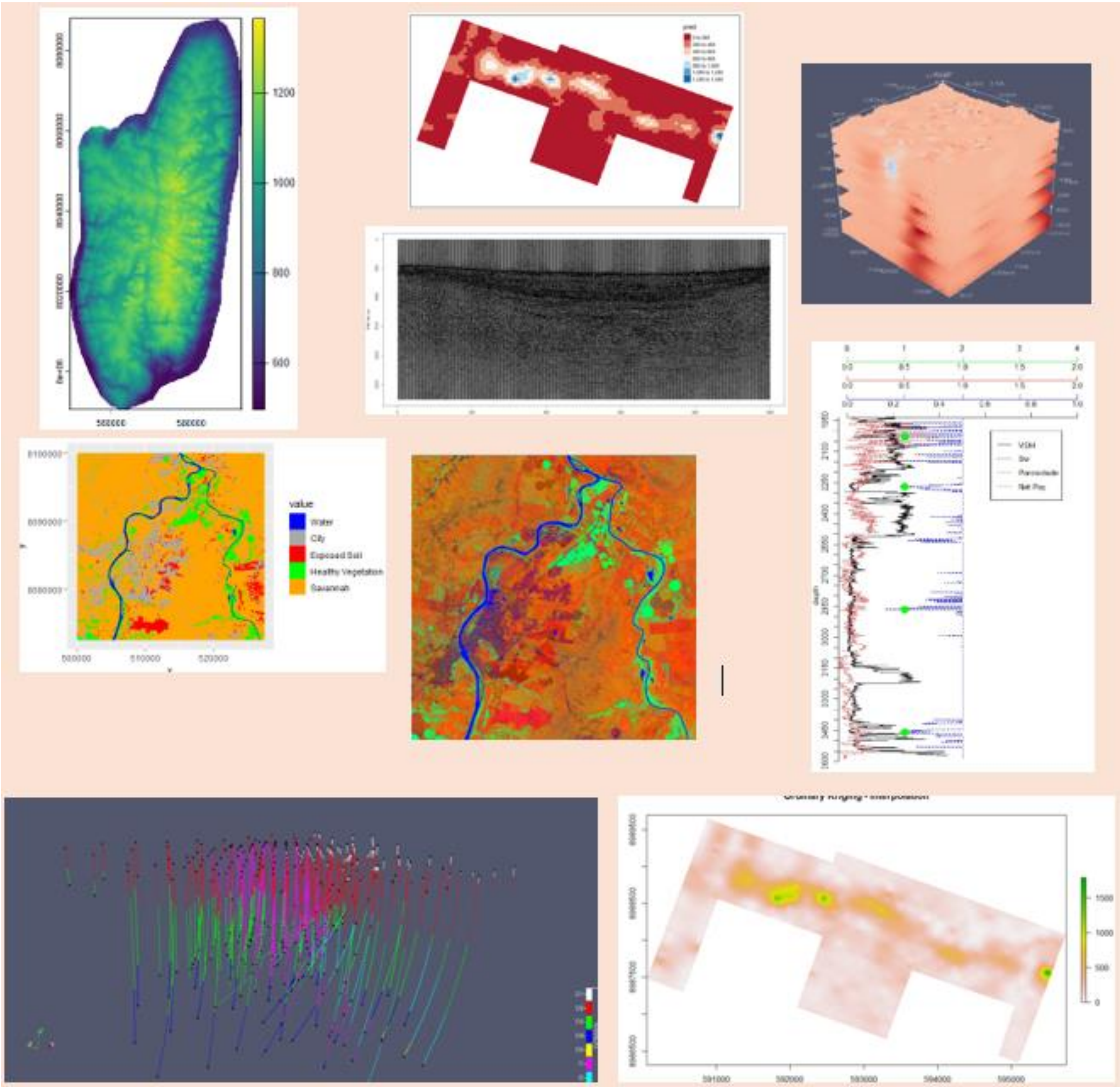
R Cookbook

Processing and Manipulating Geological spatial data with R



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Revised Edition - September 2024

Introduction

In this edition of the Cookbook, we will focus on tasks related to loading, importing, manipulating, processing and exporting geospatial data and Other geological data using R and its libraries.

We will advance progressively as we introduce new data processing and manipulation.

Libraries used:

terra	*rpostgis*	*raster*	*RColorBrewer*	
dismo	*gstat*	*gdalUtils*	*spdep*	*spgwr*
cluster	*float*	*DT*	*data.table*	*tmap*
RStollbox	*ggplot2*			

You can download this cookbook and support data at:

https://gdatasystems.com/apostilaRgeo/CookbookR_v00_eng.pdf
https://gdatasystems.com.br/apostilaRgeo/index.php

All recipes of this book should start with:

```
#Working directory where the Cookbook data is located
wd<-'C:/Users/User/cookbooksitefiles'#change according to your operating system
setwd(wd)
```

VISIT:

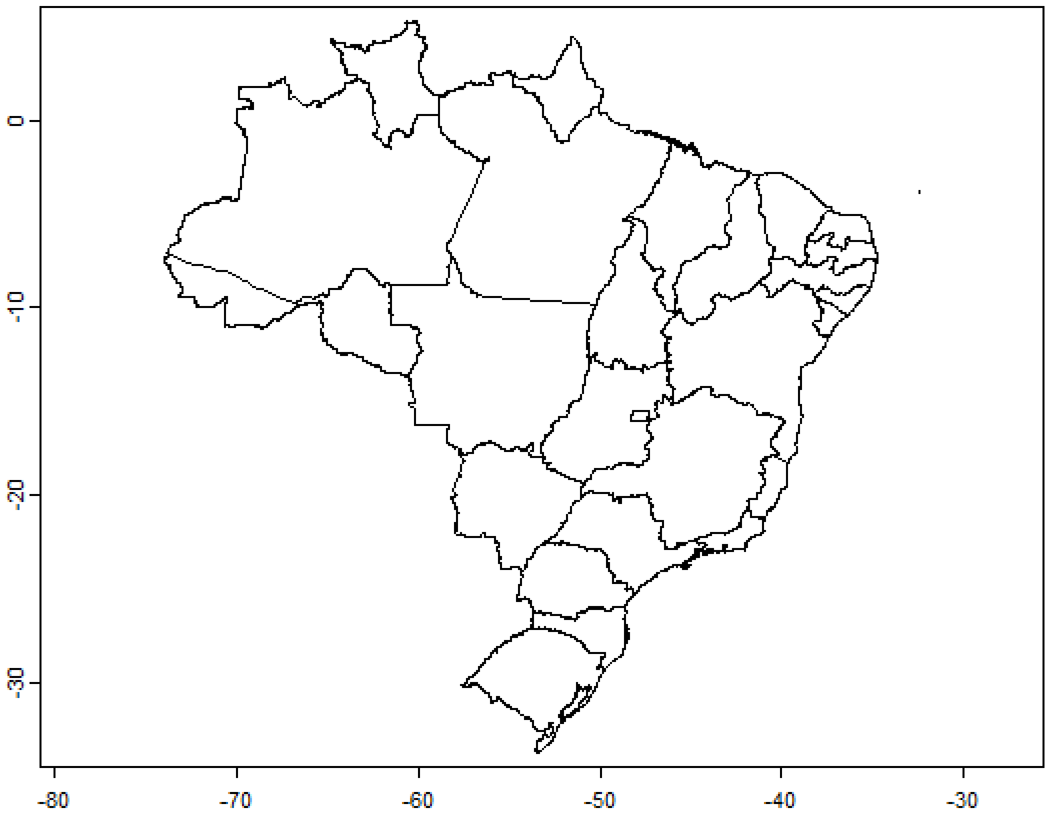
https://gdatasystems.com

1 Loading Geospatial data

Recipe - 1.1 – Loading Vectorial Data

Load, inspect and visualize a vectorial layer from a shapefile:

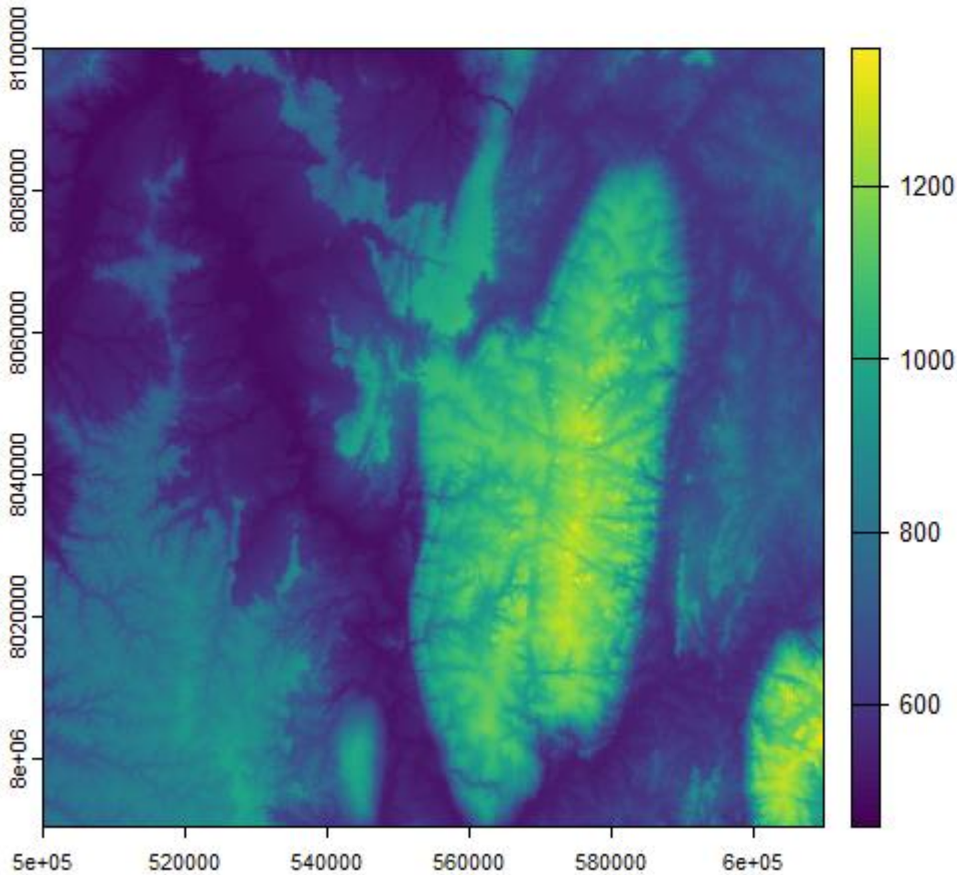
```
library(terra) #install terra using install.packages("terra")
state<-vect("estado.shp") #loads the estado.shp
state  #inspecting
 class       : SpatVector
 geometry    : polygons
 dimensions  : 27, 5  (geometries, attributes)
 extent      : -73.99024, -32.39088, -33.75136, 5.270972  (xmin,xmax,ymin,ymax)
 source      : estado.shp
 coord. ref. : lon/lat GCS_unknown
 names       :    id      nome sigla regiao_id codigo_ibg
 type        : <chr>     <chr> <chr>     <chr>      <chr>
 values      :     1      Acre    AC         3         12
                   2   Alagoas    AL         4         27
                   3  Amazonas    AM         3         13
plot(state)
```



Recipe - 1.2 – Loading Raster Data

Load, inspect and visualize a vectorial layer from a geoTiff file:

```
library(terra)
dem<-rast("dem.tif")
dem
class       : SpatRaster
dimensions  : 3650, 3649, 1  (nrow, ncol, nlyr)
resolution  : 30.08495, 30.08219  (x, y)
extent      : 5e+05, 609780, 7990240, 8100040  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
source      : dem.tif
name        : dem
plot(dem)
```



2 Creating geospatial data

Recipe - 2.1 – Creating Vectorial data

Ceating a vectorial point data from XY coordinates, georreferencing, adding atribute data and saving the vector as shapefile.

2.1.1 Creating the data:

```
longitude <- c(-116.7, -120.4, -116.7, -113.5, -115.5,-120.8, -119.5, -113.7, -
113.7, -110.7)
latitude <- c(45.3, 42.6, 38.9, 42.1, 35.7, 38.9,36.2, 39, 41.6, 36.9)
points<-cbind(longitude, latitude) #joining long-lat into a dataframe
library(terra)
pts<-vect(points)
pts
 class       : SpatVector
 geometry    : points
 dimensions  : 10, 0  (geometries, attributes)
 extent      : -120.8, -110.7, 35.7, 45.3  (xmin, xmax, ymin, ymax)
 coord. ref. :
```

2.1.2 Georreferencing:

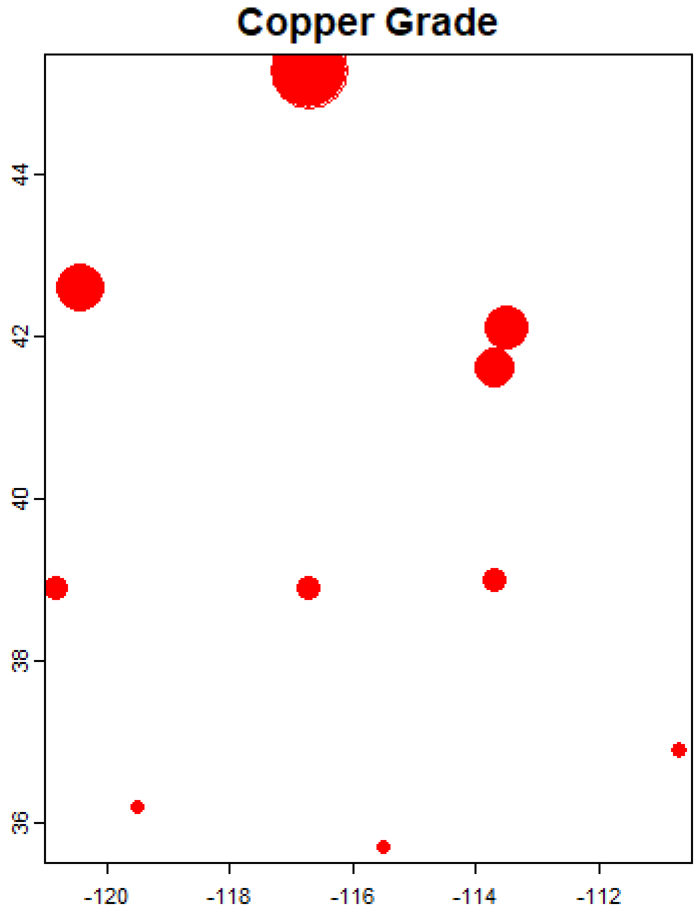
```
pts<-vect(points,crs="WGS84")
pts
 class       : SpatVector
 geometry    : points
 dimensions  : 10, 0  (geometries, attributes)
 extent      : -120.8, -110.7, 35.7, 45.3  (xmin, xmax, ymin, ymax)
 coord. ref. : lon/lat WGS 84 (EPSG:4326)
```

2.1.3 Adding attribute data:

```
df <- data.frame(ID=1:nrow(points), gradeCu=(latitude-30)^3)
df
   ID  gradeCu
1   1 3581.577
2   2 2000.376
3   3  704.969
4   4 1771.561
5   5  185.193
6   6  704.969
7   7  238.328
8   8  729.000
9   9 1560.896
10 10  328.509
ptsdf<-vect(points,crs="WGS84", atts=df)
ptsdf
 class       : SpatVector
 geometry    : points
 dimensions  : 10, 2  (geometries, attributes)
 extent      : -120.8, -110.7, 35.7, 45.3  (xmin, xmax, ymin, ymax)
 coord. ref. : lon/lat WGS 84 (EPSG:4326)
 names       :    ID gradeCu
 type        : <int>   <num>
 values      :     1    3582
                   2    2000
                   3     705
```

2.1.4 Visualizing:

```
plot(ptsdf, cex=1+ptsdf$gradeCu/500, pch=20, col='red', main='Copper Grade')
```



2.1.5 Saving as shapefile

```
writeVector(ptsdf, 'copper_points.shp', overwrite=TRUE)
```

Recipe - 2.2 – Creating Raster Data

Creating a georeferenced raster, loading it with random data, visualizing and saving as a geoTiff file.

2.2.1 Creatin the raster georeferenced as 32723 (UTM WGS84 zone 23S):

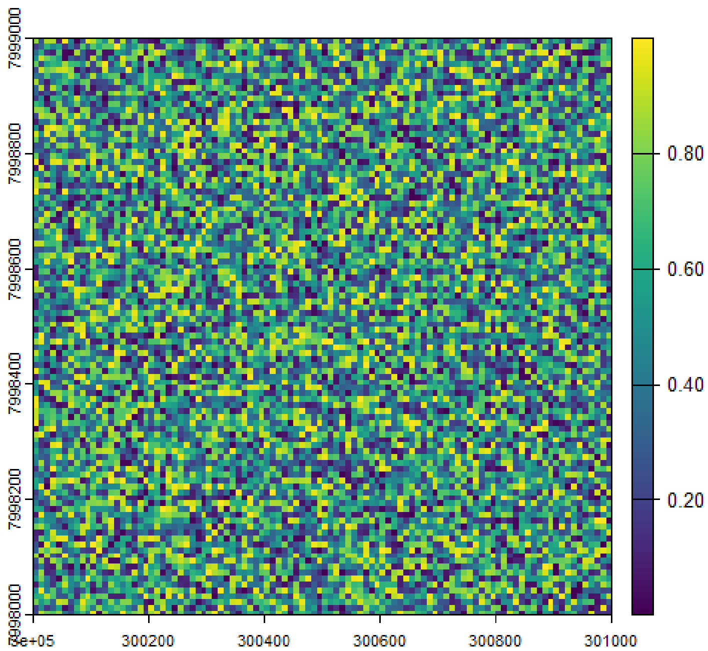
```
library(terra)
rl<-rast(ncol=100,nrow=100,xmax=301000,xmin=300000,ymin=7998000, ymax=7999000,
         crs="+init=epsg:32723")
rl
class       : SpatRaster
dimensions  : 100, 100, 1  (nrow, ncol, nlyr)
resolution  : 10, 10  (x, y)
extent      : 3e+05, 301000, 7998000, 7999000  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 23S
```

2.2.2 Adding random data values to it:

```
values(rl)<-runif(ncell(rl))
rl
class       : SpatRaster
dimensions  : 100, 100, 1  (nrow, ncol, nlyr)
resolution  : 10, 10  (x, y)
extent      : 3e+05, 301000, 7998000, 7999000  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 23S
source(s)   : memory
name        :        lyr.1
min value   : 7.768977e-05
max value   : 9.999792e-01
```

2.2.3 Visualizing the raster:

```
plot(rl)
```



2.2.4 Saving as geoTiff:

```
writeRaster(rl, 'rasternew.tif',overwrite=TRUE)
```

3 Working with Attributes/values of Geospatial data

Recipe - 3.1 – Extracting attributes from Vectorial Data

Loading a vectorial data, extracting an attribute column and saving it as a CSV file:

```
library(terra)
class       : SpatVector
 geometry    : points
 dimensions  : 6818, 24  (geometries, attributes)
 extent      : -50.94278, -39.92139, -22.86944, -14.29722  (xmin,xmax, ymin, ymax)
 source      : minasgerais_recmin.shp
 coord. ref. : lon/lat WGS 84 (EPSG:4326)
 names       : data_cadas subst_prin abreviacao      associacao associac_1
 type        :      <chr>      <chr>      <chr>           <chr>      <chr>
 values      : 2003/11/26       OURO         Au Ouro, Pirita, ~         Au
               2004/02/06    MANGANÊS         Mn              NA    Mn - Fe
               2003/11/26       OURO         Au Ouro, Pirita, ~         Au
 extrmin_x grau_de_in      metodo_geo  textura_mi        origem (and 14 more)
     <chr>      <chr>           <chr>       <chr>         <chr>
 Filoneana         NA Levantamento e~ Disseminada São Francisco
    Maciça         NA Levantamento e~    Granular São Francisco
df<-cbind(crds(arq),arq$subst_prin)
head(df)
     x                   y
[1,] "-43.7547222199999" "-20.5644444399999" "OURO"
[2,] "-43.8311111099999" "-20.56416667"      "MANGANÊS"
[3,] "-43.7616666699999" "-20.56305556"      "OURO"
[4,] "-43.77138889"      "-20.56138889"      "OURO"
[5,] "-43.76944444"      "-20.56138889"      "OURO"
[6,] "-43.77333333"      "-20.55861111"      "OURO"
colnames(df)<-c("Longitude","Latitude","Occurence")
head(df)
     Longitude           Latitude            Occurence
[1,] "-43.7547222199999" "-20.5644444399999" "OURO"
[2,] "-43.8311111099999" "-20.56416667"      "MANGANÊS"
[3,] "-43.7616666699999" "-20.56305556"      "OURO"
[4,] "-43.77138889"      "-20.56138889"      "OURO"
[5,] "-43.76944444"      "-20.56138889"      "OURO"
[6,] "-43.77333333"      "-20.55861111"      "OURO"
write.csv(df, "occurences.csv", row.names=FALSE)
```

Recipe - 3.2 – Extracting Values from Raster Data

Loading a raster data, extracting its value and saving as CSV file:

```
library(terra)
arq<-rast("dem.tif")
arq
class       : SpatRaster
dimensions  : 3650, 3649, 1  (nrow, ncol, nlyr)
resolution  : 30.08495, 30.08219  (x, y)
extent      : 5e+05, 609780, 7990240, 8100040  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
source      : dem.tif
name        : dem
elev<-values(arq)
df<-cbind(crds(arq),elev)
colnames(df)<-c("utme","utmn","elev")
head(df,n=3)
         utme    utmn elev
[1,] 500015.0 8100025  704
[2,] 500045.1 8100025  704
[3,] 500075.2 8100025  703
write.csv(df, "elevation.csv", row.names=FALSE) #A HUGE FILE BEING CREATED HERE
```

4 Reprojecting Geospatial Data

Recipe - 4.1 – Reprojecting Vector Data

Loading a vector data, reprojecting and exporting as a new shapefile:

```
library(terra)
arq<-vect("minasgerais_recmin.shp")
arq
 class       : SpatVector
 geometry    : points
 dimensions  : 6818, 24  (geometries, attributes)
 extent     : -50.94278, -39.92139, -22.86944, -14.29722  (xmin,xmax, ymin, ymax)
 source      : minasgerais_recmin.shp
 coord. ref. : lon/lat WGS 84 (EPSG:4326)
 names       : data_cadas subst_prin abreviacao      associacao associac_1
 type        :      <chr>      <chr>      <chr>           <chr>      <chr>
 values      : 2003/11/26       OURO         Au Ouro, Pirita, ~         Au
               2004/02/06   MANGANÊS         Mn              NA    Mn - Fe
               2003/11/26       OURO         Au Ouro, Pirita, ~         Au
 extrmin_x grau_de_in      metodo_geo  textura_mi         origem (and 14 more)
     <chr>      <chr>           <chr>       <chr>          <chr>
 Filoneana         NA Levantamento e~ Disseminada São Francisco
    Maciça         NA Levantamento e~    Granular São Francisco
 Filoneana         NA Levantamento e~ Disseminada São Francisco
arq2<-project(arq, "EPSG:32723")
arq2
class       : SpatVector
 geometry    : points
 dimensions  : 6818, 24  (geometries, attributes)
 extent      : -122394.4, 1043414, 7470310, 8419329  (xmin, xmax, ymin, ymax)
 coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
 names       : data_cadas subst_prin abreviacao      associacao associac_1
 type        :      <chr>      <chr>      <chr>           <chr>      <chr>
 values      : 2003/11/26       OURO         Au Ouro, Pirita, ~         Au
               2004/02/06   MANGANÊS         Mn              NA    Mn - Fe
               2003/11/26       OURO         Au Ouro, Pirita, ~         Au
 extrmin_x grau_de_in      metodo_geo  textura_mi         origem (and 14 more)
     <chr>      <chr>           <chr>       <chr>          <chr>
 Filoneana         NA Levantamento e~ Disseminada São Francisco
    Maciça         NA Levantamento e~    Granular São Francisco
 Filoneana         NA Levantamento e~ Disseminada São Francisco
writeVector(arq2, 'recmin_reprjctd.shp', overwrite=TRUE)
```

Recipe - 4.2 – Reprojecting Raster Data

Load raster data, reproject and export as a new geoTiff file:

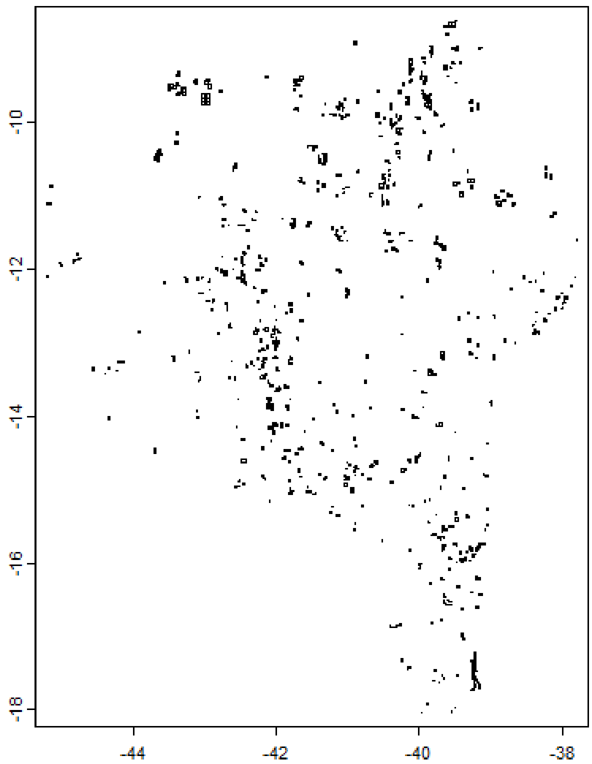
```
library(terra)
arq<-rast("dem.tif")
arq
class       : SpatRaster
dimensions  : 3650, 3649, 1  (nrow, ncol, nlyr)
resolution  : 30.08495, 30.08219  (x, y)
extent      : 5e+05, 609780, 7990240, 8100040  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
source      : dem.tif
name        : dem
arq2<-project(arq, "EPSG:4326")
arq2
class       : SpatRaster
dimensions  : 3581, 3735, 1  (nrow, ncol, nlyr)
resolution  : 0.0002778776, 0.0002778776  (x, y)
extent      : -45, -43.96213, -18.17689, -17.18181  (xmin, xmax, ymin, ymax)
coord. ref. : lon/lat WGS 84 (EPSG:4326)
source(s)   : memory
name        :       dem
min value   :  439.9265
max value   : 1369.7501
writeRaster(arq2, 'dem_reprjtctd.tif', overwrite=TRUE)
```

5 Reading Geospatial Data from Remote Database

Recipe - 5.1 –Vector Data

Loading a Postgis table (vector data) from a remote database and saving it as a local shapefile. This example is using a valid database. If you want to access a different database, replace with the proper credentials shown in red:

```
library(terra)
cstr<-"PG:dbname=dnpmba host=pg.gdatasystems.com user=droid password=devcor
       port=5432"
lyr <- vect(cstr, layer="edital") # name of vector table
lyr
 class       : SpatVector
 geometry    : polygons
 dimensions  : 708, 13  (geometries, attributes)
 extent       : -45.21476, -37.78562, -18.03977, -8.610073  (xmin, xmax, ymin,
ymax)
 source                  :   PG:dbname=dnpmba   host=pg.gdatasystems.com   user=droid
password=devcor port=5432  (edital)
 coord. ref. : lon/lat WGS 84 (EPSG:4326)
 names       :   gid     processo numero   ano area_ha              id
 type        : <int>        <chr>  <int> <int>   <num>           <chr>
 values      :   575 870509/2002 870509  2002   785.5 {23B096F9-D7C2~
                 801 872126/2006 872126  2006   996.6 {E9BA669A-1C5A~
                1212 871762/2008 871762  2008   575.6 {70DE0C14-15C8~
            fase       ult_evento             nome             subs (and 3 more)
           <chr>            <chr>            <chr>            <chr>
 DISPONIBILIDADE 2468 - DISPONI~ MARCIA OSIAS D~           ARGILA
 DISPONIBILIDADE 2468 - DISPONI~ CARLANE CLÉA R~          QUARTZO
 DISPONIBILIDADE 2468 - DISPONI~ JOSE FARIAS DE~ MINÉRIO DE VAN~
```

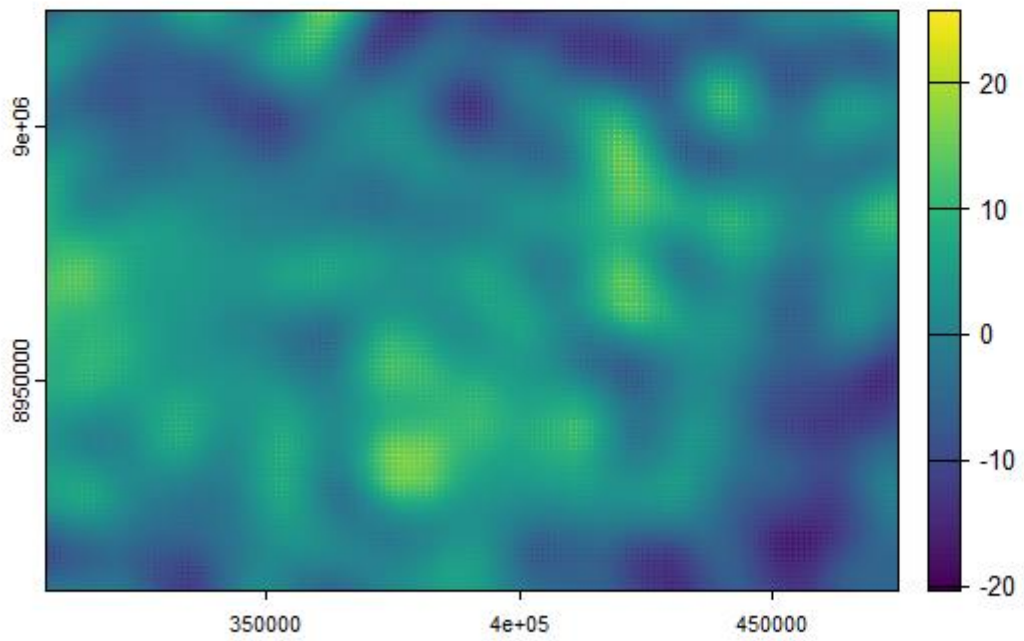



```
writeVector(lyr, 'ucusBA.shp', overwrite=TRUE)
```

Receipt - 5.2 – Raster Data

Load a Postgis raster table from a remote database and saving it as a local tiff. This example is using a valid database. If you want to access a different database, replace with the proper credentials shown in red:

```
library(terra)
cstr2<-"PG:dbname=dnpmmt host=pg.gdatasystems.com user=droid password=devcor
          port=5432 schema='public' table='sai'"
lyr <- rast(cstr2)
lyr
class        : SpatRaster
dimensions   : 382, 562, 1  (nrow, ncol, nlyr)
resolution   : 299.5464, 299.4152  (x, y)
extent       : 306437.9, 474783, 8908453, 9022829  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 21S (EPSG:32721)
source      : PG:dbname=dnpmmt host=pg.gdatasystems.com user=droid password=devcor
port=5432 schema='public' table='sai'
varname      : PG:dbname=dnpmmt host=pg.gdatasystems.com
name         : PG:dbname=dnpmmt host=pg.gdatasystems.com
plot(lyr)
```



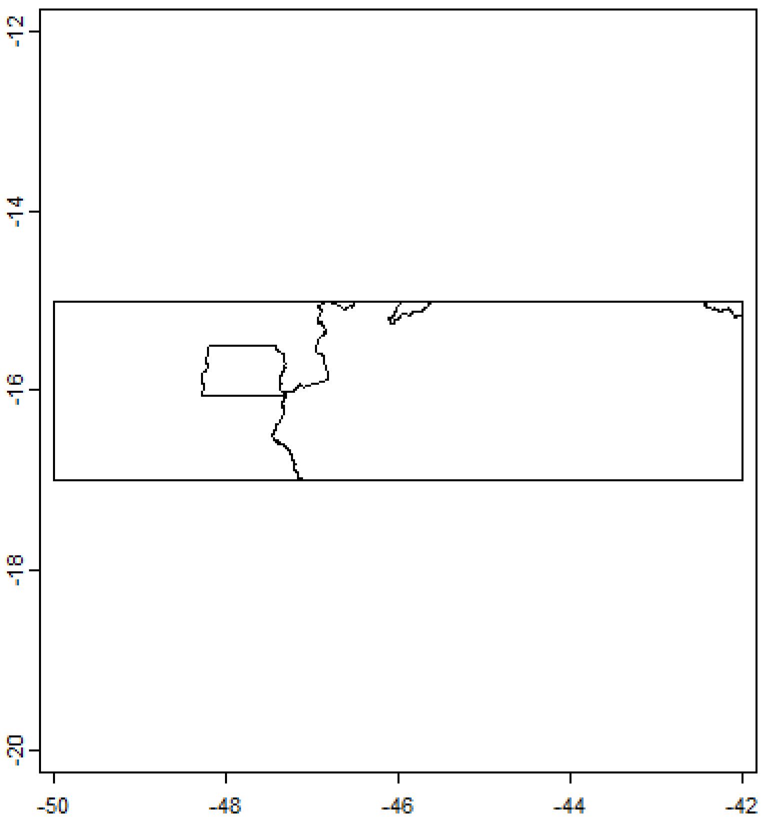

```
writeRaster(lyr, 'output.tif', overwrite=TRUE)
```

6 Cropping Geospatial Data

Recipe - 6.1 – Cropping vector using rectangle extension

Crop the loaded vector using an extension defined by the function ext(x min, x max, y min, y max).

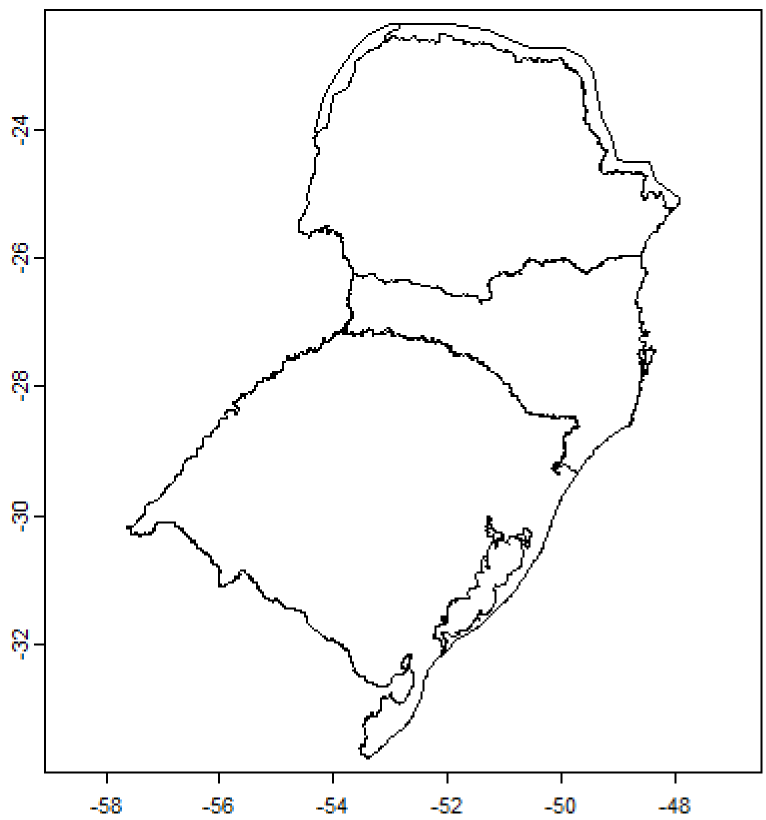
```
library(terra)
state<-vect("estado.shp") #reading shapefile estado.shp
ext<-ext(-50,-42,-17,-15)
cropped<-crop(state,ext)
cropped
 class       : SpatVector
 geometry    : polygons
 dimensions  : 4, 5  (geometries, attributes)
 extent      : -50, -42, -17, -15  (xmin, xmax, ymin, ymax)
 coord. ref. : lon/lat GCS_unknown
 names       :    id            nome sigla regiao_id codigo_ibg
 type        : <chr>           <chr> <chr>     <chr>      <chr>
 values      :     5           Bahia    BA         4         29
                   7 Distrito Federal   DF         5         53
                   9           Goiás    GO         5         52
plot(cropped)
```



Recipe - 6.2 – Cropping vector data with a shapefile

Crop the loaded vector using another vector file as mask.

