https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Soil Health Management Drives Soil Organic Matter More Than Edaphic Properties Across Working Organic Farms

Kenzo E. Esquivel[1,2], Hannah Waterhouse[3], Jennifer Thompson[4], Daniel S. Karp[5], Grace Santos[1], Yordi Gil-Santos[1], Patrick Baur[6], Alastair Iles[1], Timothy M. Bowles[1]

[1]Environmental Science, Policy, and Management, University of California Berkeley, Berkeley, 94720, USA
[2]Lawrence Livermore National Laboratory, Livermore, 94550, USA
[3]Environmental Studies, University of California Santa Cruz, Santa Cruz, 95064, USA
[4]Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg, 15374, Germany
[5]Wildlife, Fish, and Conservation Biology, Davis, 95616, USA
[6] Fisheries, Animal, and Veterinary Sciences, University of Rhode Island, 02881, USA

Correspondence to: Kenzo E. Esquivel (kesquivel@berkeley.com)

Abstract. Rebuilding soil organic carbon (SOC) on working lands plays a pivotal role in mitigating climate change and improving soil function, yet its accumulation is constrained by both management decisions and inherent soil properties. Scientists and farm advisors recommend that farmers plant cover crops, reduce tillage, and add organic amendments to increase SOC, yet the effectiveness of practices intended to improve soil health may be limited by underlying edaphic controls such as mineralogy, texture, and pH. Given that SOC consists of two distinct fractions—particulate organic matter (POM) and mineral-associated organic matter (MAOM)—which differ in their stability and response to management, a critical question emerges: How much do inherent soil properties limit the effectiveness of recommended soil health practices in increasing SOC? Despite extensive research in controlled field settings, real-world farming contexts remain less understood, limiting our ability to predict SOC gains across diverse soil conditions. Here, we evaluate how in-season and recent (<5 yr) implementation of soil health management systems on working farms affects SOC fractions and stocks across 28 organic fields growing lettuce in the Central Coast of California. We find that continuous living cover (e.g., through cover cropping) increases three measured carbon pools - free POM, MAOM, and surface soil total carbon stocks - while reduced disturbance (i.e., less tillage) increases two - free POM and MAOM. Crop diversity enhances both free and occluded POM fractions. Surprisingly, organic matter amendments do not show any relationship with any of the measured carbon pools. On average, management variables explain 3.7 times more variance than edaphic variables across carbon fractions, whereas, for carbon stocks, the opposite is true: edaphic variables explain ~2.1 times the variance compared to management. Our findings highlight that soil health practices, and in particular continuous cover, can significantly increase soil carbon levels, including both particulate and mineral-associated organic matter fractions, across diverse soil conditions.

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

1 Introduction

Rebuilding soil organic carbon (SOC) on working lands has the potential to mitigate the negative impacts of climate change and create co-benefits like increased water and nutrient retention (Abbas et al., 2020; Desjardins et al., 2005; Kopittke et al., 2022; Lal, 2016; Lessmann et al., 2022; Lorenz & Lal, 2012; Marland et al., 2003). Soil health management practices promote SOC accrual by emphasizing several principles: 1) continuous living roots (e.g., crop rotation, perennial vegetation, and cover crops); 2) minimizing soil disturbance (e.g., reducing the intensity, frequency, and depth of tillage); 3) biodiversity (e.g., crop rotation, pollinator plantings, cover crops), and 4) soil cover (e.g., mulching and crop residues) (NRCS, 2024). Organic amendments like compost, green manure, and organic fertilizers can also support healthy soils and SOC accrual (Agarwal, 2018; California Department of Food & Agriculture, 2021; Lal, 2016; Ryals & Silver, 2013). In this paper, soil health practices refer to this suite of management practices intended to build the organic matter and improve soil health.

Soil organic carbon is composed of two distinct fractions, particulate and mineral-associated, which differ in their contribution to soil functions and in their responses to management and edaphic factors (Cotrufo & Lavallee, 2022; Lavallee et al., 2020a). Particulate organic matter (POM) consists of partially decomposed plant material with high C:N ratios (Von Lützow et al., 2007, Bol et al., 2009). POM can be further classified into free POM (fPOM), which is unprotected, and occluded POM (oPOM), which is physically bound in soil aggregates, making it less accessible to microbial decay. POM is a faster cycling nutrient and energy source for microbes and decomposers, and contributes to improved soil structure (e.g., aggregate formation and stability, soil porosity, water infiltration) (Angst et al., 2023; Bu et al., 2015; Drinkwater & Snapp, 2022). Compared to mineral-associated organic matter (MAOM), POM tends to respond to management changes more rapidly. For example, increased plant biomass and incorporation of crop residue can increase POM. On the other hand, because it is physically and chemically more accessible to microbial decomposition, POM is also quite sensitive to disturbances that increase microbial activity, or that make oPOM physically accessible. (Drinkwater & Snapp, 2022; Prairie et al., 2023). Edaphic factors such as texture and mineralogy also control POM's stability through factors such as soil moisture. For example, on the one hand, finer textured soils may hold increased moisture and therefore increase microbial activity and decomposition. On the other hand, finer textured soils may also increase aggregate formation and thus physical protection of OM, decreasing mineralization (Haddix et al., 2020; Li et al., 2022; Plante et al., 2006).

Mineral associated organic matter (MAOM), in contrast, is composed of simpler carbon molecules that form chemical and physical associations with mineral surfaces. This protects MAOM from microbial decay, allowing it to persist for centuries to millennia (Kleber et al., 2015; Lehmann et al., 2020). The slower cycling of MAOM makes it an important pool for long-term carbon sequestration, soil fertility, and nutrient provisioning. MAOM formation requires smaller and simpler forms of carbon, and so its accrual is partially mediated by microbial decomposition of POM via oxidative and hydrolytic extracellular enzymes (Jilling et al., 2020; Salonen et al., 2023; Samson et al., 2020; Yu et al., 2022; Zhang et al., 2022). While increases tend to be smaller than for POM, MAOM has also been shown to increase with cover cropping, crop diversification, fertilization, and

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

tillage residue retention practices (Prairie et al., 2023; Romero et al., 2021). The ability for a soil to stabilize organic matter into MAOM is strongly influenced by its mineralogy, pH, texture, and the concentration of short-range order minerals and aluminum and iron oxides that provide reactive surfaces for carbon to sorb to. Thus, edaphic factors are thought to strongly influence MAOM formation, stability, and the carbon sequestration capacity of a soil (Heckman et al., 2018; Rasmussen et al., 2018; Wagai et al., 2020). Edaphic controls may thereby limit the effectiveness of soil health practices in increasing total MAOM.

Thus, POM and MAOM have distinct agronomic and environmental benefits, with POM relating more to near-term soil fertility and MAOM serving as a longer-term carbon reservoir. However, how POM and MAOM pools are affected by specific soil management practices across different soil types is not well understood. Generating this understanding of how soil health management influences these distinct soil carbon fractions across heterogeneous edaphic contexts would support management decisions that could prioritize the different functions of POM and MAOM, depending on farmer goals and their soil conditions.

Additionally, much of the prior agricultural SOC research has used controlled field experiments to generate mechanistic insights and isolate effects of practices while controlling for edaphic context (Maat, 2011). While valuable, extrapolating these findings to real world farming contexts that vary considerably in the use and consistency of management practices and edaphic contexts can be challenging. On-farm research complements controlled experiments to provide an understanding of how diverse practices, soil types, and climate variables affect SOC dynamics (Karlen et al., 2017; Olimpi et al., 2024; Singh et al., 2024; Sprunger et al., 2021; Williams et al., 2020).

We conducted on-farm research across 28 fields on working farms growing leafy greens in the Central Coast region of California, spanning gradients of soil health management and key edaphic characteristics. We focused on organic farms to avoid potential confounding effects of synthetic fertilizers and pesticides on observed management impacts. Our work was guided by two inter-related questions:

1) What are the relative impacts of continuous living cover, reduced soil disturbance, crop diversity, and organic amendments, on POM, MAOM, and total carbon stocks? To what extent is MAOM associated with soil enzyme activity?

2) How do soil health practices compare to edaphic factors in influencing carbon fractions and overall stocks?

Based on recent meta-analyses (Blanco-Canqui, 2022; Hu et al., 2023; Prairie et al., 2023; Vendig et al., 2023), we hypothesized that cover cropping, reduced tillage, organic amendments, and crop diversity would all increase SOC, with POM showing larger increases than MAOM. We also anticipated that increased enzyme activity would contribute to MAOM formation, while edaphic factors would primarily regulate SOC stocks via MAOM. We also expected that edaphic factors

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

would largely influence MAOM and carbon stocks, based on the importance of local mineralogy, but that POM would be influenced more by management factors.

2 Methods

2.1 Study region and sampling

2.1.1 Study area and field sites

Our work focused on 28 organic farms in San Benito, Santa Cruz, and Monterey Counties along the northern end of the California Central Coast region (Fig. 1). This region is characterized by a temperate Mediterranean climate with warm, dry summers, and wet winters (Köppen-Geiger Zone Csb: Warm-summer Mediterranean climate). Agriculture in the region consists of small-scale diversified farms, larger wholesale growers, and grazing lands (Olimpi et al., 2024). This is one of the most productive and economically significant agricultural regions in California and the United States, particularly for fresh produce (CDFA, 2022). Farms range in scale from ~0.5 ha of production to 600+ ha.

Participating farmers were identified using the USDA Organic Integrity Database and in consultation with local technical assistance providers. All selected farms grew organic lettuce to some extent. This crop was selected because of its economic importance, with lettuce and leafy greens representing the most valuable crops in the region (County of Monterey Agricultural Commissioner, 2021; San Benito County Agricultural Commissioner, 2020; Santa Cruz County Agricultural Commissioner, 2021). Given that many farmers grow lettuce, this selection allowed us to sample a wide area, explicitly selecting farms across a gradient of implemented soil health practices. Lettuces have shallow root systems and low residue return, making carbon-building management practices vital for rebuilding SOM in these systems.

