Maps and geolocalized data

Lecture 14

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CPES 2 - Fall 2022

Quick reminder

Causal approach (Behaghel et al., 2015)

- Applicants resumes randomly anonymized or not before being sent to employers

$$Y_i = \alpha + \beta D_i + \gamma An_i + \delta D_i \times An_i + \varepsilon_i$$

- $\hat{\delta}$ captures how the difference in interview rates between the minority and the majority differs between the treated and the control employers

```
summary(lm(interview ~ minority + treatment + minority*treatment,
           data_rct, weights = weight))$coefficients
```

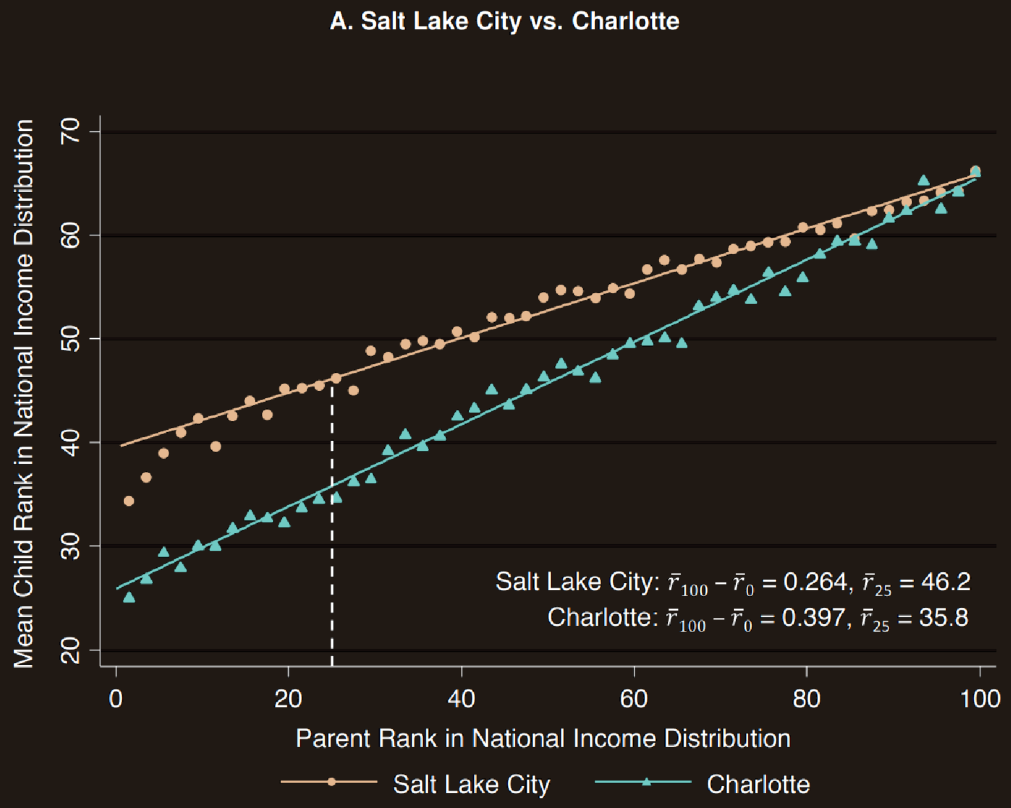
```
##                       Estimate Std. Error    t value     Pr(>|t|)
## (Intercept)         0.11638530 0.01630149  7.1395491 1.575140e-12
## minority           -0.02365790 0.02368346 -0.9989208 3.180243e-01
## treatment           0.06101349 0.02419977  2.5212424 1.181630e-02
## minority:treatment -0.10670915 0.03479712 -3.0666092 2.210982e-03
```

➜ Self-selection issue: discriminatory employers did not enter the program

Quick reminder

Correlational approach (Chetty et al., 2014)

$$\text{percentile}(y_i^c) = \alpha + \beta_{RRC}\text{percentile}(y_i^p) + \varepsilon_i$$



Relative mobility: $\widehat{\beta_{RRC}}$

Absolute mobility: $\widehat{\alpha} + 25 \times \widehat{\beta_{RRC}}$

- Strong persitence in the United-States
- Large variations across commuting zones
- Intergenerational mobility correlated with characteristics of childhood environment

Quick reminder

Structural approach (Nerlove, 1963)

- **Theoretical modeling**

$$\begin{cases} \min & C = p_L L + p_K K \\ \text{s.t.} & Y = A L^{\lambda} K^{\kappa} u \end{cases} \iff \min\ \mathcal{L} = p_L L + p_K K + \mu(Y - A L^{\lambda} K^{\kappa} u)$$

- **Regression expression**

$$\log(C) = \underbrace{\log\left(\left[\frac{\left(\frac{\lambda}{\kappa}\right)^{\kappa} + \left(\frac{\kappa}{\lambda}\right)^{\lambda}}{A}\right]^{\frac{1}{\lambda+\kappa}}\right)}_{\alpha} + \underbrace{\frac{1}{\lambda+\kappa}}_{\beta}\log(Y) + \underbrace{\frac{\lambda}{\lambda+\kappa}}_{\gamma}\log(p_L) + \underbrace{\frac{\kappa}{\lambda+\kappa}}_{\delta}\log(p_K) + \underbrace{\log\left(u^{\frac{1}{\lambda+\kappa}}\right)}_{\varepsilon}$$

- **Estimation**

$$\log(C) = \alpha + \beta\log(Y) + \gamma\log(p_L) + \delta\log(p_K) + \varepsilon \quad \Rightarrow \quad H_0 : \gamma + \delta = 1$$

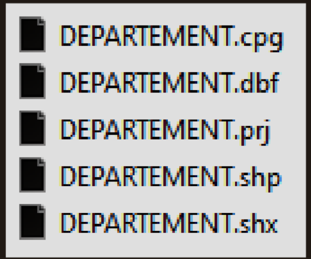
Today: Maps and geolocalized data

Today: Maps and geolocalized data

1. Geolocalized data

1.1. Shapefiles and rasters

→ The **shapefile** is a format for storing **geographic location** and associated attribute information



- Out-software it **can seem quite complicated:**
  - There are several files for a single dataset
  - Always the necessary .shp, .shx, and .dbf
  - Sometimes other files such as .prj, .cpg, etc.
- But in-software, it is **not so far from what we're used to:**
  - There is one line per geographic entity
  - And one column per variable about these entities
  - But there is one non-standard variable: the **geometry**
- The geometry can be:
  - **Points** at given coordinates: location of weather stations/of a phone
  - **Polylines** that link sets of points: rivers/roads
  - **Polygons** that link sets of points to form a closed shape: countries/land parcels

1. Geolocalized data

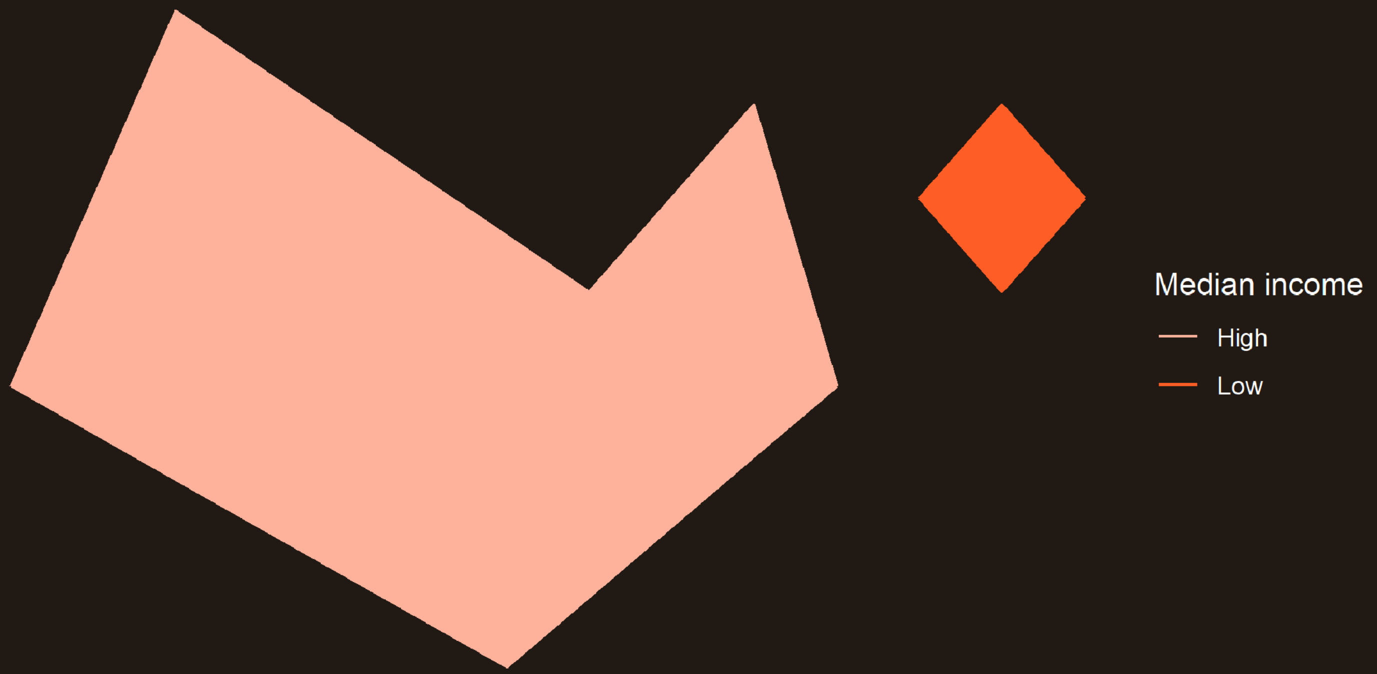
1.1. Shapefiles and rasters

- For instance consider a shapefile
  - With two observations
  - And a polygon geometry

1. Geolocalized data

1.1. Shapefiles and rasters

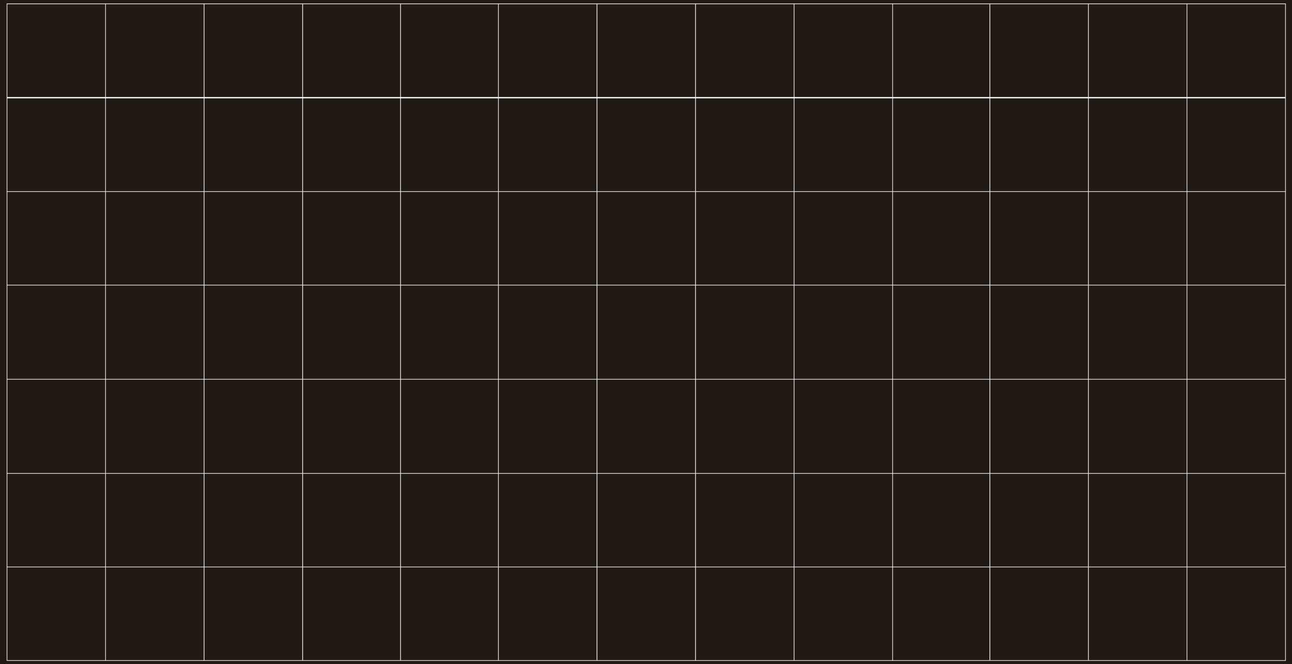
- The shapefile can also contain **attribute variable**
  - For instance the **median income** of residents of the area delimited by the polygon
  - We can plot this attribute variable using the fill aesthetic of the polygon geometry



