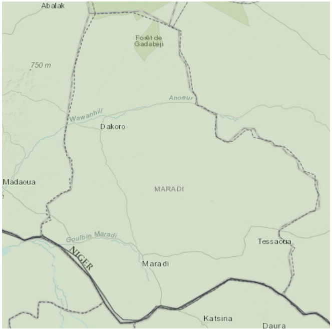
TEMPORAL ANALYSIS OF FMNR BY THE GREAT GREEN WALL PROJECT IN MARADI CITY



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A.Y. 2024-2025

Summary

The Great Green Wall

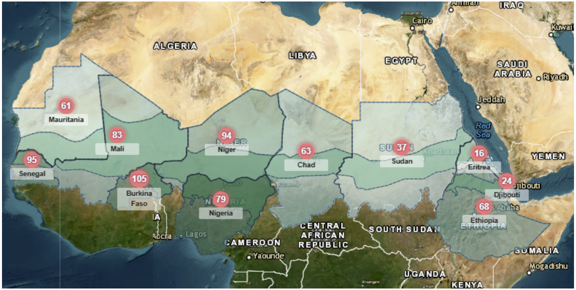


Figure: Extension of the Great Green Wall

- The Great Green Wall is an African-led movement.
- The objective is to restore 8,000 km of degraded land.
- It aims to tackle climate change, drought, famine, conflict, and migration.

Summary

Maradi

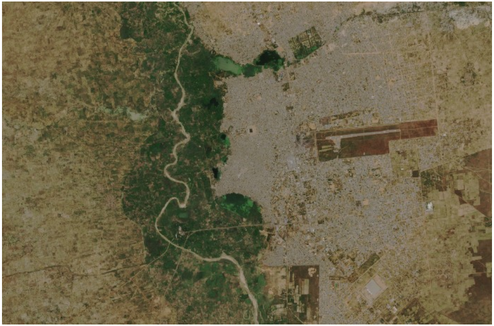


Figure: Maradi 2024

- The third largest city in Niger
- The area is critically affected by desertification
- Farmer-Managed Natural Regeneration (FMNR)

Summary

Objective

The objective of this presentation is to compare the effects of Farmer-Managed Natural Regeneration between 2017 and 2024 using Copernicus Sentinel-2 imagery and R analysis for Maradi city, to assess the strength and importance of the project.

Summary

Packages used

- library(terra)
- library(ggplot2)
- library(patchwork)
- library(viridis)
- library(devtools)
- library(imageRy)
- library(RColorBrewer)

Summary

Images used

- Four images were downloaded from Copernicus Sentinel-2
- Two images from 2017 and two from 2024
- The two images are True Color and False Color

Import

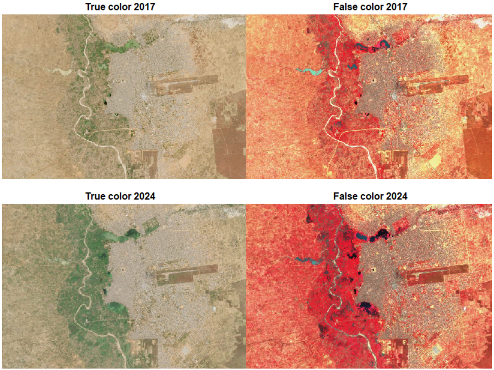
The images were imported from an external source using the `rast()` function from the terra package, loaded, and assigned to an object.

```
maradiTC17<-rast("tc251017.jpg")
maradiFC17<-rast("fc251017.jpg")
maradiTC24<-rast("tc231024.jpg")
maradiFC24<-rast("fc231024.jpg")
```

Multiframe

Let's plot all the images together.

```
par(mfrow=c(2,2))
plot(maradiTC17,main="True color 2017")
plot(maradiFC17,main="False color 2017")
plot(maradiTC24,main="True color 2024")
plot(maradiFC24,main="False color 2024")
```



