Direct yield benefits of soil carbon increases in low-carbon soils: A global meta-analysis of cover cropping co-benefits

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Abstract

Cropland management practices that restore soil organic carbon (SOC) are increasingly presented as climate solutions that provide the additional benefit of yield enhancement. But how often these benefits align at the farm level — the scale of farmers' decision-making — remains uncertain. We examined concurrent SOC and yield responses to cover cropping, including their direct connection, with a global meta-analysis. We showed that cover cropping simultaneously increased yields and SOC in 59.7% of 434 paired observations. Direct yield benefits from SOC enhancement were evident in soils with initial SOC concentrations below 9.2 g kg^{-1}. These yield benefits did not vary with nitrogen inputs or cover crop type, suggesting they are not substitutable with fertilization. In all types of soils, the largest yield increases (up to +20.2%) coincided with the largest SOC increases (up to +16.8%) when legume cover crops were integrated into systems with simplified rotations or with nitrogen inputs < 136 kg N ha^{-1} $season^{-1}$, thus providing substantial benefits for farmers and society regardless of direct effects of SOC on yield.

Background

Soil organic carbon (SOC) is considered a critical component of soil health. In agroecosystems, soil health is a metaphor that describes the degree to which soils support multiple functions beyond just crop productivity[1,2]. SOC influences multiple soil-based ecosystem services, such as nutrient cycling and retention, soil aeration and structural integrity[3], climate regulation[4], and possibly crop productivity[5]. The concentration of SOC has thus become one of the most common metrics for assessing the state of a soil's health[6].

Despite the various benefits that SOC is thought to provide[7], agricultural expansion and conventional agricultural intensification have dramatically depleted SOC across the world[8]. Practices that regenerate SOC are garnering increasing attention for their potential to restore soil functionality while simultaneously drawing down atmospheric carbon[9,10]. Cover cropping is one such cropland practice. Grown on fallow soils otherwise left bare, cover crops increase organic matter inputs to the soil in the form of crop detritus and root exudates. This in turn supports soil microbial biomass which turns over and forms microbial necromass, a key component of stable SOC[11,12]. A recent meta-analysis showed that cover cropping increases SOC by 0.32 Mg C $ha^{-1}yr^{-1}$ on average, highlighting its potential to restore some portion of the 133 Pg of global SOC that has been lost from croplands[8,13]. But the extent to which farmers will voluntarily adopt C sequestering practices hinges on more than just their potential to mitigate climate change or restore soil health[14,15].

How a practice influences crop productivity and farm profitability is central to farmers' management decisions. Cover cropping can affect both input costs (e.g., via reducing fertilizer input costs following a legume cover crop) and crop yields. Recent meta-analyses show that cover cropping typically increases crop yields[16,17]. Yield increase estimates range from 6% to 33% depending on cash crop type, cover crop type, fertilizer additions and other factors, although some studies show crop yield decreases as well[16,17]. However, since syntheses of how cover cropping affects SOC and yields have been conducted separately, it is not known how often cover cropping simultaneously increases SOC and yields (co-benefits) at the same location, increases or decreases one but not the other (trade-offs), or even decreases both SOC and yields (co-costs). Perhaps more importantly, it is also not known if there are management, edaphic, or environmental conditions in which the largest yield increases are most likely to align with the largest SOC increases. Understanding the potential for co-benefits will help inform decision-making at the farm level and will help identify areas of overlap between farm level benefits and benefits for society that might occur at regional or global scales.

When yield increases do result from cover cropping, a critical knowledge gap is the relative role of changes in SOC in driving these increases, versus other cover cropping effects, such as nutrient scavenging[18]. Understanding the role that SOC plays in yield changes under cover cropping would contribute to recent calls to better quantify the relationship between SOC and yields generally[5,19].

The widespread expectation that increasing SOC will increase crop productivity exists[8,11,20,21] because, as part of soil organic matter, SOC is related to many soil properties and functions that are important for plant productivity like nutrient and water provisioning. However, actual evidence of a relationship between SOC and yield remains contradictory and inconclusive[5,22–24]. One reason for the lack of consensus is the challenge of manipulating SOC in such a way that the effect of nutrient additions can be separated from other possible benefits of SOC[25]. Attempts to circumvent this challenge use observational data, but the lack of controls and covariation between SOC and other environmental and management variables create complex interactions that can be difficult to tease apart even using multivariate approaches[5,22]. Using similar meta-analytic techniques, recent studies have reported positive effects of SOC on yield[5,24], little to no effects[22], and negative effects[23]. In addition, observational studies examining SOC-to-yield relationships span very wide ranges of SOC[5,24]. Regional or global SOC-to-yield relationships are generally not applicable to an individual farmer making management changes since they encompass very wide ranges of SOC rather than the often modest SOC increases that occur on-farm following changes to management.

Meta-analysis of studies on agricultural practices expected to shift SOC, such as cover cropping, provides an alternative approach to quantifying the SOC-to-yield relationship[5]. By pairing treatments with relevant control values, relationships between changes in SOC and changes in yield can be quantified in such a way that eliminates the confounding effects that result from observational data (e.g., between climate or edaphic factors that influence both SOC and yields). While other effects can also confound or obscure the SOC-to-yield relationship in this approach (e.g., increases in both nitrogen availability and SOC from legume cover crops), building a broad yield model that includes such interactions can increase confidence in the causality of SOC effects.

