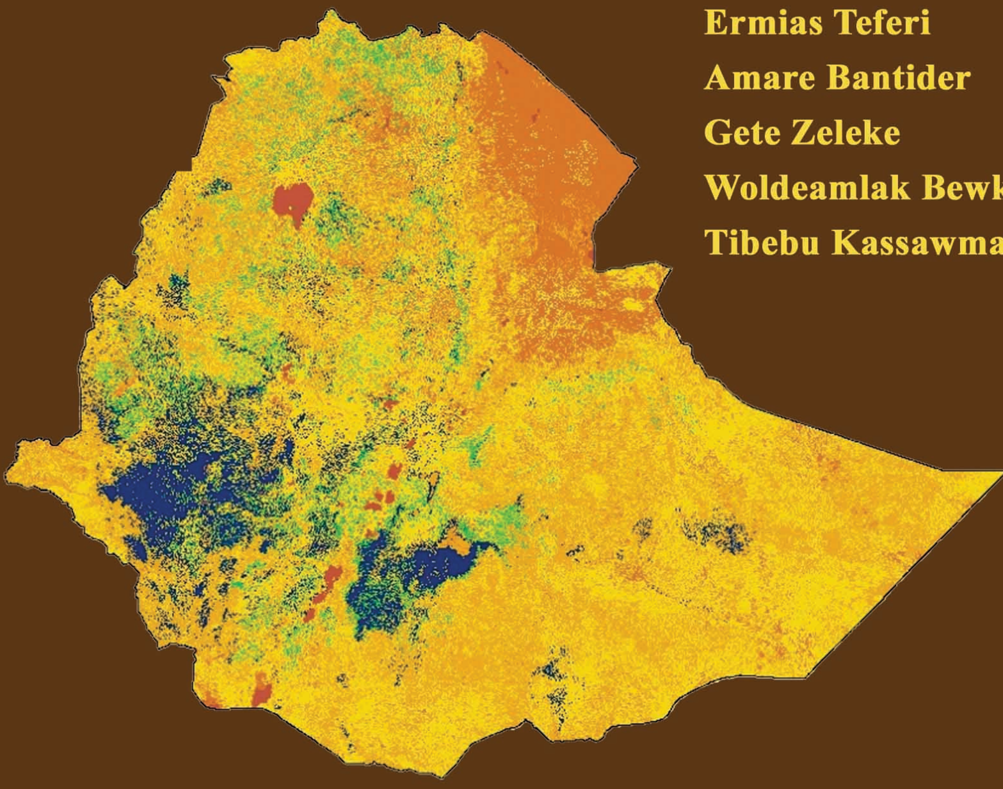
Mapping Aboveground Carbon Stocks and Emissions Induced by Land Use and Land Cover Changes in Ethiopia

A Remote Sensing Approach

Working Paper No. 3

Ermias Teferi
Amare Bantider
Gete Zeleke
Woldeamlak Bewket
Tibebu Kassawmar



Water & Land Resource Centre
Addis Ababa University

MINISTRY OF AGRICULTURE

MoARD SLM ETHIOPIA

Mapping Aboveground Carbon Stocks and Emissions Induced by Land Use and Land Cover Changes in Ethiopia: A Remote Sensing Approach

Working Paper No. 3

Ermias Teferi, Amare Bantider, Gete Zeleke, Woldeamlak Bewket and Tibebu Kassawmar

Water and Land Resource Centre, Addis Ababa University

Water and Land Resource Centre, Addis Ababa University
Rahem Building, Diaspora Square, Megenagna
P.O.Box: 3880
Addis Ababa
Ethiopia
Telephone: +251-11-661-22-36
Fax: +251-11-661-22-29
Email: info@wlrc-eth.org
https://www.wlrc-eth.org

MoARD; SLMPCM

Recommended Citation

Ermias Teferi, Amare Bantider, Gete Zeleke, Woldeamlak Bewket and Tibebu Kassawmar. 2021. 'Mapping Aboveground Carbon Stocks and Emissions Induced by Land Use and Land Cover Change in Ethiopia: A Remote Sensing Approach'. *Working Paper No. 3.* Water and Land Resource Centre, Addis Ababa University: Addis Ababa.

<u>**Disclaimer**</u>: The maps used in this working document and the boundaries may not necessarily show the Geo-political delineations.

Front cover picture: Aboveground carbon density map developed using the SM approach

Table of Contents

List of Tables

List of Figures

List of Boxes

Acknowledgments

Water and Land Resource Centre (WLRC) is greatly indebted to the Sustainable Land Management Project Coordination Office of the Ministry of Agriculture and Livestock Resource of the Federal Democratic Republic of Ethiopia for the financial support to this study as part of a project entitled, "Developing and Managing the Knowledge Base for Natural Resources in Ethiopia". The authors would like to thank Dr Matebu Tadesse and Dessalew Getnet for the editorial work which has greatly improved readability of this report.

Acronyms and Abbreviations

ACD	Aboveground Carbon Density
AGB	Aboveground Biomass
ALOS	Advanced Land Observing Satellite
APAR	Absorbed Photosynthetically Active Radiation
AVHRR	Advanced Very High Resolution Radiometry
BA	Basal Area
CA	Combine and Assign
CCI	Climate Change Initiative
CO_2	Carbon dioxide
CRGE	Climate-Resilient Green Economy
DR	Direct Remote Sensing
ECV	Essential Climate Variable
ESA	European Space Agency
FAO	Food and Agriculture Organization
FRA	Forest Resource Assessment
GHG	Greenhouse Gas
GIS	Geographic Information System
GLAS	Geoscience Laser Altimeter System
ICESat	Ice, Cloud and Land Elevation Satellite
IPCC	Intergovernmental Panel on Climate Change
LiDAR	Light Detection and Ranging
LULC	Land Use and Land Cover
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NFI	National Forest Inventory
PALSAR	Phased Array-type L-band Synthetic Aperture Radar
RADAR	Radio Detection and Ranging
RAR	Real Aperture Radar
RED	Reduced Emissions from Deforestation
REDD+	Reduced Emissions from Deforestation and Forest Degradation
SAR	Synthetic Aperture Radar
SM	Stratify and Multiply
SPOT	Systeme Probatoire D'Observation De La Terre
TCH	Top Canopy Height
UNFCCC	United Nations Framework Convention on Climate Change
WBISPP	Woody Biomass Inventory and Strategic Planning Project
WD	Wood Density
WHRC	Woods Hole Research Centre

1. Introduction

1.1 Background

Woody vegetation plays a vital role in regulating climate through carbon sequestration in its biomass. Biomass is defined as the total mass per unit area of live or dead plant material expressed in mass of dry matter per unit area. Biomass consists of aboveground biomass (AGB) and belowground biomass. AGB is defined as all living biomass above the soil, including stem, stump, branches, bark, seeds, and foliage, while belowground biomass consists of living roots (Simonian et al. 2010). AGB is a key parameter in estimating carbon emissions and removals due to land use change, and related impacts on climate (Saatchi et al. 2011; Baccini et al. 2012).

Accurate biomass estimates are also required for implementation of carbon emission reduction mechanisms from deforestation and forest degradation (REDD+) under the United Nations Framework Convention on Climate Change (UNFCCC). Biomass plays two major roles in the climate system: (i) photosynthesis withdraws CO_2 from the atmosphere and stores it as biomass, part of which is transferred to the soil when it decomposes or is stored in protected soil carbon pools; and (ii) biomass consumed by fire emits CO_2, other trace gases and aerosols to the atmosphere. Therefore, assessment of biomass and its dynamics is an essential input to climate change projection models as well as designing effective climate change mitigation and adaptation strategies. The UN Framework Convention on Climate Change (UNFCCC) has identified biomass as an Essential Climate Variable (ECV) that is needed to support the works of the UNFCCC and the Intergovernmental Panel on Climate Change (IPCC) in monitoring climate change (GCOS 2004).

Measuring and monitoring AGB has become an important research topic in recent years because of its relevance to the international climate change negotiations, specifically related to emissions from deforestation and forest degradation. This is covered under the UNFCCC's theme of reduced emissions from deforestation and forest degradation (REDD) (Gibbs et al. 2007). The concept of REDD evolved from reduced emissions from deforestation (RED), while further concepts of REDD+ and REDD++/REALU (reducing emissions from all land uses) have evolved from REDD revealing the importance of the AGB at the global scale (Gibbs et al. 2007; Sharma et al. 2013). REDD+ includes forest conservation and sustainable management and forest carbon stock enrichment, in addition to the objectives of REDD while REALU deals with emissions from all land uses and not just restricted to forests.

Woody biomass can be estimated using field measurements (e.g., tree height, stem diameter and density) by applying allometric models developed via destructive sampling and weighing of dried vegetation components. Undertaking this type of biomass assessment is difficult to conduct over large areas and it is costly, time consuming and labour intensive. As a result, national AGB inventories are often rare in sub-Saharan Africa. Yet, field measurements of biomass are essential to extrapolate field measurements to over large areas using remote sensing approaches (Goetz et al. 2009; Houghton et al. 2009). Remote sensing techniques to estimate biomass can account for the limitations of sample size, timeliness, expense and access at a range of scales (Patenaude et al. 2005). Remote sensing data can effectively provide a synoptic view over large areas and greatly increase efficiency and usefulness of the limited conventional methods (Patenaude et al. 2005). However, large area assessment of biomass is often limited by the lack of field validation datasets with comparable coverage and resolution. Since maps based on global or regional datasets are often not tailored to country-specific circumstances, their applicability at national scales needs to be better customized with appropriate case studies.

Optical remote sensing, radio detection and ranging (radar) and light detection and ranging (LiDAR) are the three main sources of remotely-sensed data for biomass estimation, with each having certain advantages over the others (Kumar et al. 2015). A number of studies have employed optical remote sensing data as the major data source for AGB estimation (e.g., Basuki et al. 2013; Lu et al. 2012). However, optical sensor data suffers from the saturation problem for forest sites with high biomass density. Radar remote sensing data is better for AGB estimation as it provides high-resolution images independent from daylight effects, cloud coverage and weather conditions for biomass estimation. Besides, Radar data can penetrate vegetation to different degrees and provide information on the amount and three-dimensional distribution of structures within the vegetation. LiDAR instruments have the ability to sample the vertical distribution of canopy and ground surfaces, providing detailed structural information about vegetation. This makes LiDAR a very good remote sensing data for accurate estimation of basal area, crown size, tree height and stem volume. However, uncertainties in the remote sensing of AGB estimation are high due to vegetation structural variations, heterogeneity of landscapes, seasonality and disproportionate data availability, among others. Given the different advantages of different data, an appropriate combination of multi-source data, such as field measurement and remote sensing monitoring, can potentially improve spatially explicit estimation of biomass over large areas.

1.2 Aim and objectives

The aim of this research was to characterize the magnitude and spatial distribution of aboveground carbon contained in woody vegetation in Ethiopia. The specific objectives were to:

i. review and synthesize different AGB estimation methods for large areas;
ii. highlight the merits and demerits of the remote sensing-based methods of AGB estimation; and
iii. characterize the magnitude and spatial distribution of aboveground carbon contained in woody vegetation in Ethiopia.

The study generates spatially-explicit carbon-density data, and provides important insights into how aboveground carbon is distributed across land cover types and landscapes. It also allows comparisons to be made among administrative units of the country, which have not been possible in past studies.

