

Faculté des sciences

Seeing The Ground Below Dense Canopies

A Structure from Motion Workflow for Generating High Accuracy Canopy Heights in a Tropical Forest

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Abstract

Forests play an active part in the carbon cycle, by storing large amounts of it as biomass. In recent years, deforestation and forest degradation have contributed to CO_2 emissions, causing a global climate change. The Democratic Republic of Congo (DRC) is the second most forested country in the world, and is undergoing land use changes through deforestation, which cause CO_2 emissions. Efforts to mitigate these emissions, and restore forest carbon stocks, such as REDD+ require monitoring of high spatial and temporal resolution. One way that this can be done is through measuring canopy heights in forests. However, current solutions such as satellite-based have too high an error and too coarse a resolution, while airborne LiDAR measurements fit precision requirements, but are too expensive for regular monitoring. Recent advances in uncrewed aerial vehicles (UAVs) and structure from motion (SfM) (a photogrammetry technique) technologies have enabled fast and cheap forest inventories for monitoring forest stands. These UAV-SfM inventories underperform in certain contexts, such as dense canopies (including the forests in the DRC), leading to underestimations of digital terrain models (DTMs) and canopy heights models (CHMs). Zhang et al. (2021) developed a high potential workflow with UAV-SfM point cloud for estimating tree heights in the dense forest of the DRC, by attaining estimations comparable to LiDAR estimations through machine learning and morphological filters to identify ground points and co-kriging to estimate a digital terrain model. In this study, we explored possibilities of this new workflow in 3 objectives. We first investigated the possibility of improving the ground detection filters by exploring the subtle structure of the point cloud. Secondly, we adapted the UAV-SfM data collection by adding oblique pictures to the photogrammetric reconstruction, to improve ground detection. Finally, we evaluated the potential for monitoring the state of forest structure through UAV-SfM by comparing our workflow to a 7-year-old LiDAR canopy height dataset. Thanks to the improved classification of ground points, the UAV-SfM DTM had a RMSE of 1.6 m and NSE of 0.84, compared to a LiDAR reference DTM. An external validation with GNSS ground sample measurements showed the error was high (RMSE = 4.8 m ; NSE = 0.68) and caused by the interpolation of ground points performing poorly in varied terrain. We also showed that oblique pictures improved ground detection, and lowered the RMSE from 4.45 m to 2.74 m on average, and, using two different angles for oblique pictures (70° and 40°), that low oblique (i.e. 70°) aided most in ground reconstruction. Finally, in evaluating the state of forest structure through canopy heights, we found that smaller trees overestimated tree heights and had a relatively high error (RMSE = 3.18 m) compared to the 7-year reference, and bigger trees (more than 40 m) had a more stable height (and lower error of RMSE = 2.12 m). Moreover, we found a RMSE of 2.04 m for the tallest tree in a plot, and deduced that the forest had remained in a similar structural state compared to 7 years ago due to absence of over/underestimation. In conclusion, thanks to an optimization of ground detection algorithms and data collection scheme (i.e., adding oblique pictures), we improved a workflow for estimating tree heights, and demonstrated

the potential for monitoring forest structure with a cheap and easy-to-use UAV-SfM workflow in the challenging context of tropical forests.

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Acronyms

AGB aboveground biomass

ALS Airborne Laser Scanning

CHM Canopy Height Model

CIR canopy interception ratio

CRR Canopy relief ratio

CV Coefficient of variation

DAP Digital Aerial Photogrammetry

DRC Democratic Republic of Congo

DSM Digital Surface Model

DTM Digital Terrain Model

EBK Empirical Bayesian Kriging

GCP Ground Control Point

GEDI Global Ecosystem Dynamics Investigation

GNSS Global Navigation Satellite System

HR height range

LAI Leaf Area Index

LiDAR Light Detection and Ranging

MVS Multi-View Stereo

NSE Nash-Sutcliffe Efficiency

OOB out-of-bag

PMF Progressive Morphological Filter

PpC population per cell

PPK Post-Processing Kinematics

RADAR Radio Detection and Ranging

REDD+ Reducing Emissions from Deforestation and Forest Degradation in Developing Countries

RF Random Forest

RGB Red-Green-Blue

RMSE Root Mean Square Error

SD standard deviation

SfM Structure from Motion

SIFT Scale-Invariant Feature Transform

SRTM Shuttle Radar Topography Mission

TLS Terrestrial Laser Scanning

UAV Uncrewed Aerial Vehicle

Chapter 1

Introduction

1.1 Forests and the Carbon Cycle

A key component of the carbon cycle, forests actively absorb atmospheric CO_2 through photosynthesis and store it as biomass (this is primary production). In the last 250 years, humans have had a profound impact on the carbon cycle, disrupting the flow from the sink that primary production represented and the sources of CO_2 (such as respiration). Indeed, one way in which the carbon cycle was disrupted is anthropogenic change in land use, or the deforestation of massive swaths of land and conversion to other land uses with less primary productivity (such as agricultural lands). In total, from 1850 to 2000, it has been estimated that 156 Pg of carbon (that is 156 trillion tons) has been released from the land (where it was stored) to the atmosphere (as CO_2) where it acts as a greenhouse gas and driver to climate change (Houghton, 2003). The impact of deforestation on the carbon cycle has been most notable in tropical forests, since they are the most productive type of forests and therefore contain the most biomass. For example, in the 1990s, it has been estimated that deforestation in the tropics alone caused a net output of 0.5 to 3 Pg of carbon per year into the atmosphere (Houghton, 2007). Efforts to mitigate climate change caused by anthropogenic emissions of greenhouse gases are afoot, such as the United Nations Framework Convention on Climate Change (UNFCCC, 2022), which has devised a unique strategy for forests. This strategy, named Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD+) involves the reducing of deforestation and forest degradation, the conservation of forest carbon stocks, a sustainable management of forests, and the increasing of current carbon stocks. To do this, the UNFCCC requires from each participating country “A robust and transparent national forest monitoring system for the monitoring and reporting of REDD+” (UNFCCC, 2022). This means that we must have a good knowledge of the distribution of carbon in forests, how the distribution will evolve through time with regard to response to climate change (which is not well known, according to Bennett et al. (2021)) and to human activities, and the effectiveness of protection and regeneration programs.

Forest carbon stocks are commonly estimated through the measure of aboveground biomass (AGB). AGB quantifies the amount (usually the mass) of C stored within a certain area, and it is widely used as it is particularly vulnerable to natural and human disturbances, as well as being a proxy for other C stocks (such as underground biomass) (Goetz and Dubayah, 2011). The direct measuring of AGB

involves cutting down trees, slicing the tree trunks, drying the slices, and weighing them. However, this is invasive and destructive for the forest, as well as extremely time-consuming (White et al., 2013). So much so that AGB was empirically modelled through allometric equations to avoid direct measuring. These equations rely on forest structural parameters, which are easier to measure. For an individual tree, the parameters are diameter at breast height, tree height, and wood density (which is specific for each tree species) (Chave et al., 2014). These parameters are more easily measured by forest inventories than directly measuring AGB, and are less prone to error because a larger number of trees can be sampled (White et al., 2013).

1.2 A Globally Significant Carbon Stock

The Democratic Republic of Congo (DRC), with its dense humid tropical forests, is the second most forested country in the world, with a total forest area of 115 million ha. It is also home to one tenth of the world's humid tropical forests. Since more than half (66.5%) of the country's forests are dense tropical humid (a very productive forest type in terms of biomass and C), an extensive monitoring effort is required to keep track of its C stocks. Indeed, even though deforestation rates are not as high as in other tropical countries, the extent of its dense tropical forest makes the DRC a top 10 country in terms of worldwide forest loss according to the National Framework-Strategy of the Democratic Republic of Congo (DRC Government, 2016). Figure 1.1 shows the locations of carbon stocks in the DRC and the places which are currently most threatened by deforestation, of which there is a large area. In the context of REDD+ and of monitoring the evolution of carbon stocks through space and time, it is important to be able to keep track of carbon losses at different spatial scales, and to preferentially preserve high-value areas (i.e. areas with a lot of carbon).

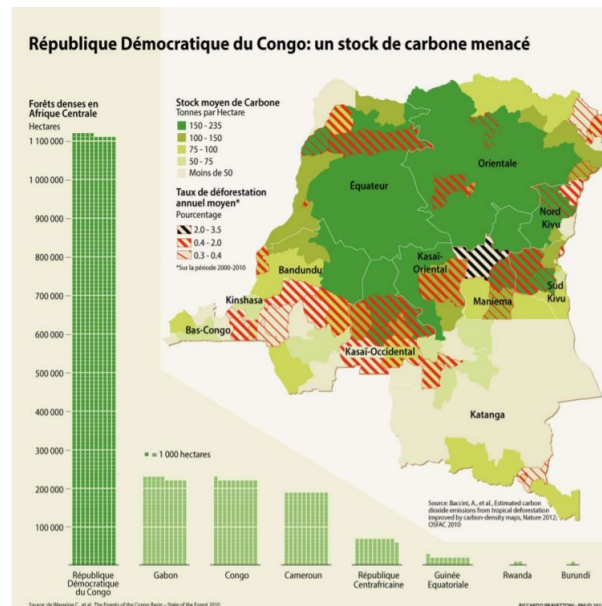


Figure 1.1: Map of the distribution of carbon stocks and deforestation rates in the DRC, with infographics showing the area of dense forests compared to other Central African countries. Figure taken from DRC National REDD+ Investment Plan 2015-2020 (DRC Government, 2015)

1.3 Tracking Forest Evolution

While AGB might be a direct representation of the amount of carbon in a forest plot, Poorter et al. (2021) argue that it is not the best metric for measuring forest structural state. The forest structural attribute that they found best estimated forest recovery was the size of the biggest tree in a plot¹. Following their logic, an optimal monitoring system would be through the measurement of tree size to track forest health. Moreover, tracking tree size at the plot level is simpler and requires less modelling than tracking AGB (so less potential errors are introduced). This study will therefore focus on canopy height estimation as a forest attribute to monitor degradation/recovery of tropical forests.

The monitoring scheme that the DRC proposed for REDD+ is in a first part through remote sensing with satellite observations for regular monitoring at the country scale, and in a second part through forest inventories for small scale and high-accuracy measurements of forest structure (REDD+ Investment Plan for 2015-2020, DRC Government (2016)).

1.3.1 Satellite Observations for Canopy Heights

Spaceborne remote sensing of forests, a large scale monitoring tool, involves three different possible types of measurements. Those are (1) optical images which are also referred to as multispectral, (2) Radio Detection and Ranging (RADAR), and (3) Light Detection and Ranging (LiDAR). Optical images are a passive mode of observation, meaning that they measure the light of the sun which is reflected by the ground. An advantage of passive spaceborne observations is the wide timescale of records of 50 years. The easiest way to monitor forests with remote sensing is through land cover dynamics, so by finding absence or presence of a forest patch in each pixel of an image. However, this is only good for a very rough estimate of forest structure. Forest structure can be estimated using the age of the forest stand, but this comes with big caveats because forest structure depends on many other factors such as land use history, soil type and climate conditions (Barbosa et al., 2014). Moreover, a forest is not homogeneous, and some finer details in the structure of the forest are missed out upon when monitoring through presence/absence. For example, forest regeneration and degradation are processes which are invisible to land cover analyses of forests, but which play a major role in determining the evolution of forest structure over time (Barbosa et al., 2014). What's more, spaceborne optical approaches sometimes have too coarse a resolution to classify patchwork landscapes of forest and small-scale agriculture, which is very widely practiced in Africa (White et al., 2016). Finally, some places in tropical regions have such a persistent cloud cover throughout the year that optical observation is impossible (Potapov et al., 2021).

Active methods of earth observation measure a signal that was emitted by the remote sensing machine itself and reflected by the ground surface. Both RADAR and LiDAR are active methods of observation. RADAR is good in that it does not depend on cloud cover, as radiowave signals can penetrate through clouds. However, RADAR observations are susceptible to underperform in complex structural contexts, as return signals tend to saturate at a certain point (Dobson et al., 1992). Moreover, RADAR tends to have a lower accuracy in elevation measurements, which is bad for smaller scale measurements of canopy heights and which Kachamba et al. (2016) showed by coupling Digital Terrain Model (DTM) estimations from Uncrewed Aerial Vehicle (UAV) with the Shuttle Radar

¹A forest area of around 1 ha

Topography Mission (SRTM) observations. In their case study, an error of more than 12 m was found, which showed that SRTM was badly correlated to canopy heights at the plot scale.

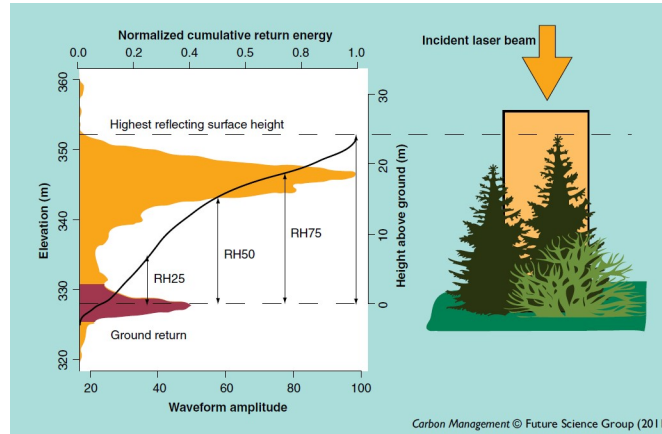


Figure 1.2: Example of the reflection of one laser pulse. On the left is the histogram of how much intensity is returned for different elevations, where brown corresponds to ground and orange to vegetation. On the right is the schematic of a patch of forest hit by a laser pulse. This whole schematic exemplifies how LiDAR is able to measure both ground and vegetation height in one pulse. Source: Goetz and Dubayah (2011)

Lastly, the process of acquiring LiDAR data involves emitting light to measure ground surface heights with high precision. This method is particularly interesting as it penetrates even the most dense canopies with high precision. This is because the emitted light signal can “separate” when reflecting off a tree element like a leaf. Part of the light signal is reflected, while the other part of the signal continues down to lower objects (i.e. the ground), enabling an estimation of canopy heights (figure 1.2). LiDAR is widely used in a variety of forest monitoring programs. The spaceborne LiDAR missions, such as Global Ecosystem Dynamics Investigation (GEDI), provide LiDAR information of Earth’s surface at a resolution of 1 km². The goal of spaceborne LiDAR missions are not mapping but a sampling of forests around the world (4% of Earth’s surface over 2 years in the case of GEDI) (Potapov et al., 2021). The most easily measurable forest attribute with LiDAR is canopy height, which is found by computing the difference between the ground elevation and top of canopy elevation. The error in elevation is generally considered to be 3-4 meters for spaceborne LiDAR (though very dependent on the measuring tool’s characteristics), though it has been argued that part of this error can be explained by errors in ground truth (especially in tropical closed canopy contexts, height measurements on the ground can lead to a Root Mean Square Error (RMSE) of 2-3 m) (Goetz and Dubayah, 2011). Compared to airborne LiDAR sampling campaigns, Potapov et al. (2021) found that the error on their canopy heights around the world was 7.2 (RMSE) with a coefficient of determination (R^2) of 0.7.

Since spaceborne LiDAR missions are only sampling missions and cover very little ground, it is impossible to use them for monitoring, and it is unlikely for a specific area of interest to overlap with a LiDAR sample. Therefore, LiDAR-derived canopy height samples were used to train models to predict canopy heights with an easier to measure and more spatio-temporally available data: optical spaceborne measurements, which cover the Earth year-round. For example, Landsat missions (8 and 9) have a return time of 15 days (covering the whole emerged Earth in that time period) at a resolution of 30 m. Even better, Sentinel-2 has a return period of 5 days for a spatial resolution of 10 m. From the GEDI sampling mission, Potapov et al. (2021) used a regression tree machine learning model to

train Landsat data in a predictive model of canopy heights. They managed to create a worldwide map of canopy heights with an RMSE of 6.6 m ($R^2 = 0.62$) when validating with GEDI data and an RMSE of 9.07 m ($R^2 = 0.61$) with Airborne Laser Scanning (ALS) validation. In both validations, however, there was an underestimation of tall tree heights (≥ 30 m high). Most recently, a new global canopy height map was created again using GEDI as training data, but this time using Sentinel-2 images for predictions and a neural network machine learning approach, which improved spatial resolution (from 30 m to 10 m). Indeed, Lang et al. (2022) got similar results with an RMSE of 7.3 m, and an underestimation of tall trees starting at 30 m. Furthermore, the mean of residuals for tropical moist broadleaf forest was 2.5 m, for an average height of 22 m.

While these results hold many advantages, such as free data availability and monitoring capabilities, they suffer from a lack of accuracy and spatial resolution for small changes in forest structure. Therefore, where very high accuracy and resolution observations are needed, forest inventories are conducted.

1.3.2 Forest Inventories

Traditional forest inventories involve the measuring of many individual trees in field campaigns. While very accurate for measuring forest structure, these inventories are time-consuming, costly, and only cover small areas. Moreover, many forests are difficult to access from the ground. Field inventories are therefore problematic for forest monitoring, as frequent inventorying of big forest areas is often required. Moreover, however accurate they are (Andersen et al. (2006) found an underestimation of 0.27 m (± 0.27) for a single sampling campaign) those measurements are very sparse, so many sampling campaigns from different research campaigns are usually combined which lead to an RMSE of tree heights that can attain 2-3 m in tropical regions (Drake et al., 2002).

Terrestrial Laser Scanning (TLS) solves one of the problems of traditional forest inventories, which is the cost in work hours. TLS is a high-resolution technique that uses a LiDAR technique for measuring distances. Fixed in one place on the forest floor, the TLS measuring apparatus can find the distance between itself and the trees and the surrounding canopy. This technique is powerful for forest inventories in that it is fast to measure tree metrics for many trees at once. Moreover, the accuracy that TLS provides in terms of AGB measurements is very high, since it very accurately reconstructs stem structure (at the centimeter scale), in which most of the biomass of the tree is stored. This measuring technique is most suited for high resolution analysis of plot-level understory structure of the forest (White et al., 2016). TLS's main drawbacks are that it requires the forest to be accessible by researchers, that the hardware for TLS is costly and the collected data is processing intensive. Moreover, while it is faster than traditional inventories, it is still not fast enough to cover large forest areas in a reasonable amount of time (Lin et al., 2018) (Roşca et al., 2018). A close alternative for ground surveying is through terrestrial photogrammetry (i.e. deducing forest structure from multi-perspective overlapping pictures of a same object of the forest taken on the ground). However, while it is both cheaper and easier to operate than TLS, it still suffers from being very time-consuming and needing the forest to be accessible on foot (Iglhaut et al., 2019).

We conclude that any kind of inventorying from the ground is problematic because it is very time-consuming for observations of a whole forest. Therefore, instead of measuring forest metrics from the

ground, we turn to high precision remote sensing from above the forest². With remote sensing, the study area does not have to be accessible by people on foot. It is also much less labor-intensive than ground forest inventories, which means that high temporal resolution monitoring is possible (Barbosa et al., 2014) (Goetz and Dubayah, 2011). An example of high-precision remote sensing in the DRC is a nationwide sampling effort to estimate the C distribution throughout the entire DRC by airborne LiDAR (Xu et al., 2017). Their method, as efficient as it was, does not fit the requirements for regular monitoring, mainly because of the operational costs of such campaigns. Indeed, regular airplane surveys of a whole country take up a lot of funds and planning.

The National Framework-Strategy of the Democratic Republic of Congo (DRC Government, 2016) prescribed for the sustainable management of forests the empowering of local communities through independent management and monitoring of their forests. We have already determined that current satellite products are either too sparse or too low spatial resolution to achieve the high accuracy and precision observations that are required, and that ground inventories are too time-consuming and costly. Therefore, to achieve the goals of low cost, high spatio-temporal resolution and high accuracy of canopy height estimation, we turn to drones, commonly referred to as UAV in the scientific literature.

1.4 UAVs - A Platform for Forest Monitoring

Paneque-Gálvez et al. (2014) posited that the use of small drones for regular monitoring of the forest by local communities could be one way of achieving the REDD+ requirements of measuring reporting and verifying. Community monitoring is good in that it can complement forest inventories. Moreover, it is a good way to keep observations independent and transparent, and can improve the local community's governance on their forests (which are also the goals of REDD+). The advantages of using small drones with a light payload (e.g., a small camera) as a monitoring tool are:

- Very high spatial resolution (a few centimeters).
- Potential for a very high temporal resolution, since the operational and maintenance costs of operating small drones are low.
- Small drones are not affected by clouds as other remote sensing techniques are, because they fly lower than clouds.
- 3D models of the forest can be generated and therefore used for finding forest structural parameters.
- The inventorying of forests is faster with drones than with traditional methods (ground surveying). The collected data are also more meaningful than sample plots.
- Drone use and data collection is easy to learn because commercial drones are made for the public and not for experts.

²Technically speaking, remote sensing is any measuring from a distance, so TLS and ground photogrammetry are forms of remote sensing. However, for the purposes of this study, we refer to remote sensing as measurements from above the canopy instead of below.

- The materials needed for drone monitoring are relatively cheap compared to other data acquisition methods (i.e. commercial satellites, airplane-borne remote sensing). Moreover, there is a high return on investment as data collection is fast.
- Small drones are able to survey areas that are otherwise inaccessible from the ground.
- They are easy to transport when conducting field missions that require travelling.

In the context of monitoring forests in the DRC, where there is a lack of resources for scientific research, poor infrastructure and logistical support and political instability (Kearsley et al., 2013), cheap, lightweight and easy to use monitoring tools are all the more important. There are of course some disadvantages to using small drones. The technology is still catching up, with a lack of integrated machines (i.e. complete systems of flying platform combined with an observation apparatus). Moreover, small drones are incapable of flying with LiDAR because of the size and weight of the observation tool. Flight time may also be limited (due to battery capacity) for electric powered drones, and weather conditions can't be rainy or very windy. Electric motors may also tend to overheat if temperatures are high, and batteries underperform in cold weather (Torresan et al., 2017).

UAVs are only platforms for transporting measuring equipment. The actual measuring apparatus commonly takes the form of a LiDAR sensor (which, mounted on a UAV is commonly referred to as ALS), or a commercial color camera.

1.5 Airborne Laser Scanning

It is possible to derive DTMs of sub-meter resolution with ALS (a DTM being a necessary first step to finding canopy heights) (Goodbody et al., 2017). With a UAV-generated ALS point cloud (the result of ALS acquisition) Goodbody et al. (2017) were able to compute a DTM with a vertical accuracy of RMSE 48 cm in a boreal forest of Canada. Moreover, it has been shown that in dense canopy cover combined with steep conditions, there was an underestimation of individual tree heights by 0.59 m (Gatzolis et al., 2010). Furthermore, in rugged and ecologically diverse stands of South Korea, Lee et al. (2018) found that the mean error on individual trees was 0.05 m, but that the absolute mean error went up to 1.38 m depending on the plot. Andersen et al. (2006) found an underestimation of trees in North America by the ALS method underestimated tree heights by 0.73 m (± 0.43). It is generally argued that, while this error is larger than ground surveys, the cost-effectiveness of ALS almost always justifies choosing it over traditional surveys. While individual tree height is easy to measure with ALS in forest contexts, many other attributes can be computed from point clouds to be compared to plot-level observations from ground surveys such as Lorey's mean height³, dominant height⁴, and AGB (White et al., 2013) (Puliti et al., 2015).

While the ALS method of acquisition of forest structure may seem like a good choice, it does have the disadvantages of requiring expertise to use, being very expensive, and requiring heavy-duty UAVs (as LiDAR equipment is cumbersome). Therefore, in recent years, there has been a push to transfer

³Lorey's mean height is a plot-scale measurement of tree height, where mean height is weighed by the basal area of the stem of each tree (Laar and Akça, 2007)

⁴A plot-scale measurement for the mean height of the dominant trees (the highest trees) in a forest plot (Laar and Akça, 2007)

from ALS data acquisition to commercial cameras. This is because it is cheaper, easier to operate, more flexible, and comparisons and transferability with ALS are easy as both return the same type of data (i.e., a point cloud) (White et al., 2013) (Goodbody et al., 2017).

1.6 Digital Aerial Photogrammetry

1.6.1 Theory of Structure Acquisition

The structure of the forest can be derived from a series of overlapping aerial pictures from UAV-borne commercial cameras through Digital Aerial Photogrammetry (DAP) methodologies (in the same way that two eyes are able to see an object's depth of perspective, a computer can “see” in 3D an object from two or more perspectives) (figure 1.3). In this way, a 3D point cloud is generated, in which each point corresponds to the absolute location of an object in the world.