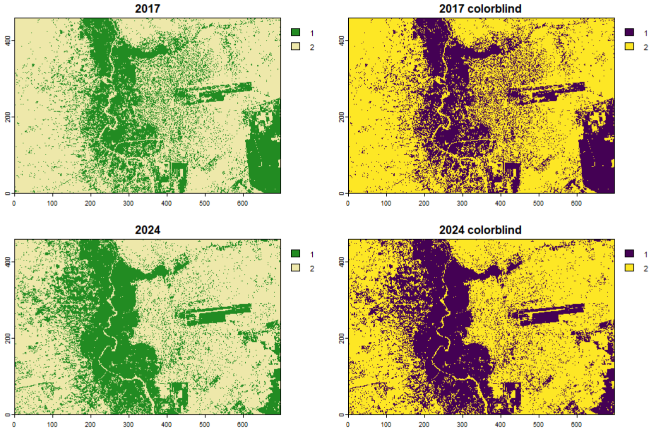
Images classification

We need to combine the True Color and NIR bands from the 2017 and 2024 images to classify.
Before, we assign the red, green, blue, and NIR bands to their respective objects.
We use the im.classify() function from the imageRy package and declare the image and the number of clusters, in this case 2.

```
bmR17<-maradiTC17[[1]]
bmG17<-maradiTC17[[2]]
bmB17<-maradiTC17[[3]]
bmI17<-maradiFC17[[1]]
bm17<-c(bmR17,bmG17, bmB17,bmI17)

bmR24<-maradiTC24[[1]]
bmG24<-maradiTC24[[2]]
bmB24<-maradiTC24[[3]]
bmI24<-maradiFC24[[1]]
bm24<-c(bmR24,bmG24, bmB24,bmI24)

Cbm17<-im.classify(bm17, num_clusters=2)
Cbm24<-im.classify(bm24, num_clusters=2)
```

Now, we want to plot everything in a multiframe that is also accessible to colorblind individuals.

```
cl <- colorRampPalette(c("forestgreen","palegoldenrod")) (100)
par(mfrow=c(2,2))
plot(Cbm17,col=cl, main="2017")
plot(Cbm17,col= viridis(2), main="2017 colorblind")
plot(Cbm24,col=cl, main="2024")
plot(Cbm24,col= viridis(2), main="2024 colorblind")
```



Frequencies and percentages

Let's calculate the frequencies and determine the percentage of the two classes using the combined bands from 2017 and 2024.

```
f17 <- freq(Cbm17)
tot17 <- ncell(Cbm17)
p17 = f17*100/tot17
# Class 1 Restored land = 33%
# Class 2 City and deserted areas = 67%

f24 <- freq(Cbm24)
tot24 <- ncell(Cbm24)
p24 = f24*100/tot24
# Class 1 Restored land = 36%
# Class 2 City and deserted areas = 64%
```

We can say that only 3% of the area was restored from 2017 to 2024.
It doesn't seem much, right? Let's not jump to conclusions.

Code for dataframe

Now, it's time to create a dataframe with the percentages we got before.
To do that, we assign the percentages of each year to the object (the year), we assign the names of the classes to the other object (classes).

```
y2017 <- c(33,67)
y2024 <- c(36,64)
classes <- c("Restored land", "City and deserted areas")
dataM <- data.frame(classes,y2017,y2024)
```

Code for graphs

Then, we create a plot using the ggplot() function from the ggplot2 package to compare the class distribution of the two images.

```
M1 <- ggplot(dataM, aes(x=classes, y=y2017, fill=classes, color=classes)) + geom
     _bar(stat="identity") + scale_fill_manual(values=c("Restored land"="
     forestgreen", "City and deserted areas"="palegoldenrod")) + scale_color_
     manual(values=c("Restored land"="forestgreen", "City and deserted areas"="
     palegoldenrod")) + ylim(c(0, 100))
M2 <- ggplot(dataM, aes(x=classes, y=y2024, fill=classes, color=classes)) + geom
     _bar(stat="identity") + scale_fill_manual(values=c("Restored land"="
     forestgreen", "City and deserted areas"="palegoldenrod")) + scale_color_
     manual(values=c("Restored land"="forestgreen", "City and deserted areas"="
     palegoldenrod")) + ylim(c(0, 100))

# Code for colorblind

M1cb <- ggplot(dataM, aes(x=classes, y=y2024, fill=classes, color=classes)) +
     geom_bar(stat="identity") + scale_fill_viridis_d(option="D") + scale_color_
     viridis_d(option="D") +  ylim(c(0, 100))
M2cb <- ggplot(dataM, aes(x=classes, y=y2024, fill=classes, color=classes)) +
     geom_bar(stat="identity") + scale_fill_viridis_d(option="D") + scale_color_
     viridis_d(option="D") + ylim(c(0, 100))
```

