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Evaluation of RapidEye Data in Determining Forest Structure and Biomass
Case study in Central Kalimantan, Indonesia

by

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Abstract

Indonesia has committed to reducing emissions from forest related issues by 26% from business as usual and by 41% with international support by 2020. Therefore, it is necessary to quantify potential biomass of the forest. Forest inventory has been carried out to provide forestry related information. However, its large forest coverage and different forest types become a distinct obstacle. RapidEye satellite imaging provides advantages in vegetation detection with a high spatial and temporal resolution. This study emphasizes the linking of remotely sensed data with field inventory. The objective of the study is mainly to evaluate the suitability of RapidEye satellite imaging in determining forest structure and biomass. Field data was obtained through field inventory in the natural laboratory of peat swamp forest (LAHG) Sebangau, Central Kalimantan. All trees having DBH of ≥ 5 cm in a 120 x 120 m plot were tallied. The plot was a single full census plot as part of a research project ***Development of an integrated forest carbon monitoring system with field sampling and remote sensing***. A subset of one ha within the plot was used for the data analysis. Individual trees above ground biomass (AGB) was estimated using three different biomass models of Brown (1997) and Chave (2005). This study shows a significant impact of wood density on overestimation of AGB with the range of 9 - 44 %. Incorporating height as a predictive variable may reduce the overestimation impact. In general, the variability of AGB estimates increase as DBH increase. Three single tiles of multi temporal Level 3A RapidEye images were evaluated. The acquisition date of each image is close to the field campaign. Image pre-processing was done to convert image digital number to its at-sensor reflectance. However, no geometric nor atmospheric correction was performed. Vegetation indices such as NDVI, GNDVI, SAVI, and NDRE were derived from corresponding image spectral bands. Different sizes of simulated rectangular grids were established with the RapidEye pixel size (5 m) as the smallest unit and 50 m as the largest grid size. Analysis of correlation revealed a consistently high positive correlation between basal area and AGB. Structural diversity shows positive correlation with AGB at 20 m grid size. Similarly, at the same grid size, vegetation indices show positive correlation with basal area, although they are low. Meanwhile, no original RapidEye bands nor vegetation indices show strong correlation with AGB. However, analysis of predictor importance shows that NDVI and NDRE have the potential to be used to determine forest structure and estimate forest AGB. Meanwhile, spatial probability analysis revealed a promising integration of field inventory and remote sensing. A clump of relatively higher correlation between image spectral values and field variables occur within a close range from the original plot position.

Keywords: Biomass, Forest inventory, Forest structure, Peat swamp forest, RapidEye

Zusammenfassung

Indonesien hat sich dazu verpflichtet die Emissionen bedingt durch forstliche Aktivitäten in der bisher gängigen Praxis um 26 % zu senken und bis Ende 2020 mit internationaler Hilfe um 41 %. Deshalb ist es notwendig die potentielle Biomasse des Waldes zu bestimmen. Es wurden Waldinventuren durchgeführt, um Informationen über das Forstwesen bereitzustellen. Jedoch wird dies bei zunehmender Waldgröße und in unterschiedlichen Waldarten ein ausgeprägtes Hindernis. Die RapidEye Satellitenbilder weisen Vorteile in Vegetationserkennung mit hoher räumlicher und zeitlicher Auflösung auf. Die vorgelegte Arbeit beschäftigt sich mit der Verknüpfung der Fernerkundungsdaten und denen der Waldinventur. Das Ziel dieser Untersuchung ist hauptsächlich die Eignung der RapidEye Satellitenbilder in Bezug auf die Bestimmung der Waldstruktur und Biomasse zu bewerten. Messdaten wurden erhoben durch die Waldinventur der natürlichen Untersuchungsstelle des Torfmoorwaldes (LAHG) in Sebangau auf Zentralkalimantan. Alle Bäume die einen BHD von ≥ 5 cm auf einer Fläche von 120 x 120 m aufwiesen wurden nachgezählt. Die Fläche wurde bereits komplett vermessen als Teil des Forschungsprojekts „Development of an integrated forest carbon monitoring system with field sampling and remote sensing“. Ein ausgewählter Hektar innerhalb der Fläche dient als Grundlage der Datenanalyse. Die oberirdische Biomasse einzelner Baum wurde mit Hilfe von drei unterschiedlichen Biomassemodellen von Brown und Chave geschätzt. Diese Studie zeigt einen signifikanten Einfluss der Holzdichte auf die Überschätzung der oberirdischen Biomasse mit Bereich von 9 – 44 %. Das Einbeziehen der Höhe als voraussagende Regelgröße kann den Einfluss der Überschätzung verringern. Im Allgemeinen nehmen die Schwankungen der Schätzung der oberirdischen Biomasse mit zunehmenden BHD zu. Drei einzelne Kacheln mit mehrzeitlichem Level 3A RapidEye Bilder wurden beurteilt. Der Erwerb jedes Bildes erfolgte zeitnah zur Inventur. Eine Bildvorverarbeitung wurde durchgeführt um die digitale Nummer des Bildes zu seiner Sensor Reflexion zu konvertieren. Allerdings wurde weder eine geometrische noch eine atmosphärische Korrektur vollzogen. Die Vegetationsanzeiger wie NDVI, GNDVI, SAVI und NDRE wurde vom Bild der zugehörigen Spektralbänder abgeleitet. Verschiedene Größen simulierter rechteckiger Gitternetze wurden mit RapidEye angelegt. Die Pixelgröße betrug 5 m als kleinste Einheit und 50m als größte Gitternetzeinheit. Die Analyse der Korrelation ergab einen durchweg hohen positiven Zusammenhang zwischen Bestandesgrundfläche und oberirdischer Biomasse. Die Strukturvielfalt zeigte eine positive Korrelation mit der oberirdischen Biomasse bei einer Gitternetzgröße von 20 m. Ähnlich, bei gleicher Gitternetzgröße, zeigten die Vegetationsanzeiger einen positiven Zusammenhang zur Grundfläche, wenn auch niedrig. Derweil haben weder die originalen RapidEye Bänder noch die Vegetationsanzeiger eine starke Korrelation mit der oberirdischen Biomasse aufgewiesen. Trotzdem ergab die Analyse der Bedeutung des Prädiktors mit der Grundfläche, dass NDVI und NDRE das Potential besitzen die Waldstruktur zu bestimmen sowie die oberirdische Waldbiomasse zu schätzen. Indes offenbarte die Wahrscheinlichkeitsanalyse eine vielversprechende Integration der Waldinventur und der Fernerkundung. Ein Klumpen von relativ hoher Korrelation zwischen Spektralbildwerten und Felddaten trat innerhalb eines engen Bereichs von der originalen Flächenposition auf.

1. Introduction

1.1. Background

Indonesia has been recognized as one of tropical countries having a large coverage of forest. The latest FAO Global Forest Resources Assessment 2010 (FRA 2010) ranked Indonesia in the 8th place worldwide with the forest coverage of 94,432 million ha or approximately 52 % of its land area, after Russian Federation, Brazil, Canada, United States of America, China, Democratic Republic of The Congo, and Australia (FAO, 2010). In another word, it makes Indonesia ranked as the third largest forest coverage among tropical countries after Brazil and Democratic Republic of the Congo. Not only its extent, different forest ecosystem types namely mangrove, swamp, peat swamp, heath forest, dryland forests from lowland to montane forests could be found here.

It is obvious that Indonesia plays an important role in the global context, especially in recent emerging issues in relation to global climate change. Forest itself considered as one of main natural resources which has roles in controlling climate and carbon flow. Forests have the function of a potential carbon storage (Brown, 2002). Losi et al. (2003) and Samalca (2007) found that approximately 50 % of the forest biomass is carbon. In addition to that, Leigh (1999) in Ghazoul (2010) stated that tropical forests produce 49 billion tones of biomass annually.

Politically, importance of forest has been acknowledged by the government of Republic of Indonesia as a potential resources to participate in the international framework. In September 2009 on climate change at the G-20 leaders summit, President Susilo Bambang Yudhoyono declared his commitment to reduce emission from forest related issues by 26% from business as usual and by 41% with international support in 2020 (Forest Climate Center, 2010).

In order to achieve the goal, measurement instruments are needed to monitor Above Ground Biomass (AGB) as the indicator of potential carbon storage, sequester, and emitter. However, its large coverage and various type of forest become a distinct obstacle in calculating forest biomass in Indonesia. Accurate and precise biomass value could be obtained by using direct method (destructive method), especially in quantifying biomass of small unit area (Bombelli et al., 2009). However, according to Gibbs et al. (2007) and Ketterings et al. (2001), the destructive method is more time consuming, expensive, and impractical for large areas. Moreover, this method will threat existence of the forest itself.

Realizing the issue, more advance researches in non-destructive biomass estimation were developed. Developing allometric equations are the most common method to estimate forest biomass based on measured variables in the field. For example, Brown (1997) gives a guideline to estimate biomass in tropical forests. Basuki et al. (2009), Ketterings et al. (2001), and Samalca (2007) use diameter at breast height (dbh) as variable to estimate individual tree biomass, while Yamakura et al. (1986) add height in addition to dbh to predict stem dry weight of the Dipterocarp forest. Hashimotio et al. (2000) use age of fallowland and include site conditions and dominant species for estimating above ground biomass of tropical lowland fallow forest. Ketterings (2001) and Chave (2005) add wood density as additional variable to estimate species-based individual tree biomass, as will be used for estimating biomass from forest inventory data in this study.

Unfortunately, these allometric equations are only applicable for known measured variables collected from forest inventory and produce only statistical estimation, yet to represent the spatial extent. In this regards, remote sensing offers an alternative method to estimate biomass for a large area and includes spatial aspect in the application.

There are some remote sensing - field inventory related researches in the tropics, but they are still limited to particular sensor, forest type and location. Optical sensor such as Landsat Thematic Mapper (TM), active remote sensing data as Synthetic Aperture Radar (SAR) and Light Detecting and Ranging (LiDAR) are the most common remotely sensed data used in biomass estimation. Using passive optical remote sensing data of Landsat Thematic Mapper (TM), Lu (2005) demonstrate the success of estimating biomass in the successional forest of Brazilian Amazon. Extensive researches on active remote sensing such as LiDAR were also showing its capacity to estimate biomass (Clark et al., 2011). Although Roy and Ravan (1996), Steiniger (2000), and Lu (2001) has shown the difficulty in estimating biomass in tropical moist region by using Landsat TM spectral features due to the complexity of forest structure.

Lu (2005) shown that forest structure has an important impact in biomass estimation using remote sensing data. Hence, it is important to evaluate the capability of remote sensing data to determine physical structure of the forest and in the same time estimating the biomass.

1.2. Objectives

The main objective of this study is to evaluate the suitability of remotely sensed data in determining forest structure and its biomass. In addition to support the main objective, structural diversity analysis, species-based biomass estimation, spectral consistency of multi temporal images, and relationship between remote sensing variables and field inventory variables will also be analyzed.

