Ground Biomass and Carbon Stock in Natural Forests - A Review

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Abstract

Carbon exists as carbon dioxide in the atmosphere and constitutes about 0.04% of the atmosphere. In the recent past, it has gained a lot of attention as a greenhouse gas, as it has potential to influence the climate pattern of the world. Anthropogenic activities like industrialisation, deforestation, forest degradation and burning of fossil fuel, has caused an increase in the level of carbon in the atmosphere and disrupted the global carbon cycle. However, nature has its own mechanism of sequestering and storing the carbon in its "reservoirs" or "sinks''. Forest plays an important role in the global carbon cycle as carbon sinks of the terrestrial ecosystem. The carbon sequestered or stored on the forest trees are mostly referred to as the biomass of the tree or forest. The Intergovernmental Panel on Climate Change identified five carbon pools of the terrestrial ecosystem involving biomass, namely the above-ground biomass, below-ground biomass, litter, woody debris and soil organic matter. Among all the carbon pools, the above-ground biomass constitutes the major portion of the carbon pool. Estimating the amount of forest biomass is very crucial for monitoring and estimating the amount of carbon that is lost or emitted during deforestation, and it will also give us an idea of the forest's potential to sequester and store carbon in the forest ecosystem. Estimations of forest carbon stocks are based upon the estimation of forest biomass. Forest's carbon stocks are generally not measured directly; however, many authors assume the carbon concentration of tree parts to be 50% or 45% of the dry biomass. This paper, aims to review and summarise the various methods and studies that were carried out to estimate the above-ground biomass of the forest.

Introduction

Carbon exists in the earth's atmosphere primarily as the gas-carbon dioxide. It constitutes a very small percentage of the atmosphere about 0.04% approximately. However, it plays an important role in supporting life on earth, as plants make themselves from it. During photosynthesis, plants take up carbon dioxide from the atmosphere, converting it into carbohydrate and releasing oxygen into the atmosphere. When these plants or trees die or are burnt, the carbon stored in them are released back into the atmosphere. This natural cycling of the carbon is maintained and controlled by a dynamic balance between biological and inorganic processes since the geological history of earth.

Nevertheless, the atmospheric concentration of carbon dioxide in the last five decades explains a disturbingly increasing trend. The rate at which carbon dioxide is being added to the atmosphere is also observed to be much faster than at any time in the past 80,000 years [1]. The carbon dioxide concentration in the atmosphere is continuously being measured and recorded since 1957 [2]. The carbon dioxide concentration in the atmosphere has increased from about 280 ppm, during the pre-industrial period, to approximately 390 ppm in the present-day [1]. The rise in the carbon dioxide level in the atmosphere is mainly caused by anthropogenic activities. In the 19th century, with the advent of industrial revolution, humans have been burning a huge amount of fossil fuels, releasing the carbon stored in it back into the atmosphere as carbon dioxide. Since the industrial insurgency, the carbon dioxide level in the atmosphere has increased tremendously causing remarkable changes in the natural global carbon cycle. Besides the combustion of fossil fuels, other human activities such as deforestation also have a considerable impact on the ability of the terrestrial biosphere to emit or remove carbon dioxide from the atmosphere. Deforestation and degradation of forests lead to emission of carbon dioxide through burning of forest biomass and decomposition of plant parts and soil carbon. These human activities have accelerated and contributed to a long-term rise in atmospheric carbon dioxide level.

With all the carbon dioxide pumped into the atmosphere from the various human activities, the planet would have been overheated rapidly if not for the nature's mechanism of sequestering the carbon from the atmosphere and storing it in its reservoirs like the oceans and the forests and soils. The nature's way of sequestering carbon from the atmosphere is a process of achieving balance of carbon dioxide levels in atmosphere and maintaining the global carbon cycle, and this cycle has been happening billions of years. However, humans have greatly disturbed this balance with various activities like combustion of fossil fuels and change in land-use patterns such as deforestation.

