

# Using ‘Copernicus Data Space Ecosystem’ API Wrapper

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## Introduction

The CDSE package for R was developed to allow access to the ‘[Copernicus Data Space Ecosystem](#)’ data and services from R. The ‘[Copernicus Data Space Ecosystem](#)’, deployed in 2023, offers access to the EO data collection from the Copernicus missions, with discovery and download capabilities and numerous data processing tools. In particular, the ‘[Sentinel Hub](#)’ API provides access to the multi-spectral and multi-temporal big data satellite imagery service, capable of fully automated, real-time processing and distribution of remote sensing data and related EO products. Users can use APIs to retrieve satellite data over their AOI and specific time range from full archives in a matter of seconds. When working on the application of EO where the area of interest is relatively small compared to the image tiles distributed by Copernicus (100 x 100 km), it allows to retrieve just the portion of the image of interest rather than downloading the huge tile image file and processing it locally. The goal of the CDSE package is to provide easy access to this functionality from R.

The main functions allow to search the catalog of available imagery from the Sentinel-1, Sentinel-2, Sentinel-3, and Sentinel-5 missions, and to process and download the images of an area of interest and a time range in various formats. Other functions might be added in subsequent releases of the package.

## API authentication

Most of the API functions require OAuth2 authentication. The recommended procedure is to obtain an authentication client object from the `GetOAuthClient()` function and pass it as the `client` argument to the functions requiring the authentication. For more detailed information, you are invited to consult the “Before you start” document.

```
id <- Sys.getenv("CDSE_ID")
secret <- Sys.getenv("CDSE_SECRET")
OAuthClient <- GetOAuthClient(id = id, secret = secret)
```

### Note

*In this document, the data.frames are output as tibbles since it renders better in PDF. However, all the functions produce standard data.frames.*

## Collections

We can get the list of all the imagery collections available in the ‘[Copernicus Data Space Ecosystem](#)’. By default, the list is formatted as a data.frame listing the main collection features. It is also possible to obtain the raw list with all information by setting the argument `as_data_frame` to `FALSE`.

```
collections <- GetCollections(as_data_frame = TRUE)
collections
#> # A tibble: 10 x 12
#>   id      title description since instrument  gsd bands constellation long.min
#>   <chr>   <chr> <chr>      <chr> <chr>      <int> <int> <chr>          <dbl>
#> 1 sentin~ Sent~ Sentinel 2~ 2015~ msi         10    13 sentinel-2    -180
#> 2 sentin~ Sent~ Sentinel 3~ 2016~ olci        300    NA <NA>          -180
#> 3 landsa~ Land~ Landsat 8~ 2013~ oli/tirs/~ 30    17 <NA>          -180
#> 4 sentin~ Sent~ Sentinel 3~ 2016~ olci        300    21 <NA>          -180
#> 5 sentin~ Sent~ Sentinel 3~ 2016~ slstr       1000    11 <NA>          -180
#> 6 sentin~ Sent~ Sentinel 3~ 2016~ slstr       1000    NA <NA>          -180
#> 7 sentin~ Sent~ Sentinel 3~ 2016~ olci/slstr 300    NA <NA>          -180
#> 8 sentin~ Sent~ Sentinel 1~ 2014~ c-sar        NA    NA sentinel-1    -180
#> 9 sentin~ Sent~ Sentinel 2~ 2016~ msi         10    12 sentinel-2    -180
```

```
#> 10 sentin~ Sent~ Sentinel 5~ 2018~ tropomi      5500      NA <NA>      -180  
#> # i 3 more variables: lat.min <dbl>, long.max <dbl>, lat.max <dbl>
```

## Catalog search

The imagery catalog can be searched by spatial and temporal extent for every collection present in the 'Copernicus Data Space Ecosystem'. For the spatial filter, you can provide either a `sf` or `sfc` object from the `sf` package, typically a (multi)polygon, describing the Area of Interest, or a numeric vector of four elements describing the bounding box of interest. For the temporal filter, you must specify the time range by either `Date` or `character` values that can be converted to date by `as.Date` function. Open intervals (one side only) can be obtained by providing the NA or NULL value for the corresponding argument.

```
dsn <- system.file("extdata", "luxembourg.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
images <- SearchCatalog(aoi = aoi, from = "2023-07-01", to = "2023-07-31",
  collection = "sentinel-2-l2a", with_geometry = TRUE, client = OAuthClient)
images
#> # A tibble: 70 x 12
#>   acquisitionDate tileCloudCover areaCoverage satellite acquisitionTimestamp~1
#>   <date>          <dbl>          <dbl> <chr>          <dtm>
#> 1 2023-07-31      98.9          1.84 sentinel-- 2023-07-31 10:47:29
#> 2 2023-07-31      99.8          20.3 sentinel-- 2023-07-31 10:47:25
#> 3 2023-07-31      99.7           5.93 sentinel-- 2023-07-31 10:47:22
#> 4 2023-07-31      99.9          16.3 sentinel-- 2023-07-31 10:47:14
#> 5 2023-07-31      99.9          92.5 sentinel-- 2023-07-31 10:47:11
#> 6 2023-07-31      99.4          22.2 sentinel-- 2023-07-31 10:47:09
#> 7 2023-07-28     100.0           4.99 sentinel-- 2023-07-28 10:37:28
#> 8 2023-07-28     100.0           5.66 sentinel-- 2023-07-28 10:37:27
#> 9 2023-07-28     100.0           4.29 sentinel-- 2023-07-28 10:37:21
#> 10 2023-07-28      99.9           4.94 sentinel-- 2023-07-28 10:37:20
#> # i 60 more rows
#> # i abbreviated name: 1: acquisitionTimestampUTC
#> # i 7 more variables: acquisitionTimestampLocal <dtm>, sourceId <chr>,
#> #   long.min <dbl>, lat.min <dbl>, long.max <dbl>, lat.max <dbl>,
#> #   geometry <POLYGON [°]>
```

We can visualize the coverage of the area of interest by the satellite image tiles by plotting the footprints of the available images and showing the region of interest in red.

```
library(maps)
days <- range(as.Date(images$acquisitionDate))
maps::map(database = "world", col = "lightgrey", fill = TRUE, mar = c(0, 0, 4, 0),
  xlim = c(3, 9), ylim = c(47.5, 51.5))
plot(sf::st_geometry(aoi), add = TRUE, col = "red", border = FALSE)
plot(sf::st_geometry(images), add = TRUE)
title(main = sprintf("AOI coverage by image tiles for period %s",
  paste(days, collapse = " / ")), line = 1L, cex.main = 0.75)
```

