Large-Scale Mapping of Forest Aboveground Biomass Retrieval from Maximum Entropy using SAR and Optical Satellite Data and Topographic Variables

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By

Pedro Rodríguez Veiga MSc
Department of Geography
University of Leicester

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ABSTRACT

Large-Scale Mapping of Forest Aboveground Biomass Retrieval from Maximum Entropy using SAR and Optical Satellite Data and Topographic Variables

A Maximum Entropy (MaxEnt) algorithm was calibrated with ground data to generate living aboveground biomass (AGB), its associated uncertainty, and forest probability maps for Mexico. The input predictor layers were extracted from Optical and Synthetic Aperture Radar (SAR) imagery, as well as from a digital elevation model. The combination of the three spatial datasets showed superior accuracy and lower relative error (0.31 and 58%) than the use of single dataset (0.12 - 0.19, and 62% - 74%) or two datasets (0.25 - 0.28, and 58% - 59%). The AGB map showed a root mean square error (RMSE) of 17.3 t C ha\(^{-1}\) and \(R^2 = 0.31\) when validated with inventory plots. The total carbon stored in forests was estimated to be 1.69 Gt C ± 1%, which agrees with the total national estimations. This new map proved to have similar accuracy as previous AGB maps of Mexico, but to be more representative of the shape of the probability distribution function of AGB in the national forest inventory data.

Different forest area masks with similar forest definitions but originating from different sensors are widely-used to constrain AGB retrievals. The use of different forest masks yielded differences of about 24.1 million ha in forest cover extent and 0.36 Gt C in total carbon stocks for Mexico. A forest cover mask derived from the combination of spatial datasets showed higher accuracy (κ=0.83) than alternative masks derived from SAR (κ=0.78) or optical datasets (κ=0.66).

This work found an increasing AGB trend with elevation in Mexico, and that the allometric relationship between AGB and canopy height (\(H\)) at plot level significantly varies within biomes and across the topographic gradient (p-value < 0.001). As a result, the amount of AGB per unit of \(H\) at higher altitudes is higher than at lower altitudes. This has implications in the use of generalised models across large areas such as those seen in the tropical carbon maps (TCMs) (Saatchi et al., 2011b, Baccini et al., 2012). TCMs show large discrepancies when compared to in-situ observations and regionally calibrated maps. The use of a single allometry (vs. regional allometry), and the calibration of the algorithm without taking into account regional variations are the main sources of the discrepancies. Errors up to 74% are found in this thesis when using the continental allometry from Saatchi et al. (2011b) over Mexico. The results show that the variability on forest ecosystems play a key role when mapping AGB at larger scales. Thus, approaches that take into account these regional variations, are the way forward to improve these products.
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I dedicate this thesis to my family, especially my father, to my wife and to my son.
PUBLICATIONS

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<td>Aboveground Biomass</td>
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<tr>
<td>AGBC</td>
<td>Aboveground Biomass Carbon</td>
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<tr>
<td>ALOS</td>
<td>Advanced Land Observing Satellite</td>
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<td>AUC</td>
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<td>BA</td>
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<td>Digital Surface Model</td>
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<td>Earth Observation Research Centre</td>
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<td>European Space Agency</td>
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<tr>
<td>EVI</td>
<td>Enhanced Vegetation Index</td>
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<tr>
<td>FAO</td>
<td>Food and Agriculture Organization of the UN</td>
</tr>
<tr>
<td>FAPAR</td>
<td>Fraction of Absorbed Photosynthetically Active Radiation</td>
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<tr>
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<td>Fraction of green Vegetation Cover</td>
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<td>International Geosphere-Biosphere Program</td>
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<tr>
<td>INEGI</td>
<td>Mexican National Institute of Statistics and Geography</td>
</tr>
<tr>
<td>INFyS</td>
<td>Mexican National Forest and Soil Inventory</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>κ</td>
<td>Cohen's kappa coefficient</td>
</tr>
<tr>
<td>K&amp;C</td>
<td>Kyoto and Carbon Initiative</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
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<tr>
<td>LCCS</td>
<td>Land Cover Classification System</td>
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<tr>
<td>xvi</td>
<td></td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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</tr>
<tr>
<td>Ln</td>
<td>Natural logarithm</td>
</tr>
<tr>
<td>LUV</td>
<td>Land Use and Vegetation map of Mexico</td>
</tr>
<tr>
<td>MAXENT</td>
<td>Maximum Entropy</td>
</tr>
<tr>
<td>MERIS</td>
<td>Environmental Satellite</td>
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<tr>
<td>MEX</td>
<td>Mexico</td>
</tr>
<tr>
<td>MIR</td>
<td>Mid-Infrared</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MRF</td>
<td>Mexico Random Forest Map</td>
</tr>
<tr>
<td>MRT</td>
<td>MODIS Reprojection Tool</td>
</tr>
<tr>
<td>MRV</td>
<td>Measurement, Reporting and Verification</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NERC</td>
<td>Natural Environment Research Council of the UK</td>
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<tr>
<td>NIR</td>
<td>Near-Infrared</td>
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<tr>
<td>NGO</td>
<td>Non-Governmental Organization</td>
</tr>
<tr>
<td>OC-SVM</td>
<td>One-Class Support Vector Machine</td>
</tr>
<tr>
<td>OLI</td>
<td>Operational Land Imager</td>
</tr>
<tr>
<td>PALSAR</td>
<td>Phased Array L-band Synthetic Aperture Radar</td>
</tr>
<tr>
<td>PCA</td>
<td>Principal Component Analysis</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability Density Function</td>
</tr>
<tr>
<td>PTC</td>
<td>Percent Tree Cover</td>
</tr>
<tr>
<td>QSCAT</td>
<td>Quickscatteredometer</td>
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<tr>
<td>REDD</td>
<td>Reducing Emissions from Deforestation and forest Degradation</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
<td>REDD+</td>
<td>Reducing Emissions from Deforestation and forest Degradation with sustainable management of forests, conservation and enhancement of forest carbon stocks</td>
</tr>
<tr>
<td>RF</td>
<td>Random Forest</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>ROC</td>
<td>Receiver Operator Curve</td>
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<tr>
<td>RSS</td>
<td>Remote Sensing Survey</td>
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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
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<tr>
<td>SDM</td>
<td>Species Distribution Model</td>
</tr>
<tr>
<td>SPOT</td>
<td>Satellite Pour l'Observation de la Terre</td>
</tr>
<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
</tr>
<tr>
<td>SVM</td>
<td>Support Vector Machine</td>
</tr>
<tr>
<td>TCM</td>
<td>Tropical Carbon Map</td>
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<tr>
<td>TM</td>
<td>Thematic Mapper</td>
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<tr>
<td>TOA</td>
<td>Top Of Atmosphere</td>
</tr>
<tr>
<td>TOC</td>
<td>Top Of Canopy</td>
</tr>
<tr>
<td>UN</td>
<td>United Nations</td>
</tr>
<tr>
<td>VCF</td>
<td>Vegetation Continuous Fields</td>
</tr>
<tr>
<td>VGT</td>
<td>Vegetation</td>
</tr>
<tr>
<td>VI</td>
<td>Vegetation Indices</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>United Nations Framework Convention on Climate Change</td>
</tr>
<tr>
<td>WSG</td>
<td>Wood Specific Gravity</td>
</tr>
<tr>
<td>WWF</td>
<td>World Wide Fund for Nature</td>
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</tbody>
</table>
Chapter 1

Introduction
1. INTRODUCTION

Planetary 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 (Hester and Harrison, 2002, Slaymaker et al., 2009). 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 CO₂ being the most significant trace gas. Changes in the amount of atmospheric CO₂ 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, 2014).

How the global carbon cycle stores and exchanges carbon within the system is crucial in understanding 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 in order 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). 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).
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 aboveground biomass of trees (AGB). Forest AGB is living organic plant material composed of 50% carbon (IPCC, 2003b) 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). Afforestation, reforestation and growth of existing forest is the major contribution to the terrestrial sink term. Monitoring AGB stored in the world’s forests is essential in order to understand the processes related to the global carbon cycle and reducing carbon emissions originating from deforestation and forest degradation.
Mapping the spatial distribution of $AGB$ is crucial in order to determine the loss of carbon stocks due to disturbances (e.g. deforestation, fires) or the gain due to new planted forest or growth (Houghton, 2005). However, the methods should not only estimate $AGB$ but also provide information about the uncertainty of the parameter itself.

Earth Observation sensors can be used to estimate $AGB$ across large areas (e.g. Santoro et al., 2011, Cartus and Santoro, 2016), but the sensitivity of the sensor to $AGB$ depends on the technology used. Each technology has its own strengths and weaknesses which are mostly related to cloud penetration and topographic effects. Most approaches also face challenges related with the absence of in-situ well distributed data samples at scales useful for remote sensing (Houghton et al., 2009), the poor availability of allometric models (Henry et al., 2011), the differences among forest definitions (Sexton et al., 2015), and the limited sensitivity of satellite sensors to $AGB$ (Patenaude et al., 2005). Additionally, $AGB$ distribution is ultimately driven by variations in tree allometries as a result of different climate conditions (Reich et al., 2014, Feldpausch et al., 2011, Chave et al., 2005).

Methods to combine different spatial datasets to exploit the specific strengths of each sensor are therefore needed. Additionally, understanding the strengths and limitations of each sensor is key to improve these methodologies.

Recent tropical carbon maps (hereafter TCMs) (Saatchi et al., 2011b, Baccini et al., 2012) make use of multi-platform earth observation datasets, and are a benchmark in the field. However, these two products only agree at coarse scales, providing dissimilar results at finer resolutions (Mitchard et al., 2013). Differences when compared to in-situ $AGB$ data or to local $AGB$ maps have also been found (Mitchard et al., 2014, Carreiras et al., 2013), but the reasons are not fully understood.

1.1. AIMS

This thesis aims to study the variability of $AGB$ across wide areas focusing on the allometric variations occurring between biomes and across the topographic gradient.

$AGB$ is estimated at country-level using locally calibrated field inventory data and different spatial datasets. The use of different spatial datasets and their combinations are explored. The contribution of the different input datasets to predict $AGB$ across different
AGB ranges is also analysed. The best combination of spatial datasets is used to map AGB and estimate forest carbon stocks at national level and their uncertainty. The probability of a pixel belonging to the forest class is also estimated, and a systematic error propagation approach to assess the uncertainty of AGB estimates at pixel scale is described.

The results from using different forest masks based on a similar forest definition but originating from different sensors are also presented. Sources of uncertainty in the approach are discussed and compared to previous AGB studies. Discrepancies due to input EO data, AGB reference data, allometries, and the geographical extent in which the algorithms were calibrated will be examined.
Chapter 2

Background
2. BACKGROUND

A peer-reviewed article with content from this chapter has been submitted:


2.1. DEFINITIONS AND CONCEPTS

2.1.1. What is a forest?

Forests sequester carbon through photosynthesis and store it primarily as living aboveground biomass of trees (AGB). AGB is defined as the mass of living organic material for a given area and includes woody and herbaceous vegetation above the soil, including stems, branches, bark, seeds, flowers, and foliage of live plants. AGB is measured in units of dry mass or carbon per unit of area (t ha⁻¹ or t C ha⁻¹, respectively). In this thesis, the term AGB is used when talking about dry mass, while AGBC is used when talking specifically about carbon. Approximately 50% of AGB is carbon (IPCC, 2003a). Therefore, AGB is a key parameter for monitoring carbon allocation in terrestrial ecosystems as it represents a basic unit to account for carbon.

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 large-scale mapping study 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 after (Wadsworth et al., 2008). Data from (Lund, 2012).

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. (2007) about definitional issues 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 un-stocked areas are considered forest or non-forest, and lacks a specific definition for deforestation.
While some international consensus or similarities exist regarding the definitions of forest and deforestation, the term forest degradation is still very broad (Schoene et al., 2007). Forest degradation is not studied in this thesis but it should be mentioned in this context. The forest degradation definition used for the FAO FRA’s is the most comprehensive. FAO (2000) considers degradation as “a reduction of canopy cover or stocking within the forest”. The report further explains the concept: “For the purpose of having a harmonized set of forest and forest change definitions, that also is measurable with conventional techniques, forest degradation is assumed to be indicated by the reduction of canopy cover and/or stocking of the forest through logging, fire, windfelling or other events, provided that the canopy cover stays above 10% (cf. definition of forest). In a more general sense, forest degradation is the long-term reduction of the overall supply of benefits from forest, which includes wood, biodiversity and other products or service” (FAO, 2000).

2.1.2. Biomes

Biomes are geographically defined areas on Earth with similar climatic conditions and having more or less the same kind of abiotic and biotic characteristics (Olson et al., 2001). There are several terms denoting identical or similar concepts, and can be considered synonyms: formation, major life form, major life zone, major community (type), ecoregion and ecofloristic zone (Rakonczay, 2002).

The first classification of biomes was based on the biological effect of temperature and rainfall on vegetation (Holdridge, 1947, Holdridge, 1967) delineating 30 “humidity provinces”. This classification was simplified by Whittaker (1962), and Whittaker (1970). Walter and Box (1976) also developed a system based on seasonality of temperature and precipitation defining 9 major biomes: equatorial, tropical, subtropical, mediterranean, warm temperate, nemoral, continental, boreal, and polar. Later, Bailey and Hogg (1986) defined terrestrial ecosystems based on climate features in four domains (polar, humid temperate, dry humid, and humid tropical), 12 divisions and subsequent sub-divisions (making a total of 98 of these subdivisions).

More recently, the World Wildlife Fund (WWF) assembled an international team of over 1000 biogeographers, taxonomists, conservation biologists, and ecologists that develop the terrestrial ecosystems classification system (Olson et al., 2001) dividing the world in 8 biogeographic realms and 14 major biomes or habitat types. These were further
subdivided into 867 terrestrial ecoregions based on biogeographical concepts. This biogeographical classification, based on such a wide consensus of experts, might better reflect the distribution of species that previous classifications based on biophysical features (e.g. rainfall and temperature). It also allows a finer classification in more numerous regions than previous systems. The major biomes can also be grouped in five categories: Tropical/Subtropical, Temperate, Dry, Polar/Montane, and Aquatic (Figure 3).

Figure 3 Global Biomes from the World Wildlife Fund (WWF) Terrestrial Ecoregions of the World dataset (Olson et al., 2001). Map modified from CIESIN (2012)

Temperate (Broadleaf, Coniferous, and Mixed forest), Mediterranean, and Boreal forest Biomes are located in developed countries. The Boreal forest biome is the largest land biome, occurring in North-America, Siberia, and North of Europe and Asia. The characteristic climate has short cool summers and long winters. Temperate and Mediterranean forests can be found in areas with a long and milder summer and short winter. Forest types characteristic of these biomes are evergreen and deciduous forests (Temperate and Boreal) and sclerophyllous forest (Mediterranean).

Forests in tropical and subtropical biomes, as well as mangroves, are characterized by a very high species richness and $AGB$ density. The climate in these areas either lack seasonality (in equatorial regions), presents double seasonality (rainy-dry seasons, in
tropical regions), or has high seasonality (subtropical regions). Typical forests are evergreen tropical rainforest, seasonal forest, and savannahs.

2.1.3. Topography
Topography studies the relief of Earth’s surface identifying landforms by recording the three dimensional structure of the terrain. This is also known as geomorphometry. Topography usually involves the generation and use of a digital elevation model (DEM). DEM is a generic term that refers to digital terrain models (DTM) and digital surface models (DSM), and sometimes is used as synonym of those. A DTM represent the bare ground surface without any object, while a DSM represents the ground surface and all the objects on it such as trees or buildings (Li et al., 2004).

Common topographic variables used in this thesis are defined here:

- Elevation: Terrain altitude. Altitude is expressed as the height above or below a predetermined reference point. This reference is usually a reference geoid.
- Slope: Inclination angle of the local surface. Slope is typically expressed as a percentage, an angle, or a ratio.
- Aspect: Compass direction that a slope faces. This corresponds to the angle from $0^\circ$ to $360^\circ$.

2.2. FOREST MONITORING PRODUCTS

Several products are globally or continentally produced to monitor land cover or forest cover changes (Table 1). These projects are generally based on satellite optical sensors with medium to coarse spatial resolutions (25 m to 5 km spatial resolution). 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. 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. No current forest monitoring program generates spatial AGB estimations at different time intervals.

Early efforts to monitor forests at global level led to the Forest Resource Assessments (FRAs) by the United Nations (UN) Food and Agriculture Organization (FAO). These
assessments are based on the analysis of forest inventory information supplied by each country and supported by expert judgements, remote sensing and statistical modelling. National Forest inventories are 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. 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. Nonetheless, 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, 2012b). 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). These assessments however do not generate spatial estimations of AGB, but national level statistics on forest cover, forest state (e.g. GSV), forest services and non-wood forest products.

The Global Remote Sensing Survey (RSS) implemented in 2009 was a systematic sampling based on units located at longitude and latitude intersections worldwide (Ridder, 2007). 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 (Potapov et al., 2011). The survey reported estimates of forest area, deforestation and afforestation at global, continental and ecological zone level for 1990, 2000 and to 2005.

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 global land cover product (Arino et al., 2005) (Figure 4). GlobCover uses data from the Environmental Satellite (MERIS) and Advanced Synthetic Aperture Radar (ASAR) on board Environmental Satellite (ENVISAT) 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.
Table 1 Global Forest Area Monitoring Programmes.

<table>
<thead>
<tr>
<th>PROGRAMME OR STUDY</th>
<th>AGENCY</th>
<th>DATA SOURCE</th>
<th>SPATIAL RESOLUTION</th>
<th>TEMPORAL COVERAGE</th>
<th>KEY ISSUES &amp; REFERENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest Resource Assessment (FRA)</td>
<td>FAO</td>
<td>National Forest Inventories</td>
<td>N/A</td>
<td>Every 5 years</td>
<td>Data sources are not globally available (FAO, 2000, FAO, 2005, FAO, 2010b, FAO, 2012b)</td>
</tr>
<tr>
<td>Global Remote Sensing Survey (RSS)</td>
<td>FAO</td>
<td>Landsat</td>
<td>N/A</td>
<td>1990, 2000, 2005</td>
<td>Systematic sample (10km x 10km) of Landsat imagery worldwide (FAO et al., 2009)</td>
</tr>
<tr>
<td>ALOS Kyoto and Carbon Initiative</td>
<td>JAXA</td>
<td>ALOS PALSAR</td>
<td>25m, 50 m, 100m, 500m</td>
<td>Annual 2007 – 2010, 2015</td>
<td>L-band SAR imagery &amp; Forest/Non-Forest mosaics (Shimada et al., 2011, Shimada et al., 2010, Shimada and Ohtaki, 2010, Shimada and Otaki, 2010)</td>
</tr>
<tr>
<td>Global Forest Loss &amp; Gain</td>
<td>University of Maryland</td>
<td>Landsat</td>
<td>30 m</td>
<td>Annual 2000 - 2014</td>
<td>Tree cover percentage at sub-pixel-level. Identifies areas of tree cover loss (annual) and gain (14 years cumulative) (Hansen et al., 2013)</td>
</tr>
<tr>
<td>Vegetation Continuous Fields</td>
<td>University of Maryland, NASA</td>
<td>MODIS</td>
<td>250 m, 500 m, 1 km</td>
<td>Annual 2000 - 2010</td>
<td>Tree cover percentage at sub-pixel-level (Townshend et al., 2011)</td>
</tr>
<tr>
<td>Percent Tree Cover</td>
<td>University of Maryland, NASA</td>
<td>Landsat</td>
<td>30 m</td>
<td>2000, 2005, 2010</td>
<td>Tree cover percentage at sub-pixel-level (Sexton et al., 2013)</td>
</tr>
<tr>
<td>GlobCover</td>
<td>ESA</td>
<td>ENVISAT</td>
<td>300 m</td>
<td>2005/06 &amp; 2009</td>
<td>Labelled according to the UN Land Cover Classification System (Arino et al., 2005)</td>
</tr>
<tr>
<td>MODIS Land Cover Type</td>
<td>NASA</td>
<td>MODIS</td>
<td>500 m</td>
<td>Annual 2001 - 2012</td>
<td>5 Global Land Cover Classification Systems (Friedl et al., 2010)</td>
</tr>
<tr>
<td>COPERNICUS Global Land Service</td>
<td>ESA</td>
<td>SPOT, and others</td>
<td>1 km</td>
<td>Several intervals from 1999</td>
<td>Vegetation Biophysical parameters (Copernicus, 2013)</td>
</tr>
</tbody>
</table>
The MODIS Land Cover Type Product (MCD12Q1) (Friedl et al., 2010) 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.

ESA’s Copernicus Global Land Service (Copernicus, 2013) 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 are generated using SPOT/VGT and PROBA-V (in development) sensors and have 1 km spatial resolution.

The ALOS Kyoto & Carbon (K&C) Initiative is an international programme 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 25 m, 50 m and 100 m spatial resolution forest/non-forest (K&C-FNF) area mosaics from resampled 10 m data every year (2007-2010, and 2015). These products estimate the forest area using a simple decision tree that is based on a threshold of the Horizontal-transmit Vertical receive (HV) polarized radar backscatter coefficient (Shimada et al., 2011, Shimada et al., 2014). This threshold is optimized regionally (e.g. North America, Africa, Amazon) due to the different forest structures. Forests are defined in this product as areas where the cover of woody vegetation exceeded 10% (Shimada et al., 2014).

Figure 4 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.
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 VCF is an annual sub-pixel-level representation of percent tree cover estimates globally (Hansen et al., 2003). 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). VCF collection 5 currently has one of the best temporal coverages (from 2000) among the medium resolution global forest monitoring products that are free of charge. This percent tree cover product is defined as the amount of skylight obstructed by tree canopies equal to or greater than 5 m in height (Hansen et al., 2003). The continuous nature of this product (versus binary classifications) allows its use according different definitions based on percent tree cover. Percent tree cover thresholds above 10%, in alignment with the FAO’s forest definition, are commonly used to create forest/non-forest binary maps (e.g. Saatchi et al., 2011b). It should be noted that VCF percent tree cover definition (Hansen et al., 2003) is slightly different from FAO’s canopy cover definition as VCF’s is based on light penetration through the canopy, while FAO’s canopy cover definition is based on crown vertical projection over the ground regardless light penetration.

Following the success of MODIS VCF, a recent 30 m resolution Landsat Percent Tree Cover (PTC) dataset has been developed, re-scaling the 250 m MODIS VCF with Landsat imagery (Sexton et al., 2013, Townshend et al., 2011) (Figure 4), but to date it is currently available for the epochs 2000, 2005, and 2010.

A data mining approach of the Landsat archive by means of the Google Earth Engine was also used to globally quantify annual forest loss (2000-2014) as well as 14 years of cumulative forest gain at 30 m spatial resolution (Hansen et al., 2013). The forest definition in this Global Forest Loss & Gain (GFLG) product can be modified according percent tree cover. Hansen et al. (2013) dataset can be freely downloaded and visualised on the website of the Global Forest Watch (GFW, 2014). 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.
2.3. STUDY AREA

Mexico is a North American country located between latitudes 14° & 33°N, and longitudes 86° & 119°W with an extension of 1,972,550 km². Mexico is covered by approximately 65 million ha of forest and 20 million ha of other wooded land (43% of the national territory) (FAO, 2005). Mexico’s topography, climate, and history of human land use are extremely diverse, leading to a wide variety of different forest habitats (Figure 5). The Tropic of Cancer acts as a divider of the country in temperate and tropical zones. The north of the country is covered by a mosaic of dry evergreen forest, deciduous forest and shrub vegetation, while the central region and the south are covered by a diverse mix of evergreen and deciduous forest, cloud forest at high elevations, shrub vegetation, savannahs, mangroves, and evergreen, deciduous and semi-evergreen tropical forests. The Yucatan peninsula is dominated in the north-west by sub-moist or dry deciduous tropical forest, while the south-east is dominated by moist evergreen tropical forest, with mangroves and areas of other hygrophilous vegetation. An increasing gradient of AGB is expected to be observed from NW (dry) to SE (humid) of the Yucatan peninsula. Mexico is also one of the countries with the highest biodiversity in the world (Mittermeier, 1997). This biodiversity is mostly concentrated in the tropical forest areas of the country.

The heterogeneous relief of Mexico leads to a wide variety of climates and vegetation types. The whole extension of the Yucatan peninsula, on the South East of the country, presents tropical moist and dry broadleaf forests in a homogenous relief (relatively flat) characterized by low elevations. The rest of the country presents a more heterogeneous relief with a wider variety of vegetation types.

The complex topography drives the different rainfall regimes over Mexico resulting in orographic rainfall. Annual precipitation increases with elevation in most of the territory and stays also high in the Yucatan peninsula (CONABIO, 2015). Large parts of the lowlands are considered arid or very arid (Garcia, 1990). Annual temperatures also follow topography and precipitation patterns, and increase from South to North (García, 1998).
2.4. IN-SITU FOREST ABOVEGROUND BIOMASS

2.4.1. Tree 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, dried, and weighted. This is a significantly laborious, expensive and impractical approach at a large scale (Ketterings et al., 2001). Therefore, non-destructive in-situ methods such as forest inventories are preferred. In-situ non-destructive measurements are broadly used for $AGB$ monitoring as their accuracy lies between 2% and 20% (Bombelli et al., 2009).

Some countries have developed modelling approaches based on forest stand variables such as tree species, site indexes and ecological regions to predict $AGB$ across wide areas (Shvidenko et al., 2007). Most forest inventories were developed to estimate commercial growing stock (i.e. cubic meters), neglecting biomass. These inventories only measure the commercial stem volume, leaving other biomass components like branches and leaves unknown. Biomass
Expansion Factors (BEFs) are used to convert growing stock in biomass accounting for the non-inventoried tree components. The use of BEFs involves a 2-step process calculation, stem volume estimation followed by the application of the expansion factors.

Non-destructive in-situ methods such as forest inventories make use of allometric models to predict AGB. 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). Biophysical parameters like tree height or diameter are commonly measured in forest inventories and other studies, and used to estimate AGB through allometric equations. Additionally, allometric equations are preferred over the BEF’s as the calculation is limited to one step instead of two, reducing the error propagation through the process.

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).

There is a large variety of allometric models for estimating tree biomass or its components (Parresol, 1999). The most commonly used mathematical model for AGB estimation uses the form of a nonlinear function (Equation 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):

\[
Y = b_0 \cdot X^{b_1}
\]

Equation 1

Several authors transform the data in order to fulfil the assumptions of linear regression (e.g. Socha and Wezyk, 2006, Reed and Tome, 1998):

\[
\ln(Y) = \ln(b_0) + b_1 \ln(X)
\]

Equation 2

Some commonly used biophysical parameters used for single tree allometric models are diameter at breast height, diameter-squared or basal area, tree height, diameter-squared x height, age and live crown length. However, if these equations are to be used to estimate AGB
at different scales based on forest inventory data and remote sensing techniques, then the equations must use standard variables that are easily measured or widely available. Chave et al. (2005) found that the most important predictors of AGB were trunk diameter, wood specific gravity, tree height, and forest type (dry, moist and wet). Diameter at breast height is the biophysical parameter most commonly available, either in national inventories or in other kind of studies. In addition, it is easier to measure and is subject to less measurement errors than other biophysical parameters. In fact, many studies use diameter alone as a tree biomass predictor (e.g. Verwijst and Telenius, 1999, Pastor et al., 1984). Tree basal area is also a common predictor (Madgwick, 1994) because it is easy to measure and obtain from all forest inventories and numerous studies.

2.4.2. In-situ reference data

Temperate and Boreal forests are usually well monitored by means of a large network of ground forest inventory field plots, and are easily accessible (except Boreal forest). In these areas there is also a good availability of allometric equations (Zianis et al., 2005).

Most tropical forests are located in developing countries, where the availability of ground reference data is a limiting factor to monitor forests. Field data and allometric models are unavailable in many of these countries with large areas of natural forests due to the geographical remoteness, lack of capacity, data paucity, high tree diversity or armed conflicts. 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 plots has been measured and few allometric equations have been developed for the forests of this region (Henry et al., 2011). As a result, data availability and subsequently allometric models are the key limiting factors for quantifying AGB.

Several international consortia such as AfriTRON (2002), RAINFOR (2000), ForestPlots (2009) and CTFS-ForestGEO (1980) aim to coordinate long-term monitoring of forest plots in tropical regions. They have established permanent sample plot networks across tropical forest using robust protocols for measurement and continuous monitoring of plots, and created databases to be used in ecological studies. These plot networks are essential for calibrating and monitoring remote sensing approaches in tropical forest areas.

Methods based on or assisted by remote sensing technology aiming to estimate forest biomass over large scales (i.e. global, biome, and continental levels) should focus on developing
methods which can be applied in areas with data availability problems while accounting for regional variability of forest ecosystems.

2.4.3. Uncertainties in the Estimation of Forest AGB

Uncertainty is the degree to which contents of a spatial dataset leave the user uncertain about the corresponding contents of the real world (Goodchild, 2005, Zhang and Goodchild, 2002). Two types of uncertainty are usually present in spatial datasets: the uncertainty of well-defined objects and the uncertainty of poorly defined objects, which is divided in vagueness and ambiguity (Klir and Yuan, 1995, Fisher, 1999). Spatial datasets can be differentiated between two concepts of geographical space and geographic variation: the discrete-object view (or classified object) and the continuous-field view (or continuous object) (Worboys and Duckham, 2004). In the case of forest AGB mapping, it can be assumed uncertainty originated from a metric estimate (AGB) and from a classified object (forest class).

