Suitability of vegetation indices for estimating above-ground biomass in a mixed-dipterocarp forest

Sarawak, Malaysia

1/9/2023

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Sarawak, Malaysia

An undergraduate thesis for the degree

Bachelor of Science in Forest and

Nature Management with a specialization in Tropical Forestry

University of Applied Sciences, Van Hall Larenstein

Colophon
Title: Suitability of vegetation indices for estimating above-ground biomass in a mixed-dipterocarp forest
Status: Final product
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Photo's: -
Map material: GIS
Thesis period: September 2022 – January 2023

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Preface

Before you lies the undergraduate thesis “Suitability of vegetation indices for estimating above-ground biomass in a mixed-dipterocarp forest”. This thesis was written to complete my bachelor's degree of science in Forest and Nature Management, with a specialization in Tropical Forestry at the Van Hall Larenstein University of Applied Sciences in Velp. The research and writing of this thesis were conducted from September 2022 to January 2023.

I could never have predicted all the exciting things I would experience when I started the study “Forest and Nature management”. I always wanted to travel to tropical countries, and this study allowed me to do so while learning about tropical ecosystems. My internship in Costa Rica was the first experience I had with a tropical country. I still consider this to be one of the best times in my life, during which I saw amazing wildlife, gained field experience, learned about different cultures, and met plenty of wonderful people. This internship prepared me for my final assignment, for which the present report was written. Traveling to a tropical country on my own was not something I ever expected to do when I started my study, however, this is exactly what I did. I spend about three months in Sarawak (Malaysia), during which field data was supposed to be gathered. Unfortunately, the fieldwork did not go as planned, due to the study area being inaccessible because of unfavourable weather conditions. Luckily, I was provided with data gathered in previous years, which I used to complete the present study. My time in Malaysia taught me a lot about myself, about traveling on my own in a completely foreign country, about dealing with setbacks when writing a report, and about another culture.

I would like to thank my supervisor Erika van Duijl for guiding me during my thesis, especially during the setbacks. I really appreciate the online meetings had when I was facing some setbacks while in Malaysia. Additionally, I want to thank Mr. Malcom Demies for guiding me during my stay in Malaysia, and for providing me with the opportunity to conduct my thesis at Forest Department Sarawak. I also want to thank all the staff members I met whilst working in the headquarters of Forest Department Sarawak for their kindness.

I also would like to thank my friends for their support and advise during the writing of this thesis. Finally, I want to thank my family as I don’t think I would have been able to achieve what I did without their patience and support.

Abstract

Forest inventories serve as a primary source for above-ground biomass and carbon stock estimations. These inventories, however, are costly and time-consuming especially over large areas with difficult terrain. Multiple remote sensing techniques can facilitate forest inventories with above-ground biomass assessments, one of these methods is the use of vegetation indices. However, studies have shown varying results on the effectiveness of vegetation indices for estimating above-ground biomass. The aim of the present study is to determine if the use of vegetation indices is a suitable method for above-ground biomass estimations in a mixed dipterocarp forest in Sarawak. The Aboveground biomass of 29 plots was measured, and these measurements were used to analysed the relationship between above-ground biomass and the reflection value displayed on vegetation indices. Regression analysis was performed on 11 vegetation indices, all of the analysed vegetation indices showed a weak and insignificant relationship with above-ground biomass. Out of all the analysed indices the RERVI had the strongest relationship with above-ground biomass, with an R2 value of 0.05. The results found in the present study indicate that the analysed vegetation indices are not suitable for estimating above-ground biomass in a mixed dipterocarp forest in Sarawak. This study, therefore, concludes that vegetation indices are not a useful tool for aboveground biomass and aboveground carbon stock assessments in a mixed dipterocarp forest in Sarawak.

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List of Abbreviations

AGB	Above-ground biomass
ALS	Airborne laser scanner
BGB	Below-ground biomass
C	Carbon
CO2	Carbon dioxide
DBH	Diameter at breast height
DME	Distance measuring equipment
EVI	Enhanced vegetation index
GIS	Geographic information system
GHG	Greenhouse gases
GVI	Greenness vegetation index
IPCC	Intergovernmental Panel on Climate Change
LiDAR	Light detection of laser imaging and ranging
MAVI	Moisture adjusted vegetation index
MDF	Mixed dipterocarp forest
MVI	Moisture vegetation index
NDVI	Normalized difference vegetation index
NDVIre2	Normalized difference vegetation index red-edge 2
NIR	Near infrared
Pg	Petagrams
RENDVI-2	Red edge normalized difference vegetation index-2
RERVI	Red-edge ratio vegetation index
RDVI	Renormalized difference vegetation index
REDD+	Reduction of emissions from deforestation and forest degradation
SAVI	Soil-adjusted vegetation index
SNAP	Sentinel application platform
SR	Simple ratio
SWIR	Short-wave infrared
TLS	Terrestrial laser scanner

1. Introduction

Developing suitable methods for estimating above-ground forest biomass on large scale is becoming increasingly important. Vegetation indices could potentially play a vital role in assessing forest above-ground biomass. However, the capability of vegetation indices to estimate above-ground biomass in different forest types remains inconsistent.

1.1 Background

The increase of greenhouse gases (GHG) in the atmosphere and their effects on the global climate is one of the biggest environmental concerns in current times. Specifically the rise of carbon dioxide (CO_2) which has been linked to an increase in mean global temperature (Ledley et al., 1999). According to Grace (2004), 60% of the increase in global temperatures is caused by an increase in CO_2. This rise of global temperature has devastating effects for both the environment and humans such as; rise in sea-level, heavy precipitation, drought and precipitation deficits, and an increase heat waves (IPCC, 2018). The most recent climate change report from the Intergovernmental Panel on Climate Change (IPCC) states that these extreme weather event have already impacted ecosystems, humans, settlements, and infrastructure (2022a). According to the report climate change has reduced food and water security, negatively affected human physical and mental health, and caused economic damages. Considerable damages have also been observed in ecosystems, with some showing an increase in irreversible losses. These damages and losses also affect humans, especially those whose livelihood depends on these ecosystems. Furthermore, the report states that if the rise in global temperatures continues climate hazards will increase which will strongly impact humans and ecosystems. In response to concerns about these rising temperatures and their effects more focus has been placed on methods that can assists with the removal of CO_2 from the atmosphere.

Currently, the only widely practiced methods that focus on the removal of CO_2 out of the atmosphere are related to forestry. These methods include; afforestation, reforestation, improved forest management, agroforestry, and soil carbon sequestration (IPCC, 2022b). Within these forests, five major carbon pools can be found: (1) above-ground biomass (AGB), (2) below-ground biomass (BGB), (3) deadwood, (4) litter, and (5) soil carbon (IPCC, 2006). Forests have the highest global contribution to biomass, 92% of all biomass is stored within forests (Pan et al., 2013) . The world's forest carbon stock is estimated to be 861 petagrams (Pg), with the highest amount (471Pg) found in tropical forests (Pan et al., 2011). In addition, the report also estimates the world's forests to serve as a carbon sink of 2.4Pg per year. The earth's surface consists of 31% of forests which is equal to 4.06 billion hectares, 46% of this surface consists of tropical forests (FAO, 2020). Despite covering about one third of the earth's surface, the contribution of forests to the global carbon stock is enormous. Xu et al. (2021) estimated that the world's forest contribute to about 72% of the total global carbon stock. Tropical forest contribute to almost half (47%) of the total global carbon stock, with 40% found in moist tropical forest and 7% in dry tropical forests. Tropical forests are the most carbon-dense forests in the world, which gives them the highest potential for carbon sequestration (Goodman & Herold, 2014).

Estimations of carbon stocks within a forest are essential for monitoring the carbon fluxes in a forest, these estimations also show the potential of forests to serve as a carbon sink (Vashum & Jayakuma, 2012). Carbon stock estimations and understanding of the sources and sinks help to improve carbon flux models, which are needed to improve projections of climate change and impacts (Kumar & Mutanga, 2017). In addition, carbon stock assessment is needed for most financing schemes and incentives such as reduction of emissions from deforestation and forest degradation (REDD+) (UNFCCC, 2016). To be able to estimate the amount of carbon stored within a forest, the mapping and monitoring of the forest biomass are needed (Koch, 2010).

Carbon stock estimations can be derived from destructive and non-destructive field measurements. The destructive method consists of harvesting and measuring all trees within a certain area. This method is highly accurate, however, this method is time-consuming, expensive, destructive, and impractical (Gibbs et al., 2007). Destructive measurements are mainly used to develop allometric equations, which can be used to estimate the AGB with non-destructive field measurements. The carbon present in the above ground part of trees can be derived from these AGB estimations. During non-destructive field measurements, specific tree properties are measured for each tree within a plot (e.g. tree species, height, diameter at breast height). Data gathered in the field can be converted into biomass/carbon with the use of allometric equations. However, estimating biomass over large areas with the use of forest inventories is labour intensive, costly, and time-consuming.

Remote sensing may facilitate forest inventories with these estimations since remote sensing offers multiple techniques which can quickly estimate biomass at a relatively low cost (Kumar et al., 2015). Because of its many advantages, the combination of field data with remote sensing , is seen as the primary source for estimating AGB over a large area (Lu, 2006). According to McRoberts & Tomppo (2007), there are four primary ways in which remote sensing enhances national forest inventories; (1) reduces costs and time spent on forest inventories, (2) Increases the precision of inventory estimates, especially over larger areas, (3) estimates forest characteristics with acceptable bias and precision for small areas with insufficient field data, (4) Produces thematic maps of the forest which are useful for management strategies.

Optical remote sensing, LiDAR, and radar have all been used for biomass estimations. Kumar et al. (2015) state that these different techniques have many potential benefits for estimating biomass however, the usefulness of each technique varies per circumstance. Optical remote sensing techniques are often used in forestry due to the high availability of free medium resolution spatial and temporal data. Numerous studies have been conducted where optical remote sensing techniques are used to estimate biomass (Steininger, 2000; Foody et al., 2003; Lu et al., 2004). One optical remote sensing technique commonly used for estimating biomass is vegetation indices. These indices calculate a single value for each pixel in an image by transforming two or more spectral bands. The purpose of a vegetation index is to highlight certain plant properties while minimizing the effects of other factors such as; soil-background reflectance, directional, or atmospheric effects (Fang & Liang, 2014). In the past decades, many vegetation indices have been developed and used for estimating biophysical parameters. Lu et al. (2004) state that the impact environmental conditions and shadows have on the reflectance value can in part be reduced by vegetation indices. This improves the correlation between AGB and vegetation indices, specifically in areas with complex vegetation structures.

The most well-known vegetation indices focus on the ratio or difference of light reflected in the red and near-infrared (NIR) part of the electromagnetic spectrum. Vegetation indices that use red and NIR bands to estimate biophysical properties have been used to estimate biophysical properties of temperate forests. However, these indices have shown little success in estimating biophysical properties of tropical forests (Foody et al., 1996; Foody et al., 2001). Boyd et al. (1999) suggest that indices which include the middle-infrared (MIR) reflectance show a stronger relationship when estimating biomass in tropical forests. Freitas et al. (2005) determined that vegetation indices which included the Short-wave Infrared (SWIR) or MIR bands showed the best performance for estimating biophysical parameters in humid forests.

Significant correlations have been established between AGB and vegetation indices in previous studies (Zheng et al., 2004; Heiskanen, 2006; Das & Singh, 2012). However, the strength of the correlation between vegetation indices and biomass strongly varies per location and vegetation type (Foody et al., 2003). Therefore, the result obtained in these studies are mainly applicable in areas which have similar vegetation types. Determining the suitability of vegetation indices to estimate biomass in a specific location is needed before this remote sensing technique can be applied to assist forest inventories.

1.2 Problem statement

Vegetation indices may facilitate forest inventories with AGB estimations. However, research done on the relationship between AGB and vegetation indices have varying results. Heiskanen (2006) conducted research in a pine forest in Finland, a strong relationship was observed between AGB and vegetation indices. The simple ratio (SR) showed the strongest linear relationship ($r^2 = 0.903$), while the Normalized Difference Vegetation Index (NDVI) showed the strongest non-linear relationship ($r^2 = 0.890$). Das & Singh (2012) tested the relationship in a moist deciduous and semi evergreen forest in India. They concluded that all six of the analysed indices were useful for biomass estimations, with the strongest relationship ($r^2 = 0.785$) found for the Ratio vegetation index (RVI). (Thakur et al., 2019) found a good relationship ($r^2 = 0.792$) between biomass and the NDVI in a dry tropical forests in India. Foody et al. (2001) analysed vegetation indices for tropical forests in the North-eastern part of Borneo. This report determined a weak and insignificant relationship between forest biomass and the analysed vegetation indices. Lu et al. (2004) analysed the correlation of 23 vegetation indices in 3 different study areas in the Brazilian Amazon basin. The conclusion of this report was that not all of the analysed indices showed a significantly relationship with AGB, Landsat band TM5 did show to be strongly correlated with forest parameters. This study also indicates that the strength of the correlation between AGB and vegetation indices strongly varied depending on the stand structure of the forest. Foody et al. (2003) analysed the transferability of predictive relations for estimating biomass with the use of vegetation indices. This research concluded that a vegetation index might accurately estimate a biophysical property of interest for a specific region however, this does not assure universal applicability. Lu (2006) also states that determining the most suitable vegetation index for a specific location is an important part of the process of remote sensing-based AGB estimation.

