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Assessment of carbon stocks in forest and its implications on global climate changes

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Abstract
The rapid changes in land use pattern have resulted into forest degradation and its adverse impact on global climate due to the emissions of green house gases (GHGs) from terrestrial and aquatic systems. The present paper reviews the methods to assess above ground biomass (AGB), below ground biomass (BGB) and soil organic carbon (SOC) in a forest catchment. It is found that out of various methods, Allometric method is the most suitable for AGB estimation, while root shoot ratio (RSR) & Allometric equations are used to assess the BGB in given forest. Out of several methods to estimate SOC, infra red spectroscopy (IRS) and Walkley & Black method is found to provide the most precise results as it has high carbon recovery rate, is less time consuming and cost effective. The Carbon stock estimation gives an idea about the quantity of carbon available in the area. A part of this 'C' stock appears as run-off in river/streams and finally in reservoirs/lakes where it is degraded via aerobic/ anaerobic degradation into GHGs which are emitted to atmosphere, thereby causing global warming and climate changes which is responsible for present changes in weather and hydrological cycles.

Keywords: forest, carbon stock, climate, soil, allometric

List of abbreviations:
AGB: Above Ground Biomass
BEFs: Biomass Expansion Factors
BGB: Below Ground Biomass
CH_4: Methane
CO_2: Carbon Dioxide
ETSs: Emissions Trading Schemes
FL: Forest Land
FOC: Forest Organic Carbon
GHGs: Green House Gases
GWP: Global Warming Potential
IPCC: Intergovernmental Panel on Climate Change
IRS: Infra Red Spectroscopy
LiDAR: Large Footprint Light Detection and Ranging
LOC: Labile Organic Carbon
LULUCF: Land Use and Land Use Cover Changes
N_2O: Nitrous Oxide
OC: Organic Carbon
REDD: Reductions in Emissions from Deforestation in Developing Countries
RSR: Root Shoot Ratio
SOC: Soil Organic Carbon
UNFCCC: United Nations Framework Convention on Climate Change

1. Introduction
The LULUCF changes and deforestation are amongst the most important factors that contribute to social and environmental challenges and hence are being faced by mankind in 21st century. Since 1750, approximately 35% of anthropogenic CO_2 emissions are found to be directly related to changes in the land use [1]. The CH_4 and N_2O are present in much lower concentrations than CO_2 in the atmosphere, but potentially cause much more

GWP, i.e. N_2O is 298 and CH_4 is 25 times more stringent GHG than CO_2 [2]. The N_2O is mainly emitted from human activities, particularly, agricultural practices. However, the impact of land use changes to global warming is difficult to quantify as GHGs are produced from diffuse sources and complex systems [1]. As per the IPCC, if the concentrations of GHG in the atmosphere continue to increase, the mean temperature at the earth's surface could rise from 1.8º to 4 ºC over 2000 level by the end of this century [2]. Climate change leads to average global temperature rise, sea level rise, melting of glaciers, changes in the habitat for plants and animals, intense droughts, hurricanes and other extreme weather events, increased wildfire risk and increasing events of floods and storms [12]. Changes in carbon stocks may occurs due to the following activities: (a) natural processes in the forest (b) indirect human influences (c) sustainable management practices viz. regeneration and harvesting in forests; (d) conversion of dense forests to other forest types; and (e) conversion of forests to cropland, grassland, wetlands, human settlements or other lands [3]. Tropical deforestation generates on an average about 1–2 billion tonnes of carbon per year during the 1990s, which is roughly 15–25% of annual global GHG emissions [4-5]. The significant sources of GHGs in most tropical countries are largely by deforestation and degradation of forest. The photosynthesis of forest vegetation and the decomposition & transformation of forest SOC is affected by climate changes which further impact the storage and dynamics of OC in forest soils [6]. Any change in land use practices may causes additional transfer of C from atmospheric CO_2 to the terrestrial environment (soil or vegetation), thus, reducing the atmospheric CO_2 concentration. More atmospheric CO_2 reduction may be achieved by (i) enhancing the net photosynthetic efficiency by planting more & more trees or grass in new areas (ii) slowing the rate of decomposition/degradation of SOC through land management (reduced intensity of tillage or altered water management).

Despite the importance of checking deforestation and associated emissions, developing countries have few economic or policy incentives to reduce the emissions from land-use changes [7]. Avoided deforestation projects were excluded from the first commitment period of the Kyoto Protocol (2008–2012), due to the concerns of reduction in fossil fuel concentration and measurement of GHG emissions reductions [8-9]. Recently, the importance of emissions reductions from tropical deforestation in future climate change policy has grown over the year. The UNFCCC has agreed to consider a new initiative led by forest-rich developing countries, who call for economic incentives to help facilitate REDD [10].

To estimate GHG emissions, the area of cleared forest and the amount of carbon stored in those forests need to be known. Several techniques to estimate forest biomass at different spatial scales, but destructive measurements of individual tree biomass are available to calibrate allometric equations (a statistical model relating the tree biomass to a set of predictors like as tree diameter and/or height, wood specific gravity or forest type) [11-13]. To effectively boost the ETSs, soil scientists are faced with the challenge of identifying and quantifying the GHGs fluxes from the soil. Suitable methodologies and protocols for monitoring SOC stocks must be developed.

