lab7_spatial

AUTHOR
Adeti Afe

Quarto

Quarto enables you to weave together content and executable code into a finished document. To learn more about Quarto see https://quarto.org.

```
1 + 1
```

```
[1] 2
```

```
guerry <- st_read("../../Lab7_data/guerry/Guerry.shp")
```

```
Reading layer `Guerry' from data source
  `G:\My Drive\GES 486\Lab7_data\guerry\Guerry.shp' using driver `ESRI Shapefile'
Simple feature collection with 85 features and 23 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 47680 ymin: 1703258 xmax: 1031401 ymax: 2677441
Projected CRS: NTF (Paris) / Lambert zone II
```

```
dir.create("../../Lab7_data/baltimore", showWarnings = FALSE, recursive = TRUE)
dir.create("../../Lab7_data/figs", showWarnings = FALSE, recursive = TRUE)
```

```
# Download ACS tract-level data for Baltimore City (geometry included)
census_year <- 2023

vars <- c(
  med_income = "B19013_001",  # Median household income
  pov_total  = "B17001_001",  # Poverty universe total
  pov_below  = "B17001_002"   # Below poverty level
)

balt_raw <- get_acs(
  geography = "tract",
  variables = vars,
  state = "MD",
  county = "Baltimore City",
  year = census_year,
  geometry = TRUE,
  output = "wide"
)
```

```
Getting data from the 2019-2023 5-year ACS
```

```
balt <- balt_raw %>%
  transmute(
    GEOID,
    NAME,
    med_income = med_incomeE,
    pov_rate   = 100 * (pov_belowE / pov_totalE),
    geometry
  )

summary(dplyr::select(balt, med_income, pov_rate))
```

```
   med_income        pov_rate                  geometry
 Min.   : 13628   Min.   : 0.6682   MULTIPOLYGON :199
 1st Qu.: 41853   1st Qu.:11.2103   epsg:4269    :  0
 Median : 56723   Median :19.8087   +proj=long...:  0
 Mean   : 64633   Mean   :21.6798
 3rd Qu.: 75744   3rd Qu.:29.1031
 Max.   :250001   Max.   :64.5951
 NA's   :4        NA's   :1
```

```
# Project to MD state plane (or any local projected CRS)
balt_proj <- st_transform(balt, 2248)  # NAD83 / Maryland

balt_nowater <- erase_water(
  balt_proj,
  area_threshold = 0.9  # erase largest 10% of water polygons
)
```

```
Fetching area water data for your dataset's location...

Erasing water area...
If this is slow, try a larger area threshold value.
```

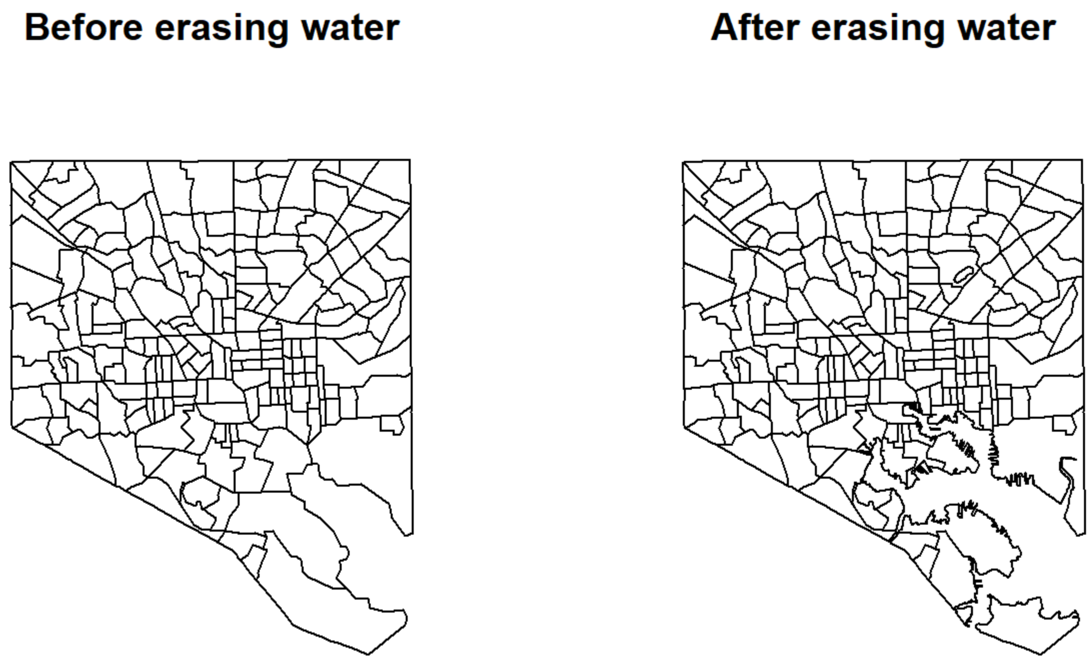
```
nrow(balt_proj)
```

```
[1] 199
```

```
nrow(balt_nowater)
```

```
[1] 199
```

```
par(mfrow = c(1, 2))
plot(st_geometry(balt_proj), main = "Before erasing water", axes = FALSE)
plot(st_geometry(balt_nowater), main = "After erasing water", axes = FALSE)
```




```r
par(mfrow = c(1, 1))
```

```r
file.exists("../../Lab7_data/figs/sigmap_ss.png")
```

```
[1] TRUE
```

```r
file.exists("../../Lab7_data/figs/lisa_cluster_ss.png")
```

```
[1] TRUE
```

```r
knitr::include_graphics(c(
  "../../Lab7_data/figs/sigmap_ss.png",
  "../../Lab7_data/figs/lisa_cluster_ss.png"
))
```

