Spatial Analysis in R

Konstantin Greger

What was offered at useR! Conference 2015?

Spatial Analysis at useR! Conference 2015 (I)

Tutorials

- *Applied Spatial Data Analysis with R* (Virgilio Gómez Rubio)
- `spatstat`*: An R package for analysing spatial point patterns* (Adrian Baddeley and Ege Rubak)

Keynote

- *How R has changed spatial statistics* (Adrian Baddeley)

Spatial Analysis at useR! Conference 2015 (II)

- *What's new in `igraph` and networks* (Gábor Csárdi)
- *Clustering US Tornadoes* (Thomas Jagger)
- *Bringing Geospatial Tasks into the Mainstream of Business Analytics* (Ian Cook)
- *Novel hybrid spatial predictive methods of machine learning and geostatistics with applications to terrestrial and marine environments in Australia* (Jin Li and Augusto Sanabria)

Spatial Analysis at useR! Conference 2015 (III)

- *Graphical Modelling of Multivariate Spatial Point Patterns* (Matthias Eckardt)
- *Spatial Econometrics Models with* `R-INLA` (Virgilio Gomez-Rubio)
- *Spatio-Temporal Analysis of Epidemic Phenomena Using the R Package* `surveillance` (Sebastian Meyer)
- *Spatial regression of quantiles based on parametric distributions* (Chenjerai Kathy Mutambanengwe)

Spatial Analysis at useR! Conference 2015 (IV)

- *Rapid detection of spatiotemporal clusters* (Markus Loecher)
- *R-package* `tmap` *- Creating thematic maps in a flexible way* (Martijn Tennekes)

My personal verdict: The latest & greatest in Spatial Analysis in R

Tutorial: "Applied Spatial Data Analysis with R"

- Topics
  - Why spatial data in R?
  - Representing Spatial Data
  - Visualizing Spatial Data
  - Accessing spatial data
  - Worked examples
    - Geostatistics
    - Point Patterns
    - Lattice Data
- Interesting but more lecture than tutorial
- Slides and data available here

Tutorial: "`spatstat`: An R package for analysing spatial point patterns"

- Topics
  - Basic statistical concepts used in spatial point pattern analysis
  - Overview of the capabilities of `spatstat`
  - Basic analysis of a point pattern dataset
    - Calculating and plotting exploratory summaries
    - Fitting Poisson, Cox, and Gibbs point process models
    - Validating and critiquing fitted models
- Didn't attend but final 20 minutes looked very promising
- Material available here (& even more here)

Keynote: "How R has changed spatial statistics"

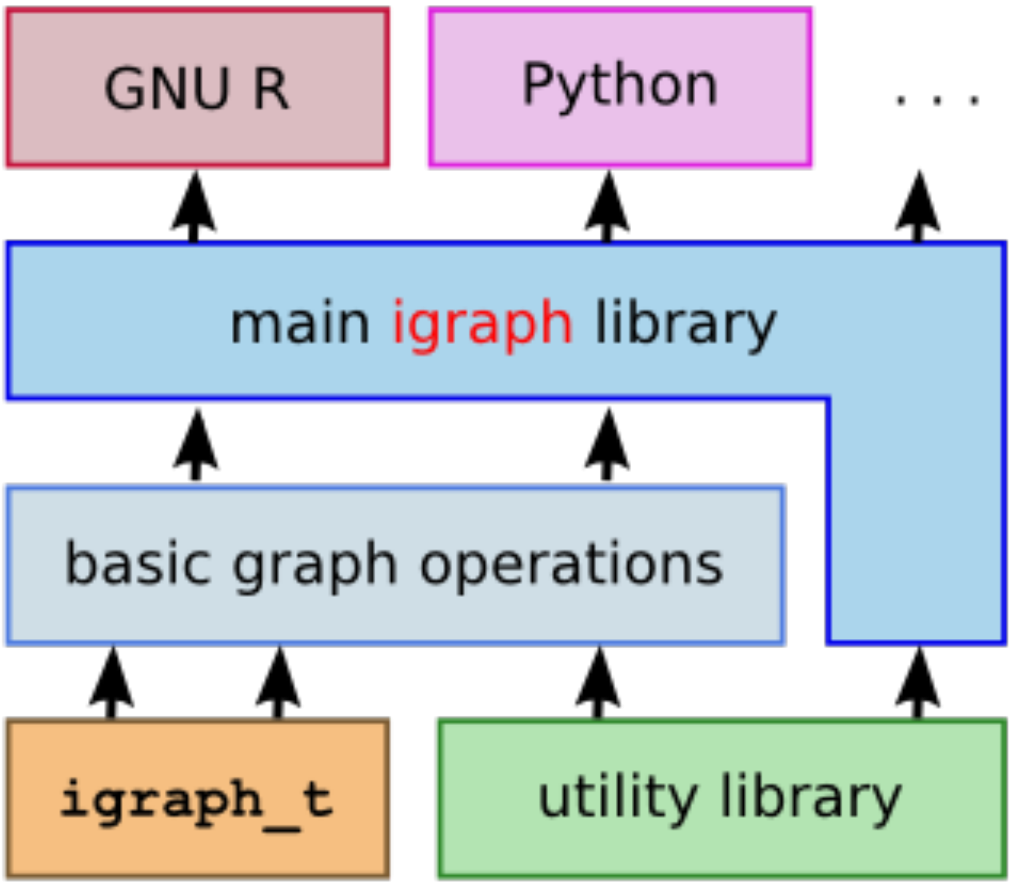
- Excellent talk by one of the luminaries of spatial analysis, author of `spatstat` package
- History and collection of revolutionary ideas (past, current and future) in spatial data analysis and statistics (esp. point pattern analysis)
- Unfortunately slides not available, yet...

