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Kaushik Saha
ICAR-National Bureau of Soil Survey and Land Use Planning
K. S. Anilkumar
anilsoils@yahoo.co.in
ICAR-National Bureau of Soil Survey and Land Use Planning
K. M. Nair
ICAR-National Bureau of Soil Survey and Land Use Planning
Lalitha M.
ICAR-National Bureau of Soil Survey and Land Use Planning
Samrat Ghosh
Bidhan Chandra Krishi Viswavidyalaya
Parinita Das
Dr Rajendra Prasad Central Agricultural University
Parvathy S.
ICAR-National Bureau of Soil Survey and Land Use Planning
James Jacob
Rubber Research Institute of India
N. G Patil
ICAR-National Bureau of Soil Survey and Land Use Planning

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Agroforestry enhances soil quality and carbon storage with carbon-credit potential across contrasting land-use systems in the Western Ghats

Kaushik Saha[1,2], K. S. Anilkumar[1]*, Nair, K. M.[1], Lalitha, M[1]., Samrat Ghosh[3], Parinita Das[4], Parvathy, S.[1], James Jacob[5], Patil, N. G[6].

[1]ICAR-National Bureau of Soil Survey and Land Use Planning, Regional Centre, Bengaluru-560 024, Karnataka, India

[2] Emergent Ventures India Private Limited, Sector-58, Gurgaon-122011, Haryana, India.

[3]Bidhan Chandra Krishi Viswavidyalaya, Mohanpur, Nadia-741235, West Bengal, India

[4]College of Basic Sciences and Humanities, Dr Rajendra Prasad Central Agricultural University, Pusa, Samastipur-848125, Bihar, India

[5]Rubber Research Institute of India, Rubber Board, Puthuppally, Kottayam 686009, Kerala, India

[6]ICAR-National Bureau of Soil Survey and Land Use Planning, Amravati Road, *Nagpur*-400033, India.

**Corresponding author: anilsoils@yahoo.co.in

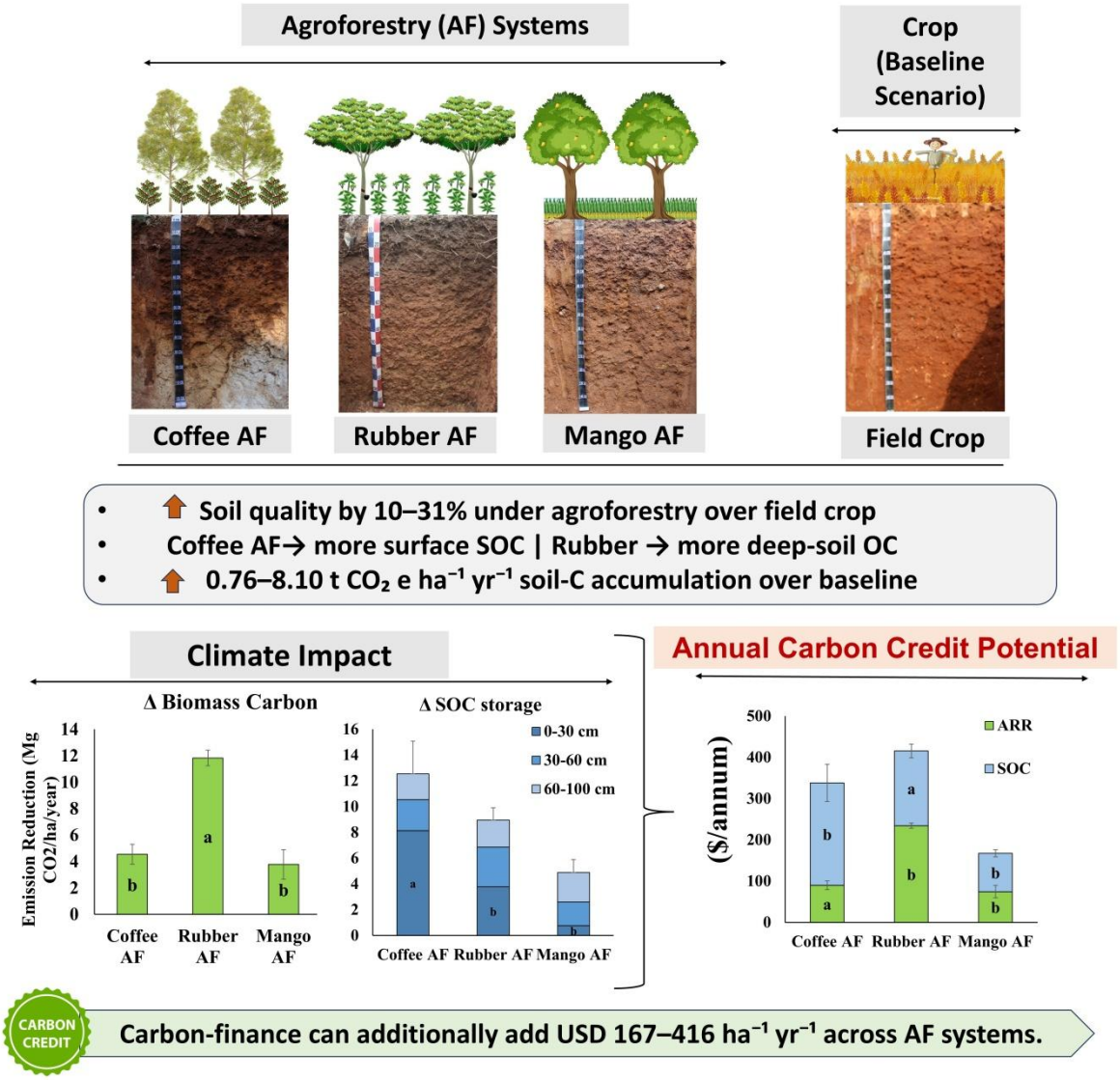
Present address: RAU Pusa, Samastipur, Bihar, India, PIN Code – 848 125

Abstract:

Agroforestry systems can improve soil quality and carbon storage while generating additional economic value through carbon financing. This study evaluated forest, coffee agroforestry (Coffee AF), rubber agroforestry (Rubber AF), mango agroforestry (Mango AF), and sole-cropping systems for soil quality, soil organic carbon (SOC) storage, biomass carbon accumulation, and indicative carbon-finance potential in the Western Ghats of Karnataka, India. SOC was assessed throughout the soil profile to capture both surface and subsurface carbon pools. Soil quality index (SQI) was higher under Coffee AF (0.655), Rubber AF (0.617), and Mango AF (0.550) than sole cropping (0.499) at 0–30 cm. Surface SOC stocks ranged from 16.6 to 88.3 Mg C ha^{-1}, with Coffee AF showing greater surface SOC storage, whereas Rubber AF recorded the highest deep-soil carbon storage. Relative to sole cropping,

annual soil-C accumulation potential was 8.1, 3.8 and 0.76 t CO_2e ha^{-1} yr^{-1} at 0–30 cm and 4.41, 5.17 and 4.12 t CO_2e ha^{-1} yr^{-1} at 30–100 cm for Coffee AF, Rubber AF and Mango AF, respectively. Biomass carbon reached 68.9, 28.8 and 22.5 t C ha^{-1} in Rubber AF, Coffee AF and Mango AF, with annual woody biomass removal potentials of 11.8, 4.6 and 3.7 t CO_2e ha^{-1} yr^{-1}, respectively. Indicative gross carbon-finance value was highest for Rubber AF (USD 415.5 ha^{-1} yr^{-1}), followed by Coffee AF (USD 338.3) and Mango AF (USD 167.3). Overall, agroforestry provides combined soil, carbon-storage and economic benefits, with Rubber AF particularly promising for deep-soil carbon storage and carbon-finance potential.

Key Words: Carbon Credit, Agroforestry, Soil quality index, Soil carbon stock, Biomass Carbon



Highlights:

- Agroforestry improved soil quality by 10–31% over sole cropping.
- Soil-C accumulation reached 0.76–8.10 t CO_2e ha^{-1} yr^{-1} across agroforestry systems.
- Coffee agroforestry increased surface soil carbon, while rubber stored more at depth.
- Carbon-finance value reached USD 167–416 ha^{-1} yr^{-1} across agroforestry systems.

Introduction:

Limiting climate warming requires rapid reductions in greenhouse-gas emissions, together with increased removal and long-term storage of atmospheric CO_2. The IPCC identifies land-based mitigation as an important component of climate action, particularly where mitigation

can be combined with food production and ecosystem restoration (IPCC, 2023). In this context, agroforestry, the deliberate integration of woody perennials with crops and/or livestock, offers a multifunctional land-use strategy that can combine agricultural production with carbon sequestration and soil restoration (Nair, 2007; Kumara et al., 2023). By increasing aboveground biomass and supplying continuous litter, root and rhizodeposition inputs, agroforestry can enhance soil organic carbon (SOC), nutrient cycling, aggregate stability and other soil-quality attributes. Meta-analyses conducted at both national and global scales indicate that agroforestry generally has positive effects on soil carbon storage compared with conventional agricultural land uses, although the magnitude and direction of responses vary with previous land use, agroforestry system, climate, stand age and soil depth (Kumara et al., 2023; Pan et al., 2025). These findings highlight the potential of integrating woody perennials into agricultural landscapes to enhance soil-C storage while providing additional ecological benefits. However, the benefits are context dependent, and agroforestry should not be regarded as a substitute for natural forests, particularly where conversion from forest to agroforestry may result in losses of existing ecosystem carbon stocks (Kumara et al., 2023). Overall, the available evidence supports agroforestry as a complementary land-management strategy for improving soil carbon storage and other soil functions while maintaining agricultural production. These findings support agroforestry as an important soil-C and climate-mitigation strategy within agricultural landscapes. However, it should not be considered a substitute for natural forests, as forest conversion to agroforestry can itself reduce C storage (Kumara et al., 2023).

The magnitude of these benefits depends strongly on system composition and management. Coffee-, rubber- and mango-based systems represent contrasting perennial agroforestry pathways. They differ in canopy structure, rooting depth, litter production, biomass accumulation and soil disturbance. Coffee agroforestry can develop a forest-like structure, with shade trees providing substantial biomass and continuous litter and root inputs. A three-decade field study showed that integrating shade trees increased SOC pools by 20–76% relative to sole coffee, demonstrating the long-term contribution of shade integration to soil-C retention (Sun et al., 2023). Recent studies also indicate that shade-tree biomass constitutes a major component of C storage in coffee agroforests (Asanok et al., 2024; Jawo et al., 2024). Rubber agroforestry provides a contrasting C pathway, combining substantial woody biomass with additional inputs from associated vegetation. Diversification can also improve soil functioning relative to rubber monoculture. In southern peninsular India, rubber

agroforestry showed 23.5% greater surface SOC and a 9.33% higher soil-quality index than rubber monoculture (Saha et al., 2025). Recent experimental evidence further indicates that rubber-based agroforestry can increase macroaggregate formation and aggregate stability, promoting SOC sequestration through physical protection of organic matter (Xu et al., 2026). Mango agroforestry similarly combines long-lived woody biomass with crop production and continuous litter- and root-derived C inputs. Indian field studies have reported improvements in SOC and soil nutrient availability under mango-based systems, indicating their potential to enhance both soil fertility and C storage. Thus, coffee, rubber and mango agroforestry can contribute to both biomass and soil-C sequestration, but the magnitude and vertical distribution of C may differ among systems because of their contrasting biological and management characteristics.

The growing recognition of these C benefits creates an opportunity to link soil restoration and climate mitigation with agricultural economics through carbon markets. Carbon crediting can provide additional economic value for demonstrable increases in biomass and soil C, potentially improving the attractiveness of tree integration where farmers face establishment costs or production trade-offs. Recent studies have quantified carbon-credit potential from Indian agroforestry systems and identified carbon finance as a potential additional income source for farmers (Kumar et al., 2024). However, total ecosystem C cannot be directly equated with creditable C. Credit generation requires a defensible baseline, additionality, permanence, uncertainty assessment and robust measurement, reporting and verification. Therefore, quantifying C gains relative to an appropriate agricultural baseline is essential for assessing the realistic carbon-finance potential of agroforestry systems (Kumara et al., 2023; Kumar et al., 2024).

Despite increasing evidence of the climate and soil-health benefits of agroforestry, comparative assessments of long-established perennial systems within a common regional context remain limited. In particular, few studies have simultaneously examined soil quality, SOC across deeper soil layers and biomass C and associated carbon market benefits. This gap is important because assessments restricted to the upper 20–30 cm may overlook substantial C stored at depth. Differences in rooting patterns and C allocation may also produce contrasting surface and subsurface SOC dynamics. Moreover, comparison with a long-term agricultural baseline is necessary to distinguish additional C storage associated with tree integration from background C dynamics under continuous cultivation. Here, we compare

long-established (>20 years) coffee-, rubber- and mango-based agroforestry systems with a >20-year continuously cultivated agricultural baseline to assess their relative potential for soil restoration and climate mitigation. Specifically, we aim to (i) evaluate soil quality and SOC storage across the 0–100 cm soil profile, (ii) quantify biomass and soil-C sequestration potential, and (iii) estimate the potential economic value of these C gains under carbon-crediting scenarios.