{r} **For Part 1**, I loaded the Guerry departments shapefile into GeoDa and explored the variable Donatns (charitable donations per capita). I created a queen contiguity spatial weights matrix (order 1) and ran Univariate Local Moran's I (LISA) on Donatns using 999 permutations. The LISA significance map shows which departments have statistically significant local clustering at common p-value thresholds, while the LISA cluster map classifies significant locations into high–high and low–low clusters, as well as high–low and low–high spatial outliers. there are clear regions where high or low donation values cluster, with a smaller number of departments behaving differently than their neighbors. ```

lab7_part2

AUTHOR
Adeti Afe

Quarto

Quarto enables you to weave together content and executable code into a finished document. To learn more about Quarto see https://quarto.org.

Running Code

When you click the **Render** button a document will be generated that includes both content and the output of embedded code. You can embed code like this:

```
1 + 1
```

```
[1] 2
```

You can add options to executable code like this

```
library(sf)
```

```
Linking to GEOS 3.13.1, GDAL 3.11.0, PROJ 9.6.0; sf_use_s2() is TRUE
```

```
library(dplyr)
```

```

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

```
library(ggplot2)
library(tidycensus)
library(tigris)
```

```
To enable caching of data, set `options(tigris_use_cache = TRUE)`
in your R script or .Rprofile.
```

```
# Use cached TIGRIS files when possible and keep geometry behavior consistent
options(tigris_use_cache = TRUE)
sf_use_s2(FALSE)
```

```
Spherical geometry (s2) switched off
```

```
# Output folder for Part 2 files
dir.create("../../Lab7_data/part2", showWarnings = FALSE, recursive = TRUE)
```

The `echo: false` option disables the printing of code (only output is displayed).

```
census_year <- 2023  # change only if your instructor requires a different year

vars <- c(
med_income = "B19013_001",
pov_total  = "B17001_001",
pov_below  = "B17001_002"
)

tracts_raw <- get_acs(
geography = "tract",
variables = vars,
state = "MD",
county = "Baltimore City",
year = census_year,
geometry = TRUE,
output = "wide"
)
```

```
Getting data from the 2019-2023 5-year ACS
```

```
tracts <- tracts_raw %>%
transmute(
GEOID,
NAME,
med_income = med_incomeE,
pov_rate   = 100 * (pov_belowE / pov_totalE),
geometry
)
```

```
tracts_proj <- st_transform(tracts, 2248)  # NAD83 / Maryland
tracts_nowater <- erase_water(tracts_proj, area_threshold = 0.9)
```

```
Fetching area water data for your dataset's location...