The present paper reviews various methods which can be used to assess above ground biomass, below ground biomass & soil carbon stocks of forests. Information can also be used as a benchmark to estimate the AGB, BGB, and SOC availability which in turn may help in estimating GHG emission potential from the available carbon in the catchment as well as from the carbon transported to reservoir/ lakes. The carbon is considered as a net contributor of GHGs to the atmosphere. Mitigation measures are also suggested to reduce the C-stock and GHG emissions from catchment and reservoirs/ lakes.

2. Measurements of Forest Carbon Stock (FOC)

The main carbon pool in tropical forest ecosystems consists of the living biomass of trees, understory vegetation, dead mass of litter, woody debris and soil organic matter. The carbon stored in the AGB of trees is the largest pool and is directly impacted by deforestation and degradation. The estimation of AGB carbon is therefore the most critical step in quantifying carbon stocks and fluxes from tropical forests. Literature review reveals that no method is yet available to directly measure forest carbon stocks across a landscape. As a result, efforts are made to develop tools and models that can 'scale up' or extrapolate destructive harvest data points to larger scales based on proxies measured in the field or from the remote sensing instruments [12-14]. At the national level, the IPCC has set up guidelines to estimate GHG inventories at different tiers of quality ranging from Tier 1 to Tier 3 [15-16]. Tier 1 is based on highly aggregated data, default combustion and emission factors. It is also important to mention that data available in all the countries can provide rough approximations which can be immediately used to calculate a nation's carbon stocks. Ground-based measurements of tree diameters and heights can be combined with predictive relationships to estimate FOCs (Tiers 2 & 3).

All emission estimates from tropical/subtropical deforestation are based on biome-average datasets in which a single numerical value of forest carbon per unit area (tonnes of C per hectare) is applied to broad forest categories or biomes [17-20]. The most primitive compilations of biome averages were made decades ago and were subsequently updated and modified by the researchers [21]. The continuous updation of biome averages makes it difficult to identify original data sources and other key information. Many contemporary estimates of FOCs are based on multiple versions or iterations of analysis. The best guesses, often employed as multiple biome averages, are combined or modified [16-18]. Table 1 provides the advantages and limitations of available methods for the estimation of FOCs.

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Table 1: Advantages and limitations of methods used to estimate forest carbon stocks.

Sl.No	Methods	Description	Advantages	Limitations	Uncertainty	References
1.	Biome averages	Estimates the average forest carbon stocks for broad forest categories based on a variety of input data sources.	• Immediately available at no cost. • Data refinements could increase accuracy. • Globally consistent.	• Fairly generalized • Data sources not properly sampled to describe large areas	High	[19-20, 89]
2.	Forest carbon inventory	Relates ground-based measurements of tree diameters or volume to forest carbon stocks using allometric relationships.	• Generic relationships readily available • Low-tech method widely understood • Can be relatively inexpensive as the field labour constitutes the major cost.	• Generic relationships not appropriate for all regions • Can be expensive and slow • Challenging to produce globally consistent results.	Low	[12, 32, 63, 88]
3.	Optical remote sensors	Make use of visible and infrared wavelengths to measure spectral indices and correlate to ground- based forest carbon measurements e.g. Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS).	• Satellite data routinely collected and freely available at global scale.	• Limited ability to develop good models for tropical forests. • Spectral indices saturate at relatively low C stocks. • Can be technically demanding.	High	[90]
4.	Very high resolution airborne optical remote sensors	Uses very high-resolution (10–20 cm) images to measure tree height and crown area and allometry to estimate carbon stocks e.g. Aerial photos, 3D Digital Aerial Imagery.	• Reduces time and cost of collecting forest inventory data. • Reasonably accurate. • Excellent ground verification for deforestation baseline.	• Applicable only to small areas (<10 000 ha). • Can be expensive and technically demanding. • No allometric relations based on crown area are available.	Low-medium	[91-92]
5.	Radar remote sensors	Uses microwave or radar signal to measure forest vertical structure e.g. Advanced Land Observing Satellite (ALOS), Phased Array type L-band Synthetic Aperture Radar (PALSAR), *European remote sensing satellite* (ERS-1), *Japanese Earth Resources Satellite* (JERS-1), Envisat.	• Satellite data are generally free. • New systems launched in 2005 to provide improved data • Can be accurate for young or sparse forests.	• Less accurate in complex canopies of mature forests because of the saturation of signals. • Mountainous terrain also increases errors. • Can be expensive and technically demanding	Medium	[93, 94]

The Table 1 shows that forest carbon inventory method is the method of choice as it can be applied to measure carbon stock in the forest area with low uncertainty and better results compared to other methods discussed above. In many countries, it may be more feasible to rely on forest carbon inventories rather than remotely sensed data to estimate FOCs, as the labor costs are often low compared to installing and managing high-tech remote-sensing equipment. However, the satellite-based estimates of FOCs will likely be more accessible over the next decade, as the new technologies emerge and technical capabilities are strengthened.

