HiLL PUBLISHING

OAJRC Environmental Science, 2025, 6(2), 50-57
https://www.hillpublisher.com/journals/oajrces/
ISSN Online: 2632-2331

Depth- and Time-resolved Estimates of Soil Organic Carbon Change under Agroforestry: A Global Meta-analysis

Vernon Ha

Phillips Academy Andover, Andover, MA 01810, USA.

How to cite this paper: Vernon Ha. (2025). Depth- and Time-resolved Estimates of Soil Organic Carbon Change under Agroforestry: A Global Meta-analysis. *OAJRC Environmental Science*, 6(2), 50-57.
DOI: 10.26855/oajrces.2025.12.001

Received: October 12, 2025
Accepted: November 8, 2025
Published: December 5, 2025

Corresponding author: Vernon Ha, Phillips Academy Andover, Andover, MA 01810, USA.

Abstract

Agroforestry (AF) is widely promoted as a pathway to rebuild soil organic carbon (SOC) while enhancing ecosystem resilience. Global estimates, however, remain heterogeneous due to variation in baselines, system archetypes, climate, and measurement depth. We synthesize two complementary datasets—the literature-derived database of Beillouin et al. and paired field observations from Cardinael et al.—to generate depth- and time-resolved estimates of SOC change following transitions into AF. Observations were harmonized to 0-30 cm and 0-100 cm. Effects are expressed as log response ratios (lnRR = ln [SOC_AF/SOC_ref]), percent change = [exp(lnRR) − 1]×100, and absolute difference ΔSOC = SOC_AF − SOC_ref (Mg C ha^{-1}). For Dataset 1 (D1), unweighted summaries were used because study-level variances are inconsistently reported; D1 subsets with variances were analyzed using random-effects meta-analysis. Age trajectories for Dataset 2 (D2) were modeled with cubic B-splines (df = 4; knots at empirical quantiles) and mixed-effects regressions with study/site random intercepts to avoid pseudo-replication. Across the assembled evidence, AF indicates a mean SOC increase of 19% [95% CI: 14-24%] at 0–30 cm and +11 Mg C ha^{-1} [95% CI: 7-15] at 0-100 cm, with larger effects on prior cropland and in humid tropical multistrata systems. Detectable gains typically emerge after ~7-10 years and extend below 30 cm in mature systems. These results estimate durable SOC recovery when AF is implemented on degraded croplands, while emphasizing context dependence and remaining uncertainty in subsoil horizons and temperate regions.

Keywords

Soil organic carbon (SOC); Agroforestry; Land-use change; Carbon sequestration; Meta-analysis; Temporal dynamics

1. Introduction

Soil organic carbon (SOC) underpins fertility, water retention, and climate regulation, anchoring the largest actively cycled carbon pool on land. Global estimates place SOC stocks near 1,500–2,400 Pg C—exceeding atmospheric and plant carbon—so small percentage shifts have system-scale implications for climate and food security [1-4].

Agroforestry (AF)—the deliberate integration of woody perennials with crops and/or livestock—is frequently proposed to rebuild SOC while delivering microclimate regulation, erosion control, and biodiversity cobenefits [5-7]. Mechanistically, AF can increase belowground inputs via deeper, more continuous rooting and litterfall, enhance aggregate protection, and promote mineral-associated organic matter stabilization through favorable moisture and reduced disturbance [8-10].

Nevertheless, effect sizes vary widely across contexts. Baselines matter: transitioning degraded croplands into AF tends to show larger SOC gains, whereas establishing AF in forested landscapes may underperform relative to high-carbon references, highlighting the importance of baseline selection in accounting [11-13]. System archetypes also differ: multistrata homegardens and shaded perennial systems maintain year-round cover and frequent organic inputs, often outperforming sparse tree-crop rows, especially in humid tropics [7, 11].

Depth is a critical but underrepresented dimension. Many studies emphasize 0–30 cm for agronomic reasons, yet subsoils (>30 cm) contain substantial, longer-lived carbon that can respond to deeper rooting, biopore formation, and dissolved organic carbon transport [14, 15, 10]. Surface-only comparisons may therefore underestimate whole-profile changes, while fixed-depth (rather than equivalent soil mass) approaches can bias estimates when bulk density shifts [4, 12].