Some tiles cover only a small fraction of the area of interest, while others cover almost the entire area.

```
summary(images$areaCoverage)
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>  1.845  5.603  15.115  19.758  20.346  92.463
```

The tile number can be obtained from the image attribute `sourceId`, as explained [here](#). We can therefore summarize the distribution of area coverage by tile number, and see which tiles provide the best coverage of the AOI.

```
tileNumber <- substring(images$sourceId, 39, 44)
by(images$areaCoverage, INDICES = tileNumber, FUN = summary)
```

# AOI coverage by image tiles for period 2023-07-01 / 2023-07-31

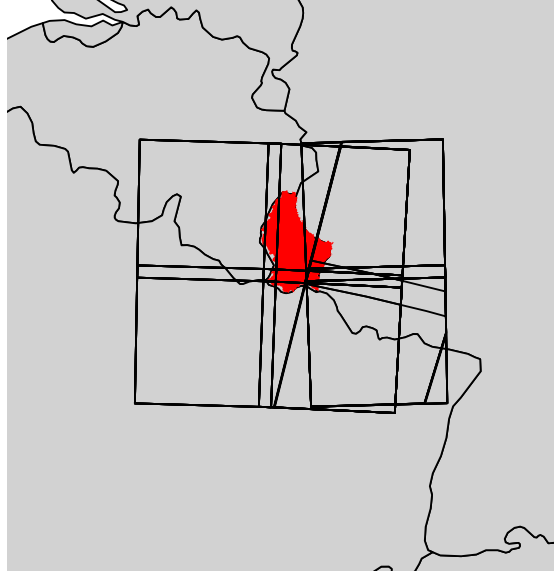


Figure 1: Luxembourg image tiles coverage

```
#> tileNumber: T31UFQ
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>  1.845  1.845   1.845   1.845  1.845   1.845
#> -----
#> tileNumber: T31UFR
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#> 16.32 16.32 16.32 16.32 16.32 16.32
#> -----
#> tileNumber: T31UGQ
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>  4.294  4.910 12.706 12.587 20.346 20.346
#> -----
#> tileNumber: T31UGR
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>  6.855 15.607 54.299 53.426 92.463 92.463
#> -----
#> tileNumber: T32ULA
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>  6.171 14.950 18.814 17.972 22.236 22.236
#> -----
#> tileNumber: T32ULV
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>  4.944  5.603  5.819  5.723  5.934  5.934
```

## Catalog by season

Sometimes one can be interested in only a given period of each year, for example, the images taken during the summer months (June to August). We can filter an existing image catalog *a posteriori* using the `SeasonalFilter()` function.

```
dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
images <- SearchCatalog(aoi = aoi, from = "2021-01-01", to = "2023-12-31",
  collection = "sentinel-2-l2a", with_geometry = FALSE, filter = "eo:cloud_cover < 5",
  client = OAuthClient)
images <- UniqueCatalog(images, by = "tileCloudCover")
dim(images)
#> [1] 81 10
summer_images <- SeasonalFilter(images, from = "2021-06-01", to = "2023-08-31")
dim(summer_images)
#> [1] 14 10
```

It is also possible to query the API directly on the desired seasonal periods by using a vectorized version of the `SearchCatalog()` function. The vectorized versions allow running a series of queries having the same parameter values except for either time range, AOI, or the bounding box parameters, using `lapply` or similar function, and thus potentially also using the parallel processing.

```
dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
seasons <- SeasonalTimerange(from = "2021-06-01", to = "2023-08-31")
lst_summer_images <- lapply(seasons, SearchCatalogByTimerange, aoi = aoi,
  collection = "sentinel-2-l2a", filter = "eo:cloud_cover < 5", with_geometry = FALSE,
  client = OAuthClient)
summer_images <- do.call(rbind, lst_summer_images)
summer_images <- UniqueCatalog(summer_images, by = "tileCloudCover")
dim(summer_images)
#> [1] 14 10
summer_images <- summer_images[rev(order(summer_images$acquisitionDate)), ]
row.names(summer_images) <- NULL
summer_images
#> # A tibble: 14 x 10
#>   acquisitionDate tileCloudCover satellite acquisitionTimestampUTC
#>   <date>          <dbl> <chr>          <dtm>
#> 1 2023-08-20          0 sentinel-2a 2023-08-20 15:51:57
#> 2 2023-07-31        2.53 sentinel-2a 2023-07-31 15:51:56
#> 3 2023-07-26        0.59 sentinel-2b 2023-07-26 15:51:56
#> 4 2023-07-11        4.38 sentinel-2a 2023-07-11 15:51:56
#> 5 2023-06-01          0 sentinel-2a 2023-06-01 15:51:54
#> 6 2022-08-25        1.18 sentinel-2a 2022-08-25 15:52:03
#> 7 2022-08-03        4.58 sentinel-2b 2022-08-03 16:01:51
#> 8 2022-07-19        1.37 sentinel-2a 2022-07-19 16:01:58
#> 9 2022-07-11        4.92 sentinel-2b 2022-07-11 15:51:57
#> 10 2022-06-19        1.91 sentinel-2a 2022-06-19 16:01:58
#> 11 2022-06-06        0.99 sentinel-2a 2022-06-06 15:51:58
#> 12 2022-06-04        2.76 sentinel-2b 2022-06-04 16:01:47
#> 13 2021-06-16        4.74 sentinel-2b 2021-06-16 15:51:51
#> 14 2021-06-06        0.38 sentinel-2b 2021-06-06 15:51:52
#> # i 6 more variables: acquisitionTimestampLocal <dtm>, sourceId <chr>,
#> #   long.min <dbl>, lat.min <dbl>, long.max <dbl>, lat.max <dbl>
```

## Evalscripts

As we shall see in the examples below, the functions that operate on remotely sensed spectral band values, such as `GetImage()` or `GetStatistics()`, require an evalscript to be passed to the `script` argument.

An evalscript (or “custom script”) is a piece of JavaScript code that defines how the satellite data shall be processed by the API and what values the service shall return. It is a required part of any request involving data processing, such as retrieving an image of the area of interest or computing some statistical values for a given period of time.

The evaluation scripts can use any JavaScript function or language structures, along with certain utility functions provided by the API for user convenience. The Chrome V8 JavaScript engine is used for running the evalscripts.