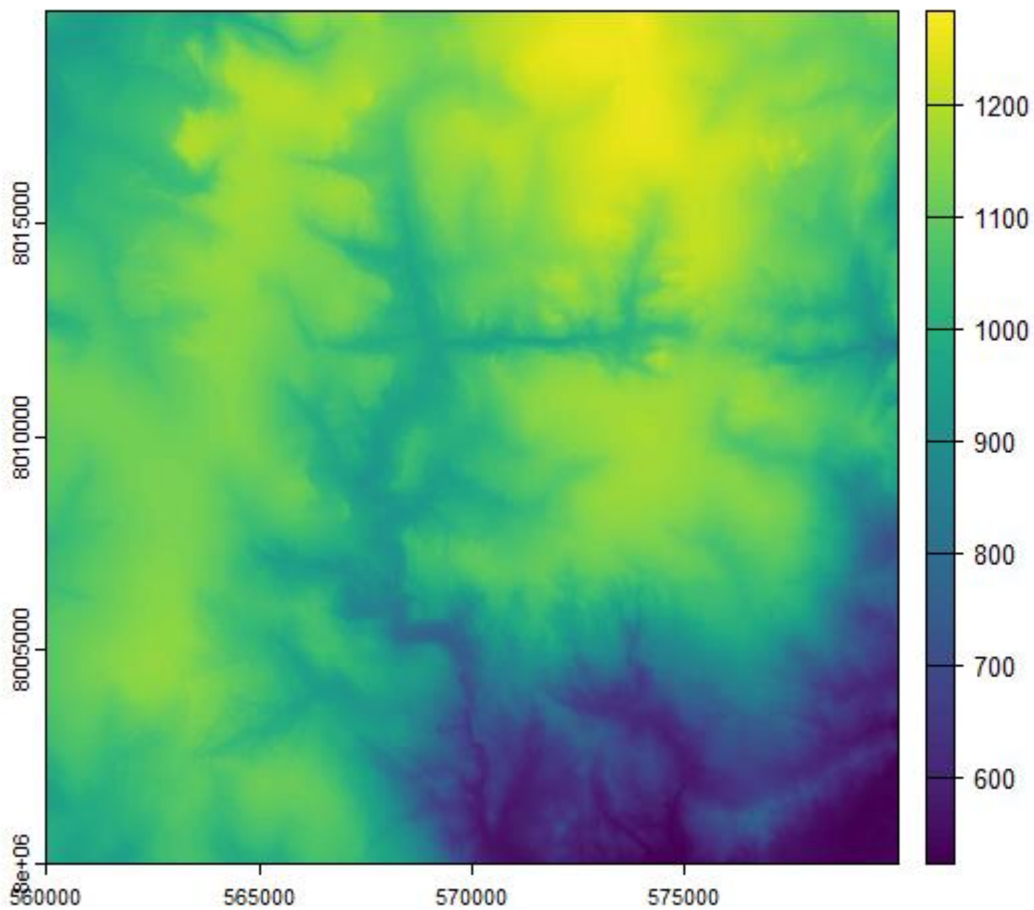
```
library(terra)
state<-vect("estado.shp") #loading  shapefile estado.shp
mask<-vect('sul.shp')# shapefile to use as mask
mask
 class       : SpatVector
 geometry    : polygons
 dimensions  : 1, 1  (geometries, attributes)
 extent      : -57.83859, -47.86047, -34.01961, -22.37426  (xmin,xmax,ymin,ymax)
 source      : sul.shp
 coord. ref. : lon/lat WGS 84 (EPSG:4326)
 names       :    id
 type        : <int>
 values      :    NA
cropped<-crop(state,mask)
cropped
 class       : SpatVector
 geometry    : polygons
 dimensions  : 5, 5  (geometries, attributes)
 extent      : -57.64272, -47.90666, -33.75136, -22.37426  (xmin,xmax,ymin,ymax)
 coord. ref. : lon/lat GCS_unknown
 names       :    id               nome sigla regiao_id codigo_ibg
 type        : <chr>              <chr> <chr>     <chr>      <chr>
 values      :    12 Mato Grosso do Sul    MS         5         50
                  18             Paraná    PR         1         41
                  23  Rio Grande do Sul    RS         1         43
plot(cropped)
```



Recipe - 6.3 – Cropping raster using rectangle extension

Crop the loaded raster using an extension defined by the function ext(x min, x max, y min, y max).

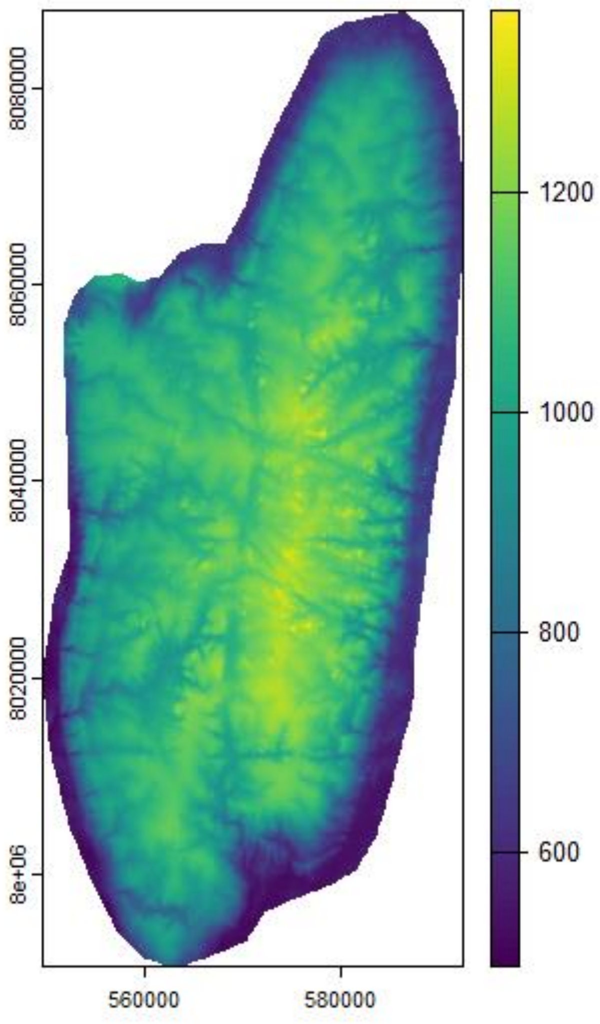
```
library(terra)
dem<-rast("dem.tif")
ext<-ext(560000,580000,8000000,8020000)
cropped<-crop(dem,ext)
cropped
 class       : SpatRaster
 dimensions  : 665, 665, 1  (nrow, ncol, nlyr)
 resolution  : 30.08495, 30.08219  (x, y)
 extent      : 559989.4, 579995.9, 7999987, 8019991  (xmin, xmax, ymin, ymax)
 coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
 source(s)   : memory
 name        :  dem
 min value   :  524
 max value   : 1284
plot(cropped)
```



Recipe - 6.4 – Cropping raster data with a shapefile

Crop the loaded raster using another vector file as mask.

```
library(terra)
dem<-rast("dem.tif")
mask<-vect('serra.shp')

mask
 class       : SpatVector
 geometry    : polygons
 dimensions  : 1, 1  (geometries, attributes)
 extent      : 549704.2, 592405.6, 7990569, 8087955  (xmin, xmax, ymin, ymax)
 source      : serra.shp
 coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
 names       :    id
 type        : <int>
 values      :    NA
cropped<-crop(dem,mask,mask=T)
cropped
 class       : SpatRaster
 dimensions  : 3237, 1419, 1  (nrow, ncol, nlyr)
 resolution  : 30.08495, 30.08219  (x, y)
 extent      : 549700.3, 592390.9, 7990571, 8087947  (xmin, xmax, ymin, ymax)
 coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
 source(s)   : memory
 name        :  dem
 min value   :  492
 max value   : 1373
plot(cropped)
```

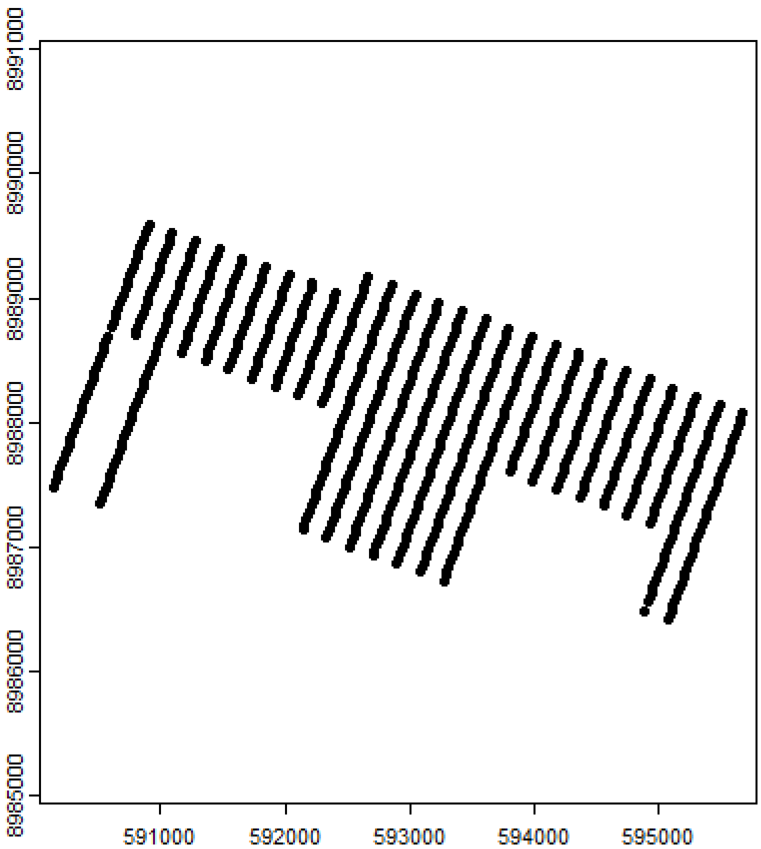


7 Working with Geological Data sources

Recipe - 7.1 – CSV format data

Structured comma separated, or any other delimiter, text data can be easily loaded into a R dataframe. The data can be transformed into geospatial data using the coordinate columns and georeferenced. The resulting data can be exported as a GIS layer too.

```
geoch<-read.csv('dado.csv')
colnames(geoch)[1]<-"sample"
library(terra)
geochem<-vect(geoch, geom=c("UTME", "UTMN"), crs="epsg:32717")
geochem
 class       : SpatVector
 geometry    : points
 dimensions  : 956, 16  (geometries, attributes)
 extent      : 590142, 595675, 8986418, 8989594  (xmin, xmax, ymin, ymax)
 coord. ref. : WGS 84 / UTM zone 17S (EPSG:32717)
 names       : ï..amostra Au_gpt    Ba    Cd    Co    Cr    Cu    Mo    Ni  Pb (and 6 more)
 type        :      <int>  <num> <num> <num> <num> <num> <num> <num> <num> <num>
 values      :          1   0.01   5.1   6.8     3    58    46     1   5.2    12
                        2   0.01    10   3.9     3    38    35     1   4.6    11
                        3   0.01   7.1   3.7     3    43    29     1     4    12
plot(geochem)
```




```
writeVector(geochem, 'geochem.shp', overwrite=TRUE)
```

The file **geochem.shp** will be used in the recipes of Chapter 8.

Recipe - 7.2 – LAS data format

Reading a LAS (Log ASCII Standard) file, visualizing the data and executing a petrophysical analysis.

7.2.1 Reading file

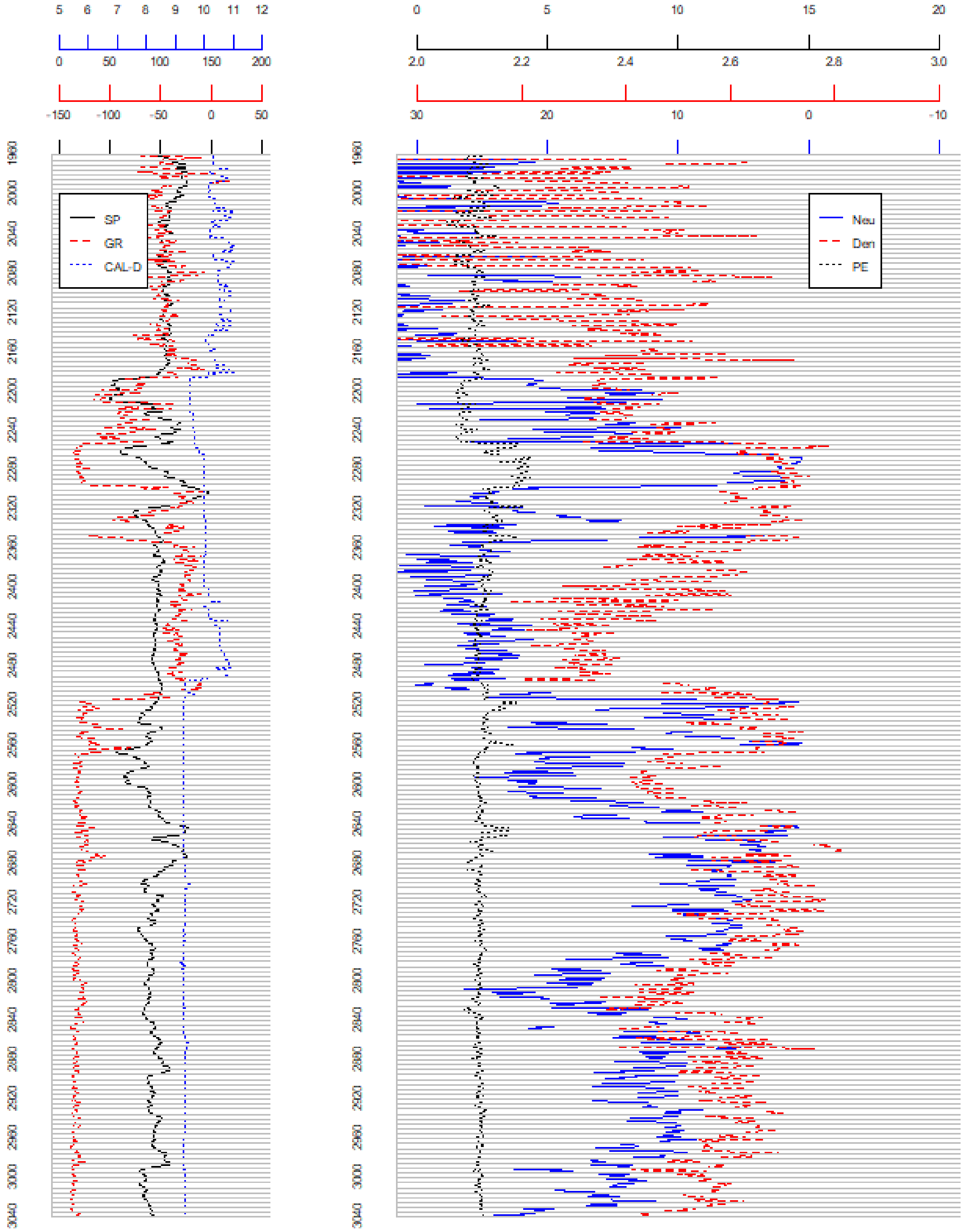
```
las<-readLines('1046531020.las')
data<-''
for (i in 1:length(las)){
 if(substr(las[i], 1, 2) == "~A"){
  data<- las[(i+1):length(las)]
  break
 }
}
hd<-''
a<-1
go<-0
for (i in 1:length(las)){
  if(substr(las[i], 1, 2) == "~C"){go<-1}
  if(substr(las[i+1], 1, 2) == "~P" || substr(las[i+1], 1, 2) == "~A" ||
  substr(las[i+1], 1, 2) == "~O"){break}
  if(go==1){
   value<-strsplit(trimws(las[i+1],"l"),'\\s{1,}')[[1]]
   hd[a]<-value[1]
   a<-a+1
  }
}
las.data<-read.table(header=TRUE, text=data)
names(las.data)<-hd
las.data[las.data==-999.2500]<-NA
las.df<-las.data[which(las.data$DEPT>250 & las.data$DEPT<3590),]
head(las.df)
      DEPT   CILD CALN  CALD     GR    ILD   ILM MINV    LWTLB CALM MNOR   NPLS   DPLS RXRT   SFL      SP   DRHO RHOB    PE
INV_RF NOR_RF
113 250.5 27.64 2.25 10.3 62.98 36.18 4.12    NA 1543.53   NA    NA 51.34 67.41    NA 0.05 114.94 -0.97 1.56 8.62
NA      NA
114 251.0 28.26 2.25 10.3 59.10 35.38 4.29    NA 1547.25   NA    NA 46.84 69.38    NA 0.05 115.51 -1.01 1.52 8.66
NA      NA
115 251.5 28.94 2.25 10.3 58.81 34.55 4.51    NA 1552.30   NA    NA 43.84 70.23    NA 0.05 116.17 -1.02 1.51 8.66
NA      NA
116 252.0 29.58 2.25 10.3 60.60 33.80 4.73    NA 1556.61   NA    NA 42.89 69.14    NA 0.05 116.52 -1.01 1.53 8.72
NA      NA
117 252.5 30.10 2.25 10.3 59.48 33.22 4.95    NA 1562.14   NA    NA 41.38 66.90    NA 0.05 116.60 -0.97 1.57 8.57
NA      NA
118 253.0 30.57 2.25 10.3 59.71 32.71 5.13    NA 1572.72   NA    NA 41.41 66.57    NA 0.05 116.58 -0.96 1.57 8.31
NA      NA
```

7.2.2 Visualizing the data

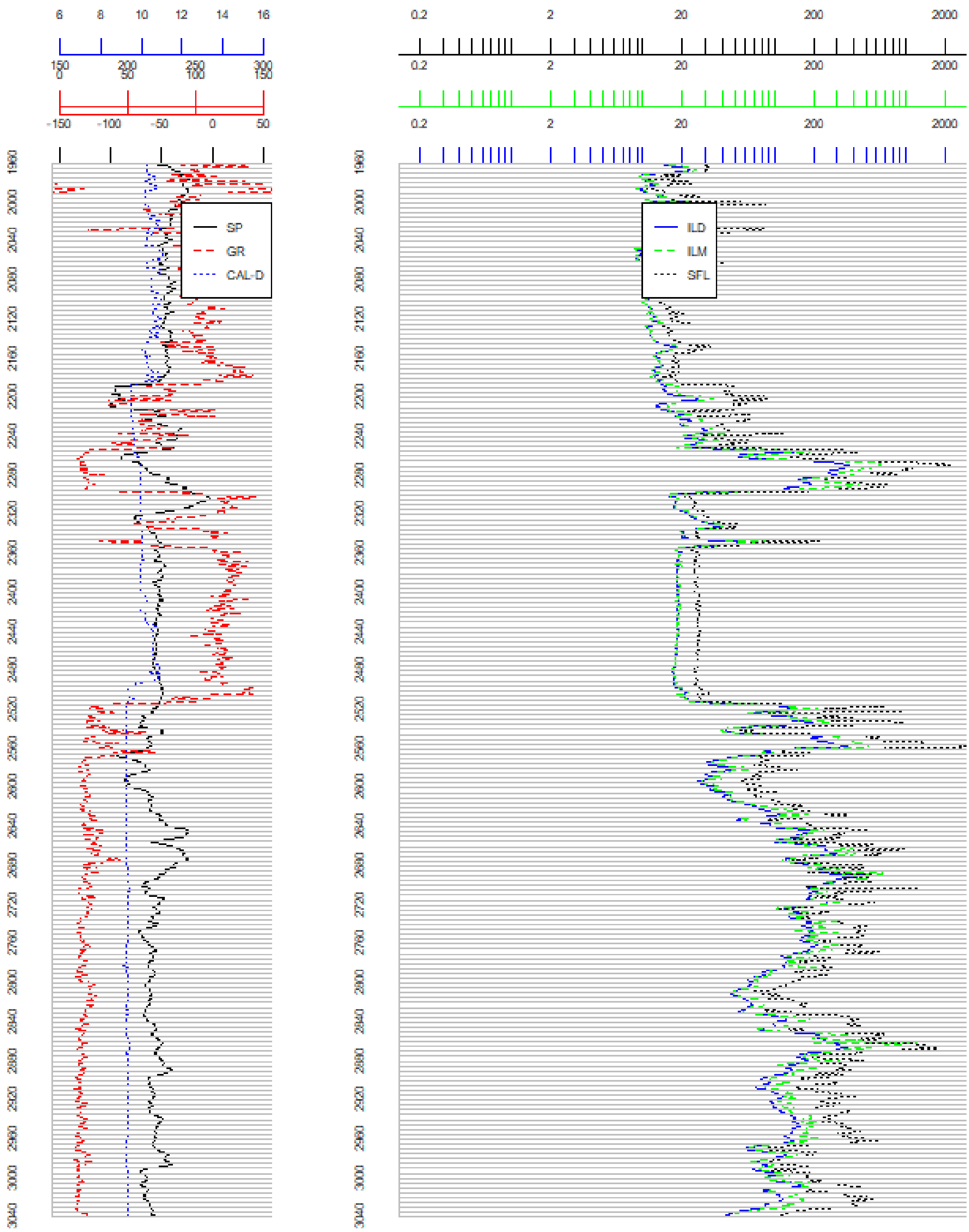
```
graf1<-function(base,topo){ #curves SP, GR and CALD /  NPLS, RHOB and PE
 par()
 dev.off()
 par(mar=c(1,2,5,2) + 0.1)
 layout(matrix(c(1,2),nrow=1), widths=c(1,2))
 plot(las.df$SP,las.df$DEPT,axes=FALSE,xlim=c(-
 150,50),type='l',xlab='', ylab='',col='black',ylim=c(topo,base))
 axis(3, xlim=c(-150,50),col='black',lwd=1,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 plot(las.df$GR,las.df$DEPT, axes=FALSE, xlim=c(0,200),
 type='l',xlab='', ylab='',col='red',lty=2, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(0,200),col='red',lwd=1,line=1.8,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 plot(las.df$CALD,las.df$DEPT, axes=FALSE, xlim=c(5,12),
 type='l',xlab='', ylab='',col='blue',lty=3, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(5,12),col='blue',lwd=1,line=3.5,cex.lab=1,cex.axis=0.5)
 axis(2,pretty(range(las.df$DEPT),500),cex.lab=1,tck=1,cex.axis=0.5,
 col='gray')
 mtext('depth',side=2,col="black",line=2)
 legend(x=5,y=base,legend=c('SP','GR','CAL-D'),lty=c(1,2,3),
 col=c('black','red','blue'), cex=0.5)
```

```
 plot(las.df$NPLS,las.df$DEPT,axes=FALSE,xlim=c(30,-
 10),type='l',xlab='', ylab='',col='blue',ylim=c(topo,base))
 axis(3, xlim=c(30,-10),col='blue',lwd=1,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 plot(las.df$RHOB,las.df$DEPT, axes=FALSE, xlim=c(2,3), type='l',
 xlab='', ylab='' ,col='red',lty=2, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(2.3),col='red',lwd=1,line=1.8,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 par(new=TRUE)
 plot(las.df$PE,las.df$DEPT, axes=FALSE, xlim=c(0,20), type='l',xlab='',
 ylab='',col='black',lty=3, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(0,20),col='black',lwd=1,line=3.5,cex.lab=1,cex.axis=0.5)
 axis(2,pretty(range(las.df$DEPT),500),cex.lab=1,tck=1,cex.axis=0.5,
 col='gray')
 legend(x=15,y=base,legend=c('Neu','Den','PE'),lty=c(1,2,3),col=c(       'blue',
'red','black'),cex=0.5)
}

graf2<-function(base,topo){ #curves SP, GR and CALD / ILD, ILM e SFL
 par()
 dev.off()
 par(mar=c(1,2,5.5,2) + 0.1)
 layout(matrix(c(1,2),nrow=1), widths=c(1,2))
 plot(las.df$SP,las.df$DEPT,axes=FALSE,xlim=c(-
 150,50),type='l',xlab='', ylab='',col='black',ylim=c(topo,base))
 axis(3, xlim=c(-150,50),col='black',lwd=1,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 plot(las.df$GR,las.df$DEPT, axes=FALSE, xlim=c(0,150),
 type='l',xlab='', ylab='',col='red',lty=2, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(0,150),col='red',lwd=1,line=1.6,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 plot(las.df$GR,las.df$DEPT, axes=FALSE, xlim=c(150,300),
 type='l',xlab='', ylab='',col='red',lty=2, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(0,150),col='red',lwd=1,line=1.9,cex.lab=1,cex.axis=0.5)
 par(new=TRUE)
 plot(las.df$CALD,las.df$DEPT, axes=FALSE, xlim=c(6,16),
 type='l',xlab='', ylab='',col='blue',lty=3, ylim=c(topo,base),lwd=1)
 axis(3, xlim=c(6,16),col='blue',lwd=1,line=3.6,cex.lab=1,cex.axis=0.5)
 axis(2,pretty(range(las.df$DEPT),500),cex.lab=1,tck=1,cex.axis=0.5,
 col='gray')
 mtext('depth',side=2,col="black",line=2)
 legend(x=12,y=base,legend=c('SP','GR','CAL-D'),lty=c(1,2,3),
 col=c('black', 'red','blue'),cex=0.5)
 plot(las.df$ILD,las.df$DEPT,axes=FALSE,xlim=c(10^-
 1,10^3),type='l',xlab='', ylab='',col='blue',ylim=c(topo,base),log='x')
 at.y <- outer(1:9, (.5*10^(-1:3)))
 lab.y <- ifelse(log10(at.y) %% 1 == 0, at.y*2, NA)
 axis(3, xlim=c(10^-1,10^3),col='blue',lwd=1,cex.lab=1,cex.axis=0.5,
 at=at.y, labels=lab.y, las=1)
 par(new=TRUE)
 plot(las.df$ILM,las.df$DEPT, axes=FALSE, xlim=c(10^-1,10^3),
 type='l',xlab='', ylab='',col='green',lty=2,
 ylim=c(topo,base),lwd=1,log='x')
 axis(3, xlim=c(10^-
 1,10^3),col='green',lwd=1,line=1.9,cex.lab=1,cex.axis=0.5, at=at.y,
 labels=lab.y, las=1)
 par(new=TRUE)
 plot(las.df$SFL,las.df$DEPT, axes=FALSE, xlim=c(10^-1,10^3),
 type='l',xlab='', ylab='',col='black',lty=3, ylim=c(topo,base),
 lwd=1,log='x')
 axis(3, xlim=c(10^-1,10^3),col='black',lwd=1,line=3.6,cex.lab=1,
 cex.axis=0.5, at=at.y, labels=lab.y, las=1)
 axis(2,pretty(range(las.df$DEPT),500),cex.lab=1,tck=1,cex.axis=0.5,
 col='gray')
 legend(x=5,y=base,legend=c('ILD','ILM','SFL'),lty=c(1,2,3),col=c('blue',
'green','black'),cex=0.5)
}
```

```
graf1(2000,3000)
```



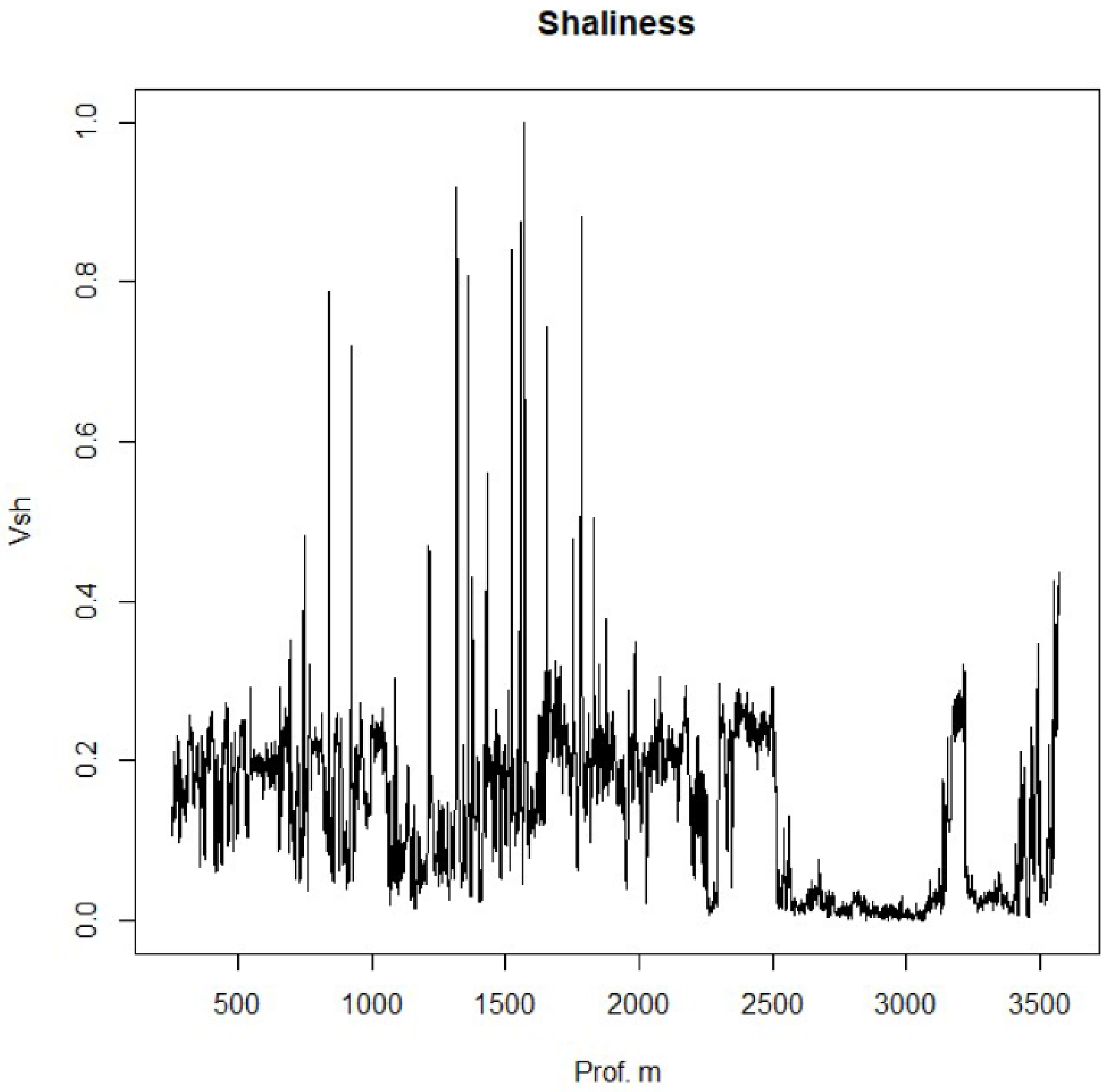
```
graf2(2000,3000)
```



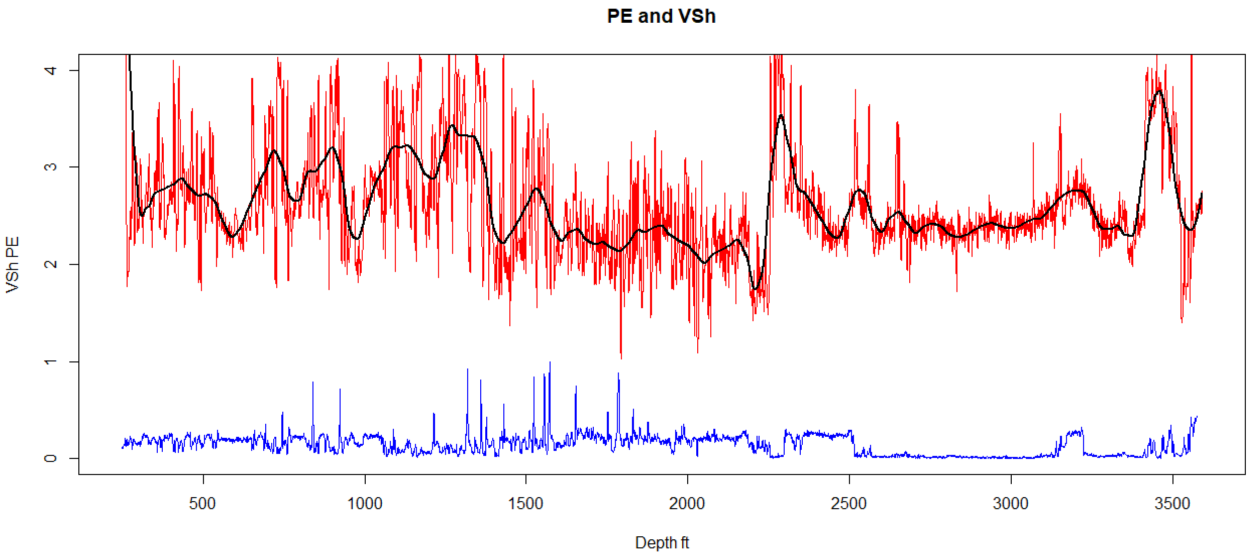
7.2.3 Petrophysical analysis

Executing the petrophysical analysis based on the data loaded above. The objective here is to show how it can be done, and several assumptions were made during the processing.

```
# SELECTING CURVES TO BE USED
petro.df<-las.df[,c(1,5,6,7,12,18,19)]
names(petro.df)<-c('depth','GR','ILD','ILM','NPLS','RHOB','PE')

#  CALCULATING SHALINESS VSh
GRmax<-max(petro.df$GR,na.rm=TRUE)
GRmin<-min(petro.df$GR,na.rm=TRUE)
petro.df$VSH<-(petro.df$GR-GRmin)/(GRmax-GRmin)
plot(petro.df$depth,petro.df$VSH,type='l',main='Shaliness',xlab='Prof.m',
ylab='Vsh')
```



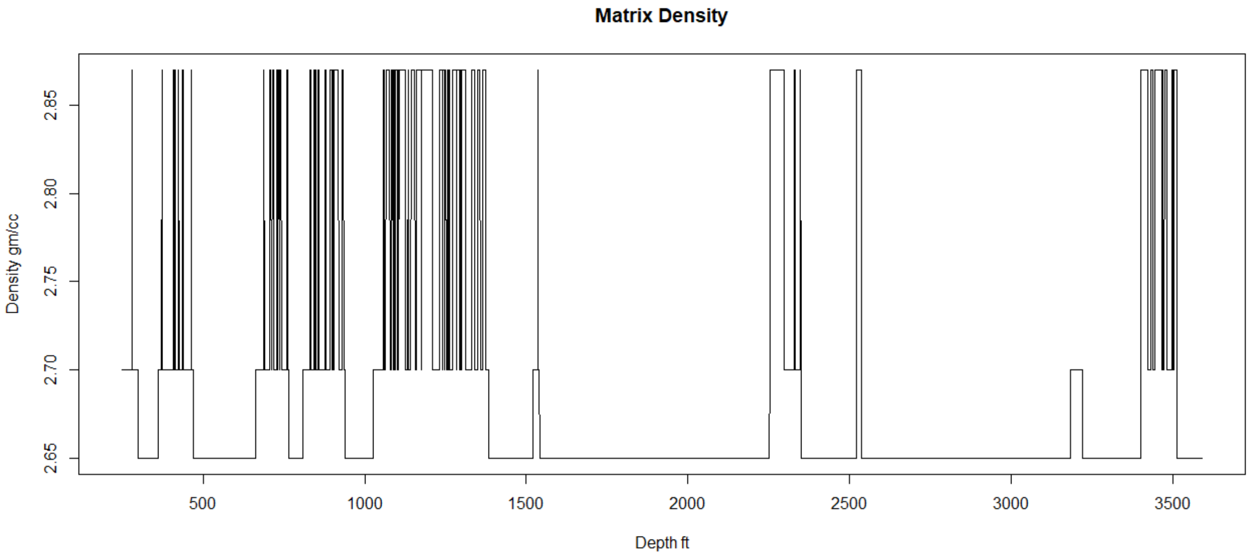

```
# CALCULATING POROSITY
lowpass.PE <- loess(PE~depth,data=petro.df, span = 0.05)
PE.lp<-predict(lowpass.PE, petro.df$depth)
plot(petro.df$depth,petro.df$PE,type='l',col='red',main='PE and VSh',
xlab='Depth ft', ylab='VSh PE',ylim=c(0,4))
lines(petro.df$depth,PE.lp,type='l',lwd=2)
lines(petro.df$depth,petro.df$VSH,type='l',lwd=.5,col='blue')
petro.df<-cbind(petro.df,PE.lp)
```



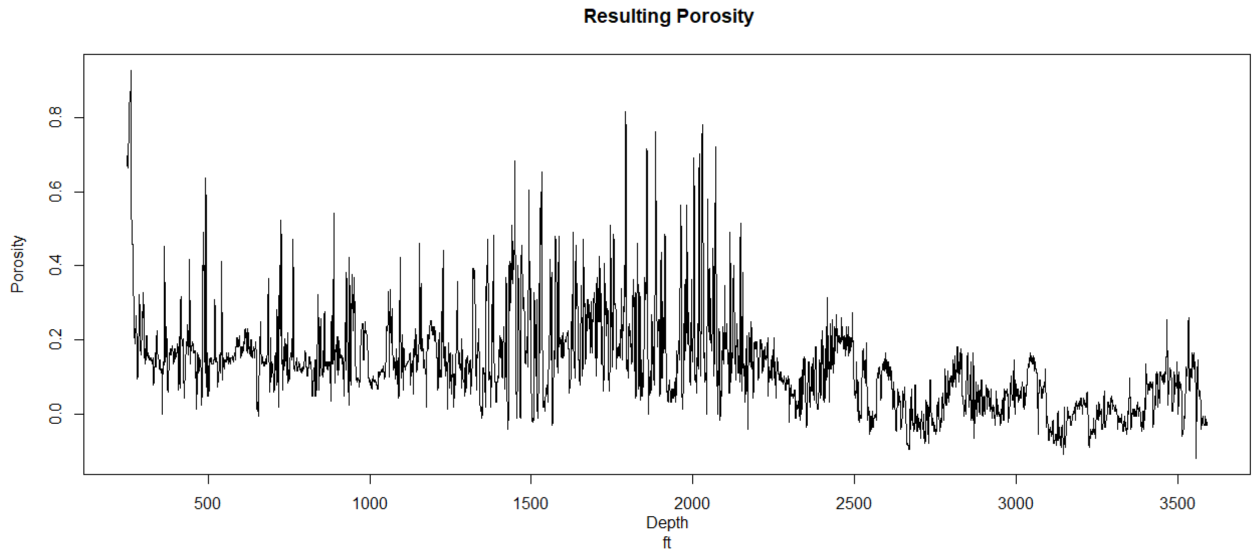
Considering the matrix porosity as 2.87 gm/cc for dolomite, 2.7 gm/cc for shale and 2.65 gm/cc for sandstone. Pe < 2.5 will be interpreted as sandstone, Pe > 2.5 will be interpreted as shale when Vsh > 0.1 otherwise dolomite.

