* [The problem](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html" \l "the-problem" \t "_blank)
* [Introduction and overview of gdalcubes](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#introduction-and-overview-of-gdalcubes)
* [Installation](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#installation)
* [Demo dataset](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#demo-dataset)
* [Creating image collections](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#creating-image-collections)
* [Creating and processing data cubes](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#creating-and-processing-data-cubes)
* [Chaining data cube operations](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#chaining-data-cube-operations)
* [User-defined functions](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#user-defined-functions)
* [Interfacing with stars](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#interfacing-with-stars)
* [Future work](https://www.r-spatial.org/r/2019/07/18/gdalcubes1.html#future-work)

[[view raw  
Rmd](https://github.com/r-spatial/r-spatial.org/blob/gh-pages/_rmd/2019-07-17-gdalcubes1.Rmd)]

**The problem**

Scientists working with collections and time series of satellite imagery  
quickly run into some of the following problems:

* Images from different areas of the world have different spatial  
  reference systems (e.g., UTM zones).
* The pixel size of a single image sometimes differs among its  
  spectral bands / variables.
* Spatially adjacent image tiles often overlap.
* Time series of images are often irregular when the area of interest  
  covers spatial areas larger than the extent of a single image.
* Images from different data products or different satellites are  
  distributed in diverse data formats and structures.

[GDAL](https://gdal.org/) and the [rgdal R  
package](https://cran.r-project.org/package=rgdal) *can* solve most of  
these difficulties by reading all relevant data formats and implementing  
*image warping* to reproject, rescale, resample, and crop images.  
However, GDAL does not know about *image time series* and hence there is  
a lot of manual work needed before data scientists can actually work  
with these data. Instead of *collections of images*, data users in many  
cases desire a regular data structure such as a four-dimensional  
[*raster data cube*](https://r-spatial.github.io/stars/) with dimensions  
x, y, time, and band.

In R, there is currently no implementation to build regular data cubes  
from image collections. The [stars  
package](https://cran.r-project.org/package=stars) provides a generic  
implementation for processing raster and vector data cubes with an  
arbitrary number of dimensions, but assumes that the data are already  
organized as an array.

**Introduction and overview of gdalcubes**

This blog post introduces the gdalcubes R package, aiming at making  
the work with collections and time series of satellite imagery easier  
and more interactive.

The core features of the package are:

* build *regular dense data cubes* from large satellite image  
  collections based on a user-defined *data cube view* (spatiotemporal  
  extent, resolution, and map projection of the cube)
* apply and chaining operations on data cubes
* allow for the execution of user-defined functions on data cubes
* export data cubes as netCDF files, making it easy to process  
  further, e.g., with  
  [stars](https://cran.r-project.org/package=stars) or  
  [raster](https://cran.r-project.org/package=raster).

Technically, the R package is a relatively lightweight wrapper around  
the [gdalcubes C++ library](https://github.com/appelmar/gdalcubes). The  
library strongly builds on [GDAL](https://gdal.org/),  
[netCDF](https://www.unidata.ucar.edu/software/netcdf/), and  
[SQLite](https://www.sqlite.org/index.html) (the full list of C++  
libraries used by gdalcubes is found  
[here](https://appelmar.github.io/gdalcubes/credits.html)).

This blog post focuses on how to use the R package gdalcubes, more  
details about the underlying ideas can be found in our recent open  
access paper in the datacube special issue of [the DATA  
journal](https://www.mdpi.com/2306-5729/4/3/92).

**Installation**

The package can be installed directly from  
[CRAN](https://cran.r-project.org/package=gdalcubes):

install.packages("gdalcubes")

Some features and functions used in this blog post are still in the  
development version (which will be submitted to CRAN as version 0.2.0),  
which currently needs a source install:

# install.packages("remotes")

remotes::install\_git("https://github.com/appelmar/gdalcubes\_R", ref="dev", args="--recursive")

If this fails with error messages like “no rule to make target …”,  
please read [here](https://github.com/appelmar/gdalcubes_R/issues/7).

