Dealing with spatial data

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0. What is spatial data?

Geospatial data is any data that contain information about a specific location on the Earth's surface. Spatial data arise in a myriad of fields and applications, so there is also a myriad of spatial data types. Cressie (1993) provides a simple and useful classification of spatial data:

1. **Geostatistical data** (air temperature values in a country),
2. **Lattice data** (unemployment rate by states),
3. **Point patterns** (the location of fires in a region).

See Montero, Fernández-Avilés, & Mateu (2015), for more details.

In this work,we focus on geostatistical data.

What we need to run geostatistical data in R?

Some useful libraries we are going to use on this article:

```r
library(climaemet) # meteorological data
library(mapSpain) # base maps of Spain

library(classInt) # classification

library(raster) # raster handling
library(sf) # spatial shape handling
library(sp) # spatial shape handling
library(gstat) # for spatial interpolation
library(geoR) # for spatial analysis

library(dplyr) # data handling
library(ggplot2) # for plots
```

Where can we find geostatistical data?

In this paper, we are going to deal with geostatistical data, specifically we are going to model the level of air temperature in Spain on **14 August 2021**.

We are going to download the data with **climaemet** package in R. **climaemet** allows to download the climatic data of the Spanish Meteorological Agency (AEMET) directly using their API. On this article we would use **climaemet (>=1.0.0)** (version not released on CRAN yet at the time of writing this article), so it is needed to install the developing version.

You can install the developing version of **climaemet** using the r-universe:

```
# Enable this universe
options(repos = c(
  ropenspain = "https://ropenspain.r-universe.dev",
  CRAN = "https://cloud.r-project.org"
))

install.packages("climaemet")
```

Alternatively, you can install the developing version of **climaemet** with:

```
library(remotes)

install_github("ropenspain/climaemet")
```

API Key To be able to download data from AEMET you will need also a free API key which you can get here.

```
library(climaemet)

# Get api key from AEMET
browseURL("https://opendata.aemet.es/centrodedescargas/obtencionAPIKey")

# Use this function to register your API Key temporarly or permanently
aemet_api_key("<MY API KEY>")
```

1. How is the structure of geostatistical data?

Geostatistical data arise when the domain under study is a fixed set D that is continuous. That is: (i) $Z(s)$ can be observed at whichever point of the domain (continuous); and (ii) the points in D are non-stochastic (fixed, D is the same for all the realizations of the spatial random function).

First, take a look of the characteristics of the stations. We are interesting in **latitude** and **longitude** attributes.

```
stations <- aemet_stations()

# Have a look on the data
stations %>%
  dplyr::select(nombre, latitud, longitud) %>%
  head() %>%
  knitr::kable()
```

nombre	latitud	longitud
ARENYS DE MAR	41.58750	2.540000
BARCELONA AEROPUERTO	41.29278	2.070000
BARCELONA, FABRA	41.41833	2.124167
BARCELONA	41.39056	2.200000
MANRESA	41.72000	1.840278
SABADELL AEROPUERTO	41.52361	2.103056

Now we can start extracting the data. We select here the daily values on **14 August 2021**:

```r
# Select data
date_select <- "2021-08-14"

clim_data <- aemet_daily_clim(
  start = date_select,
  end = date_select,
  return_sf = TRUE
)
```

We can examine the possible variables that can be analyzed. We are interested in **maximum daily temperature** named `tmax`, although the API provides also other interesting information:

```r
names(clim_data)
#>  [1] "fecha"       "indicativo"  "nombre"      "provincia"   "altitud"
#>  [6] "tmed"        "prec"        "tmin"        "horatmin"    "tmax"
#> [11] "horatmax"    "dir"         "velmedia"    "racha"       "horaracha"
#> [16] "sol"         "presMax"     "horaPresMax" "presMin"     "horaPresMin"
#> [21] "geometry"
```

On this step, we select the variable of interest on each station. For simplicity we would remove the Canary Islands on this exercise:

```r
clim_data_clean <- clim_data %>%
  # Exclude Islands from analysis
  filter(!provincia %in% c(
    "LAS PALMAS",
    "STA. CRUZ DE TENERIFE"
  )) %>%
  dplyr::select(fecha, tmax) %>%
  # Exclude NAs
  filter(!is.na(tmax))

# Plot with outline of Spain
CCAA <- esp_get_ccaa(epsg = 4326) %>%
  # Exclude Canary Islands from analysis
  filter(ine.ccaa.name != "Canarias")

ggplot(CCAA) +
  geom_sf() +
  geom_sf(data = clim_data_clean) +
  theme_light()
```

Let's plot now the values as a choropleth map:

```r
# This would be common to all the paper
br_paper <- c(-Inf, seq(15, 45, 5), Inf)
pal_paper <- hcl.colors(15, "PuOr", rev = TRUE)

ggplot(clim_data_clean) +
```