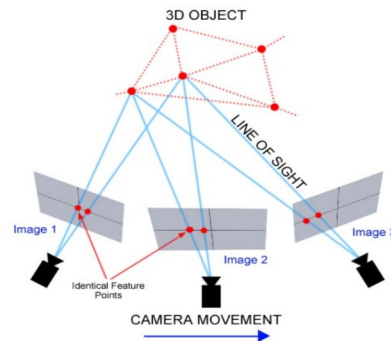


Figure 1.3: Conceptual example of 3D reconstruction with 2D images using photogrammetry principles. Source: Tokkari et al. (2017)

The Structure from Motion (SfM) workflow provides a way to model the forest structure in a way that requires little expertise, and which is similar to classic DAP reconstruction techniques⁵. However, SfM improves upon DAP in that it does not require a lot of the information that traditional photogrammetry does. For example, it does not require *a priori* knowledge of the camera's distortion on the sides of the picture or its field of view. It does not either need to know the tilt or orientation of the camera when each picture was taken (which is measured with an expensive inertial measurement unit), nor does it require a precise geolocation of the pictures to reconstruct the 3D structure of the study area (Iglhaut et al., 2019) (Dandois and Ellis, 2013) (Carrivick et al., 2016). By identifying common features (referred to as tie points) in the overlap between pictures, the SfM workflow is able to compute the three-dimensional position of that tie point. All the tie points are combined to create a sparse three-dimensional point cloud of the tie points, which can represent parts of either the canopy, the sub-canopy (such as tree stems and lower vegetation canopy) or the ground. The sparse point cloud is then densified such that the point cloud reflects forest structure (Iglhaut et al., 2019). Later, the dense point cloud can be used to estimate a Digital Surface Model (DSM), a DTM and a Canopy Height Model (CHM). DSMs represent the variations in height of the top of the point cloud. In a continuous gridded surface, each cell of a DSM raster corresponds to a local maximum, which means

⁵The SfM workflow is a type of advanced DAP reconstruction. In the following literature review, DAP will be used as a general term to include SfM and other photogrammetric workflows, for simplicity's sake.

that in the case of forests, they reflect the canopy surface’s height and structure. A DTM on the other hand is a model of the elevation under the forest, where each grid cell corresponds to the elevation of known ground points, interpolated to a gridded continuous surface. Finally, through normalization of a DSM (i.e. subtracting the ground elevation from the elevation of the canopy), a CHM can be obtained. The CHM is a raster which models the height of the trees in a forest.

1.6.2 Canopy Height Estimation in Practice

Complementary Methods

Some studies have used UAV-DAP in combination with ALS data either to estimate the DTM with ALS (and use it for normalizing the DAP point cloud), and the DSM with DAP, or by comparing the two. In one example, monitoring capabilities were studied, by comparing LiDAR and DAP in change detection of the canopy compared to a 2-year-old ALS dataset. It was found that the mean growth was estimated at 0.68 ± 0.05 m for ALS and 0.5 ± 0.05 m for DAP, which is really close (Goodbody et al., 2017). Meanwhile, Puliti et al. (2015) found that the RMSE of the dominant height estimation of a boreal forest plot had a RMSE of 0.7 m when comparing field data to a DAP canopy elevation estimation (normalized with an ALS DTM). Pioneering works in UAV DAP include Lisein et al. (2013) who found in a small plot of Belgian forest that the RMSE of a DAP CHM was 1.04 m against the RMSE of 0.83 m obtained with an ALS derived CHM, and Dandois and Ellis (2013) who obtained an R^2 of 0.87 when comparing CHMs from DAP and ALS in a temperate deciduous forest. More contemporary work includes Messinger et al. (2016) in a lowland rainforest of Brazil who estimated the error of top of canopy height between ALS and DAP to be 0.4% ($R^2 = 0.86-0.93$), and Cao et al. (2019) who compared Lorey’s mean heights measured by ALS ($R^2 = 0.91$ and relative RMSE = 9.03%) with DAP ($R^2 = 0.83$ and relative RMSE = 12.2%), and found that ALS was generally a bit higher quality at predicting forest variables (in a planted forest of east China). Furthermore, they found that plots with greater canopy heights tended to have better predictions of forest structural parameters, though a high stem density was detrimental to the accuracy of the prediction for both DAP and ALS. Finally, White et al. (2015) found, again for Lorey’s mean height a RMSE of 2.88 m (%RMSE = 8.96) for ALS, which was better than the RMSE of 4.49 m (%RMSE = 14) for DAP. They also found that the DAP canopy surface predictions were better in dense canopies, and that slope was detrimental to the prediction of height for DAP. Note that they conducted their study in a coastal temperate rainforest of western Canada. There is a lot of literature to support that DAP methodologies for estimating forest attributes are accurate, if only a bit less than ALS in most cases. There is a big caveat, however: for all the above studies comparing ALS and DAP predictions of tree heights (except Dandois and Ellis (2013)), an ALS-generated DTM was used to normalize the point cloud. This is a big problem because, as previously said, ALS data is not widely available (especially in Africa), nor is it cheap or practical. Therefore, we investigated UAV-DAP forest inventory studies which did not use any ALS data to complement DAP point clouds.

DAP as a Standalone Tool

There is good reason for using an ALS generated DTM instead of a DAP generated one, as it helps to lower prediction errors. Dandois and Ellis (2013) found that in deciduous temperate forests, a

DAP-generated DTM had errors as high as 2.49 to 5.69 m at leaf-on season in forest areas, where the DAP DTM overestimated ground elevation compared to ALS. These results were improved as time passed and technology got better. For example, Shimizu et al. (2014) found in a Cambodian seasonal tropical forest that tree height estimation had a RMSE of 1.96 m when comparing a SfM-generated DTM to ALS (and 1.72 m compared to manual measurements), but citing degraded forests and roads as gaps from which ground elevation was easily estimated and which improved predictions. For the same region of Cambodia, Ota et al. (2015) compared biomass estimations derived from point clouds normalized with a DAP and ALS generated DTM. They found that the highest levels of error happened in evergreen forests, and least in degraded forests, whereas ALS normalized clouds were consistent through different forest types. Mlambo et al. (2017) reached the same conclusions when comparing canopy heights in forests with less than 50% canopy cover (where R^2 was 0.75) and with more than 50% canopy cover (where R^2 was 0.19) which represented a very big degradation in predictions. Similarly, Wallace et al. (2016) found that errors propagated because of a badly estimated DTM using traditional DAP techniques, reaching a RMSE of 1.3 m for canopy heights (where ALS had 0.92 m of RMSE) in an Australian eucalyptus forest. More recently, in a deciduous forest (ginkgo) of mean latitudes, Shen et al. (2019) found mean errors of 1.14 m (± 1.93) when comparing ALS DTM to DAP-generated DTM. They also found that the DAP point cloud overestimated elevation when the canopy cover was dense (more than 2 m average difference), and underestimated elevation in some cases of steep slopes. Iizuka et al. (2017) found an error in tree heights of 1.7 m ($R^2 = 0.2$) in a Japanese cypress forest (considered dense by the authors) and Guerra-Hernández et al. (2018) found a mean overestimation of DAP DTMs by 1.14 m (± 1.93) in a Portuguese eucalyptus plantation. Two other notable examples in tree height estimation are Swinfield et al. (2019) who reached a RMSE of 1.85 m ($R^2 = 0.67$) in a tropical forest of Indonesia, and Panagiotidis et al. (2017) who found a RMSE of 3 m ($R^2 = 0.75$) in a Czechian forest. All of these findings show that current methods for ground detection in DAP point clouds are lacking, and that classic methods used for ALS DTM generation (Chen et al., 2017) are not adapted to DAP DTM generation, as tree height estimation consistently has a higher error. Most studies cite the lack of ground penetration through the canopy as a cause of this higher error.

1.6.3 Ground Detection in Forests

The reason that DTM generation works especially poorly in forests with dense canopy cover is that DAP approaches penetrate very poorly through dense canopies. Indeed, because of occlusion by leaves, shadows and low light beneath the canopy and general small size of canopy holes, DAP approaches tend to struggle to reconstruct ground elevation, which means that there is overestimation of elevation at ground level (figure 1.4). Shen et al. (2019) found that the more trees there are in a plot, the less ground points DAP approaches will be able to correctly map. Dietmaier et al. (2019) illustrate this very well in their study, where they compared ALS and DAP approaches in their ability to map canopy gaps in a boreal forest in Canada. Their results (figure 1.5) showed that only 8% of small gaps (0-4 m²) were accurately detected, and that the detection accuracy rose to 70% for gaps wider than 200 m².

In the case of tropical forests, the mechanism behind canopy gap creation is through the death of a single dominant tree which creates small canopy gaps (tree falls and crushes sub-canopy vegetation), while bigger canopy gaps are extremely rare. This lack of canopy gaps is one of the characteristics of old growth forests, and it differentiates them from regenerated forests (which tend to have more and

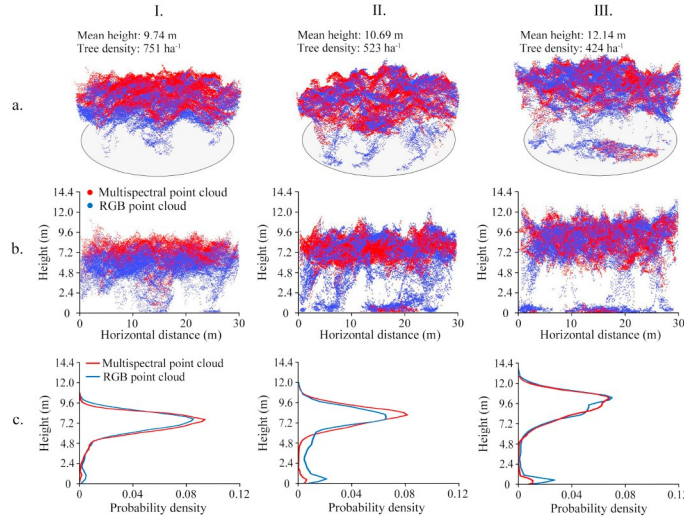


Figure 1.4: DAP point clouds generated from Red-Green-Blue (RGB) (and multispectral) imageries. a) Three dimensional representation of three point clouds, b) elevation profile of the three clouds, and c) height distribution of points in cloud relative to ground. The three point clouds represent high canopy cover (I), medium canopy cover (II), and low canopy cover (III). Source : Shen et al. (2019)

wider gaps) (Kent et al., 2015). It is unclear how many treefall gaps are created in tropical forests, and can be utilized for ground detection, because the death of dominant trees from the top canopy are stochastic and infrequent. Studies have found death rates at 1.81% per year (Lewis et al., 2004) and 5 stems per hectare per year (Bennett et al., 2021) but both these studies took into account non-dominant and dominant trees, so the rate of treefall gap creation is a lot less high than what those numbers say.

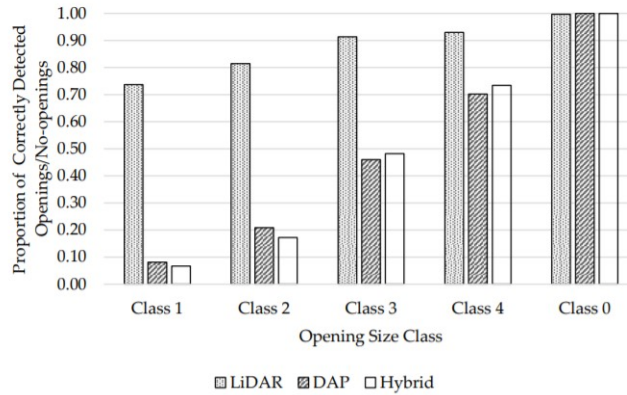


Figure 1.5: Proportion of accurately detected gaps in the canopy, depending on the area of the gap. Class 0 = no opening ; Class 1 = 0-4 m² ; Class 2 = 4-20 m² ; Class 3 = 20-200 m² ; Class 4 = >200 m². Figure taken from Dietmaier et al. (2019)

Two studies have been able to mitigate the effects of dense canopy cover for tree height estimations. Giannetti et al. (2018) found promising results with relative RMSE of 15.9% for DAP and 16.7% for ALS in an Italian beech and fir forest in volume of growing stock estimations. This was especially notable in that they argued that their workflow could be better than ALS under the combination of dense canopy covers and steep terrain. More recently, Zhang et al. (2021) developed a workflow to

identify ground points using a series of successive filters to estimate DTMs (and canopy heights) in a very dense old-growth forest in the DRC. They managed to reduce the RMSE of the DTM from 3.75 m using common DTM generation methods (Chen et al., 2017) to 2.1 m, and a canopy height error of 1.6 m at the plot level, which is comparable to what is attained in ALS derived DTMs. To do so, they included a machine learning classification (random forest) as a filtering step to remove any non-ground point.

1.7 Parameter Optimization in UAV-DAP

There is strong literature as to what are the optimal flight parameters and tools for data collection and processing of UAV DAP. Indeed, it is relatively new in forestry contexts, and sensitivity analyses were needed to know how the point clouds changed depending on the data collection for estimation of forest structural attributes. Dandois et al. (2015) studied the effects of altitude, overlap and light conditions on canopy penetration. They found that flight height did not affect penetration significantly, but front overlap improved canopy penetration, and so did sunny conditions (increase of penetration by 1 m in sunny vs. cloudy conditions). In a tropical woodland of Malawi, Domingo et al. (2019) tested the effects of image overlap, camera type (Red-Green-Blue (RGB) vs. near infrared), and image resolution on biomass predictions with a DTM-independent workflow (meaning no need for ALS data for normalization). They found that a better camera resolution increased accuracy of biomass predictions, and that a decrease in side overlap (from 80 to 70%) did not decrease accuracy if front overlap was maintained at a high level. They also found that biomass estimation models were reasonably transferable from one set of flight parameters to the other. Moreover, Frey et al. (2018) found that environmental factors which affected DAP reconstruction significantly were wind and terrain elevation, while higher overlaps positively affected reconstruction. Finally, Kameyama and Sugiura (2021) found that the best SfM software for forestry purposes (such as tree height estimation) was Pix4D, and Kameyama and Sugiura (2020) tested 64 combinations of flight height, side overlap, and front overlap and found RMSE of tree height estimations ranging from 5.1 to 7.1 m where lower flight altitudes returned better height estimations, while higher overlaps had a positive effect on the point cloud reconstruction.

A unique parameter that has rarely been studied is the use of oblique images for forest structure reconstruction, and only a few cases were found in the literature. Fritz et al. (2013) compared a DAP point cloud reconstructed from only oblique (70°) pictures to TLS for stem mapping and found promising results (with a Pearson correlation coefficient of 0.7). Lin et al. (2021) estimated Leaf Area Index (LAI) using a combination of nadir and oblique photos (85° and 70°) and found that they had a positive influence, with the 70° photos helping the most. Lin et al. (2018) used oblique photos only to estimate AGB in a sparse coniferous forest to obtain more subcanopy information, and found it was possible to get good estimates of tree heights (RMSE = 1.8 m ; $R^2 = 0.92$), though they did not compare their results to nadir DAP tree heights. Sakai et al. (2016) only compared DSMs between nadir only point clouds and oblique-augmented point clouds, and found that there was a better reproducibility when adding oblique images. Finally, Díaz et al. (2020) made the most complete analysis of the potential of oblique photos in forests. They found that oblique images improved the point accuracy in Pix4D from an RMSE of 38.7 cm to 25.1 cm (using oblique photos of two categories - less than 85° and between 85° and 70°). Moreover, the addition of oblique photos helped to improve

the estimation of tree heights by 50%, through better modelling of the structure under the canopy. They did argue that their results only applied to open canopies, with less than 85% canopy cover. All these studies point towards a significant advantage of adding oblique images to DAP reconstruction as a way of improving accuracy. However, no other forestry study was found using oblique images, making this subject one with great potential and requiring more investigation.

1.8 Research Objectives

LiDAR products (such as DTMs and CHMs) are rarely available in tropical countries (Goetz and Dubayah, 2011), which makes an integration of LiDAR DTMs with DAP forest surface products impossible for monitoring. Therefore, in the DRC, UAV-DAP must be used as a standalone tool, for both ground and canopy elevation estimations in computing and monitoring tree heights. It has been shown that it is possible, given the recent strides that UAV-DAP has recently seen in measuring forest canopy heights (Giannetti et al., 2018) (Zhang et al., 2021). These studies are very new, and their full capabilities have not yet been investigated, as they were more proof of concept. Especially Zhang et al. (2021) paved the way to monitoring canopy heights in the dense broadleaf forest of the DRC. Given their promising results, we want to further refine their process in two ways, which will make up the first two objectives of this paper.

An important step of the methodology from Zhang et al. (2021), the machine learning filtering step relied on the structure of the point cloud in order to discriminate points. They used basic structural parameters, but Almeida et al. (2020) noted that a point cloud can contain a high amount of information on the structure of a forest, which basic structural information do not reflect. We hypothesize that much more additional (and at present unexplored) valuable information is contained within point clouds to substantially improve the prediction of tree heights. The first objective of this study is therefore to include more diverse structural parameters than what was previously used to achieve a higher filtering accuracy than the 70% that Zhang et al. (2021) achieved. Further, we want to evaluate whether this new filter is capable of reconstructing a better DTM when integrated in the workflow.

Secondly, we hypothesize that flight parameters have a large influence on dense forest cloud generation and that the inclusion of oblique photos in a DAP workflow substantially enhances the ground penetration potential. Therefore, we want to investigate the impact of flight parameters during image acquisition (upstream of the SfM workflow) on the quality of ground reconstruction. Particularly, the impact of overlap between pictures will be investigated, as well as the added value of combining nadir (photos taken vertically down) and oblique photos which have been shown to be very promising in open forests (Díaz et al., 2020), though not in denser contexts.

A third and final objective will be to investigate the monitoring possibilities of our workflow by comparing canopy heights obtained through UAV-SfM to an ALS dataset obtained 7 years prior.

Chapter 2

Materials and Methods

2.1 Study Area

A field mission was carried out in August 2021 in two separate locations, both in the Tshopo province of the Democratic Republic of Congo, which is in the central Congo Basin, in the north of the country. The main city, through which we passed to go to both study areas, is Kisangani, and its coordinates are $0^{\circ}31' 0''\text{N}$; $25^{\circ}12' 0''\text{E}$ (so close to the Equator). The first location, Yangambi biosphere reserve, is 90 km west of Kisangani (figure 2.1) and most easily accessible by boat from Kisangani. Yoko forest reserve on the other hand is 30 km away from Kisangani and located to the southeast. Yoko was accessed through dirt roads, though travelling times are long (average travelling speed of 15 km/h) when roads are wet and muddy. Indeed, both in Yangambi and Yoko, rainfalls tend to be between 1500 and 2200 mm per year. While there is a long rainy season, there are two drier seasons which are short (December to January and June to August) ; note that the drier seasons only signify a reduction in the amount of rainfall (Mohymont and Demarée, 2006). Both study areas are classified as semi-deciduous-evergreen transition, and their elevation range from 350 to 500 meters above sea level. Meanwhile, the terrain does not exceed 15% in slope inclination (Réjou-Méchain et al., 2021) (Zhang et al., 2021).

2.2 UAV Data Acquisition

2.2.1 The Field Mission

The field mission took place from the 17th to the 27th of August in order to acquire UAV pictures of the forest. The Yangambi site was surveyed on August 20, 21 and 22. All surveys were done from late morning to early afternoon in order to have as vertical a sun orientation as possible, which minimized the effect of shadows. The lighting conditions ranged from overcast (August 20) to very sunny with some cumulus clouds (August 21 and 22). The wind at ground level was negligible. The launch sites (figure 2.1) for the UAV were selected at the edge of the forest for the open space and ease of access. The open space makes launching and landing easier, so that the UAV does not clip trees. The flights

on August 20 and 22 were launched from the solar panel park of Yangambi (launch site 1 on figure 2.1), which fuels the CongoFlux tower (launch site 2, figure 2.1), 2 km to the east. The launch site on August 21 was halfway up the CongoFlux tower, so approximately 30 m high, which is around the same height as the canopy. This was done in order to save battery, survey more surface and facilitate launch and landing. The Yoko launch site (launch site 3), close to the center of the village and near the main road, was also at the edge of the forest. The survey of the forest in Yoko was done on August 24 and 25. The weather conditions on August 24 were overcast, with some rain and very low clouds. August 25 was very sunny, with some cumulus clouds. No significant wind was observed on any of the two days.

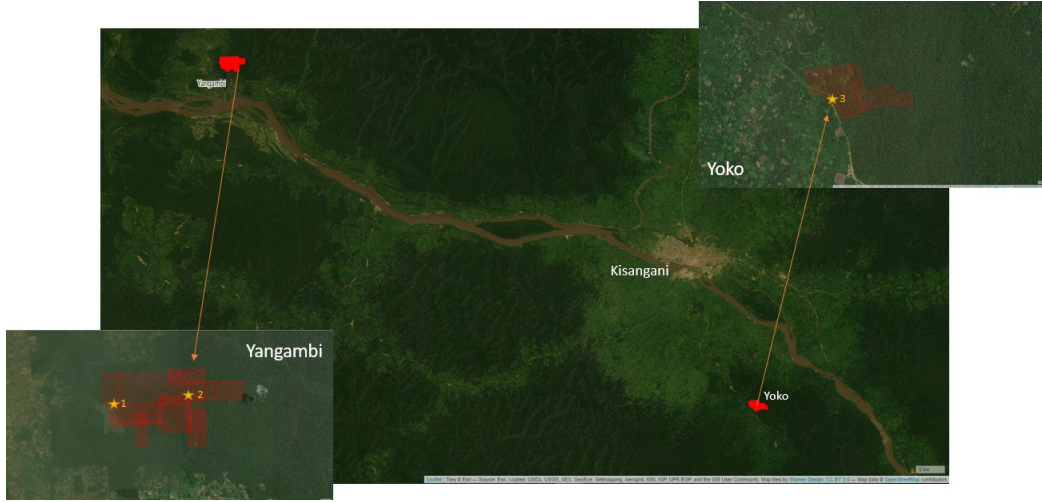


Figure 2.1: Map of Kisangani and its surroundings, zooming into Yangambi study area (bottom left) and Yoko (top right). Yellow stars correspond to the three launch sites, with 1) solar panel park ; 2) CongoFlux tower ; 3) Yoko launch site. The red surfaces represent survey area and red dots represent the locations of each picture taken in the surveys. Source of base maps: ESRI World Imagery

2.2.2 The Material

The UAV that was used was a quadcopter, which means that it could do stationary flights and vertical landings and takeoffs, unlike fixed wing UAVs (Torresan et al., 2017). This is good for forests, especially if the canopy is dense, as the launch site can be smaller without risking hitting trees. The disadvantages of using a quadcopter are that they are slower, they fly less high for less long, can therefore cover a smaller area than fixed-wing UAVs (Lin et al., 2018).

The UAV, a DJI Mavic Pro 2, had a consumer grade color camera with a field of view of 77° and a resolution of 5472×3648 pixels. This UAV was modified by Topodrone (<https://topodrone.org/>) with a high precision antenna which recorded the position of the UAV for every picture (figure 2.2b). This antenna is capable of returning a more accurate position than the one integrated in the unmodified UAV. Combined with the position measurements of a nearby base station, centimeter-level vertical accuracies and sub-centimeter horizontal accuracies could be attained through Post-Processing Kinematics (PPK) (see section 2.3). The base station position was recorded during all the UAV flights with the Emlid Reach RS+ (figure 2.2a ; <https://emlid.com/>) mounted on a ≈ 1.8 m tripod. The tripod was set at the same elevation as the launch site, some 5-10 m away, depending on the day's launch

site. Its actual position was estimated as the average of all the measures over a 2-6h average (varied depending on the day). The combination of high positional accuracy of the UAV with a nearby base station is powerful in that it does not require any Ground Control Point (GCP) to get a very accurate absolute position (Zhang et al., 2019). Thanks to this, we were able to reduce the overall positional error and to get rid of the need of GCPs for which big and accessible forest gaps are needed. This significantly reduced the amount of time and effort required as the tropical forest is large, dense, and complicated to navigate (Zhang et al., 2019) (Tomaščík et al., 2019).



(a) Picture of the two GNSS receivers (one rover and one base). Source: EMLID



(b) Picture of the Mavic DJI Pro 2 modified with an antenna (black cylinder). Source: Topodrone

Figure 2.2: Material that was used for UAV data collection

2.2.3 Flight Parameters

Flight planning and parameters for the Mavic were chosen through the Ipad application DJI GS Pro. First, a polygon covering the desired study area was drawn, and then the flight parameters were defined as in table 2.1. These parameters were kept constant for all surveys of our study area. Logistical constraints (mainly lack of electric current) made the charging of batteries difficult, and even with 10 batteries, we had to be conservative of the current we had, and try to optimize the flights to consume the least possible batteries. This is why we had a fast flight speed, and a high flight height (table 2.1), so minimal battery was used. Another constraint is that we only had 5 days of actual data collection, which made it impossible to control for light conditions. Be it overcast or sunny, the data collection had to be done, as field work in the DRC is difficult and expensive.

