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Priority science can accelerate agroforestry as a natural climate solution

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The expansion of agroforestry could provide substantial climate change mitigation (up to 0.31 Pg C yr^{-1}), comparable to other prominent natural climate solutions such as reforestation. Yet, climate-focused agroforestry efforts grapple with ambiguity about which agroforestry actions provide mitigation, uncertainty about the magnitude of that mitigation and inability to reliably track progress. In this Perspective, we define agroforestry as a natural climate solution, discuss current understanding of the controls on farm-scale mitigation potential and highlight recent innovation on emergent, high-resolution remote sensing methods to enable detection, measurement and monitoring. We also assess the status of agroforestry in the context of global climate ambitions, highlighting regions of underappreciated expansion opportunity and identifying priorities for policy and praxis.

Agroforestry – the incorporation and maintenance of trees in agricultural landscapes – is a broad term encompassing a diversity of Indigenous, traditional and modern farming practices[1–4]. These can range from scattered trees in pastures or farmscapes, to linear trees in or around fields, to forest canopies grown above crops. Agroforestry's overarching strength is its multifunctionality: adding trees to agricultural lands can provide a variety of agronomic, socioeconomic and environmental benefits[5–7]. From a climate change perspective, one key benefit is the potential for agroforestry to increase or protect carbon storage on agricultural lands. This makes agroforestry a potential natural climate solution (NCS) – a land-use practice that sequesters carbon or reduces emissions without reducing food and fibre production or eroding biodiversity[8].

Global estimates of the cost-effective mitigation potential of agroforestry range from 0.12 Pg C yr^{-1} (Griscom et al.[8]; 95% confidence interval, 0.05 to 0.21 Pg C yr^{-1}) to 0.31 Pg C yr^{-1} (Roe et al.[9]; uncertainty not estimated), making it the largest agricultural NCS opportunity, comparable to other prominent NCSs such as reforestation (0.27 Pg C yr^{-1}) and reduced deforestation (0.49 Pg C yr^{-1})[9]. Many nations intend to use agroforestry to reduce their net greenhouse gas emissions, with 40% of non-Annex I nations including agroforestry in their nationally determined contributions (NDCs) under the Paris Agreement[10]. Moreover, global agricultural lands already contain substantial woody carbon – though point estimates range widely, from 6.93 Pg C (aboveground carbon[11]) to 15.77 Pg C (aboveground[12–14]) to 37.12 Pg C (above and belowground[15,16]) (Supplementary Methods). This carbon may be

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concentrated on a small fraction of global land (<10% of agricultural lands are estimated at >5 Mg C ha^{-1} of woody biomass[11]), suggesting substantial opportunity to both conserve and expand trees within agricultural lands.

Global synopses are useful, but they are highly variable, are based on coarse assumptions, and thus cannot provide the mitigation estimates needed to inform specific land management practices. Many studies have synthesized farm-scale estimates for that purpose[17–37], arriving at broad agreement that agroforestry adoption can increase carbon storage[7], yet providing little clarity about how much. These uncertain estimates of mitigation potential, paired with the poor ability to predict changes in crop yield, revenue, ecosystem services, and other co-benefits and trade-offs of agroforestry, limit farmers' and ranchers' ability to make informed management decisions. Finally, the lack of robust, standard methodologies for monitoring, measurement, reporting and verification (MRV) limits farmers' access to climate-focused incentive mechanisms such as carbon markets or government funding.

Agroforestry has clear and viable NCS potential[38], but large uncertainties, knowledge gaps and technical hurdles remain, hindering deployment and expansion. In the couple of decades since pathbreaking reviews of agroforestry carbon sequestration[28,39–43], substantial advances have been made in scientific understanding, data availability, technical capacity and climate ambition. Here we take stock of these changes to help prioritize research and inform action during this decisive decade for constraining climate change. We review the state of our knowledge about agroforestry as an NCS (henceforth, AF-NCS) to answer four key questions: (1) What is AF-NCS? (2) How well do we understand its mitigation potential, and how can that be improved? (3) How can agroforestry locations and practices be mapped, and how can its extent and carbon density be monitored? (4) What other information and incentives will best support agroforestry adoption and expansion?

Defining agroforestry as a natural climate solution

Agroforestry is a land use, typically defined on the basis of management practices, species composition or other agro-ecological characteristics[44]. By contrast, an NCS is a land-use change, defined by the ability to mitigate climate change without decreasing food security or biodiversity. Not all land-use changes that result in agroforestry provide climate change mitigation – indeed, some agroforestry transitions can even increase atmospheric greenhouse gas concentrations (Fig. 1). Yet this is often overlooked, because the lack of an explicit definition of AF-NCS incorrectly implies that all agroforestry practices are NCSs. Here, by applying three refinements to common agroforestry definitions, we circumscribe the subset of agroforestry transitions that qualify as AF-NCS.

First, existing agroforestry definitions describe systems combining woody species (that is, shrubs or trees; hereafter 'trees'), non-woody crops or forage (hereafter 'crops'), and/or livestock. This definition does not consider whether trees are intentionally managed, but intentionality is critical for determining whether management decisions provide credible climate change mitigation. If an intentional NCS effort leads to tree incorporation or maintenance that would not have occurred under business-as-usual conditions, then it satisfies the principle of additionality and thus provides real mitigation. Though additionality can be challenging and costly to demonstrate[45], it is essential for ensuring the effectiveness of an NCS policy or intervention.

Second, existing agroforestry definitions often describe current practices without reference to prior land use, but not all agroforestry transitions benefit the climate[46]. For example, thinning or clearing of forest to establish agroforestry generally causes carbon losses[17,47], whereas establishing or enhancing tree cover on open farmland generally stores carbon[48] (Fig. 1, 'Adoption' and 'Change in management'). This means that two agroforestry systems could look similar, but their establishment could cause opposite climate forcing. Similarly, if a farmer maintains some percentage of tree cover that would otherwise have been entirely removed, this act of protection provides mitigation from avoided emissions (Fig. 1, 'Risk of removal'). Baseline setting thus helps ensure that climate-focused agroforestry efforts provide mitigation – though the questions of who sets a baseline, how, and when remain open and important ones, with potential equity implications[49].

Finally, agroforestry definitions often focus on intermixing trees with crops and/or animals, thus excluding tree-only practices that can provide carbon storage within agricultural landscapes. For example, some diversified farming systems may be excluded from agroforestry definitions because trees and crops occur as discrete patches within mosaics (for example, satoyama landscapes[50] and parcelized cut-and-carry systems[51]) rather than as fully intermixed production systems. Agricultural tree monocrops, such as orchards without crops or animals, are even more likely to be excluded from common agroforestry definitions. Yet the adoption, expansion or retention of these systems may increase net carbon storage on agricultural land[52]. Thus, although these systems are sporadically defined as agroforestry[53], we include them within our definition of AF-NCS.

Given the above, we define AF-NCS as 'the intentional establishment, increase or maintenance of trees in agricultural landscapes, providing additional net carbon storage against a business-as-usual baseline, without causing net reduction of current food and fibre production or negative impacts on biodiversity'. This definition refines standard agroforestry definitions to circumscribe the agroforestry practices that are likely to provide climate change mitigation, and it integrates the NCS definition[8] to preclude negative food security and biodiversity outcomes (for example, the replacement of diverse native grasslands with agroforestry). It provides a first-order approximation of the climate impacts of agroforestry interventions, but accurate, site-specific estimates will require careful assessment of net carbon dynamics, non-carbon climate forcing and other accounting challenges (discussed in the following section).

Estimating the mitigation potential of agroforestry

In the past decade alone, there have been more than 20 synthetic studies quantifying agroforestry carbon stocks and fluxes[17–37]. These efforts have primarily focused on carbon in aboveground and belowground woody biomass (AGB and BGB) and on soil organic carbon (SOC), and they consistently demonstrate substantial mitigation potential. However, carbon estimates vary widely across these studies, indicating a knowledge gap about the controls on farm-scale carbon sequestration and storage. This makes it challenging to accurately estimate mitigation potential at existing AF-NCS sites (because direct measurement is often cost-prohibitive) and at potential sites under consideration.

Some of this variability stems from methodological disparity. These studies vary in geographic focus and extent, quantitative methods, and data quality and criteria for inclusion. Perhaps most importantly, and typical of meta-analyses on similar topics[6], they feature limited sample sizes drawn from disjoint subsets of the total available literature: across the 21 prior analyses we reviewed, 66% of the 536 primary studies used appear only once, and just three primary studies[54–56] appear in 8 of the 21, the maximum number of repeat citations (Supplementary Fig. 1). With existing reviews basing their conclusions on small portions of the available data, understanding of AF-NCS mitigation potential remains limited.

Syntheses can also omit factors that could be key drivers of variation in agroforestry carbon storage, including bioclimate, species choice, planting density and management regime (Supplementary Table 1). Instead, previous syntheses usually stratify mitigation estimates by agroforestry practice, sometimes with coarse subdivision by a second covariate (for example, climate[17]). This is sensible, given the need to organize the vast diversity of treed agricultural systems into a

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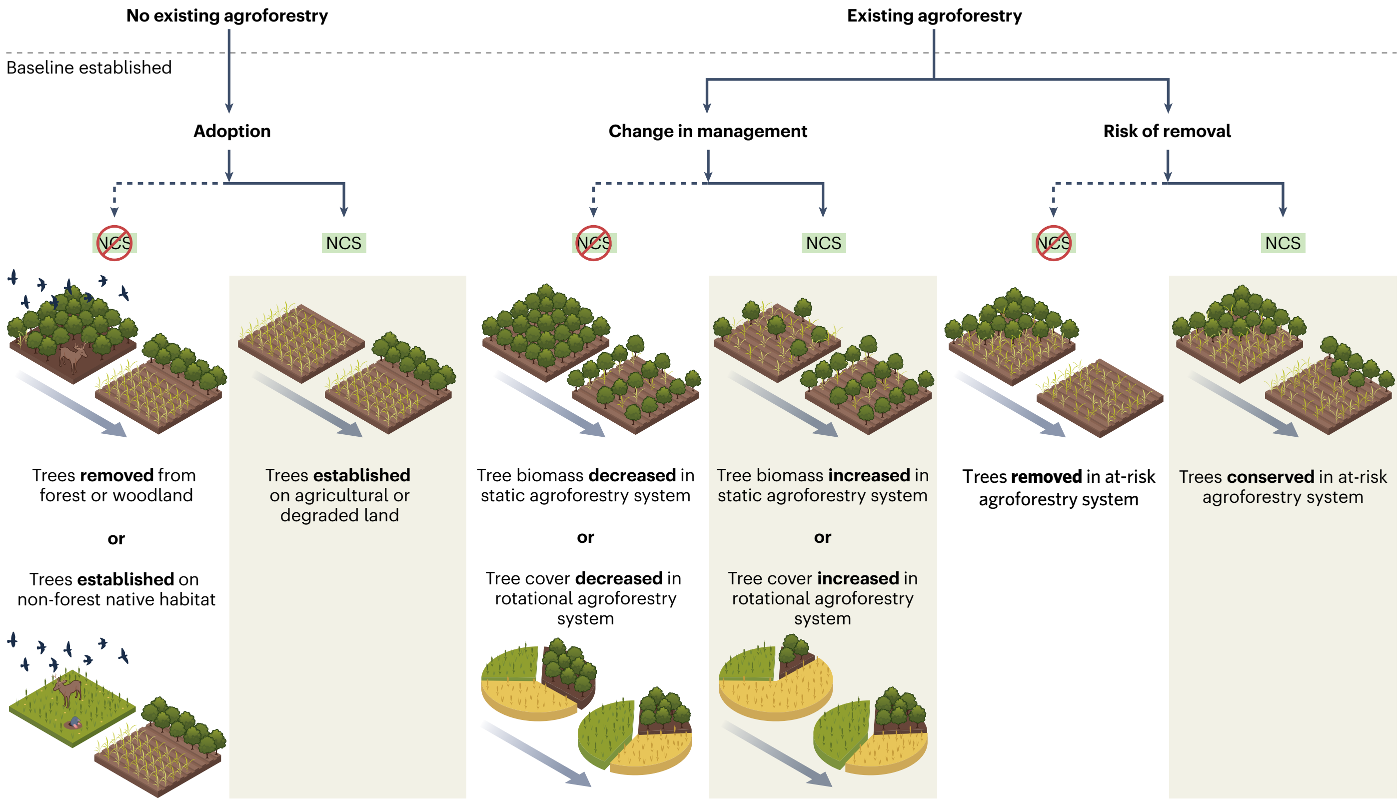