2. Methods and material

2.1. Study site

The study site was a 120 x 120 m full census plot in a small part of 50,000 ha of The Natural Laboratory of Peat Swamp Forest (LAHG) managed by Center for International Cooperation in Sustainable Management of Tropical Peatland (CIMTROP) University of Palangkaraya Indonesia. Geographically, it is located on longitude 113^{o}54.2' E and latitude 2^{o}19.2' S, approximately 20 km south of Palangkaraya, the provincial capital of Central Kalimantan (**Figure 1**.). The area is ex forest concessionaire PT Setia Alam Jaya logged over peat swamp forest. It was selectively logged over 20 years period before 2002 (Morrogh-Bernard et al., 2003).

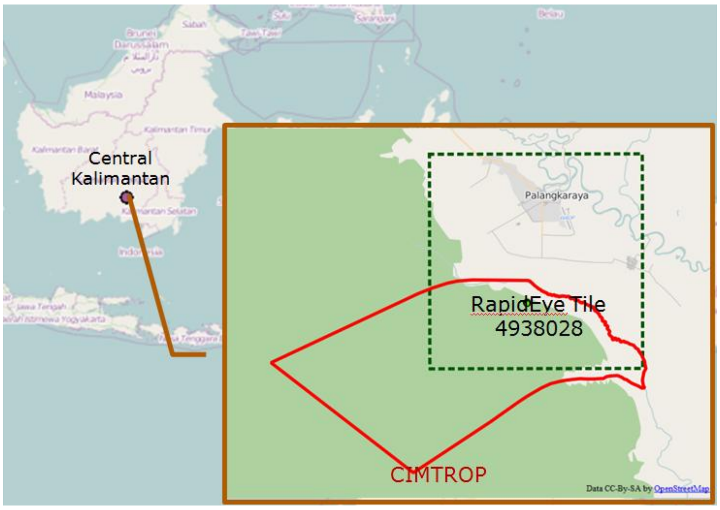


Figure 1. Location of the study area

The temperature ranged from 22.2 - 31.9 ^{o}C with mean annual temperature of 26.7 ^{o}C. The annual precipitation is 2,578 mm. During July to September, precipitation is in the range of 124 - 148 mm with the mean temperature of 26.6 - 27.2 ^{o}C (Hijmans et al., 2005). According to Peel et al. (2007), Indonesia in general categorized as tropical rainforest with the characteristic of precipitation of the driest month $\geq$ 60 mm.

The plot is laid on 12-24 masl elevation with mostly flat terrain. According to landsystem map of Kalimantan (RePPPRoT, 1986), the site belongs to Barah landsystem which has peat-covered sandy terraces consist of tropohemists, placaquods, and troposaments soil types. Peat distribution map of Wetlands International (2004) showing that the site has 4-8 m depth of peat with composition 60/40 of hemists and fibrists.

2.2. Forest inventory data

Field inventory data was obtained from a full census plot of 120x120 m as part of the project of DFG KL 894/17 "Development of an integrated forest carbon monitoring system with field sampling and remote sensing" in Sebangau, Central Kalimantan. The data used for analysis was a compiled dataset of forest inventory. It contains unique ID and records for each recorded tree in the field. The format of the dataset was geometrically corrected SHP (shapefile) which can be displayed both on GIS software and spreadsheet processing software.

2.3. RapidEye image

RapidEye™ is an earth observation satellite launched in February 2009, owned and operated by Black Bridge. It has five identical satellite constellations which orbit at the altitude of 630 km. RapidEye categorized as a high resolution sun-synchronous satellite image with 6.5 ground sampling distance at nadir and resampled to 5 m pixel in the orthorectified products. The images are collected using 12 bit multi spectral push broom imager (MSI) and converted to 16 bit images during on-ground processing. The swath width is 77 km with the capability of daily image acquisition of 5 million km^2. RapidEye is a multispectral image with five spectral bands namely Blue (440-510 nm), Green (520-590 nm), Red (630-685 nm), Red Edge (690-730 nm), and Near Infra Red/NIR (760-850 nm). Due to its spectral feature, Blackbridge claimed RapidEye as the first optical sensor which put Red Edge band which improves vegetation discrimination. The presence of Red Edge band introduced as the advantage of RapidEye among other satellites, especially in vegetation detection and discrimination purpose. The RapidEye imageries used in this study are level 3A products or orthorectified products with geometric, radiometric, and terrain corrections in a map projections (Blackbridge, 2013)

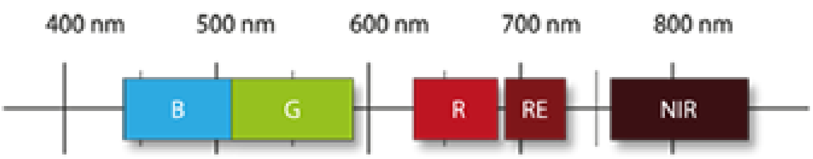


Image source: Blackbridge (2013)

Figure 2. Spectral characteristic of RapidEye

2.4. Software

There are several software used in this study, mainly statistical software and remote sensing GIS software for data analysis purpose. Both licensed and open source software are used.

Licensed:	Open source:
Microsoft office 2007	RStudio Version 0.98.994 under GNU Affero General Public License v.3
STATISTICA v.10	QGIS Desktop 2.0.1 - Dufour under GNU General Public License v.2

2.5. Field Inventory

2.5.1. Data collection

Field inventory data was carried out in natural laboratory of peat swamp forest (LAHG) Sebangau, Central Kalimantan. Field campaign was conducted during September-October 2013.

2.5.2. Variables of Interest

Tree species

Species identification is an essential variable to be included in the forest inventory. In forest management system, precise species identification is considered as the most basic step (Lacerda and Nimmo, 2010). In this study, species name is required to obtain wood density value and estimates species-based above ground biomass.

There are three major steps in tree species data handling. First step is vernacular names identification and spelling check. The identification of tree species in the field was done by local species identifier, hence the species recorded in the tally sheet were still in local name or Bahasa Indonesia. The output of this step is a list of vernacular names with a unique name and code for each species found. The next step is to find corresponding scientific or botanical name for each vernacular name. Main catalogues used as the reference were ***4000 tree species in Indonesia*** (Kartasujana, 1993), ***Indonesian Wood Atlas I - IV*** (Martawijaya et al., 1989, 2005; Abdurrohim et al. (eds), 2004; Muslich et al., 2013). The last step of the species data handling is to check botanical names collected in the previous step with the universally current accepted names.

The current tree species nomenclature reference used is based on ***The Plant List version 1.1*** database. It is a collaborative venture on plants taxonomic database management coordinated by the Royal Botanic Gardens, Kew, and Missouri Botanical Garden. It provides approximately 1.3 million of Angiosperms, Gymnosperms, Pteridophytes, and Bryophytes scientific plant name records of which more than 600 families and 17,000 plant genera are recorded (The Plant List, 2013).

Diameter at breast height

Stem diameter is the most common variable used in forest inventory. According to White (1998), stem diameter is an irreversible feature of a tree growth which is easily measured with a good precision. The ease and directly measured and usefulness in calculating basal area which is closely related to timber volume, making the diameter measurement becomes the most important tree attribute (Kleinn, 2011).

The diameter was measured at 1.3 m height or so called diameter at breast height (DBH). Diameter tape was used as the measuring device. In a flat terrain and normal tree condition, DBH measured perpendicular to stem axis at 1.3 m height above the surface level. However, there are some cases that the measurement at 1.3 m is not possible to be done due to variation of slope where the tree is standing or shape of the stem (e.g. due to buttress, roots, and other deformations). Therefore, the measurement of special case DBH performed differently as depicted in **Figure 3**.

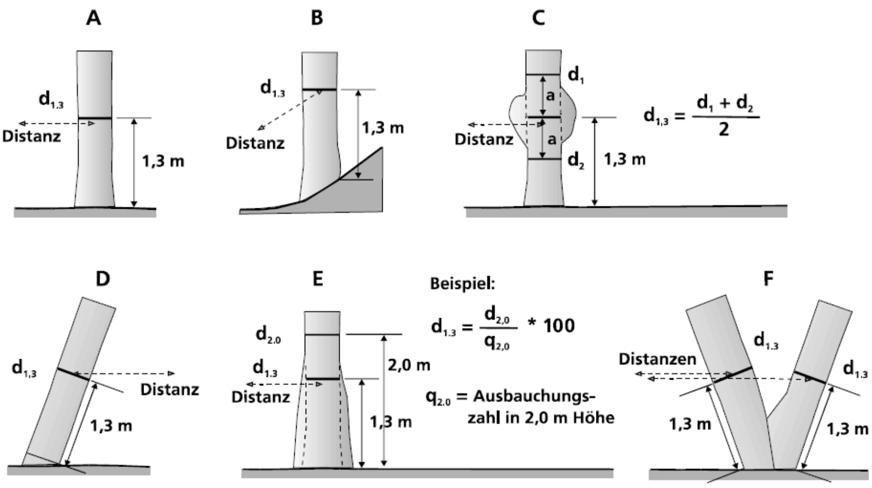


Image source: Lutz Fehrmann

Figure 3. DBH measurement at different conditions

Height

Tree height is the second most common observed variable in forest inventory after DBH. It is another single tree dimension which relatively easy to be measured directly. Height may indicate the site quality if combined with stand age and the total production of a stand is proportional to it (Van Laar and Akca, 1997; Köhl, 2006). It is widely used as predictive variable in biomass estimation, determining yield tables, and stand volume estimation (Chave et al., 2005; Kleinn, 2011). In this study, total height was used as one of variables of interest and is defined as the distance from the level of the tree top perpendicular to the surface level (Van Laar and Akca, 1997). Height may affect to the remote sensing based biomass estimation since the sensor capture the reflectance of the object, while the object should receive lights which then be reflected to the sensor.

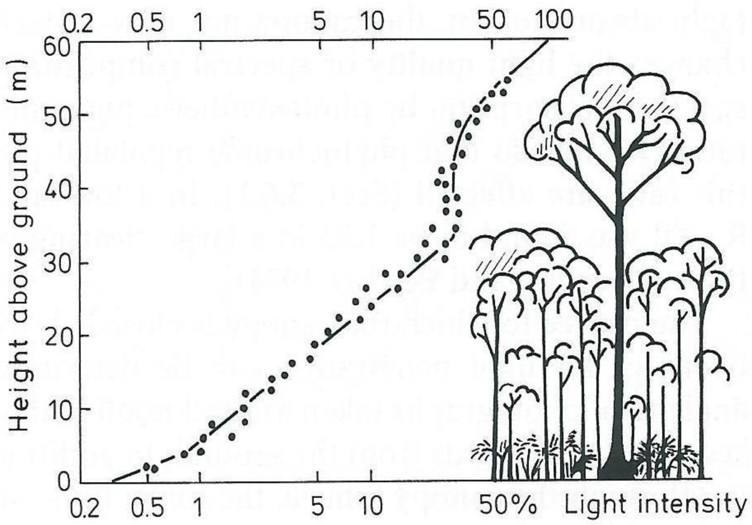


Figure 4. Relationship between height and light intensity

Wood density

Köhl et al. (2006) defined wood density as wood mass divided by its volume at a specific moisture content. Another common term of wood density is wood specific gravity (ρ), calculated as oven-dry wood at 103 ^{o}C divided by green volume and expressed in the unit of kilogram per cubic meter or gram per cubic centimeter (Chave et al., 2005). The Tree Functional Attributes and Ecological Database (World Agroforestry Center, 2014) and Global wood density database (Zanne et al., 2009) are used as reference to obtain species wood density.