As seen in chapter 2.1.1, forest is not a well-defined entity, hence a certain degree of vagueness is intrinsic to any forest area map. Fuzzy set theory is most commonly used to tackle these issues in spatial data by providing information on the degree of membership. The degree of forest class membership provides valuable information to assess the uncertainty of the forest area map. In order to further assess the validity of the modelling, an independent validation and sensitivity analysis systematically varying the model input are recommended (Goodchild, 2005, Zhang and Goodchild, 2002).

Estimation of AGB is performed at several scales, from single tree to forest stand and large scale (e.g. national scale). Single tree biophysical parameters are measured (e.g. D, H), and by means of allometric equations its AGB is estimated. The estimates are then summed up to obtain plot-level estimates, which are afterwards averaged for the whole stand or forest area. All these steps introduce some uncertainties that propagate through the data processing steps and need to be carefully and independently quantified (Chave et al., 2004). This involves several scales of prediction and propagation of errors between scales: a) Uncertainty on tree level AGB estimate due to measurement errors; b) Allometric model selection error; c) Minimum single plot size; and d) Landscape-scale representation (Figure 6).
Figure 6. The error propagation for estimating the AGB of a tropical forest from permanent sampling plots. Adapted from Chave et al. (2004)

The up-scaling of the AGB data across the landscape can be performed by simple statistics averaging over the plots (Figure 6), or by using earth observation data to model AGB across the entire area. In any case, any model prediction should be accompanied by any form of its associated confidence limits or uncertainty (Goodchild, 2005). Calculation of the uncertainty at pixel level requires a method that allows different sources of error such as seen in Figure 6 to be propagated.

2.5. CAPABILITIES AND LIMITATIONS OF EARTH OBSERVATION DATA

Before the introduction of remote sensing technologies, several approaches were used to produce AGB maps. The most well-known, simple and fast is the biome-average approach. The biome-averages are single representative values of biomass per unit area (e.g. t ha\(^{-1}\)). These biome-averages are applied to broad forest types or biomes, and have been mostly calculated and updated from analyses of country level carbon stock data archived by the United Nations Food and Agricultural Organization (FAO) (Gibbs et al., 2007). Unfortunately, estimates based on national forest inventories from some developing countries are not always reliable. However, the main advantage of using biome-averages is that the values are readily available.
at no cost, hence becoming the most important starting point for a country to assess the relative amount of carbon stocks (Gibbs et al., 2007).

Three broad types of remote sensors are currently used by Earth Observation (EO) platforms to map $AGB$: Optical, SAR, and LiDAR. The correlation between the signal received by those sensors and $AGB$ varies by sensor, forest type, slope, and other parameters. Each type of sensor has different characteristics which make them suitable for monitoring forest vegetation (Table 2) However, there is no single sensor that can currently be used for $AGB$ estimation across globally, either because of limitations in signal saturation, cloud cover persistence, or complexity of the signal retrieval due to topography. Signal saturation to $AGB$ refers to the point ($AGB$ level) where the sensitivity of the sensor signal (i.e. wavelength, reflectance) stops or where it fails to penetrate (i.e. dense canopy) (Fagan and DeFries, 2009). Additionally, the correlation of $AGB$ with different EO datasets can present regional variations due to factors such as forest structure and other environmental factors (e.g. Yu and Saatchi, 2016).

2.5.1. Synthetic Aperture Radar

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 (Figure 7).

![Figure 7](https://example.com/figure7.png)

Figure 7 Left: Illustration of Synthetic Aperture Radar Satellite basic terminology and types of backscatter originated from forest. Right: Wavelength and rate of penetration to the forest canopy. Modified from UCLA (2008)
SAR sensors transmit polarised electromagnetic waves in either the horizontal (H) or vertical (V) plane. The signal returned by the objects or earth surface can be received in either the horizontal or vertical plane. If the transmitted and received signal are in the same plane is a co-polarised configuration (i.e. HH and VV), while the combination of different planes is a cross-polarised (i.e. HV and VH). Cross-polarised data is sensitive to volume scattering elements within the forest canopy and therefore more useful for AGB estimation (Mitchard et al., 2011).

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 C-Band Sentinel-1 and L-band ALOS-2 PALSAR (Table 2). 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 - 150 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 2021. The future P-Band BIOMASS mission by ESA has the following accuracy requirements at 200 m 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\(^{-1}\).

2.5.2. Optical

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 (Lillesand et al., 2007)
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 (Foody et al., 2001, Gibbs et al., 2007). Several studies have mapped AGB at different scales (high 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. The incident electromagnetic radiation not absorbed or scattered by the atmosphere can be absorbed, transmitted, or reflected by the vegetation (Lillesand et al., 2007). Reflected radiation from targets is measure by remote sensing. Vegetation presents a diffuse reflection due to its roughness, and can be easily differentiated from other surfaces due to chlorophyll’s 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) (Figure 8)

![Figure 8 Radiation –Target Interactions with vegetation. Modified from NRC (2014).](image)

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 the high to coarse 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. Optical sensors have then a trade-off between pixel resolution and cloud-free observations availability (due to the revisiting time). High resolution (30 m) optical sensors such as Landsat have a 16-day revisiting time, which make it very challenging for obtaining cloud-free observations for large areas, while medium resolution (250 m) optical sensors such as MODIS have a 24 h revisiting time and therefore more chances to have multi-temporal cloud-free observations. 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. However, a study on tropical secondary forest in Brazil and Bolivia found the saturation to AGB of optical imagery (i.e. Landsat 5 TM) to be up to 150 t ha\(^{-1}\) (Steininger, 2000), which is as high as SAR L-band saturation to AGB. The study also found that infrared bands presented the highest correlation to AGB. Recent studies have also suggested that there is correlation of optical imagery (i.e. Landsat, MODIS) to AGB beyond the theoretical saturation due to canopy closure, especially in infrared bands (Baccini et al., 2012, Kellndorfer et al., 2011), which are sensitive to shadowing and moisture differences.

2.5.3. LiDAR

LiDAR technology consists of optical active sensors transmitting laser pulses to measure the distance to the target. LiDAR remote sensing systems can be classified according to:

- platforms: spaceborne, airborne, ground-based or hand-held
- returned signals: discrete return or waveform
- scanning pattern: profiling or scanning
footprint size (Area illuminated by the laser and from which the waveform-return signal gives information): small footprint: (<1 m diameter), medium footprint (10–30 m diameter), and large footprint (>50 m diameter).

Airborne and ground-based imaging LiDARs provide direct and very accurate measurements of canopy height the three-dimensional forest structure parameters (Asner et al., 2012) used to estimate AGB by means of allometry. LiDAR sensors do not suffer from signal saturation on the estimation of AGB, as optical and radar sensors do, because the high point density (or full waveform) allows to obtain ground returns through gaps in the canopy. In this study, however, airborne and ground platforms are not considered, as their use would be impractical at scales beyond sub-national level.

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. The GLAS LiDAR sensor on board of ICESat scanned the globe following a profiling pattern, and produced a global coverage of large full waveform signal footprints. ICESat sampled millions of approximately 65-m diameter footprints every 172-m along track in between 2003 and 2009. Canopy height can be calculated based on the relative time of the energy reflected from the floor and the canopy and received back at the instrument (waveforms) (Khalefa et al., 2013) (Figure 9). However, the vertical extent of each GLAS 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).

![Figure 9: Estimation of canopy height as a function of LiDAR GLAS vertical profile (waveform). Adapted from Drake et al. (2002)](image-url)
These profiling sensors cannot be used alone to produce wide area AGB mapping, but they are very useful in combination with other Earth Observation datasets (e.g. Baccini et al., 2012, Saatchi et al., 2011b), as they can be used as AGB reference data for calibration and validation of the algorithms (see chapter 3.2). Unfortunately, there is no current terrain profiling LiDAR satellite in orbit at the moment.

2.5.4. Current and future missions

There is a wide range of optical sensors relevant for monitoring of AGB (Table 2) as this has traditionally been the most widespread technology used by Earth Observation Satellites. In the following is expected a continuation of Landsat and Sentinel space programmes as well as other optical missions expanding the number of multispectral sensors in orbit. All these new sensors ensure the continuity of the optical archive started with the Landsat programme more than 40 years ago, as well as the large scale and low spatial resolution sensors AVHRR, MERIS and MODIS.

Governments and Space Agencies are currently starting to recognise the advantages of SAR sensors for a wide range of applications. There are more SAR instruments in space than ever before, and numbers are to increase steadily in the coming years. Current short-wavelength X-band (2.4 - 3.8 cm) SAR satellites such as the TerraSAR-X and COSMO-SkyMed constellations will be complemented by the Paz Satellite (2016) and the second generation of COSMO-SkyMed (2018-2019). C-band SAR (3.8 - 7.5 cm) satellite programmes such as Radarsat and Sentinel-1A/B will also continue with new additions in future years with the new Radarsat constellation (2018) and Sentinels 1C (2021) and 1D (no launch date yet). The only S-band satellite (Huanjing 1C) will have a continuation with NovaSAR-S (2016).

Larger wavelengths such as L-band (15 - 30 cm) ALOS-2 will have continuation with the SAOCOMS 1A and 1B. A larger wavelength than L-band is better suited to estimating high AGB levels, and the BIOMASS P-band (30 - 100 cm) sensor is very promising (Le Toan et al., 2011), which is due to be launched in 2021. The BIOMASS mission by ESA has the following accuracy requirements at 200 m 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. This will be the first spaceborne P-band SAR which will be sensitive to high AGB.

At least three Spaceborne LiDAR profiling sensors will be operational in the near future, inspired by the heritage of the ICESat satellite (GLAS sensor) that was widely used as calibration/validation dataset for AGB mapping at biome and continental levels. ICESat-2 will
be launched in 2017 with the Advanced Topographic Laser Altimeter System (ATLAS) on board. The main objective of this satellite, as with the previous ICESat, is monitoring ice sheet elevation and sea ice thickness. The mission also has a secondary objective to estimate ground surface height, canopy height, and canopy cover. However, it is not clear whether the ATLAS sensor alone will be suitable to estimate AGB in sparse forests such as the boreal taiga-tundra areas (Montesano et al., 2015).

Table 2 Operating or planned satellites used for forest mapping over large regions

<table>
<thead>
<tr>
<th>Sensor type</th>
<th>Wavelength</th>
<th>AGB Sensor Saturation*</th>
<th>Operating Sensors</th>
<th>Planned Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPTICAL</td>
<td>Visible / near-infrared (380 nm - 1 mm)</td>
<td>15 - 150 t ha⁻¹</td>
<td>Terra/Aqua MODIS, Terra ASTER, SPOT 6, SPOT 7, EO-I, DMC constellation, CBERS 4, Landsat 7 ETM+, Landsat 8 OLI, PROBA V, Sentinel 2A, Sentinel 3A</td>
<td>Amazônia-1, 1B &amp; 2, Ingenio, CBERS 4B, Sentinels (2B, 2C, 2D, 3B, 3C, 3D), Landsat 9, ALOS 3/PRISM-2</td>
</tr>
<tr>
<td></td>
<td>P Band (30 - 100 cm)</td>
<td>100 - 200 t ha⁻¹</td>
<td>BIOMASS</td>
<td></td>
</tr>
<tr>
<td></td>
<td>L band (15 - 30 cm)</td>
<td>40 - 150 t ha⁻¹</td>
<td>ALOS 2</td>
<td>SAOCOM 1A &amp; 1B, SAOCOM-CS</td>
</tr>
<tr>
<td></td>
<td>S band (7.5 - 15 cm)</td>
<td>&lt; 100 t ha⁻¹</td>
<td>Huanjing 1C</td>
<td>NovaSAR-S</td>
</tr>
<tr>
<td></td>
<td>C band (3.8 - 7.5 cm)</td>
<td>20 - 50 t ha⁻¹</td>
<td>Radarsat 1, Radarsat 2, Sentinel 1A &amp; 1B</td>
<td>RADARSAT constellation (1,2,3), Sentinels (1C, 1D)</td>
</tr>
<tr>
<td></td>
<td>X band (2.4 - 3.8 cm)</td>
<td>&lt; 20 t ha⁻¹</td>
<td>TerraSAR-X / TanDEM-X COSMO – SkyMed constellation</td>
<td>Paz, COSMO-SkyMed second generation constellation</td>
</tr>
<tr>
<td></td>
<td>Visible / near-infrared (532 &amp; 1064 nm)</td>
<td>No limit</td>
<td>ICESat 2, GEDI, MOLI</td>
<td></td>
</tr>
</tbody>
</table>

Two other LiDAR profiling sensors specifically designed for forest structure characterisation will be attached to the International Space Station (ISS). The Global Ecosystem Dynamics Investigation LiDAR (GEDI) mission on board of the ISS will be operational in 2018 (Dubayah et al., 2014). The GEDI instrument will be composed of 3 laser transmitters that will acquire 14 parallel tracks of 25 m footprints. The main objective of the GEDI mission is to quantify the spatial and temporal distribution of AGB carbon. The Multi-footprint Observation LiDAR and Imager (MOLI) will be operative in 2019 and will also be attached to the ISS (Asai et al., 2014). This sensor will have two aligned nadir-viewing LiDARs to capture multi-footprints and a multiband imager (Green, Red, and NIR) with 5 m resolution. The aim of this mission is to determine canopy height more precisely by the synergy between LiDAR and a high-resolution optical sensor able to provide information on crown size and approximate height. Unfortunately, GEDI and MOLI will not be able to obtain footprints from boreal forests (30% of world’s forest) due to the orbit characteristics of the ISS.

These LiDAR profiling sensors will provide millions of footprints containing forest structure information that could be used for calibration and validation of methods based on optical and SAR imagery. These sensors will generate key datasets for mapping AGB at large scales as they present themselves as the solution for the AGB data availability problem in many forests of the world.

### 2.6. MAXIMUM ENTROPY (MAXENT)

Jaynes (1957) postulated that a distribution which agrees with everything that is known, but avoiding any assumptions not supported by the a priori information should have maximum entropy (or uncertainty). The maximum entropy distribution is the most widespread distribution or the closest to the uniform distribution. The unknown probability distribution $\pi$ is defined over the finite space $X$ (here values of the pixels in our study area). The probability distribution $\pi$ gives a non-negative probability $\pi(x)$ to each individual element of the space $X$, and the sum of these probabilities totals 1. Therefore, the approximation of $\pi$ is the probability distribution $\hat{\pi}$, which entropy is defined as follows (Phillips et al., 2006):

$$H(\hat{\pi}) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x), \quad \text{where } ln \text{ is the natural algorithm}$$

Equation 3
Then, the constrains of $\pi$ are represented by a set of known real valued functions or features $(f_1, \ldots, f_n)$ on the space $X$. The information assumed about $\pi$ are the expectations (averages) of each feature $f_i$ under $\pi$. This feature expectation is defined as:

$$\pi[f_j] = \sum_{x \in X} \pi(x) f_i(x)$$

Equation 4

This can be approximated using a set of localities $(x_1, \ldots, x_m)$ independently drawn from $X$ according to $\pi$, so that the empirical average is:

$$\hat{\pi}[f_j] = \frac{1}{m} \sum_{i=1}^{m} f_i(x)$$

Equation 5

$\hat{\pi}[f_j]$ is used as an estimate of $\pi[f_j]$, and the objective is to find the approximate distribution of maximum entropy which satisfies the constrain that each $f_i$ match the same empirical average under $\hat{\pi}$. Based on the convex duality (Della Pietra et al., 1997), this MaxEnt distribution is equal to the maximum likelihood Gibbs distribution and proportional to the conditional probability of being positive (occurrence probability).

The MaxEnt machine learning algorithm used in this study corresponds to MaxEnt software 3.3.3k (Phillips et al., 2006, Phillips et al., 2004). As explained before, MaxEnt uses features to constrain the prior distribution. The features represent the environmental variables (here the remote sensing predictors or spatial datasets) or a function (transformation) of those. A remote sensing predictor refers in this thesis to an individual spatial variable originating from a remote sensor or spatial dataset (e.g. NDVI, elevation, SAR HV polarization, etc). The types of functions that can be used by this version of the algorithm are linear (the variable itself), product (pair-wise product combinations between remote sensing predictors), quadratic (square values of the remote sensing predictors), threshold (function that allows a “step” in the fitted function), hinge (allows a change in the gradient of the response), and categorical (for discrete remote sensing predictors) (Phillips et al., 2006, Elith et al., 2011). The algorithm will restrict by default the type of features used according to the number of occurrences available. A number of occurrences above or equal to 80 will allow by default the use of all type of features.

The algorithm can produce three different output formats for the model: raw, cumulative, and logistic. The logistic output format, which is a post-transformation of the raw output, was used in this study. The logistic output aims to estimate the closest to the probability of the species presence (probability of the class) for each pixel for the given remote sensing predictor. This is scaled from 0 to 1 being 0 the least suitable for the species and 1 the more suitable. The main
reason for this transformation is to convert the exponential model output of the algorithm into a logistic model, which will prevent the probabilities exceeding the value of 1, and making the model useful to be used with new data or for extrapolating to new areas.
Chapter 3

Literature Review
3. LITERATURE REVIEW

A peer-reviewed article with content from this chapter has been submitted:


3.1. FOREST SEMANTICS

A key challenge to map forest at a large scale is the definition of forest itself (Table 3). 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.

Table 3 Summary of attributes and minimum thresholds for the definitions of “forest” and “deforestation”. Adapted from Schoene et al. (2007)

<table>
<thead>
<tr>
<th>PARAMETERS</th>
<th>UNFCCC</th>
<th>CBD</th>
<th>FAO/FRA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young stands</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Temporarily unstocked areas</td>
<td>YES</td>
<td>--</td>
<td>YES</td>
</tr>
<tr>
<td>Forestry land use</td>
<td>--</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Min. Area (ha)</td>
<td>0.05-1.0</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Min. Height (m)</td>
<td>2-5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Crown Cover (%)</td>
<td>10-30</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Strip width (m)</td>
<td>--</td>
<td>--</td>
<td>20</td>
</tr>
<tr>
<td>Deforestation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transition from forest to non-forest</td>
<td>YES</td>
<td>N/A</td>
<td>YES</td>
</tr>
<tr>
<td>Land-use change</td>
<td>--</td>
<td>N/A</td>
<td>YES</td>
</tr>
<tr>
<td>Crown cover change (%)</td>
<td>&lt; 10 - 30</td>
<td>N/A</td>
<td>&lt; 10</td>
</tr>
<tr>
<td>Only directly human-induced</td>
<td>YES</td>
<td>N/A</td>
<td>--</td>
</tr>
</tbody>
</table>

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 un-stocked 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. Nevertheless, a forest cover map is essential in AGB mapping to avoid erroneous estimations of AGB in areas with no woody vegetation, as the remote sensing models are not usually calibrated for land covers other than forest.

The challenge becomes even greater with forest degradation. As degradation involves a reduction of standing vegetation (biomass) preserving the same forest area, measuring forest degradation is more complicated and more costly than measuring deforestation (Herold et al., 2012). In fact the more severe the degradation, the easier it is to detect using remote sensing techniques (Herold et al., 2011). As only some types of degradation can be directly detected by medium resolution sensors, indirect approaches such as monitoring human infrastructure are often used (Herold et al., 2011).

The UNFCCC definitions of forest and deforestation are ambiguous and impractical for a global study as each country applies a minimum threshold between the given ranges (Table 3). The CBD definition presents gaps related to temporal un-stocked areas, and do not have a definition for deforestation. The main challenge here is that this definition includes not only physical aspects of vegetation such as height or tree cover, but also other factors that cannot be observed by remote sensing techniques. As a result, most remote sensing studies do not specify the forest definition at use.

The forest definition plays a key role in monitoring forests. Sexton et al. (2015) demonstrated the effect of using different forest definitions to generate forest masks from remote sensing data, estimating the discrepancies in global forest extent among eight commonly used satellite products to be up to 13% of the global forest cover (Figure 10). Just within the tropics, the discrepancies between the satellite products leads to a variation in the magnitude of estimated carbon stocks of 45.2 Gt C with a value of approximately US$1 trillion (Sexton et al., 2015).
Figure 10 Agreement on the presence of forest among eight EO datasets (the number of ‘votes’ (out of eight possible) for forest cover). Larger values (in green) show agreement on the presence of forest. Conversely, values near zero (in red and black) show agreement on its absence. Yellow values (near four) represent areas of maximum disagreement over either the presence or absence of forest (Sexton et al., 2015).

By means of remote sensing techniques only “current” forest cover can be observed. Areas considered forest by national entities (according definitions) such as temporally un-stocked areas (e.g. harvested areas that will be replanted) are usually classified as deforestation or non-forested areas by remote sensing techniques (Hansen et al., 2013, Tropek et al., 2014, Hansen et al., 2014). For the same reason, forest cover present in agricultural or urban areas (which it is not considered forest according the definitions) is also usually classified as forest area by remote sensing. Therefore, it is important to be aware of this distinction between the actual forest cover seen by remote sensing and the forest defined by these organizations (which include un-stocked areas and other forestry land).

Remote sensing approaches allow the study of forest vegetation from a physical perspective (actual forest cover). Therefore, the same vegetation physical thresholds defining forest, deforestation and forest degradation, if agreed, could 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, can sometimes be included within the forest cover, especially when using coarse or medium-resolution optical sensors to monitor forest (Hansen et al., 2013, Tropek et al., 2014). To overcome this challenge, ancillary data with the location of these plantations or regionally 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).

However some forest cover products using similar definitions can also differ. MODIS Vegetation Continuous Fields (VCF), Landsat percent tree cover (PTC) and Landsat GFLG product with a 10% tree cover threshold, as well as ALOS PALSAR forest/non-forest (K&C-FNF) are examples of widely used forest cover products with similar forest definition (Saatchi et al., 2011b, Thiel et al., 2009, Shimada et al., 2011, Shimada et al., 2014, Hame et al., 2013, Hansen et al., 2013, Sexton et al., 2013). These products use FAO’s definition (10% tree cover and 5m height, but excluding temporally unstock areas) but are derived from different sensors (optical and SAR). These different forest cover products have therefore different characteristics due to the specific properties of the sensor.

The use of VCF or PTC could lead to an erroneous forest extent as the percent tree cover in sparse vegetated areas tends to be overestimated by these products (Sexton et al., 2013, Montesano et al., 2009). Likewise L-band backscatter for crops or settlements can be similar to backscatter from forest areas leading to systematic misclassification of non-forest pixels. Additionally, low biomass sparse forests and woodlands, some plantations and high biomass mangroves are often classified as non-forest by the K&C-FNF, as the signal from these is below the applied backscatter threshold (Shimada et al., 2014). Estimates of forest cover at continental level by the L-Band SAR K&C-FNF product have been found to differ as much as -15% to 42% in comparison to optical Landsat percent tree cover product (Shimada et al., 2014, Hansen et al., 2013). Additionally, these large-scale products face problems related to the regional variability of forest ecosystems across wide areas. Some of these products try to circumvent these issues with regional adjustments, such as the regional backscatter thresholding used by the K&C FNF product (Shimada et al., 2014), while other products completely lack approaches that take into account regional variations of the vegetation. As a result, a forest AGB map using any of these products as forest mask or predictor variable will have an overall unaccounted uncertainty, and lead to biased estimations of carbon stocks. How these differences affect the estimate on of carbon stocks at national and regional level has not been yet fully studied.
3.2. ALLOMETRY VARIATIONS AND PATTERNS OF AGB DISTRIBUTION

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).

The selection of appropriate equations is a crucial step when using allometry. An inappropriate choice could become the most important source of error in the estimation of AGB (Chave et al., 2004). These errors are mostly a consequence of using allometric equations outside the diameter range (Chave et al., 2004) or in a different area (Buvaneswaran et al., 2006) from which those equations were developed. Important variations obtained in C stock have been found with overestimations up to 93% when using different biomass allometric equations in the same study area (Henry, 2010).

Feldpausch et al. (2011) found that the tree allometry in between height and diameter (H:D) of trees varies across different areas and recommended to include height as predictor in biomass models. Several studies have demonstrated that diameter at breast height as well as the combination of tree height with diameter at breast height, are good predictor variables to be used in biomass equations (e.g. António et al., 2007, Chave et al., 2005, Carvalho and Parresol, 2003, Reed and Tome, 1998). The appropriateness of these biophysical parameters is not surprising since the combination of diameter and tree height in the form $D^2H$ expresses the volume of an ideal cylindrical stem.

As allometry varies due to climatic conditions, vegetation structure, species, and growth-form of trees (Keith et al., 2000, Chave et al., 2005, Feldpausch et al., 2011), the different forest biomes will present variations in allometry. Chave et al. (2005) found that forest type, based on variables such as precipitation and seasonality, was significant in tree allometry, developing different models for each forest type accordingly. In the same line, Feldpausch et al. (2011) noted the difference in the allometric H:D relationship between tropical trees from Asia, Africa and the Guyana Shield in contrast with trees from the Amazon Basin and tropical Australia, which are much shorter for any given diameter. Vicilledent et al. (2011) showed that regional models performed better than generic or theoretical models in Madagascar. It is therefore
reasonable that the use of models adapted to the regional conditions will improve biomass estimation.

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 wide regions or entire 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.

Several authors have studied LiDAR-derived biophysical canopy metrics such as maximum canopy height, Lorey’s mean canopy 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 ICESat 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. However, these canopy height models were developed using data from the United Estates and Brazil, but then used over the whole tropical region, which can be problematic due to the variability of forests worldwide.

At plot 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 allometric models which could relate plot level canopy height to $AGB$ as seen in (Saatchi et al., 2011b, Mitchard et al., 2012, Asner et al., 2012). This type of relationship at the plot, footprint 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 (i.e. plot, pixel or footprint). However, 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., 2011b, Cloude et al., 2011, Mette et al., 2004, Mitchard et al., 2012).
The allometric variations at tree level due to climatic conditions, vegetation structure, species, soil types, and other characteristics (Keith et al., 2000, Chave et al., 2005, Feldpausch et al., 2011, Reich et al., 2014) will ultimately affect the correlation between AGB and biophysical parameters like mean canopy height at plot and pixel level. 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).

GLAS footprints are used to estimate $AGB$ from allometric models and used as $AGB$ reference data for calibration and validation of different algorithms. However, the use of a single plot-level allometric model to estimate $AGB$ reference data from GLAS footprints on wide areas (e.g. continents) having only canopy height as predictor variable, as seen in Saatchi et al. (2011b), ignores the allometric variations between and within regions and can brings large errors in the estimation of $AGB$. Additionally, GLAS-derived $AGB$ reference data seems to significantly differ in comparison to field-derived $AGB$ reference data according to Mitchard et al. (2014). The reason for the differences could be linked to the single allometry used to estimate the GLAS-derived $AGB$. Nevertheless, those results however were discussed by Saatchi et al. (2015) arguing that the study had methodological flaws in the interpolation approach used by Mitchard et al. (2014), and that the 413 plots from different periods (1956-2013) used in the study only sampling 404.6 ha out of 650 million hectares of forest in the Amazon and without a rigorously designed and extensive in-situ forest inventory strategy are not representative of the $AGB$ trends in the region. Further research should therefore be done to investigate these differences.

Allometric variations at plot level across the landscape have not been sufficiently explored to be used with remote sensing. Further research is needed to develop models that capture this variability as the slopes of these allometric functions will differ across different regions or gradients. How this type of plot-level allometric relationship between $AGB$ and $H$ vary across regions has not been studied yet.

As previously discussed, regional variations in temperature, rainfall, species and soil types drive the global patterns in forest biomass distribution (Keith et al., 2000, Reich et al., 2014,
However, information on climate (i.e. temperature, etc), vegetation structure, species, or soil type are usually coarse (spatial resolution > 1km) or not globally available at the required spatial resolution.

The topography of Earth’s surface can modify the effect of climate, generate microclimates and drive the composition of species (Littell et al., 2008). Conversely, topographic information is globally available from earth observation missions such as the NASA’s Shuttle Radar Topography Mission (SRTM) (USGS, 2006) from a spatial resolution of 30 m.

Vegetation structure, allometry and biomass distribution across the landscape are strongly affected by topographic variables (Shary and Smirnov, 2013, Velízquez-Rosas et al., 2002, Pan et al., 2013a, Bispo et al., 2014, Bispo et al., 2016). Across the altitude gradient changing patterns of temperature, wind and precipitation occur over short distances, with plants being exposed to higher solar radiation, lower temperatures and stronger winds at higher altitudes and light limitations at lower altitudes (Pan et al., 2013a). Spatial patterns on the distribution of $AGB$, canopy height, and other forest parameters (Girardin et al., 2014, Buma and Barrett, 2015, Moser et al., 2008, Takyu et al., 2003) as well as allometric variations in vegetation (Pan et al., 2013a) have been previously observed in regions with elevation gradients. These studies showed a decreasing $AGB$ with elevation. The use of topographic variables as predictor parameters to assist in the estimation and upscaling of $AGB$ across large areas require of further study.