Table 2.1: UAV flight parameters for image acquisition

Parameter	Setting value
Front overlap	80%
Side overlap	80%
Camera angle	90° (nadir)
Flight height	250 m
Flight speed	14.7 m/s
Time interval b/w pictures	4.3 sec
Flight line orientation	Parallel to long side of polygon
ISO (camera sensitivity)	Automatic
Aperture time	Fast
Image format	JPEG
Ground Sample Distance	0.05 m/pixel

The survey area for Yangambi totaled 9.5 km² over the course of three days (of which 2.98 km² are overlapping with a pre-existing LiDAR dataset described in section 2.4), and 3.1 km² for Yoko.

2.3 Post-Processing Kinematics

Differential correction of position, in the form of PPK, is a method which increases the accuracy of Global Navigation Satellite System (GNSS) measurements. Indeed, due to variations in the ionosphere, troposphere and other systematic errors from the satellite and the receiver, it is impossible to get centimeter-level positional accuracy with just one GNSS receiver (White et al., 2013). However, these systematic errors can be modelled and corrected at any moment with a second GNSS receiver of known geolocation. In PPK, there are two receivers. One of them, the “base station” is of known location. In this study, it was an Emlid Reach RS+, and its precise geolocation was computed by averaging out all location records. The other GNSS receiver, the “rover”, is mobile and in this study was either the Mavic UAV (section 2.2.3) or another Emlid Reach RS+ (section 2.5).

Post-processing kinematics was used for correcting the location of all images acquired by the Mavic during flight surveys using Toposetter 2.0 Pro, and following the User Manual by Topodrone for the DJI Mavic Pro 2 PPK (<https://topodrone.org/>). For the ground sampling where we used an Emlid Reach RS+ as a rover, PPK corrections were computed in RTKLib (version 2.4.3 ; <http://www.rtklib.com/>), which is an open-source software dedicated to GNSS corrections.

2.4 ALS Dataset

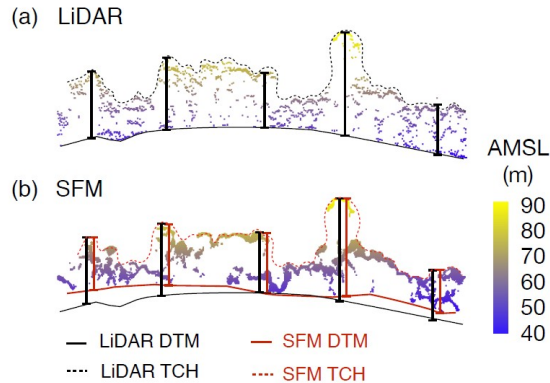


Figure 2.3: Cross-sections through ALS (a) and SfM (b) point clouds generated from the same Indonesian tropical forest area. Blue points correspond to lower elevations and yellow to higher elevations. ALS and DTM and DSM are colored in black (continuous and dashed line) while DTM and DSM are colored in red. While SfM has a higher point density, it does not reach the ground in many places, while ALS point cloud is able to accurately reconstruct the ground elevation. Source : Swinfield et al. (2019)

Because ALS is capable of penetrating through dense forest canopies (figure 2.3), it can detect ground elevation in forest environments at a sub-meter accuracy ¹, and therefore provides an elevation

¹No actual ground validation was done by Xu et al. (2017) who published this dataset. However, findings show that the RMSE varies between 0.3 and 0.8 m depending on the context (Simpson et al., 2017) ; (Salleh et al., 2015)

reference for this study. From June 2014 to February 2015, Xu et al. (2017) led an ALS sampling campaign of the forests of the entire DRC. One of the samples was collected close to Yangambi, which overlapped with our study area. Therefore, care was taken when choosing the survey area with our UAV to overlap with this preexisting dataset. The ALS dataset is a point cloud, which was processed into a DTM and DSM (Zhang et al., 2021). The DTM was created by averaging for each cell of a 5x5m grid the elevation of all points in the point cloud that were classified as “ground”. For the DSM, the maximum value of each cell in a 5x5m grid was selected. A CHM was created by subtracting the DTM from the DSM. The ALS DTM, hereafter referred to as the reference DTM, was used in later steps of the study as the ground truth for model training and validation. However, since the ALS dataset only covered a small part (213 ha) of our study area, another ground truthing method was needed.

2.5 GNSS Ground Sampling

A ground sampling mission was conducted in the forest reserve of Yoko on August 25 with the Emlid Reach RS+ GNSS receiver (named rover for this section). Its position was recorded every 2 seconds while moving under the canopy of the forest. However, GNSS signals tend to get reflected off vertical surfaces (such as tree trunks and underbrush) which increases the traveling time of the signal and creates errors in measurements. Moreover, the dense canopy reflects part of the signal before it even reaches the ground. All this means that GNSS measurements are complicated in the forest, and to mitigate this, we took care to find gaps in the canopy where the signal tends to be less disturbed.

The collected point samples were corrected by way of PPK (with the data from the base station recording in an open area at the launch site). However, even with the correction, there were too many imprecise measurements due to the closed canopy under which we sampled the location, so bad values had to be filtered out. The processing of the sample was done in three steps. The first step was to select only the points for which the PPK software found a solution. Indeed, some points were marked as “single” which means that the software RTKLib did not find an acceptable correction for that point. The second step was to remove all impossible values. The assumption that was made here was that two nearby temporal values needed to have similar spatial values. Indeed, since the rover was recording continuously, it would be impossible for the rover to travel more than a few meters in 2 seconds (the interval between two measurements). The vertical and horizontal acceleration between two temporally neighboring points were computed, and any difference greater than 2 m/s^2 on the horizontal axis and greater than 5 m/s^2 on the vertical axis was filtered out. Moreover, all points above 500 m were removed, after visual investigation of point distribution. The thresholds for this step were chosen by trial and error, with no other measure than visual interpretation of point distribution through time and space. The third and final step was to apply a low-pass filter to the filtered dataset. This was done using the Nadaraya-Watson kernel regression estimate proposed by R software (Version 4.1.1 ; <https://www.r-project.org/>), and with a bandwidth of 250.

A lot of the value thresholds and parameters for this section were subjectively chosen and this is due to the difficulties of collecting GNSS positions in a dense forest context, in only the two hours that were dedicated to this sampling.

2.6 From Images to Point Cloud

This section will only describe the implementation of the SfM workflow into the software Pix4Dmapper (Version 4.3.33 ; <https://www.pix4d.com/>), with the processing options that were used for this study. However, the theory and algorithms of the SfM workflow behind Pix4Dmapper can be found in the Annexe.

The software Pix4Dmapper works in 3 main steps, each with its own set of options. We used the “3D Maps” default settings as it best corresponded to our image acquisition methodology (aerial images with grid flight plan, mostly oriented towards the ground) and data needs (a very accurate densified point cloud). The only option that was changed was selecting “Geometrically Verified Matching” during the first step of the processing, which was only selected when the solution returned impossible camera position and orientations, and was mostly caused by bad quality images. The three steps are i) initial processing, ii) point cloud generation and iii) DSM and orthomosaic generation. Step i) produces a sparse point cloud, step ii) returns a dense point cloud. Finally, step iii) is not part of the SfM workflow, as it returns a DSM and an orthomosaic, which are a rasterized simplification of the point cloud. These two products may be useful as they are easier to handle and more commonly used in geoprocessing than point clouds.

The next section will describe the process of training a model for creating a DTM from the SfM point cloud.

2.7 Structural Parameters in DTM Reconstruction

2.7.1 From Point Cloud to DTM

In this first part, we first recreated the methodology from Zhang et al. (2021) to get a baseline in the later steps of adding more structural variables. Due to its relevance and importance to this study, the methodology will be described in this section (also represented in figure 2.4).

The first step was to find all possible points that could be ground. To do so, the SfM point cloud was simplified to a preliminary DTM of 0.5 m resolution (i.e., the value of each cell of the grid was the elevation of the lowest point contained within that cell). On this raster, a moving window found the location and height of the lowest point in a window of size 5 m. For each cell, the moving window looked at the neighborhood in a 5 m radius and found where the local minimum was in that neighborhood. The window size of 5 m was empirically found by Zhang et al. (2021) to be optimal for this methodology.

All the local minima were hereafter named candidate points.

Of these candidate points, some represent the elevation of the ground, however they often are not. Indeed, since SfM workflows especially struggle in penetrating through the dense forest canopies of forests, a lot of the candidate points are actually just the underbrush of the forest, or even a canopy if the canopy cover is particularly dense. We therefore needed a way to discriminate between candidate points that actually corresponded to the elevation of the ground, and others where the point cloud did not penetrate through the vegetation entirely. To do so, a classifier model was used, whereby the

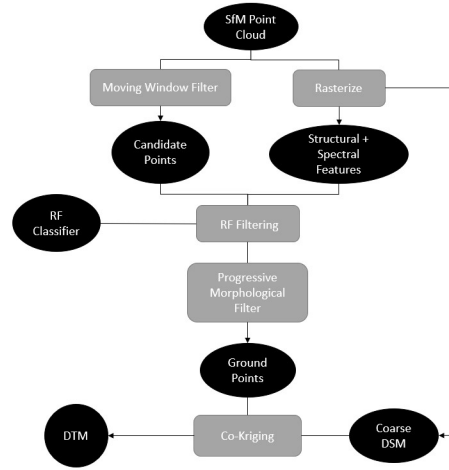


Figure 2.4: The whole procedure of getting from a point cloud to a point cloud, inspired by the methodology of Zhang et al. (2021). In black are the inputs, and in gray are the algorithms. The first input is the SfM point cloud and the final output is the DTM. For this workflow, we assume the Random Forest (RF) classifier model was already trained.

model decides which class the point is based on a set of predictive variables derived from the SfM point cloud. The goal here is therefore to be able to predict a candidate point's class based on the variables derived only from a point cloud. Since accurate predictions were required, a supervised classification was used.

The supervised classification relied on a series of candidate points whose classes were known *a priori*. In this case, they were the candidate points which were within the extent of the reference DTM (used for identifying ground truth). These candidate points were separated into training and validation data, where the training data comprised 80% of all the candidate points, and were used in the creation and parameterization of the model (i.e. the model training). Meanwhile, the other 20% (the validation data) were used in subsequent steps for the independent validation of the classifier (i.e. measuring the predictive performance of the classifier model). Note that the validation and training datasets were separated by region, so one area was defined as "training" and the other as "validation". The supervised classification needed four things to be successful : 1) a clear definition of the different classes, 2) good predictive variables derived from the point cloud which were not specific to the study area for the classifier to be transferable to other study areas, 3) a classifier model to train the data on, and 4) an independent validation.

1) Class definitions

All the candidate points which were within 2 m of the reference DTM were classified as true ground points. The 2 m threshold was justified by Zhang et al. (2021) in their exploratory analysis. The low vegetation points were defined as more than 2 m above the reference DTM, but less than 8 m higher. Finally, canopy candidate points were the ones which were 8 m or higher compared to the reference DTM.

2) Predictive variables

Predictive variables are ideally able to perfectly characterize a point and its neighborhood so that it can be distinguished between the different classes. In reality, there is a margin of error because the variables do not work perfectly. For this study, the variables were created using gridded statistics on the point cloud. Indeed, there was a lot of information to be found in the point cloud, but it was unexploitable by the model in its raw format, so it needed to be processed and converted into a series of summarizing variables. To do so, we rasterized the point cloud ; a 2D grid was created and for each cell of the grid, information and statistics were computed based on the points within the cell. There were two different types of variables which were used in the model : structural and spectral. The spectral variables exploited the RGB properties of the point cloud. There were spectral variables for each color (red, green and blue) and they represented the spectral value (= intensity of wavelength measured by the camera, so brightness of the color) for the top point and the bottom point of each cell (figure 2.5). The hypothesis for using spectral variables was that ground candidate points would have a different color than vegetation candidate points. For example, ground points could be not only darker because of shadows, but red/brown (if the soil is visible) or even a different shade of green (the ground vegetation possibly being a different color than tree leaves).

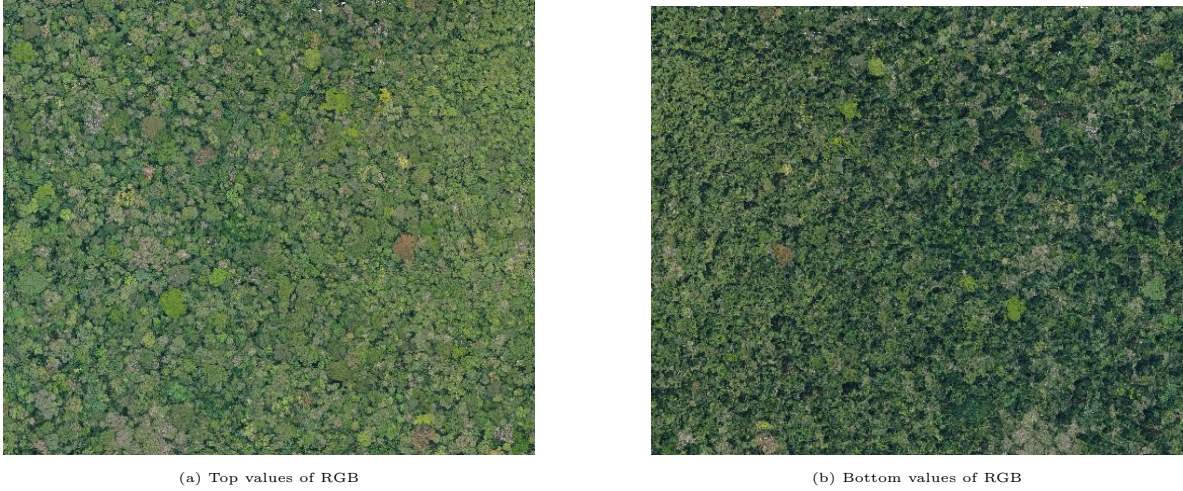


Figure 2.5: Example of difference between top and bottom values of color for spectral variables of the same forested area

To correct for differences in lighting during the moment of capture of different pictures, both top and bottom values were normalized to create two additional variables (for each color). They were normalized following equation 2.1 :

$$val_{norm} = (val - mean) / stdev \quad (2.1)$$

where val_{norm} was the normalized value of the top (or bottom) spectral value, val was the unnormalized value of the top (or bottom) spectral value, $mean$ was the mean of all the spectral values from the points in each grid cell and $stdev$ was the standard deviation of all the spectral values from the points in each grid cell. In addition to RGB spectral values, a “brightness color” was computed, and it was a combination of red, green and blue following formula 2.2 (Malepati, 2010) :

$$Y = 0.299 \times R + 0.587 \times G + 0.114 \times B \quad (2.2)$$

For this brightness color, variables for top value, bottom value, normalized top value, and normalized bottom values were computed. Combined with the variables for RGB, there were a total of 16 variables. Moreover, since variables could also have different patterns depending on the scale of computation, they were computed at different grid sizes. For all spectral variables, each raster was made with two different resolutions (i.e. grid size): 1 m and 5 m. This means that in total, 32 spectral variables were input into the classifier model.

Structural variables on the other hand are statistics on the spatial distribution of points throughout the cell, so only the 3D coordinates of the points have to be known. For each resolution, 3 structural variables were computed. They were standard deviation (SD) of elevation, height range (HR) (which was the difference between maximum and minimum elevation), and point density (population per cell (PpC)). Since ground points are most likely to be found in canopy gaps, the principle behind using structural variables is to find and characterize those canopy gaps ; the hypothesis is that in places with canopy gaps, there is a big difference of height which height range and standard deviation can reflect. The logic behind using point density was that a cell would have more points if the point cloud had better penetrated the canopy (figure 2.6). Since canopy gaps are of varying size, structural variables were computed for resolutions of 1 m, 5 m, 10 m, 20 m, and 40 m in order to capture the maximum diversity in their shapes, size, and characteristics. In total, 18 structural variables were input into the model.



Figure 2.6: Transect of the UAV-SfM point cloud illustrating the rationale behind using structural variables in random forest classifier

With the structural and spectral variables combined, a total of 50 predictive variables were computed for the study area (figure 2.7). The last thing that was needed to perform a supervised classification was the choice of the model to be used.

3) Classifier model

For this workflow, a Random Forest (RF) classifier was chosen, as this type of machine learning model has many qualities over other types of classifiers. Machine learning models (such as RF) are better for very large and varied datasets; indeed, there were 50 predictive variables and a large amount of candidate points in our dataset. Moreover, RF is easier to use than most other machine learning methods, as very little parameterization (tuning) is required. Finally, RF returns a value for the importance of each variable in the model which is practical for variable exploration, as it can inform the user on how to refine and improve the model's variables (Pal, 2005) (Zhang et al., 2021). The RF works as follows. A decision tree is “grown” out of a random subset of the available dataset, and is fit to classify

the candidate points in that subset. Many more decision trees are subsequently grown, each fit with a different subset of variables and candidate points. All these decision trees are combined to create the random forest, where each tree casts a vote as to which class a candidate point is, and the candidate point is officially classified by rule of majority. The only two parameters that needed to be set for this model were the number of trees to be used, and the depth of the trees, which is the maximum number of variables to be used in one decision tree. The RF classifier was trained in R, using the randomForest package (Version 4.7 ; <https://cran.r-project.org/web/packages/randomForest/index.html>). Once trained, the RF model returned a Gini importance index for each independent variable. The Gini importance index is a quantification of how relevant each independent variable is; a variable with a high Gini index means that it was very useful in determining the class of the training points.

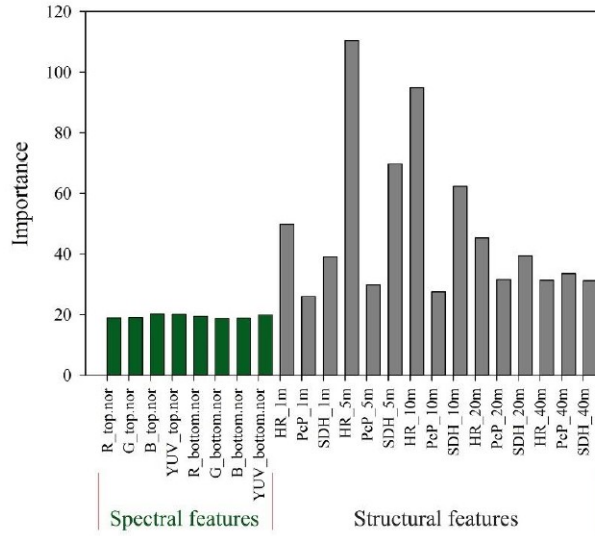


Figure 2.7: Gini’s importance of variables for RF classifier classifying ground vs. non-ground points of a UAV-SfM point cloud. YUV is the brightness, SD the standard deviation, HR the height range, PpC the point density. Source: Zhang et al. (2021).

The RF model also returned a matrix of confusion with an out-of-bag (OOB) error, with which the performance of the model could be evaluated. A matrix of confusion is a table that shows for each column the true class of the points in a dataset, and for each row the predicted class of the points in the dataset. This means that the diagonal (top left to bottom right) corresponds to points which were correctly classified, and all other cells of the matrix are misclassified points. The OOB error is computed during the model training, and it is the average percentage of misclassified points by every tree in the model. However, the OOB error and confusion matrix returned after training the model are only indicative of how well the model performs, and not a truly independent validation. Indeed, the error metrics are computed with values that are also used for fitting other trees, so there is a risk of underestimating the error of the final model. This is why we separated the original dataset into training and validation, the latter one of which was not input into the model, and which was therefore completely independent.

4) Validation

The validation of the RF model was done using a confusion matrix after having predicted the class

of each point in the validation data with the model. Further, a measure of accuracy was computed as the ratio of correctly classified points to the total number of points. A kappa index was also computed. It is similar to the measure of accuracy, but it controls for the fact that the model may have by chance correctly guessed the class of a point, and thus is less likely to overestimate the accuracy of a classification. The kappa index can take values of 0 to 1, where values of 0.8 or higher are considered very good (McHugh, 2012).

Since the end goal of this study was to generate a DTM from SfM point clouds and not just a series of ground points, we did not stop at the validation of the RF classifier only. Indeed, the full validation had to be a comparison of the reference DTM and the SfM cloud generated DTM. To do so, the predicted ground points had to first be interpolated into a continuous surface (a DTM), and this was done by following the workflow on figure 2.4 and which is described in more detail below.

As with any classifier model, there was a certain amount of error associated with the RF classifier's predictions, and the accuracy was not 100%. This was however a problem for creating a DTM, because there were only a few ground points, which meant that false ground points strongly affected the quality of the ground reconstruction. Therefore, a second filtering step was added to further remove points that did not actually correspond to the ground. This was done using a morphology-based filtering, which works under very different hypotheses than the point classification. A morphology-based filtering works under the assumption that the ground must have a certain shape. Indeed, in most contexts, there are no sharp drops or spikes in the ground, and it is relatively smooth. Therefore, the filter removed all points which would cause sharp edges or drops in the ground reconstruction (figure 2.8). In practice, the Progressive Morphological Filter (PMF) by Zhang et al. (2003) and implemented into R through the lidR package (Version 4.0 ; <https://cran.r-project.org/web/packages/lidR/index.html>) by Roussel et al. (2020) was used. This PMF worked by making a grid of the lowest point in each cell for a given resolution. If the difference in height between the grid and another point in the cell was greater than a certain value, that point was removed. The algorithm started with a small grid size and progressively increased it, each time with a different, larger threshold. In this study, the grid resolutions and height thresholds were user-defined and chosen by trial and error.

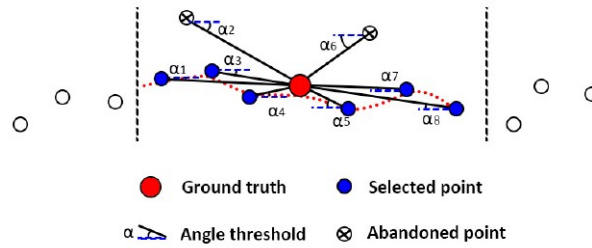


Figure 2.8: Schematic of morphological filter. The slope between the ground truth and another point determines whether a point is filtered out (source: Chen et al. (2017))

This study differed slightly from the methodology by Zhang et al. (2021), as they used a TIN filtering algorithm from a user-friendly software (Lidar360) which is very expensive. While the R implementation of PMF requires more expertise, and may slightly decrease accuracy, it was done with completely open-source algorithms, which made the methodology proposed here that much more reproducible.

After the candidate points had gone through the two different filtering steps (RF classifier + PMF),

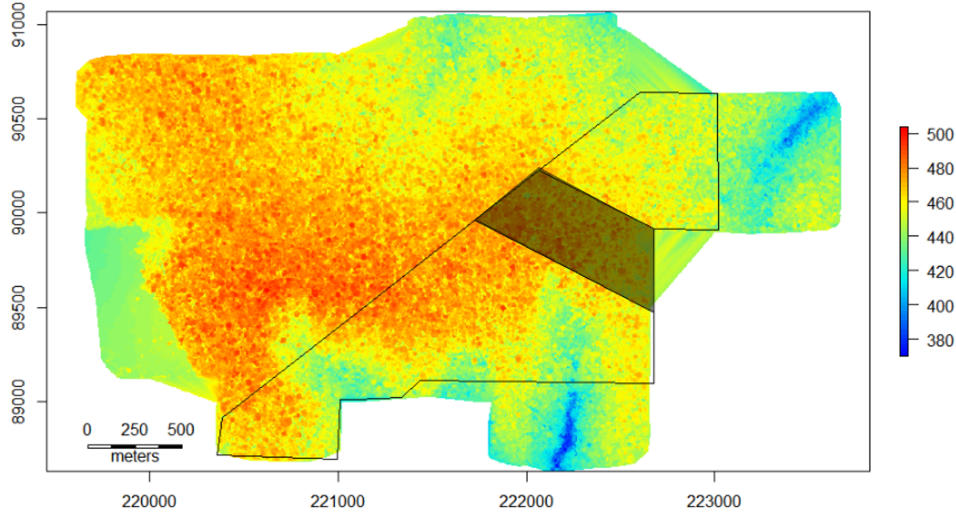


Figure 2.9: DSM of the whole Yangambi study site (resolution = 0.5 m). Warmer colors refer to high elevations, and colder colors to lower elevations. The black outline corresponds the area of the reference DTM. The shaded area corresponds to the validation area for DTM generation.

the remaining points were very likely true ground points. They could therefore be used to accurately reconstruct the ground surface under the canopy. However, since the number of ground points was so small compared to the surface that was to be modelled, advanced geostatistical methods had to be used. In geography, spatial interpolation has widely been done with kriging. In kriging, with the assumption that nearby points are spatially autocorrelated, the spatial dependency between nearby points is modelled through regression. By fitting a regression curve to the residuals of nearby points as a function of distance, the behavior of the variable through continuous space can be modelled. In the case of this study, we went one step further and used a co-kriging technique. This was done because the variable that was modelled was spatially correlated to another, more easily measurable variable. In this case, a coarse resolution DSM was used, with the assumption that the surface of the forest tends to vary in elevation at the same time as the ground underneath. Indeed, when looking at a DSM, we can take a guess at the general form that the terrain underneath (figure 2.9). The DSM of Yangambi (originally 0.5 m in resolution) was resampled to 30 m, as Zhang et al. (2021) found that this was the best correlated resolution with the underlying elevation. The co-kriging operation was done in ArcGIS Pro (Version 2.9.0 ; <https://www.esri.com/>), using the Empirical Bayesian Kriging (EBK) Regression Prediction tool. It created a 30 m resolution DTM that was subsequently resampled (by bilinear interpolation) to a 0.5 m grid to match that of the reference DTM. The bilinear interpolation is a distance-weighted average of the four closest cells, and it returns a smooth fine scale surface.