Why carbon cycle drew much attention is because carbon dioxide being the chief among the greenhouse gases, it has potentials to influence the global climate pattern [3], and it also has a relatively long residence time in the atmosphere. About 60% of the observed global climate change is attributable to this increasing carbon dioxide concentration in the atmosphere [4].

Nature has provided us with natural carbon "sinks" or "sponges" like the terrestrial ecosystem and the oceans. Forest's ecosystem is one

of the most important carbon sinks of the terrestrial ecosystem. Forest's vegetation takes up the carbon dioxide in the process of photosynthesis. In this natural process, it removes the carbon dioxide from the atmosphere and stores the carbon in the plant tissues, forest litter and soils. Thus, forest ecosystem plays a very important role in the global carbon cycle by sequestering a substantial amount of carbon dioxide from the atmosphere. This process is more prolific in a relatively new forest where the growths of the trees are still rapid. It is estimated that about 86% of the terrestrial above-ground carbon and 73% of the earth's soil carbon are stored in the forests [5]. The tropical forests are said to play a major role in the global carbon cycle, storing up to about 46% of the world's terrestrial carbon pool and about 11.55% of the world's soil carbon pool, acting as a carbon reservoir and functioning as a constant sink of atmospheric carbon [6-9]. According to a study conducted by Lugo and Brown [10], it was suggested that half of the so called "matured forests" could also sequester carbon and the rate of sequestering carbon could be further increased if human pressures are reduced or removed from these forests.

In a tropical forest ecosystem, the living biomass of trees, the understory vegetation and the deadwood, which includes the standing deadwood and the fallen deadwood like fallen stems and fallen branches, woody debris and soil organic matters constitute the main carbon pool. Among the above mentioned carbon pools, the above-ground biomass of the tree is mainly the largest carbon pool and it is directly affected by deforestation and forest degradation [11]. The change in the forest areas and the changes in forest biomass due to management and regrowth greatly influence the transfer of carbon between the terrestrial forest ecosystem and the atmosphere [12]. Hence, estimating the forest carbon stocks is mainly important to assess the magnitude of carbon exchange between the forest ecosystem and the atmosphere. Assessment of the amount of carbon sequestered by a forest will give us an estimate of the amount of carbon emitted into the atmosphere when this particular forest area is deforested or degraded. Furthermore, it will help us to quantify the carbon stocks which in turn will enable us to understand the current status of carbon stocks and also derive the near-future changes in the carbon stocks [11,12].

The Carbon Pools

According to the IPCC [13], there are five carbon pools of terrestrial ecosystem involving biomass, namely the above-ground biomass, below-ground biomass, the dead mass of litter, woody debris and soil organic matter. The carbon dioxide fixed by plants during photosynthesis is transferred across the different carbon pools. The above-ground biomass of a tree constitutes the major portion of the carbon pool. It is the most important and visible carbon pool of the terrestrial forest ecosystem [14]. Any changes in the land use system like forest degradation and deforestation has a direct impact on this component of the carbon pool. The below-ground biomass which constitutes all the live roots [13] plays an important role in the carbon cycle by transferring and storing carbon in the soil. The dead mass of litter and woody debris are not a major carbon pool as they contribute merely a small fraction to the carbon stocks of forests [14]. Soil organic matter is also a chief contributor to the carbon stocks of forests [15,16], next only to the above-ground biomass [14] and soils are a major source of carbon emissions following deforestation [17].

Generally, the estimated biomass components are the above-ground live biomass which includes the trees and shrubs excluding the roots, dead above-ground biomass like litters and fallen branches or stem, and the below-ground biomass which comprise of the roots. Our objectives of this paper are to review and summarize the various methods and studies that were carried out to estimate above-ground tree biomass and carbon stocks of forests and the benefits and limitations of these methods.

