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Bento Rodrigues dam collapse: quantification of the affected area

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Source : Senado Federal, https://commons.wikimedia.org/wiki/File:Bento_Rodrigues,_Mariana,_Minas_Gerais_(22828956680).jpg

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Bento Rodrigues dam collapse

Introduction

The Bento Rodrigues dam collapse occurred on the 5th of November 2015 in the Mariana region of Brazil as can be seen on Figure 1. The structure was supposed to hold the tailings of the Germano iron mine. The failure released an estimated 43.7 million cubic meters of toxic mine tailings in the Doce River, which caused a massive mudflow that destroyed 200 homes and killed 20 peoples. Moreover, the toxic water contaminated the riverbed and reached the Atlantic Ocean 620 kilometers downstream. The sediment load and sedimentation of the iron rich mud caused the death of millions of fishes causing the loss of livelihood for thousands of people depending on the affected river and land services. The effects are expected to be long lasting because of the high level of toxic metals in the deposited sediment and potential leaching in the water table. (Carmo et al., 2017; Fernandes et al., 2016; Garcia et al., 2017; Quaresma et al., 2020)

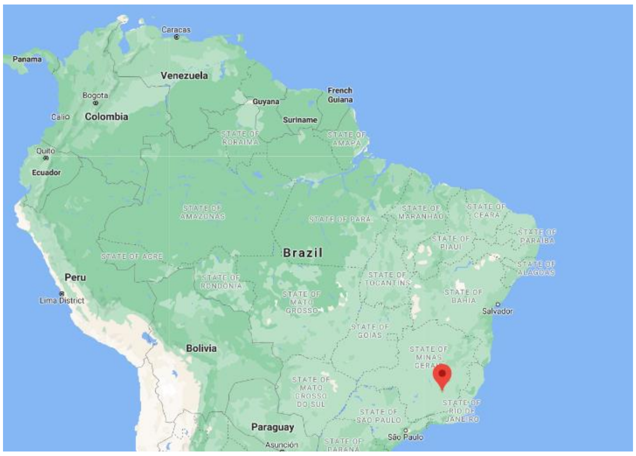

Figure 1 : Location of the Bento Rodrigues dam collapse in the Mariana region, Brazil. (maps.google.com)

The goal of this small project is to use remote sensing, in this case freely available satellite images, to quantify the affected area.

Data selection and acquisition

The event displays some characteristics that will direct my search. Firstly, the timescale is small and therefore the images should be ideally days or weeks apart at most. Secondly, the event is a flooding river, and, in some places, it might only be a couple decameters wide, meaning I should try to obtain images with a high ground resolution. Lastly, the event is an iron tailings flood, this means the images should have a IR band to sense to presence of water, and being red-brown, the visible bands could be useful.

Using GLOVIS and the prior knowledge explained before, I searched for images with low cloud cover and temporally closest to the event. This returned one before[1] image dating from the 11th October 2015 and one after[2] image dating from the 12th November 2015.

[1] Before image ID : LC08_L1TP_217074_20151011_20170403_01_T1
[2] After image ID : LC08_L1TP_217074_20151112_20170402_01_T1

Both images are from LANDSAT 8 and I downloaded them to further process in MATLAB. On Figure 2, you can observe the extent of the flood in RGB colors.

Figure 2 : Visualisation of the before (above) and after (bellow) in RGB (bands 4,3,2)

Being LANDSAT 8 images, all bands of interest have a 30 meters pixel size and we will use this characteristic to compute the affected area.

Methodology

In this section, I will present the methods I explored to quantify the affected area and the workflow I finally choose.

