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From carbon stocks to carbon fluxes: methods, challenges, and uncertainties in forest carbon sink accounting

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Abstract

Forests are central to climate mitigation, yet robust quantification of their carbon sink remains challenging. Forest carbon sinks are commonly reported as net ecosystem productivity (NEP) or net biome productivity (NBP), whereas many assessments still infer sinks from changes in biomass or soil carbon stocks, complicating the interpretation and comparability of stocks vs fluxes. Here we synthesize forest carbon sink accounting from a process-based, multi-method perspective. We first clarify the relationships among gross primary productivity, net primary productivity, NEP, and NBP, and highlight additional pathways (lateral dissolved organic carbon export, emissions of biogenic volatile organic compounds, and inorganic carbon fluxes) that are often omitted from large-scale budgets. We then critically evaluate three methodological families (field-based inventories, eddy covariance, and remote sensing) in terms of what they directly observe, the spatiotemporal scales they represent, and the assumptions required to infer NEP/NBP. Building on this comparison, we develop an integrated uncertainty framework that partitions data-, model-, and scaling-related uncertainties (including acquisition/preprocessing, model structure and parameterization, and spatiotemporal representativeness) and explain how their interactions drive divergence among sink estimates. Finally, we outline priorities for coordinated air-space-ground monitoring, advanced model-data fusion, and standardized uncertainty reporting. This review provides a clearer conceptual basis and practical guidance for reconciling stock-change and flux-based estimates toward more transparent, comparable, and policy-relevant forest carbon sink accounting.

Keywords: Forest ecosystem, Carbon sink, Eddy covariance, Forest inventory, Remote sensing, Model-data fusion

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Introduction

Forests are critical components of the global carbon cycle and serve as one of the most important natural mechanisms for mitigating climate change through their capacity to absorb and store atmospheric CO_2[1−3]. Yet despite decades of research, accurately quantifying forest carbon sinks remains scientifically challenging because forest ecosystems exhibit strong spatial heterogeneity, temporal variability, and complex ecological processes[4]. In contemporary carbon accounting, forest carbon sinks are commonly expressed as net ecosystem productivity (NEP) or net biome productivity (NBP), both of which represent carbon fluxes rather than static pools[5]. NEP integrates photosynthetic carbon uptake and ecosystem respiration, whereas NBP additionally accounts for disturbance-related carbon losses from wildfires, harvesting, insect outbreaks, storms, and other large-scale events[6,7]. Clear conceptual separation between carbon stocks (e.g., biomass, soil organic carbon) and carbon fluxes (e.g., NEP, NBP) is crucial[5]. Persistent confusion between these concepts has contributed to substantial inconsistencies in forest carbon sink assessments across studies, regions, and methodological approaches.

Forest carbon cycling extends beyond vertical CO_2 exchange between forests and the atmosphere. Lateral transport of dissolved organic carbon (DOC), emissions of biogenic volatile organic compounds (VOCs), and hydrologically mediated inorganic carbon fluxes also contribute to ecosystem carbon balance, yet these pathways have received comparatively less attention in large-scale assessments[8,9]. Neglecting such processes can lead to systematic overestimation of carbon sequestration, particularly in landscapes with strong hydrological connectivity or intense carbonate weathering[10,11]. Together with vertical CO_2 exchange, these lateral and gaseous pathways highlight that forest carbon dynamics are multidimensional and cannot be fully captured by a single measurement technique.

To quantify forest carbon sinks, several methodological families have been developed, each grounded in distinct assumptions and operating at different spatial and temporal scales[12]. Field-based inventory methods infer sink strength from changes in carbon pools, offering long-term constraints on biomass and soil carbon dynamics[13]. Eddy covariance (EC) directly quantifies net ecosystem CO_2 exchange over a tower footprint, although its interpretation depends on turbulence conditions, footprint representativeness, and careful data processing, particularly in complex terrain[14,15]. Remote sensing, using optical, LiDAR, and microwave sensors, supplies spatially continuous observations that can be integrated with empirical or process-based models to derive carbon fluxes and stock changes[16]. Because remote sensing primarily measures structural or physiological proxies, its translation into NEP or NBP depends on model design and parameterization[17]. These fundamental differences in what is being measured and how it is interpreted help explain why estimates of forest carbon sinks often diverge across methods.

Despite substantial methodological progress, comprehensive syntheses that (i) rigorously distinguish stocks from fluxes, (ii)

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explicitly incorporate 'overlooked' carbon pathways such as DOC, VOCs, and inorganic carbon fluxes, and (iii) systematically evaluate the uncertainties associated with each methodological family remain limited[18]. Such syntheses are urgently needed to support carbon neutrality strategies, national greenhouse gas inventories, and evidence-based forest management. In this review, we first outline a carbon-cycle framework that differentiates between stocks and fluxes while integrating vertical and lateral pathways. We then critically evaluate the methodological foundations, practical implementation, and uncertainty characteristics of field inventory, EC, and remote sensing-model integration approaches. Finally, we synthesize major sources of uncertainty and discuss future directions for integrated monitoring, data fusion, and standardized, transparent forest carbon accounting.

Forest carbon cycle

Understanding forest carbon sinks requires a comprehensive interpretation of how carbon enters, moves through, and exits forest ecosystems across multiple spatial and temporal scales[19,20]. Forest carbon dynamics are driven by a suite of biological, physical, and biochemical processes that collectively determine whether an ecosystem functions as a net carbon sink or source[21,22]. At the core of these dynamics are vertical exchanges of carbon between vegetation, soil, and the atmosphere[19,23]. Forests absorb atmospheric CO_2 through photosynthesis, generating gross primary productivity (GPP), part of which is returned to the atmosphere via autotrophic respiration (*Ra*) by plants, while the remainder forms net primary productivity (NPP)[24]:

$$\mathrm{NPP} = \mathrm{GPP} - Ra \tag{1}$$

Carbon entering the soil through litterfall, root exudation, and microbial decomposition undergoes further mineralization, producing heterotrophic respiration (*Rh*)[25]. These fluxes combine to determine net ecosystem productivity (NEP), a key indicator of carbon sink strength, whereas net biome productivity (NBP) extends NEP by incorporating carbon losses from natural and anthropogenic disturbances[5]:

$$\mathrm{NEP} = \mathrm{GPP} - (Ra + Rh) \tag{2}$$

$$\mathrm{NBP} = \mathrm{NEP} - D \tag{3}$$

where, *D* represents disturbance-related carbon losses (Fig. 1). Distinguishing between carbon stocks (biomass, dead organic matter, soil organic carbon) and fluxes (GPP, *Ra*, *Rh*, NEP, NBP) is therefore essential, because changes in stocks integrate multiple processes over time and space and do not directly correspond to instantaneous or annual flux balances unless they are measured repeatedly and interpreted with appropriate assumptions[26].

