```r
unique(dat$sp)
```

```
[1] "spruce"                 "pine"                   "deciduous trees"
[4] "coniferous trees"       "beech"                  "all species"
[7] "other coniferous trees" "oak"                    "other deciduous trees"
```

1.2 Germany and German states

An outline for Germany and its states is saved here:

1.3 Climate data

Some climate data (not yet completed) are available from here:

2 Getting started

In this session I aim to give you a general introduction to the course and how we developed it, some technical aspects about how we organize the course using git and gitHub. Then we will have a closer look at how to deal with spatial data in R.

Learing objectives after this session you should know

- how to use RStudio project.
- how to clone a git repository and update it.
- some familiarity with the packages `sf` and `terra` in R.

> **Preparation before the session**
>
> Please make sure you do the following the before the session:
>
> 1. Make sure R, RStudio and git is installed on your laptop.
> 2. *Optionally create an account at GitHub*
> 3. Read: Chapters 2.2 - 2.4 and 4 from Geocomputation with R https://r.geocompx.org/.
> 4. Read the basic idea of git and gitHub https://swcarpentry.github.io/git-novice/01-basics.html.

2.1 RStudio Projects

Wrong paths often lead to unnecessary problems. An easy way to avoid problems with a wrong path is to use **RStudio projects**.

To create a project:

1. Press the button shown in 1) or go to `File > New Project ...`.
2. Select `New directory` and then choose `New Project`.
3. Enter the name of the project (as shown in 4)) and the choose where on your computer you want to the place the project. A new folder with the project name will be created. If you want to create a project for this course (which I would encourage you to do), then you want to place this probably inside a folder where you have all your university courses organized.

4. Finally, press on `Create Project`.

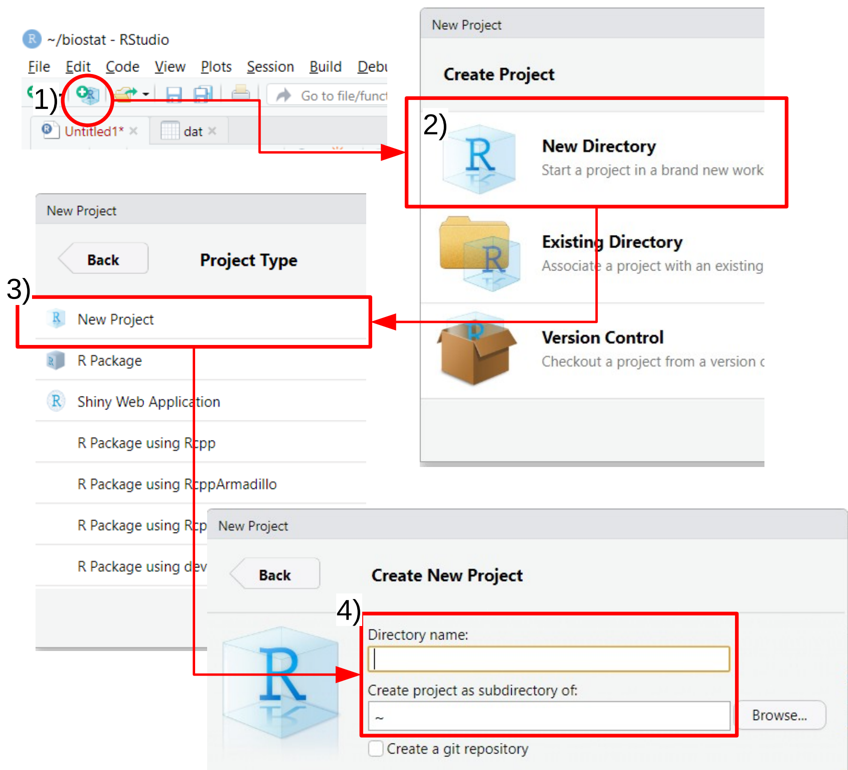


Figure 2.1: Worklfow to create a new RStudio project.

- A nice read: https://www.tidyverse.org/articles/2017/12/workflow-vs-script/
- A project has the advantage, that all paths are set with reference to the project location.
- It is a good idea, to have a directory for data in each project.

Once you created a project, there are three ways to open it:

- Double click on the project icon in the directory:

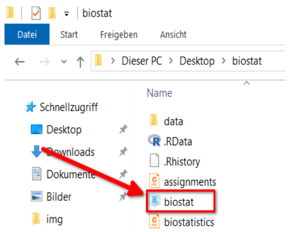


Figure 2.2: How to open an RStudio project.

Alternatively, it is possible to choose `File > Open Project` in RStudio or to select the name of a recent project on the top right in RStudio.

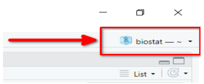


Figure 2.3: Selecting the name of a recent project.

> **Exercise 1: RStudio**
>
> 1. Create an RStudio Project for this course or clone everything from GitHub.
> 2. Make sure project clones into this directory.
> 3. Read the data set `data/dbh_1.csv`, using only **relative** paths.

3 Spatial Data

3.1 Working with vector data

- Spatial data are omnipresent.
- Basically spatial data are regular data with coordinates (so we can reference data points in space).

3.1.1 What is a GIS

> A geographic information system (GIS) is a system designed to capture, store, manipulate, analyze, manage, and present all types of spatial or geographical data (wikipedia).

3.1.2 Components of spatial data

1. Geometries
2. Attributes data

The OGC (open geospatial consortium) simple feature (SF) specification defines the following building blocks:

- Points (e.g., location of a tree),
- Lines (e.g., a road),
- Polygons (e.g., a lake).

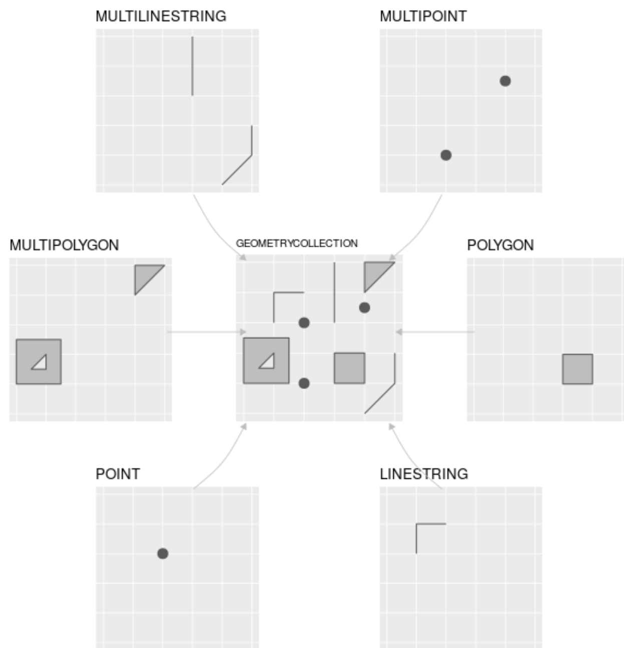


Figure 3.1: From Lovelace et al. 2021

3.1.3 Attribute data

Table with measured quantities of each subject (we often use the term *feature* in GIS).

E.g., if we were to describe the largest cities of the EU, we would obtain an attribute table like this:

Rank	City	State	Official population	Date of census/estimate	References	Image
1	London[2]	United Kingdom	8,615,246	1 June 2014	[3]	
2	Berlin	Germany	3,517,424	30 December 2013	[4]	
3	Madrid	Spain	3,165,235	1 January 2014	[5]	

Figure 3.2: Wikipedia

This data do not tell us anything of the geometries.

