ASSessment of biomass based on 2D/3D data derived from aerial stereoscopic imagery in the tropics

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Graz, 2014
STATUTORY DECLARATION

I declare that I have authored this thesis independently, that I have not used other than the declared sources / resources, and that I have explicitly marked all material which has been quoted either literally or by content from the used sources.

................................................. .................................................................
Date (Signature)
“**Tell me and I forget, teach me and I may remember, involve me and I learn.**”

*BENJAMIN FRANKLIN*
ACKNOWLEDGEMENT AND PREFACE

During my bachelor studies at the University of Graz, I developed a special interest in Remote Sensing, Geographic Information Systems and Cartography. Hence, I started studying the Masters programme Geospatial Technologies. I was very thankful for the opportunity to get an internship at Joanneum Research in 2011. In my third summer as an intern, Univ.-Prof. Dr. Mathias Sgardt agreed to supervise my thesis supporting the National Forest inventory Suriname–Pilot project.

I would like to thank Univ.-Prof. Dr. Mathias Sgardt for the advice and support during the writing of the thesis. Furthermore, I thank DI Dr. Hannes Raggam, DI Dr. Karlheinz Gutjahr and DI Dr. Roland Perko for sharing their workplace and knowledge with me in the last years at Joanneum Research.
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Thank you!
ABSTRACT

Assessment of biomass based on 2D/3D data derived from aerial stereoscopic imagery in the tropics

Keywords: Biomass, Remote Sensing, Tropical rainforest, Aerial imagery, Regression analysis

It is known that tropical rainforests are the world’s largest carbon storage. However, the amount of biomass that actually exists can only be roughly estimated, especially because terrestrial forest inventory is very demanding, cost and time expensive. Forest inventory is also the only method to map biomass directly at small-scale area. High-resolution aerial imagery and LiDAR are two methods to map biomass indirectly at a small-scale level.

In this project both high-resolution aerial images and terrestrial forest inventory data available were analysed for preselected areas of Suriname. The thesis aimed in linking terrestrially measured biomass data of High Dryland forest to features derived from aerial imagery including spectral information and height. In the thesis the term biomass is always equated with aboveground phyto-biomass, i.e. vegetation.

The thesis opens with a short introduction and a review of the state of the art containing current biomass estimation and methods used for deviation of features, sorted according to data type. It provides a description of used methods and how they are used to derive digital surface models from stereoscopic imagery, and features such as volume, forest canopy density, number of trees and statistical features based on height. This chapter also describes the outcome of the feature derivation and the arising problems and limitations. The next part shows the results of correlation and implementation and result of regression analysis, and in conclusion, a discussion and an outlook into the future are provided.
ZUSAMMENFASSUNG

Abschätzung von Biomasse anhand von 2D/3D Daten abgeleitet aus stereoskopischen Luftbildern in den Tropen

Schlüsselwörter: Biomasse, Fernerkundung, tropischer Regenwald, Luftbilder, Regressionsanalyse

Es ist allgemein bekannt, dass die tropischen Regenwälder den weltweit größten Speicher für Kohlenstoff darstellen. Die tatsächlich gespeicherte Menge an Kohlenstoff in der Biomasse kann nur grob geschätzt werden, da die terrestrische Forstinventur zur direkten Erfassung der Daten sehr aufwändig, zeit- und kostenintensiv ist. Die Forstinventur ist auch die einzige Methode, Biomasse direkt kleinräumig zu erfassen. Zwei weitere Methoden zur indirekten Erfassung in großem Maßstab sind hochauflösende Luftbilder und LiDAR.


Im ersten Teil der Arbeit wird neben der Einleitung ein Überblick über den Stand der Forschung (State of the Art) gegeben. Dieser Teil beinhaltet sowohl die aktuelle Biomasseabschätzung, als auch den Stand der Methoden, die für die Ableitung von Merkmalen verwendet werden. Im nächsten Teil werden die verwendeten Methoden zur Ableitung von Merkmalen, wie ein Oberflächenmodell, Volumen, Beschirmungsgrad, Anzahl der Bäume und statistische Auswertung, beschrieben. Hier werden auch die Ergebnisse der Merkmalsableitung und die auftretenden Probleme behandelt. Im nächsten Teil folgen das Ergebnis der Korrelation zwischen Biomasse und den einzelnen abgeleiteten Merkmalen und die Umsetzung der Regressionsanalyse. Der letzte Teil inkludiert Diskussion und Ausblick.
# TABLE OF CONTENTS

**Statutory Declaration** ........................................................................ II

**Acknowledgement and Preface** ........................................................... IV

**Abstract** ............................................................................................... V

**Zusammenfassung** ................................................................................ VI

**List of Abbreviations** ........................................................................... IX

**List of Figures** ....................................................................................... XI

**List of Tables** ......................................................................................... XIII

**List of Formulas** .................................................................................... XIII

1. **Introduction** ...................................................................................... 1
   1.1. The UN-REDD and REDD+ project as background ................................ 1
   1.2. Problem statement ........................................................................... 2
   1.3. Definitions ....................................................................................... 3
       1.3.1. Biomass .................................................................................. 3
       1.3.2. Tropics .................................................................................. 4
   1.4. Study area .................................................................................... 4
       1.4.1. Climate .................................................................................. 5
       1.4.2. Vegetation ............................................................................ 6

2. **State of the Art** .................................................................................. 9
   2.1. Terrestrial Measurements as data basis ............................................... 11
   2.2. Optical Remote Sensing Data ............................................................. 12
       2.2.1. High resolution data and aerial imagery ...................................... 12
       2.2.2. Medium resolution data ............................................................... 13
       2.2.3. Coarse resolution data ................................................................. 15
   2.3. Radar ............................................................................................. 17
       2.3.1. SAR ....................................................................................... 17
       2.3.2. LiDAR ................................................................................... 18
   2.4. GIS and Modelling ........................................................................... 20
   2.5. Integration of Data ........................................................................... 21
   2.6. Summary ....................................................................................... 23

3. **Methodology** ...................................................................................... 25
   3.1. Data Base ....................................................................................... 25
TABLE OF CONTENTS

3.1.1. SAMPLING UNITS AND FOREST INVENTORY ................................................. 25
3.1.2. BIOMASS AND VOLUME DATA ................................................................. 29
3.1.3. AIRBORNE AERIAL IMAGERY DATA ....................................................... 30
3.1.4. PRE-PROCESSING AND SOFTWARE ......................................................... 36
3.1.5. DERIVATION OF DIGITAL SURFACE MODELS ........................................ 39
3.1.6. TREETOP DETECTION .............................................................................. 45
3.1.7. SEGMENTATION – TREE CROWN DELINEATION ...................................... 46

3.2. DERIVATION OF FEATURES .......................................................................... 50
3.2.1. VEGETATION INDEX .................................................................................. 50
3.2.2. TEXTURE ................................................................................................... 51
3.2.3. FOREST CANOPY DENSITY ....................................................................... 52
3.2.4. VOLUME OF DSM – DTM –DIFFERENCE .................................................... 57
3.2.5. NUMBER OF TREES ................................................................................... 59
3.2.6. STATISTICAL FEATURES BASED ON HEIGHT .......................................... 60

4. STATISTICAL ANALYSIS ................................................................................... 61
4.1. RESULTS OF BIOMASS CALCULATION ......................................................... 61
4.2. RESULTS OF CORRELATION ......................................................................... 62
4.3. RESULTS OF REGRESSION ANALYSIS ........................................................ 63

5. DISCUSSION AND OUTLOOK ......................................................................... 70

BIBLIOGRAPHY .................................................................................................. 74

APPENDIX ........................................................................................................... 86
## LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>2D</td>
<td>2-dimensional (plane)</td>
</tr>
<tr>
<td>3D</td>
<td>3-dimensional (solid)</td>
</tr>
<tr>
<td>ADAM</td>
<td>Airborne Data and Mapping</td>
</tr>
<tr>
<td>AGB</td>
<td>Aboveground Biomass</td>
</tr>
<tr>
<td>ANRICA</td>
<td>Agency for Natural Resources Management and International Cooperation Austria</td>
</tr>
<tr>
<td>BfW</td>
<td>Bundesforschungszentrum für Wald (Austrian Research Centre for Forests)</td>
</tr>
<tr>
<td>CAF</td>
<td>Colour Array Filter</td>
</tr>
<tr>
<td>CCD</td>
<td>Charge-coupled Device</td>
</tr>
<tr>
<td>CHM</td>
<td>Canopy Height Model</td>
</tr>
<tr>
<td>CIR</td>
<td>Colour Infrared</td>
</tr>
<tr>
<td>DBH</td>
<td>Diameter at Breast height</td>
</tr>
<tr>
<td>DCM</td>
<td>Digital Canopy Model</td>
</tr>
<tr>
<td>DSM</td>
<td>Digital Surface Model</td>
</tr>
<tr>
<td>DTM</td>
<td>Digital Terrain Model</td>
</tr>
<tr>
<td>FAO</td>
<td>Food and Agriculture Organization of the United Nations</td>
</tr>
<tr>
<td>GCP</td>
<td>Ground Control Point</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
</tr>
<tr>
<td>GLAS</td>
<td>Geoscience Laser Altimeter System</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>IMPACT</td>
<td>Image Processing and Classification Toolkit</td>
</tr>
<tr>
<td>IMU</td>
<td>Inertial Measurement Unit</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>IRS</td>
<td>Indian Remote Sensing</td>
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<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
</tr>
<tr>
<td>LiDAR</td>
<td>Light Detection and Ranging</td>
</tr>
<tr>
<td>MAP</td>
<td>Main Assessment Plot</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration (USA)</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infrared</td>
</tr>
<tr>
<td>PSP</td>
<td>Principal Sampling Plot</td>
</tr>
<tr>
<td>REDD</td>
<td>Reducing Emissions from Deforestation and Forest Degradation</td>
</tr>
<tr>
<td>RGB</td>
<td>Red Green Blue (Colour Space)</td>
</tr>
<tr>
<td>RSG</td>
<td>Remote Sensing Software Graz, Software developed by JOANNEUM RESEARCH</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Full Form</td>
</tr>
<tr>
<td>--------------</td>
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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
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<tr>
<td>SBB</td>
<td>Stichting voor Bosbeheer en Bostezicht (Foundation for Forest Management and Production Control Suriname)</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite Pour l’Observation de la Terre</td>
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<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
</tr>
<tr>
<td>SU</td>
<td>Sampling Unit</td>
</tr>
<tr>
<td>UN</td>
<td>United Nations</td>
</tr>
<tr>
<td>UNEP</td>
<td>United Nations Environment Programme</td>
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<tr>
<td>UNFCC</td>
<td>United Nations Framework Convention on Climate Change</td>
</tr>
<tr>
<td>UNDP</td>
<td>United Nations Development Programme</td>
</tr>
<tr>
<td>VHM</td>
<td>Vegetation Height Model</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure 1: Survey map of Suriname ................................................................. 4
Figure 2: Climograph of Paramaribo .............................................................. 6
Figure 3: Pattern of vegetation in Suriname .................................................. 7
Figure 4: Schematic diagram of the strata of a tropical rainforest .................. 8
Figure 5: Biomass carbon map created by NASA .......................................... 9
Figure 6: Basic structure of an artificial neural network .............................. 14
Figure 7: Aboveground live biomass map ..................................................... 16
Figure 8: LiDAR acquired DSM (a), DTM (b) and CHM (c) ......................... 19
Figure 9: Schematic representation of various input layers for modelling ........ 21
Figure 10: Sampling Unit design with Principal Sample Plots in field (left) and additional plot design (right) ................................................................. 27
Figure 11: Map of the inventoried Sampling Units during National Forest Inventory Pilot Project ................. 28
Figure 12: ADAM Platform .......................................................................... 31
Figure 13: Areas overflown and forest inventory Sampling Units in Suriname .................................................. 32
Figure 14: Comparison of two different geometric resolutions ..................... 34
Figure 15: Annual distribution of precipitation in mm in Paramaribo ............ 36
Figure 16: Example for a Bayer array with 7 times 7 elements ..................... 37
Figure 17: Raw “Bayer Pattern” image (left) and interpolated RGB image (right) of a palm tree ....................... 37
Figure 18: Detail from a CIR image with band combination NIR-red-green ........ 38
Figure 19: Principle of matching using image correlation ............................ 40
Figure 20: Parameters used for Direct DSM Generation using RSG Suite Workflow .................................................. 41
Figure 21: 3D image of SU 7358 ................................................................. 42
Figure 22: Sampling Unit 5352 - Left: CIR-Orthophoto - Right: DSM .......... 43
Figure 23: Sampling Unit 5954 - Left: CIR-Orthophoto - Right: DSM .......... 43
Figure 24: Sampling Unit 5956 - Left: CIR-Orthophoto - Right: DSM .......... 44
Figure 25: Sampling Unit 6358 - Left: CIR-Orthophoto - Right: DSM .......... 44
Figure 26: Sampling Unit 7358 - Left: CIR-Orthophoto - Right: DSM .......... 45
Figure 27: Sampling Unit 5956: Treetop Detection with different crown size parameters .................................................. 46
Figure 28: Sampling Unit 5956: Region growing based on treetops ............... 47
Figure 29: Sampling Unit 5956: Segmentation based on spectral information .................................................................................. 48
Figure 30: Sampling Unit 5956: Trial of Watershed-Segmentation at different levels (Subsets – same area, same spatial extent) .................................................. 49
Figure 31: Sampling Unit 5956: Left: NDVI; Right: CIR-Orthophoto .............. 51
Figure 32: Texture in Sampling Unit 5956: Left: Third Moment; Right: Absolute Value Difference (both for NIR channel) .................................................................... 52
Figure 33: Schematic illustration of “Height Variance Approach” comparable to “SRTM Difference approach” .................................................................................. 53
Figure 34: Difference model from SAR derived DSM and SRTM – red polygon shows the referenced degradation area .................................................................................. 53
Figure 35: Tree gap masks using different threshold (here enlarging downward) .................................................................................. 54
Figure 36: Sampling Unit 5956: Comparison of forest canopy density (Visual assessment and digitally processed data) .................................................................................. 56
Figure 37: Sampling Unit 5956: Gap mask of forest canopy density ............... 57
Figure 38: Schematic illustration of the volume between calculated ground and canopy (layers are shifted for better depiction) ............................... 58
Figure 39: Sampling Unit 5956: Volume calculation (Upper left: DSM – SRTM approach; Upper right: DSM – DTM (interpolation 1st degree); Lower left: DSM – DTM (interpolation 4th degree); Lower left: DSM – DTM (interpolation 6th degree)) ........................................................................ 59
Figure 40: SU 5956: Left: DSM; Right: Pseudo-nDSM (DSM – SRTM) ................................................................. 60
Figure 41: Comparison of measured and computed AGB results .............................................................................. 66
Figure 42: Plot of model residues ......................................................................................................................... 67
Figure 43: Sampling Unit 5956: Tests for Volume calculation ................................................................. 87
LIST OF TABLES

Table 1: Advantages and Disadvantages of available data for biomass estimation 10
Table 2: Methods to estimate biomass based on diverse data 24
Table 3: Equations for calculation of biomass, basal area and commercial volume 30
Table 4: Specifications of Prosilica GE4900C digital aerial survey camera 31
Table 5: Specifications of Prosilica GC2450 digital aerial survey camera 31
Table 6: Description of the resolution dependent on altitude above ground level 33
Table 7: Results of biomass and volume calculation 61
Table 8: Regression Statistics 64
Table 9: Leave-one-out Cross-validation results (rounded) 68
Table 10: Coefficient of correlation based on 37 PSPs 86

LIST OF FORMULAS

Formula 1: Relation between altitude above ground level $h_g$, focal length $c$, a line segment $s$ and the scale denominator $m_b$ 33
Formula 2: Calculation of the size of the overlap 34
Formula 3: Normalized Difference Vegetation Index (NDVI) 50
Formula 4: Result 64
1. INTRODUCTION

1.1. THE UN-REDD AND REDD+ PROJECT AS BACKGROUND

Information in this chapter is taken from the web site of the UN [UN-REDD, 2009; UN-REDD: ABOUT REDD+, 2009], unless otherwise stated.

