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TROPICAL FOREST TYPE MAPPING BY REMOTE SENSING USING C-SAR AND OPTICAL DATA FROM SENTINEL-1 and -2

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LIST OF ABBREVIATIONS

APDS	Dzanga-Sangha Protected Area
CAR	Central African Republic
CBFP	Congo Basin Forest Partnership
COMIFAC	Central African Forest Commission
CCI	Climate Change Initiative
C3S	Copernicus Climate Change Service
DRC	Democratic Republic of the Congo
EC	European Commission
ECOFAC	Central African Forest Ecosystems
ECV	Essential Climate Variable
EO	Earth Observation
EOS	Earth Observation System
ERS	European Remote Sensing
ESA	European Space Agency
GLCM	Grey Level Co-occurrence Matrix
GRMF	Global Rainforest Mapping
JERS	Japan Earth Resource Satellite
LCCS	Land Cover Classification System
MACCS	Multi-sensor Atmospheric Correction and Cloud Screening
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectrometer
MSI	Multi-Spectral Instrument
NASA	National Aeronautics and Space Administration
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
OFAC	Observatory of the Forest of Central Africa
OSFT	Tropical Forest Spatial Observatory
RADAR	Radio Detection and Ranging
REDDAF	Reducing Emissions from Deforestation and Degradation in Africa
RIOFAC	Reinforcement and Instutionalization of the OFAC
RF	Random Forest
RS	Remote Sensing
SWIR	Short-Wave Infrared
SAR	Synthetic Aperture RADAR
S1	Sentinel-1
S2	Sentinel-2
UAV	Unmanned Aerial Vehicle
UNESCO	United Nations Educational, Scientific and Cultural Organization
WRI	World Resource Institute

INTRODUCTION

The Congo Basin forest is the second largest tropical ecosystem in the world. As global changes and anthropic degradation continually increase pressure on this valuable lung for the planet, monitoring programmes and protected areas are established in order to protect wildlife and ensure the sustainable development of forest-related activities (logging, slash and burn farming, inhabited area extension…).

Monitoring large territories require up to date documentation by continuously tracking changes. In wide inaccessible areas, remote sensing appear as a major asset to produce accurate and objective land cover mapping without travelling through entire regions.

The recent European Earth Observation Copernicus programme now provides free satellite imagery from – among others – Sentinel-1 and Sentinel-2 platforms. Very high resolution C-SAR and optical data are accessible and represent valuable data in Earth Observation domains. Those remotely-sensed data also constitute excellent raw material for current mapping programmes.

Since 2017, the RIOFAC project has been reinforcing and institutionalizing the OFAC (Observatory of the Central African Forest) by increasing its monitoring capacity of the forest, climate and biodiversity. For the mapping expertise, the UCLouvain has been consulted to produce a wide land cover of the entire Congo Basin, following many references in the remote sensing field.

In this context, this work focuses on the Protected Areas of Dzanga-Sangha, in the southwestern tip of Central African Republic. From a partnership with the local WWF organisation located in Bayanga, which is also the headquarters monitoring CAR's part of the Sanga Tri-National UNESCO park, the region has been chosen to describe the actual forest stratification, develop a forest typology and produce a forest-type mapping by remote sensing.

For this purpose, this master thesis will explore the regional context of the Congo Basin, review RS-related scientific literature, and then present the material and methodology implemented to achieve the classification of encountered tropical forest types by remote sensing. Final results, classifications and maps will be presented, described and evaluated through accuracy assessment protocols.

1. Regional context

1.1. Stakeholders in the Congo Basin

In 2005, the ECOFAC[1]'s report defines 11 Landscapes in the Congo Basin Forest, which consist 11 management units of the forest territory with typical ecosystems, located and identified (CBFP, 2005). That survey is the starting point of a global monitoring of the Congo Basin Forest, hand in hand with the establishment the same year of the Central African Forests Commission (COMIFAC[2]).

The establishment of the COMIFAC is the culmination of conferences that took place in Central Africa from 1992 with the ECOFAC program, focusing on conserving biodiversity and sustainable use of forest resources. In 1999, the Yaoundé Declaration settled the basement of sustainable management of the forest ecosystems in Central Africa (Déclaration de Yaoundé, 2005) were Heads of States proclaimed their attachment to the biodiversity preservation principle and sustainable management of Central African forest ecosystems[3]. Four years later, the conference of ministers in charge of Central African Forest[4], implemented forest legislation application and governance in Africa (AFLEG[5], 2003). This conference recognises the importance of social, economic and environmental matters concerning the tropical forest and the role of governments in the management of this resources[6].

Those international summits were the opportunity to unify all the different countries partly covered with rainforest, with a vision to recognise the environmental wealth of the African tropical flora and establish common basis of policies and intervention. Indeed, the African tropical rainforest covers territories in 6 different countries: Cameroon, Central African Republic (CAR), Democratic Republic of the Congo (DRC), Equatorial Guinea, Gabon and Republic of the Congo (Congo). Those countries represent the Congo Basin Forest Partnership (CBFP) and the preliminary Observatory of Central African forest, responsible for the first *State of the Forest* report in 2005. The Congo Basin itself is a watershed of 3.4 million km², which doesn't include Gabon and Equatorial Guinea, but covers portions of Angola, Burundi, Rwanda, South Sudan, Tanzania and Zambia.

[1] Ecosystèmes des Forêt d'Afrique Centrale.
[2] Commission des Forêts d'Afrique Centrale.
[3] « Les Chefs d'Etat proclament : Leur attachement au principe de conservation de la biodiversité et de la gestion durable des écosystèmes forestiers d'Afrique Centrale » (Déclaration de Yaoundé, 1999)
[4] Conférence des Ministres en charge des Forêts d'Afrique Centrale.
[5] Conférence ministérielle sur l'application des législations forestières et la gouvernance en Afrique.
[6] « Nous, représentants de gouvernements de pays d'Afrique, d'autres continents et la Commission Européenne, participant à la Conférence ministérielle AFLEG de Yaoundé ; (…) Reconnaissant la biodiversité des écosystèmes forestiers et le fait que ces forêts sont essentielles pour les moyens d'existence de populations africaines, en particulier les plus pauvres » (AFLEG, 2003).

The COMIFAC countries includes in total 10 states: territories of the rainforest, including Burundi and Rwanda, as well as São Tomé and Príncipe, and Chad (CBFP, 2005). The designation "Central Africa" can actually gather different combinations of countries, depending on the territories concerned or the subject to debates (United Nations, 2018; European Union, 2018; Communauté Economique et Monétaire d'Afrique Centrale, 2018). After being a backup agency in 2005 and 2006, the COMIFAC has been responsible for coordinating the *State of the Forest* from 2008 to this day through its executive arm: the Observatory of the Forests of Central Africa (OFAC).

The OFAC is now the principal hub of information for the management and preservation of the African rainforest biodiversity. Since 2017, the RIOFAC[7] project tends to reinforce and institutionalize the OFAC by increasing its monitoring capacity of the forest, climate and biodiversity, by providing a more appropriate content in relation to user's needs; and by supporting OFAC institutional participation within the COMIFAC (OFAC, 2017).

1.2. Ecological Status of Central African Republic

In 1997, Boulvert defines CAR's ecological state as a largely maintained environment, standing apart from worldwide disruptions. The country presents a tropical climate in the south and a dry climate in the north, making the vegetation vary from rainforest to savannah, including all intermediate stages. Boulvert (1997) considers the largely intact dry dense forests located eastern of the country as remains of the typical African dry forest cover largely replaced today by man-made savannah. He also confirms what was mentioned by Maley (1990) and himself (1990) about forest extend and loss: firewood consumption degrades forest significantly in the vicinity of Bangui, while forest cover grows back in rural areas emptied of its population after urban exodus. Indeed, this situation results from the fact that Central African population evolved with the lifestyle suitable for sparse groups in the natural environment, which do not suit to urban overcrowding (Cassagne, 1981).

In 1968, Suchel described 30,000 km² of rainforest in the south-west of the country, confirmed as between 36,000 and 38,000 km² by the *State of the Forest* (2006, 2008). This is the main potential logging area of the country. Protection and sustainable management of this area justify themselves as 12,000 km² of prime productive forest had already been identified in by Suchel (1968). In 1997, Boulvert observed that the preservation of this forest could be explained by the important costs of exploitation driven by its distance from the sea. Today, those 5% of the national territory appear as an important economic hub, as forest industry represent 10 to 13% of GDP and 50% in the value of exports (COMIFAC, 2006).

If it's impossible to avoid logging, which appears as economically essential for the country, the African rainforest must be managed with due diligence, in tandem with ecological

[7] Renforcement et Institutionnalisation de l'Observatoire des Forêt d'Afrique Centrale.

concerns to enable a long-term concession. Studying deforestation and reforestation rates in Central Africa, Duveiller *et al*. (2008) noted a deforestation rate of 0.6% per year in CAR. In 2013, State of the Forests publication described a decreasing rate of 2% of deforestation every 10 years, concluding that deforestation in CAR was considered as low. The country also establishes more and more legislations to manage its natural resources as good as possible. Nevertheless, the Central African Republic remains politically tenuous, with instable state institutions, and where land use is a very discontinuous process (Desclée *et al.*, 2013).

2. Litterature review

2.1. The African Tropical Forest

The Congo Basin forest is the second largest tropical rainforest in the world. In 2005, *A Preliminary Assessment* run by the Programme for Conservation and Rational Utilization of Forest Ecosystem in Central Africa (ECOFAC[8]) and financed by the European Commission (EC) estimates its extent at 2 million square kilometres, or approximately 7 degrees south and north of the equator in Africa (CBFP[9], 2005).

Figure 1. The Congo Basin Forest area (World Research Institute).

2.1.1. Dynamic change of the forest

In 1990, Maley sets out some dynamic changes of the African tropical forest. He details extension of dense forests on savannah and fallow land, but also mentions mutation of forest sectors from sempervirens to semi-deciduous flora or from light demanding to shade tolerant species. According to him, recent history of the rainforest, concerning the last three centuries, can be detailed by historical witness statements as well as by understanding current

[8] Ecosystèmes Forestiers en Afrique Centrale.
[9] Congo Basin Forest Partnership.

vegetation behaviour (Maley, 1990). At the same time, Boulvert (1990) also studies the African forest extend and loss in view of climate change and human influence. He insists on many scientists and explorers' concerns on repeated savannah fires, and on the impact of such a practice on forest ecosystems. Those fires create new types of savannah were bushes and trees disappear and grass repeatedly grow back two or three times a year. Man's action in this way has been influencing those lands for centuries (Boulvert, 1990). In her report on Mapping the Changing forests of Africa, Renfrow (2006) also observed forest regrowth on areas that used to be savannas, while forest keeps being destroyed by farmers to plant subsistence crops. If it gives hope for forest conservation and restoration projects, the overall assessment so far claims that deforestation remains more important.

Beside human behaviour responsibility in forest change, Boulvert (1990) also reported long term climatic fluctuations observed from the middle of the twentieth century and a global step back of the tropical forest driven by increasing aridity from Tertiary. The climatic variations and the impact on the Congo Basin Forest over the last 2 million years is confirmed by a UNESCO report in 2010. The forest had to adapt continuously between cold dry and warm moist periods, causing extension and regression phases. During the warmest periods, forests were reduced to forest sanctuaries, that constitutes the only remaining habitat for forest species of the Congo Basin. Global biodiversity remains very high even if it's lower than Amazonia or South-East Asia. What is typical from African rainforest is its specificity: from low to high altitude, forest houses 30 to 70% of endemic species. The continuation of the forest from the Albertine Rift to the coast of Gabon is also a very precious quality, allowing natural biological mechanisms to develop without being disrupted (UNESCO, 2010).

Compared to many other tropical forests, the African rainforest remains relatively healthy. Nevertheless, bushmeat hunting can also leads severe degradations of the forest under what looks like an undisrupted canopy. The "silent forests" phenomenon has been defined for the case where forest becomes unable to provide resources for human or wildlife, and then loses its population and fauna (CBFP, 2005).

Traditional slash and burn farming exercised by rural populations of farmers in Central Africa also have a significant impact on the forest. To make this system work efficiently, a fallow period of 15 to 25 years is needed for the soil to recover its fertility. That way of living was a balance of resource system, adapted and sustainable for small populations. Close to urban centres and alongside the roads, where population is continuously increasing, the forest resource management become more and more an issue. Fallow periods are shortened, and the natural poor fertility of soil is felt. The development of a network of paths increases the overuse of agricultural soil and facilitates the industrial exploitation of natural resources in the forest. Those activities lead to degraded forest areas, caused by rural farming and working populations, who are the first ones affected by it, ironically (UNESCO, 2010; Renfrow, 2010). The evolution of the last 30 years has mainly rejected traditional practices at the expense of new way of extraction and trading of the natural resources. Free access to rainforest can lead

to poor management from public authorities, as well as ethnical tensions or conflict concerning sovereignty over land (UNESCO, 2010).

2.1.2. Natural vegetative cover of Central African Republic

In Central African Republic, forest represents 271,000 km², mainly composed by open forest without economic value. Closed forest covers 92,000 km² split in different dense forest types: moist, half-dry, dry, and river bank woods. The south-west of the country is the only part considered as a productive forest with 38,000 km². This is the very sector where licenses for exploitation and planning (PEA10) are delivered. The south-east is also covered by 16,000 km² of dense forest with economic interest, but that part has not been exploited yet (COMIFAC, 2008). The Congo Basin land cover map prepared by UCLouvain (Verhegghen *et al.,* 2010) and published in 2010 (COMIFAC) identifies 10% of the country as lowland dense moist forest. The rest of CAR is essentially covered with Woodland (55 %), Forest-savannah mosaic (18 %), Shrubland (6 %), Tropical dry forest (5 %), and Mosaic of cultivated land and natural vegetation (2%).

Floristic studies of Boulvert in CAR during the 1970s and the 1980s are the main specific data of the country concerning vegetation species and natural ecosystems. In 1977, his catalogue makes one big distinction between the three main biomes of the country: the moist dense forest, the savannah and the dry forest (interspersed in savannah). His phytogeographic map of 1986 present a way more detailed view of the vegetative cover by combining pedological, geological, geomorphological, phytogeographic and climatic factors. The whole country is subdivided into 152 floristic stations characterized by the host rock, the altitude, the soil moisture and the floristic stand, among 16 in the dense humid forest (belonging to the Congo-Guinean domain).

[10] Permis d'Exploitation et d'Aménagement.

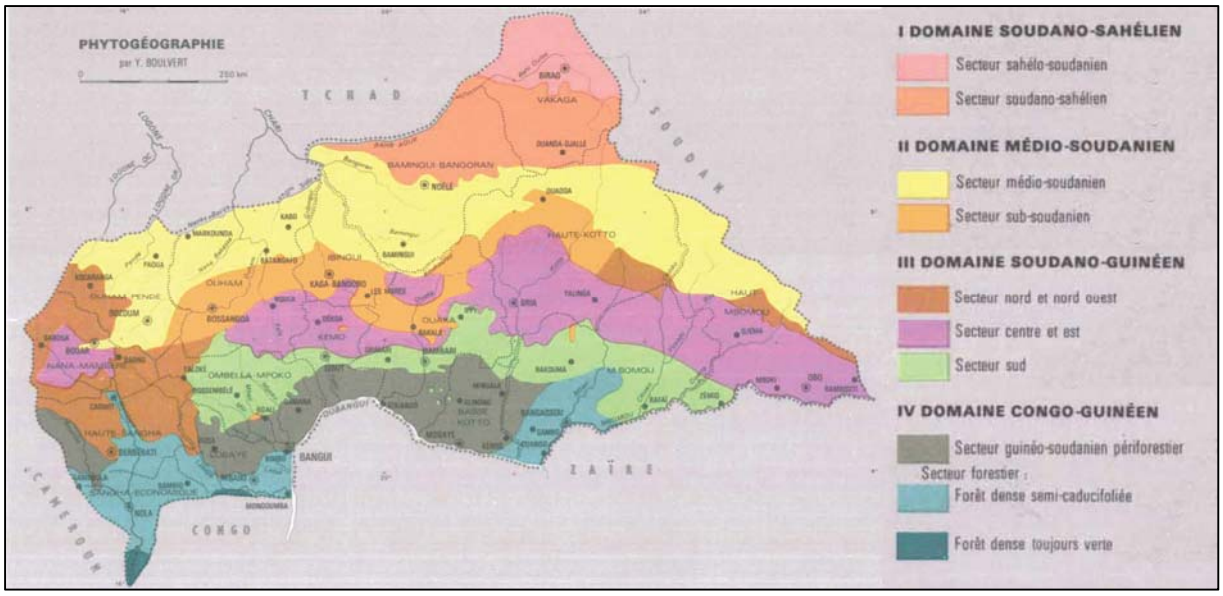


Figure 2. Phytogeographic domains of Central African Republic (Boulvert, 1986).

In 2013, a land cover study released by REDDAF[11] and OSFT[12] on the southern half of CAR (345.000 km²) was run to follow the evolution of forest cover from 1990 to 2000, and from 2000 to 2010 (*Desclée et al*., 2013). Satellite imageries from Landsat, SPOT and RapideEye computed in a remote sensing process revealed a deforestation rate of 2,41% of the rainforest during the first decade, and of 1,75% during the second one. Six land cover classes were defined for this study which shows that land keeps being recolonised by forest, but the superficies obtained with those young forests remain lower than newly deforested surface areas.

2.1.3. Challenges for nature conservation

In the light of tropical ecosystem preservation willingness, logging economic interests and political issues, producing an inventory by mapping the whole area appears as the number 1 intervention to process. The Congo Basin contains intact primary forests and lots of biodiversity sanctuaries that must be precisely located, identified and monitored. Protected areas and natural reserves for wildlife have been established since the end of the 19th century (elephant protected since 1889, gorilla protected since 1912), but the idea of protecting of the forest itself only began in the 1980s, when industrial logging has tended to show that forest could be threatened without regulation of its exploitation (CBFP, 2005).

This state of circumstances defines the main purpose of mapping: establish the actual state of the forest in terms of land cover, in order to keep it under surveillance by establishing a monitoring protocol.

[11] Reducing Emissions from Deforestation and Degradation in Africa.
[12] Tropical Forest Spatial Observatory (Observatoire Spatial des Forêts Tropicales).

2.2. Selected land cover mapping programmes by remote sensing

Remote sensing (RS) is a way of collecting data from a target object (e.g. the Earth), through a sensor loaded on a platform, to obtain and store useful information without being into direct contact with the object (ESA, 2018; NASA, 2018). The need to acquire a wide overview of terrestrial and aquatic surfaces of the Earth implies the sensor to fly aloft. Thus, first airborne platforms consisted of air balloons and aircrafts loaded with a camera until the 1960s (Graham, 1999). Those are now replaced by UAV[13] (drones) for local use with important resolution needs, or by spaceborne satellites for wide swath coverage.

Beyond photographic images taken with cameras from the 19th century, satellite sensors have tended to acquire multispectral and RADAR[14] bands allowing them to detect electromagnetic waves beyond the visible region (NASA, 2018). The measurement of radiations from a surface, naturally reflected or backscattered from a RADAR signal, determines its spectral signature, or its own specific wavelength combination (ESA, 2018). As spectral signatures of plant communities are strictly correlated to their components, their biophysical properties and the organisation of their different elements – identifying and detecting the signatures of forest types with remote sensing is the most accurate way to locate and record them over wide geographic territories (Stenberg *et al*., 2008).

Up to now, remote sensing has been used and experimented by many Earth Observation (EO) programmes, continuously improving resolutions of images and automated monitoring methodology. The following elements present the main large-scale mapping programmes focusing on vegetation land cover from the 1990's.

2.2.1. TREES programme

Tropical Ecosystem Environment Observation by Satellites was a European remote sensing programme with two major objectives: address deforestation issues in the tropical belt and at a global scale, and lead to development of new satellite remote sensing techniques (European Space Agency & Joint Research Centre, 1991).

TREES was the first experimental programme using ERS[15]-1 and ERS-2 satellites, respectively launched in 1991 and 1995 and loaded with a Synthetic Aperture RADAR (SAR) with a spatial resolution of 26 m in range (ESA, 2018). The advantage of RADAR system in remote sensing is to use wavelength reflected by land and unaffected by cloud cover, very useful in cloud and rainy territories such as tropical countries.

[13] Unmanned Aerial Vehicle.
[14] Radio Detection and Ranging.
[15] European Remote Sensing.

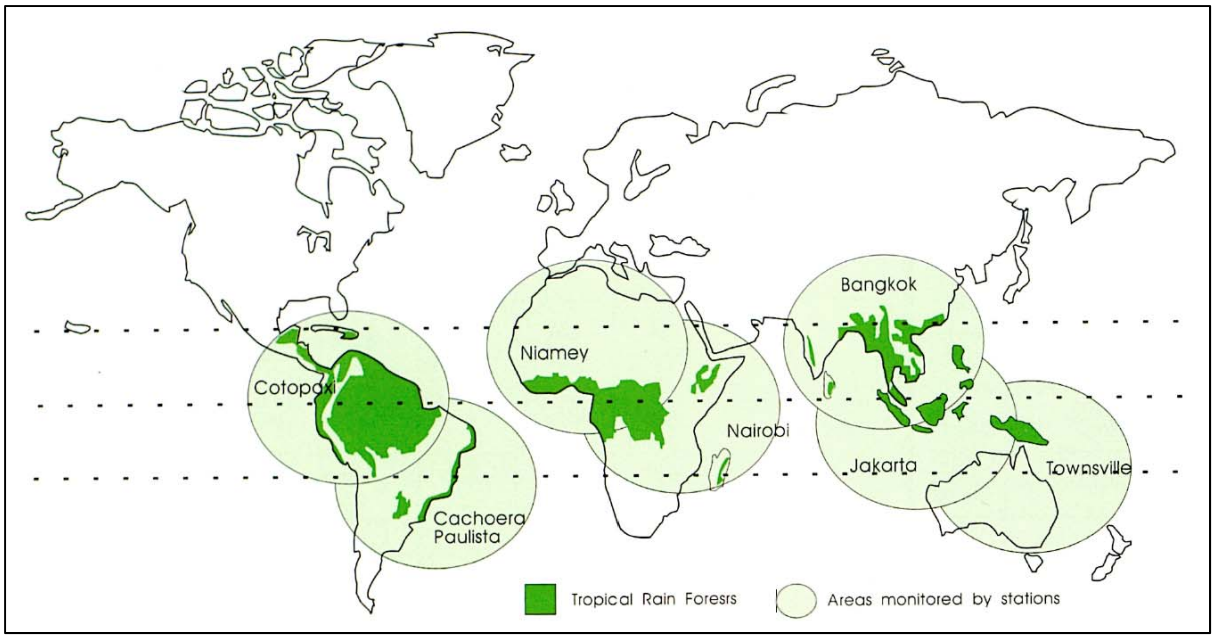


Figure 3. Localization of the tropical stations monitored in priority by full coverage in the TREES programme (JRC & ESA, 1991).

SAR technologies improve real aperture RADAR performances by using the forward motion of the radar, reflecting many pulses in sequence. This provides a better azimuth resolution, independent of the slant range, with small antennae for relatively long wavelengths. (ESA, 2018). ERS satellites use a C-band SAR (wavelength 3,75 to 7,5 cm), accurate to measure reflectance of the top layers of the vegetative cover, therefore very useful to detect gaps or swath in canopies (ESA, 2018).

For the initial phase, Advanced Very High-Resolution Radiometer (AVHRR) data were used to create and analyse a mapping of the whole tropical belt at a coarse resolution of 1 km, then higher resolution data sets were used to validate the analysis. The TREES information system provided a tropical belt inventory out of satellite imagery collecting state of the canopy information (ESA & JRC, 1991).

Observing change on vegetation cover requires so-called time series. Multidate (or multi-temporal) imagery illustrates the evolution of vegetation over time, which can be abrupt in the event of logging, or subtle in situation of regrowth (Coppin & Bauer, 1996). For this purpose, TREES used AVHRR images collected during the 1980s and the 1990s by the American National Oceanic and Atmospheric Administration (NOAA) satellites (Achard & D'Souza, 1994). Detection algorithms were used to take into consideration the local rates of change of the spectral signal differencing between time series. Thresholding those rates allowed to determine a classification system (Achard *et al*., 1998).

2.2.2. GRFM

The Global Rain Forest Mapping (GRFM) is an international programme initiated in 1995 by the National Space Development Agency of Japan (NASDA), using L-band SAR from JERS[16]-1, to generate a 100 m resolution image mosaic of the tropical belt. With a wavelength of 23.5 cm, L-band allows the signal to be relatively unaffected by leaves and collect information from under the canopy (Rosenqvist *et al*., 2000). The use of L-band SAR is very useful in specific remote sensing tasks as the signal is also very sensitive to detect above ground biomass (AGB) (Mermoz *et al.*, 2015) or flood affected soil by measuring the backscatter of standing water (Chapman *et al.*, 2015; Bwangoy *et al.*, 2009; Vizacarra, 2008).

