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Characterizing tropical forest dynamics by remote-sensing using very high resolution and Sentinel-2 images
(Upper Pulangi, Mindanao, Philippines)

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ANNs	Artificial Neural Networks
ASM	Angular Second Moment
BRDF	Bidirectional Reflectance Distribution Function
CARTs	Classification And Regression Trees
CCILC	Climate Change Initiative Land Cover
ESA	European Space Agency
ESSC	Environmental Science for Social Change
FOTO	Fourier Transform Textural Ordination
GFW	Global Forest Watch
GLCM	Grey Level Co-occurrence Matrix
IFSAR	Interferometric Synthetic Aperture Radar
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multi-Spectral Instrument
NDVI	Normalized Difference Vegetation Index
PCA	Principal Component Analysis
RF	Random Forest
SST	Simple Statistical Transformation
SVM	Support Vector Machine
SWIR	Short-Wave InfraRed
UAV	Unmanned Aerial Vehicule
VHR	Very High Resolution
WRI	World Ressource Institute

Introduction

Tropical forests are a major ecosystem on Earth as they play a crucial role in the biosphere by stocking carbon and hosting a rich biodiversity. However, this ecosystem is under an increasing pressure due to anthropogenic degradations. Human activities such as logging, farming and mining reduce tropical forest cover and therefore their ecosystem services. Among those activities such as selective logging or shifting cultivation, not always result in forest clear cut, but rather in forest degradation stages. Degraded areas can eventually regenerate and evolve through different regeneration stages, which results in what is called forest dynamics. Besides forest cover, it is thus important to look at these forest dynamics stages to consider forest condition in a monitoring process.

Given that forests represent vast areas often located on rough terrain, they are generally not easily accessible. Large *in situ* observation required for forest monitoring are therefore difficult to achieve, costly, and spatially limited. Unlike on-site observations, remote sensing is the acquisition of information without making physical contact with the object or area being observed. Remotely-sensed data is therefore widely used in forest monitoring processes, from local to global scale.

The new high resolution (10-20 m) Sentinel-2 satellites from ESA Copernicus program designed for vegetation observation shows a potential for forest monitoring, with ten spectral bands including six dedicated to vegetation (four red-edge bands and two short-wave infrared bands). Its five days revisit time allows the use of dense time-series.

The objective of this study is therefore to investigate Sentinel-2 potential for forest dynamics monitoring. In order to achieve this aim, it is required to develop a method to identify and map forest dynamic classes based on Sentinel-2 time-series, and assess its performance. To do so, dynamics at stake in the study area must be characterized, and a forest typology suitable for investigation of monitoring performance has to be established. The comparison of Sentinel-2 performance with results obtained using very high resolution (VHR) data will allow to confront this new data to a spatially sharper data type that is currently used for forest dynamic monitoring at local scale.

This master thesis is part of a collaboration with the Environmental Science for Social Change (ESSC) organization, based in Malaybalay (Mindanao, Philippines), as part of the LUCID project (UCL/UNamur/ESSC). It has been the subject of a field campaign conducted with ESSC in Bendum, (Upper Pulangi, Malaybalay) from February to March 2018.

I. Literature review

1. Tropical forests

Tropical forest is the characteristic vegetation of humid tropics, present or formerly present on all lands with sufficient and well-distributed rainfall and temperatures, located between the Tropics of Cancer and Capricorn, in South America, Africa and South-East Asia. The considerable number of species present in tropical forest makes it a major ecosystem in terms of biodiversity. Moreover, the amount of carbon stored in these forests represents one of the biggest carbon stocks on Earth, which is crucial in climate change mitigation (Richards, 1996; Baccini *et al.,* 2017).

Figure I.1 - Tropical rain forest in Mindanao, Philippines. Top right a "mother tree" emerging from the canopy. In the center, a forest gap allows soft-wood fast-growing pioneer trees to grow.

1.1 Forest types

Different tropical forests types exist, which are differentiated based on criteria such as altitude, rainfall, temperature, soils and flood-ability. For instance, in terms of rainfall, one can distinguish forests located in dryer regions of the tropics. Less dense and xerophilous forests are called *savannahs*. Forests in humid areas have roots tolerant to water inundation as with *swamp forests* along rivers and *mangroves* along the coast, which are also tolerant to salt.

Finally, the *tropical rain forest*, or *evergreen forest,* is the forest type covering most of the territories cited above. This forest type should not be confused with the term *rain forest* which is more holistic and encompasses all forests receiving heavy rainfall, including some located at higher latitudes. Among the various characteristics of tropical rain forests, the main one is that a substantial proportion of the mature vegetation community is woody, even in the presence of some epiphyte species such as vines. Tree height, which can go up to 55 meters, is also an important feature. Tropical rain forests can be subdivided into altitude-related forest types: lowland forest (< 1000 m), pre-montane forest (1000-1500 m), and montane forest (> 1500 m) (Richards, 1996).

1.2 Canopy structure

Even though canopy structure may differ depending on the forest type, a general model often accepted and described by Richards (1996) is the division of forest into strata. Generally speaking, forests can be described in five strata. The first stratum is made of herbaceous and other short plants on the ground, while the second is the shrub stratum. The three last ones are tree strata, which compose the canopy itself. The upper tree layer corresponds to the emerging trees and is therefore discontinuous (**Erreur ! Référence non valide pour un signet.**). The middle one is continuous and forms the canopy itself, with wide tree crowns. The lowest layer is comprised of spindly and irregular crowns (Richards, 1996).

1.3 Forest dynamics

Natural forest dynamics are characterized by decay and regeneration phases. In terms of decay, canopy gaps form naturally, with the main cause being the falling of large trees. A single tree can make a considerable gap of several hundred square meters and drag down other neighboring trees. Some larger areas can be cleared by natural events such as fire, intense winds, cyclones, or heavy rain leading to landslides. Trees are more likely to fall if the soil does not provide a firm anchor, meaning that tree falls are more frequent in wet climates and steep terrain with a thin soil layer (Richards, 1996). This is often referred as sylvogenetic mosaic, because of the mosaic of patches at different phases.

However, while natural forest mosaics corresponds to a dynamic equilibrium, human activities are the main driver of tropical forest decay and break this equilibrium. Logging, mining, fuelwood collection and farming lead to an overall decrease in tropical forest coverage worldwide, in terms of quantity and structure. Grainger (2013) defines degraded forest as a “temporary or permanent deterioration in the density or structure of the vegetation cover or its species composition”. It is a change in forest characteristics caused by an increase in disturbances that leads to a decreasing productive capacity.

In natural mosaics, as sometimes after anthropogenic degradation, vegetation can regrow. During what is called the “building phase”, young vegetation appears. Due to the more favorable light and rain conditions of forest gaps, those plants grow faster than the surrounding forest. The nature of vegetation regrowth depends on several parameters such as the surrounding plant communities, the soil surface state, the distance towards forested areas, the nature of the seedling bank and the illumination. Generally speaking, large and open areas with poor soil conditions will see the development of pioneer, fast-growing heliophilous species. This type of vegetation provides the shade required for slow-growing hard-wood species development, also called “pillar species”, which will form the final canopy upon maturity (Richards, 1996).

Because vegetation regrowth is part of its process, shifting cultivation (also called swidden or non-permanent agriculture) is one of the main anthropogenic drivers of forest dynamics in the tropics. After the clear cutting of a relatively small forested area, crops are grown for a few years until the area is abandoned, leading to the forest regrowth. This regrowth can be managed in a way to increase the presence of useful species for food, fiber, or medicine (Frokling *et al.,* 2009). Forest dynamics correspond therefore to different degrees of forest development.

In terms of carbon however, these sources and sinks process globally results in a net carbon loss (Baccini *et al.,* 2017). Depending on the authors, the diverse types of disturbances and vegetation regrowth are considered or not (*e.g.* selective logging is sometimes not considered). The nature of the vegetation regrowth succession is also a source of disagreement among authors.

2. Remote-sensing for forests monitoring

Unlike on-site observations, remote sensing is the acquisition of information without making physical contact with the object or area being observed. It makes use of satellites, planes or unmanned aerial vehicles (UAV) equipped with sensors to obtain data over an area or a phenomenon. Given that forests represent vast and widespread areas, often located on rough terrain, they are generally not easily accessible. Remotely-sensed data has therefore been widely used in global forest monitoring processes in the last three decades ((Achard 2002; Hansen *et al.* 2008, 2013; Achard *et al.* 2014)Achard *et al.,* 2002, 2014; Duveiller *et al.*, 2008; Food and Agricultural Organization (FAO), 1996, 2001, 2006, 2011, 2016; Hansen *et al.,* 2008, 2013).

Monitoring forest dynamic processes by remote sensing require the use of spectral, spatial and temporal measurements, with each type of indicator providing a specific type of information. These indicators can therefore be combined to better describe the occurring processes (Lambin, 1999). The user objectives, scale of the study area and image resolution are the principal factors in the selection of remotely sensed data. The user's objectives determine the scale of the study area and the nature of the classification method, and thus the suitable spatial resolution of the data (Lu et Weng, 2007).

2.1 Images used according to their spatial resolution

Remotely sensed data can be characterized by four resolution types: spatial, temporal, spectral and radiometric. The spatial resolution can be defined by the size of the smallest observable object on the ground, *i.e.* the corresponding size of a pixel (Campbell, 2002). Temporal resolution corresponds to the revisit times, *i.e.* the minimum time between two observations of a particular location. Spectral resolution refers to the number, spacing, and width of the sampled wavelength bands along the electromagnetic spectrum. Finally, the radiometric resolution is the number of different intensities of radiation a sensor is able to distinguish.

Because spatial resolution is often the most determining feature in imagery, images can be sorted depending on this characteristic: coarse resolution (1 km+), medium (30-500 m), high (5-30 m) and very high (less than 5 m). Note that this subdivision can vary between authors.

2.1.1 Coarse to medium resolution images

Because of their wide swath and for processing viability, coarse to medium resolution data are mainly used at national, continental and world scales. Their high temporal resolution (nearly daily for some data) provides ample possibilities of cloud-free observations and temporal trends.

Among the different existing global cover maps, the recent Climate Change Initiative Land Cover (CCILC) led by UCLouvain and supported by the European Space Agency (ESA) (2015) which uses 300 m resolution MERIS data provides a global view of the Earth ecosystems, including different forest classes (Figure I.2). For forests, Hansen *et al.* (2003) achieved a global forest cover map using 500 m resolution data.

However, these images are not sufficient to quantify processes occurring at smaller scales. Indeed, monitoring processes such as forest disturbances require the use of higher image resolutions, because the phenomenon involved (*i.e.* fire, windstorms, logging, shifting cultivation, etc.) most often take place at the local level (Frokling *et al.,* 2009).

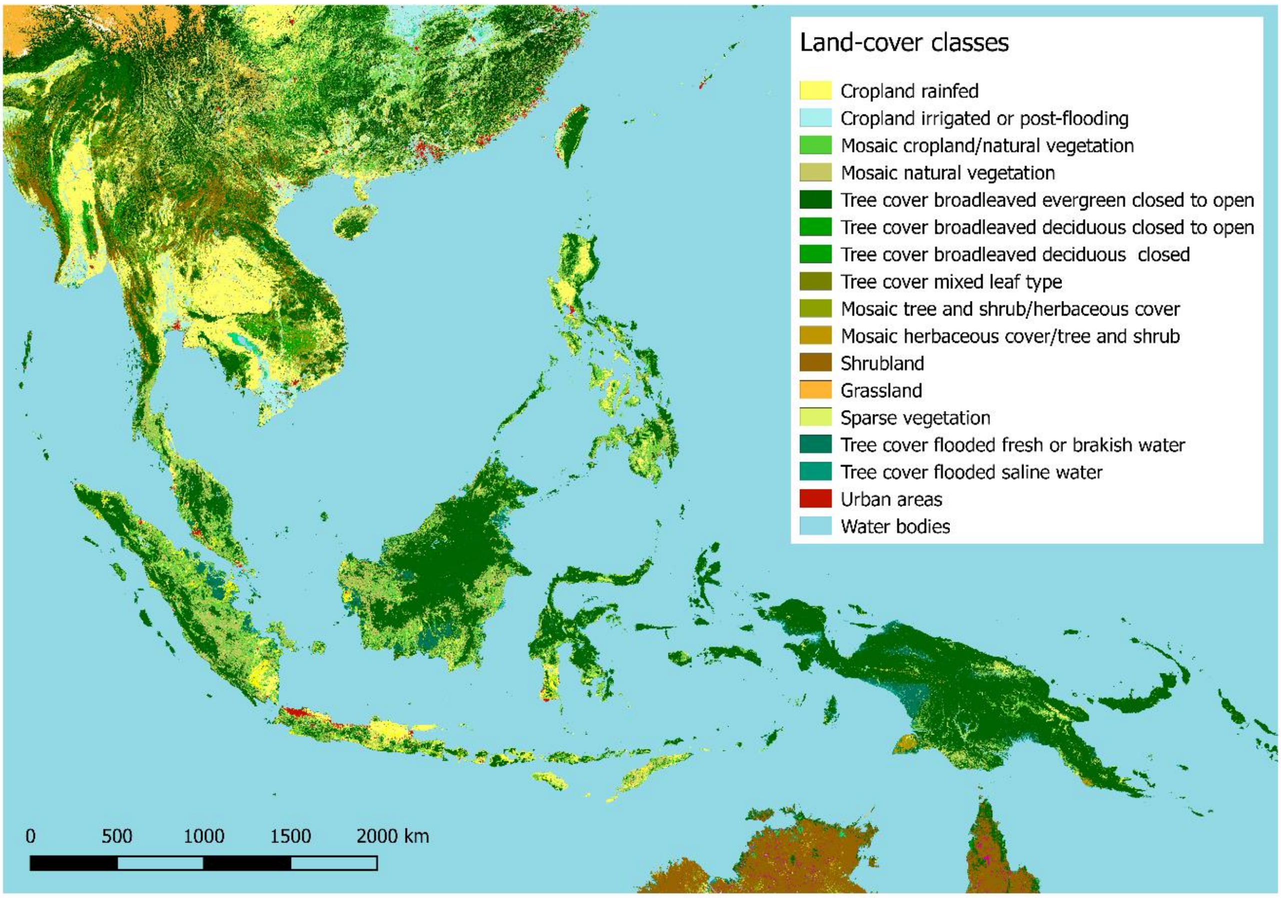


Figure I.2 - CCI Land Cover of South-East-Asia using 300 m resolution MERIS data (adapted from UCLouvain, 2015).

2.1.2 High resolution images (HR)

High resolution data, also called fine resolution data (*e.g.* Landsat (30 m), Sentinel-2 (10-20 m)) can be used to detect and map local forest processes, because their resolution suits the scale of the phenomenon well (Frokling *et al.,* 2009). The temporal resolution of HR images allows the acquisition of cloud free data and the use of frequent images for large scale process monitoring.

High resolution images are often combined with lower resolution data to quantify processes detected on these images; Hansen *et al.* (2008) combined Landsat with MODIS (250 m-500 m-1 km) data to generate tropical forest cover maps and quantify rates of forest clearing. This was later successfully achieved by using only Landsat data globally from 2000 to 2012 (Hansen *et al.,* 2013).

This resolution however, being larger than tree scale, is insufficient to extract forest canopy variables and to monitor small scale processes such as shifting cultivation or change in canopy structure.

2.1.3 Very high resolution images (VHR)

Very high resolution data (0.5m-5m) provided by space borne platforms such as IKONOS, QuickBird, Pleiades, allow a much sharper view on forests canopies. Because pixels are smaller than a tree crown, individual emerging trees can be distinguished on those images, which allows monitoring at the tree level or achieving accurate forest inventories (Wulder *et al.,* 2008; Falkowski *et al.,* 2009). Compared to coarser resolutions, VHR data allow to derive much more information from texture, which is why they are widely used (see 1.2.2 Classification methods – Texture to improve classification).

At the canopy level, VHR can lead to prediction of forest stand structure parameters, species composition, biomass estimation, local logging management, or canopy gap detection (Read *et al.,* 2003; Couteron *et al.,* 2005; Kayitakire *et al.,* 2006; Malhi & Román-Cuesta, 2008). At the tree level, variables such as top height, circumference, basal area or age can be derived from texture features on VHR images (Kayitakire *et al.,* 2009).

As of now the main limitations of VHR data are the target coverage, the cost of purchase, and the poor temporal availability which can make cloud-free images difficult to obtain in tropical regions (Frokling *et al.,* 2009). Other problems to mention are the important impact of the bidirectional reflectance distribution function (BRDF), which at this resolution can be different from one class to another as well as the topography that can cause shadowing (Barbier *et al.,* 2011).

2.1.4 The potential of Sentinel-2

The newly available Sentinel-2 (S2) images are expected to be a game-changer in vegetation observation due to its spectral and temporal characteristics designed for this purpose (Immitzer *et al.,* 2016).

Sentinel-2 satellites were recently launched (one in 2015, followed by a second in 2017) as part of the European Copernicus Earth Observation program. The combination of a high spatial resolution (up to 10 m) with a high spectral potential of 13 bands, including three red-edge bands and two short-wave infrared (SWIR) bands, makes it suitable for vegetation monitoring. The wide-swath (290 km) of its multi-spectral imager (MSI) and a five-day global revisit time for the two satellites working in tandem allow large-scale yet precise up-to-date observation (Drush et al, 2012).

Among those characteristics, its temporal resolution and the three red-edge bands are the ones that differentiate it the most from existing space borne platforms such as the Landsat program. The comparison of Sentinel-2 bands with other platforms is presented at Figure I.3.

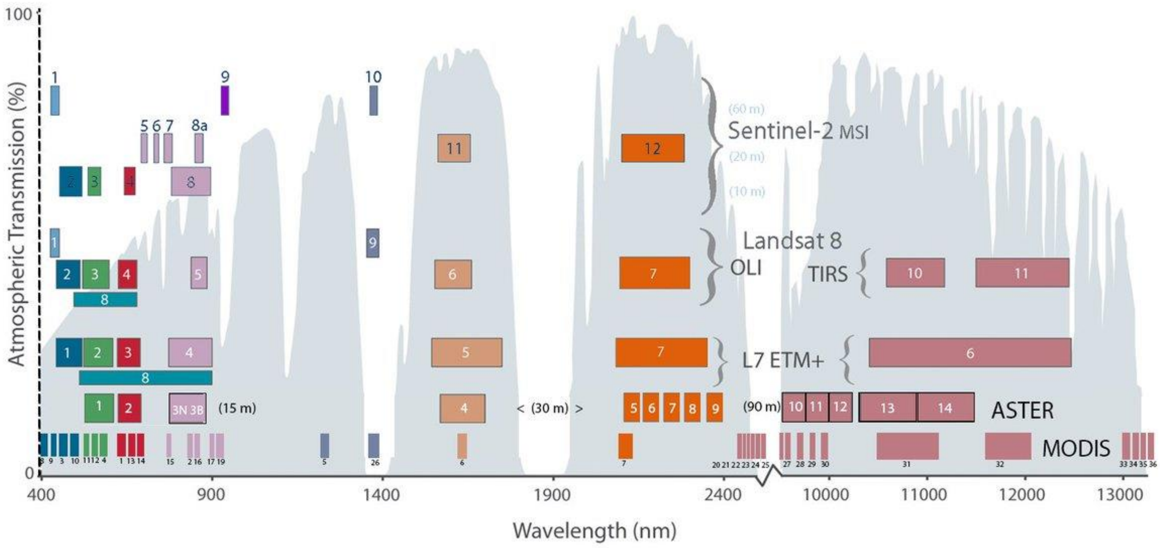


Figure I.3 - Sentinel-2 bands compared with Landsat 7, 8, MODIS and ASTER (USGS, 2017).

Immitzer *et al.* (2016) proved Sentinel-2 data suitable to map different tree species in Central Europe. Among the bands, the high value of SWIR and red-edge for forest analysis was confirmed, while the near infrared bands appeared to be the least important ones. Because Sentinel-2 data are still new, they have barely been used on tropical forest. Their potential to map local dynamic processes has not been explored by far.

Pandit *et. al.* (2018) proved Sentinel-2 data valuable to estimate above ground biomass (AGB) in community forest in Nepal.

2.2 Classification methods and related features

Besides the selection of appropriate satellite data, the classification method to be used is important as well and must be chosen according to the usage characteristics. For instance, mapping large areas requires an algorithm that can handle observation with significant noise, complex variable space, and a small number of training data relative to the size of the study area (Rodriguez et Galiano, 2012).

Classification requires the use of features, *e.g.* variables with values defining classes. Those variable values can be statistically linked to a corresponding class by classifiers. Although features are most often reflectance values for different bands on satellite data, features can be diverse and depend on the usage characteristics. In vegetation observation, vegetation indices calculated from reflectance values are widely used. In the case of forests, canopy texture features can be derived from images.

Multiple classification methods have been used to produce land cover from remotely sensed data. Classic classification methods range from unsupervised algorithms (classes are not given) such as ISODATA or K-means (cluster-based algorithms) to parametric supervised algorithms (classes are given) such as maximum likelihood. They can also be sorted in parametric (Gaussian distribution of values is assumed) and non-parametric, or per-pixel, sub-pixel and field-based. Among parametric classifiers are machine-learning algorithms, that are nowadays the main type of classifiers used in remote sensing (Lu et Weng, 2007).