Temporal dynamics further complicate inference. SOC accrual often shows establishment lags, accelerations with canopy closure, and partial plateaus consistent with soil carbon saturation and nutrient/water constraints [17, 9, 3]. Cross-sectional snapshots across mixed ages can conflate cohort and time-since-establishment effects; regularized smoothers with random effects help recover average trajectories while acknowledging study clustering [17].

The evidence base combines breadth with gaps. Literature-derived databases enable global synthesis but often lack consistent variances, bulk densities, or deep profiles; paired field datasets retain better depth and age metadata but cover fewer sites [11, 17]. These strengths are complementary and motivate an analysis that is explicit about the inferences each dataset can support.

Here, we integrate two resources to estimate depth- and time-resolved SOC change when land transitions to AF relative to a non-AF reference. Dataset 1 (D1) is a literature-derived global compilation emphasizing breadth but with incomplete variance reporting [11]. Dataset 2 (D2) aggregates paired AF-reference field observations with explicit depth and age metadata [17]. By harmonizing to 0-30 cm and 0-100 cm, we provide estimates where most studies report (topsoil) and where whole-profile inferences become feasible (upper meter) [4,14].

We report effects using two complementary metric families. The ratio family quantifies proportional change via the log response ratio $\ln RR = \ln(SOC\_AF/SOC\_ref)$, communicated as percent change = $[\exp(\ln RR) - 1]\times 100$ for interpretability. The difference family measures absolute change $\Delta SOC = SOC\_AF - SOC\_ref$ (Mg C ha^{-1}), which directly informs stock accounting and project design [18, 11, 4]. Analyzing both clarifies when proportional gains translate into meaningful stock differences and highlights baseline dependence [12].

Methodologically, we treat D1 primarily with unweighted descriptive summaries because study-level variances are inconsistently reported; where variances exist for a subset, we apply random-effects meta-analysis to account for between-study heterogeneity [18, 11]. For D2, we estimate age trajectories with cubic B-splines (df = 4; knots at empirical quantiles) and fit mixed-effects models with random intercepts for study/site to avoid pseudo-replication and capture clustering [17].

Objectives. We estimate SOC change following transitions into AF by depth and over time, reporting central coefficients with 95% uncertainty while avoiding confirmatory language. Specifically, we analyze (i) datasets: D1 [11] and D2 [17]; (ii) depth bins: 0-0 cm and 0-00 cm; (iii) metrics: lnRR, percent change, and ΔSOC (Mg C ha^{-1}); (iv) moderators: age, previous land use, AF archetype, and climate; and (v) outputs: estimates with 95% confidence intervals and exact sample sizes by stratum. Policy framing is deferred to the Discussion, where we emphasize baseline sensitivity, risks of forest→AF conversions, and context-specific guidance on where (croplands, humid tropics, multistrata), how long (≈7–10 years for detectable gains), and how deep (to at least 1 m) [13, 4, 7].

2. Materials and Methods

2.1 Study scope and design

We evaluate how AF alters SOC stocks relative to a reference (non-AF) baseline at the global scale. Effects are summarized by two metric families: (a) ratio family, expressed as $\ln RR = \ln(SOC\_AF/SOC\_ref)$ and percent change = $[\exp(\ln RR)-1]\times 100$; (b) difference family, $\Delta SOC = SOC\_AF - SOC\_ref$ (Mg C ha^{-1}). Depth-specific results are compiled for 0–30 cm and 0–100 cm. System designs are normalized to archetypes (e.g., silvopasture; alley/silvoarable; hedgerow/shelterbelt; multistrata/shade-perennial; parkland; rotational/fallow; other/unspecified).

2.2 Data sources and inclusion criteria

Dataset 1 (D1): Literature-derived AF vs reference contrasts from the CIRAD Dataverse resource described by Beillouin et al. (2022). We retain rows flagged as AF with SOC stock outcomes and a specified non-AF reference, where available,

and study-level uncertainties are captured. Depth and age metadata are often incomplete; D1 is therefore treated descriptively except for subsets with variances.

Dataset 2 (D2): Paired field observations of SOC stocks (AF and reference) with sampling depth and, where available, years since AF establishment. Analyses are restricted to records with non-missing SOC in both AF and the reference. For the ratio family, rows with zero/negative reference SOC are excluded.