Explored methods

Classifier

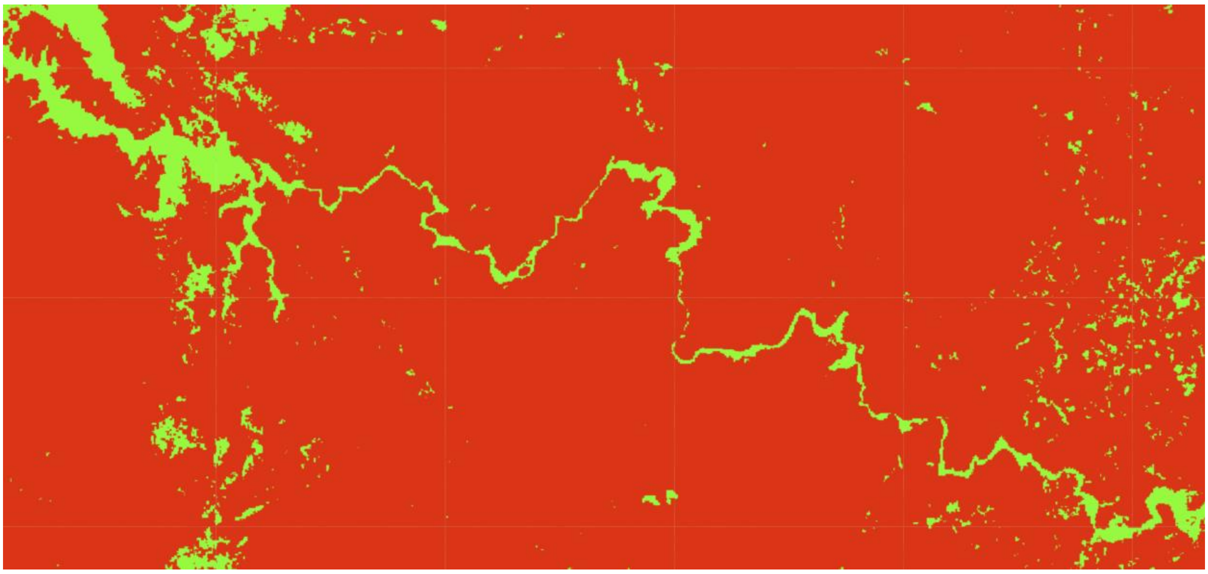

Figure 3 : Screenshot of a supervised classification of the flooded area taken from GEE explorer

At first, I tried to explore the data in Google Earth Engine (GEE) explorer and computed a model with a supervised classification. As can be observed in Figure 3, I obtained good result for the flooded zone, but to many false positive. I tried adding data points to refine the classification, but I could not obtain good enough results.

Per pixel difference on band 5

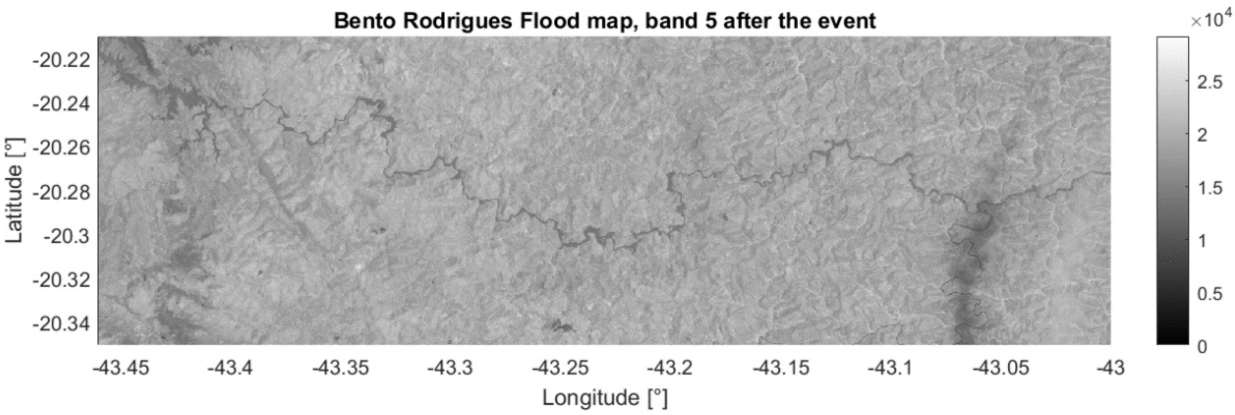

Figure 4 : Band 5 after the event of the flooded area

Exploring the data revealed, as can be seen on Figure 4, that the event is well visible on band 5, which corresponds to the NIR band. This is expected due to the high content of water in the mudflow and therefore residual moisture of the flooded areas. However, on the right of the picture, we can see a cloud shadow with similar reflectance as water.