2.2.1 Machine-learning classifiers

Machine learning algorithms such as classification and regression trees (CARTs), artificial neural networks (ANNs), or support vector machines (SVM) are increasingly used due to their advantages. In the case of a large and complex feature space, they have proven to be more efficient and accurate than conventional parametric algorithms (Rodriguez et Galiano, 2012). Their non-parametric nature makes them suitable for complex landscapes, with good boundary capability and a good combination possibility with other data (Lu et Weng, 2007).

However, techniques such as neural networks and support vector machines might be complicated to use due to the substantial number of parameters to adjust and the difficulty to automate them (Rodriguez et Galiano, 2012). It is also important to note that due to their computing-intensive aspect, they require important computing capacities to be used at large scales.

Machine learning classifiers can be grouped in ensemble classifier, with the same base classifier being used to produce repeated classifications of the same data. This allows to increase the classification accuracy (Breiman, 2001). The random forest (RF) algorithm is the main example of ensemble classifiers.

2.2.2 Random Forest

Within the growing pool of machine learning methods used nowadays in remote-sensing, Random Forest (RF) classifier is the most popular. It was designed by Breiman (2001) and has been successfully used in land cover classification (Pal, 2005). This method grows an ensemble of decision trees and lets them vote for the best class.

Concretely, a combination of Classification and Regression Trees (CARTs) are created where each classifier is generated using random training samples. Each decision tree is independently produced, and each node is split using a user-defined number of features. The number of trees is defined and creates a forest of decision trees. The classification is then made by averaging the class assignment probabilities calculated by each tree. This classification is then the new input for evaluation and each tree votes for a class membership. The membership class with the maximum votes is finally selected (Breiman, 2001), to assign an unknown pixel to a class (Pal, 2005).

The strength of this method comes from the high variance and low bias of decision trees due to their high number (Breiman, 2001). Advantages of Random Forest include its non-parametric nature, a high classification accuracy, its capability to determine variable importance, and most of all its capacity to handle a large number of features but which varies at each node. The latter means that the model less sensitive to noise, which is critical for large scale classifications. As the resampling is not based on weighting, it is also less sensitive to overtraining (Gislason *et al.,* 2006). The small number of parameters to be defined by the user makes it easier to handle compared to others machine learning algorithms such as SVM or ANNs (Pal *et al.,* 2005).

However, this model presents some disadvantages. Among them, the unknown split rules for classification, making the RF a "black box" classifier. Among the information given by the RF algorithm, the Gini index presents the features according to their importance in the classification process. However, this importance is only evaluated at the whole classification level. This means that a feature being crucial for discriminating two classes but bringing no information for other discriminations will be presented as of poor importance by the model, while it is essential to the classification. It can also over-fit the training data, making prediction more uncertain.

RF has been successfully used in several classification problems and generally achieves satisfactory results (Pal *et al.,* 2005; Gislason *et al.,* 2006). It has for example been successfully used for mapping reforested landslides using variables calculated either for each pixel (Chen *et al.,* 2014) or on image objects delineated by segmentation (Li *et al.,* 2015).

2.2.3 Texture features

The extraction of texture features may provide additional data to improve classifiers results. Image texture is a quantification of the spatial variation of image tone values. In the case of a forest, those variations are related to changes in the spatial distribution of vegetation (Franklin *et al.,* 2000). Since texture is related to the spatial resolution, it is mainly used in high to very high resolution images (Puissant *et al.,* 2006). Angular second moment, contrast, variance, homogeneity, correlation and entropy are the most relevant texture features for remote sensing (Baraldi et Parmiggiani, 1995). The main methods used for texture features extraction are described hereafter.

Grey-level co-occurrence matrices (GLCM)

GLCM (Haralick, 1973) is the main method used for texture analysis. It was designed to derive texture features from an image. In a certain area of interest, the frequency of one gray tone appearing in a specified spatial linear relationship with another gray tone is measured by a moving window. The window size, move direction, and the calculated variable have to be set. Texture features correspond to the calculated variables (*i.e.* contrast, variance, entropy, etc.). This method has been used for texture classification (Franklin, 2000) or more specifically to retrieve forest structure variables on high spatial resolution images (Kayitakire *et al.,* 2006).

Simple statistical transformation (SST)

The SST approach (Hsu, 1978) generates spatial features directly based on local neighborhood statistics calculated on a moving window. Different spatial measures were developed such as grey level average or the standard deviation. Some functions act as a smoothing operator while others act as an edge enhancement operator (Gong *et al.,* 1992).

Texture spectrum (TS)

Texture Spectrum was introduced by Wang et He (1990). The main idea is that a texture image can be decomposed into a set of essential small matrix of 3x3 pixels, called Texture Units. Texture Units are considered as the smallest complete units which best characterizes the texture aspect in the eight directions from the central pixel considered. A Texture Unit is therefore represented by eight elements, each of which has one of three possible values (0,1,2 for equal value, lower and higher value) obtained from a comparison with the neighborhood of 3 x 3 pixels around the considered pixel. Texture Unit represents the local texture aspect, and the statistics of all Texture Units in an image reveals its texture information. The occurrence distribution of Texture Units is called the Texture Spectrum. The texture features are then extracted using different algorithms and classifiers can be used (Li, 1995).

The processing of intensity values into only three values (0, 1, 2) reduces the calculation time for the pursuit statistics and eliminates the undesirable influence of both the regional intensity background along with noise in the original image.

Gabor filtering

Gabor (1946) proposed this filters method, used later in remote sensing to extract image texture feature and implement it in classifiers. Jain and Farrokhnia (1991) investigated the use of a set of Gabor filters, with different spatial frequencies, sizes and orientations to extract image texture. The results are then implemented into a clustering algorithm for classification purposes.

Fourier transform Textural Ordination (FOTO)

The FOTO method was developed by Couteron (2002) and is increasingly used in forest textural analysis. This allows to determine the forest structure by analyzing the grain texture of the canopy on high resolution images (Blanchard *et al.*, 2015). Results are well correlated with forest stand parameters (Couteron *et al.,* 2005), and with biomass in tropical forests (Proisy *et al.,* 2007).

FOTO combines a bi-dimensional Fourier transformation followed by a Principal Component Analysis (PCA) to produce textural indices. To obtain high resolution texture imagery, panchromatic and multi-spectral data can be combined, so that the whole texture gradient is available on the higher resolution of panchromatic channel (Proisy *et al.,* 2007). The region of interest is kept, while the rest of the image is masked. The image is then divided into small units (around 1 ha). The bi-dimensional Fourier transform is applied and transposes the spatial spectral radiance into the frequency domain; in other words, units are discretized into spatial frequency classes. Units with an irregular texture are mostly associated with asymmetric spectra in low frequency, while units with regular fine texture are mostly associated with steadier spectra (Blanchard *et al.,* 2015). Measurement of dispersion between radial specta of the units is achieved through a PCA. The data are distributed along two axes: one seems to represent the grain size while the other seems to describe the variation and openings in the canopy (Couteron *et al.* 2005, Ploton *et al.* 2012). An RGB texture map based on the ranking of units on the PCA axes is then made. This allows to classify vegetation texture.

Even if this method was initially developed for a single type of vegetation with closed canopy (Proisy *et al.,* 2007), it has been demonstrated that it can be used to spatially classify diverse types of land cover such as plantations, scrubland and savannah using Pleiades imagery (Blanchard *et al.,* 2015).

Some weaknesses in this method need to be mentioned. The acquisition conditions of the data can have an influence on the image texture, mostly sun-scene-sensor angles which determine shadowing (Barbier et al, 2011). A marked topography can also influence texture (Ploton, 2010).

2.3 Temporal analysis to detect forest cover change

Time-series of observations are always required to monitor land cover change (Lambin, 1999). In a changing environment, change cannot simply be seen as the difference between two conditions at different times, but rather as a continual process occurring at different speed rates on landscapes (Kennedy *et al.,* 2010). Regarding forest, "monitoring degradation can only be achieved through repetitive measurements of bio-physical attributes that characterize the land cover" (Lambin, 1999).

There are three major types of change that can be observed: seasonal, gradual and abrupt. Seasonal change is due to seasonal climatic conditions impacting the ecosystem and can be observed as an annual trend. Gradual change is more inter-annual, and can be due to different causes such as a modification in land management, vegetation regrowth, vegetation degradation, etc. Abrupt changes can be caused by deforestation, natural disasters such as landslides, or fires (Verbesselt, 2010). One of the challenges of time-series is to extract the desired features while getting rid of noise introduced by the difference in illumination, atmospheric condition, vegetation condition between images (Kennedy *et al.,* 2010).

Most of the examples presented above used a temporal component, and the majority of forest degradation mapping used time-series to achieve this goal so far (Matricardi *et al.,* 2008; Kennedy *et al.,* 2010; Margono *et al.,* 2012). Among those, Hansen *et al.* (2013) produced a global forest land-cover change for the period 2000-2017 using multi-temporal data. The temporal aspect is also a way to differentiate land-use from landcover.

The Global Forest Watch (GFW), initiated in 1997 by the World Resource Institute (WRI) also needs to be mentioned. Its goal is to produce and collect local and global forest or land cover maps, allowing to reveal forest loss and gain worldwide, with monthly up to weekly alerts on the state of forests. It is now one of the key sources for forest monitoring, and policy makers.

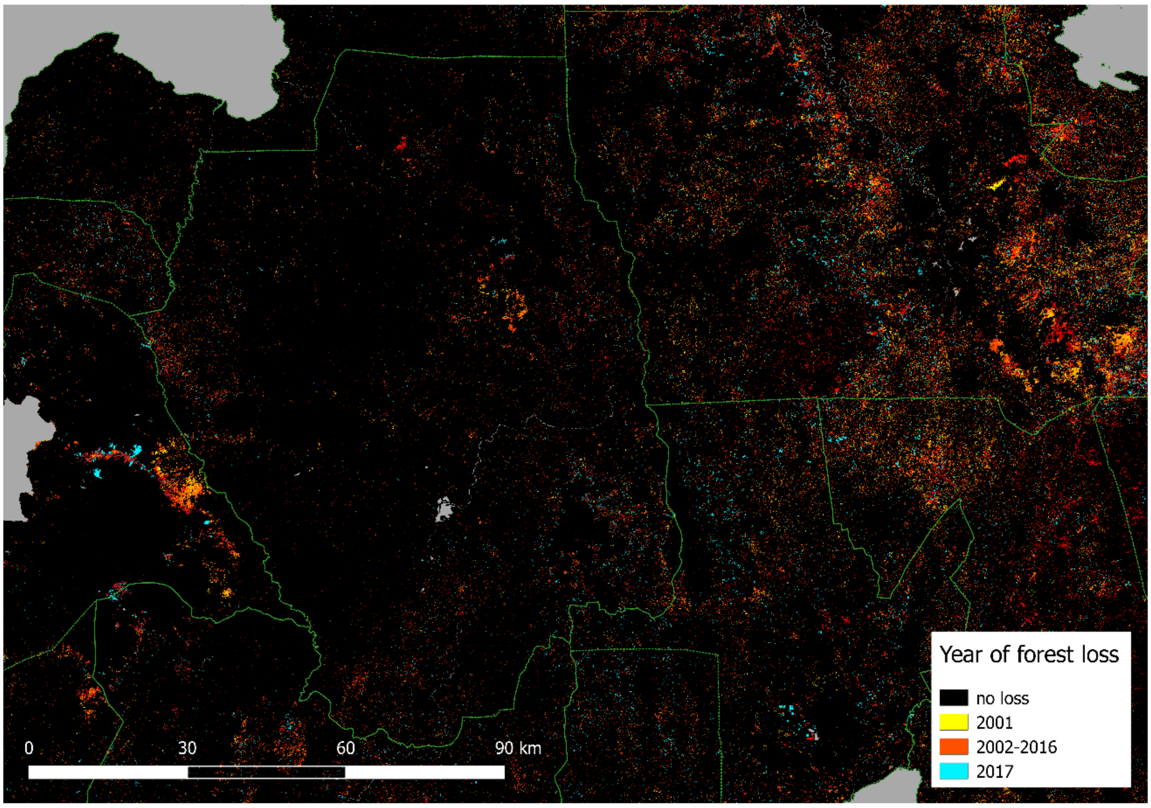


Figure I.4 – Year of forest cover loss in Bukidnon province, Mindanao, Philippines, based on Landsat (30m) data (Hansen et al., 2017).

1.3 Conclusion

Tropical rain forests are a major ecosystem facing pressure from human activities. Forest dynamics including different degradation and regeneration stages are now attracting growing interest in the assessment of forest state evolution.

Nowadays remote sensing is an essential tool for forest monitoring, both at global and regional scales. However, local dynamics have poorly been studied with space borne remote-sensing tools, mainly due to the small spatial scale of the processes (Frokling *et al.,* 2009).

In some regional applications, it appears that the choice of remotely sensed data for forest monitoring often results in a struggle between high resolution and very high resolution images. The former is easily available in terms of costs and frequency but only allow coarse forest observations at the local scale, while the latter are very costly and scarce but allow sharp analysis up to the tree level.

The newly freely available Sentinel 2 images tend to address this dilemma. Its spatial resolution of 10 to 20 m makes it sharper than classic HR images such as Landsat, but still not as sharp as VHR. However, its spectral resolution is way broader, with up to 13 bands, including red-edges and SWIR bands dedicated to vegetation analysis. This trade-off between spatial and spectral resolution allows accurate observations even at the local level. Those characteristics are complemented? by its five-day temporal resolution, designed to collect dense time series.

Even though this potential has been confirmed in the study of deciduous forest, Sentinel-2 data have not been tested so far in the case of tropical forest and especially for monitoring of forest dynamics. Exploring the potential of these datasets in this context is relevant in view of the critical role of tropical forest ecosystems and the need for improvements in monitoring their dynamics.

II. Objectives

Tropical forests are under several anthropogenic pressures that leads to vegetation dynamics. Beside classical forest/non-forest mapping, forest dynamics need to be observed as well to monitor forests state as a whole. In other words, internal dynamics needs to be assessed in addition to forest extend.

A first objective of this study is to propose a forest typology suitable for forest dynamics monitoring. Dynamics and involved land-use have to be understood and characterized.

The newly available Sentinel-2 images have a great potential in vegetation observation. A second objective is therefore to investigate the potential of Sentinel-2 time-series for tropical forest dynamics monitoring, *e.g.* to observe different forest types and vegetation succession stages. A method must be developed to map forest dynamics from these data and assess monitoring performance.

The third and last objective is to confront Sentinel-2 performances with finer spatial resolution images. Very high resolution data allows closer observation of forest canopy and it is therefore important to study the image resolution impact on the forest dynamics mapping performances in terms of accuracy and detectable typology.

III. Study area

1. Site location

This study was carried out in the Philippines, in the southern island of Mindanao, province of Bukidnon, in the Upper Pulangi watershed. The area was chosen for its variety in altitude and human practices leading to a diversity of forest dynamics types. The study area extends on the territory of *Barangays* (villages) Busdi and Saint-Peter, and more specifically around tree *sitios* (communities) located along the forest line: Bendum, Pinuwakan and Mahayag.

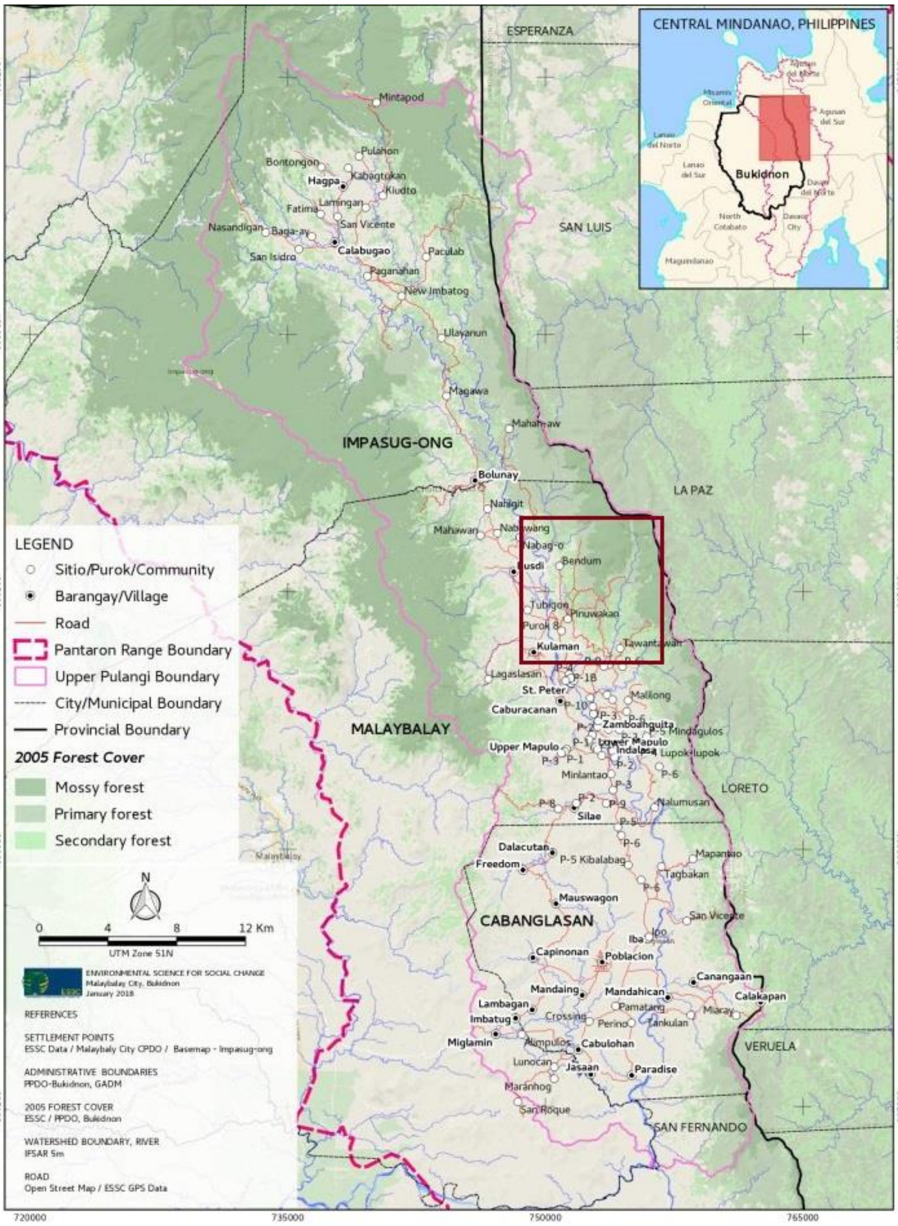


Figure III.1 – Geographic location of the study area.

2. Forest loss history

Forest loss in the Philippines has been one of the most severe in the world at the latter part of the last century (Figure III.2). This degradation is mainly due to extensive logging combined with demographic expansion, which led to upland migration and agriculture development on the newly opened lands.

Before the arrival of the Spaniards in the 16th century, approximately 90% of the Philippines was covered by forests, namely 27 million ha. At the end of the Spanish period (late 19th century), the forest cover had decreased to approximately 70% of the country's area, *i.e.* 21 million ha.

Upon the beginning of American domination at the early 20th century, mechanized forestry was developed to export timber to the US and to clear land for agriculture. After the Second World War, the country became independent and logging concessions were allocated to foreign companies making timber exportation the country's primary source of income. The logging boom during the '60s and '70s and the development of mining activities accelerated even more the deforestation process. At this time forest cover was estimated at 10.2 million ha. The country experienced the fastest deforestation rate in its history. In the '80s, many attempts were made to control forest exploitation and illegal logging, and in 1987 forest policies and guidelines were decided by the government including loging bans in certain areas and above 1000 m elevation, log exportation ban, reforestation programs, etc.

Likewise, as in the rest of the country, the Upper Pulangi region suffered from logging activities. Workers from the lowlands coming from other provinces in the Central Philippines where hired by the logging companies who then settled on the newly opened areas to farm after the companies had left. In many instances this prevented the forests to regenerate and was a source of conflict between the migrants and the indigenous locals.

Today logging activities in the region are only local and mostly for homes, but some forested areas are still cleared for cultivation mainly by migrants. The actual national forest cover extends over 7.2 million ha, around 20% of the total Philippines land area (ESSC 1999, PTFCF 2015). The study area is part of one of the largest remaining forest patch of the country.