Basal area

Basal area is defined as the cross-sectional area of the stem. Köhl et al. (2006) consider basal area as an important variable to determine stock density. In a single tree measurement, basal area is calculated as the area of the cross section at breast height (van Laar and Akca, 1997). It is assumed that basal area calculated based on circular cross section, hence the following equation is used:

$$g = \frac{\pi}{4} DBH^2$$

where g is basal area in m^2 and DBH is diameter at breast height (m).

2.6. Forest structure

Forest structure refers to stand structure and defined as spatial arrangement of the various component of the forest in horizontal and vertical structure. Horizontal structure refers to spacing of trees, species diversity, mean diameter, while structure heights of different canopy level could be interpret as vertical structure. (Lüttge, 1997; McElhinny et al., 2005).

2.6.1. Horizontal structure

Quadratic mean diameter

Unlike ordinary mean using arithmetic method, mean stem diameter is using quadratic mean.

$$QMD = \sqrt{\frac{\sum_{i=1}^{n} DBH_i^2}{n}}$$

where

QMD : Quadratic Mean Diameter
DBH : Diameter at breast height (DBH)
n : Number of tree in the stand

Stand density

Density may express crown, stem count, volume, or biomass per unit area. Köhl (2006) stated that stem per unit area provides more informative estimate of stand density than crown density. McElhinny et al. (2005) use the term of tree spacing to express the number of trees per ha as a structural attribute.

Stand basal area

Stand basal area could be used as stand volume and biomass indication (McElhinny, 2005). It has been successfully used in Costa Rica to discriminate between primary and secondary Quercus forest and successional stages in hemlock-hardwood forests (Kapelle et al., 1996; Ziegler, 2000).

2.6.2. Vertical structure

The distribution of tree height is used to illustrate the vertical stand structure in complexity of a stand structure measurement (Lu et al., 2005). In relation to remote sensing, vertical structure is important since the sensor detect the object from above, which may not represent the real 3D condition in the field.

2.6.3. Structural diversity

Stand structural diversity or stand structural complexity measures the number of different structural attributes and relative abundance of each of the attributes (McElhinny et al., 2005).

Shannon index has been widely used in diversity and ecological studies. It is also known as the Shannon-Wiener index or the Shannon-Weaver index. Stand structural diversity index used in this study is Post-hoc Shannon index. The Extensions of Shannon index is used to calculate stand diversity based on DBH, height and species proportional to basal area distribution (Staudhammer & LeMay, 2001). The following equations is used to calculate the stand structural diversity index (H'_{d+h}) and (H'_{d+h+s}).

$$H'_d = -\sum_{i=i}^{s} p_i \ln\, p_i \quad ; \qquad H'_h = -\sum_{i=i}^{s} p_i \ln\, p_i \quad ; \qquad H'_s = -\sum_{i=i}^{s} p_i \ln\, p_i$$

where

H'_d : Shannon index for DBH;
H'_h : Shannon index for height;
H'_s : Shannon index for species;

pi : the proportion of species basal area in the i_{th} DBH class, height class, or species
s : the number of diameter classes, height classes or number of species

The final index (H'_{d+h}) is the average of the diameter and height indices, while the (H'_{d+h+s}) final index is the average of the DBH, height, and species Shannon index.

2.7. Above Ground Biomass (AGB) estimation

There are numerous existing AGB estimation equations for almost all forest types in Indonesia (MoF, 2012). AGB models for peat swamp forest are also available as in Nugroho (2014) who develop a site-specific allometric equations for AGB in Riau Province. Widyasari (2010) and Novita (2010) estimates AGB and fix carbon of the peat swamp forest in Merang, South Sumatera. Jaya et al. (2007) conducted similar study in Central Kalimantan. However, those AGB models may not be suitable for other locations due to their limitations on number of tree sample, DBH range, and stand characteristics (Nugroho, 2014; Ketterings, 2001).

Nugroho (2014) suggest to combine the dataset from a wide-range of geographical area and wider DBH range of different tree species to improve the AGB models. Ludang and Jaya (2007) found that Brown (1997) equation is applicable for estimating biomass in Central Kalimantan forest. In addition, several studies recommend to incorporate wood density and height as predictive variables to reduce estimate errors (Ketterings, 2001; Chave, 2005; Nugroho, 2014). Therefore, AGB model of Brown (1997) and Chave (2005) was used to estimates AGB within the sample plot. The selection of these equations was based on the reliability of the models to estimate a broad range of tropical forests aboveground tree biomass (Chave et al., 2005). Description of the biomass model used is presented in Table 1. Mathematically, both Brown and Chave biomass models are presented as the following equations.

Brown equation

$$AGB = \exp\{-2.134 + 2.530 * \ln(DBH)\}$$

Chave equations

$$AGB = \exp\left(-2.977 + \ln\left(\rho\, DBH^2 H\right)\right)$$

$$AGB = \rho \exp\left(-1.499 + 2.148 \ln(DBH) + 0.207(\ln(DBH))^2 - 0.0281(\ln(DBH))^3\right)$$

where

AGB : Above ground biomass per tree in kg,
DBH : Diameter at breast height in cm
ρ : Wood density (oven dry mass 103 ^{o}C divided by green volume) in gr / cm^3

Table 1. Description of study site and sample source of Brown and Chave biomass model

	Brown	Chave
Number of tree sample	170	2410
Range in DBH (cm)	5 - 148	5 - 156
Locations	Australia, Asia, South America	27 study sites in Australia, Asia, Africa, Central America, South America
Forest type	Moist	Moist
Rainfall (mm)	n.a.	1,200-6,000
Adjusted r^2	0.97	n.a.

2.8. Remote sensing analysis

2.8.1. Image pre-processing

Image pre-processing refers to geometric and radiometric corrections and data errors removal (Mather, 1999). These corrections are needed to correct the images for known errors occurred during the process of collection (Jones and Vaughan, 2010). In this study, image pre-processing performed by converting image Digital Numbers (DNs) to Top of Atmosphere reflectance (ToA_{refl}). There are two major steps in this process, converting DNs to radiance and turn radiances into reflectance (Blackbridge, 2013).

Conversion of Digital Numbers (DNs) to radiance value was performed using equation:

$$RAD_{ij} = DN_{ij} * RSF_j$$

where

RAD_{ij} : Top of Atmosphere (ToA) radiance value of the pixel i in the j band (W / m^2 sr μm)
DN_i : Digital Number of pixel i of the j band
RSF_j : Radiometric Scale Factor of the j band

To convert ToA radiance to ToA reflectance, the following equation is used:

$$REF_i = RAD_i \frac{\pi * SunDist^2}{EAI_i * Cos\ (Solar\ Zenith)}$$

where

i	:	Number of the spectral band
REF_i	:	ToA Reflectance of the pixel j in the i band
RADij	:	Top of Atmosphere (ToA) radiance value of the pixel i in the j band (W / m^2 sr µm)
SunDist	:	Earth-sun distance at the day of acquisition in Astronomical Unit (AU); The value is ranged between 0.983 289 8912 AU and 1.016 710 3335 AU
EAI	:	Exo-Atmospheric Irradiance
Solar Zenith	:	Solar zenith angle in degrees (= 90^o - sun elevation)

EAI values of RapidEye spectral bands:

Blue	: 1997.8 W / m^2 µm
Green	: 1863.5 W / m^2 µm
Red	: 1560.4 W / m^2 µm
Red Edge	: 1395.0 W / m^2 µm
Near Infra Red	: 1124.4 W / m^2 µm

No further image pre-processing such as geometric correction nor atmospheric correction was performed. Geometric correction was not performed due to the product level of RapidEye used. The Level 3A RapidEye image has been processed radiometric sensor and geometrically corrected to produce orthorectified image. Fine DEMs were used to perform this geometric correction. The horizontal accuracy of this product announced at 15 m. (Blackbridge, 2013; RESTEC, 2014). The atmospheric correction was not performed due to the insufficiency of atmospheric parameters needed.

2.8.2. Image processing

In this process, original spectral bands of RapidEye image used to generate new variables, in particular vegetation indices. There are numerous vegetation indices derived from two or more original bands of the images. NDVI or Normalized Difference Vegetation Index is a powerful normalization to reduce the effect of non-uniform illumination. It is also good for Leaf Area Index (LAI) estimation (Rouse et al., 1974). The NDVI is the most widely used and become a base for further development of vegetation index. GNDVI is an example of improvement of NDVI. It improves the sensitivity in detecting dense vegetation with rather high LAI (Jones and Vaughan, 2010). In this improvement, the green band is used as a substitute for the red band. Gitelson et al. (1996) stated that GNDVI is good at detecting chlorophyll in a wider range. SAVI (Soil Adjusted Vegetation Index) corrects the effect of soil reflectance within the vegetated area (Huete, 1988). The presence of Red Edge in the spectral properties of RapidEye gives an advantage in detecting forest damage and plant stress. Therefore, Normalized Difference Red Edge (NDRE) as the modification of NDVI is expected to improve vegetation detection, tree species identification, and biomass estimation, particularly within forested area (Kärgel and Jansen, 2013; Barnes et al. 2000).

Following equations are the mathematical forms of the mentioned vegetation indices above.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

$$GNDVI = \frac{NIR - Green}{NIR + Green}$$

$$SAVI = (1 + L)\,\frac{NIR - Red}{NIR + Red + L}$$

$$NDRE = \frac{NIR - Red\ Edge}{NIR + Red\ Edge}$$

2.9. Simulated grid

Different simulated grid size have been applied to the plot. This simulated grids were established to generate artificial plots (grids) with different size. The reason behind the simulated grid establishment was due to the limitation of sample size. The inventory plot was the only plot in the study site having the particular plot design. Therefore, the plot was divided into smaller square grids as the artificial plots, regardless its spatial autocorrelation. The smallest grid having the size of image pixel (5 m) while the largest grid size is 50 m and 10 m, 20 m, and 25 m grids in between.

To analyze the plot positional effect, another simulated grid so called probability grid was generated. The underlying assumption is the probability of a field grid coincide with an image pixel. The horizontal accuracy of the RapidEye image and typical positional accuracy of handheld GPS which is reported 15 m (RESTEC, 2014;

Garmin, 2014) become a basis to set 30 m as the radius for generating the spatial probability simulated grids. There are 145 probabilities within this 30 m radius.

