Geospatial Technology Methods for Carbon Stock Assessment: A Comprehensive Review

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Abstract. Carbon stock estimation is becoming an important component for fighting against global warming. Assessment of biomass can give an idea of the amount of CO₂ that can be removed from the atmosphere by forests and other plantations. Geo-Spatial technologies, including Remote Sensing (RS) and Geographic Information Systems (GIS), offer the mean to enable rapid assessment of terrestrial biomass over large areas in a timely and cost-effective manner, allowing for the estimation of above and below ground biomass. Hence, the deployment of an integrating RS-GIS approach for precision carbon management is of high significance. This article provides a review of various RS and GIS techniques used in forest aboveground biomass mapping and monitoring as well as highpoints the associated challenges and opportunities. The review concluded that the use of RS and GIS in large-scale forest aboveground biomass assessment provides a sound alternative when compared to the use of conventional approaches. It was noted that the freely available moderate resolution optical sensors could be used reliably for estimating forest carbon stock. Furthermore, the integration of multi-sensor data in a GIS environment increased the accuracy of the estimation results. This study helps contributing to the topic in a way that it illustrates the growing developments using geospatial technologies by identifying most sensitive RS variables to measurable biophysical parameters. Furthermore, it demonstrates the usefulness of geospatial technologies for estimating terrestrial carbon sequestered. Finally, gaps, limitations and the need for further studies are underlined.

Keywords: Forest Biomass, Biophysical Parameters, GIS, Remote Sensing, Vegetation Indices.

1. Introduction
A workable definition of forest biomass is the total amount of living organic matter in trees calculated as oven-dry tons per unit area. The estimation of biomass is not an easy task, especially in areas with both complex and varying environmental conditions, as well as in low vegetation cover density areas such as arid lands. Both ecosystems require accurate and consistent measurement methods. When CO₂ gas in the atmosphere is being captured and stored in liquid or solid state, this process is called “carbon sequestration”. A process that is occurring naturally through live organic matter, trees, soils and oceans[1]. Any reservoirs or stores of carbon are called carbon pools. Storing of CO₂ occurs in three...
levels: in plants and soil (Terrestrial Sequestration), underground (Geological Sequestration) and deep in oceans (Ocean Sequestration). Terrestrial or biologic sequestration is the process of storing atmospheric CO₂ as carbon in the stems, roots of plants and soil. Photosynthesis is the process of converting CO₂ in the atmosphere to biomass stored in plants. Consequently, forests, biotic and soil, constitute large carbon pools. Carbon sequestration through forests is estimated at 2–4 gigatons annually[2]. Almost about 60% of sequestered carbon is returned to the atmosphere by the process of deforestation[3]. Therefore, a precise carbon stock estimation schema is necessary to implement carbon emission alleviation programs both, locally and globally [4]. Such studies are needed for studying and predicting long-term behavior and drivers of carbon sequestration as part of the global and climate change scenarios[5].

Forests, as both carbon sources and sinks, can play a major role in combating global climate change[6,7]. Estimation of carbon stocks and assessing the role of forest ecosystems in regional and global carbon cycles, is important for a better understanding of the impacts of land-cover changes on carbon fluxes, nutrient cycling and budgeting. Likewise, monitoring forest biomass, as a step in carbon stock estimation, is not an environmental issue only; actually, more than 190 countries are committed to take action to implement and support sustainable management of forests and enhancement of forest carbon stocks according to Paris Agreement on Climate Change[8]. Afforestation projects help in reducing the carbon footprint, hence reducing the amount of greenhouse gases (GHGs) in the atmosphere through the process of carbon sequestration[9]; such an attitude has a growing interest among policymakers and governments[10]. Similarly, plantation cropping projects, as a land use system, have the potential to contribute to carbon stocks, maintain soil biodiversity and improve soil fertility[11]. It can add economic value by providing more job opportunities, better income and food security, especially the smallholder systems in developing countries, and the timber exploitation[9,12]. The UN program for the reduction in emissions from deforestation and forest degradation (REDD+), is an international initiative to help nations earn financial incentives if they implement climate policies and if they demonstrate CO₂ emission reduction[13].