3. Stratification of the Forest Land

The stratification process consists of separating the entire 'managed' FL in forest strata to minimise the variation within each forest type (stratum). The stratification of land-use categories, especially, of the FL in the different forest types, different forest management practices and REDD activities is a key methodological challenge. Table 2 provides the criteria, carbon pool to measure AGB & BGB and methods of carbon estimation in forest area.

Table 2: Criteria, components measured and recommended methods for carbon estimation in forest area.

S. No	Criteria for stratification	Carbon pools to measure AGB & BGB	Methods for estimation	References
1.	Climate zone, ecotype, soil type & management regime within land- use types.	AGB, BGB, dead wood, litter and SOC as well as emissions of non-CO_2 gases.	Allometric equations for trees Ratio of BGB to AGB for tropical dry forest, 0.56 for < 20 tons AGB/ ha, 0.28 for > 20 tons AGB/ ha, Carbon fraction (CF), 0.47 (default value for all parts).	[16]
2.	Vegetation, soil and topography	AGB, BGB, dead wood, litter, SOC and wood products.	Allometric equations for trees, destructive harvesting for shrubs, herbs and litter Root, Shoot ratio, BGB = exp (-1.0587 + 0.8836 x ln AGB), Carbon content = 0.50. (50% of total biomass).	[95]
3.	Land-use, vegetation, slope, drainage, elevation & proximity to settlement.	AGB/ necromass, BGB (tree roots), soil carbon and standing litter crop.	Equation for moist climate, annual rainfall (1,500 – 4,000 mm) $y = 38.4908 - 11.7883 D + 1.1926 D^2$, Root, Shoot ratio = 0.10 or 0.15, Carbon content = 0.50 (50% of total biomass).	[96]
4.	As per the guidelines of IPCC.	Pools covered under the IPCC guidelines are considered.	As per IPCC guidance.	[97-98]

The Table 2 indicates that - use of stratification based on climatic zone, soil type, and slope etc. may help a country to produce verifiable quantitative estimates for its forest strata. Moreover, no distinction is made between living and dead roots so the root biomass is generally reported as total living and dead roots but difficult to compare, generalize and model the root systems due to scarcity of data, lack of accuracy & precision in the methodology used.

4. Root Shoot Ratio (RSR)

RSR, an indicator of physiological processes affecting the carbon allocation, is of significant importance in providing the estimates of BGB and AGB. Multiplying AGB by RSR is the method used to estimate BGB and carbon stocks for National Greenhouse Gas Inventories [22-24]. The RSR can be calculated to measure BGB as shown in Table 3.

Table 3: Root Shoot Ratio for the estimation of BGB [16].

Domain	Ecological zone	AGB	RSR	Range of RSR
Tropical	Rain forest	<123 Mg/ha >125 Mg/ha	0.20 0.24	0.09-0.25 0.22-0.23
	Dry forest	< 20 Mg/ha > 20 Mg/ha	0.56 0.28	0.28-0.68 0.27-0.28
Subtropical	Humid forest	<125 Mg/ha >125 Mg/ha	0.20 0.24	0.09-0.25 0.22-0.33
	Dry forest	< 20 Mg/ha > 20 Mg/ha	0.56 0.28	0.28-0.68 0.27-0.28

The Table 3 reveals that the RSR is more in the case of dry forest and less in case of humid and rain forests. It is helpful for the calculation of BGB with the help of AGB.

5. The Carbon Pools

As per IPCC (2003), five carbon pools of terrestrial ecosystem consist of biomass, namely, the AGB, BGB, the dead litter mass, woody debris and SOC. The CO_2 fixed by plants during photosynthesis is transferred across the different carbon pools [3]. The AGB of a tree constitutes the major portion of the carbon pool & is the most important and visible carbon pool of the terrestrial forest ecosystem [25]. Any change in the land use, like forest degradation and deforestation, has a direct impact on this component of the carbon pool. The BGB, constituted by all the live roots, plays an important role in the carbon cycle by transferring and storing carbon in the soil [26]. The dead litter biomass and woody debris are not a major carbon pool as these contribute to only small fraction of the carbon stocks of forests [25]. Soil organic matter is also a chief contributor to the carbon stocks of forests after AGB and soils, which are the major sources of carbon emissions following the deforestation [25, 27-29].