The evaluation scripts are passed as the `script` argument to the `GetImage()`, `GetStatistics()`, and other functions that require an evalscript. It has to be either a character string containing the evaluation script or the name of the file containing the script.

Although it is beyond the scope of this document to provide the detailed guidance for writing evalscripts, we shall provide here some tips that can help you to use the the above mentioned functions without deep understanding of the evalscripts’ internal workings. We encourage users who wish to acquire a deeper knowledge of evalscripts to consult the API [Beginners Guide](#) and [Evalscript \(custom script\)](#) documentation. You can also find a large collection of custom scripts that you can readily use in this [repository](#).

## Built-in scripts

The `scripts` folder of this package contains a few examples of evaluation scripts. They are very limited, both in number and scope, and their main purpose is to provide scripts that are used in documentation and examples. You can, of course, use them as a starting point to develop your own scripts by applying some relatively simple modifications (for example, starting from an NDVI script, replacing bands B04 and B08 with bands B8A and B11 will give a script for the NDMI - Normalized Difference Moisture Index).

## Ready-to-use examples

There is a large collection of evalscripts that you can readily use available in this [repository](#). The scripts are grouped by satellite constellation (Sentinel-1, Sentinel-2, ...) and application field (Agriculture, Disaster management, Urban planning, ...). To use one of these scripts, the simplest way is probably to use the “*Download code*” or “*Copy code*” icons in the upper right corner of the code window (see the illustration in Figure 2 below). Some indices come in several flavours (Visualisation vs. Raw Values); select the one that corresponds to your situation. If you want to do some further analysis of the images, use raw values; if you want to simply display the image, you can use the visualisation version (you will probably also export the result as a JPEG or PNG file). You can, of course, always get the raw values and then customise the visualisation in your R code. Other indices might have only one version; it will likely first compute the index value and then possibly transform it for visualisation - adapt based on your needs.

*Note:*

*The repository also contains scripts for satellite collections that are not available through CDSE.*

## Awesome Spectral Indices

‘Awesome Spectral Indices’ ([ASI](#)) is a standardized, machine-readable catalogue of spectral indices used in remote sensing for Earth Observation. It currently includes over 240 spectral indices grouped into eight application domains: vegetation, water, burn, snow, soil, urban, radar, and kernel indices. Each spectral index in ASI comes with a set of attributes such as a short and long name, application domain, formula, required bands, platforms, references, date of addition, and contributor information.

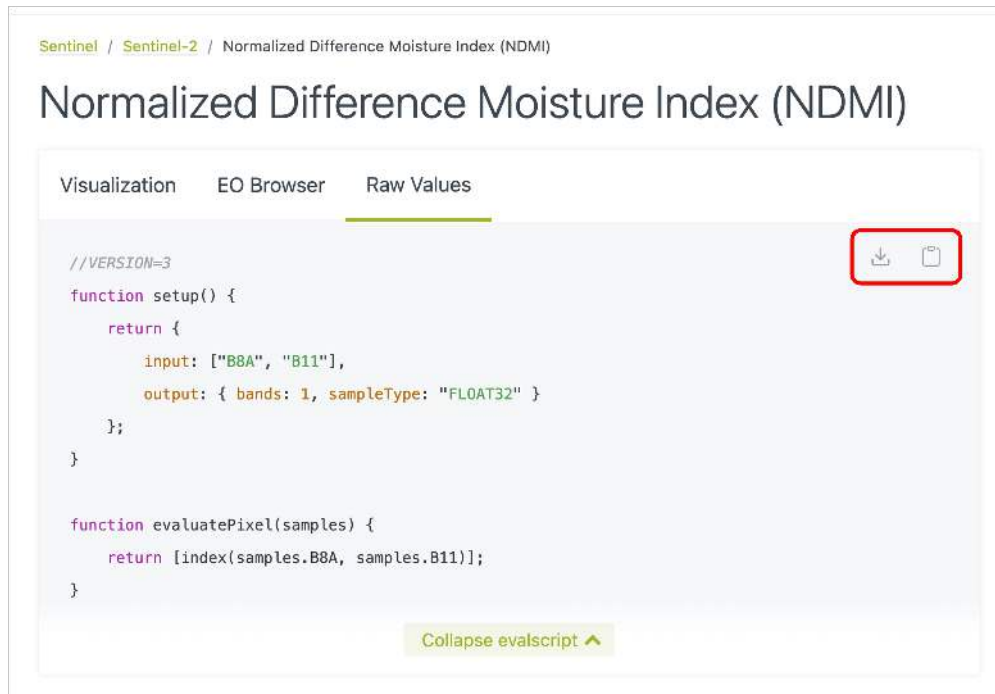


Figure 2: Using evalscript code from the repository

The R package `rsi` implements an interface to the ASI collection, providing the list of indices directly in R as a friendly `data.frame` (actually a `tibble`). These indices can now be directly used in the ‘CDSE’ package to provide the evalscript to the functions that require one. For this purpose, we have developed the `MakeEvalScript()` function that will generate the script for you based on the information contained in the `data.frame` of spectral indices produced by `rsi::spectral_indices()`.

Here is an example showing how it works.

```
si <- rsi::spectral_indices() # get spectral indices
# NDVI
ndvi <- subset(si, short_name == "NDVI") # creates one-row data.frame
ndvi_script <- MakeEvalScript(ndvi, constellation = "landsat") # generates the script
# GDVI
gdvi <- subset(si, short_name == "GDVI") # creates one-row data.frame
# GDVI requires an extra argument provided by the user
gdvi_script <- MakeEvalScript(gdvi, nex = 2, constellation = "sentinel-2")
```

The value returned by the function is a character vector with each element representing one line of the script. You can best visualise the script code by `cat(gdvi_script, sep = "\n")`, or save it to a file for later use with `cat(gdvi_script, file = "GDVI.js", sep = "\n")`. To use the generated script directly in a function, you would use something like `GetImage(..., script = paste(gdvi_script, collapse = "\n"), ...)`.

If the package `rsi` is installed, you can use a shortcut and just provide the `short_name` of the index as the first argument (instead of the one-row `data.frame`). Please note that the `short_name` is case-sensitive, although most of the names are in full upper-case. You of course still have to provide any additional arguments, if required, in the usual way. Here is an example:

```
gdvi_script <- MakeEvalScript("GDVI", nex = 2, constellation = "sentinel-2")
```

Finally, you can also define ad-hoc custom indices by providing a one-row `data.frame` crafted after the model



produced by `rsi::spectral_indices()`. Please ensure that you respect the correct formatting, particularly when writing the formula. Since the function does not use all the attributes of spectral indices but just `bands`, `formula`, `platform` and optionally `long_name` (used as a comment in the header of the script), you can provide only this information, and it does not even have to be a `data.frame`, a simple `list` will do.