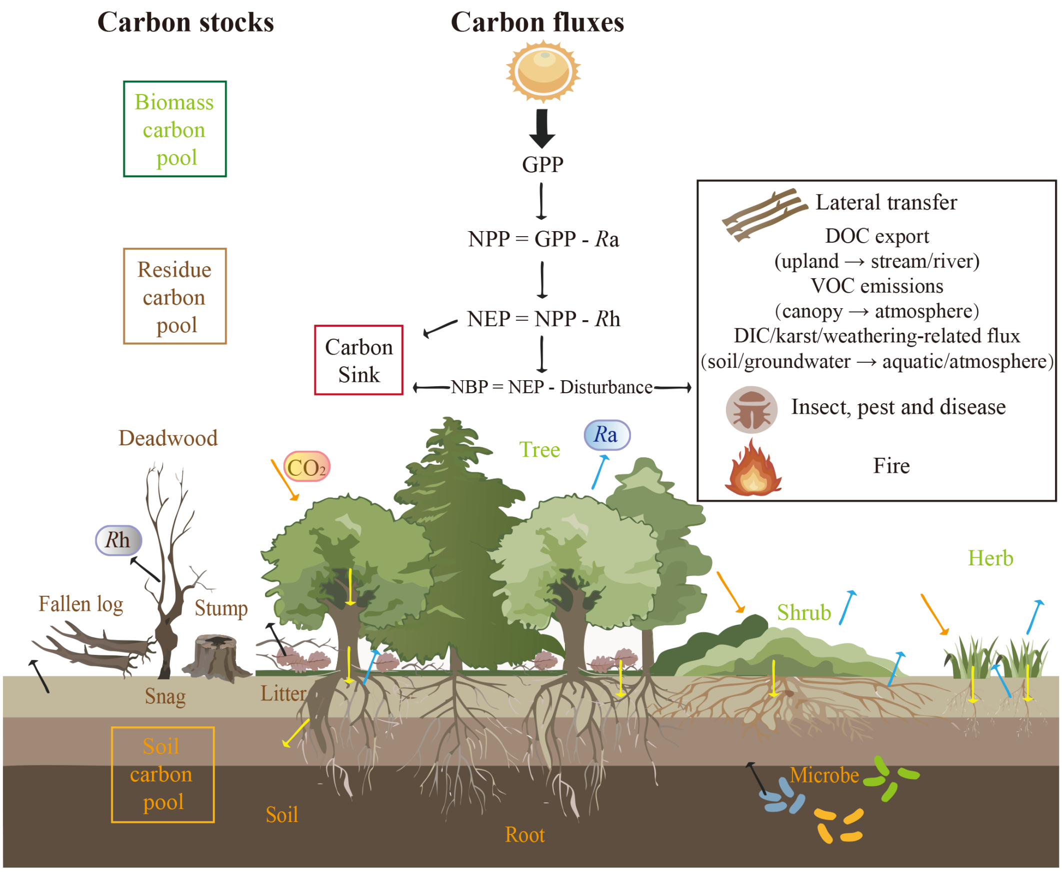

Fig. 1 Forest carbon cycle with key stocks, fluxes, and key pathways. Green indicates the biomass carbon pool (tree, shrub, herb), brown indicates the residue carbon pool (fallen log, stump, snag, litter), and orange indicates the soil carbon pool (soil, microbe). Arrows represent carbon-cycle processes: orange arrows indicate CO_2 uptake through plant photosynthesis (GPP), yellow arrows indicate carbon transfer among pools (e.g., litterfall and root inputs), blue arrows denote autotrophic respiration (*Ra*), and black arrows denote heterotrophic respiration (*Rh*). Flux relationships are shown as NPP = GPP − *Ra* and NEP = NPP − *Rh*, while net biome productivity is expressed as NBP = NEP − *D*, where *D* represents disturbance-related carbon losses (e.g., fire, pests, harvest/windthrow). The figure also highlights non-vertical pathways such as DOC export, VOC emissions, and DIC/weathering-related fluxes that can influence ecosystem carbon balance.

Beyond these well-recognized vertical fluxes, forest carbon balance is also shaped by several overlooked pathways that contribute additional complexity and uncertainty[27]. Lateral transport of dissolved organic carbon (DOC) driven by hydrological processes redistributes carbon downslope and into aquatic systems, representing a substantial, often unmeasured carbon loss in humid, mountainous, or highly weathered landscapes[28]. Forests also emit biogenic volatile organic compounds (BVOCs), including isoprene and monoterpenes, which can constitute meaningful carbon effluxes and influence atmospheric chemistry[29]. In certain geological contexts, particularly carbonate-rich or karst regions, forests participate in inorganic carbon exchanges through dissolved inorganic carbon transport and carbonate weathering, processes seldom represented in conventional assessments[30,31]. Collectively, these lateral and gaseous fluxes highlight that forest carbon cycling is not a vertically closed system and that neglecting non-CO_2 pathways can lead to systematic overestimation of ecosystem-scale carbon sinks[32]. These pathways may be particularly relevant in catchments with strong hydrological connectivity, in humid and mountainous forests, and in carbonate-rich or karst regions[28,30,31]. From an accounting perspective, their omission means that estimates based only on vertical CO_2 exchange or stock changes may not fully represent net ecosystem carbon balance[10,11]. Therefore, carbon sink estimates should be interpreted with explicit recognition of system boundaries, and of whether lateral and non-CO_2 fluxes are included or excluded.

