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Does Soil Carbon support Climate Resilient Agricultural Systems? Searching for Evidence and Developing New Measurement Tools

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Abstract

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Increasing soil organic carbon (SOC) is frequently promoted as a "win-win" strategy for agricultural management in the face of a changing climate. This framing is based on the notion that building SOC both reduces yield losses/variability by improving soil water dynamics, and that building SOC can contribute to climate change mitigation by reducing atmospheric carbon. While this framing may be useful, relationships between SOC and such outcomes are often poorly described and not quantitative. That is, it's unclear how much of an improvement to SOC is needed to reduce yield losses, whether or not that effect translates across soil types and agricultural systems, and how achievable carbon sequestration goals really are. As efforts to increase SOC in agricultural systems develop, there is a need to both better synthesize our current understanding of how it supports resilience in agricultural systems and to better monitor changes in SOC to understand its impacts on climate change adaptation and resilience. My research focuses on two broad topic areas: 1.) exploring the links between SOC, soil water dynamics, and yield outcomes, particularly under drought conditions; and 2.) developing accessible, robust measurement systems and protocols for quantifying SOC stocks at landscape scales (>100 ha) that utilize visible/near-infrared (VNIR) spectrometry.

Does Soil Carbon Support Climate Resilient Agricultural Systems? Searching for Evidence and Developing New Measurement Tools

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Dissertation overview

Background

Soil organic carbon (SOC) is the largest biologically-cycling, terrestrial carbon (C) stock, holding an estimated 1500-2400 Pg C to a depth of 1 m (Bradford et al. 2016). Modification of landscapes by humans has, however, decreased this stock by an estimated 133 Pg C (Sanderman, Hengl, and Fiske 2017), with another 30 to 203 Pg under threat of loss as climate change and land conversion accelerate decomposition processes (Crowther et al. 2016). Protecting and recapturing SOC could then be an important strategy in mitigating climate change. In a review of regional case studies, it was estimated that increasing surface SOC stocks in agricultural soils by just 0.4% globally could sequester 2-3 Pg C per year, offsetting 20-35% of annual global greenhouse gas emissions over the next 10-20 years (Minasny et al. 2017).

SOC is also an essential property of agricultural ecosystems. It provides fertility in the form of organic compounds that can be mineralized into plant available forms (Robertson et al. 2014), and it is key to formation of soil aggregates, allowing soils to form pore spaces that retain water for plant growth (Bronick and Lal 2005; Hudson 1994; Six et al. 2004; Tisdall and Oades 1982). Long-term agricultural experiments have consistently demonstrated that higher levels of SOC are positively correlated with several indicators of soil biological fertility and biophysical function, which in turn increase productivity (Rasmussen et al. 1998). A recent meta-analysis also demonstrated that this correlation scales globally across different crops and cropping systems, although effects attenuate above certain levels of SOC (Oldfield, Bradford, and Wood 2019).

Last, positive correlations between SOC and soil water dynamics are often used to suggest that by increasing SOC, producers may reduce inter-annual yield variability and improve yield resilience by mitigating yield losses during adverse weather (Iglesias et al. 2012). This message is especially poignant given that climate change is expected to increase the incidence and severity of extreme precipitation and drought events (Luber and McGeehin 2008; Meehl et al. 2007), meaning its impacts on rain-fed agriculture will likely be substantial (Urban et al. 2012).

Is increasing SOC a "win-win"?

Given evidence of its potential as a climate change mitigation solution and evidence of its impacts on agricultural productivity and resilience through improved soil water dynamics, increasing SOC is frequently promoted as a "win-win" solution for agriculture in the face of a changing climate. In this framing, agriculture can both help itself build resilience and maintain productivity, while contributing to solving the very root cause of the dangers it faces – climate change. A variety of stakeholder groups have now initiated broad-scale campaigns based on this framing and are attempting to shift agricultural production models towards ones focused on building SOC. But while these campaigns may be based on sound theories, they lack detail on the specificity of impact SOC may have and risk overpromising on outcomes.

For example, the argument that increasing SOC will decrease yield variability appears sound based on our understanding of how it impacts soil aggregate formation and structure. But very few studies have demonstrated a connection between higher SOC and reduced variability or mitigation of yield losses in drought conditions. Using yield data between the years 1949 and 1998 from several sites across an SOC gradient in China, (Pan, Smith, and Pan 2009) found that yield variability across time, measured as coefficient of variation, was lower at sites with higher SOC content. Similarly, using historic yield data from the US Department of Agriculture

(USDA) and soil data extracted from the USDA's spatial soils dataset (SSURGO), (Williams et al. 2016) found that areas with higher estimated soil water holding capacity had improved corn yield stability and decreased risk of low yields in bad weather years for corn. But these studies are cross-site comparisons in which the SOC differences between sites are substantial and may be conflated with other soil characteristics (i.e. clay content). In contrast, within a given farm, differences in SOC and soil texture are likely to be less marked, and the effects of management interventions on SOC content are likely to be relatively modest. Importantly, these studies also do not focus on separating the direct effects of different agricultural management schemes on soil water dynamics from the impacts of relative increases in SOC. Such practices have been demonstrated to have positive impacts on yield variability and outcomes (Gaudin et al. 2015), but it's unclear to what extent those impacts are mediated by changes to SOC.

Furthermore, while there may be a consensus that human activity has led to a substantial carbon debt in soils, the efficacy of managing soils for the purpose of carbon sequestration is hotly contested. Optimistic estimates are based on a presumption that the majority of this debt can be made up and in a reasonable timeframe, leading to moderate but still impactful sequestration outcomes (Fargione et al. 2018; Griscom et al. 2017; Minasny et al. 2017; Smith et al. 2008). But more skeptical opinions suggest that evidence for how different practices will impact SOC stocks is limited and that significant barriers to adoption of these practices are likely to limit the extent of those impacts (Amundson and Biardeau 2018; Schlesinger and Amundson 2019). Furthermore, as climate change alters global temperature and precipitation patterns, SOC may become more vulnerable to loss overall, negating possible positive effects of management (Crowther et al. 2016; Davidson and Janssens 2006; Natali et al. 2011; Pold et al. 2017; Pries et al. 2017).

Given these debates, it seems hardly certain that increasing SOC is indeed a "win-win." There may be few downside risks to agricultural systems from this focus in terms of the biophysical properties of soils, but a better understanding of what kinds of outcomes to expect and better tools to monitor those outcomes are essential to making evidence-based progress.

Research objectives

My research focuses broadly on two topics central to the debates outlined above:

1. Evaluating the relative impacts of management and SOC stocks on soil water dynamics and climate resilience in agricultural systems (Chapters 1 and 2). For this objective I hope to contribute research to better understand the specific impacts increasing SOC may have on agricultural systems under future climate scenarios by leveraging existing data.
2. Developing measurement tools and methods for rapidly quantifying SOC at landscape scales (Chapters 3). Our understanding of how different management schemes are impacting SOC and, hence, productivity, is often limited by a lack of data, and little research has been done at the landscape scale. For this objective I am focusing on developing tools for SOC measurement that employ inexpensive visible/near-infrared (VNIR) spectrometry and associated measurement protocols to rapidly develop spatially explicit estimates of soil carbon content at the field scale.

Summary of chapters

Chapter 1: In this chapter I will quantitatively evaluate the relative importance of soil carbon and management on soil water infiltration rates, a key soil biophysical metric and indicator of soil health, using a meta-analysis approach. This chapter corresponds to a paper of the same title that is currently in review (March 14, 2022) at the journal *PLOS ONE*.

Chapter 2: In this chapter I will assess whether soil carbon can mitigate the deleterious impacts of drought on agricultural productivity. To do so I will synthesize long-term historical data on US maize yields from the United States Department of Agriculture's National Agricultural Statistic's Service (USDA NASS) with data from digital soil maps and data on historical drought patterns to assess if higher levels of soil carbon lead to lower yield losses in the US "corn belt." This chapter corresponds to a paper of the same title published March 2021 in *Environmental Research Letters* with the following DOI - 10.1088/1748-9326/abe492.

Chapter 3: In this chapter I will assess the efficacy of a set of low-cost, open-source spectroscopy tools and digital soil mapping techniques for rapidly quantifying soil carbon content. In addition, I will simulate a potential applied use of such tools in assessing their utility in assessing field-scale soil carbon variability. This chapter corresponds to a white paper in development to report findings from the Quick Carbon research project at Yale School of Environment.

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Chapter 1: Soil carbon versus other management effects of conservation agriculture practices on soil water infiltration: A meta-analysis

Abstract:

Agricultural practices that enhance soil water infiltration could improve the resilience of agricultural systems to extreme weather events such as droughts and floods by increasing the supply of available water to crops and minimizing inundation. Several conservation agriculture practices, such as reduced tillage or cover cropping, can increase soil water infiltration relative to conventional practices. This link may be explained by increases to soil organic carbon content induced by these practices that improve soil aggregate formation and porosity, but additional effects not mediated by increases to soil carbon could also help explain such patterns. Separating and quantifying soil carbon-associated and other effects could help to inform management decisions and to better understand the specific mechanisms by which such practices might improve drought and flood resilience. We developed a dataset of paired observations of soil carbon and water infiltration rates to determine the relative effect of increases to soil carbon on soil water infiltration rates versus other effects of conservation agriculture practices, including increased living cover, reduced tillage, and organic amendments. We found that across practices increases to soil water infiltration associated with and mediated by increases to soil carbon content. For living cover, an additional, unmediated direct effect on soil water infiltration of similar magnitude was also observed. Our results support previous studies linking conservation agriculture to improved soil water dynamics but also lend greater specificity to the understanding of how and when adoption of these practices translate to improvements in soil water infiltration rates. Specifically, our data synthesis suggests that the impact of reduced tillage and organic amendments on soil water infiltration are contingent on the likelihood they will increase soil

carbon content at a given location, whereas the impacts of increased living cover manifest even in the absence of soil carbon changes.

