ASSESSMENT AND PREDICTION OF ABOVE-GROUND BIOMASS IN SELECTIVELY LOGGED FOREST CONCESSIONS USING FIELD MEASUREMENTS AND REMOTE SENSING DATA: CASE STUDY IN SOUTH EAST CAMEROON

Thesis submitted for a M.Sc. Degree in Forest Ecology and Management

University of Helsinki
Department of Forest Sciences
Viikki Tropical Resources Institute (VITRI)

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Shu Gideon Neba

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Tiedekunta/Osasto — Fakultet/Sektion — Faculty	Laitos — Institution — Department
Faculty of Agriculture and Forestry	Department of Forest Sciences, Viikki Tropical Resources Institute (VITRI)

Tekijä — Författare — Author

Shu Gideon Neba

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Tiivistelmä — Referat — Abstract

This study quantified above-ground biomass affected by selective logging in the tropical rainforest of South East Cameroon and also investigated the suitability of the density of logging roads, the density of log yards as well as variables from MODIS 250 m data (Red, NIR, MIR, NDVI, EVI) in explaining above-ground biomass logged. Above-ground biomass logged was quantified using allometric equations. The surface area of logging roads and log yards were quantified and used in the determination of above-ground biomass affected by these infrastructures based on a national reference baseline value for the forest zone of Cameroon. A comparative analysis revealed that 50% of potentially exploitable commercial tree species were effectively harvested with a harvesting intensity of 0.78 trees ha^{-1} representing an average above-ground biomass of 3.51 Mg ha^{-1}. The results also indicated that 5.65 Mg ha^{-1} of above-ground biomass was affected by logging infrastructure .i.e. 62% as compared to 38% of above-ground biomass that was logged. Correlation and regression analysis showed that the density of the logging roads explained 66% of the variation in above-ground biomass logged and 73% of the variation in above-ground biomass logged was explained by the density of the logging roads and NDVI from MODIS data. The density of log yards and the variables from MODIS data were generally weak in explaining the variation in above-ground biomass logged.

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Helsinki, May 2013
Shu Gideon Neba

Dedication

This thesis is dedicated to the life of my late father- Papa Julius Shu Ngongnjo who passed on to eternity while I was abroad pursuing this objective. Though with no formal education, Papa believed in and upheld the values of formal education by ensuring that all his nine children were able to see the four walls of a school classroom. This is one of the legacies he has left behind which will be projected through the family line over generations.

Helsinki, May 2013
Shu Gideon Neba

Table of contents

ACKNOWLEDGEMENT .... **III**

DEDICATION .... **V**

TABLE OF CONTENTS .... **VI**

LIST OF FIGURES .... **IX**

LIST OF TABLES .... **X**

ACRONYMS .... **XI**

1 INTRODUCTION **1**

1.1 BACKGROUND 1

1.2 RESEARCH OBJECTIVES 5

2 OVERVIEW OF FOREST MANAGEMENT AND SELECTIVE LOGGING IN CAMEROON **7**

2.1 FOREST MANAGEMENT 7

2.2 SELECTIVE LOGGING 8

3 THE STUDY AREA **11**

3.1 LOCATION 11

3.2 BIOPHYSICAL FACTORS 12

3.2.1 Vegetation and wildlife 12

3.2.2 Climate 13

3.2.3 Hydrography 13

3.2.4 Geology and soils 13

3.2.5 Relief 13

3.3 POPULATION 14

3.4 LOCAL ACTIVITIES 14

3.5 INDUSTRIAL ACTIVITIES 15

3.6 CONSERVATION ACTIVITIES 17

3.7 INFRASTRUCTURE AND COMMUNICATION FACILITIES 17

4 MATERIALS AND METHODS **19**

4.1 MATERIALS 19

4.1.1 Field data 19

4.1.2 Remote sensing data 20

4.2 METHODS 21

4.2.1 Processing of forest inventory data 21

4.2.2 Quantification of above- ground biomass of the commercial tree species 21

4.2.3 Quantification of above-ground biomass affected by logging roads and log yards....... 22
4.2.4 Determination of the area and the density of logging roads....................................... 24
4.2.5 Determination of the area and the density of the log yards.. 25
4.2.6 Processing of MODIS 250 m data 25
4.2.7 Data organization... 26
4.3 STATISTICAL ANALYSIS.. 26
4.3.1 Sample size 27
4.3.2 Variables 27
4.3.3 Data exploration.. 28
4.3.4 Correlation analysis... 28
4.3.5 Linear regression analysis 29
4.3.6 Interpreting the linear regression parameters... 30
4.3.7 Verification of the assumption of linear regression analysis....................................... 31
4.3.8 Testing the linear regression hypothesis 31
4.3.9 Verification of the precision of predicted above-ground biomass logged 32

5 RESULTS.. 33

5.1 ASSESSMENT OF ABOVE-GROUND BIOMASS LOGGED... 33
5.2 ASSESSMENT OF ABOVE-GROUND BIOMASS AFFECTED BY LOGGING INFRASTRUCTURE....... 34
5.3 COMPARISON OF ABOVE-GROUND BIOMASS LOGGED WITH RESPECT TO THE COMMERCIAL TREE POTENTIAL 35
5.3.1 Comparison of above-ground biomass affected with respect to the national reference baseline.. 37
5.4 CORRELATION ANALYSIS 38
5.4.1 Correlation of field measured variables with above-ground biomass logged 38
5.4.2 Correlation of MODIS variables with above-ground biomass logged.......................... 39
5.5 REGRESSION ANALYSIS 41
5.5.1 The simple linear regression model 43
5.5.2 Prediction of above-ground biomass logged using simple linear regression model...... 43
5.5.3 The Multiple linear regression model 44
5.5.4 Prediction of above-ground biomass logged using multiple linear regression model ... 44

6 DISCUSSION.. 46

6.1 EFFECTS OF SELECTIVE LOGGING ACTIVITIES ON ABOVE-GROUND BIOMASS....................... 46
6.2 CORRELATION ANALYSIS AND REGRESSION ANALYSIS 49
6.2.1 The simple linear regression model 50
6.2.2 Prediction of above-ground biomass logged using the simple linear regression model 51
6.2.3 The multiple linear regression model.. 51
6.2.4 Predicted above-ground biomass logged using multiple linear regression model......... 52

7 CONCLUSIONS AND RECOMMEDATIONS.. 54

7.1 CONCLUSION 54
7.2 RECOMMENDATIONS 55

8 REFERENCES 57

9 APPENDIX 63

List of figures

Figure 1: The forest zoning plan of Cameroon from WRI (2005) 8
Figure 2: Examples of selective logging activities in South East Cameroon 9
Figure 3: Illustration of above-ground biomass as component of carbon pool from Simon Eggleston & Nalin Srivastava (2008), AFOLU in the IPCC 2006 Guidelines............ 10
Figure 4: The location of the study site 11
Figure 5: Examples of local houses in South East Cameroon 15
Figure 6: A general view of SEBC-VICWOOD THANRY base camp and sawmill at Lokomo 17
Figure 7: Geo-localization of the forest exploitation inventory data 23
Figure 8: Geo-localization of logging infrastructure 25
Figure 9: Summary of the procedure for quantifying above-ground biomass affected by selective logging 26
Figure 10: Summary of the procedure for developing prediction models for above-ground biomass logged 32
Figure 11: A comparative analysis of above-ground biomass affected by selective logging activities 35
Figure 12: Comparative analysis of above-ground biomass of commercial trees after logging 37
Figure 13: Comparative analysis of the total above-ground biomass after logging 37
Figure 14: Correlation of above-ground biomass logged with field measured independent variables 39
Figure 15: Correlation of above-ground biomass logged with variables from MODIS 250 m data 41

List of tables

Table 1: The references of the MODIS 250 m products used in the study 20
Table 2: A list of the data used in the statistical analysis.. 27
Table 3: The correlation matrix of the dependent and the independent variables 29
Table 4: The synthesis of above-ground biomass harvested by species 33
Table 5: The synthesis of the area covered by logging infrastructure 34
Table 6: Quantity of above-ground biomass affected by selective logging activities...... 34
Table 7: A comparative analysis of above-ground biomass of commercial trees after logging 36
Table 8: Parameters of linear regression for predicting above-ground biomass logged . 42
Table 9: Prediction of above-ground biomass logged based on simple linear regression model.. 44
Table 10: Prediction of above-ground biomass using multiple linear regression 45

Acronyms

AAC	Allowable Annual Cut or ‘Assiette Annuelle de coupe’
AFOLU	Agriculture, Forestry and Other Land Use
AGB	Above-ground biomass
A.P.I.	‘Aménagement Pilote Intégré’ (Project : 1992-1996, East Cameroon)
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CBFP	The Congo Basin Forest Partnership
CCA	Contextual Classification Algorithm
CIFOR	Center for International Forestry Research
COMIFAC	Central African Forest Commission
DBH	Diameter at Breast Height (1.3 m)
EO	Earth Observation
EVI	Enhanced Vegetation Index
FMU or UFA	Forest Management Unit or Unité Forestière d’aménagement
GHG	Green House Gas emissions
GoC	Government of Cameroon
GOFC-GOLD	Global Observation of Forest and Land Cover Dynamics
GPS	Global Positioning System
IPCC	Intergovernmental Panel on Climate Change
Landsat ETM+	Land Satellite, Enhanced Thematic Mapper Plus
LUC	Land Use Change
MINFOF	Ministry of Forestry and Wildlife
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared Reflectance
QsG	Queensland Government
REDD+	Reduced Emissions due to Deforestation and Forest Degradation and the role of Conservation, Sustainable Management and the enhancement of carbon stocks

RIL	Reduce Impact Logging
SEBC	Societé d’Exploitation des Bois du Cameroun
SMA	Spectral Mixing Analysis
SPOT	Satellite Pour l’Observation de la Terre or Satellite for Earth Observation
SPSS	Statistical Package for the Social Sciences
SSV	Sales of standing Volume or ‘Ventes de coupe’
UNFCCC	United Nations Framework Convention on Climate Change
USGS	U.S. Geological Survey
UTO	Unité Technique Opérationnelle or ‘Technical Operational Unit’
WRI	World Resources Institute

1 INTRODUCTION

1.1 Background

Deforestation, forest degradation and land use change (LUC) are the main sources of carbon emissions from developing countries, accounting for 15–20% of global carbon emissions (Angelsen, 2008, UNFCCC, 2009, Kanninen et al., 2010). The increase in the concentrations of carbondioxide (CO_2) and other greenhouse gases (GHG) in the atmosphere are the main drivers of the changes in the Earth's environmental conditions and global climate (IPCC, 1990).

Since the early 1990s, there is increasing effort from the international community to combat global climate change through mitigation and adaptation. Mitigation actions are those actions that are aimed at a reduction of the carbondioxide and other GHG concentrations in the atmosphere, whereas adaptation efforts are those actions that are geared towards the reduction of the vulnerability or the enhancement of the resilience of the environment to cope with future global climatic conditions (Kanninen, 2012).

The signing of the United Nations Framework Convention on Climate Change (UNFCCC) in Rio de Janeiro in 1992 and its subsequent implementation instruments have been widely observed and recognized as important milestones in the commitment of the international community towards combating global climate change. The UNFCCC is the leading international body in addressing global climate change and the Conference of the parties (COP) is the supreme decision making body of the UNFCCC and is charged with the responsibility of coordinating the development of REDD+ (Reduced Emissions due to Deforestation and Forest Degradation and the role of Sustainable Management, Conservation, and the enhancement of carbon stocks) policy and supervising its overall development. This organ is also responsible for the final policy formulation and implementation guidelines of the REDD+ mechanism (Siwe et al., 2011). Since its creation, the COP has held 18 meetings with the most recent in Doha, Qatar, from 26 November to 7 December 2012 (UNFCCC, 2013) home page at: http://unfccc.int/meetings/items/6237.php. During COP11 in Montreal in 2005, the governments of Papua New Guinea and Costa Rica, supported by Latin American and African countries submitted a proposal for the consideration of REDD in developing countries for the post-Kyoto protocol reporting (UNFCCC, 2005, Siwe et al., 2011, Kanninen, 2012). Sustainable forest management, conservation and the enhancement of carbon stocks were subsequently considered as eligible activities under the REDD mechanism and in COP13 in Bali, the term REDD+ was adopted. The crucial role of reducing emissions from deforestation and forest degradation and the need to enhance the role of forests in the removal of greenhouse gases from the atmosphere, was recognized in COP15 in Copenhagen in December 2009, which called for the immediate establishment of the REDD+ mechanism (Reduced Emissions due to Deforestation and Forest Degradation and the role of Sustainable Management, Conservation, and the enhancement of carbon stocks) (UNFCCC, 2005, Angelsen, 2008, Kanninen et al., 2010). COP 16 requested countries engaged in the REDD+ process to elaborate national strategies or action plans, comprising a robust and transparent national forest monitoring system with sub national level monitoring and reporting, national reference emission levels or combinations of sub national forest reference levels in accordance with the national circumstance and capability, information on how safeguards are being addressed as interim measures while transitioning to a national forest reference emission level (Siwe et al., 2011, UNFCCC, 2011).

The current international REDD+ mechanism (a global climate change mitigation initiative) , sustainable forest management planning, conservation planning, economic development, improvement of local and global ecological models require the efficient assessment of the causes of deforestation and forest degradation (Carlos Souza et al., 2002, Souza and Roberts, 2005). The effective implementation of any climate change mitigation initiative in developing countries requires that there should be a constant assessment and monitoring of deforestation, forest degradation, and land use change. This entails an understanding of: (i) the aerial extent of deforestation and forest degradation, (ii) the proportion of forest biomass loss in deforestation and forest degradation, (iii) the location where deforestation or forest degradation is occurring, and (iv) the carbon content of each forest type in metric tons of carbon per hectare (Kanninen et al., 2007, Ramankutty et al., 2007, Olander et al., 2008, Baldauf et al., 2009).

Deforestation is the direct, human-induced conversion of forested land to non-forested land .i.e. a permanent conversion of forest land to other land cover or land use such as cropland, grassland, wetlands or settlements; and forest degradation is the direct, human-induced, long-term loss (persisting for a known period of time in years) or at least a known percentage of forest carbon stocks [and forest values] from a certain time reference and not qualifying as deforestation (IPCC, 2003, GOFC-GOLD, 2011). The IPCC definition of forest degradation emphasizes a decrease in carbon stocks of "forest land remaining forest land" (GOFC-GOLD, 2011). However, forest degradation also applies to a reduction of forest productivity (products and services), genes, tree vigour and quality, species composition, soils, water, nutrients and the landscape. "As widely used by forest scientists, forest degradation implies a long-term loss of productivity that is difficult to assess, especially when applied to soils, water, and the landscape" (Siwe et al., 2011).

In order to support the implementation of the REDD+ mechanism, the Intergovernmental Panel on Climate Change (IPCC) has provided guidelines to assist countries in developing carbon assessment methodologies. The guidelines are organized into three "Tiers" each providing successively increased level of accuracy. The tier I approach is the most general based on nationwide estimates of forest cover and generic forest carbon density value, tier II and III provide increased detail on carbon stock and emissions at regional and national level using a combination of plot inventory, satellite mapping and carbon modeling approaches. The achievement of tier III level of accuracy further requires that both above-ground and below-ground dead and live carbon stocks are estimated and modeled (Gregory, 2009).

Deforestation, forest degradation and land use change as sources of emissions in the tropics are caused by several factors, which are either direct or indirect factors. The direct causes of deforestation and forest degradation widely cited in literature are: expansion of agricultural land (including bioenergy production), growth of human settlements, selective timber logging, forest fires, fuel wood and charcoal collection and mining activities, while indirect causes of deforestation and forest degradation have been mostly linked to: increase in human population, change in human consumption patterns, commodity price increase, political and governance policies and practices, technological advancements, cultural factors and many others.

Methods for monitoring deforestation and LUC based on optical remote sensing technology have been relatively well developed (LAMBIN, 1999, GOFC-GOLD, 2011). However, research efforts are still ongoing to develop an efficient method for the assessment of forest degradation. Methodological difficulties in assessing forest degradation from remote sensing (widely believed to be cost effective for large scale assessments) stem from the fact that difference in reflectance between forest and degraded forest are more subtle than in the case of deforestation. The degraded forest is a complex mix of different land cover types (vegetation, dead trees, soil, shade) and the spectral signature of the degradation changes quickly (as a result of forest re-growth), i.e. in less than 2 years, making it technically challenging to assess forest degradation through optical remote sensing methods (Carlos Souza et al., 2002, Baldauf et al., 2009, Siwe et al., 2011, GOFC-GOLD, 2011).

Current literature indicates some advances made in the development of methods for mapping forest degradation developed on the basis of medium spatial resolution sensors such as Landsat, ASTER and SPOT and very high resolution sensors such as Ikonos or Quickbird, as well as aerial digital images acquired with videography (Carlos Souza et al., 2002, Souza and Roberts, 2005, Gregory, 2009, Siwe et al., 2011). A majority of the studies, which form the basis for these methods were carried out in the Amazonian tropical rainforest. Very few studies have so far been conducted in the African tropical rainforest conditions; hence the suitability and the applicability of these methods in the African tropical rainforest ecosystem have been insufficiently investigated. Considering the fact that the factors causing forest degradation may vary or may occur at different intensities in different environments, there is a need for the proper investigation of the applicability of the existing methods as well as the need to develop methods for assessing forest degradation which are directly based on the African rainforest factors of forest degradation.

The REDD+ pilot project conducted in Cameroon (Siwe et al., 2011) tested a method for mapping forest degradation caused by selective logging based on Spectral Mixing Analysis (SMA) and Contextual Classification Algorithm (CCA) techniques. Though this study concluded that remote sensing can be used to track forest degradation due to selective logging, it however observed that “there is still a gap in both research and the design of operational methods for EO-based assessment of forest degradation in COMIFAC countries,” and stressed the need for this methodological development to be addressed urgently. The same study further stressed the importance of developing a monitoring system that is robust using remote sensing technology and field measurements to track and quantify carbon fluxes due to forest degradation.

Furthermore, based on the economic situation in most developing countries, the methods based on high resolution satellite images such as Ikonos, Quickbird and aerial digital images acquired with videography are expensive and unlikely to be at the reach of a majority of the stakeholders in the forestry business as well as possible REDD+ structures in Central African countries. Persistent cloud cover is another hindrance to the full exploitation of the potential of optical remotely sensed data over the Central African rainforest ecosystem. All of these factors call for a continuous quest in the search of methodologies for a precise and accurate assessment of forest degradation in the Central African rainforest.

1.2 Research Objectives

From this background, the goal of this study is to quantify above-ground biomass affected by selective logging and to further develop models based on field measured variables and variables derived from moderate resolution free remote sensing datasets for predicting above-ground biomass in a selectively logged forest concession, with the aim of establishing proxies for the assessment of forest degradation caused by selective logging and for the quantification of the resulting carbon emissions.

