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Lidar-Based Evaluation of Pantropical Allometric Equations for Carbon Stock Estimates in Reforested Areas in Southern Ecuador

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SUMMARY (EN)

Tropical forests play a major role in tackling climate change and biodiversity conservation. In recent years, there has not only been a social interest, but also policies impose obligations to reforest large areas in order to reduce the atmospheric CO_2-concentration. Tropical reforestation has proven to be efficient in rapidly sequestering carbon and creating a habitat for biodiversity. Boosted by the carbon market, numerous corporations, organisations and countries are investing in reforestation and afforestation projects in the tropics, including in Ecuador.

Improving the quantification of above-ground biomass (AGB) is crucial for accurately monitoring carbon stocks and effectively guiding and rewarding restoration projects. Over the past decade, methods have been developed to estimate AGB using terrestrial laser scanning (TLS) data. Despite their numerous challenges in young, reforested tropical forests, TLS-derived AGB estimates can help address existing uncertainties in allometric equations.

An improved, local allometric equation constructed with TLS data of 247 trees has the potential to make better AGB and carbon stock estimates for reforested areas in the Ecuadorian Andes and Amazon. Four models are constructed and one of them was able to estimate the AGB more accurately than the commonly used pantropical allometric equation of Chave et al. (2014). The choice of allometric equation highly affects the outcome of extrapolation studies. This study's best model indicates an AGB (t/ha) of only 93% compared to the classical model. By using a local, improved allometric equation, carbon credits can be allocated in a correct way and the improved biomass estimates can support other ecological studies as well.

SAMENVATTING (NL)

Tropische bossen spelen een belangrijke rol bij de aanpak van de klimaatverandering en het behoud van de biodiversiteit. De laatste jaren is er niet alleen maatschappelijke belangstelling, maar er zijn ook beleidsmatige verplichtingen om grote gebieden te herbebossen om zo de atmosferische CO_2-concentratie te beper-ken. Tropische herbebossing is efficiënt gebleken om snel koolstof vast te leggen en daarnaast een habitat voor biodiversiteit te creëren. Gestimuleerd door de koolstofmarkt investeren tal van organisaties, bedrijven en landen in herbebossings- en bebossingsprojecten in de tropen, onder meer in Ecuador.

Verbetering van de kwantificering van de bovengrondse biomassa (BGB) is van cruciaal belang voor een nauwkeurige controle van de koolstofvoorraden en een doeltreffende begeleiding en beloning van herstelprojecten. In de afgelopen tien jaar zijn methoden ontwikkeld om de BGB te schatten met behulp van terrestrische laserscan gegevens (TLS). BGB-schattingen op basis van TLS kunnen de bestaande onzekerheden van allometrische vergelijkingen reduceren, ondanks de uitdagen die met TLS gepaard gaan in jonge, herbeboste tropische bossen.

Een verbeterde, lokale allometrische vergelijking op basis van TLS-data van 247 bomen biedt de mogelijkheid om betere BGB- en koolstofvoorraadschattingen te maken voor herbeboste gebieden in de Ecuadoraanse Andes en Amazone. Er zijn vier modellen geconstrueerd en één daarvan kon de BGB nauwkeuriger schatten dan de algemeen gebruikte pantropische allometrische vergelijking van Chave et al. (2014). De keuze van de allometrische vergelijking heeft een grote invloed op het resultaat van extrapolatiestudies. Het beste model in deze studie behaalt een BGB (t/ha) van slechts 93% ten opzichte van het klassieke model. Door gebruik te maken van de verbeterde allometrische vergelijking kunnen koolstofkredieten van herbebossingsprojecten op een correctere manier worden toegekend. Daarnaast kunnen de verbeterde biomassaschattingen ecologische studies ondersteunen.

RESUMEN (ES)

Los bosques tropicales desempeñan un rol fundamental en la lucha contra el cambio climático y la conservación de la biodiversidad. En los últimos años, no sólo ha surgido un interés social, sino también la obligación política de reforestar grandes extensiones para reducir la concentración de CO_2 en la atmósfera. La reforestación tropical ha demostrado su eficiencia para secuestrar rápidamente el carbono y crear un hábitat para la biodiversidad. Impulsadas por el mercado del carbono, numerosas empresas, organizaciones y países están invirtiendo en proyectos de reforestación y forestación en los trópicos, incluido Ecuador.

Mejorar la cuantificación de la biomasa aérea (BA) es crucial para controlar con precisión las reservas de carbono y orientar y recompensar eficazmente los proyectos de restauración. Durante la última década, se han desarrollado métodos para estimar la BA utilizando datos de escaneado láser terrestre (TLS). Las estimaciones de BA derivadas de TLS pueden ayudar a abordar las incertidumbres existentes en las ecuaciones alométricas, a pesar de sus numerosos retos en bosques tropicales jóvenes y reforestados.

Una ecuación alométrica local mejorada, construida con datos de TLS de 247 árboles, tiene el potencial de hacer mejores estimaciones de BA, y de reservas de carbono para áreas reforestadas en los Andes y la Amazonía ecuatoriana. Se construyen cuatro modelos y uno de ellos fue capaz de estimar la BA con mayor precisión que la ecuación alométrica pantropical comúnmente utilizada de Chave et al. (2014). La elección de la ecuación alométrica influye mucho en el resultado de los estudios de extrapolación. El mejor modelo de este estudio indica una BA (t/ha) de solo el 93% del modelo clásico. Si se utiliza una ecuación alométrica local mejorada, los créditos de carbono pueden asignarse de forma correcta y las estimaciones de biomasa mejoradas pueden servir de apoyo a otros estudios ecológicos.

LIST OF ABBREVIATIONS

AE	Allometric equation
AGB	Above-ground biomass
ALS	Airborne Laser System
BGB	Below-ground biomass
CDM	Clean Development Mechanism
CF	Carbon fraction
DBH	Diameter at breast height
DTM	Digital terrain model
ETS	European Trading System
FAO	Food and Agriculture Organization
GBS	Graph-based leaf-wood separation
GCF	Green Climate Fund
H	Height
IPCC	Intergovernmental Panel on Climate Change
LDG	Latitudinal diversity gradient
LF	Lower fence
LiDAR	Light detection and ranging
LMF	Lower mountain rain forest
MLS	Mobile Laser System
MSA	Multi-station adjustment
NDC	Nationally Determined Contribution
NLS	Non-linear least-square
PAE	Pantropical allometric equation
PS	Phase shift
QSM	Quantitative structure model
R	Root-to-shoot ratio
RS	Remote sensing
RSS	Residual sum of squares
SDG	Sustainable Development Goal
TLS	Terrestrial Laser Scanning
TMCF	Tropical mountain cloud forest

ToF	Time-of-flight
TSS	Total sum of squares
UF	Upper fence
UMF	Upper mountain rain forest
UNFCCC	United Nations Framework Convention on Climate Change
VCS	Verified Carbon Standard
WD	Wood density

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1. INTRODUCTION

Exceeding one or more planetary boundaries could have negative or even catastrophic consequences, due to a non-linear, abrupt environmental impact behind these thresholds (Rockström et al., 2009). Humanity has already crossed or is beyond the safe zone of four planetary boundaries: climate change, land-system change, biogeochemical flows and biosphere integrity (Steffen et al., 2015). In order to protect the Earth system, carbon emissions have to be reduced by burning less fossil fuel and counter deforestation. Reforestation is an important tool to increase the terrestrial carbon sink and mitigate atmospheric CO_2 through carbon sequestration.

The Global North bears the major responsibility to take action as they were accountable for 92% of the excess CO_2 emissions worldwide (Hickel, 2020). Because tropical forests have a great potential to store carbon, as well as a high biodiversity, the study of tropical forests and there restoration has become increasingly important in recent years (Pan et al., 2011; Locatelli et al., 2015; Raven et al., 2020). Many organisations, businesses, individuals and countries compensate for their excess greenhouse gas emission by investing in reforestation projects in the tropics (Lovell and Liverman, 2010). These carbon offset projects are rewarded with carbon credits through the Clean Development Mechanism, introduced by the Kyoto Protocol, or the Voluntary Carbon Market (UNFCCC, nd; Verra, 2022).

In Ecuador, numerous reforestation projects are currently being carried out, for example the Telenet compensation project, which is implemented by BOS+. However, effective planting, management, monitoring and quantification of these initiatives are essential for their success. Recognising this need, the COFOREC projects have been established. These projects aim to establish a long-term forest monitoring network that can accurately assess the outcomes of reforestation efforts. By collecting and analyzing data on biodiversity, ecosystem functioning, and human impacts, COFOREC contributes to the appropriate management and evaluation of reforestation projects in Ecuador. Through collaborative efforts with local and international stakeholders, COFOREC strives to ensure that these valuable restoration initiatives are sustained and optimized for the benefit of both the environment and the communities involved.

The need to monitor, manage and quantify these secondary forests has led to the development of various techniques for quantifying forest biomass and making carbon stock estimations, including destructive and non-destructive methods. A frequently used method to quantify carbon stocks in forests is the use of allometric equations, that are constructed with destructive data, to convert forest inventory data into above-ground biomass (AGB) estimations (Van Breugel et al., 2011). However, whereas many allometric equations have been developed for mature forests, only a few studies have focused on young trees (Wagner and Ter-Mikaelian, 1999).

One of the most promising, relatively new methods for forest biomass quantification is Terrestrial Laser Scanning (TLS), which has shown great potential for accurately estimating the AGB in tropical forests (Disney et al., 2019). One aim of this thesis is to compare AGB estimates derived from the TLS data with AGB estimates of multiple pantropical and local allometric equations. Additionally the quality of AGB estimates derived from the TLS data are investigated and these results are compared with traditional field inventory techniques.

A comprehension of the tropical forest ecosystem in terms of carbon and biodiversity, the effects of land use change (deforestation and reforestation) and biomass quantification methods is given in the literature review. The review is followed by a description of the specific aims, the materials and methods, the results and the discussion, where the difficulties encountered during data collection and data processing are highlighted and various AGB estimates are compared and evaluated.

Overall, this research aims to provide important insights into the use of TLS for estimating carbon stocks in young reforested tropical plots, and to contribute to our understanding of the challenges and opportunities associated with this technique.

2. LITERATURE REVIEW

2.1 Tropical forests

2.1.1 Importance and types

Tropical forests have a major role in life on Earth. Not only are these forests hotspots of biodiversity, they also store enormous amounts of carbon. Nearly 50% of the world's species are found in tropical forests and the Latin American tropical forests have the world's highest species richness (Gentry and Dodson, 1987; Raven et al., 2020). Tropical forests store a large part of the global terrestrial carbon sink and are thus a very important tool for sequestering a part of the carbon emitted by humans (Pan et al., 2011).

Several types of tropical forests can be distinguished, one of which being the tropical mountain cloud forests (TMCF). In these forests, that cover a large area of Ecuador, the net precipitation is significantly enhanced by the direct canopy interception of cloud water from persistent or frequent wind-driven clouds (Hamilton, 1995). TMCF are located at altitudes ranging from 1500 to 3300 m. At lower altitudes, up to 2500 m above sea level, the TMCF are called lower mountain rain forests (LMF) and at higher altitudes the TMCF are referred to as upper mountain rain forest (UMF) (Bruijnzeel and Proctor, 1995).

2.1.2 Biodiversity

The latitudinal diversity gradient (LDG) is a prominent global phenomenon observed across various taxa, reflecting the changing pattern of species richness with latitude (Liang et al., 2022). Higher species richness is found at lower latitudes (Fenton et al., 2023). Tropical forests are a hotspot of biodiversity. There are at least 40 000, but probably over 54 000 tropical tree species (Slik et al., 2015).

Brummitt and Lughadha (2003) state that the tropical Andes has the greatest biodiversity of all the investigated areas. Ecuador is since 1998 one of the 17 "megadiverse" countries, with only 0,06% of the global land surface but home to approximately 14% of the world's birds species, 8% of amphibians, 5% of reptiles and 8% of mammals (Mestanza-Ramón et al., 2020). Currently more than 25 000 plant species are scientifically described, with many more to be discovered (Table 2.1) (Meza, 2002). The high species diversity makes these ecosystems very valuable, but also complex. However, this exceptional diversity is threatened by habitat loss as a result of the highest deforestation rate within South America (FAO, 2006; Mosandl et al., 2008; Günter et al., 2009).

Table 2.1: The species diversity of various taxonomic groups in Ecuador (Meza, 2002).

Taxonomic Group	Total Species	Endemic Species	Endemism (%)
Plants	25 560	5 348	20,92
Vertebrates	2 794	436	15,60
Mammals	362	30	8,28
Birds	1 616	52	3,21
Reptiles	394	114	28,93
Amphibians	422	240	56,87

2.1.3 Carbon cycle

Global carbon cycle

The global carbon (C) cycle consists of three active pools that exchange C, namely the atmosphere, the oceans and the terrestrial biosphere (Falkowski et al., 2000). The carbon is distributed in different pools and C is exchanged between pools through fluxes (Figure 2.1). Enormous amounts of carbon are stored in the lithosphere, most of it in the Earth's mantle (Falkowski et al., 2000). If human influence is not considered, the total amount of C in the different pools remains largely stable. However, people do have an impact as they bring carbon from the lithosphere into the non-lithosphere by for example burning fossil fuels.

The oceans and the terrestrial biosphere absorb about half of the anthropogenic produced carbon dioxide (CO_2) and the other half leads to rising CO_2 levels in the atmosphere (Dixon et al., 1994; Schimel et al., 2001). The atmosphere is the smallest active pool (Figure 2.1), and therefore the most sensitive to an increase in CO_2. Additionally, some feedback processes enhance the susceptibility of the atmosphere to CO_2 increases. One example of a feedback mechanism is that warmer water in oceans have lower CO_2 solubility (Falkowski et al., 2000). Meaning that, when global temperatures rise due to climate change, the oceans will not be able to store as much carbon and thus more carbon would need to be stored in other pools, such as the atmosphere, to compensate leading to even higher global temperatures.