The issue that arises when using vegetation indices for AGB estimations is that the results are site dependent. Therefore, results obtained in one area cannot automatically be applied to another. This means that the usefulness of vegetation indices for estimating AGB also varies depending on the location and forest type in which the indices are analysed. The aim of this research is to determine the suitability of vegetation indices for estimating the AGB, and aboveground carbon stock in a mixed dipterocarp forest (MDF) in Sarawak.

The results of the present study could serve as an indication for the Forest Department Sarawak on the usefulness of vegetation indices for estimating AGB in mixed dipterocarp forests. This could serve as an argument for the inclusion of vegetation indices to facilitate forest inventories with forest biomass and carbon assessments.

1.3 Research objectives

The main objective of the present study is to determine if vegetation indices are a suitable predictor of AGB in a mixed dipterocarp forest in Sarawak. This research will answer the following main research question;

Which of the analysed vegetation indices is most suitable for estimating above-ground biomass in a mixed dipterocarp forest?

The following sub-research questions will also be answered;

- Which vegetation indices have the highest potential to have a strong relationship with above-ground biomass in a mixed dipterocarp forest?
- What is the average reflection value for each of the analysed vegetation indices in each plot
- How much above-ground biomass (Mg ha^{-1}) is stored in each of the analysed plots?
- Which of the analysed vegetation indices shows a significant relationship with above-ground biomass in a mixed dipterocarp forest?

2. Methods and materials

This chapter of the report gives a brief overview of the study area and discusses the methods and materials used during the present study. The study area section describes features of the study area such as; location, topography, climate, and forest type. The first section of the method will discuss how the satellite images were acquired, and how the vegetation indices with the highest potential were selected. This section is followed by information on the field data that was used in the present study, and the location of the plots. The next section includes information on the design of the plot, and the sample methods used to establish the plots. This is followed by information on how the tree measurements were conducted. The next section discusses which formulas were used to estimate the AGB of the measured trees. The final section of the methods will discuss how the regression analysis will be performed. The material section will list all materials that were used during the present study.

2.1 Study area

Malaysia is comprised of 3 federal territories and 13 states, the states are divided into districts. Within the Sarawak state, these districts are grouped into larger administrative components called divisions (Britannica, n.d.). This research was conducted in the following districts; Selangau, Tatau, Song, and Kapit (figure 1).

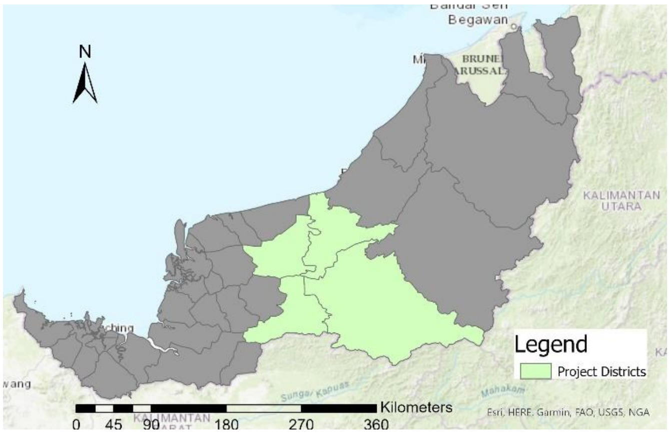

Figure 1: Districts study area

2.1.2 Climate

Sarawak has an equatorial climate with temperatures ranging between 23°C to 32°C, and humidity levels ranging between 80 to 90 percent. The districts have an annual rainfall of about 3,000 millimetres, with November being the month with the most rain (Weatherbase, n.d.).

2.1.3 Forest type

This research was conducted in a mixed dipterocarp forest, about 80% of all natural forests in Sarawak consist of this forest type. mixed dipterocarp forest have a high diversity, with many commercially valuable tree species. This forest type is grouped into lowland (0-300m), hill (301-750m), and upper (751-1200m) mixed dipterocarp forest, depending on the elevation (Forest Department Sarawak, 2021). Figure 2 gives an overview of the locations of all different forest types found in Sarawak, table 1 gives an overview of the total area for each of the forest types.

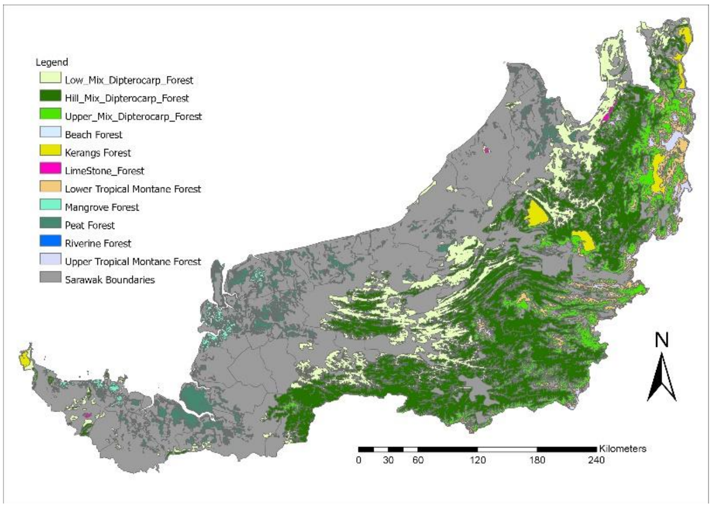

Figure 2: Forest types found in Sarawak

Table 1: Total Area forest types Sarawak

Forest type	Area (ha)	Percentage of forest area
Low Mixed Dipterocarp Forest	1,388,890	20,234%
Hill mixed Dipterocarp	2,967,280	43,228%
Upper Dipterocarp Forest	1,069,410	15,579%
Beach Forest	190	0,003%
Riverine Forest	170	0,002%
Mangrove Forest	107,130	1,561%
Peat Forest	689,000	10,038%
Kerangas	136,050	1,982%
Limestone Forest	10,860	0,158%
Lower Tropical Montane Forest	365,880	5,330%
Upper Tropical Montane Forest	129,390	1,885%
Total	6,864,250	100%

2.2 Methods

2.2.1 Satellite image acquisition

The Sentinel-2 images used in the present study were obtained from Copernicus open-access hub (ESA, n.d.). A polygon was drawn so that only satellite images of Sentinel-tile 49NFC and 49NGC were selected. An additional filter of a cloud cover between 0 and 20 percent was applied to obtain images that are largely cloud-free. The acquisition date was set between January 1st, 2017- and January 1st, 2021. This resulted in some variance between the acquisition date of the Sentinel-2 images and the date on which the fieldwork took place. This was not considered to be an issue because changes in biomass over a three-year period are minimal in general circumstances. Sentinel-2 images of the project area were selected if at least 80 percent of the plots were not covered by clouds, or covered by the shadow of a cloud.

Atmospherically corrected products (2A) with an acquisition date of the 23rd of July 2018 were used in the present study. This acquisition date was the only time between January 1st, 2017- and January 1st, 2021 on which both the Sentinel-tile 49NFC and 49 NGC were mostly cloud-free. Therefore, the images obtained on this acquisition date were deemed most suitable as input for the vegetation indices.

2.2.2 Vegetation indices

A literature review was conducted to determine which vegetation indices were most suitable to be analysed in a mixed dipterocarp forest. The vegetation indices were selected based on results obtained by other research in a similar forest type and climate.

At first, a more general search was applied, in which vegetation indices were considered to have potential in a mixed dipterocarp forest if they complied with one of the following two criteria. The first criterion which deemed an index suitable was if the index had shown a strong relationship with AGB in humid tropical forests in previous studies. The second criterion considered a vegetation index suitable if the index included bands that showed potential in humid tropical forests. Therefore, for some of these indices, the relationship with AGB in humid forests had not been analysed in previous studies. The inclusion of these indices was solely based on the bands used as input, which had shown to be sensitive in humid tropical forests. Some of the keywords used to find these indices were as follows; “biomass” “vegetation indices” “tropical forests”, “biomass” “vegetation indices” “humid forests”, “biomass” “vegetation indices” “humid tropical forests”, “AGB” “vegetation indices” “tropical forests”, “biomass” “SWIR” “tropical forests”, and “biomass” “MIR” “tropical forests”.

After the general search was done a more specific search was conducted, in which the focus was placed on vegetation indices that showed a strong relationship with AGB in a mixed dipterocarp forest. This search was more specified into vegetation indices that showed potential in a mixed dipterocarp forest in Malaysia. The keywords used to conduct these specific searches were as follows; “AGB” “vegetation indices” “mixed dipterocarp forest”, “biomass” “vegetation indices” “mixed dipterocarp forest”, “biomass” “VI’s” “mixed dipterocarp forest”, "vegetation indices" "biomass" "Malaysia", “biomass” “vegetation indices” “mixed dipterocarp forest” “Malaysia”, “biomass” “vegetation indices” “mixed dipterocarp forest” “Sarawak”, and “biomass” “vegetation indices” “mixed dipterocarp forest” “Borneo”.

The vegetation indices selected for the present study were calculated using the raster calculator in ArcGIS Pro. A spatial resolution of 20 by 20 meters was used for all of the analysed indices.

2.2.3 Field data

The study area was inaccessible during the period in which the fieldwork was planned, due to unfavourable weather conditions. Therefore field data collected in previous years was used for the present study. The Database was gathered during a project conducted by Van Hall Larenstein University of Applied Sciences for Sarawak Forestry Corporation (van der Meer et al., 2021). The database consisted of 110 main plots, each main plot consisted of two sub-plots and two sapling plots. The database contained the following forest types; Beach forest, low MDF, hill MDF, upper MDF, low montane, planted forest, oil palm plantation, mangrove, and peat forest. The field inventories were conducted throughout Sarawak in different forest types between October 2017 and March 2020. The present study focuses on mixed dipterocarp forests, therefore the following forest types were included in the results; low mixed dipterocarp forests, hill mixed dipterocarp forests, and upper mixed dipterocarp forests.

Out of the 110 plots, 88 consisted of mixed dipterocarp forests. Most plots were located in hill MDF (41) followed by low MDF (28), upper MDF contained a total of 17 plots.

All mixed dipterocarp forest plots located within Sentinel-2 tile 49 NFC and 49 NGC were used in the present study (figure 3). These Sentinel-2 tiles seemed most suitable because the acquisition date of these tiles is on the same day, therefore the images were obtained in the same atmospheric conditions. In addition, a relatively large part of the plots (31/110) was centred within these Sentinel-2 tiles. Furthermore, obtaining cloud-free Sentinel-2 images for the plots located in the north, northeast, and east of Sarawak was difficult due to the high cloud cover in these areas year-round. Table 2 gives a more detailed overview of the plot locations.

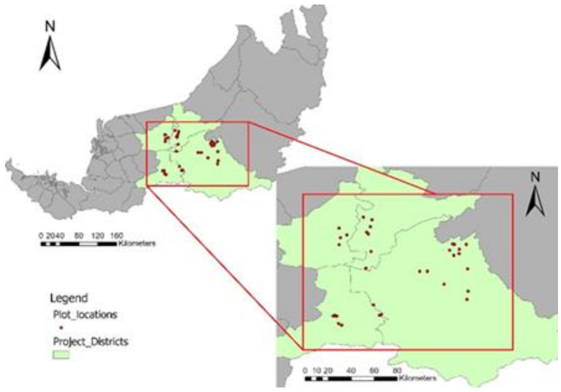

Figure 3: Plot location

Table 2: Details plot locations

Name District	Number of plots	Plot numbers	Division	Elevation range plots
Kapit	4	84,85,86,87	Kapit	151 - 486 m
Selangau	6	10,77,79,80,81,82	Sibu	107 - 474 m
Song	15	2,4,9,14,17 ,20 ,23 ,39, 49,51,69 ,70,71, 72, 73	Kapit	105 - 547m
Tatau	6	63,64,65,66, 67, 68	Bintulu	203 – 620 m

The database contained DBH and height measurements of living and standing dead trees. The vegetation indices analysed in the study mainly focus on the reflection caused by chlorophyll and water content in the leaves of living vegetation. Standing dead trees lack leaves therefore they have a limited contribution to the reflection value displayed on the vegetation indices. However, in some cases, they have a high contribution to the overall biomass within a plot. This high contribution in biomass while having a low contribution to the reflection value could result in inaccuracies when comparing the biomass to the reflection values. Therefore, all standing dead trees were excluded from the results.

Furthermore, the DBH and height measurements of the sapling plots (C) were incomplete for the following plots; 10, 14, 17, 20, 23, and 85. Because of this, AGB estimations of the sapling plots were not possible for these plots. Including AGB estimation of the sapling plot, while having incomplete data for some of the plots could lead to errors in the results. Therefore, AGB estimations of all sapling plots were excluded from the total AGB results. This meant that trees with a diameter at breast height (1.3 m, DBH) of 10 and above were included in the results.

2.2.4 Plot establishment

Distance measuring equipment (DME) was not used during the fieldwork, therefore the actual plot boundaries had to be established. Since plot boundaries had to be established, the decision was made to use rectangular shape plots, which in general are easier to establish, compared to circular plots.