The main objective of this study was to use above-ground biomass as an indicator to assess forest degradation caused by selective logging by quantifying the above-ground biomass affected in a selectively logged forest concession and also to

investigate and propose proxies for predicting forest degradation (changes in above-ground biomass levels) caused by selective logging.
The specific objectives of the study were: (i) to quantify above-ground biomass affected by selective logging activities in the study site, (ii) to investigate whether there is a relationship between the density of logging roads, the density of log yards and the quantity of above-ground biomass logged, (iii) to investigate whether there is a relationship between red reflectance, near infrared reflectance (NIR), middle infrared reflectance (MIR), normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI) derived from MODIS 250 m products and above-ground biomass logged, and (iv) to develop a model for predicting above-ground biomass logged in selectively logged forest concessions.

It is hoped that the results from the study will go to contribute to ongoing efforts in the setting up and the implementation of the climate change mitigation initiative (REDD+) in Cameroon by providing a method that would probably contribute in the assessment of carbon emissions in selectively logged forest concessions. In addition, the study will contribute to the sustainable management of the tropical rainforest of Cameroon by providing useful information on which forest management decisions could be based- both at the level of field practices as well as policy development level. The main research questions were:

- What quantity of above–ground biomass is affected by the following selective logging activities? (i) Logged trees, (ii) Construction of logging roads, (iii) Construction of log yards
- Is there a relationship between density of logging roads, the density of log yards, and above-ground biomass logged in selectively logged forest concessions?
- Is there a relationship between red reflectance, near infrared reflectance (NIR), middle infrared reflectance (MIR), normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI) derived from MODIS 250 m products and above-ground biomass logged?

The hypothesis was that:

- There is high dependency of selective logging activities on road network, which in turn creates a significant impact on above-ground biomass.

- Changes in above-ground biomass significantly correlate with i) Red reflectance, ii) Near Infrared (NIR), iii) middle infrared reflectance (MIR), iv) Normalized Difference Vegetation Index (NDVI), v) Enhanced Vegetation Index (EVI) derived from MODIS 250 m resolution products.

2 OVERVIEW OF FOREST MANAGEMENT AND SELECTIVE LOGGING IN CAMEROON

2.1 Forest management

The republic of Cameroon has a total surface area of 475000 Km^2 and the surface area of the tropical rainforest of Cameroon is estimated to be between 19.5 million and 22 million hectares (WRI, 2005, CBFP, 2006, WRI, 2007, Guiseppe et al., 2009, MINFOF, 2010, WRI, 2012).

According to the 1994 forestry law of Cameroon, the national forest estate is zoned into the permanent forest estate and the non-permanent forest estate. By definition, the permanent forest estate represents forest land that is zoned for production and conservation purposes and cannot be converted to any other land use. The permanent forest estate is comprised of the state forests and the council forests. The non-permanent forest estate by definition refers to forest land that is susceptible to being converted to other land uses than forestry. This is forest land located near villages and settlements and includes communal, community and private forests estates (see figure 1 for the detailed forest zoning system in Cameroon). The permanent forest estate is anticipated to cover at least 30% of the national territory and should represent the country's ecological diversities (vegetation types) on the completion of the land use zoning plan (GoC, 1994, WRI, 2005, WRI, 2007, Guiseppe et al., 2009, WRI, 2012).

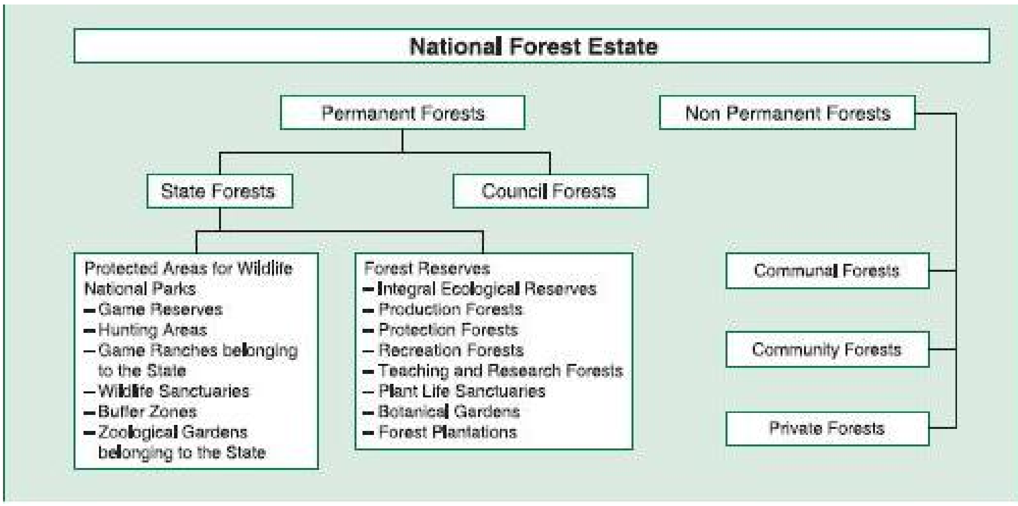


Figure 1: The forest zoning plan of Cameroon from WRI (2005)

Forest Management Units (FMUs) are production forest areas that are zoned for industrial wood production. By regulation, the surface area of a single FMU should never exceed 200.000 hectares. Wood production by local communities and councils is carried out within community and council managed forests respectively. Other production forest units called sales of standing volume (SSV) or 'ventes de coupe' (not exceeding 2500 ha) are also opened for timber production purposes and some are prioritized to national companies for a maximum three years logging period. In addition to these, there are other special permits granting individual access to forest resource exploitation, which include: (i) forest products exploitation permits, (ii) personal logging permits, (iii) timber removal permits, and (iv) timber recuperation permits (GoC, 1994, WRI, 2005, WRI, 2007, De Wasseige et al., 2009, WRI, 2012).

2.2 Selective logging

Wood harvesting in Cameroon, especially in production forests is carried out through a selective logging process. Selective logging has been described as a harvesting system practiced mainly in native forests and in hardwood plantations where a few desired and commercially valuable trees species are harvested following a predefined criteria as opposed to clear cutting where a whole forest compartment is completely clear-cut in the harvesting process. Selective harvesting is said to remove only a portion of the standing trees leaving a viable forest for natural regeneration and growth. The natural spatial configuration, stand structural elements and growth stages of the native forest are maintained by retaining at least

50 per cent basal area (which translates to about 50 per cent forest canopy cover) including habitat trees and watercourse and steep area protection zones (QsG, 2011) .

In Cameroon, the allocation of FMUs for selective logging is done through a transparent competitive public auction process where the government selects companies that have demonstrated adequate financial and technical capacities to carry out forest exploitation as well as forest management activities in the allocated forest concessions. Once attributed, companies secure long-term use rights for 15 years renewable (GoC, 1994, Guiseppe et al., 2009). Selective logging in FMUs is planned and implemented according to a pre-established management plan- an obligation imposed by the 1994 forestry law of Cameroon. The management plan defines the species to be harvested, the minimum exploitable diameter for each species which guarantees that at least 50% of the harvested tree species is able to reconstitute during the next rotation cycle, the quantity of wood to be harvested in terms of number of trees and volumes, the logging sequence for a 30 year rotation cycle and many other forest management obligations.

Photos by Shu, Sufo & Theo, July 2012

Figure 2: Examples of selective logging activities in South East Cameroon

Above-ground biomass is the carbon pool that is most affected by selective logging activities and is also one of the six carbon pools (see figure 3 below) that has been recommended for investigation in the IPCC 2006 guidelines. The activities which affect above-ground biomass during selective logging include: (i) the biomass that is taken out through the trees that are harvested (ii) the construction of logging roads and log yards and (iii) residual damage caused to the surrounding vegetation by tree fall and machinery maneuvering (Vincent Medjibe et al., 2011, Durrieu de Madron et al., 2011).

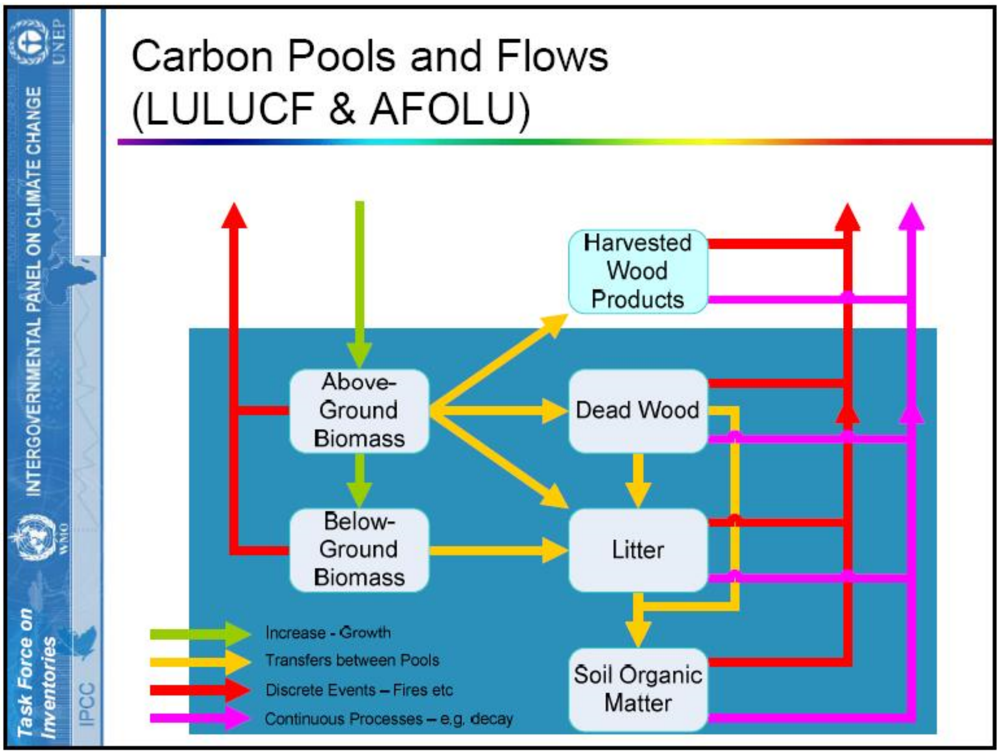


Figure 3: Illustration of above-ground biomass as component of carbon pool from Simon Eggleston & Nalin Srivastava (2008), AFOLU in the IPCC 2006 Guidelines.

3 THE STUDY AREA

3.1 Location

The study was conducted in the East Region of the Republic of Cameroon, in AAC 3-4 of FMU 10-007. FMU 10-007 is a forest management unit which covers a total surface area of 122 294 ha and was allocated for sustainable management to the forestry company SEBC-an affiliate of VICWOOD THANRY in 1998. AAC 3-4 covers a surface area of 4400 ha out of the 122 294 ha total surface area of FMU 10-007.

Geographically, FMU10-007 lies between latitudes 2°40’ and 3°09’N and longitude 15°20’ and 15°46’E. It is located in the Boumba and Ngoko division of the East region of Cameroon. Its boundaries cut across two administrative districts: Yokadouma and Moloundou. Its logging operations are guided by the prescriptions of its management plan that was elaborated in 2002 by the concession holder SEBC and approved by the then Ministry of Environment and Forestry. AAC 3-4 was selectively logged between July and December 2011 (personal communication from VICWOOD THANRY sources).

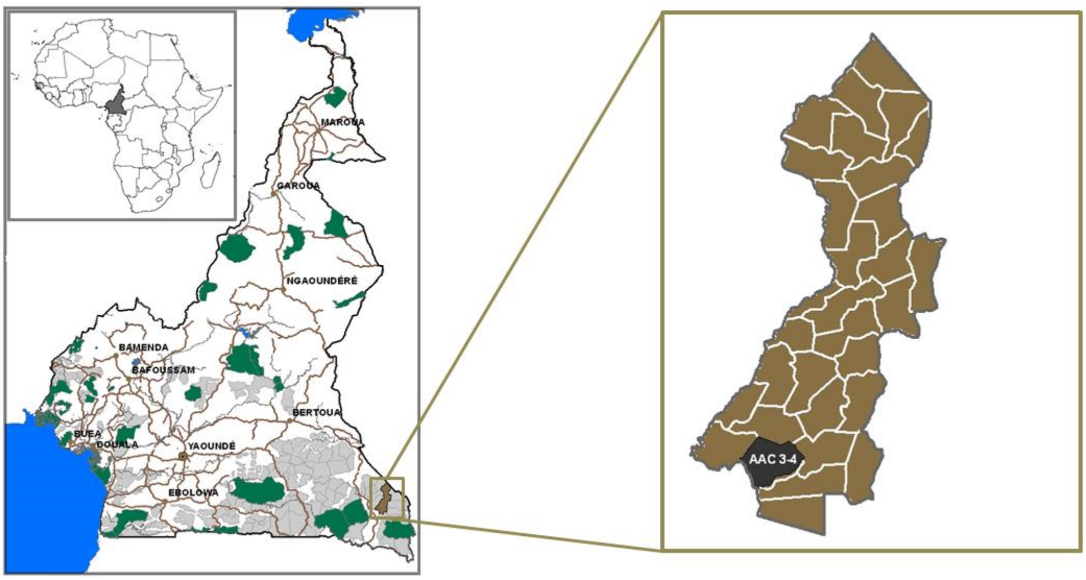


Figure 4: The location of the study site

3.2 Biophysical factors

3.2.1 Vegetation and wildlife

The vegetation type in the study site is described as semi-deciduous Guinea-congolaise dense tropical rainforest and is characteristically a mixture of evergreen forest and semi-deciduous forest which is stratified into several layers. In this forest type, trees can grow as tall as 70m and as big as 150 cm in diameter or more. Available literature indicates that the species richness and diversity in this area is very high; about 1500 different plant species grow in the area. Also, isolated pockets of swamp forest dominated by palm trees and Raphia palms bushes are encountered along the River Lokomo which forms the western boundary of the forest concession. The tree species present are mostly hardwood evergreens species and the dominant ones include: *Alstonia boonei, Celtis zenkerii, Entandrophragma angolense, Entandrophragma candollei, Entandrophragma cylindricum, Entandrophragma utile,* Eribroma oblongum*, Erythropleum ivorense, Guarea spp, Guibourtia ehié, Khaya sp, Mansonia altissima, Milicia excelsa, Pericopsis elata, Pterocarpus soyauxii, Swartzia fistuloides, Triplochyton scleroxylon* (SEBC, 2002).

Although there are no specific studies on the wildlife in FMU 10-007, literature on the East Region of Cameroon indicates that this Region is very important in terms of its diversity and abundance of wildlife resources, testified by the creation of many protected areas in this Region. The Region contains a variety of large mammals, small mammals, and avifauna. Large mammal populations include threatened species listed on the IUCN Red list of species, such as elephants (*Loxodonta africana cyclotis*), chimpanzees (*Pan troglotydes*), gorillas (*Gorilla gorilla*), buffalos (*Syncerus caffer nanus*), giant pangolins (*Manis gigantea*) antelopes (*Panthera pardus*). The population of small mammals is dominated by numerous species of monkeys and rodents, including: *Cercopithecus spp, Antherurus africanus, Cephalobus spp, Tragelaphus spekki and Colobus guereza.* The Avifauna population is dominated by dense forest species, including globally threatened species such as *Bradypterus grandis, Lobotos oriolinus, Pteronetta hartlaubii* and many other bird species (SEBC, 2002, SEFAC, 2005).

The prominent protected areas located in the zone of FMU 10-007 are the Dja biosphere reserve (one of UNESCO' s natural heritage sites in Cameroon), Lobéké national park, Boumba-Bek national park, Nki national park, and Deng Deng national park.

3.2.2 Climate

The climate is described as wet equatorial climate (also known as a Guinea type climate), meaning that it experiences high temperatures (24˚C on average). The climate is greatly influenced by the monsoon and Harmattan winds resulting in four characteristic seasons: a long dry season from December to May, a light wet season from May to June, a short dry season from July to October, and a heavy wet season from October to November. Humidity and cloud cover are relatively high, and precipitation averages 1500–2000 mm per year (SEBC, 2002, SEFAC, 2005).

3.2.3 Hydrography

The study site is described to be located within the Sangha drainage basin. The main rivers in this region are: Lokomo (which forms the natural boundary of FMU 10-007 to the west), Monguele, Lokou, Loponji, Boumba and Ngoko rivers (SEBC, 2002) .

3.2.4 Geology and soils

The geological rock basement is cratonic and dates as far back as the Precambrian and Cambrian periods; composed mainly of ancient migmatites and mica schist. Alluvial deposits dating to the quaternary period are located within valleys and other depressions. The common soil type is ferralsols (ferrallitic red soils). These ferrallitic soils are overlaid by a deep top humus layer that results from the decomposition of vegetal material. Hydromorphic soils, such as gleysols, fluvisols, and peat, are common along river banks (SEBC, 2002, SEFAC, 2005).

3.2.5 Relief

The land consists largely of monotonous, gently-undulating hills. In general, the East region of Cameroon lies on the South Cameroon plateau that forms the south-eastern half of the country. The elevation range in this region is between 200 and 1000 meters above sea level (Heckelsweiller et al., 2001).

3.3 Population

The estimate of the total local population in the vicinity of FMU 10-007 is about 7300 inhabitants, living in the following villages: Momboué, Ngolla 125, Ngolla 120, Tembé and Mikel. The ethnic groups in these villages are also described as being diverse with Baka, Bangando and Mbimo pygmies constituting the main indigenous groups. Alongside the indigenous communities are other communities such as Kounabembe and Mvong-Mvong communities which are inhabited by settlers believed to have come from other countries notably: Senegal, Mali, Mauritania, and Nigeria. However, the current experience in the area shows that there is increasing cohabitation of the Baka pygmies with people from other Bantu tribes (SEBC, 2002).

3.4 Local activities

The local populations depend on the forest for their livelihood, especially for food, medicine, handicraft and energy. They harvest various seeds, fruits, leaves, and barks, which are used either as ingredients, thickeners, or as vegetables. Baka pygmies still practice seasonal migration into the forest for gathering and harvesting fruits (based on the fruiting periods of some forest trees) or for hunting purposes as well as for visiting sacred sites for spiritual rites.

Fishing and hunting are important local activities. The Bangando, Mbimo, and Baka pygmies are traditional hunters. “Bushmeat” is the principal source of animal proteins and local income. In commercial hunting, the wildlife “bushmeat” is sold either locally or through well-organized channels of middle men to nearby towns and cities. Public transporters are highly involved in “bushmeat” business and are the main channels of “bushmeat” movement from local areas to urban centres. It is estimated that a household makes an average monthly income of 50000 fcfa (about 80€) from hunting activities (SEBC, 2002, Makazi, 2004, SEFAC, 2005).

