Multitemporal Analysis of Vegetation Health and Landscape Heterogeneity

The Impact of 2019-2020 Bushfires in the Blue Mountains National Park, Australia

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Course: Spatial Ecology in R
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Introduction

Objective: assess the ecological impact of late 2019 – early 2020 bushfires in Australia through the application of several remote sensing and statistical analysis

Study Area: Blue Mountains National Park (Australia)

Data Source: Sentinel-2 TC and FC images (Copernicus Browser)

Comparison Period: 2019 (pre-fire) – 2020 (post-fire)

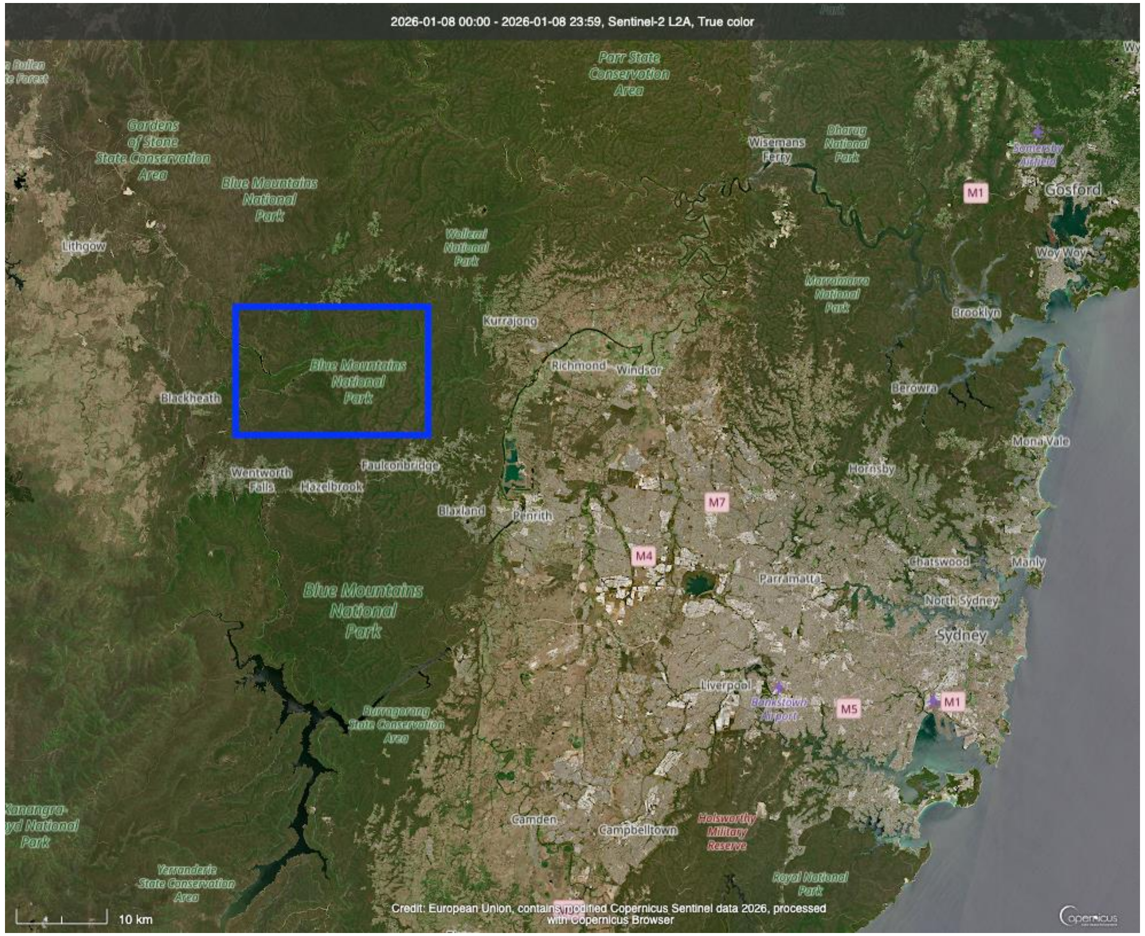
Tools: R studio

Packages

```
library(terra)
library(ggplot2)
library(patchwork)
library(viridis)
library(imageRy)
```

Study Area


DARWIN
Northern Territory
Queensland
Western Australia
South Australia
BRISBANE
New South Wales
The Blue Mountains
SYDNEY
PERTH
Great Australian Bight
ADELAIDE
CANBERRA (ACT)
Victoria
MELBOURNE
Tasmania
HOBART

