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Current and emerging technologies for carbon accounting in urban landscapes: Advantages and limitations

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ABSTRACT

Carbon capture, storage, and sequestration are crucial for mitigating climate change's adverse effects. To limit global temperature rise within the 2 °C target, it is essential to implement both artificial and natural carbon-capturing techniques and utilize renewable resources. Natural carbon sinks serve as vital resources for CO₂ reduction, but quantifying their carbon sequestration is complex due to potential CO₂ release from the upper ocean. Accurate assessment requires detailed modeling of interacting natural processes. This review critically examines various natural carbon pools, methodologies, and modeling techniques for carbon accounting, particularly in urban landscapes. The strengths and limitations of each approach are analyzed, leading to specific recommendations. Socio-economic benefits associated with natural carbon sinks are also presented. Ground and field measurements are found to be the most accurate methods, while accounting methods tend to be study-specific. Additionally, satellite earth observation, drone, and airborne measurements have significant potential for enhancing ecosystem analysis, assessment, and mapping. By comprehensively assessing these factors, this review contributes to the development of effective strategies for carbon accounting and management in diverse environments.

1. Introduction

Climate change, characterized by global warming and caused by human activities, has raised carbon emissions significantly and brought about significant sustainable development challenges to human society and the natural ecosystems (Deeksha, 2022; Liu and Li, 2012; Salimi and Al-Ghamdi, 2020). Moreover, fossil fuels released during combustion have contributed substantially to global warming over the last twenty years (Tahir et al., 2021). Coal is a particularly harmful fuel because it produces two times more carbon dioxide (CO₂) per unit of energy than natural gas. Therefore, researchers have focused on cleaner coal technologies and carbon capture and sequestration (CCS) techniques (Imteyaz et al., 2021).

Furthermore, researchers are looking at the prospect of using oil and gas reservoirs for carbon (C) sequestration because of the industry's expertise in injecting CO₂ into these sites for enhanced oil recovery (EOR) (Aldrich and Koerner, 2011). The terms carbon storage (C_{Stor}) and

carbon sequestration are interrelated (Nelson et al., 2009). However, these terms describe two different qualities of climate regulation. C_{Stor} measures the capacity of the ecosystem to hold carbon and prevents the further release of stored carbon. In contrast, carbon sequestration does not denote reducing and relocating environmental carbon emissions into long-term pools. It is a time-based process that purges carbon (evenly or unevenly) from the atmosphere, with the quantity of carbon removed varying over time. Even if a project shows positive sequestration, negative sequestration, i.e., carbon discharged into the atmosphere, can occur (over some time intervals). Thus, the temporal characteristic must be included for sequestration projects to be more accurately evaluated (Feng, 2005; Xu et al., 2023b).

Natural carbon sequestration is receiving increased attention from researchers as a viable option for cost-effective mitigation. Researchers have developed several indicators showing vegetation's significance for carbon capture (Baude and Meyer, 2023; Kolarik et al., 2023; Wang et al., 2022; Xu et al., 2023a). With binding treaties like the Kyoto

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Protocol, countries may be more driven to integrate it into their schemes to manage and reduce greenhouse gases (GHG). Urban greenery is gaining prominence as a mitigation measure for climate change because soil carbon accounts for a quarter of the natural climate solution potential, of which 40% consists of protecting existing soil carbon, while 60% includes rebuilding depleted stocks (Bossio et al., 2020; Habib and Al-Ghamdi, 2021, 2020). For example, governing bodies of many cities have adopted policies to enhance tree planting, conserve urban green spaces, and promote green roofs and facades in architecture (Mannan and Al-Ghamdi, 2021; Tahir and Al-Ghamdi, 2023). Introducing an urban green ecosystem includes decreased GHG emissions, improved air quality and thermal comfort, better-quality run-off water and flood protection, and savings in energy use.

Additionally, green spaces offer improvements in health and a wide range of recreational and psychological advantages and encourage social responsibility by taking positive measures on the environment and climate change (Mcpherson et al., 1994; Pataki et al., 2011). Although the social benefits are well-documented, the physical benefits still require more scientific investigation. For example, there is limited evidence to support the efficacy of urban vegetation in diminishing GHG emissions or the accumulation of airborne pollutants (Haase et al., 2014; Velasco et al., 2016).

1.1. Carbon emissions

CO₂ emissions contribute an estimated 50% to anthropogenic greenhouse gas emissions (Dakwale and Ralegaonkar, 2012). Compared to the mid-1800 s, mean CO₂ concentrations (399 ppm) were 40% higher in 2015, representing a 2 ppm/year average growth over the past decade. During this same period, nitrous oxide (N₂O) and methane (CH₄) levels have also substantially increased (International Energy Agency, 2016). These excessive carbon emissions have led to society's significant concern over climate change from both human and natural sources. Anthropogenic carbon emissions come from cement production, deforestation, and fossil fuel combustion, while natural sources stem from decomposition, ocean release, and respiration. The growing utilization of fossil fuels is resulting in accelerated emissions globally. Coal is the most carbon-intensive fossil fuel, with every ton of coal that is burned producing about 2.5 tons of CO₂ (Department for Environment Food and Rural Affairs, 2013). Moreover, it leads to the loss of biodiversity in the ecological system and the frequent occurrence of natural disasters (Cai et al., 2020). Thus, substantial reduction models must be applied to limit CO₂ emissions and air pollutants like SO₂ and NO_x.

1.2. Carbon capture in nature

Carbon sinks act as a primary component of the carbon cycle in nature, turning carbon into different forms by absorbing CO₂ from the atmosphere more than it emits. For example, global carbon pools and fluxes are integrated to form a global carbon cycle. These natural pools perform as carbon sinks, absorbing and moving carbon between sinks via different pathways and mechanisms (Fig. 1). The Earth's crust is the

first carbon sink, holding the highest concentration of carbon (Oberle, 2016). The other carbon pools are the stored fossil fuels underneath (4,000 PgC (Gton of carbon)) and that which is distributed in the atmosphere (750 PgC). The transformation of carbon through these pools can occur via carbon fixation from the atmosphere to plants (through photosynthesis) or via dissolution into carbonates in the oceans. Excessive release into the atmosphere causes a carbon cycle imbalance that leads to warming because the amount of accumulated CO₂ released is higher than sequestration. Carbon cycle imbalance also occurs via the acidification of oceans as the dissolution process increases.

1.3. Purpose of this study

As the accounting methods differ due to the system type or carbon pool, it is essential to determine the appropriate method to apply to a particular system. This study aims to collect and evaluate the various carbon accounting methods that have been used and developed, emphasizing urban landscapes so that researchers are provided with a guide that allows them to determine which carbon accounting methods are suitable concerning the location, geographic scale, and available resources by answering the following questions:

- What are the various methods being used for terrestrial carbon accounting, and how do they vary for different carbon pools?
- What are the limitations of these methods?
- Can a combination of different methods improve accuracy in biomass estimates and in carbon accounting?
- What approaches can be deployed based on these methods for collecting accurate data?

In addition, the drawbacks of carbon accounting methods and the challenges are discussed and presented in this work. This survey comprises of review methodology (section 2), an overview of carbon pools, fluxes, and stocks (section 3), a detailed discussion of carbon accounting methods (section 4), the socioeconomic benefits of urban landscapes (section 5), discussion (section 6) and conclusion (section 7).

2. Material and methods

The papers chosen in this review were based on methodologies that have been used and developed over the past four decades worldwide. A literature search via the Institute for Scientific Information (ISI), Web of Science (Elsevier, Springer, etc.), and the Forest Service of the United States Department of Agriculture (USDA) was done to identify relevant studies for inclusion. The search also targeted the following key search terms and Boolean operators: natural carbon sequestration in carbon pools, urban trees carbon, ecosystem carbon, ecosystem services, urban landscapes, urban forests, and environment, soil and agroforestry, and carbon storage valuation or value. The subject of "carbon sequestration" is interdisciplinary and is found in numerous published journals covering various disciplines, including planning, land use science, geography, remote sensing, ecology and landscape ecology, computational

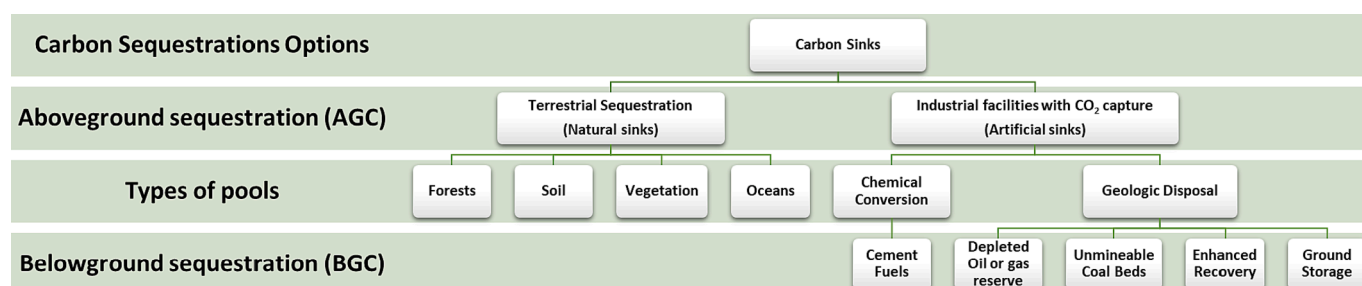


Fig. 1. Carbon sink types and carbon destination.

science, biology, planning, forestry, etc. The search returned approximately 320 records and papers concerning carbon measuring and accounting with various methods applied (based on the type of natural carbon pools). A check for content relevance was conducted, and those found to be irrelevant were excluded. Studies examining previous work were also investigated thoroughly to avoid any similarities. These checks resulted in 200 + articles included for in-depth analyses. Papers were analyzed against various carbon accounting methods and techniques (Table 1 and Fig. 2). The focus areas were selected based on the study type, and thus the method was used in accordance.

3. Carbon stocks and pools

Carbon stocks are the amount of carbon contained in a carbon pool. Different ecosystems store different amounts of carbon that depend on their ecosystem productivity (it refers to biomass generation in the ecosystem). For example, swamps and marshes store more carbon than temperate forests or cultivated lands (Fridley, 2001). During photosynthesis, the carbon fixed by plants is transported across the various carbon pools. Therefore, the way carbon gets into these ecosystems is through plants' leaves. It is a kind of carbon fixation that removes the CO₂ from the atmosphere and is stored as biomass, termed carbon stocks inside the trees (twigs, branches, trunks, leaves, etc.). The carbon is pumped from the ground to roots and eventually recycled between the trees and soil over time. There is a gradual buildup of carbon in the soil. Estimation is required when preparing an organizational carbon inventory as it is the primary source of carbon information and is recognized as an essential data source for carbon accounting (He et al., 2022; Yin et al., 2022). The United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol require national governments to provide annual inventories of all anthropogenic GHG emissions from sources and deductions from sinks.

3.1. Carbon pools

As per Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2003), there are five carbon pools of a terrestrial ecosystem related to biomass, namely: aboveground biomass (AGB), belowground biomass (BGB), soil organic carbon (SOC), the dead mass of litter and the woody debris (Fig. 3). Carbon pools are carbon reservoirs that can absorb and release carbon. The global carbon cycle comprises these pools exchanging carbon with one another, known as carbon fluxes. Carbon stocks are present in various terrestrial ecosystem carbon pools and the carbon fluxes between them (Woldemariam, 2015).

3.1.1. Carbon in aboveground biomass (AGB)

Carbon inventories and most mitigation efforts emphasize AGB for carbon accounting. Under the Kyoto Protocol, it is the main pool for afforestation and reforestation. Furthermore, carbon estimating methodologies and geographic information system (GIS) models for computing and projecting aboveground biomass is the most developed compared to other carbon pools. Biomass in non-forest land-use systems like farmland and grassland comprises non-woody perennial and annual plants that account for a small portion of the total carbon stock in the ecosystem than in forestlands. Because non-woody biomass is a part of the yearly carbon cycle and is subject to turnover annually or every few years, the net biomass carbon stock may stay relatively stable over time, even if stocks decline due to land degradation (Ravindranath and Ostwald, 2008).

3.1.2. Carbon in belowground biomass (BGB)

This denotes all living biomass of live roots and soil organic matter. However, roots less than 2 mm in diameter are often excluded since they tend to be empirically indistinguishable from soil organic matter or litter. BGB growth is defined by growth, including root collar and coarse roots. It comprised organic content in mineral and organic soils

Table 1

Carbon accounting Types and techniques used for each natural carbon pool.