Methods for Estimating Above-ground Biomass

Estimation of the accumulated biomass in the forest ecosystem is important for assessing the productivity and sustainability of the forest. It also gives us an idea of the potential amount of carbon that can be emitted in the form of carbon dioxide when forests are being cleared or burned. Biomass estimation of the forest ecosystem enables us to estimate the amount of carbon dioxide that can be sequestered from the atmosphere by the forest. The accurate assessment of biomass estimates of a forest is important for many applications like timber extraction, tracking changes in the carbon stocks of forest and global carbon cycle. Forest biomass can be estimated through field measurement and remote sensing and GIS methods [14,18].

Two methods of field measurement are available. The first one is the destructive method of tree biomass estimation. Among all the available biomass estimation method, the destructive method, also known as the harvest method, is the most direct method for estimation of above-ground biomass and the carbon stocks stored in the forest ecosystems [11]. This method involves harvesting all the trees in the known area and measuring the weight of the different components of the harvested tree like the tree trunk, leaves and branches [14,19-23] and measuring the weight of these components after they are oven dried. This method of biomass estimation is limited to a small area or small tree sample sizes. Although this method determines the biomass accurately for a particular area, it is time and resource consuming, strenuous, destructive and expensive, and it is not feasible for a large-scale analysis. This method is also not applicable for degraded forests containing threatened species [24]. Usually, this method is used for developing biomass equation to be applied for assessing biomass on a larger-scale [25,26].

The second method of tree biomass estimation is the non-destructive method. This method estimates the biomass of a tree without felling. The non-destructive method of biomass estimation is applicable for those ecosystems with rare or protected tree species where harvesting of such species is not very practical or feasible. Montès et al. [24] developed a non- destructive method for the above-ground biomass estimation of thuriferous juniper (*Juniperus thurifera* L.) woodlands in the High Central Atlas, South of Morocco. In this study [24], the biomass of the individual tree was estimated by taking into account the tree shape (by taking two photographs of the tree at orthogonal angles), physical samples of different components of the trees like branches and leaves and dendrometric measurements, volume and bulk density of the different components. Although it is a non-destructive method, to validate the estimated biomass, the trees had to be harvested and weighted. Another way of estimating the above-ground forest biomass by non-destructive method is by climbing the tree to measure the various parts [27] or by simply measuring the diameter at breast height, height of the tree, volume of the tree and wood density [14] and calculate the biomass using allometric equations [28-30]. Since these methods do not involve felling of tree species, it is not easy to validate the reliability of this method. These methods can also involve a lot of labour and time and climbing can be troublesome.

Allometric Equations for Biomass Estimation

The most widely used method for estimating biomass of forest is

through allometric equations. The allometric equations are developed and applied to forest inventory data to assess the biomass and carbon stocks of forests. Many researchers have developed generalised biomass prediction equations for different types of forest and tree species [22-25,28,31]. The allometric equations for biomass estimation are developed by establishing a relationship between the various physical parameters of the trees such as the diameter at breast height, height of the tree trunk, total height of the tree, crown diameter, tree species, etc. Equations developed for single species and for mixture of species give the estimate of biomass for specific sites and for large-scale global and regional comparisons.