2. Existing Methods of Mapping Carbon Density

Previous studies have reviewed a wide range of biomass estimation techniques. For example, Wang et al. (2009) divided estimation approaches into four: (i) process model-based, (ii) empirical model-based, (iii) biomass expansion/conversion factor or coefficient-based, and (iv) integration of plot and remotely-sensed data. Bombelli et al. (2009) also classified biomass estimation techniques into four categories: (i) harvest mapping or destructive sampling-based, (ii) non-destructive sampling-based, (iii) air-borne/space-borne remote sensing-based, and (iv) model-based (empirical and semi empirical) techniques. Lu (2006) classified the techniques used for estimation of AGB into three main categories as: (i) field measurement-based methods, (ii) remote sensing-based methods, and (iii) GIS-based methods.

The IPCC also classifies methodological approaches to carbon stock change estimation into three Tiers (Eggleston et al. 2006). For the national scale, IPCC has produced a set of guidelines for estimating greenhouse gas inventories at different tiers of quality, ranging from Tier 1 (simplest to use; globally available data) up to Tier 3 (high resolution methods specific for each country and repeated through time) (Eggleston et al. 2006).

The most commonly used approaches, which have been developed to map carbon stocks and AGB from remote sensing data, rely on calibrating satellite measurements to in-situ estimates of AGB at field condition. The approaches can be classified into three using the scheme presented by Goetz et al. (2009), namely: (i) Stratify and Multiply (SM), (ii) Combine and Assign (CA), and (iii) Direct Remote Sensing (DR) approaches (see Box 1). These methods are described in the following sub-sections.

A tier represents a level of methodological complexity. Three tiers are described for categorizing both emissions factors and activity data.

Tier 1 is the basic method, frequently utilizing IPCC-recommended country-level defaults. Tier 1 methodologies usually use activity data that are spatially coarse, such as nationally or globally available estimates of deforestation rates, agricultural production statistics, and global land cover maps.

Tier 2 can use the same methodological approach as Tier 1 but applies emission factors and activity data, which are defined by the country for the most important land uses/activities. Tier 2 can also apply stock change methodologies based on country-specific data. Country-defined emission factors/activity data are more appropriate for the climatic regions and land use systems in that country. Higher resolution activity data are typically used in Tier 2 to correspond with country-defined coefficients for specific regions and specialized land-use categories.

At **Tier 3**, higher order methods are used including models and inventory measurement systems tailored to address national circumstances, repeated over time, and driven by high-resolution activity data and disaggregated at sub-national to fine grid scales. These higher order methods provide estimates of greater certainty than lower tiers and have a closer link between biomass and soil dynamics. Such systems may be GIS-based combinations of age, class/production data systems with connections to soil modulus, integrating several types of monitoring.

Box 1. The IPCC Tier Concept

2.1. Stratify and multiply (SM) approach

Stratify and Multiply (SM) is a simple but an effective approach to derive biomass estimate/carbon stock maps at regional and national scales in which satellite data are used to derive thematic maps and field biomass data within each class are averaged. In SM approach, a single value is, or a range of values are, assigned to each of a number of land cover, vegetation type, or other thematic map classes that have been derived from satellite data (or other map sources) and placed into categories (such as Evergreen Lowland Forest, Deciduous Forest, and the like). These thematic class areas are then multiplied by the assigned values to estimate total carbon stock values. The major limitation of SM approach is the inability to consider the wide range of AGB variability within any given thematic type class. Researchers have used this approach to quantify aboveground carbon loss (e.g., Tyukavina et al. 2013; Bryan et al. 2010; Tyukavina et al. 2015).

This method does not account for the most important variation of forest carbon stocks resulting from bioclimatic gradients, such as temperature, precipitation and geologic substrate. In addition, forest carbon stocks vary within each biome according to slope, elevation, drainage class, soil type and land use history. An average value cannot adequately represent the variation for an entire forest category or country. Use of SM approach is further constrained because it is very difficult to assess the uncertainty or accuracy of source data. However, SM approach is freely and immediately available and currently provides the only source of globally consistent forest carbon information. For this reason, it continues to be the most routinely used source of forest carbon stock data. Moreover, SM method provides an important starting point for a country to assess the relative magnitude of their emissions from deforestation and degradation (IPCC Tier 1).

2.2 Combine and assign (CA) approach

This approach is an extension of the SM approach, which essentially makes use of a wider range of spatial data to extend the field-based AGB estimates. It is a method in which satellite and other spatial datasets are integrated to derive a thematic map with finer-grained strata and the field data within each stratum are averaged. For example, spatial data of population can be used together with vegetation type classes and any other spatial data layers in a geographic information system (GIS) to provide finer-grained units over which the field data can be applied. The geospatial datasets may include climate, soils, topography, population and land use information to spatially extrapolate forest inventory data and produce maps of forest carbon stocks (Brown and Gaston 1995). The advantages of this approach are: (i) different weights can be applied to various data layers in order to capture spatially-referenced phenomena, and (ii) provision of finer spatial units of aggregation is possible. Despite these advantages, this approach suffers from the following limitations: (i) a representative value to be assigned to a given spatial unit and field data may not be available to adequately characterize those units, (ii) bias associated with difficulties in assigning field plot measurements to generalized land cover classes is apparent in the CA approach, and (iii) this approach requires successive field surveys to update maps derived using GIS models, but field data are unlikely to ever be sampled adequately for monitoring purposes.

2.3 Direct remote sensing (DR) approach

The Direct Remote Sensing (DR) Approach is a method of producing carbon stock maps for large area by relating the satellite measurements directly to biomass density by calibrating them to field estimates of AGB using data driven models, such as neural networks or regression trees. The DR approach makes use of a set of field measurements to train an algorithm to develop a set of rules by which any combination of satellite observations produces a unique solution in terms of field estimated AGB (Fig. 1). Once the optimized rules are established for the training data, they are then applied to the satellite images to produce spatially continuous values of AGB for each pixel. Biomass maps have been produced using MODIS imagery for Africa, a continent of particular importance in the global carbon cycle (Williams et al. 2007), and validated using independent LiDAR datasets. Similarly, carbon stock maps have been developed for different countries using DR approach. For instance, Costa Rica (Houghton and Goetz 2008), Russia (Houghton et al. 2007), and North America (Blackard et al. 2008).

A key advantage of this approach is that the rules, once established, can potentially be adapted to a monitoring framework. The spatial unit is typically much smaller than the other approaches (i.e., the pixel size), and datasets used (satellite observations) are not only more current but also more consistent through time. Unlike land use and land cover maps required in CA and SM approaches, the satellite observations used in the DR approach are sensitive to changes at the pixel level. Thus, even fine-scale changes associated with forest degradation and afforestation can be detected. Carbon stock maps produced using the DR approach tend to show continuous map, while the CA approach produces more aggregated spatial units. Thus, a narrower range of variability within each AGB value in the DR approach indicates reduced uncertainty at any given location in a map.

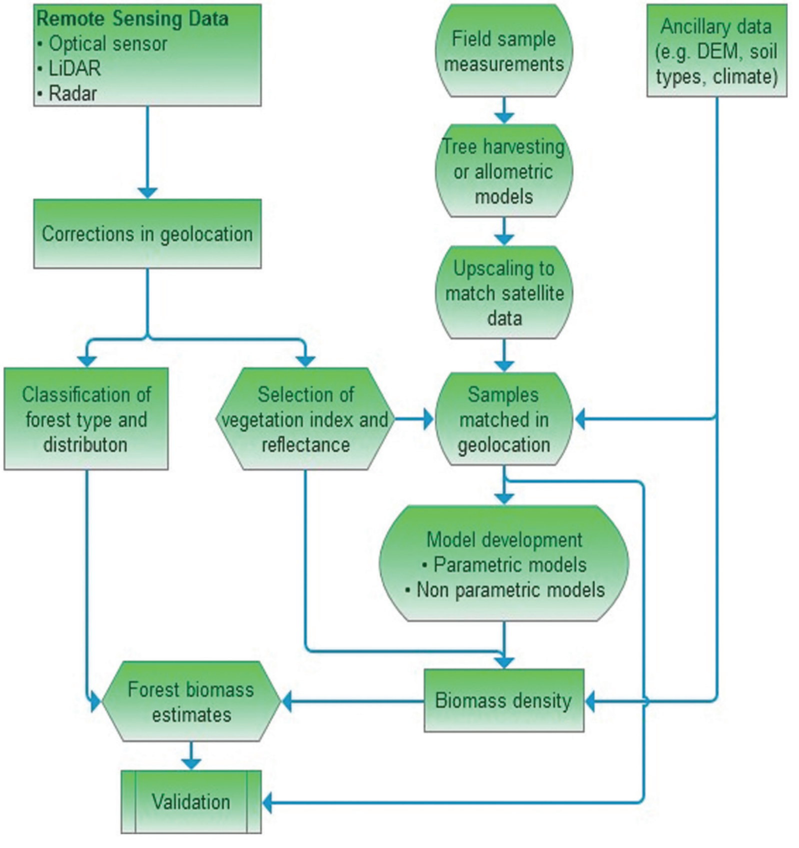


Figure 1. Flowchart for general strategy of biomass estimation modelling using remote sensing techniques

3. Remote Sensing Data for AGB Estimation

The use of RS technology for the assessment of biomass has proved to be a good alternative to the conventional methods of biomass estimation. Carbon stocks can be assessed by using remote sensing instruments mounted on satellites or airborne platforms; but, substantial refinements are needed before routine assessments can be made at national or regional scales (Baccini et al. 2004; DeFries et al. 2007). No remote-sensing instrument can measure carbon stocks directly, and thus require additional ground-based data collection (Rosenqvist et al. 2003; Drake et al. 2003). Remotely-sensed data measure other characteristics, such as crown size and forest density, which are correlated with biomass. Traditional biomass assessment methods based on field measurements are the most accurate.

However, they are difficult to conduct over large areas and are costly, time consuming, and labour intensive. The advantages of remote sensing include: the ability to obtain measurements from every location in the forest, the speed with which remotely sensed data could be collected and processed, the relatively low cost of many remote sensing data types, and the ability to collect data easily in areas, which are difficult to access on the ground. Thus, mapping carbon stocks over large areas without satellite data is clearly problematic (Houghton et al. 2001). As noted earlier in this working document, optical, radar and LiDAR sensors are the three main sources of remotely sensed data for biomass estimation (Kumar et al. 2015).

3.1 Optical Remote Sensing Data

Optical Remote Sensing (ORS) deals with those parts of electromagnetic spectrum characterized by the wavelengths from the visible to the near infrared up to thermal infrared, collecting radiation reflected and emitted from the observed surfaces. ORS systems provide two-dimensional information that can be indirectly linked to biophysical properties of vegetation and AGB and carbon stocks. ORS data have been used by several researchers for biomass estimation (e.g., Thenkabail et al. 2004; Foody et al. 2003; Baccini et al. 2004). The system provides a good alternative to the tedious hand sampling as a means of estimating biomass over large areas due to its coverage, repetitiveness and cost-effectiveness (Patenaude et al. 2005). Various spatial and temporal resolutions of optical remote sensing are available. On the basis of spatial resolution of satellite data, Lu (2006) categorized the optical sensor data for AGB estimation as fine, medium and coarse spatial resolution. High spatial resolution (<5m) data are from sensors, such as: Quickbird, WorldView, GeoEye, and DigitalGlobe. Images at high resolution offer advantages in assessing vegetation structures whereas sensors with medium resolution such as Landsat or Systeme Probatoire D'Observation De La Terre (SPOT) are useful sources for local scale biomass assessment. Coarse resolution data (>100 m) can be useful for biomass estimation at regional to continental scales since their high temporal frequency increases the probability of acquiring cloud-free data for generating consistent datasets over large areas. Examples of coarse resolution data include MODIS, national oceanic and atmospheric administration, advanced very high-resolution radiometry (AVHRR), and SPOT vegetation. AVHRR data have been the most widely used datasets for studies of vegetation dynamics on a continental scale. However, the MODIS sensor has improved spectral and spatial resolutions compared to the widely used AVHRR and provides a suite of biophysical products that are useful in biomass estimation, including vegetation indices, leaf area index, fraction of absorbed photosynthetically active radiation, gross primary production, net photosynthesis, and net primary productivity. The mid-infrared reflectance from optical remote sensing data is closely related to biomass and thus was found to be more useful in assessing alterations in vegetation characteristics compared to reflectance in the visible and near-infrared bands (Boyd 1999).