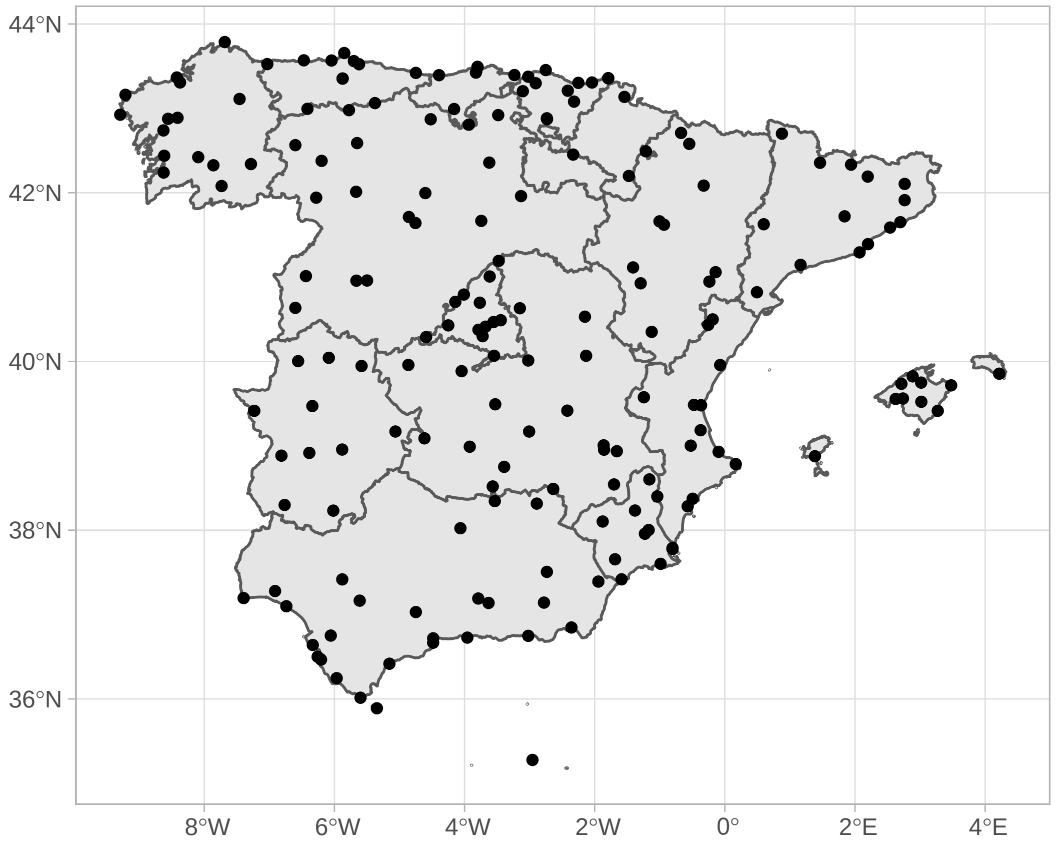


Figure 1: AEMET Stations (excl. Canary Islands)

```
geom_sf(
  data = CCAA,
  fill = "grey95"
) +
geom_sf(aes(fill = tmax),
  shape = 21,
  size = 6,
  alpha = .7
) +
labs(fill = "Max. temp") +
scale_fill_gradientn(
  colours = pal_paper,
  breaks = br_paper,
  labels = function(x) {
    paste0(x, "º")
  },
  guide = "legend"
) +
theme_light()
```

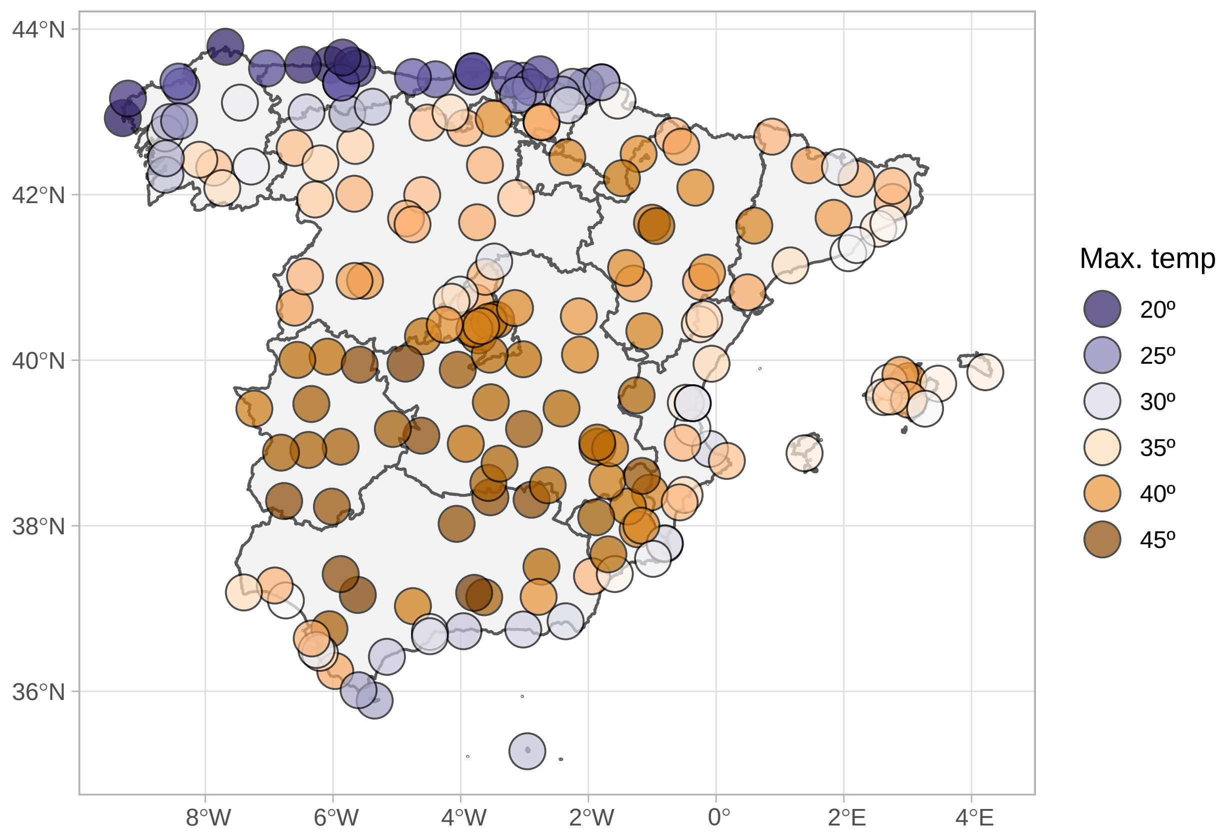


Figure 2: Max. temperature 14 Aug. 2021

2. Are independent the observations or they exhibit spatial dependence?

Everything is related to everything else. But near things are more related than distant things (Tobler, 1969).