What’s new in igraph and networks

Gábor Csárdi

2015-07-01

About igraph



The `[` operator

Imaginary adjacency matrix, queries

```
air['BOS', 'SFO']
```

```
#> [1] 6
```

```
CA <- c("LAX", "SFO", "SAN", "SMF", "SNA", "BUR", "OAK", "ONT", "SJC")
air['BOS', CA]
```

```
#> LAX SFO SAN SMF SNA BUR OAK ONT SJC
#>   7   6   1   0   0   0   0   0   1
```

The `[` operator

Imaginary adjacency matrix, manipulation

Add an edge (and potentially set its weight):

```
air["BOS", "ANC"] <- TRUE
air["BOS", "ANC"]
```

```
#> [1] 1
```

Remove an edge:

```
air["BOS", "ANC"] <- FALSE
air["BOS", "ANC"]
```

```
#> [1] 0
```

The `[[` operator

Imaginary adjacency list, adjacenct vertices:

```
air[["BOS"]]
```

```
#> $BOS
#> + 269/755 vertices, named:
#>   [1] BGR JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK
#>  [16] LAS LAS LAS MIA MIA EWR EWR EWR EWR EWR EWR EWR EWR EWR EWR
#>  [31] LAX LAX LAX LAX LAX LAX LAX PBI PBI PIT PIT PIT PIT PIT SFO
#>  [46] SFO SFO SFO SFO SFO IAD IAD IAD IAD IAD IAD IAD IAD IAD IAD
#>  [61] BDL BDL BUF BUF BUF BUF BWI BWI BWI BWI BWI BWI BWI BWI CAK
#>  [76] CLE CLE CLE CLE CLE CLT CLT CLT CLT CLT CLT CLT CLT CLT CMH
#>  [91] CMH CVG CVG CVG CVG CVG CVG CVG CVG CVG CVG DCA DCA DCA DCA
#> [106] DCA DCA DCA DCA DCA DTW DTW DTW DTW DTW DTW DTW DTW DTW DTW
#> [121] DTW DTW DTW GSO IND IND LGA LGA LGA LGA LGA LGA LGA LGA MDT
#> [136] MKE MKE MKE MSP MSP MSP MSP MSP MSP MSY MYR ORF PHF PHL PHL
#> + ... omitted several vertices
```

The `[[` operator

Imaginary adjacency list, adjacent vertices:

```
air[[, "BOS"]]
```

```
#> $BOS
#> + 256/755 vertices, named:
#>   [1] BGR JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK JFK LAS LAS
#>  [16] LAS MIA MIA MIA EWR EWR EWR EWR EWR EWR EWR EWR LAX LAX LAX
#>  [31] LAX LAX LAX LAX LAX PBI PBI PIT PIT PIT PIT SFO SFO SFO SFO
#>  [46] SFO SFO IAD IAD IAD IAD IAD IAD IAD IAD IAD BDL BDL BDL BUF
#>  [61] BUF BUF BUF BWI BWI BWI BWI BWI BWI CAK CAK CLE CLE CLE CLE
#>  [76] CLE CLE CLT CLT CLT CLT CLT CLT CLT CLT CMH CMH CVG CVG CVG
#>  [91] CVG CVG CVG DCA DCA DCA DCA DCA DCA DCA DCA DCA DTW DTW DTW
#> [106] DTW DTW DTW DTW DTW DTW DTW DTW DTW IND IND LGA LGA LGA LGA
#> [121] LGA LGA MDT MKE MKE MKE MSP MSP MSP MSP MSP MSP MSP MSP MSY
#> [136] MSY MYR PHF PHL PHL PHL PHL PHL PHL PHL PHL PHL RDU RDU RDU
#> + ... omitted several vertices
```

Pipe friendly syntax

```
g <- make_empty_graph(10) %>%
  add_vertices(5) %>%
  set_vertex_attr("name", value = LETTERS[1:5]) %>%
  add_edges(c(1,2,2,3,3,4,4,5,5,1)) %>%
  set_edge_attr("weight", value = runif(gsize(.)))
```

Easier connection to other packages

```
library(networkD3)
d3_net <- simpleNetwork(as_data_frame(karate, what = "edges")[, 1:3])
d3_net
```

Rapid detection of spatiotemporal clusters

Markus Loecher, Berlin School of Economics and Law

Hochschule für
Wirtschaft und Recht Berlin
Berlin School of Economics and Law

useR!
> sessionInfo()
[1] "June 30 - July 3, 2015"
[2] "Aalborg, Denmark"

July 2nd, 2015

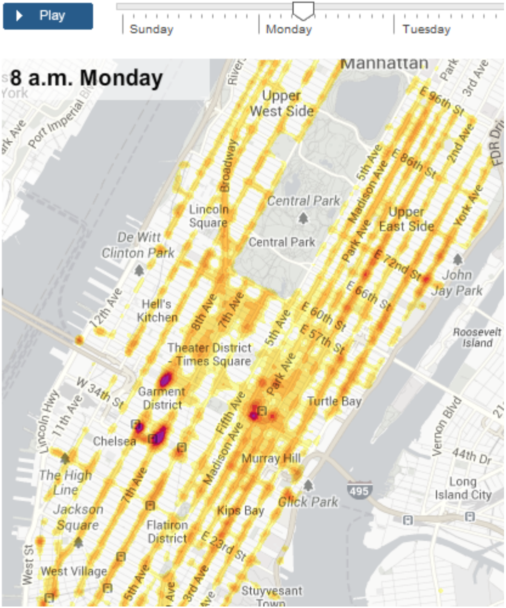
Spatiotemporal Clusters

Scoring unusual events in space and time has been an active and important field of research for decades: How do we

- distinguish normal fluctuations in a stochastic count process from real additive events ?
- identify spatiotemporal clusters where the event is most strongly pronounced ?
- efficiently graph these clusters in a map overlay ?

Supervised learning algorithms are proposed as an alternative to the computationally expensive scan statistic.
The task can be reduced to detecting over-densities in space relative to a background density.

NYC cab data


Play
Sunday
Monday
Tuesday
8 a.m. Monday
Manhattan
Upper West Side
Central Park
Lincoln Square
De Witt Clinton Park
Hell's Kitchen
Theater District - Times Square
Garment District
Chelsea
Murray Hill
Turtle Bay
Upper East Side
John Jay Park
Roosevelt Island
Long Island City
Kips Bay
Glick Park
Flatiron District
The High Line
Jackson Square
West Village
Stuyvesant Town

Hot spots

- Relatively compact areas of “high intensity”
- What is baseline ?