**Demo dataset**

We use a collection of 180 [Landsat  
8](https://landsat.gsfc.nasa.gov/landsat-8) surface reflectance images,  
covering a small part of the Brazilian Amazon forest. If you would like  
to work with the dataset on your own (and maybe reproduce some parts of  
this blog post), you have two options:

**Option A:** Download the dataset with full resolution (30 meter pixel  
size) [here](https://uni-muenster.sciebo.de/s/SmiqWcCCeFSwfuY/download)  
(67 gigabytes compressed; 190 gigabytes unzipped)

**Option B:** Download a *downsampled* version of the dataset that  
contains all images at a coarse spatial resolution (300 meter pixel  
size) [here](https://uni-muenster.sciebo.de/s/e5yUZmYGX0bo4u9/download)  
(740 megabytes compressed; 2 gigabytes unzipped)

Except for the spatial resolution of the images, the datasets are  
identical, meaning that all code samples work for both options but  
result images may look blurred when using option B. Here is the code to  
download and unzip the dataset to your current working directory (which  
might take some time):

# Option A

#download.file("https://uni-muenster.sciebo.de/s/SmiqWcCCeFSwfuY/download", destfile = "L8\_Amazon.zip")

# Option B

if (!file.exists("L8\_Amazon.zip")) {

download.file("https://uni-muenster.sciebo.de/s/e5yUZmYGX0bo4u9/download", destfile = "L8\_Amazon.zip")

unzip("L8\_Amazon.zip", exdir = "L8\_Amazon")

}

**Creating image collections**

After extraction of the zip archive, we get one directory per image,  
where each image contains 10 GeoTIFF files representing the spectral  
bands and additional per-pixel quality information. As a first step, we  
must scan all available images once, extract some metadata (e.g.  
acquisition date/time and spatial extents of images and how the files  
relate to bands), and store this information in a simple *image  
collection* index file. This file does not store any pixel values but  
only metadata and references to where images can be found.

First, we simply need to find available GeoTIFF files in all  
subdirectories of our demo dataset:

files = list.files("L8\_Amazon", recursive = TRUE, full.names = TRUE, pattern = ".tif")

length(files)

## [1] 1800

head(files)

## [1] "L8\_Amazon/LC082260632014071901T1-SC20190715045926/LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1\_pixel\_qa.tif"

## [2] "L8\_Amazon/LC082260632014071901T1-SC20190715045926/LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1\_radsat\_qa.tif"

## [3] "L8\_Amazon/LC082260632014071901T1-SC20190715045926/LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1\_sr\_aerosol.tif"

## [4] "L8\_Amazon/LC082260632014071901T1-SC20190715045926/LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1\_sr\_band1.tif"

## [5] "L8\_Amazon/LC082260632014071901T1-SC20190715045926/LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1\_sr\_band2.tif"

## [6] "L8\_Amazon/LC082260632014071901T1-SC20190715045926/LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1\_sr\_band3.tif"

To understand the structure of particular data products, the package  
comes with a set of predefined rules (called *collection formats*) that  
define how required metadata can be derived from the data. These include  
formats for some Sentinel-2, MODIS, and Landsat products. We can list  
all available formats with:

library(gdalcubes)

## Loading required package: Rcpp

## Loading required package: RcppProgress

## Loading required package: jsonlite

## Loading required package: ncdf4

## Using gdalcubes library version 0.1.9999

collection\_formats()