3.1.4 What is so special about spatial data

- Normal data with coordinates with reference to some known fixed location:

- The earth
- A country (e.g., with reference to the capital)
- A building (e.g., room map)

We often work with spatial data, that can be attributed to a unique location on the earth surface.

3.1.5 The earth is complicated

Figure 3.3: Source www.icsm.gov.au

We can start with a **Geoid**, that is the hypothetical surface of the oceans if there was no land and only gravitational forces.

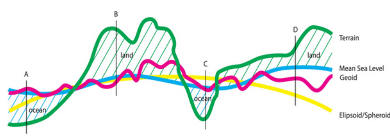


Figure 3.4: Source www.icsm.gov.au

3.1.6 Ellepsoid (= spheroid) and Datum

A geometrical approximation of the geoid, that is used to describe the sphere of the earth (we often use WGS84).

This is generally referred to as a *Datum*.

3.1.7 What is a projection

A datum is used to reference a location on an ellipsoid with:

- longitude
- latitude
- altitude

To *project* a sphere from 3D to 2D we need a set of mathematical rules, these are known as *projections*.

- The coordinate reference system (CRS) of spatial data can be referred to with a EPSG code.
- See here for a list of EPSG codes: epsg.io

3.2 Vector data in R

- Traditionally the `sp` package provided classes to work with spatial data.
- The `sp` package is replaced by the `sf` package.
- We will be using the `sf` package most of the time.

We can create simple features with `st_point()`, `st_linestring()` and `st_polygon()`. This creates a simple feature geometry (`sfg`-Object)

```
library(sf)
p1 <- st_point(c(9.23, 52.3))
p1
```

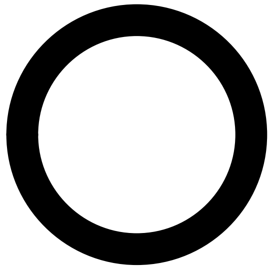
```
POINT (9.23 52.3)
```

```
l1 <- st_linestring(cbind(1:10, c(1:3, 3:1, 1:4)))
l1
```

```
LINESTRING (1 1, 2 2, 3 3, 4 3, 5 2, 6 1, 7 1, 8 2, 9 3, 10 4)
```

```
po1 <- st_polygon(list(cbind(c(1, 2, 3, 4, 1),
                             c(0, 10, 10, 0, 0))))
```

```
plot(p1)
```



Lets define the position of three trees

```
t1 <- st_point(c(103, 83))
t2 <- st_point(c(33, 73))
t3 <- st_point(c(103, 130))

t1
```

```
POINT (103 83)
```

```
t2
```

```
POINT (33 73)
```

```
t3
```

```
POINT (103 130)
```

We can now take these three trees and create a simple feature column (`sfc`-object in R) with the function `st_sfc`.

```
c1 <- st_sfc(t1, t2, t3)
c1
```

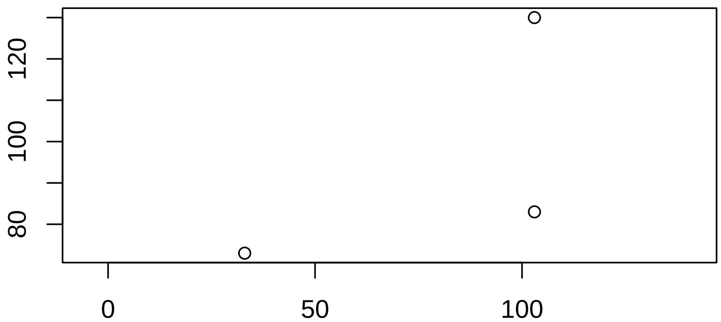
```
Geometry set for 3 features
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 33 ymin: 73 xmax: 103 ymax: 130
CRS:           NA
```

```
POINT (103 83)
```

```
POINT (33 73)
```

```
POINT (103 130)
```

```r
plot(c1, axes = TRUE)
```



Finally, we can combine the geometry with attribute data. So far we only focused on the geometries.

```r
a1 <- data.frame(
  z = c(150, 110, 167),
  sp = c("oak", "beech", "oak")
)
a1
```

```
    z    sp
1 150   oak
2 110 beech
3 167   oak
```

To do this, we call the function `st_sf()`.

```r
sf1 <- st_sf(a1, geometry = c1)
sf1
```

```
Simple feature collection with 3 features and 2 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 33 ymin: 73 xmax: 103 ymax: 130
CRS:           NA
    z    sp        geometry
```

```
1 150   oak  POINT (103 83)
2 110 beech   POINT (33 73)
3 167   oak POINT (103 130)
```

The data.frame `sf1` behaves like any other data.frame.

```r
sf1[1, ]
```

```
Simple feature collection with 1 feature and 2 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 103 ymin: 83 xmax: 103 ymax: 83
CRS:           NA
    z  sp       geometry
1 150 oak POINT (103 83)
```

```r
sf1 |> filter(sp == "oak")
```

```
Simple feature collection with 2 features and 2 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 103 ymin: 83 xmax: 103 ymax: 130
CRS:           NA
    z  sp        geometry
1 150 oak  POINT (103 83)
2 167 oak POINT (103 130)
```

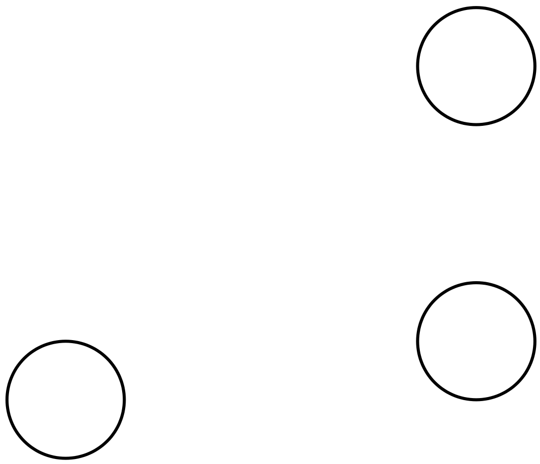
Now we can work with the spatial data, and for example add a buffer

```r
st_buffer(sf1, dist = 10)
```

```
Simple feature collection with 3 features and 2 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 23 ymin: 63 xmax: 113 ymax: 140
CRS:           NA
    z    sp                       geometry
1 150   oak POLYGON ((113 83, 112.9863 ...
2 110 beech POLYGON ((43 73, 42.9863 72...
3 167   oak POLYGON ((113 130, 112.9863...
```

`sf` is compliant with the `tidyverse` philosophy

```r
sf1 <- sf1 |> mutate(buffer = st_buffer(geometry, dist = 10))
plot(sf1$buffer)
```



