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Forest Dynamics with Sentinel 2 in Antanambe between 2005 and 2016 with the Snap Tool

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Abstract

In order to protect and sustainably manage the forest in Madagascar, which is currently one of the countries still covered by forests, it is essential to use technological advances, particularly with regard to remote sensing. It provides valuable data, and sometimes free with a wide range of spatial, spectral and temporal resolutions to meet the demands for information on forest resources that are increasingly numerous and requires ever increasing levels of accuracy. The present work presents a methodology for the analysis of forest dynamics in the Antanambe area for the period 2005-2016 for monitoring forest degradation in this forest area to be conserved. The Random Forest algorithm was used to classify a Sentinel 2 image collected on November 07, 2016 and compare with a classification result with LandSat 5 in 2005 to detect change. The per-pixel change detection of both results captured the change map to better interpret the situation.

Keywords

Random Forest, Detection Change, Remote Sensing, Forest, Madagascar

1. Introduction

The demands for information on forest ecosystems are increasing and require ever increasing levels of precision. This calls for technological advances, especially in mapping and remote sensing means (diversity and specificity of sensors and platforms) provide valuable, and sometimes free, data for a wide range of spatial, spectral and temporal resolutions [1]. There are several research works that are concerned with forest dynamics in Madagascar such as the works of [2] [3] [4] [5]. In 2007, the analysis of forest cover evolution in Madagascar is done by processing Landsat satellite images that cover the period 1990-2000-2005. This analysis gives for 1990, an area significantly less than 10.7 million hectares (RPP, 2014). This difference can relatively be identified by the fact that the 2007 analysis used a more strict determination of forest. This study estimates the total forest area to be about 9,990,000 hectares in 2000 and about 9,725,000 hectares in 2005, which means an annual deforestation rate of 0.83% for the period 1990-2000 and 0.53% between 2000 and 2005 [6]. However, this study presents an analysis of forest dynamics in the Mananara Nord Madagascar area for the period 2005-2016 with the Random Forest (RF) classification algorithm. Several studies have used and highlighted the effectiveness of the RF algorithm among existing algorithms. Based on the accuracy evaluation and visual interpretation of the resulting maps, Schneider (2012) claimed that RF is more effective than the maximum likelihood classifier and support vector machine classification. In this study, a Sentinel-2 image acquired on November 07, 2016 was used and compared to a classification result of the LandSat image in 2005 [7]. The results represent the statistics and mapping of the dynamics of the forests of Mananara Nord between 2005 and 2016.

2. Materials and Methods

2.1. Study Area

The Mananara Nord National Park is located in the northeastern part of Madagascar. More precisely, this area is located in the district of Mananara Nord and the region of Analanjorofo. Its geographical coordinates are oriented between latitude 16˚10'00" and longitude 49˚46'00". This part presents tropical rainforests. We simulated a sample on a part of this zone which the commune of Antanambe (**Figure 1**).

2.2. Presentation of the Data

A Sentinel-2 image is used that was acquired on November 07, 2016. The Sentinel-2 image comes directly from the European Space Agency (ESA) download site or more precisely in https://scihub.copernicus.eu.

The Sentinel-2 satellite is launched as part of the European Union's Copernicus program which is equipped with the MSI sensor, it consists of two satellites, Sentinel-2A and Sentinel-2B: the first was launched in June 2015 and the second in March 2016. Each of these satellites provides all-land observation every 5 days, 10 m to 60 m resolution. The MSI sensor will provide 13 spectral bands from visible to mid-infrared illustrated in **Table 1**.

In 2014, inventory work was carried out in Madagascar by [7] on forest stratification. Landsat 5 images are used for the year 2005. A classification result from this work was used in the study.