We use a global meta-analysis to determine how cover cropping affects SOC and crop yields simultaneously, and the extent to which changes in crop yield (Δ_{Yield}) are related to changes in SOC (Δ_{SOC}). We thus build on previous meta-analyses that assess how cover cropping affects SOC or yields individually by linking these responses together in a paired treatment-control meta-dataset. We asked 3 questions: 1) are co-benefits, i.e., simultaneous increases in crop yields and SOC, the most common response to cover cropping? 2) Do changes in SOC link directly to changes in yield and, if so, is this association nutrient related? 3) Regardless of direct links between SOC and yield, are there edaphic, environmental, or management conditions where co-benefits of increased SOC and yield from cover cropping are more likely to be maximized? We compiled an exhaustive database of paired yield and SOC responses to cover cropping and constructed models with important factors mediating their individual and joint responses. By building comprehensive models to identify and quantify important predictors of yield and SOC changes from cover cropping, our study not only helps with farm-level decisions regarding cover cropping, but also informs policymakers seeking to quantify the impact of cropland carbon sequestration on global food production capacity.

Results

Joint impacts of cover cropping on crop yields and SOC

Cover cropping had a strong positive effect on both SOC and yield. The modeled change across all management types and all sites was + 10.9% [95% CI: 7.5–14.5] for yield (Fig. 3A) and + 9.8% [95% CI: 7.0–12.6] for SOC (Fig. 4A). In 59.7% of the 434 paired observations in our dataset, cover cropping increased both SOC and yields (Fig. 1; top right quadrant). Trade-offs, in which either SOC or yield increased while the other decreased, accounted for about one-third of observations. In 20.7% of paired comparisons, cover crops increased SOC but decreased yield; in 12.9% of cases, cover crops increased yields but decreased SOC (Fig. 1; top left and bottom right quadrants). Co-costs, in which cover cropping negatively affected both yields and SOC, accounted for 6.7% of paired observations (Fig. 1; bottom left quadrant). Funnel plots showed no indication of publication bias (Figure S1).

Explaining variability in crop yield responses to cover cropping

Out of 29 management and environmental variables considered as possible moderators of the effect of cover crops on cash crop yield, our yield change (Δ_{Yield}) model included an interaction between SOC change (Δ_{SOC}) and initial SOC as well as rotational complexity and N fertilizer, each interacting with cover crop type (legume vs. non-legume) (Table 1). Rotational complexity is the number of different cash crop species rotated in a given plot throughout the length of an experiment and N fertilizer is the N (kg N ha^{-1}) added to both treatment and control plots in each cash crop season. Marginal R^2 of our Δ_{Yield} model was 0.27 and conditional R^2 was 0.89. Addition of edaphic variables such as soil texture and sampling depth did not improve model fit (see Table S1). The average initial SOC concentration of our dataset was 15.5 ± 9.2 g kg^{-1} (standard deviation) at an average sampling depth of 0-18.4 cm ± 7.3 cm (standard deviation). All adjusted generalized variance inflation factor (GVIF) values were below 3, indicating the effect of multicollinearity was negligible.

Δ_{Yield} Model Results			
Variable	**F-value**	**df**	**p-value**
Initial SOC	0.30	1,92	0.59
Δ_{SOC}	2.69	1,67	0.11
Cover Crop Type	0.25	1,27	0.62
Rotational Complexity	9.90	2,71	*<0.001*
N Fertilizer	31.26	1,27	*<0.001*
Absolute Latitude	1.42	1,87	0.24
Δ_{SOC} Initial SOC	4.90	1,85	*<0.05*
Rotational Complexity Cover Crop Type	20.47	2,25	*<0.001*
N Fertilizer Cover Crop Type	29.83	1,24	*<0.001*
Δ_{SOC} Cover Crop Type	2.17	1,24	*0.15*
Δ_{SOC} N Fertilization	0.01	1,63	*0.91*

Table 1. Type III ANOVA results from our Δ_{Yield} model (n = 417). df is numerator and denominator degrees of freedom, respectively, with Kenward-Roger approximation for denominator degrees of freedom. Δ_{Yield} and Δ_{SOC} are the log cash crop yield and SOC response ratios, respectively. Initial SOC is SOC (g kg^{-1}) prior to cover cropping. Cover crop type is binary categorical; legume vs non-legume coded 0 and 1,

respectively. N fertilization is in-season cash crop N fertilization (kg N ha^{-1} $season^{-1}$). Rotational complexity is the number of different cash crop species in rotation throughout the experiment. p-values in italics are considered significant at

We found that SOC changes from cover cropping (Δ_{SOC}) were directly associated with yield changes (Δ_{Yield}), but only in soils with initial SOC values of 9.2 g kg^{-1} or less (Fig. 2). In soils with initial SOC values of 5 g kg^{-1}, for instance, a 10% increase in SOC (i.e., a change from 5 g kg^{-1} C to 5.5 g kg^{-1} C) was associated with a 2.8% yield increase. In soils with initial SOC values greater than 9.2 g kg^{-1}, Δ_{SOC} was not significantly associated with Δ_{Yield}. The Δ_{SOC}-to-Δ_{Yield} relationship did not differ between cover crop types (legume vs. non-legume) and did not vary across differing levels of N fertilization.

The effect of rotational complexity on Δ_{Yield} differed between legume cover crops and non-legume cover crops (Fig. 3B, Fig. 3C). Holding all else at its average, Δ_{Yield} in legume cover crop treatments was significantly greater in continuous cash crop monocultures (+ 21.0%, 95% CI: 15.0–27.3) versus rotations with two (+ 9.3%, 95% CI: 1.7–17.5) cash crop species (Fig. 3B). For rotations with 3 or more cash crops, Δ_{Yield} from legume cover crops was not statistically different from zero. For non-legume cover crops, the magnitude of Δ_{Yield} across rotational complexity groups varied but not significantly so. At the average level of N fertilization in our dataset, non-legume cover crops significantly increased yield only in plots with 3 or more cash crops in rotation (+ 19.2%, 95% CI: 6.9–33.0) (Fig. 3C). Δ_{Yield} from non-legume cover crops in continuous monoculture and two-crop rotations was positive but overlapped zero (+ 5.1%, 95% CI: -1.0–11.5; +4.5%, 95% CI: -3.3–12.9, respectively).