1. Introduction:

Weather extremes induced by anthropogenic climate change are reducing the productivity of agricultural systems globally (Burchfield et al. 2020; Ortiz-Bobea et al. 2021; Lobell et al. 2014) and are projected to have continued, negative impacts over the next century (Dixon et al. 1994; Adams et al. 1990; Rosenzweig et al. 2014). Improving the resilience of agricultural systems to these extremes will be key to ensuring food security (Schipanski et al. 2016). Recent evidence suggests that conservation agriculture strategies, such as increasing annual living cover and greater soil organic matter, may improve resilience of yields to extreme weather events (Kane et al. 2021; Williams et al. 2016). One mechanism by which they might improve resilience is by improving water infiltration dynamics at the soil surface, ensuring that precipitation and/or irrigation events lead to a sufficient supply of plant available water (Schipanski et al. 2016; Raza, Friedel, and Bodner 2012; Stewart and Peterson 2015). Soil water infiltration rate has been identified and widely promoted as a useful, easily measured indicator that could be predictive of cropping system resilience. Cropping systems in which aboveground water more readily infiltrates may have greater water use efficiency and likely will better cope with both extreme drought and extreme rainfall.

Evidence suggests that management practices such as living cover and reduced tillage improve water infiltration (A. Basche and DeLonge 2017; A. Basche and Edelson 2017; A. Basche and DeLonge 2019; DeLonge and Basche 2018). This impact may be attributable to multiple causal factors. No-till minimizes or eliminates soil disturbance, improving soil aggregation and reduces the tortuosity of soil pores such that water infiltrates more readily (Alvarez and Steinbach 2009; Smith 2016). Similarly, increasing total annual living cover through the use of cover crops and elimination of bare fallows means aboveground cover and living roots are present throughout a greater portion of the year. Aboveground cover reduces the velocity with which precipitation meets the soil surface, reducing crusting and surface flow, while living roots increase soil aggregation and create larger macropores.

These practices can also increase soil organic matter (and hence soil carbon) content (Paustian, Larson, et al. 2019; Griscom et al. 2017; Fargione et al. 2018; Poeplau and Don 2015), and studies have linked increased soil organic matter to increased aggregate formation and porosity (Boyle, Frankenberger, and Stolzy 1989; Elliott and Efetha 1999; Franzluebbers 2002). But these organic matter responses and hence the consequences for infiltration can vary based on geographic location, soil type, and the specific manner in which a practice was implemented. As such, it remains unclear whether improvements to water infiltration following the introduction of conservation agriculture practices are largely indirect via increases in soil organic matter or are driven by other effects such as cover crops decreasing the velocity at which precipitation encounters the soil surface. Separating and quantifying the strength of effects mediated by increases to soil carbon and other effects on soil induced by management changes can inform management decisions by identifying whether the pathways of impact on infiltration rates are likely to occur at a particular location. For example, reduced tillage can but does not necessarily increase surface soil organic carbon concentrations. If its effects on infiltration are dependent on its increasing soil organic carbon then such knowledge will clarify the circumstances under which reduced tillage is likely to improve infiltration.

In this study we used a meta-analysis approach to evaluate the relative influence of soil organic carbon versus other, unmeasured effects of different conservation agriculture treatments on soil water infiltration rates. First we assembled a collection of papers by combining those from a comprehensive literature search in (A. Basche and DeLonge 2019) with a matching literature search to include publications from more recent years (2016-2021). We subset these papers to those that included data on both soil carbon and soil water infiltration. Paired observations of soil carbon and water infiltration were then analyzed to determine how these conservation management strategies influenced water infiltration and the proportional extent to which these effects were mediated through increases in soil organic carbon concentrations in surface soils versus other effects not mediated by changes to soil organic carbon concentrations.

2. Methods:

2.1. Literature search

To develop our meta-analysis database, we started with the database compiled in Basche and DeLonge (2019) **and** then filtered that database down to just those papers that also included data on soil organic matter or soil carbon**.** Extensive details on how the literature search was conducted are available in that publication and its supplementary materials, but we briefly summarize those methods here. Searches were limited to peer reviewed scientific publications until the year 2015 and were conducted using the EBSCO Discovery Service (https://www.ebsco.com/products/ebsco-discovery-service), an academic search engine that includes publications from all major scientific publishers. Search term strings all began with "infiltration W1 rate" AND "crop*" followed by additional keywords related to different conservation agricultural production systems, such as reduced tillage, cover cropping, etc. (Table 1). Searches on EBSCO Discovery Service yielded an initial 598 studies, and an additional 21 studies were identified in the USDA Natural Resource Conservation Service's soil health literature database (Kucera 2015) and manually added to the database. Basche and DeLonge (2019) then screened articles based on whether or not they included data on water infiltration rates and whether or not they included proper controls to evaluate the conservation agriculture treatment(s) being evaluated in each paper. This screening process yielded a final count of 89 articles from which they extracted data for a quantitative meta-analysis.

We further updated this bibliography to include papers from 2016 to 2021 by using the same search terms on CAB Direct. Access to EBSCO Discovery Service was no longer available, but CAB Direct includes a comparable collection of publications with a particular focus on applied life sciences, including all major agricultural research journals. This search yielded an additional 159 articles that were then screened, along with the 89 articles from Basche and DeLonge (2019), to identify those papers that contained data on soil organic matter or soil carbon for all treatments and controls. Most studies did not include data on soil organic matter or soil organic carbon at the start of the study period. As such we use data from the conclusion of the study period to allow us to make paired comparisons based on the absence/presence of treatments aligned with categories described below (i.e. we compared control values - absence of the treatment - to the treatment values). We additionally filtered to select only studies that reported soil organic matter/carbon or infiltration rate in units that could be converted to a common basis in later data harmonization steps described below. More specifically, we excluded several studies that reported soil organic matter/carbon on a mass per area basis (i.e. Mg ha^{-1}) but did not report soil depth, obfuscating conversion to a content basis (i.e. g C kg $soil^{-1}$), and we excluded one study for which infiltration rate was reported as the amount of time it took for a set volume of water to infiltrate, without specifying information needed to convert to a rate with the units cm h^{-1}. This filtering yielded a final database of 44 studies representing 191 paired comparisons and 264 complete observations.

2.2. Data preparation

Once the database was compiled we created a matrix of treatment information to match all observations. Across all studies we identified three major categories of conservation management intervention: increased living cover, reduced tillage, and organic amendment. Increased living cover was defined as treatments in which a fallow period was replaced with a cover crop or an additional cash crop. Reduced tillage was defined as treatments in which tillage was eliminated (i.e. 'no-till') or reduced in intensity or depth compared to control treatments within the study. Organic amendment included treatments in which compost, manure, or additional crop residues (i.e. green manure) were applied or left in the field. Individual treatments and observations were identified as "yes" or "no" according to these categories (Supplementary File 1). We used this categorization to develop the pairwise comparisons for each management category within each study as detailed below.

Data on mean soil water infiltration rate for each treatment were collected for each paper. In cases where multiple observations of infiltration rate were made over the course of the experiment, we recorded the observations from time points that best corresponded to paired observations of soil carbon or soil organic matter. The majority of experiments employed water infiltration methods using a ring infiltrometer or similar (Bouwer 1986) and reported either cumulative infiltration or a steady-state equivalent in units of cm h^{-1} or similar (e.g. cm min^{-1}). As such we elected to normalize all data to a cm h^{-1} basis, but to account for minor variations in methods across papers (i.e. volume of water applied, time for infiltration, size of ring, etc.), we implemented a random factor corresponding to each experiment in all models to account for these differences in methods. Additionally, we used these data to calculate log response ratios

(LRR) for each experimental treatment by taking the natural log of the ratio of the infiltration rate for each experimental treatment versus the infiltration rate of the control treatment (Eq. 1).

$$(1) \quad \text{LRR} = \ln \frac{\text{Treatment infiltration rate}}{\text{Control infiltration rate}}$$

Data on mean soil organic matter or soil carbon for each treatment were similarly collected for each paper. As with infiltration rate data, in cases where multiple observations of soil organic matter/carbon were made over the course of the experiment, we recorded the observations from time points that best corresponded to paired observations of water infiltration, or we recorded the final observation from the experiment. All soil organic matter and soil carbon data were then normalized to the same units of g C kg soil^{-1}. Since additional information to inform selection of the most appropriate conversion factor was not available in most cases, soil organic matter content data were converted to a soil carbon content basis by multiplying those values by a factor of 0.58 (Jensen et al. 2018). Papers involved different protocols for total sampling depth and depth increments, but the maximum depth to which soils were sampled in any paper was 30 cm. Given that the focus of this meta-analysis is the effect of soil carbon on water infiltration, it made most sense to focus on surface soil depths. For each paper, data from different depth increments were combined by weighting each increment by the proportion of the total sample it represented and then determining the mean soil carbon content value across all depth increments. Additionally, we accounted for these differences in methods by employing the random factor corresponding to the study, as described above. Additionally, we also calculated a LRR for soil carbon based on the ratio of soil carbon content in experimental treatments versus the soil carbon content in control treatments.