In our study, we can observe positive spatial dependence: high values of temperature are all together in the south of Spain and low temperatures are also together in the north of Spain.

```
clim_data_clean %>%
  st_drop_geometry() %>%
  select(tmax) %>%
  summarise_all(
    funs(min, max, median, sd,
      n = n(),
      q25 = quantile(., .25),
      q75 = quantile(., .75)
    )
  ) %>%
  knitr::kable()
```

min	max	median	sd	n	q25	q75
19.2	46	37.6	7.112821	195	30.85	41.55

On the next plot we divide the maximum temperature into quartiles to visualize the spatial distribution of values:

```
bubble <- clim_data_clean %>%
  arrange(desc(tmax))

# Create quartiles
cuart <- classIntervals(bubble$tmax, n = 4)
bubble$quart <- cut(bubble$tmax,
  breaks = cuart$brks,
  labels = FALSE
)

ggplot(bubble) +
  geom_sf(
    aes(
      size = quart,
      fill = quart
    ),
    col = "grey20",
    alpha = 0.7,
    shape = 21
  ) +
  scale_size(
    range = c(2, 8),
    labels = function(x) paste0("Q", x),
    guide = guide_legend()
  ) +
  scale_fill_gradientn(
    colours = pal_paper,
    labels = function(x) paste0("Q", x)
  ) +
  guides(fill = guide_legend(title = "")) +
  labs(
    size = ""
  ) +
  theme_light()
```

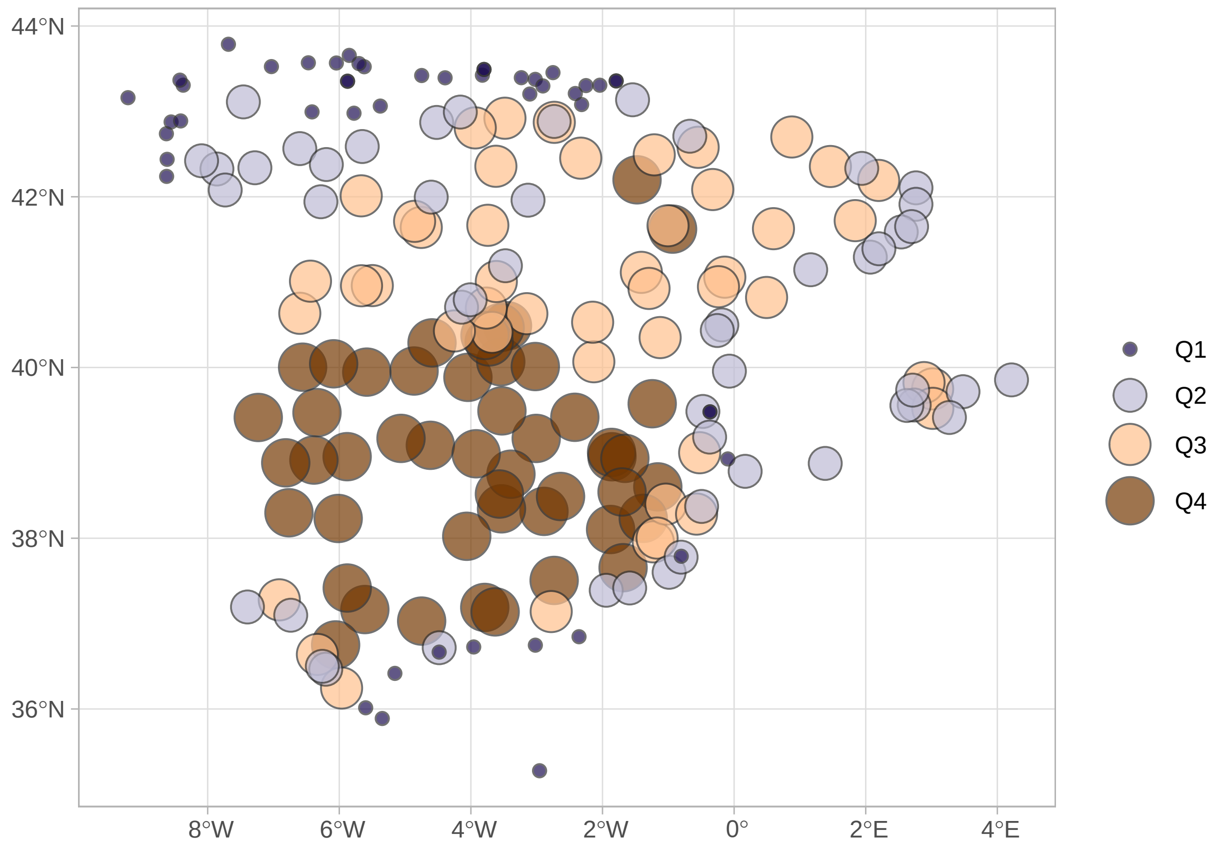


Figure 3: Max. temperature - Quartiles

3. Prepare the data as spatial object

An important thing to consider in any spatial analysis or visualization is the coordinate reference system (CRS). On this exercise, we choose to project our objects to ETRS89 / UTM zone 30N EPSG:25830, that provides projected x and y values on meters and maximizes the accuracy for Spain.

```
clim_data_utm <- st_transform(clim_data_clean, 25830)

CCAA_utm <- st_transform(CCAA, 25830)
```

Create a grid for the spatial prediction

As we need to predict values at locations where no measurements have been made, we need to create a grid of locations and perform an interpolation.