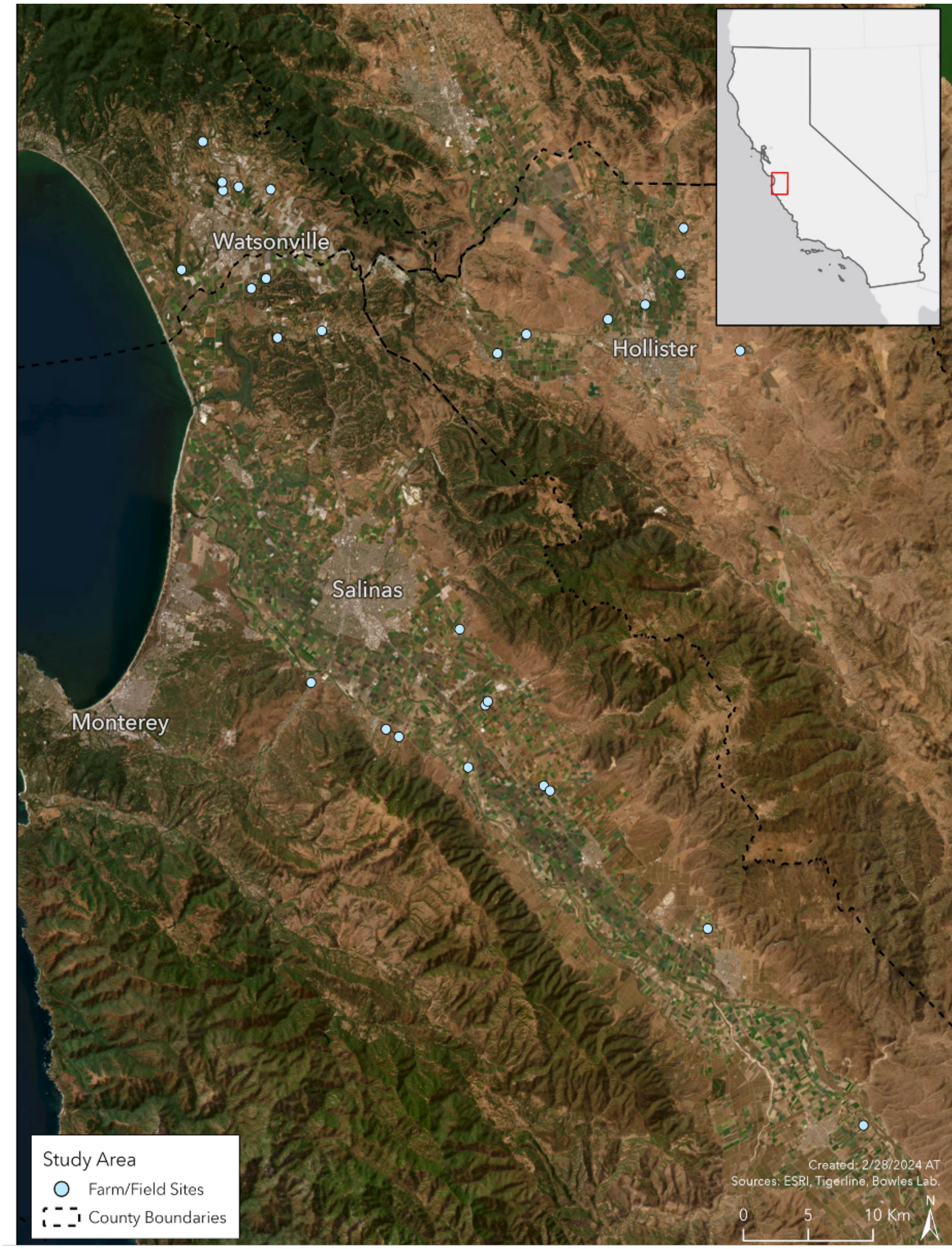


Figure 1: Map of soil sampling locations. 28 field sites span Santa Cruz, Monterey, and San Benito Counties.

2.1.2 Soil sampling

At all 28 field sites, five soil samples were collected across a 100m transect, positioned in the middle of a given lettuce field and beginning at least 10 m in from field edges. Each sample was a composite of five sub-samples, each taken from the same depth and perpendicular to the transect, 1-2m apart from each other. Soils were kept cool in an iced cooler in the field and transferred to a fridge (~ 4º C) before analysis. All samples were collected during the 2020 growing season at three time points: transplant, mid-season to represent conditions at peak nutrient uptake and plant growth (defined as peak vegetative growth, approximately 3-6 weeks after transplant, depending on the lettuce variety), and at harvest. Soils were collected from 0-15 cm for transplant, mid-season, and harvest samplings. Samples for microbial and enzyme assays were kept cold, while the other samples were air- or oven-dried for other analysis. 0-15 cm is hereafter referred to as surface soil.

Field sites were classified across four soil orders: Mollisols (20 sites), Alfisols (four sites), Entisols (three sites), and Vertisols (one site). Despite the constrained geographic area, California has a high level of soil heterogeneity as evidenced by the range of soil texture classification (Fig S1).

2.2 Lab analyses

2.2.1 Soil carbon and organic matter fractions

Bulk soil samples from harvest were oven dried at 35º C and sieved to 2 mm, and then ball milled for elemental analysis. Total carbon (TC%) was analyzed by combustion on an Elementar varioEL Cube (Elementar, Ronkonkoma, NY) for each depth. The same samples were also analyzed by combustion with a temperature ramping procedure on an Elementar SoliTOC, which measures total inorganic carbon (TIC) in addition to TOC. TIC values were negligible (<0.1%), so we consider varioEL measurements as total organic carbon (TOC).

Mid-season, 0-15 cm soil samples were air-dried, sieved to 2mm, and then fractionated by size and density into four functionally distinct pools: Dissolved organic matter (DOM), fPOM, oPOM, and MAOM.

Fractionations followed the protocol described by Haddix et al. (2020), which separates POM before and after aggregate dispersion into fPOM and oPOM. Thus, it may provide information on how management decisions impact soil aggregates, which offer short-term protection of organic matter from microbial decay.

We first separated dissolved organic matter by shaking sieved, then air-dried samples with 40 mL of DI water for 15 min before centrifuging at 2520 g for 15 min. DOM was extracted as the resulting supernatant. fPOM was then fractionated by resuspending the remaining soil pellet using sodium polytungstate solution prepared at 1.85 g cm^{-3}. The remaining oPOM and MAOM were fractionated by size (oPOM >53µm and MAOM < 53 µm), via wet sieving. High-clay soils received an additional

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

DI rinse and centrifugation, with ten additional drops of flocculants 0.25 M $CaCl_2$ and 0.25M $MgCl_2$ to help clear excess sodium polytungstate solution.

We ensured that fractions were recovered to +/- 5% of the original sample weight. Fraction samples were then oven-dried at 60° C and ball milled. Carbon in fPOM, oPOM, and MAOM fractions was measured by combustion analysis on a varioEL cube (Elementar, Ronkonkoma, NY).

2.2.2 Basic soil characteristics

Air-dried mid-season soil samples from 0-15 cm were sent to Soiltest Labs (Moses Lake, WA, USA) for analysis of texture, pH, and cation exchange capacity (CEC). pH was measured using a 1:1 soil-water slurry and a Skalar SP2000 Robotic Analyzer (Skalar, Breda, Netherlands). CEC was measured by ammonium replacement, and texture was measured by hydrometer, both following protocols by Miller et al. (2013).

Bulk density for surface soils (0 - 15 cm) was measured with 2-4 replicates per site, using a Hyprop cylindrical ring sampler with a sample volume of 250 mL (height = 12.34 cm, diameter = 5.08 cm). Samples were dried at 105 oC for 3 days. Dry soil sample mass was measured and divided by the volume of the cylindrical sampler.

2.2.3 Extracellular enzyme potential activity

Within 48 hours of soil sampling, potential extracellular enzyme activities were measured fluorometrically and photometrically using a microplate assay (Bach et al., 2013; German et al., 2011). Two grams of fresh, sieved soil were added to 100mL of 50 mM sodium acetate buffer (pH=5.5) and blended for 30 seconds. For the fluorometric assays (hydrolytic enzymes), MUF (4-methylumbelliferone) and AMC (7-amino-4-methylcoumarin) labeled substrates were used. Specifically, the enzymes glucanase/1,4-β-cellobiosidase (CBH), β-glucosidase (BG), exochitinase (NAG), and phosphatase (PHO) used the substrates MUF-cellobioside, MUF-β-glucopyranoside, MUF-N-acetyl-β-D-glucosaminide, MUF-phosphate, respectively. For the enzyme leucine-amino-peptidase (LAP), the substrate L-leucine-7-amido-4methylcoumarin was used. Samples were incubated at room temperature (22°C) in the dark and measured at 1.5 h and 3 h (excitation: 365 nm, emission: 450 nm).

The oxidative enzymes peroxidase and phenoloxidase were analyzed from the same buffered soil solution. Briefly, 0.9 mL of 20 mM L-3,4-dihydroxyphenylalanine (DOPA) was added to 0.9 ml of soil suspension in triplicates for a final concentration of 10 mM DOPA, shaken on high speed for 10 min, and centrifuged for 10 min at 14,000 g. Once plated, peroxidase samples received an additional 10 µL of 0.3% hydrogen peroxide. Absorption was measured at 450 nm at time 0 and after incubating microplates in the dark for 20 hours.

2.2.4 Soil iron fractions

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Soil iron fractions were isolated using pyrophosphate (iron complexed with organic matter), citrate-bicarbonate-dithionite (crystalline pedogenic iron), ammonium oxalate (poorly crystalline iron), and hydroxylamine hydrochloride (poorly crystalline microbially cycling iron) extractants. Pyrophosphate was extracted according to a method used by McKeague (1967). Oxalate and dithionite extractions followed protocols by Dominik & Kaupenjohann (2000) and hydroxylamine followed protocols by Lovley & Phillips (1987). The pyrophosphate, dithionite, and oxalate extractions were performed using 0.5 g of dry soil, while the hydroxylamine extraction used 1g. In brief, extractants for each fraction were added to the soils, shaken, and centrifuged, and the supernatant was diluted and measured colorimetrically using a plate reader to determine total Fe concentration. Wet extractions are not perfect in isolating their target compounds, yet in combination, they can provide meaningful insight into the different forms of iron present (Rennert, 2018).

2.3 Soil Health Management

2.3.1 Management survey

Soil health management data were collected for each of our 28 focal fields using an in-depth survey instrument created in Qualtrics (see Supplement). To ensure that questions and terms used by the survey were interpreted consistently by farmer participants, we conducted surveys in person or on the phone. This way, farmers could ask questions about our prompts, and the surveyor could provide additional context and definitions as needed. The farm management survey collected data on cover cropping, crop diversity and rotation practices, tillage, and organic inputs used by farmers over the prior five years. Questions about irrigation practices, barriers and incentives to soil health practices, and the impacts of COVID-19 were also conducted in the same survey but were not utilized in this study. Relevant parts of the survey were then collated into numeric values (i.e., counting reported crops and cover crop varieties, conversion of fertilizer applied into C and N applied based on known values from composts and application amounts etc.) for analysis. Organic amendments included farm-produced composts, composted chicken manure, and commercial organic pellet fertilizers (often derived from chicken manure and bone meal).

Notably, the management survey was specific to the field we sampled, where lettuce production was happening that season. Some sites had polycultures with multiple crops at any given time and/or cover crop mixes with high diversity. Additionally, a given field might have up to three cash crops each year.

2.3.2 Remote sensing continuous cover

To complement the management survey data about the historical use of cover cropping, we also used satellite imagery to assess continuous living cover at each farm field site via Google Earth Engine (Gorelick et al., 2017). While there was general alignment between farmer-reported cover data with the remotely sensed data, for model analyses, we defaulted to using the remote sensing metrics of continuous cover for consistency. To do so, we created a polygon for each of the 28 field sites that represented our field sampling locations. We then computed the proportion of the year with vegetation cover from 2015 until

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

2019, based on an NDVI threshold approach using Landsat and Sentinel imagery. An NDVI threshold value of 0.3 was used to separate bare soil versus sparse vegetation (Sobrino et al., 2001). From 2015 through 2019, we classified the field as having or not having vegetative cover on a monthly basis, based on this threshold. For each year, we created a proportion of cover by taking the number of months during which the mean monthly NDVI value was above the threshold and dividing this by 12. We also evaluated the presence of winter cover with NDVI values in January, though we could not distinguish winter cover versus cash crops using satellite imagery. Given that vegetation could be sparse in January, we increased the NDVI threshold to 0.5 for the 'January Mean Cover' variable. This increased NDVI threshold ensured that we only indicated winter cover crop presence when significant biomass was present.

2.3.3 Farm management standardized scores

To create interpretable management variables, we first categorized all management questions into four practice types based on Natural Resources Conservation Service soil health principles - continuous living cover, crop diversity, reduced disturbance, and organic amendments (Table 1). We did not include soil cover (i.e. mulching) as a category because it is not used in our regional lettuce production system. We then scaled individual management variables by creating a new variable, where a value of 1 indicated the highest value of a practice within our dataset. For tillage variables, such as tillage depth and frequency, we subtracted the scaled variable from 1 so that higher values indicated reduced disturbance. We then created a composite score by averaging all practices within each management category. Finally, for each category, we calculated a z-score, with a mean of 0 and a standard deviation of 1 to compare different management practices on the same scale.