We found that increased N fertilization reduced Δ_{Yield} in legume cover crop treatments but did not have a significant effect on Δ_{Yield} from non-legume cover crops (Fig. 3D, Fig. 3E). Legume cover crops in low N systems (12.9 kg N ha^{-1} $season^{-1}$, one standard deviation below the mean N fertilization of our dataset) increased yield by + 17.8% (95% CI: 11.3–24.7) and in average N systems (85.9 kg N ha^{-1} $season^{-1}$) increased yield by + 10.6% (95% CI: 4.8–16.8) (Fig. 3D). In systems receiving more than 136 kg N ha^{-1} $season^{-1}$, we found no statistically significant effect of legume cover crops. Non-legume cover crops provided yield increases in low (+ 7.5%, 95% CI: 0.9–14.4), average (+ 9.4%, 95% CI: 3.0–16.2), and high (+ 11.4%, 95% CI: 3.7–19.6) N systems (Fig. 3E).

SOC responses to cover cropping

Our Δ_{SOC} model included absolute latitude, cover crop type (legume vs non-legume), and initial SOC as variables which moderated the effect of cover crops on SOC (Table 2). Marginal R^2 was 0.11 and conditional R^2 was 0.92. Addition of other environmental and management variables such as aridity, mean annual precipitation, N and phosphorus fertilization, and tillage did not improve model fit (see Table S2 for full list).

Δ_{SOC} Model Results			
Variable	**F value**	**df**	**p-value**
Cover Crop Type	16.52	1,25	*<0.001*
Absolute Latitude	7.22	1,90	*<0.05*
Initial SOC	4.52	1,90	*<0.01*

Table 2. Type III ANOVA results from our Δ_{SOC} model (n = 434). df is numerator and denominator degrees of freedom, respectively, with Kenward-Roger approximation for denominator degrees of freedom. Δ_{SOC} is the log SOC response ratio. Cover Crop Type is binary categorical; non-legume vs legume. Absolute Latitude is the absolute value of study latitude. Initial SOC is SOC (g kg^{-1}) prior to cover cropping. p-values in italics are considered significant at

While both cover crop types significantly increased SOC, we found that legume cover crops increased SOC (+ 15.4%, 95% CI: 11.5–19.5) more than non-legume cover crops (+ 11.2%, 95% CI: 7.2– 15.3) (Fig. 4B). Cover crops became less effective at increasing SOC as absolute latitude increased (Fig. 4C). In addition, we found that the largest SOC increases occurred in sites with lower initial SOC values. In sites with initial SOC values of 6.3 g kg^{-1}, for instance, cover cropping resulted in a + 15.5% SOC increase (95% CI: 11.3–19.9) while at the average initial SOC value in our dataset of 15.5 g kg^{-1}, cover cropping increased SOC by 13.3% (95% CI: 9.4–17.2) (Fig. 4D).

Discussion

In our meta-analysis of 82 studies spanning 5 continents, we found that cover crops increased crop yields concurrently with SOC in 59.7% of 434 paired observations, thus providing a win-win outcome for farmers and society a majority of the time. Δ_{SOC} was directly associated with Δ_{Yield} only in soils with relatively low SOC prior to cover cropping. The yield benefit of increased SOC did not diminish in systems with higher N inputs and did not differ between cover crop types (legume vs non-legume), indicating that N inputs cannot substitute for changes in SOC that link to higher yields. The largest SOC increases occurred in legume cover crop treatments (+ 15.4%) and the largest yield increases also occurred from legume cover crops in systems with low to average N inputs and in 1–2 crop rotations (up to + 21.0%).

Direct relationships between changes in SOC and yield

Our experimentally based approach identified a Δ_{SOC}-to-Δ_{Yield} response that does not vary based on N inputs or with legume vs. non-legume cover crops. A negative Δ_{SOC} by N fertilization interaction would have indicated that the yield benefit from SOC was substitutable for N inputs and therefore N related. Likewise, if the Δ_{SOC}-to-Δ_{Yield} relationship differed between legume and non-legume cover crops, then some portion of the SOC benefit likely would have been a reflection of yield benefits from N fixation. In the absence of nutrient interactions with Δ_{SOC}, the link we found between Δ_{SOC} and Δ_{Yield} is likely better explained by benefits of increased SOC like reduced compaction and increased aeration[3]. Our results thus help to identify and quantify the yield benefits of soil improvement provided by SOC for which fertilization cannot substitute.

Our analysis clarifies contrasting results of observational meta-analyses regarding whether the yield benefit of additional SOC declines in higher SOC soils[5,24]. It also likely explains the finding of no relationship between yield and SOC reported in an observational meta-analysis of Danish farms[22] in which there were very few observations with SOC concentrations below 10 g kg^{-1}. The yield benefit of increased SOC that we identified is larger than that reported in a previous observational data meta-analysis. For a hypothetical increase from 5 g kg^{-1} to 8 g kg^{-1}, our model predicted a + 16.2% yield increase, compared to the + 10% yield increase previously reported[5]. Although farms with average SOC levels are unlikely to see direct yield benefits of soil improvement from increased SOC, our findings demonstrate that there is a direct material incentive for farms on degraded soils to increase SOC levels at least until 9.2 g kg^{-1}.