This grid is composed to equally spaced points over the whole extent (bounding box) of Spain. Most of the squares does not have any station, hence no observation is available. However, we would use the values of the cells that encloses any station for interpolating the data.

```r
# Create grid 5*5 km (25 km2)

grd_sf <- st_as_sfc(
  st_bbox(CCAA_utm)
) %>%
  st_make_grid(
    cellsize = 5000,
    what = "centers"
  )

# Convert to sp object - interpolation should be made with sp/raster
grd <- as(grd_sf, "Spatial") %>%
  as("SpatialPixels")
```

There are some additional steps we must perform in order to prepare our data for spatial interpolation. We ensure

```r
# Prepare the data. Change to sp for this analysis
clim_data_clean_sp <- as(clim_data_utm, "Spatial")

# Remove duplicate locations
zd <- zerodist(clim_data_clean_sp)

# Remove the duplicate rows and back to sf
clim_data_clean_nodup_sp <- clim_data_clean_sp[-zd[, 2], ]

clim_data_clean_nodup <- st_as_sf(clim_data_clean_nodup_sp)
```

4. Exploratory Spatial Data Analysis

Look the histogram, the data set is Gaussian!! Note that kriging is BLUP.

```r
ggplot(
  clim_data_clean_nodup,
  aes(x = tmax)
) +
  geom_histogram(
    aes(fill = cut(tmax, 15)),
    binwidth = 1,
    show.legend = FALSE
  ) +
  scale_fill_manual(values = pal_paper) +
  labs(
    y = "n obs.",
    x = "Max. temp (º)"
  ) +
  theme_light()
```

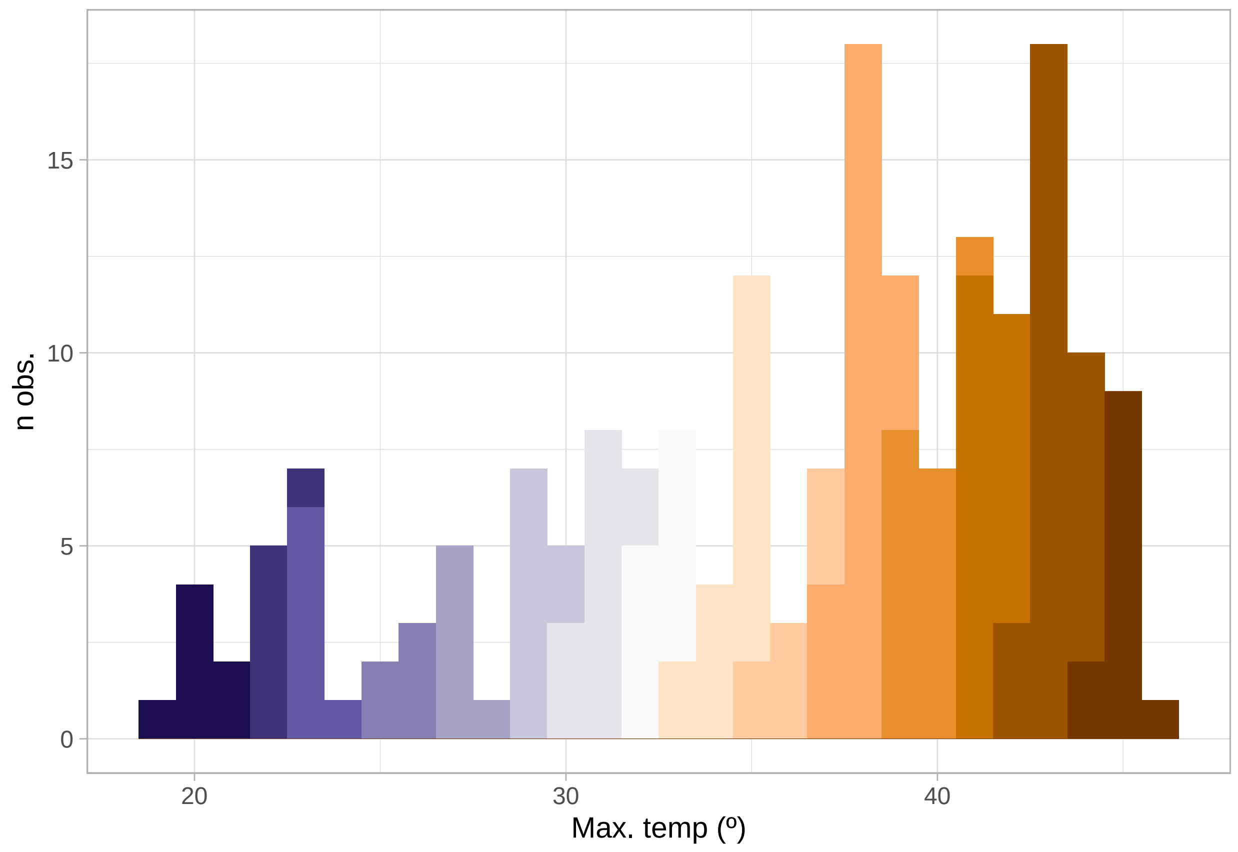


Figure 4: Max. temperature - Histogram

DIEGO: QUITARÍAMOS IDW O LO DEJAMOS PARA COMPARAR…?