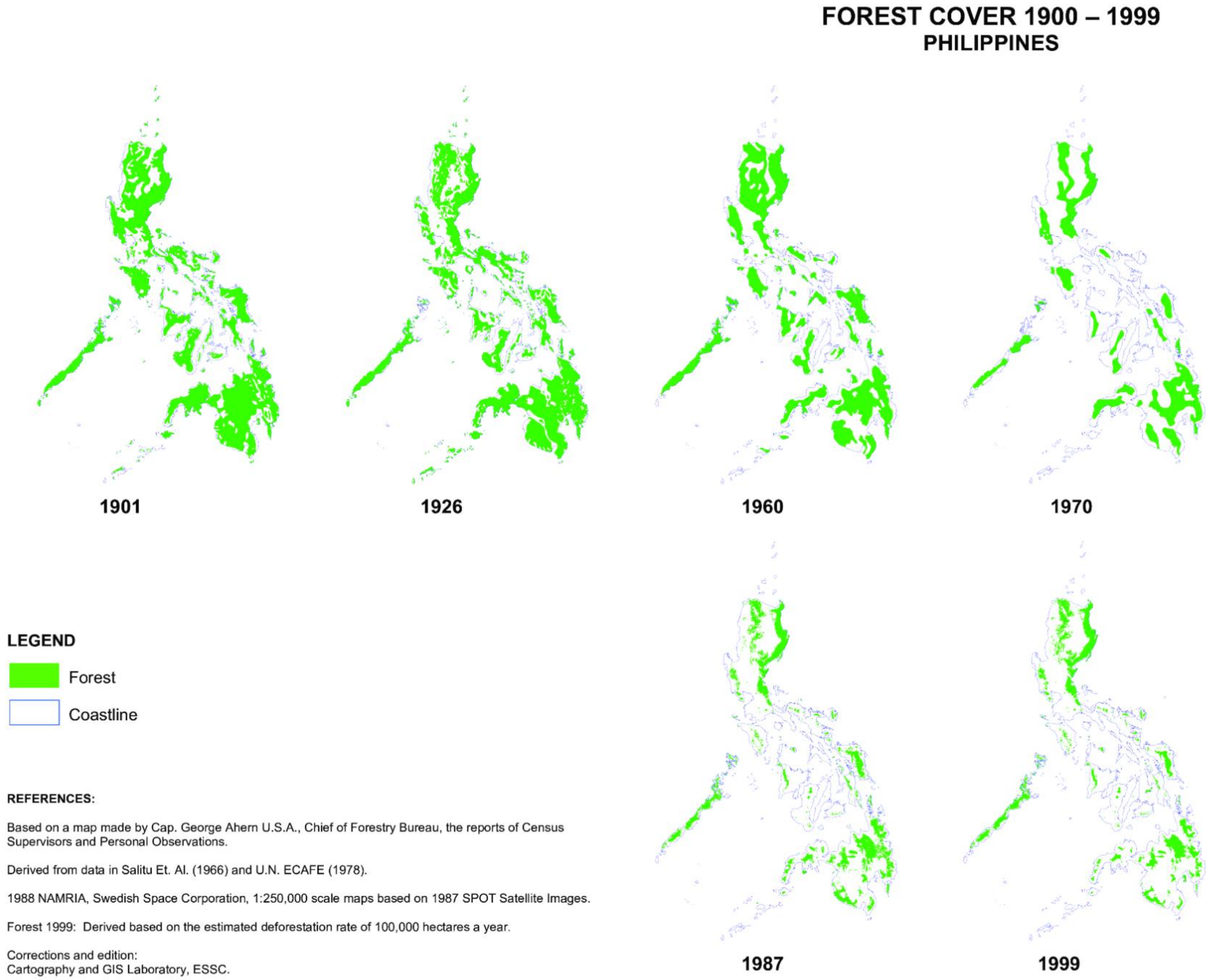


Figure III.2 – Evolution of Philippines forest cover. Data sources vary depending on the period (adapted from Walpole, 2003).

3. Forest types

Dipterocarp and mossy forests are the most prevalent and are the remaining forest types on Mindanao Island, mainly because of their high elevation due to the difficult access to logging and the log ban above 1000 m. Due to different human activities, forest dynamics are induced on dipterocarp forest. Those are spatially related and particularly elevation related, forming a toposequence. For clarity of terminology, the term "forest types" encompasses both natural forest types and anthropogenic forest dynamics types. A synthesis of local forest dynamics is represented at Figure III.10.

3.1 Dipterocarp forest

Located from the coast up to 1000 m altitude, the dipterocarp forests (also called *tropical lowland evergreen rainforest* or *pre-montane forests)* are dominated by tall trees (40-60 m) of the *dipterocarpaceae* family (Figure III.3). It used to be the most abundant forest type in the Philippines, but due to their excellent timber quality and their relatively accessible locations, these forests were severely and adversely affected by deforestation. The size and diameter at breast high (DBH) of the trees decrease with altitude, and the vegetation composition is not homogenous, but the common characteristic is a closed canopy of pillar species with emergent coppices. This forest type is called *Puwalas* (forest) in the local language.

Figure III.3 - Dipterocarp forest in Sitio Mahayag,Barangay St. Peter in the Upper Pulangi area in Northern Mindanao. Note that the effect of the slope makes tree crown appear more emerging.

3.2 Mossy forest

Mossy forests (also called *tropical upper montane forests*) are characterized by a covering layer of mosses on trees and on the ground at higher altitudes. They can be found generally above 1000 m elevation and on rocky ridges. At this region, air is permanently cloudy, moist and cold, which is why moss is so prevalent. These forests were generally not logged due to their difficult access and their low timber value in terms of volume. Interestingly they play a crucial role in the water cycle. Indeed, while they only correspond to 14% of the Upper Pulangi watershed surface, it is estimated that they contribute to around 25% of its water supply (ESSC, 2002).

Figure III.4 - Mossy forest above Bendum (+-1200 m altitude). Tree trunks are typically covered with moss and the air is saturated in humidity.

The local communities separate mossy forest into two sub-classes: *Lagiit* (transition to mossy) in the lower part and *Saldab* (mossy) in the upper part up to the top. *Lagiit* have small DBH trees covered with moss. In *Saldab*, even the ground is covered by moss. The trees have an even smaller DBH and size, and pitcher plants and climbing grasses are present and abundant.

The transition line between dipterocarp and mossy forest is characterized by the Massenerhebung effect: its altitude is proportional to the mountain top height (Grubb, 1971). In the study area, the ridge top altitude varies between 1400 m to 1500 m above sea level, with transition to mossy forest located at around 1000 m. As an illustration of this effect, Mount Apo (2954 m above sea level, the highest point of Mindanao and the Philippines) has this forest transition located between 2200 to 2500 m altitude.

3.3 Forest dynamics types due to human activities

The two main drivers of forest degradation in the region are logging activities and shifting cultivation. Depending on the nature and intensity of these practices, the resulting vegetation can differ and should therefore be classified. These forest dynamics types are well-known and described by local communities, according to their vegetation composition and former land-use. The land being clearly divided into parcels, cultivated or not, the spatial limit between types is most often clear. Only the pre-montane forest is applicable to those dynamic types, since mossy forest is located at higher altitudes and on land not fit for farming with relatively thin trees that have very low commercial value.

3.3.1 Wood extraction

The intensity of logging is the main parameter for the resulting forest dynamic types. If the primary forest (*Puwalas*) is only selectively logged, meaning that only the most valuable trees are cut (±25% of total wood volume), the result is a high canopy forest with some canopy gaps (*Kagulangan*, mature), which will eventually regenerate into *Puwalas*.

Figure III.5 - Selectively logged forest (Kagulangan) around Bendum. Light penetrates through the canopy, and young trees grow in the gap left by the selective log of valuable trees (center).

When around ±75% of total wood volume is cut, the area results in disperse tall trees forming a mainly open canopy (*Lubas Kagulangan*, between both stages). This stage is crucial since it can either regenerate into *Kagulangan* (and later *Puwalas*), or sometimes suffocate back into mixed vegetation, as explained further. Note that the difference between selectively logged and logged-over might be gradual depending on the logging intensity. It can sometimes be seen as an extended gradient of canopy gaps rather than two distinct forest classes.

In case of total clear-cutting, short vegetation will colonize the area, followed by soft-wood pioneer species (*Lubas*, "naked"), which eventually will be followed by recolonization of hard-wood pillar species.

Figure III.6 - Logged-over forest (Lubas Kagulangan). Canopy gaps represent up to half of total canopy cover. Climbing heliophilous species grow around the tree.

Forest management and protection status are disparate among communities in the study area. In Bendum, a local altitude-related log limit is decided by the community tribal council, above which logging is banned in the entire community ancestral domain (except for dead or fallen trees).

Areas owned by ESSC around Bendum are managed through *assisted natural regeneration*: tree plantation, enhancement of species diversity, control of climbing species by cutting and implementation of forest edge closure to avoid light surplus. These local forest management policies are mostly absent in the rest of the study area.

3.3.2 Shifting cultivation practices

Agricultural practice in the uplands include slash and burn. This concerns traditional indigenous plots, which have a very mixed variety of crops. A forested area is clear-cut and burned to be cultivated (*Uma*, farm lot). After a few years of cultivation, the area will be left fallow and a mixed vegetation will regrow (young regrowth, *Lubas*). The land is divided in privately owned parcels corresponding to ancestral family domains with each family tending the same lots for generations. Therefore, a defined area will be regularly farmed; the swidden fallow (*Lubas*) is clear cut and burned again to be cultivated (Figure III.7).

However, migrant-influenced sedentary practices, with mainly corn mono-culture, are spreading. This practice leads to a shorter to non-existent fallow period, and therefore a higher soil erosion and fertility loss. This erosion is even stronger on steep slopes. Because they are harder to cultivate and more subject to erosion, these areas are most often the remaining ones for farmers without land. Migrants tend to settle there and cultivate corn with little fallow, leading to important erosion and loading rivers with sediments. They became unfit for crops and are eventually abandoned.

The first colonizing species are mainly *Imperata cylindrica* (cogon grass, *salaysay*) and *Pteridium aquilinum* (ferns, *bagokbok*). The regrowth is designated according to its prominent species: *Lubas salaysayon* and *Lubas bagokbokon*. Then a mix of pioneer species including different shrubs and soft-wood trees eventually develop (Table III.1).

The interval between two farming cycles can be from one year to more than 10 years, depending on the owner's needs. If the land is abandoned on a longer period (15-20 years), pioneer trees will then be replaced by growing hard-wood pillar species, which corresponds to *Lubas Kagulangan*, later eventually leading to *Kagulangan* (±40 years) and finally *Puwalas* (±50 years).

Figure III.7 - Distinct stages of shifting cultivation. At the front a recently harvested field (Uma). Right behind, a mix of pioneer species regrowth (Lubas). Further behind, advanced soft-wood pioneer trees at forest edge.

Not included in the shifting cultivation practices but important in terms of land-use are the rubber tree plantations. They are part of the migrant sedentary cultivation practices and were traditionally not present. They are now widely present in the region, sometimes cultivated in association with coffee trees (Figure III.8). After a few years, those plantations form therefore an even-aged, mono-species, closed-canopy tree structure, that can be visually confused with forests during photointerpretation. Since rubber has to be collected every week to be sell to merchants, plantations are mainly located along the roads.

Figure III.8 - Rubber tree plantation with coffee cultivation between the rows.

Table III.1. - Summary of local forest typology and characteristics (species based on Walpole, 2003).

Forest type	Local typology	Main characteristics	Prominent species
Mossy forest	*Saldab*	Very top of the mountain (≥ ± 1200 m) Lowest tree height and DBH with mossy trunk. Moss on the ground. Tall grass, high amount of pitcher plants.	*Nepenthes truncata* *Lygodium* sp. *Agathis philippinensis* *Casuarina equisetifolia*
	Lagiit	Elevation (± 1000-1200 m). Transition between *Puwalas* and *Saldab*. Small tree height and DBH with mossy trunk.	*Nepenthes truncata,* *Palaquium foxworthyi,* *Calamus* sp.,
Pre-montane forest	*Puwalas* *(50+ years)*	*Tangile-oak* association. Closed canopy. Tallest tree height and largest DBH (altitude related).	*Shorea polysperma,* *Neotrewia cummingii,* *Calamus* sp., *Palaquium foxworthyi,*
Regenerating/ Degrading forest	*Kagulangan* *(40-50 years)*	Former limited local extraction (<±25% of total wood volume), now regenerating into *Puwalas*. Canopy gaps.	Idem as *Puwalas*
	Lubas Kagulangan *(15-40 years)*	Logged-over forest (>±75% of total wood volume) but not plowed. Growing pillar species, >20cm DBH trees. Climbing species. Degrading into *Lubas* if suffocation from climbing species, regenerating into *Kagulangan* if not.	Climbing bamboo, *Albizzia falcataria* Idem as *Puwalas* (remnants and/or young growing)
	Lubas *(1-15 years)*	Regenerating traditional swidden cultivation. Mixed pioneer species: low heliophilous vegetation, bushes, soft-wood pioneer trees (scrub).	*Musa sapientum*, Giant Fern, *Albizzia falcataria*, *Macaranga* sp., *Lithocrapus sultii*, *Ficus* sp., *Lygodium* sp.
Short vegetation regrowth	*Lubas bagokbokon*	Develop after > 4 farming cycle	Ferns (*Pteridium aquilinum*)
	Lubas salaysayon	Develop after > 6 farming cycle	Cogon (*Imperata cylindrica*)

3.3.3 *Critical stages of vegetation succession*

While vegetation stage succession might appear to be progressive in the absence of cultivation, two stages are critical and can lead to a blocked succession.

First is the early regrowth stage following a crop harvest: cogon grass and fern regrowth (*Lubas salaysayon*, *Lubas bagokbokon*). These species are generally followed by other pioneer species, but in the context of shortening farming cycles and erosion, the low remaining soil fertility and the disappearance of the seed bank lead to a dominance of this vegetation stage, adapted to poor soils.

Figure III.9 - Cogon grass cover (Lubas salysayon) and natural burning on the hills around Mahayag (Sint-Peter). This area has been covered by cogon grass since at least 20 years without any human intervention since land abandonment.

It can be expected that this elongated stage would anyway lead to an increase in soil organic matter, triggering the vegetation succession: the development of taller pioneer species, later creating the shade needed by the pillar species to grow. But in many cases, the cogon/fern mix would burn intentionally or not in dry season (April-May), leading to burned soil stage once again, though it is not cultivated (Figure III.9). This can happen annually and prevents other species to develop, while ferns and cogon grass easily regrow. The regularly burned and bare soils suffer from greater erosion and decreasing fertility, therefore reinforcing the process itself. On steep slopes, the process is even stronger due to higher soil erosion and ash lixiviation.

Cogon grass is most tolerant to poor soils thus the poorer the soil the higher the proportion of cogon compared to ferns.

The progressive vegetation succession can therefore be blocked in what can be seen as a “false climax”. In the Upper Pulangi, some hilly areas have been covered with cogon grass for more than 20 years, without any human intervention.

The second critical stage is *Lubas Kagulangan* (between *Lubas* and *Kagulangan*). Because it results from an over-logging (≤75% of total wood volume), the few remaining pillar trees form a mostly open canopy. This leads to the development of heliophilous climbing species such as *Ficus* spp. and climbing bamboos, growing up to the tree crown and possibly suffocating it, making it dies and falls, slowly sending the area back to low vegetation (*Lubas*). This is more likely to happen if the area is located next to an open one (cropland, grassland, cogon, ferns) allowing even more light to enter due to the border effect.

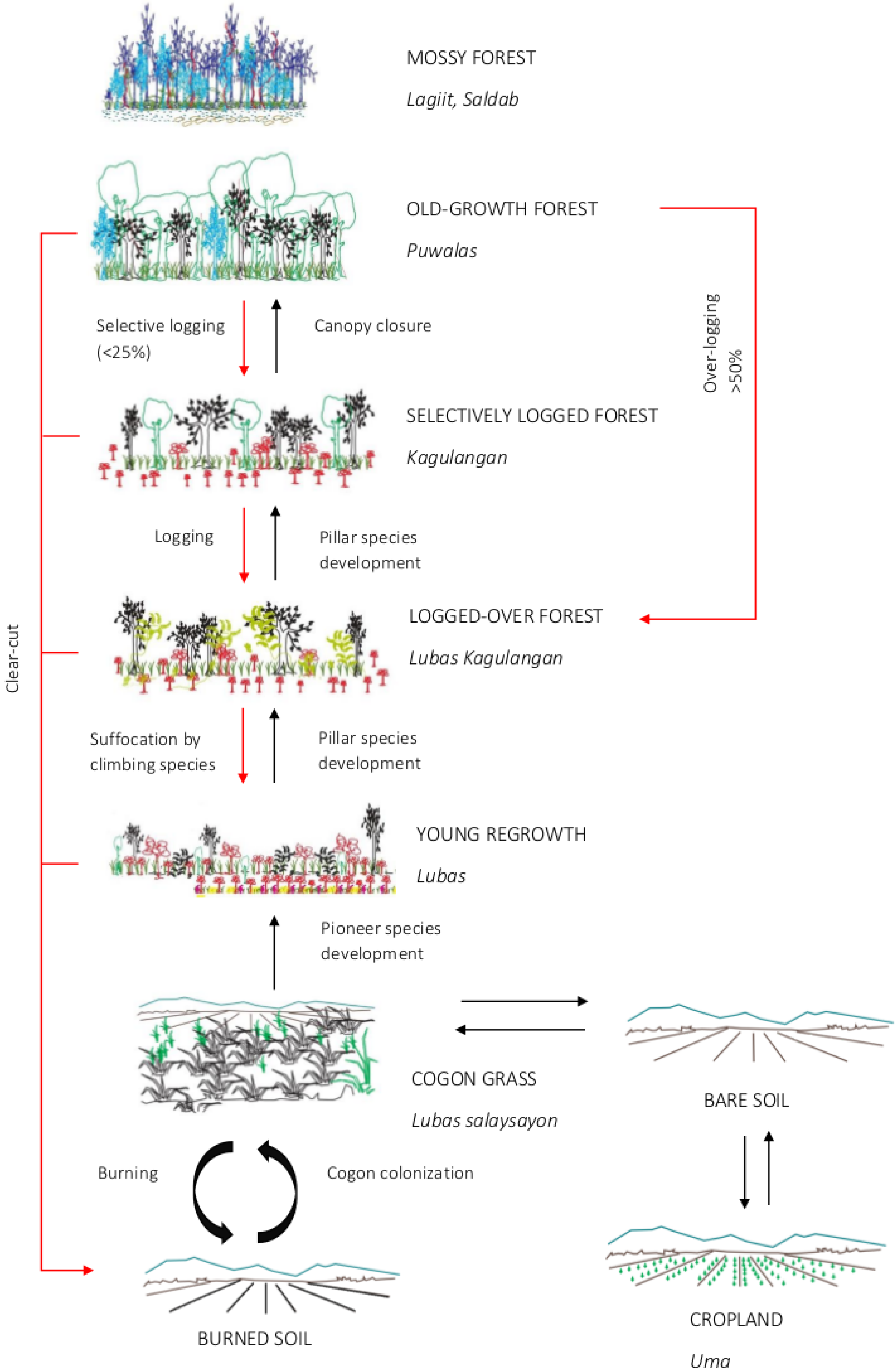


Figure III.10 – Forest dynamics cycle in the study area. Green trees represent valuable pillar species, while black trees are less valuable ones. Mossy forest is not concerned by these dynamics due to its high location and poor timber value (adapted from ESSC, 2002).

4. Spatial organization of the Upper Pulangi watershed

As in most mountainous regions, the spatial patterns of the Upper Pulangi watershed is mainly altitude-related and organized in a toposequence. Understanding this organization allows more efficient and relevant movements during a field campaign. This spatial organization is schematized at Figure III.11.

The Pulangi river is the central element of the valley, providing flat and irrigated areas to grow rice all year long. The main road is located along the river and is the backbone of human settlements. Most of the villages at the head of villages (*Barangays*) are located along this road, and their administered villages and hamlets (Sitios) are either along this road as well, or located uphill and connected by secondary roads. The bottom of the valley is therefore more densely populated, because of better connection to the road network and because rice cultivation produces more food and income.

On the emerging slopes of the valley are located secondary areas, with villages connected by secondary roads. Corn is cultivated extensively here because it does not require irrigation and can be cultivated on uneven terrain, but it is less productive and profitable than rice. The fact that uphill areas are not irrigated means that crops cannot be grown all year long. The rapid decline in fertility when a field is cultivated has led to shifting cultivation practices. This area is characterized by corn fields, various stages of vegetation regrowth and logged-over forests. Rubber tree plantations are widely present along the road, which is useful information to avoid confusion with forests.

Higher on the slopes, tall forests start with a sharp increase in inclination making cultivation next to impossible. The forest line is characterized by a first layer of selectively logged forest (*Kagulangan*) where wood is collected. Then there is the old-growth forest (*Puwalas*) and finally the mossy forest (*Lagiit, Saldab*) around 1000 m altitude.

