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Chapter

Colombian Forest Monitoring System: Assessing Deforestation in an Environmental Complex Country

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Abstract

Colombia is a key actor related with the adoption of the relevant UNFCCC provisions referred in the context of obtaining result-based payments for REDD+ actions. Since 2012, the Colombian Forest Monitoring System (SMByC, Spanish acronym) has generated wall-to-wall historical information about the deforestation process over the last 27 years at national and regional levels. The SMByC generates a methodology that integrates tools for the preprocessing and semi-automated processing of satellite imagery to detect and quantify the loss of forest cover by deforestation. Also, the SMByC has done an extensive literature review, collecting qualitative and quantitative information to identify how the drivers of deforestation (illicit crops, illegal mining and postconflict scenario) could result in an increased forest lost during a postconflict scenario. Given that Colombia is a country conformed by regions that have differentially socioeconomic and environmental conditions, the study shows how the methods could generate official information and specifies the context of deforestation process of those regions.

Keywords: forest monitoring, deforestation, drivers, postconflict

1. Introduction

The Institute of Hydrology, Meteorology and Environmental Studies—IDEAM (Spanish acronym) is the forestry authority in Colombia, among other responsibilities. Since 2012, in coordination with the Ministry of Environment and Sustainable Development, the operation of the Forest and Carbon Monitoring System for Colombia, SMByC, began as a functional tool to generate annual official information on the monitoring of the forest cover and deforestation, early warnings for deforestation, and to estimate carbon stocks and GHG emissions related to natural forests.

The SMByC complies with the provisions of the relevant decisions of the United Nations Framework Convention on Climate Change—UNFCCC and the Intergovernmental Panel on Climate Change (IPCC) in its guidelines of good practices, and operates under the principles of transparency, completeness, comparability, consistency and precision. Likewise, it complies with the requirements established by National Statistics Agency (DANE, Spanish acronym) to be considered as official information. For the generation of this type of information, the SMByC developed a specific methodology through a publicly available digital satellite image processing protocol [1, 4, 25] and updated in [23]. All the information generated by the SMByC is available on the Web page of the system, with the exception of the one that has restrictions on use, at link [2].

The information generated by the SMByC allows the IDEAM to carry out its mission activities to monitor the biophysical resources of the nation, especially those related to forest resources, generating statistics, reports, maps and official reports that give an account of their status and dynamics. More information on the indicators can be found in [3].

The main components of the SMByC are: (i) monitoring of forest/deforestation, (ii) monitoring of biomass in natural forests, and (iii) causes and agents of deforestation. The SMByC is an instrument that generates crucial information to design and implement national policies on climate change and forests.

2. Methods

2.1 Forest and deforestation definitions

We defined a forest as a piece of land mainly covered by trees that might contain shrubs, palms, guaduas, grass, and vines, in which tree cover predominates with a minimum canopy density of 30%, a minimum canopy height (in situ) of 5 m at the time of identification, and a minimum area of 1.0 ha. Commercial forest plantations, palm crops, and planted trees for agricultural production are excluded. This definition is in line with the criteria defined by the UNFCCC in decision 11/CP.7 [9], the definition adopted by Colombia under the Kyoto Protocol [10], and the definition of forest cover used by the Colombian National Greenhouse Gas Inventory [11].

Deforestation is defined as the direct and/or induced conversion of forest cover to another type of land cover in a given time [12].

2.2 Forest and deforestation monitoring

The SMByC developed a digital image processing protocol to assess the distribution, extension, and changes in forest cover in Colombia [6–8]. This protocol is implemented through the use of LANDSAT images [13]. The LANDSAT program of satellite images has several advantages for the monitoring of forest cover, such as a good record of images through time (historical availability), high temporal and spatial resolution, easy access to data, and possibilities of program permanence. The image processing protocol applied for the forest monitoring includes the following four major phases: (i) the digital preprocessing of satellite images, (ii) digital image processing, (iii) data validation, and (iv) monitoring data reporting. These phases are summarized in 12 methodological steps [14], described below in each technical phase.

2.2.1 Phase 1: digital preprocessing of satellite images

In this phase, corrections, calibrations, radiometric normalizations, exact co-registration, and reduction in atmospheric effects are applied, to assure the comparability of images and to ensure that the detection of changes is not due to this type of factors. The specific steps followed during image preprocessing are as the following:

2.2.1.1 Step 1: images select and download

For each reference year, the SMBYC downloads the entire Landsat satellite program (7 ETM+ and OLI 8), image catalog with L1T level (reflectance surface), and selects all those images with less than 90% cloud cover available between January 1 and December 31 of the reference year. We give special emphasis for the images of the last quarter of the year that compiles the highest deforestation effect, mainly at the Amazon region in Colombia.

Images affected since 2003 by the failure in the Scan Line Corrector of Landsat 7 ETM+ are processed applying a masking. To optimize this task, the SMBYC developed a specific tool implemented in QGIS® [15]. When Landsat data does not provide sufficient cloud-free coverage, images from the CBERS, RapidEye, ASTER, and Sentinel 2 satellites programs are used.

2.2.1.2 Step 2: stacking bands

In order to archive the complete images, each image is reconstructed by stacking all bands, excluding the thermal infrared wavelength bands. In case of Landsat 8 OLI, the aerosols and cirrus layers are also excluded.

Given the large number of images used (for example, more than 1400 images were used in 2015), specific algorithms have been developed to facilitate handling and processing, all of which are available for download:

- Algorithm to stack the bands [16].
- Algorithm to rename the images according to the SMBYC structure [17].
- Algorithms to extract information from Landsat metadata files [18].