Graphs

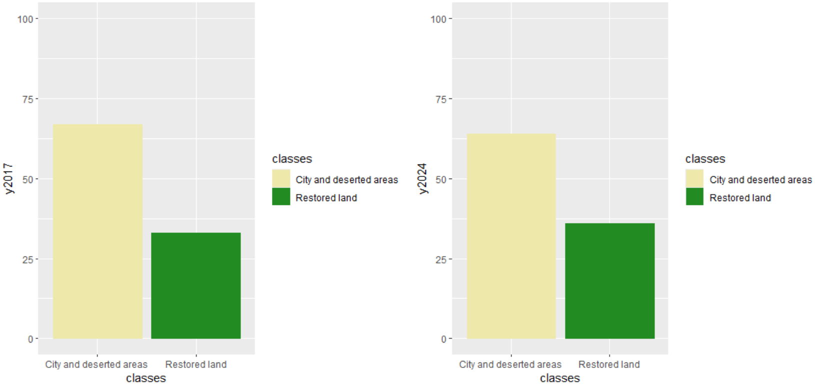


Figure: Classes percentages from 2017 and 2024

Graphs for colorblind

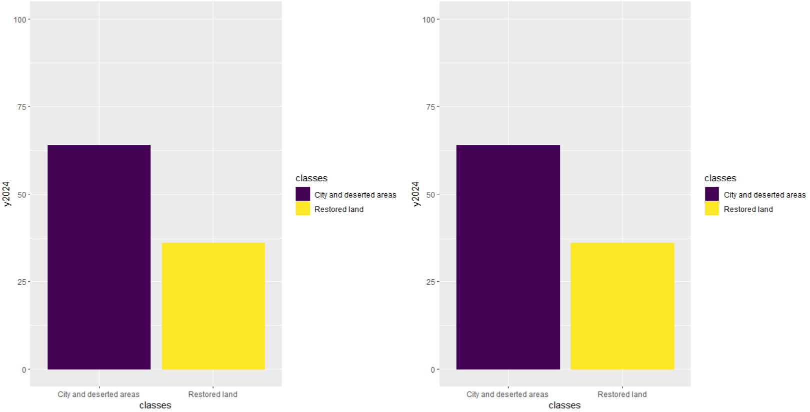


Figure: Classes percentages from 2017 and 2024 for colorblind people

DVI and NDVI analysis

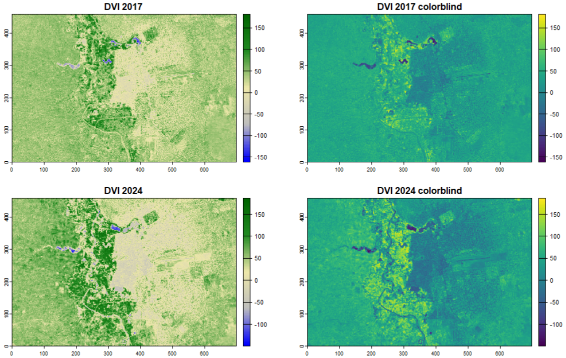
It is time to see what has changed over the years in terms of vegetation health and density; we are going to calculate the DVI (Difference Vegetation Index) and then the NDVI (Normalized Difference Vegetation Index).

```
cl1 <- colorRampPalette(c("blue", "grey", "palegoldenrod", "#228B22", "darkgreen
     "))(100) # To appreciate better the DVI and NDVI

dvi2017<-bm17[[4]]-bm17[[1]]
dvi2024<-bm24[[4]]-bm24[[1]]

ndvi2017 = dvi2017/(bm17[[4]]+bm17[[1]])
ndvi2024 = dvi2024/(bm24[[4]]+bm24[[1]])
```

DVI multiframe

We plot the result from the DVI analysis in a multiframe, also accessible to colorblind people with the viridis palette.