1. Geolocalized data

1.1. Shapefiles and rasters

- The **raster** is another type of format for storing geolocalized data
  - It works **like a picture**, with cells like pixels



1. Geolocalized data

1.1. Shapefiles and rasters

- The **raster** is another type of format for storing geolocalized data
  - It works **like a picture**, with cells like pixels
  - And each cell can take a given value, e.g. pollution observed from satellites

	0.5	0.45	0.45									
	0.45	0.45	0.4	0.2	0.2			1	1		0.9	0.85
0.4	0.4	0.4	0.3	0.2	0.2	0.5	0.6	0.8	1		0.85	0.8
0.3	0.3	0.3	0.3	0.2	0.2	0.5	0.7	0.9	1			
0.2	0.2	0.2	0.2	0.2	0.2	0.4	0.5	0.7	1			
		0.2	0.2	0.2	0.2	0.3	0.4	0.6				
				0.2	0.1	0.2	0.3					

1. Geolocalized data

1.1. Shapefiles and rasters

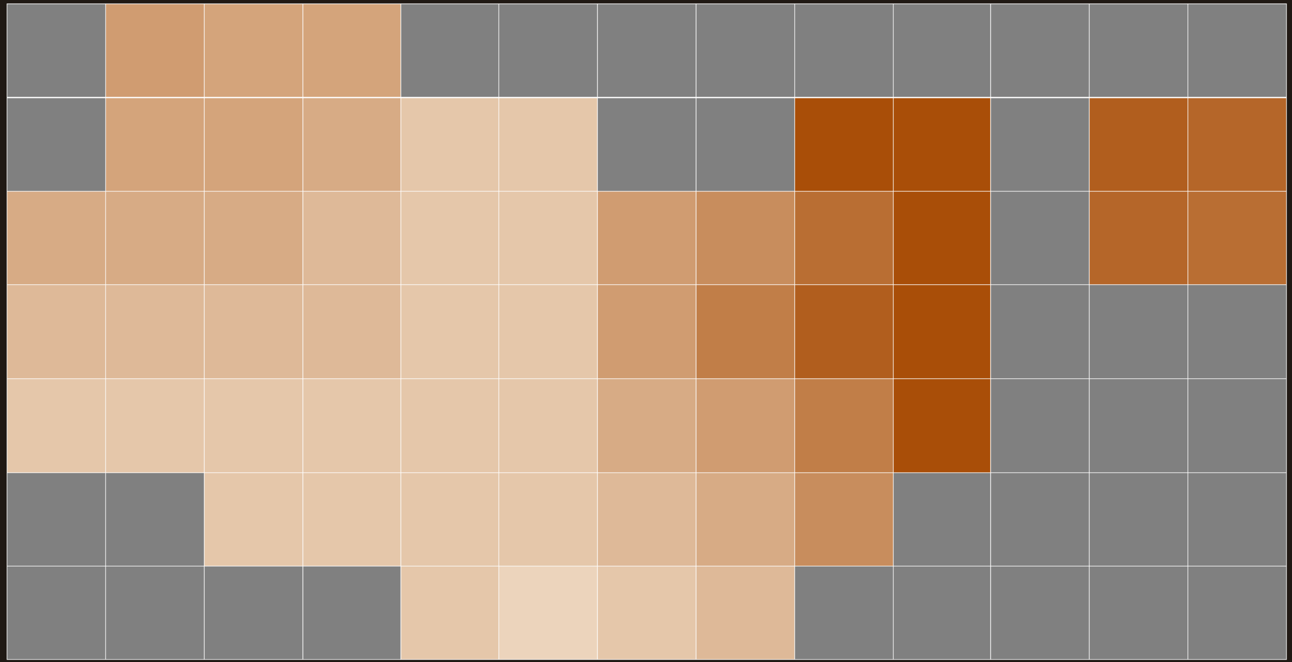
- The **raster** is another type of format for storing geolocalized data
  - It works **like a picture**, with cells like pixels
  - And each cell can take a given value, e.g. pollution observed from satellites

	0.5	0.45	0.45									
	0.45	0.45	0.4	0.2	0.2			1	1		0.9	0.85
0.4	0.4	0.4	0.3	0.2	0.2	0.5	0.6	0.8	1		0.85	0.8
0.3	0.3	0.3	0.3	0.2	0.2	0.5	0.7	0.9	1			
0.2	0.2	0.2	0.2	0.2	0.2	0.4	0.5	0.7	1			
		0.2	0.2	0.2	0.2	0.3	0.4	0.6				
				0.2	0.1	0.2	0.3					

1. Geolocalized data

1.1. Shapefiles and rasters

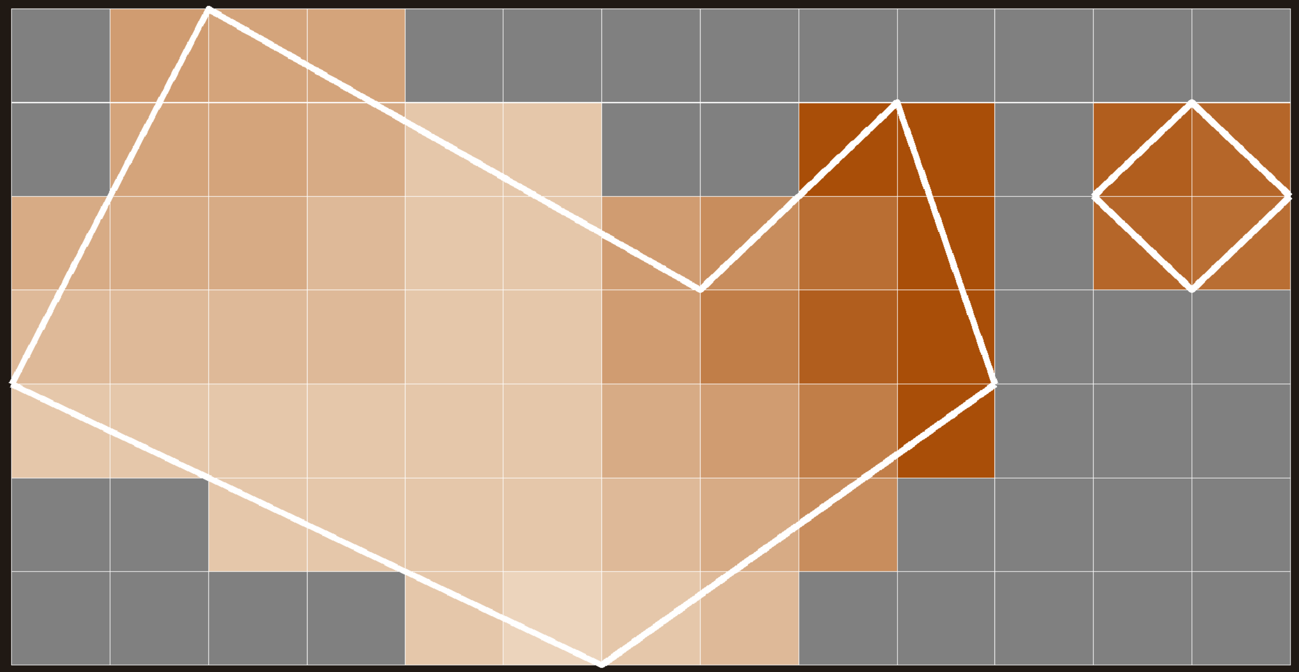
- Today we're gonna use this to estimate the relationship between **income and exposure to air pollution**
  - Using **raster** satellite data on pollution level



1. Geolocalized data

1.1. Shapefiles and rasters

- Today we're gonna use this to estimate the relationship between **income and exposure to air pollution**
  - Using **raster** satellite data on pollution level
  - And a **shapefile** to compute the average exposure in different location and merge it with income data



1. Geolocalized data

1.2. Opening geolocalized data

- We can read shapefiles in R using the `read_sf()` function from the `sf` package (data from IGN)

```
library(sf)
dep_shp <- read_sf("data/dep_shp/DEPARTEMENT.shp")
head(dep_shp, 5)
```

```
## Simple feature collection with 5 features and 5 fields
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: 0.06558525 ymin: 45.23103 xmax: 7.621946 ymax: 50.0722
## Geodetic CRS:  WGS 84
## # A tibble: 5 x 6
##   ID              NOM_DEP_M NOM_DEP INSEE_DEP INSEE_REG                  geometry
##   <chr>           <chr>     <chr>   <chr>     <chr>             <MULTIPOLYGON [°]>
## 1 DEPARTEM00000~ JURA      Jura    39        27         (((5.442842 46.84592, 5.~
## 2 DEPARTEM00000~ SEINE-MA~ Seine-~ 76        28         (((0.3875418 49.77178, 0~
## 3 DEPARTEM00000~ YONNE     Yonne   89        27         (((3.126677 47.99127, 3.~
## 4 DEPARTEM00000~ LOIRE     Loire   42        84         (((3.831716 45.99944, 3.~
## 5 DEPARTEM00000~ HAUT-RHIN Haut-R~ 68        44         (((6.923645 47.95226, 6.~
```

1. Geolocalized data

1.2. Opening geolocalized data

- We can then view the data using the `geom_sf()` geometry
  - It will understand that the `geometry` variable contains the coordinates of the polygons to be plotted

```
library(tidyverse)
ggplot(dep_shp) + geom_sf(fill = "#6794A7", color = "#014D64", alpha = .6) + theme_void()
```

1. Geolocalized data

1.2. Opening geolocalized data

- There are several **formats of raster** files (.tif, .nc, ...)
  - We're gonna use **NetCDF** satellite data on $PM_{2.5}$ from the Atmospheric Composition Analysis Group
  - So we're gonna need the packages `raster` and `ncdf4`

```
library(raster)
select <- dplyr::select # The raster packages has an overriding select function
library(ncdf4)

pm_data <- raster("data/acag_2016.nc")
pm_data
```

```
## class       : RasterLayer
## dimensions : 2300, 5000, 11500000  (nrow, ncol, ncell)
## resolution : 0.01, 0.009999999  (x, y)
## extent      : -15, 35, 36, 59  (xmin, xmax, ymin, ymax)
## crs         : +proj=longlat +datum=WGS84 +no_defs
## source      : acag_2016.nc
## names       : Hybrid.PM_2_._5...mug.m.3.
## zvar        : GWRPM25
```

- As you can see NetCDFs are complex objects:
  - **Not a simple table** with figures
  - Note that the $PM_{2.5}$ variable is Hybrid.PM_2_._5...mug.m.3.

