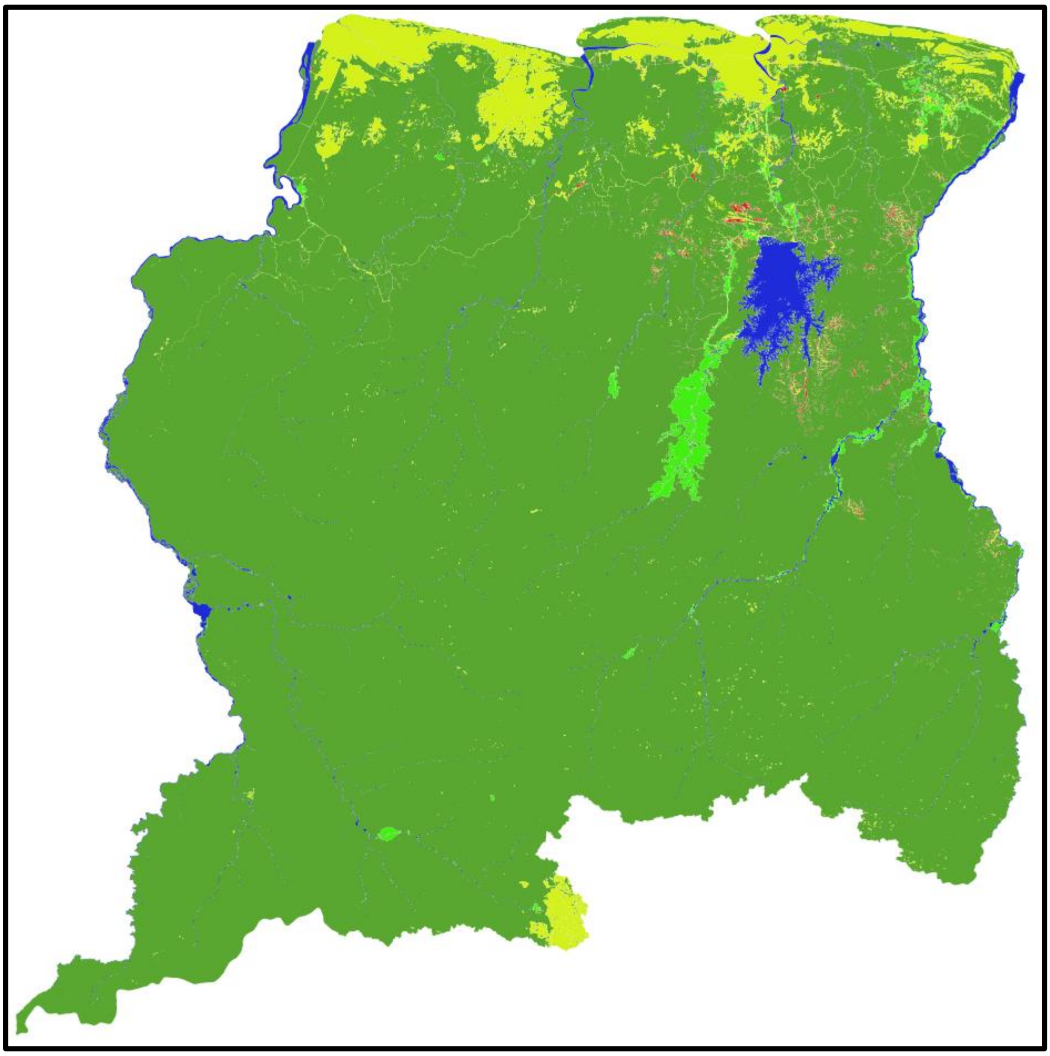
Technical report:

Forest cover monitoring in Suriname using remote sensing techniques for the period 2000-2015



Published: September 2017

Written by: Forest Cover Monitoring Unit

Foundation for Forest Management and Production Control (SBB)

Program implemented in the framework of the ACTO project "Monitoring the Forest Cover of the Amazon Region"

Technical report:

Forest cover monitoring in Suriname using remote sensing techniques for the period 2000-2015

Acknowledgements:

Rémi d'Annunzio, GIS and Remote Sensing, FAO, UN-REDD team

Anne Cécile Capel, ONF International

Amazon Cooperation Treaty Organization (ACTO), Carlos Salinas

Brazilian National Institute for Space Research (INPE)

Jenny Hewson, Conservation International

Recommended citation: SBB (2017). Forest cover monitoring in Suriname using remote sensing techniques for the period 2000-2015. Paramaribo, Suriname

Date: September 2017

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Acronyms

ACTO	Amazon Cooperation Treaty Organization
AOI	Area of Interest
CBL	Centraal Bureau Luchtkartering (Central Office for Aerial Mapping)
CC	Cloud coverage
CELOS	Centrum voor Landbouwkundig Onderzoek in Suriname (Centre for Agriculture Research in Suriname)
CELOS	Center for Agricultural Research in Suriname
cfmask	Version of Function of Mask (in C programming language)
ETM+	Enhanced Thematic Mapper Plus
FCMU	Forest Cover Monitoring Unit
FIRMS	Fire Information for Resource Management System
GCP	Ground Control Points
GDAL	Geospatial Data Abstraction Library
GHG	Greenhouse Gas
GISSAT	Geographic Information Systems Software Applications & Training
IPCC	Intergovernmental Panel on Climate Change
LBB	Suriname forest service
LULC	Land Use Land Cover
MI-GLIS	Management Instituut Global Land Information System
NFMS	National Forest Monitoring System
OLI	Operational Land Imager
ONFI	ONF International
OTB	Orfeo Tool Box
PRODES	Projeto, de Monitoramente do Desmatamento na Amazonia Legal
QA/QC	Quality Assessment, Quality Control
QGIS	Quantum Geographic Information System
REDD+	Reducing Emissions from Deforestation and Forest Degradation as well as conservation, sustainable management of forests and enhancement of forest carbon stocks
ROI	Region of Interest
SBB	Foundation for Forest Management and Production Control
SPOT	Satellite for observation of Earth
SVM	Support Vector Machine
TIFF	Tagged Image File Format
TM	Thematic Mapper

TOA	Top of Atmosphere
USGS	United State Geological Survey

Executive summary

Suriname has a long history of sustainable forest management and is known as a high forest cover, low deforestation country.
Having accurate and consistent information on forest area and forest area change is important for different reasons, including national needs and international reporting requirements, for example to access results based payments for REDD+. In June 2012, the first steps were taken in Suriname to establish the Forest Cover Monitoring Unit (FCMU). This was done in the framework of the Amazon Cooperation Treaty Organization (ACTO) project "Monitoring the Forest Cover of the Amazon region", which helps countries to strengthen their capacities to monitor the forest cover using satellite images. The FCMU, based at the Foundation for Forest Management and Production Control (SBB) in Suriname, became operational from September 2012 onwards, and was officially inaugurated by the Minister of Physical Planning, Land- and Forest Management (ROGB) on 12 November 2013. The overall goal of the FCMU is to contribute to the strengthening of the National Forest Monitoring System (NFMS) by generating information about changes regarding forest cover.
The methodology to monitor the deforestation and to produce the post-deforestation Land Use Land Cover classification is inspired by the method used by the Brazilian National Institute for Space Research (INPE) to monitor deforestation in Brazil. The method has been adjusted to Suriname's national conditions.

For the production of the forest cover data, the *"Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite"* (PRODES) method is used, which includes the use of open source software and freely available Landsat images. With this method, the classes Forest, Non-forest, Hydrography, Shifting cultivation and Deforestation are monitored. The class assignment for the areas on Landsat covered with clouds was done using the Greenest pixel composite from Google Earth Engine in combination with the Global Forest Change data from Maryland University (Hansen et al., 2013). With support from the Food and Agriculture Organization of the United Nations (FAO), the forest cover change data underwent an accuracy assessment. The underlying principle of the accuracy assessment is that it compares the mapped land classification to higher quality reference data, collected through a sample based approach. In collaboration with the Center for Agricultural Research in Suriname (CELOS), the accuracy assessment has been carried out, using Open Foris Collect Earth-software developed by the FAO[1]. The method includes a set of "good practice" recommendations for designing and implementing an accuracy assessment of a change map and estimating area based on the reference sample data. The "good practice" recommendations address three major components: sampling design, response design and analysis (Olofsson et al., 2014).

For the production of the post-deforestation Land Use Land Cover (LULC) classification, the TerraClass method is used where the deforestation mask is sub-

[1] FAO (2016). Map Accuracy Assessment and Area Estimation: A Practical Guide. National forest monitoring assessment working paper No.46/E

classified into LULC classes. In combination with national experts input, the LULC classes Agriculture, Burned areas, Infrastructure, Mining, Pasture, Secondary vegetation, Urban and Others are validated.

FCMU monitors the forest cover, but also the post-deforestation LULC classes. The results show an increasing rate in the deforestation for the period 2000-2015, where the post-deforestation LULC maps indicate that the class 'Mining' is the main driver of deforestation.

The plans for the future are to create annual deforestation maps, while the post-deforestation LULC maps will be generated every two years. Another intention is to strengthen the collaboration with other relevant institutions. Alone you can go far, but together we can go further.

1. Introduction

Suriname is one of the world's greenest countries (93 % forest cover), with **a High Forest cover and Low Deforestation (HFLD) status**.[2] However, recent trends show increasing pressure on Suriname's forest with an increase in the deforestation rate from 0.02% to 0.05% per year. In its Intended Nationally Determined Contribution (INDC) (GOS, 2015), Suriname expressed its objective to maintain its high forest cover and low deforestation rate for future generations, while promoting the uses of the forest resources and the generation of Payment for Ecosystem Services (PES). This is also in line with other policy documents, including the National Forest Policy (2006).

To be able to plan for sustainable development in balance with the forest ecosystem, countries need to have reliable and up-to-date data on the status of the forest. The National Forest Monitoring System (NFMS) aims to provide those data (SBB, 2017). One of the components of the NFMS is the Satellite Land Monitoring System (SLMS) that enables Suriname to monitor the forest cover using remote sensing techniques. The Forest Cover Monitoring Unit (FCMU), which was established in 2012 through the regional ACTO project '*Monitoring the forest cover in the Amazon region*', is responsible for the implementation of the SLMS.

This report describes the methodologies that have been developed and implemented for the generation of the Deforestation maps, the Land Use Land Cover (LULC) maps and the execution of the Quality Assessment/Quality Control (QA/QC). The report also presents the results for the historical assessment of deforestation in Suriname, including the drivers of deforestation.

Participating in a REDD+[3] mechanism can support countries to maintain the high forest cover and low deforestation rate. Since 2013, Suriname is engaged in a national REDD+ Readiness Program. The national REDD+ strategy is currently being developed, based on background studies such as "*Background Study for REDD+ in Suriname*: *Multi-Perspective Analysis of Drivers of Deforestation*, *Forest Degradation and Barriers to REDD+ Activities (DDFDB+ study)*". This study, written in 2016 and published in 2017, includes lots of data generated by the FCMU and the National Forest Monitoring System (NFMS), as presented in this report. The results presented will be one of the main input for the Forest Reference (Emission) Level (FREL/FRL).

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[2] HFLD countries have more than 50% forest cover and an annual deforestation rate which is lower than the global average of 0.22%.

[3] Reducing emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks

1.1 Suriname’s NFMS

For Suriname the forest monitoring is important for many reasons, such as providing overall support to national development processes and international reporting. This includes Suriname’s participation in the United Nations REDD+ mechanism. A vision for the National Forest Monitoring System (NFMS) of Suriname was developed by multiple stakeholders in 2014, in the context of formulating a *National Plan for Forest Cover Monitoring (FCM Plan)* (SBB, 2014).

> Vision:
>
> Suriname monitors forest cover changes in the whole country in close collaboration with multiple stakeholders, using modern technologies and local community participation in a system that provides the national and international community with the most updated and reliable information about forest cover, which is used to enforce governance on deforestation, forest degradation, land tenure and land use (changes), to sustainably manage the forest resources while maintaining resilience of forest ecosystems.

Within the *NFMS roadmap: Status and Plans for Suriname’s Forest Monitoring System* (SBB, 2017), the following principles were emphasized (Figure 1.1.):

National ownership	Multi-purpose	Streamlined with context
Phased approach	Open data accessibility and transparency	Cost-efficiency

Figure 1-1. Guiding principles for NFMS in Suriname (Source: NFMS roadmap, SBB-2017)

1.2 Capacity strengthening in NFMS

Suriname is a member of the Amazon Cooperation Treaty Organization (ACTO). Within ACTO, the eight member countries have developed the Amazonian Strategic Cooperation Agenda (2010)[4], whereby countries have agreed amongst each other to “Conserve, protect and use the renewable natural resources in a sustainable way”.

[45]http://www.otca.info/portal/admin/_upload/apresentacao/AECA_eng.pdf

Within this framework, Suriname together with the seven other countries in the Amazon rainforest, carried out the ACTO project *Monitoring deforestation, logging and land use change in the Pan Amazonian forest* Rev.1 (F), (2012-2014) financed by the International Timber Trade Organization (ITTO) and the German and Dutch Cooperation BMZ/GIZ and DGIS, followed by the project *Monitoring the Forest Cover in the Amazon Region* (2013-2018) funded by the Brazilian Development Bank (BNDES). These projects aimed to develop and implement participatory systems to monitor forest cover in the Amazon region and to strengthen existing regional coordination platforms for forest management. Specific project objectives are:

- Contribute to improving governance on matters related to deforestation, land tenure, land use change and sustainable forest management;
- Provide real time information about the extent and the condition of the forest cover to the ACTO Member Countries.

Through the participation to these projects, the Forest Cover Monitoring Unit (FCMU) was established in Suriname. This unit is located at the Foundation for Forest Management and Production Control (SBB), in the Research and Development Department. It was operational since 2012, followed by the official launch in November 2013 by the Minister of Physical Planning, Land and Forest Management (Min ROGB). The FCMU has been preparing a Satellite Land Monitoring System (SLMS) in very close collaboration with a wide range of relevant stakeholders.

Over the last years, the activities of the FCMU were directed in line with the National Plan for Forest Cover Monitoring (FCM plan, 2014[5]) composed of three major programs:

Program 1: *National capacity building on forest cover monitoring*. This program has the objective "to strengthen national capacity on forest cover monitoring, in terms of human resources, scientific and traditional knowledge, tools and technology".

Program 2: *Data generation on forest cover and its changes*. The second program of the FCM plan has the objective "to generate documented, updated and validated data on forest cover and forest cover changes, ready to be used for multiple purposes". Solid and reliable data generation is the core task of the FCMU and the backbone of forest cover monitoring.

Program 3: *Information and data sharing about forest cover and monitoring efforts.* The objective of program 3 is "to make data and information about changes in forest cover understandable and accessible to policy-makers, communities and other stakeholders". The national geoportal, developed in collaboration with UN-REDD, brings all data together and makes it accessible for the public (www.gonini.org).

Within the REDD+ program, the SLMS is further developed and expanded to be an inherent component of the National Forest Monitoring System (NFMS). This NFMS is composed of closely connected components (Figure 1.2.):

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[56]http://sbbsur.com/wp-content/uploads/2015/06/Forest_Cover_Monitoring_Plan_FCMP_Suriname.pdf

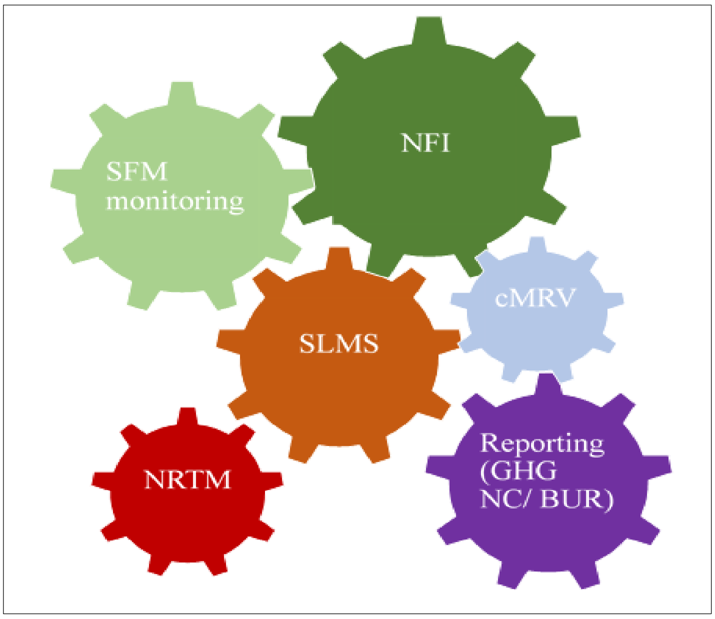

Figure 1-2. Visualization of how the NFMS subcomponents are related: National Forest Inventory (NFI); Sustainable Forest Management (SFM) monitoring; Satellite Land Monitoring System (SLMS); Community-based Measurement (C-MRV; Reporting and Verification and Near Real Time Monitoring (NRTM)

Capacity in Forest cover monitoring was also strengthened through two other regional cooperation projects:

- *REDD+ for the Guiana Shield* (www.reddguianashield.com) coordinated by ONF International (2013-2015);
- KfW-CI project: Avoided Deforestation through Consolidation and Creation of Protected Areas and Carbon Financing Mechanisms in the Guiana Region (Guyana, Suriname and Northern Brazil).

1.3 Representation of Suriname

Suriname is located on the north-eastern coast of South America, between 2° and 6° north latitude and 54° and 58° west longitude. The total land area of Suriname is estimated to be approximately 16.38 million ha according to the boundaries used for monitoring purposes, where the right river bank of the Marowijne, the Lawa and the Marowini river are the borders in the east and the left river bank of the Corantijn and the Boven-Corantijn river are the borders in the west. The southern border of the monitoring area is formed by the watershed of the Acarai mountains, Grens mountains and the Tumukhumak mountains. To better understand the changes in land area along the northern coast, a study to assess the changing coastline was carried out for a period of 30 years by Moe Soe Let V. (2016). This was used as an input to delineate a fixed area for the annual forest cover monitoring (Figure 1.3.).

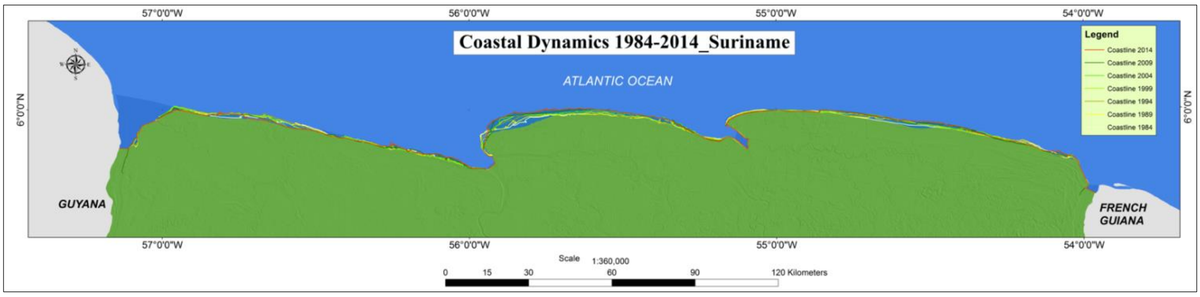

Figure 1-3. The dynamic of the northern Coast of Suriname over a period of 30 years (1984 - 2014) (Moe Soe Let V., (2016)

When it comes to the population, Suriname has approximately 540,000 citizens (ABS, 2011) and most people live in the young coastal plain. Due to the lack of infrastructure towards the interior of Suriname, the southern part of the country is sparsely populated and mostly only accessible by boat or airplane. The people living in the interior are mostly Indigenous and Tribal Peoples (ITP), relying on the forest as a source of food, fuel, medicine and land for agriculture. They perform agriculture using the shifting cultivation method, which is a traditional type of small-scale farming that involves clearing the land, burning the plant material, planting and harvesting the crops, and then abandoning the land to go fallow. Fallow periods in a shifting cultivation system vary and can be long enough to let forests regenerate in abandoned land (Katherine Lininger, 2011). In contrary to the traditional agriculture occurring in the interior, the coastal plain of Suriname has more permanent agriculture.

1.4 Definition of land use/ land cover classes

1.4.1 Definition of classes in the forest cover and deforestation maps

During the regional meeting of observation rooms in Lima, the ACTO-member countries agreed to use the following classes and the following years:

- Year 2000: forest, non-forest and clouds

- Year 2010: forest, non-forest, clouds and deforestation

Note: Suriname chose the year 2009 instead of 2010, due to too much cloud coverage in the images of the year 2010.

For national purposes, two additional classes were added (shifting cultivation, hydrography); those classes will be merged with the classes agreed upon when submitting the data to ACTO. Definition of the classes used are outlined in the Marrakesh Accords (UNFCCC 2001) and are described in the table 1.1 below.

Table 1-1. Definition of forest cover classes

Classes on the forest cover maps
Forest: Land mainly covered by trees which might contain shrubs, palms, bamboo, grass and vines, in which tree cover predominates with a minimum canopy density of 30% (or equivalent stocking level), a minimum canopy height (in situ) of 5 meters, and a minimum area of 1.0 ha. The forest definition in Suriname <u>excludes</u>: - Crown cover from trees planted for agricultural purposes (including palm trees such as coconut, oil palm etc.) - Tree cover in areas that are predominantly under urban or agricultural use. It should be noted that shifting cultivation (slash and burn agriculture) is <u>included</u> as forest as long as it is done in a traditional way so that the forest gets the chance to grow back after harvest (Workshop December 2012, Paramaribo).
Shifting cultivation: Shifting cultivation is the traditional use of the forest by indigenous and tribal peoples (ITPs). It is composed of a mosaic of small deforested pieces of land combined with fallow land at different stages of regeneration of the forest. On the Landsat images it is recognizable as a combination of small deforested patches embedded in an area of secondary forest (light green on the image). Shifting cultivation is mainly found close to the villages of indigenous and tribal communities, in the vicinity of rivers and/or roads. The forest dependent communities clearly indicate that shifting cultivation is a traditional and sustainable use of the forest (Gomes-Poma, A. & Kaus A., (1992)).
Non-forest: Land areas not covered with forest in the reference year 2000
Deforestation: Deforestation is defined as the direct and/or induced conversion of forest cover to another type of land cover after year 2000 in a given timeframe (DeFries et al., 2006[6]; GOFC-GOLD, 2009[7]).

[6]DeFries, R., Achard, F., Brown, S., Herold, M., Murdiyarso, D., Schalamadinger, B., & De Souza, C. (2006). Reducing greenhouse gas in temperate forests. Remote Sensing Reviews, 13, 207– 796 234.Emissions from Deforestation in developing countries: Considerations for monitoring and measuring, report of the Global Terrestrial Observing System (GTOS) Number 46, GOFC-GOLD report 26 (p. 23). Roma, Italia.

Clouds:

All area covered by clouds or cloud shadows on Landsat images. Clouds are currently filled where possible by using the Greenest pixel composite from Google Earth Engine and *Global Forest Change data from the Maryland University* (Hansen et al., 2013), combining the "greenest" pixel value from a series of satellite images for a specified period. Using this method can lead to almost cloud free end results.

1.4.2 Definition of classes for the post-deforestation LULC maps

To better understand the drivers of deforestation, the deforestation classes for the periods 2000-2009, 2000-2013 and 2000-2015, have been further sub-classified in land use and land cover (LULC) classes.

The definitions of these LULC classes have been streamlined with the definitions used within the regional (ACTO) context and those of the Intergovernmental Panel on Climate Change (IPCC) Good Practice Guidance for Land Use, Land-Use Change and Forestry of 2003. Table 1.2 gives an overview of the definitions of the national LULC classes and the corresponding ACTO and IPCC class.

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[7]GOFC-GOLD. (2009). Reducing Greenhouse gas emissions from deforestation and degradation in developing countries: A sourcebook of methods and procedures for monitoring, measuring and reporting, GOFC-GOLD Report version COP14-2. (F. Achard, S. Brown, R. De Fries, G. Grassi, M. Herold, D. Mollicone , Pandey, D. &C. J. Souza, Eds.) (p. 185). Alberta, Canada.

Table 1-2. Definition of Land Use Land Cover classes

Suriname LULC classes	ACTO classes	IPCC classes
Agriculture: Extensive areas with a predominance of annual cycle crops, such as grains, banana, vegetables, etc., with use of high technological standards, such as use of pesticides and mechanization, among others.	Agriculture	Cropland
Burned Area: Areas that have recently been burned.	Not observed area	---
Infrastructure: All roads excluding roads within another LULC class, as well as man-made waterways such as irrigation canals, access ways to oil wells, etc.	---	Settlements
Mining: Mining areas in current production process of gold mining (industrial and artisanal mining), sand mining, house material mining, bauxite mining, oil mining and gravel mining.	Others	Other land[8]
Other land: These are areas that do not fall under any of all LULC classes, with different coverage pattern such as savannas and others.	Others	Other land
Pasture: Pasture areas in current production process with a predominance of herbaceous vegetation, and between 90% and 100% coverage of grass species.	Pasture	Grassland
Secondary vegetation: Areas that, after the complete removal of forest vegetation, are in advanced process of regeneration of shrub and/or tree vegetation.	Secondary vegetation	Forest land
Urban: Urban patterns formed by population concentration, villages, towns or cities with differentiated infrastructure from rural areas, with density of streets, houses, buildings and other public facilities.	Urban area	Settlements

[8]In line with the 2nd National Communication on Greenhouse Gas Inventory (http://www.nimos.org/smartcms/downloads/1.%20suriname%20sncunfc%20on%20climatechange%20february%202013.pdf)

2 Materials and methods

This chapter will describe the materials and methods used for the production of the forest cover change (deforestation) data, the post-deforestation LULC data and the Quality Assessment/Quality Control (QA/QC) applied on the forest cover change data.

2.1 Overview of data used

2.1.1 Landsat Satellite data

Landsat represents the world's longest continuously acquired collection of space-based moderate-resolution remote sensing data. The archive of Landsat provides a record of observations from 1972 to the present, and will continue into the future. For monitoring the forest cover of Suriname, predominantly free Landsat images with a 30m spatial resolution are used.

Landsat data that was downloaded:

1. **Top of Atmosphere (TOA) imagery:** Landsat-5 TM, Landsat-7 ETM+, Landsat-8 Oli

The selection criteria before downloading TOA imageries are:

- The amount of cloud coverage;
- Distribution of the clouds;
- Image date (As recent images as possible in the monitoring period).

2. **Surface Reflectance imagery**[9]

The U.S. Geological Survey (USGS) is capitalizing on this valuable time series to create higher level data products that can be used to document changes of the Earth's terrestrial environment. This data is used to create cloud masks.

