The Use of LiDAR Remote Sensing in Measuring Forest Carbon Stocks

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Abstract

Atmospheric carbon levels have increased dramatically since the industrial revolution, creating an increasing concern in forming a better understanding of the global carbon budget. A key part of this budget involves forest biomass and its ability to act as a source of carbon sink or carbon gain. It is understood that terrestrial areas serve as a large source of carbon sink in terms of the global carbon budget, however the degree of spatial variation, particularly with respect to densely vegetated areas, is less certain. Advancements in LiDAR technology, an active remote sensing instrument, have been key to researchers' abilities to accurately measure these types of forest parameters. Lidar instrumentation can be used at three different scales including terrestrial, airborne, and space-born. Researchers have developed strategies involving the use of airborne lidar coupled with satellite data to develop cost-effective, high-resolution maps of carbon stocks and emissions in these densely vegetated areas. Airborne lidar has helped these researchers to observe to effects of forest degradation and secondary growth at large scales, such as the Columbian Amazon, which saw an increase in regional carbon emission of 47% from 1999 to 2009 dude to selective logging with an offset of only 18% provided by secondary growth. Great improvements have also been made with respect to space-born lidar data, particularly with the launch of ESA's Biomass satellite, which is set for launch in 2020. Biomass will assay the entire range of global vegetation on a 6-month rotation, providing useful information to create an accurate representation of the global carbon cycle. This paper will highlight the importance of lidar remote sensing in estimating forest biomass, provide information on the instrument and data processing techniques, and discuss recent work involving the application of lidar data in highly productive regions.

1. Introduction

In recent years much attention has been paid to estimating forest biomass due to its close relationship to carbon storage, which is crucial in understanding the carbon cycle in the environment. Biomass is typically defined as the oven-dry mass of the above ground portion of a particular group of vegetation (Brown, 1997, 2002), which can provide insight on how much carbon is stored in a given forested area. Global carbon emissions have increased since the industrial revolution. According to the International Energy Agency (IEA), atmospheric levels approached 400 ppm in 2012. An accurate estimation of terrestrial carbon storage is required to determine its role in the global carbon budget, to estimate the degree that anthropogenic disturbances such as land use are changing the cycle, and for monitoring mitigation efforts that rely on carbon sequestration through reforestation (Lefsky et al. 2002).

Light detection and ranging, also known as LiDAR (or lidar), an active remote sensing technology, has been instrumental in the ability to accurately measure forest inventories. Traditional remote sensing systems detect vegetation cover using passive optical-imaging sensors. Passive systems use the variability in vegetation spectral responses from the visible and near-infrared spectral regions to assay vegetation condition. These passive systems have allowed for the use of widely accepted algorithms such as the Normalized Difference Vegetation Index (NDVI) which has been correlated to vegetation structural parameters such as Leaf Area Index (LAI) of canopy the canopy (Fallah Vazirbad and Karslioglu 2011).

Unlike passive optical imaging sensors, which usually provide detailed measurements of horizontal distribution in vegetation canopies, lidar systems can produce more accurate data in both the horizontal and vertical dimensions (Lim et al., 2003). Although passive systems tend to be limited to a horizontal scope, some instruments are capable of producing three-dimensional imagery. For example, the Corona Satellite, which was declassified in 1995 was equipped with fore and aft cameras, pointing at a 15 degree angle, one forward and one backward. This orientation allowed for the creation of panoramic three-dimensional imagery (Greer 1960). Lidar-based instruments from space-borne, airborne, and terrestrial platforms combined with plot-level calibration provide a direct means of measuring forest characteristics, particularly aboveground carbon density (ACD), which were previously unachievable by passive remote sensing imagery (Asner et al., 2012).

Lidar remote sensing systems have been used to measure various kinds of forest parameters including tree height, crown size, diameter at breast height (DBH), canopy density, crown volume, tree species, and aboveground carbon density (Means et al., 1999, 2000).

Although lidar instruments are capable of producing highly accurate data over vast areas, direct estimation of carbon storage in moderate to high biomass forests remains a major difficulty. While remote sensing has had considerable success in measuring vegetation characteristics in areas where plant canopy cover is relatively sparse, quantifying vegetation structure where LAI exceeds three has been less successful (Lefsky et al., 2002). High LA1 forests, which generally have high above-ground biomass, occur in the boreal, temperate and tropical regions. These forests cover less than 35% of the Earth's terrestrial surface, yet account for 67% of terrestrial net primary productivity (NPP) and 89% of terrestrial biomass (Lefsky et al., 2002). Given their prominent role in global biogeochemistry and the likelihood that these highly productive areas could be essential for carbon sequestration, a better classification of high biomass forests using remote sensing data is needed. This paper will discuss the role of lidar remote sensing in estimating forest biomass, provide information on the instrument itself, as well as highlight recent work in implementing lidar data in highly productive regions.

2. What is Lidar

This section will discuss the basic components and principles of lidar technology. It will include a description of how lidar works, commonly used terminology and their meaning, a brief overview of applications, as well as a section on the history and development of lidar. Later sections will go into further detail explaining how lidar is used in biomass estimation, methods and models of operation, as well as the discussion of key studies in recent years.

2.1. Overview

Lidar has become an established method for collecting very dense and accurate elevation data across landscapes, shallow-water areas, glacial ice, and other designated study sites. This active remote-sensing technique uses laser light pulses compared to radar remote-sensing methods, which uses radio waves. Lidar instruments are typically flown with planes or used via satellite to gather information. They can rapidly collect data points over vast areas.

Lidar data can also be collected from ground-based mobile and stationary platforms. These later collection techniques are capable of producing extremely high accuracies and point densities, but they are limited to easily-accessible areas. The collection of elevation data using lidar has several advantages over most other methods. These advantages include higher resolutions, centimeter accuracies, and ground detection in forested terrain (NOAA 2012). The following section will discuss the basics of lidar, common terminology, a brief history, and some common applications of lidar data.

2.2. What is Lidar

LiDAR is an acronym for light detection and ranging. This is a type of remote sensing technology that emits intense, focused beams of light and measures the time it takes for the reflected beams to be detected by the sensor. This information is then used to compute ranges, or distances, to objects. In this manner, lidar is analogous to radar or radio detection and ranging. However, lidar is based on discrete pulses of laser light, allowing it to accurately detect and locate much smaller objects. Lidar instruments are able to generate three-dimensional coordinates of the target object, such as x,y,z or latitude, longitude, and elevation, which are computed from 1) this time difference between the emission and return of the laser pulse, 2) the angle at which the pulse was emitted, and 3) the absolute location of the sensor on or above the Earth’s surface.

As stated previously, there are two classes of remote sensing technologies, passive systems and active systems, which are differentiated by the source of energy used to detect the desired target. Lidar technologies are active systems because they emit pulses of light, i.e. the laser, and detect the light which is reflected back to the sensor. This ‘active’ nature allows lidar data to be collected at night when the air is usually clearer, however unlike radar, lidar cannot penetrate clouds, rain, or dust and must be used under fair weather conditions.

Lidar instruments are able to measure the Earth’s surface very rapidly at sampling rates greater than 150 kilohertz and 150,000 pulses per second. The resulting product is a densely spaced network of highly accurate georeferenced elevation points (Figure 1), often called a point cloud, that can be used to generate three dimensional representation of the Earth's surface features. Typically, lidar derived elevations have absolute accuracies of about 15-30 centimeters for the older systems data and 10-20 centimeters for more recent devices, while relative accuracies are even better. The accuracy of lidar data is an important aspect, which will be discussed in further detail in later sections.

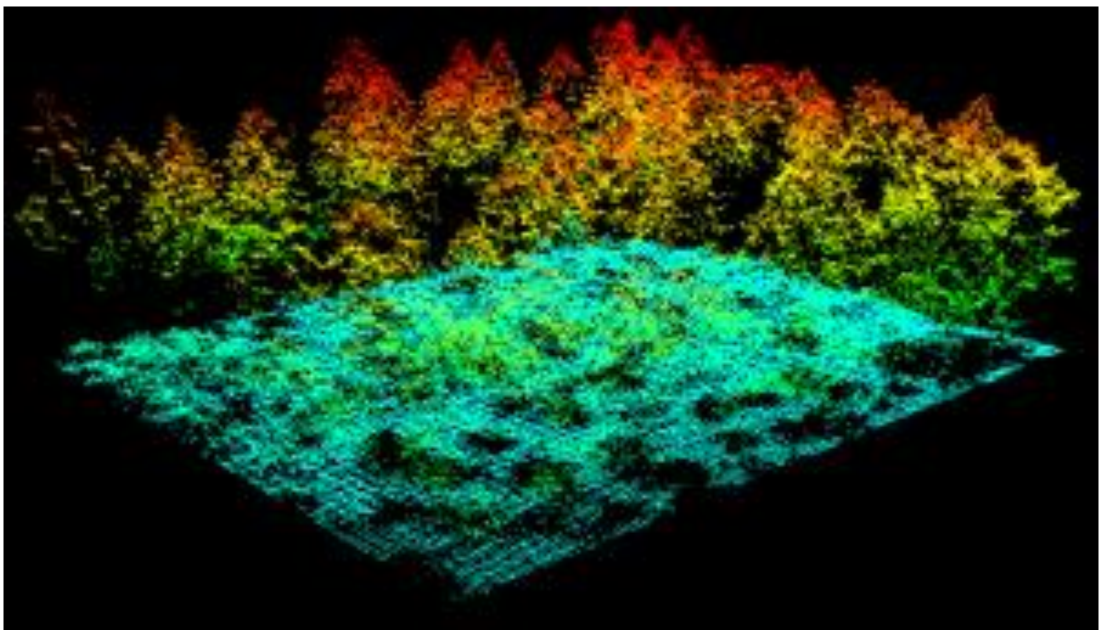

Figure 1: An example of lidar point cloud data taken of a forest canopy. These types of images are made possible due to the ability to understand the position and orientation of the sensor when laser pulses are emitted, the calculation of the three-dimensional coordinate for each laser hit, and the ability to achieve multiple hits per square meter. (Forest Inventory Research Group at UMB-INA)

2.3. Lidar Terminology

A discussion of lidar often includes technical terms that describe the level of accuracy, data collection, and the ensuing processing steps. Below is a list of several common terminologies and abbreviations associated with lidar as well as a brief description taken from the National Oceanic and Atmospheric Administration (NOAA 2012).