Aligning carbon sequestration goals with maximum yield benefits

Regardless of direct links between Δ_{SOC} and Δ_{Yield}, we found that a substantial opportunity to sequester carbon as SOC while also increasing crop yield lies in the incorporation of legume cover crops into systems with few (one to two) cash crops in rotation. Legume cover crops provided increases of + 15.4% SOC and + 21.0% yield in continuous monocrop cultures. In two crop rotations, legume cover crops increased yield by + 9.3% while the + 15.4% SOC increase remained unchanged (i.e., Δ_{SOC} did not vary across rotation types). We did not find evidence that the presence of legume cash crops like soy in more complex rotations accounted for the diminishing yield benefit of legume cover crops in more complex rotations (see Table S1). Yield benefits of crop rotational diversification are well-known[26,27] and based on our results here, appear to be redundant with legume cover crops in more complex rotational systems. In contrast, non-legume cover crops did not significantly increase yield in monocultures or simple two-crop rotations but did increase yield with three or more cash crops in rotation, although there were relatively few data points in this grouping (n = 22). This suggests a need for further research on how to optimize cover crops in more complex cash crop rotations.

We identified low to average N input systems as other key farm types where carbon sequestration goals can align with maximum yield increases through the use of legume cover crops. While Δ_{SOC} did not vary across N fertilization levels, we found that in N limited systems, the yield benefit of leguminous N fixation is relatively greater. In low N systems (defined here as 12.9 kg N ha^{-1} season^{-1}), legume cover crops increased yield by + 17.8% and increased SOC by + 15.4%. While still providing a notable yield increase, the yield benefit of legume cover crops was + 10.6% at the average level of N fertilization in our dataset (85.9 kg N ha^{-1} season^{-1}) and remained significant and positive through 136 kg N ha^{-1} season^{-1} at which point Δ_{Yield} from legumes was not distinguishable from the null (no effect). Legumes could thus allow for reducing synthetic N fertilizer inputs while maintaining yields, which also comes with environmental benefits (e.g., from reductions in greenhouse gasses from fertilizer production).

The larger SOC response from legumes compared to non-legume cover crops (+ 15.4% vs. +11.2%, respectively) contrasts with no effect of cover crop type found in prior meta-analyses[13,28], possibly due to their more limited datasets. With relatively more labile plant inputs that microbes efficiently use, legumes may be particularly effective at building soil organic matter pools, including mineral associated organic matter, that are both stable and supply N[12,29–31]. The negative relationship between latitude and Δ_{SOC} is likely related to reduced biomass production for cover crops at higher absolute latitudes[28]. Cover crops in these latitudes have less time to grow in colder conditions with less sunlight. This finding is in line with a recent meta-analysis which found the length between planting and termination to be an important predictor of SOC response[28]. Our finding that Δ_{SOC} was greatest in soils with lower initial SOC is reasonable in that a similar absolute SOC increase will translate to a larger relative change in soils with lower initial SOC levels.

Our global meta-analysis demonstrates that the goal of building soil carbon through cover cropping aligns with the goal of increasing or maintaining crop yields. Importantly, since these goals align at the site level ~ 60% of the time, benefits of higher yields for farmers are achievable concurrently with the societal benefit of carbon sequestration[10]. Non-nutrient yield benefits related to SOC (e.g., improved soil structure) were only evident in soils with below average SOC. This finding suggests that direct yield benefits from SOC increases could help motivate farmers' adoption of SOC enhancing practices in soils with low SOC, but other incentives will be needed for farmers with SOC levels greater than ~ 10 g kg^{-1}.

We therefore suggest that determining the conditions for which changes to agricultural management provide co-benefits for crop yields and SOC — rather than establishing universal relationships between SOC and yield — will be more useful for spurring agricultural transitions that produce food while also mitigating climate change. To achieve carbon sequestration goals while supporting crop yields, diversifying simplified rotations with legumes is a promising strategy given that legumes often provided the largest benefit to both SOC and yields. Likewise, in low to average N input systems, the greatest yield benefits can be aligned with the greatest SOC benefits through the use of legume cover crops. For systems with complex rotations or high N inputs, non-legume cover crops are a better choice to support yield goals while increasing SOC. Identifying when and where agricultural management practices deliver direct benefits to farmers and contribute to climate change mitigation will help with the urgent need to increase the carbon sink of agricultural lands.

Methods

Study Selection

We selected cover cropping studies according to the following criteria: 1) the experimental design includes one or more replicated cover cropping treatments, defined as a non-harvested crop grown between productive seasons; 2) the study includes a clear control as either bare fallow or spontaneous off-season regrowth (e.g., “winter weeds”); 3) data are available for both SOC and cash crop yield, each measured no more than one year apart; 4) cash crop yield is measured as fruit or grain; 5) yield and SOC are available as yearly or monthly values rather than averages across multiple years (for maximum accuracy in matching SOC values with associated yields); and 6) annual fertilizer inputs are equal across control and treatment or are administered based on pre-season soil tests. Potted plant experiments were not included in our dataset.

We began our literature search with the study lists of two recent cover cropping meta-analyses[13,17] and subsequently searched ISI Web of Science for additional studies that matched our criteria using the search string TS=((cover crop* OR catch crop OR fallow OR green manure) AND carbon AND yield). In October 2020, the date of our final search, our search string returned 2,451 studies. If an article reported only SOC data or yield data, we used key terms related to the experiment to search Google Scholar for articles reporting on the same experiment in order to fill in the missing data. In 11 instances, gray literature sources such as master’s theses, dissertations and conference proceedings were used to supplement data from peer-reviewed publications. In addition to Google Scholar searches, 36 authors were contacted for additional data or methodological clarifications, out of which 8 responded and 3 provided additional data and/or information.

Our final dataset spanned 5 continents and contained data from 82 distinct experiments gathered from 120 sources (107 peer reviewed journal articles, 6 master’s theses, 2 dissertations, 3 publicly available datasets, and 2 conference proceedings). A list of data sources used in the study along with extraction notes is provided in the supplementary material.