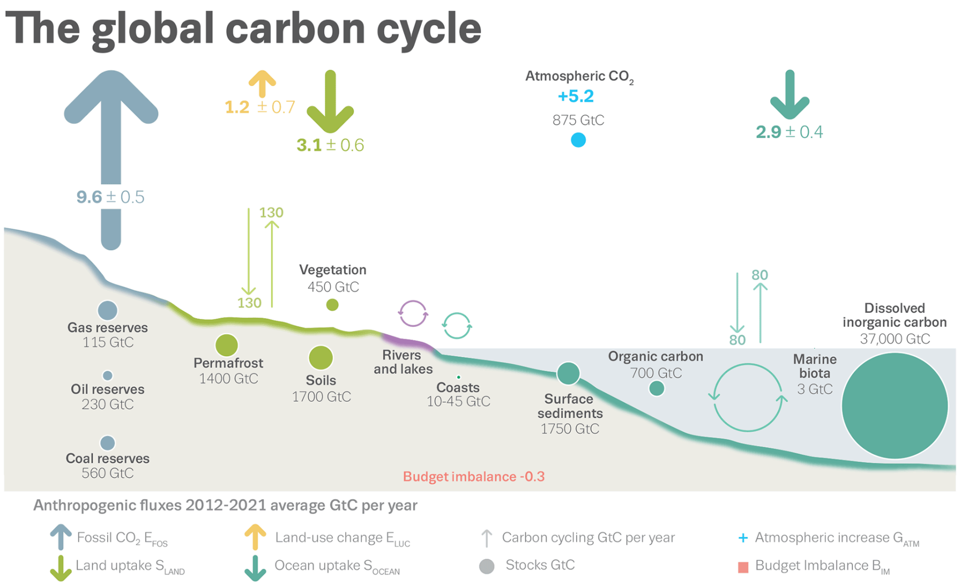


Figure 2.1: The global carbon cycle (Friedlingstein et al., 2022).

Tropical forests in the global carbon cycle

Tropical forests play an important role as carbon sink. The annual terrestrial CO_2 uptake was estimated to be 3.1 ± 0.6 GtC yr^{-1} during 2012-2021 and is expected to increase due to increasing atmospheric CO_2 concentrations and nitrogen fertilisation (Friedlingstein et al., 2022). Large amounts of the terrestrial carbon stocks are in forests, of which 55% in tropical forests (Houghton, 2005; Pan et al., 2011).

The IPCC identified five carbon pools of the terrestrial ecosystem involving biomass. Carbon is stored in above-ground biomass (AGB), below-ground biomass (BGB), litter, woody debris and soil organic matter (Vashum and Jayakumar, 2012). AGB en BGB form together the living biomass pool. The distribution of the carbon storage over the different forest compartments depends on the forest type. In tropical forests 52% of the carbon is stored in living biomass and 32% in the soil, while in boreal forests for example, there is only 20% C stored in living biomass and 60% in the soil and litter (Pan et al., 2011).

Tropical forests have a great potential to store carbon (Locatelli et al., 2015). However, disturbances such as deforestation and land degradation decrease the carbon sink capacity and on top of that, they emit carbon, turning the forests into a carbon source (Pan et al., 2011). Tropical forests are not capable of reclaiming this amount of carbon by regrowth (Hubau et al., 2020). To prevent additional loss of carbon sink potential, it is crucial to halt deforestation and forest degradation in the first place, and to encourage reforestation (IPCC, 2022).

2.2 Land use change

2.2.1 Deforestation and forest degradation

Deforestation worldwide

Tropical forests experience the highest deforestation rate of all forest types (Table 2.2). The deforestation rate is slowing down, but in the period 2015-2020 still 9,3 million ha were deforested every year. This is substantially more than the deforestation in all the other forest types combined.

Deforestation typically refers to the permanent removal of forest cover for non-forest land uses, such as agriculture, urbanization, or infrastructure development. On the other hand, degradation generally refers to the decline in the quality or health of forest ecosystems without complete removal of forest cover (Houghton, 2012).

Table 2.2: Forest area (million ha) from 1990 to 2015 in different forest ecosystems (data derived from Keenan et al. (2015)) and gross deforestation rate (millions ha/y) (data derived from FAO (2020))

	Forest area (million ha)			**Gross deforestation (million ha/y)**			
	1990	**2010**	**2015**	**1990-2000**	**2000-2010**	**2010-2015**	**2015-2020**
Tropical forest	1 965	1 797	1 770	13,80	13,20	10,30	9,30
Boreal forest	1 219	1 225	1 224	0,10	0,09	0,13	0,06
Temperate forest	618	673	684	0,49	0,54	0,53	0,31
Subtropical forest	325	319	320	1,44	1,35	0,88	0,50
TOTAL	4 128	4 015	3 999	15,83	15,18	11,84	10,17

The rate of deforestation and degradation of forests is difficult to estimate since there exists a wide variety of methods to do so. Some researchers use satellite remote sensing data, while other studies are based on national inventories (DeFries et al., 2002; FAO, 2001). It is important to consider historical land-cover changes for at least a previous twenty years to make an estimation of the carbon emissions (Ramankutty et al., 2007).

It is crucial for governments to reduce the deforestation and forest degradation rate not only because it results in loss of biodiversity but also because it emits large amounts of sequestered carbon. According to Houghton (2012) deforestation accounts for approximately 60-90% of net carbon emissions in tropical regions, and degradation for 10-40%. The range is due to the fact that it is not clear if a shift in cultivation should be categorised as deforestation or as degradation. In any case, deforestation and forest degradation remains the largest source of greenhouse gas emissions in most tropical countries (Gibbs et al., 2007).

Deforestation in Ecuador

The public attention for deforestation is largely focused on lowland tropical rain forests, such as the Amazon, even though the deforestation rate of the tropical cloud mountain forests is higher in many regions (Hamilton et al., 1995). Ecuador has the highest deforestation rate of South America (Mosandl et al., 2008). Large deforestation was manifested in the cacao boom from 1900 to the end of the 1920s and the banana boom after the Second World War (Mosandl et al., 2008). In 2005, 39% of the Ecuadorian land area was classified as forests. This is less than the average 48% in South American countries (FAO, 2006). The majority of the forests in Ecuador are tropical mountain cloud forests (TMCF). Currently the deforestation cycle starts with the extraction of valuable wood, after which the degraded land is burned and converted to pastures for cattle raising (Mosandl et al., 2008; Günter et al., 2009).

The deforestation in Ecuador is slowing down, but it is still high (Table 2.3). In the Global Forest Resources Assessment from FAO (2020) it is clear that Ecuador has a high deforestation rate in comparison to other Latin-American countries. Only Argentina and Bolivia have higher deforestation rates. The deforestation in Brazil, that is often mentioned in the media has a deforestation rate of 0,30% of its forest area, which is less than the 0,41% of Ecuador.

Table 2.3: Forest area of Ecuador divided in naturally regenerating forests and planted forests (data derived from FAO (2020)).

	Forest area (1000 ha)				**Net annual change (1000 ha/y)**		
	1990	**2000**	**2010**	**2020**	**1990-2000**	**2000-2010**	**2010-2020**
Natural	14 588	13 660	12 943	12 387	-92,7	-71,7	-55,7
Planted	44	70	85	111	2,6	1,5	2,6
TOTAL	14 632	13 731	13 028	12 498	-90,1	-70,2	-53,1

Important to note is that 100% of the planted forests in Ecuador are plantation forests (FAO, 2020). Some taxonomic groups that were present in the primary ecosystems, will never recover from land degradation, not even when a secondary forest is created (Barlow et al., 2007). On top of that, primary forests store on average around 35% more carbon than planted forests (Mackey et al., 2020). In that way, the planted forests do not have the same quality of the ecosystems that were initially present. It is thus of major importance to limit deforestation and land degradation.

2.2.2 Reforestation and afforestation in the tropics

Framing and significance

The focus of restoration projects is mainly on reforestation as a tool to mitigate carbon emissions (Locatelli et al., 2015; Schwartz et al., 2020). The IPCC estimated the potential to reduce net emissions by 2030 for different sectors (IPCC, 2022). Moreover, after renewable energy from wind and the sun, land use change have the highest potential. First "reduced conversion of forest and other ecosystem", then "carbon sequestration by agriculture" and then "ecosystem restoration, afforestation and reforestation" have the highest potential to mitigate carbon. Land use change is thus an important factor in carbon mitigation and it can go hand in hand with other SDGs (Sustainable Development Goals) (UNFCCC, 2023). The total area of the world's forests, woodlands and woody savannas could store around one-quarter of the atmospheric carbon that has to be stored in other pools to limit global warming to 1.5°C above pre-industrial levels (Masson-Delmotte et al., 2018). To achieve this, 24 million hectares of forest should be added to the global forest area every year until 2030 (Lewis et al., 2019).

Forests with trees that have rapid growth rates, such as the tropical forests are excellent to mitigate carbon emissions (Girardin et al., 2021). By restoring 15% of converted areas in the so-called priority areas, to which large parts of Ecuador belong, 60% of the expected extinctions can be avoided and 30% of the total CO_2 increase in the atmosphere can be sequestered (Strassburg et al., 2020). Tropical forests have the potential to serve as an effective carbon offset mechanism in the short- and longer-term (Silver et al., 2000; Brancalion et al., 2019).

This causes a worldwide interest of organisations, companies and countries to reforest in the tropics. Carbon offset projects and carbon credits are important actors in reforestation and afforestation projects.

Strategies

Reforestation and afforestation should not be confused. Both terms were defined by the UNFCCC (2022). Reforestation is the planting of trees on land which previously supported tree-dominated ecosystems, while afforestation is the planting of trees on land that was previously supported by non-tree dominated ecosystems.

Where plantations are desired for their productivity, a mixed-species plantation is preferred over monocultures to create a higher terrestrial biodiversity (Wang et al., 2019a). The plantation can also be embedded in intact or restored vegetation (Lamb, 1998). Another way to create higher biodiversity in a plantation is to encourage a diverse understorey beneath the plantation (Lamb, 1998). However, a restoration planting, that has the objective to reestablish the original forest ecosystem, is the best way to restore the biodiversity (Lamb et al., 2005).

Restoration with native species

The quality of reforestation and afforestation projects can be improved by planting native species, that have added values for biodiversity (Andres et al., 2022). Due to high species richness in the region, selecting suitable species for restoration is a challenge. Certain species are expected to generate desirable outcomes in restoration projects, but figuring out which species have the desired properties is still ongoing research. Andean alder (*Alnus* *acuminata*) has been proven to be able to compete with the fast growing exotic species (Günter et al., 2009; Bare and Ashton, 2016).

Another challenge is the growth of seedlings. Generally, the common procedure for seedling propagation for restoration projects is by collecting existing seeds in the forest, without considering their stage of maturity (Aguirre et al., 2008). There is a gap in knowledge on this aspect. Also the effect of management techniques, such as manual above-ground weeding and shading structures, has to be further examined since their effect is species dependent (Günter et al., 2009). The spread and implementation of the gathered knowledge should be organised by the government and small-scale farmers should be subsidised for reforestation and afforestation practices.

Trends in Ecuador

In the tropics, reforestation and afforestation are often done with monocultures of species that are interesting for the industry (Lamb et al., 2005). This is also the case in Ecuador. In 2020 more than 111 000 ha of forest was planted in the country, all of them plantations (Table 2.3). More than 90% of these plantations are planted with exotic species, mainly *Eucalyptus* spp. and *Pinus* spp. (FAO, 2006). Günter et al. (2009) claim this is due to the gap in knowledge about the early growth of native species. The successful exotic species are well studied, have a good availability of planting material and are proven to be productive and therefore preferred. Although they have a good productivity, other ecosystem services are generally lacking. The original forests provided a variety of goods e.g. qualitative timber, medicine and food, while the planted forest produce mainly pulpwood (Lamb et al., 2005). Plantations with fast growing species are able to store carbon in the short-term (Prasad et al., 2012). However, looking at the long-term, secondary forests are desired, since they enhance the carbon soil stock (Cuevas et al., 1991). Both forest types accumulate nutrients and mass, but secondary forests recirculate nutrients much faster than the plantations, which tend to store the nutrients (Lugo, 1992).

There is no such thing as one given protocol to achieve the most effective restoration, leading to reforestation and afforestation projects with varying degrees of success. More research is needed to find an effective way to reforest and restore the biodiversity and carbon sink potential of the tropical forests.

2.2.3 Carbon offset programs and carbon credits

Carbon offset is a mechanism that allows individuals, businesses, countries and organisations to compensate for their greenhouse gas emissions by investing in projects that reduce or remove carbon dioxide or other greenhouse gases from the atmosphere (Lovell and Liverman, 2010). Carbon credits are awarded when a carbon offset program is established and organisations that emit more than the defined standards can buy carbon credits to compensate for their emissions (Silver et al., 2000). This carbon offset system is the essence of the Clean Development Mechanism (CDM), as defined in the Kyoto Protocol (1997), which allows industrialised countries to implement emission-reduction programs in developing countries (UNFCCC, nd). Another important carbon credit mechanism is the Verified Carbon Standard (VCS). This program is administered by Verra, a non-profit organisation that was founded to assure quality in the voluntary carbon markets (Verra, 2022). Projects that are VCS-certified receive carbon credits that can be traded on the carbon market (Von Avenarius et al., 2018).

Afforestation and reforestation are common forestry activities in trading schemes for carbon offsets (Le et al., 2012). Tropical reforestation has the potential to serve as a carbon offset mechanism for at least 40 to 80 years, and possibly much longer (Silver et al., 2000; Saundry, 2009). With the increasing integration of carbon offsets in mandatory and voluntary programs, it is expected that the value of offset credits will rise (Richards and Huebner, 2012; World Bank, 2022a). One obstacle to incorporate forest offsets in climate policy is the risk of reversal i.e. the release of carbon back to the atmosphere due to storms, land use decisions, pests and other factors (Galik and Jackson, 2009). Sometimes failed projects are rewarded with carbon credits. These so-called phantom forests occur surprisingly frequent and threaten to undermine efforts to make planting a credible means of combating climate change by reducing carbon dioxide in the atmosphere or generating carbon credits that can be sold to companies to offset their emissions (Pearce, 2022).

