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"Global Biomass Information System"

Mapping Above Ground Biomass, Uncertainty, and Forest Area using Multi-Platform Earth Observation Datasets

Work Package 2.2

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1 EXECUTIVE SUMMARY

Forests play a vital role in the balance of terrestrial carbon as trees naturally absorb carbon dioxide (CO_2) from the atmosphere by means of photosynthesis. As a result, forest ecosystems store large amounts of carbon per year which would otherwise contribute to climate change. Forest accumulates carbon primarily in the form of living above-ground biomass of trees (AGB), which is living organic plant material composed of 50% carbon (IPCC, 2003). When forests are degraded, cleared or burned, large amounts of this carbon are released into the atmosphere as carbon dioxide and other compounds. Deforestation is the second largest anthropogenic source of carbon dioxide to the atmosphere, after fossil fuel combustion. Therefore, monitoring AGB stored in the world's forests is essential for efforts to understand the processes related to the global carbon cycle, reducing carbon emissions originating from deforestation and forest degradation, and have informed discussions on limiting greenhouse gases. However, the size and spatial distribution of forest AGB is still uncertain in most parts of the planet. Few global estimates of AGB are spatially explicit, and also very few repeat the measurements over time.

This report makes an assessment of the current state-of-the-art wide-area forest biomass mapping approaches using earth observation data. It includes a review of current global forest monitoring programmes, allometry, uncertainties, and methods for forest biomass mapping. There is no single sensor that can currently be used for AGB estimation across larger regions, either because of limitations in signal saturation, cloud cover persistence, or complex signal retrieval due to topography. The combination of different sensors by data synergy approaches makes it possible to circumvent their limitations, and exploit the specific strengths of each sensor.

A conceptual approach for a Global Biomass Information System that uses a data synergy method to combine optical, radar, and LiDAR sensors is presented. Current and forthcoming earth observation datasets from the ESA Copernicus Program (i.e. SPOT, Sentinels), JAXA (i.e. ALOS PALSAR, ALOS PALSAR-2), and NASA (i.e. MODIS, Landsat, IceSAT, IceSAT-2) can be used as inputs for this multi-sensor approach. The approach is demonstrated at both mapping scales by case studies in Mexico and in the region of Krasnoyarsk Kray (Central Siberia). The continuity of these sensors opens the possibility for designing an operational Global Biomass Information System which would allow the estimation of national carbon budgets worldwide at different time periods.

2 INTRODUCTION

2.1 FORESTS AND CARBON

Earth is undergoing significant global environmental change. The processes linked to global change are affecting the whole climate system and impacting human civilization. Understanding the effects and causes of these processes will assist human societies in devising adaptation and mitigation strategies. The United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol address the importance of reducing and monitoring greenhouse gas emissions (GHG), with CO_2 being the most significant trace gas. Changes in the amount of atmospheric CO_2 due to anthropogenic activities are altering the biogeochemical cycles that allow the recycling and reuse of carbon on Earth (global carbon cycle), and produce changes in weather patterns (IPCC, 2007).

How the global carbon cycle stores and exchanges carbon within the system is crucial to understand interactions and feedbacks with the climate system. The locations where the carbon is stored within the global carbon cycle are called carbon pools, and the rates of carbon exchanged between pools are known as fluxes, and are classified in sources (emission to the atmosphere) and sinks (uptake from the atmosphere). Knowledge of both, carbon pools and fluxes, is essential to understand the global carbon cycle. Terrestrial ecosystems play a vital role in the global carbon cycle. The terrestrial carbon pool is about three times bigger than the atmospheric pool (IPCC, 2007), and removes 30% of anthropogenic emissions from fossil fuel combustion from the atmosphere (Canadell et al., 2007). The primary source of terrestrial carbon emissions is from anthropogenic land use change, especially deforestation in the tropics, while afforestation, reforestation and growth of existing forest is the major contribution to the terrestrial sink term. Terrestrial ecosystems appear to act as a net sink (Andersson, 2009), but there are significant uncertainties (Figure 1) on the carbon fluxes between land and atmosphere in comparison with the other fluxes, still making terrestrial carbon pools and fluxes one of the major remaining uncertainties in climate science (Watson et al., 2000, Houghton et al., 2001, House et al., 2003, Houghton, 2005, Bonan, 2008).

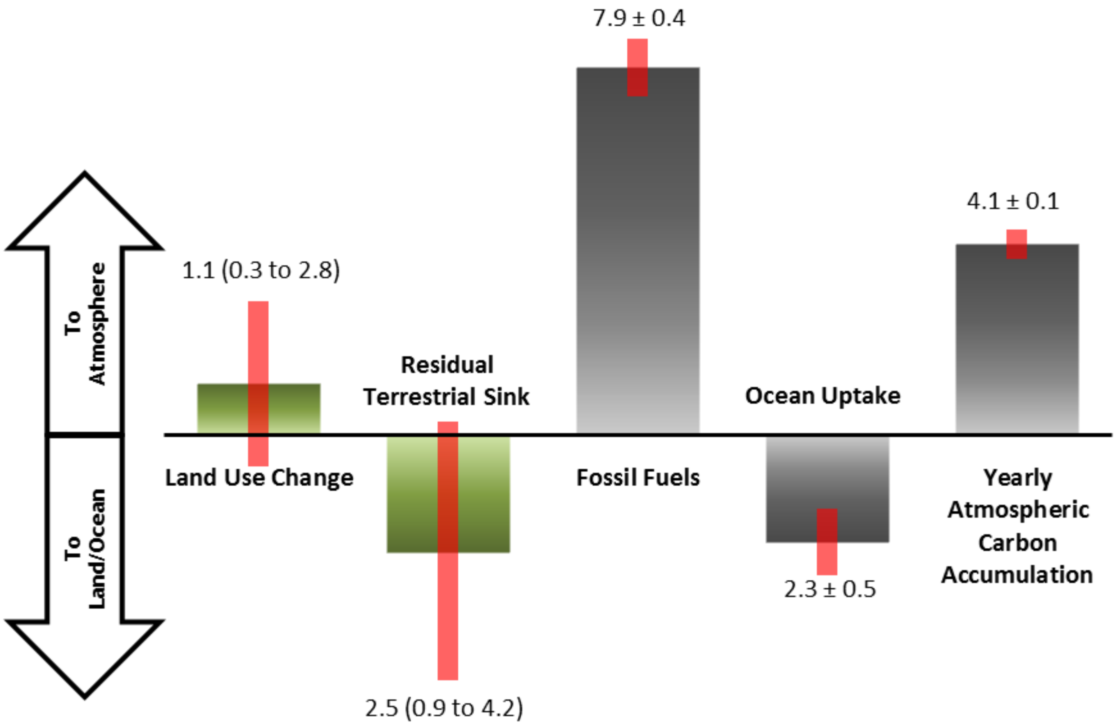

Figure 1 Global carbon flux budget for the 2000-09, partitioned into emissions to the atmosphere and uptake by the land and ocean. Fluxes related to land are coloured green. The yearly accumulation of carbon (net flux) to the atmosphere is given on the right; this is the sum of all the component fluxes but is independently measured. The uncertainties in each of the flux estimates are indicated by red error bars. Error bars from the land-related categories represent the median value from both extremes of the error range. (adapted from ESA, 2012).

Global Forests play an important role in the global carbon cycle as they cover approximately 30% of the land surface and store 45% of terrestrial carbon in the form of biomass via photosynthesis, which sequesters large amounts of carbon per year (Bonan, 2008). Forest accumulates carbon primarily in the form of living above-ground biomass of trees (AGB). Forest AGB is living organic plant material composed of 50% carbon (IPCC, 2003) as well as hydrogen and oxygen, and it is usually defined for a given area. When forests are degraded, cleared or burned, large amounts of this carbon are released into the atmosphere as carbon dioxide and other compounds. Deforestation is the second largest anthropogenic source of carbon dioxide to the atmosphere, after fossil fuel combustion and the largest source of greenhouse gas emissions in most tropical countries (Gibbs et al., 2007). Thus, monitoring AGB stored in the world's forests is essential for efforts to understand the processes related to the global carbon cycle and reducing carbon emissions originating from deforestation and forest degradation.

Biomass is an Essential Climate Variable (ECV) required by the Global Climate Observing System (GCOS) to support the work of the UNFCCC and the Intergovernmental Panel on Climate Change (IPCC) in monitoring climate change. Accurately monitoring and reporting the biomass or carbon content of forests (carbon stocks) is a requirement of different international mechanisms based on economic incentives that have been launched by the international community aiming to mitigate climate change, such as "Reducing Emissions from Deforestation and forest Degradation" (REDD+). Global estimates of AGB carbon stocks have been produced in the past to support the monitoring of CO_2 emissions from deforestation and land use change. However, the size and spatial distribution of forest AGB is still uncertain in most parts of the planet due to the difficulties measuring AGB at the ground level (ESA, 2012). Very few global AGB carbon estimates are spatially explicit. Approaches that make full use of remote sensing techniques to estimate AGB are therefore needed.

This report will first discuss current efforts to monitor forest and AGB at a global scale using traditional methods such as forest inventory ground measurements and more advanced methods based on Earth Observation data. Earth Observation is a very powerful tool to measure forest resources worldwide in an objective, efficient, and affordable manner. Earth Observation satellites use remote sensors that have different advantages and limitations to measure forest biomass. Lastly, a synergistic use of different datasets and sensors is presented in this report as the key to extract the full potential from earth observation methods.

2.2 USING EARTH OBSERVATION IMAGERY TO MEASURE ABOVEGROUND BIOMASS

Three broad types of remote sensors are used by Earth Observation platforms: Optical, Synthetic Aperture Radar (SAR), and Lidar. Each type of sensor has different characteristics which make them suitable for monitoring forest vegetation (Table 1).

Through optical remote sensing, it is possible to estimate a series of different vegetation indices such as Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI), which are mainly related to the photosynthetic components of the vegetation and therefore indirectly to AGB. This relies on an empirical relationship between green foliage and total AGB, however. In reality, forest AGB is primarily composed of the non-photosynthetic parts of trees like trunks and branches. Forest AGB can nevertheless be indirectly estimated from optical sensors based on the sensitivity of the reflectance to variations in canopy structure. Most optical approaches are based on this relationship in which signal retrieval is calibrated with ground measurements to model the spatial distribution of AGB across the landscape. Several studies have mapped AGB at different scales (medium to coarse resolution) relating ground measurements to the signal retrieved from optical sensors such as Landsat or MODIS (e.g. Avitabile et al., 2011, Baccini et al., 2008, Blackard et al., 2008).