Soil health principle	Management variable	Unit/Description	Min value	Max value	Mean	Median
Maintain continuous living cover	Winter cover	Mean presence of winter cover over prior 5 years based on January NDVI	0	1	0.44	0.40
	Continuous cover	Fraction of continuous living cover (cash and cover crops) over 5 years based on monthly NDVI	0.23	0.9	0.54	0.52
Organic amendments	Total carbon input	Kg C ha^{-1}; based on organic amendments applied during sampling season 2020	4489	2991	1926	1786
Crop rotational diversity	Cash crop richness	# of crops	3	16	5.4	5
	Crop families	# of cash crop families	1	8	4.1	4
	Cover crop richness	# of cover crop types	0	9	3	3

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

	Cover crop functional richness	Number of functional groups	0	3	1.5	2
Reduced disturbance	Bed permanence	0 = one season, 1= multiple seasons	1	0	0.1	0
	Deep tillage frequency (>12inches)	0= more than 1x per year, 1 = once per year, 2= once every few years, 3= never	3	0	1.1	0.5
	Tillage depth	Inches	42	14	28	30

Table 1: In-field management categories and included practices.

2.3 Statistical analysis

Our primary goal was to assess the relationships between management practices, soil organic carbon (SOC) fractions, and total organic carbon stocks, while accounting for site-specific edaphic variability. To do this, we used mixed-effects models, treating ‘site’ as a random intercept.

Since our goal was to assess drivers of SOC fractions rather than make predictions, we focused on hypothesis testing rather than best-fit model selection, following recommendations for similar datasets (Bradford et al., 2021; Holland, 1986; Olimpi et al., 2024). In other words, our interest was in identifying robust parameter estimates rather than maximizing explained variance. Consequently, we did not rely solely on p-values < 0.05 to interpret results (Wasserstein et al., 2019; Wasserstein & Lazar, 2016). Non-significant variables were retained to control for potential confounding effects.

First, we used random forest variable importance analyses to assess whether individual management practices (i.e., tillage depth, cash crop richness, 5-yr continuous cover; Table 1) might have a stronger impact when considered independently, rather than in a composite variable. For practices of high importance, we substituted them for composite variables in mixed models and compared results. These analyses were performed using the ‘party’ package in R (Hothorn et al., 2023).

For model construction, we first needed to select carbon variables that could reasonably be altered by management. For mineral-associated organic matter, we analysed the %C for the MAOM fraction. This was chosen so that we could investigate how much carbon was adsorbed to mineral surfaces. While this is not equivalent to saturation, which accounts for texture and mineralogy, MAOM C% is the carbon concentration in the fine, high-density particles for a given soil (i.e., regardless of soil texture, how much carbon is present in this fraction?). This is in contrast to looking at, for example, total MAOM carbon stock, which we expect to be primarily driven by the percentage of silt and clay (though increasing MAOM C% would also increase stocks).

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

For the free and occluded POM fractions, we analysed the proportional contribution of POM to the total organic carbon pool. This allowed us to account for both the %C and the relative proportion, by mass, that each POM fraction represents in each sample. This was calculated as follows:

$$fPOM_{C_{prop}} = fPOM_{C\%} * {}^{mass_{fPOM}}/_{mass_{total}} \quad (1)$$

$$oPOM_{C_{prop}} = oPOM_{C\%} * {}^{mass_{oPOM}}/_{mass_{total}} \quad (2)$$

These C_{prop} values and the total POM stock are related; thus, we also ran models with stock values to compare model results. Since no meaningful differences were found (see Supplement), we focused on C_{prop} values for POM fractions.

MAOM C%, fPOM, and oPOM C_{prop}, were subsequently transformed using a logit function. Logit transformations are useful for proportion values falling between 0 and 1, making them appropriate here (Warton & Hui, 2011). Transformations also helped in improving subsequent model fit.

Stocks were calculated assuming a depth of 15 cm as follows for MAOM, fPOM, and oPOM:

$$CStock_{MAOM} = MAOM_{C\%} * \frac{mass_{MAOM}}{mass_{total}} * BD\frac{g}{cm^3} * 15cm * 1e8\frac{cm^2}{ha} * 0.000001\frac{Mg}{g} \quad (4)$$

We calculate bulk soil carbon stocks for surface soils, again to 15 cm, as follows:

$$CStock = C\% * BD\frac{g}{cm^3} * 15cm * 1e8\frac{cm^2}{ha} * 0.000001\frac{Mg}{g} \quad (5)$$

2.3.1 Variable reduction

We used principal components analysis to create groups of related covariates for further analysis, including soil edaphic characteristics (sand content, clay content, cation exchange capacity, and dry bulk density), soil iron phases (pyrophosphate, oxalate, hydroxylamine, and dithionite extractions, described above), and extracellular enzyme activities (phosphatase, β-glucosidase, exochitinase, leucine-aminopeptidase, glucanase/ 1,4-β-cellobiosidase, peroxidase, and phenoloxidase). The first principal component axis, which captured 85.4%, 62.1% and 75.1% of variation for physical, iron, and enzyme data, respectively, was used for further analysis. PCAs were performed using the 'ade4' package in R (Dray et al., 2023). PCA figures and variable contributions to PC1 are reported in the Supplement (Fig. S5).

2.3.2 Mixed models

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

We constructed mixed-effects models to analyze the relationship between soil carbon fractions and soil edaphic properties, soil enzymes (for MAOM), and soil health management. Site was included as a random intercept to account for site-level variability and to reflect our study design while avoiding pseudoreplication (Harrison et al., 2018; Zuur et al., 2009). Models followed the general structure:

$$MAOM_{C\%\,ij} = Phys_{PC1ij} + Iron_{PC1ij} + pH_{ij} + ContCover_{Z\,i} + Disturb_{Z\,i} + CropDiv_{Z\,i} + CInput_{Z\,i} + u_i + \varepsilon_{ij} \qquad (6)$$

Where subscript PC1 indicates the use of the first principal component axis, Z reflects the use of summarized practice z-scores, and u is the random intercept for site i.

We ran an additional MAOM model including soil extracellular enzymes PC1, hypothesizing their role in processing POM into MAOM. While enzymes were positively associated with POM fractions (Fig. S3), in this case, we believe that the increase in extracellular enzymes was a response to increased POM, but does not add explanatory power as a modelled variable Cenini et al., 2016).

The same model structure was used for fPOM and oPOM. An alternative fPOM model was also implemented that replaced two of the composite management z-scores with specific practices, namely 5-year continuous cover (whereas the composite continuous cover Z score also integrates winter cover) and deep tillage frequency, which were identified via random forest analysis. Only one oPOM model was presented, as top variables from RF did not significantly alter model results. Similarly, 5-year continuous cover replaced the composite z-score in the C-stock model. The model using Continuous Cover Z is presented in the Supplement.

Models were built using 'lme4' in R (Bates et al., 2023), assuming Gaussian errors. Interactions were not modelled due to dataset limitations. Model fit was assessed via QQ plots qqnorm and multicollinearity was always found to be minimal (VIF <3; James et al., 2021; see Supplement). Logit and box-cox transformations were used for fraction and bulk carbon values respectively. Missing values (e.g., negative lab results) were imputed using five rounds of mean substitution with the 'mice' package (Alice, 2015), affecting 15 microbial biomass C/N values and 40 enzyme activity data points.

To compare effect sizes across variables on different scales, we report standardized coefficients (Gelman, 2008). We evaluate contributions of management versus edaphic variables through variance partitioning, estimating marginal R^2 values and confidence intervals via parametric bootstrapping (1000 iterations) using the 'partR2' package in R (Stoffel et al., 2024). Sensitivity analysis involved iteratively removing variables to confirm result stability, with findings reported in the Supplement (Table S6).

2.4 Estimated management outcomes

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

To facilitate interpretation of model coefficients on how management practices affect soil carbon fractions, we selected sites with contrasting use of management practices and calculated modelled changes in SOC fractions and stock. We chose these contrasting sites based on the practices that emerged as clear drivers for a given model. In all cases, these are sites that are not necessarily the highest or lowest scorers, but rather sites that have relatively high and low scores. This was done rather than selecting fixed z-scores for each practice because z-scores are a composite function of multiple practices (meaning there could be multiple practice combinations that yield the same z-score). By choosing scores from distinct farm sites, the comparisons reflect real practices rather than an arbitrary score.

We first extracted the relevant parameter coefficients from our models and applied necessary back-transformations, and then used values from the relevant management variable to estimate modelled outcomes for contrasting management implementation. Lastly, we took the difference between the high and low implementation sites (Table 2). We calculate these changes for a single model and a single practice at a time. Thus, only one practice varies, and use of all other practices are assumed to be the same, cancelling out when the difference is taken.

3 Results

3.1 Site characteristics and bulk and fraction C%

The 28 field sites encompassed a diverse range of soil edaphic characteristics and soil health practices, with practice Z-scores generally ranging between -2 and 2 (Fig. S2). Soil texture ranged from clay to loamy sand, with mean sand, silt, and clay content of 42%, 33%, and 26%, respectively (Table S2). CEC values ranged widely between 7.4 and 52.1, with a mean of 20.3 (Table S2). The bulk density of surface soil (0-15 cm) ranged from 0.88 to 1.6 g cm^{-3}, with a mean of 1.33 g cm^{-3} (Table S2). Surface soils (0-15 cm) had mean bulk soil organic carbon concentration of 1.50%, ranging from 0.74 to 3.95% (Table S2). pH values were more constrained, with a range of 6.4 to 8.4 and a mean of 7.5 (Table S2); these values are generally representative of local soil conditions that tend to be slightly alkaline. Having a similar climate across sites, with wide variation in soil physical properties and use of soil health practices allowed for identifying relationships with soil organic matter fractions.

3.2 Soil health management and edaphic impacts on MAOM C%

Mean MAOM C% was 1.73%, with MAOM-C accounting for 77.2% of the total estimated surface soil carbon stock (Fig. S3). This translates to ~19.72 Mg C ha^{-1}. Reduced tillage and continuous cover emerged as drivers of MAOM C% across the two MAOM mixed models used: In MAOM model 1 (without extracellular enzymes), the positive effect of reduced disturbance on MAOM was statistically clear at $p<0.1$ (β_{std}= 0.21; p = 0.09), while continuous cover was slightly above this threshold (β_{std}= 0.20; p = 0.105). The concentration of iron phases ($Iron_{PC1}$) and soil physical characteristics also were clearly associated with MAOM C%, with increasing amounts of poorly-crystalline (oxalate and hydroxylamine HCl -extracted) and organic