1. Geolocalized data

1.2. Opening geolocalized data

- We can **rename** the $PM_{2.5}$ variable into something more convenient

```
names(pm_data) <- "pm2.5"
```

- And convert the data into a standard dataset using the `rasterToPoints()` function
    - It will **generate a table** with 1 row per cell
    - An x variable for the longitude, y for latitude, and pm2.5 for pollution

```
head(as_tibble(rasterToPoints(pm_data)), 5)
```

```
## # A tibble: 5 x 3
##       x     y pm2.5
##   <dbl> <dbl> <dbl>
## 1 -3.38  59.0  4.60
## 2 -3.37  59.0  4.60
## 3 -3.36  59.0  4.60
## 4 -3.35  59.0  4.70
## 5 -3.34  59.0  4.70
```

1. Geolocalized data

1.2. Opening geolocalized data

- This table format allows to easily **plot raster data** using the `geom_tile` geometry:

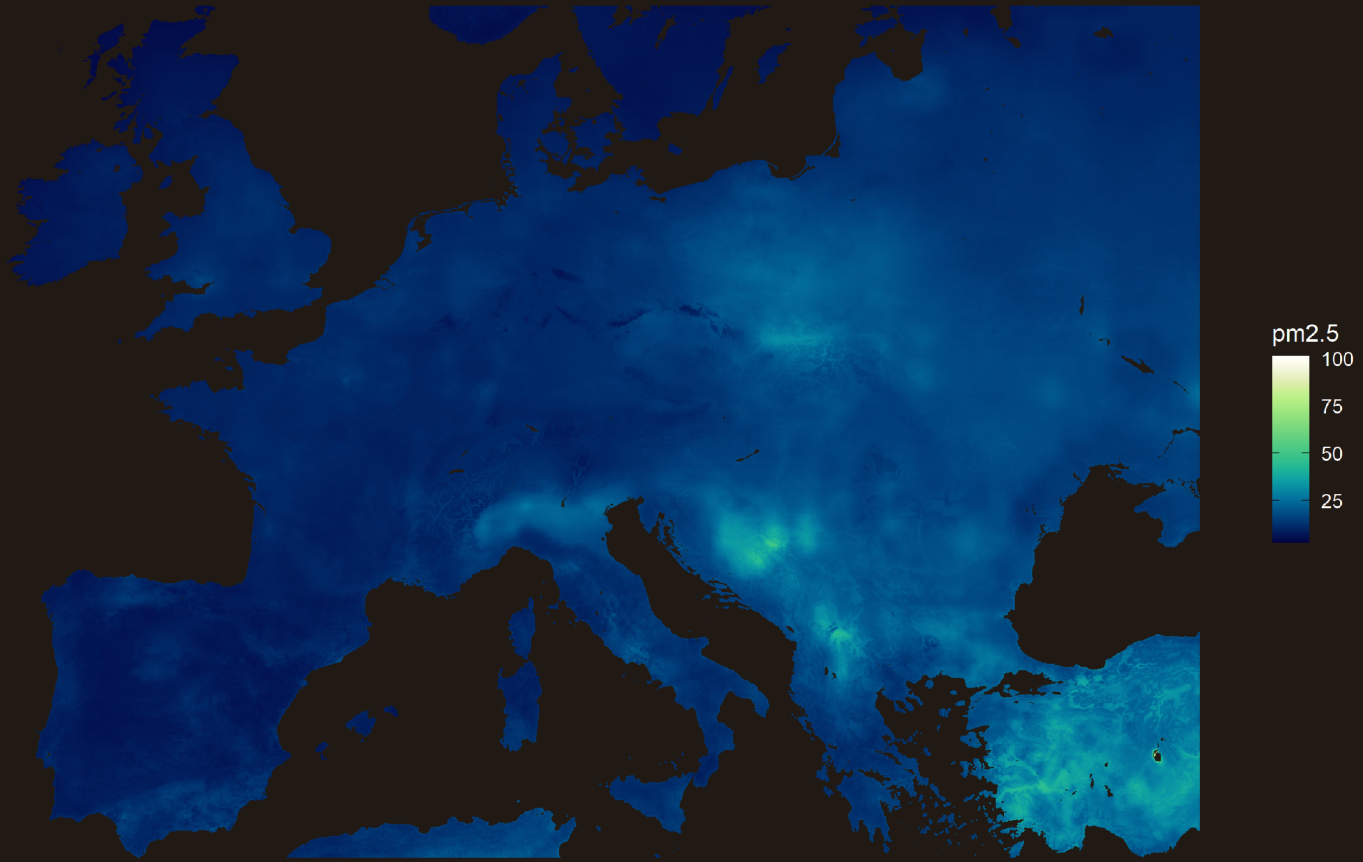
```
library(viridis) # for nice color gradient

ggplot(as_tibble(rasterToPoints(pm_data)), # Data converted in table
       aes(x = x,                          # Longitude on the x-axis
           y = y,                          # Latitude on the y-axis
           fill = pm2.5)) +                # Pollution on the fill-axis
  geom_tile() +                            # One filled square per cell
  scale_fill_viridis(option = "B",         # Nice color gradient
                     direction = -1) +     # The darker the more polluted
  theme_void()                             # Remove axes and grid
```

- This is gonna plot the 2,300 x 5,000 = 11,500,000 cells
  - With a color that is proportional to the value of `pm2.5`
  - Like the pixels of picture

1. Geolocalized data

1.2. Opening geolocalized data



1. Geolocalized data

1.3. Coordinate Reference Systems

- You might have noticed that France does not look the same on the two graphs
  - This is because we have not **reprojected the data** yet
  - But this is the **first thing to do** when working with geolocalized data

- Right now our two maps may not be in the same CRS
  - CRS stands for **Coordinate Reference System**
  - It is a model of the Earth in which each location is coded using degrees
  - WGS84 is the standard CRS used by GPS, Google maps, ...
  - But it is **not suited to all applications**

- To visualize spatial data, we need to **project the surface of the globe on a plane**
  - There is **no correct way of doing that**
  - Like you cannot flatten an orange peel without distorting it

➜ There is a tradeoff between shape and scale preservation

1. Geolocalized data

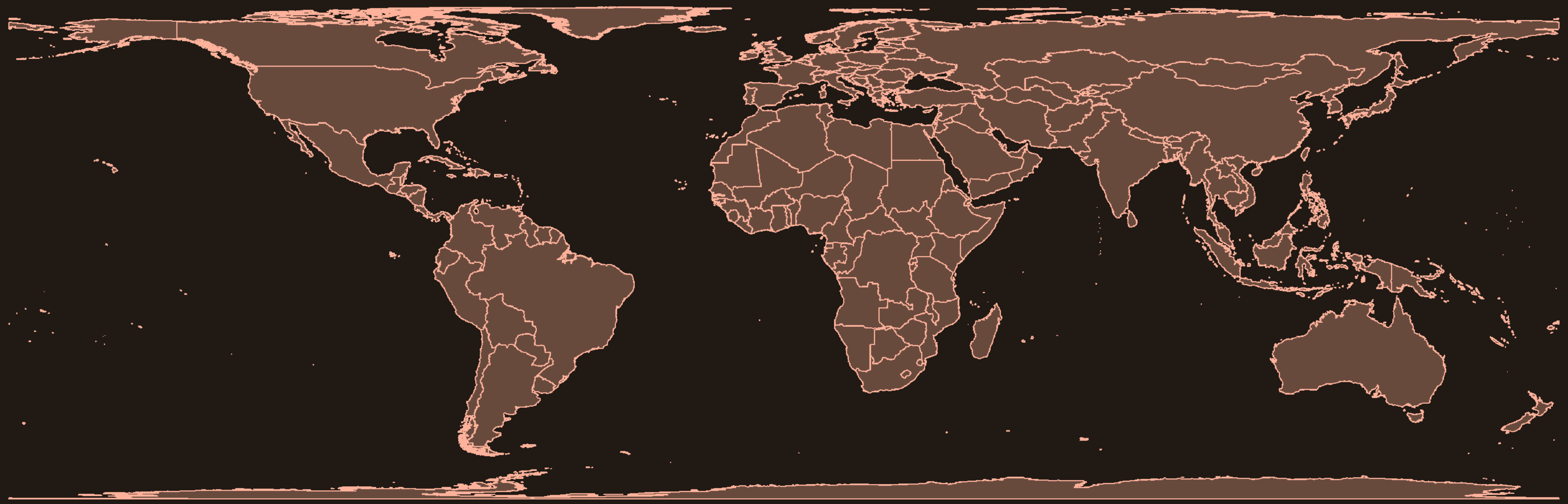
1.3. Coordinate Reference Systems

- For instance the **Mercator projection** preserves shape but distorts scale:

1. Geolocalized data

1.3. Coordinate Reference Systems

- While the **Equal-Area Cylindrical projection** preserves scale but distorts shape:



1. Geolocalized data

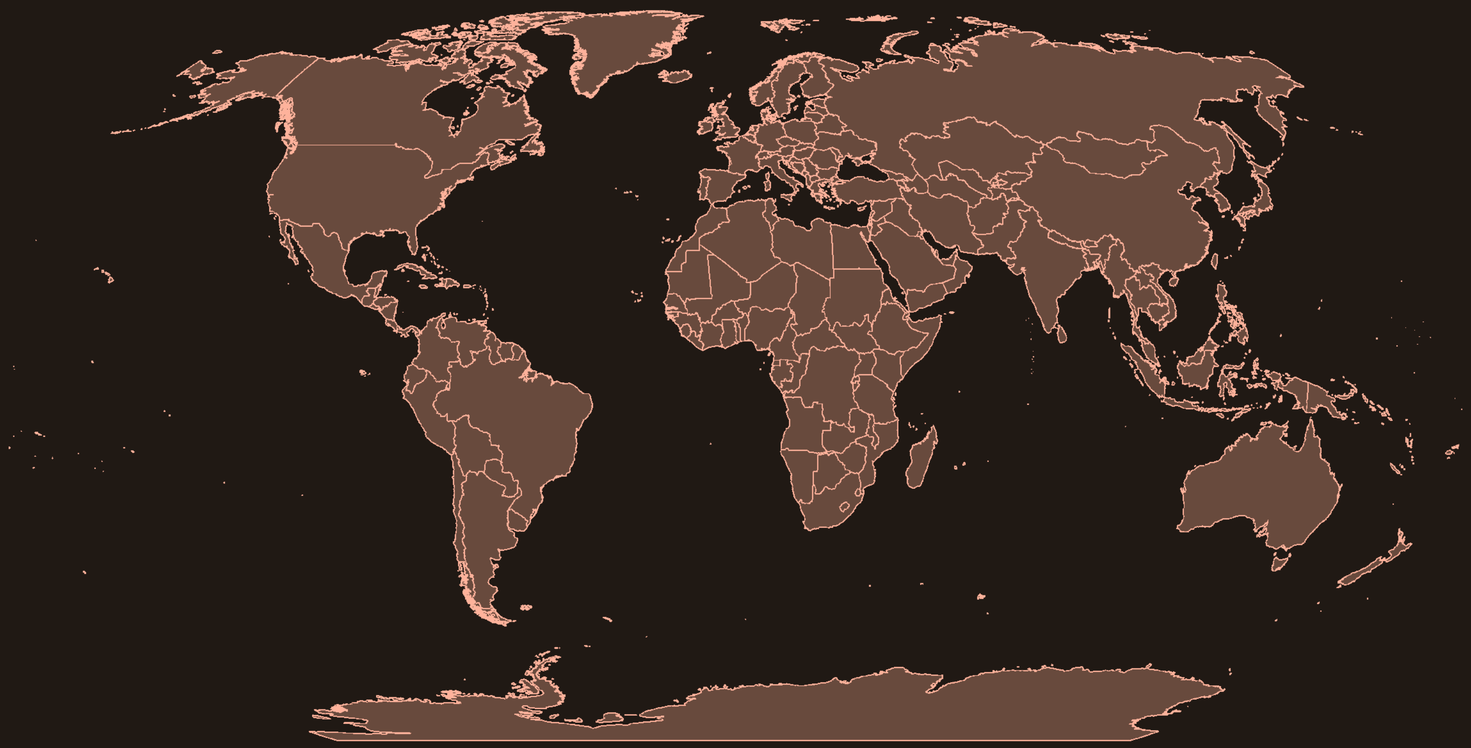
1.3. Coordinate Reference Systems

- This is also the case for the **Mollweide projection:**

1. Geolocalized data

1.3. Coordinate Reference Systems

- But most projections are in between, like the **Robin projection:**



1. Geolocalized data

1.3. Coordinate Reference Systems

- The **smaller** the **area** you want to map the **less** it is a **problem**
  - While you would have a hard time flatten the whole orange peel
  - Flattening a tiny bit of orange peel wouldn't require to distort it too much

- Even though there's **no perfect projection**, some are more suited to specific regions
  - You wouldn't use the Mercator projection if you focus on the poles

- The website epsg.io allows you to **find the appropriate CRS** for the area you want to map
  - For **France**, the recommended projection is **Lambert 93**, the corresponding EPSG code is 2154
  - The most common projection is WGS84, the corresponding EPSG code is 4326
  - What is important is that all the datasets are projected the same way

- For shapefile: `st_transform()`

```
dep_shp <- st_transform(dep_shp, "EPSG:4326")
```

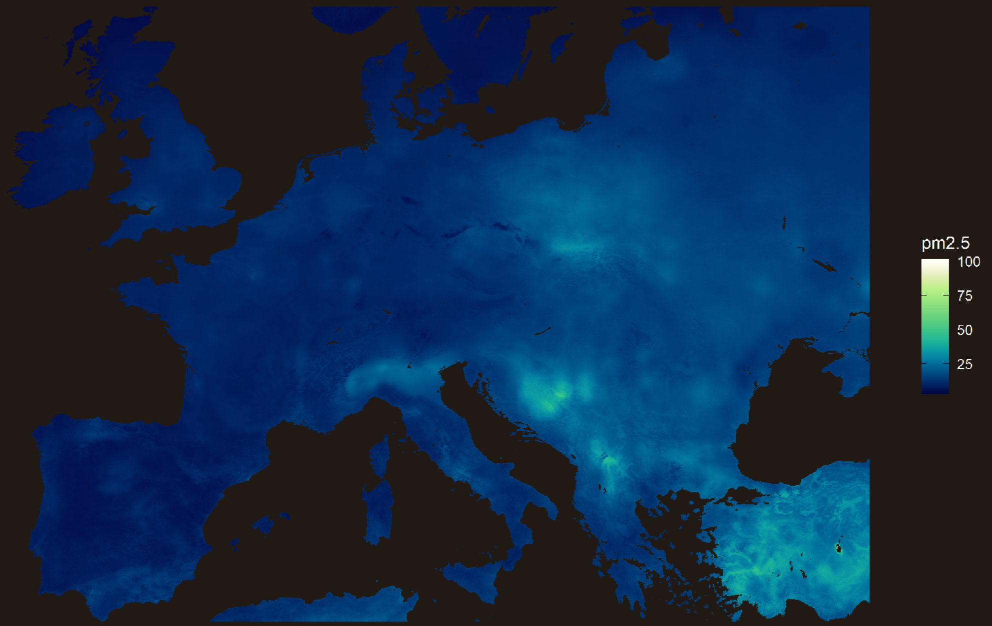
- For raster: `crs()`

```
crs(pm_data) <- "EPSG:4326"
```

1. Geolocalized data

1.3. Coordinate Reference Systems

- Data projected in WGS84:

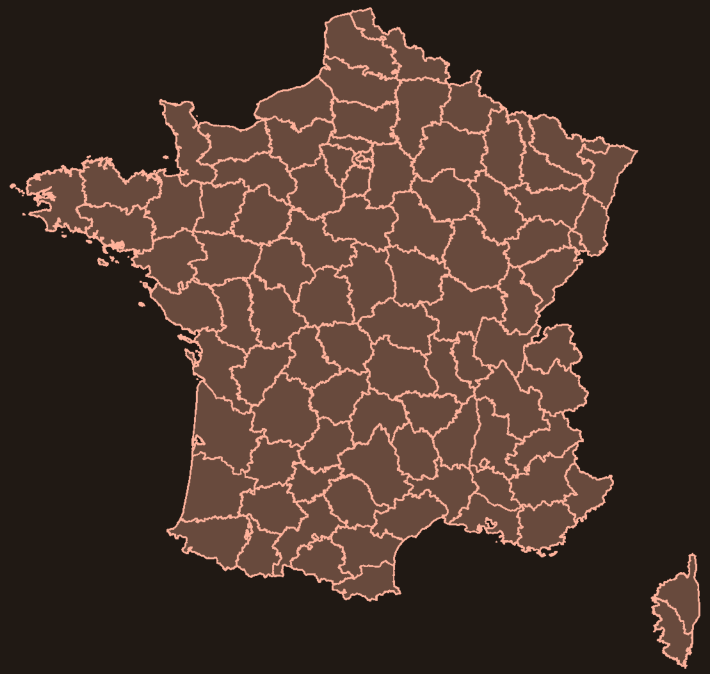


1. Geolocalized data

1.4. Subsetting geolocalized data

- To keep only metropolitan France in the shapefile, we can filter 2-digit department codes

```
dep_shp <- dep_shp %>% filter(nchar(INSEE_DEP) == 2)
```

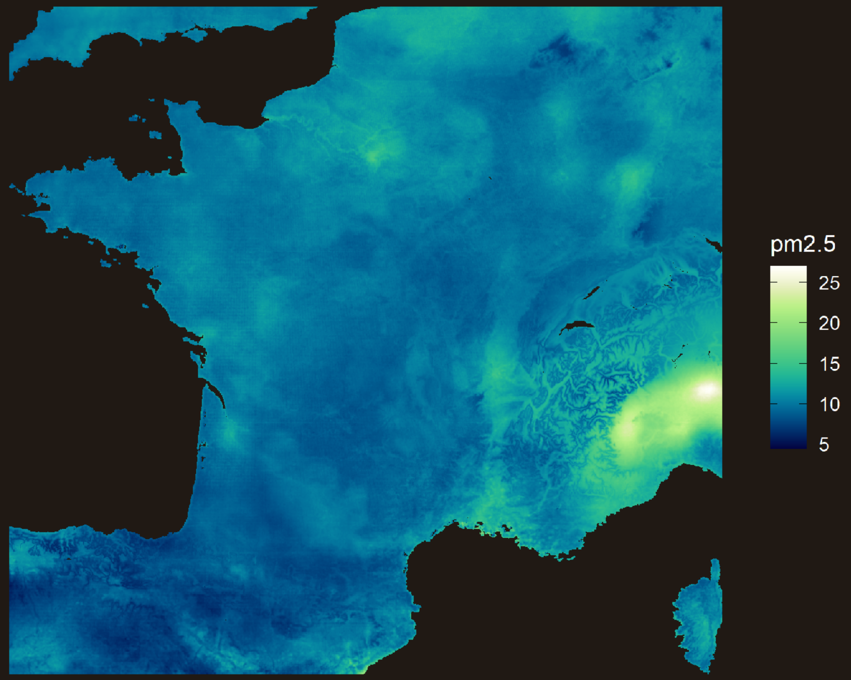


1. Geolocalized data

1.4. Subsetting geolocalized data

- Then, we can drop from the raster everything outside the longitude/latitude frame of our shapefile

```
pm_data <- crop(pm_data, extent(dep_shp))
```

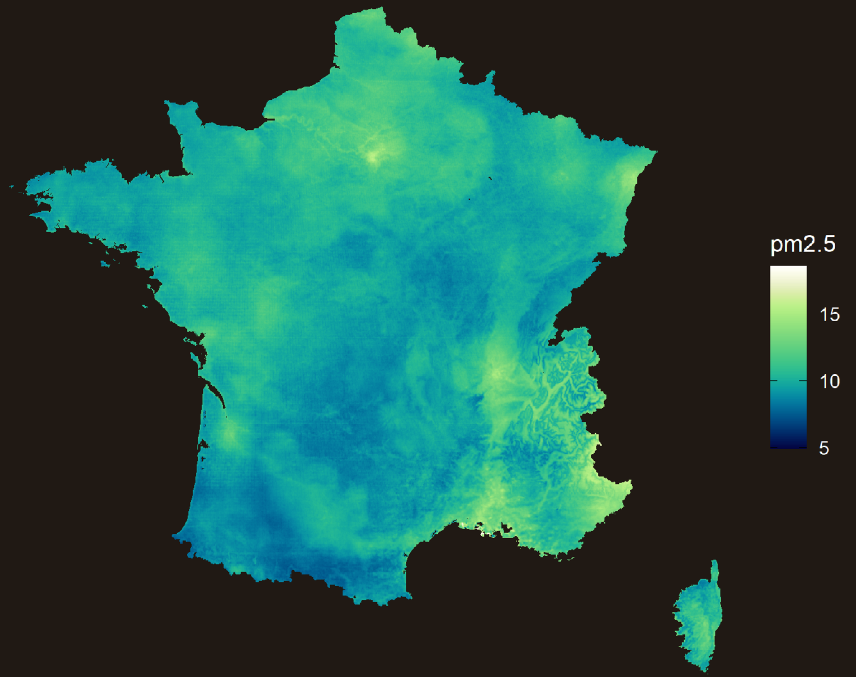


1. Geolocalized data

1.4. Subsetting geolocalized data

- We can then replace everything that is not in a polygon of the shapefile by missing values

```
pm_data <- mask(pm_data, dep_shp)
```