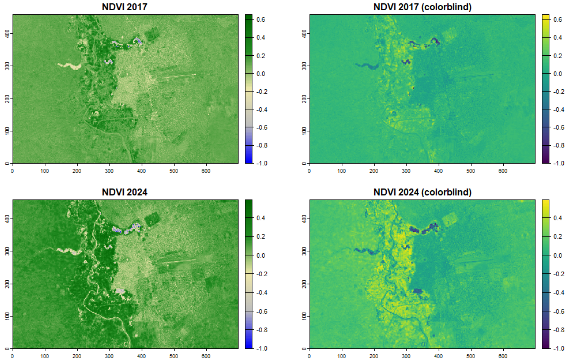
```
par(mfrow=c(2,2))
plot(dvi2017,col=cl1, main="DVI 2017")
plot(dvi2017,col=viridis(100), main="DVI 2017 colorblind")
plot(dvi2024,col=cl1, main="DVI 2024")
plot(dvi2024,col=viridis(100), main="DVI 2024 colorblind")
```



NDVI multiframe

We plot the result of the NDVI analysis.

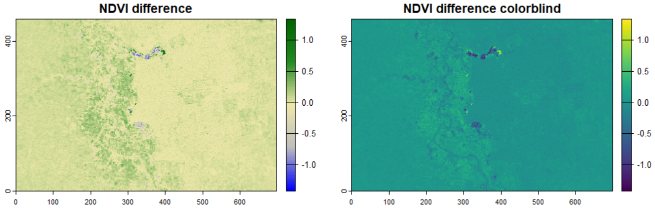
```
par(mfrow=c(2,2))
plot(ndvi2017,col=cl1, main="NDVI 2017")
plot(ndvi2017,col=viridis(100), main="NDVI 2017 (colorblind)")
plot(ndvi2024,col=cl1, main="NDVI 2024")
plot(ndvi2024,col=viridis(100), main="NDVI 2024 (colorblind)")
```



NDVI differences

- Positive values (> 0) are areas where NDVI increased from 2017 to 2024
- Negative values (< 0) are areas where NDVI decreased from 2017 to 2024

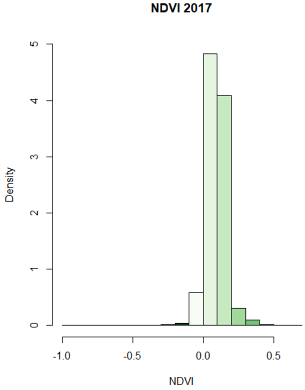
```
Difndvi=ndvi2024-ndvi2017
par(mfrow=c(1,2))
plot(Difndvi,col=cl1, main="NDVI difference")
plot(Difndvi,col=viridis(100), main="NDVI difference colorblind")
```

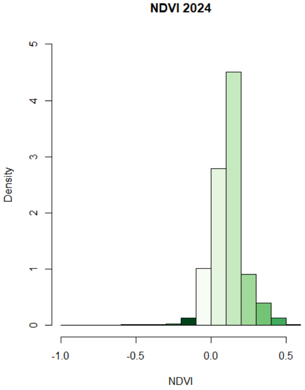


Histograms

We can visualize the results of the NDVI analysis using histograms for the years 2017 and 2024.