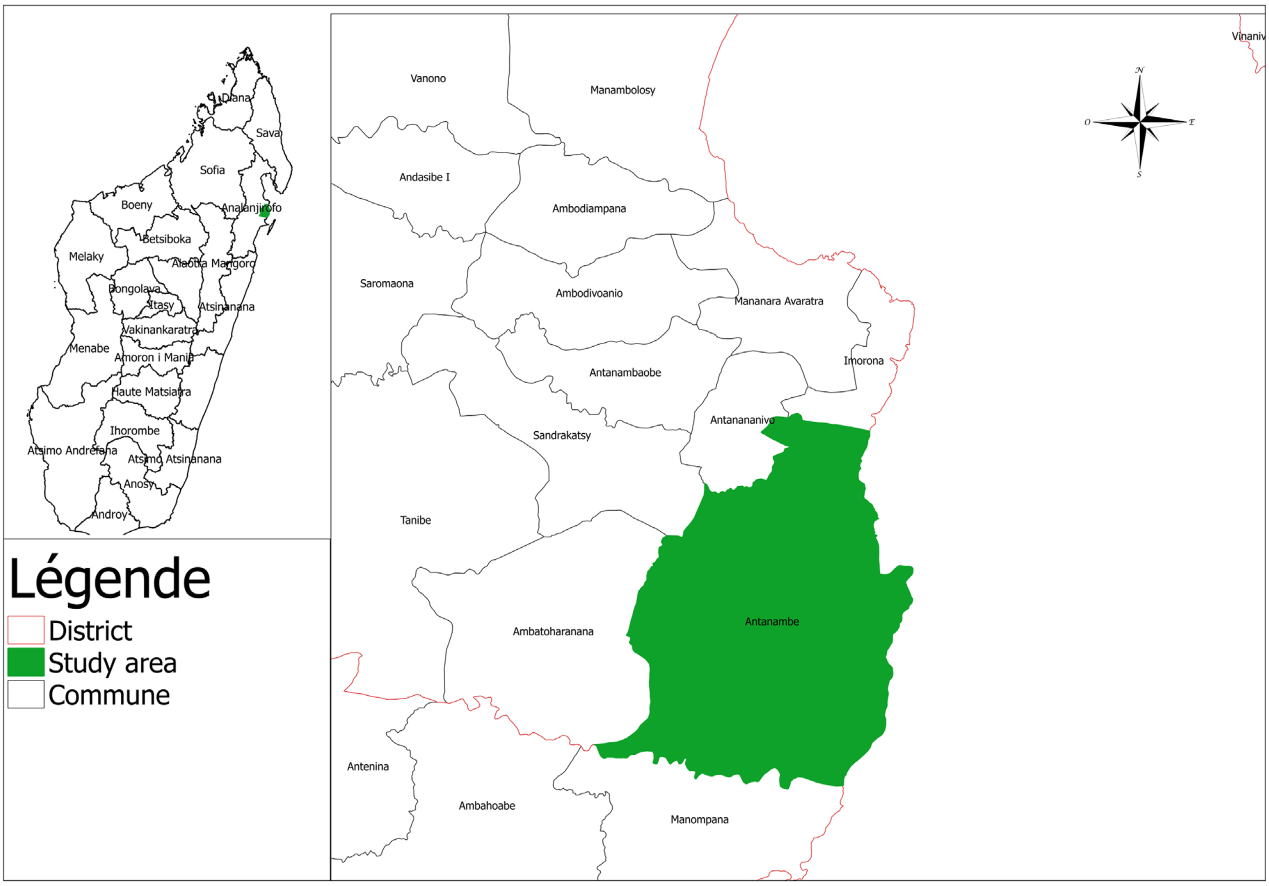

Figure 1. Study area.

Table 1. Sentinel-2 bands.

Bands	Resolution (m)	wavelength (nm)	Width of the bands (nm)
B1	60	443	20
B2	10	490	65
B3	10	560	35
B4	10	665	30
B5	20	705	15
B6	20	740	15
B7	20	783	20
B8	10	842	115
B8A	20	865	20
B9	60	945	20
B10	60	1375	30
B11	20	1610	90
B12	20	2190	180

2.3. Tool

SNAP (Sentinel Application Platform) is an ESA product specifically for processing Sentinel images. SNAP contains Sentinel toolkits with common architectures developed by Brockmann Consult, SkyWatch and CS. SNAP is an open-source solution with a number of toolboxes and plugins.