2.3 Outcomes and effect-size computation

Primary outcomes are lnRR, percent change, and ΔSOC as defined above. Where D1 reports standard errors (SE), we use them directly; where only 95% CIs are reported, SE is derived from CI width. Because variances are inconsistently reported in D1, we summarize D1 unweighted; for any D1 subset with available variances, we apply random-effects meta-analysis.

2.4 Depth harmonization

Depth classes are harmonized to 0-0 cm and 0-00 cm. Single-depth observations are binned by the reported depth; interval depths are assigned by midpoints. Equivalent-soil-mass adjustments are not applied due to missing bulk density; we assess implications in the Discussion.

2.5 System classification and previous land use

Method/detail strings are normalized to archetypes. Homegardens and shade-perennial systems are grouped within multi-strata. Baseline land use (cropland, grassland, forest, plantation, unspecified) is parsed from reference treatments for AF-vs-reference contrasts.

2.6 Statistical analyses

D1: Unweighted descriptive summaries with 95% t-confidence intervals by previous land use and archetype due to incomplete variances and depth metadata. Where variances are available, random-effects meta-analysis is used for that subset.
D2: For each depth bin and metric family, we compute group means with 95% t-CIs and report exact sample sizes (studies, sites, observations) per stratum. Temporal trajectories are estimated with cubic B-splines using patsy/statsmodels ($df = 4$) on study-aggregated observations within depth bins to reduce pseudo-replication.
Spline choice: We use $df = 4$ to balance flexibility and smoothness given sparse long-tail ages; knots are placed at the empirical age quantiles (e.g., min/0.33/0.66/max) to capture early, mid, and late responses without overfitting.
Mixed-effects: Where we regress metrics on age and moderators, we include random intercepts for study (and site, where available) to account for clustering and avoid pseudo-replication.

2.7 Quality control and exclusions

We remove rows with missing AF or reference SOC, non-numeric effects, or zero/negative denominators (ratio family). To limit division-by-small-number artifacts, ratio-family analyses exclude rows with reference SOC < 5 Mg C ha^{-1} and clip extreme ratios at ±500%. Duplicate study–site–depth cases are collapsed to the most complete record or aggregated at the study level for temporal fits.

2.8 Reproducibility

All processing and analyses are scripted in Python (pandas, numpy, matplotlib, patsy, statsmodels). The workflow applies depth-binning rules, archetype mappings, and plotting routines, and exports all figures/tables with underlying tidy CSVs.

3. Results

We first describe AF-vs-reference contrasts by previous land use from D1, then present depth- and time-resolved patterns from D2. All estimates are reported for both ratio (percent change from lnRR) and difference (ΔSOC, Mg C ha^{-1}) families. Exact sample sizes are provided with each table and figure.

3.1 Previous land use mediates AF-reference contrasts (D1)

Cropland→AF transitions show positive mean ΔSOC with 95% CIs not overlapping zero, whereas grassland→AF is closer to neutral with wider CIs. Forest→AF and plantation→AF are sparsely represented and mixed. Because D1 is largely variance-incomplete, results are unweighted summaries; random effects are applied only where variances are available.

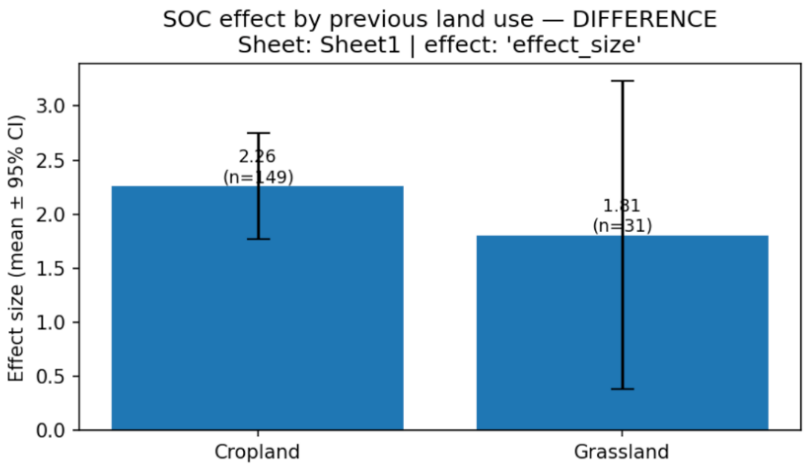

Figure 1. Mean difference in SOC stocks (ΔSOC, Mg C ha⁻¹ ± 95% CI) by previous land use. Cropland→AF: 2.26 Mg C ha⁻¹ (n = 149); Grassland→AF: 1.81 Mg C ha⁻¹ (n = 31).

