Modeling Soil Organic Carbon (SOC) in Southeast Asia: Methods and Climate Implications

Abstract: Soil organic carbon (SOC) is critical for ecosystem resilience and food security. Yet it varies in Southeast Asia, attributed to climate and land management. This study analyzes 2699 SOC values (g/kg) across nine countries and three depth classes: topsoil (0-30 cm), midsoil (30-60 cm), and deepsoil (60+ cm) to understand the drivers. We apply a complementary framework: Random Forest (RF) identifies dominant predictors, Linear Mixed-Effects Models (LMM) quantify the magnitude of their effects, and Structural Equation Model (SEM) evaluates direct and indirect pathways linking climate, management, and SOC. Across all models, precipitation and temperature is the dominant predictor of SOC. Only fertilization had a significant positive association with topsoil SOC. Land-use differences in topsoil SOC were not distinguishable once regional climate was controlled for. Tillage shows no significant association with SOC at any depth. This paper shows novelty in a convergent depth-stratified framework to an understudied region.

1. Introduction

Soils store more carbon than the atmosphere and terrestrial vegetation combined, making soil organic carbon (SOC) a central lever in global climate mitigation strategies (Gross & Harrison, 2019). Yet the capacity of soils to accumulate or lose carbon is not uniform. It depends critically on interactions between climate and land management that vary across landscapes, soil depths, and regions. In Southeast Asia (SEA), this challenge is particularly pressing: the region encompasses some of the world's most intensive and diverse agricultural systems, from paddy rice in Thailand to agroforestry in Indonesia, managed by over 100 million smallholder farmers (Tiemann & Douxchamp, 2023). Despite its scale and global significance for food security and carbon sequestration, SEA remains systematically underrepresented in global SOC databases and modeling studies (Chiew, 2024). This study addresses that gap directly: we ask which climate and management variables most strongly explain SOC concentration across SEA's agroecosystems, whether those effects are consistent across soil depths, and whether climate influences management practices in ways that complicate simple attributions of SOC change to land use.

1.1. Literature Review and Knowledge Gap

1.1.1. Soil organic carbon and the agricultural systems in Southeast Asia

Soil organic carbon is the largest terrestrial carbon pool and a key regulator of agricultural productivity, greenhouse gas emissions, and ecosystem resilience (Veldkamp et al., 2020). In tropical and subtropical systems like those of SEA, SOC dynamics are shaped by intense primary productivity, high decomposition rates under warm and wet conditions, and frequent agricultural disturbance.

Agricultural intensification across SEA has reduced SOC stocks through expansion of monocropping, reduction in fallows, heavy tillage, and reliance on synthetic inputs (Kartini et al., 2024; Hu et al., 2021). A key but underappreciated complexity is that the dominant controls on SOC change with depth. Surface horizons are biologically active and responsive to current management, while deeper horizons reflect the integration of climate and land-use legacies over decades to centuries (Gross & Harrison, 2019; Rocci et al., 2021). Most published SEA studies restrict SOC sampling to 0–30 cm layer, leaving deeper carbon dynamics poorly characterized.

Global evidence consistently identifies mean annual precipitation and temperature as dominant controls on SOC patterns. Zhou et al. (2019) found that precipitation positively predicted SOC in North and Northeast China, while temperature effects were depth-dependent: positive at the surface (through productivity enhancement) and negative at depth (through decomposition and leaching). Adhikari et al. (2018) confirmed similar patterns in temperate systems. Whether these relationships hold in the distinct climatic context of tropical SEA, where precipitation is monsoonal, temperatures are consistently high, and seasonal variability is driven more by rainfall than temperature, remains an open empirical question.

1.1.2. Methods for SOC attribution: Prediction and Causal Inference.

Two methodological traditions have dominated SOC driver research. Machine learning approaches, including Random Forest (RF), are powerful for identifying dominant predictors and capturing nonlinear interactions without distributional assumptions (Zhang et al., 2022; Pavlovic et al., 2024). However, high variable importance in RF does not distinguish direct effects from confounding: a land-use predictor may rank highly simply because land-use types cluster in climatically distinct locations rather than because management itself drives SOC change.

Linear mixed-effects models (LMMs) address part of this limitation by estimating fixed-effect slopes while explicitly controlling for hierarchical random structure (country, year). Yet LMMs treat predictors as independent and cannot represent the causal structure from climate to management to SOC. Piecewise structural equation modeling (piecewiseSEM; Lefcheck, 2016) extends this by fitting locally-estimated mixed-effects sub-models that simultaneously represent direct and indirect pathways. Liu et al (2025) demonstrated pircewiseSEM's utility for formalizing climate-management-SOC pathway analysis in China; Maaz et al. (2023) showed its advantages over additive scoring for soil health attribution. Neither study applied this framework to Southeast Asia. The critical gap this study fills is combining all three methods in a depth-stratified convergent framework, where each method's conclusions validate or complicate the others.

1.2. Research questions

This study addressed three interrelated research questions, each targeting a specific inferential limitation in the existing research:

1. Which climate and management variables are most strongly associated with SOC concentration across the region, and how do their relative differences differ by depth? We hypothesize that precipitation will be the dominant predictor of topsoil SOC, while temperature will become the primary associated factor at greater depths, consistent with depth-dependent decomposition dynamics.
2. What are the direction, magnitude, and statistical significance of associations between SOC and land-use type (annual, perennial, agroforestry), fertilization, and tillage, after accounting for climate, country, and year-level random variation? We hypothesize that agroforestry will show higher climate-adjusted SOC than annual cropping systems, given the greater structural diversity and continuous organic inputs of tree-based systems. We further hypothesize that fertilization will show a positive association with topsoil SOC. For tillage, the evidence in the literature is equivocal (Haddaway et al., 2017), and the binary encoding of tillage in this dataset precludes testing the intensity effects; we make no directional prediction.
3. Do climate variables (temperature, precipitation) show direct associations with SOC, or are there also indirect associations mediated through fertilization or tillage intensity? We hypothesize that climate-SOC associations are predominantly direct. Because fertilization decisions reflect agronomic need rather than climate, we do not expect strong climate-management covariation in this dataset. Any indirect pathway patterns would be treated as exploratory findings requiring confirmation with larger depth-specific samples.

We analyze the regional SOC dataset of Gomez et al. (2024), covering nine SEA countries from 1987 to 2023, with land-use type, binary fertilization and tillage indicators, and mean annual temperature and precipitation from CHELSA v2.1 as predictors. Section 2 describes data preparation and analytical methods. Section 3 reports results by depth levels and management variables. Section 4 interprets findings in relation to hypotheses, prior literature, and implications for SEA soil carbon policy.

2. Methods

2.1. Data Source and Overview

The soil organic carbon dataset (Gomez et al. 2024; Figshare: doi: 10.6084/m9.figshare.23736891) aggregates observations from 209 peer-reviewed articles, comprising 4341 observations on soils of cropping systems in Southeast Asia (Figure 1) from articles published between 1987 and 2023. The primary management descriptors are land use (annual, perennial, agroforestry) and intervention type (Fertilization, Tillage). Intervention variables were encoded as binary indicators (1=with treatment, 0=without treatment).