Optical sensors have great advantages for global vegetation monitoring. Vegetation can be easily differentiated from other surfaces due to its strong reflectance in near-infrared and visible green, as well as absorption in the red and blue sections of the visible spectrum (Lillesand et al., 2007). Optical sensors have been operating for a long time and have a rich archive that can be used to study vegetation changes. For example, the Landsat mission has global coverage of observations over the last 40 years. Another advantage of optical sensors is that coarse and medium resolution imagery they produce can usually be obtained for free or at a low cost. The main shortcoming of optical imagery is cloud cover as the sensors cannot "see" through clouds. This is not crucial in boreal or temperate latitudes, but can be a problem in tropical areas where there are few days a year without cloud cover. Moreover, as passive sensors, they can only operate during daylight, which reduces the number of potential revisit times in comparison with active sensors like SAR or

Lidar. Thus, the chances to obtain a cloud-free image are also diminished. The way to overcome this problem is through the use of radiometrically consistent multi-temporal datasets, but this is costly, technically demanding, and time-consuming (Los et al., 2000, Avitabile et al., 2011). Estimation of AGB by optical sensors also faces the saturation of the signal retrieval at low AGB stocks (Gibbs et al., 2007) as the signal retrieved from vegetation depends on the absorption of light from the photosynthetic parts of the plants. Optical imagery is suitable for forest area mensuration, vegetation health monitoring, and forest classification, but presents limited correlation with AGB after canopy closure.

Radars are active sensors which generate their own electromagnetic signal. They are independent of solar illumination of the target area, being able to obtain day and night observations, as well as to penetrate through haze, clouds and smoke. SAR is an airborne or spaceborne side-looking radar system that uses its relative motion, between the antenna and its target region, to provide distinctive long-term coherent signal variations used to generate high-resolution remote sensing imagery.

Each SAR satellite works within a specific radar frequency bandwidth (with corresponding wavelength), which is used to classify them in increasing wavelength size as X-, C-, S-, L- or P-band sensors. Several SAR satellites are currently operating (in orbit), including the new L-band ALOS PALSAR-2 which has been recently launched in May 2014 (Table 1).

The radar backscatter (the amount of scattered microwave radiation received by the sensor) is related to AGB as the electromagnetic waves interact with tree scattering elements like leaves, branches and stems, but their sensitivity to AGB depends on the radar wavelength (Le Toan et al., 2004). Shorter wavelengths are sensitive to smaller canopy elements (X- and C-band), while longer wavelengths (L- and P-band) are sensitive to branches and stems (Goetz et al., 2009). Longer wavelengths are theoretically more suitable for estimation of AGB as tree branches and stems comprise the highest percentage of AGB in forests. SAR backscatter sensitivity using L-band usually saturates at around 100^{-1}50 t ha^{-1} (Wagner et al., 2003, Mitchard et al., 2009). However, other authors have found higher saturation values of more than 250 t ha^{-1} for L-band (Lucas et al., 2010), and even more than 300 t ha^{-1} when combined with other SAR datasets such as X-band (Englhart et al., 2011). Nevertheless, there is no current satellite sensor in orbit (neither optical nor radar) that can offer a reasonable relationship between the observations and the high values of AGB often found in tropical areas (>400 t ha^{-1}). Even though a P-band sensor is very promising (Le Toan et al., 2011), at the moment there is only one planned satellite, the ESA Earth Explorer 8 BIOMASS mission (ESA, 2012), which will not be launched before 2020. The future P-Band BIOMASS mission by ESA has the following accuracy requirements at 200m pixel level: a RMSE of ±10 t ha^{-1} for AGB below 50 t ha^{-1}, and a relative error of ±20% for AGB above 50 t ha^{-1}.

Lidar technology consists of optical active sensors transmitting laser pulses to measure the distance to the target. In particular, airborne imaging Lidar provides direct and very accurate measurements of canopy height. Lidar sensors do not suffer from signal saturation, as optical and radar sensors do, because the signal can penetrate the canopy. Nevertheless, the vertical extent of each waveform increases as a function of terrain slope and footprint size, making this information insufficient over sloped terrain to estimate canopy height (Lefsky et al., 2007). The only spaceborne profiling Lidar sensor was the

Geoscience Laser Altimeter System (GLAS) that was aboard the NASA Ice, Cloud, and land Elevation (ICESat). This satellite operated between 2003 and 2010. There is no current terrain profiling Lidar satellite in orbit at the moment, and IceSAT-2 will not be launched until 2016.

Table 1 Operating or planned satellites used for Forest Monitoring.

Sensor	WAVELENGTH	AGB SATURATION*	OPERATING SATELLITES	PLANNED SATELLITES
OPTICAL	Visible/near-infrared (380 nm - 1 mm)	15 - 70 t ha^{-1}	Terra/Aqua MODIS, Terra ASTER, SPOT 6, Landsat 7 & 8, EO-I, DMC constellation, Sentinel 2, PROBA V, etc. High Resolution satellites	SPOT 7, Amazonia, CBER 4 & 4B, etc. High Resolution satellites
SAR	P Band (30 - 100 cm)	100 - 200 t ha^{-1}		BIOMASS
	L band (15 - 30 cm)	40 - 150 t ha^{-1}	ALOS/PALSAR 2	SAOCOM 1A, 1B Tandem-L (in study)
	S band (7.5 - 15 cm)	Not reported	Huanjing 1C	NovaSAR-S
	C band (3.8 - 7.5 cm)	20 - 50 t ha^{-1}	Radarsat 1 Radarsat 2 Sentinel 1	RADARSAT Constellation
	X band (2.4 - 3.8 cm)	< 20 t ha^{-1}	TerraSAR X Cosmo/SkyMed Tandem X	Paz
LIDAR	Visible/near-infrared (532 & 1064 nm)	No limit		ICESat 2

* Range of AGB saturation thresholds given by literature review (Imhoff, 1995, Carreiras et al., 2012, Lucas et al., 2010, Mitchard et al., 2009, Naesset, 2007, Dobson et al., 1992)

2.3 GLOBAL FOREST MONITORING

The first challenge to monitor forests at a global scale is the definition of forest itself, and consequently the definitions of deforestation and forest degradation. Forests are ecosystems dominated by trees and other woody vegetation, but there are approximately 1,500 definitions of forest worldwide based on administrative, cover, use or ecological characteristics (Lund, 2014). These different definitions are based on different concerns and interests of people and states. Legal definitions greatly differ from ecological or traditional definitions, though the characteristics and thresholds are more clearly defined. These definitions are mostly focused on setting the minimum physical thresholds for a vegetated ecosystem to be considered as a forest. Unfortunately, there is no universally agreed definition of forest (Figure 2). This situation makes any study at global scale using data generated at national level very complicated.

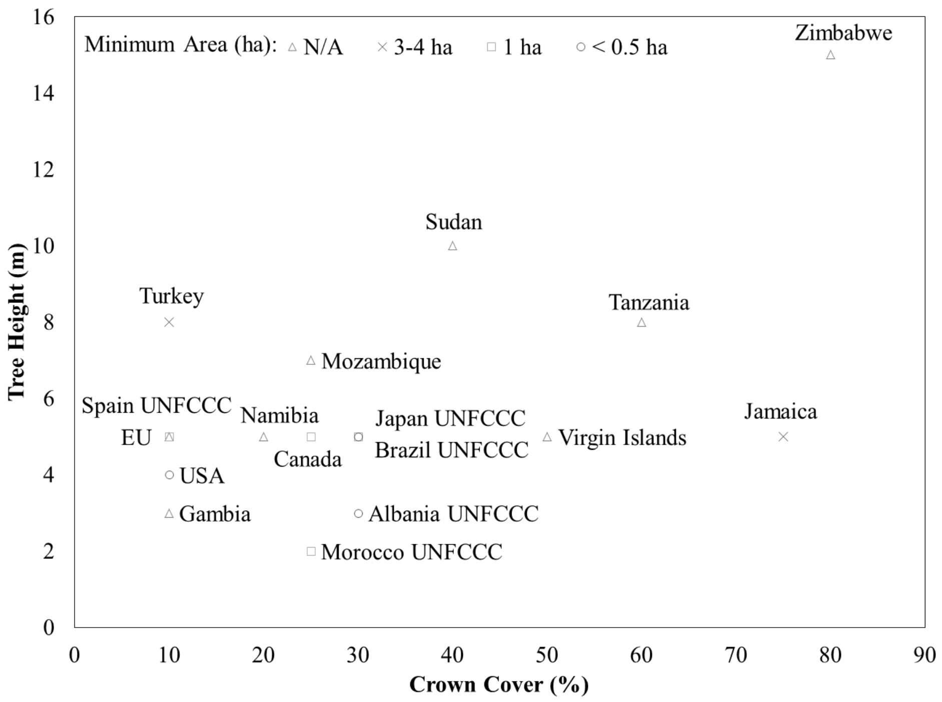

Figure 2 Minimum thresholds for tree height, crown cover and area of forest definitions used in different countries. Modified from (Wadsworth et al., 2008). Data from (Lund, 2014).

Three forest definitions and two deforestation definitions have been mainly used in different global studies, having their origin in the UNFCCC, in the Convention on Biological Diversity (CBD), and in the Forest Resource Assessment (FRA) from the Food and Agriculture Organization of the United Nations (FAO). These definitions were listed in the report Schoene et al. (2007b) about definitional issues related to REDD as follows:

DEFINITIONS OF FOREST

UNFCCC: Forest is a minimum area of land of 0.05-1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 per cent with trees having the potential to reach a minimum height of 2-5 metres at maturity in situ. A forest may consist either of closed forest formations, where trees of various storeys and undergrowth cover a high proportion of the ground, or open forest. Young natural stands and all plantations which have yet to reach a crown density of 10-30 per cent or tree height of 2-5 metres are included under forest, as are areas normally forming part of the forest area which are temporarily unstocked as a result of human intervention such as harvesting or natural causes but which are expected to revert to forest.

CBD: Forest is a land area of more than 0.5 ha, with a tree canopy cover of more than 10 percent, which is not primarily under agriculture or other specific non-forest land use. In the case of young forest or regions where tree growth is climatically suppressed, the trees should be capable of reaching a height of 5 m in situ, and of meeting the canopy cover requirement.

FAO: Land spanning more than 0.5 hectares with trees higher than 5 metres and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agriculture or urban use.

Explanatory note:

1. Forest is determined both by the presence of trees and the absence of other predominant land uses. The trees should be able to reach a minimum height of 5 m in situ. Areas under reforestation that have not yet reached but are expected to reach a canopy cover of 10 percent and tree height of 5 m are included, as are temporarily unstocked areas, resulting from human intervention or natural causes, which are expected to regenerate.
2. It includes areas with bamboo and palms provided that height and canopy cover criteria are met.
3. It includes forest roads, firebreaks and other small open areas; forest in national parks, nature reserves and other protected areas, such as those of specific scientific, historical, cultural or spiritual interest.
4. It includes windbreaks, shelterbelts and corridors of trees with an area of more than 0.5 ha and width of more than 20 m.
5. It includes plantations primarily used for forestry and protection purposes, such as rubberwood plantations and cork oak stands.
6. It excludes tree stands in agricultural production systems, for example fruit plantations and agroforestry systems. The term also excludes trees in urban parks and gardens.

