MATHÉMATIQUES
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Remote Sensing Data

Final Project

Use of the SAR Shadowing Effect for Deforestation Detection with Sentinel-1 Time Series

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Abstract : This project is part of the course "Remote Sensing Data" given at the master Mathématiques Vision et Apprentissage (MVA) at ENS Paris-Saclay. It is the work of Chloé SEKKAT (ENSAE Paris & ENS Paris-Saclay) and Arnaud LOUYS (CentraleSupélec & ENS Paris-Saclay). The goal of this project was to study and re-implement the method proposed in [1]. This method introduces a novel indicator of deforestation using Synthetic Aperture Radar (SAR) imaging and specifically a particular geometric property that appears when an area gets deforested. The authors show that this indicator is more robust to climate conditions since SAR imaging is not hindered by them (compared to optical imaging). The method relies on two key steps: shadow detection and reconstruction of deforested patches.

Contents

1 Introduction

Usually when one wants to monitor deforestation using satellite imaging, optical data is the main resource available. Many satellites actually provide Near Real Time (NRT) data allowing the constant monitoring of the evolution of the forests (for instance Sentinel-2 satellites). This comes in handy in regions where deforestation can lead to great dangers such as the Amazonian Forest. Images received from the satellite are processed as time series, hence one can use temporal changes detection techniques to detect deforestation.

However, optical images are affected by climate conditions, especially clouds and haze which can obstruct the view and make detection harder and less robust. An idea to overcome this issue is to use Synthetic Aperture Radar (SAR) imaging through C-band data. This is what is proposed by the article we studied: "Use of SAR Shadowing Effect for Deforestation Detection with Sentinel-1 Time Series" [1].

Using SAR imaging is possible since it works regardless of the weather conditions as the electromagnetic waves can penetrate the clouds and since it is an all-time sensor (acquisition is possible during night and day). Moreover, with the launch of Sentinel-1 satellites, one can have access to images every 6 or 12 days depending on the data type and the region in the world, both in ascending and in descending orbit. In this study, we implemented the method described in [1] which uses both ascending and descending orbits Sentinel-1 images in order to detect deforested patches in a given time series. This method encompasses two steps: a first step of shadow detection (crucial as deforestation is visible through shadows in SAR imaging) and a second step of reconstruction of deforested patches using both orbits. This has been done over a period ranging from 22/10/2014 to 21/07/2021 and an area over Peru (Amazonian Forest, same as in the paper).

This report is organized as follows: in Section 2, we go over the studied area along with the extraction process and the processing steps required to retrieve the backscattered signal γ_0. Section 3 will present the method and the effect at the heart of this whole technique: the shadowing effect, a geometric artifact happening alongside deforestation. In Section 4 we share our results at each key steps of the process. Finally Section 5 and 6 will respectively provide insights on how to improve the results, discuss some choices and finally conclude.

2 Data Extraction & Processing

2.1 Study Area

We chose to focus on the same area as the one given in the paper. It is a site of 600,000 ha (93 km x 65 km) over Peru, in the Amazonian Forest (Figure 1). This area spans over two tiles (WGS84) but we decided to consider only one tile : 18MUU and the associated calibrated and ortho-rectified Sentinel-1 image we get is of size (19 000, 19 000), Figure 2 (more on processing step in the following sub-sections). Considering the number of days and the fact that we use both ascending and descending orbits, having such big images means that we would have to work with more than 400GB of data. This is not practical, hence we decided to focus on a smaller patch.

In Figure 3, you can see the evolution of the chosen patch in between 2016 and 2018, with Sentinel-2 optical images (B03 band). There is indeed deforestation, especially at the center of the patch where even a road was built.

Figure 1: Studied area over Peru (image from Google Earth)