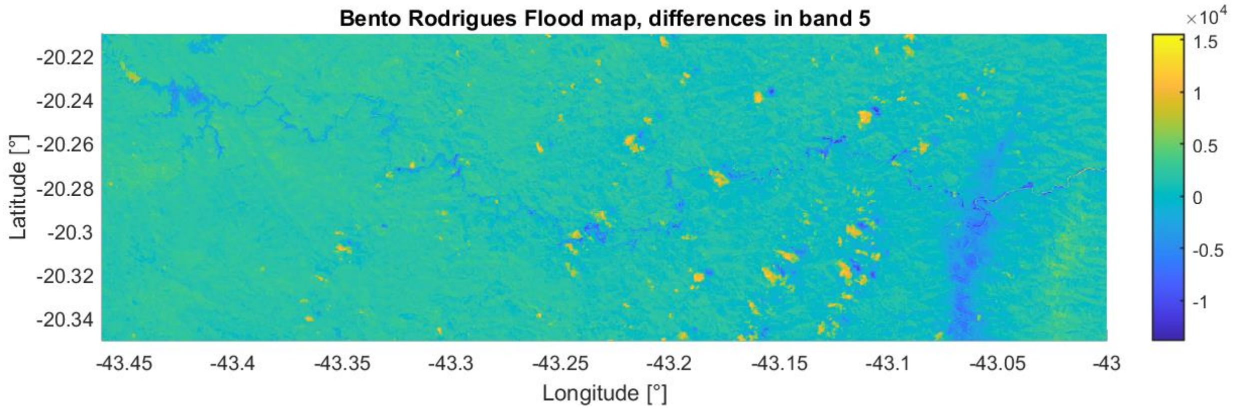

Figure 5 : Difference on band 5 of the flooded area

In order to visualize the flooded area, it is necessary to remove the static water bodies, which should not have significantly changed in the small timeframe. This is done by doing the per-pixel difference on band 5 and the results are shown on Figure 5. In this case, the flood course is well visible, but the cloud shadows pose a serious problem that will bias my results if I try to quantify the affected area.