Fig. 1 | Land-use change and carbon outcomes determine whether agroforestry is an NCS. If agroforestry does not exist before the baseline, then agroforestry adoption serves as an NCS when it increases woody and soil carbon storage without impacting biodiversity (left). If agroforestry exists at the time of baseline establishment, changing agroforestry management can serve as an NCS if it increases tree biomass or proportional tree cover in static or rotational agroforestry systems, thus increasing carbon storage (middle). Alternatively, conservation of some or all trees can serve as an NCS if those trees would have been removed under business-as-usual conditions, such that their maintenance leads to avoided emissions (right). Figure adapted from image by Vin Reed.

tractable typology. But because these typologies reflect management, not carbon dynamics, they explain a limited amount of site-to-site variation in mitigation potential. For example, 'silvopasture' (that is, trees on grazing lands) could describe systems ranging from occasional, scattered trees in pastures to livestock grazing under a closed canopy – systems that vary widely in aboveground carbon density.

As a result, estimates of carbon storage potential in prior studies have high uncertainty. For example, the carbon stock change data compiled by Cardinael et al.[17] to develop IPCC Tier 1 emission factors exhibit more variation within than between practices, with nearly 100-fold variation in silvopasture (Fig. 2 and Supplementary Methods). However, some coherent patterns appear when comparing how aboveground woody carbon (AGC) and SOC stocks change across practices (Fig. 2). The increase in AGC is greatest in multistrata systems (which can have dense and complex canopies) but is more variable in silvopasture (with its broad structural diversity) and is lower in the systems typified by scattered trees. Patterns in SOC are less clear, but SOC appears lower on average in systems that are more likely to be regularly disturbed by ploughing (that is, intercropping and silvoarable). Nonetheless, the large overlap of estimates between agroforestry types demonstrates how coarse categorical analysis and limited sample sizes can limit the utility of mitigation potential estimates.

Process-based simulation models provide an alternative approach to understanding agroforestry carbon dynamics[57], allowing for temporally and/or spatially explicit accounting of various carbon pools. However, these models may have limited utility for estimating AF-NCS mitigation potential because their structural and parametric complexity can restrict them to certain regions (for example, COMET-Farm[58]) or crops (for example, DynACof[59]) or require costly parameterization (for example, CO2FIX[60]). However, such models can be valuable when they match the system type, geographic context and accounting needs of a particular AF-NCS action.

As a path towards a generalized and comprehensive understanding of agroforestry mitigation potential, we propose a data-driven approach: a statistical model based on a database of all previously published, field-derived estimates of carbon stocks and fluxes, combined with all available information on the potential controls on that variation. The results would support everything from private project development to national emissions reporting and could even find added value from harmonization with complementary datasets (for example, any national forest inventories containing agroforestry sites). Calls for such a database have long been made[10,17,61]. We are therefore developing this database as a publicly available resource representing an exhaustive, multilingual sample of the white and grey literatures.

While this effort will help elucidate some of the principal controls on carbon storage in agroforestry systems, further progress could come from improvements in the content, quality and geographic coverage of newly reported data[41,62]. One key improvement would be standardized reporting of plot-level and site-level variables that are possible predictors of carbon storage (see Supplementary Table 1 for potential candidates). For example, bioclimate controls AGB in both natural forests[63] and agroforests[17,24], but imprecise geocoordinates in primary studies hinder climatic characterization of sites. Management variables (including pruning regimes, tillage depth and frequency, and rotation cycle lengths) are likely to influence carbon storage, so they could also be reported in a standardized and detailed way[42,64]. Other potentially important but often unreported variables include tree age distribution and species[65]. Ultimately, detailed descriptions

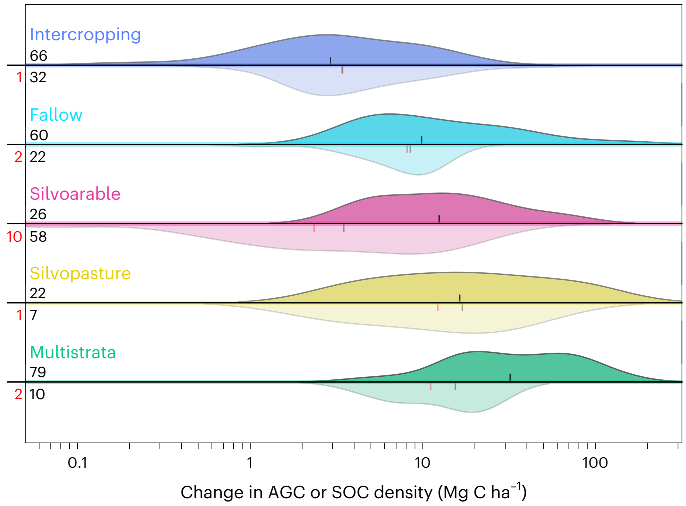

Fig. 2 | Carbon stock changes after agroforestry adoption vary within and across practices. Comparison of changes in AGC and SOC after agroforestry adoption, using data from Cardinael et al.[17]. Kernel density estimates (KDEs) show the distributions of stock changes (log_{10}-transformed for readability) for AGC (upward-facing KDEs) and SOC (downward-facing KDEs) after agroforestry adoption. The practices are ordered from top to bottom from the lowest to the highest median AGC (black ticks). The sample sizes are shown in black on the left. Negative SOC stock-change values are omitted from the KDEs because they are rare and cannot be log-transformed. Instead, the number of negative values omitted is displayed in red on the left, and the medians including negative values are displayed as red ticks. The following are brief descriptions of the systems (see Table 1 in Cardinael et al.[17] for more details): intercropping involves rows of fast-growing woody species, usually pruned as mulch for the crop rows in between and usually tropical; fallow involves sequential systems, featuring both natural and improved fallows; silvoarable involves rows of woody timber or fuel species with crop rows in between, usually temperate; silvopasture involves woody species planted on permanent grass or grazing lands; and multistrata involves one or more shade-tolerant crops grown under one or more layers of canopy, including both shade-grown commercial crops (for example, coffee and cacao) and home gardens.

of the agroforestry systems in each carbon-reporting primary study would provide maximum information for statistical modelling and thus accelerate the systematic determination of the key controls on mitigation potential.

Methods for agroforestry carbon measurements could also be improved. For AGB, this could come from the use of agroforestry-specific and species-specific allometric equations, given that accurate but costly and destructive whole-tree sampling is rarely employed[41]. Allometric equations derived from forest trees can introduce bias when the same equations are applied to open-grown agroforestry trees[66,67]. Likewise, direct measurement of BGB is expensive and difficult, so BGB is typically estimated using root–shoot ratios instead, which are also often based on forest-grown and/or unmanaged trees[68]. However, previous work has demonstrated that root–shoot ratios in agricultural systems can be influenced by increased light availability[69] or by intensive agricultural management[70] and that rooting depth and distribution can be altered by crop competition[71], suggesting that further research is needed to understand how well default root–shoot ratios reflect BGB dynamics in agroforestry. Finally, while many AGB and BGB assessments will continue to rely on field-collected tree measurements, terrestrial, drone-based, aerial and even satellite-based remote sensing methods are becoming increasingly accurate and accessible[72–74].

A variety of improvements could also be made to SOC measurements. Although agroforestry studies often quantify SOC, many fail to provide a reference measurement (that is, either before agroforestry adoption or at an adjacent non-agroforestry plot with the same land-use history). Studies that do provide a reference measurement (for example, Cardinael et al.[17]) show that SOC generally increases, though not always (Fig. 2), highlighting the critical importance of a reference against which to determine the direction and magnitude of change. Increased measurement of fine-scale spatial heterogeneity in SOC will also enable more accurate plot-level estimates, given the variation sometimes observed on small scales (for example, between rows and alleys in intercropping systems[54,75]). Additional improvements could come from measuring deeper into the soil profile than is typical (that is, >100 cm; for example, Cardinael et al.[76]), partitioning SOC into particulate and mineral-associated sub-pools to better understand residence times[41,54], and using an equivalent soil mass approach in lieu of a fixed-depth approach, to better account for the effect of land use on soil bulk density[77].

A full assessment of the mitigation potential of agroforestry may also require accounting for additional factors that are infrequently considered but potentially important. These include litter, coarse woody debris, and other dead-matter pools; CH_4 and N_2O fluxes[19,78]; and socio-ecological feedbacks (for example, fuel-wood use[79]). Non-greenhouse-gas dynamics, such as land-use-change-induced biogeophysical forcing resulting from changes in albedo, evapotranspiration or cloud dynamics, are also poorly understood but may influence net mitigation potential, especially in semi-arid and boreal regions[80,81].

Durability, or permanence, is another critical consideration, given that many agroforestry trees will not persist for the century-scale time frames targeted by many forest MRV protocols but instead may turn over on time frames closer to those laid out in newer SOC MRV protocols[82]. Estimates of durability are poorly constrained and sometimes biased, even for forest trees[83], and are only further complicated by non-stationary disturbance regimes under climate change[84]. Agroforestry trees, protected as an economic investment, could be less vulnerable to natural disturbance than unmanaged trees[85], but they could also have lower temporal durability because of wood extraction, declines in production or land-use change.

Finally, leakage is critical to NCS accounting. Leakage dynamics could reduce the mitigation of agroforestry, if agroforestry reduces crop yield and thus leads to additional land clearing. However, reverse leakage could increase agroforestry mitigation, if increased local fuel-wood production decreases fuel harvesting in nearby ecosystems[86] or if increased land-equivalent ratios improve food security on already-cleared land[87]. Leveraging synthetic-control methods to measure rates of deforestation in regions with and without agroforestry adoption, as has been done for protected areas[88], could help clarify the landscape-level outcomes of agroforestry transitions.

Mapping and monitoring agroforestry

Knowledge of where agroforestry occurs and how much carbon it stores is foundational to many of the scientific needs underlying AF-NCS implementation efforts. These include improved estimates of mitigation potential and expansion potential, and establishment of baseline tree cover extents and loss rates for MRV. However, current understanding of the spatial distribution of agroforestry is weak, with estimates of the global agroforestry extent varying fourfold, from 400 Mha (ref. 89) to 700 Mha (ref. 12) to 895 Mha (refs. 16,90) to 1,600 Mha (ref. 41). Most agroforestry mapping methods rely on remote sensing products, often by combining tree cover or AGB maps with agricultural land-cover maps[11,15,16] or by attempting to detect and classify forest management practices[12]. However, the structural variety of agroforestry systems, including both scattered trees outside forests and trees within agricultural forests (Supplementary Fig. 2), complicates mapping methodologies[10] and can introduce bias.

