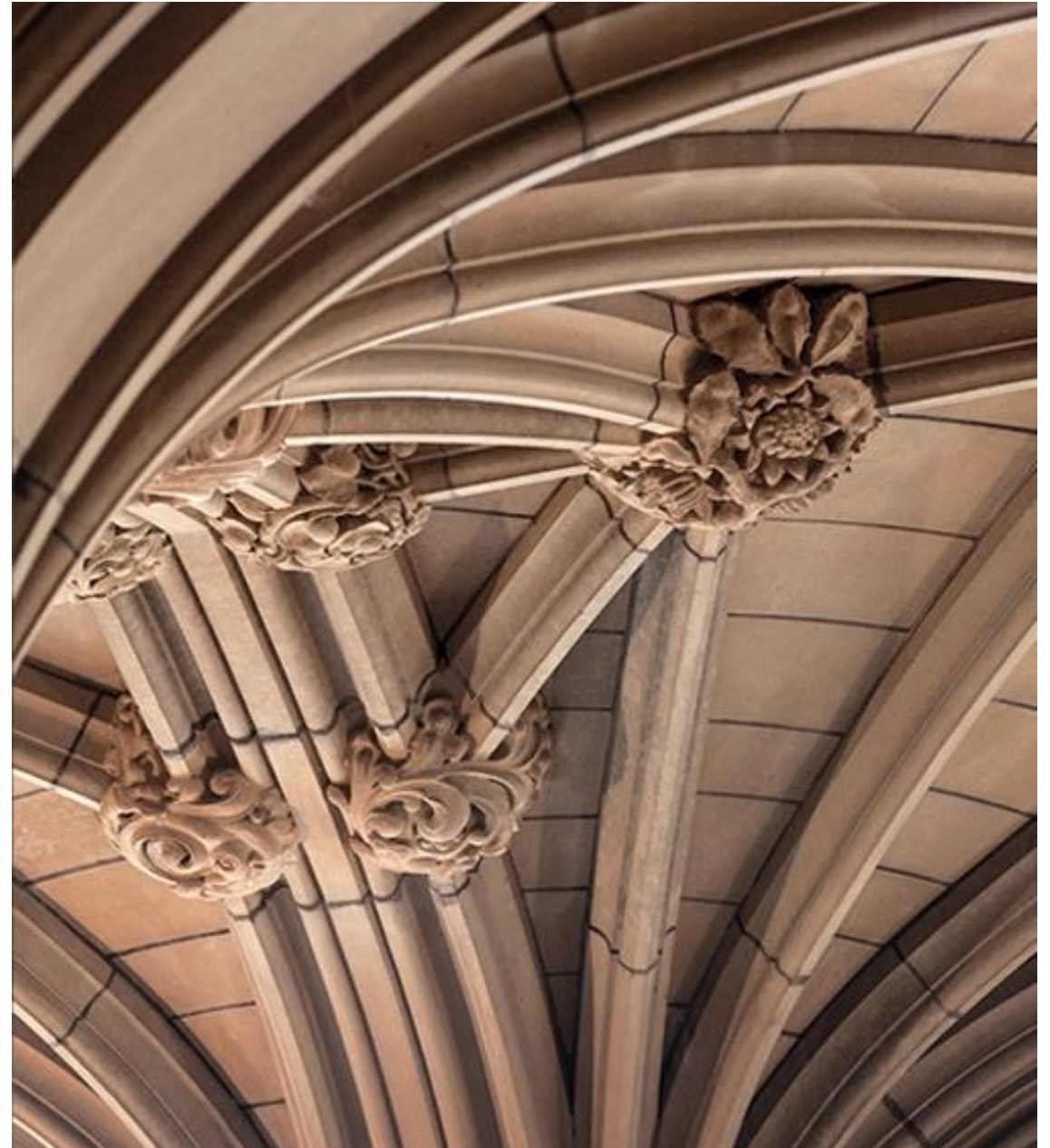


# Catchment areas, kernel densities and Inverse Distance Weighting in R

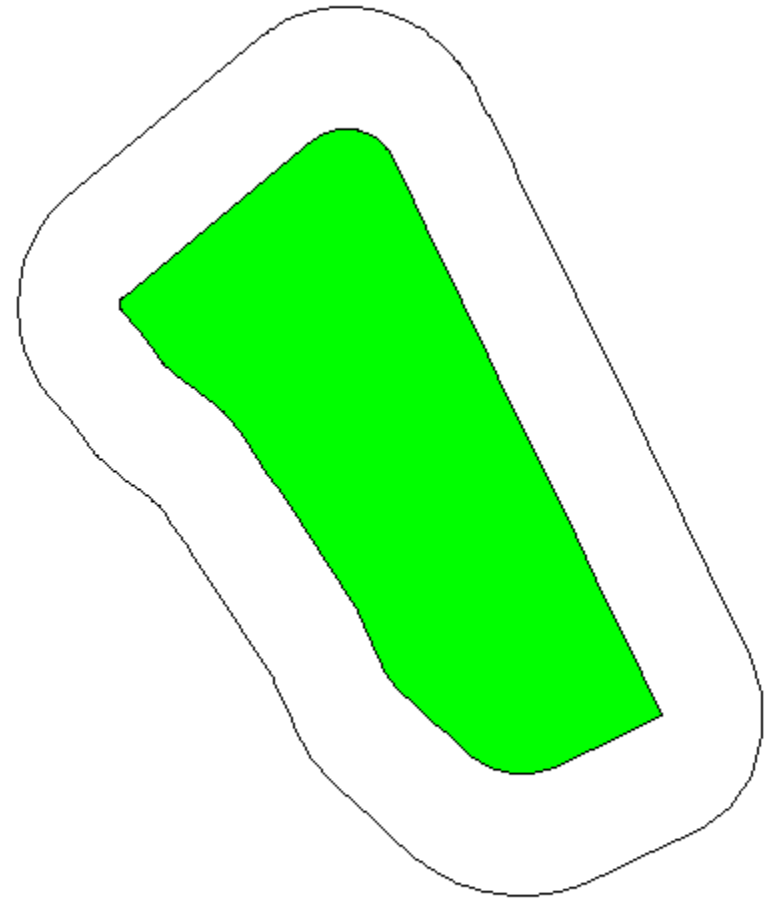
Dr Adrian Ellison  
Dr Richard Ellison

ITLS6107 Semester 2, 2017



## Simple buffers in R

- What if we wanted to do more than simply plot the area?
- If we needed to calculate the population within a distance of a location we can use several functions together.
- Alternatively, we can use the `stplanr` package's `calc_catchment` function together with our population data



## Catchment areas in R

- We first need to install and load the stplanr package
- We also need to import our population layer

```
50  
51 library(tmap)  
52  
53 tm_shape(wentworthParkBuffer) +  
54   tm_borders("black", lwd = 2) +  
55 tm_shape(wentworthPark) +  
56   tm_fill("greenyellow")  
57  
58 library(stplanr)  
59 PopulationData <- st_read("C:/otherData/GIS_DataForStudents/CensusData.gdb", "SA1_Population")  
60
```

## Catchment areas in R

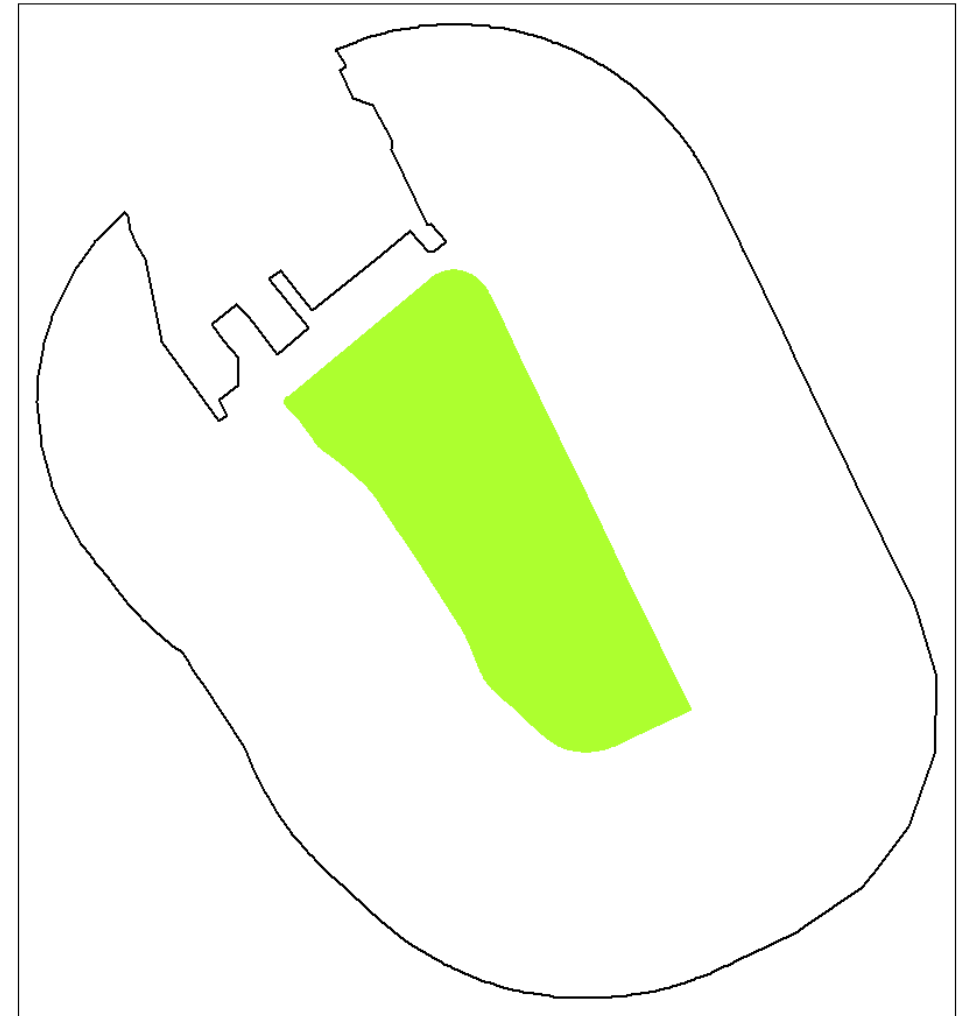
- The `calc_catchment` function takes the population layer, a layer with the location (points, lines or polygons), the distance and some other options.
- The current version requires `sp` layers so we will convert them
- We can convert the result back to an `sf` layer

```
60
61 wentworthParkCatchment <- calc_catchment(
62   polygonlayer = as(PopulationData, "Spatial"), # The layer with our population layer
63   targetlayer = as(WentworthPark, "Spatial"), # The layer with Wentworth Park
64   calccols = 'ResidentialPopulation', # The fields from the population layer to summarise
65   distance = 300, # The distance in metres
66   projection = 'austalbers', # The type of projection to use to calculate area
67   dissolve = TRUE # Return a single area for the buffer
68 )
69 wentworthParkCatchment <- st_as_sf(wentworthParkCatchment)
70
```

## Catchment areas in R

- The result can be plotted just like our previous buffer

```
70  
71 tm_shape(WentworthParkCatchment) +  
72   tm_borders("black", lwd = 2) +  
73   tm_shape(WentworthPark) +  
74   tm_fill("greenyellow")  
75
```



## Catchment areas in R

- We can use `View(WentworthParkCatchment)` to look at the summary statistics

| crimedata * WentworthParkCatchment * crime_sa1 * |                        |  |
|--|------------------------|--|
| ← → ↗ Filter                                     |                        |  |
|  | ResidentialPopulation↑ | geometry   |
| 1  | 7150.818               | list(c(151.198012484789, 151.197815686617, 151.... |