This suggests the importance of an effective project evaluation method and an accurately estimation of the stored carbon in reforested forests. The use of modern technology, including remote sensing and computer-based modeling, can improve our understanding of the multi-scale mechanisms of land use and land cover changes in our landscape (Andersson and Richards, 2001; Agrawal and Khairnar, 2019).

2.3 Quantification of forest biomass

Insights in the above-ground biomass are essential for the adequate development of management plans and to determine the carbon contents of a forest (Basantes et al., 2019). To monitor deforestation and reforestation and make correct inferences about long-term changes in biomass, it is important to quantify and follow the biomass evolution and be aware of the AGB estimation uncertainty (Chave et al., 2004). Several existing methods can be grouped in two categories: the destructive and the non-destructive methods.

2.3.1 Destructive method

A destructive method, where trees are harvested and weighted to determine the volume is often done to estimate the AGB. An alternative method for determining the volume involves submerging the harvested tree in water. By doing so, the AGB of different parts of the tree can be measured quite accurately. Since 90% of the AGB and wood productivity in tropical forests is determined by trees with a diameter of more than 10 cm, often only these trees are measured and taken into account for AGB estimations (Brown, 1997). In young reforested forests, the understorey cannot be neglected, because the overstorey is more open and the understorey has an important share in AGB. However, harvesting all trees is time consuming, not cost effective and an unsustainable technique to determine the biomass. To overcome this problem, non-destructive methods are developed, such as allometric equations (Brown et al., 1989).

2.3.2 Non-destructive methods

Allometric equations

There exist several pantropical allometric equations (PAEs), that are deduced from destructive data sets from other studies, to estimate AGB of new sites in a non-destructive way. These equations use easy measurable parameters such as diameter at breast height (DBH), tree height (H) and wood density (WD) to determine the AGB of a tropical tree. DBH and H are often measured in forest inventories, while for WD, mostly data from tables are used (Clark et al., 2001). However, the wood density of a species can vary depending on the growing conditions and altitude (Strubbe, 2013). Forest inventories can include wood density measurements by taking stem cores, but this is time intensive (Gao et al., 2017).

Some of the most known PAEs were constructed by Brown (1997), Ketterings et al. (2001) and Chave et al. (2014). Other studies evaluate these equations on a regional scale. Fayolle et al. (2013) for example compared the AGB calculated with PAE of Chave et al. (2005) with the AGB of harvested tropical trees in South-East Cameroon and noticed no significant difference. Basuki et al. (2009), on the other hand, compared the AGB in tropical lowland forests with mainly *Dipterocarp* species calculated with several PAEs and the AGB of harvested trees. The results had a variation of more than 50%, showing that PAEs are not valid for all regions and all types of tropical forest. Sometimes local allometries are needed to make a better estimation of the above-ground biomass.

Several PAEs were evaluated in young secondary forests in the north of Ecuador and all equations overestimated the above-ground biomass of trees in reforestations (Thierens, 2017). The AGB calculated with the PAEs of Chave et al. (2014) and Kenzo et al. (2010) were closest to AGB of the harvested trees, but still not accurate. In order to obtain a more correct estimate of above-ground biomass, local allometric equations for secondary forests in Ecuador should be developed.

Remote sensing

Remote sensing (RS) technology can provide a better estimation of the parameters that are difficult to measure and it is both temporary and spatially accurate (Mohd Zaki and Abd Latif, 2017). Various remote sensing data can be collected. In forest sites with relatively simple structure, optical sensor data can be sufficient, while in more complex environments, a combination with radar or laser data is preferred (Lu, 2006).

Light detection and ranging (LiDAR) is a remote sensing technique that uses laser beams to create a 3D point cloud (Dubayah and Drake, 2000). Capturing millions to billions points, a three-dimensional (3D) space of the surrounding can be constructed (Figure 2.2) (Liang et al., 2016). There are two main techniques of range measurements: phase shift (PS) and time-of-flight (ToF) methods (Liang et al., 2016). PS ranging uses continuous laser illumination and amplitude modulation of the beam at high frequency to register differences in the range. ToF LiDAR instruments, on the other hand, record the time it takes for an emitted laser to return after reflection on the target. From the range and the angle of the laser pulses the (x,y,z) coordinates are determined and a point cloud is created (Terryn et al., 2020).

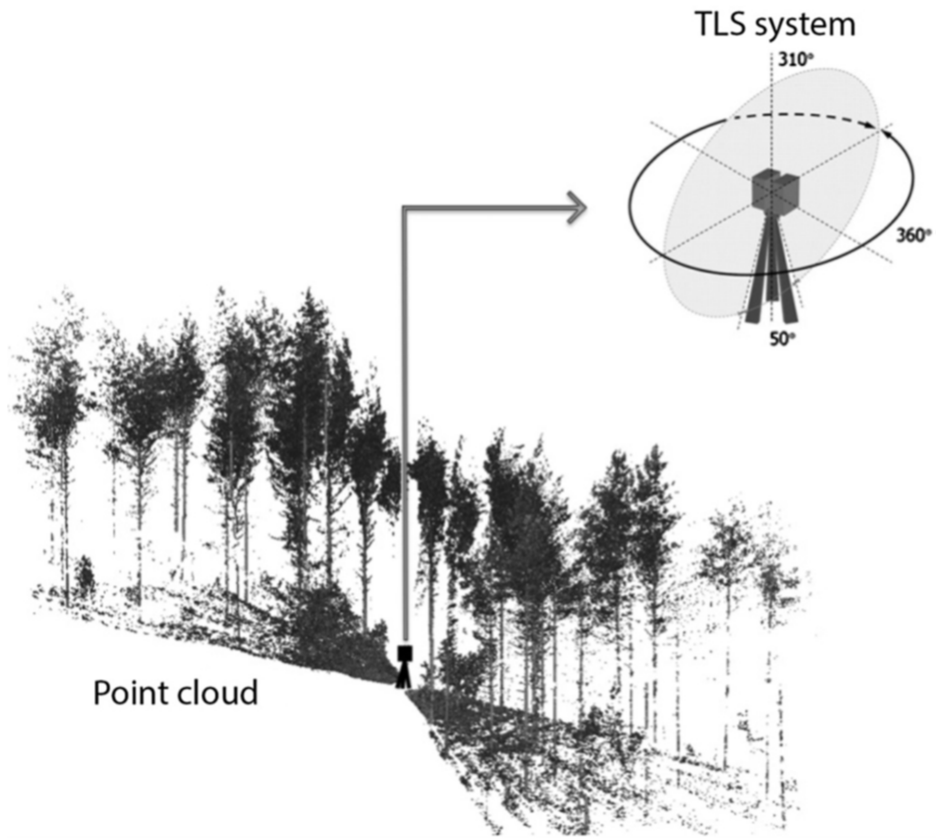


Figure 2.2: Point cloud created using terrestrial LiDAR data (Liang et al., 2016).

LiDAR data can be collected with different spatial and temporal scales and from different platforms. Compared to Airborne Laser System (ALS) and Mobile Laser System (MLS), Terrestrial Laser Scanning (TLS) has the highest level of 3D detail and provides therefore the best estimates for volume and biomass (Fowler and Kadatskiy, 2011; Gonzalez de Tanago et al., 2018; Donager et al., 2021). Different aspects have to be taken into account when deciding what forest inventory technique has to be applied. The cost of the data acquisition and data interpretation is an important factor. Depending on the desired accuracy and precision of the data, the high cost of TLS can be justified.

2.3.3 Terrestrial Laser Scanning (TLS)

Basic tree attributes, such as DBH and information about the tree position can be easily retrieved from the 3D point cloud (Liang et al., 2016). Other directly measured properties of the forest are canopy height, subcanopy topography and the vertical distribution (Dubayah and Drake, 2000). Forest structural characteristics, such as above-ground biomass are calculated from the direct measurements (Calders et al., 2015). Above-ground biomass and especially stem volume are important for the calculation of carbon stocks of forests. Comparing TLS-based estimates with the AGB of harvested trees indicates that the AGB can be estimated with high precision (Disney et al., 2019).

Terrestrial Laser Scanning (TLS) has the potential to improve AGB estimates obtained with allometric equations. Height, a frequently used parameter in allometric equations, is often difficult to measure in the field with direct measurements. Especially in dense forests with high slopes, height measurements can be challenging, leading to uncertain AGB estimations (Larjavaara and Muller-Landau, 2013). RS data, TLS data in particular, could improve the quality of the height measurements and therefore the biomass estimations (Dubayah et al., 2010; Bazezew et al., 2018; Terryn et al., 2022). However, this method still relies on allometric models that are constructed with destructive sampling data.

A different approach is the use of quantitative structure models (QSMs). QSMs are reconstructions of the complete 3D tree architecture of individual trees and these models allow volume measurements (Gonzalez de Tanago et al., 2018). The AGB per tree is then obtained by multiplying the volume with the specific wood density (Calders et al., 2015). These models are able to make very precise volume estimations (Calders et al., 2020). Calders et al. (2022) reported that the biomass carbon in temperate forests can be 1,77 times higher than what is currently estimated with allometric models. This suggests that existing allometric models should be reevaluated and other methods should be considered to make better estimations of the carbon sinks in the world.

3. AIM

The main objective of this study is to investigate the utility of terrestrial LiDAR scanning in estimating above-ground biomass (AGB) and carbon stocks in young reforested tropical areas. The study aims to identify and analyse the difficulties of the data collection and data processing and assess the quality of the results. Additionally the quality of the diameter at breast height and height measurement obtained through classical inventory surveys will be evaluated with the TLS data of these parameters.

Another aspect of the study is to compare the AGB estimates derived from the TLS data with several pantropical and local allometric equations. These equations are commonly used to estimate AGB in forest ecosystems. However, the equations may vary in accuracy and precision, depending on the forest type, age and location. This comparison is important for evaluating the performance of existing allometric equations in forest restoration efforts in South Ecuador and for identifying potential biases or limitations associated with using these equations. A more accurate, local TLS-based allometric equation is constructed, in order to make improved AGB estimates in reforested areas in the south of Ecuador.

Overall the study aims to contribute to the development of accurate and efficient methods for carbon estimations of reforestation in the tropics. The findings of this study will be useful for researchers, policy-makers and other stakeholders involved in reforestation and climate change mitigation efforts.

4. MATERIAL AND METHODS

4.1 Study area

The COFOREC II project has recently expanded their study area in the south of the country. These southern plots form the study area of this LiDAR-based research (Figure 4.1). In total, 13 plots on seven sites were scanned and their properties are summarised (Table 4.1). Four sites (Sevilla de Oro, Santa Ana, San Rafael and Aguarongo) are located in the province Azuay and three sites (Zamora, San Francisco and Numambi) in the province Zamora Chinchipe. The plots in Azuay have generally higher elevations than the plots in Zamora Chinchipe.

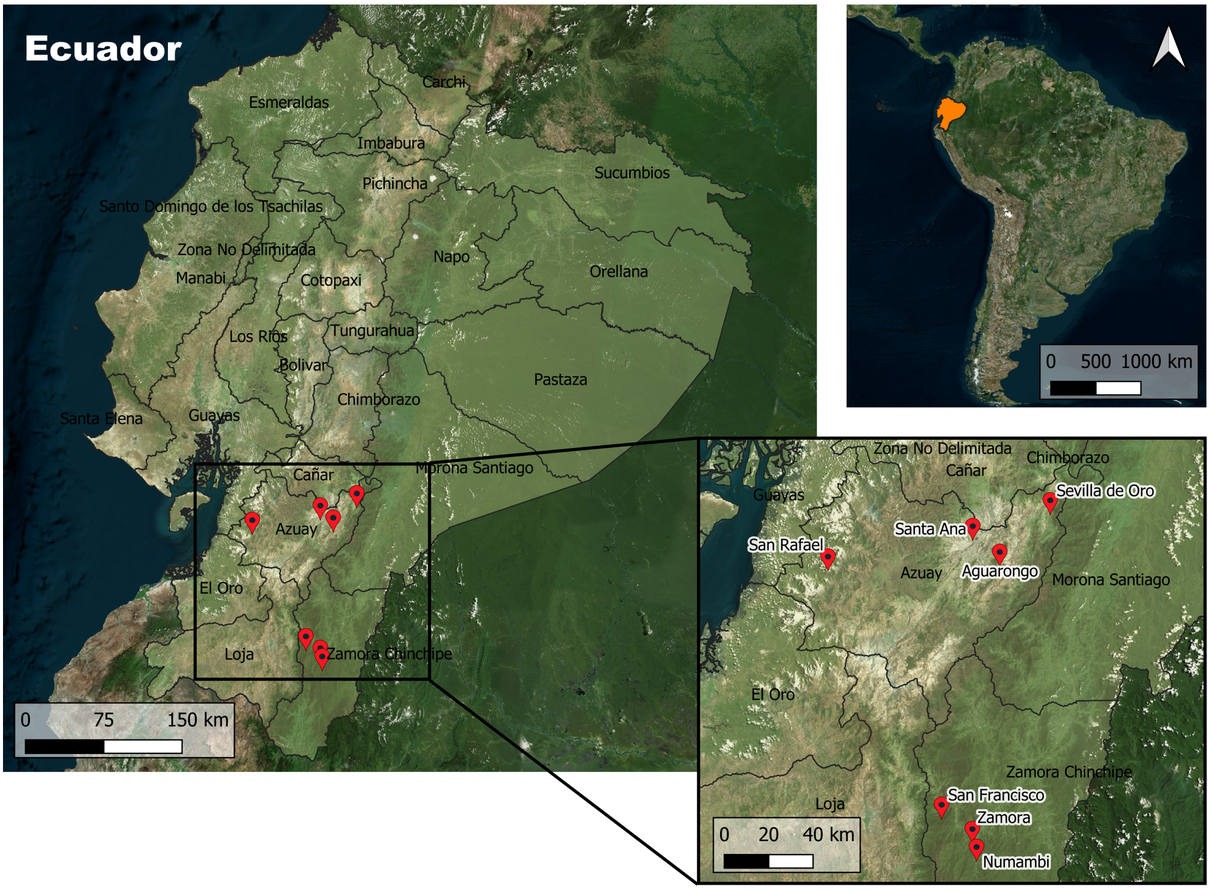


Figure 4.1: Geographical location of the study area.