REDD is an acronym for "Reducing Emissions from Deforestation and forest Degradation" and a collaborative initiative of three UN organizations: the FAO (Food and Agricultural Organization), the UNDP (United Nations Development Programme) and the UNEP (United Nations Environment Programme). The project’s goal is to support developing and emerging countries and help them use their available natural resources sustainably. A monetary value is assigned to the intact forest ecosystems and their capability to store carbon dioxide. After the assessment and quantification of stored carbon, the last step, according to UNEP [2010], is to generate carbon offset payments from developed countries to developing countries. This way, the REDD project tries to balance the economic disequilibrium “in favour of sustainable management of forests” [UNEP, 2010].

The REDD+ project aims even higher and sets its ambitious goals on the mitigation of climate change and protection through natural conservation and monitoring. According to the UN REDD, the priorities of REDD+ are “conservation, sustainable management of forests and enhancement of forest carbon stock”. At the moment, about 20 % of greenhouse gas emissions worldwide are caused by degradation and deforestation.

Suriname is a member of the UN-REDD project since the end of 2011. To implement the REDD+ project in Suriname, the pilot project National Forest Inventory Suriname (NFI) was initiated. ANRICA, the Austrian Agency for Natural Resources Management and International Cooperation, is a partner of the project. Joanneum Research Graz is involved with ANRICA. Within the pilot project, the basis for the forest inventory of the entire area of Suriname is built. In this thesis, methods for assessment of biomass are tested. Stereoscopic aerial imagery and digital surface models (DSM) serve as data base. Features such as number of trees and volume are inferred from aerial imagery and DSM and the correlation between features and biomass should reflect the distribution of biomass in the forest. The results of this thesis will be used for a more comprehensive terrestrial forest inventory in the future.
1.2. Problem statement

The estimation of above-ground biomass, i.e. vegetation as a carbon pool has become more important over the last few years, mainly due to the discussion about climate change and global warming. The anthropogenic emission of the greenhouse gas carbon dioxide is a significant component of climate change and global warming [IPCC, 2007]. The vegetation’s ability to photosynthesize, i.e. to absorb and sequester carbon will help mitigate the effects of climate change. The tropical rainforests are the world’s largest carbon storage. According to KINDERMANN et al. [2008, p. 388] tropical rainforest contains about 50 % of the world’s entire biomass, although the area occupied by tropical rainforests is just 13 % of the world’s ice-free land area.

Deforestation of tropical rainforests has two distinct effects. Firstly, during burning of biomass, the stored carbon is released into the atmosphere. Secondly, further carbon storage is lost, because forests, i.e. wood, are the most important carbon pool.

In order to quantify the extent of these processes and to establish a monitoring system, a forest inventory must be performed. Here, the area-wide data acquisition and analysis of remote sensing applications will be helpful. Information gathered will support the terrestrial forest inventory. Compared to the random forest inventory, the remote sensing applications will provide wall-to-wall coverage. Remote sensing data does not replace terrestrial forest inventory, but is an important tool for supporting and optimizing the process. By using remote sensing data and techniques, the number of terrestrial measurements can be decreased using a multi-phase inventory conception.

The aim of this thesis is to derive certain features from high-resolution aerial images of the study area and to determine biomass by linking those features to the terrestrially measured biomass. In other words, both spectral and height information of the aerial images are used in the process. The features are correlated with the existing terrestrially measured biomass in the Sampling Units, hence coherences are displayed and used for the classification of biomass by means of aerial photographs. The evaluation shows which feature and combinations of different 2D- and 3D-features perform best for the regression analysis with the biomass data from the terrestrial measurements. The results will serve as a background for a multi-phase forest inventory conception.
1.3. DEFINITIONS

1.3.1. BIOMASS

According to the FAO [2009, p. 2], biomass is the amount of dead and/or live organic matter. The term “organic matter” contains flora and fauna as well as bacteria. Most of the time, the term “biomass” is equated with the term “vegetation biomass density”, which is the mass of available biomass per area [FAO, 2009]. The units for vegetation biomass density vary: [including Brown and Lugo, 1984; Brown, Gillespie and Lugo, 1989; Chave, Riéra and Duhuios, 2001]: kg/m² (kilogram per square meter), Mg/ha (Mega gram per hectare) or t/ha (tons per hectare), among others, are used. Carbon stock can also be estimated by assuming that 50 % of the total above-ground dry biomass consists of carbon [Basuki et al., 2009], which measured in tC/ha (tons of carbon per hectare) [Brown, 2002]. Furthermore, biomass can be divided in above-ground, below-ground and dead biomass [FAO, 2009]. This thesis focuses on above-ground phyto-biomass (above-ground vegetation) and is using t/ha or kg/ha for biomass and m³/ha for the bole volume or commercial tree volume. The forest inventory involves but is not limited to measurement of the diameter at breast height (DBH), total tree height and commercial tree height, so stem volumes of standing trees including standing deadwood (standing phyto-biomass) can be calculated. Deadwood on the forest ground is not included. In this work, biomass refers to vegetation biomass density. Stored carbon in the study area is not computed in this thesis.

In the 2010 GLOBAL FOREST RESOURCES ASSESSMENT SURINAME BY THE FAO, the biomass estimation is summarized. According to this nationwide assessment, Suriname contains an AGB of 368 tons per hectare [p. 30]. The total forest area is 14,810,366 hectares, therefore the total weight of dried biomass amounts to 5,450,214,688 tons, thus approximately 5.5 billion tons [p. 30]. This estimation contains no information about the spatial distribution of the nation’s biomass. In comparison to Suriname, Austria contains only 620 million tons dried biomass on half the area of the national territory, approximately 74 tons per hectare (20 % of Suriname’s amount) [FAO, GLOBAL FOREST RESOURCES ASSESSMENT AUSTRIA, 2010, p. 34].
1.3.2. Tropics

Astronomically the tropics are defined as zones between two latitudes, where the sun reaches the zenith and is perpendicular to the earth’s surface at least once a year. They are bounded by the Tropic of Cancer at 23.5° N and the Tropic of Capricorn at 23.5° S. The sunshine duration is always about 12 hours [Weischet and Endlicher, 2008].

1.4. Study Area

The study area is the national territory of Suriname in South America and extents circa between 6° N and 1° 50’ N latitude and between 53° 56’ W and 58° 4’ W longitude [Google Inc., Google Earth, 2012]. Neighbouring countries of Suriname are Guyana in the West, Brazil in the South and on French-Guyana in the East. In the North, the country is bounded by the Atlantic Ocean.

Figure 1: Survey map of Suriname (Source: http://www.mygeo.info/landkarten/suriname/suriname_landkarte.gif, January 2014)
Suriname is one of the smallest South American countries with a total area of 163,820 km², where 156,000 km² is land area (95.23 %). According to the FAO, Suriname had a population of 534,000 people in 2012. The population density is relatively sparse and amounts 3.26 inhabitants per km² [FAO, 2012: COUNTRY PROFILE SURINAME]. The population is concentrated around the capital Paramaribo and the coastal areas. The remaining, nearly uninhabited land is mainly covered by intact tropical rainforest (primary forest) [Jonkers, 1987].

Suriname can be divided into four geomorphological zones from North to South: The Young Coastal Plain, the Old Coastal [Wong et al., 2009], the Zanderij Zone and the Interior Uplands, which consist of crystalline rocks. The Coastal Plains are between 40 km and 120 km wide. They are mostly flat and the elevation varies from mean sea level (mangroves) to a few meters. South of the Costal Plans lies the Zanderij Zone. It is the main area of deforestation in Suriname which is characterized by an undulated landscape based on soils from the Tertiary period. The remaining area of Suriname is part of the High Plain located on the Guyana-Shield. The highest elevation of the country can be found at 1280 m above sea level [Jonkers, 1987].

1.4.1. CLIMATE

Suriname is part of the humid tropics. The average yearly temperature is 27 °C. The temperature during a year averages between 23 °C and 33 °C. In Paramaribo, the average yearly rainfall is 2,200 mm. However, the precipitation is not evenly distributed over the country. It varies from 1,750 mm to more than 3,000 mm per year [FAO, 1995: SURINAME: COUNTRY REPORT TO THE FAO INTERNATIONAL TECHNICAL CONFERENCE ON PLANT GENETIC RESOURCES].

Due to the differences in precipitation rates, four time periods can be distinguished [Jonkers, 1987; FAO, 1995: SURINAME: COUNTRY REPORT TO THE FAO INTERNATIONAL TECHNICAL CONFERENCE ON PLANT GENETIC RESOURCES]. There is no distinct dry period, but rather a time period with less precipitation. The climate is humid all year around. The differences between a rainy season and a less wet season are caused by the movement of the ITCZ (Innertropical Convergence Zone) [Chave, Riéra and Dubuisos, 2001]. To simplify, periods with less precipitation are referred to as dry seasons from here on out.
- Shorter rainy season: December to January
- Shorter dry season: February to March
- Main rainy season: April to August
- Main dry season: September to November

Figure 2: Climograph of Paramaribo (Source: http://upload.wikimedia.org/wikipedia/de/8/80/Klima_paramaribo.png, modified, November 2012)

Generally in the tropics, a so-called diurnal climate predominates. In other words, the average daily fluctuation is larger than the average yearly fluctuation. Because of the high precipitation, the relative humidity of the air never dips below 75 %, within the forests it almost constantly amounts to 100 %. Due to the humid climate the degree of cloudiness is very high [POTT, 2005].

1.4.2. Vegetation

The vegetation of Suriname is mostly comprised of different forest formations. The forested area of Suriname in 2005 according to the FAO [2012, COUNTRY PROFILE SURINAME] is 147,760 km². That is 94.72 % of the land area and 90.2 % of the national
According to the FAO [2012, COUNTRY PROFILE SURINAME], 142,140 km² of the forested land was made up of primary forest in 2005, which is 96.2 % of the total forested area.

A forest is according to the FAO [2010: GLOBAL FOREST RESOURCES ASSESSMENT 2010. COUNTRY REPORT: SURINAME, p. 7] a „land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 per cent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.” In the course of this National forest inventory, the smallest mapping unit is set to 1 ha.

The tropical rainforest is characterized by its high biodiversity. KLINK and MAYER [1983] gave an example of a forest area with 1 ha size. On average, 100 to 150 trees with a minimum DBH of 25 cm inhabit that area, but only a maximum of those more than hundred trees belong to the same species. The canopy in a tropical rainforest is about 30 to 50 m high, however some trees in the emergent layer grow up to 60 m [JONKERS, 1987]. Different stages of plant growth and maturity occur at all times in tropical rainforests [POTT, 2005].
Tropical rainforests show a vertical stratification. The lowest layers, the herb and the immature layer, hardly exist since only up to 10% of the day-light reaches these near-ground layers. The immature layer is up to 6 m high. The canopy layer is 30 to 40 m high and blocks out most of the sunlight. The emergent layer exceeds the canopy layer [KLINK and MAYER, 1983].

2. State of the Art

The (remote sensing) methods used so far were mostly applied to estimate biomass on a local or regional scale in deciduous and coniferous forests of temperate latitudes and the boreal coniferous forests of high latitudes [GONZALES PATIÑO, 2011; LU, 2006]. However, tropical rainforests display more complex stand characteristics, a higher biomass density than coniferous forests and a larger variety of species [LU, 2006]. Therefore, research regarding biomass estimation in the tropics has been started, but encountered different kinds of problems. The application of optical remote sensing systems is based on information in the range of the visible light spectrum and the near infra-red, but for these sensor types the high level of cloudiness in the tropics is a limiting factor. The use of active remote sensing systems, as SAR (Synthetic Aperture RADAR) avoids that problem. Despite all the obstacles, it is possible to collect optical remote sensing data [GIBBS et al., 2007]. The following figure represents an example of biomass estimation using GLAS data. This project was conducted by NASA based on LiDAR data on NASA’s ICESat satellite, terrestrial forest sampling plots, optical and radar data and will be discussed in Chapter 2.3.2.