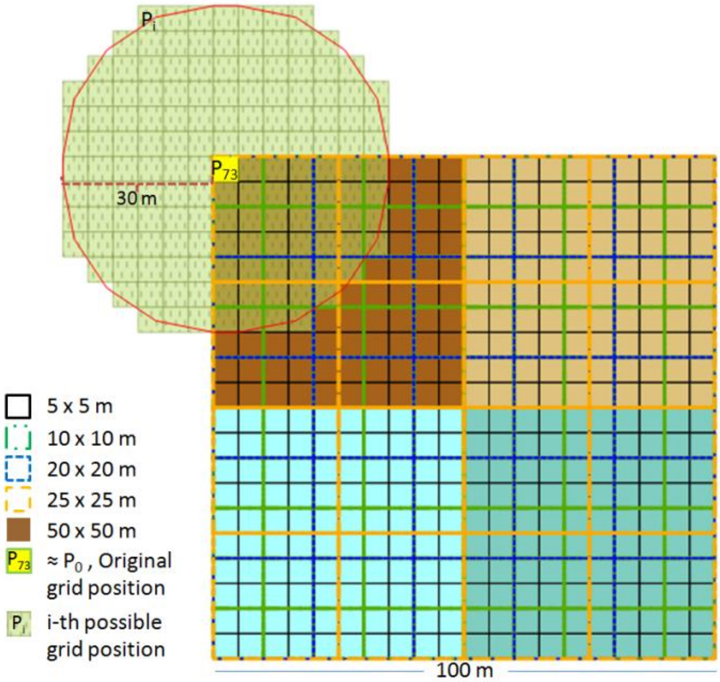


Figure 5. Simulated grid size and spatial probability grid design

2.10. Linking field and remote sensing data

2.10.1. Field inventory data aggregation

Individual records of inventory data which represent a single tree is treated as the input unit. The data is aggregated to generate variable of interests per grid. In this step, quadratic mean diameter, mean height, stand basal area, stand density, structural diversity indices as well as AGB density is calculated. The aggregation results will then be overlaid and linked with corresponding extracted image pixel value.

2.10.2. Feature extraction

In order to easier to link between the field data and remote sensing data, feature extraction is performed. In this regards, feature refers to image pixel value (ToA reflectance). Zonal statistics is selected as the method to extract the value of each RapidEye bands into corresponding simulated grids. For grids larger than pixel size, the zonal statistics assign mean of all pixel values within the grid. Each of original bands and vegetation indices is extracted independently. Fuchs et al. (2009) applied similar technique to assign average value of the pixels to the centers in the location of circular inventory plots.

2.10.3. Correlation analysis

The correlation analysis performed to investigate the correlation between field variables and remote sensing for each simulated grid. The P-pearson correlation or product-moment correlation is used to measure the strength of the linear relation between field variables and remote sensing variables. Pairs of highly correlated variables are selected and evaluated. In this process, field variables treated as dependent variables while the remote sensing variables treated as independent variables.

3. Results

3.1. Forest Inventory Data Analysis

In order to get an overview of the forest stand condition, basic statistics calculation was performed based on inventory data on each site. Overall minimum, maximum and mean value of DBH, height, and wood density were produced, as well as stand density and basal area of the forest stands. The results of this inventory data exploration presented briefly in Table 2.

Table 2. Descriptive statistics of forest inventory data

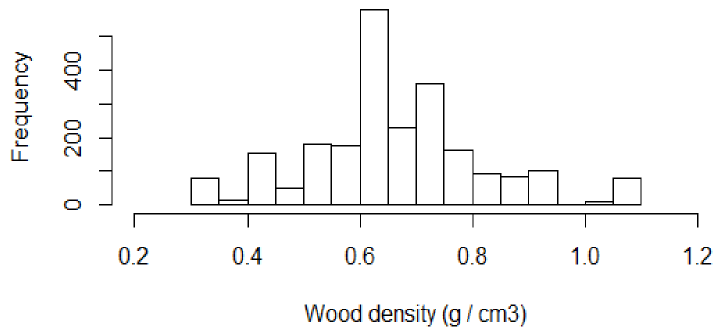
Variables	Mean	Min	Max	Sum	Variance	Std.Dev.	Coef.Var.
DBH (cm)	13.1*	5.0	59.7		45.484	6.744	60.204
Tree height (m)	12.43	1.6	32.5		20.404	4.517	36.340
Wood density (g/cm^3)	0.663	0.340	1.0575		0.024	0.154	23.236
Stand density (stems/ha)				2343			
Basal area (m^2)	0.013	0.002	0.2799	31.46	0.000	0.020	150.960
AGB Brown (ton)	0.098	0.007	3.6849	228.86	0.044	0.210	214.859
AGB Chave d, ρ (ton)	0.097	0.001	2.5920	227.24	0.047	0.217	223.994
AGB Chave d, ρ, h (ton)	0.114	0.004	3.2719	267.75	0.070	0.265	231.871

* Quadratic mean DBH

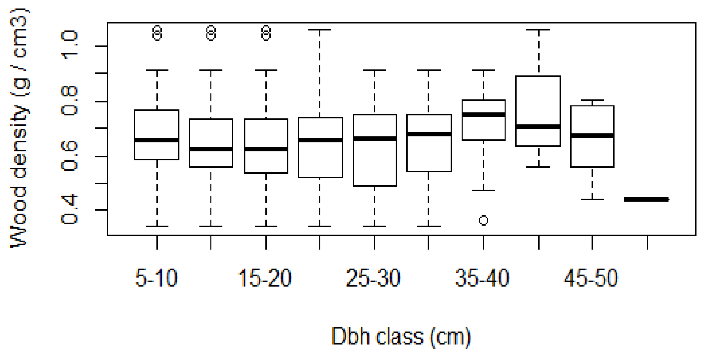
3.2. Species and wood density

There are 55 species found in Sebangau plot. These 55 species were the final identified species from 57 vernacular names, excluding the unidentified species. Of the total individuals found in the plot, the unidentified trees found were only two trees having DBH of 6.1 and 7.3 cm with the height of 4 and 3.3 m respectively. Therefore these unidentified trees shall not significantly affect the overall calculation in the latter step. Wood density (ρ) of the 55 species found in Sebangau plot ranging from 0.34 to 1.0575 g / cm^3 with an average of 0.663 g / cm^3. The average value of ρ was assigned to unidentified species as their corresponding wood density.

Trees having ρ slightly lower than the average are dominating the stand. In terms of its distribution, the variability of ρ value is almost similar between each DBH class with the most variability occur in the DBH smaller than 25 cm.



(a)



(b)

Figure 6. Wood density distribution (a) for the whole plot and (b) over DBH

3.3. Diameter distribution

From one hectare subset of full census plot, there were 2,343 trees recorded with diameter at breast height (DBH) ranging from 5 - 59.7 cm and the quadratic mean diameter of 13.1 cm. Most of the trees (59.3 %) have small DBH of 5 - 10 cm, followed by DBH 10 - 15 cm with the magnitude of 20.7 %. The trees with DBH of 15 - 30 cm occupy 17.7 % of the DBH distribution, while bigger trees having DBH more than 30 cm were recorded only as low as 2.3 %. Overall, the DBH distribution creates a reverse J-shape curve as depicted in **Figure 7.** which is typical for tropical natural forest in general (Ferreira and Prance, 1998).

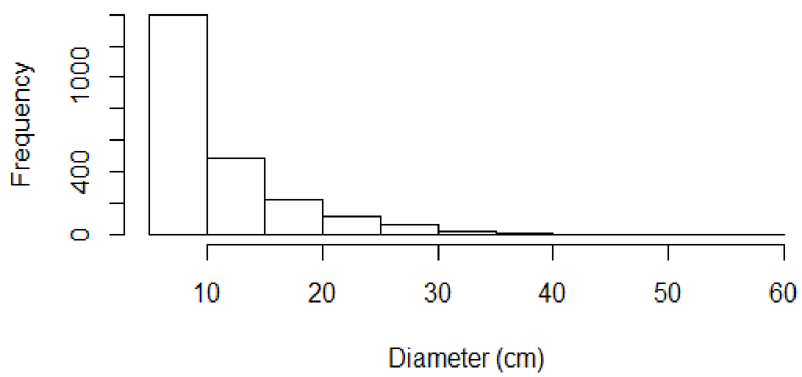


Figure 7. DBH distribution in Sebangau full census plot

3.4. Height distribution

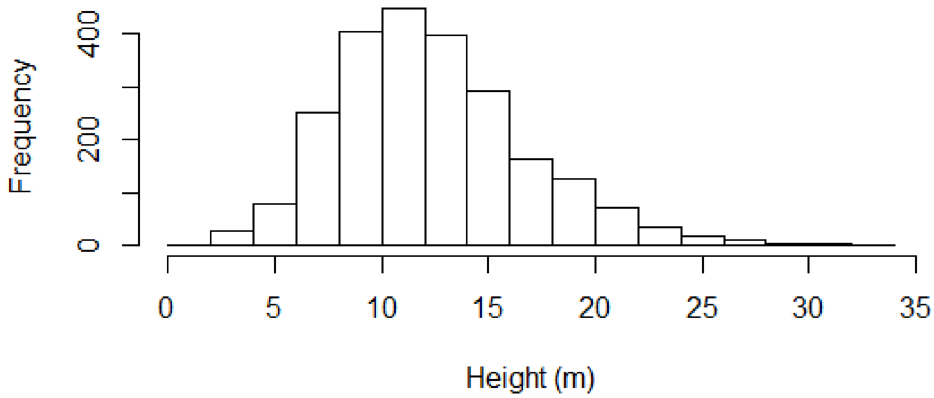


Figure 8. Tree height distribution

The tree heights are nearly normally distributed with the minimum, maximum, and mean diameter of 1.6 m, 32.5 m, and 12.43 m respectively. As depicted in **Figure 8**. the stand is dominated by trees having height of 8 - 12 m. The height distribution for each diameter class is presented in **Figure 9.** It shows that the tree height considerably increase with the diameter increase. Overall, the tree heights are normally distributed with a close-to-smooth pattern. It shows that the canopy layer has no distinct strata. However, height variability in lower diameter classes is clearly observed. In the DBH class of 5 - 10 cm and 10 - 15 cm, the height ranges are nearly the same, although the median shows that the bigger diameter class generally having higher tree.