We shall illustrate this with an example. Since the ASI spectral indices collection is very rich, rather than recreating an already existing index or creating a completely dummy ad-hoc index, we shall use a transformation of an RGB image into a greyscale image, based on [this](#) code, which strictly speaking might not be a spectral index, but can illustrate the process.

```
custom_def <- list(bands = c("R", "G", "B"),
                  formula = "0.3 * R + 0.59 * G + 0.11 * B",
                  # long_name = "Greyscale image",
                  platforms = "Sentinel-2")
custom_script <- paste(MakeEvalScript(custom_def, constellation = "sentinel-2"),
                      collapse = "\n")
```

We can now compare the greyscale and RGB images.

```
# select the day with smallest cloud cover
dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
images <- SearchCatalog(aoi = aoi, from = "2023-06-01", to = "2023-08-31",
                       collection = "sentinel-2-l2a", with_geometry = TRUE,
                       client = OAuthClient)

day <- images[order(images$tileCloudCover), ]["acquisitionDate"][[1]]
# get the greyscale image
grey_file <- file.path(tempdir(), "grey.tif")
GetImage(bbox = sf::st_bbox(aoi), time_range = day, script = custom_script,
         file = grey_file,
         collection = "sentinel-2-l2a", format = "image/tiff",
         mosaicking_order = "leastCC", resolution = 20,
         mask = FALSE, buffer = 100, client = OAuthClient)

# get the RGB image
script_file <- system.file("scripts", "TrueColorS2L2A.js", package = "CDSE")
rgb_file <- file.path(tempdir(), "rgb.tif")
GetImage(bbox = sf::st_bbox(aoi), time_range = day, script = script_file,
         file = rgb_file,
         collection = "sentinel-2-l2a", format = "image/tiff",
         mosaicking_order = "leastCC", resolution = 20,
         mask = FALSE, buffer = 100, client = OAuthClient)

# Import the rasters
rgb_img <- terra::rast(rgb_file)
grey_img <- terra::rast(grey_file)
# Rescale greyscale raster values to 0 - 1 range
mM <- terra::minmax(grey_img)
grey_img <- (grey_img - mM[1])/(mM[2] - mM[1])
# Set up plotting window for side-by-side display
old.par <- par(mfrow = c(1, 2))
# Plot RGB image
plotRGB(rgb_img) # expects layers 1,2,3 as R,G,B
# Plot greyscale image
plot(grey_img, col = grey.colors(256, start = 0, end = 1), legend = FALSE,
     axes = FALSE, mar = 0)
```



Figure 3: RGB and greyscale images of Central Park

*Caveats:*

*Kernel Spectral Indices cannot be used in this context as they do not fit into the API model (they do not operate directly on raw spectral bands).*

*The indices that are not available for the Sentinel-1, Sentinel-2 or Landsat-8/9 platforms cannot be used, as only these collections are available through the CDSE API.*

## Retrieving images

### Retrieving AOI satellite image as a raster object

One of the most important features of the API is its ability to extract only the part of the images covering the area of interest. If the AOI is small as in the example below, this is a significant gain in efficiency (download, local processing) compared to getting the whole tile image and processing it locally.

```
dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
images <- SearchCatalog(aoi = aoi, from = "2021-05-01", to = "2021-05-31",
  collection = "sentinel-2-l2a", with_geometry = TRUE, client = OAuthClient)
images
#> # A tibble: 12 x 12
#>   acquisitionDate tileCloudCover areaCoverage satellite acquisitionTimestamp-1
#>   <date>          <dbl>          <dbl> <chr>          <dtm>
#> 1 2021-05-30      100          100 sentinel-- 2021-05-30 16:01:47
#> 2 2021-05-27      16.3          100 sentinel-- 2021-05-27 15:51:51
#> 3 2021-05-25      26.5          100 sentinel-- 2021-05-25 16:01:47
#> 4 2021-05-22      100          100 sentinel-- 2021-05-22 15:51:51
#> 5 2021-05-20      24.3          100 sentinel-- 2021-05-20 16:01:47
#> 6 2021-05-17       7.17          100 sentinel-- 2021-05-17 15:51:50
#> 7 2021-05-15      28.2          100 sentinel-- 2021-05-15 16:01:47
#> 8 2021-05-12       1.35          100 sentinel-- 2021-05-12 15:51:50
#> 9 2021-05-10      92.7          100 sentinel-- 2021-05-10 16:01:45
#> 10 2021-05-07      89.6          100 sentinel-- 2021-05-07 15:51:48
#> 11 2021-05-05     100.0          100 sentinel-- 2021-05-05 16:01:45
#> 12 2021-05-02       78          100 sentinel-- 2021-05-02 15:51:48
#> # i abbreviated name: 1: acquisitionTimestampUTC
#> # i 7 more variables: acquisitionTimestampLocal <dtm>, sourceId <chr>,
#> #   long.min <dbl>, lat.min <dbl>, long.max <dbl>, lat.max <dbl>,
#> #   geometry <POLYGON [°]>
summary(images$areaCoverage)
#>   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#>   100    100     100     100    100    100
```

As the area is small, it is systematically fully covered by all available images. We shall select the date with the least cloud cover, and retrieve the NDVI values as a **SpatRaster** from package **terra**. This allows further processing of the data, as shown below by replacing all negative values with zero. The size of the pixels is specified directly by the **resolution** argument. We are also adding a 100-meter **buffer** around the area of interest and masking the pixels outside of the AOI.

```
day <- images[order(images$tileCloudCover), ]$acquisitionDate[1]
script_file <- system.file("scripts", "NDVI_float32.js", package = "CDSE")
ras <- GetImage(aoi = aoi, time_range = day, script = script_file,
  collection = "sentinel-2-l2a", format = "image/tiff", mosaicking_order = "leastCC",
  resolution = 10, mask = TRUE, buffer = 100, client = OAuthClient)
ras
#> class       : SpatRaster
#> size        : 383, 355, 1  (nrow, ncol, nlyr)
#> resolution   : 0.0001003292, 0.0001003292  (x, y)
#> extent       : -73.98355, -73.94794, 40.76322, 40.80165  (xmin, xmax, ymin, ymax)
#> coord. ref.  : lon/lat WGS 84 (EPSG:4326)
#> source(s)    : memory
#> name         : file32843161e152
#> min value    : -0.5069648
```

```
#> max value      :      0.9507549
ras[ras < 0] <- 0
terra::plot(ras, main = paste("Central Park NDVI on", day), cex.main = 0.75,
  col = colorRampPalette(c("darkred", "yellow", "darkgreen"))(99))
```