3.3. CURRENT METHODS TO MAP $AGB$

3.3.1. Types of algorithms

Several studies have aimed to map $AGB$ at different scales (Table 4). A large amount of different remotely sensed datasets are available, ranging from multispectral and hyperspectral to LiDAR and SAR from either air- or space-borne platforms. These projects are generally based on in-situ data and sensors with medium to coarse spatial resolutions (25 m to ca. 55 km). As most methods use a single sensor approach, they face the limitations of remote sensing imagery to map forest $AGB$ (signal saturation, cloud cover, topography). New methods however are aiming to combine multiple datasets in order to overcome these limitations. Data synergy approaches enable an exploitation of the specific strengths of each sensor. However, $AGB$ data availability to calibrate these methods is still an important constraint, especially at scales beyond the national level.
AGB can be directly estimated using the correlation of the remote sensor signal (e.g. reflectance, backscatter intensity, etc) to AGB. However, this approach usually faces issues related to the saturation of the signal. Alternatively, AGB can be estimated indirectly. SAR and LiDAR sensors can be used to estimate biophysical parameters such as tree canopy height (Saatchi et al., 2011b, Balzter et al., 2007b, Lefsky et al., 2005). Biophysical parameters can be used with plot level allometric models to estimate forest AGB as explained in the previous section. This approach does not suffer from the AGB / radar backscatter saturation problem.

Methods to map AGB over large spatial scales can also be separated into parametric and non-parametric approaches. Parametric approaches make assumptions on the shape (i.e., normal distribution), and on the parameters or form of the sample distribution, while non-parametric approaches only make few or no assumptions. The use of parametric models present bigger challenges for upscaling or extrapolating AGB data, as there are no current satellite observations that can be reasonably related to AGB across the whole landscape. Additionally, 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). Examples of parametric methods are multiple regression analysis (e.g. Baccini et al., 2012), or geo-statistical methods such as co-kriging (e.g. Tsui et al., 2013), whereas the k-nearest neighbour technique (e.g. McRoberts et al., 2007), random forests (Cartus et al., 2014, Baccini et al., 2012), and neural networks (e.g. Del Frate and Solimini, 2004) are examples of non-parametric methods.

Most remote sensing studies modelling AGB across the landscape report error parameters based on validations of predictions using independent datasets. Only two studies were found in the literature review providing uncertainty of the AGB estimations at pixel level (i.e. Blackard et al., 2008, Saatchi et al., 2011b). Blackard et al. (2008) produced a value of modelling uncertainty at pixel level, while Saatchi et al. (2011b) propagated four sources of error in a pixel-by-pixel basis.
<table>
<thead>
<tr>
<th>STUDY</th>
<th>UNIT</th>
<th>PIXEL SIZE</th>
<th>TEMPORAL COVERAGE</th>
<th>FOREST TYPE / SPATIAL COVERAGE</th>
<th>METHODS AND DATA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kindermann et al. (2008)</td>
<td>AGB</td>
<td>55 km</td>
<td>2005</td>
<td>Global</td>
<td>Downscaling (FAO statistics, modelled NPP)</td>
</tr>
<tr>
<td>Avitabile et al. (2014), Avitabile et al. (2016), &amp; Santoro et al. (2015)</td>
<td>AGB</td>
<td>1 km</td>
<td>2000-2008</td>
<td>Global</td>
<td>GEOCARBON project: Fusion of pan-tropical map (Avitabile et al., 2016) and boreal map (Santoro et al., 2015) Regression (VOD derived from passive microwave data calibrated by Saatchi et al. (2011b) map)</td>
</tr>
<tr>
<td>Liu et al. (2015)</td>
<td>AGB</td>
<td>27.5 km</td>
<td>1993-2012</td>
<td>Global</td>
<td>Regression (VOD derived from passive microwave data calibrated by Saatchi et al. (2011b) map)</td>
</tr>
<tr>
<td>Saatchi et al. (2011b)</td>
<td>AGB</td>
<td>1 km</td>
<td>2000</td>
<td>Tropical forest / Tropics</td>
<td>MaxEnt (GLAS. MODIS, QSCAT, SRTM, forest plots)</td>
</tr>
<tr>
<td>Baccini et al. (2012)</td>
<td>AGB</td>
<td>463 m</td>
<td>2007-2008</td>
<td>Tropical forest / Tropics</td>
<td>Random Forest (GLAS, MODIS, SRTM)</td>
</tr>
<tr>
<td>Avitabile et al. (2016)</td>
<td>AGB</td>
<td>1 km</td>
<td>2000-2008</td>
<td>Tropical forest / Tropics</td>
<td>Fusion of previous tropical maps (Saatchi et al., 2011b, Baccini et al., 2012) using forest plots and other AGB reference maps</td>
</tr>
<tr>
<td>Thurner et al. (2014)</td>
<td>AGB</td>
<td>1 km</td>
<td>2010</td>
<td>Boreal-Temperate forest / Northern boreal and temperate region</td>
<td>BIOMASAR algorithm (ENVISAT ASAR, MODIS VCF), Allometry</td>
</tr>
<tr>
<td>Santoro et al. (2015)</td>
<td>GSV</td>
<td>1 km</td>
<td>2010</td>
<td>Boreal-Temperate forest / Northern boreal and temperate region</td>
<td>BIOMASAR algorithm (ENVISAT ASAR, MODIS VCF)</td>
</tr>
<tr>
<td>STUDY</td>
<td>UNIT</td>
<td>PIXEL SIZE</td>
<td>TEMPORAL COVERAGE</td>
<td>FOREST TYPE / SPATIAL COVERAGE</td>
<td>METHODS AND DATA</td>
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<tr>
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<td>----------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Gallaun et al. (2010)</td>
<td>GSV / AGB</td>
<td>500 m / 10 km</td>
<td>2000</td>
<td>Temperate-Boreal forest / Europe</td>
<td>Downscaling by weighting the class mean values with fractional cover maps (MODIS, forest plots)</td>
</tr>
<tr>
<td>Baccini et al. (2008)</td>
<td>AGB</td>
<td>1 km</td>
<td>2003</td>
<td>Tropical forest / Africa</td>
<td>Random Forest (MODIS, forest plots)</td>
</tr>
<tr>
<td>Kellndorfer et al. (2011)</td>
<td>AGB</td>
<td>30 m</td>
<td>2000</td>
<td>Temperate – Boreal forest / USA</td>
<td>Regression Tree modelling (Landsat, NLCD land cover and canopy density, SRTM, forest plots)</td>
</tr>
<tr>
<td>Blackard et al. (2008)</td>
<td>AGB</td>
<td>250 m</td>
<td>2001</td>
<td>Temperate forest / USA</td>
<td>Classification and Regression Tree modelling (MODIS, NLCD land cover, National Elevation Dataset, forest plots)</td>
</tr>
<tr>
<td>Yin et al. (2015)</td>
<td>AGB</td>
<td>1 km</td>
<td>2001-2013</td>
<td>Temperate forest / China</td>
<td>Model Tree Ensembles (MODIS, WorldClim climate data, forest type layer, forest plots)</td>
</tr>
<tr>
<td>Du et al. (2014)</td>
<td>AGB</td>
<td>5.5 km</td>
<td>2004-2008</td>
<td>Temperate forest / China</td>
<td>Downscaling (MODIS land cover, forest plots)</td>
</tr>
<tr>
<td>Beaudoin et al. (2014)</td>
<td>AGB/ GSV</td>
<td>250 m</td>
<td>2001</td>
<td>Boreal forest / Canada</td>
<td>kNN (MODIS, forest plots)</td>
</tr>
<tr>
<td>Houghton et al. (2007)</td>
<td>AGB</td>
<td>500 m</td>
<td>2000</td>
<td>Boreal forest / Russia</td>
<td>Random Forest (MODIS, forest plots)</td>
</tr>
<tr>
<td>Saatchi et al. (2009)</td>
<td>AGB</td>
<td>5 km</td>
<td>2000-2004</td>
<td>Tropical forest / Amazon Basin</td>
<td>MaxEnt (MODIS, VCF, QSCAT, SRTM, Climate data, Soil data, forest plots)</td>
</tr>
<tr>
<td>Saatchi et al. (2007)</td>
<td>AGB</td>
<td>1 km</td>
<td>2000-2004</td>
<td>Tropical forest / Amazon Basin</td>
<td>Decision Tree Classifier (MODIS, VCF, JERS-1, QSCAT, SRTM, Climate data, Vegetation map, forest plots)</td>
</tr>
<tr>
<td>Cartus et al. (2014)</td>
<td>AGB</td>
<td>30 m</td>
<td>2005</td>
<td>Temperate – Tropical forest / Mexico</td>
<td>Random Forest (Landsat PTC, ALOS PALSAR, SRTM, Land use map, forest plots)</td>
</tr>
<tr>
<td>STUDY</td>
<td>UNIT</td>
<td>PIXEL SIZE</td>
<td>TEMPORAL COVERAGE</td>
<td>FOREST TYPE / SPATIAL COVERAGE</td>
<td>METHODS AND DATA</td>
</tr>
<tr>
<td>------------------</td>
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<td>--------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Asner et al. (2014)</td>
<td>AGB</td>
<td>100 m</td>
<td>2012-2013</td>
<td>Tropical forest/Peru</td>
<td>Random Forests (Airborne LiDAR, forest plots, Landsat-derived fractional cover, MODIS, SRTM)</td>
</tr>
<tr>
<td>Asner et al. (2013)</td>
<td>AGB</td>
<td>100 m</td>
<td>2008-2012</td>
<td>Tropical forest / Panama</td>
<td>Random Forests (Airborne LiDAR, forest plots, Landsat-derived fractional cover, MODIS, NASA Tropical Rainfall Measuring Mission, SRTM)</td>
</tr>
<tr>
<td>Avtar et al. (2013)</td>
<td>AGB</td>
<td>50 m</td>
<td>2009-2010</td>
<td>Tropical forest / Cambodia</td>
<td>Multiple Linear Regression (ALOS PALSAR, forest plots)</td>
</tr>
<tr>
<td>Lucas et al. (2010)</td>
<td>AGB</td>
<td>50 m</td>
<td>2007</td>
<td>Tropical forest / Queensland (Australia)</td>
<td>Regression (ALOS PALSAR, forest plots)</td>
</tr>
<tr>
<td>Anaya et al. (2009)</td>
<td>AGB</td>
<td>500 m</td>
<td>2001-2006</td>
<td>Tropical forest / Colombia</td>
<td>Regression (MODIS, VCF, forest plots)</td>
</tr>
</tbody>
</table>

Table Acronyms: FAO (United Nations Food and Agriculture Organization), GLC2000 (Global Land Cover 2000 Project), IPCC (Intergovernmental Panel on Climate Change), kNN (K-Nearest Neighbours), MaxEnt (Maximum Entropy), NLCD (National Land Cover Database), NPP (Net Primary Productivity), PTC (Percent Tree Cover), QSCAT (Quick Scatterometer), SRTM (Shuttle Radar Topography Mission), VOD (Vegetation Optical Depth), VCF (Vegetation Continuous Fields)
Two levels or scales for mapping $AGB$ are distinguished in this thesis, small-scale and large-scale. The small scale mapping level includes maps at sub-national (province, state or region within a country) or project level. National level mapping of small countries could also be included in this category. At this level most satellite, airborne and terrestrial sensors and methods can be applied. The second level (large-scale) includes national mapping of large countries, as well as biome, continental, and global mapping levels. At this scale only the use of satellite sensors is feasible, and not all methods are suitable.

### 3.3.2. Small-scale mapping

The methods used to map $AGB$ at this scale are generally calibrated with forest inventory plot data. However, there is an increasing tendency to use airborne LiDAR as calibration data (Asner et al., 2014, Asner et al., 2013, Perrin et al., 2016, Hudak et al., 2002, Lu et al., 2012). This type of approach relates $AGB$ field observations to airborne LiDAR data, and then calibrates the parameter retrieval from spaceborne sensors using those LiDAR datasets. As mentioned before, the use of airborne data is only feasible at national level (in the case of small countries) or below due to logistic and economic constraints.

Large-scale mapping approaches, explained in the following section, are also applicable at this level but usually not vice-versa. At small-scale mapping level more complex techniques applied to SAR data can be used to estimate other biophysical parameters such as tree canopy height, which can then be used to estimate $AGB$ indirectly from allometric models and do not suffer from the $AGB$ / signal saturation problem.

Multiple SAR images of an area, if acquired from roughly the same position in space, and with the same image geometry such as look angle, polarisation, wavelength and spatial resolution, can be combined to take advantage of the phase information contained within each complex image, in a process called SAR interferometry (InSAR). Images can be acquired simultaneously by two receiving sensors in single-pass InSAR mode (e.g. the TanDEM-X satellite constellation), or at different times by the same or different sensors in repeat-pass InSAR mode (e.g. Sentinel-1A & 1B). While the distance between the sensors’ positions in space should be sufficiently large to provide sensitivity to signal phase differences, as this distance increases there is spatial decorrelation of the signal, up to a point called the critical baseline, beyond which the phase of each image is completely decorrelated with respect to the other image (Zebker and Villasenor, 1992). From both techniques it is possible to derive Digital Surface Models (DSM) from the phase difference. This approach also requires a Digital Terrain
Model (DTM) of the ground elevation beneath the canopy to estimate canopy height (Balzter et al., 2007b) (Figure 11). The phase correlation between two acquisitions determines the reliability of InSAR measurements and is known as interferometric SAR coherence. For longer wavelengths, lower coherence between repeat-pass image pairs indicates the presence of denser vegetation, as scatterer movement between image acquisitions increases with forest growing stock volume (Tansey et al., 2004).

Figure 11 Vegetation carbon content at MonksWood National Nature Reserve derived from the canopy height models from (a) LIDAR DSM and LIDAR DTM, (b) XVV InSAR DSM and LIDAR DTM, (c) XVV InSAR DSM and smoothed interpolated LHH InSAR DTM (dual wavelength approach). Warmer colours indicate higher carbon content (range from 5 to 400 tC ha\(^{-1}\)), 21 m pixel spacing (Balzter et al., 2007b)

Polarimetric Interferometry (PolInSAR) is another SAR technique which, in contrast to single-polarisation InSAR, does not rely on an external DTM, as it estimates terrain and canopy height from the vertical heights of the scattering phase centres of the different polarimetric scattering mechanisms (Cloude et al., 2011, Papathanassiou et al., 2008, Cloude and Papathanassiou, 1998). Different polarisations interact more strongly with different scatterers, such as canopy (HV) and trunk (HH). SAR Tomography (TomoSAR) goes beyond the PolInSAR technique by using a set of multiple baselines of interferometric SAR images to generate a 3D vertical structure of the vegetation canopy based on the variation of backscattering as a function of height (Le Toan et al., 2011, Cloude, 2006). Most of these techniques are difficult to use over large areas due to the specific data requirements. Better availability of SAR sensors might circumvent these limitations.
3.3.3. Large-scale mapping

At this level data availability is the main limiting factor of AGB mapping approaches. Additionally, estimating AGB across different biomes using the same method can be very challenging due to the variations in forest structure, species composition and wood density, allometry, atmospheric effects, and vegetation moisture.

A range of non-parametric machine learning algorithms are used at national level and beyond to extrapolate AGB measured from forest plots (Blackard et al., 2008, Houghton et al., 2007, Cartus et al., 2014, Saatchi et al., 2009, Saatchi et al., 2007, Kellndorfer et al., 2011, Yin et al., 2015). This type of approach can combine different types of data. Regression methods have also been applied at this level in Colombia (Anaya et al., 2009) and Queensland (Australia) (Lucas et al., 2010). Only few studies combine datasets from different sensors, and only two of them were found to combine optical, SAR, and DEM datasets (i.e. Saatchi et al., 2007, Cartus et al., 2014).

A previous study of AGB stocks at national level used 250 m spatial resolution imagery (MODIS, DEM, and land cover layers) and forest inventory data to generate AGB maps for the United States (U.S.) by means of a classification and regression tree modelling (Blackard et al., 2008). Kellndorfer et al. (2011) used a very similar approach over the U.S. but using 30 m resolution Landsat imagery from the National Land Cover Database, the US National Forest Inventory and SRMT topographic data. Blackard et al. (2008) generated AGB, Uncertainty, and Forest Probability maps. However, the uncertainty generated by this study was only based on the relative error of the modelled prediction, lacking an error propagation approach which could allow the incorporation of other sources of uncertainty at pixel level.

Two recent map products (Baccini et al., 2012, Saatchi et al., 2011b) established a benchmark in the synergistic use of different EO datasets to map AGB across the whole tropical biome. These studies use AGB estimated from millions of GLAS footprints to calibrate their methods. The approach 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. (2011b) use three plot-level continental allometric models derived from ground data to relate GLAS-derived Lorey’s height ($H_L$) to AGB. 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 different forest biomes. These studies used machine-learning algorithms such as Random Forest (Breiman, 2001b) and MaxEnt (Phillips et al.,
2006, Phillips et al., 2004) for upscaling of the AGB across wide areas, to produce 463 m and 1 km resolution maps respectively. Saatchi et al. (2011b) reported a relative error of approximately 30% across the three continents, while Baccini et al. (2012) reported similar figures in terms of RMSE (38-50 t ha\(^{-1}\)).

One of the most innovative features of Saatchi et al. (2011b) study was the possibility of mapping the uncertainty of the AGB estimation propagating different sources of error in a pixel-by-pixel basis. Both approaches use MODIS spectral bands and the SRTM DEM as predictor variables, and in the case of Saatchi et al. (2011b) also Quicksatcaterometer data (QSCAT). These methods aim to take advantage of the full potential of the information contained in each input band, but none of these bands on its own can fully explain the variability of AGB across the landscape.

These two products provide very different results on the amount and spatial distribution of AGB at finer resolutions (Mitchard et al., 2013) (Table 5 and Figure 12). Differences when compared to in-situ AGB data or to local AGB maps have also been found (Mitchard et al., 2014, Carreiras et al., 2013), but the reasons are not fully clear. Mitchard et al. (2014) found that these maps do not agree with the spatial distribution of AGB in permanent Amazon field plots and that the uncertainties quantified in a comparison with 413 ground plots far exceed those reported by the studies. Saatchi et al. (2015) responded to Mitchard et al. (2014) arguing that, aside from methodological flaws in the interpolation approach, using 413 plots from different periods between 1956 and 2013 only represent 404.6 ha out of 650 million hectares of forest in the Amazon and without a rigorously designed and extensive in-situ forest inventory strategy are not representative of the AGB trends in the region. Nonetheless, the consistency of both products at coarser scales suggests that realistic estimates of carbon stocks can be produced over large regions. However, there are still large uncertainties in these maps and discrepancies when compared to ground data which need to be addressed. These are related to the input EO data, AGB reference data, allometries and the algorithm calibration.

The two pan-tropical carbon maps were fused using a methodology that incorporated research field observations, forest inventory plots and other high-resolution biomass maps (Avitabile et al., 2016). The method was based on bias-removal and weighted-averaging of the regional maps, and resulted in a pan-tropical map with a 15-21% lower RMSE than that of the input maps, and lower bias (mean bias 5 t ha\(^{-1}\) vs. 21 and 28 t ha\(^{-1}\) for the input maps).
Boreal and temperate forest *GSV* was mapped at 100 m and 1 km spatial resolution using hyper-temporal data series of Envisat ASAR ScanSAR backscatter imagery by means of a parametric semi-empirical model called BIOMASAR (Santoro et al., 2011). The major advantage of this parametric semi-empirical approach is that the algorithm does not rely on training data. The high uncertainty of the 100 m resolution map (average 70% relative error) was considerably reduced (average 43%) when aggregating to coarser pixels of 1 km resolution. The applicability of this C-band SAR algorithm to tropical areas with much higher *AGB* density is unclear, but adapting the algorithm to use larger SAR wavelengths such as L-band could potentially overcome this problem. Thurner et al. (2014) used the *GSV* estimated from this product in combination with specific wood density information and allometric relationships between biomass compartments (stem, branches, foliage, and roots) to produce a C stocks map for the boreal and temperate forests at ca. 1 km spatial resolution.

GSV at 500 m and *AGB* at 10 km was also mapped continentally for the whole of the European Union (Gallaun et al., 2010) using a downscaling approach that weighted the CORINE class mean GSV values extracted from forest inventories by fractional cover maps developed using MODIS data. An Africa-wide map was also produced at 1 km resolution by extrapolating data from forest plots by means of MODIS imagery and a Random Forest algorithm, producing a RMSE of 50.5 t ha$^{-1}$.

<table>
<thead>
<tr>
<th>Continent</th>
<th>Saatchi et al. (2011b) (Pg)</th>
<th>Baccini et al. (2012) (Pg)</th>
<th>Avitabile et al. (2016) (Pg)</th>
<th>Liu et al. (2015) (Pg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>113</td>
<td>129</td>
<td>96</td>
<td>126</td>
</tr>
<tr>
<td>America</td>
<td>193</td>
<td>234</td>
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<td>Asia</td>
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<td>93</td>
<td>92</td>
<td>79</td>
</tr>
<tr>
<td>Tropics</td>
<td>413</td>
<td>457</td>
<td>375</td>
<td>428</td>
</tr>
</tbody>
</table>

Comparison of *AGB* stocks for continental regions base on the coverage of Baccini et al. (2012) map.
Figure 12 Pan-tropical carbon maps from Saatchi et al. (2011b), Baccini et al. (2012), and the fused version from Avitabile et al. (2016). The bottom map shows AGB derived from GLAS footprints over forest areas using the same method and allometries as Saatchi et al. (2011b).
First global AGB maps were not based on remote sensing imagery, but on downscaling of FAO forest inventory statistics using annual net primary production NPP model outputs (Kindermann et al., 2008), and on the assignment of IPCC default AGB averages (estimated from FAO data) to GLC2000 (Bartholomé and Belward, 2005) land cover classes (Ruesch and Gibbs, 2008).

Following the same fusion approach as Avitabile et al. (2016) a global map of AGB was generated for the GEOCARBON project (Avitabile et al., 2014) fusing the boreal map from Santoro et al. (2015) and the pan-tropical map from Avitabile et al. (2016) at ca. 1 km pixel size.

An innovative approach that uses vegetation optical depth (VOD) from Earth’s passive microwave radiation was used to map AGB globally over a long time period (1993-2012) (Liu et al., 2015). The main disadvantage comes from the low energy of this radiation which only allows resolutions > 10 km. There is no ground data available at spatial scales that would allow calibration of such pixel sizes. Thus, other previous AGB maps have to be used for calibration. In Liu et al.’s (2015) study, Saatchi et al. (2011b) aggregated pixels were used. As a result, any of the uncertainties from the Saatchi et al. (2011b) map will propagate into this new product. Conversely, the long time period (1993-2012) allows a trend analysis of carbon stocks worldwide over almost 20 years. These trends are comparable in boreal and temperate areas to the trends reported by Pan et al. (2011) calculated using on ground observations for the period 2000-2007, but both studies disagree in their estimations for tropical areas where the loss of AGB is much larger in the study of Liu et al. (2015).

Estimating AGB at large-scale level and across different biomes using the same method can be very challenging due to the variations in forest structure, species composition and wood density, allometry, atmospheric effects, and vegetation moisture discussed in previous chapters. For example, the sensitivity of L-band SAR backscatter to AGB can be significantly different depending on forest types and environmental effects (Yu and Saatchi, 2016)

Additional information could therefore be used to regionalize these approaches. Regionalized methods (versus generalized methods or global methods) are defined in this thesis as methods that use regional knowledge and datasets, such as regional land cover classifications or local climatic information. Regional data can be used either as
stratification or as input variable in methods upscaling $AGB$ field measurements. It also implies the use of regional allometric models (versus single models). However, these datasets are usually available in the form of coarse spatial resolution (e.g. climate data) or coarse land cover datasets (e.g. WWF terrestrial ecosystem classification). Another higher resolution land cover classifications have also been successfully used in the past as predictor variable (Kellndorfer et al., 2011, Saatchi et al., 2007, Blackard et al., 2008, Du et al., 2014, Yin et al., 2015). However, these datasets have only very few classes or are only available to their respective study areas. Therefore, using these datasets as input for the characterization of $AGB$ at medium or high resolution is not possible or it might introduce artificial borders and unknown errors in the $AGB$ estimation. As previously discussed in the chapter 3.2 alternatively continuous predictors such as topographic variables could be used to characterize these regional variations. Topographic information is globally available from earth observation missions such as the NASA’s Shuttle Radar Topography Mission (SRTM) (USGS, 2006) and could assist in the improvement of large-scale mapping approaches.

Topographic variables have been studied to model forest structure parameters such as basal area or canopy openness in a study site in Brazil (Bispo et al., 2016), where they also explored the combination of topographic variables with SAR data to estimate $AGB$ (Bispo et al., 2014). Topographic variables have also been used as predictors in combination with other datasets to map $AGB$ across wide areas (e.g. Cartus et al., 2014, Kellndorfer et al., 2011, Saatchi et al., 2011b, Saatchi et al., 2007). However, these studies did not examine the contribution of topographic variables in comparison to Optical and SAR datasets, and neither the contribution across the $AGB$ prediction range. This information can contribute to better understand the relation between geomorphometry and $AGB$ distribution.

3.4. ALGORITHM SELECTION

As previously discussed, the use of parametric models to model $AGB$ across large scales present big challenges due to no reasonable correlation between satellite observations and $AGB$, and the lack of independence and normality of the predictors (Breiman, 2001b). Non-parametric algorithms often outperform parametric methods as forest $AGB$ distribution show autocorrelation, non-linear relationships, and temporal and spatial variable interaction (Evans and Cushman, 2009).
Maximum Entropy (MaxEnt) was selected as the ideal non-parametric algorithm to upscale AGB data to regional and global scales in this study. The MaxEnt algorithm is a flexible and general purpose algorithm that estimates the probability distribution with the maximum entropy subject to the constraints established by the input information (Phillips et al., 2006). The MaxEnt algorithm is widely used for estimation of species distribution models (SDM), and has been recently used for classification of remote sensing data (Li and Guo, 2010). MaxEnt has also been successfully used in the modelling of AGB in the pan-tropics (Saatchi et al., 2011b)

The algorithm was selected for this study by following the below criteria which is partly based on the algorithm selection criteria suggested by Pearson (2010). The order indicates the importance of each criterion:

1. Model performance in comparison to other methods (based on literature review)
2. Potential to estimate the uncertainty of the predictions at pixel level
3. The algorithm requires data on only one class (presence data)
4. Importance to determine the relative influence of different input variables on the model’s fit or predictive capacity
5. Ability to incorporate continuous and discrete environmental variables (remote sensing predictors), and to produce continuous and discrete outputs

MaxEnt presents similarities with other approaches such as generalized linear models (GLM), generalized additive models (GAM), Bayesian approaches and neural networks (Phillips et al., 2006), and has been extensively used in the fields of biogeography, conservation biology and ecology in the last years (e.g. Wollan et al., 2008, Murray-Smith et al., 2009, Cordellier and Pfenninger, 2009, Kharouba et al., 2009, Saatchi et al., 2011b). The algorithm has shown to outperform well established modelling methods such as GLM, GAM, Genetic Algorithm for Rule Set Production (GARP), and BIOCLIM (Elith et al., 2006, Guisan et al., 2007). MaxEnt has a similar performance in comparison to another machine learning algorithms such as Random Forest (Williams et al., 2009), One-Class Support Vector Machine (OC-SVM) (Li and Guo, 2010), and Boosted Decision Trees (BDT) (Elith et al., 2006, Guisan et al., 2007).

Entropy can be considered as a measure of uncertainty of probability distribution (Wang, 2008). MaxEnt maximizes mathematically this entropy (or uncertainty) to find the probability distribution that is maximally unbiased, and therefore leaving the maximum
uncertainty which is consistent with the set of constrains (Penfield Jr, 2003). The MaxEnt distribution is equal to the maximum likelihood Gibbs distribution and proportional to the conditional probability of the occurrence. Using the occurrence probabilities generated by the MaxEnt algorithm for several biomass ranges probability density functions (PDF) can be generated in a pixel-by-pixel basis (Figure 13) and then be used to estimate a single AGB value per pixel with its associated model uncertainty as seen in Saatchi et al. (2011b).

Figure 13 Example of probability density functions per pixel generated using the probabilistic outputs of the MaxEnt algorithm for several biomass ranges.

The MaxEnt algorithm requires presence-only data as input, as it uses background environmental data for the whole study area, which make it advantageous in cases of limited training data. MaxEnt outperforms other algorithms in cases of small sample sizes (Hernandez et al., 2006, Pearson et al., 2007). Continuous and categorical remote sensing predictors, as well as interactions between variables (features and functions), can be used as input. The outputs of the algorithm are continuous, but can be thresholded to obtain binary output predictions. As the MaxEnt probability distribution is mathematically well defined, the relative importance of the remote sensing predictors can be easily analysed.

The algorithm also includes a regularization feature to avoid model over-fitting. This feature refers to the smoothing of the model by making it more regular, so the fitting of a too complex model is avoided. This type of regularization so-called L1-regularization
(Tibshirani, 1996) is a common approach in model selection, and consist of trading off model fit and model complexity (Elith et al., 2011). This method is reliable and perform well, being more stable using correlated variables than for example stepwise regression, so there is no need to remove correlated variables, or pre-process covariates by using PCA and selecting dominant axes, which are more likely to degrade the results (Elith et al., 2011, Hastie et al., 2005, Wollan et al., 2008).