![Figure 5: Biomass carbon map created by NASA](http://www.jpl.nasa.gov/images/earth/20110531/earth20110531-640.jpg, April 2014)
### Table 1: Advantages and Disadvantages of available data for biomass estimation *(Source modified, Gibbs et al., 2007, p. 3; Lu, 2006, p. 1299)*

<table>
<thead>
<tr>
<th>Data</th>
<th>Description</th>
<th>Advantages</th>
<th>Disadvantages</th>
<th>Accuracy</th>
</tr>
</thead>
</table>
| Forest-inventory              | Direct measurement of diameters and heights are related through allometric equations to volumes, biomass and carbon stock  
   Methods:  
   • Destructive sampling  
   • Allometric equations  
   • Volume biomass relationships | • Allometric equations available  
   • Technically not very demanding  
   • Little cost, excluding field work | • Allometric equations not appropriate for specific regions  
   • Very small-scale  
   • Very time-consuming | High       |
| Optical remote sensing        | Parts of the visible light spectrum and the infra-red are correlated via spectral indices with the terrestrial measured biomass data  
   Methods:  
   • Based on high resolution  
   • Based on medium resolution  
   • Based on coarse resolution | • Satellite data routinely acquired and available  
   • Globally consistent | • No proper model for the description of the tropical rainforest available  
   • Technically demanding | Low        |
| LiDAR                         | Travel time measurement of laser light to measure vegetation height (VHM) and surface (DSM) – Derivation of biomass via volume based approach or single tree approach | • Capability for global estimation of carbon stock with satellite based systems  
   • Accurately estimation of vegetation structure and consequently of biomass | • Great cost  
   • Technically demanding  
   • Airborne Laser scanner are not yet acquiring large-area data (tests in the past) | High to medium |
| SAR                           | Based on RADAR-signals in microwaves range the vertical forest structure or vegetation structure can be estimated | • Satellite data are generally free  
   • New systems are developing | • Less accurate in stratified forests because of the signal scattering  
   • Mountainous terrain also increases the error  
   • High cost and technically demanding | Medium      |
| GIS                           | Model based derivation of biomass base on additional information | • Scenarios can be modelled | • Request for accurate additional information (climate data, data concerning soil, slope etc.) | ———        |
| High-resolution aerial imagery | Because of the high resolution both forest parameters based on single trees and spectral features can be included in the regression with the terrestrial measured biomass data | • Expeditiously for forest  
   • Pinpoint accuracy  
   • Ground verification | • Cover small areas  
   • No general allometric equations based on crown area available | High to medium |

There are many methods and approaches to estimate biomass or other biophysical parameters. The method used depends on the available data. The three main approaches are "based on (1) field measurement, (2) remote sensing and (3) GIS modelling" [Lu, 2006, p. 1298]. This chapter outlines the data and methods used for biomass estimation and derivation of structural forest parameters, but raises no claim to completeness.
2.1. **Terrestrial Measurements as Data Basis**

The most direct method for acquisition of the forest stock and biomass is terrestrial measurement. There are two methods to derive biomass from the field work data. The first one is called **destructive sampling**. Several measurements are taken: the DBH of each tree (according to custom in 1.3 m height from the base) before felling, the height and the diameter (every 1 to 2 m) after felling. These values are used to calculate the volume of the tree. Samples taken are then analysed in a laboratory to measure the moisture content of the wood. Based on the dry weight, the wood density is determined. Therefore, it is possible to calculate the biomass and carbon stock. After determining the biomass for a variety of trees from the same species, allometric equations can be developed. Those equations are the foundation for biomass estimation without destructive sampling [Basuki et al., 2009; Overman, Witte and Saldarriaga, 1994].

The second method, which builds upon the first, is the method of **non-destructive sampling**. Brown [2002, p. 1672] points out that “allometric biomass equations exist for practically all forests of the world”. Using these allometric equations, the terrestrially measured data (including height and DBH) can be statistically linked to biomass [Gibbs et al., 2007; Overman, Witte and Saldarriaga, 1994].

Experience has shown, that in highly species rich regions like the tropical rainforest, generic allometric equations based on diverse ecosystems can be used for biomass estimation, because the DBH “explains more than 95 % of the variation in tree biomass” [Brown, 2002, p. 1672-1673].

In summary, it can be stated that in a majority of the cases, terrestrial measurements are the foundation for a remote sensing biomass estimation approach. The terrestrially measured data functions at least as data for calibration and validation of the system, unless the derived features were not measured in a forest inventory. However, field measurement is labour- as well as cost-intensive, provides data for small areas and is more complicated in remote or inaccessible areas. As opposed to this, remote sensing offers area-wide data and has, according to Lu [2006], attracted increasing scientific interest.
2.2. **OPTICAL REMOTE SENSING DATA**

Methods to estimate biomass based on optical remote sensing data can be split in direct estimates and indirect estimates. On one hand, direct methods are approaches such as regression analysis (multiple, linear, non-linear), K nearest neighbour and neural network and indirect methods, on the other hand, are using canopy reflection models or canopy parameters. Canopy parameters include crown size and DBH and are not directly measurable in remote sensing data, but are derivable [LU, 2006; LÓPEZ BAUTISTA, 2012].

2.2.1. **HIGH RESOLUTION DATA AND AERIAL IMAGERY**

In general, so-called high resolution data does not exceed the spatial resolution of 5 m and can be acquired using airborne sensors, resulting in aerial imagery, or spaceborne sensors, such as IKONOS, QUICKBIRD and WorldView, which were already used, and in the future probably Pléiades, GeoEye etc. as well [LU, 2006; LÓPEZ BAUTISTA, 2012]. Depending on the type and the characteristics of the available data, methods and features used for biomass assessment have to be chosen. Those features are characterized in two different categories: two-dimensional or three-dimensional. 2D-features include spectral information comprising all indices and ratios and texture information. 3D-features include all types of height models and all data deduced from them. Furthermore, additional information such as a geological map or a DTM could be included in biomass modelling.

**ALVAREZ et al. [2010]** applied regression analysis in the study using UltraCAM CIR data. They looked at reflection in red, green, blue and near-infrared spectral range, NDVI and SR (Simple Ratio) in order to relate it to terrestrially measured biomass of grassland. **BROWN et al. [2005]** used aerial imagery to derive a DSM from a pine savanna. Furthermore, crown sizes and heights were manually measured and connected to allometric equations, developed from destructive field sampling, by regression analysis as well.

**MATEJKA [2009]** used CIR images and terrestrial field measurements (DBH and tree height) of a spruce forest for his research. He detected crown sizes semi-automatically based on spectral information and as a result, calculated biomass based on the derived and measured parameters.

**SLAYMAKER et al. [1999]** applied an approach including field measurement, 2D- and 3D-data using an aerial camera and a camcorder on a mixed hardwood/coniferous forest. Spectral
information and the derived DSM were used to detect crown sizes automatically. These features were linked to measured parameters like DBH. Clark et al. [2004a] focused on IKONOS data and direct methods of using spectral information (band, NDVI, texture) and statistical features based on spectral information in the tropical rainforest. Terrestrially measured biomass, DBH and canopy height over 15 m were correlated with the selected and analysed features.

Gong, Sheng and Biging [2002] focused on a "3D model-based tree interpreter". To model each conifer, optimal images acquired from different angles are needed. The optimal, model-based tree outline was optimized on the optical images, hence the model results acted as derived parameters. In this way, biomass could be modelled.

Plonton [2010] used texture analysis on IKONOS imagery and applied linear regression analysis to structural forest parameters and textural gradients on humid forests in India, but there are still problems with model calibration.

There is a variety of methods for single tree delineation [Gonzales Patiño, 2011; Jiang and Lin, 2013; Korpe, 2004; and much more], but none of them were related to biomass data.

In summary, biomass estimations based on high resolution data or aerial imagery can be conducted directly or indirectly. Features for direct estimation are spectral information, indices and texture features. Parameters from visual interpretation, single tree delineation, segmentation algorithms, etc. can be used for indirect biomass estimation. High resolution data can provide 3D-information as well. The textbook example is the derivation of DSM from stereoscopic imagery. Integration of data will be discussed in Chapter 2.5.

### 2.2.2. MEDIUM RESOLUTION DATA

In general, data with a declared medium spatial resolution can be found with resolutions ranging approximately from 10 to 100 m. Examples for sensors with medium spatial resolution are LANDSAT, SPOT, ASTER, IRS and RapidEye [Lu, 2006].

In contrast to high resolution data or aerial imagery, data with medium resolution does not display single trees. For instance, if the resolution is 15 m, a tree is depicted in one pixel, thus all spectral characteristics are mixed in one pixel. Hence, the analysis cannot be based on single trees, but on forest associations and forest types.

Castillo-Santiago, Ricker and De Jong [2010] focused on SPOT data and field measurements in tropical forests to develop a regression model using 2D-information. "7
texture measures, 8 vegetation indices, the first two principle components and the average surface reflectance of all pixels inside the field plot of the spectral bands red, green, NIR and MIR” were analysed for correlation with forest stand parameters [CASTILLO-SANTIAGO, RICKER and DE JONG, 2010, p. 2771].

FOODY et al. [2001] used Landsat TM data from Bornean tropical rainforest for a neural network analysis (see Figure 6). Artificial neural networks were developed to function in some cases similar to the human brain, to "solve complex non-linear problems. They have been used in a wide range of applications in remote sensing and image analysis including supervised classification, unsupervised classification, geometric correction, image compression, model inversion and regression analysis" [FOODY et al., 2001, p. 381]. Here, a neural network is applied to calculate biomass without previous assumptions about the data.

![Figure 6: Basic structure of an artificial neural network (Source: FOODY et al., 2001, p. 381)](image)

Li et al. [2010] used Landsat TM data from moist tropical forests and regression analysis to link independent variables to biomass data. A similar project was started by Lu et al. [2002] with Landsat TM data from moist tropical forests and regression analysis. FRANCO-LOPEZ, Ek and BAUER [2001] focused on the use of k-nearest neighbour method for estimation of forest stand characteristics of Aspen-birch and Spruce-fire dominated forest.

K-nearest neighbour method (kNN) is, according to FRANCO-LOPEZ, Ek and BAUER [2001, p. 252] (in accord with TOMPPO) the following: "The spectral distance, \( d_{pi,p} \) is computed in the feature space from the pixel \( p \) to be classified to each pixel \( p_i \) for which the ground measurement or class is known. For each pixel \( p \), take \( k \)-nearest field plot pixels (in the feature space) and denote the distances from the pixel \( p \) to the nearest field plot pixels by \( d_{pi,p}, \ldots, d_{pk,p} \) (\( d_{pi,p} \leq \ldots \leq d_{pk,p} \)). The estimate of the variable value for the pixel \( p \) is then
expressed as a function of the closest units, each such unit value weighted according to a distance function in a particular feature space." Jung et al. [2013] points out that it is important to find the optimal number of k-nearest neighbours. Franco-Lopez, Ex and Bauer [2001, p. 253] states that the kNN method is a "non-parametric classifier, where no assumption on the distribution of the data were made". With this classifier, the analysis using field data as reference resulted in a more precise estimation than with other classification methods such as Mahalanobis Distance or Euclidean Distance.

Wu and Strahler [1994] focused on modelling biomass distribution based on canopy reflectance models for coniferous forests in the USA. They summarize that three types of models were developed over time, the two-stream model, the radiative-transfer model and the geometric-optical model. The application of the geometric-optical model is based on trees as discrete objects, which were modelled by simple three-dimensional objects with one shape but different sizes using Landsat data. By modelling tree parameters such as crown radius and stand density, estimation of biomass was conducted through regression analysis [Wu and Strahler, 1994].

Asner, Hicke and Lobell [2003] summarize and discuss the opportunities for "per-pixel"-analysis of forest structure and mention types of indices and vegetation indices, spectral mixture analysis and canopy reflectance modelling, however no potential biomass estimation connected to that.

In conclusion, it must be said that there are many different approaches to estimate biomass from medium resolution data. Most approaches are based on spectral information (indices, neural network approach and kNN-approach). For models such as geometric-optical or canopy reflectance models, exterior circumstances are as important as spectral information.

2.2.3. Coarse resolution data

Coarse resolution refers to data with spatial resolution over 100 m. Sensors acquiring coarse resolution data are for instance MODIS, NOAA Advanced High Resolution Radiometer (AVHRR) and SPOT Vegetation. The use of this kind of data is limited to national, continental and global application. Furthermore mixed pixel information is a problem as well as differences in data resolution and dimension of reference data (i.e. size of field plots) [Lu, 2006].

Myneni et al. [2001] analysed the woody biomass of forests on the Northern Hemisphere using NOAA NDVI data with 8 km resolution. National forest inventory data acquired
during 18 years from 171 provinces in six countries were used for regression analysis [Myneni et al., 2001]. Saatchi et al. [2007] used MODIS data in Amazon basin to derive features such as NDVI, LAI (leaf area index) and used radar data (JERS and QSCAT), SRTM digital terrain model, climate data and a vegetation map as additional data. Due to extreme heterogeneity, available data was classified step by step by decision tree method and regression modelling. These results were intersected with the additional climate data [Saatchi et al., 2007]. A map of the final result can be seen in Figure 7.

![Figure 7: Aboveground live biomass map](Source: Saatchi et al., 2007, p. 830)

Asner, Hicke and Lobell [2003] focused research on "per-pixel"-analysis of forest structures. They summarize methods such as derivation of indices, spectral mixture analysis and canopy reflectance modelling, as mentioned in Chapter 2.2.2. Myneni, Nemani and Running [1997] did research with MODIS and AVHRR data to estimate Global Leaf Area Index (LAI) using NDVI-LAI and NDVI-FAPAR (Fraction of absorbed Photosynthetic Active Radiation). A radiative transfer model was applied and validated. Baccini et al. [2004] carried on research to estimate biomass based on multisource data (MODIS, topographic and climatic data) and statistical models on forests in California. Data were analysed using a generalized additive model (GAM).
In summation, it can be said that coarse resolution data is used to estimate biomass on a global, national or continental scale as well as the use and inclusion of additional data is advantageous.

2.3. RADAR

A requirement for high-quality optical remote sensing data is a cloud-free vision. Due to constant or recurrent cloudiness, especially in the tropics, the use of RADAR is often the only feasible way to acquire data.

2.3.1. SAR

SAR data is often used to estimate biomass, forest types and forest stand parameters [Lu, 2006]. Saturation level is a problem and a limiting factor with SAR data and depends on wavelengths, polarization and characteristics of the monitored forest [Lu, 2006, p. 1306]. According to Kurvon_en, Pulliainen and Hallikainen [1999, p. 198], saturation level for biomass retrieval "increases with decreasing frequency". Sun and Ranson [2009] point out that SAR systems can be used to measure canopy volume, especially with long wavelengths. Furthermore, they state that RADAR can be used for biomass estimation due to its sensibility to water content in vegetation and its penetrativeness for vegetation. Sun and Ranson [2009] derived a biomass map from LiDAR data (LVIS) and evaluated the capability of SAR data (including LVV, LVH, LHV and LHH backscattering parameters from polarimetric SAR) for biomass estimation in a step by step regression in a mixed hardwood and softwood forest in Maine. Kurvon_en, Pulliainen and Hallikainen [1999] used ERS-1 and JERS-1 SAR data to apply a semiempirical backscatter model based on data from conifer-dominated mixed forests in southern Finland. They point out that direct biomass retrieval from backscatter signal is limited because of a saturation level that exists, which ranges from 125 to 225 m³/ha stem volume. According to Kurvon_en, Pulliainen and Hallikainen [1999], SAR P-Band would be the most advisably band for biomass assessment, but P-Band sensors do not exist on spaceborne platforms. L-Band and C-Band were used instead. Luckman et al. [1998] used JERS-1 SAR L-Band for biomass retrieval by backscatter model as well and evaluated it with field data. The backscatter analysis resulted in a saturation level of around 60 t/ha biomass. Santos et al. [2003] also focused on biomass estimation of tropical rainforests from SAR P-Band based on
terrestrial inventory by "statistical regression using logarithmic and polynomial functions". They point out that "P-Band saturates at a higher level of biomass" than other bands [SANTOS et al., 2003, p. 484]. SANTOS et al. [2003, p. 483] remark that former studies based on AirSAR have revealed a saturation level for biomass of 20 t/ha for C-band, 40 t/ha for L-band and 100 t/ha for P-band. C-, L- and X-Band do not pierce branches and leaves due to their penetration depth compared to P-Band backscatter, which indicates boles [SANTOS et al., 2003]. DOS SANTOS et al. [2009] used SAR P-Band data to estimate biomass in dense forests of lowlands in Brazil through a heat capacity model. WILLIAMS et al. [2009] used GeoSAR X-P interferometric data alone to estimate biomass of tropical rainforests and they developed a technique to estimate biomass over 150 t/ha. DEL FRATE and SOLIMINI [2004] focused on estimation of forest biomass based on SAR data (AirSAR and SIR-C/X-SAR) through neural network algorithms.