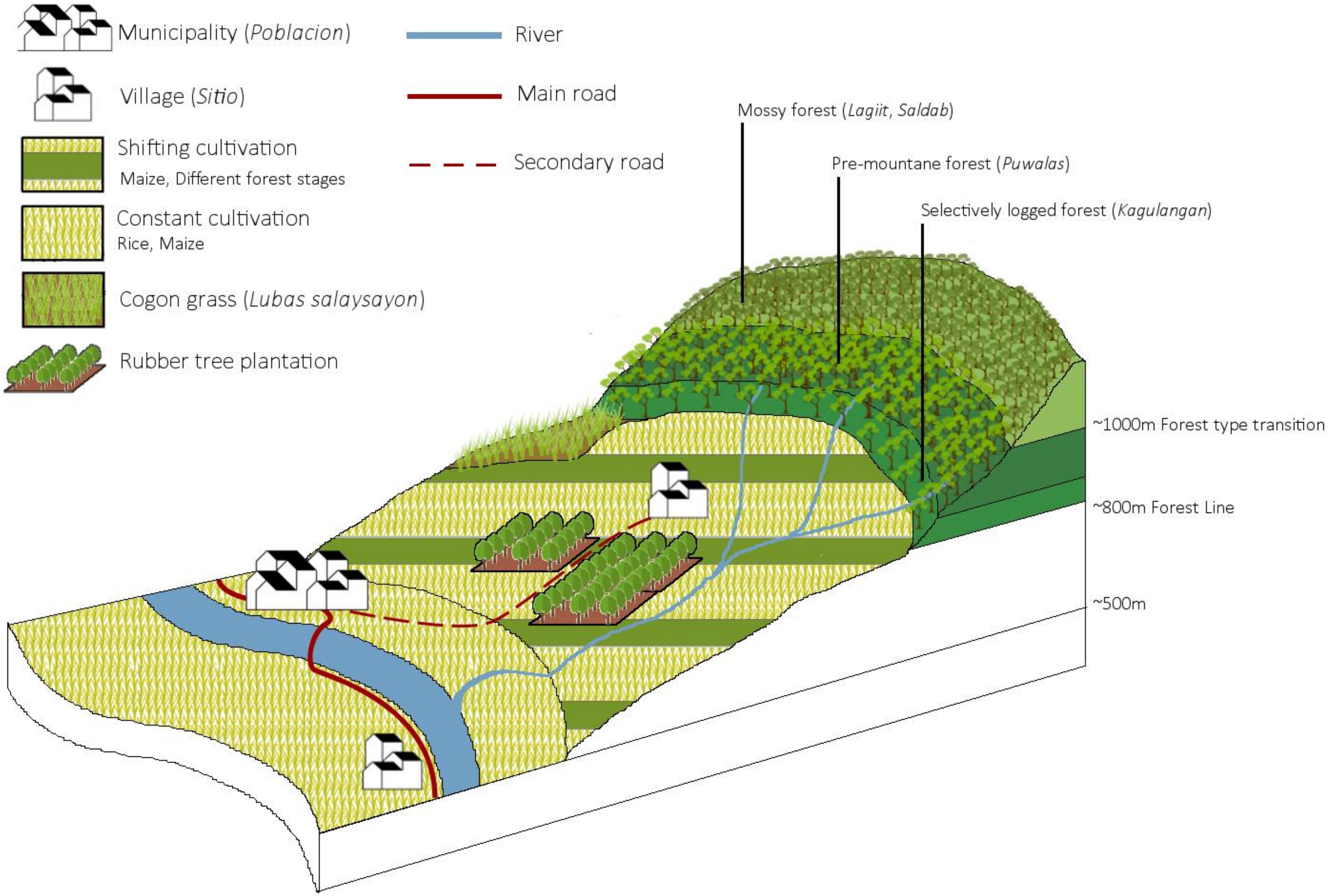


Figure III.11 – Spatial organization of the Upper Pulangi realized with local actors. Landscape is mainly organized in a toposequence. Flat areas along the main river are cultivated all year long with mainly paddy rice and are more densely populated. There is located the main road of the valley, with the head of municipalities (Poblacion) and villages along. Smaller villages are located uphill. There, the main practice is shifting cultivation. Rubber tree plantations are located along the roads. Cogon grass covers are mainly found on slopes due to higher soil erosion. The forest line starts at the net increase in slope with a first band of selectively logged forest.

IV. Materials and methods

1. Satellite data

Aside from exploring the potential of high resolution Sentinel-2 data for forest monitoring, very high resolution imagery is used in order to compare their performance and assess the impact of spatial resolution on forest typology detection and mapping. Imagery from the Pleiades satellites was chosen for its spatial resolution of 2m (multispectral) having successfully been used in tropical forest degradation mapping. This allows to confront Sentinel-2 performances with an assessed performing data type. A very high resolution image is also useful during the field campaign for photointerpretation.

1.1 Very high resolution imagery

1.1.1 Description

The Pleiades constellation is a pair of commercial agile satellites (Pleiades-1A and Pleiades-1B) launched in 2011 and 2012. They are located on the same orbit with a 90° angle between them, which allows a daily revisit of any point on the globe. Panchromatic band has a 50cm resolution and the four multispectral bands have a 2 m resolution. Those four bands are: blue (0.43-0.55 µm), green (0.50-0.66 µm), red (0.59-0.71 µm) and near-infrared (0.74-0.94 µm). The panchromatic image covers the wavelengths from 0.47 to 0.94 µm and has a radiometric resolution of 16 bits. The Pleiades image used in this study is an archive image taken by Pleiades-1B on May 25th, 2015.

1.1.2 Preprocessing

Since this image is used on the field campaign for photointerpretation of forest canopy, it is useful to increase the spatial resolution of its multispectral part for a finer usage. Therefore, a pansharpening of the image was performed. This process consists in merging high resolution (0.5 cm) panchromatic band with the lower resolution (2 m) multispectral bands to create a single 0.5 cm resolution color image. The image was pan-shapherned using the Bayesian data fusion method (Fasbender *et al.*, 2008) implemented in Orfeo Toolbox. The panchromatic band weight was set to 0.95. No atmospheric correction was achieved since multispectral radiance is already good enough for classification. In terms of geometric accuracy, the image was already orthorectified by the image provider.

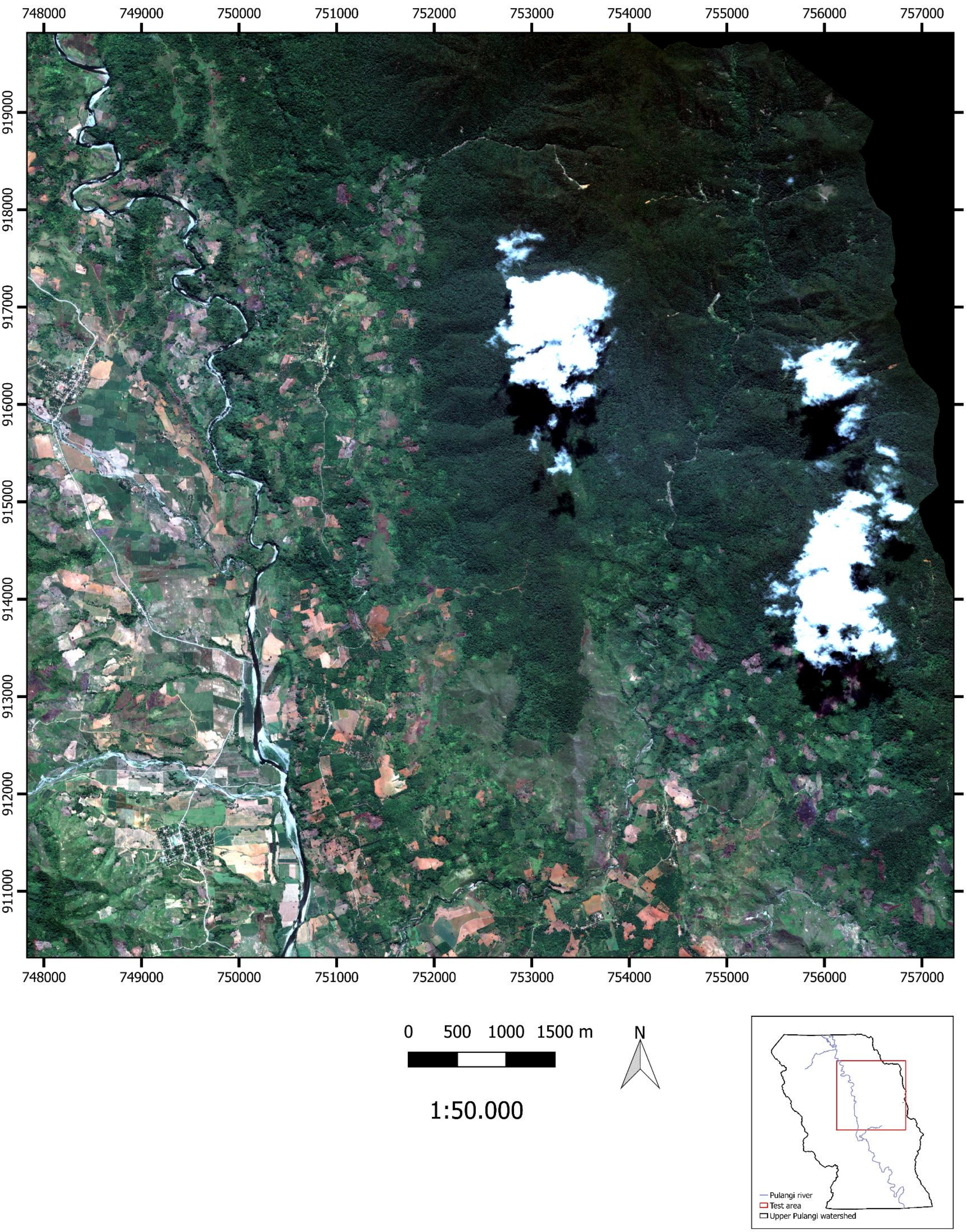


Figure IV.1 – Pleiades image (25/05/2015) subset on the test area.

Universal Transverse Mercator projection (UTM) Zone 51P
World Geodesic System 1984
Units : meters
Sources : Pleiades multispectral image (25/05/2015)
UCL-ESSC : LUCID project - Q. Marissiaux, UCLouvain-Geomatics, 2018

1.2 Sentinel-2 imagery

1.2.1 Description

Sentinel-2 image characteristics were already described in the first section. In terms of satellites, Sentinel-2A was launched in June 2015 and the first images have been available since the end of 2015. It was followed by the identical satellite Sentinel-2B launched in March 2017, with the first images being available the following July. Both satellites are positioned at opposite sides (180°) of the same orbit. The launch of the second satellite divided the global coverage time of ten days by two, making images available every five days since July 2017.

The Sentinel-2 images were downloaded by the Sen2agri software developed by the UCLouvain lab in Geomatics and funded by ESA. Since then and over our study area, only six partially cloud-free images are available on the following dates:

- 02/04/2016
- 21/07/2016
- 08/12/2016
- 08/12/2017
- 11/02/2018
- 16/02/2018

This is mainly due to the typical cloudy climate of tropical regions as well as the rugged topography with clouds observed along the mountains ridges. This low temporal availability constraints the investigation of the full potential of Sentinel-2 data.

1.2.2 Preprocessing

In order to be used, images need to be preprocessed to correct effect of atmosphere and create a cloud mask for further steps. Then, for a better forest types photointerpretation, they must be displayed in a way that visually discriminate forests.

This pre-processing was achieved by using the Sen2agri software. It provides L2A surface reflectance product, based on the Multi-sensor Atmospheric Correction and Cloud Screening (MACCS) chain, which performs atmospheric corrections and calibrate bottom-of-atmosphere reflectance values with snow, water, cloud and cloud shadow masks.

The most recent images (December 8th, 2017) was represented in a false color composite. This is shown as a combination of three bands into RGB to ease the detection of features that are not readily discernible otherwise. After testing different band combinations, it appeared that the NIR, Red and Green combination was the one that better differentiates forests in the study area. This allowed to link the field observations to the Sentinel-2 image features and therefore developing photointerpretation skills.

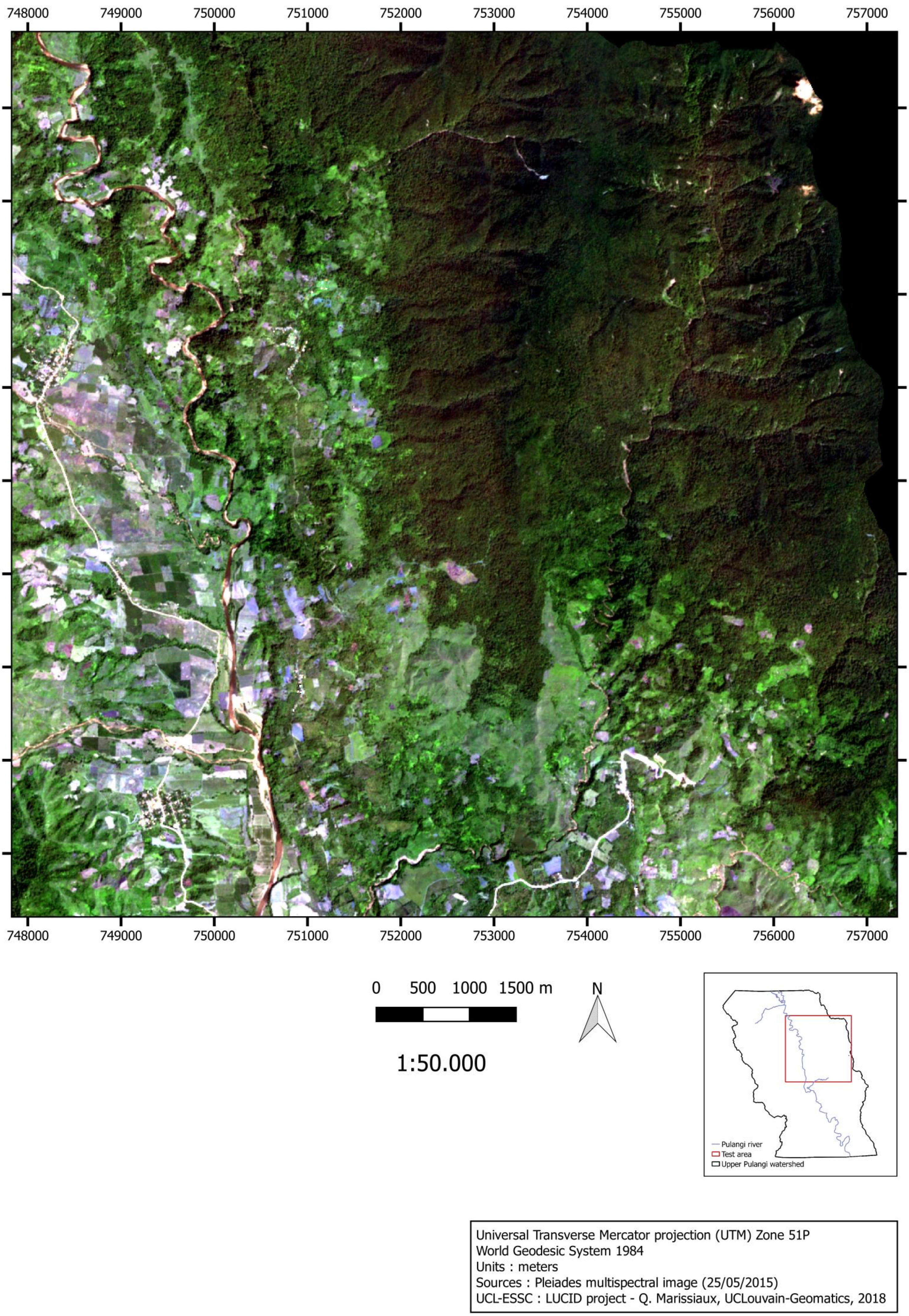


Figure IV.2 – Sentinel-2 image RGB composite (11/02/2018) subset on the test area.

2. Field data collection

Forest dynamics diversity needs to be captured and localized in order to later assess the possibilities of detecting and mapping them. Dynamics need to be understood, identified, and forest classes set. Training and validation samples for each class need to be collected to create the dataset required in the mapping processes. To do so, a field campaign was conducted for eight weeks from the end of January to end of March 2018 in the Upper Pulangi Watershed, province of Bukidnon, Mindanao, Philippines. This location was chosen for its diversity of topography and land-use leading to a variety of forest types. Data collection was achieved in collaboration with the ESSC organization that provided access to the study area, transport, authorizations from local authorities, shelter and forest guides.

2.1 Forest typology formulation

Access to local knowledge allowed a quick understanding of the spatial organization and land-use dynamics, with the corresponding forest dynamics types (see section III: Study area). In the local classification, some forest types are distinguished according to land-use or the existing dominant species. However, those distinctions might be irrelevant in terms of landcover. Therefore, some of them were assigned to more generic classes. This is the case for the *Lagiit* and *Saldab* local classes: since they are mainly differentiated based on the sub-canopy vegetation which is not detectable on remotely sensed data, those two classes were regrouped in the "mossy forest" class. Similarly, short vegetation regrowth classes such as *Lubas salaysayon*, *Lubas bagokbokon*, are distinguished according to the prominent species, but their vegetation mix is never entirely mono-specific. Therefore, they were regrouped in the "cogon grass" class since this species is widely present in all of them. The proposed forest typology to collect in situ data is presented in Table IV.1.

2.2 Field protocol

The goal of data collection is to capture the diversity inside a particular forest type, obtain representative samples, and develop photointerpretation skills. Therefore, a field protocol was established to achieve this goal in a standard way.

The protocol for field observations was as follows. In a first step, the proposed forest classes were visually linked to the Pleiades image and the Sentinel-2 false-color composite, allowing to develop photointerpretation skills. Field indicators such as typical plant species or canopy gaps extend were listed for each class (Table IV.1). A protocol for forest identification on the field was thus created: samples of interest were first located on the images by photointerpretation then the forest class was assessed on the field by observing indicators.

Areas to be visited were selected based on photointerpretation and location. Areas that could not be photointerpreted were favored to assess their class and thus improve photointerpetation skills. To obtain homogenously distributed samples on the study area, location was also considered.

Because of Sentinel-2 20 m bands, each field sample described homogeneous areas of approximately 60x60 m (30x30 m minimum). By doing so, at least one 20x20 m pixel will always entirely fall into the area. A target of 15 to 30 training samples was considered for each forest dynamics class. For each sample, forests indicators were described, and GPS coordinates of the sample center was recorded. A picture of the area on the ground was also taken to be later analyzed in case of uncertainties about the sample. This field survey was achieved by car and hiking using a Garmin GPS GPSMAP 62st and the GeoODK mobile app. The collected points were then displayed on QGIS software to establish the areas visited and those to be visited next.

A total of 180 samples were collected, with around 30 samples for each of the six classes aside from mossy forest. The later being present at the top of mountain ridges, the difficult access makes sample collection time consuming. Instead, three mountain transects were realized by walking straight from the bottom to the top of the hill and taking GPS points at forest type transitions.

Field samples were then sorted to get rid of erroneously located points. Indeed, both the GPS and the smartphone used can have an error of more than 20 m in some cases. This was mainly due to the dense forest canopy and the rugged topography such as incised riverbeds.

Table IV.1. – Identified forest dynamics classes and corresponding indicators.

	Classes	Indicators
Forest types	Mossy forest *Saldab/Lagiit*	Moss on the trunks and on the ground. Tall grass, high amount of pitcher plants (*Nepenthes truncata*). Smallest tree height and DBH.
	Old-growth forest *Puwalas*	Closed canopy. Tallest tree height (45m+) and largest DBH (altitude related).
Degradation/ regeneration stages	Selectively-logged forest *Kagulangan*	Tall pillar species. Canopy gaps (±25%)
	Logged-over forest *Lubas Kagulangan*	Growing pillar species, >20cm DBH trees. Canopy gaps (50%+) Climbing species: climbing bamboo, vines, lianas.
	Young regrowth *Lubas*	Mixed pioneer species: low heliophilous vegetation, bushes, banana trees, giant ferns, soft-wood pioneer trees (scrub).
	Cogon/ferns regrowth *Lubas salaysayon/bagokbokon*	Cogon (*Imperata cylindrica*). Ferns (*Pteridium aquilinum*)
Other	Rubber tree plantation	Rubber trees

3. Methods for forests types mapping

Methods for forest types mapping have been developed for both images types in order to compare their performances. Since their characteristics differ (4 abdns at 2 m for Pleiades and 10 bands at 10-20 m for Sentinel-2), to different methods had to be set. Indeed, wile per-pixel classification process can be used with Sen-2, it cannot be with Pleiades since its pixel size is smaller than a tree scale.

These methods are first elaborated and tested on a test zone corresponding to the field campaign area. In the case of satisfying results, the processes can be extended on a larger scale, namely part of the Upper Pulangi watershed located in the Malaybalay area. Results obtained with both methods are then compared later on.

The classification processes always require an iterative approach to enhance the final classification until a satisfying result is achieved (Figure IV.3). After the first workflow, the dataset is corrected with modifications such as the removal of noisy training data, addition of data for a given class, etc.

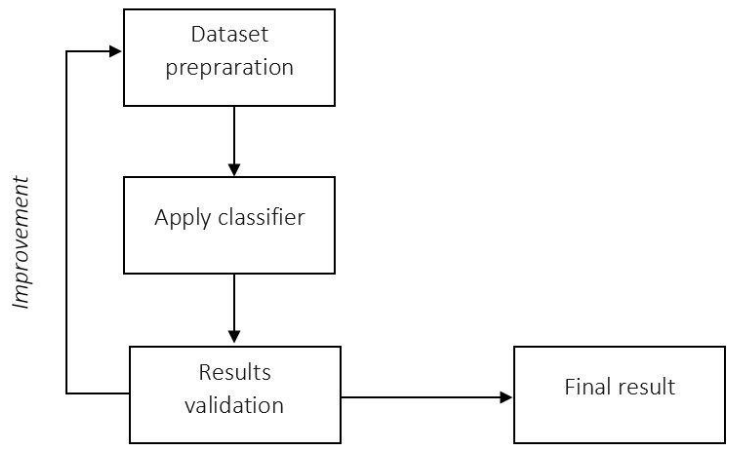


Figure IV.3 - Iterative steps of a classification process.

3.1 Very high resolution mapping of forest types

Due to its pixel size, the Pleiades image needed to undergo object-based classification. Indeed, since the pixels are smaller than a tree crown, a per-pixel classification approach would result in the prediction of different forest classes at a sub-tree scale, which makes no sense. Therefore, objects must be created by segmenting the image. The image features present in each object can then be extracted to train a model and predict classes on all objects. The complete workflow for the Pleiades image is represented in Figure IV.4. Because some classes of interest might be similar to other landcover types, a progressive hierarchical process is proposed. First to get rid of non-forested areas by avoiding confusion between dense crops and short vegetation regrowth, and in a second time to better discriminate rubber tree plantation from forests types.

3.1.1 Image segmentation

Segmentation was done using e-Cognition software from Trimble. Based on the image feature, a multi-resolution segmentation process was applied. Weights need to be given to the different bands: in this case an equivalent weight of 1 was given to the four bands. Three other parameters had to be set: the scale, shape and compactness. Different parameter values were tested until a satisfactory result was obtained, *i.e.* when created objects encompass a forest type in its diversity (for example, canopy gaps as well as emerging tree crowns are taken into a same *selectively logged* object) and with a scale similar to field observation (around 60x60 m). The segmentation process result is shown in Figure IV.5. The final chosen parameter values are presented in Table IV.2.