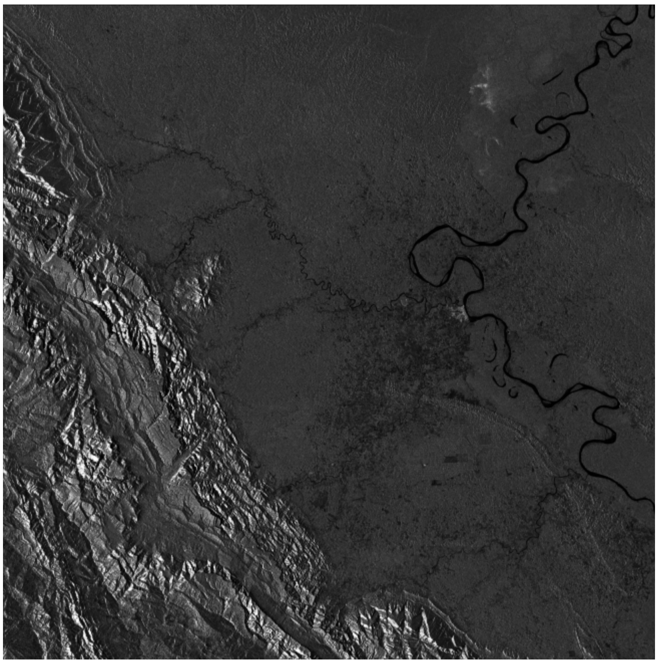
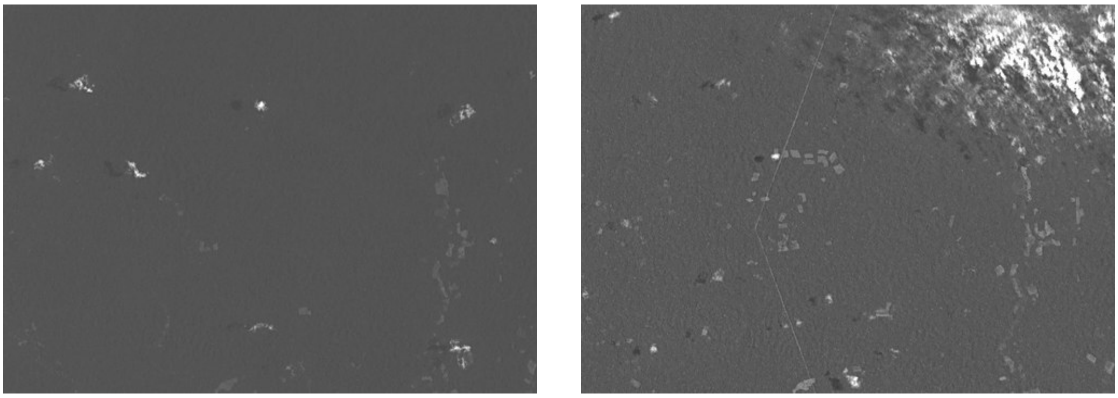


Figure 2: SAR image for Sentinel 1 covering the zone in ascending orbit



(a) Patch in 2016

(b) Patch in 2018

Figure 3: Evolution over time of the selected smaller patch (Sentinel-2 images)

2.2 Data Extraction

In order to get the data that we needed, we used the PEPs API to download SAR images from Sentinel-1 over the time period that interested us and over the geographic area of interest. We acquired the images in interferometric wideswath (IW) mode and while after 2016 we could only download data with VV+VH polarization, we used only VV in our processing.

After downloading all the images that we needed (around 400GB), we had to process them. To do that we used S1tiling from the Orfeo Toolbox to tile the different images. In fact, when the satellite flies above the geographical tile, it does not do so from east to west nor from north to south but diagonally, hence it captures the data as shown below :

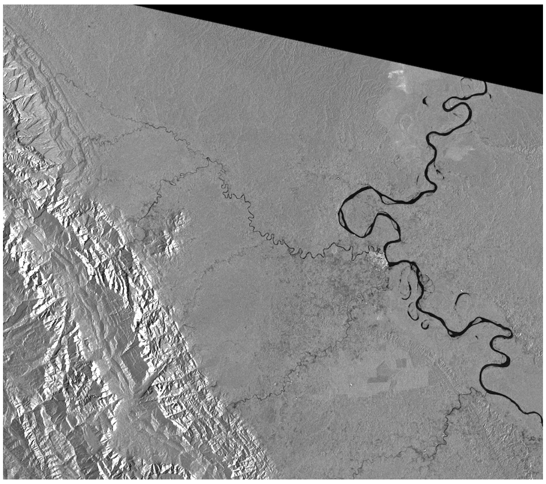


Figure 4: Partial image

So it is needed to use multiple images to fill each tile and get a full image.

2.3 Data Processing

Then, S1tiling uses the calibration metadata from each image to get γ and remove the thermal noise. Afterwards, S1Tiling use a Digital Elevation Model (DEM) from Shuttle Radar Topography Mission at 30m resolution to compensate for the difference of backscattered power due to the orientation of the terrain. This gave us an equivalent number of looks (ENL) of 4.4. Multi-looking could have been used, but given the scope of our project, we did not do it.

3 Method

In this Section, we shall motivate and present the method developed in [1].

3.1 Shadowing effect

As mentioned in the Introduction, SAR imaging can operate in all weather conditions, at any time, day or night, with or without clouds. But we still need to identify how to detect deforestation. The authors explain that this is possible thanks to the *shadowing effect*. The core idea is that a deforested patch can be spotted by looking at shadows at its edges. It is an artefact created due to the geometry of the SAR system. In a forest, if trees are being cut-out, due to their height, the electromagnetic wave of the SAR system will not be able to reach the ground at the border, as can be seen in Figure 5. Therefore, when trees are cut-out, a shadow appears or disappears depending on the orbit (ascending, descending), the orientation and the configuration (patch inside a forest, at the edge of a forest or isolated). Figure 6 is a good illustration of the various configurations that can happened.