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

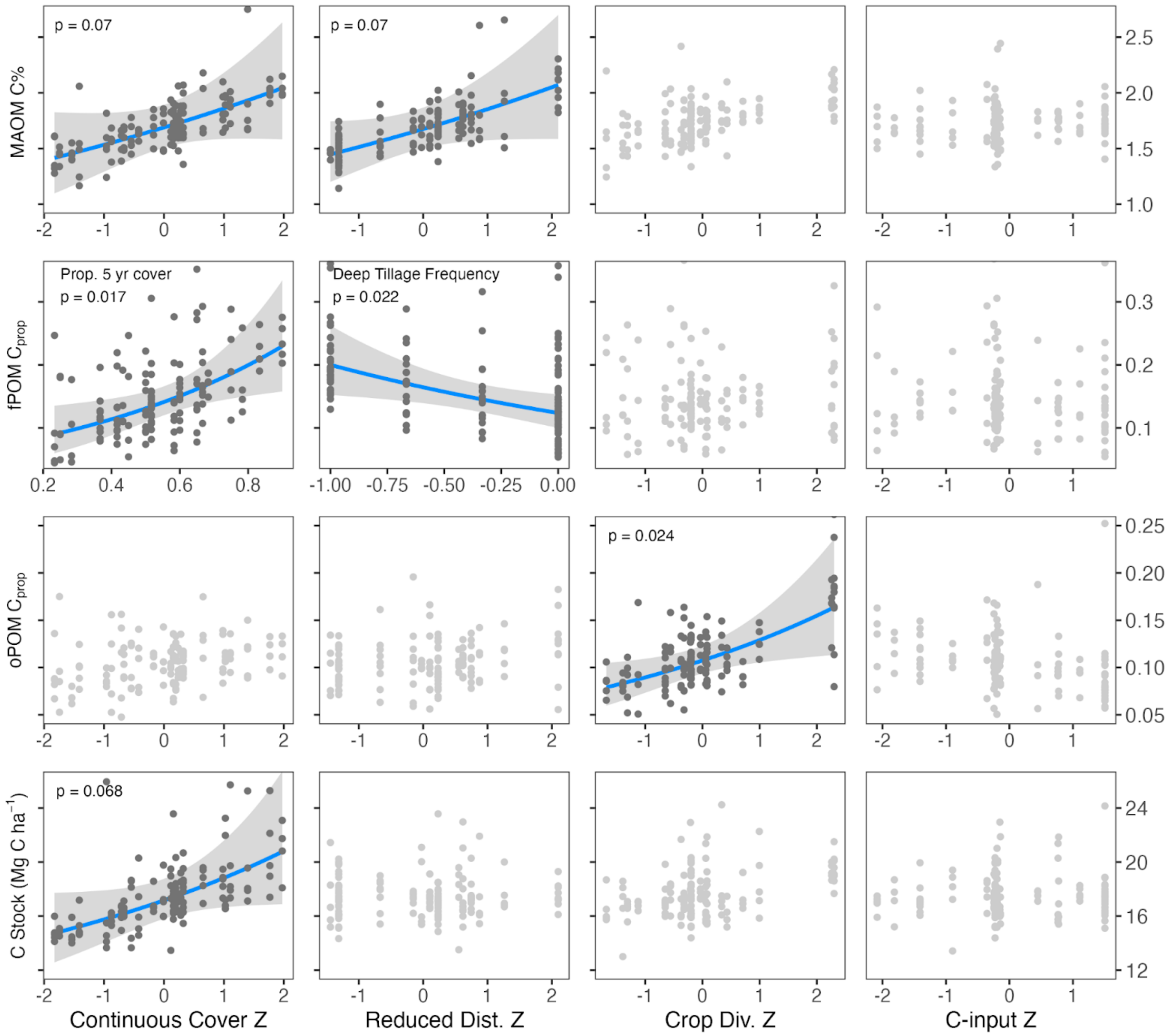
complexed (pyrophosphate-extracted) iron (β_{std} = 0.13; p = 0.023), and increasing sand content (β_{std}= 0.19; p = 0.073), corresponding to higher MAOM C%. pH was negatively associated with MAOM C% (β_{std}= -0.11; p=0.064). Standardized and unstandardized coefficient values are presented in Tables S3 and S4, respectively, alongside standard errors and p-values.

When extracellular enzyme activity was included in the model, continuous living cover and reduced disturbance remained the most important management practices ($\beta_{std\text{-}cover}$ = 0.2, p_{cover}= 0.073; $\beta_{std\text{-}dist}$ = 0.21, p_{dist} = 0.068, respectively; Fig. 2). In this model, the concentration of iron phases ($Iron_{PC1}$ primarily associated with poorly crystalline and organo-mineral fractions; see supplement) remained a positively associated variable (β_{std} = 0.1; p=0.068), while the effect of pH and physical characteristics became less clear (p_{pH} = 0.21; p_{phys}= 0.18). Meanwhile, the association with enzyme activity was clear (β_{std}= 0.1; p= 0.042), with higher enzyme activities corresponding to increased MAOM C%.

Moving from representative levels of low to high implementation of continuous living cover and winter cover increased the absolute MAOM carbon concentration (C%) by ~1.85% (Table 2; CI: 1.79 - 1.90). For tillage, low to high sites differed by absolute MAOM C% by ~1.86% (CI: 1.81 - 1.91).

MAOM1 and MAOM2 models' management variables explained approximately double the variance observed, relative to edaphic variables and enzyme activity (Fig. 3; Table S5). Edaphic variables explained less than 10% of the variance observed in our data (6.0% and 8.1%, respectively), whereas management variables explained around 20% (19% and 20%, respectively). Both MAOM models explained approximately the same amount of variance (total $R^2_{marginal}$ = 0.3 and 0.32 for models 1 and 2, respectively).

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025



340 *Figure 2: Modeled regressions for carbon fraction and stock models holding all other variables constant at mean values. Significant relationships are darker with p-values listed. Unless otherwise indicated, x-axis uses z–scores for each management category. Models MAOM 2 and fPOM 2 are visualized.*

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

	Low Score Site	High Score Site	Modeled Increase
MAOM C%			
Continuous cover	28% cover over 5 years 0% January cover	90% cover over 5 years 80% January Cover	MAOM1 (No enzyme): 1.85% C (1.79 - 1.90) MAOM2 (Enzyme): 1.86% C (1.80 - 1.91)
Reduced Disturbance	One season beds Deep till 1x per year Tillage depth = 1.07 m (42 in)	Multiple season beds Deep till 1x every few years; Tillage depth = 0.38 m (15 in)	MAOM1: 1.86% C (1.81 - 1.91) MAOM2: 1.86% C (1.77 - 1.95)
fPOM stock			
Continuous cover	23% cover over 5 yrs	90% cover over 5 years	2.76 Mg C ha^{-1} (0.67 - 11.46)
Deep tillage frequency	More than 1x per year	Never	0.62Mg C ha^{-1} (0.52 - 0.75)
oPOM Stock			
Crop Diversity	3 cash crops, no cover crops	6 cash crops, 9 species cover crop mix with 3 functional groups	4.63 Mg C ha^{-1} (4.31 - 4.97)
C Bulk Stock			
Continuous cover	28% cover over 5 years 0% January cover	90% cover over 5 years 80% January Cover	3.57 Mg C ha^{-1} (3.55 - 3.58)

Table 2: Modeled management outcomes on various carbon fractions and stocks based on back-transformed mixed-effects model coefficients, comparing high- and low-adoption sites. The sites selected are not the highest or lowest sites, but rather sites that are relatively high and low for each management category.

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

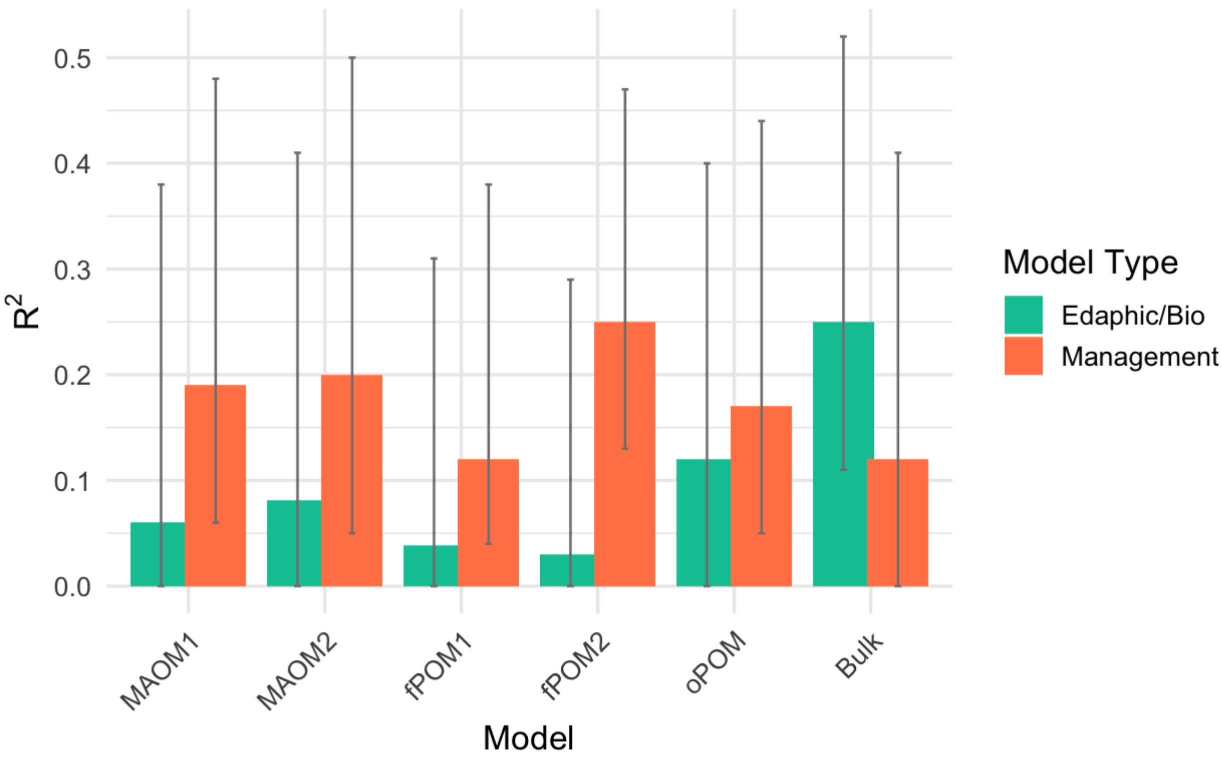


Figure 3: Marginal R^2 values for edaphic variable groupings (Physical PC1 – texture, CEC, pH, and for MAOM2, enzyme activity) and management variables (continuous cover, reduced disturbance, C input, crop diversity Z scores) with confidence intervals from bootstrapping. R^2 values and confidence intervals obtained using 'partR2' package in R. CIs estimated via parametric bootstrapping with 1000 iterations.

3.3 Soil health management and edaphic impacts on fPOM C_{prop}

Mean fPOM C% was 20.53%, with fPOM carbon accounting for 8.93% of the total estimated surface soil carbon stock (Fig. S4). This translates to ~3.54 Mg C ha^{-1}.

In the fPOM 1 model, using the model structure with all four management category scores, crop diversity and $Iron_{PC1}$ were statistically clear drivers of fPOM C_{prop} ($\beta_{std\text{-}crop\ div}$ = 0.34, $p_{crop\ div}$ = 0.083 ; $\beta_{std\text{-}iron}$ = 0.33; p_{iron} = 0.045).

As a result of Random Forest (RF) variable importance analysis (see Supplement), we ran a second model (fPOM 2) replacing continuous cover and reduced disturbance z-scores with the proportion of plant cover over the previous five years (hereafter $Cover_{prop\text{-}5yr}$), and the frequency of deep tillage, respectively. In this model, these two variables both clearly associated with fPOM C_{prop}, with an increased proportion of cover and decreased deep tillage corresponding to increased fPOM C_{prop} ($\beta_{std\text{-}}$

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

$_{cover5yr}$ = 0.46, $p_{cover5yr}$ = 0.017; $\beta_{std\text{-}deep\ till}$ = -0.40, $p_{deep\ till}$ =0.022; Fig. 2). Iron's relation was less clear in this model (p=0.13). Crop diversity drops out as a significant variable in this model ($\beta_{std\text{-}crop\ div}$ = 0.05, $p_{crop\ div}$ = 0.79).

Contrasting these individual practices across high and low implementation sites, the model predicted that a shift from 23% to 90% cover increased fPOM carbon stocks by ~2.76 Mg C/ha (CI: 0.67 - 11.46; Table 2). Going from using deep tillage more than once per year to never deep tilling increased surface soil fPOM carbon stocks by ~0.62 Mg C ha^{-1} (CI: 0.52 - 0.75).

The marginal R^2 value for the full fPOM model 1 (0.18) was lower than that of fPOM model 2 (0.31; Table S5). For the fPOM 1 model, management explained 12% of the variance, while edaphic variables explained 3.9% (Fig 3). When we substituted 'Continuous Cover' and 'Reduced Disturbance' management z-scores with individual practice variables, the management $R^2_{marginal}$ increased to 0.25, and edaphic variables decreased slightly to 0.03 (Table S5).