Brown et al. [28] developed allometric regression equations to estimate the above-ground biomass of individual tress for tropical forests as a function of diameter at breast height, total height and wood density and Holdridge life zone [32]. This estimate of Brown's biomass equation takes into account only the live trees and not the fallen litter and the standing dead trees. Nelson et al. [22] conducted a study to develop species-specific and mixed-species allometric relationships for estimating total above-ground dry weight using eight abundant secondary forest tree species in the Amazon. Chave et al. [33] proposed an estimation method for the estimation of biomass in a neo-tropical forest of French Guiana for which they have made use of published data sets providing the biomass and the diameter at breast height of felled and weighted trees. In this study, they have parameterized the regression models using 32 measurements of large trees. Ketterings et al. [34] also proposed an allometric equation for calculating the biomass of trees in the mixed secondary forest of Sumatra, Indonesia. However, the proposed equation is most suitable for trees having a diameter at breast height of 8-48 cm. Xiao and Ceulemans [23] conducted a study on a 10-year-old Scots pine to derive allometric relationships of branch and foliage biomass at branch and tree level and confirm the earlier studies conducted by Helmisaari et al. [35] on Scots pine in Finland. Segura and Kanninen [26] conducted a study in the tropical humid forest of Costa Rica to develop allometric models for estimating the stem volume, total volume (stem and branches) and the total above-ground biomass (stem, branches and foliage) for individual trees of that forest. Unlike other allometric equations found in the literature, where only the stem is taken into account for total volume, the model developed by Segura and Kanninen [26] includes the branches. The models, however, are recommended only when the diameter at breast height is between 60 and 105 cm. Aboal et al. [27] also developed allometric equations for estimating tree biomass in the Gomera laurel forest, Canary Islands. The proposed biomass equation is based on the relationship between volume and weight as they relate the diameter at breast height to the above-ground biomass. According to Aboal et al. [27], the diameter at breast height gives an idea of the volume of the tree. Kenzo et al. [36] harvested 136 trees from 23 species to measure the above-ground biomass in various tropical secondary forest trees in Sarawak, Malaysia. They also developed allometric relationships between the stem diameter at breast height, stem diameter at ground and leaf, stem and total root biomass. Their study also showed a relatively high correlation of allometric relationships between the tree height and plant-biomass. Navár [25] also developed allometric equations to estimate the biomass and carbon stocks for temperate forest and tropical dry forests of Mexico. These allometric equations are useful to estimate biomass of forests with complex diversity structure. Ryan et al. [37] carried out a study to quantify the forest carbon stock in Miombo woodland in Mozambique. They developed a new site-specific allometric equation, between stem diameter and tree stem, based on destructive harvest of 29 trees. Djomo et al. [38] also conducted a

study to estimate the total above-ground biomass of a moist tropical forest in South-western Cameroon using a locally developed mixed-species allometric equation. The choice of allometric equations has a significant effect on the biomass calculations since the forest biomass estimates vary with age of the forest, site class and stand density. Hence, the generalized allometric equations available for large landscape scales should be used with caution as the site greatly influences allometric relationships [39]. Kim et al. [40], in their study, emphasis that the sites specific allomeric equations are more accurate in predicting the forest biomass estimates on the local level as it takes into account the site effects. According to the studies conducted by Vielledent et al. [41], when biomass allometric models are not available for a given forest site, a simple height-diameter allometry is required to estimate the biomass and carbon stocks accurately from plot inventories.

There have been very few allometric equations developed specifically for lowland dipterocarp forest. Basuki et al. [31] collected the data from the lowland dipterocarp forest in East Kalimantan, Indonesia and 122 trees were sampled having a diameter at breast height (1.3m) of 6-200 cm. They then developed tree allometric equations for lowland dipterocarp forest by establishing a relationship between tree parameters such as the diameter at breast height, commercial bole height and wood density with above-ground biomass.

The forest carbon stocks are widely estimated from the allometric equations for forest biomass. Generally, the carbon concentration of the different parts of a tree is assumed to be 50% of the biomass [42] or 45% of the biomass [43]. However, Losi et al. [44] in their study estimated the carbon concentration of dry bole sample to be approximately 48% of the dry bole biomass. Djomo et al. [38] analyses the carbon content in wood with a CNS analyser and found a mean value of 46.53%. The biomass estimation of the forest can be worked out using any of the methods or in combination of the methods mentioned. At the same time, while choosing a method for biomass estimation one should keep in mind the applicability or the suitability of that method for the area or forest type or tree species. The allometric equations and regression models, for biomass estimation, also should not be used beyond their range of validity [22,45].