Table 4.1: Properties of the scanned plots: the province and site, the size (m), the age (years), the altitude (meters above sea level), the slope (%), the flank position, the mean annual temperature (MAT) (°C), the mean annual precipitation (MAP) (mm) and the climate (according to Köppen-Geiger).

Province	**Site**	**Plot ID**	**Size (m)**	**Age (y)**	**Altitude (masl)**	**Slope (%)**	**Flank position**	**MAT (°C)**	**MAP (mm)**	**Climate**
Azuay	Santa Ana	R5	20 x 20	8	3254	25	high	13.1	727	Cfb
		R6	40 x 40	8	3037	35	high	13.1	727	Cfb
	Sevilla de Oro	R11	20 x 20	9	2034	34	mid	14.4	688	Cfb
	San Rafael	R21	20 x 20	7	2574	45	mid	20.4	938	Cfb/Aw
		R23	20 x 20	7	2691	26	high	20.4	938	Cfb/Aw
	Aguarongo	R16	20 x 20	6	3155	10	high-mid	10.2	1079	Cfb
		R24	20 x 20	6	3151	16	high	10.2	1079	Cfb
Zamora Chinchipe	San Francisco	R25	20 x 20	7	1911	72	mid	15.5	1303	Af/Cfb
		R26	20 x 20	7	1906	68	mid	15.5	1303	Af/Cfb
		R27	20 x 20	7	1843	70	mid	15.5	1303	Af/Cfb
	Numambi	R34	20 x 20	8	1203	22	low	21.3	833	Af
	Zamora	R37	20 x 20	8	1143	24	high	22.0	991	Af
		R39	20 x 20	8	1002	60	mid	22.0	991	Af

Regarding climate, two distinct climate types can be identified. The plots more in the North (Aguarongo, Sevilla de Oro, Santa Ana and San Rafael) are classified as Cfb (temperate, no dry season, warm summer), while the plots in Zamora, San Francisco and Numambi have a Af (tropical, rainforest) climate. However, the Köppen-Geiger climate classification maps at 1-km resolutions published by Beck et al. (2018) show a different classification for two sites. San Rafael is classified as tropical savannah (Aw), while the observed vegetation corresponds more with a Cfb climate and San Francisco is classified as Cfb, but it is very similar to the plots in Zamora, that are Af. This shows that maps should be interpreted carefully and have to be verified with observational data.

Temperatures are generally lower in the tropical mountain cloud forests (in Azuay) which limits the growth of the planted trees more than in the Zamora rainforest. Taller trees with a higher DBH and AGB are to be expected in the reforestations in the Zamora Chinchipe province.

The tree density is lower in the plots in Azuay and also the understory is less dense. The species richness is higher in the plots in Zamora Chinchipe and average diameters and heights are higher. This indicates further development of the forest's vegetation. The difference in vegetation between the plots in Azuay and the plots in Zamora Chinchipe can be noticed (Figure 4.2).

Figure 4.2: Plots in Santa Ana (left), Sevilla de Oro (centre) and San Francisco (right).

4.2 Data collection

4.2.1 Framework

The fieldwork is part of an ongoing research project on reforestation in the Andes in southern Ecuador, the COFOREC II project. It builds upon the accomplishments of its predecessor, COFOREC, and seeks to improve the quality and quantity of data collected from permanent secondary forest plots. Additionally, COFOREC II focuses on enhancing the research skills of local ecologists through capacity building activities. The project's overall objectives include understanding natural forest responses to global change, evaluating forest recovery, assessing human pressures on forests and promoting capacity building. Collaboration with local international stakeholders, such as landowners and NGOs, is a key aspect.

This research contributes to the ecological goals of the project. Tree species and their suitability for reforestation in different areas are investigated. There are many factors that can influence their success rate, including forest management, climate, soil properties, composition... To be able to compare different sites, plant traits and their growth are monitored. The carbon stock is an important parameter to follow up the growth rate of trees. Currently, carbon stocks are determined with pantropical allometric equations, due to the lack of accurate local equations. In this study, their accuracy will be evaluated with TLS data.

4.2.2 Site selection

The observational plots in existing reforested areas were installed in 2020 and an inventory of the plots was made in 2021 and 2022. The plots in the Azuay province are at higher elevations ranging from 2000 m to 3300 m altitude. On the contrary, the plots in the Zamora province have altitudes going between 1000 m and 2000 m. The plots are often located in areas with a large slope gradient (Table 4.1). Therefore the plot dimensions were rather small to maximise uniformity in e.g. soil and climate conditions. Most plots were a square with dimensions of 20 by 20 m. Some were a bit larger and had dimensions of 40 by 40 m.

Besides observational plots, there are also experimental plots. These plots were planted in 2022 with different planting strategies to investigate the effect of mixing, shading and removal of competitive species. Due to the small size of the recently planted trees in often taller grasses, it was not possible to collect qualitative LiDAR data of the experimental plots. This gives already an indication that TLS can only be used in later stage of development of the plantations.

4.2.3 Terrestrial LiDAR scanning

General

The scanner and the supporting materials are heavy (Newnham et al., 2012), so a team of minimum two people is needed to carry and operate the equipment. Weather circumstances are an important factor (Wilkes et al., 2017). Scanning can only continue when leaves are dry and wind speeds are (very) low (Seidel et al., 2012; Wilkes et al., 2017).

To be able to achieve a coarse co-registration, four common targets between scan locations are needed (Wilkes et al., 2017). The targets are retro-reflective and can be flat, cylindrical or spherical. Here cylindrical retro-reflectors with a diameter of 5 cm were used. They were mounted on light but solid poles.

Equipment

The main instrument was a time-of-flight RIEGL VZ-400 scanner (RIEGL, 2023a). A Nikon D810 camera with a NIKKOR 14mm f/2.8D ED lens can be installed on the scaner to obtain images in the visible light range (Nikon, 2020). The use of the camera increases the scan time considerably and the camera is also an extra weight. Such images would not be used in further processing steps so that is why it was decided to not use the camera. The scanner was installed in the field using a tripod and two external 13.2 V, 18 Ah Nickel-Metal Hydride (NiMH) batteries were used as the power source (Norcell AS, nd).

Twenty retro-reflective targets and sixteen poles were brought to the field. To lay out the 10 x 10 m sample plot, a roll gauge, compass and coloured strings were needed. The materials were carried in a waterproof backpack that could also be used as a water shield to protect the scanner from precipitation.

Method

Scans and settings of the scanner

On every scanning position, two scans were taken (Figure 4.3). First, a scan in the 'up' position provides a vertical point cloud of 360° around the scanner. This scan is followed by a 'tilted' scan. Herefore the scanner is rotated 90° downwards and scans the overstorey. In this way full hemispherical data was collected, which improves canopy detail in dense forests with tall trees. A scan resolution of 40 mdeg was used, resulting in a point spacing of 34 mm at 50 m distance from the scanner. The pulse repetition rate was set at 300 kHz.

Figure 4.3: The RIEGL VZ-400 in the 'up' position (left) and the 'tilt' position (right) in San Rafael.

Scanning pattern

The method proposed by Wilkes et al. (2017) was applied to the observational plots. The first step is to lay out the sampling plot. Since the forests were dense, a 10 x 10 m sampling grid was used. Specifically, this means that there were 9 scan locations in a plot of 20 x 20 m and 25 in a 40 x 40 m plot. With the roll gauge, a distance of 10 meters was measured and the locations were marked with a coloured string. To obtain right angles in a dense vegetation on a steep slope, a compass was used. The obstructive vegetation, brambles and ferns for example, between the different scan locations, were shortened with a machete. This was necessary to allow the reflectors to be placed in a position visible to the scanner from two different locations.

The sampling pattern forms a continuous 'chain' where each scan location is linked to the previous and the previous location (Figure 4.4). Starting at Scan location 1, six targets were located between Scan location 1 and Scan location 2 (light blue on Figure 4.4). Also two targets were placed perpendicular to the scan direction, for the tilted scan. It would have been better to do the tilted scan in the scanning direction, but because of lack of experience in scanning, the tilted scans were made in the less optimal, perpendicular direction. Later, some manual targets had to be added in the co-registration step, as four common targets are needed to accurately link the scans.

Before scanning at Scan location 2, another set of eight targets were placed between Scan location 2 and 3 (light green). After performing the two scans at this location, the first eight targets between Scan location 1 and 2 (light blue) were moved and placed between Scan location 3 and 4 (orange). From now on, the last placed targets remained in their position for executing the scanning at the next location and the targets placed before were moved to the next position, this until the end of the chain was reached.

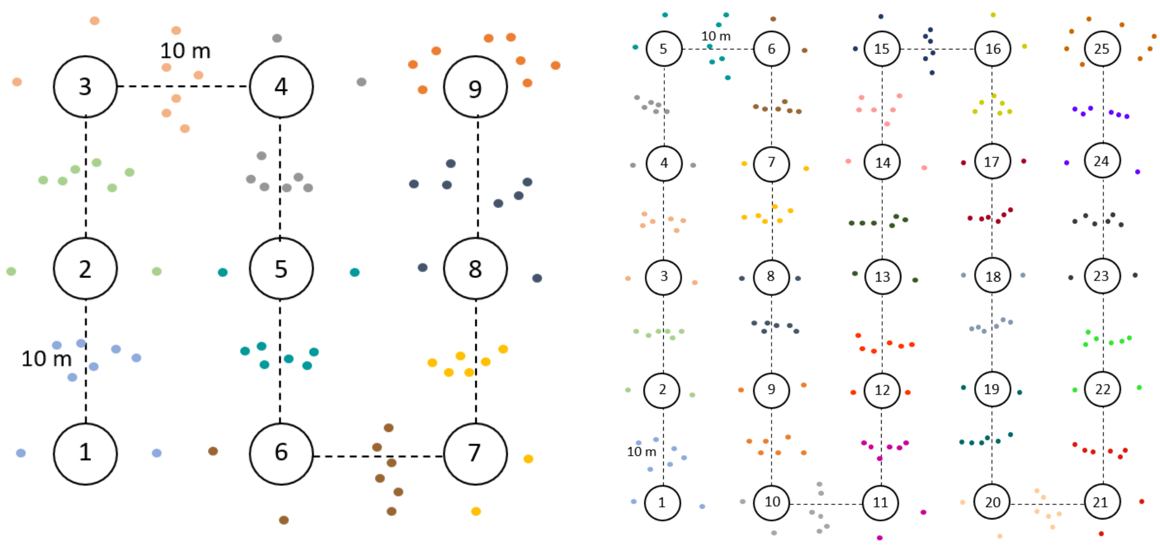


Figure 4.4: Sampling pattern used for capturing TLS data over a 20 x 20 m plot (left) and a 40 x 40 m plot (right).

The time needed to perform the scans and move the scanner and targets between every location was between 15 and 30 minutes, depending on the conditions. Topography was an important factor, since the downhill view range of the scanner is limited. The targets had to be placed high enough in order to be visible from the uphill scan location. Higher slopes increased the time needed to place the targets, but also to replace the scanner. Besides the slope, the high density of the lower vegetation affected the time, as it complicated the visibility and the accessibility.

4.3 Data processing

4.3.1 Preprocessing of the TLS data

Co-registration

The first step in the data processing is to align multiple scans of the same plot taken from different positions and angles. By doing so, a comprehensive 3D point cloud of the environment is created. This co-registration step was done in RiSCAN Pro, a software developed by RIEGL (RIEGL, 2023b). Before the co-registration, the raw data was cleaned up by filtering out undesired points. Per laser shot, all echos were kept, points with a reflectance below -25.00 dB and above 5.00 dB were deleted and so were points with a pulse shape deviation above 15.

During the co-registration, the software compares individual scans and finds the common features, the retro-reflective targets. At least four common targets are necessary to automate the co-registration. If there were not four common targets, targets had to be added manually. This was challenging in a dense forest with little reference points.

Multi-station adjustment (MSA)

Multi-station adjustment (MSA) in RiSCAN Pro improves the accuracy of the co-registration. MSA can improve the co-registration by taking plane files and poly data into account. In this case, plane files could not be used, since there were not enough registered flat surfaces. Poly data on the other hand, does not need flat surfaces and could be used for performing the MSA. A 2.5D raster of the top of the canopy was created for every scan and this poly data was used to add the scans one by one and perform the MSA.

After executing the MSA step, the scans had the optimal position and orientation and trees could be segmented. Due to limited time, only some plots were segmented. Plots in both Cfb and Af climates were selected.

Tree segmentation

Tree segmentation is the process where every tree is separated from the point cloud of the plot. All trees with a DBH of more than 5 cm were segmented in RiSCAN Pro (RIEGL, 2023b). Since the inventory data does not include palm trees, they were also not considered in the LiDAR evaluation.

One species (*Escallonia* spp.) showed difficulties to be segmented due to its high degree of branching and more bushy appearance. Further data processing on these extracted point clouds would be extremely difficult, and therefore it was decided to leave this species out. The center part of plot R6 consists mainly of this species, so the area of the plot had to be recalculated.

All tree point clouds were subsampled at 0.01 m in CloudCompareStereo (v2.12.4) (GPL software, 2023). The statistical outlier removal was performed with parameters 6 and 1.00. The first parameter specifies the number of neighbouring points that will be considered and the second is the standard deviation multiplier.

4.3.2 Above-ground biomass estimation

The above-ground biomass of the four plots: R6, R21, R26 and R39 was calculated with three different methods (Figure 4.5). Pathway 1 estimates the AGB based on the volume of the TLS data multiplied by the average wood density (WD) at plot level. In pathway 2 and 3 several existing pantropical and local allometric equations are used to estimate the AGB (Table 4.2). Diameter at breast height (DBH) and height (H) values of the TLS data (pathway 2) and of the inventory (pathway 3) are used. The results of the AGB estimates of the three pathways is compared.