Five terrestrial ecosystem carbon pools describe biomass distribution namely, above-ground biomass (AGB), below-ground biomass (BGB), litter, woody debris and soil organic matter[14]. Of the above five pools, AGB is the most visible, foremost, and dynamic, making up to 30% of the total terrestrial ecosystem carbon pool and accounts for more than 70% of total forest biomass[15]. Furthermore, AGB is the most important as it plays a major role in the atmospheric carbon fluxes due to fire, logging and land use conversions. Therefore, it should be monitored and measured along the year, not only a one-time mapping; although the estimation of forest biomass is a scientific challenge as to identify efficient methods for its assessment at regional to national-levels[13]. Producing accurate maps for biomass estimation distribution is a serious challenge which has to be addressed when calculating carbon stocks. Effective management requires constant monitoring and accurate measuring of biomass, which is a classical subject in plant population ecology[16]. Traditional assessment methods are known to be the more accurate; they are based on field measurements. Nevertheless, they are costly, intensive labor works, and difficult to implement at large scales [17][18]. Remote sensing (RS) integrated with Geographic Information Systems (GIS) techniques are widely applied to different natural resources applications and biomass assessment[19–21]. RS is capable of accurately and timely, sensing and recording forest variables over large areas and at relatively, very low cost [22]. Besides, modelling RS data within a GIS environment will augment the advantages of both technologies, permitting for the use of a wide range of ancillary and field data to the analysis, hence increasing the accuracy of the estimated AGB.

The main objective of the actual study is to review all types of methods that use geospatial technologies (RS and GIS), in biomass studies and carbon assessment. Specific objectives include:

- To highlight the growing developments on biomass and carbon estimation in terrestrial ecosystems using geospatial technologies;
- To identify significant RS variables sensitive to measurable biophysical parameters;
To underline gaps and identify limitations of RS-GIS based methods as well as to address the needs for further studies to overcome them.

2. Geospatial (RS and GIS) Methods

Field-based methods for the estimation of forest AGB and carbon stock are typically based on plots, forest inventories, and the use of allometric equations built on and derived from measurements taken using destructive in situ-measurements[4]. While direct field data measurements of biomass are the most accurate, they are not adequate to map AGB distribution at large scales. On the other hand, RS and related technologies such as GIS, proved to be practical and cost-time effective, and allows for imaging and studying inaccessible places by traditional field measurements. RS satellites data are obtainable from different sources and with varying resolutions, covering small as well as large areas at local and global scales. Different sensors with different specifications are available both passive i.e., optical and thermal, and active i.e., Radar and LiDAR sensors. Benefits and limitations of these sensors are shown in Table 1. Furthermore, GIS is a framework for spatial databases capable of assembling and analyzing geographically referenced data, building spatial models enabling the simulation of different scenarios, and allowing for real and efficient forest management. The estimation and modelling of carbon sequestered using RS and GIS methods have been receiving increasing attention and usage due to the multiple benefits they offer. In the current review we used search terms that would provide an overview of the use of geospatial technologies (RS and GIS) in estimating forest biomass and sequestered carbon. The search terms used in the literature review were: “carbon sequestration”, “carbon sequestration and remote sensing” and “carbon sequestration and GIS”. A textual search on Google Scholar was conducted to find a statistically meaningful temporal trend. To highlight the development of researches in the subject under review over time and the increase in the use of geospatial technologies (RS/GIS) in carbon sequestration (CS) studies, the search was customized to group results by ten-year intervals starting in 1951 (Figure 1). Results have shown that the amount of scientific papers considering RS in their methodologies on carbon sequestration has increased exponentially over the last two decades. This can be attributed to the launch of many satellites recently, paving the road for more images becoming available to the end user either freely or commercially [20,23–26].

Following, a systematic review was conducted in two databases other than Google Scholar, namely, Web of Science and Science Direct. The databases were last accessed in May 2020 using the search terms: “carbon sequestration”, “above-ground biomass”, “remote sensing”, and “GIS”. The search was applied to articles that were published in peer-reviewed journals only. These searches collectively yielded 2,771 results. The results were pared down to 647 by applying three criteria: (1) the results were NOT “review papers” OR “conference proceeding” papers and only restricted to research articles; (2) the study belonged to terrestrial ecosystems excluding the marine and coastal ecosystems; and (3) the study is not a duplicate from a previous search. All articles were downloaded and stored using the reference management software (ZOTERO). Based on reviewing the abstracts, the list was further reduced to 171 by retaining only articles that discuss correlation between AGB and RS-based

![Figure 1](image_url)

**Figure 1.**
Textual analysis of terms: Carbon Sequestration, Remote Sensing and GIS using Google Scholar (accessed on 11th May 2020 at 12:30 AM Abu Dhabi)
parameters, and that use GIS in the analysis (not for mapping only!). Finally, the full-text assessment of the final articles was used for the preparation of this review.