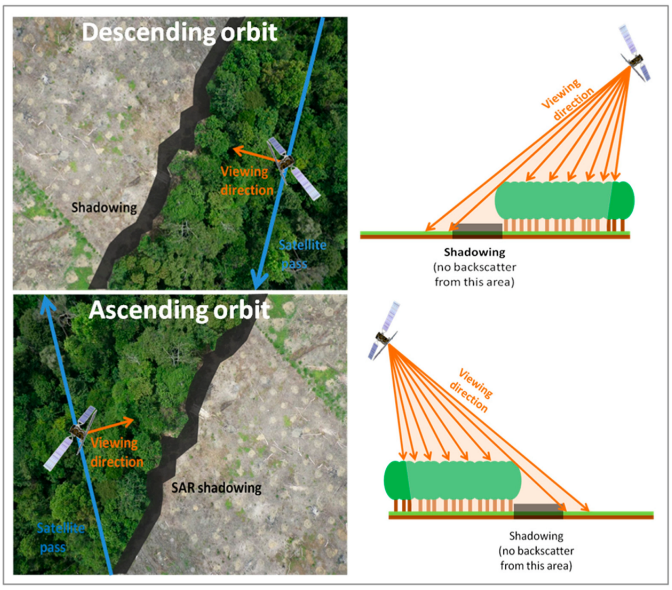


Figure 5: Illustration of the shadowing effect; extracted from the paper

The next step is to find a way to characterize the apparition of a shadow. The authors show that when a shadow appears, we observe a sudden decrease in the back-scattered signal, which is expected to be persistent over time. Therefore

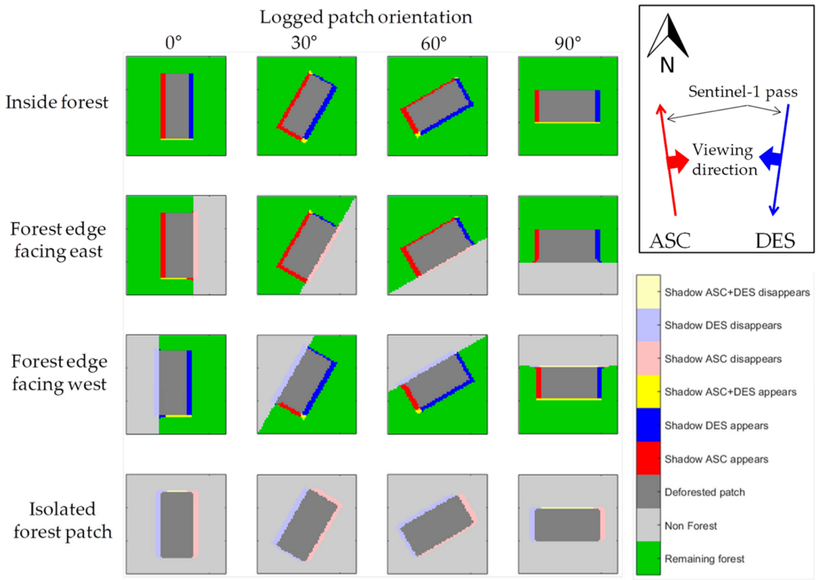


Figure 6: Possible configurations; extracted from the paper

when a patch gets deforested, we expect to see a drop in γ_0 at the border of this patch; and a small drop in γ_0 and then a gradual return to its original level inside the patch (because of the regrowth or construction happening inside the patch). This behavior is well summarized in Figure 7. In red, we have the average back-scattered signal over pixels in a shadow (i.e. at one of the borders of the deforested patch), we can see a clear drop in γ_0 happening in November 2015. The low value reached is persistent of time. While in black, we have the average back-scattered signal over pixels inside the deforested patch. When the deforestation happens, γ_0 slightly decreases before going back to its pre-disturbance value. Using this observation, we can define a mathematical tool to automatically detect the appearance of disappearance of a shadow.

3.2 Shadow detection

In [1] the authors introduce the *Radar Change Ratio* (RCR). It is a ratio between the post and pre disturbance averaged backscatter and can be used to automatically detect a sudden drop in the back-scattered signal. The reason behind the choice of a ratio over multiple dates is that a two-date ratio is more sensitive to the speckle in the image and does not ensure that the change in γ_0 stays persistent over time.