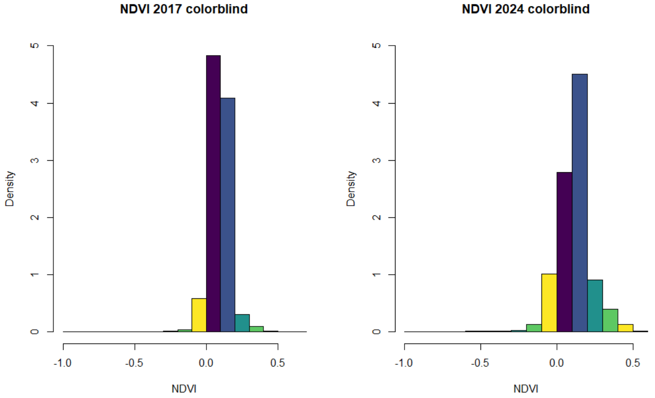
```
par(mfrow=c(1,2))
ist17 <- hist(ndvi2017, main="NDVI 2017", xlab="NDVI", nclass=20, freq=F, ylim=c
      (0,5), col=brewer.pal(9, "Greens"))
ist24 <- hist(ndvi2024, main="NDVI 2024", xlab="NDVI", nclass=20, freq=F, ylim=c
      (0,5), col=brewer.pal(9, "Greens"))
```





Histograms for colorblind people

```
par(mfrow=c(1,2))
ist17 <- hist(ndvi2017, main="NDVI 2017 colorblind", xlab="NDVI", nclass=20,
      freq=F, ylim=c(0,5), col=viridis(5))
ist24 <- hist(ndvi2024, main="NDVI 2024 colorblind", xlab="NDVI", nclass=20,
      freq=F, ylim=c(0,5), col=viridis(5))
```



PCA Analysis

1. We analyze the PCA for the year 2017.
2. We use the function im.pca and we get the variability that each axis explains
3. We combine the PCA1 and PCA2 together because they explain 86% of the total variability
4. Now we can calculate the standard deviation with the function focal

```
pca17 <- im.pca(bm17)
tot17pca <- sum(38.966791, 24.927165, 7.061764, 3.160646)

38.966791*100/tot17pca # 52.575151 variability explained by the first axis
24.927165*100/tot17pca # 33.632471 variability explained by the second axis
7.061764*100/tot17pca # 9.527942 variability explained by the third axis
3.160646*100/tot17pca # 4.264437 variability explained by the fourth axis

pc17c <- pca17[[1]] + pca17[[2]]
pcsd17 <- focal(pc17c, matrix(1/9,3,3),fun=sd)
```

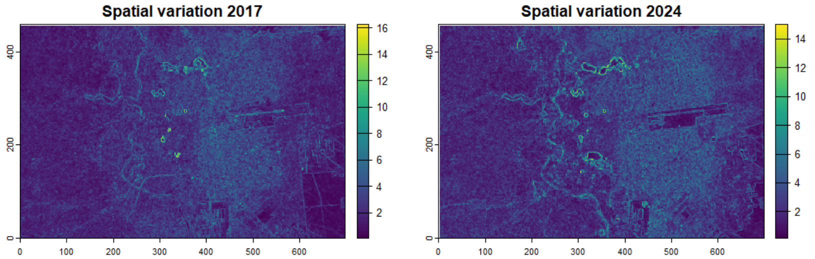
We perform the same analysis for the year 2024.

```
pca24 <- im.pca(bm24)
tot24pca <- sum(49.521251, 30.357348, 7.712667, 3.188850)

49.521251*100/tot24pca # 54.55077 variability explained by the first axis
30.357348*100/tot24pca # 33.44053 variability explained by the second axis
7.712667*100/tot24pca # 8.495987 variability explained by the third axis
3.188850*100/tot24pca # 3.512719 variability explained by the fourth axis

pc24c <- pca24[[1]] + pca24[[2]] # 88% of variability explained
pcsd24 <- focal(pc24c, matrix(1/9,3,3),fun=sd)
```

Results

We can see the results of the standard deviation analysis in a multiframe.
Some appreciable differences can be observed.

```
par(mfrow=c(1,2))
plot(pcsd17, col=viridis(100), main="Spatial variation 2017")
plot(pcsd24, col=viridis(100), main="Spatial variation 2024")
```



Summary

Conclusion

We emphasize the importance of the Great Green Wall for Africa, as what we can observe from our analyses is a slight increase in vegetation density, visible through the histograms, NDVI graphs, and PCA analysis. The latter has shown how the increase in illuminated areas reflects high variation.
Thanks for the attention!