Disturbances exert further influence on carbon dynamics by abruptly releasing carbon and altering ecosystem structure, function, and recovery trajectories[21,33]. Wildfires, insect outbreaks, storms, harvesting, and drought can significantly modify both carbon pools and fluxes, leading to discrepancies between NEP and NBP, especially in regions experiencing increasing disturbance frequency[34]. As forests progress through successional stages following disturbance, carbon allocation patterns, mortality rates, and soil respiration rates shift, complicating long-term assessments of carbon balance[35].

These interacting processes have important implications for carbon sink estimation. Because NEP and NBP quantify fluxes, methods that rely exclusively on biomass or other stock measurements can misrepresent sink strength if respiration, mortality, disturbance, and lateral transport are not explicitly considered[36]. Lateral fluxes and non-CO_2 pathways exacerbate these discrepancies by introducing additional, often unquantified, components of the carbon budget[37]. Moreover, carbon processes operate on different spatial and temporal scales—from leaf-level photosynthesis to landscape-scale disturbance mosaics—posing challenges for reconciling estimates derived from field inventories, EC, and remote sensing-model integration[38]. This process-based view provides a common basis for comparing how inventories, eddy covariance, and remote sensing model frameworks sample different parts of the same carbon budget, and why their estimates can diverge.

Carbon sink estimation methods

Accurate assessment of forest carbon sinks relies on methods that quantify either changes in carbon stocks, ecosystem-scale carbon fluxes, or model-derived estimates that integrate observations and process understanding[39]. These methods can be broadly grouped into three methodological families: field-based inventory (stock-change) methods, EC (flux) methods, and remote sensing combined with modelling. Each family targets different components of the forest carbon cycle, is grounded in different assumptions, and operates at different temporal and spatial scales[40]. A rigorous understanding of their methodological foundations, strengths, and limitations is essential for interpreting forest carbon sink estimates and for reconciling discrepancies among studies (Fig. 2; Table 1). To further illustrate how the magnitude of major carbon-cycle components varies across forest types and measurement frameworks, representative numerical ranges reported in recent studies are summarized in Supplementary Table S1.

Field-based inventory (stock-change) methods

Field-based inventory methods infer forest carbon sinks from repeated measurements of carbon pools, including living biomass, dead organic matter, and soil organic carbon[41]. In principle, changes in these pools between two time points are used to estimate a stock-based carbon sink, typically expressed as the change in total ecosystem carbon per unit time[42]:

$$C_{\text{sink}} = \frac{C_{t2} - C_{t1}}{t2 - t1} \tag{4}$$

where, C_{t1} and C_{t2} are total ecosystem carbon stocks at times $t1$ and $t2$, respectively. This stock-change estimate can be further decomposed into contributions from living biomass, residues (dead organic matter), and soil carbon pools (Supplementary File 1, Eq. 1). This stock-change framework underpins most national forest inventories and greenhouse gas reporting systems. In practice, aboveground biomass is estimated from tree measurements using allometric equations or biomass expansion factors (BEF), while belowground biomass is inferred from root-to-shoot ratios or other empirical relationships[43]. Representative allometric formulations for tree biomass and carbon-stock conversion are provided in Supplementary File 1 (Eqs 2–4), and a continuous BEF formulation that reduces bias from constant-BEF assumptions is provided in Supplementary File 1 Eq. 5. For shrubs and other woody understory components, biomass can be estimated using shrub-specific allometric relationships (Supplementary File 1, Eqs 6 and 7). Dead organic matter and soil organic carbon are quantified through litter surveys, coarse woody debris inventories, and soil sampling with laboratory analysis[44]. Equations for harvest-based understory estimation and litter carbon density calculations are summarized in Supplementary File 1 (Eq. 8), and formulations for deadwood carbon stocks (fallen logs, stumps, and snags) are provided in Supplementary File 1 (Eqs 9–12). A standard formulation for soil organic carbon density and stock estimation is provided in Supplementary File 1 (Eq. 13).

One major advantage of inventory-based methods is the ability to provide spatially explicit, long-term information on carbon stocks and their trends[13]. When sampling is representative and equations are well calibrated, aboveground biomass estimates can be relatively robust, and repeated measurements allow reliable detection of long-term carbon accumulation or loss, at stand to regional scales[45]. Inventory data also provide essential benchmarks for validating remote-sensing-derived biomass products and for calibrating process-based models[40].

However, inventory methods do not directly measure NEP or NBP, because they capture pool changes rather than fluxes[46]. Linking stock-change estimates to flux-based indicators requires assumptions about respiration, mortality, lateral transport, and disturbance processes[37]. Moreover, repeated measurements are often conducted at multi-year or decadal intervals, limiting the ability to resolve interannual variability, short-term responses to climate extremes, or transient dynamics following disturbance[47]. Soil carbon and belowground biomass remain particularly uncertain due to limited sampling density, high spatial heterogeneity, and difficulties in characterizing deep soil layers[48]. As a result, inventory-based