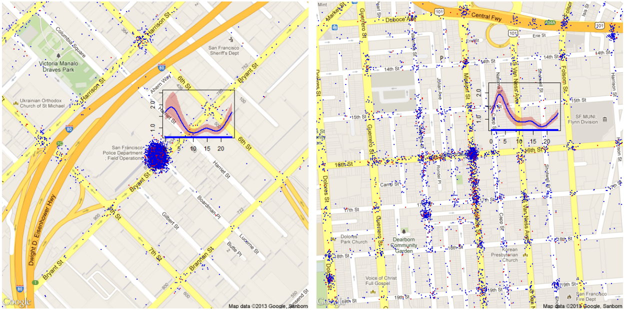
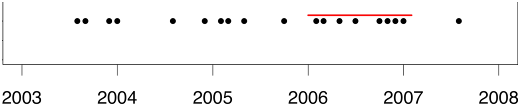


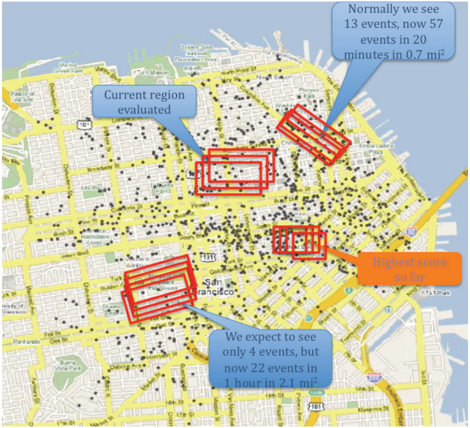
Figure: (left) One “hot spot” found where the contextual information provided by the map is invaluable. (right) Another cluster of crime activity spread along the street grid.

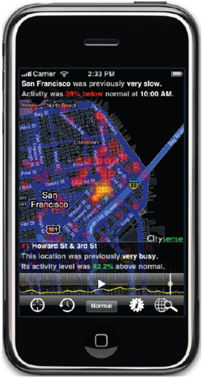
Unusual Clusters



- "Over a 5 year period there were 19 cases of a particular type of cancer reported in a town. A physician notes that there is a 1 year period that contains eight cases. "
- "On Aug 17, **the U.S. Army suspended all operations of the Black Hawk helicopter** after the third crash in 25 days. The 3 crashes were about seven times the expected rate based on the previous 5 years. ($S_{25} = 3$)"
- " **Alarming number of inmate deaths in Harris County**: In a 10 month period, 11 inmates died at the troubled Harris County Jail, which is about twice the expected rate. The U.S. Department of Justice ordered the city of Houston to pay a fine of $1000 a day until the cause was found. ($S_{10} = 11$)"

Scan Statistic





This type of spatial surveillance is computationally expensive: $O(R \cdot N^4)$

Unsupervised as Supervised Learning

Introduced in Hastie *et al* for density estimation or association rule generalizations. Problem must be enlarged with a simulated data set generated by Monte Carlo techniques

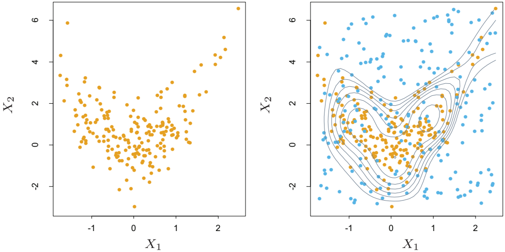


FIGURE 14.3. *Density estimation via classification. (Left panel:) Training set of* 200 *data points. (Right panel:) Training set plus* 200 *reference data points, generated uniformly over the rectangle containing the training data. The training sample was labeled as class* 1*, and the reference sample class* 0*, and a semiparametric logistic regression model was fit to the data. Some contours for* $\hat{g}(x)$ *are shown.*

In epidemiology cases and population naturally provide two classes, for anomaly detection the background "population" is taken to be some sort of average.

CART

A cluster found by a classification tree visualized on a Google map tile. The numeric labels indicate the fraction of the positive class labels.

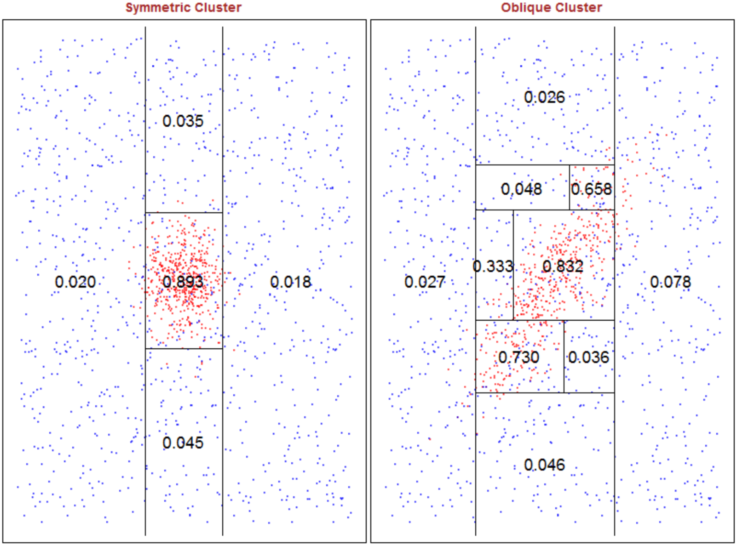
TreeHotspots

R package with new functionalities

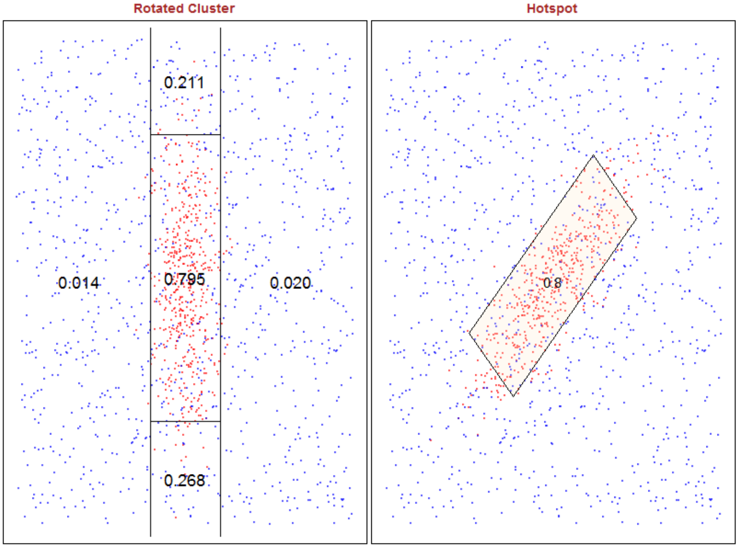
- Rotation of Data
- Visualization of selected leaves
- Overlay on maps (Google and OSM)
- User written splitting functions for *rpart*:
  - Baseline Distributions eliminate need for point augmentation
  - SatScan Poisson and Binomial Likelihood, e.g.

