EARTH OBSERVATION FOR LAND AND EMERGENCY MONITORING

EDITED BY
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Preface

The material presented in this book was produced within the European Centre of Excellence in Earth Observation Research Training, GIONET. GIONET was funded by the European Commission's Marie Curie Programme as an Initial Training Network, Grant Agreement number PITN-GA-2010-264509.

I was the scientist-in-charge of this four-year project. The 14 individual early-career researchers employed by GIONET were based in seven partner organizations, and I want to acknowledge the scientific team leaders involved in this work: Andreas Wiesmann and Urs Wegmuller at Gamma Remote Sensing Ltd, Switzerland; Chris Schmullius from Friedrich-Schiller-University Jena in Germany; Alistair Lamb at Airbus Defence and Space in the UK; Katarzyna Dabrowska-Zielinska, Stan Lewinski, Martyna Gatkowska, Zbigniew Bochenek and Agata Hoscilo at the Institute of Geodesy and Cartography in Poland; Viktor Toth at the Balaton Limnological Institute Ecological Research Centre of the Hungarian Academy of Sciences in Hungary and Stefan Voigt and Elisabeth Schöpfer at the German Aerospace Center.

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1

Earth Observation for Land and Emergency Monitoring Core Services

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The Copernicus programme is Europe's flagship operational Earth Observation programme. It is comprised of a number of core services aiming at specific user groups. Many policies and international initiatives rely on Earth Observation to deliver information services. The downstream development of new satellite applications is a rapidly growing global market and creates jobs, economic growth and prosperity for societies.

The Copernicus initiative is delivering many core monitoring services of the oceans, the land surface, air quality, climate change and the polar ice sheets. It is a laudable programme in its aspiration to provide operational long-term observations of critical parameters from space. However, it has limitations and there is room for developing new and improved innovative information services around the existing Copernicus service portfolio.

The initial operations of the European Copernicus programme from 2011 to 2014 have delivered a comprehensive range of satellite applications in support of sustainable forestry. The Geoland-2 project has established the operational Copernicus land monitoring core service, which is now implemented with a global, European, local and in-situ component. Global data products to support sustainable agriculture and forestry include surface albedo, fractionally absorbed PAR (FAPAR), fraction of PAR absorbed by vegetation for photosynthesis processes, Leaf Area Index (LAI), Top of Canopy spectral reflectance, Fractional cover (Fcover), Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Vegetation Productivity Indicator (VPI), Dry Matter Productivity (DMP), burnt area, active fires, land surface temperature, soil moisture, areas of water bodies, water level (lakes and rivers), and vegetation phenology at 1 km resolution.

At the European scale, the vector-based CORINE land cover (reference year 1990) is being updated (last produced in 2000 and 2006, and currently being updated to 2012). It consists of 44 land cover classes and uses a Minimum Mapping Unit (MMU) of 25 ha area, or a minimum width of 100 m for linear landscape structures. Land cover changes are mapped with an MMU of 5 ha by visual interpretation of high-resolution satellite imagery. CORINE has a wide range of applications, underpinning the European

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Communities policies in the domains of environment, but also agriculture, transport, spatial planning etc. The High-Resolution-Layers (HRL) at 100 m spatial resolution include two forestry data products: tree cover density and forest type. In GIO-land an additional two forest products are being produced for the European Commission's Joint Research Centre (JRC): tree cover presence/absence, and dominant leaf type at 25 m spatial resolution. The tree cover density dataset maps the level of tree cover density in a range from 0–100%, has no MMU (minimum number of pixels to form a patch) and a minimum mapping width of 20 m. The forest type products in their original 20 m resolution version consists of the dominant leaf type (MMU of 0.5 ha, 10% tree cover density threshold applied), and a support layer showing trees under agricultural use and in urban contexts (derived from CORINE and imperviousness 2009 data). For the final 100 m product trees under agricultural use and urban context from the support layer are removed.

This book introduces the reader to the outcomes from four years of research in support of the Copernicus Land Monitoring Core Service and the Emergency Monitoring Core Service.

The research was funded by the Marie Curie PEOPLE programme in Framework Programme 7, as an Initial Training Network. The GIONET project established a European Centre of Excellence in Earth Observation Research Training in 2011, when Copernicus was called "GMES" (Global Monitoring for Environment and Security), and just entered into its GMES Initial Operations phase (GIO).

GIONET trained 14 PhD researchers in academia, industry, and research centres in advanced remote sensing skills, accompanied by interpersonal, entrepreneurship and management skills. Seven organizations from five European countries employed the researchers and were supported by a large group of associated partners.

This book is structured into thematic chapters, covering Forest Monitoring (Part I), Land Cover and Land Cover Change Monitoring (Part II), Coastal Zone and Freshwater Monitoring (Part III), Land Deformation Mapping and Humanitarian Crisis Response Strategies (Part IV) and Earth Observation for Climate Adaptation (Part V). A Conclusions chapter summarizes the main findings presented in the book.

The UN initiative "Reducing Emissions from Deforestation and Forest Degradation" (REDD+) provides a strong user pull for forest information from space. In Part I on forest monitoring a concept for global forest biomass mapping is presented, making use of geographically varying forest allometric models, spaceborne profiling LiDAR (ICESAT-GLAS) and Synthetic Aperture Radar (SAR). Synergies between multi-temporal and multi-frequency interferometric radar and optical satellite data for biomass mapping and change detection are discussed and a SAR mapping application to the Congo Basin presented.

Conceived in 1985 as the CORINE programme, land cover monitoring is the most operational element of the Copernicus programme. The methodology remains largely unchanged. Part II on land cover and land cover change monitoring presents approaches that go beyond the current implementation of largely optical/near-infrared based land cover monitoring methods. Classification methods with multi-frequency, multi-temporal SAR data over semi-arid and forested African landscapes are explained and contrasted against the capabilities of optical-near-infrared high-resolution satellite images. A methodological framework for multi-scale remote sensing concludes this chapter.