- The estimated population within 300 metres of Wentworth Park is 7151

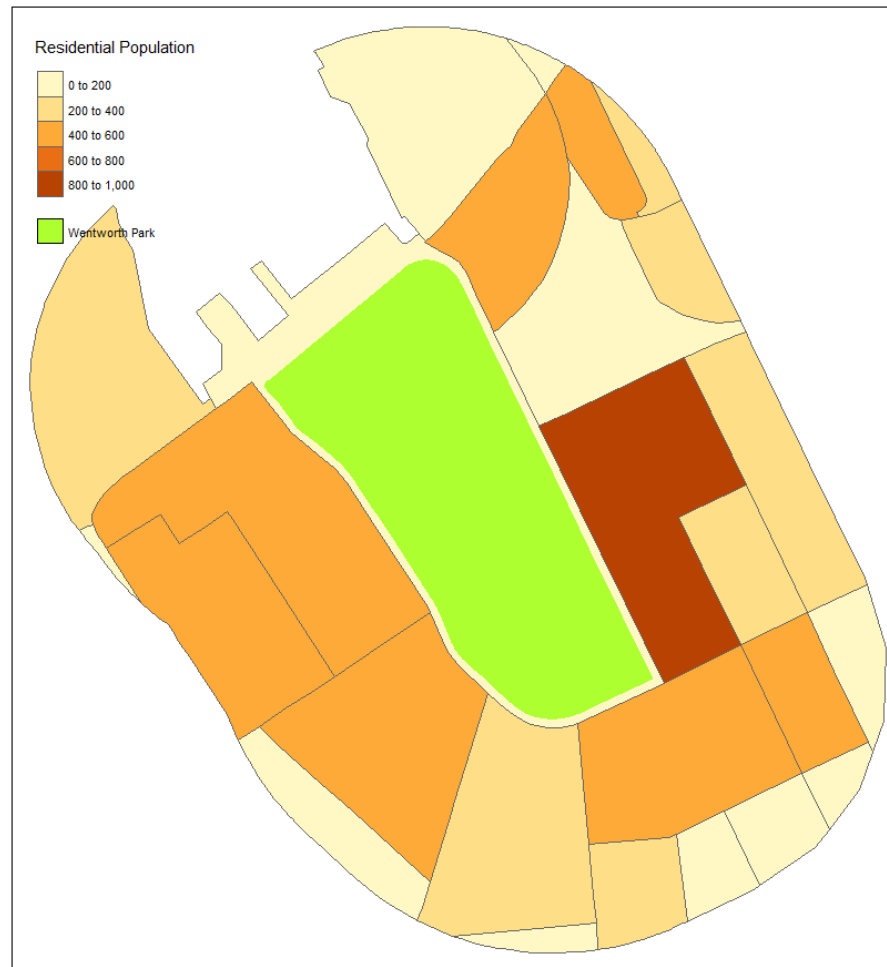
## Catchment areas in R

- If we choose `dissolve = FALSE` then we can see the population estimates for each SA1 that falls within the catchment area:

```
61 wentworthParkCatchment <- calc_catchment(  
62   polygonlayer = as(PopulationData, "Spatial"), # The layer with our population layer  
63   targetlayer = as(WentworthPark, "Spatial"), # The layer with wentworth Park  
64   calccols = 'ResidentialPopulation', # The fields from the population layer to summarise  
65   distance = 300, # The distance in metres  
66   projection = 'austalbers', # The type of projection to use to calculate area  
67   dissolve = FALSE # Return a single area for the buffer  
68 )  
69 wentworthParkCatchment <- st_as_sf(wentworthParkCatchment)  
70  
71 tm_shape(wentworthParkCatchment) +  
72   tm_fill("ResidentialPopulation", title = "Residential Population") +  
73   tm_borders() +  
74   tm_shape(wentworthPark) +  
75   tm_fill("greenyellow") +  
76   tm_add_legend("fill", labels = "Wentworth Park", col = "greenyellow")  
77
```

## Catchment areas in R

- If we choose `dissolve = FALSE` then we can see the population estimates for each SA1 that falls within the catchment area:





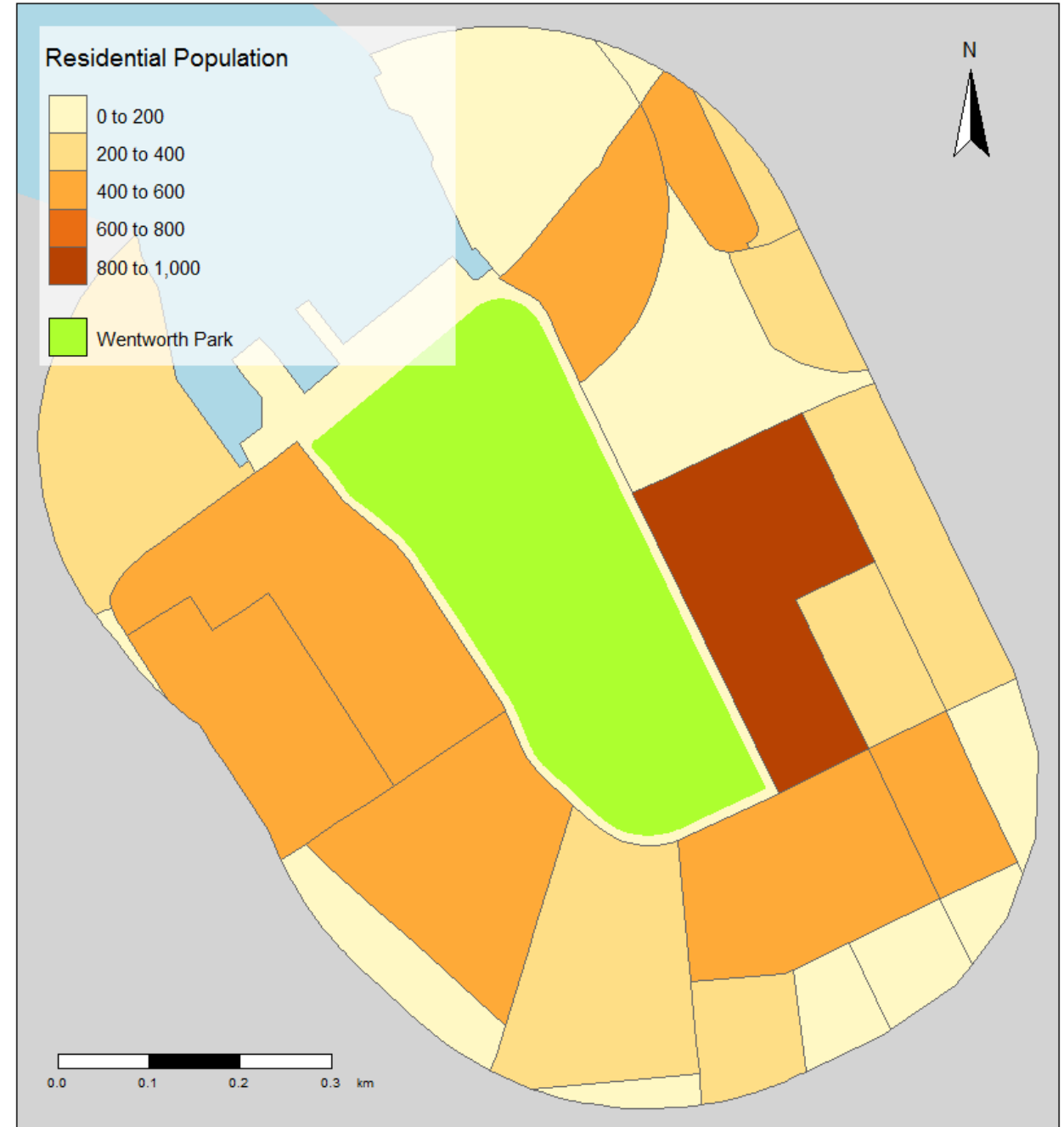
## Catchment areas in R

- We can add the original layer and make other layout changes:

```
83 tm_shape(PopulationData) +  
84   tm_fill("lightgrey") +  
85 tm_shape(WentworthParkCatchment, is.master = TRUE) +  
86   tm_fill("ResidentialPopulation", title = "Residential Population") +  
87   tm_borders() +  
88 tm_shape(WentworthPark) +  
89   tm_fill("greenyellow") +  
90   tm_add_legend("fill", labels = "Wentworth Park", col = "greenyellow") +  
91 tm_scale_bar(position = c("left", "bottom")) +  
92   tm_compass(position = c("right", "top")) +  
93 tm_layout(bg.color="lightblue", legend.bg.color = "white", legend.bg.alpha = 0.7,  
94           scale = 1.3)
```

## Catchment areas in R

- We can add the original layer and make other layout changes



## Small multiples and facets with tmap

- Sometimes you want to plot different variables on multiple small maps instead of one large map.
- The tmap package provides a way to easily display multiple variables as different themes on adjacent maps:

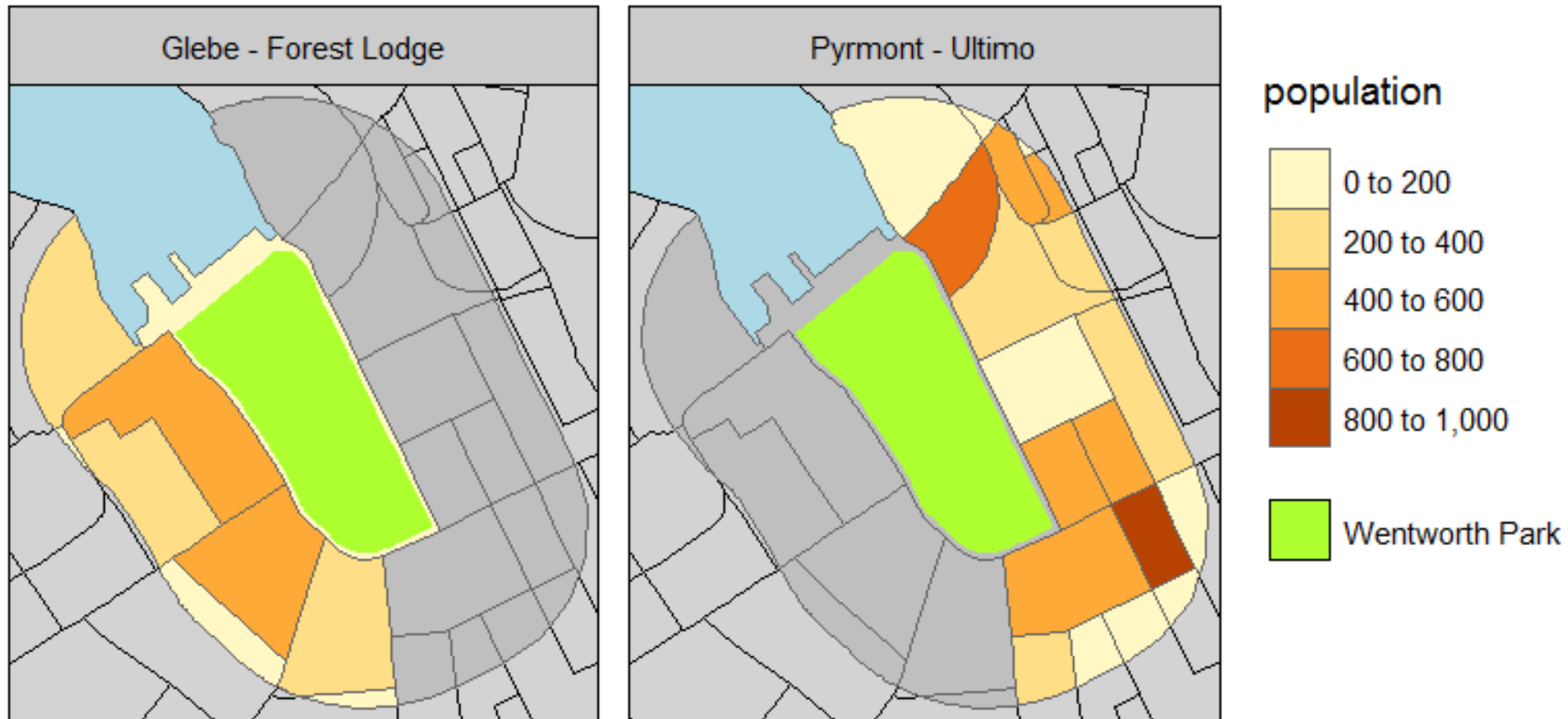


## Small multiples and facets with tmap

```
96
97 PopulationData2016 <- st_read("C:/OtherData/GIS_DataForStudents/CensusData.gdb", "SA1_Population_2016")
98
99 WentworthParkCatchment2016 <- calc_catchment(
100   polygonlayer = as(PopulationData2016, "Spatial"), # The layer with our population layer
101   targetlayer = as(WentworthPark, "Spatial"), # The layer with wentworth Park
102   calccols = c('dwelling','population'), # The fields from the population layer to summarise
103   distance = 300, # The distance in metres
104   projection = 'austalbers', # The type of projection to use to calculate area
105   dissolve = FALSE # Return a single area for the buffer
106 )
107 WentworthParkCatchment2016 <- st_as_sf(WentworthParkCatchment)
108
109 tm_shape(PopulationData2016) +
110   tm_fill("lightgrey") +
111   tm_borders(col = "black") +
112   tm_shape(WentworthParkCatchment2016, is.master = TRUE) +
113     tm_fill(c("dwelling","population"),title = c("Dwellings","Population")) +
114     tm_borders() +
115   tm_shape(WentworthPark) +
116     tm_fill("greenyellow") +
117     tm_add_legend("fill", labels = "Wentworth Park", col = "greenyellow") +
118   tm_layout(bg.color="lightblue",legend.bg.color = "white", legend.bg.alpha = 0.7,
119     scale = 1.3)
120
```