DEFINITIONS OF DEFORESTATION
UNFCCC: The direct human-induced conversion of forested land to non-forested land.
FAO: The conversion of forest to another land use or the long-term reduction of the tree canopy cover below the minimum 10 percent threshold.
Explanatory note:

1. Deforestation implies the long-term or permanent loss of forest cover and implies transformation into another land use. Such a loss can only be caused and maintained by a continued human-induced or natural perturbation.
2. It includes areas of forest converted to agriculture, pasture, water reservoirs and urban areas.
3. The term specifically excludes areas where the trees have been removed as a result of harvesting or logging, and where the forest is expected to regenerate naturally or with the aid of silvicultural measures. Unless logging is followed by the clearing of the remaining logged-over forest for the introduction of alternative land uses, or the maintenance of the clearings through continued disturbance, forests commonly regenerate, although often to a different, secondary condition. In areas of shifting agriculture, forest, forest fallow and agricultural lands appear in a dynamic pattern where deforestation and the return of forest occur frequently in small patches. To simplify reporting of such areas, the net change over a larger area is typically used.
4. Deforestation also includes areas where, for example, the impact of disturbance, over-utilization or changing environmental conditions affects the forest to an extent that it cannot sustain a tree cover above the 10 percent threshold.

The definitions of forest range from a minimum forest area of 0.05-1.0 ha, minimum tree height of 2-5 m, and minimum crown cover of 10-30%. Accordingly, deforestation can be defined as the long-term reduction of tree crown cover to below 10-30%, implying reduction of forest area. Deforestation is usually associated with land use conversion, from forest to other types such as cropland or pasture. The UNFCCC definitions are ambiguous as the minimum threshold for forest area and crown cover are ranges of values (0.05-1.0 ha and 10-30%). The CBD does not clarify if temporally unstocked areas are considered forest or non-forest, and lacks a specific definition for deforestation.

Even though the overall challenge for global monitoring of forest is very complex, the discrepancies between forest definitions used by different countries are an important issue, as estimations of forest area will differ from country to country depending on the definition used. Additionally, these definitions also have a direct impact on the technology required for monitoring forests. The minimum area considered as forest in these definitions range from 0.05 to 1 ha. This means that for a given square forest area, the minimum pixel resolution for the remote sensing imagery which will allow its detection ranges from 22x22 m (0.05 ha) to a 100x100 m (1 ha) for the UNFCCC definition, and 71x71 m (0.5 ha) for the CBD and FAO definitions. Nevertheless, higher spatial resolution is needed for assessing deforestation and forest degradation which might occur at a smaller scale. Additionally, some definitions of forest and deforestation include temporarily unstocked areas as well as forestry land use areas even if these are not currently covered by trees. This makes the estimation of forest area by remote sensing even more complicated as additional information such as land use maps are needed.

Remote sensing approaches allow the study of forest vegetation from a physical perspective. Therefore, the same vegetation thresholds defining forest, deforestation and forest degradation can be applied globally. The downside of this physical approach is that other types of woody vegetation such as oil palm plantations, which are responsible for large-scale deforestation in tropical areas, are sometimes included in the forest class, especially when using coarse or medium-resolution optical sensors to monitor forest (e.g. Hansen et al., 2013). To overcome this challenge, ancillary data with the location of these plantations or accurate remote sensing methods to differentiate these plantations from natural forest have to be implemented. Long-wavelength Synthetic Aperture Radar (SAR) sensors could play an important role as the radar signal is sensitive to forest structure such as the regular spacing patterns observed in oil palm plantations (Morel et al., 2011).

Several products are globally or continentally produced to monitor forest changes (Table 2). These projects are generally based on in-situ data and satellite optical sensors with medium to coarse spatial resolutions. The use of airborne and high resolution sensors is restricted to sub-national level or project level, as it could be impractical and the cost prohibitive at country, continental or global scale. Nevertheless, the use of these sensors on-demand can be extremely valuable for monitoring specific hot spots where deforestation is a major issue, as well as to assist in the validation of medium-resolution products. The products developed by these programmes are mostly created using optical imagery, which requires a complex and extensive data processing chain in order to produce consistent global products. The main parameters measured by these data projects are forest cover and forest type. Most of these products lack the capabilities to produce spatial AGB estimates.

Table 2 Global Forest Monitoring Programmes.

PROGRAMME OR STUDY	AGENCY	DATA SOURCE	SPATIAL RESOLUTION	TEMPORAL COVERAGE	KEY ISSUES & REFERENCE
Forest Resource Assessment (FRA)	FAO	National Forest Inventories	N/A	Every 5 years	Data sources are not globally available (FAO, 2000, FAO, 2005, FAO, 2010, FAO, 2012)
Global Remote Sensing Survey (RSS)	FAO	Landsat	N/A	1990, 2000, 2005	Systematic sample (10km x 10km) of Landsat imagery worldwide (FAO et al., 2009)
ALOS Kyoto and Carbon Initiative	JAXA	ALOS PALSAR	50 m, 500 m	Annual 2007 - 2010	L-band SAR imagery & Forest/Non-Forest mosaics (Shimada et al., 2011, Shimada et al., 2010, Shimada and Ohtaki, 2010, Shimada and Otaki, 2010)
Tree Cover Continuous Fields , Tree Cover Loss & Gain	University of Maryland	Landsat	30 m	Annual 2000 - 2012	Tree cover percentage at sub-pixel-level. Identifies areas of tree cover loss (annual) and gain (12 years cumulative) (Hansen et al., 2013)
Global Forest Watch	World Resources Institute	Landsat, MODIS, and others	30 m - 5 km (1)	Monthly quarterly, and annual from year 2000	Forest change, cover and use, alerts, crowdsourcing, etc.
Vegetation Continuous Fields	University of Maryland, NASA	MODIS	250 m, 500 m, 1 km	Annual 2000 - 2010	Tree cover percentage at sub-pixel-level (Townshend et al., 2011)
Tree Cover Continuous Fields	University of Maryland, NASA	Landsat	30 m	2000	Tree cover percentage at sub-pixel-level (Sexton et al., 2013)
GlobCover	ESA	ENVISAT	300 m	2005/06 & 2009	Labelled according to the UN Land Cover Classification System
MODIS Land Cover Type	NASA	MODIS	500 m	Annual 2001 - 2012	5 Global Land Cover Classification Systems
COPERNICUS Global Land Service	GEOLAND-2, ESA	SPOT, and others	1 km	Several intervals from 1999	Vegetation Biophysical parameters
Biomass Geo-Wiki	Several	Several (2)	30 m - 0.01 grad	2000 - 2010	Comparison AGB maps

(1) Landsat based products present 30 m spatial resolution while deforestation alerts, based on MODIS, go from 250 m up to 5 km resolution.
(2) Each product present different data sources, spatial coverage, and methods

The Forest Resource Assessments (FRAs) are based on the analysis of forest inventory information supplied by each country and supported by expert judgements, remote sensing and statistical modelling. A National Forest inventory is the most widely used method for in-situ forest monitoring due to its historic roots in national forestry administrations, its accuracy and low technical requirements. A forest inventory is a systematic collection of forest data for assessment or analysis. The approach consists of sample-based statistical methods, sometimes in combination with remote sensing and aerial imagery. In developing countries where the labour cost is low, the use of forest inventories could be a relatively cost-effective approach. The FRAs analyse information on forest cover, forest state, forest services and non-wood forest products. However, it was not until 2000 that a single technical definition for forest was used (10% crown cover). Changes in baseline information, inconsistent methods and definitions through the different FRAs make their comparison difficult (FAO, 2012). Several authors have questioned the country-level estimates of forest carbon stocks reported by the FRAs due to inadequate sampling for the national scale, inconsistent methods, and in most tropical countries figures that were based on ‘best guesses’ instead of actual measurements (Waggoner, 2009, Gibbs et al., 2007, Houghton, 2005).

The Global Remote Sensing Survey (RSS) implemented in 2009 was a systematic sampling based on units located at longitude and latitude intersections worldwide. Each sample unit consist of Landsat imagery covering an area of 10 km x 10 km, which was automatically classified into forest/non-forest areas. The survey reported estimates of forest area, deforestation and afforestation at global, continental and ecological zone level for 1990, 2000 and to 2005.

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board the Terra and Aqua satellites provides biophysical parameter datasets, which allow monitoring of biosphere dynamics. MODIS Vegetation Continuous Fields (VCF) is a sub-pixel-level representation of surface vegetation cover estimates globally (Hansen et al., 2003). The percent canopy cover per MODIS pixel refers to the amount of sky obstructed by tree canopies equal to or greater than 5 m in height (Hansen et al., 2003), which agrees with the UN Food and Agriculture Organization (FAO) definition of forest. The current version (collection 5) has been published with 250 m resolution globally. Initial results show that this version of the product is substantially more accurate (50% improvement in RMSE) than the previous 500 m version (Townshend et al., 2011). The pixel size of 250 m (ca. 6.25 ha) is still far from a pixel size of 71 m, which would be the minimum resolution that could detect a minimum unit area of forest (0.5 ha) according to the main forest definitions (Schoene et al., 2007a). Nevertheless, VCF collection 5 currently has the best temporal coverage (from 2000) among the coarse resolution global forest monitoring products that are free of charge. Following the success of MODIS VCF, a recent 30 m resolution Tree Cover Continuous Fields (VCF) dataset has been developed, re-scaling the 250 m MODIS VCF with Landsat imagery (Sexton et al., 2013) (Figure 3).

A data mining approach of the Landsat archive by means of the Google Earth Engine was also used to globally quantify annual forest loss (2000-2012) as well as 12 years of cumulative forest gain at 30 m spatial resolution (Hansen et al., 2013). This dataset together with others such as FORMA alerts (Hammer et al., 2013), which provide tree cover lost alerts every 16-days interval, can be freely downloaded and visualised on the website of the Global Forest Watch (http://www.globalforestwatch.org/). This site is a web-platform that aims to provide reliable information about forest to interested stakeholders such as governments, NGOs and companies by combining satellite technology, open data and crowdsourcing. The site also includes a forest carbon map for the year 2000 covering the tropical areas (Saatchi et al., 2011).

ESA’s Copernicus Global Land Service provides vegetation biophysical parameters at global level such as Fraction of green Vegetation Cover (FCOVER), Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), and others. The products have 1 km spatial resolution.

Biomass Geo-Wiki is a partnership project between the International Institute for Applied Systems Analysis (IIASA), University of Applied Sciences Wiener Neustadt, and the University of Freiburg. The project uses a crowdsourcing approach to compare and validate forest AGB products generated from different providers (e.g. NASA, IIASA, Friedrich-Schiller University of Jena, etc) at different spatial resolutions, for different areas and temporal coverage.

Land cover mapping provides a static representation of land cover. It does not show change in forest area, but serves as a baseline for assessment of forest cover change. Two main projects are the most representative and widely used at the moment: GlobCover and MODIS land products. GlobCover is a project from the European Space Agency (ESA) whose goal is to develop an Earth's global land cover product (Arino et al., 2005) (Figure 3). Data from the Medium Resolution Imaging Spectrometer and Advanced Synthetic Aperture Radar (MERIS) on board Environmental Satellite (ENVISAT) is used to develop a Land Cover product labelled according to the UN Food and Agriculture Organisation’s Land Cover Classification System. Two GlobCover products based on ENVISAT MERIS data at full resolution (300 m) were released by ESA for the years 2005-2006 and for 2009.