The satellite images were downloaded from different websites:

http://glovis.usgs.gov/

http://earthexplorer.usgs.gov/

https://landsatlook.usgs.gov/viewer.html

http://glcf.umd.edu/data/gls/index.shtml

http://www.inpe.br/

https://libra.developmentseed.org/

https://remotepixel.ca/projects/satellitesearch.html

[9] https://landsat.usgs.gov/sites/default/files/documents/provisional_lasrc_product_guide.pdf

https://espa.cr.usgs.gov

The Landsat images are available to download in scenes or grids. Suriname is covered with 11 Landsat scenes and each scene has a specific row and column number (see figure 2.1). To download an image for a specific area, it is important to select the correct scene. Each scene has a various amount of dates available, which enables the classes to be linked with the date of the images. For each scene, several temporal images were used, to minimize the cloud cover on the classification.

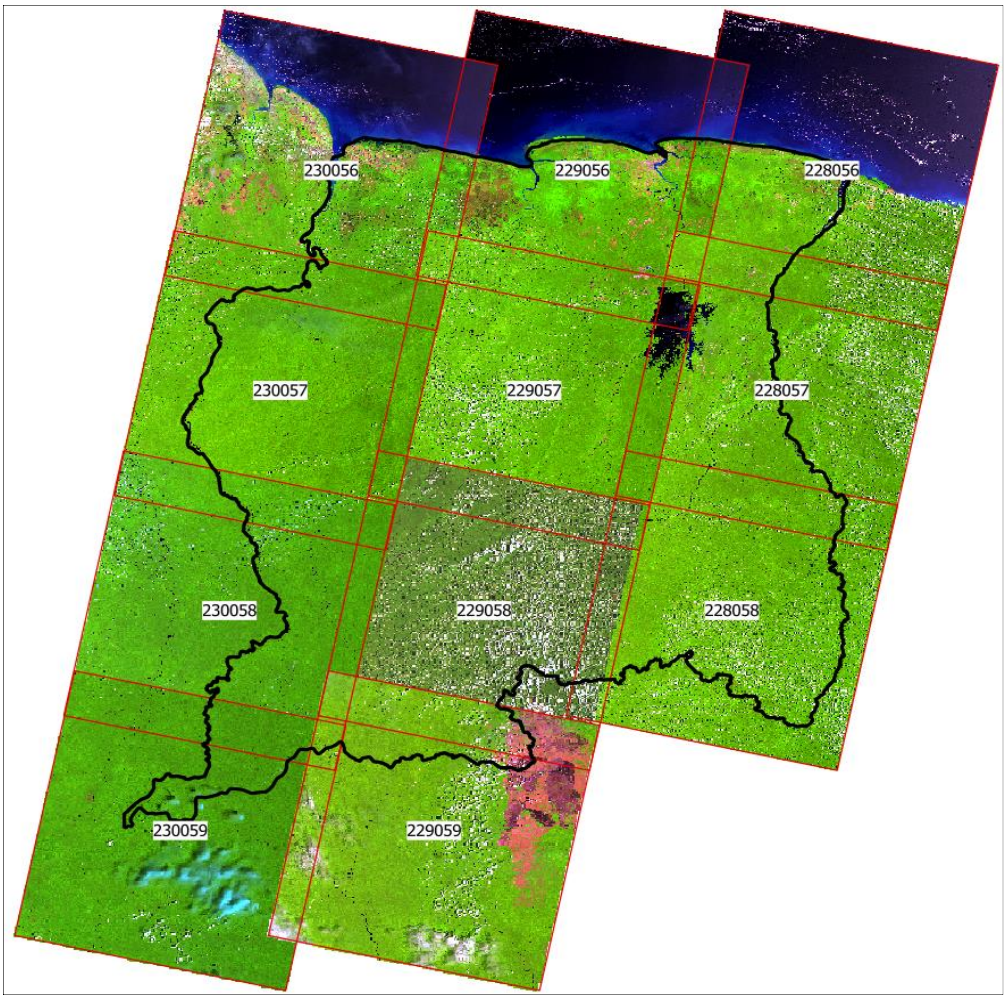


Figure 2-1. Overview of the 11 Landsat scenes covering Suriname

The overview of images used is given in Annex 1 with the row, path, sensor, date and status of georectification. Table 2.1 gives an overview of data used for the production of the forest cover data.

Table 2-1: Data used for the forest cover maps

Map produced	**Data used**		
	Satellite	**Sensor**	**Year (s)**
Basemap 2000	Landsat 5	Thematic mapper (TM)	1999, 2000 and 2001
Deforestation map 2000-2009	Landsat 5	Thematic mapper (TM)	2000-2009
Deforestation map 2009-2013	Landsat 7 Landsat 8	Enhanced Thematic Mapper plus (ETM+) Operational Land Imager (OLI)	2013
Deforestation map 2013-2014	Landsat 8 SPOT 5 and Spot 6	Operational Land Imager (OLI)	2014
Deforestation map 2014-2015	Landsat 8	Operational Land Imager (OLI)	2015
	Greenest pixel composite		2015
	Sentinel 2A[10]		2015
	Global forest change data from the University of Maryland (Hansen et al., 2013)		

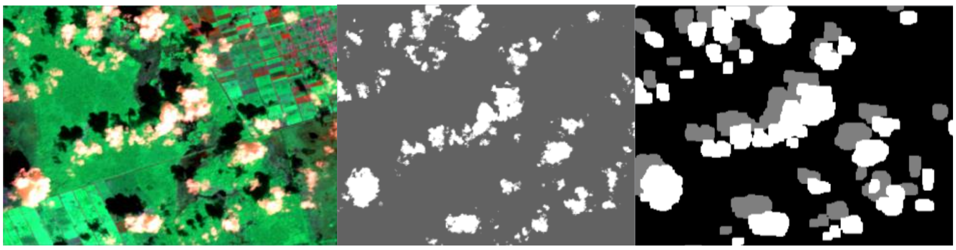
Note: All images used can be found in Annex 1

[10] https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/sentinel-2

2.1.2 Surface Reflectance satellite data

The Landsat 8 Surface Reflectance product is a Landsat Level-2 product, which is generated from the Landsat Surface Reflectance Code[11] (LaSRC). Most notably, LaSRC makes use of the coastal aerosol band to perform aerosol inversion tests, uses auxiliary climate data from MODIS and uses a unique radiative transfer model. Additionally, LaSRC hardcodes the view zenith angle to "0", and the solar zenith and view zenith angles are used for calculations as part of the atmospheric correction.

The Surface Reflectance data is used since the production of the deforestation map of 2015. This data provides a cloud, cloud shadow, snow, and water identification in the CFmask band (Table 2-1). This data is likely to present more accurate results than its companion bands (cloud_qa). The CFmask band was originally developed at Boston University in a Matrix Laboratory (MATLAB) environment to automate cloud, cloud shadow, and snow masking for Landsat TM and ETM+ images. The MATLAB Function of Mask (Fmask) was subsequently translated into open source C code at the USGS EROS Center, where it is implemented as the C version of Fmask, or CFmask. CFmask designates whether clouds, cloud shadows, snow, or water were identified in each pixel value in the Surface Reflectance product, as illustrated in figure 2.2.



Pixel Value	Interpretation
255	Fill
0	Clear
1	Water
2	Shadow
3	Snow
4	Cloud

Figure 2-2. From left to right: Landsat OLI color composite, Landsat QA-band, CFmask and the pixel values

2.1.3 Ancillary data

Within the monitoring process ancillary data was also collected and used, providing a better understanding about the activities or changes that have taken place. The ancillary data was produced by SBB and by other relevant institutes.

An example of ancillary data is the Fire Information for Resource Management System (FIRMS)[12], to provide near real-time active fire locations. Figure 2.3 explains how FIRMS data was used in the classification of deforestation. The list of ancillary data that was used is given in Annex 2.

[11] https://landsat.usgs.gov/sites/default/files/documents/lasrc_product_guide.pdf

[12] FIRMS was developed by the University of Maryland, with funds from NASA's Applied Sciences Program and the UN Food and Agriculture Organization

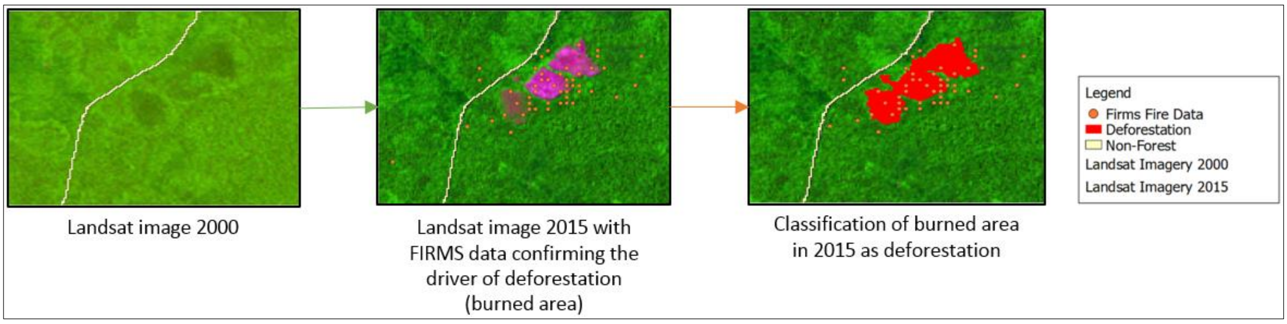


Figure 2-3. FIRMS data used in the classification of deforestation data

2.2 Method deforestation monitoring

The method for monitoring deforestation in Suriname can be divided into three main stages: Pre-processing, core-processing, and post-processing. Each stage is further subdivided in processing steps, which will be described within the following paragraphs. Figure 2.4 shows the flowchart for producing the deforestation maps.

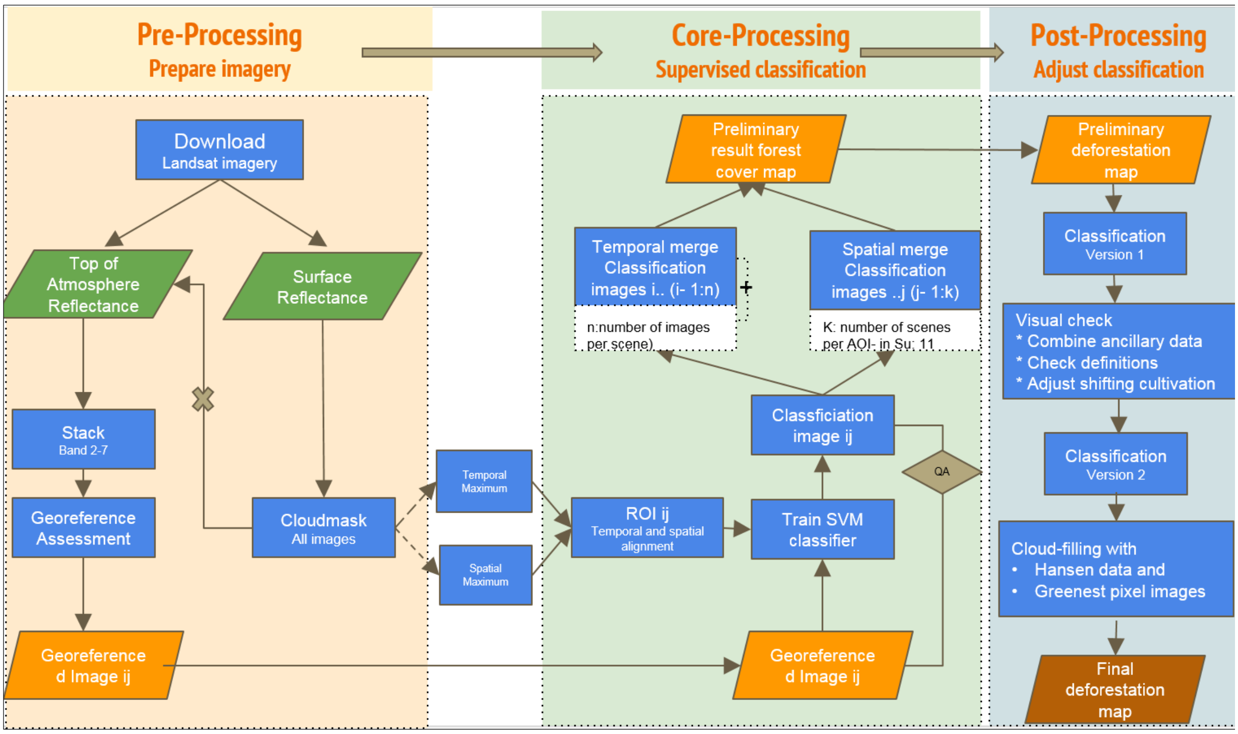


Figure 2-4. Processes flowchart for producing the deforestation map

2.2.1 Pre-Processing

The pre-processing stage contains the following steps:

1. Prepare data storage structure;
2. Downloading the imageries;
3. Georeferencing:
    a. Build color composites
    b. Selection of TOA imagery
    c. Geometric accuracy

4. Creation of Landsat mosaic (extraction and application of cloud mask);
5. Build stack image of TOA images for classification.

2.2.1.1 Data storage

Downloading Landsat images for the monitoring year is most often carried out in the beginning of the next year (e.g. the monitoring for the period 2015-2016, will be done in the beginning of the year 2017). These images are stored on the dedicated server[13] and have been catalogued by the analysis period they belong to (i.e. 2000, 2009, 2013, etc.), the sensor, the path and row (see figure 2.5.).

Ancillary data is updated continuously and are also stored in the dedicated folder.

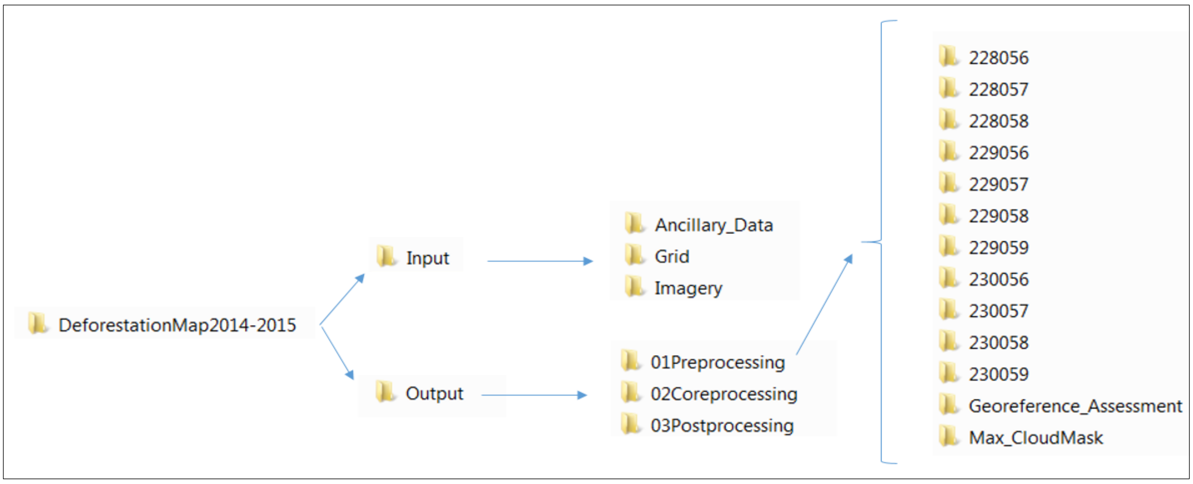


Figure 2-5: Folder structure for all the steps within the monitoring process

2.2.1.2 Sequence of TOA Imagery selection criteria

To minimize the cloud cover on selected optical Landsat images, the following selection criteria were sequentially used, selecting a maximum of 4 images. These images were then downloaded.

Monitoring period and cloud coverage

For the monitoring of the annual forest cover change, an assessment of the cloud distribution was done over the year (Mahabier V.; 2016). Based on this assessment, the period of September till November (large dry season in Suriname) was selected for yearly monitoring purposes (Figure 2.6) due to the minimum cloud coverage on the images in this period.

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13 https://docs.google.com/document/d/1uM0BK2JZwUyQvfGSO-rbAo3ry52vIF6ODIJukyvo-KA/edit

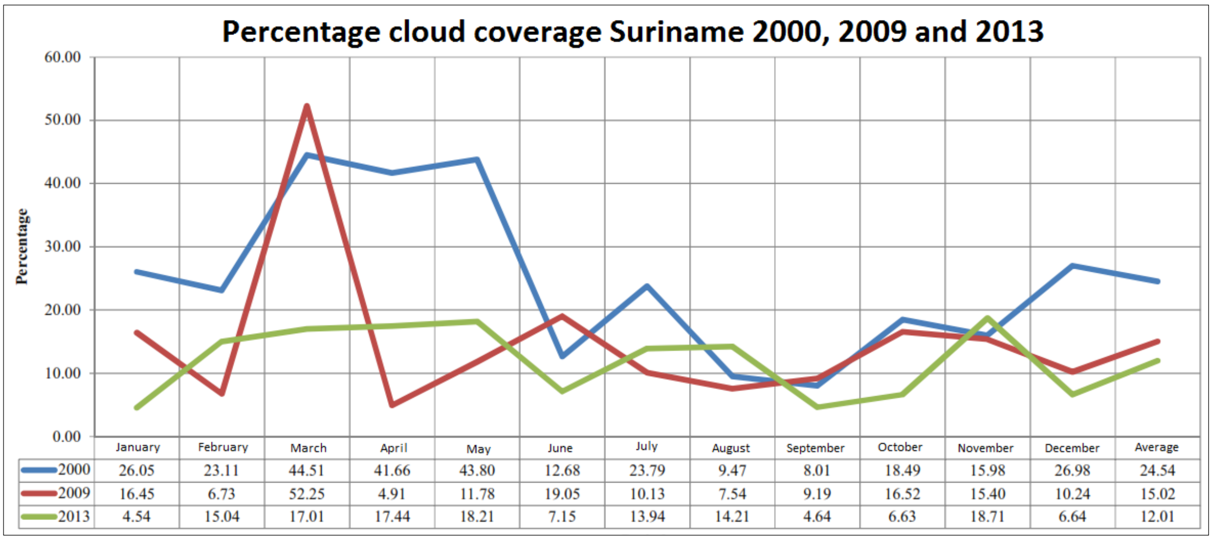

Figure 2-6: Overview average percentage cloud coverage Suriname (per month) and the yearly average adopted from NOAA/AVHRR satellite imagery from 2000, 2009 and 2013 (Mahabier V.;2016)

Because this period is at the end of each year, the results will provide a realistic estimation of the activities that took place during that year. To combine the images, first the priority image, also called the "anchor (A)" image, is selected, having the lowest cloud coverage of this period. The fill images can also be selected within this period. However, if there are images outside of the period with a lower cloud coverage, then these images are selected as fill images. An example of this selection is given in Table 2.2. The purpose of this selection is to fill in the cloud areas of the images previously selected, so the dispersion of the clouds are important within this selection process. In the deforestation monitoring year 2015, approximately 12% of the fill images are selected outside the monitoring period.

Table 2-2: Selection of imagery used for forest cover monitoring

Path	Row	CC (%)	Date (m/d/year)	Landsat ID	Selection
229	59	19.2	7/11/2015	LC82290592015192LGN00	F1
229	59	1	10/15/2015	LC82290592015288LGN00	A
229	59	21.19	11/16/2015	LC82290592015320LGN00	F2

2.2.1.3 Georeferencing

Color composites

Landsat 8 OLI data is composed of eleven spectral bands, containing reflectance information from the different wavelengths. To visualize combinations of these bands at the same time, color composites are compiled. Figure 2.7 gives an example of the color composite combining bands 4 (red), 5 (Near Infrared) and 6 (Shortwave Infrared 1). For Landsat 5 and 7, the bands 3, 4 and 5 were used.

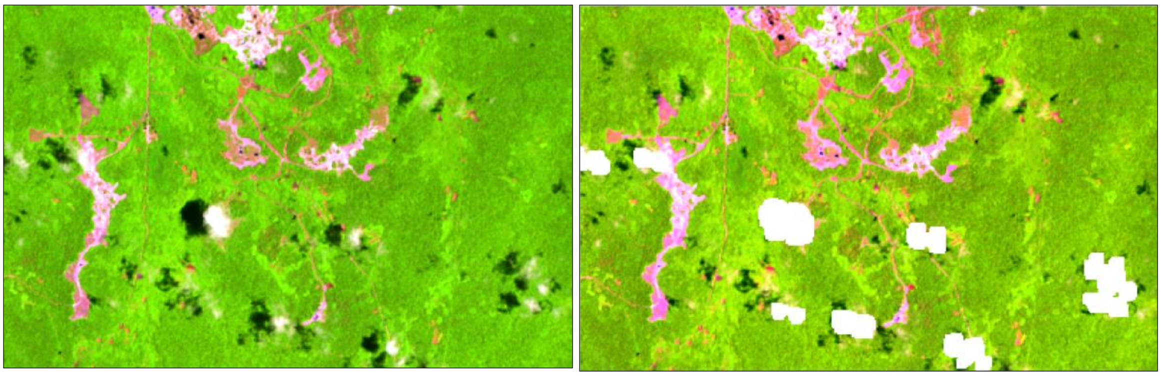

Figure 2-7: Illustration of a composite made from Landsat 8, with band combination 654 (left) and the composite with band combination 654 multiplied by cfmask (right)

Image coregistration and geometric registration

Coregistration is the process of geometrically aligning the pixels, which are representing the same area on two or more images. Precise image-to-image coregistration has to be ensured for all multi-temporal and multi-sensor datasets, because insufficient spatial fit can lead to the detection of 'false' changes (Sundaresan et al; 2007).

When downloading the Landsat images, these images already underwent a geometric registration. Especially over the last year, the United States Geological Survey (USGS) has been reprocessing much of the Landsat archive, where over 90% of the Landsat collection scenes are within a Root Mean Square Error (RMSE) of 12 meters. The RMSE defines how spatially accurate an image is. This results in the creation of a L1T *precision and terrain corrected* product, eliminating the need for further geometric correction.

Nevertheless, co-registration among images needs to be reviewed and where necessary adjusted (Hewson *et al;* 2014). To review the co-registration, an assessment was done on all downloaded images (Figure 2.8), where the Global Land Survey (GLS) data[14] is used as reference. The GLS data sets were created during a collaboration between NASA and the U.S. Geological Survey (USGS), and were designed to allow scientists and data users to have access to a consistent, terrain corrected, coordinated collection of data. All Landsat data is compared to the GLS data with control points. The control points should be points that are easy to retrieve, such as points where rivers split and other stable non-forest areas. In the attribute table, for each image, it is indicated if there is a shift between the image and the reference data (OK=No shift, 1L = shift of 1 pixel to the left, etc.) Figure 2.8 illustrates the coregistration of a Landsat image.

[14] https://landsat.usgs.gov/global-land-surveys-gls

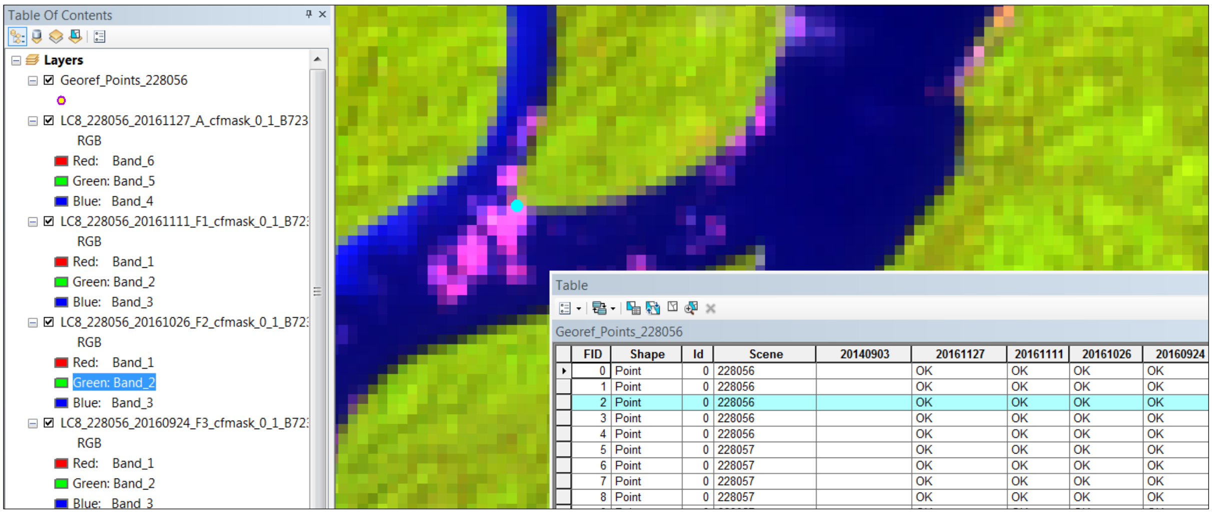

Figure 2-8: Review coregistration of Landsat images

The coregistration assessment creates an overview of the images that need to undergo a geometric registration. For the geometric registration process, a maximum of thirteen assessment points were evenly distributed over each image. This was carried out in the software QGIS, using the georeference tool. Points are spread over the Landsat scene, using a 2nd order polynomial transformation and the nearest neighbor technique, until a root mean square error (RMSE) smaller than a third of the pixel size (30m) was achieved (Figure 2.9).

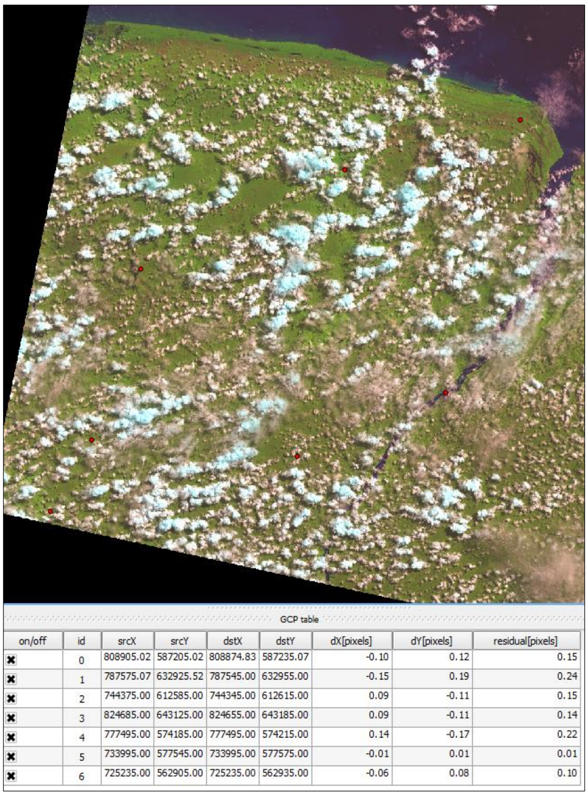

Figure 2-9: Illustration of the Ground Control Points (GCP) on a Landsat image

2.2.1.4 Create cloud-filled Landsat mosaic

A Landsat mosaic was first created temporarily (per scene) and then spatially (whole country) to support a visualization of the available Landsat data at once[15]. For the production of the cloud-filled Landsat mosaic, surface reflectance data is used. Within the process, the areas consisting clouds of all images are masked out using the CFMask band. The anchor image where clouds are masked out, is filled with data of the fill images. This cloud-filled Landsat mosaic is used for quick analyses of the changes in the forest. In the post-processing phase of the deforestation map, this image is also used for visual interpretation. The flowchart for creating a filled image is shown in figure 2.10. The same process was conducted for all scenes.