2.2.1.3 Step 3: geometric correction

For the construction of the annual image composite, it is necessary to have an exact co-registration at the pixel level among all the images acquired for each scene. The L1T products supplied by the Earth Resources Observation and Science Center (EROS) usually have an exact correspondence of the pixels. However, before performing the interpretation, a review of each image is made and those that do not meet this condition are adjusted.

2.2.1.4 Step 4: cloud masking and shadow

This allows masking and eliminates areas of clouds, banding, shadows, or haze. Before performing a change analysis, a semiautomated procedure is executed to integrate the results of the masks produced with different filtering tools implemented by the IDEAM with a QGIS Plugin named cloud masking [15], (see **Figure 1**). For additional documentation on the operation of the Cloud masking tool, refer [19].

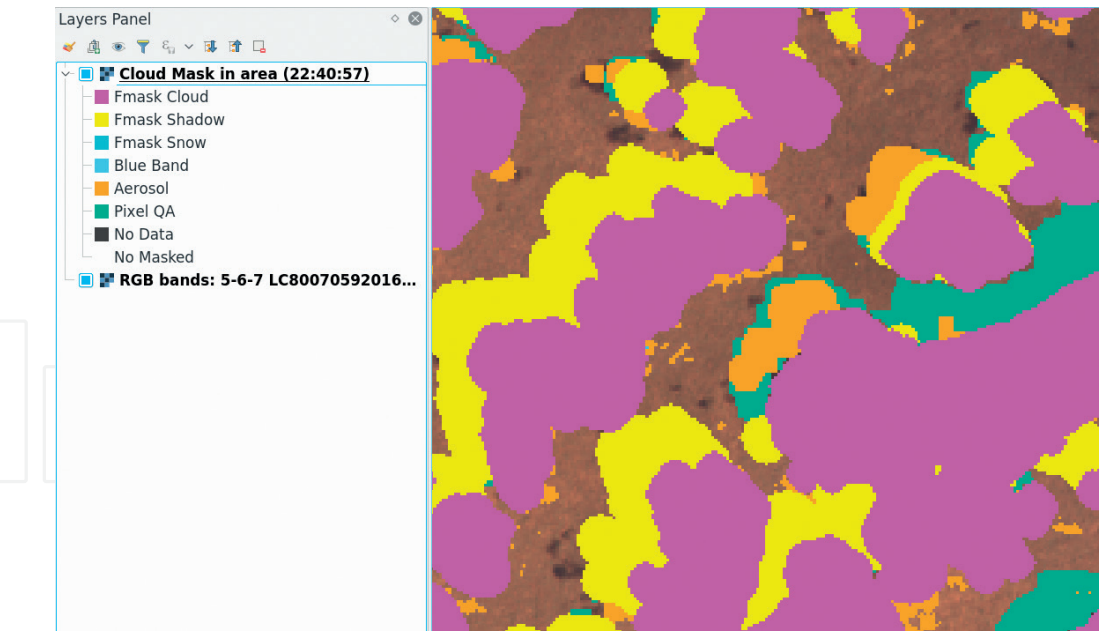


Figure 1.
Example of cloud masking filters available in tool developed by IDEAM.

2.2.1.5 Step 5: radiometric normalization

We used relative radiometric normalization of the images to adjust the radiometric values in order to reduce the variability between the images due to atmospheric differences, lighting, sensor calibration, and geometric distortions, among others. This step allows the images of different years to be comparable and ensures that the changes detected are not due to this type of factors [20, 21]. Python scripts are available to execute this procedure—ARRNorm [22].

2.2.1.6 Step 6: generation of the annual composite of images

This step uses all satellite images available for Colombia of the corresponding year, allowing for each pixel a series of annual time values that include the reflectance surface data valid for that year. The main metric used is the annual median of each spectral band, which has shown good results for the detection of changes. Thus, for each observation unit, a single radiometric value of annual reflectance surface is obtained in each one of the radiometric bands (Red, NIR, and SWIR-1 and SWIR-2). The creation of these annual composites for the whole country is done through specific tools developed in the Python language [23]. **Figure 2** shows the final result of the phase 1 using an RGB combination 453 that remarks the healthy vegetation distribution (brown tones), related mainly to forest distribution.

Although the use of the annual median values of reflectance reduces the areas without information, the error by omission could also increase if the forest cover changes occur during the last year's months. To avoid this problem, after the process described above, a visual verification and manual adjustment of the results is performed using the data of the last pixel of the year (last pixel) and the last available image of the last year's quarter.

2.2.2 Phase 2: digital image processing

This involves the automated detection of changes in forest areas using algorithms, the visual verification of detected changes, and the execution of a quality control protocol.