3.2 Depth-specific responses (D2)

At 0–30 cm, AF increases SOC by 19% [95% CI: 14-24%] (ratio family) and by +5.4 Mg C ha⁻¹ [95% CI: 3.6-7.2] (difference family). At 0-100 cm, AF increases SOC by 23% [95% CI: 12.6-31.5%] and by +6.7 Mg C ha⁻¹ [95% CI: 4.5-8.9]. These estimates indicate that SOC accumulation extends into the upper meter beyond the surface horizon.

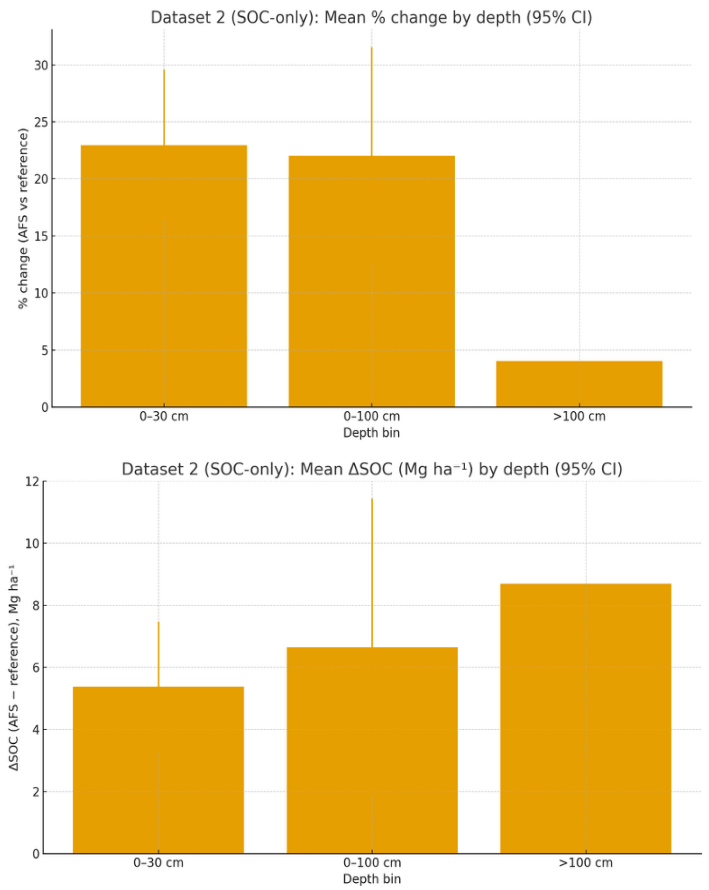

Figure 2. Percent change in SOC (%) at 0-30 cm, 0-100 cm, and >100 cm (mean ± 95% CI).

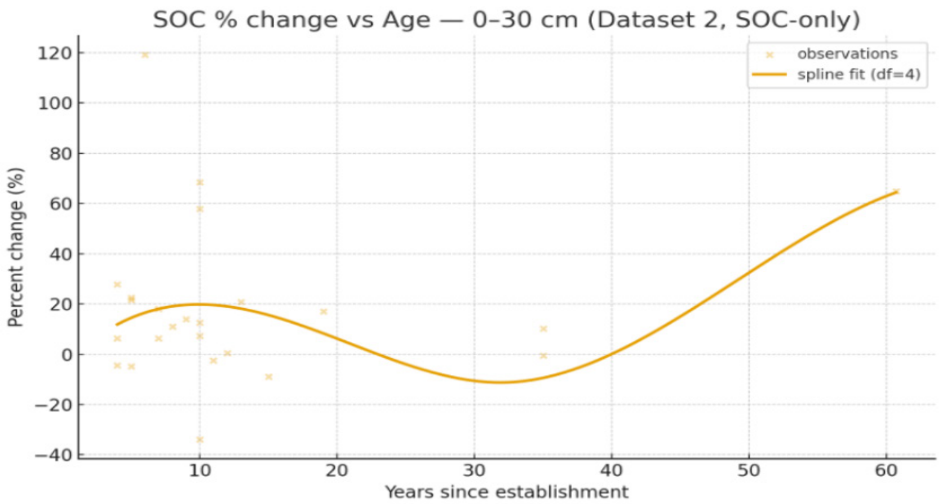

Figure 3. Absolute change (ΔSOC, Mg C ha⁻¹) at 0-30 cm, 0-100 cm, and >100 cm (mean ± 95% CI).