2.7.2 Adding Structural Variables

The first goal of this study was to improve the prediction of ground points with new and improved structural variables. These will be described in this section. For each resolution (1 m, 5 m, 10 m, 20 m, 40 m) a total of 14 new variables were created in the same way as HR, SD and PpC were computed (summarization of point cloud into grid format). They were added to the original set of predictive variables described by Zhang et al. (2021) and were defined as such :

1. Coefficient of variation (CV) as described by equation 2.3 (Almeida et al., 2020) :

$$CV = \frac{sd(Z)}{mean(Z)} \quad (2.3)$$

where Z is the elevation and sd the standard deviation. The assumption for using this variable was that if the point cloud penetrated better through the canopy, its CV would be higher.

2. Canopy relief ratio (CRR) as described by equation 2.4 (Almeida et al., 2020) :

$$CRR = \frac{mean(Z) - min(Z)}{HR(Z)} \quad (2.4)$$

where min is the minimum and HR the height range (as described in section 2.7.1). The assumption was that a canopy with a more varied relief would signify that it was less closed, and therefore the point cloud would penetrate through it better.

3. Relative point density, where we wanted to go into finer detail of how the points were distributed along the Z-axis (from top to bottom). For each cell, all the points were separated into 5 bins of equal length along the Z-axis (where the length of a bin is equal to $HR/\#$ of bins). For each bin, the relative point density was computed by the ratio of the number of points in the bin to the total number of points in the cell (the PpC). In total, 5 variables were created (hereafter named PD 1-5). These variables were created with the thinking that the distribution of heights would look different if there were gaps in the canopy or not (with more points in lower strata in places of better point cloud penetration). These metrics were inspired by Kachamba et al. (2016), and Domingo et al. (2019).
4. The skewness of the vertical distribution was computed (PDskew) as a measure of how asymmetric the distribution of elevation was. The kurtosis (PDkurt) meanwhile was a measure of how flat the distribution of elevation was (flat histogram = spread out histogram). These two variables were used in a number of forestry studies with SfM point clouds (Almeida et al., 2020) (Kachamba et al., 2016) (Domingo et al., 2019). The assumption for skewness was that a very closed canopy would be very skewed to high values (as not many points go through the canopy) and the kurtosis would be high if the elevation distribution was more spread out (and so with more height variation and a better penetration through the canopy).
5. The canopy interception ratio (CIR) described by Senn et al. (2020) was used as a basis for three variables. First, the gap fraction profile describing the understory vegetation of a point cloud was found (Bouvier *et al.*, 2015). For each voxel (a 3D pixel), the amount of points that passed through a layer $[z; z+dz]$ was computed, for all layers. With all layers assembled into a profile, the CIR could be computed as indicated by Senn et al. (2020). This computation entailed many variables, so the reader is referred to the original article for details. What is only needed to be known is that the CIR represented how the vegetation affects the penetration of water (and therefore light) through the canopy. The CIR computation returned a whole profile (figure 2.10), which was impractical to handle, as all the other variables were computed as single value rasters, so the CIR profile was transformed into three rasters which describing the shape of such a profile. The standard deviation (CGsd), the skewness (CGskew), and the kurtosis (CGkurt).
6. The entropy is an algorithm proposed by the “grid_metrics” function (lidR package). Officially

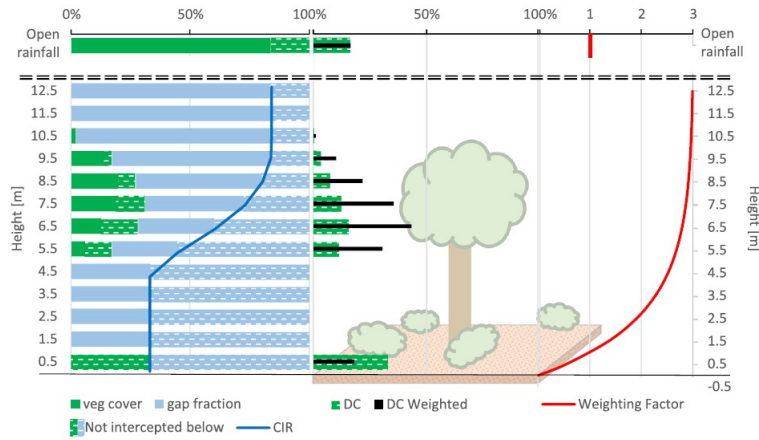
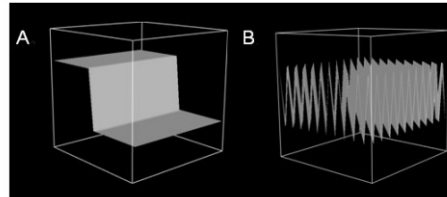


Figure 2.10: Visualization of the CIR (blue line) in a forested context. The CIR does not change from ground level to the canopy, and increases because of the canopy (schematic of forest on the right). Other metrics can be ignored in the context of this study. Source: Senn et al. (2020).

named normalized Shannon vertical complexity index, it was derived from a measure of species diversity in ecology, but was implemented in the `lidR` package to quantify the diversity and evenness of a distribution of elevation (Pretzsch, 2009). The assumption was that a complex forest structure might be representative of a better penetration through the canopy.



	Surface A	Surface B
Rumple	1.4	14.2
95th p. height	100	100
Mean height	75	75
SD height	25	25

Figure 2.11: Schematic comparison of two structures with same standard deviation and mean height, but different rumple index. Source: Kane et al. (2010)

- Finally, the last variable was the rumple index (named rumple). Proposed by the “`grid_metrics`” function, this algorithm is defined as the ratio of canopy outer surface to ground surface area (Jenness, 2004). It is close to the standard deviation of height, but the distinction is that while the standard deviation describes the one-dimensional variability of height, the rumple index describes the 3D heterogeneity of the elevation (figure 2.11). In the case of this study, the reasoning was that a low rumple index might represent a bigger canopy gap (because of less 3D heterogeneity), and would therefore lead to a higher likelihood of finding a ground point.

This new set of variables was used to train a new RF classifier model (in combination with the original variables).

2.7.3 DTM Evaluation

The quality of the UAV-SfM generated DTM was evaluated in two steps. First, it was validated in Yangambi using the validation area and comparing heights to the ALS generated DTM. Secondly, it was evaluated in Yoko with the GNSS ground sampling campaign as an external validation to measure the model's performance in a separate but similar context.

Yangambi - ALS Validation

The validation of the SfM-generated DTM ended with a comparison to the ALS-generated DTM (i.e. reference) using two statistical error indicators. The first indicator that was used is the Nash-Sutcliffe Efficiency (NSE) (equation 2.5). This indicator measures how well the simulated data (the SfM DTM) fits to the observed data (the ALS DTM), which just means that it measures how well the data fit to the 1:1 line when graphed in a plot of SfM vs. ALS. The closer the NSE is to 1, the better the model is at predicting the reference values. A NSE of 0 means that the predictions are as accurate as computing the average of all the cells in the ALS DTM. A NSE below 0 indicates that our workflow is worse at predicting the reference than a simple mean of the whole ALS DTM. In equation 2.5, the variables are n which is the number of observations (in this case number of grid cells in the DTM), O_i is the value of one observation of the ALS DTM, E_i the value of one estimation of the SfM DTM, and $\bar{O}$ the mean of the observed values. These same variables are found in equation 2.6 for computation of RMSE. This value can be interpreted as the standard deviation of the model prediction error and is computed in the same units as the DTMs (so in meters). The higher the RMSE is, the worse the model is at estimating an accurate DTM, and a perfect model would have a RMSE of 0.

$$NSE = 1 - \frac{\sum_i = 1^n (E_i - O_i)^2}{\sum_i = 1^n (O_i - \bar{O})^2} \quad (2.5)$$

$$RMSE = \sqrt{\sum_i = 1^n \frac{(O_i - E_i)^2}{n}} \quad (2.6)$$

Yoko - GNSS Validation

The point cloud for Yoko was converted into a DTM using the workflow as described in figure 2.4 and with the newly developed RF classifier from this study. The elevations of the DTM were compared to the processed elevations measured by the GNSS receiver from the ground sampling campaign (see section 2.5). Since the ground sampling was started at the launch site, a flat and open area with no trees, those elevations were guaranteed to have a minimal error. We therefore registered the validation elevation (GNSS) to the DTM using that small section. The DTM was resampled from the 0.5 m resolution to 5 m resolution using a bilinear method. Meanwhile, the validation measurements were summarized (using the mean) to a 5 m grid. The UAV-SfM DTM elevation values were then compared to the validation elevations with the RMSE and the NSE.

2.8 Variations on Flight Parameters

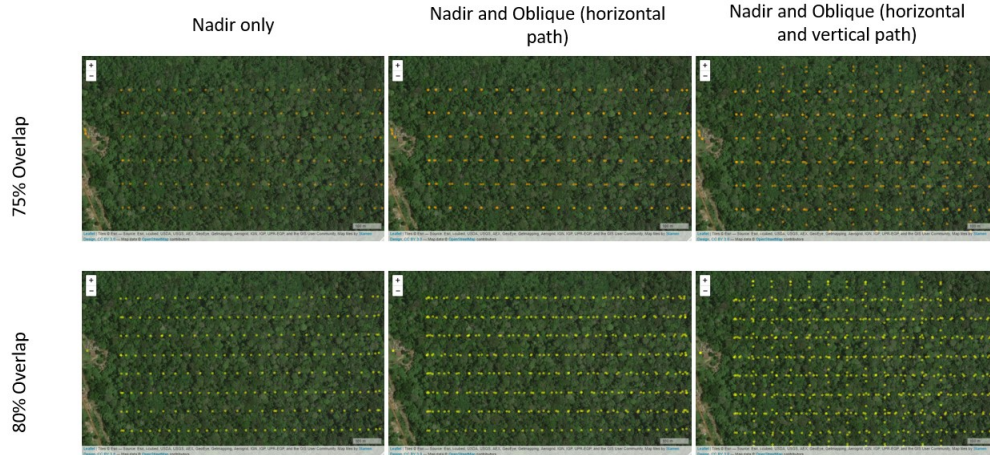


Figure 2.12: Positions of all the cameras for the generation of 6 point clouds in a region of the Yoko study area. Different rows signify different overlap proportions, and different columns signify different angles of acquisition of the camera (base map: ESRI)

A number of flights in Yoko were done to test out differences in DTM reconstruction with different proportions of overlap, and with the addition of oblique pictures acquired with different flight patterns. These tests were carried out over two different days (24 and 25 August), and with varying lighting and weather conditions (see section 2.2.3). Other than the overlap and the changing of camera angle, other parameters were kept exactly the same as for the survey flights (described in section 2.2.3). For the overlap, two different proportions were used. The control was 80% (as was used in the surveys), and the variation on overlap was of 75%. For both of these overlaps, 4 flights were carried out with an off-nadir camera angle, in addition to the nadir (looking straight down with a 90° camera angle) control flight. In the off-nadir flights, two flight patterns were tested out, with one following a parallel path to the nadir flights (hereafter referred to as horizontal path), and the other perpendicular to the nadir flights (named vertical path). Finally, two different camera angles were tested out for every combination of flight path and overlap at 70° and 40° to the horizontal axis. In total, 10 sets of pictures were generated (table 2.2). Note that, to make the reconstruction of the point cloud possible in Pix4dMapper, the pictures at a 40° angle had the top 1/3 cropped out.

The goal of the oblique pictures was to add new information to the nadir pictures, so oblique and nadir pictures were input for reconstruction together. For each combination of overlap and camera angle, three clouds were constructed. One with only nadir pictures, a second with the oblique pictures (horizontal flight path) added to nadir pictures, and a third with nadir combined to horizontal and vertical flight patterns. However, for the pictures taken at an angle of 40° , the point clouds were reconstructed separately for each flight (flights 7-10 in table 2.2). These clouds were registered (ICP algorithm from CloudCompare (<https://www.danielgm.net/cc/>)) and then merged *a posteriori*.

The reason for merging point clouds together *a posteriori* instead of directly creating a point cloud with all the desired pictures in Pix4d is that the reconstruction created a sort of "double" point cloud. The Pix4d software would recognize features and match them on all the nadir images, but would also recognize and match the same features separately for oblique pictures. The feature matching was not working. This was exacerbated by the extreme angle of the camera and very different light conditions.

Table 2.2: Variations on flight parameters

Cloud name	Overlap	Flight pattern	Camera angle	Flight date
1	75%	Horizontal	90° (nadir)	24 Aug
2	80%	Horizontal	90° (nadir)	24 Aug
3	75%	Horizontal	70°	24 Aug
4	80%	Horizontal	70°	24 Aug
5	75%	Vertical	70°	24 Aug
6	80%	Vertical	70°	24 Aug
7	75%	Horizontal	40°	25 Aug
8	80%	Horizontal	40°	25 Aug
9	75%	Vertical	40°	25 Aug
10	80%	Vertical	40°	25 Aug

All this combined made slight differences in point clouds appear (like trees being reconstructed twice separately, e.g. figure 2.13). Indeed, a Pix4d product manager highlighted in a forum (Rothenbuhler, 2017) the fact that similar issues happen with more than one flight over the same area in different lighting conditions.

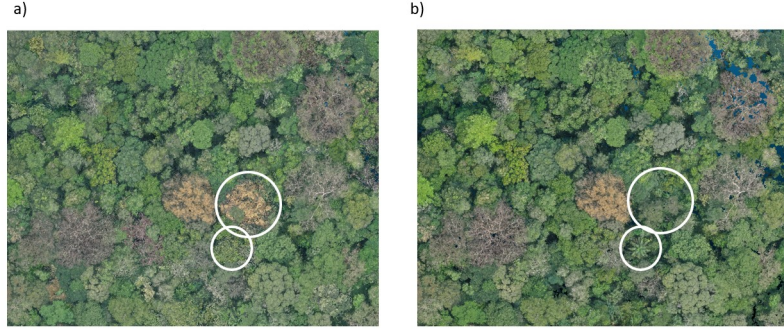


Figure 2.13: SfM point cloud of a point cloud reconstruction where a) features got twice matched in different places and b) with an accurate matching (red circles indicate places of noticeably bad reconstruction)

In the end, 10 clouds were created; 2 only nadir flights (for different overlaps), 4 clouds for nadir flights combined to horizontal oblique flights (for different overlaps and camera angles), and 4 clouds for nadir flights combined to horizontal and oblique flights (for different overlaps and camera angles) (figure 2.12).

For each of these point clouds, their DTM was reconstructed following the workflow in figure 2.4 and then tested for accuracy with GNSS ground sampling as reference, as in section 2.7.3 (which meant computing RMSE and NSE for each DTM).

2.9 Tree Heights and Monitoring

The end goal of this study was not just to create a DTM, but to create an improved tree height map of the forest in view of monitoring changing canopy heights through time. To this end, the measure of tree heights was also validated in Yangambi. The steps described in this section were done in R, and

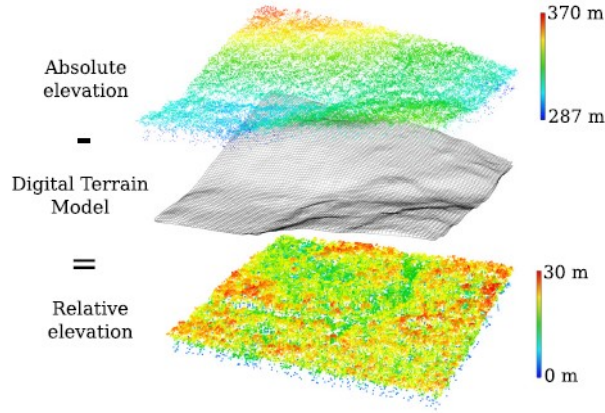


Figure 2.14: Schematic of process of normalization of a point cloud (upper) with a DTM (middle) (source: Roussel et al. (2020))

described as a standard procedure for forest point cloud analysis by Roussel et al. (2020). The SfM point cloud was first normalized with a DTM generated for the whole Yangambi study area following the workflow described in figure 2.4 and using the new RF classifier for this study (i.e. with more predictive variables). With the DTM, the point cloud could be normalized (figure 2.14). On this normalized cloud, a tree detection algorithm was used. For this case, a simple moving window was used to find all the local maxima (Popescu and Wynne, 2004). The window was defined as circular with a diameter of 20 m, and the minimum height of a tree was defined at 20 m.

Once the tree top locations were found, the point cloud was converted to a CHM (conversion from normalized point cloud to grid of maximum heights in each cell) for delineating the crown of each tree top. The crowns were found following the algorithm described in Dalponte and Coomes (2016). In this study, the default values of the algorithm implementation into R by the lidR package were used as thresholds. This crown delineation method has the advantage of being computationally very fast, which is why it was selected. For each crown, maximum height from the UAV-SfM CHM and reference CHM were compared (taken as the 99th percentile to remove possible outliers). Moreover, to compare canopy heights at a larger scale (the plot), we aggregated the CHMs to a 40 m resolution by computing the mean of all CHM values in a 40 m grid and by computing the 99th quantile (close to the maximum height, but removing any possible outliers). For each comparison (tree level and plot level), error metrics (RMSE and R^2) were computed. Furthermore, a subset of only high quality UAV-SfM DTM predictions was separated for each comparison and error metrics were computed on those subsets. The high quality values were defined as a difference between reference and UAV-SfM DTMs of less than 2 m. These high quality subsets were done for the sake of evaluating UAV-SfM and its monitoring capabilities while controlling for bad DTM estimations, but they held very little significance as the quality was defined through the use of the reference DTM (and the goal of this study was to find a ALS DTM independent method of estimating tree heights).

Chapter 3

Results

3.1 SfM Reconstruction

This first part of the results focused on an exploratory analysis of the UAV-SfM point cloud and its fit to the reference ALS dataset.

3.1.1 Surface and Geolocation Accuracy

After SfM reconstruction from images to dense point cloud, a DSM was generated (figure 3.1a). It was then compared to a similarly generated DSM of the reference (ALS) point cloud (figure 3.1c)¹. The comparison shows a good fit to the 1:1 line, with a slight overestimation by the UAV-SfM method (figure 3.1b). Numerically compared, the R^2 of 0.95 was high, which lead us to conclude that the data collection by UAV-SfM was well georeferenced. Since the RMSE of 1.29 m was still high, and the R^2 not as good as what we would hope for with PPK correction of the images for the SfM point cloud creation, we conclude that slight errors crept into the data processing. This will be discussed in the Discussion (4).

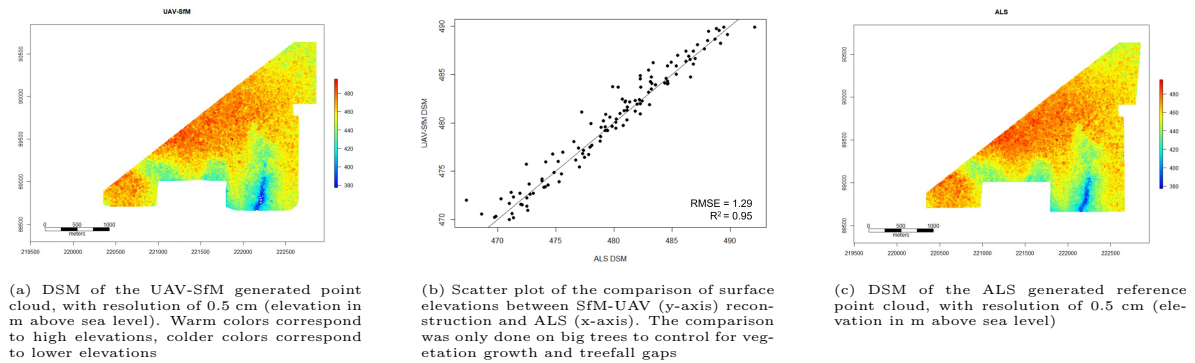


Figure 3.1: DSM reconstruction and comparison of methods

¹A bigger map of figures 3.1a and 3.1c can be found in the Annexe (figures 6.2 and 6.3)

3.1.2 Ground Reconstruction Capabilities

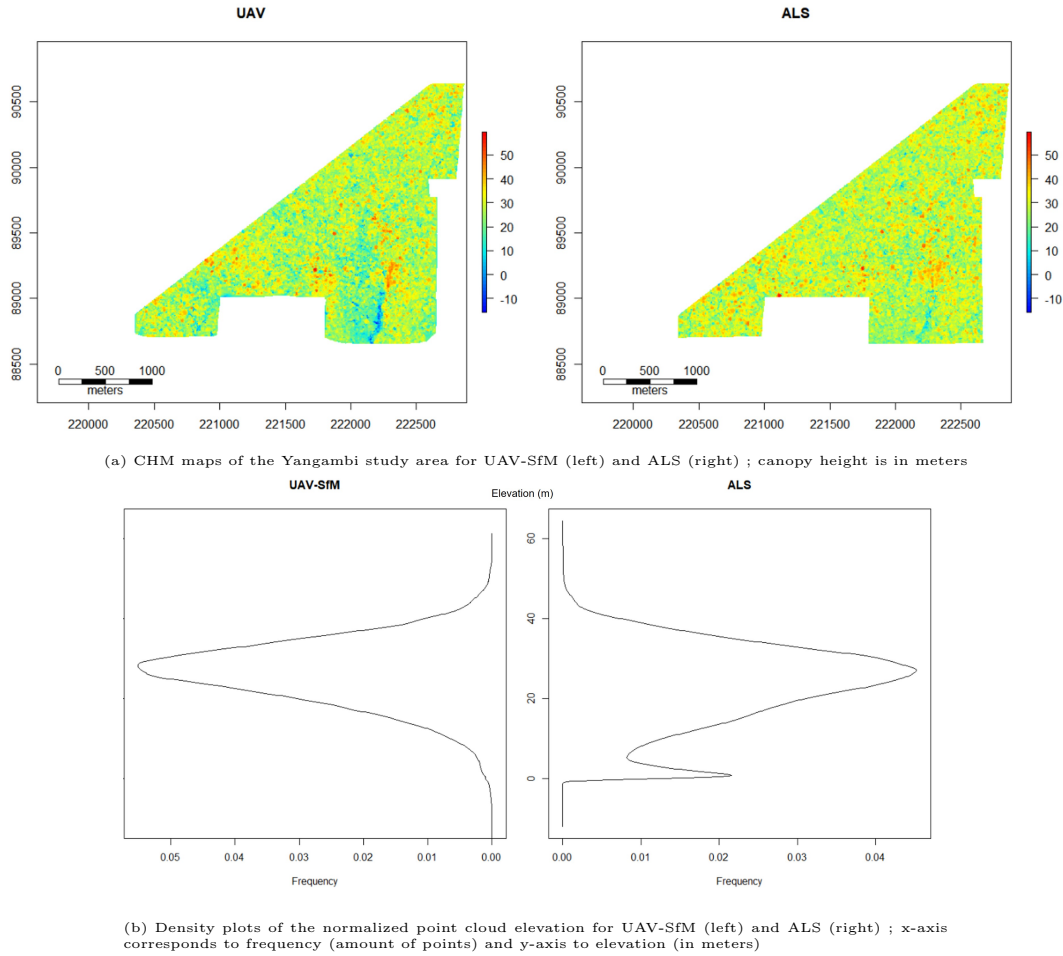


Figure 3.2

In order to determine the capabilities of ALS and UAV-SfM point clouds at detecting ground, both point clouds were normalized with the reference DTM (as in figure 2.14) and elevation distribution was compared. Visually, the CHMs looked very similar (figure 3.2a). Further, we looked at elevation distribution of the whole normalized cloud (figure 3.2b). This showed that there was a peak in ground points for the ALS point cloud, while this peak was barely noticeable for the UAV-SfM distribution, which meant that very little points actually corresponded to ground. However, even fewer points went under an elevation of 1 m, which meant that when the SfM workflow was able to reconstruct ground points, it did so accurately (figure 3.2b). For the same study region, the ALS dataset contained 11.93 million points, of which 276 024 were considered as ground points (points within 1 meter of the reference DTM). This meant that about 2.3% of the total ALS point cloud consisted of ground points and that there were approximately 1370 ground points per hectare. Meanwhile, the UAV-SfM point cloud contained 88.45 million points of which 173 201 (0.19%) were ground points. The UAV-SfM methodology was indeed good at reconstructing surface, but worse at penetrating through the canopy and to the ground below than the ALS dataset was (figure 3.2b). Indeed, we found a total of 860 ground points per hectare in the UAV-SfM point cloud. We finally saw that ground points in the SfM method

were clustered in some places, which probably corresponded to treefall gaps (figure 3.3). Moreover, there were many points in the river channel, and few where trees were highest, in the east/northeast of the study area. The ground points were only clustered toward the west of the river channel (blue) so a factor other than slope was probably at play here. Furthermore, in the densest parts of the forest (on the plateau of the east/northeast, red colors), the canopy penetration of the UAV-SfM point cloud was the worst.