2.3. LRR models

We analyzed data for each type of management intervention (living cover, reduced tillage, and organic amendment) separately. Initial statistical analyses were based on evaluating the relationship of LRRs of water infiltration rate against LRRs of soil carbon. All analyses were conducted in the R statistical computing environment (R Core Team 2020). Models were constructed as linear mixed effects models using the *lme4* package (Bates et al. 2020) and included soil carbon LRR as a fixed effect, study as a random effect, and water infiltration LRR as the dependent variable. Additionally, model estimation was weighted by length of study to account for the possibility that longer-term studies would have resulted in greater changes to soil carbon concentrations. To assess whether model results were sensitive to individual studies, we also conducted a Jackknife sensitivity analysis. This sensitivity analysis entailed iteratively removing each study from the database and re-fitting the same model with data from that study removed. Evaluating how model terms changed in each instance indicated whether or not overall results from the complete database were strongly influenced by an individual study.

2.4. Meta-regression models

In addition to models based on LRRs, we also used a series of linear mixed effects models for each practice category to test the relationship between soil carbon and practice changes on infiltration rate. These models were also fit using the *lme4* package (Bates et al. 2020) with soil carbon as a fixed effect, management category as a fixed effect, an interaction effect between these two fixed effects, study as a random effect, and water infiltration rate as the dependent variable. As with the LRR models, model estimation was weighted by length of study to account for the possibility that longer-term studies would have resulted in greater changes to soil carbon concentrations. Prior to model fitting, all observations of each independent variable were standardized so that coefficient estimates would also be standardized. Data standardization was done by subtracting the mean of a given variable from each observation and then dividing that value by 2x the standard deviation of that variable (Gelman 2008).

2.5. Path analyses

Finally, we also conducted a series of confirmatory path analyses for each management category to evaluate if causal pathways linking differences in practices to differences in soil carbon and finally to differences in soil water infiltration rates emerged in our data. We used a piecewise structural equation modeling approach using the *piecewiseSEM* package (Lefcheck, Byrnes, and Grace 2019). For each management category, models were fit to estimate both the direct effect of management on water infiltration rate (cm h^{-1}) and the effect of management as mediated through soil carbon content. Within each piecewise model component, models were fit using a linear mixed effects model with study as a random factor to account for differences in methods, and length of study as a weighting factor to account for the possibility that longer-term studies may result in greater soil carbon changes and therefore greater effects on water infiltration. Prior to model fitting, all observations of each independent variable were standardized so that coefficient estimates would also be standardized. Data standardization was done by subtracting the mean of a given variable from each observation and then dividing that value by 2x the standard deviation of that variable (Gelman 2008), *2.6. Publication bias analysis*

Finally, to assess whether or not our database exhibited a publication bias, we estimated summary statistics on the proportion of studies in our database that had positive LRRs for either soil carbon concentration or infiltration rate. Additionally, we developed forest plots (Andrade 2020) to visual potential bias across papers.

3. Results:

3.1. Database

The final database included 44 studies representing 191 paired comparisons and 264 complete observations. The majority of studies focused on tillage (29 studies), but the number of paired comparisons was relatively equal across the three practice groupings (reduced tillage, n = 73; living cover, n = 53; organic amendment, n = 65). Studies represented a variety of cropping systems across five continents (North America, South America, Asia, Australia, Africa). The majority of studies were located in India (n = 22), followed by the United States (n = 7). All remaining studies were from a variety of individual countries (Supplementary Table 1).

Across studies, implementation of conservation practices generally resulted in increases to soil carbon content quantified as a positive log response ratio (LRR) of soil carbon in treatments versus controls. However, the size of this effect varied across our practice groupings (Figure 1). Increased living cover had the greatest effect (mean LRR = 0.22), while organic amendments and reduced tillage had similar effects (mean LRR = 0.15). For infiltration rate, increased living cover had the greatest effect (mean LRR = 0.36), followed by organic amendment (mean LRR = 0.28), and finally reduced tillage (mean LRR = 0.13).

Since not all studies included a measure of error for treatment effects, our evaluation of publication bias was limited to an assessment of the distribution of estimated effects across studies. For infiltration rate, 65% of paired comparisons in living cover studies had a positive LRR, 64% in organic amendment studies, and 90% in tillage studies. For soil carbon, paired comparisons exhibited a more predominantly positive trend (living cover = 82% positive LRR; organic amendment = 95% LRR; reduced tillage = 86% positive LRR). However, in all three practice categories there were negative observations meaning that, although many pairwise comparisons were positive, the distribution of effect sizes for most results were centered near zero (Figure 1). When these results were grouped by study into tree plots, similar patterns were evident (Supplementary Figures 1-6), indicating an overall positive trend but no evidence of exclusion of negative or near-zero results.

3.2. LRR models

Across all practice categories, LRR model results demonstrated that management-induced changes to soil carbon were associated with increases in soil water infiltration rates. Soil carbon increases via reduced tillage appeared to have the greatest effect (β = 1.38), followed closely by soil carbon increases via organic amendment (β = 1.16). The effect size of soil carbon increases via increased living cover were considerably smaller in comparison (β = 0.45). Based on the Jackknife sensitivity analysis, we found minimal evidence across each practice category that any one study had an outsize effect on the observed results. Coefficient estimates when a paper was removed remained within the 95% confidence intervals of coefficient estimates when the whole database was used.

3.3. Meta-regression models

Initial results from the meta-regression models suggested that the relative importance of direct management versus soil carbon change effects on soil water infiltration rate differed across practice categories. For both organic amendments and reduced tillage, models indicated that soil carbon had a positive, significant effect ($\alpha = 0.05$) on soil water infiltration rate and presence/absence of the conservation agriculture practice had a non-significant ($p > 0.05$) effect. The opposite was true for increased living cover, which had a positive, significant effect for presence/absence of practice, albeit one with substantial standard error ($\beta = 0.24$; β-SE = 0.10; $p = 0.02$), and a non-significant soil carbon effect. No significant interaction effects were observed.

Jackknife sensitivity analyses indicated that meta-regression results for the increased living cover and organic amendments categories were sensitive to an individual paper (Figure 3). Specifically, when Lal et al. (1978) was removed from the database, the coefficient for presence/absence of the living cover practice in the model decreased and was no longer significant ($\beta = 0.02$; $p = 0.13$). Additionally, a positive, significant interaction effect of soil carbon and presence/absence of practice emerged ($\beta = 0.07$; $p < 0.01$), indicating that in the presence of increased living cover, infiltration rate increased with soil carbon content. Treatments in Lal et al. (1978) included multiple different cover types used in place of a fallow period, which served as the control. All cover treatments had a higher infiltration rate than the fallow control treatment, and differences were variable ranging from 37 to 143 cm h^{-1} greater than the control. As such, this study had very high leverage, and the large spread in outcomes was responsible for the high standard error of the coefficient for presence/absence of practice in the model on the full database. Based on this sensitivity analysis, we elected to remove this study from the database for reporting of meta-regression results (Figure 3) and when conducting path analyses.

For the organic amendments category, removing Moebius-Clune et al. (2008) substantially increased the coefficient for soil carbon (β = 0.35 to 0.67), but other effects remained similar. Examining the data from Moebius-Clune et al. (2008) revealed that an individual treatment with high soil carbon content had the lowest infiltration rate, so when included in the model, data from this treatment suppressed the estimate of the effect of soil carbon. Conversely, when Wang et al. (2016) was removed from the database, the effect of soil carbon decreased (β = 0.35 to 0.17), and a small but significant effect for presence/absence of practice emerged (β = 0.35; p < 0.01). Examining the data from this paper, an individual treatment with the highest soil carbon content had substantially higher infiltration rate than other treatments. In both cases, however, the directionality and significance of the affected coefficients remained the same, so we retained these studies in the database for path analyses.

3.4. Path analyses

Results of path analyses were largely consistent across each practice category. For each category, presence of the practice had a positive effect on soil carbon content, and higher soil carbon content had a positive effect on soil water infiltration rate (Figure 4). This pattern indicates that the effect of management changes (i.e. presence/absence of the practice) on soil water infiltration rate were mediated by increases to soil carbon content. In addition to this mediated effect, increased living cover also had a direct, positive effect on soil water infiltration rate.

4. Discussion:

Our results suggest that among the studies we summarized, conservation agricultural management practices that increase soil carbon content relative to "business as usual" controls also increase soil water infiltration rates. Results from LRR models indicated that management-induced increases to soil carbon content were associated with relatively higher soil water infiltration rate. Meta-regression models suggested that increased soil carbon content had a positive effect on infiltration rates, and path analyses extended these results by revealing that conservation agriculture practices likely had an indirect, mediated effect on soil water infiltration rate driven by increasing soil carbon content. The exception was increased living cover, which also increased soil water infiltration rate through mechanisms not associated with changes in soil carbon content.