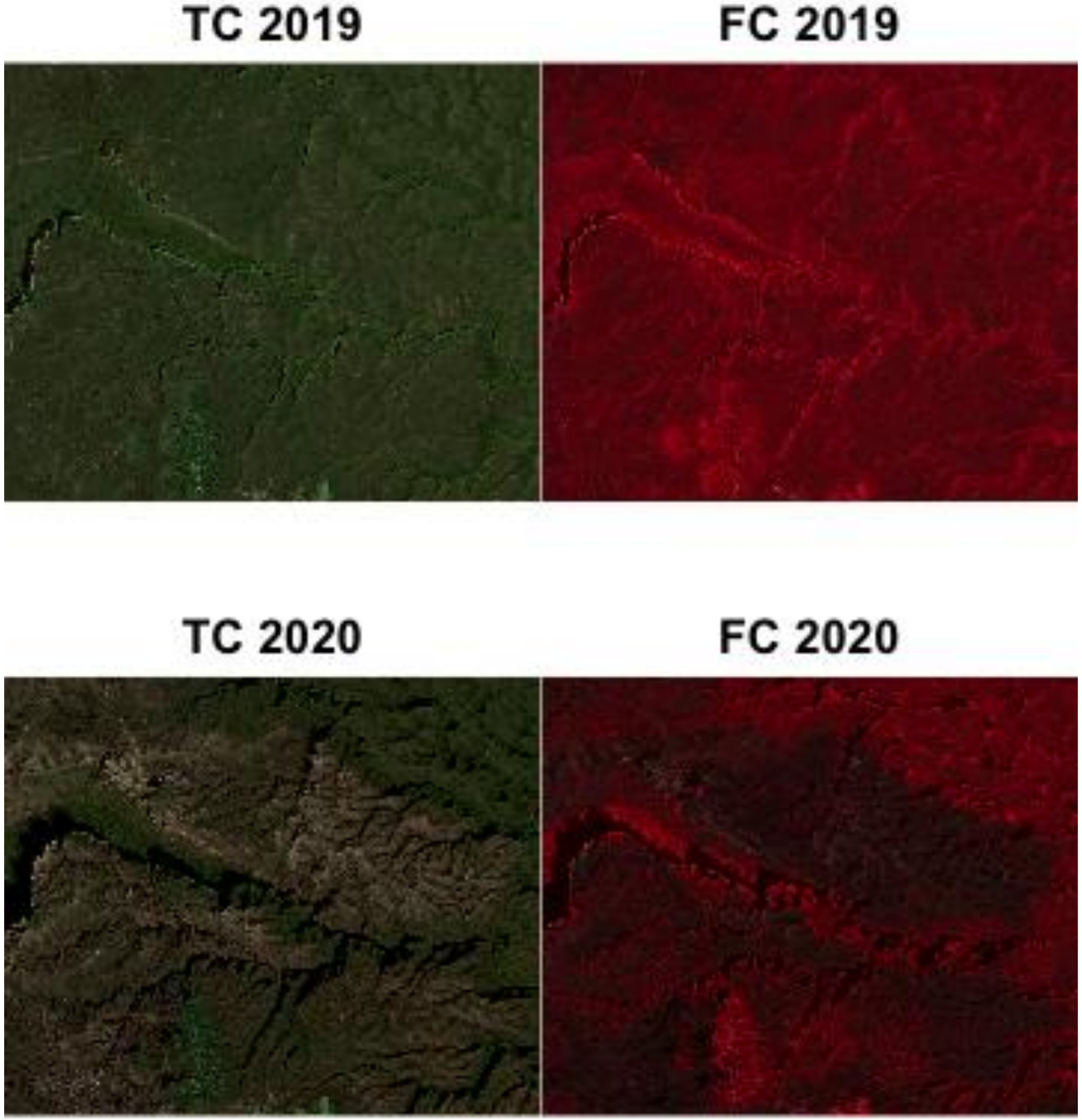

2026-01-08 00:00 - 2026-01-08 23:59, Sentinel-2 L2A, True color
Blue Mountains National Park
Lithgow
Blackheath
Kurrajong
Richmond
Windsor
Wentworth Falls
Hazelbrook
Faulconbridge
Blaxland
Penrith
Parramatta
Liverpool
Camden
Campbelltown
Sydney
North Sydney
Chatswood
Manly
Hornsby
Berowra
Brooklyn
Gosford
Woy Woy
Mona Vale
M1
M4
M5
M7
10 km
Credit: European Union, contains modified Copernicus Sentinel data 2026, processed with Copernicus Browser