The local populations also carry out farming activities, mainly for subsistence and only the surplus is sold. Shifting cultivation and mixed cropping are the local farming practices. The crops fields are generally small in size (less than 0.5 ha) on average. The common food crops that are grown include: cassava, cocoyams, plantains, groundnuts, maize, and sugar cane. Also, coffee, cocoa and plantains are grown as cash crops (SEBC, 2002).

Indian bamboos and rattans are used for local handicrafts mainly: baskets, chairs, beds and shelves. Local houses are thatch and mud houses constructed from local materials: mats made out of Raphia palms leaves for roofing and poles from different tree species for erecting the walls of houses. The main building material for Baka pygmies are tree barks and maranthaceae leaves.

A) Local Bantu house B) Local Baka pygmy house

Sources: http://en.wikipedia.org/wiki/File:Njem_house_in_Cameroon.jpg and http://fortheinterim.com/wp-content/uploads/2011/03/pygmies2.jpg.

Figure 5: Examples of local houses in South East Cameroon

3.5 Industrial activities

Commercial timber logging, mining, and safari hunting are the main industrial activities in this region. The forestry industry is the oldest industrial activity and has been mostly dominated by European and other multinational companies. However, since 1994 when the forestry policy of Cameroon introduced the notion of council and community forests, local communities and councils are also increasingly involved in the management of forest for timber production purposes.

Safari hunting which is also a common activity in the East region is regulated by the Cameroonian forestry law and all its application texts that set the modalities for carrying out this activity. The hunting zone ‘ZIC’ n°28 which covers a surface area of 82406 ha and was allocated to NGONG SAFARI, partly overlaps with the southern portion of FMU 10-007 (SEBC, 2002).

The mining sector in Cameroon is currently growing in importance as a major economic activity. Several mineral exploration projects are underway in the East Region where large deposits of gold, cobalt, iron and aluminium have been identified. Exploration and exploitation permits are also currently being allocated to different mining companies. Through the Interactive Forestry Atlas of Cameroon, it has become obvious that a majority of the mining permits in the East Region are either overlapping with production forest concessions or with protected areas. This situation is seemingly going to be a potential source of conflict between the main stakeholders: mining permit holders and industrial forestry companies and or conservation organizations.

The FMU 10-007 is surrounded by other production forests namely: FMU 10-008 and FMU 10-009 that belong to the Group SEFAC/SEBAC, FMU 10-005 that belongs to STBK company, FMU 10-011 and FMU 10-001-2-3-4, belonging to SAB and CFC respectively, which are affiliates of VICWOOD THANRY (SEBC, 2002, WRI, 2005, WRI, 2007, WRI, 2012).

The forest exploitation activities and the other industrial activities offer substantial employment opportunities to the local populations, as well as to people from outside the region. It has been observed that the forestry activities and other industrial activities in the East Region have attracted migrants from other parts of Cameroon who form a great proportion of the work force in the different companies. VICWOOD Thanry sources indicate that about 377 people are currently employed at the site in Lokomo. From this number, about 65 people are working in the sawmill which has a monthly production capacity of 10000 m^3 and the remaining 312 people work in other forestry operations. In addition to the sawmill belonging to VICWOOD THANRY, other sawmills in the zone are SEFAC/SEBAC in libongo, SIBAF in Kika, CFE in Yokadouma, CIBC in Gribi and CFE in Yokadouma. These sawmill and the related forestry activities provide great employment possibilities; thus contributing to the economic stability and a general improvement in the standard of living of the people. The workers of the various companies live in base camps constructed by the companies. The base camps have grown into highly dense settlements booming with a variety of privately owned ‘petit-trade’ businesses as well as other social amenities that are either provided by the company or by private owners’ resident within the base camps.

A) General view of the base camp

(B) A side view of one of the sawmill facilities

Photo by Shu, July 2012

Figure 6: A general view of SEBC-VICWOOD THANRY base camp and sawmill at Lokomo

3.6 Conservation activities

The government of Cameroon created a Technical Operation Unit in the South East of Cameroon in 1999; known by its French acronym UTO Sud-Est. It has a total surface area of 2300000 ha and its objective is to ensure the integrated management of the natural resources of this zone. This UTO covers production forests, national parks, Safari and community-managed wildlife hunting zones. The activities of UTO Sud-Est are supported by WWF, through its Jengi project, and the GIZ (formerly GTZ) through its project for the protection of natural forests in Cameroon. These international organizations are also working to protect the rich wildlife resources of the East region, which is currently reported to be under the threat of extinction due to deforestation and the “bushmeat” trade (Heckelsweiller et al., 2001, SEBC, 2002, Makazi, 2004, SEFAC, 2005, WWF, 2013).

3.7 Infrastructure and communication facilities

Despite the many industrial scale activities in the East region, the road infrastructure is generally seen as being underdeveloped. A majority of the roads in the region are loose earth surface roads which though are used throughout the year, their practicability during the rainy season is sometimes near impossible. Forest roads (roads constructed and maintained by forestry companies) are relatively more practicable all year round as a result of constant maintenance compared to the state owned roads.

FMU 10-007 is connected by an 18 km long forest road to the transnational n° 10 which links the East Regional headquarters Bertoua to the northern part of the Republic of Congo, passing through Yokadouma and Moloundou. In addition to these, a well maintained network of forest roads exist within the forest concession and serve as the main channels for the evacuation of harvested tree logs to the sawmill. Timber products from the sawmill are evacuated to the export port in Douala mainly by road, and a limited quantity by train from Belabo railway station.

Telephone and internet services (operated by the principal providers: MTN Cameroon and ORANGE Cameroon) are now available in the Base camp of SEBC-VICWOOD THANRY at Lokomo. These facilities have greatly improved communication on-site as well as with the external world.

4 MATERIALS AND METHODS

4.1 Materials

The data used in this study came from two principal sources: field collected data and remote sensing data.

4.1.1 Field data

The data which was collected in the field include: forest exploitation inventory data which was used for calculating above-ground biomass of the commercial trees species, the location and area of logging roads and log yards which were used to assess the quantity of above-ground biomass affected by the former and the later.

The forest exploitation inventory data was obtained from the Forest Management Department of VICWOOD THANRY. This data comprised two phases of inventory data: an initial inventory of all principal commercial tree species at exploitable diameter found in AAC 3-4 and a second inventory comprising only the trees that were effectively logged in AAC 3-4 in 2011. The minimum exploitable diameter is different for different tree species in Cameroon. The average exploitable diameter for the different tree species in this study (based on the forest exploitation inventory data) are summarized on table 4 below. According to VICWOOD THANRY sources, the initial inventory was carried out using the services of a consultant and the final inventory was conducted by an internally constituted team. Both datasets were collected through a systematic inventory of 61 counting blocks of 1000 m x 1000 m. The blocks were further divided into 250 m x 1000 m sub plots or counting units. However, due to the irregular form of the study site, some peripheral blocks did not have the standard dimensions, resulting in blocks which had sizes that were smaller than the standard block size. Therefore, the counting block sizes varied from 1-100 ha (See figure 8 below). The initial inventory was carried out in December 2010 while the final inventory was conducted between January and July 2011, (VICWOOD THANRY, personal communications). The data comprised of a systematic recording of all the commercial tree species based on the minimum exploitable diameter of each species. The information recorded on the field data sheets included the DBH of the trees, the tree identification information (mostly common names of the trees and an assigned inventory code), and the bole quality class. The relative location of the individual trees were positioned on a field sketch maps ‘les croquis’ on which other biophysical characteristics of the forest were also indicated.

The logging roads and log yards were measured during field work which was conducted in June and July 2012. The field measurements were carried out by a team of three persons; comprising of a team leader and two assistants. All the roads were systematically tracked using a handheld Garmin 76 GPS Map CSX and Arcpad Mobile GIS units. The width of each road was measured and the road type identified and recorded on field data collection sheets. The perimeters of the log yards were also systematically tracked and each log yard identified with a code as used by the company.

4.1.2 Remote sensing data

The remote sensing datasets were used for correlation and regression analysis and included: red band reflectance, near infrared, middle infrared, normalized difference vegetation index, and enhanced vegetation index derived from 16 day MODIS 250 m composites.

The MODIS satellites acquire data daily, but cloud free observations are composited for 8, 16 and 32 days periods. The data sets were obtained through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC) at (https://lpdaac.usgs.gov/get_data). Data for three consecutive 16 day composites were selected for the study periods due to observed variability in the datasets. The data was acquired for the periods: December 2010-January 211 (considered as 2010 period) and December 2011-January 2012 (considered as 2011 period). These periods correspond to the condition of the forest before selective logging and after selective logging, respectively. MODIS data is delivered in single band Geotiff file format that are projected in the geographic Latitude/longitude coordinate system.

Table 1: The references of the MODIS 250 m products used in the study

Data ID	Data description	Date
MOD13Q1.A2011353.h19v08.005.2012005012455	MODIS 250 m	12/2011
MOD13Q1.A2010353.h19v08.005.2011006040443	MODIS 250 m	12/ 2010

4.2 Methods

4.2.1 Processing of forest inventory data

The forest exploitation inventory data was converted into a digital format dataset by geo-localizing (positioning the trees on their relative field locations) using ArcGIS 10 software. Geo-localization of the data was carried out through on-screening digitizing, using the field data sheets and field sketched inventory maps 'les croquis' as support documents. The dataset was then attributed based on information presented on the field data sheets.

4.2.2 Quantification of above- ground biomass of the commercial tree species

The forest exploitation inventory data as described in section 4.1.1 above was used to calculate the above-ground biomass of the trees inventoried in the study area. The parameters found in the datasets that were useful for calculating above-ground biomass were the tree species names and the diameter at breast height (DBH) of the individual trees. Above-ground biomass was estimated through the use of species specific allometric equations. The equations were computed in MS excel and the volumes of the individual trees calculated accordingly. The calculated tree volumes were then used alongside the species specific wood densities of the different tree species to calculate the above-ground biomass of the individual trees. The general biomass equation for moist tropical rainforest developed by Chave et al. (2005) was used for tree species whose species specific allometric equations could not be located. The equations1 and 2 below are the general forms of the equations for the estimation of above-ground biomass based on tree volume and wood density (equation 1) and the general biomass equation for moist tropical rainforest (equation 2).

$$AGB\ (Mg) = Wood\ volume\ (m^3) \times Species\ specific\ wood\ density\ (Kg/m^3) \ldots\ldots\ [1]$$

$$AGB\ (Mg) = \rho * exp\ (-1.499+2.148 ln\ (D) +0.207(ln(D))^2-0.0281(ln(D))^3) \ldots\ldots\ [2]$$

Where AGB is above-ground biomass

The allometric equations used for volume estimation were extracted from (Henry et al., 2011). The equations were selected according to the following criteria: for each species, the first consideration was given to allometric equations that were developed using data collected in Cameroon, if these were unavailable; equations developed with data collected in different countries, but with similar climatic and ecological characteristics to those of Cameroon were considered. The third and final option was then to use the general biomass equation for moist tropical rainforest developed by (Chave et al., 2005) in the cases were the equations were unavailable based on the first two criteria. The equations selected were also equations that use DBH as the only input parameters since that was the only available parameter in the forest exploitation inventory data that could be used for this purpose.

In total, 26 allometric equations were used in the estimation of above-ground biomass of the trees. From this number, 25 equations were species specific equations for the estimation of tree volumes and one general equation for the direct estimation above-ground biomass. 23 of these equations i.e. about 96% were observed to be equations developed using data collected in other countries and just 2 equations i.e. about 7% were equations constructed with data collected in Cameroon. The list of the species specific allometric equations used for the calculations are presented in appendix 1.

The species specific wood density values used in the study were extracted from the databases of FAO and the World Agroforestry Center which are available on the respective webpages of these organizations that were accessed on 23/10/2012 at: http://www.fao.org/docrep/w4095e/w4095e0c.htm, http://www.worldagroforestry.org/sea/Products/AFDbases/WD/asps/DisplayDetail.asp?SpecID=2. The average wood density (580 kg/m^3) for moist tropical forest trees (Brown, 1997) was used for the cases where the species specific wood density was unavailable from those two sources. The above-ground biomass for the individual trees was calculated and the quantity per hectare was computed.

4.2.3 Quantification of above-ground biomass affected by logging roads and log yards

In order to quantify the above-ground biomass affected by logging roads and log yards, a national reference baseline value of above-ground biomass for the forest zone of Cameroon was used. This value (292.7 Mg ha^{-1}) was extracted from

(MINFOF. and FAO., 2005) which is a report of the national forestry resources inventory of Cameroon, conducted by the Ministry of Forestry and Wildlife (MINFOF) in collaboration with the Food and Agricultural Organization of the United Nations (FAO), from 2003-2004. The calculation of the national reference baseline for the forest zone was based on trees ≥ 10 cm in DBH (MINFOF. and FAO, 2005). The above-ground biomass affected by logging roads was obtained through the multiplication of the surface area of the roads by the national reference baseline value of 292.7 Mg ha^{-1}. The above-ground biomass affected by the construction of log yards was calculated by following the same procedure. The above-ground biomass affected by logging roads, log yards and that of the trees logged was then expressed per hectare and subtracted from the reference baseline value to assess the amount of above-ground biomass remaining in the study area after selective logging activities.

Similarly, a second reference baseline above-ground biomass was established for the commercial tree species in the study area based on the initial inventory data of all the commercial tree species in the study site. This dataset comprised all the commercial tree species indicated in the management plan and that have attained the minimum exploitable diameter. The second phase inventory (inventory of trees that were effectively logged) was then use to make the comparative analysis.

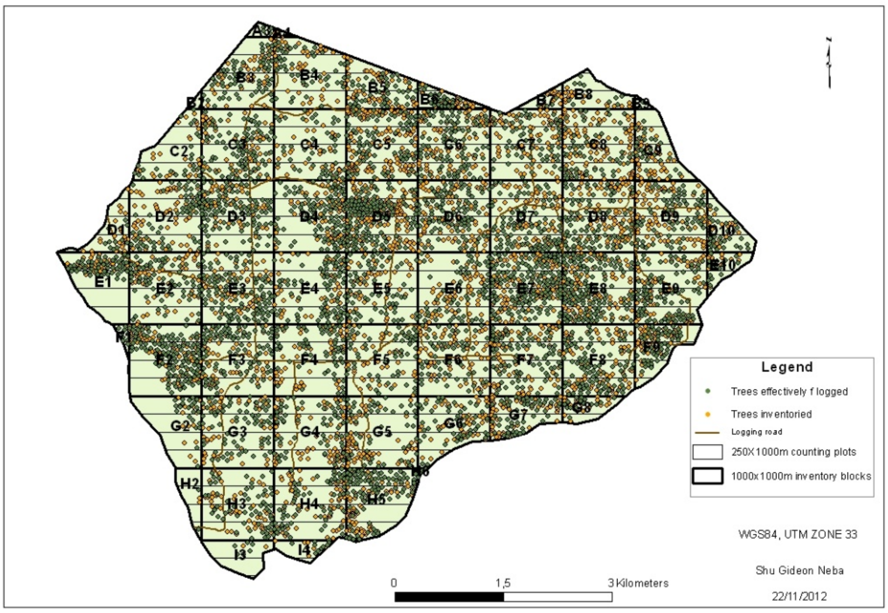


Figure 7: Geo-localization of the forest exploitation inventory data

4.2.4 Determination of the area and the density of logging roads

The field traced logging roads were uploaded onto an ArcGIS file geodatabase, edited and attributed accordingly. The information entered in the attribute table of logging roads were the width measurements of the roads, and the road category. The length of each road was generated automatically by the software. The naming of the roads followed the nomenclature used by the company which categorizes the logging roads into principal roads, secondary roads and tertiary roads. The principal road is the main centrally located axis in the logging site which also connects the logging site to the base camp. The secondary logging roads are the main branches from the principal road to different sections within the logging site and the tertiary logging roads are off shoots of the secondary roads connecting to the different log yards. The area of the logging roads were quantified using the width and length measurements in GIS ArcGIS 10 software. These were subsequently summarized by logging road categories. The density of the roads was calculated for each sample plot and expressed in km ha^{-1}.

The length of the skid trails (tracks used by the skidders to evacuate logs from the positions where they are felled to the log yards) were calculated using the relational factor of 41.4 +/- 8.2m length of skid trails per tree logged in a primary forest established by (Iskandar et al., 2006). The trees effectively logged in the study area were used as the basis for calculating the total length and the density (km ha^{-1}) of the skid trails in each sample plot. The density of the calculated skid trails and the density of the field measured roads were then combined and used in correlation and regression analysis. This approach was adopted because at the time of field work, the skid trails in the study area were no longer accessible and so could not be measured directly from the field.

4.2.5 Determination of the area and the density of the log yards

The field collected log yard dataset was also stored in a filegeodatabase. The perimeter of each log yard was converted into a polygon surface feature and its area calculated with the help of the 'calculate geometry' function in ArcGIS. The density of the log yards (ha ha^{-1}) was also calculated for each sample block.

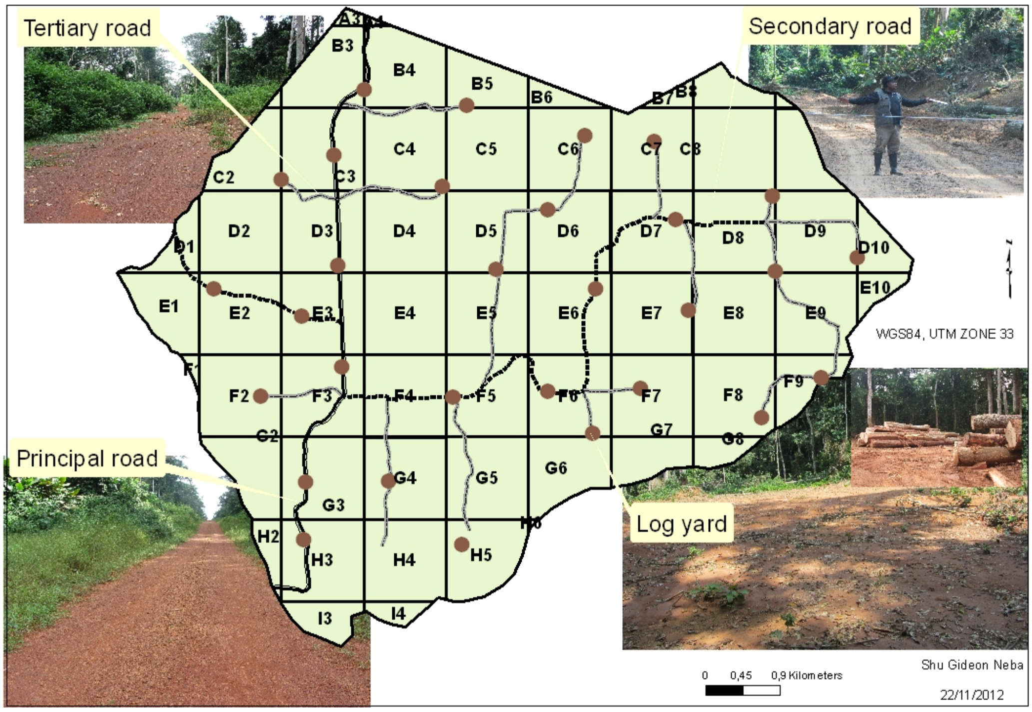


Figure 8: Geo-localization of logging infrastructure

4.2.6 Processing of MODIS 250 m data

The variables of interest (red reflectance, near infrared, middle infrared, normalized difference vegetation index, and enhanced vegetation index) were extracted from the MODIS data. The mean value was calculated for each of the variables based on the three consecutive composites that were obtained for each of the study periods. This approach helped to normalize the observed variation in the data values. The mean value of each variable was then computed for the entire sample plots with the help of the "Zonal Statistics as table" function in ArcGIS- Spatial Analyst extension. The execution of this function required as input data the single band geotiff file for each variable and the vector file of the sample plots. The "Zonal Statistics as table" function then aggregated the pixels corresponding to each sample plot and computed the mean value for each plot. This information was automatically populated in the attribute table of the sample plots in their corresponding rows and column positions. The "Zonal Statistics as table" function offers the possibility to calculate many other statistics as desired.

