

Maps in R!

ST465— Making Maps in R

Today we'll go over how to make maps in R and how to work with spatial data sets. Some of the key R packages that we'll work with are `tmap`, `mapview` for map making and `sf`, `spData`, `spDataLarge` for working with spatial data.

```
## R packages
setwd(getwd())
library(rmarkdown)
library(tmap) ## Very commonly used -- to make static and interactive plots
library(mapview)
library(leaflet)
library(shiny)
library(tidyverse)
library(spDataLarge) ## Data sets -- use commands in notes to download
library(spData) ## Data sets
library(sf) ## simple features
```

tmap

Let's work with the `world` and `coffee` data sets. For each, identify the type of object it is and its coordinate reference system (CRS).

```
#data("world")
world
```

```
## Simple feature collection with 177 features and 10 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: -180 ymin: -89.9 xmax: 180 ymax: 83.64513
## Geodetic CRS: WGS 84
## # A tibble: 177 x 11
##   iso_a2 name_long continent region_un subregion type area_km2
## * <chr> <chr> <chr> <chr> <chr> <chr> <dbl>
## 1 FJ Fiji Oceania Oceania Melanesia Sovereign country 19290.
## 2 TZ Tanzania Africa Africa Eastern Africa Sovereign country 932746. 5
## 3 EH Western Sahara Africa Africa Northern Africa Indeterminate 96271.
## 4 CA Canada North America Americas Northern America Sovereign country 10036043. 3
## 5 US United States North America Americas Northern America Country 9510744. 31
## 6 KZ Kazakhstan Asia Asia Central Asia Sovereign country 2729811. 1
## 7 UZ Uzbekistan Asia Asia Central Asia Sovereign country 461410. 3
## 8 PG Papua New Guinea Oceania Oceania Melanesia Sovereign country 464520.
## 9 ID Indonesia Asia Asia South-Eastern Asia Sovereign country 1819251. 25
## 10 AR Argentina South America Americas South America Sovereign country 2784469. 4
## # ... with 167 more rows
```

```
coffee_data
```

```
## # A tibble: 47 x 3
##   name_long      coffee_production_2016 coffee_production_2017
##   <chr>          <int>          <int>
## 1 Angola                NA                NA
## 2 Bolivia                 3                 4
## 3 Brazil              3277             2786
## 4 Burundi                37                38
## 5 Cameroon               8                 6
## 6 Central African Republic      NA                NA
## 7 Congo, Dem. Rep. of           4                 12
## 8 Colombia             1330             1169
## 9 Costa Rica               28                 32
## 10 Côte d'Ivoire           114                130
## # ... with 37 more rows
```

```
world_coffee = dplyr::left_join(world, coffee_data, by = "name_long")
world_coffee
```

```
## Simple feature collection with 177 features and 12 fields
## Geometry type: MULTIPOLYGON
## Dimension:      XY
## Bounding box:  xmin: -180 ymin: -89.9 xmax: 180 ymax: 83.64513
## Geodetic CRS:  WGS 84
```

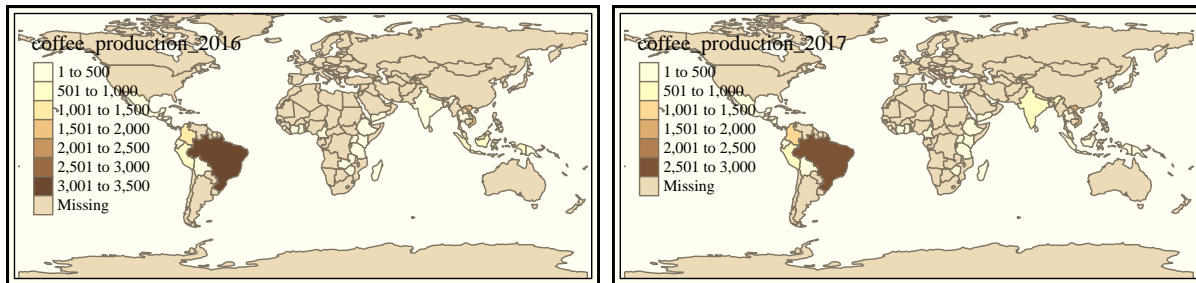
```
## # A tibble: 177 x 13
##   iso_a2 name_long      continent      region_un subregion      type      area_~1      p
##   <chr>  <chr>          <chr>          <chr>      <chr>          <chr>      <dbl>  <dbl>
## 1 FJ     Fiji          Oceania        Oceania    Melanesia      Sovereign count~ 1.93e4  8.86
## 2 TZ     Tanzania        Africa         Africa     Eastern Africa  Sovereign count~ 9.33e5  5.22
## 3 EH     Western Sahara  Africa         Africa     Northern Africa  Indeterminate   9.63e4  NA
## 4 CA     Canada          North America Americas    Northern America  Sovereign count~ 1.00e7  3.55
## 5 US     United States    North America Americas    Northern America  Country         9.51e6  3.19
## 6 KZ     Kazakhstan      Asia           Asia       Central Asia     Sovereign count~ 2.73e6  1.73
## 7 UZ     Uzbekistan        Asia           Asia       Central Asia     Sovereign count~ 4.61e5  3.08
## 8 PG     Papua New Guinea  Oceania        Oceania    Melanesia      Sovereign count~ 4.65e5  7.76
## 9 ID     Indonesia         Asia           Asia       South-Eastern Asia  Sovereign count~ 1.82e6  2.55
## 10 AR    Argentina        South America Americas    South America     Sovereign count~ 2.78e6  4.30
## # ... with 167 more rows, and abbreviated variable names 1: area_km2, 2: gdpPercap, 3: coffee_production
```