Table IV.2 - Set of parameter values for the multi-resolution segmentation process of the eCognition software.

Parameters	**Set values**
Band weights	1,1,1,1
Scale	80
Shape	0.8
Compactness	1

Once the segmentation was done, image features for each object were extracted. Features comprise the four mean band values inside the segment, the four-band standard deviation, the mean brightness, and six texture features derived from the grey-level co-occurrence matrix. Certain texture features were chosen among the 14 described by Haralick (1973) because they were found to be the most relevant for forests types sensing (Kaykatire, 2006). These texture features are: angular second moment (ASM), contrast, variance, homogeneity, correlation and entropy. The segments and corresponding feature values were exported in shapefile format.

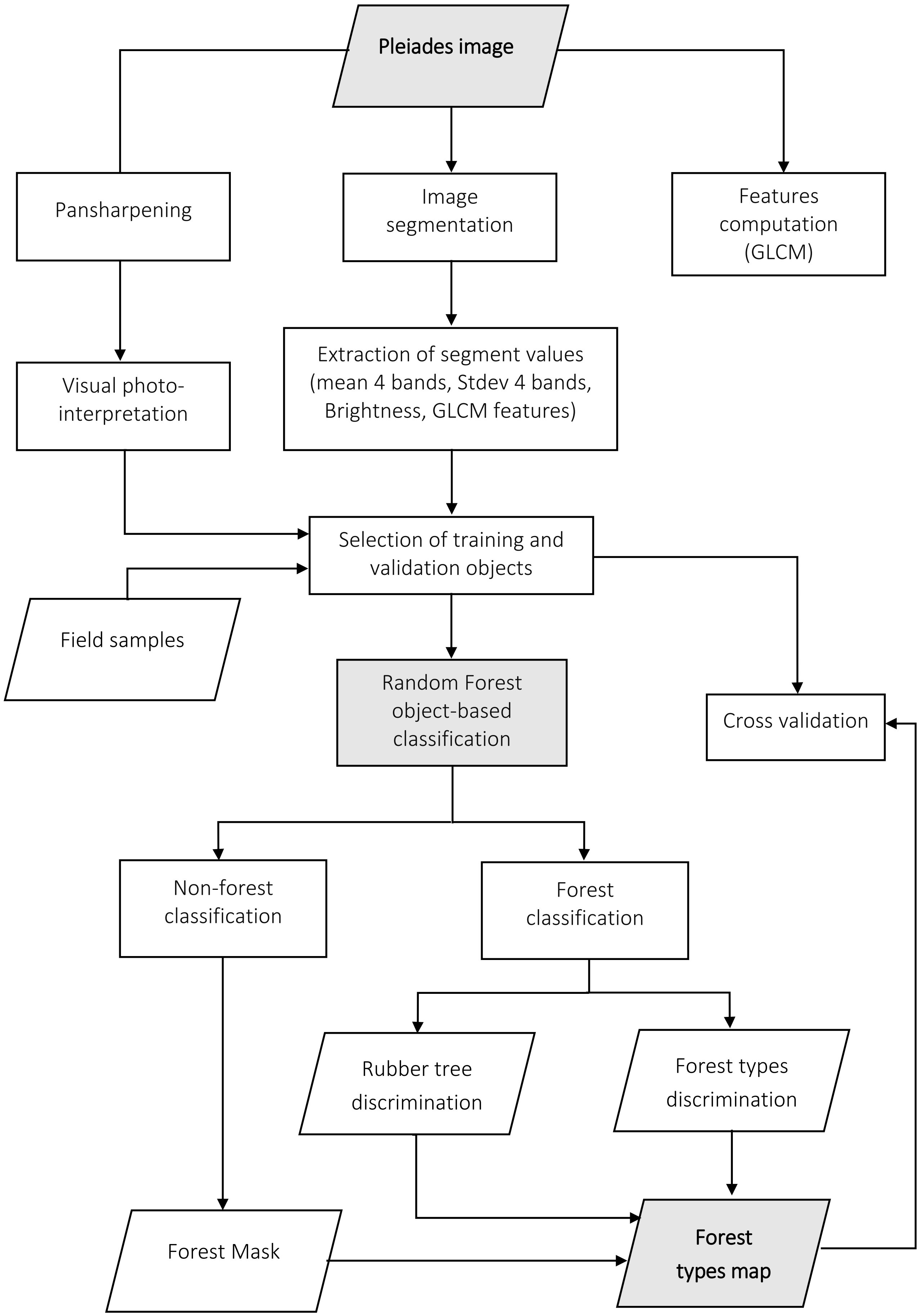


Figure IV.4 - Pleiades image processing, classification and mapping workflow

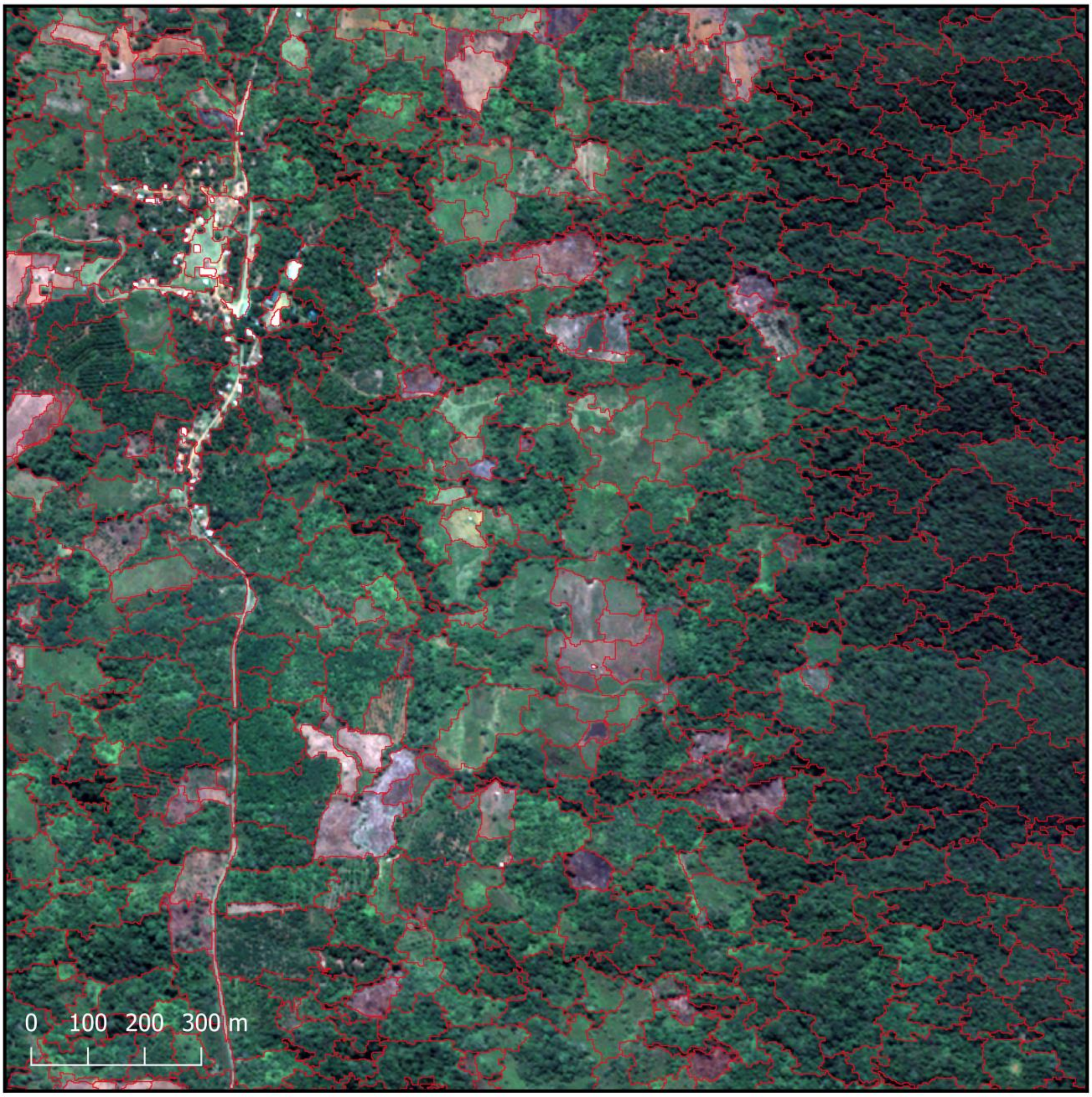


Figure IV.5 – Pleiades image objects obtained by segmentation. Zoom on Bendum village, fields and forest line.

3.1.2 Training and validation dataset preparation

Once the objects available with the corresponding features, a dataset was established based on the field samples. They were represented by GPS points (center of the sample) positioned on the segmented image. If one falls within an object, the class of the sample is given to the object. A sample can be cover by two or three objects, thus the number of objects in the final dataset is higher than the original number of field samples. In addition, some segments were given a class using photo-interpretation to further extend the dataset.

3.1.3 Classification process and cross validation

Because of the pixels size, a per-object classification is chosen to assign a class to the objects out of the training dataset. The classifier used is the Random Forest algorithm since it is powerful, easy to handle, and above all less sensitive to noise which was crucial in this study. Indeed, forest classes may be confused in terms of spectral signature partly because of similar tree species and canopy structures. The entire classification process was performed in the R programming language using the “randomForest” package.

The object dataset needs to be split into training and validation data. The more training data the model receive the better the prediction, but on the other hand more validation objects means a better accuracy assessment. A compromise in the split must be decided. Therefore, in the object dataset, a random 75/25 ratio is chosen for training/validation data. However, because of the small number of object dataset compared to the number of classes, the accuracy assessment varies largely when repeated. Increasing the proportion of validation data would mean a decrease in model prediction.

Therefore, a 4-fold cross-validation process is chosen. It consists in a random split of the dataset into four folds. Three folds out of four are chosen to perform model training, while the last fold is used for validation. The process is then repeated by choosing another fold for validation and the three others for training. This is repeated three times until all four groups were used for validation. The four accuracy assessments obtained are then averaged into one overall accuracy assessment. In other words, validation is performed with the whole dataset, but a given sample was never used for training and validation at the same time.

At each stage of the 4-fold process, 75% of the dataset is randomly selected as training data, while the rest is left for validation. The model is first trained by relating the object features with the corresponding classes. Classes for the other objects are then predicted. Predicted classes on the validation objects and their true class are confronted to assess model accuracy, which correspond thus to the ratio of correct predictions. A confusion matrix is computed, confronting truth and prediction for each class in order to detect problematic classes and confusions.

The resulting prediction is then combined with the polygon shapefile in QGIS to be displayed as a map. A visual inspection is realized with the help of the “swipe” tool in QGIS. This tool allows a precise visual comparison between the predicted class and the original image. A total of 728 samples constitute the dataset.

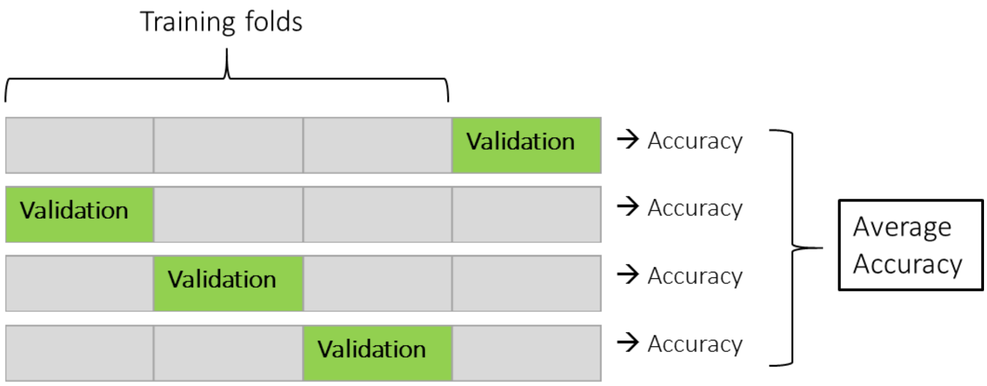


Figure IV.6 - 4-fold cross validation process. Dataset is split into four folds out of which three are selected for model training and the last one for validation. The process is reiterated three times by using each time a different fold for validation. The four model accuracy assessments obtained are then averaged into an overall one.

3.2 Sentinel-2 mapping of forests types

Compared to the Pleiades images, the 10 m spatial resolution of Sentinel-2 data allows a per-pixel classification. Indeed, pixel scale corresponds to several tree crowns and encompasses both trees and canopy gaps, which makes them representative of the forest class. With six dates being available, the process described here was used for the different dates individually, for all of them at once, and for dates regrouped by year. The three images of 2016 were tested on the one hand and the December 2017 and two February 2018 images on the other.

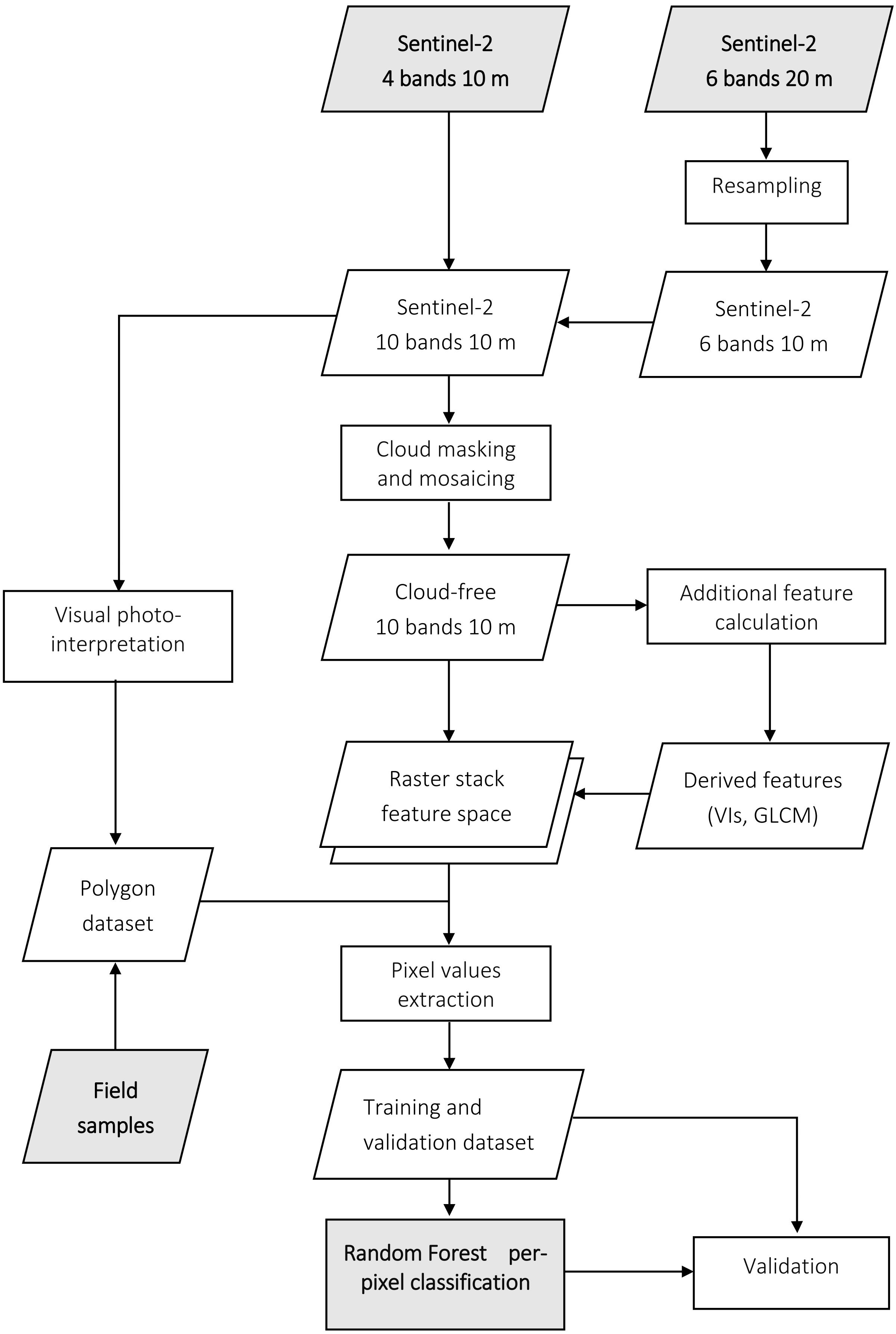


Figure IV.7 – Sentinel-2 image classification process workflow.

3.2.1 Polygon dataset preparation

In order to delimitate pixels concerned by a given sampled area, polygons are drawn based on collected GPS data using GIS software. The limits of polygons are set by photointerpretation to cover the whole single class area concerned by the sample. Additional polygons are added through photointerpretation. These polygons encompassed therefore all pixels related to the sampled area. Depending on the date of the images used, the polygon dataset is adjusted since the landcover can change from one year to another.

3.2.2 Resampling and cloud mosaicking

Since six of the Sentinel-2 bands only have a 20 m spatial resolution, they had to be resampled into 10 m resolution so that they could be stacked with the four 10 m bands. ArcMap (from the ArcGIS suite of ESRI) was used for this resampling.

Clouds were then removed from the resulting ten band images. This was done using the cloud mask (CM) provided by the Sen2agri output. The mask contained various levels of cloud intensity and cloud shadows, but because only few clouds were present and for ease of calculation, all these cloud levels were set to a single cloud value. The resulting mask was therefore a raster file composed of cloud and non-cloud areas represented by 1 or 0. This mask was then applied on cloudy images to select cloudy areas and substitute them with the corresponding values of the cloud-free image, ideally the closest in time. This can be summarized by the following procedure:

$$\begin{aligned} &Cloud\ free\ surface\ reflectance\ Im1 \\ &\quad = Cloudy\ surface\ reflectance\ \ Im1 * (1 - CM) \\ &\quad + cloud\ free\ surface\ reflectance\ Im2 * CM \end{aligned}$$

3.2.3 Features computation

Additional features were computed from the 10 cloud-free band values using GIS software. Normalized difference vegetation index (NDVI) was calculated from the reflectance values of Red and NIR bands following the equation:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

3.2.4 Pixel value extraction

The next steps are realized using a developed R script in which the different raster files (band values and newly computed features) are entered as input. The raster files are stacked and compose the feature space of the classification process.

The polygon dataset is then added, and the raster stack pixel values located inside the polygons are extracted and put together in a data frame, with the corresponding class value of the polygons. The extraction rule is that a pixel is considered for extraction if its center is located inside the polygon extent. The obtained dataset is therefore a pool of pixel values with an allocated class, with no distinction of the polygon from which the pixels originate.

3.2.5 Model training and prediction

The Random Forest classifier designed by Breiman (2001) was used for classifying the image, for the same reasons mentioned in the Pleaides classification process. The classifier was performed in the R programming language using the “randomForest” package.

The dataset was randomly split between training and validation samples in a 3:1 ratio. The training data was given as input in the model. The Gini index was returned, which brought information on the discriminating power of input features. A ranking was established and plotted, allowing to identify and compare feature importance in the model.

3.2.6 Model validation

The trained model was then used to predict classes on the validation pixels. Compared to a prediction on the entire raster stack, this method had a substantial advantage in reducing the computation time of prediction. Since validation is only completed on pixels with known classes, a full prediction on the whole raster extent would be unnecessary and time consuming. A comparison between prediction and known classes leads to an accuracy assessment and a confusion matrix. It is important to note that this is therefore a model accuracy assessment and not a validation of the whole produced landcover. As explained previously, the dataset can then be improved, and the process iterated until a satisfying result is reached.

V. Results and discussion

To assess Sentinel-2 data potential and compare it with very high resolution data, classification methods performed for both images were evaluated. For each process, model accuracy, effect of classifications on the proposed forest classes, and features importance are presented and discussed. Because collected samples are not homogenously spatially distributed among the study area, performance assessment corresponds to the calibration assessment of the model.

1. Very high resolution classification

The Pleiades image was segmented and object-based classified. Results obtained are presented here. Model prediction accuracy, feature importance and the resulting forest map are analyzed. To avoid confusion between forest classes and other landcover types, an initial forest/non-forest classification was performed. Rubber tree plantations were then discriminated from forest types. This process was done for every test carried out.

1.1 Model performance evaluation

Classification performance is evaluated by computing ratio of correct to incorrect model predictions. As mentioned before, the ratio of training and validation data was set to 75%/25% of the dataset, composed of field samples and additional photo interpreted ones.

Because this method consists in a 4-folds cross-validation, the model accuracy assessment presented corresponds to an overall mean value of the four validation stages. Confusion matrices are calculated to identify prediction omission and commission. Because the random data split of the 4-fold process do not systematically select the same number of samples for each class, it is not possible to average the four confusion matrices obtained. Therefore, a single computed matrix was systematically selected among the four folds. Arbitrarily, the first one out of four obtained was chosen.

In order to assess the discrimination of proposed forest classes, a first classification was done for all forest classes. To test the importance of the eight texture features derived from GLCM, two classifications were achieved. The classifier was first used without texture features and then with them. Doing so allows a finer assessment than the Gini index alone.

1.1.1 All proposed forest classes

The model calibration assessments resulting from the cross validation for each classification step are presented in Table V.1. Because predictions can either be correct or not, they follow a binomial law. Therefore, a Bernoulli test was used to calculate confidence intervals. The resulting map is presented in Figure V.1.