The signal was horizontally polarised from JERS-1 sensor and back to it (HH) to collect maximum reflectance from horizontal surface. In this way, holes in the canopy and open forests were specifically detected from the high reflectance of the signal with the ground. As a second step, a downsampling to 12.5 m of the full-resolution scenes was processed. The objective of GRFM was to provide open-access data sets to the international science community to improve the global understanding of tropical ecosystems (Rosenquist *et al*., 2000).

2.2.3. MODIS Land cover

Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the 5 sensors loaded on the NASA's satellite Terra. Terra was launched in 1999 and remains the flagship of the American Earth Observing System (EOS), carrying sensors from United States (CERES, MISR and MODIS), Japan (ASTER) and Canada (MOPITT). MODIS is used for global land cover, using a coarse resolution of 250 m to 1 km with a 2,330 km wide swath (NASA, 2018). That coarse resolution remains a more manageable choice for wide remote sensing work such as tropical forest monitoring (Renfrow, 2006), as tiles are 10 degrees by 10 degrees at the equator (LPDAAC, 2018), or cover approximately 12.400 km². With a maximum of 2 days repeat circle and 36 spectral bands, MODIS observes large-scale changes in the biosphere, from aerosols in the atmosphere to photosynthetic activity, with a view to monitor ecosystem distribution and land use (NASA, 2018).

The advantage of ranging 36 different wavelength and frequencies is to capture very detailed spectral characterization of objects through hyperspectral imaging (HIS). To reduce the hardware complexity of HIS, multispectral imaging (MSI) appears as the most practicable alternative: instead of sampling the whole spectra, a few predeterminate narrowband filters are selected for each task depending on the target object's spectral features (Jia *et al*., 2015).

[16] Japan Earth Resources Satellite.

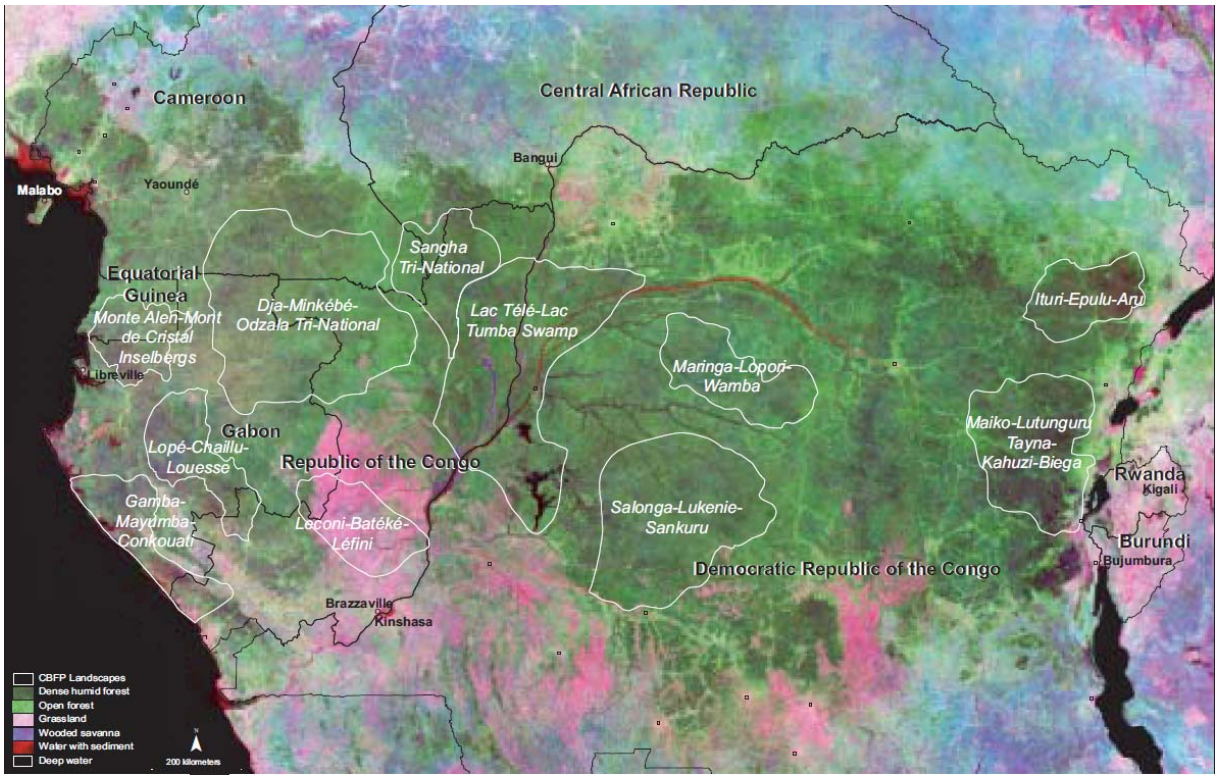


Figure 4. Localization of the 11 landscapes of the Congo Basin forest on a composite image made of MODIS data acquired between 1999 and 2002 (CBFP, 2005).

First treated images of MODIS were acquired in 2000. To create a global land cover with 17 land classes, among 11 natural vegetation types. The automated methods for categorizing land cover provides frequent monitoring of any place on earth with a spatial resolution of 1 km (Perkins, 2001). Concerning Tropical Africa, images from 1999 to 2002 were needed to obtain a cloud-free global view of the Congo Basin Forest, were 6 land cover types were determined, among 4 vegetation types. The map created was used to locate the 11 landscapes on which conservation activities of the CBFP will focus (CBFP, 2005).

2.2.4. GLC-2000

Coordinated by Europe's JRC, Global Landcover Cover Project is the result of a 14 month-daily data acquisition in order to create an harmonised land cover around the world. The year 2000 was then considered as a reference period to monitor environmental changings over the years. The programme was using the VEGA 2000 dataset, composed of VEGETATION programme imagery (EC, 2019). The VEGETATION 1 instrument was loaded on the SPOT[17]-4 mission, launched in 1998. The 4 sensors provides continuous measurements at 1 km resolution in the visible and IR domains, graded on chlorophyll spectral signature, with the objective of monitoring agriculture, forestry and environmental areas for local or regional use (VEGETATION, 2019).

[17] Satellite Pour l'Observation de la Terre.

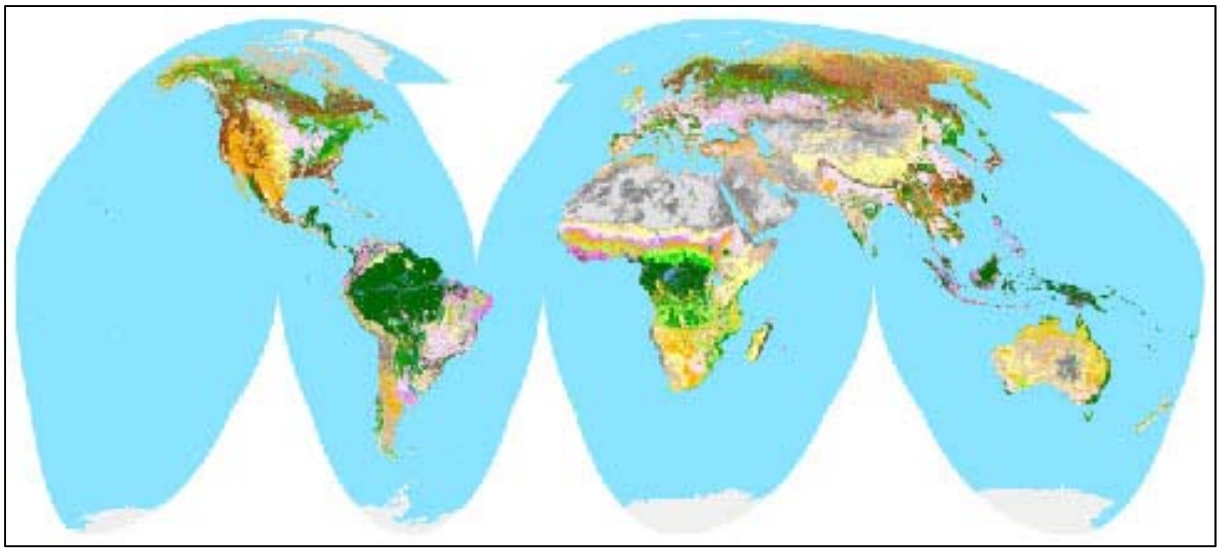


Figure 5. Global Land Cover mapping project 2000 (JRC, 2019).

Images in VEGA 2000 dataset were orthorectified and resample to 1 km resolution. The land cover project uses the 22 classes from the FAO Land Cover Classification System (LCCS), among 18 vegetation-cover dedicated, plus 4 for artificial surfaces, bare areas, water bodies and snow. The global classification gathers products from 21 regional areas of the world, defined according to their landscape and geographic morphologies, which previously had been mapped and classified with the 22 LCCS classes, before being put together to form the final product (EC, 2019).

2.2.5. ESA GlobCover

From the ESA's initiative in partnership with the JRC, the EEA[18], the FAO, the UNEP[19], the GOFC-GOLD[20] and the IGBP[21], the GlobCover project was led thanks to the success of previous GLC-2000 programme, using time series from MERIS[22] imagery on board the Envisat platform. Two land covers are available. Released in 2008, GlobCover 2005 used an 18 month time series from December 2004 to June 2006 to produce the first global landcover map with a resolution of 300 meters. This global landcover programme was also the first automated service using level 1B imagery as inputs, including pre-processing treatments to final classification. Later, GlobCover 2009 released a second global mapping available since December 2010, using imagery from the whole year 2009, which fully demonstrated the workability of the automated GlobCover Chain. The final product uses the official 22 classes of the LCCS (ESA, 2019; Bontemps *et al*., 2011).

[18] European Environmental Agency.
[19] United Nations Environment Program.
[20] Global Observation for Forest and Land Cover Dynamics.
[21] International Geosphere-Biosphere Programme.
[22] Medium Resolution Imaging Spectrometer.

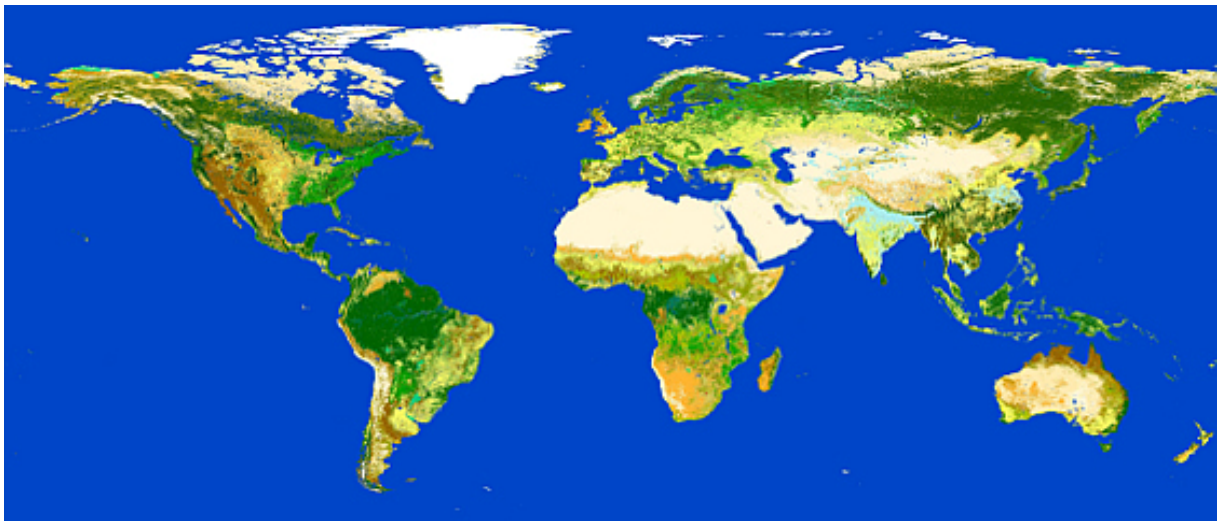


Figure 6. GlobCover 2009 mapping project (ESA).

2.2.6. CCI land cover

ESA's Climate Change Initiative began in 2010, and is the first earth observation programme to add temporal dimension in land cover monitoring. In a time of global change and environmental challenges, the objective was to use and process satellite imagery from the 1990's to 2015, to observe the evolution of Essential Climate Variables (ECVs) established in 1992 by the Global Climate Observing System (GCOS). The evolution of the land cover is one variable of the terrestrial monitoring project. For this purpose, earlier images from MERIS, SPOT-VGT and SAR sensors have been used to classifying each period with the same 300 meter resolution and the 22 LCCS classes (Hollmann *et al*, 2013; Downy, 2016). The first long time series of global annual land cover maps from 1992 to 2015 was produced from a multi-sensor approach by a consortium led by UCLouvain.

2.2.7. Copernicus programme

Copernicus is a European Union's Earth Observation Programme, offering information services based on satellite Earth Observation and in situ data (Copernicus, 2018). Out of its monitoring environmental programmes, Copernicus produces cartographic data freely available for public or private users, in the fields of ecology, agriculture, climate change, urban sprawl, transport, territory planning, seascapes… The open source policy of this civil programme ensures independence and autonomy of EU, as well as a top-rank place in global initiatives. Its three main data collecting tools are the Sentinels (Copernicus-dedicated satellites), third-party satellites and on-site surveys (Copernicus, 2018).

The Sentinel-1 mission is a constellation of two sun-synchronous satellites, Sentinel-1A and Sentinel-1B, sharing the same orbit and respectively launched in 2014 and 2016. Those satellites carry a C-band SAR. That wavelengths allow imagery by cloudy weather or low-light illumination, in a resolution down to 10 m with a swath up to 400 m. Each of the two satellites

has a 12 day repeat cycle. Combined, the mission enable imagery from any point on earth every 6 days (ESA, 2018).

The twin satellites of the Sentinel-2 mission carry wide-swath, high resolution, multi-spectral imaging sensors, and revisit under the same viewing angle every 5 days. With its 13 spectral bands, Sentinel-2 provides imagery with a resolution from 10 to 60 m with a swath of 290 km. The mission was initiated in 2015 and focuses on land monitoring (ESA, 2018).

The Sentinel-3 mission focuses on sea and ocean monitoring, while Sentinel-4, -5 and -5P are complementary elements of the same constellation monitoring air quality and atmospheric dynamic, and Sentinel-6 surveys topography of the global ocean (ESA, 2018).

Besides Atmosphere and Marine Environment monitoring systems, Climate Change, Emergency Management and Security, Copernicus offers a Land Monitoring service (CLMS). Initiated in 2006, CLMS service monitors land cover changes, among vegetation state and water cycle (ESA, 2018). Environmental variables from the earth's surface such as albedo, temperature, moisture and vegetation indexes are continuously generated to supply the Earth Observation Satellite database (Lacaze *et al*., 2013). From those observations, CLMS provides Pan-European High Resolution Layers (HRLs) from specific land cover characteristics. Two productions of HRLs, in 2012 and 2015, provide complementary, improved and specific land cover products (Copernicus, 2019). Concerning forest, available raster layers are related to tree cover density, dominant leaf type and forest type in a resolution of 20 or 100 meters. Sensing situations in 2012 and 2015 permit the creation of change products, detailing evolution between the to periods. Additional support layers also details information on trees in agricultural or urban context (Langanke, 2017).

Using Sentinel-2 imagery, the CCI land cover team led by UCLouvain produced in 2016 the first a prototype map of Africa, with a resolution of 20 meters using 10 classes. Another prototype map of Meso America was also generated in 2018 with a resolution of 10 meters (ESA, 2018).

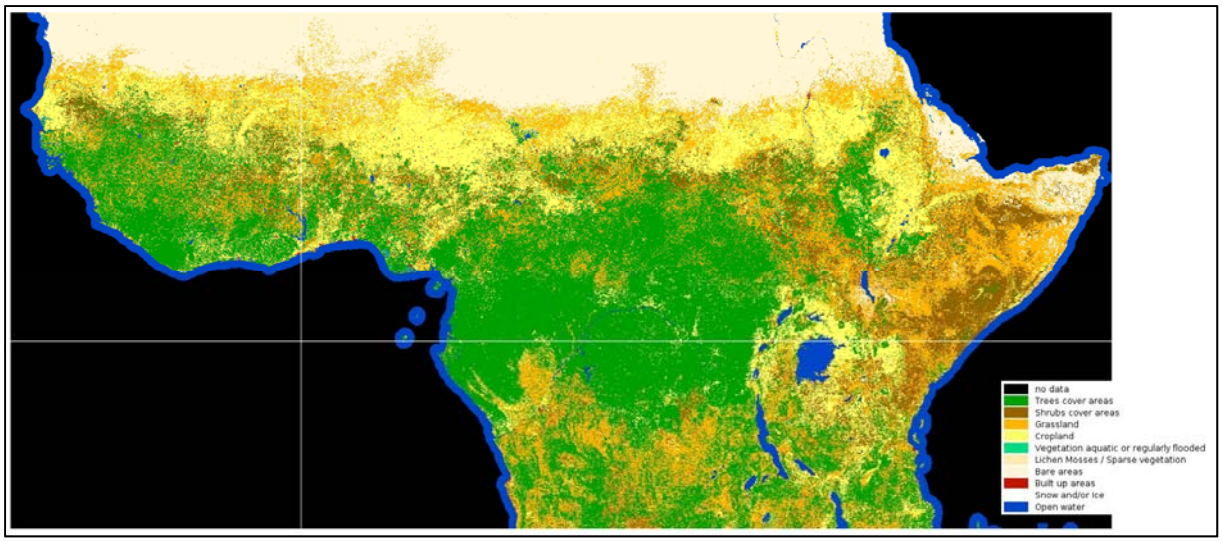


Figure 7. Central Africa on the S2 prototype land cover map of Africa produced by UCLouvain and released in 2016 (ESA).

As another follow-up of the CCI and the recent Copernicus programme, the Copernicus Climate Change Service (C3S) continues the land cover mapping evolution with PROBA-V platform to release 2016 to 2019 maps. Another 100 meters global map for 2015 using 18 LCCS classes was produced for the Copernicus Global Land Services (CGLS). C3S uses earth observation data in a climate change perspective, in order to produce past, current and predictive information about landcover evolution in Europe and worldwide (Copernicus, 2019).

2.2.8. Global Forest Watch

Global Forest Watch (GFW) programme was launched in 1997 by the World Resource Institute (WRI) to quantify global forest loss in order to inform governments and wood industry about their implementation in deforestation (GFR, 2019). The programme uses MODIS and Landsat imagery, GlobCover maps, and crowdsourcing initiatives. GFW also have strong multimedia and IT partners such as Google and ESRI, and many other governmental and NGO's environmental agencies, constituting an international mapping network providing transparency in forest monitoring (Showstack, 2014; GFR, 2019; WRI, 2002). The website provides GIS dataset and publishes periodic global and local forest watch report and forest atlas from Central Africa. In 2014, GFW opened its free-access online platform monitoring global forest and its evolution in near-real time. The interactive map can be consulted and displayed to show forest loss/gain/changes in recent year time.

2.2.9. Synthesis

In today's sprawling international context of Central Africa, global shared objectives and common documentation appear essential to improve collective work consistency. The natural limits of vegetation are therefore more appropriate than artificial administrative borders to determine spatial scale of monitoring. As the final goal is the mapping of the whole Central African Forest, experimental work accomplished in regional places must be considered in a

way that sustains a global application. Remote sensing has proven itself to be the most relevant tool on such an undertaking: technological developments provide continuous improvements of satellite imagery resolutions and sensing accuracy; and the wide swath and frequent repeated circles of current satellites represent great assets for spatial and temporal analyses.

2.3. Forest type classification by remote sensing

Merging different data sources (combining multidate images from different sensors) in order to obtain a synthetic view may be the best way to produce land cover mapping in cloudy and rainy equatorial regions (Verhegghen & Defourny, 2010). Times-series can also reveal distinctive seasonal phenology, useful to identify specific forest stations (Moreau & Defourny, 2013). Repeated data acquisition in long period also allows to detect changes in ecosystems, in addition to their actual state (Immitzer *et Al.*, 2016). This procedure brings out the heterogeneity of forest types in what appears like homogenous canopies (Gond *et al.*, 2013).

Textural analysis is a complementary intervention to radiometric data measurement to detail classification (Benelcadi, 2014), and become more and more useful with the improvement of imagery resolution (Coburn & Roberts, 2004). In addition to be a heterogenous visual perception, the texture of a surface can be defined by the variation of the radiometric intensity between pixels belonging to the same component. The textural information can be comprehended with different scales. In their paper concerning A multiscale texture analysis procedure for improved forest stand classification, Coburn & Roberts recommend texture analysis processes with window from 5x5 to 15x15 pixels (2004).

2.3.1. Effectiveness of combining optical and SAR-C images

Remote sensing studies tend to combine optical and SAR images to upgrade accuracies of their models. Features and data from both image types provide reflectance and natural spectral signature from object, as well as texture information from the RADAR backscattering signal (Kaplan & Avdan, 2018; Mngadi *et al.*, 2019).

Optical and RADAR sensors have different ways to get remotely sensed data from Earth. A RADAR sensor is an active sensor, which means that an electromagnetic signal is sent by the platform itself, while the sensor measures the backscattering from the surface. Optical sensor only work by collecting the natural reflectance of electromagnetic waves produced by natural sources of energy, mostly the Sun. The C-band wavelength and the capability of the sensor to send a signal by itself make C-SAR to be fully independent and unimpacted from light and atmospheric conditions (ESA, 2019).

2.3.2. Temporal analysis

Multitemporal data increase the potential of classification when vegetation goes through different phenological phases. If those changes are obvious during a yeartime of crop-type mapping (Benson *et al.*, 2018), tropical forest undergoes flooding and drought periods, as well as selective leaf fall in its canopy. Comparing different times in a period also reveal physical evolution in forest such as deforestation and regrowth (Coppin & Bauer, 1996). In the case of a multitemporal remote sensing analysis, selected features have to correspond with the different times of the year when those changes are the most distinct. Using multi-seasonal SAR data adds complementary features to a dataset, in addition to optical data (Numbisi *et al*., 2018).

2.3.3. Texture features: Haralick's GLCM

Robert Haralick *et al.* (1973) created texture features to identify objects in an image. Considering an image as a matrix where each pixel is a value, he developed mathematical algorithms to export new raster data. As the matrix assigns a grey-tone value to every cell, two-dimensional analysis in a determined moving window computes statistical results from a specific cell in comparison with its neighbouring cells. The variation of those grey values (corresponding to reflectance of backscattering intensity in single-band image) over space defines the textural nature of an object.

Haralick's GLCM is one of the most common algorithms for computing texture measures which can be used as to illustrate and reflect specific texture changing in an image (Kim, Madden & Warner, 2009). There are two main categories of texture features: edge-highlighting and patch-interior features. The first one will create new objects from edges between classes while the second will categorise the texture of the object itself, more useful in forest types mapping (Hall-Beyer, 2017). From the 14 GCLM-extracted features suggested by Haralick, a selection has to be made for every purposes, according to available algorithms and to the nature of the examined items (Mamat *et al*., 2016).

2.3.4. Machine-learning classifier: Random forest

Many machine-learning classifiers have been used to map landcover using remotely sensed data, from unsupervised algorithms (cluster-based, where classes are not given) such as ISODATA or K-means to supervised parametric supervised algorithms (where classes are given beforehand) such as maximum likelihood (Jensen, 2005; Rodriguez et al., 2012).

Random forest (RF) is a supervised machine-learning classifier which constructs a collection of independent tree-structured classifiers and let them vote for the most popular class. (Breiman, 2001). This classifier has been used in many studies that have proven its relevance and efficiency in remote sensing projects and image analysis (Immitzer *et al.*, 2016). To be effective, a RF has to be trained to be able to recognise and classify data into classes. In

the case of forest type mapping, training zones in satellite images have to be delimited and categorised as samples for each of the defined classes in order to train the model to associates data from those training zones to the corresponding categories. Once the classifier is trained and the specific model is created, it can be used to classify wider areas and evaluate according to its accuracy. Random Forest classifier takes its name from the ensemble of decision trees created and the random use of training samples during the training process.

Different RF model can be trained and used for the same purpose with different features to evaluate the most relevant input bands (Numbisi *et al*., 2018). The classifier can learn over optical and RADAR, as well as vegetation indices or texture features. In case of cloud presence, light mist or punctual artefacts affecting reflectance, object of pixel can be classified into the wrong classes (Ienco *et al*., 2018). The problem doesn't exist with SAR imagery, where the backscattering isn't influenced by any external factor (except ongoing rainfall during acquisition) and provide a more steady data for RF classification.

2.3.5. Synthesis

Good preliminary knowledges of the target object – the tropical forest – and a good overview of the sensors – Sentinel-1 and -2 – are necessary to proceed an accurate remote sensing tasks. Forest types can be discriminated depending on a pre-existing scientific literature, the visual interpretation of satellite imagery and in-situ surveys. An accurate classification depends on thorough scientific observations, good comprehension of technological tools and relevant use of analytical procedures. To step forward into the remote sensing progress, the final goal is to dig more deeply in detailing forest stands, from previous classifications.