## Small multiples and facets with tmap

- Sometimes we want different features/rows to be displayed separately rather than different variables
- We use the `tm_facets()` function to split our rows into groups for display

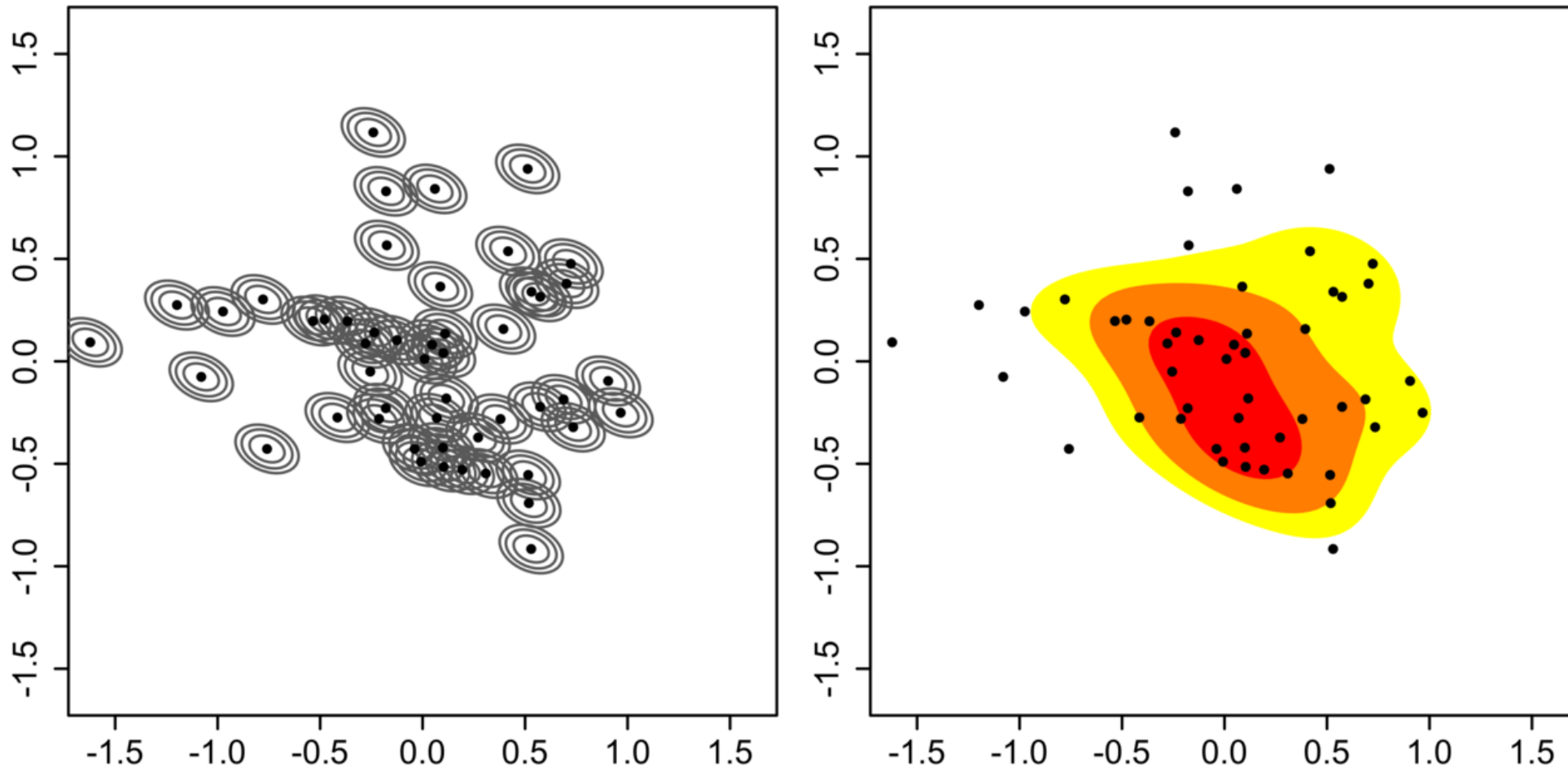


## Small multiples and facets with tmap

```
122 tm_shape(PopulationData2016) +  
123   tm_fill("lightgrey") +  
124   tm_borders(col = "black") +  
125 tm_shape(WentworthParkCatchment2016, is.master = TRUE) +  
126   tm_fill("population") +  
127   tm_borders() +  
128   tm_facets("SA2_NAME16") +  
129 tm_shape(WentworthPark) +  
130   tm_fill("greenyellow") +  
131   tm_add_legend("fill", labels = "wentworth park", col = "greenyellow") +  
132   tm_layout(bg.color="lightblue", legend.bg.color = "white", legend.bg.alpha = 0.7,  
133             scale = 1.3)
```

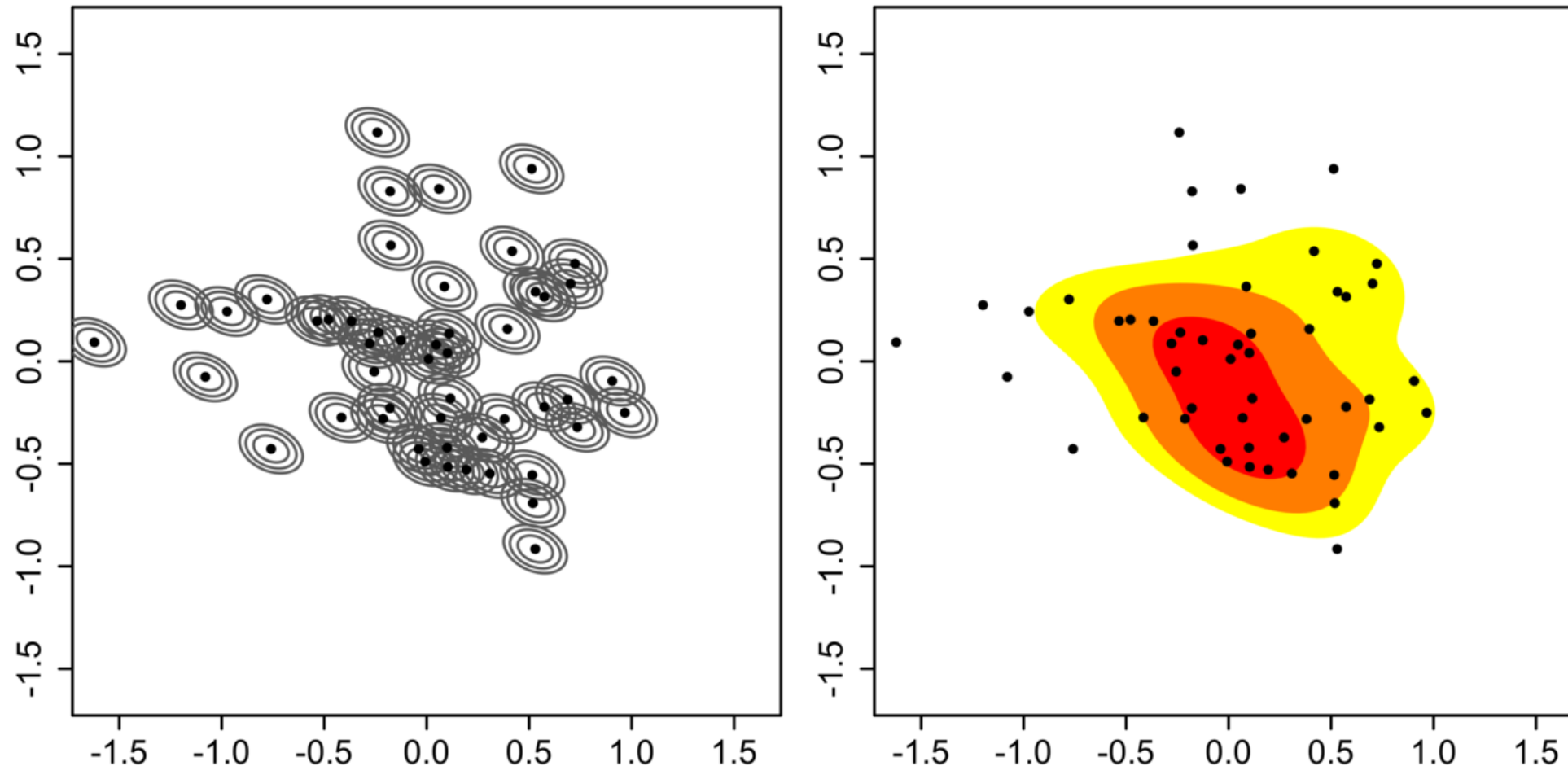
# What is spatial kernel density estimation?

- Computes a distribution of values along two dimensional space using small “buffers”



# What is spatial kernel density estimation?

- Allows us to calculate the spatial density and distribution of point data





## Kernel density estimation in R

- Many possible methods of calculating kernel densities in R using functions from different packages
- In almost all cases, requires a projected layer
  - Means we must project our crimelocs layer:

```
crimelocs <- spTransform(crimelocs, CRS(get_proj4(3308)))
```

- We are converting to the NSW Lambert projection
- 3308 is a standard code (EPSG) for this projection
  - 4326 is the code for Unprojected WGS 1984