In conclusion, SAR data has a large capability to estimate biomass, especially in the tropics not dependent on weather conditions or sunlight. On the other hand, the saturation level in areas with over 100 or 150 t/ha biomass can be problematic and a limiting factor.

2.3.2. LiDAR

LiDAR (Light Detection And Ranging) is an important method for assessment of biomass because LiDAR systems can measure some forest components directly such as canopy heights [LU, 2006]. The use of airborne LiDAR for biomass estimation of large areas is very cost-intensive. ASNER et al. [2010] focused on integration of satellite image data, airborne LiDAR data and field plot biomass assessments in large areas in the lowlands of an Amazon forest. Satellite data were used to classify forest cover, degradation or deforestation. Then LiDAR data were calibrated with terrestrial measured field plot data to computed biomass and carbon content. For calculation of carbon content several features were used but mean canopy profile height was the best predictor. LEFSKY et al. [2002] did research on deriving forest biomass in temperate deciduous forests, in temperate coniferous forests and in boreal coniferous forests using LiDAR and field data. LEFSKY et al. [2002] used Multiple Regression analysis to compare diverse features including mean canopy profile height, which reflects the vertical structure of the canopy, mean canopy height squared, canopy cover and canopy cover multiplied with other features. An equation was found, which included mean canopy height squared. JÄRNSTEDT et al. [2012] used kNN estimation method (cf. chapter 2.2.2) to compare terrestrially measured forest stand variables such as diameter at breast height or basal area with both
LiDAR data and photogrammetric DSM or CHM, but direct estimation of biomass was not conducted. Järnstedt et al. point out that using LiDAR data leads to better results in estimation. López-Bautista [2012] did research on biomass estimation in a subtropical forest in Nepal. GeoEye-data for segmentation, terrestrially measured field data and LiDAR data were used. Clark, Clark and Roberts [2004b] used a small-footprint LiDAR for a study in the evergreen tropical rainforest. From last pulse signals, a DTM was interpolated and used to derive a DCM (Digital canopy model). Linear regression was used to compare terrestrially measured tree heights to heights derived from DCM, but no comparison with biomass was conducted.

Figure 8: LiDAR acquired DSM (a), DTM (b) and CHM (c) (Source: Kellner, Clark and Hofton, 2009)

Drape et al. [2002] tried to predict forest stand parameters including biomass in a wet tropical forest in Costa Rica using LiDAR data. Stepwise Multiple Regressions resulted in multiple-term equations, which led to $R^2 > 0.9$ for AGB and QMSD (quadratic mean stem diameter). Hyypä et al. [2001] focused on extracting tree parameters from LiDAR data acquired in a boreal forest in Finland. A 3D-model was generated and tree parameters were derived by using segmentation, but no biomass estimation was conducted. Chen et al. [2012] applied (statistical) mixed-effects modelling to combine LiDAR data and
vegetation data from aerial imagery in a study area in the Sierra Nevada, California. Mixed-effect models are beneficial here, because model parameters do not have to be constants but can rather be described as variables. So for biomass modelling, the sample plots do not have to be divided in vegetation types and analysed separately but can rather be analysed together, which increases the number of available data. Further information on LiDAR application in forestry can be found in Lim et al.’s review “LiDAR remote sensing of forest structure” [2003].

Baccini et al. [2008] used coarse resolution MODIS data in combination with terrestrial measurements for biomass estimation, using a regression tree in the tropics and with GLAS data (Geoscience Laser Altimeter System). GLAS acquired spaceborne LiDAR data using a LiDAR-sensor mounted on the ICESat Satellite (The Ice, Clouds and Land Elevation Satellite) between 2003 and 2010, and was stopped due to technical problems [NASA, ICESAT]. Saatchi et al. [2011] focused on the application of the abovementioned GLAS data. They mapped above- and belowground biomass of all tropical forests using spaceborne LiDAR data, terrestrial inventory plots, radar data and optical imagery. LiDAR measured tree heights were related to terrestrial measurements and the result was extrapolated to entire available areas in the tropics.

In summary, similar to the SAR method, LiDAR has also a large capability to determine the amount of biomass. Future research will be more focused on LiDAR and data integration to take advantage of different sensor systems. In contrast to passive optical sensors, LiDAR data contributes the vertical structure of canopy and three-dimensional information.

### 2.4. GIS AND MODELLING

This chapter contains a short review about modelling and GIS modelling approaches for biomass estimation. Modelling is a broad term and aims to simplify complex issues. It includes the use of various algorithms and diverse input data with varying degrees of resolution. When working with models, the degree of accuracy can be chosen as well as whether the model should be empirically or physical based.

Many other modelling approaches exist. Here, only a few selected ones are presented. Brown and Gaston [1995] did research on GIS based modelling of biomass in tropical forests of Africa. Data such as population density, elevation, vegetation maps, climate and soil data served as spatial base data. Thus, potential biomass distribution was modelled...
using a combination of weighted layers. Furthermore, the potential biomass was reduced to actual biomass by including population density and the degree of degradation. ASNER, HICKE and LOBELL [2003] summarized pixel-based approaches of forest structure, including physically based canopy reflectance modelling. Radiative transfer models are among this field of modelling as well as geometrical-optical models and reflectance models based on canopy photon theory.

![Schematic representation of various input layers for modelling](http://geosphere.gsapubs.org/content/2/4/236/F2.large.jpg, April 2014)

In summary, the expression “modelling” wholly depends on the definition. Modelling can be related to regression modelling as well as sophisticated physically based transfer models or empirical GIS modelling. Modelling does not depend on remote sensing data, but could be inclusive of it.

### 2.5. **Integration of Data**

Integration of data from different sources or sensors has the goal of using advantages of different data types and to avoid disadvantages to glean best possible results. Theoretically, there is any number of possible combinations of data. Therefore, the selection of data combination depends on the availability of data for the study area and
the problem. *Lu [2006]* points out that integration of *Landsat* TM and SAR data, for instance, has led to better model results for basal area estimation, but that more research could be done on this topic. This paragraph gives a brief overview of the state of the art of data integration. *Gautam et al. [2010]* focused on data integration for biomass estimation in the tropics. Data and technologies used were airborne ALS data because of its ability to penetrate multilayer canopies. It provides vertical information, satellite data, due to its extent and dimension, and field measurement data, for calibration and validation. *Sun and Ranson [2009]* used LiDAR data and samples to show which capabilities SAR data have to estimate biomass through stepwise regression. They point out that SAR data can be used with certain qualifications to the radar wavelength. *Lefsky, Cohen and Spies [2001]* focused on comparison of diverse optical sensor data (*Landsat* TM (single date and multitemporal data), ADAR data and AVIRIS data) and LiDAR data using 92 sampling plots in the coniferous forests of Western Oregon, USA. Methods used were techniques such as regression analysis, computing texture images, calculation of indices, principal component analysis and more. The study shows that the LiDAR (SLICER) data lead to the best results when it comes to estimation of forest structure parameters. *Chen et al. [2012]* focused on mixed-effect models (compare chapter 2.3.2). In case of integration of data, they point out that in previous studies, integration of LiDAR data with data acquired from radar or optical sensors does not always improve the result. Furthermore, they state that other studies could achieve better results by integration of LiDAR and optical data. *Baccini et al. [2004]* tried to integrate additional data, such as precipitation, temperature and elevation, with MODIS data to estimate biomass in coarse resolution of forests in California, USA. A generalized additive model (GAM) was performed in the first place to detect conjunction between the remote sensing data and the used additional data. Subsequently biomass was predicted using a random forest model. *Asner et al. [2010]* used satellite data, LiDAR data and field plots for biomass mapping in Peru. Multitemporal satellite data were used to distinguish and map 26 types of vegetation classes. With this vegetation map, the study area was stratified and investigated using LiDAR metrics. To interpolate or regionalise the findings, statistical distribution was investigated for each vegetation class.

Ultimately, current research has emphasized the integration of data, to benefit from advantages of different sensors and to adjust weaknesses of systems. Many possible combinations can result in beneficial effects for biomass estimation, although more research is needed to develop effective approaches and suggestive combinations.
2.6. **SUMMARY**

To summarise, there are as many methods to derive biomass and forest stand parameters as there are available data and data combinations. Most of the methods used for biomass estimation were developed and applied in areas with relatively simple forest stand structures like boreal coniferous forests or coniferous forests in general. Transferring these models or applications to study areas with significantly more sophisticated stand characteristics certainly leads to problems. However, for research in tropical rainforests for example, new application and models has to be developed and tested and existing approaches has to be changed or modified, respectively. Forest inventory including field work is necessary to calibrate and validate the applications used. Data acquired with LiDAR sensors seems to have the most potential when it comes to biomass assessment, but LiDAR systems do not acquire large-area data. Optical remote sensing imagery is available in diverse spectral, radiometric and spatial resolutions. So the integration of it depends on the problem statement of the project and/or the temporal availability of data, because, focussing on the tropics, cloudiness can be a tremendously limiting factor. Radar data is not restricted through weather conditions but copes with a saturation level problem on biomass. GIS data tends to be complex and time-consuming and is sometimes limited to discrete data, whereas remote sensing data depicts continuous data. Table 2 on the next page provides an overview.
<table>
<thead>
<tr>
<th>Data</th>
<th>Characteristics</th>
<th>Methods</th>
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<tr>
<td>Forest inventory</td>
<td>Field work</td>
<td>Direct:</td>
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<td>Terrestrially measured</td>
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<td></td>
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<td>Destructive sampling</td>
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<tr>
<td>Fine-spatial resolution</td>
<td>Max. 5 m resolution</td>
<td>Indirect:</td>
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<td>optical data and aerial</td>
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<td>Allometric equations</td>
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<td>imagery</td>
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<td>Medium-spatial resolution</td>
<td>10 to 100 m resolution</td>
<td>Multiple Regression analysis</td>
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<td>optical data</td>
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<td>Modelling</td>
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<td>Coarse-spatial resolution</td>
<td>More than 100 m resolution</td>
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<td>optical data</td>
<td></td>
<td>Regression models</td>
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<td>LiDAR</td>
<td>Measurement of vertical canopy structure</td>
<td>LiDAR metrics: direct use for biomass estimation</td>
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<tr>
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<td>Regression</td>
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<td></td>
<td>Modelling (e.g. mixed effect modelling)</td>
</tr>
<tr>
<td>SAR</td>
<td>Independent of weather conditions, saturations level problem</td>
<td>Regression models</td>
</tr>
<tr>
<td>GIS and modelling</td>
<td>Based on additional data, physically based models, empirically based models</td>
<td>Backscatter model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Interferometry</td>
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<tr>
<td></td>
<td></td>
<td>Modelling:</td>
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<tr>
<td></td>
<td></td>
<td>Abovementioned algorithms (neural network, kNN, canopy reflectance model, etc.)</td>
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<tr>
<td></td>
<td></td>
<td>Geometrically based models</td>
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</table>
3. METHODOLOGY

In this chapter contains the methods used in course of the thesis are depicted and the results of biomass calculation are presented. It starts with a description of the data followed by the derivation of features. Unless stated otherwise, the research was done at Joanneum Research Graz – DIGITAL. The biomass of all sampling plots was calculated by the author, based on formulas and data from ANRICA and SBB.

3.1. DATA BASE

The data base was built from terrestrial forest measurements and high resolution aerial imagery (RGB and NIR) which were acquired during the course of a pilot project for the “National Forest Inventory Suriname”, and were used for DSM extraction. In addition to the aerial images, terrestrial forest measurements from the same project in Suriname were available, beginning in January 2013.

Since the remote sensing data has to be combined with the National Forest Inventory data, aspects of aerial imagery need to be of high quality, including geometrical and spectral resolution. HILDEBRANDT [1996] points out that aerial photographs are best suited for forest inventory. He also mentions that it best suits to cover relatively large areas with high resolution.

Based on terrestrial measurements, biomass was calculated using allometric equations. Aerial imagery was base for calculation of orthoimages and DSMs, which made up the data base for treetop detection and segmentation methods.

3.1.1. SAMPLING UNITS AND FOREST INVENTORY

The Sampling Units for the pilot project were selected randomly and distributed with regularity nationwide to the specifications of a national forest inventory. Another approach would be using random and irregular distributed Sampling Units, which was not done here.

SABOROWSKI and DAHM [1997, p. 92] point out that “stratification is a classification of the inventory area into sub-areas defined by auxiliary variables and the following the selection of a predetermined number of sampling units of each of the subregions.” Auxiliary variables used for classification are forest type, age of stands and more. This reduces the
sampling error in the inventory [SABOROWSKI and DAHM, 1997]. However, stratification was not applied in the course of the pilot project, but might be applied in subsequent forest inventory project in Suriname. In the current project, Sampling Plots generated by a regular grid were chosen based on different forest types in order to measure representative samples. Gibbs et al. [2007] point out that stratification of the area is necessary to avoid over- and underestimation. When the area of the via stratification classified subunits is known, the measured information can be statistically projected on the entire area of the same stratum. The stratification is needed because the ecological associations of plants emerge inherently grouped. Moreover through stratification it can be guaranteed that the entire variation of forest associations is mapped and scaled. Gibbs et al. [2007] point out that in the course of national forest inventory, additional information such as geological subsoil, soil type, runoff characteristics, topography, land use, etc., shall be included to evaluate the spatial variation in a better way.

The regular grid for the field inventory in Suriname is built in distances of 20 km. The single Sampling Units (SU) of the grid are the size of 750 x 750 m and are subdivided systematically in 8 or 12 Principal Sample Plots (PSP) and the PSP furthermore in 20 Main Assessment Plots (MAP) and are measured and mapped systematically [see SBB and ANRICA, 2013].