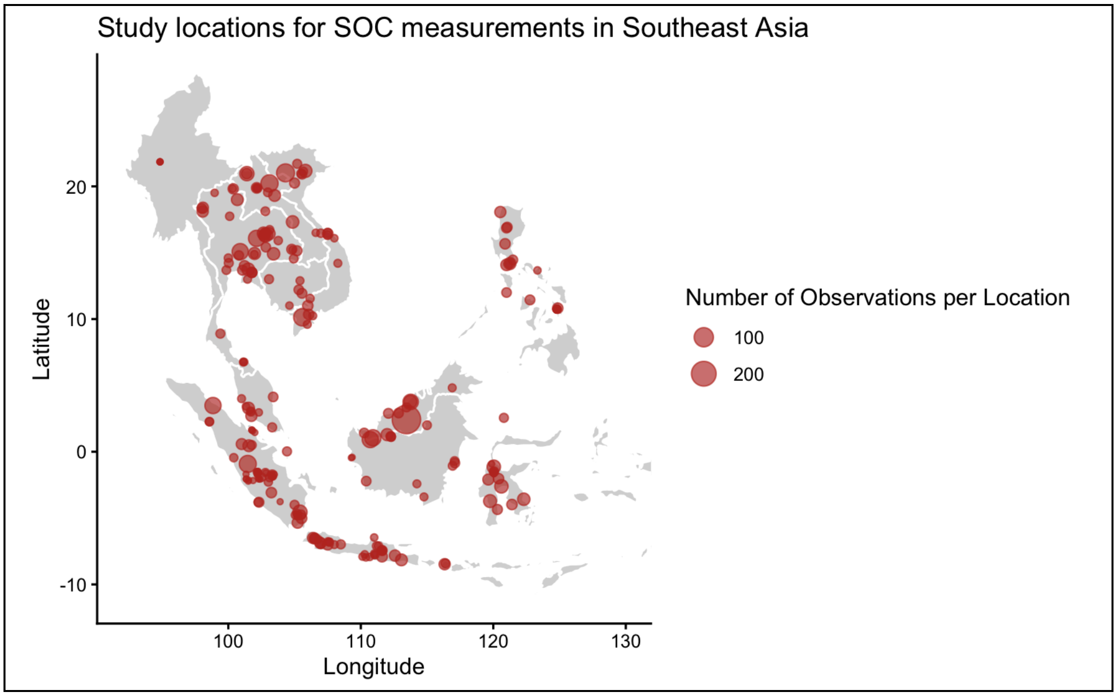

Figure 1: Maps of the studied location for SOC measurements in Southeast Asia

2.2. Data Preparation and Inclusion Criteria

Observations were retained if they (1) reported at least one SOC measurement with identifiable depth information; (2) included at least one management descriptor, and (3) were georeferenced by country or coordinate. Variables with more than 50% missing values were excluded. After removing rows with extensive missing data across key predictors, 2699 observations were available for analysis. All data preparation was conducted in R (version 4.4.0; R Core Team, 2024).

Mean annual precipitation (bio12, mm) and mean annual temperature (bio1, °C) were appended to all observations using CHELSA v2.1 climatologies (1981–2010) and site coordinates (Karger et al., 2021). Because CHELSA represents long-term climatological averages rather than year-of-measurement conditions, these variables capture site-level climatic context rather than inter-annual variability.

SOC concentrations reported in diverse units were harmonized to g/kg (concentration), the focus of this analysis (approximately 62% of observations). Because SOC data were strongly right-skewed (raw g/kg: min = 0.30, median = 16.7, mean = 88.6, max = 960.0), log-transformation was applied before all modeling (Table 1).

Unit	Min	Median	Mean	Max
g/kg	0.3014	16.7	88.55	960
Log g/kg	-1.199	2.815	3.039	6.867
mg/ha	2.72	21.42	32.79	245.41
Log mg/ha	1.001	3.064	3.176	5.503

Table 1. Summary of reported and log-transformed SOC values.

Depth observations were classified into three levels based on the midpoint of the reported depth range: topsoil (0–30 cm; 71.5% of observations, n = 1935), midsoil (30–60 cm; 13%, n = 351), and deepsoil (60+ cm; 15.5%, n = 423). The midpoint was computed as (lower bound + upper bound) / 2. A one-way ANOVA confirmed that depth class has a significant effect on log-SOC [$F(2, 2696) = 239.6$, $p < 0.001$], with shallower levels exhibiting higher SOC concentrations. All models were subsequently run separately for each depth level.

2.3. Analytical Framework

This study employs a sequential three-model framework, as each model answer one research question. All models are depth-stratified, treating each depth level as an independent analytical unit.

2.3.1. Random Forest

Random Forest (RF) is an ensemble method that fits many regression trees on bootstrap samples and aggregates predictions. It captures nonlinear relationships and predictor interactions without distributional assumptions. Variable importance was quantified using permutation-based %IncMSE (percent increase in mean squared error upon variable permutation), which measures predictive degradation when each predictor is excluded. A higher %IncMSE indicates greater importance. Separate RF models were fit for each depth class using temperature, precipitation, and the management category variable as predictors of log-SOC. Model fit was assessed using R-squared and root mean squared error (RMSE). Models were implemented with the randomForest package in R (Liaw & Wiener, 2002) with ntree = 500 and set.seed(123) for reproducibility.

2.3.2. Linear Mixed-Effects Model (Estimation)

Linear Mixed-Effects Model (LMM) estimates the direction, magnitude, and significance of fixed-effect predictors while controlling for spatial and temporal clustering. Country and sampling year were included as crossed random intercepts, accounting for non-independence among observations from the same country. The model is structured as:

$$\log(\mathrm{SOC}_i) = \beta_0 + \beta_1 \mathbf{LandManagement}_i + \beta_2 \mathbf{Temp}_i + \beta_3 \mathbf{Precip}_i + u_{\mathrm{country}[i]} + v_{\mathrm{year}[i]} + \varepsilon_i$$

Where β_0 is the fixed intercept; β_1,β_2,β_3 are fixed-effect coefficients for Land Management (fertilization, tillage, agroforestry, annual, perennial), Temperature, and Precipitation, u and v are country and year random intercepts.

Agroforestry was the reference category for land-use comparisons with annual and perennial crops. Models were fit using the lme4 package (Bates et al., 2015). Effect sizes are reported as log-scale coefficients with 95% confidence intervals. R-squared was computed using the MuMIn package (Barton, 2024).

2.3.3. Piecewise Structural Equation Modeling (Pathway Analysis)

Piecewise SEM (piecewiseSEM; Lefcheck, 2016) was used to test direct and indirect pathways between climate, management, and SOC. Unlike global SEM, piecewiseSEM fits locally-estimated sub-models, preserving the mixed-effects structure of a Linear Mixed-Effect Model while simultaneously estimating pathway coefficients. We specified two pathway models: (1) a fertilization model, where fertilization intensity (binary: 1 = with, 0 = without) was the mediating variable and climate variables were upstream predictors; and (2) a tillage model with the same structure. All SEM sub-models included country as a random intercept. SEM sub-models include country as a random effect, excluding year because year was not a significant source of variance in the sub-model outcome variables (fertilization intensity, tillage intensity); the full country + year structure is maintained in the standalone LMMs.

Path coefficients are reported as standardized estimates. Because land-use categories (Annual, Perennial, Agroforestry) are nominal factors that cannot serve as response variables in the SEM framework, their climate-adjusted associations with SOC were estimated separately using Estimated Marginal Means (EMMs) from the fitted LMMs, holding temperature and precipitation at their dataset means (emmeans package; Lenth, 2024). Tillage models at 60+ cm were not fit due to insufficient cases (n = 2 with tillage). A minimum of 100–200 cases per model and 5–10 observations per parameter were required for analysis following Lefcheck (2016).

All pathway associations in the SEM framework are observational and reflect co-variation in this cross-sectional dataset. The term "indirect pathway" refers to a statistical association pattern (climate co-varies with management, which in turn co-varies with SOC) and should not be interpreted as established causal mediation without experimental support.

Management Variables	Depth 0-30 cm	Depth 30-60 cm	Depth 60+ cm
Fertilization: with/without	733/207	86/19	64/8
Tillage: with/without	36/49	10/16	2/8 (excluded)
Annual (land use)	754	169	229
Perennial (land use)	838	176	285
Agroforestry (land use)	196	45	52

Table 2. Observation counts by management pathway and depth class for PiecewiseSEM models. Fertilization models met the minimum case threshold at all depths. Tillage at 60+ cm was excluded (n=2 with tillage).

3. Results.

All analyses were run separately for three depth levels. A one-way ANOVA confirmed that log-SOC differed significantly across depth class (Figure 2) [$F(2,2696 = 239.6, p < 0.001$]. Topsoil exhibited the highest median log-SOC (median = 3.03 log g/kg, corresponding to approximately 20.7 g/kg); midsoil showed lower and more variable values (median = 1.91 log g/kg, approximately 6.7 g/kg); and deepsoil showed the widest interquartile range (median = 1.51 log g/kg, approximately 4.5 g/kg) (Figure 2).