4.1. Implications for management

These results are consistent with previous studies showing that conservation agriculture practices increase water infiltration (Basche and DeLonge 2019) and also reflect research results from grazing systems in which increases to soil carbon and increases to water infiltration co-occur (DeLonge and Basche 2018). Yet they lend greater specificity as to how such practices might increase soil water infiltration by highlighting the relative importance of increases to soil carbon content versus other mechanisms of impact. Although data on the mechanism by which increases in soil carbon facilitate greater infiltration is not available to us across the studies we evaluated, a plausible, well-documented mechanism is that an increase in soil organic carbon in such systems is, in part, the result of increases in soil macroaggregates and hence greater porosity (A. Basche and DeLonge 2017; Elliott and Efetha 1999; Lado, Paz, and Ben-Hur 2004; Boyle, Frankenberger, and Stolzy 1989). Additional research would be needed to discern if this mechanism explains the impacts of conservation practices on infiltration rates in the studies included here. If it does, then to improve the resilience of agriculture to droughts, one option will be to promote practices that build and sustain soil macroaggregate concentrations.

Notably, cover crops can increase water stable aggregate formation independent of their effects on soil organic carbon accrual (Villamil et al. 2006; Rorick and Kladivko 2017). One way in which living cover is expected to increase macroaggregate formation and abundance is by maintaining living fine roots and mycorrhizae in the soil, whose collective activities such as exudation fuel microbial growth, providing the materials needed for microaggregates to aggregate into macroaggregates (Carter, Kunelius, and Angers 1994; Six et al. 2004). In addition, living cover intercepts rain drops before they hit the surface of otherwise-exposed, mineral soils, preventing the destruction of aggregates and resulting decreases in the porosity of the soil surface (Smith 2016). Regardless of the exact mechanism(s) by which living cover increases infiltration, our results do suggest that increased living cover increases soil water infiltration independent of impacts on soil carbon. As such, even when increased living cover does not translate to greater soil organic carbon given variation in factors such as soil texture that are out of a producer's control (Poeplau and Don 2015), adoption of practices such as winter cover cropping in temperate systems or replacing a bare fallow period may nevertheless improve the resilience of an agricultural system to extreme weather events such as floods and droughts.

A number of recent studies have provided evidence that conservation agriculture systems and soil organic carbon are key in supporting the resilience of agricultural systems to weather extremes, particularly drought (Kane et al. 2021; Williams et al. 2016; Bowles et al. 2020). This pattern is arguably supported by evidence that increased soil carbon content can improve water holding capacity of similarly-textured soils (Hudson 1994). But more recent work across a greater diversity of soil types suggests that the actual effects of soil organic carbon content on water holding capacity may be more limited than previously thought and effects are more pronounced on sandy soil types with lower baseline matric potential (Minasny and McBratney 2018; Libohova et al. 2018). There is a mismatch, then, between the evidence that increased soil organic carbon supports yield resilience and emerging evidence that suggests soil organic carbon has only a modest effect on soil water holding capacity. This inconsistency suggests that additional soil properties influenced by soil carbon content, but not captured by laboratory measures of soil water holding capacity, might in part be responsible for increased resilience of yields recorded in the field. Our results suggest that improved soil water infiltration may be such a property. Specifically, increasing the belowground capture of precipitation for crop use by reducing runoff may be equally important to resilience as is improving the capacity of a soil to retain that water under a vapor pressure deficit as a result of carbon accrual. If so, that fact would support the argument that soil water infiltration is an essential, easily-measured metric of soil health that could help in verifying and tracking improvements to cropping system resilience. By comparison, soil carbon is more difficult and expensive to measure and can take several years before a change is measurable (Harden et al. 2017; Paustian, Collier, et al. 2019).

4.2. Study limitations and ways forward

Given the inclusion criteria we set for this meta-analysis, our final database was a relatively limited number of papers. Furthermore, most articles only reported treatment means for soil organic carbon and water infiltration rate and did not report statistics on variance, and the majority were based on studies in India on cropping systems specific to the region. These factors limit how generalizable our results are to locations outside the areas and cropping systems included in the papers we used and make it impossible to quantify how measurement error may have impacted the results. Our meta-analysis reinforces the need for controlled experiments to report variance statistics in addition to means and/or to publish raw data in conjunction with articles to improve their usefulness to future research and meta-analyses. Additionally, several of the papers retrieved in our initial searches included data on soil water infiltration but no data on soil organic carbon or related properties such as aggregation or porosity. Given past research that indicates a mechanistic connection between these properties and water infiltration, and given the results presented here that appear to confirm the importance of increasing soil organic carbon to increase water infiltration, future studies could provide greater value by evaluating all these properties together.

Additionally, the limitations of our database similarly suggest a need for more detailed study of the impacts of specific practices on soil carbon and soil water infiltration. We classified practices into three broad categories but within each of those categories there was substantial variation in management. For example, reduced tillage is often broadly defined as tillage systems that leave 30-50% of previous crop residues on the soil surface (Doval 2019). This definition could include a range of tooling approaches, including chisel plows, disks, or no-till, all of which vary in degree of soil disturbance and tillage depth. The broader category definition may then foster misguided expectations as to how introducing reduced tillage will alter water infiltration rates. Our results suggest that expectations around the impact of reduced tillage on infiltration should be prefaced on how likely a subsequent increase in soil carbon is at a given location. Yet the size of the impact on soil organic carbon is likely dependent on the specific type of reduced tillage, with practices within that category that produce the least soil disturbance being expected to have the greatest positive effect on soil carbon (Aguilera et al. 2013; Luo, Wang, and Sun 2010; Angers and Eriksen-Hamel 2008). Similarly, whereas the likelihood of organic amendments to increase total soil carbon content is more assured than that of reduced tillage given that they are a direct subsidy of carbon to the soil, properties such as soil texture will likely mediate the impact of such management strategies on total soil carbon content and hence water infiltration rates. Our findings therefore identify the need for infiltration studies to report not only changes in soil carbon contents, but also information on specific practice types and soil properties that modulate how adoption of a practice is likely to translate into impact on soil water infiltration and hence agricultural resilience under drought.

Results of our bias analysis confirmed that the patterns reported here are not the result of systematic publication bias. Similarly, results of our sensitivity analyses suggest that the observed effects were generally robust against outlying studies and different ranges of observed change in soil organic carbon content, except in the case of increased living cover studies, where the removal of one study (Lal et al. 1978) resulted in substantive changes to estimates of model coefficients. Both of these analyses suggest that despite the limited number of studies we found that matched our criteria, our results were not the consequence of biased reporting in the literature or outlying studies. Nonetheless, ensuring future experiments that evaluate management-induced changes to soil water infiltration rate also study changes to soil organic carbon would help to resolve the underlying mechanisms and also guide management interventions, intended to improve soil water availability, that are tailored to what is achievable at a site. For example, our findings suggest that cover crops should be the preferred intervention in systems where building soil carbon content is more difficult to achieve, given they appear to impact soil water infiltration rates by mechanisms beyond soil carbon change.

5. Conclusions:

Through a meta-analysis of peer-reviewed literature we found evidence that reduced tillage and organic amendments increased soil water infiltration rates and that these increases were associated with increasing soil organic carbon content. Additional effects of these management interventions, not mediated by increases to soil organic carbon, were small to non-existent. By contrast, increasing living cover had a greater overall effect on improving soil water infiltration rate than reduced tillage or organic amendments and this effect was likely mediated both through increases to soil organic carbon content and unmeasured effects of increasing living cover on soils. We suggest that these increases are likely attributable to changes in soil structural properties such as aggregation and porosity, which can be associated with increases in soil organic carbon but have also been shown to increase with the introduction of increased living cover independent of increases in soil organic carbon content (Basche and DeLonge 2017; Rorick and Kladivko 2017).

Our findings can help guide management recommendations and inform anticipated success for increasing infiltration rates. For example, increasing living cover appears to be a strategy for increasing soil water infiltration that will be effective regardless of how soil carbon contents respond. Whereas the effects of reducing tillage or organic amendments on water infiltration appear to depend on the success of those practices for increasing soil carbon content. Further, our results raise the possibility that the observed relationship between soil carbon content and resilience of yields to drought events may, at least in part, be mediated by increases to soil water infiltration. Future research focused on resilience should aim to more explicitly connect management, soil organic carbon, water infiltration, and yield resilience under drought to clarify underlying mechanisms and provide more informed quantitative expectations for how management recommendations relate to desired outcomes.