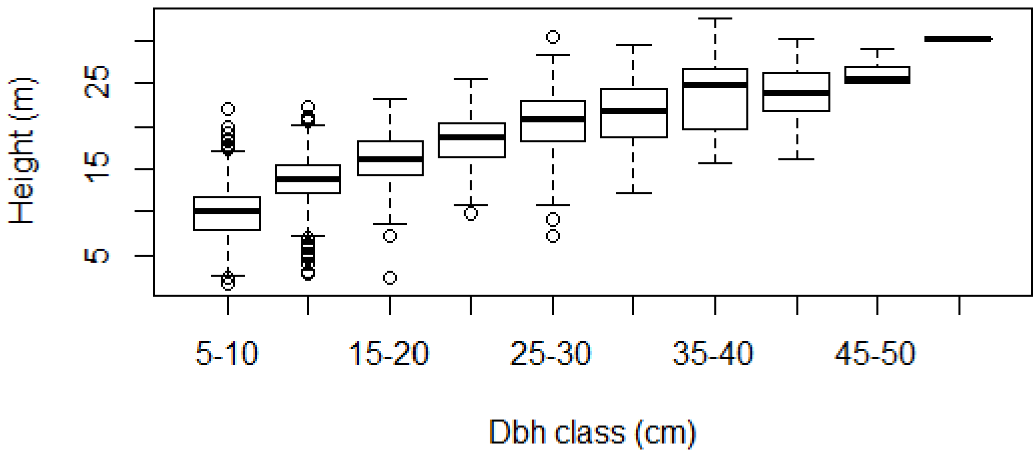


Figure 9. Tree height over DBH

3.5. Forest structure

There are four measures to indicate the forest structure, they are species diversity, diameter diversity, height diversity and combination of diameter and height diversity so called structural diversity measure (Table 3.). Since all diversity measures calculated based on the proportion of its basal area in terms of species, DBH, and height, the interpretation of the value could be equalized. From the calculated Shannon-Weaver index and its extensions, species diversity has a higher value than DBH and height diversity. However, in regards to their maximum values, all diversity indices show relatively high value. The extended Shannon-Weaver indices show the overall structural diversity of the stand which is moderately high.

Table 3. Forest structure related indices

Species diversity		DBH diversity		Height diversity		Structural diversity	
H'_s	Max H'_s	H'_d	Max H'd	H'_h	Max H'h	H'_{d+h}	H'_{d+h+s}
3.430	4.007	2.056	2.303	1.593	1.946	1.825	2.360

3.6. Biomass estimation

Individual tree above ground biomass (AGB) estimations based on three different equations resulting different magnitude of estimates. Brown (1997) equation show smooth exponential increase of AGB with the increase of DBH. The variability of AGB on each DBH class is obviously low since this equation use only DBH as independent variable to estimate AGB of individual trees. In comparison with the result of using Brown equation, AGB estimates using Chave (2005) equations show different result. Incorporating wood density/WD (ρ) produce more variability in the AGB estimates. The AGB estimates tend to be over estimate with a significant variability within DBH class. However, by using another Chave equation which incorporate height as independent variable after DBH and wood density, individual tree AGB is tend to be closer with the result by using Brown equation, although the variability within each class is still remain. From all equations used, the AGB variability is increase as DBH increase. **Figure 10.** shows the individual tree AGB estimates over DBH for all AGB equations used.

Smaller trees with the DBH less than 10 cm can have AGB of as low as 0.05 ton per tree. As the DBH reach 20 cm, individual AGB is estimated to increase more than ten folds.

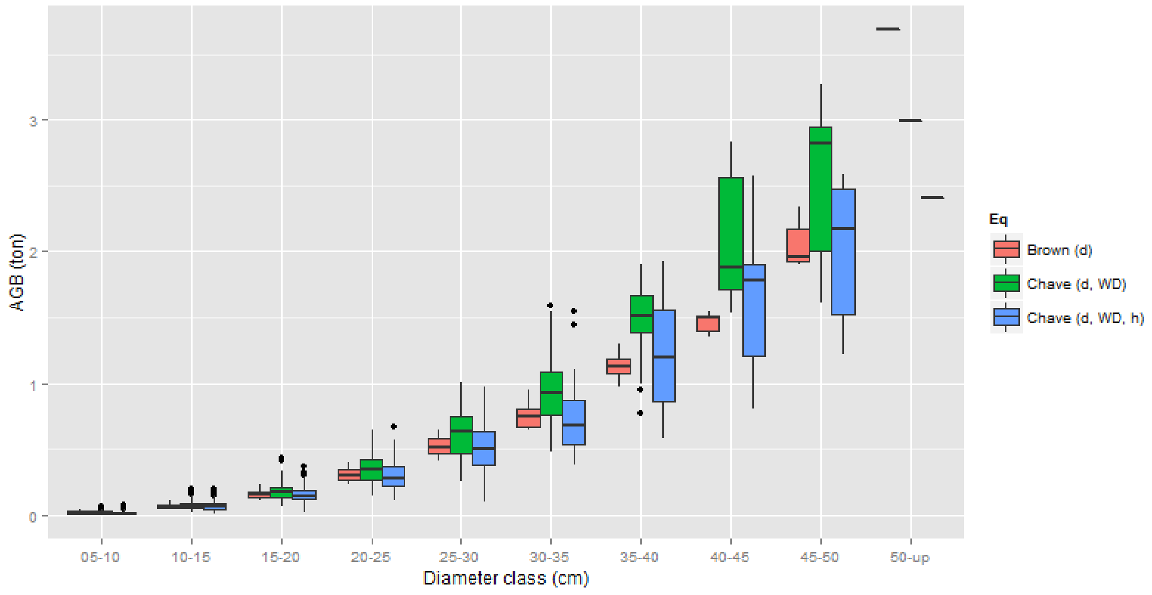


Figure 10. Individual tree AGB distribution over DBH

In terms of AGB density, estimated total AGB within the plot using Brown equation is 228.86 t/ha. Chave equation with DBH and wood density as predictive variables gives an estimate of 267.75 t/ha, while another Chave equation with height as additional variable is at the magnitude of 227.24 t/ha. Horizontally, AGB tend to increase from the lower DBH class to middle DBH class, significantly decrease at the mid-DBH class, and slowly decrease as DBH increase. On average, DBH of 5-30 cm contribute 72.16 % to the total AGB, while DBH of 30-50 cm having proportion of 26.58 %. A single tree having DBH of 59.7 cm contribute 1.26 % to the total AGB of the plot.

Similar to the AGB distribution over DBH class, AGB distribution over tree height class shows an increase from the shorter tree to the mid-height class (15 - 20 m). The biomass density continuously decrease afterwards. Different magnitude of AGB estimates between height classes are also clearly observed. The biggest difference in AGB is observed within the 15-20 m class with a magnitude of 12.06 ton/ha.