### 3.5. SUMMARY, GAPS AND RESEARCH QUESTIONS

The distribution of AGB is globally driven by temperature (Reich et al., 2014). Variations on allometry can explain these patterns (Keith et al., 2000, Chave et al., 2005, Feldpausch et al., 2011). Large-scale AGB mapping methods face the challenge to account for this variability. Climatic variables are generally coarse to be used as input in these methods and biome class datasets might introduce artificial boundaries. As vegetation structure, allometry and biomass distribution across the landscape are strongly affected by topographic variables (Shary and Smirnov, 2013, Velízquez-Rosas et al., 2002, Pan et al., 2013a, Bispo et al., 2014, Bispo et al., 2016), those could be used as alternative predictor parameters for improving the methods.

Tree-level allometric models are the main tool to estimate ground AGB data, while remote sensing techniques based on SAR and LiDAR profiling sensors require plot-level allometric models to relate pixel or footprint derived biophysical parameters to AGB. Current approaches only rely on canopy height as predictor to develop these plot-level models to be applied over wide areas or even continentally (Saatchi et al., 2011b, Mitchard et al., 2012, Asner et al., 2012). However, the variation of the plot-level allometric relationship between AGB and canopy height among different biomes and across the topographic gradient has not being explored. Mitchard et al. (2014) compared in-situ derived AGB data to GLAS-derived AGB data, showing significant differences between the datasets. The results however were contested by Saatchi et al. (2015) due to limitations of the in-situ data related to the sampling, distribution and acquisition time. Therefore, these differences should be further explored with appropriate in-situ datasets.

Estimating carbon stocks using earth observation techniques is complex and presents several challenges related to the data availability and the methodology. The definition of forest itself is crucial when estimating biomass across wide areas. Large differences in
forest cover estimation can be found when using products with different forest definitions (Sexton et al., 2015). Even products using the same or similar forest definition have also be found to differ (Shimada et al., 2014). The effect of these differences at national scale have not been explored yet, neither the effects on national carbon stocks.

Optical and SAR imagery have different sensitivity to AGB due to the nature of each sensor (Imhoff, 1995, Carreiras et al., 2012, Lucas et al., 2010, Mitchard et al., 2009, Naesset, 2007, Dobson et al., 1992, Steininger, 2000). SAR imagery has in theory a higher AGB saturation point than Optical imagery according to the literature, but some studies have also found that optical infrared imagery might have correlation to AGB beyond its theoretical saturation point, especially on the infrared bands (Baccini et al., 2012, Kellndorfer et al., 2011, Steininger, 2000). However, all these sensors have limitations for AGB estimation across larger regions due to signal saturation, cloud cover persistence, or complex signal retrieval due to topography.

The use of non-parametric machine learning algorithms make possible to exploit the specific strengths of each sensor and are more suitable to model complex ecological systems such as forests (Evans and Cushman, 2009). However, only few methods combine different types of spatial datasets for AGB estimation, and none of them have explored their prediction contribution across the AGB range.

Only few large-scale AGB maps (global or continental) are currently available. The most relevant are the TCMs (Saatchi et al., 2011b, Baccini et al., 2012) which make used of a combination of EO datasets to map AGB across the whole tropical region. However, these maps present important discrepancies when compared (Mitchard et al., 2013). Several scales of prediction and propagation of errors between scales can be defined and analysed when estimating AGB, including errors from tree level measurements, allometries, minimum plot-size (within plot/pixel variability), and landscape representation. How these types of uncertainty can explain the difference between current AGB maps has not been properly studied.

3.5.1. Gaps in the literature

During the review of the literature the following gaps and areas were discovered that require more focus:
Several studies have investigated patterns of allometric variation at tree level but very few had done it at plot level.

No studies have been found that investigated the variation of plot-level allometric relationship between AGB and canopy height across the topographic gradient.

Very few studies have used topographic variables extracted from a DEM as AGB stand-alone predictors or in combination with other datasets.

Few studies have investigated the combination of three types of spatial datasets (Optical, SAR and DEM) to estimate AGB. No studies have been found to analyse the prediction contribution of each dataset across each AGB range.

Only one study has been found that compares forest cover products based on different definitions. No study has been found that compares the effect on carbon stocks from the use of different forest cover products based on the same definition but originating from different sensors.

Only one study has been found that compares the TCMs (calibrated with GLAS derived AGB data) to in-situ derived AGB data. However, this study only reported the differences, and it was contested based on the appropriateness of the in-situ dataset. No study has been found to directly compare GLAS derived AGB data footprints to in-situ derived AGB data plots. Therefore, further research is needed to clarify the sources of those differences.

Only one study has compared the widely used TCMs to each other, but no study has compared them to other regional maps and to in-situ data.

3.5.2. Research questions

Based on the review of the current literature the following gaps/questions will be addressed in this thesis in the respective chapters:

- Chapter 5:
  
  Question 1. Does the allometric relationship between canopy height and AGB at plot level vary across biomes and the topographic gradient? How does this relationship vary across the topographic gradient?

  Question 2. Which spatial dataset (Optical imagery, SAR imagery, and DEM) can better predict AGB across wide areas? Do topographic variables contribute to a better prediction of AGB distribution across the landscape? Is there an increase in the prediction power of the models if
spatial predictors are combined in comparison to stand-alone dataset modelling?

- Chapter 6:

  Question 3. What is the relative importance across the AGB range of Optical, SAR and DEM datasets when combined to estimate forest biomass stocks?

  Question 4. To what extent forest cover products based on the same forest definition but generated from different sensors differ from each other? Does the combination of different types of spatial datasets (Optical, SAR, and DEM) increase the accuracy of forest masks? What is the effect of the selection of a forest area mask on the estimation of carbon stocks at national level?

- Chapter 7:

  Question 5. Where are the main discrepancies among current carbon maps over Mexico? What are their sources? To what extent does the use of reference data derived from GLAS footprints instead of reference data derived from forest inventories impact AGB mapping?
Chapter 4

General Methods & Data
4. GENERAL METHODS & DATA

4.1. CALIBRATION AND VALIDATION DATA

Plot level measurements collected for the Mexican National Forest and Soil Inventory (INFyS) by the Comision Nacional Forestal (CONAFOR) will be used in this thesis. The plots cover the whole range of forest types in Mexico. AGB for this study refers to forest aboveground density, which is defined as the tons of living aboveground biomass of vegetation (leaves, branches and trunks) per hectare. Litter and dead wood are excluded from the definition of AGB in this study, due to the lack of data available.

Table 6 Plot datasets used in this study

<table>
<thead>
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<th>Dataset</th>
<th>Nr plots</th>
<th>Sampling</th>
<th>Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>INFyS</td>
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<td>Stratified systematic sampling. Plots located in a 5 km x 5 km &amp; 10 km x 10 km grids</td>
<td>Four rectangular/circular 0.04 ha sub-plots (0.16 ha) per primary circular sampling unit (1 ha)</td>
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<td>INFyS training</td>
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<td>Only used for calibration</td>
</tr>
<tr>
<td>INFyS validation</td>
<td>1,265</td>
<td>Random stratified sampling of forest types and AGB ranges</td>
<td>Only used for validation</td>
</tr>
<tr>
<td>Forest/Non-Forest binary class validation</td>
<td>198</td>
<td>Stratified systematic sampling. Plots located in a 100 km x 100 km grid</td>
<td>Square area with 300 m of side visually classified in forest and non-forest using Google Earth high resolution imagery. Only used for validation</td>
</tr>
</tbody>
</table>

The INFyS is a national in-situ database that provides accurate and current information on the size, spatial distribution and condition of forest resources (SEMARNAT, 2004). This information is used to support the development of national policies for sustainable development and to promote forestry sector activities. The ground plot dataset from INFyS contains the data of 17,171 plots comprising of four 400 m² (0.04 ha) rectangular (tropical forest and mangrove) or circular (other forest and arid vegetation) sub-plots positioned in an inverted ‘Y’ with respect to the North, representing a circular area of 56.42 m radius (1 ha) systematically located across forested areas in Mexico for the
period 2004-2012 (Figure 14). Therefore, a total area of 0.16 ha is sampled at each location. The shape of the subplot is determined by the difficulty to set circular sub-plots in dense tropical forest areas.

![Figure 14 Mexican INFYs sample plot consisting of 1 ha primary unit and four 400 m² sub-units (0.16 ha sampled area) for forest and arid vegetation (left) and tropical forest and mangroves (right)](image)

The sampling distance between centres of the plots is 5 x 5 km in forest areas and mangroves, and 10 x 10 km in dry tropical forest and semi-arid vegetation (Figure 15). These distances were decided based on ecological and economical (timber and non-timber) importance of each forest ecosystem.

A total of 339 biomass allometric equations and 214 species-specific wood densities (MRV, 2015) were used by CONAFOR to estimate tree-level AGB following a protocol for allometric model selection which prioritises the use of species-specific and regional models and wood densities within their diameter range of applicability. If more than one equation is available the equation with highest $R^2$ or regional (closest spatial location) is selected. If no species-specific model is available, the same procedure is followed at higher levels (genus and forest type). Due to the lack of species- or genus-specific allometries for all tree species, generalized models are also used (Chave et al., 2005, Brown, 1997) for approximately half of the plots in the INFYs database (Cartus et al., 2014).
Most plots have been measured twice during this period. In these cases the average of both measurements was used if the second measurement was higher or relatively similar to the first measurement. This was done to better represent the $AGB$ at reference year (2008) of the INFyS measurements (2004-2012), and to reduce sampling errors by having two measurements per pixel. If the second measurement was significantly lower, it was assumed that the forest area was cleared during the period, and therefore the plot was removed from the analysis. Several primary units were also excluded due to the lack of geographical coordinates. A total of 16,613 plots from the INFyS dataset were finally retained for the final analysis. The primary sampling sites from INFyS were divided into a training dataset (15,348 plots) and a validation dataset (1,265 plots), comprising 90% and 10% of the data respectively (Figure 15). The sub-sampling of the validation dataset was based in a random stratified sampling of forest types and $AGB$ ranges. The training dataset was used for the calibration of the $AGB$, uncertainty and FP maps. The remaining 10% of the INFyS primary sampling plots were excluded from the analysis and used as an independent validation dataset for the $AGB$ map.
Figure 15 Land Use and Vegetation map of Mexico (INEGI, 2009). Training dataset (black dots) and validation dataset (red dots) comprising 90% and 10% of the INFyS data respectively.
An independent forest/non-forest binary class validation dataset of points systematically located following a triangular mesh pattern over Mexico was generated. The validation points were separated 100 km from each other over the landscape allowing the generation of 198 points. Each point was assigned to the class “forest” or “non-forest” based on a visual classification of a square area with 300 m of side around the point using true-colour composite imagery available in Google Earth from 2008 and the closest available years. The imagery available was very high resolution (below 1 m) from the DigitalGlobe constellation (i.e. IKONOS, QuickBird, etc). In this task the LUV dataset was also used as a reference of the potential vegetation for each site. Tree canopy cover (using FAO’s canopy cover definition) of more than 10% of the area was defined as “forest”. Each square was also sub-divided in small squares to facilitate the interpretation of 10% tree cover over the pixel (Figure 16). This assessment was done by 3 different geographers. No disagreement was found among their interpretations.

Figure 16 Example of forest plot classified for the forest/non-forest binary class validation dataset using Google Earth engine. DigitalGlobe imagery is used to assess the plot.

4.2. EARTH OBSERVATION DATA

MODIS Vegetation Index (VI) 16-day products (MOD13Q1) (NASA, 2008) over Mexico (9 mosaic tiles) were acquired from the USGS (USGS, 2012). MODIS VI is generated from atmosphere-corrected bidirectional surface reflectance daily observations. MODIS VI layers were used to generate NDVI, EVI, Blue, Red, MIR, and NIR layers for the greenest vegetation period (here highest NDVI). The highest NDVI values in Mexico
occur between July and August; here the period from June to September is used. Maximum values of NDVI and EVI products as well as averages of the reflectance bands were then generated for this period using the reliability layers to discard pixels covered by snow, ice or clouds (see ANNEX 1 for more details).

A hole-filled version of the Shuttle Radar Topography Mission-SRTM (USGS, 2006) at 250m resolution was obtained from the International Centre for Tropical Agriculture (CIAT) (Jarvis et al., 2008). The product from SRTM consist on a DSM. However, the USGS refers to this product as DEM, so this term is used in this thesis for SRTM. The DEM was used to estimate topographic variables such as elevation, slope and aspect of the terrain and included as predictors.

Slope-corrected, orthorectified, and radiometrically calibrated ALOS PALSAR backscatter intensity mosaics at 50 m resolution for both polarisations (HH and HV) were obtained from JAXA (JAXA, 2014) for the years 2007, 2008, and 2009. A destriping process (Shimada and Isoguchi, 2002) is applied by JAXA to equalize the intensity differences between neighbouring strips due to seasonal and daily differences in surface moisture conditions. Strips with remaining significant striping were excluded. Multi-temporal averaged mosaics were aggregated to 250 m resolution to reduce speckle. The K&C-FNF product at 100 m resolution was also obtained from the same repository and aggregated at 250 m resolution based on a majority rule.

MODIS Vegetation Continuous Fields-VCF (MOD44B) product (DiMiceli et al., 2011) with 250 m resolution for the year 2008 were also acquired from the Global Land Cover Facility (GLCF). MODIS VCF imagery was reprojected and mosaicked using the MODIS Reprojection Tool (MRT). The FNF and the VCF were not used as modelling input for the MaxEnt algorithm but as forest/non-forest masks.

The Mexican Land Use and Vegetation map (LUV) vector file developed by the Mexican National Institute of Statistics and Geography (INEGI) was also acquired (INEGI, n.d.).

The Copernicus programme, formerly known as Global Monitoring for Environment and Security (GMES), from the European Commission aims to establish long-term Earth Observation capacity for Europe. The Copernicus Global Land service provides global coverage of biophysical parameters at 1km resolution generated from the VEGETATION (VGT) sensor on board of the French satellites SPOT-4 and SPOT-5 (Satellite Pour
l'Observation de la Terre). Imagery from the SPOT-VGT sensor generated by the Copernicus Global Land Service was acquired for the period 2007-2010. Four vegetation bio-geophysical products were acquired (Copernicus, 2013):

- Leaf Area Index (LAI), defined as half the total area of green elements of the canopy per unit of horizontal ground area. This includes all vegetation layers quantifying in some way for the thickness of the vegetation.
- Normalized Difference Vegetation Index (NDVI) is a widely used indicator of vegetation greenness defined as
  \[ NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \], where \( R_{NIR} \) and \( R_{RED} \) are the spectral reflectance in the near infrared and red wavebands respectively.
- Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), defined as the fraction of the incoming solar radiation absorbed by green leaves of living photosynthetic organisms.
- Fraction of Green Vegetation Cover (FCOVER), defined as the fraction of ground area covered by green vegetation.

The products correspond to the GEOV1 version developed by the GEOLAND2 project. The LAI, FAPAR, and FCOVER products are derived from the VGT sensor. The algorithm is based on the fusion between MODIS and CYCLOPES products and are estimated by a Neural Network applied on Top Of Canopy (TOC) input reflectances (red, near-infrared and shortwave infrared) normalized over a period of 30 days (Baret et al., 2013). NDVI is estimated by TOC reflectances (red and near-infrared) normalized by inversion of a kernel-driven reflectance model (Baret et al., 2013). The products are provided at a 10 days interval, but these are the result of 30 days composite of VGT observations. The product can be supplied in 10°x10° tiles or continental tiles. Average annual composites mosaics were generated for the period 2007-2010 for each of these products (See ANNEX for more details).
<table>
<thead>
<tr>
<th>Spatial Dataset</th>
<th>Resolution</th>
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<th>Layers</th>
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<tbody>
<tr>
<td>16-Day MODIS VI (2008)</td>
<td>250 m</td>
<td>MODIS</td>
<td>NDVI, EVI, Blue, Red, MIR, NIR</td>
</tr>
<tr>
<td>ALOS PALSAR (2007-2009)</td>
<td>50 m</td>
<td>ALOS PALSAR</td>
<td>HV, HH</td>
</tr>
<tr>
<td>Digital Elevation Model (2000)</td>
<td>90 m</td>
<td>SRTM</td>
<td>Elevation, Slope, Aspect</td>
</tr>
<tr>
<td>ALOS K&amp;C-FNF (2008)</td>
<td>100 m</td>
<td>ALOS PALSAR</td>
<td>Forest / Non-Forest</td>
</tr>
<tr>
<td>MODIS VCF (2008)</td>
<td>250 m</td>
<td>MODIS</td>
<td>Percent Tree Cover</td>
</tr>
<tr>
<td>Copernicus Global Land Service – VGT (2007-2010)</td>
<td>1 km</td>
<td>SPOT-4 &amp; -5</td>
<td>LAI, NDVI, FAPAR, FCOVER</td>
</tr>
</tbody>
</table>

VI, Vegetation Indices; NDVI, Normalized Difference Vegetation Index; EVI, Enhanced Vegetation Index; SRTM, Shuttle Radar Topography Mission; MIR, Mid-Infrared; NIR, Near-Infrared; LAI, Leaf Area Index; FAPAR, Fraction of Absorbed Photosynthetically Active Radiation; FCOVER, Fraction of Green Vegetation Cover

### 4.3. ALLOMETRIC MODELS

The aboveground biomass relationships at plot level will be modelled using a general allometric equation. If any of the assumptions of linear regressions is violated, the regression model may be inefficient or biased. The assumptions are:

- linearity of the relationship between dependent and independent variables
- independence of the errors (no serial correlation)
- homoscedasticity (constant variance) of the errors
- normality of the error distribution

Conformity will be tested by graphical methods, such as plots of residuals versus predicted values, normal probability plots of the residuals, and partial regression plots.

Generally, in the analysis of allometric relations, residual heteroscedasticity occurs, with an increase in the residual variance of the dependent variable with an increase in the values of independent variable. In these cases a logarithmic (or natural log) form of the equation is recommended to satisfy the condition of homoscedasticity for the regression analysis (Pardé, 1980). Kleinbaum et al. (1998) cited the three primary reasons for using data transformations:
1. To stabilize the variance of the dependent variable, if the homoscedasticity assumption is violated
2. To normalize the dependent variable, if the normality assumption is noticeably violated
3. To linearize the regression model, if the original data suggest a model that is nonlinear in either the regression coefficients or the original variables

Therefore, the biomass equations will be linearized as follows:

\[ \ln(AGB) = \ln(b_0) + b_1 \cdot \ln(B_p) + \varepsilon \]  \hspace{1cm} \text{Equation 6}

where \( AGB \) is the total aboveground biomass per ha (dependent variable), \( B_p \) is a biophysical parameter (predictor variable), \( b_0 \) and \( b_1 \) the model parameters, and \( \varepsilon \) is the regression error. Biophysical parameters that can be used as predictors in allometric models include growing stock volume (GSV), and mean canopy height (\( h \)).

Then, the models will be back-transformed as follows:

\[ AGB = b_0 \cdot B_p^{b_1} \times CF \]  \hspace{1cm} \text{Equation 7}

where \( CF \) is a correction factor calculated as

\[ CF = e^{(\text{MSE}/2)} \]  \hspace{1cm} \text{Equation 8}

where MSE is the mean square error of the regression.

The \( CF \) accounts for the back-transformation regression error when using linear models with ln-transformed data in allometry (Baskerville, 1972).

**4.4. METHODS**

A recent study (Saatchi et al., 2011b) demonstrated the possibility of modelling a continuous biophysical parameter by combining the probabilistic outputs generated from a MaxEnt algorithm, and estimate the uncertainty of the estimation on a pixel-by-pixel basis. This is a key reason for the selection of the MaxEnt algorithm for this study.

The MaxEnt \( AGB \) distribution modelling approach used in this thesis is shown in Figure 17. The term “biomass distribution model” (BDM) refers to the probabilistic output generated by the MaxEnt algorithm for a specific biomass range. One-class classifications
of remote sensing imagery, as seen in Li and Guo (2010), will be carried out for each AGB class to generate probabilistic outputs (BDMs). As explained before, the probability calculated by the MaxEnt algorithm is equal to the Gibbs probability which is proportional to the conditional probability of the class (here AGB class) (Li and Guo, 2010). In numerous iterations for each AGB class, the weights for combining the remote sensing predictors are adjusted to maximise the average sample likelihood (training gain), and to estimate the distribution over the whole region extent. The higher the probability for the pixel, the more suitable the pixel is for representing the same characteristics as the training pixels.

Figure 17 Theoretical framework and components of the MaxEnt AGB distribution model approach. The number of predictors per spatial dataset is shown in parenthesis.

In this study, we use remote sensing predictors, commonly used to map vegetation, to produce one-class BDM for each AGB class, instead of the climatic information
commonly used in species distribution modelling. Therefore, the occurrences for each AGB class can be represented as localities (x and y map coordinates) sharing the “geographical space” with the remote sensing predictors. The values of the remote sensing predictors are extracted at the localities and used in the multidimensional “environmental space” to calibrate the BDM (Figure 18). Therefore, the models do not make use of the geographic proximity for calibration (Elith and Leathwick, 2009, Pearson, 2010), but this is already inherent of the models by means of the spatial autocorrelation of biomass, reflected in the remote sensing imagery.

Figure 18 Connection between field observations (localities) from two different AGB ranges and remote sensing data in the geographical space (left), their relationship in the environmental space (centre), and the model predictions (probabilities) in the geographical space (right). The distribution and distance between field observations is very different in both spaces (Partly based on Elith and Leathwick, 2009).

This approach allows the synergistic use of different types of sensors to scale up the AGB ground measurements. This approach is an modified version of the method by Saatchi et al. (2011b), which uses the probability logistic outputs from the MaxEnt algorithm to produce AGB and uncertainty maps.

This study assumes a geographic finite space X formed by a set of discrete grid cells. A set of points representing recorded values of AGB (occurrences) are the localities of the model (training dataset). The implementation of this probabilistic method requires the set of AGB localities to be classified into AGB classes. The training data has to be converted in discrete AGB ranges to generate several BDMs, which are then combined to obtain continuous AGB estimations, therefore increasing the demand on sampling size. This step is however needed to allow the calculation of the pixel level uncertainty. Stockwell and
Peterson (2002) found that for species distribution models, ten samples were enough to achieve 90% of the maximum accuracy, with 50 samples to reach maximum accuracy. Saatchi et al. (2011b) suggested that at least 100 samples should be used as training data for each BDM to assure best results, but this might be related to the minimum training set needed by this version of algorithm (80 samples) to use all the features (linear, product, quadratic, threshold, and hinge) (Phillips et al., 2006).

Thus, the minimum number of plots per class was set in 100. The set of calibration $AGB$ plots is classified into 11 $AGB$ classes. Thus, the training dataset was divided in 11 classes by 20 t ha$^{-1}$ intervals (0-20 t ha$^{-1}$, 21-40 t ha$^{-1}$, ..., >200 t ha$^{-1}$) and a probability distribution map for each class was generated. These $AGB$ class probabilities were combined to generate a pixel-by-pixel PDF, which was then used to estimate a single $AGB$ value per pixel. $AGB$ map for Mexico. A Forest $AGBC$ map was also generated using the INFyS average $AGB$-to-carbon ratio for Mexico of 0.48 in order to estimate carbon stocks.

The remote sensing predictors consist of datasets that contain information correlated to $AGB$ such as reflectance (Optical), backscatter intensity (SAR), and topographic variables (DEM). The $AGB$ classes are used in combination with the set of remote sensing predictors defined in the space $X$ as inputs for the MaxEnt algorithm. Using this input, the aim is to estimate the probabilistic distribution of each $AGB$ class (BDM) (Figure 19).

Figure 19 Example of BDMs 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.
Once the BDMs are generated for each AGB class, the continuous values of AGB for each pixel are calculated as the weighted average AGB per pixel with the probabilities as weights (Equation 9). The uncertainty of the AGB prediction ($\epsilon_{\text{prediction}}$) is calculated from the root mean square error ($\sigma_{\text{AGB}}$) obtained per pixel. The following equations are used (Saatchi et al., 2011b):

$$\overline{AGB} = \frac{\sum_{i=1}^{N} P_i^n \overline{AGB}_i}{\sum_{i=1}^{N} P_i^n}$$  \hspace{1cm} \text{Equation 9}

$$\epsilon_{\text{prediction}} = \sigma_{\text{AGB}} / \overline{AGB} \times 100$$  \hspace{1cm} \text{Equation 10}

$$\sigma_{\text{AGB}} = \sqrt{\frac{\sum_{i=1}^{N} (\overline{AGB}_i - \overline{AGB})^2 P_i}{\sum_{i=1}^{N} P_i}}$$  \hspace{1cm} \text{Equation 11}

where $\overline{AGB}$ is the AGB prediction per pixel, and $P_i$ is the probability estimated by MaxEnt for each AGB range $\overline{AGB}_i$ (average value within class i). The power of the probability $n$ is used to weight the predicted value towards the maximum probability closest to the true value when other probabilities are small. This study uses $n = 3$. As explained in Saatchi et al. (2011b), $n = 3$ preserves the skewness in distributions for each pixel, and produce the best results based on a cross-validation test.

The total uncertainty at pixel level is composed of 4 sources of error which are assumed to be random and independent. The flexibility of the method allows more error terms to be added if needed. These errors are propagated using the following the equation proposed by Saatchi et al. (2011b) and based on Chave et al. (2004):

$$\epsilon_{\text{AGB}} = (\epsilon_{\text{measurement}}^2 + \epsilon_{\text{allometry}}^2 + \epsilon_{\text{sampling}}^2 + \epsilon_{\text{prediction}}^2)^{1/2},$$  \hspace{1cm} \text{Equation 12}

This error propagation equation is not only used to generate estimates of uncertainty at pixel level, but also as framework to assess the discrepancies and possible sources of error in other AGB map products. The values of these errors are adapted based on current literature (Chave et al., 2004, Saatchi et al., 2011b, Weisbin et al., 2014, Mitchard et al., 2011) and the type of data used:

$\epsilon_{\text{measurement}}$: the measurement error of tree level parameters such as diameter and tree height averaged at plot level (Chave et al., 2004). This component was assumed to be 10% for this study (Mitchard et al., 2011).
\( \varepsilon_{\text{allometry}} \): this is the error in using allometric equations to estimate \( AGB \) at plot level. The allometric model selection protocol of INFyS prioritises the use of species-specific and regional models and wood densities within their diameter range. This study assumes an average error of 11% in estimating \( AGB \) using allometric equations with species-specific wood densities and within their diameter range based on findings by Chave et al. (2004).

\( \varepsilon_{\text{sampling}} \): This error originates from the variability of \( AGB \) within the pixel area (6.25 ha) and depends on the size of the plots used to upscale the \( AGB \) measurements to the pixel level. This error is approximated using data from Chave et al. (2003) on the \( AGB \) variability of a 50 ha plot. Chave et al. (2003), using the sampling size equation for 95% confidence interval, found that a minimum of 160 plots of 0.04 ha are needed to estimate the biomass of a 50 ha plot with a ±10% uncertainty. This means that a sampling intensity of 12.8% (0.04x160/50) is needed. By assuming the same variations in the 6.25 ha pixel, the number 0.04 ha plots needed to reach the same sampling intensity will be 20. Each pixel uses 1 or 2 INFyS primary units containing four to eight 0.04 ha subplots respectively. Thus, the uncertainty of the \( AGB \) estimation will increase and be confined between 15.8% \((10 \times \sqrt{20}/8)\) and 22.4% \((10 \times \sqrt{20}/4)\). The higher value is used in this thesis (22.4%).

\( \varepsilon_{\text{prediction}} \): This is the error calculated for each pixel from the prediction probabilities of the MaxEnt model. This error also accounts for the representativeness of the sampling sites of the true distribution of \( AGB \) in the region (Saatchi et al., 2011b).

In order to avoid non-zero \( AGB \) estimates in non-forest pixels, the forest area has to be masked. The locations of forest inventory plots are also used as training data to run the MaxEnt algorithm in order to generate a Forest Probability (FP) distribution map. These plots are located in forest areas according the CONAFOR definition of forest. However, only plots with canopy cover above 10% and canopy height above 5 m are used as training data here, according to the FAO forest definition (FAO, 2010b) and to other forest area products (MODIS VCF and ALOS PALSAR K&C-FNF).

As the probability calculated by the MaxEnt algorithm is equal to the Gibbs probability and is proportional to the conditional probability of the class (i.e. forest class) (Li and Guo, 2010), forest inventory plots were used as training data to generate a country-wide
forest probability map. The same remote sensing predictors used to develop the AGB and uncertainty maps are used for the FP map. The resulting map provides an equivalent to the conditional probability of each pixel to be forest (as defined by FAO). At the pixel level this probability can not only be used to create a binary forest mask based on a probability threshold, but also as a parameter to assess the reliability of the forest area mask itself. The forest probability layer is equivalent to a fuzzy forest class membership layer (e.g. Hattab et al., 2013) going from 0% (most uncertain) to 100% (less uncertain).