Optical remote sensing uses the technique of modelling based on biomass–vegetation index relations to estimate aboveground biomass. Optical sensors collect data from aboveground vegetation only and have been used mainly for aboveground biomass assessment using a range of vegetation indices, such as ratio vegetation index, normalized difference vegetation index and soil adjusted vegetation index. Alternatively, optical remote sensing data can be used to obtain indirect estimates of absorbed photosynthetically active radiation (APAR) from the red and infrared reflectance characteristics of the vegetation (Ruimy et al. 1994). The APAR gives an indication of how efficiently absorbed energy is converted into dry biomass by a vegetation type (Monteith 1972).

3.2. RADAR (active microwave) data

Active microwave sensors (radar) generate their own illumination by transmitting pulses of microwave radiation and measure quantity and time delay of energy backscattered from the area of interest. Therefore, images can be acquired day and night, completely independent of solar illumination. The term RADAR is an acronym for Radio Assisted Detection and Ranging. Microwaves are electromagnetic radiation with wavelengths from 1mm to 30cm. Microwaves easily penetrate clouds, and images can be acquired independently of weather conditions. Radar is based on the principle of echolocation-transmit a signal and measure the echoes that return sometime later. The two types of imaging radars most commonly used are: Real Aperture Radar and Synthetic Aperture Radar (SAR). Real Aperture radars are often called Side Looking Airborne Radar. Both Real Aperture Radar and Synthetic Aperture Radar are side-looking systems with an illumination direction usually perpendicular to the flight line. The difference lies in the resolution of the along-track, or azimuth direction. SAR uses signal processing to synthesize an aperture that is hundreds of times longer than the actual antenna by operating on a sequence of signals recorded in the system memory. SAR offers certain unique capabilities that have advantages over optical sensors which are as follows: (a) all weather capability (penetration capability through clouds), (b) day and night capability (independent of intensity and sun illumination angle), (c) penetration through vegetation, soil sand and dry snow to a certain extent, and (d) sensitivity to surface roughness, dielectric properties and moisture (in liquid or vapour forms).

SAR data can be acquired in X band (8–12GHz), C band (4–8GHz), L band (1–2GHz), and P band (0.3–1GHz). The list of SAR satellite sensors working under different bands is given in Table 1. L-band data have been proven valuable for AGB estimation (Kurvonen et al. 1999; Sun et al. 2002). However, low or negligible correlations were found between C-band backscatter and AGB (Le Toan et al. 1992). Polarization of the SAR signals is an important parameter of SAR data that interacts variably due to different orientations and structures of the features. Polarization of the electromagnetic waves refers to the direction of electric field and depends upon the interaction between signals and the reflectors. Microwave sensors emit signals in horizontal (H) or vertical (V) polarizations. In VV polarisation, both emitted and reflected signals have vertical polarization (Ghasemi et al. 2011). The longer wavelengths (L and P band) and the HV polarization are most sensitive to AGB (Sun et al. 2002). Longer wavelengths (L and P bands) with cross-polarizations (HV and VH) produced better result for biomass-related studies than short wavelengths (X and C bands) with co-polarizations (HH or VV) (Hamdan et al. 2011). C band is preferred for lower vegetation biomass estimations (Ghasemi et al. 2011). The two most widely used approaches used for forest biomass estimations are: (1) using backscatter values, and (2) interferometry technique, along with polarimetric analyses.

Previous researches have shown the potential of radar data in estimating AGB (Sun et al. 2002; Treuhaft et al. 2004). Sinha et al. (2015) reviewed the application of radar remote sensing for biomass estimation. Lucas et al. (2004) reviewed SAR data for AGB estimation in tropical forests and temperate and boreal forests.

There are some drawbacks of using SAR that needs to be overcome. Unlike the optical data, the cost of SAR data is a serious constraint in the development of commercial technology for AGB estimation. Processing of SAR involves certain complex steps that can be performed in specific software. SAR data acquisition and processing incur huge cost. Compared to optical data, the x- and y-resolutions are not the same because range resolution varies with local incident angle. Interpretation requires good understanding of microwave frequency interaction with various targets, as data interpretation is affected by occurrence of speckles and image distortions due to undulating terrains. In rugged or mountainous regions, topographic factors such as slope and aspect can considerably affect vegetation reflectance, resulting in spurious relationships between AGB and backscattering values. Hence, removal of topographic effects is necessary. Layover occurs when the radar beam reaches the top of a tall object before it reaches the base. The top of the object is displaced toward the radar from its true position on the ground and laid over the base of the feature. Under moderate slope conditions, though the radar return from foot reaches first followed by the top, the ground range will be less than the actual ground distance, causing compression in the image called foreshortening. Shadows occur toward the far range, behind vertical features or slopes with steep sides. Since the radar beam does not illuminate the surface, shadowed regions will appear dark on an image as no energy is available to be backscattered.

Table 1. A list of SAR satellite sensors working under different frequency bands

No.	Sensor	Operation	Frequency band	Institution/ Country	Remark
1	Seasat	1979	L(HH)	NASA/JPL, USA	First civilian SAR satellite
2	ERS-1/2	1991-2000 /1995-2011/	C(VV)	ESA, Europa	European SAR satellites
3	Radarsat-1	1995-today	C(HH)	CSA, Canada	First Canadian SAR satellite
4	SRTM	Feb. 2000	C(HH+VV) and X(VV)	NASA/JPL, USA; DLR, Germany; ASI, Italy	Shuttle Radar Topography Mission, 1st space-borne interferometric SAR
5	ENVISAT/ ASAR	2002 - 2012	C(dual)	ESA, Europa	1st SAR satellite with transmit/receive module
6	ALOS/ PALSAR	2006 - 2011	L(quad)	JAXA, Japan	Advanced Land Observing satellite
7	TerraSAR-X/ TanDEM-X	2007- today 2010-today	X(quad)	DLR/Astrium, Germany	1st bi-static radar in space, resolution up to 1m
8	Radarsat-2	2007-today	C(quad)	CSA, Canada	Resolution up to 1mx3m
9	COSMO-Skymed-1/4	2007-today	X(quad)	ASI/MiD, Italy	Constellation of four satellites (1m resolution)
10	RISAT-1	2012-today	X(quad)	ISRO, India	
11	HJ-1C	2012-today	S(VV)	CRESDA/CAST/ NRSCC, China	Constellation of four satellites
12	Kompsat-5	2013-today	X(dual)	Korea multi-purpose	KARI, Korea
14	PAZ	2013-today	X(quad)	Constellation of TerraSAR-X and TanDEM-X	CDTI, Spain
15	ALOS-2	2013-today	L(quad)	Resolution up to 1mx3m	JAXA, Japan
16	Sentinel-1a/1b	2014-today	C(dual)	Constellation of two satellites	ESA, Europe

3.3. LiDAR

LiDAR, which stands for Light Detection and Ranging, is an active remote sensing method that uses electromagnetic energy in the optical range to detect an object (target), determine the distance between the target and the instrument (range), and deduce physical properties of the object. Lasers for terrestrial applications generally have wavelengths in the range of 0.9 - 1.064 μm, where vegetation reflectance is high. One drawback of working in this range of wavelengths is absorption by clouds, which impedes the use of LiDAR during cloudy conditions. In LiDAR systems, the time interval is detected between sent and return laser pulses which are backscattered from an object. LiDAR point cloud of returns generates a 3D digital representation of the vegetation structure in which each point is characterized by XYZ coordinates (Cote et al 2011). Thus, LiDAR sensors directly measure the three-dimensional distribution of plant canopies as well as sub-canopy topography. Thus, they provide high-resolution topographic maps and highly accurate estimates of vegetation height, cover, and canopy structure. Carbon stocks of woody vegetation are estimated by applying allometric height–carbon relationships (Hese et al. 2005).

Large-footprint of LiDAR sensors far exceeds the capabilities of radar and optical sensors to estimate carbon stocks for all forest types (Drake et al. 2003). Airplane mounted LiDAR instruments are too costly to be used for more than a small area. LiDAR sensors mounted on satellites provide global coverage. Currently, the geoscience laser altimeter system (GLAS) is the only LiDAR operating space-borne system. GLAS is an important part of the U.S. government's National Aeronautics and Space Administration (NASA) earth science enterprise carried on the ice, cloud and land elevation satellite (ICESat) (Afzal et al. 2007). GLAS data are intended to be used mainly for scientific studies of sea ice elevation (Zwally et al. 2002); but, they are also suitable for the estimation of tree canopy height (Lefsky et al. 2005; Duncanson et al. 2010). GLAS data have been shown to have a fairly close correlation with canopy height and aboveground biomass measured on ground plots in tropical and temperate forests (Lefsky et al. 2005). Previous researches demonstrated that LiDAR data are promising for estimating AGB and carbon stock (e.g., Sun et al. 2008).

3.4. Multi-sensor or multisource synergy

Reliable estimates of biomass cannot be expected from a single sensor on any satellite mission, whether radar, LiDAR or optical. Using these measurements in a synergistic manner can potentially overcome the limitations of each (radar, LiDAR or optical). AGB maps at moderate resolution have been produced for the entire tropical belt by integrating various satellite observations (Saatchi et al. 2011; Baccini et al. 2012). The use of multi-sensor or multi-resolution data has the potential to improve AGB estimation performance (Asner et al. 2010). However, the time, cost and labour involvement in image processing will be significantly increased.

Radar provides an efficient means for assessment of AGB and it can overcome important limitations of optical remote sensing. Although LiDAR is perhaps the most suitable single sensor for biomass estimation, synergistic use of optical and SAR sensors would be the obvious choice due to their availability, cheaper cost and shorter time of processing. Synergistic use of multi- temporal optical, radar and LiDAR sensors can potentially be the best combination in remote sensing integrated with the use of model-based approach (semi-empirical) for the estimation of biomass. See Box 2.

In response to the urgent need for improved mapping of global biomass and the lack of any current space systems capable of addressing this need, the BIOMASS Mission was proposed to the Call for Ideas released in March 2005 by the European Space Agency (ESA) for the third cycle of Earth Explorer Core missions. BIOMASS was selected in May 2006 for Assessment Study (phase 0) and in March 2009 for Feasibility Study (phase A). The BIOMASS Mission was planned to be launched in 2020 and would carry a polarimetric P-Band SAR sensor capable of providing the urgently needed global knowledge about biomass. The objectives of the mission were: 1) to quantify the magnitude and distribution of forest biomass globally to improve resource assessment, carbon accounting and carbon models; and 2) to monitor and quantify changes in terrestrial forest biomass globally, on annual basis or shorter, leading to improved estimates of terrestrial carbon sources (primarily from deforestation); and terrestrial carbon sinks due to forest regrowth and afforestation.