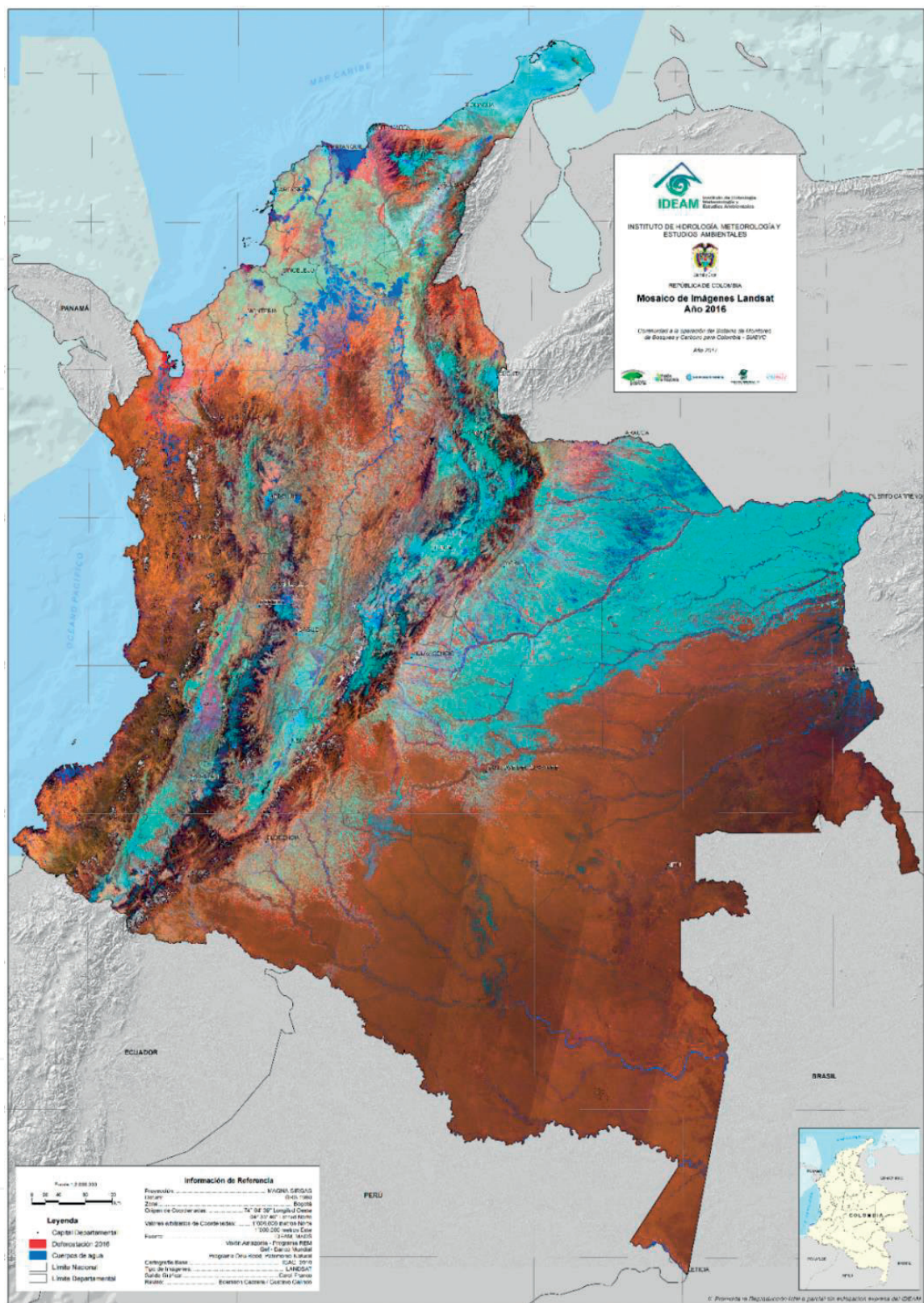


Figure 2.
Annual image composite of surface reflectance for the year 2017 (Landsat ETM and Landsat 8 OLI images from January 1 to December 31).

2.2.2.1 Step 7: detection of changes

To identify forest cover change, a direct and automated method is used applying the principal component analysis (PCA), over the image annual composite generated in the previous step, to then make a reclassification of the values of the pixels to the value of the corresponding class. The legend and the values assigned in the

reclassification for each class are as follows: (1) stable forest, (2) stable nonforest, (3) deforestation, (4) regeneration, and (5) without information (corresponding to masked data). To adjust the areas without information detected for each reporting period, a time series analysis is applied to verify the temporal consistency. For this process, the information from the most recent reporting period is considered, and the areas “without information” are adjusted compared with the other reporting periods.

2.2.2.2 Step 8: visual verification of the changes detected

Once the PCA process has been executed by scene or set of scenes, each interpreter codes each pixel to the corresponding thematic class, obtaining a preliminary forest change map with the following classes or strata:

1. Stable forest
2. Deforestation
3. No information
4. Regeneration
5. Stable Nonforest.

For this step, each interpreter uses the following information: (i) the last images of each reference year, (ii) the annual composite images for each reference year, and (iii) the median compounds for the last quarter of the reference year. By implementing this step, we seek to evaluate and revise the first version of the map of forest cover change in order to identify inconsistencies with respect to the changes detected in previous years and to generate an adjusted version of the map.

2.2.2.3 Step 9: quality control

The quality control process involves monitoring all the technical steps executed, from the download of the satellite images and the intermediate products to the final results of the Forest Change Map and Forest Cover Map. The SMByC has consolidated a set of tools to guarantee the quality, completeness, and consistency of the data, through a Python script executed in ArcGIS© to produce quality control reports for each scene.

2.2.3 Phase 3: thematic accuracy assessment

Thematic accuracy assessment allows generating reliability metrics of the official forest monitoring data generated to: (1) avoid bias, which means to avoid a systematic underestimate or overestimate of forest cover and forest change, and (2) to reduce uncertainty as much as possible [24], in line with guidelines proposed by the Global Forest Observation Initiative (GFOI). This procedure applies user's precision (commission error) and the producer's precision (omission error) following recommendations developed by [25] over the forest change map. For the execution of thematic accuracy assessment, a team of four experts is formed under the following structure:

- A leader of the evaluation, in charge of coordinating the interpreters, who designs and implements a probabilistic sample. The leader performs the consolidation and verification of the interpretation as well as the accuracy analysis.