Carbon Stocks Type	Carbon Accounting Technique	References
Above ground carbon: Trees species & Litterfall	Ground sampling	(Clark et al., 1986a) (Nowak, 1993) (Dewar and Cannell, 1992) (Mcpherson et al., 1994) (Suwanmontri et al., 2013) (Wotherspoon et al., 2014) (Clark et al., 1986b) (Rowntree and Nowak, 1991) (Peper et al., 2001) (Oren et al., 2001) (Strohbach and Haase, 2012) (Nowak and Crane, 2002) (Dorendorf et al., 2015) (Nowak et al., 2013) (Baral and Guha, 2004) (Nowak et al., 2013)
	Allometric equations	(Soares et al., 2011) (McPherson et al., 2011) (Flocks et al., 2011) (Parmehr et al., 2016) (Birge et al., 2019) (Birge and Berger, 2019) (Riley et al., 2018) (Riley and Gardiner, 2020) (Hynynen et al., 2005) (Salminen et al., 2005) (Siipilehto et al., 2007) (Ahtikoski et al., 2011, 2012) (Mönkkönen et al., 2014) (Hynynen et al., 2014) (Triviño et al., 2015) (Rowntree and Nowak, 1991) (Mcpherson et al., 1994) (Brack, 2002) (Nowak et al., 2003) (Myeong et al., 2006) (Churkina, 2008) (Jenkins et al., 2003) (Churkina et al., 2010) (Crowther et al., 2015) (Nowak et al., 2008b) (Pouyat et al., 2006) (Oren et al., 2001) (Resh et al., 2002) (Edmondson et al., 2012) (Buchholz et al., 2014) (Zhu et al., 2017) (Dorendorf et al., 2015) (Beesley, 2012; Graham et al., 2019; Lemma et al., 2006) (Kaye et al., 2005; Miller and Fujii, 2011; Pouyat et al., 2006; Rossi and Rabenhorst, 2019) (Nadelhoffer et al., 1999) (Crowther et al., 2016)
	Urban Forest Effect (UFORE) model CTCC (CTCC, 2023) & iTree (i-Tree, 2019)	
Belowground: Soil Organic Carbon & Roots	MOTTI stand simulator (Metla, 2013)	
	Tree Density (Tree species Distribution) (Forest sizes)	
Carbon Fluxes and Transfers	Field Sampling	
	Automated mapping (Remote Sensing & GIS) Estimations by: (Mapping) (GIS) (Thematic Mapping) Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) (Stanford University, 2019)	

(continued on next page)

Table 1 (continued)

Carbon Stocks Type	Carbon Accounting Technique	References
Balances	Eddy covariance method (Eddy Pro)	(Baldocchi, 2003) (Papale et al., 2006) (Qun and Huizhi, 2013) (Campioli et al., 2016) (Swain et al., 2018) (Zhao et al., 2019)
	Carbon fixation model (CO ₂ FIX)	(Dewar and Cannell, 1992) (Schelhaas et al., 2004) (Masera et al., 2003) (Groen et al., 2006) (Lemma et al., 2007) (Negash and Kanninen, 2015)
	CASA model	(Potter and Klooster, 1997) (Tang et al., 2014) (Xu et al., 2018) (Cao et al., 2016) (Feng et al., 2008)
	Statistical analysis (ANOVA model)	(Miller and Fujii, 2011) (Cardinael et al., 2015) (Cardinael et al., 2012) (Lemma et al., 2006) (Raciti et al., 2012)
	Land use/ Land cover change	(Churkina et al., 2010) (Buisson et al., 2019) (Pataki et al., 2006) (Viglizzo et al., 2016) (Viglizzo et al., 2019)

(including peat) at a depth determined by the country and applied continuously throughout time. When empirically indistinguishable, fine live roots (smaller than the specified diameter limit for BGB) are incorporated with soil organic matter (Food and Agriculture Organization of the United Nations, 2005). Soil can be a viable source or sink of atmospheric carbon and plays a crucial role in climate policymaking, depending on the organizational practices adopted. Soil performs a vitally important aspect of carbon sequestration (Adhikari and Hartemink, 2016; Lal, 2014; Minasny et al., 2017; Oren et al., 2001; Pouyat et al., 2006; Villanueva-López et al., 2019).

3.1.3. Soil organic carbon (SOC)

SOC holds the potential of natural climate solutions with a percentage of 25%. Within the soil carbon, carbon is divided into protecting organic matter and restoring the stock depleted through the carbon fluxes (40% and 60%, respectively) (Bossio et al., 2020). On the other hand, many crops have roots that only reach around one meter below the earth. It is unclear what factors influence the lifespan of below-ground C in various forms. As a result, a greater knowledge of these mechanisms is essential for improving C sequestration. Moreover, the quality and ability to support biomass production determine its potential for sequestration.

3.1.4. Carbon in woody and other debris/litter

Fine litter on the forest floor (fruits, leaves, twigs, bark pieces, branches less than 10 cm diameter, etc.), dead trees and snags, and laying deadwood bigger than 10 cm diameter make up the amount of detritus in a forest. Fine litter biomass density varies between 2 and 16 Mg ha⁻¹ (average of 6 Mg ha⁻¹ or less than 5% of AGB), with greater values in damp situations. However, there is no obvious trend in the database (Brown and Lugo, 1982). The fine litter quantity on the forest floor reflects the difference in litterfall inputs (dead plant organic matter) and decomposition outputs (which is a process of supplying nutrients to the soil), which differ significantly across the tropics and environmental conditions (Suseela, 2019). The microbial decomposers in soil receive resources from litter inputs, which they use to release plant-available nutrients like nitrogen (N) and store organic carbon (Kerdran et al., 2020).

3.2. Fluxes, Transfer, and Balances

Carbon transport from one pool to another is known as carbon flux. Fluxes are typically stated as a rate, with units representing the amount of a substance transported during a given time period. All of the major pools and fluxes of carbon within the ecosystem are evaluated for carbon assessment and accounting; a single carbon pool might sometimes contain many flows, both adding and withdrawing carbon collectively.

Carbon flux accounting directly measures carbon flow into and out of the terrestrial environment. Eddy covariance is a technique used by cutting-edge sensors to continually monitor carbon exchange between all carbon pools in an ecosystem and the atmosphere. Flux-based estimates are appropriate for supplying net carbon exchange information (Forest Research, 2022). Carbon flow studies are also crucial for validating estimation methodologies across various pools. Fig. 4 portrays the major pools and fluxes in the earth's carbon cycle. Arrows designate fluxes, while boxes indicate carbon pools. The net ecosystem exchange (NEE) is the difference between CO₂ captured via gross primary production (GPP) and loss through respiration, ultimately determining whether the ecosystem is a net carbon source or sink. The NEE shows the net CO₂ traded vertically between the land surface and the atmosphere.

4. Carbon accounting methods

Estimating the biomass and the carbon contents of forestry and woodland and all other terrestrial ecosystems and their rate of change is vital in the carbon accounting system. These estimates are usually calculated using a combination of suitable techniques (Fig. 5). The optimal approach to adopt is determined by the assessment's objectives, location, geographic scale, and resources available to conduct the evaluation. The most robust and cost-effective carbon stock accounts will combine all four methodologies. There are four ways for carbon stock estimations:

i. Ground Sampling techniques of carbon in biomass

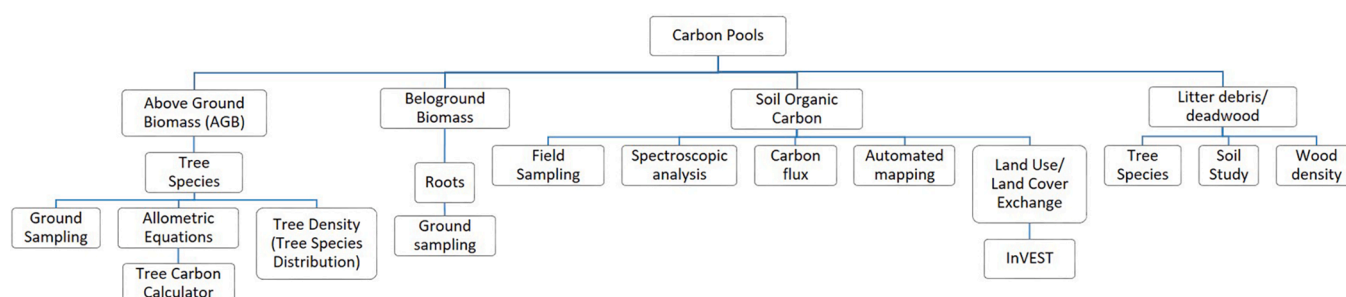


Fig. 2. The carbon accounting methods for natural carbon sequestration pathways.

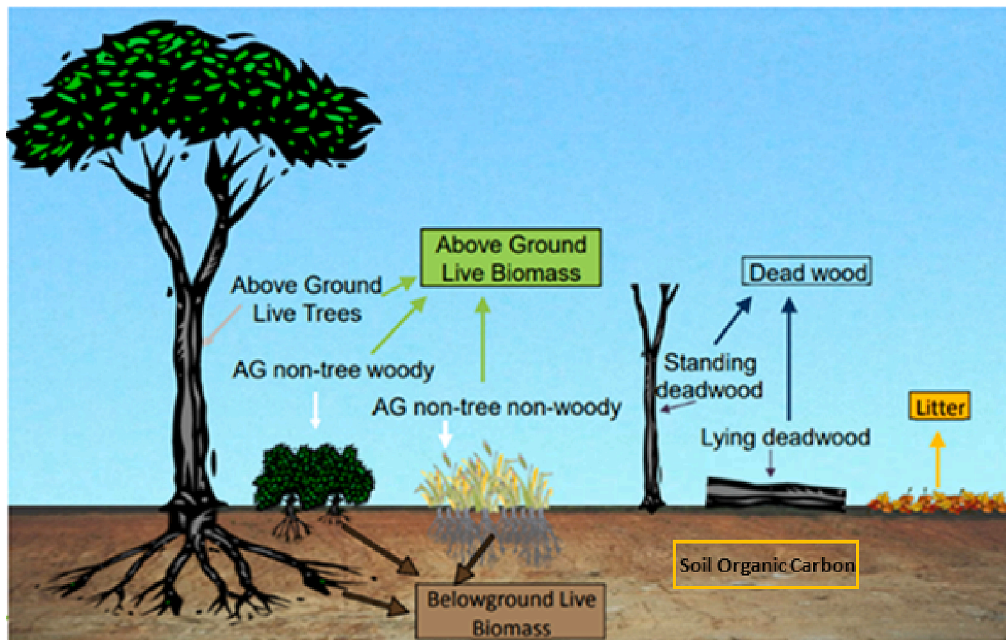


Fig. 3. Pictorial representation of carbon pools of a terrestrial ecosystem (Snowdon et al., 2002).

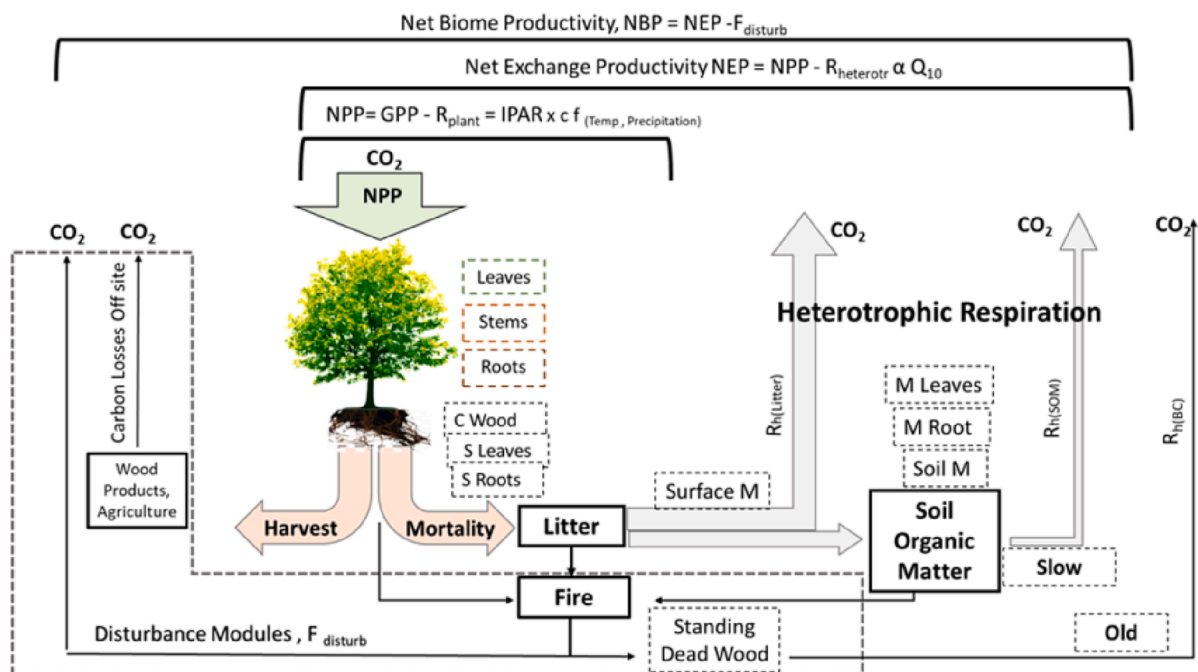


Fig. 4. Major pools and fluxes in the earth's carbon cycle (Battle et al., 2000).

