Using NDVI to assess vegetation damage after wildfires

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30-01-2025

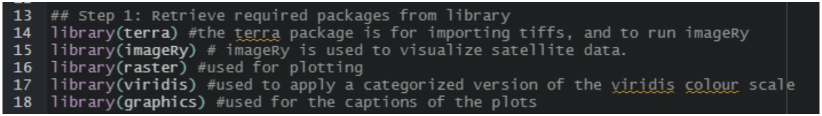
Introduction

Using sentinel 2 data to analyse the effects of two wildfires on vegetation health

- **Location:** Deurnse Peel, Brabant, the Netherlands
- **Habitat type:** swamps, shrubs, forests, and peatlands
- **Fire 1:** 20 april 2020 - 16 june 2020, 710 hectares damaged
- **Fire 2**: 31 august 2022, 41 hectares damaged

Data collection

The data is collected from the Copernicus Dataspace Browser. We use Sentinel-2 data. Throughout this project we use the following packages:

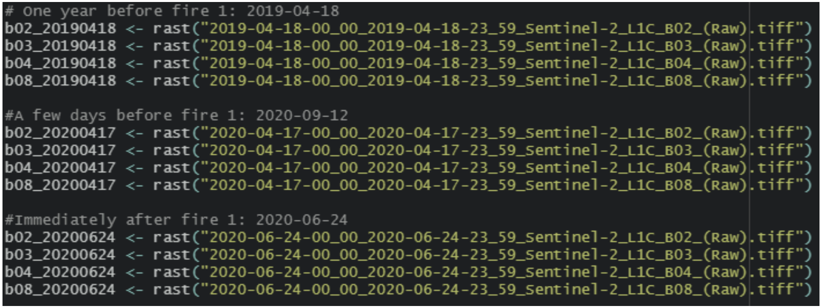


```
## Step 1: Retrieve required packages from library
library(terra) #the terra package is for importing tiffs, and to run imageRy
library(imageRy) # imageRy is used to visualize satellite data.
library(raster) #used for plotting
library(viridis) #used to apply a categorized version of the viridis colour scale
library(graphics) #used for the captions of the plots
```

Figure: Code for importing packages

Data collection

The rast() function, from the terra package, is used to import the tiff images we need.

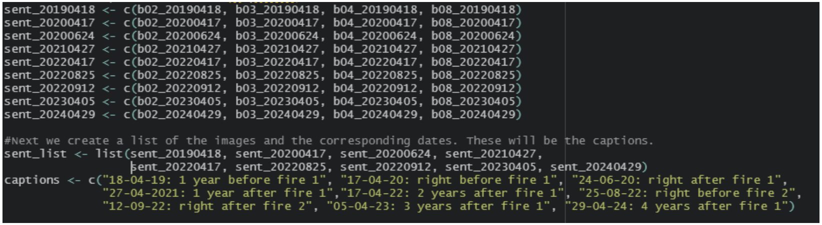


```
# One year before fire 1: 2019-04-18
b02_20190418 <- rast("2019-04-18-00_00_2019-04-18-23_59_Sentinel-2_L1C_B02_(Raw).tiff")
b03_20190418 <- rast("2019-04-18-00_00_2019-04-18-23_59_Sentinel-2_L1C_B03_(Raw).tiff")
b04_20190418 <- rast("2019-04-18-00_00_2019-04-18-23_59_Sentinel-2_L1C_B04_(Raw).tiff")
b08_20190418 <- rast("2019-04-18-00_00_2019-04-18-23_59_Sentinel-2_L1C_B08_(Raw).tiff")

#A few days before fire 1: 2020-09-12
b02_20200417 <- rast("2020-04-17-00_00_2020-04-17-23_59_Sentinel-2_L1C_B02_(Raw).tiff")
b03_20200417 <- rast("2020-04-17-00_00_2020-04-17-23_59_Sentinel-2_L1C_B03_(Raw).tiff")
b04_20200417 <- rast("2020-04-17-00_00_2020-04-17-23_59_Sentinel-2_L1C_B04_(Raw).tiff")
b08_20200417 <- rast("2020-04-17-00_00_2020-04-17-23_59_Sentinel-2_L1C_B08_(Raw).tiff")

#Immediately after fire 1: 2020-06-24
b02_20200624 <- rast("2020-06-24-00_00_2020-06-24-23_59_Sentinel-2_L1C_B02_(Raw).tiff")
b03_20200624 <- rast("2020-06-24-00_00_2020-06-24-23_59_Sentinel-2_L1C_B03_(Raw).tiff")
b04_20200624 <- rast("2020-06-24-00_00_2020-06-24-23_59_Sentinel-2_L1C_B04_(Raw).tiff")
b08_20200624 <- rast("2020-06-24-00_00_2020-06-24-23_59_Sentinel-2_L1C_B08_(Raw).tiff")
```