Let γ_i be the back-scattered signal of a pixel at date d_i. The changes in

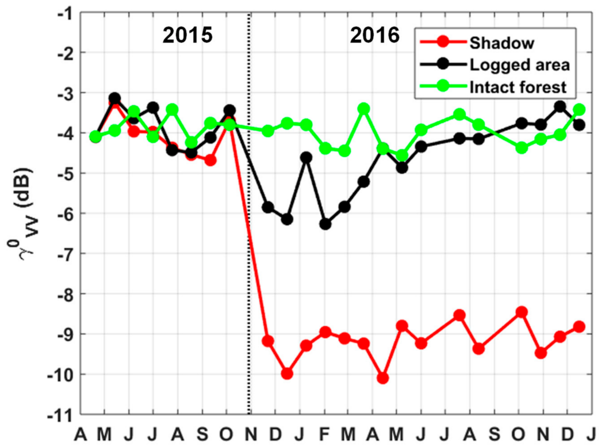


Figure 7: Expected behavior of γ_0 around a deforested patch; extracted from the paper

backscatter between dates d_i and d_{i+1} can be measured as:

$$RCR_i = \frac{M_a}{M_b} \tag{1}$$

where:

$$M_b = \frac{1}{X_b} \sum_{j=i-X_b+1}^{i} \gamma_j \text{ and } M_a = \frac{1}{X_a} \sum_{j=i+1}^{i+X_a} \gamma_j \tag{2}$$

X_b is the number of images to take into account before date d_i and X_a is the number of images to take into account after date d_{i+1}. As such, the RCR can be seen as an averaged derivative of γ_0. In order to choose the values of X_a and X_b there are several ideas to keep in mind. First, the higher the number of images we consider (i.e. the higher X_a and X_b), the lower the speckle effect and the lower the number of outliers. However, if we require too much images to compute the RCR, we cannot perform deforestation detection in NRT. Indeed, we would need X_a images "in the future", hence delaying detection. This implies that X_a must not be too big. As the authors did, we chose $X_a = 3$. Regarding the choice of X_b, in theory it can be as large as one wants and the larger it is, the more robust is the RCR to seasonal changes and environmental effects (which affects γ_0). Following the choice of the authors, we took $X_b = 5$.

In Section 4 we present the results we got with our method. Before showing

the results, there is another step needed to fully exploit the RCR in shadow detection.
Say that we are now focusing a on single pixel, we shall consider the stack of Sentinel-1 images and hence obtain a time series for that pixel, representing its evolution through time. At each point in time, we consider the whole stack of images we have (with, in our setting, 3 images post date d_i and 5 images pre date d_i). A shadow is said to be detected if:

$$\min RCR_i < \lambda \text{ dB} \tag{3}$$

where λ is a chosen threshold and i is the date index. The former is to be chosen depending on the polarization (VV, VH or VV+VH), the local incidence angle θ and characteristics of the area under scrutiny. Following the guidelines of the authors, we chose to take $\lambda = -4.5$ dB. We applied this threshold on the whole RCR time series to detect pixels which might have been inside a shadow. As explained in Section 2, we chose to work with images with only VV polarization before 12/2016 and VV+VH afterwards (after having discussed it with our supervisors and due to availability constraints). Note that the authors pointed out that there was not much difference between the various polarization, they had similar performances.

Formally, we create an "image" where each pixel's value correspond to its minimum RCR over the time series. Then we apply a simple mask to get pixels for which their minimum is lower than -4.5 dB. The resulting image displays the shadows that were detected and these shadows are supposed to represent edges of deforested patches. From that resulting image, we could see an important number of outliers (especially in ascending orbit because we had more images). These were filtered out using sieving i.e. by keeping only segments of more than 16 consecutive pixels (at a 10 meters pixel size). Our first choice of implementation was to consider, for a given pixel, one pixel at the top, one pixel at the bottom, one at the left, one at the right and the 4 diagonal ones. However, after comparing the results on several deforested patches, there were still too many outliers. This is because in that case we were considering shadows that were "too big" and not only representing borders of deforested patches. Hence we decided not to take into account the pixels in diagonal. The results, again when compared on various deforested patches, were better and we could clearly see the correspondences between the right edges and the ground truth patches (found thanks to optical images such as the one in Figure 3). For images in descending orbit, we kept the same threshold of 16 consecutive pixels, but since we have less images than in the ascending orbit (less available images on PEPS for unknown reasons), there is less noise/speckle affecting the RCR.

Now that we have obtained two images, one for ascending orbit and one for descending orbit, which give us the shadows we detected i.e. the edges of the deforested patches, we must then devise an algorithm to match them and finally reconstruct the deforested patches.

3.3 Reconstruction of deforested patches

In order to recover the size and shape of the patches that are deforested, we used the fact that the viewing angle is not the same depending on the orbits. For the ascending orbit (resp. descending) the satellite is looking from west to east (resp. east to west). Thus, with each orbit, we get a different side of the patches, as seen in Figure 6.

We then get the outline of each patches and we just need to take the convex hull of each sets of detected pixels to recover the whole size and shape. It is useful to note that for a given patch we will always detect its west side using the ascending orbit and east side with the descending one.

4 Results

This Section represents the results we got on a particular area of the smaller patch we considered (Figure 3). On this area, one can distinguish both deforested and intact patches as well as a road at the center (see Figure 8 for the corresponding optical image).

Figure 8: Considered patch in 2018; source: Google Maps.