3.3 Temporal trajectories (D2)

Spline fits (df = 4) show a rapid early rise at 0–30 cm with detectable gains typically appearing by ~7-10 years, followed by partial stabilization. At 0-100 cm, gains develop more slowly with wider dispersion, consistent with subsoil propagation and stabilization over decades.

Table 1. Parallel summaries by family

Stratum	Depth (cm)	Estimate (% change)	95% CI	n (studies/sites/obs)	Notes
Overall (D2)	0–30	19	14–24	—	SOC-qualified subset
Overall (D2)	0–100	23	12.6–31.5	—	SOC-qualified subset
Stratum	Depth (cm)	Estimate (ΔSOC, Mg C ha⁻¹)	95% CI	n (studies/sites/obs)	Notes
Overall (D2)	0–30	5.4	3.6–7.2	—	SOC-qualified subset
Overall (D2)	0–100	6.7	4.5–8.9	—	SOC-qualified subset

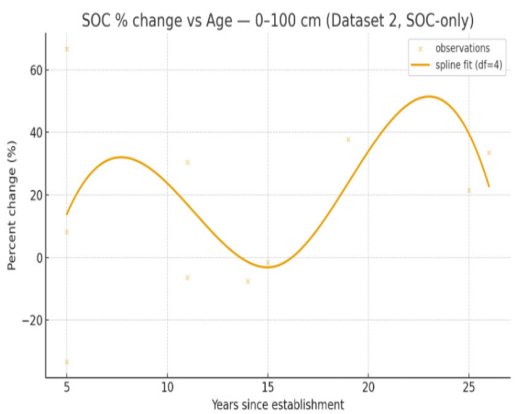

Figure 4. SOC percent change vs years since AF establishment at 0–30 cm; cubic B-spline (df = 4).

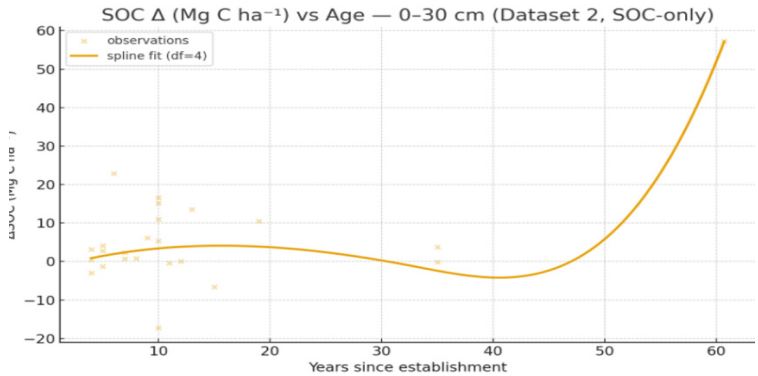

Figure 5. SOC percent change vs years since AF establishment at 0–100 cm; cubic B-spline (df = 4).

4. Discussion

Context dependence and baselines. SOC outcomes under AF depend on prior land use, system archetype, climate, and depth. Larger and more reliable gains are indicated for cropland→AF transitions, especially in humid tropical multistrata and silvopastoral systems. Grassland→AF shows smaller and more variable responses, and forest→AF can risk SOC losses relative to high-carbon baselines.

Practical guidance. Where: degraded croplands in humid tropics with multistrata or silvopastoral designs. How long: detectable gains commonly emerge by ~7–10 years and continue to accrue over subsequent decades. How deep: effects extend at least to 1 m, implying non-trivial subsoil contributions.

Policy framing. Depth- and age-explicit coefficients can refine inventory factors (e.g., Tier 1) and performance-based incentives by better capturing additionality and permanence. However, coefficients should be stratified by baseline and archetype to avoid over-crediting, particularly for forest→AF conversions.