3. Objectives

The main objective of this work is to develop a forest type mapping method using time series of Sentinel-1 and -2 imagery and experiment its practicability in Bayanga, in a way that could reveal methodological assets and errors to avoid in the Congo Basin wide mapping. The final output of this process is the vegetation cover map from the whole study area, including the surroundings of Bayanga and the nearby Dzanga Protected Area.

As this work constitutes a master thesis in the remote sensing field, this is also the opportunity to design and experiment a whole RS workflow, from satellite imagery analysis and on-site data acquisition to complete mapping.

The first step is to accustom to satellite imagery, remote sensing principles and classification methods. Theorical preparation is very important to get to know scientific achievements until today and continue the research by exploring new applications.

Second, data acquisition includes a field work in order to identify typical forest types in Bayanga representative of the Congo Basin Forest. As no recent forest stratification has been made of the area since the 1980's, this study is the opportunity to suggest a current regional forest typology and provide the actual land cover of it. As a partnership was established with the local WWF facilities to set up our field campaign, the map produced focuses on the Dzanga protected area, where most of the monitored wildlife's habitats are located. The stay in the middle of an African tropical forest is also the opportunity to discover local customs and knowledges.

Then, back from the field, work focuses on data analysis and classification processes. The experimental method described in this paper explores the interest of combining optical data from Sentinel-2 with SAR data from Sentinel-1, in order to obtain reflectance, textural and seasonal data from a single yeartime. The ability of SAR images to be effective in cloudy conditions can be very useful in moist regions such as the Congo Basin and complete the temporal data when optical images can only be gathered from dry season times and clear skies. This approach is led to confirm the complementarity between the two sensors in near-real time forest type mapping by remote sensing.

4. Study area: the Dzanga-Sangha Protected Areas

Only one of the 11 Landscapes described in 2005 (CBFP) includes a part of the CAR: The Sangha Tri-National (STN) Forest Landscape, covering the whole ecosystem spectrum of the rainforest in 7,500 km², almost untouched by current human civilisation. The Landscape gathers three adjacent National Parks: Lobéké NP in Cameroon, Nouabalé-Ndoki NP in Congo, and the Dzanga-Ndoki NP in south-western tip of CAR. Wildlife such as gorillas, chimpanzees and elephants, and an exceptional floristic wealth can be observed trough those parks. Thanks to a global environmental management, the landscape conserves a very high biodiversity and precious habitats for endangered species (UNESCO, 2018). Dzanga-Sangha (DS) Special Reserve is surrounding the only dense rainforest block in CAR. The area was already described in 1968 by Jean-Bernard Suchel as limited to the extreme south-west of the country, south from a line from Bangui to Berbérati, and covering 30,000 km² (Cahiers d'outre-mer). Suchel observes that the primary forest only appears south from Nola, on both sides of the Sangha River. This is the very territory occupied 50 years later by the DS reserve, today officially called the Dzanga-Sangha Protected Area (APDS[23]).

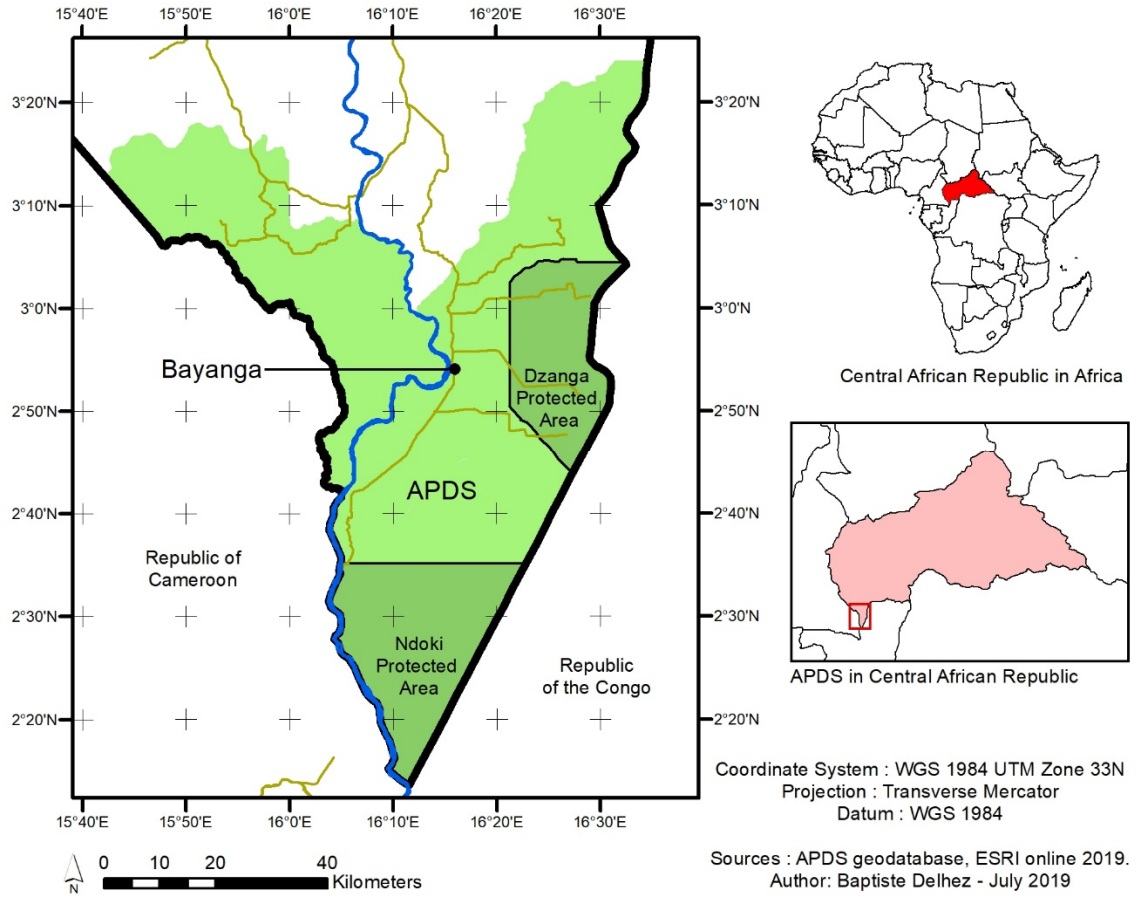


Figure 8. The Dzanga-Sangha Protected Areas in Central African Republic.

[23] Aires Protégées de Dzanga-Sangha.

The mapping work on the town of Bayanga and the nearby Dzanga Protected Area, representing 2000 km² of mostly dense rainforest. This perimeter correspond to the area where field samples have been acquired and where all the different forest types (described below) are represented. This specific zone have been delimited for the final map to constitue a practical tool for everyday life in the surroundings of Bayanga, as well as a state of the forest in the protected area where wildlife, gorillas and elephants reserves among others, are monitored by WWF. This monitoring work is led from headquarters stationned in Bayanga and out-posts of obervation in the protected area itself.

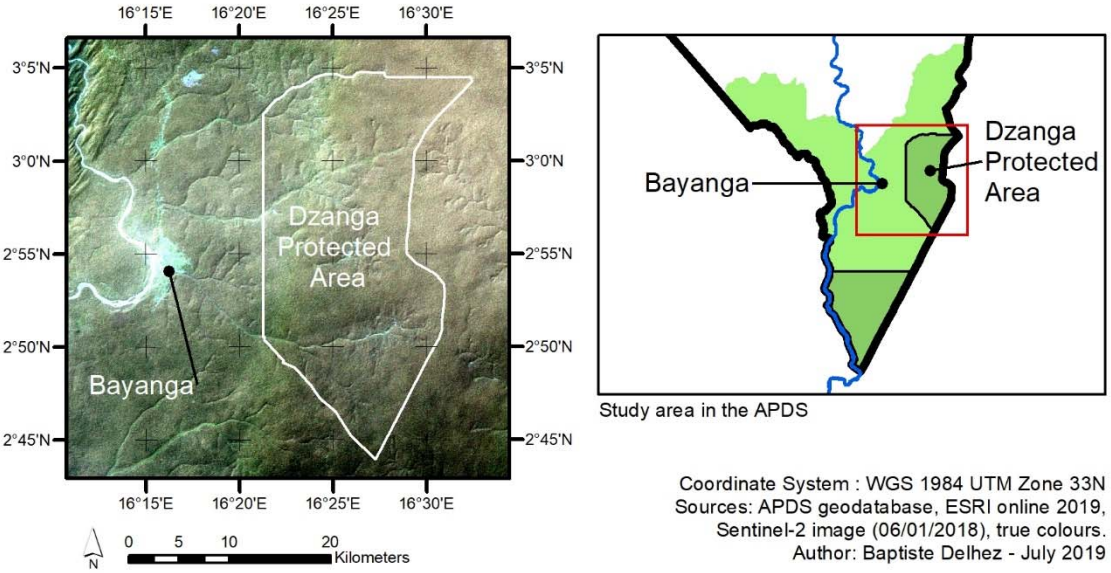


Figure 9. Study area delimitation : mapping work objective in the APDS.

APDS's archives indicate that several logging companies have been active in the region: Slovenia Bois from 1970 to 1985, Groupe Bonneau from 1987 to 1988, Sangha Bois from 1989 to 1990, SYlvicole des Bois from 1992 to 1997, and then Société des Bois de Bayanga from 1999 to 2005 (APDS Archives, WWF Bangui, 2019). Today, no logging is permitted inside the APDS delimitation, only old logging road are still visible in satellite imagery. Since 2014, two logging visa have been granted to SINFOCAM and STBC north of the APDS and they have been active in their delimited area, as it can be observed on the online Global Forest Watch mapping application.

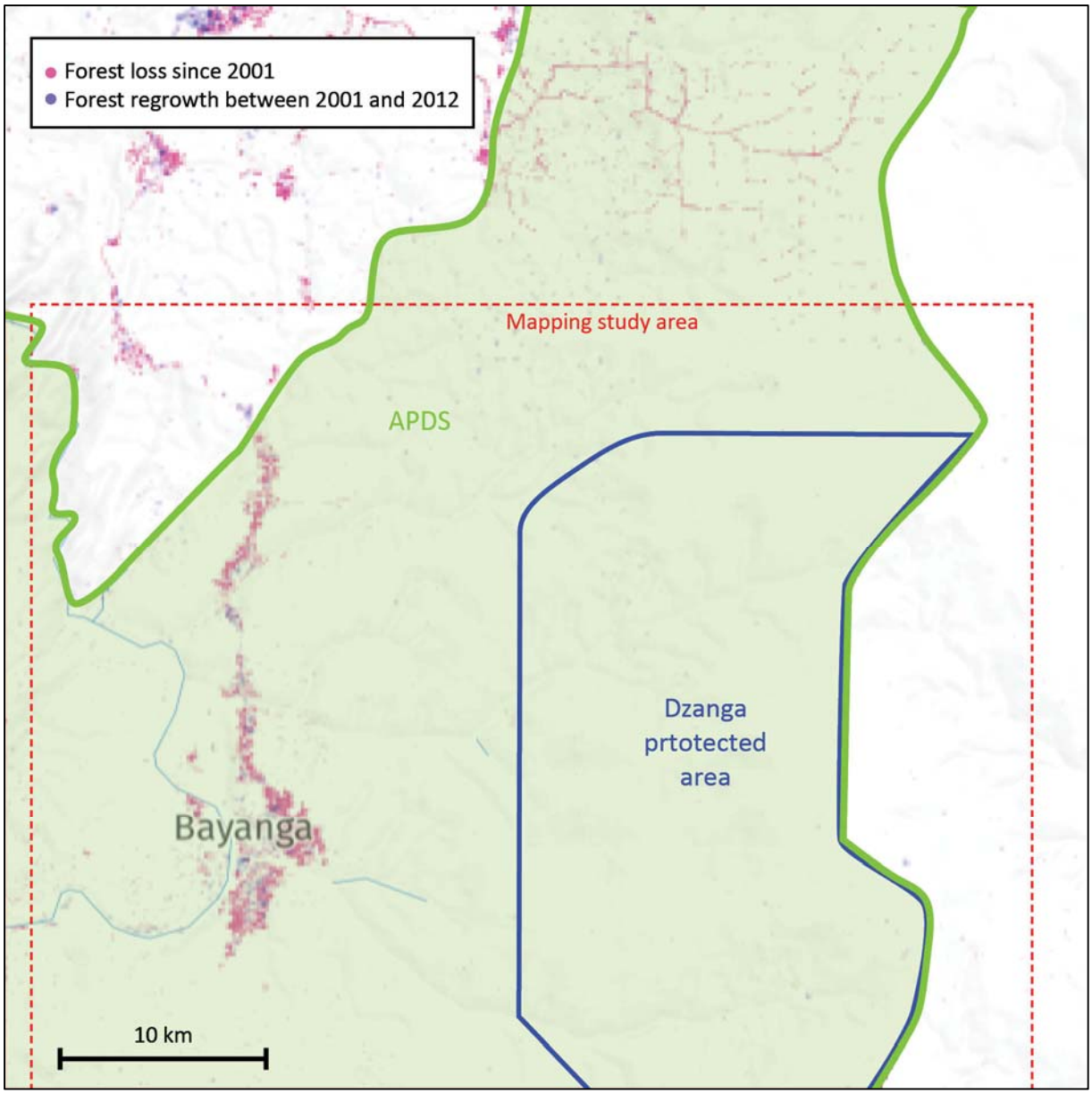


Figure 10. Forest loss and regrowth in the surroundings of Bayanga since 2001 (Background map: Global Forest Watch, 2019).

The map above seems to confirm that no industrial logging have been committed in the forests around Bayanga since 2001 at least. On the other hand, what looks like urban expansion of villages and punctual slashing spots are clear to see in Bayanga's agricultural clearance, in nearby forests and alongside the road north through all the small inhabited hamlets. Domestic slashing seems to be the main deforestation cause in the area. Reforestation remain anecdotal. Furthermore, logging sites north of the region are clear to see through all the exploitation roads. This zone is out of the mapping project delimitation, and of course out of any protected area, but still monitored by the ADPS region.

5. Materials and methods

5.1. Available cartographic resources

The only available cartographic documentation of the region come from the national pedologic and phytogeographic maps of Central African Republic, realised by Yves Boulvert in the 1980's. Those data constituted essential assets providing scientific knowledge of the territory during the field campaign.

5.1.1. Boulvert's pedologic map (1983)

Yves Boulvert was the first scientist to describe ecosystems in CAR. After his Catalogue of Central African Republic's Flora (1977), his pedologic map (1983) was the most detailed data available to described natural geography of the country at that time. The map is very useful to understand landscape construction and relief in the APDS. Some pedologic stretches correspond quite exactly to optical reflectance signals in S2 images. This is why soil characteristics must be taken into account in forest types description.

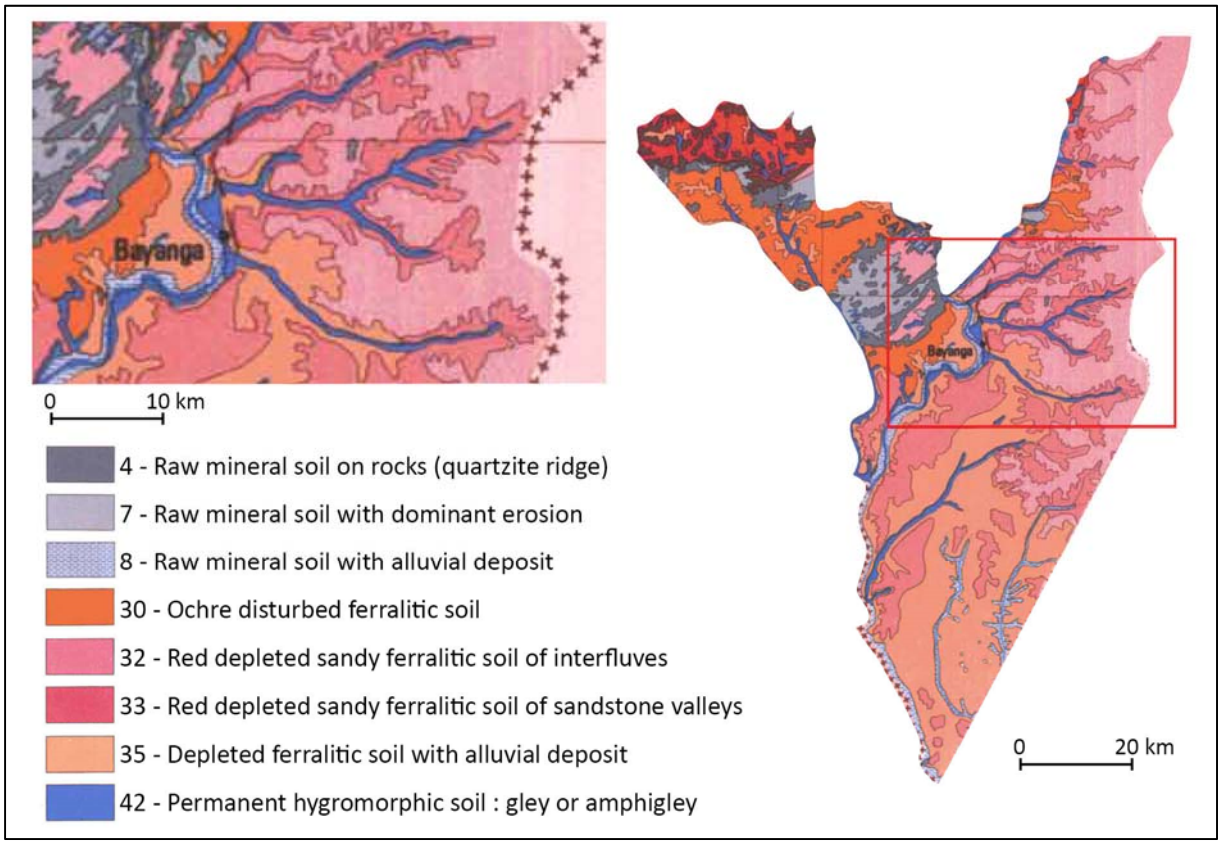


Figure 11. Study area and APDS extraction from Boulvert's pedologic map of Central African Republic (1983).

5.1.2. Boulvert's phytogeographic map (1986)

On Boulvert's phytogeographic map of CAR (1986), vegetation formations in the APDS, seems to be quite similar to actual forest cover. The map doesn't take logging into consideration, but natural forest stands are represented in way that they still match the natural field condition. Six different forest formations are present in the APDS, all belonging to the Congo-Guinean domain.

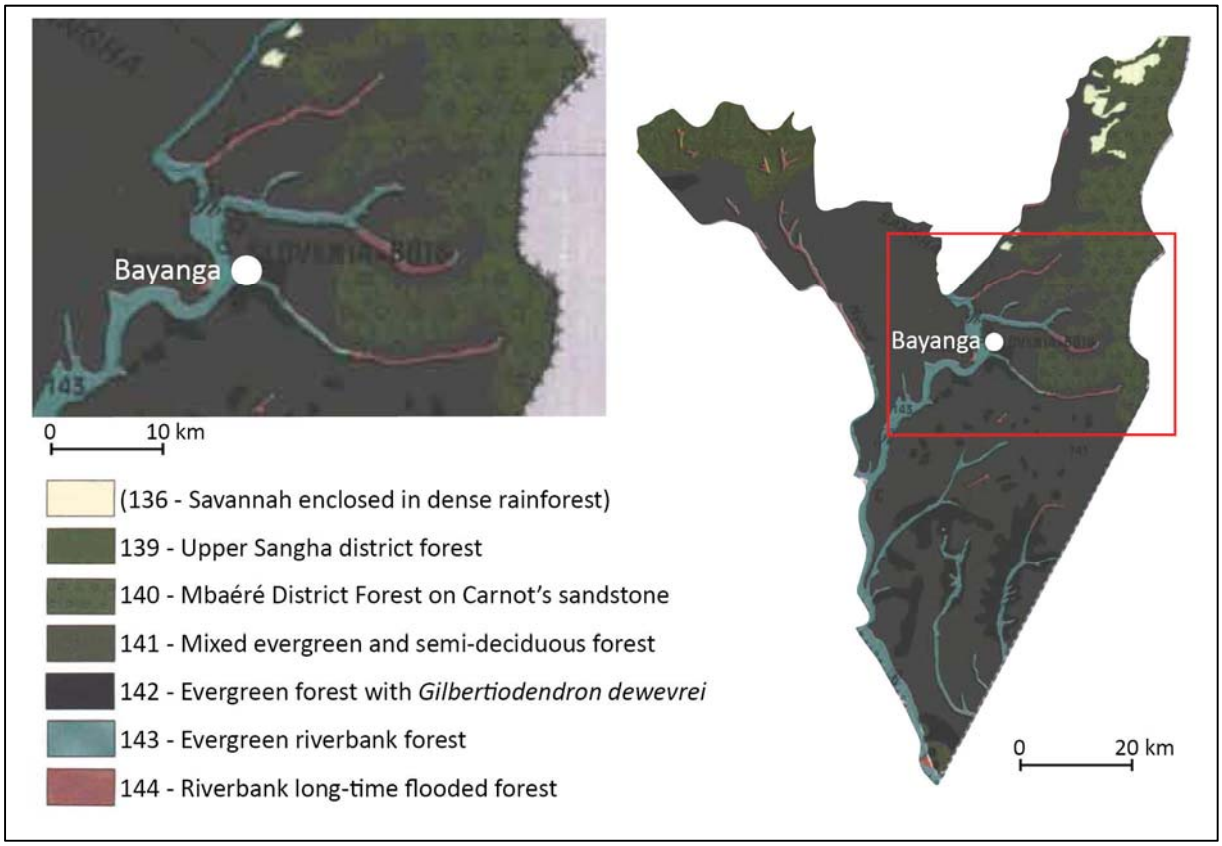


Figure 12. Study area and APDS extraction from Boulvert's phytogeographic map of Central African Republic (1986).

Forest type 140, Forest on Carnot's sandstone, confirms the idea of taking soil data into consideration to classify vegetation groups. Topography, pedology, hydromorphy and vegetation are all linked on the field and constitute visible indicators to describe a station.

5.1.3. APDS forest types (2008)

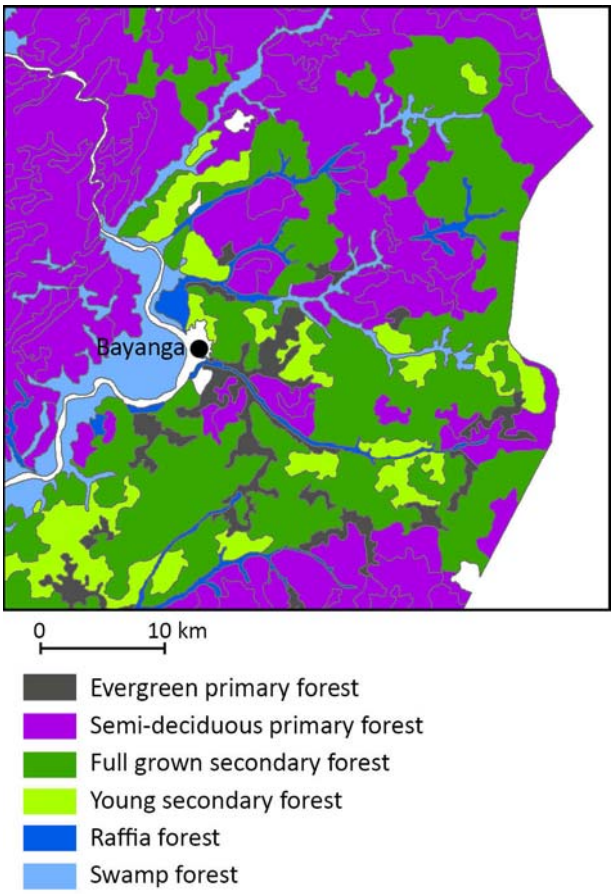


Figure 13. Forest types classification around Bayanga in 2008 (WDPA, Ministry of Water and Forest in Central African Republic).

The most recent data given by the Central African Ministry of Water and Forest in Bayanga is a shapefile categorising all forest types is the southwestern part of the country. The documents represent the situation 11 years ago and contributed to name the different forest classes encountered. Nevertheless, there was no information on how or by whom it was made; forest types don't really match the actual forest covers and some appellations tend to indicate that they use generic names, common to the whole Congo Basin Forest without seeking local specification. For example, Riparian forest in the APDS do not stand for Raffia formation unlike many places in DRC and Congo Republic. In this map, semi-deciduous primary forest are split into 3 categories : young, disturbed and old. Once again, the terms are confusing to describe primary (=old growth) forests. In the light of the above, this map can be used for information purposes only.