4.1 Shadow detection

As per described in Section 3, the first step towards detecting a shadow is looking at the evolution of the back-scattered signal of each pixel in order to compute the RCR. In Figure 9, you can see the averaged temporal variation of γ_0 over a small number of pixels which are located at the border of a deforested patch. Starting in June-July 2017, there is a sharp decrease in the back-scattered signal. The new lower level of γ_0 reached is then maintained over several months. This is the excepted behavior when a shadow appears. The red dash is the average M_b (5 images before) and the green one is M_a (3 images after). Thanks to these two quantities we can compute the RCR at date July 2017, which is represented by the black dash. The RCR can indeed be seen as an average derivative, quantifying the drop.

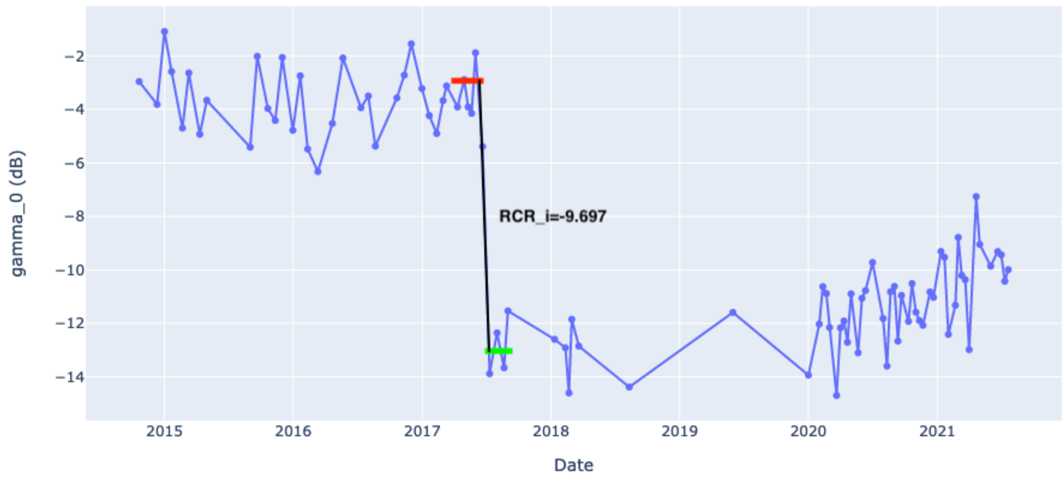


Figure 9: Temporal variation of γ_0 at the border of a deforested patch

Recall Figure 7 extracted from the paper, we replicated it over our own dataset in Figure 10. For the deforested patch under scrutiny, we have a large sudden decrease in the back-scattered signal when the shadow appears (blue line), the decrease remains persistent over time. Inside the patch (red line), there is a slight decrease in γ_0 before it gradually goes back to its original value. Finally, the evolution of γ_0 of pixels over an intact patch remains stable over time.

The next step is to compute the corresponding RCR over the whole timeline, this can be seen in Figure 11. We can see the peak in July 2017; it is the date at which the minimum RCR is reached for that bunch of pixels. To simplify, one can consider that this is the RCR of a single pixel. Once the minimum of -9.6 dB is reached, the RCR goes back to its original level (pre-disturbance). Again, this is as expected and described by the authors in [1].

Since $\min RCR_i = -9.6 < -4.5$ dB for i = 07/2017, the algorithm will select this pixel to have been inside a shadow at date i. It will tell us that in this pixel there was a shadow which appeared in July 2017. What is left is to run the algorithm over all pixels in the considered patch. Results are displayed in Figure 12.

If a pixel is in color a shadow was detected, if not, no shadow have been detected over the period we considered. Clearly there are more outliers in ascending orbit. This is partly due to the fact that we have less available images in descending orbit. This is also due to the fact that we did not apply major