5.1. Methods to assess the AGB pool in the forest

The most common method to estimate AGB of forests includes the combination of forest inventories with allometric biomass regression equations and airborne or satellite-based remote-sensing techniques [5]. Recent remote-sensing technique like LiDAR enables detailed assessments of spatial variations in AGB over large spatial scales but the accuracy depends on the calibration with field data [30-31]. Thus, allometric models are a crucial link in the estimation of forest AGB stocks [32]. Two methods of field measurement are available. (i) The destructive direct method of tree biomass estimation for estimating the ABG and the carbon stocks stored in the forest ecosystems [11]. It involves harvesting of all trees in the known area and measuring the weight of different components of harvested tree like the tree trunk, leaves & branches including weight of oven dried components [25, 33]. The method is not only limited to a small area or small tree sample size but is time and resource consuming, destructive, expensive, can be feasible for a large scale analysis and therefore is not applicable to degraded forests with threatened species [34]. But it can be used for developing biomass equations that may be used to assess biomass on a larger-scale [35]. (ii) The second method also known as, the non-destructive method can estimate the biomass of a tree without felling and is applicable for those ecosystems with rare or protected tree species, where harvesting of tree species is not very practical or feasible. In a study by Montes et al. [34], the biomass of the individual tree was estimated by taking into account the tree shape, physical samples of different components of the trees like branches and leaves and dendrometric measurements, volume and bulk density of the various components. Another way of estimating the AGB by this method is by climbing up the tree in order to measure the various parts [36] or by simply measuring the diameter at breast height, volume of the tree, height of the tree and wood density to calculate the biomass using allometric equations [37]. Since these methods do not involve felling of tree species, it is difficult to validate the reliability of this method which requires a lot of labour & time and the climbing can also be troublesome.

A reliable estimation of AGB should consider the spatial variability, tree and forest metrics (allometric models). Several papers have appeared in literature on AGB estimates in tropical forests around the world [38-42], while the research on BGB estimation is relatively limited to tropical areas [7, 22, 43-47]. As the root systems have particular features and require specific procedures, the measurements are time consuming, costly, qualitative, focussed only on one specific application and are often not representative of large areas as these generally involve a small number of root systems. In some cases, new methods (3D root architecture data analysis) can also be used to compute the continuous spatial distribution of coarse root volume, biomass and specific length of root [10].

5.1.1. Comparison of allometric models for mixed forests as a function of tree diameter and volume

Allometric equations can be used to accurately estimate the biomass and/or carbon stock in forest ecosystems. The mixed species tree biomass regression models were used for AGB estimation of natural and plantation forests as shown in Table 4. To accurately estimate the forest biomass, it is preferable to develop allometric equations for tree diameter and/or height, because once the equations are developed, the disturbance e.g. destruction of the forest stand can be avoided and it may be possible to cover large study areas [12, 48]. Moreover, the adequacy of this estimation is usually high even when there are many tree species within the same forest stand [49]. Research reported that the selection of the most appropriate allometric equations for a target forest is important to accurately estimate the forest biomass because the developed equations differ significantly between forest types as shown in Table 4. In most of the cases, DBH is largely used for the estimation of AGB because it saves time, cost and energy. Allometric models using diameter and height of trees are rarely reported since height (H) is often difficult to measure in the field due to time and cost constraints.

Table 4: Regression equations for the estimation of AGB for mixed-species forest

Sl. No	Regression equations	R^2		References
		Natural plantation	Plantation forest	
1.	$AGB = \exp\{-2.134+2.530 \times \ln(D)\}$	0.80	0.83	[50]
2.	$AGB = 42.69-12.800(D) + 1.242\ (D^2)$.	0.87	0.84	[50]
3.	$AGB= - 12.05+0.876(BA)$	0.98	-	[99]
4.	$AGB =11.27+6.03(BA)+1.83(H)$	0.94	-	[99]
5.	$AGB = 21.297- 6.953\ (D) + 0.740\ (D^2)$	0.87	0.84	[50]
6.	$AGB = \exp[-3.114+0.972 \times \ln(D^2H)]$	0.87	0.65	[100]
7.	$AGB = \exp[-2.409+0.952 \times \ln(D^2H)]$	0.88	0.67	[100]
8.	$AGB = \exp\ (-2.00+2.42) \times \ln(D)$	0.82	0.76	[39]
9.	$AGB = \exp[-0.37+0.33 \times \ln(D) + 0.933 \ln (D)^2 \times 0.122 \ln (D)^3]$	0.93	0.91	[51]
10.	$AGB = 1.276 + 0.034(D^2{\times}H)$	0.86	0.63	[52]
11.	$AGB = 38.4908 - 11.7883(D) + 1.1926\ D^2$	0.88	0.85	[100]
12.	$\ln(AGB) = 1.201 + 2.196{*}\ln(DBH)$	0.96	-	[55]
13.	$\ln(AGB) = (–0.744) + 2.188{*}\log(DBH) + 0.832{*}\log(WSG)$	0.97	-	[55]
14.	$\ln(AGB) = (–1.499) + 2.148{*}\ln(DBH) + 0.207{*}\ln(DBH)^2 – 0.0281{*}\ln(DBH)^3 + \ln(WSG)$	1.00	-	[12]
15.	$\ln(AGB) = (–2.977) + \ln (WSG{*}DBH^2{*}H)$	0.99	-	[12]
16.	$\ln(AGB) = (–2.289) + 2.649{*}\ln(DBH) – 0.021{*}\ln(DBH)^2$	0.98	-	[102]
17.	$\ln (AGB) = –2.025 + 2.459{*}\ln(DBH)$	0.84	-	[101]

Where; AGB in kilogram (kg); Diameter at breast height (DBH or D) in cm; H (tree height) in meters; WSG or WD is wood density (g /cm^3); BA, basal area (m^2).