Figure: Code for data. This step is repeated for nine dates in total: 18-04-2019, 17-04-2020, 24-06-2020, 27-04-2021, 17-04-2022, 25-08-2022, 12-09-2022, 05-04-2023, and 29-04-2024

Data preparation

Now we stack our .tiff filles (one file per band per date) into stack per date. This enables us to use im.plotRGB (package: imageRy) efficiently. We also create a string of captions, corresponding to each stack of bands.



```
sent_20190418 <- c(b02_20190418, b03_20190418, b04_20190418, b08_20190418)
sent_20200417 <- c(b02_20200417, b03_20200417, b04_20200417, b08_20200417)
sent_20200624 <- c(b02_20200624, b03_20200624, b04_20200624, b08_20200624)
sent_20210427 <- c(b02_20210427, b03_20210427, b04_20210427, b08_20210427)
sent_20220417 <- c(b02_20220417, b03_20220417, b04_20220417, b08_20220417)
sent_20220825 <- c(b02_20220825, b03_20220825, b04_20220825, b08_20220825)
sent_20220912 <- c(b02_20220912, b03_20220912, b04_20220912, b08_20220912)
sent_20230405 <- c(b02_20230405, b03_20230405, b04_20230405, b08_20230405)
sent_20240429 <- c(b02_20240429, b03_20240429, b04_20240429, b08_20240429)

#Next we create a list of the images and the corresponding dates. These will be the captions.
sent_list <- list(sent_20190418, sent_20200417, sent_20200624, sent_20210427,
                  sent_20220417, sent_20220825, sent_20220912, sent_20230405, sent_20240429)
captions <- c("18-04-19: 1 year before fire 1", "17-04-20: right before fire 1", "24-06-20: right after fire 1",
              "27-04-2021: 1 year after fire 1","17-04-22: 2 years after fire 1", "25-08-22: right before fire 2",
              "12-09-22: right after fire 2", "05-04-23: 3 years after fire 1", "29-04-24: 4 years after fire 1")
```

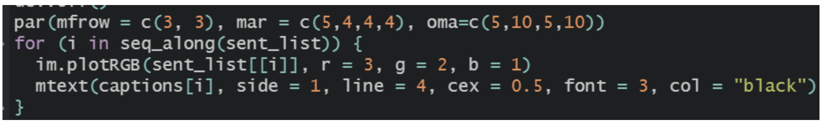
Figure: Code for stacking and listing all our data

Creating a natural colour image

The first thing we do is to create a natural colour image. To do this we use im.plotRGB. Some details:

- Since the exact step is repeated nine times, once per date, we make a for() loop for the step.
- A natural colour image consists of bands 4, 3, and 2, as red, green, and blue, respectively.
- Given that band 1 is not in our list, band 4 becomes 3, 3 becomes 2, and 2 becomes 1.

Code for natural colour images



```
par(mfrow = c(3, 3), mar = c(5,4,4,4), oma=c(5,10,5,10))
for (i in seq_along(sent_list)) {
  im.plotRGB(sent_list[[i]], r = 3, g = 2, b = 1)
  mtext(captions[i], side = 1, line = 4, cex = 0.5, font = 3, col = "black")
}
```

Figure: The loop that creates nine natural colour images

Natural colour images

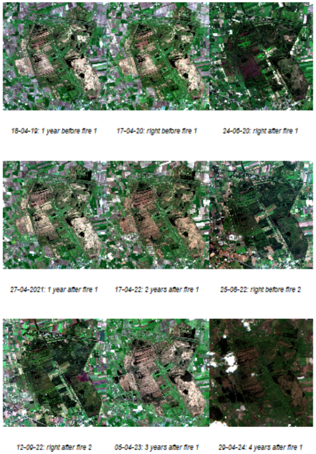

18-04-19: 1 year before fire 1
17-04-20: right before fire 1
24-06-20: right after fire 1
27-04-2021: 1 year after fire 1
17-04-22: 2 years after fire 1
25-08-22: right before fire 2
12-09-22: right after fire 2
05-04-23: 3 years after fire 1
20-04-24: 4 years after fire 1