Data Compilation and Extraction

We quantified the effect of cover crops on yield and SOC using the log response ratio, calculated as the natural log of the cover crop treatment value divided by that of the respective bare fallow control. Within a given study, a treatment value was matched to a control value in the response ratio (RR) only if both groups differed in no other respect than the use of cover cropping (e.g., same tillage regime, same N application, etc.) and if the treatments were sampled at the same time. This aspect of our study design allowed us to control for confounding effects that would otherwise be introduced in a direct comparison of raw values between studies such as environmental conditions, management decisions, or edaphic factors. In the case of the yield response to cover cropping, our use of the RR allowed us to make comparisons across crops with different morphological characteristics (e.g., tomatoes vs. cotton) because weight units are normalized by the ratio. Site-level initial SOC values were not available for some of the studies in our dataset. To approximate missing site-level values, we used the earliest SOC sample available for the non-cover crop control, assuming that the field had likely been under a no-cover crop planting regime prior to the initiation of the cover cropping experiment. Although differing sampling depths across studies have the potential to obscure trends when comparing raw SOC values, we did not find that sampling depth was a significant predictor of initial SOC values in our dataset. We therefore opted to test initial SOC effects using raw SOC values.

Data Analysis

We collected sampling variances when available to assign weights to data points. However, only 30% of studies reported some form of variance. Following previous work, we chose instead to weight our observations using sample size of the treatment and control groups which gave high weight to larger, well-replicated studies[32–34]. Our weighting formula (Eq. 1) includes the common weighting ratio based on treatment group sample size (n_t) and control group sample size (n_c) as well as a correction term dividing by the total number of observations contributed by a given study (N). This additional step is meant to ensure that no study contributes a disproportionate amount to the final model simply because it contained more extractable data points than another[35].

(Eq. 1) $\mathrm{W} = \frac{n_t \times n_c}{n_t + n_c} \times \frac{1}{N}$

We modeled study site as a random effect to account for the non-independence of these data points, and nested sampling year within study site to account for temporal non-independence. To build models for both Δ_{SOC} and Δ_{Yield}, we implemented a model selection process which utilized Akaike Information Criterion (AIC)[36] scores to select final predictors which we had hypothesized may be mechanistically related to Δ_{SOC} or Δ_{Yield}. Variable relevance was determined by comparing weighted mixed effect models of each variable as a solitary predictor of each response variable against the corresponding model containing only the intercept. Because of incomplete data for certain predictor variables, model comparisons between the solitary predictor and the intercept-only model were done using complete data subsets for the solitary predictor. If the regression containing the solitary predictor variable resulted in an AIC score more than two units below that of the intercept-only regression (i.e., ΔAIC < 2), the variable was included in our final multiple regression model. We did not perform any further model selection because complex model selection decisions are often subjective and can change results considerably[37]. For our Δ_{Yield} model, we tested interaction terms between Δ_{SOC} and soil texture metrics, as well as an interaction between Δ_{SOC} and initial SOC (SOC concentration prior to cover cropping), as per previous findings[5]. Lastly, we tested interaction terms between cover crop type (legume vs non-legume) and yield predictor variables whose effects we hypothesized may be influenced by N fixation such as N fertilization, rotational complexity and Δ_{SOC}.

In both models, we checked for collinearity among variables using generalized variance inflation factors (GVIF) with the following adjustment to allow for comparability across variables with differing degrees of freedom[38] (df): $AdjustedGVIF = (GVIF)^{\frac{1}{2df}}$. We considered adjusted GVIF values of 3 and higher to indicate potential collinearity[39]. Variables with foreseeable problems of collinearity such as mean annual temperature and precipitation, absolute latitude, and aridity index were assessed separately in multiple regressions on the basis of AIC.

All analyses were performed using R Statistical Software v4.2.0[40]. We built mixed effect regressions using the package 'lme4'[41] and determined fixed effect F-values using a type III ANOVA in the 'stats' package[40]. We used the package 'emmeans' to quantify interaction effects[42]. We used pairwise comparison in the package 'emmeans' to determine significant differences among levels of categorical variables using a = 0.05 with a Bonferroni adjustment for multiple comparisons[43]. To determine the significance of different levels of our moderating factors, we checked to see whether their 95% confidence intervals (95% CI) overlapped zero, with no overlap indicating a rejection of the null (zero effect) at a = 0.05. We used the Kenward-Roger approximation for denominator degrees of freedom in all p-value calculations[44].

Declarations

Author contributions

I.V., T.M.B., and L.P. conceived the ideas and designed methodology; I.V. and G.D.L.C. collected the data; I.V., A.G., and K.E. analyzed the data; I.V. and T.M.B. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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Conflict of Interest

The authors have no conflicts of interests related to this work.

Data Availability

Data used in this meta-analysis are available from the Dryad Digital Repository, accession.