## CHIRPS\_v2\_0\_daily\_p05\_tif | Image collection format for CHIRPS v 2.0

## | daily global precipitation dataset (0.05

## | degrees resolution) from GeoTIFFs, expects

## | list of .tif or .tif.gz files as input.

## | [TAGS: CHIRPS, precipitation]

## CHIRPS\_v2\_0\_monthly\_p05\_tif | Image collection format for CHIRPS v 2.0

## | monthly global precipitation dataset (0.05

## | degrees resolution) from GeoTIFFs, expects

## | list of .tif or .tif.gz files as input.

## | [TAGS: CHIRPS, precipitation]

## L8\_L1TP | Collection format for Landsat 8 Level 1 TP

## | product [TAGS: Landsat, USGS, Level 1, NASA]

## L8\_SR | Collection format for Landsat 8 surface

## | reflectance product [TAGS: Landsat, USGS,

## | Level 2, NASA, surface reflectance]

## MxD10A2 | Collection format for selected bands from

## | the MODIS MxD10A2 (Aqua and Terra) v006 Snow

## | Cover product [TAGS: MODIS, Snow Cover]

## MxD11A1 | Collection format for selected bands from

## | the MODIS MxD11A2 (Aqua and Terra) v006 Land

## | Surface Temperature product [TAGS: MODIS,

## | LST]

## MxD11A2 | Collection format for selected bands from

## | the MODIS MxD11A2 (Aqua and Terra) v006 Land

## | Surface Temperature product [TAGS: MODIS,

## | LST]

## MxD13A3 | Collection format for selected bands from

## | the MODIS MxD13A3 (Aqua and Terra) product

## | [TAGS: MODIS, VI, NDVI, EVI]

## Sentinel2\_L1C | Image collection format for Sentinel 2 Level

## | 1C data as downloaded from the Copernicus

## | Open Access Hub, expects a list of file

## | paths as input. The format works on original

## | ZIP compressed as well as uncompressed

## | imagery. [TAGS: Sentinel, Copernicus, ESA,

## | TOA]

## Sentinel2\_L1C\_AWS | Image collection format for Sentinel 2 Level

## | 1C data in AWS [TAGS: Sentinel, Copernicus,

## | ESA, TOA]

## Sentinel2\_L2A | Image collection format for Sentinel 2 Level

## | 2A data as downloaded from the Copernicus

## | Open Access Hub, expects a list of file

## | paths as input. The format should work on

## | original ZIP compressed as well as

## | uncompressed imagery. [TAGS: Sentinel,

## | Copernicus, ESA, BOA, Surface Reflectance]

The “L8\_SR” format is what we need for our demo dataset. Next, we must  
tell gdalcubes to scan the files and build an image collection. Below,  
we create an image collection from the set of GeoTIFF files, using the  
“L8\_SR” collection format and store the resulting image collection  
under “L8.db”.

L8.col = create\_image\_collection(files, "L8\_SR", "L8.db")

L8.col

## A GDAL image collection object, referencing 180 images with 17 bands

## Images:

## name left top bottom

## 1 LC08\_L1TP\_226063\_20140719\_20170421\_01\_T1 -54.15776 -3.289862 -5.392073

## 2 LC08\_L1TP\_226063\_20140820\_20170420\_01\_T1 -54.16858 -3.289828 -5.392054

## 3 LC08\_L1GT\_226063\_20160114\_20170405\_01\_T2 -54.16317 -3.289845 -5.392064

## 4 LC08\_L1TP\_226063\_20160724\_20170322\_01\_T1 -54.16317 -3.289845 -5.392064

## 5 LC08\_L1TP\_226063\_20170609\_20170616\_01\_T1 -54.17399 -3.289810 -5.392044

## 6 LC08\_L1TP\_226063\_20170711\_20170726\_01\_T1 -54.15506 -3.289870 -5.392083

## right datetime

## 1 -52.10338 2014-07-19T00:00:00

## 2 -52.11418 2014-08-20T00:00:00

## 3 -52.10878 2016-01-14T00:00:00

## 4 -52.10878 2016-07-24T00:00:00

## 5 -52.11958 2017-06-09T00:00:00

## 6 -52.09798 2017-07-11T00:00:00

## srs

## 1 +proj=utm +zone=22 +datum=WGS84 +units=m +no\_defs

## 2 +proj=utm +zone=22 +datum=WGS84 +units=m +no\_defs

## 3 +proj=utm +zone=22 +datum=WGS84 +units=m +no\_defs

## 4 +proj=utm +zone=22 +datum=WGS84 +units=m +no\_defs

## 5 +proj=utm +zone=22 +datum=WGS84 +units=m +no\_defs

## 6 +proj=utm +zone=22 +datum=WGS84 +units=m +no\_defs

## [ omitted 174 images ]

##

## Bands:

## name offset scale unit nodata image\_count

## 1 AEROSOL 0 1 180

## 2 B01 0 1 -9999.000000 180

## 3 B02 0 1 -9999.000000 180

## 4 B03 0 1 -9999.000000 180

## 5 B04 0 1 -9999.000000 180

## 6 B05 0 1 -9999.000000 180

## 7 B06 0 1 -9999.000000 180

## 8 B07 0 1 -9999.000000 180

## 9 EVI 0 1 -9999.000000 0

## 10 MSAVI 0 1 -9999.000000 0

## 11 NBR 0 1 -9999.000000 0

## 12 NBR2 0 1 -9999.000000 0

## 13 NDMI 0 1 -9999.000000 0

## 14 NDVI 0 1 -9999.000000 0

## 15 PIXEL\_QA 0 1 180

## 16 RADSAT\_QA 0 1 180

## 17 SAVI 0 1 -9999.000000 0

Internally, the output file is a simple SQLite database. Please notice  
that our collection does not contain data for all possible bands (see  
image\_count column). Depending on particular data download requests,  
Landsat 8 surface reflectance data may come e.g. with some  
post-processed bands (like vegetation indexes) that can be used if  
available.