The Table 4, shows that the generic allometric equations for natural plantations including height was developed by Chave et al. [12] who found the best equation with the highest R^2 of 1.00 and the lowest as 0.80 as estimated by FAO. 3.2.4. [50]. For plantation forest, the highest regression coefficient of 0.91 was estimated by Chambers et al. [51] and lowest (0.63) by Brown and Iverson [52]. The allometric equations based on the regression coefficient (R^2>0.90) discussed above might be useful for calculation of the AGB in forest area. As reported by IPCC, the field measurements of FOC though provide more accurate estimates of the forest biomass but are labour & resource intensive and time consuming as well[3]. The choice of an appropriate allometric equation requires low uncertainties in forest biomass stock estimates. The allometric equations are often preferred for estimating forest biomass, due to fact that it is a nondestructive indirect measurement of biomass, cheaper and less time consuming. This indirect method makes use of 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. The regression of AGP in different forest as a function of tree diameter and volume is given in Table 5, from which it can be seen that in all forest, SE from 2.44-7.37 indicates lesser uncertainty i.e. low variation in data for the estimation of AGB.

Rates of biomass accumulation are dependent on the different climatic conditions and eco-regions. The mean value given by Rai and Proctor [53] was found three times more than the estimation of Chan et al., [54]. Similar results were obtained when the results of Chan et al. [54] equation was compared with the results by Yamakura et al. [49] and Basuki et al. [55] for primary rain forests in East Kalimantan, Indonesia. These results emphasize the importance of tree height in the estimation of forest biomass. In addition, these findings indicate that tropical rain forests has higher biomass productivities than seasonal forests regardless of different climatic and topographic conditions. This suggests that various size classes of diameters and/or heights as well as different species must be considered to estimate biomass in any eco-region. The literature reveals that the higher variation are found in the mean estimation of AGB based on equations for primary rain forests, moist tropical forest, logged-over forest and mixed secondary forest. It is important to emphasise that the site-specific allometric relationships are vital for accurate estimation of biomass. Different forest types reflect different growth patterns giving different recovery rates of biomass accumulation.

5.1.2. Errors and bias in the estimation of the above carbon stock

Four types of uncertainties are associated with AGB estimates of tropical forests [32]: inaccurate measurements of variables, wrong allometric models, sampling uncertainty and poor representativeness of the sampling network. Vieira et al. [56] demonstrated the effect of inaccurate height measurement, for example a stem with a DBH of 20 cm and a height of 13 m gave an AGB of 153.0 and 127.0 kg respectively, when using the tool of Chave et al., [12]. With the same DBH, but one metre more height, the estimated AGB becomes 164.1 and 136.6 Kg, with an increase of about 7% and 5% biomass respectively. The LiDAR data and small footprint LiDAR data can also be used to retrieve indirect tree height estimates. The elevation difference within the footprint particularly for large footprint, LiDAR data can be substantially compared to the predominant tree height making it difficult to accurate estimate the tree height [57]. Terrestrial laser scanning (TLS) can also be used to estimate the tree height indirectly at plot level. However as the tree height, branching frequency and stand density increase, the quality of information obtained from the terrestrial laser scanner decreases due to inherent occlusion effects, increasing point spacing and the related uncertainty.

Most research is based on considering 10–30 sample trees per species which seems to be too low for biomass estimation of large countries in the tropics. The accuracy of biomass estimation ultimately depends on the accuracy of the original measurements used to develop biomass assessment tools like allometric models; BEF and generic equations and species group specific volume-to-biomass models [58-59]. BEFs are strongly dependent on the stand structure [60] and site characteristics/features [58, 61] and extrapolation with BEFs may lead to biased results when compared with local biomass equations [62] indicating the importance of representativeness and the risks of extrapolation.

Therefore, the lack of representativeness is the major drawback with current biomass equations. The sampling of sufficient trees is time consuming and costly for the purpose of acquiring the information on species and size distribution in a forest. Grouping all species even in species-rich tropical forests, may produce multiple/simple regression equations with high R^2 (>0.95) [63]. Therefore, use of regression equations stratified by eco-regions or species group (broadleaf or conifer) might increase the accuracy and precision of the equations which is based on a large number of trees spanning over wider range of diameters apart from the assess where unique plant forms occur for which development of regression equations is recommended [63].

There is, therefore, an urgent need to validate and test the reliability of allometric models for country and/or a specific region. The allomertic equation/ regression equations with high R^2 (>0.90) may help to predict the biomass in a particular eco-region but may not be applicable to other eco-regions due to climatic conditions, site specificity and forest types.

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Table 5: Regressions of AGB in forest as a function of tree diameter and height.