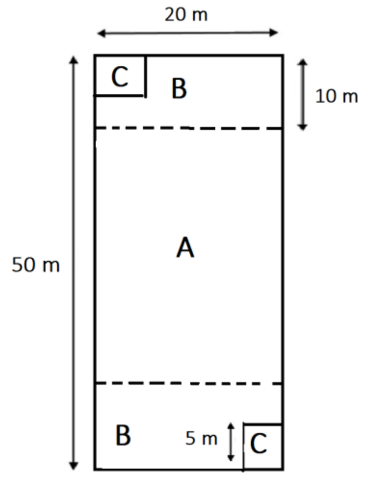

Figure 4: Plot lay-out

Rectangular-shaped plots of 20 by 50 meters (0.1 hectare) were during the field inventories. The plots were divided into a main plot (20 x 50 m), two subplots (2 x 20 x 10 m), and two sapling plots (2 x 5 x 5 m). An overview of the plot layout is shown in figure 4. The main plots included trees with a DBH of 30 cm or greater. Trees with a DBH ≥ 10 cm and < 30 cm were recorded in the subplots. Within the sapling plot, all trees with a DBH equal to or greater than 2 and smaller than 10 cm were recorded.

The sample plots used during the fieldwork were randomly selected with the use of ArcMap. Firstly the classify tool was used to determine the location of the logging roads within the study area, the logging roads were used to access the plot locations. To ensure easy accessibility, the randomly selected plots needed to be within a reasonable distance from the logging roads. Because of this, a buffer of 500 meters was placed around the logging roads. This buffer was used to ensure that the randomly selected plot would fall within a distance of 500 meters from the nearest access point. The potential sampling locations were created, with the create random points tool in ArcMap. However, the potential plots should not be located too close to the logging roads, since logging activities could cause disturbances to the plots. Therefore all points which were located within 80 meters of the centre of a logging road were removed from the potential plots.

Even though the original coordinate point was randomly selected, the placement of the other three corner points was done in the field. To avoid any bias when establishing the plot a set of rules was applied in the field when selecting the other corner points. The plot consisted of four corners; A, B, C, and D. The A-corner consisted of the original coordinate point that was randomly selected in ArcMap. The B-corner was placed directly east of the A-corner, the C-corner north of the A-corner, and the D-corner north of the B-corner (figure 5). The coordinates of each corner point were measured in the field with a handheld GPS.

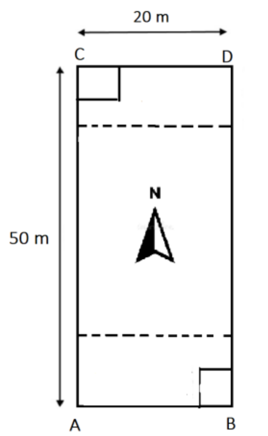

Figure 5: Plot Corner points

2.2.5 Tree measurements

All species within the plot were identified and recorded by their common name and scientific name. The identification of the species was important to determine the wood density, which was needed as input for the allometric equation.

The DBH of each tree included in the measurements was recorded. Measurements were taken with a diameter tape, all recordings were in centimetres (rounded to one decimal point). Boundary trees were included when the centre of the tree at DBH was within the plot boundary. Different DBH classes were measured in the three different plot sizes. Within the A-plots (main plots) all trees with a DBH ≥ 30 cm were measured. The B-plots (sub-plots) included all trees with a diameter ≥ 10 cm and < 30 cm, and the C-plots (sapling plots) measured all trees with a DBH between 2 and 10 cm. Table 3 gives an overview of the different plots and the DBH sizes measured. The surface area of the B and C plots has to be multiplied by two because each main plot consists of two B and two C plots.

Table 3: Tree measurements in different plots

Plot dimensions	Surface area (m^2)	Tree size measured, DBH (cm)
50 x 20 m	1,000	≥ 30 cm
10 x 20 m (x 2)	200 (x 2)	≥ 10 - < 30 cm
5 x 5 m (x 2)	25 (x 2)	≥ 2 - 10 cm

Table 4 displays how measurements were conducted in certain exceptional circumstances. All data were recorded on a field form, this field form can be found in the appendices (appendix A). Information such as plot corner coordinates, inventory team, date, and elevation was recorded on the field form.

Table 4: Methods of measuring DBH for special circumstances

Special circumstance	**Measuring method**
Trees growing on slopes	Measurements took place at the uphill side of the slope
Leaning trees	Measurement tape followed the tree stem axis, to ensure correct DBH measurement
When irregularities occur at DBH (e.g. swellings, depressions, branches)	DBH measurements were taken above the irregular feature
Trees with buttresses at (or above) DBH	Measurements took place 30cm above the end of the buttress
Forked trees	1. If split is slightly above DBH, measurements took place just underneath the split 2. If the split of the trees is below DBH, the DBH of both trees were measured individually

2.2.6 Estimation on above ground biomass of living vegetation

The AGB was estimated for each of the analysed sample plots, these estimations were based on an allometric equation. Chave et al. (2014) developed an allometric equation model which can be applied to a wide range of tropical vegetation types. Multiple allometric equation models were developed, the most suitable model depends on the parameters measured in the field. Model four is advised by Chave et al. (2014) for AGB estimation, therefore this model was used in the present study when all necessary parameters were recorded. The equation (1) of model 4 used the parameters; height (total tree height), DBH, and wood density. Whenever total tree height measurements were not recorded, the equation (2) of model 7 was used. Model 7 used DBH, wood density, and an environmental variable as input parameters, therefore model 7 is suitable in the absents of height measurements. The equations developed by Chave et al. (2014) were also used by the Forest Department Sarawak for AGB estimation in a mixed dipterocarp forest (Forest Department Sarawak, 2021).

$$AGBi = 0.0673 * (pD^2H)^{0.976} \quad (1)$$

$$AGBi = exp\,[-1.803 - 0.976E + 0.976\,ln(p) + 2.673\,ln(D) - 0.0299[ln(D)]^2] \quad (2)$$

Where:
AGBi = Above-ground biomass of the analysed tree (kg/tree)
p = Wood specific gravity of analysed tree (g cm^{-3})
D = diameter at breast height of the analysed tree (diameter in cm at 1.30 meters)
H = Height of the analysed tree (m)
E = Environmental variable

The environmental variable was a necessary covariable to determine the tree diameter-height relationship. This environmental variable depended on the coordinates of analysed plot, the value was derived from an R script provided in the supplementary information by Chave et al. (2014). Due to the script being provided, detailed knowledge of R was not needed to be able to obtain the environmental variable. The R script developed by Chave et al. (2014) only needed the longitude and latitude coordinates of a location as input, based on this input the R script derived the E-value for that area. Therefore the plot coordinates for all plots which had tree records without height measurements were placed into the R script.

The value for the wood-specific gravity was obtained from the wood density database developed by ICRAF (n.d.). Whenever the wood gravity of a specific species was not available, the average wood density of the genus was used.

The AGB of each tree inside a plot was combined to determine the total AGB for each sampling plot. The AGB per hectare of a sampling plot was derived with the use of a scaling factor. Each plot (main, sub, and sapling) used a different scaling factor to determine the AGB per hectare. Table 5 gives an overview of the scaling factor used to determine the AGB per hectare for the sample plots. Both the B- and C-plots are multiplied by two because each main plot consisted of two B- and two C-plots. The total AGB per hectare of a plot was determined by combining the AGB per hectare of all sampling plots. The amount of carbon per hectare for each plot was also determined, this value was derived from the total AGB per hectare. A scaling factor of 0.47 was used to convert AGB into carbon, this factor is also used in the forest inventory reports by Forest Department Sarawak (Forest Department Sarawak, 2021).

Table 5: Scaling factor per plot

Plot dimensions	Surface (m2)	Scaling factor
5 x 2 m x 2	20	500
10 x 20 m x 2	400	25
50 x 20 m	1,000	10

2.2.7 Regression analysis

The biomass estimated within the plots served as sample points that were used for the regression analysis. Simple linear regression was performed to determine if there is a significant relationship between AGB and the analysed vegetation indices. A regression model allows one to estimate the value of one variable based on the measured value of another variable (Cohen et al., 2013). To develop the regression models, the AGB per hectare within each plot was compared to the average reflection value of that plot.

The coordinates of each corner point were measured in the field, these coordinates were then placed into ArcGIS Pro. The coordinates points were used to create the plots in ArcGIS Pro. The vegetation indices analysed during the present study had a spatial resolution of 20 by 20 meters. Therefore, the total surface of a plot consisted of multiple pixels, which all have a specific value. To be able to develop the regression model the average reflection value found within each plot was needed. The zonal statistic tool was used to obtain a single value for each index in each plot. The zonal statistics tool determined the reflection value of each pixel that lies within the plot boundaries, the tool then calculates the average pixel value within the plot boundaries. If only one coordinate point of a plot was recorded, all neighbouring pixels to the coordinate point were used as input.

To determine if there is a significant relationship between the AGB and the reflection value of the vegetation indices, an alpha level of 0.05 was used as the threshold.

2.2.8 Materials

All materials and software programs that were needed to conduct this research are mentioned in table 6. For each item listed, the table indicates what the function of the listed material was during the forest inventories. Table 7 gives a full overview of all software programs that were needed to analyse the data gathered in the field.

Table 6: Materials needed for forest inventories

Material	**Function**
Measuring tape (20 m)	Measuring the boundaries of the sample plots
DBH measuring tape	Measuring the diameter at breast height (1.30) for each of the analysed trees
Field form	To record all data measured in the field
Handheld GPS	To accurately determine the exact location of the researchers in the field
Poles + tape	Set out plot boundaries

Table 7: Software programs used

Software program	**Function**
Sentinels Application Platform (SNAP)	Atmospherically correct sentinel-2 images, cloud removal
ArcGIS pro ArcMap	To develop base maps of the area, create the vegetation indices, calculate the overall biomass/carbon, generate random sample points
R	To Derive the “E” value (allometric equation)
Access	Process the field-data

3. Results

This chapter analyses the obtained results of the present study. The first part of this chapter consists of a literature review of the vegetation indices which were analysed during this study. The chapter discusses the reasoning behind the selection of these vegetation indices. This part is followed by the results of the selected vegetation indices, with a visual display of the selected indices and a table that contains the reflection values for each index and the corresponding plot. This section is followed by the results obtained from the field inventories, in which the AGB per hectare of the plots is displayed. The final part of the results consists of the statistical analysis, in which the results of the regression analysis are shown for each of the analysed indices.

3.1 Vegetation indices

3.1.1 Vegetation indices selection

The selection of the most suitable vegetation indices was one of the most important parts of this research. Therefore a literature review was done to determine which vegetation indices had the highest potential to distinguish differences in biomass in a mixed dipterocarp forest. The selected indices have either; 1) shown potential in other research done on the relationship between vegetation indices and biomass in a humid tropical forest, or 2) Used bands shown to be sensitive to the biophysical properties of humid tropical forests. However, Vegetation indices that are well-known and often used in biomass studies like the normalized difference vegetation index (NDVI) were also analysed. Table 8 gives an overview of the selected indices, and the authors of the indices. The table gives the Sentinel-2 bands used in the formula of the vegetation index to avoid confusion, mainly with the indices that include SWIR and MIR.

The NDVI is one of the most well-known vegetation indices, which mainly focuses on enhancing the signal of vegetation in conditions with low biomass (Huete et al., 1997). The results obtained by studies analysing the relationship between NDVI and AGB have varying outcomes. This variation is mainly caused by the location of the study area in which the NDVI is analysed (Lu et al., 2004). A strong relationship between the reflection value displayed by the NDVI and AGB has been found in forested areas (Lee & Nakane, 1997; Heiskanen, 2006; Gizachew et al., 2016). These strong correlations are mainly found in forests with relatively low biomass, however, Hussain et al. (2019) found a strong relation in a tropical forest in a tropical wet evergreen forest in India as well. This is in contrast with most studies done on the relation between NDVI and AGB in areas with high biomass (Sader et al., 1989; Foody et al., 1996; Foody et al., 2003; Lu et al., 2004). The main limiting factor for the NDVI is the saturation at higher levels of biomass (Thenkabail et al., 2000; Van Der Meer et al., 2001; Huete et al., 2002). Furthermore, the soil brightness also strongly influences the NDVI (Huete & Jackson, 1988; Todd & Hoffer, 1998).

The enhanced vegetation index (EVI) is similar to the NDVI, however, the EVI also includes the blue band. The inclusion of the blue band does not result in more data on biophysical properties, it is mainly included to reduce atmospheric noise in the image. Furthermore, the EVI includes the adjustment factors; G, C1, C2, and L to correct canopy background noise and atmospheric influences. The adjustment factors C1 and C2 use the blue band to correct for influences of aerosols in the red band. The L-factor is in place to overcome issues with the soil background brightness (Jiang et al., 2008). The values used for the adjustment factors in this study can be found in table 8 Because of these adaptation factors the EVI is considered to be more sensitive to higher levels of biomass. Huete et al. (2002) observed the EVI to remain sensitive in areas with high levels of biomass like the amazon. Furthermore, Huete et al. (1997), found the EVI to show minimal saturation problems in various temperate and tropical biomes. They conclude that vegetation indices that use higher weighting coefficients in the near-infrared perform best in high-density forests. Eckert (2012) analysed the potential of high spatial resolution images for estimating biomass and carbon in a tropical humid rain forest. A strong relationship was observed between the EVI and biomass in a non-degraded forest area. Pandapotan Situmorang et al. (2016) found a relatively strong relationship (R^2 = 0.83) between biomass and the EVI in a production forest in Indonesia. However, research conducted by Anaya et al. (2009) found no relationship between EVI and forest biomass in Colombia. The adjustment factors used in the EVI require the reflectance value of the Sentinel-2 bands. Therefore all Sentinel bands used in the formula given in table 8 are divided by 10,000.