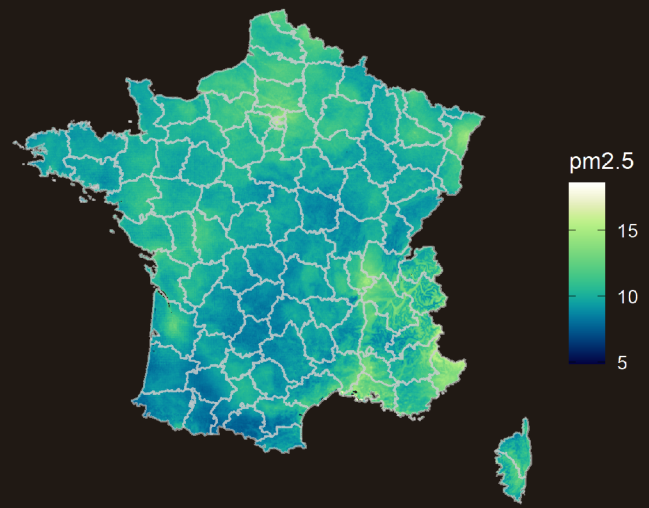


1. Geolocalized data

1.4. Subsetting geolocalized data

- The two datasets can now be overlaid:

```
ggplot() +
  geom_tile(data = as_tibble(rasterToPoints(pm_data)), aes(x = x, y = y, fill = pm2.5))  +
  geom_sf(data = dep_shp, fill = NA, color = alpha("grey20", .6)) +
  scale_fill_viridis(option = "A", direction = -1) + theme_void()
```



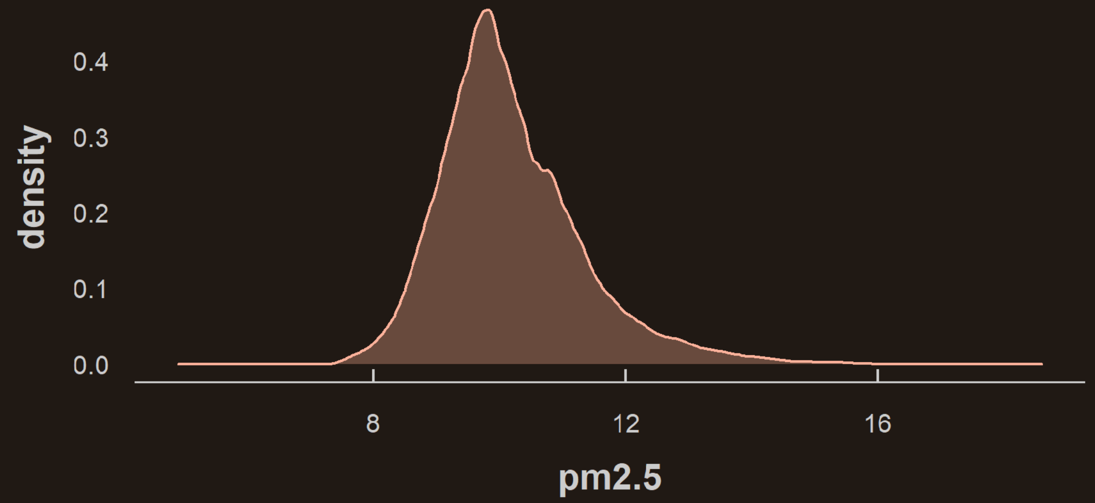
1. Geolocalized data

1.4. Subsetting geolocalized data

- We do not see much variation… Let's take a look at the $PM_{2.5}$ distribution

```
subset_data <- as_tibble(rasterToPoints(pm_data))

ggplot(subset_data, aes(x = pm2.5)) +
  geom_density(fill = "#6794A7", color = "#014D64", alpha = .6)
```



- There are **few** very high and very low **values that stretch the scale**

  → *To better visualize the variations, we can **discretize the variable into deciles***

1. Geolocalized data

1.4. Subsetting geolocalized data

- To convert a continuous into deciles we should:
    1. Arrange the values in ascending order
    2. Compute the ratio of their index over N to get something $\in (0;1]$
    3. Multiply by the desired number of quantiles and take the ceiling
    4. Set as factor so that R does not interpret it as continuous

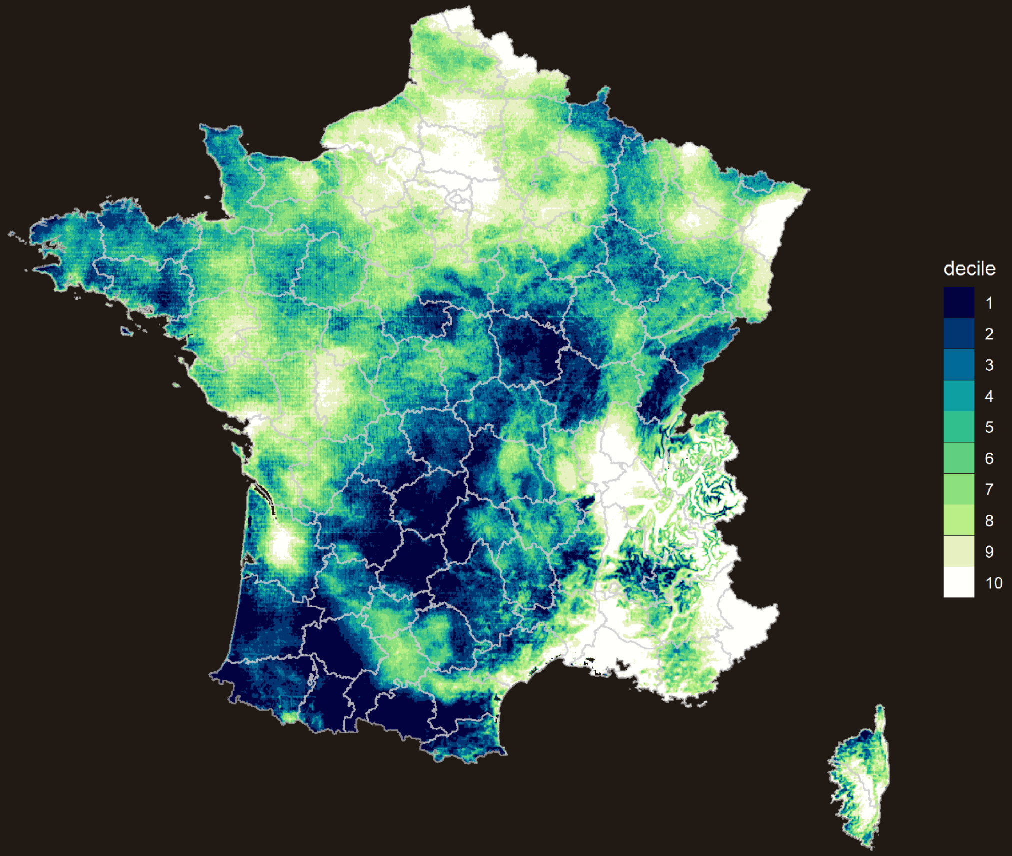
```
subset_data <- subset_data %>%
  arrange(pm2.5) %>%
  mutate(decile = as.factor(ceiling(10 * row_number()/n())))
```

- And plot the deciles instead of the continuous values

```
ggplot() +
  geom_tile(data = subset_data, aes(x = x, y = y, fill = decile))  +
  geom_sf(data = dep_shp, fill = NA, color = alpha("grey20", .6)) +
  scale_fill_viridis_d(option = "A", direction = -1) + theme_void()
```

1. Geolocalized data

1.4. Subsetting geolocalized data



Practice

First, make sure we're on the same page

```r
# Load packages
library(tidyverse)
library(viridis)
library(sf)
library(raster)
select <- dplyr::select
library(ncdf4)

# Import data
dep_shp <- read_sf("data/dep_shp/DEPARTEMENT.shp")
pm_data <- raster("data/acag_2016.nc")

# Reproject data
dep_shp <- st_set_crs(dep_shp, "EPSG:4326")
crs(pm_data) <- "EPSG:4326"

# Rename PM 2.5 layer
names(pm_data) <- "pm2.5"
```

Practice

08:00

1) Filter only the Île-de-France region both in the shapefile and the raster

Hint: The Île-de-France geographic code is 11

2) Plot the $PM_{2.5}$ concentration in Île-de-France and overlay the department shapefile

You've got 8 minutes!

Solution

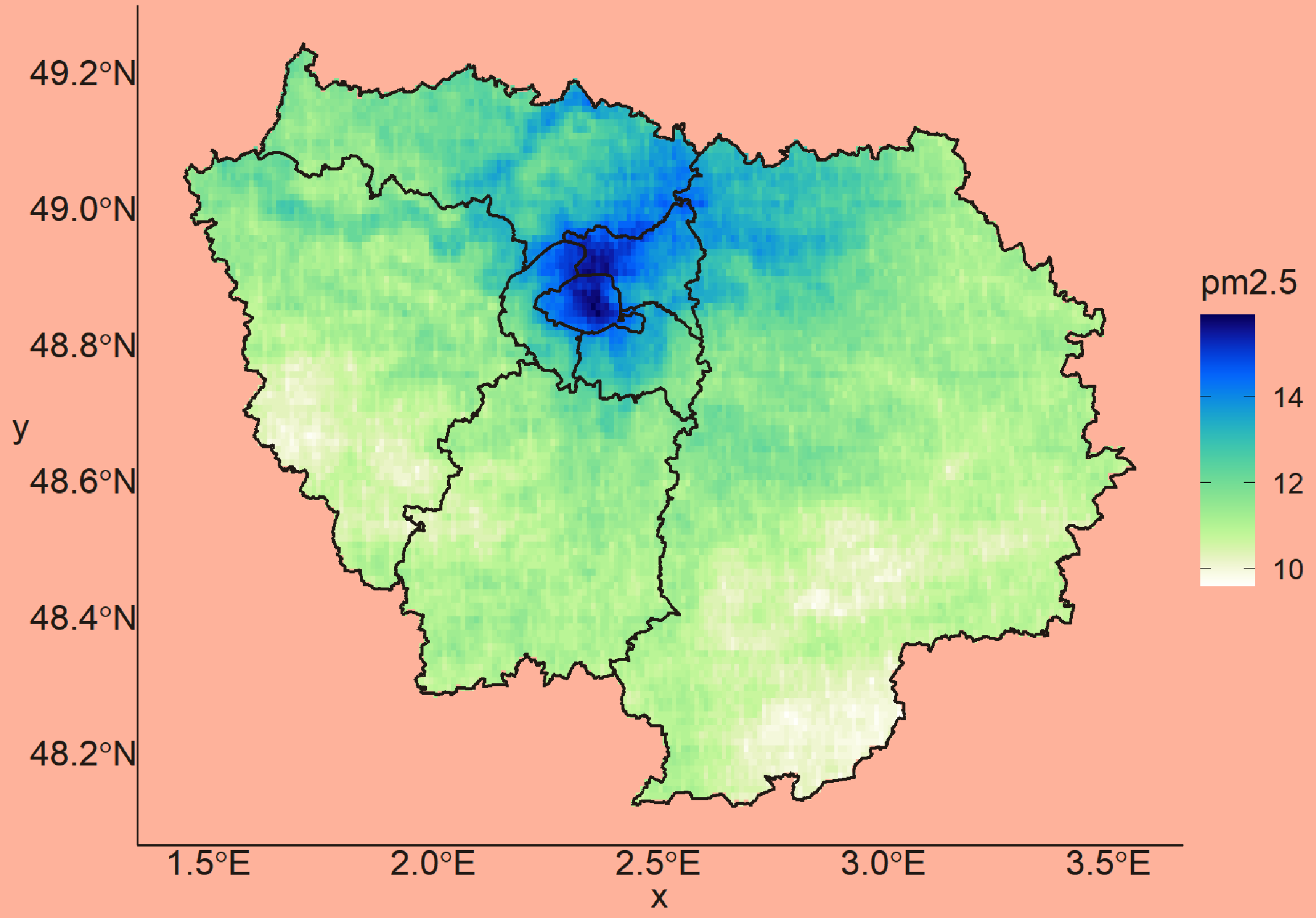
1) Filter only the Île-de-France region both in the shapefile and the raster

```
# Filter only departments of Île-de-France in shapefile
dep_shp <- dep_shp %>% filter(INSEE_REG == 11)
# Drop fromraster everything outside the lon/lat frame of the shapefile
pm_data <- crop(pm_data, extent(dep_shp))
# Replace everything that is not in a polygon of the shapefile by NA
pm_data <- mask(pm_data, dep_shp)
```