The European Water Framework Directive requires monitoring of the ecological status and water quality of all major water bodies and their habitats. Earth Observation is only beginning to influence this application area. In Part III on coastal zone and freshwater monitoring, a study of salt marsh habitats in Wales is presented. Salt marshes are regarded as effective buffers against sea level rise and can be mapped with multi-sensor data to support Integrated Coastal Zone Management. Freshwater applications focus on the ecology of emergent and submerged macrophytes in Lake Balaton, Hungary, using airborne hyperspectral and LiDAR remote sensing to map the extent of reed dieback syndrome, and satellite remote sensing to map and monitor optically active water quality parameters, such as chlorophyll-a as a proxy for phytoplankton biomass and blooms.

The recent past was characterized by many humanitarian crises and natural disasters. Part IV of this book describes the use of radar interferometry for land deformation mapping applications and demonstrates the use of machine learning algorithms in the context of humanitarian crisis response strategies. After a short review on radar interferometry, a new hybrid method using Differential SAR Interferometry/Persistent Scatterer Interferometry for ground-motion monitoring from spaceborneSAR data is demonstrated and applied to different land cover types. Chapter 12 describes the use of spaceborne SAR and ground-based radar interferometry for mapping landslide displacements in the Swiss Alps. New methods for the detection of small-scale land surface feature changes in complex humanitarian crisis situations are demonstrated, transferring machine learning algorithms to environmental remote sensing.

With an increasing likelihood that mankind is unable or unwilling to respond effectively to the causes of climate change, there is a widening recognition that we will have to adapt to its impacts. In Part V on Earth Observation for climate adaptation, a study on remote sensing of wetland dynamics as indicator of water availability in semi-arid Africa is presented, using time series of optical and SAR satellite imagery. Satellite observations of drought events and crop stress in Europe conclude this chapter.

The book presents a collection of original research findings interspersed with selected review chapter and intends to serve as a compendium on the state-of-the-art in remote sensing in support of land and emergency monitoring going beyond the current operational monitoring services in Copernicus.

I am grateful to the GIONET team for the inspiring and productive work over the past four years, in particular to my colleagues at the University of Leicester, UK, Airbus Defence and Space (formerly Astrium GEO-Information Services), UK, Gamma Remote Sensing AG, Switzerland, the Institute of Geodesy and Cartography (IGIK) in Warsaw, Poland, Friedrich-Schiller-University in Jena, Germany, the Hungarian Academy of Sciences – Centre for Ecological Research and the German Aerospace Center (DLR), and the associated partners in the Joint Research Centre of the European Commission in Ispra, Italy, University of Stirling, UK, University of Padova, Italy, the National Observatory of Athens, Greece, Chalmers University in Sweden, and the companies Trimble, Germany, EXELIS Visual Information Solutions Ltd., UK, SpectoNatura, UK, BlackBridge, Germany, DANKO Plant Breeding in Poland, Envirosense, Hungary, and Earth Observation Services in Germany.

It has been a privilege and a pleasure to coordinate the international team of 14 early-stage researchers who were working towards their doctoral degrees in this unique international research environment.

Part I

Forest Monitoring

2

Methodology for Regional to Global Mapping of Aboveground Forest Biomass: Integrating Forest Allometry, Ground Plots, and Satellite Observations

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2.1 Forests and Carbon

Earth is undergoing significant global environmental change. The processes linked to global change are affecting the whole climate system and impacting human civilization. Understanding the effects and causes of these processes will assist human societies in devising adaptation and mitigation strategies. The United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol address the importance of reducing and monitoring greenhouse gas emissions (GHG), with CO_2 being the most significant trace gas. Changes in the amount of atmospheric CO_2 due to anthropogenic activities are altering the biogeochemical cycles that allow the recycling and reuse of carbon on Earth (global carbon cycle), and produce changes in weather patterns [1].

How the global carbon cycle stores and exchanges carbon within the system is crucial to understand interactions and feedbacks with the climate system. The locations where the carbon is stored within the global carbon cycle are called carbon pools, and the rates of carbon exchanged between pools are known as fluxes, and are classified in sources (emission to the atmosphere) and sinks (uptake from the atmosphere). Knowledge of both carbon pools and fluxes is essential to understand the global carbon cycle. Terrestrial ecosystems play a vital role in the global carbon cycle. The terrestrial carbon pool is about three times bigger than the atmospheric pool [1], and removes 30% of anthropogenic emissions from fossil fuel combustion from the atmosphere [2]. The primary source of terrestrial carbon emissions is from anthropogenic land use change; especially deforestation in the tropics, while afforestation, reforestation and growth of existing forest is the major contribution to the terrestrial sink term. Terrestrial ecosystems appear to act as a net sink [3], but there are significant uncertainties 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 [4–8].

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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 [8]. 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 [9] 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 [10]. Thus, monitoring *AGB* stored in the world's forests is essential for efforts to understand the processes related to the global carbon cycle and reducing carbon emissions originating from deforestation and forest degradation.

Biomass is an Essential Climate Variable (ECV) required by the Global Climate Observing System (GCOS) to support the work of the UNFCCC and the Intergovernmental Panel on Climate Change (IPCC) in monitoring climate change. Accurately monitoring and reporting the biomass or carbon content of forests (carbon stocks) is a requirement of different international mechanisms based on economic incentives that have been launched by the international community aiming to mitigate climate change, such as "Reducing Emissions from Deforestation and forest Degradation" (REDD+). Global estimates of *AGB* carbon stocks have been produced in the past to support the monitoring of CO_2 emissions from deforestation and land use change. However, the size and spatial distribution of forest *AGB* is still uncertain in most parts of the planet due to the difficulties measuring *AGB* at the ground level [11]. Very few global *AGB* carbon estimates are spatially explicit. Approaches that make full use of remote sensing techniques to estimate *AGB* are therefore needed.