Spectral Structure

True Color and False Color

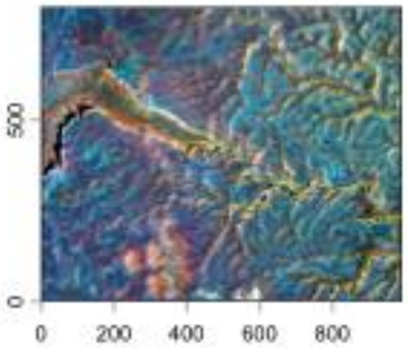
```
tc19 <- rast("2019_TC.jpg")
fc19 <- rast("2019_FC.jpg")
tc20 <- rast("2020_TC.jpg")
fc20 <- rast("2020_FC.jpg")

par(mfrow=c(2,2))
plot(tc19, main = "TC19")
plot(fc19, main = "FC19")
plot(tc20, main = "TC20")
plot(fc20, main = "FC20")
```

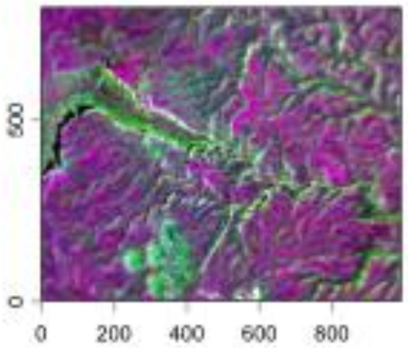
The differences between 2019 and 2020 can also be observed in the visible spectrum.
False Color composition emphasizes some large areas of reduced NIR reflection caused by the bushfires.

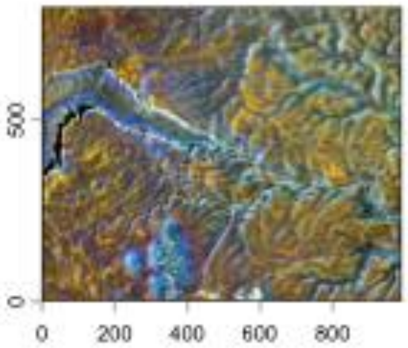


Visual Interpretation (RGB plots)

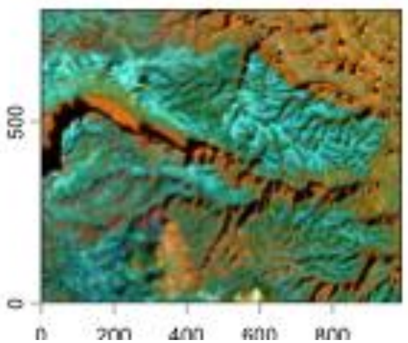
2019

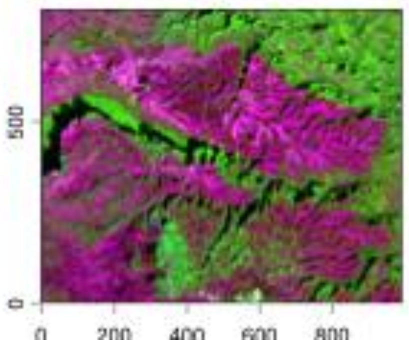


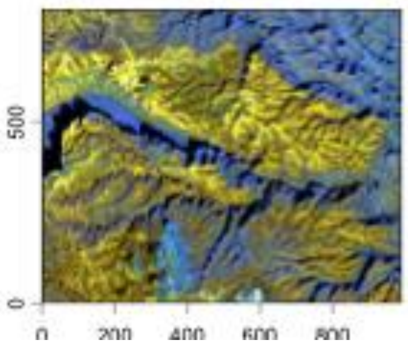




2020







NIR on red: 2020 red color is less continuous -> reduction in NIR reflectance.

NIR on green: 2020 more defined patches -> Increased spatial contrast.

NIR on blue: 2020 more landscape heterogeneity.

Multispectral RGB colouring highlights an increase in spatial heterogeneity between 2019 and 2020. While the overall geomorphological structure remains recognizable, post-fire images show a more fragmented spectral pattern, consistent with vegetation health reduction and patchy recovery following the disturbance.