5.1.4. Digital elevation model

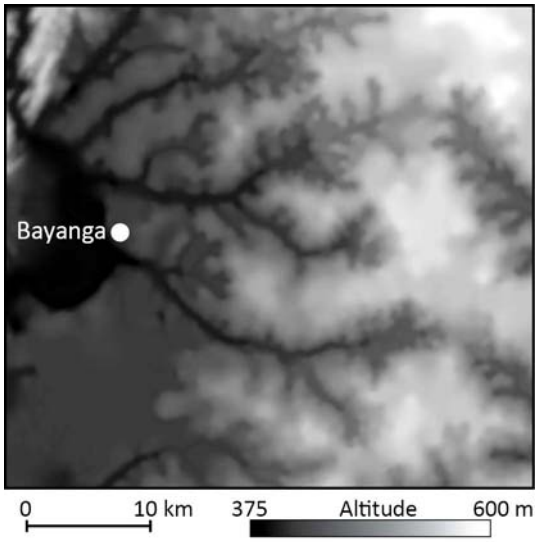


Figure 14. Digital elevation model around Bayanga (APDS geodatabase, 2019).

The digital elevation model (DEM) reveals clearly the topographic stiuation of Bayanga. Alongside the river, the town has been established on the upper bank, with less flooding risks. All the small valleys of contributing rivers are well visible and connected to the main Dzanga riverbed. The highest parts of this delimited region culminate to 600 meters, constitued by the rocky ridges northwest and the eastern sandstone plateaus.

5.2. Satellite imagery

Three types of satellite imagery were used for on-site data collection and forest type classification. Optical and SAR data contributed to the knowledge and discovery of the region from different spectral points of view. Hereafter are detailed the different media used for this work.

5.2.1. Pleiades reconnaissance imagery

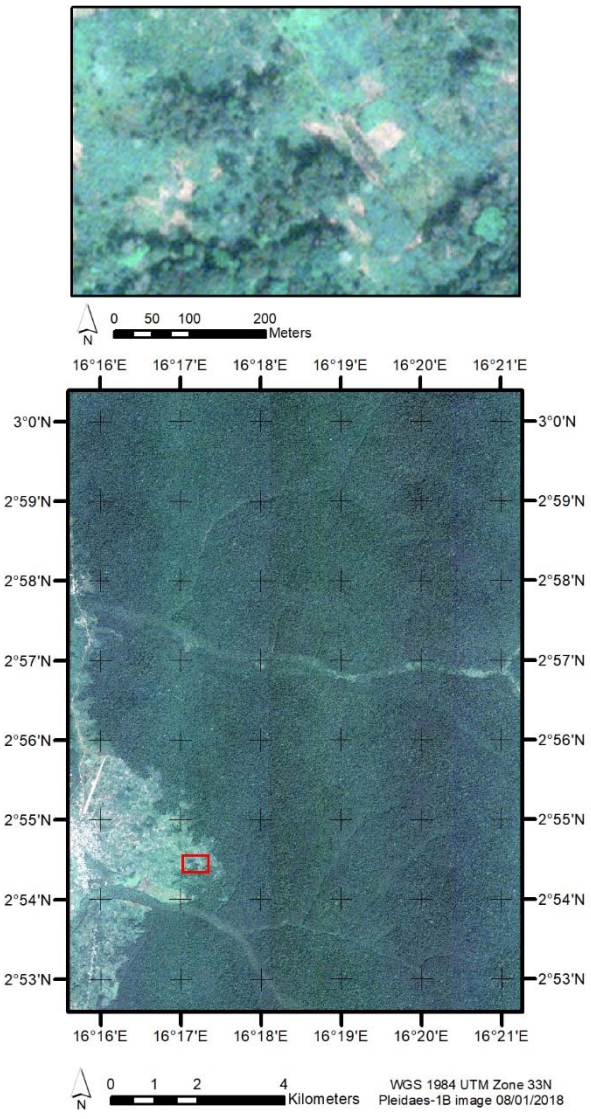


Figure 15. Figure X. Pleiades image from the 08/01/2018, used as reconnaissance data in the surroundings of Bayanga during the field work.

Pleiades mission (satellites 1A and 1B) have been initiated in 2011 and are public-private platforms and sensors depending on the CNES[24] and Airbus Defense and Space (Satellite Imaging Corporation, 2019).

Pleiades 1A and 1B satellite sensors have, with 4 spectral bands R-G-B-NIR and 1 panchromatic band synthesising the mean reflectance of the 4 bands. Surface reflectance is measured with a spatial resolution of 2 meters, but the panchromatic resolution of 50 cm allow to increase the image performance to a multispectral resolution of 50 cm. The high resolution of those images makes them very useful as reconnaissance data for local expedition in distant country.

The image at the left was the best acquisition before going to Bayanga (clearing in the lower left of the image) and helped to anticipate which kind of territory and landscapes the study was facing, and later to recognise in true colours forest stands discovered on the field.

[24] Centre National d'Etudes Spatiales (France).

5.2.2. Sentinel-2 optical data imagery

With 13 spectral bands, Sentinel-2 sensor has been designed to be effective in land cover discimination and very accurate in forest type detection (Immitzer *et al*., 2016). The 6 bands with a resolution of 20 meters have proven to be the most accurate to discriminate forest types (Mngadi *et al.,* 2019). Moreover, the aerial water vapour always present up the Congo Basin have a huge impact on short wavelengths corresponding to the visible part of the spectrum (Blue-Green-Red), modifying reflectance distinctly from a date to another. This is why this remote sensing work only uses those 6 bands as optical features. S2 Images (level1c) have been pre-processed and atmospherically corrected according to MACCS[25] protocol, producing two main TIFF files gathering respectively the four 10-m and the six 20-m resolution bands. In the output MACCS folder, the ATB file produced includes 2 bands corresponding to water vapour content and aerosol optical thickness, informing that atmospheric parameters have been taken in account. Nevertheless, unsatisfying visual assessment to 10-m resolution bands confirms the idea of not using them.

Table 1. Spectral resolution of the Sentinel-2 sensors and output data after MACCS preprocessing computation (EOS, 2019; ESA, 2019).

Sentinel-2 spectral bands		Central wavelength	Spatial resolution	MACCS output MSI		Used in this work
				Used	File name	
Band 2	Blue	490 nm	10 m	x	…_FRE_R1	
Band 3	Green	560 nm	10 m	x		
Band 4	Red	665 nm	10 m	x		
Band 8	NIR	842 nm	10 m	x		
Band 5	Vegetation Red Hedge	705 nm	20 m	x	…_FRE_R2	x
Band 6	Vegetation Red Hedge	740 nm	20 m	x		x
Band 7	Vegetation Red Hedge	783 nm	20 m	x		x
Band 8a	Narrow NIR	865 nm	20 m	x		x
Band 11	SWIR	1610 nm	20 m	x		x
Band 12	SWIR	2190 nm	20 m	x		x
Band 1	Coastal aerosol	443 nm	60 m			
Band 9	Water vapour	940 nm	60 m			
Band 10	SWIR - Cirrus	1375 nm	60 m			

With a colour composition using band 5-7-11, a S2 image from the 11/01/2018 was the main source carried on during the field work. The colour composition was found very useful to observe the different vegetation formations in the surrounding of Bayanga.

[25] Multi-mission Atmospheric Correction and Cloud Screening.

A composite image was created to increase the temporal suitability and attenuate speckle noise in the S2 data. The images establishes the mean reflectance of the 5 only cloud-free images in the last yeartime before the field campaign, all taken during the dry season from December 2017 to February 2018 (using all 6 bands with spatial resolution of 20 meters):

- S2A: 01/01/2018 and 11/01/2018
- S2B: 27/11/2017, 06/01/2018 and 05/02/2018

To snap with Sentinel-1 images (described below) resolution, every 20-m resolution band has been resampled to 10 meters and exported as a raster feature, to constitute a basic optical feature.

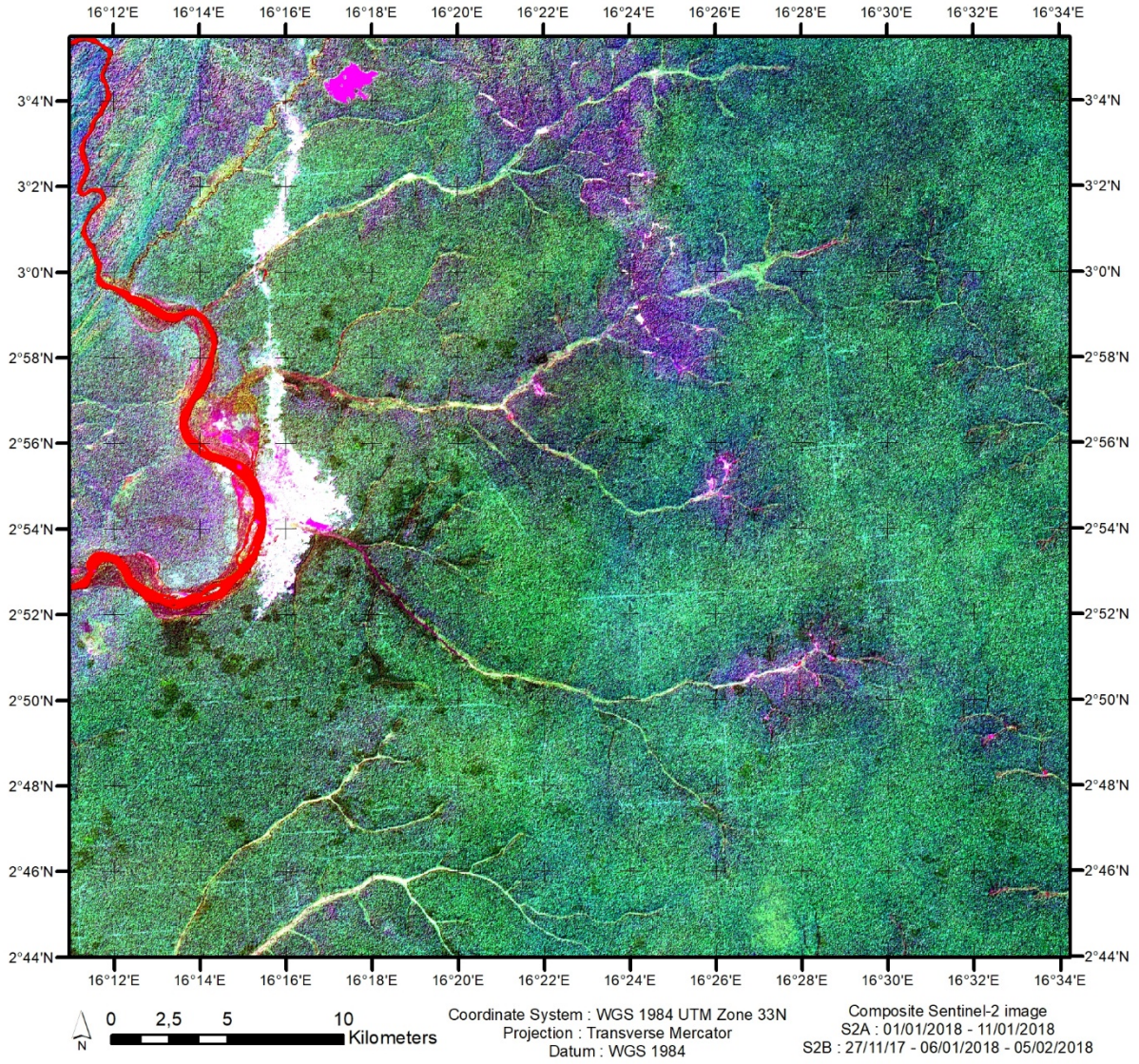


Figure 16. Composite Sentinel-2 image centered on Bayanga and the eastern Dzanga protectd area; made out of 5 dry-season cloudless images (from december 2017 to february 2018); colour composition using bands 5-7-11 (2 red hedge bands and 1 SWIR band).

5.2.3. Sentinel-1 C-SAR data imagery

RADAR images from Sentinel-1 are C-band SAR data, with a wavelength from 3,75 to 7,5 cm (8 to 4 GHz). The data used for this project is high resolution Level-1 Single Look Complex (SLC) images in Interferometric Wide swath (IW) mode, resampled to a resolution of 10 meters and constituting Standard-class products with a DV (dual VV+VH) polarization (ESA, 2019).

Table 2. C-SAR bands in Sentinel-1 images (ESA, 2019).

C-bands	Polarization	Resolution
Band 1	VV	10 m
Band 2	VH	10 m
Band 3	Ratio VV/VH	10 m

The whole S1 archive from 2018 which completely covers the study area have been pre-processed by Juliette Dalimier (UCLouvain) with a first Lee filter and a second multitemporal filter to attenuate speckle.

As another temporal filter, the computation of the mean backscattering of each band was realised using the 54 images from S1A and S1B the full 2018 archive. This image and its 3 bands are used as the basic features for all S1 texture feature extraction.

The mean backscattering from dry season (8 images from January and February 2018) and wet season (10 images from July and August 2018) have also been computed to create two more S1 composite images. Thereafter, those 6 temporal features have been used to calculate the backscattering deviation between the two periods, to light up backscattering changes through the year and generate one seasonal feature for each of the 3 bands.

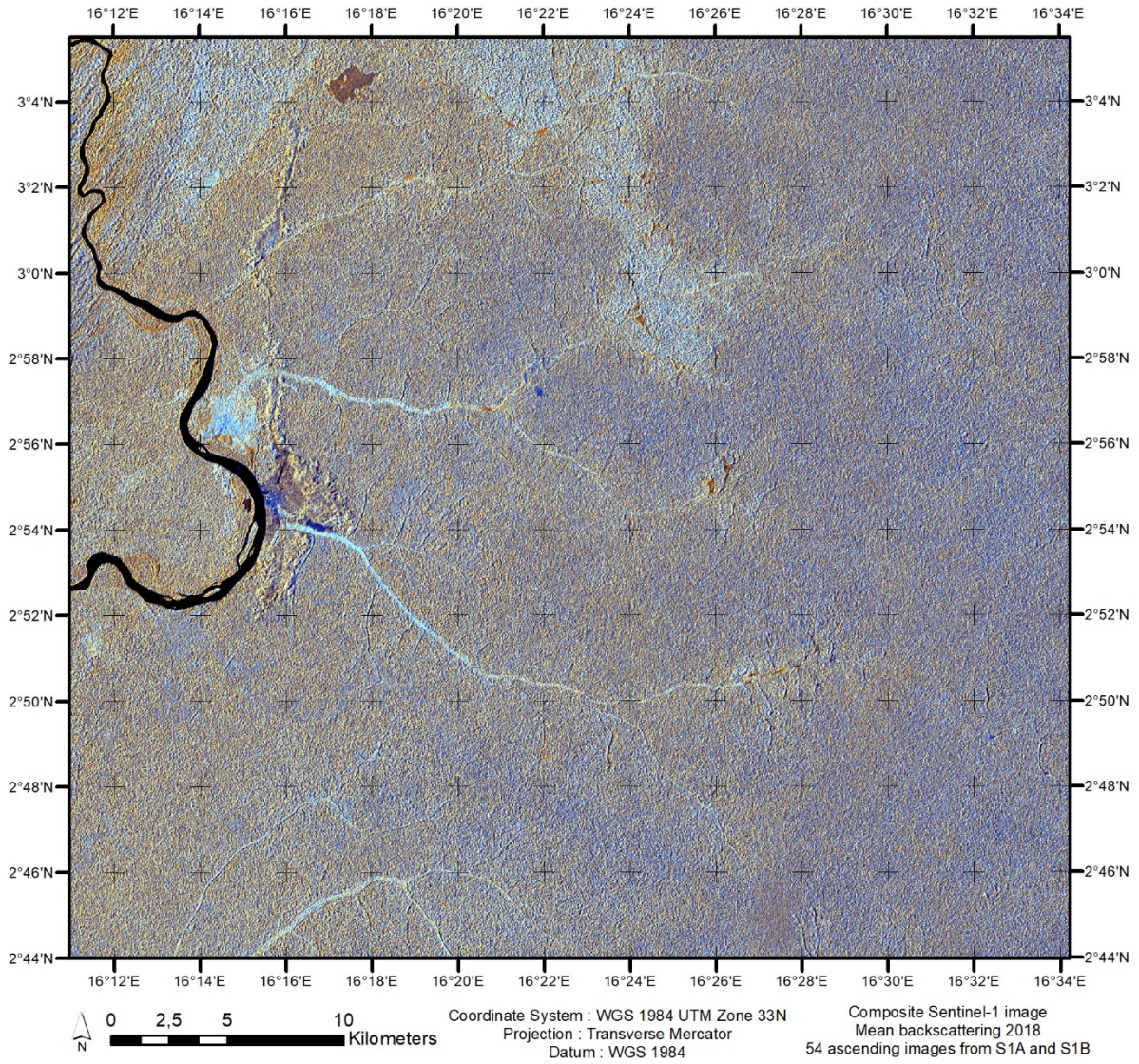


Figure 17. Composite Sentinel-1 image centered on Bayanga and the eastern Dzanga protected area: mean backscattering of the 3 bands in 2018, made out of 54 S1A and S1B ascending images.

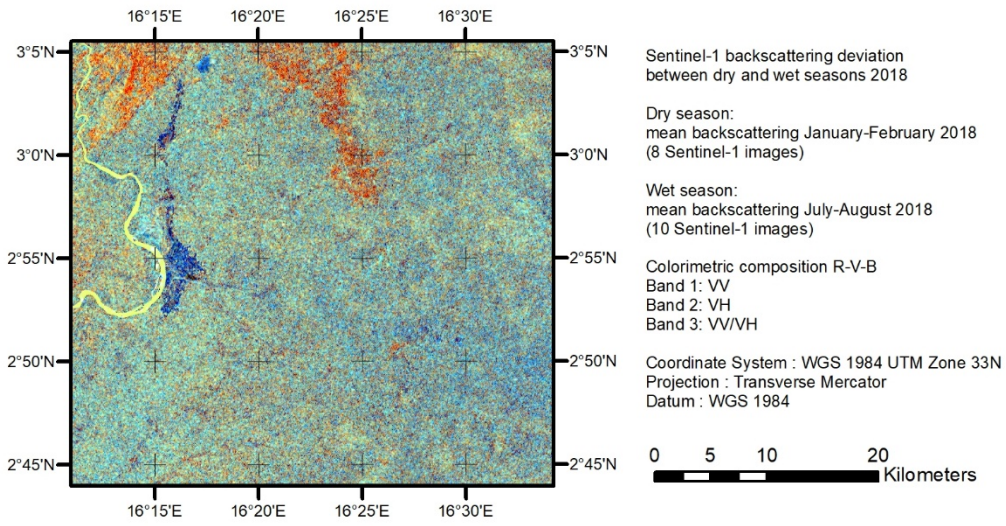


Figure 18. Sentinel-1 backscattering deviation (3 bands) between dry and wet seasons 2018.

5.3. On-site data collection

In order to understand and identify local forest dynamics and ecosystems, satellite imagery acquisition demands additional field campaign data. In-situ observations allow to associate reflectance and backscattering information in optical and RADAR images with ground objects and land cover. The field knowledge acquired with this method enable to develop photointerpretation skills and confirm comprehensive reading of a satellite image. This field campaign in the APDS's forests was completed through a stay of 6 weeks in Bayanga in the local WWF's facilities.

The mapping work is a university project, which means no particular request was made from the field in the first way. No recent state of the forest was available either in a way that could be used as a starting or comparison point for further developments. Field forms had been prepared to report field observation on forest stand in every visited sample. Beside general information's (datum, point number) and geographic descriptions of every station (slope, hydrology and comment), the field protocol was to describe a maximum of 5 strata in forests, using Braun-Blanquet (1932) vegetation abundance indices. This method was quickly aborted because of the complexity of apprehending unfamiliar vegetation formations and because local knowledges was missing to operationalise such a documentation. Strata quantitative description was replaced by two local indices: canopy closure and understory closure.

Table 3. Quantitative description of canopy and understory closure as finally used on the field.

	Very open	Open	Closed	Very closed
Canopy closure: vertically-projected cover	< 25 %	25-50 %	50-75 %	> 75 %
Understory closure: horizontal visibility	> 15 meters	10-15 m	5-10 m	< 5 m

A general description of the vegetation was made in every station in the purpose of finding indicator species and typical elements. The first week, an agent from the Ministry of water and forests accompanied the field surveys and helped distinguish tree height, canopy cover, and general observation. Primary and secondary forests were clearly named but the difference between old secondary forest and primary ones weren't always clear to distinguish. Besides general forest observation and very precise or small element encountered, characterizing forest types at that level didn't seem to be a regular and familiar practice in the region.

The whole point of travelling through the forest was to locate homogenous forest stands and take their coordinate position with the GPSmap 62 (Garmin) in order to acquire several sample of all the identified forest type and compare them on the satellite images. As forest

stands weren't easy to recognise from Western European eyes, the method quickly switched to a pre-encoding of all the point to visit before taking the road, then the visit straight to those points in the forest by following the GPS indications. In this way, proper stands were visited and samples came directly from the centre of homogenous vegetation formations as observed on S2 imagery.

Homogenous forest stands needed to represent at least a square with 60-m sides, to prevent GPS and image geometric errors. Indeed, the S2 image used as roadmap had a resolution of 20 meters. In addition, dense canopies make it difficult to acquire a GPS precision inferior to 10 m, 7 m being the best potential value, rarely possible.

In total, 20 days of approximately 6-hour walks have been conducted to obtain 204 valid samples in total, from each of the 8 forest types defined in situ. Dozens of bad samples from edges and unprecise cover have been removed, useless. All samples are used as validation data for each classification, while additional regions of interest are selected to train models.

The main road companions during the whole duration of this field campaign were BaAka pigmies hired as trackers. No one goes into the APDS forest without a BaAka tracker who leads the ways with machete blows. Living directly out of forest make local pigmies very familiar with the natural surroundings and all the danger that might be encountered. Elephants were the main detour factor during walks. BaAka pigmies have a really good knowledge of plants, their uses, properties and value, but they name most of them in their own language, which makes it very difficult to write down for later translation. Available local-made bilingual plants lists didn't really help identify scientific names. Those long walks permitted little by little to learn or understand local use or custom but the open communication was a very long process that might have needed way more weeks on site to be pursued.

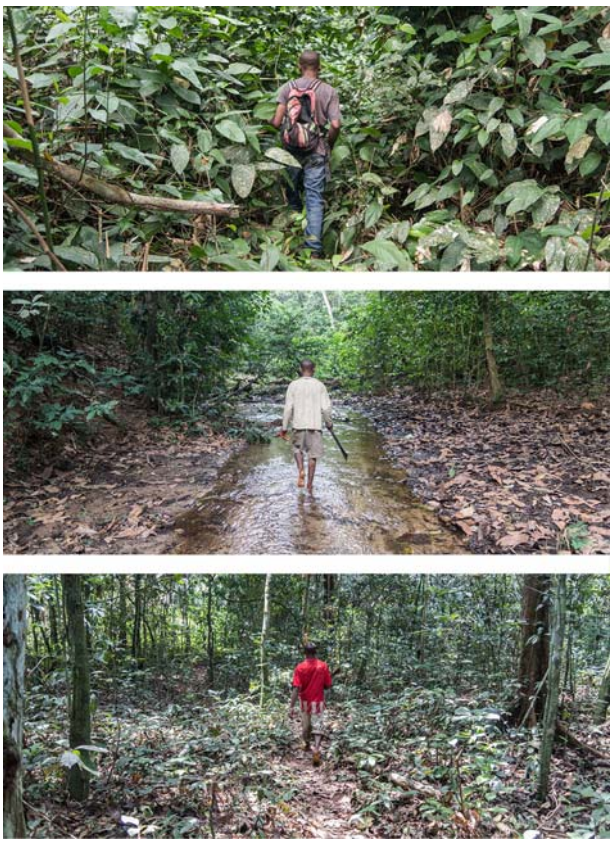


Figure 19. Felix Mesan, BaAka pigmy tracker, opening the road during field tours.

5.4. On-site forest types observed

5.4.1. Preliminary comments

Forest type have been observed with a specific spectral signature on a S2 image, then visited on-site, located and compared with existing documentation and then named and described properly. Those following descriptions are the result of long walks in the forest, discussion with locals and reflections, but no official forest typology have been obtained from any authority for the purpose of this mapping study.

The concept of Primary forest is often discussed by the scientific community nowadays. Often considered as natural and free from human disturbance[26], global warming tends to show that no place worldwide still remains how it would have been without human presence on Earth. Plus, the argument of human damages, considered as artificial amongst all contributors, is null if we consider BaAka pygmies as the natural inhabitants of the forest, and still exploiting its resources for subsistence. Regarding that all forests around Bayanga are full of small natural disturbances and signs of human back and forths, the primary forest term simply defines a forest free of industrial logging for the following classifications.

Figure 20. Everyday's life and natural signs of distubances in old-growth forests : (A) Burnt and felled trunk for honey extraction – (B) Manioc crops in a natural forest fall – (C) Elephant road.