LAS- and abbreviation for laser file format. The LAS file format is a public file format for the interchange of three dimensional point cloud data between data users. LAS is a binary file format that maintains information specific to the lidar nature of the data while not being overly complex.

RMSE- abbreviation for root mean square error, which is a measure of the accuracy of the data. This is similar to the measure of standard deviation if there is no bias in the data.

FVA- Fundamental Vertical Accuracy. A measure of the accuracy of the data in open areas at a 95% confidence level. This is calculated from the RMSE using the equation $RMSE \times 1.96 = FVA$

Classification- data that have been processed to define the type of object from which the pulses have been reflected. The most common categorization is to classify the data sets for points that are considered “bare earth” and those that are not, which are “unclassified”.

Return Number- many lidar systems are able to capture the first, second, third, and last return from a single laser pulse. The return number can be used to help determine what the reflected pulse is from such as the canopy, understory, or surface.

Point Spacing- a measure of how close the laser points are to each other, which is analogous to the pixel size of aerial images. The point spacing determines the resolution of the derived gridded products.

Pulse Rate- the number of discrete laser emissions per second. Systems used more recently have been able to emit up to 300,000 pulses per second. More common data collection methods are on the order of 50,000 to 150,000 pulses per second.

Intensity Data- a measurement of the strength of the laser return. These values represent how well the object reflected to wavelength of light used by the laser system (usually in nanometers). These data resemble a black and white photo but cannot be interpreted as such.

RTK GPS (Real Time Kinematic GPS)- a satellite navigation that uses the carrier phase that transmits the Global Positioning System signal instead of the GPS signal itself. The actual GPS signal has a frequency of about 1 megahertz, while the carrier wave has a frequency of about 1500 megahertz. The carrier phase is much more costly to use, however it produces a much more accurate position in relation to its higher frequency.

DEM or Digital Elevation Model- a surface created from elevation point data to represent the surface topography. A DEM is more often and easily used in a geographic information system (GIS) or computer-aided design (CAD) application than the raw point data it originates from.

2.4. Principles and Techniques

The basic concepts of lidar technology are fairly straightforward (Figure 2). That is, measure the time it takes a laser pulse to strike an object then return to the sensor, which has a known location due to direct georeferencing systems, determine the distance using the travel time, record the laser angle, then compute where the reflecting object (surface, tree, canopy, etc.) is located in three dimensions using this information. However, to achieve such a high level of accuracy, this process is much more complicated. It is crucial to know the location of the airplane (within about one centimeter) as if flies at speeds over 100 miles per hour, shifting in all directions, while keeping track of hundreds of thousands of lidar pulses per second. Fortunately, several technologies have been implemented which make this type of rapid data capture possible including the use of the Global Positioning System (GPS) and precision gyroscopes which allow for an accurate measurement of the of the aircraft's absolute location.

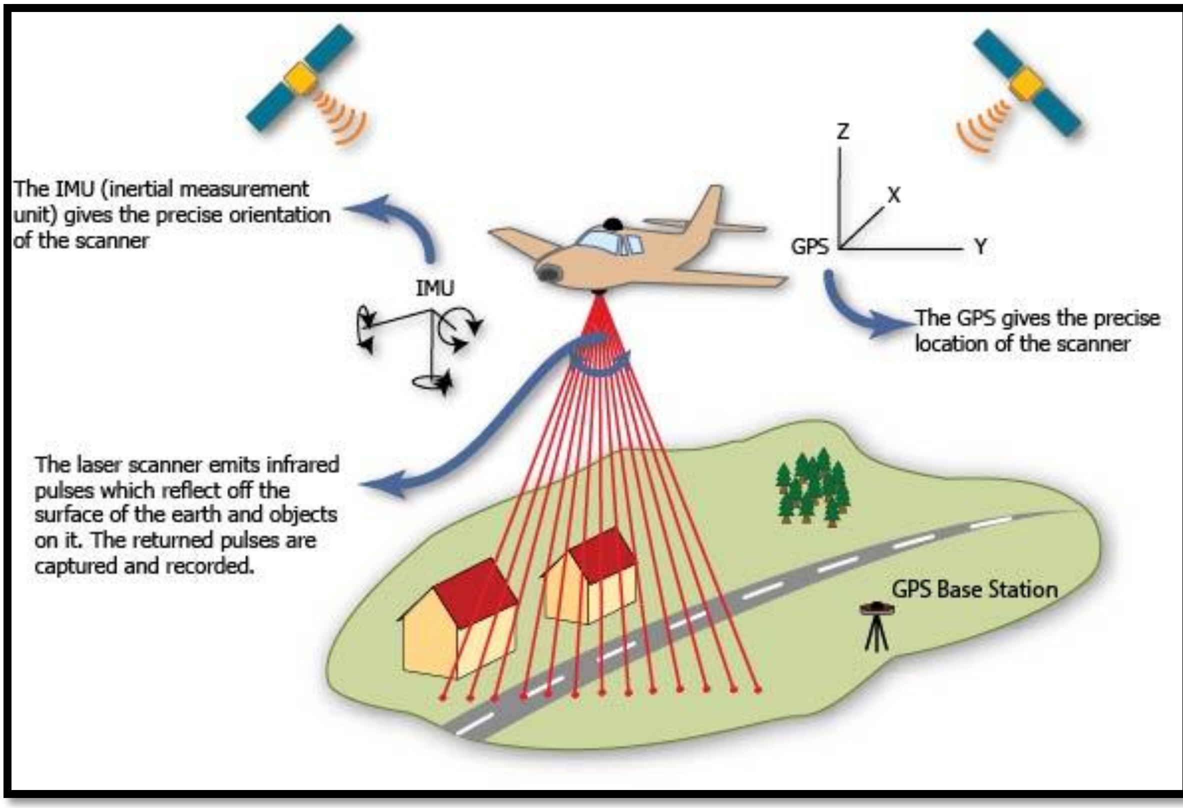

Figure 2: A schematic diagram of airborne lidar remote sensing. Georeferencing of lidar points uses GPS to derive the position of the aircraft, INS to determine the pointing direction of the sensor, and the lidar range to extrapolate the coordinates of a target point on the ground. Source: Geospatial Modeling and Visualization.

Key advancements in Inertial Navigations Systems (INS) or Inertial Measuring Units (IMU) have been influential in making the exact positioning of the plane possible. These types of systems are capable of measuring movement in all directions and combining these measurements into a single position. Although major advances have been made, these systems are not perfect and lose precision after just a few seconds. To account for this lack of this lack of precision, a very highly sophisticated GPS unit, which records several types of signals from the GPS satellites, is used to “update or reset” the INS or IMU every few seconds. The GPS positions are recorded by the plane and ground station with a known position. The ground station is used to provide a correction factor to the GPS position recorded by the plane.

Much like the INS and IMU's, lidar systems have improved considerably in recent years. Early commercial units were capable of 10,000 points or 10 kilohertz per second and were much larger. More recent instruments are lighter, compact, have higher angular precision, and can process multiple laser returns in the air. This is done by emitting a second laser pulse before returns from the previous laser shot are received, which allows for pulse rates of over 300,000 or 300 kilohertz per second. Multiple return systems, which are quite common, can capture up to five returns per pulse. This can increase the amount of data by 30% or more (100,000 pulses/second ~ 130,000 returns/second) and increases the ability to study the three-dimensional structure of features above the ground surface such as the forest canopy and understory. The different forms of data acquisition, including multiple returns, will be discussed in greater detail in later sections.

2.5. Overview of Applications

As stated previously, lidar has several advantages over many other remote sensing techniques. Chief among these advantages are high accuracies, high point density, large coverage, and the ability to resample quickly and efficiently. This allows for the possibility to map discrete changes at a very high resolution and cover large areas uniformly, quickly, and accurately. Some common applications of lidar data include updating and creating flood maps, coastal change mapping, and forestry studies. The need for more accurate flood insurance maps was a major driver in the development and use of lidar data. It allowed researches to more accurately delineate flood boundaries, resulting in a more precise interpretation of flood insurance policies. Mapping the coastal zone is an application the highlights the use of lidar data along with Geographic Information Systems (GIS), which increases the utility of both data sets. The coastal zone changes on very short timescales, is densely populated, and contains many natural habitats that are highly dependent on elevation. With an increasing concern over sea-level rise, lidar data can be applied to restoration solutions in critical areas, as well as sustainable planning to minimize future impacts. Forest biomass estimation often involves plot sampling which are then extrapolated to represent an entire forest stand. These methods are often very costly, time consuming, and make it difficult to study forested areas that are not easily accessible. Lidar data can be used to count trees and measure tree height, crown width, and crown depth. From these measurements, the standing volume of timber can be estimated on an individual tree basis, or at the stand level with a larger footprint. Although the use of lidar data covers a wide range of applications, this paper will focus more closely on its use in forest ecology, with a particular focus on biomass estimation.