The field data acquisition started in January 2013, which resulted in the step by step development of the database. The calculation of biomass, tree volumes and basal area was conducted by the author. The allometric equations were provided by ANRICA and can be found in Pearson, T., Walker, S. and Brown, S. [2005, p. 43]. The formula for biomass calculation is a generally valid equation for moist tropical rainforest (see also Chapter 3.1.2). For comparison with aerial images, only trees with more than 20 cm DBH were included due to the height and crown overlap of bigger trees. Another reason was that trees with a DBH more than 20 cm contain the highest amounts of biomass. The derived data later on acted as a foundation for the regression with the features from the aerial images.
The field work was conducted progressively. First, 5 Sampling Units, which were relatively easy accessible, were mapped, measured and used for analysis. That way, the current 140 Sampling Units, for which aerial images are available, are successively inventoried in the subsequent National Forest Inventory Project.

Figure 10: Sampling Unit design with Principal Sample Plots in field (left) and additional plot design (right) (Source: SBB and ANRICA, 2013)
The unique ID of the Sampling Units is a composite of the first two numbers of the UTM zone 21 N – Coordinates of the centre of the SU. In this thesis, five inventoried Sampling Units were used – SU 5352, SU 5954, SU 5956, SU 6358 and SU 7358.
The available aerial images were analysed by the members of the field assessment teams and in the first step, forest areas were distinguished from non-forest areas. Afterwards, the following forest types were designated in the process of visual stratification and mapping in aerial images:

1. High Dryland forest  
2. Mangrove forest  
3. Marsh forest  
4. Swamp forest  
5. Low xerophytic forest  
6. High xerophytic forest  
7. Bamboo forest  
8. Liana forest  
9. Shifting cultivation  
10. Secondary forest  
11. Planted forest

An attempt was made to define a further attribute from the aerial imagery: the stocking density. The field teams tried to assign the attributes low, medium and high stocked to forest areas. In the course of the field work, it became more and more evident that the assignment of stocking density was difficult and challenging to map on aerial images because of the small-scale heterogeneity of the forest types. It is to be hoped that a combination of terrestrial field work and interpretation of aerial imagery will lead to better results for stocking density. In future, the judgement based on experience is required for determination of the stocking density based only on aerial imagery. Another feature was attributed: the level of disturbance. Forest types were classified in “No disturbance”, “Disturbed by logging” and “Other disturbance” [SBB and ANRICA, 2013]. High Dryland forest covers the largest areas in Suriname and is the dominate forest type. Therefore, the focus of derivation of regression equations was on this forest type.

3.1.2. BIOMASS AND VOLUME DATA

In the course of the thesis, data of 5 inventoried Sampling Units was used - SU 5352, SU 5954, SU 5956, SU 6358 and SU 7358. The terrestrial measurements were used as
reference data, digitally processed and resulted in biomass estimations for the 5 Sampling Units used.

The terrestrially acquired parameters were DBH, number of trees, commercial height, total height and plenty of descriptive quality parameters. One of the descriptive quality parameters is the crown health, which is important for remote sensing evaluation. With the abovementioned parameters, biomass, basal area and commercial volume were calculated using the following formulas. Since biomass is target value for regression analysis, all the other mentioned parameters are important for the remote sensing approach to estimate the biomass.

### Table 3: Equations for calculation of biomass, basal area and commercial volume

<table>
<thead>
<tr>
<th>Equations for</th>
<th>Formula</th>
<th>Information from</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Biomass</strong> (Moist tropical forest)</td>
<td>$\text{Biomass [kg]} = e^{-2.289+2.649\ln DBH - 0.021\ln DBH^2}$</td>
<td>PEARSON, T., WALKER, S. and BROWN, S., 2005, p. 43</td>
</tr>
<tr>
<td><strong>Basal area</strong></td>
<td>$BA [m^2] = \frac{DBH^2}{100} \times \frac{\pi}{4}$</td>
<td>DR. MICHAEL KLEINE</td>
</tr>
<tr>
<td><strong>Commercial volume</strong></td>
<td>$\text{Com Vol [m}^3]\text{]} = BA [m^2] \times \text{Com height [m]} \times 0.75$</td>
<td>DR. MICHAEL KLEINE</td>
</tr>
</tbody>
</table>

According to KORPELA [2004], only trees with at least a small part of the crown exposed to sunlight are detectable in aerial imagery. Therefore, trees with seriously damaged or broken crowns, which are not detectable in aerial imagery, were excluded from biomass data. Results of biomass calculation per Sampling Unit are shown in Table 7 (Chapter 4.1).

### 3.1.3. AIRBORNE AERIAL IMAGERY DATA

The flights campaign over the study area took place in September 2012 and was performed by JOANNEUM RESEARCH GRAZ – DIGITAL. The remote sensing platform used - called ADAM - was developed at JOANNEUM RESEARCH GRAZ – DIGITAL and in an abbreviation for “Airborne Data and Mapping”. The flights were conducted with a small aircraft, a Cessna on which the ADAM platform was mounted. The imaging sensors of Joanneum Research consist of an aerial survey camera “PROSILICA GE4900C” and an infrared aerial survey camera “PROSILICA GC2450”. Furthermore, a GPS-receiver and an inertial measurement unit (IMU) were part of the platform [detailed information in SOMMER, 2012].
Figure 12: ADAM Platform (Source: SOMMER, 2012, p. 36)

Table 4: Specifications of Prosilica GE4900C digital aerial survey camera (Source: ALLIED VISION TECHNOLOGIES and JOANNEUM RESEARCH)

<table>
<thead>
<tr>
<th>Prosilica GE4900C</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Resolution</strong></td>
</tr>
<tr>
<td><strong>Sensor type</strong></td>
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<tr>
<td><strong>Sensor</strong></td>
</tr>
<tr>
<td><strong>Sensor size</strong></td>
</tr>
<tr>
<td><strong>Cell size</strong></td>
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<tr>
<td><strong>Bit depth</strong></td>
</tr>
<tr>
<td><strong>Raw modes</strong></td>
</tr>
<tr>
<td><strong>Supplementary equipment</strong></td>
</tr>
</tbody>
</table>

Table 5: Specifications of Prosilica GC2450 digital aerial survey camera (Source: ALLIED VISION TECHNOLOGIES and JOANNEUM RESEARCH)

<table>
<thead>
<tr>
<th>Prosilica GC2450</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Resolution</strong></td>
</tr>
<tr>
<td><strong>Sensor type</strong></td>
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<tr>
<td><strong>Sensor</strong></td>
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<tr>
<td><strong>Sensor size</strong></td>
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<tr>
<td><strong>Cell size</strong></td>
</tr>
<tr>
<td><strong>Bit depth</strong></td>
</tr>
<tr>
<td><strong>Raw Modes</strong></td>
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</tbody>
</table>
The data acquisition took place in several lines from north to south. Previously defined Sampling Units were overflown and surveyed. The definition of the locations and numbers of Sampling Units took place in the first phase of the project conducted by SBB and ANRICA. Previously measured forest inventory spots, so-called Carbon Plots, were covered by aerial photographs, too.

**Figure 13:** Areas overflown and forest inventory Sampling Units in Suriname (Source: *SBB and ANRICA, 2013*)
The target resolution was 20 cm on the ground. The following formula displays the relation between flying altitude above ground level, the focal length and the scale denominator.

\[
\frac{c}{h_g} = \frac{1}{s} \text{ or } \frac{1}{m_b}
\]

**Formula 1:** Relation between altitude above ground level \(h_g\), focal length \(c\), a line segment \(s\) and the scale denominator \(m_b\) (Source: Based on Hildebrandt, 1996, p. 116)

<table>
<thead>
<tr>
<th>Focal length (c) in mm</th>
<th>Altitude above ground level in m</th>
<th>Scale denominator (m_b)</th>
<th>Resolution in cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>500</td>
<td>1000</td>
<td>10</td>
</tr>
<tr>
<td>50</td>
<td>1000</td>
<td>2000</td>
<td>20</td>
</tr>
<tr>
<td>50</td>
<td>1500</td>
<td>3000</td>
<td>30</td>
</tr>
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</table>

A constant focal length of 50 mm and a target resolution of 20 cm results in a flying altitude of about 1000 m. As one can see in Figure 14, images with a resolution of 20 cm can be used to identify single trees and branches, in contrast to images with a resolution of 100 cm. The image with 100 cm resolution was resampled to this geometric resolution to show the difference between 20 cm and 100 cm resolution. The image with 20 cm resolution is the original image.
The coverage of the image is in turn related to the flying altitude above ground level and the surface of the areas overflown. In case of flat terrain and stable flying altitude of 1000 m above ground level, one photograph covers an area of 974.4 m x 649.6 m, which results in an area of 0.6329 km².

The overlap area of the images acquired, which is very important for stereoscopic (3D) processing, marginally varies from plot to plot. To achieve sufficiently good results, the overlap for the stereoscopic processing has to be more than 60 % in flight direction and at least 30 % across to flight direction. In mountainous areas with large drops, the overlaps should nevertheless amount to at least 70 % in flight direction and at least 40 % across to flight direction [ARBEITSGRUPPE FORSTLICHER LUFTBILDINTERPRETEN, 2012]. According to SOMMER [2012], a higher degree of overlap increases the quality of the DSMs derived as mentioned before. To calculate the overlap size, the length of one side of the photograph (S) and the length of the baseline (B) is needed.

\[
\text{Overlap} \, [%] = \left(1 - \frac{B}{S}\right) \times 100
\]

**Formula 2: Calculation of the size of the overlap** (Source: KAUFMANN, 2010, Chapter 2.3.2)

With a baseline of 165 m, the overlap is approximately 75 %. To get an overlap size of 60 % on flat terrain, the baseline needed to be 260 m.

LEBERL et al. [2010, p. 1123] mentions the advantages of digitally sensed images which include “the cost-free increase of overlap between images”. An overlap of 80 % in flight
direction means that an object point exists in 8 images. That implies that the image block is more stable and thus systematic error decreases. Using more images during image matching also means more image information and more precise canopy models [paragraph see SOMMER, 2012; KRAUS, 2004]. Furthermore, HIRSCHMÜLLER [2008] developed a matching algorithm that uses all available images for matching, which results in an increase of geometric accuracy. In this thesis the standard stereo approach was applied due to better results during the matching process, mention in Chapter 3.1.5.

Certain difficulties occur during data acquisition in the tropics. Due to humid climate, the degree of cloudiness is very high. A large amount of clouds is constant at low elevations. The cloud ceiling, which is a limiting problem for optical satellite remote sensing data, can be underflown. If the cloud ceiling during a flight is underflown, the conditions of illumination change to diffuse light. This can cause problems with camera calibration, when the camera is calibrated to sunlight. The position of the sun is another factor in the planning of flights, since the position of the sun is different compared to the temperate latitudes. An image flight in the temperate latitudes often takes place at noon in order to achieve the optimum illumination for the aerial imagery. In the tropics at noon, the sun is located perpendicular or nearly perpendicular and causes a total reflection and as a consequence an overexposure or blooming on the images. Furthermore, at noon the first clouds appear on the sky which reduces the quality of the photographs. Therefore, it is recommended to conduct image flights in the tropics in the mornings. Another criterion for flight planning, as mentioned before, is the season of the year respective to the annual variability of precipitation. Since Suriname has no real dry season, but a period of time with less precipitation, it is recommended to schedule image acquisition during that period of time (see Chapter 1.4.1).
Within the humid tropics, the factor phenology is largely neglectable. In climates where seasons or distinct dry or rainy seasons are distinguished, the time of data acquisition has to be scheduled according to the phenology [ARBEITSGRUPPE FORSTLICHER LUFTBILDINTERPRETEN, 2012].

3.1.4. PRE-PROCESSING AND SOFTWARE

The software used for image processing is the Remote Sensing Software Graz (RSG) package developed by Joanneum Research Graz – DIGITAL. Furthermore, the software library IMPACT (Image Processing and Classification Toolkit) by JR was used, which also belongs to the image processing software package. Unless stated otherwise, all processes were performed with the software packages of Joanneum Research Graz.

Firstly, the aerial images available in a memory-saving raw image format had to be imported and pre-processed. After that, the data was processed to derive height information and other features in 2D or 3D, described in the following chapters.
The raw image data is available in a compressed format. This format is the so-called “Bayer Pattern”-format, named after a scientist who invented a colour array filter (CAF), overlaid on digital aerial cameras. With this CAF it is possible to acquire colour images with 3 channels using just one charge-coupled device (1 channel). That colour array is built of 50% green, 25% red and 25% blue pixels (see Figure 16). To obtain images with three colour channels, a process called “Demosaicing” has to be carried out. In this process, the missing pixels lying in-between are interpolated and the RGB-information is split into three channels [see BAYER, 1976; PERKO, 2004].

![Figure 16: Example for a Bayer array with 7 times 7 elements (Source: PERKO, R., 2004, p. 98)](image1)

![Figure 17: Raw “Bayer Pattern” image (left) and interpolated RGB image (right) of a palm tree](image2)
The next step is the importation of data, the removal of geometric distortion and of the vignetting effect. The importation of data is conducted in RSG by reading the image data and the additional data and subsequently a descriptor file in XML-format. For all image-related information, the so-called .rsx-file is created. However, for information regarding interior and exterior orientation, a so-called parameter file (.PAR) is generated.

4-channel images from RGB-image and NIR-image were created through registration. The registration is realised through image correlation, where identical object points were identified. After resampling to the same pixel size, both RGB-image and NIR-image were stacked to a CIR-image. The imagery used later existed as CIR images with band 1 (NIR), band 2 (red), band 3 (green) and band 4 (blue). In Figure 18, an example of a CIR image in the tropical rainforest with a palm is shown.

All the above mentioned processing steps were conducted in one workflow, the so-called “RSG Suite”, implemented in RSG.

The next step revolved around the orthorectification of the images, also in the “RSG Suite”-Workflow. The coordinate system used is UTM 21 N (WGS 84).

The interior and exterior orientation of the camera is known from camera calibration, GPS and IMU data. There are no GCPs available in the entire study area, which is not a problem since direct geocoding is applied.
The parameters of exterior orientation are acquired using GPS and IMU. Through integration of GPS and IMU, the results concerning position have a high absolute accuracy and provide the three parameters of position. Furthermore, the inertial measurement unit, which is has to be fixed to the camera, provides angles which can be related to roll, pitch and yaw angles through boresight calibration \[\text{paragraph see Cramer, Stallmann and Haala, 2000; Kraus, 2004; Jacobsen, 2001}\].

When it comes to information regarding terrain, only the SRTM elevation model was available for the study area. After orthorectification, the orthoimage shows the features of a map, because the distortions caused by terrain are removed. The orthoimage is also resampled to a homogeneous pixel size \[\text{see Albertz, 2001; Gonzalez Patiño, 2011}\]. The orthorectified images are used in forestry to delineate areas, to describe stocks and they serve as a base for the determination of areas and are needed to update maps Heurich [2006]. To cover larger areas, in this case a Sampling Unit, a mosaic of orthoimages is needed. The orthoimage mosaics are produced by RSG Workflow.