The MODIS Land Cover Type Product (MCD12Q1) provides data characterizing five global land cover classification systems and is offered free of charge. The land cover product is an annual 500 m spatial resolution product derived through a supervised decision-tree classification method.

The ALOS Kyoto & Carbon (K&C) Initiative is an international project led by Japan Aerospace Exploration Agency (JAXA). Coordinated by JAXA Earth Observation Research Centre (EORC), the programme focuses on producing data products primarily from the Phased Array L-band Synthetic Aperture Radar (PALSAR) sensor on-board the Advanced Land Observing Satellite (ALOS). The main product from the K&C program is the 50 m spatial resolution forest/non-forest (FNF) area mosaics from resampled 10 m data every year (2007-2010) (Figure 3). The method for developing this map is based on backscatter intensity threshold (Shimada et al., 2011).

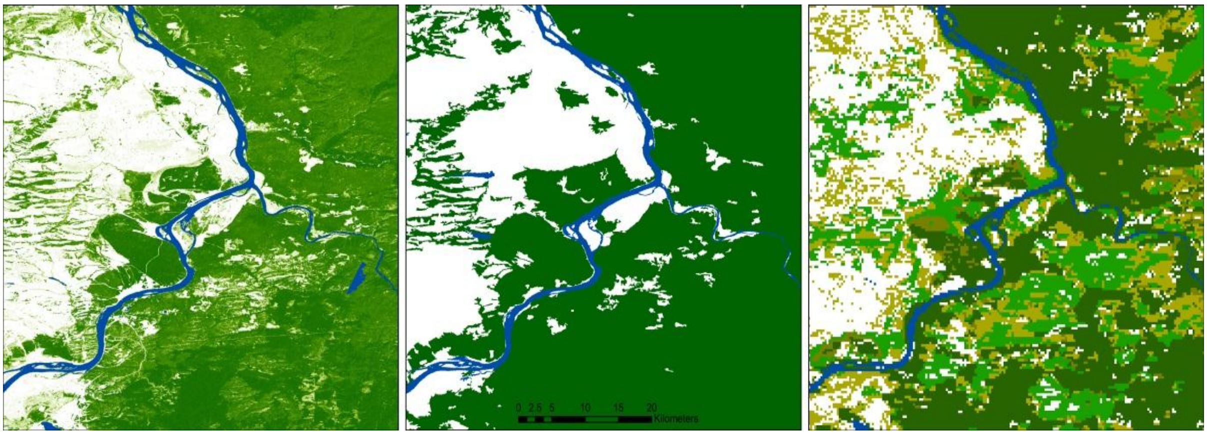

Figure 3 Area in Central Siberia. Left: Landsat Tree Cover Continuous Fields 30 m resolution (2000) (Raw data:(Sexton et al., 2013)), Centre: Forest/Non Forest K&C Initiative Product 50 m resolution (2010) (Raw data: © JAXA), Right: Globcover 300 m resolution (2009) (Raw data: © ESA 2010 and UCLouvain). Green colours denote forest and white colour non-forest area.

2.4 REMOTE SENSING AND ALLOMETRY

AGB is accurately and directly measured through in-situ destructive sampling methods. Through these methods entire trees are felled and the different tree components are separated and weighted in-situ, resulting in a significantly laborious, expensive and impractical approach at a large scale (Ketterings et al., 2001). Non-destructive in-situ methods such as forest inventories make use of allometric models to predict AGB. In-situ non-destructive measurements are broadly used for AGB monitoring as their accuracy lies between 20% and 2% (Bombelli et al., 2009). Biophysical parameters like tree height or diameter are commonly measured in forest inventories and other studies, and used to estimate AGB through allometric equations.

Derivation of allometric relationships is based on the allometry of living organisms. Allometry is the condition of geometric similitude which results when geometry and shape are conserved among organisms differing in size (Niklas, 1994). It works as a 'rule of proportions' between organism components and their whole. Allometric biomass regressions are developed by measuring biomass of entire trees or their components and regressing these data against some more easily measured variables (Pastor et al., 1984). The use of allometric equations has been shown to be a cost-efficient technique due to the use of existing and easily-measured variables. Common examples of these variables are tree height (*H*), basal area (*BA*), wood specific gravity (*WSG*), or diameter at breast height (*D*).

The most commonly used mathematical model for AGB estimation uses the form of a nonlinear function (Eq. 1), where Y is the total aboveground tree dry biomass or any other tree component, b0 and b1 are parameters, and X is the biophysical parameter used for prediction (António et al., 2007):

$$Y = b_0 \cdot X^{b_1} \qquad \textit{Eq. 1}$$

Allometric models have been traditionally developed to be used in national forest inventories or specific studies. The samples used to create these models are usually delimited to the area under study. Such models are generally developed for specific species and sites (West et al., 1991, Saint-André et al., 2005, Muukkonen, 2007, Návar, 2009). In temperate and boreal forested areas, there is a large availability of allometric equations (Zianis et al., 2005). Unfortunately, these equations are not easily available for developing countries in tropical regions with large areas of natural forests due to the geographical remoteness, lack of research studies, data paucity, high tree diversity or armed conflict situations. The Congo Basin is a clear example of the scarcity of ground samples. Even though the Congo basin is one of the largest forested areas in the world, only a small number of allometric equations have been developed for the forests of this region (Henry et al., 2011). Several studies found that allometric models could be generalised by the incorporation of additional variables that explain the regional variability, such as *WSG*, and developed models for specific regions or forest biomes based on a large number samples (Brown, 1997, Ketterings et al., 2001, Chave et al., 2005). Generalized equations are frequently used in tropical areas, but are just recommended in cases where no local models are available (Chave et al., 2004). Moreover, Feldpausch et al. (2011) suggested that height should be included in any allometric model as the *H:D* allometry varies by geographic location, environment and forest structure.

Few allometric models relating remote sensing-derived biophysical parameters (usually canopy height) to AGB are presently available (e.g. Asner et al., 2012, Saatchi et al., 2011, Cloude et al., 2011, Mette et al., 2004, Mitchard et al., 2012). This kind of relationship at the plot or pixel scale is conceptually similar to relationships at tree level. The main difference is that the relationship is established between the biophysical parameter and the AGB of all trees inside the area of interest. At tree level, AGB can be accurately calculated from *H*, *D,* and *WSG* (Feldpausch et al., 2012, Vieilledent et al., 2011, Chave et al., 2005) using generalized models. Remote sensing can measure *H* but cannot directly measure *WSG*. The use of allometric models calibrated with regional ground data can circumvent this problem and provide accurate estimates of AGB (Fagan and DeFries, 2009). Moreover, the use of additional forest structure variables can also improve the estimates (Popescu et al., 2003, Palace et al., 2008). Forest biomes or ecological regions present different tree allometries depending on climatic conditions, vegetation structure, species, soil types, and other characteristics, which ultimately affect the correlation between AGB and biophysical parameters like mean canopy height at plot and pixel level. It seems therefore logical to develop regional models that capture the regional variability, as the slopes of these allometric functions will differ from region to region (Figure 4). Regional allometry has not been sufficiently explored to be used with remote sensing, but its use could improve AGB estimation worldwide.

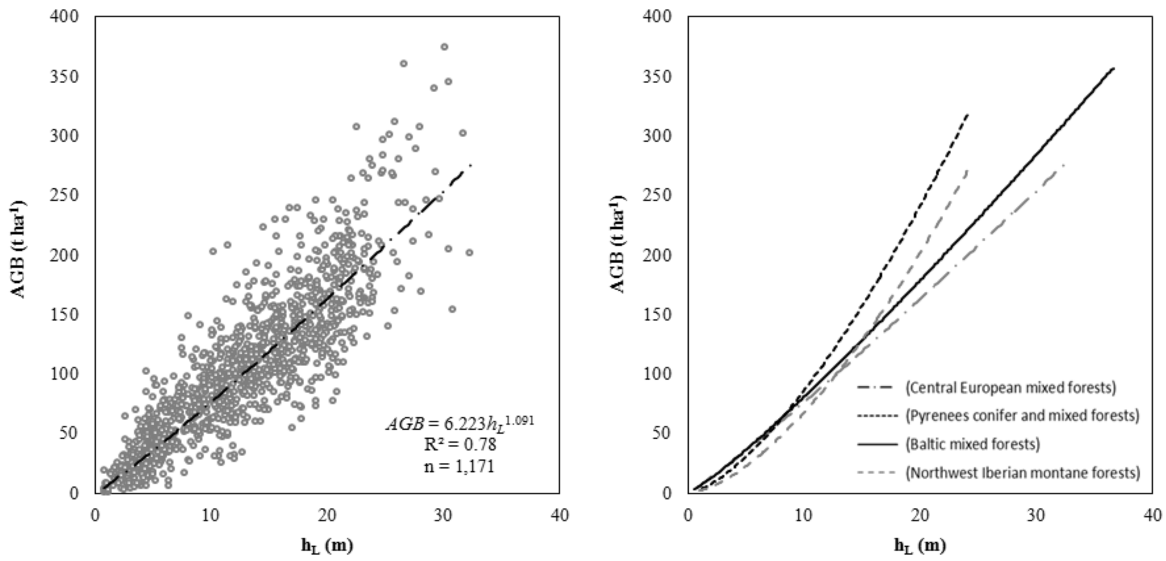

Figure 4 Left: Plot-level allometric model relating AGB to Lorey's mean canopy height for the Central European Mixed Forest ecological region. Right: Allometric models for different ecological regions in Europe.

New techniques applied to SAR and Lidar sensors can be used to estimate biophysical parameters such as tree canopy height (Saatchi et al., 2011, Balzter et al., 2007b, Lefsky et al., 2005). Biophysical parameters can be used with regional allometric models to estimate forest AGB. This approach does not suffer from the AGB / radar backscatter saturation problem. AGB can be mapped by SAR from interferometric height models in combination with allometry (Balzter et al., 2007b). This approach requires a ground Digital Terrain Model (DTM), which is not always easy to obtain. Polarimetric Interferometry is another SAR technique which, in contrast to single-polarisation interferometry, does not rely on an external DTM, as it estimates terrain and canopy height from the different polarimetric scattering mechanisms (Cloude et al., 2011, Papathanassiou et al., 2008, Cloude and Papathanassiou, 1998). It relies on the coherence of two SAR scenes taken over the same site, either within a short time window or simultaneously from two slightly different positions within a certain distance range or baseline. SAR Tomography goes beyond the polarimetric interferometry technique by using a multi-baseline of interferometric SAR images to generate a 3D vertical structure of the vegetation based on the variation of backscatter scattering as a function of height (Le Toan et al., 2011, Cloude, 2006).