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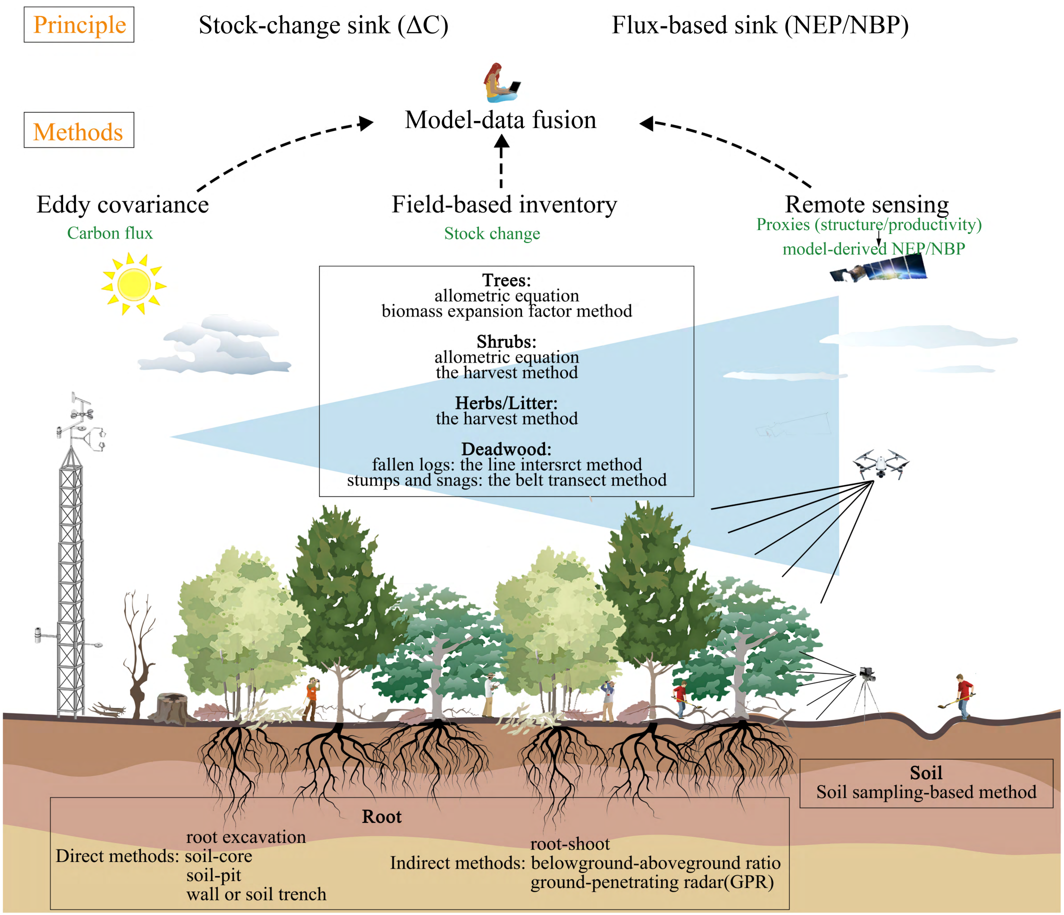

Fig. 2 Major approaches for estimating forest carbon sinks. Conceptual comparison of three method families: field-based inventory (stock-change, ΔC), eddy covariance (flux-based NEE/NEP), and remote sensing-model integration (structure/productivity proxies translated to model-derived NEP/NBP). The diagram emphasizes model-data fusion and cross-method complementarity for upscaling and interpretation.

estimates of forest carbon sinks can diverge substantially from flux-based estimates, especially in systems with frequent disturbances, rapid succession, or pronounced climatic variability[49].

Recent methodological developments aim to narrow these gaps and bring stock-change estimates closer to flux-based interpretation[50]. Key advances include the establishment of permanent sample plots with more frequent remeasurement, refinement of species- and region-specific allometric equations, expansion of soil sampling into deeper and stony horizons, and tighter integration between inventory plots and remote sensing for spatial upscaling[39]. These improvements enhance the robustness of stock-based assessments and facilitate more consistent comparison with EC- and model-based flux estimates. Nevertheless, inventories remain most powerful for characterizing long-term trends in biomass and soil carbon, while inferences about NEP and NBP must be made cautiously and with transparent documentation of underlying assumptions.

Eddy covariance (flux) methods

The eddy covariance (EC) technique is unique among forest carbon sink estimation methods in that it directly measures ecosystem-scale CO_2 exchange between the land surface and the atmosphere at high temporal resolution[15]. By capturing fluctuations in vertical wind velocity and CO_2 concentration, EC provides estimates of the turbulent CO_2 flux:

$$Fc = \overline{w'c'} \tag{5}$$

where, w' denotes deviations of vertical wind speed from its mean, and c' denotes deviations of CO_2 concentration. If canopy storage is non-negligible, especially under stable conditions, net ecosystem exchange (NEE) is computed as the sum of the turbulent flux and the storage term (Supplementary File 1, Eqs 14 and 15). NEE is then converted to net ecosystem productivity (NEP) by sign convention[51]:

$$\mathrm{NEP} = -\mathrm{NEE} \tag{6}$$

With additional information on disturbance and management-related carbon losses, flux-based estimates can be extended from NEP to approximate NBP over appropriate time scales.

The main strength of EC is its ability to continuously monitor ecosystem-scale CO_2 fluxes from minutes to years, thereby capturing diurnal cycles, seasonal dynamics, interannual variability, and responses to climatic and biotic drivers[52]. EC time series support detailed process studies, evaluation of model performance, and assessment of how climate extremes and management interventions influence forest carbon balance[53]. Multi-site syntheses and flux networks (e.g., FLUXNET) have produced important insights into biome-level patterns of carbon uptake and have provided critical constraints for global carbon budget analyses[54].

However, EC accuracy depends strongly on the physical assumptions underpinning the method. It requires sufficient turbulence and the applicability of Monin-Obukhov similarity theory; conditions that are often violated at night, in stable boundary layers, or in

Table 1. Comparative summary of major approaches for forest carbon sink estimation and key uncertainty characteristics.

