Remote Sensing Time Series Database for Deforestation Detection*

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Abstract. We present a database containing Native Forest and Deforested remote sensing time series for the Argentine Chaco Forest for the period 2000 - 2020. Deforested time series have the deforestation date indicated with a monthly resolution between 2002 - 2016. This database was created with a near real-time deforestation detection task in mind. We show that this database is appropriate for that purpose, and later we explore other applications.

Keywords: Deforestation · Time Series · Remote Sensing.

1 Introduction

The Gran Chaco is the second-largest Forest in South America. In the last two decades, this forest has experienced an intense process of deforestation, being one of the most affected areas on the planet [1, 2]. The Argentine Chaco Forest represents 62% of the Gran Chaco; the most recent report indicates a deforestation rate of 125.000 ha/year for the period 2016 - 2019 [6]. Consequences are multiple and diverse: loss of biodiversity and of ecosystem services such as carbon sequestration and storage, water provision, loss of indigenous culture and the maintenance of human health [3–5]. This process is a clear example of deforestation driven by agribusiness expansion [7], soybean being the proximate driver in the Argentine Chaco [8].

At the end of 2007 the Argentina Congress approved the Federal Law 26331/ 2007 (The Forest Law). The Forest Law requires each province to approve in a participated way (i.e., by involving local and indigenous communities) a set of Territorial Regulation of Native Forests (Ordenamento Territorial Bosques Nativos, OTBN) within one year. No deforestation can be authorized unless such OTBN has been approved. Furthermore, Argentina is part of the ONU-REDD Programme (The United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation) from 2010 and from 2015 is also part of the REDD+ program (reducing emissions from deforestation and forest

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degradation in developing countries, and the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries).

In the frame of the Forest Law and REDD+, it is essential to monitor deforestation in Native Forests in a timely manner. Given the geographical extension of the region involved, one appropriate approach is the use of Remote Sensing methods, focusing on automatic techniques. But the development of algorithms for near-real time deforestation detection cannot be carried out without a database specifying *when* and *where* deforestation occurred in the past. These data should be used:

1. As a training set for the development of algorithms under the Supervised Learning paradigm.
2. To evaluate the performance of the algorithms developed, under the Supervised Learning paradigm or any other paradigm.

For these purposes, it was necessary to build that database. In general, both the spatial scope and the plausibility of these algorithms will depend on the geographical representativeness, quality and quantity of data available, so the total number of data required is usually large. This also implies that it is essential to obtain an accessible and systematic database.

In this manuscript, we will explain the steps implemented to construct this database. It consists of a group of time series of the MODIS MOD13Q1 product, corresponding to Native Forest pixels and Deforested pixels with a known deforestation date in the period 2002 - 2016. As an intermediate product, a layer with geolocated information in vector format (GIS) was also created. This layer contains information of deforestation dates at monthly resolution.

2 Study Area

The Gran Chaco is a geographical region located mainly in the territories of Argentina, Paraguay and Bolivia, and a small part of Brazil. The Argentine part of the Gran Chaco covers an approximate area of 620,000 km^2, making it the largest forest of the country. The Argentine Chaco can be divided into two large ecoregions, the Dry Chaco and the Humid Chaco. The Dry Chaco, in turn, can be divided in the Semiarid, Arid and Serrano Chaco.

The Semiarid, Arid and Serrano Chaco forest presents a mean annual rainfall that varies from 500 to 800 mm, which differs from the ∼1300 mm of the Humid Chaco. Precipitation and hydrological anomalies have more impact on the Humid Chaco, being the vegetation of the other areas better adapted to rainfall stress and temperature variation. The vegetation in the Arid Chaco consists of mixed xenophile forests dominated by deciduous or semi-deciduous species, and shows a stationary growth season related to the rainfall pattern [9]. The dominant vegetation is *Aspidosperma quebracho-blanco* (white quebracho) and *Schinopsis lorentzii* (red quebracho) subtropical seasonal forests. The Humid Chaco is characterised by mixed xenophile forests and the presence of wetlands, whose phenology is influenced by climatic conditions and flood pulses. Both areas are classified as open dry forest (20 % of tree crown cover) with two strata [6].