**Creating and processing data cubes**

To create a raster data cube, we need (i) an image collection and (ii) a  
*data cube view*, defining *how* we look at the data, i.e., at which  
spatiotemporal resolution, window, and spatial reference system. For a  
quick look at the data, we define a cube view with 1km x 1km pixel size,  
yearly temporal resolution, covering the full spatiotemporal extent of  
the image collection, and using the web mercator spatial reference  
system.

v.overview = cube\_view(extent=L8.col, dt="P1Y", dx=1000, dy=1000, srs="EPSG:3857",

aggregation = "median", resampling = "bilinear")

raster\_cube(L8.col, v.overview)

## A GDAL data cube proxy object

## Dimensions:

## name low high size chunk\_size

## 1 t 2013.0 2019.0 7 16

## 2 y -764014.4 -205014.4 559 256

## 3 x -6582280.1 -5799280.1 783 256

##

## Bands:

## name type offset scale nodata unit

## 1 AEROSOL float64 0 1 NaN

## 2 B01 float64 0 1 NaN

## 3 B02 float64 0 1 NaN

## 4 B03 float64 0 1 NaN

## 5 B04 float64 0 1 NaN

## 6 B05 float64 0 1 NaN

## 7 B06 float64 0 1 NaN

## 8 B07 float64 0 1 NaN

## 9 EVI float64 0 1 NaN

## 10 MSAVI float64 0 1 NaN

## 11 NBR float64 0 1 NaN

## 12 NBR2 float64 0 1 NaN

## 13 NDMI float64 0 1 NaN

## 14 NDVI float64 0 1 NaN

## 15 PIXEL\_QA float64 0 1 NaN

## 16 RADSAT\_QA float64 0 1 NaN

## 17 SAVI float64 0 1 NaN

As specified in our data cube view, the time dimension of the resulting  
data cube only has 7 values, representing years from 2013 to 2019. The  
aggregation parameter in the data cube view defines how values from  
multiple images in the same year shall be combined. In contrast, the  
selected resampling algorithm is applied when reprojecting and rescaling  
individual images.

If we are interested in a smaller area at higher temporal resolution, we  
simply need to define a data cube view with different parameters,  
including a specific spatiotemporal extent by passing a list as extent  
argument to cube\_view. Below, we define a data cube view for a 100km x  
100km area with 50m pixel size at monthly temporal resolution.

v.subarea = cube\_view(extent=list(left=-6320000, right=-6220000, bottom=-600000, top=-500000,

t0="2014-01-01", t1="2018-12-31"), dt="P1M", dx=50, dy=50, srs="EPSG:3857",

aggregation = "median", resampling = "bilinear")

raster\_cube(L8.col, v.subarea)

## A GDAL data cube proxy object

## Dimensions:

## name low high size chunk\_size

## 1 t 201401 201812 60 16

## 2 y -600000 -500000 2000 256

## 3 x -6320000 -6220000 2000 256

##

## Bands:

## name type offset scale nodata unit

## 1 AEROSOL float64 0 1 NaN

## 2 B01 float64 0 1 NaN

## 3 B02 float64 0 1 NaN

## 4 B03 float64 0 1 NaN

## 5 B04 float64 0 1 NaN

## 6 B05 float64 0 1 NaN

## 7 B06 float64 0 1 NaN

## 8 B07 float64 0 1 NaN

## 9 EVI float64 0 1 NaN

## 10 MSAVI float64 0 1 NaN

## 11 NBR float64 0 1 NaN

## 12 NBR2 float64 0 1 NaN

## 13 NDMI float64 0 1 NaN

## 14 NDVI float64 0 1 NaN

## 15 PIXEL\_QA float64 0 1 NaN

## 16 RADSAT\_QA float64 0 1 NaN

## 17 SAVI float64 0 1 NaN

The raster\_cube function always returns a proxy object, meaning that  
neither any expensive computations nor any data reads from disk are  
started. Instead, gdalcubes delays the execution until the data is  
really needed when users call plot(), or write\_ncdf(). However, the  
result of our call to raster\_cube can be passed to data cube  
operators. For example, the code below drops all bands except the  
visible RGB bands and, again, returns a proxy object.