3.4 Soil health management and edaphic impacts on oPOM C_{prop}

Mean oPOM C% was 0.87%, with oPOM carbon accounting for 2.28% of the total estimated surface soil carbon stock (Fig. S4). This translated to ~2.28 Mg C ha^{-1}.

For oPOM C_{prop}, crop diversity and $Iron_{PC1}$ were the two statistically clear driving variables ($\beta_{std\text{-}crop\ div}$ = 0.36, $p_{crop\ div}$ = 0.024; $\beta_{std\text{-}iron}$ 0.40, p_{iron} = 0.001; Fig. 2). Like fPOM, we used two individual practice variables that emerged from RF analysis ($Cover_{prop\text{-}5yr}$ and tillage depth), but this did not notably change model results (see Supplement).

Contrasting a low crop diversity field with 3 cash crops, to a high diversity site with 6 cash crops and 9 species of cover crops, the oPOM carbon stock had a modeled increase of 4.63 Mg C ha^{-1} (CI: 4.31 - 4.97; Table 2).

Marginal R^2 values showed the similar trend of management variables explaining more variance than edaphic variables ($R^2_{marginal\text{-}edaphic}$ = 0.12, $R^2_{marginal\text{-}management}$ = 0.17; Fig. 3), though the difference was not as pronounced as it was for MAOM or fPOM. The model as a whole, similar to other fractions, explained ~29% of the observed variance in our data (Table S5).

3.5 C stock and management

Continuous cover and $PC1_{Phys}$ emerged as clear drivers of bulk carbon stocks in the surface soil ($\beta_{std\text{-}cover}$=0.015, p_{cover} =0.068; $\beta_{std\text{-}phys}$ = -0.021, p_{phys} = 0.0074; Fig. 2).

Contrasting sites with high and low implementation of continuous cover, increasing the cover proportion from 23 to 90% and winter cover from 0 to 80% increases carbon stock in the top 15cm by ~3.57 Mg C ha^{-1} (CI: 3.55 - 3.58; Table 2). The marginal R^2 value for carbon stocks is 0.25 for edaphic and 0.12 for management variables, and the total model R^2 is 0.34 for the bulk carbon models (Fig. 3; Table S5).

4 Discussion

4.1 Relative impacts of soil health management on POM, MAOM, and carbon stocks

We found that that soil health practices, and in particular continuous living cover, significantly influenced multiple carbon fractions and overall carbon stocks across working organic farms spanning a wide range of edaphic conditions. Reduced disturbance also increased MAOM C% and fPOM, while crop diversity was linked to increases in oPOM. These results underscore the potential for various land management strategies to drive carbon accumulation in functionally distinct organic matter fractions across a range of agricultural soils.

Continuous living cover emerged as a significant variable across most models, indicating importance for multiple carbon pools. We found that fields with higher levels of continuous living cover over the previous 5 years had significantly higher fPOM, MAOM, and overall carbon stocks. This may be mediated through increased aggregate stability, steady belowground carbon inputs via rhizodeposition, and above and belowground plant biomass that is incorporated into soils (Gentsch et al., 2024; White et al., 2020). These carbon inputs may support microbial activity and processing that is key for MAOM accumulation, and may also increase dissolved organic matter in soils, which can also sorb to minerals to form MAOM (Kallenbach et al., 2016; Liang et al., 2017; Sokol et al., 2019). Recent global meta-analyses similarly found that cover crops increased POM by nearly 14.5 - 15% and MAOM carbon by 5.6 - 7% relative to bare soil controls (Wooliver & Jagadamma, 2023; Hu et al., 2023). This increase in MAOM was accentuated in long-term experiments (>10 years), indicating that continuous cover over extended periods may be important for MAOM accrual in particular.

Reduced tillage was also positively linked to increased MAOM C, and reducing deep tillage increased fPOM. Reducing tillage can help preserve soil structure and limit microbial degradation of physically protected POM and MAOM (Conceição et al., 2013; Grandy & Robertson, 2007). While the increase in fPOM might be expected with decreased tillage intensity, it was less expected to see MAOM also significantly higher for fields with lower tillage intensity. Consistent with our findings, Samson et al. (2020) observed increased Fine Organic Matter (FOM)—analogous to MAOM—in reduced tillage systems. While Wooliver & Jagadamma (2023) found no direct tillage effect on MAOM in their meta-analysis, they suggest that overall SOC declines under tillage result from increased microbial decomposition of the MAOM pool. Decreased fPOM may result from accelerated decomposition due to disturbance, but it is also possible that deep tillage moves fPOM from surface soils down the soil profile, thus reducing the fPOM observed in surface soils (Angers & Eriksen-Hamel, 2008; Martins et al., 2015). Fractionations of deeper soil samples would be needed to confirm this hypothesis.

Crop diversification also emerged as an important practice for POM fractions. This follows a recent meta-analysis which found that, while POM generally increases with cropping system intensification (eliminating fallows, increasing number of crops grown per year, planting cover crops, inclusion of perennials), this trend is not as clear for systems that incorporate multiple

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

crops (Prairie et al., 2023). That said, they still found that bi- and polyculture systems as well as perennial intercropping show increases for POM (Prairie et al., 2023). Importantly, diversified cropping systems contribute to the formation of stable macroaggregates, which are particularly important for oPOM (Gentsch et al., 2024; G. Li et al., 2024).

Surprisingly, our analysis found no apparent influence of organic amendments on carbon fractions or stocks. While non-significant, the coefficient values for all but MAOM are negative. This finding was unexpected since studies show increases in SOC following application of compost, manures, and other organic amendments (Aguilera et al., 2013; Bian et al., 2024; Bolinder et al., 2020; Samson et al., 2020; White et al., 2020). The discrepancy between the findings from our on-farm study and these experimental studies needs further investigation. We speculate that one reason for this discrepancy could be that the timescales and quantities required for amendments to increase SOC were not represented at our farm sites and study design. Further investigation of carbon inputs revealed negative bivariate correlations with POM fractions, suggesting a potential priming effect, wherein adding nutrient-rich amendments may increase microbial activity, leading to increased decomposition of POM fractions (Fig. S8). Nevertheless, we found that organic amendments correlate with lettuce yield (Esquivel et al., in prep; Supplement), affirming the importance of this practice for organic growers.

This on-farm research complements manipulative experiments that have limited generalizability to real world conditions but greater causal inference. We addressed one limitation of observational studies that hampers causal interpretation, selection bias, by including key edaphic factors that not only impact soil organic matter outcomes of interest but also possibly decisions regarding soil health management (Larsen et al 2019). Repeated sampling over longer timescales would enable additional causal insight into relationships between soil health management and soil carbon dynamics from on-farm research. Future on-farm work could also account for interactions between practices and between practices and edaphic conditions. While we account for all practices simultaneously in our models, it is possible that, for example, simultaneous increases in tillage and continuous cover might have an especially positive impact on carbon fractions. To do so would require more resources to sample more sites, with possible tradeoffs for the number and types of measurements collected.

Additionally, it is important to note that these findings may not hold for different crop types, such as perennial or tree crops and non-vegetable systems with different rooting depths and soil residue inputs. Non-organic systems may also have different dynamics with the addition of synthetic pesticides and fertilizers, though we observe high SOC variability even within these organic systems.

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

4.2 Management versus edaphic impact on soil carbon

While soil health management clearly influenced each of the focal carbon pools, we also find that edaphic characteristics, and in particular higher levels of soil iron, emerged as an important explanatory variable in most models.

Poorly crystalline iron (oxalate and hydroxylamine HCl extracted) and organo-mineral (pyrophosphate extracted) complexes are well known to provide sorption sites to stabilize MAOM, as we confirmed in our MAOM models. We find that the pyrophosphate-extracted iron fraction has the strongest relationship with MAOM carbon concentration (Fig. S6), underscoring the importance of organo-mineral stabilization in these Central Coast soils. These metal phases, though imperfectly isolated by wet extraction, provide valuable insights into soil carbon stabilization and turnover (Masiello et al., 2004; Rennert, 2018). Mineral-organic associations protect low-molecular-weight carbon inputs and contribute to long-term carbon storage (Rasmussen et al., 2018; Wagai et al., 2020; Wu et al., 2023). Despite the known importance of iron and other minerals in associating with organic carbon, relatively few studies on agricultural soil carbon include this as a measured variable. This is likely because iron does not have a direct impact on the growth of most crops or on the agricultural suitability of soils, thus iron is not generally included in routine agronomic evaluations of soils (Zhu et al., 2013).

Soil iron fractions also play a key role in fPOM and oPOM accumulation. Many of the studied soils contain high-activity smectitic soils and amorphous minerals such as short-range order iron minerals, which can encourage greater aggregate stability and physically protect both POM and MAOM (Six et al., 2004; Wu et al., 2023). Across ecosystem types, Yu et al. (2022) found oxalate-extractable Fe predicted POM contribution to total SOC. In our dataset, while iron mineralogy is significantly positive for almost all models, its positive relationship is especially clear ($p = 0.001$) for oPOM, suggesting that soil iron is critical for increasing the proportion of oPOM (Ren et al., 2024; Wang et al., 2019). This appears to be driven largely by a relationship with Pyrophosphate-extractable iron (Fig. S7).

Despite the consistency of iron as an important variable in our models, we found that soil health management variables still explain more of the variance than edaphic variables across MAOM, fPOM and oPOM models. This finding was surprising, particularly for MAOM, given the importance of soil pH and texture in shaping sorption dynamics and drivers of SOC persistence (Rasmussen et al., 2018). While edaphic and climatic conditions govern the decomposition of the POM pool, our study finds that management variables that control POM inputs appear more important than inherent soil characteristics. A recent meta-analysis with pH values ranging from 4 to 8 similarly found that cover cropping impacts on POM and MAOM were not strongly influenced by soil texture and pH (Wooliver & Jagadamma, 2023). Altogether this finding demonstrates that, despite variable edaphic conditions (clay percentage ranges from 5-60% and sand from 5-77%; Table S2), on-farm management practices have the potential to significantly increase POM and MAOM fractions in agricultural soils with benefits for soil health and fertility.

The only model where edaphic variables explained more variance was for the carbon stock model. This is unsurprising as higher proportions of clay and silt in a soil increases the surface area for carbon sorption (Georgiou et al., 2022; Wu et al., 2023). While our models indicate significant impacts of management on MAOM, which comprises the largest fraction of the overall carbon stock, this apparent discrepancy is explained by our use of carbon percentage for MAOM rather than MAOM carbon stock. Our result aligns with other work showing that SOM in agricultural soils is more related to soil texture than management factors (Williams et al., 2020). Interestingly, iron concentration is not quite significant for bulk soil carbon stock. This may indicate that, while important when looking at specific carbon fractions, that texture is a stronger edaphic factor driving overall carbon stocks.

Importantly, while soil texture is a key predictor of carbon stocks, most agricultural soils are highly undersaturated – meaning that there is a lot of remaining surface area on which carbon could sorb – relative to uncultivated soils (Georgiou et al., 2022; Rasmussen et al., 2018). Thus, agricultural management is still essential for increasing soil carbon stocks.

Finally, while enzyme activity was only considered for one of our MAOM models, we find that it correlates positively with MAOM-C%. This is likely due to the breakdown of plant polymers and subsequent microbial contributions to MAOM formation (Whalen et al., 2022). However, the directionality of enzyme activity is usually not clear for MAOM or POM fractions, and correlations tend to be stronger for POM fractions (Cenini et al., 2016; Grandy et al., 2007). In our dataset, enzyme activity strongly correlates with the fPOM fraction, but we omit enzymes as a predictor variable for POM models due to uncertainty in the direction of effects (Fig. S3). Although root exudates and extracellular enzymes can destabilize MAOM, their positive correlation with MAOM C% in our study suggests a net contribution to its formation (Jilling et al., 2021; H. Li et al., 2021).