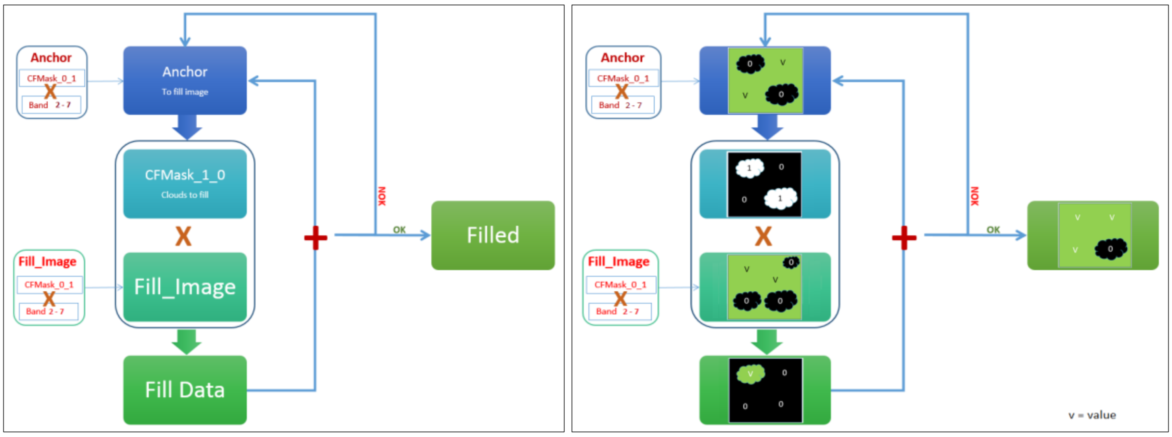

Figure 2-10: Flow diagram of creating cloud-free mosaic (left), with the illustration (right)

Extract and apply cloudmask

For each individual image a (binary) mask is created that represents areas which are covered with clouds on that image. To do this, the CFmask is extracted from the surface reflectance image data. The formula to extract the clouds and cloud shadow is "cfmask" = 2 OR "cfmask" = 4 (see table 3.3). This is done using Raster Calculator in QGIS.

Before building the stack of all bands, a cloud mask is applied on spectral bands 2-7. This process is done with a model "Apply Cloudmask" built in QGIS (Figure 2.11).

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[15] The following link contains a report of creating a cloud-free mosaic with Surface Reflectance Data:

https://docs.google.com/document/d/1JoYJ5yZQ7RlFpGKke5H-ti-BRPYaLDeJkTnwv1jIjEA/edit

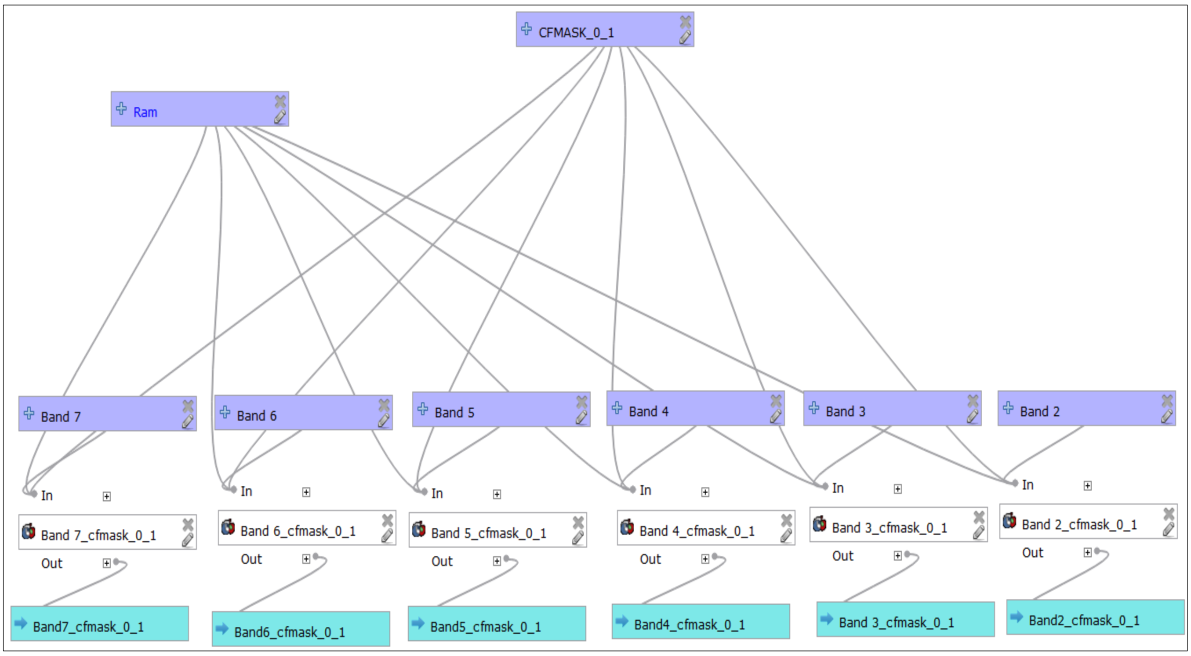


Figure 2-11: Model built in QGIS to "apply cloudmask" process

Fill anchor image with data from fill images

With raster calculator, data from fill images is extracted and added to the anchor image, where clouds persisted.

Build spatial mosaic

Spatially, all images are added to create a cloud filled mosaic of Landsat data. Figure 2.11 illustrates how an anchor image is filled with 3 fill images.

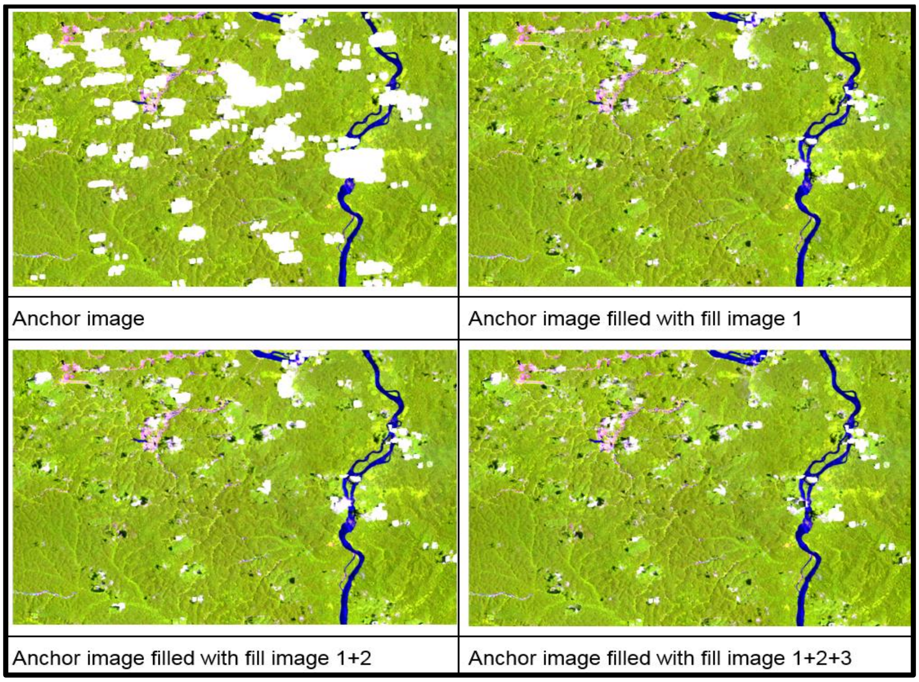


Figure 2-12: Example of an anchor image successively filled with fill image 1, 2 and 3

2.2.1.5 Build stack image of TOA images bands 2-7

Prior to this process, tests were conducted in order to know which image stack gives the best SVM classification result.

Therefore three image stacks were created with and without indices, i.e. an image stack with the bands 2 till 7, an image stack with the bands 2 till 7 and a Normalized Difference Vegetation Index (NDVI), and an image stack with the bands 2 till 7 and a Normalized Difference Water Index (NDWI). The reason for not including band 1 and band 9 is that these bands are useful for respectively coastal and aerosol studies and cirrus cloud detection[16].

Results have indicated that no significant difference was found in the classification results when adding indices such as NDVI and NDWI. So, it has been decided to choose an image stack of band 2 till 7 to create an image composite, which will be used in the core-processing step for the SVM classification. The Landsat bands 2-7 are stacked in the numerical order as virtual raster and saved as a tiff format. The images that were used are given in Annex 1.

2.2.2 Core-Processing: Supervised Vector Machine classification

Support vector machines (SVMs) developed by Vapnik (V. Vapnik, 1995), have gained wide acceptance because of their high generalization ability for a wide range of applications. SVMs are particularly appealing in the remote sensing field due to their ability to successfully handle small training data sets, often producing higher classification accuracy than the traditional methods (Mantero et al., 2005). The Support Vector Machine is one of the state-of-the-art techniques for classification tasks (V. Vapnick, 1999). This classification technique is also used in various regional studies, such as the regional gold mining study "Monitoring the impact of gold mining on the forest cover and freshwater in the Guiana Shield" (Rahm M. et al., 2014), where promising results have been generated. The SVMs learning phase consists in finding a set of parameters, for which many effective techniques have been proposed (J.C. Lin, 2002). However, the search for the optimal parameters does not complete the learning phase of the SVM: a set of additional variables (hyperparameters) must be tuned (training data/supervised learning) in order to find the SVM characterized by optimal performance in classifying a particular set of data. This phase is usually called model selection and is strictly linked with the estimation of the generalization ability of a classifier, as the chosen model is characterized by the smallest estimated generalization error (B.L. Millenova et al.; 2005), (D. Anguita et al.; 2005), (B. Skoelkopf et al.; 2002), (J. Shawe-Taylor et al.; 2000).

[16] https://landsat.usgs.gov/what-are-band-designations-landsat-satellites

The supervised classification is also used within the core-processing phase of the deforestation maps, creating the version 1 map, using Orfeo Toolbox[17] in the open source software QGIS. The classification process includes 5 main steps (Figure 2.13.):

1. Create training samples;
2. Compute image statistics;
3. Train SVM classifier (build the model);
4. Create image classification;
5. Analyze the classification and
6. Create mosaics of classifications.

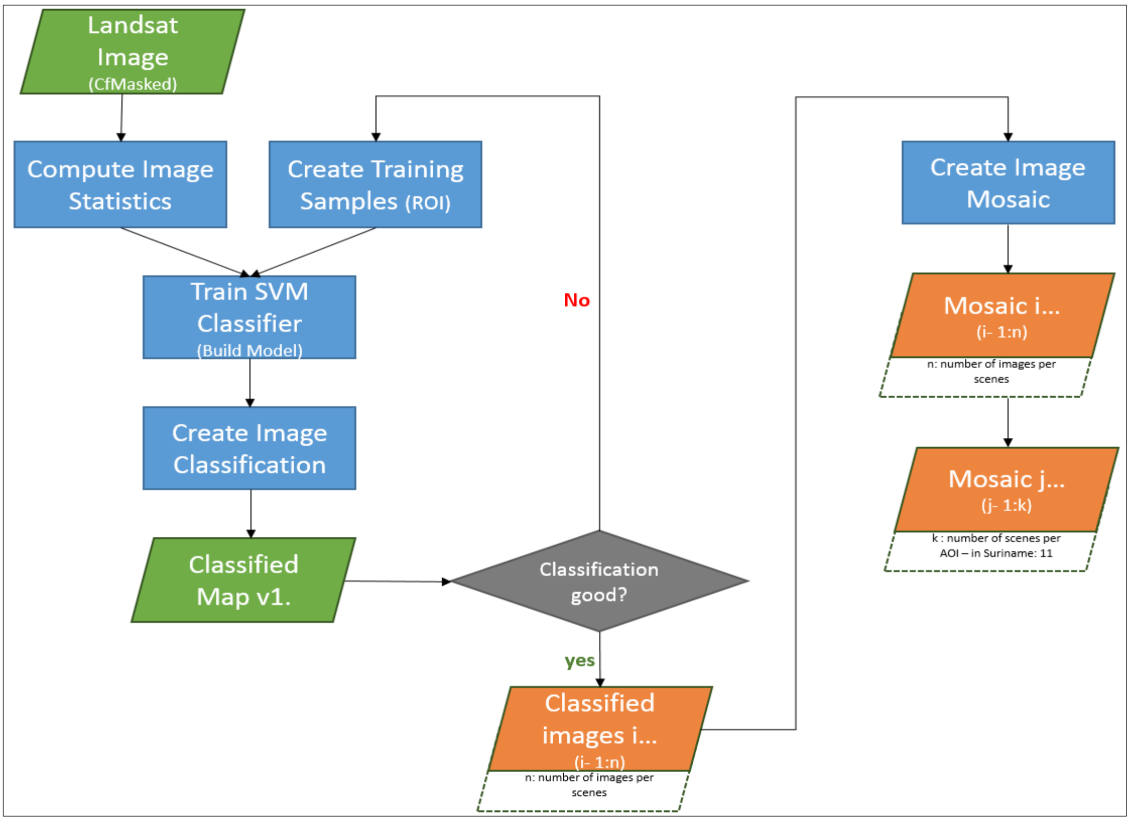


Figure 2-13: Flowchart of the SVM classification

[17] https://www.orfeo-toolbox.org/

2.2.2.1 Create training sets

Several techniques have been proposed for obtaining a probabilistic estimate in the SVM classification, which can be divided in two main categories: practical and theoretical methods (D. Anguita et al.; 2005), (K. Duan et al.; 2003). Practical methods typically rely on well–known and reliable statistical procedures, whose underlying hypotheses, however, cannot be always satisfied or are only asymptotically valid (R.Kohavi; 1995). Theoretical methods, instead, provide deep insights on the classification algorithms and are based on rigorous approaches to give a prediction, in probability, of the generalization ability of a classifier.

For the production of the deforestation maps of Suriname the practical method is used. Practical methods usually split the available set of data in two independent subsets: one is used for creating a model (training set), while the other is used for computing the generalization error estimation (hold-out set) (V.Vapnik; 2000), (T. Poggio et al.; 2004), (P.L.Bartlett et al.; 2002).

The creation of a model, consists of a set of training samples also known as Regions Of Interest (ROI). ROIs are created, based on visual interpretation of input data (Landsat imagery). Selecting training samples from each class separately often improves the classification accuracy of the resulting SVM classifiers. Each class consists of a range of pixel values (digital numbers), which are observed as various reflectances on a satellite image (for example the Non-forest class reflect the colors pink to purple (composite of bands 654)). As much of these variations in reflectances can then be samples for each class (Figure 2.14). Each class was trained by giving values to the training polygons referring to the following classes:

- 0= no data : clouds extracted by the cloud mask
- 1= hydrology : all water bodies
- 2= forest : all forest areas, including shifting cultivation
- 3= non-forest : all bare soil areas

Small clouds, not detected by the cloudmask, will be visually adjusted in the post-processing phase.

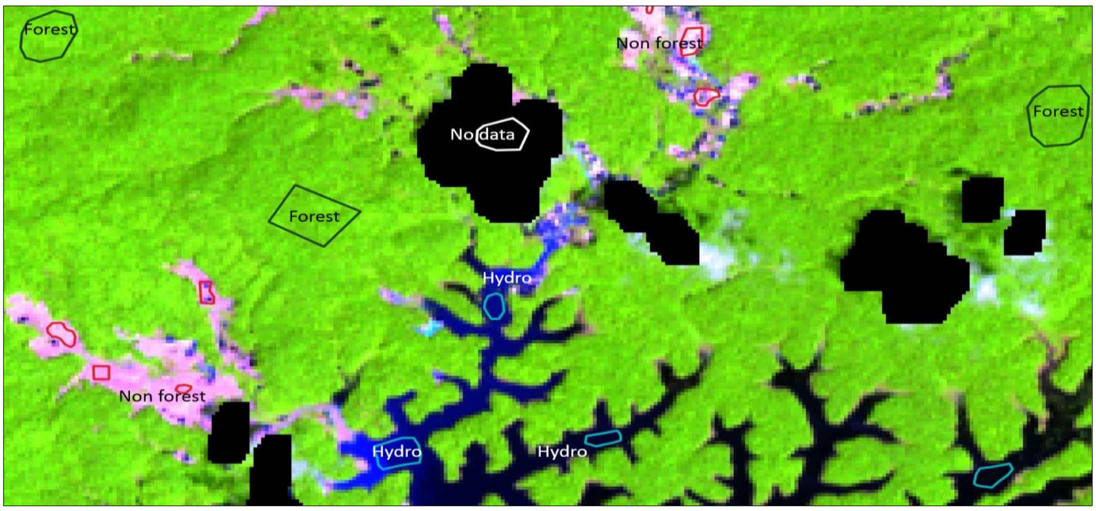
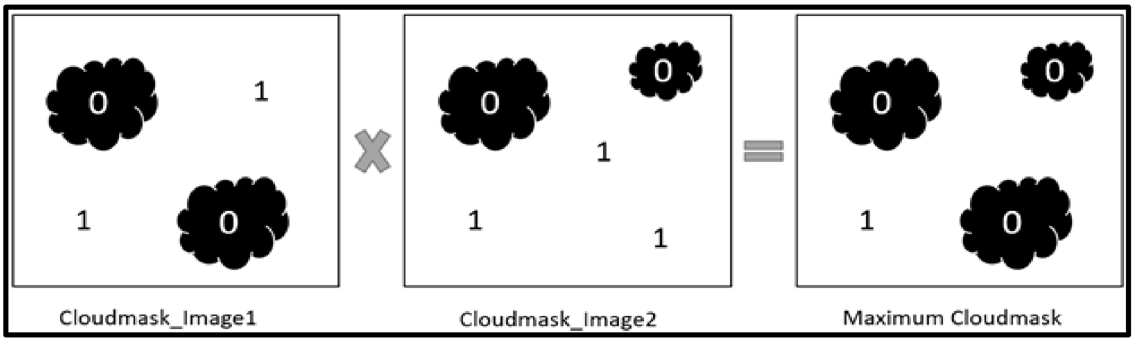
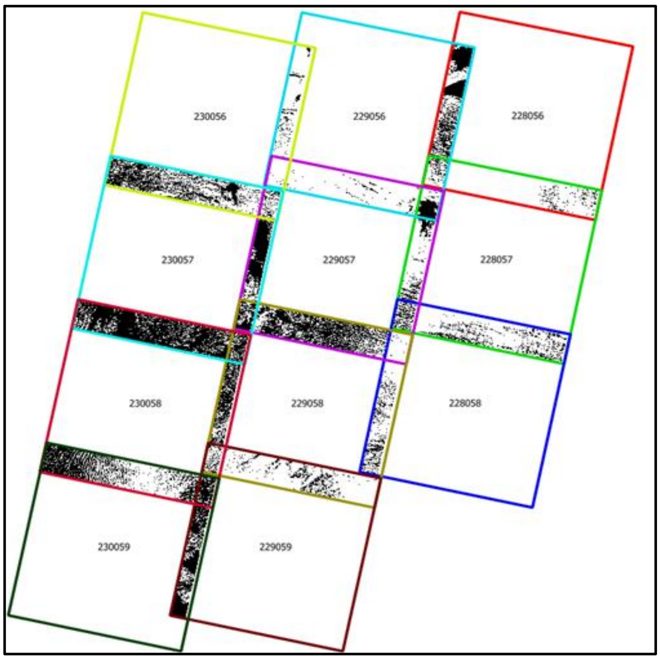


Figure 2-14: Overview of the ROIs in each class

Classification alignment

The version 1 deforestation map is a mosaic created from the classification per scene, where Suriname is covered by 11 Landsat scenes. For each scene, approximately 3 images are classified temporally. The temporal and spatial classification has to be streamlined, by as much as possible re-using training samples. To produce training samples that can be re-used, various types of cloud masks are created. These cloud masks give an overview of the areas, where temporal and spatial overlaps between images, consists of comparable land cover data for each image. These types are given in table 2.3. The cloud masks are produced with the Surface Reflectance data which can be downloaded from the USGS website. For the cloud masks, the CFmask is used where pixel value 4 and 2 are extracted.

Table 2-3: The various types of cloud masks created

No	Type	Description	Use
1	Maximum temporal cloud mask	For each scene the individual cloud masks are multiplied with each other to show the area where there is data on all images.	Temporally matching ROI's for no-change areas to conduct a consistent SVM classification
	 Illustration shows the multiplication between temporal cloud masks in the tool Raster calculator in QGIS		
2	Cloud mask anchor at overlaps	For all the overlapping areas between the scenes, a cloud mask is created showing the area where no clouds are on both neighboring scenes. This is created with the cloud mask of the anchor images.	Spatially draw matching ROI's at overlapping scenes for spatial classification alignment
	 		

To make sure that the classifications are aligned, a reference classification is produced for scene 228056. The neighboring scenes of the reference classification can then be classified and so on. The sequence of the classification of the scenes is given in figure 2.15.

Sequence

Scene	Spatial alignment check with:
228056	Reference Scene
229056	228056
228057	228056
229057	228057 229056 (228056)
230056	229056
230057	230056 229057 (229056)
228058	228057
229058	228058 229057 (228057)
230058	230057 229058 (229057)
229059	229058 (228058)
230059	230058, 229059 (229058)

Overlapping areas with neighboring scenes

Figure 2-15:Overview of the sequence in which the classification occurs per scene

2.2.2.2 Compute image statistics

This application computes a global mean and standard deviation for each band of a set of images and optionally saves the results in an XML file. The output XML is intended to be used as an input for the Train Images Classifier application to normalize the samples before training.

2.2.2.3 Train SVM image classifier

The 'Train SVM Image Classifier' performs a classifier training from multiple pairs of input images and the created ROI's (see previous section). Samples are composed of pixel values in each band optionally normalized using an XML statistics file produced by the 'Compute Images Statistics' application. The SVM (Support Vector machine) is trained, which creates a model file. This file contains the "memory" of the training step.

2.2.2.4 Create image classification

This application performs an image classification based on a model file produced by the Train Images Classifier application. Pixels of the output image will contain the class labels decided by the classifier.

2.2.2.5 Create mosaics of classification

In order to create mosaics of classification, a spatial alignment and temporal alignment should be executed first. These steps are described below, in this paragraph.

Spatial alignment

First the difference in classification results in the overlapping area is checked. If the classifications differ, the ROIs are assessed and adjusted till classifications are aligned. Figure 2.16 shows an example of the confusion between the non-forest and hydrography class. This is corrected by reselecting the ROI's and repeating the SVM-Classification.

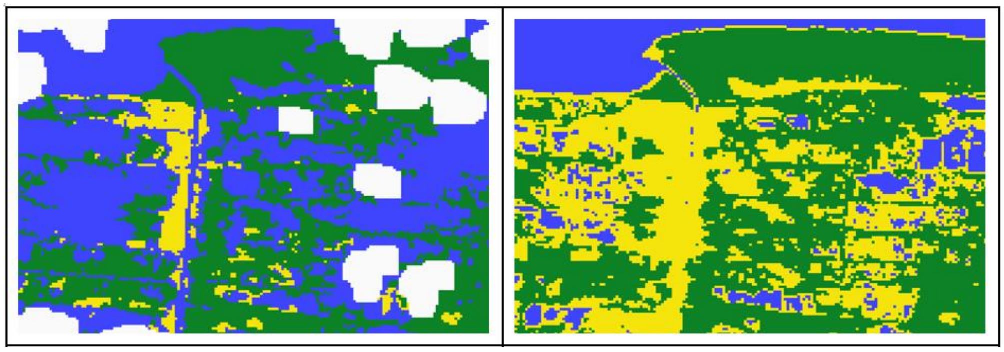


Figure 2-16: Neighboring scenes, where the classification of overlapping areas do not match.

Subsequently, the transition at the edge between the scenes is checked (e.g. when the river continues across the edges of the scene, it should continue smoothly). In figure 2.17 the edge of the two images can be observed by the division of the light and dark image.

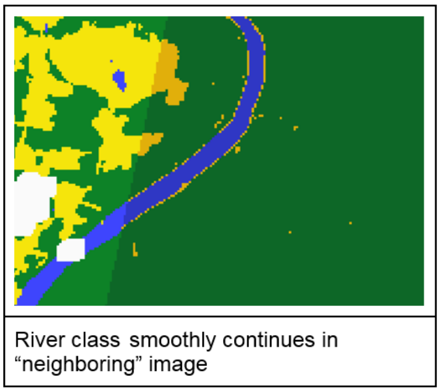
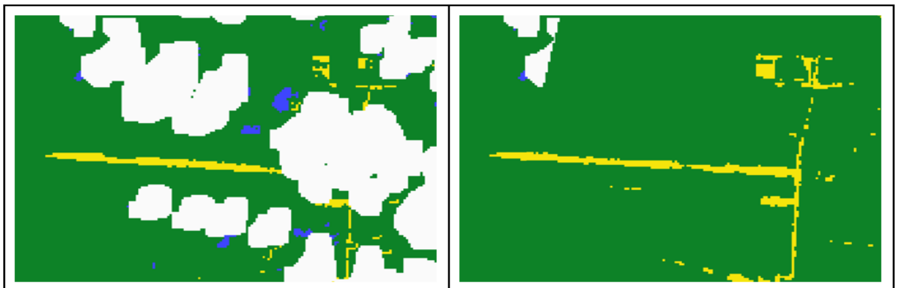


Figure 2-17: Classification of neighboring scenes showing a smooth transition

Finally the transition at edges of cloud-filled areas by the "neighboring" filled image is checked. Figure 2.18 shows the transition at edges of cloud-filled areas by the "neighboring" filled image.