Code for RGB plots

```
# Extracting the bands from 2019 images. Useful to classify the objects and extract more information from the data.
# From the TC image I'm taking the red (r), blue (b) and green (g) bands.
r19 <- tc19[[1]]
g19 <- tc19[[2]]
b19 <- tc19[[3]]
# From the FC image I'm taking the NIR band.
nir19 <- fc19[[1]]
# Combining the bands in a single object.
stack19 <- c(r19, g19, b19, nir19)

# Extracting the bands from 2020 images.
# From the TC image I'm taking the red (r), blue (b) and green (g) bands.
r20 <- tc20[[1]]
g20 <- tc20[[2]]
b20 <- tc20[[3]]
# From the FC image I'm taking the NIR band.
nir20 <- fc20[[1]]
# Combining the bands in a single object.
stack20 <- c(r20, g20, b20, nir20)

# Visualizing the images with different colors:
par(mfrow=c(3,2))
im.plotRGB(stack19, r=4, g=2, b=3)
im.plotRGB(stack19, r=1, g=4, b=3)
im.plotRGB(stack19, r=1, g=2, b=4)
im.plotRGB(stack20, r=4, g=2, b=3)
im.plotRGB(stack20, r=1, g=4, b=3)
im.plotRGB(stack20, r=1, g=2, b=4)
```

Vegetation Health Index
DVI = NIR -red

2019: DVI range covers from -75 to 179.
2020: DVI range covers from -90 to 200.

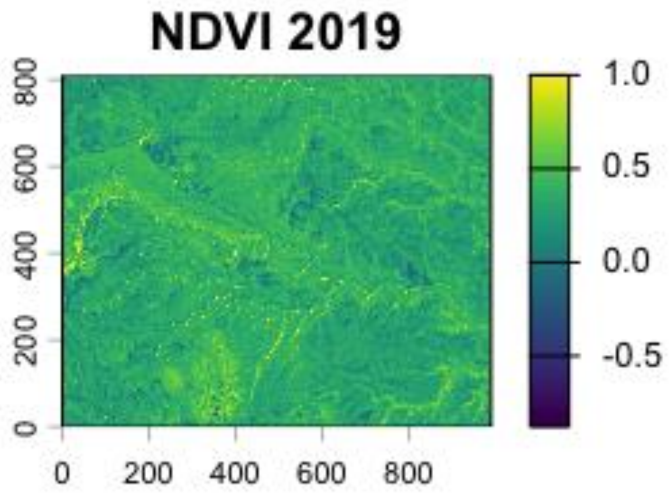
- **Decrease in minimum range** in 2020 (-90). This indicates areas where red reflectance exceed the NIR reflectance, a clear sign of clorophyll loss: with less photosynthesis, red wavelengths are less absorbed and so vegetation is less or stressed.

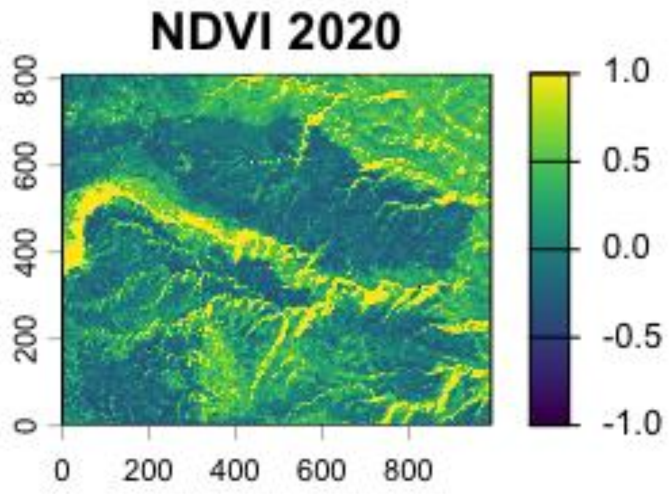
- **Higher maximum value** in 2020 (200), it's likely not due to better vegetation, but rather to different atmospheric illumination or the high overall reflectance of exposed bare rocks or soil, which can reflect strongly across the entire spectrum.