4.3 Implications for management and policy

Our findings suggest that increasing continuous living cover and reducing deep tillage on working lands could significantly increase MAOM C%, POM, and overall carbon stocks. According to data from the U.S. Census of Agriculture, the percent of available cropland planted with cover crops nationally is 5.6%, and in California, 4.8% (LaRose & Myers, 2019). In our focal region of the Central Coast of California, a recent remote sensing analysis revealed that only ~6% of farmland had winter cover crops, and ~60% of farmers left their fields fallow through the winter (Thompson et al., 2023). Similarly, based on our survey and local knowledge of production systems in California, the use of reduced tillage practices is quite rare (Mitchell et al., 2007). The low use of continuous cover and reduced tillage across California and the US indicates a significant opportunity for increasing cropland carbon sequestration. Policy and conservation incentive programs should focus on supporting farmers in adopting cover cropping practices, and other means of increasing living cover, while recognizing that the barriers that different groups of farmers face vary widely and that many barriers exist at structural levels beyond the farm requiring policies tailored to different farming contexts (Carlisle et al., 2022; Esquivel et al., 2021).

In California, the Healthy Soils Program (HSP), whose goal is explicitly tied to increasing SOC in agricultural lands, has allocated over 2/3 of its grant funding towards carbon amendments like compost, amounting to nearly $56 million in 2021 alone (Babin et al., 2025; California Department of Food and Agriculture, 2022). Our study suggests that the context and timescales of compost application may be critical in generating measurable changes in SOC and highlights the need for further research to understand the precise conditions under which such amendments may be a valuable strategy for carbon sequestration on working lands.

4.5 Conclusion and future directions

This on-farm study examined the impact of soil health management on mineral and particulate carbon fractions and surface soil carbon stocks across 28 actively managed farms. It provides valuable insights into real-world farming practices across diverse soil textures and their effects on carbon in different functional fractions. Sampling soils directly from working farms provides insight into the impacts of heterogeneous cropland management that are difficult to assess in controlled field experiments. The use of our management gradient provides a continuous measurement of the level of use of a given practice that allows for unique insights on the impact of various levels of management practice utilization.

Ultimately, we found that cultivating continuous living plant cover, reducing tillage, and increasing crop diversity can enhance both the slower-cycling MAOM fraction and the more dynamic POM fraction. The dominance of the MAOM fraction in overall carbon stock suggests its potential for long-term carbon sequestration in agricultural soils. Notably, maintaining continuous cover emerged as a significant factor in increasing MAOM, fPOM, and overall soil carbon stocks in surface soils.

Furthermore, across various soil textures, these management practices showed significant potential to boost carbon stored in MAOM, fPOM, and oPOM fractions. This research complements mechanistic and experimental trials, highlighting that soil health management is effective in increasing soil organic carbon fractions and stocks across a diverse range of soil types. This underscores the importance and potential of soil health management as a climate mitigation strategy across working agricultural lands.

5 Acknowledgements

Thank you to Kait Libby, Amiri Taylor, Melanie Rodriguez, Arely Ortiz, and Anna Barcellos for the mountain of lab work conducted over the last several years to make this work possible. A huge thank you to the interdisciplinary team of researchers who have supported this work. We appreciate Annie Taylor, who created the site map image. This work was supported by an NSF Coupled Natural Humans Systems (#1824871) and USDA-NIFA Grant (#2019-67019-29537) funding. We also want to thank UC Berkeley's Graduate Division, the William & Lisa Liu Fellowship, the Ford Foundation, and the Switzer Foundation for providing fellowship funding.

References

Abbas, F., Hammad, H. M., Ishaq, W., Farooque, A. A., Bakhat, H. F., Zia, Z., Fahad, S., Farhad, W., & Cerdà, A. (2020). A review of soil carbon dynamics resulting from agricultural practices. Journal of Environmental Management, 268, 110319. https://doi.org/10.1016/j.jenvman.2020.110319

Agarwal, R. K. (2018). Carbon Capture, Utilization and Sequestration. BoD – Books on Demand.

Aguilera, E., Lassaletta, L., Gattinger, A., & Gimeno, B. S. (2013). Managing soil carbon for climate change mitigation and adaptation in Mediterranean cropping systems: A meta-analysis. Agriculture, Ecosystems & Environment, 168, 25–36. https://doi.org/10.1016/j.agee.2013.02.003

Alice, M. (2015, October 4). Imputing missing data with R; MICE package | R-bloggers. https://www.r-bloggers.com/2015/10/imputing-missing-data-with-r-mice-package/

Angers, D. A., & Eriksen-Hamel, N. S. (2008). Full-Inversion Tillage and Organic Carbon Distribution in Soil Profiles: A Meta-Analysis. Soil Science Society of America Journal, 72(5), 1370–1374. https://doi.org/10.2136/sssaj2007.0342

Angst, G., Mueller, K. E., Castellano, M. J., Vogel, C., Wiesmeier, M., & Mueller, C. W. (2023). Unlocking complex soil systems as carbon sinks: Multi-pool management as the key. Nature Communications, 14(1), 2967. https://doi.org/10.1038/s41467-023-38700-5

Babin, N., Tan, J., Church, S. P., & Radulski, B. (2025). Systemic change or input substitution? The impact of the Healthy Soils Program on agroecological transitions within California food systems. Agroecology and Sustainable Food Systems. https://www.tandfonline.com/doi/abs/10.1080/21683565.2025.2472770

Bach, C. E., Warnock, D. D., Van Horn, D. J., Weintraub, M. N., Sinsabaugh, R. L., Allison, S. D., & German, D. P. (2013). Measuring phenol oxidase and peroxidase activities with pyrogallol, l-DOPA, and ABTS: Effect of assay conditions and soil type. Soil Biology and Biochemistry, 67, 183–191. https://doi.org/10.1016/j.soilbio.2013.08.022

Bates, D., Maechler, M., Bolker [aut, B., cre, Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., Grothendieck, G., Green, P., Fox, J., Bauer, A., simulate.formula), P. N. K. (shared copyright on, & Tanaka, E. (2023). lme4: Linear Mixed-Effects Models using "Eigen" and S4 (Version 1.1-35.1) [Computer software]. https://cran.r-project.org/web/packages/lme4/index.html

Bian, Q., Zhao, L., Cheng, K., Jiang, Y., Li, D., Xie, Z., Sun, B., & Wang, X. (2024). Divergent accumulation of microbe- and plant-derived carbon in different soil organic matter fractions in paddy soils under long-term organic amendments. Agriculture, Ecosystems & Environment, 366, 108934. https://doi.org/10.1016/j.agee.2024.108934

Blanco-Canqui, H. (2022). Cover crops and carbon sequestration: Lessons from U.S. studies. Soil Science Society of America Journal, 86(3), 501–519. https://doi.org/10.1002/saj2.20378

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Bol, R., Poirier, N., Balesdent, J., & Gleixner, G. (2009). Molecular turnover time of soil organic matter in particle-size fractions of an arable soil. Rapid Communications in Mass Spectrometry, 23(16), 2551–2558. https://doi.org/10.1002/rcm.4124

Bolinder, M. A., Crotty, F., Elsen, A., Frac, M., Kismányoky, T., Lipiec, J., Tits, M., Tóth, Z., & Kätterer, T. (2020). The effect of crop residues, cover crops, manures and nitrogen fertilization on soil organic carbon changes in agroecosystems: A synthesis of reviews. Mitigation and Adaptation Strategies for Global Change, 25(6), 929–952. https://doi.org/10.1007/s11027-020-09916-3

Bradford, M. A., Wood, S. A., Addicott, E. T., Fenichel, E. P., Fields, N., González-Rivero, J., Jevon, F. V., Maynard, D. S., Oldfield, E. E., Polussa, A., Ward, E. B., & Wieder, W. R. (2021). Quantifying microbial control of soil organic matter dynamics at macrosystem scales. Biogeochemistry, 156(1), 19–40. https://doi.org/10.1007/s10533-021-00789-5

Bramble, D. S. E., Ulrich, S., Schöning, I., Mikutta, R., Brandt, L., Poll, C., Kandeler, E., Mikutta, C., Konrad, A., Siemens, J., Yang, Y., Polle, A., Schall, P., Ammer, C., Kaiser, K., & Schrumpf, M. (2024). Formation of mineral-associated organic matter in temperate soils is primarily controlled by mineral type and modified by land use and management intensity. Global Change Biology, 30(1), e17024. https://doi.org/10.1111/gcb.17024

Bu, R., Lu, J., Ren, T., Liu, B., Li, X., & Cong, R. (2015). Particulate Organic Matter Affects Soil Nitrogen Mineralization under Two Crop Rotation Systems. PLOS ONE, 10(12), e0143835. https://doi.org/10.1371/journal.pone.0143835

California Department of Food & Agriculture. (2021). Healthy Soils Program. https://www.cdfa.ca.gov/oefi/healthysoils/

California Department of Food & Agriculture. (2022). California Agriultural Statistics Review 2021-2022 (Agricultural Statistics Review).

California Department of Food and Agriculture. (2022). 2021 Healthy Soils Program—Incentives Program: Applications Selected For Award. https://www.cdfa.ca.gov/oefi/healthysoils/docs/2021-HSPIncentive-SelectedProjects.pdf

Carlisle, L., Esquivel, K., Baur, P., Ichikawa, N. F., Olimpi, E. M., Ory, J., Waterhouse, H., Iles, A., Karp, D. S., Kremen, C., & Bowles, T. M. (2022). Organic farmers face persistent barriers to adopting diversification practices in California's Central Coast. Agroecology and Sustainable Food Systems, 46(8), 1145–1172. https://doi.org/10.1080/21683565.2022.2104420

Cenini, V. L., Fornara, D. A., McMullan, G., Ternan, N., Carolan, R., Crawley, M. J., Clément, J.-C., & Lavorel, S. (2016). Linkages between extracellular enzyme activities and the carbon and nitrogen content of grassland soils. Soil Biology and Biochemistry, 96, 198–206. https://doi.org/10.1016/j.soilbio.2016.02.015

Conceição, P. C., Dieckow, J., & Bayer, C. (2013). Combined role of no-tillage and cropping systems in soil carbon stocks and stabilization. Soil and Tillage Research, 129, 40–47. https://doi.org/10.1016/j.still.2013.01.006

Cotrufo, M. F., & Lavallee, J. M. (2022). Chapter One - Soil organic matter formation, persistence, and functioning: A synthesis of current understanding to inform its conservation and regeneration. In D. L. Sparks (Ed.), Advances in Agronomy (Vol. 172, pp. 1–66). Academic Press. https://doi.org/10.1016/bs.agron.2021.11.002

County of Monterey Agricultural Commissioner. (2021). Monterey County Crop & Livestock Report: Salad bowld of the world.