Figure: Natural colour images before- and after fires 1 and 2

NDVI

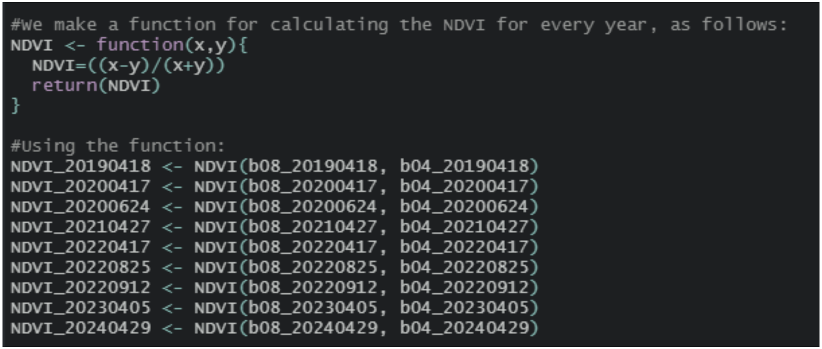
The natural colour image does not give us that much information. As an alternative, we try the Normalized Difference Vegetation Index (NDVI). With sentinel-2 data, NDVI is given as:

$$NDVI = (B8 - B4)/(B8 + B4) \tag{1}$$

$$NDVI = (NIR - RED)/(NIR + RED) \tag{2}$$

We write a function to do this in R:

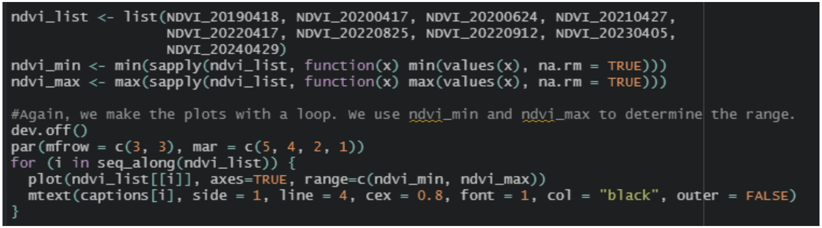
NDVI in R



```
#We make a function for calculating the NDVI for every year, as follows:
NDVI <- function(x,y){
  NDVI=((x-y)/(x+y))
  return(NDVI)
}

#Using the function:
NDVI_20190418 <- NDVI(b08_20190418, b04_20190418)
NDVI_20200417 <- NDVI(b08_20200417, b04_20200417)
NDVI_20200624 <- NDVI(b08_20200624, b04_20200624)
NDVI_20210427 <- NDVI(b08_20210427, b04_20210427)
NDVI_20220417 <- NDVI(b08_20220417, b04_20220417)
NDVI_20220825 <- NDVI(b08_20220825, b04_20220825)
NDVI_20220912 <- NDVI(b08_20220912, b04_20220912)
NDVI_20230405 <- NDVI(b08_20230405, b04_20230405)
NDVI_20240429 <- NDVI(b08_20240429, b04_20240429)
```

Figure: Code for calculating NDVI in R

NDVI visualisation



```
ndvi_list <- list(NDVI_20190418, NDVI_20200417, NDVI_20200624, NDVI_20210427,
                  NDVI_20220417, NDVI_20220825, NDVI_20220912, NDVI_20230405,
                  NDVI_20240429)
ndvi_min <- min(sapply(ndvi_list, function(x) min(values(x), na.rm = TRUE)))
ndvi_max <- max(sapply(ndvi_list, function(x) max(values(x), na.rm = TRUE)))

#Again, we make the plots with a loop. We use ndvi_min and ndvi_max to determine the range.
dev.off()
par(mfrow = c(3, 3), mar = c(5, 4, 2, 1))
for (i in seq_along(ndvi_list)) {
  plot(ndvi_list[[i]], axes=TRUE, range=c(ndvi_min, ndvi_max))
  mtext(captions[i], side = 1, line = 4, cex = 0.8, font = 1, col = "black", outer = FALSE)
}
```