2.4. Methodology

The Sentinel-2 image that we acquired is at pre-processing level 2a, *i.e.* it is no longer necessary to make the radiometric and geometric correction. We continue the pre-processing by combining the mono-spectral bands into a single multi-spectral band because when downloading Sentinel-2 images to the ESA site, the images are still separated into channels, so we need a transformation to obtain a multi-spectral image. Then, we cut the study area in order to minimize the processing time.

The NDVI thresholding technique is used for a pre-classification to discriminate vegetation to other land cover types [8]. NDVI values can range from −1 and 1. Higher values of the index correspond to the presence of dense and healthy vegetation cover. They are generally between 0.1 and 0.7 while clouds and snow result in NDVI values close to 0 [9].

The supervised classification [10] was used to determine the forest cover of the study area. We implemented the existing Random forest algorithm in the SNAP tool which is particularly effective in identifying relationships between a variable to be explained and explanatory variables [11].

To wait for the objective, we performed change detection between the 2016 classified Sentinel-2 image and the 2005 classification result from LandSat 5 [12] [13] [14]. The methodology is illustrated in **Figure 2**.

3. Results and Discussions

3.1. Vegetation Index NDVI

We have here a pre-classification result after the NDVI calculation. This index uses the near infrared band (PIR) and the red band (R) of the satellite image. In the case of Sentinel-2 images, the PIR is the eighth band and the R is the fourth band.

$$\mathrm{NDVI} = (PIR - R)/(PIR + R) \tag{1}$$

By applying Equation (1), we have the result presented in **Figure 3** where the higher values of the index correspond to the presence of a dense and healthy vegetation cover.

3.2. Random Forest

Supervised classification is used using the Random forest algorithm. It is a classification algorithm based on parallel learning on multiple decision trees that improves prediction accuracy [11]. After integrating the field validation points, the SNAP tool gave the confusion matrix presented in the **Table 2** below, which deduces an acceptable Kappa index of 94, 8863%. The result is presented in two classes (forest and non-forest) in **Figure 4**.

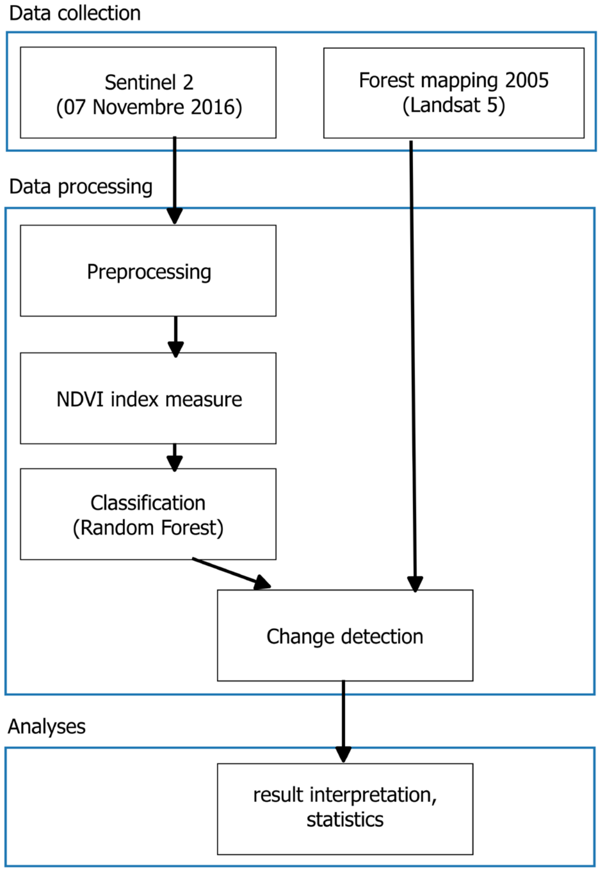

Figure 2. Methodology.