Erasing water area...
If this is slow, try a larger area threshold value.
```

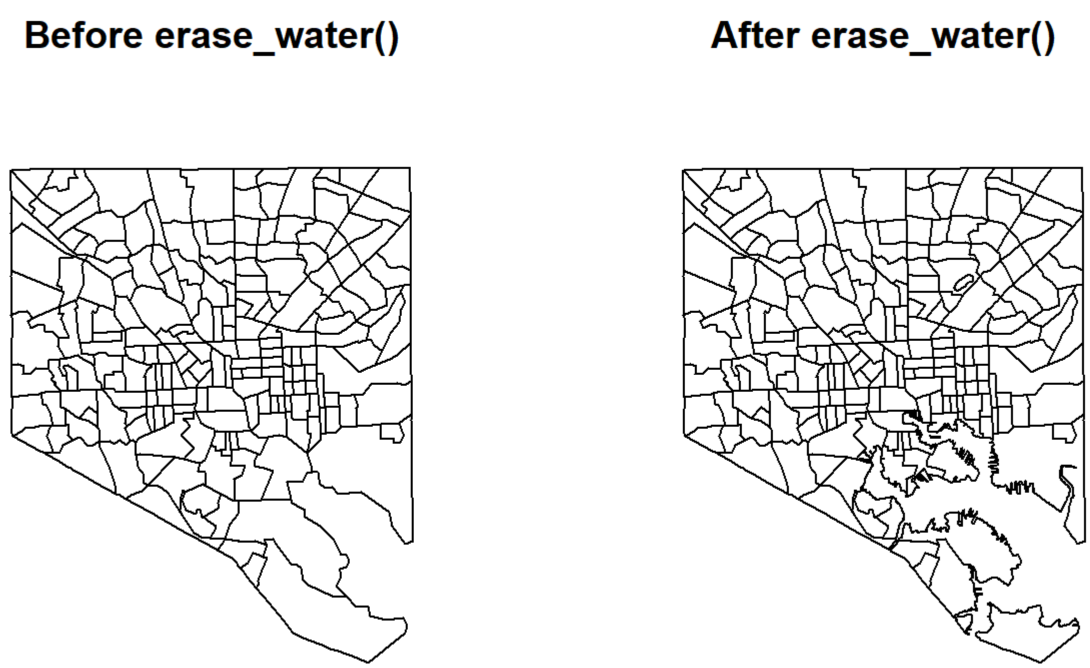
```
out_base <- "../../Lab7_data/part2/baltimore_income_poverty_nowater"

# remove any existing shapefile components first (shp/dbf/shx/prj/etc.)
unlink(paste0(out_base, ".*"))

st_write(
  tracts_nowater,
  dsn = paste0(out_base, ".shp"),
  driver = "ESRI Shapefile",
  append = FALSE
)
```

```
Deleting layer `baltimore_income_poverty_nowater' using driver `ESRI Shapefile'
Writing layer `baltimore_income_poverty_nowater' to data source
  `../../Lab7_data/part2/baltimore_income_poverty_nowater.shp' using driver `ESRI Shapefile'
Updating existing layer baltimore_income_poverty_nowater
Writing 199 features with 4 fields and geometry type Unknown (any).
```

```
par(mfrow = c(1, 2))
plot(st_geometry(tracts_proj), main = "Before erase_water()", axes = FALSE)
plot(st_geometry(tracts_nowater), main = "After erase_water()", axes = FALSE)
```

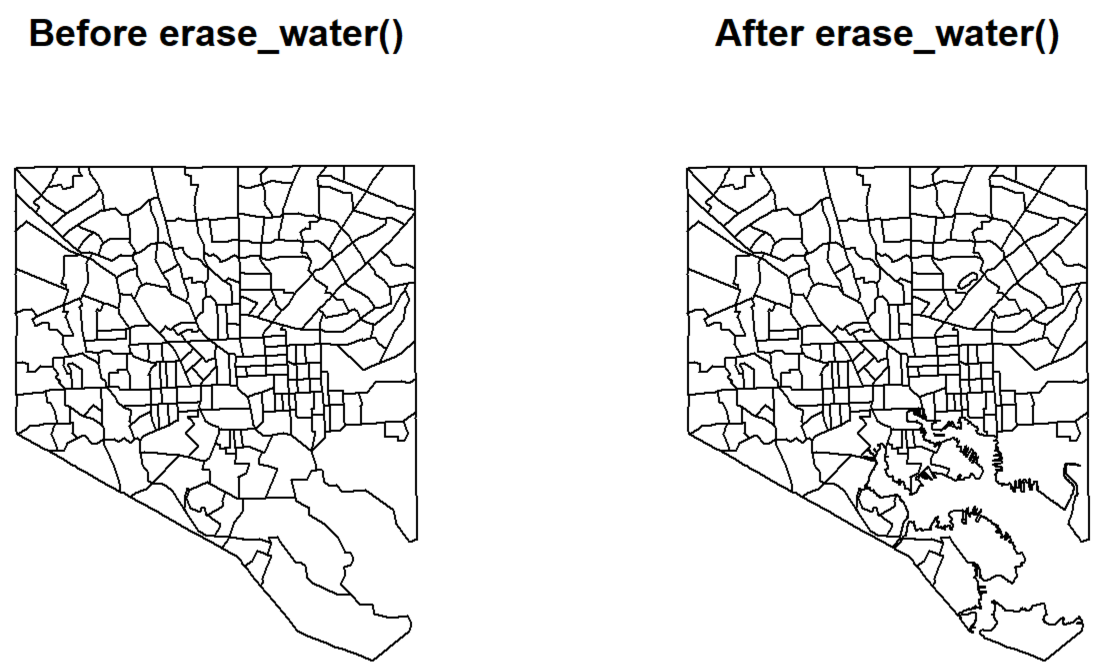