Chaco Forest is affected by both anthropogenic and non-anthropogenic forcings. The most important non-anthropogenic driver of phenology is climate change, which is disturbing both typical precipitation and temperature regimes. In particular, seasonal forests in north-western Argentina have experienced an increase in rainfall during the past decades. At the same time, a pronounced decrease in rainy days with changes in rainfall distribution patterns is observed in moist semi-deciduous forests in the north-east, which are also experiencing an increment in mean temperatures [10–12]. Finally, extensive areas are affected by cattle ranching (*puesteros*), selective logging and firewood extraction, with negative effects on the forest structure, particularly a reduction in tree aboveground biomass, and changes in species composition and subregion functioning [2, 12].

For the purpose of this analysis, we defined six Pilot Areas of similar surface (250.000 ha), based on environmental characteristics and the availability of fieldwork. Each site represents particular conditions of environmental constraints (mainly precipitation and temperature) and therefore different vegetation composition (Fig. 1). Pilot Areas A, B and C were located in the Semiarid Chaco, D in Humid Chaco, E Dry Chaco and F in Serrano Chaco forest.

It is important to note that for representing the Semiarid Chaco subregion we used three Pilot Areas (A, B and C). This is related to the fact that this is a large area both in latitude and longitude, encompassing large gradients of both precipitation and temperature. Therefore, the Pilot Areas were selected in order to capture the expected variability of forest dynamics inside this subregion.

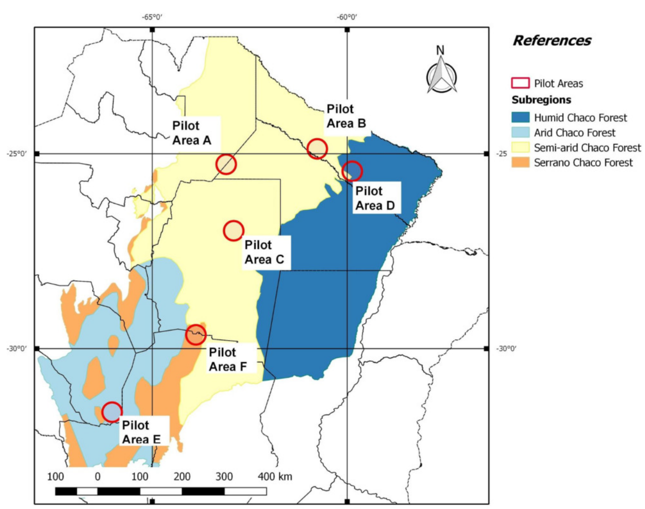

Fig. 1. Chaco Forest subregions map over Argentina and Pilot Areas.

3 Data and Methods

Our methodology consisted of 3 main steps. In Step 1, we mapped monthly deforestation in the Pilot Areas for the period 2002 - 2016, obtaining a Geographical Information System (GIS) of Monthly Deforestation. In Step 2, we describe other relevant layers that do not correspond to Native Forest, but were not included in Step 1. Finally, in step 3 we used the layers previously described to extract MODIS MOD13Q1 time series for deforested areas, Native Forest and other relevant classes.

3.1 Monthly Deforestation GIS

We mapped monthly deforestation by visual interpretation of Landsat images using Google Earth Engine (GEE), which include Landsat 7 ETM+ from 2002 to 2014 and Landsat 8 OLI/TIRS from 2013 to 2016. To minimize the effects of clouds and cloud shadows, we used a cloud score algorithm available in GEE. We then created monthly composite of Landsat images using the percentile 75 at the band and pixel level of all available images for that month.

We used as primary sources the Red Agroforestal Chaco Argentina (REDAF, [2, 13]) and Unidad de Manejo del Sistema de Evaluación Forestal (UMSEF, [14]) annual deforestation maps. Both sources characterize deforestation in the Chaco Forest using Landsat imagery for the period studied, containing geospatial vector data (*shapefiles*) with deforested regions and its corresponding year. For each deforested region present in the primary sources, we estimated the month of deforestation by visually determining the Landsat monthly composite image in which the deforestation event is first visible. If images were not available due to cloud or other reasons, the number of months with no available images before the deforestation event was registered in a *cloud* metadata field, along *month* and *year*. If a geometry primary identified with a specific year was partially transformed in several month or years, the annual geometry was divided into as many plots as clearance processes occurred. Criteria for defining plots by visual interpretation was the disruption of spatial continuity with strong evidences of human action. Transformed plots by human action are regularly shaped and have defined limits, while transformations due to natural agents (e.g. fire) are irregularly shaped.