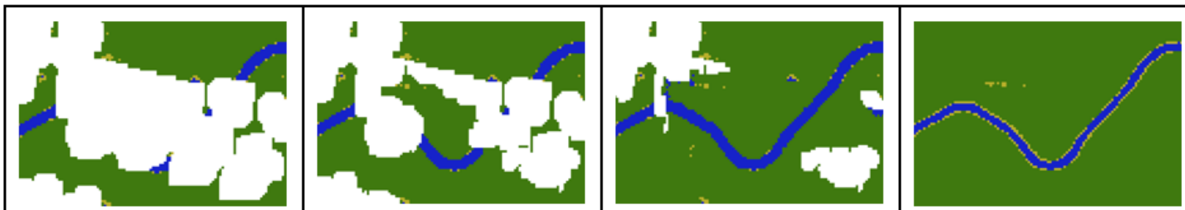
Cloud covering infrastructure T-junction in overlapping area.	Clouds filled with classification of "neighboring" filled image gives an expected continuation/ representation of infrastructure

Figure 2-18: The transition at edges of cloud-filled areas by the "neighboring" filled image.

Temporal alignment

The classification results of fill images with anchor image and "neighboring" filled image are checked. Figure 2.19 shows the transition changes of the anchor image to the neighboring image.

1. Transition at edges of cloud-filled areas by the fill images (similar as spatial alignment).
2. Difference in classification results *between fill images and "neighboring" filled image* for cloud gaps (areas) within the overlapping area.
3. Transitions between classification results of the Fill images at the cloud areas with the classification results of the "neighboring" filled image.



Anchor	Anchor + Fill 1	Anchor + Fill 1+Fill 2	Filled image "neighboring" River

Figure 2-19: Transition changes of the anchor image to the neighboring image

Temporal and spatial merge of SVM classification

For spatial and temporal merge of the SVM classification results, the tool *Mosaic to New Raster* in ArcGIS is used. After the border values on all images are set to "No Data", the images are organized in the order they should be filled, where after the option "FIRST" is used to combine the values of the areas with overlapping information. This results in a first forest cover map (Figure 2.20). In this result clouds persist, because the cloud mask algorithm does not detect small clouds and detected clouds are not entirely filled with data of temporal Landsat images. These remaining cloud (no-data) areas are in the post-processing filled with the greenest pixel composite, Global Forest Change and Sentinel 2A data.

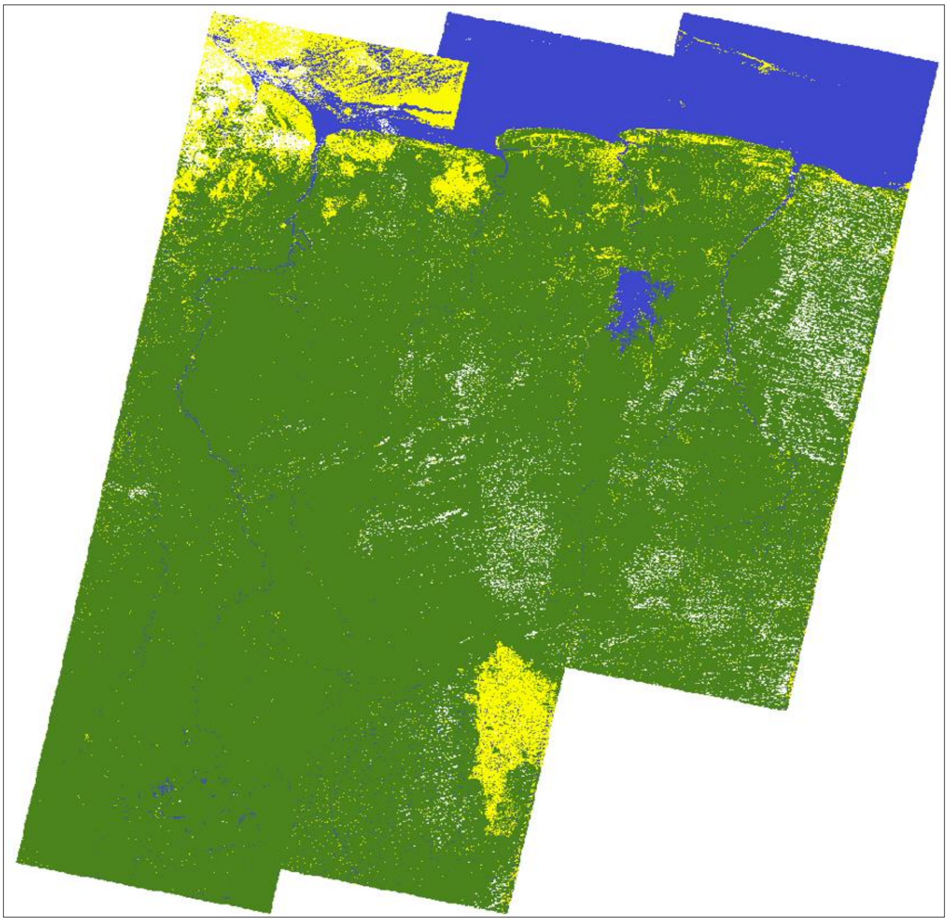


Figure 2-20: Version1 SVM classification result

2.2.3 Post-Processing

In this sub-paragraph all the processes within the post-processing stage are explained. The post-processing is divided into 3 phases:

1. Database setup;
2. Manually adjust the results of the semi-automatic classification, by doing visual checks using Landsat imagery and ancillary data;
3. Fill clouds with other data i.e. Global forest change data (Hansen et al 2013), Greenest pixel composite from Google Earth engine and Sentinel 2A imagery.

Post-Processing is carried out in TerraAmazon[18]. TerraAmazon freeware offers a multi-user environment and provides a geographical user interface for the open source software PostgreSQL. TerraAmazon is developed by the Brazilian agency for Space Research INPE and is used for the yearly deforestation maps produced within the PRODES-program.

2.2.3.1 Database setup

To have increased control over data entry and management of the information that the database holds, 3 databases are set up. Each database has a different group of information:

1. Database containing the supervised classification;

2. Database containing the Landsat color composite (band combination of 654);

3. Database containing the ancillary data.

2.2.3.2 Classification adjustments

The results from the version 1 semi-automatic classification in the core-processing phase are visually checked, using the software TerraAmazon. This software has a multi-user environment, allowing simultaneous editing in the data layer.

The results of the SVM classification were first vectorized in QGIS, then imported into TerraAmazon. In TerraAmazon it was visually adjusted using the corresponding Landsat image and ancillary data. Some examples of the classifications are shown in the table below. In some areas the deforestation is underestimated, while in other areas the deforestation is overestimated in the semi-automatic classification.

Narrow areas being deforested, is often not classified in the semi-automatic process, but is clearly visual. This is an underestimation of the deforested areas and is added to the class deforestation (Figure 2.21).

[18] http://terraamazon.org/

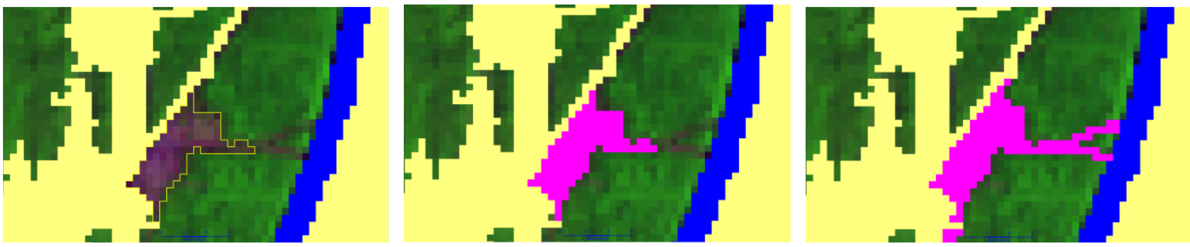


Figure 2-21: Illustration of visually adjusting underestimations of deforestations in Terra Amazon: The first image shows the borders of the deforested areas in yellow as results from the SVM and can be confirmed and classified as deforestation (in the second image

In order to visually correct the deforested areas produced by the SVM classification, some ancillary data has been used. An example is the gold mining data produced during the regional study with ONFi. As long as the deforested area covers 1ha or 11 pixels, it can be classified as the class Deforestation. If it does not cover the area of 1ha or 11 pixels, then it belongs to the class that corresponds to its surrounding area.

Shifting cultivation plots, smaller than 1 ha were also identified as deforested areas, during the SVM classification. This is an overestimation of the deforestation class. The plots are only classified as Deforestation, when they are greater than 1 ha or cover 11 pixels. Plots that are smaller than 1 ha belong to the shifting cultivation class. Shifting cultivation is classified as an extensive area that contains plots smaller than 1 ha (see figure 2.22).

The non-forest class are the areas that were not covered with forest since 2000. These areas could also be identified during the SVM classification as deforestation. This can be checked with Landsat images from 2000 to see if it was still forest or already deforested in 2000.

Figure 2.22 illustrates areas that are classified as deforestation in the semi-automatic process.

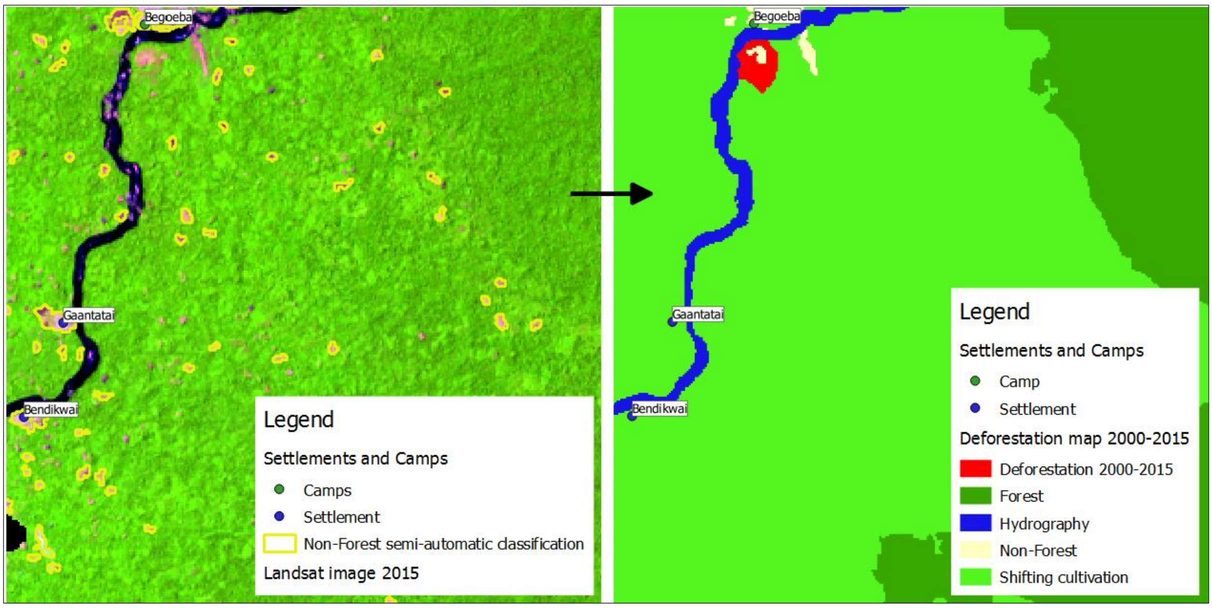


Figure 2-22: Shifting cultivation areas, detected as deforestation in the semi-automatic process, but that are classified as shifting cultivation in the post-processing phase

2.2.3.3 Cloud-filling

In version 2 of the forest cover classification, clouds persisted. Figure 2.23 below show the dispersion of clouds on the forest-non forest data for the periods 2000, 2000-2009, 2009-2013, 2013-2014 and 2014-2015.

		
Basemap 2000 (Total Cloud area = 174500 ha)	Deforestation map 2000-2009 (Total Cloud area= 357508 ha)	Deforestation map 2009-2013 (Total Cloud area= 415971 ha)
		
Deforestation map 2013-2014 (Total Cloud area =7020 ha)	Deforestation map 2014-2015 (Total Cloud area 242818 ha)	

Figure 2-23:. Overview of cloud coverage for the periods 2000, 2000-2009, 2009-2013, 2013-2014 and 2014-2015.

The visualization of the cloud dispersion given above, show that the majority of the clouds are in the Southern part of Suriname. The majority of this part of Suriname is covered with forest, and the activities in this forest area are low, due to the difficult accessibility. There are clouds which also covers the deforestation and shifting cultivation class, but this area of clouds is relatively small.

To finalize the historical assessment of deforestation, the clouds were removed by using the Global Forest Change data, produced by Maryland University (Hansen et al., 2013).

The processes for cloud filling are:
1. Compare FCMU data with Global Forest Change data from Maryland University;
2. Reclassification of clouds with Global Forest Change data from Maryland University;
3. Reclassification of residual clouds with Greenest pixel composite;
4. Finalizing the data by checking class transitions.

Global Forest Change data from Maryland University consists of results from a time-series analysis of Landsat images in characterizing global forest extent and change from 2000 through 2014. The data that was used is explained in table 2.4 below.

The greenest pixel composite from google earth engine is a composite of an image collection, where each image has an NDVI band. Each pixel of the composite then contains the maximum NDVI from the collection.

Table 2-4: Description of Global Forest Change data from Maryland University (Hansen et al., 2013) that were used

Global Forest Change data	**Description**
Tree canopy cover for year 2000 (treecover 2000)	Tree cover in the year 2000, defined as canopy closure for all vegetation taller than 5m in height. Encoded as a percentage per output grid cell, in the range 0–100.
Global forest cover loss 2000–2014 (loss)	Forest loss during the period 2000–2014 on an annual basis, defined as a stand-replacement disturbance, or a change from a forest to non-forest state. Encoded as either 1 (loss) or 0 (no loss).
Global forest cover gain 2000–2012 (gain)	Forest gain during the period 2000–2012 on an annual basis, defined as the inverse of loss, or a non-forest to forest change entirely within the study period. Encoded as either 1 (gain) or 0 (no gain).
Year of gross forest cover loss event (lossyear)	A disaggregation of total forest loss to annual time scales. Encoded as either 0 (no loss) or else a value in the range 1–13, representing loss detected primarily in the year 2001–2014, respectively.

Ad 1. Compare FCMU data with Global Forest Change data from Maryland University

The data produced by the Forest Cover Monitoring Unit (FCMU) was compared with the Global Forest Change data from Maryland University. The objective of this comparison was to know the differences between these two datasets in order to assess the compatibility.

Table 2.5 shows a table with two classes of tree crown cover percentage (0-30% and 30-100%) from Global Forest Change data, and the classes Clouds, Forest, Hydrography, Non-forest and Shifting cultivation of the Basemap 2000 produced by FCMU. Following conclusions can be drawn:

- **Forest:** There is a 99% overlap of the forest class with the class 30-100% crown cover, meaning that there is a very high similarity between the FCMU data and the Global Forest Change data from Maryland University data.
- **Clouds**: Most of the clouds overlap with the class 30-100% crown cover, meaning that most of the clouds can be reclassified as forest according to the Global Forest Change data from Maryland University.
- **Shifting cultivation:** A high percentage of shifting cultivation coincides with the class 30-100% crown cover. Shifting cultivation is a type of small-scale farming that involves clearing the land, burning the plant material, planting and harvesting the crops, and then abandoning the land to go fallow. In Suriname, the shifting cultivation plots are traditionally cultivated for 1 to 3 years and fallow periods vary from 3 to 15 years, letting the forest regenerate on the abandoned land (Helstone and Playfair, 2014). According to Ribeiro Filho *et al.* (2013), in most cases shifting cultivation can be seen as a sustainable activity without long-term negative impact on the soil and where fallow periods, which are long enough, mimic forest ecosystems. The forest dependent indigenous and tribal communities clearly indicate that shifting cultivation is a traditional and sustainable use of the forest (Gomes-Poma and Kaus, 1992; AAE and Tropenbos International Suriname 2017). Analysis conducted by SBB, using multi-year forest loss data (Hansen *et al.*, 2013) has shown that most shifting cultivation patches (>90%) are smaller than the minimum mapping unit of 1 hectare.
- **Hydrography**: An overlap with the 30-100% crown cover was found, mostly along the rivers borders. This is caused by the differences in water level. The National data includes the maximum water level.
- **Non-Forest**: An overlap was found with the class 30-100% crown cover. For the class Non-forest these overlaps represent areas in the coastline, rice plantations, abandoned plantations, swamps and urban areas.

Table 2-5: Matrix showing Global Forest Change data and Basemap 2000

		Global Forest Change data (treecover 2000)		TOTAL
		0-30% Crown cover	30-100% Crown cover	
Basemap 2000	CLOUDS	36.06	174463.74	174499.81
	FOREST	14046.25	14876431.49	14890477.73
	HYDROGRAPHY	260050.36	71428.52	331478.88
	NON-FOREST	425960.53	351314.45	777274.97
	SHIFTING CULTIVATION	1766.27	191327.71	193093.98
	TOTAL	701859.47	15664965.90	16366825.37

Ad 2. Reclassification of clouds with Global Forest Change data of Maryland University

The criteria that was used for the reclassification of Clouds for Basemap 2000 is shown in table 2.6 below.

Table 2-6: Criteria for reclassification of clouds

Basemap 2000	Global Forest Change data		Reclassification class
	Treecover 2000	Loss per year	
Clouds	Tree crown cover ≥ 30%	Cover loss = 0	Forest
	Tree crown cover < 30%	Cover loss > 0	Non-forest

Table 2.7 illustrates the method used to reclassify clouds. The tree cover 2000 was divided in ten classes from 0% to 100% with an interval of 10%. The first class is 1 and the last class is 10. In the first example of table 2.9 the tree cover of the Global Forest Change data is 1 (between 0% and 10%) and the loss year has the value 0 (no loss). This means that the Cloud of Basemap 2000 should be reclassified as Non-Forest. For the second row of the table the Cloud of Basemap 2000 should be reclassified as Forest, based on the Global Forest Change Data where the tree cover is 10 (between 90% and 100%) and no loss of forest cover has taken place.

Table 2-7: Examples of cloud reclassifications

FCMU data		Global Forest Change Data		
Basemap 2000	Deforestation map 2009	Tree cover	Loss Year	Cloud reclassification
CLOUDS	NON FOREST	1	0	NON FOREST
CLOUDS	FOREST	10	0	FOREST

Ad 3. Reclassification of clouds with greenest pixel composite

After filling the clouds with the forest loss data and the tree cover data, a visual cross check was done with the Greenest pixel composite downloaded from google earth engine.

For the Forest class, 100 random polygons were visually inspected with the greenest pixel composite. If all the polygons appear to have a high NDVI value on this composite, then the reclassification from Clouds to Forest is accepted. For the Non forest classes all polygons were visually inspected with Greenest pixel composite.

An example of the Cloud filling assessment is shown in Figure 2.24. If the Cloud polygon completely falls on Forest or Non-forest it will be classified according to that specific class.

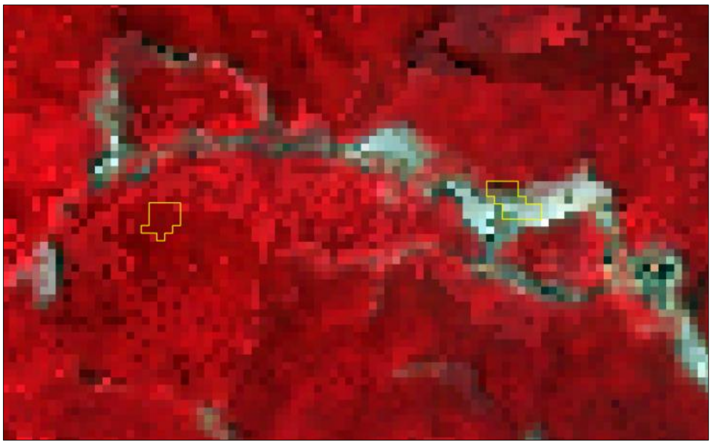


Figure 2-24: An example of the assessment "Clouds" filling with Greenest pixel composite. The Cloud polygon is illustrated with yellow borders. The cloud on the left is reclassified as Forest and the cloud on the right is reclassified as Non-forest.

Ad 4. Reclassification of clouds with Sentinel 2A data

Since 2015, Sentinel 2A imagery became available and can also be used to assign the land cover data to cloudy areas that persist on Landsat imagery. Figure 2.25 shows the areas covered with clouds that persisted on Landsat imagery, which are clearly seen as forest on Sentinel 2A imagery.

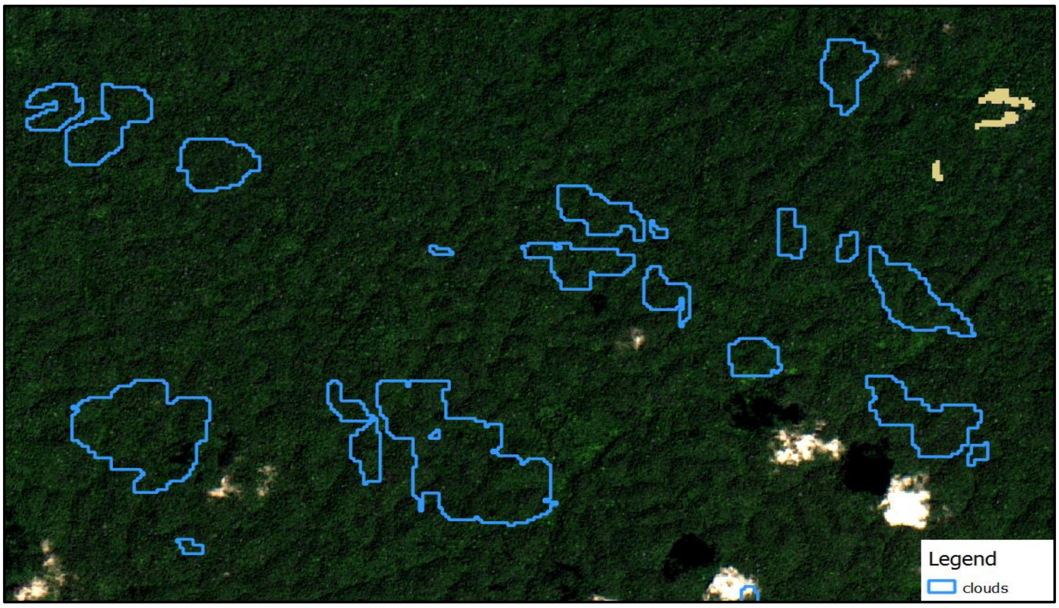


Figure 2-25: Clouds reclassification to forest with Sentinel 2A imagery

2.3 Method post-deforestation Land Use Land Cover (LULC) maps

Currently, four Deforestation maps are produced for the periods 2000-2009, 2009-2013, 2013-2014 and 2014-2015, where for the periods 2000-2009, 2000-2013 and 2000-2015 post-deforestation Land Use Land Cover (LULC) maps have been produced. The methodology is based on digital data (available satellite imageries and ancillary data) and non-digital data (field experience of experts and stakeholders).

The method for creating the LULC map requires several steps to be taken. These are:

a. Carrying out an internal classification, using ancillary data;
b. Validating the internal classification by gathering input data from stakeholders through work sessions;
c. Final classification with the gathered input data from stakeholders;
d. Assessing the total classified area that is validated.

The flowchart for producing a post-deforestation LULC map is given in Figure 2.26.

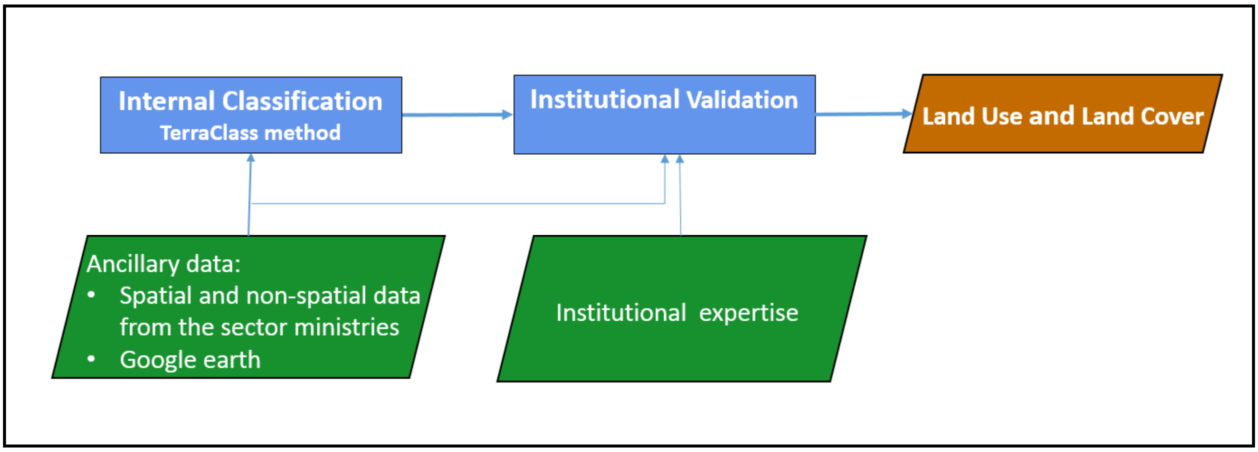


Figure 2-26: Flowchart for producing post-deforestation LULC maps

2.3.1 Internal classification

A preliminary classification, using ancillary data, was performed in the software TerraAmazon. The deforested areas were classified into the following LULC classes: Agriculture, Pasture, Urban area, Secondary vegetation, Mining, Infrastructure, Burned area and Others.

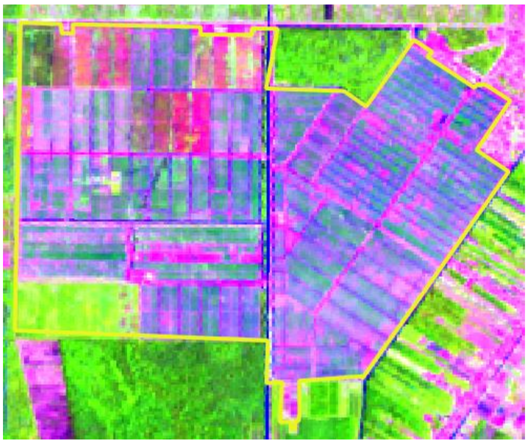
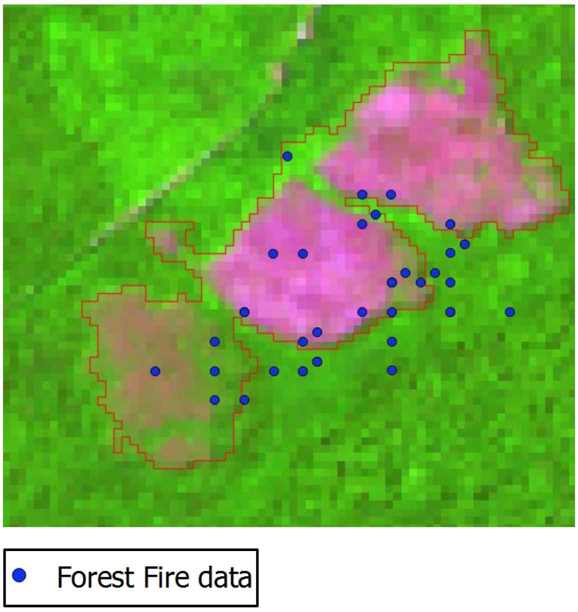
Ancillary data are GIS complementary data that can be used for decision making within the classification. The types of ancillary data that have been used are given in table 2.8.