Resulting processing.

```
petro.df$ro.matrix <- ifelse(petro.df$PE.lp >=2.75, ifelse(petro.df$VSH
<0.1,2.87,2.7), 2.65)
plot(petro.df$depth,petro.df$ro.matrix,type='l',main='Matrix
Density',xlab='Depth ft',ylab='Density gm/cc')
petro.df$phi<-(petro.df$ro.matrix-petro.df$RHOB)/(petro.df$ro.matrix-1)
```



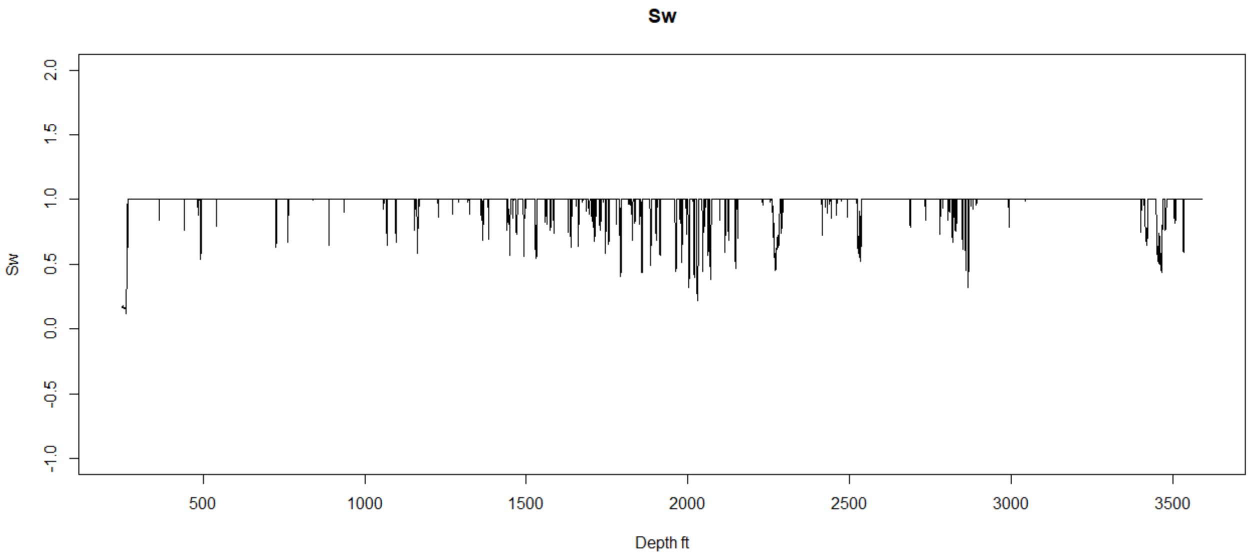

```
plot(petro.df$depth,petro.df$phi,type='l',main=' Resulting Porosity',xlab='Depth
ft', ylab='Porosity')
```



The next step is calculating the Rw from an interpreted water zone. Note that will be applying to the entire well as an overall example. The precise procedure would be applying to intervals instead. Thus, we will apply a unique Rw that may not be appropriate to the entire well because the water zone resistivity is expected to change with depth.

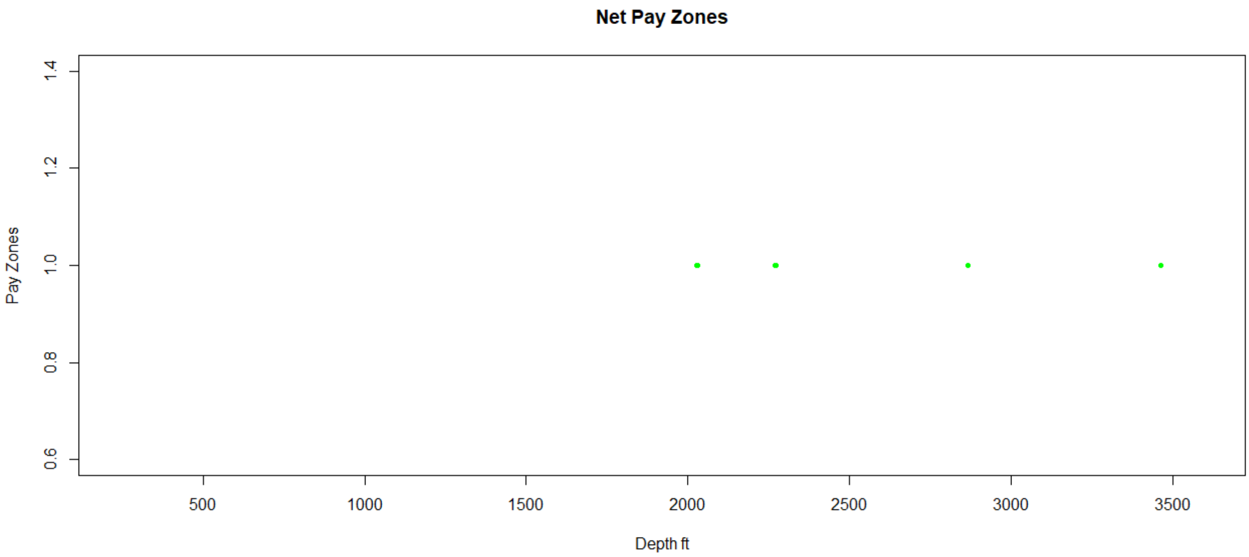
We assumed that the depth of 3042 ft shows a low resistivity, and it is porous (sandstone).
Now we will calculate the Sw using:

```
# CALCULATING THE SW
petro.df[petro.df$depth == 3042,]

     depth    GR   ILD   ILM  NPLS RHOB   PE        VSH    PE.lp ro.matrix       phi
5696  3042 14.91 17.93 19.78 25.97 2.38 2.35 0.01037538 2.428599      2.65 0.1636364

Rt<-petro.df[petro.df$depth == 3042,]$ILD
phiT<-petro.df[petro.df$depth == 3042,]$phi
Rw<-phiT*phiT*Rt
Rw
[1] 0.4801091

petro.df$Sw<-1/petro.df$phi*sqrt(Rw/petro.df$ILD)
index<- petro.df$Sw > 1
petro.df$Sw[index]<- 1
index<- petro.df$Sw < 0
petro.df$Sw[index]<- 1
plot(petro.df$depth,petro.df$Sw,type='l',main='Sw',xlab='Depth ft',
ylab='Sw', ylim=c(-1,2))
```



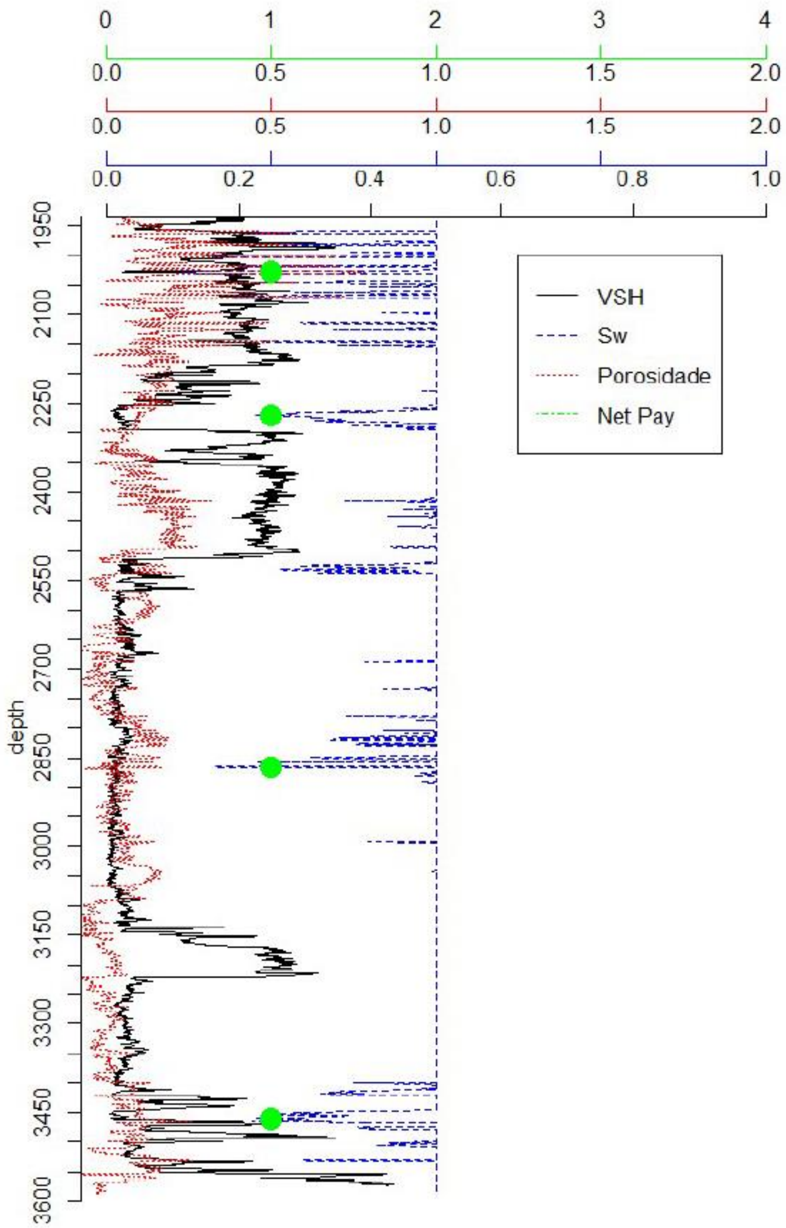
Net Reservoir is the zone where VSh is low and the porosity is high. The Net Pay is the zone inside the Net Reservoir where the water saturation is low. Here we used the cut values as 0.05 for Vsh, 0.1 for Porosity and 0.5 for Sw to define our Net Pay Zone(s).

```
# CALCULATING THE NETPAY
petro.df$net.pay<-ifelse(petro.df$phi>0.1,ifelse(petro.df$VSH<0.05,
ifelse(petro.df$Sw<0.5,1,NA), NA),NA)
plot(petro.df$depth,petro.df$net.pay,type='l',main='Net Pay Zones',
xlab='Depth ft',ylab='Pay Zones',lwd=5,col='green')
```




```
# A BETTER PLOT
dev.off()
par(mar=c(1, 4, 8, 4) + 0.1)
plot(petro.df$VSH,petro.df$depth,axes=FALSE,xlim=c(0,1),type='l',xlab=
'', ylab='',col='black',ylim=c(3600,2000))
axis(3, xlim=c(0,1),col='black',lwd=1)
par(new=TRUE)
plot(petro.df$Sw,petro.df$depth, axes=FALSE, xlim=c(0,2),
type='l',xlab='', ylab='',col='blue',lty=2, ylim=c(3600,2000),lwd=1)
axis(3, xlim=c(0,2),col='blue',lwd=1,line=2)
par(new=TRUE)
plot(petro.df$phi,petro.df$depth, axes=FALSE, xlim=c(0,2),
type='l',xlab='', ylab='',col='red',lty=3, ylim=c(3600,2000),lwd=1)
axis(3, xlim=c(0,2),col='red',lwd=1,line=4)
par(new=TRUE)
plot(petro.df$net.pay,petro.df$depth, axes=FALSE, xlim=c(0,4),
type='l',xlab='', ylab='',col='green',lty=4,ylim=c(3600,2000),lwd=15)
```

```
axis(3, xlim=c(0,4),col='green',lwd=1,line=6)
axis(2,pretty(range(petro.df$depth),100))
mtext('depth',side=2,col="black",line=2)
legend(x=2.5,y=2000,legend=c('VSH','Sw','Porosidade','Net
Pay'),lty=c(1,2,3,4),col=c('black','blue','red','green'))
```



Recipe - 7.3 – SEG-Y Data Format

Reading and interacting with SEG-Y files used to store Seismic and GPR surveys. This example should work with most of the SEG-Y data without big modifications.

SEG-Y files are divided into three main parts (generically speaking); General header (3200 bytes of text Header plus 400 bytes of binary header); binary trace header (240 bytes); and trace binary data.

7.3.1 Reading the text header data

```
hdbn<-c('JOB_ID_NO','LINE_NUMBER','REEL_NUMBER','TRACES_PER_RECORD',
'AUXS_PER_RECORD','SAMPLE_RATE','SAMPLE_RATE_FIELD','NSAMPLES','NSAMPL
ES_FIELD','FORMAT_CODE','ENSEMBLE_FOLD','TRACE_SORT','VERTICAL_SUM','S
WEEP_FREQ_START','SWEEP_FREQ_END','SWEEP_FREQ_LENGTH','SWEEP_TYPE','SW
EEP_TRACE_NO','SWEEP_TAPER_LENGTH_START','SWEEP_TAPER_LENGTH_END','SWE
EP_TAPER_TYPE','CORRELATED_TRACES','BINARY_GAIN','AMP_RECOVERY_METHOD'
,'UNITS','SIGNAL_POLARITY','VIBRATOR_POL_CODE','UNUSED','SEGY_FORMAT_R
EVISION_NO','SEGY_FIXEDLEN_FLAG','SEGY_NO_TEXTFHEADERS','UNUSED')
con <- file("1104-30A.segy","rb")
library(float) #install float using install.packages("float")
cabe.texto<-c('bogus','data')
for(i in 1:40){
dec<-readBin(con,"raw",size=1,n=80)
cabe.texto[i]<-
paste0(iconv(rawToChar(dec,multiple=T),'cp500','utf8'), collapse='')
}
cabe.texto
[1] "C 1 CLIENT MMS                        COMPANY GECO                 CREW NO         "
 [2] "C 2 LINE 1104-30A    AREA PHASE-30A                  MAP ID                        "
 [3] "C 3 REEL NO 17784MIG0 DAY-START OF REEL      YEAR      OBSERVER                    "
 [4] "C 4 INSTRUMENT: MFG              MODEL            SERIAL NO                       "
 [5] "C 5 DATA TRACES/RECORD        AUXILIARY TRACES/RECORD       CDP FOLD              "
 [6] "C 6 SAMPLE INTERVAL        4 SAMPLES/TRACE  2750 BITS/IN     0 BYTES/SAMPL        0"
 [7] "C 7 RECORDING FORMAT        FORMAT THIS REEL       MEASUREMENT SYSTEM             "
 [8] "C 8 SAMPLE CODE: FLOATING PT 032 FIXED PT     FIXED PT-GAIN     CORRELAT          "
 [9] "C 9 GAIN  TYPE: FIXED     BINARY     FLOATING POINT     OTHER                     "
[10] "C10 FILTERS: ALIAS     HZ  NOTCH     HZ  BAND     -     HZ  SLOPE    -            "
[11] "C11 SOURCE: TYPE AIRGUN    NUMBER/POINT         POINT INTERVAL                    "
[12] "C12     PATTERN:                             LENGTH        WIDTH                  "
[13] "C13 SWEEP: START     HZ  END      HZ  LENGTH       MS  CHANNEL NO     TYPE        "
[14] "C14 TAPER: START LENGTH       MS  END LENGTH       MS  TYPE                       "
[15] "C15 SPREAD: OFFSET         MAX DISTANCE        GROUP INTERVAL                     "
[16] "C16 GEOPHONES: PER GROUP     SPACING     FREQUENCY     MFG          MODE          "
[17] "C17     PATTERN:                             LENGTH        WIDTH                  "
[18] "C18 TRACES SORTED BY: RECORD     CDP     OTHER                                    "
[19] "C19 AMPLITUDE RECOVERY: NONE      SPHERICAL DIV       AGC    OTHER                "
[20] "C20 PROJECTION : SPHEROID :                            "
[21] "C21 FAMILY 1 DEFAULTS: DATA TRACES/RECORD        AUXILIARY TRACES/RECORD          "
[22] "C22                    SAMPLE INTERVAL          SAMPLES/TRACE                     "
[23] "C23 FAMILY 3 DEFAULTS: SAMPLE INTERVAL          SAMPLES/TRACE                     "
[24] "C24 CENTRAL MERIDIAN :  0  0 0.0 E    ORIGIN PARALLEL :  0  0 0.0 N               "
[25] "C25 FALSE NORTHING :      0.0 FALSE EASTING :      0.0 UNIT TO METER :0.000000  "
[26] ""
[27] "C27 MXYMRGOV 15.06.22 12- 8-88 A6602IM4 0526     1104-30                          "
[28] "C28                                                                               "
[29] "C29                                                                               "
[30] "C30                                                                               "
[31] "C31                                                                               "
[32] "C32                                                                               "
[33] "C33                                                                               "
[34] "C34                                                                               "
[35] "C35                                                                               "
[36] "C36                                                                               "
[37] "C37                                                                               "
[38] "C38                                                                               "
[39] "C39                                                                               "
[40] "C40 END EBCDIC                                                                    "
```

7.3.2 Reading the binary header data

```
seek(con,3200) #posicioning at the byte 3201 (starts with 0)
cabe.bin<-c(1.0,1.7)
passo<-1
```

```
for (i in passo:(passo+2)){
cabe.bin[passo]<-readBin(con,'int',size=4,endian='big')
passo<-passo+1
}
for (i in passo:(passo+23)){
cabe.bin[passo]<-readBin(con,'int',size=2,endian='big')
passo<-passo+1
}
cabe.bin[passo]<-0
seek(con,3500)
passo<-passo+1
for (i in passo:(passo+2)){
cabe.bin[passo]<-readBin(con,'int',size=2,endian='big')
passo<-passo+1
}
cabe.bin[passo]<-0
seek(con,3600)
cabecalho.bin<-data.frame(field=hdbn,value=cabe.bin)
cabecalho.bin
                         field value
1                    JOB_ID_NO   526
2                  LINE_NUMBER  1104
3                  REEL_NUMBER    30
4            TRACES_PER_RECORD     1
5              AUXS_PER_RECORD     0
6                  SAMPLE_RATE  4000
7            SAMPLE_RATE_FIELD     0
8                     NSAMPLES  2751
9             NSAMPL\nES_FIELD  2751
10                 FORMAT_CODE     1
11               ENSEMBLE_FOLD     1
12                  TRACE_SORT     4
13                VERTICAL_SUM     2
14          S\nWEEP_FREQ_START     0
15              SWEEP_FREQ_END     0
16           SWEEP_FREQ_LENGTH     0
17                  SWEEP_TYPE     0
18            SW\nEEP_TRACE_NO     0
19     SWEEP_TAPER_LENGTH_START    0
20       SWEEP_TAPER_LENGTH_END    0
21          SWE\nEP_TAPER_TYPE     0
22           CORRELATED_TRACES     0
23                 BINARY_GAIN     0
24         AMP_RECOVERY_METHOD     0
25                       UNITS     1
26             SIGNAL_POLARITY     0
27           VIBRATOR_POL_CODE     0
28                      UNUSED     0
29 SEGY_FORMAT_R\nEVISION_NO       0
30           SEGY_FIXEDLEN_FLAG    0
31        SEGY_NO_TEXTFHEADERS     0
32                      UNUSED     0
```

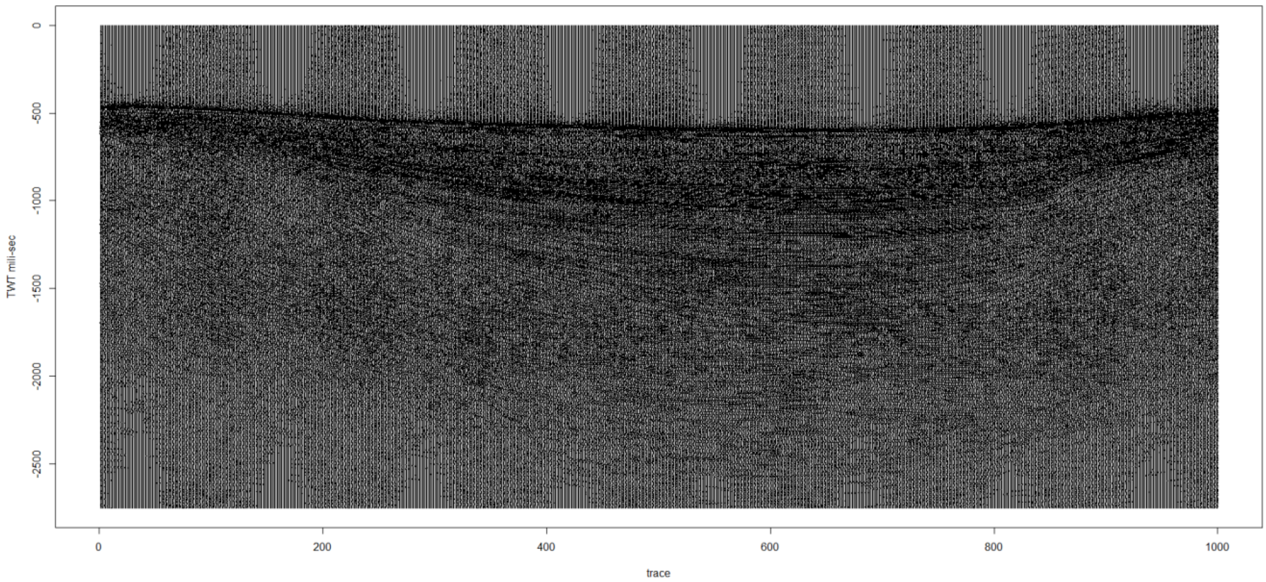
7.3.3 Combining the trace header and trace vector into a dataframe

```
tam.arq<-file.info('1104-30A.segy')$size
tam.arq
[1] 50995140
rep.cabecalho<-cabecalho.bin[31,2]
rep.cabecalho
numero.samples<-cabecalho.bin[8,2]
numero.samples
[1] 2751
num.tr<-(tam.arq-3600-3600*rep.cabecalho)/(240+numero.samples*4)
num.tr
[1] 4535
conta<-c(7,4,8,2,4,46,5,2,3,4,6,1,2)
byte.me<-c(4,2,4,2,4,2,4,2,2,2,2,2,4)
tr.bin<-c(1,2)
l.cabe.tr.bin<-list(data.frame(campo='oi',valor=1))
l.tr<-list(c(1,2,3))
traco<-c(1,2,3)
for (i in 1:num.tr){
tbc<-0
for (a in 1:13){
for (c in 1:conta[a]){
tr.bin[tbc]<-readBin(con,'int',size=byte.me[a],endian='big')
tbc<-tbc+1
```

```
}
}
frame<-data.frame(valor=tr.bin)
l.cabe.tr.bin[[i]]<-frame
for(s in 1:numero.samples){
traco[s]<-readBin(con,'double',size=4,endian='big')
}
l.tr[[i]]<- as.single (traco)
}
close(con)
segY<-list(cabe.texto,cabecalho.bin,l.cabe.tr.bin,l.tr)
```

7.3.4 Plotting the Result

```
plot(((segY[[4]][[1]])/40)+1,c(-1:-numero.samples),type='l',
xlim=c(1,1000), xlab='trace', ylab='TWT mili-sec',lwd=0.02)
for(i in 2:1000){
lines(((segY[[4]][[i]])/40)+i,c(-1:-numero.samples),type='l',lwd=0.02)
}
```



Recipe - 7.4 – OASIS-MONTAJ XYZ Data Format

Oasis Montaj XYZ geophysical data are normally in the following formats:

```
/ ------------------------------------------------------------------------------
/ XYZ EXPORT [05/11/10]
/ DATABASE [F:\1100\DVD_01\GDB\1100_MAGLINE.gdb : SUPER]
/ ------------------------------------------------------------------------------
/
/ X Y FIDUCIAL GPSALT BARO ALTURA MDT MAGBRU MAGCOM MAGCOR...
/=========  ==========  ===========  ==========  ==========  ==========  ==========
=======...
/
Line 10010
170583.35 8895511.73 26618.0 423.09 426.67 109.01 322.03 24287.7188 24286.1147
24272.3286...
```

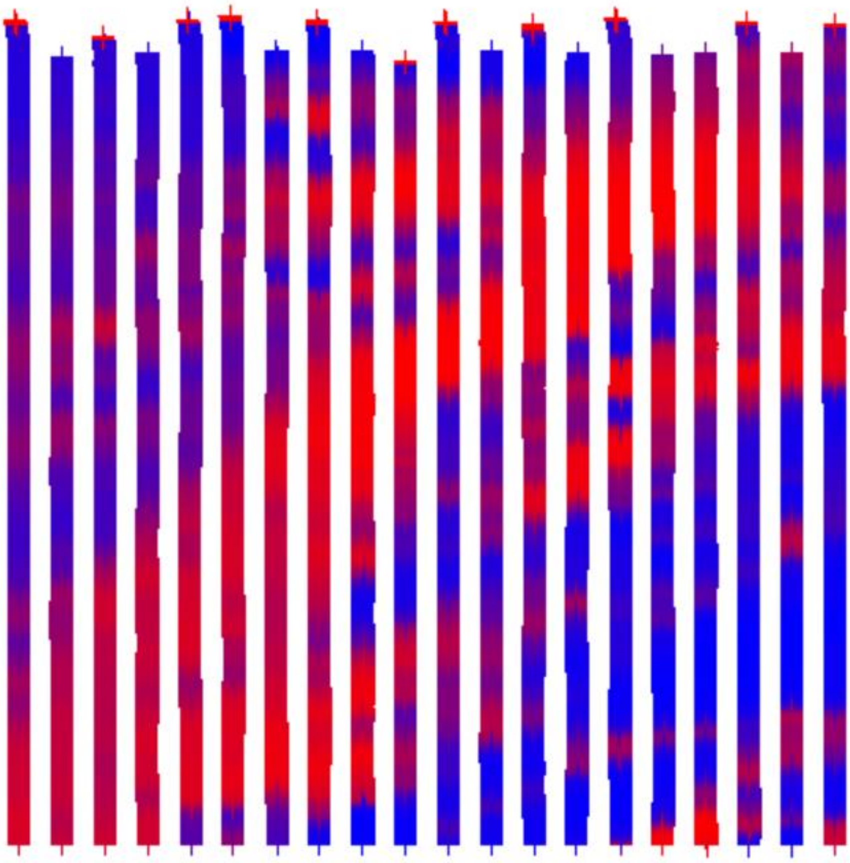
Or

```
/ ------------------------------------------------------------------------------
/ XYZ EXPORT [05/11/10]
/ DATABASE [F:\1100\DVD_01\GDB\1100_GAMALINE.gdb : SUPER]
/ ------------------------------------------------------------------------------
/
/ X Y FIDUCIAL GPSALT BARO ALTURA MDT CTB KB UB ....
/========== ========== ========== ========== ========== ========== ==========...
/
Line 10010
170583.28 8895543.28 1752.0 422.61 426.67 107.69 314.92 1644 151 52 ...
170582.68 8895622.11 1753.0 422.09 424.89 106.13 315.96 1616 132 55 ...
170581.96 8895701.04 1754.0 422.19 425.78 106.93 315.26 1655 132 56 ...
```

Creating a dataframe with the XYZ data. If the file you have is in GDB format you can easily convert it to XYZ using Oasis Montaj Viewer.

```
xmi<-180000
xma<-190000
ymi<-8940684
yma<-8950684
flcon<-file('1099_MAGLINE.XYZ',open='r')
# reading first lines
tmp <- readLines(flcon, n=5)
# retrieving column names
coluna <-c(strsplit(substring(readLines(flcon, n=1),11),"\\s+")[[1]],'line/tie')
n.co<-length(coluna)+1
# reading additional lines until the data
tmp <- readLines(flcon, n=2)
lin<-c('a')
o<-1 #define o índice
lineOrTie<-'vazio'
while (length(line <- readLines(flcon, n = 1, warn = FALSE)) > 0) {
  if(substring(line,2,3)=='ie' || substring(line,2,3)=='in'){
     if(substring(line,2,3)=='ie')lineOrTie<-'Tie'
     if(substring(line,2,3)=='in')lineOrTie<-'Line'
    }else{
     v<-as.numeric(strsplit(line, "\\s+")[[1]][2])
     w<-as.numeric(strsplit(line, "\\s+")[[1]][3])
     if(v>xmi & v<xma & w>ymi & w<yma){
      lin[o]<-paste(line,lineOrTie)
      o<-o+1
     }
   }
}
close(flcon)
r <- strsplit(sub("^\\s+","",lin), "\\s+")
s <-as.data.frame(do.call(rbind, r))
names(s)<- coluna
cols = c(1:(ncol(s)-3))
s[,cols] = apply(s[,cols], 2, function(x) as.numeric(as.character(x)))
```

```
# converting to SpatVector and ploting
library(terra) #install terra using install.packages("terra")
sgeo<-vect(s, geom=c("X", "Y"), crs="epsg:32721")
library(raster) #install raster using install.packages("raster")
mag<-as(sgeo, "Spatial")
plot(mag,col=colorRampPalette(c('blue','red'))(length(mag$MAGIGRF))[rank(mag$MA
GIGRF)])
```



Recipe - 7.5 – UBC Data Format

UBC mesh-model 3D are structured in the following format:

msh file format:

$$
\begin{array}{cccc}
\mathrm{NE} & \mathrm{NN} & \mathrm{NZ} & \\
\mathrm{E}_o & \mathrm{N}_o & \mathrm{Z}_o & \\
\Delta\mathrm{E}_1 & \Delta\mathrm{E}_2 & \cdots & \Delta\mathrm{E}_{NE} \\
\Delta\mathrm{N}_1 & \Delta\mathrm{N}_2 & \cdots & \Delta\mathrm{N}_{NN} \\
\Delta\mathrm{Z}_1 & \Delta\mathrm{Z}_2 & \cdots & \Delta\mathrm{Z}_{NZ}
\end{array}
$$

Where:
- NE NN NZ number of points at each direction
- Eo No Zo origin coordinates
- ΔE(1 to N) spacing between data in E direction (W to E)
- ΔN(1 to N) spacing between data in N direction (S to N)
- ΔZ(1 to N) spacing between data in Z direction (Top to Base)

mod file format:

$$
\begin{array}{l}
m_{1,1,1} \\
m_{1,1,2} \\
\vdots \\
m_{1,1,NZ} \\
m_{1,2,1} \\
\vdots \\
m_{1,j,k} \\
\vdots \\
m_{NN,NE,NZ}
\end{array}
$$

Where:
- Each m{i,j,k} is the property in the [i,j,k]^{th} model cell.
- \([i, j, k]=[1, 1, 1]\) is defined as the cell at the top, south-west corner of the model.
- The total number of lines in this file should equal NN x NE x NZ.
- The model ordering is performed first in the z-direction (top-to-bottom), then in the easting, and finally in the northing.