The BIOMASS Mission is designed to address this limitation in our knowledge of the Earth and its functioning. It will aid in building a sustained global carbon monitoring system that improves over time, thus helping nations to quantify and manage their ecosystem resources, and to improve national reporting. Its value will also extend well beyond the mission's lifetime: since biomass in undisturbed forest changes relatively slowly, the maps produced during the mission will provide realistic values for calculations of emissions based on deforestation maps produced by other means, such as optical or shorter wavelength radar sensors.

Box 2. The BIOMASS Mission

3.5 Available aboveground biomass maps

3.5.1 An improved pan-tropical biomass map (Avitabile et al., 2016)

Using a novel data fusion approach, Avitabile et al. (2016) have integrated two existing large-scale biomass maps (Saatchi et al. 2011; Baccini et al. 2012) with local high-quality biomass data into an improved pan-tropical aboveground biomass map of woody vegetation at 1 km resolution for the 2000s. (The fused map and the corresponding reference dataset can be freely downloaded from http://lucid.wur.nl/datasets/high-carbon-ecosystems/).

Baccini et al. (2012) estimated the carbon density (Mg C ha^{-1}) of aboveground live woody vegetation for the pan-tropics at a spatial resolution of 500m using a combination of remote sensing (LiDAR) and field data for the period 2007–2008. Saatchi et al. (2011) mapped the total carbon stock in live biomass, above- and belowground, using a combination of data from 4,079 in-situ inventory plots and LiDAR samples of forest structure to estimate carbon storage, plus optical and microwave imagery (1-km resolution) for the early 2000s.

3.5.2 AGB map of African savannahs and woodlands at 50 m (Bouvet et al., 2018)

Bouvet et al. (2018) produced the first continental map of the AGB of African savannahs and woodlands at a resolution of 50 m, using the data sources presented in Table 2. The map is built using a Bayesian inversion of an L-band SAR mosaic from ALOS PALSAR (HH and HV polarizations), with the help of 144 reference plots. This approach allows estimating AGB until 85 Mg·ha^{-1} approximately, while dense forests and non-vegetated areas are masked out using the ESA CCI Land Cover dataset. The resulting map is visually compared with existing AGB maps and it is validated using a cross-validation approach and a comparison with AGB estimates obtained from LiDAR datasets, leading to a root mean squared difference (RMSD) of 8 to 17 Mg·ha^{-1}. The data can be downloaded from www. theia-land.fr/en/products/african-biomass-map.

Table 2. Data sources for aboveground biomass and related parameters

Reference	Scale	Data sources	Parameter	Spatial resolution	Reference year
Saatchi et al. (2011)	Pantropical	GLAS-MODIS+Quick-SCAT + Field measurements	Aboveground biomass	1km	2000
Baccini et al. (2012)	Pantropical	GLAS + MODIS	Aboveground biomass	500 m	2007–2008
Avitabile et al. (2016)	Pantropical	GLAS+-MODIS+Quick-SCAT	Aboveground biomass	1km	
Bouvet et al. (2018)	African Savannahs and woodland	ALOW PALSAR mosaic	Aboveground biomass	50 m	2010
Woods Hole Research Centre (WHRC)	Pantropical	LiDAR and Radar	Vegetation height	30m	2007

3.6 Limitations of remotely-sensed data and potential solutions

Remote sensing-based AGB estimation has many advantages over traditional field measurement methods. For example, it avails the possibility to estimate AGB at different scales. However, several factors can affect accuracy of the remote sensing-based AGB estimation, such as insufficient sample data, atmospheric conditions, complex biophysical environments, area of land considered, availability of software, spatial resolution of remotely-sensed data, or mixed pixels, among others (Lu et al. 2006). In remote sensing-based AGB research, the major uncertainty sources may arise from the collection of AGB sample data, the atmospheric correction, the registration errors between remotely sensed data and AGB sample data, selection of suitable remote sensing-derived variables, and algorithms used to develop AGB estimation models. Understanding and identifying the sources of uncertainties and then devoting efforts to improving them are critical in improving AGB estimation performance. For example, stratification of the remotely-sensed data based on ancillary data, such as agro-ecological zones, was shown to be an effective way to improve estimation accuracy within each stratum (Katila and Tomppo 2001).

Different sensor data have their own characteristics in reflecting land surfaces, and hence, understanding the strengths and weaknesses of different types of sensor data is important for selecting suitable sensor data for AGB estimation in a specific situation. Optical sensor data are suitable for the retrieval of horizontal vegetation structures such as vegetation types and canopy cover; but it is not suitable for estimation of vertical vegetation structures, such as canopy height, which is one of the critical parameters for biomass estimation. On the other hand, LiDAR and Radar data are suitable for estimating vertical vegetation structures. Thus, integration of different sources of remotely-sensed data (e.g., optical and radar/LiDAR) has the potential to improve AGB estimation because it potentially reduces the mixed pixels and data saturation problems and incorporates radar information in the new dataset. Data fusion of multi-sensor or multi-resolution data takes advantage of the strengths of distinct image data for improvement of visual interpretation and quantitative analysis. Previous researches have obtained a good result through integration of optical and radar data (Haack et al. 2002; Townsend 2002).

Difficulty in obtaining optimal variables required for biomass estimation is another limitation of remote sensing-based biomass estimation. Obviously, not all variables are useful in modelling due to high inter-variable correlation or weak relationships with biomass. Identification of optimal variables for biomass estimation in a particular area is still poorly understood due to the differences in sensor data and the complex biophysical environments of the study areas. Thus, it is necessary to develop accurate methods that can identify optimal variables needed for biomass estimation modelling in the context a given area.

4. Materials and Methods

4.1 Data sources

4.1.1 Pan-tropical map of vegetation height (LiDAR and Radar)

Recently, researchers from Woods Hole Research Centre (WHRC) produced a dataset of below a hectare scale estimates of forest heights across the tropics (http://whrc.org/publications-data/datasets/detailed-vegetation-height-estimates-across-the-tropics/). The team combined more than 17,000 radar images from the Japanese ALOS satellite with LiDAR point height measurements from NASA's ICESat/GLAS mission to develop three continental scale models for the Americas, Africa, and Asia for the year 2007. The models allow for the continuous mapping of vegetation height up to 15 m height based on sensitivity of the models. The vegetation height postings were provided at 30 m horizontal pixel spacing (Table 2, Fig. 2).

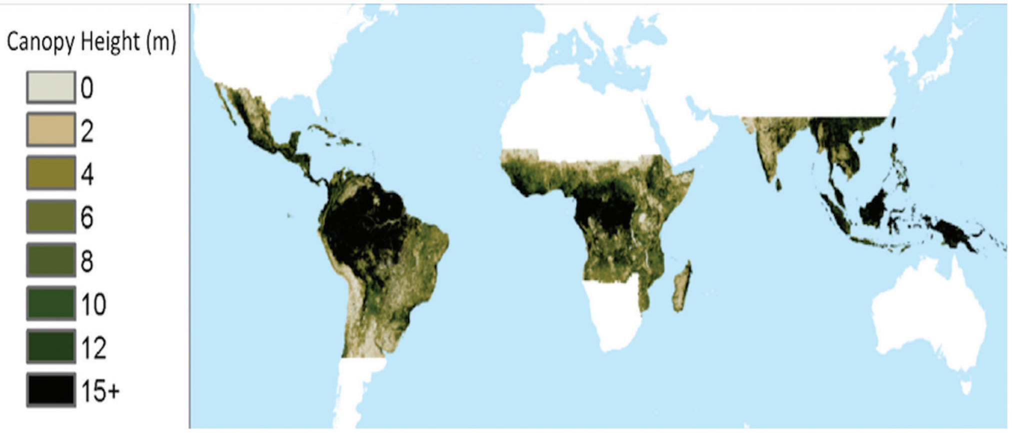


Figure 2. Pan-tropical map of vegetation height developed from LiDAR and Radar instruments

Source:*http://whrc.org/publications-data/datasets/detailed-vegetation-height-estimates-across-the-tropics/*

Despite the advantages of the fine spatial resolution and global coverage, WHRC's map has some limitations. These are: (1) LiDAR sensors have incomplete spatial and temporal coverage; capturing information from only a small part of the earth's surface over a multi-year mission, (2) seasonality of environmental and climatic effects like rain can lead to uncertainties in the dataset, and (3) the map works well for trees with heights up to 15 to 20 meters, depending on location. These limitations may be overcome in future satellite missions, which aim to acquire global radar images rapidly. Besides, another similar mission for LiDAR called the Global Ecosystem Dynamics Investigation (GEDI), which is underway, will have much denser observation points.

4.1.2 National land use and land cover data (30m)

The Stratify & Multiply (SM)/biome-average approach of estimating carbon stock requires good quality land use and land cover (LULC) data at national scale. The LULC data used in this research was obtained from the knowledge management project (WLRC, 2018). This LULC data was used as a basis for carbon biomass and carbon stock calculations. The apparent bias in the SM/ biome-average approach is associated with difficulties in assigning field plot measurements to the more generalized land cover categories. The complete description about the land use and land cover classes is given in Appendix 2.

4.2 Computation of AGB for Ethiopia

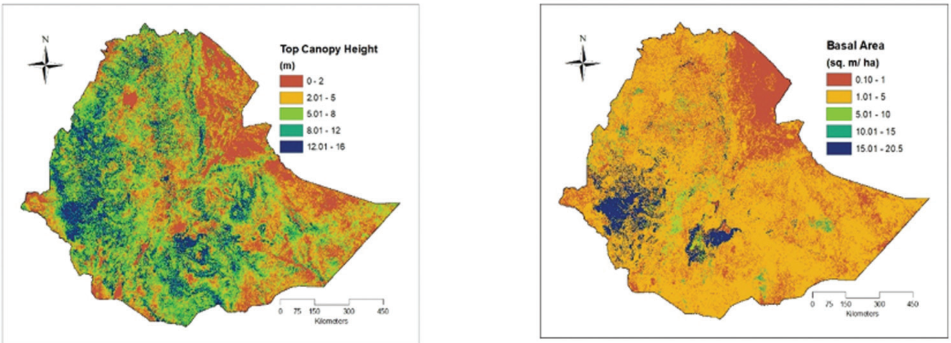
4.2.1 Generalized ACD equation (Asner and Mascaro 2014)

To date no sensor has been developed that is capable of providing direct measurement of biomass. Biomass can be inferred indirectly using surrogate variables that are correlated with biomass. For example, vegetation height and stem density are strongly correlated with biomass. Quantifying the relationship between biomass and forest height is the base for estimating biomass from LiDAR retrieved height (e.g., Lefsky et al. 2005; Saatchi et al. 2011). As recommended by Asner and Mascaro (2014), a generalized approach for estimating Above-ground Carbon Density (ACD, in Mg C ha^{-1}) in tropical landscapes uses a simple power-law function. It uses top canopy height (TCH, in m) as shown in Fig. 3a, stand basal area (BA; in m^2 ha^{-1}) as shown in Fig.3b and the weighted mean wood density (WD; in g cm^{-3}) to estimate ACD as follows:

$$ACD_{General}=3.836*TCH^{0.281}*BA^{0.972}*WD^{1.376}$$

$$WD=1.541*TCH^{-0.278}$$

BA map was developed from forest inventory data obtained from FAO (2018) (Fig. 3b). Asner and Macro (2014) used a network of 754 field inventory plots distributed across a wide range of tropical vegetation types, climates and successional states and found that LiDAR-based top-of-canopy height (TCH), BA and WD explained 92.3% of the variation in ACD (RMSE = 17.1 Mg C ha^{-1}). The advantage of using this equation is that ACD can be predicted solely as a function of TCH. The Pan-tropical maps of vegetation height developed from LiDAR and Radar instruments were used to represent TCH (Fig. 3a). Asner and Mascaro (2014) suggested that the general LiDAR approach can be applied in any tropical vegetation type with relatively few apriori inputs.