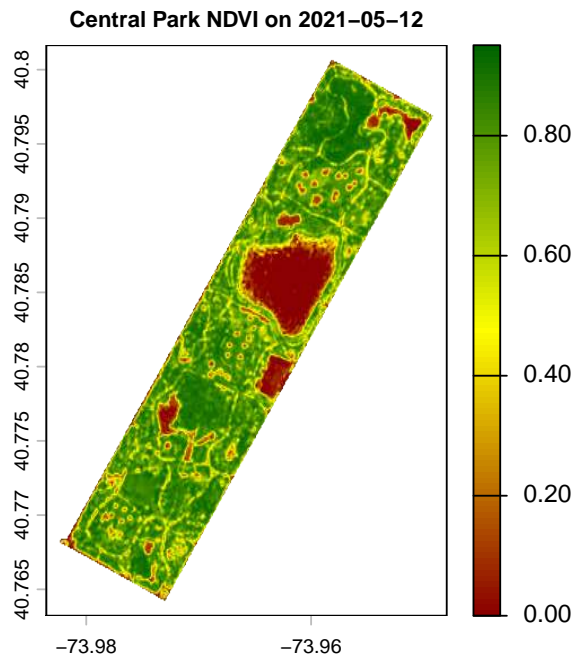


Figure 4: Central Park NDVI raster

## Retrieving AOI satellite image as an image file

If we don't want to process the satellite image locally but simply use it as an image file (to include in a report or a Web page, for example), we can use the appropriate script that will render a three-band raster for RGB layers (or one for black-and-white image). Here we specify the area of interest by its bounding box instead of the exact geometry. We also demonstrate that the evaluation script can be passed as a single character string, and provide the number of pixels in the output image rather than the size of individual pixels - it makes more sense if the image is intended for display and not processing.

```
bbox <- as.numeric(sf::st_bbox(aoi))
script_text <- paste(readLines(system.file("scripts", "TrueColorS2L2A.js",
  package = "CDSE")), collapse = "\n")
cat(c(readLines(system.file("scripts", "TrueColorS2L2A.js", package = "CDSE"), n = 15),
  "..."), sep = "\n")
#> //VERSION=3
#> //Optimized Sentinel-2 L2A True Color
#>
#> function setup() {
#>   return {
#>     input: ["B04", "B03", "B02", "dataMask"],
#>     output: { bands: 4 }
#>   };
#> }
```

```

#>
#> function evaluatePixel(smp) {
#>   const rgbLin = satEnh(sAdj(smp.B04), sAdj(smp.B03), sAdj(smp.B02));
#>   return [sRGB(rgbLin[0]), sRGB(rgbLin[1]), sRGB(rgbLin[2]), smp.dataMask];
#> }
#>
#> ...
png <- tempfile("img", fileext = ".png")
GetImage(bbox = bbox, time_range = day, script = script_text,
  collection = "sentinel-2-l2a", file = png, format = "image/png", buffer = 100,
  mosaicking_order = "leastCC", pixels = c(600, 950), client = OAuthClient)
terra::plotRGB(terra::flip(terra::rast(png), direction = "vertical"))

```



Figure 5: Central Park image as PNG file

## Retrieving a series of images in a batch

It often happens that one is interested in acquiring a series of images of a particular zone (AOI or bounding box) for several dates, or the images of different areas of interest for the same date (probably located close to each other so that they are visited on the same day). The `GetImageBy*`() functions (`GetImageByTimerange()`, `GetImageByAOI()`, `GetImageByBbox()`) facilitate this task as they are specifically crafted for being called from a `lapply`-like function, and thus potentially be executed in parallel. We shall illustrate how to do this with an example.

```

dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
images <- SearchCatalog(aoi = aoi, from = "2022-01-01", to = "2022-12-31",
  collection = "sentinel-2-l2a", with_geometry = TRUE,
  filter = "eo:cloud_cover < 5", client = OAuthClient)

```

```

# Get the day with the minimal cloud cover for every month -----
tmp1 <- images[, c("tileCloudCover", "acquisitionDate")]
tmp1$month <- lubridate::month(images$acquisitionDate)
agg1 <- stats::aggregate(tileCloudCover ~ month, data = tmp1, FUN = min)
tmp2 <- merge.data.frame(agg1, tmp1, by = c("month", "tileCloudCover"), sort = FALSE)
# in case of ties, get an arbitrary date (here the smallest acquisitionDate,
# could also be the biggest)
agg2 <- stats::aggregate(acquisitionDate ~ month, data = tmp2, FUN = min)
monthly <- merge.data.frame(agg2, tmp2, by = c("acquisitionDate", "month"), sort = FALSE)
days <- monthly$acquisitionDate
# Retrieve images in parallel -----
script_file <- system.file("scripts", "NDVI_float32.js", package = "CDSE")
tmp_folder <- tempfile("dir")
if (!dir.exists(tmp_folder)) dir.create(tmp_folder)
cl <- parallel::makeCluster(4)
ans <- parallel::clusterExport(cl, list("tmp_folder"), envir = environment())
ans <- parallel::clusterEvalQ(cl, {library(CDSE)})
lstRast <- parallel::parLapply(cl, days, fun = function(x, ...) {
  GetImageByTimerange(x, file = sprintf("%s/img_%s.tiff", tmp_folder, x), ...),
  aoI = aoI, collection = "sentinel-2-l2a", script = script_file,
  format = "image/tiff", mosaicking_order = "mostRecent", resolution = 10,
  buffer = 0, mask = TRUE, client = OAuthClient)
})
parallel::stopCluster(cl)
# Plot the images -----
par(mfrow = c(3, 4))
ans <- sapply(seq_along(days), FUN = function(i) {
  ras <- terra::rast(lstRast[[i]])
  day <- days[i]
  ras[ras < 0] <- 0
  terra::plot(ras, main = paste("Central Park NDVI on", day), range = c(0, 1),
    cex.main = 0.7, pax = list(cex.axis = 0.5), plg = list(cex = 0.5),
    col = colorRampPalette(c("darkred", "yellow", "darkgreen"))(99))
})