Several authors have studied Lidar-derived biophysical canopy metrics such as maximum canopy height, Lorey's mean height (h_L) and the height of median energy (HOME) to characterize forest vertical structure (Lefsky, 2010, Sun et al., 2008, Balzter et al., 2007a, Balzter et al., 2007b, Hinsley et al., 2006, Bradbury et al., 2005, Drake et al., 2002). In recent studies (Lefsky, 2010, Simard et al., 2011), spaceborne profiling Lidar from the GLAS sensor was used to create global maps of forest canopy height. The maps estimated top canopy height (Simard et al., 2011), and h_L (Lefsky, 2010) from the full waveform of the GLAS footprints (area illuminated by the laser and from which the waveform-return signal gives information). Lorey's mean canopy height is the basal area weighted height of all trees. At plot and Lidar footprint level h_L shows a robust relationship with AGB (Lefsky, 2010). The size of the GLAS footprints (< 0.4 ha) is comparable to most forest plots sizes (0.02 - 1 ha). Therefore, there are plenty of data available for developing regional models which could relate canopy height to AGB as seen in (Saatchi et al., 2011, Mitchard et al., 2012, Asner et al., 2012).

3 SYNERGY OF REGIONAL ALLOMETRY, IN-SITU MEASUREMENTS, AND MULTI-PLATFORM EARTH OBSERVATION DATASETS

There is no sensor that can currently be used for AGB estimation across larger regions, either because of limitations in signal saturation, cloud cover persistence, or complex signal retrieval due to topography. Several studies have aimed to map AGB at global, biome, or continental levels using a variety of methods. Products mapping forest AGB and Carbon stocks globally (Kindermann et al., 2008), continentally (Baccini et al., 2008, Schepaschenko et al., 2011), in the tropical (Saatchi et al., 2011, Baccini et al., 2012), temperate and boreal regions (Thurner et al., 2014), as well as growing stock volume continentally (Gallaun et al., 2010), and in boreal regions (Santoro et al., 2011) have recently been published. Together with the limitations of remote sensing imagery to map forest AGB, all these products also face important challenges regarding ground data availability to calibrate their approaches. Most of these studies use methods for combination of multiple datasets in order to circumvent such limitations. Data synergy approaches make possible to exploit the specific strengths of each sensor. For example, Lidar sensors can be used for estimation of AGB samples across the landscape, while SAR sensors in combination with optical sensors can be used for forest area estimation and extrapolation of the measurements.

There are a number of parametric and non-parametric approaches to extrapolate values of AGB to larger spatial scales using remote sensing imagery. Multiple regression analysis, k-nearest neighbour technique (k-NN), co-kriging, random forests, and neural networks are some examples. Parametric models should not be used for extrapolating AGB data, as there are no current satellite observations that can be reasonably related to AGB across the whole landscape. Moreover, the assumptions in parametric models of independence and multivariate-normality are often violated (Breiman, 2001b). As complex ecological systems like forests show non-linear relationships, autocorrelation, and variable interaction across temporal and spatial scales, the use of non-parametric algorithmic methods often outperform parametric methods (Evans and Cushman, 2009).

Two recent papers (Baccini et al., 2012, Saatchi et al., 2011) mapped the spatial distribution of AGB and Carbon in the tropics using synergistic approaches based on the use of AGB estimated from GLAS footprints (Figure 5). The approach described by Baccini et al. (2012) relates GLAS waveforms to AGB using a model calibrated by ground plots directly located under the GLAS footprints, while Saatchi et al. (2011) uses 3 continental allometric models derived from ground data to relate GLAS-derived Lorey's mean canopy height to AGB. As discussed in the previous section, the use of a model for each continent might better explain the allometric regional variability than a single model, but might still introduce a great amount of uncertainty when applied to very different forest biomes such as temperate coniferous and tropical rainforest. The studies use non-parametric approaches such as Random Forest (Breiman, 2001a) and MaxEnt (Phillips et al., 2006, Phillips et al., 2004) for extrapolation of the AGB across wide areas, to produce 463 m and 1 km resolution maps respectively. One of the most innovative features of using MaxEnt is the possibility of mapping the uncertainty of the AGB estimation on a pixel-by-pixel basis. Both approaches use MODIS and SRTM products, and in the case of Saatchi et al. (2011) also

Quickscatterometer data (QSCAT). None of these products can solely explain the variability of AGB across the landscape, but the methods used by these studies aim to take advantage of the full potential of the information contained in each product.

The studies showed though important differences in the amount and distribution of AGB Carbon (Figure 5). These differences nearly disappear at coarser resolutions when data is aggregated to biome or country scale (Mitchard et al., 2013).

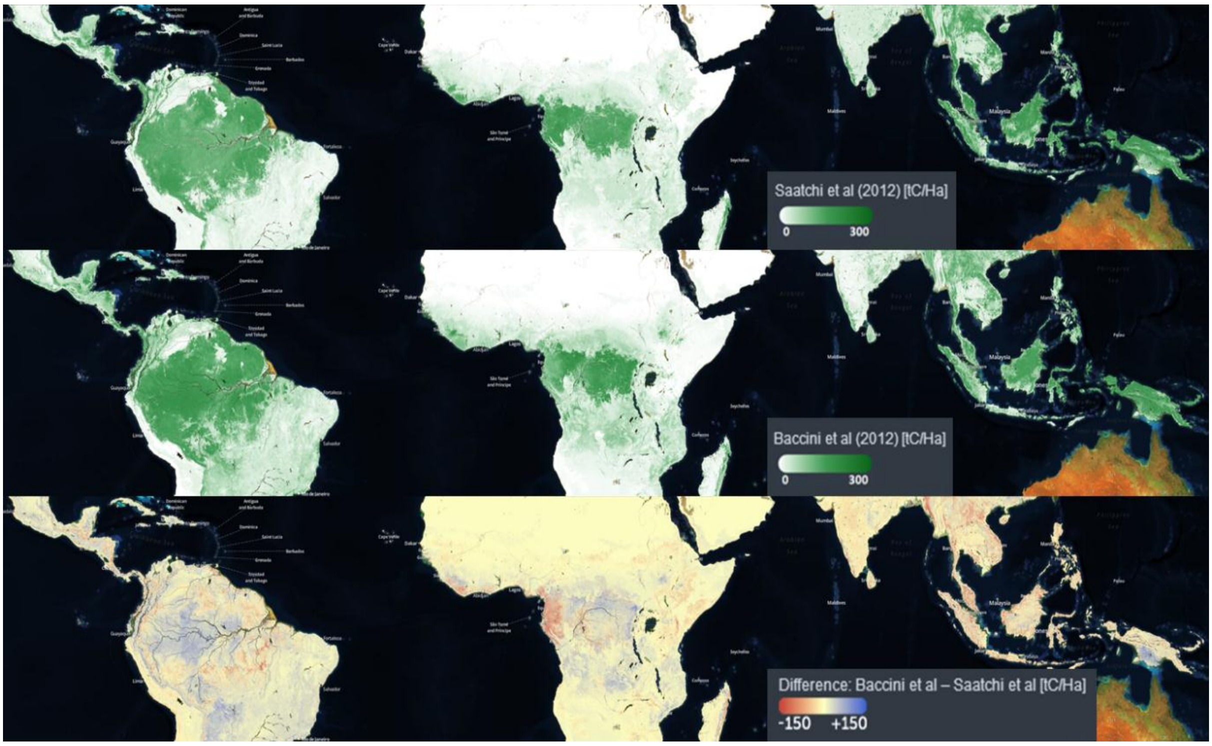

Figure 5 Comparison of Pan-Tropical maps from Saatchi et al. (2011) and Baccini et al. (2012) done by Mitchard et al. (2013). Images from http://carbonmaps.ourecosystem.com.

Most of the differences between both maps could be explained by the allometric models used to estimate AGB, different ground and remote sensing data, modelling techniques, pixel sizes, and temporal coverage (Mitchard et al., 2013). There are still large uncertainties in these maps which need to be addressed in further research, but the consistency of both products at coarser scales suggest that realistic estimates of carbon stocks can be produced over large regions.

3.1 GLOBAL FOREST AGB MAPPING CONCEPT

Based on the previous examples, it is possible to define a general concept for global AGB mapping (Figure 6) using a combination of datasets from different remote sensors by means of a non-parametric approach such as MaxEnt to extrapolate the AGB calibration data. These AGB data could be directly obtained from forest inventory datasets, or by means of regional allometric models relating AGB to remote sensing-derived biophysical parameters such as mean canopy height calculated from GLAS-footprints.

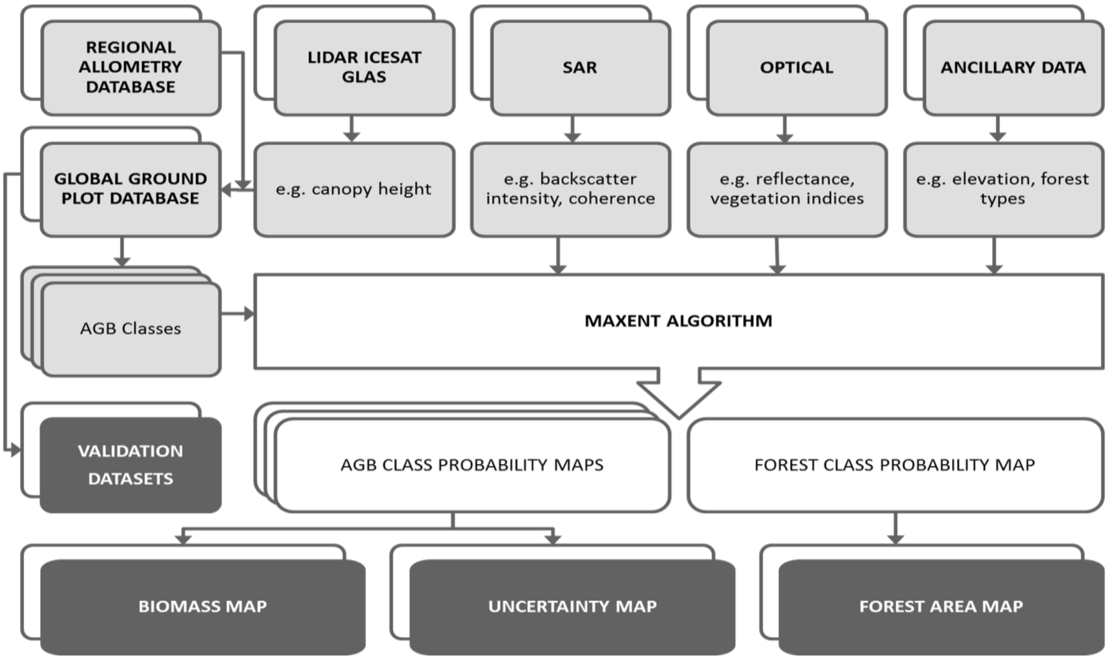

Figure 6 Global AGB mapping method proposed for a Global Biomass Information System.

The proposed approach uses a MaxEnt classification algorithm (Phillips et al., 2006, Phillips et al., 2004) to scale up the AGB plots either measured in the ground or from GLAS footprints. The AGB plots are classified by AGB class intervals (e.g. 0-20 t ha^{-1}, 21-40 t ha^{-1}, and so on) to create different AGB training datasets. These datasets are used in combination of the remote sensing imagery as inputs for the MaxEnt algorithm. The algorithm estimates the target probability distribution with the maximum entropy (closest to uniform) which is subject to the constrains established by the set of the remote sensing variables (Phillips et al., 2006). Through numerous iterations the weights of these variables are adjusted to maximize the average sample likelihood (training gain), and then used to estimate the distribution over the whole space for each of the AGB classes (Figure 7).