For example, the data from Chapman et al.[11] (hereafter the 'Chapman map'), despite being the most comprehensive global attempt to map agroforestry, excludes locations with >25% tree cover because

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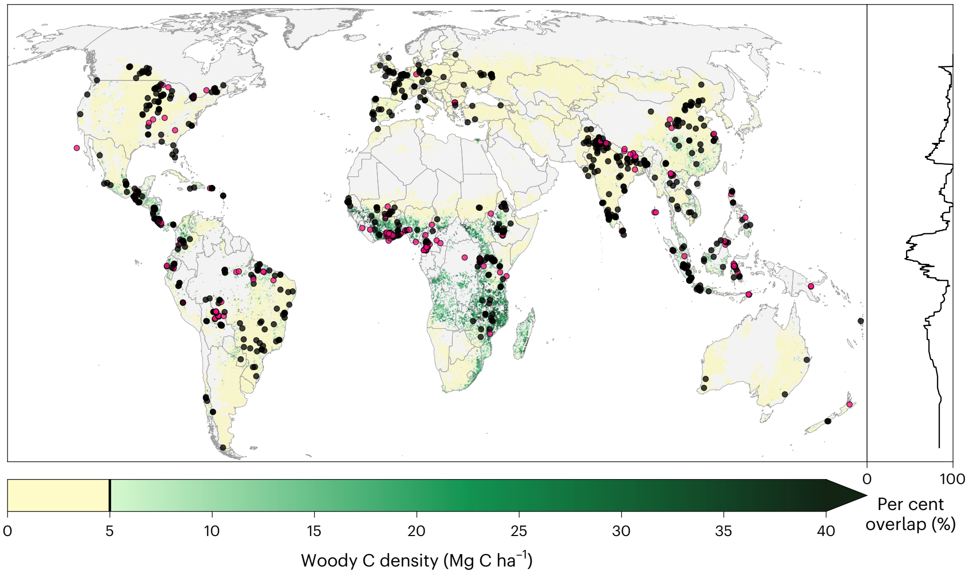

Fig. 3 | Global comparison between remote sensing of agroforestry and site locations gathered from literature. The global distribution of woody carbon density in agricultural lands (grazing lands and croplands) is shown for the year 2000. Following the methodology of ref. 11, we distinguish land with densities >5 Mg C ha^{-1} as 'agroforestry' and depict carbon density in those locations with an increasing green scale. Known agroforestry locations (n = 992) pulled from 528 primary studies (Supplementary Methods) are overlaid as black circles for sites that overlap with our 3-km-aggregated Chapman dataset and as pink circles for the remaining sites that do not overlap. In the right panel, we display the percentage of known agroforestry sites covered by the map within a latitudinal sliding window, showing that the majority of the missed sites are clustered within moist tropical and subtropical regions (Supplementary Methods). Figure adapted with permission from ref. 11, Wiley.

of the inability to distinguish closed-canopy agroforestry (for example, multistrata systems) from non-agricultural forests. This methodological choice, though inevitable, disproportionately omits data in regions where agroforestry tends to be closed-canopy (for example, the moist tropics; Fig. 3). Because closed-canopy systems tend towards higher AGC (Fig. 2), this leads to underestimates of carbon storage potential that propagate through to IPCC and peer-reviewed analyses[9,38]. Indeed, remote sensing estimates of agroforestry AGC appear 65% lower within the Chapman map on average (12.5 Mg C ha^{-1} versus 36.2 Mg C ha^{-1} when comparing Cardinael et al.[17] sites that overlap with the Chapman map with all Cardinael sites), and field measurements are 51% lower when making the same site comparison (11.0 Mg C ha^{-1} versus 24.9 Mg C ha^{-1}; Supplementary Fig. 3 and Supplementary Methods).

Agroforestry systems often feature small plot sizes with fine-scale heterogeneity in tree cover and thus in carbon density, limiting the utility of best-available, moderate-resolution (30-metre) global datasets. These small plot sizes are exemplified by the fact that the low precision of many published study site coordinates (less than half of the studies we reviewed report coordinates to at least three decimal places of coordinate precision (~110 m; Fig. 4a) makes it difficult to confidently identify the corresponding agroforestry plots within aerial imagery (such as the Latin American coffee system in Fig. 4b). Their fine-scale heterogeneity (for example, Fig. 4b) results in a large discrepancy between field-derived and remotely sensed carbon estimates (Supplementary Fig. 4) – one with limited room for improvement by increasing temporal (Supplementary Fig. 4) or spatial (Supplementary Fig. 5) alignment between field-derived and remote sensing datasets. Primarily, improved mapping and MRV will probably require increased spatial resolution that matches or exceeds the characteristic heterogeneity of the systems being monitored. In some systems, effective MRV may also require temporal resolution sufficient to detect complex AGC dynamics (for example, the two periods of biomass accumulation observed in Fig. 4c) or improved spectral resolution to improve discrimination between target agroforestry systems and other land cover.

Fortunately, the trend towards higher-resolution, machine-learning-based mapping promises substantial progress. One major area of work is in detection, which can help answer the question of where agroforestry occurs. This can be particularly important for regional or jurisdictional efforts, for which the locational information that is a prerequisite for MRV may not be readily available. The structural heterogeneity across agroforestry systems (Supplementary Fig. 2) poses a substantial challenge for detection and typically means that different methods are used to detect open-canopy versus closed-canopy agroforestry systems.

The detection of open-canopy agroforestry systems can utilize methods for mapping trees outside forests. These methods can map dispersed tree cover even when the canopy area of individual trees is smaller than the nominal pixel size of moderate-resolution datasets. This has revealed numerous examples of dispersed tree cover that was systematically overlooked in previous analysis[91–93]. Some trees-outside-forests algorithms use global, publicly available satellite imagery of the highest available resolution (for example, 10-metre Sentinel data[93–95]) to estimate tree cover in non-forest landscapes. Others use high-resolution (for example, between 5 and 0.5 metres) imagery, from regional aerial campaigns or from commercial satellite archives, to delineate and count individual trees[74,92,96]. Both approaches have their strengths and drawbacks, and both could be useful starting points for developing methods to distinguish open-canopy agroforestry trees from other trees outside forests (that is, to distinguish between the light and dark yellow segments in Supplementary Fig. 2). Some precedent exists for this[97], but much work remains to be done.

Because there is little spectral signature distinction between closed-canopy agroforests and non-agricultural forests (that is, between the light and dark green segments in Supplementary Fig. 2), these two land-cover types are challenging to distinguish. Recent approaches thus tend to analyse higher-resolution data with sophisticated methods, including time-series analysis[98], analysis of non-optical imagery (for example, synthetic-aperture radar (SAR)[99]), deep learning[100] and data fusion[101]. Much work is still needed to discover accurate, generalized solutions[101], but this is an active research area. Recent work demonstrating that a tree-delineation algorithm developed for trees outside forests[92] can also delineate trees within forests[74] suggests

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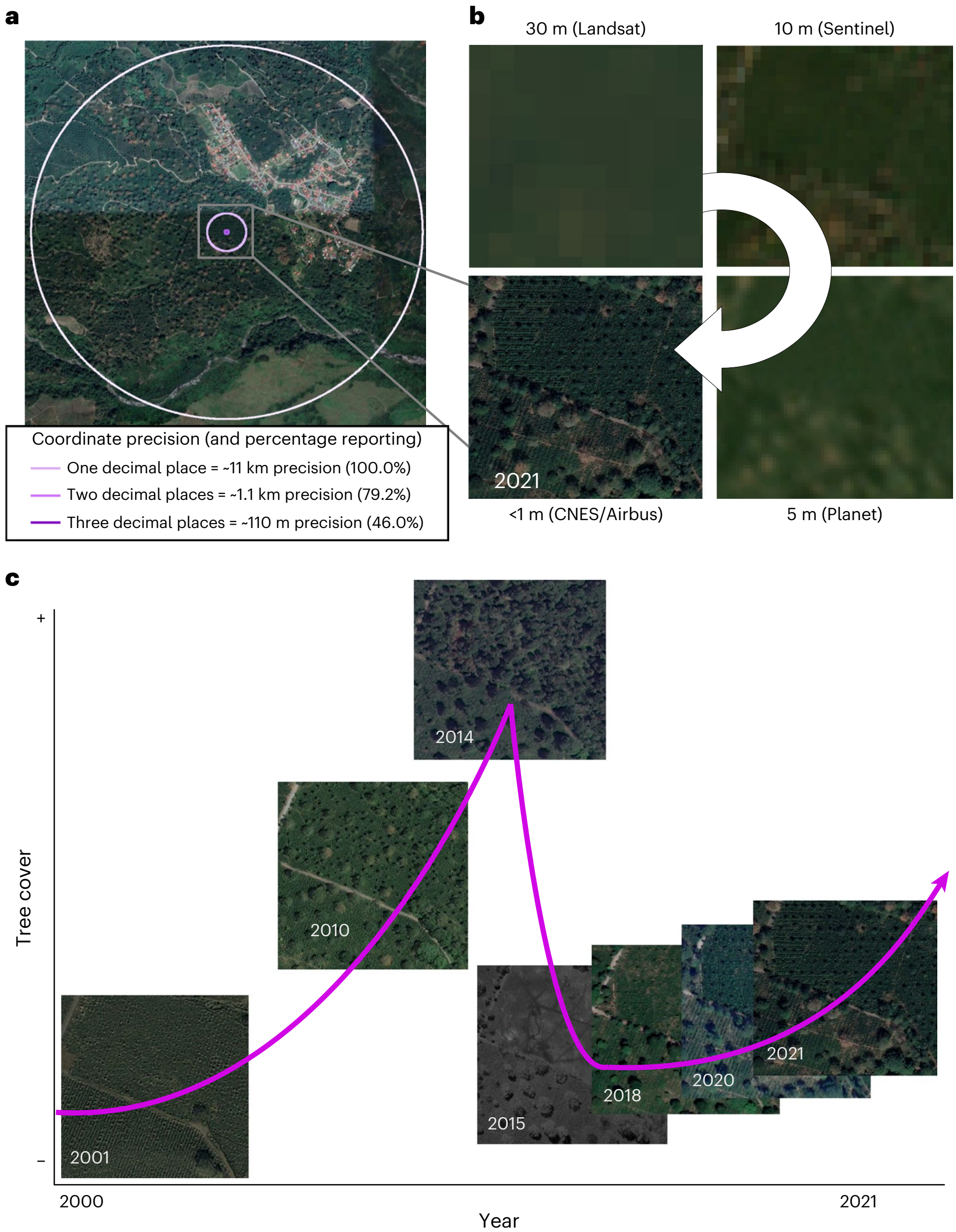

Fig. 4 | Importance of spatial precision, spatial resolution and temporal dynamics in remote sensing of agroforestry. a, Spatial precision: regional aerial image of the surroundings of a Latin American coffee agroforestry system explored in **b** and **c**. The image is annotated with radii depicting increasing levels of decimal-degree precision (expressed in approximate metres at the equator) associated with geographic coordinates collected from 465 primary studies that measured agroforestry carbon (increasing from one decimal place (that is, ~11 km precision), in light purple; through two decimal places (that is, ~1.1 km), in purple; to three decimal places (that is, ~110 m), in dark purple). In the legend, we display the percentage of field sites reported at each of the three levels of precision. Without high precision, it is difficult to confidently identify study systems in aerial imagery or to use previously published estimates as training data for spatial modelling efforts. **b**, Spatial resolution: the coffee agroforestry system indicated by the grey box in **a**, shown in remote sensing imagery of increasing resolution. All images are from the same roughly one-month period (Landsat, 10 March 2021; Sentinel, 24 February 2021; Planet, February 2021; CNES/Airbus, February 2021). **c**, Temporal dynamics: the coffee agroforestry system from **b**, shown in a multi-year time series of publicly available Maxar/CNES/Airbus aerial imagery, all captured during the same three months of the year. Approximate tree cover trajectory is visualized as a purple line. The image labelled '2021' is identical to the 2021 image in **b**. If only 2001 and 2014 imagery were available, the time-averaged tree cover would be overestimated, whereas if only 2001 and 2015 imagery were available, the time-averaged tree cover would be underestimated. Image in **a** adapted from Google Earth © 2023 Maxar Technologies/CNES/Airbus.

the possibility of detecting agroforestry systems across a range of tree densities.