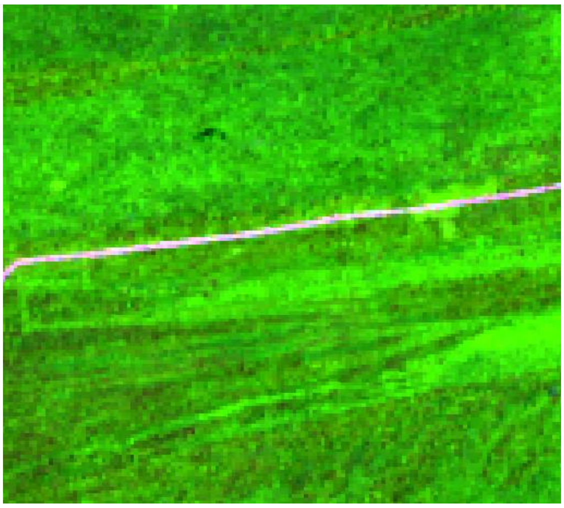
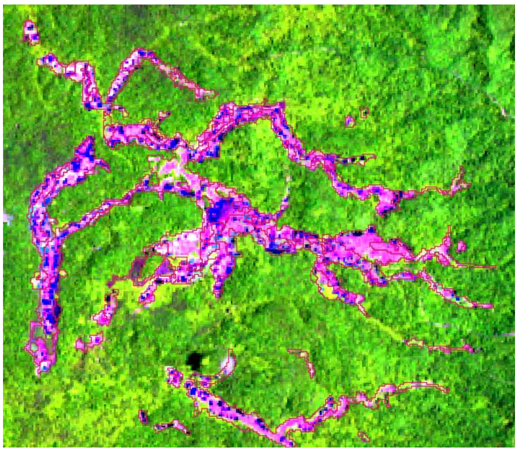
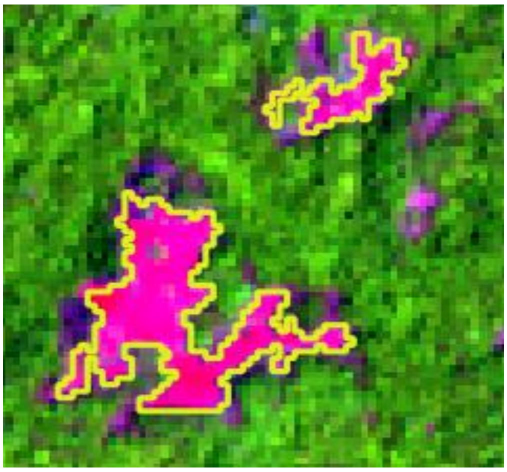
Table 2-8: Overview of the GIS ancillary data used for the LULC map

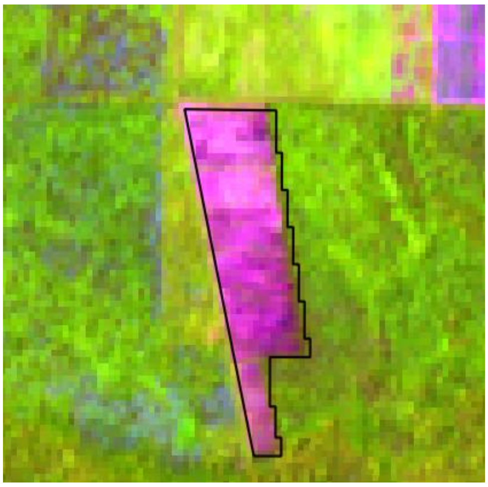
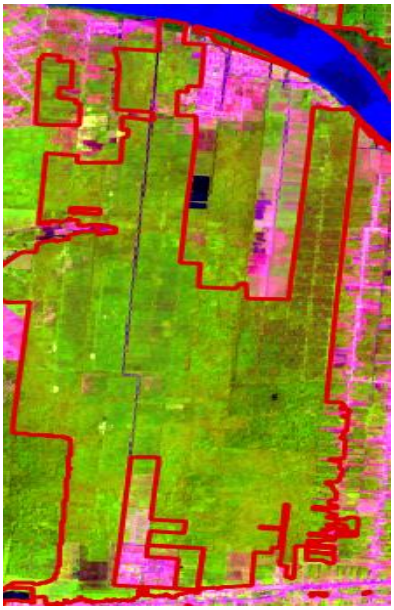
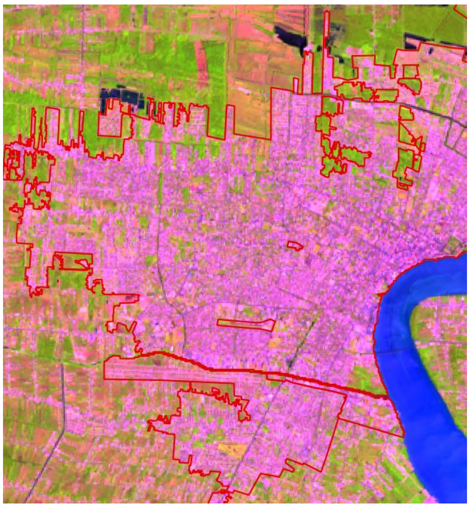
Type of data	**Description**	**Source**
Woodlandings	The woodlandings are locations of areas, where the logged wood is gathered, before transporting it to the sawmill.	SBB
Gold mining data 2015	The gold mining data has been generated within a regional project by ONFi.	SBB
Ecosystem map 1978	The Ecosystem map consists the coastal part of Suriname and has been produced by Teunissen / Stinasu 1978 with aerial photographs (Central Bureau for Aerial Survey, Paramaribo, 1970-1973) and reconnaissance soil maps (Department of Soil Survey, Paramaribo, 1978).	Teunissen
Centraal Bureau Luchtkartering (CBL) maps	Land cover data, based on aerial imagery from the period 1956-1964, was previously produced by the cartographic company 'Centraal Bureau Luchtkartering (CBL)'. This data is produced for several regions of Suriname, and on different scales (40000, 50000, 100000).	MI-GLIS
Mining concession data	Data that indicates the locations and state of mining concessions in Suriname	GMD
Geological map	Data that shows the geological deposit in specific locations	GMD
SRTM data (incl.HAND)	With the Shuttle Radar Topography Mission (SRTM) data, the HAND data is produced based on the digital elevation model. The HAND data includes the height above the nearest waterways.	SBB
Ports data	Data that gives an overview of the registered ports in Suriname.	MAS
Airstrips and airports	Data that gives an overview of the registered airstrips and airports	Gum-air
Settlements	Data that gives an overview of villages and important places among villages	SBB & RO

Table 2.9 gives an overview of the LULC classes and their appearance. Based on their patterns, color, shape and texture, the polygons were assigned to specific LULC classes.

Table 2-9: Visual interpretation of the LULC classes on satellite images

Class	Appearance on image
Agriculture	
Burned area	

Infrastructure	
Mining	
Others	

Pasture	
Secondary vegetation	
Urban	

2.3.2 Institutional validation

After conducting the internal classification, FCMU organized several work sessions with other relevant stakeholders from the different sector ministries and institutions (List of stakeholders in Annex 4). The purpose of the work session was to validate the internal classification, including national expertise and field experience from the partner institutions. Additionally, this provides a collaboration platform, supporting knowledge exchange between partners[19]. Figure 2.27 shows an example where construction material data from GMD validate parts of the class "Mining". An overview of the proportion of the different classes assessed by the stakeholders can be found in Annex 5. Based on the available data and feedback of the stakeholders, the final classification was done.

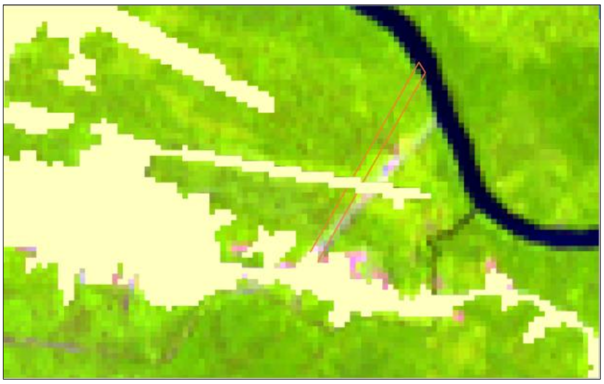


Figure 2-27: An example where the construction material concession shape file, which was produced by the GMD, was used as ancillary data

2.4 Method QA/QC

True values of land cover area and land cover change area vary from the areas that can be extracted directly from the map. The true areas can be calculated after an accuracy assessment has been carried out and a classification error matrix has been created (Olofsson, Foody, Stehman, & Woodcock, 2013). The underlying principle of the accuracy assessment is that it compares the mapped land classification to higher quality reference data, collected through a sample based approach. The higher quality reference data can be obtained through ground collected data, but as this is expensive and labor intense it is more commonly obtained through satellite imagery or aerial photography with finer spatial resolution than the data that was used to create the map data.

[19] For more detailed information regarding the LULC worksession, see the following link for the LULC worksession report (in dutch): https://docs.google.com/document/d/1VaMfeLWjyQjX8bm8kfmkQnZg5dQVA7in0M1B1AbKVR8/edit#heading=h.jpjzt36fl5p1

The procedures used to estimate the forest cover and forest cover change area are agreed upon as suitable to access result-based payments through a REDD+-mechanism[20].

The accuracy assessment was carried out in collaboration with the research institution CELOS, by applying Collect Earth-software developed by the FAO[21]. The method includes a set of "good practice" recommendations for designing and implementing an accuracy assessment of a change map and estimating area based on the reference sample data (FAO, 2016). The method will be further described in this paragraph.

The set of "good practice" recommendations mentioned above, address three major components: sampling design, response design and analysis (Olofsson, Foody, Herold, Stehman, Woodcock, & Wulder, 2014) .With this method the forest cover change data for the periods 2000-2009 and 2009-2015 underwent an accuracy assessment. The steps that were performed during the accuracy assessment are given in the process flow in figure 2.28.

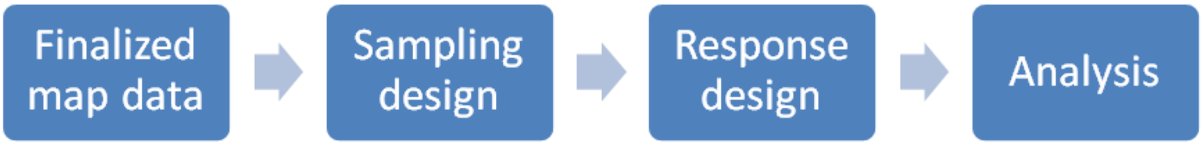


Figure 2-28: Process flow for the execution of Quality assessment and Quality control (QaQc)

2.4.1 Finalize the map data

The first step is a general quality control check of the map data. Before executing the accuracy assessment on the forest cover change data, the map data should be considered to be final.

From the produced maps, the following map classes were assessed:

- Forest 2015
- Non-forest
- Hydrography
- Shifting cultivation 2000
- Shifting cultivation 2000-2009
- Shifting cultivation 2009-2015
- Deforestation 2000-2009
- Deforestation 2009-2015

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[20]http://www.gofcgold.wur.nl/documents/SecondAccuracyAssesssmentWS_2017/Report_OsloAAmeeting_20170828_OnlineVersion.pdf

[21] http://www.openforis.org/tools/collect-earth.html

2.4.2 Sampling design

The sampling design determines for which subset of the map reference data will be collected. To make sure no rare/smaller classes, such as deforestation are missed or under-represented, a stratified random sampling approach will be implemented. This allows for increasing the sample size in these smaller classes. This approach is a common approach for uncertainty analysis (Cakir, Khorram, & Nelson, 2006).

The sampling design was carried out in the Shiny app from RStudio, using an algorithm developed by UN-REDD, including a user-friendly interface. Now, the sampling design can also be done in the System for earth observations, data access, processing & analysis for land monitoring (SEPAL[22]), a cloud-based platform.

Following steps were followed:

- **Input map:** The final map data, which should be assessed, were selected. Also the minimum mapping unit of 1ha (10000 m^2) and the resolution of imagery used for mapping was assigned (30m resolution). The minimum mapping unit of 1 ha is covered by approximately 11 pixels of a satellite image.
- **Map areas**: The areas for each of the map categories are calculated at this step in order to calculate the overall and stratified sample size.
- **Classes to include**: The expected accuracies of the classes were selected. Common classes occupy the majority of the map and are expected to have high user accuracies, so they got a higher confidence assigned. The common classes are: Forest, Non-forest and Hydrography. Rare classes such as land covert change classes, which occupy a small portion of the map area, are expected to have lower user accuracies, so these classes got a low confidence assigned. The rare classes are: Deforestation and Shifting cultivation. This measure will influence the overall sample size. More classes with lower confidence will increase the overall sample size.
- **Sampling size:** In the sampling design, the sample size for each map category was calculated to ensure that the sample size is large enough to produce sufficiently precise estimates of the area of the class (GFOI, 2014). The final samples can be manually adjusted, taking into account that the minimum amount of samples should be at least 30 in order to be representative.
- **Response design**: A total of 873 samples were used in the response design. The sampling points were drawn and exported as a Collect Earth file. The number of points per class were randomly distributed for each of the map classes, which is illustrated in figure 2.29.

[22] https://sepal.io/

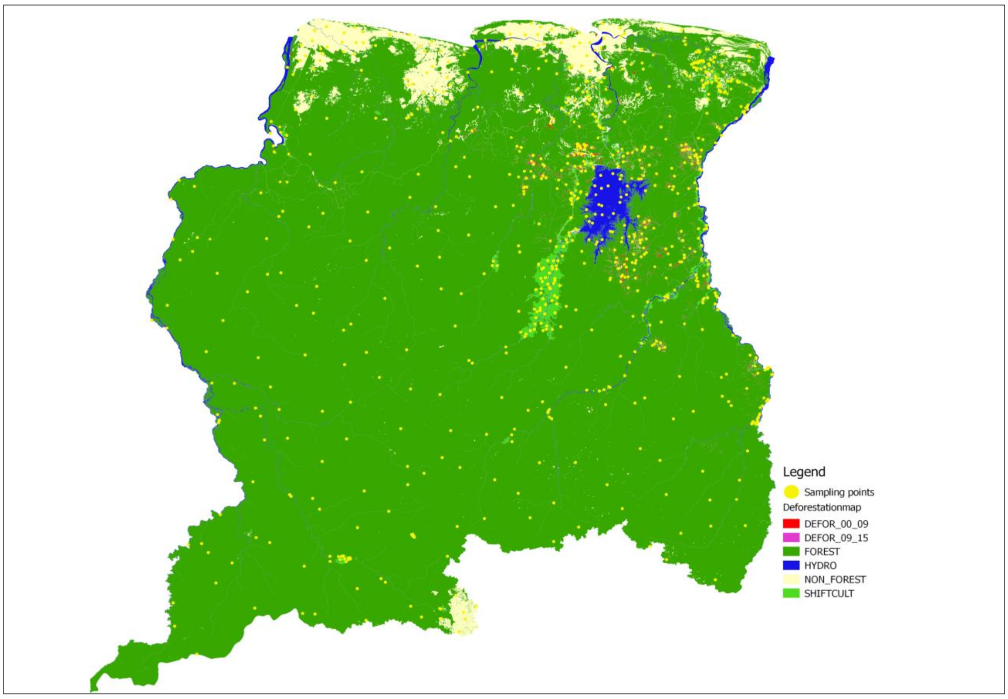


Figure 2-29: Overview of the distribution of sample points on the map classes

2.4.3 Response design

The sampling points are imported in Google Earth via Open Foris Collect Earth. Open Foris Collect Earth provides a fast, easy and flexible way to set up a survey with a user-friendly interface. This Google Earth plugin allows the practitioner to visually assess the land cover/use of sample locations with the freely available data from Google Earth, Google Earth Engine and Bing maps. By clicking on a sample, a window pops open which allows one to select the class, assign how certain the user is about the classification and adding a comment (optional). Figure 2.30 illustrates the window which opens in Google earth to execute the response design.

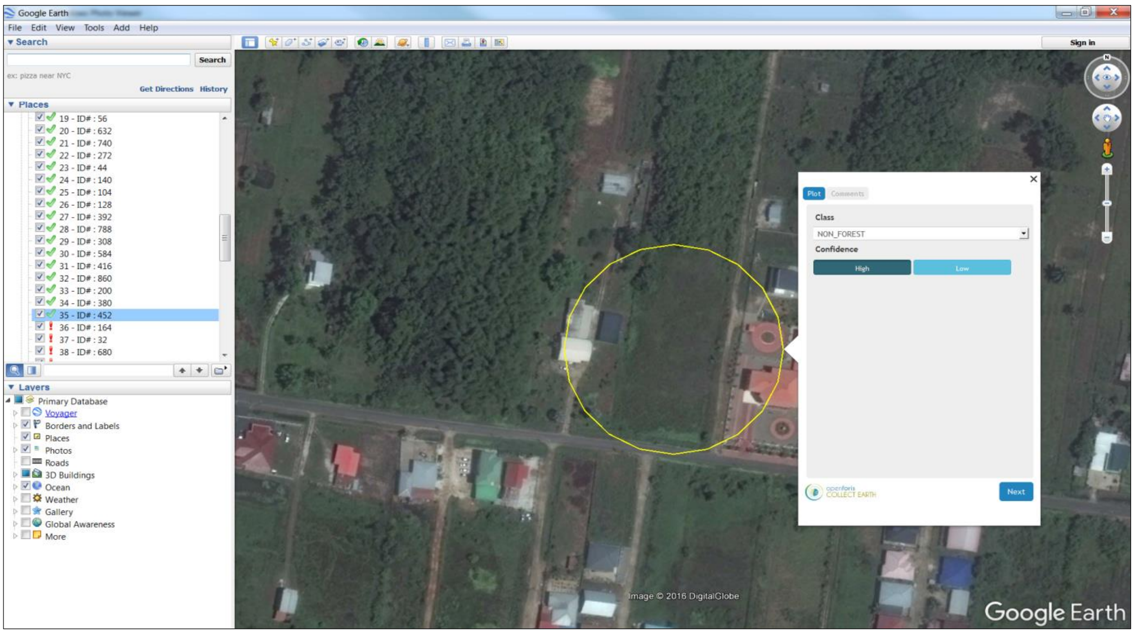


Figure 2-30: Sample on a non-forest area bases on google earth imagery

To know when the change in the forest cover has occurred, a clip of annual time series of Landsat and Sentinel-2A images has been made in R with a box around the sample points (Figure 2.31). The boundary box has a 500m distance from the sample point. Annual time series have been created of each year, from 2000-2015. The last box in the right down corner shows a graphic indicating the NDVI values in each year of the sample point.

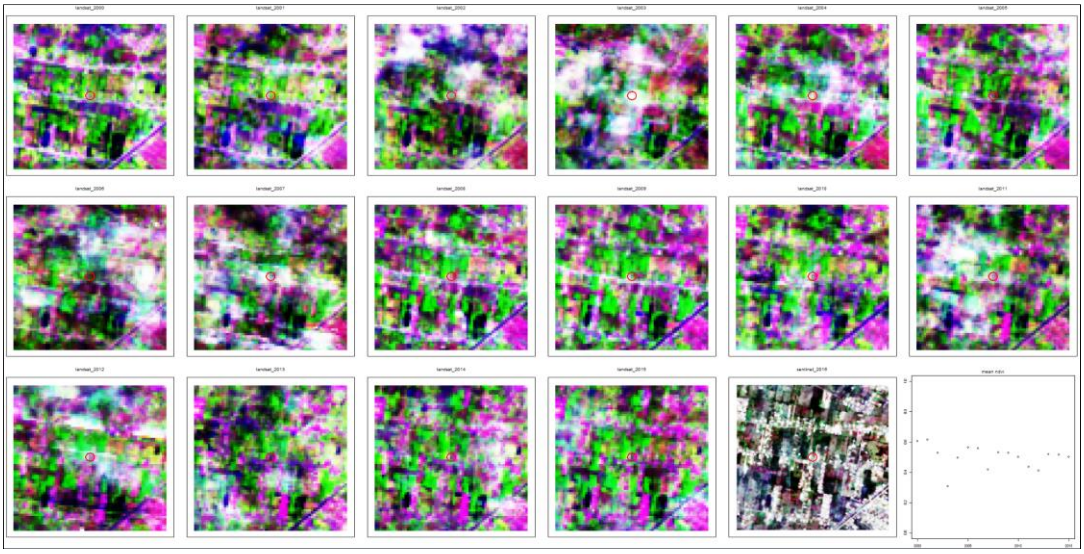


Figure 2-31: Clip of annual time series

2.4.4 Analysis protocol

The analysis protocol includes all steps that lead to a decision whether the map and reference data are in agreement for the subset of the data that was sampled.

After analyzing the 873 samples, 739 were analyzed as high confidence in the classification and 134 as low confidence samples. The low confidence samples were excluded from further analyses.

The results for accuracy assessment analyses are presented in an html-file. The objective of this file is to create confusion matrices and calculate bias corrected estimates and confidence intervals around these estimates.

The accuracy assessment analysis contains three steps that have been executed:

1) Input map: the final map has been selected and two files were necessary:
    a. The validation file must contain a column with the classified reference data and a column with the original map data.
    b. The area file should contain the map areas and the corresponding map class. The area file can be generated in the Accuracy Assessment Design application.
2) Check: it was verified that all classes with their areas are represented
3) Results: the input was filtered and calculated. These results were used for quick analyses and for the report.

The resulting data from the response design have been further analyzed in Ms-Excel where an error/confusion matrix is created. The error matrix is a simple cross-tabulation of the class labels allocated by the classification of the remotely sensed data against the reference data for the sample sites. The error matrix organizes the acquired sample data in a way that summarizes key results and aids the quantification of accuracy and area. The main diagonal of the error matrix highlights correct classifications, while the off-diagonal elements show omission (the columns) and commission errors (the rows).

The User's Accuracy (UA) and the Producer's Accuracy (PA) are also given in the confusion matrix. UA corresponds to error of commissions (inclusion) and PA corresponds to error of omissions (exclusion).

3 Results and discussions

In this chapter the results of the Deforestation maps and post-deforestation LULC maps are presented. To better understand the dynamic of the change classes, several spatial analysis have been executed.

3.1 Deforestation maps

Up to now, the FCMU has produced a base map of the year 2000 and four deforestation maps for different periods: 2000-2009, 2009-2013, 2013-2014 and 2014-2015, containing the following classes: Forest, Non-forest, Shifting cultivation, Hydrography and Deforestation. The intention is to produce the deforestation map yearly beginning from 2014. An overview of the above mentioned Deforestation maps are shown in figure 3.1.

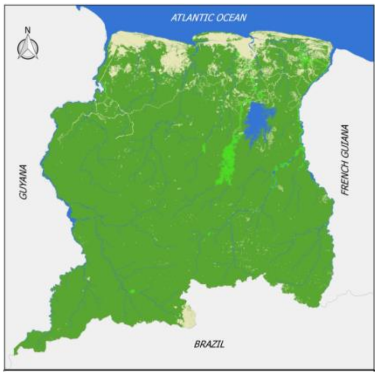
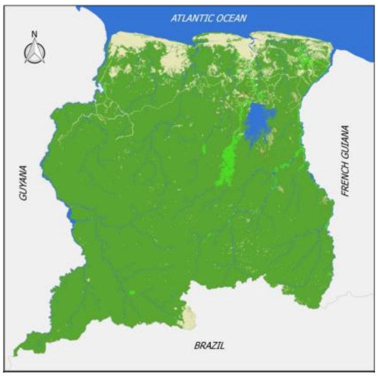
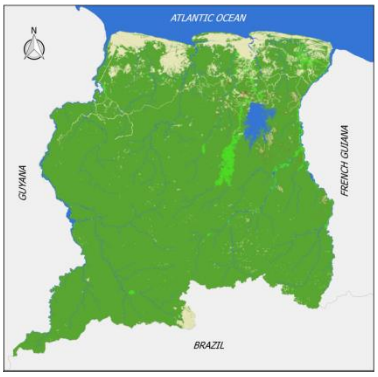
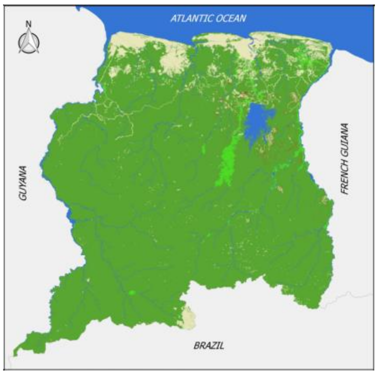
Basemap 2000	Deforestation map 2000-2009	Deforestation map 2009-2013
		
Deforestation map 2013-2014	Deforestation map 2014-2015	
		

Figure 3-1: Basemap 2000 and the Deforestation maps for the period 2000-2009, 2009-2013, 2013-2014 and 2014-2015

Figure 3.2 provides a visualization of the regions with different degrees of intensity of deforestation for the different periods.

In the period 2000-2009 the hotspots were accumulated near Balingsoela, Meriankreek, Lelygebergte/Sarakreek, Tapanahony River and Benzdorp. In 2009-2013 the hotspots were in the same areas as before, including Brownsberg. In the period 2013-2014 the hotspots shifted to Balingsoela and Meriankreek, while the intensity in Benzdorp was low. For 2014-2015 the hotspots were Balingsoela, Meriankreek, Brownsberg, Lelygebergte/Sarakreek and Tapanahony River.