(a) Top Canopy Height

(b) Basal area map estimated from land cover based basal area data from ENFI (2018)

Figure 3. Spatially-distributed parameters used to estimate aboveground carbon density, using Asner and Mascaro (2014) method

4.2.2 Stratify and multiply/biome-average approach

The major factors affecting the amount of carbon stored in woody vegetation are climate, vegetation type, and geography (Stas 2014). The biome-averages approach assumes that approximations of aboveground biomass of a landscape can be made based on geographically-explicit datasets zones (Gibbs et al. 2007; Houghton 1999). Biome average values of biomass and carbon density were based on national forest inventory data (FAO 2018). The area of each LULC class was multiplied by the assigned values of biomass/carbon in order to estimate total carbon stock values. This approach is relatively simple to implement using a limited set of published data available at low or no cost. Moreover, biomes represent the most important variation of woody biomass carbon stocks because they account for major bioclimatic gradients, such as temperature, precipitation and geologic substrate.

However, carbon stocks of woody vegetation vary further within each biome according to slope, elevation, drainage, soil type and land-use history. Hence, an average value cannot adequately represent the variation for an entire woody vegetation category or country. Thus, the biome average approach does not capture finer-scale spatial heterogeneity of carbon stocks; the accuracy of the estimates can be increased via data refinements such as use of good quality LULC data. The LULC data used in this approach was produced at 30 m spatial resolution from Landsat images.

Biomass and carbon values were derived from the National Forest Inventory (NFI) conducted between 2014 and 2016 (Box 3; Appendix 1) (FAO 2018). A total of 627 sampling units were established with every sampling unit covering an area of 1 km^2 and composed of 4 plots. The sampling design chosen for NFI was stratified systematic cluster sampling. Using available geospatial layers of Ethiopia and large-scale ecological studies, the whole country was classified into five strata, which was a macro ecological characterization of five macro areas. The number of sampling units from the strata varied depending on estimated probabilities to find trees and forests. See Box 3.

In collaboration with the Food and Agriculture Organization of the United Nations (FAO), the Ministry of Environment, Forest and Climate Change conducted a national forest inventory (NFI) at 631 sampling units covering the entire country between 2014 and 2016. The NFI cooperation was aimed at addressing the shortage of quantified information on the current status of forest cover and spatial information regarding forestry's underestimated contribution to the national economy. The cooperation was extended to strengthening the implementation of the National Forest Monitoring and Measurement Reporting and Verification system. It was also meant to support Ethiopia's initiative to "Reduce Emissions from Deforestation and Forest Degradation" through satellite-based monitoring, and measurement of emissions.

Important outputs were produced after conducting multiple steps of NFI and satellite image analysis. Emission factors, basal area, aboveground biomass (AGB), belowground biomass (BGB), count of trees, shrubs and saplings, biomass of deadwood, and litter were estimated from the NFI data at subnational level. The extent of changes in forest cover and land use between 2000 and 2013 was used as a reference level to measure changes in historical carbon emissions from deforestation. It is from this reference level that Ethiopia's effort in reducing atmospheric carbon dioxide by implementing REDD+ activities will be measured to get performance-based payments. The NFI and mapping quantified how much forest resources were found and where, so that adequate information can be obtained for planning, management and utilization of forests. This information would help to better quantify the forestry sector's contribution to the national gross domestic product. The aggregated information from the NFI and spatial analysis can be used as primary baseline information for various decision-making processes in forest development, biodiversity and conservation studies and the formulation and assessment of forest policy, law and regulations.

Box 3. Ethiopia's National Forest Inventory

4.3 Estimating aboveground carbon loss

The national-level aboveground carbon (AGC) loss was assessed by employing the SM (Stratify and Multiply) approach. The SM approach requires a national-scale land cover change dataset (*activity data* in the IPCC terminology, Eggleston et al. 2006) and Δmean AGC density estimates for each land cover type (IPCC *emission factors*, here referred to as *carbon data*). AGC loss within a study region or a country is the following:

$$\text{AGC loss} = \sum_{i=1}^{n} \Delta AD_i \, CD_i$$

Where ΔAD_i (activity data) denotes the change in the extent of a given land cover type i, and CD_i (carbon data) represents average carbon content of vegetation per land cover type.

5. Estimated Biomass and Carbon Stock

5.1 Total biomass and carbon stock of Ethiopia

Aboveground biomass and aboveground carbon stock maps were produced using the SM approach and Generalized ACD Equation at 30 m spatial resolution for the entire Ethiopia (Fig. 4 and Fig. 5). The SM approach produced an AGB map based on high quality LULC data developed for the year 2016 and NFI data. Thus, we assume the SM approach gives a more realistic estimate. The AGB estimates from the Generalized ACD Equation were higher than the SM estimates in most land cover classes of the country. The total amount of aboveground biomass and aboveground carbon stock for Ethiopia were estimated to be 1993 Mt (million tons) and 1294 million tons of carbon, respectively (Table 3).

Table 3. National-level biomass carbon stocks estimates (M t C) using biome average approach

No	Land use and land cover	Area (M ha)	Aboveground Biomass (M t)	Biomass (M t)	Aboveground Carbon (M t)	Carbon (M t)
1	Forest	6.96	912.45	1181.14	456.16	590.39
2	Woodland	27.69	227.6	302.35	114.63	152.01
3	Shrub/bush	28.14	240.88	316.86	121.28	158.71
4	Cropland	17.33	148.34	194.96	74.17	96.7
5	Grassland	12.71	71.67	92.64	35.83	46.89
6	Wetland	0.44	2.50	3.21	1.26	1.60
7	Afroalpine	0.23	1.43	1.88	0.71	0.95
8	Riverine	0.95	7.14	9.23	3.62	4.57
9	Agroforestry	1.53	201.76	258.10	100.89	129.04
10	Plantation	0.67	54.78	69.61	27.42	34.77
11	Cropland with trees	4.10	121.81	154.62	.70	77.51
12	Others	13.38	2.41	2.41	601.20	1.20
	Total	114.12	1992.77	2587.01	997.87	1294.34

The estimated national carbon stock based on the Woody Biomass Inventory and Strategic Planning (WBISPP) Project data was 2763.7 million tons (WBISSP 2005). This is similar to the national carbon stock reported by Nune et al. (2013) amounting to 2.5 billion tons for the year 2005.

According to the SM map, the highest AGC (456.16 million tons of carbon) was found in the forest landscapes of the country and the lowest values (0.71 million tons of carbon) were associated with Afroalpine vegetation class. Biomass and carbon stock are generally high in forest areas, reflecting the role of forest in the carbon cycle. Next to the forest landscape, the AGC values of shrub/bush and woodland were high, amounting to about 121.3 million and 114.63 million tons of carbon stock, respectively. The total area covered by the woody vegetation landscape is 64.4 million ha[1]. That accounts for 56.44% of the total area of the country. The woody vegetation landscape, in the context of the present study includes: forest (6.96 M ha), woodland (27.69 M ha), shrub/bush (28.14 M ha), riverine (0.95 M ha) and plantation (0.67 M ha). The total amount of aboveground biomass stock from woody vegetation was 1,879.1 Mt (million tons) and the aboveground carbon stock from the landscape was estimated to be 723.1 million tons (Table 3).

Making comparison for national carbon stocks based on different forest definitions is difficult. The major land cover classes which the present study identified as forest are: high forest, dry forest, degraded natural forest, and church forest. Dense woodland class is not considered as forest category. Accordingly, the country's total forest area was estimated at about 6.96 million ha and its aboveground carbon stock was estimated to be 456.16 million tons (Table 3). Our result is in line with the findings of WBISSP (2005) that estimated the aboveground carbon stock in the country to be 434.19 million ton of carbon over the 4.07 million ha of forest (Table 4).

1 The area covered by the woody vegetation landscape is computed from the total area covered by forest (6.96 M ha), woodland (27.69 M ha), shrub/bush (28.14 M ha), riverine (0.95 M ha), and plantation (0.67 M ha).

Table 4. Table 4. Mean aboveground carbon density and total carbon stocks in major forest categories of Ethiopia (WBPP 2005)

Forest category	Area (million ha)	AGC density (tons ha-1)	Total AGC stock (million tons)
High forest	4.07	106.68	434.19
Woodland	29.55	42.75	1263.26
Plantation	0.50	123.00	61.50
Shrubland	26.40	36.04	951.46
Lowland bamboo	1.07	47.50	50.83
Highland bamboo	0.03	84.23	2.53
Total	61.62		2763.77

Since different reports use different definitions for forest, using national reporting will obviously influence global carbon accounting based on national estimations. For example, the WBISPP (2004) defines forest as “land with relatively continuous cover of trees, which are evergreen or semideciduous, only being leafless for a short period, and then not simultaneously for all species. The canopy should preferably have more than one story”. Whereas, FAO defines forest as, “land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 per cent, or trees able to reach these thresholds in-situ” (Simonian et al., 2010).

Several other studies reported different estimates of national forest carbon stocks. For example, Houghton (1999) estimated 153 million tons of national forest carbon stocks based on the biome-average approach and Gibbs and Brown (2007) gave an estimate of 867 million tons. Simonian et al (2010) reported a value of 172 Mt for the year 2010. The estimation of the present study (Table 5) is not consistent with these estimates. The discrepancy could be due to the differences in the methods and tools applied variability in soil, topography, and forest type.