Although some regions may have experienced multiple deforestation and regrowth regimes between 2002 and 2016, we only considered the first deforestation per region, and once labelled as deforested, we stopped monitoring it as subsequent time steps. Each individual plot was incorporated as a polygon shape into the GIS.

Once this process was finished, a post-processing stage was carried out to study the quality and internal consistency of this database. Some error correction steps were also implemented. Although a complete report of this stage is beyond the scope of this manuscript, this evaluation included: duplicated instances, missing values, valid values, positional accuracy, valid geometries, overlapping

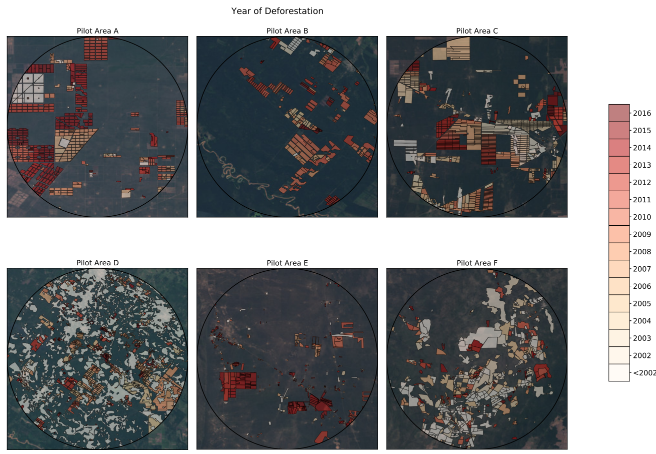

Fig. 2. Year of deforestation for each geometry present in the Monthly Deforestation GIS. The background image is a Landsat composite for January 2017.

geometries, completeness, etc. A complete report of this stage is available upon request from the authors. The resulting GIS can be seen in Fig. 2 and 3.

3.2 Other Relevant Layers

The Monthly Deforestation GIS produced in Step 1 contains information on native forest regions converted to agricultural plots in the period 2002 - 2016 at monthly temporal resolution. However, there are other regions that do not correspond to undisturbed native forest, but that are not included in this database. These are regions whose date of deforestation is not so easy to define, because of the underlying process involved in its generation, or because the area involved is negligible compared to the regions converted to agricultural use. Some examples of these areas are roads, and places with small scale logging and/or extensive farming (*puesteros*). These regions need to be considered if we want to achieve a database where Native Forest and Disturbed Forest are clearly differentiated. For that purpose, we will use two databases, the Road Network from the Instituto Geográfico Nacional (IGN, [15]), and the Land Cover Classification from UMSEF.

Road network The road network is composed of different types of roads - primary road, secondary road, rural trail, etc. It is not a static layer, as new roads are constantly being opened, particularly on active deforestation fronts. However, the area affected by these is negligible compared to the area associated

Fig. 3. Month of deforestation for each geometry present in the Monthly Deforestation GIS. In white, Road Network from the IGN database. The background image is a Landsat composite for January 2017

with agricultural plots, so it is not necessary for the purposes of this work to obtain database with the temporal evolution of the road network. However, it is necessary to consider its presence to differentiate disturbed and undisturbed native forest.

A GIS of the road network is generated by the IGN at national level, which we delimited to each Pilot Area (Fig. 3). A visual inspection showed that several paths and roads are not included in the database.

Land Cover Class Database The classification proposed by the Food and Agriculture Organization of the United Nations (FAO), through the Forest Resources Assessment to the Year 2000 (FRA 2000, [16]), adapted to the characteristics and particularities of Argentina [6], defines the following land cover classes:

- **Forest**: Lands that constitute a natural ecosystem that present a tree cover of native species greater than or equal to 20% with trees that reach a minimum height of seven meters.
- **Other wooded land**: Lands that constitute a natural ecosystem with a tree cover of native species between 5 and 20 % with trees that reach a minimum height of 7 meters; or with a tree cover of native species greater than or equal to 20 % where the trees are less than seven meters high; or that present at least 20 % shrub cover of native species with shrubs with a minimum height of half a meter. Palm groves and reed beds are included.