Although, the field measurements give a more accurate estimate of the forest biomass, it is labour and resource intensive and time consuming. Therefore, allometric relationship is often the preferred method for estimating forest biomass as this method provides a non-destructive and indirect measurement of biomass and comparatively, it is less time consuming and less expensive. The estimation of biomass with the help of allometric equation is considered to be a non-destructive method or an indirect method as these equations uses only the indicator parameter obtained from the forest inventories to estimate the biomass. However, the allometric equations developed for biomass estimation need to be validated. And for the validation of the biomass equations, cutting and weighting of tree components are required [24,37,38,40,46].

Use of Remote Sensing and GIS for Biomass Estimation

The measurement of field data is the most conventional method for estimating the forest biomass. Although, this method of forest biomass estimation is the most accurate method for the purpose, it is strenuous, expensive, time consuming and destructive (which may not be very practical for those forest ecosystems with threatened or rare or protected plant species). Moreover, it is applicable for only a small sample of trees and small-scale analysis. Therefore, remote sensing technology is expected to provide a solution for the above mentioned

challenges. Remote sensing is a process of acquiring data from a distance of an object, area or a phenomenon by analyzing the data through instruments without being in contact with the object or area which is/ are being examined. Remote sensing technology provides a synoptic view of the surface area of interest, thereby capturing the spatial variability in the attributes of interest. A major advantage of remote sensing technology is that it can obtain information about an area of interest that is difficult to access or inaccessible. Remote sensing has enabled us to monitor natural resources on a continental, even on a global scale. It is also the only realistic and cost-effective way of acquiring data over a large area.

Remotely sensed data are useful for mapping and monitoring vegetation, land cover and land-use change. Forest's carbon stocks can be evaluated using remote sensing technology. Several studies have been conducted to estimate the forest biomass using the data of remote sensing with the data collected from the field [47-51].

Nelson et al. [47] conducted a study to determine the utility of laser profiling data for the estimation of forest biomass and volume. In this study, they co-related the data of forest biomass and volume, obtained from field measurements taken from specific plots of the laser flight lines, with the corresponding estimates of forest canopy height obtained from the laser profiling. Steininger [52] conducted a study to examine the potential of Landsat TM images in estimating the above-ground biomass of tropical secondary forests. Lu [53] also conducted another study to estimate the above-ground biomass in the Brazilian Amazon using Landsat TM data. The study showed that the use of Landsat TM image for estimating forest above-ground biomass is more successful for successional forest rather than mature forests. Lefsky et al. [54] estimated the above-ground biomass in three biomes-temperate deciduous, temperate coniferous and boreal coniferous, using LiDAR remote sensing. LiDAR remote sensing is designed to allow the signal to penetrate the canopy. LiDAR systems send out pulses of laser light and measure the signal return time to directly measure the height and vertical structures of forests. They compared the LiDAR-measured canopy structure with the field measurements of above-ground biomass and found that a single equation can be used to relate the remotely sensed canopy structure to the above-ground biomass for all the three biomes with distinctly different forest communities. Omasa et al. [55] proposed a methodology for estimating carbon stocks using a high resolution, helicopter-borne 3-dimensional (3-D) scanning LiDAR system. The study was conducted in a Japanese cedar forest, and the LiDAR system measures the 3-D canopy structure of every tree in the forest. The study demonstrates that the allometric relationship between the tree height and carbon stocks will enable estimation of the total carbon stocks stored in the forest. Popescu [56] found that LiDAR data can be used to measure precisely the biophysical parameters of individual trees such as the diameter at breast height (dbh) which is one of the commonly used variables for biomass estimation of forest. Hudak et al. [57] evaluated and found that repeated LiDAR surveys along with field sampling and statistical modeling can be successfully used for accurately estimating high resolution and spatially explicit biomass and carbon dynamics in conifer forests. Ene et al. [58] conducted a study to assess the accuracy of LiDAR-based biomass estimation where they used the airborne laser scanning (ALS) sampling approach. Their finding suggested the systematic ALS assisted survey was more efficient than the ground-based inventory.