- Three interpreters, with extensive experience in visual and digital interpretation, who are trained to apply the forest definition in medium-resolution optical images.

2.2.3.1 Step 10: sampling design

This analysis consists of the implementation of a stratified random sampling. The size of the sample (n) is selected following [26]. The assigned proportion of each class uses a proportional allocation based on the area of each stratum compared to the total area allocated [27]. The proportions of each of the strata are based on the forest change map for the reference year, which are as follows: (1) stable forest, (2) stable nonforest, and (3) deforestation. Additionally, each stratum is subdivided based on a deforestation risk map that identifies two main areas (low risk and high risk) based on the historical trends of deforestation.

Equation (1) shows the math expression used to calculate the proportion (w_i) of mapped area ($A_{m,i}$) for each stratum i , related to the total area of all classes (A_{tot}):

$$W_i = \frac{A_{m,i}}{A_{tot}} \quad (1)$$

The classes with the largest mapped area are assigned a p -value of 0.9, considering that these classes have a high accuracy, while the change classes, high-risk deforestation areas (DEF-AR) and low-risk deforestation areas (DEF-BR), are assigned a p -value of 0.8, considering that for these classes, there is a greater uncertainty and therefore less accuracy.

The standard error (S_i) associated to each class is calculated as the square root of the variance. The total size of the sample (n) is calculated as the sum of the products of the area ratio (w_i), associated to each class i , multiplied by the standard errors (S_i) of each class, and divided by a general standard error of the classification (S_o), squared Eq. (2)

$$n = \left[\frac{\sum_{i=1}^n (W_i S_i)}{S_o} \right]^2 \quad (2)$$

For each reference year, a value of 0.005 is assumed for the expected general standard error of classification. The assigned proportion of each stratum is based on a simplified approach to the optimum, based on the proportion of area of each stratum compared to the total area allocated. Thus, the smallest strata are adjusted by minimizing the variance estimator for the accuracy of these user classes, in accordance with the recommendations of [25].

2.2.3.2 Step 11: sampling implementation

The sampling implementation, as well as the sampling point interpretation, is done in Acatama, a self-developed software that is available for QGIS at <https://bitbucket.org/smbyc/qgisplugin-acatama>.

2.2.3.3 Step 12: sampling points interpretation

The interpreter team performs a visual interpretation of each unit of verification (point), applying the forest and deforestation definitions adopted by the SByC. This procedure is applied using Acatama tool [14] that allows defining a fixed spatial reference scale for interpretation, using all the satellite data available.

During this procedure, we also perform the classification and identify the nonclassified samples (**Figure 3**).

We used the satellite data as reference data for the sampling point interpretation for periods before and after annual composite generated in Step 6. Also, we used Google Earth Engine, Bing images, or other high-resolution image repositories if available.

2.2.3.4 Step 13: error matrix and confidence intervals

Thematic accuracy assessment of the forest cover and deforestation data for the reference year is done by constructing a confusion matrix [20], using the data generated in the previous step. Subsequently, from the error matrix, a new matrix is constructed and is expressed in terms of the proportion of the estimated area.

2.2.4 Phase 4: calculations and reports

To calculate the deforested area between two analysis periods, only the areas with available data in the two analysis periods are considered, so the associated (un)certainly that the event occurred in the period is analyzed.

Forest losses detected after one or several dates without information were not included in the reports in order to avoid overestimated rates due to different factors (e.g., high cloudiness or sensor failures). After each deforestation monitoring period, an analysis of consistency of the time series is performed, verifying that each pixel marked as deforestation has not been marked in the previous periods (at least 6 years) as deforested. If this is the case, the most recent result is corrected and marked as no forest (NB) or the specific area is reviewed retrospectively. The same procedure is applied for “forest recovering,” maintaining the same check process in which a pixel marked as deforested could not be assigned as “forest” class until after 6 years.