Detection is only the starting point for reliable monitoring and measurement. Except for the minority of projects that fund field-based protocols, this will probably depend on remote sensing. And given the coarseness and uncertainty of agroforestry emission factors, remote-sensing-based monitoring will probably require not only tracking agroforestry extent over time but also estimating carbon stocks and their temporal changes. Efforts are already underway to improve methods for estimating AGB and AGC using publicly available data from space-based optical, lidar and/or SAR sensors[102]. These state-of-the-art products may have improved accuracy, enabling more accurate and more frequent estimation of incremental stock changes over time. However, their moderate resolution will probably still fail

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to capture the fine-scale spatial heterogeneity of some agroforestry systems, for the reasons discussed above. One alternative is the application of similar methods to higher-resolution satellite, aerial or drone imagery[103], producing pixel-based carbon stock change estimates that may better align with field-based values. Another is the combination of high-resolution tree-delineation methodologies with location-relevant tree allometrics, providing the novel ability to make tree-by-tree stock change estimates[74,104,105]. For SOC, the other major pool of interest, estimates are not only limited by coarse spatial scale and considerable uncertainty but are also predominantly detectable only in open cropland[102], so progress is likely to depend on some combination of improvements in statistical and mechanistic modelling.

Higher resolution will doubtless play a role in improving AF-NCS mapping and MRV. However, efforts to use high-resolution data will need to navigate the analytical trade-offs that can arise — limited spectral and temporal resolution or spatial extent, increased data volume or processing time[106], and complications caused by image variability within single tree crowns[107]. They will also need to handle the common challenges of accessibility of quality, cloud-free imagery, technical capacity, and affordability of data acquisition and computation. Ultimately, high-resolution MRV systems may need to be developed and parameterized on a regional and case-by-case basis, especially given the potential for variability in monitoring needs and objectives (for example, some applications may wish to distinguish tree monocrops (such as orchards and woodlots) from trees intercropped with food or fodder[108], or to identify rotational systems using change detection methods[109]). Purpose-built workflows could benefit from the ability to develop unique, strategic analyses combining higher spatial-resolution and/or spectral-resolution optical datasets, object-based tree-inventory approaches, lidar or SAR imagery, texture metrics, and/or phenology[99,101], but such analyses would require substantial technical investment. Meanwhile, for regions where such investment remains cost-prohibitive, as well as to improve the worldwide perspective on AF-NCS, the development of a coarser but global agroforestry monitoring system (akin to Global Forest Watch[110]) could be a worthwhile objective.

Potential and implications of agroforestry expansion

To help motivate and spatially prioritize investment, multiple studies have estimated or mapped the global mitigation potential of AF-NCS. These efforts have focused on modelling locations where agroforestry is biophysically possible, only sometimes adding constraints to maintain crop yield or ensure cost-effectiveness[8,9,11]. These results, aggregated to the globe, suggest that cost-effective potential is as high as 1.12 Pg CO_2 yr^{-1} (ref. 9), placing agroforestry among the most promising NCSs.

Combining these estimates of mitigation potential[9] with data on contemporary woody carbon density in agricultural lands[11], NDC ambitions[10,111] and levels of economic development[112] provides a telling look at the global status of AF-NCS. Potential additional agricultural woody carbon density is dramatically higher than current density on all continents except Africa, where contemporary woody carbon density is close to the modelled capacity in many regions (Fig. 5a). Furthermore, woody carbon density is significantly higher in countries that mention agroforestry in their NDCs ($n = 81$) than in those that do not ($n = 81$; Welch's t-test, $P = 1.92 \times 10^{-5}$), yet potential additional density shows no such difference ($P = 0.397$; $n_{NDC} = 80$, $n_{non\text{-}NDC} = 77$). Given the general inverse relationship between economic development and agricultural tree cover, much of the global opportunity lies in Global North countries, which rarely mention agroforestry in their NDCs despite being among the highest-potential nations (Fig. 5b).

This mismatch between potential and ambition suggests that agroforestry awareness is greatest in nations where trees remain

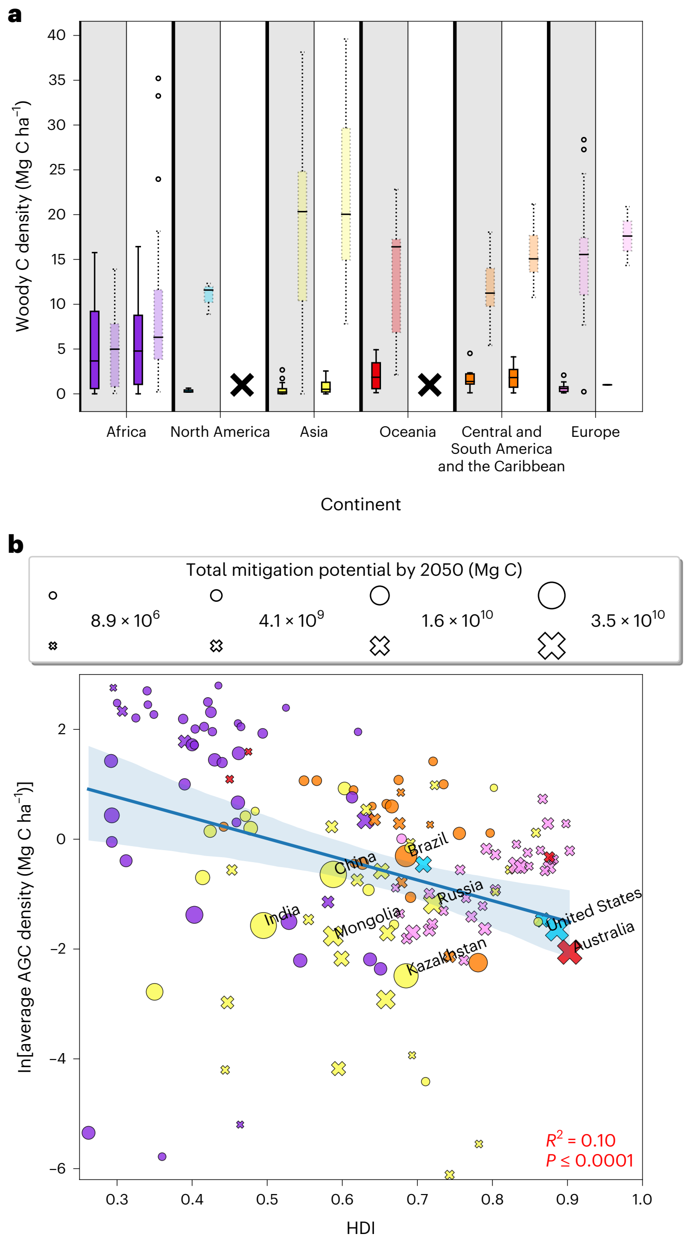

Fig. 5 | Variation in current and potential additional agroforestry carbon storage. a, For each continent, the distributions of circa-2000 ('current', solid boxes; data from country estimates in Chapman et al.[11]) and potential (transparent boxes; data from Roe et al.[9]) agroforestry carbon density are depicted as box plots (with a median centre line, first- and third-quartile box limits, whiskers extending to 1.5× the interquartile range, and outliers plotted outside them), differentiating countries that mention agroforestry in their NDCs (white columns) and those that do not (grey columns) using agroforestry NDC data from Rosenstock et al.[10], supplemented with data from the International Union for Conservation of Nature[111]. Two continents (North America and Oceania) have no countries that mention agroforestry in their NDCs and so have bold Xs displayed in the corresponding columns. **b**, Countries' year-2000 log-transformed average agricultural woody carbon density[11] versus year-2000 Human Development Index (HDI[112]). While the relationship varies across continents, the overall relationship is negative and significant ($P \leq 0.0001$; the trend line is fitted as a simple linear regression and plotted within its 95% confidence interval). The countries are colour-coded by continent (as in **a**), styled by whether or not they mention agroforestry in their NDCs (circles for yes; crosses for no)[10,111], and sized by modelled cumulative AF-NCS mitigation potential by 2050[9]. Countries in the 95th percentile of cumulative mitigation potential are labelled in black.

a dominant feature in agricultural landscapes. This highlights a need to promote a broader understanding and awareness of the value of agroforestry across diverse economic, social and cultural contexts. Much of agroforestry research has focused on developing small-scale systems that improve economic outcomes and increase the food and climate security of the rural poor. However, there is also a need to continue developing and expanding viable mechanized agroforestry systems in regions with expansive, monocrop agriculture, to increase carbon storage and support biodiversity and ecosystem services[4,113]. Because broad-scale agroforestry adoption may impose costs (for example, more complicated management and longer pay-off times for tree crops versus annual crops), especially in temperate climates, there is a need for targeted research aimed at lowering barriers to adoption. The growing appetite for NCSs to meet net-zero commitments[114] might present an opportunity for the private and public sectors to catalyse essential research and development in this area.

The future of AF-NCS will depend on the improved incorporation of agroforestry into MRV systems and thus incentive mechanisms, across sectors and geographic scales. In national emissions inventories, agroforestry reporting is typically piecemeal and uncoordinated, primarily because the diversity of agroforestry systems is divided between the two categories of 'Agriculture' and 'Land Use, Land Use Change, and Forestry' that comprise the IPCC approach to Agriculture, Forestry, and Other Land Use (AFOLU) accounting, and further subdivided across nationally defined land-use types within them[10]. The result is a complete lack of standardization and a near invisibility of agroforestry across NDC reporting streams[10]. Remote sensing can provide the most reliable and globally consistent source of AFOLU activity data, but, as discussed above, open-canopy and closed-canopy agroforestry systems pose major and distinct challenges. Emergent tree-based remote sensing methods may signal a globally consistent approach to comprehensive AFOLU emissions accounting[74], and the development of an algorithm that can detect the full diversity of agroforestry systems could provide a unified home for agroforestry within that, while also reducing dependence on still-uncertain emission factors. That, in turn, could provide traction for the further integration of AF-NCS into incentive mechanisms for land-based mitigation efforts, especially in developing nations, where agroforestry already makes a major contribution to the production of food, fodder, fibre and forest products. Examples of such mechanisms include not only voluntary carbon markets but also national[115] and regional[116] government programmes, as well as the most prominent international mechanism, REDD+. Despite the heavy focus of REDD+ on natural forests, 17.5% of projects in a public database already utilize agroforestry[117], and emergent jurisdictional initiatives that promote agroforestry signal growing opportunity (for example, in Acre, Brazil[118]). Improved ability to monitor agroforestry adoption could enable the integration of AF-NCS actions into broader programmes and frameworks, such as the Bonn Challenge and the forest landscape restoration paradigm[119].