### 3.1.5. Derivation of Digital Surface Models

One purpose of the thesis is the generation of Digital Surface Models (DSM) to depict the canopy surface at best for evaluation of canopy height, treetop detection and calculation of volume of DSM – DTM (Digital Terrain Model) - Difference, which is currently not available and has to be approximated. The only accessible information on elevation is the SRTM elevation model, which does not depict true ground elevation. SRTM elevation data is acquired using Radar C-Band and X-Band [NASA, JPL, 2005]. The NASA, JPL [2005] also points out that the 5.6 cm wavelength used does not penetrate vegetation very well. Thus, no ground elevation is depicted in areas of tropical rainforest with dense vegetation. The SRTM data are a rough approximation. For the study area, the SRTM elevation model with a resolution of 90 m is available. The SRTM is nevertheless needed for orthorectification of the aerial images.

The steps of DSM Generation are conducted in RSG and IMPACT in the “RSG Suite”-Workflow. The function of the workflow is outlined in the following paragraphs. The information is based on Joanneum Research - Digital, Sommer [2012] and Kraus [2004]. Firstly, tie points in the overlapping areas of the images are searched for automatically and through point matching transferred on the corresponding areas of other images.
within the same flight line. Linking all the images used of a chosen area, a tie point adjustment can be conducted. With that adjustment, the relative accuracy of the images of one block can be optimized since there are no GCPs for improvement of the absolute accuracy available. The relative accuracy for the used image blocks was determined with maximum 1 Pixel, i.e. 20 cm, deviation. The absolute accuracy is not specified. Next, the image matching was conducted which requires so-called epipolar registered input images. To register two images epipolar, they are rotated and shifted, so that there is just a disparity in one direction left [see KRAUS, 2004; JOANNEUM RESEARCH]. This procedure restricts the search area for the matching process (used parameters see Figure 20). The method of Semi-Global-Matching is an algorithm, according to HIRSCHMÜLLER [2008]. This algorithm requires strictly epipolar input images because the search area is one-dimensional. Through image correlation, similar or - more preferably - the same pixels are detected in search and reference images (see Figure 19). Similarity is expressed in the cost function used. The pixel with the lowest cost that is detected is the most similar pixel. The offset of search pixel to reference pixel is subsequently used to calculate the disparity maps [SOMMER, 2012].

**Figure 19: Principle of matching using image correlation** (Source: SOMMER, 2012, p. 64 according to RSG)

For DSM Generation a sequential matching approach was used only, because the baselines of the multi baseline approach were too large with a sequential overlap of about 75 %. However, the multi baseline approach had worse results as the traditional sequential approach in implemented benchmarks.

The so-called disparity maps are the results of all SGM matching processes and are computed using cost functions. After that, east, north and height values for each pixel were calculated through spatial point intersection based on least square method. Finally, the single DSMs were merged [RAGGAM, 2006; SOMMER, 2012].
According to GONZALES PATIÑO [2011, p.35], problems during derivation of DSMs and image matching can result from regions with little texture, diverse discontinuities of objects, reoccurring structures, ambiguous structures of objects, occultation, shading, objects in motion, sheer materials and radiometric artefacts such as reflections. The most important factors causing problems in forest areas can be overlap, occultation and shading of the canopy. The forest soil is usually not visible.

It was feasible to generate a DSM from aerial stereoscopic imagery, but it is sophisticated to derive precise ground information, i.e. DTM, to calculate a VHM (Vegetation Height Model). Precise DTM generation requires ground information, which is difficult to provide based on optical data in areas with dense vegetation, because only gaps and clearings are visible in optical data. Thus, only a rough DTM was generated and interpolated using visible terrain information located in gaps and clearings. Generation of precise DTMs in study areas with dense vegetation requires LiDAR data, which were not available in this project. LiDAR is an active system that penetrates vegetation, even dense vegetation
according to Gautam [2010]. Integrating LiDAR data in this project could improve the accuracy of vegetation height measurements, thus the accuracy of volume of DSM – DTM - Difference.

Regarding positional accuracy of orthorectified aerial imagery the expected accuracy depends on the specifications and calibration of the sensors used. The GPS specification of GPS of the ADAM platform permits an accuracy assessment in the range below 1 m [Novatel, 2011]. The inertial measurement unit used was the iMAR IMU-FSAS with a specified angular random walk of 0.15 °/√h [Novatel, 2014]. According to Sommer [2012], who analysed the ADAM platform performance, a positional accuracy of ± 5 cm can be accomplished through post-processing of GPS/IMU data. The camera accuracy was tested at a test area in course of platform calibration. The result revealed that the 3D accuracy in XY is about 30 cm, in Z below 80 cm.

Figure 21: 3D image of SU 7358
The orthophotos were used to generate an orthoimage mosaic of the Sampling Units. This mosaic and the DSMs of all Sampling Units are presented here to provide an overview about the spatial patterns of the natural landscape. Also a stream and a road transecting the Sampling Units can be seen. Afterwards, only Sampling Unit 5956 is presented as an example.

Sampling Unit 5352 is located entirely in High Dryland forest, except for a small area with liana forest, identifiable in the upper left quarter with lower vegetation. There is also a stream of flowing water recognizable in both optical imagery and DSM.

Sampling Unit 5954 is located completely in High Dryland forest.
Sampling Unit 5956 is mostly located in High Dryland forest. The part at the very bottom is located in high xerophytic forest.

Only a little more than half of Sampling Unit 6358 is only located in High Dryland forest. The right part is located in marsh forest.
Sampling Unit 7358 is completely located in High Dryland forest. This study area is situated next to a road.

### 3.1.6. Treetop Detection

According to HIRSCHMUGL [2008, p. 28], treetop detection includes “determination of exact location of a tree”. Based on that, the number of trees and the tree height can be measured. The tree height would be a result of the difference of detected absolute tree height and DTM. Measuring the tree height based on single trees was not performed as part of the thesis. The only way of determine the exact number of trees in tropical rainforests is terrestrial forest inventory. In dense heterogeneous rainforests it is considered improbable to derive the quantity of trees from optical imagery or DSM. According to KORPELA [2004], simple forest structure with regular crown sizes, only one tree layer and non-overlapping branches that do not blend into each other would be a good condition for treetop detection. This method was considered anyways because the number of big trees detected can be related to biomass.

The treetop detector is based on a Local Maximum Approach, which is described in HIRSCHMUGL [2008, pp. 28] and WANG, GONG and BIGING [2004]. The treetop detection was conducted with IMPACT. In the IMPACT implementation, it is necessary to indicate an average crown size. As a result, the treetops are detected as local maximums in the DSM with predefined average crown size.

It is very challenging to detect all trees of the closed canopy of a tropical rainforest. The local maximum approach used is dependent on the input parameter of average crown size.
size, as can be seen in Figure 27. The main problem is that the crown sizes of tropical rainforest are extremely varied. If the average crown size parameter is set too small, many treetops are detected on one large crown. This happens because deciduous tree crowns are different compared to coniferous tree crowns, which are coned, wide and expansive crowns with spreading branches. If the average tree size parameter is set higher, smaller trees are not detected anymore. Another problem is the layer structure of the tropical rainforest. Trees located in lower layers are not detected very well, because of shading and overlapping. Depending on the forest type, the number of trees in very homogenous areas of closed canopy is also underestimated, because if the canopy appears plain, no treetop can be detected.

Average crown size 10 m  
Average crown size 7 m  
Average crown size 5 m  
Average crown size 3 m  

Figure 27: Sampling Unit 5956: Treetop Detection with different crown size parameters

3.1.7. SEGMENTATION – TREE CROWN DELINEATION

According to HIRSCHMUGL [2008], segmentation always aims in generating regions instead of point positions. The application of tree crown delineation or segmentation resulted in
features such as shape, size and number of tree crowns. The approaches tested for tree crown segmentation were based on a watershed segmentation algorithm, a region growing algorithm based on height and on spectral information. These approaches were tested in the course of this thesis.

The first 3D-approach was the application of the watershed algorithm. Application of this algorithm may be envisioned as incremental flooding of a topographic relief. Thus, so-called watersheds are detected and depicted as regions. Information regarding the function of the algorithm comes from Hirschmugl [2008]. First, the derived DSM was filtered using median filter with different kernel sizes varying from 5 to 50 pixels. Before starting the algorithm, the DSM has to be inverted, so that the tree crowns are seen as basins. Results are depicted in Figure 30.

Another 3D-approach is the region growing algorithm. So-called seed pixels are required as a starting condition. The detected treetops were used as seed pixels, described in Chapter 3.1.6. Starting from all treetops, the region is enlarged until two adjacent regions contact each other. This approach is heavily dependent on the accuracy of the detected tree crown. Through analysis of the application it was revealed that the size of detected tree crowns is dependent on the seed pixels. The seed pixels, on the other hand are dependent on the average tree crown factor used. The treetops extracted are not correct because on giant crowns, more than one treetop is detected. This information displays the same information as the treetop detection, thus it is redundant.

![Figure 28: Sampling Unit 5956: Region growing based on treetops](image_url)
The last approach in 2D is a region growing algorithm based on optical images, thus using spectral information [see HIRSCHMUGL, 2008, Chapter 7.2.2]. This algorithm needs a seed pixel to start the region growing process. Also here, the treetops detected, described in Chapter 3.1.6 were used as seed pixels. The neighbouring pixels are included or excluded through thresholds. The candidate pixels are checked for predefined criteria and hence included or excluded from the region. This method was tested with very little success. The spectrally extremely heterogeneous canopy of the tropical rainforest results in an overestimation of treetops per tree in the course of treetop detection.

![Sampling Unit 5956: Segmentation based on spectral information](image)

*Figure 29: Sampling Unit 5956: Segmentation based on spectral information*

The segmentation results have shown that none of the segmentation methods could be used in further analysis because no approach provided representative results. It is extremely challenging to detect single crowns in tropical deciduous forests characterized by huge heterogeneous crowns. Using the watershed algorithm, the result of segmentation depends on the degree of filtering, i.e. smoothing. Different filtering approaches were tested resulting in unsatisfying outcomes (see Figure 30). Either under- or overestimation was the consequence. Overestimation occurred when the kernel size for filtering was set too small, for example 10x10. When small trees were located and outlined, large tree crowns were detected as four or five trees. Underestimation occurred when the kernel size for filtering was set too large, for example 50x50. When large tree crowns were detected correctly, smaller crowns were aggregated to one segment. Results show that the canopy is too heterogeneous to derive complete tree crowns. Only spectrally homogeneous parts of crowns were segmented and many spectrally different
small areas were segmented as well. This approach was rejected due to unsatisfying results. None of the segmentation results could be used in further analysis.

Figure 30: Sampling Unit 5956: Trial of Watershed-Segmentation at different levels (Subsets – same area, same spatial extent)
3.2. Derivation of Features

Data base for the derivation of features to be correlated with terrestrial biomass are the aforementioned NIR-orthoimages, the DSM, the results of treetop detection and the segmentation. These are used to derive the following features.

3.2.1. Vegetation Index

Vegetation indices have a long tradition of being used in remote sensing. The first indices developed were used more than 30 years ago ([Asner, Hicke and Lobell, 2003]). Vegetation indices are based on radiation and are evaluated based on pixels.

In former studies, spectral indices were related to biomass. In most cases, ratios concerning red or infrared wavelengths, such as NDVI, are used. The NDVI accumulated during the growing season reflects the biomass potential. This may be useful for study areas with a distinct growing season but it is less important in study areas such as tropical rainforests ([Dong et al., 2003]). Furthermore, vegetation indices were mostly calculated when coarse or medium resolution data was available. According to Dong et al. [2003] and Freitas, Mello and Cruz [2005], the NDVI in humid tropical forests or old growth forests tends to saturate. Freitas, Mello and Cruz [2005, p.359] point out that including NDVI in biomass estimation can lead to bad outcomes in some cases and to good results in others.

Besides the generally known Normalized Difference Vegetation Index (NDVI), plenty other vegetation indices were developed over time. Asner, Hicke and Lobell [2003] list them, including Simple Ratio (SR), Perpendicular Vegetation Index (PVI), Global Environment Monitoring Index (GEMI), Soil-Adjusted Vegetation Index (SAVI), Atmospherically resistant Vegetation Index (ARVI), Enhanced Vegetation Index (EVI) and Leaf Area Index (LAI) to name a few. In the course of this thesis the most widely used NDVI was applied.

\[
NDVI = \frac{IR - RED}{IR + RED}
\]

Formula 3: Normalized Difference Vegetation Index (NDVI) (Source: Foody, 2001, p. 380)
The NDVI was computed for the area of the Sampling Units. The author assumed that using NDVI for forest biomass estimation in the tropics would represent a random factor, especially using high resolution imagery. The assumption is based on the knowledge that there is no distinct growing season and that there is no strong connecting link between leaf vitality of an old-growth forest and underlying biomass distribution, for example. In the absence of a growing season there is no period of time in which significantly more reflection of infra-red wavelengths is recorded. This method was tested and mean and standard deviation were computed for both PSP and MAP Units. Whether it is reasonable to use it in a regression analysis will be discussed in Chapter 5.

Figure 31: Sampling Unit 5956: Left: NDVI; Right: CIR-Orthophoto

3.2.2. Texture

Another feature considered important is image texture. According to Albertz [2001], texture is the patterning of an image area or the physical configuration of all image pixels. Single pixels do not reveal information about image texture. It also depends on the image scale, i.e. resolution, of input data.

Lu [2006] points out that using image texture alone is not sufficient for biomass modelling. Furthermore, image texture is even more important than spectral information in study areas with complex forest characteristics such as moist tropical forest. Lu [2006] states that the challenge is to find the texture features that correlate with biomass, because many features do not.
In the course of this thesis, two algorithms implemented in the Joanneum Research software IMPACT were tested - the Absolute Value Difference algorithm with kernel size 5x5 and the Third Moment algorithm also with kernel size 5x5. Both, third moment and absolute value difference algorithm are based on a grey level co-occurrence matrix, which is designed to detect differences in intensity of grey levels, hence image texture. According to GONZALES PATIÑO [2011], are grey level co-occurrence matrices a function to calculate second-order texture parameters. That means that spatial distribution and distance are included in analysis. Texture is also dependent on image scale, i.e. resolution [GONZALES PATIÑO, 2011, p. 102]. Because of the high resolution of the images and the heterogeneous canopy, the texture value varies greatly in size. Correlation shows that there is no relationship to biomass (see Chapter 4.2).