– **Other land**: Land not classified as forest or other wooded land as defined above. Includes agricultural land, meadows and pastures, built-on areas, barren land, water bodies, etc.

Deforestation is usually reported over Forest Lands and Other Wooded Lands by the UMSEF. This implies that, *a priori*, both classes can be combined to represent Native Forest. We used a 2006 UMSEF Land Cover Class GIS to differentiate each land cover class in each Pilot Area.

3.3 MODIS MOD13Q1 Time Series

The Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1) data are generated every 16 days at 250 meter spatial resolution [17]. For the area under study, we used tiles h12v11 and h12v12. Each tile covers an area of approximately 1200x1200 km, or 4800x4800 pixels. They are easily and freely available from many sources. Each image contains the following layers:

1. Two vegetation index layers, NDVI and EVI.
2. Four MODIS reflectance bands (in brackets, the corresponding band number from MODIS): red (1), near-infrared (NIR,2), Blue (3), and mid-infrared (MIR, 7).
3. One exhaustive quality layer, Vegetation Index Quality Assessment, and a summary quality layer, the pixel reliability index.
4. Four observation layers: View zenith angle, Sun zenith angle, Relative azimuth angle and Day of Year.

Images were used from February 18, 2000 (first available image of the product) until February 02, 2020, a total of 20 years or 460 images. The layers that contain relevant information from the terrain are the reflectance bands and the Vegetation Indices, which must be preprocessed before they can be used. Preprocessing these series involves the following steps:

1. **Delimitation to Pilot Areas**.
2. **Quality Filtering**. As we have mentioned, the MOD13Q1 product has two quality bands. The first, Quality Assessment, is a 16-bit band that contains detailed information on the quality of the generated product, in a total of 9 different parameters. Pixel Reliability contains simplified categories of data that describe the general quality of pixels, grouping them into 5 categories: No Data (Value: -1), Good Data (0), Marginal Data (1), Snow/Ice (2) and Cloudy (3). A detailed description of both quality bands can be found in the User's Guide [17]. For the purposes of this manuscript, we selected those data whose reliability was high (Good Data, Value 0), and the rest was discarded. In all cases, more than 90% of the data was preserved. No missing data (-1) or Snow/Ice were present, and neither a strong trend or seasonal pattern were found in the Marginal or Cloudy Data.

3. **Scaling and Interpolation**. Both reflectances and vegetation products are distributed as signed 16-bit integers. These values must be scaled to values that have physical meaning, i.e. between 0.0 and 1.0 for reflectances, and between -0.2 and 1.0 for vegetation products. After quality filtering, the series contain missing values. These values were imputed with a linear interpolation on the values of the same series.

Once the series have been preprocessed, we must assign the corresponding class (Deforested, Forest, Other Wooded Land, and Other Land) for each pixel inside the pilot areas. This is equivalent to identifying those points of the MODIS grid that are within each geometry that makes up the Monthly Deforestation GIS and the Land Cover Class GIS. However, precautions must be taken not to mix classes. To that end, buffers were created around each geometry, both towards the interior and the exterior. The size of the buffer used was 0.75 times the maximum distance between grid points. The same process was applied to the Road Network database. We took precautions to avoid assigning one pixel to different classes.

After each pixel was assigned to its corresponding region, time series were grouped in four classes: Deforested, Forest, Other Wooded Land and Other Land. No series were extracted from the buffers region or the road networks.

Before continuing with an analysis of the database obtained, we want to address one key aspect of the decision making process here involved, which is the choice of MODIS MOD13Q1 product. We can summarize this decision in the form of three question and their answers:

1. **Is MODIS MOD13Q1 pixel size appropriate for deforestation detection in the Chaco Forest?** The pixel size of the product is 6.25 hectares, which could be considered coarse for many applications. However, [2] reports a mean plot size of 61.99 $\pm$ 0.29 hectares for the Dry Chaco Forest and that mean plot size is increasing in time. A preliminary analysis of the Monthly Deforestation GIS agrees with [2] results. Moreover, a visual inspection reveals plots tend to be rectangular. This implies that an average of 10 pixels is expected from each deforested plot before buffering.
   Another aspect that was considered is that this coarse resolution facilitates computational processing. Each image occupies 220 Mbs in memory, so all the imagery used in the creation of this database are close to 200 Gigabytes in memory. The imagery in Landsat resolution (30 m) would occupy in the order of 70 times mores.
2. **Is MODIS MOD13Q1 scientific datasets suitable for deforestation detection?** MODIS MOD13Q1 is a Level 3 product specially designed for vegetation monitoring. The NDVI and EVI indices are a common and broadly accepted choice for this and many other tasks involving forest monitoring.
3. **Is MODIS MOD13Q1 temporal resolution appropriate for near real-time deforestation detection in the Chaco Forest?** There are at least two issues to address in this question. The first is the relationship

between the resolution of the Monthly Deforestation GIS and the MODIS MOD13Q1. The second, perhaps more important, involves the temporal dynamic of the deforestation process. Regarding the first issue, there is a trade-off between the temporal resolution of the ground-truth database and the product used for detection; higher product resolution is preferable, because that means that a faster detection is possible, although validation can only be done at the database temporal resolution. This is the case here presented. Regarding the second issue, deforestation dynamics presents different forms. However, the main driver of deforestation, and the one we are mainly concerned here, is agribusiness. To our knowledge, there are not reports regarding daily, weekly or even monthly deforestation rates, apart from those derived from the annual reports. In that sense, the Monthly Deforestation GIS here presented is unique, since it can be used to better study deforestation dynamics and drivers at a finer time scale. We expect - given the order of magnitude of the deforested plots, and the incidence of deforestation process derived from annual reported rates and the ones obtained from our Monthly Deforestation GIS - that 16 days temporal resolution will be appropriate for near-real time.

The answers provided here are the *a priori* assumptions we used for choosing MODIS MOD13Q1 product. In the Results section we will see that it is, in fact, a suitable choice.

4 Results

We have arrived to a MODIS MOD13Q1 Time Series Database which contains four classes of instances: Deforested, Forest, Other Wooded Land and Other Land. The number of instances for each Pilot Area and class can be seen in Table 1. Each instance consists of twelve time series 460 elements long; six of those time series contain bio-physical information about the ground (Vegetation Indices and Reflectances). Although Quality Filtering has already been done, both quality time series are still available for re-analysis. The four observation layers are also included for the same reason.

Table 1. Number of instances by Land Cover Class and Pilot Area.

Pilot Area	Deforested	Forest	Other Wooded Land	Other Land
A	2230	21629	515	260
B	1851	17598	2957	1881
C	2825	17697	338	1037
D	1223	8212	479	2
E	880	704	25673	2064
F	3254	2237	9007	4763

Each group of time series are saved in *npy* format, native to NumPy [18, 19] and easily open with Python. Each group series has associated a *metadata* archive, in *csv* format. Fields of this metadata are:

- *idx_setDM*: Index corresponding to the instance in which the pixel associated with this series was contained in the Monthly Deforestation database.
- *year*: Year in which the corresponding instance in the Monthly Deforestation database was deforested. Valid values range from 2002 to 2016.
- *month*: Month in which the corresponding instance in the Monthly Deforestation database was deforested. Valid values range from 1 to 12.
- *clouds*: Number of unavailable monthly Landsat composite images before deforestation was registered in Monthly Deforestation database.
- *imputed_clouds*: binary variable indicating if *clouds* was imputed.
- *longitude* and *latitude*: geographic coordinates of the pixel associated with the series.

All metadata fields, except *longitude* and *latitude*, contain null values, besides those corresponding to the Deforested series.

There are several aspects that could be studied from this database, most of them exceeding the scope of this manuscript. In the remaining of this work, we will address that a) Forest and Deforested time series are different, showing long-term change in behaviour after the deforestation date, and b) this database can be used for near-real time deforestation detection, at least for all Pilot Areas except Pilot Area F. We will address these aspects with a visual analysis. In Fig. 4 we show a random NDVI Forest time series and a random Deforested time series for each Pilot Area. Time series are presented without any filtering or resampling, only Quality Filtering mentioned in Section 3.3. All time series present a strong annual seasonality. Forest and deforested time series look alike until the date of deforestation. After that date, Deforested series show a change in behaviour, except for Pilot Area F. This change corresponds to land management after deforestation.