Sl. No	Location type	Forest type	Species	MAP (mm)	MAT (˚C)	No. of sample	Diameter Range (cm)	Mean AGB	Regression equation	Wood density (g/cm^3)	SE (%)	SL	References
1.	World moist tropical	MT	Mixed	-	-	170	5-148	32.17	In (AGB) = 2.53 × In (D)–2.13	0.71	4.77	0.40	[103]
2.	Kalimantan, Indonesia	PR	Mixed	1862	26	76	5-148	34.29	In (AGB) = 2.62 × In (D)–2.30	0.36-0.81	5.32	0.21	[49]
3.	India, Karnataka	PR	Mixed	6500	22	189	12.4-60.9	61.80	In (AGB) = 2.12 × In (D)–0.435	0.49-0.98	7.37	0.00	[53]
4.	Kalimantan, Indonesia	PR	Mixed	2000	27	122	6-200	34.75	In (AGB) = 2.196 × In(D) – 1.201	0.60	4.32	0.18	[55]
5.	Sumatra, Indonesia	MSF	Mixed	3000	26	29	7.6-48.1	20.22	In (AGB) = 2.59 ×In (D) –2.75	0.60	3.09	1.00	[104]
6.	Kalimantan, Indonesia	ESF	Mixed	1800	28	191	3.2-20.3	17.44	In (AGB) = 2.44 ×In (D) – 2.51	0.29-0.47	2.47	1.00	[105]
7.	Sarawak, Malaysia	ESF	Mixed	2600	27	136	0.11-28.66	17.34	$AGB= 0.0829 \times D^{2.43}$	0.35	2.44	1.00	[47]
8.	Sarawak, Malaysia	LOF	Mixed	4010	25	30	1.0-44.1	25.34	$AGB= 0.1525 \times D^{2.43}$	0.50	3.41	0.98	[106]
9.	Bago, Myanmar	MDF	Mixed	1900	25	160	1.2-25.4	18.82	$AGB= 0.069 \times D^{2.533}$	0.1-0.86	2.79	-	[54]
10.	Sarawak, Malaysia	LOF	Mixed	4010	25	30	1.0-44.1	19.56	$AGB= 0.1083 \times (D^2H)^{0.80}$	0.50	2.46	0.94	[106]
11.	Thailand	MIX	Mixed	1434-2721	-	119	-	24.32	$AGB= 0.0430 \times (D^2H)^{0.95}$	-	3.76	0.31	[107]
12.	Bago, Myanmar	MDF	Mixed	1900	25	160	1.2-25.4	18.15	$AGB= 0.063 \times (D^2H)^{0.86}$	0.1-0.86	2.49	-	[54]
13.	Northern Costa Rica, Europe	MIX	Mixed	4000	23.7	19	15.7-35.9	-	$AGB= 21.297 - 6.95(D) + 0.7403(D)^2$	0.62	-	0.92	[40]

Where; MT = moist tropical, PR = primary rain forest, MSF = mixed secondary forest, ESF = early successional secondary forest, LOF = logged-over forest, MDF = mixed deciduous forest, Mix = mixture of dry monsoon, monsoon-savanna, savanna, and rain forest, MAP = Mean annual precipitation, MAT = Mean annual temperature, SE = Standard error, SL = Significance level, n = number of samples.

5.2. Assessment of BGB pool in the forest

BGB constitutes about 30 % of AGB [64-65] which is estimated for most carbon mitigation projects and national GHG inventories using RSR or allometric equations. One of the most common methods for root biomass estimation is the RSR in which the root biomass is estimated from easily measured shoot biomass [66]. This method is currently widely used to estimate BGB and carbon stocks [22-24]. The method is not really precise due to considerable variability being encountered in the data, natural variability in forests and the use of different sampling methods, but also due to the lack of a systematically/statistically experimental design implemented [63]. Root biomass can also be estimated by another indirect method (without digging) using allometric models or equations [7], but such models/equations need calibration based on large amounts of data collected by reliable excavation methods as shown in Table 6.

Table 6: Methods to measure Carbon stocks in forests area.

Sl. No	Types of biomass	Methods of carbon stock estimation	Empirical formula	References
1.	BGB	Allometric equations	BGB = 0.02186 x DBH $^{2.487}$	[108]
			BGB = Exp [–1.0587 + 0.8836*ln(AGB]	[22]
		Root ,Shoot ratio	BGB= AGB x Root, Shoot ratio	[16]
2.	Deadwood and Litter	Gain–Loss" or "Stock-Difference" methods.	----	[3,16, 102]
3.	SOC	Dichromate Methods	Soil mass (t/ha) = [area (10,000 m^2 /ha) × depth (0.3 m) density (t/m^3)] SOC (t/ha) = [soil mass in 30 cm layer × SOC concentration (%)] / 100	[102, 109-110]

Despite the importance of below-ground parts in plant production, estimation of root mass and its distribution in the profile by direct method is still very difficult and time consuming and no single reliable methodology is available [67]. Difficulties in harvesting roots in their totality, particularly for deep root systems, [68] may lead to global underestimates of root mass in forest ecosystems. Consequently, the depths are not standardized but the depth selected in a given study is assumed to capture practically all the roots.