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Figures

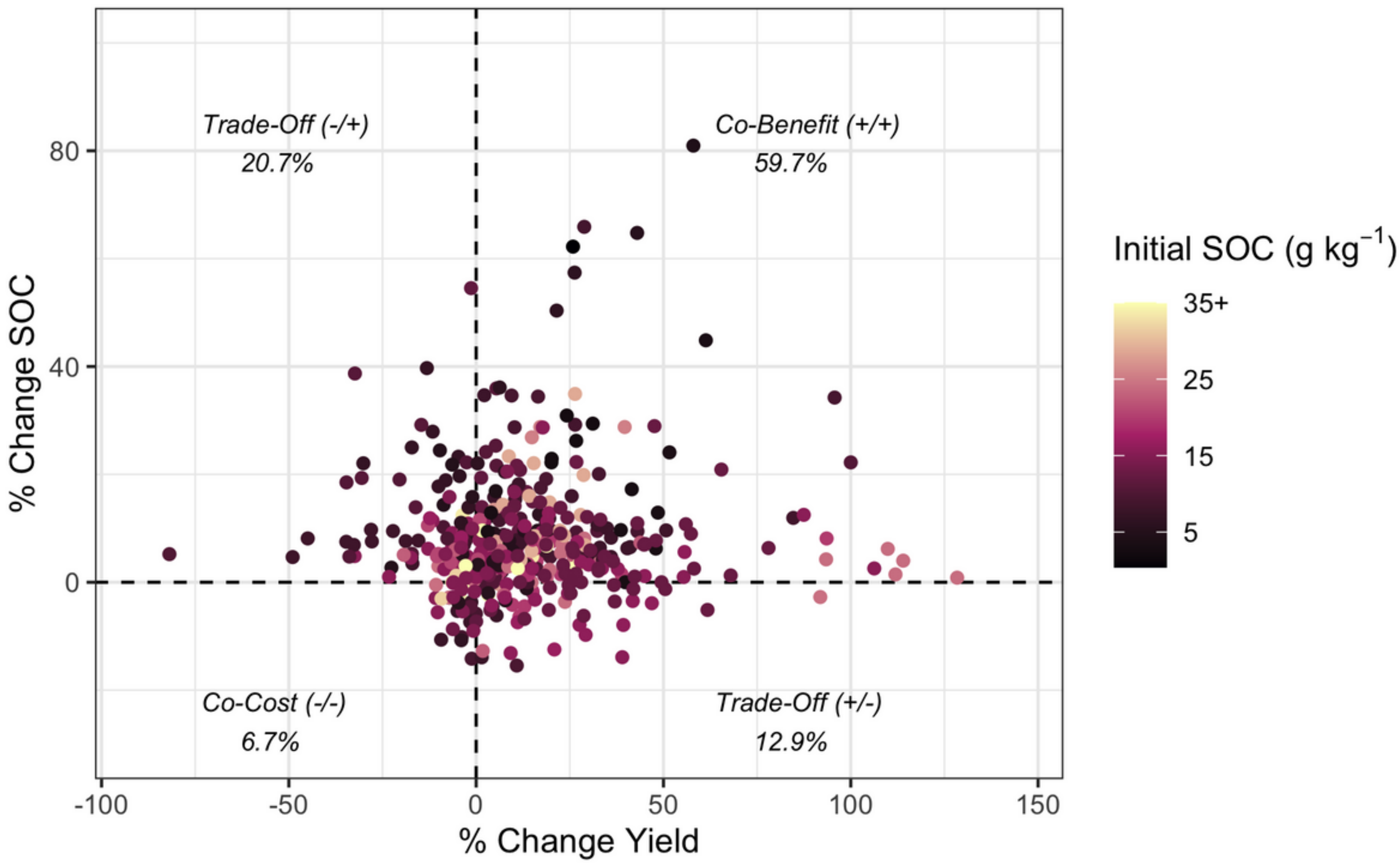

Figure 1

Scatterplot of co-occurring SOC and yield changes from cover crops (n = 434). In 59.7% of observations, SOC increases occurred alongside yield increases from cover crops (i.e., provided co-benefits). In 20.7% of observations, cover crops increased yield, but decreased SOC, and in 12.9% cover crops decreased SOC but increased yield (trade-offs). Cover crops decreased both SOC and yield in 6.7% of data points (co-costs). 2 outlier points have been cut off from the limits of this graph to aid in visualization of the data.