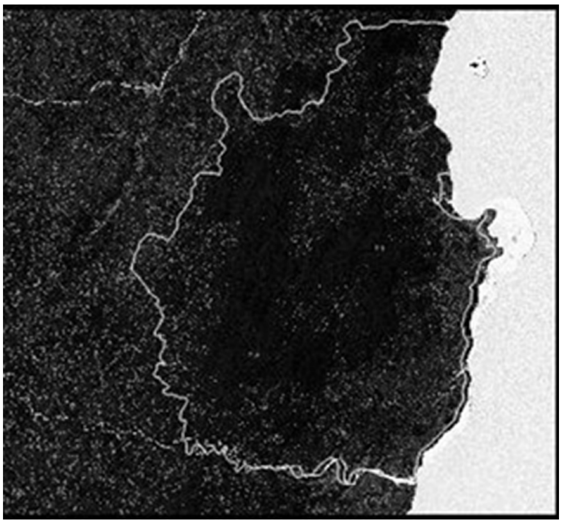

Figure 3. NDVI result.

Table 2. Confusion matrix.

Classes	Forest	No forest	Production accuracy
Forest	99.31	1.76	60.38
No forest	0.69	98.24	39.62

3.3. Change Detection

Change detection consists in comparing the classification in 2005 with Landsat 5 and the classification in 2016 with Sentinel 2 (**Figure 5**).

The transition matrix (**Table 3**) represents the percentage change in pixels for the two classes (Forest and No-Forest) between the two dates of 2005 and 2016.

According to the table, 70.044% of the forests classes and 75.652% of the no-forests classes remain stable the two dates of 2005 and 2016. During this 11-year period, the analysis shows a significant deforestation (Forest → Non-Forest) of 29.956% but also regeneration (Non-Forest → Forest) of 24.348%. The result is presented in **Figure 6**.

In terms of area, 16,687 ha of forest has been lost in 11 years. This means that there is a significant deforestation between two dates 2005 and 2016 (**Table 4**).

According to the Strategic Environmental and Social Assessment of Madagascar's REDD+ program, the annual deforestation rate for the rainforest ecoregion

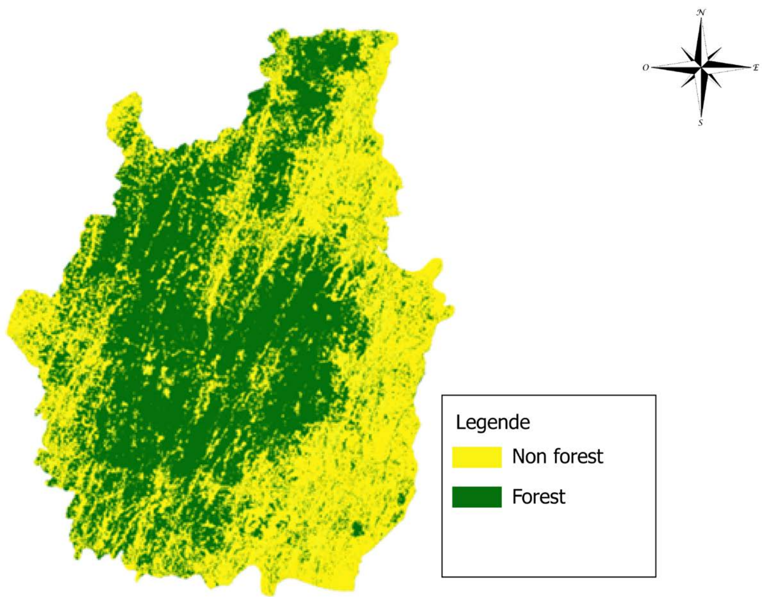

Figure 4. Classification with Random Forest.