In order to create the binary forest mask from the probabilities, a threshold must be identified. A threshold which maximises the $\kappa$ coefficient of agreement with the validation dataset (Pearson et al., 2002), a threshold where sensitivity equals specificity (Hattab et al., 2013, Freeman and Moisen, 2008), a threshold that maximises the sum of sensitivity and specificity (Hattab et al., 2013, Freeman and Moisen, 2008), and a threshold corresponding to a 5% error of omission (Li and Guo, 2010, Pearson et al., 2004) have been recommended in previous studies as threshold optimization criteria. This FP layer mask is used to delimit the region in which the MaxEnt algorithm uses background samples and generates the BDMs, to only areas covered by woody vegetation (Elith et al., 2011). This step is essential to avoid erroneous estimations of AGB in areas with no woody vegetation, as the model is not trained for land covers other than forest.

LUV forest mask, MODIS VCF with a 10% threshold (hereafter VCF$_{10\%}$), and K&C-FNF. The K&C-FNF product is based on a HV backscatter threshold which is optimized for wide areas. Another forest mask was generated from the HV backscatter layer by optimizing a threshold for Mexico using the validation dataset. The best results were obtained with a HV backscatter threshold of $-14.5\text{dB}$ (hereafter FNF$_{-14.5\text{dB}}$). The accuracy of these forest area masks were assessed against the forest/non-forest validation dataset.
Chapter 5

Forest Aboveground Biomass Variability in the Forests of Mexico
5. FOREST ABOVEGROUND BIOMASS

VARIABILITY IN THE FORESTS OF MEXICO

A peer-reviewed article with content from this chapter has been published:


5.1. INTRODUCTION AND AIMS

The Mexican National Forest and Soil Inventory (INFyS) of the Comision Nacional Forestal (CONAFOR) is a rigorously designed and extensive ground-based national forest inventory that provides accurate and current information on the size, spatial distribution and condition of forest resources (SEMARNAT, 2004).

The tree-level allometric relationship between tree canopy height and tree \( AGB \) has been found to change in between regions (Feldpausch et al., 2011, Feldpausch et al., 2012). This study hypothesizes that the plot-level allometric relationship between \( AGB \) and plot canopy height varies significantly between regions (here biomes), and across the elevation gradient due to changes in climatic conditions ultimately originated by topography. This study also analyses in which direction the slope of the allometric relationship between \( AGB \) and \( H \) changes across the elevation gradient. This can demonstrate that topographic variables could be used as a proxy spatial predictors to estimate \( AGB \) across the landscape.

The ground plot data from this inventory can be integrated with earth observation data to map \( AGB \) over the whole country. Several satellite sensors can be used to scale up \( AGB \) in-situ data to wider areas. The most used types are optical sensors that contain information related to the photosynthetic parts (chlorophyll content) of the vegetation (e.g. Baccini et al., 2012), and SAR sensors (e.g. Santoro et al., 2011) which contain information related with the volume of the vegetation, but DEM datasets have also been used in the past (e.g. Bispo et al., 2016). In this chapter, the in-situ data from the INFyS dataset is analysed. The correlation of the in-situ measured \( AGB \) to three types of spatial
datasets is assessed. Optical (MODIS) imagery, SAR (ALOS PALSAR) imagery and topographic variables from a DEM (SRTM) are explored.

This chapter therefore will address the following research questions:

Question 1. Does the allometric relationship between canopy height and AGB at plot level vary across biomes and the topographic gradient? How does this relationship vary across the topographic gradient?

Question 2. Which spatial dataset (Optical imagery, SAR imagery, and DEM) can better predict AGB across wide areas? Do topographic variables contribute to a better prediction of AGB distribution across the landscape? Is there an increase in the prediction power of the models if spatial predictors are combined in comparison to stand-alone dataset modelling?

5.2. SPECIFIC DATA AND METHODS

The final INFyS dataset is used in this chapter. Remote sensing imagery sensitive to forest from different sensors and other ancillary datasets were collected from different sources (see methods section). Those are mosaicked, co-registered and aggregated to 250 m spatial resolution. Scatterplots and spatial trend plots were used to initially assess the correlation of AGB to the remote sensing predictors. Scatterplots of remote sensing variables versus in-situ AGB were generated for Mexico. Then, the response of each remote sensing variable was averaged and plotted by 10 t ha\(^{-1}\) AGB intervals in order to generate trendlines. Additionally, trend analysis of the three-dimensional distribution of AGB was performed over the latitudinal (North-South) and longitudinal (East-West) gradients. The INFyS in-situ plots were interpolated using universal Kriging geostatistical interpolation as in Ter Steege et al. (2003), and represented in the x,y plane, while the AGB values were extracted and projected in the x,z (East-West) and y,z (North-South) planes as scatterplots together with their trend lines (polynomials), allowing then to assess the longitudinal and latitudinal trends.

The INFyS in-situ dataset is analysed to evaluate allometric differences between biomes and across the elevation gradient. An Analysis of Covariance (ANCOVA) is used to assess whether the mean of the dependent variable (AGB) varies in relation to a covariate (H) across levels of the categorical independent variables (biomes and elevation range).
The log-transformed data (\(LnAGB\) and \(LnH\)) are used for the analyses to satisfy the conditions of homoscedasticity, normal distribution, and the linear dependency of the covariate.

The scaling relationship at plot level between \(AGB\) and \(H\) across the altitudinal gradient was then explored analysing the variation of the scaling exponents and slopes from the allometric relationships as in Pan et al. (2013a). The INFyS dataset is used to generate allometric models for different biomes and elevation ranges. The plots were divided by biomes and by elevation ranges of 500 m elevation intervals with the average value of the each range assigned as follows: 250 m, 750 m, 1,250 m, 1,750 m, 2,250 m, and 2,750 m. Next, average \(AGB\) values were also estimated by aggregating plots by 3 m canopy height intervals. Allometric models by biome and by elevation range were then developed relating average \(AGB\) to average canopy height following the procedure explained in the general methods section (chapter 3.2.).

Optical, SAR and topographic spatial dataset have shown to be directly or indirectly correlated to \(AGB\). To assess the relative importance of each spatial dataset to estimate \(AGB\), the MaxEnt methodology is used to generate \(AGB\) maps with different combinations of spatial datasets. Sensitivity analyses are performed based on AUC, model gain, \(R^2\), RMSE, Bias and Rel. RMSE. The MaxEnt algorithm estimates AUC and model gain by bootstrapping 25% of the training data. Accuracy (\(R^2\)), root mean square error (RMSE), Bias and Relative RMSE are estimated using the independent INFyS validation dataset. The analysis compares the use of a single dataset, the use of two and the combination of all three datasets. Seven different combinations of spatial datasets are generated as follows:

- ALOS PALSAR: 2 bands (HH and HV)
- MODIS: 6 bands (NDVI, EVI, Blue, Red, MIR, and NIR)
- SRTM: 3 bands (elevation, slope and aspect)
- MODIS+SRTM: 9 bands (NDVI, EVI, Blue, Red, MIR, NIR, elevation, slope and aspect)
- ALOS+SRTM: 5 bands (HH, HV, elevation, slope and aspect)
- ALOS+MODIS: 9 bands (HH, HV, NDVI, EVI, Blue, Red, MIR, and NIR)
- ALOS+MODIS+SRTM: 11 bands (HH, HV, NDVI, EVI, Blue, Red, MIR, NIR, elevation, slope and aspect)
5.3. RESULTS

An AGB spatial trend analysis of the INFyS dataset (Figure 20) was used to assess the AGB spatial patterns exhibited by the in-situ data in Mexico. The trend analysis shows certain anisotropy with a slight trend of increasing AGB from West to East and from North to South. The analysis shows a peak of AGB in the central part of the country where the mountain belts converge, and an increasing trend from the dry tropical forests in the northwest of the Yucatan peninsula towards the humid tropical forests of the southeast.

Figure 20 Trend analysis of AGB distribution across latitudinal (North South) and longitudinal (East-West) gradients in Mexico projected in the x,z (East-West) and y,z (North-South) planes as scatterplots together with their trend lines (polynomials). Darker colours denote low AGB while lighter colours denote high AGB in the geostatistical interpolation map projected in the x,y plane (left). Histogram of AGB distribution based on the Mexican forest inventory dataset (INFyS) (right)

The average forest AGB for the country is estimated based on the INFyS dataset in approximately 53 t ha\(^{-1}\). Maximum AGB values recorded in this dataset are as high as 400 t ha\(^{-1}\), but very few plots have values above 200 t ha\(^{-1}\) (Figure 20). Scatterplots and trend lines showed the correlation of INFyS in-situ measured AGB versus remote sensing variables (Figure 21).
Figure 21 Scatterplots of INFyS in-situ measured $AGB$ versus remote sensing variables used in this study. Warmer colours indicate higher point density. Trend lines and $R^2$ are generated from the square points (average value of the variables per each 10 t ha$^{-1}$ interval $AGB$ range). Frequency spider-diagram per $AGB$ class is used for elevation aspect.
The analysis of AGB by elevation gradient shows two point-cloud clusters. One of the clusters is the Yucatan peninsula. The Yucatan peninsula (South-East part of the country) presents a wide range of AGB, including some of the highest AGB measured in Mexico. This area is mostly covered by moist tropical forest and the terrain is mostly flat and near sea level altitude. The biggest cluster corresponds with the rest of the country and shows a possible altitudinal gradient. The highest correlation to EO data was found between biomass and the ALOS PALSAR HV polarization backscatter followed by the MODIS MIR reflectance.

The exploration of the INFyS dataset per vegetation type (Table 8) show that the Oyamel (Abies forest) forests have the highest average AGB measured in the country followed by medium semi-deciduous tropical forests and Ayarin (Pseudotsuga and Picea forest) forests. These also have the tallest average canopy heights together with tall semi-evergreen tropical forests. The lowest average AGB was measured in low tropical thorn forests and low deciduous tropical forests, and the lowest average canopy height was measured in Tascate (Juniperus forest) and gallery forests. The highest average crown cover occurs in the medium deciduous tropical forests and Oyamel forests, while the lowest occurs in low tropical thorn forests and pine forests. Despite the crown cover figures, the forests with highest average of number of trees per hectare are the medium semi-deciduous tropical forests, low semi-evergreen tropical forests, and medium semi-evergreen tropical forests.

Around 35% of the inventory plots were located in tropical forest types, while temperate forests account for more than 60% of the plots. In contrast, the percentage of forest area by those forest types is 44% and 48% respectively. The difference is due to the reduced sampling intensity used in dry tropical forest, where plots are located in a 10km x 10km grid instead of a 5km x 5km used in temperate forest.

Table 8 Average forest parameters estimated from the INFyS dataset

<table>
<thead>
<tr>
<th>Forest types</th>
<th>AGB (t ha⁻¹)</th>
<th>H (m)</th>
<th>Nr trees per ha</th>
<th>Crown Cover (%)</th>
<th>Percentage of total plots (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud</td>
<td>58.8</td>
<td>9.2</td>
<td>341.8</td>
<td>65.3</td>
<td>2.50</td>
</tr>
<tr>
<td>Oyamel (Abies)</td>
<td>132.5</td>
<td>13.3</td>
<td>371.1</td>
<td>78.1</td>
<td>0.36</td>
</tr>
<tr>
<td>Ayarin (Pseudotsuga &amp; Picea)</td>
<td>69.1</td>
<td>9.3</td>
<td>370.2</td>
<td>43.0</td>
<td>0.05</td>
</tr>
<tr>
<td>Cedar</td>
<td>53.1</td>
<td>6.8</td>
<td>358.5</td>
<td>47.7</td>
<td>0.05</td>
</tr>
<tr>
<td>Pine</td>
<td>48.8</td>
<td>8.2</td>
<td>319.1</td>
<td>39.6</td>
<td>8.39</td>
</tr>
<tr>
<td>Forest types</td>
<td>AGB (t ha⁻¹)</td>
<td>H (m)</td>
<td>Nr trees per ha</td>
<td>Crown Cover (%)</td>
<td>Percentage of total plots (%)</td>
</tr>
<tr>
<td>------------------------------</td>
<td>--------------</td>
<td>-------</td>
<td>----------------</td>
<td>----------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Tascate (Juniperus)</td>
<td>28.1</td>
<td>5.0</td>
<td>288.1</td>
<td>24.3</td>
<td>0.71</td>
</tr>
<tr>
<td>Pine-Oak</td>
<td>58.4</td>
<td>7.2</td>
<td>420.6</td>
<td>53.2</td>
<td>10.36</td>
</tr>
<tr>
<td>Oak-Pine</td>
<td>61.2</td>
<td>8.4</td>
<td>406.5</td>
<td>51.0</td>
<td>15.47</td>
</tr>
<tr>
<td>Oak</td>
<td>42.8</td>
<td>6.1</td>
<td>324.8</td>
<td>42.3</td>
<td>24.46</td>
</tr>
<tr>
<td>Gallery</td>
<td>51.8</td>
<td>4.5</td>
<td>471.9</td>
<td>42.5</td>
<td>0.01</td>
</tr>
<tr>
<td>Mangrove</td>
<td>46.8</td>
<td>6.7</td>
<td>382.3</td>
<td>41.3</td>
<td>0.93</td>
</tr>
<tr>
<td>Tall evergreen tropical</td>
<td>44.1</td>
<td>8.6</td>
<td>308.0</td>
<td>49.7</td>
<td>4.48</td>
</tr>
<tr>
<td>Tall semi-evergreen tropical</td>
<td>64.0</td>
<td>9.8</td>
<td>471.0</td>
<td>55.7</td>
<td>0.30</td>
</tr>
<tr>
<td>Medium deciduous tropical</td>
<td>38.0</td>
<td>7.7</td>
<td>374.0</td>
<td>80.4</td>
<td>0.03</td>
</tr>
<tr>
<td>Medium semi-evergreen tropical</td>
<td>61.8</td>
<td>8.4</td>
<td>624.8</td>
<td>57.3</td>
<td>9.35</td>
</tr>
<tr>
<td>Medium semi-deciduous tropical</td>
<td>74.0</td>
<td>9.2</td>
<td>752.6</td>
<td>59.6</td>
<td>11.77</td>
</tr>
<tr>
<td>Low deciduous tropical</td>
<td>26.6</td>
<td>6.3</td>
<td>388.4</td>
<td>48.5</td>
<td>9.61</td>
</tr>
<tr>
<td>Low thorn tropical</td>
<td>14.8</td>
<td>5.3</td>
<td>240.8</td>
<td>21.9</td>
<td>0.23</td>
</tr>
<tr>
<td>Low evergreen tropical</td>
<td>30.5</td>
<td>9.2</td>
<td>221.9</td>
<td>42.1</td>
<td>0.01</td>
</tr>
<tr>
<td>Low semi-deciduous tropical</td>
<td>44.6</td>
<td>8.2</td>
<td>452.1</td>
<td>47.4</td>
<td>0.13</td>
</tr>
<tr>
<td>Low semi-evergreen tropical</td>
<td>56.8</td>
<td>8.1</td>
<td>749.0</td>
<td>46.0</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Note: INEGI classifies tropical forest according its size (height):
- Tall forest and medium semi-evergreen tropical forest corresponds to moist forest
- Low forest and medium semi-deciduous tropical forest corresponds to dry forest

The in-situ data indicates that the amount of AGB per given ha varies per biome, and that the highest values of AGB occur at the lowest and at the highest elevation ranges. The data also shows that biomes are related to altitude ranges as tropical and temperate coniferous forests occur at the highest altitudes while mangroves, tropical dry and tropical moist forests occur at the lowest. In intermediate altitudes it is possible to observe an increasing trend in the amount of AGB per ha (Figure 22).
Figure 22. Boxplots of AGB per biome (a), elevation per biome (b), and AGB per elevation range (c). The central mark of each box represents the median, while the lower and upper limits of the box represent the 25th and 75th percentile respectively. The whiskers cover the range of extreme values. Crosses represent maximum outliers.

An analysis of covariance for AGB, using canopy height ($H$) as covariate, was performed to explore the effects of biome and elevation on the relationship between AGB and $H$. Data from five biomes was used in the analysis: Tropical and Subtropical Moist Broadleaf Forest, Tropical and Subtropical Dry Broadleaf Forest, Tropical and Subtropical Coniferous Forest, Temperate Coniferous Forest, and Mangrove Forest. The 500 m interval elevation ranges described in the methods section of this chapter with average values 250 m, 750 m, 1,250 m, 1,750 m, 2,250 m, and 2,750 m were also used. These revealed that AGB for a given $H$ varied significantly with biome, elevation, and with interaction amongst these factors (p-value < 0.001 in all cases) (Table 9).

Table 9 Summary of F-probabilities and significances of Biome and Elevation range (group factors) from the analysis of covariance using LnAGB as dependent variable and LnH as covariate

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum Squares</th>
<th>Degrees Freedom</th>
<th>Mean Square</th>
<th>F-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariate (LnH)</td>
<td>7,473.2</td>
<td>1</td>
<td>7,473.2</td>
<td>10,697.8</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Between (Elevation)</td>
<td>45.7</td>
<td>5</td>
<td>9.1</td>
<td>13.1</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Between (Biome)</td>
<td>29.5</td>
<td>4</td>
<td>7.4</td>
<td>10.6</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Between (Elevation * Biome)</td>
<td>98.2</td>
<td>12</td>
<td>8.2</td>
<td>11.7</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Within</td>
<td>18,104.9</td>
<td>25,9</td>
<td>0.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>26,756.1</td>
<td>25,9</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Allometric models per different biomes were generated using the INFyS dataset. It can be observed that for any given $H$ the $AGB$ can vary considerably (Figure 23).

Figure 23 Allometric models relating $AGB$ to $H$ per biome in Mexico. $AGB$ as a function of a $H$ of 13.5 m is marked with vertical and horizontal lines as example.

In Figure 21 and Figure 22 two different trends in the relation between $AGB$ and altitude can be distinguished. Above approximately 250 m of altitude the $AGB$ increases along the elevation gradient, while below that altitude $AGB$ does not follow the same trend and show a high average $AGB$. The INFyS plots located below 250 m correspond to the Yucatan Peninsula. The Yucatan peninsula is predominantly flat and is located at sea level. It can be observed how the average $AGB$ estimation increases per elevation range, and even more meaningful is the amount of $AGB$ ($t \text{ ha}^{-1}$) per unit of $H$ (meter) at each elevation range (Figure 24). When plots from the Yucatan peninsula are excluded from the INFyS ground data, the gradient ($AGB$ per unit of $H$) becomes more evident (Figure 24). This shows that the allometric relationship between $AGB$ and $H$ varies within the region as a function of relief (elevation), as seen in the analysis of covariance.
Allometric models using the log-transformed values were developed relating average \( AGB \) to average \( H \) at different elevation ranges. The slopes (scaling exponents or allometric factors - \( \alpha \)) and intercepts (\( \beta \)) of these models were then plotted against the elevation range (Figure 25).

The intercepts of the allometric models noticeably increase with elevation range while the model slope slightly decreases. Despite the slight decrease in the model slopes, for any given \( H \) the \( AGB \) increases with elevation as previously seen in Figure 24 due to the substantial increment of the intercepts along the elevation gradient. As a result, forest plots with the average \( H \) in Mexico (i.e. 7.2 m) will have approximately 69 t ha\(^{-1} \) at higher
elevations and only 44 t ha\(^{-1}\) at lower altitudes (average 57\% higher AGB for the average \(H\) at higher altitudes). Similar occurs with a \(H\) of 10 m which will have an AGB of approximately 90 t ha\(^{-1}\), while forest in lower elevations and the same \(H\) (10 m) will only have 65 t ha\(^{-1}\) of AGB (38\% higher AGB in plots at higher altitudes for a given \(H\) of 10 m). However, due to the more pronounced model slope in lower attitudes (below 750 m), forests above 12 m in \(H\) presents higher AGB than at intermediate altitudes (but still no higher than forests above 2750 m).

Seven different AGB maps were generated using the same calibration in-situ data, and seven different combinations of spatial datasets as predictors (Figure 26). The maps are calibrated only using reference data from forest areas. As a result, the algorithm is not calibrated to make estimates over other land cover types. This is evident when visualizing the different maps (Figure 26). The map using only SRTM as predictor estimates very high AGB in low altitude areas with gentle slope (as in the Yucatan peninsula), even though no vegetation is present in some of these areas. This effect is also observed in the maps using SRTM in combination with another sensor. MODIS and ALOS PALSAR have problems but in a lesser degree. MODIS does not work over agricultural areas, where it seems to over-estimate AGB, while ALOS PALSAR seems to have problems over bare and desert sandy areas as well as wetlands where it clearly overestimates the AGB. This shows the importance of an appropriate forest area mask when developing forest AGB maps. This will be further explored in the next chapter.

Sensitivity analysis were performed to assess the different combinations of spatial datasets (MODIS, ALOS PALSAR and SRTM). The results show that the use of at least two spatial datasets can substantially increase the accuracy and reduce the error. The use of MODIS optical data alone or combined with ALOS PALSAR or SRTM allows the modelling to predict at higher maximum levels of AGB. The results however show that the combination of the three spatial datasets showed superior accuracy and lower relative error (0.31 and 58\%) than the use of single dataset (0.12 - 0.19, and 62\% - 74\%) or two datasets (0.25 - 0.28, and 58\% - 59\%) (Figure 27).
Figure 26 AGB maps generated by the MaxEnt method using different combinations of spatial predictors (no forest mask is used): a) ALOS, b) MODIS, c) SRTM, d) ALOS+SRTM, e) ALOS+MODIS, f) MODIS+SRTM, and g) ALOS+MODIS+SRTM
Figure 27 Sensitivity analysis of different combinations of input data. Parameters tested: AUC and Model gain (from MaxEnt performance metrics), Maximum $AGB$ estimated by the model (from output $AGB$ maps), Bias, R², RMSE, and rel. RMSE (from independent INFyS validation dataset).
5.4. SUMMARY AND DISCUSSION

The AGB measured by the INFlyS in-situ data were analysed in terms of spatial distribution, forest types, biomes and topographic gradient. The trend analysis showed a peak of AGB in the central part of the country where the mountain belts converge and an increasing trend from the dry tropical forests in the northwest of the Yucatan peninsula towards the humid tropical forests of the southeast. Low tropical thorn forests present the lowest AGB (14.77 t ha\(^{-1}\)) in the country. AGB per given ha increases in Mexico from West to East and from North to South of the country. Some of the highest AGB per ha occur in the moist tropical forest of the Yucatan peninsula (Mexican’s South-East). Oyamel and Ayarin forests are scarce in Mexico in comparison to other forest types, but the average AGB measured by the in-situ plots is the highest in Mexico (132.54 t ha\(^{-1}\) and 69.10 t ha\(^{-1}\) respectively). These forests are located in the central mountainous areas of Mexico with some of the highest altitudes and precipitation rates in Mexico (Vidal-Zepeda, 1990).

When comparing the in-situ measured AGB to the signal retrieved by the EO datasets, the highest correlations are found for the ALOS PALSAR HV polarization and the MODIS MIR reflectance, while the lowest correlations correspond to MODIS EVI and the topographic aspect. The high correlation of ALOS PALSAR HV polarization to AGB agrees with the literature as L-band SAR backscatter has the highest AGB saturation of all sensors currently in orbit (Imhoff, 1995, Carreiras et al., 2012, Lucas et al., 2010, Mitchard et al., 2009, Naesset, 2007, Dobson et al., 1992). The high correlation of the optical MODIS MIR band to AGB also agrees with recent studies which found strong correlation of infrared imagery to AGB even beyond the theoretical saturation limit of optical imagery (Baccini et al., 2012, Kellndorfer et al., 2011). However, it is surprising the low correlation of MODIS EVI to AGB compared to NDVI, as EVI is generated to be more sensitive than NDVI over dense vegetation conditions (NASA, 2008). The analysis of the in-situ data also showed that the amount of AGB varies per biome and elevation. Correlation to AGB was found with elevation. The highest values of AGB occur at the lowest and at the highest elevation ranges, with an evident increasing trend at intermediate altitudes. This correlation is more significant when excluding data from the Yucatan peninsula (wide flat area at sea level).
This chapter revealed that AGB for a given H varies significantly with biome, elevation, and with interaction amongst these factors. This study also found that there is an increasing trend in the model intercepts and a slight decreasing trend in the model slopes of the allometric relationships between AGB and H across the elevation gradient. This results in higher amount of AGB per unit of H at higher altitudes than at lower altitudes. However, this does not occur across the whole range of H as the allometric model slopes are more pronounced at the lowest attitudes (below 750 m). Once the H of forests at low altitudes goes above of approximately 12 m, the AGB for those forest is higher than at intermediate altitudes, but still slightly lower than at the highest altitudes (> 2750 m). This scaling relationship at plot level between AGB and H across the altitudinal gradient can explain the AGB altitudinal trend observed in this study. Spatial patterns of AGB, H, and other forest parameters (Girardin et al., 2014, Buma and Barrett, 2015, Moser et al., 2008, Takyu et al., 2003) as well as allometric variations in vegetation (Pan et al., 2013a) have been previously observed in other regions with elevation gradients.

Moser et al. (2008) found a decreasing trend on AGB with increasing elevation due to climatic and edaphic factors by studying five forest stands of montane forest in Ecuador. The same trend was also found by Takyu et al. (2003) in Kalimantan montane rainforest. This study also noticed that the geological substrate and the nutrient content of the soil have an important effect on this trend. Girardin et al. (2014) found a decreasing trend not only on AGB but also on H with increasing elevation in the Amazon to Andes transition zone related to a decrease in forest richness with elevation. These decreasing trends occurs in the transition from lowland Amazon rainforest at lower altitudes to cloud forest at higher altitudes in Ecuador, Peru and Bolivia. Conversely, in Mexico the transition goes from tropical moist forests at the lowest elevations, tropical dry forests at low and mid altitudes, to tropical and temperate coniferous forests at the highest altitudes.

The change in the scaling allometric relationship at plot level, and ultimately the increasing trend in AGB with elevation seen in this study could be the result of increases in annual precipitation with elevation in Mexico as pointed out by Cartus et al. (2014). All of these studies took place on elevation gradients with small ranges of annual precipitation and in all cases annual precipitation was above 2000 mm. In contrast this chapter analysed tropical dry forests with annual precipitations below 500 mm to coniferous forests with more than 4500 mm (CONABIO, 2015), which might explain to a certain degree the different results.
Similarly, approximately 50% of the Mexico is classified as arid or semiarid (Garcia, 1990) and therefore very susceptible to drought. Those areas are mostly located at low altitudes in Mexico. Drought has been found to affect vegetation growth and ultimately increase tree mortality (Allen et al., 2010), which could explain the differences in allometry found in this chapter. Some of the highest AGB densities in Mexico occur at Oyamel (Abies) and Ayarin forests (Pseudotsuga & Picea) which are located at the highest altitudes with the highest precipitation and lowest drought risk. Alternatively, it could also be related to human interactions with the landscape as seen in Wang et al. (2001), as higher elevations have less human-related disturbances (e.g. degradation, land use change) than lower elevations.

Based on the results of this chapter, the retrieval of AGB across large areas presents itself as a challenging task due to the regional variability of the allometry across biomes and topographic gradient. The incorporation of coarse biome categorical data as spatial predictor might generate artificial borders and bring unknown errors to the estimation, so it is not contemplated in this thesis. Nevertheless, as biomes are strongly characterized by forest types, which in most cases can be differentiated by the optical spectrum, this information is intrinsic to optical sensors. Topographic variables can act as a proxy for climate variations (i.e. temperature and rainfall) and can be incorporated by the use of a DEM such as SRTM. The Optical and SAR imagery as well as topographic variables explored in this chapter showed to be significantly correlated to AGB.

This chapter demonstrated that the three types of spatial datasets (Optical, SAR, and DEM) contain distinct information that can be combined by means of this approach to produce better estimations than with a single dataset approach. The combination of 11 remote sensing predictors from ALOS PALSAR, MODIS, and SRTM datasets showed better accuracy and lower relative error (0.31 and 58%) than using a single sensor (0.12 - 0.19, and 62% - 74%) or combining two sensors (0.25 - 0.28, and 58% - 59%).
Chapter 6

Magnitude, Spatial Distribution and Uncertainty of Biomass Carbon stocks in the Forests of Mexico
6. MAGNITUDE, SPATIAL DISTRIBUTION AND UNCERTAINTY OF BIOMASS CARBON STOCKS IN THE FORESTS OF MEXICO

A peer-reviewed article with content from this chapter has been published:


A peer-reviewed book chapter with content from this chapter is currently in press at the time of submission of this dissertation


6.1. INTRODUCTION AND AIMS

Different forest area products such as MODIS Vegetation Continuous Fields (VCF) and ALOS PALSAR based forest maps are often used to estimate carbon stocks (Saatchi et al., 2011b, Thiel et al., 2009, Shimada et al., 2011). MODIS VCF is an annual sub-pixel-level representation of percent tree cover estimates globally (Hansen et al., 2003) at 250 m spatial resolution. Percent tree cover is defined as the amount of skylight obstructed by tree canopies equal to or greater than 5 m in height (Hansen et al., 2003). Percent tree cover thresholds above 10% are commonly used to create forest/non-forest binary maps (Saatchi et al., 2011b). The ALOS Kyoto & Carbon (K&C) Initiative is an international programme led by Japan Aerospace Exploration Agency (JAXA) whose main products are 25-50 m spatial resolution forest/non-forest area maps for the years 2007 to 2010. These products estimate the forest area using a simple decision tree that is based on a threshold of the Horizontal-emit Vertical receive (HV) polarized radar backscatter coefficient (Shimada et al., 2011). These different forest masks have different
characteristics due to the specific properties of the sensor that was used. For example, the use of VCF could lead to an erroneous forest extent as tree cover in sparse vegetated areas tend to be overestimated by this product (Sexton *et al.*, 2013). These errors could lead to biased carbon stocks calculations and an overall high uncertainty of the forest AGB map.