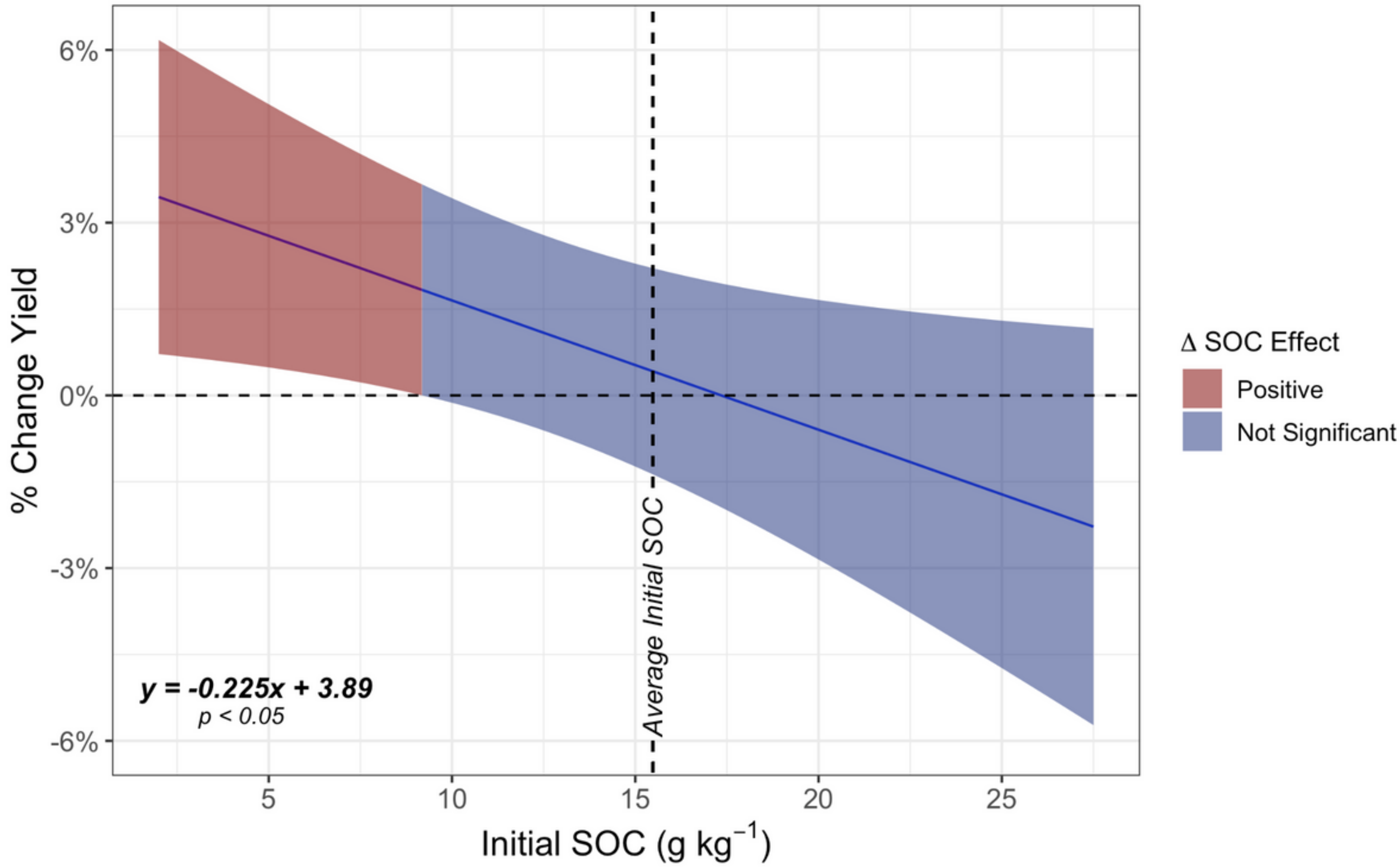

Figure 2

Yield change associated with a 10% increase in SOC (e.g., from 5 g kg^{-1} to 5.5 g kg^{-1}) at differing levels of initial SOC. Initial SOC is SOC (g kg^{-1}) prior to cover cropping (0-18.4 cm depth on average). Shaded bands are 95% CIs. Increased SOC is positively associated with yield (red) only in sites with below average initial SOC. 90% of observations fell within the initial SOC range shown.