![Texture in Sampling Unit 5956: Left: Third Moment; Right: Absolute Value Difference (both for NIR channel)](image)

**3.2.3. FOREST CANOPY DENSITY**

Forest canopy density, also known as canopy closure or crown coverage, is another important parameter characterizing forest stands. Forest canopy density is defined as the ratio of the visible ground and vegetation [JOSHI et al., 2006; AZIZI, NAJAFI and SOHRABI, 2008]. In study areas with vegetation in several layers, this ratio tends to saturate. To derive forest canopy density values, the proportion of trees and tree gaps is used. For estimation of forest gaps, terrain information is necessary to ensure that variation of
vegetation height, depicted from the DSM only, does not depend on terrain and elevation. The SRTM was used to reduce the terrain influence because there was no better DTM available. Thus, the SRTM was used to pseudo-normalize the DSM generated.

The lowest areas of this pseudo-nDSM are assumed to be gaps in the canopy, at least in the top layer of canopy (comparable to Figure 33). A similar approach termed “SRTM Difference approach” was tested by Deutsch et al. [2013] in a tropical rainforest using a SAR-derived DSM and SRTM. Results of Deutsch et al. [2013] can be seen in Figure 34.
Tree canopy gap masks using 3 different empirically thresholds were generated (see Figure 35). The ratio of gap pixels to tree pixels in a defined area results in forest canopy density. According to visual inspection, the gap detection has shown satisfactory results.
Forest canopy density is the only feature where a ground truth via aerial image interpretation is available. The ground truth data was collected by Dr. Michael Kleine. He tried to assign forest canopy density in the study area of SU 5956 to 5 classes via visual interpretation. Classes were divided in 0 % - 20 %, 20 % - 40 %, 40 % - 60 %, 60 % - 80 % and 80 - 100 % canopy cover. Furthermore, forest canopy density was compared to this
ground truth. Figure 36 shows that the results of computed forest canopy density overestimates the degree of canopy closure, which was visually assigned. A possible explanation for overestimation could be incorrect visual interpretation of the aerial imagery. When the underlying layer of the canopy is located in areas with shadows, visual image interpretation could determine this area as a forest gap. Interpretation of a combination of DSM and aerial image could reveal more information about forest gaps.

![Figure 36: Sampling Unit 5956: Comparison of forest canopy density (Visual assessment and digitally processed data)](image)

The parameter of forest canopy density tends to saturate. A possible reason is that, when the forest canopy density remains at 100% in dense forests, the underlying biomass varies and thus, a dense canopy reveals no information about the amount of underlying biomass. This is the problem in tropical rainforests, because the estimation of the number of underlying layers of vegetation is the critical point in biomass estimation. Hence, forest canopy density has to be considered critically.
3.2.4. VOLUME OF DSM – DTM – DIFFERENCE

Due to the absence of terrain information, different tests to generate a rough DTM, from stereo images in combination with SRTM terrain model for volume calculation were conducted. Two approaches were tested: In the first approach, the available SRTM was included and a negative Z-shift was added. As explained in Chapter 3.1.5, the SRTM does not depict true terrain information. The SRTM was shifted empirically to the lowest elevation of DSM, derived from the aerial photographs. The volume of the underlying pixel is calculated (see Figure 38). The second approach to approximate a DTM is based on the prior extracted gap mask. The height information in the gaps was minimum filtered and the pixels lying the lowest were used to interpolate a DTM. Because the real appearance of ground is not known, different degrees of polynomials were used for interpolation. Therefore, DTM ranging from linear interpolation to interpolation using sixth degree polynomials were used and the volume was calculated according to the method used in the first approach. By using these different degrees of polynomials, variation in volume amount occurs.
First degree of interpolation depicts a simple terrain structure, a plain or a ramp. Raising the degree of interpolation depicts a more complex terrain structure. To illustrate the aforementioned, results of volume calculation for a Sampling Unit are shown in Figure 39.
3.2.5. NUMBER OF TREES

The number of trees is a feature derived from treetop detection. The treetops detected represent the number of trees. The algorithm requires an input parameter called average crown size, as mentioned in Chapter 3.1.6. The algorithm, applied for the treetop
detection, is using 3 m, 5 m, 7 m and 10 m as average crown size. As a consequence, the analysis results in 4 different numbers of treetops per unit of area. The problem, also mentioned in Chapter 3.1.6, is that when the average crown size parameter is set too small, the number of trees is overestimated, because on large tree crowns, more than one treetop is detected. This feature was calculated for the Sampling Units.

3.2.6. Statistical features based on height

To analyse height information, the areas covered by the field inventory were tested by using statistical features based on height for both MAP Units (10 x 10 m) and PSP (20 x 100 m). A pseudo-nDSM was generated by calculating the difference of DSM and SRTM in order to reduce the influence of terrain (see Figure 40). Volume of DSM - DTM is one of the features based on height, but is described separately in Chapter 3.2.4. The mean height of a defined area was analysed via DSM. Mean height, not to be confused with mean stand height, represents the mean height of all pixels based on the variation of height the difference of canopy and terrain model. Additionally, the standard deviation, which depicts the variation around the mean value, was calculated. According to Sommer [2012], standard deviation represents a measurement for roughness. The more gaps or emergent trees exist, the more variation in height data can be analysed, and the higher is the value of standard deviation of height. In other words, the rougher the canopy, the more variation in height can be analysed. The analysis was conducted using the original DSM and the pseudo-normalized DSM (DSM – SRTM).

The result for standard deviation of height for DSM and pseudo-nDSM ranged from about 3.5 to 13.5 m.

Figure 40: SU 5956: Left: DSM; Right: Pseudo-nDSM (DSM – SRTM)
4. STATISTICAL ANALYSIS

All 2D- and 3D-features generated were evaluated statistically by correlation analysis. Afterwards, the features, that correlated best with biomass, were used for regression analysis. The evaluations were based on MAP Units (10 x 10 m) and on PSP (20 x 100 m). First, the results of biomass calculation are presented, followed by the results of correlation analysis between biomass and all the derived features. The last chapter is focusing on implementation and results of regression analysis.

4.1. RESULTS OF BIOMASS CALCULATION

The results of terrestrial measurement and biomass calculation as described in Chapter 3.1.2 are presented here.

Table 7: Results of biomass and volume calculation

<table>
<thead>
<tr>
<th></th>
<th>AGB in kg</th>
<th>AGB in t</th>
<th>Number of trees</th>
<th>Number of trees /ha</th>
<th>Basal area/ha</th>
<th>Number of trees/SU</th>
<th>Commercial Volume in m³</th>
<th>Commercial Volume in m³/ha</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 PSP</td>
<td>333881.159</td>
<td>333.881</td>
<td>208.676</td>
<td>283</td>
<td>176.875</td>
<td>18.904</td>
<td>9949.219</td>
<td>306.440</td>
</tr>
<tr>
<td>SU 5352</td>
<td>402299.954</td>
<td>402.300</td>
<td>251.437</td>
<td>330</td>
<td>206.250</td>
<td>22.175</td>
<td>11601.563</td>
<td>393.839</td>
</tr>
<tr>
<td>8 PSP</td>
<td>342916.916</td>
<td>342.917</td>
<td>244.941</td>
<td>246</td>
<td>175.714</td>
<td>21.397</td>
<td>9883.929</td>
<td>326.590</td>
</tr>
<tr>
<td>SU 5954</td>
<td>256817.508</td>
<td>256.818</td>
<td>160.511</td>
<td>218</td>
<td>136.250</td>
<td>19.222</td>
<td>7664.063</td>
<td>258.515</td>
</tr>
<tr>
<td>7 PSP</td>
<td>408884.980</td>
<td>408.885</td>
<td>255.553</td>
<td>324</td>
<td>202.500</td>
<td>22.482</td>
<td>11390.625</td>
<td>476.142</td>
</tr>
<tr>
<td>SU 6358</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8 PSP</td>
<td>342916.916</td>
<td>342.917</td>
<td>244.941</td>
<td>246</td>
<td>175.714</td>
<td>21.397</td>
<td>9883.929</td>
<td>326.590</td>
</tr>
<tr>
<td>SU 7358</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7 shows a large variation of the calculated biomass for High Dryland forest. The question is whether the variation can be observed also in the derived features and consequently in the regression analysis. The amount of terrestrially measured biomass, i.e. AGB, for the 5 Sampling Plots is between 160 and 255 tons per hectare. This is roughly the amount of biomass that BROWN [1997] mentioned as a biomass value for Upland
forests in Suriname which is 255 tons per hectare. It has to be considered that the amount of biomass calculated does not include any trees with a DBH < 20 cm, as well as undergrowth.

4.2. Results of Correlation

A correlation analysis was conducted first to display relationships between features derived from aerial photos and biomass, i.e. biomass and commercial volume measured in the field plots. Terrestrial biomass measurements were available for 5 Sampling Units. 37 PSP were located in High Dryland forest (see Chapter 3.1.1). The correlation was applied to both the 740 MAP-Units (10 x 10 m) and the 37 PSP (20 x 100 m), which were associated with High Dryland forest. All features were correlated with AGB (above ground biomass). Results of correlation analysis for 37 PSP can be found in the Appendix.

The Pearson correlation coefficient was calculated to display the coherences between above ground biomass and single features such as forest canopy density. Because the correlation coefficient only displays linear coherences, the Spearman coefficient of correlation was calculated as well. The Spearman coefficient of correlation is often used because it requires ranked values. It is more stable to outliers and a linear coherence is not required according to ECKSTEIN [2013]. The comparison of Pearson correlation coefficients shows that there is a big difference between PSP and MAP data. Responsible is the so-called “edge effect”. The small-area MAP Units with a size of 10 x 10 m are responsible for this effect. Often, the tree trunk is not located within the MAP Unit, but the large tree crown is located within the MAP Unit after all and thus detected by methods of digital image processing. This effect decreases with increasing size of study area, i.e. PSP Units (20 x 100 m), but still exists in PSP Units.

Correlating all 37 PSP Units in terms of biomass with the features derived, the best positive coefficient of correlation (Pearson) is 0.316 using DSM standard deviation and 0.342 (Spearman) using volume 5 (interpolation 5th degree). The low correspondence might be due to the “edge effect” described above. The best negative coefficient of correlation (Pearson) amounts to -0.365 and -0.967 (Spearman) using number of trees based on 10 m average crown size.

If the 8 PSPs of one single Sampling Units are used for correlation, the Pearson coefficient of correlation amounts best to 0.85 (SU 5352) using biomass and volume 6 (interpolation 6th degree). The correlation, using the 37 PSPs of all 5 available Sampling Units (see
Chapter 3.1.1), amounts to more than -0.8 (forest canopy density), for instance. A reason of the improvement of the correlation coefficient could be the reduction of the “edge-effect” the bigger the research area becomes. However, it has to be mentioned that 5 Sampling Units are not statistically sufficient to make reliable statements. The results of correlation did not reveal a strong coherence between the derived features and biomass. Hence, this led to the assumption that the results of regression might not be very good as well. The “edge-effect”, the underestimation of forest gaps and the lack of precise terrain information are problems when it comes to derivation of features. When these problems can be solved, also the results of correlation and the results of regression will improve hopefully.

4.3. Results of Regression Analysis

Multiple Regression Analysis was used to link biomass or related parameters to the features derived from the aerial images. "Multiple Regression involves target-oriented relation of a feature with multiple other variables. The aim is to investigate the specific influence of each variable related to the first, independent variable or feature. However, in case of multiple correlation analysis the mutual coherence between a group of features and another group of features is analysed" (TRANSLATED FROM VOß, W., 2004, p. 511). In terms of Multiple Regression, “groups of features” have to be explained. A group of features means all parameter values of one feature.

Multiple Regression is commonly referred to as a linear statistical method to relate features to display mathematical relations. The results from Multiple Regression are the coefficients $R^2$ and adjusted $R^2$ as parameters for model quality, error values and a significance test. According to SCHÄFER [2009], the aim of Multiple Regression is to describe coherences in quantity, the way other regression functions also do.

The analysis was performed using Microsoft Excel Software – Regression Analysis. The confidence level was assumed with 95 %. The features used were chosen after correlation analysis and thus iteratively applied in Multiple Regression.

The output of the regression implemented is listed, described and interpreted here. The formula derived is only valid for the forest type "High Dryland forest" and study areas in size 20 x 100 m. In this case, 37 available PSPs were used. A larger number of PSPs, not only from the “High Dryland forest” forest type will be available soon. At the time of
finishing the work for this thesis, only 5 SUs, including 37 PSP located in High Dryland forest, were available and thus, used for analysis.

Variables:

[1] Volume of DSM - DTM (interpolation 5) – difference

[2] Forest canopy density 1

[3] DSM Standard deviation

[4] DSM – SRTM Mean

[5] Trees - detection 10 m

Formula 4: Result


Table 8: Regression Statistics

<table>
<thead>
<tr>
<th>Regression Statistics</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.656</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.430</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.338</td>
</tr>
<tr>
<td>Standard Error in kg</td>
<td>11033.784</td>
</tr>
<tr>
<td>Observations</td>
<td>37</td>
</tr>
<tr>
<td>Significance F</td>
<td>0.0027</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>t-Statistics</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.693</td>
</tr>
<tr>
<td>Volume of DSM - DTM (interpolation 5) – difference</td>
<td>2.592</td>
</tr>
<tr>
<td>Forest canopy density 1</td>
<td>-3.240</td>
</tr>
<tr>
<td>DSM Standard deviation</td>
<td>-2.078</td>
</tr>
<tr>
<td>DSM - SRTM Mean</td>
<td>1.968</td>
</tr>
<tr>
<td>Trees - 10 m</td>
<td>-1.789</td>
</tr>
</tbody>
</table>
The interpretation is based on *Fahrmeir, Kneib and Lang [2009]*. The Standard error in this case depicts the standard deviation about the regression and is computed from the predicted data with 11033.78 kg or 23.4 % (see Figure 42). The adjusted R² is one main result in terms of quality parameters. The adjusted R² corrects the influence of the number of variables on the coefficient of determination. Here, with a result of 0.338, the regression model does not predict the observations well. The standard error is at about 23 % and therefore relatively high. The significance F is about 0.0027 (see Table 8), which means that the model is statistically significant using a confidence level of 95 %. P-values for each variable can be found in the analysis output. These define the individual probability, that the variables are not significant. P-values (see Table 8) should also be below 0.05, i.e. below 5 %. The t-statistics are values that state the significance at confidence level > 95 %. If the values are greater or less than 2 or -2 respectively, the values are significant.