2) Plot the $PM_{2.5}$ concentration in Île-de-France and overlay the department shapefile

```
ggplot() +
  # Plot the raster
  geom_tile(data = as_tibble(rasterToPoints(pm_data)), aes(x = x, y = y, fill = pm2.5))  +
  # Plot the shapefile
  geom_sf(data = dep_shp, fill = NA) +
  # Custom scale
  scale_fill_viridis(option = "B") + theme_void()
```

Solution


49.2°N
49.0°N
48.8°N
48.6°N
48.4°N
48.2°N
y
1.5°E
2.0°E
2.5°E
3.0°E
3.5°E
x
pm2.5
14
12
10

Overview

1. Geolocalized data ✓

- 1.1. Shapefiles and rasters
- 1.2. Opening geolocalized data
- 1.3. Coordinate Reference Systems
- 1.4. Subsetting geolocalized data

2. Geographic variables

- 2.1. Import from csv
- 2.2. Zonal statistics
- 2.3. Centroids and distance

3. Wrap up!

Overview

2. Geographic variables

2.1. Import from csv

- Geographic variables can simply be stored in csv:
  - The Gini index of inequality of countries
  - The unemployment rate of departments
  - The number of inhabitants of cities
  - ...

- In this case you can simply
  - Import the csv data you need
  - Join it to the shapefile as you would do with any other data

➜ *Let's study the relationship between income and exposure to air pollution at the city level in Île-de-France*

- We need:
  1. To import the shapefile of cities in Île-de-France
  2. To import and join median income by city

2. Geographic variables

2.1. Import from csv

- Import shapefile of cities in Île-de-France and project it in WGS84

```
idf_shp <- read_sf("data/idf_shp/idf.shp")
idf_shp <- st_set_crs(idf_shp, "EPSG:4326")
head(idf_shp, 5)
```

```
## Simple feature collection with 5 features and 5 fields
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: 1.643507 ymin: 48.36067 xmax: 2.365918 ymax: 49.17332
## Geodetic CRS:  WGS 84
## # A tibble: 5 x 6
##   NOM_COM     INSEE_COM INSEE_DEP INSEE_REG POPULATION                 geometry
##   <chr>       <chr>     <chr>     <chr>          <int>       <MULTIPOLYGON [°]>
## 1 Haute-Isle  95301     95        11               278 (((1.691893 49.07523, 1.~
## 2 Ambleville  95011     95        11               372 (((1.691683 49.12863, 1.~
## 3 Chalou-Mou~ 91131     91        11               431 (((2.043785 48.36067, 2.~
## 4 Morsang-su~ 91434     91        11             20909 (((2.36231 48.64807, 2.3~
## 5 Vienne-en-~ 95656     95        11               416 (((1.74087 49.07267, 1.7~
```

2. Geographic variables

2.1. Import from csv

- Join csv data on median income by city and plot together with department shapefile
  - We shall make sure that the **join variable(s)** have the **same name and class**

```
insee_data <- as_tibble(read.csv("data/insee_2016.csv"))
head(insee_data, 1)
```

```
## # A tibble: 1 x 3
##   INSEE_COM CITY  MED16
##       <int> <chr> <dbl>
## 1     75056 Paris  26.8
```

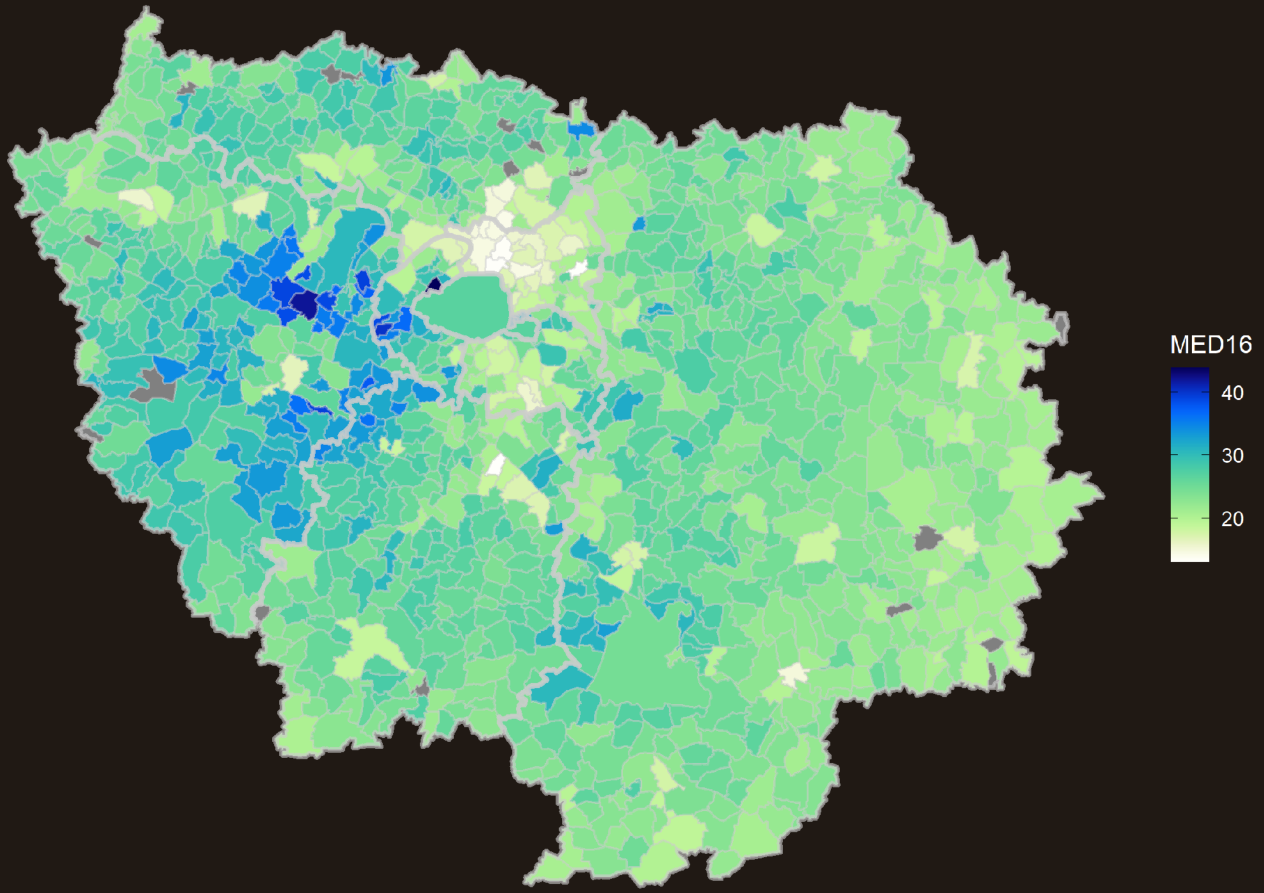
- Same name but not same class

```
idf_shp <- idf_shp %>% mutate(INSEE_COM = as.numeric(INSEE_COM)) %>% left_join(insee_data)

ggplot() + geom_sf(data = idf_shp, aes(fill = MED16), color = alpha("grey20", .4)) +
  geom_sf(data = dep_shp, fill = NA, color = alpha("grey20", .6), size = 1.2) +
  scale_fill_viridis(option = "B") + theme_void()
```

