The R-spatial package ecosystem and openEO for analysing Earth Observation data

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Why do we use Data Science languages, and Open Source?

The aim of science is communication:

- DS languages summarise and abstract problems, and allow reproducing the computational steps of a study
- open source lets anyone scrutinize computation, it allows to
  - learn,
  - understand,
  - critisize and
  - extend

`https://github.com/edzer/LPS22`

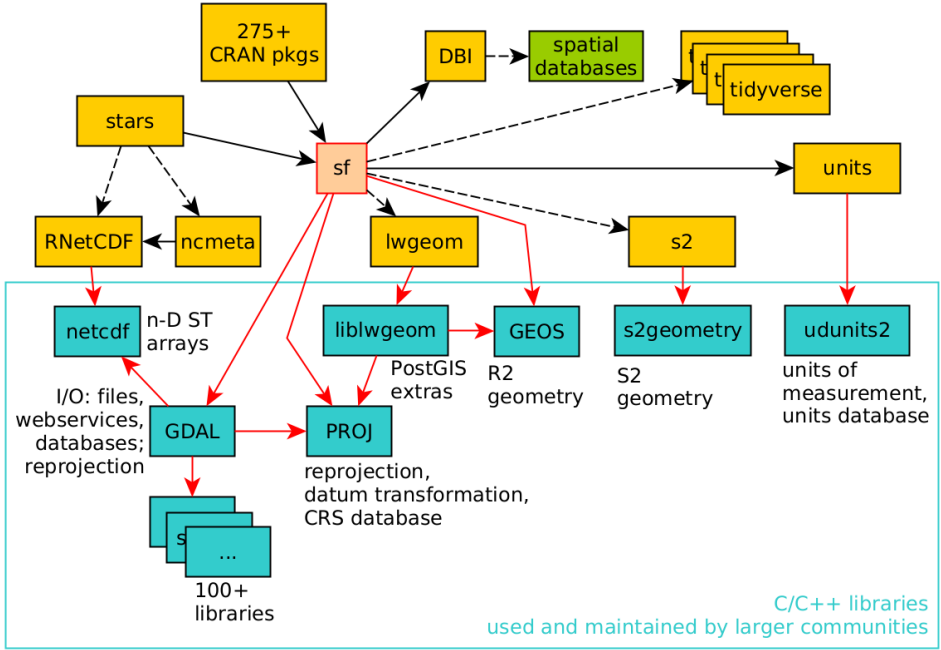
What is R, and R-Spatial?

Why do people use R?

- .. it is a free software environment for statistical computing and graphics
- it is extendible
- it runs on Win/OSX/Linux, and has no package install hell
- it has strong support for spatial data, and spatial statistics

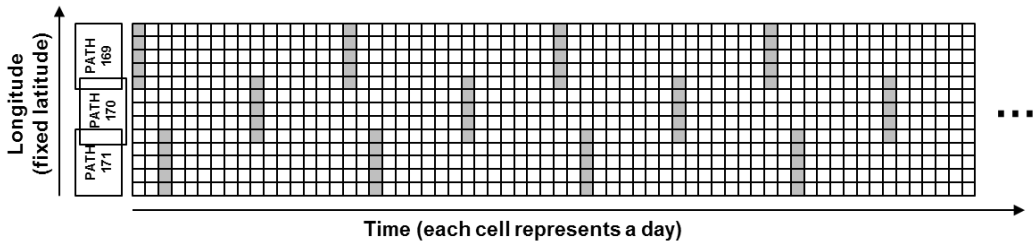
Why do people use R-Spatial?