4.2.7 Data organization

The datasets created for the study were either spatial or non-spatial datasets. The spatial datasets were stored in ArcGIS 10 'file geodatabase' file format. The non-spatial datasets were stored in MS excel file formats and IBM SPSS statistics file format.

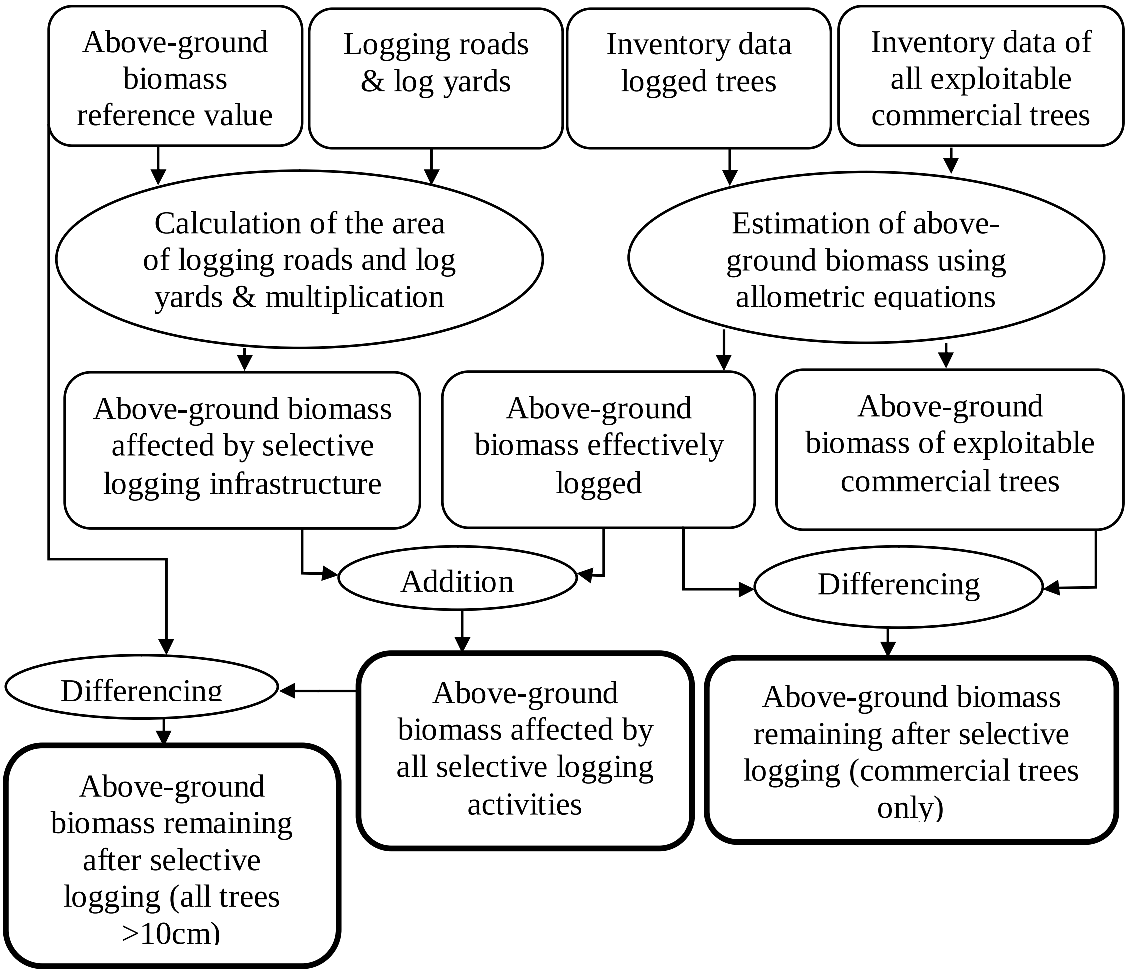


Figure 9: Summary of the procedure for quantifying above-ground biomass affected by selective logging

4.3 Statistical analysis

Statistical analyses were carried out using IBM SPSS Statistic 20. The datasets were first explored and checked for any possible abnormalities (outliers and leverages). They were further analyzed to ensure that the data fulfilled the different assumptions for the linear regression analysis. The analyses that were carried out included: correlation analysis to investigate possible relationships between the variables (see table 5 below), regression analysis to determine the necessary parameters for developing a model for predicting above-ground biomass logged.

4.3.1 Sample size

The original sample size for the study was 61 plots with a plot size range from 1-100 ha. However, from data exploration activities (see section 4.3.3 below), it was realized that outliers and leverages observed in the datasets were resulting from sample plots that were less than 30 ha in size. Also, in order to ensure that the remote sensing information analyzed for any sample plot came from at least 5 pixels of MODIS data, a threshold plot size was taken at 33 ha and this gave a total of 49 plots that were used for the correlation and regression analysis. The variables calculated were further harmonized and made comparable over the sample plots by computing the per hectare unit value of the variable for all sample plots.

4.3.2 Variables

The variables that were used in the correlation and regression analysis are summarized in table 2.

Table 2: A list of the data used in the statistical analysis

Variable	Type of variable	Description / Source
AGB logged	Dependent	From forest exploitation inventory data
Density of logging roads*	Independent	Field measured road lengths combined with calculated lengths of skid trails
Density of log yards**		Field measurements
EVI		MODIS 250m products (December 2010 & 2011)
MIR		
NDVI		
NIR		
Red reflectance		

AGB = Above-ground biomass (Mg ha^{-1}), *Expressed as Km ha^{-1}, **expressed as ha ha^{-1}

4.3.3 Data exploration

Data exploration involved checking the different datasets for any possible abnormalities. Three tools in IBM SPSS statistics software were used for data exploration: boxplots for checking the possible presence of outliers and leverages (extreme values in the datasets). The identified outliers and leverages were excluded from the analysis after establishing the possible reason for their presence in the datasets. Histogram and P-P plots were used for checking the normal distribution of regression residuals (see appendix 4 & 5) and scatterplots were used to verify the linear relationship between the dependent variable-above-ground biomass logged and the field measured and remote sensing independent variables (Melissa and Curda, 2007, Buxton, 2008, Chi and Foregger, 2013).

4.3.4 Correlation analysis

The correlation analysis was carried out with the aid of the bivariate correlation function in IBM SPSS Statistic 20. The purpose of this analysis was to identify possible associations between the independent variables and dependent variable (see table 2 above). The correlation analysis makes a comparison of all input variables and the output is a matrix table with corresponding comparisons. The important parameters for interpreting the correlation analysis are the Pearson Correlation Coefficient and the probability value (sig). The Pearson Correlation Coefficient ranges from -1 to 1 and the more the Pearson Correlation Coefficient approaches the extreme value -1 and 1, the stronger the association between the variables under investigation. A negative Pearson Correlation Coefficient indicates a negative relationship (meaning that when one of the variables increases, the other decreases), while a positive Pearson Correlation Coefficient signifies a positive relationship (meaning that as one variable increases, the other also increases). The significance of the association is given by probability value (sig), which is the probability of the null hypothesis being true. It is significant if it is less than the significant level stated for the null hypothesis (usually 0.05 or 0.01). In SPSS, the significant associations are marked with an asterisks and the level of significance is also indicated (Melissa and Curda, 2007, Buxton, 2008). The correlations of the different variables are presented on tables 3 and appendix 3 below. The correlation of the variables then served as the basis for a stepwise regression analysis and the subsequent selection of the variables for the development of a simple linear regression model and a multiple linear regression model for predicting above-ground biomass logged.

Table 3: The correlation matrix of the dependent and the independent variables

Independent variables	Parameters	Above-ground biomass logged ha^{-1}
Logging road density Km ha^{-1}	Pearson Correlation	.813**
	Sig. (2-tailed)	.000
Log yard density ha ha^{-1}	Pearson Correlation	.398**
	Sig. (2-tailed)	.005
EVI	Pearson Correlation	-.023
	Sig. (2-tailed)	.876
MIR	Pearson Correlation	.242
	Sig. (2-tailed)	.094
NDVI	Pearson Correlation	-.333*
	Sig. (2-tailed)	.020
NIR	Pearson Correlation	.077
	Sig. (2-tailed)	.598
RED reflectance	Pearson Correlation	.290*
	Sig. (2-tailed)	.043

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
N = 49= sample size

4.3.5 Linear regression analysis

Stepwise linear regression analyses were carried out in IBM SPSS statistics software to identify the variables and the corresponding model parameters for the development of models for predicting above-ground biomass logged (the lone dependent variable analyzed in the study). The stepwise linear regression analysis method in backward mode is used when multiple independent variables are being regressed while simultaneously removing those that are unimportant in explaining the variation in the dependent variable. In this regression analysis method, the independent variables are also analyzed for collinearity using the "collinearity diagnostics function". Collinearity indicates how the explanatory variables correlate with each other. If two explanatory variables have a strong correlation, they both have about the same strength in explaining the dependent variable i.e.

either of the variables is sufficient in explaining the variation in the dependent variable as the addition of the other variable does not bring in any additional information. The “VIF” which stands for variance inflation factor is one of the ways to determine collinearity in SPSS. VIF values around 1 are reasonable and show that there is no collinearity between the variables. A VIF value which is higher than 10 indicates that the variables are collinear (IDRE-UCLA and Leeds University websites available at http://www.ats.ucla.edu/stat/spss/webbooks/reg/chapter2/spssreg2.htm, accessed on 28/02/2013 and http://www.geog.leeds.ac.uk/courses/other/statistics/spss/stepwise/; accessed on 20/01/2013 respectively).

In this study, the VIF values and the correlation coefficients (appendix 3) were used to determine collinearity between the independent variables. For the variables that were collinear, the first that was selected by the stepwise regression process was retained for the model.

4.3.6 Interpreting the linear regression parameters

The parameters that were used in interpreting and selecting the best fit models were:

The R^2 statistic: The R^2 statistic is an indicator of the “goodness of fit” of the model. It represents the percentage of the variation in the response (dependent) variable that is explained by the explanatory (independent) variables used in the model. This means that the higher the R^2 statistic, the better the model fits the data. Also the "adjusted R^2" statistic can be used to judge how well the model fits the dataset. The "adjusted R^2" statistic downward adjusts the R^2 statistic when additional variables are added to the model. This is useful in telling if one regression model fits the data better than another based on whether the adjusted R^2 statistic for the two models is higher or lower when other variables are added into the model. The **Standard Deviation (SD)** is a measure of the variation around the predicted value and so is important for the determination of the precision of the prediction. **The unstandardized coefficients** show the contribution of the independent variable(s) in explaining the dependent variable. The **standardized coefficients** report the effects of each independent variable on the dependent variable in standard deviations and permits for a direct strength comparison between the independent variables used in the model. The **significance of the statistical test of each independent variable**, which tests the probability whether the correlation between the independent variables and the dependent variables was due to chance i.e. random sampling error (SPSS Tutorials, 2013).

The above parameters were interpreted for the two regression models from the stepwise regression analysis and were the basis for the decision on the best fit model.

4.3.7 Verification of the assumption of linear regression analysis

Finally, the assumptions for linear regression analysis were verified as follows:

The linearity of the regression model was checked by producing scatterplots of the explanatory variables (density of logging roads and NDVI) against the response variable (above-ground biomass logged). The normal distribution of the regression residuals (approximates for the error terms) was verified through histogram plots and P-P plots of the regression standardized residuals (see appendix 5).

4.3.8 Testing the linear regression hypothesis

The aim of this test was to find out whether at the 5% significance level the data provided sufficient evidence to conclude that the density of the logging roads and NDVI were useful predictors for above-ground biomass logged. The conclusions from this test were made from the interpretation of the slope lines of the simple and the multiple linear regression models. The assumption for this test were that the slope lines of the linear regression models = 0, in other words that there is no relationship between the dependent variable (above-ground biomass logged) and the independent variables (density of logging roads and NDVI). The hypothesis for the test was formulated thus:

H0:$\beta = 0$ (density of logging roads and NDVI are not useful predictors of above-ground biomass logged), Ha: $\beta \neq 0$ (density of logging roads and NDVI are useful predictors of above-ground biomass logged. The null hypothesis was either rejected or accepted at the significance Level $\alpha = 0.05$ at the critical p-value ≤ 0.05. That is the null hypothesis was rejected if the slope of the regression line was not equal to zero otherwise it was accepted.

4.3.9 Verification of the precision of predicted above-ground biomass logged

The following values were used to verify the precision of the predictions made by the simple linear regression model: minimum, mean, mean ± SD and maximum values of the density of the logging roads dataset. The precision of the multiple linear regression model was verified by using nine different combinations of the mean and mean ± SD of the density of the logging roads and the NDVI values in running the model. The confidence interval of the predictions (predicted mean value and predicted value) was set at 95%. The precision of the predictions was judged from the standard error of the predicted mean value as well as from comparisons with the measured mean value of above-ground biomass logged.

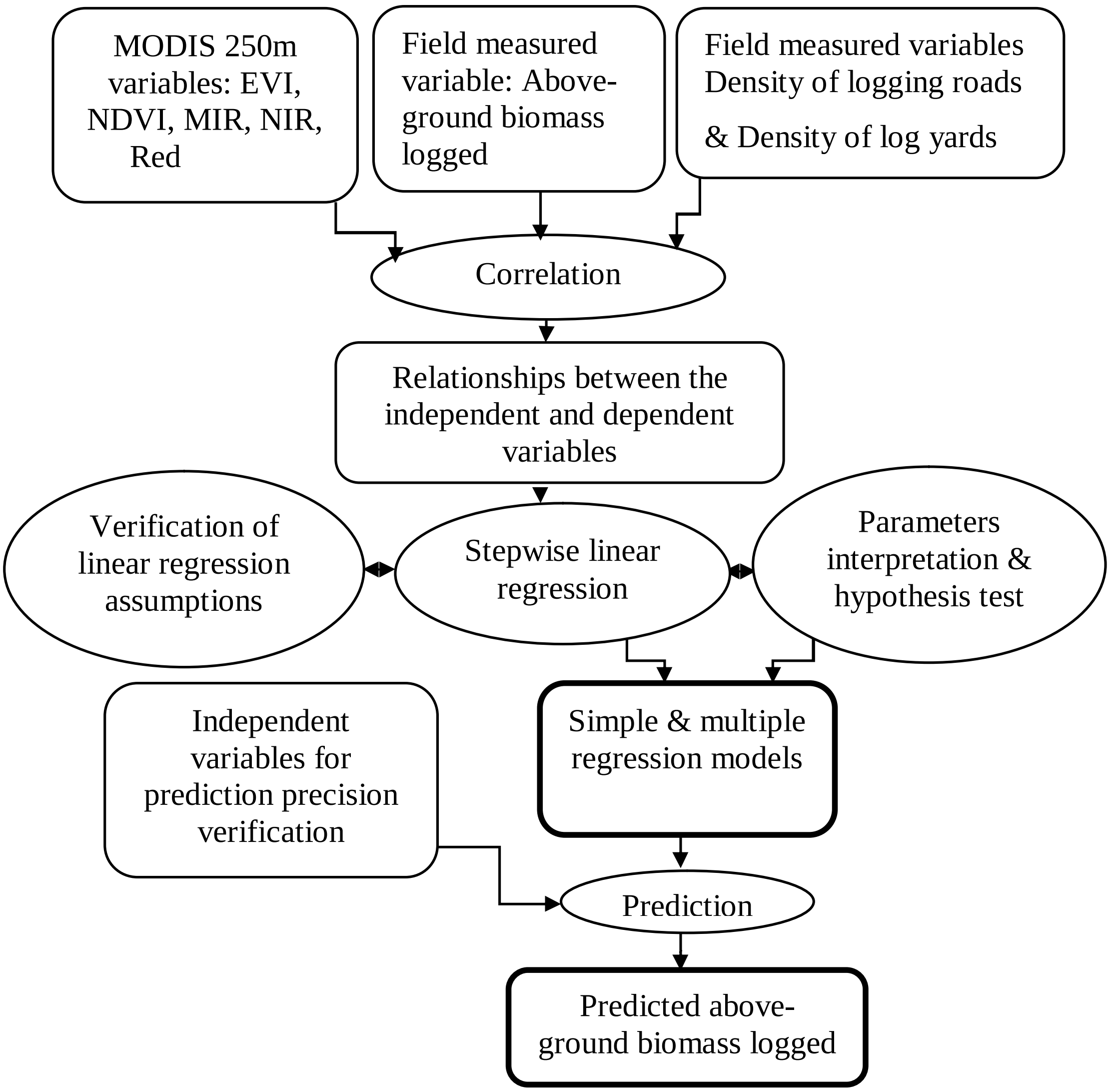


Figure 10: Summary of the procedure for developing prediction models for above-ground biomass logged

5 RESULTS

5.1 Assessment of above-ground biomass logged

The results indicated that 0.78 trees were logged per hectare, representing about 3.51 Mg ha^{-1} of above-ground biomass harvested. Species wise, *Triplochyton scleroxylon* was the species that was highly harvested (68.08% of all the trees harvested and 0.53 tree ha^{-1}). It also accounted for about 58.4% of the total above-ground biomass logged per hectare. *Entandrophragma cylindricum* was the second highest tree species logged (18.3% of the trees logged and 0.14 tree ha^{-1}). It accounted for 31.1% of the total above-ground biomass harvested (see table 7 below).