Method and material

2.1. Study area and site description

The study was conducted across five contrasting land-use systems—forest, coffee agroforestry (Coffee AF), rubber agroforestry (Rubber AF), mango agroforestry (Mango AF), and sole-cropping systems—in Chikkamagaluru district, Karnataka, India. The district encompasses the Western Ghats escarpment and adjoining plateau regions and exhibits substantial variability in rainfall, elevation, topography, soils, and vegetation. The Western Ghats create a pronounced rainfall gradient, with humid high-rainfall areas adjoining relatively dry rain-shadow regions, and the district falls within the Hilly, Southern Transition, and Central Dry agro-climatic zones. Site selection followed a stratified approach to minimize environmental variability within land-use categories. The reconnaissance-level soil map of Karnataka (Shivaprasad et al., 1998) was used to identify broad soil groups, while agro-climatic zones were considered to delineate areas with relatively similar climatic and vegetation characteristics. Sampling sites were subsequently selected considering soil type, climate, topography, and land-use history. Forest sites were used as a reference benchmark representing relatively undisturbed ecosystems and predominantly comprised tropical wet evergreen (TWE) forests developed mainly on Alfisols and Ultisols, supporting large-canopy species such as Alstonia spp., Tectona grandis, and Dipterocarpus indicus. Historical land-use records, supplemented by farmer interviews and information from local agricultural officials, were used to identify mature agroforestry systems, and only sites with at least 20 years of established agroforestry management were included. Coffee AF sites consisted of plantations maintained under moderate shade-tree density (100–500 trees ha^{-1}), with intentionally retained or planted shade trees and associated crops such as black pepper. Rubber AF sites had a minimum 20-year agroforestry history, with banana and turmeric commonly cultivated during the initial establishment phase and shade-tolerant intercrops such as cowpea present at the time of sampling. Mango AF sites were initially intercropped with ragi, turmeric, and

millets during the first 7–10 years, after which increasing canopy development and shade favoured crops such as cowpea and black pepper, with dragon fruit present only as a minor experimental component at selected sites. Sole-crop sites represented areas with a continuous history of annual cropping, predominantly involving ragi, millet, and paddy. The spatial distribution of sampling sites across the five land-use systems is presented in Fig. 1. At each site, structured survey sheets were used to document land-use history, soil and nutrient management, agronomic inputs, crop productivity, intercrop composition, and supplementary farm-based income-generating activities.

2.2. Soil sampling and laboratory analysis

Fifteen representative soil profiles were examined across the five predominant land-use categories, with three profiles selected for each category. Sampling locations were selected to capture differences in soil type, topography and climatic conditions using the 1:500,000-scale soil-mapping units of Karnataka as the spatial framework. At each location, a soil pit was excavated to the underlying lithic contact or bedrock, allowing the complete sequence of genetic horizons to be characterized. Profile description and taxonomic classification followed the USDA Soil Taxonomy (Soil Survey Staff, 2022). Approximately 2 kg of soil was collected from each horizon, air-dried, gently disaggregated and passed through a 2-mm sieve before laboratory analysis.

Particle-size distribution was determined using the international pipette method. Sand (2000–50 μm) was separated following mechanical dispersion and sieving, whereas silt and clay fractions were quantified from sedimentation measurements (Jackson, 1979). Bulk density was measured by the core method (Blake and Hartge, 1986). Soil pH was determined potentiometrically using a 1:2.5 soil-to-water ratio. Exchangeable acidity was extracted with 1 N KCl, while extractable acidity was determined using a $BaCl_2$–triethanolamine (TEA) buffer adjusted to pH 8.2, followed by titrimetric determination (Sarma et al., 1987). Soil pH was additionally measured in 0.01 M $CaCl_2$ and 1 M KCl according to Reeuwijk (1992). Organic carbon in the <2-mm fraction was determined by the Walkley–Black wet oxidation procedure (Walkley and Black, 1934). Exchangeable Ca, Mg, K and Na were extracted with 1 N ammonium acetate at pH 7.0 and measured by atomic absorption spectrophotometry (Reeuwijk, 1992). Exchangeable Al was extracted using 1 M KCl and quantified by titration. Base saturation was calculated as the proportion of total exchangeable bases relative to the cation exchange capacity (CEC), expressed as a percentage.

2.3 Soil quality evaluation

A Principal Component Analysis (PCA) was performed on 28 soil physicochemical and exchangeable properties to identify the dominant variables controlling soil quality and to derive a Minimum Data Set (MDS), following the soil-quality assessment framework of Doran and Parkin (1994) and Mukherjee and Lal (2014). Principal components with eigenvalues >1.0 were retained according to the Kaiser criterion (Kaiser, 1960), and Varimax rotation was applied to improve the interpretability of variable loadings (Waswa et al., 2013). Variables with loadings within 10% of the maximum loading for each retained component were initially considered for inclusion in the MDS. Where variables were strongly correlated, the variable with the greater overall correlation was retained as the representative indicator (Andrews and Carroll, 2001).

The selected indicators were transformed into dimensionless scores using nonlinear scoring functions (NLSFs), with the direction of scoring determined by the expected relationship between each indicator and soil quality (Liebig et al., 2001; Raiesi, 2017). Indicators showing a monotonic response were scored using the sigmoidal function with a slope coefficient of ±2.5 (Raiesi, 2017; Bandyopadhyay and Maiti, 2021):

$$NLSF=a/[1+(Xi/Ximean)b] \quad \text{(Eq. 3)}$$

Where a represents the maximum score, X_i is the measured value of the indicator, Xmean is its mean value, and b is the slope coefficient. For properties for which intermediate values represent optimum soil conditions, a Gaussian-type function was applied following the "midpoint-is-optimum" concept (Liebig et al., 2001). The Soil Quality Index (SQI) was subsequently calculated using a weighted-additive approach. Indicator weights were assigned according to the contribution of each retained principal component to the total variance (Andrews et al., 2002; Ray et al., 2014). SQI was first calculated for individual soil horizons and subsequently aggregated for the 0–30, 30–60, 60–100 and >100 cm depth intervals for each land-use category.

2.4. Estimation Soil carbon stock

Soil organic carbon stocks were estimated from SOC concentration, soil depth, bulk density and coarse-fragment content using the approach of Ellert et al. (2001), modified following Szatmári et al. (2021):

$$SOCstock = C \times d \times BDd \times 0.1 \times (1\text{-}CF) \quad \text{(Eq. 4)}$$

where C% is the SOC concentration (%), d is the thickness of the soil layer (cm), BDd is the bulk density of the fine-earth fraction (<2 mm; g cm^{-3}), and CF is the volumetric fraction of coarse fragments (>2 mm). The term (1−CF) accounts for the proportion of fine earth within the soil volume. SOC stocks were calculated separately for 0–30, 30–60, 60–100 and >100 cm depth intervals. Weighted mean values were used where individual horizons did not coincide exactly with the predefined depth intervals.