Retrieving the data from mesh and model files:

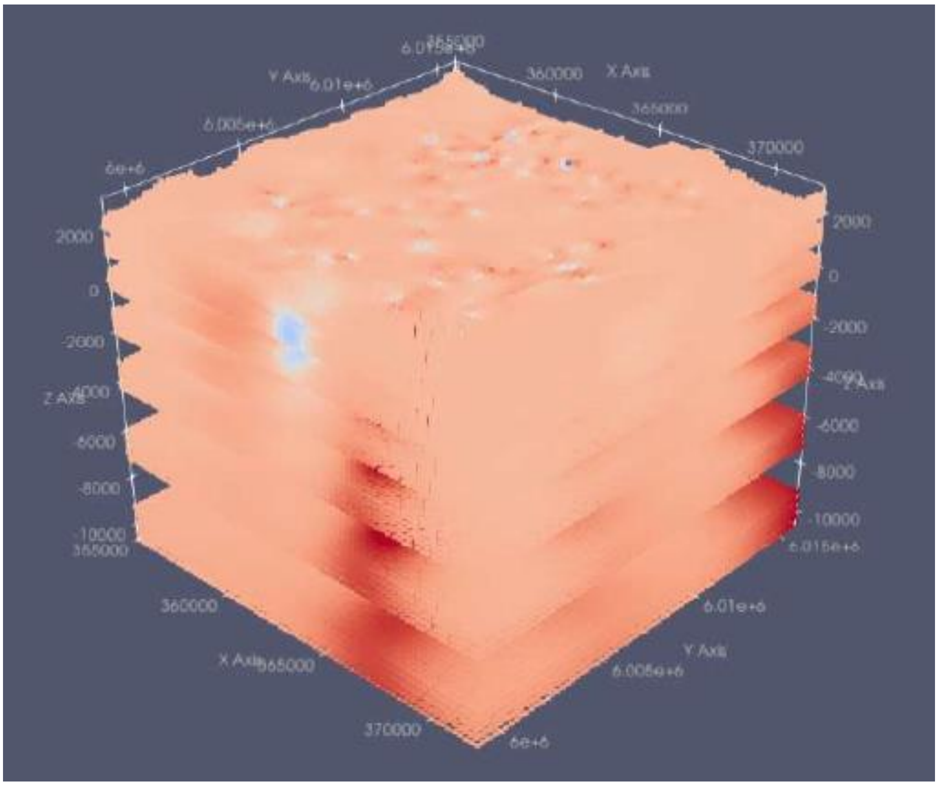
```
file<-file('arquivo_mesh.msh',open='rt')
GV<-list()
GV[[1]]<-scan(file,what=1,nlines=1,sep=" ")
GV[[2]]<-scan(file,what=1,nlines=1,sep=" ")
GV[[3]]<-scan(file,what=1,nlines=1,sep=" ")
GV[[4]]<-scan(file,what=1,nlines=1,sep=" ")
GV[[5]]<-scan(file,what=1,nlines=1,sep=" ")
close(file)
GV[[6]]<-data.frame(z=NA,x=NA,y=NA,v=read.table('arquivo_model.mod')$V1)
names(GV)<-c('dimension','origin','deltaX','deltaY','deltaZ','values')
```

```
GV$deltaX<-na.omit(GV$deltaX)
GV$deltaY<-na.omit(GV$deltaY)
GV$deltaZ<-na.omit(GV$deltaZ)
summary(GV)
          Length Class      Mode
dimension  3     -none-     numeric
origin     3     -none-     numeric
deltaX    69     -none-     numeric
deltaY    69     -none-     numeric
deltaZ    40     -none-     numeric
values     4     data.frame list
```

loading the coordinates into the dataframe 'values' and exporting it as ubc.csv file:

```
coordz<-GV$origin[3]+GV$deltaZ-GV$deltaZ*seq(1:GV$dimension[3])
GV$values[1]<-coordz
coordx<-rep(GV$origin[1],GV$dimension[1])
coordxx<-coordx-GV$deltaX+GV$deltaX*seq(1:GV$dimension[1])
coordxxx<-rep(coordxx, each=GV$dimension[3])
GV$values[2]<-coordxxx
coordy<-rep(GV$origin[2],GV$dimension[2])
coordyy<-coordy-GV$deltaY+GV$deltaY*seq(1:GV$dimension[2])
coordyyy<-rep(coordyy, each=GV$dimension[1]*GV$dimension[3])
GV$values[3]<-coordyyy
GV$values<-na.omit(GV$values)
write.csv(GV$values,'ubc.csv',row.names=F)
```

Visualizing the ubc.csv file using Paraview (using Table to Po point Filter):



Recipe - 7.6 – Moving Exploration data to a Remote Database

This is not an R receipt, but it can be useful for the next recipe.
To move exploration data to a PostgreSQL server following the instruction below:

On the server create a database **geodb** using:
$ *createdb geodb --encoding=utf-8*

Create the file create.sql using a text editor:

```
CREATE TABLE collar(
holeid      varchar(50) NOT NULL,
x           numeric(6,2) NOT NULL,
y           numeric(6,2) NOT NULL,
z           numeric(6,2) NOT NULL,
enddepth    numeric(6,2)NOT NULL,
UNIQUE(holeid));

CREATE TABLE survey(
holeid      varchar(50) NOT NULL,
_at         numeric(4,1) NOT NULL,
azm         numeric(5,2) NOT NULL,
dip         numeric(4,2)NOT NULL,
UNIQUE(holeid,_at));

CREATE TABLE assay(
holeid      varchar(50) NOT NULL,
_from       numeric(4,1) NOT NULL,
_to         numeric(4,1) NOT NULL,
au          numeric(4,2));

CREATE TABLE litho(
holeid      varchar(50) NOT NULL,
_from       numeric(4,1) NOT NULL,
_to         numeric(4,1) NOT NULL,
domain      varchar(10),
rocktype    varchar(10),
weath       varchar(10));
```

Save the file locally at the server and run:
$ *psql -d geodb -f create.sql*

Upload the data from the files collar.csv, assay.csv, survey.csv and litho.csv into the geodb database using:
$ *psql geodb*
geodb =# \copy collar (holeid,x,y,z,enddepth) FROM 'collar.csv' DELIMITER ',' HEADER CSV
geodb =# \copy assay FROM 'assay.csv' DELIMITER ',' HEADER CSV
geodb =# \copy survey FROM 'survey.csv' DELIMITER ',' HEADER CSV
geodb =# \copy litho FROM 'litho.csv' DELIMITER ',' HEADER CSV
geodb =# GRANT SELECT ON ALL TABLES IN SCHEMA public to user;

Don't forget to replace user by the real database username.

Recipe - 7.7 – Drilling Data Desurvey

Executing a drillhole desurvey using the data located at a remote PostgreSQL database.

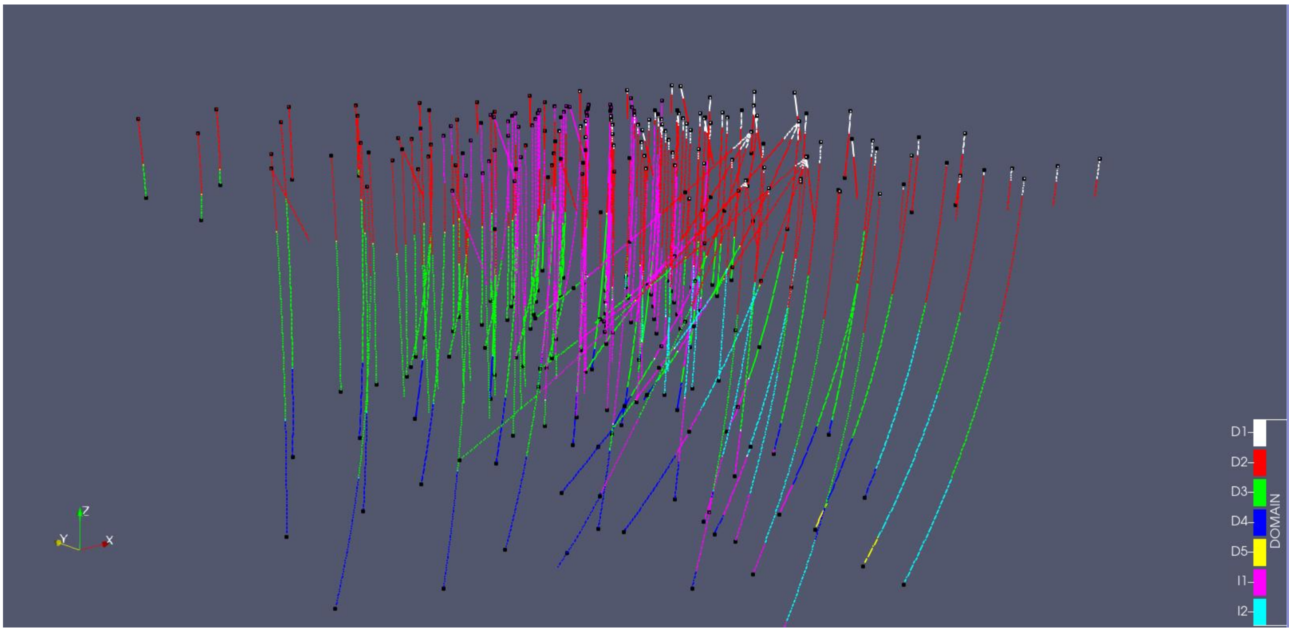
Server: **pg.gdatasystems.com**
User: **droid**
Password: **devcor**

User the server and server credentials to run this recipe.

```
library(RPostgreSQL) #install RPostgreSQL using install.packages("RPostgreSQL")
con<-dbConnect(PostgreSQL(),host='pg.gdatasystems.com',user='droid',
password='devcor',dbname='geofoss')

dat <- dbGetQuery(con, "select c.holeid as hole, c.x as x, c.y as
y, c.z as z, a.au as au, a._from as prof, l._from as profl, a._to as
toa, l._to as tol, (a._to-a._from) as lena, (l._to-l._from) as lenl,
l.domain, l.rocktype, l.weath from collar as c, assay as a, litho as
l where c.holeid = a.holeid and l.holeid=c.holeid and l._from between
a._from and (a._to-0.02) order by hole,prof")

collar <- dbGetQuery(con, "select c.holeid as hole,s._at as prof, c.x
as x, c.y as y, c.z as z, s.dip as dip, s.azm as az from collar as c,
survey as s where c.holeid = s.holeid and s._at=0")
# if dip is positive uncoment this line-------------------------------
collar$dip <- collar$dip*-1

station <- dbGetQuery(con, "SELECT holeid as hole, _at as prof, null
as x, null as y, null as z, dip as dip, azm FROM survey order by
holeid,prof")

station$dip <- station$dip*-1
d2r <- function(x) { x * pi/180}
tresD<-function(co,es){
 linha <- data.frame()
 for(i in 1:nrow(co)){
 x <- co[i,3]
 y <- co[i,4]
 z <- co[i,5]
 di <- 0
 fur <- es[es[[1]]==co$hole[[i]],]
 fur <- fur[order(fur$prof),]
 ro <- nrow(fur)
 for(j in 1:ro){
 ang <- fur[j,7]
 d <- fur[j,2]-di
 di <- d+di
 dip <- fur[j,6]
 if(j>1)dip <- fur[(j),6]-(fur[j,6]-fur[(j-1),6])/2
 deltaz <- d*sin(d2r(dip))
 r <- d*cos(d2r(dip))
 x <- round(x+r*sin(d2r(ang)))
 y <- round(y+r*cos(d2r(ang)))
 z <- round(z+deltaz)
 linha<-
rbind(linha,data.frame(hole=fur[j,1] ,prof=fur[j,2],x=x ,y=y
,z=z,dip=fur[j,6],az=fur[j,7]))
 }
 }
 lin <- linha
 lin <- lin[order(lin$hole,lin$prof),]
 return(lin)
}
Spts <- tresD(collar,station)
calculo <- function(azt,azb,dt,db,dp){
 dt <- (90-dt)
 db <- (90-db)
 dbt <- db-dt
 abt <- azb-azt
```

```
 d <- acos(cos(d2r(dbt))-sin(d2r(dt))*sin(d2r(db))*(1-cos(d2r(abt))))
 r <- 1
 if(d==0){r <- 1}
 else{r <- 2*tan(d/2)/d}
 x = 0.5*dp*(sin(d2r(dt))*sin(d2r(azt))+ sin(d2r(db))*sin(d2r(azb)))*r
 y = 0.5*dp*(sin(d2r(dt))*cos(d2r(azt))+ sin(d2r(db))*cos(d2r(azb)))*r
 z = 0.5*dp*(cos(d2r(dt))+cos(d2r(db)))*r
 return(c(x,y,z))
}
calcXYZ<-function(hole,depth){
 dadoxyz <- c(0.0,0.0,0.0)
 t <- Spts[which(Spts$hole==hole & Spts$prof <=depth),]
 t <- t[order(-t$prof),]
 b <- Spts[which(Spts$hole==hole & Spts$prof > depth),]
 if(dim(t)[1] == 0){return (c(0,0,0))}
 di <- b[1,2]- t[1,2]
 rga <- t[1,6] - b[1,6]
 stp <- rga/di
 dpt <- depth-t[1,2]
 pang <-stp*dpt
 if(dim(b)[1] >= 1){
 res <- calculo(t[1,7], b[1,7],t[1,6], t[1,6]-pang, dpt)
 return(c((t[1,3]+res[1]), (t[1,4]+res[2]), (t[1,5]+res[3])))
 }
 else{
 res <- calculo(t[1,7], t[1,7], t[1,6], t[1,6], dpt)
 return(c((t[1,3]+res[1]), (t[1,4]+res[2]), (t[1,5]+res[3])))
 }
}
for(i in 1 : dim(dat)[1]){
 dado <- calcXYZ(dat$hole[i],dat$prof[i])
 dat$x[i] <- dado[1]
 dat$y[i] <- dado[2]
 dat$z[i] <- dado[3]
}
colnames(dat)<-c("BHID","X","Y","Z","AU","FROM","FROML","TO",    "TOL","LENGTH",
"LENHTL","DOMAIN","ROCKTYPE","WEATH")
write.csv(dat,"RDESURVEYED.CSV",row.names = FALSE)
write.csv(Spts,"SURVEY_PTS.CSV",row.names = FALSE)
```

Visualizing the files created above using Paraview (using Table to Po point Filter):



8 2D Point Interpolation

In this chapter we will use the file **geoqui.shp** created in recipe 7.1.

Recipe - 8.1 – Distance Matrix

In here we gather the distance between points as a matrix using spDists that takes two objects Spatial* (in this example we use the same object twice) and a third parameter informing if the data is Euclidean (ex. UTM) or Longitude / Latitude.

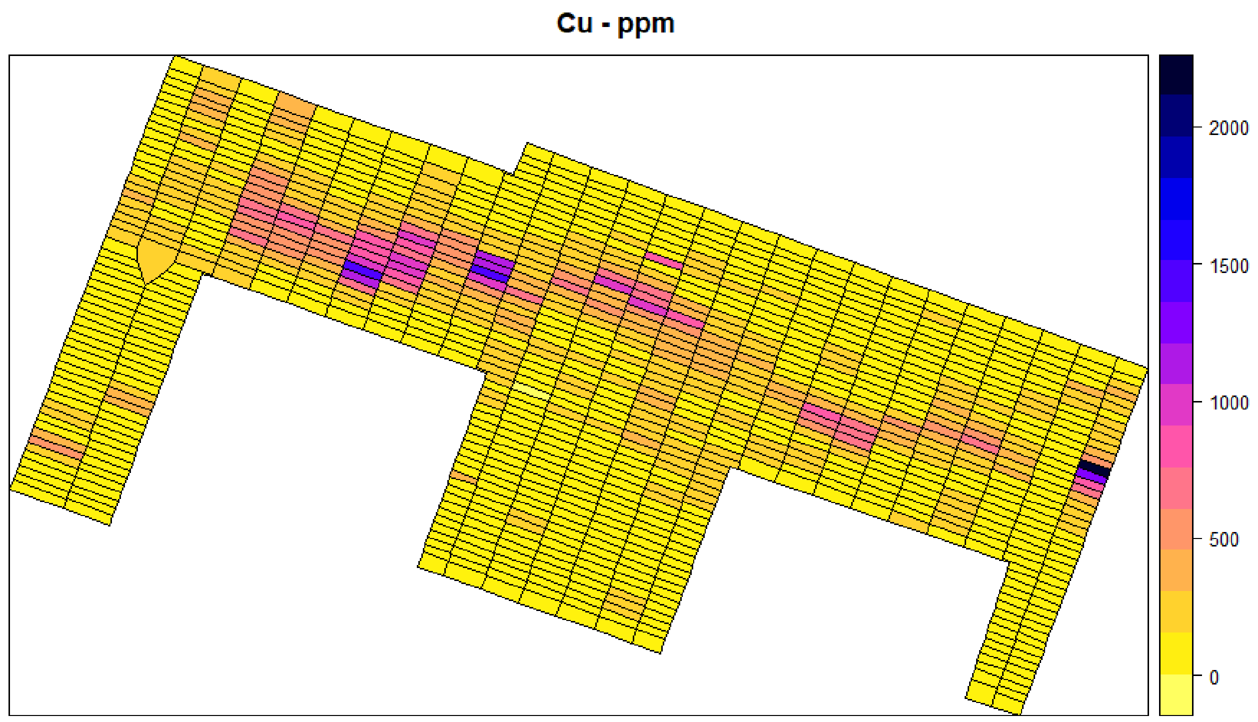
First, we create a distance matrix followed by the creation of a matrix of the inverse of the distance normalized to 1:

```
library(terra)
dado<-vect('geoqui.shp')
dado
 class       : SpatVector
 geometry    : points
 dimensions  : 956, 16  (geometries, attributes)
 extent      : 590142, 595675, 8986418, 8989594  (xmin, xmax, ymin, ymax)
 source      : geoqui.shp
 coord. ref. : WGS 84 / UTM zone 17S (EPSG:32717)
 names       : amostra Au_gpt    Ba    Cd    Co    Cr    Cu    Mo    Ni    Pb
 type        :   <int>  <num> <num> <num> <num> <num> <num> <num> <num> <num>
 values      :       1   0.01   5.1   6.8     3    58    46     1   5.2    12
                     2   0.01    10   3.9     3    38    35     1   4.6    11
                     3   0.01   7.1   3.7     3    43    29     1     4    12
 (and 6 more)

dist<-distance(dado, y = dado)
rownames(dist)<-dado$amostra
colnames(dist)<-dado$amostra
dist[1:6,1:6] #visualizing the first six lines and 6 rows
          1         2         3         4         5         6
1   0.00000  40.16217  79.71198 120.20815 159.42396 199.91998
2  40.16217   0.00000  39.56008  80.05623 119.26860 159.76545
3  79.71198  39.56008   0.00000  40.49691  79.71198 120.20815
4 120.20815  80.05623  40.49691   0.00000  39.21734  79.71198
5 159.42396 119.26860  79.71198  39.21734   0.00000  40.49691
6 199.91998 159.76545 120.20815  79.71198  40.49691   0.00000

#inverse of the distance normalized to 1
w<-1/dist
w[!is.finite(w)] <- NA
rtot<-apply(w,1,sum,na.rm=TRUE)
wnorm<-round(w/rtot,8)
wnorm[1:6,1:6]
           1          2          3          4          5          6
1         NA 0.04343730 0.02188549 0.01451263 0.01094275 0.00872617
2 0.04105078         NA 0.04167556 0.02059413 0.01382332 0.01031943
3 0.02005059 0.04040114         NA 0.03946652 0.02005059 0.01329587
4 0.01298204 0.01949313 0.03853496         NA 0.03979226 0.01957732
5 0.00960954 0.01284488 0.01921907 0.03906411         NA 0.03782981
6 0.00755341 0.00945184 0.01256219 0.01894417 0.03728870         NA
```

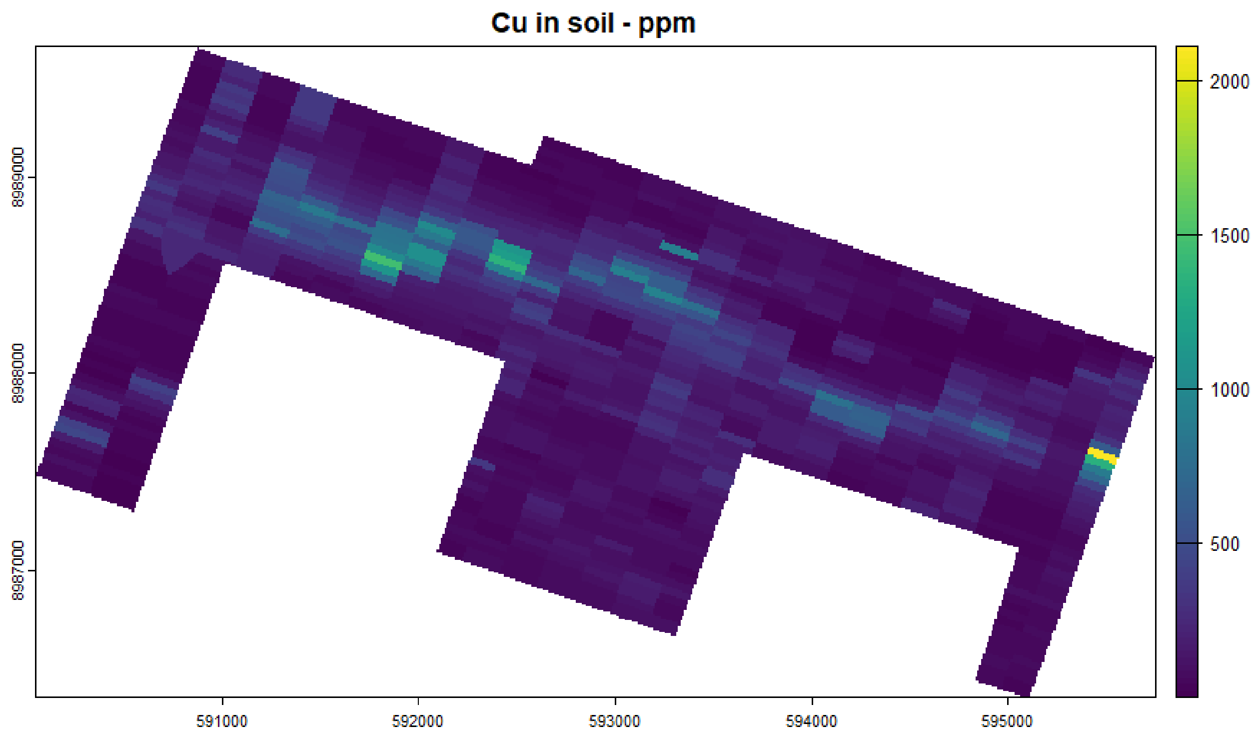
Recipe - 8.2 – Voronoi

Generating Voronoi Polygons to store each individual data point and using a mask shapefile (ot.shp) to cut out the data outside the points domain. Followed by the rasterization of the result.

```
library(dismo) #install dismo using install.packages("dismo")
library(terra)
dado<-vect('geoqui.shp')
 OGR data source with driver: ESRI Shapefile
 Source: "C:\Users\andre.costa\Documents", layer: "geoqui"
 with 956 features
 It has 16 fields
 Integer64 fields read as strings:  amostra V
dado
 class       : SpatVector
 geometry    : points
 dimensions  : 956, 16  (geometries, attributes)
 extent      : 590142, 595675, 8986418, 8989594  (xmin, xmax, ymin, ymax)
 source      : geoqui.shp
 coord. ref. : WGS 84 / UTM zone 17S (EPSG:32717)
 names       : amostra Au_gpt    Ba    Cd    Co    Cr    Cu    Mo    Ni    Pb
 type        :   <int>  <num> <num> <num> <num> <num> <num> <num> <num> <num>
 values      :       1   0.01   5.1   6.8     3    58    46     1   5.2    12
                     2   0.01    10   3.9     3    38    35     1   4.6    11
                     3   0.01   7.1   3.7     3    43    29     1     4    12
 (and 6 more)
mask<- vect('ot.shp')
 OGR data source with driver: ESRI Shapefile
 Source: "C:\Users\andre.costa\Documents", layer: "ot"
 with 1 features
 It has 1 fields
 Integer64 fields read as strings:  id
mask
 class       : SpatVector
 geometry    : polygons
 dimensions  : 1, 1  (geometries, attributes)
 extent      : 590050, 595746.7, 8986354, 8989662  (xmin, xmax, ymin, ymax)
 source      : ot.shp
 coord. ref. : WGS 84 / UTM zone 17S (EPSG:32717)
 names       :    id
 type        : <int>
 values      :    NA
v<-voronoi(dado)
Loading required namespace: deldir
vor<- crop(v,mask)
spplot(vor,'Cu',col.regions=rev(get_col_regions()), main="Cu - ppm")
```



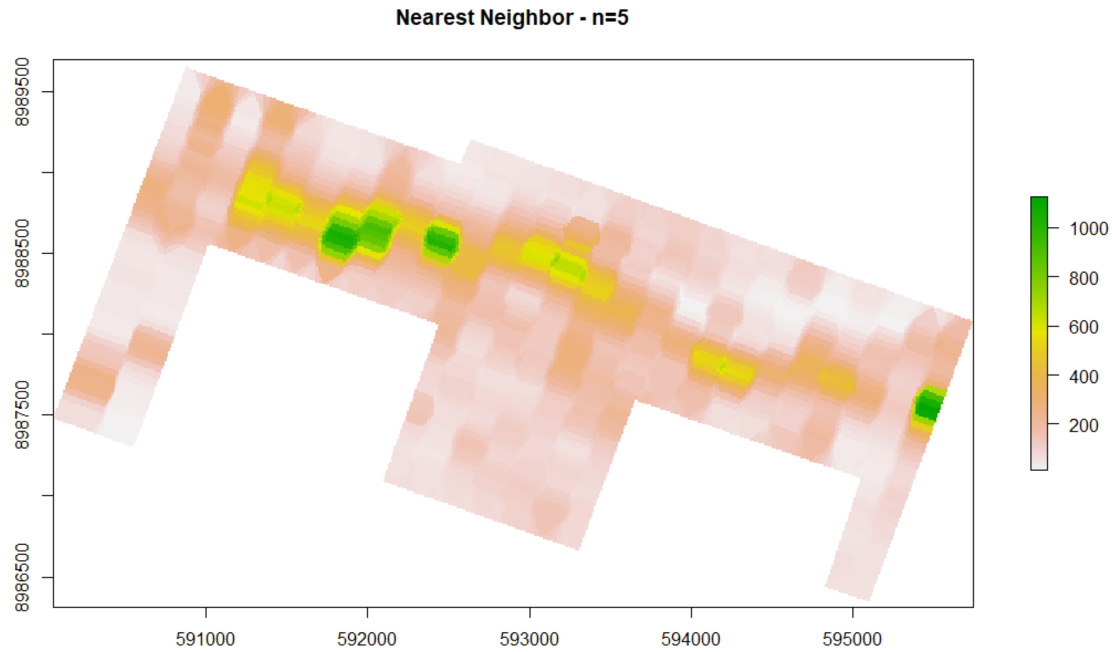

```
rast<-rast(mask,res=10)
v.rast<-rasterize(vor,rast,'Cu')
plot(v.rast,main='Cu in soil - ppm')
```



Recipe - 8.3 – Nearest Neighbor

Nearest Neighbor Interpolation Method.

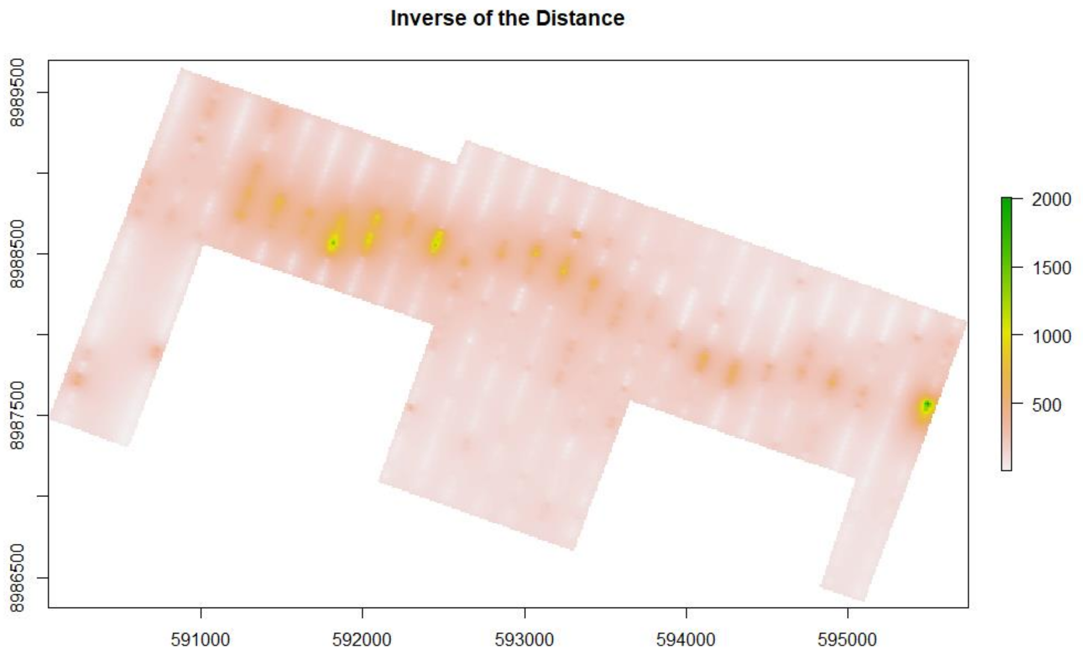
```
library(terra)
library(raster)
dado<-as(vect('geoqui.shp') , "Spatial")
 OGR data source with driver: ESRI Shapefile 
 Source: "C:\Users\andre.costa\Documents", layer: "geoqui"
 with 956 features
 It has 16 fields
 Integer64 fields read as strings:  amostra V 
dado
class       : SpatialPointsDataFrame 
features    : 956 
extent      : 590142, 595675, 8986418, 8989594  (xmin, xmax, ymin, ymax)
crs         : +proj=utm +zone=17 +south +datum=WGS84 +units=m +no_defs 
variables   : 16
names       : amostra, Au_gpt,  Ba, Cd,  Co,   Cr,   Cu, Mo,  Ni, Pb, Sb, Sc,   V,  Y, Zn, ... 
min values  :       1,   0.01,   1,  1,   3,    1,    1,  1,   1,  3,  5,  3,   3,  1,  1, ... 
max values  :    1008,   1.06, 272, 25, 123, 1219, 2115, 49, 143, 83, 19, 41, 386, 79, 66, ... 
(and 6 more)
mask<- vect('ot.shp')
 OGR data source with driver: ESRI Shapefile 
 Source: "C:\Users\andre.costa\Documents", layer: "ot"
 with 1 features
 It has 1 fields
 Integer64 fields read as strings:  id 
mask
 class       : SpatVector 
 geometry    : polygons 
 dimensions  : 1, 1  (geometries, attributes)
 extent      : 590050, 595746.7, 8986354, 8989662  (xmin, xmax, ymin, ymax)
 source      : ot.shp
 coord. ref. : WGS 84 / UTM zone 17S (EPSG:32717) 
 names       :    id
 type        : <int>
 values      :    NA
rast<-raster(as(mask, "Spatial"),res=10)
library(gstat)
metodo<-gstat(formula=Cu~1,locations=dado,nmax=5,set=list(idp=0))
vmp<-interpolate(rast,metodo,debug.level=0,index=1)
vmpmsc<-mask(vmp,as(mask, "Spatial"))
plot(vmpmsc,main='Nearest Neighbor - n=5')
```



Recipe - 8.4 – Inverse of the Distance Weighted

IDW interpolation Method.