Table V.1 - Model accuracy assessments for each classification steps and corresponding confidence intervals based on a Bernoulli test.

	Classification	Model Accuracy	CI (95%)
Without texture	Forest mask	0.956	0.940 - 0.971
	Rubber trees	0.884	0.858 - 0.906
	Forest types	0.708	0.674 - 0.742
With texture	Forest mask	0.962	0.946 - 0.975
	Rubber trees	0.950	0.932 - 0.965
	Forest types	0.730	0.697 - 0.763

It turns out that the model is accurate for around 70% of forest type predictions. Adding texture features only improve classification by around 2%. However, rubber tree classification is improved by 7% by adding texture, going from around 88% to 95%. Adding GLCM texture features is therefore valuable for distinguishing rubber tree plantations from forest types. The forest mask obtained reached an accuracy of around 95% in both cases, allowing it to be used.

Concerning forest types, it is important to look at the confusion matrix obtained to localize misclassification. This consists in a table confronting model predictions to the true class of the segments. The confusion matrix for forest types classification with texture features is presented in **Erreur ! Source du renvoi introuvable.**.

The main confusion occurs between the selectively logged and logged-over classes. Indeed, the model confuses them in almost one out of two cases. This confusion can be explained by the similarity between these forest classes. Indeed, the proportion of logging and therefore canopy gaps is more a gradient rather than two clearly distinct classes. Even if selectively logged and logged over refer to different land use dynamics, forested areas do not always clearly correspond to one class but are sometimes rather halfway between both.

On the other hand, classes such as cogon grass and young regrowth are almost never omitted, which is expected due to their more different characteristics than other classes. Mossy forest, although sharing similar characteristics with old-growth forest (*i.e.* some tree species in common but from different dimensions), appears not to be confused with other classes.

Because it seems that most of confusion occurs between selectively logged and logged-over classes, it was decided to combine those classes into one. This new merged class is simply called “logged forest” and corresponds therefore to all forests that were logged but not clear-cut.

Table V.2- Confusion matrix for forest types classification with textures. Reference classes are on the top, predicted classes on the left. Sample number for each class is represented between brackets.

		Reference					
	Total Pop.: 90	**Cogon grass** (13)	**Young regr.** (21)	**Logged – over** (17)	**Select. logged** (18)	**Old - growth** (12)	**Mossy** (9)
Prediction	**Cogon grass** (11)	11	0	0	0	0	0
	Young regr. (22)	2	19	1	0	0	0
	Logged -over (16)	0	1	9	6	0	0
	Select. logged (20)	0	1	7	9	2	1
	Old – growth (13)	0	0	0	3	10	0
	Mossy (8)	0	0	0	0	0	8

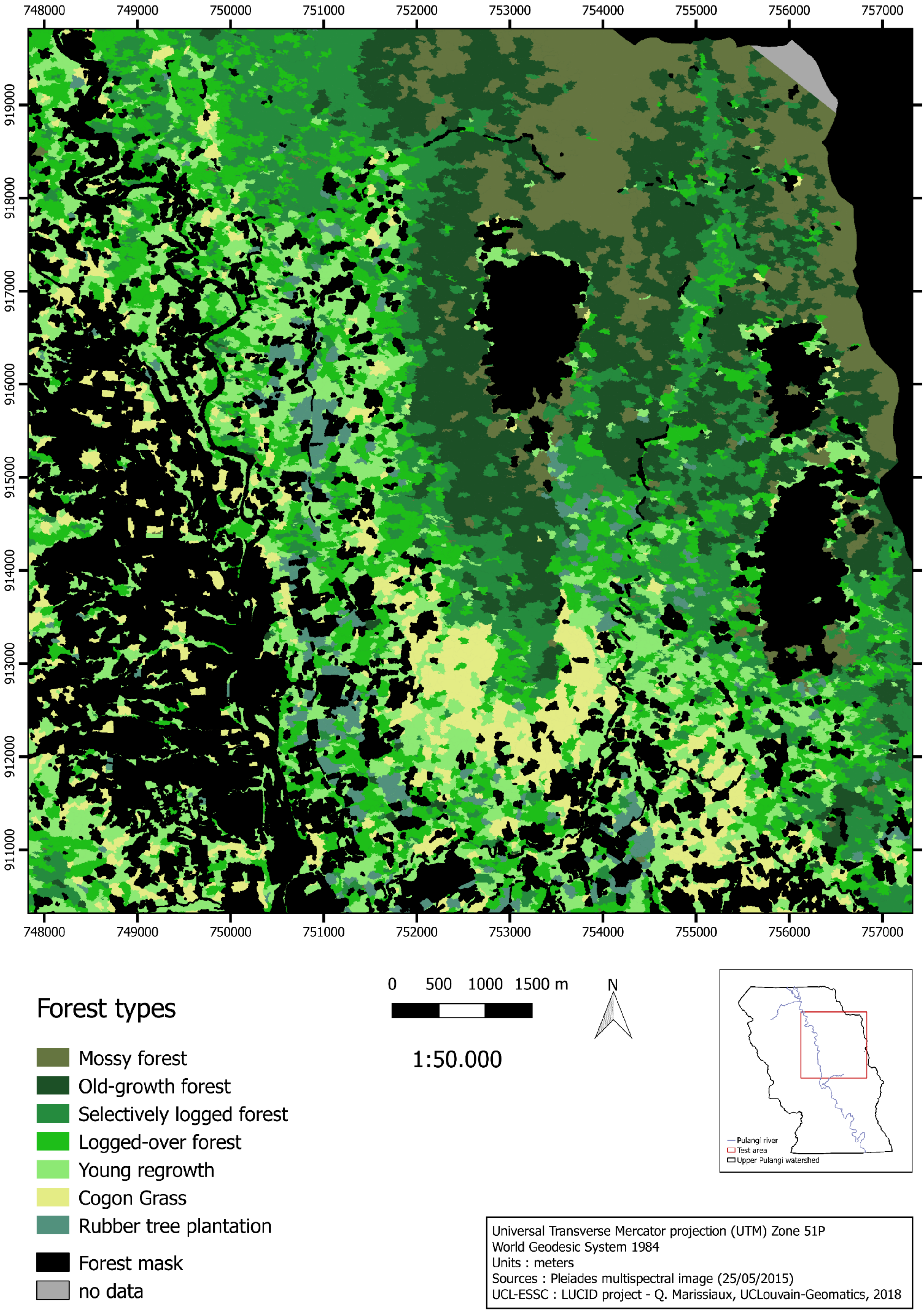


Figure V.1 – Pleiades image classification on test area for the proposed forest classes

1.1.2 Combined selectively logged and logged-over classes

The classification process was repeated with the combined selectively logged and logged-over forest classes, meaning that the model was trained again with the new class. A total of five forest classes were therefore used. Because texture had proven to be useful, it was directly included in the feature space. The resulting map is presented in Figure V.2. The map accuracy assessment and confidence interval are presented in Table V.3.

Table V.3 - Model accuracy assessment for forest types classification using the combined selectively logged and logged-over classes.

	Classification	**Model Accuracy**	**CI (95%)**
With texture	Forest types	0.842	0.813 – 0.868

As expected, model prediction accuracy is improved, from 73% to 84% with the combined classes. This accuracy is the best reached with Pleiades image in this study. The new confusion matrix is presented in Table V.4. Fewer omission and commission errors are present. The most important error remaining appears to be the omission of young regrowth class as the new partially logged class.

Table V.4 - Confusion matrix for forest types classification with combined selectively logged and logged-over classes. Sample number for each class is represented between brackets.

		Reference				
	Total Pop.: 89	**Cogon grass** (18)	**Young regr.** (20)	**Partially logged** (33)	**Old - growth** (9)	**Mossy** (9)
Prediction	**Cogon grass** (16)	16	0	0	0	0
	Young regr. (17)	2	15	1	0	0
	Partially logged (36)	0	5	30	1	0
	Old – growth (12)	0	0	3	8	1
	Mossy (8)	0	0	0	0	8

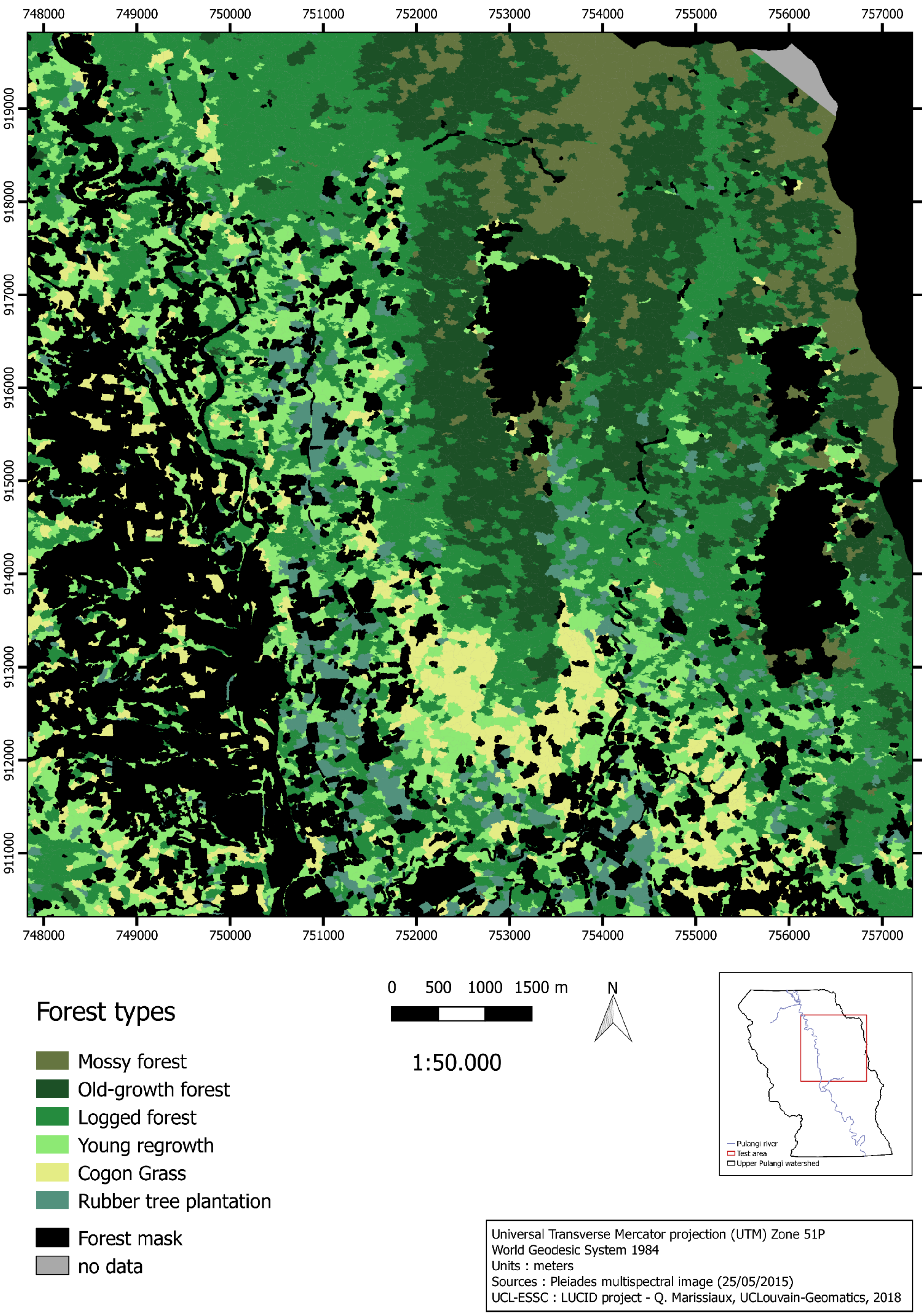


Figure V.2 - Pleiades image classification on test area for proposed forest classes with merged selectively logged and logged over classes.

1.2 Feature importance

Evaluation of feature importance allows to understand their relevance and link them with class physical properties. It allows to detect what parts of the data makes it suitable for forest types discrimination.

The Random Forest classifier includes a feature importance assessment that is determined after model training. The Gini index measures the average gain of purity by splits at tree nodes of a given feature. If the feature is useful, it tends to split mixed labeled nodes into pure single class nodes. The features are ranked according to their decreased effect on the Gini index.

It is however important to point out that this ranking concerns the tree build globally. Therefore, a feature being crucial for a split between two classes but useless for all other splits will appear low in the ranking, although it is essential for the classification process.

1.2.1 Forest mask

In the case of forest/non-forest classification, the feature importance is represented in Figure V.3. It is the mean NDVI value of the segments that distinguishes best. This result can be expected since NDVI assesses the amount of vegetation, which is probably the main difference between bare soil/crop areas and forested areas. Max diff corresponds to the maximum value difference between bands value. The RGB bands then follow as most differentiating features.

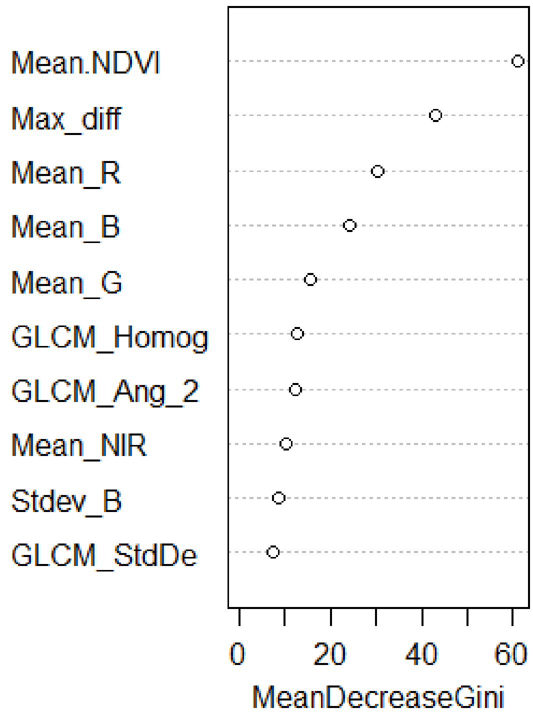


Figure V.3 - Feature importance ranking depending on their decrease effect on the Gini index for the forest mask (Mean = mean value inside the object, Ang_2 = Angular second moment, Stdev = Standard deviation.).

1.2.2 Rubber trees

In the case of discrimination of rubber trees plantation from forest types, adding texture features proved to increase model prediction accuracy from 88% to 95%. When looking at the mean decrease Gini index ranking, it appears that standard deviation and correlation GLCM texture features are the most distinguishing of all features. When adding texture features, it is those two in particular that actually impact classification accuracy, while the other GLCM features are ranked much lower. Its proves that standard deviation and correlation have a discriminative power for rubber tree plantation and forests. This might be due to the structure of rubber tree plantation: it could be due to their regular spatial pattern with lines of gaps between tree rows.

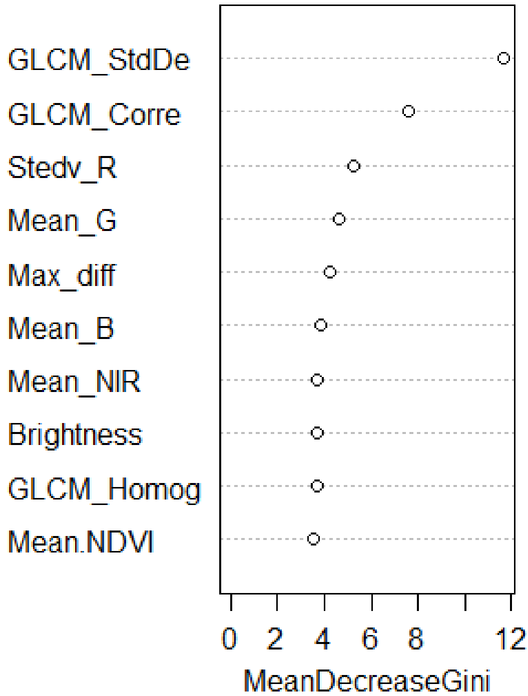


Figure V.4 - Features importance ranking depending on their decrease effect on the Gini index for rubber tress discrimination (Mean= mean value inside the object, Ang_2 = Angular second moment, Stdev = Standard deviation.).

1.2.3 Forest types

In the forest types classification, on the other hand, texture features have little discriminating power. Feature importance ranking is not as clear as previous classifications, but among the top five are the standard deviation of NIR and Blue bands, and the three RGB band mean values.

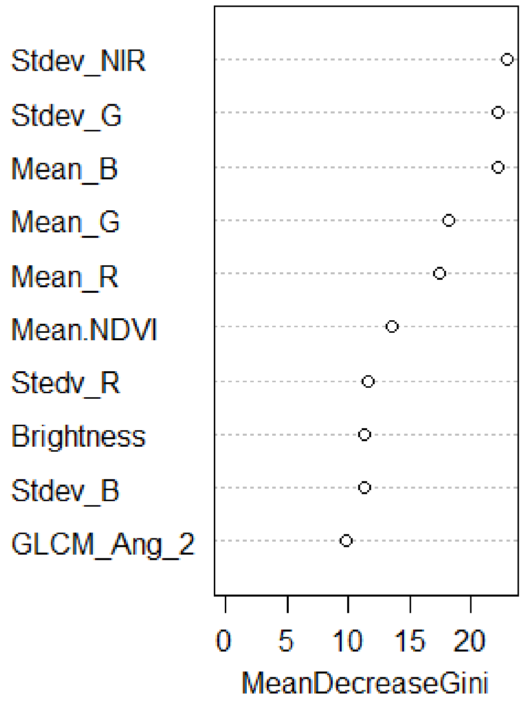


Figure V.5 - Feature importance ranking depending on their decrease effect on the Gini index for forest types (Mean= mean value inside the object, Ang_2 = Angular second moment, Stdev = Standard deviation.).

1.3 Map analysis

Because it is the best result obtained with Pleaides, the classification process involving the combined selectively logged and logged-over classes was applied to the whole Upper Pulangi watershed areas located within the Malaybalay City boundaries. The resulting forest types map is presented in Figure V.6. Because the whole watershed area is not available in the Pleiades images, some areas are missing on the map. Visual inspection shows a more contrasted result than simple model accuracy assessment.

In the case of rubber trees for example, while the model shows 95% accuracy, many objects outside of the validation dataset are predicted as rubber while it is clear that they cannot be. This assessment, without collected samples *in situ*, is made possible by the understanding of the spatial organization of the area. Indeed, due to their position on high hilly slopes far from any road, many objects predicted as rubber can be assumed as confused with what should be selectively logged forest or old growth forest.

Topographically, when looking at the hillsides of the valley, the forest types toposequence presented in the spatial organization seems to be well represented.

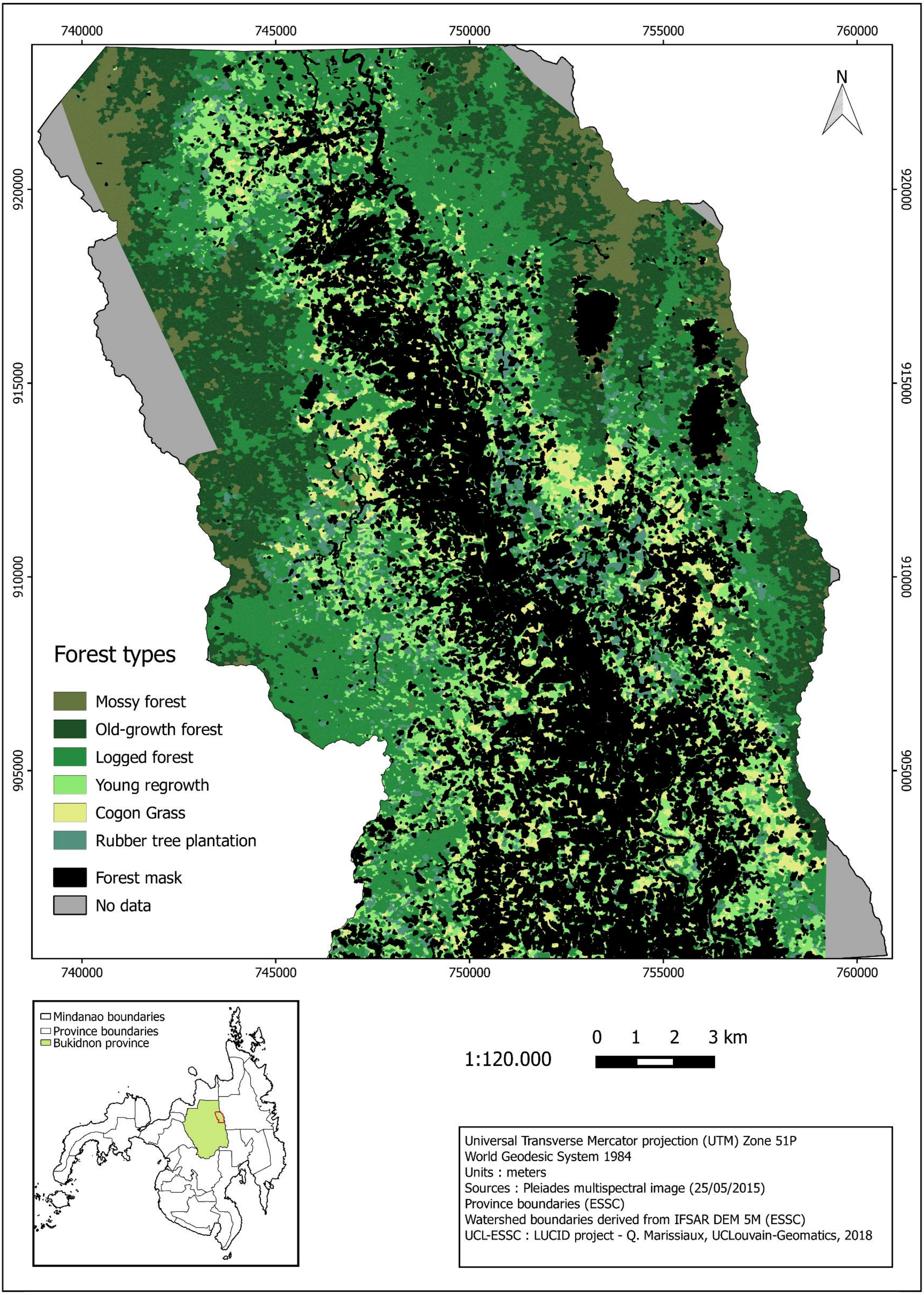


Figure V.6 – Pleiades image classification on the Upper Pulangi watershed for proposed forest classes with merged selectively logged and logged over classes

2. Sentinel-2 classification

The Sentinel-2 images were per-pixel classified, and the method performance was evaluated in the same way as for the VHR image, namely by assessing model calibration accuracy, feature importance and analysis of the resulting forest map. As mentioned before, the ratio of training and validation data was set to 75%/25% of the dataset, composed of field samples and completed with photo-interpreted ones based on the Pleiades image. Validation was achieved per-pixel, *i.e.* 25% of pixels dataset not used for model training were classified and compared to corresponding reference class values. 10 m resolution was used for validation. For the same reason mentioned for the Pleiades images, and to allow a better comparison between methods later on, the same hierarchical classification process as for the VHR image was performed. Results obtained are presented here.