Regardless of improvement in policy frameworks, the future of AF-NCS on the ground ultimately hinges on the decisions of many individual farmers and ranchers to adopt or maintain agroforestry. This, in turn, depends on local decision-making contexts that enable and incentivize agroforestry and minimize barriers. Governments and non-state actors wishing to promote AF-NCS must continue developing research, policies and programmes to address the various barriers and enablers, including land-tenure rights and security, access to technical knowledge and training, credit access and short-term funding, market development and access, and market failures and misaligned incentives[120–123]. From an NCS perspective, the fact that agroforestry climate mitigation is predominantly a public benefit, rather than a private benefit to the farmer, creates a market failure that can serve as a major barrier[120]. Carbon markets and other payment schemes can help rectify this, transmuting public benefits into private ones[124] – especially as agricultural MRV protocols mature[82]. However, many of the other potential agroforestry benefits may accrue to farmers directly and thus more directly influence their decisions[122,124]. Enthusiasm about the many potential benefits of AF-NCS is justified but must be paired with recognition that the actual outcomes of agroforestry adoption are complex and context-dependent[125] and can impose important trade-offs. Realistic knowledge of outcomes is frequently lacking[120], but mechanistic modelling[57], meta-analysis[6,7] and local co-development of applied research[121,125] will all play important roles in generating the knowledge needed to inform farmers' decisions about whether and how to adopt agroforestry.

Conclusions

Decades of research demonstrate agroforestry's potential to help mitigate climate change while also improving agricultural livelihoods and sustainability. However, an extensive and prioritized scientific effort is needed to transition AF-NCS from potential to practice. Synthesizing existing knowledge to elucidate the factors driving the climate outcomes of agroforestry actions is a first critical step. Simultaneously, improved reporting of carbon stocks and covariates can help further reduce the uncertainty of mitigation estimates. Improvements in remote sensing methods and in the quality and quantity of spatial data will enhance agroforestry mapping abilities, opening opportunities to develop more rigorous, replicable and consistent MRV protocols. Finally, the successful expansion of AF-NCS will depend on an outsize, decentralized effort to incentivize agroforestry investment and remove barriers, not only in developing nations but across all suitable agricultural lands. Agroforestry's greatest strength is its multifunctionality. Agroforestry not only has the potential to provide climate change mitigation – the focus of this Perspective – but also can play a crucial role in a holistic, systemic response to climate change, supporting adaptation and enhancing the resilience of the global food system while improving rural livelihoods.

Data availability

All data used in this study are publicly available from their original providers via the supplementary materials and/or requests to the corresponding authors of the originating peer-reviewed publications, except the summary data we gathered about previous agroforestry meta-analyses and the agroforestry site geographic coordinate data that we collected from the primary literature. We have made all data available in our GitHub repository (http://github.com/naturalclimatesolutions/AF_as_NCS; https://doi.org/10.5281/zenodo.8209212).

Code availability

All code used for this study is provided at http://github.com/naturalclimatesolutions/AF_as_NCS (https://doi.org/10.5281/zenodo.8209212).

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Author contributions

D.E.T.H., S.C.C.-P., S.Y., M.A., D.B., R.C., S.K., T.S.R., S.S.-H., F.S., M.S., B.T. and S.W. conceived the study and analyses. D.E.T.H., S.C.C.-P., S.Y., R.C., T.S.R., M.S. and B.T. gathered the data. D.E.T.H. analysed the data and prepared the figures, with input from all authors. D.E.T.H. and S.C.C.-P. wrote the manuscript, with contributions from all authors.

Competing interests

The authors declare no competing interests.

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Priority science can accelerate agroforestry as a natural climate solution

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SUPPLEMENTARY INFORMATION:

Priority Science Can Accelerate Agroforestry as a Natural Climate Solution

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SUPPLEMENTARY METHODS

Overall

The concepts and content for this paper developed out of a workshop "Agroforestry as a Natural Climate Solution: Cultivating the Science" hosted by TNC in 2021, as well as a series of structured discussions that followed. Analysis and plotting were done primarily in Python (version 3.9.12)[126] using standard-library modules and a number of third-party Python packages[127–134], with some preprocessing also done in Google Earth Engine[135] and R (version 4.0.5)[136].

Comparisons between global estimates of agroforestry land area, carbon stocks, and mitigation potential

Any cited global estimates of agroforestry land area, carbon stocks, and mitigation potential were gathered directly from publications or their supplemental materials, where available[8,9,11,15,16,41,89,90], and were converted to common units as necessary (Mha, Pg C, and Pg C yr^{-1}, respectively). In the case of Zomer *et al.*[16] estimates, we assumed that carbon represents the same fraction of tree biomass in that study as in their previous study[15]. We estimated global agroforestry AGC stocks by summing the Global Forest Watch AGB map[13] (the basis for the Chapman *et al.*[11] map, developed using the methods laid out by Zarin *et al.*[14]) within all 'agroforestry' pixels, then multiplying by the IPCC-recommended carbon:biomass ratio of 0.47 to estimate AGC.

Literature-coverage across previous meta-analyses

As part of our larger database-construction effort, we collected the underlying primary studies covered by 21 previous synthetic reviews (all of the reviews we found that included a systematic method for identifying primary studies)[17–37], as part of a much larger search across over 25,000 papers. We combined all of the primary studies in a single spreadsheet, annotated each primary study with all of the meta-analyses that drew data from it, then summarized the resulting matrix to calculate the total number of primary studies that occurred at least once, the percentage and number of primary studies covered by only N meta-analyses, and the maximum N for which the number of primary studies was greater than zero, and plotting the result (Fig. S1).

Comparison between AGC and SOC *in situ* estimates

We chose the original aboveground woody carbon (AGC) and SOC data from Cardinael *et al.*[17] as our field carbon dataset (henceforth, 'Cardinael data') because it was the most rigorous and comprehensive compilation available to us, given that the authors collected detaield information on agroforestry practice types, carbon estimates, their geographic coordinates, and related covariates to generate IPCC Tier 1 default emission factors.

To visualize variation in Cardinael data estimates of AGC and SOC stock changes after agroforestry adoption, both within and between agroforestry practices, we first reclassified practices in the Cardinael dataset to allow for comparative analysis: we folded data from shaded perennial-crop systems (which had no SOC data) into the multistrata class, and we dropped data from parklands (which has only 7 AGB samples and 2 SOC samples) and hedgerows (which report carbon stocks per kilometer hedgerow length, rather than per hectare). (See Cardinael *et al.*[17] Table 1 for full-detail definitions of agroforestry system types.) We then produced a series of horizontal, split violin plots, colored by agroforestry practice (Fig. 2). Each violin depicts a kernel density estimate (KDE) of AGC stock-change estimates above its central axis (i.e., upward-facing, solid color) and of SOC stock-change estimates below (downward-facing, transparent color). Medians of the values depicted in the KDEs are plotted as black ticks on the central axis; medians calculated including the negative stock-change values that are necessarily omitted from the log-transformed KDEs are depicted as red ticks superimposed on the SOC data (as this is the only pool with negative stock-change values). The counts of values represented by the AGC and SOC KDEs are provided in black at the left (above and below the x axes, respectively), and the count of omitted negative SOC stock-change values is provided at the far left, in red.

Comparison between *in situ* and remotely sensed AGC estimates

To compare *in situ* AGC estimates (displayed in Figure 2) to remotely sensed estimates, we used Google Earth Engine (GEE[135]) to extract remotely-sensed woody carbon density estimates at the geographic coordinates of each *in situ*. We extracted these values from two maps of aboveground woody biomass: 1.) the Chapman *et al.*[11] map of aboveground woody biomass in global agricultural lands ca. 2000 (but with pixels set to zero where forest loss occurred between 2000 and 2014 according to Hansen *et al.*[137]; henceforth, the 'Chapman map'); and 2.) the precursor to the Chapman map, a global woody biomass ca. 2000 that is not masked to only agricultural lands (based on a global extension of the Zarin *et al.*[14] algorithm and available through Global Forest Watch[13]; henceforth, the 'Zarin map'). We chose these two datasets because comparison between them would allow us to elucidate potential underestimation in current global estimates of agroforestry mitigation potential. This is because: a.) the Chapman map is generally considered our best current understanding of global variation in agricultural woody biomass (and hence, by proxy, global variation in agroforestry), and estimates derived from this map[9] factor into current IPCC estimates for global agroforestry mitigation potential[38]; yet, b.) the Chapman map is derived from a subset of the full biomass data and is masked to only pixels covered by global maps of either cropland or pastureland, then masked again to only pixels with ≤25% tree cover (i.e., 'forest' pixels), using Landsat-derived tree-cover data[137]. Because of this relationship, the Chapman map is expected to miss closed-canopy agroforestry systems with characteristically high biomass (e.g., multistrata systems), and thus to underestimate global agroforestry mitigation potential.

Before extracting map values, we first combined the crop and pasture Chapman layers per the Chapman methods[11]: we resampled the coarser-resolution pastureland dataset to the nominally 30-meter resolution of the cropland dataset, kept the more-refined cropland values wherever they were available, kept pasture land values elsewhere, and masked out all pixels having no value for either layer. We then converted each biomass map from its native units (Mg biomass ha^{-1}) to the common carbon units of the Cardinael data (Mg C ha^{-1}) by multiplying by 0.47 (as above), before finally extracting values at Cardinael *in situ* estimates.

We plotted published estimates against remotely sensed estimates (Fig. S3). We included only points that fell within unmasked values for at least one of the two map datasets (Chapman or Zarin; some points did not intersect with either dataset and thus are not included). We also styled the points to differentiate between those that intersect both the Chapman and Zarin maps (circles) and those that are missed by the Chapman map (stars), then used that same styling to differentiate between: the mean *in situ* and remotely-sensed values for the points intersecting both the Zarin and Chapman maps (larger, black, hollow circle); and the mean values for all points, including those that only intersect the Zarin map (larger, black, hollow star). The discrepancies along the axes give an indication of the underestimation likely embedded in Chapman-based estimates of mitigation potential used by Roe *et al.*[9] and by IPCC[38]. To visualize exact-zero values (which occur in remote sensing data but not in *in situ* data), we plotted them within the shaded gray region at the bottom of the plot, along an artificial zero line superimposed onto the log-transformed axes and represented by the tick label '∅', below the y-axis broken stick.

To explore the potential drivers of divergence between published and remote-sensing estimates — and thus the potential for refinement of agroforestry carbon estimates using AGB remote sensing data at moderate (i.e., Landsat) resolution — we collected ancillary data on a pair of potential predictors of this discrepancy, then summarized them statistically. (Note that we consider the published estimates as the 'targets' of the remote sensing estimates because, despite measurement error, they are likely to be much closer to the true values, given that they are detailed, continuous-valued, plot-based field measurements.) We then calculated divergence as the difference between a published measurement and its remotely sensed estimate (such that a negative divergence indicates overestimation by remote sensing data and a positive divergence indicates underestimation).

One potential explanatory factor of divergence is the difference in measurement years between remote-sensing data (ca. 2000) and published data (variable). We reviewed each primary study associated with the Cardinael data and noted the year of data collection associated with each measurement, either as directly reported in the primary study (when available) or else however the year could be best estimated from description of field efforts within the primary study (with the year prior to publication serving as the best available estimate when no more refined information was available). We then calculated time discrepancy as the difference between the published measurement year and the remote sensing measurement year (i.e., 2000), such that negative time discrepancies indicate measurements collected prior to 2000 and vice versa. We ran and plotted (Fig. S4) the simple linear regression (SLR) model $divergence_{meas} \sim \beta_0 + \beta_1\ discrepancy_{time} + \varepsilon$, then used the t-test associated with coefficient β_1 to test the null hypothesis that variation in divergence is uncorrelated with variation in time discrepancy (versus our alternative hypothesis that there is a positive, linear relationship between the two, given that sites with published estimates predating remote sensing estimate would usually be overestimated by remote sensing, and vice versa, excepting the potential for vegetation-clearing events that occur between the collection dates of published and remotely sensed data).