2.6. History

Lidar technology was originally developed over 40 years ago for meteorological uses relating to mapping particles in the atmosphere. These ground based systems had far less positional complexity than airborne mapping devices. The development of global positioning systems in the 1980's opened up the applications to moving sensors, or airborne lidar. Lidar gained further recognition in the 90's with the development of the first commercial airborne lidar system, along with several government projects such as SHOALS and NASA's Clementine project. With such a gain in popularity in recent years, the further development of lidar, along with its ability to obtain large amounts of detailed data, has allowed for the standardization of data formats and processing techniques, making this instrument even more alluring to research scientists spanning a wide range of fields including meteorology, geology, transportation, ecology, agriculture, and archaeology.

3. The Use of Lidar in Biomass Estimation

Although lidar can be used for a variety of study areas this paper will focus more closely on its use in biomass estimation and measuring carbon storage in forested areas. Section 3 covers the systems of lidar including the three different types of platforms: space-borne, airborne, and terrestrial. It will also discuss how data is acquired using lidar technology in first and last return, multiple return, and full wave form.

3.1. Systems

Lidar systems make use of the time of flight principle of phase-based differences to measure the distances of objects. As discussed earlier, this is done by detecting the time interval between the sent and return laser pulses which are backscattered from an object. The lidar point cloud of returns generates a three-dimensional digital representation of the vegetation structure in which each point is identified by a set of XYZ coordinates (See figure 2) (Maas et al 2008, Cote et al 2011).

A lidar system consists of a laser ranging unit, a scanning instrument such as an oscillating mirror or rotating prism, and a direct geo-referencing navigation unit (which uses the global positioning systems – GPS and inertial navigation system- INS discussed above). The choice of the platform depends mainly on the desired application and scale of study. Space-borne systems map the globe for researchers and experimental purposes. Airborne systems collect data for national or regional investigations. Terrestrial platforms are frequently used to produce three dimensional models of man-made structures or small scale natural resource studies such as small forested areas. With several different systems, the basic principle and technical specification for a sensor installed on a platform such as an Earth orbiting satellite, airplane, helicopter, tripod, or vehicle changes due to the variety of desired applications (Shan and Toth 2009).

In most cases, commercial systems are designed to receive data from a small footprint, such as a 0.20-3.00 meter diameter depending on the flying height and beam divergence, with higher repetition frequency (Mallet and Bretar 2009). These systems acquire a high point density and an accurate height determination. However, small footprint systems often miss tree tops which cause under estimation in tree height. Therefore, it is hard to define whether the ground has been detected under dense vegetation or not, making it difficult to estimate ground and tree heights (Dubayah and Blair 2000). On the other hand, large footprint systems such as those with a 10-70m diameter, increase the chance to hit both the ground and the tree top which eliminates the biases of small footprint systems. Therefore, the return waveform gives a record of vertical distribution of the captured surface within a wider area, providing important information for biomass estimation. The first experimental full waveform topographic systems were large footprint systems which were mostly carried by satellite platforms. At higher flying heights, pulses must be fired at a lower frequency and with a higher energy to penetrate into the forest canopy as much as possible (Fallah Vazirbad and Karslioglu 2011, Mallet and Bretar 2009).

3.1.1. Space-borne

Until recently, the geoscience laser altimeter system (GLAS) was the only lidar operating space-born system. GLAS was an important part of the NASA earth science enterprise carried on the ice, cloud, and land elevation satellite (ICESat) from January 12, 2003 (Afzal et al., 2007). This instrument contained three lasers, each of which had a 1064 nm lidar channel for surface altimetry and dense cloud heights and a 532 nm lidar channel for the vertical distribution of clouds and aerosols (NASA, 2007). The main objective of the GLAS instrument was to measure the ice sheet elevations and changes in elevation through time. Secondly, GLAS detected clouds, atmospheric aerosol vertical profiles, terrain elevation, vegetation cover, and sea ice thickness (Figure 3). ICESat was ultimately limited by the failure of the three lasers onboard GLAS in October 2009 and retired later in February 2010. Fortunately, the European Space Agency has developed a new satellite known as BIOMASS which is set for launch in 2020. The Satellite will be equipped with a P-Band Synthetic Aperture Radar (PAR), which aid in the development of highly accurate maps of tropical, temperature and boreal forest biomass (ESA 2012). As discussed earlier, these forest systems contain rather dense vegetation making it difficult to acquire data using terrestrial and airborne technology. BIOMASS will ultimately aid in improving the understanding of the global carbon cycle and reduce uncertainties of carbon stocks and fluxes associated with the terrestrial biosphere (ESA 2012).

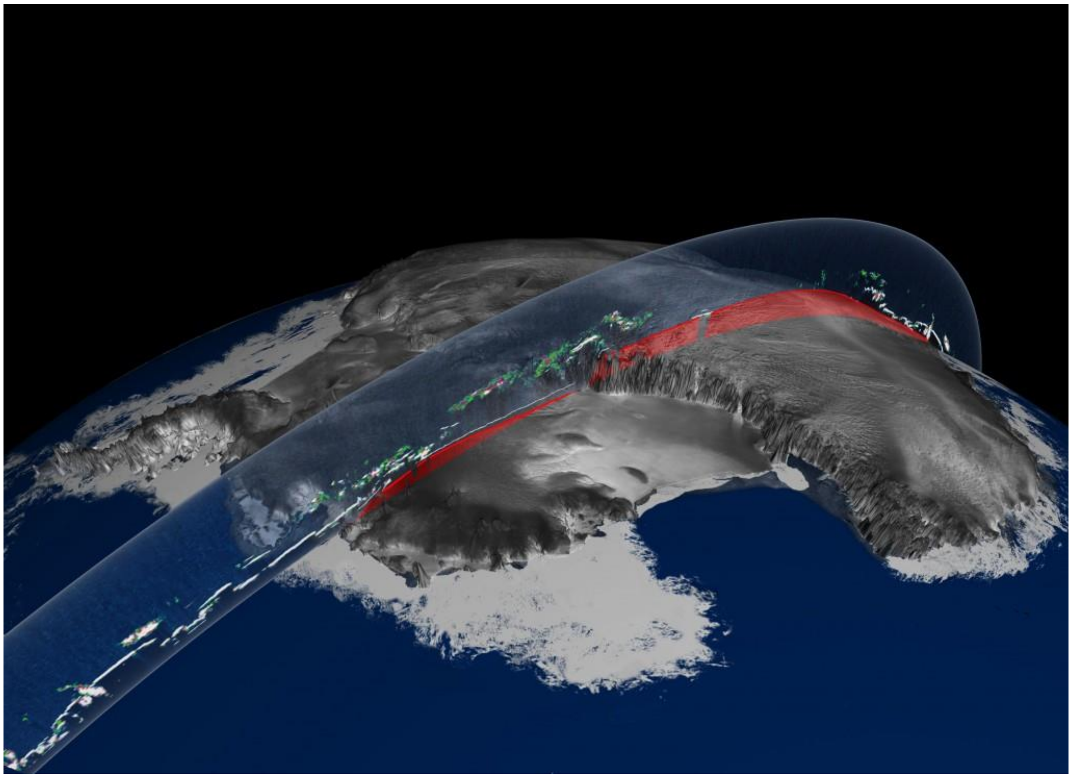

Figure 3: An illustration of ice sheet elevation and cloud data over Antarctica taken from the GLAS instrument onboard ICESat in February 2003. Source: NASA

Nevertheless, only a small number of studies have used airborne lidar data to evaluate the DTM which was derived from satellite laser altimetry GLAS data over forested areas. GLAS which only operated on board ICESat, records the full waveform returns, and provides a high precision elevation data with nearly global spatial coverage at a low end user cost (Fallah Vazirbad and Karslioglu 2011). Space-borne data are mainly used to model the global canopy height for evaluating carbon budget (Xing et al., 2010). Duong et al. (2007, 2009) compared terrain and feature heights derived from the satellite (GLAS) observations with a nationwide airborne lidar dataset (the Actual Height model of the Netherlands: AHN). Their findings showed little difference between the two derived heights with an average below 25 cm over bare ground and urban areas. Over forests, the differences were even smaller, but with a slightly larger standard deviation of about 60 cm (Chen, 2010). Harding et al. (2001) used GLAS full waveform data to generate an average forest canopy height model (CHM). Their results highlighted the variations of important canopy attributes including height, depth, and the over-story, mid-story, and under-story forest layers. Sun et al. (2007,2008) applied GLAS waveforms to estimate the forest canopy height in the flat area in Northern China mountains. They found that the ICESat-derived forest height indices were well correlated with the field-measured maximum forest height ($R^2 = 0.75$).