Red-edge vegetation indices make use of the region between the visible red and the NIR part of the electromagnetic spectrum. Indices derived from red-edge bands are highly sensitive to dense vegetation and less prone to saturation (Mutanga & Skidmore, 2004; Forkuor et al., 2020). Laurin et al. (2016) showed that red-edge and green vegetation indices were able to distinguish differences in canopy densities. Schumacher et al. (2016) determined that red-edge indices are an important indicator for estimating wood volume. Models used to estimate wood volume improved significantly with the use of red-edge indices in forests in a semi-arid region. Research done by Imran et al. (2020) compared broadband vegetation indices such as NDVI to narrowband indices. They found the narrowband red-edge vegetation indices to be a superior predictor for vegetation biomass over the broadband indices. This was especially the case for forested areas with a high density, in which the red-edge indices seem to overcome saturation issues. The strongest relationship was found between biomass and the red edge normalized difference vegetation index-2 (RENDVI-2). Research done by Adan (2017) in a lowland dipterocarp forest in Malaysia also found similar results, with narrowband red-edge indices having the strongest relationship with AGB. The index with the strongest relationship with biomass was the red-edge ratio vegetation index (RERVI), the RENDVI also showed a relatively strong relationship.

The RENDVI analysed by Adan (2017) was originally proposed by Fernández-Manso et al. (2016) as the normalized difference vegetation index red-edge 2 (NDVIre2), which is an adaptation to the NDVIre proposed by Gitelson and Merzlyak (1994). Therefore from now on, the present report refers to the original name of the RENDVI, which is the NDVIre2. The name of the RENDVI-2 was not altered because the formula used for this vegetation index by Imran et al. (2020) could not be found in other reports.

As mentioned in the introduction, indices that include the MIR or SWIR bands seem to have the best performance for estimating biophysical parameters in tropical forests. The SWIR bands can discriminate moisture content in soils and vegetation (USGS, 2019). The usage of the SWIR band makes vegetation indices more sensitive to absorption by leaf moisture (Horler and Ahern, 1986). Studies conducted in a tropical moist deciduous forest in India also found the SWIR band to be strongest related to biomass (Yadav & Nandy, 2015; Nandy et al., 2017). The same result was found in China by Yang et al. (2019), who concluded that only SWIR band 5 of Landsat TM data was significantly sensitive to tropical forest biomass. Foody et al. (1996) found vegetation indices using MIR more strongly related to tropical forest biomass than indices using red or NIR. Boyd et al. (1999) also found the MIR to have the strongest relationship with biomass in tropical forests in Cameroon, stating that MIR reflectance is more sensitive to forest changes in forest structure than visible and NIR reflectance. In addition, a strong relationship between the MIR reflectance and biomass was observed by Steininger (2000) in a secondary forest in Brazil. Lu et al. (2004) analysed the correlation between AGB and Landsat Thematic Mapper spectral responses for three different testing sites. The MIR was most strongly correlated with AGB in two of the three testing sites. Because of these findings, this study included some indices that use the SWIR and MIR bands. The SWIR and MIR bands are combined in this section because there is some overlap between the region of the SWIR and MIR in different studies. For example; Lu et al. (2004) labels band 5 and 7 of the Landsat Thematic Mapper as MIR bands, while the United States Geological Survey labels these bands as SWIR bands (USGS, 2019).

The moisture vegetation index (MVI) proposed by Sousa and Ponzoni (1998), was developed to detect changes in timber volume with the use of MIR reflectance values. A comparison was made between the NDVI and the MVI in the Atlantic rainforest by Freitas and Cruz (2003) to see how well both indices perform in dense canopies. MVI showed to be less sensitive to saturation and to be more sensitive in dense canopies. The relationship between MVI and forest structure was again analysed by Freitas et al. (2005) in South-eastern Brazil. The NDVI and two versions of the MVI were analysed, using Landsat 7 satellite images. The first MVI (MVI-5) used SWIR band 5 as input, The second (MVI-7) used band 7 which is a MIR band. MVI-5 and MVI-7 both performed best in dense humid forests, however, MVI-5 did show to be more consistent in all regression models. Therefore, Freitas et al. (2005) indicate that MVI-5 has the highest potential in dense mature tropical forests. Roy and Ravan (1996) found similar results in a mixed forest type in India, they found that models which used MIR bands showed higher reliability for biomass estimations.

A mention of the variation of MIR in different studies should be made here, mainly due to the variation in the wavelength that is used in different studies. Sousa and Ponzoni (1998) proposed MVI-5 and MVI-7, which use bands 5 (1.55-1.75 µm) and 7 (2.08-2.35 µm) of Landsat 5, both these bands are labeled as MIR bands in their study. Boyd et al. (1999) also concluded the MIR wavelength to be useful for estimating biomass in tropical forests with the use of an index similar to the MVI-5/MVI-7. However, Boyd et al. (1999) used a MIR index proposed by Kaufman and Remer (1994), who used AVHRR channel 3, which has a wavelength of 3.55-3.93 µm. The present study only included the MVI-5 and MVI-7 proposed by Sousa and Ponzoni (1998) because neither Sentinel-2 nor Landsat 7/8/9 have bands in a wavelength similar to the bands analysed by Boyd et al. (1999). During the present study Sentinel-2 images were used therefore the input bands for MVI-5 and MVI-7 are different, however, the wavelengths of the Sentinel-2 input bands (band 11 and band 12) are similar.

The Moisture Adjusted Vegetation Index (MAVI), was developed to reduce background reflectance and topographical Effects (Zhu et al., 2014). The MAVI proved to be strongly correlated with LAI in mixed forest types in a subtropical climate zone in China. The MAVI seems to be more strongly correlated to LAI due to the incorporation of the red, NIR, and SWIR bands. No relationship between MAVI and biomass was analysed in this study. However, LAI is an indicator of forest biomass (Gupta et al., 2000). Therefore a strong correlation with LAI would suggest that this index might also be useful for biomass estimations. In addition, the index includes a SWIR band, which has been suggested to be used in tropical forests, as discussed above. Furthermore, MAVI showed to have a stronger correlation to LAI than some of the more well-known vegetation indices (e.g. NDVI, SAVI). The original MAVI was developed based on Landsat-5 data, therefore the SWIR band used varies slightly from the Sentinel-2 SWIR band used in this study. SWIR band 11 was used as input for this study since this band is closest to the range (1.5–1.75 µm) used in the original study.

The simple ratio (SR) is another well-known vegetation index, which displays the ratio of reflected light between the NIR and red wavelength. The ratio between NIR/red strongly emphasizes the difference in reflectance of the bands in areas with vegetation. Additionally, the index minimizes problems of variable illumination due to topography (Silleos et al., 2006). The SR is very similar to the previously mentioned RENDVI, however, it uses the red band instead of the red-edge band. The SR proved to have a strong relationship with biomass in an open to sparsely treed pine forest in Canada (Chen et al., 2012). A Strong relationship between AGB and the SR was also found in a coniferous and deciduous forest in the Himalayan region in India (Ghosal et al., 2022). Furthermore, the SR was seen as an effective predictor of biomass for a mangrove forest in the Philippines (Baloloy et al., 2018). These studies indicate that the SR has a high potential to estimate AGB in different locations and different forest types. However, the main reason to include the index in this study is due to the findings of Rasib et al. (2018). This study was conducted in a mixed dipterocarp forest in peninsular

Malaysia, which is the same forest type and the same country as the present study. A strong relationship was found between AGB and the simple ratio (SR) with an R^2 value of 0.72

Another well-known vegetation index is the tasseled cap transformation, developed by Kauth and Thomas (1976). The tasseled cap transformation reduces the volume of data with a minimal loss of information. Three transformations were developed to obtain different levels of information about the surface, these transformations have different coefficients which are applied to the bands. The three transformations emphasize brightness, greenness, and wetness. The present study analysed the greenness (TC-2) and wetness (TC-3) indices since these indices emphasize vegetation (TC-2) and soil and canopy moisture (TC-3). The indices include a total of six bands; blue, green, red, NIR, SWIR-1, and SWIR-2. The coefficients applied to the bands by TC-2 are meant to emphasize the signal of vegetation (Silleos et al., 2006). The TC-2 and TC-3 had a relatively strong relationship with AGB in a plantation forest in Ethiopia (Geda, 2021). This strong relationship was also found by Shen et al. (2018) in a mixed forest region in China. Their study area consisted of three main forest types; subtropical evergreen broadleaved, evergreen broadleaved, and tropical monsoon forest. Their results indicate both TC-2 and TC-3 have a strong relationship with AGB. Uttaruk and Laosuwan (2018) also found TC-2 to have the strongest relationship with AGB in a dry dipterocarp forest in Thailand, the relationship between TC-3 and AGB was not analysed during this study. The coefficients developed by Kauth and Thomas (1976) are sensor-dependent, therefore the exact coefficients used for the tasseled cap transformations depend on the satellite data used during the study (Sheng et al., 2011). Shi and Xu (2019) proposed coefficients for the Sentinel-2 sensor, these coefficients are used in this study.

Table 8: Vegetation indices analysed during this study

Vegetation index	Formula	Symbology	Author index
Normalized difference vegetation index	$NDVI = \frac{\mathrm{B8} - \mathrm{B4}}{B8 + B4}$		Rouse et al., 1974
Enhanced vegetation index	$EVI = \mathrm{G}\frac{\mathrm{B8} - \mathrm{B4}}{\mathrm{B8} + \mathrm{C1} * \mathrm{B4} - \mathrm{C2} * \mathrm{B2} + \mathrm{L}}$	G = 2.5 C1 = 6 C2 = 7.5 L = 1	Huete et al. 1997
Normalized Difference Vegetation Index red-edge 2	$NDVIre2 = \frac{\mathrm{B8} - \mathrm{B6}}{B8 + B6}$		Fernández-Manso et al. (2016)
Red edge normalized difference vegetation index-2	$RENDVI - 2 = \frac{\mathrm{B7} - \mathrm{B4}}{\mathrm{B7} + \mathrm{B4}}$		Imran et al. (2020)
Red-edge ratio vegetation index	$RERVI = \frac{B8}{B6}$		Cao et al., 2016
Moisture vegetation index-5	$MVI5 = \frac{\mathrm{B8} - \mathrm{B11}}{\mathrm{B8} + \mathrm{B11}}$		Sousa & Ponzoni, 1998
Moisture vegetation index-7	$MVI7 = \frac{\mathrm{B8} - \mathrm{B12}}{B8 + B12}$		Sousa & Ponzoni, 1998
Moisture adjusted vegetation index	$MAVI = \frac{\mathrm{B8} - \mathrm{B4}}{\mathrm{B8} + \mathrm{B4} + \mathrm{B11}}$		Zhu et al., 2014
Simple ratio	$SR = \frac{\mathrm{B8}}{\mathrm{B4}}$		Jordan, 1969
Tasseled cap greenness	$TC - 2 = -0.2818(B2) - 0.3020(B3) - 0.4283(B4) + 0.3138\ (B8) - 0.1341(B11) - 0.2538\ (B12)$		Original: Kauth & Thomas (1976) Sentinel-2 adaptation: Shi and Xu (2019)
Tasseled cap wetness	$TC - 3 = 0.1763(B2) + 0.1615(B3) + 0.0486(B4) - 0.0755(B8) - 0.7710(B11) - 0.5293(B12)$		Original: Kauth & Thomas (1976) Sentinel-2 adaptation: Shi and Xu (2019)

3.1.2 Vegetation indices value per plot

Table 9 gives an overview of all of the plots and the corresponding average reflection value for all of the analysed indices.