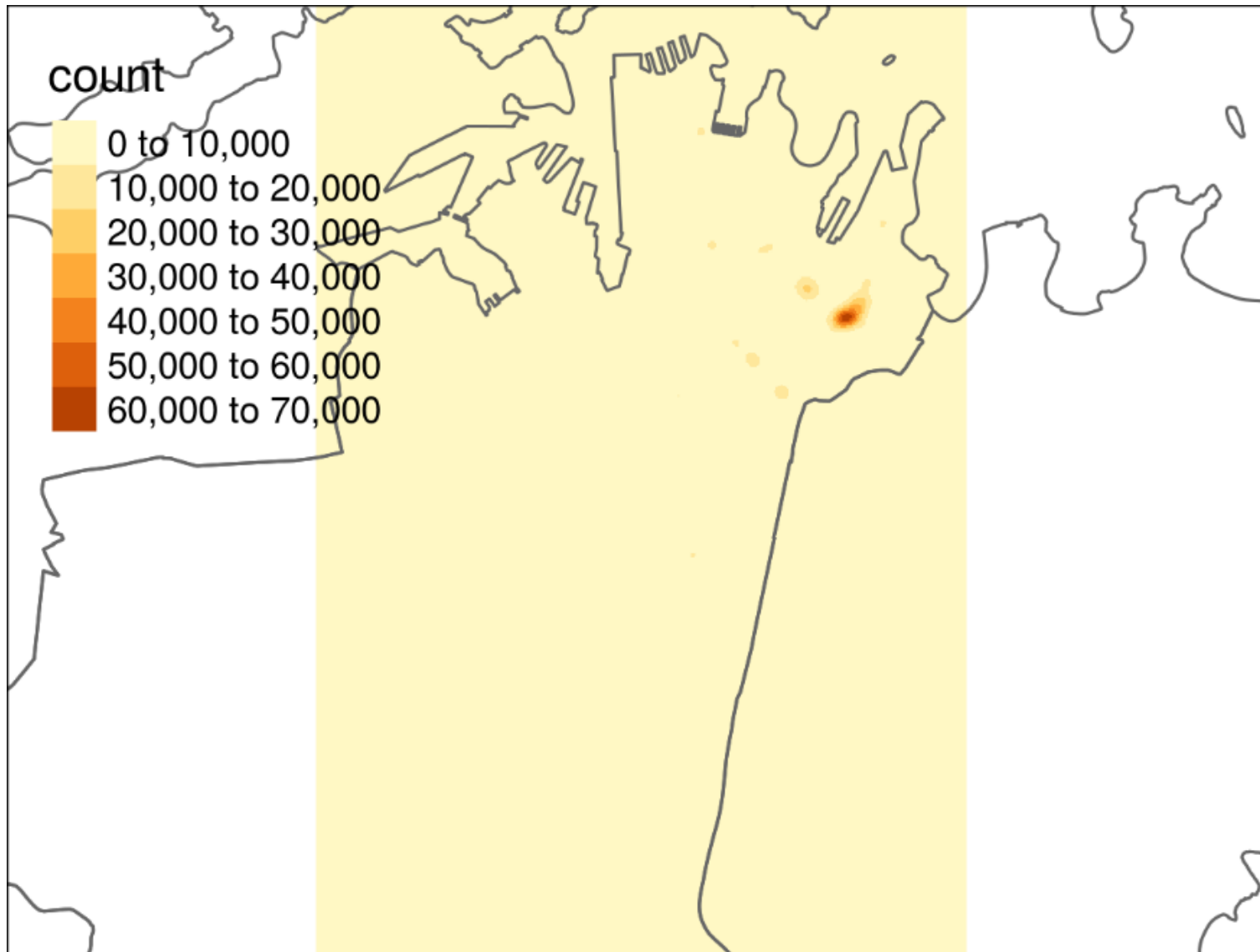
# Kernel density estimation in R

- The **tmaptools** package contains a spatial kernel density function called **smooth\_map**

```
crimekd <- smooth_map(crimelocs)
tm_shape(crimekd$raster) + tm_raster(col="count")
```

- The `smooth_map` function computes the kernel density and returns the results in several formats:
  - Raster
  - Line (similar to contour lines or isobars)
  - Polygons
- We can plot the result using `tmap`

## Kernel density estimation in R



# Kernel density estimation in R

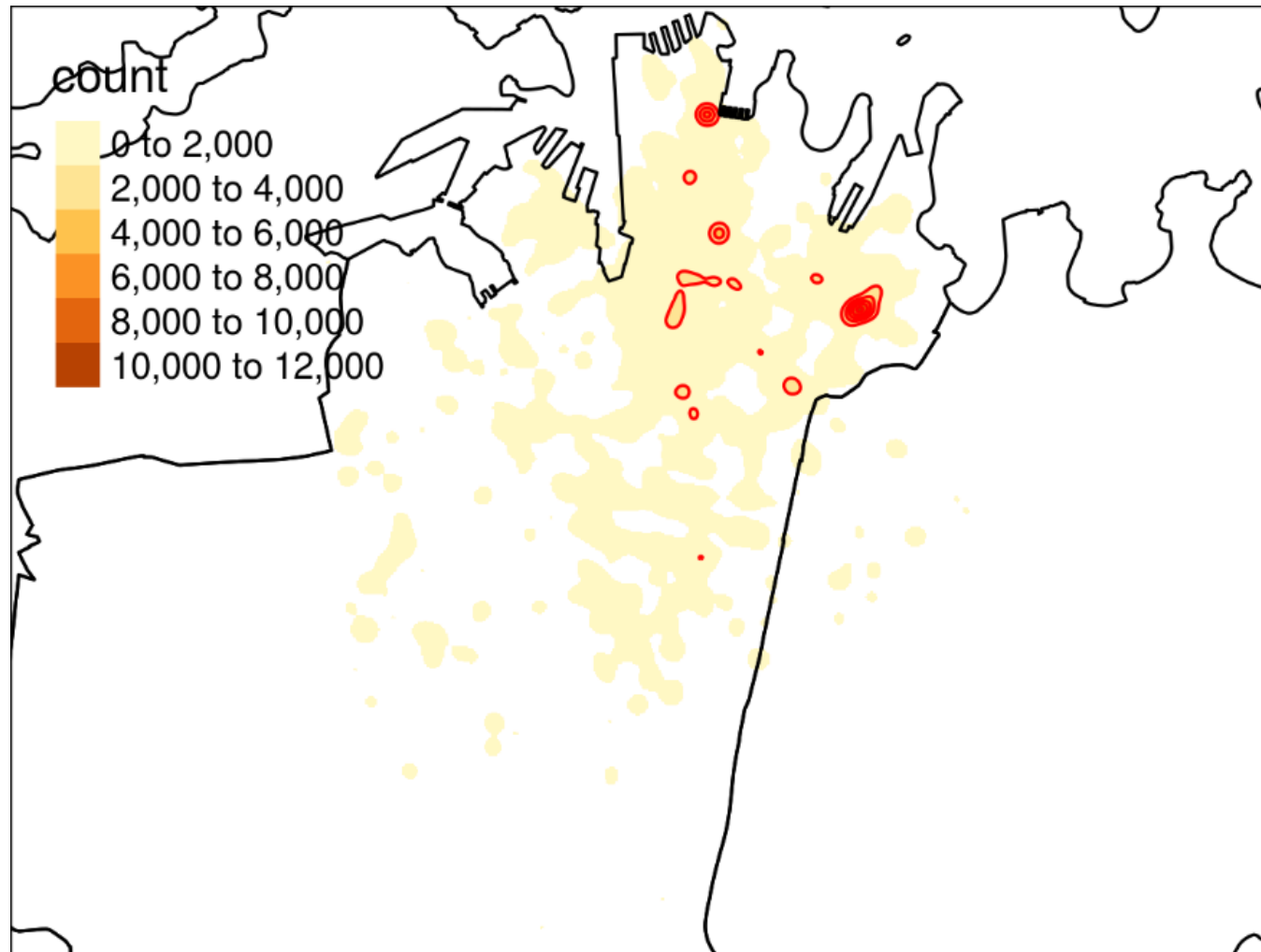
- We can adjust the map to make it a bit clearer:

```
sydsa4 <- readOGR("E:/data/CensusData.gdb", "Sydney_SA4")
sydsa4 <- spTransform(sydsa4, CRS(get_proj4(3308)))

tm_shape(crimekd$raster[which(crimekd$raster$count > 100),]) +
  tm_raster(col="count", alpha=0.75) +
tm_shape(crimekd$iso) +
  tm_lines() +
tm_shape(sydsa4) +
  tm_borders(col="black")
```

# Kernel density estimation in R

- Kernel density for assaults only:



## Comments on kernel density estimation

- Kernel density estimation is a relatively simple method of determining the locations of spatial clusters based on point data.
- The default options (that we used) uses an algorithm to determine the size of each band (i.e., the distribution used) but you can change this if you want specific proportions for the bands (quartiles, etc.).
- Many ways of computing kernel densities in R

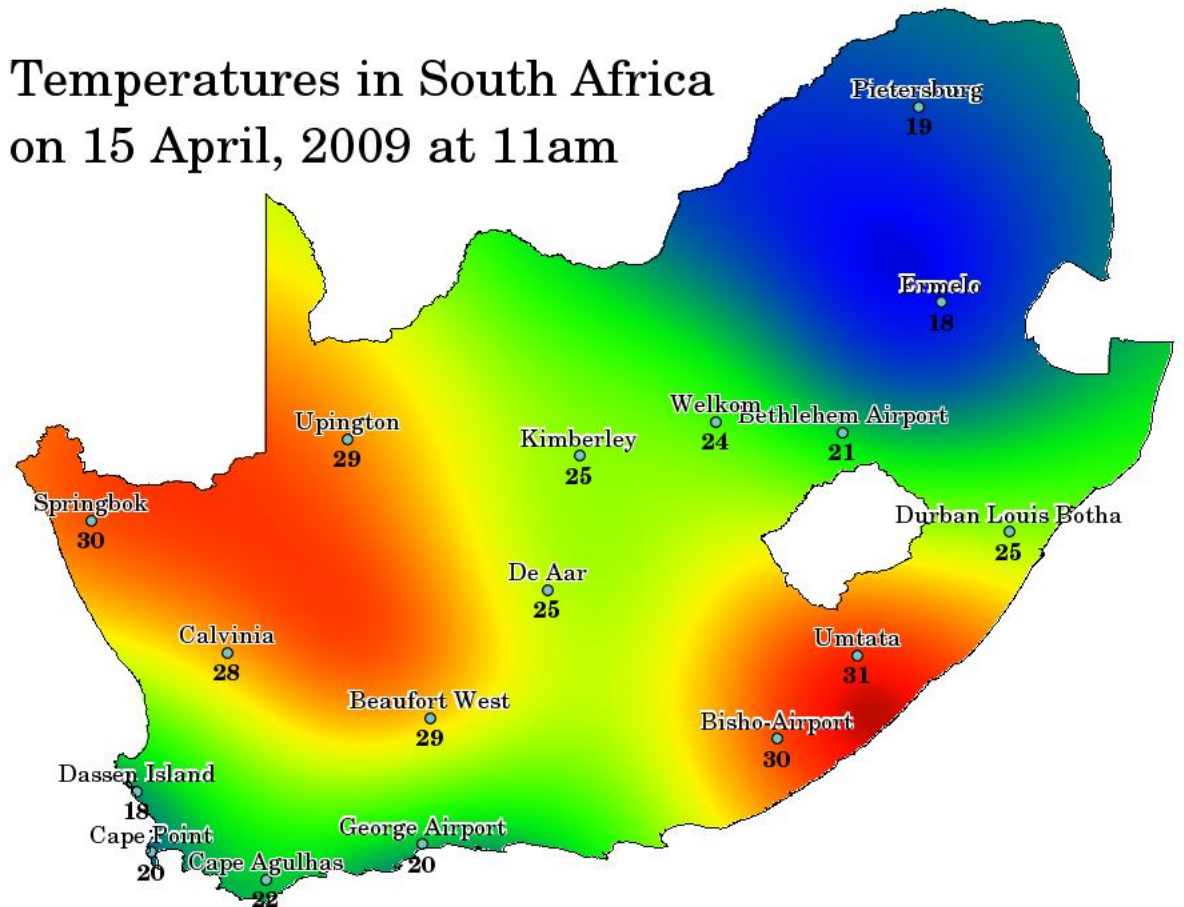
## Comments on kernel density estimation

- For some datasets you will need to create a new `SpatialPointsDataFrame` by merging a non-spatial dataset with the coordinates from a `SpatialLayer`
  - More on this later...