Around two thirds of these studies used passive sensors, mainly optical (with different spatial resolutions), while the remaining third used active sensors (almost equally split between RADAR and LiDAR) (Figure 2). Half of the studies using optical sensors used coarse spatial resolution (>100 meters) sensors like MODIS and SPOT VEG. While more than one third used moderate spatial resolution (~10-100 meter) sensors like Landsat, IRS, and SPOT. Additionally, around 20% of these studies used fine spatial resolution sensors (sub-meter to 5 meters) like IKONOS, Quickbird and World View. To improve the accuracy of estimating AGB, integration of more than one sensor is becoming a trend (around 17% of the reviewed studies), as well as the integration with GIS-based approaches (around 14% of the reviewed studies). It was observed that more than 60 studies were conducted using these two approaches. In addition, it was found that the studies that tend to estimate AGB at plant species levels, instead of forests or mixed species, were increasing.

Using RS, GIS and modeling to study the current state of carbon sequestration and its future dynamics, are promising and have a potential ability as an innovative approach to tackle the ecological assessment problems[27]. RS-based methods have seen widespread use among the research community thanks to their unique characteristics either in data collection or in results presentation. RS data can sense and record spatial variability, spatial distributions, spatial patterns of forests and assess their changes over time[28]. Figure 2 shows the proportion of utilizing different sensors with a different number of bands, and costs for biomass and carbon sequestered estimation. Noteworthy that most of these studies run on boreal and tropical forests with a small portion run on other ecoregions/forest ecoregions. This could be due to the early availability of geospatial technologies in the northern developed countries (boreal forests) and the relative importance of the tropical rainforests to the global carbon cycle (Figure 3). RS data are nowadays abundant and widely available for a fraction of the cost required only a decade ago. For example, archived and recent Landsat imageries are freely downloadable from the USGS website, providing a globally consistent record since 1972; likewise, other resources are being published and added to the internet. Despite the successful application of many sensors in AGB estimation, selecting the “right” sensor is associated with the specific data availability of the area under study, project budget, technical skill requirements for data interpretation and software packages.

Table 1. A summary of limitations and benefits of Optical, RADAR, and LiDAR sensors used for estimating the Above Ground Biomass (AGB) of standing forests.
**Fine spatial resolution**

- **Hyperspectral**: V. High
- **RADAR Sensors**: High
- **LiDAR Sensors**: V. High

*It was calculated according to $R^2$ value.

**High (>40%), Moderate (≤40% and >30%), Low (≤30% and >20%), and V. Low (<20%).

Furthermore, RS data are used as input to GIS, where GIS is then used as a spatial platform for data layering and database building to perform spatial data analysis and map creation. Not only does this save time, but it also allows for faster and better communication between research centers across the globe[29]. A repository of various data sources (e.g., forest inventory, land use maps, elevation and RS data) can be used to measure vegetation parameters over large areas[30]. GIS is usually employed to process model inputs and to visualize results[29]. A hybrid classification approach within GIS, has improved land use and land cover (LULC) classification, forest and biomass mapping using Landsat data[30,31,32]. Results show that an integration of RS and spatial analysis functions in GIS improves the overall classification result from 50.12% to 74.38%[33].

RS and GIS methods are widely used to collect information about forest biomass and other vegetation’s structure variables. Moreover, they are very efficient in monitoring and mapping vegetation distribution at large scales and quantifying its productivity [20,23–26]. The process for mapping vegetation using geospatial technology consists in several steps. First, apply image preprocessing to improve the quality of original images. Second, determine the level of vegetation classification (at a community level or species level). Third, identify the correlation between the vegetation types and spectral characteristics of remotely sensed imagery. Finally, translate the spectral classes into vegetation types by assigning each pixel in the scene to one of the vegetation categories defined in a vegetation classification system. Classification methods are broadly based on the pixel-based classification (PBC) approach or the object-oriented based classification (OOC) approach. Both methods have their advantages and disadvantages depending on their areas of applications and, most importantly, the RS datasets that are used for information extraction[33].