Another potential explanatory factor is the level of precision of the geographic coordinates associated with the published measurements summarized by Cardinael *et al*. For each published measurement, we quantified coordinate precision by calculating the mean number of decimal points prior to either a repeating digit or the final digit in the reported latitude and longitude values of the measurement's geographic coordinates. We ran and plotted (Fig. S5) the simple linear regression (SLR) model $divergence_{meas} \sim \beta_0 + \beta_1\ |precision_{space}| + \varepsilon$, then used the t-test associated with coefficient β_1 to test the null hypothesis that variation in divergence is uncorrelated with variation in spatial precision (versus our alternative hypothesis that there is a negative fitted relationship between the two, given that we expected to see a cone of heteroskedasticity narrowing to the right as divergence drops toward zero with increasing coordinate precision).

<u>Comparison of known agroforestry study locations and global agroforestry maps</u>

To compare the distribution of known agroforestry locations to global maps estimating agroforestry locations, we collected geographic coordinates of known agroforestry study sites, then plotted those coordinates on top of raster maps from two distinct mapping efforts (in a global equal-area projection; World Eckert IV; EPSG:54012). To help interpret both map overlays, we calculated both maps' latitudinal rolling averages of agroforestry site coverage (defined as the fraction of agroforestry sites that fall within a map's non-masked pixels), then showed the results as a vertical line plot to the right of each map, including a solid, bold line for the paired map at left and a dotted, faint line for the comparator map. We extracted point coordinates of agroforestry study sites documented in the scientific literature, as part of our wider database-construction effort. These points (N=992) come from a total of 528 studies, including those covered by previous agroforestry carbon-sequestration meta-analyses and additional relevant studies we have already processed, providing as comprehensive and unbiased a representation of the spatial distribution of known agroforestry study sites as we are currently capable. When locations were reported with identifiable place names but without coordinates, we made reasonable best effort to digitize the locations using visual inspection on Google Maps or Google Earth. For coordinates reported as bounding boxes rather than points, we plotted the box centroids.

The raster data used (Figure 3) is a map of agricultural woody biomass from Chapman *et al.*[11]). To produce this figure, we color-mapped the Chapman map so as to distinguish between pixels ≤ 5 Mg C ha^{-1} (i.e., 'non-agroforestry') and pixels > 5 Mg C ha^{-1} (i.e., 'agroforestry'), per Chapman *et al.*[11] methods, and we plotted known agroforestry study sites as black circles (where they overlap with Chapman map) and red circles (where they do not overlap). To reduce the RAM required for visualization, we aggregated the Chapman to approximately 3 km resolution on GEE before exporting it as a GeoTIFF. We used this aggregated dataset, rather than the native-resolution (~30 m) Chapman map, to visualize the overlap between the Chapman map and the known study sites, for two reasons: 1.) extraction of the native-resolution map shows that the majority of the known sites do not overlap with the Chapman map, both because of the inherently patchy nature of the Chapman map's input agricultural masks and because of the known sites' geographic imprecision being often much greater than the 30 m nominal resolution of the Chapman map; and 2.) the sites that still do not overlap with Chapman map, even after aggregation to approximately 3 km, provide a better indication of regions where known sites are a considerable distance from any valid Chapman values, and thus indicate regions where overlap is poor not only because of the intrinsic uncertainty of both datasets (which occurs globally) but also because of any bias embedded in the Chapman map.

<u>Depiction of spatial precision and resolution and temporal dynamics in an exemplary agroforestry system</u>

To demonstrate some common considerations for remote sensing-based monitoring of agroforestry, related to spatial precision, spatial resolution, and temporal dynamics, we hand-selected a known agroforestry study site, then plotted both contemporaneous remote-sensing imagery of the site's region (Figure 4a) and of the site itself across varying spatial resolutions (Figure 4b), as well as plotting coregistered and equal-resolution imagery of the site through time, starting in 2001 and proceeding until the present (Figure 4c). We selected our site based on the requirement that it have high coordinate precision (and thus could be readily identified in aerial imagery) and that it have ample, cloud-free, publicly-available imagery, taken in roughly the same time of year, for all of our target satellite and aerial remote sensing datasets (which we determined by methodical visual inspection). Our final site cannot be published openly, to maintain anonymity, but is a coffee agroforestry system in Latin America.

To produce a series of concentric circles depicting the spatial uncertainty associated with coordinates of increasing degrees of precision, we displayed the default GEE basemap imagery for our site's region, then overlaid on that image circles of radii corresponding to 1 decimal degree of coordinate precision (i.e., roughly 11 km at the equator), 2 decimal degrees (i.e., roughly 1.1 km at the equator), and 3 decimal degrees (i.e., roughly 110 m at the equator). We then estimated the coordinate precision associated with the geographic coordinate points we were able to collect from sites reported in the primary the literature (i.e., the point data displayed in Figure 3, but excluding sites that were originally reported as bounding boxes rather than points, as well as sites that we manually digitized from place names reported without point coordinates) and calculated the percentage of those measurements ≥ each of the three levels of precision displayed in Figure 4a. To estimate precision, we used the same method described in the section 'Comparison of in situ and remotely sensed AGC estimates', above.

To compare spatial resolutions between remote sensing imagery (Figure 4b), we first loaded three public datasets of increasing resolutions into GEE from the GEE data catalog (30 m: Landsat 8 Collection 2 Tier 1 top-of-atmosphere reflectance data; 10 m: Sentinel-2 MultiSpectral Instrument Level-2A reflectance data; and 5m: the Planet Tropical Americas basemaps, produced under the NICFI program and made available by Planet's GEE integration functionality). Given that we relied on Google Earth (GE) to explore the temporal record of high-resolution aerial imagery (© CNES/Airbus, Maxar Technologies) at our chosen site (see next paragraph), we then filtered our loaded satellite datasets to the most recent GE-displayed year that overlaps with all of the available satellite archives (i.e., to 2021). Next, we sorted the resulting annual series of Landsat and Sentinel images by increasing cloud-cover, then used the dates of the top (i.e., highest-quality) images to choose a three-month period of the year within which to compare images across spatial resolution (and across time; next paragraph). Finally, we plotted each of a set of 4 images (Landsat, Sentinel, Planet, and CNES/Airbus), using cloud-free imagery that was as close in date as possible, and manually scaling reflectance values to visually match color palettes as closely as possible. For each plotted image, we captured a high-resolution screenshot (using the default screenshot tool provided by Linux Pop!_OS 21.10) of an identical rectangular area, framed using polygons plotted onto the maps in GEE.

To produce a time series of same-season imagery for our site (for Figure 4c), we used GE to frame the same rectangular area as in Fig. 4b. We then perused the record of high-resolution (i.e., sub-meter) aerial imagery (© CNES/Airbus, Maxar Technologies) to screenshot coregistered, maximally-zoomed imagery of our site for any cloud-free images available within our chosen three-month period of any year. For demonstrative purposes, we placed those images in 2d space (time, tree cover), then superimposed the approximate trajectory of tree cover observed at the site over time.

Comparison of current and potential agricultural woody C, by NDC ambition, continent, and country

To compare current and potential agricultural woody carbon density by continent, we combined ca. 2000 estimates from Chapman *et al.*[11] (using tabular, country-level estimates extracted from their supplemental information) with cost-effective mitigation potential estimates from Roe *et al.*[9] (country-level estimates extracted from supplemental information). We converted Chapman map data from Mg biomass ha^{-1} to Mg C ha^{-1} by multiplying by 0.47 (as above), then calculated a single, mean-density value as the average of cropland and pastureland densities, weighted by the relative national land areas of each. We merged the two resulting tabular datasets, then merged onto them a tabular dataset of agroforestry ambitions expressed in NDCs. We produced this NDC dataset using the data from Rosenstock *et al.*[10], which indicates whether or not each non-Annex I country mentions (either explicitly or implicitly; see Rosenstock *et al.* methods for details) agroforestry activities within their Paris Agreement NDC, then supplementing that with similar but less-detailed IUCN NDC data[111] gathered by Chapman *et al.*[11] for Annex I countries. Finally, we merged that table onto a country-boundaries dataset, then assigned countries to continents for stratified analysis. We used the resulting dataset to create a continent-colored, paired box-and-whisker plot of the resulting dataset, plotting both current density (solid colors) and potential density (transparent colors), both for countries that do not mention agroforestry in their NDCs (gray vertical sections of the plot) and those that do (white vertical sections) (Fig. 5a; plots depict a median center line, 1st- and 3rd-quartile box limits, whiskers extending to 1.5x the inter-quartile range, and outliers plotted outside them). To determine whether current and/or potential agricultural woody carbon densities differ significantly between countries with expressed agroforestry NDC ambitions and those without, we ran an independent, two-sided Welch's t-test (to account for unequal variances) of the current, area-weighted average agricultural woody carbon densities of countries in those two categories ($n_{NDC} = 81$ $n_{non\text{-}NDC} = 81$), as well as an identically structured t-test of the cost-effective, potential densities modeled by Roe *et al.* [9] ($n_{NDC} = 80$, $n_{non\text{-}NDC} = 77$).

To depict that data by country, in comparison to an indicator of economic development, we first downloaded Human Development Index (HDI) data from the UNDP (using year-2000 data[112], to match the year for which current woody carbon densities are estimated) and merged that onto the tabular dataset explained above. We then produced a scatterplot comparing year-2000 average agricultural woody carbon density (ln-transformed) to year-2000 HDI (Fig. 5b). We colored each country's point by continent (as in Fig. 5a), styled it to indicate whether it mentions agroforestry in its NDC (circles) or not (X's), and sized it according to cumulative, cost-effective agroforestry mitigation potential by year 2050 (as estimated by Roe *et al.*[9]), labeling countries in the 95th percentile of cumulative potential. Finally, we used SLR to estimate and plot (within the 95-percent confidence interval) the model $ln(woody\_C_{2000}) \sim \beta_0 + \beta_1 HDI_{2000} + \varepsilon$, then reported the R2 and p-value.

Estimation of percent of REDD+ projects using agroforestry

To estimate the percent of REDD+ projects that incorporate agroforestry, we first downloaded the full version 4.2 dataset from the “International Database on REDD+ projects and programs: Linking Economics, Carbon and Community” (ID-RECCO)[117]. We then calculated the percent of projects listing ‘agroforestry’ among their activity details (i.e., the percent of rows in sheet ‘1. Projects’ with the term ‘agroforestry’ included in the contents of the column ‘Details for Afforestation/Reforestation activity’).