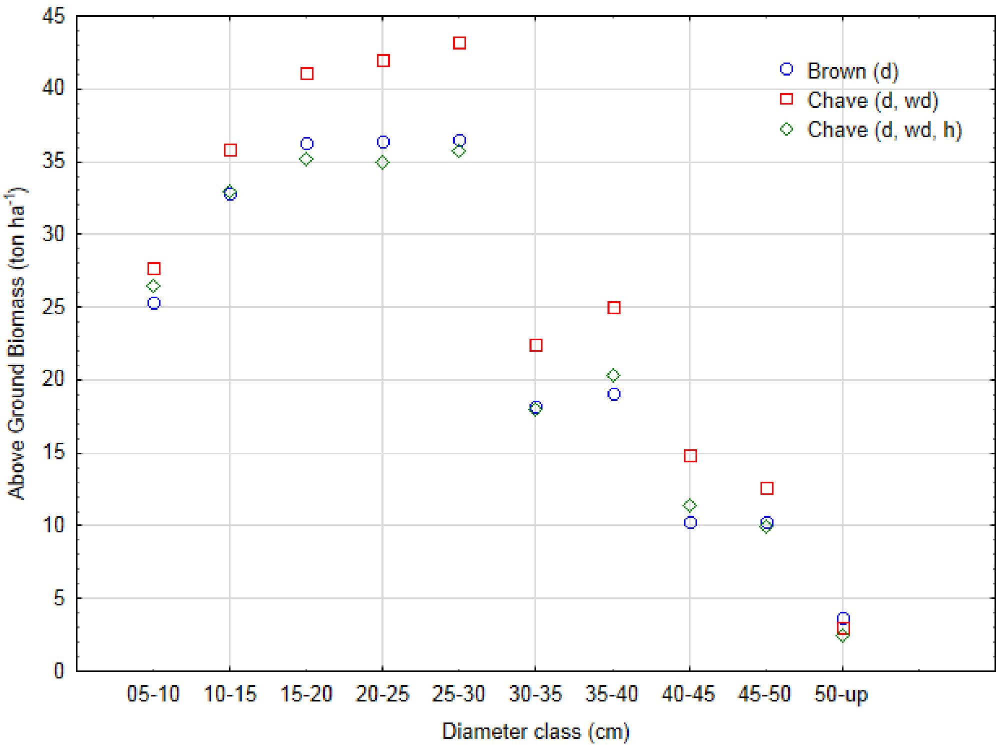


Figure 11. AGB distribution over DBH class

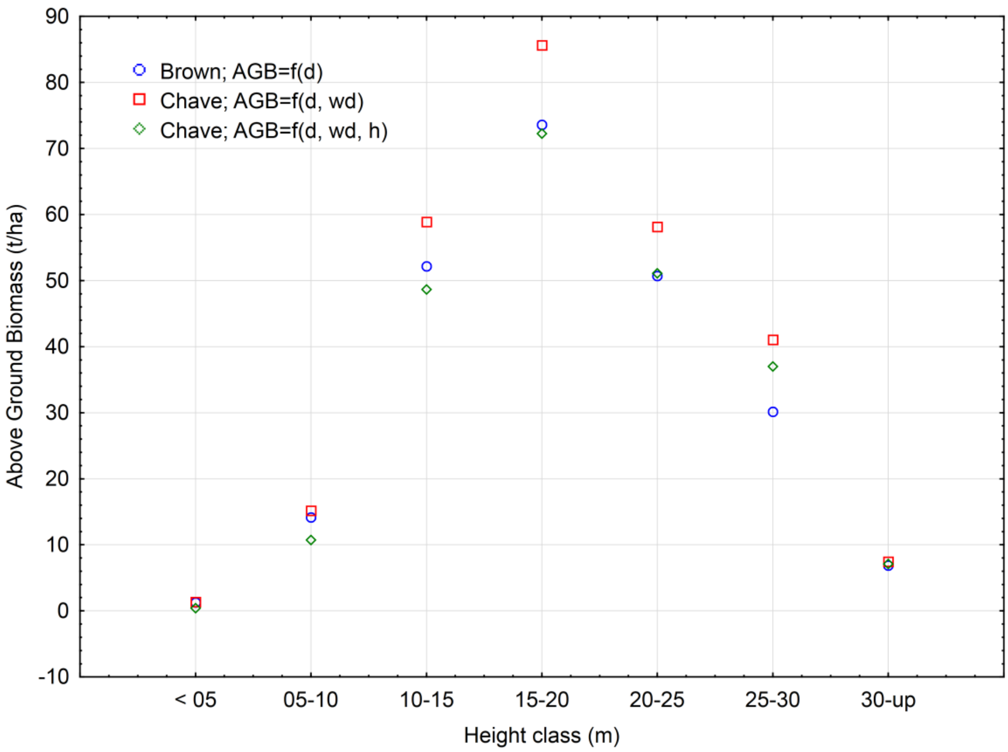


Figure 12. AGB distribution over height class

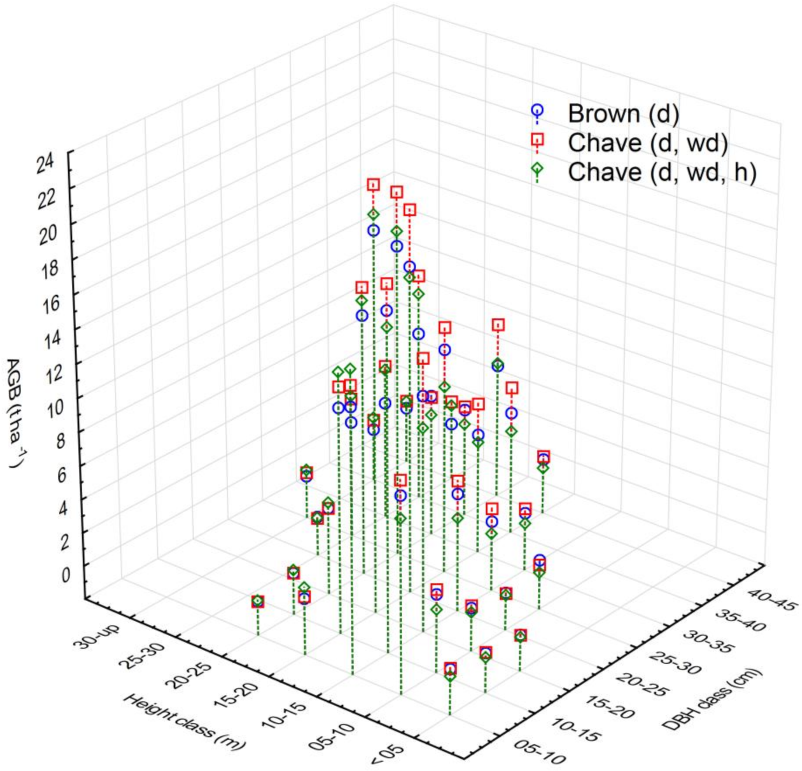


Figure 13. AGB distribution over DBH and height classes

Figure 13. show the biomass distribution in 3D, using DBH class and height class as the X and Y axis. Meanwhile AGB value from different equations is used as the Z axis. It shows that the peak value is in the mid-class of both DBH and height. Smaller AGB are observed in the surrounding of the peak. It is also clear that different biomass models giving different AGB estimates, in particular within the mid-class of DBH and height.

3.7. RapidEye images evaluation

The evaluation of RapidEye in this study is limited to its spectral characteristic only. This evaluation is necessary since the relationship analysis between Rapideye image involve the pixel value and field variables. The spectral analysis identified spectral differences between each different acquisition data.

In general, ToA reflectance of each original band vary between acquisition dates. Overall, ToA reflectance of RapidEye image acquired in September 20, 2013 is higher than the one acquired in October 06, 2013, while the image acquired in September 26, 2013 having the highest range of all.

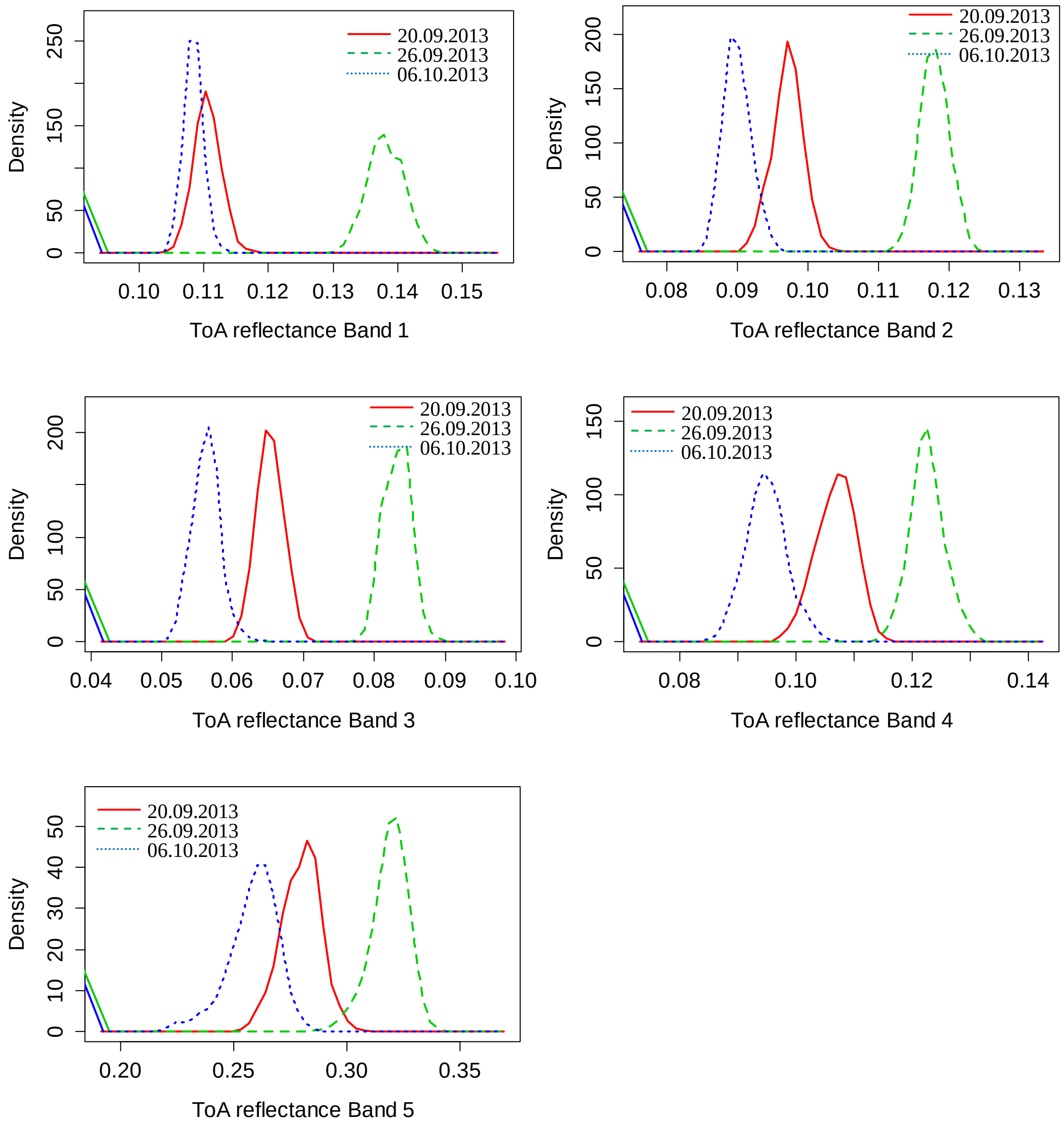


Figure 14. RapidEye original band ToA reflectance distribution from different acquisition dates

Vegetation indices derivation giving advantages in terms of value distribution. It may reduce the difference in ToA reflectance of a band with different acquisition dates. **Figure 14.** shows the value of indices for each acquisition date. By calculating NDVI, the difference between each image tile is still observable. GNDVI shows a very good image matching in terms of pixel value distribution, especially for the image acquired in September 20, 2013 and October 6, 2013. SAVI made all the three images into almost the same range of spectral value. Similarly, NDRE made the images having spectral value ranged from 0.4 - 0.5.

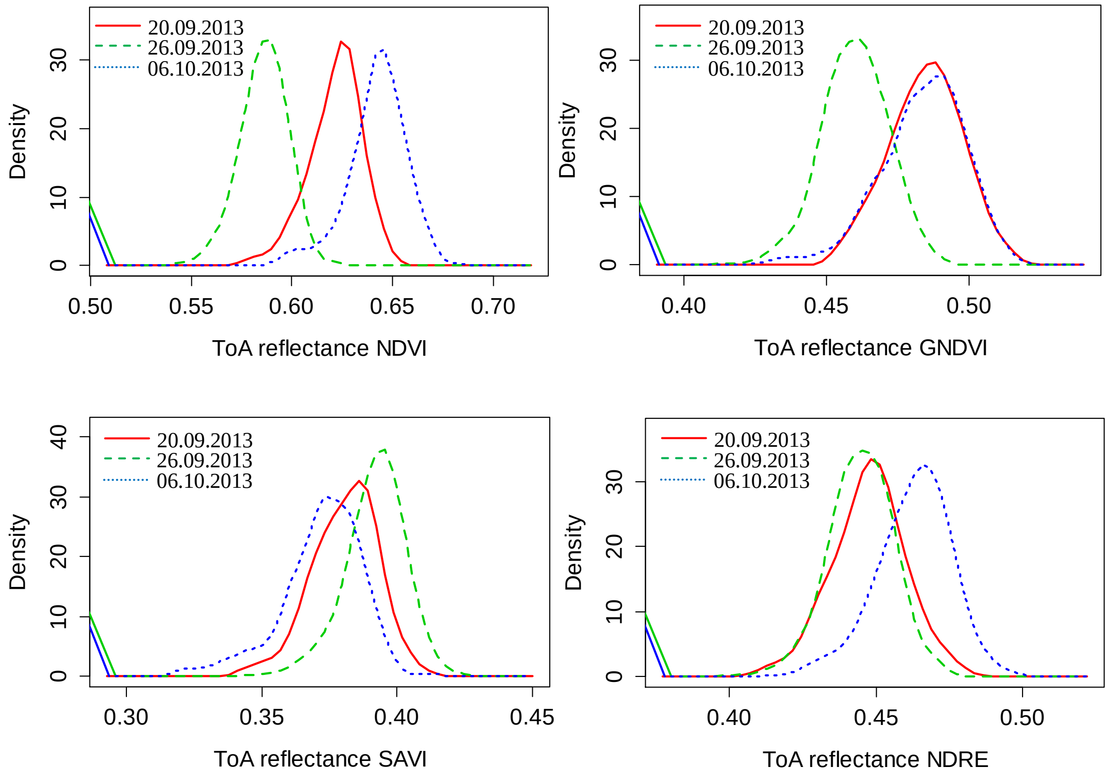


Figure 15. Vegetation indices distribution from different acquisition dates

3.8. Analysis of relationship between variables

Relationship between variables or variables correspondence is analyzed in this chapter. There are three different relationships to analyzed, they are forest structure and AGB relationship, image spectral and forest structure relationship, and image spectral and AGB relationship.

