "Bird Observations ",
       title = "Bird Observations within each HOLC Grade in LA County") +
  theme_minimal()

# View plot
bird_grade_plot
```




```
# Save figure
ggsave(here::here("figs", "bird_grade_plot.png"))
```

The graph above shows that HOLC grade C has the most bird observations, which contradicts the statements in Ellis-Soto et.al 2023 which say less bird observations in historically redlined zones (i.e. zones C-D). This can be due to the other factors that influence biodiversity that were included in Ellis-Soto's study – vegetation, open space, population density, and climate. Although we looked at population density, these other factors can truly reveal how thriving the biodiversity is in these redlined regions.