SUPPLEMENTARY FIGURES

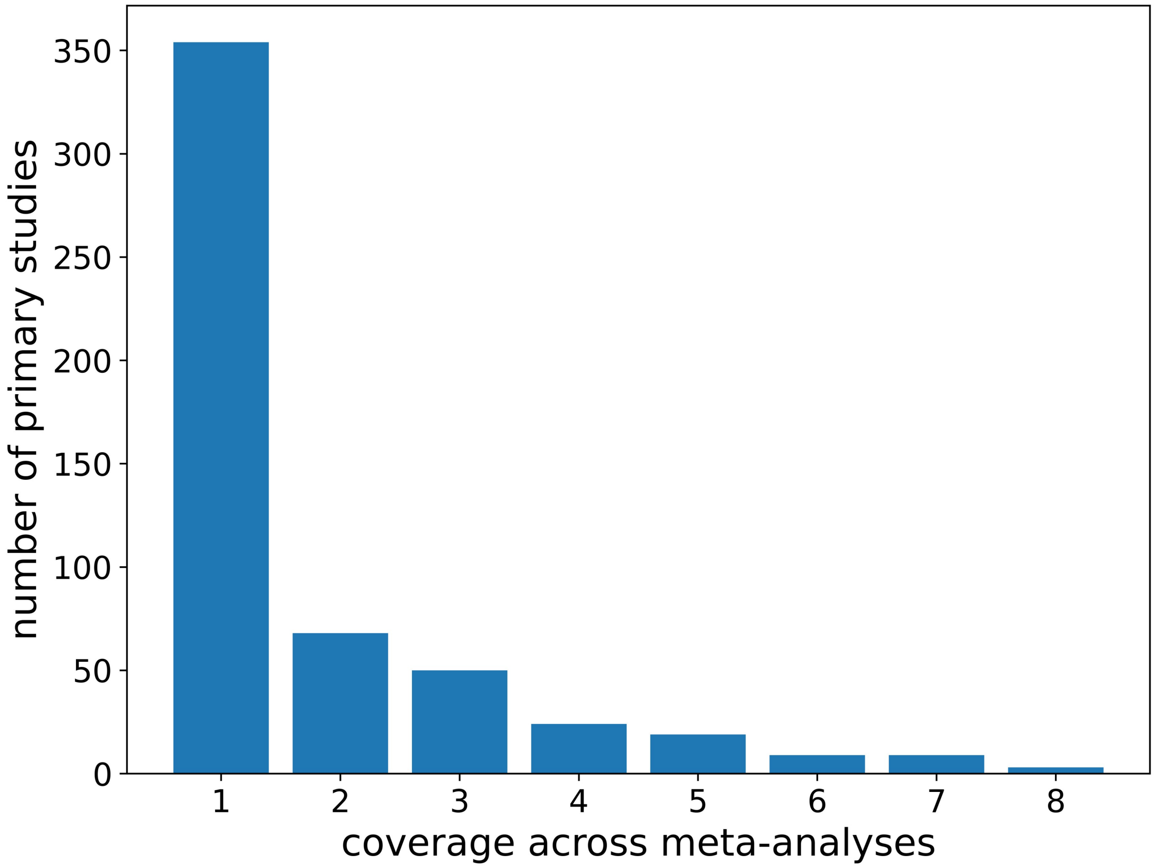

Figure S1: Coverage of primary studies in agroforestry carbon syntheses. Plot shows the number of primary studies having each of the values of 'coverage' (i.e., number of syntheses in which the primary study's data was used), up to the highest observed coverage of 8 (out of a maximum potential coverage of 21).

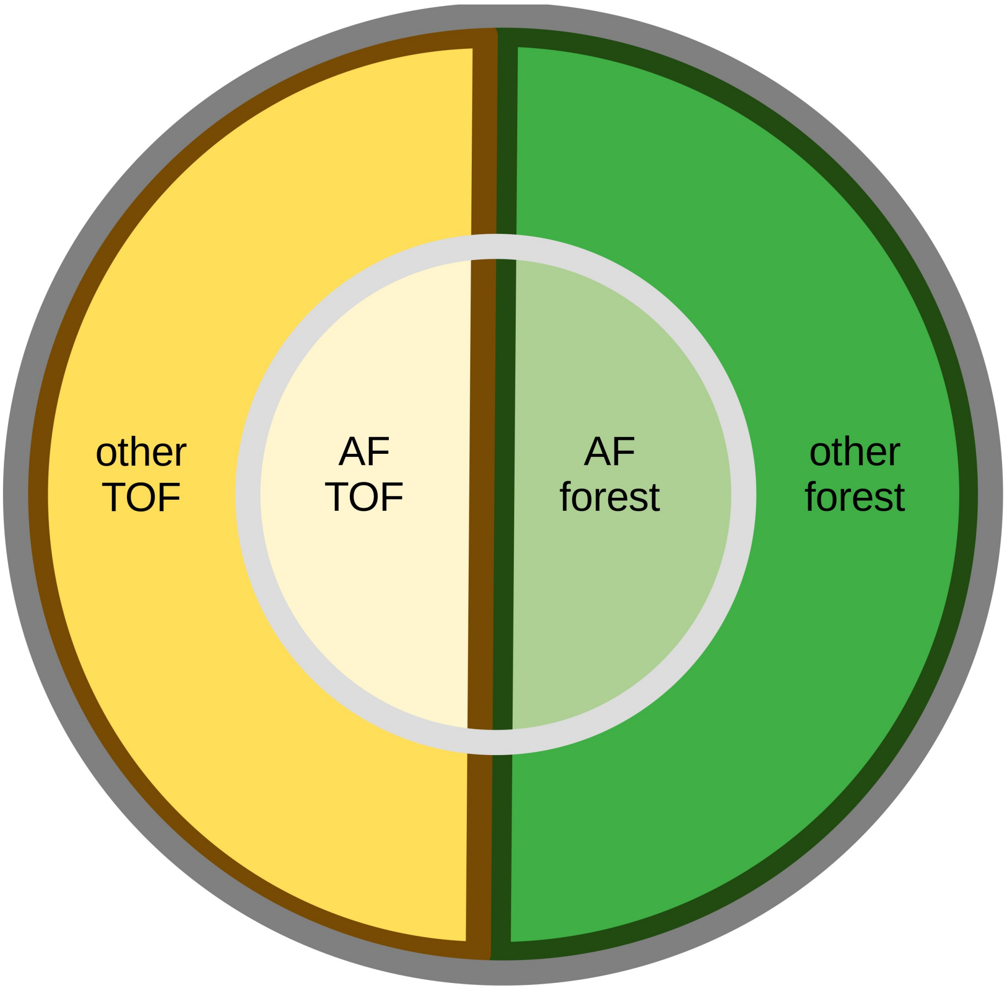

Figure S2: Conceptual organization of global trees. A diagram representing all of the world's trees (outer, dark gray circle), divided between trees outside forest (TOF; dark brown half circle) and trees within forest (dark green half circle)), and simultaneously divided between non-agroforestry trees (bright-colored segments) and agroforestry trees (pale-colored segments, within the inner, light gray circle). (Diagram segments are arbitrarily scaled.) Remote sensing and MRV methodologies often rely on the classification of pixels into forest and non-forest categories, such that agroforestry systems can be considered as consisting of TOF (i.e., open-canopy systems) or forest trees (i.e., trees in closed-canopy systems). Comprehensive carbon accounting frameworks for the agriculture, forestry, and other land use (AFOLU) sector may be able to leverage emergent, tree-based (rather than pixel-based) remote sensing methodologies to circumvent this complication.

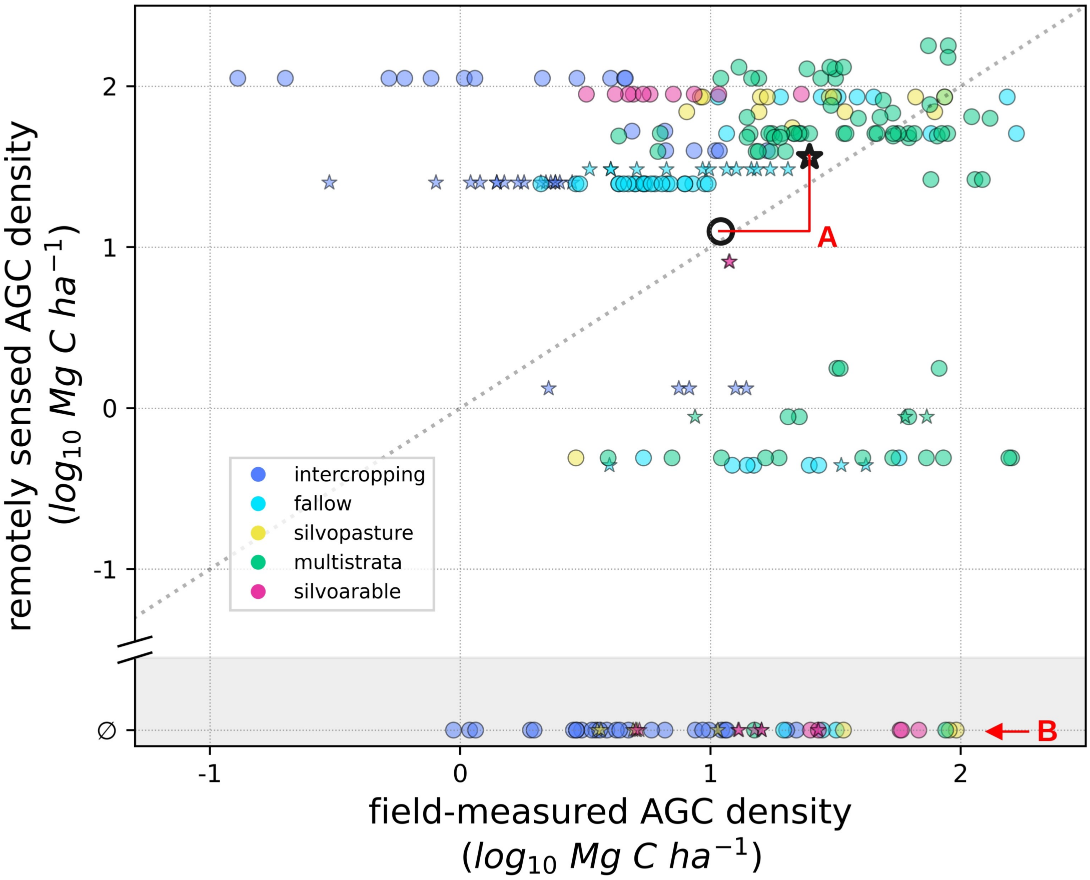

Figure S3: Comparison between field-measured and remotely sensed agroforestry aboveground carbon (AGC) stocks. There is little apparent correspondence between AGC stocks measured at field sites described in the primary literature (N=273) and AGC estimates derived from the highest-resolution global remote sensing product available. The x-axis shows the same, $\log_{10}$-transformed AGC data as that displayed in Figure 2, and the y-axis shows $\log_{10}$-transformed values extracted from the unmasked 30-meter global biomass map available from Global Forest Watch[13] — the precursor to the Chapman *et al.*[11] agroforestry map, prior to exclusion of non-agricultural pixels and high-tree-cover pixels. The expected 1:1 line is also shown. Point style indicates whether a site falls within a pixel included in the final Chapman map (circles) or not (stars). We also show the means of only Chapman-covered sites (large black circle) and for all sites (large black star), highlighting that sites not included in the Chapman map lead to lower mean mitigation potential estimates in both field-measured and remotely sensed data (red annotation 'A'); the downward bias in remote sensing data propagates through peer-reviewed publications[9] and IPCC reports[38] derived from the Chapman map. Sites in the gray-shaded region below the y-axis broken stick have zero remotely-sensed AGC, yet vary widely in their field-measured estimates (red annotation 'B'). We also note that the discrepancy between field-measured and remotely sensed agroforestry AGC is largely insensitive to temporal misalignment (Fig. S4) and entirely unrelated to the spatial precision of published field coordinates (Fig. S5). These challenges reinforce the known limitations of moderate-resolution data for agroforestry mapping and carbon estimation.