Mexico is taking part in the Reduction of Emission from Deforestation and Forest Degradation (REDD+) to obtain economic incentives for preserving its forest. A Measurement, Reporting and Verification (MRV) program at national level is being developed to evidence its efforts. To achieve that, Mexico already has a dense network of forest inventory plots nation-wide. Developing an efficient and transparent MRV system required by the international community requires approaches that combine remote sensing and ground data to produce spatially explicit AGB estimations at scales in which this network of forest inventory plots cannot provide accurate local estimates of AGB.

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 percent, or trees able to reach these thresholds in situ” (FAO, 2012a). Forest area products using FAO’s definition (or similar) and originating from different optical and SAR sensors are often used in vegetation studies. The Mexican Land Use and Vegetation map (LUV) developed by the Mexican National Institute for Statistics and Geography (INEGI) uses a combination of visual interpretation of optical imagery and field verifications to create a land use and vegetation class vector layer with a scale of 1:250,000 (125 m raster spatial resolution) over the whole Mexican territory (INEGI, 2009). This product has been found rather generalized and therefore not recommended for AGB mapping (Cartus *et al.*, 2014). Additionally, the definition of forest for Mexico used in this product do not use biophysical parameters commonly used such as minimum canopy cover or canopy height which can be “seen” by remote sensing imagery (e.g. FAO, 2012a), but rather describes types of forest in the country based on several characteristics such as species composition, soils, elevation and climate (INEGI, 2014). MODIS Vegetation Continuous Fields (VCF) and ALOS PALSAR forest/non-forest (K&C-FNF) are examples of widely used forest area products generated from optical and SAR imagery with similar forest definition (Hansen *et al.*, 2003, Shimada *et al.*, 2014).

The previous chapter has concluded that the regional variability of the allometry across biomes and topographic gradients make it challenging for retrieving AGB for large-scale
areas based on EO data, and found that the combination of optical, SAR and DEM datasets are more accurate and have less error than the use of stand-alone sensor or combination of two sensors. As different datasets have different types of information it is important to calculate the contribution of each predictor on the AGB estimation. Additionally, it might be even more important calculating the contribution of each dataset (optical, SAR, and DEM) across the whole AGB prediction range. This will help to understand which dataset is better fit to estimate AGB at different AGB levels.

The previous chapter also showed that algorithms only calibrated with data from forest areas do not properly predict AGB over other land cover types, which underlines the importance of using an appropriate forest mask. Therefore it is crucial to understand to what extent the use of a different forest mask can affect the estimation of forest carbon stocks at national level. This chapter focuses on forest masks that use the same forest definition but are generated from different sensors. This is being studied by assessing the AGB stocks in Mexico at country level in a spatially explicit fashion for each forest mask.

The chapter illustrates how to estimate the probability of forest presence and how to generate a forest mask by combining different datasets, as well as how to use the error propagation approach to generate the associated uncertainty of the AGB estimations at pixel level.

This chapter addresses the following research questions:

**Question 3.** What is the relative importance across the AGB range of Optical, SAR and Topographic datasets when combined to estimate forest biomass stocks?

**Question 4.** To what extent forest cover products based on the same forest definition but generated from different sensors differ from each other? Does the combination of different types of spatial datasets (Optical, SAR, and DEM) increase the accuracy of forest masks? What is the effect of the selection of a forest area mask on the estimation of carbon stocks at national level?

### 6.2. SPECIFIC DATA AND METHODS

The same remote sensing predictors are used to generate the FP map and the AGB class probability layers. The remote sensing predictors from three datasets (MODIS, ALOS
PALSAR (and SRTM) are used, as they have shown the best performance in the previous chapter.

The MaxEnt algorithm performance assessment is made by bootstrapping 25% of the training data. The variable importance by AGB class was analysed as the relative contribution to the MaxEnt model gain by sensor. This is done to circumvent the existing correlation between remote sensing predictors which belong to the same sensor (e.g. HV and HH SAR backscatter polarization layers).

Models are also evaluated using all variables, excluding one variable each time, and also using one variable in isolation each time. A permutation assessment is also carried out for each remote sensing predictor by randomly permuting the training data and re-evaluating the model. A large drop in AUC means that the model heavily depends on that variable. The drop in AUC is then normalised to percentage relative values. In this study, the variable importance is assessed by combining the relative importance of each remote sensing predictor by sensor and per different AGB class. This is done to circumvent the existing correlation between remote sensing predictors which belong to the same sensor (e.g. HV and HH SAR backscatter polarization layers).

The FP layer is used to generate a binary forest/non-forest mask based on a probability threshold as explained in the general methods section (chapter 4.1). The probability threshold corresponding to the 5% of the error of omission in the training data obtained from the MaxEnt algorithm was 27%, for the equal sensitivity and specificity 46%, and for the maximum sensitivity plus specificity 35%. The highest κ obtained from the validation for the forest masks generated from the FP map occurs for the probability threshold of 25%. Therefore, a forest/non-forest layer is generated using the lowest threshold (hereafter FP25%).

The K&C-FNF product and the ALOS PASAR with a -14.5db threshold (FNF_{14.5 db}) were also used to generate forest masks. MODIS VCF with a 10% tree cover is also used (VCF_{10%}). The forest classes of the LUV dataset were also used as forest mask. A visual comparison between the forest area defined by these products gives an idea of the existing differences between them (Figure 28).
Figure 28 Forest extent defined by the LUV map, by the FP\textsubscript{25\%}, by VCF\textsubscript{10\%}, and by K&C-FNF. Dark grey represents forest and light grey non-forest. The location of validation points (n=198) is displayed in the LUV map.

The independent dataset was used to estimate the overall uncertainty of the AGB map. The uncertainty map generated by the MaxEnt approach was used to analyse the uncertainty in terms of biomass levels and forest types.

A multi-scale analysis of AGBC stocks derived by the INFyS dataset and the map was carried out following the approach used by (Cartus \textit{et al.}, 2014) at municipality and state level. The average AGBC per ha for each municipality/state was calculated as the mean of the values from the INFyS plots, weighted by the forest type proportional area (coniferous forest, mixed coniferous-broadleaved forest, broadleaved, moist tropical forest, dry tropical forest, and mangrove forest). The INEGI land use and vegetation (LUV) map was used accordingly for this purpose.

6.3. RESULTS

Jackknife analyses based on AUC changes are used to assess the importance of each prediction variable. MaxEnt models are run with each single variable in isolation. Then, models using all variables together are run excluding one single variable each time. The former shows the importance of each variable to individually predict AGB, while the latter
shows which variables have more information that is not included in the other variables. The results show that ALOS PALSAR HV and MODIS MIR are the most important layers used in isolation, while SRTM aspect and MODIS NIR are the least important. Additionally, ALOS PALSAR HV and SRTM elevation are the layers that contain more information not included in any other layer, because the AUC drops the most when these variables are excluded. In contrast, excluding SRTM aspect or MODIS NIR results in the smallest decreases in AUC (Figure 29).

![Figure 29 Average AUC of AGB map for single variable models and all variables together (left). Average AUC of AGB map for models excluding a single variable (right) (note: y-axis has different scaling).](image)

The algorithm performance of the final AGB class probability layers using the combination of all prediction variables from ALOS PALSAR, MODIS, and SRTM products showed an average AUC=0.93 (training data) and AUC=0.90 (validation data), and for all cases P<0.001. The AUC for the FP map was 0.82 (training data) and 0.81 (validation data), with P<0.001.

The variable importance analysis of the remote sensing inputs shows that the main input layers contributing to the MaxEnt prediction of AGB, are ALOS PALSAR HV polarization, MODIS MIR and SRTM elevation. This is expected, as those were the layers with a high information content that is not included in any other variable. Due to the high correlation between layers from the same sensor, the remaining layers have lower importance. The analysis is also performed grouping the variables by remote sensor (dataset type). The overall percent contributions of ALOS PALSAR, MODIS and SRTM
to model $AGB$ were 50.9%, 32.9%, and 16.2% respectively, while permutation importance values were 49.9%, 37.7%, and 12.4%. In the case of the FP map, the percent contribution of ALOS PALSAR is 77.5%, while MODIS and SRTM contributions are 16.8% and 5.6% respectively. Permutation importance values for the FP map were 56.7%, 32.3%, and 11.0%.

When exploring the contribution of each remote sensing instrument to the $AGB$ class probability layers, ALOS PALSAR was the most important input layer to predict $AGB$ for the most abundant $AGB$ classes up to 100-120 t ha$^{-1}$ with percent contributions in the range of 60% to 75%, and was still relevant up to 180 t ha$^{-1}$ in the range 30% to 40% (Figure 30). Above 120 t ha$^{-1}$ MODIS becomes more important with 50% contribution. SRTM contribution gradually increases from approximately 10% in the lower $AGB$ ranges to 30-40% above 180 t ha$^{-1}$.

![Figure 30 Percent contributions to the $AGB$ map by spatial dataset per biomass range (lines, left axis) and frequency INFyS plots (columns, right axis)](image)

The decline in the contribution of ALOS PALSAR in the estimation for $AGB$ above 100-120 t ha$^{-1}$ is in agreement with the saturation effect that can be seen in the literature for L-band backscatter (Wagner et al., 2003, Mitchard et al., 2009). After this point the weight of the estimation fluctuates among products.
The FP$_{25\%}$, FNF$_{14.5\, \text{dB}}$, and VCF$_{10\%}$ forest masks are compared to the LUV map in order to assess in which areas this products disagree with the LUV map (Table 10). The LUV map is a land cover product which includes actual and potential land use and cover; whereas the forest maps developed in this chapter are based on a physical threshold approach that only includes actual vegetation cover independently from the land use. Nevertheless, the comparison of these products gives an insight on the types of land cover, such as grassland or shrub, where these products fail to discriminate from forest vegetation.

Table 10 Partial validation matrix showing disagreement between the forest area defined by the LUV map and the forest area masks, shown as total area per land use class (M ha).

<table>
<thead>
<tr>
<th>INEGI - Land Use and Vegetation Types</th>
<th>Totals</th>
<th>FP$_{25%}$</th>
<th>FNF$_{14.5, \text{dB}}$</th>
<th>VCF$_{10%}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropland</td>
<td>33.12</td>
<td>8.25</td>
<td>8.10</td>
<td>12.62</td>
</tr>
<tr>
<td>Grassland or Pasture</td>
<td>31.02</td>
<td>7.43</td>
<td>7.02</td>
<td>15.53</td>
</tr>
<tr>
<td>Other Vegetated land</td>
<td>6.53</td>
<td>0.36</td>
<td>0.37</td>
<td>1.21</td>
</tr>
<tr>
<td>Savannah</td>
<td>0.31</td>
<td>0.17</td>
<td>0.17</td>
<td>0.29</td>
</tr>
<tr>
<td>Shrub Vegetation</td>
<td>55.09</td>
<td>3.64</td>
<td>6.81</td>
<td>11.74</td>
</tr>
<tr>
<td>Urban &amp; Non-Vegetated land</td>
<td>2.92</td>
<td>0.43</td>
<td>1.09</td>
<td>0.72</td>
</tr>
<tr>
<td>Total Disagreement</td>
<td>20.28</td>
<td>23.56</td>
<td>42.10</td>
<td></td>
</tr>
</tbody>
</table>

The three masks present the most severe disagreements with the LUV map in croplands, grasslands, pasture, savannah, and shrub vegetation. These land cover types usually have some woody vegetation at sub-pixel level. However, the VCF$_{10\%}$ layer cannot discriminate between these land cover types and forest as well as FNF$_{14.5\, \text{dB}}$ and the FP$_{25\%}$ layers. According to the LUV map, the VCF$_{10\%}$ layer classifies almost the whole savannah and half the croplands, grasslands and pastures in Mexico as forest. The total area misclassified as forest according to LUV by the VCF$_{10\%}$ layer is twice as high as that by the other layers (Table 10). The FNF$_{14.5\, \text{dB}}$ and FP$_{25\%}$ layers substantially improve the agreement with the LUV map in comparison to the VCF$_{10\%}$ map. Both maps yield similar results, having the largest disagreements with the LUV map in cropland, grassland, pasture and shrub areas. The FNF$_{14.5\, \text{dB}}$ map has the largest disagreement with urban and
non-vegetated areas in comparison to the other products. The FP25% map reduces the disagreement with the LUV map in shrub vegetation, and urban & non-vegetated land in comparison to the FNF-14.5dB mask. The above results show the strengths of optical imagery to detect green vegetation, but at the same time its weakness as in most cases it cannot differentiate between forest and other types of vegetation such as croplands, grasslands, and scrublands. ALOS PALSAR can discriminate other types of vegetation from forest, as the backscatter signal depends on the volume and structure of the vegetation, but it can get false positives from other natural or artificial structures such as city buildings. However, the combination of both types of imagery produces the most balanced results in terms of accuracy and reliability.

$A_{GB}$ maps were generated by using the forest masks from optical (VCF10%), SAR (K&C-FNF and FNF-14.5 dB), and a combination of optical, SAR, and DEM (FP25%) and then compared in terms of extent and carbon stocks. The $A_{GB}$ map with a forest mask derived from optical data (VCF10%) has 24.1 million ha more (33%) in forest extent than the map with a mask originated from SAR (K&C-FNF), and up to 0.36 Gt C higher (23%) total carbon stocks. This difference can be converted to 1.32 Gt CO$_2$-e and an economic value of $12.2$ billion.

The total $A_{GB}C$ estimated for Mexico using the VCF10% forest mask was the highest (1.92 Gt C) (Table 11). Differences in the total $A_{GB}C$ between optical (VCF10%) and SAR (FNF-14.5 dB and K&C SAR) were in the range between 16% and 23%. It is apparent that VCF10% tends to overestimate forest cover in comparison with the other products due to the misclassification of areas such as croplands, grassland and other sparse vegetated areas as forest, generating artificially inflated values of forest carbon stocks. This result shows that the use of different forest masks can have a significant effect on the total forest carbon stock estimated for a country. The carbon stock estimated using the LUV mask is lower than the official 1.68 Gt C reported to FAO (FAO, 2010a), but close to Cartus et al. (2014) estimations of 1.53 Gt C.

The $A_{GB}$ map using the FP25% forest mask (hereafter MEX-1) presents the highest $\kappa$ and forest probability, and the lowest average uncertainty at pixel scale (Table 11). The MEX-1 map estimates the total forest cover as 77.25 M ha, from which a total $A_{GB}C$ stock for Mexico of 1.69 Gt C can be inferred, by summing the total $A_{GB}$ of all forest pixels and using the Mexican $A_{GB}$-to-carbon ratio (0.48). The uncertainty at national
level can be calculated by increasing the sample area and propagating the pixel errors from pixel to national scale. The relative uncertainty is constrained below ±1% for the entire MEX-1 map for Mexico. The final AGB, uncertainty and forest probability maps are displayed in Figure 31.
<table>
<thead>
<tr>
<th>Forest mask (threshold)</th>
<th>Forest Probability (%)</th>
<th>Forest Area ( \kappa )</th>
<th>Overall Accuracy</th>
<th>Forest Cover (M ha)</th>
<th>Average ( AGBC ) (t C ha(^{-1}))</th>
<th>Average Uncertainty (±%)</th>
<th>Total ( AGBC ) (Gt C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FP(_{25%})</td>
<td>0.47</td>
<td>0.83</td>
<td>0.92</td>
<td>77.25</td>
<td>21.8</td>
<td>49.3</td>
<td>1.69</td>
</tr>
<tr>
<td>FNF(_{14.5\ dB})</td>
<td>0.45</td>
<td>0.78</td>
<td>0.89</td>
<td>80.21</td>
<td>20.6</td>
<td>49.9</td>
<td>1.65</td>
</tr>
<tr>
<td>K&amp;C-FNF</td>
<td>0.44</td>
<td>0.72</td>
<td>0.87</td>
<td>73.80</td>
<td>21.2</td>
<td>51.1</td>
<td>1.56</td>
</tr>
<tr>
<td>VCF(_{10%})</td>
<td>0.36</td>
<td>0.66</td>
<td>0.83</td>
<td>97.80</td>
<td>19.6</td>
<td>57.7</td>
<td>1.92</td>
</tr>
<tr>
<td>LUV</td>
<td>0.43</td>
<td>0.56</td>
<td>0.79</td>
<td>67.27</td>
<td>21.8</td>
<td>50.2</td>
<td>1.47</td>
</tr>
</tbody>
</table>
Figure 31 A) Aboveground biomass, B) Biomass uncertainty, and C) Forest probability maps for Mexico ca. 2008. Maps are masked by a 25% probability threshold (FP_{25%}).
The AGB map was validated against the independent plot dataset (10% INFyS dataset) resulting in a $R^2$ of 0.31 for the whole country. The RMSE and bias at pixel scale were 36.1 t ha$^{-1}$ (17.3 t C ha$^{-1}$) and -3.6 t ha$^{-1}$ (-1.7 t C ha$^{-1}$) (Figure 32).

Figure 32 Validation of the Mexican AGB map using an independent plot dataset. Warmer colours indicate higher point density. Solid line: $y = x$.

The average rel. RMSE across the whole map was 58%. However, the highest uncertainty values primarily occur in the lowest AGB ranges (Figure 33) where the sub-pixel variability (i.e. vegetation gaps or other non-forest cover within the pixel) plays an important role. This error originates from the difference of size between the plots used as AGB reference data and the pixel size of the remote sensing imagery ($\epsilon_{\text{sampling}}$ in this study). The area covered by AGB below 20 t ha$^{-1}$ across Mexico has a considerable extent, but the total amount of AGB present in those areas is relatively small in comparison (Figure 10). Nevertheless, these areas contribute to most of the uncertainty showed by the MEX-1 map. Some of these pixels are areas with small amounts of sparse woody vegetation encroachments which may have a 10% canopy cover, but in many cases might not be considered a forest in the sense of FAO as those have to be of at least 0.5 ha or 20 m in width which is below the pixel size used in this study.

The high uncertainty in those areas gives an insight into the challenges of assessing AGB changes between different periods for areas with low biomass density. This error is mostly originating from the plots used to train MaxEnt. A 6.25 ha pixel size is much larger than
the INFyS plot area (0.16 ha per 1 ha) used to upscale the AGB measurements. The error associated with the AGB variability at sub-pixel scale ($\varepsilon_{\text{sampling}}$) leads to a very high uncertainty through error propagation (Equation 12). This uncertainty could be reduced using larger sample plots (e.g. 1 ha sampled area plots) to reduce the error originated from the sub-plot variability as suggested by previous studies (Saatchi et al., 2011a, Montesano et al., 2014).

Figure 33 a) Uncertainty, b) RMSE, c) Total Area, and d) Total AGB by AGB class. Average AGB and its uncertainties also vary within forest types (Figure 34). These differences arise from the MaxEnt algorithm error term ($\varepsilon_{\text{prediction}}$) due to weak correlations between remote sensing data layers and AGB for certain forest types and AGB levels (e.g. caused by signal saturation at high biomass). Evergreen forests have the highest AGB per hectare in Mexico. The map shows higher relative errors for deciduous forest than evergreen forest, perhaps due to the broadleaved phenology. Even though the optical data used in this study were acquired within the vegetation growing season, the SAR imagery was acquired in different seasons. The forest structure and hence the backscatter signal from deciduous trees under leaf-on or leaf-off conditions will be different. Evidence for this effect is shown by the correlation between L-band SAR backscatter and leaf area index (Dabrowska-Zielinska et al., 2014, Canisius and
Fernandes, 2012, Kovacs et al., 2013). Wetlands also increase the uncertainty, because of the soil moisture effect on radar backscatter that produces vegetation-surface specular reflection due to inundation (Yu and Saatchi, 2016). The use of additional SAR wavelengths or texture information generated from the SAR data might better characterise forest structure and can contribute to better estimations in those forest types. The new BIOMASS satellite mission (Le Toan et al., 2011, ESA, 2012) to be launched in 2020 will be less affected by small scattering elements due to the large wavelength of the P-band sensor.

The agreement between MEX-1 map and the Mexican forest inventory was assessed through a multi-scale analysis. The MEX-1 map converted to AGBC values by means of a 0.48 carbon ratio, and the LUV map were used here. The average carbon stock showed a good agreement between the MEX-1 and the INFyS ground plots dataset with R² of 0.76 for the municipality level (ranging from 3.7 km² to 54.8·10³ km², average 1.1·10³ km²) and 0.94 for the state level (ranging from 1.6·10³ km² to 242.9·10³ km², average 61.8·10³ km²) (Figure 35).

Figure 34 Average AGB and its associated uncertainty by forest type in Mexico.
Measurements of $AGB$ in combination with its uncertainty can improve the quality of biomass stock estimations. The current chapter presented a feasible approach to estimate forest probability, $AGB$ and its associated uncertainty using in-situ data and a combination of freely available Earth observation datasets. Satellite remote sensing data at 250 m spatial resolution were used to map all forest lands of Mexico. A combination of SAR, optical and elevation datasets (ALOS PALSAR, MODIS, and SRTM) were used, and the contribution of each dataset to the $AGB$ estimation per biomass range is reported. The carbon stocks of Mexico and its uncertainty are analysed in terms of spatial distribution, forest types, forest masks and biomass ranges. The use of different forest masks can have a large impact on the estimation of national carbon stocks. Even forest masks generated from different sensors using a similar forest definition (i.e. from the FAO) present large discrepancies in forest extent and total carbon stocks.

The contribution of each predictor variable to $AGB$ estimation has been reported and discussed. The results show that ALOS PALSAR HV and MODIS MIR are the most important predictor variables to predict $AGB$ as stand-alone predictor. The results also show that ALOS PALSAR HV and SRTM elevation are the layers that contain more information not included in any other layer. This implies that ALOS PALSAR is essential for $AGB$ estimation and MODIS MIR and SRMT elevation greatly contribute to improve the estimates. It is interesting that MODIS MIR has a higher contribution to $AGB$
estimation than traditional vegetation indices such as NDVI. This agrees with recent studies (Baccini et al., 2012, Kellndorfer et al., 2011) that found correlation to AGB beyond the theoretical saturation point of optical imagery in infrared bands explained by shadowing and moisture differences.

A further analysis was also performed to assess the contribution by dataset type (Optical, SAR, and DEM) across the AGB range. As expected, SAR imagery holds the weight of the AGB prediction up to the theoretical saturation point around 150 t ha$^{-1}$ (Wagner et al., 2003, Mitchard et al., 2009), thereafter the contribution of each sensor varies but a higher contribution of optical and elevation data is noticeable on the higher biomass ranges. This seems to be due that none of the products can solely explain the amount of AGB at this high range. MODIS optical imagery might contain, as previously mentioned, information from the mid-infrared layer which allows contributing to the estimation of AGB at this high ranges. The high contribution of SRTM for the highest AGB ranges (above 160 t ha$^{-1}$) also stands out, which can be explained due to the distribution of forest AGB in Mexico across the topographic gradient and has also been observed in chapter 5 and in a previous study (Cartus et al., 2014). Some of the highest values of AGB per ha in Mexico occur at the highest altitudes and slopes (and precipitation), where Ayarín and Oyamel forests are located (from 1,500 m – 2,000 m altitude). These forests are characterised by tree species such as Pseudotsuga, Picea and Abies and canopy heights above 30 - 40 m. The lowest AGB usually occurs at the lower areas with relatively flat terrain. The only exception to this gradient can be observed in the Yucatan peninsula, where high AGB values can be found at low elevation and flat terrain. These results demonstrate that topographic information incorporates regional information that helps to better predict AGB in wide areas.

The forest mask generated from the forest probability layer (FP$_{25\%}$) was compared to a forest mask developed from SAR imagery (K&C-FNF and FNF$_{-14.5dB}$, ALOS PALSAR L-band), and to a mask developed from optical imagery (VCF$_{10\%}$). When compared to the LUV dataset, the VCF$_{10\%}$ mask appears to overestimate forest cover due to a misclassification of grassland, pasture, cropland, sparse vegetation and shrub as forest. This effect is thought to be caused by the difficulty of optical sensors to distinguish different types of vegetation greenness (Sexton et al., 2013, Montesano et al., 2009). The FP$_{25\%}$, FNF$_{-14.5dB}$, and K&C-FNF masks lead to more accurate classifications of forest and non-forest. Very high values of uncertainty occurred at low biomass ranges and at
forest types characterised by high soil moisture. The use of different forest masks based on the same forest definition but originating from different sensor type has a significant effect in the total amount of AGBC stocks. A 23% higher total AGBC stocks were calculated when using MODIS VCF_{10\%} as forest mask instead of K&C-FNF. The difference were higher (30%) when compared to the LUV forest mask.

This study showed similar results to map AGB, uncertainty and forest probability at 250 m resolution than a similar study carried over the whole U.S. which used 250 m MODIS imagery, SRTM and land cover layers (Blackard et al., 2008) (Rel. RMSE of 51-92% versus the 58% in this study). However, the error reported by this study (17.3 t C ha^{-1}) is slightly higher than the error reported by Cartus et al. (2014) in Mexico (14.4 t C ha^{-1}) using Landsat PTC, ALOS PALSAR and SRTM. The multi-scale comparison between the INFyS in-situ data and this study showed a good agreement at municipality and state level (R^2 of 0.76 and 0.94 respectively). This is expected as uncertainties from AGB estimation “average out” at larger scales as seen by other studies (Santoro et al., 2011, Saatchi et al., 2011b, Cartus et al., 2014).

The AGB, Uncertainty, and Forest Probability maps presented in this chapter can be used to reduce the uncertainties estimating carbon stocks in Mexico, as well as to assess the carbon losses originated from disturbances such as deforestation and fire, or gains due to new planted forest and forest growth. The map can therefore be useful in the national reporting of greenhouse gases.

The approach presented here is applicable to imagery from sensors that are currently in orbit (MODIS and ALOS-2 PALSAR). These results confirm that a locally trained MaxEnt approach can provide accurate estimates at spatially coarse scale. However, this is not the case at the scale of the field plot data (1 ha inventory plots), where relative accuracies such as the ones expected from the BIOMASS mission (Le Toan et al., 2011) are not achieved. The map presented here has quantified different sources of uncertainty (measurements, allometry, sampling, and remote sensing prediction) at pixel scale using an error propagation model. The remote sensing prediction error presents the largest error term. This error term increases with biomass level, mostly due to saturation of the signal at high biomass.
Chapter 7

Uncertainty of Aboveground Biomass Carbon Maps
7. UNCERTAINTY OF ABOVEGROUND BIOMASS CARBON MAPS

A peer-reviewed article with content from this chapter has been published:


7.1. INTRODUCTION AND AIMS

Forest aboveground biomass carbon (AGBC) stocks in Mexico for the FAO Forest Resource Assessments were estimated by the Comision Nacional Forestal (CONAFOR). Saatchi et al. (2011b) mapped AGBC over the whole tropical region for the first time (including Mexico) using satellite datasets at 1 km spatial resolution, and estimated the uncertainty of AGBC on a pixel scale by combining the probabilistic outputs generated from the MaxEnt algorithm with data from ICESat GLAS LiDAR footprints and MODIS, Quick Scatterometer (QSCAT) and SRTM. Later work by Baccini et al. (2012) mapped AGBC in the tropics (partially covering Mexico) at 500 m resolution using ICESAT-GLAS LiDAR, MODIS and SRTM, but without spatial uncertainty estimation.

These two products are widely used by the research community even as calibration for other AGB maps (e.g. Liu et al., 2015, Avitabile et al., 2016, Harris et al., 2012). Liu et al. (2015) used Saatchi et al. (2011b) aggregated map pixels to calibrate large pixels (>10 km) of vegetation optical depth to calculate AGB change across a 20 year period. As a result, any of the uncertainties from the Saatchi et al. (2011b) map will propagated into this product. Liu et al. (2015) estimations of AGB loss in the tropics largely disagree with estimations based on ground data (Pan et al., 2011) (Figure 36).
Figure 36 Comparison of AGB change in the period 2000 - 2007 between Pan et al. (2011) and Liu et al. (2015)

These tropical carbon maps for the year 2000 by Saatchi et al. (2011b) (hereafter TCM-1) and for the year 2005 by Baccini et al. (2012) (hereafter TCM-2) are consistent in their methods but show large discrepancies in AGB (Mitchard et al., 2013). They also disagree with the official carbon estimations for Mexico from in-situ data (FAO, 2010a) and with ground data and locally calibrated products in other regions (Hill et al., 2013, Mitchard et al., 2014, Carreiras et al., 2013). Several reasons have been suggested for these differences (Mitchard et al., 2013, Mitchard et al., 2014). Mitchard et al. (2014) found that the TCMs do not agree with the spatial distribution of AGBC in the Amazon and that the uncertainties far exceed the reported by the TCMs based on a comparison to 413 in-situ plots. Saatchi et al. (2015) made a critique of this study arguing that, aside from the methodological flaws in the interpolation approach used by Mitchard et al. (2014), 413 plots from different periods (1956-2013) only sampling 404.6 ha out of 650 million hectares of forest in the Amazon and without a rigorously designed and extensive in-situ forest inventory strategy are not representative of the AGB trends in the region. In this chapter, in contrast, the AGBC maps are compared to a large systematic stratified sampling inventory of the forests in Mexico (i.e. INFyS).