2. Geographic variables

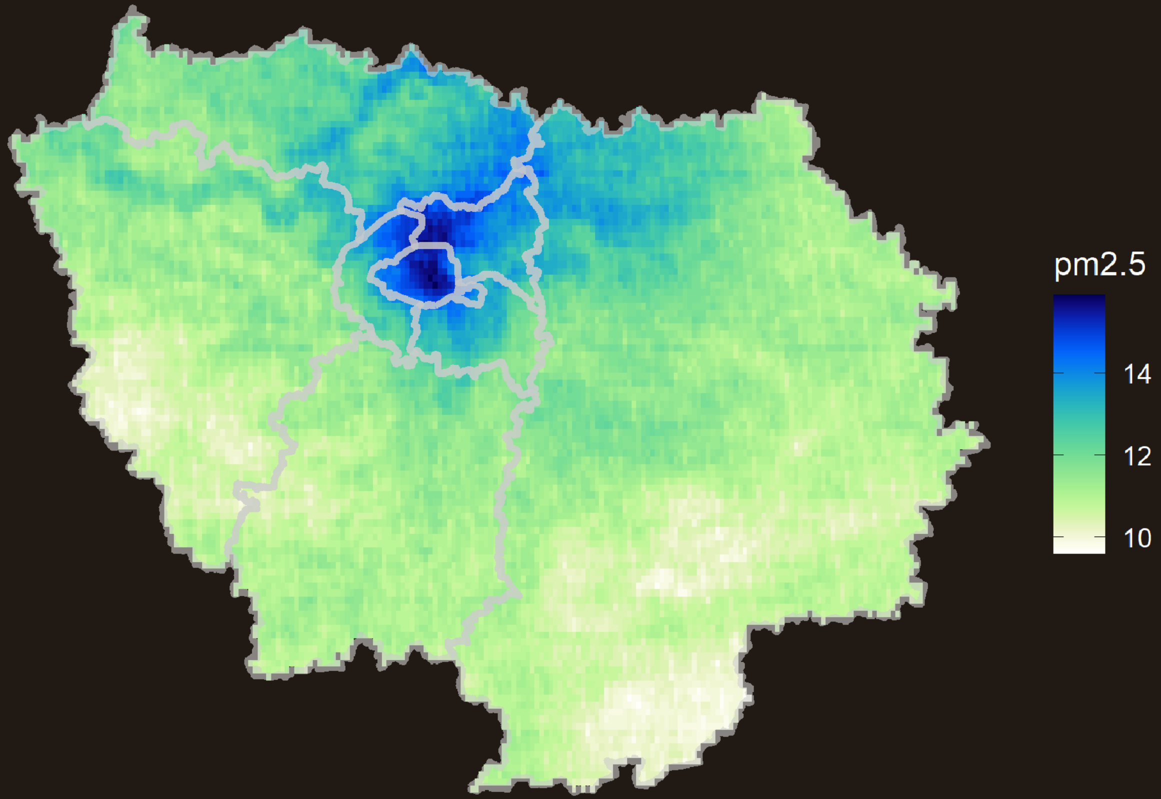
2.1. Import from csv



2. Geographic variables

2.2. Zonal statistics

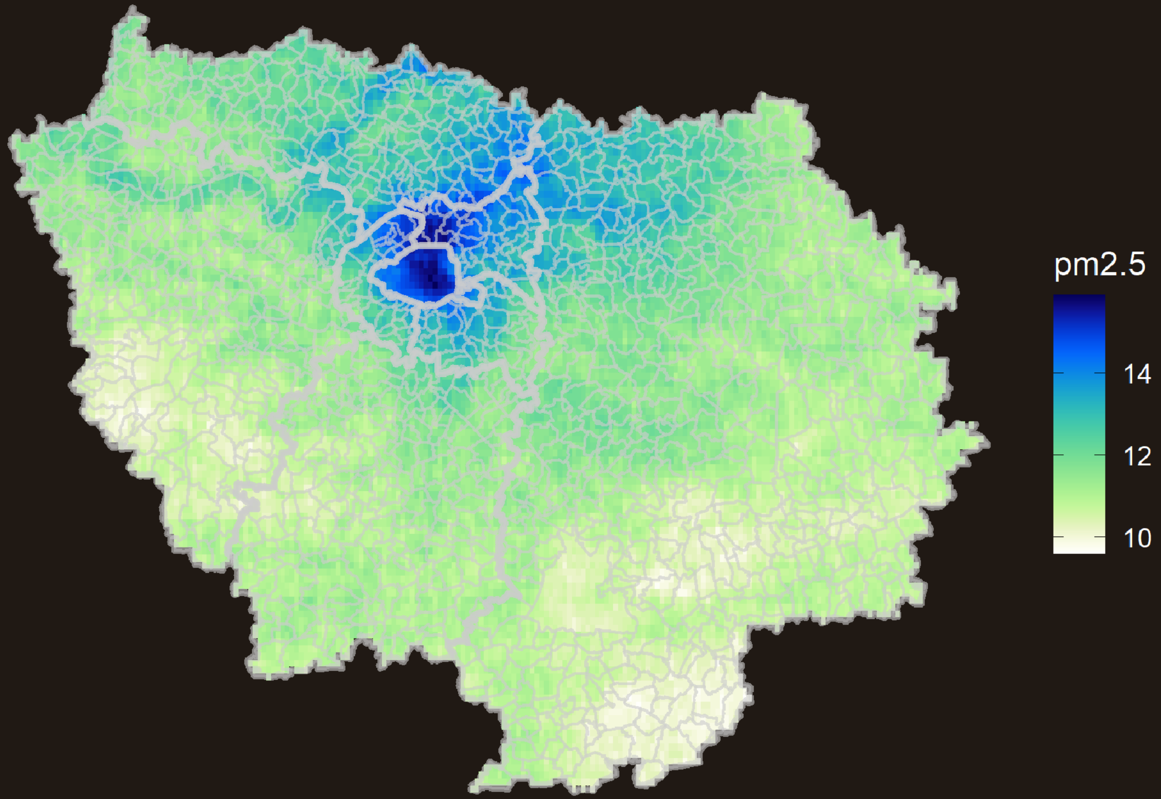
- Right now we have pollution at the cell level in our raster



2. Geographic variables

2.2. Zonal statistics

- And a shapefile delimiting the cities in which we want to know the pollution level



2. Geographic variables

2.2. Zonal statistics

- This is the principle of **zonal statistics:**
    - Compute **statistics on areas delimited by a shapefile from values of a raster**
    - We want the average $PM_{2.5}$ value of the cells that fall within the municipality geometry
    - With our shapefile and raster that cover the same area and are projected the same way

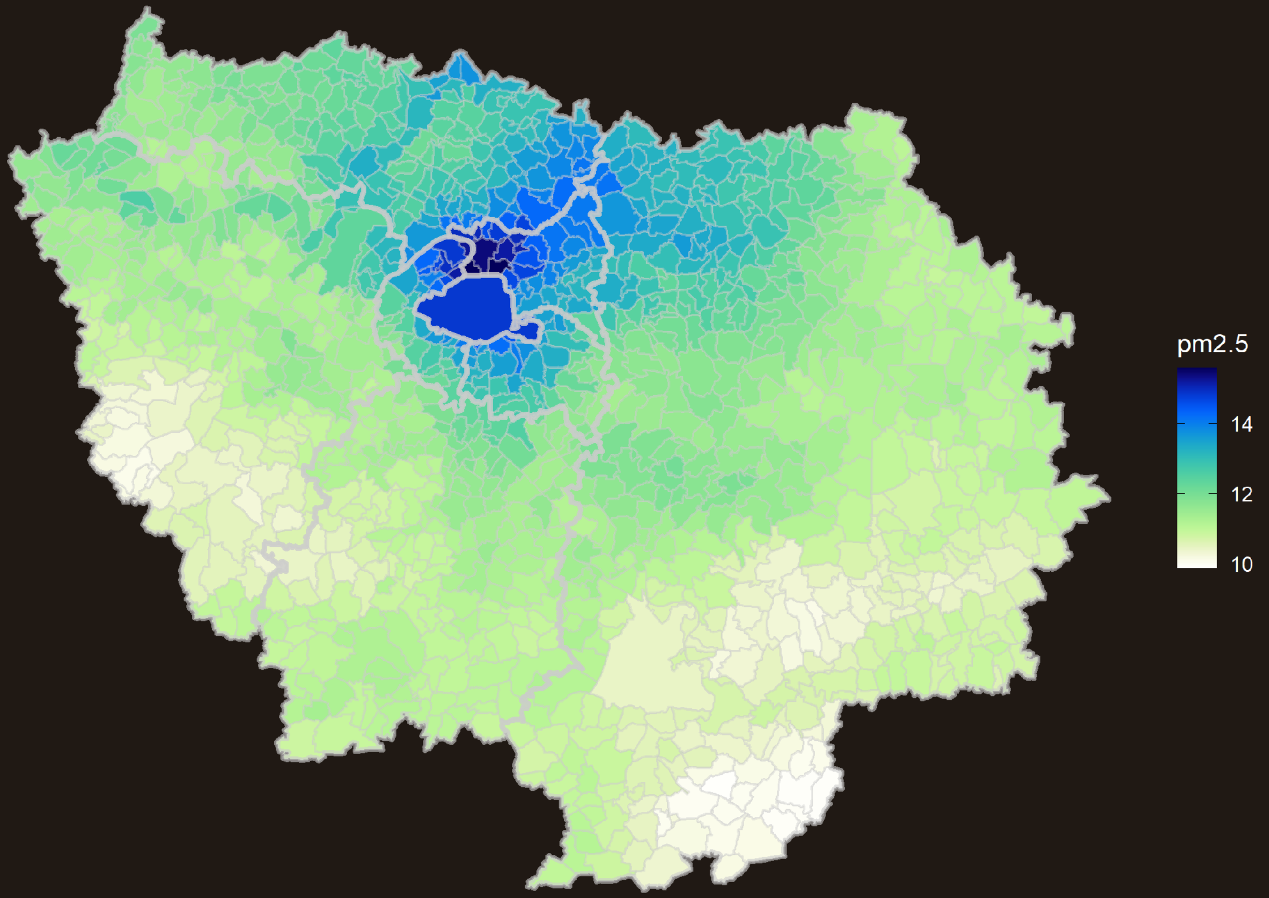
- In R zonal statistics can be computed with the function **extract()**
    - **x:** the data containing the values to compute statistics from
    - **y:** the data delimiting the zones in which to compute statistics
    - **FUN:** the statistic to compute (min, max, median, mean, ...)

```
idf_shp <- idf_shp %>% mutate(pm2.5 = extract(x = pm_data, y = ., fun = mean))

ggplot() +
  geom_sf(data = idf_shp, aes(fill = pm2.5), color = alpha("grey20", .4)) +
  geom_sf(data = dep_shp, fill = NA, color = alpha("grey20", .6), size = 1.2) +
  scale_fill_viridis(option = "B") + theme_void()
```

2. Geographic variables

2.2. Zonal statistics



2. Geographic variables

2.2. Zonal statistics

- We now have in the same dataset:
  - Average exposure to $PM_{2.5}$
  - Median income
  - Both at the city level

→ Let's do the regression

```
stargazer(lm(pm2.5 ~ MED16, idf_shp),
          type = "text",
          keep.stat = c("n", "rsq"))
```

```
##
## ========================================
##                  Dependent variable:
##              ---------------------------
##                        pm2.5
## ----------------------------------------
## MED16                -0.051***
##                       (0.007)
##
## Constant             13.037***
##                       (0.183)
##
## ----------------------------------------
## Observations           1,250
## R2                     0.040
## ========================================
## Note:        *p<0.1; **p<0.05; ***p<0.01
```

2. Geographic variables

2.3. Centroids and distances

Results indicate that at the city level in Île-de-France, an increase of 1,000 euros is associated with a reduction of 0.05 µg/m^3 in the concentration of $PM_{2.5}$, ceteris paribus

- But could this **effect** just be due to the **distance to Paris?**
  - Maybe richer individuals tend to live away from the urban center
  - And thus to be less exposed to pollution

- We need to **control** for the distance to Paris
  - To do so we can find the location of the **centroid** of each municipality with st_centroid()
  - It corresponds to the arithmetic mean position of all the points in the polygon

```
idf_shp <- idf_shp %>%
  mutate(centroid = st_centroid(geometry))

ggplot() +
  geom_sf(data = idf_shp$geometry, fill = "#6794A7", color = "#014D64", alpha = .6) +
  geom_sf(data = idf_shp$centroid, color = "#014D64") + theme_void()
```

2. Geographic variables

2.3. Centroids and distances

2. Geographic variables

2.3. Centroids and distances

- Note that the centroid of a polygon can be outside the polygon
  - Take for instance the municipality Les Ulis:

2. Geographic variables

2.3. Centroids and distances

- To compute distances we should first convert the centroid variable into a longitude and a latitude variable

```
idf_shp <- idf_shp %>%
  group_by(INSEE_COM) %>%
  mutate(cent_lon = unlist(centroid)[1], cent_lat = unlist(centroid)[2])
```

- And store the coordinates of Paris

```
paris <- idf_shp %>%
  filter(NOM_COM == "Paris") %>%
  select(cent_lon, cent_lat) %>% st_drop_geometry() # Specific function to drop geometry

paris
```

```
## # A tibble: 1 x 2
##   cent_lon cent_lat
## *    <dbl>    <dbl>
## 1     2.34     48.9
```

2. Geographic variables

2.3. Centroids and distances

- We can now compute the distance between each centroid and that of Paris using `geodist_vec()`

```
library(geodist)
idf_shp <- idf_shp %>% mutate(dist_paris = geodist_vec(x1 = cent_lon, y1 = cent_lat,
                                                        x2 = paris$cent_lon, y2 = paris$cent_lat,
                                                        measure = "geodesic") / 1000)
```