Table 9: Average reflection value per plot

Plot nr	Vegetation index										
	NDVI	EVI	NDVIre2	RENDVI2	RERVI	MVI5	MVI7	MAVI	SR	TC-2	TC-3
2	0.82	0.50	0.10	0.83	1.23	0.34	0.59	0.57	10.83	232.08	-1603.65
4	0.86	0.48	0.10	0.86	1.22	0.36	0.66	0.60	13.27	320.33	-1255.86
9	0.87	0.54	0.14	0.86	1.34	0.37	0.67	0.61	15.29	394.52	-1662.21
10	0.87	0.51	0.14	0.87	1.36	0.41	0.70	0.63	16.29	374.38	-1299.09
14	0.88	0.57	0.08	0.88	1.19	0.33	0.66	0.60	15.46	305.95	-1603.82
17	0.85	0.51	0.11	0.85	1.25	0.30	0.62	0.56	11.83	232.22	-1489.97
20	0.83	0.42	0.12	0.86	1.28	0.35	0.65	0.57	11.51	227.90	-1476.15
23	0.88	0.71	0.09	0.89	1.19	0.32	0.63	0.60	15.57	426.14	-2193.24
39	0.88	0.49	0.11	0.88	1.25	0.35	0.67	0.60	14.55	279.85	-1276.09
49	0.88	0.54	0.11	0.87	1.25	0.34	0.66	0.59	14.52	283.40	-1457.05
51	0.89	0.53	0.11	0.88	1.26	0.37	0.68	0.61	16.43	387.28	-1581.61
63	0.89	0.54	0.11	0.89	1.25	0.34	0.66	0.60	15.96	286.07	-1396.76
64	0.88	0.59	0.07	0.89	1.18	0.33	0.64	0.60	16.84	351.81	-1724.76
65	0.89	0.55	0.08	0.88	1.19	0.33	0.64	0.60	16.35	321.44	-1582.27
66	0.87	0.46	0.09	0.89	1.21	0.34	0.64	0.60	15.06	282.15	-1316.64
67	0.87	0.45	0.08	0.88	1.14	0.31	0.63	0.58	14.46	224.25	-1302.74
68*	0.83	0.52	0.14	0.84	1.32	0.34	0.60	0.58	11.82	223.25	-1652.16
69*	0.76	0.44	0.11	0.79	1.27	0.30	0.61	0.53	7.82	90.02	-1427.45
70	0.87	0.63	0.09	0.76	1.21	0.30	0.59	0.55	11.65	244.56	-2057.05
71	0.84	0.53	0.10	0.86	1.22	0.30	0.57	0.52	10.39	-9.65	-1773.74
72	0.87	0.51	0.12	0.87	1.28	0.35	0.65	0.60	14.60	327.80	-1596.27
73	0.84	0.54	0.12	0.86	1.28	0.35	0.65	0.59	12.54	293.35	-1494.63
77	0.87	0.60	0.11	0.89	1.28	0.37	0.68	0.61	15.34	452.82	-1798.01
79	0.81	0.48	0.08	0.62	1.16	0.16	0.42	0.37	6.00	-502.11	-1982.42
80	0.87	0.61	0.10	0.88	1.21	0.38	0.68	0.61	13.95	389.90	-1663.47
81	0.85	0.47	0.12	0.84	1.29	0.35	0.67	0.59	13.24	307.80	-1458.46
82	0.86	0.55	0.10	0.86	1.30	0.37	0.68	0.61	13.49	341.30	-1437.94
84	0.85	0.56	0.12	0.81	1.29	0.38	0.67	0.61	13.18	416.72	-1719.85
85	0.87	0.59	0.07	0.87	1.17	0.33	0.65	0.59	15.08	377.16	-1762.86
86	0.84	0.55	0.10	0.86	1.22	0.33	0.64	0.58	11.94	295.34	-1583.40
87	0.85	0.58	0.07	0.85	1.17	0.30	0.61	0.55	11.44	143.98	-1831.34

*Plot (partially) covered by clouds

A boxplot for each of the analysed indices was created to display the distribution of the values for the different indices. The results of the calculated vegetation indices were placed underneath boxplots to visualise the differences between the indices (figure 6). A larger visual display of the vegetation indices with more details is shown in appendix B.

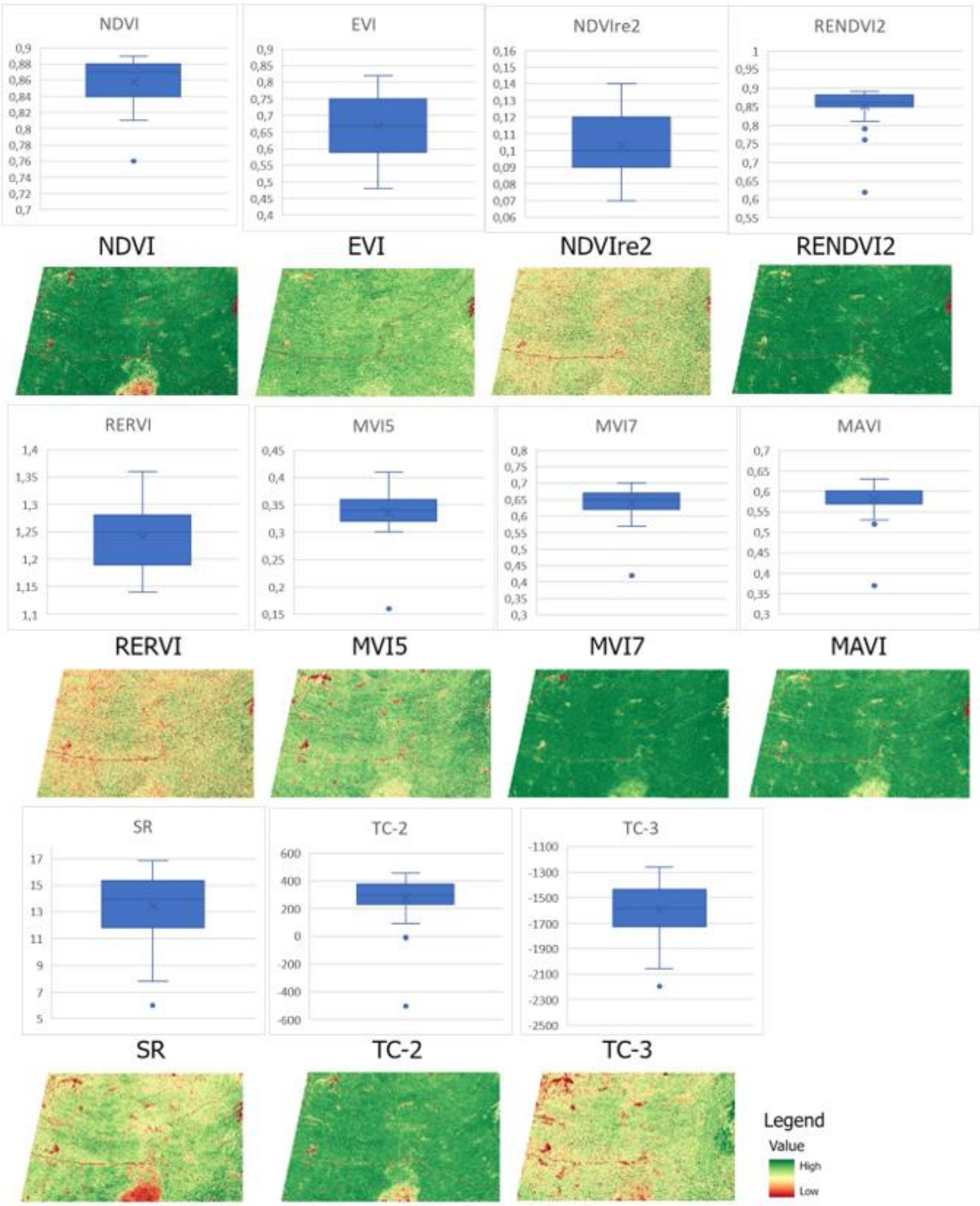

Figure 6: Boxplot and visual display for each of the analysed vegetation indices

3.2 Above-ground biomass estimation

3.2.1 Above-ground biomass in different MDF classes

To determine if there was a significant difference in biomass found in the different classes of mixed dipterocarp forests a one-way ANOVA test was used. The results of the test showed that there was no significant difference in AGB between the different classes of mixed dipterocarp forest when using a threshold of 0.05 (table 10). Because of this, all three classes of mixed dipterocarp forests were combined and used as input for the statistical analysis. The boxplot in figure 7 displays the distribution of the AGB values in the different forest types.

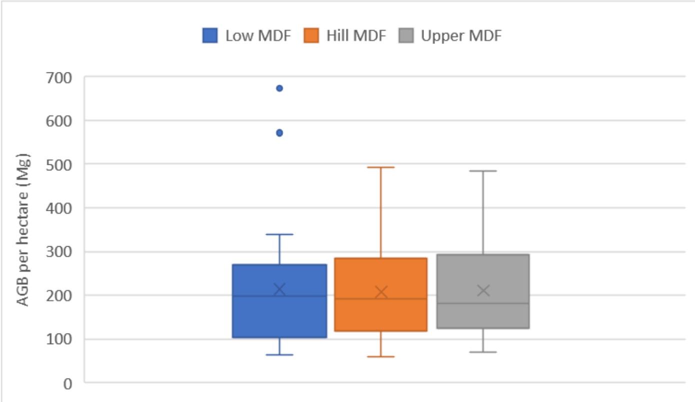

Figure 7: Distribution of AGB per hectare in lowland MDF (0-300m), hill MDF (301-750m), and upper MDF (751-1200m)

Table 10: ANOVA-test low, hill, and upper MDF

Source of Variation	***SS***	***df***	***MS***	***F***	***P-value***	***F crit***
Between Groups	758.5823	2	379.2911	0.025609	0.974723	3.103839
Within Groups	1,258,904	85	14810.63			
Total	1,259,662	87				

3.2.2 Field data results

The AGB per hectare was analysed for a total of 31 main and sub-plots. The field data shows that the total AGB per hectare ranged from 62.58 Mg (plot 79) to 672.90 Mg (plot 17), with an average of 245.33 Mg ha^{-1}. The average aboveground tree carbon stored within a mixed dipterocarp forest was found to be 115.30 C Mg ha^{-1}.

Within the main plots, the lowest amount of AGB was found in plot 4 with a total of 2.07 Mg ha^{-1}. The highest amount of AGB in the main plots was found in plot 17, with a total of 560.03 Mg ha^{-1}. An average AGB of 162.79Mg ha^{-1} was found in the main plots. Four of the analysed plots (17, 23, 63, 67) had one (plot 23,63,67) or two (plot 17) trees with a DBH greater than 100, these four plots also contained the highest amount of total AGB in the main plots. Within the sub-plots, the lowest amount of AGB was found in plot 51 (26.63 Mg ha^{-1}), and the highest amount in plot 84 (182.05 Mg ha^{-1}). On average an AGB of 82.54 Mg ha^{-1} was found in the sub-plots. An overview of the AGB and the above-ground carbon found in the analysed plots is given in table 11. A more detailed overview of the AGB values for the sub- and the main plots is given in Appendix C.

Table 11:Total AGB and above-ground carbon per hectare per plot

Plot ID	**Elevation (m)**	**Main plot AGB (Mg ha^{-1})**	**Subplot AGB (Mg ha^{-1})**	**Total AGB (Mg ha^{-1})**	**Total above ground carbon (Mg ha^{-1})**
2	128	22.07	81.47	103.54	48.66
4	116	2.07	77.25	79.32	37.28
9	120	42.84	28.58	71.41	33.56
10	297	76.00	41.24	117.24	55.10
14	355	190.76	99.55	290.31	136.45
17	105	560.03	112.87	672.90	316.26
20	469	102.04	75.35	177.39	83.37
23	459	315.53	77.82	393.34	184.87
39	311	90.42	42.87	133.30	62.65
49	147	213.34	29.28	242.62	114.03
51	158	102.73	26.63	129.36	60.80
63	339	420.75	72.03	492.78	231.61
64	216	129.14	111.74	240.89	113.22
65	203	155.70	128.26	283.96	133.46
66	232	123.31	88.60	211.91	99.60
67	281	475.64	95.83	571.47	268.59
68	620	258.26	106.73	365.00	171.55
69	465	120.13	98.46	218.60	102.74
70	547	240.02	140.44	380.46	178.82
71	536	174.96	96.00	270.96	127.35
72	213	141.82	56.04	197.85	92.99
73	398	224.12	165.87	389.99	183.30
77	474	80.92	112.56	193.49	90.94
79	203	28.86	33.72	62.58	29.41
80	107	111.68	85.93	197.61	92.88
81	178	149.77	83.00	232.77	109.40
82	149	134.41	36.49	170.89	80.32
84	290	49.81	182.05	231.86	108.97
85	486	159.37	69.39	228.76	107.52
86	151	113.21	33.88	147.09	69.13
87	286	36.63	68.92	105.55	49.61

3.3 Statistical analysis

To determine the relationship between AGB and vegetation indices simple linear regression analysis were performed. In total 29 out of the 31 plots could be used to perform the analysis due to partial cloud cover above plots 68 and 69. The AGB per hectare for each of the plots was compared to the average reflection value of the analysed index of that plot.

3.3.1 Regression analysis

Simple linear regression was used to determine whether the reflection value displayed on a vegetation index had a significant relationship with the measured AGB in the plots. An alpha level of 0.05 was used to determine if the relationship between AGB and an index was significant or not. No significant relationship was found between any of the analysed vegetation indices and the measured AGB. The next section shortly discusses each of the analyse indices and shows the scatter plots.

3.3.1.1 NDVI

The NDVI showed the second best relationship between reflection value and AGB, the result indicates that the reflection value displayed on the NDVI explains 4.9% of the measured AGB ($F(1,27) = 1.402$, $p = 0.247$). However, there is no significant relationship between the NDVI value and AGB. The two plots with the highest measured AGB do not seem to display a high NDVI value (figure 8).