Figures:

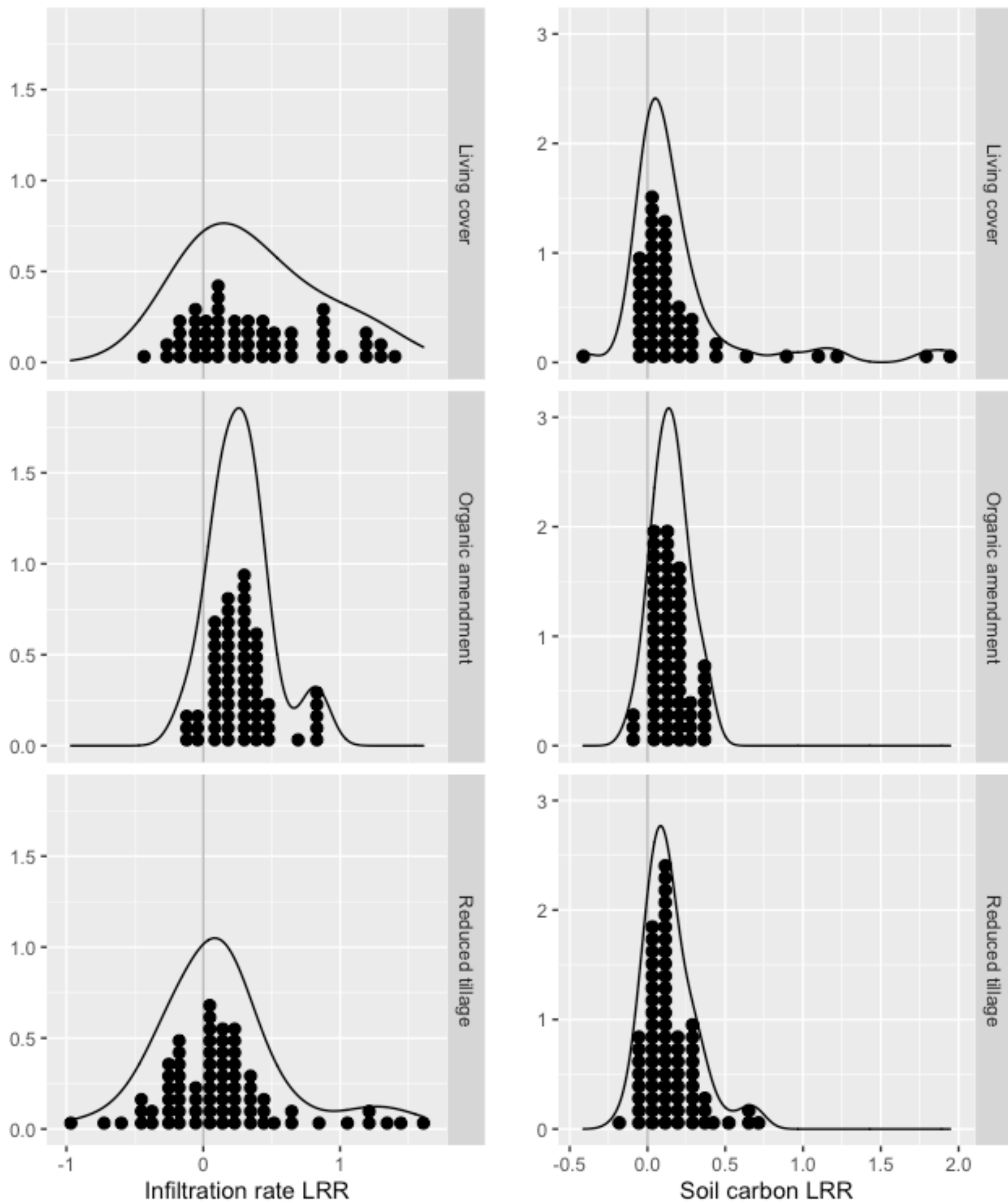

Figure 1. Distribution of log response ratios of infiltration rates and soil carbon content of experimental treatments as compared to controls across all studies in each management intervention category. Lines represent a smoothed kernel density estimate for each distribution, and the y axis represents the probability density function at each LRR bin. Dots represent the number of observations for each LRR bin.

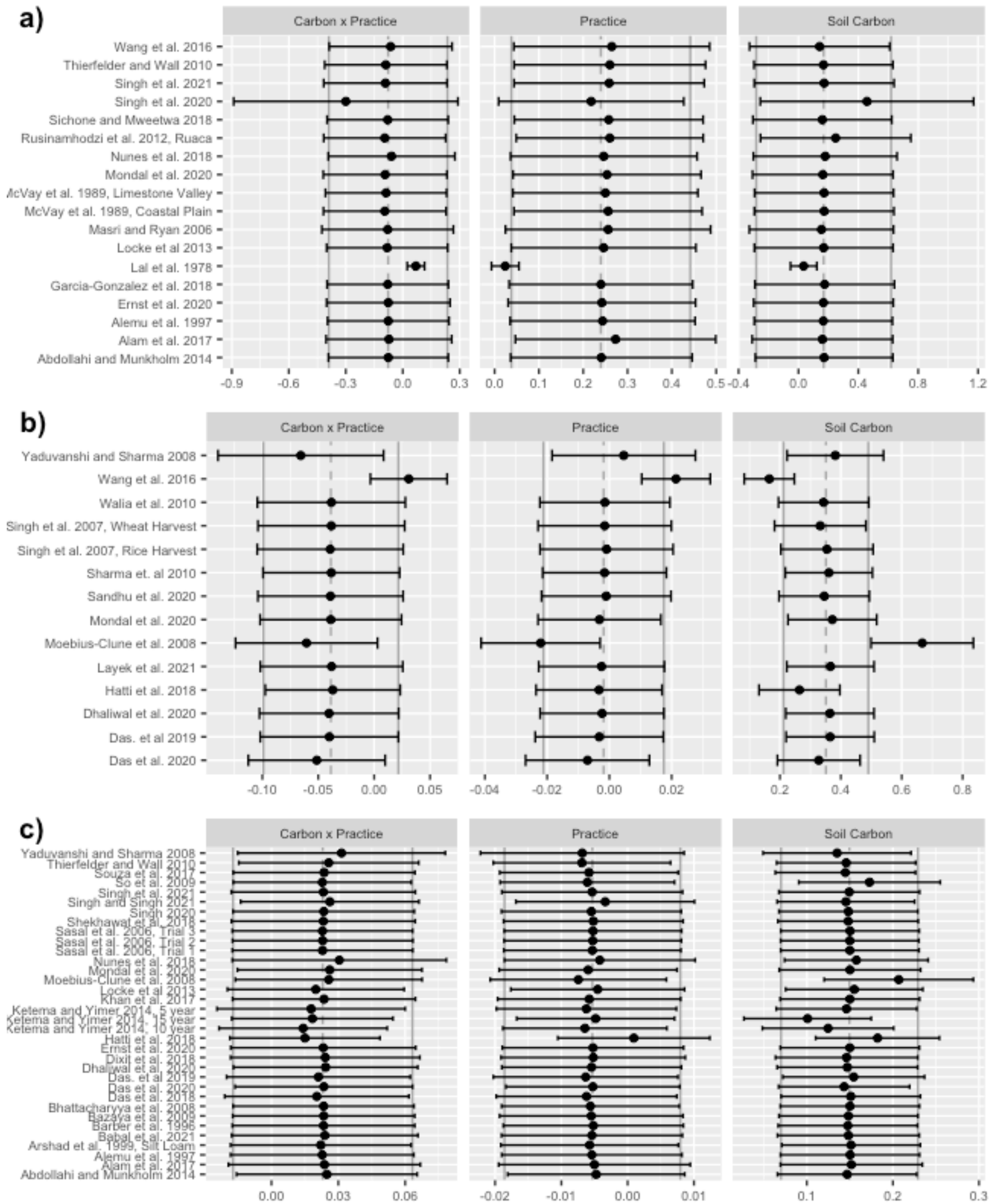

Figure 2. Jacknife sensitivity analysis across practice categories (a = living cover, b = organic amendments, c = reduced tillage). Dot plots represent the 95% confidence intervals of models testing effects specified in meta-regression models when the corresponding paper is removed from the database. Dashed vertical line represents the mean coefficient estimate when the entire database is used, and solid vertical lines represent the 95% confidence intervals when the entire database is used.