Figure: Code for visualising the NDVI of each date

NDVI visualisation

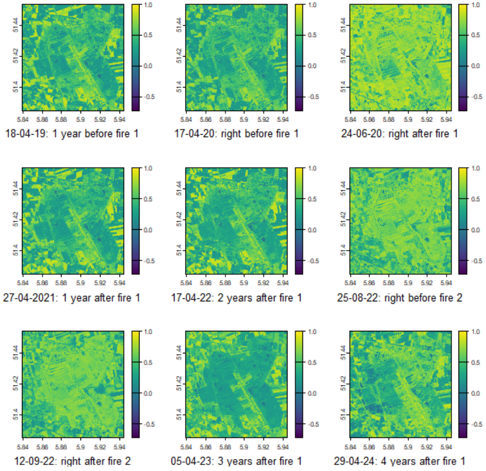

18-04-19: 1 year before fire 1
17-04-20: right before fire 1
24-06-20: right after fire 1
27-04-2021: 1 year after fire 1
17-04-22: 2 years after fire 1
25-08-22: right before fire 2
12-09-22: right after fire 2
05-04-23: 3 years after fire 1
29-04-24: 4 years after fire 1

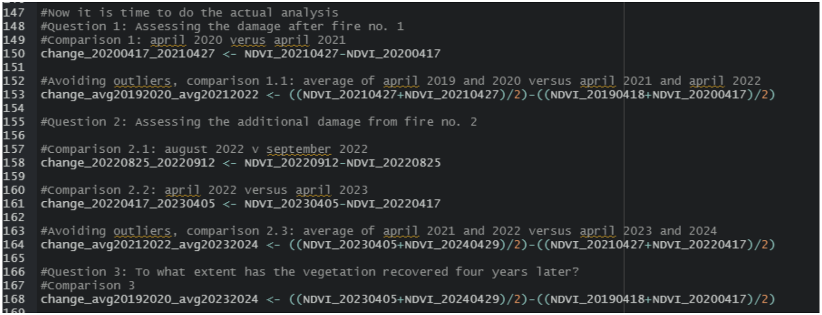
Figure: NDVI for each date

Calculating the changes in NDVI values

Now it is time to compare the before- and afters for each fire. We make five comparisons:

- **Before/after fire 1:** April 2020 versus April 2021
- **Before/after fire 1, no outliers:** Average April 2019/20 versus Average April 2021/22
- **Before/after fire 2:** April 2022 versus April 2023
- **Before/after fire 2, no outliers:** Average April 2021/22 versus Average April 2023/24
- **Before/after both fires, no outliers** Average April 2019/20 versus Average April 2023/24

Code for calculating NDVI changes

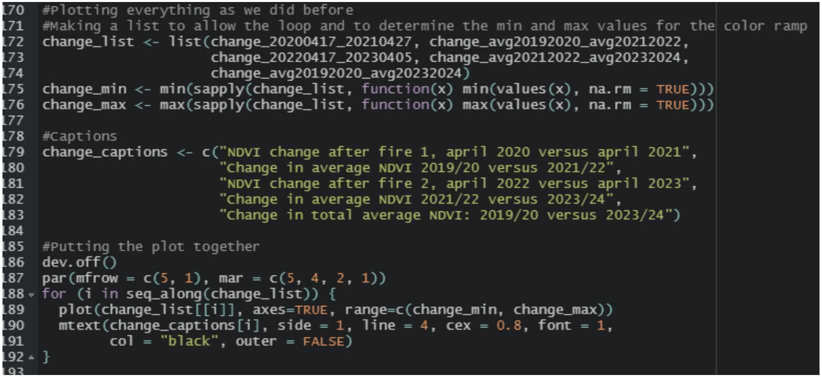


```
#Now it is time to do the actual analysis
#Question 1: Assessing the damage after fire no. 1
#Comparison 1: april 2020 verus april 2021
change_20200417_20210427 <- NDVI_20210427-NDVI_20200417

#Avoiding outliers, comparison 1.1: average of april 2019 and 2020 versus april 2021 and april 2022
change_avg20192020_avg20212022 <- ((NDVI_20210427+NDVI_20210427)/2)-((NDVI_20190418+NDVI_20200417)/2)

#Question 2: Assessing the additional damage from fire no. 2

#Comparison 2.1: august 2022 v september 2022
change_20220825_20220912 <- NDVI_20220912-NDVI_20220825

#Comparison 2.2: april 2022 versus april 2023
change_20220417_20230405 <- NDVI_20230405-NDVI_20220417

#Avoiding outliers, comparison 2.3: average of april 2021 and 2022 versus april 2023 and 2024
change_avg20212022_avg20232024 <- ((NDVI_20230405+NDVI_20240429)/2)-((NDVI_20210427+NDVI_20220417)/2)

#Question 3: To what extent has the vegetation recovered four years later?
#Comparison 3
change_avg20192020_avg20232024 <- ((NDVI_20230405+NDVI_20240429)/2)-((NDVI_20190418+NDVI_20200417)/2)
```