3.1.2. Airborne

An extensive test of the laser profiler was performed at the Stuttgart University (1990) where Differential Global Positioning System (DGPS) and Inertial Measurement Unit (IMU) was integrated in the laser system for the first time, which provided precise positioning and orientation (attitude) of the airborne platform (Fallah Vazirbad and Karslioglu 2011). Soon after that, the scanning mechanism was designed by Optech Company (Canada - ALTM system). The laser profiler was developed in forestry research by NASA's Goddard space flight center (GSFC) on the basis of Riegl laser rangefinder. It contained a 20 ns wide laser pulse and repetition rate of 2 kHz. There are three main commercial suppliers of airborne laser scanning systems, Optech International Inc., Leica Geosystem, and Riegl which are producing data for the forest inventory and biomass estimation researches. Besides these commercial systems, a number of other systems built by US government research agencies are offered for scientific research purposes, like NASA, ATM, RASCAL, SLICER, Laser Vegetation Imaging Sensor (LVIS), and ScaLARS (Fallah Vazirbad and Karslioglu 2011). LVIS has been developed by NASA for topography mapping, elevation, and forest coverage studies (Figure 4). A special design of scanning system such as the full waveform is required for the scanning of vegetation covered regions to capture the reflected pulse in different returns. This scanner has been used mostly throughout the United States (California, eastern states) and Central America (Costa Rica and Panama). It was also applied in Amazonian forests of Brazil to generate direct measurements of canopy height and a relative aboveground biomass map. (Shan and Toth, 2009)

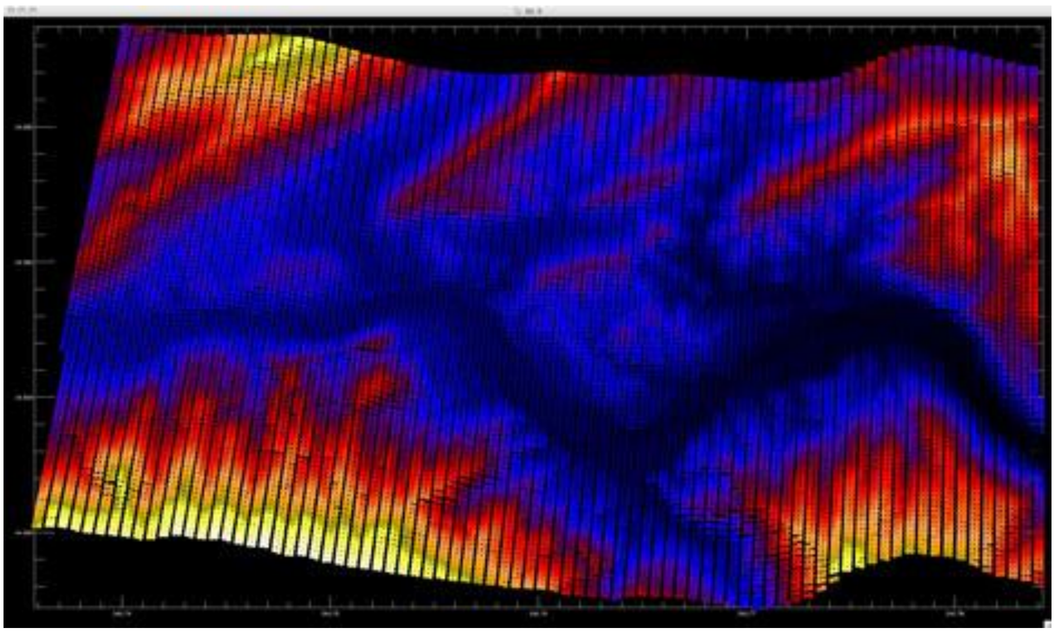

Figure 4: An example of NASA's LVIS scan and beam pattern. This image contains approximately 100 beams across a 2km wide swath. Colors represent surface elevation (blue is low, white/yellow is high). Source: NASA

Perhaps one of the most advanced and influential airborne systems developed in recent years is the Carnegie Airborne Observatory. The CAO is a unique aircraft equipped with specialized optical, chemical, and laser sensors, which together form AToMS, or the Airborne Taxonomic Mapping System. AToMS allowed its founder, Gregory Asner, and his team to create high-resolution, three-dimensional maps of vegetation structure and plant communities throughout tropical forests. While typical satellite forest monitoring programs provide a breadth of coverage, CAO offers immense detail, capturing images of individual trees at a rate of 500,000 or more per minute. This system has the ability to transform how tropical research is conducted. It can help alleviate uncertainties about carbon emissions from deforestation and different forms of forest management, both of which are critical to REDD, the U.N. program for Reducing Emissions from Deforestation and forest Degradation. The findings of the CAO and the use of lidar in tropical forest management will be discussed in further detail in later sections.

3.1.3. Terrestrial

Ground-based, or terrestrial, lidar systems are generally used in close-range, high accuracy applications, making them difficult to use in areas where large coverage is needed. The systems can be classified by two measuring techniques, pulse ranging or time of flight (TOF) and phase measuring technique. Other classifications are also available in relation to the angular scanning technique and coverage of scanner. These include Panorama, Hybrid, and Camera scanners. Panorama scanners carry out distance and angular measurements providing 360˚ angular coverage within the horizontal plane. Types of laser scanners, which perform unrestricted scanning around the rotation axis, fall in the category of Hybrid scanners. The third category of scanners carrying out distance and angular measurements over a limited angular range and in a specific field of view is called Camera scanners (Shan and Toth, 2009). For the range measurements, it is necessary to obtain information about the exterior orientation elements (positions and orientation or attitude angles) of platforms of the terrestrial laser scanner which can be detected during the calibration procedure. Sensitivity of tree volume estimates, which are related to different error sources in the spatial trajectory of the terrestrial lidar, has been analyzed by (Palleja et al. ,2010) where they found that the tree volume is very sensitive to the errors in determining distance and orientation angle. Cote et al. (2011) proposed to estimate the tree structure attributes by means of terrestrial Lidar. They concluded that the main limitation of the use of terrestrial system was the effect of object shading and wind. When considering biomass estimation terrestrial laser scanning may best contribute as a support system to airborne and space-borne lidar.

3.2. Data Acquisition

The measurement process of the laser scanner can be represented by the frequency, intensity, phase, and the travel time of the sent and returned signal. The transmitted and received energy are formulated similar to the Radar equation (Shan and Toth, 2009). This can be expressed as an integral (Mallet and Bretar, 2009) and the range is measured in pulsed systems as seen below:

$$R = c \times t/2 \qquad \text{Equation 1}$$

Where c is the speed of light, t is the two way laser light travel time, and R is the distance measured (Shan and Toth 2009). The equation of the continuous waveform can be used as follows:

$$R = 0.5\ (\emptyset/2\pi)\lambda \qquad \text{Equation 2}$$

Where θ is the phase difference and λ is the wavelength which is operationally between 600 and 1000nm (the Electromagnetic infrared range). This interval is not eye-safe, therefore the optimum performance must be balanced against safety considerations (Fallah Vazirbad and Karslioglu 2011).

In addition to positional data, each lidar observation must also contain the scan angle for each shot together with the measurement of reflectance from the target. Since the calculation of range for the detected pulse involves the elapsed time, the precision of time measurement is of vital importance, especially considering that 7ns sensitivity is needed to distinguish 1m object. This plays a decisive role in the scanning of vegetated areas. In some methods a fraction is used as a constant in the sent and return pulse. In other methods, a centroid of the pulses is taken as a time of reference (Fallah Vazirbad and Karslioglu 2011).

The characteristics of forest inventory from both discrete return (first, last, multi returns) and full waveform recordings are extensively studied by different Lidar approaches such as tree crown detection and biomass estimation (Harding et al., 2001; Coopes et al., 2004; Jang et al., 2008; Brantberg et al., 2003), which will be further discussed below.

3.2.1. First Return, Last Return

Lidar systems can be categorized by the way they process the waveform reflections for each pulse as well as the size of the footprint they record. Systems that record footprints up to 100cm are often called small footprint systems which typically contain frequencies around 15kHz (Heritage and Large, 2009). Early small footprint systems recorded the range only up to the first reflecting object of the first pulse in discrete returns. Fundamentally, a map of all first pulses would result in a model showing only the height of all surface objects. This requires the recording of the last reflecting object in each return signal if there is more than one reflectance, which is often referred to as the last pulse. Although the last pulse data has the potential to penetrate vegetation canopies, in can never be assumed that the last pulse actually reaches the ground and is not reflected form a higher point of the canopy. Also, where low vegetation is involved, the first and last pulse may be too close together to generate a reliable range and ultimately leads to overestimation of the terrain height.

Discrete returns have had considerable use in the literature. Coopes et al. (2004) used airborne discrete returns to indicate canopy crown and height while Lim and Treitz (2004) collected airborne discrete first and last returns to estimate aboveground biomass. First and last returns are also used by Thomas et al. (2006) but the effects of which are not explained on the results of canopy height models.

Fallah Vazirabad and Karslioglu (2010) extracted the tree tops experimentally from the first pulse data because it contains more canopy returns than the ground ones. In discrete return systems, the small diameter of footprints and the high repetition rates of these systems allow for high spatial resolution, which can yield dense distributions of sampled points. Therefore, discrete return systems are preferred for detailed mapping of ground and canopy surface. Lastly, these types of data are readily and widely available, with ongoing and rapid development in forestry studies.

3.2.2. Multi Return

The capability of detecting different returns in the closely placed terrain surfaces depends on instrument parameters such as the laser pulse width (the shorter the better), detector sensitivity, response time, system signal to noise performance, and a few others. In the case of discrete returns more detectors are needed. With this technology the number of pulses between first pulse and last pulse is limited by the number of detectors. That is, the more detectors available, the more pulses that can be used. Thus, there are systems with a second and third pulse aside from the first and last pulse record. In contrast to small footprint systems, large footprint systems (10-100 m) open up the possibility of recording the entire return pulse. Discrete return airborne laser systems (ALS) have the benefit of providing data over a large area, but are restricted by their laser pulse return density (points/m^2 ratio). A system's multiple return recording capabilities are able to produce a point cloud density between 1 and 20 points/m^2 optimistically. Often this level of point density is unsatisfactory to produce a comprehensive 3D model, especially in the vertical view (Moorthy et al. 2011).

When multiple return lidar is used the amount of signal returned as the pulse passes through the canopy triggers the recording of an x,y,z point location at several locations within the canopy and ground surface (see Figure 5). As the laser pulse is reflected by the canopy and sub-canopy forest structure the amount of laser light available to record returns decreases with depth as it penetrates the vegetation. Therefore the number of first and second returns is typically much larger than additional or last of many returns. In order to detect the ground surface in dense forested areas it is often needed to increase the amount of energy per pulse, lower the flight altitude to decrease the pulse travel distance, or increase the pulse density.