Desjardins, R. L., Smith, W., Grant, B., Campbell, C., & Riznek, R. (2005). Management Strategies to Sequester Carbon in Agricultural Soils and to Mitigate Greenhouse Gas Emissions. In J. Salinger, M. V. K. Sivakumar, & R. P. Motha (Eds.),

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Increasing Climate Variability and Change: Reducing the Vulnerability of Agriculture and Forestry (pp. 283–297). Springer Netherlands. https://doi.org/10.1007/1-4020-4166-7_14

Dominik, P., & Kaupenjohann, M. (2000). Simple spectrophotometric determination of Fe in oxalate and HCl soil extracts. Talanta, 51(4), 701–707. https://doi.org/10.1016/s0039-9140(99)00324-0

Dray, S., Dufour, A.-B., Thioulouse, and J., Jombart, with contributions from T., Pavoine, S., Lobry, J. R., Ollier, S., Borcard, D., Legendre, P., & Chessel, S. B. and A. S. B. on earlier work by D. (2023). ade4: Analysis of Ecological Data: Exploratory and Euclidean Methods in Environmental Sciences (Version 1.7-22) [Computer software]. https://cran.r-project.org/web/packages/ade4/index.html

Drinkwater, L. E., Midega, C. A. O., Awuor, R., Nyagol, D., & Khan, Z. R. (2021). Perennial legume intercrops provide multiple belowground ecosystem services in smallholder farming systems. Agriculture, Ecosystems & Environment, 320, 107566. https://doi.org/10.1016/j.agee.2021.107566

Drinkwater, L. E., & Snapp, S. S. (2022). Advancing the science and practice of ecological nutrient management for smallholder farmers. Frontiers in Sustainable Food Systems, 6. https://doi.org/10.3389/fsufs.2022.921216

Emde, D., Hannam, K. D., Midwood, A. J., & Jones, M. D. (2022). Estimating Mineral-Associated Organic Carbon Deficits in Soils of the Okanagan Valley: A Regional Study With Broader Implications. Frontiers in Soil Science, 2. https://doi.org/10.3389/fsoil.2022.812249

Esquivel, K., Carlisle, L., Ke, A., Olimpi, E., Baur, P., Ory, J., Waterhouse, H., Iles, A., Karp, D. S., Kremen, C., & Bowles, T. M. (2021). The "sweet spot" in the middle: Why do mid-scale farms adopt diversification practices at higher rates? Frontiers in Sustainable Food Systems. https://doi.org/10.3389/fsufs.2021.734088

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. Statistics in Medicine, 27(15), 2865–2873. https://doi.org/10.1002/sim.3107

Gentsch, N., Riechers, F. L., Boy, J., Schweneker, D., Feuerstein, U., Heuermann, D., & Guggenberger, G. (2024). Cover crops improve soil structure and change organic carbon distribution in macroaggregate fractions. SOIL, 10(1), 139–150. https://doi.org/10.5194/soil-10-139-2024

Georgiou, K., Jackson, R. B., Vindušková, O., Abramoff, R. Z., Ahlström, A., Feng, W., Harden, J. W., Pellegrini, A. F. A., Polley, H. W., Soong, J. L., Riley, W. J., & Torn, M. S. (2022). Global stocks and capacity of mineral-associated soil organic carbon. Nature Communications, 13(1), 3797. https://doi.org/10.1038/s41467-022-31540-9

German, D. P., Weintraub, M. N., Grandy, A. S., Lauber, C. L., Rinkes, Z. L., & Allison, S. D. (2011). Optimization of hydrolytic and oxidative enzyme methods for ecosystem studies. Soil Biology and Biochemistry, 43(7), 1387–1397. https://doi.org/10.1016/j.soilbio.2011.03.017

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Grandy, A. S., Neff, J. C., & Weintraub, M. N. (2007). Carbon structure and enzyme activities in alpine and forest ecosystems. Soil Biology and Biochemistry, 39(11), 2701–2711. https://doi.org/10.1016/j.soilbio.2007.05.009

Grandy, A. S., & Robertson, G. P. (2007). Land-Use Intensity Effects on Soil Organic Carbon Accumulation Rates and Mechanisms. Ecosystems, 10(1), 59–74. https://doi.org/10.1007/s10021-006-9010-y

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Haddix, M. L., Gregorich, E. G., Helgason, B. L., Janzen, H., Ellert, B. H., & Francesca Cotrufo, M. (2020). Climate, carbon content, and soil texture control the independent formation and persistence of particulate and mineral-associated organic matter in soil. Geoderma, 363, 114160. https://doi.org/10.1016/j.geoderma.2019.114160

Harrison, X. A., Donaldson, L., Correa-Cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., Robinson, B. S., Hodgson, D. J., & Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ, 6, e4794. https://doi.org/10.7717/peerj.4794

Heckman, K., Lawrence, C. R., & Harden, J. W. (2018). A sequential selective dissolution method to quantify storage and stability of organic carbon associated with Al and Fe hydroxide phases. Geoderma, 312, 24–35. https://doi.org/10.1016/j.geoderma.2017.09.043

Holland, P. W. (1986). Statistics and Causal Inference. Journal of the American Statistical Association, 81(396), 945–960. https://doi.org/10.1080/01621459.1986.10478354

Hothorn, T., Hornik, K., Strobl, C., & Zeileis, A. (2023). party: A Laboratory for Recursive Partytioning (Version 1.3-14) [Computer software]. https://cran.r-project.org/web/packages/party/index.html

Hu, Q., Thomas, B. W., Powlson, D., Hu, Y., Zhang, Y., Jun, X., Shi, X., & Zhang, Y. (2023). Soil organic carbon fractions in response to soil, environmental and agronomic factors under cover cropping systems: A global meta-analysis. Agriculture, Ecosystems & Environment, 355, 108591. https://doi.org/10.1016/j.agee.2023.108591

James, G., Witten, D., Hastie, T., Tibshirani, R., & Taylor, J. (2023). An introduction to statistical learning: With applications in python. Springer Nature.

Jilling, A., Kane, D., Williams, A., Yannarell, A. C., Davis, A., Jordan, N. R., Koide, R. T., Mortensen, D. A., Smith, R. G., Snapp, S. S., Spokas, K. A., & Stuart Grandy, A. (2020). Rapid and distinct responses of particulate and mineral-associated organic nitrogen to conservation tillage and cover crops. Geoderma, 359, 114001. https://doi.org/10.1016/j.geoderma.2019.114001

Jilling, A., Keiluweit, M., Gutknecht, J. L. M., & Grandy, A. S. (2021). Priming mechanisms providing plants and microbes access to mineral-associated organic matter. Soil Biology and Biochemistry, 158, 108265. https://doi.org/10.1016/j.soilbio.2021.108265

Kallenbach, C. M., Frey, S. D., & Grandy, A. S. (2016). Direct evidence for microbial-derived soil organic matter formation and its ecophysiological controls. Nature Communications, 7(1), Article 1. https://doi.org/10.1038/ncomms13630

Karlen, D. L., Goeser, N. J., Veum, K. S., & Yost, M. A. (2017). On-farm soil health evaluations: Challenges and opportunities. Journal of Soil and Water Conservation, 72(2), 26A-31A. https://doi.org/10.2489/jswc.72.2.26A

Kleber, M., Eusterhues, K., Keiluweit, M., Mikutta, C., Mikutta, R., & Nico, P. S. (2015). Chapter One - Mineral–Organic Associations: Formation, Properties, and Relevance in Soil Environments. In D. L. Sparks (Ed.), Advances in Agronomy (Vol. 130, pp. 1–140). Academic Press. https://doi.org/10.1016/bs.agron.2014.10.005

Kopittke, P. M., Berhe, A. A., Carrillo, Y., Cavagnaro, T. R., Chen, D., Chen, Q.-L., Román Dobarco, M., Dijkstra, F. A., Field, D. J., Grundy, M. J., He, J.-Z., Hoyle, F. C., Kögel-Knabner, I., Lam, S. K., Marschner, P., Martinez, C., McBratney, A. B., McDonald-Madden, E., Menzies, N. W., … Minasny, B. (2022). Ensuring planetary survival: The centrality of organic carbon in balancing the multifunctional nature of soils. Critical Reviews in Environmental Science and Technology, 52(23), 4308–4324. https://doi.org/10.1080/10643389.2021.2024484

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Lal, R. (2016). Soil health and carbon management. Food and Energy Security, 5(4), 212–222. https://doi.org/10.1002/fes3.96

LaRose, J., & Myers, R. (2019). Adoption of Soil Health Systems Based on Data from the 2017 U.S. Census of Agriculture. Soil Health Institute. https://soilhealthinstitute.org/app/uploads/2021/11/Soil-Health-Census-Report.pdf

Larsen, A.E., Meng, K., Kendall, B.E., 2019. Causal analysis in control–impact ecological studies with observational data. Methods in Ecology and Evolution 10, 924–934. doi:10.1111/2041-210X.13190

Lavallee, J. M., Soong, J. L., & Cotrufo, M. F. (2020). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. Global Change Biology, 26(1), 261–273. https://doi.org/10.1111/gcb.14859

Lehmann, J., Hansel, C. M., Kaiser, C., Kleber, M., Maher, K., Manzoni, S., Nunan, N., Reichstein, M., Schimel, J. P., Torn, M. S., Wieder, W. R., & Kögel-Knabner, I. (2020). Persistence of soil organic carbon caused by functional complexity. Nature Geoscience, 13(8), 529–534. https://doi.org/10.1038/s41561-020-0612-3

Lessmann, M., Ros, G. H., Young, M. D., & de Vries, W. (2022). Global variation in soil carbon sequestration potential through improved cropland management. Global Change Biology, 28(3), 1162–1177. https://doi.org/10.1111/gcb.15954

Li, G., Yu, C., Shen, P., Hou, Y., Ren, Z., Li, N., Liao, Y., Li, T., & Wen, X. (2024). Crop diversification promotes soil aggregation and carbon accumulation in global agroecosystems: A meta-analysis. Journal of Environmental Management, 350, 119661. https://doi.org/10.1016/j.jenvman.2023.119661

Li, H., Bölscher, T., Winnick, M., Tfaily, M. M., Cardon, Z. G., & Keiluweit, M. (2021). Simple Plant and Microbial Exudates Destabilize Mineral-Associated Organic Matter via Multiple Pathways. Environmental Science & Technology, 55(5), 3389–3398. https://doi.org/10.1021/acs.est.0c04592

Li, H., Van den Bulcke, J., Mendoza, O., Deroo, H., Haesaert, G., Dewitte, K., De Neve, S., & Sleutel, S. (2022). Soil texture controls added organic matter mineralization by regulating soil moisture—Evidence from a field experiment in a maritime climate. Geoderma, 410, 115690. https://doi.org/10.1016/j.geoderma.2021.115690

Liang, C., Schimel, J. P., & Jastrow, J. D. (2017). The importance of anabolism in microbial control over soil carbon storage. Nature Microbiology, 2(8), 1–6. https://doi.org/10.1038/nmicrobiol.2017.105

Lorenz, K., & Lal, R. (2012). Cropland Soil Carbon Dynamics. In R. Lal, K. Lorenz, R. F. Hüttl, B. U. Schneider, & J. von Braun (Eds.), Recarbonization of the Biosphere: Ecosystems and the Global Carbon Cycle (pp. 303–346). Springer Netherlands. https://doi.org/10.1007/978-94-007-4159-1_14

Lovley, D. R., & Phillips, E. J. P. (1987). Rapid Assay for Microbially Reducible Ferric Iron in Aquatic Sediments. Applied and Environmental Microbiology, 53(7), 1536–1540. https://doi.org/10.1128/aem.53.7.1536-1540.1987

Maat, H. (2011). The history and future of agricultural experiments. NJAS: Wageningen Journal of Life Sciences, 57(3–4), 187–195. https://doi.org/10.1016/j.njas.2010.11.001

Marland, G., West, T. O., Schlamadinger, B., & Canella, L. (2003). Managing soil organic carbon in agriculture: The net effect on greenhouse gas emissions. Tellus B: Chemical and Physical Meteorology, 55(2), 613–621. https://doi.org/10.3402/tellusb.v55i2.17042

Martins, B. H., Cavigelli, M. A., Buyer, J. S., Maul, J. E., Reeves III, J. B., & Martin-Neto, L. (2015). Chemical Evaluation of Soil Organic Matter Structure in Diverse Cropping Systems. In Labile Organic Matter—Chemical Compositions, Function, and Significance in Soil and the Environment (pp. 195–217). John Wiley & Sons, Ltd. https://doi.org/10.2136/sssaspecpub62.2014.0041

Masiello, C. A., Chadwick, O. A., Southon, J., Torn, M. S., & Harden, J. W. (2004). Weathering controls on mechanisms of carbon storage in grassland soils. Global Biogeochemical Cycles, 18(4). https://doi.org/10.1029/2004GB002219

McKeague, J. A. (1967). An evaluation of 0.1 m pyrophosphate and pyrophosphate-dithionite in comparison with oxalate as extractants of the accumulation products in podzols and some other soils. Canadian Journal of Soil Science, 47(2), 95–99. https://doi.org/10.4141/cjss67-017

Miller, R. O., Gavlak, R., & Horneck, D. (2013). Soil, Plant and Water Reference Methods for the Western Region (4th Edition). https://www.naptprogram.org/files/napt/publications/method-papers/western-states-methods-manual-2013.pdf

Mitchell, J. P., Klonsky, K., Shrestha, A., Fry, R., DuSault, A., Beyer, J., & Harben, R. (2007). Adoption of conservation tillage in California: Current status and future perspectives. Australian Journal of Experimental Agriculture, 47(12), 1383–1388. https://doi.org/10.1071/EA07044

Olimpi, E. M., Ke, A., Baur, P., Carlisle, L., Esquivel, K., Glaser, T., Snyder, W. E., Waterhouse, H., Bowles, T. M., Kremen, C., & Karp, D. S. (2024). Ungrazed seminatural habitats around farms benefit bird conservation without enhancing food borne pathogen risks. Landscape Ecology.