```r
par(mfrow = c(1, 1))
```

```r
list.files("../../Lab7_data/part2")
```

```
 [1] "balt_bilisa_cluster.png"
 [2] "balt_bilisa_sig.png"
 [3] "balt_bivar_moralnonlocal_global.png"
 [4] "balt_bivar_moran_global.png"
 [5] "balt_queen.gal"
 [6] "baltimore_income_poverty_nowater.dbf"
 [7] "baltimore_income_poverty_nowater.shp"
 [8] "baltimore_income_poverty_nowater.shx"
 [9] "baltimore_income_poverty_nowater_geoda..dbf"
[10] "baltimore_income_poverty_nowater_geoda..prj"
[11] "baltimore_income_poverty_nowater_geoda..shp"
[12] "baltimore_income_poverty_nowater_geoda..shx"
```

```r
par(mfrow = c(1, 2))
plot(st_geometry(tracts_proj), main = "Before erase_water()", axes = FALSE)
plot(st_geometry(tracts_nowater), main = "After erase_water()", axes = FALSE)
```



```
par(mfrow = c(1, 1))
```

```
getwd()
```

```
[1] "G:/My Drive/GES 486/Lab7_spatial"
```

```
normalizePath("../../Lab7_data/part2")
```

```
[1] "G:\\My Drive\\Lab7_data\\part2"
```

```
list.files("../../Lab7_data/part2", full.names = TRUE)
```

```
 [1] "../../Lab7_data/part2/balt_bilisa_cluster.png"
 [2] "../../Lab7_data/part2/balt_bilisa_sig.png"
 [3] "../../Lab7_data/part2/balt_bivar_moralnonlocal_global.png"
 [4] "../../Lab7_data/part2/balt_bivar_moran_global.png"
 [5] "../../Lab7_data/part2/balt_queen.gal"
 [6] "../../Lab7_data/part2/baltimore_income_poverty_nowater.dbf"
 [7] "../../Lab7_data/part2/baltimore_income_poverty_nowater.shp"
 [8] "../../Lab7_data/part2/baltimore_income_poverty_nowater.shx"
 [9] "../../Lab7_data/part2/baltimore_income_poverty_nowater_geoda..dbf"
[10] "../../Lab7_data/part2/baltimore_income_poverty_nowater_geoda..prj"
[11] "../../Lab7_data/part2/baltimore_income_poverty_nowater_geoda..shp"
[12] "../../Lab7_data/part2/baltimore_income_poverty_nowater_geoda..shx"
```

```
file.exists("../../Lab7_data/part2/baltimore_income_poverty_nowater.shp")
```