[26] NOTE: Primary forest do not have official definition in dictionaries. If the meaning of the adjective *primary* refers to first in importance, fundamental, elementary and natural (Harrap's dictionary, 2004; Collins Concise English dictionary, 2019), it's not clearly defined in forestry. If we check to popular references, Wikipedia article defines Old-growth forest, also named primary, as late-seral forest, (…) without significant disturbance (…) classified as climax community (Wikipedia, 2019). The French article on the same subject is more ideologic, mentioning the terms virgin and intact, never destroyed (…) nor fragmented (…) by man (Wikipedia, 2019), without taking in consideration disturbance made by animals and natural catastrophe.

5.4.2. Evergreen primary forest

Figure 21. Very open understory in a monospecific evergreen primary forest.

The monospecific forest stands of *Gilbertiodendron dewevrei* (Limbali) are very easily recognizable on the field. The dense and steady, closed to very closed canopies also appear as dark patterns on satellites images, and is already delimited in Boulvert's phytogeographic map (1986, cfr. Figure X) The limited natural light reaching the understory and the dense leaf litter restrain the development of the herbaceous layer and tree regeneration, which generates a very open understory easy to walk through. As the Limbali's have brittle wood, it's common to hear them fall and pretty rare to observe a subjects broader than 100 cm in diameter. Those forests are called monospecific or "monodominant", to recognize the dominant character of the main tree species by including herbaceous companion species, more or less present in the understory depending to canopy holes : *Marantochloa mildbraedii, Megaphrynium macrostachyum, Trachyphynium braunianum …*

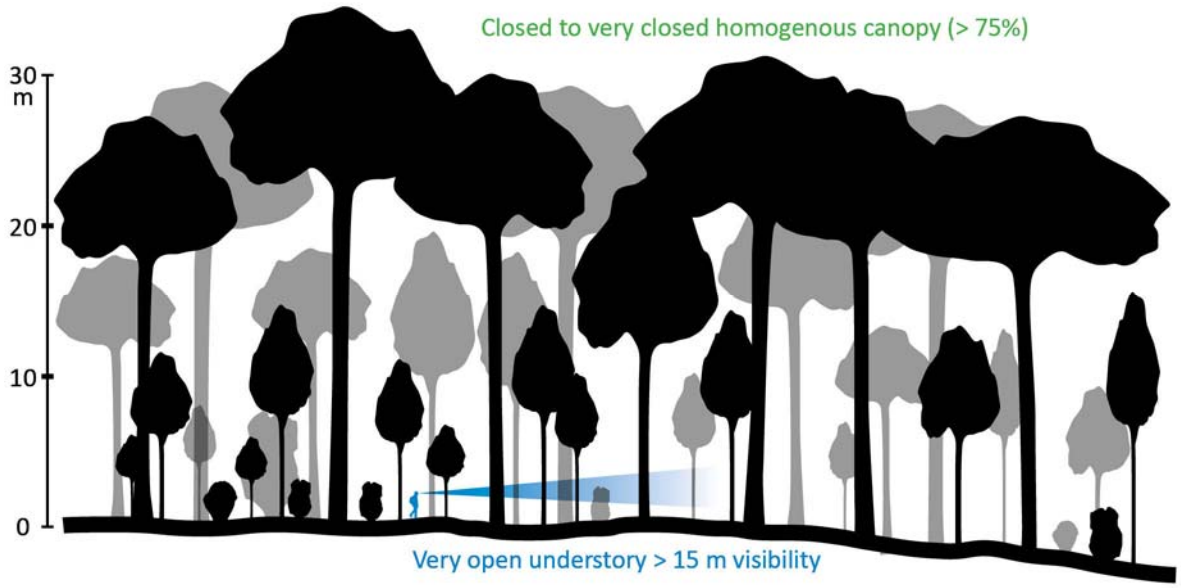


Figure 22. Schematic representation of an evergreen primary forest..

5.4.3. Semi-deciduous primary forest

Figure 23. Semi-deciduous mixed primary forest.

Semi-deciduous primary forests include the tallest and broadest trees in the APDS. This dense mixed forest type gathers lots of tree, shrub, liana and herbaceous species in mature forest stands, currently located in places with difficult access: riverbanks, uneven terrain, bottom of valley… which probably explains how they remained relatively intact.

Very old trees are present in those forests and it is very frequent to encounter large buttress trunks close to 4 meters in diameter, every 200 to 500 meters depending on location. The great biodiversity of those stands shapes irregular forest and canopies, from 25 to 45 meters high and variable closed understories. Those stands correspond to dense evergreen semi-deciduous forest in Boulvert's phytogeographic map (1986, cfr. Figure. 12), in specific places of valley's rejuvenated ferralitic soils located in Boulvert's pedologic map (1983, cfr. Figure. 11).

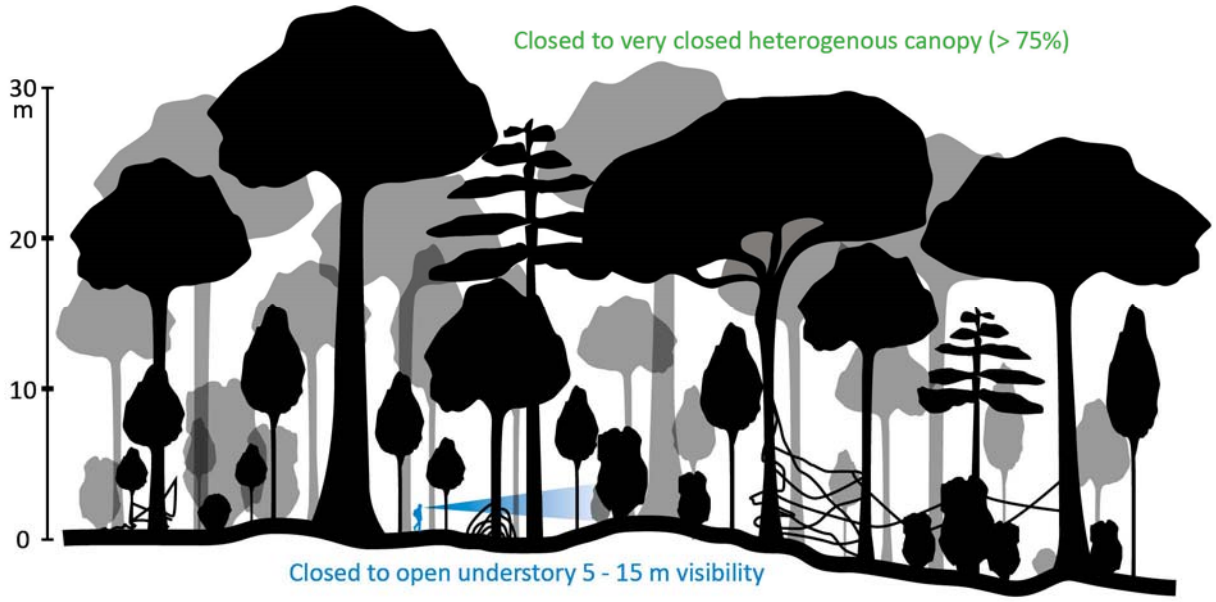


Figure 24. Schematic representation of a semi-deciduous primary forest.

5.4.4. Rocky primary forest

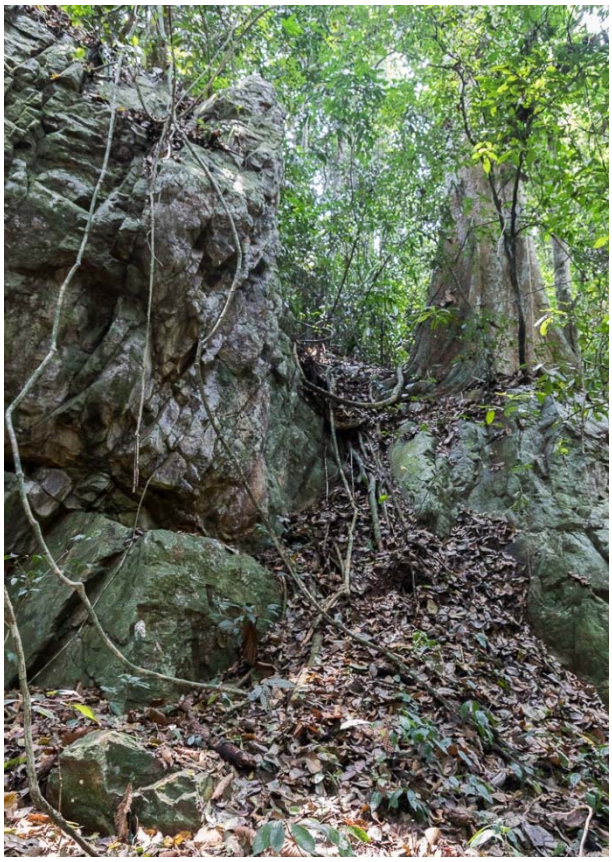


Figure 25. Primary forest on rocky hills.

Rocky forest present different types of physiognomy and are mainly characterized by their location on rocky ridge (up to 550 meters high when Dzanga River lies at 375 meters at Bayanga's shore) with steeply upwards slopes (up to 100% or more). This broken relief creates a very different forest station than the mountain plateau east of Bayanga and peaking at the same height. The rocky outcrop covers from 10% to 50% of the ground and can be located in Boulvert's pedologic map (1983, cfr. Figure. 11) as quartz ridges and young eroded soil.

Canopy height can go up to 30-35 meters when the depth of the soil allows full growth of trees. Otherwise, the rocky forest culminates from 10 to 20 meters, with a dense understory full of bushes and lianas.

Figure 26. Schematic representation of a rocky primary forest.

5.4.5. Old secondary forest

Figure 27. Dense understory in an old secondary forest.

The APDS's 2008 forest type map was a huge help to locate old secondary forests and distinguish from young ones, as the can be very close in appearances. Secondary forest present a pretty advanced stage of development. Tree can gradually reach the full growth height until the nearby semi-deciduous old-growth forests. The understory cover depends on the canopy closure, from open holes to very closed old stands. When the natural light can reach the ground, a very closed herbaceous/shrub layer mainly composed of *Marantaceae* and lianas species grow up to 5 meters and create a dense vegetation, very slow and difficult to cross. In Boulvert's phytogeographic map (1986, cfr. Figure. 12), old secondary forest correspond to dense mixed forest on Carnot's sandstone plateau which implies two hypothesis : either old secondary forests have been less logged because of their further location from the main road, or the soil conditions are responsible from a better regrowth of the forest than on less stable sandy soil.

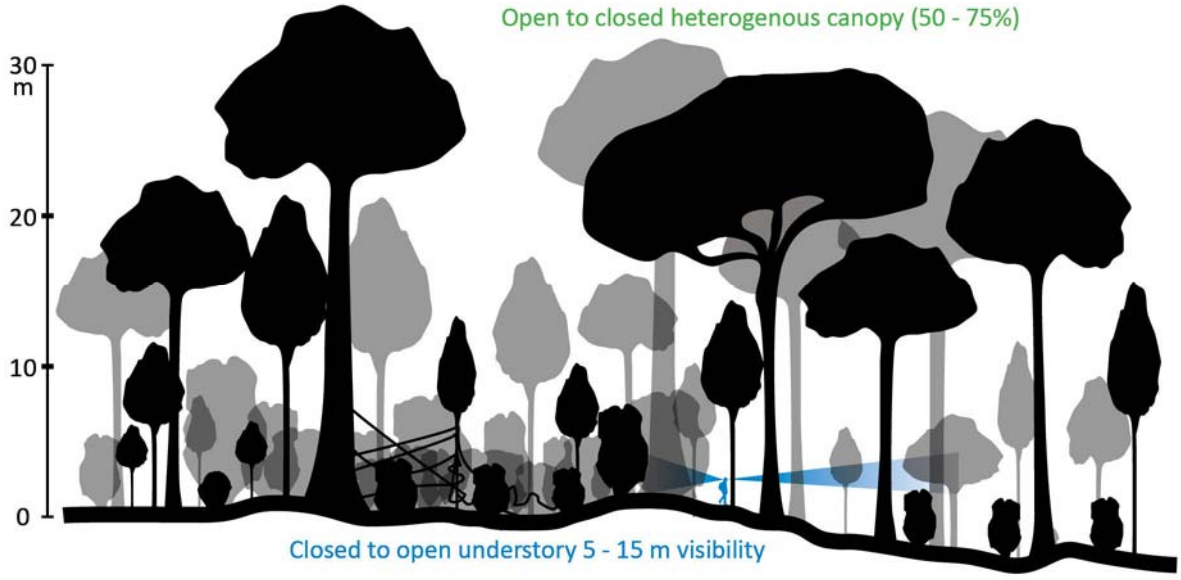


Figure 28. Schematic representation of an old secondary forest.

5.4.6. Young secondary forest

Figure 29. Pioneer vegetation in a young secondary forest.

The young secondary forests are regrowth of the forest from 20 to 40 years. The palm tree *Calamus deerratus* (Rattan) is an indicator species in holes of young stands. Due to their location, close to the main road and to the inhabited hamlets, these young forests are still frequently crossed by local population, so that they don't benefit from their full regrowth potential.

The irregular canopies can reach a height from 25 to 30 meters but the trunks are all inferior to 75 cm in diameter. Tree cover progress from open to closed canopy, but the tree foliage remain lighter than in the elder forest stands. The understory is generally closed to very closed, full of bushes and lianas forming a dense mixed inferior layer.

Figure 30. Schematic representation of a young secondary forest.

5.4.7. Wetland forest

Figure 31. Flooded forest with vegetation on the upper positions.

Depending on the nearby forest types, wetland forests are characterized by different heights, covers and stages of vegetation. The main characteristic of those remains in their partially/temporally flooded soil. This forest type is located in riverbanks, as a transitional field between dry forest and watercourse.

The ground is basically made of hollows and bumps, where the vegetation occupies the upper positions. Different level of flooding are observed, from the bank to the river : dry bare soil in the hollows, muddy soil around trees and bushes, and flooded forest until 50 cm during the dry season. Water tends to rise from 1 to 2 meters during the wet season in those places, which makes forest landscapes completely different, as well as optical reflectance and RADAR backscattering in satellite imagery.

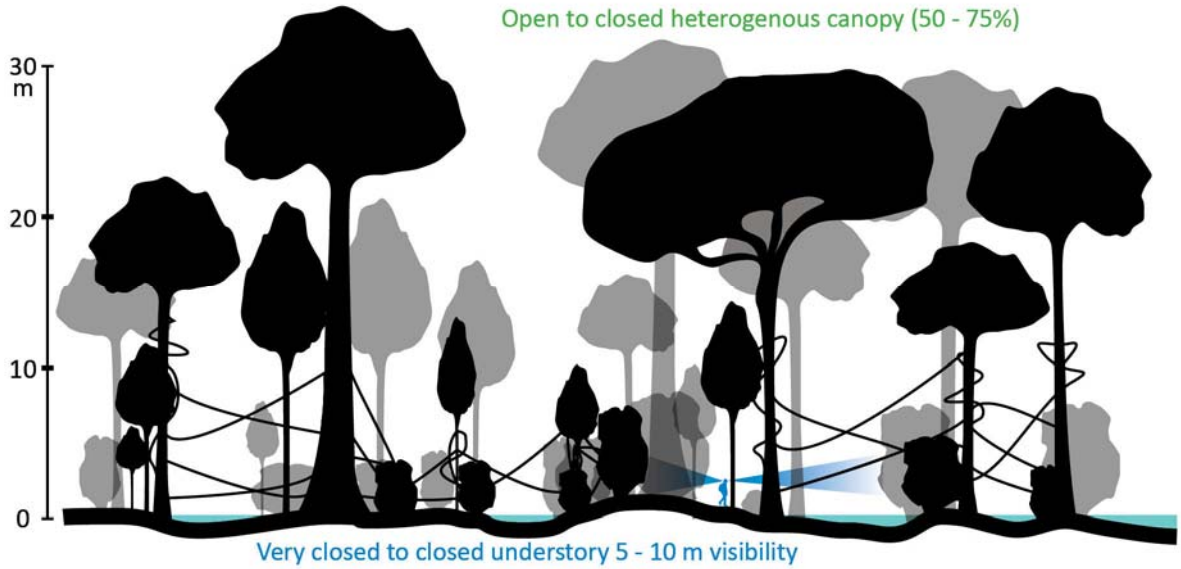


Figure 32. Schematic representation of a wetland forest.

5.4.8. Low riparian forest

Figure 33. African bamboo growing in the middle of a river stream.

Low riparian forests are located close to the mouth of small rivers when they flows into the Dzanga river, until 10 to 20 meters in altitude up the stream (over 15 to 25 km depending on the slope). African bamboo stands grow right in the middle of the watercourses forming mounds in the middle of the stream, where fern grow as companion species. The open bamboo canopy culminates at 15 meters with an heterogenous cover interspersed with water.

During dry season, watercourses are 1 meter deep with a slow stream, making it possible to cross or to walk slowly up or down from the middle of the sandy river bed. Banks are in general almost at the same level, which makes them very muddy.

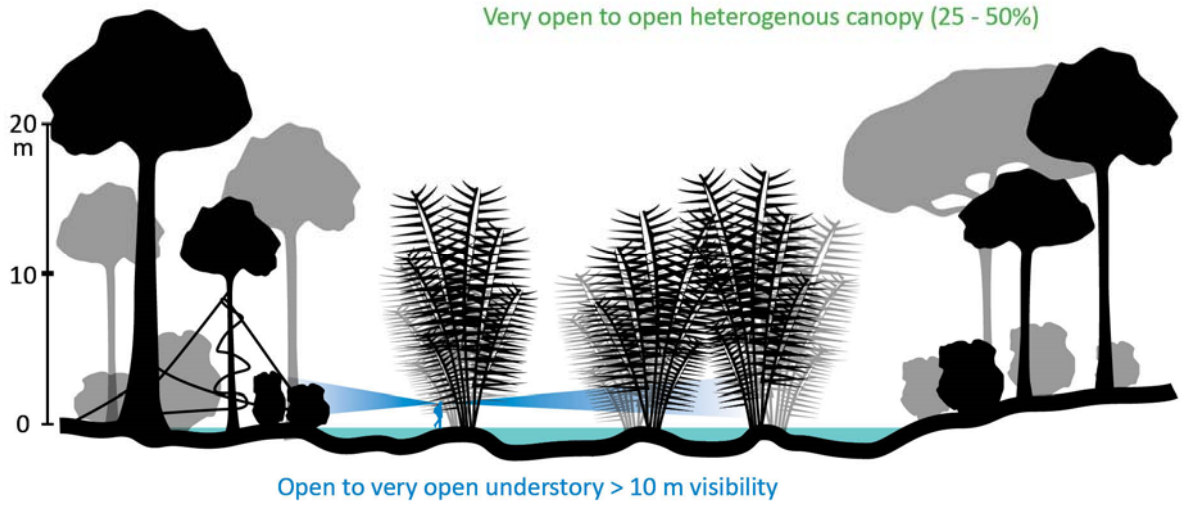


Figure 34. Schematic representation of a low riparian forest.

5.4.9. High riparian forest

Figure 35. Open vegetation from a high riparian forest.

Located in upper streams from the spring down to the valley, high riparian forests are rather low plant formations interrupting the nearby forests, but are still punctuated with sparse high trees, in addition to being fully part of the natural ecosystem. This vegetation grow in the gentle stream of the upper rivers, in 20 to 50 cm water during the dry season. A very dense bush/herbaceous layer with many different species grows up to 5 meters high. As very few trees grow directly in the middle of the stream, the vegetation grow in a very open field, very warm and sunny. The soil alternate from muddy swamp to sandy stable bed. The changing of the soil's consistency at every step already slow the pace, but the dense vegetation is the real constraint to move in those formations.

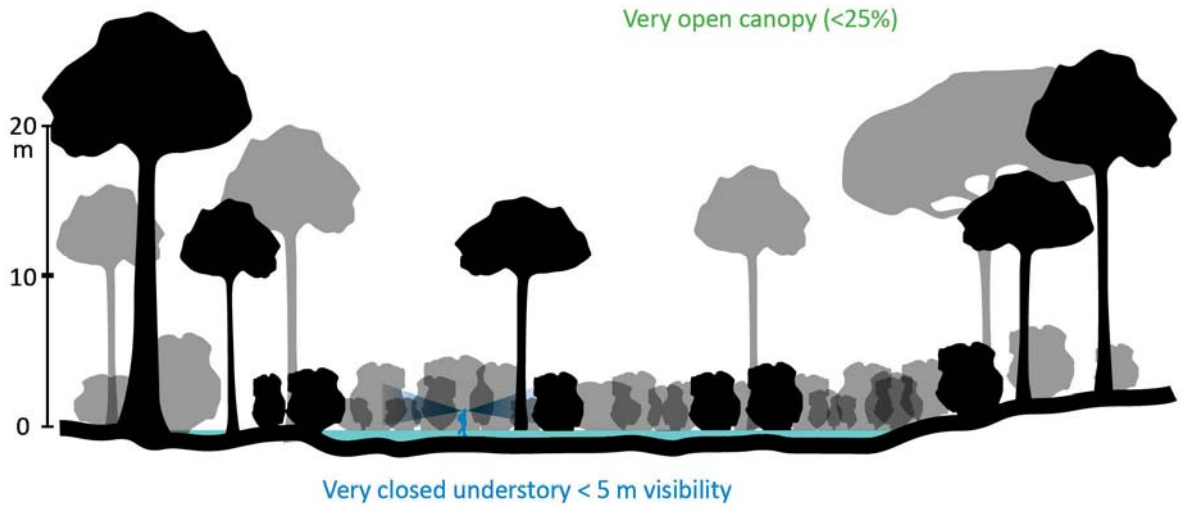


Figure 36. Schematic representation of a high riparian forest.

5.5. Forest types mapping

5.5.1. How to deal with textural canopies

What should be classified as homogenous forest stands doesn't necessarily appear with a consistent spectral signature. Satellite data acquired with a resolution of 10 of 20 meters record many small unwanted artefacts (shadow, reflection) that may trouble pixel-based classification (cfr. Appendix 1.). Temporal filter allow to attenuate speckle and ephemeral reflection but doesn't smooth classes sufficiently to provide a uniform source material. Additional spatial filters applied with a defined window scale can be used to measure spatial information and create useful texture features (Hall-Beyer, 2017; Mamat *et al*., 2016; Hu *et al*, 2018). Segmentation in another way of providing useful features out of satellite imagery, grouping pixels by minimising heterogeneity inside each segment (Baatz & Schäpe, 2000). Combining the two methods, the mean value of extracted texture features can also be measured in segmented polygons to create new object-based texture features.

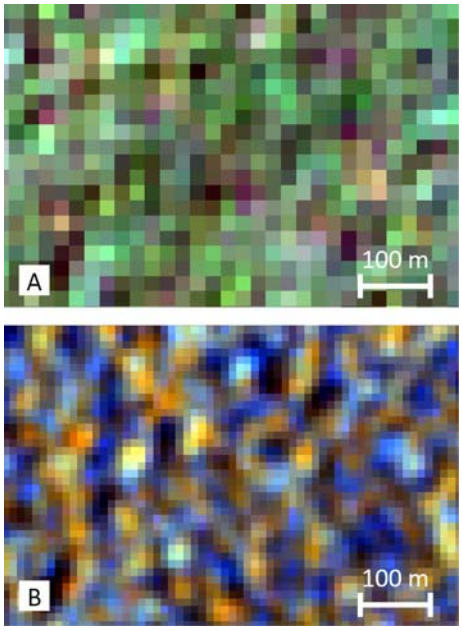


Figure 37. Heterogeneous (A) reflectance on a S2 images and (B) backscattering from a S1 images; at the same place in a single forest type (young secondary forest).