### 2.1. Biophysical Parameters

RS tools detect and measure the different biophysical parameters of the vegetation growth based on the assumption that their body parts are growing at different degrees[34]. Those parameters are in fact detected by remote sensing because of the influence of the spectral characteristics of vegetation on the spectral signature measured by remote sensors. While spectral reflectance is primarily affected by chlorophyll content in vegetation, it is also influenced by vegetation density, shadow, texture, soil moisture and roughness[35,36] and constitutes one of the RS variables used in estimating biomass. The biophysical parameters used for estimating biomass include leaf area index (LAI), chlorophyll content, leaf nutrient concentration, crown measurements (crown area and crown diameter), height, DBH, stand basal area and greenness of canopy. All these parameters are used to estimate biomass traditionally, but only some are applicable for RS based estimation (Figure 3).

![Figure 3. Percentages of different biophysical parameters used in RS based estimation of AGB.](image-url)
For example, a high logarithmic correlation was found between AGB and LAI, when using ALOS POLSAR and UK-DMC2 in Malaysia to calculate LAI of oil palm [34,37],[38]. Although, it was concluded that an increase of the LAI shows a proportional increase in the spectral reflectivity or Normalized Difference Vegetation Index (NDVI) during the initial growth stage; however, no significant increase was recorded after full canopy cover was attained due to sensor saturation[38]. Nonetheless, hyperspectral RS has the ability to sense and record reflectances in many “narrow bands”; this is very advantageous for extracting vegetation parameters, such as chlorophyll content, LAI, and leaf nutrient concentration[39].

Large scale aerial photographs have been extensively used to measure various forest parameters, such as tree height, crown closure, crown diameter, etc.[40,41]. Multiple regression analysis and canopy reflectance models were applied to RS data for an indirect estimation of forest biomass, through determining tree canopy parameters, like crown diameter using [42]. The area of the crown can be measured by satellite imageries and, thus, biomass estimation. It was concluded that the medium-resolution or more detailed spatial resolution data could be used for the crown coverage[43]. Object-based image analysis was used to detect and delineate crown projection area (CPA), which is the canopy area that is covered by an individual tree [29,34]. IKONOS data (spatial resolution 4 m) was effectively used in estimating crown projected area, DBH and stem density[44]. An average tree crown size for hardwood stands could be estimated through measurement of tree crown size from IKONOS and Quickbird images [45].

LiDAR and Radar can be used to retrieve information about the height of trees. The height proved to be a potentially successful indicator for age in oil palms, for example, and it is widely used in estimating forest biomass[34]. Radar backscatters (P and L bands) are positively correlated not only to tree height and age but also to other major biophysical forest parameters such as DBH, basal area, and total AGB[46]. The three-dimension (3D) components of vegetation canopy structure can be measured using LiDAR, which is widely used in the estimation of forest biophysical parameters (Table 1). LiDAR data are used for both measurements of biophysical parameters such as tree height and stand volume, and in biomass estimation. However, the two-dimensional data (2D) have some limitations in estimating vertical vegetation structures such as canopy height, a critical biophysical parameter for biomass estimation (Table 1). Lately, some optical sensors instruments for stereo mapping like IKONOS, and SPOT have been providing stereo viewing capability that can be used to develop vegetation canopy height, hence improving biomass estimation performance [47]. Likewise, SPOT 5 HRS was used for forest height estimations in Bavaria and Spain, while 3-D information derived from SPOT 5 stereo imagery was tested to map forest parameters stem diameter, stem volume and tree height[48,49].