We've created a new data set called `world_coffee`, what type of object is it and what is its CRS?

Let's plot the spatial object using the R package `tmap`.

```
## tmap_mode "view" set to interactive viewing
tmap_mode("plot")
facets = c("coffee_production_2016", "coffee_production_2017")

tm_shape(world_coffee) +
  tm_polygons(facets) +
  tm_facets(nrow = 1, sync = TRUE)
```



Now let's use the World data set (not that world and World are different data sets.)

```
data("World")
World
```

```
## Simple feature collection with 177 features and 15 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: -180 ymin: -89.9 xmax: 180 ymax: 83.64513
## Geodetic CRS: WGS 84
```

```
## First 10 features:
```

##	iso_a3	name	sovereignty	continent	area	pop
## 1	AFG	Afghanistan	Afghanistan	Asia	652860.000	[km^2] 284
## 2	AGO	Angola	Angola	Africa	1246700.000	[km^2] 127
## 3	ALB	Albania	Albania	Europe	27400.000	[km^2] 30
## 4	ARE	United Arab Emirates	United Arab Emirates	Asia	71252.172	[km^2] 4
## 5	ARG	Argentina	Argentina	South America	2736690.000	[km^2] 405
## 6	ARM	Armenia	Armenia	Asia	28470.000	[km^2] 29
## 7	ATA	Antarctica	Antarctica	Antarctica	12259213.973	[km^2]
## 8	ATF	Fr. S. Antarctic Lands	France	Seven seas (open ocean)	7257.455	[km^2]
## 9	AUS	Australia	Australia	Oceania	7682300.000	[km^2] 21
## 10	AUT	Austria	Austria	Europe	82523.000	[km^2] 89

##	income_grp	gdp_cap_est	life_exp	well_being	footprint	inequality	HPI
## 1	5. Low income	784.1549	59.668	3.8	0.79	0.42655744	20.22535 MULTIPOLYGON
## 2	3. Upper middle income	8617.6635	NA	NA	NA	NA	NA MULTIPOLYGON
## 3	4. Lower middle income	5992.6588	77.347	5.5	2.21	0.16513372	36.76687 MULTIPOLYGON
## 4	2. High income: nonOECD	38407.9078	NA	NA	NA	NA	NA MULTIPOLYGON

```
## 5    3. Upper middle income  14027.1261    75.927      6.5      3.14 0.16423830  35.19024 MULTIPOLYGON
## 6    4. Lower middle income   6326.2469    74.446      4.3      2.23 0.21664810  25.66642 MULTIPOLYGON
## 7    2. High income: nonOECD 200000.0000      NA      NA      NA      NA      NA MULTIPOLYGON
## 8    2. High income: nonOECD 114285.7143      NA      NA      NA      NA      NA MULTIPOLYGON
## 9     1. High income: OECD   37634.0832    82.052      7.2      9.31 0.08067825  21.22897 MULTIPOLYGON
## 10   1. High income: OECD   40132.6093    81.004      7.4      6.06 0.07129351  30.47822 MULTIPOLYGON
```

HPI stands for “Happy Planet Index” and provides a quantification of a country’s “happiness”. More information here: <https://happyplanetindex.org> Let’s check it out:

```
tmap_mode("view")

tm_shape(World) +
  tm_polygons("HPI")
```

Let’s look at the HPI along with economy type:

```
tmap_mode("view")
tm_shape(World) +
  tm_polygons(c("HPI", "economy")) +
  tm_facets(sync = TRUE, ncol = 2)
```