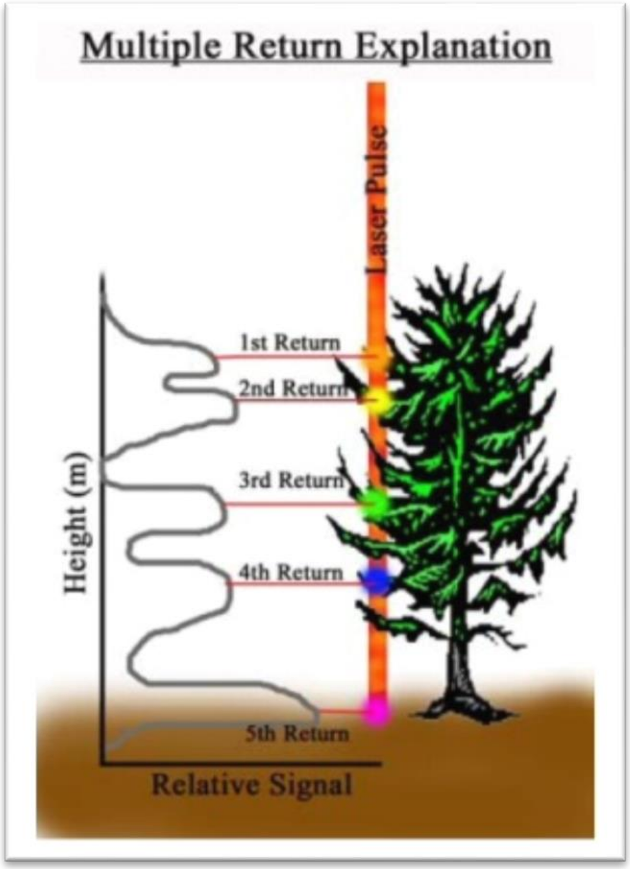

Figure 5: An example of multiple lidar returns from an individual tree. The amount of laser light available decreases with depth in the forest canopy, making it difficult to survey densely forested areas. Source: Pennsylvania State University: Department of Geography.

3.2.3. Full Wave Form

The problems which are mentioned previously in first and last pulse systems for vegetated regions can be alleviated with full waveform technology (Shan and Toth, 2009). For full waveform lidar, energy is reflected back above a specific noise threshold and recorded for given time intervals (see Figure 6). The sensitivity of the sensor is at the level of a few photons per interval (typically 15 cm), and as a result, even small volumes of vegetation can influence the shape of the return waveform. The waveform data can be translated into a detailed description of vertical canopy distribution (location, density, and volume), and can be used to model light transmittance in forest canopies. With full waveform lidar data, canopy heights can be calculated by converting the elapsed time difference between peaks in the amplitude into range values. The advantage of full waveform data is the fact that there is enough precision in the vertical recording for a better estimation of the vertical distribution of trees structure. These devices have been primarily designed for measuring vegetation properties. Extensive research (Harding et al, 2001; Lefsky et al., 2001, 2002; Reitberger et al., 2009) has shown that waveform shape is directly related to canopy biophysical parameters including canopy height, crown size, vertical distribution of canopy, biomass, and leaf area index.

Harding et al. (2001) discussed the canopy height profile detection from full waveform raw data provided by SLICER. The advantages of full waveform recording include an enhanced ability to characterize canopy structure, the ability to concisely describe canopy information over increasingly large areas, and the availability of global data sets. Examples of these data include airborne systems such as SLICER and LVIS, and satellite data like of GLAS. The other advantage of full waveform systems is that they record the entire time varying power of the return signal from all illuminated surfaces on the canopy structure. It is also important to note that previous space-borne lidar data provides only full waveform recordings (Lefsky et al., 2002).

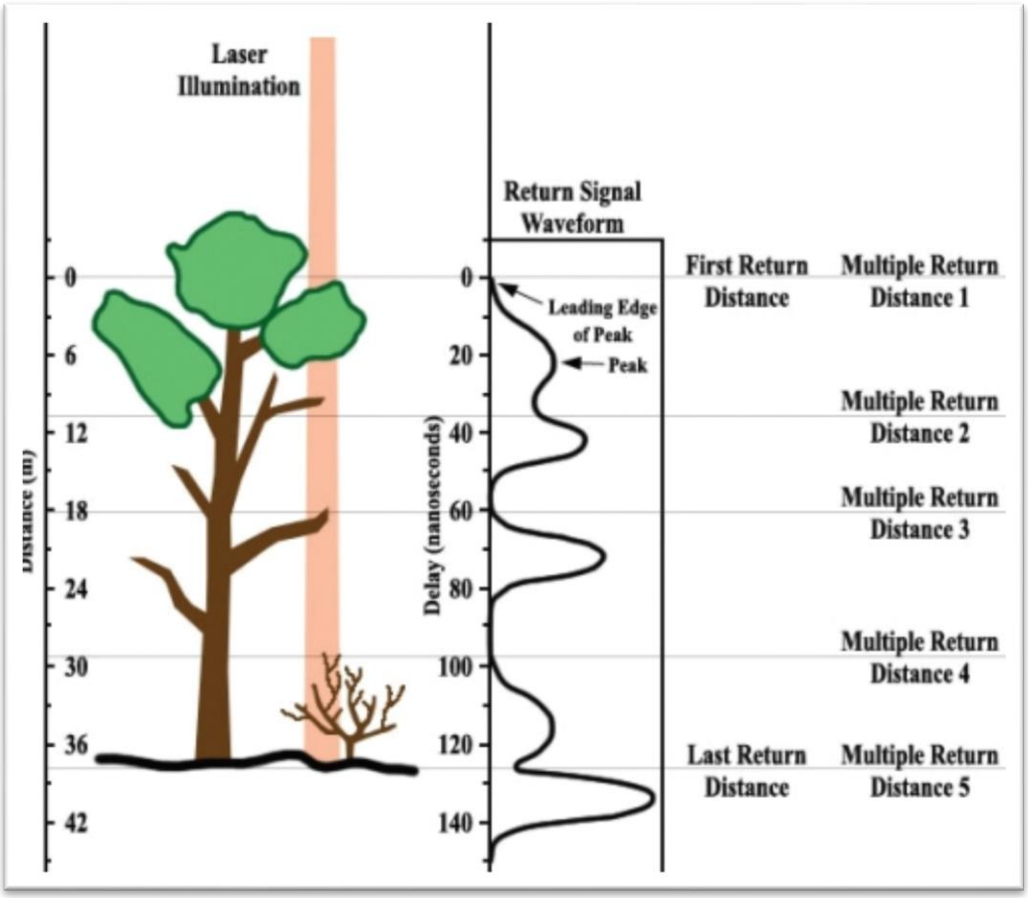

Figure 6: In a full waveform lidar the entire return pulse is digitized and recorded. In a discrete multiple-return lidar only the peaks are recorded. The greater precision of full waveform lidar creates a more accurate representation of forest canopy structure compared to multiple return data (see Figure 5).Source: Pennsylvania State University: Department of Geography

4. Methods and Models

This section is organized into two parts containing data pre-processing and methods. Data pre-processing methods in turn are divided into four parts. In the filtering methods section some efficient algorithms are explained in minor detail. Apart from different interpolation methods the generation of the digital terrain model (DTM), digital surface model (DSM), and canopy height model (CHM) is also discussed. Quality assessment of laser data is carried out within section

4.1.4. Additionally, the quality of filtering methods, interpolation methods, DTMs, DSMs, and CHMs results and their performances are also evaluated. The methods section considers those methods used in biomass estimation as well as other single tree and tree characteristic detections. Later sections will discuss the applications of lidar using the models for biomass estimation, recognizing the advantages of lidar systems for biomass estimation.

4.1. Data Pre Processing

Data pre-processing is a critical step to consider when using lidar data. Choosing the proper filtering method plays an important role in the quality of results. In this way, the quality of the results cannot be expected to be better than the data accuracy itself. However, all interpolation methods are more than capable of generating precise three-dimensional models considering the vast quantity of readily available lidar data.

4.1.1. Filtering

The purpose of filtering is to remove vegetation points from the data. Figure 7 shows all points before filtering (left) and the terrain points left after filtering is complete (right). The terrain points extracted from the point cloud of lidar data sets are used as an input to generate Digital Terrain Models (DTM). The first pulse data sets contain vegetation points and terrain points in the forest area. Numerous kinds of filtering methods have been developed to classify the terrain and vegetation points in the point cloud (Pfeifer et al., 2004; Tovari and Pfeifer, 2005). Different concepts for filtering, with different complexity and performance characteristics have been proposed in mainly four categories such as morphological, progressive densification, surface based, and segmentation based filters. There are also developments, extensions, and variations for these filter methods.

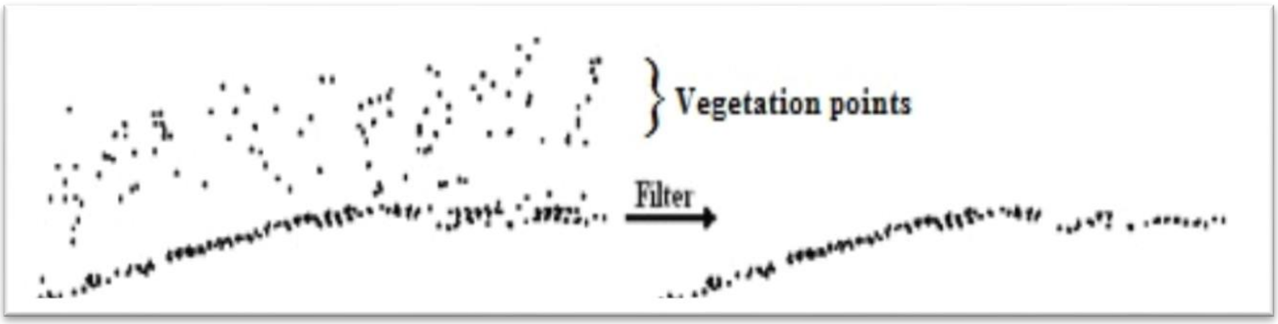

Figure 7: The use of filtering to remove vegetation points. This allows for the creation of DTM's or digital terrain models. (Fallah Vazirabad and Karslioglu 2011).