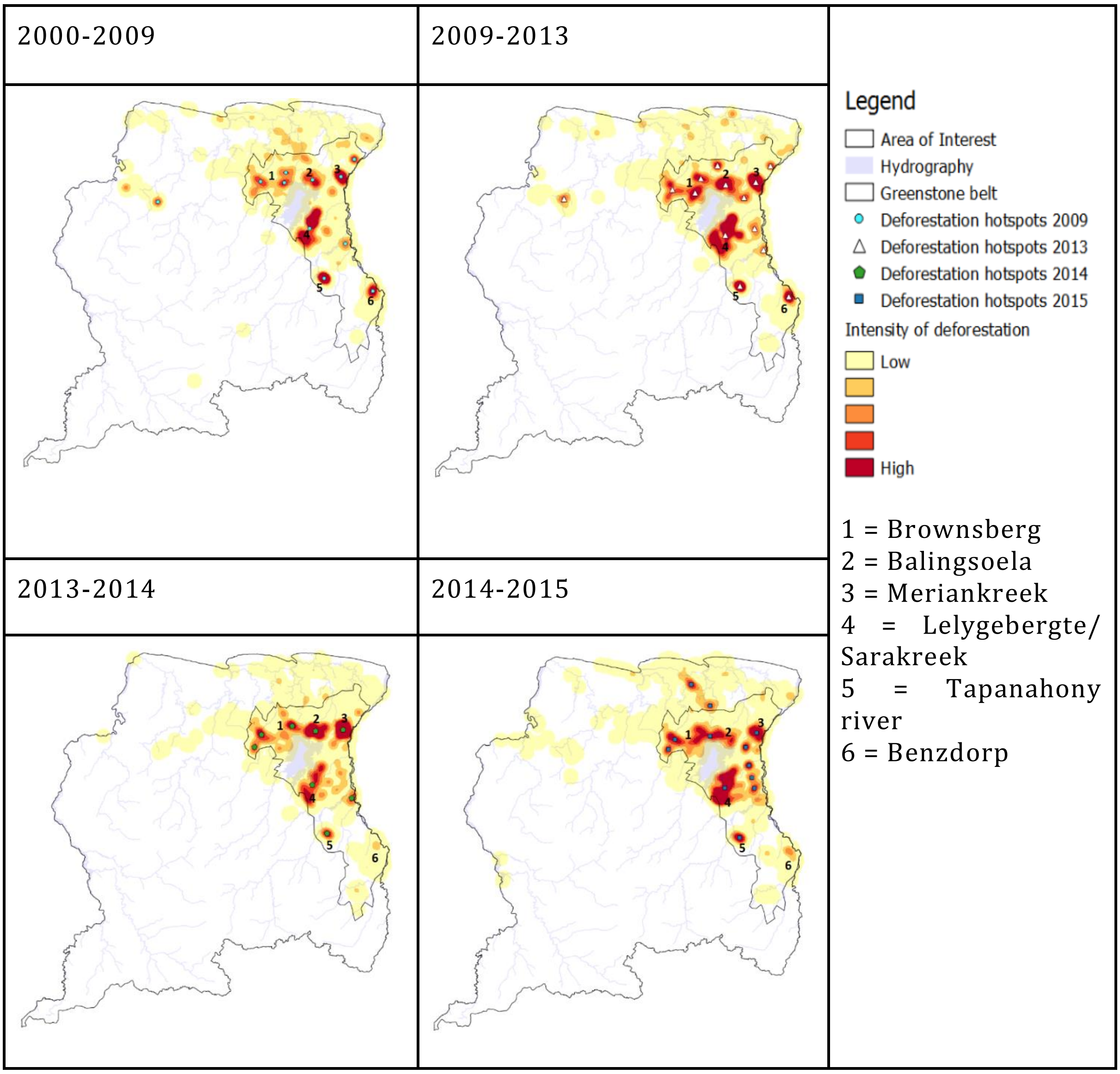


Figure 3-2: Overview of the level of intensity of deforestation for the periods 2000-2009, 2009-2013, 2013-2014 and 2014-2015

These results show that the areas with high intensity of deforestation shifted during the time to specific locations. The shift to other areas can be due to the accessibility, the detection of gold, advanced technology or return to former gold mines to take residues of gold. The latter is explained in the DDFDB+ study, where mines have been re-accessed 4-5 times with the use of more advanced equipment.

The map in figure 3.3 shows that most shifting cultivation appear along the upper-basin of the Suriname River, where settlements are present. The existence of shifting cultivation near settlements is expected, because the people living here rely on the forest as a source of food, fuel, medicine and land for agriculture (Lininger K., 2011). Another study also shows that distance to settlements is one of the important variables (Kasanpawiro, 2015).

It is also remarkable that the deforested areas are located around the Brokopondo Lake, which is part of the Greenstone belt. Based on field knowledge and interviews with the Geological Mining Services and Commission Regulation Gold mining sector, deforestation due to alluvial (mostly informal) gold mining takes place in the vicinity of streams (Rahm, et al., 2015). There were two large-scale gold mining companies operational in Suriname, known as IAMGOLD and Newmont. Both of these companies are located north of the Lake.

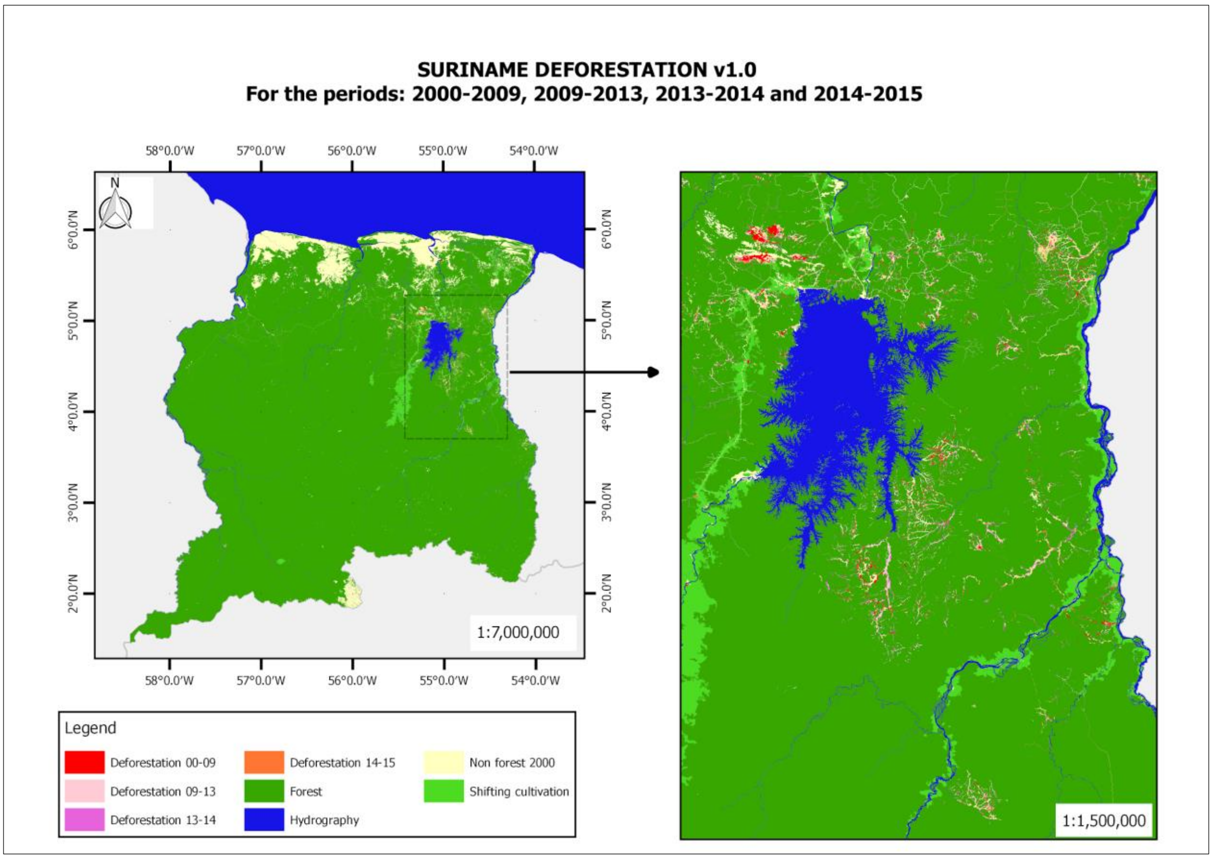


Figure 3-3: Deforestation map of Suriname for the time periods: 2000-2009, 2009-2013, 2013-2014 and 2014-2015

3.2 Area estimations after accuracy assessment

After executing the accuracy assessment, a stratified estimated area and confidence intervals are calculated for each class present in the Deforestation map[23].

Table 3.1 shows the map area, stratified estimated area, and confidence interval for each class.

Table 3-1: Corrected area estimation and confidence interval

Class	Map area (ha)	Stratified estimated area (ha)	Confidence interval (ha)
Deforestation 2000- 2009	24,784	33,051	5,361
Deforestation 2009-2013	30,833	32,071	2,388
Deforestation 2013-2014	17,222	15,757	2,082
Deforestation 2014-2015	12,308	9,442	1,620
Forest 2015	14,963,593	15,044,605	48,089
Hydrography	331,239	335,084	30,891
Non-forest	777,139	717,346	56,163
Shifting cultivation 2000	190,734	172,374	14,007
Shifting cultivation 2000-2009	14,334	13.158	6,783
Shifting cultivation 2009-2015	4,639	6,366	5,086

[23] For more detail regarding the accuracy assessment results, see the QA/QC report written by FCMU (2016) with the following link: https://docs.google.com/document/d/1BvmlOWSZ8hI3N6hfUq3gmu_BHiUiTxlenLpgWZY_eoU/edit

3.3 Development of Deforestation

3.3.1 Temporal change in deforestation rate

Based on the QA/QC results of the land cover classes mentioned above, the deforestation rate can be calculated. In figure 3.4, the deforestation trend is given during the different time period 2000-2015. It can be concluded that there is a significant increase in deforestation comparing the period 2000-2009 with the period 2009-2015. Currently it seems to stabilize around 0.07%. It should be considered that, taking into account the cloud cover and the relatively small deforestation, annual estimations might not provide a clear understanding of the trend. Therefore, it might be better to calculate averages over a period of two years.

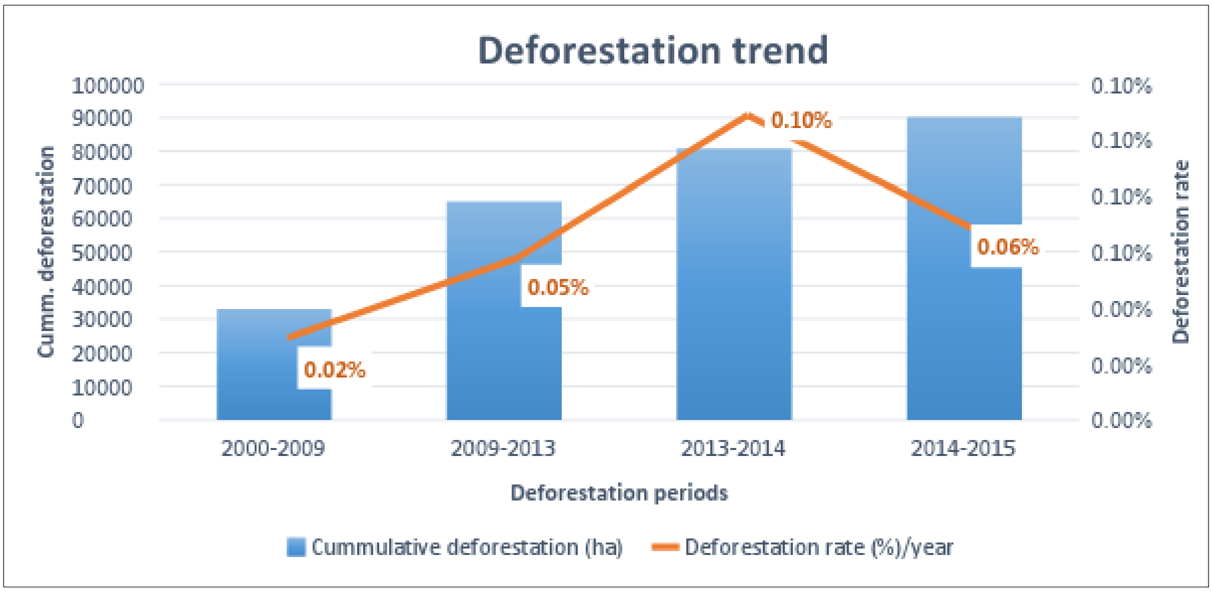


Figure 3-4: Deforestation trend for different periods from year 2000 till 2015

The increase and decrease of the deforestation rate can be explained by the results of the post-deforestation LULC maps, where mining is shown to be the main driver of deforestation. The degree of gold mining activities seem to have a link with gold prices. Figure 3.5 shows the relation between the gold price and the deforestation. The gold price increased from 2009 till 2012 and decreased after 2012 till 2015. The same trend appears for the deforestation rate, but there is a delay of approximately two years after the gold price changed.

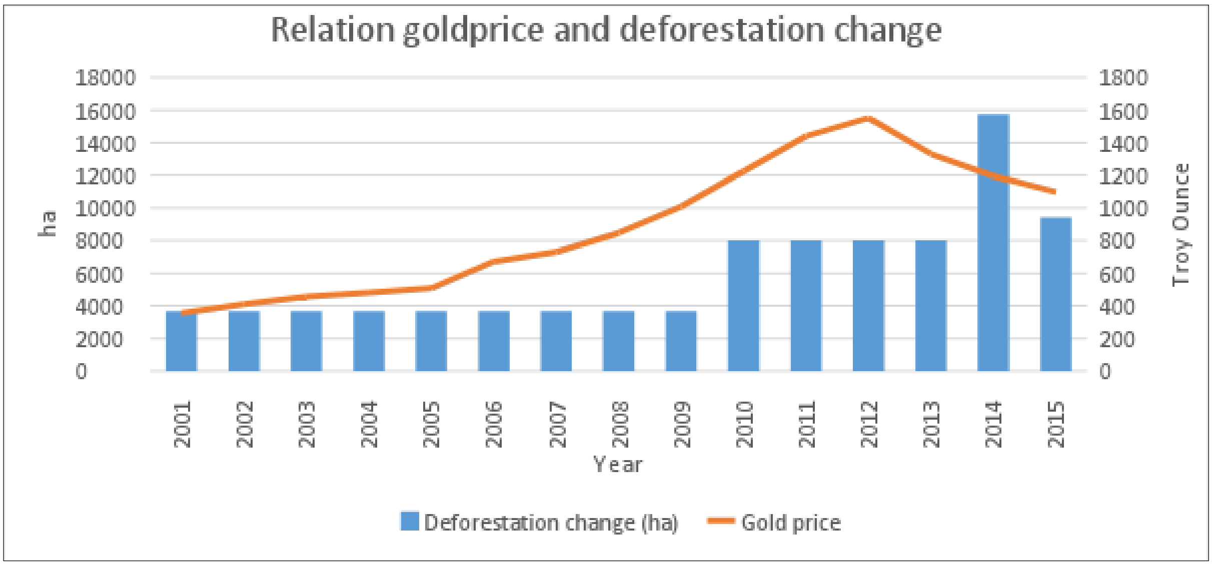


Figure 3-5: Relationship between the gold price and the deforestation change from 2001-2015

3.3.2 Deforestation by driver

The post-deforestation LULC map of 2000-2015 is given in figure 3.6 and the corresponding areas are given in table 3.2 below, including the areas of the periods 2000-2009 and 2000-2013.

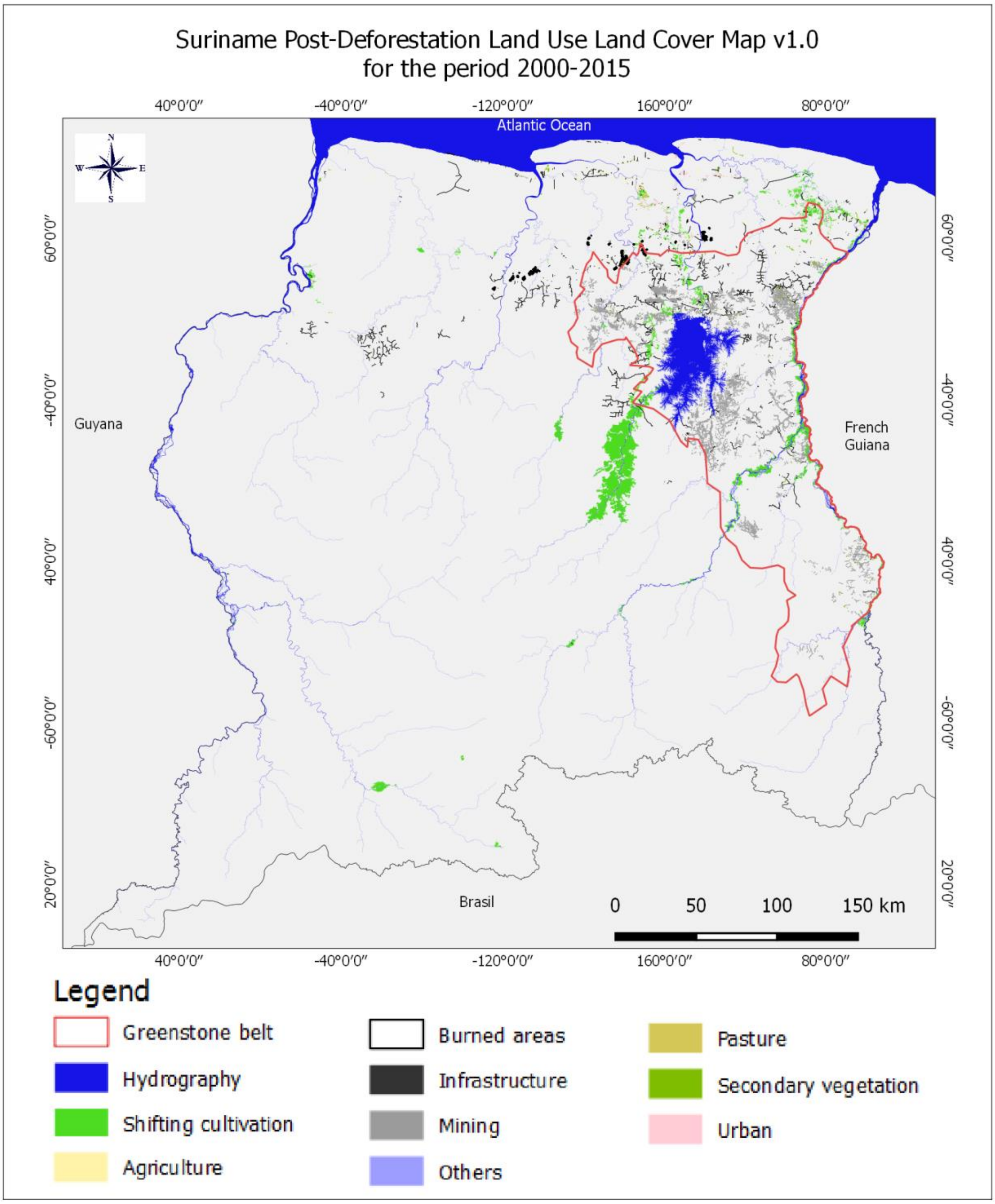


Figure 3-6: Overview of the Post-deforestation LULC map 2000-2015

Table 3-2: Map areas of the post-deforestation LULC maps

LULC classes*	2000-2009 (ha)	2000-2013 (ha)	2000-2015 (ha)
Mining	19,494	41,797	62,102
Infrastructure	2.829	7,498	12,964
Urban	1,027	1,714	3,424
Burned areas	243	2,052	2,502
Agriculture	872	1,286	2,213
Secondary vegetation	0	940	1,205
Pasture	150	228	455
Others	169	101	281
Total deforestation	24,784	55,616	85,146

Figure 3.7 illustrates the percentage of LULC classes relative to the total deforestation for the period 2000-2015. Mining covers about 72.9% of the total deforestation, where 95% of the mining takes place in the Greenestone belt. Gold mining covers 54.8% of the mining area (Rahm, et al., 2017). According to the DDFDB+ study (SBB *et al.,* 2017) gold mining is an important economic activity in Suriname, which provides employment to marginal groups of the society. Besides Mining as the main driver of deforestation, Infrastructure and Urban are also two large LULC classes covering respectively 15.2% and 4.0% of the total deforestation. Furthermore, the area of Secondary vegetation increases from 940 till 1.205 ha from 2013 to 2015, covering only 1.4% of the deforestation in the period 2000-2015. Detection of this class started in the second monitoring period 2000-2013 where deforestation areas from 2000-2009 were analyzed whether forest regeneration occurred.

All road infrastructure was mapped within the period 2000-2015. The results of this activity show that a total length of 11.700 km roads is mapped including roads from both coastal and interior area. There are less roads leading to the southern part of Suriname. Previous research shows that deforestation is more likely to occur nearby roads. Roads lead to accessibility of areas, which can result in various human activities.

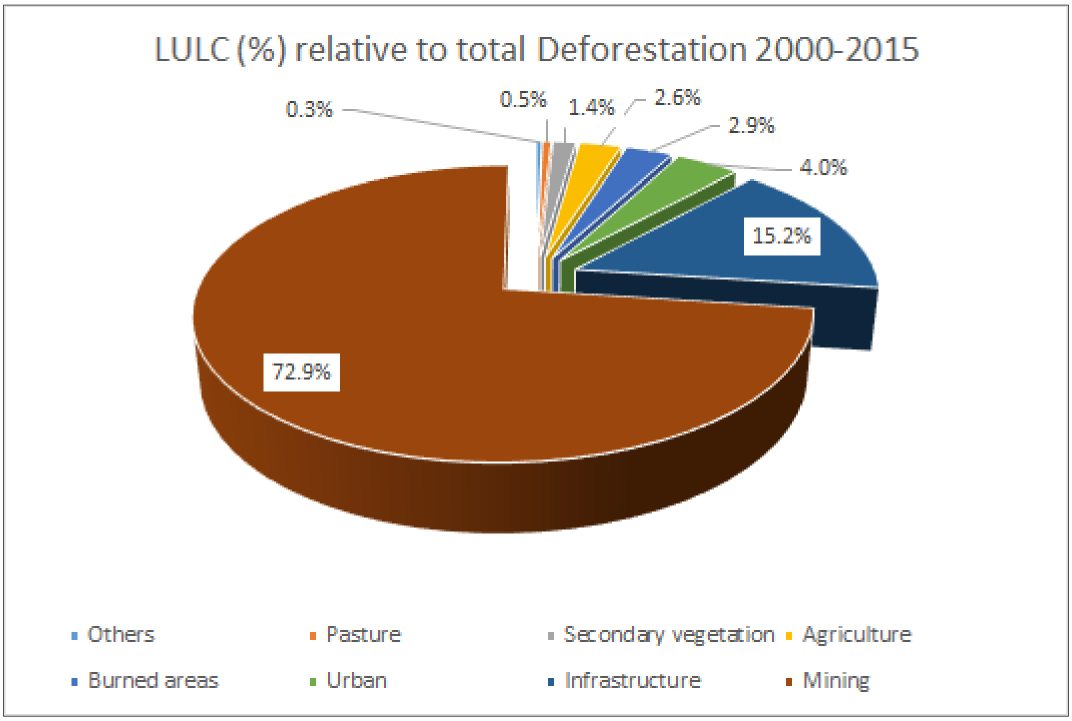


Figure 3-7: Pie-Percentage of each LULC class for the period 2000-2015

Table 3.3, 3.4 and 3.5 show the Land Use Change matrices between the following maps: Basemap 2000, Post-deforestation map 2000-2009, 2000-2013 and 2000-2015.

Table 3-3: Land Use Change matrix between 2000 and 2009 based on map areas

		LULC2009								
		AGRICULTURE	BURNED AREAS	FOREST	INFRA-STRUCTURE	MINING	OTHERS	PASTURE	SHIFTING CULTIVATION	URBAN
Basemap 2000	AGRICULTURE (NA)	---	---	---	---	---	---	---	---	---
	BURNED AREAS (NA)	---	---	---	---	---	---	---	---	---
	FOREST	871	243	15026292	2767	19519	169	148	14736	846
	INFRA-STRUCTURE (NA)	---	---	---	---	---	---	---	---	---
	MINING (NA)	---	---	---	---	---	---	---	---	---
	OTHERS (NA)	---	---	---	---	---	---	---	---	---
	PASTURE (NA)	---	---	---	---	---	---	---	---	---
	SHIFTING CULTIVATION	1	---	---	61	61	---	---	192743	183
	URBAN (NA)	---	---	---	---	---	---	---	---	---

Table 3-4: Land Use Change matrix between 2009 and 2013 based on map areas

		LULC2013									
		AGRICULTURE	BURNED AREAS	FOREST	INFRA-STRUCTURE	MINING	OTHERS	PASTURE	SECONDARY VEGETATION	SHIFTING CULTI-VATION	URBAN
LULC 2009	AGRICULTURE	706	0	0	10	2	0	0	125	0	30
	BURNED AREAS	0	238	0	0	0	0	0	4	0	0
	FOREST	555	1759	14994265	4786	22360	95	28	123	1752	516
	INFRA-STRUCTURE	2	0	0	2407	231	0	0	180	0	7
	MINING	3	0	0	70	19041	1	0	457	0	21
	OTHERS	0	53	0	100	4	5	0	7	0	1
	PASTURE	0	0	0	2	0	0	145	2	0	0
	SHIFTING CULTIVATION	7	0	0	80	365	0	54	4	206759	222
	URBAN	14	2	0	41	14	0	1	38	0	917

Table 3-5: Land Use Change matrix between 2013 and 2015 based on map areas

		LULC 2015									
		AGRICULTURE	BURNED AREAS	FOREST	INFRA-STRUCTURE	MINING	OTHERS	PASTURE	SECONDARY VEGETATION	SHIFTING CULTIVATION	URBAN
LULC2013	AGRICULTURE	1286	0	0	0	0	0	0	0	0	0
	BURNED AREAS	0	2052	0	0	0	0	0	0	0	0
	FOREST	685	452	14963545	5399	19843	95	70	229	2939	987
	INFRA-STRUCTURE	0	0	0	7333	4	92	0	44	0	26
	MINING	0	0	0	8	41932	0	0	31	0	0
	OTHERS	0	0	0	0	0	86	0	7	0	8
	PASTURE	0	0	0	0	0	0	228	0	0	0
	SECONDARY VEGETATION	0	0	0	0	46	0	0	891	0	4
	SHIFTING CULTIVATION	241	0	0	218	439	8	157	0	206749	684
	URBAN	0	0	0	2	0	0	0	3	0	1709

3.3.3 Deforestation for the different districts

Figure 3.8 shows a map with the distribution of the total deforestation (absolute deforestation) from the period 2000-2015 over the country. Sipaliwini and Brokopondo seem to have the highest absolute deforestation while Paramaribo seems to have the lowest absolute deforestation. Most of Paramaribo is already deforested before 2000 and therefore less forest is present to be deforested.