$$\left(\frac{c}{E[c]}\right)^{c} \cdot \left(\frac{C-c}{C-E[c]}\right)^{C-c}$$

Simulations



Simulations



SF crime data, on map

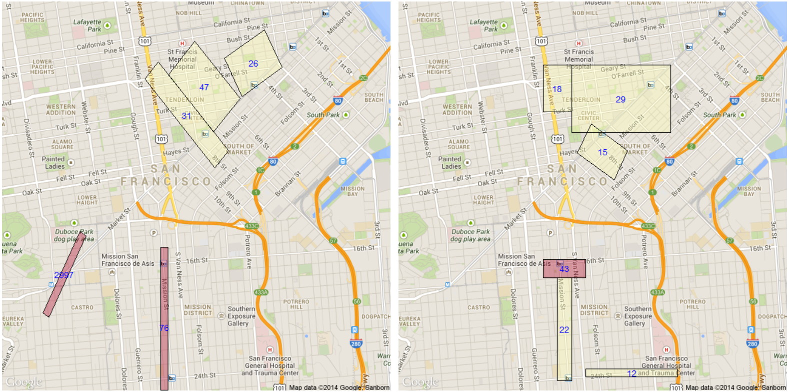


Figure: positive class is given by (left) drug crimes and (right) robbery related incidents.

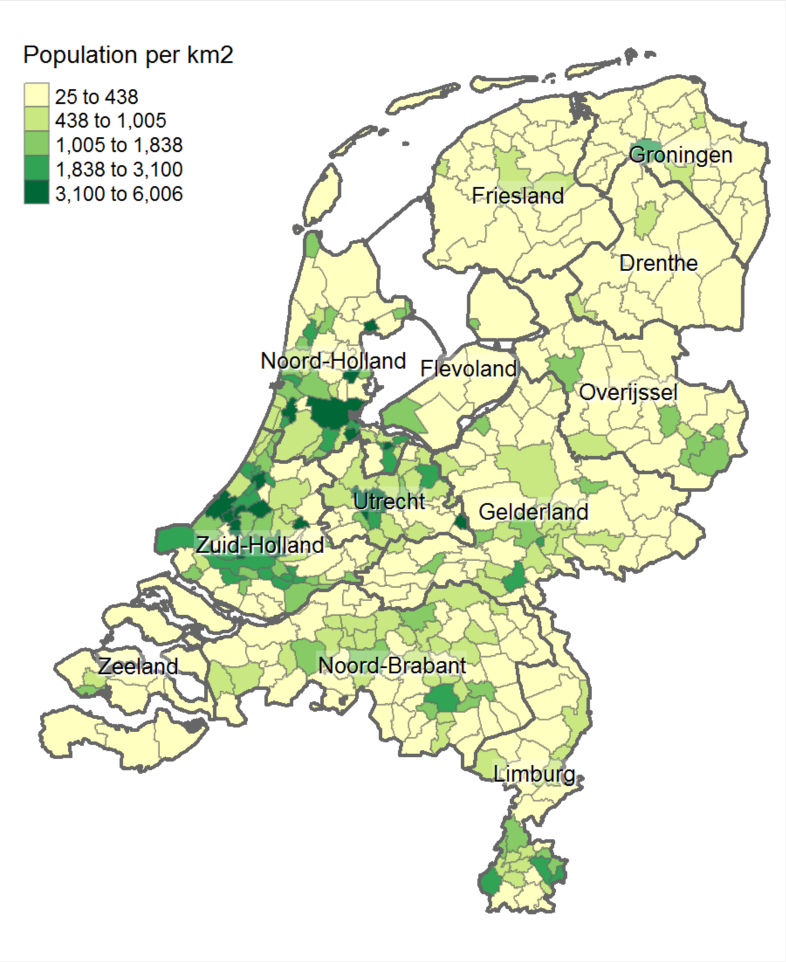
R-package tmap

Creating thematic maps in a flexible way

Martijn Tennekes

Statistics Netherlands

Thematic map



= Thematic map

Layered approach

A Layered Grammar of Graphics (Wickham, 2010)
Implemented in **ggplot2**

Defaults
- Data
- Aesthetics

Layers
- Data
- Aesthetics
- Geometry
- Statistics
- Position

Scales

Coordinates

Facets

Group

1

1 or more

Layered approach in **tmap**

Shape specification
- Spatial object
  - Types:
    - ◊ Polygons
    - • Points
    - ⁄ Lines
    - # Raster
  - Data
- Map projection
- Bounding box

Layers
- Aesthetics
- Statistics
- Scale

Facets

Building a thematic map

```
tm_shape(NLD_muni,
         projection="rd") +
```

```
tm_fill()
```

Building a thematic map

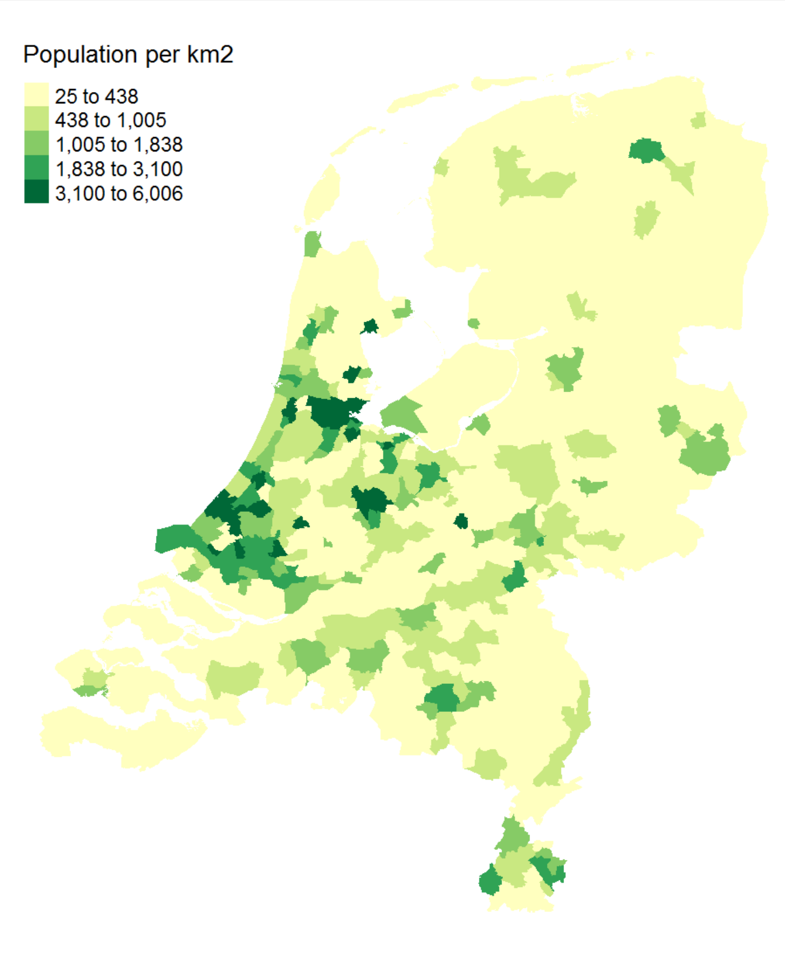
```
tm_shape(NLD_muni,
         projection="rd") +
```

```
tm_fill("blue")
```