The morphological filter was derived by Vosselman (2000) from the mathematical morphology definition. This method assumes that the smaller the distances between a ground point and its neighboring points, the lesser the height difference, which allows for the proper identification and elimination of outliers. The progressive densification filter, which was developed by Axelsson (2000), works progressively by classifying points which belong to the ground. Surface based filters assume from the beginning that all the points lying on the ground form a surface. Then a fitting procedure is applied to extract the points which do not belong to the ground (Pfeifer et al. 2001). Segmentation filters are developed as the fourth category. This method involves the division of points into segments which are located within defined thresholds such as the distance and height difference between neighbor points.

The experimental comparison of filtering algorithms with manual methods for DTM extraction is introduced by Sithole and Vosselman (2004) to show the suitability of filters with the terrain shape. In comparison with other filtering methods, the segment base filter has turned out to be a more reliable method in steep slope terrain extraction using a surface growing method (Fallah Vazirabad and Karslioglu 2011). The most important part in this method is the accuracy assessment and parameter tuning. These processes for the segmentation method are performed by Vazirabad and Karslioglu (2009) as shown in Figure 8. Segmented terrain points are colored as brown and green while white points are assumed to be the vegetation points in forest area.

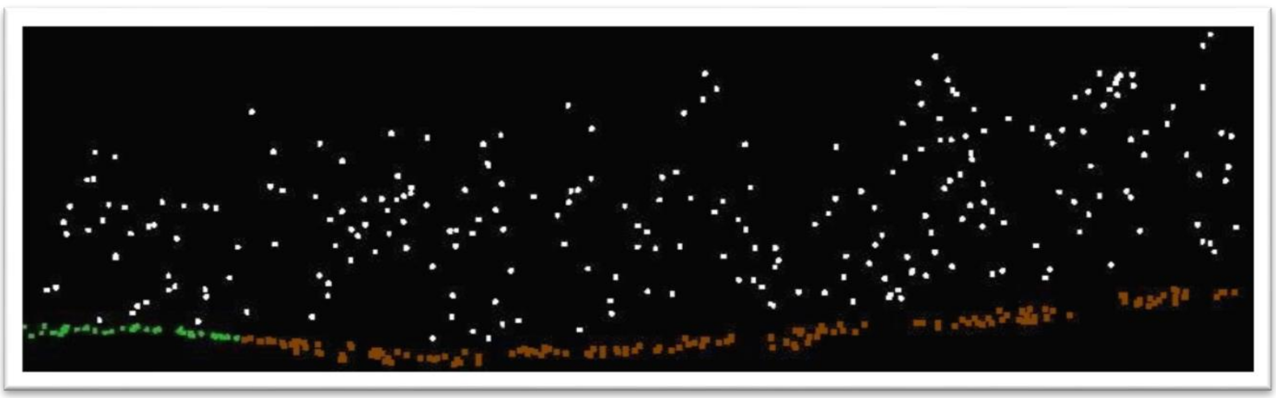

Figure 8: An example of the segmentation method showing a point cloud from the vertical view (Fallah Vazirabad and Karslioglu 2011).

4.1.2. Interpolation

Interpolation is necessary to produce digital models from lidar point cloud data. The idea of interpolation is rather simple as is uses the nearest neighbor method to estimate elevation (Maune, 2007). This involves searching for the set of nearest points where a new elevation value is then selected as the same value of the nearest point as opposed to taking the average of all points. An important problem associated with the nearest neighbor method is the zigzag appearance of the surface (see figure 8). This can be attributed to the selecting of the nearest point method by defining Voroni diagrams or Theissen polygons (Fallah Vazirabad and Karslioglu 2011). Because of this, some types of averaging methods should be applied to the set of known nearest elevation points. Therefore, a weighted average such as an inverse distance weighting (IDW) can be introduced which works with the distances between points (Monnet et al, 2010; Bater and Coops, 2009).

In lidar data, especially in vegetated areas, distances are not related to the elevations. In contrast, kriging or geostatistical approaches provide better results (Heritage and Large, 2009). However, they require more mathematically complex and computationally intensive algorithms. Since dense data is always available, rapid interpolation methods such as the nearest neighbor are preferred to use for rough surfaces in the forest areas (Fallah Vazirabad and Karslioglu, 2010).

Riano et al. (2003) investigated the performances of spline and nearest neighbor interpolation methods to generate DTMs. Spline interpolation is a special form of piecewise polynomial. The interpolation error in the DTM can be small even when applying the low degree polynomial. They concluded that there were no large differences between the spline and nearest neighbor results while the spline computation was three times slower. Hollaus et al. (2010) described the derivation of DSM employing the least square fitting method to compare it with kriging interpolation. They introduced a moving least square fitting technique which selects the highest points in the search window as surface points. This technique finds the best fitting surface to the set of points by minimizing the sum of squares of the residuals of the points from surface. The results of this study showed that the least square fitting technique produced high precision DSM on rough surfaces while it needs more computational time (Fallah Vazirabad and Karslioglu, 2011).

4.1.3. DTM, DSM, CHM

The terrain model function, which is described in equations 3 and 4, is computed from 3D points where n is the number of points (Shan and Toth, 2009) (Equaiton 4). Heights are stored at discrete, regularly aligned points, and the interpolated height as the height of the grid must be given within a grid mesh. These grid heights are obtained by interpolation methods explained previously in subsection 4.1.2. These methods consist of nearest neighbor, IDW, kriging, spline, and least square fitting.

$$4z = f(x, y) \qquad \text{Equation 3}$$

$$p_i = (x_i, y_i, z_i), i = 1, \dots n \qquad \text{Equation 4}$$

An alternative method to the interpolations is known as triangular irregular network (TIN) data structure. The original points are used for reconstructing the surface in the form of TIN. For large point sets, triangular networks are more effective than the time consuming methods which are mentioned before. Digital surface models (DSM) are generated from noise removed Lidar data and represent the canopy top model. Digital terrain model (DTM) is basically produced by the laser pulse returns which are assumed to be on the terrain. (van Aardt et al., 2008). By subtracting DTM from DSM, CHMs can be obtained which can be seen in Figure 9. This process results in a digital description of the difference between tree canopy points and the corresponding terrain points.

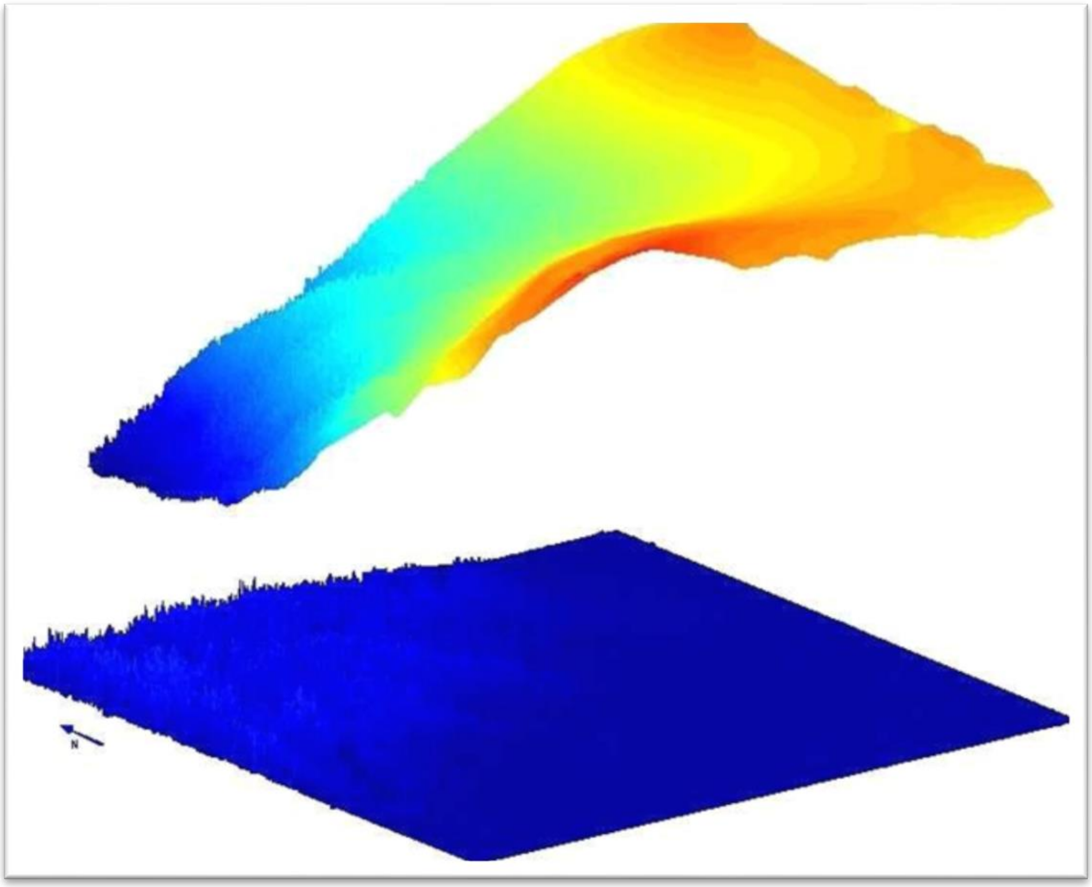

Figure 9: Example result of subtracting the DTM from the DSM, which provides a digital description of the difference between tree canopy points and the corresponding terrain points (Fallah Vazirabad and Karslioglu 2011).