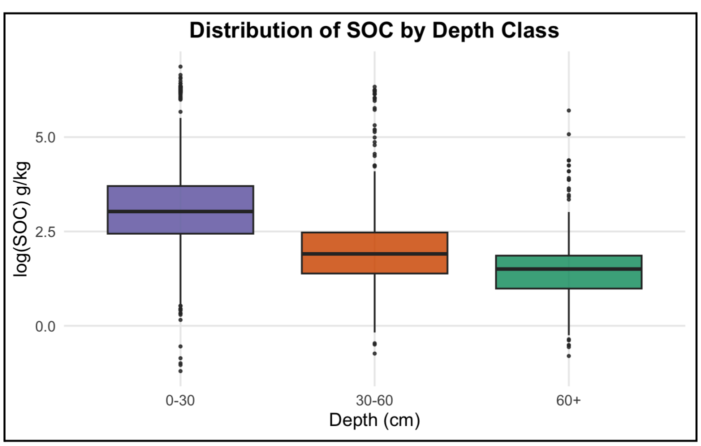

Figure 2. Boxplots of log-transformed SOC (g/kg) by depth class. Topsoil shows the highest median; deepsoil shows the widest interquartile range.

Climate coverage across the dataset spanned a precipitation range of 577–4920 mm (mean: 1,893 mm) and a temperature range of 14.6–29.3°C (mean: 25.8°C) (Figure 3). Countries with the highest observation counts were Indonesia, Thailand, and Vietnam, while East Timor and Myanmar were the least represented. Land-use observations comprised 63.7% of all records, with annual and perennial crops accounting for approximately 88% of land-use observations.

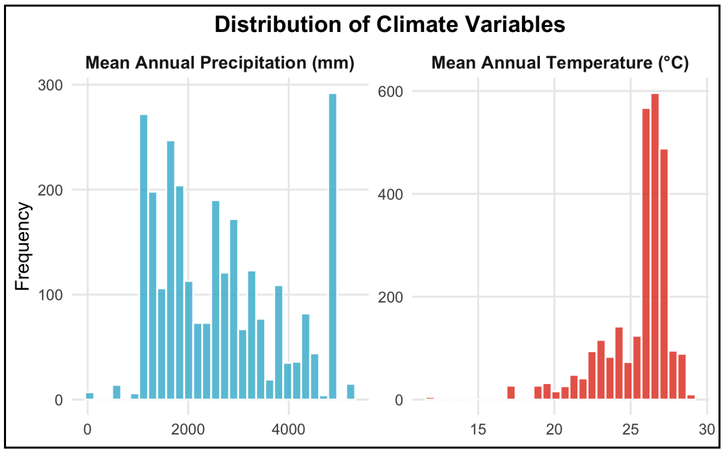

Figure 3: Distributions of mean annual precipitation (mm) and mean annual temperature (°C).

3.1. Random Forest (RF). Which environmental and management variables are most predictive of SOC concentration across the region?

Random Forest (RF) achieved a strong predictive fit across all three depths (Figure 4). Topsoil $R^2 = 0.87$ (RMSE = 0.54 log g/kg); midsoil $R^2 = 0.78$ (RMSE = 0.65 log g/kg); deepsoil $R^2 = 0.80$ (RMSE = 0.44 log g/kg). These results indicate that the selected climate and management predictors explained between 74% and 88% of SOC variability across depth levels, with topsoil showing the highest predictive accuracy.

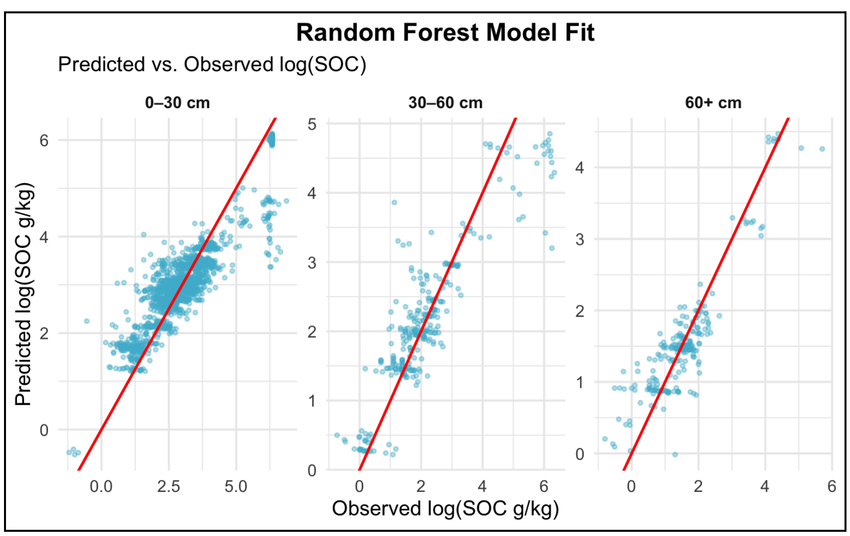

Figure 4. Random forest predicted vs. observed log SOC (g/kg) by depth class. There is a slight underprediction at extremely high values in topsoil (0-30cm).

Variable importance, as shown in Figure 5, shifted systematically with depth. At topsoil, precipitation was the strongest predictor (%IncMSE = 47), followed by the management variable (%IncMSE = 38) and temperature (%IncMSE = 36), consistent with the hypothesis that precipitation drives surface SOC via enhanced productivity and organic matter inputs. At midsoil and deepsoil, temperature and precipitation ranked approximately equally (%IncMSE is just over 40 each), with management declining to third (%IncMSE = 34 for midsoil and %IncMSE = 27 for deepsoil). This progressive shift from precipitation-dominant to temperature-dominant with depth supports Research Question 1 and is consistent with the hypothesis that thermal regulation of decomposition and carbon stabilization becomes the primary associated factor in deeper horizons.

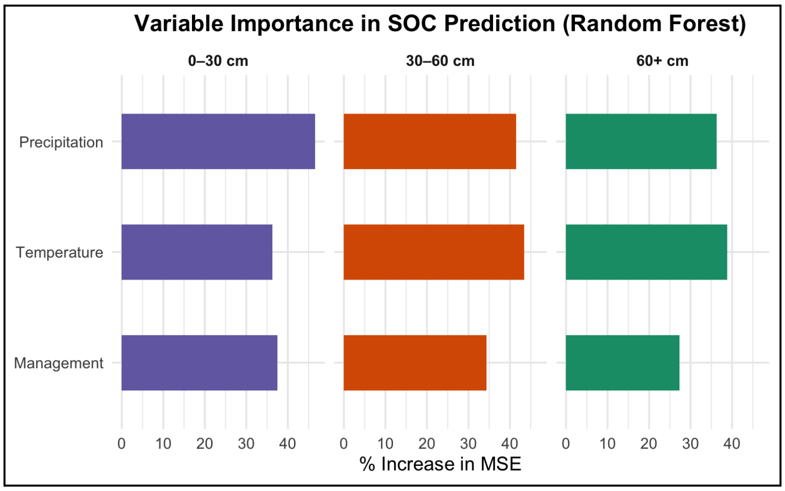

Figure 5. Variables importance (%IncMSE) by depth class.

An important structural note on the Random Forest management predictor: the variable secondary_descriptor encodes all management categories, land-use types (Annual, Perennial, Agroforestry), and intervention types (Fertilization, Tillage), as a single multi-level factor. This design is appropriate for a general ranking of broad predictor relationships (climate vs. management vs. depth), because it captures the collective predictive signal of all management variation in the dataset. However, it does not permit attribution of importance to individual management practices, nor does it separate the predictive contributions of land-use type from those of fertilization or tillage within the management category. The LMMs in Section 3.2 address this by fitting separate models for land use, fertilization, and tillage with individual fixed-effect estimates and confidence intervals.

3.2. Linear Mixed-Effect Model: What are the specific impacts of land management and climate on SOC when accounting for spatial and temporal clustering?