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

2.2 Using Earth Observation Imagery to Measure Aboveground Biomass

Three broad types of remote sensors are used by Earth Observation platforms: Optical, Synthetic Aperture Radar (SAR), and LiDAR. Each type of sensor has different characteristics, which make them suitable for monitoring forest vegetation. Detailed explanation and examples on the use of different earth observation sensors and techniques to estimate *AGB* can be found in Chapter 3 of this book or in other literature [e.g. 12]. The following is a brief summary of techniques and sensors available to measure biophysical parameters of vegetation.

Through optical remote sensing, it is possible to estimate a series of different vegetation indices such as Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI), which are mainly related to the photosynthetic components of the vegetation and therefore indirectly to *AGB*. This relies on an empirical relationship between green foliage and total *AGB*, however. In reality, forest *AGB* is primarily composed of the non-photosynthetic parts of trees like trunks and branches. Forest *AGB* can nevertheless be indirectly estimated from optical sensors based on the sensitivity of the reflectance to variations in canopy structure. Most optical approaches are based on this relationship in which signal retrieval is calibrated with ground measurements to model the spatial distribution of *AGB* across the landscape. Several studies have mapped *AGB* at different scales (medium to coarse resolution) relating ground measurements to the signal retrieved from optical sensors such as Landsat or MODIS [e.g. 13–15].

Optical sensors have great advantages for global vegetation monitoring. Vegetation can be easily differentiated from other surfaces due to its strong reflectance in near infrared and visible green, as well as absorption in the red and blue sections of the visible spectrum [16]. Optical sensors have been operating for a long time and have a rich archive that can be used to study vegetation changes. For example, the Landsat mission has global coverage of observations over the last 40 years. Another advantage of optical sensors is that coarse and medium resolution imagery they produce can usually be obtained for free or at a low cost. The main shortcoming of optical imagery is cloud cover, as the sensors cannot "see" through clouds. This is not crucial in boreal or temperate latitudes, but can be a problem in tropical areas where there are few days a year without cloud cover. Moreover, as passive sensors, they can only operate during daylight, which reduces the number of potential revisit times in comparison with active sensors like SAR or LiDAR. Thus, the chances to obtain a cloud-free image are also diminished. The way to overcome this problem is through the use of radiometrically consistent multi-temporal datasets, but this is costly, technically demanding, and time-consuming [13,17]. Estimation of *AGB* by optical sensors also faces the saturation of the signal retrieval at low *AGB* stocks [10] as the signal retrieved from vegetation depends on the absorption of light from the photosynthetic parts of the plants. Optical imagery is suitable for forest area mensuration, vegetation health monitoring, and forest classification, but presents limited correlation with *AGB* after canopy closure.

Radars are active sensors, which generate their own electromagnetic signal. They are independent of solar illumination of the target area, being able to obtain day and night observations, as well as to penetrate through haze, clouds and smoke. SAR is an airborne or spaceborne side-looking radar system that uses its relative motion, between the antenna and its target region, to provide distinctive long-term coherent signal variations used to generate high-resolution remote sensing imagery (Figure 2.1).

Each SAR satellite works within a specific radar frequency bandwidth (with corresponding wavelength), which is used to classify them in increasing wavelength size as X-, C-, S-, L- or P-band sensors. Several SAR satellites are currently operating (in orbit), including the new L-band ALOS-2 PALSAR, which was launched in May 2014 (Table 2.1).

The radar backscatter (the amount of scattered microwave radiation received by the sensor) is related to *AGB* as the electromagnetic waves interact with tree scattering elements like leaves, branches and stems, but their sensitivity to *AGB* depends on the radar wavelength [18]. Shorter wavelengths are sensitive to smaller canopy elements (X- and C-band), while longer wavelengths (L- and P-band) are sensitive to branches

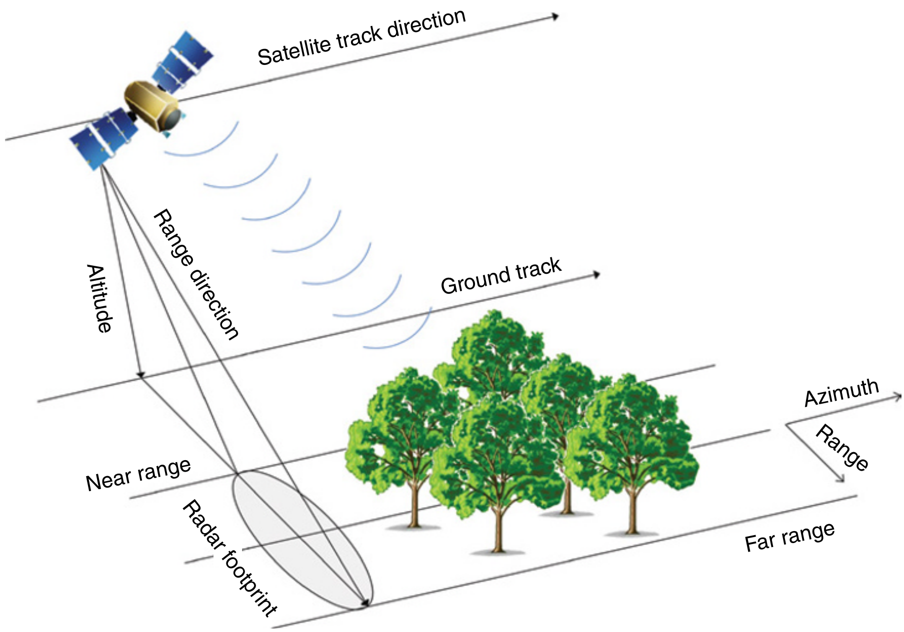

Figure 2.1 Illustration of Synthetic Aperture Radar Satellite basic terminology.

Table 2.1 Operating or planned satellites used for forest monitoring.