Image texture is an important property which gives information about an object or a selected region in an image. Studies have been carried out using texture measurements with optical data and SAR data for biomass estimation. Sarker and Nichol [59] explored the potential of optical imagery using ALOS AVNIR-2 texture indices for biomass estimation and obtained a significant improvement while using the ratio of texture parameters. Eckert [60] also obtained similar results in the estimation of forest carbon and biomass while using the texture measurement from WorldView-2 satellite data. In another study by Cutler et al. [61], a combination of SAR image texture and LANDSAT TM data were used for the estimation of tropical forest biomass. The result of this study suggested that inclusion of SAR texture with multi-spectral data can be successfully applied to a predictive relation at times and space other than which it was developed for. Although, texture measurements demonstrate a promising result for biomass estimation, it requires further investigation.

Baccini et al. [50] estimated the forest biomass for eighteen National Forests in California. For the estimation of forest biomass, they used a combination of data sources like remotely sensed data, topographic information and climatic variables, to map the above-ground biomass. They found that the estimate of forest biomass at the regional scale with this method gives a pretty much accurate estimates of the above-ground biomass.

Remote sensing data has become an important tool for the estimation of forest biomass. Biomass estimation using remotely sensed data is an emerging technology and it is being increasingly used to inventory forest biomass. Satellite-based estimates of carbon stock are likely to become more accessible over the next few years [11]. However, remote sensing data does not directly estimate the amount of biomass that is present in the forest. It only measures the parameters which are correlated to biomass like the tree height, crown size, forest density, forest type, forest volume, leaf area index, etc. Remote sensing data coupled with the field-based measurement of the forest is used to estimate the above-ground biomass. The field measurements are commonly used to develop predictive models or allometric equations for biomass and to validate the results obtained from the remotely sensed data. Once it is validated the remotely sensed data can be used to estimate the forest biomass for wider area where there is very little or no field measurement data available.

An overview of Forest Biomass Estimation in India

Tiwari and Singh [62] described a method for mapping biomass using black-and-white aerial photograph and ground survey data (non-destructive sampling) through a case study in Kumaun Himalaya. They subdivided the various forest types into five classes based on crown cover. The circumference at breast height ≥ 31.5 cm and the ground-measurement of crown cover was recorded for each tree in the sample plot. They then construct a regression equation relating the total above-ground biomass and crown cover. They suggested the use of generalized species equation for dominant and generalized interspecies equation for sub-ordinate species over individual species biomass equation as there might be differences in the composition and proportion of species due to factors like slope and aspects. Although, biomass inventories can be made using aerial photographs with a minimum non-destructive sampling, it was impossible to identify individual sub-ordinate species from the aerial photographs. The aerial coverage also does not provide sufficient data to make a generalization of the forest ecosystem across the country, as it is highly heterogeneous [63].

Rai and Proctor [64] carried out a study in the Western Ghats to estimate the above-ground tree biomass. The biomass was estimated by harvest method and deriving a regression equation relating the biomass fraction with the log transformations of diameter at breast height. They