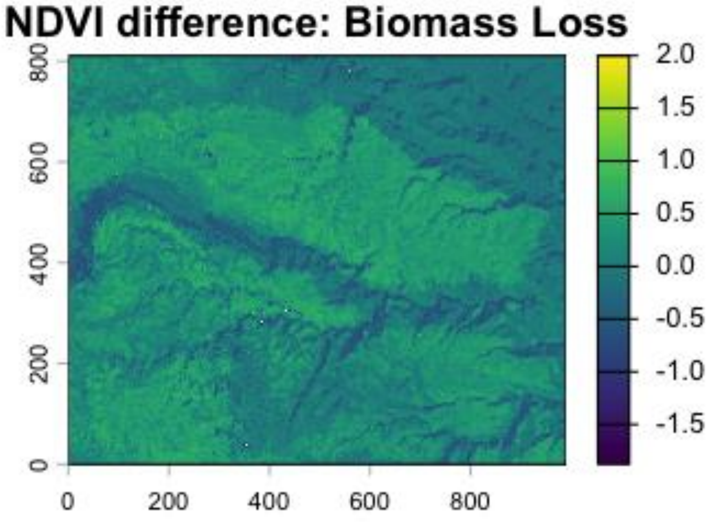
DVI consent to observe the raw physical behavior of the spectral of the NIR-red bands and the direct loss of photosynthetic efficiency.

NDVI is essential to normalize the data by filtering out potential "noise" caused by different illumination or atmospheric conditions.

Vegetation Health Index
NDVI







2019: mean elevated and homogeneous values. Spatial continuous consistency along valleys and slopes. Structurally stable landscape.
2020: generalized diminution of NDVI values, large areas with low NDVI. Pattern more fragmented and more evident contrast between near patches. Caused by the loss of biomass, by the vegetation's stress and by the disomogeneous effects of fire.

Code for NDVI

```
ndvi19 <- (nir19 - r19)/(nir19 + r19)
ndvi20 <- (nir20 - r20)/(nir20 + r20)

par(mfrow=c(3,1))
plot(ndvi19, col=viridis(100), main="NDVI 2019")
plot(ndvi20, col=viridis(100), main="NDVI 2020")

ndvi_diff <- ndvi19 - ndvi20
plot(ndvi_diff, col=viridis(100), main="NDVI difference: Biomass Loss")
```

Landscape Structure

Data Compression (PCA)

- **Data Reduction:** Sentinel-2 provides multiple spectral bands (Red, Green, Blue, NIR) that are often highly correlated and redundant.

- **Information Concentration:** PCA transforms these bands into new, uncorrelated variables called Principal Components.

- **Variance captured:** In this study, the first two components (PC1 and PC2) explain **~76.59%** (2019) and **~70.15%** (2020) of the total landscape variability.

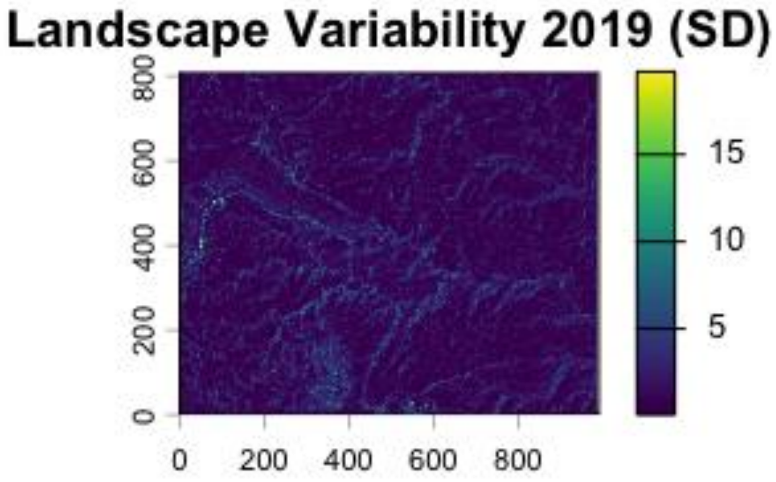
- **Objective:** Isolating the most important ecological signals to calculate spatial heterogeneity without the "noise" of redundant data.