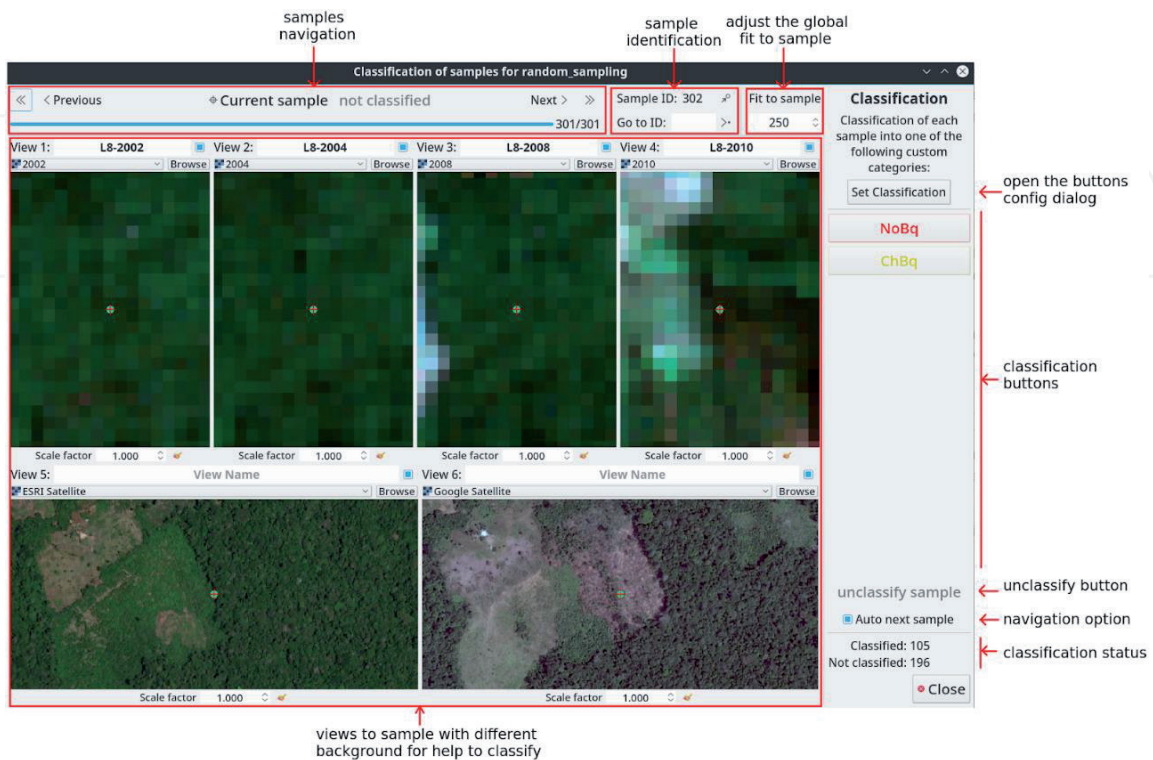


Figure 3.
Acatama QGIS© tool. Verification window for sampling point interpretation.

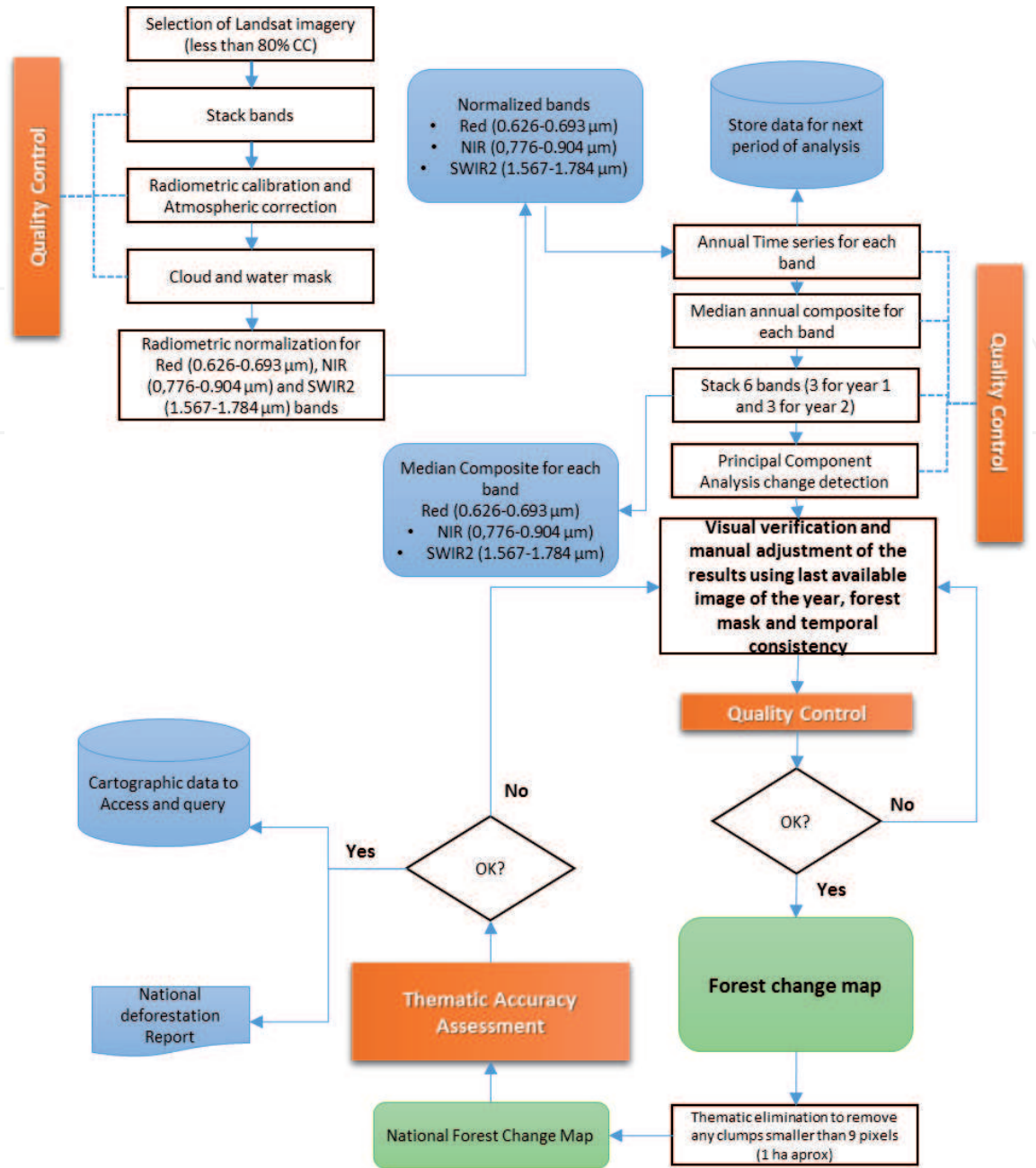


Figure 4. Methodological workflow applied in the digital image processing protocol V.2 (Source [11]).