```

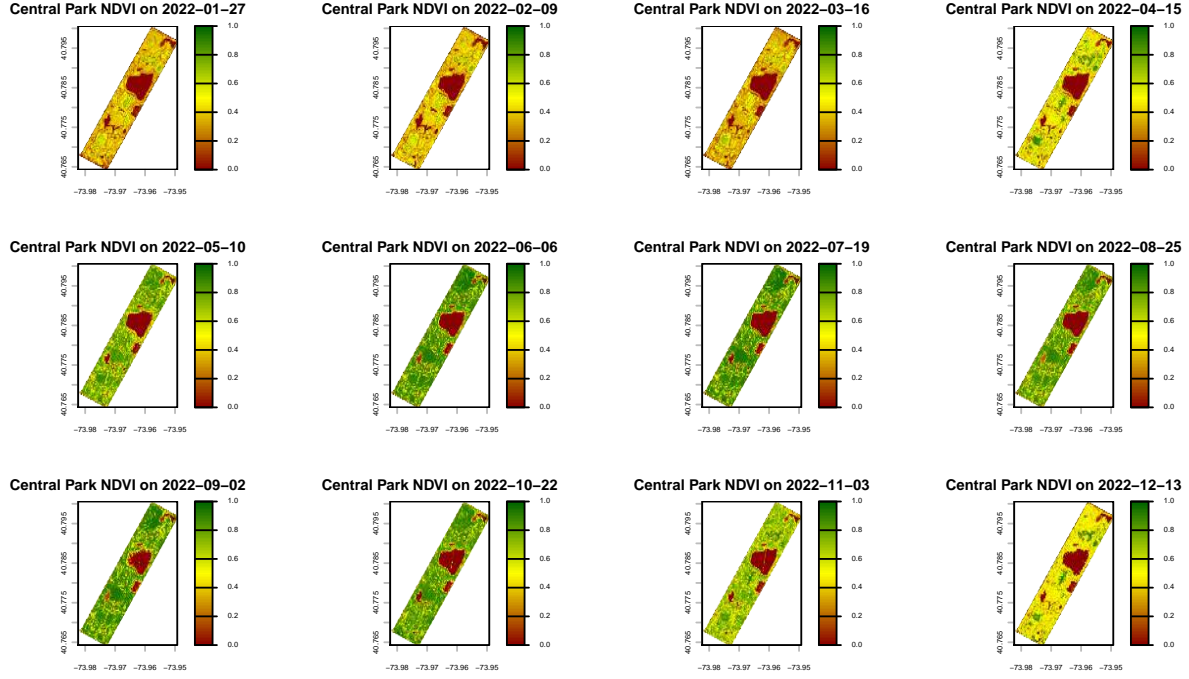


Figure 6: Central Park monthly NDVI

In this particular example, parallelisation is not necessarily beneficial as we are retrieving only 12 images, but for a large number of images, it can significantly reduce the execution time. Also note that we have limited the list of images to the tiles having cloud cover < 5% using the `filter` argument of the `SearchCatalog()` function.



## Retrieving statistics

If you are only interested in calculating the average value (or some other statistic) of some index or just the raw band values, the [Statistical API](#) enables you to get statistics calculated based on satellite imagery without having to download images. You need to specify your area of interest, time period, evalscript, and which statistical measures should be calculated. The requested statistics are returned as a `data.frame` or as a `list`.

## Statistical evalscripts

All general rules for building evalscripts apply. However, there are some specifics when using evalscripts with the Statistical API:

- The `evaluatePixel()` function must, in addition to other output, always return also `dataMask` output. This output defines which pixels are excluded from calculations. For more details and an example, see [here](#).
- The default value of `sampleType` is `FLOAT32`.
- The `output.bands` parameter in the `setup()` function can be an array. This makes it possible to specify custom names for the output bands and different output `dataMask` for different outputs.

It should be noted that the scripts generated by the `MakeEvalScript` function can be directly used to retrieve the statistical values.