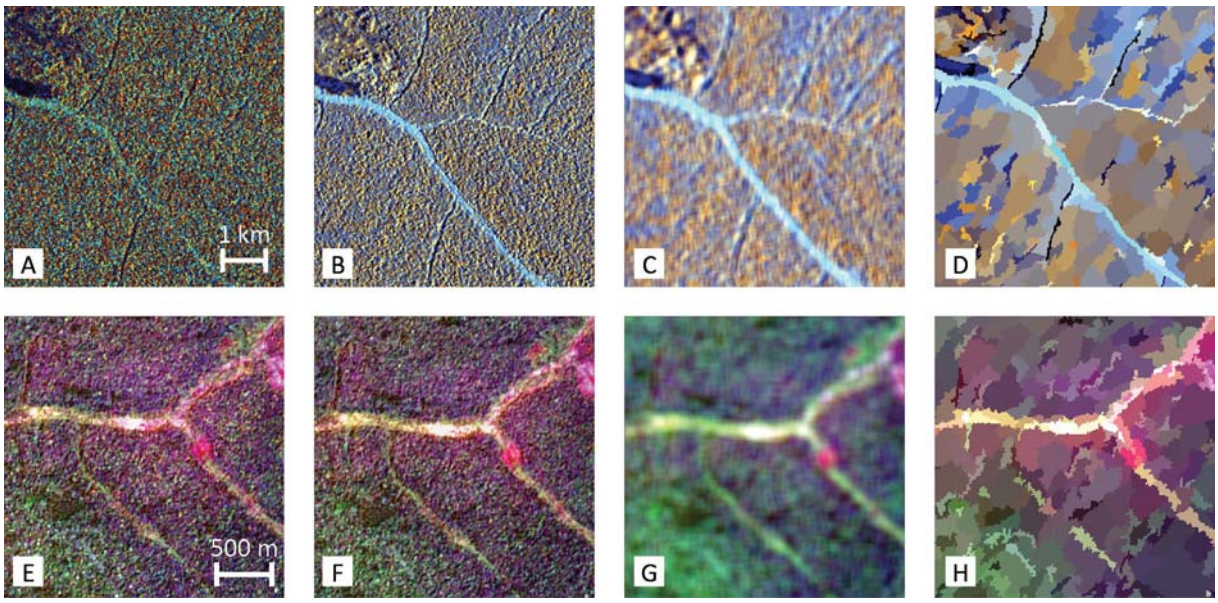


Figure 38. Satellite images and computed filter, feature and segmentation possibilities.
Upper row (3 bands from Sentinel-1 C-SAR images): (A) Single-date image, (B) annual mean backscattering of 54 images, (C) Haralick's GLCM mean value extraction from a 7x7 window, (D) Segmented image, mean backscattering exported in every segmented polygon;
Lower row (bands 5-7-11 from Sentinel-2 optical images): (E) Single-date image, (F) dry season mean reflectance of 5 images, (G) Haralick's GLCM mean value extraction from a 7x7 window, (D) Segmented image, mean reflectance exported in every segmented polygon.

- ***Texture features extraction***

Texture measurements quantitatively describe relationships between every pixel of the image with the neighbouring pixels. The global extracted feature is composed by a continuous measure of spatial information extracted from satellite imagery (Hall-Beyer, 2017; Kaplan & Avdan, 2018).

Using Haralick's texture feature extraction tool, four patch-interior focused texture features derived from the GLCM have been selected to complete this mapping project's dataset: Energy, Inverse Different Moment (measures the texture homogeneity), Mean and Sum Average. With an X and Y radius of 7 pixels, a moving window of 15x15 have been determined for all texture extraction, corresponding to the territory's and landscape's spatial shapes and highlighting homogeneous classes. All the texture features have been extracted from the S1 mean backscattering 2018. GLCM mean value have also been extracted from S2 reflectance data and S1 seasonal backscattering deviation, as spatial filter.

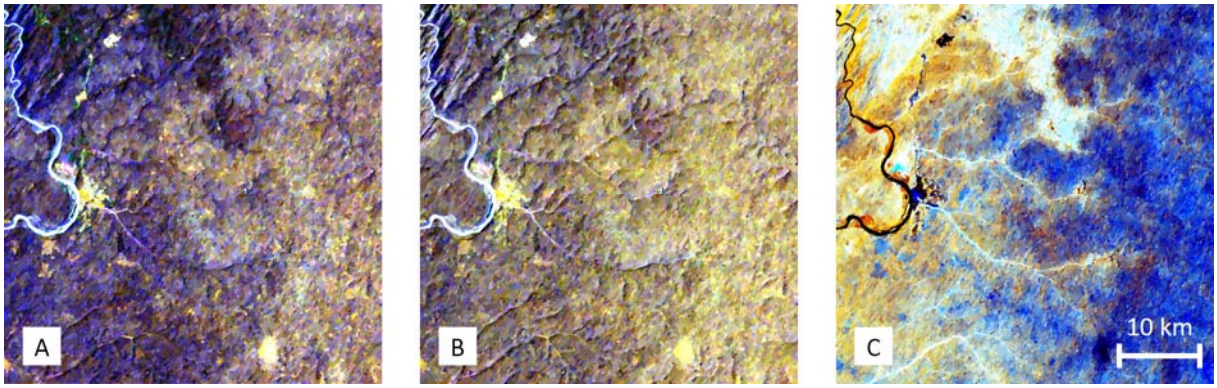


Figure 39. Images made of Haralick's textural features extracted from S1 mean backscattering 2018 of bands 1-2-3: (A) energy, (B) homogeneity and (C) sum average.

- ***Topographic Position Index***

Only used to detect rocky ridges (last surmised class), the Topographic Position Index (TPI) is derived from the DEM, and attribute pixel values according to the relative position of an area in a topographic context: high value to ridges and peaks (elevated from the context), low value to valleys and cavities (lower from the context) and intermediate value to flat areas and regular slope (equal to mean context). Mean values have been derived from the GLCM in a 100x100 moving window to focus on wide geographic objects, as illustrated in Boulvert's pedologic map (1983). This additional feature is essential to classify the rocky forest type, made of heterogenous classes.

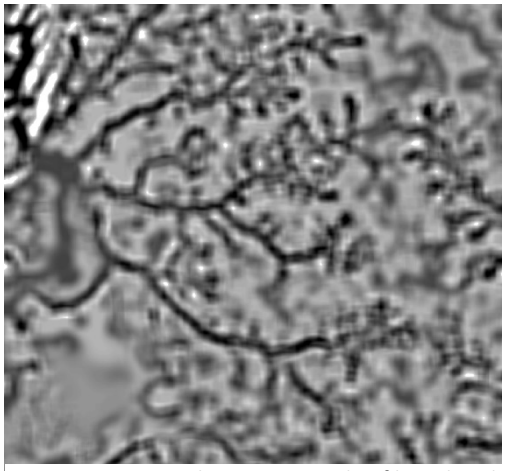


Figure X. Topographic Position Index filtered with Haralick's mean GLCM value in a 100x100 moving window: highlight of the rocky ridges in the northwestern corner (white spots).

- ***Image segmentation***

Multi-resolution segmentation[27] algorithm has been proven to be very fully reliable in object based image analysis, maximizing the intra-object homogeneity through a number of input features (Witharana *et al*., 2014; Chen *et al*., 2019). The right delimitation of the narrow rivers and valleys were the limiting factor imposing the minimum level of scale, shape and compactness parameters[28]. On the other hand, forest stands have tended to be segmented as wide and heterogenous as possible to include reflectance variations in the same class. Lots of trials and errors are necessary to obtain a proper segmentation: too broad creates imprecise shapes, too specific decompose forest stands into shadows and reflections and creates irrelevant objects. To delimit and segment visible forest stands corresponding to the reality discovered on the field, only the six composite bands from S2 optical data have been used as input features.

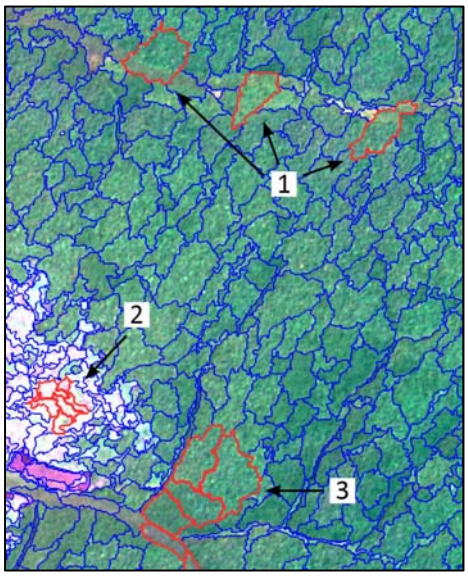


Figure 40. Figure x. Visual check of a multi-resolution segmentation:
(1) irrelevant coarse segmentation, (2) useless detailed zone, (3) proper delimitation of forest stands.

Each of the bands have been given an equivalent weight of 1, and the tree others parameters have been tested with several value to obtain a segmentation corresponding to the scale of studied objects. The final segmentation performed for this work used a scale factor of 80, a shape parameter of 0.7 with a compactness of 0.5. Polygons extracted from this segmentation can be used to calculate mean value from others S1 data, related features and TPI, to create a full object-based dataset.

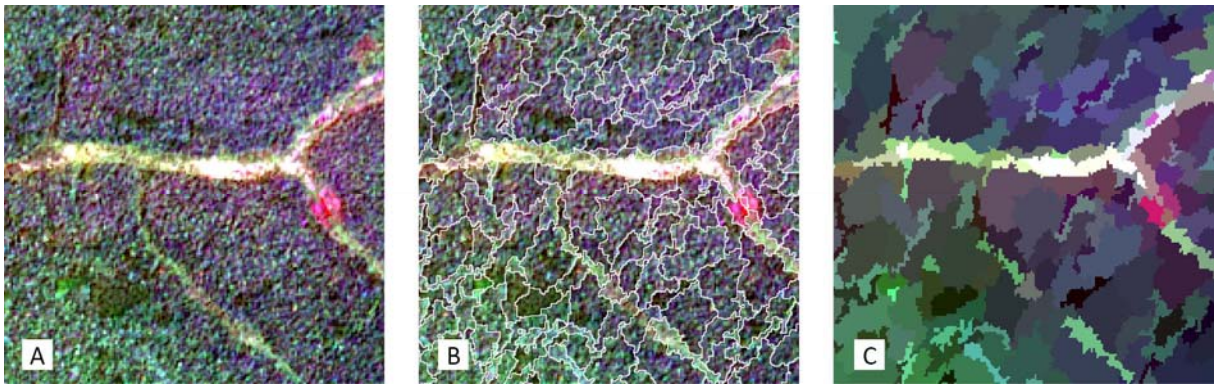


Figure 41. Segmentation of a pixel-based raster image into an object image using eCognition Developer; (A) Sentinel-2 image as input, (B) Segmentation polygons, (C) Object-based image made of exported mean reflectance in every polygon.

[27] Performed with eCognition Developer from Trimble.
[28] See appendix 1. Coarse classification induced by coarse image segmentation.

5.5.2. Dataset production : workflows

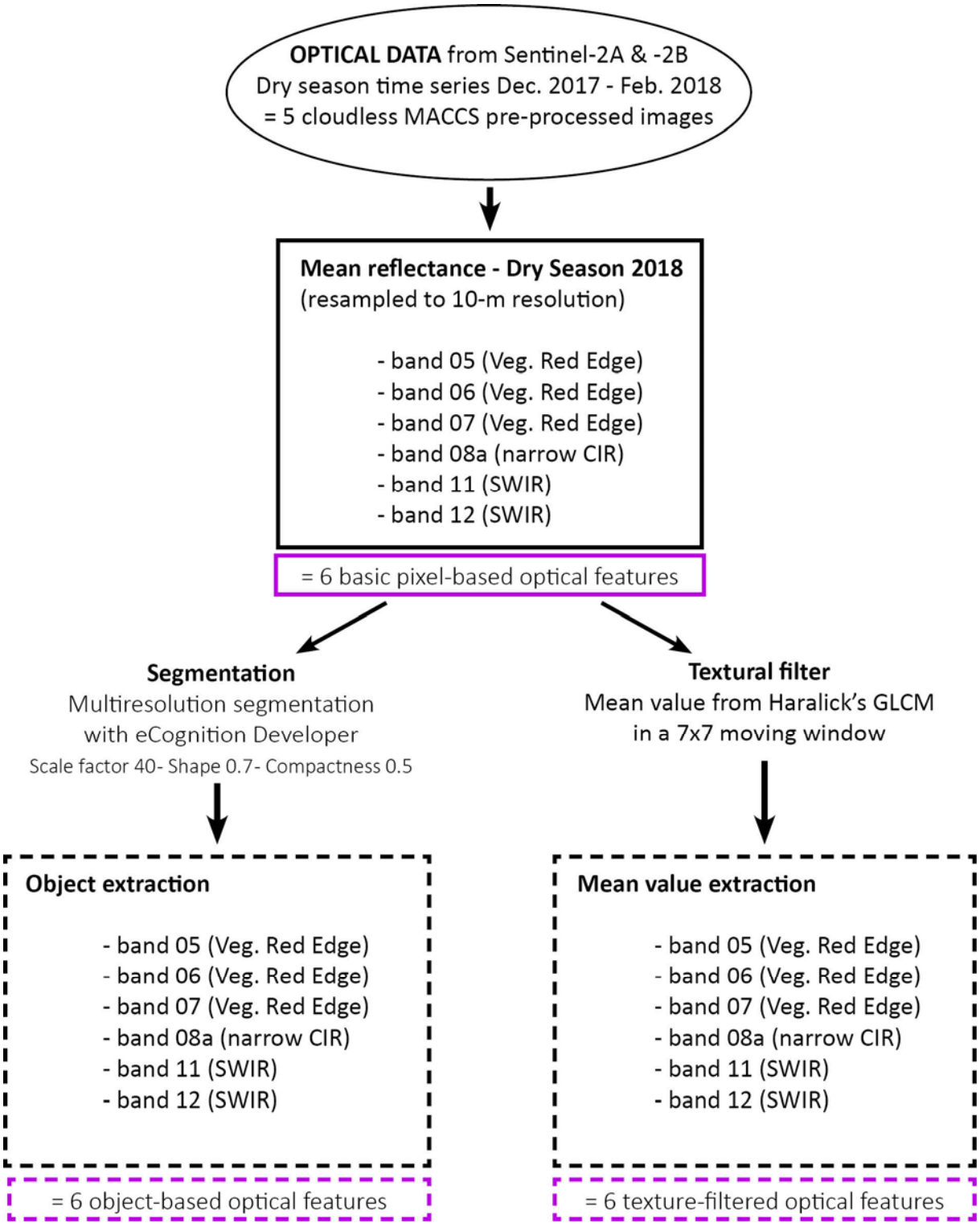


Figure 42. Feature extraction and dataset constitution out of S2 optical data.

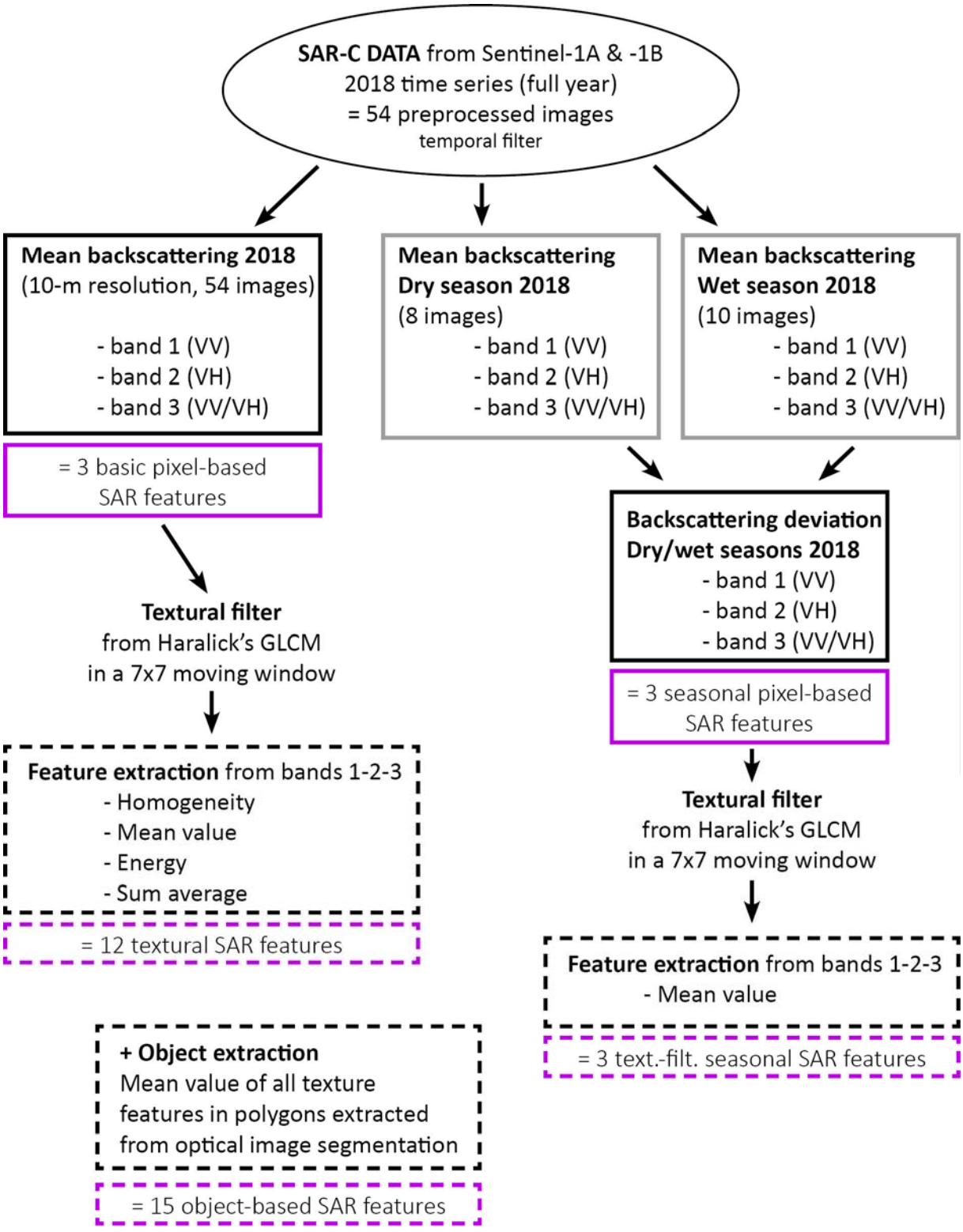


Figure 43. Feature extraction and dataset constitution out of S1 SAR data.

5.5.3. Classifying in three phases

First attempts to classify revealed the complexity of discriminating 8 forest types and 1 non-forest class in a single classification. This is why a forest mask created first, discriminating forest and non-forest areas, and concentrating following classifications straight on the right land cover (Verhegghen *et al*. 2010; Ernst *et al*. 2010). Preliminary tests also tended to misclassified rocky forests. The class happens not be a proper forest type by itself but is rather an additional topographic/geographic characteristic of the field in specific areas, constructed by variable forest types in rocky mountains. Samples acquired on the field confirms the existence a specific forest station in the mountains, even though its heterogeneous spectral signature shows mixed old and young, open to closed canopies. To ensure proper spectral classification in the mountains, by adding geographic topic in specific rocky areas, the rocky forest type is first removed from forest type classification, then added as a superimposed class in related areas.

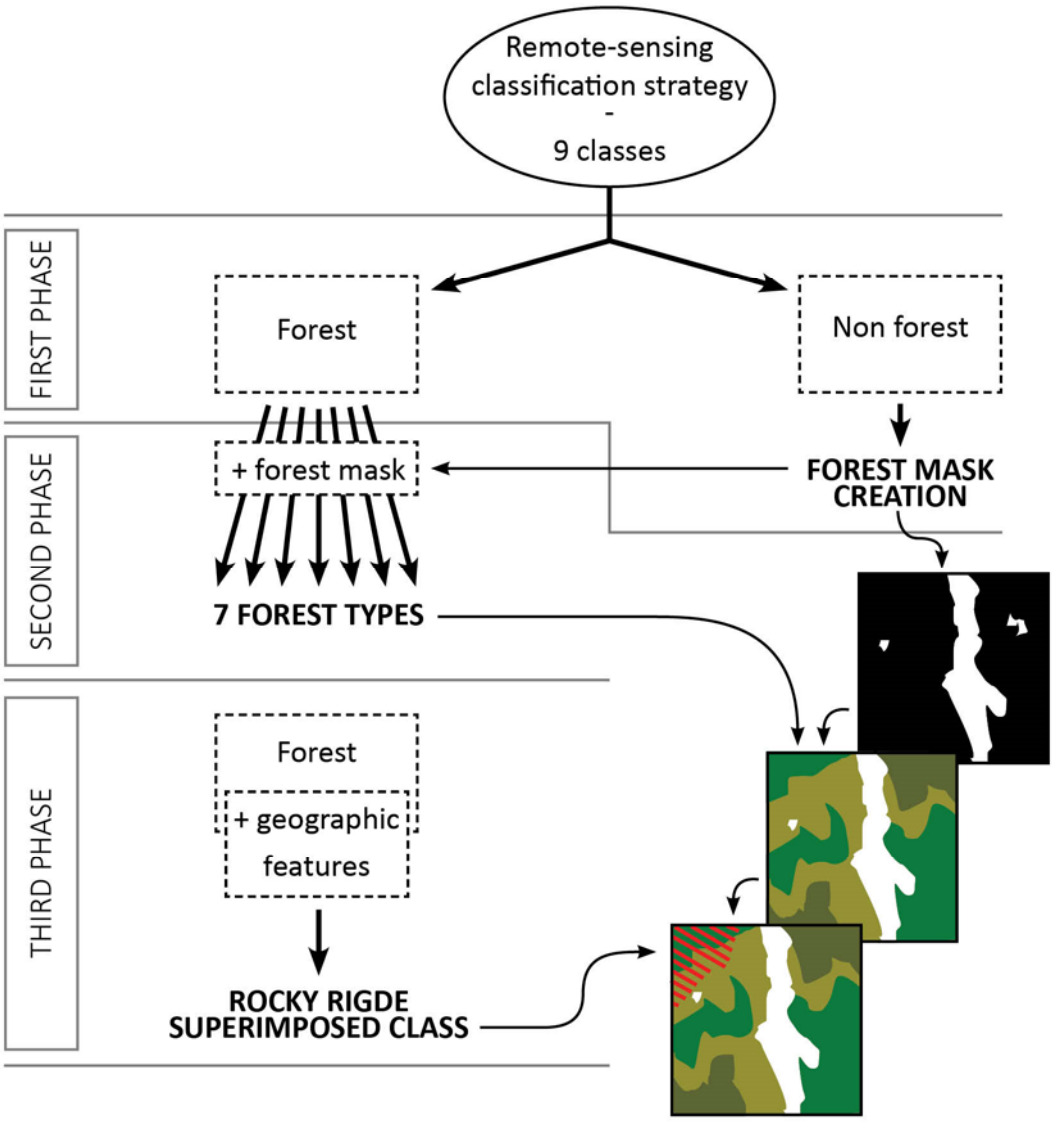


Figure 44. Remote sensing classification workflow in three phases.

5.5.4. Dataset composition

Object-based and pixel-based approaches need to use the same features to be properly compared. For the object-based method, mean value from all S1 features have been calculate in every segmented polygon and then rasterized to complete the dataset. On the other hand, all the features used for the pixel-based classification have been filtered through Haralick's textural indices which minimize textural heterogeneity in the canopy.

Here is the complete list of features for both object-based and pixel-based method:

- **Object-based dataset** (mean value of all features in segmented polygons)
  - Sentinel-2 mean reflectance from dry season 2018:
    - Bands 5-6-7-8a-11-12
  - Sentinel-1 mean backscattering 2018:
    - Bands 1-2-3
  - Texture extraction from Haralick's GLCM of S1 mean backscattering 2018:
    - Band 1-2-3: energy
    - Band 1-2-3: homogeneity
    - Band 1-2-3: sum average
  - Sentinel-1 backscattering deviation between dry and wet seasons 2018:
    - Bands 1-2-3
  - Mean value from Haralick's GLCM in a 100x100 moving window of the Topographic Position Index (only for rocky ridge superimposed class):
    - 8-bits rendered value raster

- **Pixel-based dataset**
  - Mean value from Haralick's GLCM in a 15x15 moving window of Sentinel-2 imagery mean reflectance from dry season 2018:
    - Bands 5-6-7-8a-11-12
  - Textural extraction from Haralick's GLCM in a 15x15 moving window of Sentinel-1 mean backscattering 2018:
    - Bands 1-2-3: mean
    - Bands 1-2-3: energy
    - Bands 1-2-3: homogeneity
    - Bands 1-2-3: sum average
  - Mean value from Haralick's GLCM in a 15x15 moving window of Sentinel-1 backscattering deviation between dry and wet seasons 2018:
    - Bands 1-2-3
  - Mean value from Haralick's GLCM in a 50x50 moving window of the Topographic Position Index (only for rocky ridge superimposed class):
    - 8-bits rendered value raster

5.5.5. Training and validation samples

Training samples used in the following classification are all delimited by photointerpretation, away from the validation samples, to represent every forest type for further classification. The 204 acquired field samples have been useful to describe forest types and are also used as validation samples to calculate model accuracy. For the forest mask, 76 additional non-forest field samples collected by Dorian Lessire[29], are also used as validation data.