3.8.1. Forest structure and above ground biomass relationship

Analysis of relationship between forest structure and above ground biomass is performed within the simulated grid size. **Figure 16.** to **Figure 20.** show the superiority of basal area among other structural attributes in relation to AGB. Simulations show that stand basal area is strongly correlated with all AGB models. Table 4. shows the significant high correlation coefficient between stand basal area and AGB which remain above 0.86 for each simulated grid size and AGB models. Another structural attribute having relatively high correlation with AGB is quadratic mean diameter (QMD). The highest correlation coefficient between QMD and AGB is within ten meters grid which has value of 0.81, 0.84, and 0.80 for Brown model, Chave eq.1 and Chave eq. 2 respectively. As visually observed in **Figure 18.** structural diversity measures are having relatively high correlation with all AGB models within the 20 m grid size. The extensions of Shannon index to DBH, height and species has the second highest correlation coefficient after stand basal area. In contrary, stand density and species diversity have low correlation for each simulated grid size and AGB models.

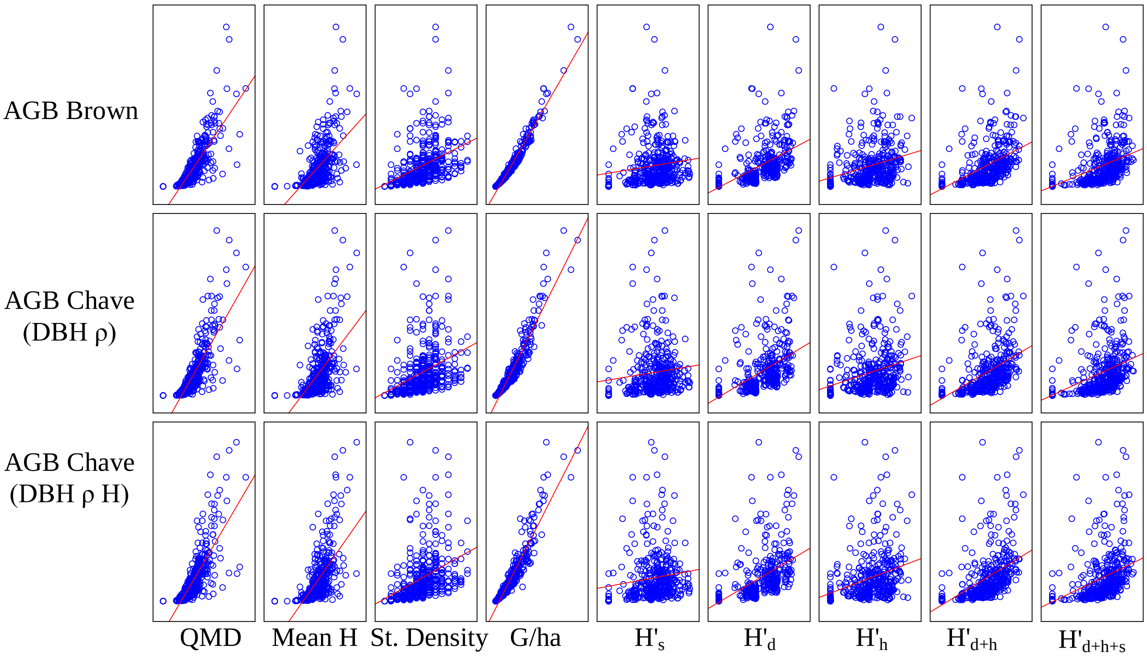


Figure 16. Scatterplot between diversity attributes and AGB at five meter grid size (n = 400)

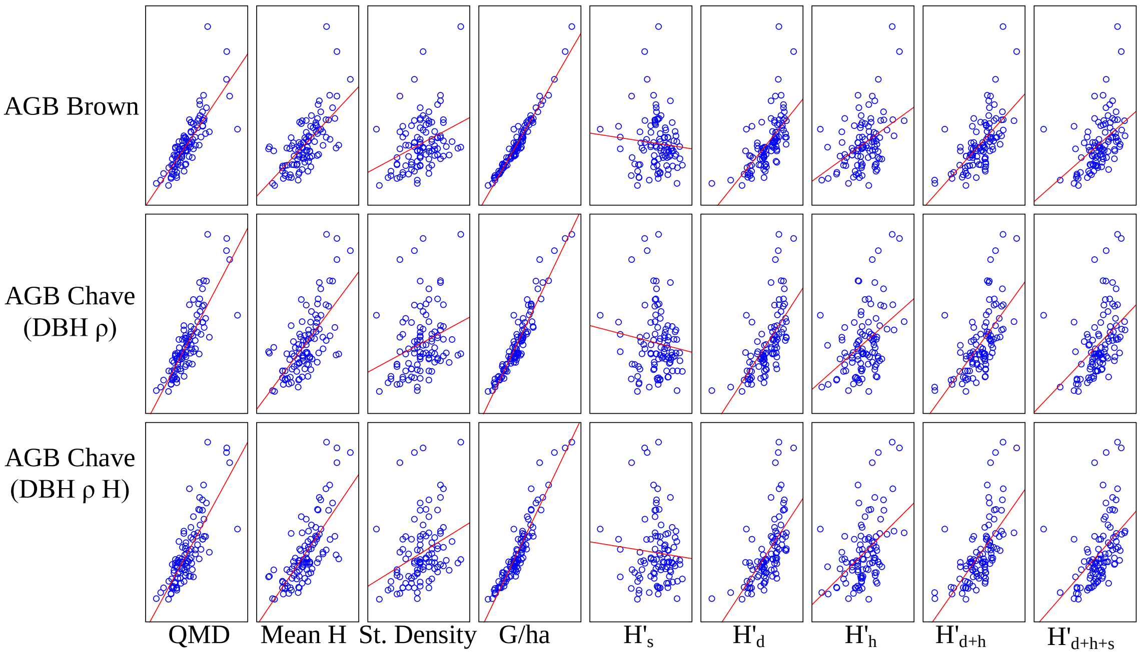


Figure 17. Scatterplot between diversity attributes and AGB at ten meter grid size (n = 100)

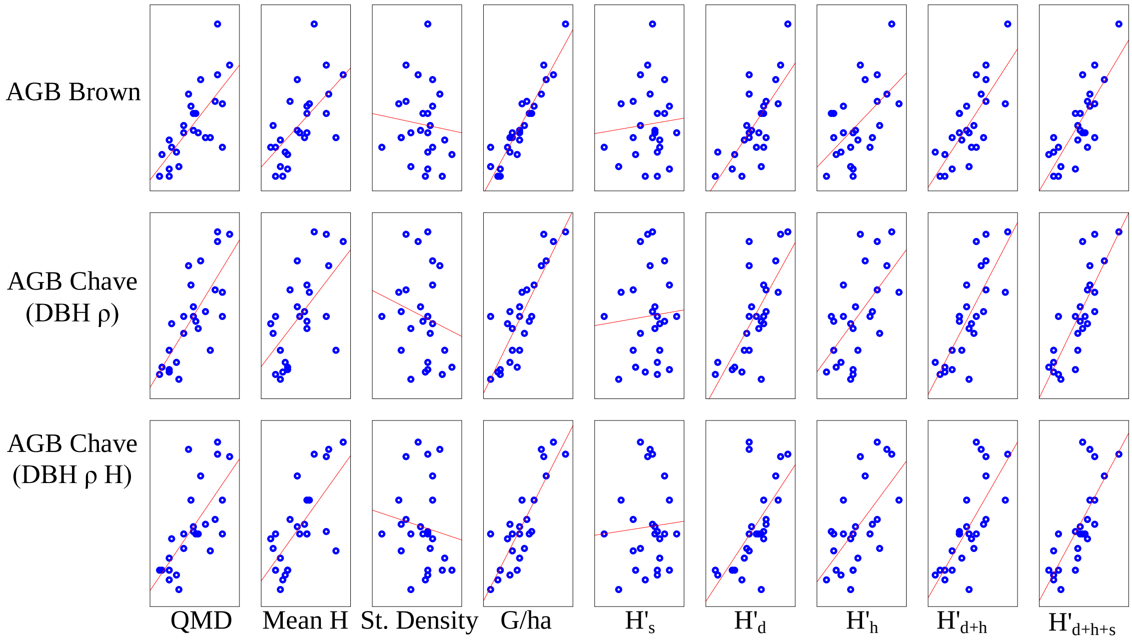


Figure 18. Scatterplot between diversity attributes and AGB at 20 m grid size (n = 25)

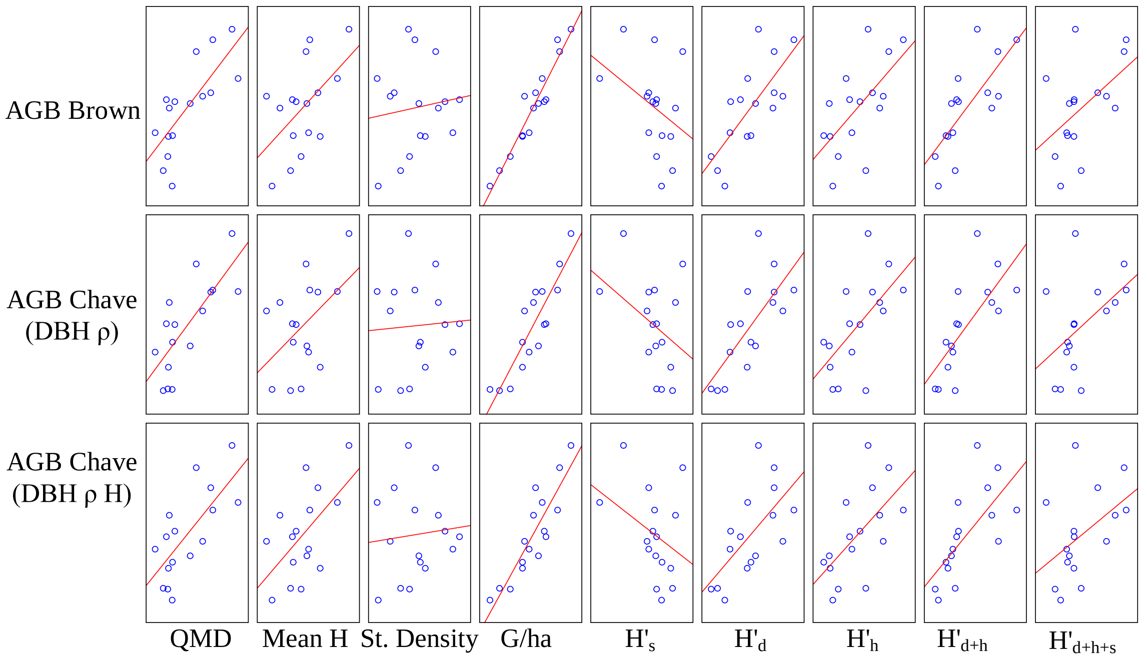


Figure 19. Scatterplot between diversity attributes and AGB at 25 m grid size (n = 16)