3.2.1 Creating spatial points from a data frame

Of course there is an easier way to create `st_points` from a `data_frame`

```r
sta <- read.csv(here::here("data/weather/feb2015.csv"))
head(sta, 2)
```

```
  X id Feb1 Feb2 Feb3 Feb4 Feb5 Feb6 Feb7 Feb8 Feb9 Feb10 Feb11 Feb12 Feb13
1 1 44  0.4  0.6  0.2 -1.5 -1.4 -1.7  0.6  3.4  5.5   5.4   3.8   1.6   2.4
2 2 71 -2.0 -2.7 -6.8 -6.1 -4.9 -4.9 -6.2 -4.3 -3.0  -0.4  -1.9  -2.2  -0.3
  Feb14 Feb15 Feb16 Feb17 Feb18 Feb19 Feb20 Feb21 Feb22 Feb23 Feb24 Feb25 Feb26
1   4.1   1.7   1.4   0.7   1.6   2.1   3.9   3.8   2.2   3.6   4.1   4.0   6.2
2   1.0  -2.6  -2.2  -3.6  -2.9  -0.7   2.5   1.7  -0.4   0.3   1.0   0.6   0.0
  Feb27 Feb28    lon     lat
1   4.9   3.3 8.2370 52.9335
2   0.5   0.1 8.9784 48.2155
```

```r
sta <- st_as_sf(sta, coords = c("lon", "lat"))
head(sta, 2)
```

```
Simple feature collection with 2 features and 30 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 8.237 ymin: 48.2155 xmax: 8.9784 ymax: 52.9335
CRS:           NA
  X id Feb1 Feb2 Feb3 Feb4 Feb5 Feb6 Feb7 Feb8 Feb9 Feb10 Feb11 Feb12 Feb13
1 1 44  0.4  0.6  0.2 -1.5 -1.4 -1.7  0.6  3.4  5.5   5.4   3.8   1.6   2.4
2 2 71 -2.0 -2.7 -6.8 -6.1 -4.9 -4.9 -6.2 -4.3 -3.0  -0.4  -1.9  -2.2  -0.3
  Feb14 Feb15 Feb16 Feb17 Feb18 Feb19 Feb20 Feb21 Feb22 Feb23 Feb24 Feb25 Feb26
1   4.1   1.7   1.4   0.7   1.6   2.1   3.9   3.8   2.2   3.6   4.1   4.0   6.2
2   1.0  -2.6  -2.2  -3.6  -2.9  -0.7   2.5   1.7  -0.4   0.3   1.0   0.6   0.0
  Feb27 Feb28               geometry
1   4.9   3.3  POINT (8.237 52.9335)
2   0.5   0.1 POINT (8.9784 48.2155)
```

3.2.2 IO of spatial data

Often we want to read and write vector data from existing file:

```r
ger <- st_read(here::here("data/ger/ger_states_3035.shp"))
```

```
Reading layer `ger_states_3035' from data source
  `/Users/jsigner/ownCloud - jsigner@uni-goettingen.de@owncloud.gwdg.de/Documents/L_Lehre/M_a
  using driver `ESRI Shapefile'
Simple feature collection with 16 features and 1 field
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 4031295 ymin: 2684102 xmax: 4672253 ymax: 3551343
Projected CRS: Lambert_Azimuthal_Equal_Area
```

```r
ger
```

```
Simple feature collection with 16 features and 1 field
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 4031295 ymin: 2684102 xmax: 4672253 ymax: 3551343
Projected CRS: Lambert_Azimuthal_Equal_Area
First 10 features:
                  state                       geometry
1               Hamburg MULTIPOLYGON (((4333619 340...
2         Niedersachsen MULTIPOLYGON (((4109540 339...
```

```
3               Bremen MULTIPOLYGON (((4222786 334...
4  Nordrhein-Westfalen MULTIPOLYGON (((4230505 326...
5               Hessen MULTIPOLYGON (((4298290 316...
6      Rheinland-Pfalz MULTIPOLYGON (((4169461 308...
7    Baden-Württemberg MULTIPOLYGON (((4221076 273...
8               Bayern MULTIPOLYGON (((4355236 271...
9             Saarland MULTIPOLYGON (((4109218 294...
10              Berlin MULTIPOLYGON (((4565934 327...
```

Writing vector data

Similarly, it is possible to write geographic data from R, using the function `st_write()`.

3.2.3 Transforming the coordinate reference system (CRS)

```r
st_crs(ger)
```

```
Coordinate Reference System:
  User input: Lambert_Azimuthal_Equal_Area
  wkt:
PROJCRS["Lambert_Azimuthal_Equal_Area",
    BASEGEOGCRS["WGS 84",
        DATUM["D_unknown",
            ELLIPSOID["WGS84",6378137,298.257223563,
                LENGTHUNIT["metre",1,
                    ID["EPSG",9001]]]],
        PRIMEM["Greenwich",0,
            ANGLEUNIT["Degree",0.0174532925199433]]],
    CONVERSION["unnamed",
        METHOD["Lambert Azimuthal Equal Area",
            ID["EPSG",9820]],
        PARAMETER["Latitude of natural origin",52,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8801]],
        PARAMETER["Longitude of natural origin",10,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8802]],
        PARAMETER["False easting",4321000,
            LENGTHUNIT["metre",1],
            ID["EPSG",8806]],
```

```
        PARAMETER["False northing",3210000,
            LENGTHUNIT["metre",1],
            ID["EPSG",8807]]],
    CS[Cartesian,2],
        AXIS["(E)",east,
            ORDER[1],
            LENGTHUNIT["metre",1,
                ID["EPSG",9001]]],
        AXIS["(N)",north,
            ORDER[2],
            LENGTHUNIT["metre",1,
                ID["EPSG",9001]]]]
```

We did not set CRS for `sta` when creating it. We *know* that `sta` is in geographic coordinates (i.e., EPSG = 4326)

```r
st_crs(sta) <- 4326 # epsg code
st_crs(ger) == st_crs(sta)
```

```
[1] FALSE
```

In order to work with both data sets `ger` and `sta`, we have to transform one of them.

Transform to projected CRS

```r
sta <- sta |> st_transform(st_crs(ger))
st_crs(ger) == st_crs(sta)
```

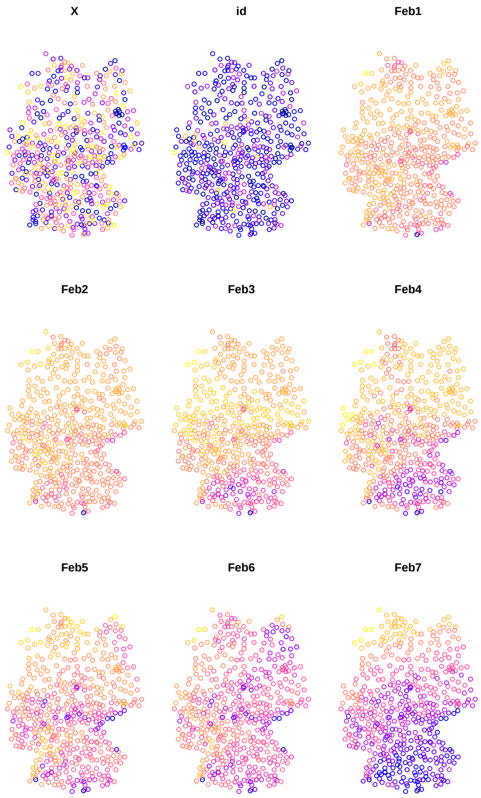
```
[1] TRUE
```

3.2.4 Plotting spatial data

The plot command works with `sf`-objects. By default up to 10 attributes are displayed.