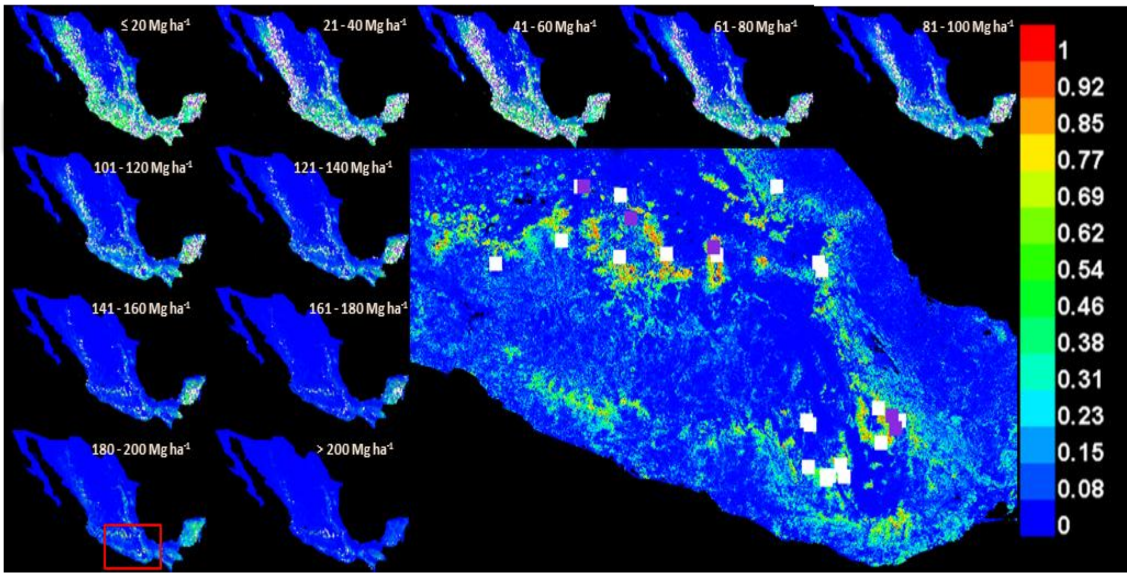

Figure 7 Probability distribution maps generated by the MaxEnt algorithm with pixels ranging from 0 (least suitable) to 1 (most suitable) for each biomass range. White squares represent training data and violet squares represent test data.

The higher the probability estimated for the pixel is, the more suitable the pixel is for presenting the same characteristics as the training pixels. The current study make use of an adapted version of the method in Saatchi et al. (2011), which uses the probability outputs from the MaxEnt algorithm to produce the AGB and Uncertainty maps. Continuous AGB map are created by assigning the AGB values corresponding to the maximum probability weighted mean per pixel, while the uncertainty of the AGB prediction ($\varepsilon_{\mathrm{prediction}}$) was calculated from the root mean square error ($\sigma_{\widehat{\mathrm{AGB}}}$) obtained per pixel. The following expressions were used (Saatchi et al., 2011):

$$\widehat{\mathrm{AGB}} = \frac{\sum_{i=1}^{N} P_i^n \mathrm{AGB}_i}{\sum_{i=1}^{N} P_i^n} \qquad \textit{Eq. 2}$$

$$\varepsilon_{\mathrm{prediction}} = \sigma_{\widehat{\mathrm{AGB}}} / \widehat{\mathrm{AGB}}\,\mathrm{x}100 \qquad \textit{Eq. 3}$$

$$\sigma_{\widehat{\mathrm{AGB}}} = \sqrt{\frac{\sum_{i=1}^{N} (\mathrm{AGB}_i - \widehat{\mathrm{AGB}})^2\, P_i}{\sum_{i=1}^{N} P_i}} \qquad \textit{Eq. 4}$$

where $\widehat{\mathrm{AGB}}$ is the AGB prediction per pixel, and P_i is the probability estimated by MaxEnt for each AGB range AGB_i (median value of the range).

The total uncertainty at pixel level is composed of 4 sources of error which are assumed to be random and independent. Those are propagated, using the following the expression:

$$\varepsilon_{\mathrm{AGB}} = (\varepsilon^2_{\mathrm{measurement}} + \varepsilon^2_{\mathrm{allometry}} + \varepsilon^2_{\mathrm{sampling}} + \varepsilon^2_{\mathrm{prediction}})^{1/2}, \qquad \textit{Eq. 5}$$

The values of these errors have to be adapted to the input data used using this error propagation approach. The following example illustrates the errors assumed for 1 ha ground sampling plots and 250 m (6.25 ha) imagery used as training datasets:

$\varepsilon_{\mathrm{measurement}}$: the measurement error of tree level parameters such as diameter and tree height averages out at plot level Chave et al. (2004). This component is therefore assumed error free for 1 ha primary sampling sites.

$\varepsilon_{\mathrm{allometry}}$: the error in estimating AGB by using allometric equations with species-specific wood densities and within their diameter range of applicability averages 11% based on findings by Chave et al. (2004).

$\varepsilon_{\mathrm{sampling}}$: as explained by Saatchi et al. (2011), this error is divided in 2 parts: the representativeness of sampling sites of the true distribution of AGB in the region, and the error associated to the variability of AGB within the pixel area (6.25 ha). The first part is accounted for in the error calculated from the MaxEnt probabilities, and the second part is estimated to be 5% for sampling sites of 1 ha (Chave et al., 2004).

$\varepsilon_{\mathrm{prediction}}$: the error calculated for each pixel from the prediction probabilities of the MaxEnt model

This approach generates AGB and Uncertainty maps covering the whole territory even though these maps were created using only forest AGB data as training data. Non-forested areas should be masked out. Therefore, the locations of the forest plots are used as training data to generate a Forest Probability (FP) map. The same remote sensing layers used to develop the AGB and Uncertainty map are used for the FP map. Only plots with canopy cover above 10% and mean canopy height above 5 m according to the FAO forest definition (FAO, 2010) are used as training data. The probability calculated by the MaxEnt algorithm is equal to the Gibbs probability and proportional to the conditional probability of the class (Li and Guo, 2010). Therefore, the resulting map provides a conditional positive probability of each pixel to belong to the class forest. At the pixel level, this probability can be not only used to create a binary forest/non-forest map based on a probability threshold, but also as a parameter to assess the reliability of the forest area map itself.

In order to create a binary forest/non-forest map from the probabilistic output, a threshold must be identified. A threshold which maximizes the Kappa statistic of agreement with the validation dataset (Pearson et al., 2002), or the threshold probability corresponding to a 5% omission rate for the validation dataset (Li and Guo, 2010, Pearson et al., 2004) have been recommended in previous studies. For this study a threshold corresponding with the 5% of the test omission rate is used as initial reference. Then, several probabilities around this value are validated against a validation dataset. The closest value to the initial probability threshold with the highest Kappa statistic is selected as optimum threshold. This forest area map developed using a combination of optical and SAR imagery has shown to be more accurate than forest area maps developed by only one sensor (Rodriguez-Veiga et al., 2014a)

Remote sensing imagery suitable for the kind of method can be classified by sensor according its spatial resolution, defining two mapping levels: Global or Regional, and Sub-National (

Table 3). These two levels can be used in a Global Forest Biomass Information System to report the status of AGB at different time intervals. Global or Regional level maps at 1 km-250 m spatial resolution could be annually generated, while Sub-National level maps with less than 150 m spatial resolution could be generated in a 3-5 year interval.

Table 3 Mapping levels and proposed imagery.

MAPPING LEVELS	TEMPORAL RESOLUTION	SPATIAL RESOLUTION	SATELLITE SENSORS		
			OPTICAL	SAR	LIDAR
Global or Regional	1yr	1 km-250 m	MODIS, SPOT VGT, PROBA-V, MERIS Archive	ALOS PALSAR, ALOS PALSAR-2, BIOMASS	IceSAT archive, IceSAT-2
Sub-National	3-5 yr	< 150 m	Landsat, Sentinel-2	ALOS PALSAR, ALOS PALSAR-2, BIOMASS	IceSAT archive, IceSAT-2

AGB, Uncertainty and Forest Probability maps can be globally generated using the presented approach. Even though ground data is not globally available, lidar footprints from the IceSAT GLAS archive and future IceSAT-2 could be used to obtain millions of AGB estimates which will be added to the ground data to train the algorithm (e.g. Saatchi et al., 2011, Baccini et al., 2012). Crowdsourcing is also becoming an important source of data for the research community, and projects such as Geo-Wiki (http://www.geo-wiki.org/) shows how geographical research can be benefited. Therefore a global approach to map forest biomass should take advantage of all these sources of data.

Global annual mosaics of L-Band ALOS PALSAR backscatter slope corrected, ortho-rectified, and radiometrically calibrated have been recently made available by the K&C Initiative with a spatial resolution of 50 m for the period 2007-2010 (Shimada and Ohtaki, 2010). Data from ALOS PALSAR-2 (since 2014) will also be processed to obtain such annual mosaics. The continuity of this mission ensures the availability of long wavelength SAR imagery.

MODIS products are globally available and can be used in combination with those datasets. Moreover, the use of Landsat imagery instead of MODIS, in combination with ALOS PALSAR, opens the possibility of generating higher spatial resolution maps (Rodriguez-Veiga et al., 2014b) aiming to satisfy sub-national level monitoring requirements. Consistent continental-scale science-quality Landsat mosaics with a level of pre-processing similar to MODIS products currently exist for the United States and Alaska (Roy et al., 2010) through the Web-Enabled Landsat Data (WELD) project. This project is currently producing global mosaics (http://globalmonitoring.sdstate.edu/projects/weldglobal/) for six 3-year epochs spaced every 5 years from 1985 to 2010, which will allow the use of consistent Landsat imagery for wide area mapping.

The following case studies (sections 3.2 and 3.3) demonstrate the implementation of this approach at the both mapping levels proposed by this report.

3.2 CASE STUDY GLOBAL/REGIONAL LEVEL: FOREST AGB, UNCERTAINTY, AND FOREST PROBABILITY FOR MEXICO

Forest inventory sampling units of 1 ha for calibration of the MaxEnt algorithm were used to map AGB in combination with three different remote sensing products: MODIS 250 m reflectance bands and vegetation indices, SRTM digital elevation model, and ALOS PALSAR L-band dual polarization imagery (Rodriguez-Veiga et al., 2014a, Rodriguez-Veiga et al., in press). L-band SAR backscatter intensity signal is relatively sensitive to AGB up to 150 t ha^{-1} and provides a different type of information than SRTM and MODIS. The Area Under the Receiver Operator Curve - AUC (Phillips et al., 2006, Phillips et al., 2004) was used to examine the performance of the final AGB maps using different combinations of these datasets (Figure 8). The average AUC increased from a minimum of 0.79 (single product) to a maximum of 0.93 using the three products combined (Rodriguez-Veiga et al., 2014a).