5.2.1. Methods of estimation of BGB

Two direct methods are used to estimate root biomass and it involves sampling individuals or multi-tree plots [23]. Single-tree excavation (STE) method consists of removing the tree root system from the soil and tracing each root individually from the stump to root tip. Volumetric Soil-Root Sample (VSRS) method requires the excavation of a given volume of soil and sorting the roots contained in that volume. These volumetric samples range from traditional auger cores and monoliths to Voronoi polygons [7, 23]. In in-situ imaging method, the roots are seen through a tube [69] or a transparent pane of glass [70] inserted into the soil. Though, biomass can be estimated by these imaging methods [71] but the results are obtained because these methods require a correction factor to convert length to root mass [72]. Of the direct methods, the first method (STE) is now considered as a standard method for coarse-root biomass [23]. On the other hand, for fine and medium roots, all the above-mentioned techniques provide highly variable biomass estimates. Millikin and Bledsoe [73] found that the root mass density of blue oak using the monolith method was at least 50% higher than that obtained by the core method for the youngest trees, while the reverse trend was observed for larger trees. For fine and medium roots, the choice is somewhat determined from the researcher's personal experience, preference, equipment, the time taken and available finances rather than accuracy and precision.

Part of the problem lies in substantial below-ground spatial heterogeneity and the highly variable allocation of photosynthates to roots [67]. In addition, fine-root dynamics are subject to many biotic and abiotic factors that vary in time and space. These factors include soil type, soil temperature, moisture, nutrient availability, tree age, trees species as well as the impacts of insects, fungi and other soil microorganisms [74-75].

5.3. Soil organic carbon (SOC) pool

Increasing SOC stocks are widely discussed as a short to mid-term implementable solution to the rising atmospheric GHG concentrations, as soils are the largest carbon reservoir of terrestrial carbon cycle. In 2005, about 10 – 12% of anthropogenic GHGs (N_2O & CH_4) emissions were contributed by agricultural activities, livestock and rice farming. The net CO_2 flux from soils was estimated at only 0.04 Gt/year [76]. Carbon storage in soils is the balance between the input of dead plant material and losses from decomposition and mineralization of organic matter. Under aerobic conditions, most of the carbon entering the soil returns to the atmosphere by autotrophic root and heterotrophic respiration. DayCent model was developed to simulate ecosystem dynamics for agricultural, grassland, forest and savanna ecosystems for the prediction of GHG emissions [77-78]. DayCent used more mechanistic sub models to simulate daily plant production, uptake of plant nutrient, trace gas fluxes (N_2O, CH_4), NO_3 leaching, and soil water and temperature [77, 79]. Factors affecting the CO_2 production and emissions from the soil are given in Table 7.

Table 7: Parameters affecting the CO_2 production and emissions from the soil.

Sl. No	Factors	Effects	References
1.	**Physical Conditions**		
	a) Soil temperature	The CO_2 emission is not possible below 5^0C, but logarithmic increase from 20 to 40^0C.	[111]
	• Soil moisture	Increasing CO_2 emission with increase in soil moisture up to an optimum level, above which it reduces drastically.	[112]
	• Temperature- moisture interaction	Re-wetting a dry soil considerably increases CO_2 efflux.	[113]
	• Crop seasonality	Soil respiration is highest during the crop growing season. The seasonal CO_2 flux is high in spring followed by summer, autumn, and winter.	[114]
2.	**Soil Conditions**		
	• Texture	Soil texture affects microbial activity, water and air diffusion rates, thus CO_2 formation.	[115]
	• pH	Directly related to microbial activity	
	• Salinity	Excess amounts of salts have adverse effects on soil microbial processes.	
	• Others	Microbial activity can be inhibited by the presence of toxic material in the soil and thus, CO_2 emissions.	
3.	**Soil Management**		
	• Manure application	Application of large quantities of organic/farm yard manure can increase CO_2 emission in the soil.	[116]
	• Fertilizer application	The application of N fertilizer may increase acidity and reduce microbial activity in soil.	[117]
	• Tillage	Tillage activities can promote soil aeration which increases CO_2 emission in soil.	[118]

As stated above, the agricultural activities directly produce and release about 10-12 % of the atmospheric GHGs such as CO_2, CH_4, N_2O [76]. Similar to the concerns about the pool, there exists a significant uncertainty regarding the estimate of GHG fluxes (CO_2, CH_4) from world soils. Eddy Covariance (EC) measurement of CO_2 flux is valuable in this regard as it can cover longer time periods spanning a year or more (Post et al. 2001). Due to the heterogeneity of SOC distribution, the samples required to accurately estimate SOC stocks at large scales suitable for carbon trading is high. Goidts et al., [80] found an increase in coefficients of variation (CV) from 5–35 % in SOC stocks. Inadequate sampling procedures produced biasness in data resulting in inaccurate estimations of SOC stocks [81]. Gaudinski et al., [82] found that calculation of CO_2 flux is very sensitive to the estimation of rock content in soil. The details of method to evaluate SOC are given in Table 8, from which it is seen that Walkley and Black method is suitable to calculate SOC from terrestrial biosphere due to high recovery rates, low cost and need of less time [83]. Recently, IRS has been applied to measure numerous soil properties including OC content and composition in bulk soils and soil fractions due to its being fast, inexpensive, non-destructive, and requiring little/no sample pre-treatment [84-85].