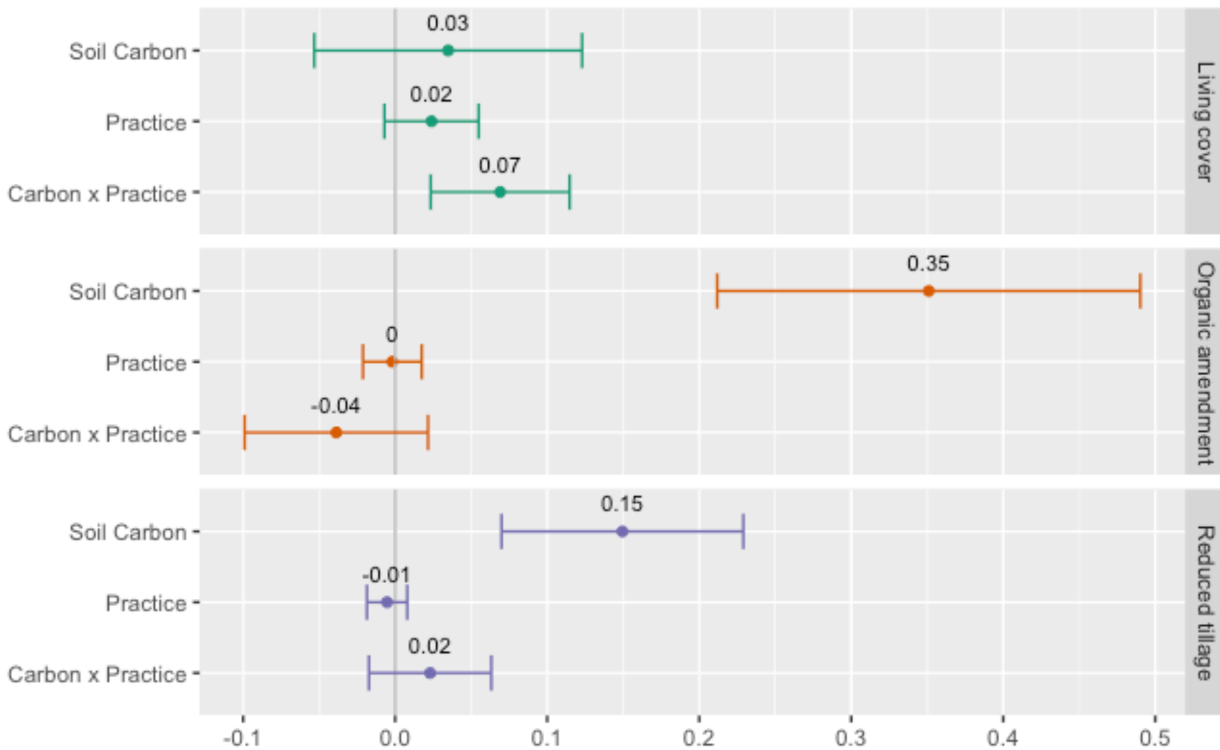

Figure 3. Beta coefficient estimates for meta-regression models relating presence of conservation agriculture practices and soil carbon content to soil water infiltration rate for each practice category. Dots represent mean beta coefficient estimates (with exact values shown in numerals above the dots), bars represent 95% confidence intervals. Estimates for the living cover are based on models excluding Lal et al. 1978.

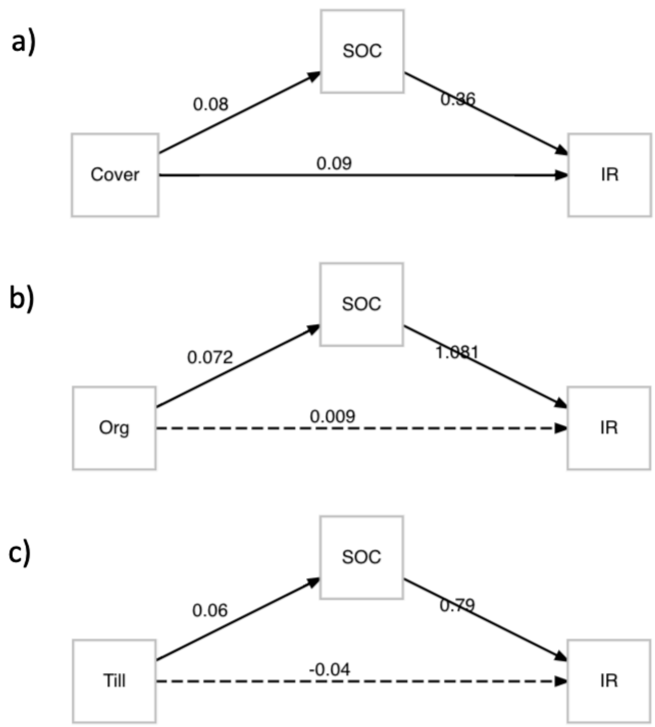

Figure 4. Diagrams of path analysis models across all practice categories (a = living cover, b = organic amendment, c = reduced tillage). Boxes represent variables in the path analysis, lines represent estimated relationships, and numbers over lines represent the estimated coefficient. Solid lines indicate the relationship is significant at a confidence level of α = 0.05, and dashed lines are non-significant at the same confidence level.

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Supplementary Information:

Paper	Location
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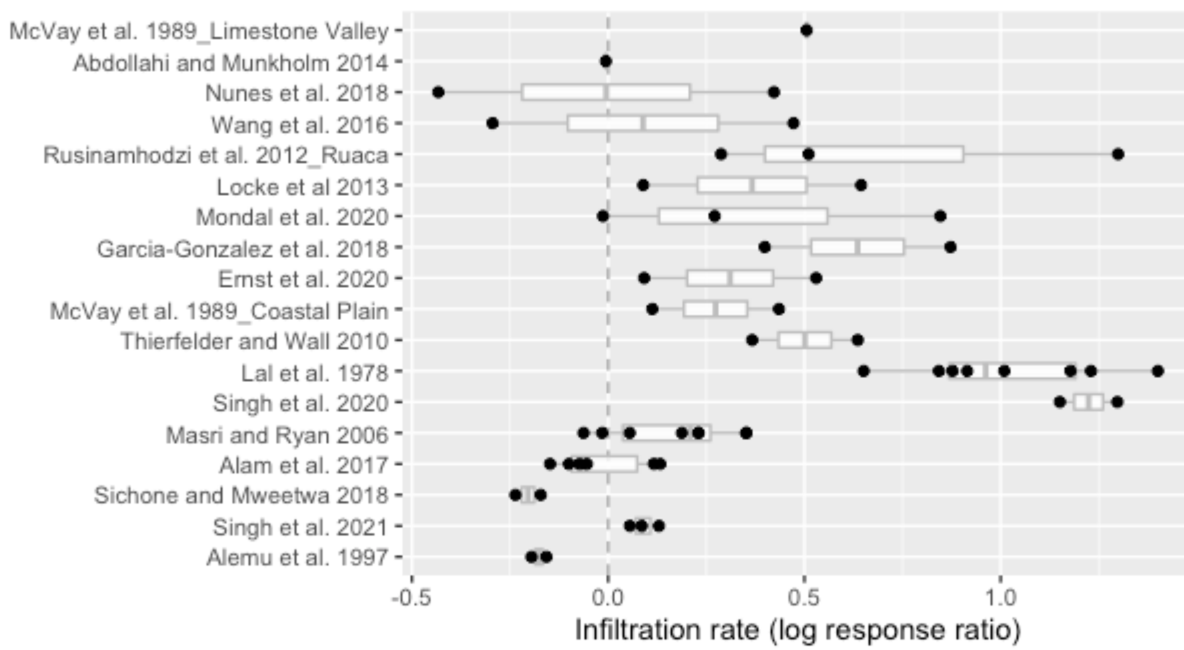
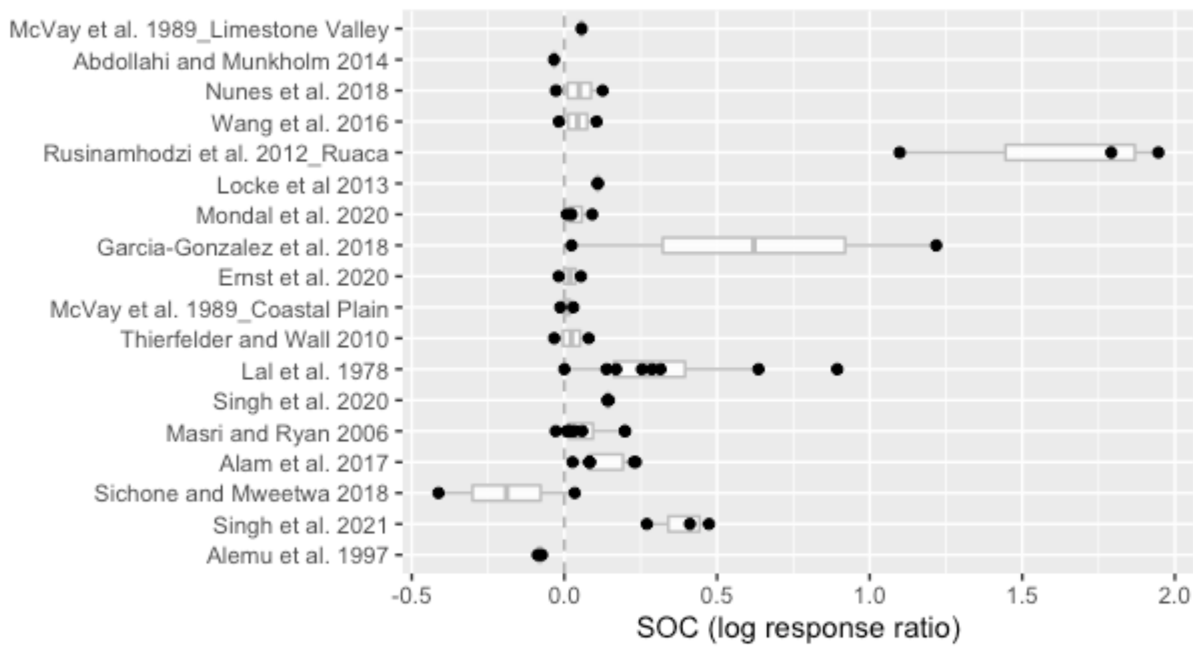
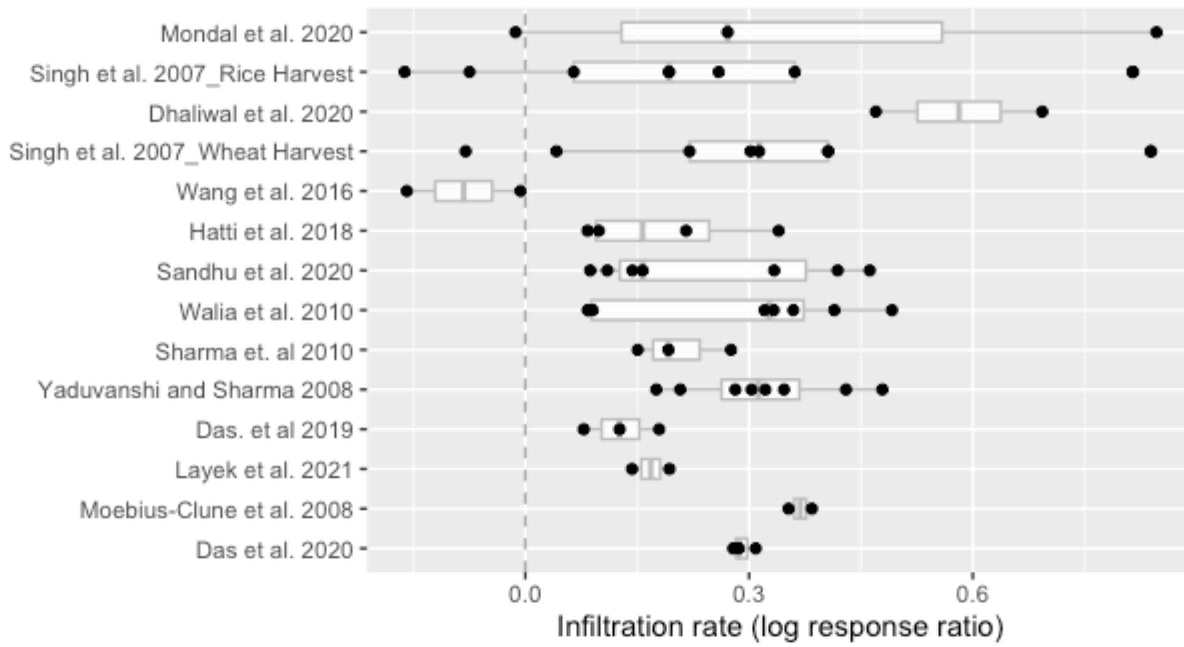
Supplementary Table 1. Studies used in this analysis and geographic locations of those studies.