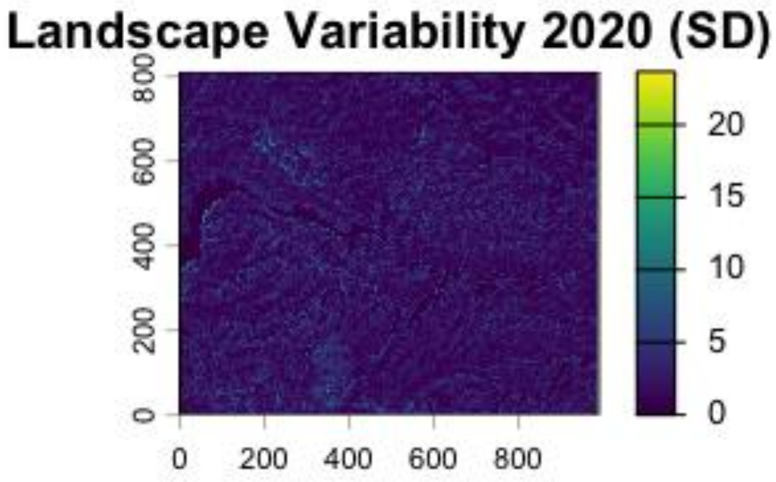
Code for PCA

```
# Running the Principal Component Analysis on the 2019 stack.
pca19 <- im.pca(stack19)

# Standard Deviations obtained from R:
# pca1 = 22.300805
# pca2 = 13.894895
# pca3 = 8.694020
# pca4 = 2.365775

# Calculating the total variability as the sum of SDs of the
components.
tot19pca <- sum(22.300805, 13.894895, 8.694020, 2.365775)
# 47.2555

# Estimating the percentage of information represented by each
axis.
22.300805*100/47.2555 # 47.19% (PC1)
13.894895*100/47.2555 # 29.40% (PC2)
8.694020*100/47.2555 # 18.40% (PC3)
2.365775*100/47.2555 # 5.01% (PC4)

# PC1 and PC2 together cover ~76.59% of the original
information, which is enough to describe the landscape
structure.
compactpca19 <- pca19[[1]] + pca19[[2]]
```

```
# Running the Principal Component Analysis on the 2020 stack.
pca20 <- im.pca(stack20)

# Standard Deviations obtained from R:
# pca1 = 30.18312
# pca2 = 28.80024
# pca3 = 19.72079
# pca4 = 5.34542

# Calculating the total variability as the sum of SDs of the
components.
tot20pca <- sum(30.18312, 28.80024, 19.72079, 5.34542)
# 84.04957
# It's interesting to notice that total variability is almost doubled
between 2019 (47.26) and 2020, this is due to the disorder
caused by the fires.

# Estimating the percentage of information represented by each
axis.
30.18312*100/84.04957 # 35.91% (PC1)
28.80024*100/84.04957 # 34.26% (PC2)
19.72079*100/84.04957 # 23.46% (PC3)
5.34542*100/84.04957 # 6.36% (PC4)

# PC1 and PC2 together cover ~70.15% of the original
information, which is enough to describe the landscape
structure.
compactpca20 <- pca20[[1]] + pca20[[2]]
```

Landscape Heterogeneity (SD)





2019: SD values generally low and spatially coherent, relative homogeneous landscape with variability associated to main geomorphological structures.
2020: While maintaining a similar global distribution, increment of variability, with a stronger presence of high SD pixels (yellow) and a more fragmented distribution. Outputs consistent with an heterogenous stress event like fire. The fire acted as a "disturbing agent" thet broke the spatial continuity noticed in 2019 and generated "disorder".

Differences between 2019 and 2020 are mainly expressed in terms of fine-scale spatial heterogeneity and highlight a general increment in spatial complexity in post-fire period.

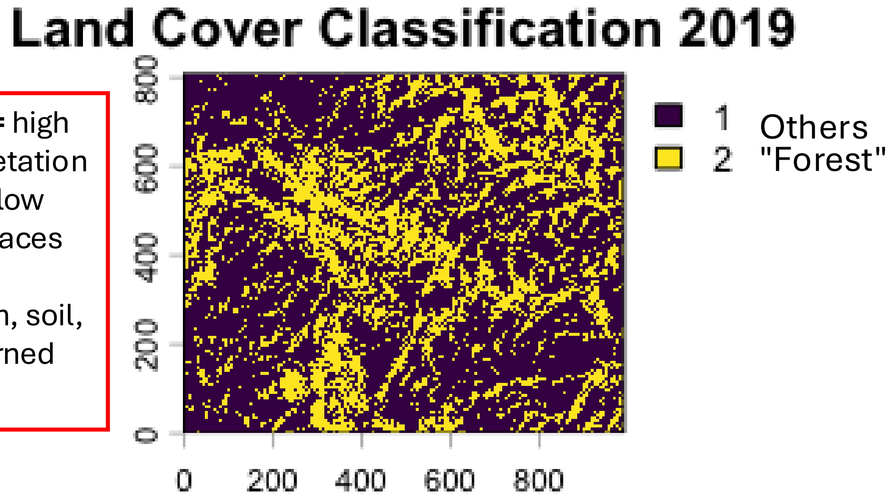
Code for SD

```
# Calculating the Standard Deviation (pcsd19), based on the principal components, to measure the spatial hetereogeneity of the landscape. I'm applying focal() function to calculate SD in a 3x3 moving window.

# Areas with high SD indicate high landscape complexity.

pcsd19 <- focal(compactpca19, matrix(1/9,3,3), fun=sd)


# Calculating the Standard Deviation (pcsd20), based on the principal components, to measure the spatial hetereogeneity of the landscape. I'm applying focal() function to calculate SD in a 3x3 moving window.

pcsd20 <- focal(compactpca20, matrix(1/9,3,3), fun=sd)


par(mfrow=c(2,1))

plot(pcsd19, col=viridis(100), main = "Landscape Variability 2019 (SD)")

plot(pcsd20, col=viridis(100), main = "Landscape Variability 2020 (SD)")
```