The AGB estimates based on TLS data (pathway 1) are used to construct four new allometric equations. Finally in pathway 4, the inventory of all plots is used as an input for the new allometric equations and one existing allometric equation (Chave et al. (2014)) to estimate the AGB of the COFOREC II project in South Ecuador.

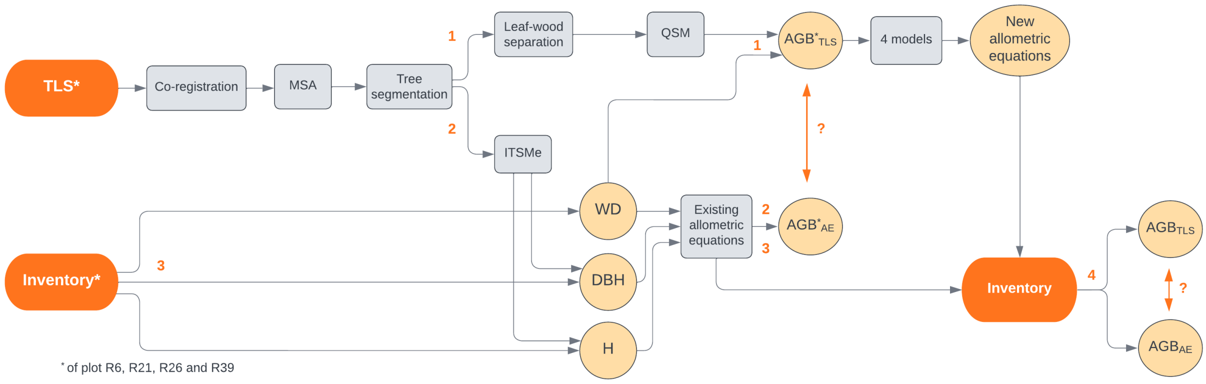


Figure 4.5: Flowchart of the pathways to estimate the above-ground biomass (AGB). Pathway 1, 2 and 3 estimate the AGB of the four plots (R6, R21, R26 and R39). Pathway 1 is TLS-based, while pathway 2 and 3 use existing allometric equations (AE). In pathway 4, the AGB of all COFOREC II plots in South Ecuador is estimated with the new models (AGB_{TLS}) and with one existing allometric equations (AGB_{AE}).

Pathway 1: TLS data and QSMs

In order to make a TLS-based AGB estimation, the wood volume has to be calculated. A first step is to separate the point cloud of the segmented trees into a wood point cloud on one hand, and a leaf point cloud on the other hand. The graph-based leaf-wood separation method (GBS) was used (Tian and Li, 2022a). The technique constructs a graph representation of the LiDAR point cloud data and creates shortest-path features. The shortest path represents the most direct route between two points in a graph, and by considering these paths, the method can effectively capture and analyse the structural patterns of LiDAR point cloud data. This automatic, robust method can outperform two other state-of-the-art leaf-wood separation methods (Tian and Li, 2022b).

Quantitative structure models (QSMs) reconstruct details of a tree in sets of small of cylinders. The cylinders have different diameters, representing the variety in branch and stem structure and size (Raumonen et al., 2013). The models were constructed with the wood point clouds in Matlab with the TreeQSM (v.2.4.1) software (Raumonen et al., 2013; The MathWorks Inc., 2022). With these QSMs, tree volumes were calculated, and by multiplying the volume with the wood density from the inventory, above-ground biomass values were obtained. The results of the QSM-based AGB estimation are compared with the results of the AGB estimates using existing allometric equations.

Pathway 2: TLS data and allometric equations

The DBH and H were extracted from the point clouds of the segmented trees using the ITSMe package in R (R Core Team, 2018; Terryn et al., 2023). Values for DBH were obtained by two different functions of the package (*plot_dbh_fit_pcs* and *plot_circle_fit_pcs*). A comparison of the results showed that in many cases, the two methods had a similar result, although sometimes one function was able to produce a correct diameter while the other over- or underestimated the DBH. In some cases, neither of the two functions was able to obtain a DBH value. In these cases, the DBH was measured manually on the point cloud using a measuring tool in RiSCAN Pro. The values of these parameters were compared with the DBH and H measurements of the inventory, in order to check whether there is a difference. The TLS derived DBH and H and the average plot level WD from the inventory were an input for the allometric equations (Table 4.2) to make AGB estimates.

Pathway 3: inventory data and allometric equations

Inventory data for DBH is available for the same year as the TLS field campaign (2022), while the height measurements are done one year before. The DBH of all trees with a diameter of at least 5 cm was measured at 1.3 m with a diameter tape and the height was measured with a hypsometer. The inventory also includes wood density values for every tree estimated with the oven-dry method (data from 2022). Hence the exact location of the trees is not known, the trees of the point cloud could not be linked to the same tree in the inventory and species determination was impossible. Therefore, WD values per plot were calculated as the mean of the wood densities of the trees. DBH, H and WD of the inventory were used as an input in several existing allometric equations (Table 4.2) to estimate the AGB.

Pathway 4: extrapolation to the project

According to four models, four new allometric equations were constructed and used to estimate the AGB of all plots in the COFOREC II project in South Ecuador (Figure 4.5). For this extrapolation, the DBH, H and WD of all trees in the inventory are needed as an input for these equations. As a reference, the AGB is also estimated with the equation of Chave et al. (2014). The outcomes are compared and the effect of the selected allometric on the AGB estimates is investigated.

Table 4.2: Allometric equations used for above-ground carbon (AGB) estimation of single trees. The parameters are diameter at breast height (DBH) in cm, height (H) in m and wood density (ρ) in g/cm³.

AGB_{tree} (kg)	**Variable(s)**	**Forest Type**	**Diameter Class (cm)**	**Region**	**Source**
$e^{-2.314+2.530 \cdot \ln(DBH)}$	DBH	Mature forest (moist)	5-148	Pantropical	Brown (1997)
$0.0673 \cdot (\rho \cdot DBH^2 \cdot H)^{0.976}$	DBH H WD	Mature forest (moist)	>5	Pantropical	Chave et al. (2014)
$0.11 \cdot \rho \cdot DBH^{2+0.62}$	DBH WD	Secondary forest	7.6-48.1	Sumatra	Ketterings et al. (2001)
$e^{-2.232+2.422 \cdot \ln(DBH)}$	DBH	Secondary forest	0.9-40	Colombia	Sierra et al. (2007)
$e^{-3.416+2.633 \cdot \ln(DBH)}$	DBH	Secondary forest	2-15	Ecuador	Thierens (2017)
$0.0776 \cdot (\rho \cdot DBH^2 \cdot H)^{0.940}$	DBH H WD	Secondary forest	15-75	Ecuador	González et al. (2018)

4.3.3 Construction of local allometric equations

Several allometric models are already developed for estimating the above-ground biomass. Widely used models are the ones from Chave et al. (2014) and Brown et al. (1989). Furthermore, Overman et al. (1994) evaluated multiple regression models for above-ground biomass estimation in the Amazon rainforest. Four allometric regression models were selected (Table 4.3) and after removal of the outliers, the parameters were estimated using the TLS-based AGB estimates (pathway 1).

Table 4.3: Allometric regression models for estimation of individual tree biomass. The variables are diameter at breast height (DBH) in cm, height (H) in m and wood density (ρ) in g/cm³. The models estimate the parameters a, b and/or c.

No.	Regression model	Variable(s)	Source
1	$AGB = a \cdot (DBH^2 \cdot H \cdot \rho)^b$	DBH, H, ρ	Chave et al. (2014)
2	$AGB = e^{a+b \cdot \ln(DBH)}$	DBH	Brown (1997)
3	$AGB = e^{a+b \cdot \ln(DBH^2 \cdot \rho)}$	DBH, ρ	Overman et al. (1994)
4	$AGB = e^{a+b \cdot \ln(DBH^2)+c \cdot \ln(\rho)}$	DBH, ρ	Overman et al. (1994)

The outliers were analysed with the Tukey's fence method. This method identifies data point outside a lower and an upper fence (LF and UF respectively). The lower fence is calculated as $LF = Q1 - 1.5 \cdot IQR$, and the upper fence as $UF = Q3 + 1.5 \cdot IQR$, where Q1 and Q3 are the first and third quartile and IQR is the interquartile range. After identifying the outliers for DBH, H and AGB, only the outliers for H were removed. The outliers for DBH were the trees with higher DBH and since they are not common, they were identified as an outlier. However, these trees are an important part of the total AGB and cannot be neglected for the construction of the models and therefore they were not removed. On the contrary, the outlier for the height variable (only one tree) had a large effect on the accuracy of the models and was removed.

Non-linear least-square (NLS) estimates of the parameters were made (R Core Team, 2018). R-squared is generally not a useful goodness-of-fit measure for most nonlinear regression models, but the NLS estimation technique is an exception. The NLS estimator seeks to minimise the sum of squares of residual errors thereby making R-squared applicable to NLS regression models (Date, 2021). A higher R^2 value indicates a stronger fit of the model to the data, implying that the predicted AGB by the model better replicates the observed AGB.

R-squared is calculated as follows:

$R^2 = 1 - \frac{\text{Residual sum of squares (RSS)}}{\text{Total sum of squares (TSS)}}$, with

$$RSS = \sum_{i}^{N} (y_i - y_{pred_i})^2 \qquad \text{and} \qquad TSS = \sum_{i}^{N} (y_i - y_{mean})^2$$

4.4 Carbon stocks and credits according to the voluntary carbon market

Verra (2013), a main player on the voluntary carbon market, proposes a method to estimated the carbon stocks and the CO_2-equivalents in forests. Firstly, the above-ground biomass (AGB) should be estimated with destructive sampling or with allometric equations. Here, the four constructed models and the pantropical allometric equation of Chave et al. (2014) were applied, so the different outcomes can be compared.

When the AGB is known, the below-ground biomass (BGB) is calculated using a root-to-shoot ratio (R). For secondary tropical forests that have an AGB of less than 125 t/ha, a root-to-shoot ratio of 0.42 is used (Intergovernmental Panel on Climate Change, 2003). The BGB (t/ha) is calculated relatively to the AGB (t/ha) with the formula: $BGB = R \cdot AGB = 0.42 \cdot AGB$.

Normally the non-tree woody biomass of the forest should also be measured with destructive sampling or allometric equations, but since there is no data for these plots, this is neglected here. This study did not take soil organic carbon into account either. The carbon stock (tC/ha) is retrieved from the total biomass using the carbon fraction (CF) of dry matter. The default value is 0.47 (Verra, 2013). Summarised, carbon stocks are calculated according to the formula:

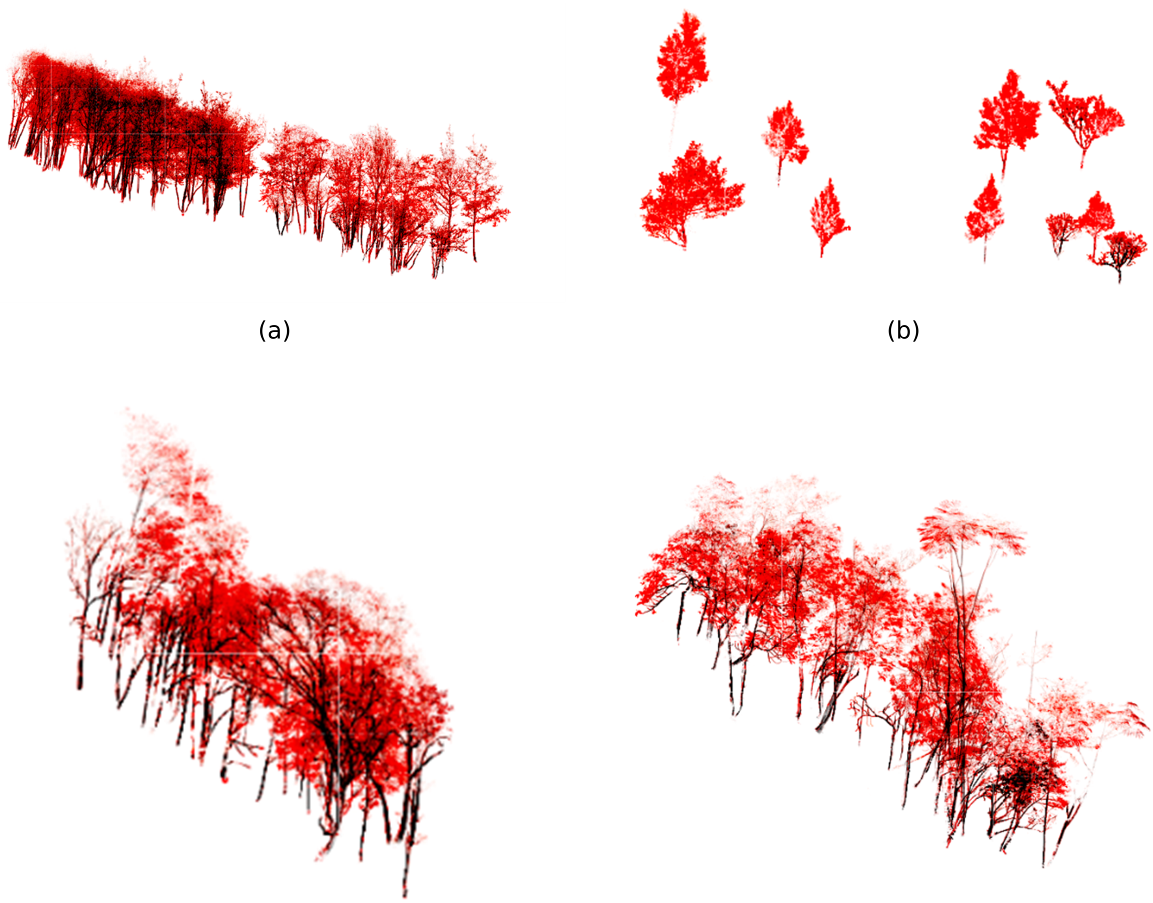
$$C_{stock} = CF \cdot (AGB + BGB) = 0.47 \cdot (AGB + 0.42 \cdot AGB) = 0.6674 \cdot AGB.$$

The CO_2-equivalent (CO_{2e}) is commonly used to measure the price of carbon emissions or carbon credits in the context of carbon markets and pricing mechanisms. It takes the global warming potential of different greenhouse gases relative to carbon into account. CO_{2e} (tCO_{2e}/ha) is calculated out of the carbon stock with the formula: $CO_{2e} = 44/12 \cdot C_{stock}$.