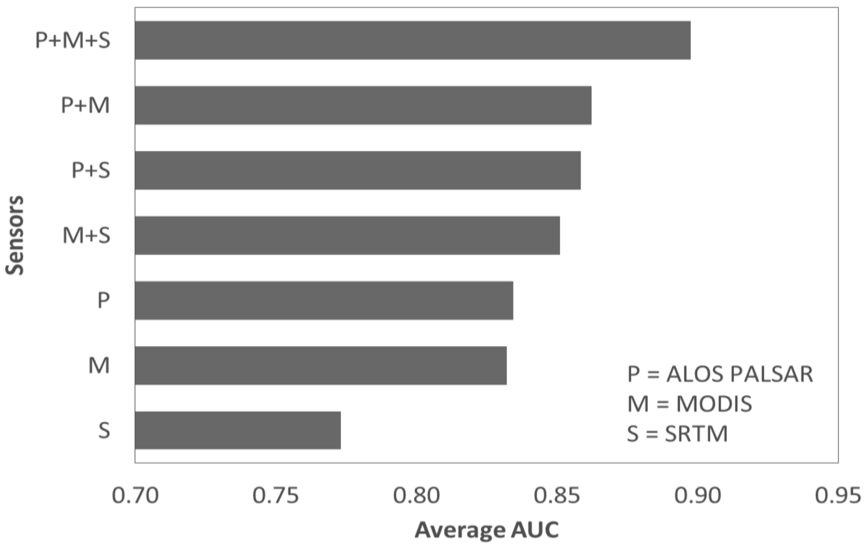

Figure 8 Jackknife analyses based on AUC by sensor showed the importance of dataset combinations.

Wall-to-wall 250 m resolution (6.25 ha) AGB and uncertainty maps (Figure 9, A & B) were developed using this method.

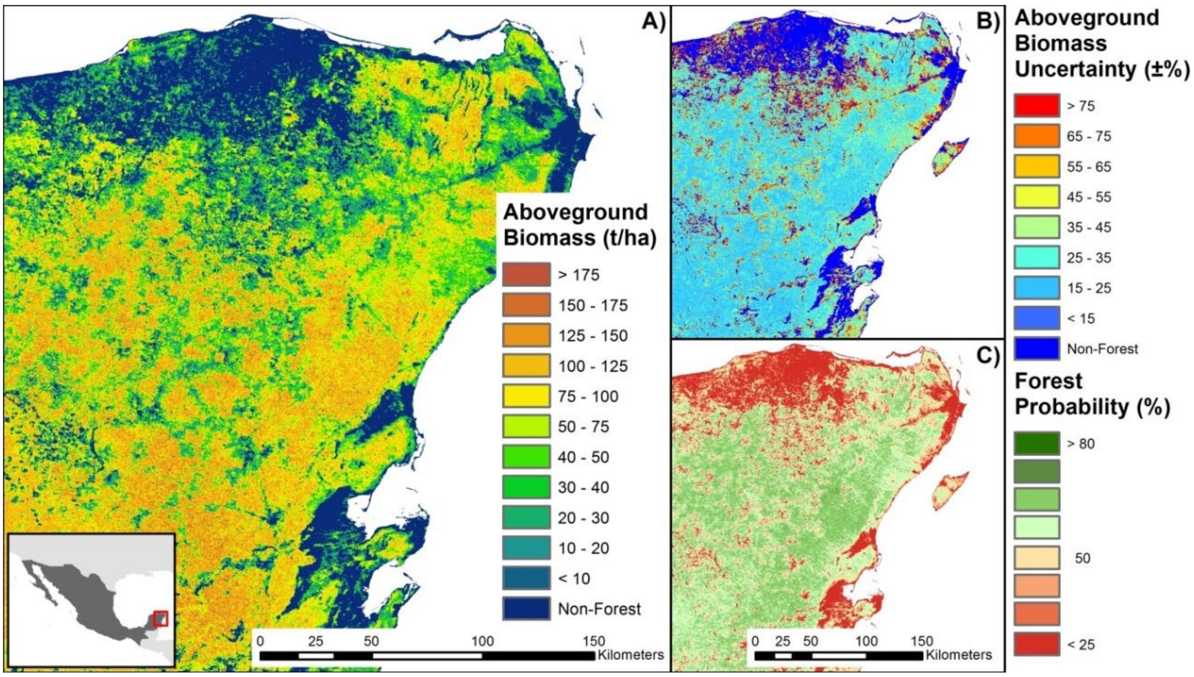

Figure 9 East of Yucatan Peninsula maps at 250 m resolution of A) AGB, B) AGB-Uncertainty, and C) Forest Probability. Maps A) and B) are masked by the forest probability map C) thresholded by 25%.

The variable importance for generation of the AGB map by the MaxEnt algorithm was analysed as groups of variables belonging to the same remote sensing product. The overall per cent contribution of ALOS PALSAR explains approximately 50.9%, while MODIS and SRTM products were 32.9%, and 16.2% respectively. The analysis of variable contributions by different biomass classes shows that ALOS PALSAR product was the most important variable to predict biomass for the most abundant biomass classes (up to 100-120 t ha^{-1}) and was still very relevant up to 180 t ha^{-1} (Figure 10). Above 120 t ha^{-1} the contributions fluctuated among products. This could be explained by the saturation of the sensitivity of L-band to AGB at approximately 150 t ha^{-1} described by several studies (Wagner et al., 2003, Mitchard et al., 2009).

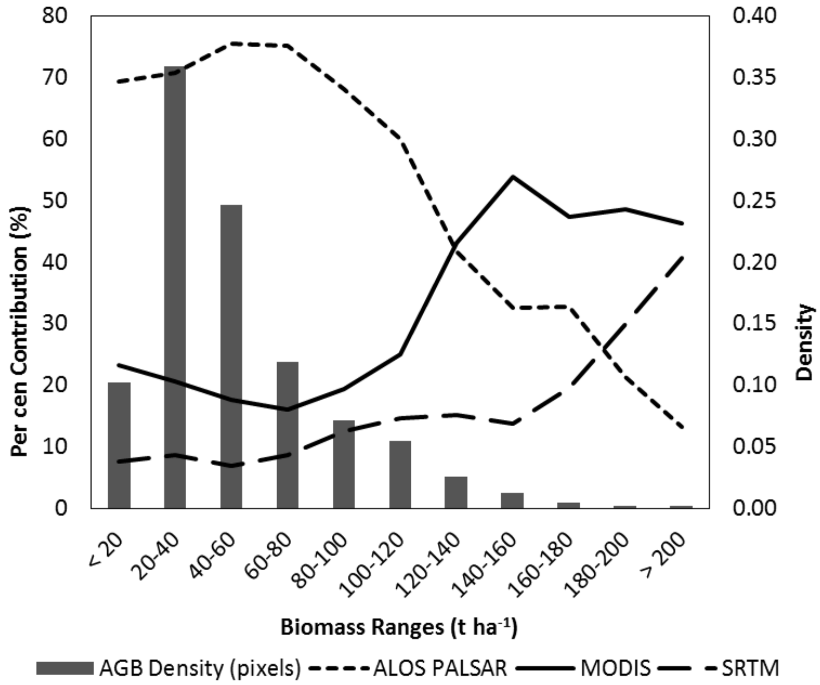

Figure 10 Lines represent per cent contributions to the AGB map per biomass range. The columns represent the density of each biomass range (map pixels).

A forest mask was created using the forest probability map and compared to forest masks created from MODIS VCF and ALOS PALSAR. MODIS VCF and ALOS PALSAR are commonly used to create binary forest/non-forest area maps in several studies by means of a threshold approach (e.g. Saatchi et al., 2011, Shimada et al., 2011, Thiel et al., 2009). A visual comparison of these forest maps to the forest area defined by the Land Use and Vegetation map of Mexico (INEGI, 2009) revealed evident problems for both products to delineate the appropriate forest area in Mexico (Figure 11 A). This is not surprising in the case of MODIS VCF, which appears insufficiently accurate in regions with sparse vegetation where tends to overestimate tree cover (Sexton et al., 2013) (Figure 11 C). The ALOS PALSAR product clearly improves over MODIS VCF, but still presents some inaccuracies in mountainous areas non-vegetated or covered by shrub (Figure 11 D). The forest probability map was validated in comparison to several threshold-based MODIS VCF and ALOS PALSAR forest/non-forest binary maps. The Kappa statistic for the Forest Probability map was 0.83, while for ALOS PALSAR and VCF forest maps were 0.78 and 0.66 respectively. The forest probability product combines the advantages of optical and SAR imagery bypassing their individual problems to differentiate forest vegetation (Figure 11 B).

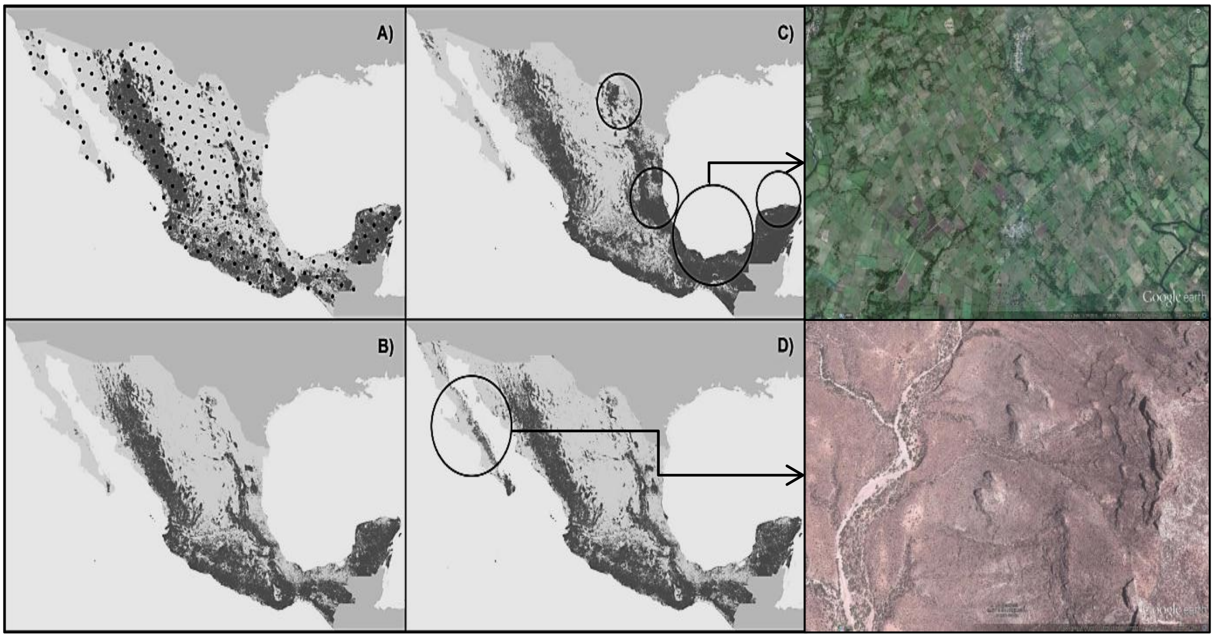

Figure 11 Forest area mask delineated by A) Mexico Land Use and Vegetation map (dots represent the location of the validation points), B) Forest Probability map (25% threshold), C) MODIS Vegetation Continuous Fields (10% tree cover threshold), and D) ALOS PALSAR HV (-14.5 dB threshold). Circles in C) show areas of sparse vegetation and agricultural land misclassified as forest in the MODIS VCF product, and the Circle in D) shows an area of shrubland in a mountainous region misclassified as forest in the ALOS product. High resolution Imagery extracted from Google Earth (Data: Google, INEGI, Digital Globe).