Figure: Code for calculating the difference in NDVI values

Code for plot of all NDVI changes

This is the code for plotting all five images. It follows the same structure as before, when we plotted nine images of individual NDVI values.



```r
#Plotting everything as we did before
#Making a list to allow the loop and to determine the min and max values for the color ramp
change_list <- list(change_20200417_20210427, change_avg20192020_avg20212022,
                    change_20220417_20230405, change_avg20212022_avg20232024,
                    change_avg20192020_avg20232024)
change_min <- min(sapply(change_list, function(x) min(values(x), na.rm = TRUE)))
change_max <- max(sapply(change_list, function(x) max(values(x), na.rm = TRUE)))

#Captions
change_captions <- c("NDVI change after fire 1, april 2020 versus april 2021",
                     "Change in average NDVI 2019/20 versus 2021/22",
                     "NDVI change after fire 2, april 2022 versus april 2023",
                     "Change in average NDVI 2021/22 versus 2023/24",
                     "Change in total average NDVI: 2019/20 versus 2023/24")

#Putting the plot together
dev.off()
par(mfrow = c(5, 1), mar = c(5, 4, 2, 1))
for (i in seq_along(change_list)) {
  plot(change_list[[i]], axes=TRUE, range=c(change_min, change_max))
  mtext(change_captions[i], side = 1, line = 4, cex = 0.8, font = 1,
        col = "black", outer = FALSE)
}
```

Figure: Code for plot of all NDVI changes

NDVI changes plot

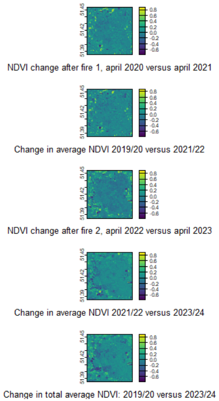
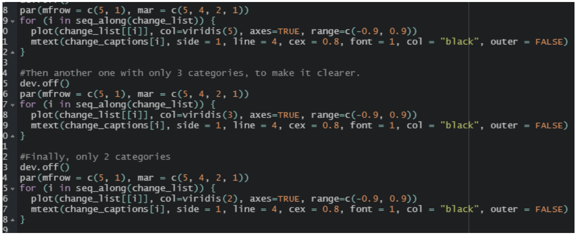

51.45
51.42
51.39
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
NDVI change after fire 1, april 2020 versus april 2021
Change in average NDVI 2019/20 versus 2021/22
NDVI change after fire 2, april 2022 versus april 2023
Change in average NDVI 2021/22 versus 2023/24
Change in total average NDVI: 2019/20 versus 2023/24

Figure: Changes in NDVI

Categorical changes

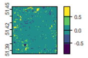
This is a bit difficult to read. As an alternative we make the plots categorical: this is easier for the human eye. The min and max values are artificially symmetrical: this makes it easier to visualize positives and negatives.



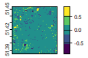
```
par(mfrow = c(5, 1), mar = c(5, 4, 2, 1))
for (i in seq_along(change_list)) {
  plot(change_list[[i]], col=viridis(5), axes=TRUE, range=c(-0.9, 0.9))
  mtext(change_captions[i], side = 1, line = 4, cex = 0.8, font = 1, col = "black", outer = FALSE)
}

#Then another one with only 3 categories, to make it clearer.
dev.off()
par(mfrow = c(5, 1), mar = c(5, 4, 2, 1))
for (i in seq_along(change_list)) {
  plot(change_list[[i]], col=viridis(3), axes=TRUE, range=c(-0.9, 0.9))
  mtext(change_captions[i], side = 1, line = 4, cex = 0.8, font = 1, col = "black", outer = FALSE)
}

#Finally, only 2 categories
dev.off()
par(mfrow = c(5, 1), mar = c(5, 4, 2, 1))
for (i in seq_along(change_list)) {
  plot(change_list[[i]], col=viridis(2), axes=TRUE, range=c(-0.9, 0.9))
  mtext(change_captions[i], side = 1, line = 4, cex = 0.8, font = 1, col = "black", outer = FALSE)
}
```

Figure: Code to make the colour scheme categorical: 5, 3, and then 2 categories.