Method	Field-based inventory	Eddy covariance	Remote sensing
Concept	Stock-change accounting (ΔC) from repeated measurements of ecosystem carbon pools (AGB/DOM/SOC) using allometry/BEF	Real-time measurement of CO_2 fluxes in forest ecosystems by an *in situ* eddy covariance system	Satellite observations provide structure/productivity proxies; NEP/NBP is inferred via models
Temporal resolution of measured data	Repeated pool measurements at multi-year intervals (typically 5–10 years)	High-frequency flux measurements (typically 10–30 Hz, commonly stored as 30-min aggregates)	Sensor revisit intervals from days to weeks; annual products typically derived after compositing/model integration
Sampling	Discrete point sampling	Tower-based flux footprint (variable source area depending on wind and stability)	Areal continuous observation
Resources	High labor and time costs	High instrument and maintenance costs	Data access, preprocessing, and substantial computing; requires ground/flux data for calibration/validation
Model	Allometric/BEF and stock-change accounting	Flux processing and gap-filling, and partitioning	Empirical/ML upscaling; LUE; process-based; data assimilation
Advantage	Long-term, policy-relevant stock accounting; spatially explicit pool estimates; robust for biomass trends when sampling and allometry are well calibrated	Direct, continuous ecosystem-scale CO_2 exchange (tower footprint) with high temporal resolution; captures diurnal-interannual variability	Wide spatial coverage; repeated observations of canopy structure/condition; efficient regional-to-global mapping; long time-series availability (sensor dependent)
Limitation	Coarse temporal resolution; allometry/BEF and sampling bias; high uncertainty in SOC/belowground pools; disturbance/harvest attribution gaps; ΔC-to-NEP/NBP conversion is assumption-rich and scale-dependent	Low turbulence / stable stratification; gap-filling/partitioning choices; advection & complex terrain; footprint representativeness	Cloud/saturation; sensor/preprocessing (atmospheric/geometric/terrain); indirect inference; model structural uncertainty; scaling mismatch
Main factors influencing uncertainty	Sampling design, plot representativeness, allometric equations/BEF, belowground biomass, SOC heterogeneity, remeasurement interval	Gap fraction, nighttime low turbulence, u* filtering, gap-filling, flux partitioning, advection, terrain complexity, footprint representativeness	Cloud contamination, signal saturation, atmospheric/geometric/terrain correction, sensor type, calibration data, model structure, scaling mismatch
Application Scale	Tree-level Stand-level Regional scale National scale	tower footprint (~10^2–10^4 m radius; context dependent) network synthesis	Stand-level Regional scale National scale Global scale
Primary observed variable	ΔC in pools (AGB/DOM/SOC)	NEE (→NEP via sign convention; NBP requires disturbance/management losses)	Structure/productivity proxies (AGB, LAI, fPAR, GPP/NPP) and model-derived NEP/NBP

complex terrain[15]. In such cases, CO_2 produced near the surface may not be fully transported to the measurement height, leading to underestimation of ecosystem respiration[55]. Nighttime data gaps and low-turbulence periods are therefore ubiquitous in EC records[56]. Contrary to simplified explanations that attribute missing data mainly to instrumental or environmental interference, the primary cause of these gaps is insufficient turbulence and non-stationary high-frequency time series[57]. To generate continuous annual NEP estimates, EC data must be subjected to systematic quality control and gap-filling. Established approaches such as Marginal Distribution Sampling (MDS) and, more recently, machine-learning methods like random forests and neural networks, have become standard practice in flux networks[58]. A simplified formulation illustrating lookup-table-type gap-filling under similar meteorological conditions, consistent with the logic of MDS, is provided in Supplementary File 1 (Eq. 16). While these methods greatly improve data completeness, they also introduce methodological uncertainty, with gap-filling choices and parameter settings potentially shifting annual NEP values by non-trivial amounts[59].

Terrain and footprint characteristics represent additional sources of uncertainty. EC is best suited to flat, homogeneous surfaces, whereas many forested landscapes are characterized by complex topography, heterogeneous vegetation, and advective flows[60]. In such settings, horizontal and vertical advection, drainage flows, and spatial variability in source areas can violate the assumptions of the EC method and bias flux estimates[61]. Despite ongoing advances in footprint modelling and correction strategies, these issues remain particularly challenging in mountainous and highly heterogeneous regions[62]. EC data also require flux partitioning to separate GPP from ecosystem respiration, as well as additional information to account for disturbance-related carbon losses, harvested biomass removal, and lateral carbon fluxes[37,63]. Consequently, EC provides an essential but incomplete picture of forest carbon sinks and is most powerful when combined with complementary data sources, particularly remote sensing and inventory observations for spatial upscaling and independent constraints.

Remote sensing and model-based approaches

Remote sensing and modelling together provide the spatially continuous perspective necessary to assess forest carbon sinks at regional to global scales[64,65]. Unlike inventory and EC methods, which are inherently site-based, remote sensing delivers repeated observations of canopy structure, vegetation condition, and environmental drivers over large areas[66]. These observations do not directly measure NEP or NBP but can be translated into carbon fluxes or stock changes when integrated with empirical, semi-empirical, or process-based models[67].

Optical remote sensing systems, such as those on board Landsat, Sentinel-2, and MODIS, provide information on spectral reflectance, vegetation indices, leaf area index, and canopy cover[68]. These metrics are widely used to estimate GPP and NPP through light-use-efficiency models and to monitor vegetation dynamics[69,70]. However, optical signals saturate at high biomass and are strongly affected by clouds, aerosols, and atmospheric conditions[71]. LiDAR instruments—airborne, terrestrial, and spaceborne—complement optical systems by providing three-dimensional information on canopy height, vertical structure, and stand density, enabling more accurate estimation of aboveground biomass[72]. Microwave sensors, including synthetic aperture radar (SAR) and vegetation optical depth products, can penetrate the canopy and are sensitive to woody biomass and canopy water content, although they are influenced by soil moisture, incidence angle, and terrain[73].

To translate these diverse observations into carbon sinks, remote sensing is coupled with several modelling frameworks. Empirical models use regression or machine-learning relationships between remote-sensing-derived variables and field-based biomass or flux measurements[54]. Light-use-efficiency models simulate GPP and NPP from absorbed photosynthetically active radiation and environmental modifiers, but requires explicit representation of respiration and disturbance processes to approximate NEP[70]. Process-based ecosystem models incorporate photosynthesis, respiration, allocation, and decomposition, often driven by climate data and constrained by remote-sensing products such as leaf area index or biomass[74]. Hybrid approaches, such as data assimilation frameworks and machine-learning emulators trained on EC or inventory data, have emerged as powerful tools for upscaling NEP and NBP[54]:

$$GPP = \varepsilon \max \times f_{PAR} \times f(T) \times f(VPD) \tag{7}$$

where, εmax is maximum light-use efficiency, f_{PAR} is the proportion of photosynthetically active radiation absorbed, and $f(T)$ and f(VPD) represent limitation functions for temperature and vapor pressure deficit, respectively. These models estimate GPP (or NPP) and therefore require additional parameterization of autotrophic and heterotrophic respiration, and disturbance-related carbon losses, to derive NEP or NBP[65].