Building a thematic map

```
tm_shape(NLD_muni,
         projection="rd") +
```

```
tm_fill("population",
        convert2density=TRUE,
        style="kmeans",
        title="Population per km2") +
```

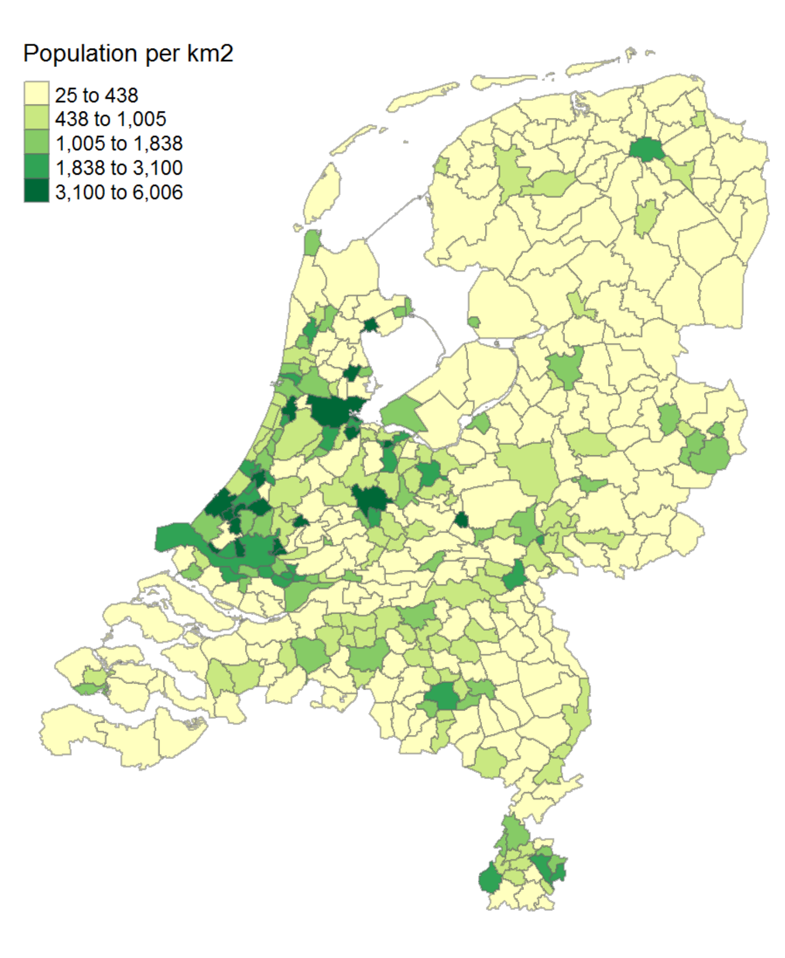


Building a thematic map

```
tm_shape(NLD_muni,
         projection="rd") +
```

```
tm_fill("population",
        convert2density=TRUE,
        style="kmeans",
        title="Population per km2") +
```

```
tm_borders(alpha=.5) +
```

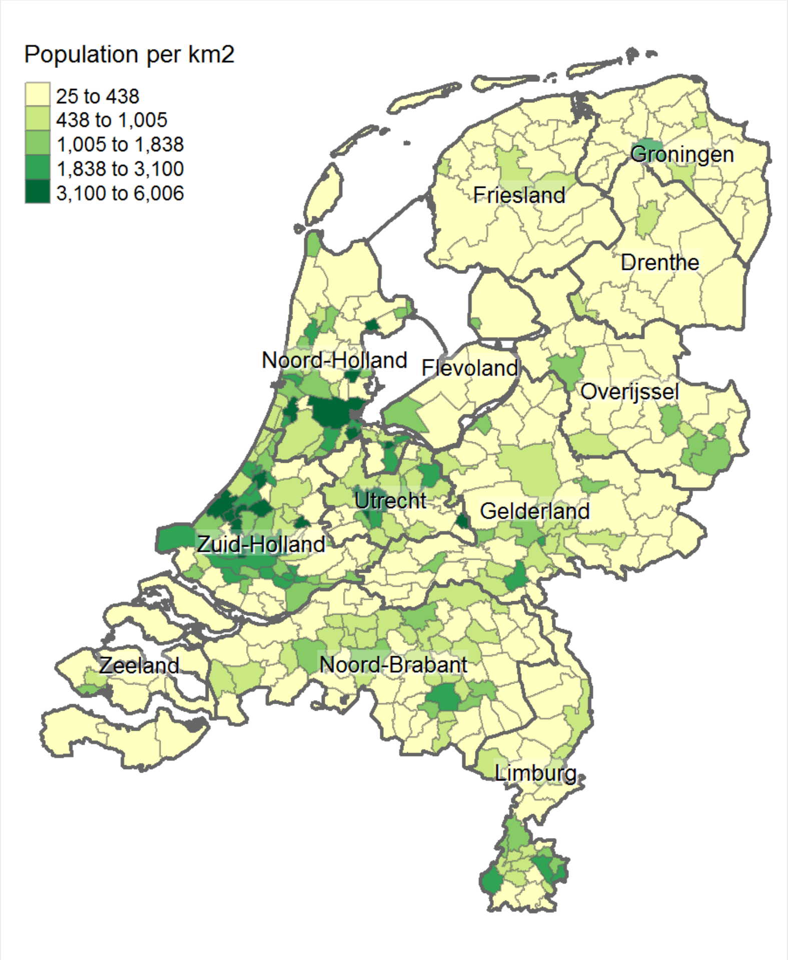


Building a thematic map

```
tm_shape(NLD_muni,
         projection="rd") +
```

```
tm_fill("population",
        convert2density=TRUE,
        style="kmeans",
        title="Population per km2") +
```

```
tm_borders(alpha=.5) +
```




```
tm_shape(NLD_prov) +
```