Temporality is a crucial asset of Sentinel-2 data. To assess its impact, the developed method was used in three different ways: for a single date, for the six dates as a whole, and for the dates regrouped by years. The latter corresponds to the tree dates of 2016 (02/04, 21/07, 08/12) regrouped, while the December 2017 image is regrouped with the two early February 2018 images, because of proximity in time. Even though it allows a comparison of years with the same number of images, the first group is homogenously split along the year while images of the second group are temporally close to each other. Concerning the single date, the February 16th, 2018 image was chosen because being the closest in time to the field campaign and therefore best corresponding to the collected samples.

2.1 Model performance

In the same way as the VHR method, classification performance was evaluated by computing ratio of correct to incorrect model predictions. Confusion matrices are calculated to localize predictions errors and confusion between classes.

Unlike the 2 m resolution Pleiades image, GLCM texture features were not added to the feature space for Sentinel-2 classification given the more limited textural information on 10 to 20 m pixel resolution images compared to VHR images, and extensive computation time.

Resulting model classification accuracies and corresponding 95 % confidence intervals are presented in Table V.5. Prediction accuracy increases when adding dates. Indeed, the random forest classifier will reach better results with a larger feature space. The strongest increase in classification accuracy occurs in the forest types discrimination, going from 87 % accuracy for one date to 96 % for six dates. This suggests that proposed forest classes have different spectral signatures depending on temporality. In terms of confidence intervals, 95 % are on a thousandth scale, which means that model prediction is accurate.

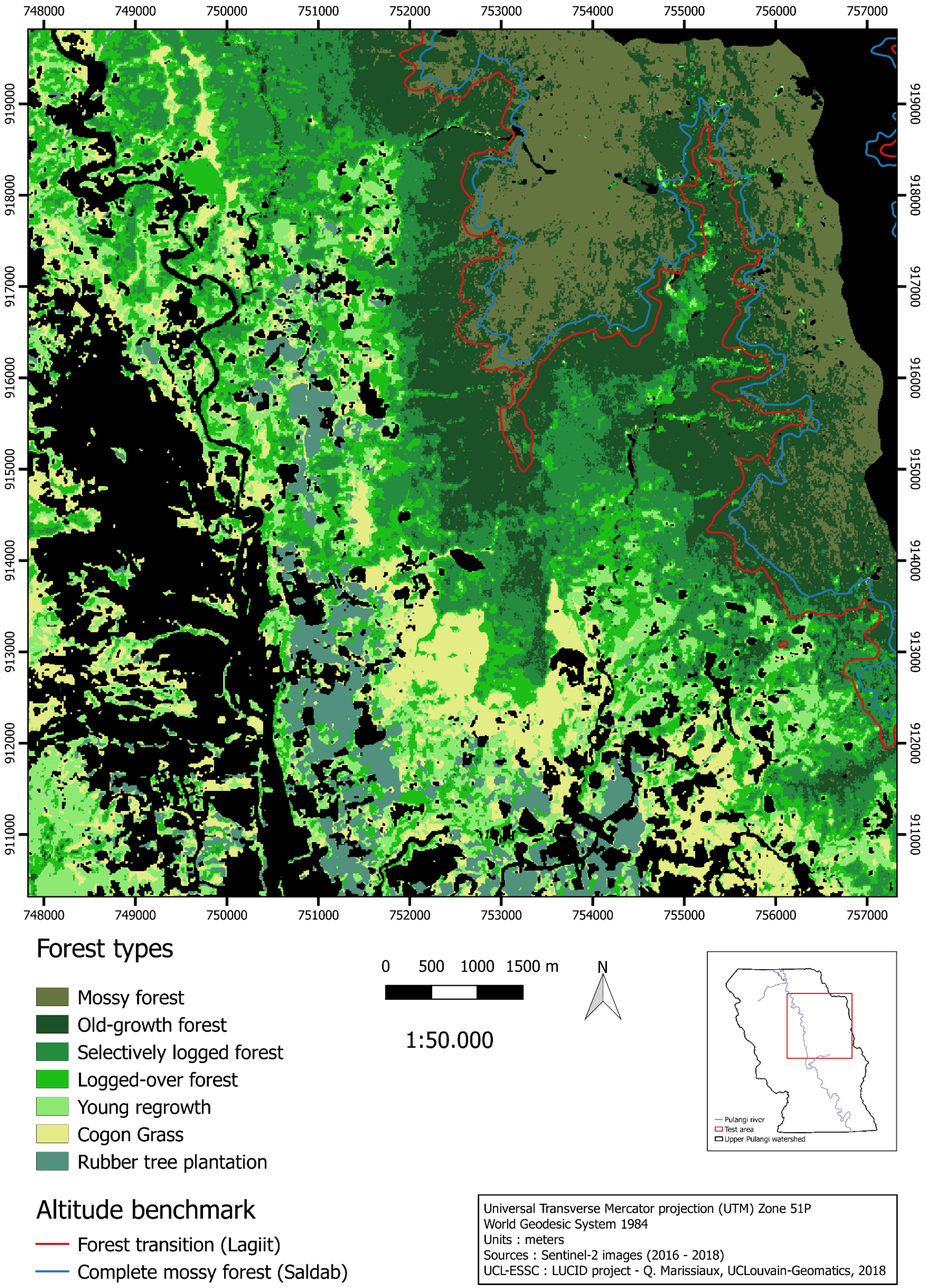


Figure V.7 - Sentinel-2 all six images classification on test area for proposed forest classes.

Table V.5 - Model classifications accuracies and corresponding 95 % confidence intervals for tested temporalities.

Classification	Images used			
	1 date	**3 dates 2016**	**3 dates 2018**	**All 6 dates**
Forest mask	0.977	0.989	0.988	0.997
	0.963-0.986	0.987-0.991	0.985-0.986	0.996 - 0.998
Rubber trees	0.976	0.991	0.987	0.991
	0.961-0.985	0.988-0.992	0.985-0.990	0.989 - 0.993
Forest types	0.872	0.943	0.925	0.959
	0.864-0.879	0.938-0.949	0.919-0.931	0.955-0.964

With the confusion matrix presented in Table V.6, no clear confusion appears. It coincides with the 96 % accuracy assessment, which tends to show no confusion.

However, what needs to be mentioned is that validation was achieved by randomly selecting 25 % of pixels among the pixel dataset. Since it is a per-pixel validation, spatial correlation has an impact on these results. Indeed, if a pixel is selected in the middle of a certain class patch, it is less likely to be misclassified since neighbor pixels have been used for model training. Accuracy assessments presented can therefore be overrated.

Table V.6 - Confusion matrix for all six dates forest types classification. Sample number for each class is represented between brackets.

		Reference					
	Total Pop: 7084	**Cogon grass** (1148)	**Young regr.** (761)	**Logged -over** (1303)	**Select. logged** (1531)	**Old - growth** (1673)	**Mossy** (670)
Prediction	**Cogon grass** (1150)	1132	14	4	0	0	0
	Young regr. (757)	14	716	25	2	0	0
	Logged - over (1274)	0	27	1210	36	1	0
	Select. logged (1526)	2	2	64	1444	14	0
	Old – growth (1712)	0	2	0	49	1646	17
	Mossy (665)	0	0	0	0	12	653

2.2 Feature importance

As with the Pleiades feature importance assessment, mean decrease in Gini index value given by the random forest algorithm is used. It allows to determine which Sentinel-2 bands are the most relevant for tropical forest types discrimination.

2.2.1 Single date

Feature importance for a single date is presented in Table V.7. For the forest mask, NDVI is the most discriminating feature. In the case of rubber trees separation from forest types it is the two SWIR bands that are ranked at the top, followed by a red-edge band. Regarding forest types classification, SWIR bands are at the top as well, with blue band and red-edge bands.

Table V.7 - Top 5 features ranked by importance of their decrease effect on the Gini index for one single date.

Forest mask	Rubber trees	Forest types
NDVI	SWIR2	SWIR1
Red-edge 1	SWIR1	SWIR2
R	Red-edge 1	B
Red-edge 4	B	Red-edge 2
G	G	Red-edge 1

2.2.2 All six dates

Looking at feature importance for several dates allows to confirm their role since each feature is represented several times (six times in this case). Table V.8 represents the top 10 features (on a total of 66) ranked by importance for each classification. Full ranking for forest types classification is presented in Figure V.8. Full ranking for forest mask and rubber trees are listed in appendix.

Table V.8 – Top 10 features ranked by importance of their decrease effect on the Gini index for all six dates combined. Images are chronologically listed, from date 1 to 6.

Forest mask	Rubber trees	Forest types
Date 4 - NDVI	Date 2 - R	Date 1 - SWIR2
Date 3 - NDVI	Date 1 - Red-edge 2	Date 1 - SWIR1
Date 4 - R	Date 5 - SWIR2	Date 4 - B
Date 4 - B	Date 1 - SWIR1	Date 2 - SWIR1
Date 1 - NDVI	Date 2 - B	Date 5 - SWIR2
Date 5 - NDVI	Date 1 - Red-edge 3	Date 4 - SWIR2
Date 2 - NDVI	Date 2 - G	Date 6 - B
Date 1 - SWIR2	Date 6 - SWIR2	Date5 - B
Date 6 - NDVI	Date 4 - Red-edge 4	Date 4 - SWIR1
Date 1 - B	Date 2 - NDVI	Date 2 - SWIR2

In the case of the forest mask, it clearly appears that NDVI is the most discriminating feature, since all of the six indices are present in the top ten. This confirms the fact that NDVI contributes for a major part in discriminating wooded areas from other landcover classes. Regarding rubber tree discrimination from forests, it appears as an heterogenous ranking where the date has an influence on the discriminating power. It seems however that SWIR and red-edge bands have a strong influence on classification. These bands are dedicated to vegetation observation, which makes them suitable for discriminating close vegetation types such as wooded plantations and forests.

Finally, when looking at forest types classification, it happens that SWIR bands are the most discriminating features. Seven of them are in the top 10, and all 12 of them (two SWIR bands per images for six images in total) are present in the top 20 (Figure V.8). Blue band has also a strong discrimination power since five out of six are present in the top 20, which is almost entirely made of SWIR and blue bands. This SWIR and blue bands differentiating power confirms comparable results from literature (Immitzer *et al.*, 2016). However, having the blue band as a good discriminating feature might be difficult to explain since it corresponds to atmospheric reflectance, among others.

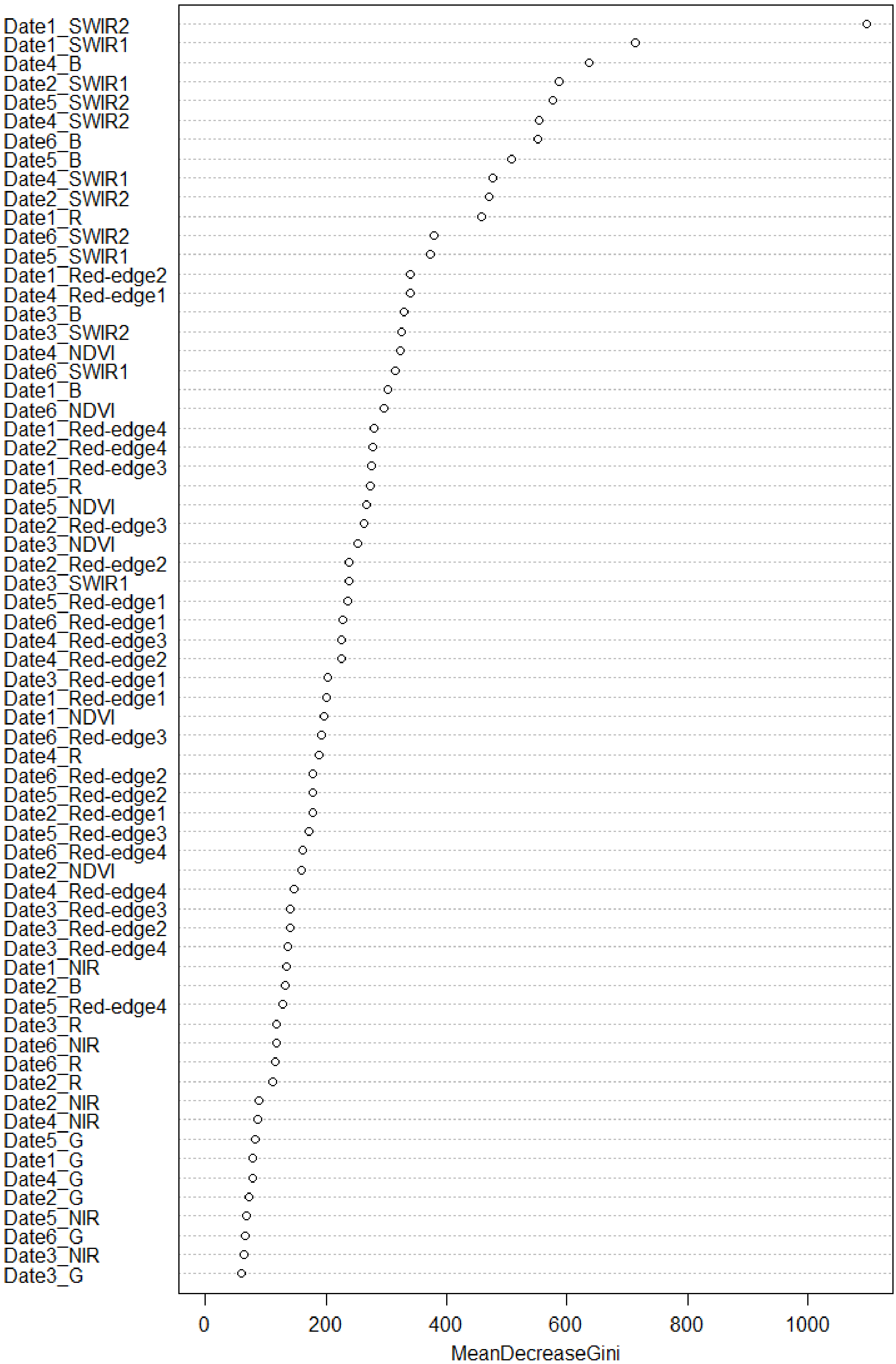


Figure V.8 – Features importance ranking by mean decrease effect on the Gini index, for all six images. Dates are chronologically numbered. SWIR and blue bands are the most discriminating features for forest types classification.

2.3 Map analysis

Visual inspection reveals spatial map characteristics. Effect of topography, transition between classes and general aspect are detailed.

The forest types toposequence is well represented on the resulting prediction. The transition band between old growth and mossy forest was measured on the field and is represented on an IFSAR digital elevation model (5 m resolution) on Figure V.7. Per-pixel classification gives mixed prediction of both classes in this area, which shows that this method allows to represent transition between forest types. Even though altitude related, mossy forest location can vary depending on the orientation of slopes and tend to be more present on ridges even if they are lower located. The transition was measured on the west slope were model prediction appears to be correct. On the east slope however, it seems that mossy forest is located higher in altitude. Mossy forest on ridges seems to be well detected. As illustration, it is well present on the narrow ridge south of the main hill.

When looking at degraded forest classes, a forest edge effect is detected by the model. Indeed, logged-over classes are represented by dense vegetation developing below canopy to the light overflow. This overflow is due to the large canopy gaps of this forest class but can also be due to proximity to forest edge, where light flows from the flanks. Logged-over class is detected at forest edges, with selectively logged forest inward. It is also detected along rivers, where the vegetation free area allows more light to come in. This river effect is confirmed by looking at the topography lines on Figure V.7.

When looking at the watershed map in Figure V.9, the west hill side (middle left side of the map extend) presents what seems to be a significant effect of exposure. Indeed, predicted forest types seems to follow the hill topography. This might be an effect of the scaling up process, with all the training samples being aggregated on one side of the area.

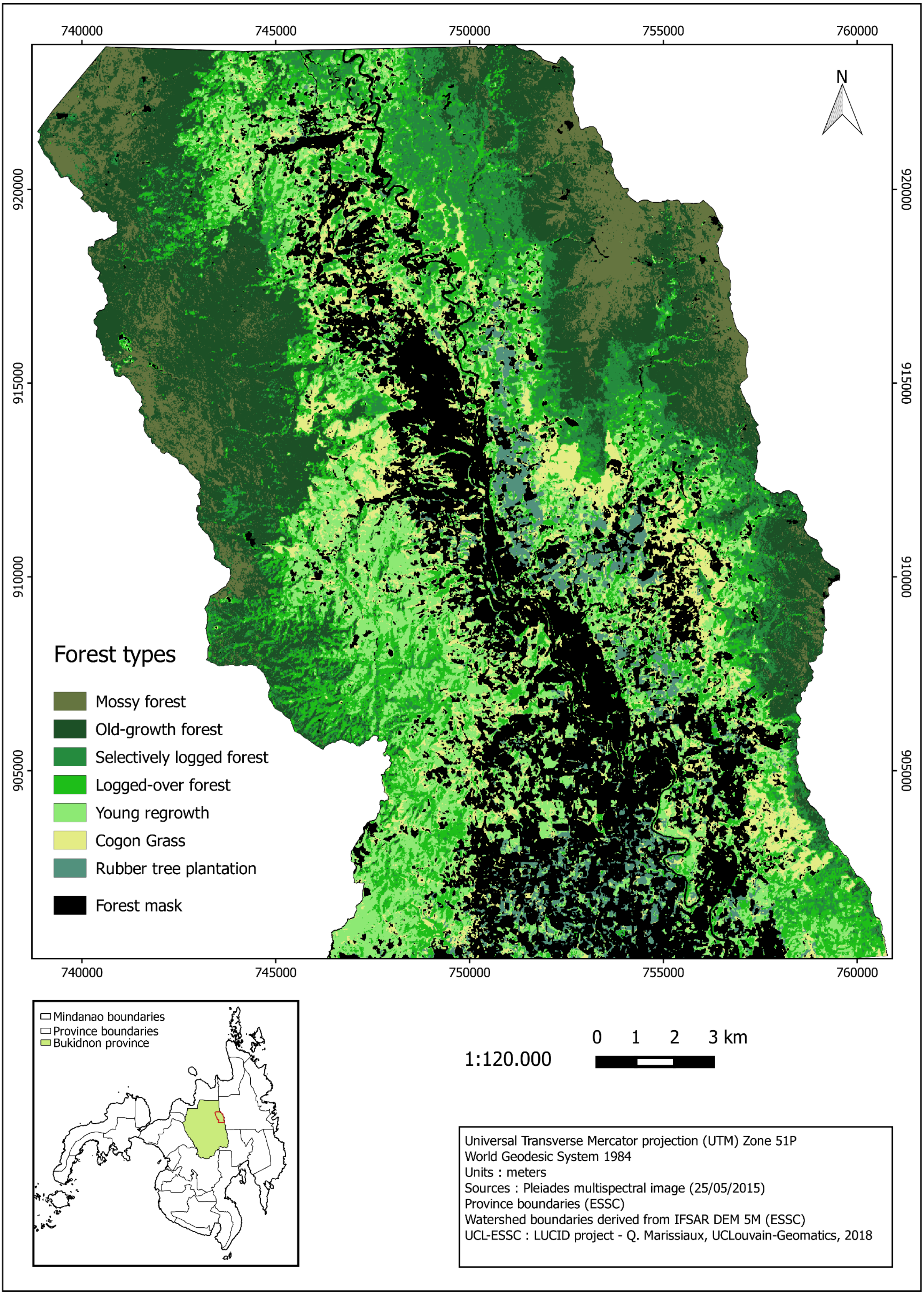


Figure V.9 – Sentinel-2 all six dates classification of the Upper Pulangi watershed for proposed forest classes

3. Methods comparison

It is interesting to compare the two developed methods in order to put into perspective their suitability for tropical forest mapping.