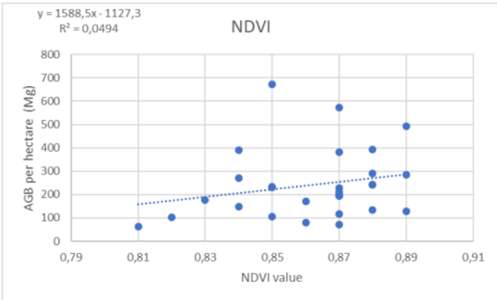

Figure 8: Scatter plot NDVI

3.3.1.2 EVI

No significant relationship was found between the EVI and AGB ($F(1,27) = 0.438$, $p = 0.514$), with the model explaining 1.6% of the variation in measured AGB. When analysing the scatter plot it again shows a relatively low reflection value for the two plots with the highest amount of AGB (figure 9).

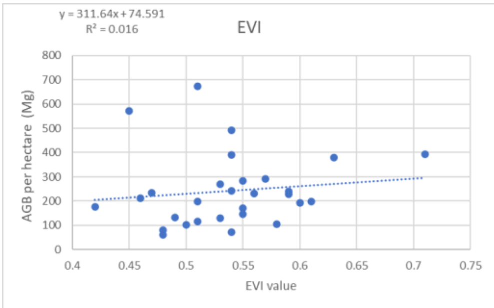

Figure 9: Scatter plot EVI

3.3.1.3 NDVIre2

The NDVIre2 model could explain 1.6% of the variation in measured AGB. There was no significant relationship between the NDVIre2 values and the measured AGB. The scatter plot shows relatively low reflection values for plots with high levels of AGB (figure 10). Furthermore some of the plots that had the lowest amounts of AGB display a high and low reflection values for the NDVIre2.

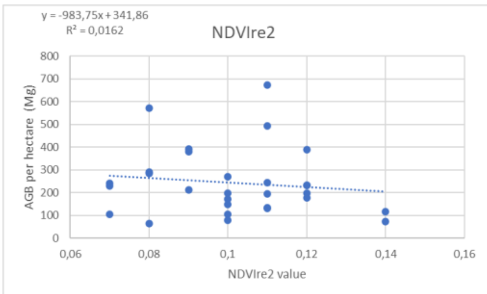

Figure 10: Scatter plot NDVIre2

3.3.1.4 RENDVI-2

The RENDVI-2 showed no significant relationship with AGB. The RENDVI-2 model could explain 3.7% of the variance in measured AGB. The scatter plot shows that most of the points are clustered around the 0.86 value (figure 11).

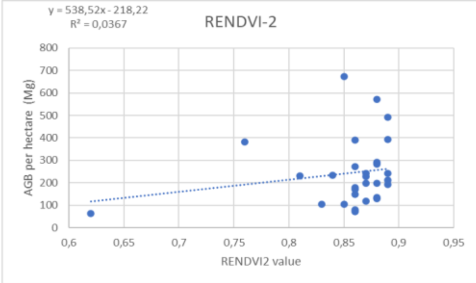

Figure 11: Scatter plot RENDVI-2

3.3.1.5 RERVI

The RERVI had the strongest relationship with AGB. However, No significant relationship was observed between the RERVI and AGB. With the model being able to explain 5.0% of variance in measured AGB. The scatter plot shows a negative relationship between the RERVI and AGB. The plots in which high levels of AGB were measured again showed to be outliers (figure 12).

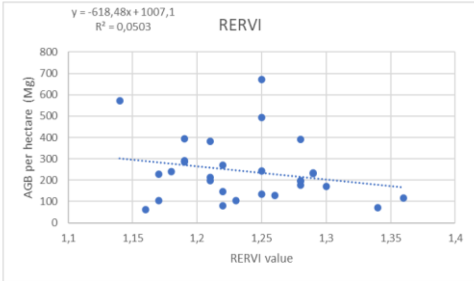

Figure 12: Scatter plot RERVI

3.3.1.6 MVI-5

The model of the MVI-5 was able to explain 2.1% of the AGB, and showed no significant relationship. The scatter plot shows a very low reflection value for the plot with the lowest AGB, however, high reflection values can also be found for plots with low amount of AGB (figure 13).

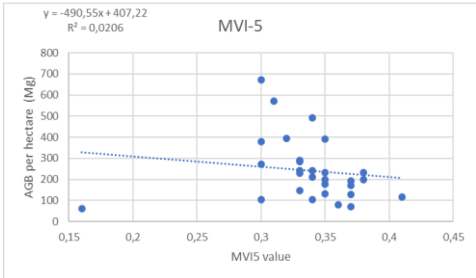

Figure 13: Scatter plot MVI-5

3.3.1.7 MVI-7

The MVI-7 also did not show a significant relationship with AGB. The model of the MVI-7 performed worse than the MVI-5, the model could explain less than 1% of the measured AGB. The scatter plot does not show any pattern, with both low and high reflection values for low levels of AGB (figure 14).

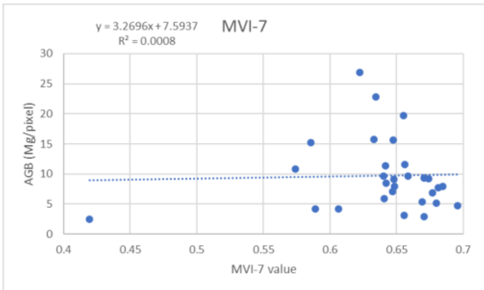

Figure 14: Scatter plot MVI-7

3.3.1.8 MAVI

The MAVI shows similar results as the MVI-7, with no significant relationship and the model being able to explain less than 1% of the AGB. The scatter plot of the MAVI (figure 15) is similar to that of the MVI-7. With most of the data points clustering around the 0.6 value.

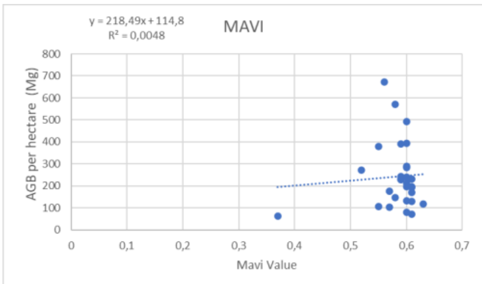

Figure 15: Scatter plot MAVI

3.3.1.9 SR

The SR model could explain 1.6% of the measured AGB, and was also found to be insignificant. The pattern displayed by the scatter plot is similar to that of the NDVI, with the outliers being the two plots with the highest amount of AGB (figure 16). Furthermore, some low AGB points display a high reflection value.

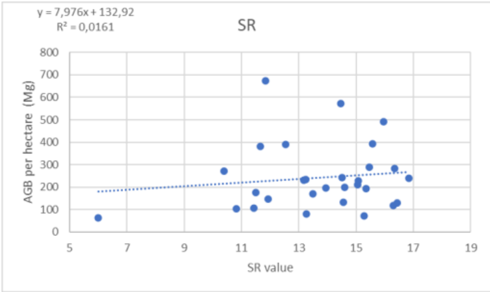

Figure 16: Scatter plot SR

3.3.1.10 TC-2

The greenness tasseled cap index (TC-2) also showed no significant relationship with AGB. When analysing the scatter plot it seems that the plots with a high amount of biomass show a relatively low reflection value (figure 17). The model of the TC-2 could explain less than 1% of the variance in AGB.

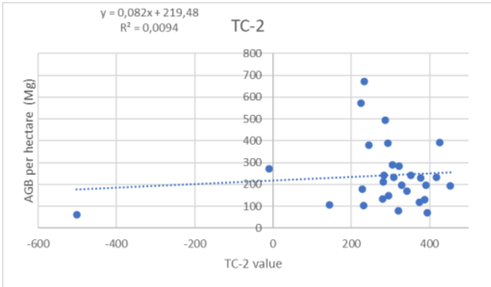

Figure 17: Scatter plot TC-2

3.3.1.11 TC-3

Out of all of the analysed indices, the TC-3 showed the weakest relationship with AGB. The scatter plot does not display any clear pattern (figure 18). Especially the low AGB values seem to display both high and low reflection values.

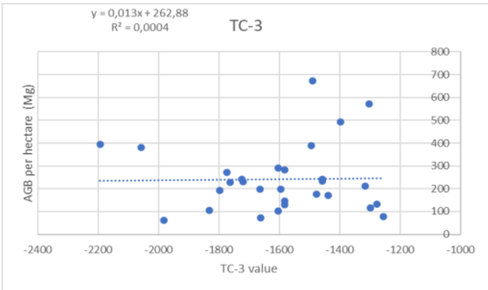

Figure 18: Scatter plot TC-3

None of the analysed indices showed a significant relationship with the measured AGB. An overview of the regression analysis for each of the analysed indices is given in table 12.

Table 12: Results linear regression

Vegetation index	**Equation**	**R^2**	**Standard error**	**F**	***P*-value**
NDVI	y = 1588.5x - 1127.3	0.049	1341.713	1.402	0.247
EVI	y = 311.64x + 74.591	0.016	470.776	0.438	0.514
NDVIre2	y = -983.75x + 341.86	0.016	1474.680	0.445	0.510
RENDVI-2	y = 538.52x - 218.22	0.037	531.005	1.029	0.320
RERVI	y = -618.48x + 1007.1	0.050	517.088	1.431	0.242
MVI-5	y = -490.55x + 407.22	0.021	650.947	0.568	0.458
MVI-7	y = 47.768x + 211.55	0.000	550.634	0.008	0.932
MAVI	y = 218.49x + 114.8	0.005	606.943	0.130	0.722
SR	y = 7.976x + 132.92	0.016	12.017	0.441	0.513
TC-2	y = 0.082x + 219.48	0.009	0.162	0.257	0.616
TC-3	y = 0.013x + 262.88	< 0.000	0.122	0.011	0.916

3.3.2 Regression analysis without outliers

Additional regression analysis was performed, in which outliers were left out of the input data. The first, third, and interquartile range was used to determine whether a data point was considered an outlier or not. The following decision rule was used;

- Lower bound; first quartile – 1.5 * interquartile range
- Upper bound; third quartile + 1.5 * interquartile range

This decision rule gave an upper bound of 20.40, and a lower bound of -3.71. This resulted in the exclusion of plot number 17 and 67, which both exceed the upper bound value. The EVI shows a significant relationship with AGB when plots 17 and 67 are excluded from the input data. EVI shows the strongest relationship, with the model explaining 20.4% of the AGB ($F(1,25) = 6.424$, $p = 0.018$). Most of the other indices also improved, however, they still did not show a significant relationship with AGB (table 13). The RERVI, which had the strongest relationship with the inclusion of the outliers, showed a decline in the strength of the relationship when plots 17 and 67 were removed.

Table 13: Results linear regression without outliers

Vegetation index	Equation	R^2	Standard error	F	*P*-value
NDVI	*y = 1844.4x - 1376.3*	0.134	939.077	3.857	0.061
EVI	*y = 816.49x - 228.45*	0.204	322.135	6.424	0.018
NDVIre2	*y = -661.74x + 281.37*	0.014	1101.885	0.361	0.554
RENDVI-2	*y = 455.61x - 175.15*	0.053	384.262	-852.399	502.090
RERVI	*y = -302.61x + 589.21*	0.022	406.838	0.553	0.464
MVI-5	*y = 6.6818x + 211.71*	0.000	488.271	0.000	0.989
MVI-7	*y = 218.46x + 73.915*	0.012	399.296	0.299	0.589
MAVI	*y = 407.14x - 23.678*	0.034	436.636	0.869	0.360
SR	*y = 12.013x + 49.003*	0.072	8.594	1.954	0.174
TC-2	*y = 0.1274x + 178.34*	0.046	0.116	1.214	0.281
TC-3	*y = -0.0962x + 58.661*	0.043	0.090	1.136	0.297

4. Discussion

This chapter discusses the results obtained in the present study and compares the results to those found in other studies. Furthermore, the limitations of the present study are discussed.

4.1 Vegetation indices

The following 11 vegetation indices were deemed to have the highest potential to show a strong relationship with AGB in a mixed dipterocarp forest; NDVI, EVI, NDVIre2, RENDVI-2, RERVI, MVI-5, MVI-7, MAVI, SR, TC-2, TC-3. Noticeable is the variation in the distribution of the data when analysing the boxplots and the visual displays of the different indices. Some of the analysed indices like the RENDVI-2, MVI-5, MVI-7, MAVI, and TC-2 seem to have a very limited distribution of the data. Whilst the NDVI, EVI, NDVIre2, RERVI, SR, and TC-3 show to have more spread in the reflection values found within the plots.

4.2 Above-ground biomass plots

The results of the field data showed an average of 162.79Mg ha^{-1} in the main plots and an average of 82.54 Mg ha^{-1} in the sub-plots. The average total AGB found within the plots was 245.33 Mg ha^{-1}. The presence of large trees seemed to have a strong impact on the overall AGB. Trees with a DBH greater than 100 cm were found in 4 out of the 28 analysed plots (17, 23, 63, and 67), these plots were also the plots in which the highest overall AGB was found. Especially plot 17 and 67 had a high total AGB, which seems to be caused mainly by the presence of one or two large trees in the main plots.