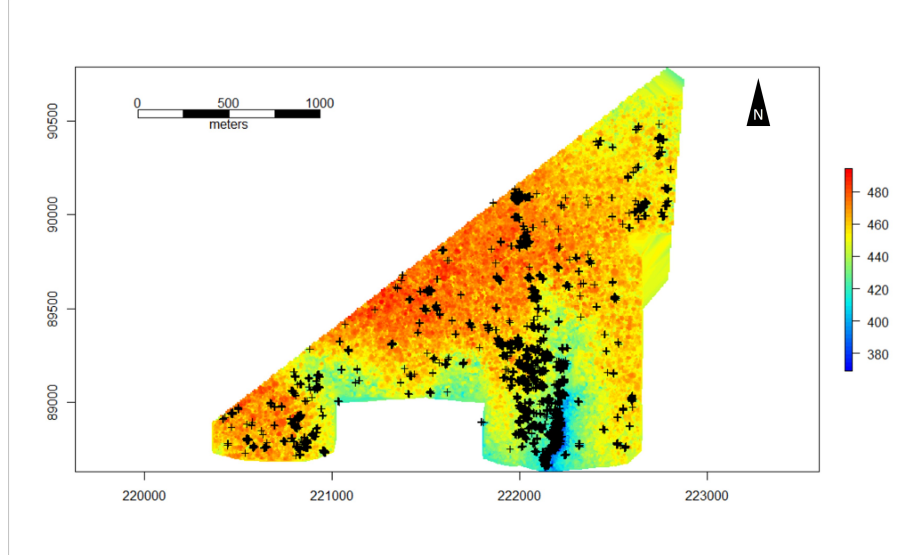


Figure 3.3: Locations of the UAV-SfM points within 1 m of the reference DTM (black crosses) overlaid on a UAV-SfM DSM of the Yangambi study area.

3.2 Structural Parameters in DTM Reconstruction

3.2.1 Ground Point Classification

This section is divided in two steps. First, the RF classifier was trained with the original workflow's variables, and for the second step, the new variables were added to the classifier. For both these steps, the same training and validation datasets were used. These included 8068 candidate points (i.e. local minima) for the training and 1647 points for the validation (distributed as in figure 2.9). Only around 4% of these candidate points actually did correspond to ground points, which justified the use of a classification scheme (Annexe - figure 6.4).

Original Method

After having trained the RF model with basic structural variables only (the original way), the internal error (OOB error) was 19.4%. Moreover, the validation dataset returned an accuracy of 85%, and the kappa index was of 0.46. From this test of accuracy, we focused on the amount of “false ground” points (so points which were falsely classified as ground). Of all the validation points, a total of 67

were predicted to be ground, of which 39 were accurately classified. This means that 40% of all the predicted ground points were misclassified.

The variables in this model which turned out to be most important in classifying the candidate points were height range (for both 5 m, 10 m, and 20 m resolution) and standard deviation for 10 m resolution. The most important resolution for point density was 40 m (in 10th place) and the most important spectral variable was the normalized bottom red value at 5 m (in 13th place) (Annexe - figure 6.5).

In the subsequent step, the PMF, all 67 predicted ground points were input into the algorithm. With this PMF filter, an additional 19 points were removed as being “false ground”. This left us with 47 ground points for the DTM reconstruction. Finally, we compared the elevation of these 47 ground points to the reference DTM, and found that 37 (78%) were within 2 m distance to the DTM.

New Method - Added Variables

The new RF model (with added structural variables) had an internal error of 16.7% and an accuracy of 87%, which was only 2% better than the original RF classifier. However, we found that the kappa value, a more robust diagnostic of classification, was 0.54 which was a more meaningful increase. Moreover, we found that in terms of ground prediction, 51 ground points were correctly classified from a total of 66 predicted ground points. This means that the RF classifier badly classified a candidate point 23% of the time, which is a lot better than the previous 40%. Note that, for both this updated RF classifier and the original one, many true ground points were misclassified during the prediction. In fact, only 32% of the true ground points were selected with the original classifier, and 34% were selected with the updated classifier. This means that a lot of points that could be helpful in further steps were removed during the classification.

In terms of variable importance, the two highest were the height range variable for 5 m and 10 m resolution. In third was the coefficient of variation (10 m resolution), then height range (20 m), coefficient of variation (5 m), standard deviation (10 m), and entropy (10 m) in 7th place. The rest of the list can be found in Annexe - figure 6.6). The first occurrence of a spectral variable (again normalized bottom red value with 5 m resolution) was only in place 39. We can therefore conclude that the new structural variables did help in the classification, though original structural variables were clearly still very important.

Of the 66 predicted ground points from the RF classifier validation, the PMF filter removed 31 of them, which left the presumed “true ground” at a number of 35 for the DTM reconstruction. Of these 35 ground points, 30 were correctly identified as ground, while the other 5 were too high compared to the DTM. We can deduce that this updated workflow is better at correctly identifying ground points, even if it does not identify more of them. Indeed, the accuracy of the original workflow was 78% while here it was improved to 85%.

3.2.2 Yangambi DTM Evaluation

The original workflow’s ground points, after having been interpolated using co-kriging, had a large error where the elevation was generally overestimated compared to the reference DTM (figure 3.4).

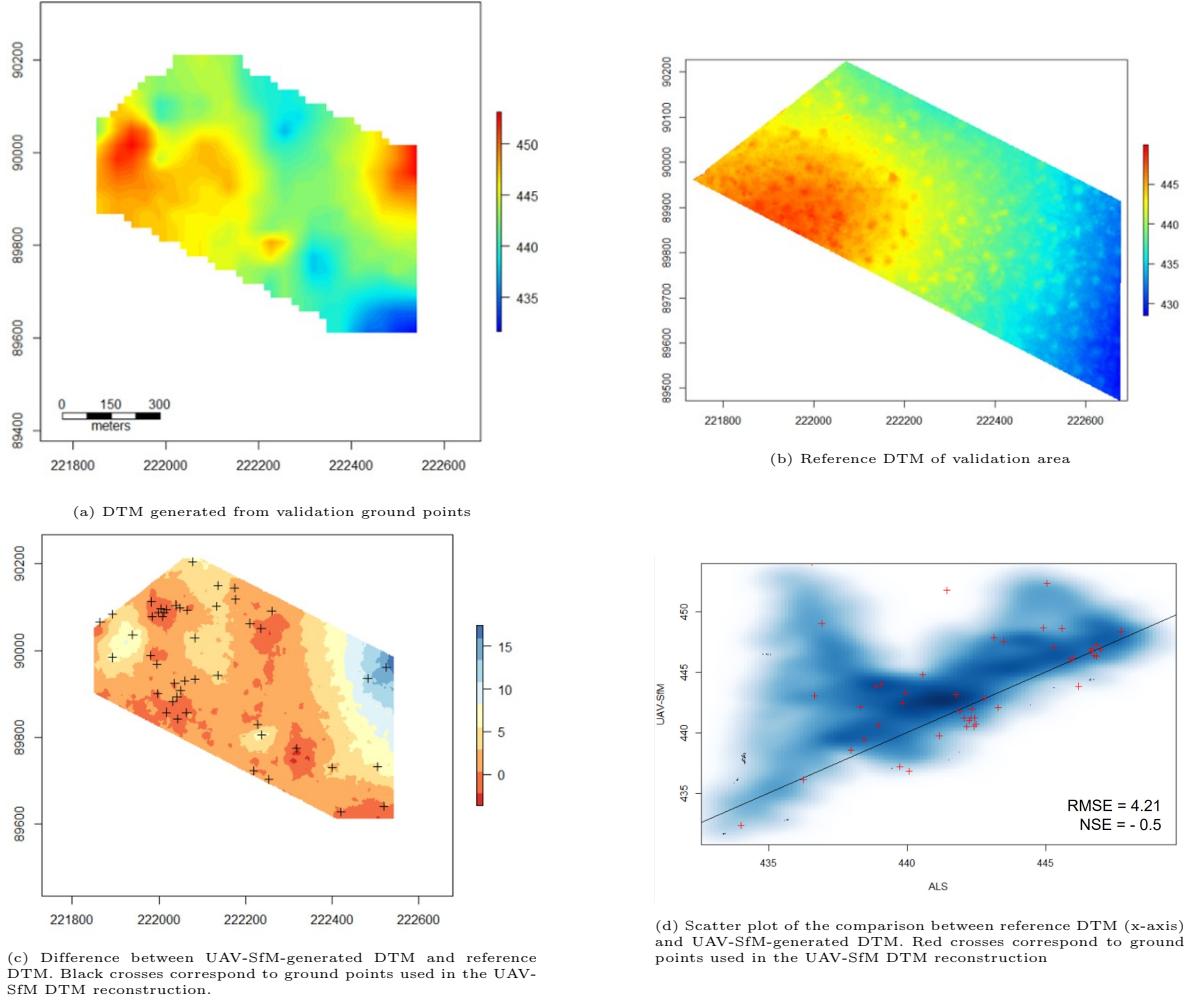


Figure 3.4: Validation of the UAV-SfM-generated DTM from ground points identified by a series of successive filters (including a RF classifier from Zhang et al. (2021)) with the reference DTM

The western part of the DTM was the most overestimated (15 m difference) because of two misclassified ground points (figure 3.4c). Moreover, a wide area had more than 5 m difference with the reference (northeast and west) and that is because of at least 4 or 5 points (figure 3.4d). We concluded from this that the three successive filters were not enough to accurately produce a DTM, as the RMSE was 4.21 m and the NSE was negative. By manually removing the two westernmost points which overestimated the elevation by more than 10 m, we found that the errors were reduced to 2.66 m for the RMSE and 0.4 for the NSE. However, these values were still high, and more than what was expected.

All things constant except for the new RF classifier, we found that this DTM reconstruction was better (figure 3.5a). Indeed, the RMSE was of 1.63 m and the NSE 0.84 without manually removing a single point. The points here were more spatially clustered, and there were few in the center of the validation area. Thanks to the co-kriging however, the UAV-SfM DTM was underestimated by at most 4 meters (figure 3.5c). Moreover, looking at the scatter plot (figure 3.5d), we found that the SfM-generated DTM generally underestimated elevation for most of the surface, including the cluster of 5-6 points in the northwest of the validation area (most of the blue in figure 3.5d is under the 1:1

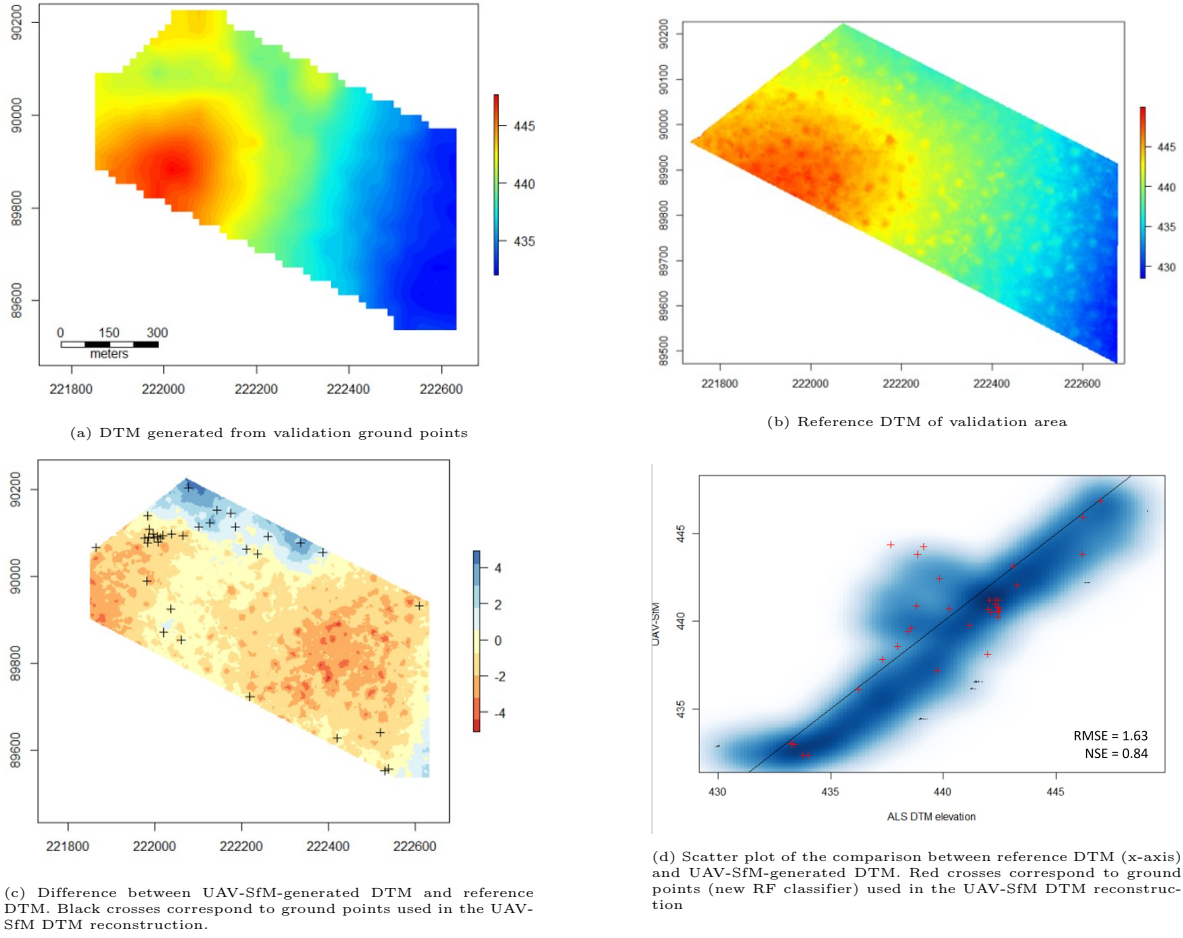
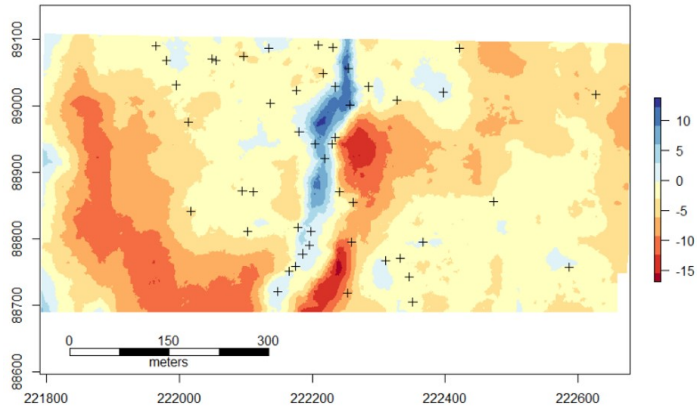
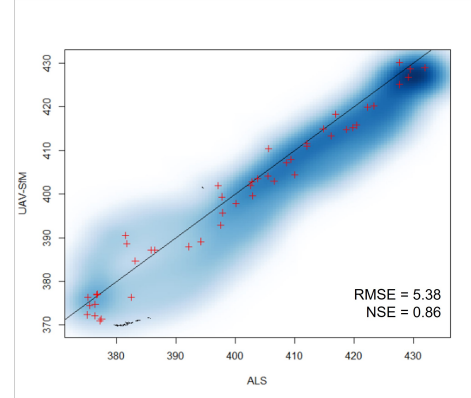


Figure 3.5: Validation of the UAV-SfM-generated DTM from ground points identified by a series of successive filters (including a RF classifier created in this study) with the reference DTM

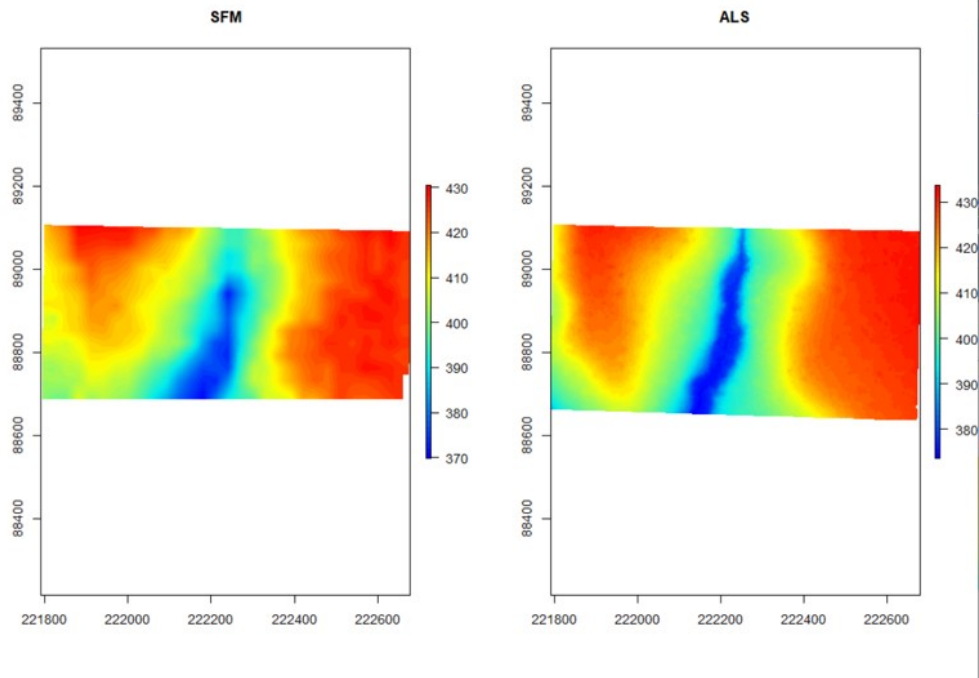
line). Note also that the reconstruction of the DTM was affected by the small size of ground points. Indeed, a DTM reconstruction was made of the entire Yangambi study area, and our validation area was extracted from it. When we did this, most of the ground points were exactly the same. However, the scatter plot fit a lot better to the 1:1 line, and there was no underestimation of the elevation by the UAV-SfM DTM. Thanks to this, the RMSE was brought down to a lower 1.35 m, and the NSE was 0.91 (Annexe - figure 6.7). There was no underestimation in this case, because the co-kriging did not fit its regression curve onto underestimated ground points, but on a much larger zone of generally better fitting ground points. We therefore concluded that the cluster of underestimated points negatively affected the DTM reconstruction as they weighed too much in the co-kriging model, and that a higher amount of data is beneficial. However, this conclusion must be taken with care, as the co-kriging was fit over part of the training data, which is not a good statistical practice. As a final side note, we found that the cluster of ground points corresponded to the location of the CongoFlux tower (<https://www.congo-biogeochem.com/congoflux>) which is positioned in a relatively large forest clearing. However, this tower and the clearing surrounding it were made after the ALS data collection. This means that there was either a georeferencing error between the reference and our UAV-SfM-generated DTM, or that the reference DTM overestimated the elevation at that spot.



(a) Difference between UAV-SfM generated DTM and reference DTM. Black crosses correspond to ground points used to reconstruct UAV-SfM-generated DTM



(b) Scatter plot of the difference in elevation between reference DTM (x-axis) and UAV-SfM-generated DTM. Red crosses correspond to ground points used to reconstruct the UAV-SfM-generated DTM



(c) DTM generated from ground points using RF classifier from this study and workflow (left) compared to reference DTM

Figure 3.6: Comparison of DTMs between reference and UAV-SfM in an independent area from training and validation with slopes

Set aside from the validation and the training, part of the UAV-SfM point cloud containing higher slopes and which overlapped with the reference DTM was analyzed. This was done to quantify the performance of our new workflow in a slope and stream channel context (south of the Yangambi study area) which is usually considered more challenging. We found that the bottom of the stream channel (dark red spot, center south of figure 3.6a) was underestimated by the UAV-SfM-generated DTM. Moreover, there was a difference in the placement of the slope between the reference and UAV-SfM west of the channel. Indeed, the slope on the UAV-SfM DTM was closer to the river channel, which created a blue area of overestimation compared to the reference DTM (figure 3.6a).

3.2.3 Yoko External Validation

As a test of performance of the methodology, a DTM was made and validated in Yoko. In this case, contrary to Yangambi, ground points were identified only with the new RF classifier. On a surface of 3.1 km^2 , and with a point cloud containing 81.88 million points, 960 ground points were identified (so 0.001% of the original cloud, figure 3.7a). The forest here is part old growth (dense and tall), especially in the east of the study area, and part secondary forest (short and less dense), especially in the north and west. There were even roads, a railroad track and a village which were completely open and free of canopy. As in Yangambi, the ground detection worked least well in old-growth and tall forest plots, and better with low trees, like in regenerating forest plots. Interestingly, the RF classifier identified very few ground points in completely open spaces, where in theory there would be the largest clusters of ground points. This is probably due to the fact that the classifier relied so much on variation in structure to find ground points in dense canopies that it was trained to see completely flat ground as the top of a canopy. We can confirm this hypothesis by the fact that points were most clustered where the open spaces met the edge of the forest (like a road and clearing edges). Note that the CHM of the Yoko study area can be found in the Annexe (figure 6.8).

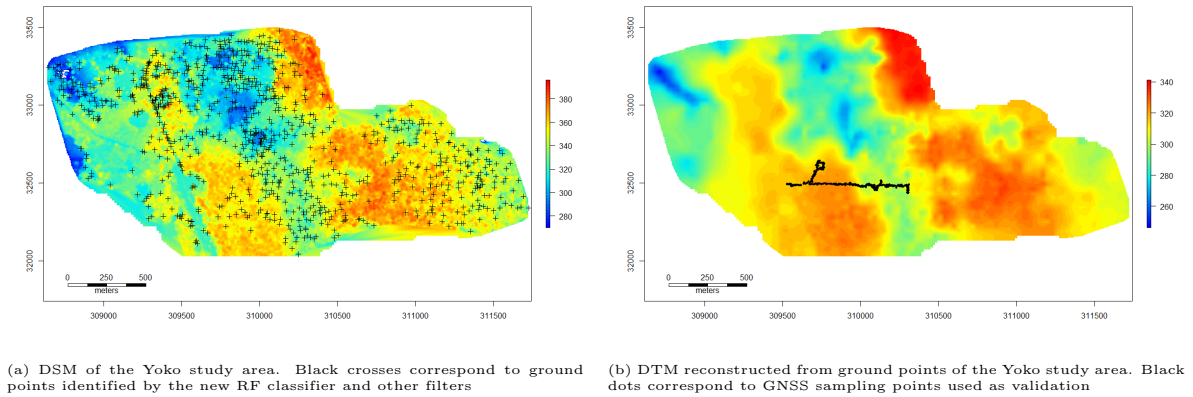
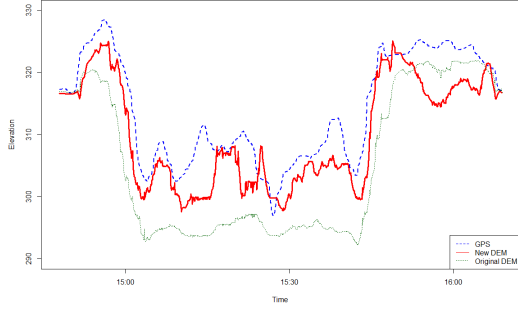
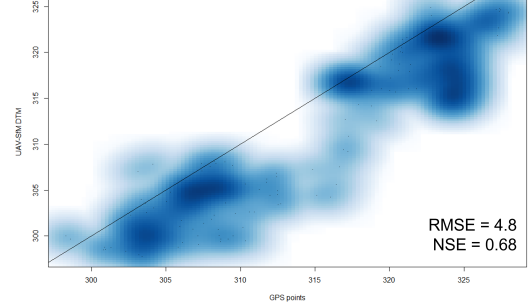


Figure 3.7: Surface and terrain reconstruction of the Yoko study area from UAV-SfM point cloud

The DTM reconstruction of the Yoko study area (figure 3.7b) was compared to the ground elevation sampling campaign that was done with the GNSS receiver. While there was some correspondence in the elevation profile and variations at the meter scale corresponded, the DTM was generally underestimated compared to the GNSS measurements (figure 3.8a). In addition, the biggest height difference was found at a place of completely flat ground, and the slopes had a very similar elevation to the reference. Another DTM, one created by Zhang et al. (2021) (Annexe - figure 6.9) underestimated elevation even more, especially in low elevations. Moreover, it did not measure well the small variations in terrain down slope. Numerically, the error between the GNSS sample elevations and our new DTM was 4.8 m for the RMSE and 0.68 for the NSE (figure 3.8b). The scatter plot showed that there were some big clusters of points which were well estimated (part of the down slope, and top of the slope). As a further proof that the new DTM was better than the original one, created with the previous RF classifier, the RMSE between GNSS sample elevation and DTM was 9.40 m (NSE = -0.21). There was indeed a big improvement of 5 m between the original and the new method.