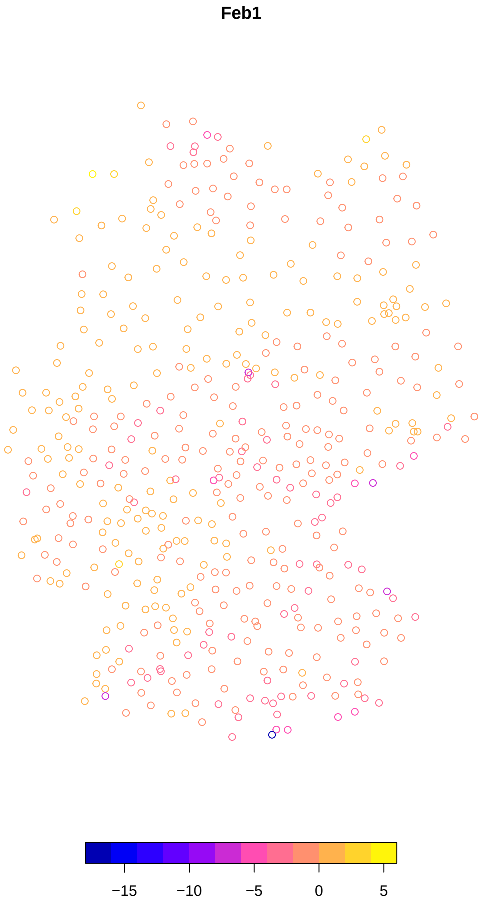
```r
plot(sta)
```

```
Warning: plotting the first 9 out of 30 attributes; use max.plot = 30 to plot
all
```



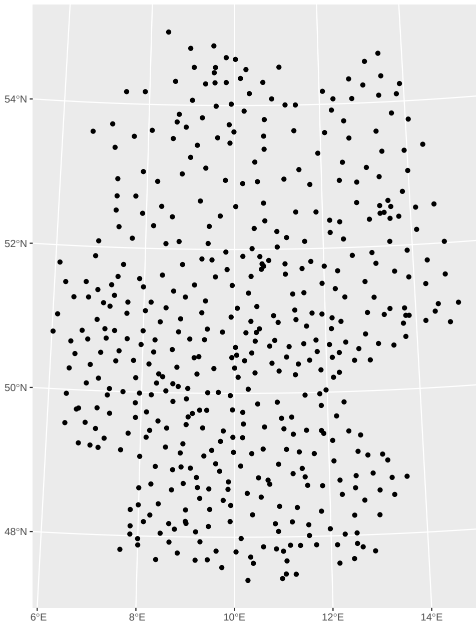
We can pick specific attributes (i.e, columns) with:

```
plot(sta[, "Feb1"])
```



`ggplot2` can be used plot spatial data. There is a `geom` for spatial data called `geom_sf()`. By default the geometry column is used (the one that is returned or set with `st_geometry()`).

```
ggplot(sta) + geom_sf()
```

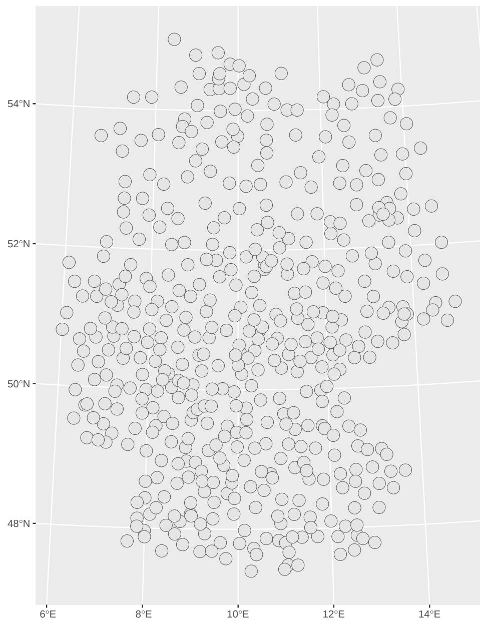


But different geometry columns can be used. We buffer each weather station with 10 km.

```
sta1 <- sta |>
  mutate(buffer = st_buffer(geometry, dist = 1e4))
```

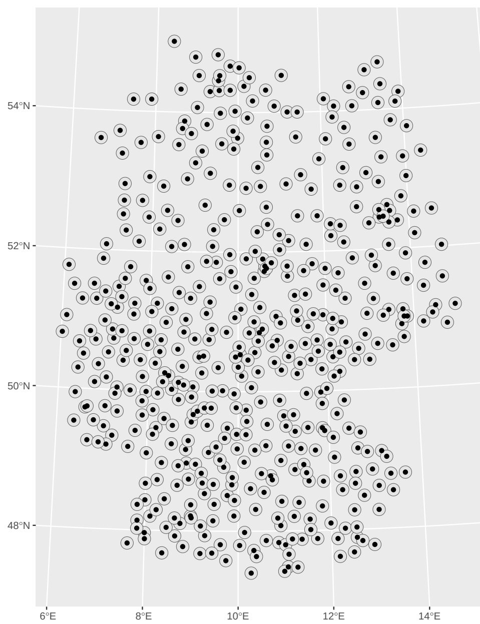
The geometry is still the column with the unbuffered points, but we can plot the buffered points by explicitly calling the new geometry.

```
ggplot(sta1) + geom_sf(aes(geometry = buffer))
```



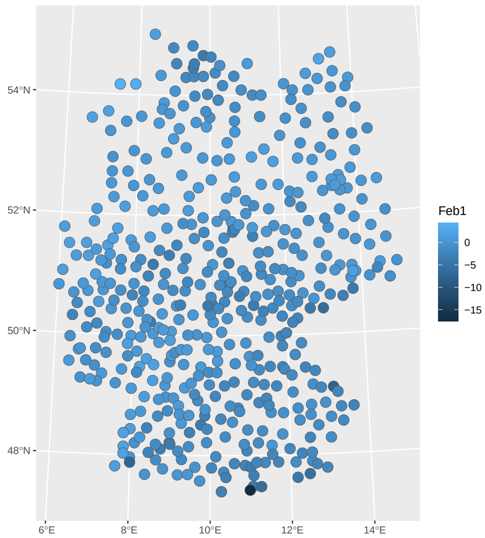
We could even plot geometries:

```
ggplot(sta1) +
  geom_sf(aes(geometry = buffer)) +
  geom_sf(aes())
```



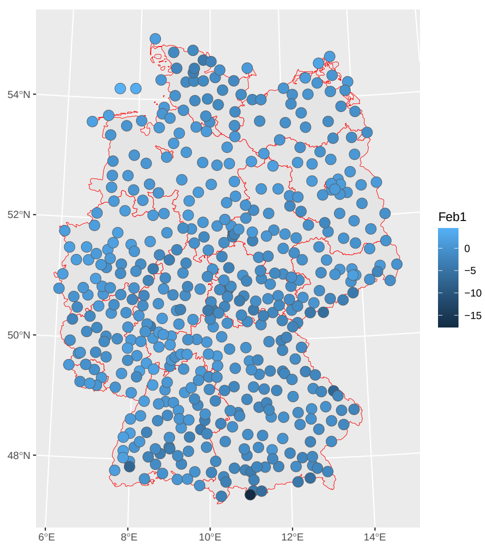
We can use aesthetics for colors and fill as with non-spatial data.

```r
ggplot(sta1) +
  geom_sf(aes(geometry = buffer, fill = Feb1))
```



We can also combine several layers:

```r
ggplot(sta1) +
  geom_sf(data = ger, col = "red") +
  geom_sf(aes(geometry = buffer, fill = Feb1))
```

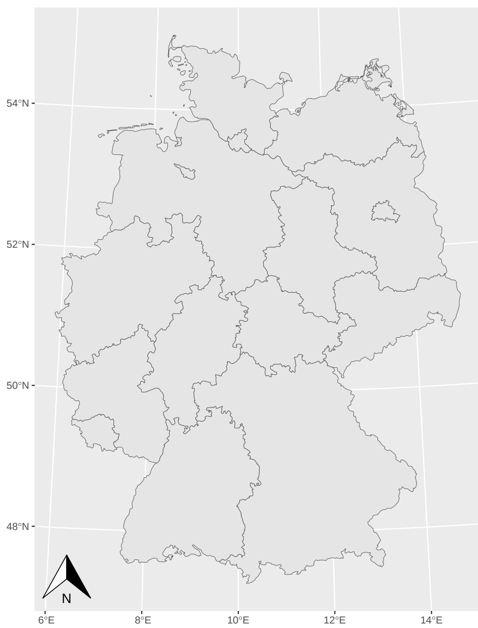


Funcitonally can be extended with `ggspatial`:

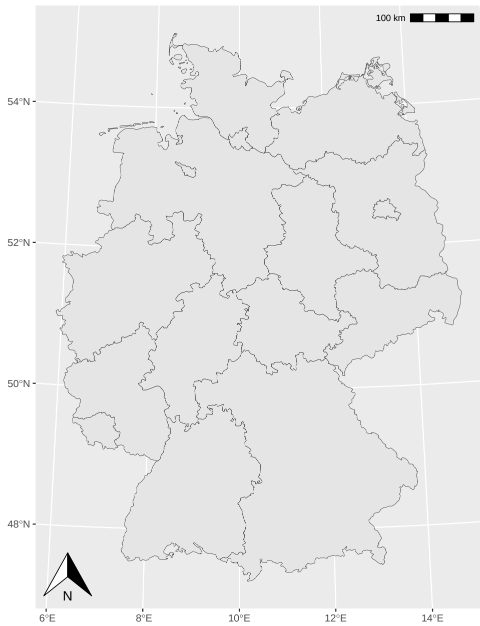
Often we need to annotate a map with north arrows and scale bars. This can be achieved with the package `ggspatial` or `ggsn`. We will use the package `ggspatial` here.

- `annotation_north_arrow()` adds a north arrow to the map.
- `annotation_scale()` adds a scale to the map.

```
library(ggspatial)
ggplot() +
  geom_sf(data = ger) +
  annotation_north_arrow()
```




```
ggplot() +
  geom_sf(data = ger) +
  annotation_north_arrow() +
  annotation_scale(location = "tr")
```



We can even add a map tile as background with the function `annotation_map_tile()`:

```
ggplot() + annotation_map_tile() +
  geom_sf(data = ger, fill = NA)
```

```
Zoom: 5
```

- The package `tmap` offers many functions to create maps from geographic data in R. A good introduction can be found here: https://geocompr.robinlovelace.net/adv-map.html.
- The package `mapView` makes it very easy to create interactive maps.

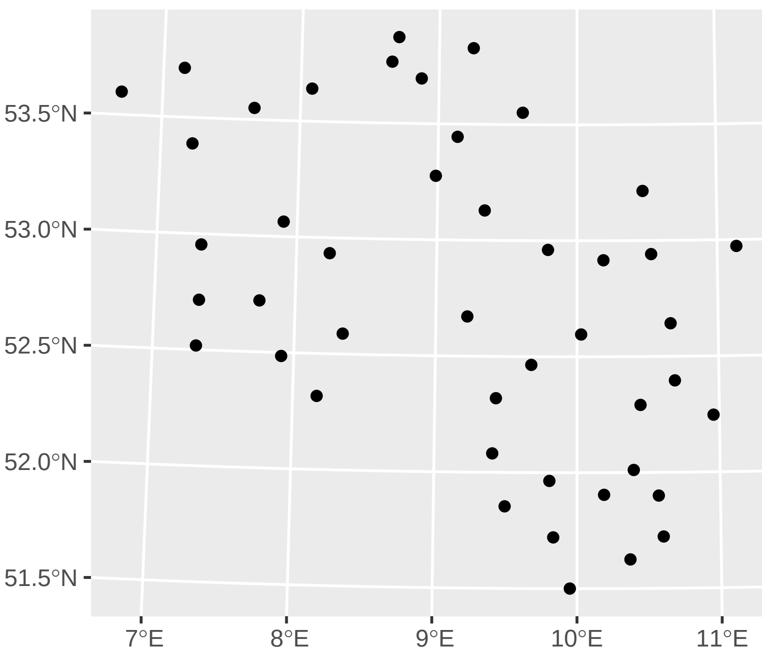
3.2.5 Spatial subsets

`[` works also for spatial data. E.g.,

```
nds <- filter(ger, state == "Niedersachsen")
```

Now we can get all weather stations from Lower Saxony with

```
ggplot(sta[nds, ]) + geom_sf()
```



3.2.6 Topological relations

These describe the *spatial* relationship between two or more features. Some of the most commonly used functions are:

- `st_intersects()`

- `st_disjoint()`
- `st_within()`
- `st_touches()`

All of these functions have an argument `sparse` that is by default set to `TRUE`.

For example, which weather stations are within which state?

```r
st_within(sta, ger)
```

```
Sparse geometry binary predicate list of length 488, where the
predicate was `within'
first 10 elements:
 1: 2
 2: 7
 3: 8
 4: 2
 5: 5
 6: 8
 7: 13
 8: 8
 9: 6
 10: 8
```

If `sparse = FALSE` we get

```r
st_within(sta, ger, sparse = FALSE) |> head()
```

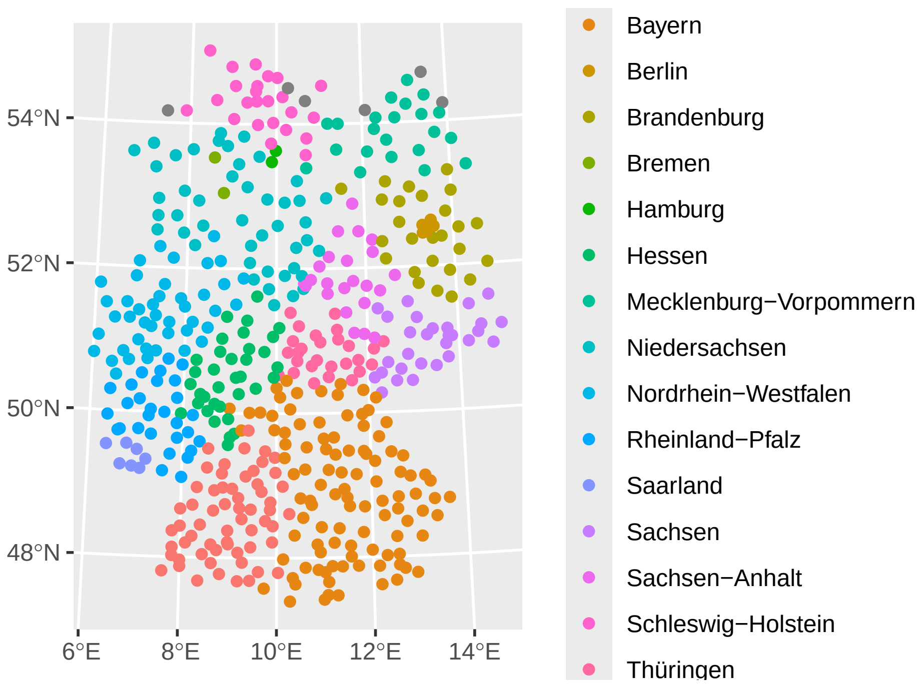
```
      [,1]  [,2]  [,3]  [,4]  [,5]  [,6]  [,7]  [,8]  [,9] [,10] [,11] [,12]
[1,] FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[2,] FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE
[3,] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE
[4,] FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[5,] FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[6,] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE
     [,13] [,14] [,15] [,16]
[1,] FALSE FALSE FALSE FALSE
[2,] FALSE FALSE FALSE FALSE
[3,] FALSE FALSE FALSE FALSE
[4,] FALSE FALSE FALSE FALSE
[5,] FALSE FALSE FALSE FALSE
[6,] FALSE FALSE FALSE FALSE
```

3.2.7 Spatial joins

Analogous to non-spatial joins, there is a function called `st_join()`, which *joins* attributes based on their locations from two data sets.