2.5. Estimation of above-ground and below ground biomass of trees and total carbon sequestration potential of agroforestry systems:

Aboveground biomass of dominant tree species was estimated using random plot sampling. Within each 20 × 20 m sampling plot, tree diameter at breast height (DBH) and tree density were recorded. Species-specific equations published by the Forest Survey of India (FSI, 1996, 2021) were used to estimate tree volume and biomass.

Total ecosystem C stock was calculated by combining aboveground tree biomass C, belowground biomass C and SOC. Carbon sequestration was expressed as CO_2-equivalent by applying the molecular-weight conversion factor of 44/12 (3.667) to the estimated carbon stock (Ajit et al., 2013).

2.6 Carbon credit and pricing

For the purpose of this assessment, one carbon credit was considered equivalent to one tonne of CO_2-equivalent (tCO_2e) removed from or avoided in the atmosphere, subject to the applicable permanence and accounting requirements (Mitchell et al., 2024). The potential for carbon-credit generation was evaluated within the framework of established carbon-accounting principles. Existing forest areas were not considered for A/R-based crediting; consequently, the analysis focused on the three agroforestry systems, with continuously cultivated field crop representing the baseline land-use scenario.

Additional SOC storage under each agroforestry system was estimated relative to the field-crop baseline. Apparent annual SOC accrual was derived by relating the estimated difference in SOC stock to the mean age of the respective plantation systems. The resulting apparent annual C gains were converted to CO_2-equivalent and used to estimate indicative carbon-credit potential. Because carbon prices vary substantially among standards, project types, market segments and transaction periods, the economic assessment was conducted using the assumed voluntary carbon-market price applicable to the study period. For 2025, a reference price of approximately ₹1,544 (US$19.8) per tCO_2e was adopted (VCM, 2025). The resulting values represent indicative carbon-revenue potential rather than guaranteed carbon-credit income, as actual issuance and realized prices depend on project additionality, baseline determination, permanence, uncertainty, validation/verification and market conditions.

2.6 Statistical analysis

Statistical analysis was carried out using the IBM-SPSS-23.0. Differences between the different land use systems and within each soil depth intervals were evaluated with Duncan's multiple range test at $P \leq 0.05$. PCA and correlation analysis was carried out through R studio.

3. Results:

3.1 Changes in Soil Quality Index (SQI) and Key Soil Properties

Principal component analysis (PCA) of 28 soil variables identified five principal components (PCs) with eigenvalues >1, explaining 72.1% of the total variance. PC1 (27.2%) was dominated by base saturation (BS), PC2 (15.2%) by organic carbon (OC), PC3 (14.1%) by sand, PC4 (8.6%) by dry bulk density (BDd), and PC5 (7.0%) by exchangeable sodium percentage (ESP), which were selected as MDS indicators (Table S1).

Figure 2a presents SQI and the contributions of individual MDS indicators across land uses and soil depths. At 0–30 cm, SQI followed the order Forest (0.704) > Coffee AF (0.655) > Rubber AF (0.617) > Mango AF (0.550) > Crop (0.499), with higher BS and OC contributions under Forest and Coffee AF. Despite the highest OC contribution, Rubber AF had lower SQI due to reduced BS, whereas Mango AF showed lower BS and OC contributions. At 30–60 cm, SQI declined across all land uses, with Forest and Coffee AF

maintaining higher BS and OC contributions; Rubber AF and Mango AF showed comparable SQI (0.538), while Crop recorded the lowest SQI (0.465). At 60–100 cm, a similar pattern persisted, although OC contributions remained comparable among agroforestry systems. Rubber AF showed a pronounced decline in BS contribution, whereas Crop exhibited the lowest ESP contribution. At >100 cm, Forest and Coffee AF maintained higher SQI, while Rubber AF remained constrained by low BS and sand contributions despite its relatively high OC contribution. Overall, Forest consistently exhibited the highest SQI, whereas Crop showed the lowest soil quality across the profile.

3.2 *Changes in soil organic carbon stock (SOC stock)*

SOC stocks varied significantly among land-use types across the soil profile ($p < 0.05$; Fig. 3a). In the 0–30 cm layer, SOC stocks ranged from 16.6 to 88.3 Mg C ha^{-1} and followed the order: Forest > Coffee AF > Rubber AF > Mango AF > Field crop. Forest soils exhibited significantly greater SOC storage than all other land uses within the upper 100 cm of the soil profile. In contrast, SOC stocks under Rubber AF, Coffee AF, and Mango AF were statistically comparable in the 30–60 cm and 60–100 cm layers ($p < 0.05$). Below the control section (>100 cm), the distribution pattern changed markedly, with Rubber AF recording the highest SOC stock, followed by Forest, Coffee AF, Mango AF, and Field crop ($p < 0.05$; Fig. 3a). Field crop consistently exhibited the lowest SOC stock across all soil depths.

Depth-wise SOC distribution further revealed distinct carbon allocation patterns among land-use systems (Fig. 3b). Coffee AF showed pronounced SOC accumulation in the surface layer (0–30 cm), followed by a significant decline in the subsoil (30–100 cm), indicating limited carbon allocation to deeper horizons ($p < 0.05$). In contrast, Mango AF maintained statistically similar SOC stocks throughout the 0–100 cm profile, suggesting a more uniform vertical distribution of carbon. Rubber AF exhibited the greatest deep-soil carbon allocation, with maximum SOC storage occurring below 100 cm, followed by the surface (0–30 cm) and subsurface (30–100 cm) layers ($p < 0.05$; Fig. 3b). Forest and Field crop displayed broadly similar depth-wise allocation patterns, although total SOC stocks remained significantly higher under Forest across the entire profile.

3.3 *Total biomass carbon, annual carbon removal, and estimated carbon credit under varied agroforestry systems*

In accordance with the accounting principles of major carbon standards (CDM, 2006; Verra, 2023), only the woody biomass of trees was considered for carbon removal estimation, whereas biomass from cultivated and regularly pruned crops was conservatively excluded as non-tree biomass. Total biomass carbon stock (above- and below-ground) varied substantially among land-use systems, following the order: Forest (294.3 t C ha^{-1}) > Rubber AF (68.9 t C ha^{-1}) > Coffee AF (28.8 t C ha^{-1}) > Mango AF (22.5 t C ha^{-1}) (Fig. 4).