- it solves problems, they know how
- many problems need *statistical* analysis, e.g. for model inference or assessing prediction errors
- complex graphs are easy to make
- friendly and diverse commmunity support


275+
CRAN pkgs
DBI
spatial
databases
tidyverse
stars
sf
units
RNetCDF
ncmeta
lwgeom
s2
netcdf
n-D ST
arrays
liblwgeom
GEOS
s2geometry
udunits2
PostGIS
extras
R2
geometry
S2
geometry
units of
measurement,
units database
I/O: files,
webservices,
databases;
reprojection
GDAL
PROJ
reprojection,
datum transformation,
CRS database
...
100+
libraries
C/C++ libraries
used and maintained by larger communities

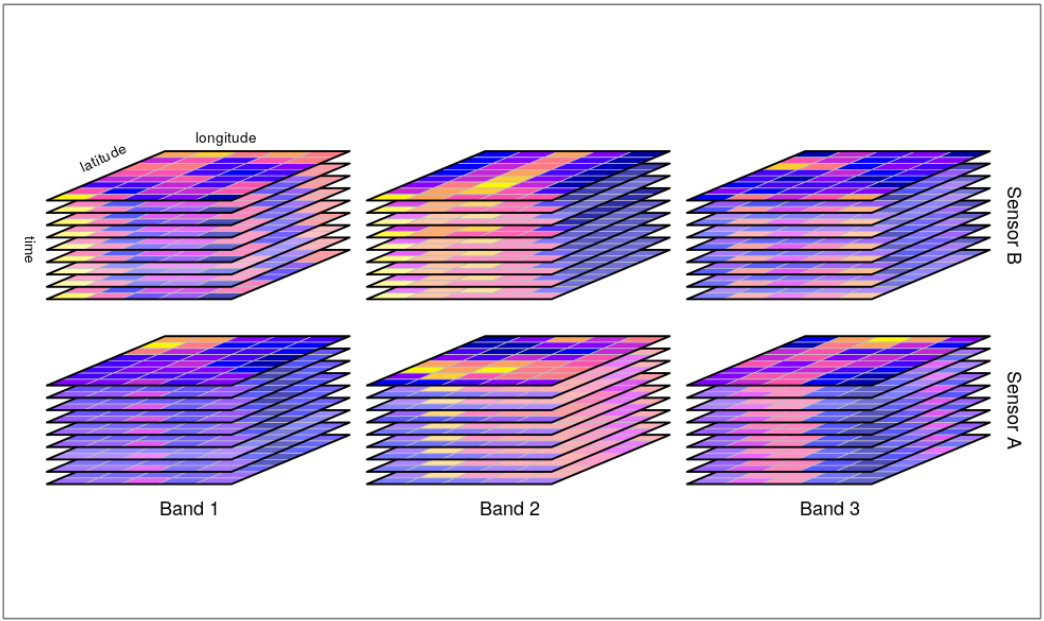
Data cubes, image collections

What we have:



Appel, M., Lahn, F., Buytaert, W. & Pebesma, E. (2018). Open and scalable analytics of large Earth observation datasets: from scenes to multidimensional arrays using SciDB and GDAL. ISPRS Journal of Photogrammetry and Remote Sensing, 138, 47-56.

What we want:


longitude
latitude
time
Sensor B
Sensor A
Band 1
Band 2
Band 3

Or even:

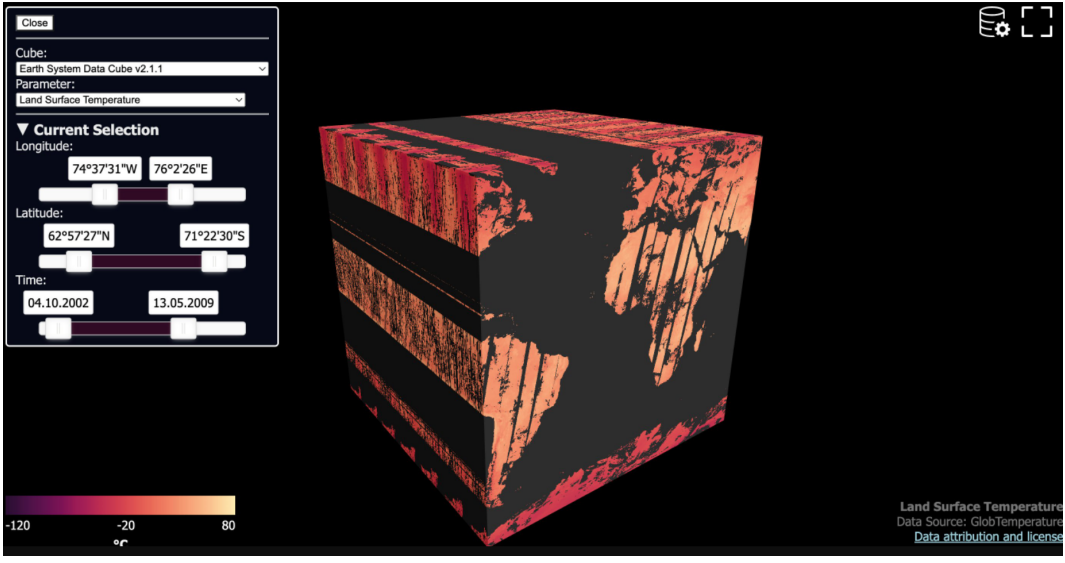


Figure 1: https://twitter.com/miguelmahechag1/status/1528653878798991360

How to cube?

Need to choose:

- spatial resolution: not everything needs to be done always at observation resolution
- target CRS, in case e.g. multiple UTM zones are covered
- spatial and/or temporal aggregation/interpolation *methods*

It seems unlikely that major EO datasets are *distributed* as cubes, because

- there is no one-fits-all
- the “best” cube seems application dependent

Creating cubes from image collections

- on-the-fly, GEE, openEO: data cube *views*
- explicitly: e.g. using R package `gdalcubes`

package gdalcubes

```
library(gdalcubes)
L8.files = list.files("/home/edzer/data/L8_cropped", pattern = ".tif",
                recursive = TRUE, full.names = TRUE)
L8.col = create_image_collection(L8.files, format = "L8_SR",
                out_file = "L8.db")
v.overview = cube_view(srs="EPSG:3857", extent=L8.col,
        dx = 500, dy = 500, dt = "P1Y", resampling = "nearest",
        aggregation = "median")
```

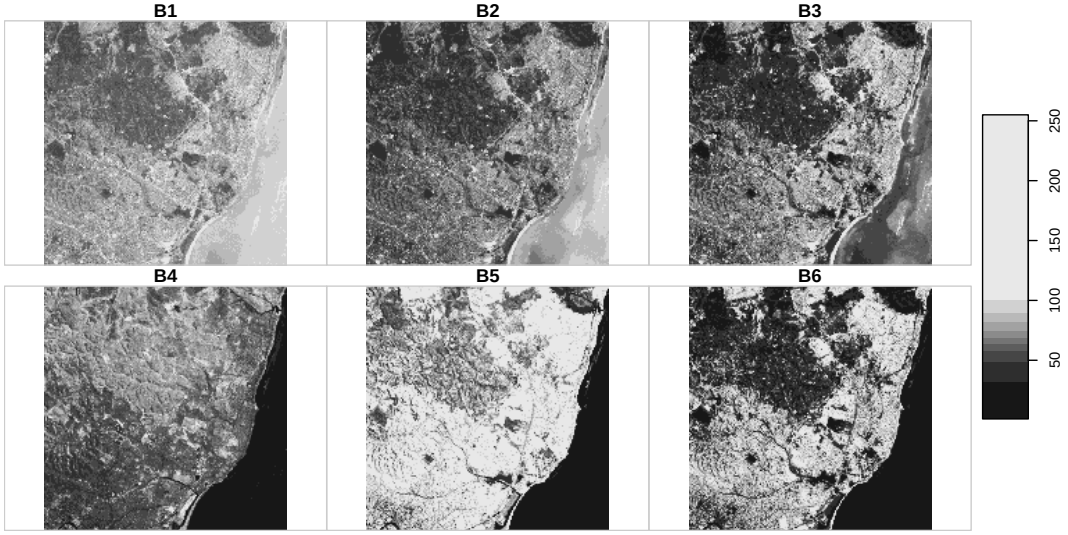
```
v.overview
## A data cube view object
##
## Dimensions:
##                  low              high count pixel_size
## t               2013              2019     7        P1Y
## y -1096876.57818711 -993876.578187112   206        500
## x -7370181.54841633 -7235181.54841633   270        500
##
## SRS: "EPSG:3857"
## Temporal aggregation method: "median"
## Spatial resampling method: "near"
L8.cube.overview = raster_cube(L8.col, v.overview)
L8.cube.overview.rgb = select_bands(L8.cube.overview,
    c("B02", "B03", "B04"))
# write_ncdf(L8.cube.overview.rgb, "L8.nc")
```