LMMs estimated fixed-effects associations between management and climate predictors and log-SOC at each depth, controlling for country- and year-level random variation. Random effect variance patterns differed across depth level (Figure 6). At the topsoil level, year variance (Std. Estimate = 0.316) and country variance (Std. Estimate = 0.084) were both modest, reflecting relatively consistent SOC-management patterns across the sampling period. At midsoil, year variance increased (Std. Estimate = 0.794) while country variance remained moderate (Std. Estimate = 0.259). At deepsoil, both year (Std. Estimate = 1.205) and country (Std. Estimate = 1.278) variance were large and approximately equal, indicating that deep SOC is structured strongly along both national and temporal axes. Marginal R^2 values (fixed effects only) were low across all depths: 0.027, 0.058, and 0.147 at topsoil, midsoil, and deepsoil, respectively. Conditional R^2 (including random effects) were substantially higher: 0.428, 0.577, and

0.929, confirming that country-level and year-level clustering accounts for the dominant share of SOC variance, particularly at deepsoil.

3.2.1. Topsoil (0-30cm)

Contrary to the hypothesis that agroforestry would show higher climate-adjusted SOC, neither annual nor perennial systems differed significantly from agroforestry at the topsoil. Annual systems showed no significant association (Coefficient = −0.016 log g/kg; 95% CI: −0.228 to +0.196; $p = 0.880$), and perennial systems were similarly indistinguishable from agroforestry (Coefficient = +0.003; 95% CI: −0.191 to +0.196; $p = 0.977$). This confirms that land-use type does not significantly differentiate topsoil SOC once climate and random structure are accounted for. Tillage was not significant (Coefficient = −0.027; 95% CI: −0.163 to +0.110; $p = 0.703$). Fertilization was the only significant positive management predictor (Coefficient = +0.217; 95% CI: 0.110 to 0.323; $p < 0.001$), confirming hypothesis 2 for this predictor. Among climate predictors, precipitation was positively and significantly associated with topsoil SOC (Coefficient = +0.801 in the fertilization model; Coefficient = +0.165 in the land-use model; both $p < 0.001$), while temperature was not significant in the land-use model (Coefficient = −0.034, $p = 0.234$). The marginal R^2 of 0.027 indicates that the fixed effects explain only 2.7% of topsoil SOC variance; the remaining explained variance (conditional $R^2 = 0.428$) is attributable to country- and year-level clustering.

3.2.2. Midsoil (30-60cm)

At midsoil, annual cropping systems were significantly associated with lower SOC relative to agroforestry (Coefficient = −0.972; 95% CI: −1.642 to −0.303; $p = 0.005$). Perennial systems also showed a negative association but did not reach significance (Coefficient = −0.537; 95% CI: −1.207 to +0.133; $p = 0.118$). These results provide partial support for hypothesis 2: agroforestry is associated with substantially higher subsoil carbon than annual systems, though the perennial comparison is inconclusive at this depth. Fertilization was positive (Coefficient = +0.308) but not significant ($p = 0.141$), likely reflecting limited statistical power ($n = 58$ fertilization observations at midsoil) and a singular fit warning. A singular fit indicates that the dataset has a lack of information that prevents the model to estimate all parameters precisely. Neither temperature (Coefficient = −0.008, $p = 0.933$) nor precipitation (Coefficient = +0.080, $p = 0.585$) was a significant fixed-effect predictor at midsoil in the LMM, despite both ranking highly in RF importance.

3.2.3. Deepsoil (60+ cm)

Deepsoil results diverged markedly from topsoil patterns. Both temperature and precipitation showed significant negative associations with deep SOC: temperature (Coefficient = −0.547; 95% CI: −0.694 to −0.401; $p < 0.001$) and precipitation (Coefficient = −0.452; 95% CI: −0.635 to −0.269; $p < 0.001$). This finding contrasts sharply with the positive surface associations and is the study's most ecologically significant result. At deepsoil, climate appears to drive decomposition and leaching processes that deplete rather than build subsoil carbon stocks (Gross & Harrison, 2019; Rocci et al., 2021). No management predictor reached significance: annual (Coefficient = −0.346; 95% CI: −0.702 to +0.010; $p = 0.059$), perennial (Coefficient = −0.220; $p = 0.234$), and fertilization (Coefficient = +0.394; $p = 0.093$) all had confidence intervals spanning or nearly spanning zero. The marginal R^2 of 0.147 is the highest of the three depth levels, driven almost entirely by the significant negative climate fixed effects; the conditional R^2 of 0.929 confirms that country and year clustering dominate deepsoil SOC variation.

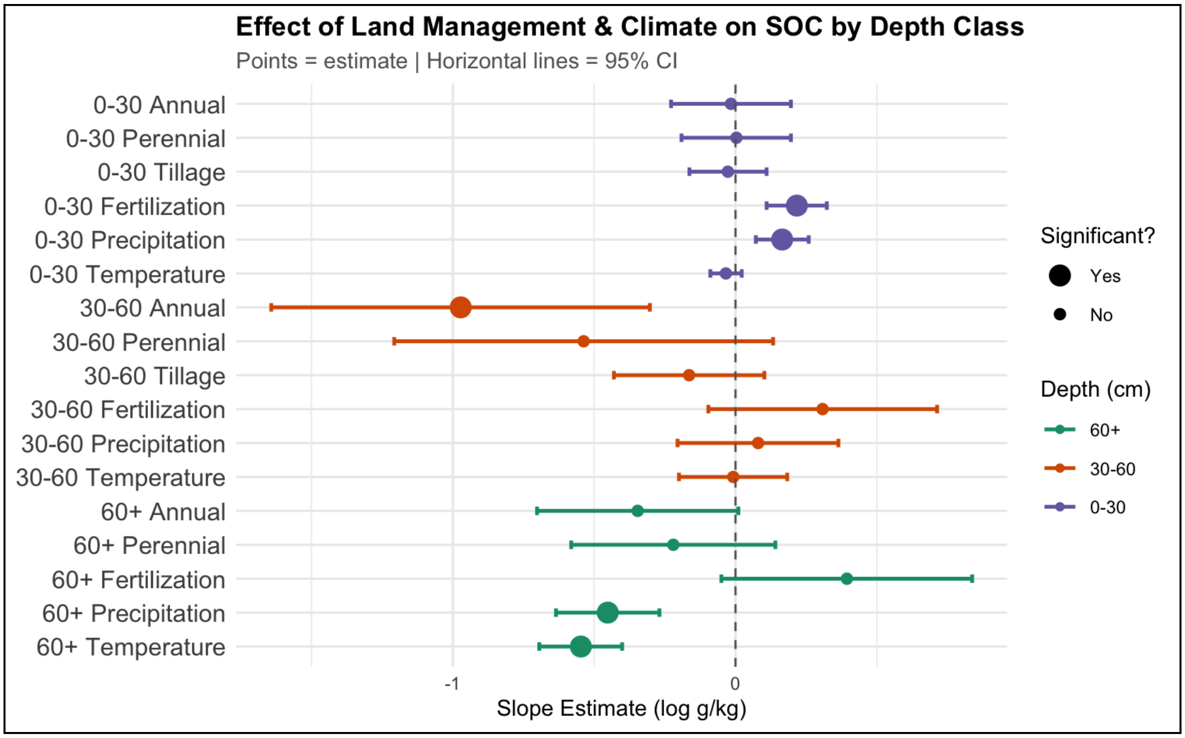

Figure 6. Effect and magnitude of temperature, precipitation, and land management (fertilization, tillage, annual and perennial vs. agroforestry) on SOC values by depth level.

3.3. Piecewise SEM: Pathway Analysis

3.3.1. Fertilization pathways

At topsoil (0–30 cm), neither temperature nor precipitation was significantly associated with fertilization intensity, indicating that climate does not co-vary meaningfully with fertilizer application in this dataset at this depth. Fertilization was significantly and positively associated with topsoil SOC, consistent with the LMM finding. Temperature and precipitation both showed direct positive associations with topsoil SOC in the SEM, with precipitation dominant.