Sensor	Wavelength	**AGB* saturation	Operating satellites	Planned satellites
LIDAR	Visible/near-infrared (532 & 1064 nm)	No limit		ICESat 2, GEDI (sensor attached to ISS)
SAR	P Band (30–100 cm)	100–200 $t\,ha^{-1}$		BIOMASS
	L band (15–30 cm)	40–150 $t\,ha^{-1}$	ALOS-2 PALSAR	SAOCOM 1A, 1B NISAR
	S band (7.5–15 cm)	Not reported	Huanjing 1C	NovaSAR-S NISAR
	C band (3.8–7.5 cm)	20–50 $t\,ha^{-1}$	Radarsat 1 Radarsat 2 Sentinel 1	RADARSAT Constellation
	X band (2.4–3.8 cm)	<20 $t\,ha^{-1}$	TerraSAR X Cosmo/SkyMed Tandem X	Paz
OPTICAL	Visible/near-infrared (380 nm–1 mm)	15–70 $t\,ha^{-1}$	High Resolution satellites, Terra/Aqua MODIS, Terra ASTER, SPOT 6 & 7, Landsat 7 & 8, EO-I, DMC constellation, Sentinel 2 & 3, PROBA V, and others	High Resolution satellites, Landsat 9, Ingenio, Amazonia, CBERS 4 & 4B, and others

* Range of *AGB* saturation thresholds found in the literature [21,22,25–28].

and stems [19]. 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 $t\,ha^{-1}$ [20,21]. However, other authors have found higher saturation values of more than 250 $t\,ha^{-1}$ for L-band [22], and even more than 300 $t\,ha^{-1}$ when combined with other SAR datasets such as X-band [23]. 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 [24], at the moment there is only one planned satellite, the ESA Earth Explorer 8 BIOMASS mission [11], which will not be launched before 2021. The future P-Band BIOMASS mission by ESA has the following accuracy requirements at pixel level (200 m × 200 m): an RMSE of ±10 $t\,ha^{-1}$ for *AGB* below 50 $t\,ha^{-1}$, and a relative error of ±20% for *AGB* above 50 $t\,ha^{-1}$.

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

- platforms: spaceborne, airborne, or ground-based
- returned signals: discrete return or wave form
- scanning pattern: profiling or scanning
- footprint[1] size: small footprint: (<1 m diameter), medium footprint (10–30 m diameter), and large footprint (>50 m diameter).

Airborne imaging LiDAR provides direct and very accurate measurements of canopy height. LiDAR sensors do not suffer from signal saturation, as optical and radar sensors do, because the signal can penetrate the canopy. Nevertheless, the vertical extent of each waveform increases as a function of terrain slope and footprint size, making this information insufficient over sloped terrain to estimate canopy height [29]. However, the use of airborne and ground platforms would be too costly and impractical at national, continental or global level [10].

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. 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 [29]. There is no current LiDAR satellite in orbit at the moment. ICESat-2 will be launched in 2017, and the Global Ecosystem Dynamics Investigation LiDAR (GEDI) mission, which will attach a LiDAR profiling sensor to the International Space Station (ISS), will not be operative until 2020. 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. 30,31].

1 Area illuminated by the laser and from which the waveform-return signal gives information.

2.3 Global Forest Monitoring

The first challenge to monitoring forests at a global scale is the definition of forest itself, and consequently the definitions of deforestation and forest degradation. Forests are ecosystems dominated by trees and other woody vegetation, but there are approximately 1500 definitions of forest worldwide based on administrative, cover, use or ecological characteristics [32]. 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 2.2). This situation makes any study at global scale using data generated at national level very complicated.

The remote sensing approaches allow the study of forest vegetation from a physical perspective. Therefore, the same vegetation thresholds defining forest, deforestation and forest degradation can be applied globally. The downside of this physical approach is that other types of woody vegetation such as oil palm plantations, which are responsible for large-scale deforestation in tropical areas, are sometimes included in the forest class, especially when using coarse or medium-resolution optical sensors to monitor the forest [e.g. 34]. To overcome this challenge, ancillary data with the location of these plantations or accurate remote sensing methods to differentiate

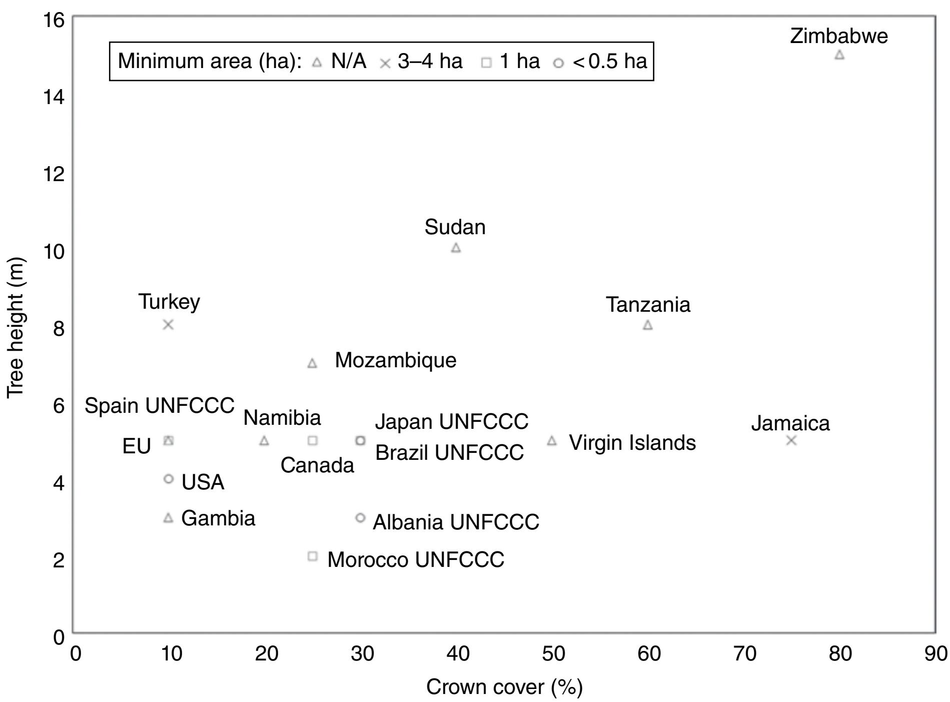

Figure 2.2 Minimum thresholds for tree height, crown cover and area of forest definitions used in different countries. Modified from [33]. Data from [32].