## Retrieving simple statistics

Besides the time range, you have to specify the way you want the values to be aggregated over time. For this you use the `aggregation_period` and `aggregation_unit` arguments. The `aggregation_unit` must be one of `day`, `week`, `month` or `year`, and the `aggregation_period` providing the number of `aggregation_units` (days, weeks, ...) over which the statistics are calculated. The default values are “1” and “day”, producing the daily statistics. If the last interval in the given time range isn’t divisible by the provided aggregation interval, you can skip the last interval (default behavior), shorten the last interval so that it ends at the end of the provided time range, or extend the last interval over the end of the provided time range so that all intervals are of equal duration. This is controlled by the value of the `lastIntervalBehavior` argument.

```
dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
script_file <- system.file("scripts", "NDVI_CLOUDS_STAT.js", package = "CDSE")
daily_stats <- GetStatistics(aoi = aoi, time_range = c("2023-07-01", "2023-07-31"),
  collection = "sentinel-2-l2a", script = script_file, mosaicking_order = "leastCC",
  resolution = 100, aggregation_period = 1, client = OAuthClient)
weekly_stats <- GetStatistics(aoi = aoi, time_range = c("2023-07-01", "2023-07-31"),
  collection = "sentinel-2-l2a", script = script_file, mosaicking_order = "leastCC",
  resolution = 100, aggregation_period = 7, client = OAuthClient)
weekly_stats_extended <- GetStatistics(aoi = aoi,
  time_range = c("2023-07-01", "2023-07-31"), collection = "sentinel-2-l2a",
  script = script_file, mosaicking_order = "leastCC", resolution = 100,
  aggregation_period = 1, aggregation_unit = "w", lastIntervalBehavior = "EXTEND",
  client = OAuthClient)
daily_stats
#> # A tibble: 26 x 9
#>   date      output      band      min      mean      max      stDev sampleCount
#>   <date>    <chr>      <chr>    <dbl>    <dbl>    <dbl>    <dbl>      <int>
#> 1 2023-07-01 statistics ndvi_value 0      2.97e-1 7.81e-1 2.02e-1      1120
#> 2 2023-07-01 statistics cloud_cover 0      1.10e+2 2.55e+2 5.78e+1      1120
```



```

#> 3 2023-07-04 statistics ndvi_value 0 1.31e-3 8.09e-2 7.35e-3 1120
#> 4 2023-07-04 statistics cloud_cover 9.8 e+1 1.28e+2 1.45e+2 2.74e+0 1120
#> 5 2023-07-06 statistics ndvi_value 0 5.93e-1 9.41e-1 3.15e-1 1120
#> 6 2023-07-06 statistics cloud_cover 3.8 e+1 1.38e+2 2.55e+2 3.45e+1 1120
#> 7 2023-07-09 statistics ndvi_value 9.02e-3 1.44e-2 1.82e-2 1.60e-3 1120
#> 8 2023-07-09 statistics cloud_cover 1.28e+2 2.05e+2 2.55e+2 4.52e+1 1120
#> 9 2023-07-11 statistics ndvi_value 0 5.86e-1 9.23e-1 3.08e-1 1120
#> 10 2023-07-11 statistics cloud_cover 1.08e+2 1.27e+2 1.37e+2 3.69e+0 1120
#> # i 16 more rows
#> # i 1 more variable: noDataCount <int>
weekly_stats
#> # A tibble: 8 x 10
#>   from to output band min mean max stDev sampleCount
#>   <date> <date> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <int>
#> 1 2023-07-01 2023-07-07 statisti~ ndvi~ 0 0.593 0.941 0.315 1120
#> 2 2023-07-01 2023-07-07 statisti~ clou~ 38 138. 255 34.5 1120
#> 3 2023-07-08 2023-07-14 statisti~ ndvi~ 0 0.586 0.923 0.308 1120
#> 4 2023-07-08 2023-07-14 statisti~ clou~ 108 127. 137 3.69 1120
#> 5 2023-07-15 2023-07-21 statisti~ ndvi~ 0 0.341 0.876 0.238 1120
#> 6 2023-07-15 2023-07-21 statisti~ clou~ 0 123. 255 65.5 1120
#> 7 2023-07-22 2023-07-28 statisti~ ndvi~ 0 0.551 0.864 0.283 1120
#> 8 2023-07-22 2023-07-28 statisti~ clou~ 0 159. 255 67.8 1120
#> # i 1 more variable: noDataCount <int>
weekly_stats_extended
#> # A tibble: 10 x 10
#>   from to output band min mean max stDev sampleCount
#>   <date> <date> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <int>
#> 1 2023-07-01 2023-07-07 statisti~ ndvi~ 0 0.593 0.941 0.315 1120
#> 2 2023-07-01 2023-07-07 statisti~ clou~ 38 138. 255 34.5 1120
#> 3 2023-07-08 2023-07-14 statisti~ ndvi~ 0 0.586 0.923 0.308 1120
#> 4 2023-07-08 2023-07-14 statisti~ clou~ 108 127. 137 3.69 1120
#> 5 2023-07-15 2023-07-21 statisti~ ndvi~ 0 0.341 0.876 0.238 1120
#> 6 2023-07-15 2023-07-21 statisti~ clou~ 0 123. 255 65.5 1120
#> 7 2023-07-22 2023-07-28 statisti~ ndvi~ 0 0.551 0.864 0.283 1120
#> 8 2023-07-22 2023-07-28 statisti~ clou~ 0 159. 255 67.8 1120
#> 9 2023-07-29 2023-08-04 statisti~ ndvi~ 0 0.574 0.909 0.301 1120
#> 10 2023-07-29 2023-08-04 statisti~ clou~ 119 128. 132 1.02 1120
#> # i 1 more variable: noDataCount <int>

```

In this example we have demonstrated that a week can be specified as either 7 days or 1 week.

## Retrieving statistics with percentiles

Besides the basic statistics (min, max, mean, stDev), one can also request to compute the percentiles. If the percentiles requested are 25, 50, and 75, the corresponding output is renamed 'q1', 'median', and 'q3'.

```

daily_stats <- GetStatistics(aoi = aoi, time_range = c("2023-07-01", "2023-07-31"),
  collection = "sentinel-2-l2a", script = script_file, mosaicking_order = "leastCC",
  resolution = 100, aggregation_period = 1, percentiles = c(25, 50, 75),
  client = OAuthClient)
head(daily_stats, n = 10)
#> # A tibble: 10 x 12
#>   date output band min q1 median mean q3 max
#>   <date> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>

```

```
#> 1 2023-07-01 statistics ndvi_v~ 0 1.35e-1 2.72e-1 2.97e-1 4.67e-1 7.81e-1
#> 2 2023-07-01 statistics cloud_~ 0 1.2 e+2 1.28e+2 1.10e+2 1.28e+2 2.55e+2
#> 3 2023-07-04 statistics ndvi_v~ 0 0 0 1.31e-3 0 8.09e-2
#> 4 2023-07-04 statistics cloud_~ 9.8 e+1 1.28e+2 1.28e+2 1.28e+2 1.28e+2 1.45e+2
#> 5 2023-07-06 statistics ndvi_v~ 0 4.07e-1 7.28e-1 5.93e-1 8.35e-1 9.41e-1
#> 6 2023-07-06 statistics cloud_~ 3.8 e+1 1.28e+2 1.28e+2 1.38e+2 1.36e+2 2.55e+2
#> 7 2023-07-09 statistics ndvi_v~ 9.02e-3 1.34e-2 1.45e-2 1.44e-2 1.54e-2 1.82e-2
#> 8 2023-07-09 statistics cloud_~ 1.28e+2 1.69e+2 2.16e+2 2.05e+2 2.48e+2 2.55e+2
#> 9 2023-07-11 statistics ndvi_v~ 0 3.98e-1 7.24e-1 5.86e-1 8.22e-1 9.23e-1
#> 10 2023-07-11 statistics cloud_~ 1.08e+2 1.27e+2 1.28e+2 1.27e+2 1.28e+2 1.37e+2
#> # i 3 more variables: stDev <dbl>, sampleCount <int>, noDataCount <int>
weekly_stats <- GetStatistics(aoi = aoi, time_range = c("2023-07-01", "2023-07-31"),
  collection = "sentinel-2-l2a", script = script_file, mosaicking_order = "leastCC",
  resolution = 100, aggregation_period = 7, percentiles = seq(10, 90, by = 10),
  client = OAuthClient)
head(weekly_stats, n = 10)
#> # A tibble: 8 x 19
#>   from to output band min P.10.0 P.20.0 P.30.0 P.40.0
#>   <date> <date> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <dbl>
#> 1 2023-07-01 2023-07-07 statistics ndvi_v~ 0 0 0.241 0.535 0.649
#> 2 2023-07-01 2023-07-07 statistics cloud_~ 38 1.22e+2 128 128 128
#> 3 2023-07-08 2023-07-14 statistics ndvi_v~ 0 0 0.246 0.530 0.651
#> 4 2023-07-08 2023-07-14 statistics cloud_~ 108 1.24e+2 126 128 128
#> 5 2023-07-15 2023-07-21 statistics ndvi_v~ 0 3.20e-2 0.111 0.184 0.242
#> 6 2023-07-15 2023-07-21 statistics cloud_~ 0 0 96 128 128
#> 7 2023-07-22 2023-07-28 statistics ndvi_v~ 0 0 0.237 0.520 0.612
#> 8 2023-07-22 2023-07-28 statistics cloud_~ 0 6.3 e+1 122 141 150
#> # i 10 more variables: P.50.0 <dbl>, mean <dbl>, P.60.0 <dbl>, P.70.0 <dbl>,
#> # P.80.0 <dbl>, P.90.0 <dbl>, max <dbl>, stDev <dbl>, sampleCount <int>,
#> # noDataCount <int>
```