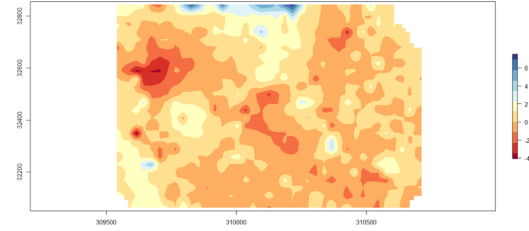
(a) Elevation profile (m) of the GNSS points as a function of the time those samples were taken, and corresponding DTM elevations of each GNSS sample. New DEM (red line) is the DTM which was created by the workflow and RF model trained in this paper. Original DEM (green dashed line) is a DTM created by Zhang et al. (2021) using the same workflow as this study but using another RF model using less detailed variables. GPS (blue dashed line) are GNSS measurements of altitude, used as ground truth.



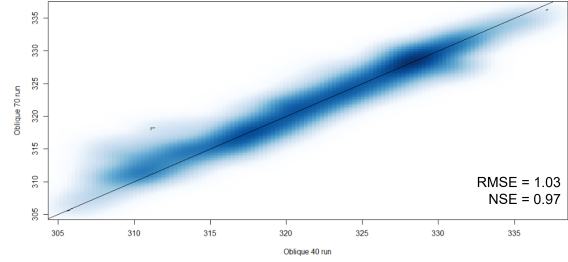
(b) Scatterplot of GNSS sample elevation (x-axis) against UAV-SfM DTM generated from the new workflow (y-axis)

Figure 3.8: Validation graphs comparing the GNSS sample elevations and the UAV-SfM DTMs

A Tangent on Stability



(a) Difference between two identically generated DTMs from the same point cloud



(b) Scatter plot of two identically generated DTMs from the same point cloud. Oblique 40 run refers to the DTM that was used to compare to high oblique point clouds (i.e. 40°) and oblique 70 run refers to the DTM used to compare to low oblique point clouds.

Figure 3.9: Comparison of two identically generated DTMs from the same point cloud.

Stability is here defined as how reproducible a DTM is from one time to the other, each time using our same workflow. We first compared two DTMs generated from the exact same point cloud (one created for the comparison with high oblique point clouds and one for the comparison with low oblique point clouds), which we called first and second run. In this case, there were only some minor differences between the two, which were caused by a small bug in the RF classification (a point with the same probability for two classes gets randomly classified as one class or the other). In terms of ground points, on an area of 0.87 km^2 , there were 110 points in the first run and 109 in the second run, due to the classification bug. By comparing the two DTMs, we found that the RMSE between the two rasters was 1.03 m and the NSE was of 0.97. The two DTMs fit very well to the 1:1 line, and in a couple isolated spots, there were slight variations (figure 3.9). All in all and apart from the small variations, the very high NSE showed that the stability within the generation from a same point cloud is good.

The second test of stability was done on two different point clouds. Both were generated in the same way from photos taken on the same day, but one of them (the point cloud which produced the

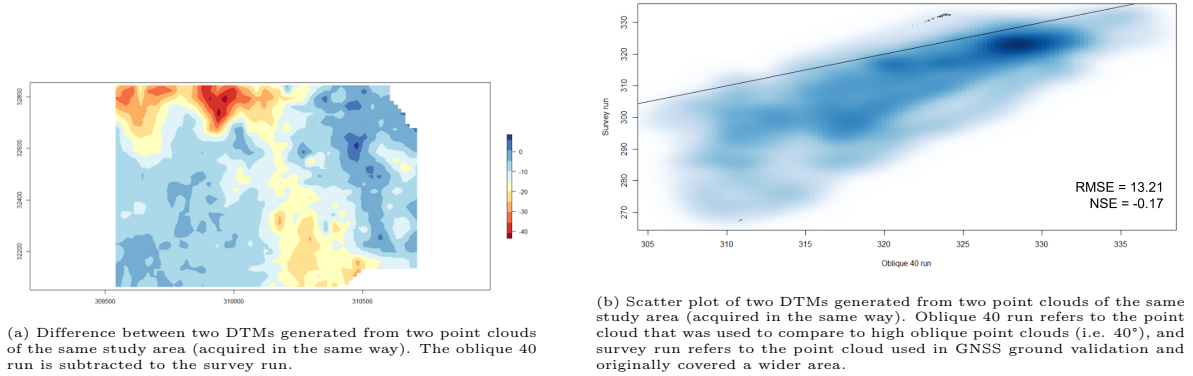


Figure 3.10: Comparison of two identically generated DTMs from two different but identically generated point clouds

third DTM) covered a wider area. For the purposes of this test, the DTM was first produced over the whole study area, then cropped to fit to the first DTM. In this case, the reconstruction was very bad, and the third DTM overestimated the elevation, especially in the lower elevations. The RMSE was 13.21 m and the NSE was negative, which showed that the stability in the reconstruction was very bad (figure 3.10). The bad correspondence between the two DTMs may have been slightly affected by a vertical registration error, but some other, more significant factors were probably at play here, such as differences in kriging regression models. We concluded from this that the reproducibility of this DTM generation workflow in our case was bad when using different input point clouds.

3.3 Variations on Flight Parameters

In this section, we analyzed how different flight parameters affected DTM reconstruction. All the DTMs that were made can be found in the Annexe with their corresponding CHM (figures 6.10 and 6.12). Moreover, each DTM and CHM was compared to one control DTM/CHM, and those comparisons can also be found in the Annexe (figures 6.11 and 6.13). We found that the DTM reconstruction for each point cloud was acceptable, as all of them mirrored the same general landform shapes. However, the errors tended to be high and relatively stochastic at a finer scale.

Table 3.1: Average error metrics for same flight parameters

Flight parameter variation	RMSE	NSE
Nadir	4.45	0.73
+ Horizontal	3.68	0.82
+ Vertical	2.74	0.90
Low oblique (70°)	2.91	0.88
High oblique (40°)	3.5	0.83
75% overlap	4.04	0.77
80% overlap	3.21	0.86

To compare the quality of our DTMs with the ground truth from Yoko (the GNSS sampling), we computed error metrics (RMSE and NSE) and made scatter plots (figure 3.11 for high oblique com-

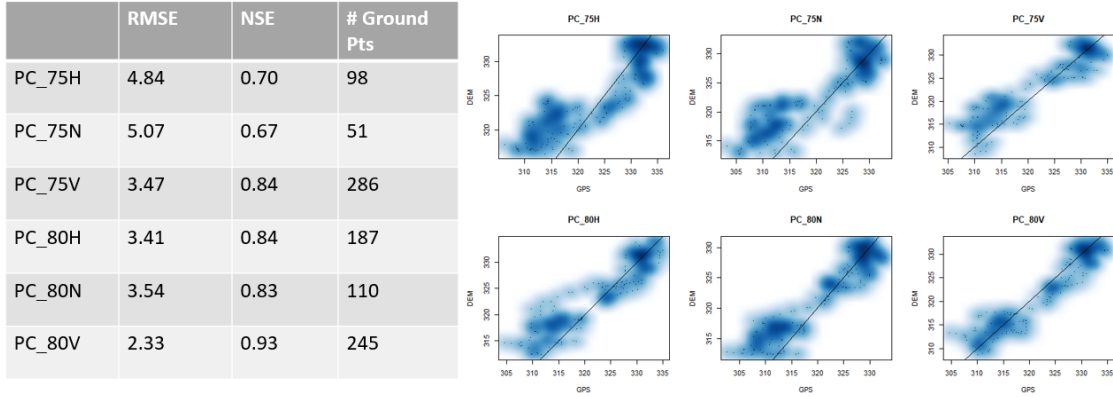


Figure 3.11: Comparison of GNSS ground sampling elevation and DTMs with varying flight parameters including angle of high oblique picture (40°), overlap (75 or 80%), and direction of flight path for oblique pictures (H/N/V for horizontal, nadir (= no oblique pic), and vertical). Left is the table of the error metrics and number of ground points used in DTM reconstruction, and right are the individual scatterplots

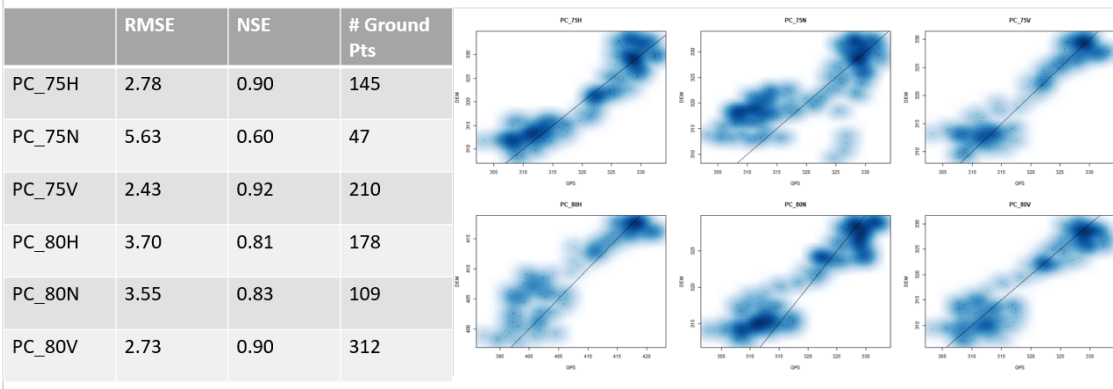


Figure 3.12: Comparison of GNSS ground sampling elevation and DTMs with varying flight parameters including angle of low oblique picture (70°), overlap (75 or 80%), and direction of flight path for oblique pictures (H/N/V for horizontal, nadir (= no oblique pic), and vertical). Left is the table of the error metrics and number of ground points used in DTM reconstruction, and right are the individual scatterplots

parisons and 3.12 for low oblique comparisons). We found the lowest error and highest correspondence to the 1:1 line to be the DTM generated from the point cloud with 80% overlap, combining vertical and horizontal high oblique (40°) and nadir pictures. This was also the point cloud which required the most pictures and most post-processing work. This DTM was closely seconded by the one made from vertical and horizontal low oblique (70°) and nadir pictures, with a 75% overlap, which required both less work and fewer pictures. The worst DTM was from the nadir only point cloud with 75% overlap. The second to last was the 75% overlap point cloud with high oblique pictures added to it (horizontal flight lines). We then grouped the error metrics by averaging them out by common characteristic (same overlap, same level of obliqueness, and same pattern of flight lines). The results (table 3.1) showed that 1) low oblique point clouds were better at reconstructing the ground than high oblique, 2) a higher degree of overlap (i.e. 80%) was better, and 3) nadir was worse than nadir combined with horizontal flight lines (for oblique pictures) which itself was worse than nadir and horizontal combined with vertical flight lines (for oblique pictures).

3.4 Tree Heights and Monitoring

With the validation DTM of Yangambi, we normalized the point cloud and did additional validation on the resulting CHM. We compared the UAV-SfM CHM from Yangambi to the ALS-generated CHM (the reference).

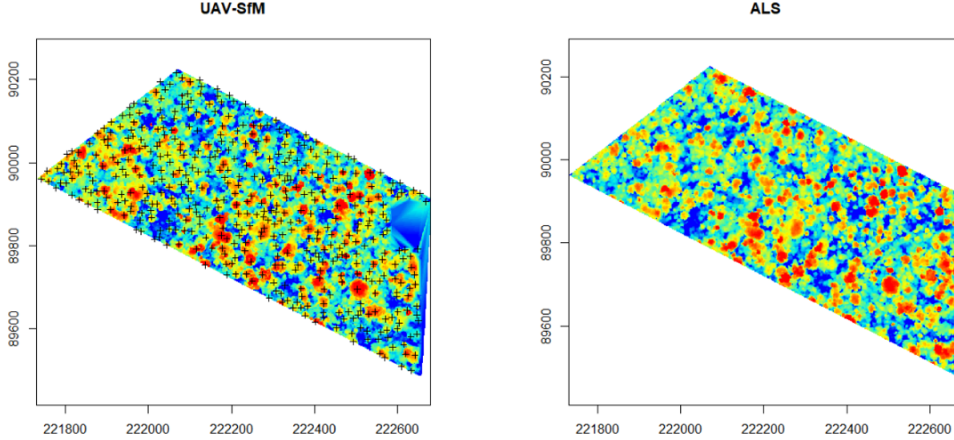
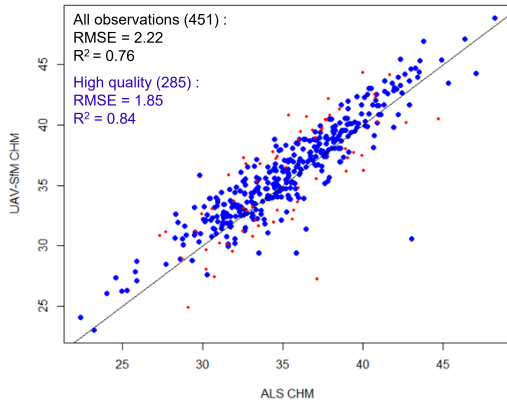


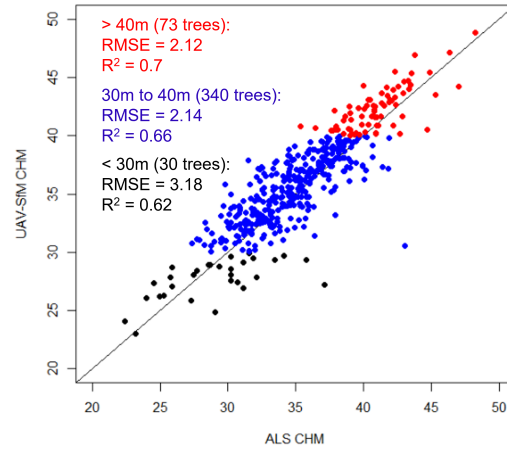
Figure 3.13: CHMs of UAV-SfM and ALS (reference). The UAV-SfM CHM had values of 0-60 m (cold to warm colors) and the blue spot in the top right is an edge artifact. The ALS CHM had values of 0-48 m (cold to warm colors). Black crosses (left) correspond to tree tops of more than 20m.

A first visual look (figure 3.13) showed that the two CHMs were very similar to each other, except for some treefall gaps in the UAV-SfM CHM which were not in the reference CHM (e.g., extreme north of figure 3.13). A total of 451 trees of more than 20 m were found, and 285 of those were in a zone of high quality DTM (see figure 3.5c). The estimation of tree top elevation had a RMSE of 2.22 m and R^2 of 0.76, which improved to 1.85 m and 0.84 after removing bad quality trees (figure 3.14a). Even though there was a good improvement, there still remained an error, which was probably caused by growing vegetation between the two data collection dates. Moreover, when separating the trees into height cohorts (figure 3.14b), the RMSE went from a high 3.18 m for the trees under 30 m high, to 2.14 m for trees 30 to 40 m tall, and 2.12 m for the highest trees. At the plot level, there were a total of 229 observations (= 40 m grid cells) of which 160 were high quality. For the mean plot elevation, the RMSE was improved from 2.37 m to 1.66 m and the R^2 from 0.61 to 0.72 (figure 3.14c). Meanwhile, the 99th quantile of plot elevation returned errors of 2.04 m and 0.74 respectively for RMSE and R^2 . Finally, when removing bad quality plots, the error was improved to 1.96 m (RMSE) and 0.84 (R^2) (figure 3.14d). The gain in quality between all observations and only high quality was very little for the plot-level 99th quantile compared to the decrease in RMSE for mean plot elevation.

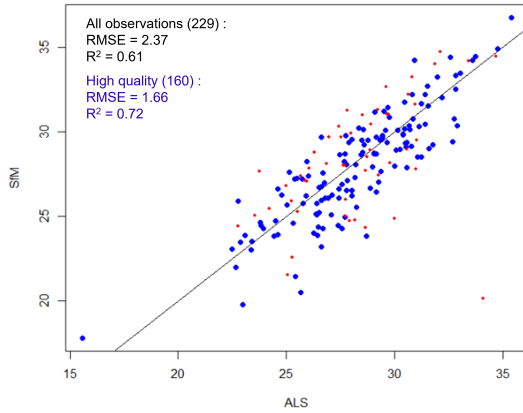
In conclusion, we found that the CHM was best estimated at the plot level (for the 99th quantile), and that the worst estimation was at individual tree scale for trees less than 30 m high. This is probably due to lower vegetation growing faster than already tall trees in a forest. Indeed, the high trees and plot scale comparisons controlled better for those kinds of variations (high trees and plots being more stable in the forest structure). Finally, removing bad estimations was least beneficial at the plot scale (99th quantile metric), and most beneficial for plot-scale mean height.



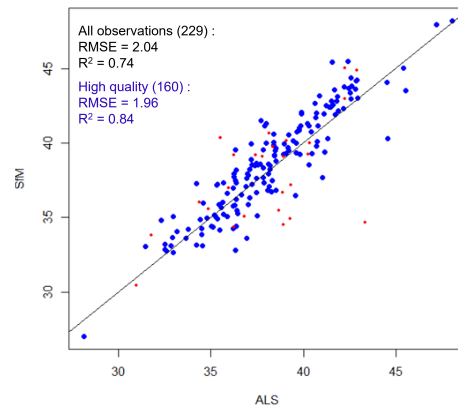
(a) Tree scale scatter plot of ALS tree heights and UAV-SfM tree heights. Blue dots correspond to high quality observations and red dots correspond to bad quality observations.



(b) Tree scale scatterplot of ALS tree heights and UAV-SfM tree heights. Black dots correspond to trees of less than 30 m (in the UAV-SfM CHM), blue dots correspond to trees between 30 m and 40 m, and red dots correspond to trees higher than 40 m.



(c) Plot scale scatter plot (mean plot elevation) of ALS and UAV-SfM normalized clouds. Blue dots correspond to high quality observations and red dots to bad quality observations



(d) Plot scale scatter plot (99th quantile) of ALS and UAV-SfM normalized clouds. Blue dots correspond to high quality observations and red dots to bad quality observations

Figure 3.14: Plot and tree level validation of UAV-SfM CHM with reference (ALS) CHM

Chapter 4

Discussion

4.1 Ground Detection

First, the number of actual ground points produced varied strongly within the DTM (figure 3.3). The worst part in regard to ground detection was clearly the plateau. Moreover, the west side of the river channel (at the south of the Yangambi study zone) contained a lot more ground points than the east side. The lighting conditions were the same for the acquisition of both those sites (overcast) so this cannot explain the difference between the two sides as light occlusion should have been the same. The fact that there were more ground points on the west side suggests other factors, which may have an environmental cause. Indeed, the west side of the river channel (figure 3.3) contains less high trees and a seemingly generally less dense forest than the east side.

All in all, there were ground points scattered across the whole study area, which was a good thing for later DTM generation. Moreover, we found that ground detection is possible in all kinds of lighting conditions through the dense canopy. Though no rigorous testing was done, the weather ranged from overcast to very sunny for different areas of the point cloud, and while that may have impacted ground detection, big enough holes in the canopy were detected regardless. It was indeed a strength to be able to sample in varying light conditions, as logistical factors dictated sampling times more than weather during our field work. In the future however, if the researcher has a choice, we would recommend conducting the data collection in sunny conditions, following the findings of Dandois et al. (2015) who found SfM point clouds penetrated better through the canopy in sunny conditions. We would also investigate using HDR (combining pictures of different exposures into one image to compensate for the big differences in lighting between ground and top of canopy) as Dandois et al. (2015) suggested. Finally, we found that a 250 m flight height for the UAV was accurate enough to obtain a reasonable ground detection. Though Kameyama and Sugiura (2020) found that lower flight heights (i.e., 60 m) were better for optimal point cloud reconstruction, it is not known how much it helps for ground detection. Furthermore, we maintain that a higher flight height is necessary to optimize data collection times and UAV battery.

4.2 Objective 1 - An Improved RF Classification

4.2.1 The RF Classifier Before and After

Before adding new variables, the RF classifier was first reproduced as described by Zhang et al. (2021). In this state, the RF classifier (and other steps of the methodology) returned a DTM which had a very high error ($RMSE = 4.21$ m) compared to what Zhang et al. (2021) achieved (i.e., a $RMSE$ of 2.1 m). Most of the error came from two grossly misidentified ground points. Even by removing manually those two points (something which would be impossible without a reference), the $RMSE$ was still 0.5 m higher than Zhang et al. (2021). From this we were able to come to two conclusions. Firstly, the DTM reconstruction was worse if there were very badly identified points than if there were just no points (and therefore interpolation). So the classification needed to accurately classify a point as “ground” but there was less of an impact if it misclassified a true ground point as something else. The second conclusion is that the wider study area and different landform of said study area than Zhang et al. (2021) probably contributed most to the very high, $RMSE$ as it was the only thing that was really changed between our study and theirs. Since RF classifiers are a black box in terms of precise impacts of variables, it cannot be known whether this classifier was fit differently. However, our guess is that the fit was similar, since the variable importances matched well with Zhang et al. (2021) (figure 6.5).

Random forest is a black box when it comes to predictions, so while we know the importance of each variable, we have no real information on how exactly the variables help in determining how they affect the decisions. What we do know is that the RF relies heavily on structure, and the presence of high elevation variation. This is confirmed by the fact that in the completely flat terrain of the Yoko village, the only ground points which were identified were at the edge of the forest. An unexplored perspective which Zhang et al. (2021) also mentioned was the combination of the RF (and other filtering steps from this study) with the cloth simulation filter, which works better in environments of dense ground points, and is quite user-friendly with open-source implementations in CloudCompare and R (Zhang et al., 2016). RF is a very specific modelling technique, and it does not perform well when extrapolating, which means that it can’t adapt to new situations. This means that while the RF classifier worked in the context of the DRC’s semi-deciduous-evergreen transition forest, it is unlikely to extend to other contexts of more open canopies. While this is of course a big restriction, this technique already has the potential of mapping a very large quantity of highly productive land area by itself, due to the large surface area of forests in the DRC.

4.2.2 DTM Generation and Validation

By creating a second RF classifier with more structural variables, the filtering was improved, which dramatically impacted the DTM reconstruction. Regarding the new structural variables which were used, a similar pattern to the basic structural variables was found, where smaller resolution (5-10 m) tended to have more importance. The new variable that was most helpful was the coefficient of variation, though it is very close to standard deviation in its computation, so probably redundant information to the basic standard deviation variables. Since RF does not need variables to be independent of one another, this is not a problem, but it does beg the question whether we really need to compute it. The entropy variable was important for a couple of resolutions, and so were some variables describing

the canopy gap profile. Mostly, the basic structural parameters still remained most important. Not to be deterred, while the new variables added complexity and computation time to the workflow, the DTM reconstruction was greatly improved thanks to this new classifier. Indeed, the 1.6 m of RMSE was very good given the context of dense forests with very few ground points. This was done in an area of very low relief variability (15 m total), which probably favored the DTM reconstruction, as it is a very predictable context.

With this low an error, and the low cost at which we were able to obtain the DTM, this method becomes very powerful, as a good DTM is the basis for all forestry studies through point clouds, as they generally need normalization through ALS which is expensive and hard to obtain (Barbosa et al., 2014). Indeed, the context of dense tropical forest is a very challenging one, so attaining a high accuracy, and later improving upon it showed the strength and potential of this workflow.

The validation in Yoko was less successful, returning a high degree of error ($\text{RMSE} = 4.8 \text{ m}$), and low correlation ($\text{NSE} = 0.68$). However, it was still an improvement to the previous DTM that was generated by Zhang et al. (2021). While the general terrain elevation was correctly modelled, it was the finer details of terrain variation, both at the top and bottom of the valley, which were less well modelled (figure 3.8a). The impact of the variation in terrain will be discussed in the next section. One possible source of error was related to the data which was used as ground truth. GNSS are bad in forest contexts (White et al., 2013), and elevation is poorly computed under dense canopies. Indeed, a lot of post-processing was required to remove all the noise, and still some probably remained.