- ii. Field measurements (using allometric equations or regression models)
- iii. Explicit spatial analyses (Mapping the ecosystem)
- iv. Carbon accounting models

4.1. Ground sampling and experimental analyses

Ground sampling is applied to AGB and BGB as it gives the highest accuracy measurements and valuation of carbon content. However, plot sampling for large shrubs and trees may not be practical (Catchpole and Wheeler, 1992). To get precise measurements, ground sampling for AGB

requires demolishing several samples, leading to an inefficient method concerning the environment. Therefore, it is more common to take BGB sampling, where samples can be easily collected and analyzed experimentally (Kaye et al., 2005; Miller and Fujii, 2011; Pouyat et al., 2006; Rossi and Rabenhorst, 2019). Another alternative and valuable technique is biomass estimation (Catchpole and Wheeler, 1992). It should be noted that sampling is an initial necessity for determining accuracy in assessment for both AGB and BGB while using remote sensing or modeling techniques using flux measurements gives the highest accuracy measurements and valuation of carbon content.

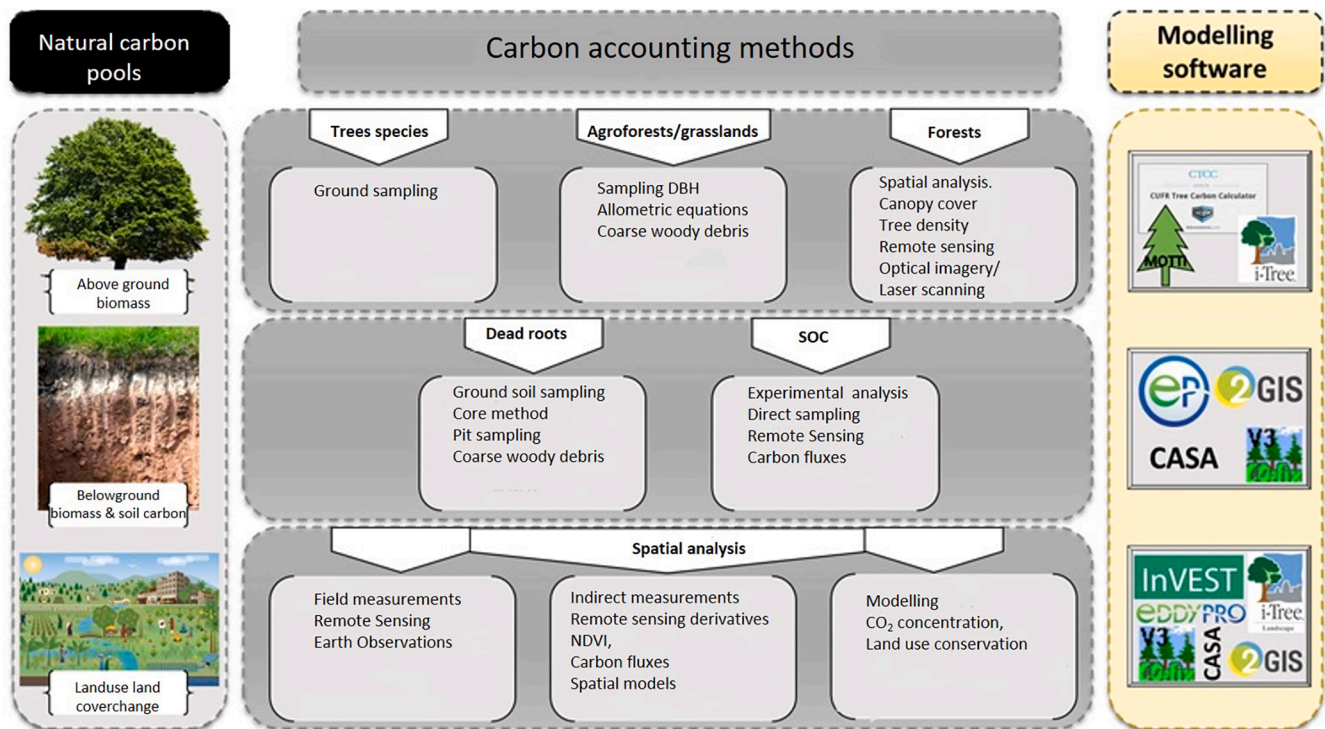


Fig. 5. Approaches for carbon accounting across different carbon pools.

4.1.1. Aboveground carbon

AGB measurement methods include non-destructive, harvesting (destructive), or combining these two accounting methods (double sampling). The destructive method directly measures standing biomass from a known area's plots. Vegetation biomass is clipped and removed for weighing within the plots. Similarly, for harvesting herbaceous plants (forbs, grasses, and grass-like plants), AGB is clipped and removed from the aboveground plant parts within the plot (Natural Resources Conservation Service and Institute, 2000). For shrubs, entire plants may be collected, but separation into wood and leaf components may be required.

4.1.1.1. Destructive Measurements. The destructive method requires the total removal of a living tree with all the content (roots, stems, branches, and leaves) to acquire the exact measurement of the tree biomass carbon. To determine the contents of tree species' aboveground carbon, three trees are destructively harvested (of each species). Roots are separated from aboveground tree components, such as the trunk, twigs (residual branches stemming from secondary branches), primary (branching directly off the trunk), and secondary (first branching off primary branches) (Miller and Fujii, 2011; Thevathasan and Gordon, 2004; Thomas et al., 2020; Wotherspoon et al., 2014). Arbitrarily, five to ten disk samples of the size of 2–3 cm are cut along the tree component axis and are subsampled to determine the moisture content at the harvesting time. To remove the water content so that the biomass can be expressed on a dry-matter basis, the subsamples are oven-dried at 65 °C until they attain a steady dry weight (Catchpole and Wheeler, 1992). Moisture content and dry biomass are calculated from each tree component's dry and wet weight subsamples. Then, five to ten sawdust samples from the disks are analyzed to determine the percentage of C in the respective tree components. Carbon concentration can then be multiplied by dry biomass to find the C content (Wotherspoon et al., 2014). Determining the total C pool at the system level requires adding all C pools (AG-C and BG-C for trees and SOC).

In contrast, calculations of total fluxes are based on inputs and outputs of litterfall C, root turnover, assimilation by trees, inputs/outputs of

crop C, and C leachate from data collected in the estimations (Peichl et al., 2006). Such studies can be applied to Agroforestry to quantify C and N content above and below-ground in a tree-based intercropping (TBI) system and compare it to a conventional agricultural system, as well as to study C dynamic changes at the "system-level" between tree ages (Wotherspoon et al., 2014). Wood dust and C content are measured with LECO CR-12 dry combustion Carbon Analyzer (LECO Corporation, MI, USA).

4.1.1.2. Non-destructive Measurements. In a non-destructive study, trees are collected on randomly located plots for all land uses. Tree data collection includes trunk diameter at breast height (DBH), species, and tree height. The total shrub area can be measured on each plot, while for individual shrubs, diameters are measured 6 in. (15 cm) above the ground line on every tenth plot (Mcpherson et al., 1994). Biomass equations can vary depending on what portion of the tree biomass is calculated, whether oven-dry or fresh weight is estimated, and what diameter ranges are used to develop the equations. Tree biomass is dispersed with about 20% of the biomass in the crown, 60% in merchantable stem (to 10 cm top), and 20% in the stump/root system. To compute the C contents in a tree, the equation is multiplied by specific factors depending on each tree type (fresh-weight, dry-weight, merchantable, conifers, and hard wood trees) (Clark et al., 1986b; Nowak, 1993). Factors considered in C accounting include thinning, mortality, dead wood, and litterfall as C stocks (Dewar and Cannell, 1992). Statistical methods ensure adequate sample collections to detect changes that should be considered in measuring biomass and consider stratification of the land area for collecting a representative variability of samples of the plant communities being monitored (Angerer et al., 2016). In estimating tree diameter (year $x + 1$), the average diameter growth is added to the existing tree diameter (year x). The amount of C sequestered annually is the difference in estimated C_{stor} between years x and $x + 1$. To evaluate the quantity of C sequestered due to tree growth, tree mortality is excluded from the final calculation (Mcpherson et al., 1994). Another way of measuring C experimentally, is by using an instrument to measure the C income through the living leaves of a tree

(Suwanmontri et al., 2013). This instrument, known as Portable Photosynthesis System Li-6400 (LI-COR Inc., USA), measures the CO₂ assimilation and analyzes CO₂ absorption rate measurements of each common species from 10 leaves of different trees for 7 h a day (2 days for one species). Apart from CO₂ absorption, the instrument simultaneously measured photosynthetically active radiation (PAR), the actual environmental conditions, leaf and ambient temperature, and CO₂ concentration in the air.

Non-linear regressions were formed to find a singular relationship between each species' net C assimilation and environmental variables. Various regression functions can be applied: logistic, rise-to-max exponential, and sigmoidal, with the hill and Gaussian functions showing a peak, i.e., increasing external factors after a peak, negatively affect absorption, while the latter showed a level-off maximum, i.e., the CO₂ absorption saturation point to the external factors. CO₂, PAR clearly affects tree CO₂ absorption, and the rate of CO₂ absorption in the same environmental condition depends on the tree species. These non-linear models can help compare CO₂ absorption with other plants (Suwanmontri et al., 2013).

4.1.2. Belowground carbon

Belowground biomass sampling technologies are less established and utilized in the field less frequently. Furthermore, the methodologies for measuring belowground biomass for various land-use systems are not uniform (PCC, 2006). Root biomass is given as a total of live and dead roots since alive and dead roots are rarely distinguishable. The method employed varies on the site conditions, vegetation type, and precision required, although root-to-shoot ratio and allometric equations are the most widely utilized in carbon inventory studies. The root-to-shoot ratio considered is 1:5 (20% of the AGB).

As in tillage systems, management practices can highly influence the SOC distribution within the soil profile, especially where the soil environment is altered. Such changes to the soil environment will affect accumulation in different layers of the soil profile or soil carbon

retention (Olson and Al-Kaisi, 2015). To quantify the C content found in the BGB, the soil should be excavated, in replicates, from the area to be studied with certain patterns taken into consideration (site selection, sampling method plan, sampling timing, type of soil to be studied, and type of sampling) as shown in Fig. 6.