```
[1] TRUE
```

For Part 2, I picked **Baltimore City, Maryland** because it's a river/coastal place (it sits along the Patapsco River and Baltimore Harbor). Using `tidycensus`, I pulled **census-tract** data for two variables that should be connected: **median household income** (ACS `B19013_001`) and a **poverty rate** that I calculated from ACS poverty counts (`B17001_002` divided by `B17001_001`, times 100). After downloading the tracts with geometry, I projected them to and used `erase_water()` to remove the big water areas so the layer focused on land tracts. I saved that processed layer as a shapefile called `baltimore_income_poverty_nowater.shp`.

After that, I opened the no-water shapefile in **GeoDa**, created **queen contiguity weights (order 1)**, and explored the relationship between the two variables. I ran **Global Bivariate Moran's I** using **poverty rate** and the **spatial lag of median income**, and I got a Moran's I of **-0.391**, which lines up with what you'd expect: places with higher poverty tend to be near places with lower income, and vice versa. Then I ran **Bivariate Local Moran's I (BiLISA)** with **999 permutations** to see where that relationship shows up on the map. GeoDa produced a **BiLISA significance map** and a **BiLISA cluster map**, and it also added result fields to the attribute table (like `LISA_I`, `LISA_CL`, and `LISA_P`). I exported those GeoDa results into a new shapefile named `baltimore_income_poverty_nowater_geoda.shp`. For the assignment requirement, I rendered this section to **HTML** and then exported/printed it to **PDF**.

For the QGIS part, I loaded the GeoDa results shapefile (`baltimore_income_poverty_nowater_geoda.shp`) and made a polished map that shows the relationship using the `LISA_CL` categories. I set up the symbology so the legend reads clearly (Not Significant plus the BiLISA cluster/outlier categories), and I built a print layout with all the standard map elements.

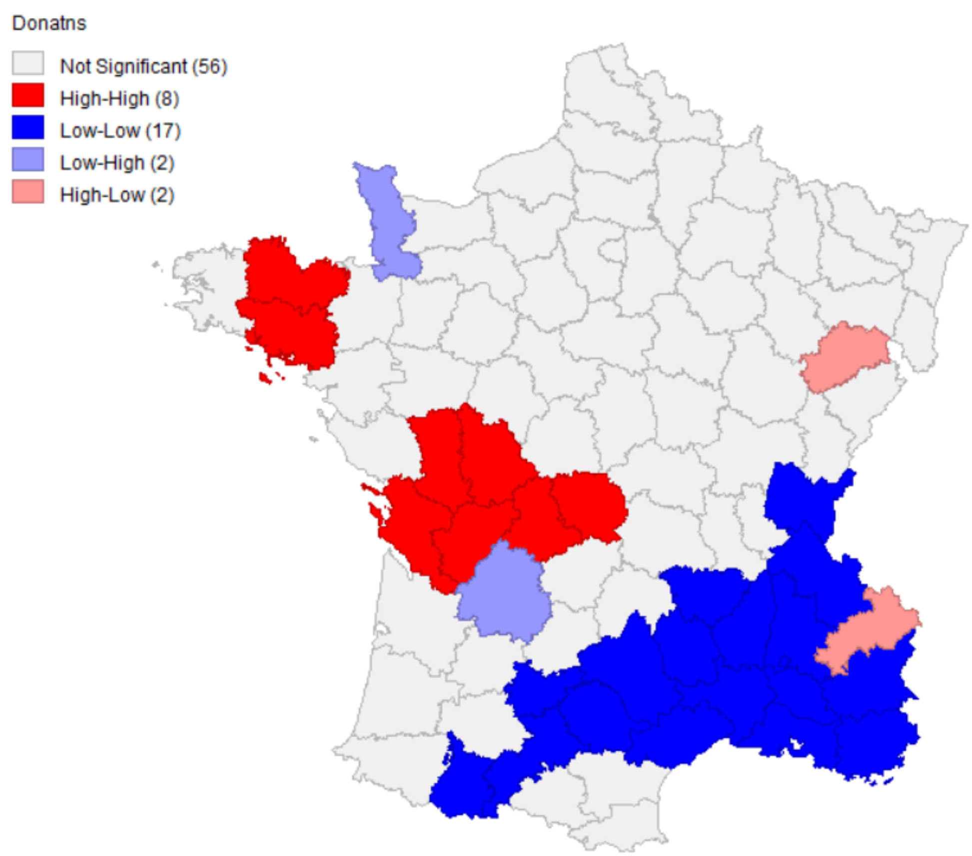