Table 4: The synthesis of above-ground biomass harvested by species

Tree species	DME average	Tree count	%	Count ha^{-1}	AGB ha^{-1}	% AGB ha^{-1}
E. angolense	108	9	0.26	0.002	0.012	0.3
E.candollei,	120	37	1.07	0.008	0.077	2.2
E.cylindricum	103	632	18.34	0.144	1.092	31.1
E. utile	110	14	0.41	0.003	0.023	0.7
Erythropleum ivorense	79	92	2.67	0.021	0.089	2.5
Guarea spp,	78	61	1.77	0.014	0.046	1.3
Guibourtia ehié	105	2	0.06	0.000	0.004	0.1
Khaya sp	86	26	0.75	0.006	0.022	0.6
Mansonia altissima	43	3	0.09	0.001	0.001	0.0
Milicia excels	115	6	0.17	0.001	0.012	0.3
Pericopsis elata	80	109	3.16	0.025	0.029	0.8
Pterocarpus soyauxii	58	106	3.08	0.024	0.051	1.4
Swartzia fistuloides,	63	3	0.09	0.001	0.002	0.1
T. scleroxylon	104	2346	68.08	0.533	2.049	58.4
Total	-	3446	100	0.783	3.51	100

AGB= Above-ground biomass (Mg ha^{-1}), DME average = Average diameter exploited per species, # of trees = total number of trees logged, E= Entandrophragma, T = Triplochyton

5.2 Assessment of above-ground biomass affected by logging infrastructure

The results showed that the logging infrastructure (principal logging roads, secondary logging roads, tertiary logging roads and log yards) covered a total surface area of 85.04 ha out of the 4400 ha that made up the study area. The results further indicated that the tertiary roads covered 41.0% of the total infrastructure area, secondary roads 29.8%, principal logging roads 23.2% and log yards 6.0% (see table 5 below).

Table 5: The synthesis of the area covered by logging infrastructure

Logging infrastructure	Length (m)	Width (m)	Area (ha)	Percentage
Tertiary logging roads	23246.15	15	34.87	41.0
Secondary logging roads	12661.49	20	25.32	29.8
Principal logging roads	7892.78	25	19.73	23.2
Log yards	-	-	05.12	06.0
Total	-	-	85.04	100

In terms of the quantity of above-ground biomass affected, the results revealed that 38.3 % of the above-ground biomass was logged, 25.3% was affected by the construction of tertiary roads, 18.3% by the construction of secondary roads, 14.3% by the construction of principal logging roads and 3.8% by the construction of log yards (see table 6 and figure 11 below).

Table 6: Quantity of above-ground biomass affected by selective logging activities

Logging infrastructure	Above-ground biomass affected Mg ha^{-1}	Percentage
Tertiary logging roads	2. 23	25.3
Secondary logging roads	1.68	18.3
Principal logging roads	1.31	14.3
Log yards	0.34	3.8
Logged trees	3.51	38.3
Total	9.16	100

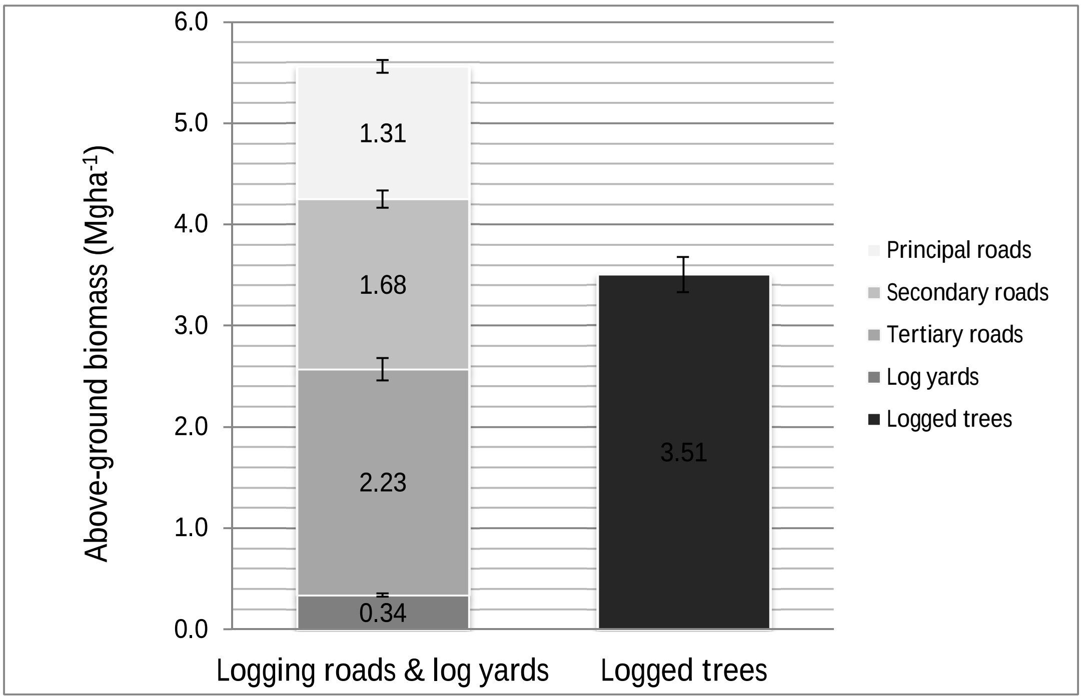


Figure 11: A comparative analysis of above-ground biomass affected by selective logging activities

5.3 Comparison of above-ground biomass logged with respect to the commercial tree potential

The analysis showed that 50% (15,436 Mg) of the total above-ground biomass of valuable commercial tree species that were inventoried in the study area was effectively logged and about 50% was unlogged or remained in the plots after the selective logging process. (See table 7 & figure 12 below).

Table 7: A comparative analysis of above-ground biomass of commercial trees after logging

Tree species	Total above-ground biomass inventoried	Total above-ground biomass	Total above-ground biomass remaining (Mg)
Alstonia boonei	37	0	37
Amphimas pterocarpoides	1,227	0	1,227
Aningeria altissima	8	0	8
Aningeria robusta	7	0	7
Autrenella congolensis	64	0	64
Ceiba pentandra	213	0	213
Celtis zenkerii	433	0	433
Coeloncaryon preussi	64	0	64
Detarium macrocarpum	249	0	249
Entandraphragma angolense	103	52	51
Entandraphragm candollei	590	338	252
Entandraphragm cylindricum	7,801	4,804	2,996
Entandraphragm utile	177	102	75
Eribroma oblongum	242	0	242
Erythrophleum ivorense	669	390	279
Gambeya africana	20	0	20
Guarea sp	334	203	132
Guibourtia ehié	49	16	33
Khaya sp	219	95	124
Mansonia altissima	87	4	83
Milicia excelsa	125	52	74
Nesogordonia papaverifera	59	0	59
Ongokea gore	207	0	207
Pericopsis eleta	176	130	46
Piptadeniastrum africanum	60	0	60
Pterocarpus soyauxii	466	223	243
Pycnanthus angolensis	35	0	35
Swartzia fistuloides	32	10	22
Terminalia superba	270	0	270
Triplochyton scleroxylon	16,496	9,017	7,479
Total	30,521	15,436	15,086

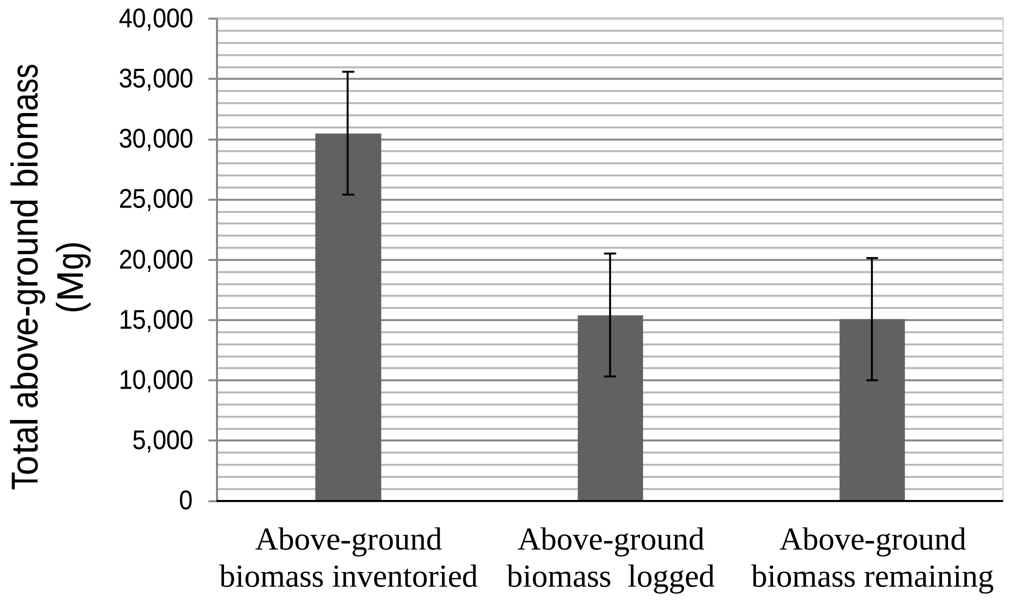
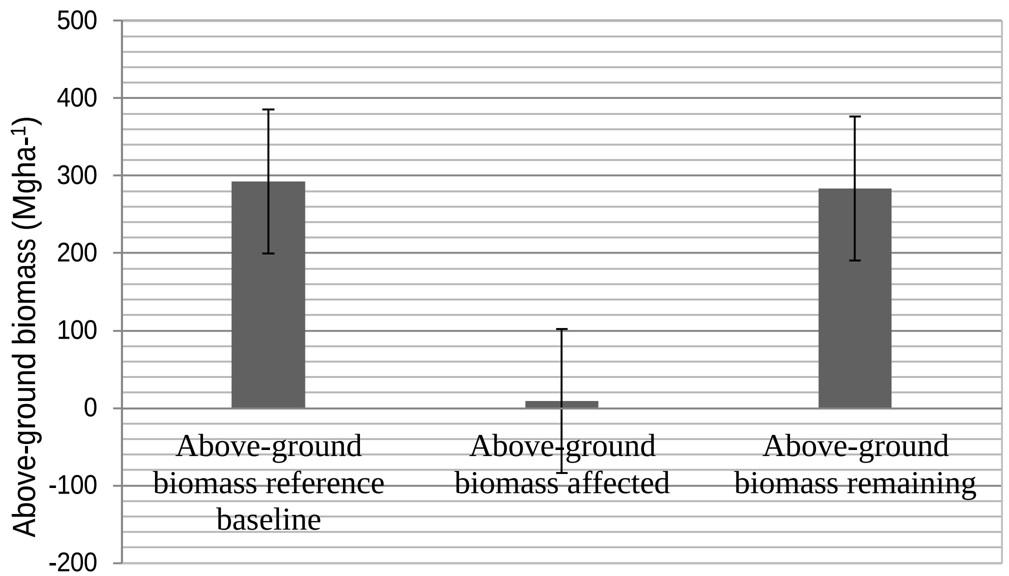


Figure 12: Comparative analysis of above-ground biomass of commercial trees after logging

This figure shows the quantity of above-ground biomass of commmercial tree species that was inventoried, the quantity that was logged and the quantity that remained unlogged after selective logging activities in the study area.

5.3.1 Comparison of above-ground biomass affected with respect to the national reference **baseline**



N.B. The above-ground biomass reference baseline (292.7Mg ha^{-1}) was extracted from MINFOF (2005)

Figure 13: Comparative analysis of the total above-ground biomass after logging

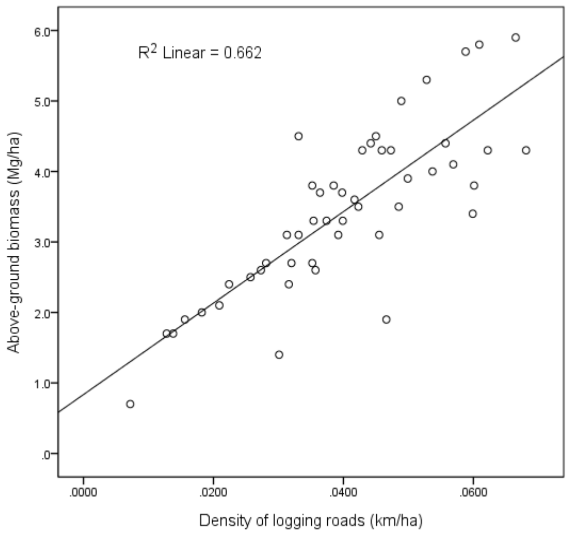
This figure shows the above-ground biomass available in the study area (based on a national reference baseline value), the quantity that was logged and the quantity that remained after selective logging. It indicates that from an intitial national reference baseline of 292.7 Mg ha^{-1} of above-ground biomass, 9.16 Mg ha^{-1} (3%) was affected by selective logging actives (logged trees, the construction of logging roads and log yards), while 283.54 Mg ha^{-1} (97 %) of above-ground biomass was unaffected.

5.4 Correlation analysis

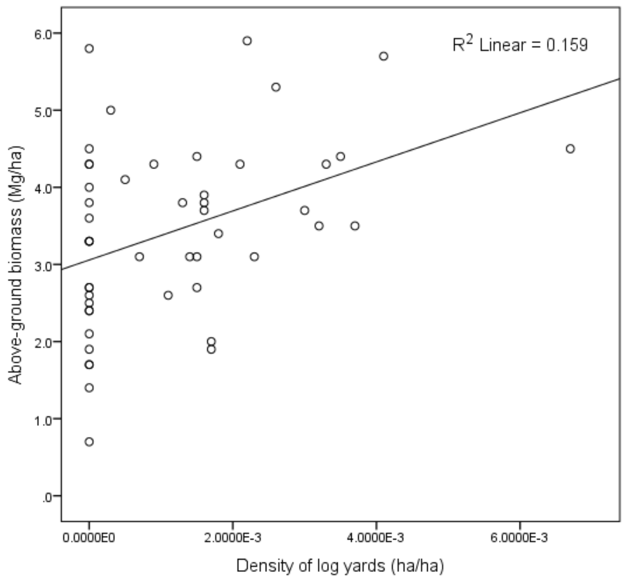
The purpose of the correlation analysis was to investigate possible relationships between the list of selected independent variables and the dependent variable-above-ground biomass logged. The results from the valid comparisons as revealed by the correlation analysis (table 3 above) are presented in the following subsections.

5.4.1 Correlation of field measured variables with above-ground biomass logged

The results showed that the density of logging roads had a strong significant positive correlation with above-ground biomass logged (Pearson correlation coefficient =0.813, sig =0.000), while the density of log yards showed a weak positive correlation with above-ground biomass logged (Pearson correlation coefficient = 0. 398, sig = 0.005). The scatterplots elucidating the correlations between above-ground biomass logged and the density of logging roads as well as above-ground biomass logged and the density of log yards are presented in Figure 14 A and B below.



A) Correlation between density of logging roads and above-ground biomass logged

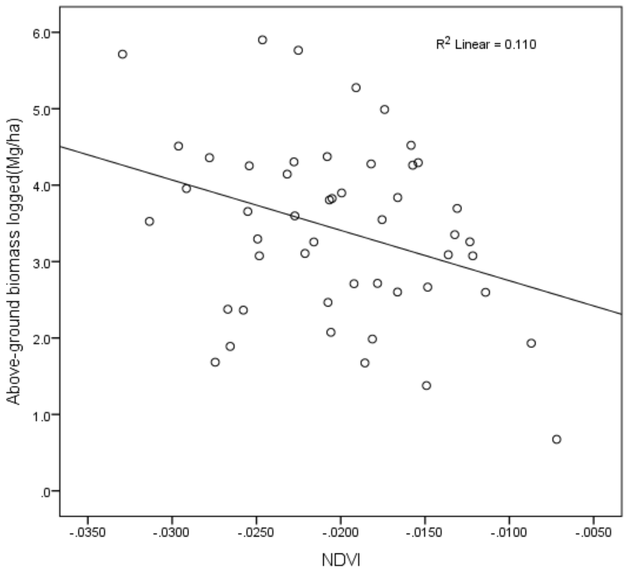


B) Correlation between density of log yards and above-ground biomass logged

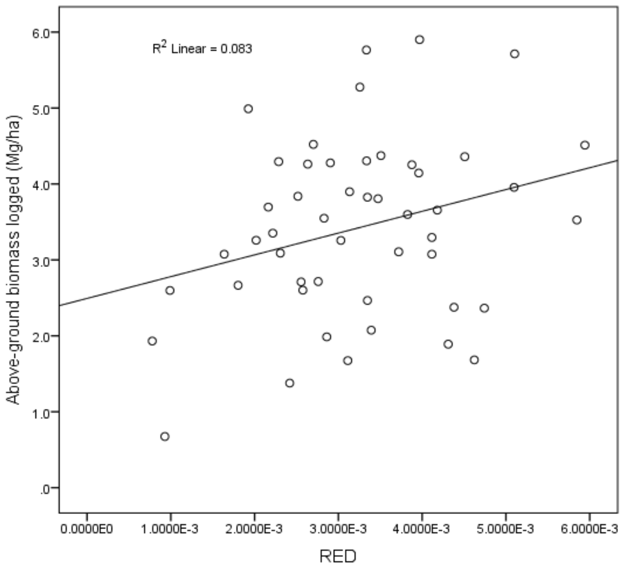
Figure 14: Correlation of above-ground biomass logged with field measured independent variables

5.4.2 Correlation of MODIS variables with above-ground biomass logged

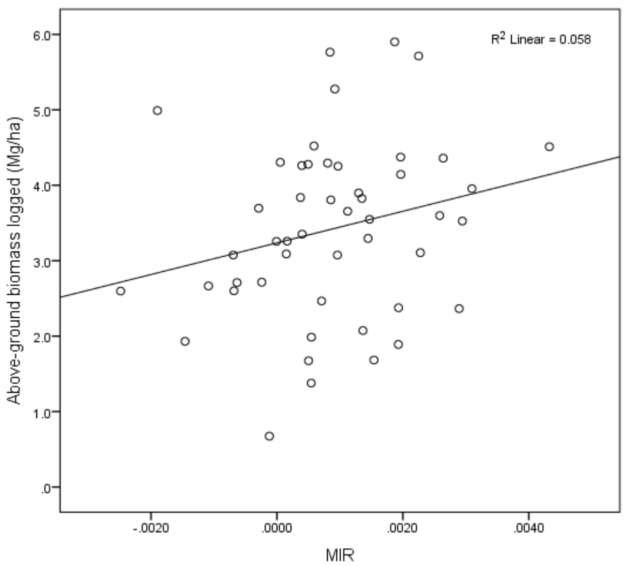
The independent variables derived from MODIS 250 m products showed weak associations with above-ground biomass logged. The relationships as revealed by the analysis were as follows: NDVI showed a weak negative correlation with above-ground biomass logged (Pearson correlation coefficient = -0.333, sig = 0.020), EVI also showed a weak negative correlation (Pearson correlation coefficient = -0.023 and sig = 0.876). On the other hand, MIR, NIR and red band reflectance all showed weak positive correlations with above-ground biomass logged. MIR (Pearson correlation coefficient = 0.242, sig = 0.096), NIR (Pearson correlation coefficient = 0.077, sig = 0.598) and red band reflectance (Pearson correlation coefficient = 0.290, sig = 0.043). The scatterplots elucidating the correlations between above-ground biomass logged and the remote sensing derived independent variables are shown in figure 15 (A-E) below.