While remote-sensing-and-modelling approaches offer unparalleled spatial coverage and the ability to monitor forest carbon dynamics over large regions, they also inherit the uncertainties of both data and model components[64]. Sensor noise, atmospheric correction errors, geometric misregistration, and terrain effects can propagate into biomass and productivity estimation[75,76]. Model structure and parameterization further influence the magnitude and spatial pattern of simulated carbon sinks[77]. Moreover, scaling mismatches between the footprints of flux towers, inventory plots, and remote-sensing pixels complicate calibration and validation[78]. Despite these challenges, remote sensing and modelling are indispensable for constructing large-scale forest carbon sink assessments and for linking site-level observations to national and global carbon budgets[65]. Their reliability depends critically on the availability of high-quality ground and flux data for calibration and evaluation, as well as on transparent treatment of uncertainties.

Synthesis of methodological roles

In summary, field-based inventory, EC, and remote sensing-model integration methods illuminate different aspects of forest carbon sinks. Inventory approaches are most suitable for long-term trends in carbon stocks; EC uniquely resolves high-frequency ecosystem-scale fluxes, and remote sensing-model frameworks enable spatially explicit mapping and upscaling. None of these methods alone can fully characterize NEP and NBP across scales and disturbance regimes. Their effective use, therefore, requires not only a clear understanding of their individual strengths and limitations, but also an explicit strategy for multi-method integration and cross-validation.

Method choice should be guided by the study objective and spatiotemporal scale. At plot and stand scales, field inventories and EC observations provide the most direct constraints on stock changes and ecosystem CO_2 exchange, and are therefore indispensable for model calibration and validation. At regional to national scales, remote sensing combined with empirical or light-use-efficiency modelling offers spatial continuity and repeated coverage, but requires careful cross-scale harmonization with plot and tower data. At global scales, products and frameworks such as MOD17, FLUXCOM, and DGVM ensembles enable consistent long-term assessments, yet their credibility depends on systematic benchmarking against inventories and flux networks. This scale-aware perspective clarifies why single-method estimates diverge and motivates multi-method integration as the default strategy.

Direct cross-method comparison studies further highlight that methodological differences are not uniform across carbon-cycle components (Table 2). Campioli et al.[79] showed that eddy-covariance and biometric methods produced different estimates of NEP, whereas ecosystem respiration and gross primary production were generally more comparable, with stronger discrepancies in boreal forests where smaller net fluxes make source-sink classification more sensitive to methodological differences[79]. Site-level comparisons also show that convergence among inventory-based stock change, eddy-covariance-based cumulative NEP, and model estimates depends strongly on stand age, spatial representativeness, and the treatment of disturbance history and detrital pools[49]. These findings indicate that multi-method cross-validation is especially informative when methods are compared within the same ecosystem and over matched temporal windows, rather than interpreted as isolated estimates from different sites or periods.

Representative recent studies further illustrate that the reported magnitude of major forest carbon-cycle components varies substantially across forest types and methodological frameworks (Supplementary File 1). Across eddy-covariance-based studies, mean annual GPP and ecosystem respiration are often on the order of approximately 1,400–1,700 and 1,090–1,370 g C m^{-2}·yr^{-1}, respectively, while annual NEP/NEE can range from near neutral to well above 1,000 g C m^{-2}·yr^{-1} depending on forest type, stand origin, and site conditions[80,81]. At broader scales, biome- or region-level estimates may show lower mean GPP than site-level tower studies because of spatial aggregation and model-assisted scaling[54]. By contrast, NBP is typically lower than NEP once harvest and disturbance losses are included, highlighting the importance of accounting boundaries[34,37]. Ra and Rh are even more method-sensitive

Table 2. Representative studies for cross-method comparison of forest carbon sink estimates.

Forest system	Methods compared	Variables compared	Main finding relevant to this review	Ref.
Forest sites across boreal, temperate, and tropical zones	Eddy covariance (EC) vs biometric methods (BM)	Annual NEP, Reco, and GPP	EC and BM produced different estimates of NEP, whereas Reco and GPP were generally more comparable. Methodological discrepancies were more pronounced in boreal forests, where net fluxes are smaller and source-sink classification is therefore more sensitive to methodological differences.	[79]
Coastal Douglas-fir stands, British Columbia, Canada	Inventory-based stock change, EC-flux-tower estimates, and CBM-CFS3 model estimates	ΔC and cumulative ΣNEP	Cross-method comparison required explicit matching of inventory measurements, tower-based fluxes, and model estimates over comparable periods. The study showed that interpretation of agreement among methods depends strongly on topography, disturbance history, stand structure, and footprint-weighted comparison between tower fluxes and inventory plots.	[49]

because they usually depend on partitioning approaches or independent process-based modelling rather than direct ecosystem-scale observation[82]. DOC and BVOC fluxes are generally much smaller in carbon magnitude than CO_2-based fluxes, but they can still be important for carbon-budget interpretation, especially in hydrologically connected systems or when chemically reactive carbon losses are considered[83−85]. These examples underscore that numerical comparisons across studies should always be interpreted together with the monitoring approach, temporal coverage, and whether disturbance, lateral export, and non-CO_2 pathways are included[37,49,79].

Uncertainty in forest carbon sink estimation

Uncertainty in forest carbon sink estimation arises from multiple sources across data collection, methodological application, model structure, and spatiotemporal scaling[86]. Because inventory, EC, and remote sensing-model methods quantify different components of the carbon cycle, their estimates often diverge unless uncertainties are explicitly identified and addressed. Conceptually, uncertainties can be grouped into aleatory components (e.g., measurement noise and sampling variability) and epistemic components (e.g., incomplete process representation, parameter uncertainty, and scale mismatch). Importantly, uncertainty sources are not independent; they can propagate and accumulate along the estimation chain, from data acquisition and preprocessing to model parameterization, scaling, and aggregation, ultimately affecting the credibility and comparability of sink estimates.