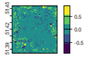
Categorical changes



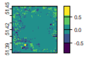
NDVI change after fire 1, april 2020 versus april 2021



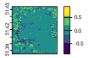
Change in average NDVI 2019/20 versus 2021/22



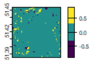
NDVI change after fire 2, april 2022 versus april 2023



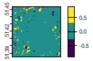
Change in average NDVI 2021/22 versus 2023/24



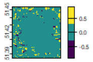
Change in total average NDVI: 2019/20 versus 2023/24



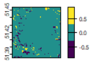
NDVI change after fire 1, april 2020 versus april 2021



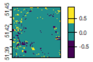
Change in average NDVI 2019/20 versus 2021/22



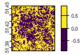
NDVI change after fire 2, april 2022 versus april 2023



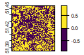
Change in average NDVI 2021/22 versus 2023/24



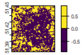
Change in total average NDVI: 2019/20 versus 2023/24



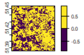
NDVI change after fire 1, april 2020 versus april 2021



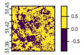
Change in average NDVI 2019/20 versus 2021/22



NDVI change after fire 2, april 2022 versus april 2023



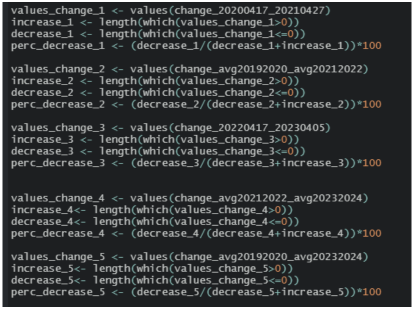
Change in average NDVI 2021/22 versus 2023/24



Change in total average NDVI: 2019/20 versus 2023/24

Counting values

To be certain we also calculate the percentage of negative values for each change tile. This is done as follows:



```
values_change_1 <- values(change_20200417_20210427)
increase_1 <- length(which(values_change_1>0))
decrease_1 <- length(which(values_change_1<=0))
perc_decrease_1 <- (decrease_1/(decrease_1+increase_1))*100

values_change_2 <- values(change_avg20192020_avg20212022)
increase_2 <- length(which(values_change_2>0))
decrease_2 <- length(which(values_change_2<=0))
perc_decrease_2 <- (decrease_2/(decrease_2+increase_2))*100

values_change_3 <- values(change_20220417_20230405)
increase_3 <- length(which(values_change_3>0))
decrease_3 <- length(which(values_change_3<=0))
perc_decrease_3 <- (decrease_3/(decrease_3+increase_3))*100


values_change_4 <- values(change_avg20212022_avg20232024)
increase_4<- length(which(values_change_4>0))
decrease_4<- length(which(values_change_4<=0))
perc_decrease_4 <- (decrease_4/(decrease_4+increase_4))*100

values_change_5 <- values(change_avg20192020_avg20232024)
increase_5<- length(which(values_change_5>0))
decrease_5<- length(which(values_change_5<=0))
perc_decrease_5 <- (decrease_5/(decrease_5+increase_5))*100
```

Figure: Code for calculating percentage showing negative NDVI change

Observed value changes

We get the following results:

- **April 2020 versus April 2021:** 50.5 percent was negative
- **Average April 2019/20 versus April 2021/22:** 53 percent was negative
- **April 2022 versus April 2023:** 66 percent was negative
- **Average April 2021/22 versus April 2023/24:** 39 percent was negative
- **Average April 2019/20 versus April 2023/24:** 38 percent was negative

Two possible conclusions: (1) vegetation recovers quickly (2) NDVI is not suitable for this type of land (e.g. lot of water)

Sources

- Copernicus Sentinel data [2025]. Retrieved from Copernicus Browser [24 01 2025], processed by ESA.
- RStudio version 1.4.1106
- R version 4.4.2
- Staatsbosbeheer (n.d.). Natuurbrandbeheersplan Deurnsche Peel en Mariapeel. Staatsbosbeheer.