NDWI on bands 3 and 5

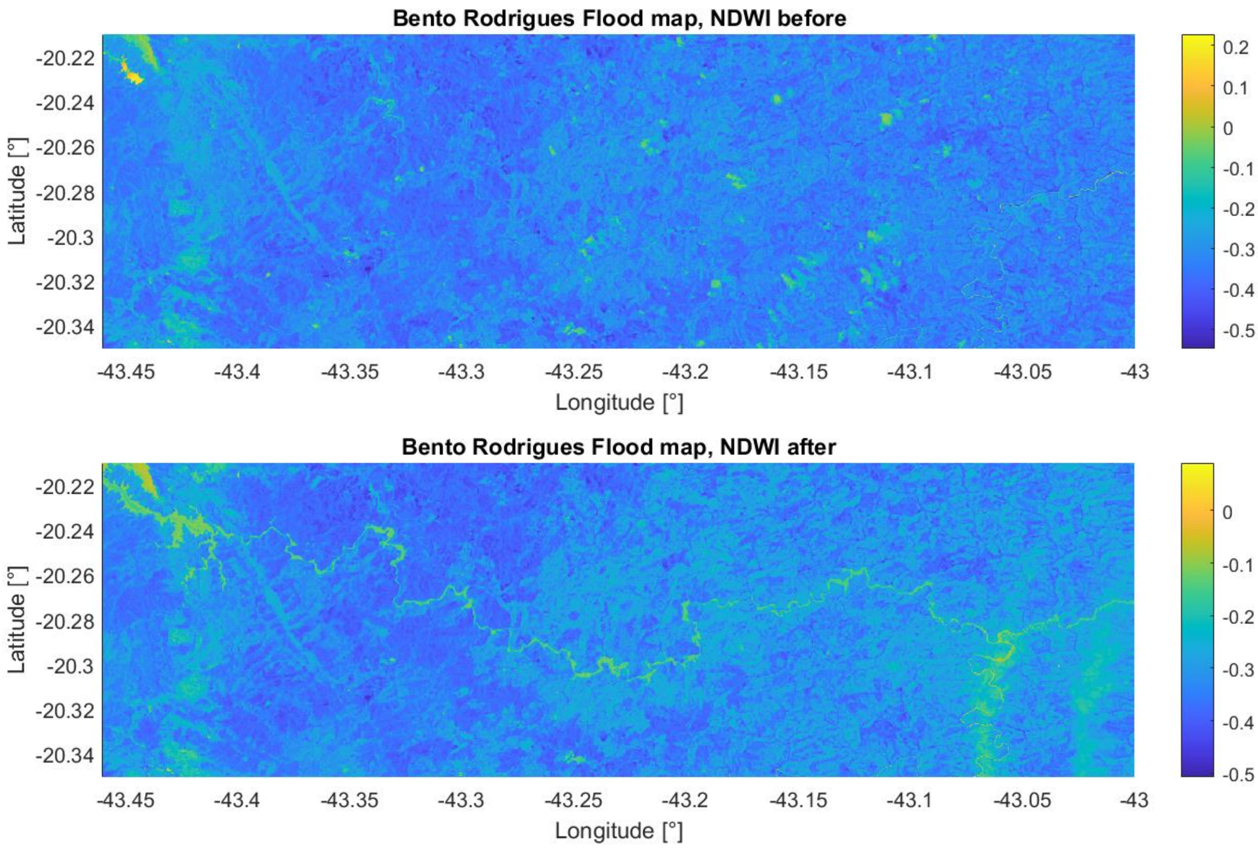

Figure 6 : NDWI before and after the flood

The Normalized Difference Water Index (NDWI) refers to at least two indexes related to water. The one suited for the detection of water bodies uses the green and NIR bands, bands 3 and 5 respectively fort LANDSAT 8 (McFeeters, 1996). Figure 6 displays the NDWI before and after the event. The course of the Doce River appears a lot wider after the flood and I assume that even if the area is not flooded anymore, the deposition of water rich sediments up to 3m high (Carmo et al., 2017) changes the reflectance significantly and allows us to visualize the event. I also tried other variation of NDWI, but they did not provide as good results as the bands 3 and 5 version. The NDWI seemed to be an appropriate way to quantify the area affected by the flood and in the next section I will develop the workflow I adopted.

Final workflow

For the final workflow I chose to work with the NDWI and did the difference between after and before in order to subtract any feature that are normally part of the region. I realized however that, even if the NDWI is supposed to be normalized, there was a bias by plotting the histogram. This can be expected as I kept the raw pixel value for the bands and did not imadjust. To counter that, I instead normalized the NDWI and then did the difference. This gave a much better result (less influence from the clouds) in the flood map. From that I chose an appropriate threshold by sampling multiple points that were affected by the flood. I then classified the image using the threshold and simultaneously counted the TRUE pixels. Finally, I multiplied the number on TRUE pixels by the area of a pixel and got the estimated affected area.

```
count = 0;                  % the TRUE pixels counter
[m,n] = size(a_b5);         % get the size of the array
flood = NaN(m,n);           % pre-allocation of the flood array
thres = 1.5;                % threshold for the flooded pixels
pixel_size = 30;            % groud resolution of the bands
% Loop
for i=1:m
    for j=1:n
        if diff(i,j)>thres          % selecting with threshold
            flood(i,j) = 1;         % if true, setting pixel to 1
            count = count + 1;      % if true, add 1 to the counter
        else
            flood(i,j) = 0;         % if false, set pixel to 0
        end
    end
end
area = count * pixel_size^2 ;       % flooded area in [m^2]
```

In the next section, I will present the result of this method, and compare it with the simple NDWI difference.