The age-normalized annual carbon removal potential from woody biomass differed significantly among agroforestry systems, with Rubber AF recording the highest removal rate (11.8 t CO_2 ha^{-1} yr^{-1}), followed by Coffee AF (4.6 t CO_2 ha^{-1} yr^{-1}) and Mango AF (3.7 t CO_2 ha^{-1} yr^{-1}) (Fig. 5a). Soil carbon removal, estimated from SOC stock gains relative to sole field crops, exhibited contrasting depth-wise patterns. In the surface soil (0–30 cm), Coffee AF achieved the highest apparent annual SOC removal (8.1 t CO_2 ha^{-1} yr^{-1}), followed by Rubber AF (3.8 t CO_2 ha^{-1} yr^{-1}) and Mango AF (0.76 t CO_2 ha^{-1} yr^{-1}) ($p<0.05$; Fig. 5b). In contrast, the subsurface layer (30–100 cm) showed the greatest carbon removal under Rubber AF (5.17 t CO_2 ha^{-1} yr^{-1}), followed by Coffee AF (4.41 t CO_2 ha^{-1} yr^{-1}) and Mango AF (4.12 t CO_2 ha^{-1} yr^{-1}) (Fig. 5b).

Economic valuation based on biomass-derived carbon credits indicated that Rubber AF generated the highest annual revenue potential from woody biomass carbon accumulation (USD 234.1 ha^{-1} yr^{-1}), followed by Coffee AF (USD 89.8 ha^{-1} yr^{-1}) and Mango AF (USD 74.7 ha^{-1} yr^{-1}) (Fig. 5c). Revenue derived from SOC sequestration, however, was highest under Coffee AF (USD 248.4 ha^{-1} yr^{-1}), followed by Rubber AF (USD 181.3 ha^{-1} yr^{-1}) and Mango AF (USD 92.7 ha^{-1} yr^{-1}). Consequently, the combined annual indicative carbon credit potential was greatest for Rubber AF (USD 415.5 ha^{-1} yr^{-1}; ₹39,474 ha^{-1} yr^{-1}), followed by Coffee AF (USD 338.3 ha^{-1} yr^{-1}; ₹32,138 ha^{-1} yr^{-1}) and Mango AF (USD 167.3 ha^{-1} yr^{-1}; ₹15,898 ha^{-1} yr^{-1}).

4. Discussion:

4.1 Influence of agroforestry systems on soil quality and soil carbon storage

Soil quality varied consistently among land-use systems, with SQI highest under Forest, followed by Coffee AF, Rubber AF, Mango AF and Crop, and generally declining with depth (Fig 2a). The higher SQI under Forest and Coffee AF was primarily associated with greater base saturation (BS) and organic carbon (OC) contributions (Fig 2b), consistent with greater

organic-C inputs, nutrient recycling and improved soil physical condition under agroforestry systems (Singh et al., 2022; Angadi et al., 2025). BS was a major discriminator, remaining high under Forest (0.271–0.243) and Coffee AF (0.253–0.221) but declining markedly under Rubber AF, particularly below 60 cm (0.132–0.119), potentially reflecting depletion of exchangeable Ca and Mg and acidification of the exchange complex (Liu et al., 2019; Saha et al., 2025; Liu et al., 2024), whereas higher BS under forest may be associated with deep rooting, nutrient recycling and litter-derived base-cation return (Fig 2b). The OC contribution declined with depth but remained comparatively high under agroforestry; below 60 cm, contributions were similar among Coffee AF (0.135–0.137), Rubber AF (0.133–0.157) and Mango AF (0.131–0.135), indicating continued C retention in deeper soil through root turnover, rhizodeposition and dissolved-C transport (Krüger et al., 2024). In contrast, sand became an important limiting indicator in Rubber AF, Mango AF and Crop, with its depth-wise contribution likely reflecting inherent profile development and land-use effects because particle-size distribution is strongly governed by parent material and pedogenesis. The Rubber AF–Mango AF contrast further shows that high OC did not necessarily translate into higher SQI: Rubber AF retained relatively high OC but was constrained by lower BS and sand, whereas Mango AF had comparable OC but somewhat greater BS. The marked decline in Rubber AF soil quality at depth is consistent with reported subsoil acidification, increased exchangeable Al and nutrient depletion under long-term rubber cultivation (Liu et al., 2024). Crop consistently recorded the lowest SQI, declining from 0.499 at 0–30 cm to 0.373 at >100 cm, driven by combined limitations of OC, sand and particularly ESP. Long-term cultivation can alter exchangeable cation balances and subsoil chemical conditions, whereas agroforestry can improve ESP and SOC across the soil profile. Overall, the results indicate a depth-dependent shift from OC- and BS-driven soil quality in surface soil towards stronger physical and chemical constraints in deeper layers, with perennial vegetation maintaining superior soil functioning compared with sole cropping (Singh et al., 2022; Angadi et al., 2025; Sirimalle et al., 2025). This improvement in soil functioning under perennial vegetation was also reflected in the magnitude and distribution of soil organic carbon (SOC) storage across the soil profile.

Among the studied land-use types, forest soils exhibited the greatest SOC storage within the upper 100 cm, providing a benchmark for the C-storage capacity of relatively undisturbed ecosystems. Forest SOC stocks at 0–30 cm (88.3 ± 2.88 Mg C ha^{-1}) and 30–60 cm (55.54 ± 31.11 Mg C ha^{-1}) were comparable with values reported for forest ecosystems across the Western and Eastern Ghats of peninsular India (Seen et al., 2010; Sreekanth et al.,

2013; Kothandaraman et al., 2020; Saha et al., 2024). Because forest conversion to cropland generally results in substantial SOC depletion (Kissinger, 2020; Chort and Öktem, 2024), agroforestry represents a potential pathway for recovering part of this C deficit while sustaining agricultural production. Among the agroforestry systems, coffee AF retained the greatest proportion of surface SOC (Fig. 3a), with stocks only 24% lower than forest, compared with 56% and 76% lower stocks under rubber and mango AF, respectively. The relatively high SOC under coffee AF likely reflects the continuous and diverse C inputs from shade trees and coffee plants through litterfall, fine-root turnover, pruning residues and rhizodeposition (Tumwebaze and Byakagaba, 2016; Lugo-Pérez et al., 2023; Sun et al., 2023), supplemented by persistent ground cover. Moreover, high-quality litter inputs can promote aggregate formation and physical protection of SOC (Sinha et al., 2026). Rubber AF also maintained considerably greater surface SOC than cropland and mango AF, although its storage was lower than that of coffee AF. In rubber-based systems, however, inter-row cultivation associated with short-duration intercrops such as turmeric and pineapple can increase soil disturbance and SOC turnover (Joseph et al., 2022), although integration with intercrops can still improve soil quality and C storage relative to rubber monoculture (Saha et al., 2025). Mango AF, in contrast, showed only a marginal 17% increase in SOC over cropland, potentially reflecting greater periodic inter-row cultivation for weed control and water management, which may disrupt aggregates and accelerate SOC turnover. These surface differences, however, did not persist uniformly with increasing soil depth, highlighting the importance of considering the vertical distribution of SOC rather than surface stocks alone.