- We can plot this new variable

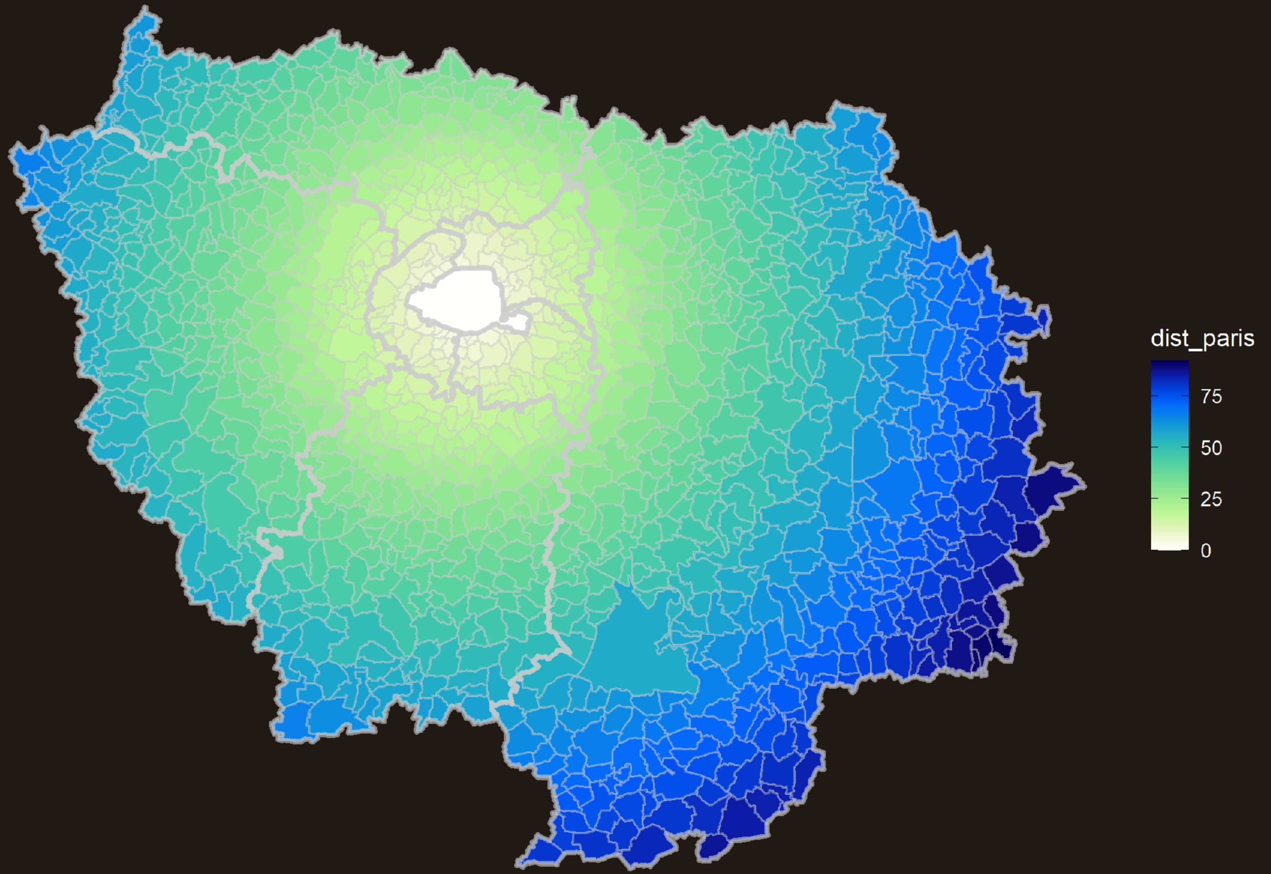
```
ggplot() +
  geom_sf(data = idf_shp, aes(fill = dist_paris), color = alpha("grey20", .4)) +
  geom_sf(data = dep_shp, fill = NA, color = alpha("grey20", .6), size = 1.2) +
  scale_fill_viridis(option = "B") + theme_void()
```

- And add it in the regression

```
stargazer(lm(pm2.5 ~ MED16 + dist_paris, idf_shp), type = "text", keep.stat = c("n", "rsq"))
```

2. Geographic variables

2.3. Centroids and distances



2. Geographic variables

2.3. Centroids and distances

```
##
## ========================================
##                  Dependent variable:
##               ---------------------------
##                         pm2.5
## ----------------------------------------
## MED16                 -0.092***
##                        (0.005)
##
## dist_paris            -0.041***
##                        (0.001)
##
## Constant              15.749***
##                        (0.131)
##
## ----------------------------------------
## Observations            1,250
## R2                      0.620
## ========================================
## Note:        *p<0.1; **p<0.05; ***p<0.01
```

- Once controlling for distance to Paris, the coefficients associated with median income is even more negative
  - Distance to Paris has opposite relationships with pollution and median income
  - Richer municipalities tend to be closer to Paris
  - But also to be less polluted than poorer municipalities

- In Île-de-France the relationship between exposure to $PM_{2.5}$ and median income (in thousand euros) is even stronger than with distance to Paris (in km)
  - Both coefficients are significant at 99% confidence level

Overview

1. Geolocalized data ✓
- 1.1. Shapefiles and rasters
- 1.2. Opening geolocalized data
- 1.3. Coordinate Reference Systems
- 1.4. Subsetting geolocalized data

2. Geographic variables ✓
- 2.1. Import from csv
- 2.2. Zonal statistics
- 2.3. Centroids and distance

3. Wrap up!

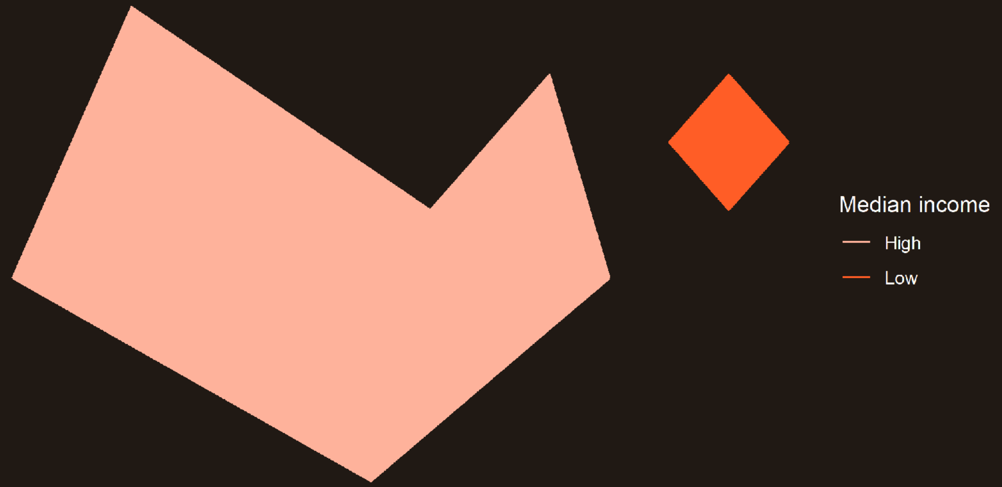
3. Wrap up!

Shapefiles and rasters

Two main types of geolocalized datasets:

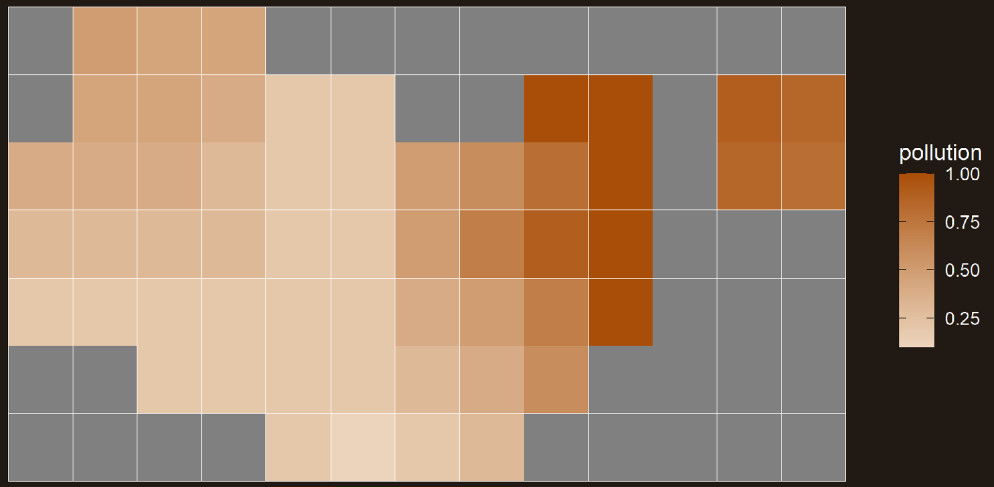
Shapefiles

- One row per entity/one column per variable
- A geometry variable with the coordinates of the points/polylines/polygons



Rasters

- Works like a picture, with cells like pixels
- And each cell can take a given value, e.g. pollution observed from satellites



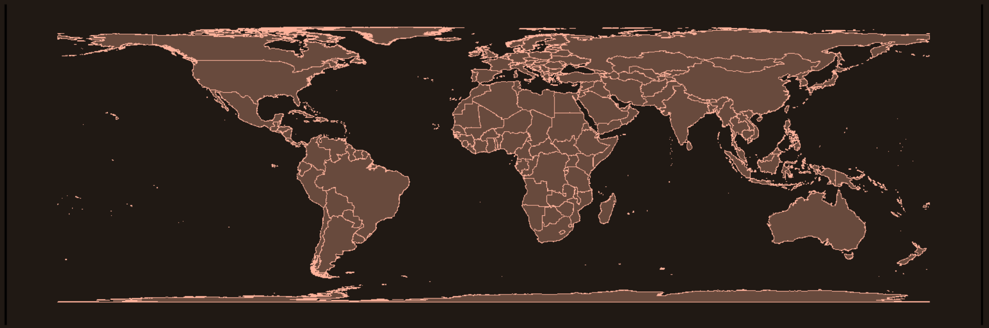
3. Wrap up!

Coordinates Reference Systems

- A Coordinate Reference System (CRS) is a model of the Earth in which each location is coded using degrees
  - It allows to **project the surface of the globe on a plane**
  - But there is a **tradeoff** between preserving:

Shape (like the Mercator projection)

Scale (like the Equal-Area Cylindrical projection)



  - Most projections are somewhere in between
  - For France: Lambert 93 projection (EPSG:2154)

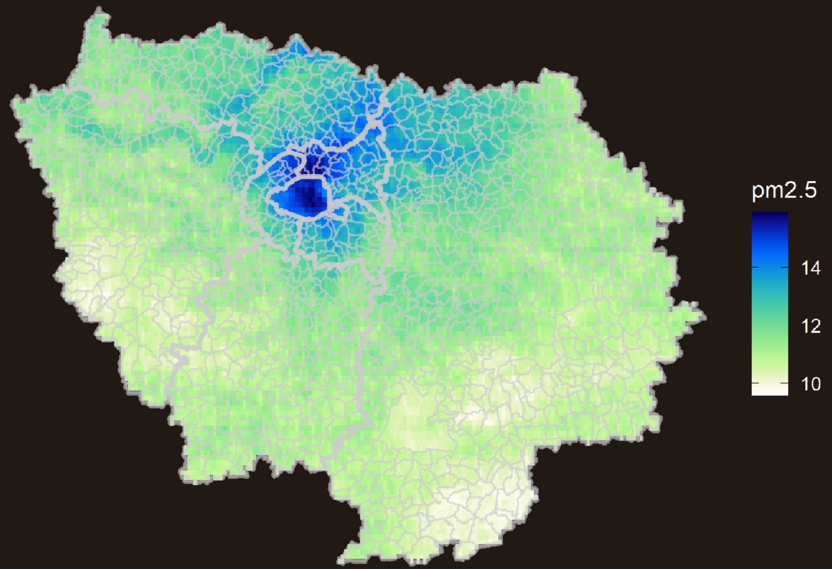
→ *First thing to do:* ***reprojection***

3. Wrap up!

Operations on geolocalized data

Zonal statistics

- Computing statistics on areas delimited by a shapefile from values of a raster
  - Project shapefile and raster the same way
  - Compute the mean/max/... of cell values



Centroids

- The centroid is the arithmetic mean position of all the points in the polygon
  - To compute distances between polygons
  - A centroid is not always within its polygon