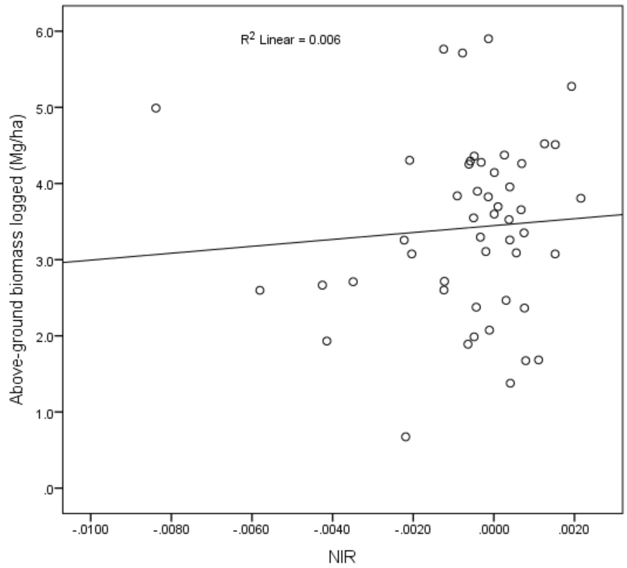
(A) The correlation between NDVI and above-ground biomass logged



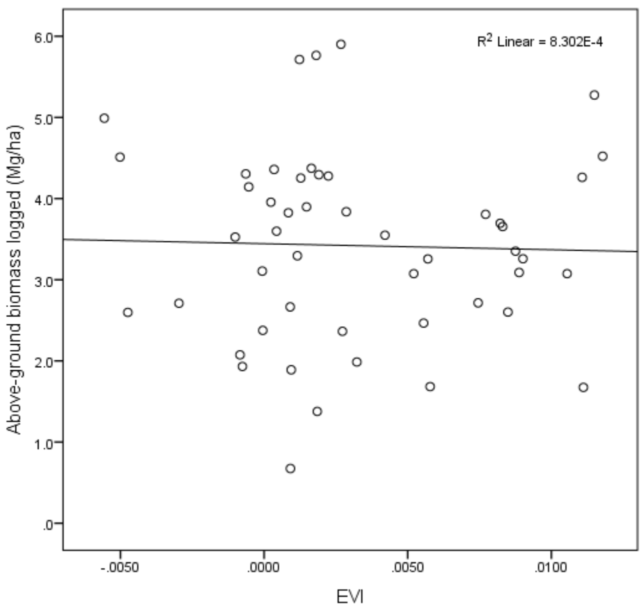
(B) The correlation between red band reflectance and above-ground biomass logged



(C) The correlation between MIR reflectance and above-ground biomass logged



(D) The correlation between NIR reflectance and above-ground biomass logged



(E) The correlation between EVI and above- ground biomass logged

Figure 15: Correlation of above-ground biomass logged with variables from MODIS 250 m data

5.5 Regression analysis

The stepwise linear regression analysis between the field measured independent variables and the dependent variable suggested two models: a simple linear regression model and a multiple linear regression model that are useful for predicting above-ground biomass logged. The parameters of these models are presented in table 8 (A-D) below, while the model equations and predictions made to assess the precisions of the predictions from the models are presented in sections 6.4.1 & 6.4.2.

Table 8: Parameters of linear regression for predicting above-ground biomass logged

A: Descriptive Statistics of the datasets			
Variables	Mean	Std. Deviation	N
Above-ground biomass logged (Mg ha^{-1})	3.431	1.1626	49
Road density (km ha^{-1})	0.040	0.0146	49
NDVI	-201.67	58.760	49

B: Model Summary[c]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.813[a]	.662	.654	.6836	.662	91.850	1	47	.000
2	.852[b]	.725	.713	.6226	.064	10.652	1	46	.002

a. Predictors: (Constant), Road density (km ha^{-1})
b. Predictors: (Constant), Road density (km ha^{-1}), (NDVI)
c. Dependent Variable: Above-ground biomass logged (Mg ha^{-1})

C : Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	0.835	.288		2.901	.006	0.256	1.414
	Road density (km ha^{-1})	64.882	6.770	0.813	9.584	.000	51.263	78.502
2	(Constant)	-0.095	0.387		-0.246	.806	-0.875	0.684
	Road density (km ha^{-1})	62.851	6.198	0.788	10.141	.000	50.375	75.326
	NDVI	-0.005	0.002	-0.254	-3.264	.002	-0.008	-0.002

a. Dependent Variable: Above-ground mass logged (Mg ha^{-1})

D: ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42.921	1	42.921	91.850	.000[b]
	Residual	21.963	47	.467		
	Total	64.884	48			
2	Regression	47.051	2	23.525	60.682	.000[c]
	Residual	17.833	46	.388		
	Total	64.884	48			
a. Dependent Variable: Above-ground biomass logged Mg ha^{-1}						
b. Predictors: (Constant), Road density km ha^{-1}						
c. Predictors: (Constant), Road density km ha^{-1}, NDVI						

5.5.1 The simple linear regression model

The simple linear regression model is based on the density of the logging roads (Km ha^{-1}) as the input independent variable. This model strongly predicted above-ground biomass logged (R^2=0.66, sig=0.000). This result indicates that 66% of the variation in above-ground biomass logged (Mg ha^{-1}) is explained by the variation in the density of the logging roads (Km ha^{-1}) with a 0.000 significant level. The value of the slope of the linear of regression line is 64.882; hence the null hypothesis is rejected. The model equation is as follow:

$$\mathbf{Y = 0.835 + 64.882\ X \ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]}$$

Where: Y= above-ground biomass logged in Mg ha^{-1}, X= density of logging roads in km ha^{-1}

5.5.2 Prediction of above-ground biomass logged using simple linear regression model

The 95% confidence interval (CI) for predicted above-ground biomass logged (Mg ha^{-1}), using the simple linear regression model is summarized in table 9 below. The table shows the values of the density of the logging roads (km ha^{-1}) that were used for the predictions, the predicted value of above-ground biomass logged (Mg ha^{-1}), the standard error (S.E) of the predicted mean values of above-ground biomass logged, the confidence interval (CI) of the predicted mean values and the confidence interval for any predicted value of above-ground biomass logged (Mg ha^{-1}).

Table 9: Prediction of above-ground biomass logged based on simple linear regression model

AGB = above-ground biomass, S.E = Standard error, LMCI = Lower confidence interval limit of predicted mean, UMCI = Upper confidence interval limit of predicted mean, LC I = Lower confidence interval limit of predicted value, UCI = Upper confidence interval limit of predicted value, min = minimum value, Max = Maximum value and SD= Standard deviation

density of logging roads (km ha^{-1})	AGB logged Mg ha^{-1}	S.E of predicted mean	95% confidence interval for predicted mean		95% confidence interval for predicted value	
			LMCI	UMCI	LCI	UCI
0.007 (min)	1.302	0.243	0.814	1.790	-0.157	2.761
0.025 (mean-SD)	2.457	0.141	2.174	2.741	1.053	3.861
0.040 (mean)	3.430	0.098	3.234	3.627	2.041	4.820
0.055 (mean+SD)	4.404	0.141	4.120	4.687	2.999	5.808
0.068 (Max)	5.254	0.214	4.823	5.684	3.813	6.694

5.5.3 The Multiple linear regression model

The multiple linear regression model is based on the density of the logging roads (Km ha^{-1}) and NDVI as input independent variables. It strongly predicted above-ground biomass logged (R^2 = 0.73, sig = 0.002). This indicates that 73% of the variation in above-ground biomass logged (Mg ha^{-1}) is explained by the variation in the density of the logging roads and NDVI with a 0.002 significance level. The slope of the multiple regression model (62.851 for X_1 and - 0.005 for X_2) indicates that the slope of the regression line is not zero, hence the null hypothesis is similarly rejected. The model equation is presented below.

$$\mathbf{Y = -0.095 + 62.851X_1 - 0.005021X_2 \ldots\ldots\ldots\ldots\ldots\ldots [4]}$$

Where: Y = above-ground biomass logged in Mg ha^{-1}, X_1 = density of logging roads density km ha^{-1}, and X_2 = NDVI

5.5.4 Prediction of above-ground biomass logged using multiple linear regression model

The 95% confidence interval (CI) for the predicted above-ground biomass logged using the multiple linear regression model is summarized in table 10 below. The table shows the values of the density of the logging roads (km ha^{-1}) and NDVI values that were used for the predictions, the predicted value of above-ground biomass logged (Mg ha-1), the standard error (S.E) of the predicted mean values of above-ground biomass logged, the confidence interval (CI) of the predicted mean values and the confidence interval for any predicted value of above-ground biomass logged (Mg ha-1).

Table 10: Prediction of above-ground biomass using multiple linear regression

AGB = above-ground biomass, S.E = Standard error, LMCI = Lower confidence interval limit of predicted mean, UMCI = Upper confidence interval limit of predicted mean, LC I= Lower confidence interval limit of predicted value, UCI = Upper limit of confidence interval of predicted value.

Density of logging roads km ha^{-1}	NDVI	AGB logged Mg ha^{-1}	S.E predicted mean	95% confidence interval for predicted mean		95% confidence interval for predicted value	
				LMCI	UMCI	LCI	UCI
0.040	-142.995	3.136	0.127	2.881	3.391	1.857	4.415
0.040	-260.532	3.726	0.127	3.470	3.981	2.447	5.005
0.040	-201.764	3.431	0.089	3.252	3.610	2.165	4.697
0.025	-201.764	2.513	0.127	2.258	2.769	1.234	3.792
0.055	-201.764	4.374	0.129	4.115	4.633	3.094	5.653
0.025	-260.532	2.808	0.161	2.484	3.132	1.513	4.103
0.025	-142.995	2.218	0.150	1.916	2.521	0.929	3.508
0.055	-260.532	4.668	0.152	4.363	4.974	3.378	5.958
0.055	-142.995	4.079	0.162	3.752	4.406	2.783	5.374

6 DISCUSSION

6.1 Effects of selective logging activities on above-ground biomass

The results showed that only 50% of the potentially harvestable commercial trees were effectively logged and that the average number of trees logged per hectare was 0.78 trees, representing about 3.51 Mg ha^{-1} of above-ground biomass logged in AAC 3-4. Also, the above-ground biomass logged (3.51 Mg ha^{-1}) was lower than the quantity affected by the construction of the logging roads and log yards which showed a value of 5.65 Mg ha^{-1} of above-ground biomass affected.

The total above-ground ground biomass of a tree is given by the partial biomass multiplied by the biomass expansion factor (BEF) (Henry et al., 2011). In this study, only the partial biomass (biomass of tree logs) was calculated as the biomass expansion factor was not applied in the calculations that used equations in the form of the general equation (1). This means that the above-ground biomass calculated based on those equations was probably underestimated.

The activity level comparison reveals that the trees logged accounted for 38.3% of the total above-ground biomass affected, while the tertiary logging roads accounted for the loss of 25.3%. The secondary logging roads and the principal logging roads were responsible for 18.3% and 14.3% of the total above-ground biomass affected respectively. The least impact on above-ground biomass was observed from the log yards which were responsible for only 3.8% of the total above-ground biomass affected. Furthermore, a comparison of the total above-ground biomass affected by the selective logging against the initial quantity of above-ground biomass available in the study site (based on the national reference baseline value) indicated that selective logging activities affected just 3% of the initial quantity of above-ground biomass available in the study area.

From the above, analysis it is observed that a greater quantity of above-ground biomass was affected by the construction of the logging roads and the log yards (about 59% of the total affected above-ground biomass) as opposed to 41% which was valuably logged or harvested. This shows that though the intensity of wood harvesting is low, there is high impact on above-ground biomass coming from the development of the associated infrastructure. The magnitude of the impact decreased in the order tertiary logging roads, secondary logging roads, principal logging roads and Log yards.

The high density of the tertiary logging roads compared to the other categories of the logging roads are indicative of the fact that many of such roads are required for a successful selective logging operations in the field. This high density of the tertiary logging roads is possibly explained by the fact that they constitute the end branches of the road network connecting each log yard to the main evacuation point or the sawmill; thus a good number of the tertiary roads are required in order to access and evacuate wood stored in the log yards. Although some log yards were observed to be located along the principal and secondary logging roads, a majority of this infrastructure is found at the end points of the tertiary roads. These analysis also show that though the tertiary logging roads are smallest in terms of width (15 m), they are important in length and this is the plausible explanation for the high impact on above-ground biomass, when compared to that of the secondary logging roads and the primary logging roads which are larger (20 m and 25 m) respectively.

As already indicated above, 0.78 trees were logged per hectare and the total measured impact of selective logging on above-ground biomass was (3%), indicating that 97% of above-ground biomass is unaffected by selective logging activities. This leads to the conclusion that selective logging activities were observed to have a low impact on above-ground biomass in the study area.

This finding is in general agreement with previous research work conducted in Cameroon and in other countries of the Congo Basin where it has been established that the maximum number of trees harvested during selective logging is 4 trees per hectare. The results of the project A.P.I Dimako, in South East Cameroon from 1992-1996; summarized in (Durrieu de Madron et al., 1998) indicates that 0.35 trees were logged per hectare in a forest that is selectively logged for the first time and that 0.77 trees (10.8 m^3 ha^{-1}) was harvested in a forest that is being logged for a second time. Also, a study in CIB concessions in the north of the Republic of Congo showed that 0.53 trees were logged per hectare, corresponding to about 11 m^3 and 10.20 t C ha^{-1} (Brown et al., 2008). Similarly, a study conducted in ‘Monts de Cristal' in Gabon has also reported a logging intensity of 0.82 trees per hectare (Vincent Medjibe et al., 2011) . Also, other regional studies (Ruiz Perez et al., 2005) have equally established that between 0.7- 2.0 trees are logged per hectare in selective logging activities across Central African countries.

A direct comparison of the results from the analysis of the impact of the construction of the different logging infrastructure has not been very feasible because most researchers who have worked on the subject have tend to group and report the impact of logging roads just as one category "roads" without differentiating the road categories. Nonetheless, the report of the REDD+ pilot study which was conducted in the same zone in 2010 indicated that 16.55 ha of logging roads were constructed in a certified forest concession and 15.77 ha of roads were constructed in a forest concession which was uncertified. The interpretation of these figures is that the same quantity of above-ground biomass was affected by logging roads in the certified and the uncertified forest concession. The same study however indicated that the area of skid trails in the certified concession was bigger than that in the uncertified concession; which is also similarly interpreted. Another study by (Tamungang, 2010) in AAC 2-3 of FMU 10-064 found out that logging roads and log yards covered a total surface area of 54.22 ha. From these values, it is estimated that 4.3 Mg ha^{-1} of above-ground biomass was affected by logging roads and log yards which is reasonably close to the quantity observed in this study (5.65 Mg ha^{-1}).

Through the above results and analysis, the general observed trend is a low impact of selective logging activities on above-ground biomass. Though this study investigated only some of the factors of selective logging activities that have an impact on above-ground biomass, it is presumed that a full assessment of all the other factors could likely see a change in some of the values presented in this document, but it is unlikely to reverse the trend of the findings of this research. This position is further strengthened by the conclusions of the 2010 REDD+ pilot project in Cameroon which established that "currently Cameroon has low historical rates of deforestation and forest degradation but developments in other related sectors are likely to increase the pressure on forest related resources in the future, and Cameroon likewise other Congo Basin countries will stand to lose in a REDD+ system which is based on historical deforestation and forest degradation rates only".

6.2 Correlation analysis and regression analysis

The observed relationship between the density of logging roads and above-ground biomass logged was not surprising because roads development is an important feature associated with selective logging as the roads provide access to the location and the evacuation of harvested trees as well as for the passage of the heavy machinery used in selective logging operations. Because of this high dependency of selective logging operations on roads, it is expected that the greater the number of trees harvested the more the number of roads (or length) of the roads that would be constructed. This dependency of selective logging operations on the construction of roads has been used as a tool to monitor the evolution of selective logging within forest concessions and also to track illegal logging activities. The Interactive Forestry Atlas of Cameroon developed by the World Resources Institute (WRI) makes use of this knowledge and is helping forestry administrations in 6 countries of the Congo Basin in their effort to efficiently monitor the evolution of selective logging in authorized forest concessions and also to identify illegal logging both in authorized forest concession and in unauthorized locations (WRI, 2005, 2007, 2012). The tool works by combining logging roads tracked from satellite images and the boundaries of the forest concession (where logging is supposed to be occurring) in a GIS system and making visual interpretations.

It was however, surprising to discover a weak association between the density of log yards and above-ground biomass logged. One would expect a strong relationship between these two variables from the reasoning that a large log yard will be required to store many trees harvested and a small one will be required for few trees harvested. The results were unable to bring out this relationship and a probable explanation to this finding is linked to the experimental design which made it impossible to capture the relationship. The log yards were analyzed per sample plots, but as can be observed from figures 7 & 8 above, there are sample plots where harvesting occurred but which do not have log yards. This means that the harvested wood in such plots was transported and stored in a log yard located elsewhere. Therefore, monitoring the wood flow to different log yards and using the log yards as the samples was necessary for capturing this relationship rather than comparing above-ground biomass logged in each plot by the size of the log yard in the plot as was done in the study.

The weak correlation of the remote sensing variables derived from MODIS 250 m products: red band reflectance, Near infrared reflectance (NIR), Middle infrared reflectance (MIR), Normalized Difference Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) is probably due to the spatial resolution of the data (250 m pixel size) which may be very coarse to capture and differentiate the effects of selective logging activities at this spatial resolution.

6.2.1 The simple linear regression model

The stepwise linear regression modeling method proposed a simple linear regression model and a multiple linear regression model for predicting above-ground biomass logged in the study site. The simple linear regression model is based on the density of logging roads as explanatory variable and the multiple linear regression model is based on the density of the logging roads and NDVI from MODIS 250 m as explanatory variables for the prediction of above-ground biomass logged.

The results revealed that the simple linear regression model has an R^2 value of 0.66 and a significance level of 0.001. This means that 66% of the variation in the above-ground biomass logged is explained by the variation in the density of the logging roads with a 0.001 significance level. The slope of the linear regression line is 64.882, indicating that the slope of the regression line is not zero, hence the null hypothesis is rejected. Therefore, there is sufficient evidence to conclude that the density of the logging roads is useful as predictor of above-ground biomass logged. The value for the slope of the regression line is positive meaning that the relationship between the density of the logging roads and the above-ground biomass logged is positive; i.e. above-ground biomass logged will increase with increasing density of logging roads.