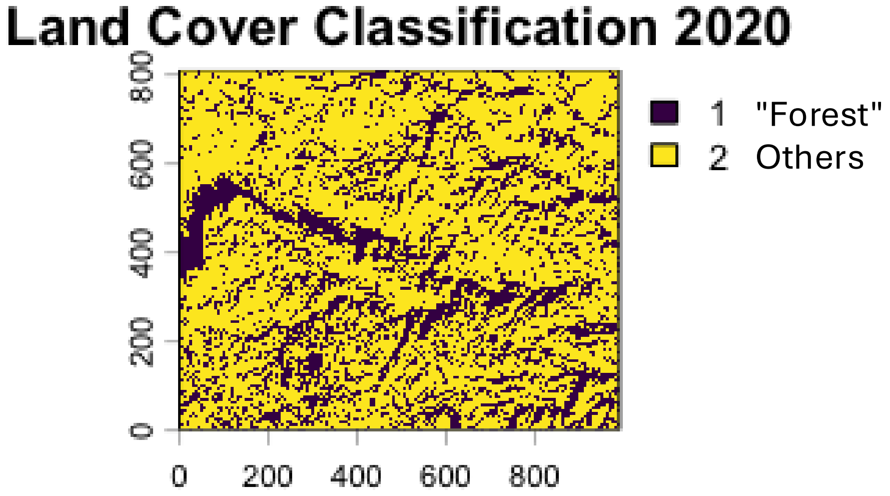
Quantifying Change

Land Cover Classification

2019: "Forest" coverage -> 31.89005%
2020: "Forest" coverage -> 29.38597%
Net loss = ~2.5% of "Forest" coverage



"**Forest** "= high NDVI vegetation
Others = low NDVI surfaces (stressed vegetation, soil, rocks, burned areas)