Table 5. National-level forest biomass carbon stocks estimates (M t C)

Approach	References	Forest biomass carbon stocks estimate (M t C)
Compilation of harvest data	Olson et al. (1983); Gibbs (2006)	183
	Houghton (1999); DeFries et al. (2002)	153
	Eggleston et al. (2006)	553
Forest inventory	Brown (1997); Archard et al. (2004)	168
	Gibbs and Brown (2007)	867
	WBISSP (2005)	434
	FRA (2010)	172

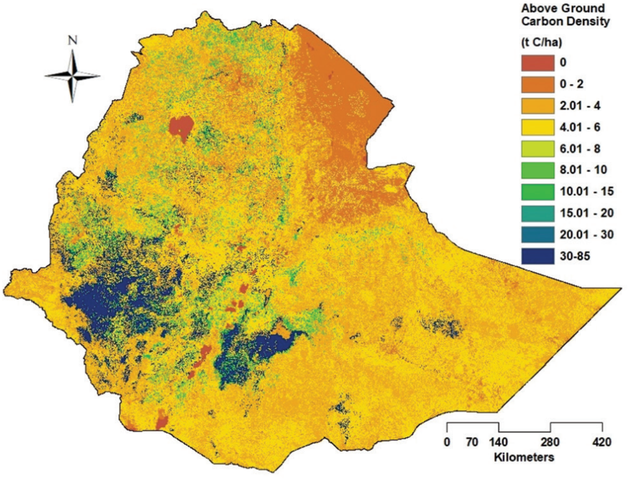


Figure 4. Aboveground carbon density map developed using the SM approach

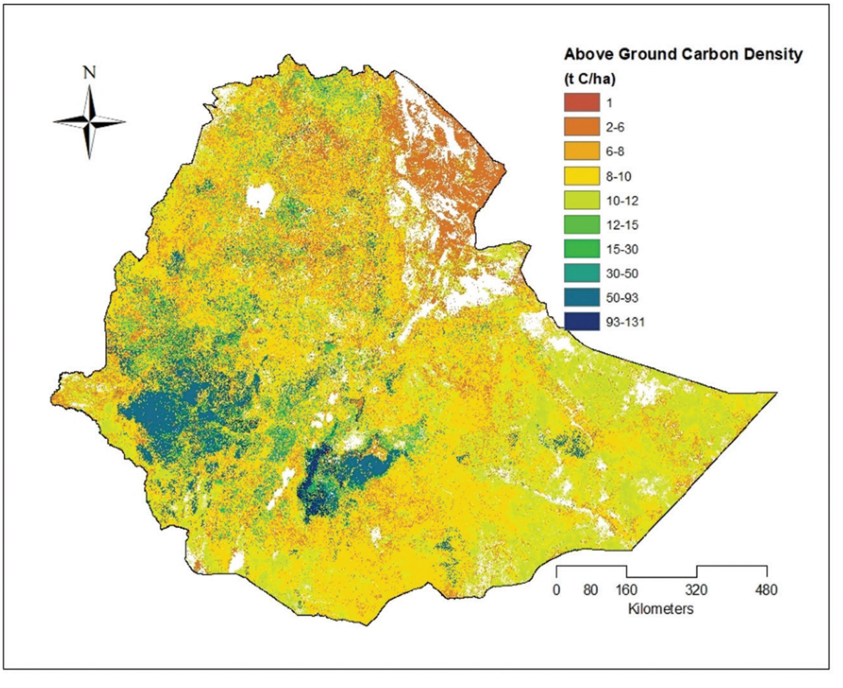


Figure 5. Above-ground carbon density map developed using the Generalized Equation

5.2. Comparison of recent aboveground carbon maps

Our estimate of AGC of Ethiopia revealed strong disagreement with previous estimates of total AGC ranging from 997.87 to 2065.09 M ton (Table 6). The Avitable et al. (2016) Map revealed CA estimate of 823.915 M ton, an estimate which is relatively close to the 998 M ton CA value; whereas, the Bouvet Map indicated a much higher CA estimate of 2065 M ton. Estimates of AGC density of forest from both the Generalized Equation and SM map are higher than published Ethiopia-wide data. For example, Watson et al. (2013) estimated an area-weighted mean forest carbon stock across the forests of the Bale Mountains to be 195 ton C/ha. However, if we take the AGC density values of forest in Africa, our finding is consistent and falls within the range of 20–454 t C/ha (Eggleston et al., 2006; Gibbs et al. 2007; Baccini et al. 2008).

Table 6. Comparison table of Aboveground Carbon Density maps

No	LULC	Area (ha)	This research		Previous AGC maps	
			SM approach	Generalized ACD Equation	Bouvet Map	Avitable Map
1	Forest	6958911	456.16	491.87	203.86	314.630
2	Woodland	27687981	114.63	279.99	663.20	121.595
3	Shrub/bush	28140225	121.28	278.40	534.29	111.605
4	Cropland	17329795	74.17	168.86	216.70	95.960
5	Grassland	12707412	35.83	88.15	159.94	58.705
6	Wetland	438703	1.26	2.82	5.57	2.060
7	Afroalpine	227249	0.71	1.73	1.57	2.305
8	Riverine	951796	3.62	8.89	21.74	6.160
9	Agroforestry	1526063	100.89	94.75	36.65	21.250
10	Plantation	668011	27.42	32.82	11.39	3.955
11	Cropland with trees	4101252	60.70	74.43	70.25	29.575
12	Others	13383506	1.20	27.69	139.93	56.115
			997.87	**1550.40**	**2065.09**	**823.915**

5.3 Carbon emission/removals of Ethiopia (1986 - 2016)

Changes in LULC can either reduce or increase the AGB amount over time depending on the change types. Detecting the changed pixels is thus critical because only biomass in these grid cells should be used to constrain LULCC emissions. For Ethiopia, due to LULC changes, total aboveground carbon stock increased by 219.56 Mt CO_2e between 1986 and 2016 (Table 7). Changes from vegetated class to non-vegetated class led to carbon storage loss, while changes from non-vegetated class to vegetated class led to increased carbon storage. Change from cropland to a more vegetated class contributed the most to the total carbon storage gain of 82%, with the total amount of carbon storage reaching 179.85 Mt CO_2e. Conversions from forest and woodland to less-vegetated classes were found to be the largest sources of carbon storage decline among all LULC changes.

All changes from forest to other classes led to carbon storage losses, with the total amount reaching 125.51 Mt CO_2e (4.18 Mt CO_2e/yr), mainly contributed by the changes from forests to agroforestry and woodland. Forest to cropland conversion caused a carbon loss of 8.47 Mt CO_2e (0.28 Mt CO_2e/yr). Decreases in forest and woodland classes resulted in aggregated carbon losses of 247.32 Mt CO_2e. Carbon loss from forest degradation (113.73 Mt) was greater than that of deforestation (conversion of forest to cropland (8.14 Mt) and cropland with trees (10.3)) between 1986 and 2016. These losses were counterbalanced by conversion of non-vegetated area to vegetated areas through expansion of plantation forest. For example, under Climate-Resilient Green Economy (CRGE), the government of Ethiopia has set a target to cover 7 million ha of land by plantation forest by the year 2030. In terms of carbon sink, conversions from cropland to a more vegetated class were found to lead to the largest increase in carbon stock, amounting to 179.85 Mt CO_2e. The largest contributing LULC change types were cropland to cropland with trees (72.38 Mt CO_2e), cropland to agroforestry (70.84 Mt CO_2e), cropland to forest (12.21 Mt CO_2e) and cropland to plantation forest (11.37 Mt CO_2e).

The above findings of carbon loss or gain show that changes in LULC contribute to climate change in Ethiopia. The livestock, crop, and forestry sectors together contributed 88% of the total greenhouse gas (GHG) emissions in 2010, amounting to 150 Mt CO_2e (CRGE 2011). The emission from forestry was estimated to be 55 Mt CO_2e. The causes for GHG emissions in forestry were deforestation and forest degradation (CRGE 2011).

Table 7. Aboveground carbon storage change per land use land cover change between 1986 and 2016 (million t C)

1986 \ 2016	F	WL	SHB	CL	GL	We	Af	R	Ag	Pl	CWT	O	Total
F	0.00	-23.21	-8.47	-8.14	-1.28	-0.04	-0.11	-1.87	-53.68	-18.37	-10.3	-0.04	-125.51
WL	139.7	0.00	-158.18	-25.7	-19.87	-0.11	0.00	-1.21	-17.78	-10.74	-27.76	-0.15	-121.81
SHB	30.98	50.93	0.00	-21.74	-39.12	-0.40	-0.04	0.7	10.01	14.56	-28.71	-0.48	16.68
CL	12.21	3.26	5.02	0.00	4.55	0.00	0.00	0.15	70.84	11.37	72.38	0.07	179.85
GL	14.48	11.4	26.51	-37.91	0.00	0.95	0.07	0.33	28.27	17.09	27.1	-0.37	87.93
We	0.92	0.33	0.62	0.44	1.54	0.00	0.00	0.04	1.17	0.11	0.37	0.00	5.54
Af	5.13	0.04	0.00	-0.15	-0.04	0.00	0.00	0.00	0.22	0.18	-0.18	0.00	5.21
R	66.92	6.75	-3.08	-1.36	-0.59	-0.18	0.00	0.00	4.91	1.87	-2.6	-0.04	72.60
Ag	13.82	0.44	-0.7	-5.35	-0.48	0.00	0.00	0.07	0.00	2.64	-9.06	0.00	1.39
Pl	1.47	0.29	-0.18	-0.59	-0.15	0.00	0.00	0.11	10.41	0.00	0.55	0.00	11.92
CWT	18.19	0.66	1.14	-19.65	-0.51	-0.04	0.00	0.07	53.57	3.45	0.00	0.00	56.87
O	2.57	1.80	7.99	4.40	3.30	0.07	0.00	0.92	1.43	4.29	2.13	0.00	28.89
Total	306.39	52.69	-129.32	-115.76	-52.65	0.26	-0.07	-0.7	109.38	26.44	23.91	-0.99	219.56

***F=Forest, WL=woodland, SHB=shrub/bush, CL=cropland, GL = grassland, We=wetland, Af=Afroalpine, R=Riverine vegetation, Ag =Agroforestry, P=Plantation, CWT=Cropland with trees, O = Others**

Note: The emission/removal is expressed as tons of carbon dioxide equivalent (t CO_2e). The carbon stock was converted to emission/ removal by multiplying with 44/12. 44/12 is the ratio of the molecular weight of carbon dioxide to that of carbon

6. Conclusions

A first spatially-explicit map of aboveground biomass and carbon stocks of forests along with other woody vegetation at 30 m spatial resolution was produced for the entire Ethiopia. The map provides decision makers and land managers in Ethiopia with a new tool for forest resource management and carbon stock assessment in a data-scarce environment where forest inventory plots are sparse. Moreover, the carbon emissions and removals due to land use and land cover changes between 1986 and 2016 in Ethiopia were estimated using Landsat satellite images and data from forest inventory plots. This study also demonstrated the use of new remote sensing-based maps of forest parameters recently produced over large areas, such as the forest canopy height map, for mapping carbon stock at the national scale.

Limitations of the approaches followed by this study (due to classification errors and aggregation of biome average approach) do not allow for replacement of local and high-spatial resolution field-based monitoring activities. However, our approach could have produced more accurate estimations if the national forest inventory data collected in 2014 were available in the form of geospatial dataset. Thus, the future direction of this study could be mapping of above ground carbon density through integration of national forest inventory geospatial data with freely available high-resolution space-borne SAR sensors, such as ALOS/PalSAR).

References

Achard, F., Eva, H. D., Mayaux, P., Stibig, H. J., and Belward, A. 2004. Improved estimates of net carbon emissions from land cover change in the tropics for the 1990s. Global Biogeochemical Cycles, 18(2).

Afzal, R. S., Anthony, W. Y., Dallas, J. L., Melak, A., Lukemire, A. T., Ramos-Izqueirdo, L., and Mamakos, W. 2007. The geoscience laser altimeter system (GLAS) laser transmitter. IEEE Journal of Selected Topics in Quantum Electronics, 13(3): 511-536.

Asner, G. P., and Mascaro, J. 2014. Mapping tropical forest carbon: Calibrating plot estimates to a simple LiDAR metric, Remote Sensing of Environment, 140: 614-624.

Asner, G.P., Powell, G.V., Mascaro, J., Knapp, D.E., Clark, J.K., Jacobson, J., Kennedy-Bowdoin, T., Balaji, A., Paez-Acosta, G., Victoria, E. and Secada, L. 2010. High-resolution forest carbon stocks and emissions in the Amazon. Proceedings of the National Academy of Sciences, 107(38): 16738-16742.

Avitabile, V., Herold, M., Heuvelink, G.B., Lewis, S.L., Phillips, O.L., Asner, G.P., Armston, J., Ashton, P.S., Banin, L., Bayol, N. and Berry, N.J. 2016. An integrated pan-tropical biomass map using multiple reference datasets. Global Change Biology, 22(4): 1406-1420.