The surface SOC contrast, however, diminished markedly with depth. SOC stocks under coffee, rubber and mango AF were statistically comparable at 30–60 and 60–100 cm (Fig. 3a), indicating that the strong surface-C advantage of coffee was largely confined to the upper soil. This pattern is consistent with evidence that litter-derived C inputs in coffee primarily enhance surface SOC, whereas deeper SOC accumulation is increasingly regulated by root distribution, mineral interactions and stabilization processes (Chatterjee et al., 2019). Conversely, Mango AF maintained relatively uniform SOC across the 0–100 cm profile, potentially reflecting greater belowground C allocation through its extensive rooting system. Below 100 cm, Rubber AF exhibited the highest SOC stock, possibly reflecting the deep, actively cycling root system of rubber and greater incorporation of root-derived C into deeper soil. Such depth-dependent storage is particularly relevant to C persistence because subsoil

SOC is generally less accessible to microbial decomposition and more strongly protected through mineral association and physical mechanisms than surface SOC (Hicks Pries et al., 2023; Zhou et al., 2024; Bolan et al., 2026). Thus, the controls on SOC shifted from surface C inputs and management to belowground C allocation and depth-dependent stabilization with increasing soil depth. From a carbon-sequestration perspective, these findings demonstrate that the magnitude of surface SOC alone does not fully capture the long-term C-storage potential of agroforeforestry systems; the vertical distribution and persistence of SOC must also be considered, with coffee AF showing the strongest surface-C recovery and rubber AF showing notable potential for deeper, more persistent C storage.

4.2 Indicative carbon credit potential under varied agroforestry systems

Carbon crediting can provide an important economic incentive for transitioning from input-intensive monocultures to multifunctional agroforestry by monetizing additional biomass and soil-C sequestration that is otherwise not reflected in farm income. Recent Indian studies have demonstrated substantial C-sequestration and carbon-finance potential of agroforestry systems (Kumara et al., 2023; Kumar et al., 2024; Singh et al., 2024; Vikrant et al., 2025). In the present study, long-established (>20 years) coffee-, rubber- and mango-based agroforestry systems were assessed against a >20-year continuously cultivated cropland baseline. Surface SOC accumulation was highest under coffee AF (8.13 t CO_2 ha^{-1} yr^{-1}), followed by rubber (3.77) and mango (0.76 t CO_2 ha^{-1} yr^{-1}), whereas subsurface SOC accumulation (30–100 cm) was highest under rubber (5.20), followed by coffee (4.41) and mango (4.12 t CO_2 ha^{-1} yr^{-1}). Considering the 0–100 cm profile, the estimated soil-C value ranged from USD 92.72 to 248.40 ha^{-1} yr^{-1} under the assumed carbon-price scenario. Biomass C sequestration was highest under rubber AF (11.82 t CO_2 ha^{-1} yr^{-1}), followed by coffee (4.53) and mango (3.77 t CO_2 ha^{-1} yr^{-1}), corresponding to USD 74.60–234.18 ha^{-1} yr^{-1}. Integration of soil and biomass C resulted in the highest estimated carbon-finance potential under rubber AF (USD 415.5 ha^{-1} yr^{-1}; ~₹39,474 ha^{-1} yr^{-1}), followed by coffee (~₹32,138 ha^{-1} yr^{-1}) and mango (USD 167.3 ha^{-1} yr^{-1}; ~₹15,898 ha^{-1} yr^{-1}). These values represent potential carbon revenue under the assumed price and accounting framework, rather than guaranteed credit income, as actual issuance depends on additionality, baseline, permanence, uncertainty and robust MRV (Kumar et al., 2024; Gokhale and Singh, 2025).

The economic significance of these C gains is particularly important because agroforestry can involve a production trade-off relative to monoculture. Excessive shade or

sub-optimal tree density can reduce crop yields through competition for light, water and nutrients, as reported for shaded coffee systems (Schnabel et al., 2018; Mokondoko et al., 2022; Cornelius et al., 2024). Thus, agroforestry should not simply replace monoculture, but should be designed to balance crop productivity with biomass production, SOC accumulation and ecosystem services. This trade-off is especially relevant in the Western Ghats, where plantation expansion has contributed to substantial land-use transformation, while rubber monoculture has also been associated with declining soil quality and C storage (Gaucherel et al., 2017; Karthika et al., 2022; Saha et al., 2025). Carbon finance therefore offers a mechanism to partially compensate farmers for potential production trade-offs by creating an additional income stream from climate mitigation while maintaining agricultural production. In this context, the contrasting performance of the studied systems is particularly relevant: coffee AF showed the strongest surface-SOC recovery, whereas rubber AF combined substantial deep-soil C storage with the highest biomass accumulation and overall carbon-finance potential. Rather than promoting a universal shift from monoculture, our findings support economically optimized agroforestry in which crop yield, tree density and C sequestration are jointly managed. With appropriate carbon accounting, farmer-oriented MRV and equitable benefit sharing, carbon finance represents a substantial opportunity to make climate-smart agroforestry economically attractive to farming communities.

Conclusion:

This study demonstrated the potential of forest and agroforestry systems, coffee, rubber, and mango, to improve soil quality and enhance carbon storage compared with continuous sole cropping in the Western Ghats of Karnataka. Forest recorded the benchmark soil quality and total carbon stocks, followed by coffee, rubber, mango, and sole-cropping systems. Among the agroforestry systems, coffee showed the greatest surface SOC accumulation, whereas rubber exhibited the highest biomass carbon accumulation and greater carbon storage in deeper soil layers. The combined contribution of soil and biomass carbon resulted in substantial indicative carbon-finance potential, with rubber showing the highest overall value, followed by coffee and mango. These economic benefits highlight the potential of agroforestry to generate additional income from carbon financing while simultaneously improving soil quality and supporting climate-change mitigation. However, the relatively small sample size, observational design, and absence of repeated temporal measurements limit direct attribution of carbon accumulation to agroforestry management. The estimated carbon values should therefore be interpreted as indicative rather than verified carbon credits.

Future research should expand sampling across comparable agro-climatic regions, establish long-term monitoring of soil and biomass carbon, and integrate robust carbon-accounting frameworks to quantify creditable removals and optimize agroforestry management for both productivity and carbon income.