These TCMs maps have been globally calibrated (continentally in the case of TCM-1) using AGB reference data derived from GLAS height metrics and global or continental allometric models solely based on canopy height, which might explain why they do not fully capture the spatial variation of AGB. The most recent assessment covering the whole of Mexico is the map of forest aboveground carbon stocks for the year 2005 by Cartus et
The previous chapter presented an approach to map AGB, uncertainty and forest probability using three types of spatial datasets (Optical, SAR and DEM) over Mexico, and analysed the contribution of each dataset across the AGB range. The chapter also studied to what extent forest cover products based on the same forest definition but...
generated from different sensors differ from each other, and what is the effect of the selection of a forest area mask on the estimation of carbon stocks at national level. The carbon stocks of Mexico and its uncertainty were analysed in terms of spatial distribution and forest types. In this chapter, the resulting map for Mexico developed in the previous chapter (MEX-1), the TCM-1, TCM-2, and the MRF for Mexico are compared. These AGBC stock maps were generated at different spatial resolutions following different approaches. MEX-1 and MRF are regionally calibrated and incorporate topographic data and in-situ AGBC estimations based on species specific and regional allometry, while the TCMs are calibrated across the whole tropical region and do not use in-situ data nor regional allometry to estimate AGBC.

The amount and spatial distribution of the AGBC maps are compared to INFyS in-situ data across the Mexican territory. The differences among these products will be analysed in the framework of the error propagation approach used in this thesis. Input EO datasets, AGB reference data, allometric models and upscaling methods used by these studies will be analysed in order to explain the differences between those products.

The following questions will be explored in this chapter:

Question 5. Where are the main discrepancies among current carbon maps over Mexico? What are their sources? To what extent does the use of reference data derived from GLAS footprints instead of reference data derived from forest inventories impact AGB mapping?

### 7.2. SPECIFIC DATA AND METHODS

The TCM-1, TCM-2, and MRF maps were provided by their respective authors. These maps use AGBC (t C ha\(^{-1}\)) as biomass unit. Therefore, MEX-1 is converted to AGBC units by means of the AGB-to-Carbon ratio of 0.48 to allow the comparison. Maps were co-registered and aggregated to the same resolution when compared (1 km). The spatial extent among all maps is restricted to the geographical space covered by TCM-2, as this map does not fully cover the whole Mexican territory (Figure 37). This covers approximately southern half of the country. The area is bounded by a square with NW coordinate 110°42′41.9″W, 23°24′13.6″N and SE coordinate 86°28′37.7″W, 14°27′32.1″N.
7.2.1. Comparison to in-situ data

The AGBC map predictions were compared to the in-situ INFyS data. The spatial variability of the maps is examined by trend analysis. Trend analyses of the three-dimensional distribution of AGBC were performed over the latitudinal (North-South) and longitudinal (East-West) gradients. The coordinates of the INFyS in-situ plots were used to extract sample points from the maps (MEX-1, TCM-1, TCM-2, and MRF). These values were projected in the x,z (East-West) and y,z (North-South) planes as scatterplots together with their trend lines (polynomials). This allows then to assess the longitudinal and latitudinal trends.

Histograms displaying the AGBC frequency distribution for each dataset were also processed and compared to the INFyS in-situ AGBC histogram. Each histogram was also divided in 8 quantiles (same number of occurrences per AGBC bin) for comparison. The similarity between the histogram of the INFyS dataset and the histogram of each AGBC map was also assessed based on the correlation ($R^2$) between the frequency values from both histograms for each 1 t C ha$^{-1}$ bins.

Global Moran’s I Index (Moran, 1950, Getis and Ord, 2010) is also used to assess the spatial pattern (spatial clustering) of the AGB predictions of each map over forest areas (delineated by the LUV mask) within each state. States were used as spatial units for this analysis instead of ecoregions (Figure 37). The reason is that the size of the states in the study area is more homogeneous than the size of ecoregions, which have extreme large
and small sizes. The tests were individually run per AGB map at each state. The locations of the INFyS plots were used to extract values from each map and assess the different degree of spatial clustering per state. The index evaluates whether a spatial pattern is clustered, dispersed, or random. P-values are also estimated to assess the significance of the index. All input parameters are set equally with exception of the size windows. This is specific of each state due to the difference in size among states. Therefore, index values with significant p-value are comparable per state among map products, giving an indication of the intensity of spatial clustering or spatial dispersion. However, the indexes are not comparable in between states.

7.2.2. Comparison at Biome and Ecoregion level

Biome and ecoregion level comparisons were performed using the WWF biome classification dataset by Olson *et al.* (2001). AGB map estimates are compared to average AGB estimates from the INFyS in-situ plots falling within the biome or ecoregion area. This area completely overlaps 4 forest biomes and 25 ecoregions (Figure 38):
7.2.3. Exploring sources of uncertainty

The next step is to explore map differences with a focus on the different sources of uncertainty described in the error propagation equation used in this thesis ($\epsilon_{\text{measurement}}, \epsilon_{\text{allometry}}, \epsilon_{\text{sampling}}, \text{and} \epsilon_{\text{prediction}}$) (Equation 12). Therefore, the maps will be assessed based on those possible sources of error, which are ultimately related to the different EO datasets used as predictor variables, the $AGB$ reference data used for calibration, the allometric models used to estimate $AGB$, and the different methods used for upscaling $AGB$ across the landscape (Figure 39).

The GLAS LiDAR footprint dataset used to create the TCM-1, with canopy heights estimated by Lefsky (2010) models, was provided alongside the TCM-1. The number of GLAS footprints over forest in the Mexican territory was 97,872. The single allometric model for the American continent (Saatchi et al., 2011) was used to estimate $AGB$ from each footprint. Footprints in high relief (slopes above 10%) were removed from the dataset using the SRTM layer in an attempt to minimise errors.

Three grids of hexagons with different edge sizes (10 km, 50 km, and 100 km corresponding to 260 km$^2$, 6,500 km$^2$, and 26,000 km$^2$ respectively) were generated over Mexico. Those were overlapped to the INFyS and GLAS datasets, and an average $AGB$ value from each dataset was assigned to each hexagon. Only hexagons with at least 5 INFyS plots and 5 GLAS footprints were used for comparison to reduce the error related to the sub-pixel variability (Baccini et al., 2012). These grids are used to explore whether there are differences in the spatial distribution of $AGB$ between the datasets at aggregated scales.
Figure 39 Schematic of the different methods, inputs and outputs of the carbon maps analysed in this chapter. Right-lower corner: relative scaling between plots/footprints (circles – solid line) and pixels (square – dotted line) for a) MEX-1, b) MRF, c) TCM-1, and d) TCM-2. Note that a) contain 2 primary units per pixel, and c) and d) contain at least 5 footprints per pixel.
In order to have a comparison between overlapping or nearly-overlapping plots, an additional grid of squares with 1 km² was generated. The grid was overlapped to the GLAS footprint dataset and average AGB values were assigned to the 1 km² squares, reducing the sampled estimations to 11,686 squares. Additionally, pixels using less than 5 GLAS footprints were also discarded as before, further reducing the number to 6,348 pixels. The AGB sampling size error due to within pixel variability associated to assign the value of at least 5 GLAS footprints of 0.25 ha each to 1 km² squares (100 ha) is approximately bounded between 17.8%-22.8% (Saatchi et al., 2011b). The values from those squares were compared to values from the INFyS in-situ plots also overlapping the squares (henceforth type I overlap - 130 plots). INFyS plots within 500 m of distance from the centre of the plot to the border of the squares were also included in the analysis (type II overlap – 294 plots), making a total of 424 plots (Figure 40).

Figure 40 Method to compare AGB pixels derived from GLAS footprints and from in-situ INFyS plots. a) GLAS footprints over forest (light grey 1 km² squares) were selected (black circles) and over non-forest squares (white squares) discarded (grey circles), b) At least 5 GLAS footprints per square were used (black circles), or otherwise discarded (grey circles) c) Average AGB estimated from the GLAS footprints were assigned to the squares (dark grey), d) the values of GLAS AGB squares (dark grey) were compared to the AGB from in-situ INFyS plots within the square (type I overlap), e) AGB of INFyS plots outside the GLAS AGB square but within 500 m were also compared (type II overlap). Note that the size of GLAS footprints, INFyS plots and squares in this figure are proportional to reality.

Canopy height estimated from GLAS footprints by means of Lefsky (2010) models is $H_L$, which is the basal area weighted height of all trees, while the in-situ data is defined as the arithmetic mean height of all the trees within the plot ($H$). In order to compare both
canopy heights, the model developed by Yu (2013) relating $H_L$ to $H$ is used. This model was developed using forest plot inventory data from the U.S.

$$H = 1.4635 \cdot H_L^{0.80925}$$

Equation 13

The MaxEnt approach from the previous chapter was used to generate a new AGBC map over Mexico. In this chapter the MODIS optical dataset used in the previous chapter is replaced by a Copernicus-SPOT 1 km optical dataset. The other datasets from previous chapter (ALOS PALSAR and SRMT) were aggregated to 1 km spatial resolution and also used.

7.3. RESULTS

7.3.1. Comparison to in-situ data

The studies present different quantities and spatial distribution of AGBC stocks in Mexico (Figure 41). Trend analysis of the three-dimensional distribution of AGBC was performed over the latitudinal (North-South) and longitudinal (East-West) gradients. There are considerably different spatial trends in the southern-central part of the country, where the TCM-1 and TCM-2 maps display significantly higher amounts of AGBC in comparison to the in-situ data, MRF, and the MEX-1 map. The MRF map and MEX-1 map show similar spatial patterns in the distribution of AGBC as well as the overall amount of AGBC stocks. However, the MEX-1 map characterises the increasing trend in AGBC from the dry tropical forests in the northwest of the Yucatan peninsula towards the humid tropical forests of the southeast much more realistically.
Figure 41 AGBC maps and longitude-latitude AGBC trend analysis (Z-axis represents AGBC) showing different amount and spatial distribution of AGBC: a) Plots INFyS in-situ data (oversized for visualization purposes), b) MEX-1, c) MRF (Cartus et al., 2014), d) TCM-1 (Saatchi et al., 2011b), and e) TCM-2 (Baccini et al., 2012). All maps have been aggregated to 1km spatial resolution for comparison.

The total AGBC estimated by the MEX-1 map for the year 2008 was 1.69 Pg C (21.6 t C ha⁻¹), which agrees with the national estimations of 1.68 Pg C reported to FAO (FAO, 2010b), but very different from TCM-1 and TCM-2 (2.24 and 1.95 Pg C respectively). If the LUV mask is used then the estimate was 1.47 Gt C, which is very close to the MRF map estimate (1.53 Gt C). Some of differences between TCM-1 and TCM-2 have previously been discussed (Mitchard et al., 2013). When comparing these pan-tropical maps, the MRF map, the MEX-1 map and the in-situ data, the different temporal coverage might not be sufficient to explain the differences. Both tropical carbon maps (TCM-1 and TCM-2) present very high values of AGBC per ha, which strongly disagree with INFyS ground measurements.
The AGBC in-situ INFyS data comes from a large systematic stratified sampling inventory design over Mexico and it is assumed to be the most representative of the AGBC real distribution in this study. In order to compare the AGBC estimations of these maps and the in-situ data, the locations of the in-situ plots are used to extract the predictions from each map and generate AGBC histograms (Figure 42).

The MEX-1 map presents similar results to the MRF map in terms of spatial distribution and stocks of AGBC. Both used the in-situ INFyS dataset as AGBC reference data, but this study used Maximum Entropy algorithm to upscale the measurements while MRF used Random Forest. MRF has a smaller RMSE than MEX-1, but the MRF map tends to overestimate small AGBC values while high values are underestimated. This is apparent when comparing the histograms of AGBC, as MRF has a very narrow distribution in comparison to the INFyS in-situ dataset and the MEX-1 map (Figure 42). MEX-1 histogram represents the variation in the INFyS in-situ data much more realistically than any other map examined here.

The correlation between the frequencies of the INFyS dataset and the frequencies of MEX-1 (using the same bins) is 0.76, which is much higher than the correlation of INFyS with MRF, TCM-1, and TCM-2 frequencies (0.62, 0.42, and 0.04, respectively) (Figure 42). MEX-1’s histogram distribution better matches the INFyS in-situ data in comparison to any other map.

The two tropical carbon maps (TCM-1 and TCM-2) have similarly high AGBC per ha, which exceeds the AGBC expected in Mexico according to the INFyS field plots. Dividing the histogram into quantiles shows that 50% of the occurrences for TCM-1 and TCM-2 are above 50 t C ha\(^{-1}\), although the INFyS in-situ data suggest no more than 13% (Figure 42).
Figure 42 a), b), c) & d) Histograms of carbon maps predictions. Dash line: INFyS in-situ plot data histogram; e) Lower limit of histogram quantiles (same number of occurrences per bin). f) Correlation between INFyS histogram frequencies and maps frequencies (using the same 1 t C ha⁻¹ bins). INFyS location points were used to extract values from the carbon maps and produce their respective histograms.

The RMSE of MEX-1 is slightly higher than in MRF but the AGBC distribution found in the in-situ data is better represented by MEX-1, especially for the highest and lowest AGBC ranges. As observed in Figure 42 and Figure 43, areas where high AGBC is expected according to INFyS ground data consistently have a lower estimation in the MRF map than in MEX-1, and areas where low values are expected the estimation of the MRF map is higher than the one in MEX-1. However, when comparing the maps specifically generated for Mexico (MEX-1 and MRF) to the TCMs (TCM-1 and TCM-2) the differences are considerable.
Figure 43 Differences mean AGBC between MEX-1 and MRF at 250 m spatial resolution. Warmer colours indicate that MEX-1 presents higher carbon stock while cooler colours indicate that MRF has a higher estimation.

Moran’s I index tests at state level (Figure 44) showed that all maps present different spatial autocorrelation index values (all p-values < 0.001). Moran’s I Index ranges from -1 to 1 with positive values indicating spatial clustering (high AGB values cluster near other high values, and low AGB values cluster near other low values), and negative values indicating spatial dispersion. As expected due to the spatial autocorrelation of AGB, all Moran’s index values were positive indicating different degrees of spatial clustering. Small states in the centre of the country present the larger differences between map products. The states in the Yucatan peninsula present almost identical index for the MEX-1 and MRF maps. MEX-1, MRF, and TCM-2 present similar relative values of Moran’s I index in most of the states, while TCM-1 presents several discrepancies. The remote sensing imagery used in each of these studies is the main responsible for these trends in spatial clustering.
Figure 44 Moran's I Index within state by AGB map. Note: Different size windows were used per state to compute the index (due to the large different in size among states). Therefore, index values are comparable per state among map products, but not among states.

7.3.2. Comparison at Biome and Ecoregion level

The LUV layer was used as forest mask with all the AGBC maps. Average AGBC values per biome and ecoregion (Olson et al., 2001) were then extracted.

TCM-1 and TCM-2 present higher average AGBC values for all biomes. INFyS in-situ data, MEX-1 and MRF agree in all biomes with the exception of Mangroves, where INFyS data presents slightly higher average AGBC than MEX-1 or MRF but still lower than TCM-1 and TCM-2 (Figure 45). The reason for this difference was discussed in the previous chapter, as uncertainty increases in those areas due to the soil moisture effect on the radar backscatter. AGBC estimation over mangroves does not fully agree with any of the products analysed in this chapter. Mapping the AGBC of mangroves without the use of SAR imagery (which is affected by soil moisture), may be the way to proceed. However, this will probe to be most challenging as SAR imagery has demonstrated in this study to have the highest correlation to AGBC in comparison to optical imagery or
topographic variables. The use of a land cover to mask out or independently calibrate mangrove forests might also be an alternative.

Figure 45 Average AGBC values per Biome for INFyS dataset, MEX-1, MRF, TCM-1, and TCM-2

The MEX-1 map presents the highest accuracy at ecoregion level (R²=0.54) followed by MRF (R²=0.48) (Figure 46). It can be observed that the TCMs have very large discrepancies with INFyS in almost every ecoregion (Figure 46) with estimations even 4-5 times higher in some ecoregions.

MEX-1 and MRF were generated using the INFyS data as training dataset. Therefore similitude was anticipated to the INFyS estimates. However, the large differences between those maps and the pan-tropical maps, with estimations 5 fold higher than the in-situ data for some ecoregions, are difficult to explain. The different temporal coverage of the maps it is not sufficient to explain these differences. The reason for these should be related to the calibration data, the EO data, the allometry and/or the geographical extent in which the algorithms were used by these studies.
Figure 46 Left: Correlation between the average AGBC values estimated from the maps and the INFyS data at ecoregion level (n = 25). Linear trend lines are forecasted forwards and backwards for easier comparison. Dashed red line: y = x. Right: Average AGBC values per ecoregion for MEX 1, MRF, TCM-1, and TCM-2. Columns correspond to the INFyS values. Only ecoregions completely overlapped by all maps are included in the analysis.
7.3.3. Exploring source of uncertainties

The maps present differences that can be associated to the different source of uncertainties described in the error propagation equation used in this thesis ($\varepsilon_{\text{measurement}}$, $\varepsilon_{\text{allometry}}$, $\varepsilon_{\text{sampling}}$, and $\varepsilon_{\text{prediction}}$) (Equation 12). This section explores the EO datasets used as predictor variables, $AGB$ reference data used for calibration, the allometric models used to estimate $AGB$, and the different methods used for upscaling $AGB$ across the landscape. The main differences are summarized in Table 13, which can be used as reference for the following sub-sections.

Table 13 Comparison of AGBC maps based on EO datasets, $AGB$ reference data, allometric models, and the scale of the calibration

<table>
<thead>
<tr>
<th>Map</th>
<th>AGB data</th>
<th>Allometry type</th>
<th>EO predictors*</th>
<th>Ratio plot/pixel area</th>
<th>Pixel size (m)</th>
<th>Algorithm** / Scale of calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEX-1</td>
<td>In-situ</td>
<td>Regional tree allometry</td>
<td>O,S,D</td>
<td>2.6%</td>
<td>250</td>
<td>ME / National</td>
</tr>
<tr>
<td>MRF</td>
<td>In-situ</td>
<td>Regional tree allometry</td>
<td>O,S,D,Ot</td>
<td>ca.16%</td>
<td>30</td>
<td>RF / National</td>
</tr>
<tr>
<td>TCM-1</td>
<td>GLAS</td>
<td>Continental plot allometry</td>
<td>O,D,Ot</td>
<td>&gt; 2%</td>
<td>1000</td>
<td>ME / Continental</td>
</tr>
<tr>
<td>TCM-2</td>
<td>GLAS</td>
<td>Generalized tree allometry</td>
<td>O</td>
<td>&gt; 8%</td>
<td>500</td>
<td>RF / Global</td>
</tr>
</tbody>
</table>

*Optical (O), SAR (S), DEM (D), Other (Ot); **MaxEnt (ME), Random Forest (RF)

EO datasets

MEX-1 and MRF were generated using different EO datasets, spatial resolutions (250 m vs 30 m) and algorithms (MaxEnt vs Random Forest). However, as seen before the amount and spatial distribution of the $AGB$ predictions are very similar when aggregated to the same scale (250 m) (Figure 43). This section hypothesizes that the use of different input EO datasets from the same type (e.g. optical) do not significantly change the final $AGB$ map due to the robustness of the approach. Therefore, this new map should show similar quantities and distribution.

This was assessed by generating a new AGBC map at 1 km spatial resolution using the same data as in the previous chapter with exception of the optical data. This new map was generated using ALOS PALSAR, SRTM and SPOT VGT optical data from Copernicus - ESA (NDVI, FAPAR, LAI, and FCOVER) instead of MODIS (henceforth MEX-2). The contribution of each type of sensor to generate MEX-2 was analysed following the same procedure as in the previous chapter. As expected, the contribution of
the different optical, SAR and DEM sensors follows the same pattern as in MEX-1, even though different optical imagery is used (Copernicus-SPOT VGT instead of MODIS) (Figure 47).

Figure 47 Percent contributions to the AGB MEX-2 map by sensor per biomass range

The amount and spatial distribution of both maps is very similar, having the MEX-2 map 1 t C ha\(^{-1}\) higher average \(AGBC\) at pixel level. This difference is further reduced to 0.93 t C ha\(^{-1}\) at state level (Figure 48). Moreover, the total \(AGBC\) estimated at country level for MEX-2 was only a 5% higher than MEX-1 (1.78 Pg C vs 1.69 Pg C). The same calibration data and algorithm were used in both maps. A different input optical data was used to generate MEX-2, but the difference between the maps is 5% in total \(AGBC\), which shows the robustness of the approach as long as three types of datasets are used (optical, L-band SAR, and DEM).
Figure 48 AGBC map for Mexico using optical MODIS datasets, MEX-1 (upper left) and Copernicus-SPOT datasets, MEX-2 (upper right) at 1 km spatial resolution. The maps are masked by the forest area mask generated in the previous chapter. Differences in average AGBC at 1 km pixel level (lower map). Warmer colours indicate MEX-2 has higher average AGBC while cooler colours indicate that MEX-1 has higher estimation.
MEX-1 uses 250 m remotely sensed images (compared to 1000 m in the TCM-1, 500 m in TCM-2, and 30 m in the MRF). MEX-1 and MRF used SAR, Optical and DEM data. Both use L-band imagery as SAR dataset. TCM-1 used radar Ku-band instead. Different MODIS optical products at different resolutions were used by all the studies with the exception of MRF that used Landsat optical data. Nevertheless, all datasets have some limitations to estimate AGB. The use of datasets that are more or less correlated with AGB will have an impact in the prediction error ($\epsilon_{\text{prediction}}$). As seen in chapter 5, the use of optical, L-band SAR and DEM datasets types combined provides the best results in comparison to single dataset or the combination of two. As L-band has a wavelength that physically interacts more with forest AGB components than Ku-band (with no former known correlation to AGB), this error should be smaller for MEX-1 and MRF as the model should perform better estimating AGB. Additionally, TCM-1 showed a different trend of spatial clustering than the other AGB maps. This could be the result of using imagery non-correlated to AGB such as the Ku-band which generates a different spatial pattern.

**Map AGB Reference Data (in situ-derived AGB vs GLAS-derived AGB)**

The AGB reference data used by the different maps to calibrate the algorithms differs. Two types of reference data were used:

- In situ-derived AGB (INFyS ground plots) by MEX-1, MEX-2 and MRF
- GLAS-derived AGB (Profiling LiDAR footprints) by TCM-1 and TCM-2

GLAS LiDAR metrics have to be further processed to estimate $H_L$ and AGB. As seen in Figure 42, the maps using GLAS LiDAR footprints as reference data (TCM-1 and TCM-2) show comparable results as also seen in Mitchard *et al.* (2013), but a different histogram distribution than INFyS in-situ data at the same sampling points.

In MEX-1, MEX-2 and in the MRF map, an INFyS plot dataset with 0.16 ha of sampled area (per 1 ha primary unit) is used as training data for 250 m (6.25 ha), 1000 m (100 ha) and 30 m (0.09 ha) resolution pixels, respectively. In TCM-1 and TCM-2 a dataset of ~0.4 ha GLAS LiDAR footprints were used to calibrate imagery with 1000 m (100 ha) pixels. Only pixels with at least 5 footprints were used. The percentage of area covered by the plot/footprint in relation to the pixel size is for MEX-1 2.6% if accounting only sampled plot area, for MEX-2 0.16%, for TCM-1 at least 2%, and for TCM-2 at least 8% (Figure 39). MRF uses the average value of the all the pixels covering the 1 ha plot to
calibrate the model as the INFyS plot is several times larger than the 30 m pixel. Therefore the calibration is done at least 1 ha pixel size (equivalent to at least 100m resolution). Therefore the sampling intensity for MRF is < 16%.

TCM-1 and TCM-2 use the average value of the footprints falling inside the pixel, which can be 5 or more. The training data is a key issue for the TCM-1 and TCM-2 when training the algorithm with medium-coarse pixels. MODIS land cover product MCD12Q1 (Friedl et al., 2010) with 500m resolution was used by TCM-1 to discard footprints falling on non-forest land cover classes before calibration. However, the sub-pixel variability in coarse pixels can be very high, so the \( H_L \) estimated from those footprints might refer to forest, bare soil, crops, a house, or any other feature in the landscape. All these approaches face problems related to the \( AGB \) variability within the pixel, due to the difference between the sampled areas of the calibration plots and the area of the pixels \( (\epsilon_{\text{sampling size}}) \). This uncertainty could be reduced using larger sample plots (e.g. 1 ha sampled area plots) to reduce the error originated from the sub-plot variability as suggested by previous studies (Saatchi et al., 2011a, Montesano et al., 2014).

As observed in Figure 49, the \( AGB_C \) estimated by the in situ INFyS data and the GLAS footprint data significantly differ even when compared at different scales. At larger scales the natural variability is lower than at the fine scale, but the differences are still substantial. The larger differences occur on the Yucatan peninsula, where the GLAS dataset consistently underestimates the \( AGB_C \) in comparison to the INFyS in-situ data with differences ranging from 87.5 t C ha\(^{-1}\) to >100 t C ha\(^{-1}\). This can be related to the canopy height and allometric models used to estimate \( AGB \) from the GLAS dataset, indicating that the Yucatan peninsula presents a different regional allometry. This seems to disagree with the actual map predictions of TCM-1, which present higher \( AGB_C \) values that the quantities shown by the GLAS reference data. Therefore, another factor has a stronger effect on the map predictions of TCM-1.

INFyS ground data used by MEX-1 and the MRF map consist of non-destructive measurements of diameter and tree-height, which error \( (\epsilon_{\text{measurement}}) \) averages out to 10% at stand level (Chave et al., 2004, Mitchard et al., 2011). In contrast, TCM-1 uses three models to estimate \( H_L \) from the GLAS LiDAR footprints, while TCM-2 uses a single multiple regression model to directly estimate \( AGB \) from the GLAS LiDAR footprint metrics. TCM-1 estimates \( H_L \) using Lefsky’s models (Lefsky, 2010). These canopy height
models were developed using data from the U.S. and Brazil, but then used over the whole tropical region. The RMSE for those models was ±4.9 m for needleleaf forest, ±3.3 m for broadleaved forest, and ±6.9 m for mixed forest. The large RMSE in the canopy height models could lead to very large errors in the estimation of AGB by means of allometry. The AGB multiple regression model used by TCM-2 presents a standard error of 45.2 t ha\(^{-1}\) (Baccini et al., 2012).

An accurate estimation of canopy height or AGB from GLAS footprints in smooth and homogeneous forest areas is feasible, but in areas with dense forest cover, high relief or heterogeneous forest cover the estimation is complex and inconsistent (Duncanson et al., 2010). The latter, describes most of the forest areas in Mexico, as with the exception of the forest in the Yucatan peninsula, forest areas in Mexico are predominantly heterogeneous and covering mountain ranges. Forest height estimates from GLAS footprints metrics over sloped terrains might have large biases, causing overestimation of the calculated tree height (Mitchard et al., 2013). In the pan-tropical maps (TCM-1 and TCM-2) footprints falling in sloped areas were filtered out from the analysis. However this was done using a medium resolution (90 m) elevation layer (SRTM) which does not ensure the reliability of the filtering method. \(H_L\) estimated from GLAS footprints over Mexico should therefore be used with caution as those might be largely overestimated. In this context, the errors from the \(H_L\) models in TCM-1 and from the GLAS multiple regression model in TCM-1 will increase the value of the \(\varepsilon_{measurement}\) and partially to \(\varepsilon_{allometry}\).
Figure 49 Comparison between AGBC reference data estimated from INFyS in-situ measurements and from GLAS footprints measurements at different levels (Hexagons of 10, 50 and 100km) over Mexico. At least 5 plots and 5 GLAS footprints per hexagon are required to be displayed in the maps.
**Allometry**

Allometric models are used to estimate AGB from the training data (INFyS plots or GLAS footprints). These models are constructed as power functions, so a small error on the predictor variables (e.g. diameter, height) could lead to large errors in the estimation of AGB for a given area (Henry, 2010). In these studies, 2 types of allometries are found: a) tree-level allometries relating tree parameters such as D to tree AGB; and b) footprint-level (or plot-level) allometries that relate plot-level parameters such as mean canopy height to plot AGB.

The non-destructive measurements (tree diameter and height) from the INFyS dataset were used with a total of 339 tree biomass allometric equations by CONAFOR to estimate tree-level AGB following a protocol for allometric model selection (CONAFOR, 2012). This protocol prioritises the use of species-specific models within their diameter range of applicability. Tree level AGB measurements were aggregated to estimate AGB at plot level. This dataset was used by MEX-1 and the MRF map.

Three continental allometric models were used to relate that GLAS footprint $H_L$ to AGB in the TCM-1 map. Ground data from 493 plots overlaying GLAS footprints was used to estimate plot-level AGB by aggregating tree-level AGB estimated using the 3-parameter pan-tropical allometric equations (Chave *et al.*, 2005) with $H$, $D$, and wood density. From this in-situ AGB dataset, 298 plots were used to create the American continental model relating $AGB$ to $H_L$ estimated from the GLAS LiDAR footprints in TCM-1 (Saatchi *et al.*, 2011b). The use of a single allometric model for a whole continent might be an important source of error ($\varepsilon_{allometry}$). Different biomes and forest types present different tree allometries (Chave *et al.*, 2005, Feldpausch *et al.*, 2011). The plot level allometric relationships between AGB and canopy height differ by biome and even by altitudinal gradient as seen in chapter 5. The ground plots used in TCM-1 to develop the American continental allometric model were mostly located in the Amazon forest region (Saatchi *et al.*, 2011b). The use of that model to estimate AGB from the GLAS footprints covering Mexico might lead to large errors.