A soil profile describes the horizons and their thickness and provides context for data interpretation and collection (Schoeneberger et al., 2012). Challenges can occur in sampling soil spatially; soils vary vertically (depth) and horizontally (across the land), and to understand what the plant's soil properties are actually exposed to during the different periods of the plant life cycle, heterogeneity must also be considered, when soils are sampled (Perkins et al., 2013). For soil organic matter (and C content) extraction and measurements, sampling methods depend majorly on the depth of the soil to be excavated. It is remarked as 1 m for average digging with the first two topsoil horizons (Nayak et al., 2019). Inaccurate results can occur by measuring SOC only within the top layer of the soil profile because low and high temporal changes due to soil erosion occur primarily on this horizon (Olson and Al-Kaisi, 2015). However, the characteristic of organic matter differs from layer to layer and reaches a maximum depth of one meter. In a European study that tested at various depths, no carbon reduction under sealed surfaces was observed. The sampling depth was 15–100 cm for non-vehicle load bearing and 40–100 cm for vehicle load-bearing areas with soil sealing (Edmondson et al., 2012). As most soil C comes from the roots rather than leaf litter and shoots, a distance of two-meter roots could sequester far more C than is presently captured (Kell, 2012). Urban areas can store substantial amounts of carbon (Churkina et al., 2010). The soil bulk density analyses showed that up to 10–20 kg m⁻² (100–200 Mg ha⁻¹) can be stored in soil depending on the soil depth, climate zone, and habitat type (Dorendorf et al., 2015). The upper fifteen centimeters of lawn soil are limited to organic C_{stor}. In comparison, below thirty centimeters, the material consists of substantial amounts of the alkaline building remains and augmented sandstone parent material. Dissolved organic carbon (DOC) leached directly from the surface of applied

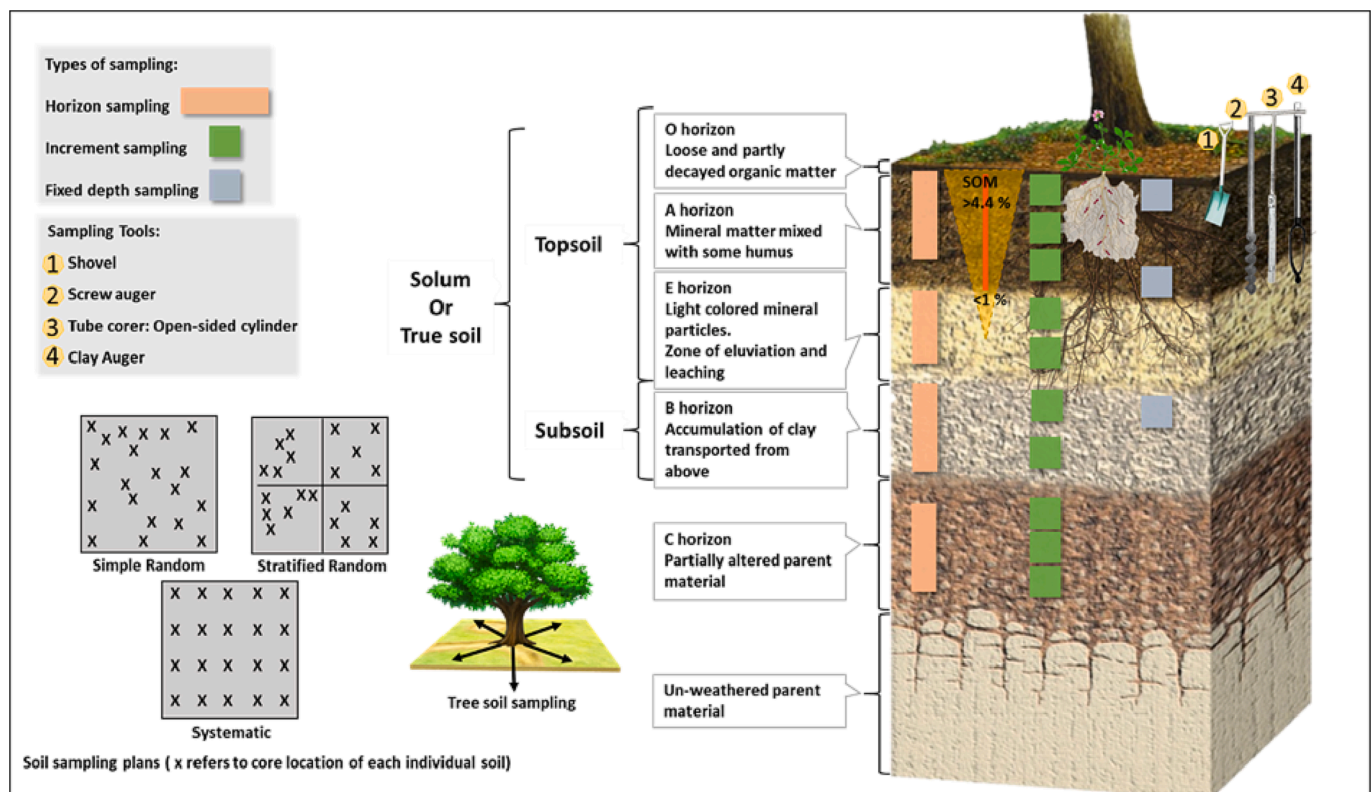


Fig. 6. Soil sampling methods for soil organic matters SOC. Types of sampling from (Schoeneberger et al., 2012).

compost mulch amendment is very mobile to a soil depth of fifteen centimeters but not at a depth of thirty centimeters; this verifies that the soluble organic C fraction is limited in vertical redistribution to the deeper technic horizons (Beesley, 2012). Soil sampling plans can be designed either by systematic sampling (Line transect and belt transect methods), simple random, stratified random sampling, approximation, or transection methods (Al-qahtani, 2018; Resh et al., 2002). The biotope-type cadaster of a district, field, or city can be utilized to create a stratified random survey of organic C stored in soil and trees. The cadaster is constructed from initial existing air photography, maps, and ground surveys and updated continuously to yield a wide-ranging data set of varying resolutions (Dorendorf et al., 2015). A transect method (Graham et al., 2019; Rossi and Rabenhorst, 2019) or a geological survey (Lemma et al., 2006; Miller and Fujii, 2011) can be applied using several sampling locations to equate SOC in herbaceous biomass systems comparative to alternative land-uses, if they are placed at uniformly spaced intervals, along the transect or to study the effect of time on accumulating SOC between old and new soils (Miller and Fujii, 2011). Accurate measurements of baseline data and bulk density (dry soil mass by its core volume) must be assigned to get correct SOC sequestration valuations (Al-qahtani, 2018; Dorendorf et al., 2015; Graham et al., 2019; Nadelhoffer et al., 1999). To account for stored C in urban areas, some studies examine proxies' areas (Dorendorf et al., 2015) or used values derived from other land uses showed that there was less organic C stored in urban vegetation than in urban soils (Churkina et al., 2010; Edmondson et al., 2012; Pouyat et al., 2006). There is potential to sequester substantial amounts of SOC in urban soils, especially in residential areas, because fewer annual soil disturbances and management inputs help increase net SOC (Pouyat et al., 2006). Moreover, the distribution variation throughout the regional LUC is important in approximating urban SOC pools (especially wetlands) (Miller and Fujii, 2011; Pouyat et al., 2006). The collected samples are dried for carbon accounting, and their bulk density and mass are measured. Since the same horizon thickness value is used to determine the soil bulk density and C stocks within the horizon on an aerial basis, this method helps correct potential errors introduced by compaction (Rossi and Rabenhorst, 2019). Total C and N are usually measured via dry combustion (at 950 °C) using a CN-Analyzers (LECO CHN-2000 analyzer (LECO Corporation, St. Joseph, MI) (Rossi and Rabenhorst, 2019)), (LECO-1000, LECO Corporation, St. Joseph, MI, USA (Kaye et al., 2005)) or (Vario MAX cube, Elementar Analysensysteme GmbH, Hanau, Germany (Al-qahtani, 2018)). For inorganic C, the soil is combusted at 1300 °C in a LECO CR-412 carbon analyzer (LECO Corporation, MI, USA).

4.1.3. Estimation for litter and debris

The dead wood amount in tropical forests is difficult to quantify and varies greatly. It could be a significant source of organic matter, accounting for anything from less than 10% to more than 40% of a forest's aboveground biomass, depending on the age and climate of the forest. Table 2 shows an overview of estimates of other forest component biomass density represented as a percentage of aboveground biomass in trees. Due to a lack of data on this important forest component, the total quantity of biomass in a forest can be underestimated.

Table 2
Estimates summary for forest components shown as the percent of AGB in trees (Sandra Brown, 1997).

Elements	% of matured forest's AGB
Understorey	< 3%
Belowground (roots)	4% – 30%
Fine litter (dead plant material)	< 5%
Dead wood	5% – 40%

4.2. Allometric equations and regression models

The size and age of urban trees influence ecosystem services (ES) and management costs. In the literature, researchers have developed allometric equations to calculate biomass for each measured tree in the urban domain (Nowak, 1993; Nowak et al., 2013; Nowak and Crane, 2002). AGB prediction equations convert entire tree biomass (based on the root-to-shoot ratio) and equations that yield dry-weight biomass by multiplying fresh-weight biomass by species- or genus-specific-conversion factors. These conversion factors stem from the average moistness contents of species. Open-grown trees tend to have less AGB for equal breast height and diameter maintained than forest-derived biomass equations predict. At the same time, adjustments were not developed for trees in more natural environments. A single analytical equation for an extensive range of diameters for species was obtained by combining multiple equations used for separate species and produced results within 2% of the original estimates, using multiple equations for total C_{stor} (Fig. 7). Average values were used from equations of the same genus if no allometric equation was available for an individual species. The average from all conifers or broadleaf equations was applied if no genus equations existed. The standard error is given for C report sampling error because the estimation error is either: unknown, greater than the reported sampling error, includes the ambiguity of using biomass equations and conversion factors (that may be significant), or has a measuring error (Nowak and Crane, 2002). Applying equations for the same species for the same family, genus, or species is a common approach used in estimating C and N accumulation and biomass production by trees (Jenkins et al., 2003; Mcpherson et al., 2016; Strohbach and Haase, 2012) as summarized in Table 3. Allometric equations also allow for further predictions of estimated C stored by the trees (Nowak, 1993); for example, planting ten million urban trees per year over one decade (1991–2000) that survive over fifty years will enable 77 million Mg of C to be stored by a tree population of 100 million by 2040. In addition, this will evade the production of 286 million Mg of C. Over the next fifty years, this brings stored and avoided C to a total of 363 million Mg, as shown in Fig. 8.

US forest ecosystems store roughly 52.5 billion Mg of C, 31% in live trees, 59% in soils, 9% in litter, humus, and woody debris, and 1 % in live understory vegetation (Nowak, 1993). However, their predictive capability and span of application are limited due to narrow geographic regions, small sample sizes, young trees or excellent condition trees only, and few species. Moreover, the allometry of trees managed in agroforestry systems and within different environments is still not comprehended because allometric equations are derived from forest-grown trees. These trees have a different canopy architecture and growth rate from those in alley-cropping growth conditions. This leads to substantial over- and under-estimations of biomass. Trees also have a high morphological and physiological plasticity to adapt to resource limitations like solar radiation, nutrients, and water. These changes are dependent on soil and site-specific climatic conditions and impact allometric equations (Thomas et al., 2020). Mcpherson et al. (Mcpherson et al., 1994) and D. J. Nowak et al. (D. Nowak et al., 2008a) found that the biomass in Chicago's street trees was 20% lower than predicted from allometric equations. However, it was discovered that current allometric equations might overestimate some urban tree species' biomass while underestimating others (McPherson et al., 2011, 1999).

To estimate the errors, one can apply the Bootstrap method that repeats the C_{stor} calculation by means of the corresponding equations and their stated residual standard error. The C_{stor} for each plot is summed. The procedure is repeated one thousand times, creating a thousand repetitions of 10 plots per land cover, each varying slightly because of the residual standard error of the allometric equations (Strohbach and Haase, 2012). This makes it possible to compare computed mean C_{stor} in trees from one city to another. Thus, in comparing research findings, it is important to consider the differences in geology, historical backgrounds, and climate of cities and the methodologies. Davies et al. (Davies et al.,

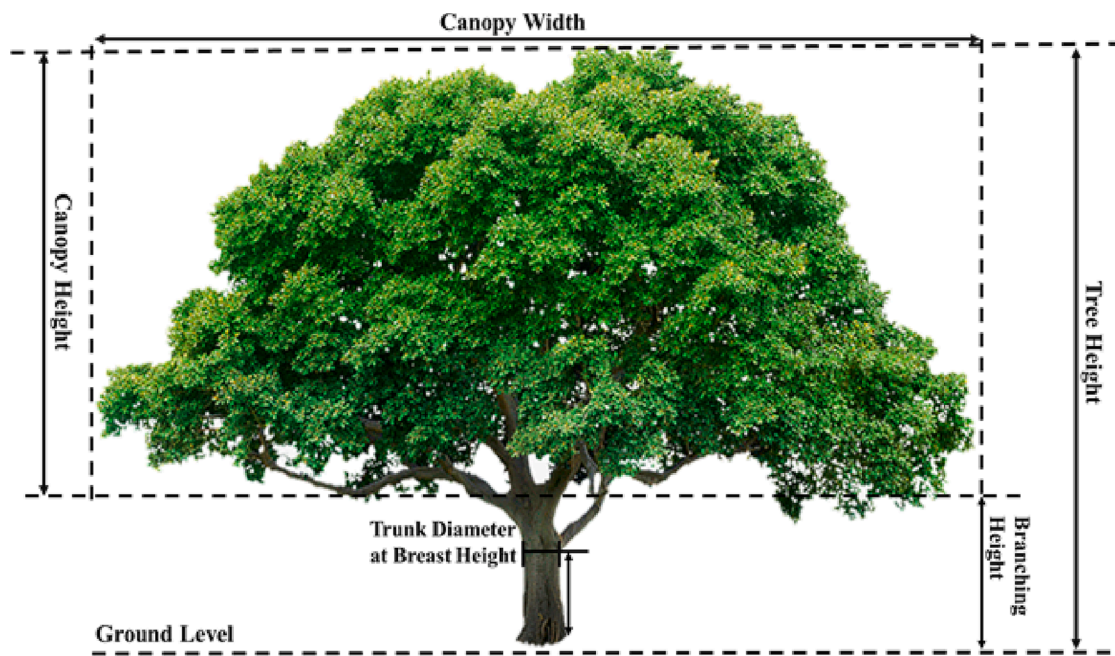


Fig. 7. Allometric equations variables (Trunk diameter DBH, tree height, can canopy cover).