The uncertainty of the AGB estimations varies by regions and by biomass ranges showing lower uncertainty in areas with high biomass levels, and higher uncertainty in areas with low biomass density.

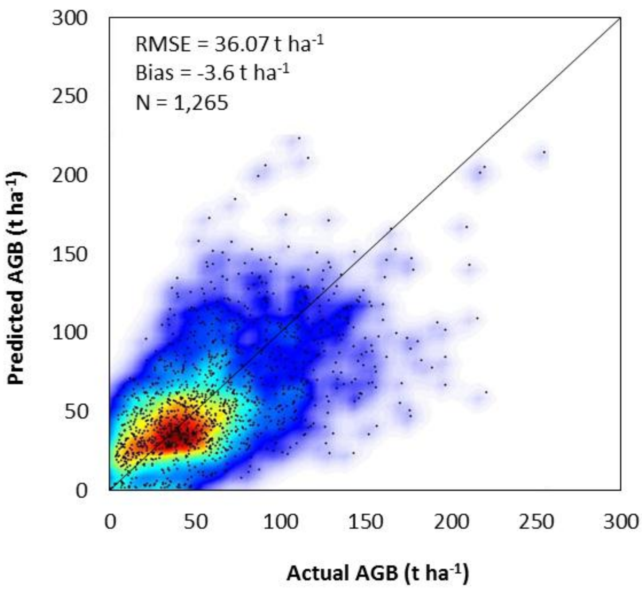

Figure 12 Validation of the AGB map using an independent plot dataset. Warmer colours indicate higher point density. Solid line: y = x.

The average uncertainty at pixel level was estimated in ±40.0% by pixel aggregation of the errors. Using the forest/non-forest binary mask developed by this study (Figure 11 B) to exclude non-forest pixels, the average pixel level uncertainty of the map decreases to ±35.6%. The map showed a relative error of ±44.5% (RMSE 36.07 t ha^{-1}) by validation against an independent dataset (Figure 12). As mentioned before, the BIOMASS mission by ESA is expected to achieve better accuracy levels once is operative beyond 2020. Nevertheless, these maps achieve good accuracy levels in areas that can be easily identified by the use of the corresponding uncertainty map.

3.3 CASE STUDY SUB-NATIONAL LEVEL: ABOVEGROUND BIOMASS MAPPING IN CENTRAL SIBERIA USING ALLOMETRY, LANDSAT, AND ALOS PALSAR

Landsat imagery instead of MODIS in combination with ALOS PALSAR allows the generation of 50 m spatial resolution maps (Rodriguez-Veiga et al., 2014b). The Russian live biomass plot database (IIASA, 2007) was used to develop a regional allometric model relating growing stock volume (GSV) to AGB (Figure 13). GSV is calculated based on the volume of stems, while AGB included the mass of stems, branches, leaves & needles. The model only uses regional data from the ecological regions occurring in Krasnoyarsk Kray. This model was used to convert GSV forest inventory data from 2010 (Assessment of Northern Eurasian Forests - ZAPAS project) to AGB estimates for the Krasnoyarsk Kray region in Central Siberia.

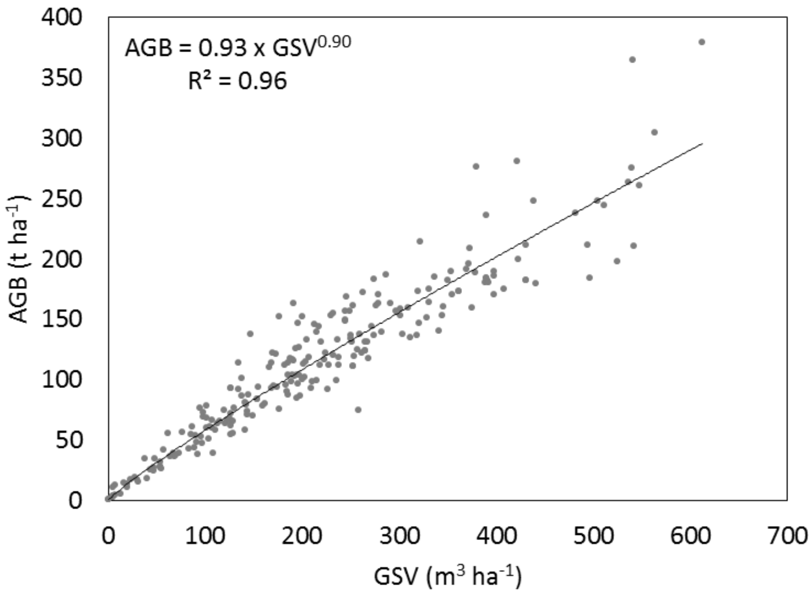

Figure 13 Regional allometric model relating GSV to AGB.

ALOS PALSAR dual polarization imagery for year 2010 (HH and HV) slope corrected, ortho-rectified, and radiometrically calibrated from the Kyoto & Carbon Initiative (K&C) 50 m resolution mosaics, and cloud-free reflectance bands and NDVI from Landsat Global Land Survey (GLS) imagery for the year 2010 were used in this study. Different categorical land cover datasets from the ZAPAS project (http://zapas.uni-jena.de/) were also explored as an additional mapping input. The forest/non-forest (FNF) product generated from the K&C program was used as forest area mask.

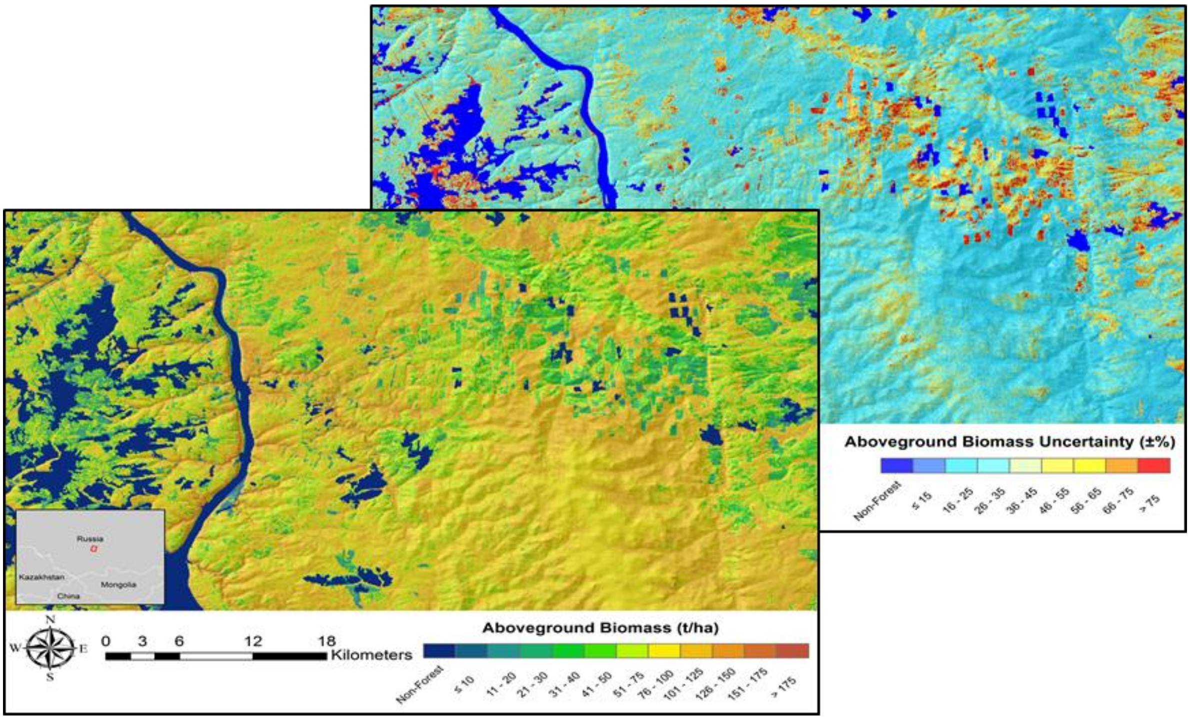

Figure 14 AGB and Uncertainty maps of part of the Krasnoyarsk Kray federal region in Central Siberia at 50 m spatial resolution.

The resulting map presents a 33% relative error estimated by an independent dataset (Rodriguez-Veiga et al., 2014b). This kind of product aims to satisfy sub-national level monitoring requirements (Figure 14).

4 CONCLUSIONS

This report has discussed current approaches to the mapping and monitoring of aboveground forest biomass from optical, radar and LiDAR sensors, and their limitations. A method using a maximum entropy approach for the estimation of AGB from a combination of selected geospatial input datasets is presented. Case studies showed the different spatial resolutions that can be achieved based on different inputs and the relative importance of the different types of sensors in the generation of the AGB maps. Additionally, it was shown that improved forest area maps can also be obtained within the same approach. The accuracy of the AGB estimates and the forest area was studied using error propagation methods, and validated by independent forest inventory datasets.

A conceptual approach for a Global Biomass Information System is presented. It is based on two hierarchical mapping scales and uses the synergies between data products from optical, radar and LiDAR data. It is applicable to the current and forthcoming series of new satellites from the ESA Copernicus Program (i.e. Sentinels), JAXA (i.e. ALOS PALSAR-2), and NASA (i.e. Landsat, IceSAT-2). Nevertheless, this approach presents certain requirements to be carried out by governments, spaces agencies, and the research community for its feasibility:

1. The development of a geodatabase of regional allometric models that could relate remote sensing-derived biophysical parameters to biomass at GLAS-footprint or pixel level

2. Access to an extensive global dataset of AGB ground data for calibration and validation purposes collected from forest inventories, research studies and other sources such as crowdsourcing
3. Continuation of the GLAS IceSAT measurements interrupted in 2010 by means of the IceSAT-2 satellite (to be launched in 2016).
4. Continuation and expansion of optical missions and projects such as MODIS, PROBA-V, Sentinel-2, and Landsat WELD (Roy et al., 2010), which allow the generation of radiometrically consistent global datasets
5. Continuation of long wavelength SAR satellite missions such as the new L-band ALOS PALSAR-2 (launched in May 2014) and the future P-band BIOMASS expected not before 2020.

Such approaches clearly require a strong collaboration and data sharing agreement between the Japanese, European and US space agencies. It is possible within limits to generate global AGB maps with accuracies that make them meaningful. They do not read the expected accuracies achievable from the BIOMASS mission by ESA, but appear as the best way to obtain quality AGB estimations for the period before this mission.

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