The average carbon found in the plots is somewhat lower than the results found by the Forest Department Sarawak. The average aboveground tree carbon stored within a mixed dipterocarp forest was found to be 115.30 C Mg ha^{-1} in the present study. Forest Department Sarawak found an average of 143.25 C Mg ha^{-1} (Forest Department Sarawak, 2021). Three reasons could be the cause of the differences in measured AGB. Firstly, both reports used models developed by Chave et al. (2014) for estimating AGB. However, Forest Department Sarawak used model 7, while the present study mainly used model 4. A second explanation is the specific classification of forest type in which the studies were conducted. Since the forest inventories conducted by Forest Department Sarawak (2021) consisted of 16.4% of totally protected areas. A higher number of large trees can likely be found within these totally protected areas, which could explain the overall higher average per hectare found by Forest Department Sarawak. A third reason for finding a lower average per hectare in the present study is the exclusion of the sapling plots. The exclusion of these plots did result in an underestimation of the total AGB.

4.3 Regression analysis results

The capability of vegetation indices to estimate AGB varies strongly depending on forest type and location. This study aimed to determine if vegetation indices are a suitable predictor of AGB in mixed dipterocarp forests in Sarawak. The results indicate that there is no significant relationship between the AGB measured in the field and the reflection value displayed on the analysed vegetation indices. The relationship between AGB and the vegetation indices proved to be relatively weak, with the strongest model of the RERVI being able to explain 5.0% of the observed variance in AGB. Most indices improved their relationship with AGB when outliers in AGB were removed from the input data. The EVI showed a significant relationship with AGB when outliers were removed from the dataset. However, the relationship remained weak, with the model (EVI) being able to explain 20.4% of the AGB. The findings of this study suggest that none of the analysed vegetation indices is a suitable predictor of AGB in a mixed dipterocarp forest in Sarawak.

Most noticeable about the results are the low and insignificant relationships of the indices that were specifically developed for tropical forests, and thus supposedly more sensitive to higher levels of biomass. One of the problems that stand out is the reflection value of plots with a very high amount of AGB. Vegetation indices are known to have issues with saturation in high amounts of biomass (Mutanga & Skidmore, 2004). However, in the present study, the opposite was observed, plots with a very high amount of AGB displayed a relatively low reflection value. During the analysis of the main plots, it was already noticed that the highest amount of AGB was found in plots that contained one or two large trees with a DBH greater than 100, this was most noticeable in plots 17 and 67. These large trees had a high impact on the overall AGB found in the plots, however, they did not seem to cause the same effect on the reflection value of the vegetation indices. Therefore it seems that one of the problems of the analysed vegetation indices is the inability to explain high amounts of AGB caused by a singular large tree.

The additional analysis in which AGB outliers were excluded makes clear that the inability to explain high amounts of AGB is not the only issue for the analysed indices. The NDVI, NDVIre2, RENDVI-2, RERVI, MVI5, MVI7, MAVI, SR, TC-2, and TC-3 all remained to show a weak and insignificant relationship when the AGB outliers were removed. When analysing tables 9,11, and the scatter plots it is noticeable that the lower levels of AGB also show a strong variation for all of these indices. Only the EVI shows somewhat of a pattern, in which low AGB values display low reflection values and vice versa (with exception of the very high AGB value, as discussed above). The other indices display varying reflection values for the plots with a low amount of AGB. All of the other indices seem to display both high and low reflection values in the plots with low amounts of AGB.

Results obtained in the present study contradict the results obtained by the literature that was used when these indices were selected. All of the selected indices have shown a strong relationship with AGB in studies done in the past. The reason for these differences in strength could be explained by the results obtained by Foody et al. (2003), this study highlights the problem of vegetation indices when transferring results obtained from one site to another. Foody et al. (2003) analysed the relationship between AGB and vegetation indices and found that the strength of the relationship varied strongly between testing sites. Lu et al. (2004) found similar effects, with a strong variation in results obtained by the indices in different testing sites. Therefore the strong relationships found in other studies do not guarantee that the same relationship would be found in the present study.

Even when taking the issues with transferability into account, the contradicting results between the present study and other studies conducted in mixed dipterocarp forests were unexpected. Adan (2017) conducted research in a mixed dipterocarp forest in Malaysia and found relatively strong relationships between AGB and red-edge vegetation indices, specifically the RERVI (R^2 = 0.64). In the present study, a non-significant and weak relationship (R^2 = 0.05) was found between the RERVI and AGB. The differences in results for the RERVI could partially be explained by the different methodologies used in both studies.

Adan (2017) separated total biomass into two groups; upper canopy biomass, and lower canopy biomass. The lower canopy biomass was estimated based on the DBH and allometric equations, similar to the method used in the present study. However, the upper canopy biomass was estimated using the DBH and airborne laser scanner data (ALS) for height estimations, this could have resulted in more accurate biomass estimations. Furthermore, Adan (2017) removed outliers based on the pixels in which a tree was found. A tree was excluded from the database if the pixel in which a tree was found did not fall completely within the boundaries of the plot. In addition, a terrestrial laser scanner (TLS) was used to determine the location of each tree within the plot on the Sentinel-2 images. This made it possible to determine the exact biomass value of each pixel within the plot, and thus the ability to use each pixel within the plot as a sample point for the regression analysis.

Because of this methodology, Adan (2017) had almost four times as many sample points, with presumably a higher accuracy, whilst having a similar number of field plots as the present study. The AGB per pixel approach used by Adan (2017) could result in a better representation of singular large trees. Since the high AGB of the singular tree was linked to the pixel in which the tree is found, instead of an average of all pixels within the plot as in the present study.

Another study conducted by Rasib et al. (2018) in a mixed dipterocarp forest in peninsular Malaysia found a relatively strong relationship between biomass and the simple ratio (SR). Rasib et al. (2018) found the strongest relationship when comparing the SR to the AGB of 100 random sample points (R^2 = 0.72). At first, this seems like a strong contrast with the present study, however, a strong decrease in the strength of the relationship occurred when the sample size was increased. When increasing the sample size from 100 to 250, the R^2 decreased from 0.72 to 0.02, which is similar to the results obtained in the present study (R^2 = 0.02). Because of this, it seems that the strong relationship obtained by Rasib et al. (2018) when analysing a smaller sample size, is not representative of the predictive capability of the SR in a mixed dipterocarp forest.

Uttaruk and Laosuwan (2018) also conducted research in a dry dipterocarp in Thailand. They found a relatively strong relationship between TC-2 (R^2 = 0.81) and AGB. Similar results were not obtained in the present study, in which the TC-2 and TC-3 showed one of the weakest relationships with the AGB. The main reason for the differences in results again seems to be caused by the sample size used. As shown by Rasib et al. (2018), a smaller sample size could result in high relationships caused by chance. Uttaruk and Laosuwan (2018) used a relatively small sample size of 12 plots, this could explain why the TC-2 obtained such a high R^2 value.

The moisture indices (MVI-5, MVI-7, and MAVI) were included in the analysis because of the inclusion of the SWIR band, besides the red and the NIR band. The inclusion of the SWIR band has been shown to make vegetation indices more sensitive to biomass in tropical forests (Yadav & Nandy, 2015; Nandy et al., 2017; Yang et al., 2019). The MVI-5 and MVI-7 both also proved to have a strong relationship with AGB in dense humid forests (Freitas et al., 2005). The results of the present study show that none of the moisture indices proved to have a strong relationship with AGB in a mixed dipterocarp forest. These results are similar to the finding of Basuki et al. (2012), which was also conducted in a mixed dipterocarp forest. Basuki et al. (2012) also found a weak and non-significant relationship between AGB and the MVI-5 (R^2 = 0.02) and the MVI-7 (R^2 = 0.04). Adan (2017) found similar results when analysing the relationship between indices that combined the NIR and SWIR bands in a mixed dipterocarp forest in Malaysia. A weak relationship was found for all analysed moisture indices. Therefore it seems that the SWIR bands are less sensitive to AGB in mixed dipterocarp forests.

So far, mainly studies that contradict the results found in the present study have been discussed however, there are studies that agree with the findings of the present study. Foody et al. (2001) analysed the relationship between AGB and 230 vegetation indices in Malaysia. The results indicated that all of the 230 analysed vegetation indices were weakly and insignificantly related to forest biomass. In addition, Lu et al. (2004) also found a large amount of the analysed indices to have a weak and insignificant relationship with AGB, with strong variations between testing sites. A study by Lu et al. (2002) concluded that vegetation indices alone were not suitable to establish effective biomass estimation models. Lu et al. (2002) stated that vegetation indices are weakly related to biomass because of the use of red and NIR bands, which were shown to be weakly correlated to biomass. Similar results were found in a study by Wang et al. (2005), in which most of the analysed vegetation indices were weakly correlated with biomass. Therefore Wang et al. (2005) concluded that vegetation indices are insufficient for establishing effective models to predict biomass. As mentioned above, the results obtained when analysing the larger sample size by Rasib et al. (2018) are also similar to those obtained in the present study.

4.4 limitations

One of the limitations found in the present study is the relatively small sample size used. Outliers had a strong impact on the predictive capability of the models, as shown by the additional analysis. A larger sample size could have limited the impact of these outliers and thus given a better indication of the potential of the predictive models.

Field data could not be gathered as intended due to unfavourable weather conditions. Therefore, older source data were used which was gathered in a longer time frame of approximately a three-year period (2017-2020). Only one Sentinel-2 image (2018) was deemed suitable to use as input since it was the only image during this time period with minimal cloud cover. No large changes in biomass due to the growth of the woody biomass are expected in a timeframe of three years. However, other natural causes such as diseases and storms could have affected the overall AGB during this period. Therefore, having a Sentinel-2 acquisition date close to the field inventory date would be optimal for comparing the field data to the Sentinel-2 image. The greater the difference between the field-inventory date and the Sentinel-2 acquisition date, the higher the chances are that changes in forest structure have occurred. Therefore, the Sentinel-2 image used in the present study might not have represented the exact same situation as was observed during the field inventories. This could have resulted in errors in some of the plots when comparing the AGB to the reflection value. Preferably a smaller time period was used, with a Sentinel-2 acquisition date close to the date on which the field data were gathered.

The sapling plots were excluded from the AGB assessment, due to incomplete DBH and height measurements in some of the sapling plots. The exclusion of these plots resulted in an underestimation of the total AGB found within the plots. The inclusion of these sapling plots would have given a more accurate representation of the actual situation.

As observed during the analysis of the field data, the presence of a single large tree strongly impacted the total AGB inside a plot. However, a single large tree mainly affects the reflection value of one pixel inside the plot. The use of an average reflection value based on all pixels inside the plot might have limited the capability of the models to express high reflection values caused by a single tree. A pixel-based approach similar to Adan (2017) might be more capable to express strong reflection values when a high amount of AGB is caused by a single large tree.

5. Conclusion

Remote sensing techniques, such as the use of vegetation indices, may facilitate forest inventories with AGB estimations. Studies, however, have shown varying results regarding the effectiveness of vegetation indices for estimating AGB. The present study aimed to investigate the usefulness of vegetation indices for estimating AGB in a mixed dipterocarp forest in Sarawak, Malaysia. The following conclusion was found regarding the main research question;

Which of the analysed vegetation indices is most suitable for estimating above-ground biomass in a mixed dipterocarp forest?

Out of 11 analysed indices, the RERVI showed to be most suitable for predicting AGB in a mixed dipterocarp forest. However, the relationship was weak and insignificant, as it was for all of the analysed vegetation indices. The outcomes of the present study imply that vegetation indices are not suitable as predictors of AGB in a mixed dipterocarp forest.

The strength in relationship between AGB and 11 vegetation indices was analysed in the present study. A total of 29 plots were used as input for the regression analysis, for each plot the measured AGB was linked to the reflection value displayed on the vegetation indices. No significant relationship was found between the analysed vegetation and the measured AGB. An additional analysis was performed in which outliers of AGB were excluded. This analysis showed improvements for most of the indices, with the EVI showing a significant relationship with the AGB. However, the relationship with AGB remained rather weak.

Most noticeable was the inability of the models to explain high amounts of AGB. Plots with a high amount of AGB did not show any sign of saturation, but rather a lack of reflection signal. The presence of large trees and the method used to determine the reflection value of the plots could be a reason for this phenomenon.

5.1 recommendations

The results of the present study indicate that the analysed vegetation indices are not suitable as a predictor for AGB in a mixed dipterocarp forest. The following recommendations are made for future studies;

- Future studies should examine if a pixel-based approach AGB-reflection value approach results in stronger relationships between AGB and the reflection values.

- Future studies should analysed if the relationship between AGB and vegetation indices improves with the use of high-resolution satellite images.

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Appendices

Appendix A: Field form

Plot nr. : ……………………………………… Date:………………………………….