Baccini, A.G.S.J., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A. and Samanta, S. 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Climate Change, 2(3): 182-185.

Baccini, A., Friedl, M.A., Woodcock, C.E. and Warbington, R. 2004. Forest biomass estimation over regional scales using multisource data. Geophysical Research Letters, 31(10).

Basuki, T. M., Skidmore, A. K., Hussin, Y. A., and Van Duren, I. 2013. Estimating tropical forest biomass more accurately by integrating ALOS PALSAR and Landsat-7 ETM+ data. International Journal of Remote Sensing, 34(13): 4871-4888.

Blackard, J.A., Finco, M.V., Helmer, E.H., Holden, G.R., Hoppus, M.L., Jacobs, D.M., Lister, A.J., Moisen, G.G., Nelson, M.D., Riemann, R. and Ruefenacht, B. 2008. Mapping U.S. forest biomass using nationwide forest inventory data and moderate resolution information. Remote Sensing of Environment, 112 (4):1658-1677.

Bouvet, A., Mermoz, S., Le Toan, T., Villard, L., Mathieu, R., Naidoo, L. and Asner, G.P. 2018. An above-ground biomass map of African savannahs and woodlands at 25m resolution derived from ALOS PALSAR. Remote Sensing of Environment, 206(2018): 156-173.

Boyd, D. S. 1999. The relationship between the biomass of Cameroonian tropical forests and radiation reflected in middle infrared wavelengths (3.0-5.0 mu m). International Journal of Remote Sensing, 20(5): 1017-1023.

Brown, S. 1997. Estimating biomass and biomass change of tropical forests: a primer (Vol. 134). Rome: FAO.

Brown, S., and Gaston, G. 1995. Use of forest inventories and geographic information systems to estimate biomass density of tropical forests: application to tropical Africa. In: African Greenhouse Gas Emission Inventories and Mitigation Options: Forestry, Land-Use Change, and Agriculture, pp. 51- 62. Dordrecht: Springer.

Bryan, J., Shearman, P., Ash, J., and Kirkpatrick, J. B. 2010. Estimating rainforest biomass stocks and carbon loss from deforestation and degradation in Papua New Guinea 1972–2002: best estimates, uncertainties and research needs. Journal of Environmental Management, 91(4): 995 - 1001.

Climate-Resilient Green Economy (CRGE). 2011. Ethiopia's Climate-Resilient Green Economy, Green Economy Strategy. Addis Ababa, Ethiopia: Federal Democratic Republic of Ethiopia

Côté, J. F., Fournier, R. A., and Egli, R. 2011. An architectural model of trees to estimate forest structural attributes using terrestrial LiDAR. Environmental Modelling & Software, 26(6): 761-777.

DeFries, R. S., Houghton, R. A., Hansen, M. C., Field, C. B., Skole, D., and Townshend, J. 2002. Carbon emissions from tropical deforestation and regrowth based on satellite observations for the 1980s and 1990s. Proceedings of the National Academy of Sciences, 99(22): 14256-14261.

DeFries, R., Achard, F., Brown, S., Herold, M., Murdiyarso, D., Schlamadinger, B., and de Souza Jr, C. 2007. Earth observations for estimating greenhouse gas emissions from deforestation in developing countries. Environmental Science & Policy, 10(4): 385-394.

Drake, J. B., Knox, R. G., Dubayah, R. O., Clark, D. B., Condit, R., Blair, J. B., and Hofton, M. 2003. Above-ground biomass estimation in closed canopy neotropical forests using lidar remote sensing: Factors affecting the generality of relationships. Global Ecology and Biogeography, 12(2): 147-159.

Duncanson, L. I., Niemann, K. O., and Wulder, M. A. 2010. Estimating forest canopy height and terrain relief from GLAS waveform metrics. Remote Sensing of Environment, 114(1):138-154.

FAO (Food and Agriculture Organization of the United Nations). 2018. Ethiopia's National Forest Inventory-Final Report. Addis Ababa: FAO.

Foody, G. M., Boyd, D. S., and Cutler, M. E. 2003. Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. Remote Sensing of Environment, 85(4): 463-474.

GCOS (Global Climate Observing System). 2003. Second report on the Adequacy of the Global Observing System for Climate in Support of the UNFCCC. GCOS–82 (WMO/TD No. 1143). Geneva, Switzerland: World Meteorological Organization.

Ghasemi, N., Sahebi, M. R., and Mohammadzadeh, A. 2011. A review on biomass estimation methods using synthetic aperture radar data. International Journal of Geomatics and Geosciences, 1(4): 776-788.

Gibbs, H. K. 2006. Olson's Major World Ecosystem Complexes Ranked by Carbon in Live Vegetation: An Updated Database Using the GLC2000 Land Cover Product (NDP-017b, a 2006 update of the original 1985 and 2001 data file). United States. doi:10.3334/CDIAC/LUE.NDP017.2006.

Gibbs, H. K., Brown, S., Niles, J. O., and Foley, J. A. 2007. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. Environmental Research Letters, 2(4):1 -13.

Goetz, S.J., Baccini, A., Laporte, N.T., Johns, T., Walker, W., Kellndorfer, J., Houghton, R.A. and Sun, M. 2009. Mapping and monitoring carbon stocks with satellite observations: a comparison of methods. Carbon Balance and Management, 4(2): 1 - 7.

Hamdan, O., Aziz, H. K., and Rahman, K. A. 2011. Remotely sensed L-band SAR data for tropical forest biomass estimation. Journal of Tropical Forest Science, 23(3):318 - 327.

Bombelli, A., Avitabile, V., Balzter, H., Marchesini, L.B., Bernoux, M., Brady, M., Hall, R., Hansen, M., Henry, M. and Herold, M. 2009. Biomass—assessment of the status of the development of the standards for the terrestrial essential climate variables. Rome, Italy: Food and Agriculture Organization-Global Terrestrial Observation System.

Hese, S., Lucht, W., Schmullius, C., Barnsley, M., Dubayah, R., Knorr, D., Neumann, K., Riedel, T. and Schröter, K. 2005. Global biomass mapping for an improved understanding of the CO2 balance—the Earth observation mission Carbon-3D. Remote Sensing of Environment, 94(1): 94 - 104.

Houghton RA, Butman D, Bunn AG, Krankina ON, Schlesinger P, Stone TA. 2007. Mapping Russian forest biomass with data from satellites and forest inventories. Environmental Research Letters, 2(4):1 - 7.

Houghton, R.A. and Goetz, S.J., 2008. New satellites offer a better approach for determining sources and sinks of carbon. Eos Transactions of the American Geophysical Union, 43: 417 - 418.

Houghton, R. A., Hackler, J. R., and Cushman, R. L. 2001. Carbon Flux to the Atmosphere from Land-use Changes: 1850 to 1990. Tennessee, USA: Carbon Dioxide Information Analysis Center (CDIAC), Oak Ridge National Laboratory (ORNL).

Houghton, R. A., Hall, F., and Goetz, S. J. 2009. Importance of biomass in the global carbon cycle. Journal of Geophysical Research: Biogeosciences, 114(G00E03):1 - 13.

Eggleston, H S, Buendia, L, Miwa, K, Ngara, T, and Tanabe, K. 2006. IPCC guidelines for national greenhouse gas inventories. Japan: Institute for Global Environmental Strategies.

Kumar, L., Sinha, P., Taylor, S., and Alqurashi, A. F. 2015. Review of the use of remote sensing for biomass estimation to support renewable energy generation. Journal of Applied Remote Sensing, 9(1): 097696(1 - 28).

Kurvonen, L., Pulliainen, J., and Hallikainen, M. 1999. Retrieval of biomass in boreal forests from multitemporal ERS-1 and JERS-1 SAR images. IEEE Transactions on Geoscience and Remote Sensing, 37(1): 198 - 205.

Le Toan, T., Beaudoin, A., Riom, J., and Guyon, D. 1992. Relating forest biomass to SAR data. IEEE Transactions on Geoscience and Remote Sensing, 30(2): 403 - 411.

Lefsky, M.A., Harding, D.J., Keller, M., Cohen, W.B., Carabajal, C.C., Del Bom Espirito-Santo, F., Hunter, M.O. and de Oliveira, Jr, R. 2005. Estimates of forest canopy height and aboveground biomass using ICESat. Geophysical Research Letters, 32(22): L22S02(1-4).

Lu, D. 2006. The potential and challenge of remote sensing-based biomass estimation. International Journal of Remote Sensing, 27(7): 1297 - 1328.

Lu, D., Chen, Q., Wang, G., Moran, E., Batistella, M., Zhang, M., Vaglio Laurin, G. and Saah, D.2012. Aboveground forest biomass estimation with Landsat and LiDAR data and uncertainty analysis of the estimates. International Journal of Forestry Research, vol. 2012: 1 - 16.

Lucas, R. M., Moghaddam, M. and Cronin, N. 2004. Microwave scattering from mixed-species forests, Queensland, Australia. IEEE Transactions on Geoscience and Remote Sensing, 42(10): 2142-2159.

Monteith, J. L. 1972. Solar radiation and productivity in tropical ecosystems. Journal of Applied Ecology, 9(3): 747 - 766.

Nune, S., Kassie, M. and Mungatana, E. 2013. Forest resource accounts for Ethiopia. In Implementing environmental accounts (pp. 103-142), R.M. Hassan and E.D. Mungatana (eds.). Dordrecht: Springer.

Olson, J.S., Watts, J.A. and Allison, L.J. 1983. Carbon in live vegetation of major world ecosystems (No. DOE/NBB-0037). TN (USA): Oak Ridge National Laboratory.

Patenaude, G., Milne, R., and Dawson, T. P. 2005. Synthesis of remote sensing approaches for forest carbon estimation: reporting to the Kyoto Protocol. Environmental Science & Policy, 8(2): 161-178.

Rosenqvist, Å., Milne, A., Lucas, R., Imhoff, M., and Dobson, C. 2003. A review of remote sensing technology in support of the Kyoto Protocol. Environmental Science & Policy, 6(5): 441-455.

Ruimy, A., Saugier, B., and Dedieu, G. 1994. Methodology for the estimation of terrestrial net primary production from remotely sensed data. Journal of Geophysical Research: Atmospheres, 99(D3): 5263-5283.

Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S. and Petrova, S. 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences, 108(24):9899-9904.

Sharma, L. K., Nathawat, M. S., and Sinha, S. 2013. Top-down and bottom-up inventory approach for above ground forest biomass and carbon monitoring in REDD framework using multi-resolution satellite data. Environmental Monitoring and Assessment, 185(10): 8621-8637.

Simonian, L., Hernández Munguía, J.G., Arana Noguera, G.A., Thomas, L., Middleton, J. and Phillips, A. 2010. Global forest resources assessment 2010: main report (No. FAO FP-163). Rome (Italy): FAO.

Sinha, S., Jeganathan, C., Sharma, L. K., and Nathawat, M. S. 2015. A review of radar remote sensing for biomass estimation. International Journal of Environmental Science and Technology, 12(5): 1779-1792.

Stas, S. M. 2014. 'Above-ground biomass and carbon stocks in a secondary forest in comparison with adjacent primary forest on limestone in Seram, the Moluccas, Indonesia'. CIFOR Working Paper, (145).

Sun, G., Ranson, K. J., and Kharuk, V. I. 2002. Radiometric slope correction for forest biomass estimation from SAR data in the Western Sayani Mountains, Siberia. Remote Sensing of Environment, 79(2-3): 279 - 287.