# Inverse distance weighting

- Sometimes you may have point data with values for specific locations but want to (spatially) interpolate the value for areas between these locations.
- Frequently used for weather observations

Temperatures in South Africa  
on 15 April, 2009 at 11am

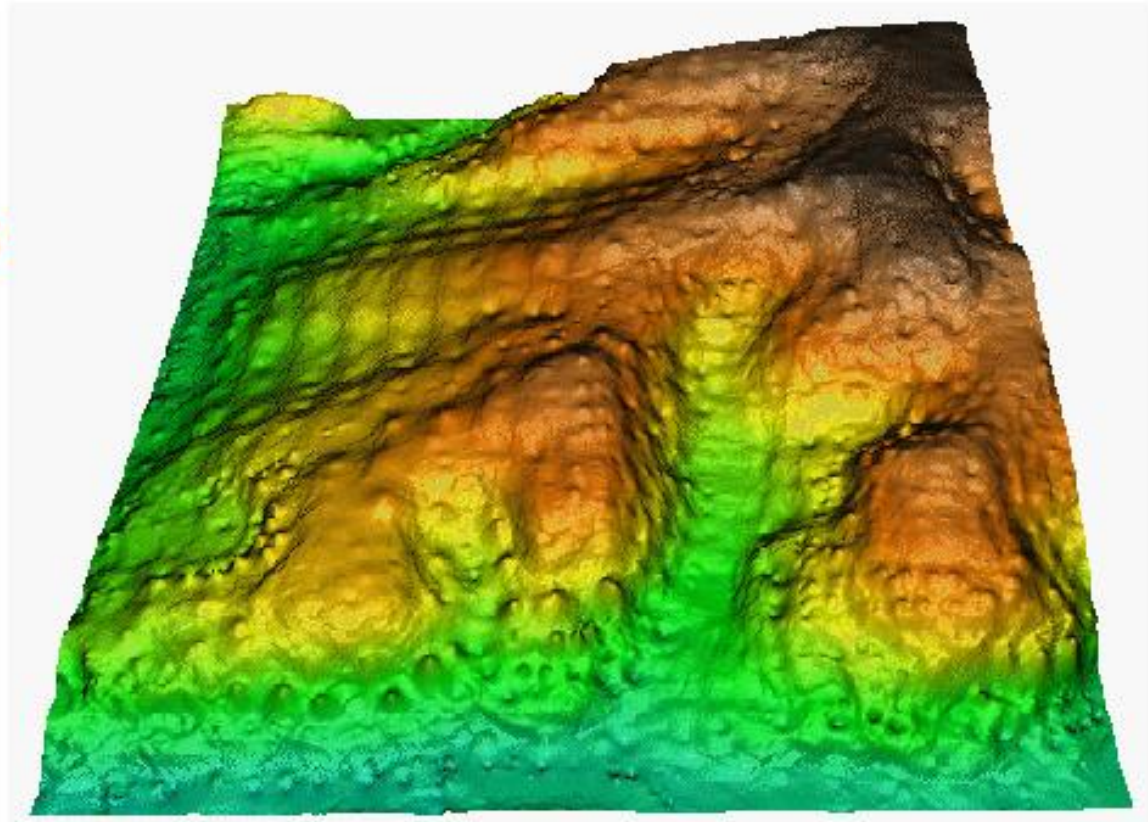
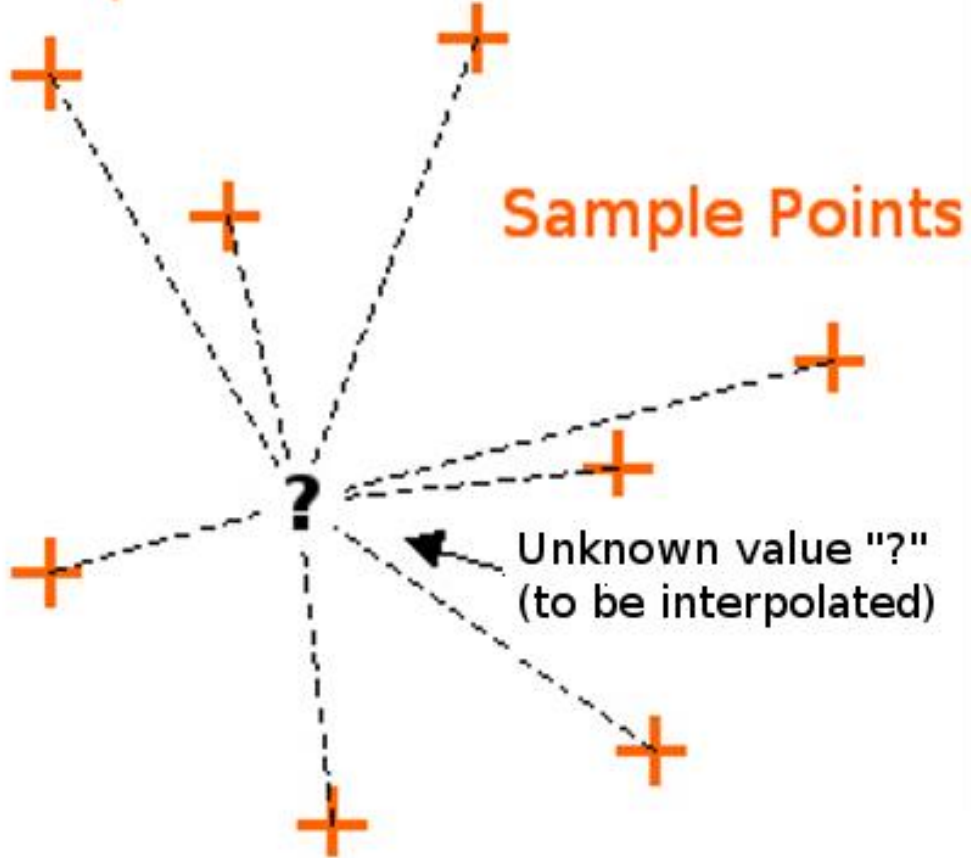




# Inverse distance weighting

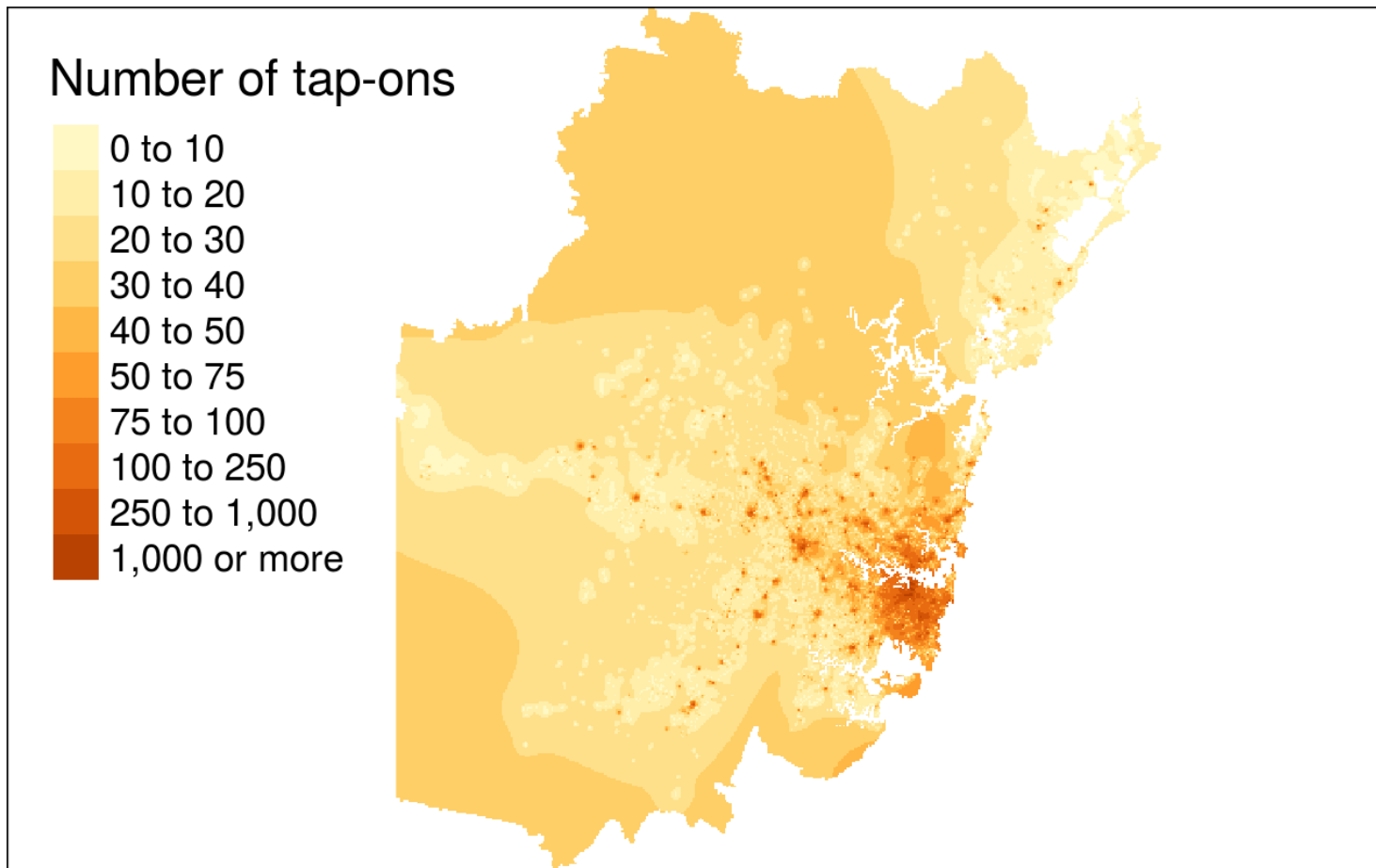
- Works by weighting the values of each known point by the distance to the unknown points the value is being calculated for.

Sample Points



# Inverse distance weighting

- The same method can be used to create a plot that show continuous changes in values for point data.



## Inverse distance weighting

- In R we can use the **idw** function in the **gstat** package to run an inverse distance weighting procedure
- Recall that we loaded this package earlier
- We will need our opal data layer we used for the first assignment and need to project it to a projected coordinate system:

```
opaldata <- readOGR("E:/data/opaldata","sydney_tapon_nums")  
opaldata <- spTransform(opaldata, get_proj4(3308)) # Transform to NSW Lambert Projection
```

## Inverse distance weighting

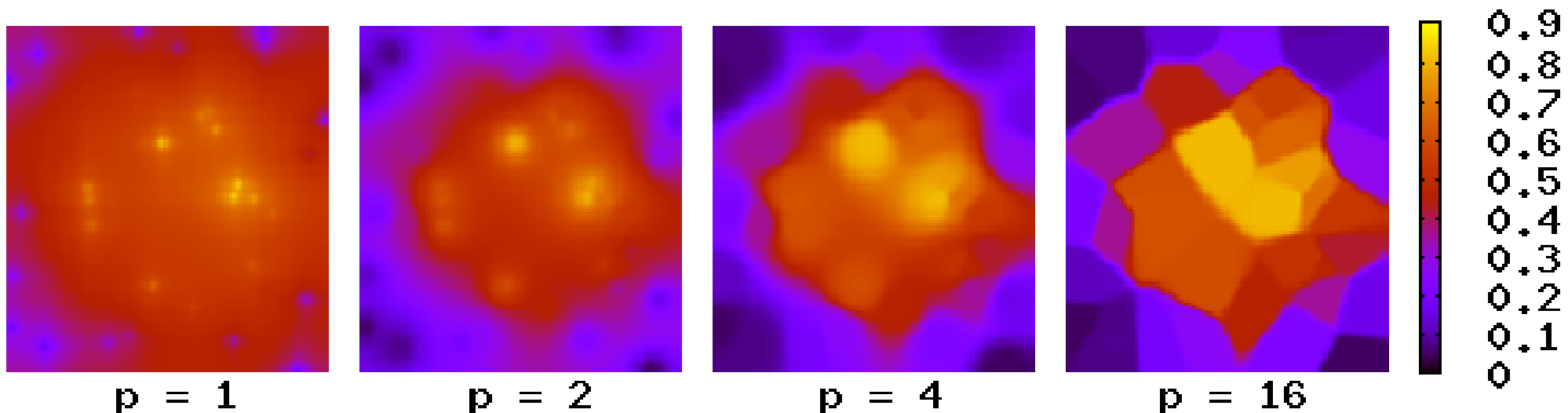
- To use the **idw** function we will need to create a new raster grid for points to interpolate
- In R we can assign a value to a function output, sometimes makes it easier to read and avoids copying the whole dataset to a new object

```
# Create a new table (i.e., "Data Frame") with the coordinates of our new raster layer
rastergrid <- as.data.frame(spsample(opaldata, "regular", n=250000))
# Change the names of our columns to "X" and "Y"
names(rastergrid) <- c("X", "Y")
# Tell R that our data.frame should be a SpatialLayer
coordinates(rastergrid) <- c("X", "Y")
# Tell R that our points are a point grid
gridded(rastergrid) <- TRUE
# Tell R that we want a full grid (not just points)
fullgrid(rastergrid) <- TRUE
# Set the projection to the projection of our opal layer
proj4string(rastergrid) <- proj4string(opaldata)
```