3.1 Impact of data characteristics

Images characteristics are the main influence on resulting classifications. With respect to spatial resolution, VHR 2 m pixels are unsuitable for per-pixel classification, and variations among them are high, which implies segmentation for object-based classification, with each feature being averaged on the object. Sentinel-2 10 and 20 m resolution allows a detailed mapping without requiring segmentation, because its pixel size is suitable. Indeed, 10 m is just larger than tree crown scale, and 20 m bands allows to encompass both tree crowns and canopy gaps, which allows to take wooded areas spectral variations into account while getting rid of tree-scale ones.

In terms of spectral information, the 4 bands of VHR image limits the classifier discriminating power and particularly between two proposed forest classes. Sentinel-2 10 bands on the other hand, allows a discrimination of all proposed forest classes thanks to its two SWIR bands. These bands purposely designed for vegetation mapping have proven to be valuable in this case of tropical forest types.

The temporal aspect of Sentinel-2 though under-represented in this study due to the low number of available images, still proves its value for classification accuracy enhancement. The single VHR image on the other hand could not allow such enhancement.

3.2 Models performance

While the 2 m resolution Pleiades image requires segmentation for an object-based classification, Sentinel-2 data can be per-pixel classified. This main difference impacts mapping.

The per-pixel classification allows representation of transition areas between forest types, which is impossible in an object-based approach. Object-based classification however gives visually cleaner results which would be better in the case of crop mapping. In natural forested areas, mixed pixels and patches can reflect local variation and can be useful to represent. These variations are not represented in the objects.

VHR image gives more spatial information and allows to derive texture features. But computing these texture features along with image segmentation turns out to be a time-consuming processes even for a small area such as the study site, which strongly limits applications to larger scales. The Sentinel-2 classification process, on the other hand, is way faster and shows less limitations in surface applications.

On model performance itself, the Sentinel-2 process appears to be the better between the two. When it comes to model prediction accuracy, it is higher with around 95% for all proposed classes while Pleiades has a 85 % accuracy at best and with two classes combined. This statement must be nuanced since validation processes have not been conducted in the same way. In the case of Sentinel-2, the per-pixel validation is susceptible to spatial correlation and is therefore over-estimated. Validation is however more precise because of the large number of pixel evaluated, compared to the low object numbers in the Pleiades validation process which gives a more variable assessment.

3.3 Maps crossing

In order to quantify differences in predictions from both methods, resulting maps are crossed. Because one is vector format and the other in the form of a raster file, one of them must be transformed into the other format. Because segmentation had given satisfying results, it was decided that the Sentinel-2 per-pixel prediction be transformed into objects from Pleiades segmentation. To get object attributed class, a majority voting is achieved inside each object.

The two object-based maps can thus be compared and contrasted. Because of different cloud condition and temporality, forest masks are spatially different. If an object is predicted as forest mask in at least one of the two maps, the object is not considered for comparison. Because the VHR best result was achieved with combined selectively logged and logged-over classes, predictions for both classes were merged as well in Sentinel-2 results for a fair comparison. A confusion matrix between both outputs' given classes is computed to localize disagreements between methods.

Predictions of methods coincide in 57 % of objects on the Upper Pulangi watershed, presented in **Erreur ! Source du renvoi introuvable.**. When looking at the crossing table, some strong disagreements appear. The main ones are between rubber trees and young regrowth, with more rubber trees prediction subject to disagreement than agreement. Then comes mossy and old-growth forest, and old-growth with partially logged. What it seems to reflect here are two different ways of setting limits between classes being part of a gradient. Because of the object-based process, the given classes are actually the most likely ones in the entire area of the object, while in reality a gradient could be occurring there.

This is even more true in the case of majority voting of the pixel-based Sentinel-2 process, where the given class is the most represented one. It means that an object overlaying a transition between two classes will receive the value of the main one even if they are almost equally distributed. This can partially explain disagreements between neighboring classes.

Table V.9 – Prediction crossing for both methods in number of predicted objects. Sample number for each class is represented between brackets.

		Reference					
	Total Pop.: 34930	**Cogon grass** (1994)	**Young regr.** (8726)	**Partially logged** (12974)	**Old - growth** (8016)	**Mossy** (1675)	**Rubber tree** (1545)
Prediction	**Cogon grass** (1711)	1025	568	37	13	14	54
	Young regr. (8666)	801	4626	2183	274	39	743
	Partially logged (16097)	97	2730	9404	3411	105	350
	Old – growth (4977)	5	55	711	3523	675	8
	Mossy (1679)	14	24	108	689	841	3
	Rubber trees (1800)	52	723	531	106	1	387

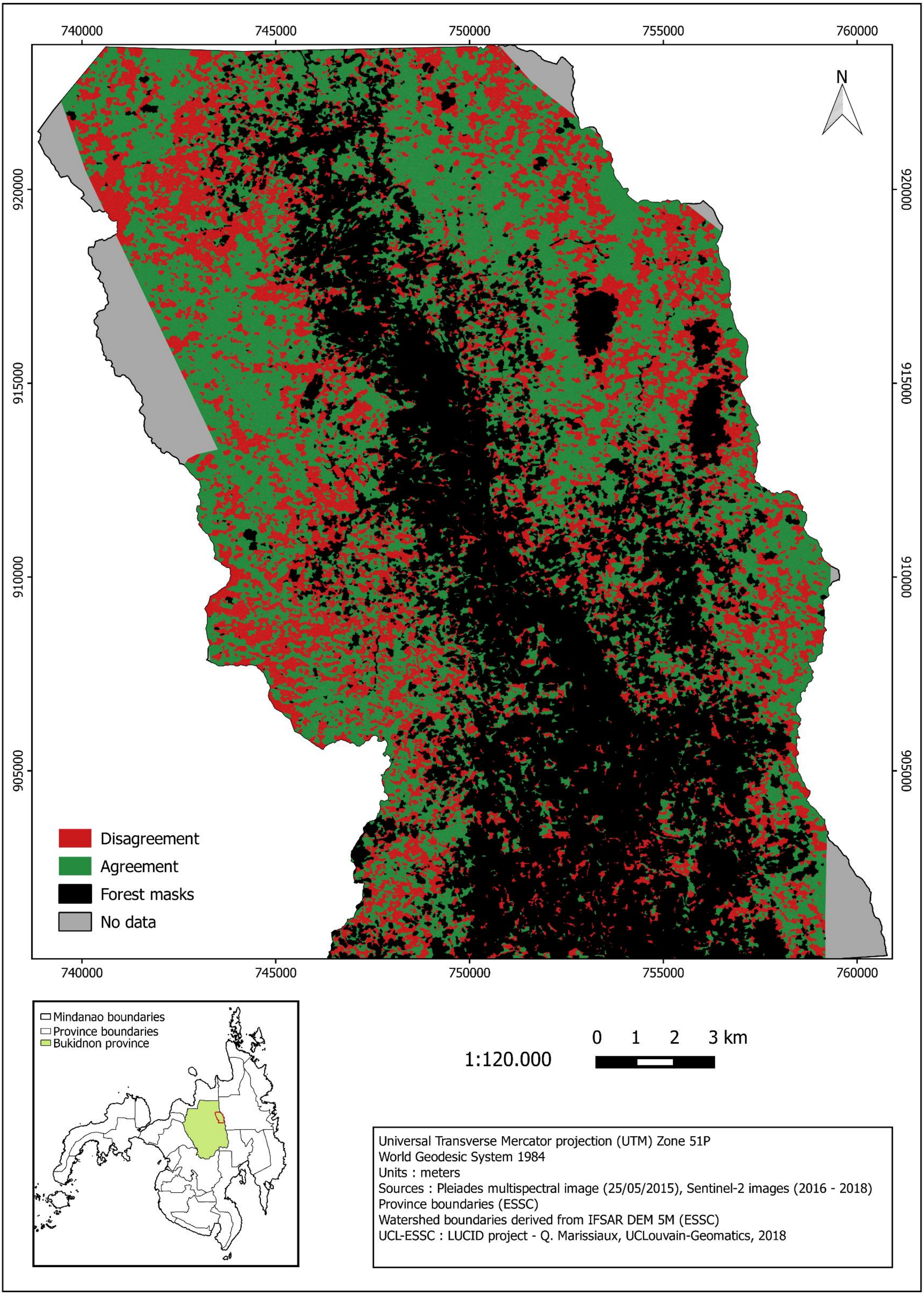


Figure V.10 – Classifications crossing based on objects from Pleiades image segmentation.

4. Model application for a complete landcover

Because the Sentinel-2 classification proved to be accurate (>90 %), the developed method was applied to obtain a fully usable landcover map product of the Upper Pulangi watershed, tailored for the local partner, ESSC. To do so, non-forest classes must be added, and classification must be post-processed to obtain a visually cleaner result with a greater readability

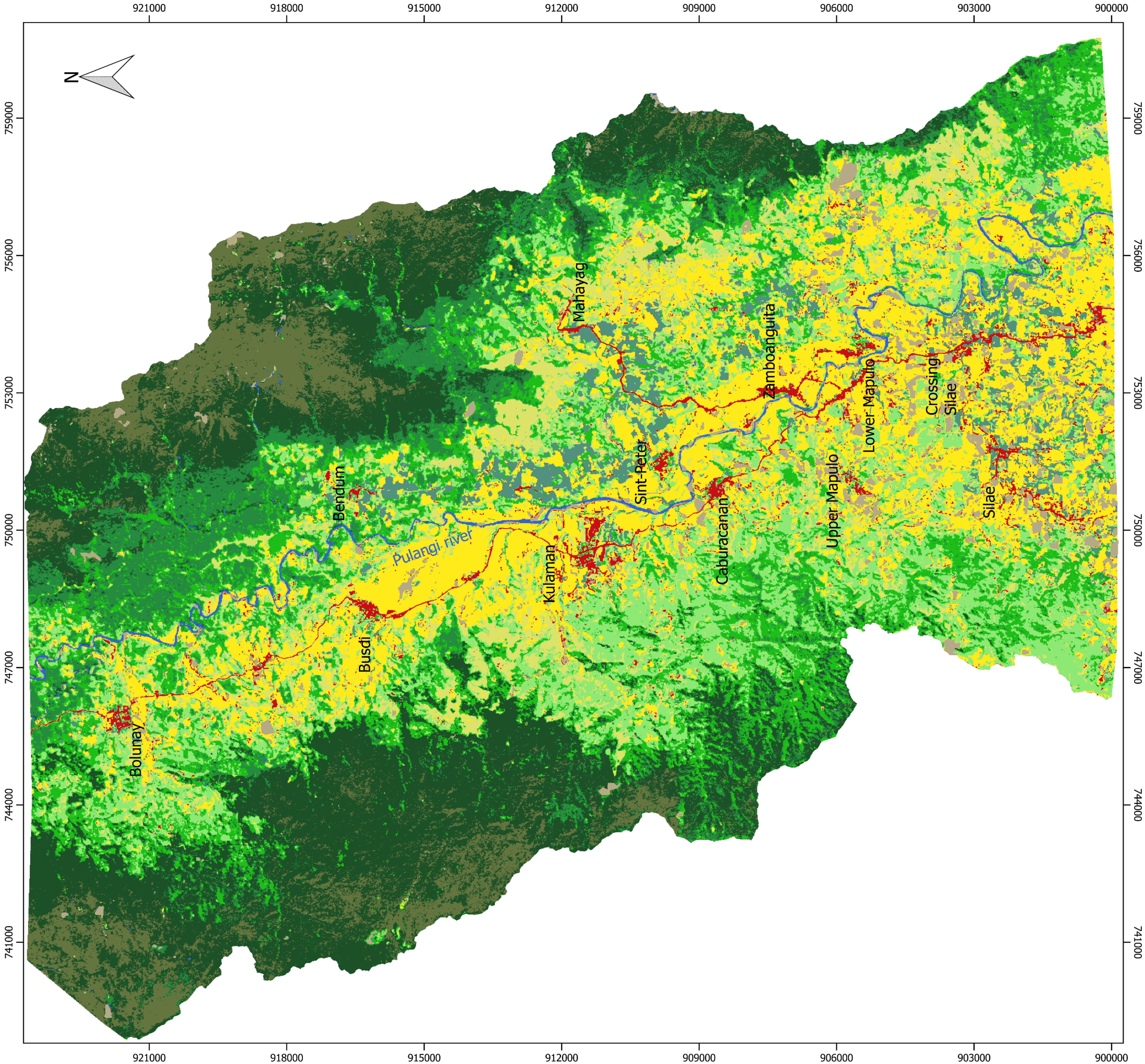
The same hierarchical method as the one developed was used, but what the forest mask was is now discriminated into four non-forest classes: built up areas including villages and roads, croplands, water and bare soil. The later was added because of areas of exposed gravel and mud located along the river, and because of open areas inside forests (from localized landslides or clear cutting) that are not cultivated. The dataset for non-forest classes was constituted by photo-interpretation of Sentinel-2 images.

Non-forest classes model prediction is validated the same way as forest classes prediction, *i.e.* by randomly selecting 25% of pixels dataset for model prediction, later compared to the reference classes. The model reaches 98.5 % prediction accuracy, which means little omission and commission errors in the confusion matrix.

Due to the per-pixel classification process, single pixels or small patches can occur. In the case of non-forest classes, these cannot be exact since croplands or built up areas correspond to a certain minimum size. This is also true for rubber tree plantations. This is why filters are applied to obtain a visually cleaner result.

A majority filter was applied, which consist in this case in a 3x3 moving window where the central pixel value is changed based on the majority value of surrounding pixels. Noisy pixels are filtered differently for rubber trees than for non-forest classes. Because rubber trees plantations always possess a large and geometric shape, all other smaller patches predicted are wrong, and a strong filter must be applied. It is made possible by the hierarchical classification process, with rubber being on an apart layer. The eight neighboring pixels are considered for majority, which makes small patches disappear but can trim larger patches angles. The result is that only larger patches remain, with rounded corners. In the case of non-forest classes, a lighter filter is applied to preserve detected roads, that are only one or two pixels wide. The four adjacent pixels are only considered for majority. This filter was applied two times. Forest classes are left intact to preserve edges and transition effects represented by clouds of single pixels.

Because of the limited number of images, some cropland appears as bare soil because these were not cultivated at the time the pictures were taken. A few local misclassifications occur and were therefore manually corrected.



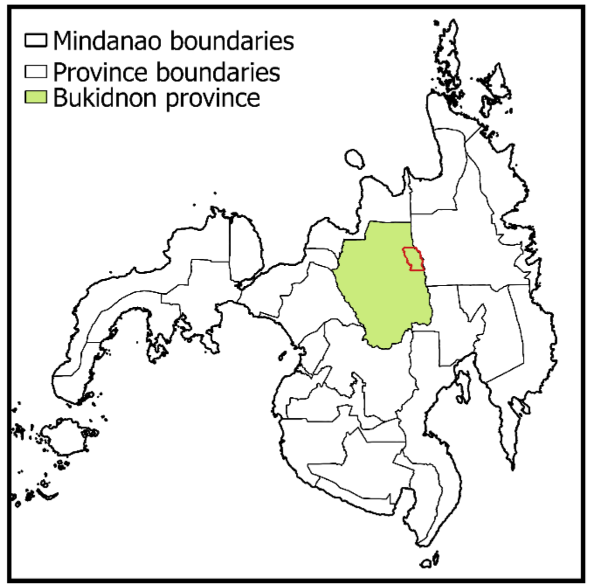
Upper Pulangi landcover

Malaybalay, Province of Bukidnon, Philippines

1:80.000

- Mossy forest
- Old-growth forest
- Selectively logged forest
- Logged-over forest
- Young regrowth
- Cogon grass
- Rubber tree plantation
- Cropland
- Bare soil
- Built-up surface
- Water

Universal Transverse Mercator projection (UTM)
Zone 51P
World Geodesic System 1984
Units : meters
Sources : Sentinel-2 images (2016-2018)
Province boundaries (ESSC)
Watershed boundaries derived from IFSAR DEM 5M (ESSC)
UCL-ESSC : LUCID project - Q. Marissiaux, UCLouvain-Geomatics, 2018



VI. Conclusion

Tropical forest plays an important role in the biosphere, being an important biodiversity and carbon stock. It is under constant anthropogenic pressure. Some human activities such as selective logging or shifting cultivation not always result in forest clear cut, but rather in forest degradation. Areas can eventually regenerate, which results in what is called forest dynamics. It is thus important to look at these forest dynamics stages rather than forest cover only. Remote-sensing offers faster and cheaper ways to monitor forests than field observation only, from local to global scale. The new high resolution (10-20m) Sentinel-2 satellites from ESA Copernicus program designed for vegetation observation shows a potential for forest monitoring, with 10 spectral bands and a five days temporal resolution.

The objective of this study was to investigate Sentinel-2 potential for forest dynamics monitoring. To this purpose, it was required to develop a method to identify and map forest dynamic classes based on Sentinel-2 time-series. To do so, dynamics at stake in the study area needed to be characterized, and a forest typology suitable for monitoring had to be established. Because very-high resolution data was the main data type used for local forest dynamics monitoring, the developed Sentinel-2 method had to be confronted to a developed VHR mapping method in order to further assess its possibilities.

Thanks to the field campaign conducted on the study area in Upper Pulangi, Mindanao, Philippines, a typology of six forest dynamics classes have been proposed. The two developed methods for monitoring these classes are based on two different classification processes due to differences in images spatial resolution. The VHR is segmented and per-object classified with the use of computed texture features, whereas Sentinel-2 images are per-pixel classified. Random forest algorithm was selected because it presents suitable characteristics and is the main machine learning classifier used nowadays. Due to the cloudy climate of the study area, only six Sentinel-2 images were available, which constraints the investigation of the full potential of these data.

This study shows that even in limited temporal availability, Sentinel-2 data is suitable to discriminate all six proposed forest classes from the established typology. Model prediction accuracies score above 90%. The use of the six available images as a whole shows an increase in model accuracy compare to single-date classification. Grouping images per year (2016 and 2018) presents limited differences in terms of forest types cover, meaning that a larger time scale is required to monitor evolution of forest dynamics in the area. In terms of features, the most important ones for forest classes discrimination proved to be the two short-wave infrared (SWIR) bands, followed by the blue band. Although dedicated to vegetation observation, the four red-edge bands only showed importance to discriminate rubber tree plantations from forest classes.

The method developed for VHR shows less accurate model prediction, with an overall accuracy of 70% and the confusion of two proposed classes. Combining them into one lead to an increase in classification accuracy up to 85%. The 2 m pixel resolution being smaller at sub-tree scale, per-pixel classification was unappropriated. The image was therefore segmented, and per-object classified. GLCM texture features were computed as additional features. It appears that standard deviation of near-infrared and green bands were the most discriminating features for forest classes along with the blue band, whereas texture features had a minor role. However, standard deviation and correlation texture features extracted from the GLCM proved to be the most important to differentiate rubber tree plantations from forest classes.

To compare both methods, the Sentinel-2 per-pixel classification had to be transformed in a similar format as the VHR map. Therefore, a majority voting was carried out on the Sentinel-2 predicted pixel values inside the VHR objects. The confrontation of both results showed an agreement on prediction of less than 60%. This can be explained by the majority voting process and the similarities between some forest classes. In terms of performance comparison however, the Sentinel-2 based method showed more accurate predictions and was able to discriminate all proposed classes, unlike the VHR method. This added to the costs, temporal and spatial availability, makes Sentinel-2 a suitable data source for tropical forest dynamics monitoring.

Because it was proven efficient, the Sentinel-2 developed method was applied to obtain a usable map product in the form of a full landcover of the Upper Pulangi watershed. Non-forest classes (croplands, built-up areas, water, bare soil) were added to the classification process to obtain the landcover map.

Further researches could deeper investigate the temporal potential of Sentinel-2 data for forest dynamics monitoring with the use of denser time-series, even though difficult to obtain in tropical climate. In terms of spatiality, studies at larger scale would allow to determine method robustness on a more heterogenous landscape and detect potential model over-fitting.

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Characterizing tropical forest dynamics by remote-sensing using very high resolution and Sentinel-2 images

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Résumé

Tropical forest is a major Earth ecosystem, in terms of extend, biodiversity and carbon stock. Anthropogenic degradations put this ecosystem under increasing pressure. Some practices such as selective logging or shifting cultivation however, not always lead to net forest cover loss, but rather in a change in forest structure. Vegetation regenerate through different stages, which results in what is called forest dynamics. Observing those dynamics allow a more accurate monitoring.

Remote-sensing offers faster and cheaper ways to monitor forests, from local to global scale, than *in situ* observations. ESA new Sentinel-2 satellites designed for vegetation observation shows promising perspectives for forest monitoring. It is therefore important to investigate its potential in the case of tropical forest dynamics.

This study is based on a collaboration with the Environmental Science for Social Change (ESSC) organization in Mindanao, Philippines, and has been the subject of a field campaign in February-March 2018.

Forest dynamics at stake in the study area are characterized, and a typology suitable for monitoring is established. Two methods to detect and map the proposed forest classes are developed, one based on a Sentinel-2 images per-pixel classification, the other one based on a very high resolution image (Pléiades) per-object classification.

The Sentinel-2 method turns out to be able to discriminate all proposed forest classes, with a 95% classification accuracy. The most discriminating features are the two short-wave infrared (SWIR) image bands followed by the blue band. The very high resolution method shows a confusion between two close classes and an overall model prediction accuracy of 70%. Combining the confused classes into one makes prediction reach 85% accuracy.

By comparing both developed methods, the Sentinel-2 per-pixel classification prove to be more accurate, but also to better represent transition areas between classes than the Pleiades method. An Upper Pulangi watershed full landcover is realized as application of the developed method.

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