Regarding the computed results, the variables DSM – SRTM Mean and Trees – 10 m are at the limit of significance. According to t-statistics and p-values of the two aforementioned variables, it can be stated that the significance is not perfect. The two variables were not excluded from the regression analysis because a shifting of the model would occur through change. This means, that other apparently good variables, result in a poor outcome and bad significance values through elimination of too many variable. Tests were performed by removing the variable(s) mentioned with the result that the significance of the other variables dropped and as a consequence only one or two would remain with poor model quality.
In Figure 41, biomass calculated and biomass measured for the 37 PSPs were compared. The abscissa in Figure 41 shows the amount of terrestrially measured biomass in comparison to ordinate, which shows the computed biomass values using derived features and regression analysis. Evidently, the calculated amount of biomass is overestimated in lower range of biomass, whereas the model tends to underestimate the amount of biomass in range of high biomass.

The amount of 5 Sampling Units or 37 Principal Sampling Plots with forest type "High Dryland forest" is statistically sufficient to generate a significant model, but the result is very unstable with a large range of variation, i.e. standard error, of about 11 tons. On the other hand, there is a large natural range of variation the tropical rainforests, as it can be seen in the crown sizes, which vary extremely. More data, such as more inventoried Sampling Units with High Dryland forest, could stabilise the regression model.
The analysis shows that these results are too poor for further biomass calculation only based on aerial images. However, a combination of terrestrial measurements and analysis of aerial imagery can significantly reduce the number of terrestrial Sampling Units, even with low accuracy of the resulting model. Corresponding simulations are performed by the employees of BfW. The result shows that integration of 2D and 3D data derived from aerial stereoscopic imagery has a large capability to estimate biomass in combination with terrestrial measurements and to apply it to larger areas. This can lead to more precise calculations of tropical biomass as so far has been implemented.

As validation method the so-called leave-one-out cross-validation (LOO-CV) was chosen. The LOO-CV was conducted as following: In every step one PSP was left out and a biomass formula such as the result above was calculated using N-1 datasets. Using this new derived formula, the biomass for the left out plot was calculated. This procedure was conducted until every plot was left out once. The results are shown in Table 9. The mean variance of the cross-validation results is about the standard error of the regression.
model and amounts to 10.25 tons, which is comparable with the residues shown in Figure 42.

Table 9: Leave-one-out Cross-validation results (rounded)

<table>
<thead>
<tr>
<th>SU</th>
<th>PSP</th>
<th>Measured Biomass in t</th>
<th>Calculated Biomass in t</th>
<th>Difference in t</th>
</tr>
</thead>
<tbody>
<tr>
<td>SU 5352 11</td>
<td>63.182</td>
<td>70.256</td>
<td>7.074</td>
<td></td>
</tr>
<tr>
<td>SU 5352 12</td>
<td>45.332</td>
<td>51.423</td>
<td>6.091</td>
<td></td>
</tr>
<tr>
<td>SU 5352 21</td>
<td>41.195</td>
<td>53.994</td>
<td>12.799</td>
<td></td>
</tr>
<tr>
<td>SU 5352 22</td>
<td>42.602</td>
<td>44.447</td>
<td>1.845</td>
<td></td>
</tr>
<tr>
<td>SU 5352 31</td>
<td>40.572</td>
<td>38.658</td>
<td>-1.913</td>
<td></td>
</tr>
<tr>
<td>SU 5352 32</td>
<td>33.901</td>
<td>45.410</td>
<td>11.509</td>
<td></td>
</tr>
<tr>
<td>SU 5352 41</td>
<td>39.000</td>
<td>47.989</td>
<td>8.989</td>
<td></td>
</tr>
<tr>
<td>SU 5352 42</td>
<td>28.097</td>
<td>41.529</td>
<td>13.432</td>
<td></td>
</tr>
<tr>
<td>SU 5954 11</td>
<td>27.481</td>
<td>42.233</td>
<td>14.752</td>
<td></td>
</tr>
<tr>
<td>SU 5954 12</td>
<td>40.607</td>
<td>57.638</td>
<td>17.031</td>
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</tr>
<tr>
<td>SU 5954 21</td>
<td>36.144</td>
<td>54.432</td>
<td>18.288</td>
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</tr>
<tr>
<td>SU 5954 22</td>
<td>38.228</td>
<td>44.796</td>
<td>6.568</td>
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<td>SU 5954 31</td>
<td>45.048</td>
<td>40.418</td>
<td>-4.630</td>
<td></td>
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<td>SU 5954 32</td>
<td>77.541</td>
<td>37.640</td>
<td>-39.901</td>
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<td>SU 5954 41</td>
<td>71.490</td>
<td>61.262</td>
<td>-10.228</td>
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<tr>
<td>SU 5954 42</td>
<td>65.762</td>
<td>56.996</td>
<td>-8.766</td>
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<td>SU 5956 11</td>
<td>47.612</td>
<td>39.204</td>
<td>-8.408</td>
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<td>59.468</td>
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<td>59.405</td>
<td>47.784</td>
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<td></td>
</tr>
<tr>
<td>SU 5956 41</td>
<td>47.617</td>
<td>48.597</td>
<td>0.980</td>
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<td>48.840</td>
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<td>48.349</td>
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<td></td>
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\[ \sum \]

\[ \begin{array}{ll}
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\[ \text{Mean} \quad 10.255 \]
5. DISCUSSION AND OUTLOOK

In conclusion, derivation of features derived from aerial images in dense tropical rainforests describing biomass have proven to be quite problematic and sophisticated. Both the size of crowns and the height of the canopy vary greatly and thus influence 3D processing. It is a challenge to inventory parts of the primary forest and to acquire aerial photographs. Main challenges in the field of terrestrial forest inventory are inaccessibility, positioning and orientation. With respect to image acquisition, the main challenges were the degree of cloudiness, the weather conditions and the conditions of illumination.

Terrestrial measurements of five Sampling Units were available in size of 750 x 750 m. The Sampling Units contain 37 PSPs in size of 20 x 100 m, which are situated in High Dryland forest and used for analysis. In terms of biomass calculation from terrestrial measurements, a formula, valid for moist tropical forests, was applied. Only trees with a DBH greater than 20 cm were included in the analysis due to visibility on aerial imagery and those trees containing the most biomass. The results of terrestrial measurements for AGB ranged from about 160 t/ha to about 255 t/ha. That is approximately the amount of biomass that former studies on large areas of tropical rainforest have resulted in.

The pre-processing of aerial images included demosaicing, devignetting and importation of the images. To generate aerial images including a NIR channel, a CIR stack was conducted. For orthorectification, the post-processed GPS and IMU data were used. Through direct geocoding, the aerial images were orthorectified using the SRTM of the study area as the only available elevation model. It should be noted that the SRTM used is not an accurate terrain model, especially because the radar signal is scattered by the dense vegetation and does not penetrate through to the ground. Also, the geometric resolution of the SRTM is at 90 m and therefore very coarse. Nevertheless the SRTM was used because of a lack of another DTM.

In terms of photogrammetric processing, direct geocoding (see Chapter 3.1.4) was conducted, but no GCPs were available to improve the accuracy. Hence, during a tie point adjustment, the relative accuracy of the images was enhanced and resulted in about 20 cm variation. Following through image correlation, image matching and spatial point intersection, a DSM was derived. There is no way to verify the positional accuracy of the DSM, besides sensor specifications, camera calibration and post-processing of GPS/IMU data. Furthermore, forest inventory staff visually estimated the accuracy during field work using orthoimages. The accuracy was tested in Graz, which resulted in about 30 cm in XY and 80 cm in Z. The same accuracy can be transferred to the project in Suriname.
The DSM derived was analysed and statistical features, to be correlated with, were derived. For that purpose, the original DSM and a “pseudo-normalized” DSM were used. For normalization the only available elevation data, the SRTM, was used to try to minimize the influence of the terrain. Again, it has to be mentioned that the SRTM is not an accurate terrain model and that application of LiDAR derived DTM is recommended, if available. Mean and standard deviation of the height values of both DSMs mentioned were calculated. Mean height, not to confuse with mean stand height, depicts the average height value of an analysed unit. The standard deviation of height represents a feature for roughness of canopy and a measure for the level of detail of DSMs.

Treetops were detected as data base to derive the number of trees, using a local maximum approach with a required input parameter of average crown size. It is almost impossible to detect the correct number of treetops in tropical rainforests, only terrestrial forest inventory can. The reason for using this feature was the assumption that few detected treetops would display bigger trees and hence more available biomass. The perfect conditions for treetop detection would be a simple forest structure with equal crown, only one tree layer with branches that are not overlapping and not blending into each other. Those conditions do not apply to tropical rainforests. Therefore, treetop detection leads to under- or overestimation of treetops depending on the setting of the input parameter “average crown size”.

Tree crown segmentation to derive shape, size and number of tree crowns did not provide satisfying results. Three different approaches were tested, but none of them led to accurate tree segments. Problems coming along with segmentation are the spectral heterogeneity of tree crowns, the thick vegetation of tropical rainforests and the dense canopy. Applying the watershed algorithm, the result of segmentation depended on the degree of filtering. Without filtering, the heterogeneous crowns of deciduous trees were segmented in countless small areas. The region growing algorithm was based on detected treetops and resulted in redundant information. The segmentation algorithm based on spectral data brought out countless small segments, because even branches of one tree are not homogenous in terms of spectral information.

The vegetation index was another feature evaluated because of its common use and long tradition. The first critical point with using NDVI is that the tropical rainforest has no distinct growing season where reflection in the spectral range of near infrared is more dominant than usual. Furthermore, NDVI tends to saturate in old-growth forests and tropical forests, according to sources. It was calculated because, despite all the problems, it led to good results in some studies, in others the outcome was not as good. After determination of the correlation coefficient, the NDVI was rejected, too.
Image texture was another feature calculated but not used, because correlation analysis showed no coherence to biomass. It only depends on the spatial patterns and different intensities of the spectral information, i.e. on 2D-information. Using images with 20 cm resolution resulted in a very fine-grain texture image, which was generated additionally based on the heterogeneous canopy of the tropical rainforest. Correlation revealed no relationship to biomass and thus, the feature was rejected.

Forest canopy density is the tree to tree gaps ratio. To derive the gaps in the DSM, the SRTM was used for normalization. By applying empirical thresholds, the gaps were detected and the forest canopy density was calculated. This feature tends to saturate in comparison with biomass because when the canopy density reaches 100 %, the biomass amount can increase unrestricted. Forest canopy density of one Sampling Unit was validated through visual interpretation of aerial images. It shows that derivation of forest canopy density leads to a slight overestimation of digitally derived forest canopy density as compared with visual assessments of Dr. Michael Kleine, a partner of ANRICA. A possible explanation is that the detection of small gaps in a photogrammetrically derived DSM always underestimates the size of gaps because of shadowing in aerial images and as a result problems within the matching process occur. On the other hand, a reason for overestimation of forest canopy density can be incorrect visual interpretation of the images.

Another approach was to derive volume. In this case, volume was defined by the DSM-DTM difference, not to be confused with timber volume. Since no precise DTM exists, a rough DTM was generated using ground information in previously detected forest gaps. The volume was calculated as the difference of DSM-DTM. The analysis of this feature revealed good results. Better information could be gained, if a LiDAR DTM was available.

The numbers of trees was a feature directly deduced from treetop detection. Four different numbers of trees were calculated using an average crown size of 3 m, 5 m, 7 m and 10 m as input parameters for the treetop detection algorithm. As mentioned previously, the number of trees is most likely overestimated, because more treetops are detected on huge tree crowns, but can also be underestimated.

All features were calculated for both MAP units and PSPs. This led to the so-called “edge-effect” problem. The MAP units (10 x 10 m) are probably a good choice for terrestrial forest inventory to keep track of the investigated area. However, the extent of MAP units is much too small for analysis based on remote sensing, because the diameter of a tree crown is frequently bigger than 10 m. Thus, the “edge-effect” occurs when the entire tree crown or at least a large visible part is located and detected by image analysis within the MAP unit, but the inventoried tree trunk is not located within the MAP unit and
consequently no biomass is mapped in that area and vice versa. Using PSP (20 x 100 m), the “edge-effect” decreases but is not neglectable. Analysis based on the five Sampling Units reduces the effect even more, according to the coefficient of correlation. Apart from that, five Sampling Units are not statistically sufficient to make reliable statements. Correlation analysis revealed the best features. The “edge-effect” was also apparent using MAP units, because the correlation coefficient according to Pearson did not exceed 0.25, the Spearman coefficient of correlation did not exceed 0.19, thus further analysis was focused on PSPs. For regression analysis, a volume feature, the forest canopy density, the DSM standard deviation of height, the DSM – SRTM mean height and a treetop feature based on 10 m average crown size were used. The DSM – SRTM mean height had poor results in Pearson correlation analysis, but better results in Spearman correlation analysis. The result of regression analysis shows that the quality of the model is poor and does not predict the observations well. In terms of significance, the results are satisfying. The residues for the regression model did not reveal a systematic error. The standard error amounted to approximately 11 tons.

In summary, this model results are too poor to use it for further biomass estimation. However, there is a huge capability of using high resolution aerial imagery for biomass estimation in the tropics. More data could stabilize the regression model or lead to better results in regression analyses. A more stable model could be applied to larger areas to estimate biomass from aerial imagery. A reason for the unstable regression model is the small number of Sampling Units and the small number of PSPs used. More than 37 PSPs are necessary to derive a stable model because of the high variability of the biomass. When it comes to a new inventory, the size of the Sampling Units, i.e. PSP and MAP units, should be chosen larger and adapted to the prevailing tree crown size in order to minimize the “edge effect”. Moreover, the author recommends including LiDAR data in further studies. This would enhance the quality of the features derived, particularly volume of DSM-DTM Difference, forest canopy density and number of trees. Also integration of data acquired by diverse sensors and platforms will be a research need in the future.
**BIBLIOGRAPHY**


KAUFMANN, V. [2010]: Photogrammetrie. LV 509.503, VO 2010, Institute of Remote Sensing and Photogrammetry, Graz University of Technology


Sommer, C. [2012]: Ableitung eines Aufnahmekonzepts für die Erstellung von digitalen Oberflächenmodellen aus hoch redundanten Luftbildern im Forstbereich. Master thesis, Graz University of Technology, p. 103


Vor, W. [2004]: Taschenbuch der Statistik. 2. Auflage, Fachbuchverlag Leipzig im Carl Hanser Verlag, München, Wien, p. 756


Online-Sources:


Google Inc. [2012]: Google Earth [Version: 6.2.2.6613] [Software], Available from: http://earth.google.com


UNEP [2010]: UN-REDD Programme. [WWW]. Available from: http://www.unep.org/forests/Portals/142/docs/UN-REDD%20FAQs%20%5B11.10%5D.pdf, last access: June 2014
Table 10: Coefficient of correlation based on 37 PSPs

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Figure 43: Sampling Unit 5956: Tests for Volume calculation