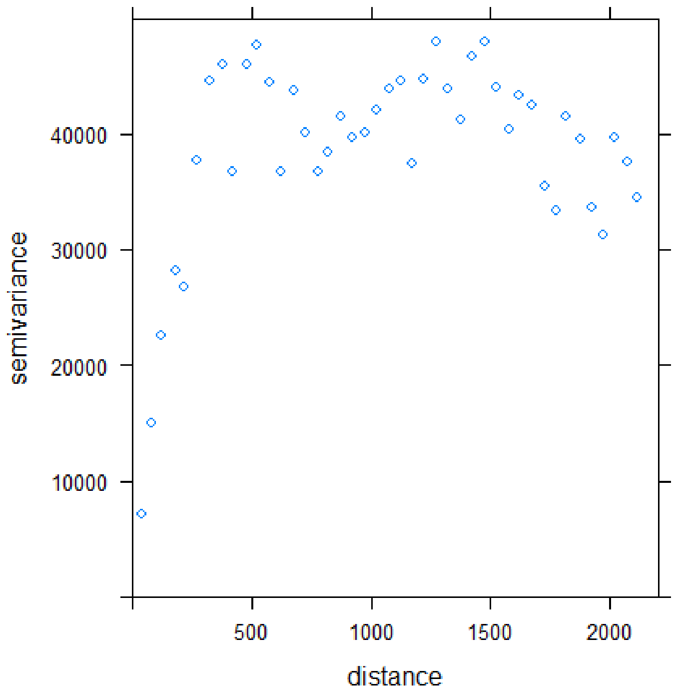
```
library(terra)
library(raster)
dado<-as(vect('geoqui.shp') , "Spatial")
 OGR data source with driver: ESRI Shapefile 
 Source: "C:\Users\andre.costa\Documents", layer: "geoqui"
 with 956 features
 It has 16 fields
 Integer64 fields read as strings:  amostra V 
dado
class       : SpatialPointsDataFrame 
features    : 956 
extent      : 590142, 595675, 8986418, 8989594  (xmin, xmax, ymin, ymax)
crs         : +proj=utm +zone=17 +south +datum=WGS84 +units=m +no_defs 
variables   : 16
names       : amostra, Au_gpt,  Ba, Cd,  Co,   Cr,   Cu, Mo,  Ni, Pb, Sb, Sc,   V,  Y, Zn, ... 
min values  :       1,   0.01,   1,  1,   3,    1,    1,  1,   1,  3,  5,  3,   3,  1,  1, ... 
max values  :    1008,   1.06, 272, 25, 123, 1219, 2115, 49, 143, 83, 19, 41, 386, 79, 66, ... 
(and 6 more)
mask<- vect('ot.shp')
 OGR data source with driver: ESRI Shapefile 
 Source: "C:\Users\andre.costa\Documents", layer: "ot"
 with 1 features
 It has 1 fields
 Integer64 fields read as strings:  id 
mask
 class       : SpatVector 
 geometry    : polygons 
 dimensions  : 1, 1  (geometries, attributes)
 extent      : 590050, 595746.7, 8986354, 8989662  (xmin, xmax, ymin, ymax)
 source      : ot.shp
 coord. ref. : WGS 84 / UTM zone 17S (EPSG:32717) 
 names       :    id
 type        : <int>
 values      :    NA
rast<-raster(as(mask, "Spatial"),res=10)
library(gstat)

metodo <- gstat(formula=Cu~1, locations=dado)
idw<-interpolate(rast,metodo)
idwmsc <-mask(idw,as(mask, "Spatial"))
plot(idwmsc,main='Inverse of the Distance')
```



Recipe - 8.5 – Kriging

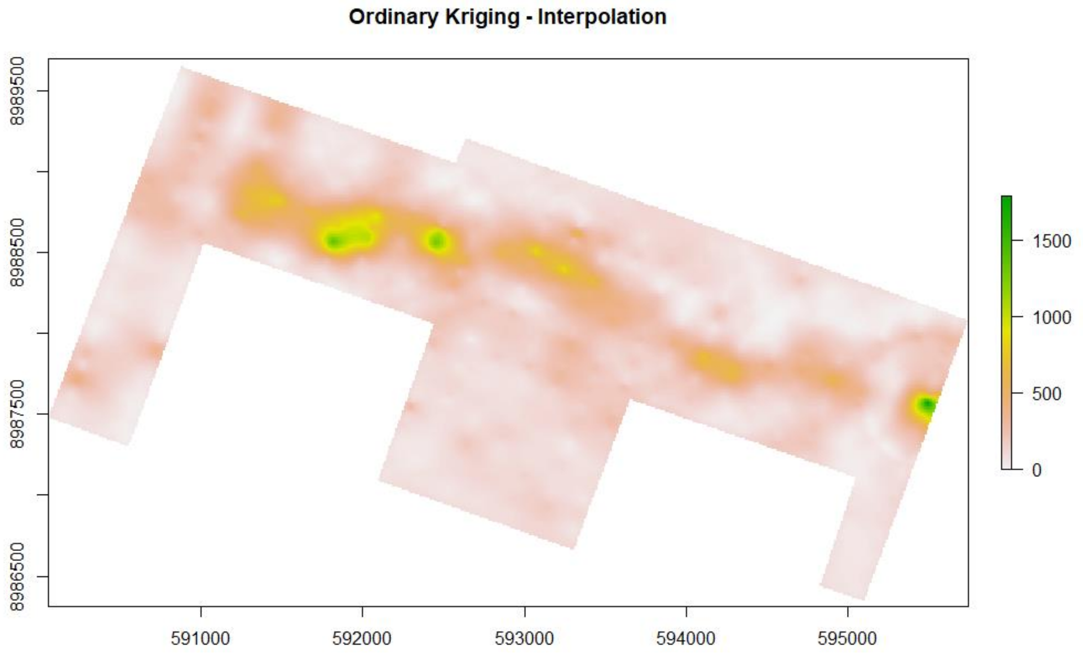
Ordinary kriging Interpolation Method.

```
library(terra)
library(raster)
dado<-as(vect('geoqui.shp') , "Spatial")
 OGR data source with driver: ESRI Shapefile
 Source: "C:\Users\andre.costa\Documents", layer: "geoqui"
 with 956 features
 It has 16 fields
 Integer64 fields read as strings:  amostra V
dado
class        : SpatialPointsDataFrame
features     : 956
extent       : 590142, 595675, 8986418, 8989594  (xmin, xmax, ymin, ymax)
crs          : +proj=utm +zone=17 +south +datum=WGS84 +units=m +no_defs
variables    : 16
names       : amostra, Au_gpt,  Ba, Cd,  Co,   Cr,   Cu, Mo,  Ni, Pb, Sb, Sc,   V,  Y, Zn, ...
min values  :       1,   0.01,   1,  1,   3,    1,    1,  1,   1,  3,  5,  3,   3,  1,  1, ...
max values  :    1008,   1.06, 272, 25, 123, 1219, 2115, 49, 143, 83, 19, 41, 386, 79, 66, ...
(and 6 more)
mask<- vect('ot.shp')
 OGR data source with driver: ESRI Shapefile
 Source: "C:\Users\andre.costa\Documents", layer: "ot"
 with 1 features
 It has 1 fields
 Integer64 fields read as strings:  id
mask
 class        : SpatVector
 geometry     : polygons
 dimensions   : 1, 1  (geometries, attributes)
 extent       : 590050, 595746.7, 8986354, 8989662  (xmin, xmax, ymin, ymax)
 source       : ot.shp
 coord. ref.  : WGS 84 / UTM zone 17S (EPSG:32717)
 names        :    id
 type         : <int>
 values       :    NA
library(gstat)
krig.met <- gstat(formula=Cu~1, locations=dado)
vario <- variogram(krig.met, width=50)
f.v <- fit.variogram(vario, vgm(c("Sph","Gau","Exp")))
plot(vario)
```

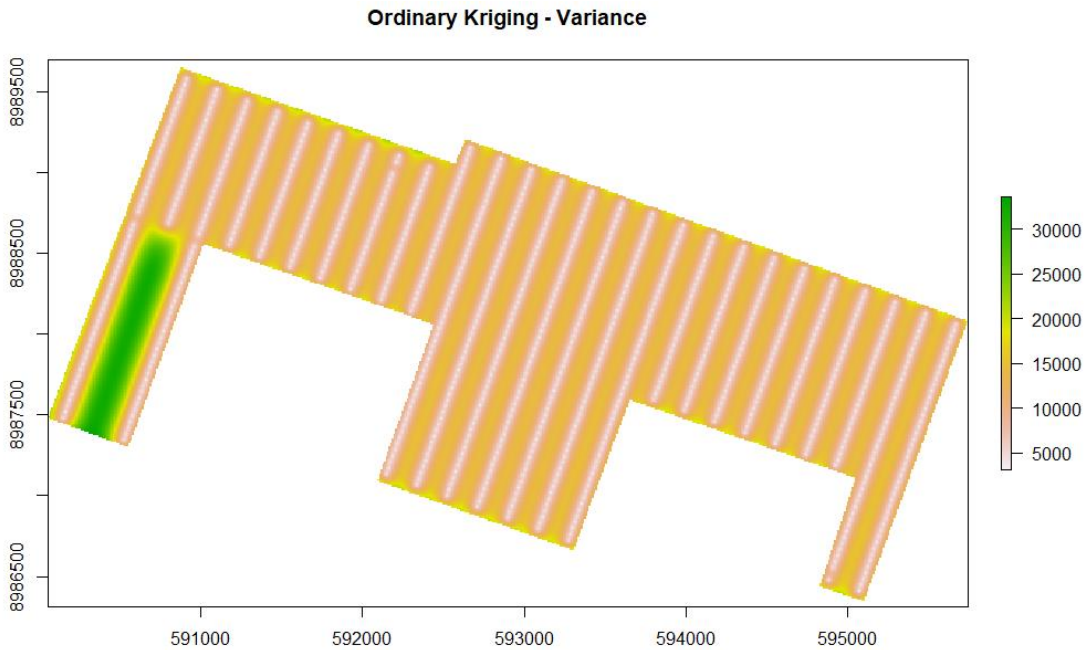



```
f.v  #semivariogram parameters
```

```
  model      psill     range
1   Nug  1679.221   0.0000
2   Sph 39454.770 398.5911
krig<- gstat(formula=Cu~1, locations=dado, model=f.v)
ur<- raster(as(mask, "Spatial"),res=10)
ugri <- as(ur, 'SpatialGrid')
kri.pred<-predict(krig,ugri)
ko <- brick(kri.pred)
ko <- mask(ko, as(mask, "Spatial"))
names(ko) <- c('Interpolation', 'Variance')
plot(ko$Interpolation, main='Ordinary Kriging - Interpolation')
```




```
plot(ko$Variance, main= 'Ordinary Kriging - Variance')
```



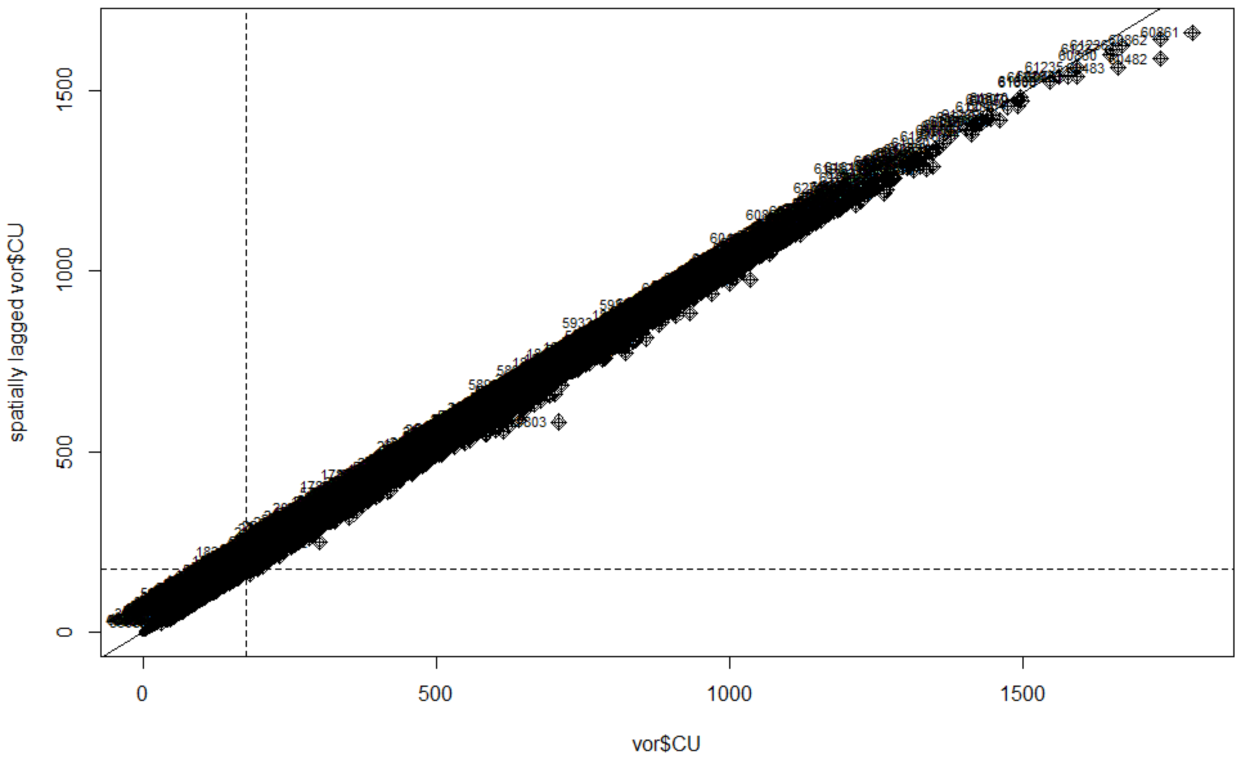
Save the resulting kriging as the best result achieved to be used on the following recipes in this chapter.

```
xyz <- rasterToPoints(ko$Interpolation)
colnames(xyz)<-c("UTME","UTMN","CU")
write.csv(xyz, "best.csv", row.names=FALSE)
```

Recipe - 8.6 – Spatial Autocorrelation (Moran Test)

In here we show how to execute a Moran Test.

```
library(terra)
library(raster)
geoq<-read.csv('best.csv')
geoqui<-vect(geoq, geom=c("UTME", "UTMN"),crs="+init=epsg:32717")
mask<- vect('ot.shp')
v<-voronoi(geoqui)
vor<-crop(v,mask)
library(spdep)
vizin<-poly2nb(as(vor,'Spatial'))
vizin
 Neighbour list object:
 Number of regions: 78521
 Number of nonzero links: 622292
 Percentage nonzero weights: 0.01009305
 Average number of links: 7.925167
lista.vz<-nb2listw(vizin)
lista.vz
 Characteristics of weights list object:
 Neighbour list object:
 Number of regions: 78521
 Number of nonzero links: 622292
 Percentage nonzero weights: 0.01009305
 Average number of links: 7.925167

 Weights style: W
 Weights constants summary:
       n         nn     S0       S1       S2
 W 78521 6165547441 78521 19901.57 314248.9
mo<-moran.test(vor$CU,lista.vz)
mo
      Moran I test under randomisation
 data:  vor$CU
 weights: lista.vz

 Moran I statistic standard deviate = 554.44, p-value < 2.2e-16
 alternative hypothesis: greater
 sample estimates:
 Moran I statistic       Expectation          Variance
      9.960117e-01     -1.273561e-05      3.227192e-06
moran <- moran.plot(vor$CU, listw = nb2listw(vizin, style = "W"))
```

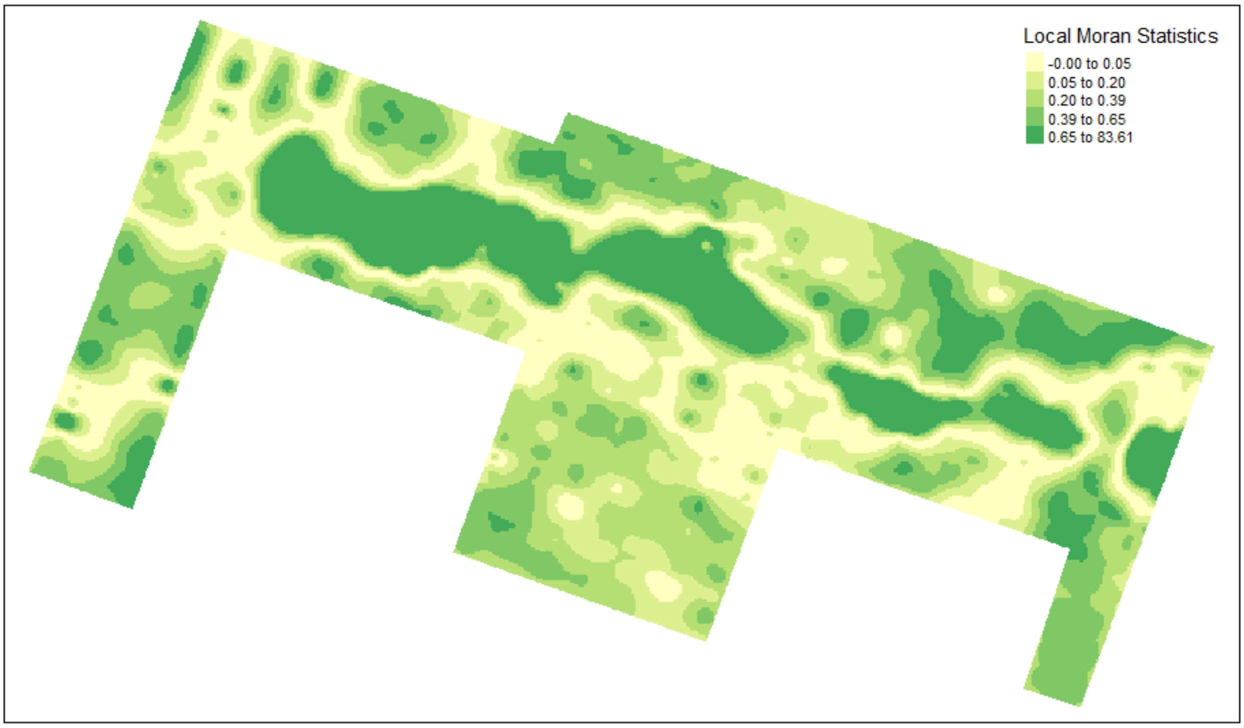



```
mo.local <- localmoran(x=vor$CU, listw = nb2listw(vizin, style = "W"))
head(mo.local)
         Ii          E.Ii      Var.Ii      Z.Ii Pr(z != E(Ii))
1 0.4750409 -6.075008e-06 0.15900022 1.191345     0.23351802
2 0.4558659 -5.627332e-06 0.11046110 1.371633     0.17017784
3 0.5046008 -6.470802e-06 0.08467637 1.734093     0.08290158
4 0.4748128 -5.991551e-06 0.06720340 1.831607     0.06700997
5 0.4350343 -5.444376e-06 0.07124471 1.629869     0.10312927
6 0.3950668 -4.841281e-06 0.09503146 1.281570     0.19999369
```

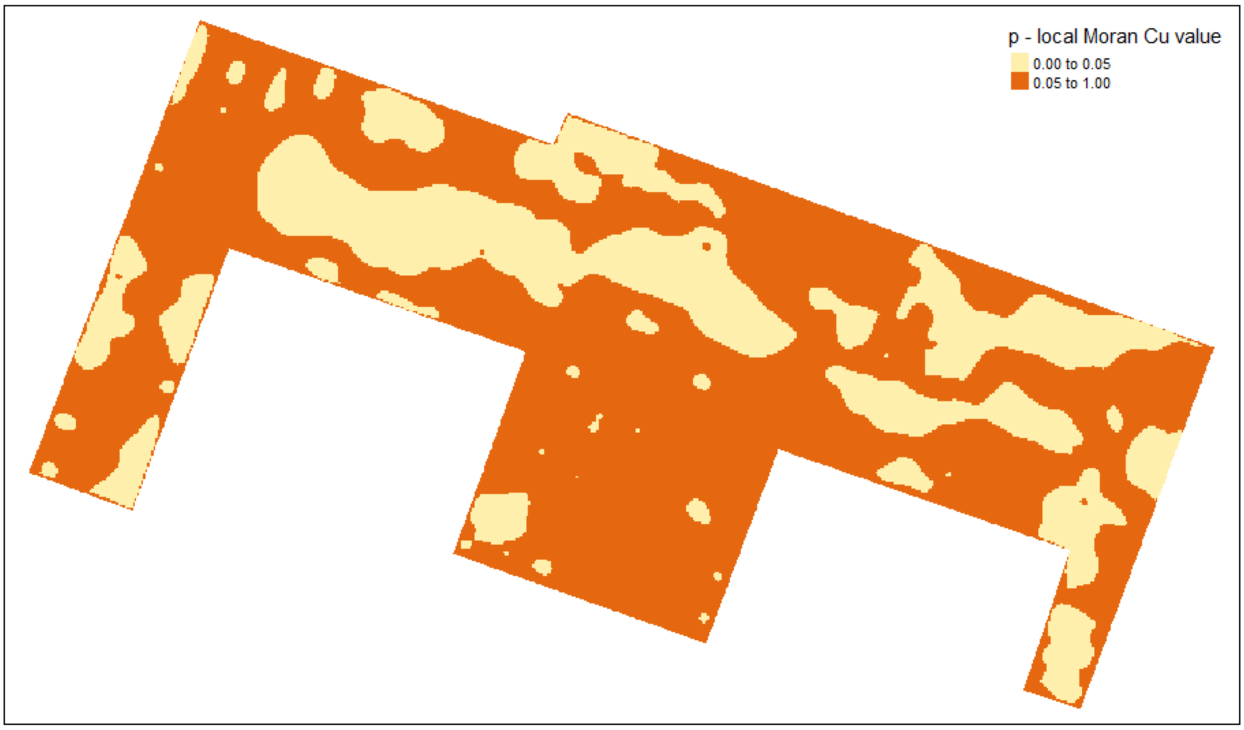
Where:

Ii	Local Moran Statistic
E.li	Expected Local Moran Statistic
Var.li	Variance of Local Moran Statistic
Z.li	Standard deviation of Local Moran Statistic
Pr()	p-value of Local Moran Statistic

```
mapa.moran<-cbind(vor,mo.local)
library(tmap)
mm<-as(mapa.moran,'Spatial')
tm_shape(mm) + tm_fill('Ii',style='quantile',title='Local Moran Statistics')
```



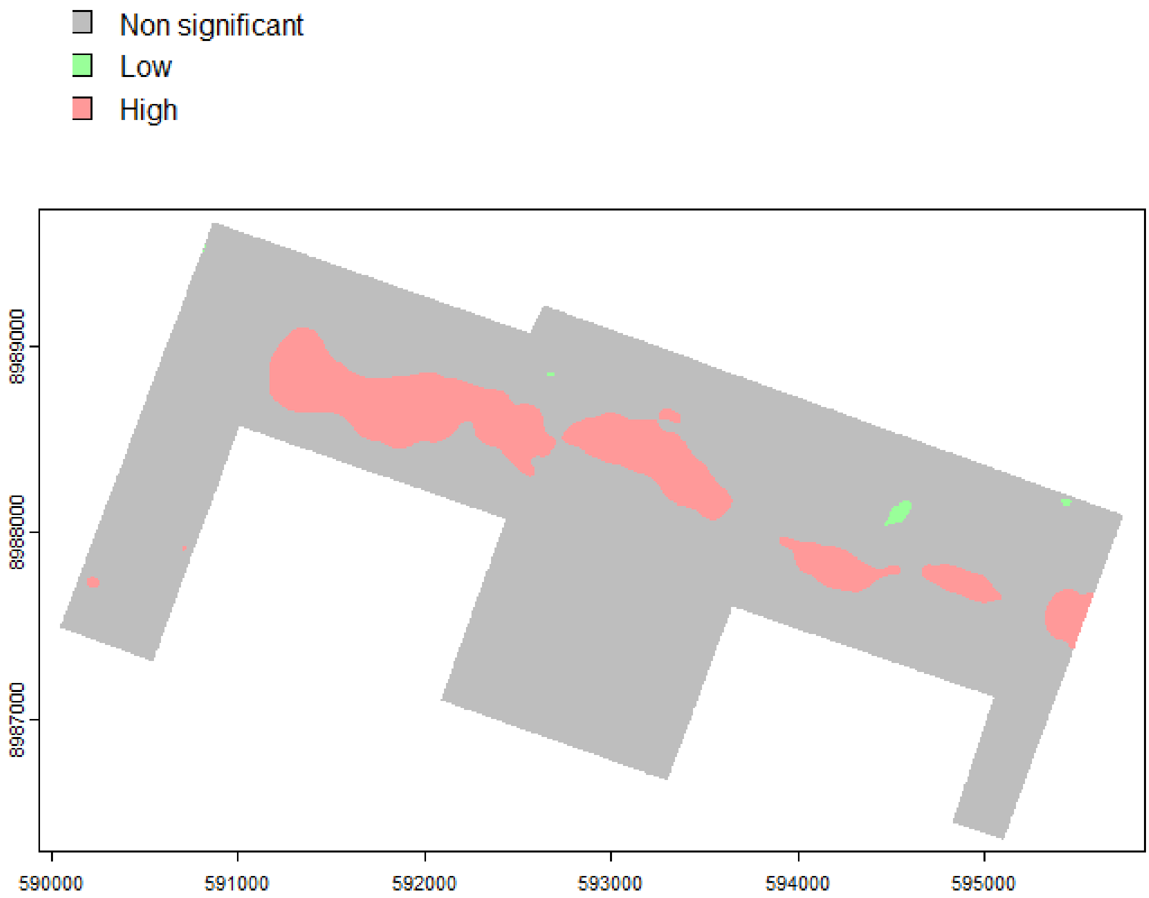

```
tm_shape(mm)+tm_fill('Pr(z != E(Ii))',n=10,style='fixed',breaks= c(0,0.05,1),
title = 'p - local Moran Cu value')
```



Recipe - 8.7 – LISA (Local Indicators of Spatial Association)

Creating a map categorizing the relation of each element has with its neighbor .

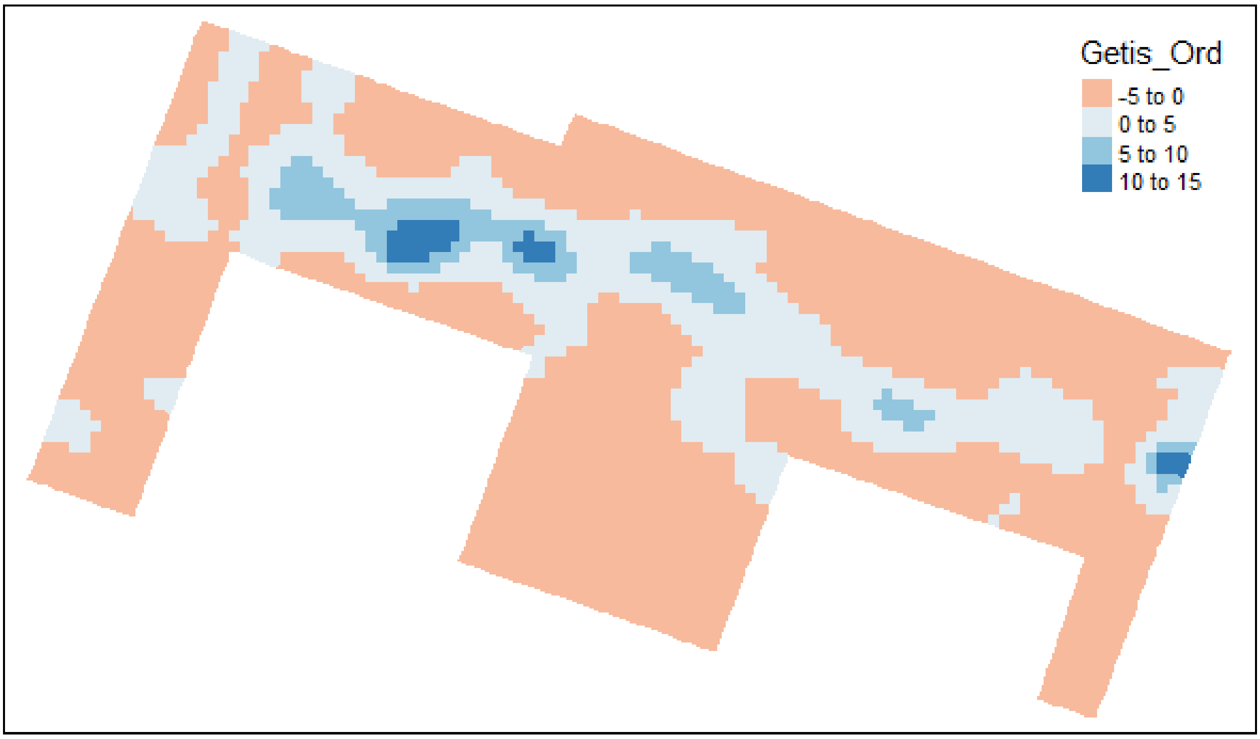
```
library(terra)
library(raster)
geoq<-read.csv('best.csv')
geoqui<-vect(geoq, geom=c("UTME", "UTMN"),crs="+init=epsg:32717")
mask<- vect('ot.shp')
v<-voronoi(geoqui)
vor<-crop(v,mask)
library(spdep)
vizin<-poly2nb(as(vor,'Spatial'))
lista.vz<-nb2listw(vizin)
mo<-moran.test(vor$CU,lista.vz)
mo.local <- localmoran(x=vor$CU, listw = nb2listw(vizin, style = "W"))

qua<-vector(mode='numeric',length=nrow(mo.local))
media.Cu<-vor$CU-mean(vor$CU)
media.mo<-mo.local[,1]-mean(mo.local[,1])
significancia<-0.1
qua[media.Cu >0 & media.mo>0]<-2
qua[media.Cu <0 & media.mo>0]<-1
qua[mo.local[,5] >significancia]<-0
quebras <- c(0,1,2)
cores <- c('grey',rgb(0,1,0,alpha=0.4),rgb(1,0,0,alpha=0.4))
plot(vor,border=NA,col=cores[findInterval(qua,quebras,all.inside=FALSE)])
box(which='outer',lty='blank')
legend('bottomleft',legend=c('Non significant','Low','High'),fill=cores,
bty="n",border=F)
```



Recipe - 8.8 – Getis-Ord Gi*

Using Getis-Ord Gi* method, a.k.a. as hot-spot analysis.

```
library(terra)
library(raster)
mask<- vect('ot.shp')
dado<-as(vect('geoqui.shp') , "Spatial")
library(gstat)
krig.met <- gstat(formula=Cu~1, locations=dado)
vario <- variogram(krig.met, width=50)
f.v <- fit.variogram(vario, vgm(c("Sph","Gau","Exp")))
krig<- gstat(formula=Cu~1, locations=dado, model=f.v)
ur<- raster(as(mask, "Spatial"),res=50)
ugri <- as(ur, 'SpatialGrid')
kri.pred<-predict(krig,ugri)
ko <- brick(kri.pred)
ko <- mask(ko, as(mask, "Spatial"))
names(ko) <- c('Interpolation', 'Variance')
xyz <- rasterToPoints(ko$Interpolation)
colnames(xyz)<-c("UTME","UTMN","CU")
write.csv(xyz, "bestLR.csv", row.names=FALSE)
geoq<-read.csv('bestLR.csv')
geoqui<-vect(geoq, geom=c("UTME", "UTMN"),crs="+init=epsg:32717")
v<-voronoi(geoqui)
vor<-crop(v,mask)
library(spdep)
vizin2<-dnearneigh(coordinates(as(vor,"Spatial")),0,80)
lista.vz2<-nb2listw(vizin2,style='B')
go.local <- localG(vor$CU, lista.vz2)
go.local <- cbind(vor,as.matrix(go.local))
names(go.local)[2]<-'Getis_Ord'
library(tmap)
tm_shape(as(go.local, "Spatial")) + tm_fill("Getis_Ord", palette = "RdBu", style
= "pretty")
```

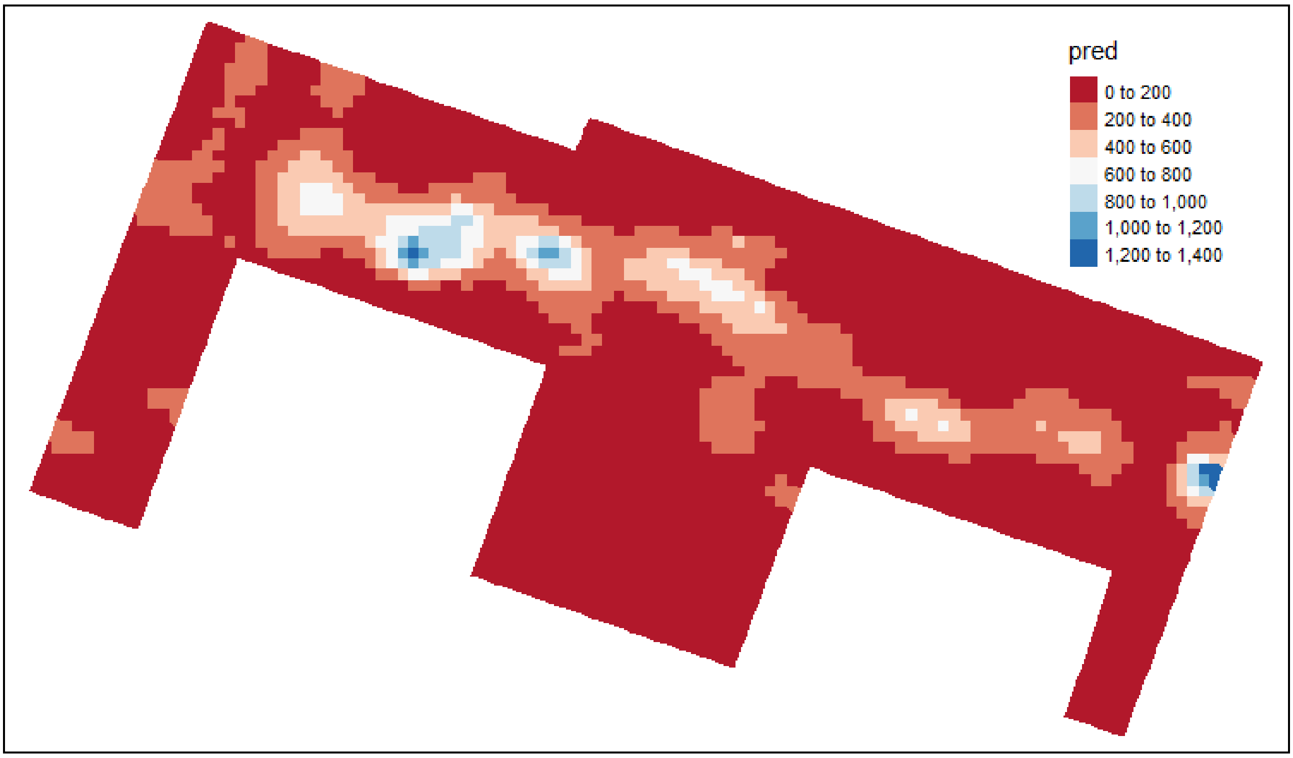


Recipe - 8.9 – GWR (Geographically Weighted Regression)

The package spgwr is used in this test. Using gold to predict copper. First, we create an ordinary kriging base for gold the same way we did for copper previously.

```
library(terra)
library(raster)
mask<- vect('ot.shp')
dado<-as(vect('geoqui.shp') , "Spatial")
library(gstat)

krig.met <- gstat(formula=Au_gpt~1, locations=dado)
vario <- variogram(krig.met, width=50)
f.v <- fit.variogram(vario, vgm(c("Sph","Gau","Exp")))
krig<- gstat(formula=Au_gpt~1, locations=dado, model=f.v)
ur<- raster(as(mask, "Spatial"),res=50)
ugri <- as(ur, 'SpatialGrid')
kri.pred<-predict(krig,ugri)
ko <- brick(kri.pred)
ko <- mask(ko, as(mask, "Spatial"))
names(ko) <- c('Interpolation', 'Variance')
xyz <- rasterToPoints(ko$Interpolation)
colnames(xyz)<-c("UTME","UTMN","AU")
write.csv(xyz, "best_au.csv", row.names=FALSE)

krig.met <- gstat(formula=Cu~1, locations=dado)
vario <- variogram(krig.met, width=50)
f.v <- fit.variogram(vario, vgm(c("Sph","Gau","Exp")))
krig<- gstat(formula=Cu~1, locations=dado, model=f.v)
ur<- raster(as(mask, "Spatial"),res=50)
ugri <- as(ur, 'SpatialGrid')
kri.pred<-predict(krig,ugri)
ko <- brick(kri.pred)
ko <- mask(ko, as(mask, "Spatial"))
names(ko) <- c('Interpolation', 'Variance')
xyz <- rasterToPoints(ko$Interpolation)
colnames(xyz)<-c("UTME","UTMN","CU")
write.csv(xyz, "best_cu.csv", row.names=FALSE)

geoqui1<-read.csv('best_cu.csv')
geoqui2<-read.csv('best_au.csv')
geoqu<-data.frame(geoqui1,geoqui2$AU)
colnames(geoqu)<-c("UTME","UTMN","CU","AU")
geoqui<-vect(geoqu, geom=c("UTME", "UTMN"),crs="+init=epsg:32717")
v<-voronoi(geoqui)
vor<-crop(v,mask)
library(spgwr)
faixa.gwr<-gwr.sel(vor$CU~vor$AU,data=as(vor, "Spatial"), adapt=TRUE)
Adaptive q: 0.381966 CV score: 55716070
Adaptive q: 0.618034 CV score: 57387225
Adaptive q: 0.236068 CV score: 52874806
Adaptive q: 0.145898 CV score: 48211707
Adaptive q: 0.09016994 CV score: 42392348
Adaptive q: 0.05572809 CV score: 36204448
Adaptive q: 0.03444185 CV score: 31505155
Adaptive q: 0.02128624 CV score: 26530922
Adaptive q: 0.01315562 CV score: 22098388
Adaptive q: 0.008130619 CV score: 18115633
Adaptive q: 0.005024999 CV score: 12528538
Adaptive q: 0.00310562 CV score: 10384401
Adaptive q: 0.001919379 CV score: 6209050
Adaptive q: 0.001186241 CV score: 3825456
Adaptive q: 0.0007331374 CV score: 3679102
Adaptive q: 0.000894264 CV score: 3700954
Adaptive q: 0.0006924473 CV score: 3673672
Adaptive q: 0.000427956 CV score: 3618510
Adaptive q: 0.0002644913 CV score: 2934807
Adaptive q: 0.0001634646 CV score: 2351761
Adaptive q: 0.0001010267 CV score: 2772414
Adaptive q: 0.0002041547 CV score: 2481491
Adaptive q: 0.0001634646 CV score: 2351761

modelo.gwr<-gwr(vor$CU ~ vor$AU, data= as(vor, "Spatial"),adapt=faixa.gwr,
hatmatrix=TRUE, se.fit=TRUE)
modelo.gwr
Call:
```

```
gwr(formula = vor$CU ~ vor$AU, data = vor, adapt = faixa.gwr,
    hatmatrix = TRUE, se.fit = TRUE)
Kernel function: gwr.Gauss
Adaptive quantile: 0.0001634646 (about 0 of 3141 data points)
Summary of GWR coefficient estimates at data points:
                    Min.     1st Qu.      Median     3rd Qu.        Max.  Global
X.Intercept.   -782.815      24.123      80.045     157.451    1707.361  115.51
vor.AU       -58106.717    -118.601    1360.545    4167.845   65895.934 1489.71
Number of data points: 3141
Effective number of parameters (residual: 2traceS - traceS'S): 2675.557
Effective degrees of freedom (residual: 2traceS - traceS'S): 465.4425
Sigma (residual: 2traceS - traceS'S): 21.73402
Effective number of parameters (model: traceS): 2092.351
Effective degrees of freedom (model: traceS): 1048.649
Sigma (model: traceS): 14.47965
Sigma (ML): 8.366411
AICc (GWR p. 61, eq 2.33; p. 96, eq. 4.21): 34822.47
AIC (GWR p. 96, eq. 4.22): 24350.5
Residual sum of squares: 219860.1
Quasi-global R2: 0.9975564
gwr.res<-as.data.frame(modelo.gwr$SDF)
names(gwr.res)
[1] "sum.w"   "X.Intercept."    "vor.AU"    "X.Intercept._se"     "vor.AU_se"         "gwr.e"
[7] "pred"    "pred.se"         "localR2"   "X.Intercept._se_EDF" "vor.AU_se_EDF"     "pred.se.1"
gwr.final<-cbind(as(vor, "Spatial"),as.matrix(gwr.res))
library(tmap)
tm_shape(gwr.final) + tm_fill("pred", palette = "RdBu", style = "pretty")
```



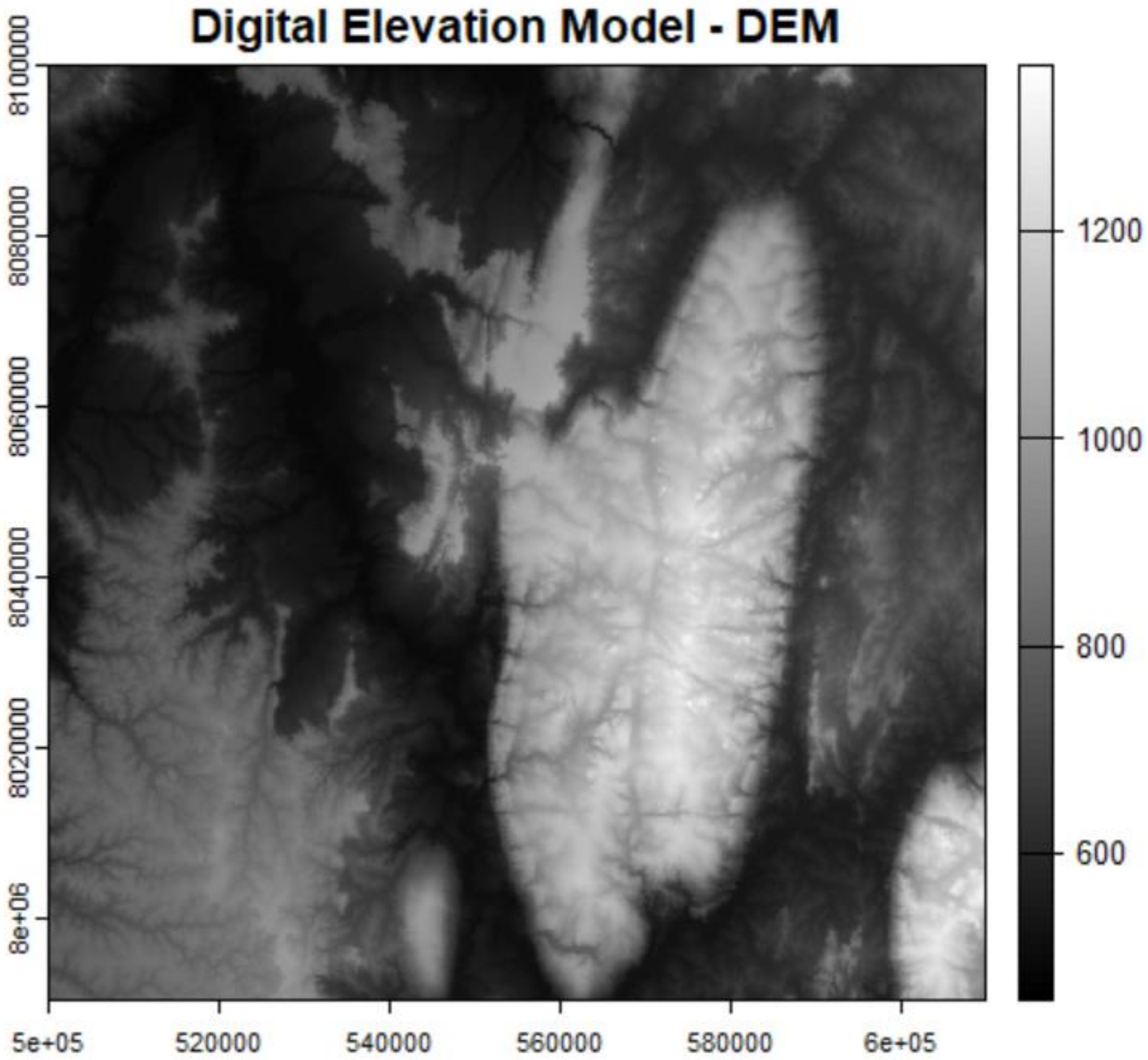
A high correlation for gold to predict copper is observed using GWR.