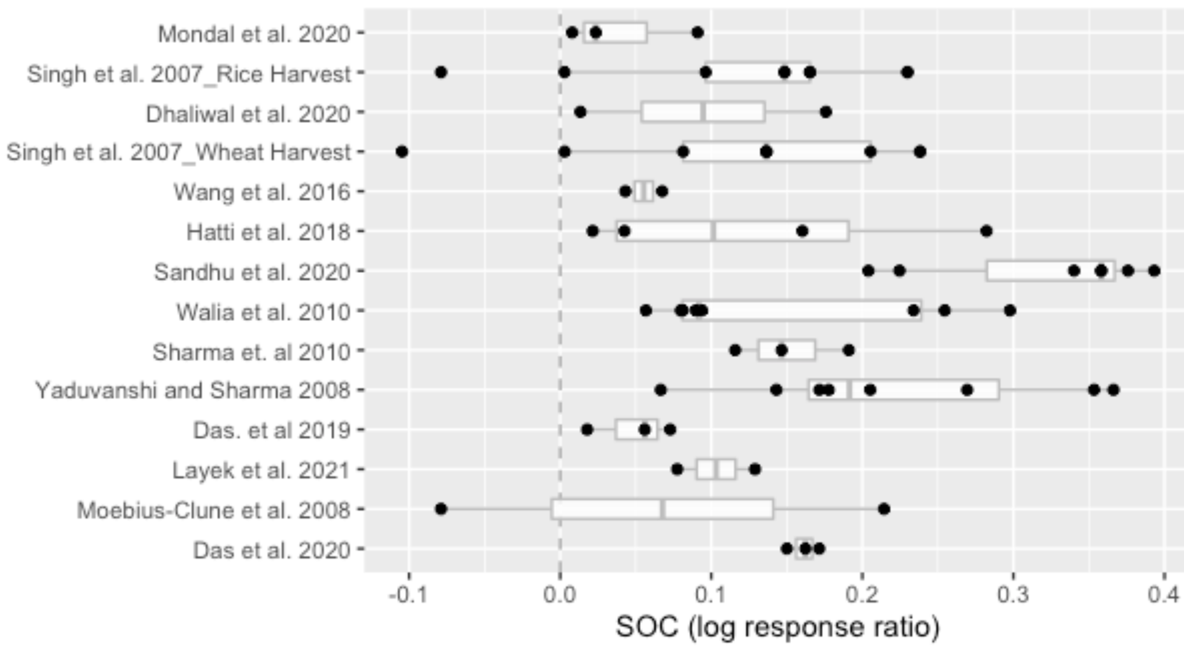
Supplementary figure 1. Tree plot of IR LRR values for increased living cover studies.



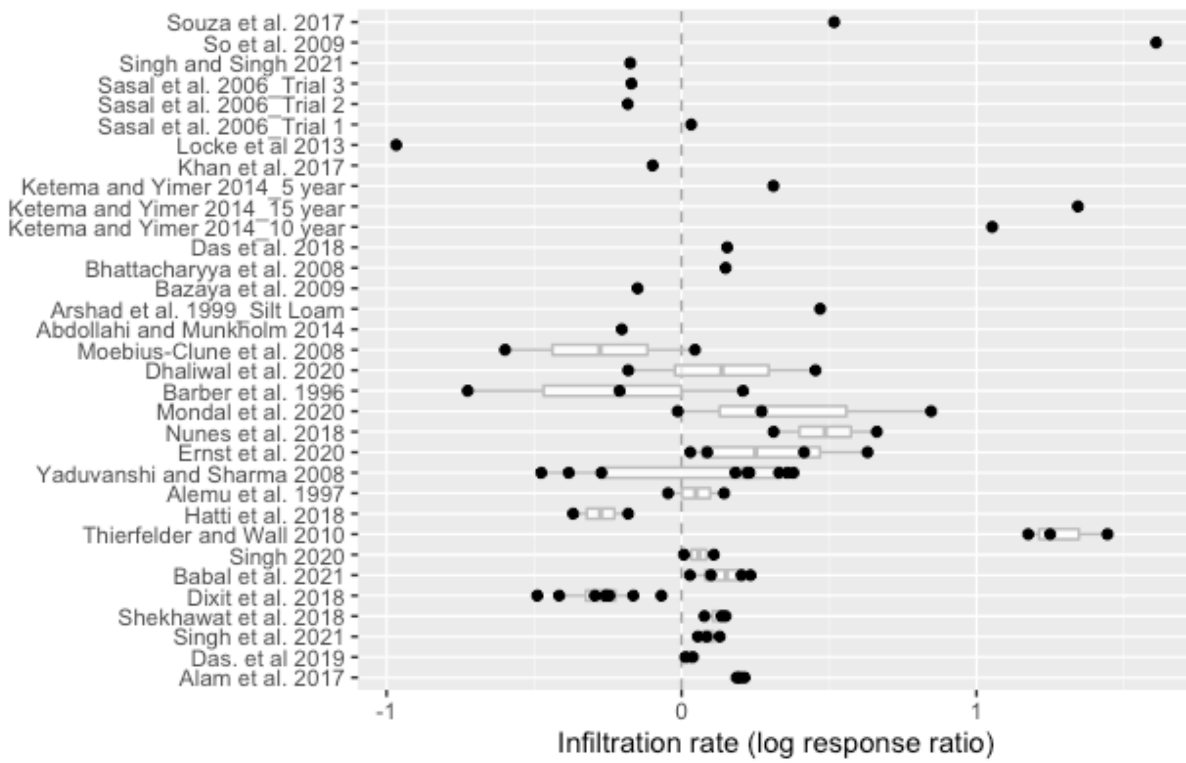
Supplementary figure 2. Tree plot of SOC LRR values for increased living cover studies.



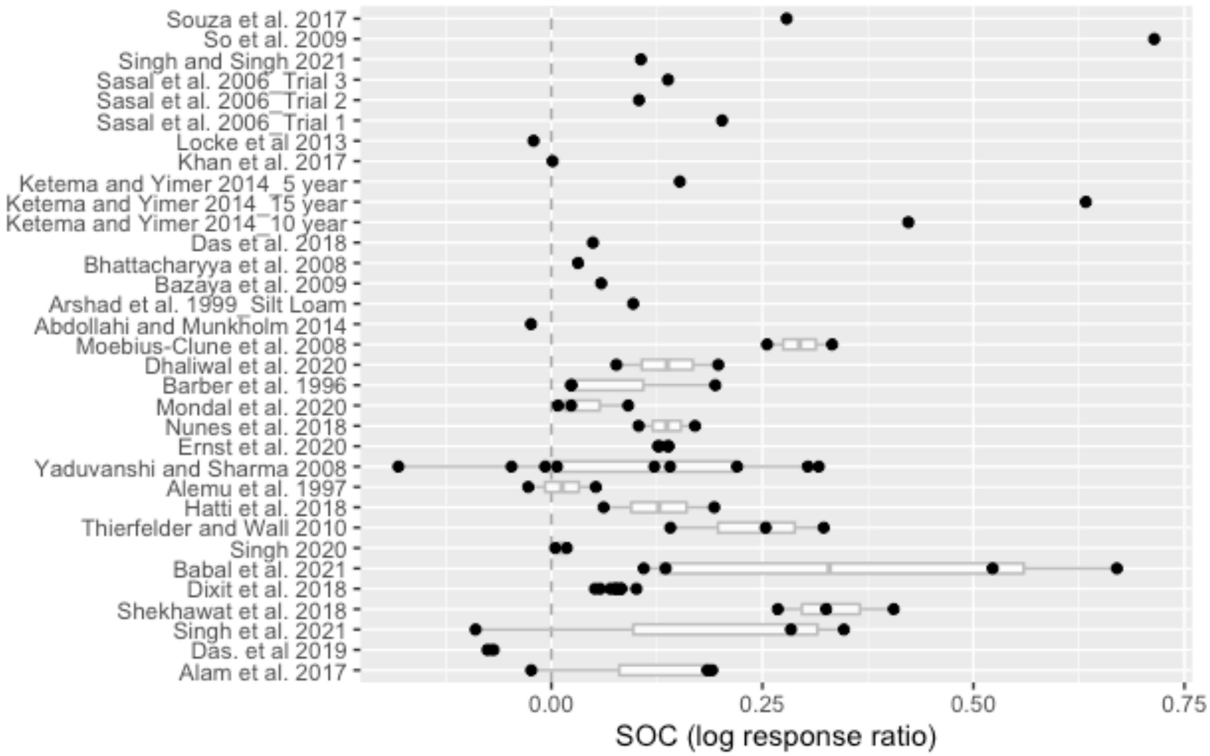
Supplementary figure 3. Tree plot of IR LRR for organic amendment studies.