At midsoil (30–60 cm), temperature showed a marginally non-significant negative association with fertilization intensity. Temperature and precipitation both showed strong positive associations with midsoil SOC. The non-significant [temperature → fertilization] path is noted because its direction and magnitude are consistent with hypothesis 3, but it does not constitute evidence of an indirect pathway. This pattern warrants investigation with a larger subsoil dataset.

At deepsoil (60+ cm), no significant [climate → fertilization] associations were found (temperature: $p = 0.17$; precipitation: $p = 0.3$). Fertilization's direct association with SOC was not significant, mirroring the LMM result. Temperature showed a very large standardized association with deepsoil SOC, while precipitation showed an insignificant association with SOC. The anomalously large temperature standardized estimate at deepsoil is discussed in Section 4.2.

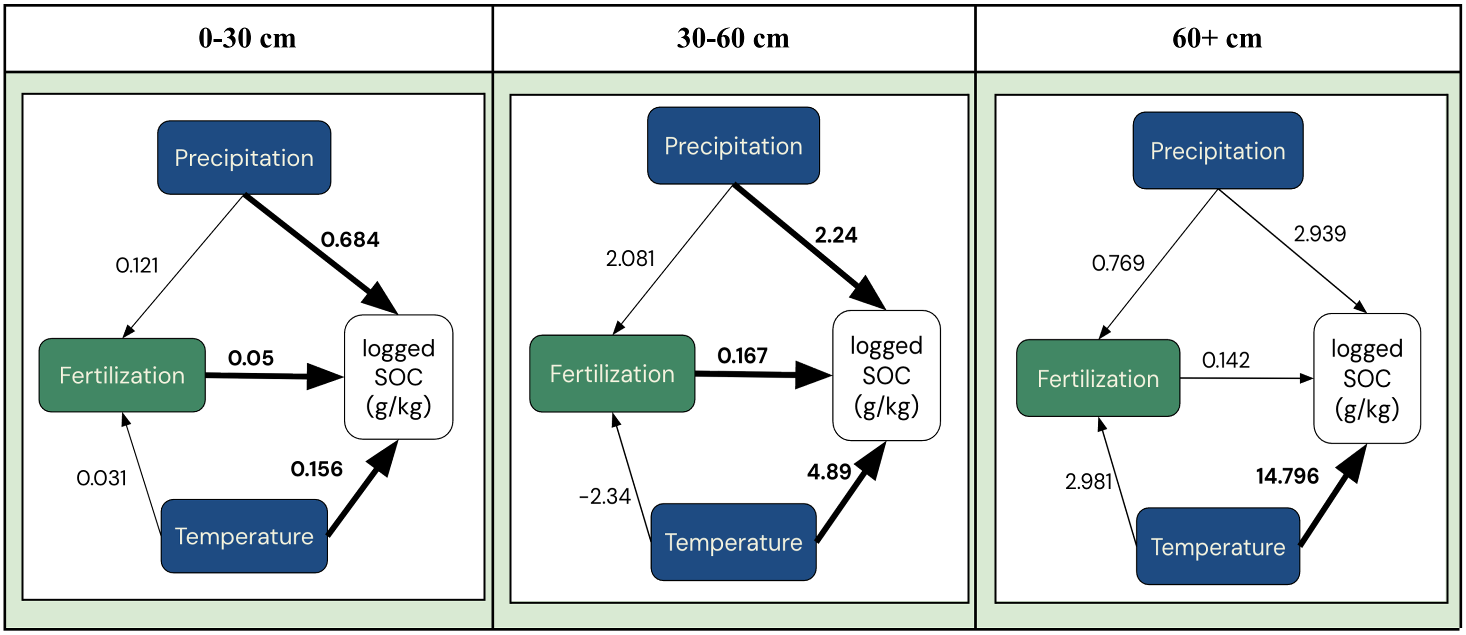

Figure 7: PiecewiseSEM path diagrams for fertilization intensity at 0-30cm, 30-60cm, 60+ cm. Thick arrows indicate significance ($p < 0.05$). Labeled numbers indicate standardized estimates

3.3.2. Tillage pathways

At the topsoil (0-30 cm), temperature showed a marginally non-significant positive effect on tillage intensity, while precipitation was significant. Tillage had no significant direct association with topsoil SOC (Figure 8). The midsoil (30-60cm) tillage SEM did not converge. With n = 10 tillage observation at midsoil, several countries contributed only one or two treated records, making the country random intercept unidentifiable under piecewiseSEM. At deepsoil (60+ cm), n=2 with tillage precluded model fitting entirely.

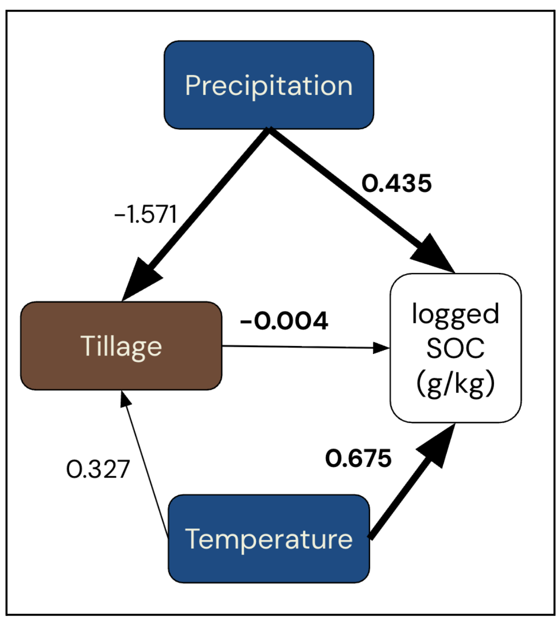

Figure 8: PiecewiseSEM path diagrams for tillage pathways at 0-30cm. The midsoil (30-60cm) (n=10) and deepsoil (60+ cm) (n=2) model did not converge due to insufficient tillage observation per country. Thick arrows indicate significance ($p < 0.05$). Labeled numbers indicate standardized estimates.

3.3.3. Land-use associations with Estimated Marginal Means (EMMs)

Climate-adjusted SOC values for each land-use type were estimated via EMMs from the depth-specific LMMs, holding temperature and precipitation at dataset means (Figure 9). At topsoil (0–30 cm), EMMs were nearly identical across land-use types: Agroforestry (emmean = 3.03 log g/kg; equivalent to 20.7 g/kg), Annual (emmean = 3.01; equivalent to 20.3 g/kg), and Perennial (emmean = 3.03; equivalent to 20.7 g/kg). The overall test across land-use types was not significant ($p = 0.8$), indicating that once regional climate variation is controlled, land-use type does not detectably differentiate topsoil SOC at this spatial scale. This refutes hypothesis 2 that agroforestry would show higher climate-adjusted topsoil SOC, and is one of the study's most consequential findings for regional land-use policy.

At midsoil (30–60 cm), a separation emerged: Agroforestry showed the highest climate-adjusted SOC (emmean = 3.15 log g/kg; equivalent to 23.3 g/kg), followed by Perennial (emmean = 2.61; equivalent to 13.6 g/kg) and Annual (emmean = 2.17; equivalent to 8.8 g/kg). This ordering is directionally consistent with tree-based systems providing deeper root carbon inputs and reduced mechanical disturbance at intermediate depths (Yadav et al., 2021), though wide confidence intervals due to small agroforestry sample sizes ($n = 45$ at midsoil) limit formal inference. At deepsoil (60+ cm), EMMs converged: Agroforestry (emmean = 1.89; equivalent to 6.6 g/kg) > Perennial (emmean = 1.67; equivalent to 5.3 g/kg) > Annual (1.55; equivalent to 4.7 g/kg), with fully overlapping confidence intervals. The convergence of EMMs at deepsoil, combined with non-significant management fixed effects at this depth (Section 3.2.3), confirms that land-use type does not detectably differentiate deep SOC in this dataset.