# Inverse distance weighting

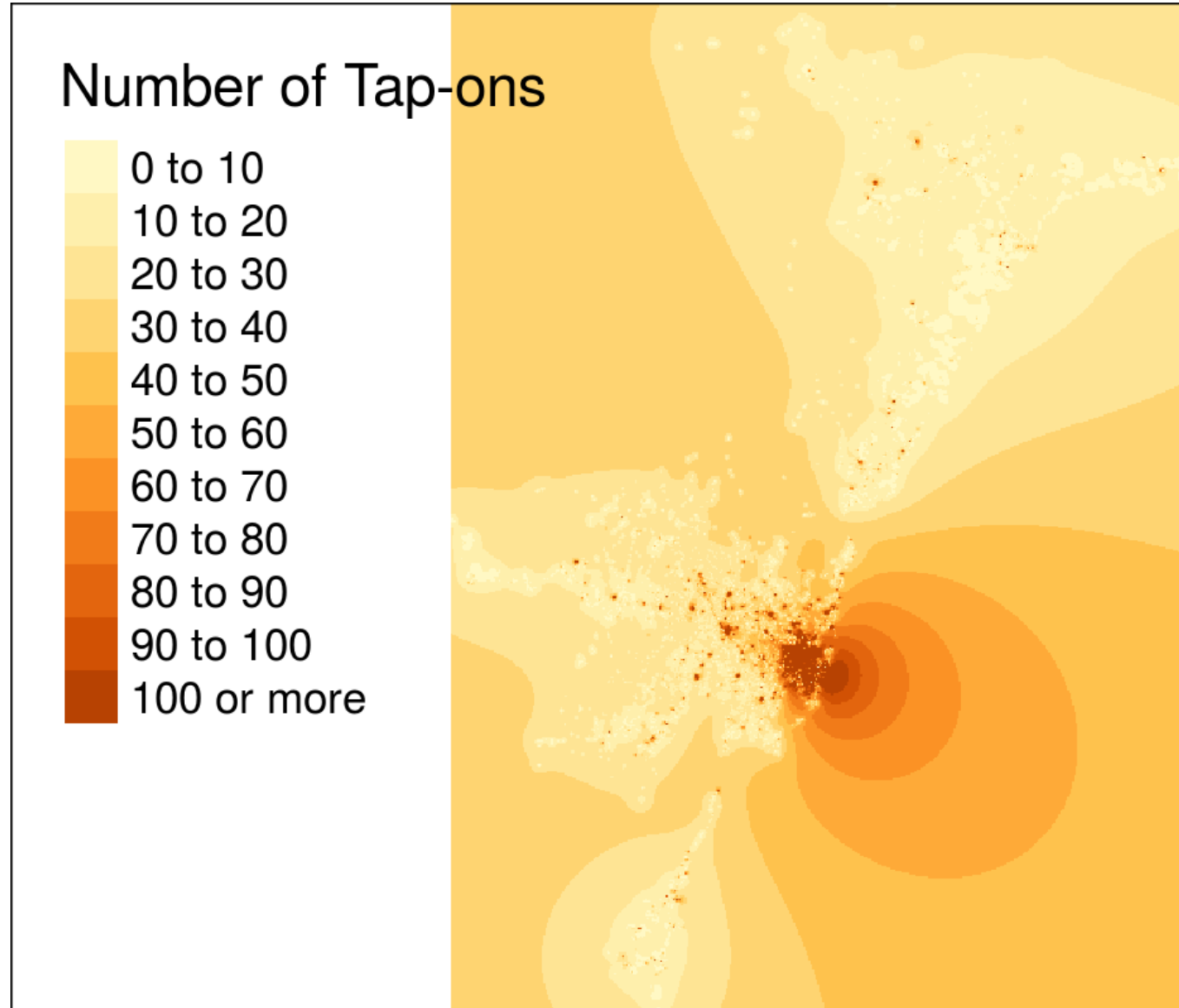
- Running the IDW function requires us to tell R how to calculate the unknown values
- We do this by specifying a function where the  $\sim$  means “is a function of”
- We can then convert the result into a raster layer

```
opalidw <- idw(num_tapons ~ 1, opaldata, newdata=rastergrid, idp = 2.0)  
opalidwr <- raster(opalidw)
```



## Inverse distance weighting

- Plotting the results shows that what is returned is a raster layer that covers the whole grid
- Completely ignores geography!



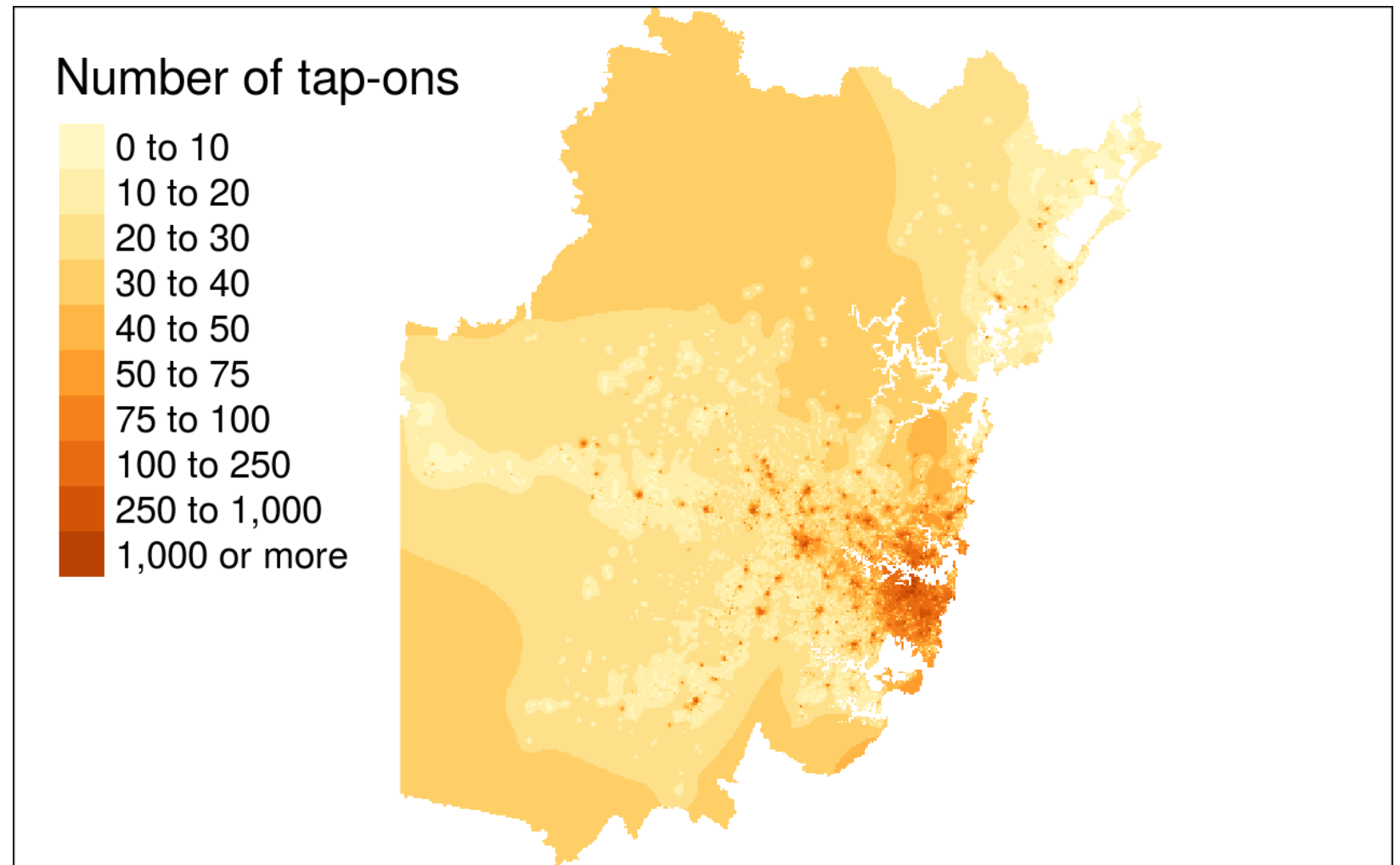
## Inverse distance weighting

- We need to remove areas outside our geographic boundary using the **mask** function from the **raster** package
  - Plot the result and set different colours based on the ranges in the “breaks” argument:

```
opalidwrcrop <- mask(opalidwr, sydsa4)
tm_shape(opalidwrcrop) +
  tm_raster(breaks = c(0,10,20,30,40,50,75,100,250,1000,Inf))
```

# Inverse distance weighting

- Now respects (somewhat) the geography





## Inverse distance weighting

- If necessary we can convert our raster layer to a line layer:

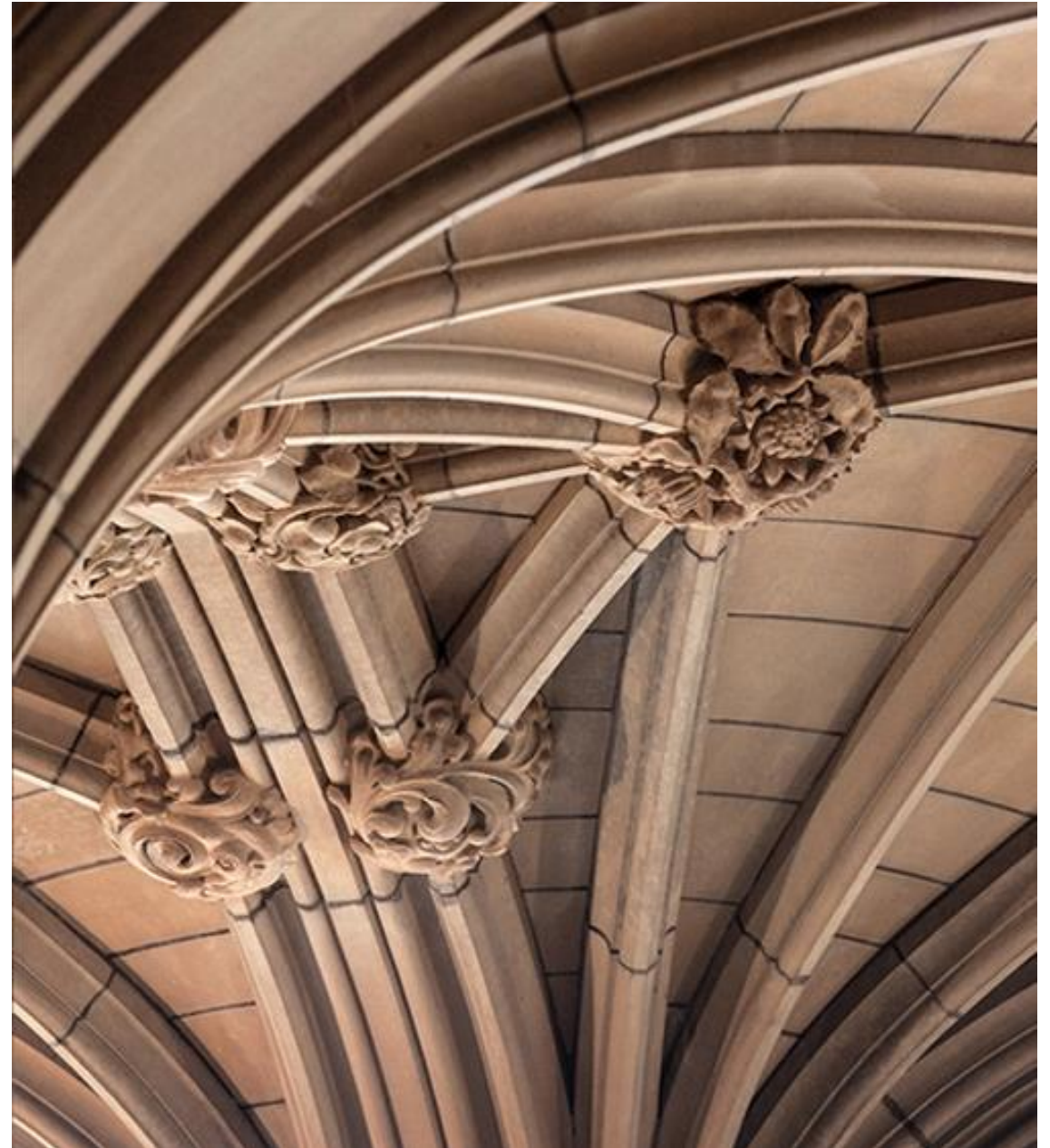
```
opalcontours <- rasterToContour(  
  opalidwr,  
  levels=c(0,10,20,30,40,50,75,100,250,1000,Inf)  
)  
  
tm_shape(opalcontours) +  
  tm_lines(col="level")
```