Sun, G., Ranson, K. J., Kimes, D. S., Blair, J. B., and Kovacs, K. 2008. Forest vertical structure from GLAS: An evaluation using LVIS and SRTM data. Remote Sensing of Environment, 112(1): 107 - 117.

Thenkabail, P. S., Enclona, E. A., Ashton, M. S., Legg, C., and De Dieu, M. J. 2004. Hyperion, IKONOS, ALI, and ETM+ sensors in the study of African rainforests. Remote Sensing of Environment, 90(1): 23 - 43.

Treuhaft, R. N., Law, B. E., and Asner, G. P. 2004. Forest attributes from radar interferometric structure and its fusion with optical remote sensing. AIBS Bulletin, 54(6): 561-571.

Tyukavina, A., Baccini, A., Hansen, M.C., Potapov, P.V., Stehman, S.V., Houghton, R.A., Krylov, A.M., Turubanova, S. and Goetz, S.J. 2015. Aboveground carbon loss in natural and managed tropical forests from 2000 to 2012. Environmental Research Letters, 10(7): p.074002.

Tyukavina, A., Stehman, S.V., Potapov, P.V., Turubanova, S.A., Baccini, A., Goetz, S.J., Laporte, N.T., Houghton, R.A. and Hansen, M.C. 2013. National-scale estimation of gross forest aboveground carbon loss: a case study of the Democratic Republic of the Congo. Environmental Research Letters, 8(4): p.044039.

Wang, G., Oyana, T., Zhang, M., Adu-Prah, S., Zeng, S., Lin, H., and Se, J. 2009. Mapping and spatial uncertainty analysis of forest vegetation carbon by combining national forest inventory data and satellite images. Forest Ecology and Management, 258(7): 1275 -1283.

WBISPP (Woody Biomass Inventory and Strategic Planning) Project. 2005. A strategic plan for the sustainable development, conservation and management of the woody biomass resources: Final report. Addis Ababa: Ministry of Agriculture.

Williams, C. A., Hanan, N. P., Neff, J. C., Scholes, R. J., Berry, J. A., Denning, A. S., and Baker, D. F. 2007. Africa and the global carbon cycle. Carbon Balance and Management, 2(1): 1-13.

Water and Land Resource Center (WLRC). 2018. Land Use and Land Cover Mapping, Change Detection and Characterization of Ethiopia. Addis Ababa, Ethiopia: WLRC.

Zwally, H.J., Schutz, B., Abdalati, W., Abshire, J., Bentley, C., Brenner, A., Bufton, J., Dezio, J., Hancock, D., Harding, D. and Herring, T. 2002. ICESat's laser measurements of polar ice, atmosphere, ocean, and land. Journal of Geodynamics, 34(3-4):405-445.

Appendix 1: Tree biomass and carbon by biome

Land use and land cover types (2016)	Equivalent class, ENFI (FAO,2018)	t ha-1					
		AGB	BGB	B	AGC	BGC	C
Afroalpine; Grassland	Natural grassland	5.8	1.8	7.5	2.9	0.9	3.8
Afroalpine; Erica bush	Woodland	7.4	2.7	10.1	3.7	1.4	5.1
Agroforestry; Banana	Perennial crop	78.4	24.3	102.7	39.2	12.2	51.4
Agroforestry; Banana and Mango	Perennial crop	78.4	24.3	102.7	39.2	12.2	51.4
Agroforestry; Coffee	Coffee plantation	169.2	45.7	214.9	84.6	22.8	107.4
Agroforestry; Dense	Perennial crop	78.4	24.3	102.7	39.2	12.2	51.4
Agroforestry; Enset	Perennial crop	78.4	24.3	102.7	39.2	12.2	51.4
Agroforestry; Enset and Coffee	Average of Perennial crop and Coffee plantation	123.8	35	158.8	61.9	17.5	79.4
Agroforestry; Enset and Khat	Perennial crop	78.4	24.3	102.7	39.2	12.2	51.4
Agroforestry; Enset, Banana and Mango	Perennial crop	78.4	24.3	102.7	39.2	12.2	51.4
Agroforestry; Crop with Khat	Mixed annual and perennial crop	29.7	8	37.7	14.8	4	18.9
Bare land	Barren land	0.2	0.1	0.2	0.1	0	0.1
Church forest	Evergreen forest	149.6	43.6	193.3	74.8	21.8	96.6
Cropland	Annual crop	8.6	2.7	11.3	4.3	1.3	5.6
Cropland with trees	Mixed annual and perennial crop	29.7	8	37.7	14.8	4	18.9
Croplands on hilly terrain	Annual crop	8.6	2.7	11.3	4.3	1.3	5.6
Degraded hills; Exposed rock or soil	Barren land	0.2	0.1	0.2	0.1	0	0.1
Dense shrub and bush	Woodland	7.4	2.7	10.1	3.7	1.4	5.1
Dense woodland	Woodland	7.4	2.7	10.1	3.7	1.4	5.1
Dryland forest; Deciduous dry region forest	Deciduous forest	83.4	24.5	107.9	41.7	12.3	54
Exposed rock; rock with grass	Barren land	0.2	0.1	0.2	0.1	0	0.1
Exposed sand	Barren land	0.2	0.1	0.2	0.1	0	0.1
Exposed surface	Barren land	0.2	0.1	0.2	0.1	0	0.1
Grassland; Drained and dry grassland	Natural grassland	5.8	1.8	7.5	2.9	0.9	3.8

Land use and land cover types (2016)	Equivalent class, ENFI (FAO,2018)	t ha-1					
		AGB	BGB	B	AGC	BGC	C
Grassland; Wet/ undrained	Marsh	3.8	1	4.8	1.9	0.5	2.4
High forest; Moist evergreen; Coffee undergrowth	Evergreen forest	149.6	43.6	193.3	74.8	21.8	96.6
Homestead plantation	Average of broadleaved and coniferous planted forest	82	22.15	104.2	41.05	11.1	52.05
Irrigated fields	Annual crop	8.6	2.7	11.3	4.3	1.3	5.6
Large Scale Investment; Big farms	Annual crop	8.6	2.7	11.3	4.3	1.3	5.6
Marsh	Marsh	3.8	1	4.8	1.9	0.5	2.4
Mixed forest; enriched degraded natural forest	Semi-deciduous forest	28.3	11.7	39.9	14.1	5.8	20
Open shrub and bush	Wooded grassland	9.1	2.6	11.8	4.6	1.3	5.9
Open woodland	Wooded grassland	9.1	2.6	11.8	4.6	1.3	5.9
Plantation forest	Average of broadleaved and coniferous planted forest	82	22.15	104.2	41.05	11.1	52.05
River course	Barren land	0.2	0.1	0.2	0.1	0	0.1
Riverine vegetation	Wooded wetland	7.5	2.2	9.7	3.8	1.1	4.8
Salt flats	Barren land	0.2	0.1	0.2	0.1	0	0.1
Savanna grassland	Natural grassland	5.8	1.8	7.5	2.9	0.9	3.8
Shifting cultivation	Fallow	6.4	2.2	8.5	3.2	1.1	4.3
Swamp	Wooded wetland	7.5	2.2	9.7	3.8	1.1	4.8
Urban	Built-up area	Masked					
Urban and dense rural settlement	Built-up area	Masked					
Water body	Perennial river	Masked					

*ENFI: Ethiopia's National Forest Inventory, AGB=Above Ground Biomass, BGB=Below Ground Biomass, B=Biomass, AGC=Above Ground Carbon, BGC=Below Ground Carbon, C=Carbon

Appendix 2: Description of land use land cover classes

No	Land use land cover classes	Description
1	Forest	High forest; Moist evergreen; Coffee undergrowth Dryland forest; Deciduous dry region forest Church forest; Mixed forest; enriched degraded natural forest
2	Woodland	Open woodland; Dense woodland
3	Shrub/bush	Open shrub and bush; Dense shrub and bush
4	Cropland	Shifting cultivation; Cropland; Croplands on hilly terrain; Irrigated fields; Large Scale Investment; Big farms
5	Grassland	Grassland; Drained and dry grassland; Grassland; Wet/undrained; Savannah grassland
6	Wetland	Swamp; Marsh
7	Afroalpine	Afroalpine; Erica bush; Afroalpine; Grassland
8	Riverine	Riverine vegetation
9	Agroforestry	Agroforestry: Enset, Khat, Enset and Khat, Coffee, Enset and Coffee, Bannana, Bannana and Mango,
10	Plantation	Homestead plantation, Plantation forest
11	Cropland with trees	Cropland with trees
12	Others	Water body; Urban and dense rural settlement; Bareland; Degraded hills; Exposed rock or soil; Exposed rock; rock with grass; River course; Salt flats; Exposed sand; Exposed surface; Urban

About the Authors

Ermias Teferi, is a postdoctoral research fellow within the UKRI-GCRF supported Water Security and Sustainable Development Hub project with a specific task of Catchment Hydrology research at WLRC and Newcastle University. He is also an Associate Professor at the Centre for Environment and Development, Addis Ababa University. He received his PhD in Hydrology and Water Resources from Technical University of Delft and UNESCO-IHE Institute for Water Education, the Netherlands, in July 2015. Ermias has researched and published in the areas of soil and water management, hydrology & water resources, remote sensing & GIS, climate & disaster risk management, sustainable land management, and land change science.

Amare Bantider is a Resource Governance and Socio-Economic Research Division Director at Water and Land Resource Centre, Addis Ababa University and an Associate Professor of Geography and Natural Resource Management at the Centre for Food Security, College of Development Studies Addis Ababa University. He has researched and published in the areas of on watershed management, soil and water conservation, climate change adaptations, climate change and variability, land use and land cover dynamics, natural resource governance, which have continued to be areas of his research interests.

Gete Zeleke, with a PhD in Natural Resources Management and long years of research, development, and leadership experience, is Director General of Water and Land Resource Centre, Addis Ababa University and a Fellow of the Ethiopian Academy of Sciences. He has researched and published over 50 peer-reviewed articles and book chapters in the areas of land degradation, modelling, integrated landscape management, landscape transformation, sustainability, land use changes. His research and development interests are in the areas of land degradation, integrated landscape management, landscape transformation sustainability.

Woldeamlak Bewket, with a PhD in Production Ecology & Resource Conservation from Wageningen University, The Netherlands, and long years of research and teaching experience, is a Professor of Environmental Studies at the Department of Geography & Environmental Studies, Addis Ababa University. His research interest is in the interdisciplinary areas of environmental change and natural resource management. He has published extensively in refereed periodicals and most of his works are widely cited in the related literature. He is a fellow of the Ethiopian Academy of Sciences.

Tibebu Kassawmar, with a PhD in Geography and Sustainable Development and long years of research and development experience, is Head of the Land Use Systems and Geoinformatics Division at Water and Land Resource Centre, Addis Ababa University. He has researched and published in the areas of land use and land cover dynamics, landscape transformation, land use systems analysis, natural resources management, remote sensing and geoinformatics. His research interests are in the areas of remote sensing, mapping and monitoring land use systems, spatial modeling, landscape transformation analysis, land degradation assessment.

Water & Land Resource Centre
Addis Ababa University

Water and Land Resource Centre, Addis Ababa University
Rahem Building, Diaspora Square, Megenagna
P.O.Box: 3880
Addis Ababa
Ethiopia
Telephone: +251-11-661-22-36
Fax: +251-11-661-22-29
Email: info@wlrc-eth.org
https://www.wlrc-eth.org

Print @ Eclipse +251 115 572222/23