2.2. Vegetation Indices for AGB estimation RS-based models

Many studies are using vegetation indices (VIs) to estimate biomass (Figure 4) [50–53]. VIs are considered important applications for the study of spectral reflectance of vegetation. They can be used to identify and map land vegetation cover with accuracy by reducing soil background effects, atmospheric conditions and sun view angles[22,54]. They are indicators of vegetation vigor and show better sensitivity than individual spectral bands for the detection of biomass[55]. A strong and significant relationship have been manifested between VI’s and vegetation biomass [28,56,57]. In a study on the Anatolian pine forests, it has been shown that VI’s calculated using Landsat TM data, presented better estimation of AGB with an R² equal to 0.606 while, it was only 0.465 when using individual band reflectance[58].
AGB models can be developed using many available predictors, grouped into two distinct categories: reflectance of individual bands and VI’s. Different VI’s have been developed these include: normalized difference vegetation index (NDVI), difference vegetation index (DVI), simple ratio (SR), ratio vegetation index (RVI), global environmental monitoring index (GEMI), soil adjusted vegetation index (SAVI), enhanced vegetation index (EVI), tasseled cap index of wetness (TCW), tasseled cap index of greenness (TCG), tasseled cap index of brightness (TCB), normalized difference fraction index (NDFI), and many others. The ability of VI’s to separate the vegetation from its background varies from one ecoregion to another, and from plant species to another. Common vegetation indices used, include NDVI, EVI, and SAVI, in order to estimate biophysical variables such as LAI, Absorbed photosynthetically active radiation (APAR) and biomass[46]. A regression model using NDVI and reflectance in bands 3 and 4 of IKONOS were implemented for estimation of AGB for oil palm in Africa with 64%-72% accuracy[59]. In another region, it was found that the NDFI of Landsat ETM+ data has better performance for estimating AGB for oil palm in Malaysia with R-value equal to 0.8[60]. Additionally, the Normalized Difference Index (NDI) of green and red bands succeeded in separating oil palms from their background using a histogram dissimilarity metrics[61]. Nonetheless, any new VI should be tested before generalization. For example, Landsat TM was used in Eastern China to calculate VI’s with shortwave infrared spectral bands (SWIR), they were found to have a higher correlation with AGB in complex forest stand structures; while VI’s calculated using near-infrared bands (NIR) performed better in relatively simple forest stand structures[28]. It was concluded that the choice of adequate VI’s depends on the type of ecosystem, the environmental conditions and the spectral information available. In another case study in forests in Bogotá, Colombia, the best AGB estimation was achieved using RVI with R² of 0.582. Alternatively, it was concluded that atmospheric and topographic correction proved to be vital in improving prediction models, especially in high aerosol and rugged terrain[4].

However, some studies had shown poor relationships between biomass and VI’s as compared to using raw bands. Two optical sensors (Landsat TM and SPOT 5) were used to assess their efficiency and evaluate disparities in forest composition and AGB in Sabah, Malaysia[62]. It was found that NDVI derived from SPOT 5 can distinguish between pristine forests and oil palm plantations. However, they concluded that the spectral variables were limited in their effectiveness in differentiating between forest types and in estimating their biomass. In fact, the reflectance values of bands 3 (red sensitive) and 4 (near infrared sensitive) of Landsat are strongly correlated with the field-based AGB values while both the VI’s derived from Landsat TM and SPOT 5 (such as NDVI) are weakly correlated with the field-based AGB values[63]. Landsat data saturation is a well-recognized problem, it is considered as an important factor resulting in inaccurate forest AGB estimation, especially in dense forests with high AGB (> 130 Mg.ha⁻¹), as well as with non-homogeneous forest structures[28]. Spectrally, NDVI saturation could have led to underestimation of biomass carbon at certain places. The underestimated biomass was referred to the shadow effect resulting in decreased overall reflectance during their study to derive spectrally modeled AGB of coniferous forests of Western Himalaya[64]. Contrarily, they referred to the overestimated biomass in other places of their study area due to mixing up of reflectance contributed by soil and crown cover, which leads to an increase in overall reflectance[64]. In another
study area, no clear evidence of data spectral saturation at higher biomass value in open canopy woodlands[65]. To estimate total living biomass of miombo woodlands of Tanzania, Landsat 8 OLI-derived NDVI was proposed as suitable auxiliary information tool for carbon monitoring in the context of the United Nation (UN) program (REDD+)[65].