Data-related uncertainties are particularly substantial. Field-based inventories face challenges stemming from sampling design, measurement precision, and the application of species- or region-specific allometric equations[87]. Soil carbon estimation is especially uncertain due to spatial heterogeneity in bulk density, gravel content, and decomposition dynamics[88]. As soil carbon frequently constitutes the largest pool in forest ecosystems, errors in its measurement can substantially influence stock-change assessments[89]. Meanwhile, EC observations are sensitive to the atmospheric conditions that underpin Monin-Obukhov similarity theory[90]. Nighttime underestimation of ecosystem respiration remains a persistent issue resulting from insufficient turbulence and non-stationary time series, necessitating rigorous gap-filling procedures[59]. Choices regarding u* thresholds, gap-filling algorithms, whether MDS or machine-learning-based, and energy balance closure corrections can cumulatively shift annual NEP estimates by notable margins[56,58]. Flux footprints are also highly sensitive to terrain complexity and surface heterogeneity, conditions under which standard EC assumptions may not hold[78,91].

Remote sensing data introduces its own suite of uncertainties linked to sensor performance, data preprocessing, and environmental variability. Optical sensors are limited by cloud cover and saturation in high-biomass forests, while LiDAR measurements vary with point density, occlusion, and canopy penetration[68,92]. Microwave sensors such as SAR or vegetation optical depth (VOD) are influenced by soil moisture, incidence angle, and terrain-induced distortion[73]. Radiometric and geometric correction further propagate uncertainty into biomass or productivity estimation[75]. Importantly, mismatches between the spatial footprints of inventory plots, EC towers, and remote sensing pixels create representativeness challenges that complicate model calibration and validation[79,93].

Model-based uncertainties stem from structural simplifications, parameterization choices, and the difficulty of representing disturbance regimes and belowground processes. Light-use-efficiency models typically simulate only GPP or NPP and require assumptions to convert these values into NEP, while process-based models still struggle to capture forest mortality, root dynamics, microbial processes, and the effects of compound disturbances[74]. Machine-learning models offer flexibility but often lack interpretability and may perform poorly when extrapolated beyond the training domain[54,90]. Additional variability across model outputs is introduced by parameter uncertainty, such as variability in carbon allocation, respiration sensitivity, turnover rates, and soil decomposition parameters[94].

Spatial and temporal scaling further amplify uncertainties. Inventory-based ΔC values integrate multi-year changes, while EC detects hourly fluctuations and remote sensing provides observations at discrete intervals[78]. It is difficult to reconcile these disparate temporal resolutions, especially in ecosystems with dynamic disturbance histories or rapid successional transitions. Lateral carbon fluxes, such as the export of dissolved organic carbon, erosion, and hydrological redistribution, are often unmeasured yet can significantly influence the net carbon balance[63]. When disturbances or lateral fluxes are unaccounted for, carbon sinks may be systematically overestimated[95].

Addressing these uncertainties requires integrating advances in model-data fusion, error propagation analysis, Monte Carlo simulation, Bayesian inference, and multi-model ensemble averaging[94]. Improving the consistency of measurement protocols, strengthening cross-scale calibration between field, flux, and remote sensing observations, and explicitly representing disturbance and lateral fluxes will enhance the reliability and comparability of forest carbon sink assessments[63,86,93]. Transparent uncertainty quantification is therefore indispensable for advancing forest carbon science and supporting policy-relevant carbon accounting frameworks.

Conclusion and future perspectives

Forests play fundamental roles in global climate regulation through their capacity to sequester atmospheric CO_2, yet accurately quantifying this carbon sink remains a significant scientific challenge. This review has clarified the conceptual distinctions between carbon stocks and carbon fluxes, integrated overlooked carbon pathways such as lateral dissolved organic carbon transport, volatile organic compounds, and inorganic carbon exchanges, and provided a critical evaluation of the major methodological approaches used to estimate forest carbon sinks. Field-based inventory, EC flux measurements, and remote sensing-model integration each capture different dimensions of the forest carbon cycle and operate under distinct assumptions, sampling constraints, and spatiotemporal resolutions (Fig. 3). Their inherent differences help explain why forest carbon sink assessments often diverge, particularly in regions with strong environmental heterogeneity or complex disturbance histories[96].

Despite substantial methodological progress, uncertainties remain pervasive across all components of carbon sink estimation. Inventory methods are affected by sampling design, variability in biomass equations, and difficulty in measuring belowground and soil carbon pools[79]. EC data are subject to turbulence limitations, gap-filling uncertainties, terrain-induced distortions, and the inability to directly capture disturbance-related carbon losses[59,90]. Remote sensing introduces sensor-specific errors, radiometric and