## Final questions on kernel densities or IDW?

# Databases with R and ArcGIS

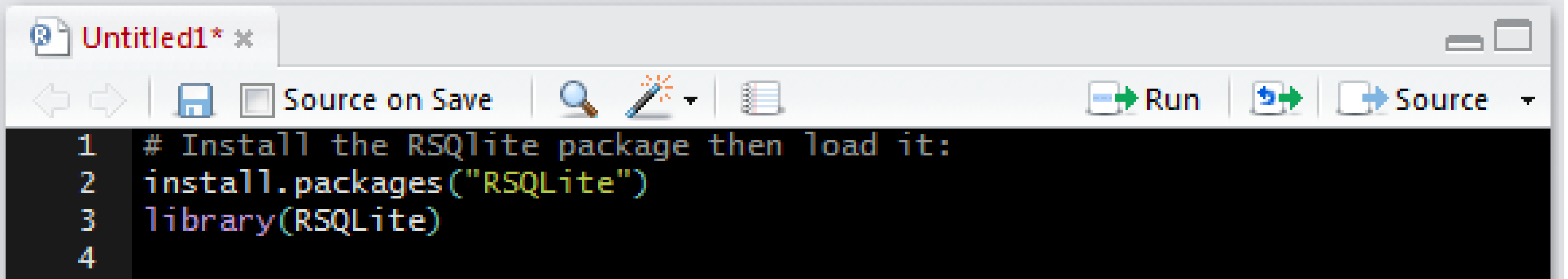
Dr Adrian Ellison  
Dr Richard Ellison

ITLS6107 Semester 2, 2017



## Install the RSQLite package

- For this session we will be using the RSQLite package
- Recall that to install and load a package in R we run:



The screenshot shows an R script editor window with a toolbar at the top. The toolbar includes icons for navigation (back, forward), saving, a 'Source on Save' checkbox, a search icon, a 'Run' button with a green arrow, and a 'Source' button with a blue arrow. The script content is as follows:

```
1 # Install the RSQLite package then load it:  
2 install.packages("RSQLite")  
3 library(RSQLite)  
4
```

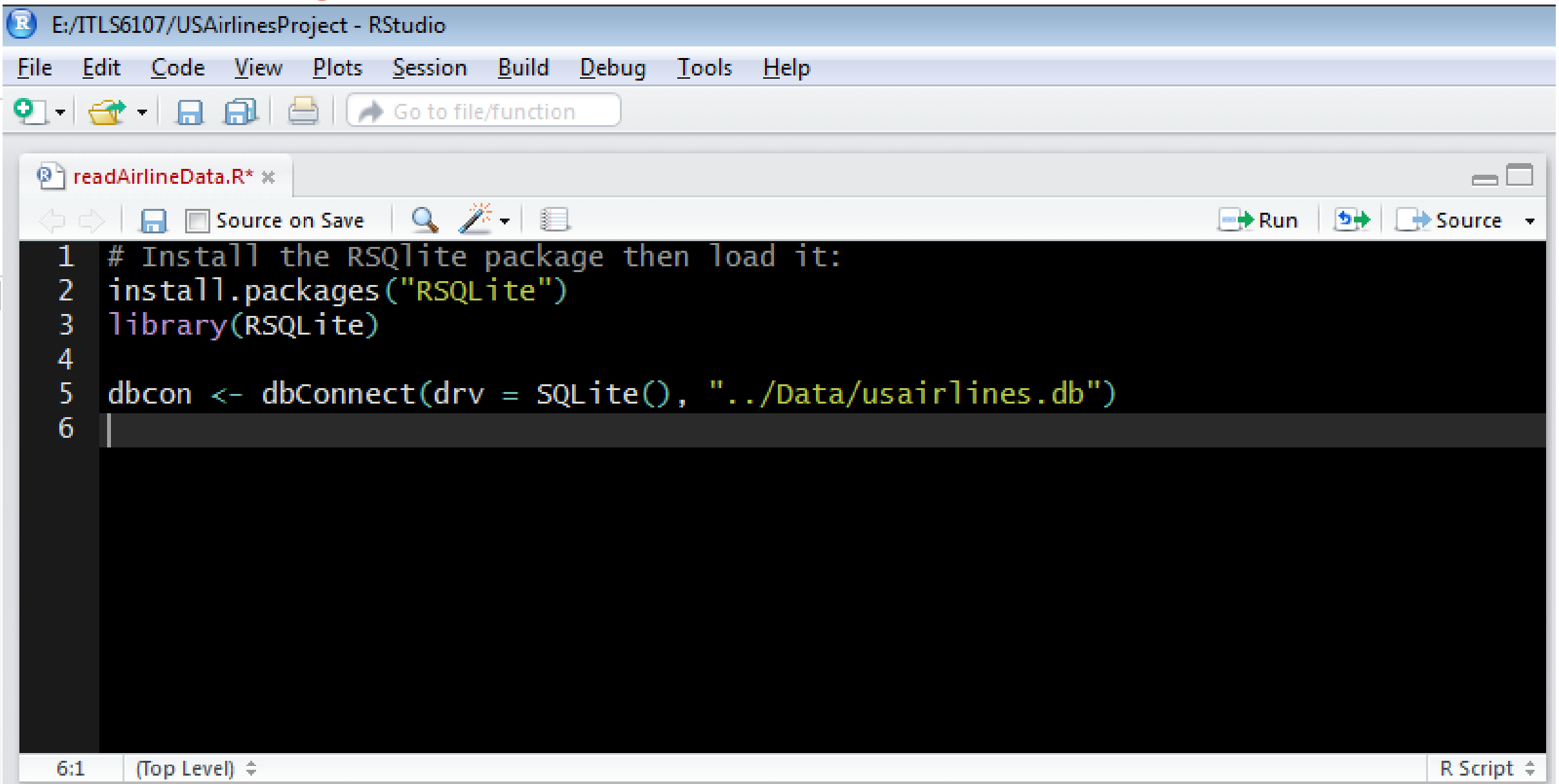
## SQLite and RSQLite

- SQLite is a flat-file database that supports using SQL queries as if it were a standard relational database
  - Frequently used for small databases where data integrity is not important (e.g., iPhone and Android apps)
  - Not a good idea to use it for very large or complex databases
  - Has some restrictions in how it can be used
    - Not able to delete fields!
- Main advantages are:
  - Quick to setup
  - No need to install anything special to use it
  - Can run spatial queries using the Spatialite extension (needs installation)

## SQLite and RSQLite

- The RSQLite package is used to access an SQLite database in R
  - Similar packages are available for standard relational databases:
    - RMySQL (for MySQL)
    - RPostgreSQL (for PostgreSQL)
    - Etc.
  - All are used in the same way (with a few minor differences)

# Connecting to the database



The screenshot shows the RStudio application window. The title bar reads "E:/ITLS6107/USAirlinesProject - RStudio". The menu bar includes File, Edit, Code, View, Plots, Session, Build, Debug, Tools, and Help. The toolbar contains icons for file operations and a search bar labeled "Go to file/function". The script editor shows a file named "readAirlineData.R\*" with the following R code:

```
1 # Install the RSQLite package then load it:
2 install.packages("RSQLite")
3 library(RSQLite)
4
5 dbcon <- dbConnect(drv = SQLite(), "../Data/usairlines.db")
6
```

The status bar at the bottom indicates the cursor is at line 6, column 1, and the file is an "R Script".

## US domestic flights database

- For this session we will be using a database that contains all domestic flights in the United States in November 2015.
  - Contains 467,972
- The full dataset contains all flights from 1987 to (currently) November 2015
  - Approximately 130 million flights
- Two tables:
  - flights – Table containing all the flight data
  - airports – Table containing all the airports (the same as the .csv file on Blackboard)



## flights table

- Year/Month/DayOfMonth/DayOfWeek – Columns for the date of the flight (all integers)
- ArrTime/DepTime – Actual arrival and departure times in 24 hour times as 4 digit numbers
- CRSArrTime/CRSDepTime – Scheduled arrival and departure times
- UniqueCarrier – IATA code for the airline
- FlightNum – Flight number (excluding the airline code)
- TailNum – Identifier of the aeroplane
- ArrDelay – Minutes the flight was delayed (negative if early)
- Origin/Dest – IATA Airport code of origin/destination
- Others

## Interacting with the database

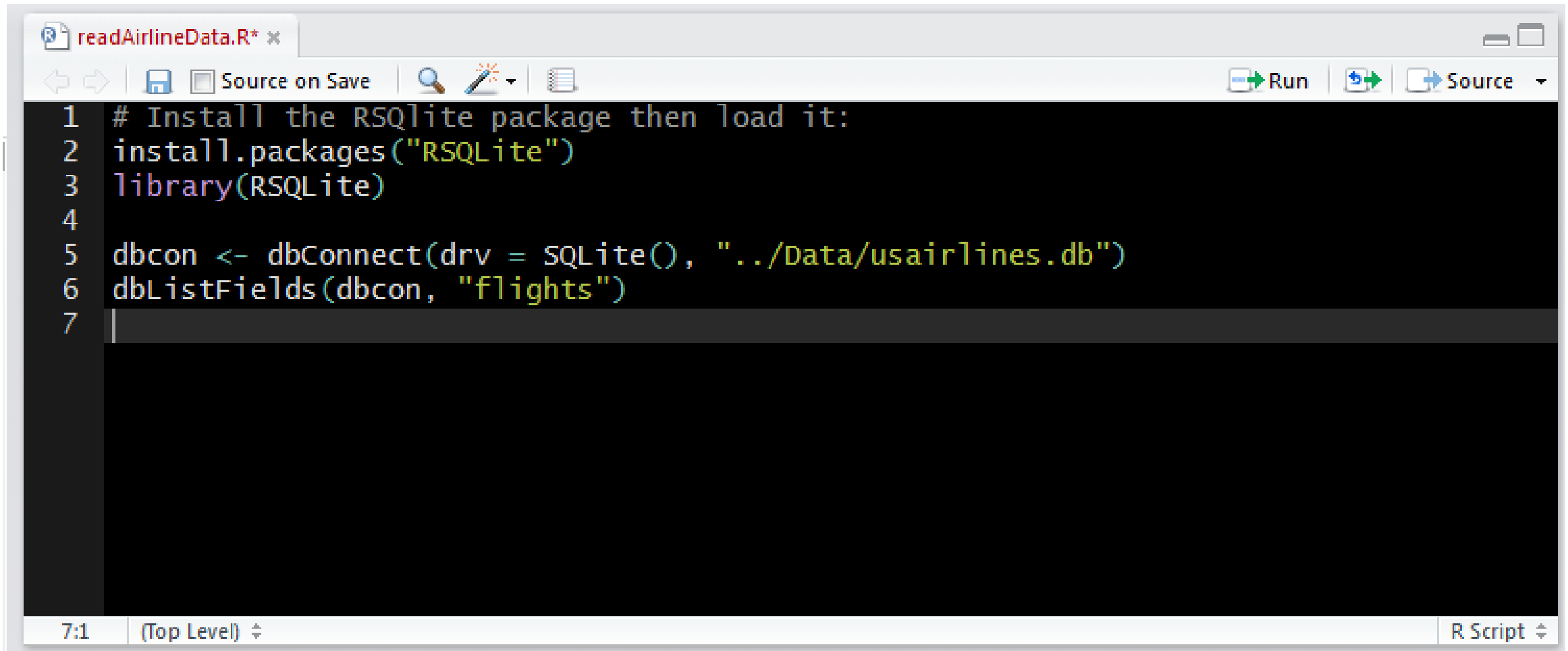
- RSQLite includes several methods for interacting with SQLite
  - `dbListTables()` – List the tables in the database
  - `dbFetch()` – Used to get results in sets (rather than all at once)
  - `dbGetQuery()` – Used to get all the results of a query at the same time
  - `dbReadTable()` – Read a whole table into R
  - `dbGetRowCount()` – Tells you many rows there are in your result
  - Others

## Interacting with the database

- We will mostly use `dbGetQuery()` but `dbFetch()` is useful if you want to download large amounts of data
- `dbGetQuery()` returns the results of your query as a standard R dataframe
- Need to think carefully about what you actually need to retrieve from the database
  - Do you need the individual records or do you want to run aggregate analyses?