2011) and McPherson et al. (McPherson et al., 2016) attempted to overcome many of these limitations by constructing an urban tree database (UTD) that holds measurements for almost fifteen thousand urban park and street trees. They created nearly four hundred allometric equations for the tree species across the U.S. Eight equations for each of the twenty most abundant species constitute a “set.” Tree age can be used to predict species DBH. Where remote sensing is applied, DBH is predicted, in some cases, by average crown diameter, and consequently, additional data can be acquired.

4.3. Explicit spatial analysis

To fully capture the C cycle and fluxes through the entire ecosystem, it is essential to get the whole frame of ecosystem boundaries through explicit spatial analysis. It automatically demonstrates the carbon fluxes distribution by studying the biogeochemical cycles and land use land cover change (LUCC) in large-scale areas, regions, cities, continents, and even globally (Pataki et al., 2006; Tang et al., 2018). It provides a scientific foundation for industrial distribution change, land planning, and C management activity spatial adjustment. A macro-scale scale is a large-scale unit used to measure and describe the dynamics of weather and climate factors (Viglizzo et al., 2016). Creating stronger linkages between C management and prediction and earth system processes research disciplines will improve the co-representation of managed and natural systems needed in decision-making (Pataki et al., 2006; West et al., 2018). Scale sensitivities govern the type of service being modeled. For example, dynamic flow models like sediment erosion are the most sensitive to spatial resolution, whereas stock estimates like C_{stor} are the most susceptible to aggregation across scales (Grafius et al., 2016). Satellite earth observation and drone and airborne measurements have huge potential to refine analysis, assessment of ecosystems and their services, and mapping. Optical, radar, high-resolution QuickBird satellite images (Galidaki et al., 2017; McPherson et al., 2011; Vihervaara et al., 2017), and light detection and ranging (LiDAR) technology can provide high-resolution quantification for land-cover and biomass assessments (Angerer et al., 2016; Lesiv et al., 2019; McPherson et al., 2011). This data can be employed for direct measurements or to collect the input information for the models (Davies et al., 2011; Zhang et al., 2017). Image-based methods offer larger area mapping using vast

numbers of temporal databases of satellite imagery, and spectral indices offer a method to monitor biomass (Asrar et al., 1985; Franklin, 1986; Franklin and Hiernaux, 1991; Roy and Ravan, 1996). In studying estimates of forest C density, LiDAR data achieves higher accuracy and lower uncertainty than QuickBird. This is because LiDAR allows for higher biomass-to-height correlation and undercounting of trees by the crown detection algorithm (with an overall accuracy of 70–97%) (Gonzalez et al., 2010). As evidenced by the integration and comparison of multisource data, LiDAR proves to be the best single sensor for estimating biomass, as height metrics usually outperform cover metrics.

Moreover, integrating optical data into methodologies increases biomass estimation accuracy (Galidaki et al., 2017). A data-based classification of the ecosystem mapping methods was done by Vihervaara et al. (Vihervaara et al., 2018). It consists of three types of measurements: direct, indirect, and modeling systems. Depending on the type of analysis required and the amount of data available, the mapping analysis can be chosen and used, as shown in Fig. 9.

4.3.1. Direct measurements

Field observation is the primary approach allowing for substantially accurate measurements regarding quantification, mapping, and assessment of ES. In the natural sciences, data collection has traditionally centered on field observations and direct measurements (based on physical units). National or regional sample systems, such as biodiversity surveys, national forest inventories, or land cover measurements, can include them (Vihervaara et al., 2018). Moreover, field analysis uses two models, combined with GIS, empirical coefficient, and ecological network (Negash and Kanninen, 2015), to clarify the C metabolism process network consisting of natural and socio-economic C metabolism of several classes of vegetation (Nowak and Crane, 2002; Pouyat et al., 2006) from similar climatic zones across the globe and with a time-lapse measurement (Raciti et al., 2012). Another method includes surveys that provide a quick overview of the study and select what other models can be utilized in mapping and assessment (Liu and Li, 2012). They can also be used for C density comparison by reflecting top-down landscape policies from the local authority level (Davies et al., 2011) and location-based analysis for GHG inventory approaches (Li et al., 2017). The role of surveys in ecosystem assessment and decision support is crucial as they can be used to evaluate uncertainties of other methodologies.

Table 3

Urban C_{stor} in vegetation in some cities with climate and methods used for assessment. Modified from (Strobbach and Haase, 2012).

City	Climate	Method	Tree Carbon Storage (Mg C ha ⁻¹)	Reference
Overall mean US cities	Varied	Aboveground C in trees, stratified random sampling across the land cover (canopy cover)	14.1 (average) 7.2–35.8 (range)	(Rowntree and Nowak, 1991)
Oakland, CA, USA	Warm, with dry summer	Aboveground and belowground C in trees, stratified random sampling across land cover	11.0 (average) 0.5–27.9 (range)	(Nowak, 1993)
Chicago II USA	Snow climate and humid	Aboveground and belowground C in trees, stratified random sampling across the city area	14.1 (average) 7.2–35.8 (range)	(Mcpherson et al., 1994)
Mean USA cities	Varied	Aboveground C in trees, UFORE model, and field data	0.5–4.7 (2.51)	(Nowak and Crane, 2002)
Hamburg	Warm and humid	Aboveground C in trees allometric equations and below-ground sampling	2.74	(Dorendorf et al., 2015)
Barcelona, Spain	Warm and dry summer	Aboveground and belowground C in trees, UFORE model, and field data	11.2 (average) 0.3–33.3 (range)	(Chaparro and Terradas, 2009)
Leicester, United Kingdom	Warm and humid	Aboveground C in vegetation, stratified random sampling across the land cover, and land ownership	3.1631.6 (average) 1.4–288.6 (range)	(Davies et al., 2011)
Karlsruhe, Germany	Warm and humid	Aboveground C in trees, inventory data of forests, and linking field data to the remote sensing material	3.23	(Kändler et al., 2011)
Leipzig, Germany	Warm and humid	Aboveground C in trees, stratified random sampling across land cover	1.18	(Strobbach and Haase, 2012)
Cities in Middle Korea	Snow climate, dry winter	Aboveground and belowground C in trees, stratified random sampling across two land cover classes	4.7–7.2 (urban) 26–60.1 (natural)	(Jo, 2002)
Hangzhou, China	Warm and humid	Forest inventory, trees in built areas are missing	30.3 (average)	(Zhao et al., 2010)

The digital remote sensing method offers an objective, observable, fast, and effective way to analyze urban forest dynamics. Accuracy assessment allows researchers to determine the quality of the remotely sensed data. It is highly accurate when used in tandem with data derived from aerial photos, close to the time of satellite overpass, or with ground reference data (Powell et al., 2018; Qun and Huizhi, 2013). Remote sensing is not expected to provide better accuracy of biomass estimates at the stand or plot level. However, field-based biomass estimations are essential in calibrating and verifying remote-sensing methodologies (Galidaki et al., 2017). Remote sensing technology boosts technical support, allowing a more accurate study of the LUCC impact on the terrestrial ecosystem C cycle and improved monitoring of change and land use over time (Raciti et al., 2012). The emergence of software like ArcGIS provides additional possibilities (Zhang et al., 2018). Combining

remote sensing, GIS, and empirical data allows for a better spatial expression between the C emissions and LUCC relationship (Vihervaara et al., 2012). Remote sensing is usually used in tandem with GIS to measure the LUCC, representing high-value C sinks, like forests with young trees and wetlands converted into urban built-up areas (Pan et al., 2019). With a 10 – 100 m range, it is defined as the medium spatial resolution in the remote sensing literature (Tang et al., 2018; Vihervaara et al., 2012). Predictive regression models can be generated for forested areas in various biomes. These models link tree density to GIS layers and spatially explicit remote sensing layers of typography, vegetation characteristics, climate, and anthropogenic land use (Crowther et al., 2015). A single forest tree density map (on a per-hectare scale) is produced via regressions run in an algebra framework map. Equation coefficients and intercepts are applied independently to each pixel (Tuanmu and Jetz, 2014). To quantify aboveground C density annual changes of tropical woody live vegetation, Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data can be used for a given period and provide direct, measurement-based evidence (Baccini et al., 2019).

4.3.2. Indirect measurements

Derivatives of remote sensing and Earth observation are used to get the quantitative capacity ES indirectly. These measurements include normalized difference vegetation index (NDVI), land cover change, surface temperatures, and primary production. Their importance depends on the sources they are derived from. For instance, NVDI is a spectral index derived from red and infrared spectral band differences. At the same time, land cover change results from the automated classification of remote sensing images or visual interpretation (Vihervaara et al., 2018). NDVI can be obtained from MODIS on the EOS-1Terra satellite, providing an annual assessment of global land coverage with high resolution (Angerer et al., 2016; Baccini et al., 2019; Qun and Huizhi, 2013) or from the red or near-infrared bands of Landsat thematic mapper (TM) imagery (Franklin, 1986). C_{stor} can be quite easily obtained via image analysis, as the image normalization methods in detecting changes over time appear promising (Myeong et al., 2006; Vihervaara et al., 2018; Xu et al., 2018; Zhang et al., 2017). Some synthetic data can be acquired through the National Aeronautics and Space Administration's (NASA) Airborne Visible/InfraRed Imaging Spectrometer (AVIRIS) (Dungan, 1998); such results usually provide illustrative information only. Spatial prediction methods differ in accuracy depending on sample size and specific case (Dungan, 1998). They also integrate both high-performance parallel computing (through shuttle radar topography mission (SRTM) tiles for canopy height extraction and biomass and C estimations) and GIS-based geospatial analysis (Kumar et al., 2015; Lesiv et al., 2019; Tang et al., 2018).

4.3.3. Land use/Land cover change (LUCC)

LUCC and changes in urban systems C sequestration dynamics can be more complex than those in natural ecosystems due to intrinsic natural factors, as well as extrinsic human activities (Xu et al., 2018). LUCC data can be divided into forest, residential, or other developed classes (developed open space, industrial, commercial, and institutional) (Raciti et al., 2012). The LUCC information can be combined into an ecosystem process model to improve the accuracy of the C cycle dynamics and can be studied based on activity or land accounting (Fig. 10). Additionally, a C sink map of a study region can be created, based on the most current land use map, with classes of vegetation types included (cultivated crops, grass, shrubs, forest, pasture, and both herbaceous and woody wetlands) (Davies et al., 2011; Pan et al., 2019), or by forest type and plantation (pine or eucalyptus plantations, pastures, grassland, and riparian forests) (Vihervaara et al., 2012).

4.3.4. Urban tree distribution

The urban trees' C_{stor} estimation study by Nowak (Nowak, 1993) used canopy cover analysis to estimate the C budget. There have been several explicit efforts to compute the ES provision at a city-wide scale.

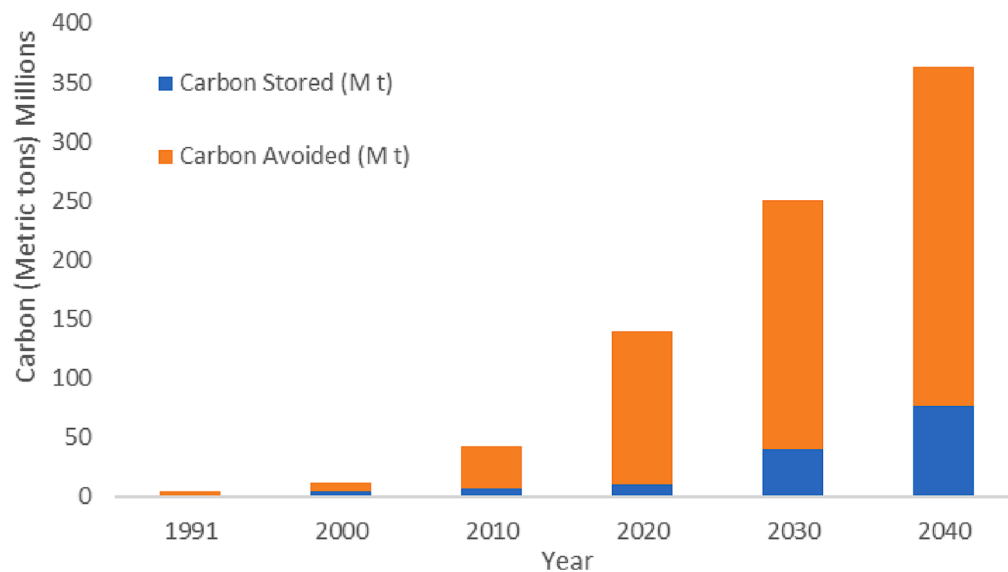


Fig. 8. The amount of accumulated C is stored and avoided with the assumption of 10 million urban trees planted (with no tree mortality assumption), data taken from (Nowak, 1993).