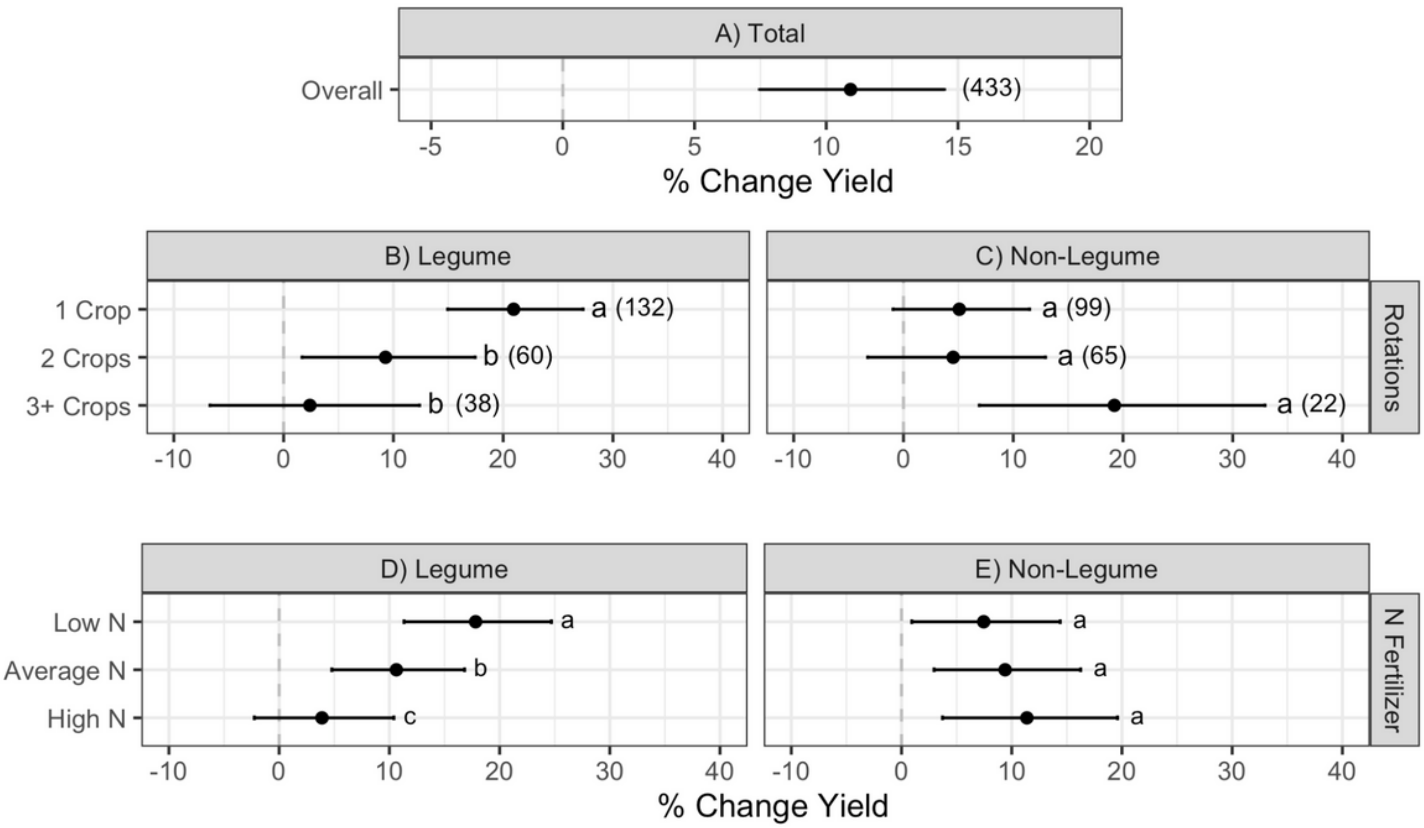

Figure 3

Cash crop yield change from cover cropping at different levels of rotational complexity ("rotations") and N fertilizer (kg N ha^{-1} $season^{-1}$) in our yield model. Selected N fertilizer levels are dataset mean ± sd with low, average, and high N corresponding to 12.9, 85.9, 158.9 kg N ha^{-1} $season^{-1}$, respectively. Rotational complexity ("Rotations") is a count of the number of different cash crop species rotated on a given plot across the length of the experiment. Yield change estimates are shown for both legume and non-legume cover crops. Letters are pairwise comparison results with different letters indicating significantly different effect sizes at

. Numbers in parentheses are observations in each grouping (not included for N fertilizer because displayed estimates correspond to selected values along a continuous axis rather than groupings). Error bars are 95% CIs.

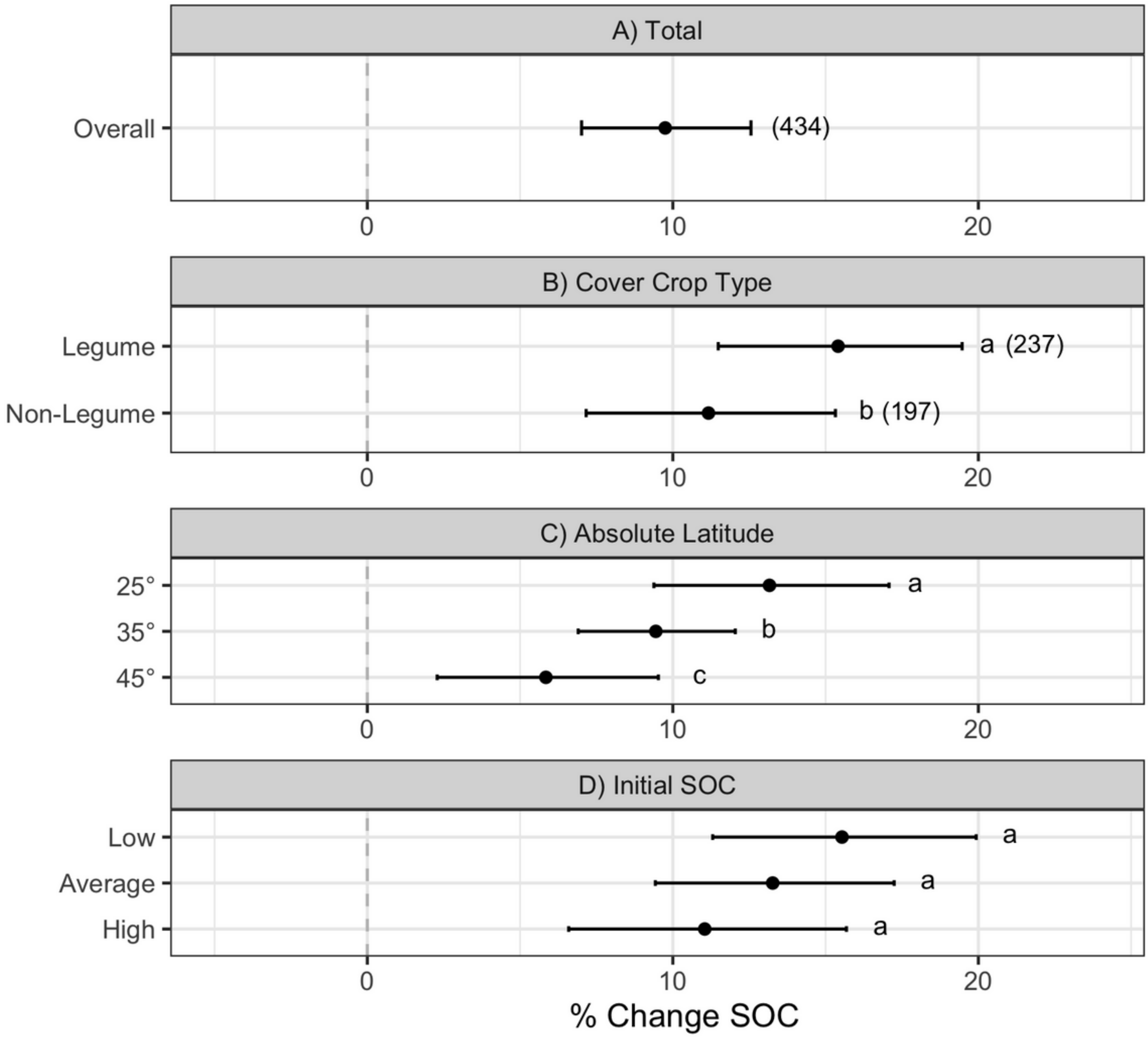

Figure 4

SOC change from both cover crop types (legume vs non-legume) as well as SOC change estimates at selected values of absolute latitude in our yield model. Absolute Latitude is the absolute value of study latitude. Initial SOC is SOC prior to cover cropping (selected values are dataset mean ± sd with low, average, high corresponding to 6.3 g kg^{-1}, 15.5 g kg^{-1}, 24.7 g kg^{-1}, respectively). Cover Crop Type is binary categorical; non-legume vs legume. Letters are pairwise comparison results with different letters indicating significantly different effect sizes at

. Numbers in parentheses are observations in each grouping (not included for absolute latitude and initial SOC because displayed estimates correspond to selected values along a continuous axis rather than groupings). Error bars are 95% CIs.

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