The implementation of this methodology allowed to identify the changes in forest cover (expressed in hectares) for the last 27 years in Colombia, generating reports for the years 1990, 2000, 2005, 2010, and 2012, and five annual reports for the years 2013–2017. **Figure 4** presents the workflow implemented. Additional information is available at [28].

3. Results and discussion

3.1 Forest cover in Colombia

In 2017, the natural forest area in Colombia was 59'312.369 ha, which represented 51.9% of the continental and insular Colombian territory (**Figure 5**). At a regional level, some provinces show high forest cover like Amazonas (97.3%), Vaupés (96.5%), and Guainía (92.9%). Likewise, other departments like Atlántico (1.4%), Sucre (2.6%), and Cesar (8.7%) have the smallest area of their territory with natural forests.

3.2 Patterns of forest loss in Colombia

In the last 27 years (1990–2017), Colombia lost more than 6.7 million ha of natural forest. Only in the last 5 years (2013–2017), a forest loss of 783,899 ha was identified. Deforestation has mainly been concentrated in the so-called “Colombian Amazon deforestation arc,” located between the departments of Putumayo, Caquetá, Meta, and Guaviare. Other deforestation hotspots are Serranía de San Lucas (Antioquia and Bolívar departments), Chocó department, and Catatumbo (Norte de Santander department) (see **Figure 5**).

In regional terms, the Colombian Amazon presented the highest deforestation in the last 5 years (2013–2017), accumulating 46% of the total deforestation, especially in areas



Figure 5. Forest cover in Colombia for the year 2017 (green) and deforestation distribution for the period 2013–2017 (red).

such as the so-called “Sabanas del Yari—4” (limits of Meta and Caquetá departments), northwest of the Guaviare department—2, Meta department—3, and the middle and lower sectors of the Río Caguán basin—1 (Caquetá department), (**Figure 6**).

During 2017, the deforestation in Colombia raised to 219,973 ha, an increase of 23% compared with the deforestation reported for the year 2016. In total, 65% of forest loss was concentrated in the Colombian Amazon deforestation arc.

It is important to mention that deforestation is ostensibly less in areas such as National Natural Parks, Indigenous Lands, and Afro Colombian community Lands, compared with the rest of the country. In 2017, in 723 municipalities, at least 1 ha was deforested.

Overall, 74% of the deforestation in the whole country was concentrated in 25 municipalities, being San Vicente del Caguán (Caquetá department), Cartagena del Chairá (Caquetá department), San José del Guaviare (Guaviare department), La Macarena (Meta department), and Calamar (Guaviare department), the ones with the largest deforested area.

3.3 Rates of forest loss

At the national level, in 2017, the deforestation rate in Colombia was -0.38 , which is the highest value of the last 17 years, only overpassed by the rates registered in the

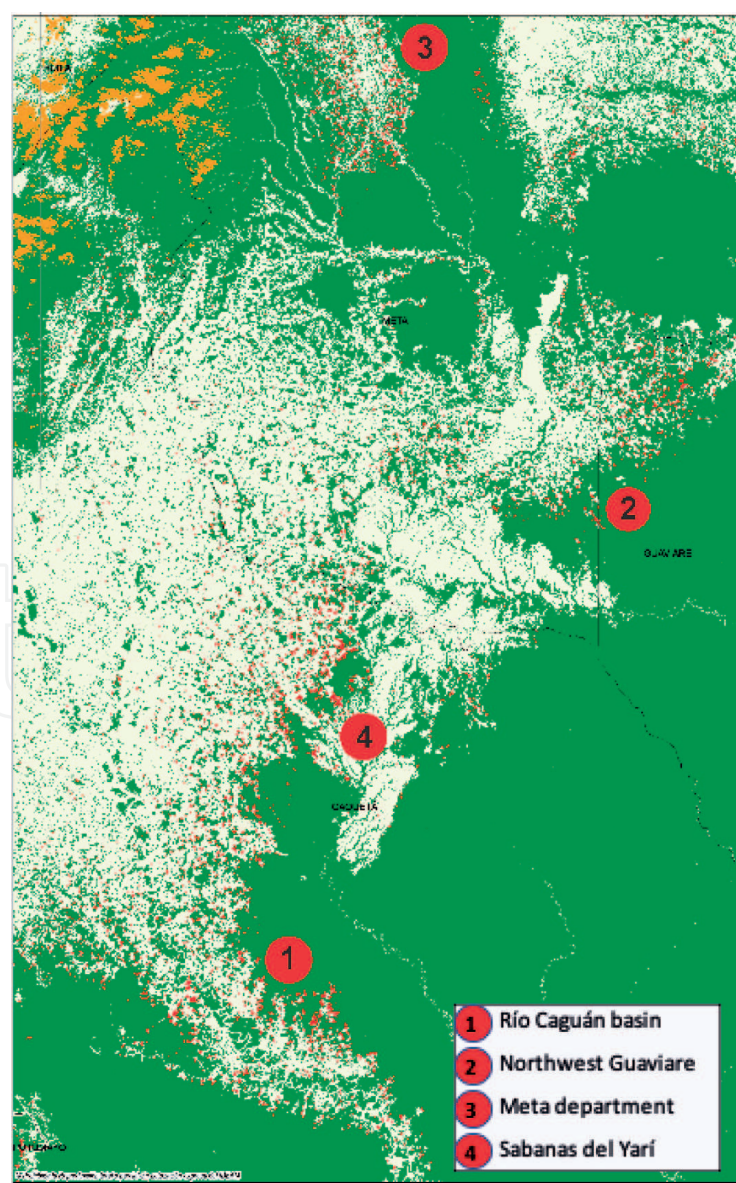


Figure 6.
Main deforestation hotspots in the Colombian Amazon (period 2013–2017).