5. RESULTS

5.1 Tree segmentation

In total 277 trees were segmented. In the plots of Santa Ana (R6), San Rafael (R21), San Francisco (R26) and Zamora (R39) respectively 175, 11, 39 and 52 trees were segmented (Figure 5.1). The side and top perspective of the two plots in the Azuay province demonstrate the clear difference in tree density (Figure A.1). The two plots in the Zamora Chinchipe province on the other hand, are more similar in tree density and structure (Figure A.2).



(a) (b) (c) (d)

Figure 5.1: The side perspective of the four plots where trees were extracted. (a) Plot R6 in Santa Ana. (b) Plot R21 in San Rafael. (c) Plot R26 in San Francisco. (d) Plot R39 in Zamora.

The size of R21, R26, R39 is 20 x 20 m or 0.04 ha, while R6 is 40 x 40 m. However, the middle part (0.06 ha) of R6 is not segmented (Figure A.1). This is due to the presence of *Escallonia* trees, that are unsuitable for further calculations, resulting in an effective segmented area of 0.1 ha. In conclusion, only considering trees with a DBH ≥ 5 cm, R6 has the highest tree density of 1750 trees/ha followed by R39, R26 and R21 with tree densities of 1300, 975 and 275 respectively.

5.2 Evaluation of the inventory data

5.2.1 Wood density

Analysing the wood density (WD) indicates a variation depending on the location. The mean wood density is 353.37 kg/m³, 498.16 kg/m³, 263.13 kg/m³ and 566.70 kg/m³ in plot R6, R21, R26 en R39 respectively. The mean wood density of the four plots is 394.21 kg/m³. The average wood density of all trees in the 52 plots of the inventory is 440.05 kg/m³.

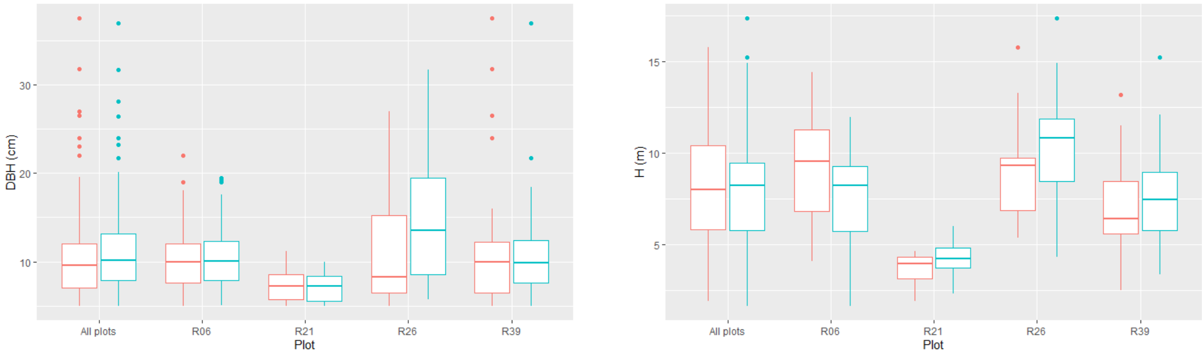
5.2.2 Diameter at breast height

The diameter at breast height (DBH) calculated with the ITSMe package resulted in some incorrect values and in some cases neither one of the functions was able to calculate the DBH. The failed DBH measurements occur when the trunk branches under 1.3 m or when stem of the tree is not positioned upwards. In total 31 manual DBH measurements were done.

The distribution of the diameter at breast height (DBH) measurements of the inventory and the DBHs calculated with the TLS data is overall similar (Figure 5.2a). The DBH measurements with the two methods are not significantly different in plots R6, R21 and R39. In plot R36 however, the DBH measured with the TLS data is significantly larger than the DBH of the inventory data ($p = 0.0045$).

5.2.3 Height

The distribution of the height measurements is due to the time gap harder to compare (Figure 5.2b). The height measurements of the inventory were one year before the TLS field campaign, thus higher height values are expected in the latter. The tree heights measured with the TLS are higher in plots R21, R26 and R39 (p-values of 0.1702, 0.0199 and 0.1856 respectively), while the TLS tree heights in plot R6 are lower compared to the inventory data ($p = 4.3 \times 10^{-6}$).



(a) (b)

Figure 5.2: The distribution of two variables for the allometric equation. Data from the inventory (red) and from the TLS (blue). (a) Diameter at breast height (DBH) in cm. (b) Height (H) in m.

5.3 Above-ground biomass estimation

5.3.1 TLS above-ground biomass estimation

Quality of the quantitative structure models

The quality of the quantitative structure models (QSMs) was visually assessed by overlaying the point clouds and the models (Figure 5.3). This visual representation clearly demonstrates the software's ability to generate accurate QSMs, even for smaller trees. In total, 247 QSMs are generated. This is 89% of all the segmented trees. In plot R6, R21, R26 and R39 QSMs of respectively 90, 100, 92 and 81% of the trees are constructed.

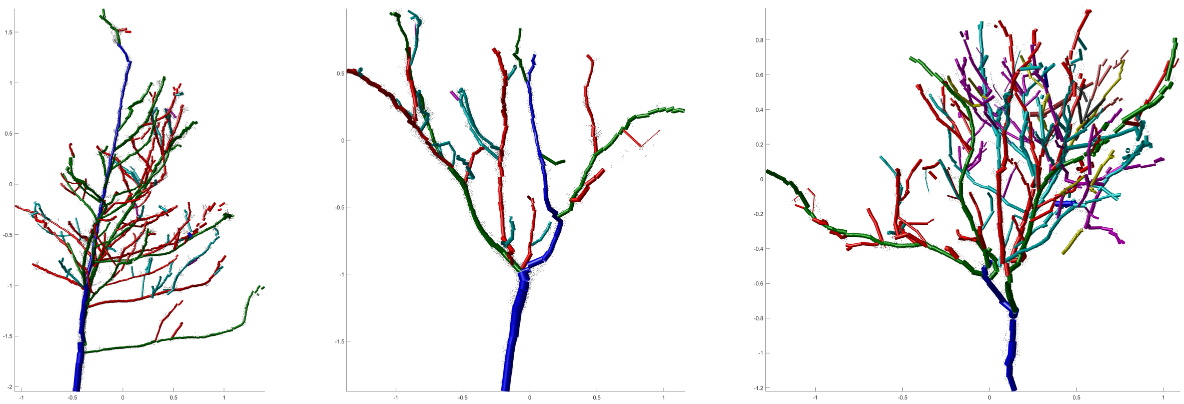


Figure 5.3: Quantitative structure models (QSMs) of three trees in plot R21 overlaid on their corresponding point clouds.

Volume calculations

The QSMs incorporate the volumes of different size of branches. The volume on plot level highly depends of the chosen branch diameter limit (Figure 5.4). The incorporation of the volume of branches that have a low diameter leads to an overestimation of the total volume (Demol et al., 2022). It is thus important to select an appropriate volume threshold. Here, the volume of branches with a diameter of 5 cm or more were taken into consideration, hence the inflection point of the graph is situated around this volume. However, it could be discussed to consider also branches with a diameter between 4 and 5 cm.

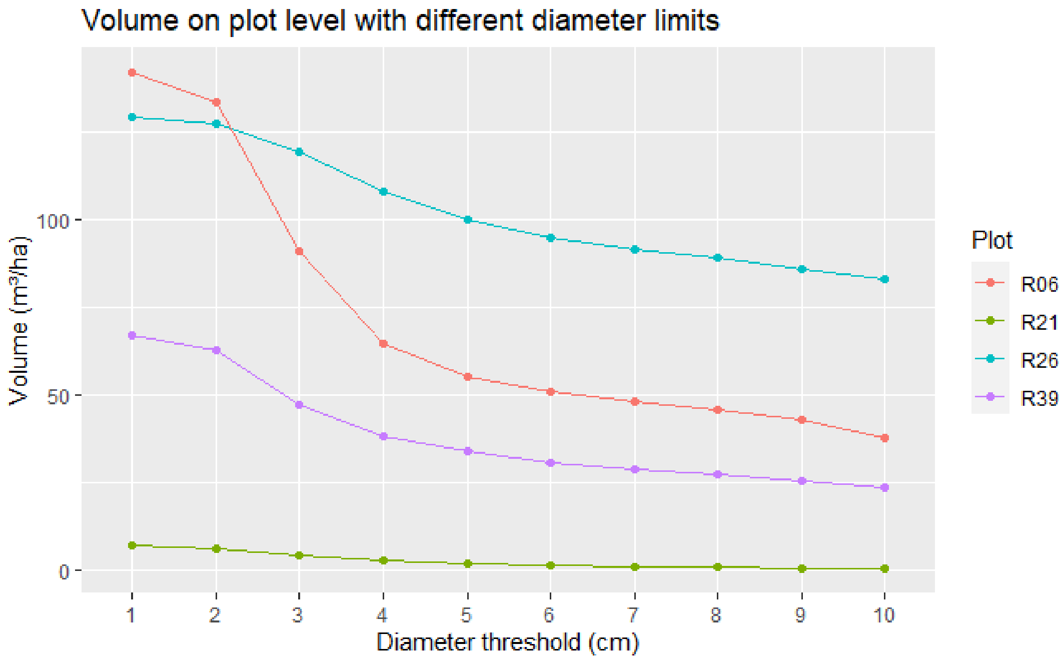


Figure 5.4: The total volume (m^3/ha) in function of the branch diameter threshold (cm).

5.3.2 Evaluation of existing allometric equations

The estimates of above-ground biomass (AGB) at tree level obtained using different allometric equations show significant divergence, particularly for larger tree diameters (Figure 5.5). The local allometry of González et al. (2018) approximates the AGB values the best, especially for larger DBH, but still overestimates the AGB. The second best approximation is by the equation of Chave et al. (2014). The allometric equations of Thierens (2017), Sierra et al. (2007), Ketterings et al. (2001) and Brown (1997) overestimate the AGB, mainly for trees with higher DBH, which is important since these trees have relatively higher contributions to the AGB at plot level.

Upon closer examination of the results for smaller trees with diameters between 5 and 10 cm, determining the most accurate allometric equation for estimating above-ground biomass (AGB) becomes more challenging. The estimates tend to converge more closely in this range. However, it is clear that the allometric equations proposed by Sierra et al. (2007) and Brown (1997) consistently overestimate the AGB.

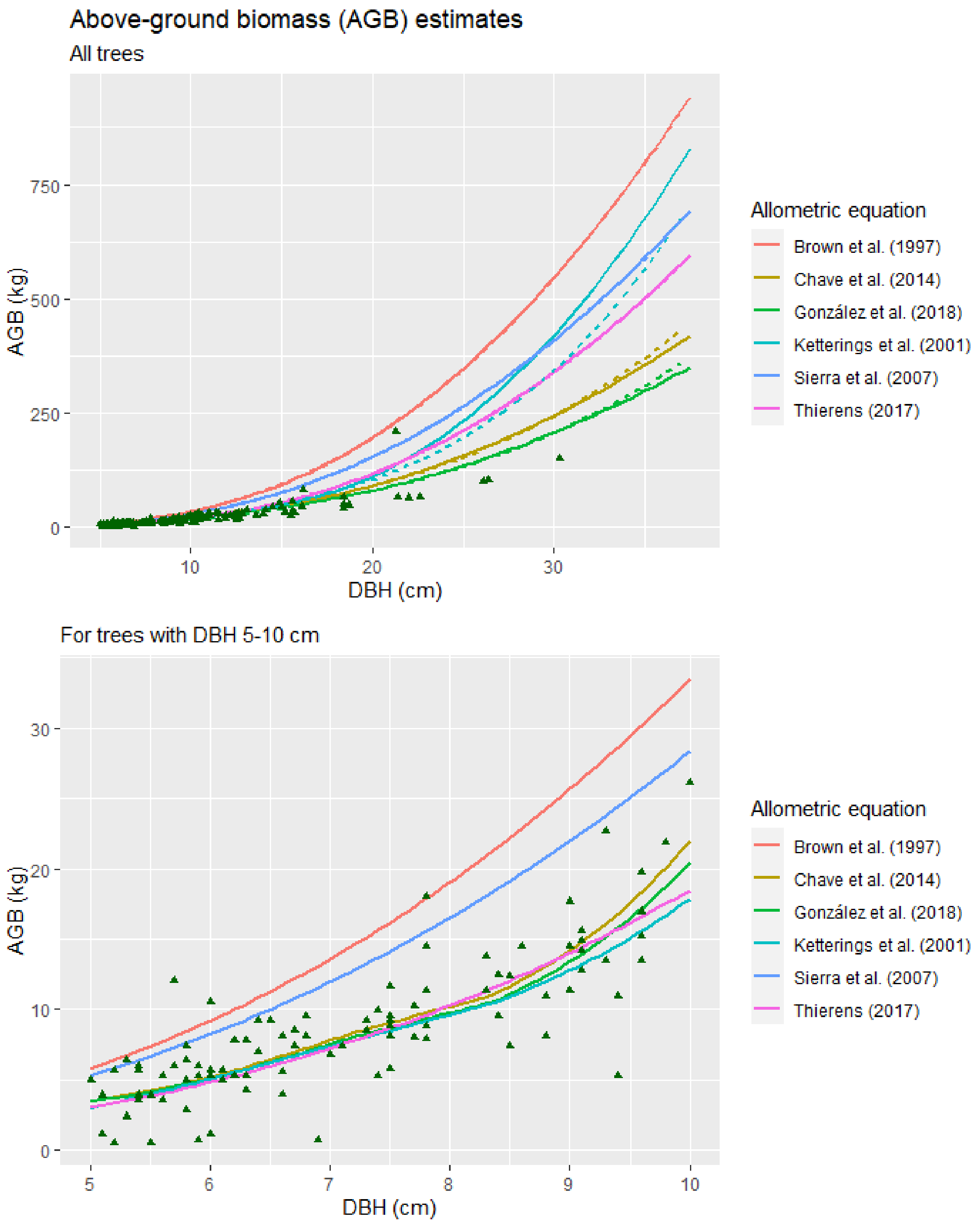


Figure 5.5: Above-ground biomass (AGB) estimates in kg with the allometric equations of Brown (1997); Chave et al. (2014); González et al. (2018); Ketterings et al. (2001); Sierra et al. (2007); Thierens (2017). Full lines are calculated with diameter at breast height (DBH) in cm and height (H) measurements of the inventory data (pathway 3) and dashed lines with DBH and H measurements of the TLS data (pathway 2). The AGB of the trees as a result of the QSMs, constructed with the TLS data (pathway 1), are plotted with green triangles. Wood density values are the means of the plots.