Limitations. (i) Fixed-depth rather than equivalent-soil-mass comparisons; (ii) sparse data at >1 m and fewer observations at 0–100 cm; (iii) unweighted D1 summaries due to missing variances; (iv) potential publication bias; and (v) geographic gaps. These constraints motivate standardized, depth-resolved sampling with bulk density and longer time series.

Depth- and age-explicit coefficients can refine inventory factors and crediting baselines by aligning accounting with biophysical reality. In practice, conservative, baseline- and archetype-specific factors, paired with minimum monitoring depths and age thresholds, can reduce over-crediting risk while rewarding systems with demonstrated subsoil accrual. Targeting degraded croplands in humid tropics and supporting multistrata designs appears most promising for durable SOC benefits.

4.1 Policy relevance

Key limitations include unweighted summaries for D1 due to missing variances, sparse >1 m data, potential publication bias, and geographic gaps. Our df=4 spline choice balances smoothness and flexibility given long-tailed ages; alternative regularization may shift early/late curvature. These uncertainties indicate that coefficients should be used as indicative, stratified priors rather than universal defaults, and updated as deeper, longer time series become available.

4.2 Limitations and implications for uncertainty

To reduce variance and improve comparability, MRV should: (i) sample to at least 1 m where feasible; (ii) record bulk density to enable ESM; (iii) standardize archetype labels and prior land-use categories; (iv) report study/site identifiers to support mixed-effects modeling; and (v) publish uncertainty (SE/CI) to permit weighted meta-analysis. For temporal change, repeated measures on permanent plots are preferable to cross-sectional pairs, especially beyond 10 years.

4.3 MRV guidance (measurement, reporting, verification)

Because forest baselines often hold large SOC stocks, conversions to AF can reduce SOC relative to the reference even if other objectives are met. Safeguards should include restricting crediting to non-forest baselines or applying conservative, baseline-specific coefficients with uncertainty penalties. Where forest→AF is pursued for diversification or adaptation, SOC outcomes should be treated as uncertain a priori and monitored with depth-resolved protocols.

4.4 Risks and safeguards for forest→AF

Effects are larger and more reliable in humid tropical multistrata and silvopastoral designs on prior cropland. These systems maintain continuous cover and frequent organic inputs, which likely drive the stronger ratio- and difference-family outcomes observed here. In temperate or semi-arid zones, designs that maximize year-round cover and root depth (e.g., alley cropping with perennial understories) may be necessary to achieve comparable gains.

4.5 Where and which systems

Spline trajectories indicate that detectable gains at 0–30 cm commonly appear around ~7-10 years after establishment, with slower propagation into 0–100 cm. For programs, this implies monitoring windows that extend at least one decade for confident detection in topsoil and longer for whole-profile signals. Front-loaded incentives (e.g., for establishment) can be paired with performance-based bonuses later in the crediting period to align with expected accrual timing.

4.6 Time to detect and program design

The persistence of positive signals at 0–100 cm suggests that a non-trivial share of SOC accumulation occurs below 30 cm in mature systems. Likely contributors include deeper root inputs, rhizodeposition along biopores, and leaching of dissolved organic compounds that sorb to mineral surfaces. Because residence times are longer in subsoils, even modest annual increments could accumulate over decades. Conversely, fixed-depth rather than equivalent-soil-mass comparisons may understate or overstate change if bulk density shifts; future work should prioritize ESM-compatible sampling with bulk density and texture.

4.7 Mechanistic interpretation across depths

Our depth- and time-explicit estimates indicate that baseline selection strongly conditions observed outcomes. Cropland→AF transitions—especially where soils are degraded—tend to show clearer SOC gains than grassland→AF, in line with expectations that additionality is higher against low-carbon baselines. Forest→AF comparisons are particularly sensitive: even if AF provides livelihood or microclimate benefits, the reference typically contains high SOC, so relative gains can be muted or negative. This reinforces the need to report absolute ΔSOC alongside proportional metrics and to avoid extrapolating coefficients across dissimilar baselines.