We do not know the state of each weather station in `sta`. We can get the state using a spatial join.

```
sta <- st_join(sta, ger)
ggplot(sta, aes(col = state)) + geom_sf()
```



3.3 *Optional: What is GDAL?*

The Geospatial Data Abstraction Library (GDAL) is a computer software library for reading and writing raster and vector geospatial data formats (e.g. shapefile), and is released under the permissive X/MIT style free software license by the Open Source Geospatial Foundation. As a library, it presents a single abstract data model to the calling application for all supported formats. It may also be built with a variety of useful command line interface utilities for data translation and processing. Projections and transformations are supported by the PROJ library. (from Wikipedia)

3.3.1 Accessing GDAL

- From command line (this can be tedious)
- Within R use the `gdalUtilities` package.
    - We can still do all the manipulation from within R.
    - **But** the data are not read into R.

```r
library(terra)
```

```
terra 1.8.42


Attaching package: 'terra'


The following object is masked from 'package:tidyr':

    extract
```

```r
(clc <- rast(here::here("data/dem_goe1.tif")))
```

```
class       : SpatRaster
dimensions  : 1127, 1464, 1  (nrow, ncol, nlyr)
resolution  : 25, 25  (x, y)
extent      : 4297325, 4333925, 3140100, 3168275  (xmin, xmax, ymin, ymax)
coord. ref. : ETRS89_ETRS_LAEA
source      : dem_goe1.tif
name        : dem_goe1
```

```r
system.time(
  clc <- project(clc, "epsg:4326")
)
```

```
   user  system elapsed
  0.334   0.021   0.363
```

The same with `gdalwarp()`:

```r
library(gdalUtilities)
```

```
Attaching package: 'gdalUtilities'

The following object is masked from 'package:sf':

    gdal_rasterize
```

```r
system.time(
  gdalwarp(
    srcfile = here::here("data/dem_goe1.tif"),
    dstfile = here::here("data/dem_goe1_4326.tif"),
    t_srs = 'EPSG:4326')
)
```

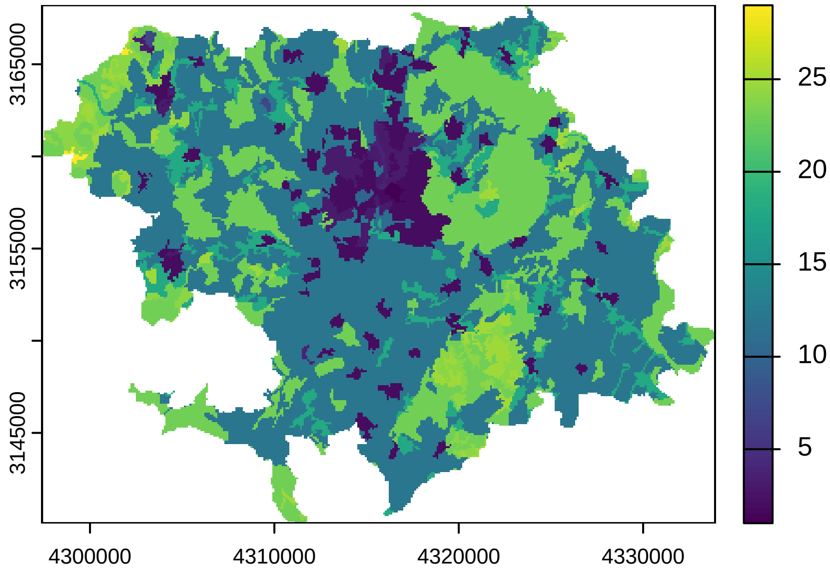
```
   user  system elapsed
  0.038   0.014   0.059
```

3.4 Cut to features

```r
gdalwarp(here::here("data/clc_europe.tif"),
         here::here("data/clc_goe.tif"),
         ot = "Int16",
         dstnodata = -128,
         cutline = here::here("data/goe.gpkg"),
         crop_to_cutline = TRUE,
         overwrite = TRUE)
```

```
Warning in CPL_gdalwarp(source, destination, options, oo, doo, config_options,
: GDAL Message 1: The definition of projected CRS EPSG:3035 got from GeoTIFF
keys is not the same as the one from the EPSG registry, which may cause issues
during reprojection operations. Set GTIFF_SRS_SOURCE configuration option to
EPSG to use official parameters (overriding the ones from GeoTIFF keys), or to
GEOKEYS to use custom values from GeoTIFF keys and drop the EPSG code.
```

```r
r1 <- rast("data/clc_goe.tif")
plot(r1)
```



Exercise 2: Vector data

Use the following data set

```r
set.seed(123)

df1 <- data.frame(
  x = runif(100, 0, 100),
  y = runif(100, 0, 100),
  crown_diameter = runif(100, 1, 15),
  sp = sample(letters[1:4], 100, TRUE)
)
```

1. Use `df1` and create a geometry column.
2. Buffer each tree with its canopy radius.
3. Calculate the crown area of each tree and save it in a new column (hint, you my want to use the function `st_area()`).
4. Find the tree with the largest canopy area.
5. Find the tree with the largest canopy area for each species.

3.5 Working with raster data

The package **terra** (`raster` in the past) is dedicated to work with raster data.

```r
library(terra)
r <- rast(here::here("data/raster/feb_1_2015.tif"))
r
```

```
class       : SpatRaster
dimensions  : 170, 125, 1  (nrow, ncol, nlyr)
resolution  : 5000, 5000  (x, y)
extent      : 4040863, 4665863, 2696181, 3546181  (xmin, xmax, ymin, ymax)
coord. ref. : ETRS89-extended / LAEA Europe (EPSG:3035)
source      : feb_1_2015.tif
name        : feb_1_2015
min value   : -15.064530
max value   :   4.273138
```

`rast()` is a very generic function to create all kind of rasters. It can also be used to create a raster from scratch:

```r
x <- rast()
x
```

```
class       : SpatRaster
dimensions  : 180, 360, 1  (nrow, ncol, nlyr)
resolution  : 1, 1  (x, y)
extent      : -180, 180, -90, 90  (xmin, xmax, ymin, ymax)
coord. ref. : lon/lat WGS 84 (CRS84) (OGC:CRS84)
```

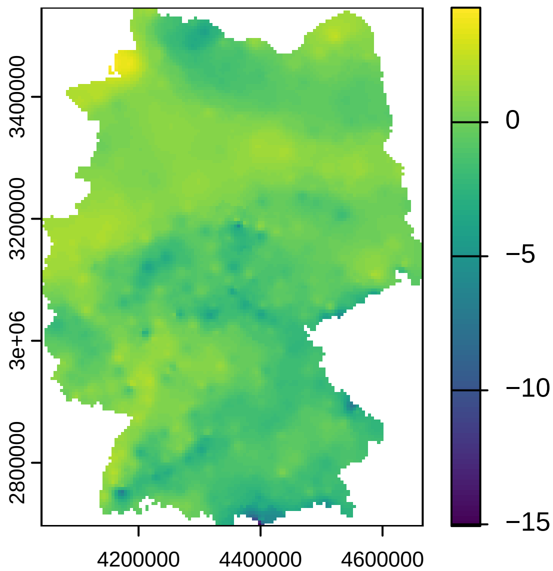
Or by defining an extent

```r
x <- rast(xmin = 0, xmax = 100, ymin = 0, ymax = 100, res = 10)
x
```

```
class       : SpatRaster
dimensions  : 10, 10, 1  (nrow, ncol, nlyr)
resolution  : 10, 10  (x, y)
extent      : 0, 100, 0, 100  (xmin, xmax, ymin, ymax)
coord. ref. :
```

The generic `plot()` command works well for continuous raster data.

```r
plot(r)
```