Plante, A. F., Conant, R. T., Stewart, C. E., Paustian, K., & Six, J. (2006). Impact of Soil Texture on the Distribution of Soil Organic Matter in Physical and Chemical Fractions. Soil Science Society of America Journal, 70(1), 287–296. https://doi.org/10.2136/sssaj2004.0363

Prairie, A. M., King, A. E., & Cotrufo, M. F. (2023). Restoring particulate and mineral-associated organic carbon through regenerative agriculture. Proceedings of the National Academy of Sciences, 120(21), e2217481120. https://doi.org/10.1073/pnas.2217481120

Rasmussen, C., Heckman, K., Wieder, W. R., Keiluweit, M., Lawrence, C. R., Berhe, A. A., Blankinship, J. C., Crow, S. E., Druhan, J. L., Hicks Pries, C. E., Marin-Spiotta, E., Plante, A. F., Schädel, C., Schimel, J. P., Sierra, C. A., Thompson, A., & Wagai, R. (2018). Beyond clay: Towards an improved set of variables for predicting soil organic matter content. Biogeochemistry, 137(3), 297–306. https://doi.org/10.1007/s10533-018-0424-3

Ren, L., Yang, H., Li, J., Zhang, N., Han, Y., Zou, H., & Zhang, Y. (2024). Organic fertilizer enhances soil aggregate stability by altering greenhouse soil content of iron oxide and organic carbon. Journal of Integrative Agriculture, S209531192400217X. https://doi.org/10.1016/j.jia.2024.05.026

Rennert, T. (2018). Wet-chemical extractions to characterise pedogenic Al and Fe species – a critical review. Soil Research, 57(1), 1–16. https://doi.org/10.1071/SR18299

Romero, C. M., Hao, X., Hazendonk, P., Schwinghamer, T., Chantigny, M., Fonteyne, S., & Verhulst, N. (2021). Tillage-residues affect mineral-associated organic matter on Vertisols in northern Mexico. Geoderma Regional, 27, e00430. https://doi.org/10.1016/j.geodrs.2021.e00430

Ryals, R., & Silver, W. L. (2013). Effects of organic matter amendments on net primary productivity and greenhouse gas emissions in annual grasslands. Ecological Applications, 23(1), 46–59. https://doi.org/10.1890/12-0620.1

Salonen, A. R., Soinne, H., Creamer, R., Lemola, R., Ruoho, N., Uhlgren, O., Goede, R. de, & Heinonsalo, J. (2023). Assessing the effect of arable management practices on carbon storage and fractions after 24 years in boreal conditions of Finland. Geoderma Regional, 34, e00678. https://doi.org/10.1016/j.geodrs.2023.e00678

Samson, M.-E., Chantigny, M. H., Vanasse, A., Menasseri-Aubry, S., Royer, I., & Angers, D. A. (2020). Management practices differently affect particulate and mineral-associated organic matter and their precursors in arable soils. Soil Biology and Biochemistry, 148, 107867. https://doi.org/10.1016/j.soilbio.2020.107867

San Benito County Agricultural Commissioner. (2020). San Benito County Crop & Livestock Report.

Santa Cruz County Agricultural Commissioner. (2021). Santa Cruz County Agricultural Crop and Livestock Report.

Setia, R., Verma, S. L., & Marschner, P. (2012). Measuring microbial biomass carbon by direct extraction – Comparison with chloroform fumigation-extraction. European Journal of Soil Biology, 53, 103–106. https://doi.org/10.1016/j.ejsobi.2012.09.005

Silva, L. C. R., Doane, T. A., Corrêa, R. S., Valverde, V., Pereira, E. I. P., & Horwath, W. R. (2015). Iron-mediated stabilization of soil carbon amplifies the benefits of ecological restoration in degraded lands. Ecological Applications, 25(5), 1226–1234. https://doi.org/10.1890/14-2151.1

Singh, P., Kawa, N. C., & Sprunger, C. D. (2024). “More questions than answers”: Ohio farmers’ perceptions of novel soil health data and their utility for on-farm management. Agroecology and Sustainable Food Systems, 48(1), 74–92. https://doi.org/10.1080/21683565.2023.2270928

Six, J., Bossuyt, H., Degryze, S., & Denef, K. (2004). A history of research on the link between (micro)aggregates, soil biota, and soil organic matter dynamics. Soil and Tillage Research, 79(1), 7–31. https://doi.org/10.1016/j.still.2004.03.008

Sobrino, J. A., Raissouni, N., & Li, Z.-L. (2001). A Comparative Study of Land Surface Emissivity Retrieval from NOAA Data. Remote Sensing of Environment, 75(2), 256–266. https://doi.org/10.1016/S0034-4257(00)00171-1

Soil Health | Natural Resources Conservation Service. (2024, April 1). https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soils/soil-health

Sokol, N. W., Sanderman, J., & Bradford, M. A. (2019). Pathways of mineral-associated soil organic matter formation: Integrating the role of plant carbon source, chemistry, and point of entry. Global Change Biology, 25(1), 12–24. https://doi.org/10.1111/gcb.14482

Sprunger, C. D., Culman, S. W., Deiss, L., Brock, C., & Jackson-Smith, D. (2021). Which management practices influence soil health in Midwest organic corn systems? Agronomy Journal, 113(5), 4201–4219. https://doi.org/10.1002/agj2.20786

Stoffel, M. A., Nakagawa, S., & Schielzeth, H. (2024). partR2: Partitioning R2 in GLMMs (Version 0.9.2) [Computer software]. https://cran.r-project.org/web/packages/partR2/index.html

Thompson, J. B., Symonds, J., Carlisle, L., Iles, A., Karp, D. S., Ory, J., & Bowles, T. M. (2023). Remote sensing of hedgerows, windbreaks, and winter cover crops in California’s Central Coast reveals low adoption but hotspots of use. Frontiers in Sustainable Food Systems, 7. https://doi.org/10.3389/fsufs.2023.1052029

Vendig, I., Guzman, A., De La Cerda, G., Esquivel, K., Mayer, A. C., Ponisio, L., & Bowles, T. M. (2023). Quantifying direct yield benefits of soil carbon increases from cover cropping. Nature Sustainability, 6(9), Article 9. https://doi.org/10.1038/s41893-023-01131-7

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Von Lützow, M., Kögel-Knabner, I., Ekschmitt, K., Flessa, H., Guggenberger, G., Matzner, E., & Marschner, B. (2007). SOM fractionation methods: Relevance to functional pools and to stabilization mechanisms. Soil Biology and Biochemistry, 39(9), 2183–2207. https://doi.org/10.1016/j.soilbio.2007.03.007

Wagai, R., Kajiura, M., & Asano, M. (2020). Iron and aluminum association with microbially processed organic matter via meso-density aggregate formation across soils: Organo-metallic glue hypothesis. SOIL, 6(2), 597–627. https://doi.org/10.5194/soil-6-597-2020

Wang, P., Wang, J., Zhang, H., Dong, Y., & Zhang, Y. (2019). The role of iron oxides in the preservation of soil organic matter under long-term fertilization. Journal of Soils and Sediments, 19(2), 588–598. https://doi.org/10.1007/s11368-018-2085-1

Warton, D. I., & Hui, F. K. C. (2011). The arcsine is asinine: The analysis of proportions in ecology. Ecology, 92(1), 3–10. https://doi.org/10.1890/10-0340.1

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA Statement on p-Values: Context, Process, and Purpose. The American Statistician, 70(2), 129–133. https://doi.org/10.1080/00031305.2016.1154108

Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a World Beyond "p < 0.05." The American Statistician, 73(sup1), 1–19. https://doi.org/10.1080/00031305.2019.1583913

Whalen, E. D., Grandy, A. S., Sokol, N. W., Keiluweit, M., Ernakovich, J., Smith, R. G., & Frey, S. D. (2022). Clarifying the evidence for microbial- and plant-derived soil organic matter, and the path toward a more quantitative understanding. Global Change Biology, 28(24), 7167–7185. https://doi.org/10.1111/gcb.16413

White, K. E., Brennan, E. B., Cavigelli, M. A., & Smith, R. F. (2020). Winter cover crops increase readily decomposable soil carbon, but compost drives total soil carbon during eight years of intensive, organic vegetable production in California. PLOS ONE, 15(2), e0228677. https://doi.org/10.1371/journal.pone.0228677

Williams, H., Colombi, T., & Keller, T. (2020). The influence of soil management on soil health: An on-farm study in southern Sweden. Geoderma, 360, 114010. https://doi.org/10.1016/j.geoderma.2019.114010

Wu, S., Konhauser, K. O., Chen, B., & Huang, L. (2023). "Reactive Mineral Sink" drives soil organic matter dynamics and stabilization. Npj Materials Sustainability, 1(1), Article 1. https://doi.org/10.1038/s44296-023-00003-7

Ye, C., Huang, W., Hall, S. J., & Hu, S. (2022). Association of Organic Carbon With Reactive Iron Oxides Driven by Soil pH at the Global Scale. Global Biogeochemical Cycles, 36(1), e2021GB007128. https://doi.org/10.1029/2021GB007128

Yu, W., Huang, W., Weintraub-Leff, S. R., & Hall, S. J. (2022). Where and why do particulate organic matter (POM) and mineral-associated organic matter (MAOM) differ among diverse soils? Soil Biology and Biochemistry, 172, 108756. https://doi.org/10.1016/j.soilbio.2022.108756

Zhang, Z., Kaye, J. P., Bradley, B. A., Amsili, J. P., & Suseela, V. (2022). Cover crop functional types differentially alter the content and composition of soil organic carbon in particulate and mineral-associated fractions. Global Change Biology, 28(19), 5831–5848. https://doi.org/10.1111/gcb.16296

Zhu, X., Silva, L. C. R., Doane, T. A., & Horwath, W. R. (2013). Iron: The Forgotten Driver of Nitrous Oxide Production in Agricultural Soil. PLOS ONE, 8(3), e60146. https://doi.org/10.1371/journal.pone.0060146

https://doi.org/10.5194/egusphere-2025-3440
Preprint. Discussion started: 3 September 2025

Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. (2009). Mixed Effects Modelling for Nested Data. In A. F. Zuur, E. N. Ieno, N. Walker, A. A. Saveliev, & G. M. Smith (Eds.), Mixed effects models and extensions in ecology with R (pp. 101–142). Springer. https://doi.org/10.1007/978-0-387-87458-6_5