3. Gaps and limitations
Although RS proved efficient in saving time and money, however, this technology cannot achieve its goal without additional field and data measurement[13,66,67]. Nevertheless, the amount of fieldwork required with RS is mostly reduced. This should not lead to totally reject traditional methods in estimation AGB, instead taking the advantages of geospatial technologies methods to accelerate and enhance existing methods through process integration and modelling[68]. Geospatial technologies can be a modern alternative to traditional methods in estimation AGB and will continue to advance; however, it does not come without its limitations and drawbacks[69]. The technologies used in the RS process include satellites, aerial photography devices such as drones, computers and sensors are all extremely costly. The maintenance of these technologies can also be costly, requiring specialized care and trained professionals. Likewise, using computers to analyze the incoming data requires training and skills, such as being able to read the GIS maps and make sense of the incoming RS imagery. When using RS in ecological subjects like estimating AGB and carbon sequestration, uncertainties are high because of heterogeneity of landscapes, species composition, vegetation structural variations, soil properties, climatic variability and seasonality, disproportionate data availability and human activities; which have a significant impact on biomass distribution and change tendency[5,17,70]. Also, no RS sensors can measure forest carbon stock directly without additional ground-based collection[13,66,67]. Forest biomass at any point in time is affected by disturbance; likewise, forest structure is also influenced by environmental conditions, ecological processes of tree growth, mortality, and decomposition[26,71]. These issues must be considered when applying RS change detections studies, and dense time-series records are required to accurately monitor forest change in dynamic systems.

4. Recommendations & Conclusions
This review paper is supporting the consensus of thousands of scientific papers over the last five decades. Geospatial technologies such as RS and GIS proved to be practical, feasible and provide an adequate validation for AGB assessment monitoring, modeling and management of carbon sequestration. Such technologies can provide a tool for countries, especially developing ones to measure, map, monitor, model and manage their carbon stocks in biomass and soil.

There are many methods suggested for estimating forest biomass with varying advantages and shortcomings. The fieldwork-based methods are the most accurate, but they are destructive, time consuming, expensive and labor intensive. Building allometric equations can help alleviate these disadvantages. Unfortunately, most of the actual allometric equations are developed for mixed species and not tailored for specific species and most of them are built for specific sites and ecosystems (less applicable for arid regions). Thus, it is recommended to build allometric biomass equations integrable with RS variables and relying more on RS techniques to estimate biomass and carbon stock (crown and height attributes). Carbon sequestered rates, especially for plant species that have economic values, can be reached by building special Geo-databases. This should fill the gap and improve our ability to estimate the potentiality of plant species and ecosystems types for sequestering CO₂.

 Solely using RS may not always be possible without ground measurements, such as soil sampling and field results validation, required in all stages for any estimate in biomass research. The best fit methodology encompasses RS-GIS data analysis combined with fieldwork. The proposed procedures comprise three steps: pre-field work to identify areas of interest for sampling, field-works which include sample collection and measurement of plant characteristics, and finally a post-field activity that aims at processing and analyzing the RS data and validation of the model. Measuring forest biomass remotely and consistently over large areas greatly varies with the type of instrument and the platform. Raised difficulties could be tackled and solved using different sensors options, innovative methods, and
avoiding the limitations that relate to many aspects like scale, costs, error associated & uncertainties. High resolutions RS data are the most accurate but are costly; however, moderate resolution satellite data, such as Landsat, has proved to be effective in estimating above ground biomass with good accuracy, and consequently calculating the carbon stock. Furthermore, available long archived satellite data provide us with invaluable historical data to monitor the change of carbon stock over time. Developing algorithms that combine more than one remote sensor is highly important in order to estimate carbon sequestered. In AGB estimation studies, it is important to consider the effects of bioclimatic factors depending on parameters like plant age, species, forest type, rainfall, topography, vegetation structural variations, heterogeneity of landscapes, and seasonality. One of the common challenges to achieve this is to map the spatial pattern of vegetation and soil carbon and produce geo-referenced estimates of carbon to give a better understanding of carbon dynamics and quantify the regional and global carbon budget. In addition, it provides a strong knowledge to decision makers to identify what and where is the essential action to take.

The UN program for the reduction in emissions from deforestation and forest degradation (REDD+), is an international initiative to help nations earn financial incentives if they implement climate policies and if they demonstrate CO₂ emission reductions. Geospatial approaches are powerful tools to help implementing the REDD+ agenda through monitoring and continuous assessment of the efforts of all nations for sustainable management of carbon stock in all ecosystems.

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