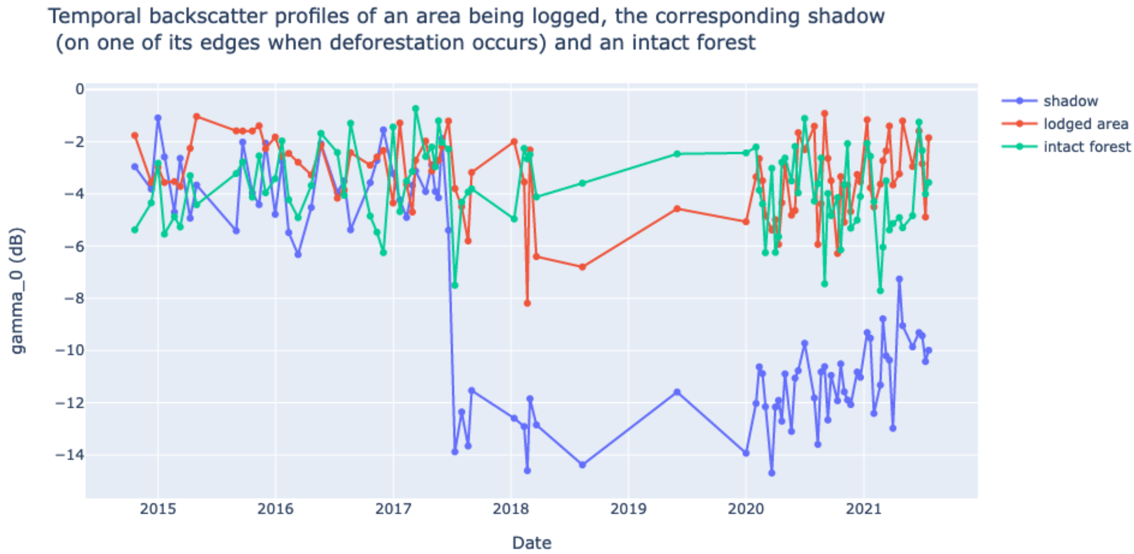


Figure 10: Behavior of the temporal back-scattered signal on our 4x3 patch in ascending orbit

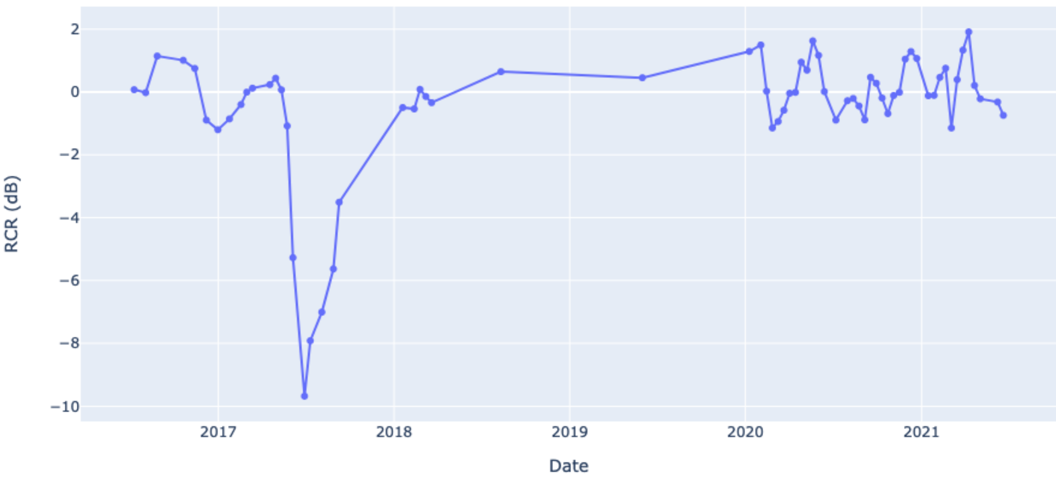
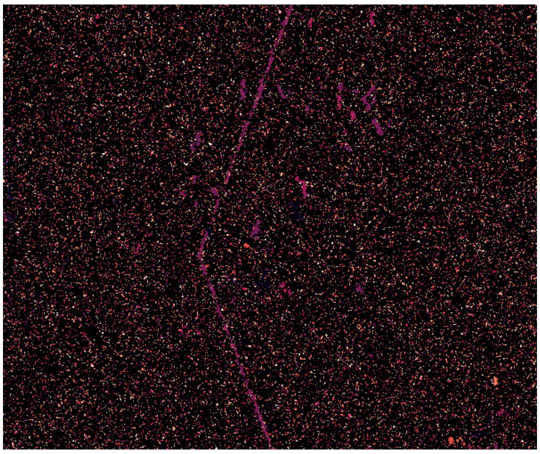


Figure 11: Corresponding temporal variation of the Radar Change Ratio

denoising techniques (note that the RCR can already be seen as a sort of denoising technique since we average multiple images) such as SAR2SAR [2] or multi-looking (as seen during the lectures). To filter outliers we empirically chose a threshold of 16 consecutive pixels. In the paper, the authors chose 4 but their final


(a) Ascending orbit

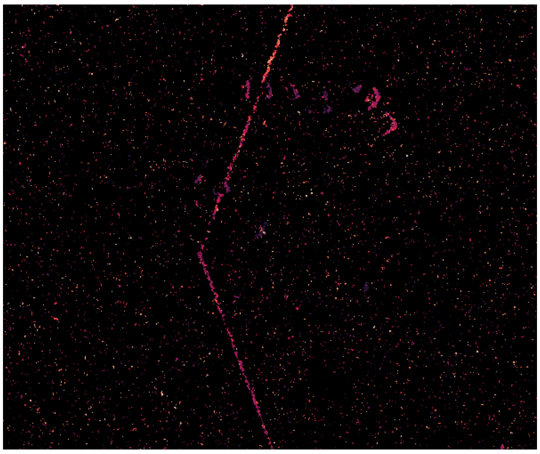
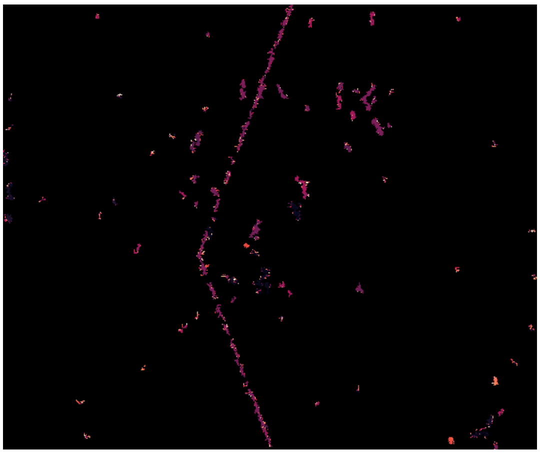