L8.cube.rgb = select\_bands(raster\_cube(L8.col, v.overview), c("B02","B03","B04"))

L8.cube.rgb

## A GDAL data cube proxy object

## Dimensions:

## name low high size chunk\_size

## 1 t 2013.0 2019.0 7 16

## 2 y -764014.4 -205014.4 559 256

## 3 x -6582280.1 -5799280.1 783 256

##

## Bands:

## name type offset scale nodata unit

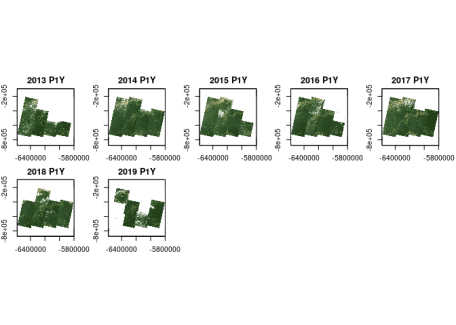
## 1 B02 float64 0 1 NaN

## 2 B03 float64 0 1 NaN

## 3 B04 float64 0 1 NaN

Calling plot() will eventually start computationn, and hence might  
take some time:

system.time(plot(L8.cube.rgb, rgb=3:1, zlim=c(0,1200)))



## user system elapsed

## 16.367 0.605 17.131

**Chaining data cube operations**

For the remaining examples, we use multiple threads to process data  
cubes by setting:

gdalcubes\_options(threads=4)

We can chain many of the provided data cube operators (e.g., using the  
pipe %>%). The following code will derive the median values of the RGB  
bands over time, producing a single RGB overview image for our selected  
subarea.

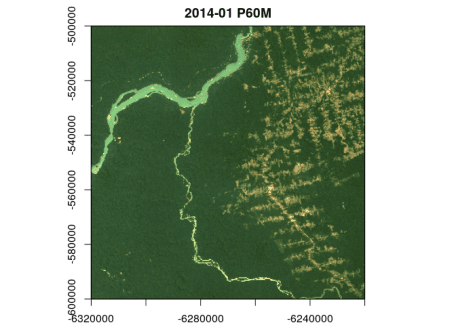
suppressPackageStartupMessages(library(magrittr)) # use the pipe

raster\_cube(L8.col, v.subarea) %>%

select\_bands(c("B02","B03","B04")) %>%

reduce\_time("median(B02)", "median(B03)", "median(B04)") %>%

plot(rgb=3:1, zlim=c(0,1200))



Implemented data cube operators include:

* apply\_pixel apply one or more arithmetic expressions on individual  
  data cube pixels, e.g., to derive vegetation indexes.
* reduce\_time apply on or more reducers over pixel time series.
* reduce\_time apply on or more reducers over spatial slices.
* select\_bands subset available bands.
* window\_time apply an aggregation function or convolution kernel  
  over moving time series windows.
* join\_bands combines the bands of two indentically shaped data  
  cubes.
* filter\_pixel filter pixels by a logical expression on band values,  
  e.g., select all pixels with NDVI larger than 0.
* write\_ncdf export a data cube as a netCDF file.

In a second example, we compute the normalied difference vegetation  
index (NDVI) with apply\_pixel and derive its maximum values over time:

suppressPackageStartupMessages(library(viridis)) # use colors from viridis package

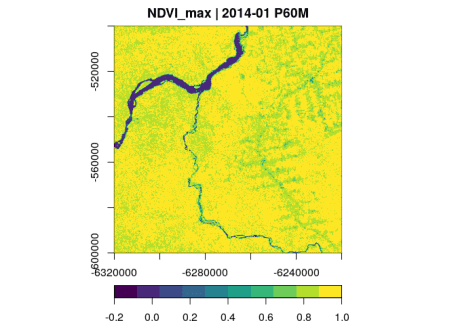
raster\_cube(L8.col, v.subarea) %>%

select\_bands(c("B04","B05")) %>%

apply\_pixel(c("(B05-B04)/(B05+B04)"), names="NDVI") %>%

reduce\_time("max(NDVI)") %>%

plot(zlim=c(-0.2,1), col=viridis, key.pos=1)



**User-defined functions**

Previous examples used character expressions to define reducer and  
arithmetic functions. Operations like apply\_pixel and filter\_pixel  
take character arguments to define the expressions. The reason for this  
is that expressions are translated to C++ functions and all computations  
then are purely C++. However, to give users more flexibility and allow  
the definition of user-defined functions, reduce\_time and  
apply\_pixel also allow to pass arbitrary R functions as an argument.  
In the example below, we derive the 0.25, and 0.75 quantiles over NDVI  
time series. There is of course no limitation what the provided reducer  
function does and it is thus possible to use functions from other  
packages.