For Part 3, the main takeaway is that **poverty rate and neighboring median income are strongly related in space** in Baltimore City. The negative global bivariate Moran's I (**-0.391**) shows the overall pattern: higher-poverty tracts tend to be surrounded by lower-income areas, while lower-poverty tracts tend to be surrounded by higher-income areas. The BiLISA maps add the geography by showing exactly which tracts form statistically significant patterns and where the most obvious clusters and outliers are. The `erase_water()` step mattered because Baltimore has a lot of shoreline and harbor water, and removing water makes the tract layer cleaner and more representative of actual neighborhoods; the before/after maps show how the study area becomes more focused on land tracts, which makes the interpretation of the GeoDa weights and clusters more straightforward.

Adeti Afe
GES 486 Lab 7
November 25th, 2025

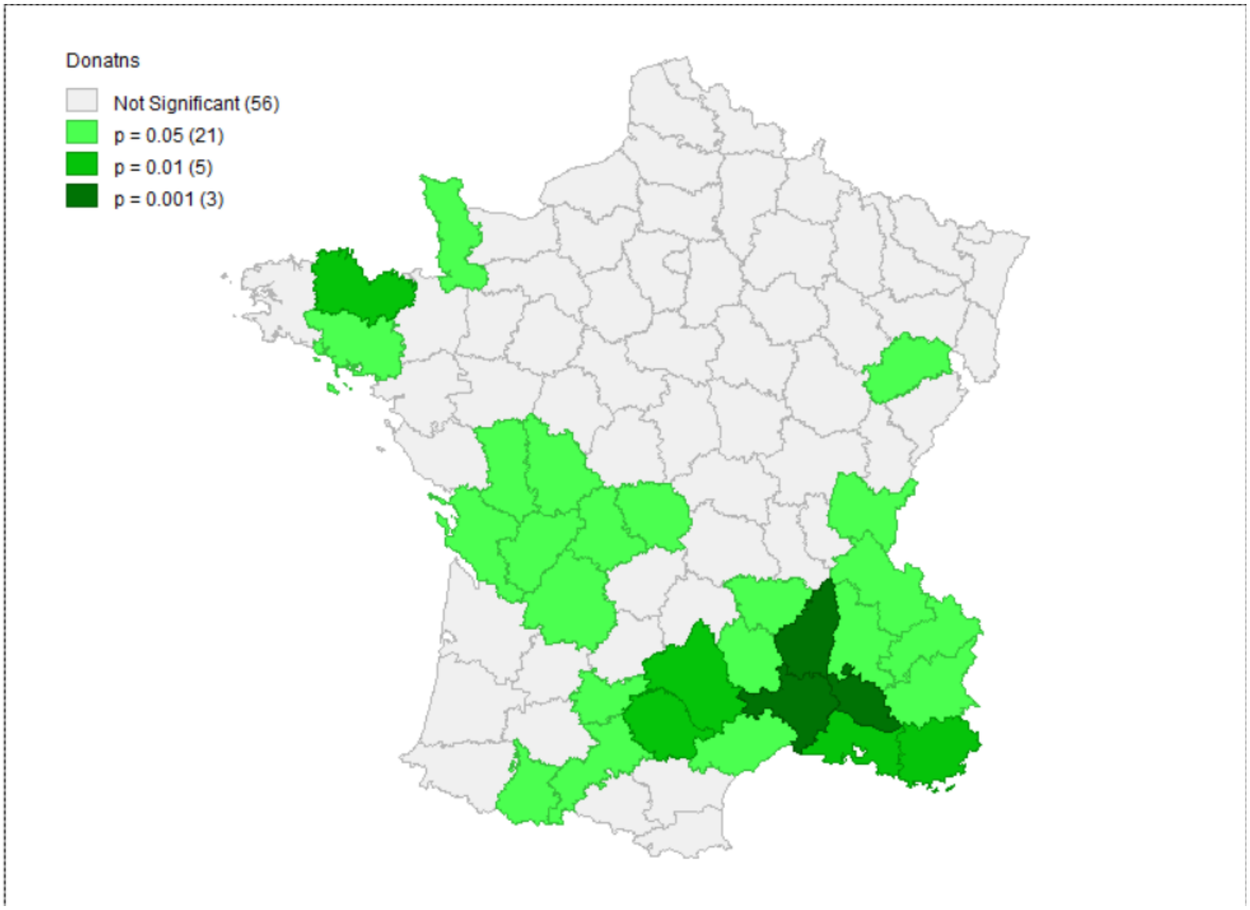
All my maps are included here and correspond to the part 1 and 2 QMD attached above.