1990s. At the regional level, there were departments with deforestation rates ostensibly lower than the national average, such as the case of the departments of Amazonas (-0.01%), Vaupés (-0.04%), and Vichada (-0.09%). On the contrary, the deforestation rate in Antioquia (-0.96), Caquetá (-0.92), and Guaviare (-0.8) was ostensibly higher than the national average. In these cases, the government should put special attention because they are well above the average world deforestation rate of -0.21% [26], and even above countries such as Indonesia (-0.7%) or Bolivia (-0.5%).

3.4 The early warning system

The implementation of the described methodology has allowed to identify the main recent active cores of deforestation for the year 2018. IDEAM generates four deforestation early warning bulletins per year that are available through the institutional platform. These bulletins are based on the digital image processing of low spatial resolution (MODIS Terra/Aqua), medium spatial resolution (sentinels 1 and 2), and high spatial resolution satellite data (Planet Scope), with the use of automated change detection algorithms, to detect quarterly (inclusive monthly) the main forest loss cores. With these bulletins, users can know the distribution and geographic location of the early alerts (including specific coordinates) or the location of the active deforestation nuclei (maps with tonalities indicate the magnitude of the alert), to detect the forest areas with loss of natural forest (**Figure 7**). This information is useful as a basis for effective control to carry out timely actions against activities such as the illegal mining, illicit crops, praderization, illegal logging, conversion to agricultural crops, and forest fires, among others.

In 2018, it was identified that the arc of deforestation in the Colombian Amazon is the area that concentrated the greatest warning of deforestation, mainly in the first and fourth quarters. Other areas with active deforestation cores are Catatumbo (Norte de Santander department), Serranía de San Lucas (Antioquia and Bolívar departments), Paramillo (Antioquia and Córdoba departments), and some sectors of Cauca and Chocó departments.

Likewise, the IDEAM performs an analysis of active fires [29] as a proxy of active deforestation, which monitors the possible occurrence of burning areas or active fires. This platform (see **Figure 8**) allows to access active fire information on a daily basis or an aggregated basis for the national, departmental, and regional levels since 2000.

3.5 Drivers and agents of deforestation

Agricultural and livestock activities generate the greatest pressures on natural areas, by establishing productive systems that are characterized by low levels of productivity and for promoting new zones of colonization or expansion from the existing ones [30]. Traditional agricultural production represents about 10% of the total agricultural productive area of the country [2, 31]. The activity represented about 7% of the new land transformed between 2005 and 2012, mainly impacting the Andean and Amazonian regions, among which 86% of the agricultural land transformed in Colombia is distributed. However, livestock, especially cattle, which is one of the main economic activities of the country, appears as the main driver of deforestation at the national level. Overall, we have estimated that 51% of the total forest loss was due to the increase of areas in pastures, in theory to settle livestock productive systems [11].

The production of illicit crops, in particular coca leaf, has also been recognized as an important cause of deforestation [32]. Although its direct impact is usually reduced compared to other causes of deforestation, the fragmentation of the forest matrix caused by this driver has a decisive indirect impact on the advance of the agricultural frontier [4]. In 2017, the estimated proportion of forest loss due to illegal



Figure 7.
Deforestation early warning persistence for the year 2018.

crops is 6% [33] and is primarily concentrated in the hotspots of deforestation of the country. Another smaller but still important driver of deforestation is forest fires related to land tenure conflicts, certain agricultural management practices, activities such as hunting, pest and weed control, and expansion of crops and pastures for livestock [34, 35]. In our work, we identified that 2800 ha were deforested by 117 fires in 61 municipalities, which is equivalent to 2.3% of the total deforested in the period of 2014–2015 [4, 36]. Likewise, illegal mining is having an important effect on forest loss. In total, we quantified the direct loss of natural forest cover associated with alluvial gold exploitation activities in 2681 ha for the year 2014 [37]. In 2015, deforestation associated with alluvial gold mining reached 7890 ha (7% of national deforestation) and was concentrated mainly in three natural regions (Pacific, Andes, and Caribbean) [33]. A study carried out by UNODC and the Government of Colombia indicates that 38% of the territory affected by alluvial gold exploitation at the national level registers the presence of illicit crops [5, 37]. In the territories affected by coca, the phenomenon of alluvial gold exploitation has been growing rapidly, in a pattern of clear spatial and social association between the two activities [4].