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 [35].

Several products are globally or continentally produced to monitor forest changes (Table 2.2). These projects are generally based on in situ data and satellite optical sensors with medium to coarse spatial resolutions. The use of airborne and high-resolution sensors is restricted to sub-national level or project level, as it could be impractical and the cost prohibitive at country, continental or global scale. Nevertheless, the use of these sensors on demand can be extremely valuable for monitoring specific hot spots where deforestation is a major issue, as well as to assist in the validation of medium-resolution products. The products developed by these programmes are mostly created using optical imagery, which requires a complex and extensive data processing chain in order to produce consistent global products. The main parameters measured by these data projects are forest cover and forest type. Most of these products lack the capabilities to produce spatial *AGB* estimates.

The Forest Resource Assessments (FRAs) are based on the analysis of forest inventory information supplied by each country and supported by expert judgements, remote sensing and statistical modelling. A National Forest inventory is the most widely used method for in situ forest monitoring due to its historic roots in national forestry administrations, its accuracy and low technical requirements. A forest inventory is a systematic collection of forest data for assessment or analysis. The approach consists of sample-based statistical methods, sometimes in combination with remote sensing and aerial imagery. In developing countries where the labour cost is low, the use of forest inventories could be a relatively cost-effective approach. The FRAs analyse information on forest cover, forest state, forest services and non-wood forest products. However, it was not until 2000 that a single technical definition for forest was used (10% crown cover). Changes in baseline information, inconsistent methods and definitions through the different FRAs make their comparison difficult [39]. 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 [7,10,47].

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

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board the Terra and Aqua satellites provides biophysical parameter datasets, which allow monitoring of biosphere dynamics. MODIS Vegetation Continuous Fields (VCF) is a sub-pixel-level representation of surface vegetation cover estimates globally [48]. The percent canopy cover per MODIS pixel refers to the amount of sky obstructed by tree canopies equal to or greater than 5 m in height [48], which agrees with the UN Food and Agriculture Organization (FAO) definition of forest. The current version (collection 5) has been published with 250 m resolution globally. Initial results show that this version of the product

Table 2.2 Global Forest Monitoring Programmes.

Programme or study	Agency	Data source	Spatial resolution	Temporal coverage	Key issues and reference
Forest Resource Assessment (FRA)	FAO	National Forest Inventories	N/A	Every 5 years	Data sources are not globally available [36–39]
Global Remote Sensing Survey (RSS)	FAO	Landsat	N/A	1990, 2000, 2005	Systematic sample (10 km × 10 km) of Landsat imagery worldwide [40]
ALOS Kyoto and Carbon Initiative	JAXA	ALOS PALSAR	25 m/50 m/100 m	Annual 2007–10	L-band SAR imagery & Forest/Non-Forest mosaics [41–44]
Tree Cover Loss & Gain	University of Maryland	Landsat	30 m	Annual 2000–12	Identifies areas of tree cover loss (annual) and gain (12 years cumulative) [34]
Global Forest Watch	World Resources Institute	Landsat, MODIS, and others	30 m– 5 km[(1)]	Monthly quarterly, and annual from year 2000	Forest change, cover and use, alerts, crowdsourcing, etc.
Vegetation Continuous Fields	University of Maryland, NASA	MODIS	250 m, 500 m, 1 km	Annual 2000–10	Tree cover percentage at sub-pixel-level [45]
Tree Cover Continuous Fields	University of Maryland, NASA	Landsat	30 m	2000	Tree cover percentage at sub-pixel-level [46]
GlobCover	ESA	ENVISAT	300 m	2005/06 & 2009	Labelled according to the UN Land Cover Classification System
MODIS Land Cover Type	NASA	MODIS	500 m	Annual 2001–12	5 Global Land Cover Classification Systems
COPERNICUS Global Land Service	GEOLAND-2, ESA	SPOT, and others	1 km	Several intervals from 1999	Vegetation Biophysical parameters
Biomass Geo-Wiki	Several	Several[(2)]	30 m–0.01 grad	2000–10	Comparison *AGB* maps

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

is substantially more accurate (50% improvement in RMSE) than the previous 500 m version [45]. The pixel size of 250 m (ca. 6.25 ha) is still far from a pixel size of 71 m, which would be the minimum resolution that could detect a minimum unit area of forest (0.5 ha) according to the main forest definitions [49]. Nevertheless, VCF collection 5 currently has the best temporal coverage (from 2000) among the coarse resolution global forest monitoring products that are free of charge. Following the success of MODIS VCF, a recent 30 m resolution Tree Cover Continuous Fields (VCF) dataset has been developed, re-scaling the 250 m MODIS VCF with Landsat imagery [46] (Figure 2.3).