9 Manipulating Digital Elevation Models

Recipe - 9.1 – DEM

Loading a raster file with the Digital elevation Model:

```
library(terra)
dem<-rast('dem.tif')
plot(dem,col=grey(0:100/100),main='Digital Elevation Model - DEM')
```



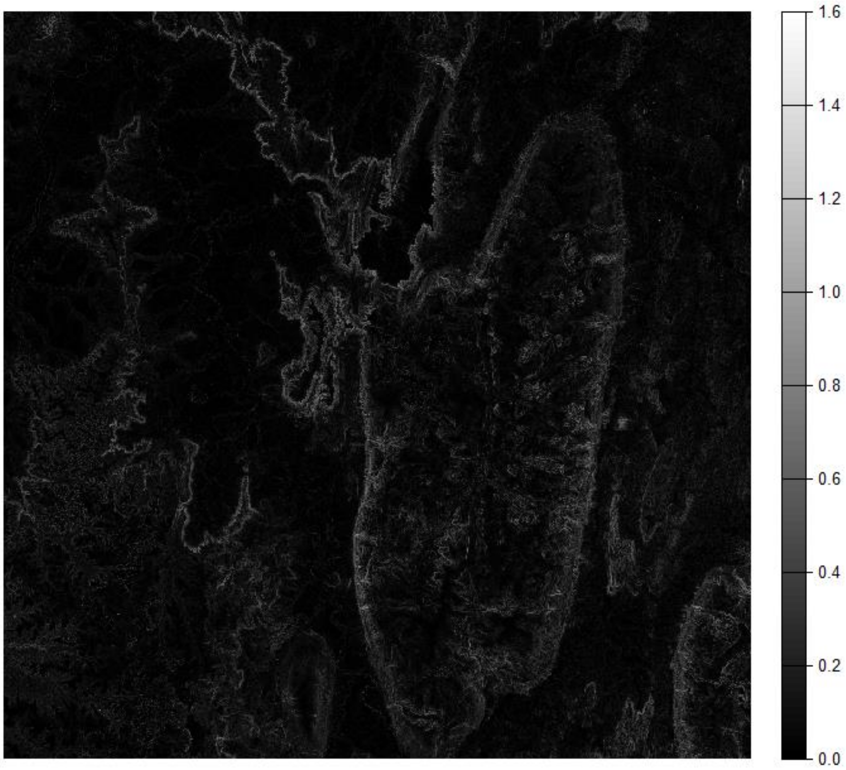
Recipe - 9.2 – Extracting derivative images from DEM

From a digital elevation model, it is possible to derivate several other images that can be used for geomorphological studies, such as:

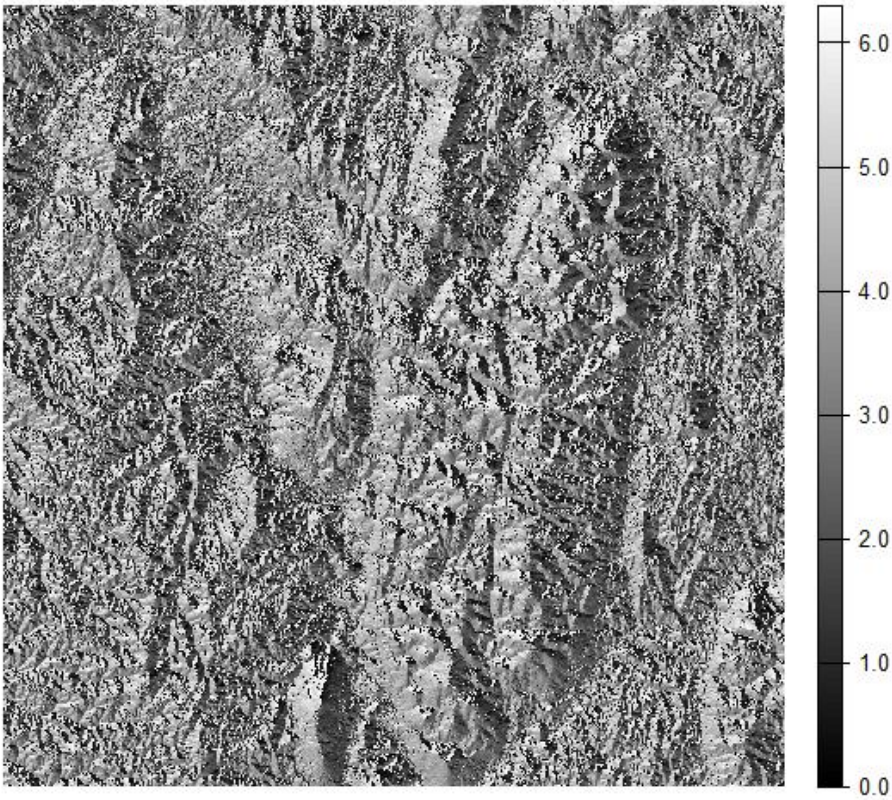
- Slope
- Aspect
- TPI -Topographical Position Index
- TRI – Topographic Roughness Index
- Roughness
- Flow Direction

```
library(terra)
dem<-rast('dem.tif')
slope<-terrain(dem,v='slope',unit='radians')
aspect<-terrain(dem,v='aspect',unit='radians')
tpi<-terrain(dem,v='TPI')
tri<-terrain(dem,v='TRI')
roughness<-terrain(dem,v='roughness')
flowdir<-terrain(dem,v='flowdir',unit='radians')
```

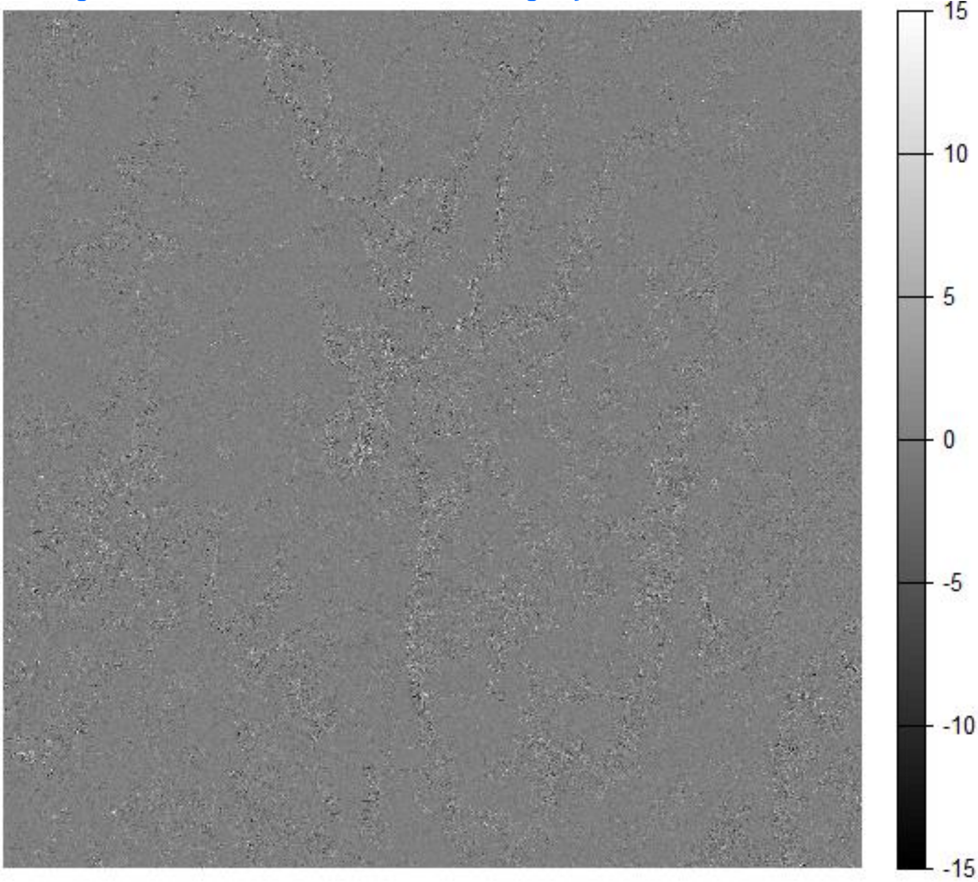
```
plot(slope,range=c(0,1.6),axes=FALSE,col=grey(0:100/100))
```



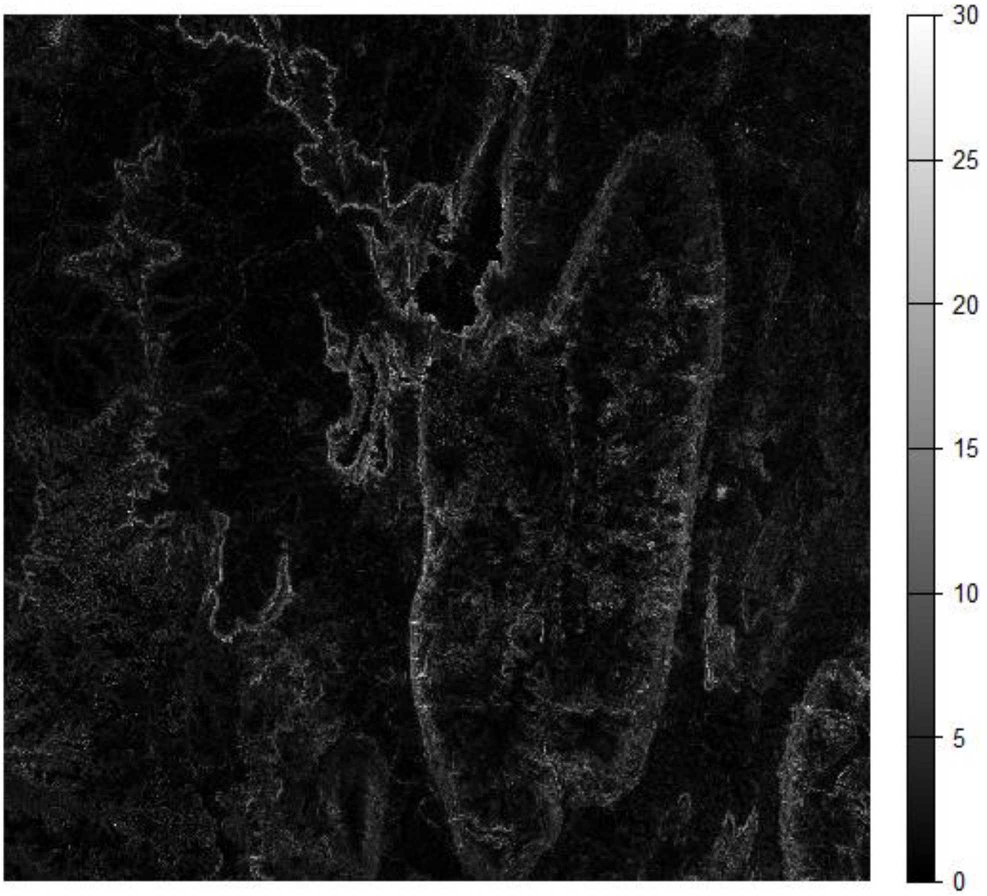
```
plot(aspect,range=c(0,6.3),axes=FALSE,col=grey(0:100/100))
```



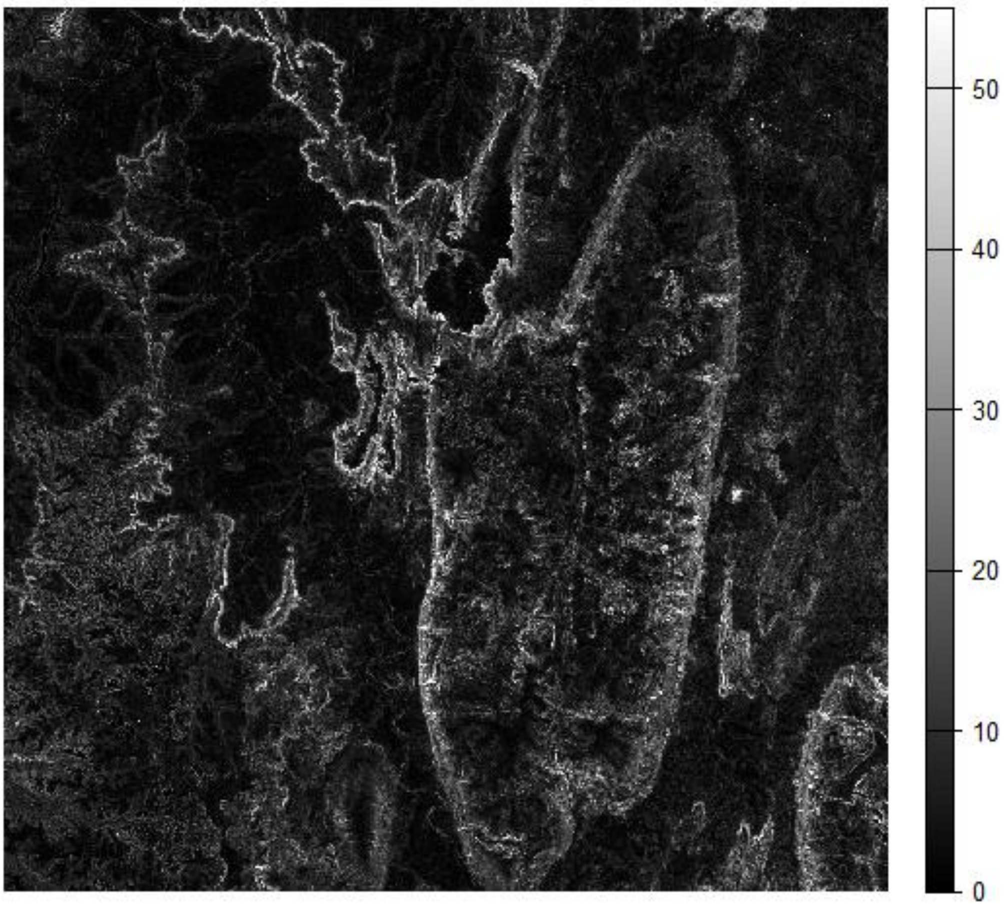

```
plot(tpi,range=c(-15,15),axes=FALSE,col=grey(0:100/100))
```



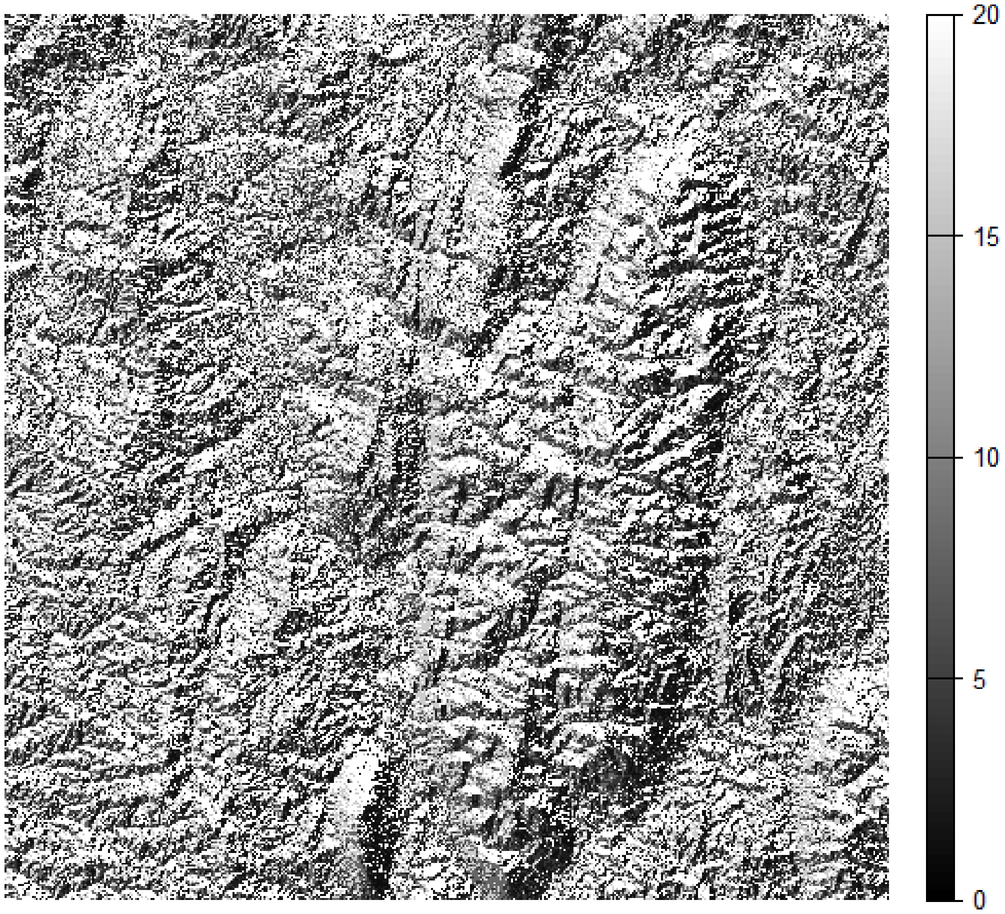
```
plot(tri,range=c(0,30),axes=FALSE,col=grey(0:100/100))
```




```
plot(roughness, range=c(0,55),axes=FALSE,col=grey(0:100/100))
```



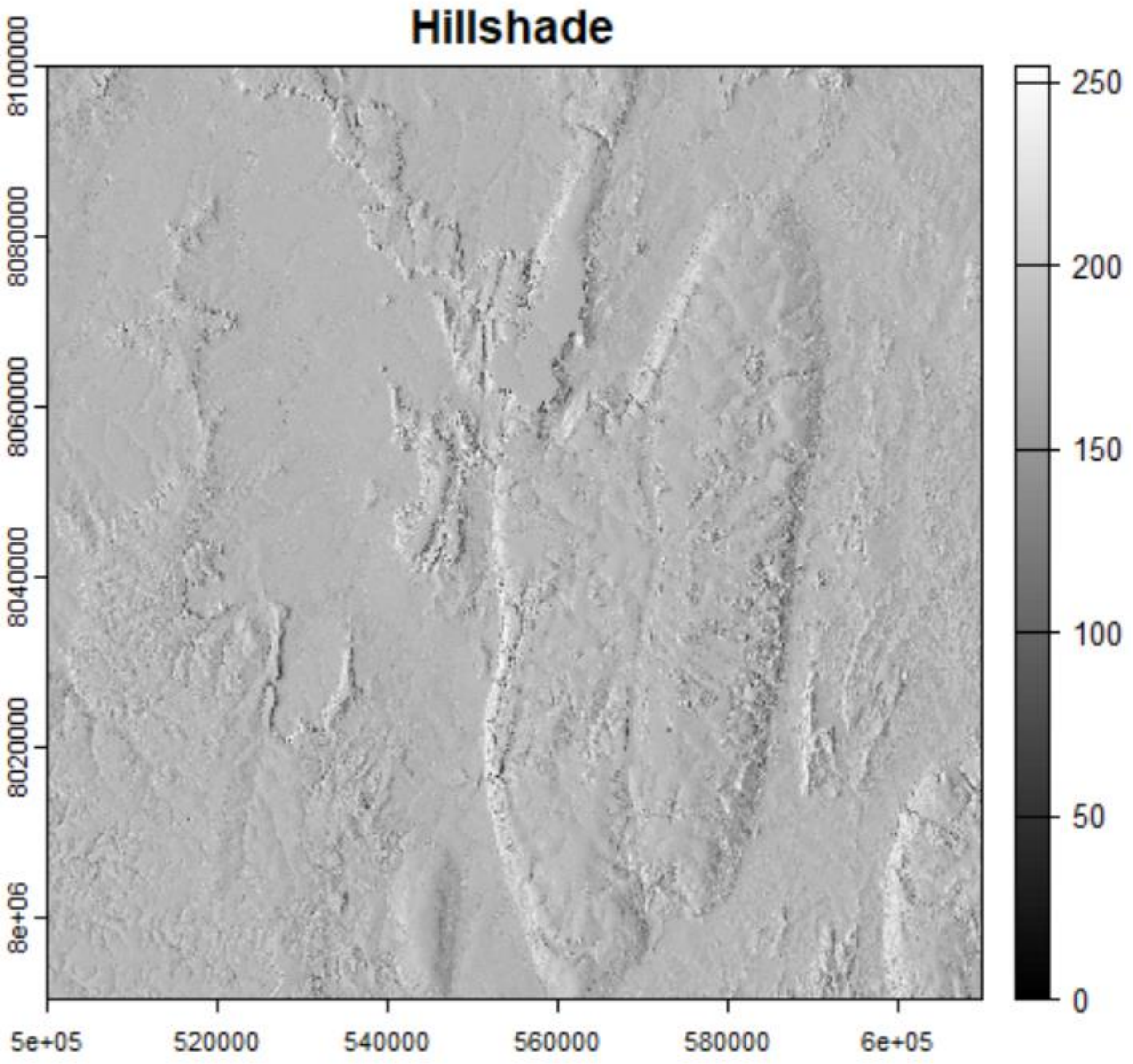
```
plot(flowdir,range=c(0,20),axes=FALSE,col=grey(0:100/100))
```



Recipe - 9.3 –Hillshade

Creating a hillshade using DEM aspect and gradient and saving it as a geoTiff.

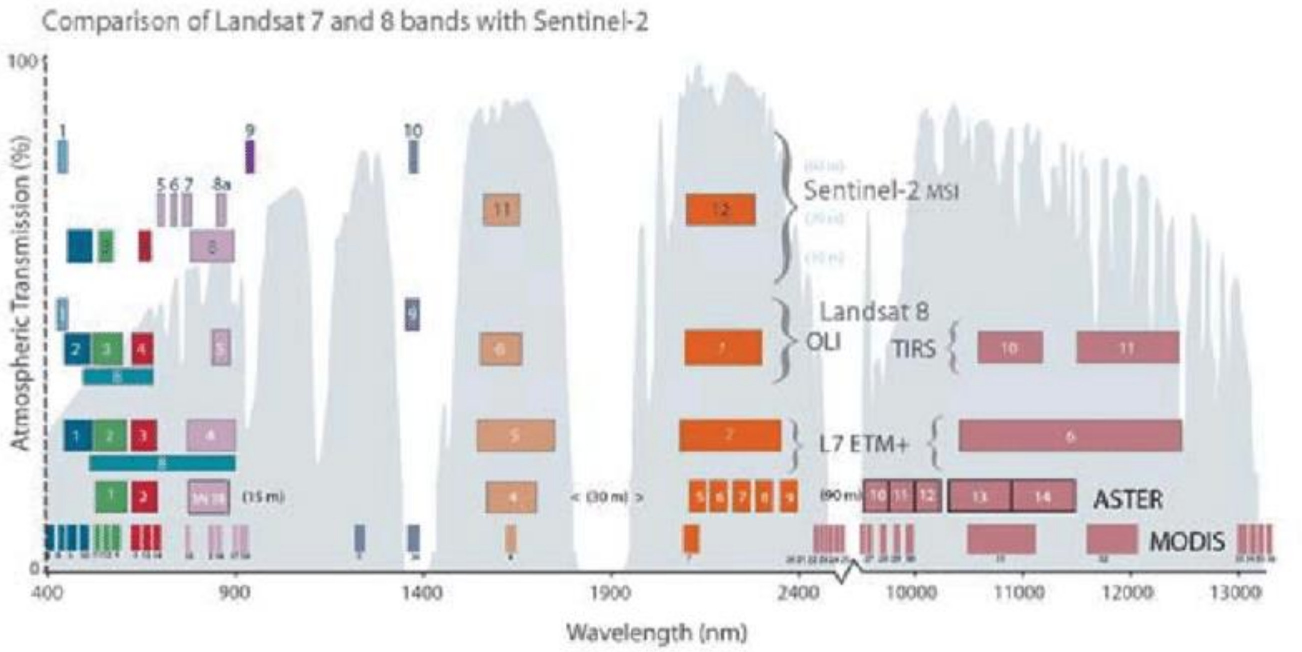
```
library(terra)
dem<-rast('dem.tif')
gradiente<-terrain(dem,v='slope',unit='radians')
aspecto<-terrain(dem,v='aspect',unit='radians')
relevo<-shade(gradiente,aspecto,angle=45,direction=270,normalize= TRUE)
plot(relevo,col=grey(0:100/100),zlim=c(0,250),main='Hillshade')
```




```
writeRaster(relevo,'hillshade.tif',overwrite=TRUE)
```

10 Satellite Images and Normalized Indexes

Spectral bandwidth can vary according with the satellite used to acquire them. They can be divided into visible (blue, green and red bandwidth), Very near infra-red (VNIR or red edge), near infra-red (NIR), Short wave infra-red (SWIR) and thermal bandwidth.



We will be working here with sentinel2 images (ESA) with the bands 2, 3, 4, 5, 6, 7, 8A, 11 and 12. The following composites are created:

- Visible (VIS)
- Very Near Infra-Red (VNIR or Red Edge)
- Near and Short-Wave Infra-Red (NIR+ SWIR)

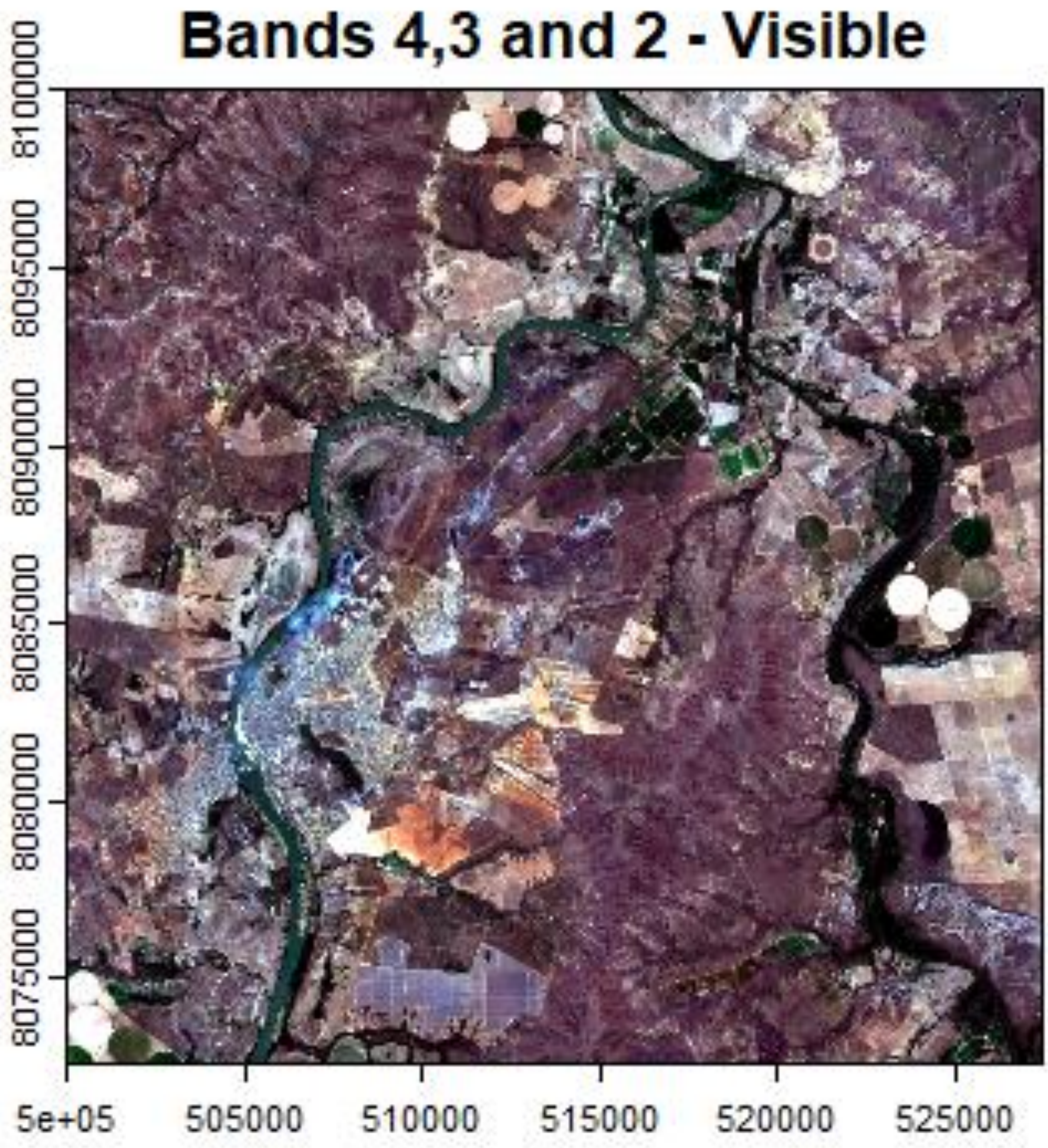
The following Indexes are presented here:

- NDVI
- NDVIre1
- SAVI
- NDWI
- MNDWI
- NDMI
- NDTI
- NDBI

Recipe - 10.1 – TCC Visible

Visible or true color composite.