4.2.3 Technical Considerations

The question of course is if adding 70 new variables is worth the computational effort. Indeed, the whole process of creating a DTM from a point cloud of 3 square kilometers easily took 8+ hours on a laptop (16Gb of RAM ; Intel Core i7 processor ; 1Tb hard drive), and that is not even counting the SfM point cloud generation (19 hours on a dedicated PC with 32Gb of RAM). However, if the DTM is generated for monitoring purposes, it only has to be created once, as the terrain changes much less fast compared to the canopy. Therefore, an extra effort to get a much better quality DTM may not be that bad an idea, especially with mostly open source materials (ArcGIS excluded ; though some experimenting for interpolation in R was done, nothing was officialized). Moreover, repetition of DTM acquisition over a monitoring period might help to lower even further the error, as different conditions (especially lighting) might help to better detect canopy gaps

4.2.4 Varied Terrain and Interpolation

The one less good step from this workflow was the co-kriging. It was for example what caused the overall underestimation of the validation DTM (figure 3.5d). Indeed, there was a cluster of ground points which were underestimated, and they were given a lot of weight, because the number of the low number of points over which the co-kriging regression was fit. We would expect the co-kriging to be better estimated over a wider area, as more points would give less weight to one particular cluster. We showed this was the case, as when the DTM was estimated over the whole Yangambi study area, the RMSE was further lowered to 1.35 m. Care must however be taken not to take this error as an actual result of this study, as this lowering was attained by fitting the co-kriging regression on part

of the training area (which is bad modelling practice). A further argument against our co-kriging is in the particular context of varied terrain. Indeed, varied terrain tends to be underrepresented in our study areas, so when there were areas of higher slopes (e.g., a river channel), the interpolation did not work well, leading to high errors. This was especially apparent during the stability analysis of two different point clouds, as one of the co-kriging regressions had been fit over only a small area (with high terrain variability) and the other over a wider area (so variable terrain was underrepresented). In that case, the lower elevation (down slope) was very badly estimated compared to when varied terrain was better represented (figure 3.10). Moreover, while Shen et al. (2019) found that SfM point clouds underestimated elevation in slopes, we found that this was not so clear-cut. There was indeed a worse error when it came to computing slope elevation (especially in Yangambi), but we found both overestimations and underestimations of the ground depending on the context and location.

A possible endeavor would be to look into adding other covariates extracted from the DSM such as slope and surface roughness. Moreover, more advanced regression techniques exist, such as random forest interpolation with covariates. It is an interesting prospect, as random forest regression does not have as strict requirements as generalized linear modelling does. Moreover, it requires less decision-making of the parameters by the user (as co-kriging does), which would make the interpolation more user-friendly.

4.3 Objective 2 - Oblique Pictures and Overlap

For this part, we had two hypotheses. The first one was that a higher degree of overlap would help better reconstruct the ground points in the point cloud, and this worked. It has been shown already that point cloud reconstruction is better with a higher degree of front overlap (Kameyama and Sugiura, 2020) (Dandois et al., 2015). Here, we did not evaluate the point cloud quality, but only canopy penetration. It was found that it was better when overlap proportion was higher, as Dandois et al. (2015) found in a sparse canopy cover. Indeed, generally more ground points were found, and the DTM reconstruction was better, with average decrease of almost 1 m in RMSE and an increase from 0.77 average NSE to 0.86, which were big improvements. If only using nadir pictures, a 75% overlap is not recommended, as there was a very clear lack of ground points, which prevented a good DTM reconstruction.

Moreover, the real stride that was achieved was in using oblique photos to better describe the structure of a dense forest. Indeed, this capability had already been proven for sparse forests, and it had been questioned whether it was also better for closed canopies (Díaz et al., 2020). The worry here was mainly that ground points would be misidentified. Indeed, the RF classifier was not trained for point clouds including oblique pictures, and these better describe the structure, on which the RF classifier heavily depends. This turned out to be unfounded as oblique pictures increase DTM accuracy in most cases, and the more oblique pictures there were, the better ground detection was. In particular, oblique pictures may have helped on and near slopes, which is particularly interesting. It is also clearly helpful to have crisscrossing flight lines for oblique picture acquisition.

Between having high oblique (40°) or low oblique (70°), we strongly recommend low oblique. Indeed, the high oblique required a lot of post-processing and individual computations of point clouds and registration instead of just inputting all the pictures into the Pix4d software. This was a lot of work,

and the DTM reconstruction was on average not better. Moreover, the high oblique returned bad canopy estimations, which is detrimental to monitoring in future steps.

Overall, oblique pictures have once again demonstrated their potential in bettering forest inventories (especially following Díaz et al. (2020) and Sakai et al. (2016)). It takes longer to acquire the data, as one or two more flights are required for every one nadir flight, but we estimate that it is worth the effort. Especially since Sakai et al. (2016) found that DSMs acquired with oblique pictures were more reproducible and accurate, tree height estimation could be bettered through better modelling of the canopy in addition to better modelling of the ground. Finally, in the future, more flights might not be necessary with some large UAVs being able to take both oblique and nadir pictures in one flight.

4.4 Objective 3 - Tree Heights and Monitoring

As a third objective, we measured the error of tree height estimation with UAV-SfM, and from there evaluated the monitoring potential of our workflow. Tree heights were also computed, as they are very commonly used in the forestry literature to evaluate point clouds.

Firstly, at the plot level, we found a RMSE of almost 2 m for maximum height, which was nearly unimpacted by bad DTM estimations. This was not the case for the mean elevation at the plot level, which saw a decrease of 0.7 m error with better DTM estimations. This means that maximum elevation is probably better for monitoring, even if its error is higher (as it did not need the DTM to have a lower error). Indeed, according to Poorter et al. (2021), maximum tree size in a plot was the best indicator for monitoring forest evolution through time. Moreover, these results were on par with older studies in deciduous environments (Dandois and Ellis, 2013) and even more recent work under tropical conditions (Swinfield et al., 2019) who found a R^2 of 0.67 (against ours of 0.74) and (Tokkari et al., 2017) who found a same coefficient of determination as us under sparse canopy cover. Moreover, this study even held up against other DTM-dependent height estimations, such as Cao et al. (2019) ($R^2 = 0.83$), though these studies tended to reach coefficient of determination closer to 0.9 (Messinger et al., 2016) (Cao et al., 2019) and a RMSE closer to 1 m (Lisein et al., 2013) (White et al., 2015). Moreover, for the plot-based analyses, we found no overestimation by SfM which could have happened due to the 7-year time gap between our data collection and the reference. While the error was probably partly explained by the time gap, we can hypothesize that the state of the forest in Yangambi stayed more or less the same, remaining undisturbed.

At the individual tree level, we did find growth of trees, as smaller trees (less than 30 m) had a higher RMSE than higher trees (40 m or higher). Indeed, we found that the error (which was caused by overestimation) decreased the higher the tree was. This is logical as trees tend to have an asymptotic growth, and it proves that our workflow is able to track changes at the individual tree level in a dense forest. Indeed, most of the error was explained by growth, as the high quality tree estimations did not reduce the RMSE by much.

4.5 Geolocation Accuracy

The error of point cloud reconstruction in UAV-SfM was high compared to ALS, but the fit to 1:1 line was relatively good, when comparing absolute elevations of canopy heights (figure 3.1b). This error was not much impacted by the growing of vegetation, as only very high tree tops were selected to show the positional accuracy of the point cloud (those tend to grow much less than smaller trees). The high error was in part caused by a problematic geolocation, during the point cloud creation. The point cloud of Yangambi was created in three separate parts in an effort to reduce computation time and ease the load on the computer’s memory during the Pix4d processing. However, when the three point clouds were merged *a posteriori*, some errors crept in when manually registering both clouds for the merging. This error probably played some part in subsequent analyses, as some areas of the point cloud were not accurately registered to the reference ALS point cloud. When looking at the scatter plot (figure 3.1b), we see that only certain points are further from the 1:1 line. All these points were clustered in the north of the Yangambi point cloud (which confirms the fact that only part of the point cloud was badly registered).

Measures were taken to reduce the possible impact of such registration errors. For the tree height validation, plot-level analyses reduced the impact of such errors, and for tree-level analyses the tree crowns were delineated and then local maxima in SfM and ALS CHMs were taken from the delineated crowns, which reduced the impact of geolocation errors. Finally, for the DTM estimation (which was the least controlled for geolocation) no artifacts were apparent, and the errors coming from elevation estimation likely outweighed geolocation errors. Moreover, since the variations in elevation are less fine scale (as the canopy surface is), we can still have a good level of confidence in the accuracy of our errors. Finally, Goodbody et al. (2017) showed that a difference in canopy reconstruction always exists when comparing ALS and SfM point clouds, since ALS returns a less dense point cloud, it may slightly underestimate the tree top elevation. This underestimation is however quite small (0.2 m according to Goodbody et al. (2017)), but may have explained part of the error in figure 3.1b.

Chapter 5

Conclusion

Through this study, we showed the high potential of UAV-SfM point clouds in forest monitoring of dense tropical forests such as the ones in the Tshopo province in the DRC. Dense canopy covers, which are characteristic of moist tropical forest, have been shown to return bad estimations of subcanopy features with a SfM workflow, as this method cannot penetrate well through the canopy cover. Recent advances have however shown not only the potential in using UAV-SfM as a standalone tool for forest monitoring when other types of data are unavailable, but have done so in challenging contexts, namely in steep terrain (Giannetti et al., 2018) and in dense canopy cover (Zhang et al., 2021). Taking as a starting point the workflow that Zhang et al. (2021) proposed, and through the optimization of a series of steps throughout their workflow, we were able to improve ground reconstruction and further monitoring possibilities of such an approach.

The DTM reconstruction of the ground under dense canopies was optimized in two ways. First, the algorithm for identifying ground points was expanded and improved upon through the use of a large quantity of variables describing the structure of the SfM point cloud. This improved the accuracy of the filtering by 7%, but more importantly, this led to a reduction of the error of the DTM by 2.61 m (to a RMSE of 1.6 m), which brought us closer to what other more established methods (such as ALS) can achieve. The only downfall that was found was the interpolation, which worked variably well, and could be refined.

Further, we devised a better data collection scheme through the use of oblique pictures, a novel way to increase the point cloud penetration through dense canopies. Thanks to combining oblique and vertical pictures in the point cloud reconstruction by SfM, we were able to achieve a RMSE of 1 m better than the scheme that was used by Zhang et al. (2021).

Finally, we evaluated how this new DTM could be used for monitoring purposes, and determined that the estimation of the size of tall trees at the individual and at the plot level (with our DTM as normalization) was almost as good as a ALS generated DTM. Thanks to the plot-level analysis, we suggested that the forest of Yangambi has been in a steady state and that no degradation had happened in the 7 years. Herein lies the strength of the workflow proposed in this paper, as the point cloud reconstruction is user-friendly and easy to do, the materials are relatively cheap in a research context, the workflow, while requiring some expertise in geoprocessing was done through open-source

and shareable material, and the simplicity of using tree heights as an indicator of the state of the forest (as Poorter et al. (2021) proposed) removes the need for additional models for estimating AGB and possibly new errors.

In total, from 10 days of field work (including 5 of travelling), we were able to survey and assess the state of 12.6 km² of forest in difficult logistical conditions, and with a comparatively low budget to ALS acquisition. Moreover, Puliti et al. (2017) argued that forest inventories can be upscaled in cost-effective methods through the sampling and continuous monitoring of forest plots using UAVs, and could be integrated into the countrywide monitoring scheme of the DRC for REDD+, for protecting and preventing the destruction of high-value forest areas. For example, forest height measurement schemes could be standardized, and errors controlled for in the whole DRC, which could even help to create an upscaled model of tree heights through Landsat or Sentinel images (Potapov et al., 2021) (Lang et al., 2022). Indeed, a regional model could further help in reducing the error of tree height estimations through optical satellite images.

A totally other perspective is to go into high-precision AGB models. This is done a lot, including by Zhang et al. (2021), but with UAV high precision multispectral data (which we already have in Yoko as part of this sampling campaign), AGB could be estimated at the tree level, if individual trees could be classified according to their species.

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Chapter 6

Annexe

6.0.1 SfM Workflow Description

The SfM workflow consists of 3 main steps (figure 6.1). In order from start to finish, they are the Scale-Invariant Feature Transform (SIFT), the structure from motion (SfM), and finally the Multi-View Stereo (MVS) algorithms. One must not confuse SfM, which is an algorithm, and only one step of the SfM workflow, which refers to the whole process of going from a series of overlapping images to a dense point cloud.

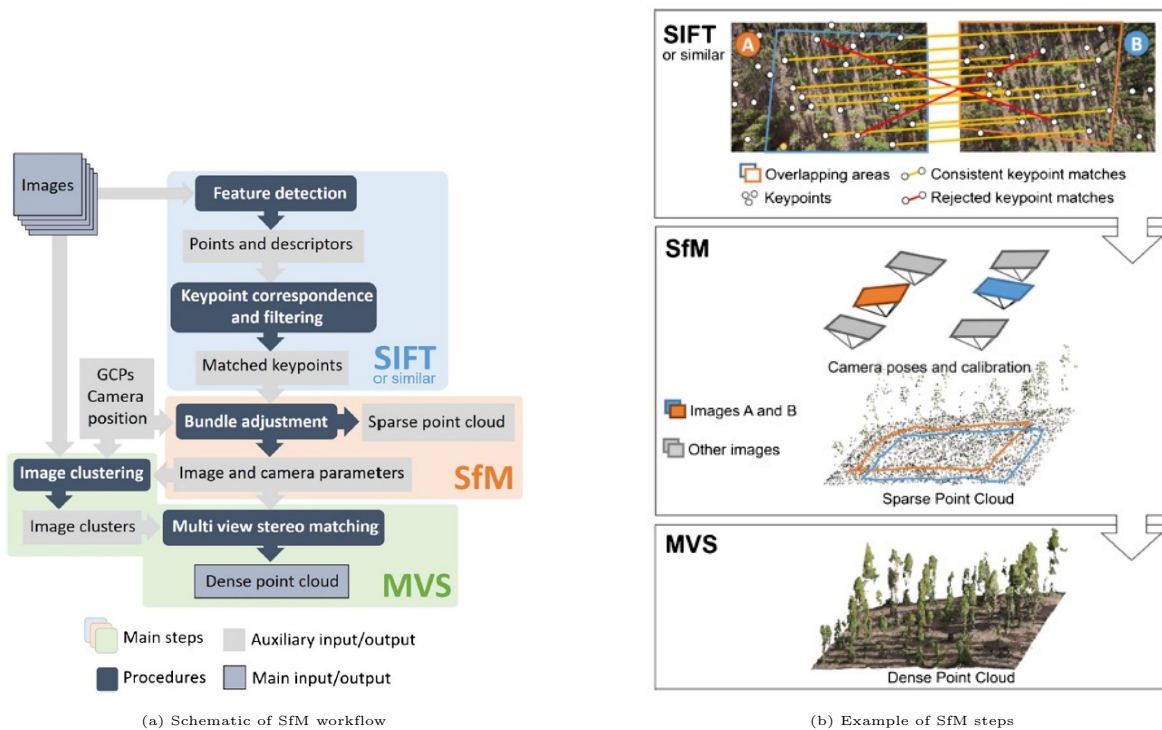


Figure 6.1: Main steps of the SfM workflow (source: Iglhaut et al. (2019))

The first main step, SIFT, uses as input only the set of overlapping images. This means that the accurate geolocation of each picture comes in at a later time. In this step, for each picture, an algorithm finds all the easily identifiable features. These features, referred to as keypoints are sets of pixels that do not vary with changes in orientation and scale, which means that they can be identified on many different pictures from different angles and different conditions (e.g. lighting or flight height). When all the keypoints for each individual image are found, each keypoint is matched to other images. The coherence of each matching is then checked, so matches that are geometrically out of line with the rest of the matches are rejected (see figure 6.1b, the red lines in the SIFT step). The matched keypoints that remain are used in the next step of the workflow, which is the SfM algorithm (Iglhaut et al., 2019) (Carrivick et al., 2016).

The SfM algorithm simultaneously computes the 3D position of the keypoints, the position and orientation of the camera at the time each picture was taken, and intrinsic camera parameters. The intrinsic camera parameters include the field of view, and the lens distortions which occur on the edges of a picture. The simultaneous optimization of all these parameters at the same time is what is called the bundle adjustment (figure 6.1a). The output of this algorithm is a sparse 3D point cloud where all points have an accurate relative position to each other, but with no absolute position in a geographic reference system. This is where the precise geolocation of each picture is useful, as the point cloud is accurately georeferenced at this point in the workflow. To summarize, first the 3D positions of keypoints relative to each other are first found, and secondly all the points are collectively georeferenced with the coordinates of the images. We can now understand why SfM workflows require so much less expertise than traditional photogrammetry. It is because photogrammetry requires information on location, orientation and distortion of the camera for each picture before being able to reconstruct a point cloud, whereas SfM computes all of these parameters simultaneously to reconstructing the point cloud and without any input from the user (James and Robson, 2014) (Iglhaut et al., 2019) (Dandois and Ellis, 2013).

The sparse point cloud is however only an intermediate product, as it offers little information on the structure of the forest in the observed study area. Therefore, the third and final step refines the resolution of the point cloud to create a dense point cloud, which is the end product of the SfM workflow. It is however, very computationally heavy to densify a point cloud using the MVS algorithms, so images are clustered thanks to the GPS coordinates associated to each image (“image clustering” in figure 6.1a). The internal workings of these algorithms are usually not described in the literature, but the interested reader is referred to the book “Structure from Motion in the Geosciences“ by Carrivick et al. (2016) which gives a concise description of the SfM workflow from start to finish. In the dense point cloud, not only does each point have a 3D positional value, there are also RGB values for each point, which means that the point cloud can be colorized to the colors in the images (figure 6.1b).

6.0.2 Results - Extra Figures

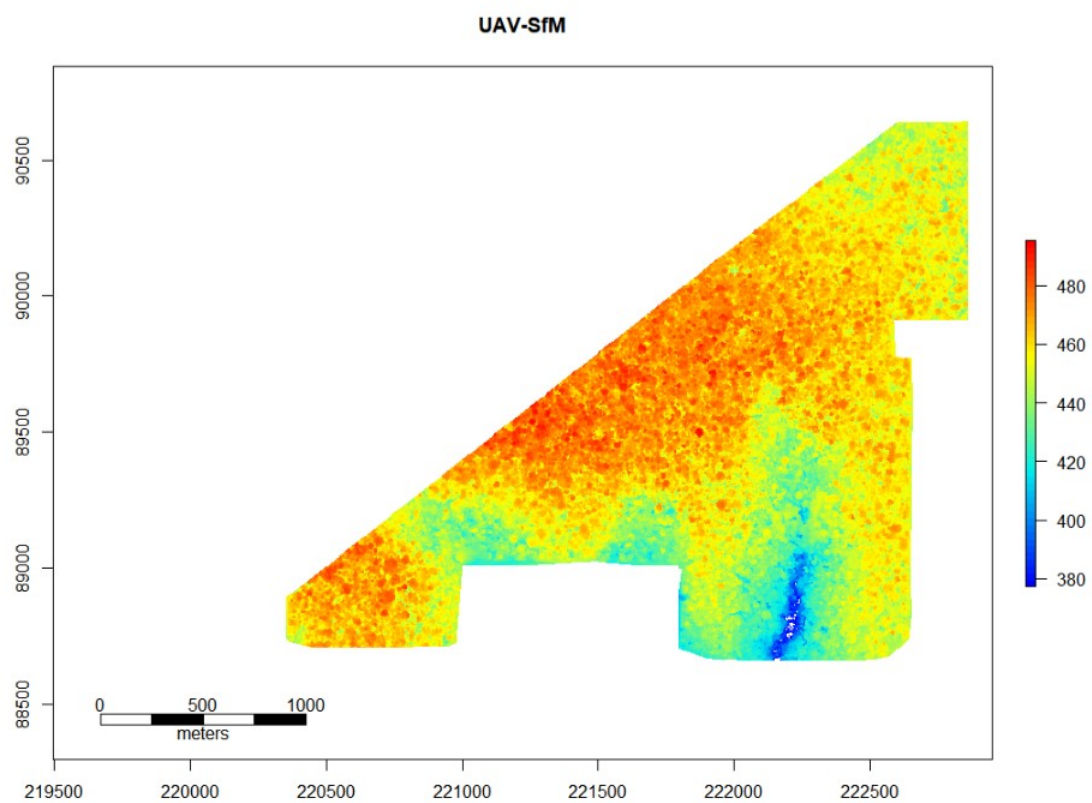


Figure 6.2: Larger scale reproduction of figure 3.1a ; DSM of the Yangambi study area, from the UAV-SfM point cloud

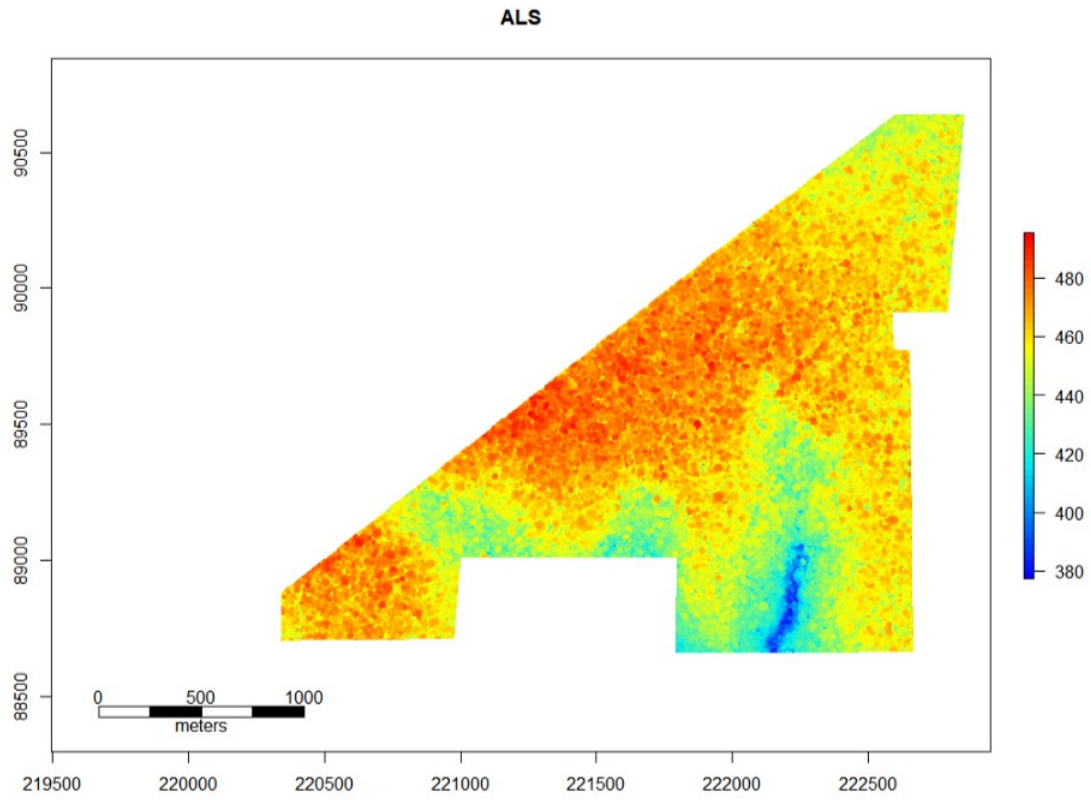


Figure 6.3: Larger scale reproduction of figure 3.1a ; DSM of the Yangambi study area, from the ALS reference point cloud

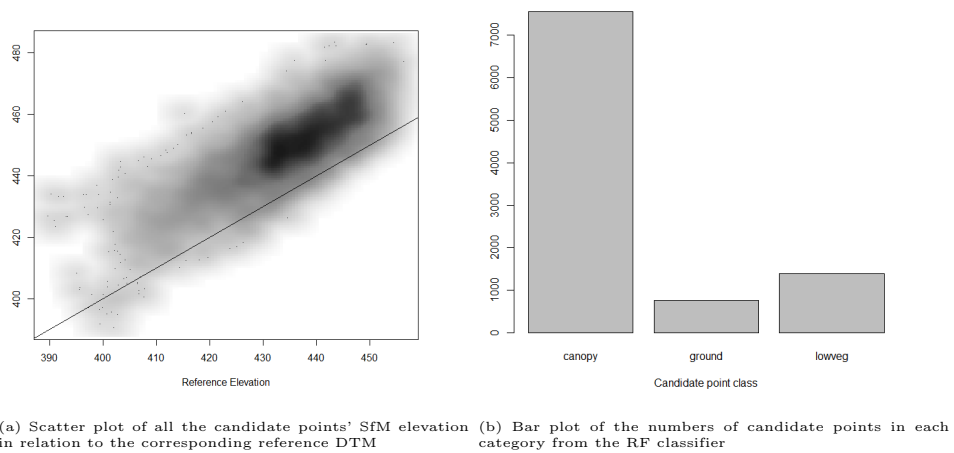


Figure 6.4: Analysis of candidate points in relation to reference DTM



Figure 6.5: Bar plot of the relative importance of variables in the RF classifier (original variables) as described by the mean Gini decrease