A data mining approach of the Landsat archive by means of the Google Earth Engine was also used to globally quantify annual forest loss (2000–12) as well as 12 years of cumulative forest gain at 30 m spatial resolution [34]. This dataset together with others such as FORMA alerts [50], which provide tree cover lost alerts every 16-days interval, can be freely downloaded and visualised on the website of the Global Forest Watch (www.globalforestwatch.org/). This site is a web-platform that aims to provide reliable

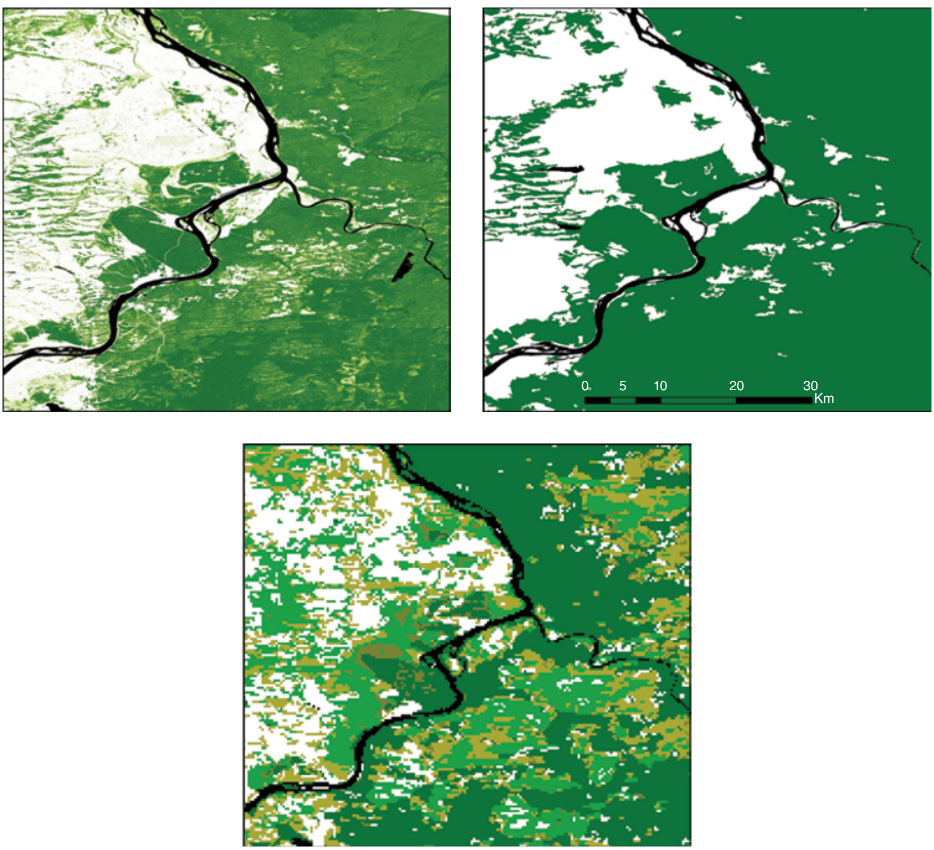

Figure 2.3 Area in Central Siberia. Left: Landsat Tree Cover Continuous Fields 30 m resolution (2000) (Raw data: [46]), Centre: Forest/Non Forest K&C Initiative Product 50 m resolution (2010) (Source data provided by JAXA as the ALOS high level product © JAXA, METI), Right: GlobCover 300 m resolution (2009) (Source Data: © ESA / ESA GlobCover Project, led by MEDIAS-France/POSTEL). Green colours (grey colours in printed version) denote forest, black colour water bodies, and white colour non-forest area.

information about forest to interested stakeholders such as governments, NGOs and companies by combining satellite technology, open data and crowdsourcing. The site also includes a forest carbon map for the year 2000 covering the tropical areas [31].

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

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

Land cover mapping provides a static representation of land cover. It does not show change in forest area, but serves as a baseline for assessment of forest cover change. Two main projects are the most representative and widely used at the moment: GlobCover and MODIS land products. GlobCover is a project from the European Space Agency (ESA) whose goal is to develop an Earth's global land cover product [51] (Figure 2.3). Data from the Medium Resolution Imaging Spectrometer and Advanced Synthetic Aperture Radar (MERIS) on board Environmental Satellite (ENVISAT) is used to develop a Land Cover product labelled according to the UN Food and Agriculture Organisation's Land Cover Classification System. Two GlobCover products based on ENVISAT MERIS data at full resolution (300 m) were released by ESA for the years 2005–06 and for 2009.

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

The ALOS Kyoto & Carbon (K&C) Initiative is an international project led by Japan Aerospace Exploration Agency (JAXA). Coordinated by JAXA Earth Observation Research Centre (EORC), the programme focuses on producing data products primarily from the Phased Array L-band Synthetic Aperture Radar (PALSAR) sensor on-board the Advanced Land Observing Satellites (ALOS and ALOS-2). The main products from the K&C programme are the 25 m, 50 m and 100 m spatial resolution forest/non-forest (FNF) area mosaics from resampled 10 m data every year (2007–2010 and 2015 onwards) (Figure 2.3). The method for developing this FNF product is based on a decision-tree classification that applies different backscatter intensity thresholds [41].

2.4 Remote Sensing and Biomass Allometry

AGB is accurately and directly measured through in situ destructive sampling methods. Through these methods entire trees are felled and the different tree components are separated and weighted in situ, resulting in a significantly laborious, expensive and impractical approach at a large scale [52]. Non-destructive in situ methods such as forest inventories make use of allometric models to predict *AGB*. In situ non-destructive measurements are broadly used for *AGB* monitoring as their accuracy lies between

20% and 2% [53]. Biophysical parameters like tree height or diameter are commonly measured in forest inventories and other studies, and used to estimate *AGB* through allometric equations.

Derivation of allometric relationships is based on the allometry of living organisms. Allometry is the condition of geometric similitude, which results when geometry and shape are conserved among organisms differing in size [54]. It works as a "rule of proportions" between organism components and their whole. Allometric biomass regressions are developed by measuring the biomass of entire trees or their components and regressing the data against some more easily measured variables [55]. 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, basal area, wood specific gravity, or diameter at breast height.