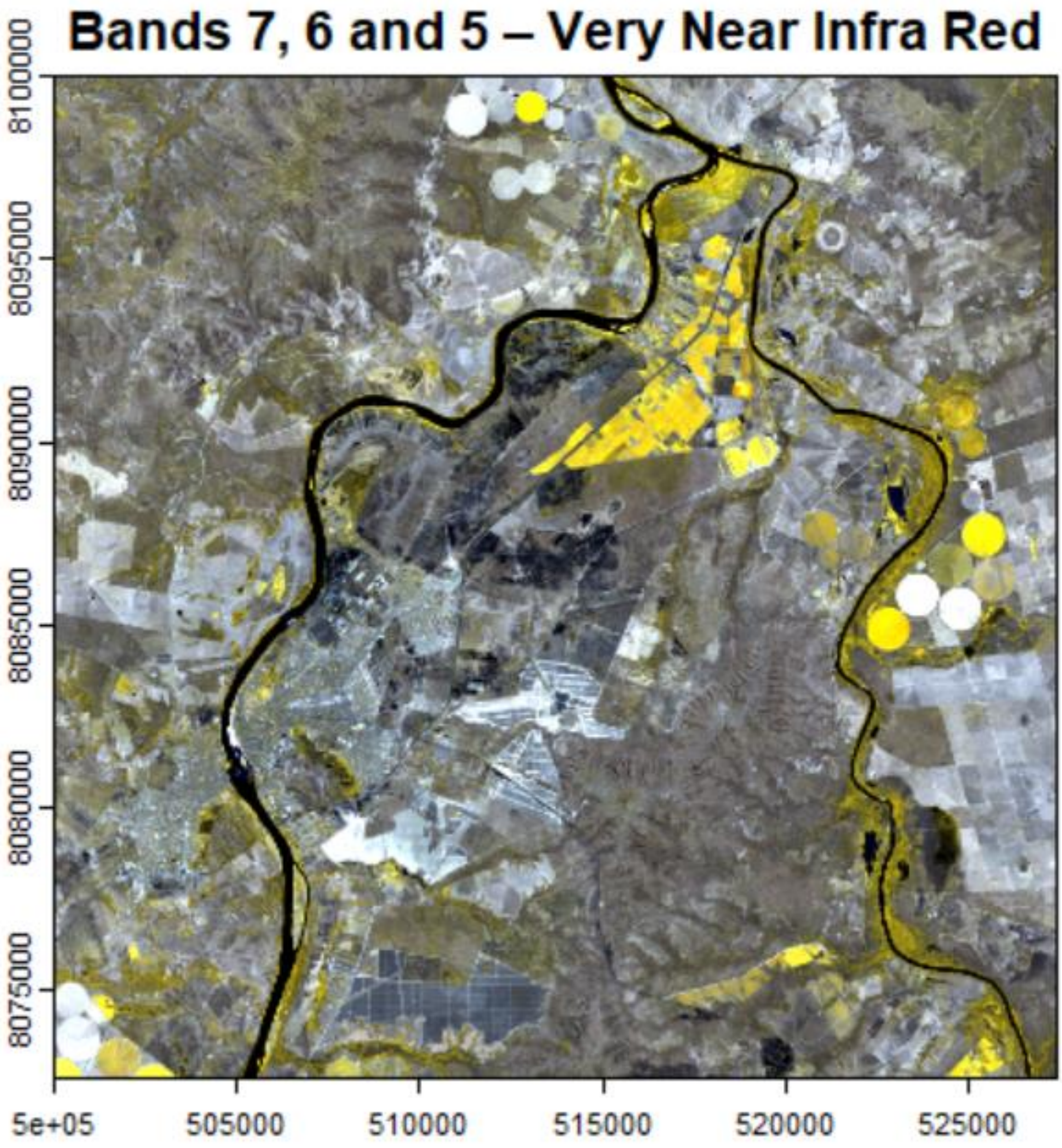
```
library(terra)
filenames <- paste0('B0', 4:2, "_20m.jp2")
tcc4_3_2<-rast(filenames)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(tcc4_3_2,e)
plotRGB(rc,stretch='lin',axes=TRUE,main='Bands 4,3 and 2 - Visible',
mar=c(6,6,6,6))
```



Recipe - 10.2 – FCC VNIR

VNIR or Red-Edge false color composite.

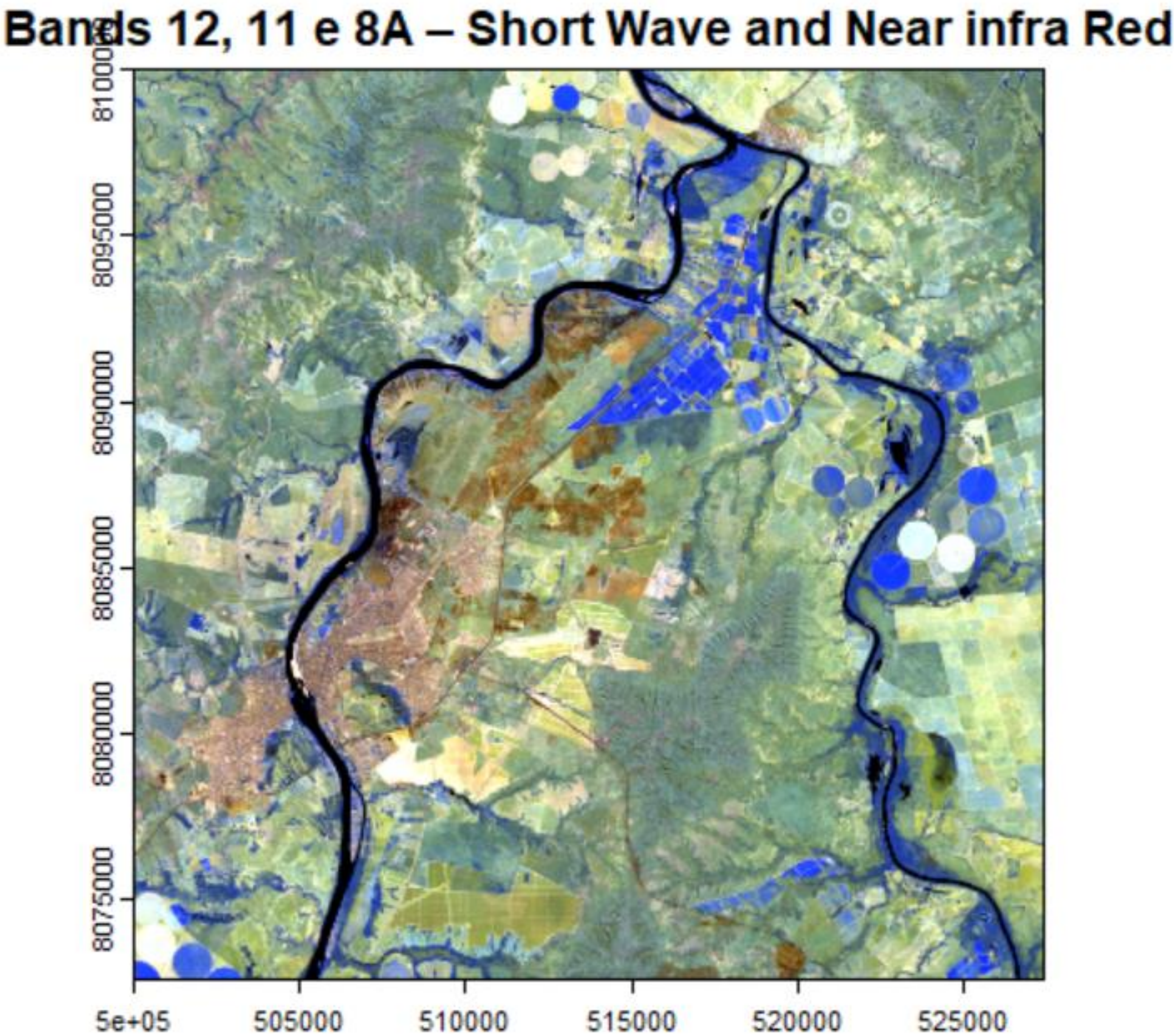
```
library(terra)
filenames <- paste0('B0', 7:5, "_20m.jp2")
fcc7_6_5<- rast(filenames)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(fcc7_6_5,e)
plotRGB(rc,stretch='lin',axes=TRUE,main='Bands 7, 6 and 5 - Very Near Infra
Red' , mar=c(6,6,6,6))
```



Recipe - 10.3 – FCC SWIR+NIR

SWIR+NIR false color composite.

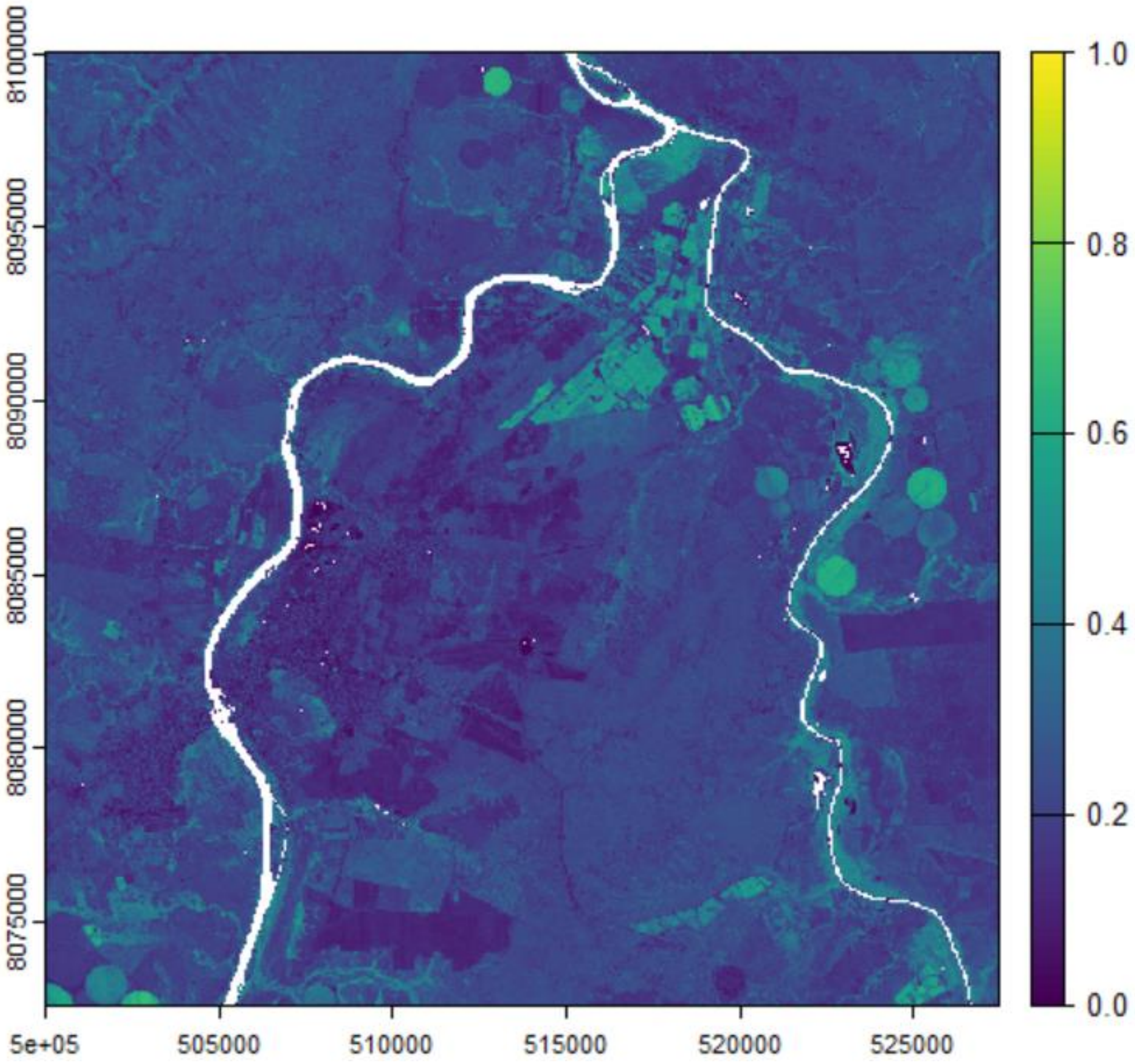
```
library(terra)
filenames <- paste0('B',c('12','11','8A'), "_20m.jp2")
fcc12_11_8a<- rast(filenames)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(fcc12_11_8a,e)
plotRGB(rc,stretch='lin',axes=TRUE,main='Bandas 12, 11 e 8A – Short Wave and
Near infra Red' , mar=c(6,6,6,6))
```



Recipe - 10.4 – NDVI

NDVI (Normalized Difference Vegetation Index).

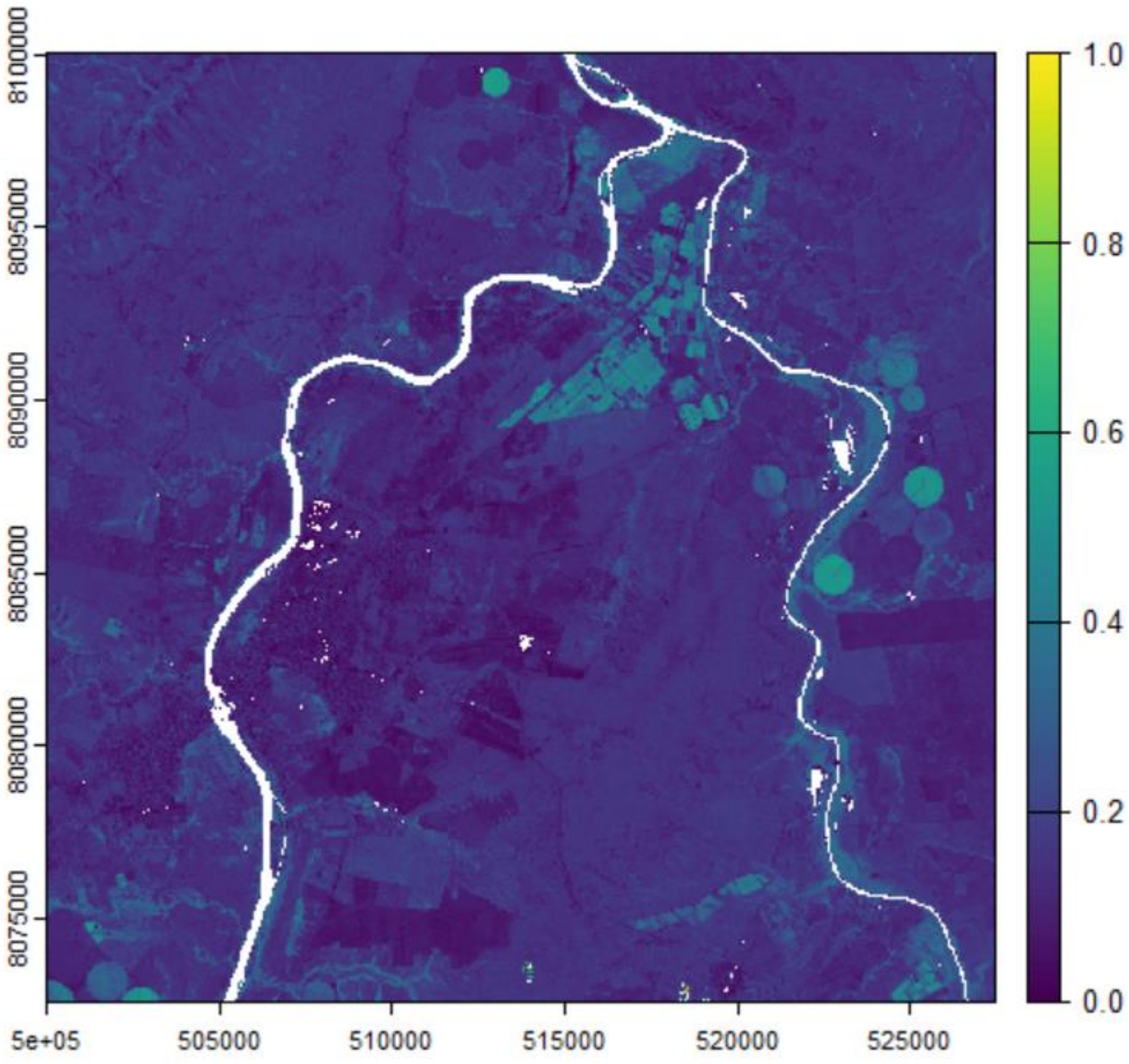
```
library(terra)
nir<-rast('B8A_20m.jp2')
vermelho<-rast('B04_20m.jp2')
ndvi<-(nir-vermelho)/(nir+vermelho)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(ndvi,e)
plot(rc,axes=TRUE ,range=c(0,1))
```



Recipe - 10.5 – NDVIre1

NDVIre1 (red-edge-based Normalized Difference Vegetation Index).

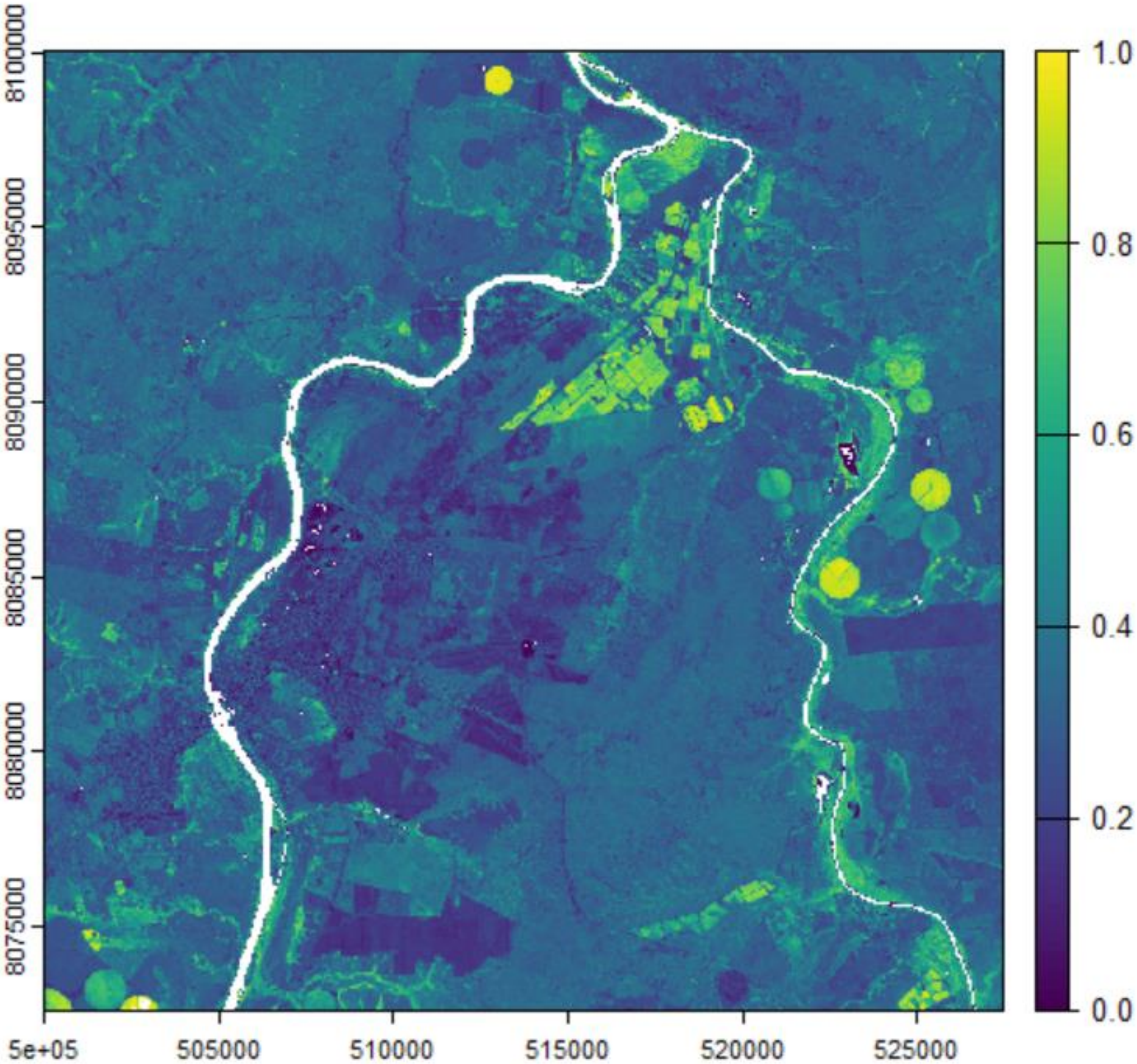
```
library(terra)
vnir<-rast('B05_20m.jp2')
nir<-rast('B8A_20m.jp2')
ndvire<-(nir-vnir)/(nir+vnir)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(ndvire,e)
plot(rc,axes=TRUE,range=c(0,1))
```



Recipe - 10.6 – SAVI

SAVI (Soil Adjusted Vegetation Index).

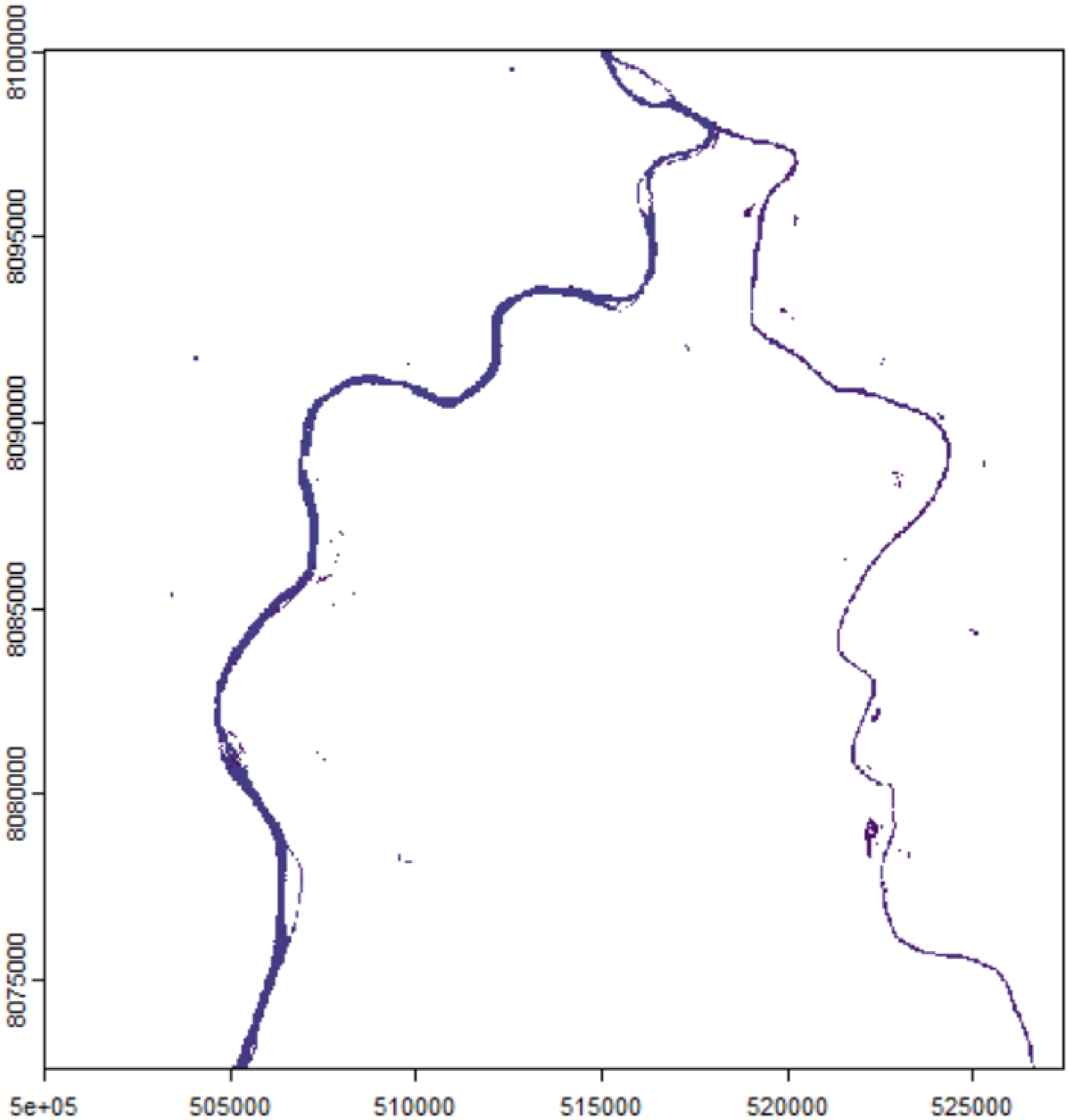
```
library(terra)
nir<-rast('B8A_20m.jp2')
vermelho<-rast('B04_20m.jp2')
savi<-(nir-vermelho)/(nir+vermelho+0.5)*1.5
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(savi,e)
plot(rc,axes=TRUE,range=c(0,1))
```



Recipe - 10.7 – NDWI

NDWI (Normalized Difference Water Index).

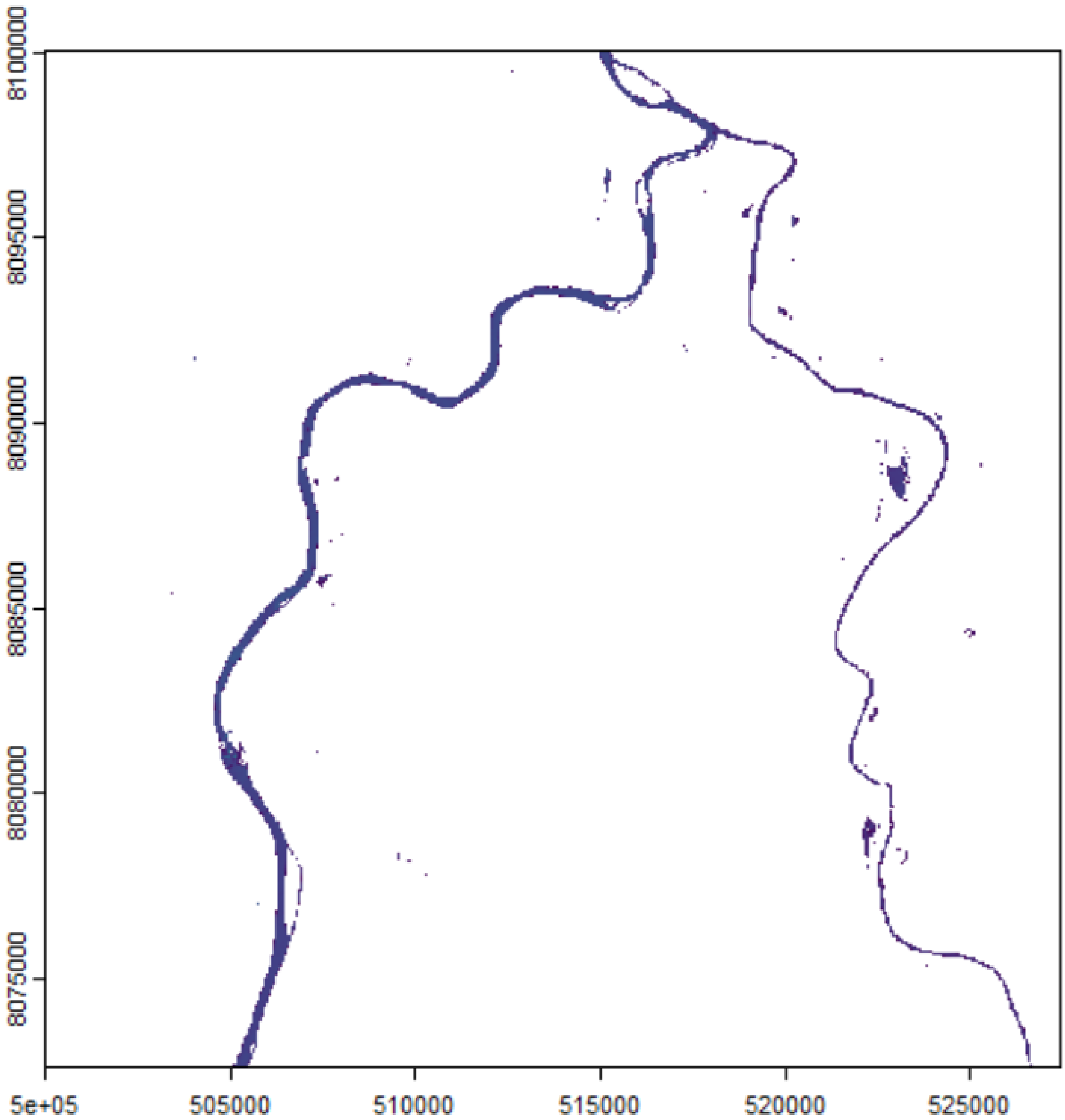
```
library(terra)
green<-rast('B03_20m.jp2')
nir<-rast('B8A_20m.jp2')
ndwi<-(green-nir)/(green+nir)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(ndwi,e)
plot(rc,axes=TRUE,legend=FALSE,range=c(0,1))
```



Recipe - 10.8 – MNDWI

MNDWI (Modified Normalized Difference Water Index).

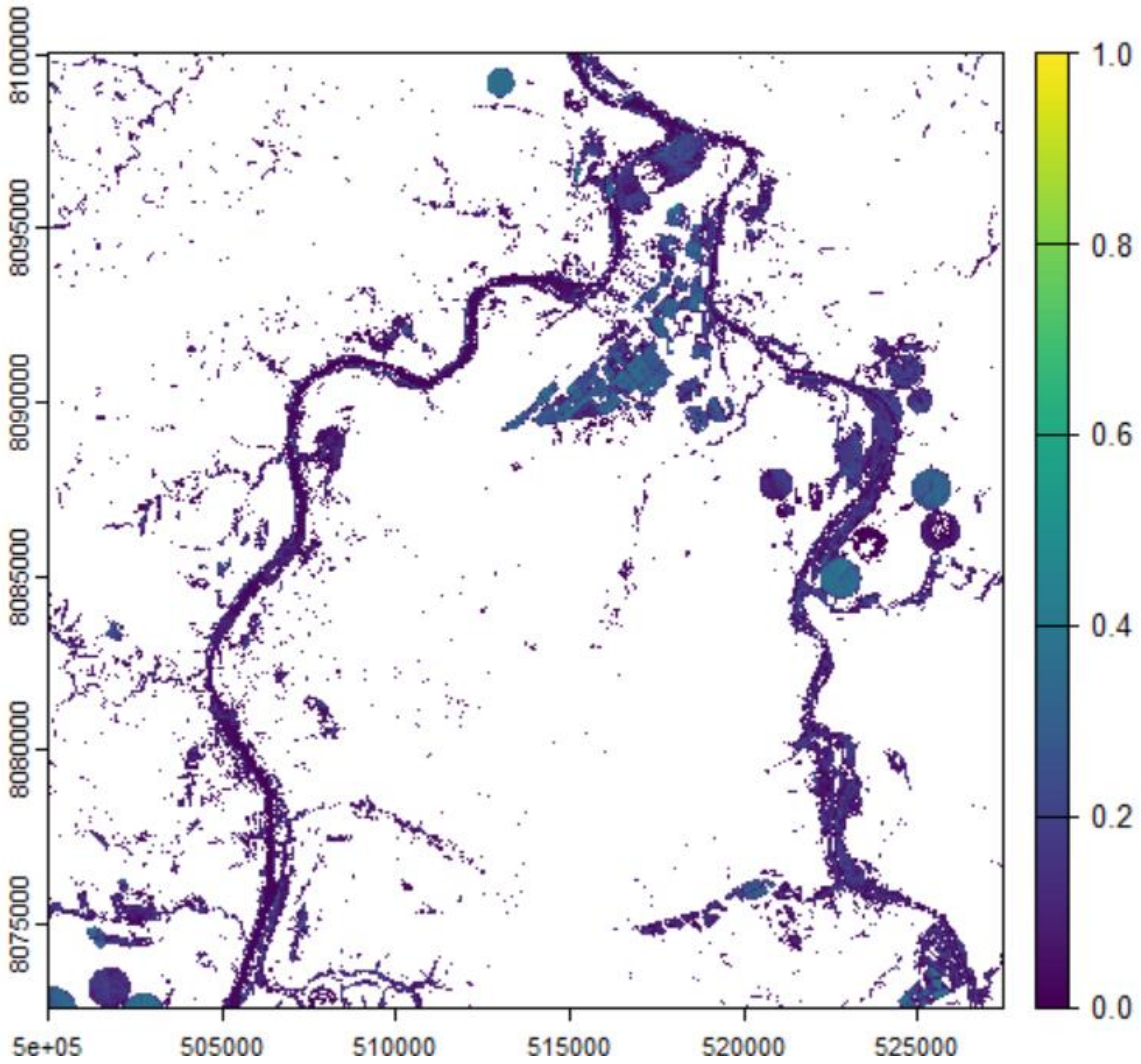
```
library(terra)
green<-rast('B03_20m.jp2')
swir<-rast('B11_20m.jp2')
mndwi<-(green-swir)/(green+swir)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(mndwi,e)
plot(rc,axes=TRUE,legend=FALSE,range=c(0,1))
```



Recipe - 10.9 – NDMI

NDMI (Normalized Difference Moisture Index).

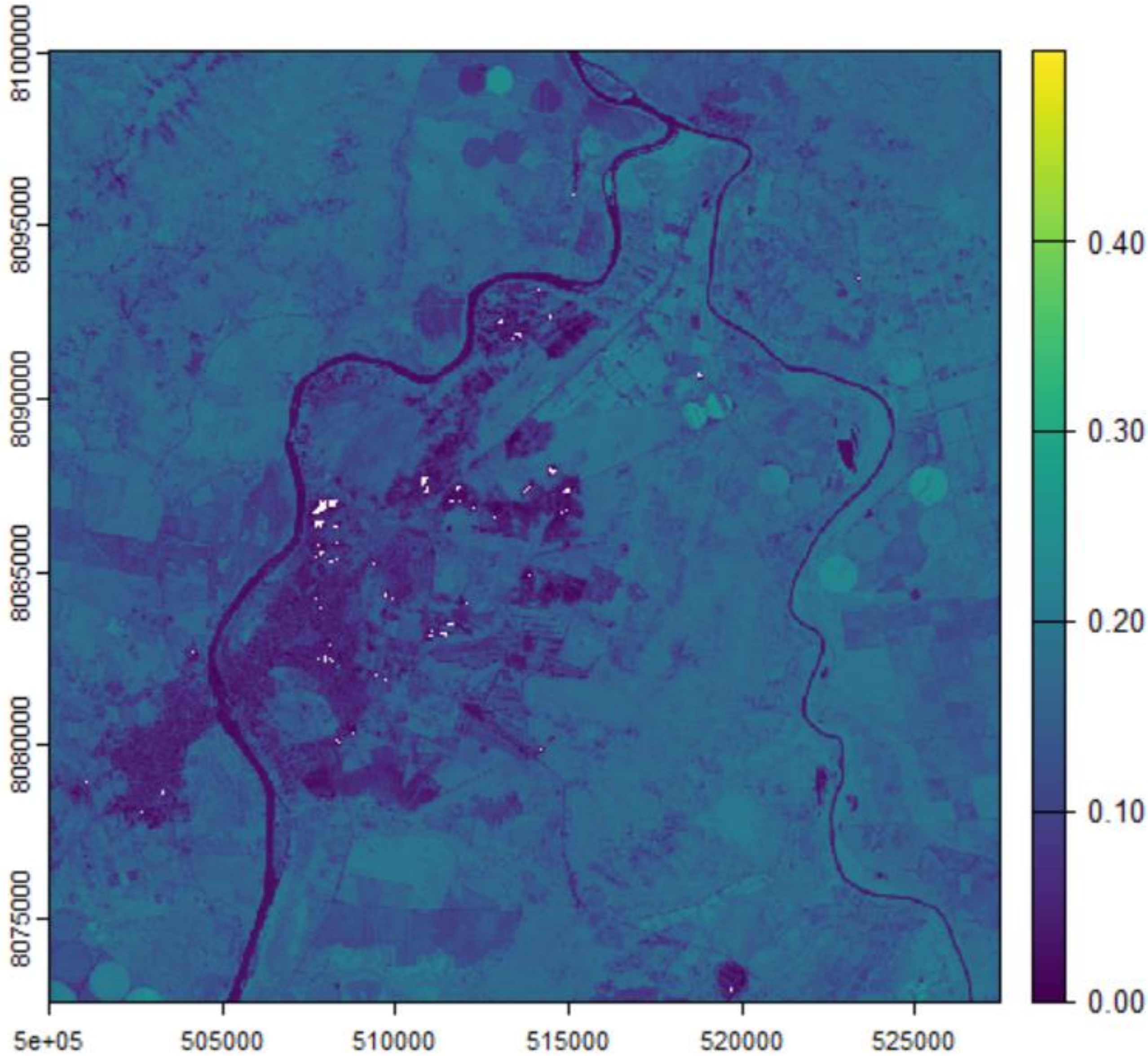
```
library(terra)
nir<-rast('B8A_20m.jp2')
swir<-rast('B11_20m.jp2')
ndmi<-(nir-swir)/(nir+swir)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(ndmi,e)
plot(rc,axes=TRUE,range=c(0,1))
```



Recipe - 10.10 – NDTI

NDTI (Normalized Difference Tillage Index).