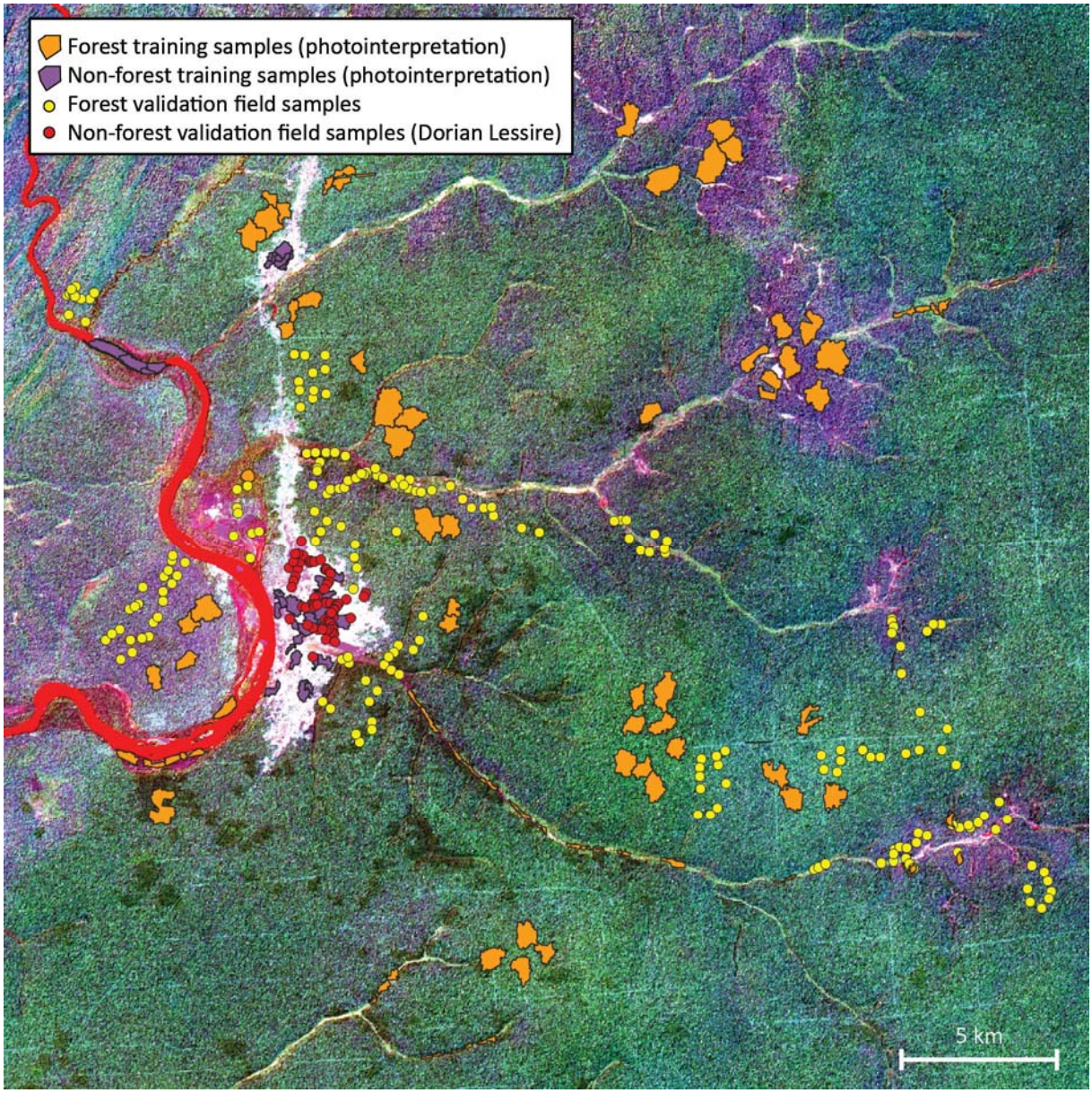


Figure 45. Figure X. Set of the 60 x 60 m samples acquired (n=204) during the field campaign in the APDS around Bayanga, and localization of the additional regions of interest delimited as training samples afterwards (background: Sentinel-2a image from the 11/01/2018, used as road map in situ.

[29] Student at UCLouvain working on the full land cover of the same study area.

Field conditions were decisive in sample collection and determined their spatial distribution. The closest and most accessible places were first visited to ensure a minimum number of samples in every class. As a second step, heterogenous forest types like semi-deciduous primary forest, and old and young secondary forests were way more visited then others ones, mainly because sample acquisition was combined with forest documentation. On the other hand, forest types such as evergreen primary forest, low and high riparian forests were very recognisable and didn't need lots of tours to be properly documented. Otherwise, outposts located east of Bayanga allowed us to spend the night in local accommodations and then access further areas in one day walk. The rocky area was only accessible by boat (northwest samples on the map above), this why only nine samples correspond to that class, all acquired in one day.

5.5.6. Classification accuracy assessment

A confusion matrix is generated with every classification. All validation samples acquired on the field matches with a corresponding forest type described for this work. The confusion matrix details where every validation sample has been classified and gives quantitative evaluation of the model performance. Mitchell (2018) detailed how errors in a confusion matrix can come from either deficiencies in the data (inaccurate sample) or model misspecification (inaccurate classification). As the map accuracy has to be performed by comparison to a reference dataset and as no previous relevant forest type classification has been found of the study area, the accuracy assessment is fully dependent on the field samples for this work.

Table 4. Assessment method with a confusion matrix to evalutate the accuracy of classification model: F-scores and overall accuracy calculations (from Fawcett, 2005).

	Class 1	Class 2	Class ...	Class j	**User's Accuracy (UA %)**
Samples 1 (corresponding to class 1)	$Samples\ 1_1$	$Samples\ 1_2$	...	$Samples\ 1_j$	$Samples\ 1_1 \Big/ \sum_{x=1}^{j} Samples\ 1_x$
Samples 2 (corresponding to class 2)	$Samples\ 2_1$	$Samples\ 2_2$	...	$Samples\ 2_j$	$Samples\ 2_2 \Big/ \sum_{x=1}^{j} Samples\ 2_x$
Samples ...	...	...	...	...	...
Samples i (corresponding to class j)	$Samples\ i_1$	$Samples\ i_2$	...	$Samples\ i_j$	$Samples\ i_j \Big/ \sum_{x=1}^{j} Samples\ i_x$
Producer's accuracy (PA %)	$\frac{Samples\ 1_1}{\sum_{y=1}^{i} Samples\ y_1}$	$\frac{Samples\ 2_2}{\sum_{y=1}^{i} Samples\ y_2}$	...	$\frac{Samples\ i_j}{\sum_{y=1}^{i} Samples\ y_j}$	

F-score of each classes	**Overall accuracy**
$= \frac{2}{\frac{1}{UA} + \frac{1}{PA}}$	$= \sum_{y=x=1}^{i,j} Samples\ y_x \Big/ \sum_{x=1}^{j} \sum_{y=1}^{i} Samples\ y_x$

Two main quantitative indicators are used to assess the accuracy of evaluated methods: F-scores and the overall accuracy. In addition, producer's accuracy will only be used to describe rocky ridge classification.

The F-score is calculated from the User's Accuracy (also called recall) and the Producer's Accuracy (also called precision) of each class, both corresponding to the percentage of samples classified in the corresponding class divided respectively by the total sum of the same samples; and by the total sum of samples in the same class. F-score corresponds to the harmonic mean between those two values and measures the accuracy of a single class in a model.

The overall accuracy represent the proportion of validation samples well classified in every class in relation to the total sum of all validation samples. The model accuracy it gives the probability of every field samples to be classified in the corresponding forest type.

Forest types represent different percentages of the study area, which do not always correspond proportionally to the number of samples acquired in every class. As no reference map is available to process map accuracy, weights can be attributed to each sample types corresponding to every class, according to their extent. For an example, if a forest type covers 50% of the map, the number of its validation sample has to be corrected to represent 50% of the validation dataset. Weighted validation samples enable to calculate the map accuracy, which gives the probability of every pixel of the map to be classified in the corresponding forest type.

6. Results and discussion

To evaluate the potential of the object-based and the spatial-filtered pixel-based datasets, every classification is executed twice to experiment both inputs. For each classification, a quantitative assessment is realised to evaluate model performance through the overall accuracy and F-scores of each classes. The results are also discussed and set into the context by mentioning the limited acquisition of field samples and the imprecisions related to field conditions and sample acquisitions. Two more qualitative visual approaches are made for every classification to evaluate the geographic consistency and the graphical rendering of every output map, with a view to its use as a valuable tool.

6.1. Forest mask

The forest mask has been first realised to remove non-forest land cover, irrelevant to this work, and to focus further classifications on forest cover. For the classifications of the two datasets to be fully comparable, the same regions of interest have been chosen to train models. Those ROI have been delimited to cover equally object- and pixel-based datasets in a relevant way. The binary classification models show high scores of respectively 97% and 99%. Those results must be balanced with the fact that most of the samples have been acquired in obvious classes. Moreover, misclassified samples are all located in forest edges, which exact delimitations remain ambiguous as no quantitative description of what defines forest cover have been made. This forest mask is based on mean reflectance and textural analysis and is fully appropriate for the further steps of this work, but does not reflect any tree density threshold below which vegetation is no longer considered as forest.

Table 5. Model accuracy assessment from object-based and pixel-based datasets for the forest mask classification.

	Object-based classification		Pixel-based classification	
	F-scores	Overall accuracy	F-scores	Overall accuracy
Forest	98%	**97%**	99%	**99%**
Non-forest	95%		98%	

The following figures illustrate how segmented images reveal coarser cut in the progressive transition from the dense forest to clearances and villages. Object-based classification depend on the level of segmentation, which attributes textured values to intermediate objects half on the forest limit. The F-scores of the non-forest class correspond to this observation: from 95% object-based to 98% pixel-based, the second dataset provide a more accurate classification of the non-forest areas and create smoother and more natural edges by including holes and clearances regardless to their spatial context.

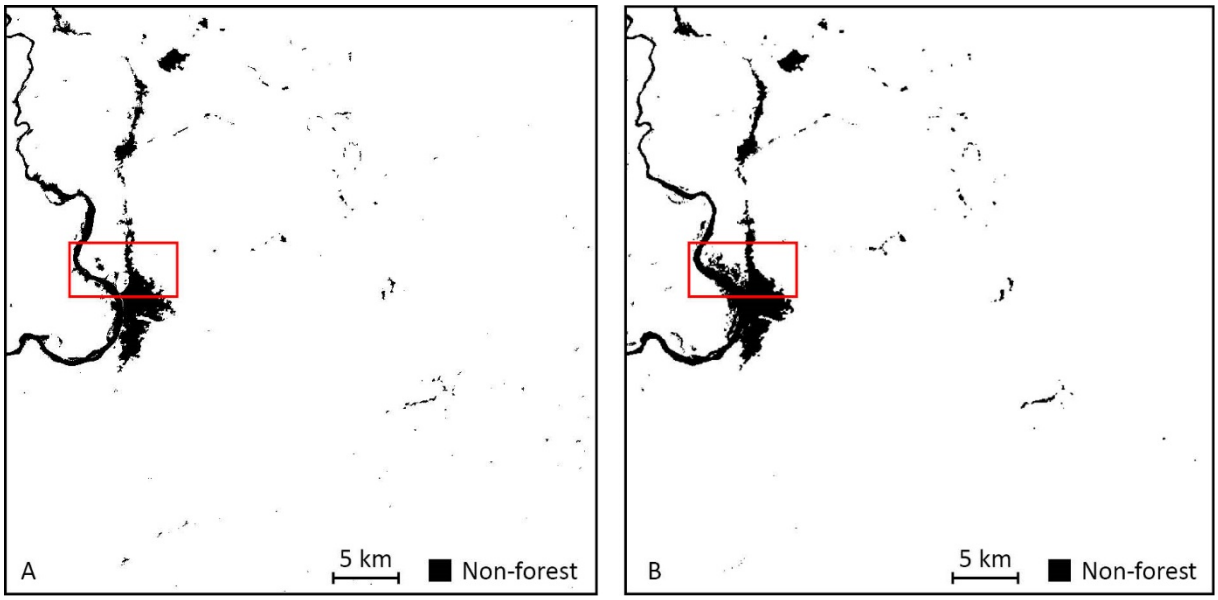


Figure 46. Forest masks created (A) object-based and (B) pixel-based.

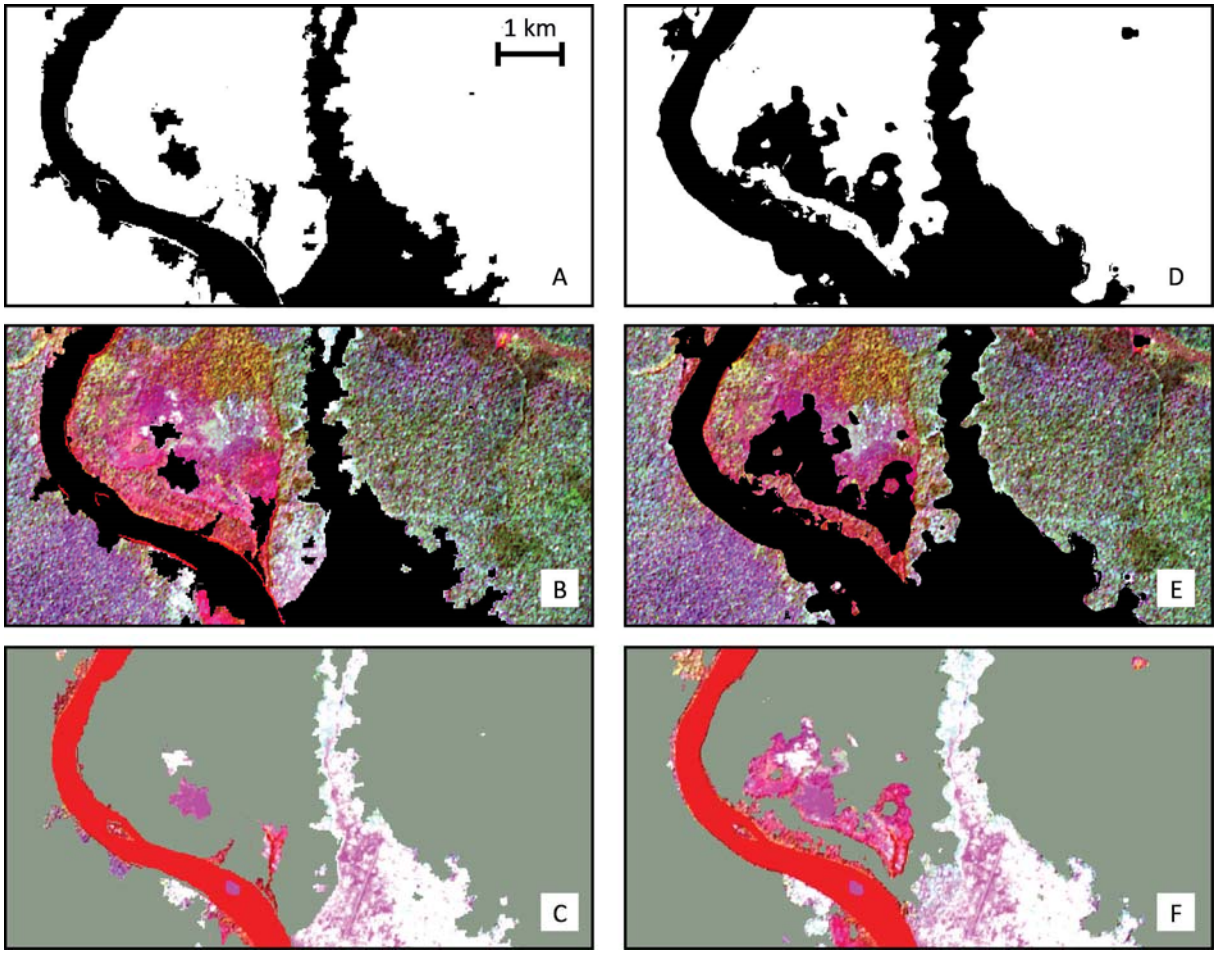


Figure 47. Focus on the northern limit of Bayanga and the swampy Mossapoula river's mouth (contributing to the Dzanga river) for qualitative evaluation of the object-based and the pixel-based classifications.
Left column (object-based classification): (A) Forest mask with (B) forest patches included and (C) non-forest patches included.
Right column (pixel-based classification): (D) Forest mask with (E) forest patches included and (F) non-forest patches included.

6.2. Forest types

6.2.1. Preliminary classifications

The same regions of interest have been used as a starting point from the forest mask, allocated over the 7 main forest types, to train classification models. Several tests have been processed and those training samples have been adjusted or extended to provide the best results possible. Successive classifications can be improved by adding training samples in areas where classification creates incorrect land cover. When adding a new sample leads to an overrepresentation of the referred class, the model indicates that the samples assigned to the class includes a too wide range of the feature values and must be reduced to a more specific focus.

The training sample adjustments have been realised through several trials and errors to obtain the weighted overall accuracies of 80.6% for the object-based classification and 72.4% for the pixel based classification. Weighting classes increases the overall accuracy by 15% for the object-based method, mainly due to the tree main classes: old secondary forests, primary semi-deciduous forest and young secondary forest. Before weighting, the three of them obtain high F-scores between 70 and 80%, and represent 93% of the surface area.

From the same model overall accuracies of 65.2%, the two classification obtain a very different map accuracy after weighting, which illustrates how the accuracy assessment can transform medium to high results, according to the method used. As weighted F-scores produce very high unrealistic values next to the model overall accuracies, unweighted model F-scores are kept to assess class accuracies.

Table 6. Model and map accuracy assessment from object-based and pixel-based datasets for the forest type classification.

	Pixel-based dataset		Pixel-based dataset	
Classes	F-Scores	Weight	F-Scores	Weight
Primary evergreen	38%	1,4%	38%	5,1%
Pr. semi-deciduous	80%	16,9%	78%	20,4%
Old secondary	74%	64,2%	76%	58,3%
Young secondary	72%	12,8%	70%	13,7%
Wetland	24%	1,6%	24%	0,8%
Low riparian	64%	0,1%	67%	0,1%
High riparian	43%	2,8%	43%	1,6%
Overall accuracies	65,7%	**80,6%**	65,2%	**72,4%**

A visual qualitative comparison from both method can be made in terms of graphic representation of the territory. It reveals that object-based approach produced accurate land cover but also creates artificial land shapes, tending to streamline reality and attenuate heterogeneous canopies. Object-based approach provided a coarser classification but also recreates textural irregularities in canopies, providing a more natural understanding of forest heterogeneity.

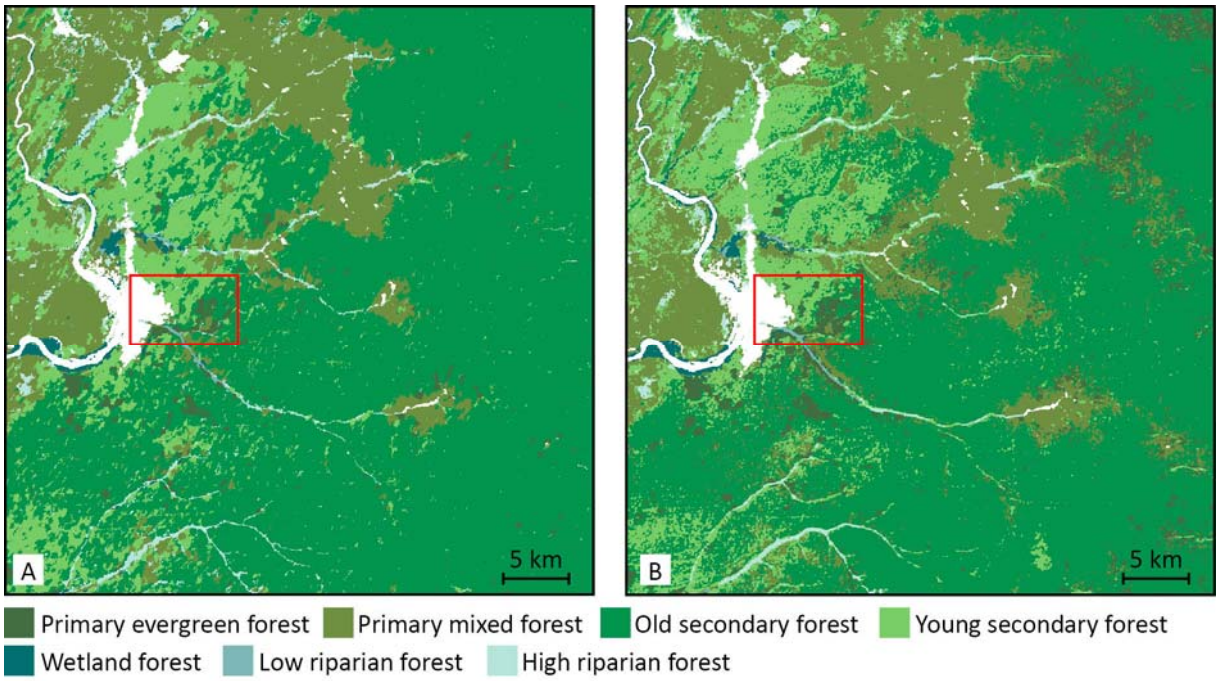


Figure 48. Forest types classified (A) object-based and (B) pixel-based.

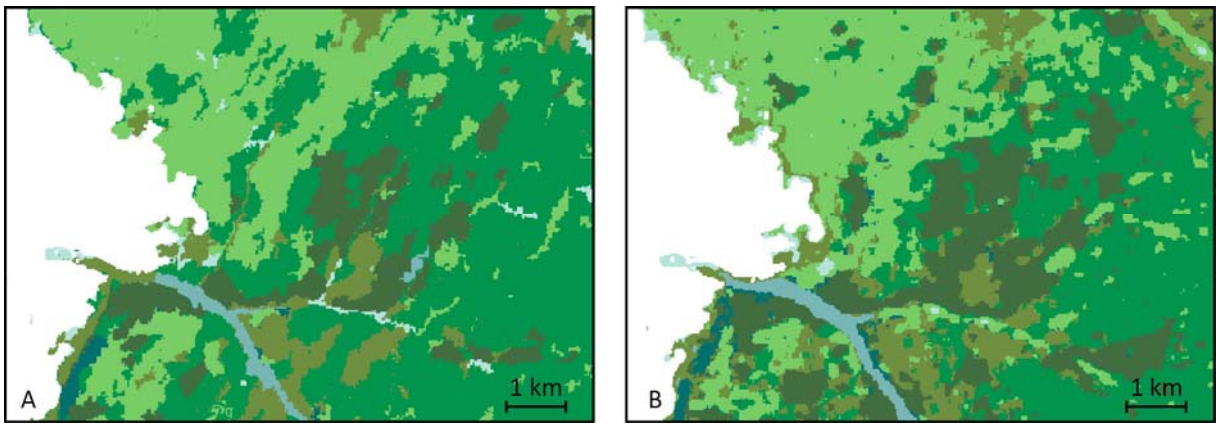


Figure 49. Focus on the eastern limit of Bayanga and the small valleys drilled by Yandoumbe's river (contributing to the Dzanga river) for qualitative evaluation of the object-based and the pixel-based classifications.
(A) Object-based forest type classification; (B) pixel-based forest type classification.

6.2.2. Morphologic comprehension of classes

Classification and accuracy assessment must be balanced with an additional factor related to field conditions: misclassified sample acquisition due to inaccurate comprehension of encountered forest types. Canopy structure is the main element taken into account to discriminate forest types by remote sensing. Forest types including hydromorphic, topographic or soil descriptions which differentiate them from one another won't be relevant if a dense canopy hides those characteristics from sensing.

Constraints from sample acquisition and field geomorphology affect F-scores while visual evaluation can be fully acceptable: wide patches of primary evergreen forest appears to be well classified in exported maps but some related samples have been taken in too small stands, which tends to be nested in the surrounding class, in both object-based and spatial-filtered pixel-based approaches.

More specifically, samples taken in primary evergreen forest tends to be classified as semi-deciduous primary forest, which indicates indeed a wrong large-scale perception of monospecific forest stands, or the presence of small patches of monospecific stands in semi-deciduous forests. Several samples are also classified as wetland, expressing the situation where primary evergreen forest is floodable.

Wetlands and low riparian forests are also very misclassified because of their heterogenous canopy, taking different forms and corresponding to variable feature values. Those types of vegetation make it very difficult to train without producing a model where flooded areas appears everywhere on the map. Finally, the narrowness of high riparian forests induces misclassification mainly for two reasons. In the object-based approach, the forest type classification is fully dependant to the accuracy of the segmentation, which can be relevant and delimitate objects properly, or too coarse and completely erases the existence of small streams. In other case, the stream is not event visible on the image, its presence is only discernible through the canopies because of the reduction of foliage's density. If so, high riparian forest tends to be classified as young secondary forest with a feature signature similar to sparse forests. These observations confirms that field experience is very important to produce objective validation data, and also to recognize relevant samples from ambiguous spots. For the accuracy assessment to be fully effective, more samples should be taken in a more relevant way, for an example by acquiring 50% of obvious located samples, and the other 50% in small patches, edges or uneven terrain. On the other hand, the classification of a streams tends to show that the best validation system would be to collect observation data at regular intervals along their whole lengths.

As misclassified samples collected in specific forest types tend to be mostly attributed to one other particular class, what the model will classify as part of the class tends to illustrate

what forest morphology is actually included in in every class. Therefore, high riparian forest is the only type which is always scattered through the whole map in every classification, in places where rivers obviously don't stream (hill peaks, wide hillsides, visited forest hedges). Instead of concluding to an inaccurate model calibration, the class must be reinterpreted as open forests. The vegetation cover described for high riparian forest matches for wide clearance and sparse forests where canopy tend to be very open with a very dense bush/herbaceous layer. This class will be renamed for the final classification.