The most commonly used mathematical model for *AGB* estimation uses the form of a non-linear function (Eq. 2.1), where Y is the total aboveground tree dry biomass or any other tree component, b_0 and b_1 are parameters, and X is the biophysical parameter used for prediction [56]:

$$Y = b_0 \cdot X^{b_1} \tag{2.1}$$

Allometric models have been traditionally developed to be used in national forest inventories or specific studies. The samples used to create these models are usually delimited to the area under study. Such models are generally developed for specific species and sites [57–60]. In temperate and boreal forested areas, there is a large availability of allometric equations [61]. Unfortunately, these equations are not easily available for developing countries in tropical regions with large areas of natural forests due to the geographical remoteness, lack of research studies, data paucity, high tree diversity or armed conflict situations. The Congo Basin is a clear example of the scarcity of ground samples. Even though the Congo basin is one of the largest forested areas in the world, only a small number of allometric equations have been developed for the forests of this region [62]. Several studies found that allometric models could be generalised by the incorporation of additional variables that explain the regional variability, such as wood density, and developed models for specific regions or forest biomes based on a large number samples [52,63,64]. Generalized equations are frequently used in tropical areas, but are just recommended in cases where no local models are available [65].

Few allometric models relating remote sensing-derived biophysical parameters (usually canopy height) to *AGB* are presently available [e.g. 31,66,67–69]. This kind of relationship at the plot or pixel scale is conceptually similar to relationships at tree level. The main difference is that the relationship is established between the biophysical parameter and the *AGB* of all trees inside the area of interest. At tree level, *AGB* can be accurately calculated from tree height, diameter and specific wood density [64,70,71] using generalized models. Remote sensing can measure tree height but cannot directly measure wood density. The use of allometric models calibrated with regional ground data can circumvent this problem and provide accurate estimates of *AGB* [72]. Moreover, the use of additional forest structure variables can also improve the estimates [73,74]. Forest biomes or ecological regions present different tree allometries depending on climatic conditions, vegetation structure, species, soil types, and other characteristics, which ultimately affect the correlation between *AGB* and biophysical parameters like mean canopy height at plot and pixel level. It seems therefore logical to develop regional models that capture the regional

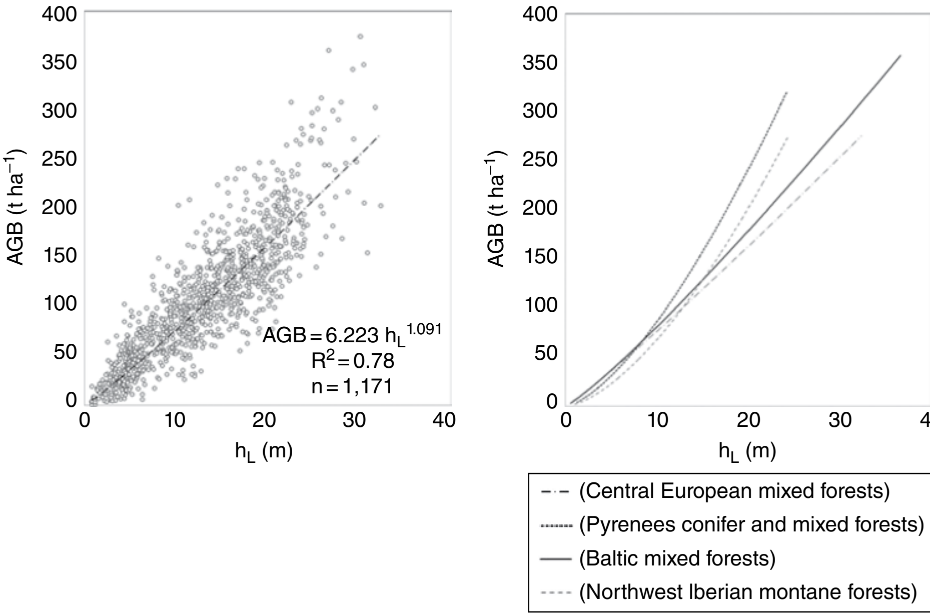

Figure 2.4 Left: Plot-level allometric model relating *AGB* to Lorey's mean canopy height (h_L) for the Central European Mixed Forest ecological region. Right: Allometric models for different ecological regions in Europe.

variability, as the slopes of these allometric functions will differ from region to region (Figure 2.4). Regional allometry has not been sufficiently explored to be used with remote sensing, but its use could improve *AGB* estimation worldwide.

New techniques applied to SAR and LiDAR sensors can be used to estimate biophysical parameters such as tree canopy height [31,75,76]. Biophysical parameters can be used with regional allometric models to estimate forest *AGB*. This approach does not suffer from the *AGB*/radar backscatter saturation problem. *AGB* can be mapped by SAR from interferometric height models in combination with allometry [75]. This approach requires a ground Digital Terrain Model (DTM), which is not always easy to obtain. Polarimetric Interferometry is another SAR technique, which in contrast to single-polarisation interferometry, does not rely on an external DTM, as it estimates terrain and canopy height from the different polarimetric scattering mechanisms [67,77,78]. It relies on the coherence of two SAR scenes taken over the same site, either within a short time window or simultaneously from two slightly different positions within a certain distance range or baseline. SAR Tomography goes beyond the polarimetric interferometry technique by using a multi-baseline of interferometric SAR images to generate a 3D vertical structure of the vegetation based on the variation of backscatter scattering as a function of height [24,79].

Several authors have studied LiDAR-derived biophysical canopy metrics such as maximum canopy height, Lorey's mean height (h_L) and the height of median energy (HOME) to characterize forest vertical structure [75,80–85]. In recent studies [80,86], spaceborne profiling LiDAR from the GLAS sensor was used to create global maps of forest canopy height. The maps estimated top canopy height [86] and Lorey's mean canopy height (h_L) [80] from the full waveform of the GLAS footprints (area illuminated by the laser and from which the waveform-return signal gives information). Lorey's mean canopy height is the basal area weighted height of all trees. At plot and LiDAR footprint level h_L shows a robust relationship with *AGB* [80]. The size of the GLAS footprints (<0.4 ha) is comparable to most forest plots sizes (0.02–1 ha). Therefore, there are plenty of data available for developing regional models, which could relate canopy height to *AGB* as seen in [31,66,69].