In addition, the value of the slope indicates that a unit change in the density of the logging roads (km ha^{-1}) will result in an increase of 64.882 of above-ground biomass logged (Mg ha^{-1}). Furthermore, the 95% confidence interval of the slope of the regression line falls between 51.263 and 78.502 Mg ha^{-1}. Therefore, with 95% certainty, the study is able to confirm that the slope of the simple linear regression model falls within between 51.263 and 78.502 Mg ha^{-1}.

6.2.2 Prediction of above-ground biomass logged using the simple linear regression model

The predicted above-ground biomass logged using the minimum, the mean ± SD and the maximum values from the density of the logging roads dataset were observed to fall within the range of 1.302 - 5.254 Mg ha^{-1}. The mean value of above-ground biomass logged calculated from field measured data was 3.431 Mg ha^{-1}. Also, the standard deviation (SD) of the predicted mean value was 0.683 while the standard errors (S.E) of the predicted values ranged from 0.09 - 0.243. These statistics all indicate a good precision of the predictions of above-ground biomass logged using the simple linear regression model. Naturally, it was observed that the predicted values were very close to the mean value of the field measured above-ground biomass logged when the predictor values were selected close to the mean value of the density of the logging roads data set, and that extreme predicted values were obtained when selected predictor values were further away from the mean value i.e. with increasing standard deviations from the mean values of the predictor variable, the precision of the model decreased. Therefore, the precision of the model in predicting above-ground biomass logged is observed to be high when the density of the logging roads values are within mean ± SD and outside this range, the precision tends to diminish. Also, the 95% confidence interval (CI) of the predicted mean values was observed to be more precise than the 95% confidence interval of the predicted values. The difference between the two Confidence intervals is that the former is for the predicted mean values whereas the latter is for any predicted value.

6.2.3 The multiple linear regression model

The multiple linear regression model using both the density of the logging roads (km ha^{-1}) and NDVI values derived from MODIS 250 m products gave an R^2 value of 0.73 with a 0.000 significance level; indicating that 73% of the variation in above-ground biomass logged was explained by the variation in the density of the logging roads (km ha^{-1}) and NDVI. This model also shows that by including the NDVI values in the simple linear regression model gave a reward of a 7 percent increase in the performance of the model.

Like in the simple regression model, the slope of the multiple regression model (62.851 for X_1 and - 0.005 for X_2) indicates that the slope of the regression line is not zero, hence the null hypothesis is rejected. Hence, it is similarly concluded that there exist sufficient evidence to confirm that the density of the logging roads (km ha^{-1}) and NDVI values from MODIS 250 m products are useful predictors for predicting above-ground biomass logged (Mg ha^{-1}). The value for the slope of X_1 is positive, indicating a positive relationship, while that for X_2 is negative, similarly indicating a negative relationship.

These values of the slope line further indicate that a unit change in the density of the logging roads(km ha^{-1}) corresponds to a change in above-ground biomass logged of 62.851 (Mg ha^{-1}) and a unit change in NDVI results in a change of -0.005 (Mg ha^{-1}) of above-ground biomass logged as soon as the two explanatory variables are independent. The 95% confidence interval for the slope of the regression line (50.375 and 75.326 for the density of the logging roads) and (-0.008 and -0.002 for NDVI) also implies that with 95% certainty, this study is able to confirm that the slope of the regression line of the multiple linear regression model falls within the above indicated intervals for X_1 and X_2 respectively.

6.2.4 Predicted above-ground biomass logged using multiple linear regression model

The predicted above-ground biomass logged using different combinations of the mean ± SD of the two explanatory variables (the density of the logging roads (km ha^{-1}) and NDVI were observed to range from 2.218 - 4.668 Mg ha^{-1}. Comparing the range of the values of the predicted above-ground biomass logged to the mean value of above-ground biomass logged calculated from field measured data (3.431 Mg ha^{-1}), it is observed that the predicted range is very closed to the field measured mean value. Also, the standard deviation (SD) of the predicted mean value was 0.623 and the standard errors (S.E) of the predicted values ranged from 0.089 - 0.162. These statistics also indicate a good precision of the multiple linear regression model in predicting the above-ground biomass logged. The combination of the mean values of the two predictor variables gave a predicted above-ground biomass logged value that was the same as the field measured mean value of above-ground biomass logged. The 95% confidence interval for the predicted mean values and that of the predicted values were generally shorter when compared to those of the simple linear model. Hence, the multiple linear model is more precise than the simple linear regression model.

The collinearity diagnostic analysis indicated that the red band reflectance showed collinearity with NDVI (see the correlation coefficients in appendix 3 and the VIF values in appendix 6). This means that the Red band reflectance is also important in predicting above-ground biomass logged but it was excluded from the multiple linear regression model because it introduced no additional information in the model when the NDVI values were already used. Therefore, in the absence of NDVI data, the red band reflectance data if available can be used in the multiple linear regression model for predicting above-ground biomass logged. The contributions of the density of the log yards, EVI, NIR, and MIR in explaining the variation in above-ground biomass logged were very marginal and so were not very useful for predicting above-ground biomass logged.

Finally, both models were observed to meet the assumptions of linearity (see figures 14 & 15 above) and the normal distribution of the regression residuals (see appendix 5) of linear regression modeling.

7 CONCLUSIONS AND RECOMMEDATIONS

From the findings of this study the following conclusions and recommendations can be made:

7.1 Conclusion

The study used forest exploitation inventory data and field measured data of selective logging infrastructure to quantity above-ground biomass affected by selective logging operations. The different methods used efficiently estimated above-ground biomass loss (forest degradation) as a result of selective logging. These techniques are presumably more time and cost efficient in the assessment of above-ground biomass loss when compared to traditional methods at the same scale of measurement. This means that these different techniques can be combined to easily assessed forest degradation (measured in this study as the loss of above-ground biomass).

The feasibility of using these methods for the assessment of above-ground biomass is further made possible by the increasing ease to access accurate forest exploitation data in Cameroon. Also, there currently exist national and international initiatives in Cameroon and other countries within the Congo Basin that are developing up-to-date spatial datasets of forestry activities. For instance, the Interactive Forestry Atlas Projects of WRI in six countries of the Central African region contains datasets on logging roads within forest concessions tracked from satellite images. This data is updated on an annual basis and is a potential source of data for such analysis.

Furthermore, the study has also developed two models for predicting above-ground biomass logged (indicator of forest degradation). Both models gave a good precision in predicting above-ground biomass logged. These are very useful tools in assessing above-ground biomass logged, considering that the data required for the implementation of these models is now easily obtainable through the different sources as indicated above.

The information generated in this study is useful for forest management decision making. For instance, the analysis of the impact of the development of selective logging infrastructure on above-ground biomass is useful information that can support decisions on RIL strategies. Also, knowledge of the intensity of selective logging in Cameroon is equally important for making management decisions which have both economic as well ecological significances. For instance, an understanding of trees remaining in the forest after selective logging can serve as a basis for a decision on promoting certain tree species in the international market as strategy to reduce pressure on well-known and commonly harvested tree species.

Also, the different above-ground biomass calculations can be further used to determine the quantity of carbon that is released into the atmosphere by each activity through the conversion factor below:

Carbon released = above-ground biomass affected x 0.5……......................... [5]

7.2 RECOMMENDATIONS

This study is able to make two sets of recommendations: recommendations on the future improvement of the study and recommendations on other related study lines that are still necessary in supporting the quest for new and easy ways to assess above-ground biomass in degraded African tropical rainforest ecosystems.

Concerning the improvement of the current work, the original plan of this study envisaged the use of Landsat7 and other medium resolution images for the correlation and regression analysis. However, as a result of the poor quality of Landsat images (cloud cover, effect of stripes) and the fact that this is only a student project with insufficient funding, all the desired datasets could not be afforded. Therefore, any future studies which is able to use higher resolution data than MODIS products is likely to improve, the remote sensing component of this study.

Also, the data for the lengths of the skid trails used was calculated based on conversion factors in published literature. Therefore, there is need to repeat the analysis with actual field measured skid trails values. Based on the experience of this study, the best time to measure the skid trails in the field is during active logging so as to benefit from the facilitation of the forest teams to access the skid trails. Another reason is that the skid trails tend to close up faster than the logging roads and their accessibility sometimes after the logging operations (from about 6 months after the logging operations has ended) could pose a real problem.

In addition, it is probably more logical to correlate the above-ground biomass logged and effectively stored in each log yard with the area of the log yard as it was observed that all the sample plots did not necessary have log yards, indicating that the trees harvested in such plots were transported and stored in log yards elsewhere and this wood flow needs to be monitored for any assessment of the area of the log yards against above-ground biomass logged.

With regards to complimentary studies, this study recommends that, additional investigations to add to the existing knowledge on damage caused in logging gaps and linear regression models using similar variables be tested for this kind of damage as well. Finally, sustainable management strategies in the African tropical rainforest such as RIL should pay particular attention to the optimization of the construction of tertiary logging roads since from this study; it was observed that the greatest impact on above-ground biomass was caused by this road category.

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9 APPENDIX

Appendix 1: List of species specific wood densities used in the study

N°	Species	Specific wood density (KgM^3)
1	*Alstonia boonei*	0.380
2	*Amphimas pterocarpoides*	0.580*
3	*Aningeria altissima*	0.420
4	*Autrenella congolensis*	0.680
5	*Ceiba pentandra*	0.280
6	*Celtis zenkerii*	0.600
7	*Coeloncaryon preussi*	0.560
8	*Detarium macrocarpum*	0.720
9	*Entandrophragma angolense*	0.450
10	*Entandrophragma candollei*	0.590
11	*Entandrophragma cylindricum*	0.550
12	*Entandrophragma utile*	0.530
13	*Eribroma oblongum*	0.600
14	*Erythrophleum ivorense*	0.720
15	*Gambeya africana*	0.769
16	*Guarea sp*	0.480
17	*Guibourtia ehié*	0.670
18	*Khaya sp*	0.440
19	*Mansonia altissima*	0.580*
20	*Milicia excelsa*	0.580*
21	*Nesogordonia papaverifera*	0.660
22	*Ongokea gore*	0.881
23	*Pericopsis eleta*	0.580*
24	*Piptadeniastrum africanum*	0.689
25	*Pterocarpus soyauxii*	0.610
26	*Pycnanthus angolensis*	0.481
27	*Swartzia fistuloides*	0.820
28	*Terminalia superba*	0.520
29	*Triplochyton scleroxylon*	0.320

- * Mean wood density for moist tropical rainforest (Brown 1997)

Appendix 2: Allometric equations for tree species from Henry et al. (2011)

N°	Species	Equation (m3)	Calibration range of X	Location	Reference	Year
1	Alstonia boonei	Y =ρ*exp(-1.499+2.148ln(D)+0.207(ln(D))2-0.0281(ln(D))3)		General Equation	Chave et al.	2005
2	*Amphimas pterocarpoides*	Y=ρ*exp(-1.499+2.148ln(D)+0.207(ln(D))2-0.0281(ln(D))3)		General Equation	Chave et al.	2005
3	*Aningeria altissima*	log10Y= LOG10(0.0006245)+2.114×LOG10(X)	D1.3 in cm (1, 200)**	Ghana	Wong , J.L.G.	1990
4	*Autrenella congolensis*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
5	*Ceiba pentandra*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
6	*Celtis zenkerii*	AGB =ρ*exp(-1.499+2.148ln(D)+0.207(ln(D))2-0.0281(ln(D))3)		General Equation	Chave et al.	2005
7	*Coeloncaryon preussi*	AGB =ρ*exp(-1.499+2.148ln(D)+0.207(ln(D))2-0.0281(ln(D))3)		General Equation	Chave et al.	2005
8	*Detarium macrocarpum*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
9	*Entandrophragma angolense*	Y= 10.82×(X^1.89)	D1.3 in m (0.01, 0.8)*	Gabon	Bilé Allogho, J.	1999
10	*Entandrophragma candollei*	Y= 10.82×(X^1.89)	D1.3 in m (0.01, 0.8)*	Gabon	Bilé Allogho, J.	1999
11	*Entandrophragma cylindricum*	Y= 2.003–1.094×X+11.89×(X^2)	D1.3 in m (0.8, 1.69)*	Api-Cameroon	Palla, F., Louppe, D., et al	2002
12	*Entandrophragma utile*	Y= 10.82×(X^1.89)	D1.3 in m (0.01, 0.8)*	Gabon	Bilé Allogho, J.	1999
13	*Eribroma oblongum*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
14	*Erythrophleum ivorensis*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.6)*	Gabon	Bilé Allogho, J.	1999
15	*Gambeya africana*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
16	*Guarea sp*	Y= 9.72×(X^(2.46))	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
17	*Guibourtia ehié*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
18	*Khaya sp*	Y= 10.82×(X^(1.89))	D1.3 in m (0.01, 0.8)*	Gabon	Bilé Allogho, J.	1999
19	*Mansonia altissima*	Y= –0.524+13.127×(X^2)	D1.3 in m (0.2, 1.69)**	Ivory Coast	Akindele, S.O.	2005
20	*Milicia excelsa*	Y= 1.05+10.08×(X^2)	D1.3 in m (0.01, 0.7)*	Gabon	Bilé Allogho, J.	1999
21	*Nesogordonia papaverifera*	Y= 0.04+9.07×(X^2)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
22	*Ongokea gore*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
23	*Pericopsis elata*	log10Y= LOG10(0.0006426)+2.058×LOG10(X)	D1.3 in cm (1, 200)**	Ghana	Wong , J.L.G.	1990
24	*Piptadeniastrum africanum*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
25	*Pterocarpus soyauxii*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.7)*	Gabon	Bilé Allogho, J.	1999

26	*Pycnanthus angolensis*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.6)*	Gabon	Bilé Allogho, J.	1999
27	*Swartzia fistuloides*	Y= 9.72×(X^2.46)	D1.3 in m (0.01, 0.4)*	Gabon	Bilé Allogho, J.	1999
28	*Terminalia superba*	Y= 0.19+10.46×(X^2)	D1.3 in m (0.01, 1.69)**	Gabon	Groulez, et al.	1984
29	*Triplochyton scleroxylon*	Y= 0.000209×(X^(2.3528))	D1.3 in cm (1, 80)*	Cameroon	Palla, F., Louppe, D., et al	2002

General equation = General biomass Equation for Moist tropical rainforest

Original references of allometric equations presented in the above table referenced by Henry et al. (2011)

Akindele, S.O. 2005. Volume functions for commontimber species of Nigeria’s forests – a technical document. ITTO, UBC, Federal University of Technology, Vancouver, Canada. Akure, Nigeria

Bilé Allogho, J. 1999. Etude sur les ressources forestières du Gabon. FAO, Rome

Groulez, J. & Wood, P.J. 1984. Terminalia superba, monographie. Centre technique forestier tropical, Commonwealth Forestry Institute.

Palla, F. & Louppe, D. 2002a. Obeché. CIRAD, Montpellier

Palla, F. Louppe, D. & Forni, E. 2002c. Sapelli. CIRAD

Wong, J.L.G. 1990. Forest resources management project temporary sample plot inventory computer program manual. ODA (UK).

Appendix 3: Correlation matrix from the correlation analysis of the studied variables

Correlations									
		AGBloggedha	logyardensityhaha	Rdskidtraildensitykmha	EVI_diff	MIR_diff	NDVI_diff	NIR_diff	RED_diff
AGBloggedha	Pearson Correlation	1	.398**	.813**	-.023	.242	-.333*	.077	.290*
	Sig. (2-tailed)		.005	.000	.876	.094	.020	.598	.043
	N	49	49	49	49	49	49	49	49
logyardensityhaha	Pearson Correlation	.398**	1	.466**	-.084	.384**	-.288*	.206	.346*
	Sig. (2-tailed)	.005		.001	.566	.006	.045	.155	.015
	N	49	49	49	49	49	49	49	49
Rdskidtraildensitykmha	Pearson Correlation	.813**	.466**	1	-.045	.136	-.100	.009	.078
	Sig. (2-tailed)	.000	.001		.757	.352	.492	.949	.596
	N	49	49	49	49	49	49	49	49
EVI_diff	Pearson Correlation	-.023	-.084	-.045	1	-.132	.242	.555**	-.141
	Sig. (2-tailed)	.876	.566	.757		.367	.094	.000	.335
	N	49	49	49	49	49	49	49	49
MIR_diff	Pearson Correlation	.242	.384**	.136	-.132	1	-.776**	.666**	.879**
	Sig. (2-tailed)	.094	.006	.352	.367		.000	.000	.000
	N	49	49	49	49	49	49	49	49
NDVI_diff	Pearson Correlation	-.333*	-.288*	-.100	.242	-.776**	1	-.349*	-.966**
	Sig. (2-tailed)	.020	.045	.492	.094	.000		.014	.000
	N	49	49	49	49	49	49	49	49
NIR_diff	Pearson Correlation	.077	.206	.009	.555**	.666**	-.349*	1	.532**
	Sig. (2-tailed)	.598	.155	.949	.000	.000	.014		.000

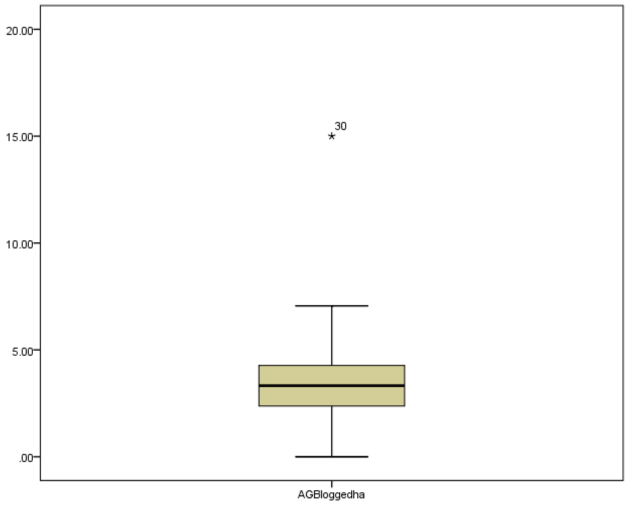
	N	49	49	49	49	49	49	49	49
RED_diff	Pearson Correlation	.290*	.346*	.078	-.141	.879**	-.966**	.532**	1
	Sig. (2-tailed)	.043	.015	.596	.335	.000	.000	.000	
	N	49	49	49	49	49	49	49	49

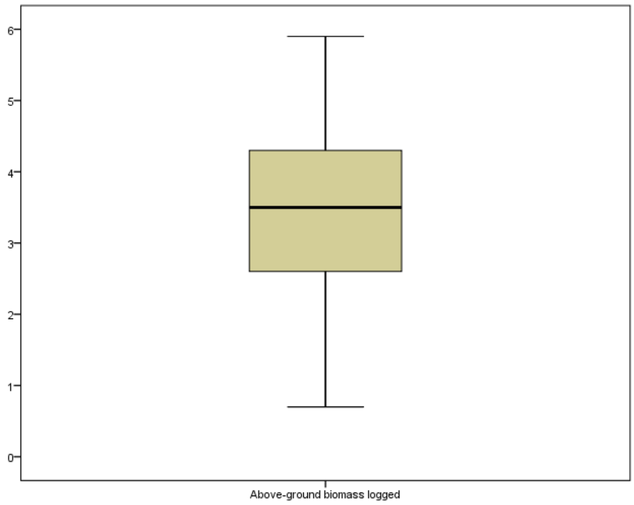
**. Correlation is significant at the 0.01 level (2-tailed).