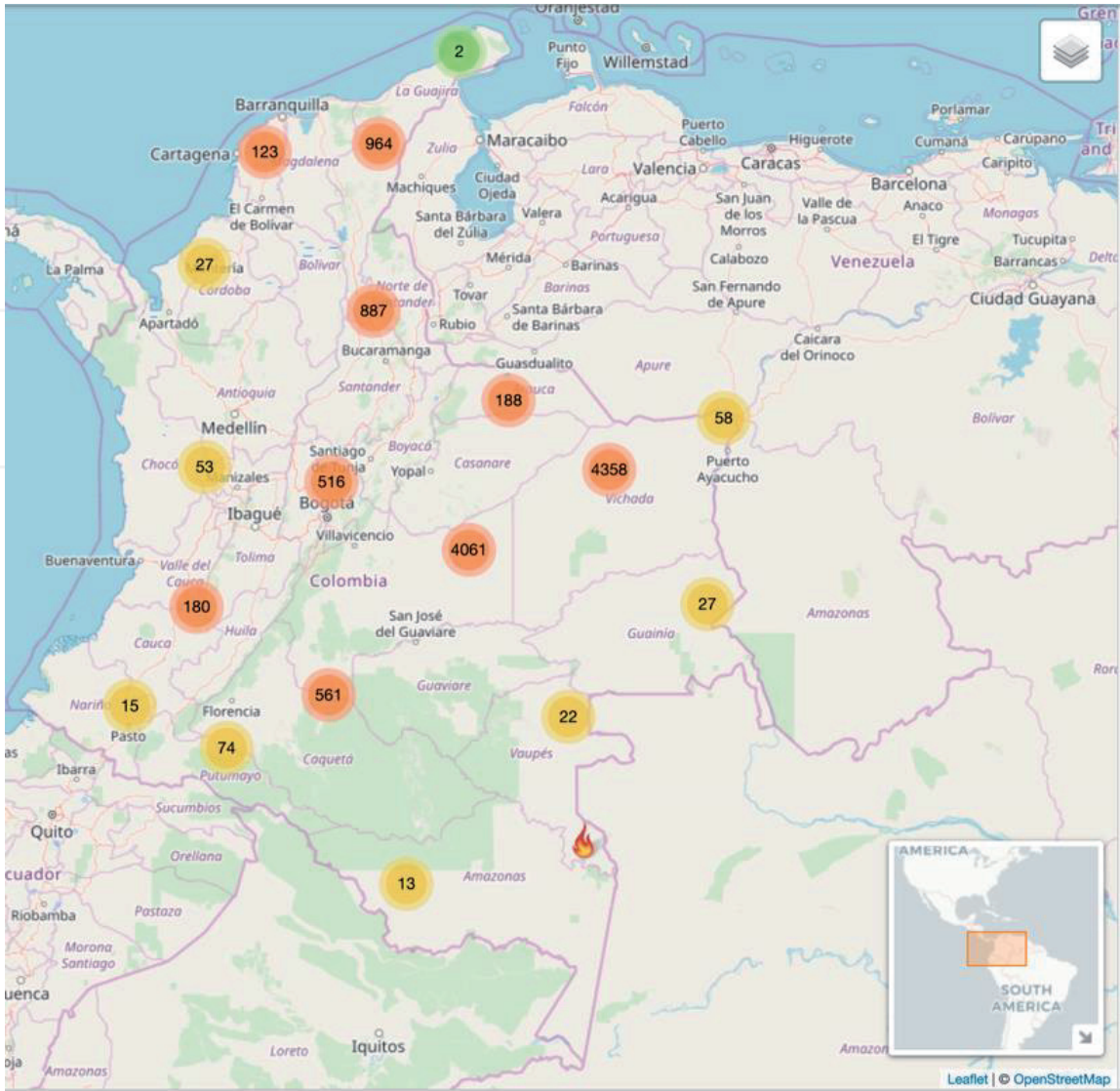


Figure 8.
Active fire platform at IDEAM's web portal [29].

Finally, since the peace talks began between Colombia's government and the Revolutionary Armed Forces of Colombia (FARC) in 2012, experts warned that the postconflict period could have negative consequences of forests, mainly due to access to areas that were restricted during the conflict and the lack of planning for the sustainable development of these territories [38, 39]. In the vast majority of cases, the areas with the greatest forest presence and the threat of deforestation are located in small- and medium-sized municipalities (up to 100,000 inhabitants), where the end of the conflict would surely increase its development at expenses of the removal of vast areas covered by natural forests. Even in the most environmentally optimistic postconflict scenario, it can be expected that at least during a transitional period, the first economic benefits at the end of the conflict will come from the abundant natural capital available in the region. In this context of accelerated economic growth with few restrictions, forests will continue to be one of the most affected resources [4].

4. Conclusions

Colombia is considered a forestry country. The natural forest area covers 59'312.369 ha, which represents 51.9% of continental and insular Colombian territory. Nevertheless, in the last 27 years (1990–2017), Colombia lost more than 6.7 million ha

of natural forest, and in the last 5 years (2013–2017), the estimated forest loss was of 783,899 ha. This finding ranks Colombia within the top 15 countries with one of the highest forest covers on earth (52%) and shows the high utility and need to maintain and improve the Forest and Carbon Monitoring System for Colombia—SMByC.

Overall, the SMByC is a prominent tool to help the country to accomplish with its commitments in terms of minimizing deforestation and carbon emissions in the coming decade. Forest monitoring indicators have a special importance to follow one of the goals established at 2030 for the Sustainable Development Goals—SGD, related to the conservation of at least 50% of the continental and insular territory covered by forests. Here, we show that based on the optimal use of digital image processing protocol, it is possible to generate reliable official information on the distribution, extension, and changes in forest cover at the national level. The SMByC will certainly play a key role on facing the expected changes of the ongoing climate change.

Since many of the armed conflicts in tropical regions occur in areas with high forest cover, like the one we have had in Colombia, the main challenges for both society and government are to take advantage of the great opportunity contributing toward peace-building, reducing deforestation, while promoting sustainable development [40].

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