6.2.1. Classification as training samples

To ensure well classified training samples, intersection between classes of the two classification described above have been selected as training samples, to train new models.

For those next classifications, the mean extent of each class from the two previous classification are considered in sample weighting. The final map accuracies are lower than previous classification, with 77.1% for object-based and 70.7% for the pixel-based, but F-scores now testify to better representativeness of each class. Only wetlands remain inferior to 50%, which confirm the fact that the class and related samples have been described imprecisely.

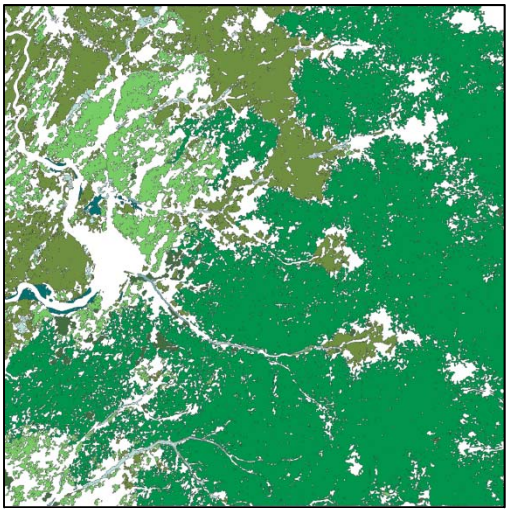


Figure 50. Training samples used for the final forest type classification: made from the intersections between the object-based and pixel-based previous classifications.

Table 7. Model and map accuracy assessment from object-based and pixel-based datasets for the final forest type classification.

	Object-based dataset		Pixel-based dataset	
Classes	F-Scores	Weight	F-Scores	Weight
Primary evergreen	50%	3,3%	50%	3,3%
Primary mixed	78%	18,7%	84%	18,7%
Old secondary	78%	61,2%	72%	61,2%
Young secondary	67%	13,3%	63%	13,3%
Wetland	28%	1,2%	30%	1,2%
Low riparian	59%	0,1%	56%	0,1%
High riparian	55%	2,2%	50%	2,2%
Overall accuracies	65,7%	**77,1%**	65,2%	**70,7%**

On the other hand, visual qualitative assessment is way more satisfying: both classification providing way better realistic information's about canopy texture, corresponding to natural landscapes, small valleys and degradation caused by former logging roads. With the

highest overall accuracy, the object-based classification would be considered as the best referenced map to assess further map accuracies, but the rendering of pixel-based approach appears as way more detailed with regards to small land shapes such as valleys and river streams, and will be used as main support for the final mapping.

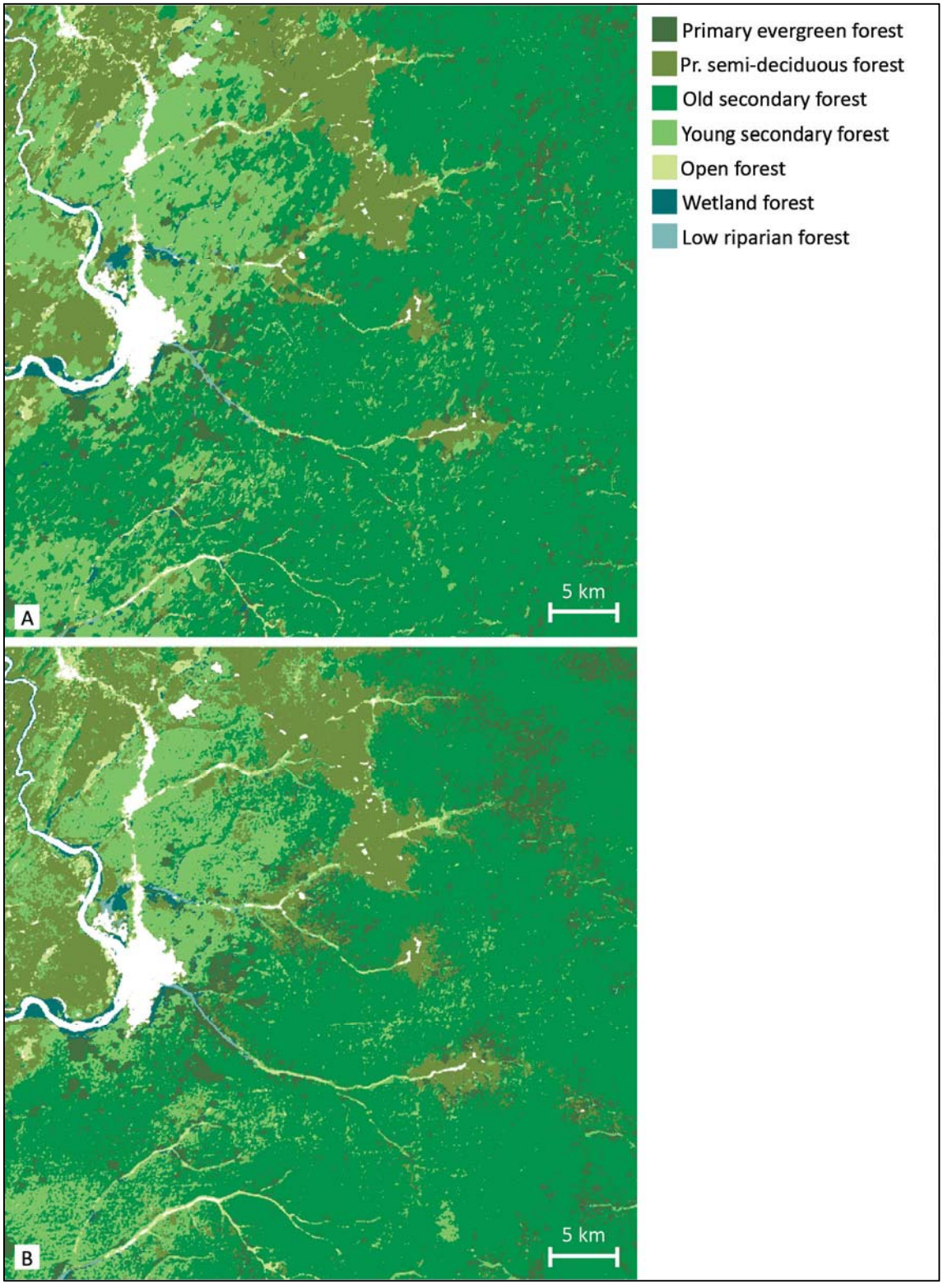


Figure 51. Forest types classified (A) object-based and (B) pixel-based.

6.3. Rocky ridges

Rocky ridge classification have been performed by adding TPI as additional feature to the dataset. The results shows that topography has been the main discriminating factor in ridge classification. Using all 204 samples to validate model, overall accuracy present incorrect high scores up to 97%, considering the fact that all non-rocky samples have been well classified. On the opposite, producer's accuracies of the two classification are very low, with 11% for object-based- and 33% for pixel-based approach, describing the situation where very few rocky area-related samples have been well classified. The main reason for that inaccuracy is that the model focuses on the highest values of the TPI, including only highest peaks. Samples acquired in the hills have all been acquired at too altitude on the slopes, and are thus all located in a maximum of 500 m from delimitated rocky areas.

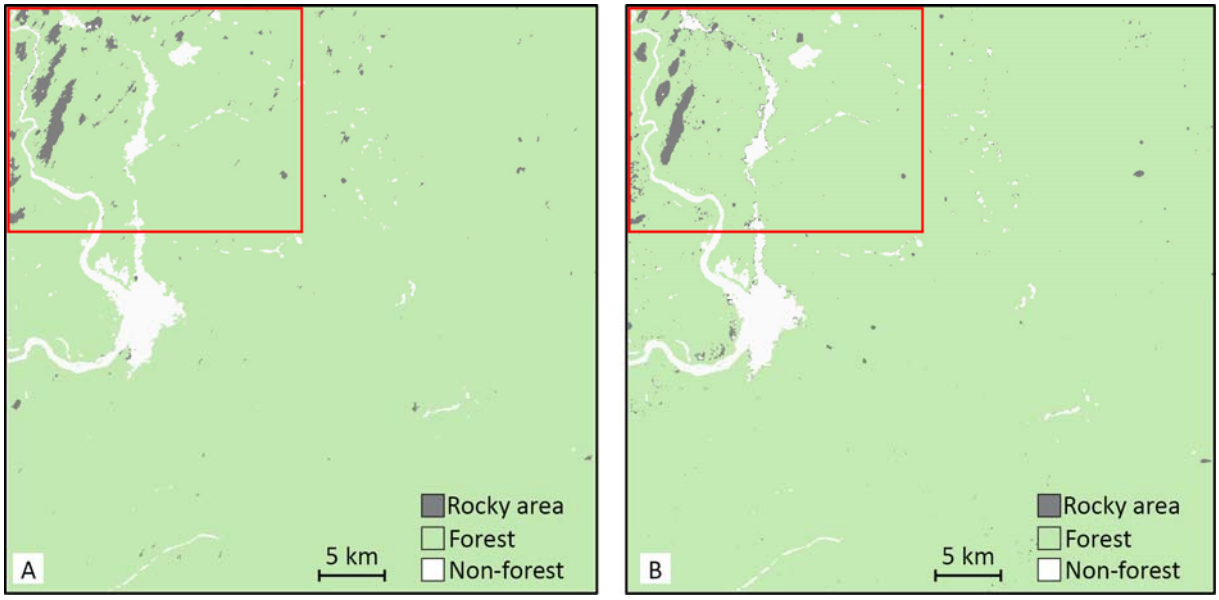


Figure 52. Rocky ridge remotely sensed (A) object-based and (B) pixel-based.

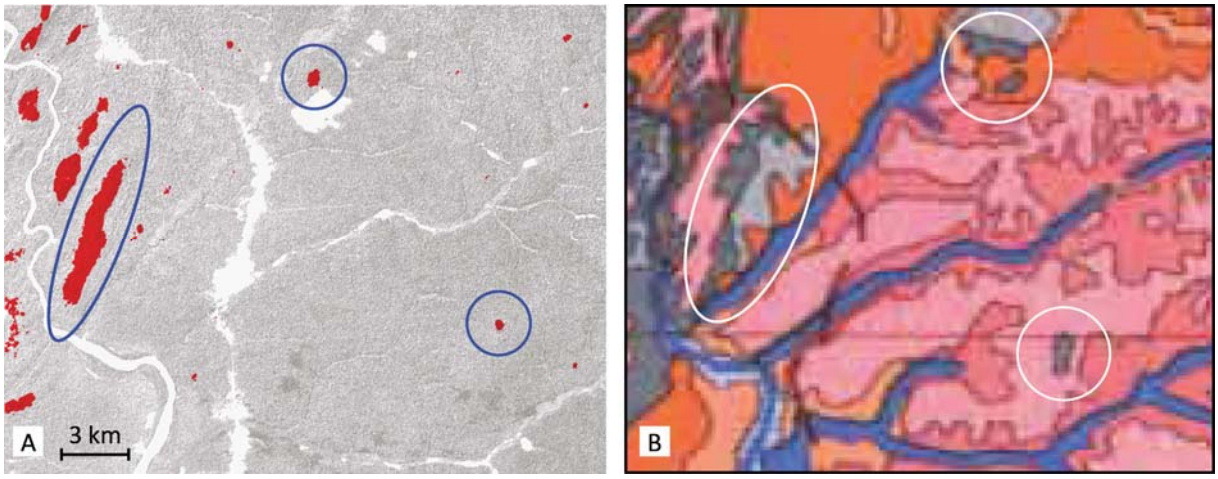


Figure 53. Visual assessment of the rocky ridge classification (intersection of both classifications) with Boulvert's pedologic map (1983).

Above, a visual accuracy assessment have been made, comparing rocky pattern intersecting the two classification with rocky outcrop on Boulvert's pedologic map (1983). It appears that the two main rocky spots revealed by the classification, east of the high well-known rocky ridges, seems to correspond to rocky areas on Boulvert's map. Just as the main western ridge on the classification occupies a narrower range than what was witnessed in the reality (rocky samples) were all in the periphery of the ridge), the spot additional evaluated spot seems way smaller than on related spots from Boulvert's map.

The same remark concerning misclassified classes from above can be applied in this context: rocky areas are covered with very heterogenous canopies and vegetation formations, unlikely classified as one homogenous class. So far, TPI was the only reliable feature for the classification. What can be deducted from output rocky patterns is that rocky land stretches way beyond the small areas of high peaks revealed by the model. To remove small artefacts essentially produced by the pixel-based method, the intersection of both classification have been processed, and patterns superior to 10 hectares selected to constitute the basic layer of rocky areas. To match rocky land cover witnessed on the field as well as getting closer to Boulvert's map information, a buffer of 500 m have been applied to the selected polygons, to constitute final delimitation of rocky areas on the map. This class extent provide an artificial overall accuracy of 100%, which would have to be properly assessed by collecting validation samples in the revealed rocky area in the eastern remote places.

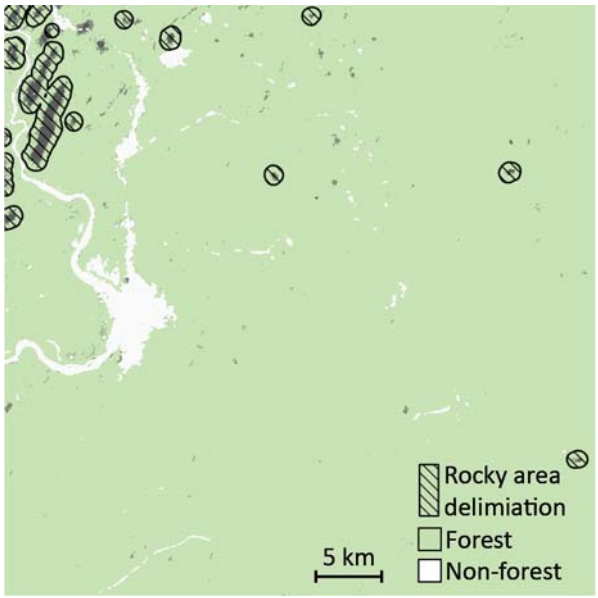


Figure 54. Final delimitation of rocky ridges, superimposed to forest types in the final mapping of the area.

7. Complete land cover

Combing all three classification phases, a full land cover mapping have been produced and provided a significant geographic tool for the region. Quantitative accuracy assessment showed quite low results (71% map accuracy for forest types) despite detailed representation of the territory items and good visual qualitative assessment. Validation method and forest type descriptions must be completed and maybe differently developed and described to achieve high model and map overall accuracies.

The map below combines a non-forest mask with a forest stratification layer, superimposed by the rocky area layer. A majority filter have applied to forest types using a 3x3 moving window in order to remove eventual salt and pepper effect and create a more compact patterns. The Dzanga River, mains roads and contours have been added to illustrated geographic and territorial landmarks. Non-forest class includes the rural complex, the main roads, the clearance and the savannah, all constituted by a combination of sand, grass and bare or artificial field.

DZANGA PROTECTED AREA
Forest stratification
(APDS, Central African Republic)

1/ 140.000e

N

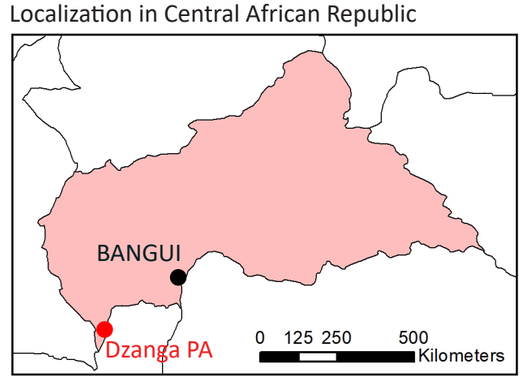
0 2 4 8 Kilometers

- Evergreen primary forest
- Semi-deciduous primary forest
- Old secondary forest
- Young secondary forest
- Open forest
- Non forest
  - Rural complex
  - Main roads
  - Clearances
  - Savannah
- Wetland
- (Low) Riparian forest
- Dzanga River
- Rocky areas

Universal Transverse Mercator Projection
System: WGS 1984 UTM Zone 33N
Datum: World Geodesic System 1984

UCLouvain/AGRO/ELIE/Geomatics
August 2019

Localization in Central African Republic



Author: Baptiste DELHEZ

CONCLUSION

In the context of the RIOFAC's initiative to improve monitoring services in the Congo Basin, a state of the forest in the surrounding of Bayanga (Central African Republic) have been established in partnership with the WWF organization. This work achieved the objective of combining optical and SAR imagery from Copernicus programme in order to characterize forest types in the surroundings of Bayanga and the nearby Dzanga protected area. Remote sensing methodology have proven to be a very fast and accessible way to map wide areas where access remain uncertain.

The output product is a full land cover of the study area produced out of very high resolution imagery from Sentinel-1 and -2. One year S1 archive and one dry season (3 month) of S2 archive constitutes the main source material to complete this study. On the land cover map, the Dzanga Rivers, main roads and contours have been added as landmarks to create a useful geographic tool.

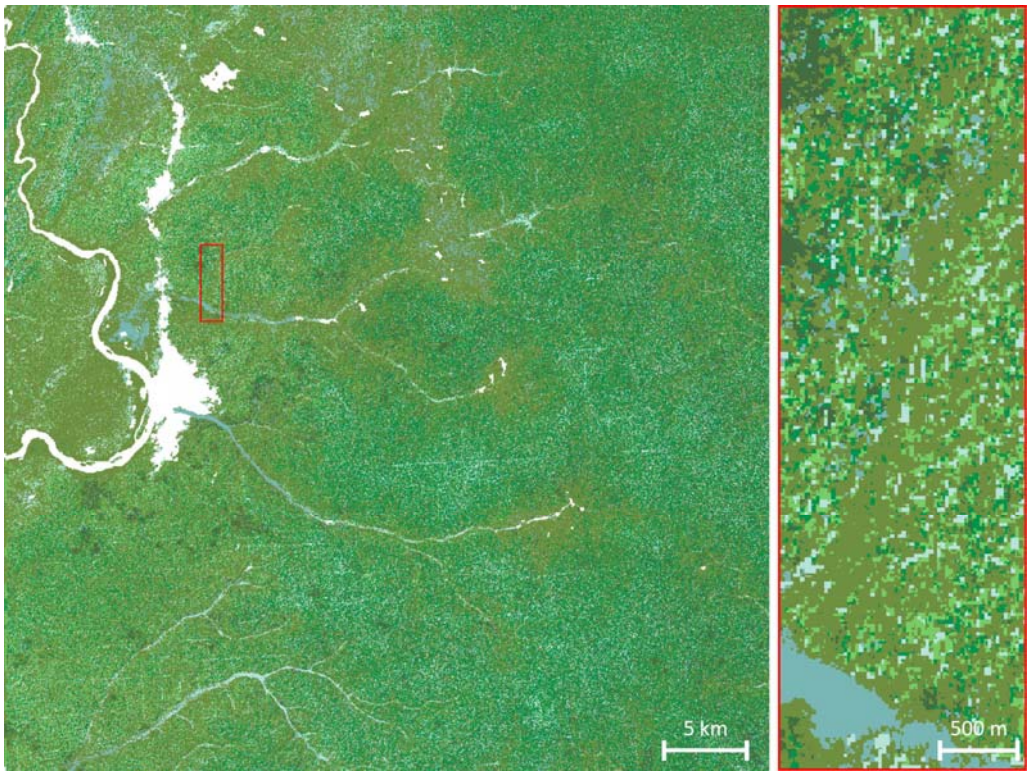
As a new forest typology have been created, the next step would the validation assessment from the local WWF and Bayanga's inhabitants. Uncertainty in forest type classification and rocky area determination revealed the lack of relevance from field-acquired validation samples. The final map showed debatable overall accuracies: model accuracy of 99% for the forest mask, map accuracy of 71% for the forest types and evaluated map accuracy of 100% after post-processing of the rocky patterns revealed in the classification.

The superimposed class revealed itself as a good way to integrate a transversal forest type, not strongly correlated with canopy structure, but defining proper field characteristics. This methodology illustrates how forest types classification can first focus on canopy covers and structures, while field indicator related to topography or hydromorphy can constitute superimposed patterns defining subtypes of in the forest.

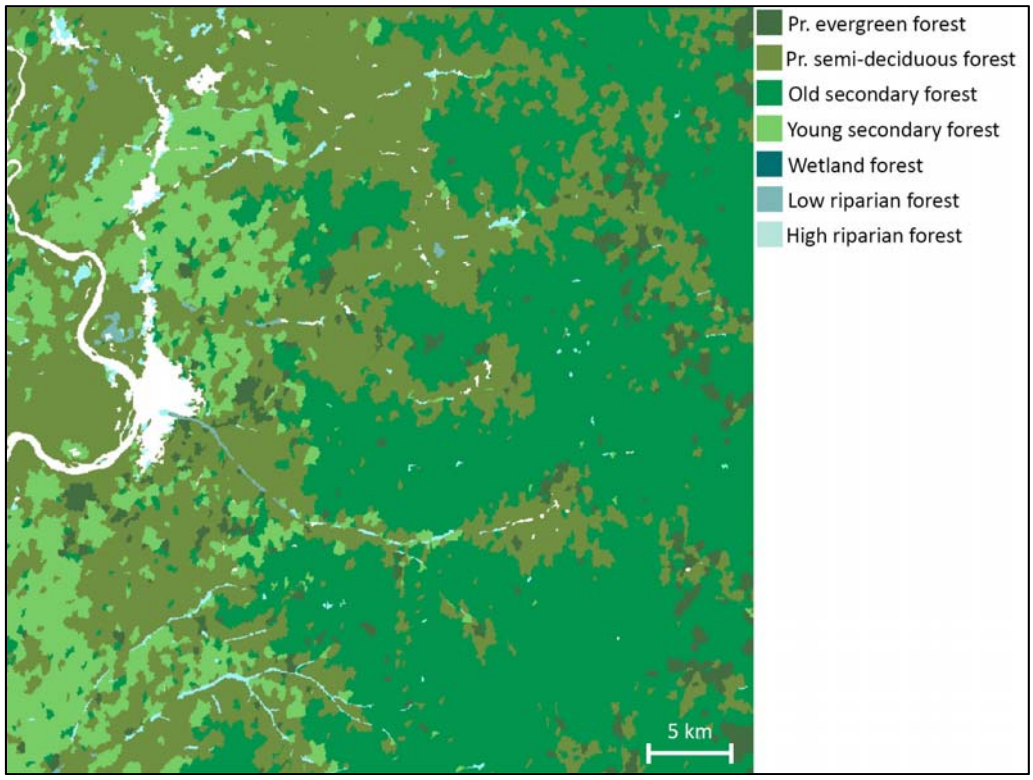
As this work represent a full methodology to develop and map forest stratification in a remote tropical region, every step from field sample collection, satellite data acquisition, classification method and validation assessment can improved by field and methodological experience.

An extensive further work would allow to specify a field protocol providing relevant validation dataset in sparsely documented regions. The whole classification method could also be simplified by determining discriminating features during the process and reduce the energy and time given to dataset production. New projects in similar environments could be the opportunity to increase the potential of near-real time mapping by remote sensing.

APPENDICES



Appendix 1. Pixel-based classification using unfiltered images revealing unclear output map.



Appendix 2. Coarse classification induced by coarse image segmentation.

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TROPICAL FOREST TYPE MAPPING BY REMOTE SENSING USING C-SAR AND OPTICAL DATA FROM SENTINEL-1 and -2

Baptiste DELHEZ

The Congo Basin forest is the second largest tropical ecosystem in the world. As global changes and anthropic degradation continually increase pressure on this valuable lung for the planet, monitoring programmes and protected areas are established in order to protect wildlife and ensure the sustainable development of forest-related activities (logging, slash and burn farming, inhabited area extension…).

Monitoring large territories require up to date documentation. In wide inaccessible areas, remote sensing appear as a major asset to produce accurate and objective land cover mapping without travelling through entire regions. The recent European Earth Observation Copernicus programme now provides free satellite imagery from – among others – Sentinel-1 and Sentinel-2 platforms. Very high resolution C-SAR and optical data are accessible and represent valuable data in Earth Observation domains. Those remotely-sensed data also constitute excellent raw material for current mapping programmes.

Since 2017, the RIOFAC project has been reinforcing and institutionalizing the OFAC (Observatory of the Central African Forest) by increasing its monitoring capacity of the forest, climate and biodiversity. For the mapping expertise, the UCLouvain has been consulted to produce a wide land cover of the entire Congo Basin, following many references in the remote sensing field.

From a partnership with a local WWF organization located in Bayanga (Central African Republic), the APDS region has been chosen as study area, to describe the actual forest stratification, develop a forest typology and produce a forest-type mapping by remote sensing. The output product of this master thesis is a full land cover of the study area produced out of very high resolution imagery from Sentinel-1 and -2.

As this work represent a full methodology to develop and map forest stratification in a remote tropical region, every step from field sample collection, satellite data acquisition, classification method and validation assessment can improved by field and methodological experience.

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