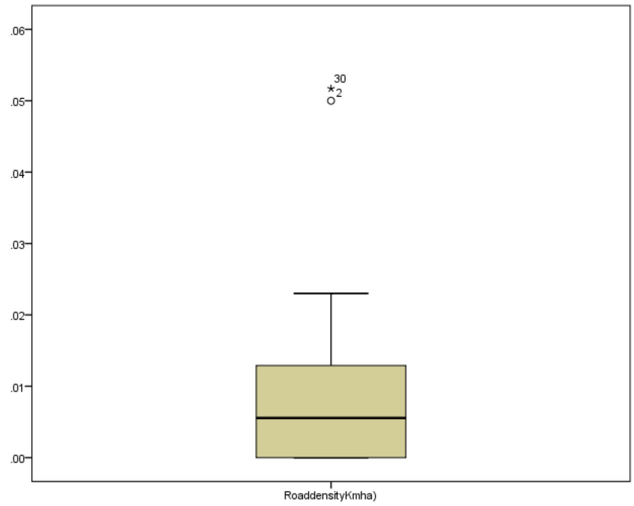
*. Correlation is significant at the 0.05 level (2-tailed).

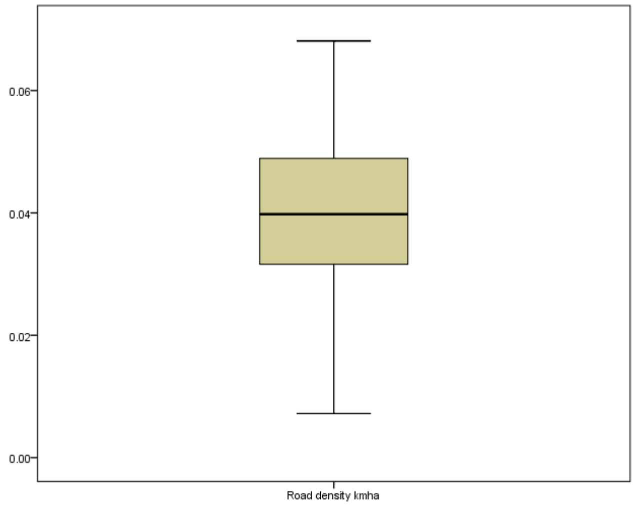
Appendix 4: Output from data exploration for possible abnormalities in the datasets

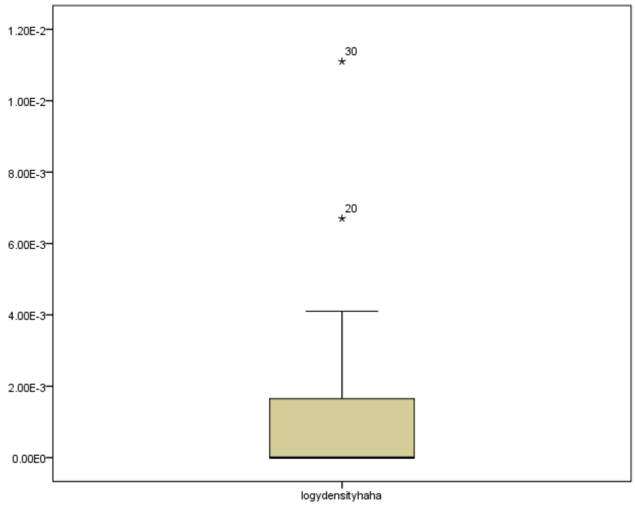
Before data editing After data editing

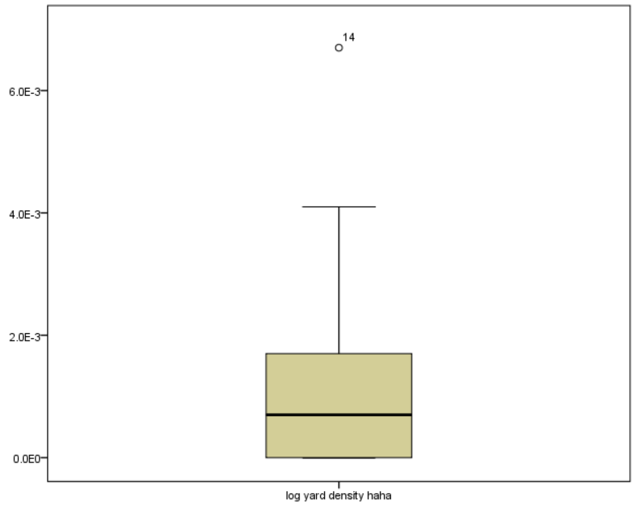


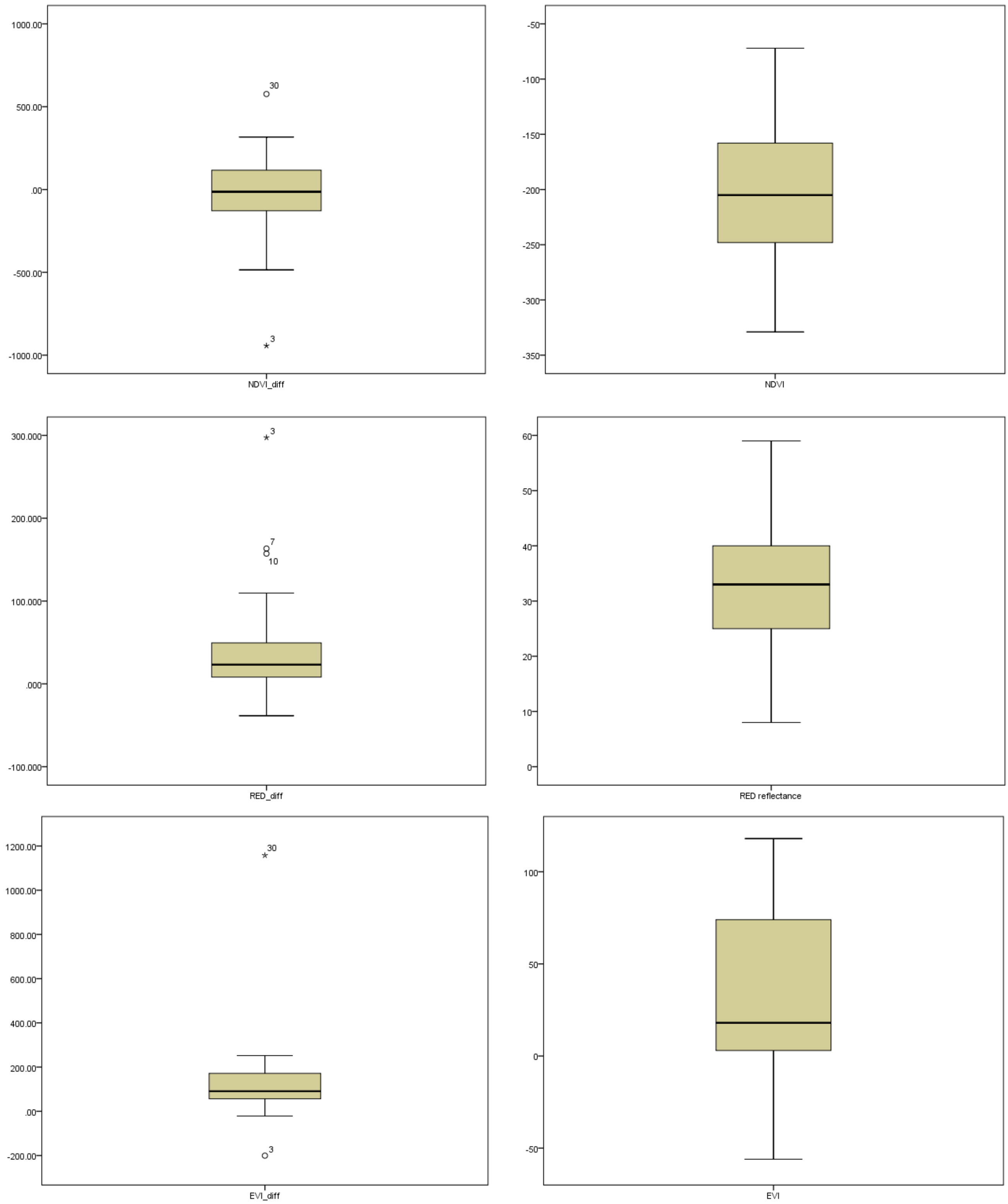


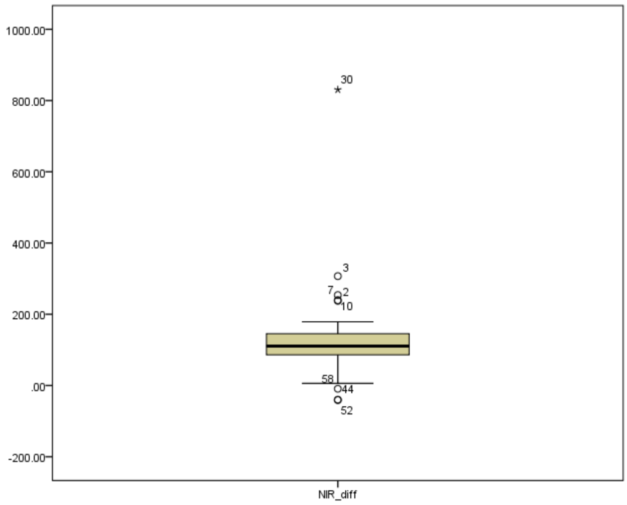


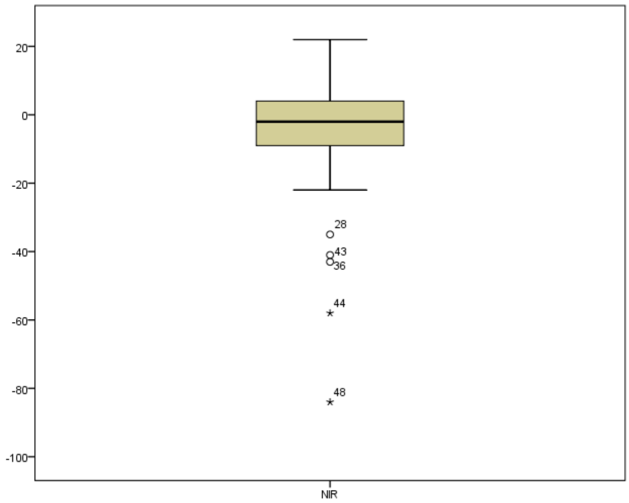


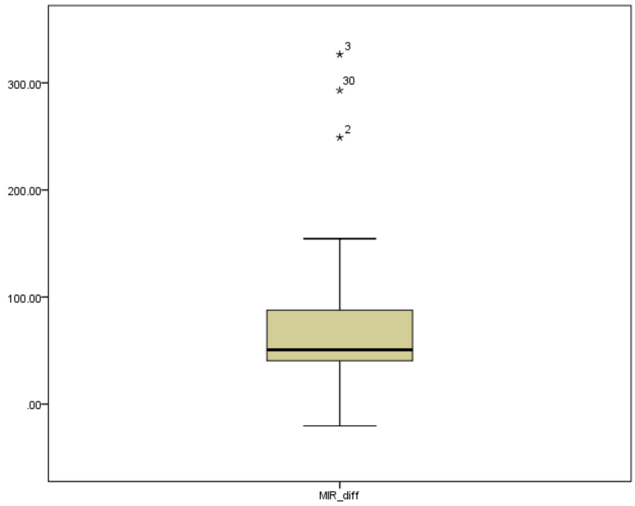


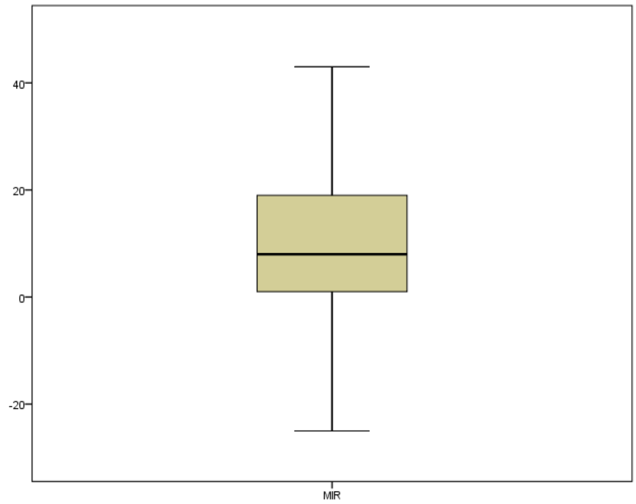



1000.00
500.00
.00
-500.00
-1000.00
30
3
NDVI_diff
-50
-100
-150
-200
-250
-300
-350
NDVI
300.000
200.000
100.000
.000
-100.000
3
7
10
RED_diff
60
50
40
30
20
10
0
RED reflectance
1200.00
1000.00
800.00
600.00
400.00
200.00
.00
-200.00
30
3
EVI_diff
100
50
0
-50
EVI

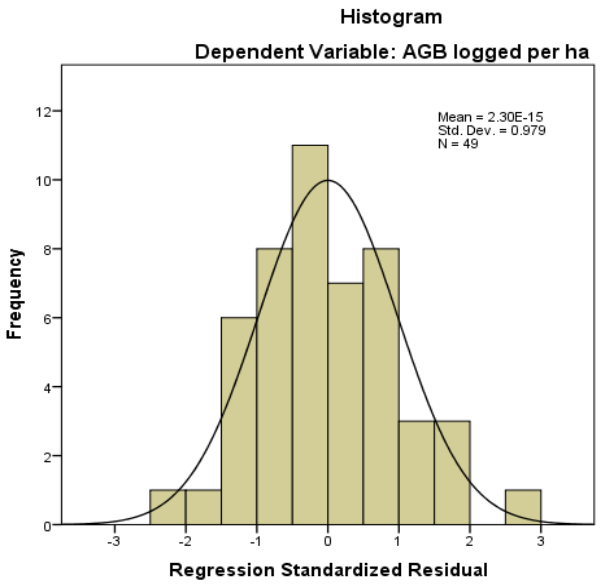

1000.00
800.00
600.00
400.00
200.00
.00
-200.00
30
3
7
2
10
58
44
52
NIR_diff

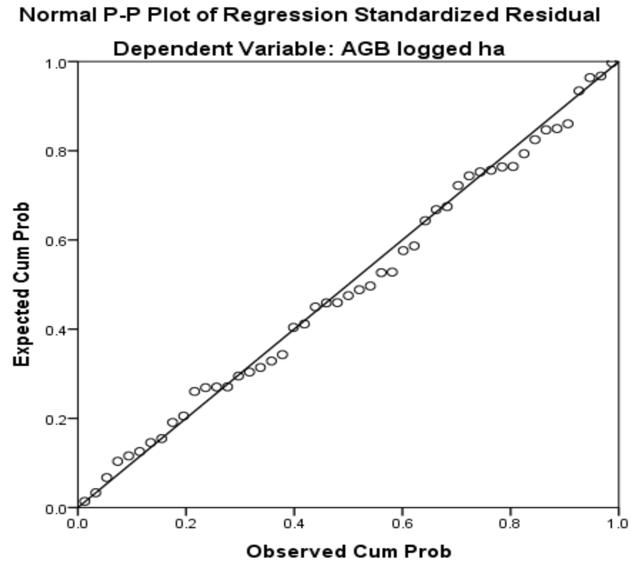

20
0
-20
-40
-60
-80
-100
28
43
36
44
48
NIR

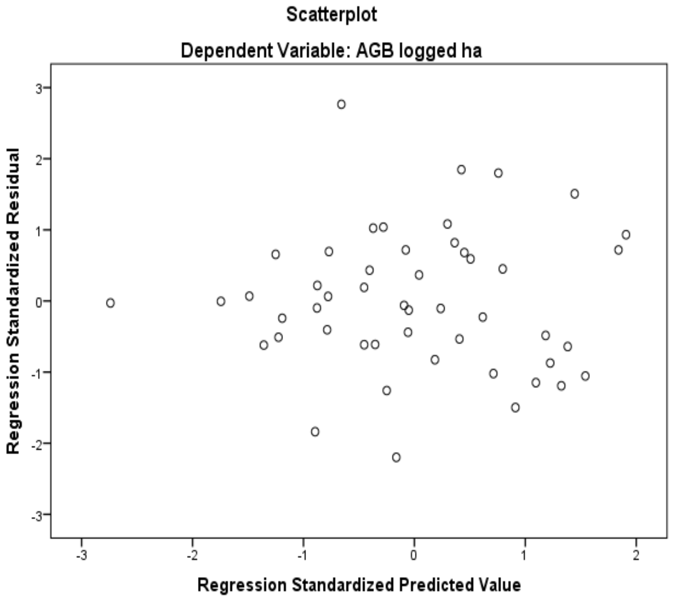

300.00
200.00
100.00
.00
3
30
2
MIR_diff


40
20
0
-20
MIR

Appendix 5: Histogram & P-P plots for checking the normality of regression residuals







Appendix 6: A list of independent variables excluded by the stepwise regression

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	logyardensityhaha	.025[b]	.261	.796	.038	.783	1.277	.783
	EVI_diff	.014[b]	.164	.871	.024	.998	1.002	.998
	MIR_diff	.134[b]	1.591	.118	.228	.982	1.019	.982
	NDVI_diff	-.254[b]	-3.264	.002	-.434	.990	1.010	.990
	NIR_diff	.070[b]	.818	.418	.120	1.000	1.000	1.000
	RED_diff	.229[b]	2.887	.006	.392	.994	1.006	.994
2	logyardensityhaha	-.057[c]	-.624	.536	-.093	.725	1.380	.725
	EVI_diff	.079[c]	.989	.328	.146	.941	1.063	.934
	MIR_diff	-.156[c]	-1.276	.209	-.187	.395	2.532	.395
	NIR_diff	-.021[c]	-.254	.801	-.038	.878	1.139	.869
	RED_diff	-.234[c]	-.781	.439	-.116	.067	14.915	.067