Is this a random behaviour or its a characteristic of the database? Mean and 2.5 - 97.5 percentile spread around the mean are shown in Fig. 5 for all NDVI time series, grouped by class (Forest and Deforested), and Pilot Area. Cumulative percentage of deforested series present on the database is also shown (we remark that the Cumulative Deforestation shown there is a feature of our database, and it does not reflect the ground truth of this process). Mean time series for each class differs as deforestation accumulates. Moreover, spread around the mean also increases. Again, Pilot Area F seems to be the exception.

We have shown that Forest and Deforested series are different, individually with a random example (Fig. 4), and on average (Fig. 5). Although changes in the deforested time series shown in Fig. 4 suggest that there is an immediate change in the series near the date of deforestation, Fig. 4 and Fig. 5 emphasize the long-run effect of deforestation. What we want to address now is the short-term change in time series behaviour around the date of deforestation, because that is the information that will be useful in a near-real time deforestation detection scheme.

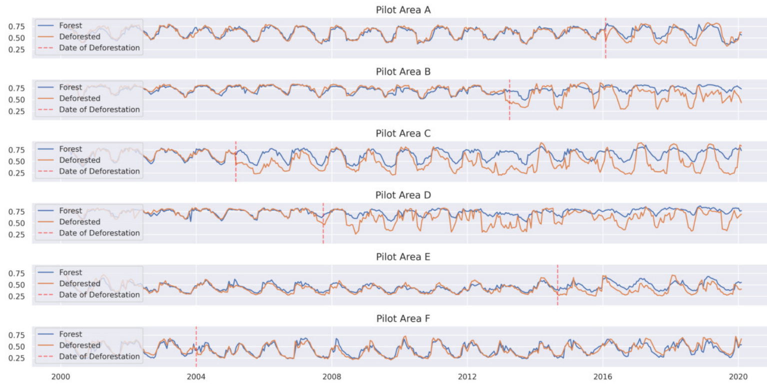

Fig. 4. One random Forest and Deforested NDVI time series for each pilot area. We cannot assure that Forest series remain undisturbed after 2017.

For this end, we took all deforested time series for which its *cloud* metadata was equal to zero. We resampled these series to monthly frequency. Then, we cut a segment three years previous to deforestation date (month/year) and two years later. We did the same for a same number of Forest time series randomly chosen, and then plotted mean and 2.5 - 97.5 percentile spread around the mean. This is shown in Fig. 6.

We found that NDVI reaches it lowest mean value around the date of deforestation for Pilot Areas A to D. Spread around the mean also shows that NDVI values of deforested series are lower than it forest counterpart. This can also be seen in Fig. 7, where we plotted NDVI distribution for the date of deforestation. Histograms for each class are clearly different, even for Pilot Area E and F. However, this difference seems to be carried along time since the start of the segments for those Pilot Areas, in particular to Pilot Area F, so it does not imply that it is useful for near real-time detection. Although not shown, this behaviour repeats in the other series (EVI and reflectances).

5 Conclusions

We arrived to a MODIS MOD13Q1 Time Series database for six Pilot Areas of 250,000 ha in the Argentine Chaco Forest, three in the Semiarid Chaco, and one in the Humid, Arid and Serrano Chaco each. Time Series are grouped in four classes: Deforested, Forest, Other Wooded Land, and Other Land. Deforested series carry information about deforestation events in the period 2002 - 2016, although Time Series span the period 2000 - 2020.

This database was developed with near real-time deforestation detection in mind. The suitability for this task was addressed, showing that Deforested and Forest series are different in the long-run but also at the date of deforestation for at least four of the six pilot areas considered. However, database usefulness is not limited to this task. Some possible examples of usage are:

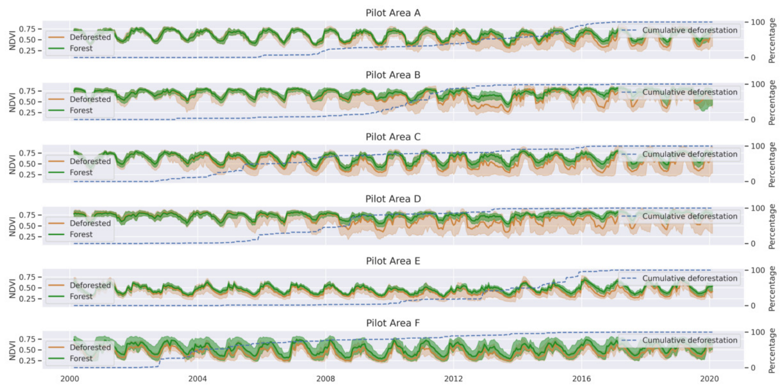

Fig. 5. Mean and 2.5 - 97.5 percentile spread around the mean for Forest and Deforested NDVI time series. We cannot assure that Forest series remain unperturbed after 2017.

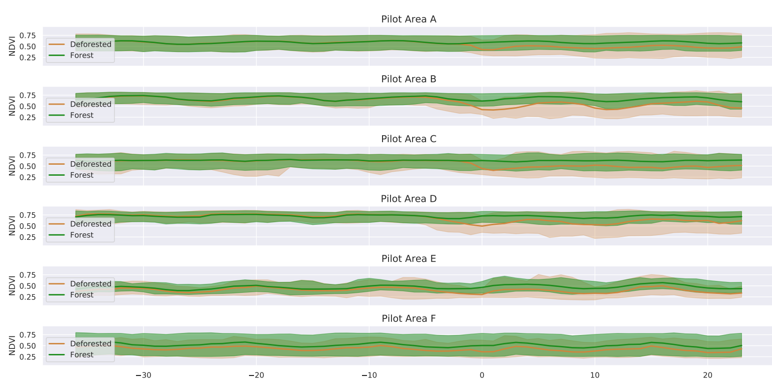

Fig. 6. Mean and 2.5 - 97.5 percentile spread around the mean for all NDVI Deforested series aligned at date of deforestation, per Pilot Area. The same number of Forest time series was randomly chosen and aligned for comparison.

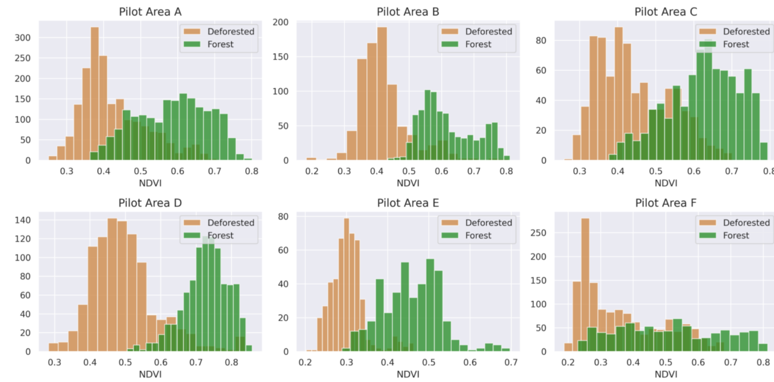

Fig. 7. Histogram of NDVI values at date of deforestation for Deforested series and a same number of Forest series randomly chosen.

- Forest-only time series are suitable to study forest phenology and dynamics. Deforested series can be used to study land use and management after deforestation.
- This database is suitable for the development, optimization and evaluation of breakpoint detection methods. Some of the breakpoints present in the time series are subtle and are dissimulated by the seasonality, noise, and sometimes trend, of the series.
- This database is also appropriate for the development, optimization and evaluation of Time Series Clustering techniques. Four classes per each Pilot Area ensure an interesting variety of time series groups.
- Another challenge present in this database is the incidence of the deforestation process. Although deforestation is very high from an ecological point of view, from a statistical point of view its incidence is low. For example, the maximum number of series deforested in a month for Pilot Area A is 137 (November 2014), which corresponds to an incidence in the order of 1 in 500, with an average of 25 series per month, which corresponds to an incidence in the order of 1 in 3000.

Database Availability Database, along with a first-approach Jupyter Notebook, is available upon request at `estebanroitberg@gmail.com`. Database size is 5.7 Gb, 48 files (4 *.npy* files and 4 *.csv* per Pilot Area). There is also available a Jupyter Notebook with a thorough report of the post-processing stage of the Monthly Deforestation GIS (at the time of the writing of this manuscript, only in Spanish).

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