5.3.3 Construction of local allometric equations

All regression models fitted to the TLS data are statistically significant (Table 5.1). Model 1 has the highest R-squared and is therefore the best model. This model is only slightly better than the frequently used allometric equation of Chave et al. (2014), that has an R^2 of 0.957 for this study.

The higher the amount of variables incorporated in a model, the better its performance. The simplest model, with only DBH as a variable, has the least accurate above-ground biomass estimation.

Table 5.1: Regression models equations for estimation of individual tree above-ground biomass (kg). All regression equations fitted to the TLS data are statistically significant ($p < 0.001$). The variables are diameter at breast height (DBH) in cm, height (H) in m and wood density (ρ) in g/cm^3. Parameters a, b and/or c are estimated and R^2 indicates the goodness of fit of the model.

No.	Regression model	Parameter(s)	R-squared
1	$AGB = a \cdot (DBH^2 \cdot H \cdot \rho)^b$	a = 0.0655 b = 0.9700	0.958
2	$AGB = e^{a+b \cdot \ln(DBH)}$	a = -1.5776 b = 1.9472	0.687
3	$AGB = e^{a+b \cdot \ln(DBH^2 \cdot \rho)}$	a = -1.5494 b = 1.2097	0.937
4	$AGB = e^{a+b \cdot \ln(DBH^2)+c \cdot \ln(\rho)}$	a = -1.4115 b = 1.2086 c = 1.3415	0.940

The most accurate estimation of the AGB (kg) at tree level (model 1) is obtained with three variables: diameter at breast height (cm), height (m) and wood density (g/cm^3), with the equation:

$$AGB_{tree} = 0.0655 \cdot (DBH^2 \cdot H \cdot \rho)^{0.970}$$

5.4 Carbon stocks and carbon dioxide equivalents

5.4.1 Cumulative above-ground biomass

The four constructed models and the allometric equation of (Chave et al., 2014) are used to estimate the above-ground biomass of all trees (DBH ≥ 5 cm) in the COFOREC II project in south Ecuador (pathway 4). The area of all plots is 4.48 ha.

The cumulative AGB of the inventory trees, divided by 4.48 to rescale the AGB to ton per hectare, is highly dependant on the selected model (Figure 5.6). However, all models show that the largest part of the AGB is determined by the largest trees (steep increase in the beginning). When smaller trees are added to the cumulative AGB, it does not lead to a big increase of the total AGB.

Model 3 and 4 indicate higher AGB than Chave et al. (2014) and model 1 and 2 result in less AGB per hectare. The best model is model 1, but some models have very similar R^2 so it is not clear what the effective AGB is. The AGB will probably be situated in the range of the outcomes of the different models, i.e. between 26 and 38 ton/ha.

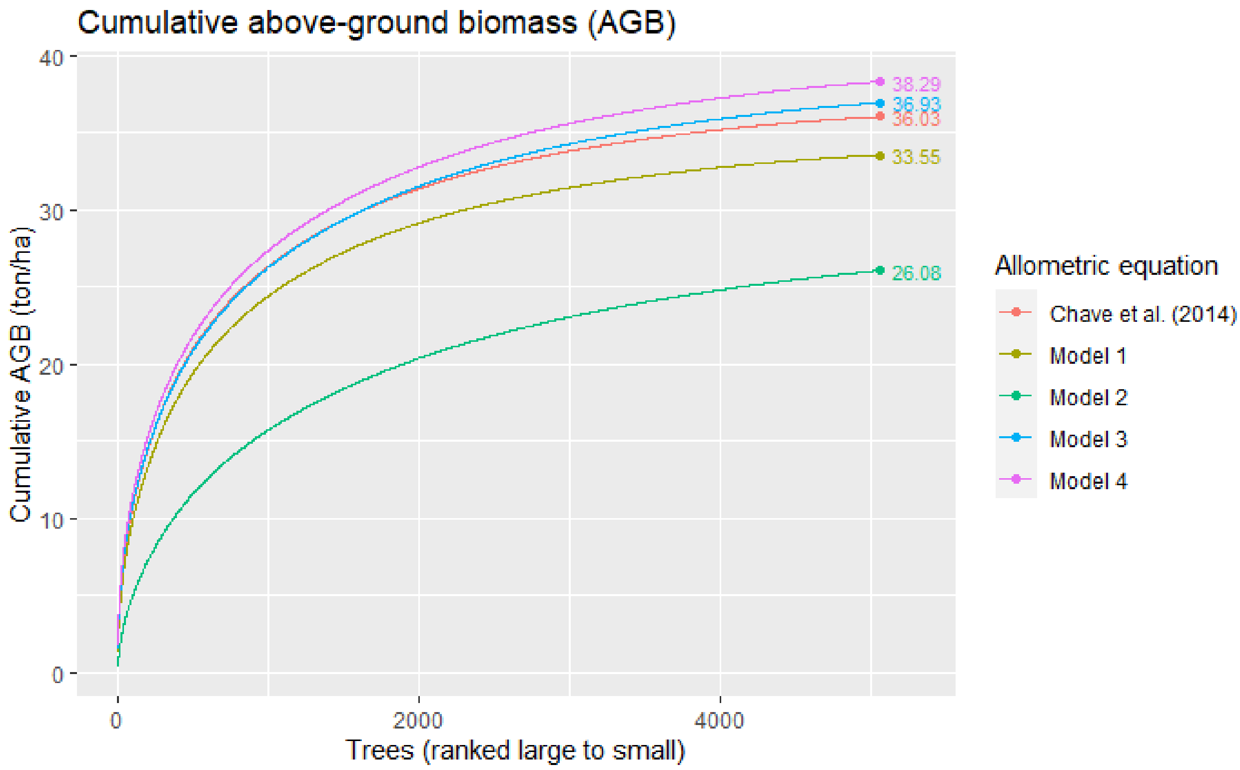


Figure 5.6: Above-ground biomass (AGB) (t/ha) of all trees (DBH ≥ 5 cm) in the COFOREC II project, South Ecuador, as a result of estimates with the four models of the study and Chave et al. (2014) as a reference. The AGB of 5056 trees (t/ha) of the inventory data are ranked from high to low AGB.

5.4.2 Carbon dioxide equivalents

The above-ground biomass is used to determine the below-ground biomass, carbon stock and CO_2-equivalent (Table 5.2). The CO_{2e} ranges from 63.82 to 93.70 tCO_2. This study's best model, model 1, is only 93% of the outcome of Chave et al. (2014), while the second best model, model 4, is 106% of Chave's outcome.

Table 5.2: Average above-ground biomass (AGB), below-ground biomass (BGB), carbon stocks (C_{stock}) and CO_2-equivalents (CO_{2e}) per hectare of the observational plots of the COFOREC II project in the south of Ecuador, as a result of different allometric equations.

Equation	AGB (t/ha)	BGB (t/ha)	C_{stock} (tC/ha)	CO_{2e} (tCO_2/ha)	Relative to Chave et al. (2014) (%)
Chave et al. (2014)	36.03	15.13	24.05	88.17	100.00
Model 1	33.55	14.09	22.39	82.10	93.12
Model 2	26.08	10.95	17.41	63.82	72.38
Model 3	36.93	15.51	24.65	90.37	102.50
Model 4	38.29	16.08	25.55	93.70	106.27

6. DISCUSSION

6.1 Bottlenecks and opportunities of TLS

6.1.1 Data collection

One drawback of TLS is the use of expensive and heavy materials. The scanner and its supporting materials have a high cost and can weigh over 20 kg, resulting in difficult transport (Newnham et al., 2012). Another disadvantage is the strong dependency on weather conditions (Wilkes et al., 2017). Raindrops can interfere with laser beams and branches moving in the wind and produce a ghosting effect in the resulting point cloud. Scanning can only continue when leaves are dry and wind speeds are low (Seidel et al., 2012; Wilkes et al., 2017). Consequently, field campaigns are best planned during dry seasons.

Additionally, TLS is not universally applicable to all forest types. Trees must have a certain volume to obtain qualitative data. An attempt was made to scan newly planted plots to determine the initial biomass, but due to the small size of the trees (height < 1 m), the samplings were too subject to movement by the wind, even in calm conditions. Furthermore, the presence of similarly sized grass made it difficult to differentiate the seedlings. Dense, shrubby forests also pose a challenge, as finding suitable positions for the scanner without obstruction becomes problematic. Moreover, steep slopes introduce difficulties, as the scanner needs to be positioned nearly level and its downward view is limited, making it harder to place the retro-reflective targets. However, newer scanners that no longer require these targets can solve this issue.

In conclusion, data collection using TLS presents several challenges, including the high cost and weight of the equipment, weather dependency, limited applicability to certain forest types and difficulties posed by topography. Despite these limitations, TLS offers the advantage of collecting highly detailed data that provides numerous opportunities for ecological research.

6.1.2 Data processing

Tree segmentation

Even though the tree segmentation is done manually and has high accuracy, there are some limitations. It is a very time consuming process and in dense forests it is sometimes hard to differentiate which points belong to which tree. Some floating or stand alone points can be attributed to the wrong tree or missed causing inaccurate individual tree point clouds.

Besides, trees with a DBH of less than 5 cm may have been overlooked and therefore not segmented.

Additionally, the trees on the edges are a source of uncertainty. In field inventories there is an existing protocol on what to do with trees that are situated on, or close to the border of the plot. In the three dimensional point cloud, the exact borders of the plot or not visible, leading to the falsely incorporation or exclusion of some trees that may have large contribution to the AGB at plot level.

Diameter and height measurements

The unexpected significantly higher DBHs in plot R36 of the TLS data compared to the inventory data could be due to difficulties delineating the plot. In TLS data the edge is not clear, leading to the incorporaton of more, larger trees in the data set, while they are in fact not in the inventory. It could also be because of incorrect measurements in the field. Since the amount of trees in the inventory data and in the TLS data is almost the same, the difference in diameter measurements is attributed to measurement errors during the field campaign of the inventory. Nevertheless, field campaigns are in general able to measure DBH in an accurate way.

It is not straightforward to draw conclusions on the accuracy of the height measurements since the gap in time. The higher tree heights of the TLS data in plots R21, R26 and R39 could be attributed to growth only, or to a combination of growth and incorrect height measurements. The lower heights in plot R6 with the TLS data of 2022 compared to the inventory data of 2021 could be explained by the fact that this plot is very dense, resulting in incorrect height measurements of both methods due to occlusion. Height measurements remain an uncertain factor in the estimation of biomass, especially in dense forests with high crown closure.

Above-ground biomass estimates

The quality of the AGB estimates depends highly on the quality of the data. In dense forests with a lot of occlusion, the terrestrial scanner is not always able to obtain qualitative data of the top of the canopy. This is an important downside not only for the construction of QSMs for AGB estimates, but also for height measurements. Some allometric equations include height as a parameter, but one should be aware of the high uncertainty that goes with height measurements in the tropics. It would be useful to have height measurements from the same year to assess the error in this parameter, as TLS is capable of producing accurate height measurements in less dense forests (Wang et al., 2019b). However, obtaining reliable height data in young plantations can still be challenging.

One bottleneck, typical for tropical forest is the uncertainty of the leaf-wood separation process. In temperate forests, the scanning is done in leaf-off conditions, but this is not possible in tropical forests with evergreen species. Therefore it is important to use an accurate and robust leaf-wood separation method in order to be able to estimate the volume of the woody biomass (Tian and Li, 2022b).

Another important factor of uncertainty is the branch diameter threshold of the volume estimation with QSMs. If branches with a very small volume are considered, the AGB is overestimated. Branches with a diameter of less than 5 cm can account for 80% or more of the overestimation (Demol et al., 2022). Demol et al. (2022) attribute the overestimations primarily to scanner characteristics and co-registration errors rather than to suboptimal QSM parameterisation. It could be interesting to determine the volume of some trees after having scanned them with a destructive method and compare the results with the QSM volume with different diameter thresholds to check which threshold leads to the best estimation.

Another issue is related to trees that have a more "bushy" appearance. It was not possible to make QSMs of *Escallonia* spp., the species that covered the center part of plot R6, due to a high degree of branching. Developing TLS-based species specific allometric models is not manageable for this kind of trees and here, it may be necessary to develop models with a destructive method.

6.1.3 Data interpretation

If the inventory data would include GPS coordinates or the x-y coordinates of the trees within the plot, it would be possible to connect the trees of the traditional inventory to the TLS-generated point cloud. This would enable a direct comparison of DBH and H measurements. Consequently, the accuracy of AGB estimates would be enhanced, as each tree could be assigned its specific wood density value, instead of relying on plot averages.

In general, it is important to be aware of the accumulated uncertainties associated with data collection and processing. Methodological differences, as well as assumptions of wood density create uncertainties in AGB estimates (Disney et al., 2019). Wood density can vary greatly depending on the region, species and the phylogenetic characteristics (Chave et al., 2006). To account for this variation, TLS data can be supplemented with wood density measurements, instead of using wood density values from literature.