Declarations:

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

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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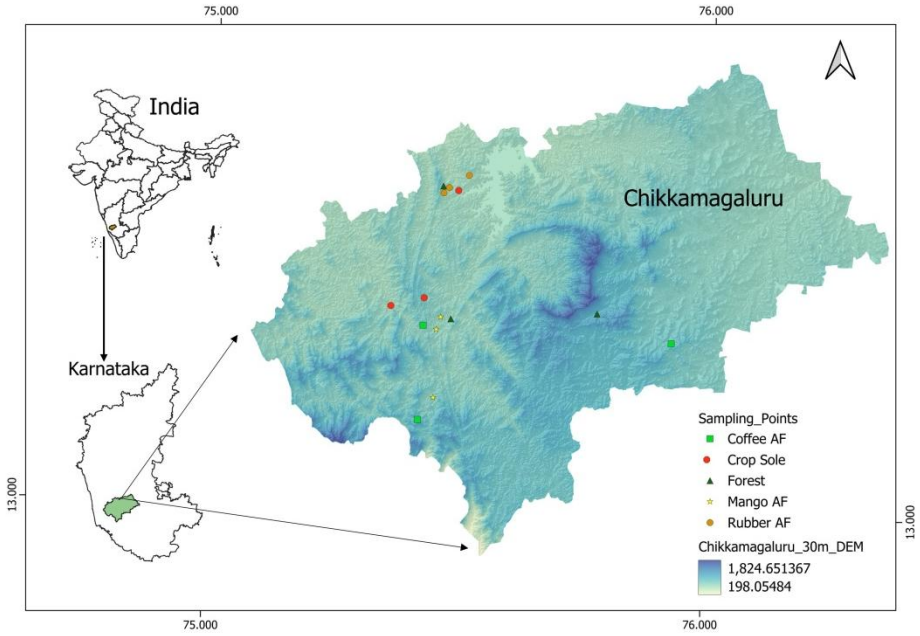
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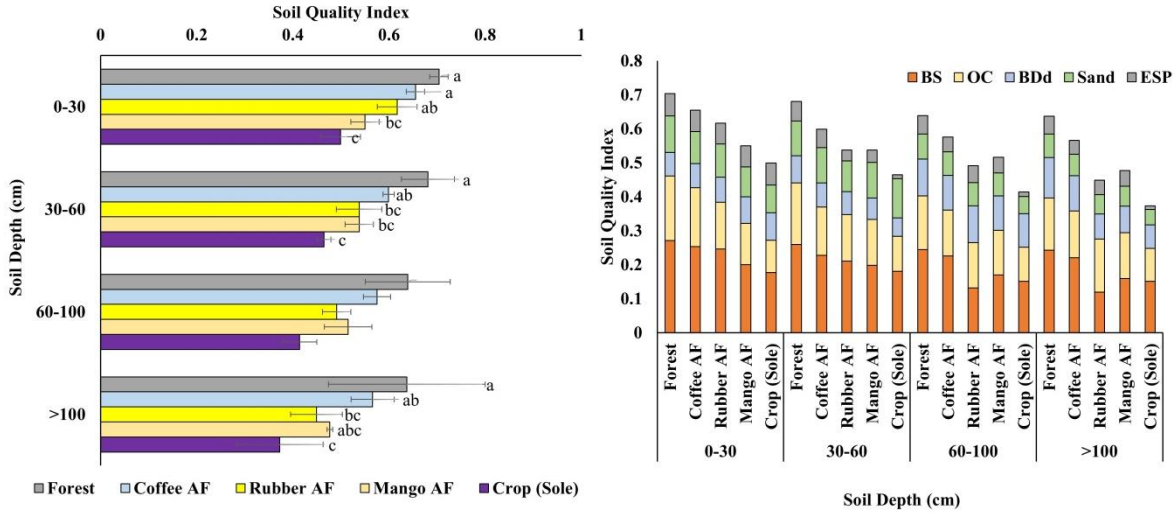
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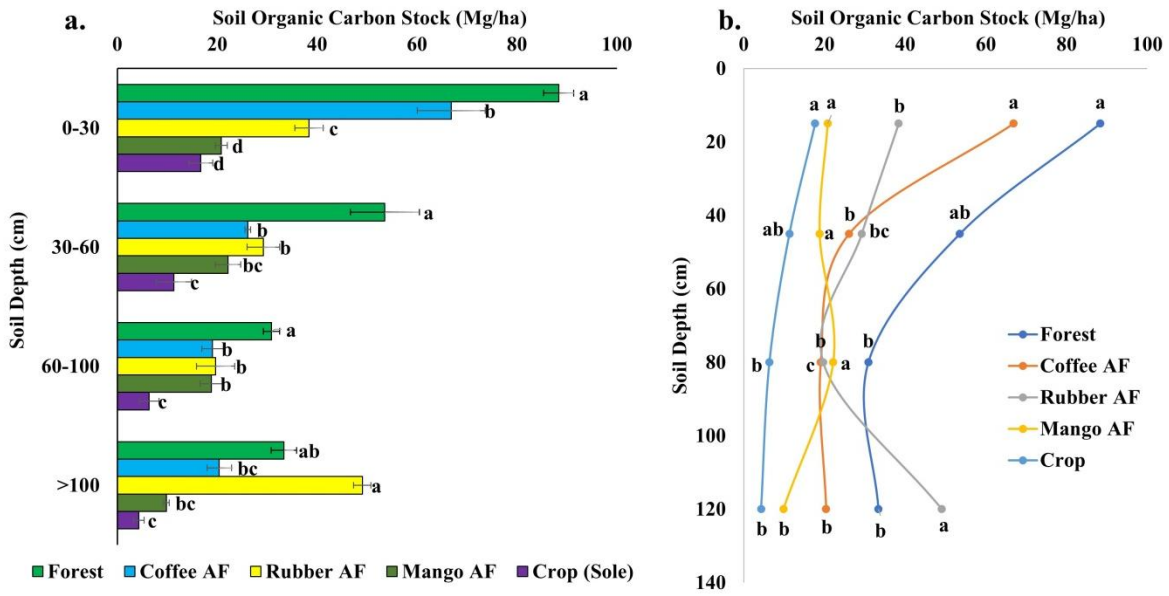


705

706 Fig.1. Location map of different study sites. forest, coffee AF (agroforestry), rubber AF,
707 mango AF and filed crop under Chikkamagaluru district of Karnataka state, India.