Table 3. Transition matrix.

Percentage of pixels per class		Initial state (2005)	
		Forest	No forest
Final state	Forest	73.044%	24.348%
(2016)	No forest	26.956%	75.652%

Table 4. Surface changed.

Areas (Ha)		
Forest	63,071.2	46,383.3694
No forest	1288.1636	17,975.9942

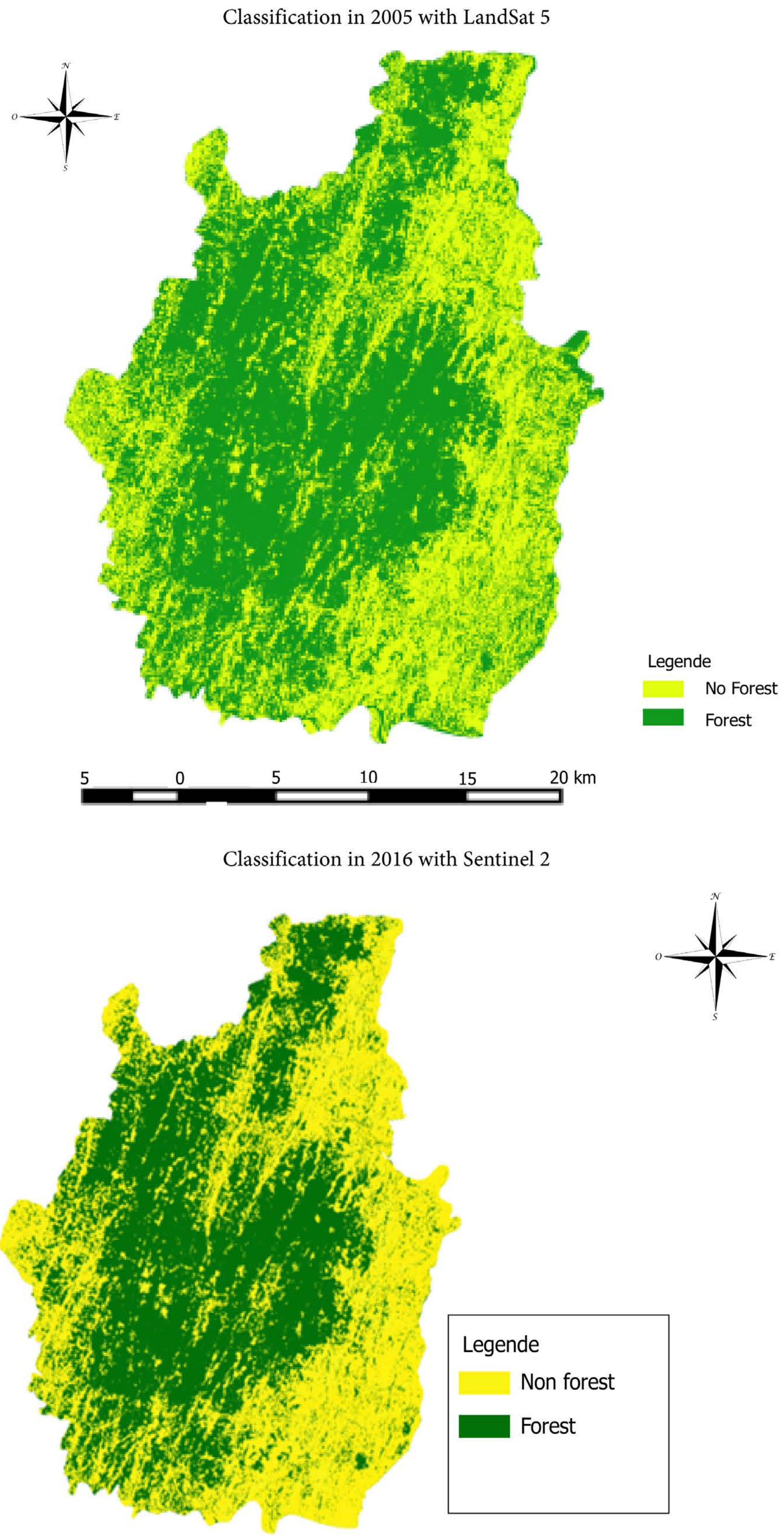

Figure 5. Classification results.