v.16d = cube\_view(view=v.overview, dt="P16D")

raster\_cube(L8.col, v.16d) %>%

select\_bands(c("B04", "B05")) %>%

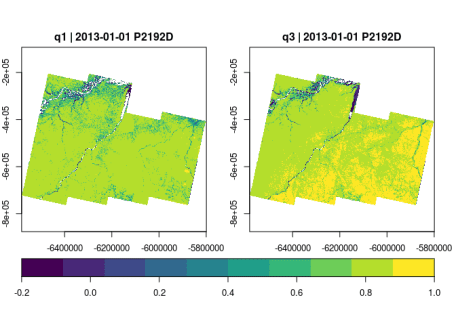
apply\_pixel(c("(B05-B04)/(B05+B04)"), names="NDVI") %>%

reduce\_time(names = c("q1","q3"), FUN = function(x) {

quantile(x["NDVI",], probs = c(0.25, 0.75), na.rm = TRUE)

}) %>%

plot(col=viridis, zlim=c(-0.2,1), key.pos=1)



However, there are some things, users need to keep in mind when working  
with user-defined functions:

1. Users should provide names of the output bands and make sure that  
   the function always return the same number of elements.
2. When executed, the function runs in a new R session, meaning that it  
   cannot access variables in the current worskspace and packages must  
   be loaded within the function if needed.
3. Ideally, users should carefully check for errors. A frequent cause  
   for errors is the presence of NA values, which are abundant in  
   raster data cubes from irregular image collections.
4. In the current version, only apply\_pixel and reduce\_time allow  
   for passing user-defined functions.

**Interfacing with stars**

The stars package is much more generic and supports higher dimensional  
arrays and hence supports e.g. data from climate model output. It also  
does not assume data to be orthorectified, i.e. it works also with  
curvilinear grids and hence supports data as from Sentinel-5P. In  
contrast, gdalcubes concentrates on multispectral image time series (4d)  
only.

gdalcubes currently comes with a simple as\_stars() function, writing a  
data cube as a (temporary) netCDF file, which is then opened by  
read\_stars. The stars object holds bands as attributes. If needed  
(e.g. for ggplot below), st\_redimension converts attributes to a new  
dimension.

suppressPackageStartupMessages(library(ggplot2))

suppressPackageStartupMessages(library(dplyr))

suppressPackageStartupMessages(library(stars))

x = raster\_cube(L8.col, v.overview) %>%

select\_bands(c("B02","B03","B04")) %>%

as\_stars()

x

## stars object with 3 dimensions and 3 attributes

## attribute(s), summary of first 1e+05 cells:

## B02 B03 B04

## Min. : 123.8 Min. : 174.1 Min. : 112.1

## 1st Qu.: 209.9 1st Qu.: 397.3 1st Qu.: 247.2

## Median : 295.0 Median : 497.9 Median : 380.3

## Mean : 457.6 Mean : 653.0 Mean : 563.5

## 3rd Qu.: 476.7 3rd Qu.: 686.5 3rd Qu.: 662.6

## Max. :9419.0 Max. :9780.7 Max. :10066.2

## NA's :79497 NA's :79497 NA's :79497

## dimension(s):

## from to offset delta refsys point

## x 1 783 -6582280 1000 +proj=merc +a=6378137 +b=... FALSE

## y 1 559 -205014 -1000 +proj=merc +a=6378137 +b=... FALSE

## time 1 7 NA NA POSIXct FALSE

## values

## x NULL [x]

## y NULL [y]

## time 2013-01-01,...,2019-01-01

ggplot() +

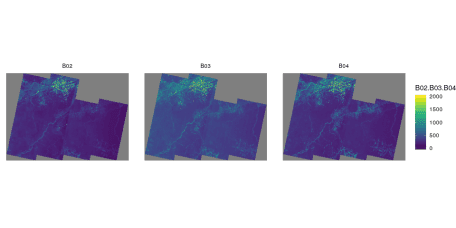
geom\_stars(data = slice(st\_redimension(x), "time", 5)) +

facet\_wrap(~new\_dim) +

theme\_void() +

coord\_fixed() +

scale\_fill\_viridis(limits=c(0, 2000))



**Future work**

There are many things, which we didn’t cover in this blog post like  
applying masks during the construction of data cubes. More importantly,  
a question we are very much interested in at the moment is how far we  
can go with gdalcubes and stars in cloud computing envrionments, where  
huge image collections such as the full Sentinel-2 archive are already  
stored. This will be the topic of another blog post.