LO HE METIDO MAS ADELANTE

5. Kriging Ordinary

GEMA, AQUI YO PONDRIA MAS CHICHA…

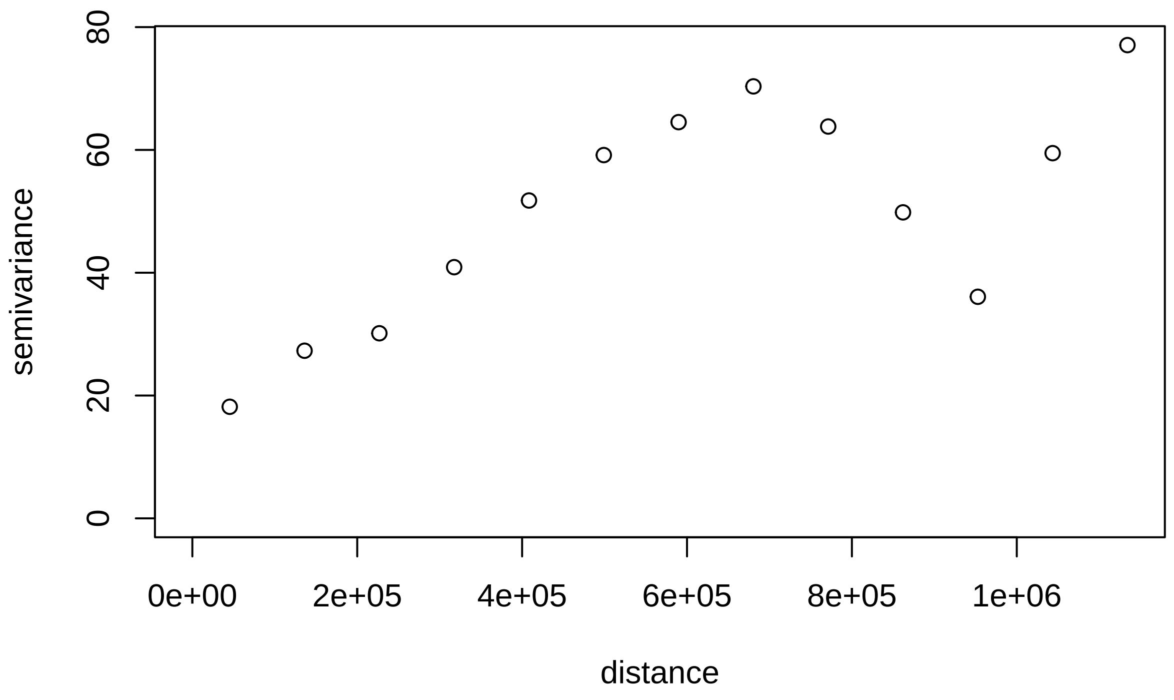
Prepare the geospatial object with geoR package

```
library(geoR)

mydata.geo <- clim_data_clean_nodup %>%
  st_coordinates() %>%
  as.data.frame() %>%
  mutate(
    lon = X,
    lat = Y
  ) %>%
  select(-X, -Y) %>%
  bind_cols(tmax = clim_data_clean_nodup$tmax)

mydata <- as.geodata(
  obj = mydata.geo,
  coords.col = 1:2,
  data.col = 3
)
```

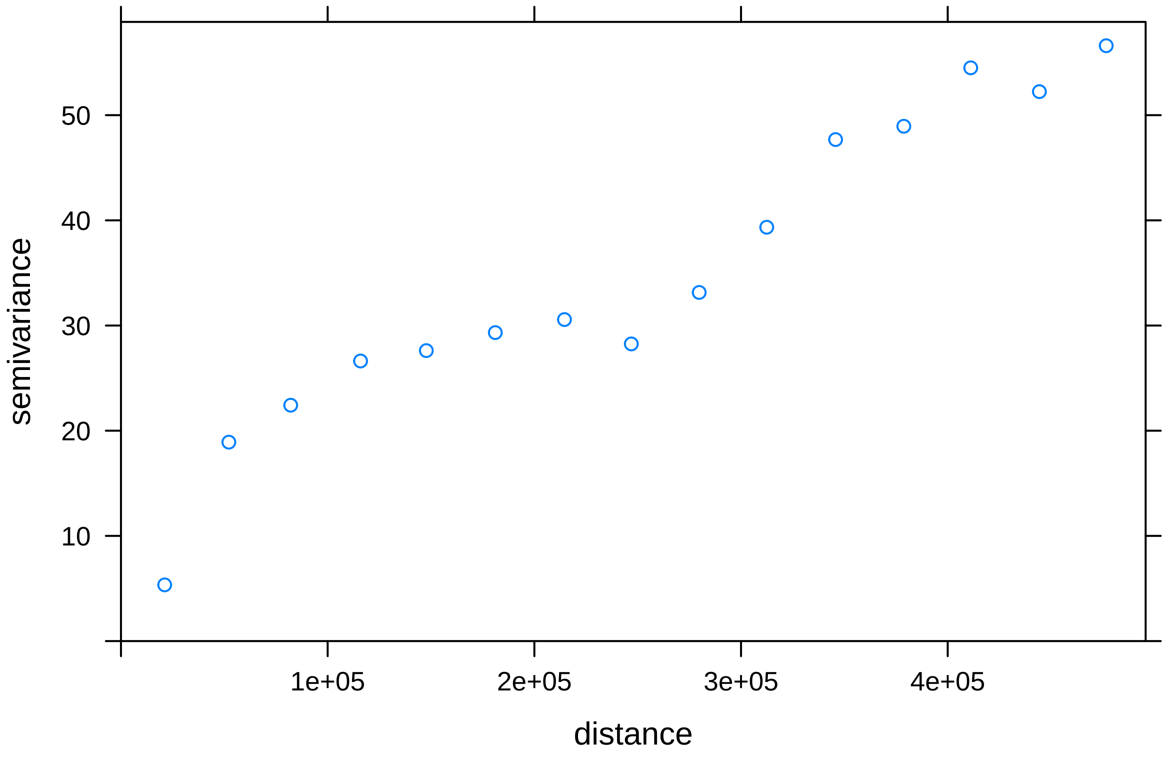
The semivariogram function require a more depth study. Now, we show two different functions to fit the empirical semivariogram to a theoretical semivariogram.

GEMA, CAMBIÉ El DIA, PUEDES REVISAR LOS PARAMETROS? NO ME SALE...