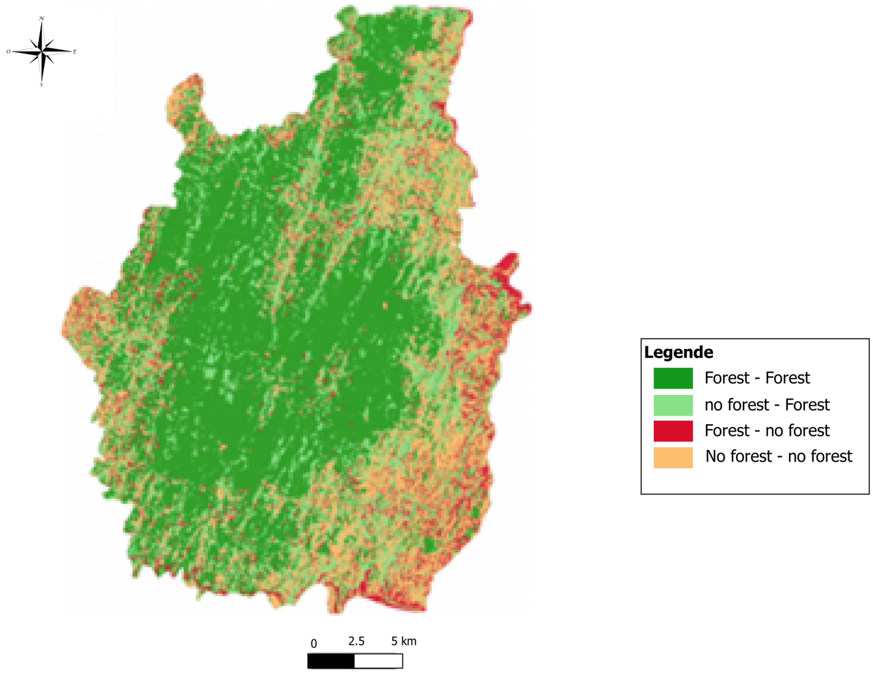

Figure 6. Change map.

in Madagascar is 0.94% per year for the period 2010-2013. The Analanjorofo region is found among the regions with the highest annual deforestation rate. In terms of area, the Analanjorofo region lost 24,000 ha of forest for the period 2010-2013. Surveys conducted by ONE in 2016 were able to group four root causes of deforestation and forest degradation: The weakness of governance and institutions, the non-rational use of forest resources and forest areas, the weak coordination of the development of rural areas to the detriment of forests and the rural poverty and the lack of alternatives development alternatives.

4. Conclusion and Perspectives

In this experience, we retain the technique of monitoring deforestation by remote sensing. This computerized solution is a facilitating means for experts in the field of environmental management that offers interesting results generally without direct contact to all the studied covers. We performed a supervised classification of a part of the National Park of Mananara Nord, in the commune of Antanambe by the satellite image Sentinel 2 acquired in 2016. This result is compared to a LandSat 5 classification in 2005 to detect the change between these two dates. The analysis shows the existence of more deforestation than generation in the study area. Deforestation monitoring mobilizes many entities in Madagascar. The results play a very important role for decision making in the field of environmental conservation in Madagascar. For this, the discussion is open for the capitalization of the experience in the form of knowledge that can be reused in another study area or other input data. The technique is applicable to a wider coverage such as the whole of Madagascar by inserting task automation (workflow) and parallel processing in the distributed system (cloud computing, grid computing) in order to optimize processing time.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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