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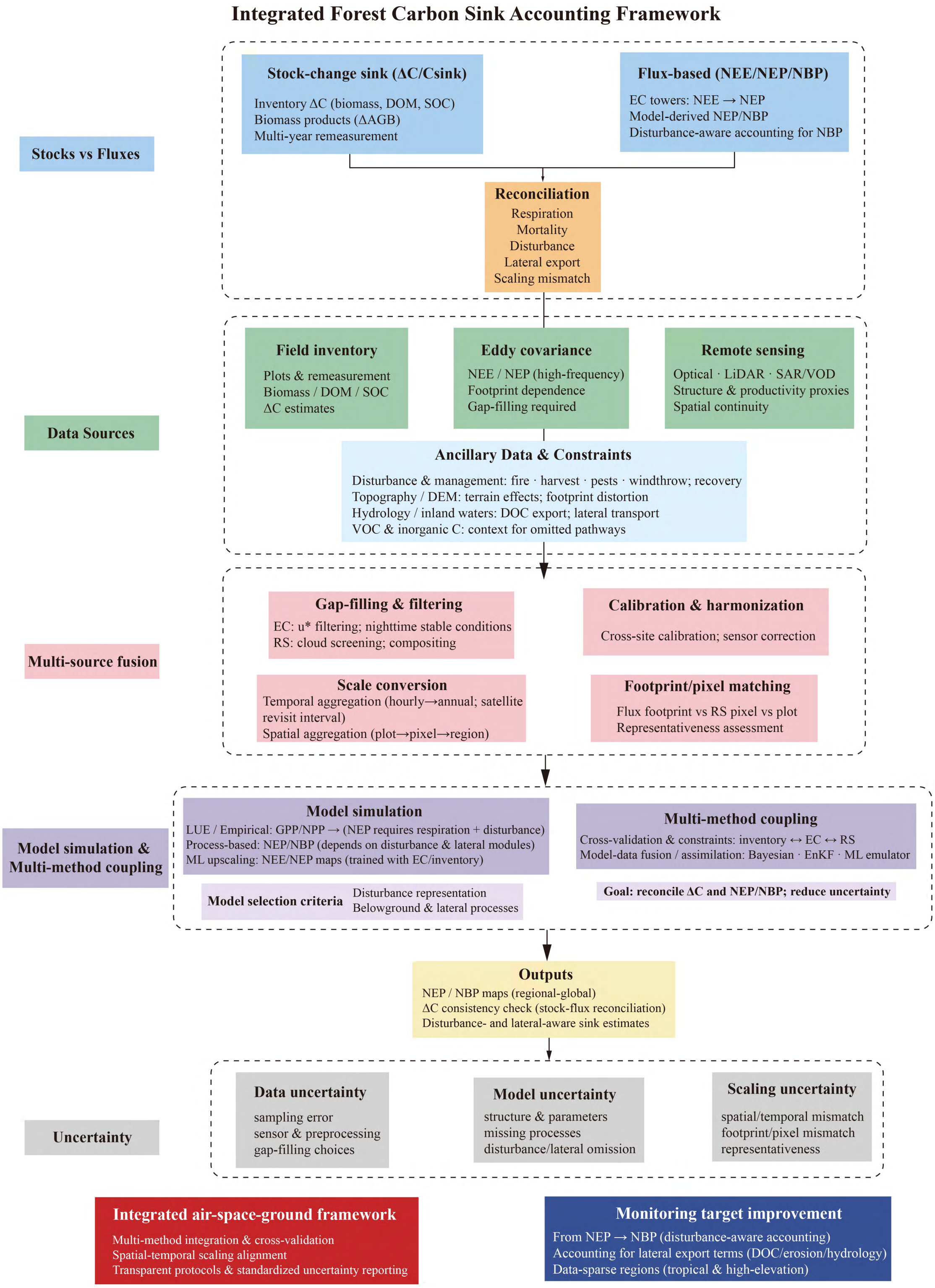

Fig. 3 Integrated framework for reconciling stock-change and flux-based sink estimates. Workflow linking ΔC/C_sink and NEE/NEP/NBP through a reconciliation step that considers respiration, mortality, disturbance, lateral export, and scaling mismatch. Inputs include inventory, eddy covariance, remote sensing, and ancillary constraints (disturbance/management, topography/DEM, hydrology/DOC, and VOC/inorganic-carbon context). The framework summarizes key fusion steps (gap-filling/filtering, calibration, scale conversion, footprint/pixel matching), model pathways, and uncertainty partitioning (data, model, scaling), and concludes with an air-space-ground monitoring strategy. Abbreviations: ΔC, change in ecosystem carbon stock; Csink, stock-change carbon sink estimated as ΔC per unit time; NEE, net ecosystem exchange; NEP, net ecosystem productivity; NBP, net biome productivity; EC, eddy covariance; DOM, dead organic matter; SOC, soil organic carbon; ΔAGB, change in aboveground biomass; DEM, digital elevation model; DOC, dissolved organic carbon; VOC, volatile organic compounds; u*, friction velocity threshold used for EC quality filtering; RS, remote sensing; LiDAR, Light Detection and Ranging; SAR, synthetic aperture radar; VOD, vegetation optical depth; LUE, light-use efficiency; GPP, gross primary productivity; NPP, net primary productivity; ML, machine learning; EnKF, Ensemble Kalman Filter.

geometric correction uncertainties, and the challenge of converting structural or spectral proxies into meaningful carbon flux estimates[64,65,76]. Model-based approaches further amplify uncertainty through structural simplifications, parameter sensitivity, and incomplete representation of disturbance, mortality, and soil processes[97]. These uncertainties, combined with mismatches in spatial and temporal scaling, underscore the urgent need for more integrated and transparent frameworks for forest carbon sink accounting.

Looking forward, several avenues are critical for advancing the scientific rigor and policy relevance of forest carbon sink assessments. First, integrating multi-source observations through coordinated air-space-ground monitoring systems will allow more robust cross-validation and reduce method-specific biases[98,99]. Second, advances in data fusion, Bayesian inference, and machine-learning-based model-data integration can enable more accurate parameter estimation and reconcile discrepancies among different methods[54,100]. Third, explicit representation of disturbance regimes, lateral carbon fluxes, and recovery trajectories is essential for moving from NEP-based assessments toward more comprehensive NBP evaluations[37,63,101]. This is especially important in environments where hydrological export, VOC emissions, or inorganic carbon exchanges are likely to contribute non-negligibly to the overall carbon budget. Fourth, standardized protocols for measurement, preprocessing, uncertainty quantification, and reporting will greatly enhance comparability across studies, regions, and national inventories[97]. Finally, tropical forests, high-elevation ecosystems, and other data-sparse regions should be prioritized for future monitoring due to their sensitivity to climate change and their disproportionate contribution to global carbon budgets[102].

By strengthening methodological integration, improving data quality and model representation, and establishing unified standards for uncertainty quantification, the scientific community can move toward more accurate, consistent, and policy-relevant assessments of forest carbon sinks. Such progress is vital not only for advancing ecological understanding but also for informing climate mitigation strategies and supporting global commitments to carbon neutrality.

Author contributions

The authors confirm their contributions to the paper as follows: methodology, conceptualization, data collection, visualization, writing – original draft: Yue He; methodology, conceptualization, data collection, visualization: Yutong He, Yang Y; methodology: Pan B, Zhang Y; conceptualization: Chen F; revise the paper: Zhang X; supervision: Bai J; supervision, project administration, funding acquisition, conceptualization, writing – review and editing: Zhang S. All authors reviewed the results and approved the final version of the manuscript.

Data availability

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study. All information summarized in the tables was obtained from published literature.

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Conflict of 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.

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