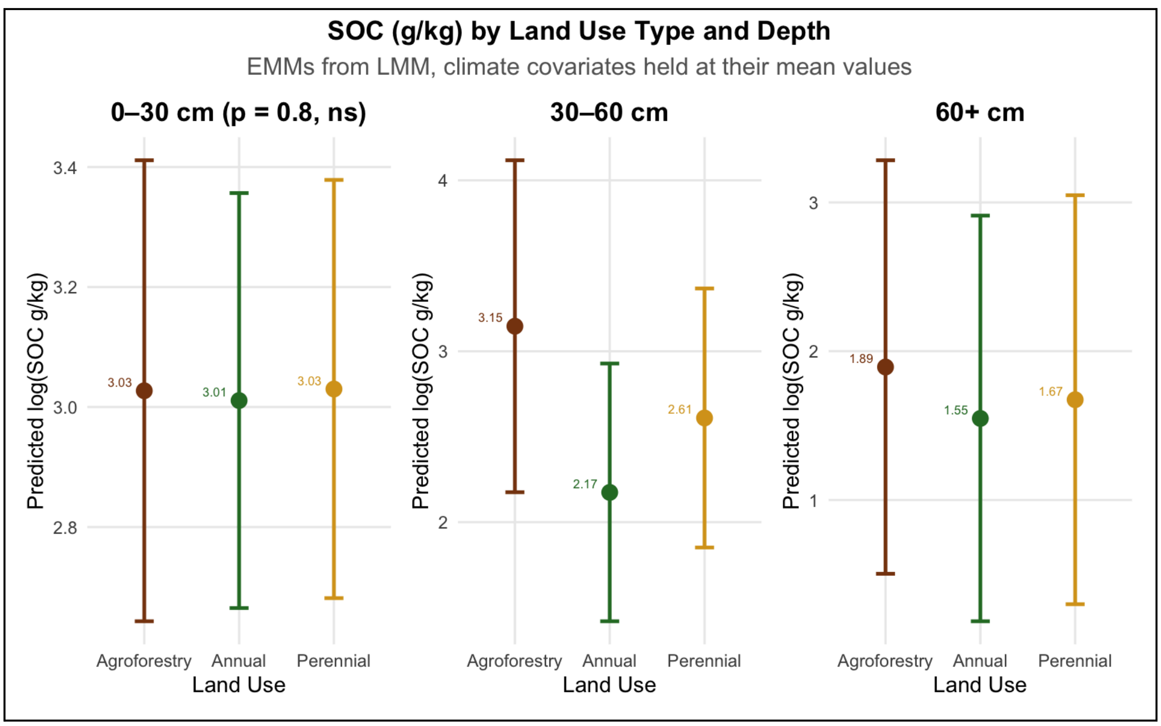

Figure 9. EMMs for land-use types at 0-30cm, 30-60cm, and 60+ cm.

4. Discussion

This study evaluated associations between climate (temperature, precipitation) and management variables (land-use type, fertilization, tillage), and soil organic carbon (SOC) concentration across three soil depth levels in Southeast Asia. Three principal findings emerge from the corrected model outputs. First, precipitation is the dominant positive climate predictor at topsoil. In contrast, at deepsoil both temperature and precipitation show significant negative associations with SOC. This directional reversal constitutes the study's most ecologically important result and aligns with the depth-dependent decomposition patterns described by Zhou et al. (2019) and Gross & Harrison (2019). Second, land-use type does not significantly differentiate topsoil or deepsoil SOC in LMM or the EMM analysis; at midsoil, only annual systems show a significant negative association relative to agroforestry. Third, fertilization is the only management practice with a significant positive association with SOC, while tillage shows no significant association at any depth.

4.1. Convergence of Models

The methods converge on precipitation as the dominant positive predictor of topsoil SOC: RF ranks precipitation highest (%IncMSE = 47), the fertilization LMM confirms a strong positive precipitation effect, and piecewiseSEM identifies precipitation as the largest direct pathway to topsoil SOC. Temperature also shows a significant positive direct association in the fertilization SEM, though this is not replicated in the land-use LMM. As noted in Section 3.2.1, this divergence reflects subsample heterogeneity: the fertilization subsample captures climatically distinct sites where temperature and SOC co-vary positively. The safest cross-model summary is that precipitation robustly and positively predicts topsoil SOC across all specifications, consistent with prior evidence that rainfall drives surface SOC through enhanced primary productivity and reduced decomposition in tropical systems (Zhou et al., 2019; Adhikari et al., 2018). This directly answers the motivation laid out in the Introduction: of the climatic variables that drive SOC in tropical SEA, precipitation, not temperature, dominates at the surface.

The most important methodological finding is the mutual confirmation between Linear Mixed-Model (LMM) and Estimated Marginal Means (EMM) results at the topsoil. In both analyses, land-use type does not significantly differentiate topsoil SOC. The EMM analysis independently confirms this: climate-adjusted means cluster near 2.92–2.98 log g/kg across all three land-use types with no significance. This dual confirmation rules out the possibility that the EMM null result was an artifact of climate adjustment; the unadjusted LMM also finds no significant land-use effect. This finding speaks directly to a concern raised in Section 1.1.2: prior site-level studies (Yadav et al., 2021; Udomkun et al., 2025) documented SOC advantages for agroforestry, but those comparisons rarely controlled for the climatic gradients that co-determine both land-use placement and SOC.

4.2. Depth-dependent dynamics

The depth-stratified design reveals a three-tier climate gradient that directly addresses the gap identified in the literature review that most Southeast Asia studies restrict sampling to 0-30 cm (Tan & Kuebbing, 2023), missing the qualitatively different dynamics at greater depths. At topsoil, precipitation is the dominant positive predictor (Coefficient = +0.165, $p < 0.001$ in the land-use model; Coefficient = +0.801, $p < 0.001$ in the fertilization model), consistent with precipitation driving productivity and organic matter inputs in this monsoonal, tropical environment. In tropical Southeast Asia, temperature may not emerge as an independent predictor of topsoil SOC once country- and year-level clustering are accounted for, consistent with the idea that SOC at this depth is often more strongly structured by land use, soil properties, and moisture than by temperature alone (Gross & Harrison, 2019; Zhou et al., 2019) At midsoil, all climate predictors lose significance in the LMM after absorbing random variation, while management legacy effects are detectable: annual systems show significantly lower midsoil SOC relative to agroforestry (Coefficient = −0.972, $p = 0.005$). Year-level variance rises from 0.316 to 0.794, reflecting the accumulation of temporally variable management inputs in the subsoil. At deepsoil, the climate signal reverses: both temperature (Coefficient = −0.547, $p < 0.001$) and precipitation (Coefficient = −0.452, $p < 0.001$) show significant negative associations with SOC. Warmer and wetter sites have lower deep SOC than cooler, drier highland sites. This is consistent with the depth-dependent decomposition mechanism described by Zhou et al. (2019) for Chinese soils by Gross & Harrison (2019) more broadly: at depth, thermal energy and dissolved organic carbon leaching driven by precipitation deplete rather than accumulate carbon, particularly in the heavily weathered Acrisoles and Ferralsols that dominate Southeast Asia (European Commission & FAO, 2023).

The directional reversal at deepsoil is robust in the Linear Mixed-Model, but the piecewiseSEM gives a positive temperature standardized estimate (Std.Est. = 14.8, $p < 0.05$). This is directional conflict between frameworks at deepsoil, which is a consequence of model specification. The SEM subsample for deepsoil fertilization is small (n = 30) and produced a singular fit (year variance = 0), meaning year-level structure was not captured. Without year random effects, the SEM's temperature path captures both genuine temperature associations and year-level confounds. The LMM with the full deepsoil land-use sample (n = 190) and proper country and year hierarchical structure is the appropriate estimator at this depth. The negative temperature and precipitation effects in the LMM reflect a genuine ecological pattern: in the high-temperature, high-rainfall lowland sites that dominate the deepsoil sample, accelerated decomposition and leaching reduce subsoil carbon stocks relative to the cooler, drier highland sites also present in the dataset. In short, the LMM result is trustworthy because it uses the full deepsoil sample with proper random structure. The SEM's conflicting positive estimate is an artifact of a small and structurally compromised subsample and should not be interpreted as a competing ecological signal.