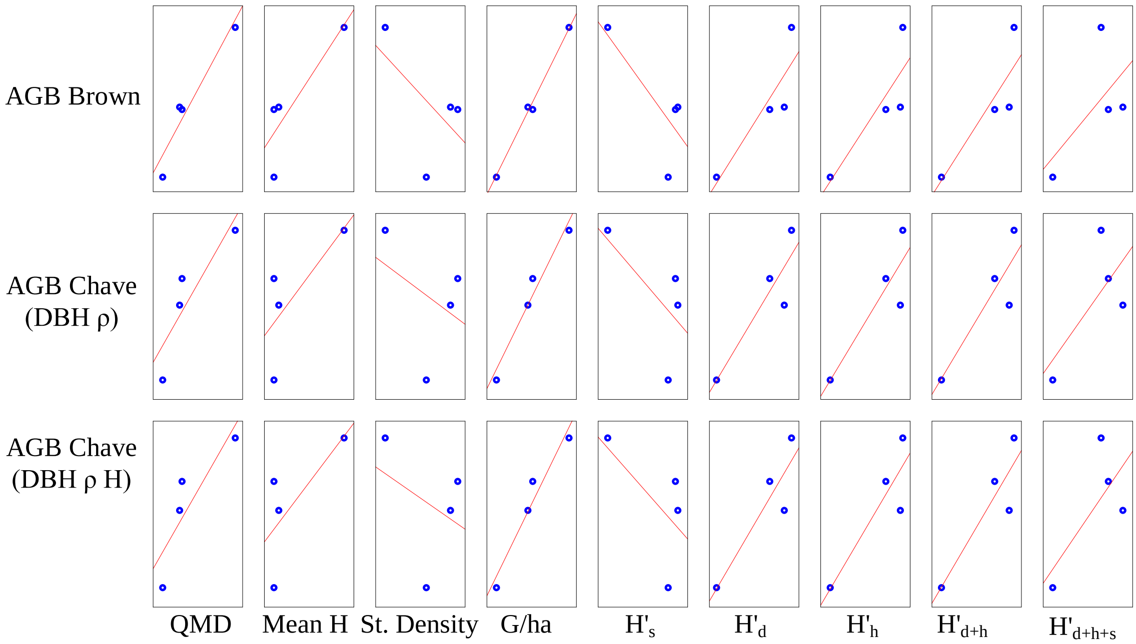


Figure 20. Scatterplot between structural attributes and AGB at 50 m grid size (n=4)

Table 4. Correlation coefficient of structural attributes and AGB

Biomass model	Structural attributes	Grid size				
		5m	10 m	20 m	25 m	50 m
		N = 400	N = 100	N = 25	N = 16	N = 4
Brown	QMD	0.79*	0.81*	0.71*	0.75*	0.96*
	Mean height	0.56*	0.67*	0.63*	0.54*	0.87
	Stand density	0.41*	0.35*	-0.10	0.13	-0.57
	Stand basal area	0.98*	0.98*	0.94*	0.96*	1.00*
	H's	0.14*	-0.09	0.08	-0.37	-0.77
	H'd	0.50*	0.66*	0.72*	0.73*	0.87
	H'h	0.28*	0.43*	0.57*	0.62*	0.84
	H'$_{d+h}$	0.46*	0.64*	0.77*	0.74*	0.86
	H'$_{d+h+s}$	0.36*	0.48*	0.80*	0.50*	0.61
Chave (DBH, ρ)	QMD	0.78*	0.84*	0.74*	0.76*	0.89
	Mean height	0.56*	0.68*	0.61*	0.49	0.75
	Stand density	0.37*	0.28*	-0.19	0.06	-0.38
	Stand basal area	0.95*	0.95*	0.86*	0.89*	0.98*
	H's	0.12*	-0.12	0.07	-0.38	-0.63
	H'd	0.48*	0.66*	0.71*	0.73*	0.89
	H'h	0.26*	0.43*	0.60*	0.62*	0.88
	H'$_{d+h}$	0.43*	0.64*	0.78*	0.73*	0.89
	H'$_{d+h+s}$	0.33*	0.46*	0.81*	0.49	0.70

Biomass model	Structural attributes	Grid 5 m	10 m	20 m	25 m	50 m
Chave (DBH, ρ, H)	QMD	0.76*	0.80*	0.69*	0.72*	0.87
	Mean height	0.60*	0.74*	0.68*	0.58*	0.72
	Stand density	0.38*	0.32*	-0.13	0.09	-0.35
	Stand basal area	0.94*	0.94*	0.86*	0.89*	0.98*
	H's	0.13*	-0.08	0.06	-0.35	-0.61
	H'd	0.48*	0.64*	0.63*	0.65*	0.90
	H'h	0.30*	0.48*	0.62*	0.60*	0.89
	H'_{d+h}	0.45*	0.66*	0.74*	0.68*	0.90
	H'_{d+h+s}	0.35*	0.50*	0.76*	0.46	0.72

* significant at $p < 0.05$

3.8.2. Images spectral and structural attributes relationship

Analysis of relationship between images spectral and structural attributes in the original grid position showing no correlation between Rapideye original bands nor the vegetation indices and structural attributes. However, grid-specific correlation analysis show a consistent correlation of NDVI and SAVI with the stand density.

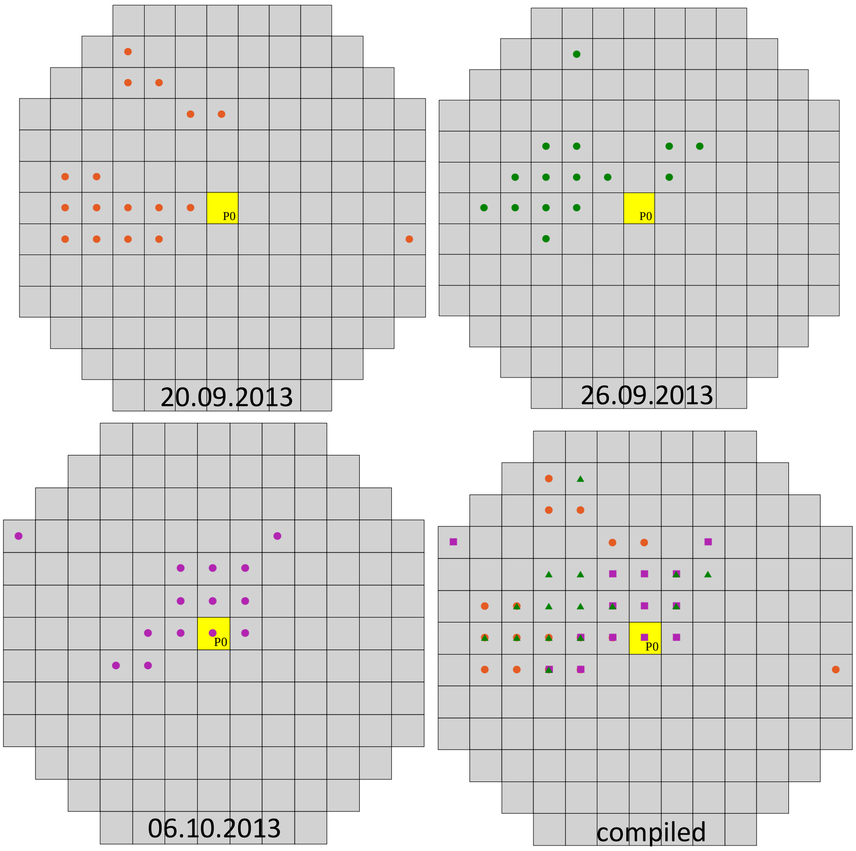


Figure 21. Distribution of the highest coefficient correlation of NDVI and stand density within probability grids

3.8.2. Images spectral and aboveground biomass relationship

The analysis of correlation between image spectral and aboveground biomass show no correlation in the original grid position. Simulation using simulated grid size giving no improvement in increasing the correlation coefficient. Simulation of probability grids show similarly.

4. Discussion

The estimation of forest biomass is an essential key element to determine carbon stocks and their changes over time. Such estimates are needed as basis for carbon accounting on large areas. The choice of a biomass model is thereby a serious factor of uncertainty for market mechanisms like e.g. REDD. This study shows that different models applied to the same data collected in the Sabangau National park in Kalimantan result in significantly different estimates of above ground biomass and carbon stocks. As these field observations are also used as ground truth for remote sensing analysis and to produce e.g. carbon maps, the accuracy of these final products is as much affected by these problems as any other statistical estimate of mean values. One of the major problems in this context is how the final choice of a specific model could be justified. Both applied models (Brown 1997, Chave 2005) are generalized models that are derived based on compiled data from the whole humid tropics. They are here applied to a local population that is in the humid tropics but is also a special example in many respects. Swamp forests cannot necessarily be compared to the mean growing conditions in the humid tropics. Further, the species mixture and forest structure found in the study site is special to this biotope. The common statistical estimates on the model performance, like e.g. the reported R^2 of the models is in both cases very high ($R^2>0.9$). However, these statistics are derived from the dataset used for model development and refer to the model performance in this population exclusively. They do not allow any conclusion on how well the models fit a certain local population. In the actual case it is likely, that the data used by Chave and Brown do not contain any trees from swamp forests at all.

It is interesting to note that the difference between the two Chave models applied here, and that is a consequence of considering the actual wood density of the existing tree species, is relatively large. At the same time predictions of the model of Chave become more similar to those of the Brown model, if the height variable is considered. This could also be evidence on the special characteristics of tree species in the swamp forest. Compared to trees growing on mineral soils, the poor nutrition in a swamp might lead to much slower growth of the trees. From temperate forests, where trees only grow in a certain period, it is known that slow growth is often related to higher wood density. The wood density might also help to "adapt" the general model to the special site conditions in the actual case.

The results show that, depending on the choice of a model, different estimates could be derived. As no own data from destructive sampling was collected in the study site, a final decision about a suitable model is not possible. Therefore the model predictions would need to be compared to a sufficient number of own observations on single tree biomass. This is a very usual case in carbon projects.

As for the remote sensing data, it is surprising that none of the RapidEye spectral bands are able to capture the variability of the biomass in the field. The RapidEye has been advertised as so called vegetation detector. With the Red Edge band as its prime unique feature, RapidEye is expected to easily characterize vegetated area, including estimate the biomass. In the one hand, Red Edge band provides the advantages in monitoring health status as the function of chlorophyll within the forest. On the other hand, it has no correlation with the forest aboveground biomass. However, the correlation between vegetation indices and stand density show a promising result to determine horizontal structure of the forest, although it needs further investigation.

5. Conclusion

The study found that species identification may contribute to the uncertainty on estimation of Above Ground Biomass (AGB), in particular species based AGB estimation. Wood density value found to be significantly affect to the estimation of individual tree biomass which in turn affecting the estimation of the forest stand.

The simulated grid size demonstrates an alternative option to analyze inventory data from a small sample area. Image processing by applying spectral enhancement such as vegetation indices may reduce the difference of original spectral band in a multi series RapidEye data. Vegetation indices gives a promising result in determining forest structure, although it is still limited to stand density as a horizontal structural attribute. However, further investigation is needed to evaluate the capability of RapidEye image spectral to estimate aboveground biomass.

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I hereby assure that this thesis was exclusively made by myself and that I have used no other sources and aids then the ones enlisted

Göttingen, 30.09.2014 Edwine Setia Purnama