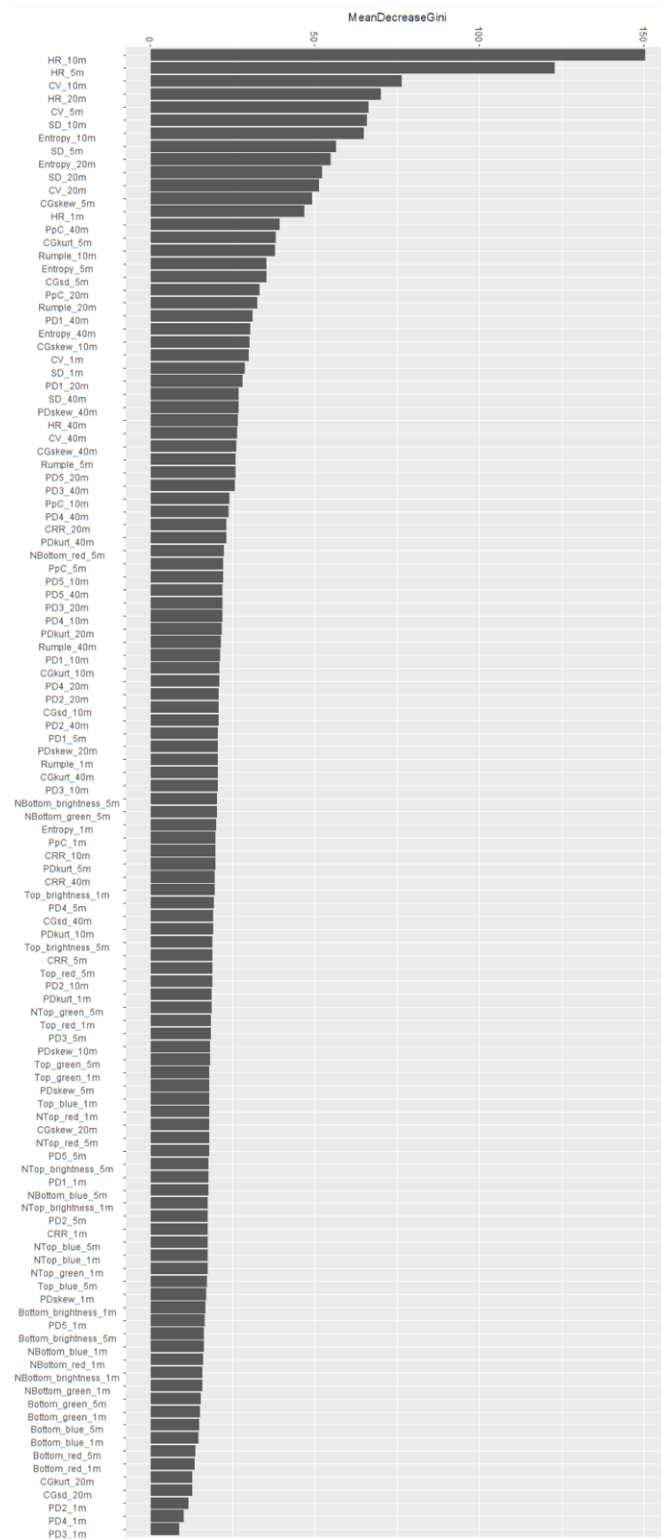
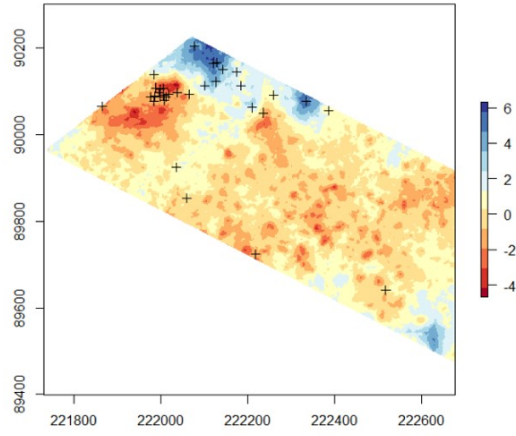
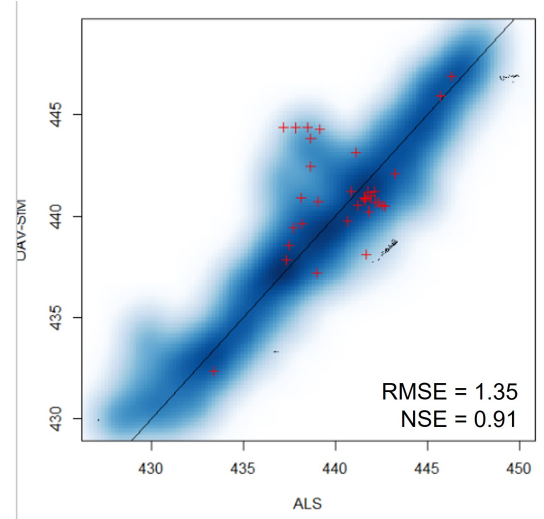


Figure 6.6: Bar plot of the relative importance of variables in the RF classifier (updated variables) as described by the mean Gini decrease



(a) Difference between UAV-SfM-generated DTM from the complete Yangambi study area reconstruction and the reference DTM. Black crosses correspond to UAV-SfM ground points identified by our workflow



(b) Scatter plot of the reference DTM elevation (x-axis) and UAV-SfM-generated DTM elevation (y-axis). Red crosses correspond to UAV-SfM ground points identifier by our workflow

Figure 6.7: Validation of UAV-SfM-generated DTM which was created for the whole Yangambi study area (including training and validation zones)

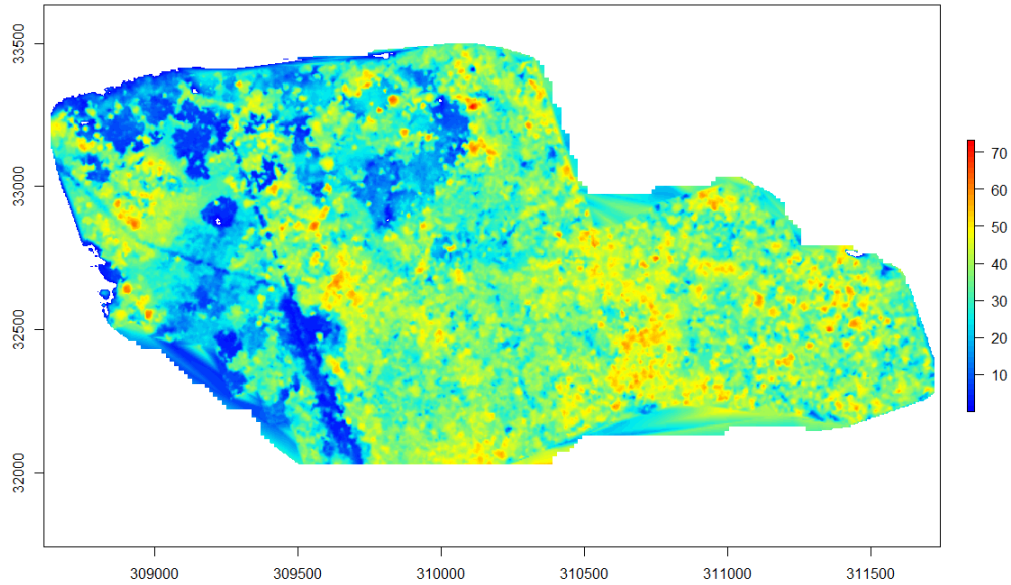


Figure 6.8: CHM of the Yoko study area (elevation is in meters)

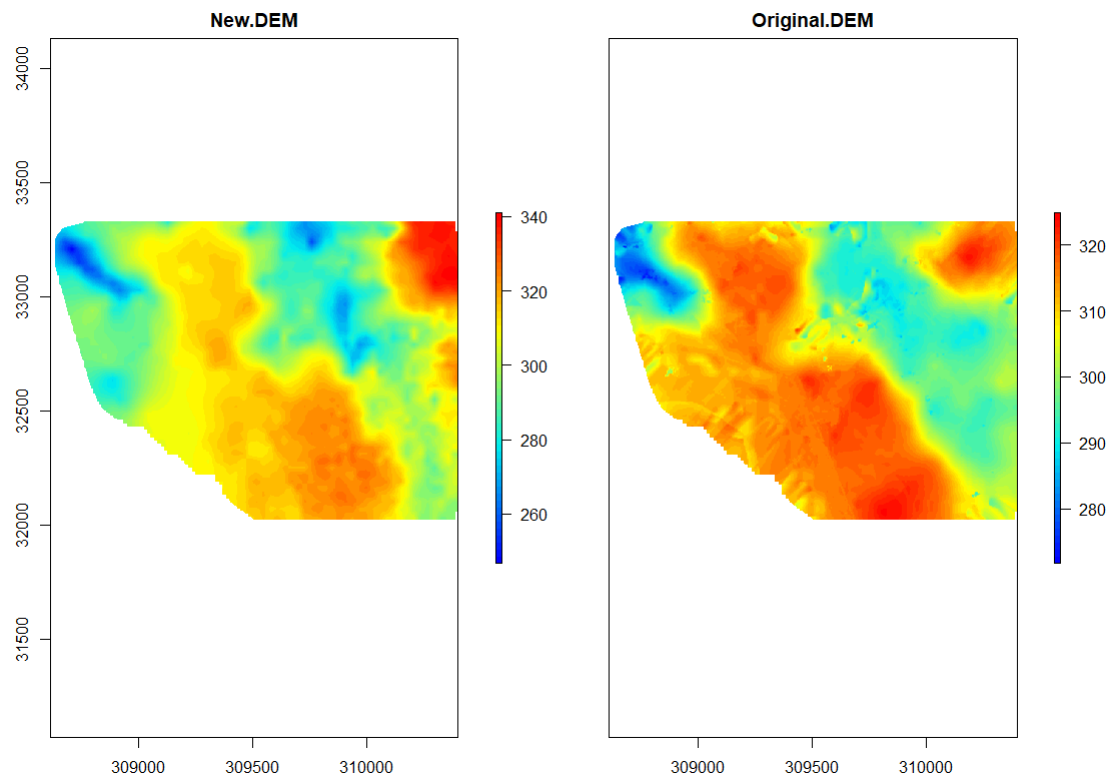
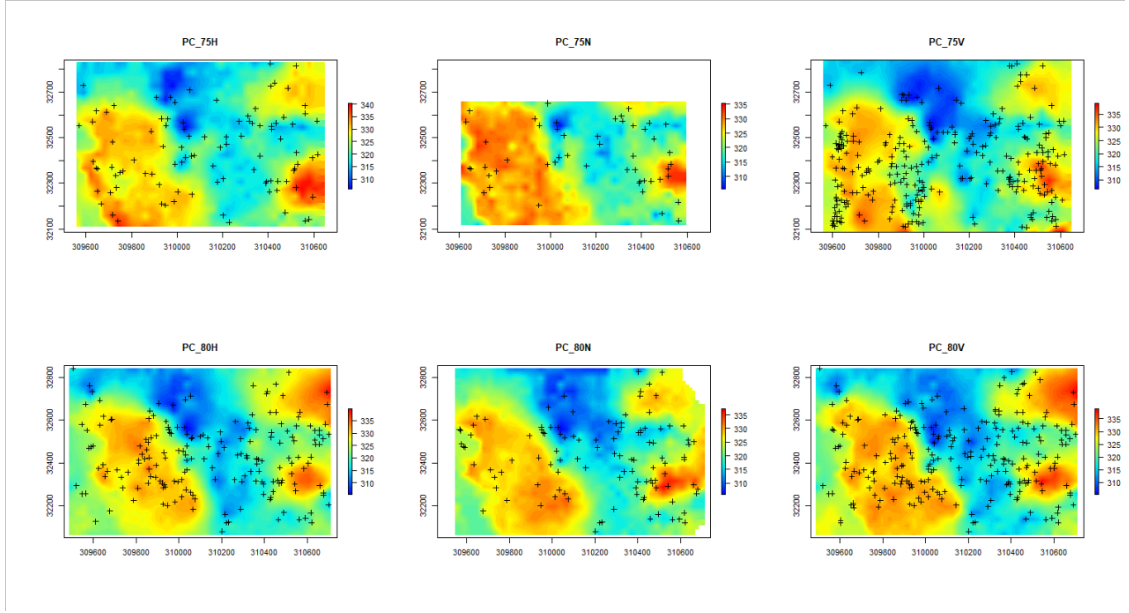
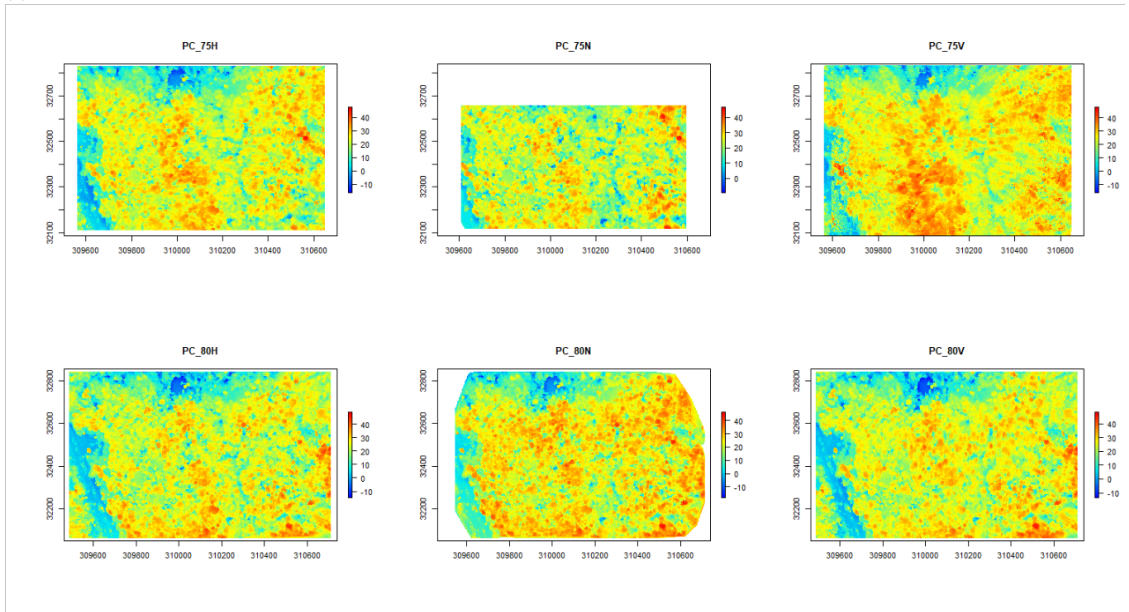


Figure 6.9: DTMs of part of the Yoko study area with new DTM (left) and original DTM (source: Zhang et al. (2021)). Elevation is in meters



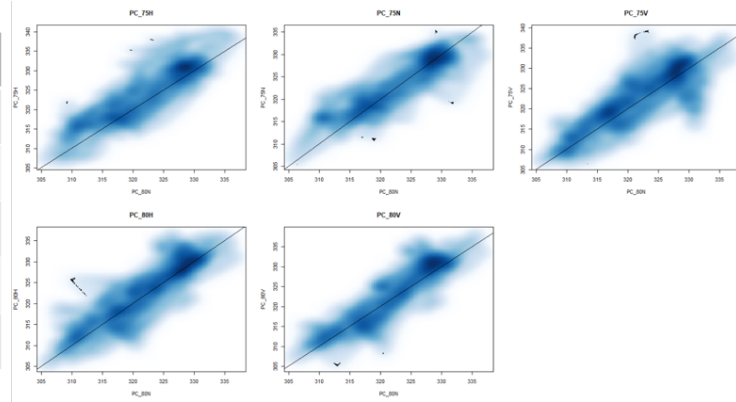
(a) DTM reconstruction for each combination of flight parameter. Black crosses are identified ground points used in the DTM reconstruction



(b) CHMs for each combination of flight parameter

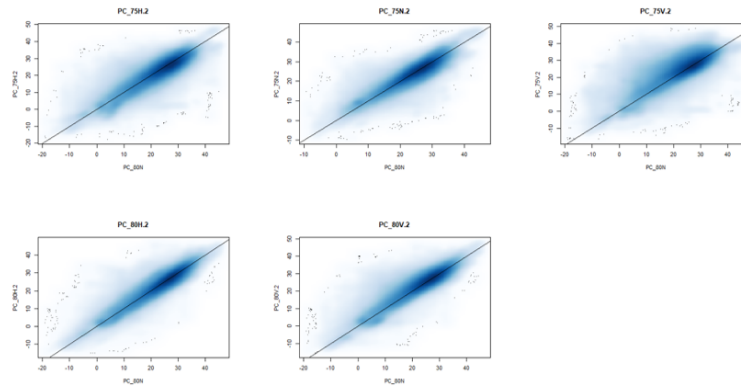
Figure 6.10: Ground and canopy reconstruction for point clouds collected with different flight parameters (40° oblique photos). PC_ stands for point cloud, 80/75 stands for the percentage of overlap and H/N/V stand for horizontal, nadir and vertical (the flight lines, H and V included oblique photos).

	RMSE	NSE
PC_75H	3.54	0.70
PC_75N	2.69	0.82
PC_75V	3.50	0.70
PC_80H	2.89	0.78
PC_80V	2.75	0.81



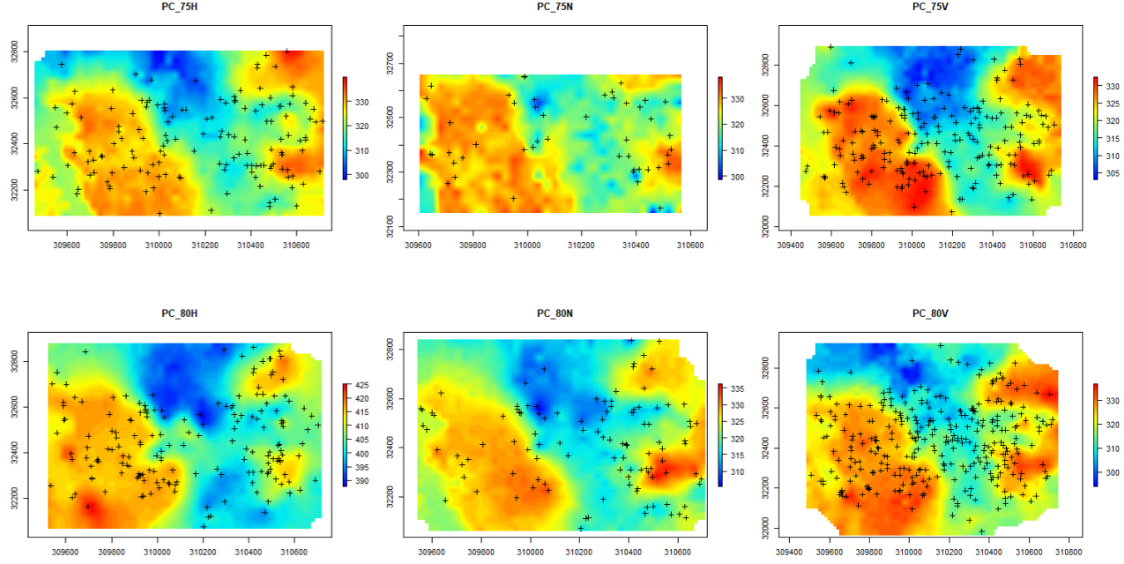
(a) Comparison between DTMs for each combination of flight parameters and the control DTM. On the left are error metrics and on the right are corresponding scatter plots (x-axis = control ; y-axis = variation)

	RMSE	NSE
PC_75H	4.40	0.75
PC_75N	3.25	0.79
PC_75V	6.07	0.53
PC_80H	3.29	0.86
PC_80V	3.83	0.82

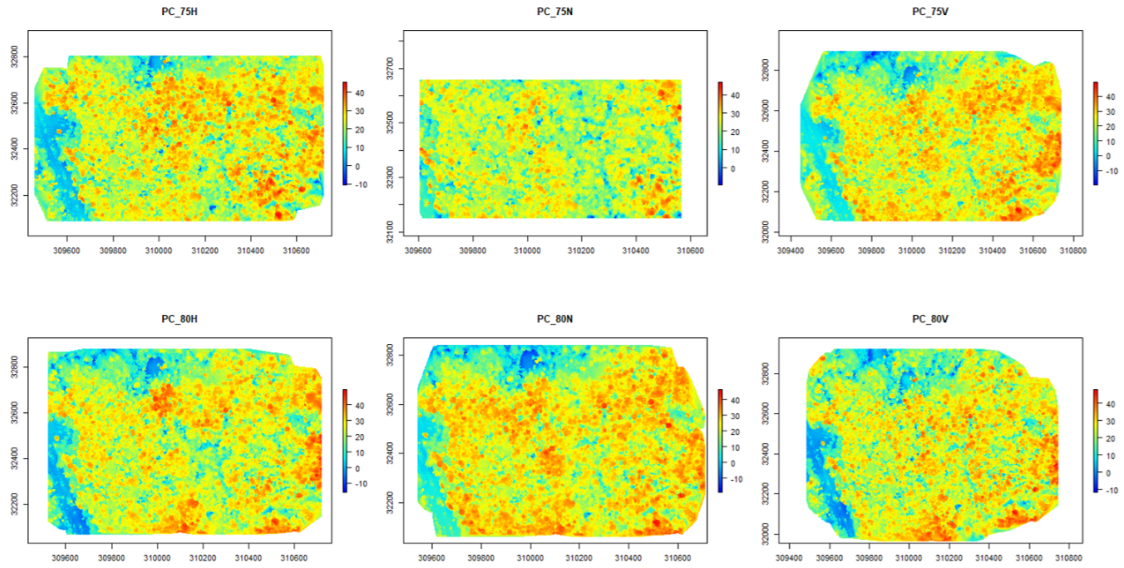


(b) Comparison between CHMs for each combination of flight parameters and the control CHM. On the left are error metrics and on the right are corresponding scatter plots (x-axis = control ; y-axis = variation)

Figure 6.11: Comparisons of DTMs and CHMs with varying flight parameters (40°oblique pictures). The control DTM and CHM was PC_80N (80% overlap, nadir pictures only)

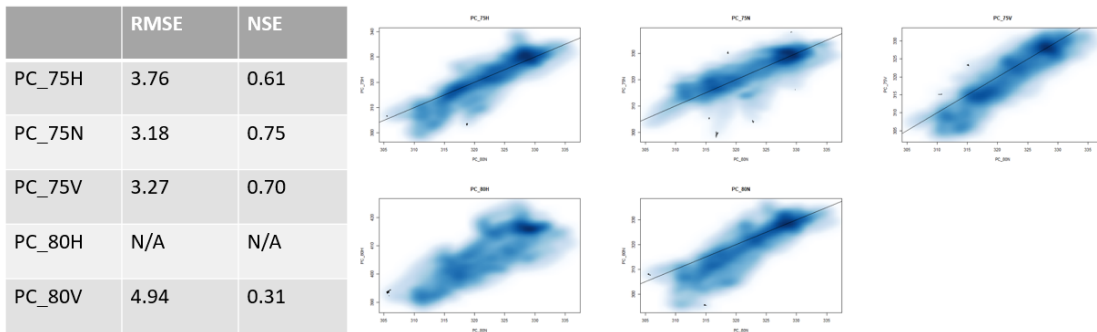


(a) DTM reconstruction for each combination of flight parameter. Black crosses are identified ground points used in the DTM reconstruction

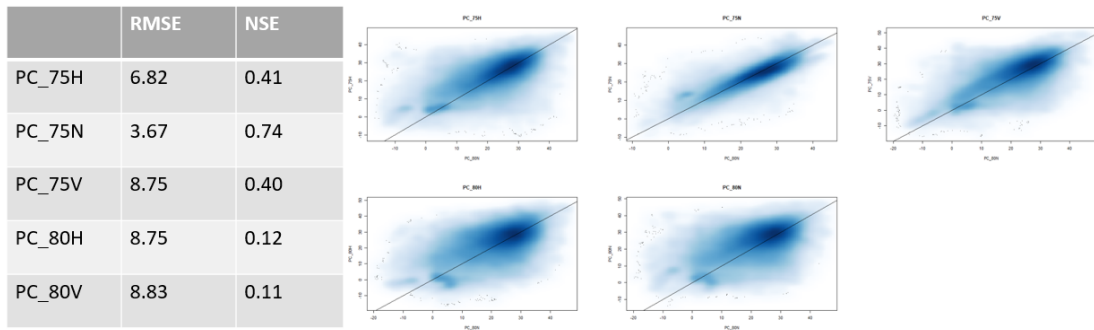


(b) CHMs for each combination of flight parameter

Figure 6.12: Ground and canopy reconstruction for point clouds collected with different flight parameters (70°oblique photos). PC_ stands for point cloud, 80/75 stands for the percentage of overlap and H/N/V stand for horizontal, nadir and vertical (the flight lines, H & V included oblique photos).



(a) Comparison between DTMs for each combination of flight parameters and the control DTM. On the left are error metrics and on the right are corresponding scatter plots (x-axis = control ; y-axis = variation)



(b) Comparison between CHMs for each combination of flight parameters and the control CHM. On the left are error metrics and on the right are corresponding scatter plots (x-axis = control ; y-axis = variation)

Figure 6.13: Comparisons of DTMs and CHMs with varying flight parameters (70°oblique pictures). The control DTM and CHM was PC_80N (80% overlap, nadir pictures only)

Autobiography

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