We continue to make maps, this time with the `metro` data set. What information is provided? What is the geometry type and what is the CRS?

```
## reading in data
data(metro)
metro
```

```
## Simple feature collection with 436 features and 12 fields
## Geometry type: POINT
## Dimension:      XY
## Bounding box:   xmin: -123.1193 ymin: -37.814 xmax: 174.7667 ymax: 60.16925
## Geodetic CRS:   WGS 84
## First 10 features:
##      name              name_long iso_a3 pop1950 pop1960 pop1970 pop1980 pop1990 pop2000 pop2010
## 2      Kabul              Kabul   AFG  170784  285352  471891  977824  1549320  2401109  3722000
## 8    Algiers El Djazair (Algiers) DZA  516450  871636  1281127  1621442  1797068  2140577  2432000
## 13   Luanda              Luanda   AGO  138413  219427  459225  771349  1390240  2591388  4508000
## 16 Buenos Aires      Buenos Aires ARG  5097612  6597634  8104621  9422362  10513284  12406780  14245000
## 17   Cordoba          Cordoba   ARG  429249   605309  809794  1009521  1200168  1347561  1459000
## 25   Rosario          Rosario   ARG  554483   671349  816230  953491  1083819  1152387  1298000
## 32   Yerevan          Yerevan   ARM  341432   537759  778158  1041587  1174524  1111301  1065000
## 33  Adelaide          Adelaide   AUS  429277   571822  850168  971856  1081618  1141623  1217000
## 34  Brisbane          Brisbane   AUS  441718   602999  904777  1134833  1381306  1666203  2033000
## 37  Melbourne          Melbourne AUS  1331966  1851220  2499109  2839019  3154314  3460541  3951000
```

```
tmap_mode("view")
tm_basemap("Stamen.Watercolor") +
tm_shape(metro) + tm_bubbles(size = "pop2020", col = "red") +
tm_tiles("Stamen.TonerLabels")
```

You can also play around with the style in `tmap`.

```
tmap_style("classic")
## tmap style set to "classic"
## other available styles are: "white", "gray", "natural", "cobalt", "col_blind", "albatross", "beaver"

tm_shape(World) +
  tm_polygons("HPI", legend.title = "Happy Planet Index")
```

We can also look through some data from New Zealand. As the others, what type of object is it and what is the CRS? How it different from others and why might that be the case?

```
## New Zealand
nz
```

```
## Simple feature collection with 16 features and 6 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: 1090144 ymin: 4748537 xmax: 2089533 ymax: 6191874
## Projected CRS: NZGD2000 / New Zealand Transverse Mercator 2000
## First 10 features:
```

##	Name	Island	Land_area	Population	Median_income	Sex_ratio		
## 1	Northland	North	12500.561	175500	23400	0.9424532	MULTIPOLYGON	(((1745493 600
## 2	Auckland	North	4941.573	1657200	29600	0.9442858	MULTIPOLYGON	(((1803822 590
## 3	Waikato	North	23900.036	460100	27900	0.9520500	MULTIPOLYGON	(((1860345 585
## 4	Bay of Plenty	North	12071.145	299900	26200	0.9280391	MULTIPOLYGON	(((2049387 583
## 5	Gisborne	North	8385.827	48500	24400	0.9349734	MULTIPOLYGON	(((2024489 567
## 6	Hawke's Bay	North	14137.524	164000	26100	0.9238375	MULTIPOLYGON	(((2024489 567
## 7	Taranaki	North	7254.480	118000	29100	0.9569363	MULTIPOLYGON	(((1740438 571
## 8	Manawatu-Wanganui	North	22220.608	234500	25000	0.9387734	MULTIPOLYGON	(((1866732 566
## 9	Wellington	North	8048.553	513900	32700	0.9335524	MULTIPOLYGON	(((1881590 548
## 10	West Coast	South	23245.456	32400	26900	1.0139072	MULTIPOLYGON	(((1557042 531

```
legend_title = expression("Area (km"2*)")
map_nza = tm_shape(nz) +
  tm_fill(col = "Land_area", title = legend_title) + tm_borders()
map_nza + tm_style("bw")
```

```
map_nza + tm_style("classic")
```

```
map_nza + tm_style("cobalt")
```

```
map_nza + tm_style("col_blind")
```