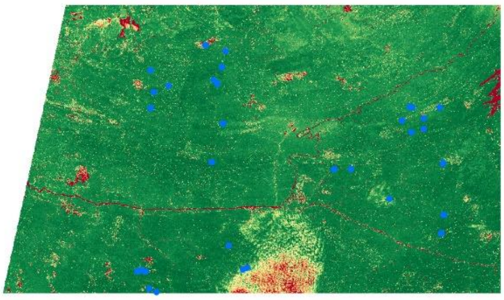
Plot coordinates: ……………………………………………………………………………

Group members: ……………………………………………………………………………
X-coordinates A corner :…………………… Y-coordinates A corner:…………………
X-coordinates B corner:……………………. Y-coordinates B corner:…………………..
X-coordinates C corner:……………………. Y-coordinates C corner: …………………
X-coordinates D corner:…………………… Y-coordinates D corner:…………………
Slope:………………………………….. Elevation:………………………………..
Coordinate system: **WGS-1984 (Decimal degree)**

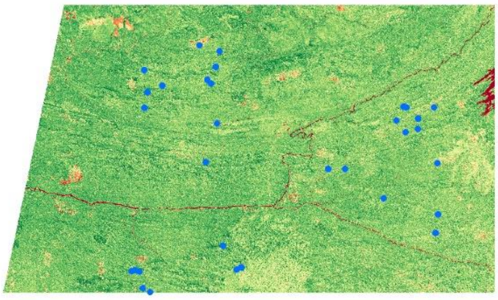
Common name	**Scientific name**	**Tree ID**	**DBH (cm)**	**Height (m)**	**Sub-plot**
Remarks					

Appendix B: Display vegetation indices

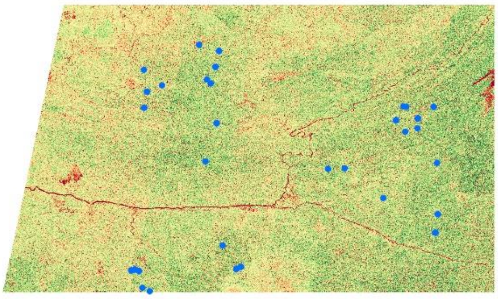
NDVI



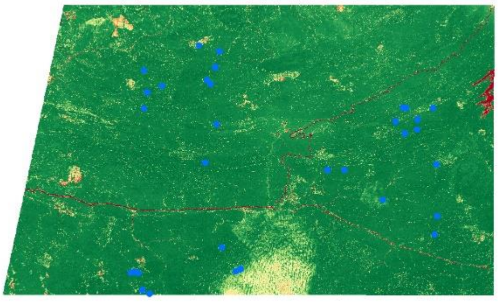
EVI



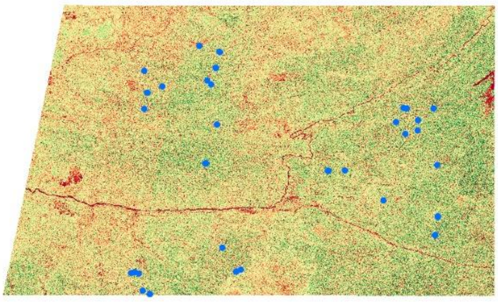
NDVIre2



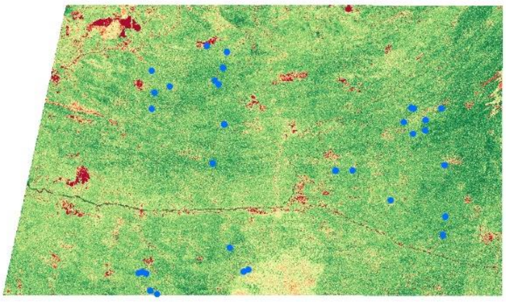
RENDVI-2

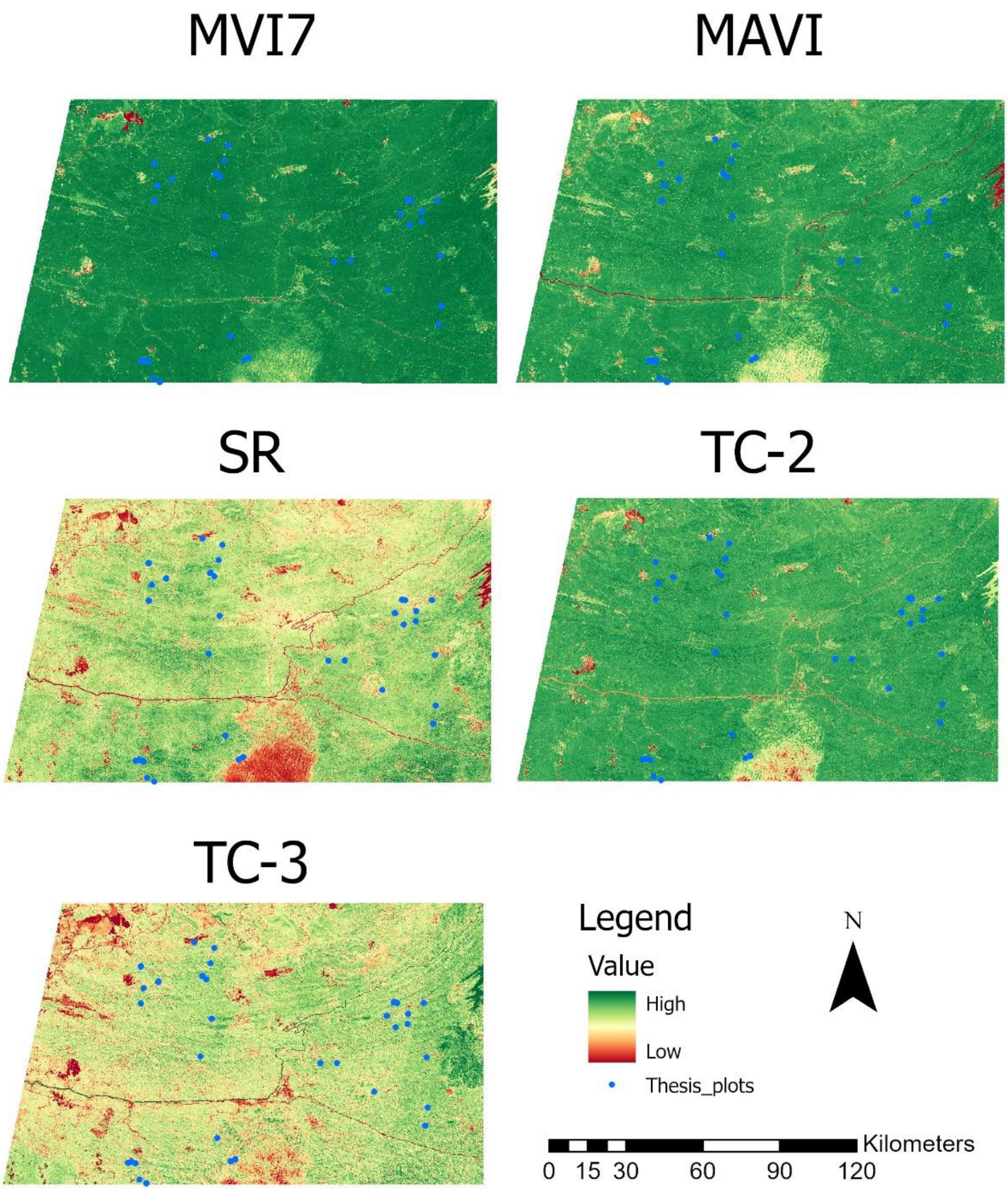


RERVI



MVI5




MVI7
MAVI
SR
TC-2
TC-3
Legend
Value
High
Low
Thesis_plots
N
Kilometers
0 15 30 60 90 120

Appendix C: Field data main and sub-plots

					DBH (cm)			Height (cm)			AGB Mg ha^{-1}
Plot nr.	Sample plot	Size plot (m^2)	DBH class (cm)	Number of trees	min	max	mean	min	max	Mean	
2	Main	1,000	≥ 30	3	30.8	36.7	33.1	20	23	22	22.07
	Sub	400	≥ 10 - < 30	20	10	28.6	15.4	13	28	18	81.47
4	Main	1,000	≥ 30	1	30.7	30.7	30.7	10	10	10	2.07
	Sub	400	≥ 10 - < 30	20	11	29.4	18.2	6	26	16	77.25
9	Main	1,000	≥ 30	5	30	42.9	35.4	17	27	21	42.84
	Sub	400	≥ 10 - < 30	13	10	24.5	14.0	6	18	14	28.58
10	Main	1,000	≥ 30	10	30	49	37.1	12	27	19	76.00
	Sub	400	≥ 10 - < 30	11	14	28.8	19.7	7	15	12	41.24
14	Main	1,000	≥ 30	14	31.9	54	39.2	18	45	27	190.76
	Sub	400	≥ 10 - < 30	20	11	28	18.2	8	29	16	99.55
17	Main	1,000	≥ 30	13	32	120	60.0	15	40	27	560.03
	Sub	400	≥ 10 - < 30	21	10	29.1	18.4	9	25	17	112.87
20	Main	1,000	≥ 30	8	30.2	54.5	37.3	24	32	27	102.04
	Sub	400	≥ 10 - < 30	25	10	23.8	15.0	12	20	15	75.35
23	Main	1,000	≥ 30	13	31.2	140	50.4	15	40	25	315.53
	Sub	400	≥ 10 - < 30	21	11	26	16.9	8	20	15	77.82
39	Main	1,000	≥ 30	9	31.1	49	41.2	18	27	23	90.42
	Sub	400	≥ 10 - < 30	19	11	23.8	14.2	8	20	12	42.87
49	Main	1,000	≥ 30	12	32.2	75	46.1	12	28	21	213.34
	Sub	400	≥ 10 - < 30	16	10	25	14.2	7	18	10	29.28
51	Main	1,000	≥ 30	6	36	60	50.7	15	27	21	102.73
	Sub	400	≥ 10 - < 30	7	13	28.5	19.1	7	16	11	26.63
63	Main	1,000	≥ 30	23	30.1	135	43.3	19	35	24	420.75
	Sub	400	≥ 10 - < 30	15	11	27.7	19.0	13	20	16	72.03
64	Main	1,000	≥ 30	8	30	78	44.1	19	30	24	129.14
	Sub	400	≥ 10 - < 30	26	10	27.7	17.7	8	19	16	111.74
65	Main	1,000	≥ 30	11	30	80	40.2	19	34	24	155.70
	Sub	400	≥ 10 - < 30	28	11	26.9	17.9	6	20	16	128.26
66	Main	1,000	≥ 30	14	31.2	56.9	39.5	17	27	22	123.31
	Sub	400	≥ 10 - < 30	23	10	29.4	18.0	6	20	15	88.60
67	Main	1,000	≥ 30	19	30.8	130	50.6	17	34	23	475.64
	Sub	400	≥ 10 - < 30	25	11	28.4	16.8	10	26	16	95.83
68	Main	1,000	≥ 30	19	30	80	41.5	14	31	22	258.26
	Sub	400	≥ 10 - < 30	28	11	29.5	16.5	8	20	16	106.73
69	Main	1,000	≥ 30	11	30.5	55.5	39.3	18	27	23	120.13
	Sub	400	≥ 10 - < 30	29	10	28	16.0	9	18	16	98.46
70	Main	1,000	≥ 30	16	30.2	80	44.3	18	29	23	240.02
	Sub	400	≥ 10 - < 30	28	10	29.3	17.7	4	21	16	140.44
71	Main	1,000	≥ 30	12	30.5	58	42.1	20	29	25	174.96
	Sub	400	≥ 10 - < 30	22	12	28.1	16.3	6	22	15	96.00
72	Main	1,000	≥ 30	13	30	42.9	37.6	17	27	24	141.82
	Sub	400	≥ 10 - < 30	16	12	21.1	16.4	10	18	16	56.04
73	Main	1,000	≥ 30	15	30	57.2	42.9	22	28	25	224.12
	Sub	400	≥ 10 - < 30	32	10	29	17.5	10	23	17	165.87
77	Main	1,000	≥ 30	9	30.1	41.8	35.9	15	25	21	80.92
	Sub	400	≥ 10 - < 30	25	11	28.1	19.7	10	21	14	112.56
79	Main	1,000	≥ 30	4	30.1	35.1	33.4	20	25	24	28.86
	Sub	400	≥ 10 - < 30	13	10	28.8	15.2	5	15	10	33.72
80	Main	1,000	≥ 30	10	30.1	50.2	38.8	22	27	26	111.68
	Sub	400	≥ 10 - < 30	18	10	29.5	17.7	7	27	16	85.93
81	Main	1,000	≥ 30	13	30.5	55.5	38.8	17	27	24	149.77
	Sub	400	≥ 10 - < 30	20	11	27.1	17.1	7	25	15	83.00
82	Main	1,000	≥ 30	11	31.1	55.5	41.7	20	35	24	134.41
	Sub	400	≥ 10 - < 30	10	12	27.1	18.6	10	17	13	36.49
84	Main	1,000	≥ 30	5	31.4	45.5	37.7	20	25	23	49.81
	Sub	400	≥ 10 - < 30	29	11	29.5	19.3	10	25	20	182.05
85	Main	1,000	≥ 30	11	30.3	65	42.2	18	26	23	159.37
	Sub	400	≥ 10 - < 30	16	11	28.2	17.0	10	22	17	69.39
86	Main	1,000	≥ 30	10	33	55	41.1	20	25	23	113.21
	Sub	400	≥ 10 - < 30	10	12	22	15.3	10	20	17	33.88

87	Main	1,000	≥ 30	1	70.6	70.6	70.6	25	25	25	36.63
	Sub	400	≥ 10 - < 30	17	11	27	16.2	15	25	19	68.92