The canopy height estimated from GLAS footprints and the canopy height measured in the INFyS ground plots cannot be directly compared. The canopy height estimated from GLAS footprints is $H_L$, while the in-situ data is $H$. The plot-level allometric model for the American continent developed by Saatchi *et al.* (2011b) was used to estimate AGB. The
estimated $H_L$ from the GLAS LiDAR footprints was used as predictor for the model. The estimated $AGB$ was then converted to $AGBC$ using the 0.48 $AGB$-to-Carbon ratio (Figure 50). Then, the model developed by Yu (2013) was used to convert the $H$ measured from the INFyS ground data into $H_L$. When comparing those GLAS estimates of $AGBC$ and $H_L$ to the ground measurements from the INFyS dataset, $AGBC$ GLAS estimations are generally lower, especially over the Yucatan peninsula (Figure 50). The $H_L$ histograms are remarkably similar, while the $AGB$ histograms greatly differ. Moreover, average $AGBC$ for the INFyS dataset almost doubles the average $AGBC$ from the GLAS dataset (25.2 t C ha$^{-1}$ vs 14.8 t C ha$^{-1}$, 70% difference). Conversely, $H_L$ is just slightly lower in the GLAS footprints with only 1.4 m lower canopy (22% difference) than the average $H_L$ for the INFyS datasets. This result shows that, even though the GLAS sensor measures similar $H_L$ values when compared to the ground data (note that the RMSE for the $H_L$ models range from ±3.3 m to ±6.9 m), the use of a continental allometric model to calculate $AGB$ generates a different result in comparison to the ground data (Figure 50).
Figure 50 Spatial distribution of a) INFyS plot $AGBC$ values, b) GLAS footprint $AGBC$ values, c) INFyS plot $H_L$ values, and d) GLAS footprint $H_L$ values. Histogram comparison of both datasets for values of $AGBC$ (upper right graph) and $H_L$ (lower right graph).
In order to make a direct comparison between the datasets, the overlapping pixels of the 1,000 m raster created using the GLAS footprints are compared to the values of the overlapping in-situ INFyS plots (type I overlap) and to the 500m-buffer INFyS plots (type II overlap). The results show a significant negative bias in the estimation of $AGBC$ for the Yucatan peninsula (-29.8 t C ha$^{-1}$), while in the rest of the country the bias is positive (32.2 t C ha$^{-1}$) (Figure 51).

Figure 51 $AGBC$ estimated for GLAS footprints compared to $AGBC$ estimated by in-situ INFyS plots in a) the Yucatan Peninsula and b) the rest of Mexico (type I overlap, 130 plots) and c) the Yucatan Peninsula and d) the rest of Mexico (type I + type II overlap, 424 plots)

The model developed by Yu (2013) was also used to convert the $H$ measured from the INFyS ground data into $H_L$. Then, the allometric model developed by Saatchi et al. (2011b) for the American continent was used to estimated $AGBC$ for each plot. When comparing the $AGBC$ estimated using Saatchi et al. (2011b) model to the INFyS $AGBC$ original value from the field, it can be observed the same type of error as with the GLAS footprints. A very high relative error ($\pm 74.2\%$) and negative bias (-8.9 t C ha$^{-1}$) are
observed, which contrast with the ±15.8% relative error of the model reported for the whole continent by Saatchi et al. (2011b) (Figure 52).

Figure 52 Scatterplot of AGBC estimations using the allometric model for the American continent developed by Saatchi et al. (2011b) (INFyS $H_L$ data as predictor variable for the model) versus INFyS AGBC original estimation

Part of this large error (Figure 51 and Figure 52) can be associated to the $H_L$ estimation by means of the Lefsky (2010) GLAS canopy height models, or to the Yu (2013) model to convert between $H$ and $H_L$. The remaining error is explained by the different structure, species composition and wood density between the forest in Mexico and the forest in the Amazon region. The ground data used for developing the allometric model was located in the Amazon. These two regions present different allometric relationships between AGBC and canopy height, with the data suggesting that Mexican forest have generally lower AGBC and lower canopy heights than Amazon forests, but Mexican forests present higher values of AGBC at lower canopy heights than the Amazon forests. The TCM-2, as previously seen, presumably presents a similar type of modelling error, as AGBC was estimated from GLAS footprints by means of a single multiple-regression model for the whole tropical region. Moreover, TCM-2 ground estimations used to calibrate the multiple-regression model are based in the 2-parameter pan-tropical tree level allometric equation (Chave et al., 2005) using only D and wood density, which have a tendency to estimate higher AGB values than the 3-parameter pan-tropical equation used in TCM-1,
which also includes $H$ (Chave et al., 2005, Banin et al., 2012). This can largely explain why TCM-2 has higher $AGBC$ estimations than TCM-1, even though they use similar GLAS calibration data.

Allometric relationships between biophysical parameters, such as canopy height and $AGB$, have been found to vary among regions (Keith et al., 2000, Chave et al., 2005, Feldpausch et al., 2011). The use of a single plot-level allometric model having only canopy height as predictor variable, and therefore ignoring the allometric variations between and within regions, brings large errors ($\epsilon_{allometry}$) in the estimation of $AGB$ from GLAS footprints.

**Scale of algorithm calibration**

The algorithm used might also play an important role explaining the differences among the maps. MEX-1 and MRF (Figure 43) generated similar results even though were obtained using different algorithms and EO data. In those cases, the algorithm did not have a significant influence, but the scale or geographical extent at which the algorithms are calibrated can be relevant. The calibration data sampling might lack representativeness of the true distribution of $AGB$ in Mexico ($\epsilon_{prediction}$).

The $AGBC$ derived by GLAS footprints was upscaled to the whole continent for the TCM-1, and to the whole tropical region for TCM-2. In the case of TCM-1, the amount of footprints over the Amazon accounted for 85% of the footprints used as input for the American continent map while the footprints over Mexico accounted only for the 5% of the total, making the calibration of the algorithm mostly based on Amazon data (Saatchi et al., 2011b). Thus, the weight of GLAS-derived $AGBC$ footprints over Mexico in the algorithm calibration of TCM-1 was relatively small. As the MODIS imagery used for calibration saturates at relatively low biomass once the canopy is closed, the high values of $AGB$ from the GLAS footprints in the Amazon were assigned to pixels in Mexico with similar canopy closure, even though the amount of $AGB$ in Mexico is significantly lower than in the Amazon. Therefore, the representativeness of sampling footprints of the true distribution of $AGB$ in Mexico (accounted for by $\epsilon_{prediction}$) was not adequate. This explains the large differences between the $AGBC$ GLAS-derived estimations over Mexico and the TCM-1 map estimations.
The same can be said for the TCM-2 as the algorithm was trained to upscale the data over the whole tropical region (Baccini et al., 2012). Therefore, a more regional or biome-specific algorithm calibration approach might generate better results.

### 7.4. SUMMARY AND DISCUSSION

This chapter explored the differences between carbon stock assessments done in Mexico against in-situ data. The substantial differences reported at different spatial levels reveal the challenges to estimate $AGBC$ stocks country-wide. The TCMs (TCM-1 and TCM-2) present discrepancies in the amount and spatial distribution of carbon stocks in Mexico when compared to the in-situ forest inventory data at different scales (pixel, ecoregion, biome, and country level), while MEX-1 and MRF agreed with INFyS estimates. The divergent $AGBC$ estimates of TCM-1 and TCM-2 when compared to in-situ data, agree with the findings of Mitchard et al. (2014), despite Saatchi et al. (2015) critique.

The TCMs are widely accepted and used as input in several research studies (e.g. Harris et al., 2012, Liu et al., 2015, Avitabile et al., 2016). Understanding why these maps do not agree with in situ data is essential. TCM-1 and TCM-2 presents larger estimates of $AGB$ than any other map over Mexico. $AGB$ calibration data (in situ-derived vs. GLAS-derived) is crucial in explaining the differences. While MEX-1 and MRF are locally calibrated using field inventory data, the TCM-1 and TCM-2 are globally calibrated using $AGBC$ estimated from GLAS LiDAR footprints. The consistently higher estimations of TCM-1 might explain the larger total loss of $AGB$ in tropical areas estimated by Liu et al. (2015) with an approach calibrated with TCM-1, in comparison to Pan et al. (2011), which used ground measurements (Figure 36).

The total carbon stocks estimated by MEX-1 (1.69 Pg C) agrees with data reported to FAO (FAO, 2010a). The products developed specifically for Mexico (MEX-1 and MRF) better represent the amount and spatial trends of $AGBC$ stocks in the country when compared to the in-situ data. The differences between both maps are below a 10% of the total $AGBC$. MRF presents a lower RMSE than MEX-1, but the later better agrees with the histogram distribution of the in-situ data.

The INFyS dataset is assumed to be the most accurate dataset in this thesis but it also has limitations. The INFyS database might underestimate $AGBC$ for certain forest types as trees with less than 7.5 cm in diameter are not measured. The number of trees not being
measured in humid tropical forest might be insignificant in terms of $AGBC$, but this might not be the case for tropical dry forest where trees with diameters below 7.5 cm can account for 26-40% of the total $AGBC$ in the plot (Jaramillo et al., 2003).

$AGBC$ derived by INFyS ground plots and $AGBC$ estimated by GLAS footprints used to calibrate TCM-1 were directly compared at different aggregation levels. Differences above 87.5 t C ha$^{-1}$ were found in the Yucatan peninsula. The reason for these differences is the allometry used by TCM-1. The use of a plot-level allometric model developed in another region (i.e. Amazon) in TCM-1, generates large errors in the estimation of $AGBC$ for Mexico up to ±74.2% of rel. RMSE in comparison to ground data. The average canopy height estimated from GLAS footprints (used as predictor in the allometric model) and canopy height from INFyS plots agrees when compared, which indicates that allometry is the main cause for these differences, as this model does not account for the variation in the allometric relationship between regions. The use of tree-level allometry in TCM-2 without $H$ as predictor variable as explained by Chave et al. (2005) and Banin et al. (2012) appears as the main reason for the very high estimations of $AGBC$ in TCM-2 (Mitchard et al., 2013).

Conversely, the $AGBC$ estimations from the GLAS footprints over Mexico do not seem to agree with the TCM-1. The calibration of the algorithm to upscale $AGBC$ data over the whole American continent in TCM-1 (Saatchi et al., 2011b) causes that the predictions are mostly based on training data from the Amazon region. Additionally, the effect of using Ku-band on TCM-1 might also introduce unknown errors when upscaling the $AGBC$ estimations. The use of a single regression model using only optical data as predictor to upscale the $AGBC$ measurements to the whole tropical area in TCM-2 (Baccini et al., 2012) might have the same effect.

The results of this chapter suggest that the use of regional allometry and algorithm calibration approaches that take into account regional variations are the way forward to improve these products.
Chapter 8

Discussion, Research Contributions and Conclusions
8. DISCUSSION, RESEARCH CONTRIBUTIONS AND CONCLUSIONS

8.1. INTRODUCTION AND AIMS

This chapter identifies the original contributions of the research and presents the major findings. A general discussion and conclusion from previous chapters is summarize here addressing the main research questions of this thesis. Limitations of the research and future research to be built from this study are also presented.

8.2. ORIGINAL RESEARCH CONTRIBUTIONS

This thesis advances the study of AGB mapping across wide areas by means of original research contributions.

Chapter 5 studied AGB estimations of in-situ inventory plots in Mexico in terms of spatial distribution, forest types, biomes and topographic gradient, and found different trends in AGB distribution across Mexico. Allometric models were also developed by elevation range to study how the allometric relationship between AGB and H varies across the altitudinal range in Mexico. The chapter assessed the correlation of layers from MODIS, ALOS PALSAR and SRTM to AGB, and by means of a sensitivity analysis on a MaxEnt algorithm, found the best combination of different spatial datasets to predict AGB.

Chapter 6 demonstrates the use of a locally calibrated MaxEnt approach using in-situ data, MODIS, ALOS PALSAR and SRTM to map forest probability, AGB and its associated uncertainty across the entire country of Mexico (approximately 1.97 million km²) at 250 m resolution. The results were validated using an independent dataset, and the agreement of the map estimates to the in-situ estimates was analysed at municipality and state level. Jackknife analyses were used to find the most important spatial predictors and to assess which predictors contain more information not included in any other predictor. In addition, it was the first time that this importance contribution analysis was designed to find and report the contribution of each spatial dataset per biomass prediction range. The spatial representation of the uncertainty also allowed to analyse the uncertainty
of the estimations by AGB range and by forest type. An independent validation was performed to assess the accuracy of different forest masks based on the same forest definition but originated from different sensors. The chapter also reports on how the selection of forest mask can impact the calculation of total carbon stocks at country level.

Biomass Carbon maps in Mexico were compared to in-situ forest inventory data in Chapter 7. Each map was generated using different datasets and approaches, which have resulted in substantial differences in the amount and distribution of AGB stocks in Mexico at pixel, ecoregion, biome, and even country level. GLAS-derived AGB (used as calibration by TCM-1 & TCM-2) were also compared to in-situ derived AGB (used by MEX-1 & MRF), which allowed to find what the main sources of these differences are.

8.3. GENERAL DISCUSSION

This study demonstrated that regional variations of forest ecosystems play an important role when mapping AGB at large scales. Trends on AGB distribution across Mexico were found to be related to geographical location, with AGB increases from West to East and from North to South. The average AGB was also found to vary per biome and across the elevation range in Mexico. The highest values of AGB occur at the lowest and at the highest elevation ranges, with an evident increasing trend at intermediate altitudes. This result disagree with previous studies in Ecuador, Peru, Bolivia, and Kalimantan (Girardin et al., 2014, Buma and Barrett, 2015, Moser et al., 2008, Takyu et al., 2003) where AGB tend to decrease with elevation and is linked to climatic and edaphic factors, geological substrate, nutrient content and species richness.

In this study the increasing AGB trend can be explained due to changes on the allometric relationship between canopy height and AGB at plot/pixel level per biome and across the topographic gradient. This variation might be related to increases in annual precipitation with elevation and therefore the less likelihood of droughts, but it could also be related to the lower impact of human interactions as Wang et al. (2001) found in another study in China. The allometric variations between AGB and H found in this study have large implications for studies using plot level allometry solely based on canopy height on pixels or GLAS footprints to estimate AGB reference data such as the TCMs (Saatchi et al., 2011b, Baccini et al., 2012).
A regionally calibrated approach with the best available information from SAR (ALOS PALSAR) and optical imagery (MODIS), DEM information (SRMT) and AGB reference data calculated from species specific and regional tree allometry (INFyS) is used to improve AGB retrievals nationwide. A set of 250 m resolution national maps of AGB, its associated uncertainty and forest probability were generated using a MaxEnt approach. The synergistic use of the three datasets showed better accuracy and lower relative error than using a single sensor or combining two sensors.

The correlation of ALOS PALSAR HV polarization to AGB was found to be the highest followed by MODIS MIR. The contribution of ALOS PALSAR saturates at approximately 150 t ha⁻¹, which agrees with the literature as L-band SAR backscatter has the highest AGB saturation of all sensors currently in orbit (Imhoff, 1995, Carreiras et al., 2012, Lucas et al., 2010, Mitchard et al., 2009, Naesset, 2007, Dobson et al., 1992). Additionally, optical MODIS MIR seems to contribute to AGB estimations beyond its theoretical saturation point as seen in previous studies (Baccini et al., 2012, Kellndorfer et al., 2011). DEM information was also shown to be an essential contribution to the retrieval of the high AGB ranges in Mexico with information not contained in the other datasets which agrees with other studies (Bispo et al., 2014). This can ultimately be explained by the increasing AGB trend with elevation found in this thesis.

In the case of forest cover mapping, a forest cover map nationally calibrated using the combination of EO datasets (optical, SAR, DEM) presented better accuracy than widely used forest area products globally calibrated and generated from SAR and optical imagery (i.e. MODIS VCF, K&C-FNF). Sexton et al. (2015) demonstrated the effect of using different forest definitions to generate forest masks from remote sensing data, estimating the discrepancies in global forest extent among eight commonly used satellite products to be up to 13% globally. This thesis however showed differences up to 33% in forest extent nationally when using forest masks based on the same forest definition but different sensor technology. This is equivalent to a 23% difference in carbon stocks for the country. The large differences in carbon stocks found in this study are relevant to international mechanisms aiming to preserve or enhance forest carbon stocks at national level, and should be taken into account when designing MRV programs.

The uncertainties found in the AGB mapping approach presented in this dissertation do not fully meet the expected accuracies from the BIOMASS mission (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$^{-1}$ at 200m resolution), which is planned for launch in 2020 (Le Toan et al., 2011, ESA, 2012). The results suggest that using training plots that match the resolution of the remote sensing imagery should improve the results by reducing the error originated from the sub-plot variability as suggested by previous studies (Saatchi et al., 2011a, Montesano et al., 2014).

Current maps of carbon stocks present large discrepancies in the amount and spatial distribution of AGB estimated in Mexico. The previous carbon map in Mexico using INFyS as calibration data (MRF) has a smaller RMSE than the map from this thesis (MEX-1), but the MRF map tends to overestimate small AGBC values while high values are underestimated. This is apparent when comparing the histograms of AGBC, as MRF has a very narrow distribution in comparison to the INFyS in-situ dataset and the MEX-1 map. MEX-1 histogram represents the variation in the INFyS in-situ data much more realistically than any other map examined here.

Widely used TCMs based on GLAS-derived AGB reference data present the largest discrepancies in comparison to maps generated using ground forest inventory data (MEX-1 & MRF). This thesis demonstrated that the differences between both calibration-datasets are related to the allometries used with GLAS-derived AGB, but that the differences between the final maps are also related to calibrating the algorithm over large scales (above continental) instead of a regional calibration. As a result, the TCMs show a completely different histogram function in Mexico when compared to the forest inventory ground data, having very high estimations of AGB compared to in-situ data. The results suggest that the use of regional allometry and algorithm calibration approaches that take into account regional variations, are the way forward to improve these products.

### 8.4. CONCLUSIONS

This dissertation studied different aspects of AGB mapping across wide areas, from the variability on the allometric relationships occurring between biomes and across the topographic gradient, the synergistic combination of spatial datasets, the effect on carbon stocks from the selection of different forest masks, to the discrepancies among carbon products. The research questions, set in chapter 3, and answers to those are summarize as follows:
Question 1. Does the allometric relationship between canopy height and AGB at plot level vary across biomes and the topographic gradient? How does this relationship vary across the topographic gradient?

The ANCOVA of INFyS data showed that AGB (dependent variable) for a given $H$ (covariate) varies significantly with biome, elevation (categorical independent variables), and with interaction amongst these factors (p-value < 0.001 in all cases).

This study also found that there is an increasing trend in the model intercepts and a slight decreasing trend in the model slopes of the allometric relationships between AGB and $H$ across the elevation gradient. This results in higher amount of AGB per unit of $H$ at higher altitudes than at lower altitudes. Forests with the average canopy height in Mexico (7.2 m) will have a 57% more AGB at higher altitudes. However, this does not occur across the whole range of $H$ as the allometric model slopes are more pronounced at the lowest altitudes (below 750 m). This scaling relationship at plot level between AGB and $H$ across the altitudinal gradient can explain the AGB altitudinal trend observed in this study.

Question 2. Which spatial dataset (Optical imagery, SAR imagery, and DEM) can better predict AGB across wide areas? Do topographic variables contribute to a better prediction of AGB distribution across the landscape? Is there an increase in the prediction power of the models if spatial predictors are combined in comparison to stand-alone dataset modelling?

Optical (MODIS), SAR (ALOS PALSAR) and DEM (SRTM) spatial datasets were used to assess the correlation of the signal retrieved by the EO datasets to in-situ measured AGB. The highest correlations were found for the ALOS PALSAR HV polarization and the MODIS MIR reflectance, while the lowest correlations corresponded to MODIS EVI and the topographic aspect.

Sensitivity analysis were then performed to assess the different combinations of spatial datasets to predict AGB. The results show that the use of at least two spatial datasets can substantially increase the accuracy and reduce the error ($R^2$ and rel. RMSE). The results however show that the combination of the three spatial datasets showed superior accuracy and lower relative error (0.31 and 58%) than the use of single dataset (0.12 - 0.19, and 62% - 74%) or two datasets (0.25 - 0.28, and 58% - 59%)
Question 3. What is the relative importance across the AGB range of Optical, SAR and DEM datasets when combined to estimate forest biomass stocks?

The contribution of each spatial dataset to the estimation of the AGB class probability layers was analysed. SAR (ALOS PALSAR) was the most important input layer to predict AGB for the most abundant AGB classes up to 100-120 t ha\(^{-1}\) with percent contributions in the range of 60% to 75%, and was still relevant up to 180 t ha\(^{-1}\) in the range 30% to 40%. Above 120 t ha\(^{-1}\) Optical (MODIS) becomes more important with 50% contribution. DEM (SRTM) contribution gradually increases from approximately 10% in the lower AGB ranges to 30-40% above 180 t ha\(^{-1}\). The decline in the contribution of ALOS PALSAR in the estimation for AGB above 100-120 t ha\(^{-1}\) is in agreement with the saturation effect that can be seen in the literature for L-band backscatter (Wagner et al., 2003, Mitchard et al., 2009). After this point the weight of the estimation fluctuates among products.

Question 4. To what extent forest cover products based on the same forest definition but generated from different sensors differ from each other? Does the combination of different types of spatial datasets (Optical, SAR, and DEM) increase the accuracy of forest masks? What is the effect of the selection of a forest area mask on the estimation of carbon stocks at national level?

Forest masks from optical (VCF\(_{10\%}\)), SAR (K&C-FNF and FNF\(_{14.5\text{ dB}}\)), and a combination of optical, SAR, and DEM (FP\(_{25\%}\)) were compared. The forest mask derived from the combination of different types of spatial datasets (FP\(_{25\%}\)) presented the highest overall accuracy (0.92) and \(\kappa\) (0.83). Forest masks derived from optical (VCF\(_{10\%}\)) and SAR (K&C-FNF and FNF\(_{14.5\text{ dB}}\)) exhibited lower overall accuracies (0.83, 0.87, and 0.89 respectively) and \(\kappa\) (0.66, 0.72, and 0.78 respectively).

When compared to the LUV dataset, other land cover types are misclassified as forest by the VCF\(_{10\%}\) as twice more often than FNF\(_{14.5\text{ dB}}\) and FP\(_{25\%}\). The VCF\(_{10\%}\) layer classifies almost the whole savannah and half the croplands, grasslands and pastures in Mexico as forest. FNF\(_{14.5\text{ dB}}\) and FP\(_{25\%}\) yield similar results, having the largest disagreements with the LUV map in cropland, grassland, pasture and shrub areas. The FNF\(_{14.5\text{ dB}}\) map has the largest disagreement with urban and non-vegetated areas in comparison to the other products. The FP\(_{25\%}\) map reduces the disagreement with the LUV map in shrub vegetation, and urban & non-vegetated land in comparison to the FNF\(_{14.5\text{ dB}}\) mask.
The AGB map with a forest mask originated from optical data (VCF10%) has 24.1 million ha more (33%) in forest extent than the map with a mask derived from SAR (K&C-FNF), and up to 0.36 Gt C higher (23%) total carbon stocks. This difference can be converted to 1.32 Gt CO2-e and an economic value of $12.2 billion. Even when using the same forest definition, forest masks originating from different sensors can have a significant effect on the total forest carbon stock estimated for a country.

Question 5. Where are the main discrepancies among current carbon maps over Mexico? What are their sources? To what extent does the use of reference data derived from GLAS footprints instead of reference data derived from forest inventories impact AGB mapping?

The total AGBC estimated for Mexico in this thesis (MEX-1) was 1.69 Pg C, which agrees with the national estimations of 1.68 Pg C reported to FAO (FAO, 2010b), but very different from TCM-1 and TCM-2 (2.24 and 1.95 Pg C respectively). The TCMs present discrepancies in the amount and spatial distribution of carbon stocks in Mexico when compared to the in-situ forest inventory data at different scales (pixel, ecoregion, biome, and country level), while MEX-1 and MRF agreed with INFyS estimates.

The products developed specifically for Mexico (MEX-1 and MRF) better represent the amount and spatial trends of AGBC stocks in the country when compared to the in-situ data. The differences between both maps are below a 10% of the total AGBC. MRF has a smaller RMSE than MEX-1 (14.4 vs 17.3 t C ha⁻¹), but MEX-1 histogram represents the variation in the INFyS in-situ data much more realistically than any other map examined here. The TCMs have similarly high AGBC per ha, which exceeds the expected in Mexico according to the INFyS field plots. The comparison showed that 50% of the occurrences for TCM-1 and TCM-2 are above 50 t C ha⁻¹, although the INFyS in-situ data indicates no more than 13%. MEX-1, MRF, and TCM-2 present similar spatial clustering (values of Moran’s I index) in most states, while TCM-1 presents several discrepancies.

TCMs present higher average AGBC prediction values for all biomes than in-situ INFyS data, MEX-1 and MRF. The MEX-1 map presents the highest accuracy at ecoregion level (R²=0.54). TCMs estimation are 4-5 times higher than INFyS in some ecoregions.

AGBC derived by GLAS footprints (used to calibrate TCM-1) presented large discrepancies when compared to AGBC derived by INFyS ground plots over the whole...
Mexican territory. *AGBC* was estimated from the GLAS footprints using a continental allometry. The largest discrepancies were located on the Yucatan peninsula (average differences above 87.5 t C ha\(^{-1}\)). However, the average canopy height estimated from GLAS footprints (before used as predictor in the allometric model) and canopy height from INFyS plots agrees when compared. The reason for these differences is therefore the allometry used by TCM-1 developed in another region (i.e. Amazon).

This was further studied by using the model from TCM-1 with the in-situ data, which showed errors in the estimation of *AGBC* up to ±74.2% of rel. RMSE in comparison to actual *AGBC* ground data values. GLAS-derived *AGBC* estimates also showed a significant negative bias in the estimation of *AGBC* when validated with overlapping INFyS plots for the Yucatan peninsula (-29.8 t C ha\(^{-1}\)), while in the rest of the country the bias is positive (32.2 t C ha\(^{-1}\)).

Conversely, the *AGBC* estimations from the GLAS footprints over Mexico do not seem to agree with the TCM-1 map. The upscaling of *AGBC* data over the whole American continent in TCM-1 causes that the algorithm calibration is mostly based on training data from another region, as most of the GLAS footprints (85%) were from the Amazon forest. Therefore, the results suggest that the use of a single continental allometry (vs. regional allometry), and the calibration of the algorithm without taking into account regional variations are the main sources of the discrepancies.

8.5. LIMITATIONS OF THE RESEARCH

The reader of this thesis should keep in mind that the spatial datasets used in this research are limited to ALOS PALSAR, MODIS, and DEM at 250m spatial resolution. The use of other type of sensors (e.g. with different SAR wavelengths), as well as higher spatial and temporal resolution datasets might further contribute to this topic.

This thesis assumes the INFyS in-situ data as the most representative dataset of the true distribution of *AGB* in the region, as it is a rigorously designed and extensive ground-based forest inventory. This assumption could however be contested as seen in Saatchi *et al.* (2015), which argued that there is no proof that measures by field plots are superior to remotely sensed measures (e.g. GLAS footprints).
This thesis uses validation matrix to calculate $\kappa$ for each forest mask. However, the use of $\kappa$ has been discussed as seen in Pontius Jr and Millones (2011). This thesis also compared overall accuracy of each forest mask and the disagreement with LUV to complement the validation.

### 8.6. FUTURE RESEARCH DIRECTIONS

Future work should examine the use of higher spatial resolution datasets (e.g. Sentinels). The use of different types of data such as the future L-Band SAR should also be investigated. The use of more complex SAR products such as coherence or interferometric height instead of backscatter intensity used in this thesis could also further improve the estimates.

Research should also focus on a better characterisation of the sources of error, and how the spatially distributed per-pixel error propagates to aggregated scales.

The development of appropriate allometric models to be used with the forthcoming LiDAR profiling sensors (ICESat-2, GEDI and MOLI) should also be considered, as this could be used for calibration of optical and SAR imagery such as Sentinels, ALOS-2 PALSAR and BIOMASS mission. This could be in the form of regional allometry or with the incorporation or additional forest structure variable calculated from GLAS footprints that could complement canopy height (e.g. basal area, crown density).
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10. APPENDIX

Figure A1. Diagram processing steps MODIS VI product

Figure A2. Diagram processing steps MODIS VCF product

Figure A3. Diagram processing steps SRTM product
Figure A4. Diagram processing steps ALOS PALSAR product Mexico

Figure A5. Diagram processing steps LUV product Mexico

Figure A6. Diagram processing steps Copernicus Land products Mexico

Pre-processing done by JAXA/JPL: calibration, geometric correction, geocoding, speckle reduction, composite, resampling
Figure A7. Diagram data preparation for MaxEnt approach
Figure A8. Diagram MaxEnt approach implementation