4.3. Land Management: Fertilization, tillage, and land use systems

Fertilization is the only management practice with a significant positive association with SOC in this dataset, and this association is restricted to topsoil. The piecewiseSEM confirms this is a direct effect, not mediated through climate co-variation. This finding aligns with the site-level evidence from Northeast Thailand, where Oechaiyaphum et al. (2020) found organic amendments increased topsoil SOC by 16-20% and with global meta-analyses showing 20-30% increases from fertilization (Alvarez, 2025). At midsoil and deepsoil, fertilization linear mixed models (LMMs) produced singular fits, and sample sizes were small (n = 58 and n = 30, respectively), precluding reliable inference. The directional positive association remains positive, but neither is significant. These underpowered results do not constitute evidence of null effects at depth; a well-powered subsoil fertilization study remains needed.

Tillage shows no significant association with SOC at any depth. At topsoil, the piecewiseSEM does show temperature as a significant direct predictor of topsoil SOC in the tillage model and precipitation as marginally significant, but neither climate variable significantly predicted tillage intensity itself, not no direct [climate → tillage → SOC] pathway exist. No tillage effects were modeled at midsoil and deepsoil. These convergence failures are themselves informative: they confirm that the available data are insufficient to estimate a country-adjusted tillage-SOC association below 30 cm, regardless of true effect size. Any conclusions about subsoil tillage effects require datasets with substantially larger and more geographically balanced subsoil tillage representation. Across all depths, these results represent the absence of a detectable binary tillage presence/absence signal, not evidence that tillage intensity is inconsequential for soil carbon. This is consistent with Tan and Kuebbing (2023), who found that reduced tillage did not reliably increase SOC below 40cm and that results varied substantially with measurement protocol. Targeted studies with larger, geographically balanced samples with continuous tillage intensity measures are needed before any conclusions about tillage effects can be drawn from this dataset.

The depth-stratified land-use EMMs reveal two distinct patterns that together define the study's most policy-relevant finding of this study. At topsoil (0-30cm), climate-adjusted EMMs are statistically indistinguishable across land-use types. Combined with the LMM result, this confirms that at the regional cross-national scale, land-use type does not drive topsoil SOC. The literature review's idea that agroforestry produces higher SOC than annual systems (Yadav et al., 2021; Satdichanh et al., 2023), reviewed in Section 1.1.2, is not supported at the topsoil in this dataset once the climatic context is controlled. At midsoil (30–60 cm), agroforestry shows the highest climate-adjusted EMM, substantially exceeding perennial and annual systems. This depth-selective advantage of agroforestry is consistent with its tree-based root architecture providing carbon inputs below the tillage-affected layer, and is precisely where surface-only SOC measurement would miss the signal entirely. At deepsoil, EMMs converge (Agroforestry 1.89, Perennial 1.67, Annual 1.55) with fully overlapping confidence intervals, confirming that land-use type is not a detectable differentiator of deep SOC in this dataset.

4.4. Implications for climate-smart soil management in Southeast Asia

The dominance of precipitation as the leading positive driver of SOC at the surface, and its increasingly complex role at depth, has direct implications for how Southeast Asian countries should approach soil carbon management under a changing climate. As regional precipitation becomes more variable under climate projections, maintaining adequate soil moisture through water management practice - cover cropping, mulching, agroforestry canopy cover, and irrigation design - may be the highest leverage intervention for protecting surface SOC stocks. This is consistent with the regional smallholder context where Tiemann & Douxhcamp (2023) identified water management as a key constraint on SOC stability across Southeast Asia. At deepsoil, however, the negative climate associations mean that the same warm, wet lowland environments that support high surface productivity are structurally associated with depleted subsoil carbon. This creates a climate constraint on deep carbon accumulation that cannot be overcome through surface management intervention. Lowland irrigated rice systems in Indonesia, Thailand, and Vietnam may have comparatively constrained subsoil carbon accumulation because flooded conditions alter decomposition dynamics and can limit microbial mineralization rates, although the strength of this effect is system- and depth-dependent (Oechaiyaphum et al., 2020; Gomez et al., 2024).

Fertilization's consistent positive effect on SOC across depth supports investment in organic amendment programs for smallholder farmers, who represent the majority of agricultural land managers in the region (Tiemann and Douxchamp, 2023). However, the lack of significant land-use effects at the regional scale when climate is controlled suggests that land-use transitions alone, without complementary climate-adapted practices, may be insufficient to reliably increase SOC across diverse site conditions. Context-specific, locally adapted recommendations will be essential.

Finally, the finding that midsoil and deepsoil respond differently to management and climate than topsoil directly challenges the adequacy of surface-only monitoring for carbon credit programs and national SOC reporting. Most current carbon credit programs and national soil carbon inventories in Southeast Asia rely on 0-30 cm measurements. These miss the amplified management legacy associations at midsoil and the negative climate associations and deepsoil that imply systemic carbon loss in warming lowland systems. Monitoring - Report - Verify (MRV) frameworks for soil carbon should prioritize depth-stratified, standardized sampling, particularly in countries (Indonesia, Thailand, Vietnam) with the highest research density and greatest potential for scaled soil carbon management.

4.5. Limitations and future directions

Several limitations should be acknowledged. First, the dataset aggregates observations from studies with heterogeneous sampling protocols, analytical methods, and measurement years, introducing noise that may attenuate true management effects, particularly for tillage. Second, the nominal treatment of land-use categories in SEM (via EMMs rather than as structural mediators) means that indirect land-use pathways cannot be formally tested. Third, important pedological covariates, including soil texture, bulk density, and pH, were not consistently available across the dataset, limiting the ability to control for soil physical properties that independently influence SOC.

Future work should prioritize within-country sub-analyses to reduce climatic confounding of land-use comparisons, and should incorporate soil texture and bulk density as covariates wherever available. Seasonality indices and drought frequency metrics would improve on mean annual climate values as predictors. A longitudinal experiment dataset, particularly in underrepresented countries such as East Timor and Myanmar, is needed to establish temporal dynamics and causal mechanisms. Other management dimensions not captured in this dataset, including organic amendment type, crop residue management, irrigation frequency, and crop rotation complexity, warrant targeted investigation.

5. Conclusion

Using a convergent framework of Random Forest, Linear Mixed-Effects Models, and piecewise Structural Equation Modeling across three soil depth strata, this study documents systematic, depth-dependent shifts in the climate and management variables associated with SOC concentration in SEA agroecosystems. At topsoil, precipitation is the dominant positive predictor, and fertilization is the only management practice with a significant positive association with SOC. Land-use type does not significantly differentiate topsoil SOC in either the LMM or the EMM comparison. At deepsoil, both temperature and precipitation show significant negative associations, indicating that warmer and wetter lowland sites are associated with depleted subsoil carbon, the study's most ecologically important finding. Land-use type does not significantly differentiate topsoil SOC in either the LMM or EMM analysis; at midsoil, only annual systems show a significant deficit relative to agroforestry.

The depth-stratified design reveals a three-tier structure, management-responsive topsoil, management-legacy-dominated midsoil, and climate-constrained deepsoil, which is invisible in surface-only analyses. This finding has direct implications for carbon accounting: monitoring frameworks relying exclusively on 0–30 cm measurements miss both the amplified management legacy associations at midsoil and the qualitatively different climate patterns at deepsoil. As Southeast Asian countries develop soil carbon monitoring and verification frameworks for national climate commitments and emerging carbon markets, standardized, depth-stratified sampling protocols are essential. This study provides the first convergent multi-method, multi-depth analysis of SOC drivers across the region and establishes a reproducible analytical template for future large-scale observational SOC research in tropical agroecosystems.

References

Adhikari, K., et al. (2018). Assessing soil organic carbon stock of Wisconsin, USA, and its fate under future land use and climate change. Science of the Total Environment, 667, 833–845. https://doi.org/10.1016/j.scitotenv.2019.02.420

Alvarez, R. (2025). Increasing soil organic carbon by applying farm-made organic fertilizers as a function of soil depth: A global synthesis. *Science of The Total Environment*, *991*, 179933.