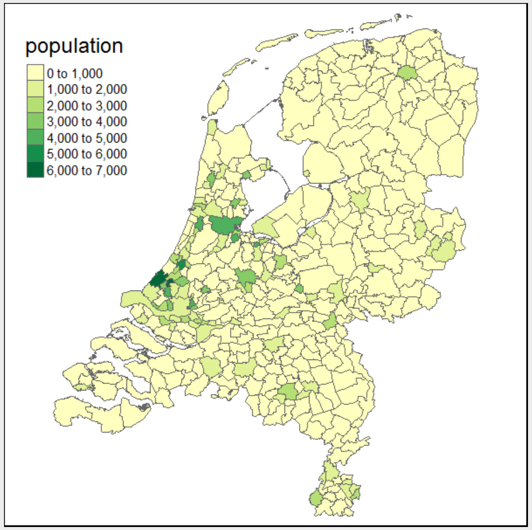
```
tm_borders(lwd=2) +
```

```
tm_text("name", size=.8, shadow=TRUE,
  bg.color="white", bg.alpha=.25)
```

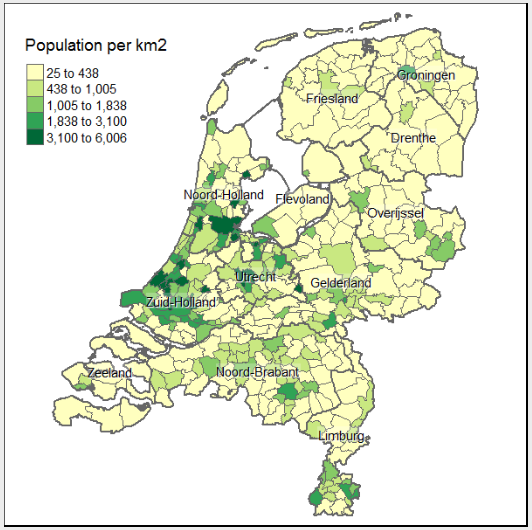
Quick thematic map

- Quick thematic map: qtm
- Wrapper for the main plotting method

```
qtm(NLD_muni)
```

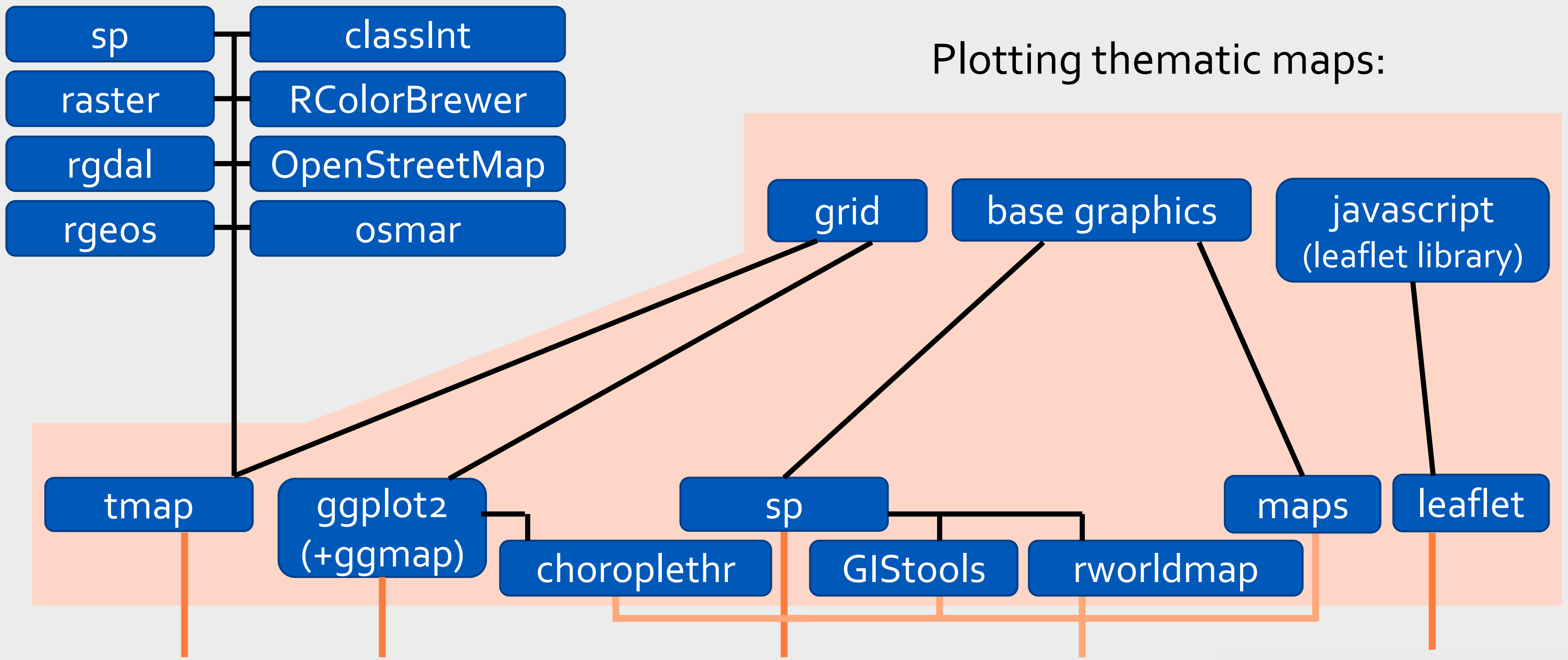



```
qtm(NLD_muni,
    fill="population",
    convert2density=TRUE)
```




```
qtm(NLD_muni,
  fill="population",
  convert2density=TRUE,
  fill.style="kmeans",
  fill.title="Population per km2") +
qtm(NLD_prov, fill=NULL,
  text="name", text.size=.7,
  borders.lwd=2,
  text.bg.color="white",
  text.bg.alpha=.25, shadow=TRUE)
```

tmap and the field



+ Easy to use
+ Flexible
+ Layer based
+ OSM
+ Small multiples
- New syntax
- Not interactive (yet)