2.5 Synergistic Use of Regional Allometry, in situ Measurements, and Spaceborne Profiling LiDAR, with Optical and SAR Imagery for Biomass Mapping

There is no sensor that can currently be used for *AGB* estimation across larger regions, either because of limitations in signal saturation, cloud cover persistence, or complex signal retrieval due to topography. Several studies have aimed to map *AGB* at global, biome, or continental levels using a variety of methods. Products mapping forest *AGB* and carbon stocks globally [87], continentally [14,88], in the tropical [30,31], temperate and boreal regions [89], as well as growing stock volume continentally [90], and in boreal regions [91] have recently been published. Together with the limitations of remote sensing imagery to map forest *AGB,* all these products also face important challenges regarding ground data availability to calibrate their approaches. Most of these studies use methods for combination of multiple datasets in order to circumvent such limitations. Data synergy approaches make possible to exploit the specific strengths of each sensor. For example, LiDAR sensors can be used for estimation of *AGB* samples across the landscape, while SAR sensors in combination with optical sensors can be used for forest area estimation and extrapolation of the measurements.

There are a number of parametric and non-parametric approaches to extrapolate values of *AGB* to larger spatial scales using remote sensing imagery. Multiple regression analysis, k-nearest neighbour technique (k-NN), co-kriging, random forests, and neural networks are some examples. Parametric 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. Parametric models present bigger challenges for extrapolating *AGB* data, as there are no current satellite observations that can be reasonably related to *AGB* across the whole landscape. Moreover, the assumptions in parametric models of independence and multivariate-normality are often violated [92]. 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 [93].

Two recent papers mapped the spatial distribution of *AGB* in the tropics using synergistic approaches based on the use of GLAS footprints for the estimation of *AGB* [30,31]. The approach described by Baccini *et al.* [30] relates GLAS waveforms to *AGB* using a model calibrated by ground plots directly located under the GLAS footprints, while Saatchi *et al.* [31] uses three continental allometric models derived from ground data to relate GLAS-derived Lorey's mean canopy height to *AGB*. As discussed in the previous section, the use of a model for each continent might better explain the allometric regional variability than a single model, but might still introduce a great amount of uncertainty when applied to very different forest biomes such as temperate coniferous and tropical rainforest. The studies use non-parametric approaches such as Random Forest [94] and MaxEnt [95,96] for extrapolation of the *AGB* across wide areas, to produce 463 m and 1 km resolution maps respectively. One of the most innovative features of using MaxEnt is the possibility of mapping the uncertainty of the *AGB* estimation on a pixel-by-pixel basis. Both approaches use MODIS and SRTM products, and in the case of [31] also Quickscatterometer data (QSCAT). None of these products can solely explain the variability of *AGB* across the landscape, but the methods used by these studies aim to take advantage of the full potential of the information contained in each product.

2.5.1 Global Biomass Monitoring Approach

Based on the previous examples, it is possible to define a general concept for *AGB* mapping (Figure 2.5) using a combination of datasets from different remote sensors by means of a non-parametric approach such as MaxEnt to extrapolate the *AGB* calibration data. These *AGB* data could be directly obtained from forest inventory datasets, or by means of regional allometric models relating *AGB* to remote sensing-derived biophysical parameters such as mean canopy height calculated from Spaceborne LiDAR.

A baseline *AGB* map can be developed and updated at predefined time intervals (e.g. every 3–5 years). If annual products are needed for periods in between updates, those

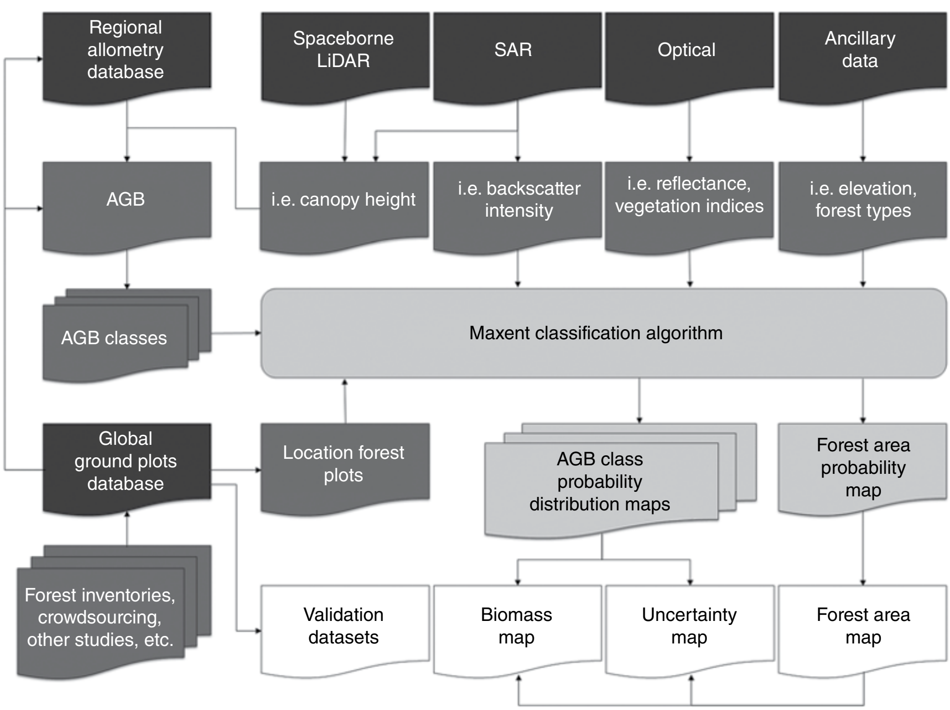

Figure 2.5 *AGB* mapping method proposed for a Global Biomass Monitoring Approach.