gdalcubes understands STAC collections, using R package rstac

package stars

```
library(stars)
file_name = system.file("tif/L7_ETMs.tif", package = "stars")
(r = read_stars(file_name))
## stars object with 3 dimensions and 1 attribute
## attribute(s):
##               Min. 1st Qu. Median     Mean 3rd Qu. Max.
## L7_ETMs.tif      1      54     69 68.91242      86  255
## dimension(s):
##      from  to  offset delta                       refsys point values x/y
## x       1 349  288776  28.5 SIRGAS 2000 / UTM zone 25S FALSE   NULL [x]
## y       1 352 9120761 -28.5 SIRGAS 2000 / UTM zone 25S FALSE   NULL [y]
## band    1   6      NA    NA                           NA    NA   NULL
```

```
plot(r)
```



```
read_stars(file_name, proxy = TRUE) |>
   st_set_dimensions("band", c("B1", "B2", "B3", "B4", "B5", "B6")) -> r
r
## stars_proxy object with 1 attribute in 1 file(s):
## $L7_ETMs.tif
## [1] "[...]/L7_ETMs.tif"
##
## dimension(s):
##      from  to  offset delta                       refsys point    values
## x       1 349  288776  28.5 SIRGAS 2000 / UTM zone 25S FALSE      NULL
## y       1 352 9120761 -28.5 SIRGAS 2000 / UTM zone 25S FALSE      NULL
## band    1   6      NA    NA                           NA    NA B1,...,B6
```

- lazy: delays reading pixels and subsequent computations until needed (plot, download)

Vector data cubes

```
r |> st_bbox() |> st_as_sfc() |> st_sample(10) -> pts
(e <- st_extract(r, pts))
## stars object with 2 dimensions and 1 attribute
## attribute(s):
##               Min. 1st Qu. Median  Mean 3rd Qu. Max.
## L7_ETMs.tif    11   44.25   60.5 59.35      79  131
## dimension(s):
##          from to offset delta                       refsys point
## geometry    1 10     NA    NA SIRGAS 2000 / UTM zone 25S  TRUE
## band        1  6     NA    NA                           NA    NA
##                                                        values
## geometry POINT (296565.3 9112856),...,POINT (291353.6 9115558)
## band                                                  B1,...,B6
```

```r
as.data.frame(e) |> dim()
## [1] 60  3
as.data.frame(e) |> head(3)                # "long"
##                   geometry band L7_ETMs.tif
## 1 POINT (296565.3 9112856)   B1          89
## 2   POINT (295004 9118257)   B1          69
## 3   POINT (290961 9116739)   B1          61
st_as_sf(e) |> as.data.frame() |> dim()
## [1] 10  7
st_as_sf(e) |> as.data.frame() |> head(3) # "wide"
##   B1 B2 B3 B4 B5 B6                  geometry
## 1 89 76 48 12 13 13 POINT (296565.3 9112856)
## 2 69 60 55 80 89 53   POINT (295004 9118257)
## 3 61 47 36 66 62 33   POINT (290961 9116739)
```