Brokopondo, Wanica and Para happens to have respectively 3.7%, 1.9%, and 1.5% of the district area covered by deforestation.

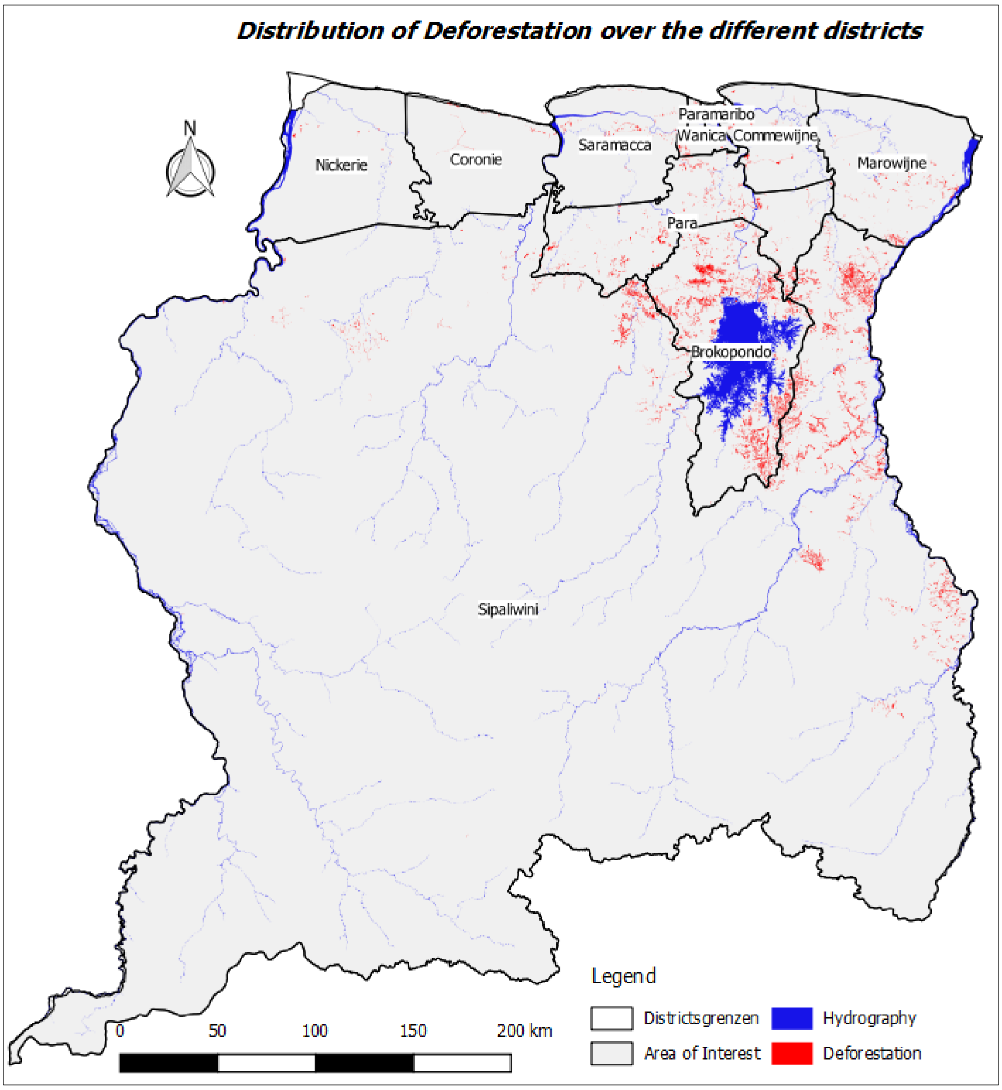


Figure 3.8 Figure 3-8: Map showing the distribution of deforestation over the country

Within each district the deforestation area is divided by the forest area from 2000, present in the district. The percentages in the column chart shown in figure 3.9, represent how much forest from 2000 is converted into deforested area in the period 2000-2015 per district. The following districts have the highest percentage of forest converted into deforestation in the period 2000-2015: Paramaribo (29.8%), Wanica (11.6%) and Brokopondo (4.9%). Sipaliwini has a low percentage (0.3%) of relative deforestation, but the highest absolute deforestation. This district is the largest district with 12.800.000 ha forest in 2000.

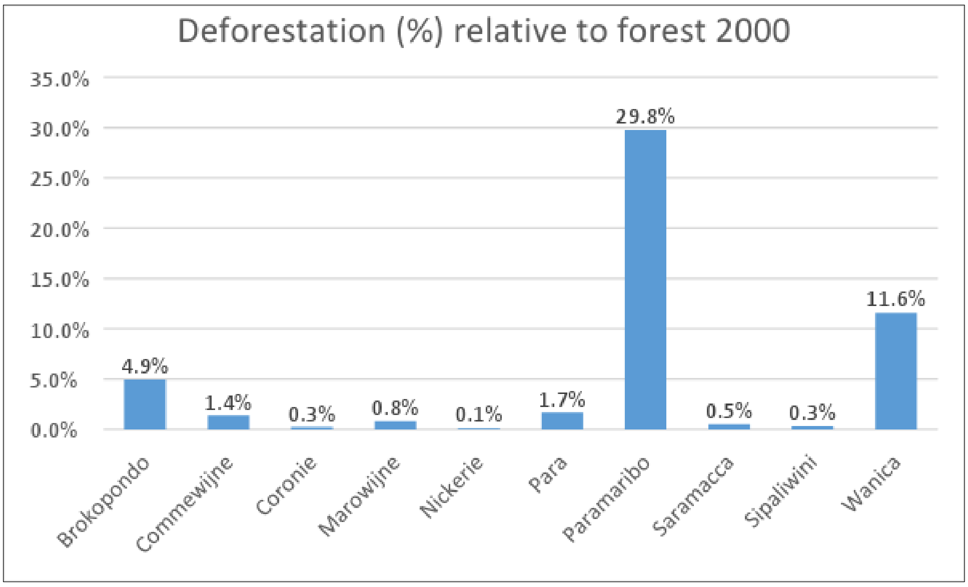


Figure 3-9: Chart showing percentage of deforestation 2000-2015 relative to forest 2000 within each district

Figure 3.10 shows the trend of the annual deforestation in the different periods of respectively Wanica, Brokopondo and Sipaliwini from 2000 till 2015. In Sipaliwini the yearly deforestation increases from 2000 till 2014 and decreases in 2015, while in Wanica no significant change in the yearly deforestation is observed for the different periods. The districts Sipaliwini and Brokopondo have the highest absolute deforestation meaning that the most deforestation appears in these districts respectively 3.7% and 1.9% of the total deforestation from 2000 till 2015.

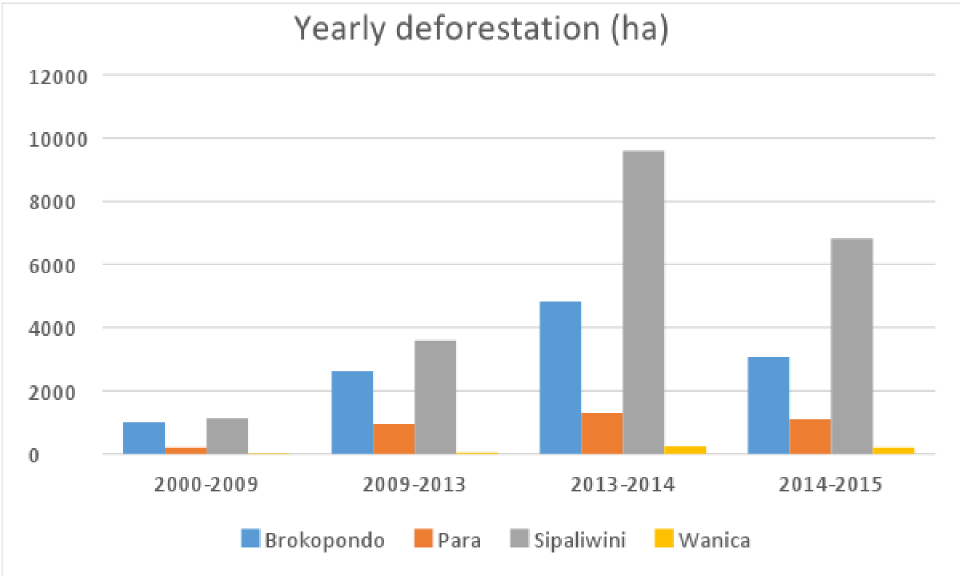


Figure 3-10: Graphic showing the annual deforestation over the different periods for district Para, Wanica, Brokopondo and Sipaliwini

Figure 3.11 shows the drivers of deforestation for the period 2000-2015 for the districts Para, Brokopondo, Sipaliwini and Wanica as one chart.

In Wanica and Paramaribo, the main drivers are Urban, Agriculture and Pasture class, with respectively 36%, 28% and 25%. According to the General statistic office of

Suriname (2015), Wanica and Paramaribo have the highest population density, explaining the urban expansion as main driver.

The main drivers in Brokopondo and Sipaliwini is Mining and Infrastructure. These districts are partly covered by the Greenstone belt, where gold reserves are present. In Sipaliwini, more infrastructure was constructed due to logging activities in the forest belt than in Brokopondo.

In Para, the main drivers are Mining, Burned areas and Infrastructure with respectively the following percentages 33%, 26% and 21%. These burned areas are mostly located in the savannahs and were created by the local communities. The land use of these areas are not yet known and for that reason it is classified as Burned areas.

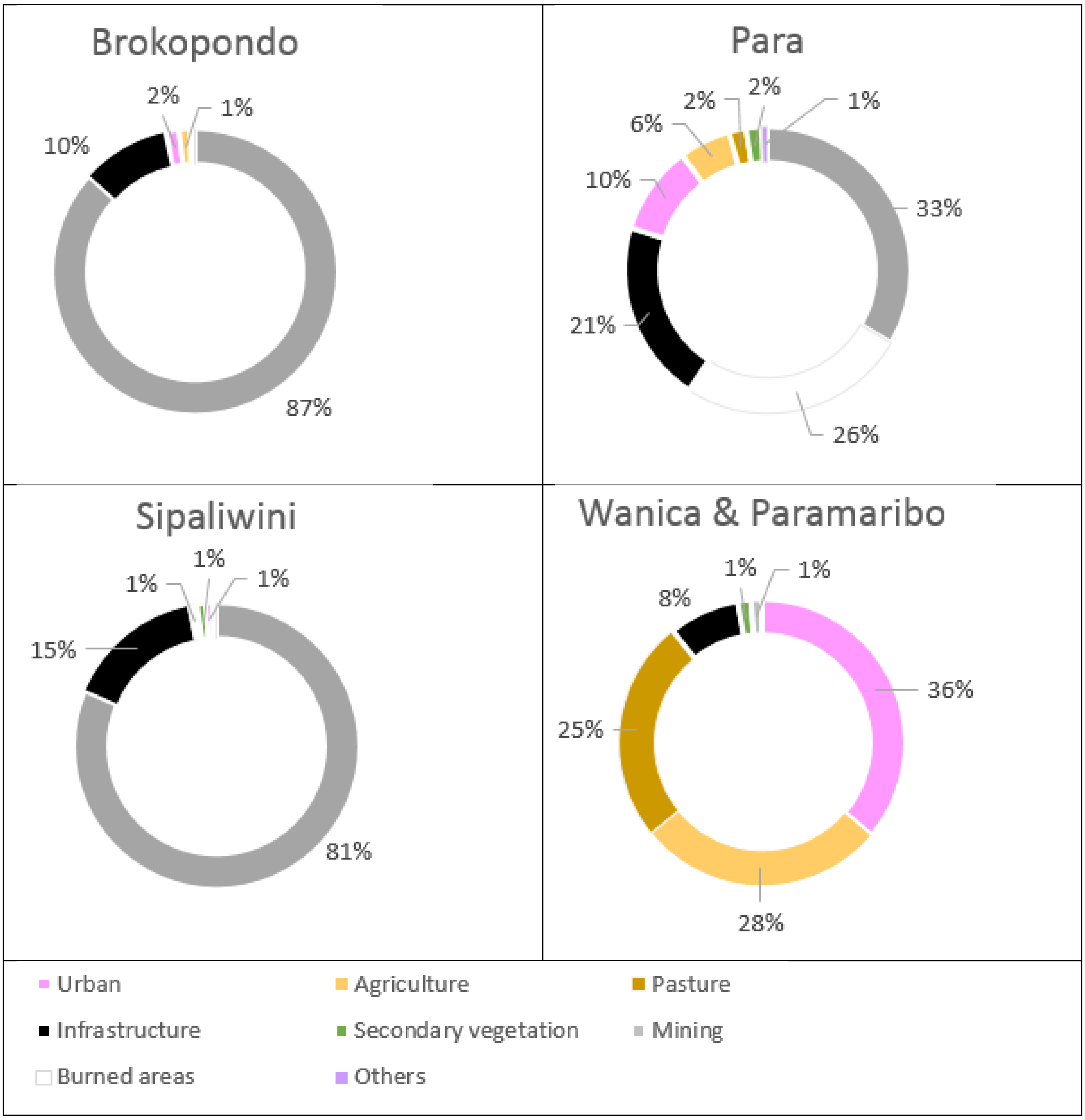


Figure 3-11: Overview of the division of LULC classes for the period 2000-2015

3.3.4 Forest cover

Table 3.6 shows the percentage of the forest cover per year. According to this figure, the forest cover remained approximately 93% from 2000 till 2015.

Table 3-6: Forest cover per year in percentage

Year	Stratified Estimated area	Percentage
2000	15,314,395	93.57%
2001	15,310,723	93.55%
2002	15,307,050	93.52%
2003	15,303,378	93.50%
2004	15,299,706	93.48%
2005	15,296,033	93.46%
2006	15,292,361	93.44%
2007	15,288,689	93.41%
2008	15,285,016	93.39%
2009	15,281,344	93.37%
2010	15,273,326	93.32%
2011	15,265,309	93.27%
2012	15,257,291	93.22%
2013	15,249,273	93.17%
2014	15,233,516	93.08%
2015	15,224,073	93.02%
2016	15,212,687	92.95%

The forest cover status of each district in the year 2015 is shown in figure 3.12. In Sipaliwini and Para the forest covers more than 80% of the district area, while in Marowijne, Saramacca, Brokopondo, Commewijne, and Nickerie the forest covers between 60-80% of the district area. Wanica and Paramaribo contain less than 20% of forest cover. An explanation for these two districts could be the high population density (ABS, 2013) and the relatively small district area.

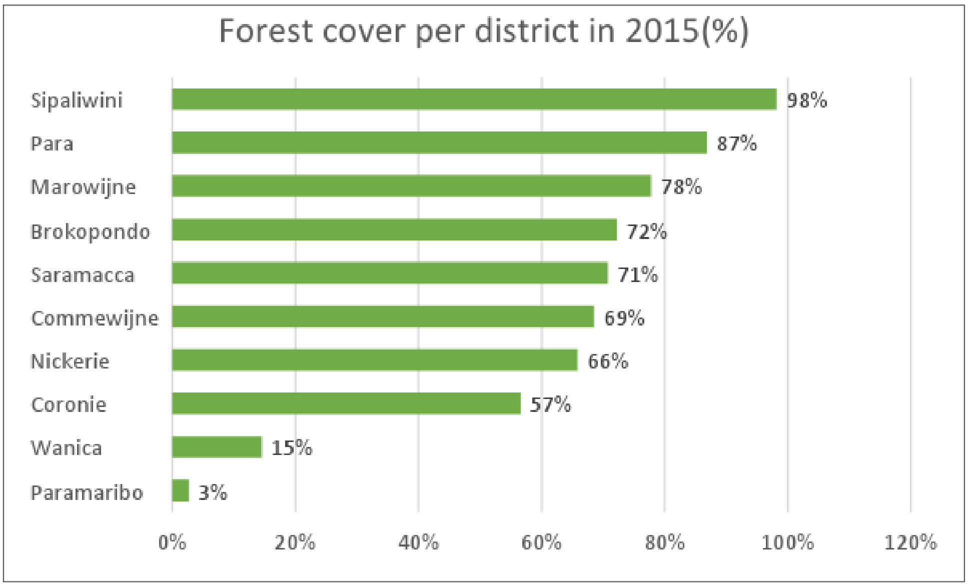


Figure 3-12: Percentage forest cover 2015 for each district

3.3.5 Development of shifting cultivation

Figure 3.13 shows the absolute shifting cultivation over the different periods since 2000. It should be noted that based on the results of the accuracy assessment that the uncertainty of this increase is very high and further detailed research is recommended.

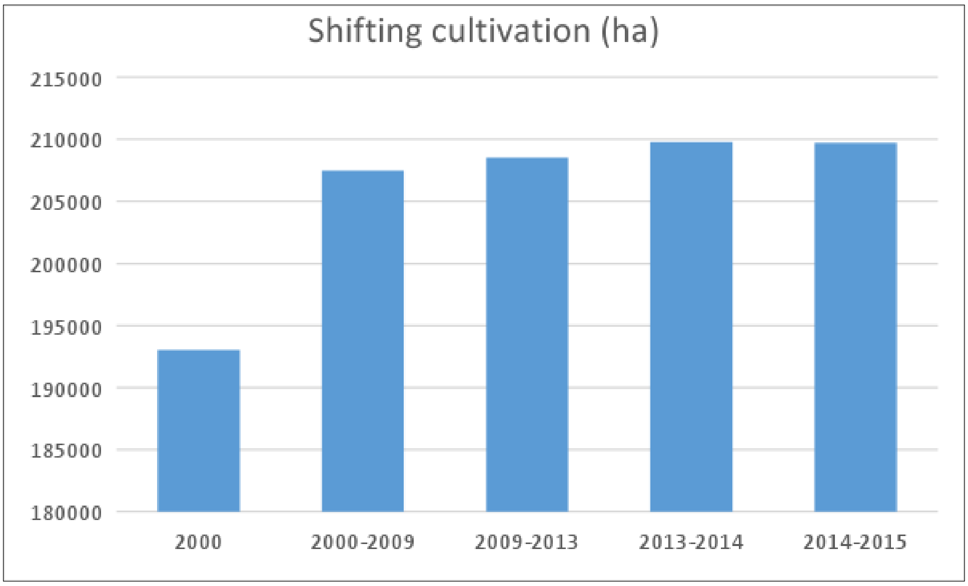


Figure 3-13: Shifting cultivation trend from 2000 till 2015

The green color on the map in figure 3.14 shows the distribution of Shifting cultivation over the country. According to the map most of the shifting cultivation can be found in Sipaliwini, Marowijne, Brokopondo and Para.

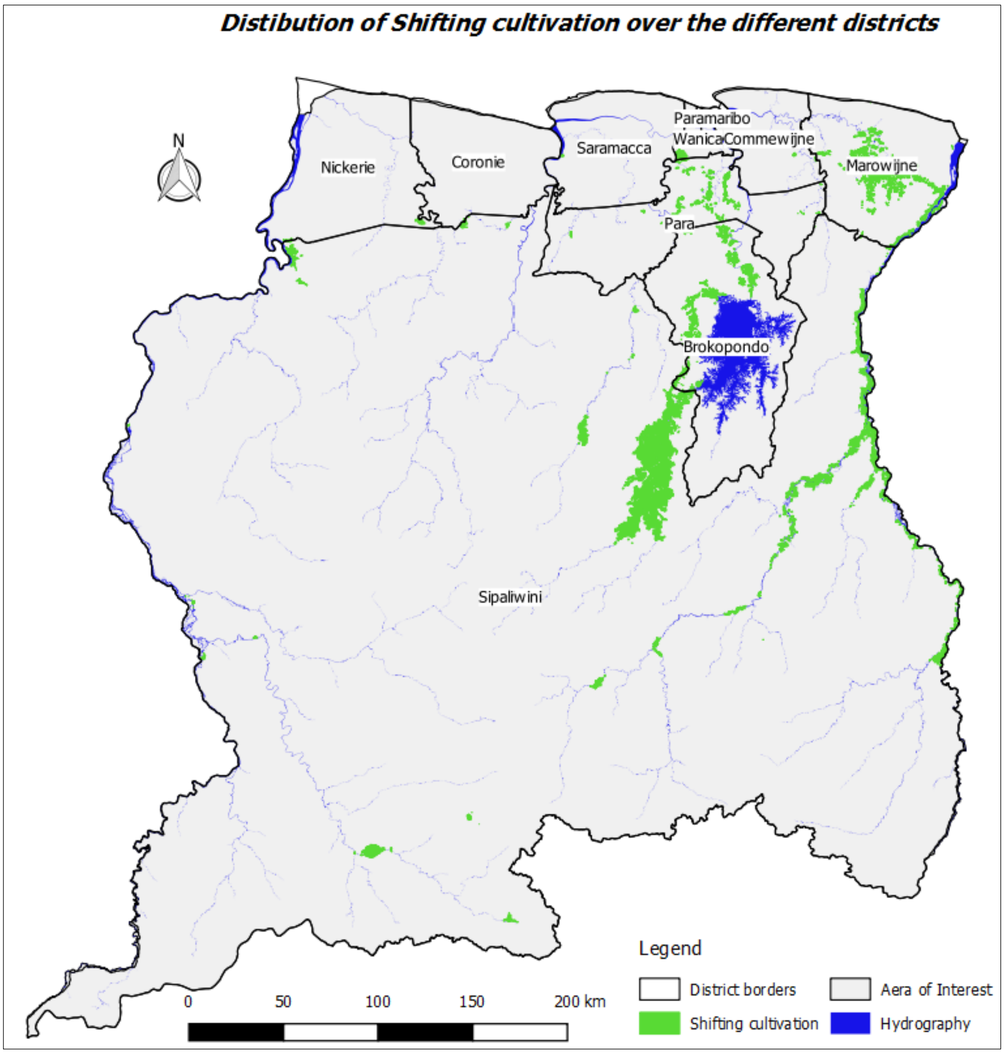


Figure 3-14: Map showing the distribution of shifting cultivation over the country

The percentage of the area of shifting cultivation occurring within Sipaliwini, Marowijne, Brokopondo and Para in the period 2000-2015 are respectively 75%, 11%, 9%, and 3% (figure 3.15). This can be explained by the fact that in these four districts most of the settlements are found.

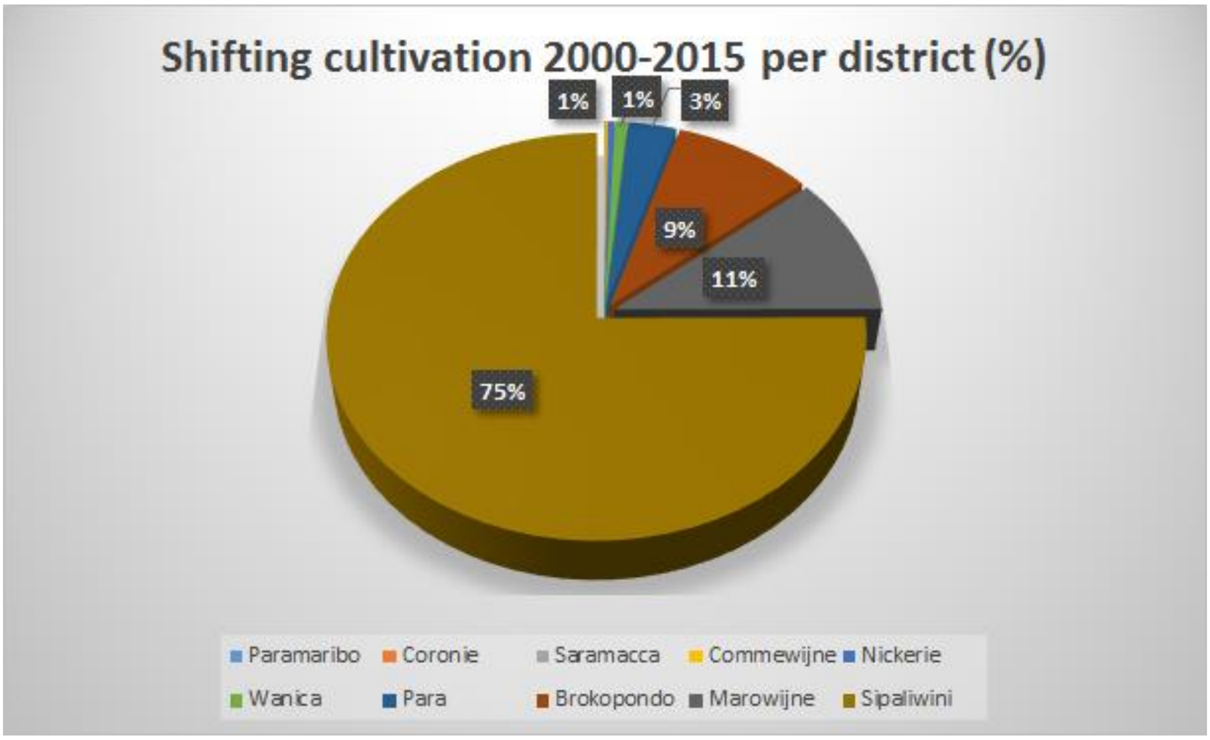


Figure 3-15: Percentage of the area of shifting cultivation occurring within each district

Figure 3.16 shows the amount of settlements per districts based on the collaboration work done by the Ministry of Regional Development and SBB. The settlements are divided between Amerindian and Maroon. In figure 3.20 the location of these settlements are shown over the different districts.

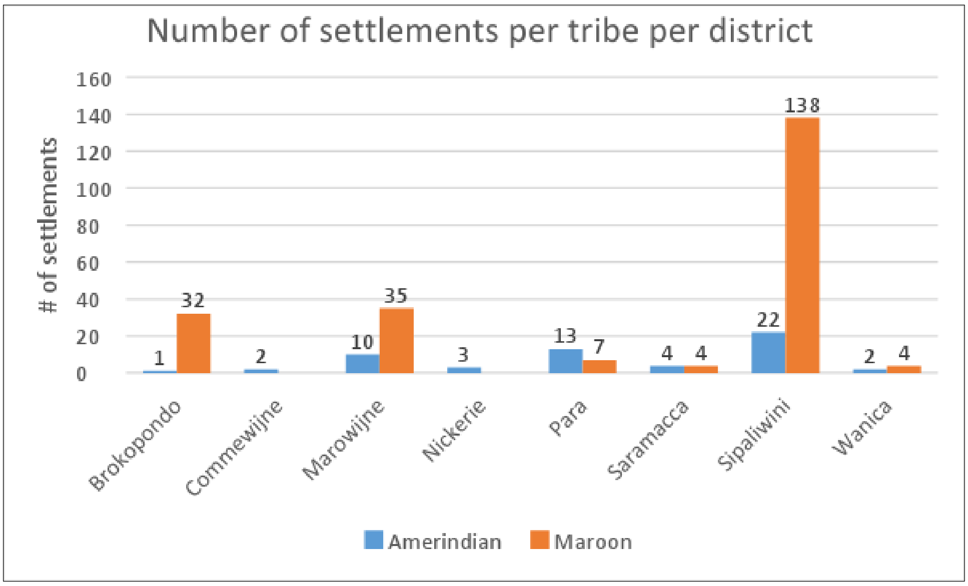


Figure 3-16: Diagram showing the numbers of settlements divided in Amerindian and Maroon

Most of the settlements occur in Sipaliwini, Marowijne, Brokopondo and Para, respectively 160, 45, 33 and 20 settlements (Figure 3.17). In Sipaliwini more Maroon settlements are present than Amerindian, while in Para the case is vice versa.