(b) Descending orbit

Figure 12: Detected shadows (in color) before sieving.

Equivalent Number of Looks is 27.4 (ours is 4.4). They applied a multi-image filter to decrease the speckle effect while preserving the spatial resolution.
Once sieving has been done, we get the following images (Figure 13). There are much more cleaner and one can recognized the two opposite sides of each deforested patches, which we will use to reconstruct them.


(a) Ascending orbit

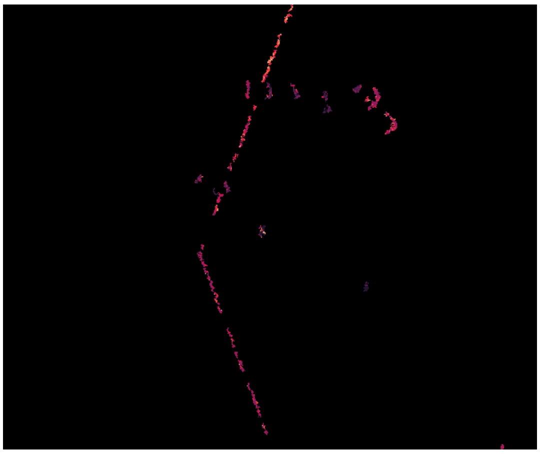

(b) Descending orbit

Figure 13: Detected shadows (in color) after sieving.

4.2 Reconstruction of deforested patches

Using the information above and the data from both orbits we get :

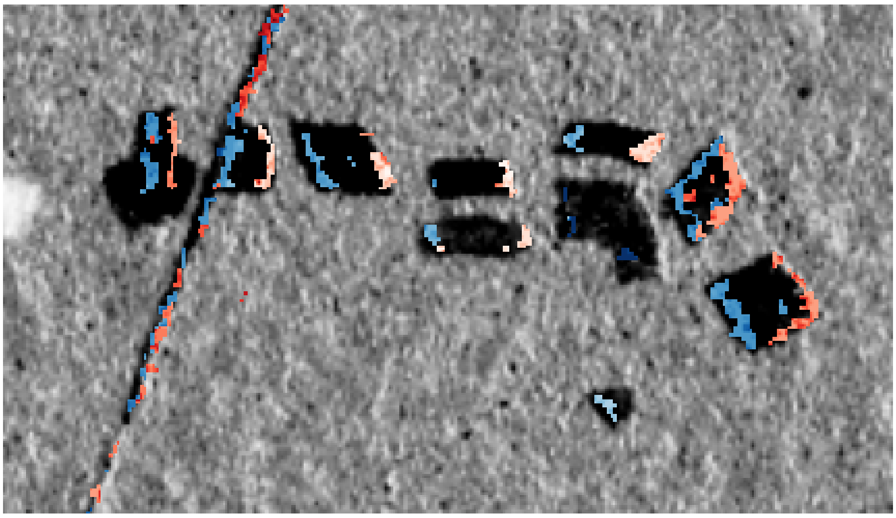


Figure 14: Shadow detected from each orbits (blue - ascending, red - descending)

It is clear, that using this information, we can recover the different patches by associating one blue cluster with a red one, and taking the convex hull of all these pixels.

Other possibilities can be used and we implemented a fast and simple algorithm which give the following results :

Figure 15: Reconstructed patches

The idea behind the algorithm which gave the result above is to go through each line and every time we get a detection from the ascending orbit on a pixel p, we check if we have a detection on p' from the descending orbit in the line of a predefined length (let's say 10 pixels for instance) on the left of p. If we have, we color the output image from p to p'. As there is still noise in our data and detection algorithm, some artefacts may appear but we recover the position and the rough shape of the deforested patches. It is also very fast.