openEO: R client

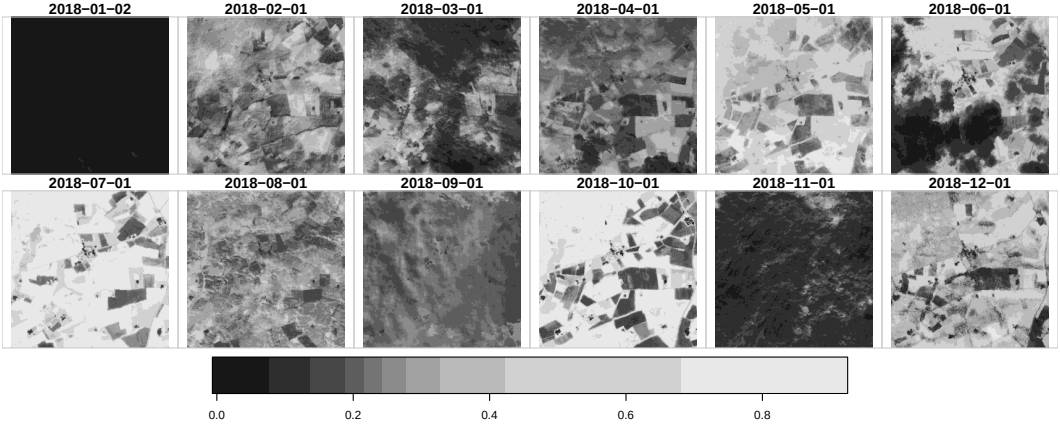
Connect, load collection:

```
library(openeo)
con = connect("https://openeo.cloud")
login()
# list_collections()
collection = "SENTINEL2_L2A"
bbox = list(west = 7, east = 7.01, south = 52, north = 52.01)
bands = c("B04", "B08")
time_range = list("2018-01-01", "2019-01-01")
p = processes()
data = p$load_collection(id = collection, spatial_extent = bbox,
          temporal_extent = time_range, bands = bands)
```

Process (asynchronous):

```
ndvi = function(data, context) {
  red = data[1]; nir = data[2]; (nir-red)/(nir+red)
}
calc_ndvi = p$reduce_dimension(data = data, dimension = "bands",
    reducer = ndvi)
intervals = ... ; labels = ...
temp_period = p$aggregate_temporal(data = calc_ndvi,
    reducer = function(data, context) p$median(data),
    intervals = intervals, labels = labels, dimension = "t")
result = p$save_result(data = temp_period, format="NetCDF")
job = create_job(graph = result,
    title = "ndvi.nc", description = "ndvi.nc",
    format = "netCDF")
start_job(job = job$id) # use the id of the job (job$id) to start the job
status(job)
dwnld = download_results(job = job$id, folder = "./") # when finished
```

```
r = read_stars("openEO.nc")
plot(r)
```



UDF: user-defined functions

local exploration, remote execution

1. obtain a small cube section, using `openeo::get_sample()`, as `stars` object
2. explore locally, developing an analysis function
3. push *exactly* the same function as UDF to the openEO backend
4. show, explore, or download the results

- At the back-end, the "full" data cube is chunked, and pulled through the UDF, again as `stars` sub-cubes.
- Currently works with `reduce_dimension` and `apply_dimension`, so that the backend *knows* which chunking strategy to use

Vision

1. Minimize modification of the script

- extend `stars_proxy` objects to "cubed" remote image collections
- running locally or in cloud, with minimal adaptation
- use UDF: test locally, deploy remotely

2. Add syntactic sugar

```
# after connect()/login():
get_collection("SENTINEL2_L2A") |>
    filter(bbox, time_range, bands) |>
    st_apply(~band, ndvi) |>
    aggregate("months", median) |>
    mapview()
```

Further packages:

- `raster`, now `terra`: stop at 3 dimensions, directly read GDAL datasets, no vector data cubes; focus on scalable and high performance
- `sits`: trains ML models and predicts using EO *time series* ; used operationally by INPE for mapping land use change in Brazil; see https://e-sensing.github.io/sitsbook/

Discussion

- vector data cubes arise naturally from raster data cubes (by sampling, aggregating over polygons)
- Data Science is multi-lingual; language cross fertilization is useful
- R-spatial welcomes new contributions, and developers willing to take responsibility
- use or search for `#rspatial` on Twitter
- Get involved, get in touch!