## Showing a full list of fields in the database

- Once we have connected to the database we can get more information about the database:



```
readAirlineData.R* x
Source on Save Run Source
1 # Install the RSQLite package then load it:
2 install.packages("RSQLite")
3 library(RSQLite)
4
5 dbcon <- dbConnect(drv = SQLite(), "../Data/usairlines.db")
6 dbListFields(dbcon, "flights")
7
```

7:1 (Top Level) R Script

## Running a simple query on the database

- The `dbGetQuery()` function is used to query the database:

```
dbGetQuery(dbcon, "SELECT COUNT(*) FROM flights")
```

Database connection

COUNT(\*) retrieves the number of rows

The “flights” table

The query as a string

- Remember that the standard requires double speech marks around field names – SQLite does not require this

## Running a simple query on the database

- Tells us the number of rows in our flights table:

```
>  
> dbGetQuery(dbcon, "SELECT COUNT(*) FROM flights")  
COUNT(*)  
1      467972  
> |
```

## Running a simple query on the database

- Remember, to retrieve all the fields in a table we use a SELECT \* FROM... query
  - LIMIT says to only return the first x observations

```
8 dbGetQuery(dbcon, "SELECT COUNT(*) FROM flights")
9 someflights <- dbGetQuery(dbcon, "SELECT * FROM flights LIMIT 10")
10 View(someflights)
```

# Running a simple query on the database

readAirlineData.R\* ✕ someflights ✕

← → ↺ Filter

|   | Year | Quarter | Month | DayofMonth | DayOfWeek | FlightDate | UniqueCarrier | AirlineID | Carrier | TailNum | FlightNum |
|---|------|---------|-------|------------|-----------|------------|---------------|-----------|---------|---------|-----------|
| 1 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N944DL  | 2605      |
| 2 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N982AT  | 2607      |
| 3 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N941DL  | 2608      |
| 4 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N973DL  | 2609      |
| 5 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N973DL  | 2609      |
| 6 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N553NW  | 2610      |
| 7 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N315NB  | 2611      |
| 8 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N331NW  | 2612      |
| 9 | 2015 | 4       | 11    | 3          | 2         | 2015-11-03 | DL            | 19790     | DL      | N993AT  | 2613      |

Showing 1 to 10 of 10 entries



## Calculating summary statistics using the database

- Using a database provides a powerful method of quickly calculating summary statistics without needing to import the data into R:
- SQLite provides functions for some summary statistics
  - Average: `AVG()`
  - Minimum: `MIN()`
  - Maximum: `MAX()`
  - Sum: `SUM()`
  - Number of observations: `COUNT()`
- Other databases provide many more of the standard statistical functions
  - Median, Standard deviation, etc.

## Calculating summary statistics using the database

- We can use different variations of the same query to look at the average values of different fields, or multiple fields in the same query:

```
12 dbGetQuery(dbcon, "SELECT AVG(DepDelay) FROM flights")
13 dbGetQuery(dbcon, "SELECT AVG(ArrDelay) FROM flights")
14 dbGetQuery(dbcon, "SELECT AVG(DepDelay), AVG(ArrDelay) FROM flights")
15
```

- These queries return a statistic for the whole table.
  - What if we want to look at the average delay by airline?

# Calculating summary statistics using the database

- We use the **GROUP BY** clause to calculate different statistics for each value of the field(s) listed after the **GROUP BY** clause.

```
15  
16 dbGetQuery(dbcon, "SELECT AVG(DepDelay), AVG(ArrDelay) FROM flights GROUP BY UniqueCarrier")  
17
```

- Gives us exactly the same output but separated by airline.
- Problem is, which airline is which?

```
> dbGetQuery(dbcon, "SELECT AVG(DepDelay)  
  AVG(DepDelay)  AVG(ArrDelay)  
1      6.402242    0.7649010  
2      1.702294   -1.9056631  
3      7.071485    1.4081670  
4      4.536911   -3.1714571  
5      7.015785    4.3196702  
6     11.607884   11.0926188  
7     -1.724768   -2.7144754  
8      6.905491    0.2095050  
9      8.559721    7.4592680  
10     6.725366    4.8402478  
11    11.165944    0.2783549  
12     5.720724    0.1148873  
13     7.793868    0.9845355  
> |
```

## Calculating summary statistics using the database

- We use the **GROUP BY** clause to calculate different statistics for each value of the field(s) listed after the **GROUP BY** clause.

```
18 dbGetQuery(dbcon, "SELECT UniqueCarrier, AVG(DepDelay), AVG(ArrDelay) FROM flights
19      GROUP BY UniqueCarrier")
```

- We tell the database to return UniqueCarrier as a column in our results
- We can change the UniqueCarrier field to another field name to look at
  - Airports
  - Day of the month
  - Day of the week
  - Aircraft

|    | UniqueCarrier | AVG(DepDelay) | AVG(ArrDelay) |
|----|---------------|---------------|---------------|
| 1  | AA            | 6.402242      | 0.7649010     |
| 2  | AS            | 1.702294      | -1.9056631    |
| 3  | B6            | 7.071485      | 1.4081670     |
| 4  | DL            | 4.536911      | -3.1714571    |
| 5  | EV            | 7.015785      | 4.3196702     |
| 6  | F9            | 11.607884     | 11.0926188    |
| 7  | HA            | -1.724768     | -2.7144754    |
| 8  | MQ            | 6.905491      | 0.2095050     |
| 9  | NK            | 8.559721      | 7.4592680     |
| 10 | OO            | 6.725366      | 4.8402478     |
| 11 | UA            | 11.165944     | 0.2783549     |
| 12 | VX            | 5.720724      | 0.1148873     |
| 13 | WN            | 7.793868      | 0.9845355     |

## Using joins in the database

- In ArcGIS, using a (non-spatial) join allows us to link two tables by a common attribute.
  - ArcGIS does this by querying the File Geodatabase tables we want to join.
- The equivalent procedure can be run using SQL

## Using joins in the database

- In ArcGIS, using a (non-spatial) join allows us to link two tables by a common attribute.
  - ArcGIS does this by querying the File Geodatabase tables we want to join.
- The equivalent procedure can be run using SQL

```
dbGetQuery(dbcon, "SELECT * FROM flights INNER JOIN airports  
ON flights.Origin = airports.IATA_Code  
LIMIT 10")
```

**ON** tells us what attributes to join by

Attributes in the **ON** clause  
are specified by the format:  
TableName.FieldName

**INNER JOIN** tells the database  
to only return matching rows

## Using joins in the database

- If we want all fields from the flights table but only some from the airports table we can change our SELECT statement to:

```
dbGetQuery(dbcon, "SELECT flights.*, airports.latitude_deg, longitude_deg  
FROM flights INNER JOIN airports  
ON flights.Origin = airports.IATA_Code  
LIMIT 10")
```

Fields in the **SELECT** statement are specified the same way as in the **ON** clause. We can also specify them without the table name if the field name is unique in both tables.

Attributes in the **ON** clause are specified by the format: `TableName.FieldName`

**INNER JOIN** tells the database to only return matching rows

## Are there clusters of delayed flights?

- If we only want to look at flights that depart more than 20 minutes (or another value) late, we can use the WHERE clause to retrieve only flights that match that condition:

```
lateflights <- dbGetQuery(dbcon,  
  "SELECT flights.*, airports.latitude_deg, longitude_deg  
  FROM flights INNER JOIN airports  
  ON flights.Origin = airports.IATA_Code  
  WHERE DepDelay > 20")
```

- We are saving the results of our query to the (new) **lateflights** dataframe



## Are there clusters of delayed flights?

- Once we have our data in R we need to convert it to a spatial format R understands
- We are looking at the origin airports only so we are using point data
- Remember to load the **sp** and **sf** packages
- Our data was imported from SQLite as character data but we need the coordinates as numeric so we also need to convert them:

```
37 library(sp)
38
39 lateflights$longitude_deg <- as.numeric(lateflights$longitude_deg)
40 lateflights$latitude_deg <- as.numeric(lateflights$latitude_deg)
```

## Are there clusters of delayed flights?

- We then create our spatial object using the `st_as_sf()` function.
- Try plotting the points

## Are there clusters of delayed flights?

- United States is recognisable but there are some outliers
  - Which airports are these?

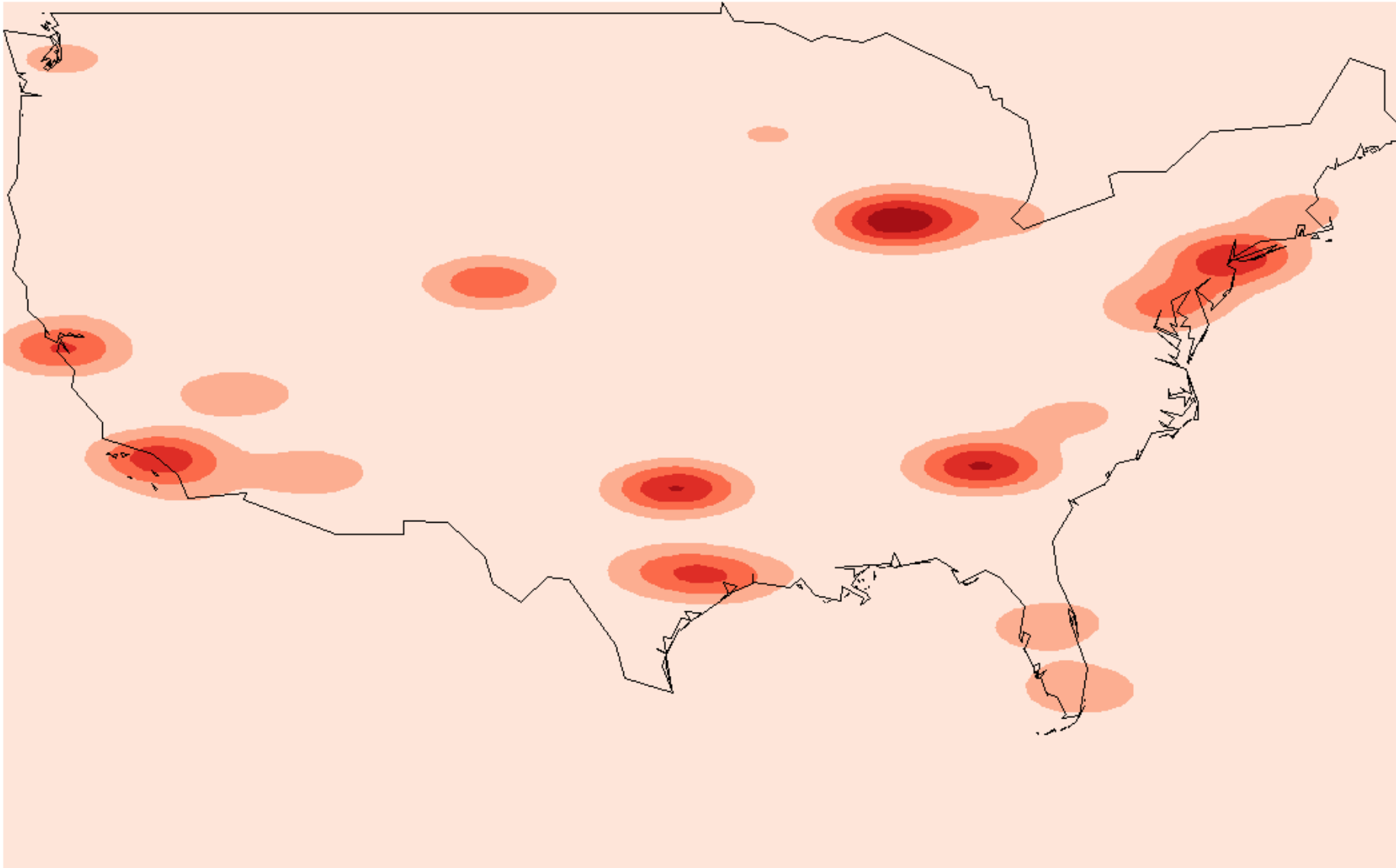


## Are there clusters of delayed flights?

- We want to know where these delayed flights occurred
  - Are they concentrated in a specific area or more spread out?



## Are there clusters of delayed flights?



## Other methods of interacting with databases in R

- The dplyr package provides functionality to interact with databases using its standard functions:
  - `group_by()`
  - `mutate()`
  - `summarise()`
  - Others...
- The postGIStools package provides functions for working with spatial Postgres databases that automatically converts the result into a spatial table in R and the `st_read` function can also read from spatial databases.