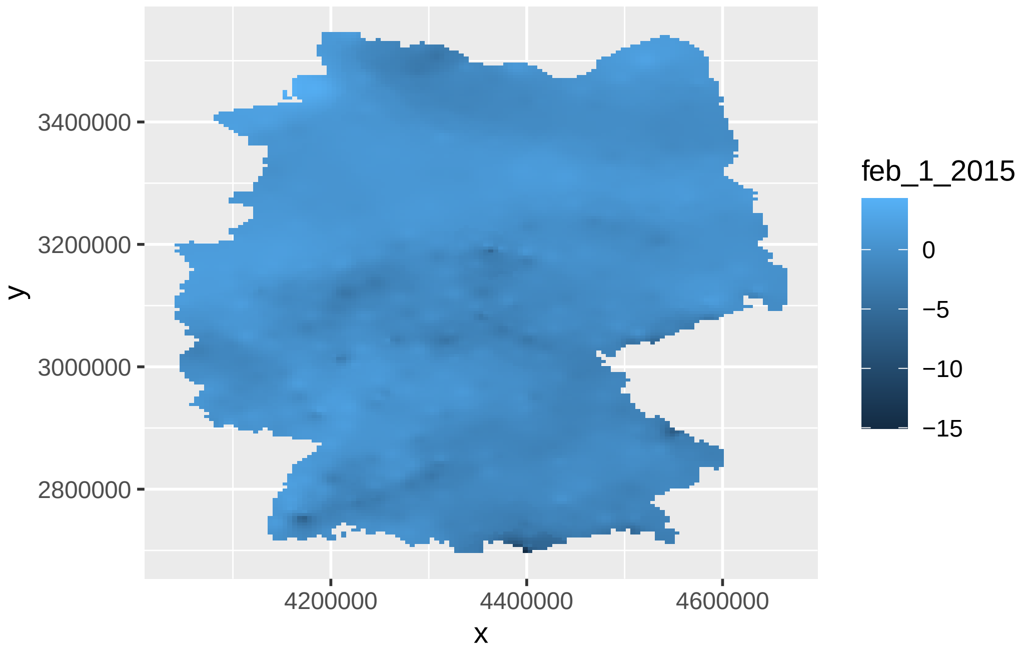


Much more flexibility to plot can be achieved with `ggplot2`. The way to plot raster data with `ggplot2` is to 1) convert the raster to a data frame (`rasterToPoints()`) and then 2) use `geom_raster()`.

```r
d <- as.data.frame(r, xy = TRUE)
```

Now we can create a plot using `ggplot2` and `d`. Alternatively, `as.data.frame(r, xy = TRUE)` also works.

```r
ggplot(d, aes(x, y, fill = feb_1_2015)) + geom_raster()
```



3.5.1 About a raster

We can get the resolution of a raster with the function `res()`

```r
res(r)
```

```
[1] 5000 5000
```

The dimensions (i.e., the number of rows and columns) with `dim()`. Note, `nrow()` and `ncol()` also exist for raster.

```r
dim(r)
```

```
[1] 170 125   1
```

The extent of a raster can be obtained with function `extent()`

```
ext(r)
```

```
SpatExtent : 4040863.15800447, 4665863.15800447, 2696180.93186771, 3546180.93186771 (xmin, xm
```

Finally, the CRS can be obtained with `projection()`

```
crs(r)
```

```
[1] "PROJCRS[\"ETRS89-extended / LAEA Europe\",\n    BASEGEOGCRS[\"ETRS89\",\n        ENSEMBL
```

- The projection of a raster can also be transformed using `project()`.
- Caution: if the values of the raster continuous set `method = "bilinear"` otherwise set `method = "near"` to use nearest neighbor interpolation. Other options include `cubic` and `cubicsplines`.

3.5.2 Accessing values of a raster

The functions `setValues()` and `getValues()` can be used to set or obtain the values of a raster, respectively.

```
head(values(r))
```

```
     feb_1_2015
[1,]        NaN
[2,]        NaN
[3,]        NaN
[4,]        NaN
[5,]        NaN
[6,]        NaN
```

Alternatively the `[`-function also works.

```
head(r[])
```

```
     feb_1_2015
[1,]        NaN
[2,]        NaN
[3,]        NaN
[4,]        NaN
[5,]        NaN
[6,]        NaN
```

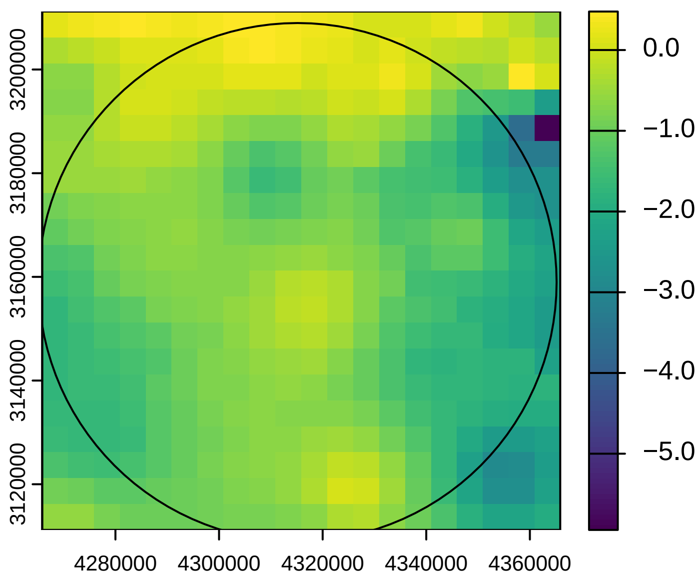
3.5.3 Cutting rasters

The function `crop()` allows to 'cut' a raster to an arbitrary bounding box.

```
g <- data.frame(x = 9.915803, y = 51.54128) # Goettingen
g <- st_as_sf(g, coords = c("x", "y"), crs = 4326)
g <- st_transform(g, crs = crs(r))
gb <- st_buffer(g, dist = 5e4)
```

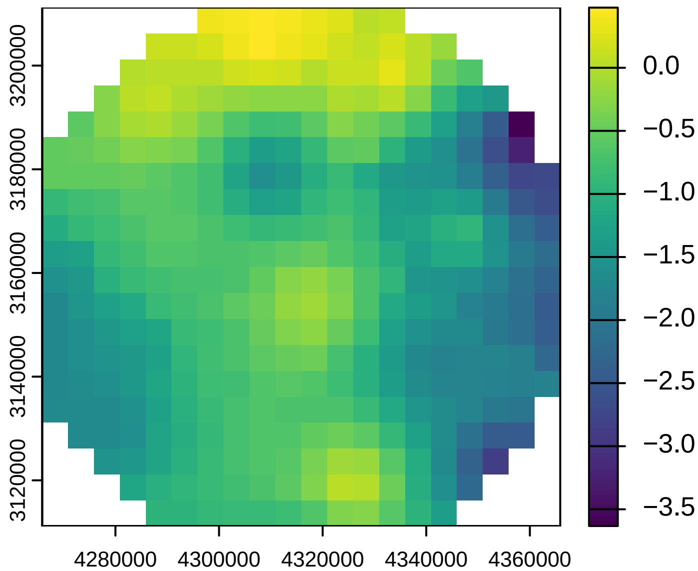
Next, we can crop the raster to the bounding box of Göttingen:

```
gr <- crop(r, gb)
plot(gr)
plot(gb, add = TRUE)
```



In order to set values that are outside the feature to `NA`, we will have to use the function `mask()`

```
g2 <- mask(gr, gb)
plot(g2)
```