4.1.4. Quality Assessment

Quality assessment is necessary for each step of pre-processing. Although the utilization of lidar technology has increased in different applications, the development of standard methodologies for the quality assurance of these systems and quality control of the derived data has not followed the same trend. A frequently adopted procedure for quality evaluation is the comparison of LiDAR data and ground control points. Aside from being expensive, this approach is not accurate enough for the verification of the horizontal accuracy, unless specifically-designed targets are utilized. The filtering methods mentioned before are likely to fail facing with outliers in the data, complexity of the terrain, and small vegetation which is completely. Most of filter algorithms start with the minimum height in data. Thus the most effective error is the negative outliers which are originated from multi path errors and errors in range finder. The vegetation on the slope also produces difficulties in filter algorithms because of the reflected pulses returning from the neighbor points. Therefore, filtering methods need some initial threshold values, which are usually defined by experience and prior information about the data and terrain characteristics.

Fallah Vazirabad and Karslioglu (2011) demonstrate that the quality of segmentation filter deteriorates with increasing point spacing of ALS point cloud looking at Type I and Type II errors (table 1). Large Type I error leads to a reduced DTM accuracy as a consequence, because many vegetation points will be included in DTM generation. The Type II error induces some effects resulting from the fact that measured elevation values in lidar data are replaced by interpolated values for DTM, which cause a zig-zag pattern in the DTM modeling (Figure 10).

Table 1: An example of Type I and Type II errors taken from Fallah Vazirabad and Karslioglu (2011).

Filter		Reduced		Sum
		Terrain	Off-terrain	
Original	Terrain	A	B	A+B
	Off-terrain	C	D	C+D
Sum		A+C	B+D	(Total) T=(A+B+C+D)
Type I = (B*100)/(A+B) & Type II = (C*100)/(C+D) Total Errors = (B+C)*100/T				

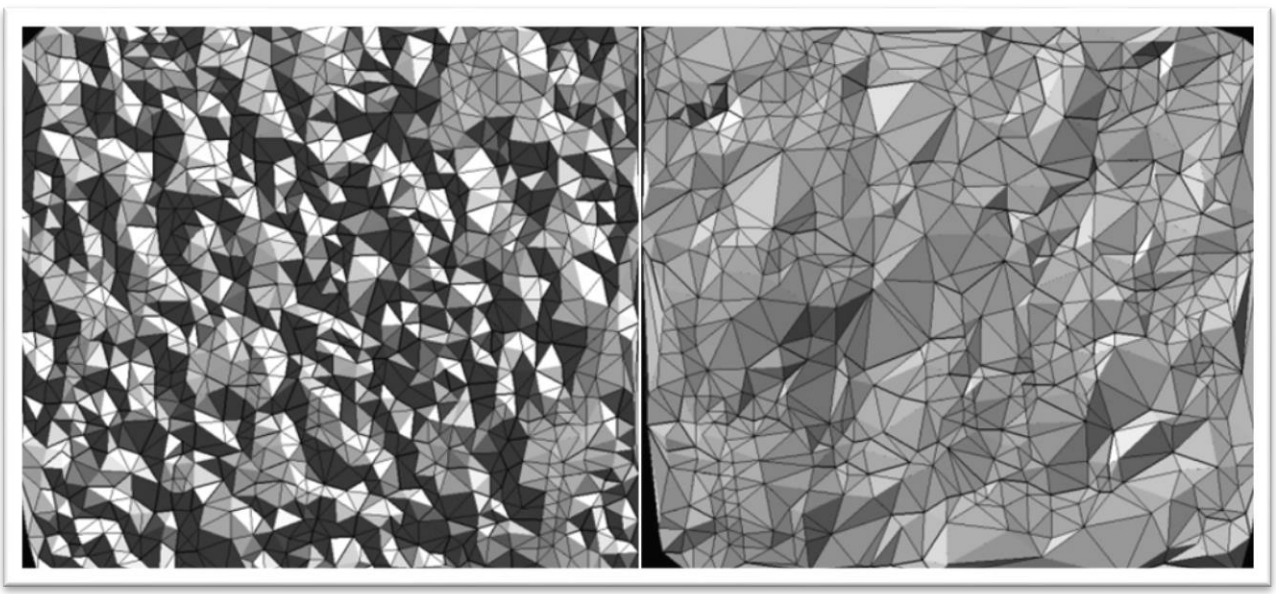

Figure 10: An example of poor filtering (left) and proper filtering (right). The zig-zag pattern created when replacing lidar elevation data with interpolated values for DTM is easily noticed in the left figure. (Fallah Vazirabad and Karslioglu 2011).

4.2. Methods

Extracting forest characteristics from lidar data for biomass estimation can be classified into two categories, (1) height distribution with its statistical analysis and (2) single tree detection containing its location and characteristics. A conventional model of biomass estimation is introduced by Thomas et al. (2006), which is given as: b x dbh^2 x height, where b is the coefficient. This equation was developed for the whole tree as well as the components of the stem wood, stem bark, branches, and foliage. Once the metrics (dbh and height) are measured for each plot, the equation can be established to estimate biomass and biomass components. The coefficient b is a variable which is related to the tree species. Measurements for the deriving of forest biomass include destructive sampling which is the input of regression modeling. For this, sample trees are measured, felled, and weighted (Popescu et al, 2004). The mass of components of each tree is then regressed to one or more dimensions of the standing tree. As discussed in the previously, biomass has also been estimated by means of formerly developed models using lidar, which relies on tree characteristics extraction such as height, dbh, and crown size. Crown size is not used directly in the estimation procedure but it is useful for extracting the tree species. All developed models and their parameters for biomass estimation must be calibrated on the basis of tree characteristics. For this, four models were studied by Salmaca (2007). These include the power function, log transformed model, fractional power transformation, and explanatory function. The Power function is developed for north of the United States, the Log transformed model is described by a linear function, the fractional power transformation is referred to linearized curvilinear model, and the explanatory function is constituted by a polynomial model (Fallah Vazirabad and Karslioglu 2011). Under these models the Log transformed model is recommended which delivers the results with the unit of kilogram per every tree (Fallah

Vazirabad, 2007). Accordingly, tree characteristics extraction by lidar data plays an important role in the biomass estimation model.

Bortlot et al. (2005) proposed to locate trees by an image processing module using the data of small footprint Lidar system. This method assumes that the tree crown is circular, trees are taller than surroundings, and tree tops tend to be convex. The algorithm begins by generating a CHM and works by a shadow search method to find the crown boundaries which is related to tree tops. After defining a threshold and fitting the circles to the smoothed and generalized CHM, the circles should present the top of actual trees. The algorithm eliminates the small trees which are close to tall ones, because it searches for related high point neighboring. They conclude that tree heights are associated with canopy volume and therefore should be related to the biomass. They used the tree heights detected from image processing as variables for a stepwise multiple linear regression to find an equation for biomass prediction. They evaluated the results with highly significant (>95%) carrying out an efficient field measurement to calibrate the number of trees which are detected by an algorithm based on their height. Small trees are not included in this evaluation.

Lefsky et al. (1999) developed equations relating height indices to canopy area and biomass. Their research indicated that there are some differences in the predictive ability of the height indices. These differences are small, and statistically non-significant. However, the canopy structure information, which is summarized in the median, mean, and quadratic mean canopy height indices, improved the stand canopy estimation related to the maximum canopy height. They defined the relation between tree height, H and dbh as:

$$dbh = (H/19.1)^{2.1}. \qquad \text{Equation 5}$$

They concluded that the result of the model using stepwise multiple regressions causes a higher variance value than those from the simple linear regression referring to the CHM. However, the predictions of the stand attributes were less applicable to the CHM than the height indices. Stepwise multiple regressions of basal area and biomass using the canopy height profile vector as independent variables increase the importance of the field measured regression equations (Fallah Vazirabad and Karslioglu 2011).

Fallah Vazirabad and Karslioglu (2009) investigated biomass estimation using the method of single tree detection. The lidar data segmentation filtering method was applied to point clouds to distinguish canopy points from the terrain points which are used for the generation of a DTM. The CHM was then obtained by subtracting the DSM (from original data) from DTM as discussed previously. A single tree detection method was employed to locate trees and detect the height of each tree top. The diameter at breast height (at 1.37 m from ground) was extracted from the close relation with the tree height which is defined by field measurements for the evaluation. A log transformed model could then be applied for biomass estimation on the basis of the dbh variable.

4.2.1. Single Tree Detection, Tree Characteristic Detection

The objective of many previous studies was to validate the tree detection, tree height estimation, crown size estimation for volume, and biomass estimation of different forest types. Nelson et al (1988) used discrete Lidar data to collect forest canopy height data. Two logarithmic equations were tested to find the best model. They used a height distribution method and analyzed a statistical approach. Falkowski et al (2006) described and evaluated spatial wavelet analysis (SWA) techniques to estimate the location, height, and crown diameter of individual trees from Lidar data. Two dimensional hat wavelets were convolved with a CHM to identify local maxima within the wavelet transformation image. Their findings correlated well with estimated derived using established methods that required prior knowledge or the tree height-crown diameter relationship. They suggested that the SWA could potentially allow for the automated, large scale, remote estimation of numerous tree characteristics.

Anderson et al. (2006) developed a methodology for acquiring accurate individual tree height field measurements within 2 cm accuracy using a total station instrument. They utilized these measurements to establish the expected accuracy of tree height derived from small and large footprint lidar data. Their results showed that the accuracy of small footprint lidar data changes according to the tree species. The comparison has shown that tree heights, which are retrieved from small footprint lidar, are more accurate than the result of large footprint data. Hopkinson (2007) investigated the influence of flight altitude, beam divergence, and pulse repetition frequency on laser pulse return intensities and vertical frequency distributions within a vegetated environment. The investigation showed that the reduction in the pulse power concentration by widening the beam, increasing the flight altitude, or increasing the pulse repetition frequency results in slightly reduced penetration into short canopy foliage and increased penetration into tall canopy foliage, while reducing the maximum canopy return heights.