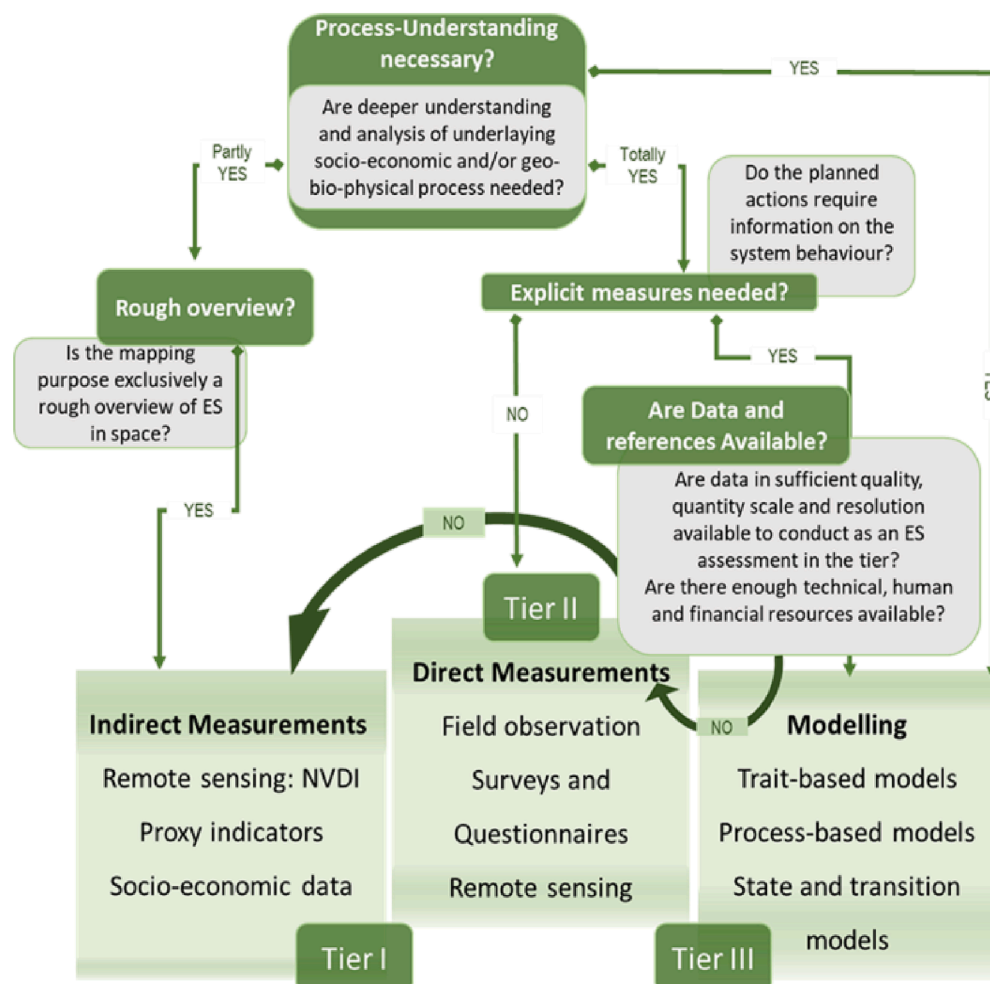


Fig. 9. Decision-tree guidelines for selecting ES mapping tiers, (). adapted from Vihervaara et al., 2018

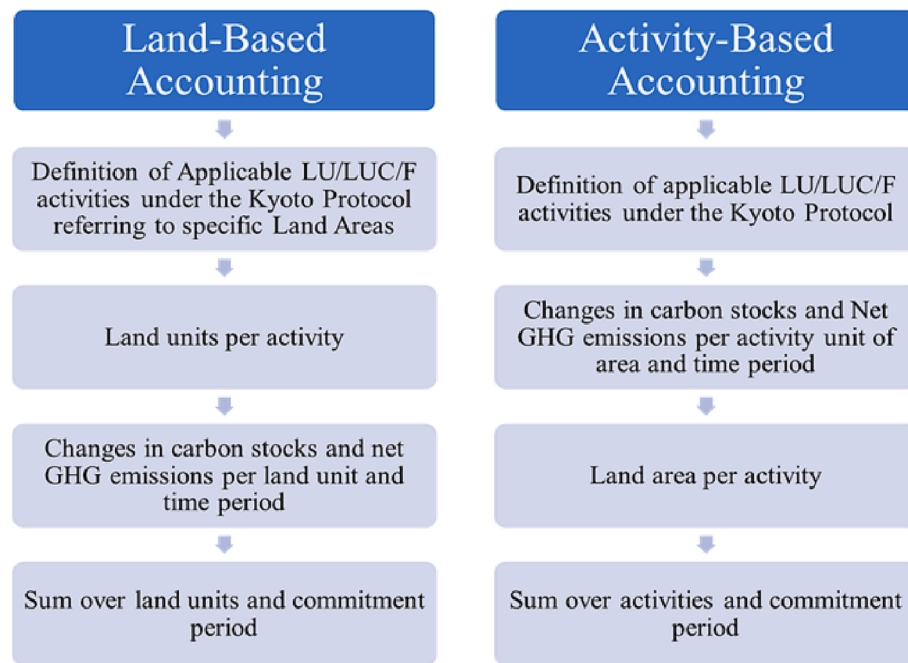


Fig. 10. Carbon accounting approaches based on land-use changes adopted from (Land-use, 2000) .

The perception remains that urban ecosystems have a lower value because they are relatively small and heavily modified by humans (Nowak and Crane, 2002; Pouyat et al., 2006). However, urban areas as an entire ecosystem of both a driver of CO₂ emissions and C cycling in urban soils and plants must be thoroughly comprehended (Pataki et al., 2006). In terms of city scale, some cities acted as C sources (Li et al., 2017), while other regions were in the process of transitioning from C sources to C sinks (Lesiv et al., 2019; Nowak and Crane, 2002; Pouyat et al., 2006). Later, the characteristic of C stock distribution within a city analyzed the C emissions discrepancy of land components like slums, urban green areas, and built-up areas (Li et al., 2017; Pan et al., 2019), and the spatial distribution of C sinks spatial distribution of many urban forests (McPherson et al., 2005). These studies concentrated not on the gradient change of C uptake and emissions but on the discrete form (Zhang et al., 2018). High spatial resolution LUCC data sets typically include natural and semi-natural classes like human-related and biophysical, including their interactions (Churkina, 2008; Strohbach and Haase, 2012). To gauge the role urban forests play in climate change, the amount of sequestration and C_{stor} by urban trees is quantified (Larondelle and Haase, 2013). Remotely sensed data on biomass was used, with exceptional accuracy and spatial resolution, for the investigation of the entire pantropic (including tropical Africa, America, and Asia using remotely sensed data on biomass) and associated land cover with the aid of multi-sensor satellite data (Chaplin-Kramer et al., 2015) and LiDAR (Baccini et al., 2012) to estimate AGB. Additional LUCC studies were done in the rural lands in Brazil, Paraguay, Argentina, and Uruguay (Viglizzo et al., 2019) and parts of the Mediterranean ecosystem (Galidaki et al., 2017). Because it is imperative to map values to create conservation strategies that combine sustainable forest use and regional forest protection, explicit spatial approaches have been employed in mapping rent distribution across the biome of non-timber forest products (NTFPs) (Strand et al., 2018). Satellite imagery is employed to generate annual estimates of the amount of C stored in tree forests. However, in interpreting the relationships between AGB increase and other C stock attributes, one must consider that this imagery also captures shrub and herb productivity (Powell et al., 2018). As C accounts for half the dry-weight biomass of trees, spectral indices can also be applied to detecting C_{stor} changes in trees (Davies et al., 2011; Powell et al., 2018). As location-based inventory delivers explicit spatial information,

it can be used for environmental education, improved mitigation policy-making, and in-depth examination of the relationship between city landscapes and GHG emissions distribution, which is beneficial to low C practice, city research (Li et al., 2017), and the emission discounting influences economic decisions (Fearnside et al., 2000; Watson et al., 2000).

4.3.5. Statistical analysis

Statistical analyses are usually applied to these systems to measure the accuracy of study outcomes. Analysis of variance (ANOVA) model, least square method, Tukey–Kramer test, or a combination of two of these analyses can be opted. ANOVA utilizes a one or two-way approach to analyze statistical data such as gaseous C fluxes (Feng et al., 2008; Miller and Fujii, 2011); a tree's DBH with height class as a factor (Martinez-Falero et al., 2016); effects on the soil N and SOC pools within a tree species and given site (Raciti et al., 2012; Resh et al., 2002; Thomas et al., 2020); soil core ID and total SOC concentration and other soil properties (Cardinael et al., 2015; Lemma et al., 2006). ANOVA can also be enhanced with a functions package (to fit linear and non-linear mixed-effects models) like the LMER Convenience Functions package for R to calculate the upper bound P- values for the effect of the microbial community in the SOC richness. ANOVA can also be combined with the least square method to assess litter decomposition and plant biomass production (Miller and Fujii, 2011). Additionally, ANOVA can be combined with the Tukey-Kramer test to determine and compare the significance of variation and difference between the data analyzed (Cardinael et al., 2015; Raciti et al., 2012).

4.4. Modeling systems and approaches

Many models were developed to estimate and analyze the forest functions/structures, attributes (such as tree health, species composition, species diversity, diameter distribution, and native vs. exotic species distribution), C sequestration, and economic aspects. The urban forest effects (UFORE/i-tree) model (USDA Forest Service et al., 2006) assists users in quantifying urban forest functions and structure using meteorological data, local hourly air pollution, and standardized field data from randomly located plots. It also calculates values and forest functions related to tree effects on building energy use, air pollution,

global warming potentials, and GHGs (Nowak et al., 2007). Backed by peer-reviewed research and varied data collection techniques, UFORE forecasts the financial values of regulating urban ecosystems (UESs) by urban forests using a revealed preference approach (D. Nowak et al., 2008a). Because of the data inputs of this approach, the model is usually applied to a single or numerous closely related UESs (Haase et al., 2014). Richness, abundance, size class of native and exotic tree species, and diversity can also be quantified. For example, a survey of inner-city residential and vacant lots and suburban residential lots was completed using the i-Tree eco model and demonstrated that inner-city and suburban residential lots supported three times fewer trees, less tree diversity, and fewer native and exotic trees than inner-city vacant lots (McPherson et al., 2011). Since the program outputs are ultimately based on various assumptions of mathematical relationships and available data, estimates can be expected to change as computational methods evolve and data sources change over time. In addition, while geographically inclusive, the relatively low data resolution creates a higher margin of error within spatially diverse urban areas (Riley and Gardiner, 2020).

Another example of an ecosystem model is InVEST (Integrated Valuation of Environmental Services and Tradeoffs) which permits users to value and map multitudinous ES (Tao et al., 2015). It has accessible options and is widely used to create large-scale scenario models to assess a broad range of freshwater and marine ecosystems and terrestrial and over twenty sub-models (Bottalico et al., 2016). InVEST can estimate biodiversity conservation, economic values and levels of ES, and market value of commodities provided by the landscape through LUCC patterns (Pathak et al., 2019; Shukla et al., 2018). Additionally, the model can also evaluate the economic and social importance of the C sequestration, highlighting tradeoffs and synergies between multiple ES, market returns to landowners, and biodiversity conservation (Nelson et al., 2009; Sharp et al., 2018). The impacts of future land-use change on sequestration or C_{stor} can be modeled using C_{stor} estimates found in the literature (Nelson et al., 2009). The InVEST model does have a few drawbacks. It assumes a linear change in C sequestration over time, uses an oversimplified C cycle, and potentially inaccurate discounting rates (Sharp et al., 2018). Moreover, C sequestration studies built on sub-type LUCC are insufficiently understood (Polasky et al., 2011; Zhang et al., 2017).