The same also works with polygons.

```
bdl <- st_read(here::here("data/ger/ger_states_3035.shp"))
```

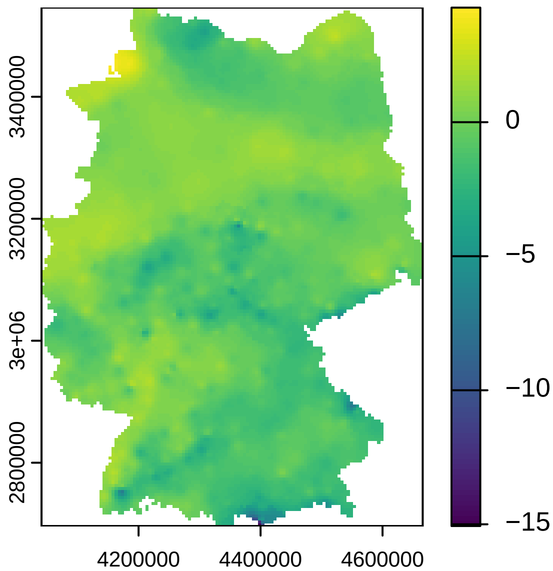
```
Reading layer `ger_states_3035' from data source
  `/Users/jsigner/ownCloud - jsigner@uni-goettingen.de@owncloud.gwdg.de/Documents/L_Lehre/M_a
  using driver `ESRI Shapefile'
Simple feature collection with 16 features and 1 field
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 4031295 ymin: 2684102 xmax: 4672253 ymax: 3551343
Projected CRS: Lambert_Azimuthal_Equal_Area
```

```
bdl <- st_transform(bdl, crs(r))
by <- bdl[bdl$state == "Bayern", ]
temp_bayern <- mask(crop(r, by), by)
```

3.5.4 Raster algebra

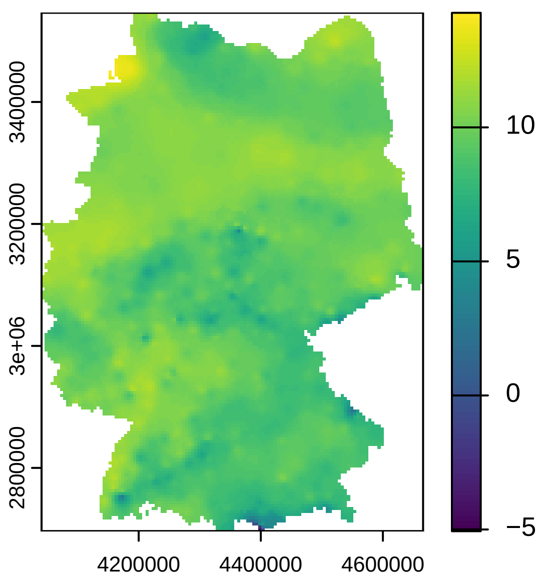
We can work with raster data like any other data. This is often referred to as raster algebra.

```
plot(r)
```



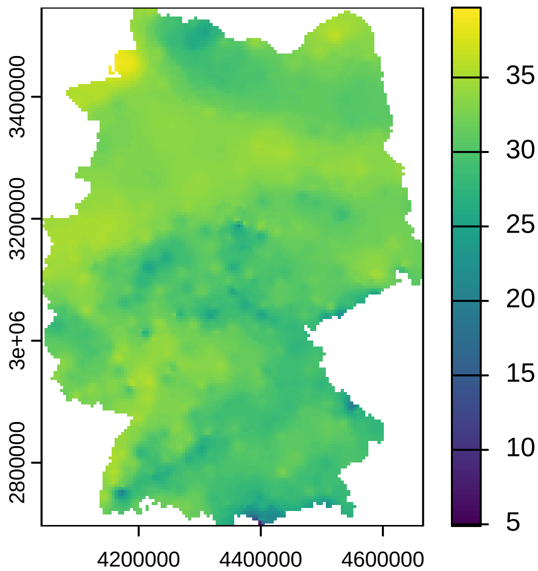
Arithmetic operators

```
plot(r + 10)
```



Temperature in degrees Fahrenheit:

```
plot(r * 1.8 + 32)
```

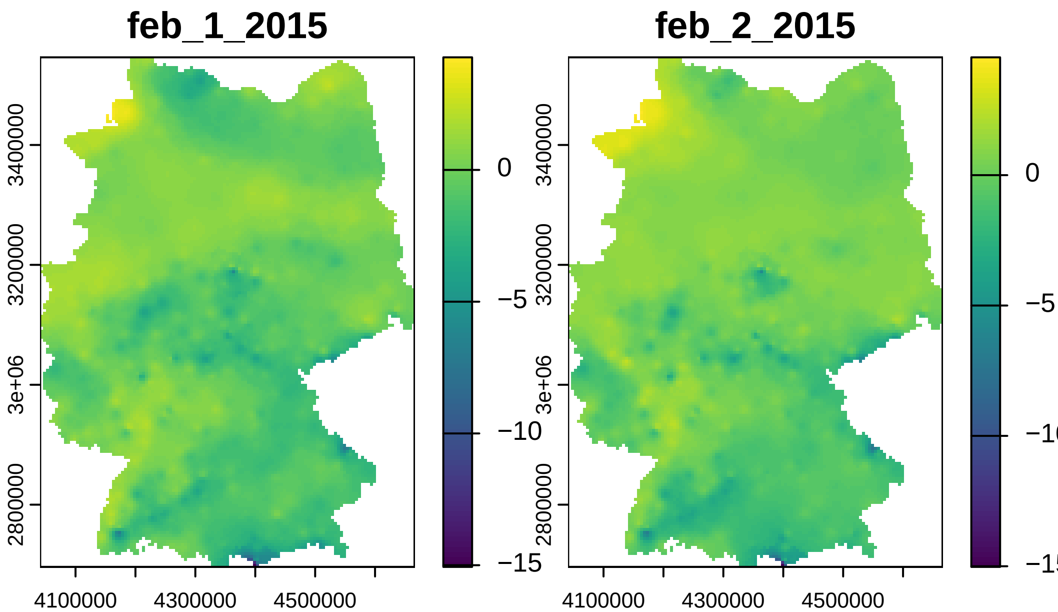


3.5.5 Working with many rasters simultaneously

The function `rast()accepts a list of rasters. Alternatively different rasters can be combined with thec`-function.. It is important that all rasters have the same extent and resolution.

```
r1 <- rast(here::here("data/raster/feb_1_2015.tif"))
r2 <- rast(here::here("data/raster/feb_2_2015.tif"))
r <- rast(list(r1, r2))
r <- c(r1, r2)
```

```
plot(r)
```



The implementation of multiple rasters is very powerful and most functions that we have seen up to now also work with multiple rasters. E.g., `crs()`, `crop()`, `mask()` and raster algebra.

Note, `dim()` now gained a third dimension:

```r
dim(r)
```

```
[1] 170 125   2
```

Exercise 3: Wokring with raster data

The aim of this exercise is to get you start working with raster data.

1. Load the Digital Elevation Model (DEM) of Germany saved in `data/raster/dem_3035.tif`.
2. What is the spatial resolution and the CRS of the raster?
3. Cut the DEM to the state of Lower Saxony (use the data set on German states for this; `data/ger/ger_states_3035.shp`).
4. What is the mean elevation of Lower Saxony?
5. Find all pixels in Lower Saxony that have an elevation of 100 m or more. What is the percentage of Lower Saxony with an elevation of 100 m or more?
6. Create a plot of Lower Saxony (using the elevation as a background with an appealing fill color; *hint: have a look at the `rcartocolor` package*), a scale and a north arrow.