Fallah Vazirabad and Karslioglu (2010) used a technique based on the searching for the local maximum canopy height to detect individual trees with variable window size and shape. The method detects tree location, number of trees, and the height of each single tree. The variable window size and shape solved the problems of small tree detection and not detectable CHM margin regions. They emphasized the importance of field measurements and reference information evaluation. Popescu and Zhao (2008) developed a method for assessing crown base height for individual trees using lidar data in forests to detect single tree crowns. They also investigated the Fourier and wavelet filtering, polynomial fit, and percentile analysis for characterizing the vertical structure of individual tree crowns. Fourier filtering was used for smoothing the vertical crown profile. The investigation resulted in the detection of 80% of tree crown correctly.

Moorthy et al. (2011) utilized terrestrial laser scanning to investigate the individual tree crown. From the observed 3D laser pulse returns, quantitative retrievals of tree crown structure and foliage were obtained. Vigorous methodologies were developed to characterize indicative architectural parameters, such as tree height (R^2= 0.97, rmse = 0.21m), crown width (R^2= 0.97, rmse = 0.13m), crown height (R^2= 0.86, rmse = 0.14m), crown volume (R^2= 0.99, rmse = 2.6m. It seems that the first pulse return from the upside view of an individual tree in terrestrial laser scanning brought about the low performance in crown height while the other characteristics were detected well.

Riano et al. (2004) estimated leaf area index (LAI) and crown size using lidar data. They concluded that LAI was better estimated using larger search windows while the crown size was better estimated using small window size. They generated the vegetation height above the ground for each laser pulse using interpolated values extracted from DTM. They also applied spline function interpolation in order to obtain the height above the ground. However, in this work it is not specified whether the first or last return was used to extract the canopy height, which effects the results significantly.

5. Examples of Studies in Estimating Carbon Stocks

As stated previously, remote sensing has had notable success in measuring vegetation characteristics in areas of low leaf area indices (>3). On the other hand, quantifying vegetation structure where LAI exceeds three has been less successful (Lefsky et al., 2002). It is well known that high LA1 forests, which generally have high above-ground biomass, occur in the boreal, temperate and tropical regions. These forests cover less than 35% of the Earth's terrestrial surface, yet account for 67% of terrestrial net primary productivity (NPP) and 89% of terrestrial biomass (Lefsky et al., 2002). Gaining a better understanding of these areas above ground biomass values will allow for a more accurate estimation of terrestrial carbon storage, which will help to more properly evaluate the global carbon budget.

It was not until recently that the use of lidar to monitor large scale tropical forest carbon stocks was even considered. The high diversity of Amazon forests, coupled with the relatively high cost of operation and small geographic coverage create two painstaking obstacles to consider when using this data collection method. However, in 2010 Asner and his colleagues showed that when combined with a strategic use of satellite data, airborne lidar can yield cost-effective, high- resolution maps of forest carbon stocks and emissions. This potential was not previously realized at large geographic scales, which would be applicable to an international REDD (Reduced Emissions from Deforestation and Degradation program). REDD has the potential to connect carbon emitters with governments positioned to reduce forest carbon losses through monetary compensation, which could greatly reduce global carbon emissions. In addition to offsetting emissions, REDD could provide indirect support for biodiversity conservation through reduced habitat loss, thus providing a unique solution to the ongoing tension between conservation interests and other land-use needs in tropical forest regions such as the Peruvian Amazon (Asner et al 2012).

Asner and his colleagues applied their new multi-scale, multi-temporal method to analyze carbon stocks and emissions throughout 4.3 million ha of Amazon forest in the Department of Madre de Dios, Peru, an area twice that of Costa Rica's forests. The Madre de Dios region has undergone relatively moderate land-use change throughout the past several years. However, the paving of the Interoceanic Highway in 2006, along with new timber concessions and an increase in gold mining, land-use pressure has drastically increased (Asner et al. 2012). With such alterations to the landscape being made, Asner sought to better understand the sources of spatial and temporal variability in carbon stocks and emissions throughout this large region of the Amazon. The study approach involved four steps: the regional mapping of vegetation type and condition using moderate-resolution satellite data, regionally stratified large-scale sampling of vegetation canopy 3-D structure using airborne LiDAR, converting LiDAR vegetation structural data to aboveground carbon density using LiDAR allometrics which were developed at a limited number of field plots, and finally integrating the satellite maps with the calibrated lidar data to set a regional, high-resolution baseline carbon estimate, and mapping of carbon emissions into the future (Asner et al 2012).

Asner's approach was able to discover previously unknown variation in carbon storage at multiple scales based on both geologic substrate and forest type. They found that from 1999 to 2009, emissions from land use totaled 1.1% of the standing carbon throughout the region. They also found that types of forest degradation, such as selective logging, increased regional carbon emissions by 47% over deforestation alone, and secondary growth provided and offset of only 18% against total gross emissions (Asner et al. 2012). Most countries in tropical regions rely on tier-I estimates issued by the Intergovernmental Panel on Climate Change (IPCC) which are based on average carbon values assigned for biomes. When applied to this study area, the tier-I estimate indicated a much greater amount of above ground biomass, perhaps highlighting the fact that forest carbon densities are not homogeneous at a variety of scales. Although the estimations may be lower, Asner's methods generate very high-resolution and accurate results, which would likely yield increased investment per unit of carbon. Developing monitoring capacities at higher accuracies and using procedures similar to those done by Asner's group can ultimately provide an increased carbon credit, boosted carbon sequestration, and improved biodiversity protection.

Another benefit to this method of high-resolution carbon stock and emissions monitoring is the fact that the costs of implementation continue to decrease. Satellite data costs are decreasing, and most major data sources are free of charge to end users. The Carnegie Institution is making its CLASlite available for free to noncommercial organizations throughout the Amazon region. Lidar, like aerial photography in the 70's and 80's, is rapidly expanding throughout the world with uses in a range of environmental sectors, with airborne lidar mapping companies operating in the Americas, Europe, Africa, Asia, Australia, and the Pacific. The analysis of this 4.3 million ha project was done at a cost of less than $0.08/ha, while more recent work in Madagascar has reduced the cost to about $0.06/ha (Asner et al. 2012). Aside from its accuracy and cost effectiveness, this procedure can be scaled up to the national level. This ground breaking work done by Greg Asner and his colleagues can serve as a future framework for studies to follow. Further research can perhaps provide the necessary data for programs like REDD to gain a better understanding of the global carbon budget, particularly in diverse tropic regions, allowing them to better reduce global carbon emissions while increasing carbon storage.

Aside from the work done by Asner and colleagues at the Carnegie Airborne Observatory, several others have studied the capabilities of remote sensing in densely forested areas. Dubayah et al. (2010) measured forest structure and biomass dynamics over the tropical forests of La Selva Biological Station in Costa Rica. Their results comparing lidar footprints between study years showed canopy top height changes similar to those expected based on land cover types. Gibbs et al (2007) reviewed a range of methods, including lidar remote sensing, available to estimate national-level forest carbon stocks. They were able create the first complete set of national-level forest carbon stock estimates. Clark et al (2010) aimed to evaluate small footprint, discrete return lidar data for the estimation of aboveground biomass in a Costa Rican tropical rain forest landscape. They concluded that of all lidar and hyperspectral metrics analyzed, lidar vegetation height is the strongest predictor of biomass in densely forested areas. Although these researchers, and several others, were able to achieve some level of success in using lidar to measure forest characteristics in densely forested areas, they have all noted the need of a space-borne system to map carbon stocks and flux at the broad spatial scales needed to support global carbon-emission regulation.

Although the work done by those discussed above has caused great advancements in the understanding of the global carbon budget, the launch of ESA's Biomass satellite will perhaps provide an unprecedented level of understanding of the world's forests in the carbon cycle. Biomass will exploit the unique sensitivity of P-band SAR together with advanced retrieval methods to measure forest biomass, height, and disturbance across the entire biomass range every six months (ESA 2012). Biomass marks a major step forward compared to existing and planned satellite missions because of the distinctive capabilities of P-band SAR. These include P-band's high sensitivity to biomass, its ability to display temporal coherence over repeat phases separated by several weeks allowing it to retrieve forest vertical structure for the first time from space, and lastly its high sensitivity to disturbances and temporal changes in biomass. By exploiting these capabilities Biomass will create a unique archive of information on the world's forests, shedding new light on an accurate representation of the global carbon cycle.

6. Conclusion

Lidar remote sensing has proven to be a useful tool in the estimation of forest biomass receiving substantial attention in literature in recent years. Airborne lidar has the advantages of variable flying height systems and therefore collects more precise data with respect to terrain shape. There are many full waveform airborne lidar operational systems, but several substantial challenges still exist such as the vast data processing required and the ability to penetrate densely forested areas. The investigation on the point density of lidar data shows that having a sufficient number of points has a large impact on the filtering results. The results of segmentation filtering shows a high capability of adaptation in different landscapes, but it requires the right choice of segmentation parameters relating to the point density. Point spacing also plays an important role for the selection of the interpolation method with respect to the DTM, DSM, and CHM resolution. Although several advancements have been made in the use of lidar, more studies are required to continue the improvement of the various approaches discussed here. With a rising concern over the global carbon budget, further development of lidar systems, particularly space-borne, will be crucial in mapping and monitoring the role of the world's forests in carbon storage.

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