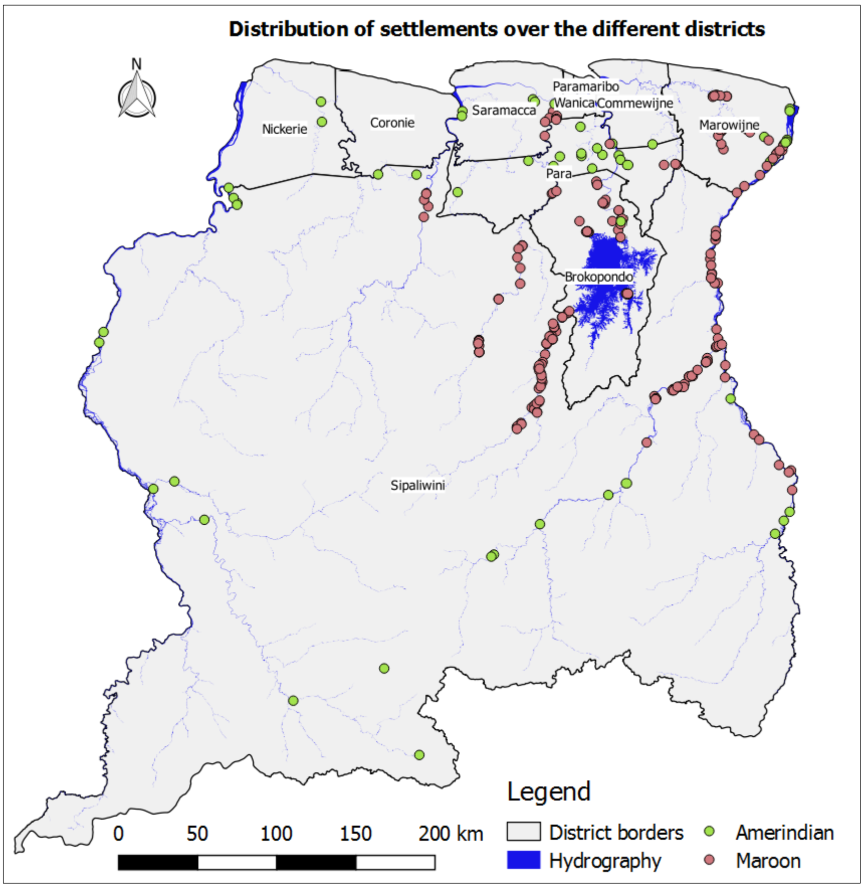


Figure 3-17: Map showing the distribution of settlements over the country

Figure 3.18 shows the percentage of shifting cultivation proportionally expressed in each district area. Therefore, the shifting cultivation area is divided by the district area. In Marowijne, Wanica, and Brokopondo, shifting cultivation covers respectively 4.87%, 3.72%, and 2.63% in each of the district area. In Paramaribo no shifting cultivation is present. Commewijne, Coronie, Nickerie, and Saramacca contain less than 1% of shifting cultivation. However, most of the permanent agriculture areas appears within these districts. For example, in Nickerie the rice and banana agriculture are present, while in Commewijne and Saramacca mainly citrus agriculture areas are present.

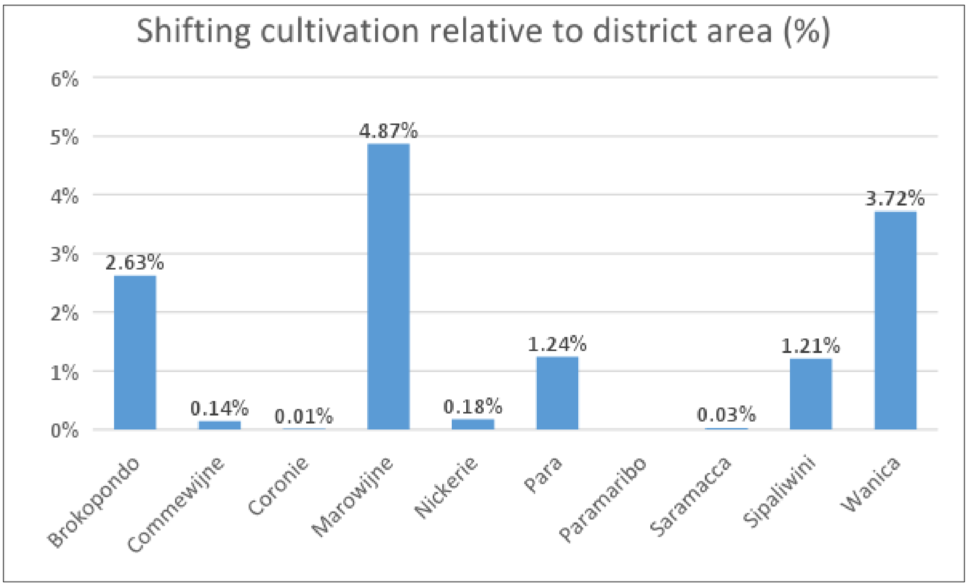


Figure 3-18: Histogram of the percentage of shifting cultivation proportional to district area

4 Conclusion and perspectives

So far, the FCMU has produced the following maps: Basemap 2000, Deforestation maps for the periods 2000-2009, 2009-2013, 2013-2014 and 2014-2015 containing the classes: Forest, Non-forest, Hydrology, Shifting cultivation and Deforestation.

Also post-deforestation LULC maps for the periods 2000-2009, 2000-2013, and 2000-2015 containing the classes Agriculture, Pasture, Mining, Secondary vegetation, Urban, Infrastructure, Others and Burned areas, were produced in collaboration with relevant national stakeholders.

Based on the deforestation maps the following conclusions can be made:

Areas with a high intensity of deforestation fall within the Greenstone belt and changed between specific areas (hotspots) during the deforestation monitoring period 2000-2015. The hotspots are Balingsoela, Meriankreek, Lelygebergte/Sarakreek, Tapanahony river, Benzdorp and Brownsberg. Most of the deforestation is located around the Brokopondo Lake due to the fact that it is part of the Greenstone belt, which contains gold reserves. Besides this, the presence of streams in this area facilitates the alluvial gold mining activity. Along the upper-basin of the Suriname River most shifting cultivation is present due to the occurrence of settlements.

Furthermore, the Quality Assessment/Quality Control that has been performed on the deforestation maps achieved an overall accuracy of 99%. Hereby stratified estimated areas with a confidence interval have been calculated for each class of the deforestation map.

Based on the analysis of the development of deforestation, the following conclusions can be made:

- The deforestation rate has been increasing from 0.02% in the period 2000-2009 to 0.05 % in the period 2009-2015
- The deforestation rate due to gold mining has a strong relation with the gold prices
- The following districts have a high percentage of deforestation expressed in terms of proportion by district area: Brokopondo (3.7%), Wanica (1.9%), and Para (1.5%)

Most of the deforestation appears in the districts Sipaliwini and Brokopondo, respectively 3.7% and 1.9% of the total deforestation in Suriname. The main drivers in Brokopondo and Sipaliwini are mining and infrastructure.

The percentage of forest cover for the whole country remained approximately 93% from 2000 to 2015. Therefore, Suriname still meets the requirements of a High Forest cover and Low Deforestation country.

The analysis on the development of shifting cultivation shows that a significant increase of shifting cultivation was noticed for the period 2000-2009, where after the trend appears to remain stable. Most of the shifting cultivation occur within the districts Sipaliwini (75%), Marowijne (11%), Brokopondo (9%) and Para (3%). This also has a link with the occurrence of settlements within these districts.

Finally, based on the post-deforestation LULC maps that cover the period 2000-2015, the main driver of deforestation in Suriname is mining. The validation of the post-deforestation LULC maps was done in collaboration with other relevant stakeholders, who have more expertise and field knowledge about the LULC classes.

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Annex 1: Overview of the satellite images used

Table a1-Overview of the Landsat images used for generating the Basemap 2000

Row	Path	Sensor	Date	Georectified
56	228	ETM+	1999-11-21	No
	228	ETM+	2000-11-21	No
	229	ETM+	2000-08-10	No
	229	ETM+	2000-09-03	Yes
	229	ETM+	2000-10-29	No
	230	ETM+	1999-11-03	No
	230	ETM+	2001-09-05	No
57	228	TM	2000-09-12	Yes
	228	ETM+	2000-11-15	Yes
	229	ETM+	1999-11-28	No
	229	ETM+	2000-08-10	No
	229	ETM+	2001-09-14	
	230	ETM+	2001-09-05	No
	230	ETM+	2001-11-07	No
58	228	ETM+	1999-09-18	Yes
	228	ETM+	2000-09-12	Yes
	229	ETM+	2000-06-05	yes
	230	ETM+	2002-09-08	No
59	229	ETM+	1999-11-28	Yes
	229	TM	2000-09-03	Yes

	229	ETM+	2000-09-11	Yes
	230	ETM+	2002-09-08	No

Table a2-Landsat images used for generating the Deforestation map 2000-2009

Row	Path	Sensor	Date	Georectified
56	228		2009-08-04	No
	229		2009-09-28	No
	230		2009-11-06	No
57	228		2009-09-05	No
	229		2009-11-15 (eastern part)	No
	229		2009-09-28 (western part)	No
	230		2009-09-19	No
58	228		2009-10-23	Yes
	229		2009-09-23	Yes
	230		2009-09-03	No
59	229		2009-09-28	No
	230		2009-09-03	Yes

Table a3- An overview of the Landsat images to fill clouds from 2000 within Deforestation map 2000-2009

Row	Path	Sensor	Date	Georectified
56	228	TM	1997-08-03	No
	228	TM	1997-09-04	No
	228	TM	2003-10-07	No

	228	TM	2003-10-23	No
	228	TM	2005-07-08	No
	228	TM	2005-07-24	No
	228	TM	2005-08-25	No
	228	TM	2005-09-26	No
	229	TM	1998-09-14	No
	229	TM	2004-04-07	No
	229	TM	2004-08-29	No
	229	TM	2004-11-17	No
	229	TM	2005-09-17	No
	229	TM	2005-10-03	No
	229	TM	2005-10-19	No
	229	TM	2005-11-20	No
	229	TM	2007-07-21	No
	230	TM	1998-08-04	No
	230	TM	1998-10-23	No
	230	TM	2004-10-23	No
57	228	TM	1997-08-03	No
	228	TM	2003-10-23	No
	228	TM	2003-10-07	No
	228	TM	2004-08-22	No
	228	TM	2004-11-10	No
	228	TM	2004-12-12	No

	228	TM	2005-07-08	No
	228	TM	2005-07-24	No
	228	TM	2005-08-25	No
	229	TM	1996-09-08	No
	229	TM	1996-10-10	No
	229	TM	2003-11-15	No
	229	TM	2006-09-04	No
	229	TM	2006-10-06	No
	230	TM	1996-08-14	No
	230	TM	2004-09-21	No
	230	TM	2004-10-23	No
	230	TM	2006-08-10	No
	230	TM	2006-09-27	No
58	228	TM	1995-07-29	Yes
	228	TM	1997-09-18	Yes
	228	TM	2004-10-09	Yes
	229	TM	2004-10-23	Yes
	230	TM	2004-11-10	Yes
	230	TM	2006-10-06	No
59	229	TM	1997-09-11	No
	229	TM	2003-11-15	No
	229	TM	2004-09-14	No
	229	TM	2004-11-17	No

	229	TM	2004-12-03	No
	229	TM	2004-12-19	No
	229	TM	2006-10-06	No
	229	TM	2006-10-22	No
	230	TM	1995-07-11	No
	230	TM	1995-08-28	No
	230	TM	1995-09-13	No
	230	TM	1997-10-04	Yes
	230	TM	2004-01-25	No
	230	TM	2004-09-21	No

Table a4- An overview of the images used for Deforestation map 2009-2013

Row	Path	Sensor	Date	Georeferenced
56	228	OLI	2013-08-15	
	229	OLI	2013-08-06	
	229	OLI	2013-09-23	
	230	OLI	2013-06-26	
	230		2013-09-30	
57	228		2013-08-15	
	228	OLI	2013-11-03	
	229	OLI	2013-08-22	
	229	OLI	2013-08-22	
	230	OLI	2013-11-17	

58	228	ETM+	2013-10-10	yes
	228	ETM+	2013-09-24	
	228		2013-11-03	yes
	229	OLI	2013-06-19	yes
	230	OLI	2013-10-16	
59	229	OLI	2013-09-23	yes
	230	OLI	2013-10-16	

Table a5-An overview of the used images for Deforestation map 2013-2014

Row	Path	Sensor	Date	Type	Georeferenced
56	228	OLI	2014-09-03	Anchor image	
	228	OLI	2014-09-19	Fill1 image	
	228	OLI	2014-07-01	Fill2 image	
	229	OLI	2014-09-26	Anchor image	
	229	OLI	2014-10-28	Fill1 image	
	229	OLI	2014-05-21	Fill2 image	
	230	OLI	2014-10-19	Anchor image	
	230	OLI	2014-09-17	Fill1 image	
	230	OLI	2014-03-09	Fill2 image	
	230	OLI	2014-07-31	Fill3 image	
	230	OLI	2015-10-06		
57	228	OLI	2014-09-03	Anchor image	
	228	OLI	2014-10-05	Fill1 image	

	228	OLI	2014-07-17	Fill2 image	
	228	OLI	2015-09-22		
	229	OLI	2014-09-26	Anchor image	
	229	OLI	2014-10-28	Fill1 image	
	229	OLI	2014-08-25	Fill2 image	
	229	ETM+	2014-01-21		
	229	ETM+	2014-06-30		
	229	ETM+	2014-08-01		
	229	ETM+	2014-10-04		
	230	OLI	2014-10-03	Anchor image	
	230	OLI	2014-09-17	Fill1 image	
	230	OLI	2014-10-19	Fill2 image	
	230	OLI	2014-04-10	Fill 3 image	
	230	OLI	2014-07-15		
	230	ETM+	2014-08-08		
	230	ETM+	2014-09-25		
	230	ETM+	2014-10-11		
	230	OLI	2015-09-20		
	230	OLI	2015-10-22		
58	228	OLI	2014-09-03	Anchor image	
	228	OLI	2014-10-05	Fill1 image	
	228	OLI	2014-07-17	Fill2 image	
	228	OLI	2014-08-02	Fill 3 image	

	228	ETM+	2014-07-09		
	228	ETM+	2014-08-10		
	228	ETM+	2014-09-27		
	228	ETM+	2014-11-30		
	229	OLI	2014-10-28	Anchor image	
	229	OLI	2014-09-26	Fill1 image	
	229	OLI	2014-08-25	Fill2 image	
	229	OLI	2015-10-15		
	230	OLI	2014-07-15	Anchor image	
	230	OLI	2014-08-16	Fill1 image	
	230	OLI	2014-01-20	Fill2 image	
	230	OLI	2014-03-09	Fill3 image	
	230	OLI	2015-10-22		
	230	OLI	2015-09-20		
59	229	OLI	2014-10-28	Anchor image	
	229	OLI	2014-09-26	Fill1 image	
	229	OLI	2014-12-15	Fill2 image	
	229	OLI	2014-11-13	Fill3 image	
	230	OLI	2014-07-15	Anchor image	
	230	OLI	2014-07-31	Fill1 image	
	230	OLI	2014-10-19	Fill2 image	
	230	OLI	2014-01-20	Fill3 image	
	230	OLI	2015-09-20		

	230	OLI	2015-11-07		

Table a6-An overview of the SPOT5 images used for reducing clouds

KJ	JOB	Sensor	Date	Georeferenced
687-341	GU_005114	J	2014-09-04	yes
687-342	GU_004736	J	2014-09-04	yes
688-343	GU_005084	J	2014-07-30	yes
688-343	GU_005178	J	2014-11-16	yes
687-342	GU_004736	J	2014-09-04	yes
687-343	GU_004724	J	2014-07-14	yes
687-344	GU_005064	J	2014-07-14	yes
688-344	GU_005126	J	2014-10-16	yes
688-345	GU_005137	J	2014-10-16	yes
688-346	GU_005136	J	2014-10-16	no
682-340	GU_005169	J	2014-11-05	yes
685-339	GU_005030	J	2014-04-02	yes
682-340	GU_005169	J	2014-11-05	yes
683-340	GU_004748	J	2014-11-16	yes
682-339	GU_005171	J	2014-11-05	yes
682-340	GU_005169	J	2014-11-05	yes
683-340	GU_004748	J	2014-11-16	yes
682-340	GU_005169	J	2014-11-05	yes
683-340	GU_004748	J	2014-11-16	yes

Table a7-An overview of the SPOT 6 images used to reduce the clouds

Scene	SPOT 6 id
228-57	IMG_SPOT6_PMS_201409251343101_ORT_1270945101_R1C11
229-56	IMG_SPOT6_PMS_201409251343101_ORT_1270945101_R1C11
229-57	IMG_SPOT6_PMS_201409251343101_ORT_1270945101_R1C11

Table a8- An overview of Landsat images used to produce the Deforestation map 2014-2015

Row	Path	Sensor	Date	Type	Georeferenced
56	228	OLI	2015-09-22	Anchor image	No
	228	OLI	2015-10-24	Fill1 image	No
	228	OLI	2015-06-02	Fill2 image	No
	229	OLI	2015-10-15	Anchor image	No
	229	OLI	2015-09-29	Fill1 image	No
	229	OLI	2015-09-13	Fill2 image	No
	230	OLI	2015-10-06	Anchor image	No
	230	OLI	2015-10-22	Fill1 image	No
57	228	OLI	2015-09-22	Anchor image	No
	228	OLI	2015-10-24	Fill1 image	No
	229	OLI	2015-08-	Extra Image	No

			05		
	229	OLI	2015-10-15	Anchor image	No
	229	OLI	2015-09-13	Fill1 image	No
	230	OLI	2015-10-22	Anchor image	No
	230	OLI	2016-09-20	Fill1 image	No
	230	OLI	2015-10-06	Fill2 image	No
58	228	OLI	2015-09-22	Anchor image	No
	228	OLI	2015-07-04	Fill1 image	No
	229	OLI	2015-10-15	Anchor image	No
	229	OLI	2015-09-13	Fill1 image	No
	230	OLI	2015-10-22	Anchor image	No
	230	OLI	2015-09-20	Fill1 image	No
59	229	OLI	2015-10-15	Anchor image	No
	229	OLI	2015-07-11	Fill1 image	No
	229	OLI	2015-11-16	Fill2 image	No
	230	OLI	2015-09-20	Anchor image	No

	230	OLI	2015-11-07	Fill1 image	No

Annex 2: Overview of the ancillary data

Data	Source	Year	Additional remarks
Ecosystem map of the Northern Suriname	Teunissen P.	1978	The Ecosystem map consists the coastal part of Suriname and has been produced by Teunissen / Stinasu 1978 with aerial photographs (Central Bureau for Aerial Survey, Paramaribo, 1970-1973) and reconnaissance soil maps (Department of Soil Survey, Paramaribo, 1978).
Topographic maps with scales 1: 40000,1: 50000 and 1:100000	MI-GLIS	1970s	Land cover data, based on aerial imagery from the period 1956-1964, was previously produced by the cartographic company 'Centraal Bureau Luchtkartering (CBL)'. This data is produced for several regions of Suriname, and on different scales (40000, 50000, 100000).
Fire Information for Resource Management System (FIRMS)	NASA EOSDIS FIRMS, LANCE	2000-2009	Freely downloadable from the internet
Road layer	SBB	Continuously updated	Roads registered with a GPS
Logging compartments	SBB	Continuously updated	Compartments where logging takes place, registered in the field with a GPS
River	GISSAT	Unknown	Shapefile of the rivers based on the topographic maps
Settlements	SBB &RO	Continuously updated	Data that gives an overview of villages and

			important places among villages
Google Earth and Bing maps	Google Bing maps	Continuously updated	Combination of low, mid and high resolution data, to be consulted via the internet
Airstrips and airports	Gum-air		Data that gives an overview of the registered airstrips and airports
Creeks	CELOS/SBB		
Forestry Concessions	SBB	Continuously updated	Produced by SBB
Landings/ Log yards	SBB	Continuously updated	A point layer registered with GPS where logs are collected for transportation
Protected areas	SBB/LBB		
Processed Shuttle Radar Topography Mission (SRTM) data	SRTM		
Lake	GISSAT		
Gold Mining shapefiles	SBB	2014	Produced during the ONFI project “Monitoring the impact of gold mining on the forest cover and freshwater in the Guiana shield”
Greenstone belt	SBB		
Tracks	SBB	Continuously updated	Produced by SBB during field visits to the logging concessions
Camps	SBB	Continuously updated	Produced by SBB during field visits to the logging

			concessions
Mining concession data	GMD		Data that indicates the locations and state of mining concessions in Suriname
Geological map	GMD		Data that shows the geological deposit in specific locations
SRTM data (incl.HAND)	SBB		With the Shuttle Radar Topography Mission (SRTM) data, the HAND data is produced based on the digital elevation model. The HAND
Ports data	MAS		Data that gives an overview of the registered ports in Suriname.

Annex 3: Definitions of classes by ACTO and IPCC

LULC classes	
ACTO	IPCC 2003
Secondary vegetation: Areas that after the complete removal of forest vegetation, are in advanced process of regeneration of shrub and/or tree or have been used for practicing forestry or permanent agriculture with the use of native or exotic species.	**Forest land**: This category includes all land with woody vegetation consistent with thresholds used to define forest land in the national GHG inventory, sub-divided into managed and unmanaged, and also by ecosystem type as specified in the IPCC Guidelines. It also includes systems with vegetation that currently fall below, but are expected to exceed, the threshold of the forest land category.
Agriculture: Extensive areas with a predominance of annual cycle crops, especially grains, with use of high technological standards, such as use of certified seeds, inputs, pesticides and mechanization, among others.	**Cropland**: This category includes arable and tillage land, and agro-forestry systems where vegetation falls below the thresholds used for the forest land category, consistent with the selection of national definitions.
Pasture: Pasture areas in current production process with a predominance of herbaceous vegetation, and between 90% and 100% coverage of grass species.	**Grassland**: This category includes rangelands and pasture land that is not considered as cropland. It also includes systems with vegetation that fall below the threshold used in the forest land category and are not expected to exceed, without human intervention, the threshold used in the forest land category. The category also includes all grassland from wild lands to recreational areas as well as agricultural and silvi-pastural systems, subdivided into managed and unmanaged consistent with national definitions.
Urban Area: Urban patterns formed by population concentration, villages, towns or cities with differentiated infrastructure from rural areas, with density of streets, houses, buildings and other public facilities.	**Settlements**: This category includes all developed land, including transportation infrastructure and human settlements of any size, unless they are already included under other categories. This should be consistent with the selection of national definitions.
Hydrography: Set the presence of surface water in the area, including seas, lakes,	**Wetlands**: This category includes land that is covered or saturated by water for all or part of the year (e.g., peatland) and

river, lagoons and bays.	that does not fall into the forest land, cropland, grassland or settlements categories. The category can be subdivided into managed and unmanaged according to national definitions. It includes reservoirs as a managed sub-division and natural rivers and lakes as unmanaged sub-divisions.
Others: These are areas that do not fall under any of all project classes, with different coverage pattern such as rock outcrops, river beaches, sandbars and others.	**Other**: This category includes bare soil, rock, ice, and all unmanaged land areas that do not fall into any of the other five categories. It allows the total of identified land areas to match the national area, where data are available.
Not Observed Area: Areas that have their interpretation rendered impossible by the presence of clouds or cloud shadow, at the time of passage for satellite images acquisition, in addition to areas recently burned. Burned areas are included in the Not observed-class, because it is not clear for what land use these areas are burned.	

Annex 4: Overview of stakeholders

	Institutes
1	Center for Agricultural Research in Suriname (CELOS)
2	Management Institute for Land Registration and Land Information System (MI-GLIS)
3	Geological Mining Services (GMD)
4	NV Grasshopper Aluminium Company (NV GRASSALCO)
5	Maritime Authority Suriname (MAS)
6	Ministry of Trade and Industry (HI)
7	Ministry of Agriculture, Animal Husbandry and Fisheries (LVV)
8	Ministry of Public Works (OW)
9	Ministry of Regional Development (RO)
10	Ministry of Physical Planning, Land-and Forestry Management (RGB)
11	National Institute for Environment & Development (NIMOS)
12	Presidential Commission to Regulate the Gold Sector (OGS)
13	Planning Office Suriname (SPS)
14	Foundation for Forest Management and Production Control (SBB)

Annex 5 – Overview of the proportion of classes validated by the stakeholders

Table b-5: Proportion of the areas that are validated for the period 2000-2009

2000- 2009	Area_ha	Area_Validated (ha)	Validated (%)
Agriculture	1096	159	15%
Burned areas	305	275	90%
Infrastructure	3554	2348	66%
Mining	24492	24125	99%
Others	212	0	0%
Pasture	188	159	84%
Urban	1290	504	39%
Total	31138	27570	
Total validated	88.54%		

Table b-6: Results of the validation process for the period 2000-2013

2000- 2013	Area_ha	Area_Validated (ha)	Validated (%)
Agriculture	1297	752	58%
Burned Areas	2070	1301	63%
Infrastructure	7561	5342	71%
Mining	42151	41674	99%
Others	102	0	0%
Pasture	230	108	47%
Secondary vegetation	948	0	0%
Urban	1728	885	51%
Total	54790	49310	
Total validated	90.00%		

Table b-7: Results of the validation process for the period 2000-2015

2000- 2015	Area_ha	Area_Validated (ha)	Validated (%)
Agriculture	2066	1382	67%
Burned Areas	2337	1445	62%
Infrastructure	12106	8537	71%
Mining	57990	57388	99%
Others	262	0	0%
Pasture	425	197	46%
Secondary vegetation	1125	0	0%
Urban	3197	1344	42%
Total	77443	68911	0
Total validated	88.41%		