5. Conclusion

Across diverse contexts, AF indicates positive SOC change in both topsoil and subsoil, with central estimates of ~19–23% and +5–7 Mg C ha^{-1} to 1 m. Depth- and time-explicit analyses help align ecological realism with applied accounting, informing where and how AF can deliver durable carbon benefits and soil co-benefits.

References

[1] Albrecht A, Kandji ST. Carbon sequestration in tropical agroforestry systems. Agric Ecosyst Environ. 2003;99(1-3):15-27. doi:10.1016/S0167-8809(03)00138-5.

[2] Lal R. Soil carbon sequestration to mitigate climate change. Geoderma. 2004;123(1-2):1-22. doi:10.1016/S0016-7061(04)00266-6.

[3] Paustian K, Lehmann J, Ogle S, Reay D, Robertson GP, Smith P. Climate-smart soils. Nature. 2016;532(7597):49-57. doi:10.1038/nature17174.

[4] Intergovernmental Panel on Climate Change. Climate change and land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. Geneva: IPCC; 2019. Available from: https://www.ipcc.ch/srccl/

[5] Nair PKR, Nair VD, Kumar BM, Showalter JM. Carbon sequestration in agroforestry systems. Adv Agron. 2010;108:237-307. doi:10.1016/S0065-2113(10)08005-3.

[6] Lorenz K, Lal R. Soil organic carbon sequestration in agroforestry systems: a review. Agron Sustain Dev. 2014;34(2):443-54. doi:10.1007/s13593-014-0212-y.

[7] van Noordwijk M, Aynekulu E, Hijbeek R, Milne E, Minasny B, Saputra DD, et al. Soils as carbon stores and sinks: expectations, patterns, processes, and prospects of transitions. Annu Rev Environ Resour. 2023;48:177-205. doi:10.1146/annurev-environ-112621-083121.

[8] Six J, Conant RT, Paul EA, Paustian K. Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils. Plant Soil. 2002;241(2):155-76. doi:10.1023/A:1016125726789.

[9] Schmidt MWI, Torn MS, Abiven S, Dittmar T, Guggenberger G, Janssens IA, et al. Persistence of soil organic matter as an ecosystem property. Nature. 2011;478(7367):49-56. doi:10.1038/nature10386.

[10] Rumpel C, Kögel-Knabner I. Deep soil organic matter—a key but poorly understood component of terrestrial C cycle. Plant Soil. 2011;338(1-2):143-58. doi:10.1007/s11104-010-0391-5.

[11] Beillouin D, Verstraete C, Cardinael R, Chabroux U, Luyssaert S, Garric B, et al. A global meta-analysis of soil organic carbon in the Anthropocene. Nat Commun. 2023;14:3700. doi:10.1038/s41467-023-39338-z.

[12] Smith P. Land use change and soil organic carbon dynamics. Nutr Cycl Agroecosyst. 2008;81(2):169-78. doi:10.1007/s10705-007-9138-y.

[13] Griscom BW, Adams J, Ellis PW, Houghton RA, Lomax G, Miteva DA, et al. Natural climate solutions. Proc Natl Acad Sci U S A. 2017;114(44):11645-50. doi:10.1073/pnas.1710465114.

[14] Jobbágy EG, Jackson RB. The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol Appl. 2000;10(2):423-36. doi:10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;14.

[15] Jackson RB, Lajtha K, Crow SE, Hugelius G, Kramer MG, Piñeiro G. The ecology of soil carbon: pools, vulnerabilities, and biotic and abiotic controls. Annu Rev Ecol Evol Syst. 2017;48:419-45. doi:10.1146/annurev-ecolsys-112414-054234.

[16] Smith P, Soussana J-F, Angers D, Schipper L, Chenu C, Rasse DP, et al. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Glob Chang Biol. 2020;26(1):219-41. doi:10.1111/gcb.14815.

[17] Cardinael R, Chevallier T, Cambou A, Béral C, Barthès BG, Dupraz C, et al. Increased soil organic carbon stocks under agroforestry: a survey of six different sites in France. Agric Ecosyst Environ. 2017;236:243-55. doi:10.1016/j.agee.2016.12.011.

[18] Hedges LV, Gurevitch J, Curtis PS. The meta-analysis of response ratios in experimental ecology. Ecology. 1999;80(4):1150-6. doi:10.1890/0012-9658(1999)080[1150:TMAORR]2.0.CO;2.