QMD Part 1

Cluster map:

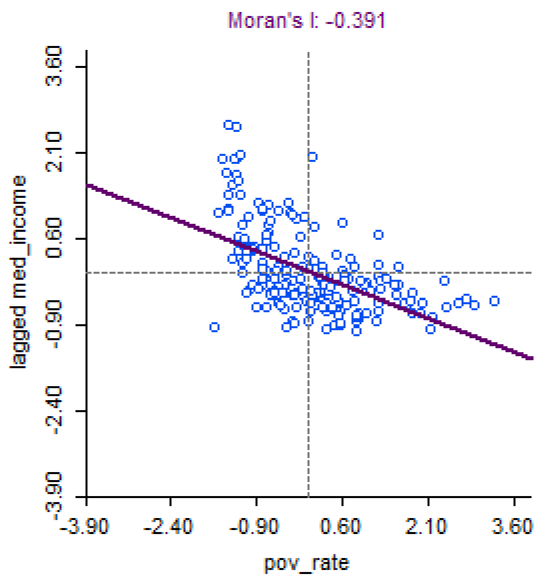


Significance map:

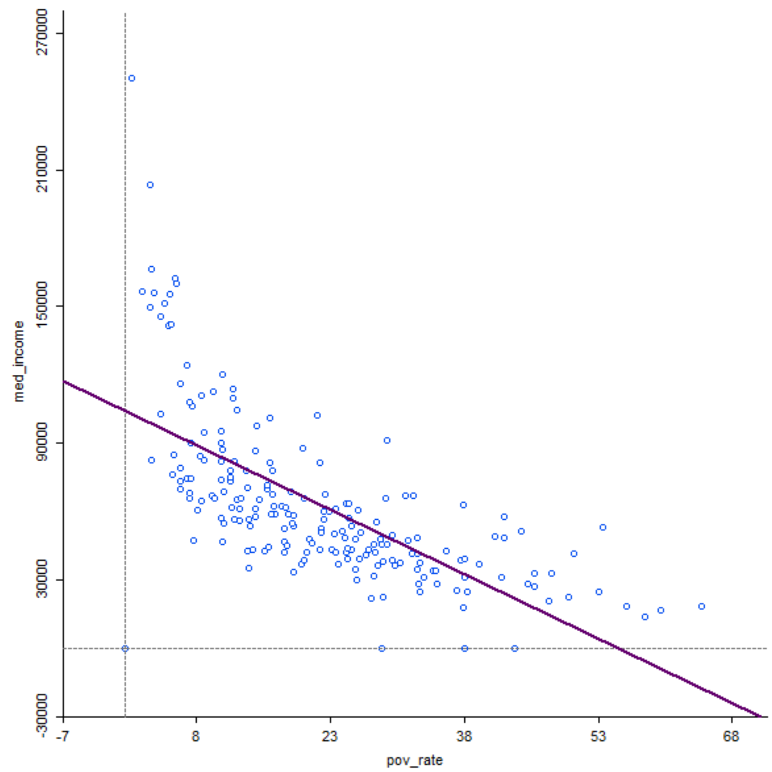


Qmd Part 2:

Moran I

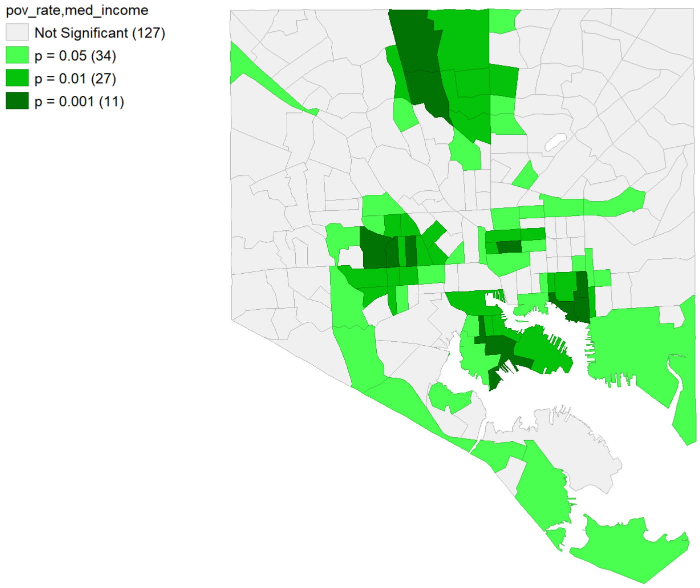


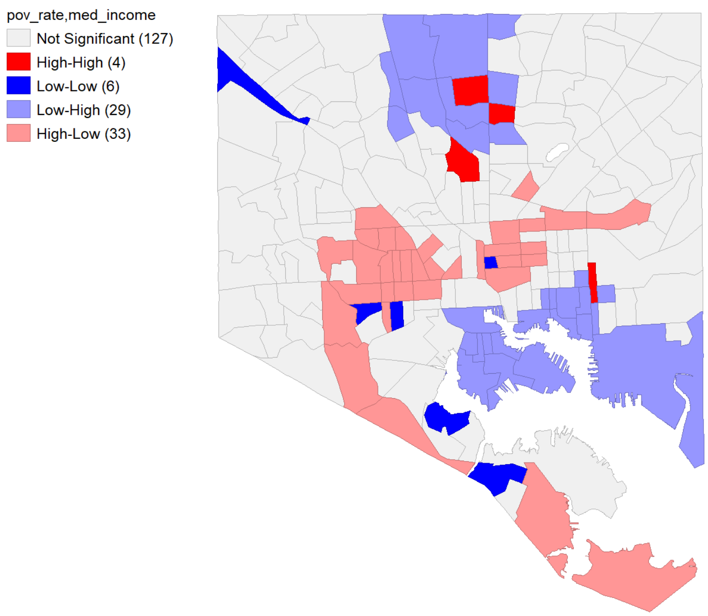
Local Moran I



#obs	R^2	const a	std-err a	t-stat a	p-value a	slope b	std-err b	t-stat b	p-value b
199	0.450	103870.271	3742.753	27.752	0	-1879.214	147.949	-12.702	0.000
0	0	0	0	0	0	0	0	0	0
199	0.450	103870.271	3742.753	27.752	0	-1879.214	147.949	-12.702	0.000

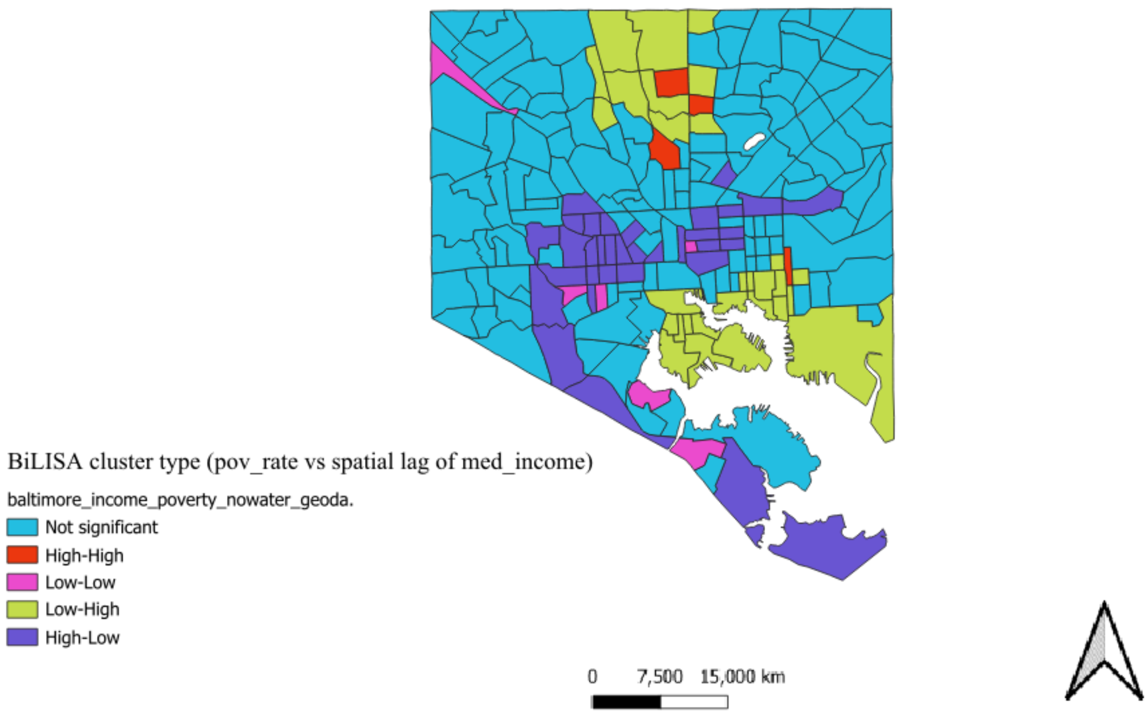
Chow test for sel/unsel regression subsets: can't compute


pov_rate,med_income
Not Significant (127)
p = 0.05 (34)
p = 0.01 (27)
p = 0.001 (11)


pov_rate,med_income
Not Significant (127)
High-High (4)
Low-Low (6)
Low-High (29)
High-Low (33)

Part 2: QGIS

Baltimore City Tracts: Poverty Rate vs Neighboring Median Household Income (BiLISA Cluster Map)



Explanations to QMD part 3 given at the end of qmd part 2 quarto document pdf.