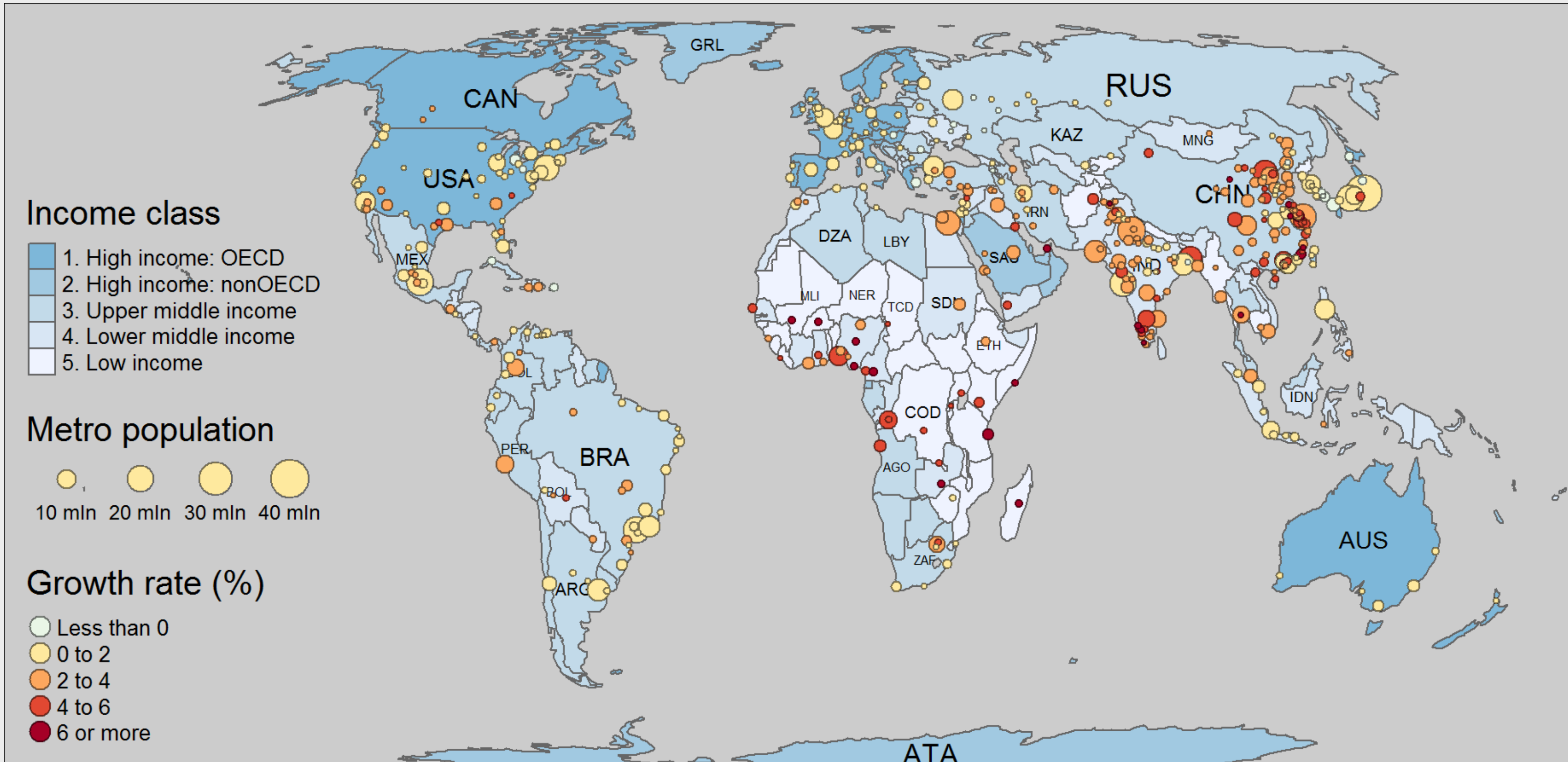
+ Grammar of graphics
+ Familiar syntax
- Processing required:
  - Shape to be fortified
  - Layout to be polished

+ Familiar syntax
- Do-it-yourself!