6.2 Allometric equation

6.2.1 Evaluation of existing allometric equations

The performance of the different allometric models had some unexpected results. It was anticipated that the models developed specifically for secondary forests (Ketterings et al. (2001), (Sierra et al., 2007), (Thierens, 2017) and (González et al., 2018)) would consistently provide more accurate AGB estimates compared to the models of Chave et al. (2014) and Brown (1997) that are developed for mature forests, considering the distinct ecological characteristics of forest types.

Contrary to the expectation, Chave et al. (2014) showed better AGB predictions then most other allometric equations. Only the local allometric equation of González et al. (2018) had better AGB estimates. The high accuracy of the Chave et al. (2014) model can be attributed to its larger sample size (approximately 4000 trees) compared to the smaller sample sizes of the other models, typically around 150 trees.

The model developed by González et al. (2018) provides the closest approximation of the AGB in this study. This can be attributed to the fact that the model was established in the same region as this study. However, it appears that the model still tends to overestimate the AGB.

6.2.2 Improved allometric equation

The best equation to estimate the AGB at tree level of this study has an R^2 of 0.958 and the equation of Chave et al. (2014) has an R^2 of 0.957. The accuracy of the equations is very similar, but when estimates are made per hectare, the outcome is quite different. The AGB with this study's best model is only 93% if the outcome of Chave's equation, indicating that the equation of Chave et al. (2014) tend to overestimate the AGB, especially at plot level. The allometric equation of this study presents an improvement model, however further improvement is still possible. Only a few trees with larger DBH were incorporated in the model and they influenced the model highly, since they were identified as outliers. More data, especially of larger trees, will lead to improved allometric equations and above-ground biomass estimates.

6.2.3 Carbon credits

Ecuador has the goal to reforest 210 000 ha of cleared land, as noted in its Nationally Determined Contribution (NDC). To achieve its REDD+ action plan, it received more than 100 000 million USD from the Green Climate Fund (GCF) and from the governments of Germany and Norway (Serrano, 2022). A large capital is invested and can also be recovered through carbon credits.

Right before the Russian invasion in Ukraine, the value of carbon credits was the highest on the Emissions Trading System (ETS) of the European Union (World Bank, 2022b). One ton of CO_2 equivalent was worth approximately 109 USD or 100 euro in February 2022. Nowadays, the prices are slightly lower, but they are expected to rise, because of the increasing interests and efforts. The World Bank reported that the global carbon pricing revenue increased with 60% in 2021 compared to 2020, with a total revenue around 84 billion USD.

If the outcome of this study is extrapolated to the 210 000 ha of reforested area, an estimation of revenue through carbon credits can be made for the above- and below-ground carbon (1 tCO_2 = 109 USD). The carbon stock estimates 8 years after the reforestation is highly dependent on the selected allometric equation for AGB estimates. If the commonly used equation of Chave et al. (2014) is used, the reforested areas will be worth 1.851 billion USD in carbon credits. However, using the best model of this study results in 1.717 billion USD. This is a difference of almost 17 million USD per year. After all, all outcomes remain predictions and a large part of the carbon stock, the soil organic carbon, is not accounted for. This extrapolation is surely not an accurate estimate but it gives an indication of the range in outcome of several methods.

It is important to be aware of this uncertainty and use the most accurate equation possible when estimating the AGB. Local constructed allometric equations have the potential to be more accurate than pantropical allometric equations. For large reforestation projects, the costs of the use of TLS can certainly be justified, considering that this study, accounting the transportation and labour hours costed approximately 15 000 USD. A more elaborated set up, to have a larger sample data set, would also be defensible.

Overall, high-quality data contributions are crucial not only for financial considerations, but they also hold an enormous value for ecological research. TLS data can play a vital role in various studies investigating for example the links between carbon stock and functional traits, vertical structure, and even in comparative analyses of reforestation success across different regions.

7. CONCLUSION

The main objective of this research was to investigate the utility of terrestrial laser scanning (TLS) in the estimation of above-ground biomass, specifically in reforested areas in the south of Ecuador. TLS has shown many bottlenecks in young, dense forests. The disadvantages are mainly the high cost of the equipment and difficulties in data collection and processing. The challenges during data collection are the weather dependency and the limited applicability of TLS in newly planted areas and for species that have a shrubby shape. Data processing has shown difficulties in the tree segmentation step and the construction of the quantitative structure models (QSM). In plots with high occlusion, height measurements are inaccurate and some segmented trees do not have a complete point cloud. QSMs cannot be constructed for trees with missing parts, and neither for trees with a shrubby form. This indicates that for some species, TLS is not a useful tool to estimate the AGB and species-specific allometric equations should be constructed, using another, perhaps destructive method.

Despite the challenges that come with TLS, it is shown to be a good method to make improved above-ground biomass estimates of reforested areas using a local TLS-based allometric equation. Since quantifying AGB with TLS requires only a fraction of the efforts and time as compared to destructive harvesting, it can be a powerful tool in AGB upscaling. A local allometric equation is developed with higher accuracy than the commonly used pantropical allometric equation of Chave et al. (2014). However, the estimates with this equation are only slightly better than the ones with Chave's equation. The equation can be improved by enlarging the data set that it is fitted on, so it incorporates larger trees better, and more trees from different growing conditions are represented. Actually, 13 plots are scanned and pre-processed, but only four are segmented due to time constraints. TLS data of the remaining 9 plots is available for further tree segmentation and QSM construction. By doing so, the size of the data set could increase from 247 to approximately 400 trees. The plots are all situated in a quite small geographical area, so an even better allometric equation could be constructed for this region.

Improved allometric equations are important for better AGB and carbon stock estimates. It can influence the decision making process on where to primarily reforest in order to capture as much carbon as fast as possible and have the greatest climate mitigation effects. Besides, a more accurate estimation of the above-ground biomass leads to a more correct allocation of carbon credits. In that way, initiators are rewarded and motivated to carry out reforestation projects.

It is also important to have better carbon stock estimates to avoid an overestimation of the terrestrial carbon stock. This improvement is necessary to guide the implementation of effective nature restoration projects, which are vital for preventing a catastrophic climate collapse and addressing the ongoing biodiversity crisis.

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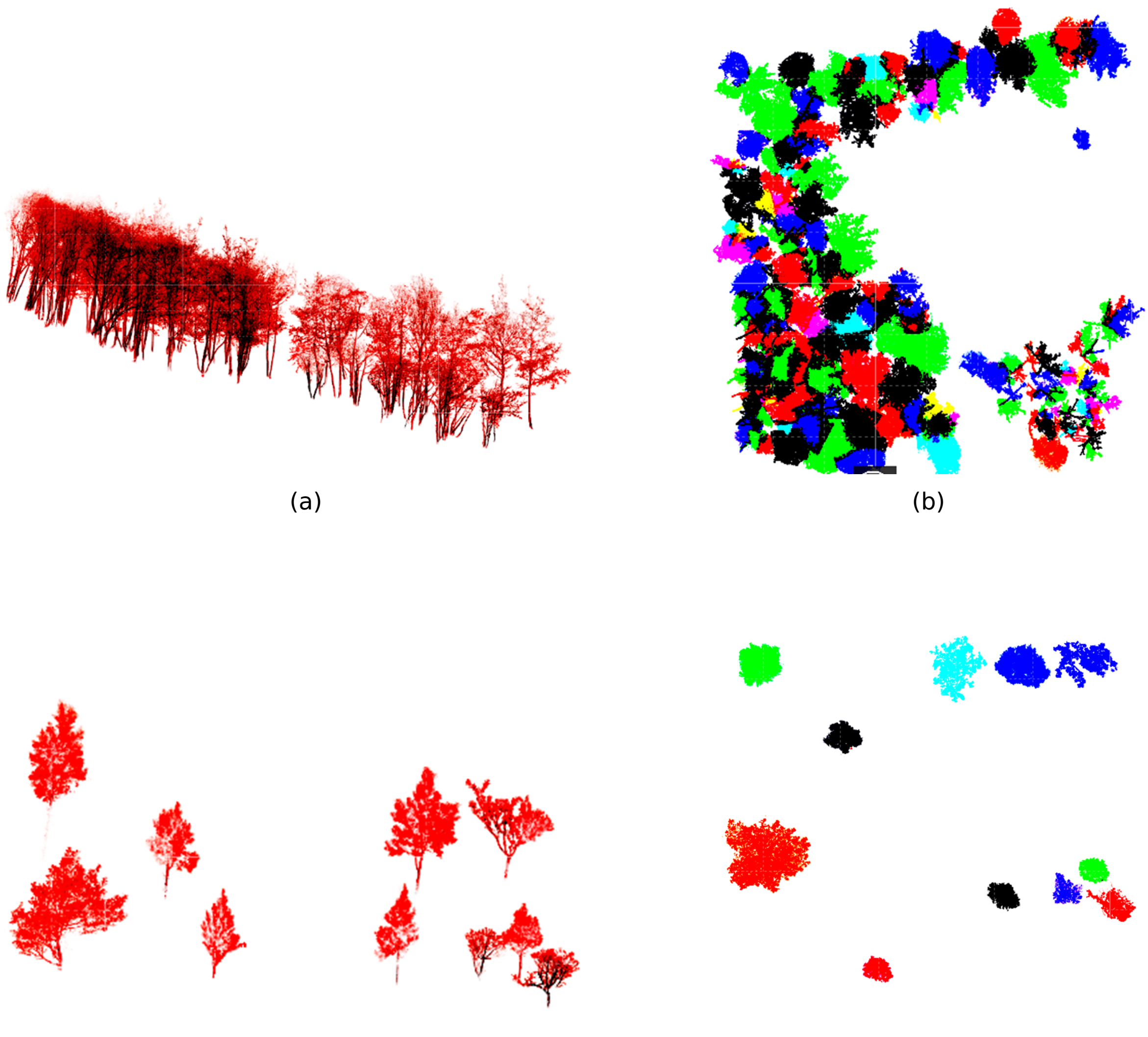
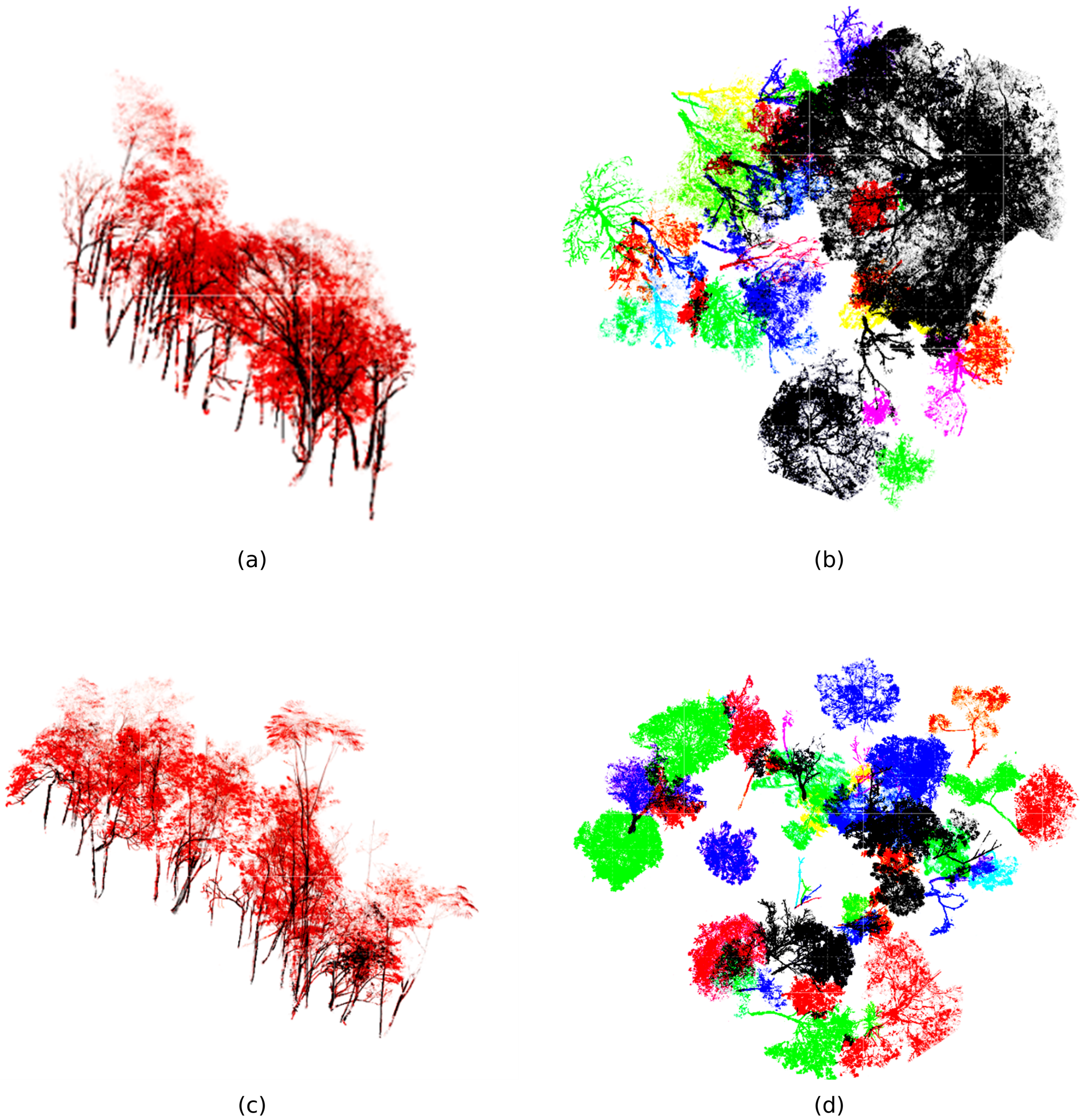
APPENDIX A



(a) (b) (c) (d)

Figure A.1: Segmented plots in the Azuay province: Santa Ana (R6) and San Rafael (R21) from two perspectives. (a) Side-view R6. (b) Top-view R6. (c) Side-view R21. (d) Top-view R21.



(a) (b) (c) (d)

Figure A.2: Segmented plots in the Zamora-Chinchipe province: San Francisco (R26) and San Zamora (R39) from two perspectives. (a) Side-view R26. (b) Top-view R26. (c) Side-view R39. (d) Top-view R39.