Results

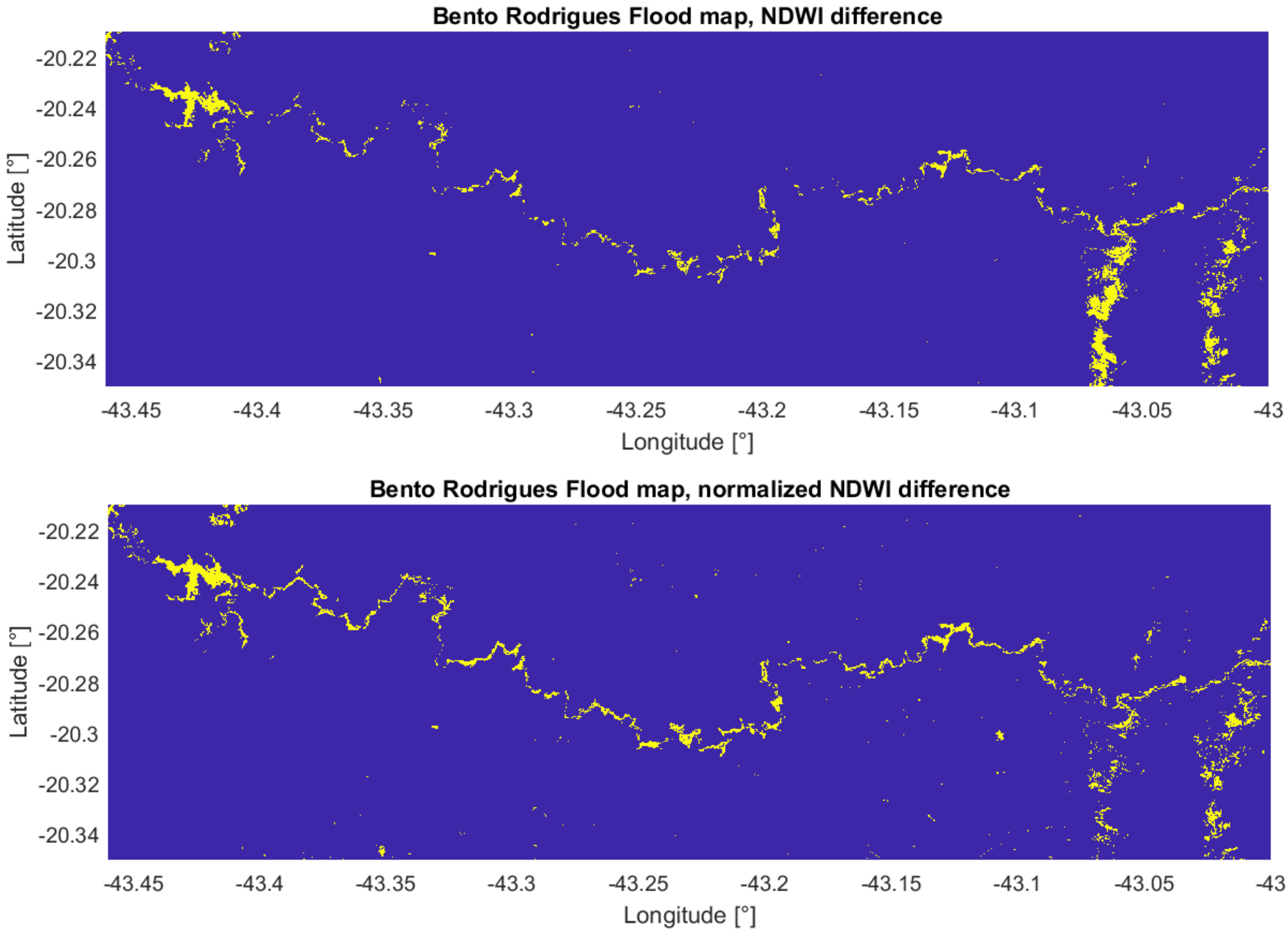

Figure 7 : Comparison of the NDWI and normalized NDWI flood map

On Figure 7, we can observe the supperiority of the normalized NDWI. It is able supress a bit more of the clouds and cloud shadows in the lower right part of the image, and the flooded zone of the river are more in line with what can be visually observed in the corresponding zones. It is also important to note that the number on TRUE pixel is almost exactly matched between the two maps, revealing the most effective method.

Looking more closely at the normalized NDWI flood map, we see there is still a small number of false positive, and that the clouds and cloud shadows are still visible. However the flooded zone are better defined, especially in the north-west, where the flood originated, and the flooding was the most subsantial.

An important thing to note is that with this method of difference, the before river course is substracted in the resulting the flood map, it is correct in terms of flooding, but it ommits the fact the riverbed itself has been polluted by the toxic sediments.

In the end, the flooded area I was able to compute is 18.5km^2. Which is in the neighborhood of other estimation of the disater that range from 15km^2 to 22km^2 (Carmo et al., 2017; Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis [IBAMA], 2015; Segura et al., 2016).

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