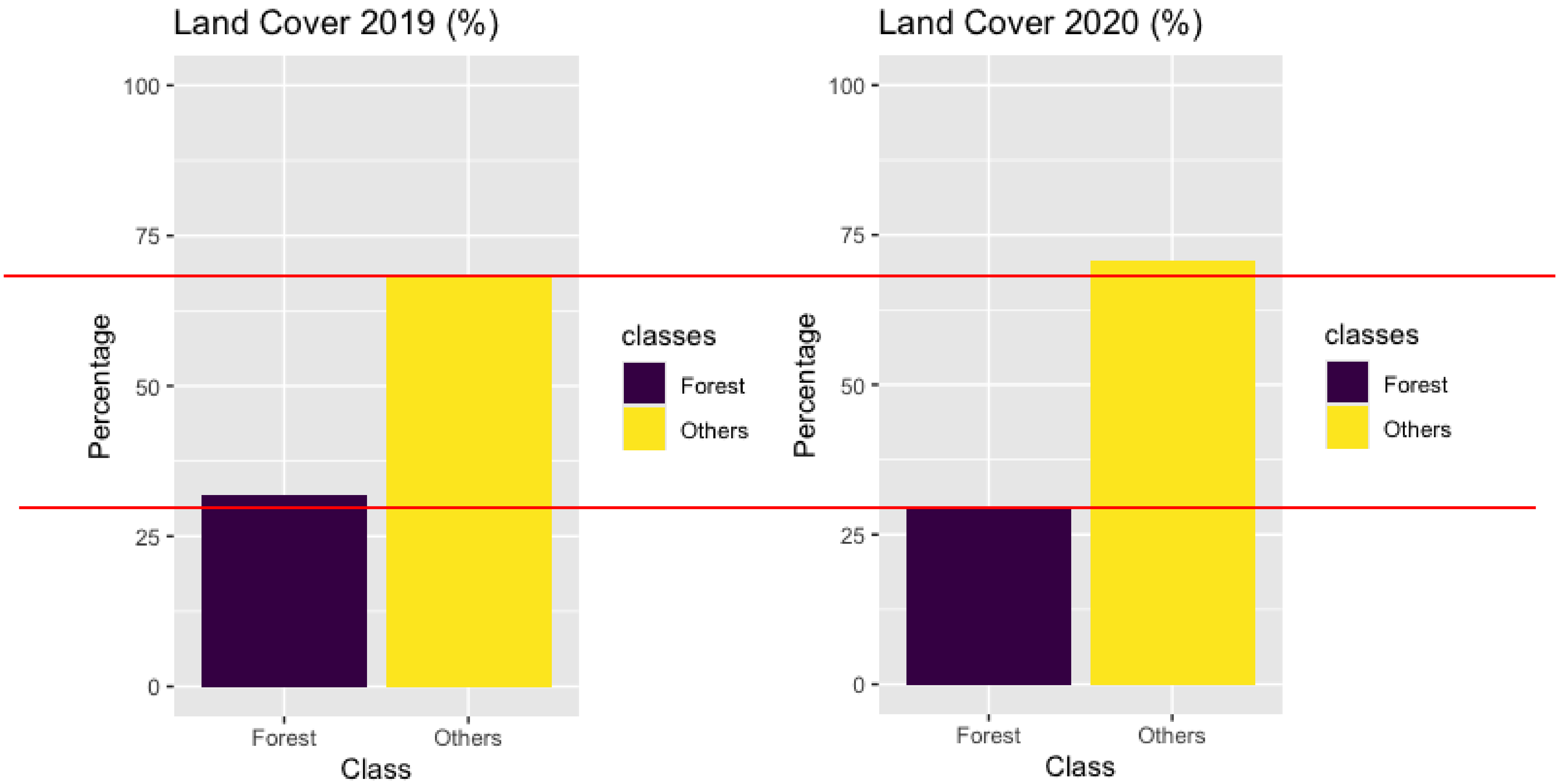
2019: large and continuous patches of the two classes. Reflects moderate landscape variability and a structural stable environment, consistent with a healthy forest.
2020: increased fragmentation and a more irregular distribution of small patches.

Due to **unsupervised classification** function the numbers of the two classes are inverted between 2019 and 2020. The classification results indicate a reduction of 2.5% in Forest class in 2020 after bushfires.
Although, because the classification is unsupervised, class proportions represent changes in spatial configuration and spectral similarity rather than true gain or loss in forest covered area. This pattern is consistent with the general loss of NDVI in 2020 and increased landscape fragmentation.

Code for Classification

```
# Classifying the image into 2 clusters: "Forest" (vegetation) and Others (rocks/water/bare soil).
cl19 <- im.classify(stack19, num_clusters=2)
cl20 <- im.classify(stack20, num_clusters=2)

# Calculating the frequencies to get the percentage of land cover of each land cover class.
f19 <- freq(cl19) # Number of pixels for each class
tot19 <- ncell(cl19) # Total number of pixels in the image
p19 <- f19*100/tot19 # Percentage for each class
p19
# Class 1 ("Forest") = 31.89005%
# Class 2 (Others) = 68.10995%

f20 <- freq(cl20)
tot20 <- ncell(cl20)
p20 <- f20*100/tot20
p20
# Class 1 (Others) = 70.61403%
# Class 2 ("Forest") = 29.38597%

par(mfrow=c(2,1))
plot(cl19, main = "Land Cover Classification 2019")
plot(cl20, main = "Land Cover Classification 2020")
```

Statistical Synthesis (ggplot2)



Code for ggplot2

```
# Building a dataframe to visualize the class percentage from 2019 and 2020.
y19 <- c(31.89, 68.11) # Forest, Others
y20 <- c(29.39, 70.61) # Forest, Others
classes <- c("Forest", "Others")
# Creating the dataframe
dataF <- data.frame(classes, y19, y20)
dataF

# Visualizing a clear quantitative representation
F19 <- ggplot(dataF, aes(x=classes, y=y19, fill=classes)) + geom_bar(stat="identity") +
scale_fill_viridis_d(option="D") + ylim(c(0, 100)) + labs(title="Land Cover 2019 (%)", y="Percentage",
x="Class")
F20 <- ggplot(dataF, aes(x=classes, y=y20, fill=classes)) + geom_bar(stat="identity") +
scale_fill_viridis_d(option="D") + ylim(c(0, 100)) + labs(title="Land Cover 2020 (%)", y="Percentage",
x="Class")
F19 + F20
```

Thank you!