In [1], the authors proposed an improvement on the previous method. By using the slight decrease of the logged areas in γ around the time of deforestation, they applied a higher threshold of $-3dB$ for the detection and used it to fuse the different shadows :

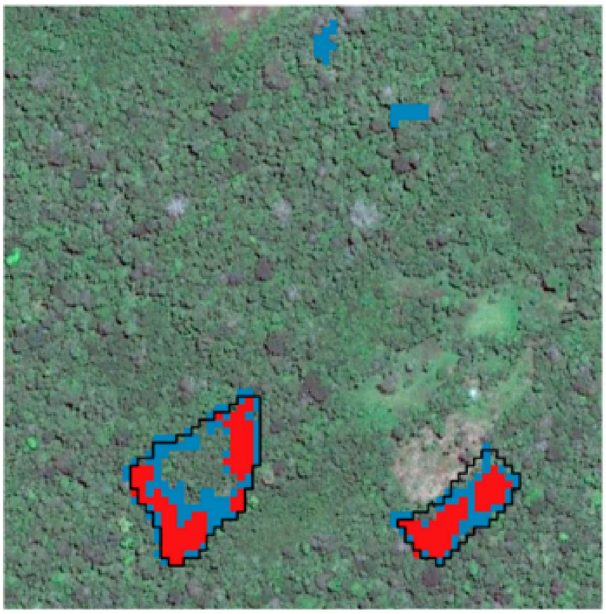


Figure 16: In red is the shadows, in blue the pixels matched by the $-3dB$ threshold

As you can see above, it is then possible to group the shadows from each side of the patches by merging them if they touch the same blue patch, then taking the boundary of all the pixels by using a convex hull function is easy. We were not able to use this method because our data was too noisy and we could not find a relevant threshold. The difference with the authors data is our lower ENL which could have hindered us.

5 To go further

The method developed in the studied paper is meant to provide an alternative to NRT monitoring of forests through optical images. Even though we were not able to evaluate it quantitatively (lack of ground truth), this method seems to perform quite well qualitatively (as we showed with our study case). However we believe that it could be improved throughout several ideas. The first one implies a discussion over the choice of some parameters.

As the authors pointed out, the thresholds applied on the minimum RCR and the potentially deforested areas, namely -4.5 dB and -3 dB, were chosen empirically. They tested several values and found out that these were the best for the area under scrutiny. However as these thresholds depend on the polarization, the local incidence angle θ and characteristics of the area, they need to be tuned manually for each area. This is time consuming. It would be great to have an automatic means of computing them. A way to do so would be to use statistics derived from reference samples. For instance, the RCR could be approximated by an intensity ratio (as, again, it can be seen as an averaged derivative of the back-scattered signal).

Regarding the orbits, in our experiments we used both in order to reconstruct the deforested patches as it appeared to be the most robust way to do so. Indeed, when we have both sides of the detected deforested patches, the false positive rate is decreased and the matching easier. In configurations where one does not have access to both orbits, special care should be given to disappearing shadows to help with the detection of deforested patches' edges.

A shortcoming of our experiments is the lack of denoising/despeckling methods applied before computing the RCR. In order to improve detection rate, the algorithm could benefit from using multi-looking filtering or deep-learning based methods such as SAR2SAR [2] to reduce the strong radiometric noise characteristic of SAR imaging. Note that the sensitivity to geometric distortions (lateral viewing and high incidence angle) have already been taken into account during the calibration and ortho-rectification with a DEM process. By decreasing the speckle in the images, we could consider using less images before and after the date d_i when computing the RCR.

The key point is reducing X_a (fixed at 3 in our experiments) in order to apply the method in NRT applications. The lower X_a, the more this method is suited for NRT monitoring. But the lower X_a, the higher the false positive rate due to the presence of more speckle. By using a despeckling method beforehand, one might be able to reduce X_a.

Finally, one could want to combine both SAR and optical images. We could imagine a system where SAR imaging is used as a baseline, always available and operational (all weather and time conditions sensors), whose results are being backed by classical optical imaging tools (e.g. computation of temporal changes in NDVI).

6 Conclusion

In this project we implemented the algorithm proposed by Bouvet et al. in [1]. This method aims at detecting deforestation through the use of SAR imagining. The latter is very useful since it works regardless of the weather conditions and the time of day. The method builds on the geometric properties induced by SAR acquisition system, namely that when a part of the ground is not reached by the electromagnetic wave, the signal is not back-scattered and hence a shadow appears on the final SAR image. It also heavily builds on the accessibility to NRT SAR images in both ascending and descending orbits at a high temporal rate (6 to 12 days). The algorithm qualitatively works well and is quite fast (modulo the size of the images being handled). We tested it on a smaller area than the one chosen in the paper and were able to detect deforested patches in between 2016 and 2018.

References

[1] Alexandre BOUVET, Stéphane MERMOZ, Marie BALLÈRE, Thierry KOLECK et Thuy LE TOAN : Use of the sar shadowing effect for deforestation detection with sentinel-1 time series. *Remote Sensing*, 10(8), 2018.

[2] Emanuele DALSASSO, Loic DENIS et Florence TUPIN : SAR2sar: A semi-supervised despeckling algorithm for SAR images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14:4321–4329, 2021.