CASA (Carnegie–Ames–Stanford approach) is a simulation model that pools together climate, multi-year satellite, and other land surface databases to predict regional or global biosphere–atmosphere interchange of water, energy, and trace gases from soils and plants. The model is driven by global monthly solar radiation, climate and satellite input data, soil, and vegetation types and can directly evaluate the net primary production (NPP), i.e., the incoming quantity of energy and C into ecosystems (Xu et al. CASA has been used in multiple simulations for ecosystem C flux predictions and used to validate terrestrial NPP fluxes in specific sites against CO₂ sampling stations (Neigh, 2008). The model is employed for aboveground net primary productivity (ANPP), which is particularly important for predicting global C cycle changes and directional climate changes (Cao et al., 2016). However, the CASA biosphere model shows that the annual production of CO₂ from fossil fuel emissions is a tenth of that of annual CO₂ production from soils (Potter and Klooster, 1997). At the same time, the model also illustrates that this is offset because plants absorb CO₂ in amounts equal to that produced by the soils. The model also shows that 60% of CO₂ produced is absorbed in tropical latitudes, permitting researchers to gain better insight into land changes and tropical deforestation's impact on atmospheric trace emissions and their roles in global biogeochemical cycles. CASA is an integral part of NASA's Earth Science Enterprise (ESE), as independent observations continually refine and validate its approach. Their data inform policymakers on how human actions impact the global environment.

The most widely used technique for flux measurements is Eddy covariance Technique (EddyPro); developed by LI-COR, the EddyPro

model processes eddy covariance (EC) data. It measures fluxes of CO₂ by using a micro-meteorological technique and Biometric Methods (BM) to quantify CO₂ exchange between terrestrial ecosystems and atmosphere net ecosystem production (NEP) (Campioli et al., 2016). It can also compute fully processed methane and other trace gas fluxes, water vapor (evapotranspiration), and energy. The EC technique is founded on the mass balance principle, as seen in Fig. 11. The schematic explains that, during stationary and horizontally homogenous conditions of a studied volume, the turbulent vertical flux (Z_{ref}) should equal $S(z)$, the integral over all sinks and sources. Eddies create related variations in vertical wind speed (w') and scalar concentration (s'). This results in the efficient transport of energy and mass vertically. Thus, the greatest accuracies are achieved during steady atmospheric conditions and when vegetation is homogeneous and situated upwind on flat terrain for an extended distance. The EC method is considered an advanced method of estimating turbulent fluxes of CO₂. It can still be used for more complex landscapes and turbulent atmospheric conditions. However, when applying EddyPro in these conditions, flux divergence, advection, and atmospheric storage measurements must be included to quantify CO₂ exchange between the atmosphere and the biosphere. It is a scale-appropriate method that allows scientists to assess the net CO₂ exchange of a whole ecosystem and measure ecosystem CO₂ exchange across a wide time range—from hours to years (Baldocchi, 2003; Qun and Huizhi, 2013). Carbon exchange processes and the responses to ecological factors in a meadow grassland at a wide-scale ecosystem using long-term continuous EC measurements are compared (Zhao et al., 2019). During the dry and wet seasons, periodic and seasonal changes in carbon dioxide, methane, and energy interchange from irrigated lowland rice-rice ecosystems were examined using an open-path EC system (Swain et al., 2018). Long-term continuous EC measurements were taken to test inter-annual fluctuations of potential C sink potential and source for grasslands (Zhao et al., 2019). It used long-term continuous EC measurements to study the C exchange processes and the responses to environmental factors in a meadow steppe in a wide-scale ecosystem.

Zhao et al. (2019) took long-term continuous EC measurements to test inter-annual fluctuations of potential C sink potential and source for grassland. Combining EC instruments with a digital camera to capture time-lapse images at a fixed location setup can better understand the relationship between C flux dynamics and canopy development. A methodology presented by Papale et al. (2006) has been integrated into the European EC measurements database with a new standardized set of corrections. Terrestrial Ecosystem Respiration (TER) and Gross Primary Production (GPP) uncertainties associated with these corrections were assessed in Europe for eight different forest sites. The outcome proved that standardized data processing is required to underpin inter-annual variability and provide effective comparison across biomass. Such analysis was also performed in the Arctic to examine the average relative flux uncertainties under stable and unstable stratification (Aalstad, 2015).

Carbon fixation approach (CO2FIX): The CO2FIX is an open-source simulation software based on the concept of the C flow model and works to enumerate C fluxes and stocks in wood products, soil organic matter, and forest biomass chain. CO₂ fixation takes place through photosynthesis, converting solar into chemical energy that aids plants and other living organisms in developing and growing (Baldocchi, 2003). Growth of stem volume and pattern of allocation to foliage, roots, and branches are input into the CO2FIX biomass module and tabulated to determine the balance of C (between growth and turnover, harvest, and mortality) for a one-year time interval; it can be applied to deciduous forests, monocultures, coniferous forests, or mixed tree stands (Schelhaas et al., 2004). Continuous C build-up occurs on the forest floor in non-woody and woody biomass litter. Part of this biomass transforms into soil organic matter during each cycle and decomposes into CO₂. The model assumes: that the yearly tree growth pattern remains constant, there is no ground vegetation, and quantiles of C lost to recalcitrant soil organic matter or in groundwater are minimal (Dewar and Cannell,

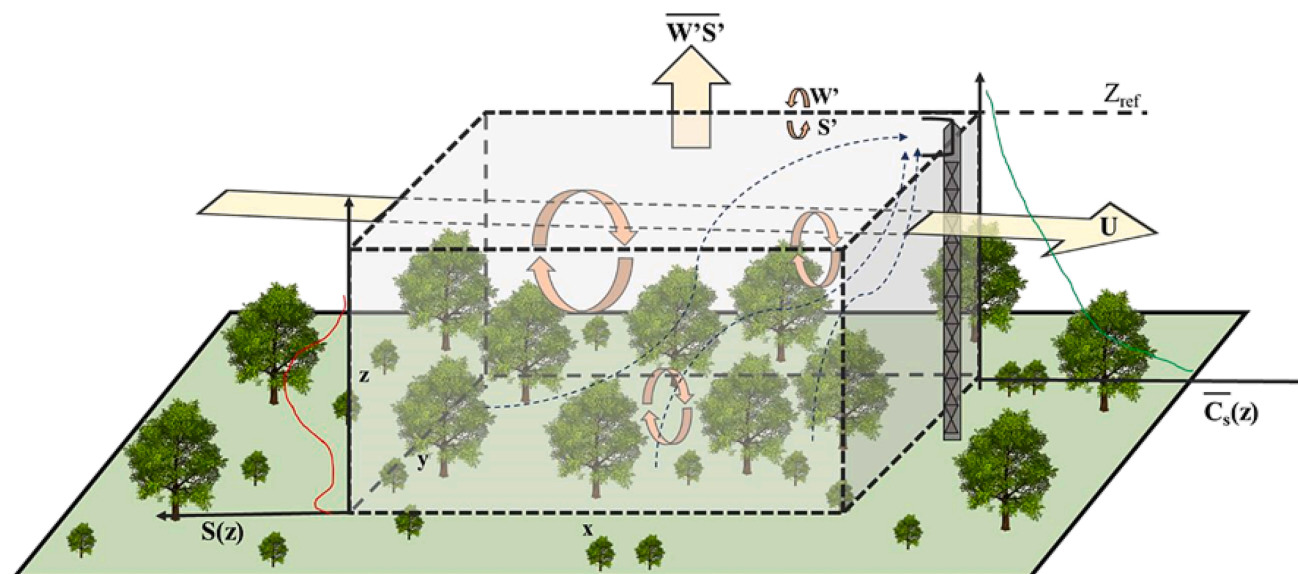


Fig. 11. A schematic explanation of the Eddy covariance technique principle. Edited from (Finnigan et al., 2003; Launiainen, 2011).

1992). The model was enhanced into the programmed software, CO2FIX Version 3.1, and is categorized into six modules: bioenergy, financial, C accounting, biomass, and soil. The bioenergy module calculates biomass use over fossil fuels for energy production. The financial module allows cost and revenue inputs for different scenarios to compare project profitability for different scenarios. The C accounting model enables users to simulate C fluxes and stocks and determine how many C credits a project can generate for different crediting systems. The soil module defines soil C dynamics and decomposition in well-drained soils. (Schelhaas et al., 2004). CO2FIX Version 3.1 has worldwide applications: afforestation projects, multiple cohort forest ecosystems, and selective logging systems (Groen et al., 2006). It is an extremely useful tool that has been utilized for the IPCC's climate assessments in the context of the Kyoto Protocol.

5. Socioeconomic benefits of urban landscapes

5.1. Air pollution removal

Urban shrubs and trees act to rid large volumes of air pollutants, improving the health of humans and the environment. Once inside the leaf, gases diffuse into the leaf's intercellular spaces and are absorbed by water films, reacting with inner-leaf surfaces or creating acids (Smith, 1990). Trees also remove pollution by intercepting airborne particles and absorbing them into the tree. They are only temporal retention sites as particles are usually washed off by rain or dropped to the ground with twigs and leaf fall (Nowak et al., 2006). A modeling study using pollution concentration and hourly meteorology exhibited an estimated total pollution removal of 711,000 metric Mg valued at almost \$4B in U.S.

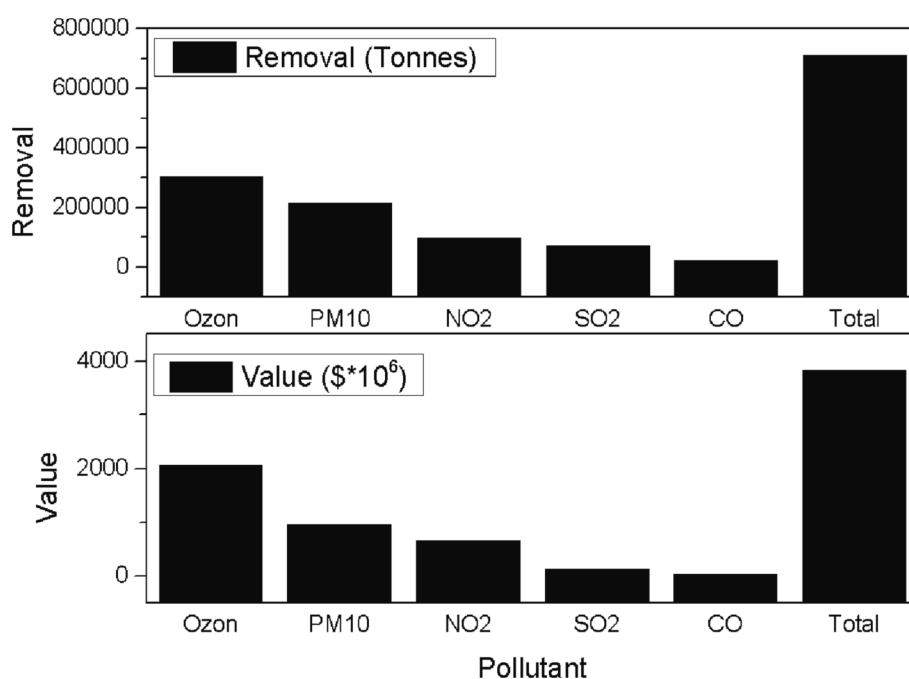


Fig. 12. Potential removal of some air pollutants by trees with economic values estimations using the typical range published in leaf dry deposition velocities, data taken from (Lovett, 1994; Nowak et al., 2006).

cities by urban trees (Fig. 12). A benefit-cost analysis study of Modesto, California's urban forest, indicated that avoided emissions, due to energy-saving devices, of nitrogen dioxide (NO₂), volatile organic compounds (VOC), and particulate matter, with a diameter of 10 µm (PM₁₀) were minor, totaling approximately 7.2 Mg with a value just under \$70 K. However, there was a considerable benefit in pollution uptake (particulate interception and pollution deposition), totaling 157 Mg valued at nearly \$1.4 M. This translated to an average savings of almost \$16/tree. Thus, the total benefit was significant, with net air-quality savings coming primarily from pollutant uptake (McPherson et al., 1999). In addition to improving air quality through pollution removal, integrated studies reveal that urban tree canopy cover management can improve air and health quality and reduce air temperature. Because percentage gains in air quality due to pollution removal are small, combining this effort with increased urban tree canopy cover, i.e., urban management, allows for a significant total effect (Nowak et al., 2006). During daylight hours, when water transpires from tree leaves, urban trees have the greatest impact on ozone, NO₂ and SO₂, whereas removal of particulate matter, intercepted by both bark and leaf surface, happens around the clock and throughout the year. Furthermore, removal of carbon monoxide (CO) also occurs around the clock, during in-leaf season and at a much lower rate than for the other pollutants.