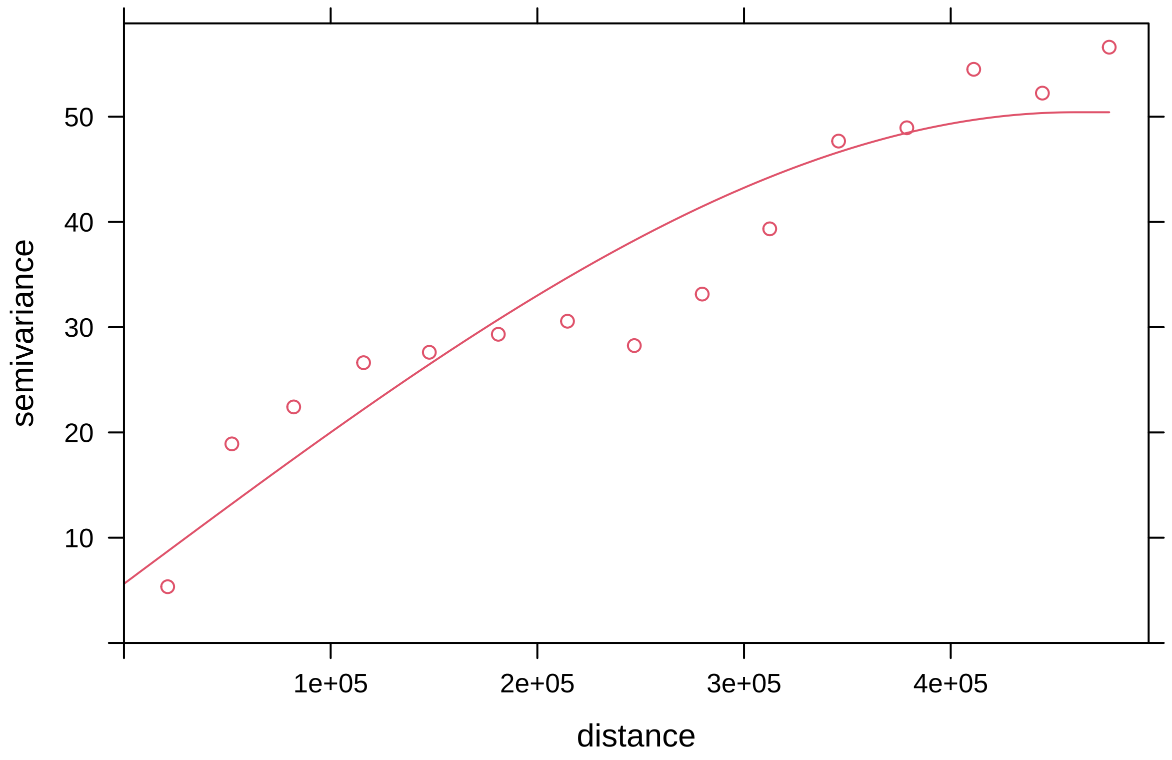
```
vario.b <- variog(mydata, coords = mydata$coords, data = mydata$data)
#> variog: computing omnidirectional variogram
plot(vario.b)
```



```
# eyefit() is an interactive function to play with the types and parameters of semivariogram.
# eyefit(vario.b)
#  cov.model sigmasq       phi tausq kappa kappa2 practicalRange
# spherical   30 826374.98 22.43  <NA>   <NA>     826374.98

# Fit the semivariogram by eye in gstat()
vgm <- variogram(tmax ~ 1, clim_data_clean_nodup_sp)
plot(vgm)
```



```
fit.var <- fit.variogram(vgm, model = vgm(0, "Sph", 826374.98, 30))

# Plot empirical (dots) and theoretical semivariograms (line)
plot(vgm, fit.var, col = 2)
```



6. Compute ordinary kriging and plot the results

There are different kinds of kriging depend on the characteristics of the spatial process: simple, ordinary or universal kriging (external drift kriging), kriging in a local neighborhood, point kriging or kriging of block mean values and conditional (Gaussian or indicator) simulation equivalents for all kriging varieties.

In this work we deal with ordinary kriging, the most widely used kriging method. It serves to estimate a value at a point of a region for which a variogram is known, using data in the neighborhood of the estimation location.

```
kriged <- krige(tmax ~ 1,
  clim_data_clean_nodup_sp,
  grd,
  model = fit.var
)
#> [using ordinary kriging]
```

We now plot the results to see a representation of the results:

```

kriged_df <- as.data.frame(kriged, xy = TRUE, na.rm = TRUE)

ggplot() +
  geom_tile(
    data = kriged_df,
    aes(
      x = coords.x1,
      y = coords.x2,
      fill = var1.pred
    )
  ) +
  geom_sf(
    data = CCAA_utm,
    col = "black",
    fill = NA
  ) +
  scale_fill_gradientn(
    colours = pal_paper,
    breaks = br_paper,
    labels = function(x) {
      paste0(x, "º")
    },
    guide = guide_legend(
      reverse = TRUE,
      title = "Max. temp\n(kriged)"
    )
  ) +
  theme_light() +
  theme(
    panel.background = element_blank(),
    panel.grid = element_blank(),
    panel.border = element_blank(),
    axis.title = element_blank()
  )
```

By last, we plot the variance of the estimation:

```
ggplot() +
  geom_tile(
    data = kriged_df,
    aes(
      x = coords.x1,
      y = coords.x2,
      fill = var1.var
    )
  ) +
  geom_sf(
    data = CCAA_utm,
    col = "black",
    fill = NA
  ) +
  geom_sf(
    data = clim_data_clean_nodup,
    col = "black",
    shape = 1
  ) +
  scale_fill_gradientn(
```