Table 8: Problems identified and suggested mitigation measures.

Sl. No	Ecosystem	Problems	Strategy	Potential land-management change	Potential for LULC changes	References
1.	Forests	Deforestation causes soil erosion and rise in temperature in nearby area.	• Carbon sequestration	• Lengthen timber harvest-regeneration rotation. • Increase forest management intensity (increase in forest density, forest fertilization, thinning, reduction in fire fuel to reduce severe fires, management of insects and diseases).	• Reduce logging frequency. • Convert lands to forest (afforestation). • Preserve forest and avoid deforestation	[119-120]
			• Mitigation of net GHG emissions	• Reduce logging impacts	• Reduce deforestation	
2.	Croplands	• Rice crop emitting more CH_4 because of anaerobic condition into the soil, as compared to other crop because the requirement of water is not much more as compared to rice crop. • Cropland requires fertilizer and pesticides, after degradation thereby emitting NO_2 gas into the atmosphere.	• Soil carbon sequestration	• Reduce crop tillage • Change crop mix to high-residue crops and crop rotations • Increase winter cover crops • Increase efficiency of crop fertilization • Reduce summer fallow • Restore agricultural land • Use biochar	• Convert to grassland and perennial crops.	[121-122]
			• Mitigation of CH_4 and N_2O emission.	• Improve crop tillage • Improve crop mix • Increase efficiency of crop fertilization • Expand irrigation	• Reduce rice acreage	[118, 123-124]
3.	Grasslands/ shrub lands	• Degradation of shrub/ grassland causes soil erosion. • It also releases CO_2 in to the atmosphere.	• Soil carbon sequestration	• Modify grazing management practices. • Improve efficiency of fertilizer. • Allow natural succession towards native shrub and forest. • Restore degraded rangelands		[125-126]
			• Mitigation of net GHG emissions	• Reduce severe rangeland fires	• Reduce conversion of grassland to energy producing crops.	[127-129]

It is also successfully used to measure SOC in-situ, which is a reliable and low-cost method for assessing SOC stocks on the field scale, thereby resolving the problem of inadequate data resolution [86]. Kumar et al., [83] also found that out of the total SOC, LOC is largely responsible for the GHG emissions in soil/lakes/reservoirs. Several studies measured only the carbon changes in the top 20 to 30 cm of the soil profile and therefore do not shows any effect of leaching and activity by earthworms on the movement of carbon down the profile. In addition, temporal sampling of SOC measurements tends to be sparse, inadequate in number and time interval to estimate SOC decomposition rates [87].
From the Table 7, it is concluded that GHG emissions from the soil is affected by reduced tillage, extended rotations, temperature, pH, increased crop use efficiency of fertilizer-N and use of chemical or natural inhibitors of nitrification. Proper management of soils and crops also help to reduce GHG emissions by storing atmospheric 'C' as soil organic matter.

6. Problems due to C-stocks and remedial measures

As stated elsewhere, a forest consists of several components i.e. AGB and BGB. The presence of this organic matter in natural forests may cause natural process of degradation to release GHG depending on the prevailing environment in soil/sediments [11, 13]. The runoff from degraded areas is carried during flooding to river and streams which ultimately reaches the reservoirs/lakes and finally settle at the bottom. The organic matter undergoes aerobic or anaerobic conditions prevailing at the bottom and releases significant quantities of GHG gases into the atmosphere thereby causing global warming. Depending on whether CO_2 /CH_4/N_2O is in significant quantity, the global warming impact is accordingly measured. These gases bring serious climate changes affecting the environmental processes.
The long term climate change effects may be minimized by applying catchment area treatment of degraded area using high photosynthetic efficiency, conservation of forest, stopping the flow of forestry organic matter to river/reservoirs and recovery of GHGs as a source of energy from reservoir, if GHG production is significant. The problems identified and suggested mitigation measures are however discussed in Table 8, it shows that the mitigation of net global carbon emissions requires both reduction in the sources of N_2O/CH_4/CO_2 to the atmosphere as well as maintaining and increasing the terrestrial carbon sinks.

7. Conclusions

Forests, the largest carbon pool on earth, act as a major sources and sinks of carbon in nature. IPCC Tier 1 is useful for the estimation of national level forest carbon stocks and helps countries and policy-makers to predict climate changes/carbon sequestration. Allometric models can be used to predict stand and landscape AGB. Correlation between AGB and BGB and RSR is found within a narrow range. Thus, the default RER or Allometric equations could be used to assess the C-stocks of a given forest. Out of the several methods, IRS, and Walkley and Black method is found as the best method to calculate SOC due to high recovery of carbon, low cost and less time requirement. Satellite-based forest carbon stocks estimation may be more useful in future.

The estimation of C-stock gives an idea about the quantity and quality of carbon available in the area and also how it does behaves in water bodies, where the carbon is ultimately degraded to GHGs emissions to the atmosphere causing global warming and climate change impacts ,which affect entire ecosystem significantly. The suggestion of suitable mitigation measures is also given in order to reduce the GHG emissions.

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