found that the total bole and branch biomass was always within the 95% confidence limit of the total, above-ground biomass estimates and this observation was based on actual weighing of a large numbers of trees and are on fairly large sites (0.44-1ha.). Lodhiyal and Lodhiyal [21] also carried out a study in Bhabar forest of Central Himalaya to estimate e the biomass in a 5-, 10- and 15-years Shisham (Dalbergia sissoo Roxb.) forests planted after clear cutting mixed broad-leave tree species. 100 trees were measured in each forest type for height and diameter at breast height and grouped the trees of each forest into three diameter classes. They adopted the selective harvest technique for biomass estimation. Twelve trees in each forest were harvested, and regression equations for each component were developed for biomass estimation. The total biomass was obtained by adding biomass of each diameter class. They observed an increase in the total vegetation biomass with an increase in the age of the forest. Mani and Parthasarathy [65] developed allometric equation to estimate the above-ground biomass in the tropical dry evergreen forest of peninsular India. They calculated the biomass of a tree ≥ 3.18 cm diameter at breast height using two linear regression equations-one using basal area and the other using basal area and height. They found that the basal area and above-ground biomass obtain a positive correlation for all the sites. Their study supports the use of basal area value to provide effective estimates of above-ground biomass in tropical dry evergreen forests. Using the allometric equation developed by Mani and Parthasarathy [65], Mohanraj et al. [66] estimated the biomass and carbon stocks of different forest types in Kolli hills, Tamil Nadu. Devi and Yadava [19] also carried out a study to assess the above-ground biomass in the semi-evergreen tropical forest of Manipur using harvest method. They also found a positive correlation between the diameter at breast height of tree species and the above-ground biomass of tree components. The plots for sampling in the above studies have been randomly selected, and this may over- or under-sample as the patterns in nature are clumpy and not likely to be randomly distributed. Stratification of the sampling schemes increases efficiency of the survey by reducing unnecessary sampling and also ensures that major variations are being sampled [11]. Singh et al. [67] established allometric equations for the estimation of biomass for three tree species having a diameter at breast height < 10 cm. There have been limited studies attempted to develop such equations. They identified six 0.1 ha plots, which were well spread over the plantation of the size 44 ha. They have obtained a highly significant allomeric equation for all the components of the three species.

Many studies are also being carried out in India to estimate forest biomass and forest carbon stocks using remotely sensed data and GIS techniques [68-71]. Aspects (direction of slope with respect to the sun), and slopes (angle of geographical terrain) were observed to affect the biomass estimation of dry tropical forest [70]. Ramachandran et al. [68] conducted a pilot study to estimate the carbon stocks in the natural forests of Eastern Ghats of Tamil Nadu using GIS techniques and satellite data of IRS LISS III. In another study by Kale et al. [69] the potential of the forests in the Western Ghats to sequester carbon dioxide was estimated using ground-based observation in combination with satellite remote sensing data. For their study, they used the satellite data of Landsat TM, and IRS LISS III. In these studies [68,69], the forest type mapping and digital elevation models were prepared using 20 m contours and 15 m contours respectively. Ramachandran et al. [68] concluded with an emphasis on the need to have carbon databank for all types of forest in India to study carbon sequestration potential for better management of forests. Recent studies have made conjunctive use of remote sensing data and ground or field inventory data [72,73]. Thakur and Swamy [72] estimated forest biomass of Barnawpara

Sanctuary, Chattisgarh using remote sensing and ground data. It was found that there is a strong correlation between C and N densities of forest with NDVI and biomass. According to the study of Ravikumar et al. [73], the combination of satellite and forest inventory data reduces uncertainties in aboveground biomass estimation.

The first estimates of woody growing stock of India's forest was made by Forest survey of India in 1995 using forest's inventory data (1965-1990), thematic maps and forest cover data. This information is the main input for the estimation of carbon stocks for different institutions and scientists. Forest Survey of India carried out another project during 2008-10 to estimate the carbon stock of Indian forests between 1994-2004 by using remotely sensed data of sample areas and field survey method [74]. Sheikh et al. [75] also estimated the carbon storage in India's forest biomass for the year 2003, 2005 and 2007 using secondary data of growing stock data [76-78] and satellite data. According to their study, there has been a continuous decrease in the carbon stock in India's forest biomass since 2003, despite a slight increase in forest cover.

Summary and Conclusion

Forests are the largest carbon pool on earth. It acts as a major source and sinks of carbon in nature. Thus, it has a potential to form a chief component in the mitigation of global warming and adaptation to climate change. Estimation of the forest carbon stocks will enable us to assess the amount of carbon loss during deforestation or the amount of carbon that a forest can store when such forests are regenerated. The principal element for the estimation of forest's carbon stocks is the estimation of forest biomass. Although there has been numerous studies carried out to estimate the forest biomass and the forest carbon stocks, there is still a further need to develop robust methods to quantify the estimates of biomass of all forest components and carbon stocks more accurately.

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