5.2. Economic benefits of carbon sequestration

There is an increasing research effort to study the action and inaction of CO₂ reduction and quantify a global perspective on the economics of CO₂ reduction. Studying C sinks and using real economic estimations can quantify the economic benefits associated with enhancing the natural C sinks. Moreover, the evaluations do not solely count the C reduction but include all benefits, i.e., energy savings, air quality, stormwater prevention, etc.

5.2.1. Natural carbon sinks

Researchers in Chicago analyzed links between forest functions and values with vegetation structure, discovering that trees in the region removed almost 5,575 metric Mg of air pollution, equating to just over \$9M in clean air and approximately 316,000 metric Mg of C annually was sequestered. Furthermore, up to \$90 per dwelling unit could be saved in annual cooling and heating expense with just a ten percent increase in planting three trees per building lot or increasing tree cover by 10 % due to lower summertime air temperature, reduction in neighborhood wind speeds, and increased shade once trees matured. Researchers estimated the services of the trees contributed to a net present value (NPV) of about \$400, while the long-term benefits exceeded twice the NPV costs (McPherson et al., 1997). The researchers also analyzed the economic benefits of urban forests in Modesto, California, using the UFORE/iTree Eco model (McPherson et al., 1999) with evidence that residents benefitted more than twice from an estimated 92,000 public trees to residents than the cost of maintaining these trees. In fact, researchers monetized the benefits at \$4.95 million (about \$27 per resident or \$54 per tree).

To determine the economic benefits of cultural UESs, like green area aesthetics, hedonic pricing methods can be applied, i.e., the price of a good is related to the services it provides or its characteristics. For example, in two Finnish towns, an investigation showed clear evidence that positive benefits were attained by the nature and social functions of the towns' urban forests. In contrast, negative results were achieved concerning the towns' timber production. The takeaway from this investigation emphasizes the importance of defining municipal urban forest policies (Tyrväinen, 2001).

5.2.2. Urban ecosystem services (UES) analysis

A comprehensive investigation discovered that most UES research had been undertaken at the city scale in China, Europe, North America, and China with assessment methods involving GIS, valuation, and

biophysical models. Moreover, the research conclusions have not translated into substantial land-use policy. The research indicates that to get a more accurate assessment of the actual value of UESs. This complete regional portrait highlights the concept of ecosystem tradeoffs, and the spatially explicit approaches (in an urban context) are required (Haase et al., 2014). In one study, Luck et al. (2009) analyzed the socioeconomic impact of urbanization on Australia's urban vegetation for 20 years. They found a strong correlation between urban vegetation and socioeconomics. They concluded that the properties in the areas with higher urban vegetation ratios are of higher values than that of regions with lower vegetation ratios. Another study (Richards and Thompson, 2019) suggested that urban ecosystems provide numerous benefits, including health, leisure opportunities, and environmental regulations.

Furthermore, in rural areas, payments for ecosystem services (PES) programs are being employed to encourage environmental management reforms and conservation efforts, while cities have rarely adopted this strategy. The authors highlighted the potential benefits of PES for managing, preserving, and protecting urban ecosystems. Additionally, Boyd and Banzhaf (2011) defined a public policy demand for standardized units of ecosystem measurement via an inventory of measurable ecosystem services. They concluded that most ecosystem services must be acquired by the government and not through markets, making them public goods that fall short of effective oversight and lack market provision. Thus, governments need to be held accountable and communicate trends in ecological conditions, paving the way for services defined by performance accounting. Although weighing the relative value of services would pose challenges, it is a starting point for governments to systematically tally what is important about nature, making this approach similar to socio-cultural valuation methods.

6. Discussion

This study summarizes the carbon accounting methods and tools for the ecosystem and the effectiveness of such methods and tools. The methods to assess carbon estimates/fluxes are summarized in Fig. 13. Sound scientific and technical knowledge is required to select a carbon accounting method/tool for a particular habitat/region. It is generally agreed that remote sensing is a widely used advanced technique. AGB is the most accurate carbon pool that can be estimated through remote sensing because it covers a large area and is relatively inexpensive to measure. Field measurements, a well-developed and accurate method for large areas, are the most expensive component of sampling-based methods (Tomppo, 2006). The amount of data from each method depends on the source's quality and the trade-offs that must be made between accounting accuracy and costs of resources and time. Remote sensing data are integrated with empirical data to measure biomass and, subsequently, carbon stocks, either directly using allometric relationships or indirectly based on characteristics like canopy cover (Rose-nqvist et al., 2003).

Additionally, indices that combine reflection from various spectral regions can be utilized to estimate biomass. It is necessary to make indirect estimations utilizing empirical relationships, such as canopy cover, indices from different bands, or net primary production (NPP), which combines environmental data with remotely sensed data. For instance, it can be difficult to interpret remote sensing data/images into meaningful insights. Long-term data comparison may also be difficult because remote sensing systems' sensors, bandwidth, or maintenance may have changed over time. It is necessary to have expertise in managing data from these procedures (Sensing and Techniques, 2008). Therefore, combining various remote sensing data types with field measurements is an appropriate method for evaluating alternative land-use systems or regions and, consequently, for determining carbon stocks. It also has the advantage of tracking changes in carbon stocks and land use over an extended period.

For the BGB estimate, a proportion or function of the AGB pool is considered because of the complexity of the methods and the more

Carbon Estimation Techniques

Remote sensing	Models	Field measurements	Mapping and survey	Allometric equations
<ul style="list-style-type: none"> • LIDAR • RADAR • SAR • PALSAR • GEDI • Laser scanning (spaceborne) • Optical imagery etc. • LANDsat 7 	<ul style="list-style-type: none"> • i-Tree • CTCC • Eddy Covariance • CASA • CO2fix • INVEST • MOTTI etc. 	<ul style="list-style-type: none"> • Plot sampling • Harvesting • Point sampling • Eddy tower • Vegetation indices(NDVI) • Bulk density (litterfall) • DBH Measurements etc. 	<ul style="list-style-type: none"> • Transect method • Line/strip methods • LULC • Soil carbon density • Plot size • Sampling density • Arial photography etc. 	<ul style="list-style-type: none"> • Regression models • Allometric equations • Biometric approach • Mean biomass density method • DBH values • Biomass conversion w.r.t. Volume • MRM (MEAN ratio method) etc.

Fig. 13. Summary of carbon estimation techniques.

human efforts involved in field measurements, especially for forestlands. Additionally, since root biomass is not disrupted and no fresh planting is done, BGB for such systems is not expected to be damaged. When root biomass equations that are appropriate for the species or the project location are unavailable, field measurements may be used instead (Hairiah et al., 2001). Furthermore, estimations of carbon flux using suitable ecosystem models must be considered, as this process is a continuous one that is greatly influenced by land use and management (Paustian et al., 1997).

Measuring the deadwood and litter debris pools concurrently with the AGB pool measurement is simple and low-cost. Similar to AGB, the stock change measuring approach might be used to estimate litter biomass with little additional expense or labor. Expert judgment is required to determine whether the dead organic matter should be assessed, especially given that it makes up only approximately 10% of the total carbon stocks in forests and that annual litter production estimates are difficult and time-consuming. However, the accurateness of biomass or C estimations depends on the initial data used to develop allometric and general equations and biomass factors (Wirth et al., 2004; Wutzler et al., 2008), in addition to species-specific volume-to-biomass models. Ground sampling and satellite imaging methods can be used to classify the ecosystem precisely. Moreover, regional and biome-specific research, as well as the calculation of wood-based debris (Keller et al., 2004; Palace et al., 2007), may refine the carbon content estimates (Mäkinen et al., 2006).

Landsat has been frequently employed for medium spatial resolution image development. However, in some cases, because of the limitation of the optical sensors, radar and LiDAR are used instead. LiDAR data of large and small footprints can also be utilized to extract indirect tree height forecasts. However, the elevation variations within the footprint, mostly for big footprints, can be significant, making it more challenging to approximate tree height with high accuracy.

Contrary to field inventory, where data is frequently confined to small regions, remote sensing (space-borne or airborne) typically offers uninterrupted spatial information over large areas. For carbon flux estimations and statistical models, such as eddy covariance, LUCC, and vegetation indices can produce forecasts regarding carbon exchange among ecosystems and the atmosphere (NDVI). If there is any inconsistency in the carbon estimations, it can be due to the following:

- Imprecise variable measures, such as instrument and calibration errors
- Unsuitable allometric equations
- Sampling uncertainty
- The sampling network is poorly represented.

The lack of adequate and high-precision AGB sample plots is a key obstacle to constructing AGB estimate models and validating and assessing the accuracy of AGB estimation results. AGB estimate using remote sensing is a difficult process. Many factors can influence AGB estimate performance, including environmental conditions, mixed pixels, data concentration, diverse biophysical factors, inadequate sample data, observed remote sensing variables, and the methods used (Qureshi et al., 2012). The factors such as time, cost, and expertise for some of the above-mentioned methods are listed in Table 4. Future studies may integrate multi-source data that entails accurate remote sensing implementation, GIS, and modeling tools. The variability of biomass estimations at the local level can be reduced by improving the resolution of input maps and using more recent GIS techniques as technology develops. When new data becomes available, validation should be performed.

7. Conclusion and outlook

This review identifies natural carbon sinks, pools, and sequestration pathways. The carbon accounting methods are classified based on planned study types or data availability required to measure the carbon stocks and fluxes. In addition, benefits from the natural carbon capture systems are discussed from a socio-economic perspective. Some of the highlights and key challenges are as follows:

- It is essential to consider the accuracy of the measurement during the analysis. Ground and field measurements are the most accurate method applied, as the data provided is exact. However, some difficulties are associated with generalizing results unless the measurement was made on a large scale and widely randomized.
- The soil bulk density analyses show that carbon up to 10–20 kg m⁻² can be stored in soil depending upon the soil depth, climate zone, and habitat type.

Table 4

Comparison of different accounting methods in terms of time, cost, and expertise.

Method	Time	Cost	Expertise	Accuracy	Remarks
Models based	Effective	Costly	Complex	Low	Spatial scale is limited Large-area coverage
Remote sensing	Effective	Costly	Simple	Low	
Forest Inventory	Effective	Economical	Simple	Low	
Eddy Covariance	Effective	Costly	Complex	Low	For BGB Spatial scale is limited
Carbon flux	Effective	Economical	Simple	Low	
Field Measurements	Time-consuming	Costly	Simple	High	
Allometric Equations	Effective	Economical	Simple	Low	

- Research showed that live sampling provided the highest accuracy; however, it is a destructive method that is not recommended except for soil sampling and some restricted analyses.
- Collecting field data for the whole ecosystem is sometimes not approachable (with big forest measurements or in large-scale analysis). The ecosystem elements are not always acquirable and are generally not cost or time-effective.
- Satellite earth observation and drone and airborne measurements have huge potential to refine analysis, assessment of ecosystems and their services, and mapping.
- LiDAR is the best single sensor for estimating biomass, as height metrics usually outperform cover metrics.
- Estimation calculations were able to provide good quantitative measurements. However, when leveled to a large scale with higher biodiversity (big city or state), uncertainties reached 40%.
- In assessing carbon sequestration projects, it is critical to account for time regarding carbon storage estimates and compares carbon sinks and other climatic change mitigation options.
- Combining remote sensing, GIS, and empirical data allows for a better spatial expression between the carbon emissions and LUC relationship.
- The various accounting approaches differ in how they treat the concept of time. The accounting approach chosen to investigate sequestration options is typically study-specific. Countries and regions are free to choose the accounting method that best fits their sequestration program.
- Although these estimations did not provide entirely accurate values, they can be used as indicators demonstrating the considerable impact and benefits that the trees and biome systems had on reducing atmospheric carbon and other pollutants.
- The natural carbon sinks greatly benefit pollution uptake (particulate interception and deposition). The integrated studies revealed that urban tree canopy cover management could improve air and health quality and reduce air temperature.

CRediT authorship contribution statement

Salma Habib: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Furqan Tahir:** Data curation, Formal analysis, Investigation, Visualization, Writing – review & editing. **Fabiha Hussain:** Formal analysis, Investigation, Visualization, Writing – review & editing. **Nadine Mac-auley:** Formal analysis, Investigation, Writing – review & editing. **Sami G. Al-Ghamdi:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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