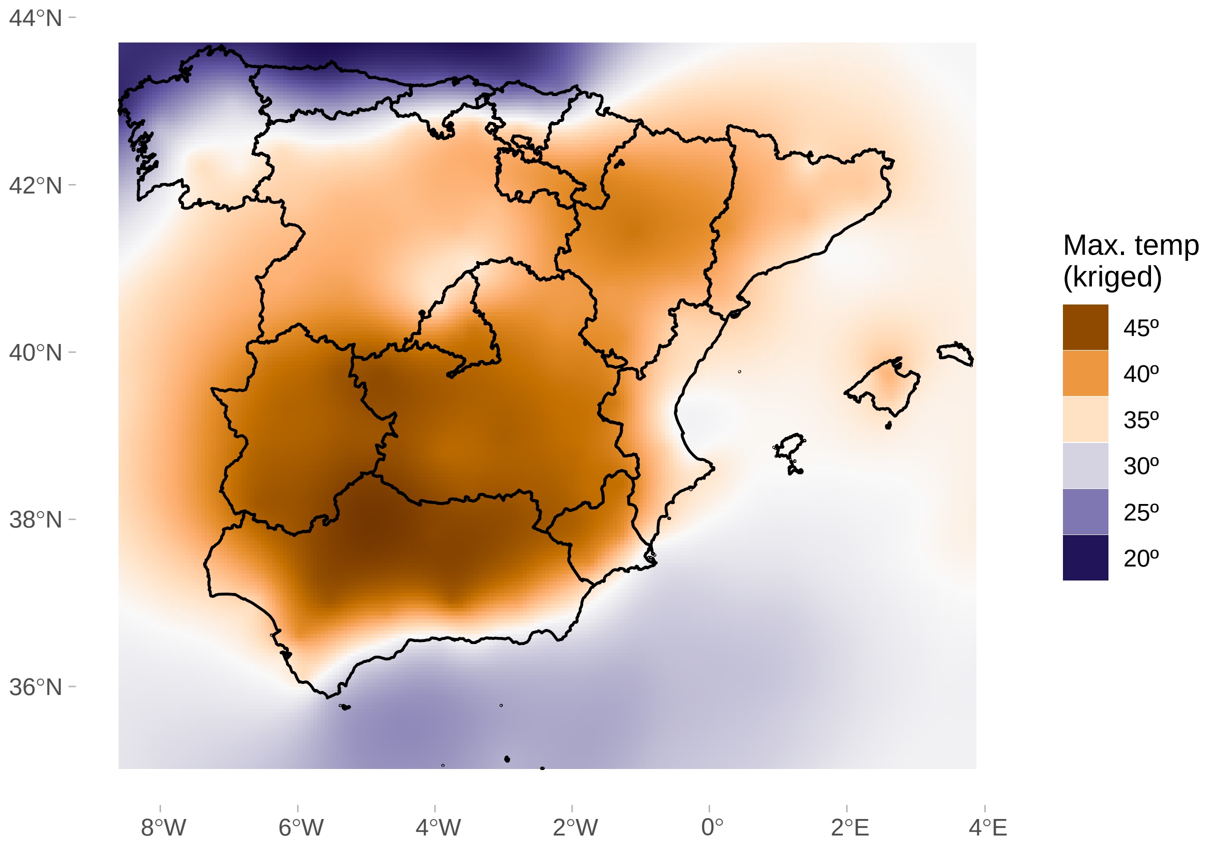


Figure 5: Ordinary Kriging - Results

```
    # Special palette
    colours = c(
      "green4", "white",
      hcl.colors(10, "PuRd",
        alpha = .7,
        rev = TRUE
      )
    ),
    breaks = c(-Inf, 6, 10, 15, 20, 30, Inf),
    guide = guide_legend(
      reverse = TRUE,
      title = "Variance"
    )
  ) +
  theme_light() +
  theme(
    panel.background = element_blank(),
    panel.grid = element_blank(),
    panel.border = element_blank(),
    axis.title = element_blank()
  )
```