Aroca-Fernandez, J. M., Diez-Pastor, J. F., Latorre-Carmona, P., Elvira, V., Camps-Valls, G., Pascual, R., & Garcia-Osorio, C. (2025). A Collaborative Platform for Soil Organic Carbon Inference Based on Spatiotemporal Remote Sensing Data. *arXiv preprint arXiv:2504.13962*.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. Journal of Statistical Software, 67(1), 1–48.

Barton, K. (2024). MuMIn: Multi-model inference. R package version 1.48.4.

Carrascosa, A., Moreno, G., Cotrufo, M. F., Frade, C., Rodrigo, S., & Rolo, V. (2025). Improved management increases soil mineral-protected organic carbon storage via plant-microbial-nutrient mediation in semi-arid grasslands. *Soil*, *11*(2), 911-937.

Chiew, S. (2024). *Investigating Soil Organic Carbon Dynamics: Implications for Sustainable Agriculture and Climate Change Mitigation in Southeast Asia* (Doctoral dissertation, Murdoch University).

De Morais, C. P., McMeekin, K., & Nault, C. (2024). Scalable solution for agricultural soil organic carbon measurements using laser-induced breakdown spectroscopy. *Scientific Reports*, *14*(1), 15272.

Drexler, S. (2022). Benchmarking soil organic carbon to support agricultural carbon management: A German case study. Journal of Plant Nutrition and Soil Science. https://doi.org/10.1002/jpln.202200007

European Commission, JRC, and FAO. 2023. Soil Atlas of Asia. Publications Office of the European Union, Luxembourg. 208 pp. ISBN 978-92-79-26715-4, doi 10.2788/52319.

Gomez, C., et al. (2024). A dataset for soil organic carbon in agricultural systems for the Southeast Asia region. Scientific Data. https://doi.org/10.1038/s41597-024-03213-3

Gross, C. D., & Harrison, R. B. (2019). The case for digging deeper: soil organic carbon storage, dynamics, and controls in our changing world. *Soil Systems*, *3*(2), 28.

Haddaway, N. R., Hedlund, K., Jackson, L. E., Kätterer, T., Lugato, E., Thomsen, I. K., ... & Isberg, P. E. (2017). How does tillage intensity affect soil organic carbon? A systematic review. *Environmental Evidence*, *6*(1), 30.

Hu, W., Zhai, X., Du, S., & Zhang, X. (2021). Impacts of slope and longitudinal ridge on soil organic carbon dynamics in the typical Mollisols sloping farmland (China). *Eurasian Soil Science*, *54*(6), 951-963.

Karger, D. N., Conrad, O., Böhner, J., Kawohl, T., Kreft, H., Soria-Auza, R. W., Zimmermann, N. E., Linder, H. P., Kessler, M. (2021). Climatologies at high resolution for the Earth's land surface areas. EnviDat. https://www.doi.org/10.16904/envidat.228.

Kartini, N. L., Saifulloh, M., Trigunasih, N. M., Sukmawati, N. M. S., & Mega, I. (2024). Impact of long-term continuous cropping on soil nutrient depletion. *Ecological Engineering & Environmental Technology*, *25*.

Lefcheck, J.S. (2016). piecewiseSEM: Piecewise structural equation modelling in R for ecology, evolution, and systematics. Methods in Ecology and Evolution, 7(5), 573–579. https://doi.org/10.1111/2041-210X.12512

Lenth, R. V. (2024). emmeans: Estimated marginal means, aka least-squares means. R package version 1.10.0.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. R News, 2(3), 18–22.

Liu, Y., et al. (2025). A causal prediction method for soil organic carbon storage change estimation, with Shaanxi Province as a case study. Computers and Electronics in Agriculture. https://doi.org/10.1016/j.compag.2025.109377

Maaz, T., et al. (2023). Measuring the immeasurable: A structural equation modeling approach to assessing soil health. Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2023.161900

Oechaiyaphum, K., et al. (2020). Impact of long-term agricultural management practices on soil organic carbon and soil fertility of paddy fields in northeastern Thailand. https://doi.org/10.1016/j.rsci.2020.04.003

Parvizi, Y., & Fatehi, S. (2025). Geospatial digital mapping of soil organic carbon using machine learning and geostatistical methods in different land uses. *Scientific Reports*, *15*(1), 4449.

Pavlovic, M., Ilic, S., Ralevic, N., Antonic, N., Raffa, D. W., Bandecchi, M., & Culibrk, D. (2024). A deep learning approach to estimate soil organic carbon from remote sensing. *Remote Sensing*, *16*(4), 655.

R Core Team. (2024). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Ren, X., Zhu, B., Bah, H., & Raza, S. T. (2020). How tillage and fertilization influence soil N2O emissions after forestland conversion to cropland. *Sustainability*, *12*(19), 7947.

Rocci, K. S., Lavallee, J. M., Stewart, C. E., & Cotrufo, M. F. (2021). Soil organic carbon response to global environmental change depends on its distribution between mineral-associated and particulate organic matter: A meta-analysis. *Science of the Total Environment*, *793*, 148569.

Satdichanh, M., Dossa, G. G., Yan, K., Tomlinson, K. W., Barton, K. E., Crow, S. E., ... & Harrison, R. D. (2023). Drivers of soil organic carbon stock during tropical forest succession. *Journal of Ecology*, *111*(8), 1722-1734.

Shiferaw, H., Gebremedhin, A., Solomon, N., Taye, G., & Zenebe, A. (2020). Comparative study on spatial variability of topsoil moisture content and carbon stocks as influenced by land use and soil and water conservation structures in the semi-arid Ethiopian highlands. *Physical Geography*, *41*(5), 389-406.

Tan, S., and Kuebbing, S. (2023). A synthesis of the effect of regenerative agriculture on soil carbon sequestration in Southeast Asian croplands. Agriculture, Ecosystems and Environment. https://doi.org/10.1016/j.agee.2023.108450

Tiemann, T., & Douxchamps, S. (2023). Opportunities and challenges for integrated smallholder farming systems to improve soil nutrient management in Southeast Asia. *World Development Sustainability*, *3*, 100080.

Udomkun, P., Rupngam, T., Müller, J., Masso, C., Boonupara, T., & Kaewlom, P. (2025). A Critical Review of Regenerative Soil Management: A Novel Scoring System for SOC and GHG Emissions in Southeast Asia. *Soil Use and Management*, *41*(3), e70118.

Veldkamp, E., Schmidt, M., Powers, J. S., & Corre, M. D. (2020). Deforestation and reforestation impacts on soils in the tropics. *Nature Reviews Earth & Environment*, *1*(11), 590-605.

Xu, Y., et al. (2025). Perennial rice cultivation as an ecologically sustainable approach. Soil and Tillage Research. https://doi.org/10.1016/j.still.2025.106499

Yadav, G. S., Kandpal, B. K., Das, A., Babu, S., Mohapatra, K. P., Devi, A. G., ... & Barman, K. K. (2021). Impact of 28-year-old agroforestry systems on soil carbon dynamics in Eastern Himalayas. *Journal of Environmental Management*, *283*, 111978.

Zhang, W. C., Wan, H. S., Zhou, M. H., Wu, W., & Liu, H. B. (2022). Soil total and organic carbon mapping and uncertainty analysis using machine learning techniques. *Ecological Indicators*, *143*, 109420.

Zhou, Y., Hartemink, A. E., Shi, Z., Liang, Z., & Lu, Y. (2019). Land use and climate change effects on soil organic carbon in North and Northeast China. *Science of the Total Environment*, *647*, 1230-1238.

Generative AI Statement

During the preparation of this work, generative AI tools were used to assist the software development. ChatGPT (model GPT -4o) was used to identify R libraries needed, outline visual format of models result, and assist with debugging. Grammarly was used to check for standard English grammar and sentence structure. These tools are strictly limited to technical aids for code implementation and language refinement. All conceptual modeling, statistical analyses, model specifications, and scientific intepretations remain original work.