mapview

Let's use `mapview` now, another common R package for constructing spatial maps. We'll use the `trails` and `franconia` data set. What kind of objects are they and what is its CRS?

```
trails
```

```
## Simple feature collection with 543 features and 3 fields
## Geometry type: MULTILINESTRING
## Dimension:      XY
## Bounding box:   xmin: 528933.9 ymin: 5415754 xmax: 715816.7 ymax: 5597457
## Projected CRS: WGS 84 / UTM zone 32N
## First 10 features:
##                                     FGN      FKN      district
## 1                                003756/Kunigundenweg 003756 Oberfranken MULTILINEST
## 2 004037/Jakobsweg (Almerswind-Coburg-Lichtenfels-Bamberg-Nuernberg) 004037 Oberfranken MULTILINEST
## 3                                005160/Steigerwaelder Jakobsweg (Bamberg-Uffenheim) 005160 Oberfranken MULTILINEST
## 4                                022650/Sieben-Fluesse-Wanderweg 022650 Oberfranken MULTILINEST
## 5                                005316/Rennsteigverein 1896 e.V. / Bamberger Rennsteig 005316 Oberfranken MULTILINEST
## 6                                012029/Steigerwald-Panoramaweg 012029 Oberfranken MULTILINEST
## 7                                013633/Frankenwaldverein / Markgrafenweg 013633 Oberfranken MULTILINEST
## 8                                023964/Rot-Main-Auen-Weg 023964 Oberfranken MULTILINEST
## 9                                007443/Jean-Paul-Weg 007443 Oberfranken MULTILINEST
## 10                               007443/Jean-Paul-Weg 007443 Oberfranken MULTILINEST
```

```
franconia
```

```
## Simple feature collection with 37 features and 6 fields
## Geometry type: MULTIPOLYGON
## Dimension:      XY
## Bounding box:   xmin: 8.975926 ymin: 48.8625 xmax: 12.27535 ymax: 50.56422
## Geodetic CRS:   WGS 84
## First 10 features:
##      NUTS_ID  SHAPE_AREA SHAPE_LEN CNTR_CODE      NAME_ASCII      geometry
## 1    DE241  0.006736012  0.3926225      DE  Bamberg, Kreisfreie Stadt MULTIPOLYGON (((10.92581 49...
## 2    DE242  0.008424469  0.6247263      DE  Bayreuth, Kreisfreie Stadt MULTIPOLYGON (((11.58157 49...
## 3    DE243  0.005982341  0.5185471      DE    Coburg, Kreisfreie Stadt MULTIPOLYGON (((10.95355 50...
## 4    DE244  0.007329480  0.4569815      DE      Hof, Kreisfreie Stadt MULTIPOLYGON (((11.93067 50...
## 5    DE245  0.146698316  3.4819699      DE      Bamberg, Landkreis MULTIPOLYGON (((10.87615 50...
## 6    DE246  0.159489736  3.6242023      DE      Bayreuth, Landkreis MULTIPOLYGON (((11.70657 50...
## 7    DE247  0.074698748  2.6954234      DE      Coburg, Landkreis MULTIPOLYGON (((10.88654 50...
## 8    DE248  0.079746707  1.7712298      DE      Forchheim MULTIPOLYGON (((11.26376 49...
## 9    DE249  0.112934151  2.7544708      DE      Hof, Landkreis MULTIPOLYGON (((11.91988 50...
## 10   DE24A  0.081960299  1.9393830      DE      Kronach MULTIPOLYGON (((11.36979 50...
```

What does it look like if we only plot the trails data?

```
trails%>%
  mapview()
```

What about the franconia data set?

```
franconia%>%
  mapview()
```

We'd like to plot the trails onto the map, but they're not the same CRS. In lecture, we saw that we can use a suite of functions starting with `st_` to modify a spatial object. We'll use a few here to change the crs and plot the data sets together:

```
## first, using st_transform() function we changed the CRS
trails %>%
  st_transform(st_crs(franconia)) %>%
  st_intersection(franconia[franconia$district == "Oberfranken", ]) %>%
  st_collection_extract("LINE") %>%
  mapview(color = "red", lwd = 3, layer.name = "trails") +
  mapview(franconia, zcol = "district", burst = TRUE)
```

Lastly, suppose you also wanted to know about any breweries along the trails. Let's check out the **breweries** data set. What kind of object is it and what is its CRS?

```
breweries
```

What does a map of the breweries look like?

```
breweries%>%
  mapview()
```

Let's combine them all:

```
trails %>%
  st_transform(st_crs(franconia)) %>%
  st_intersection(franconia[franconia$district == "Oberfranken", ]) %>%
  st_collection_extract("LINE") %>%
  mapview(color = "red", lwd = 3, layer.name = "trails") +
  mapview(franconia, zcol = "district", burst = TRUE) +
  breweries
```

tmap

What if we tried to do this in tmap?

```
tm_shape(franconia) + tm_fill("district") +
tm_shape(trails) + tm_lines() +
tm_shape(breweries) + tm_dots()
```