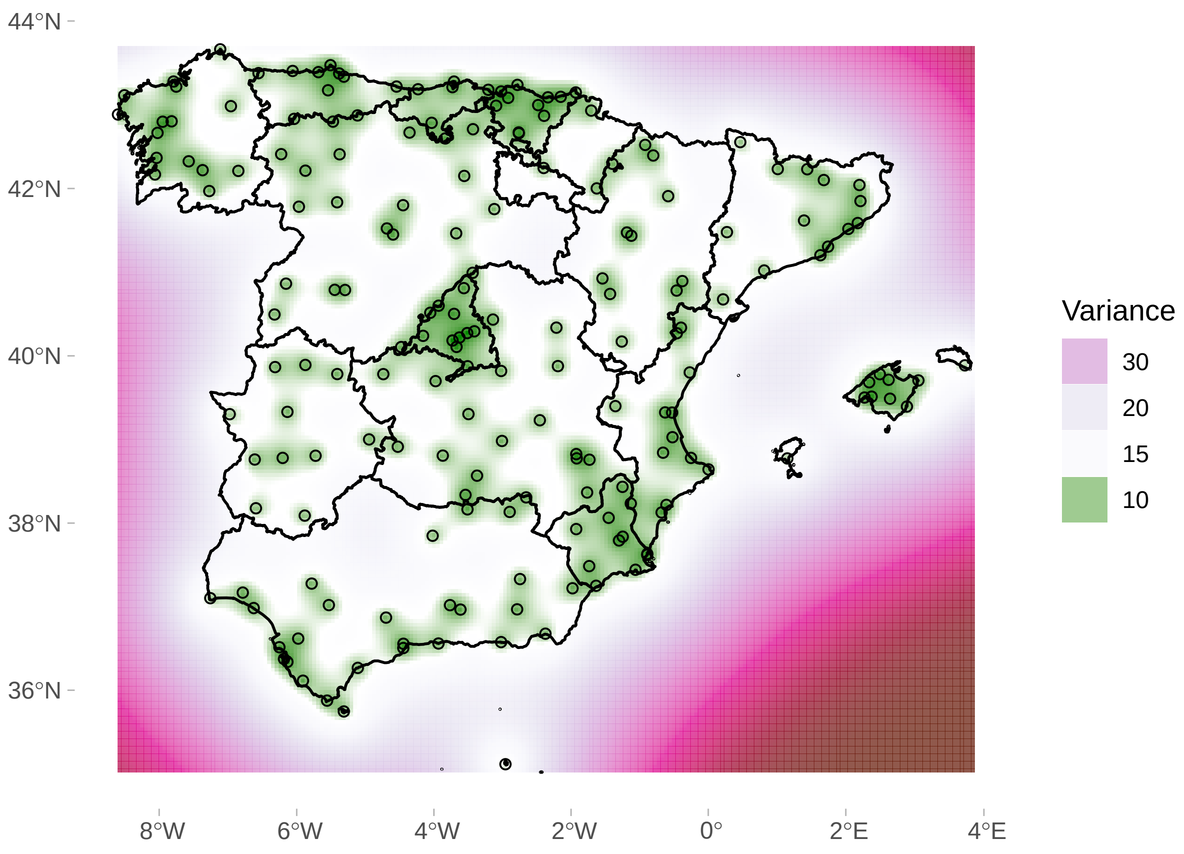


Figure 6: Ordinary Kriging - Variance

7. Kriging versus IDW (GEMA)

On this section we would compare kriging vs. the Inverse Distance Weighted (**IDW**) method, that is one of several approaches to perform spatial interpolation. We recommend this article on how to perform these analysis on **R**.

```
idw <- idw(tmax ~ 1,
  clim_data_clean_nodup_sp,
  newdata = grd,
  idp = 2.0
)
#> [inverse distance weighted interpolation]

idw_df <- as.data.frame(idw, xy = TRUE, na.rm = TRUE)

# Prepare for facetting

idw_facet <- idw_df %>%
  mutate(method = "IDW")

all_methods <- kriged_df %>%
  mutate(method = "Kriging") %>%
  bind_rows(idw_facet)

# Reorder for facets
all_methods$method <- factor(all_methods$method, levels = c("Kriging", "IDW"))

# Plot and compare
ggplot(all_methods) +
  geom_tile(
    aes(
      x = coords.x1,
      y = coords.x2,
      fill = var1.pred
    )
  ) +
  facet_wrap(vars(method),
    ncol = 2
  ) +
  geom_sf(
    data = CCAA_utm,
    col = "black",
    fill = NA
  ) +
  scale_fill_gradientn(
    colours = pal_paper,
    breaks = br_paper,
    labels = function(x) {
      paste0(x, "º")
    },
    guide = guide_legend(
      title = "Max. temp",
      direction = "horizontal",
      keyheight = 0.5,
      keywidth = 2.5,
      title.position = "top",
      title.hjust = 0.5,
      label.hjust = .5,
      nrow = 1,
      byrow = TRUE,
      reverse = FALSE,
      label.position = "bottom"
    )
  ) +
  theme_void() +
  theme(
    legend.text = element_text(
      size = 10
    ),
    legend.title = element_text(
      size = 11
    ),
    legend.position = "bottom"
  )
```

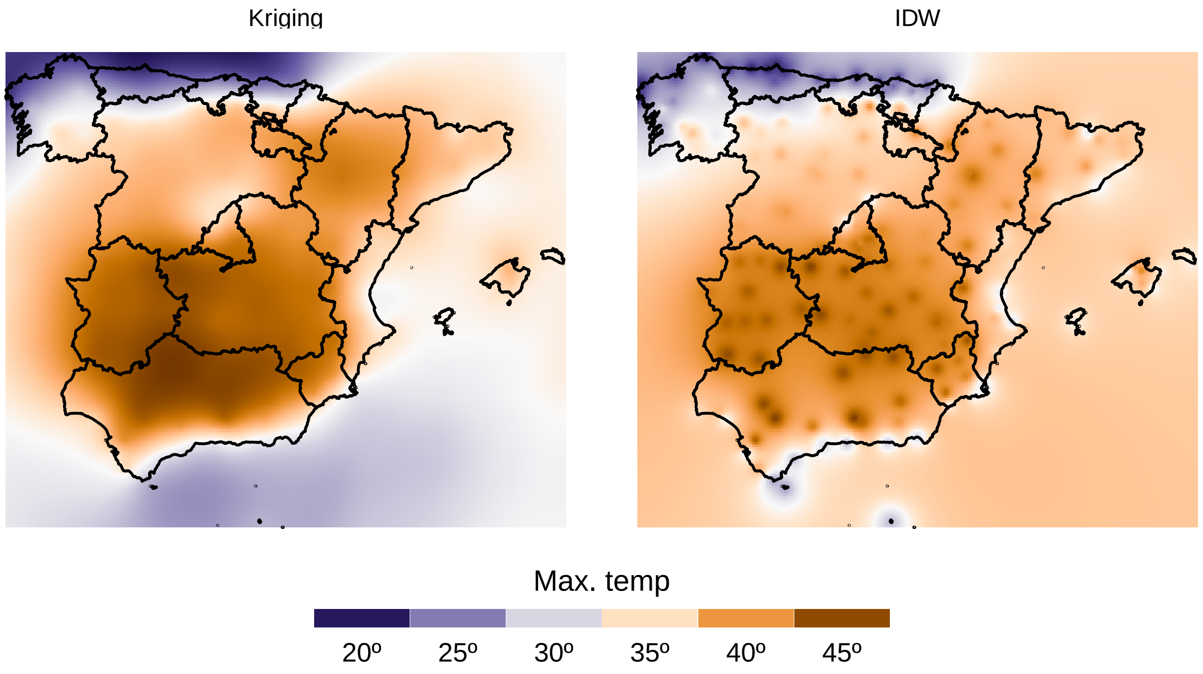


Figure 7: Comparison of kriging vs. IDW

References

Cressie, N. A. C. (1993). *Statistics for spatial data*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119115151

Montero, J., Fernández-Avilés, G., & Mateu, J. (2015). *Spatial and spatio-temporal geostatistical modeling and kriging*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118762387

Tobler, W. R. (1969). Geographical filters and their inverses. *Geographical Analysis*, *1*(3), 234–253. https://doi.org/10.1111/j.1538-4632.1969.tb00621.x