## Retrieving a series of statistics in a batch

Just as when retrieving satellite images, one can be interested in acquiring a series of statistics for a particular zone (AOI or bounding box) for several dates, or the statistics of different zones for the same periods. The `GetStatisticsBy*`() functions (`GetStatisticsByTimerange()`, `GetStatisticsByAOI()`, `GetStatisticsByBbox()`) facilitate this task as they are specifically crafted for being called from a lapply-like function, and thus potentially be executed in parallel. The following example illustrates how to do this.

```
dsn <- system.file("extdata", "centralpark.geojson", package = "CDSE")
aoi <- sf::read_sf(dsn, as_tibble = FALSE)
ndvi_script <- paste(MakeEvalScript(
  list(
    bands = c("N", "R"),
    formula = "(N - R)/(N + R)",
    long_name = "Normalized Difference Vegetation Index",
    platforms = "Sentinel-2"
  ),
  constellation = "sentinel-2"), collapse = "\n")
seasons <- SeasonalTimerange(from = "2020-06-01", to = "2023-08-31")
lst_stats <- lapply(seasons, GetStatisticsByTimerange, aoi = aoi,
  collection = "sentinel-2-l2a", script = ndvi_script, mosaicking_order = "leastCC",
  resolution = 100, aggregation_period = 7L, client = OAuthClient)
```

```

weekly_stats <- do.call(rbind, lst_stats)
weekly_stats <- weekly_stats[order(weekly_stats$from), ]
row.names(weekly_stats) <- NULL
head(weekly_stats, n = 5)
#> # A tibble: 5 x 10
#>   from      to      output band   min  mean  max stDev sampleCount
#>   <date>    <date>    <chr>  <chr> <dbl> <dbl> <dbl> <dbl>      <int>
#> 1 2020-06-01 2020-06-07 default index   -1 0.408 0.868 0.521      1120
#> 2 2020-06-08 2020-06-14 default index   -1 0.539 0.943 0.389      1120
#> 3 2020-06-15 2020-06-21 default index   -1 0.556 1      0.502      1120
#> 4 2020-06-22 2020-06-28 default index   -1 0.396 0.850 0.412      1120
#> 5 2020-06-29 2020-07-05 default index   -1 0.569 0.930 0.379      1120
#> # i 1 more variable: noDataCount <int>

```

## Copernicus Data Space Ecosystem services status

If you encounter any connection issues while using this package, please check your internet connection first. If your internet connection is working fine, you can also check the status of the Copernicus Data Space Ecosystem services by visiting [this](#) webpage. It provides a quasi real-time status of the various services provided. Once you are on the webpage, scroll down to Sentinel Hub, and pay particular attention to the Process API (used for retrieving images), Catalog API (used for catalog searches), and Statistical API (used for retrieving statistics).

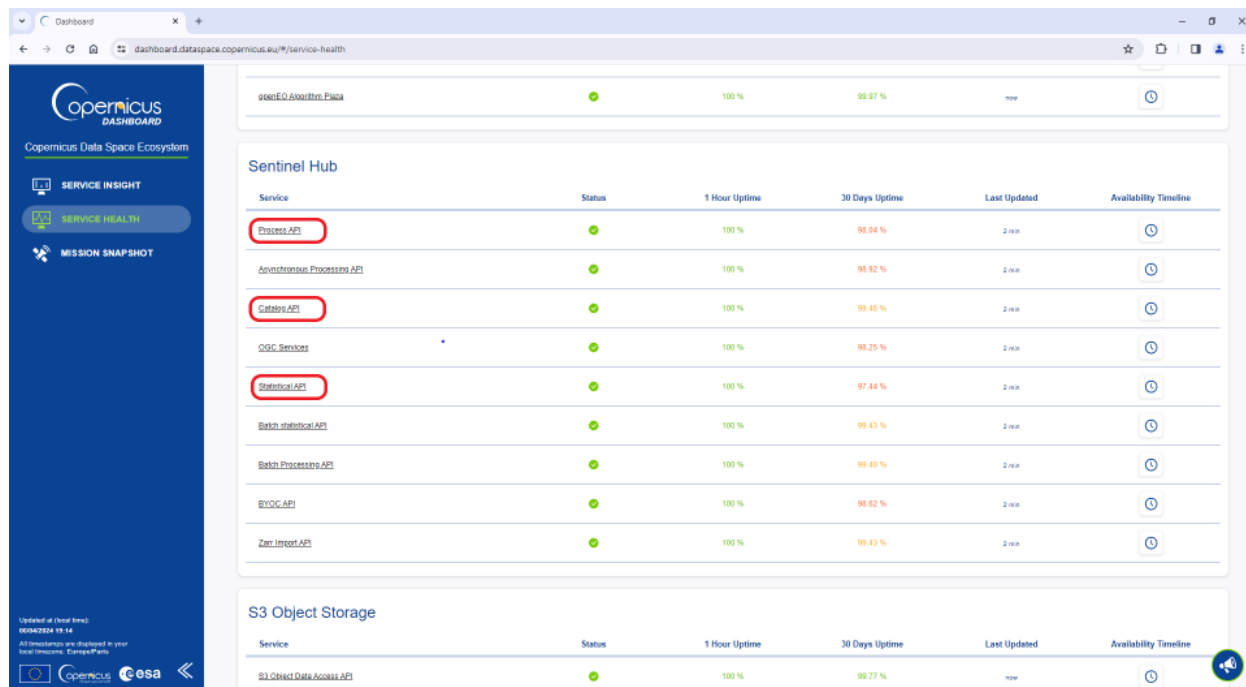


Figure 7: Copernicus Data Space Ecosystem Service Health