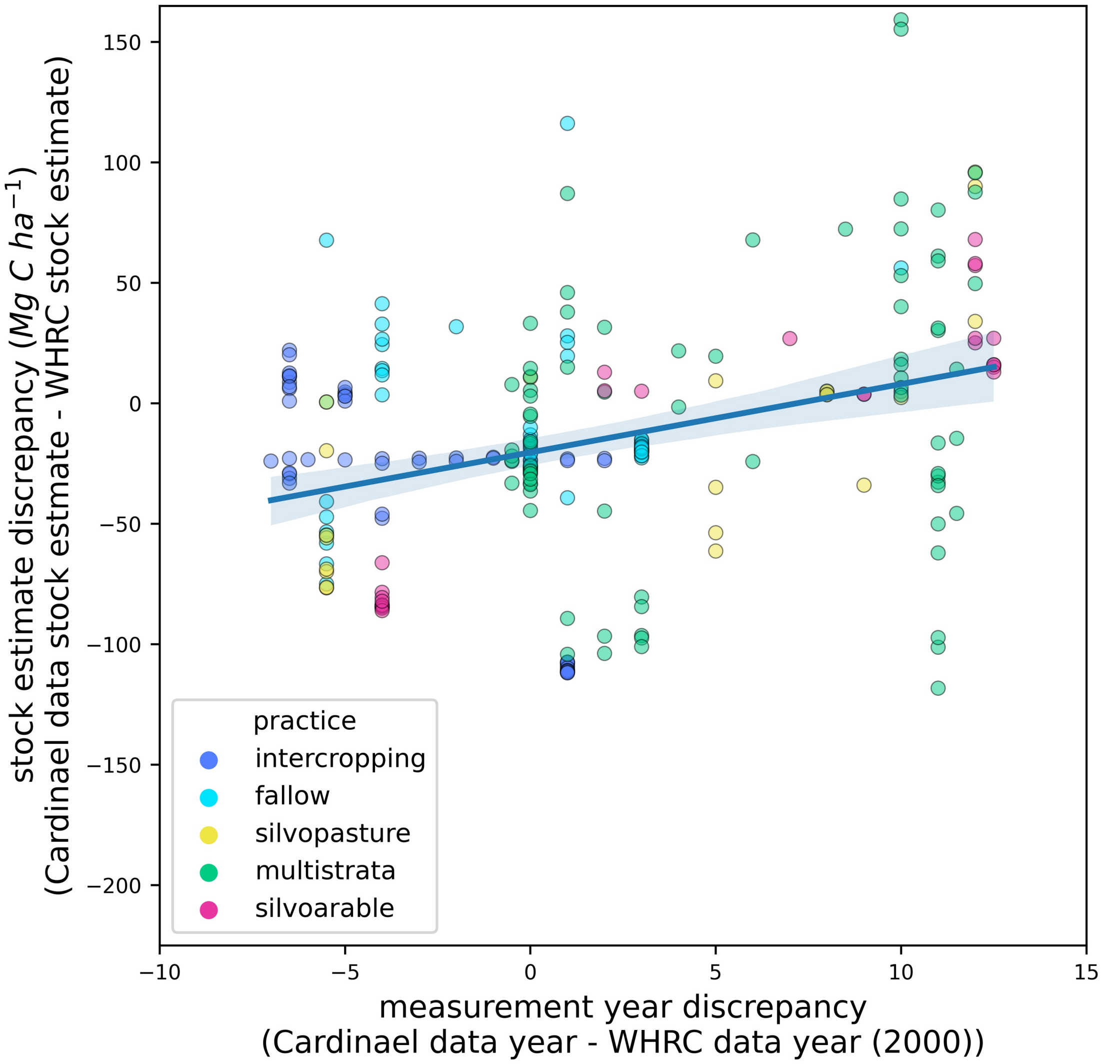

Figure S4: Discrepancy between published and remote sensing carbon stock estimates is partially attributable to discrepancy in data-collection years. The difference between published and remotely-sensed estimates increases as a function of the difference between their collection years ($R^2 = 0.112$). The slope of the relationship is positive and significant (slope=2.837 Mg C ha^{-1} yr^{-1}; $p = 1.29\times10^{-7}$). This suggests some room, albeit quite limited, for improvement in AF carbon stock measurement using moderate-resolution remote sensing data. Only 13.18% of measurements have the same year as the remote sensing dataset (year 2000), 48.45% differ by up to 5 years, 22.87% differ by between 5 and 10 years, and 15.50% differ by more than 10 years. Sites are colored by AF practice, as in Fig. 2.

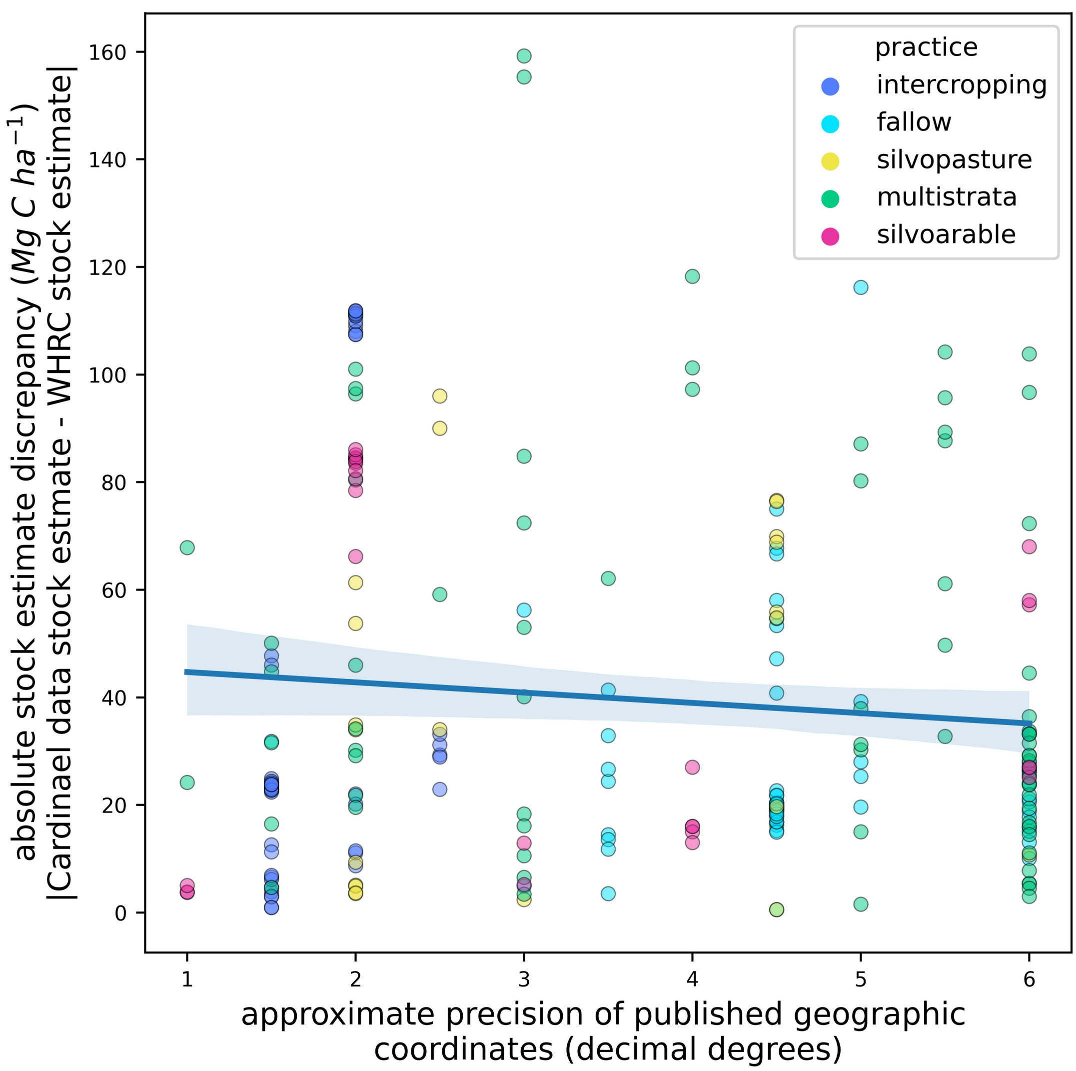

Figure S5: Discrepancy between published and remote sensing carbon stock estimates is not related to spatial precision of published geographic coordinates. The difference between published and remotely-sensed estimates has no significant linear relationship with the spatial precision of the decimal-degree geographic coordinates reported in AF field studies ($R^2 = 0.0093$). The slope of the relationship is indistinguishable from 0 (slope=-1.911 Mg C ha^{-1} $degree^{-1}$; $p = 0.14$). If increasing imprecision improved the ability of moderate-resolution remote sensing imagery to estimate AF aboveground carbon stocks then the scatterplot would be expected to be heteroskedastic (with greater variance at left) and to exhibit a significant negative slope. Sites are colored by AF practice, as in Fig. 2

SUPPLEMENTARY TABLES

Table S1: Potential predictors of variation in agroforestry carbon stocks and fluxes that have been mentioned in previous studies, other than the commonly used categorical variable of agroforestry practice type (e.g., [17,18,25,35,36,138])

Potential predictor	**References**
Previous land use	Demessie *et al.* 2014[139], Lorenz *et al.* 2014[140], van Straaten *et al.* 2015[47], Chatterjee *et al.* 2018[25], De Stefano and Jacobson 2018[18]
Age of system	Fassbender 1998[141], Oelbermann *et al.* 2004[142], Demessie *et al.* 2014[139], Lorenz *et al.* 2014[140],Chatterjee *et al.* 2018[25], Ma *et al.* 2020[29], Corbeels *et al.* 2019[143]
Soil management practices (e.g., tillage, application of plant residue)	Hulugalle *et al.* 1990[144], Fassbender 1998[141], Albrecht *et al.* 2003[43], Soto-Pino *et al.* 2009[145], Winans *et al.*. 2014[146], Dhyani *et al.*. 2016[53], Shrestha *et al.* 2018[31]
Soil class	Demessie *et al.* 2014[139], Muñoz-Rojas *et al.* 2015[147], Hübner *et al.* 202[21]
Soil fertility	Amézquita *et al.* 2009[148]
Initial SOC	Minasny *et al.* 2017[149], Corbeels *et al.* 2019[143]
Clay content	Demessie *et al.* 2014[139], Lorenz *et al.* 2014[140], Hübner *et al.* 2021[21]
Altitude	Amézquita *et al.* 2009[148], Nath *et al.* 2021[33]
Climate	Lorenz *et al.* 2014[140], Cardinael *et al.* 2018[17], Ma *et al.* 2020[29], Ahirwal *et al.* 2021[36], Hübner *et al.* 2021[21], Nath *et al.* 2021[33]
Topography	Amézquita *et al.* 2009[148], Demessie *et al.* 2014[139]
Mean annual temperature	Amézquita *et al.* 2009[148], Dhyani *et al.*. 2016[53], Ahirwal *et al.* 2021[36], Hübner *et al.* 2021[21]
Mean annual precipitation	Dhyani *et al.*. 2016[53], Ahirwal *et al.* 2021[36], Hübner *et al.* 2021[21]
Vegetation management (e.g., pruning frequency)	Romero *et al.* 1991[150], Oelbermann *et al.* 2004[142]
Tree density	Somarriba *et al.* 2008[151], Demessie *et al.* 2014[139]
Tree species	Albrecht *et al.* 2003[43], Oelbermann *et al.* 2004[142], Somarriba *et al.* 2008[151], Demessie *et al.* 2014[139], Wotherspoon *et al.* 2014[152], Dhyani *et al.* 2016[53]
Tree functional type (e.g., coniferous, broadleaf; N-fixing)	Demessie *et al.* 2014[139], Lorenz *et al.* 2014[140], Mayer *et al.* 2022[23]
Tree diversity	Demessie *et al.* 2014[139], Lorenz *et al.* 2014[140], Islam *et al.* 2015[153], Lovell *et al.* 2018[154], Ma *et al.* 2020[29]

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