+ Less DIY work
- New syntax
- Limited possibilities

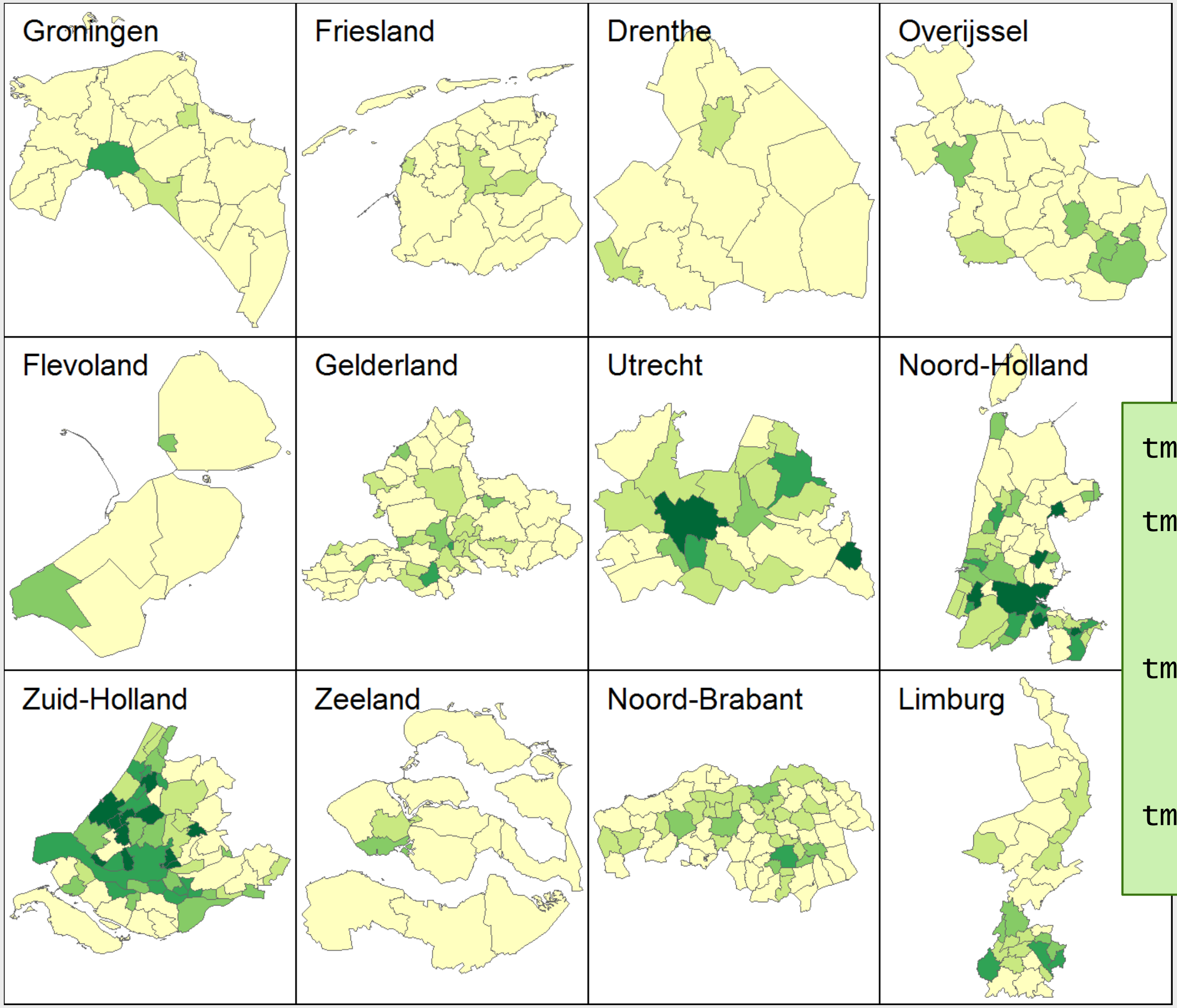
+ Interactive
+ Flexible
+ Layered based
+ OSM
- Small multiples
- New syntax
* Lower level (w.r.t. tmap)

Example: choropleth + bubble map




```
tm_shape(World) +
  tm_polygons("income_grp", palette="-Blues", contrast = .5,
    title="Income class",) +
  tm_text("iso_a3", size="AREA") +
tm_shape(metro) +
  tm_bubbles("pop2010", col = "growth",
    border.col = "black", border.alpha = .5, style="fixed",
    breaks=c(-Inf, 0, 2, 4, 6, Inf), palette="-RdYlBu",
    title.size="Metro population", title.col="Growth rate (%)") +
tm_layout_World(bg.color = "gray80")
```

Small multiples



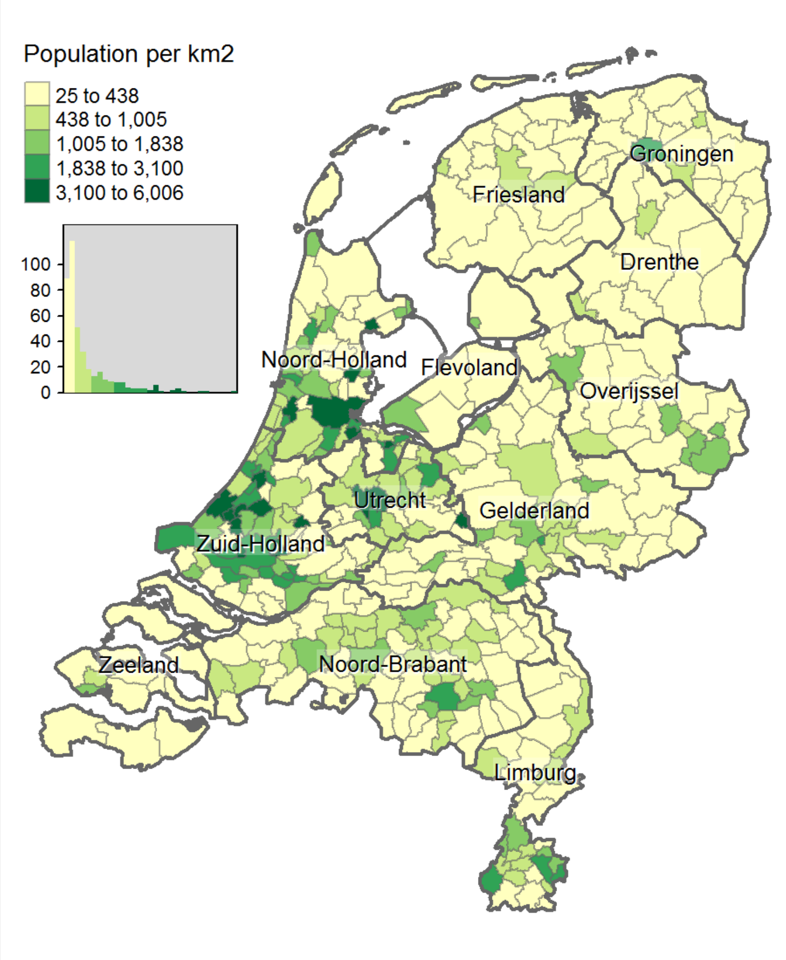

```
tm_shape(NLD_muni) +

tm_polygons("population",
  style="kmeans",
  convert2density = TRUE) +

tm_facets(by="province",
  free.coords=TRUE,
  drop.shapes=TRUE) +

tm_layout(legend.show = FALSE,
  outer.margins=0)
```

Histogram




```
tm_shape(NLD_muni, projection="rd") +
  tm_borders(alpha = .5) +
  tm_fill("population",
    convert2density = TRUE,
    style= "kmeans",
    title="Population per km2",
    legend.hist = TRUE) +
tm_shape(NLD_prov) +
  tm_borders(lwd=2) +
  tm_text("name", size=0.8,
    shadow=TRUE, bg.color="white",
    bg.alpha=.25) +
tm_layout(draw.frame=FALSE,
  bg.color="white",
  inner.margins=c(.02, .05, .02, .02),
  legend.hist.bg.color = "grey85")
```

Overall a great conference