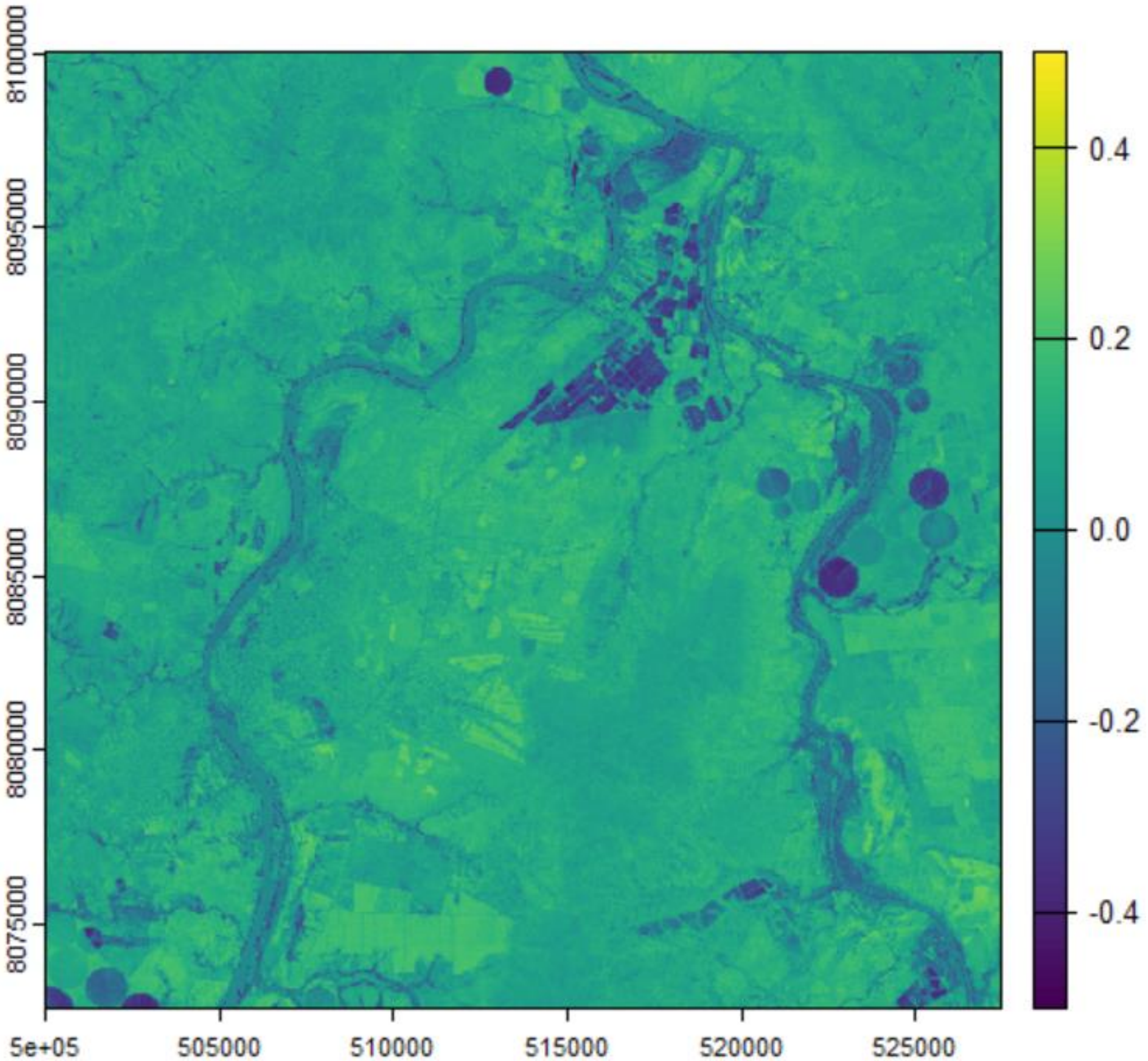
```
library(terra)
swir1<-rast('B11_20m.jp2')
swir2<-rast('B12_20m.jp2')
ndti<-(swir1-swir2)/(swir1+swir2)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(ndti,e)
plot(rc,axes=TRUE,range=c(0,0.5))
```



Recipe - 10.11 – NDBI

NDBI (Normalized Difference Built-up Index).

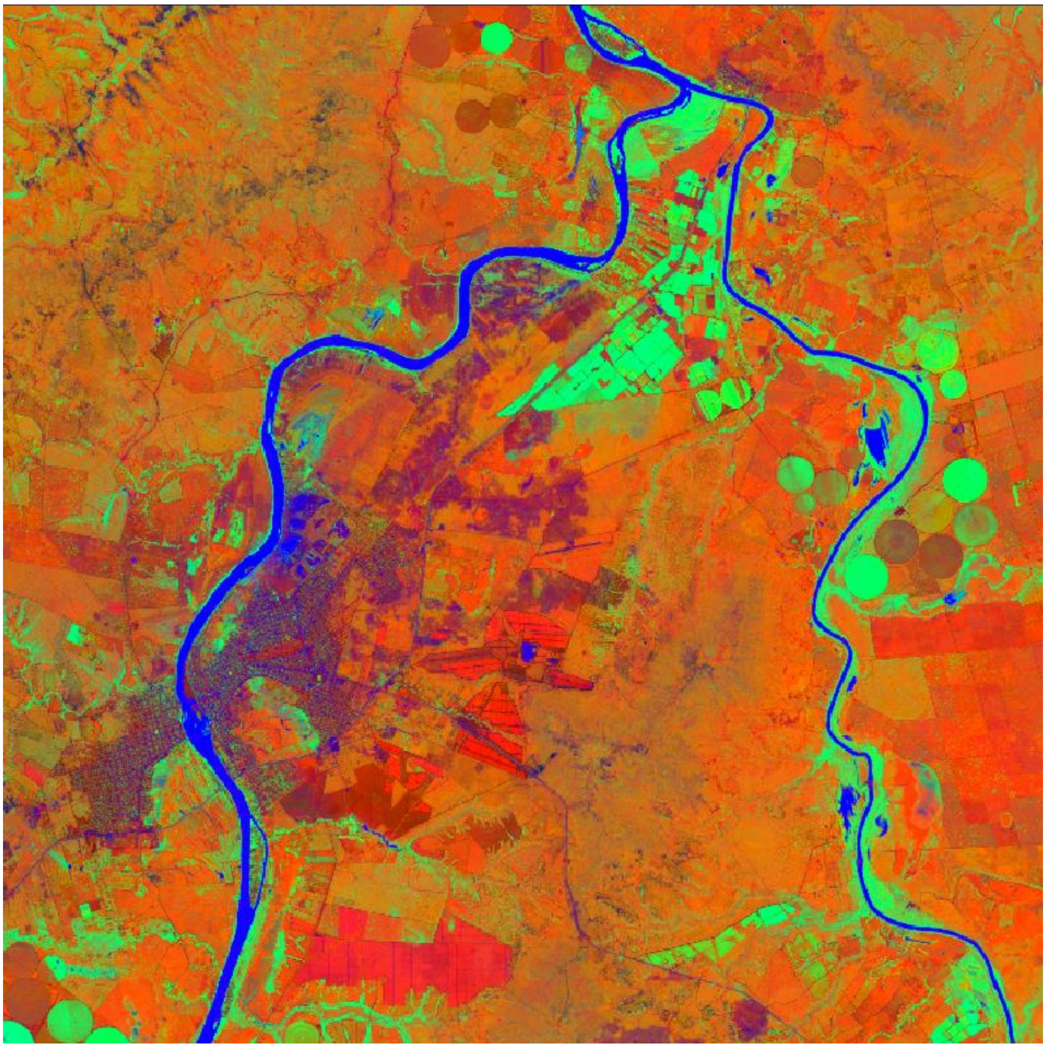
```
library(terra)
nir<-rast('B8A_20m.jp2')
swir<-rast('B11_20m.jp2')
ndbi<-(swir-nir)/(swir+nir)
e <- ext(499980, 527430, 8072590,8100040)
rc<-crop(ndbi,e)
plot(rc,axes=TRUE,range=c(-0.5,0.5))
```



Recipe - 10.12 – RGB composite with indexes

Creating a classification FCC image RGB with the indexes MNDWI (Blue), SAVI (Green) and NDBI+NDTI (Red).

```
library(terra)
nir<-rast('B8A_20m.jp2')
vermelho<-rast('B04_20m.jp2')
savi<-(nir-vermelho)/(nir+vermelho+0.5)*1.5
green<-rast('B03_20m.jp2')
swir<-rast('B11_20m.jp2')
mndwi<-(green-swir)/(green+swir)
swir1<-rast('B11_20m.jp2')
swir2<-rast('B12_20m.jp2')
ndti<-(swir1-swir2)/(swir1+swir2)
nir<-rast('B8A_20m.jp2')
swir<-rast('B11_20m.jp2')
ndbi<-(swir-nir)/(swir+nir)
e <- ext(499980, 527430, 8072590,8100040)
rgb<-rast(list(ndbi+ndti,savi,mndwi))
rcrgb<-crop(rgb,e)
plotRGB(rcrgb,stretch='lin')
writeRaster(rcrgb, indexes.tif', overwrite=TRUE)
```

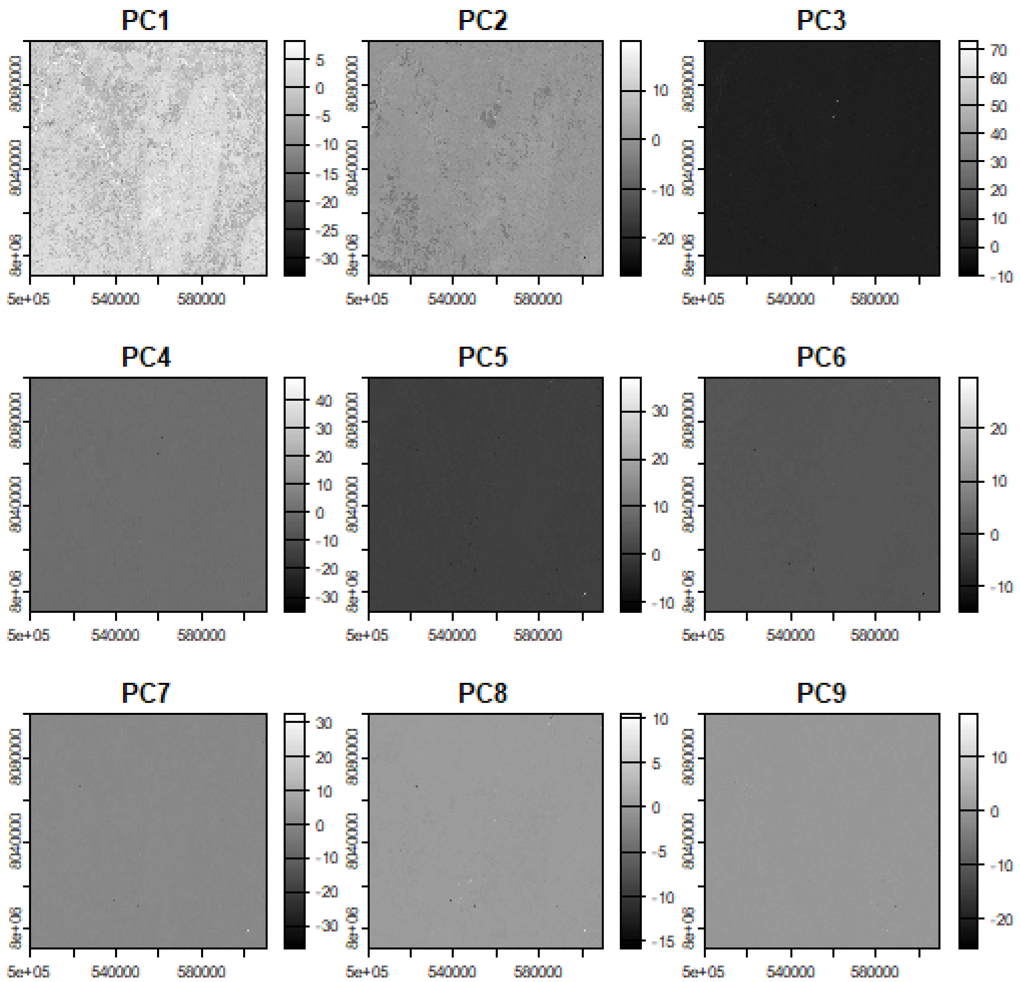


11 Advanced satellite image processing

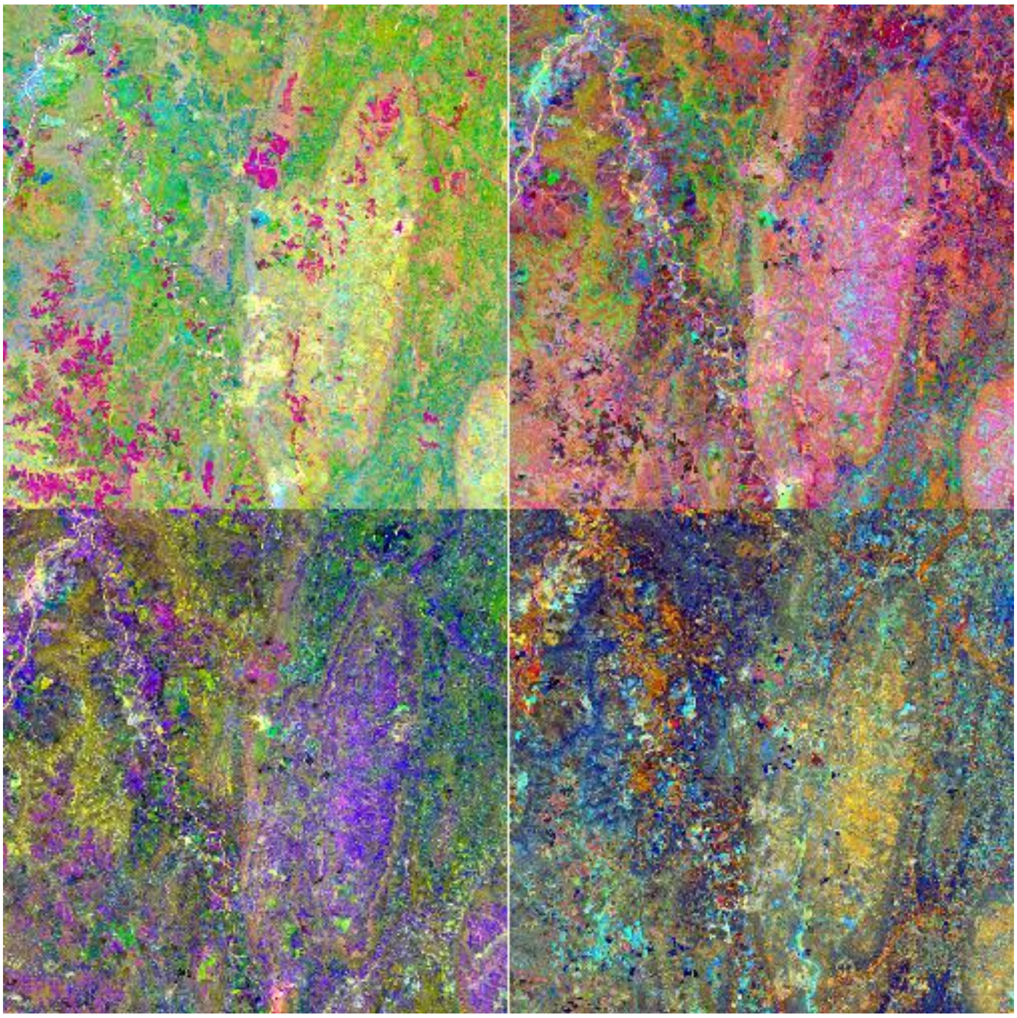
Recipe - 11.1 – PCA

Creating a Principal Component Analysis (PCA) by loading all bands with same resolution (2, 3, 4, 5, 6, 7, 8A, 11 and 12) on a SpatRaster object and execute the PCA.

```
library(terra)
rlis<-c("B02_20m.jp2","B03_20m.jp2","B04_20m.jp2","B05_20m.jp2","B06_20m.jp2",
"B07_20m.jp2","B8A_20m.jp2","B11_20m.jp2","B12_20m.jp2")
rlis2<-c("b2","b3","b4","b5","b6","b7", "b8a","b11","b12")
sentinel<-rast(rlis)
names(sentinel)<-rlis2
set.seed(1)
amostra <- spatSample(sentinel, 300000,method="random")
pca <- prcomp(amostra, scale = TRUE)
rm(amostra)
pca
Standard deviations (1, .., p=9):
[1] 2.5013165 1.3679497 0.6039902 0.4215913 0.3048038 0.2968446 0.2802938 0.2076735 0.1639242

Rotation (n x k) = (9 x 9):
           PC1        PC2          PC3        PC4         PC5         PC6         PC7          PC8         PC9
b2  -0.3162025 -0.2320622 -0.815739281 -0.4095477 -0.08747453  0.04109089 -0.05010989  0.031012661 -0.01379107
b3  -0.3687928 -0.1370622 -0.193331645  0.5862211  0.45532814 -0.18406493  0.45459507  0.126958259 -0.01395845
b4  -0.3770770 -0.1772968  0.074984493  0.2998913 -0.30954832 -0.07939164 -0.34219088 -0.263856469  0.66481823
b5  -0.3875970 -0.0605321  0.105833744  0.2603263 -0.43205877 -0.10680666 -0.25781674  0.007790049 -0.70888736
b6  -0.3045409  0.4373218 -0.009146478  0.1081630 -0.12972038  0.78848093  0.13684802  0.201314573  0.08023160
b7  -0.2661544  0.5173791 -0.015049521 -0.1031059  0.48539072 -0.24427509 -0.56828982  0.179660082  0.01085614
b8a -0.2684434  0.5145304  0.043052373 -0.2538508 -0.20887038 -0.35783075  0.47315466 -0.448271831  0.02025474
b11 -0.3540186 -0.2316913  0.415203567 -0.4004747 -0.10396148 -0.17407037  0.20126868  0.619399635  0.15146809
b12 -0.3325883 -0.3389823  0.325286320 -0.2894144  0.44233833  0.32711634 -0.03468634 -0.505796451 -0.15875327
pcis<-predict(sentinel,pca,filename='pcis.tif',overwrite=TRUE)
plot(pcis,col=grey(0:100/100))
```



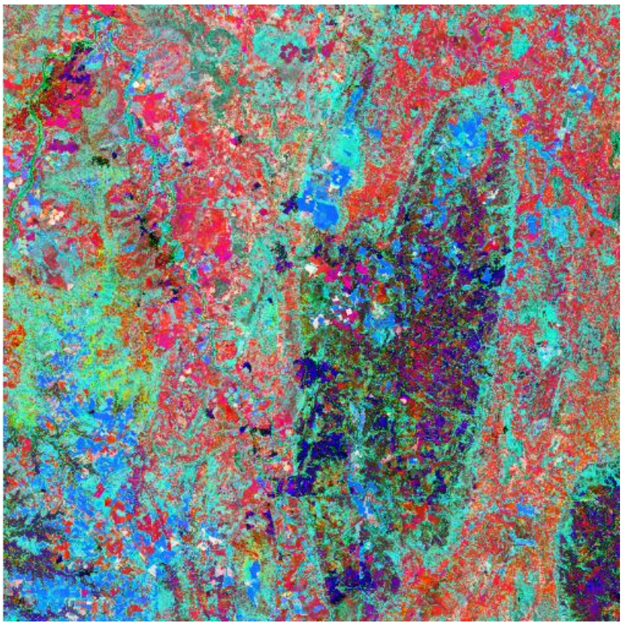
```
dev.off()
par(mfrow=c(2,2))
plotRGB(pcis,r=1,g=2,b=3,stretch='lin')
plotRGB(pcis,r=1,g=3,b=5,stretch='lin')
plotRGB(pcis,r=3,g=4,b=5,stretch='lin')
plotRGB(pcis,r=5,g=6,b=7,stretch='lin')
```



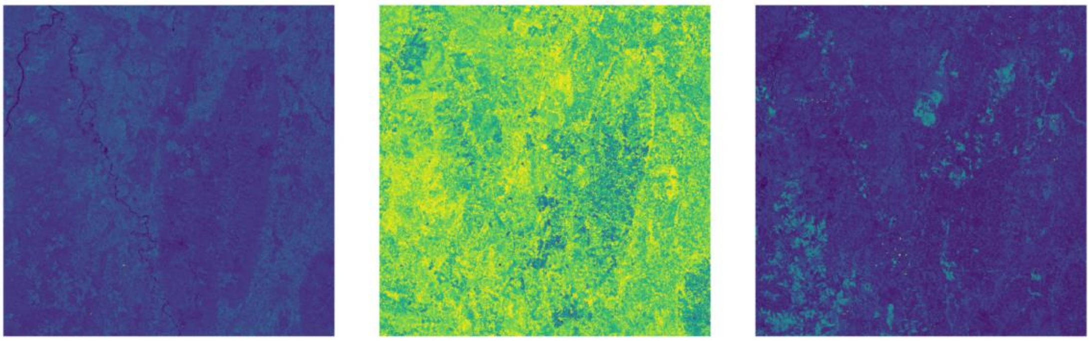
Recipe - 11.2 – IHS

HIS decomposition from a RGB composite (bands 12, 11 and 8A).

```
library(terra)
fcc.rgb<-rast(c('B12_20m.jp2','B11_20m.jp2','B8A_20m.jp2'))
Nor<-fcc.rgb/32767
Nor
class       : SpatRaster
dimensions  : 5490, 5490, 3  (nrow, ncol, nlyr)
resolution  : 20, 20  (x, y)
extent      : 499980, 609780, 7990240, 8100040  (xmin, xmax, ymin, ymax)
coord. ref. : WGS 84 / UTM zone 23S (EPSG:32723)
source      : spat_s9YbPQxviLyJU8U_3384.tif
names       : B12_20m, B11_20m, B8A_20m
min values  :       0,       0,       0
max values  :       1,       1,       1
I<-(Nor[[1]]+Nor[[2]]+Nor[[3]])/3
S<-1-(3/(Nor[[1]]+Nor[[2]]+Nor[[3]]))*min(Nor[[1]],Nor[[2]],Nor[[3]])
H<- acos((0.5*((Nor[[1]]-Nor[[2]])+(Nor[[1]]-Nor[[3]])))/(sqrt((Nor[[1]]-
Nor[[2]])^2+((Nor[[1]]-Nor[[3]])*(Nor[[2]]-Nor[[3]])))))
ihs<-c(I,H,S)
plotRGB(ihs,stretch='hist')
```



```
dev.off()
par(mfrow=c(1,3))
plot(I,axes=FALSE,legend=FALSE)
plot(H,axes=FALSE,legend=FALSE)
plot(S,axes=FALSE,legend=FALSE)
```

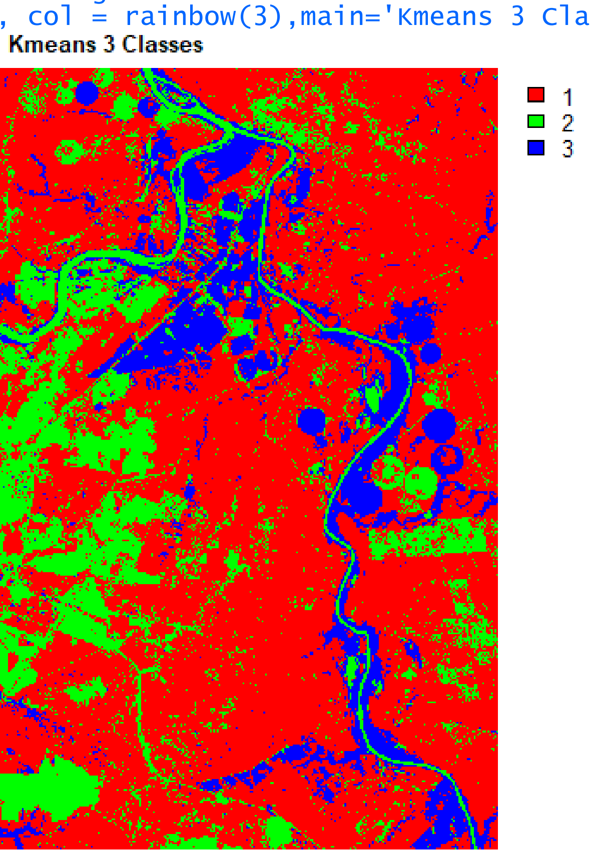


12 Image Classification

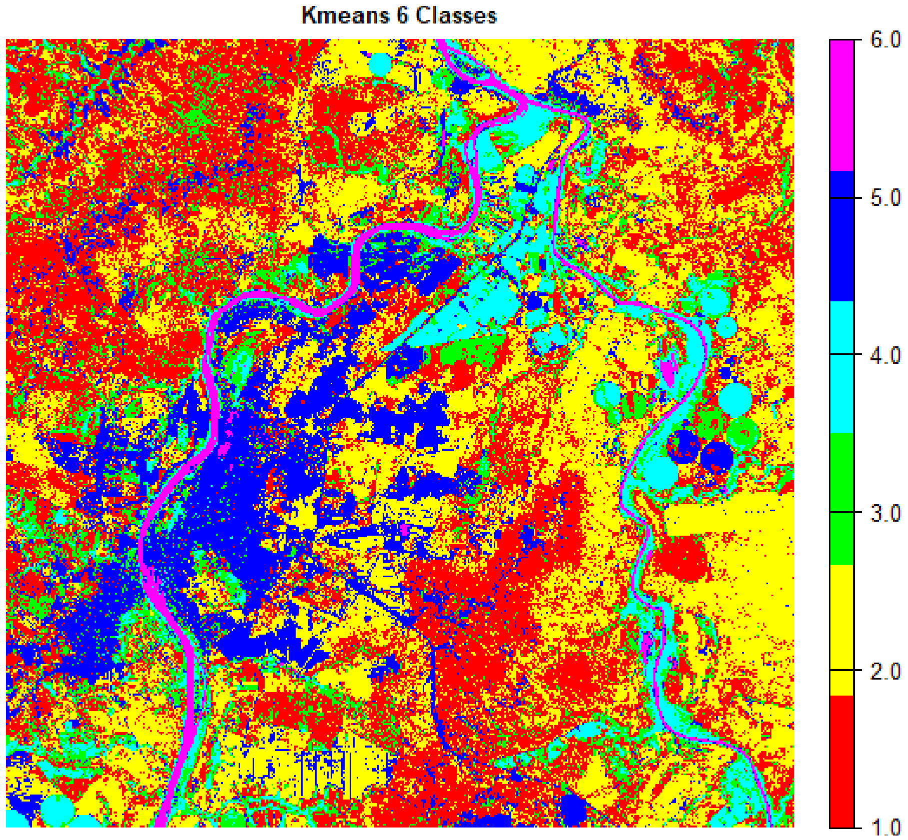
Recipe - 12.1 – Kmeans

Executing unsupervised KMeans classification on indexes composite MNDWI, SAVI and NDBI+NDTI.

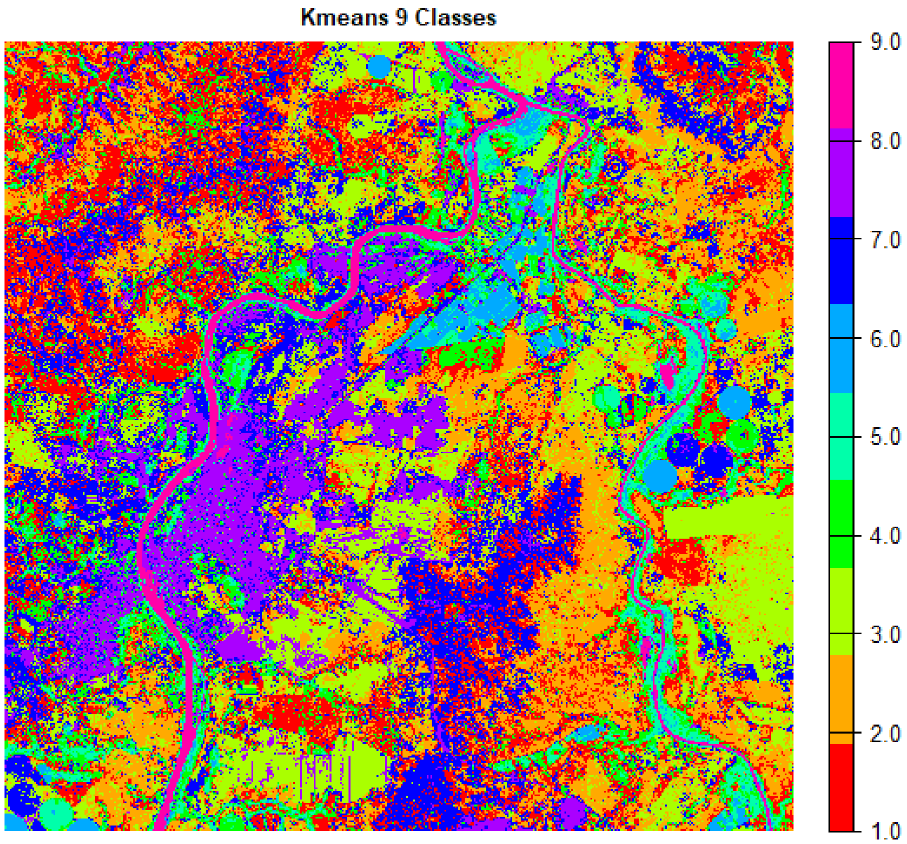
```
library(terra)
library(cluster) #install cluster using install.packages("cluster")
nir<-rast('B8A_20m.jp2')
vermelho<-rast('B04_20m.jp2')
savi<-(nir-vermelho)/(nir+vermelho+0.5)*1.5
green<-rast('B03_20m.jp2')
swir<-rast('B11_20m.jp2')
mndwi<-(green-swir)/(green+swir)
swir1<-rast('B11_20m.jp2')
swir2<-rast('B12_20m.jp2')
ndti<-(swir1-swir2)/(swir1+swir2)
nir<-rast('B8A_20m.jp2')
swir<-rast('B11_20m.jp2')
ndbi<-(swir-nir)/(swir+nir)
e <- ext(499980, 527430, 8072590,8100040)
rgb<-rast(list(ndbi+ndti,savi,mndwi))
rgbi<-crop(rgb,e)
img<-c(rgbi[[1]],rgbi[[2]],rgbi[[3]])
ar <- values(img) #loading  raster into a vector
values <- which(!is.na(ar)) #índice de valores válidos (valores não NA)
ar <- na.omit(ar) #removing NA from vector
Result <- clara(ar,3,samples=500,metric="manhattan",pamLike=T)
kmraster3 <- rast (rgbi[[1]])
values(kmraster3) <- Result$clustering
Result <- clara(ar,6,samples=500,metric="manhattan",pamLike=T)
kmraster6 <- rast(rgbi[[1]])
values(kmraster6) <- Result$clustering
Result <- clara(ar,9,samples=500,metric="manhattan",pamLike=T)
kmraster9 <- rast(rgbi[[1]])
values(kmraster9) <- Result$clustering
plot(kmraster3, legend=T,axes=F, col = rainbow(3),main='Kmeans 3 Classes')
```



```
plot(kmraster6, legend=T,axes=F, col = rainbow(6),main='Kmeans 6 Classes')
```



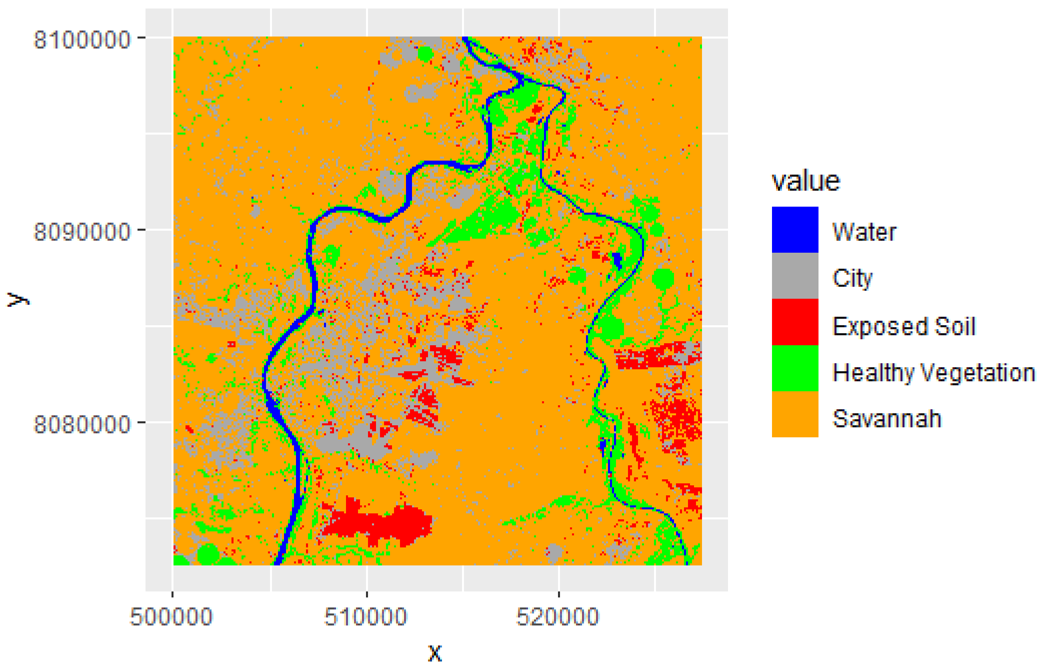

```
plot(kmraster9, legend=T,axes=F, col = rainbow(9),main='Kmeans 9 Classes')
```



Recipe - 12.2 – SAM

Applying supervised Spectral Angle Mapper (SAM) to classify the indexes composite MNDWI, SAVI and NDBI+NDTI.

```
library(terra)
library(RStoolbox) #install RStoolbox using install.packages("RStoolbox")
nir<-rast('B8A_20m.jp2')
vermelho<-rast('B04_20m.jp2')
savi<-(nir-vermelho)/(nir+vermelho+0.5)*1.5
green<-rast('B03_20m.jp2')
swir<-rast('B11_20m.jp2')
mndwi<-(green-swir)/(green+swir)
swir1<-rast('B11_20m.jp2')
swir2<-rast('B12_20m.jp2')
ndti<-(swir1-swir2)/(swir1+swir2)
nir<-rast('B8A_20m.jp2')
swir<-rast('B11_20m.jp2')
ndbi<-(swir-nir)/(swir+nir)
e <- ext(499980, 527430, 8072590,8100040)
rgb<-rast(list(ndbi+ndti,savi,mndwi))
rgbi<-crop(rgb,e)
library(raster) #install raster using install.packages("raster ")
## training endmember
pontos <- data.frame(x = c(506009, 507004,512952,504937,518565), y = c(8084856,
8084148,8083483,8085263,8081092))
endmembers <- extract(rgbi, pontos)
rownames(endmembers) <- c("Water","City","Exposed Soil","Healthy Vegetation",
"Savannah")
## Classification based on minimum angle
samCl <- sam(rgbi, endmembers, angles = FALSE)
library(ggplot2) #install ggplot2 using install.packages("ggplot2 ")
ggR(samCl, forceCat = TRUE, geom_raster=TRUE) + scale_fill_manual(values =
c("blue", "darkgray","red","green","orange"), labels = c("Water","City","Exposed
Soil","Healthy Vegetation", "Savannah"))
```



Goiânia - GO, September 20, 2024