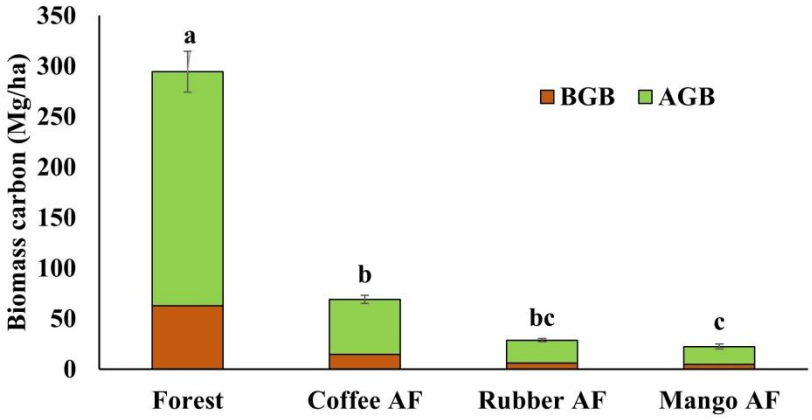


708
709 Fig 2: Vertical distribution of (a) Soil quality index (SQI) and (b) soil properties selected
710 through minimum data set (MDS) under different land use systems (LUS). Here, BS: Base
711 saturation; OC: organic carbon; BDd: dry bulk density; ESP: Exchangeable sodium
712 percentage. Data are expressed as the mean of LUSs and depth points with different
713 lowercase letters indicate significant differences among the LUSs ($p < 0.05$; the tested method
714 was one-way analysis of variance (ANOVA, $p < 0.05$) followed by Duncan's Multiple Range
715 Test test.). Study sites are forest, Coffee AF (agroforestry), rubber AF, mango AF and filed
716 crop.



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718 Fig 3: (a) Soil organic carbon stock (SOCs) under different land use systems (LUS) and (b)
719 SOC distribution under different LUSs at varied soil depth function. Data are expressed as
720 the mean and bars with different lowercase letters indicate significant differences among the
721 LUTs ($p < 0.05$). Study sites are forest, Coffee AF (agroforestry), rubber AF, mango AF and
722 filed crop.



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724 Fig 4: Biomass carbon stock (SOCs) under different land use systems (LUSs). AGB: Above
725 ground biomass carbon and BGB: below ground biomass carbon. Data are expressed as the
726 mean and bars with different lowercase letters indicate significant differences among the
727 LUTs ($p < 0.05$). Study sites are forest, Coffee AF (agroforestry), rubber AF and mango AF.

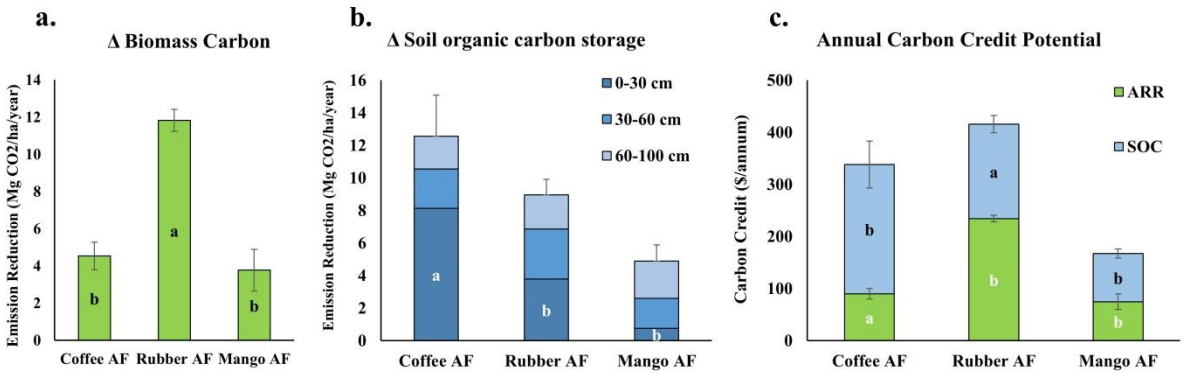


Fig 5: (a) Annual biomass carbon increment (b) annual soil carbon increment and (c) Carbon credit potential under agroforestry (AF) systems. ARR indicates the credit generated through afforestation of shade trees and SOC indicates credit generated through soil organic carbon increment. Data are expressed as the mean and bars with different lowercase letters indicate significant differences among the LUTs ($p < 0.05$). Study sites are Coffee AF (agroforestry), rubber AF and mango AF.

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751 Supplementary Table 1: : Principal components, eigenvalues and component matrix variables

Soil parameter	PC1	PC2	PC3	PC4	PC5
Eigenvalue	7.88	4.42	4.1	2.48	2.04
% variance	27.17	15.24	14.14	8.55	7.03
Cumulative variance	27.17	42.41	56.55	65.1	72.13
Weight factor	0.377	0.211	0.196	0.119	0.098
Sand	0.2	0.03	**0.86***	-0.06	0.16
Silt	-0.15	-0.17	-0.21	0.2	0.25
Clay	-0.15	0.05	**-0.85**	-0.05	-0.31
Gravel	0.05	0.21	-0.57	0.49	0.04
BDw	0.05	-0.07	-0.13	**0.9***	0.06
BDd	0.13	-0.14	-0.06	**0.87**	-0.02
pH W	**0.83**	0.14	0.17	0.16	-0.18
pH $CaCl_2$	**0.88**	0.09	-0.03	0.18	0.12
pH KCl	**0.83**	0.01	-0.19	0.19	0.11
EC	0.01	-0.32	-0.58	-0.2	0.32
OC	0.1	**0.9***	0.26	-0.11	0.23
TOC	0.07	0.87	0.13	-0.14	0.18
Ca	0.71	0.5	0.27	-0.12	-0.1
Mg	0.64	0.36	0.48	0.03	-0.05
Na	0.23	0.51	0.2	0.05	0.75
K	0.45	0.19	-0.05	0	0.16
Total exchangeable cation	0.73	0.72	0.49	0.33	-0.08
$BaCl_2$ Acidity	0.14	0.12	0.75	-0.29	0.04
Ex H	-0.49	-0.18	0.31	0.37	0.04
Ex Al	-0.78	0.11	-0.12	-0.15	-0.12
CEC	0.31	**0.87**	-0.04	-0.15	-0.03
BS	**0.88***	0.16	0.37	-0.06	0.02
Al Saturation	**-0.82**	-0.06	-0.08	-0.02	0.04
CEC:Clay	0.37	0.51	0.65	-0.06	-0.08
Ca:Mg	-0.07	0.09	-0.25	-0.42	-0.42
ECP	**0.86**	0.16	0.27	-0.12	-0.12
EMP	0.65	0.13	0.49	0.08	-0.05
ESP	0.14	0.12	0.22	-0.04	**0.92***

752 Boldface factor loadings are considered highly weighted (weighted when within 10% of
753 variation of the highest factor loading in each factor).
754 Bold-stared soil attributes correspond to the indicators included in the MDS

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