Supplementary figure 4. Tree plot of SOC LRR for organic amendment studies.



Supplementary figure 5. Tree plot of IR LRR values for reduced tillage studies.



Supplementary figure 6. Tree plot of SOC LRR values for reduced tillage studies.

Chapter 2: Soil organic matter protects US maize yields and lowers crop insurance payouts under drought

Abstract:

Higher levels of soil organic matter improve soil water retention, meaning they could mitigate agricultural yield losses from drought. Yet evidence to support such claims is mixed and incomplete. Using data from 12,376 county-years in the United States of America, we show that counties with higher soil organic matter are associated with greater yields, lower yield losses, and lower rates of crop insurance payouts under drought. Under severe drought, an increase of 1% soil organic matter was associated with a yield increase of 2.2 ± 0.33 Mg ha^{-1} (32.7 bu ac^{-1}) and a 36 ± 4.76% reduction in the mean proportion of liabilities paid. Similar, yet smaller, effects were found for less severe levels of drought and this effect was reduced as soil clay content increased. Confirmatory pathway analyses indicate that this positive association of soil organic matter and yields under drought is partially explained by positive effects of soil organic matter on available water capacity and cation exchange capacity, but that soil organic matter may be imparting yield protection via mechanisms not fully captured by those metrics. Overall, our results suggest soil organic matter predicts yield resilience at regional scales in the United States. We argue that data on soil organic matter should be used in agricultural policy and financial planning, with our analyses providing quantitative evidence of the co-benefits of soil organic matter believed fundamental to advancing soil health and carbon sequestration initiatives.

1. Introduction

Rain-fed agriculture, which made up 75% of global cropland use as of 2000 (Portmann, Siebert, and Döll 2010), is highly susceptible to extreme weather conditions, such as heat and drought. Extreme heat accelerates plant development, effectively shortening growing season length and reducing harvest index, and in extreme instances, extreme heat causes plant reproductive failures, such as kernel abortion in maize, that drastically reduce yields (Hsiao, Swann, and Kim 2019; Craufurd and Wheeler 2009; Sage and Kubien 2007). Similarly, drought leads to elevated vapor pressure deficit which can lead to increased transpiration by plants, closing of stomata, and ultimately reduced rates of photosynthesis that slow plant growth and reduce grain yields (Lobell et al. 2013; 2014). Climate change is predicted to increase the incidence and severity of droughts and floods (Luber and McGeehin 2008; Meehl et al. 2007), thereby increasing the risk of crop failures and yield losses (Urban et al. 2012). Conservative estimates for maize suggest yields could drop between 20-80% in the US under plausible future climate scenarios (Hsiao, Swann, and Kim 2019; Lobell et al. 2014; Schlenker and Roberts 2009). Such scenarios threaten global food security and suggest that resilience planning to mitigate these impacts is necessary.

Increasing soil organic matter can increase soil water holding capacity on similarly textured soils (Minasny and McBratney 2018; Hudson 1994) and improve water infiltration (Boyle, Frankenberger, and Stolzy 1989; Elliott and Efetha 1999; Franzluebbers 2002) by supporting greater aggregate formation and, hence, a greater volume of pore spaces (Lado, Paz, and Ben-Hur 2004). Researchers have argued that soils with higher organic matter can retain more water under vapor pressure deficit, protecting crops from losses induced by extreme heat and drought better than low organic matter soils (Iizumi and Wagai 2019; Carminati and Javaux 2020; Bot and Benites 2005). Yet recent work suggests the actual effect of soil organic matter on plant available water is modest (Minasny and McBratney 2018; Libohova et al. 2018), and it is unclear whether these effects on water retention are great enough to reduce drought-induced yield losses. Studies have demonstrated that higher soil organic matter is associated with lower long-term interannual yield variability at regional scales (Williams et al. 2016; Pan, Smith, and Pan 2009). But lower variability is not necessarily indicative of greater resilience or protection against yield losses and/or crop failure under adverse conditions. Some field-level studies have shown that practices known to increase soil organic matter can protect yields (Bowles et al. 2020; Gaudin et al. 2015), but these do not explicitly test the relative effect of organic matter and do not provide information at county or regional scales which are arguably most relevant to policy initiatives. Furthermore, these studies did not attempt to quantify how the effect of soil organic matter on yields does or does not scale under different drought conditions.

In light of these evidence gaps, we quantified the impact of soil organic matter on agronomic risk to drought in the United States of America. We analyzed county-level maize (*Zea mays* L.) yield and crop insurance payouts in the US from 2000 - 2016 in combination with soil characterization data and county-level Standardized Precipitation Evapotranspiration Index (SPEI) data. Data were gathered for 754 counties where maize production was predominantly rain-fed, representing a total of 12,376 county-years, 5945 of which experienced drought conditions over the summer growing season. We hypothesized that counties with higher levels of soil organic matter in surface soils (0-30 cm depth) where most of the fine-root biomass is found, would be less prone to yield losses in drought years given expected positive effects of soil organic matter on crop water availability and that, as a result, a lower proportion of crop insurance liabilities would be paid out in drought years.

2. Methods

2.1. Data collection

2.1.1. Maize yield data

We collected mean maize (*Zea mays* L.) yield (Mg ha^{-1}) data for all US counties between the years 2000 to 2016 for which maize yield data were available from the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS) (USDA NASS Staff 2018) accessed via the *rnassqs* package (Potter et al. 2019) in the R v.3.6.3 statistical software environment (R Core Team 2020). Data were limited to the years 2000-2016 to minimize the confounding effect improvements in maize genetics may have on yield data and because other data used to estimate drought incidence in each county detailed below were only available beginning in the year 2000. We removed data from counties in which corn was not grown for at least 16 of the 17 years in the study period. Yield data were then detrended on a county basis per the method detailed in Lu et al. 2017 (Lu, Carbone, and Gao 2017). Briefly, we fit a locally weighted regression (LOWESS) model wherein yield was the dependent variable and year was the independent variable. Models were fit using the R package *caret* (Kuhn et al. 2020) using a 10-fold cross validation approach wherein the span parameter was constrained to a range of 5-10 years and the degree parameter was allowed to be either 1 (linear) or 2 (polynomial). We then added the yearly residuals of these models to the long-term county average yield to estimate detrended yield for each county-year in the study period, and we also divided the observed yield by the predicted yield of these models for each county-year to estimate yield anomaly.

Because soil organic matter might protect yields by improving soil water dynamics, irrigation could mask the effects of soil organic matter on agricultural resilience. As such, we restricted the analysis to primarily non-irrigated acres. We also retrieved data from USDA NASS

(USDA NASS Staff 2018) via the *rnassqs* (Potter et al. 2019) on the total number of corn acres harvested in each county-year and the total number of irrigated corn acres harvested in each county-year for the US Agricultural Census years of 1997, 2002, 2007, and 2012. The US Agricultural Census is conducted every 5 years, so data on irrigation within our study period is only available for those years. We then calculated the percent of maize-growing acres that were irrigated in each county for each census year, averaged those figures across all four census years, and filtered yield data to those counties in which corn-growing acres were on average ≤5% irrigated during the study period and in which average acres irrigated had a standard deviation of ≤1% across the four census years for which data were retrieved.

2.1.2. Drought data

We retrieved county-level Standardized Precipitation-Evapotranspiration Index (SPEI) figures from the Center for Disease Control (National Environmental Public Health Tracking Network 2018). SPEI is a multi-scalar drought index based on the similar Standardized Precipitation Index (Vicente-Serrano et al. 2012; Vicente-Serrano, Beguería, and López-Moreno 2009). Differences between cumulative monthly precipitation and potential evapotranspiration are calculated for a chosen time scale (i.e. 1 month, 3 months, etc.). These figures are then standardized based on a log-logistic distribution so that they are comparable across locations. The CDC dataset we used is based on a 1-month standardization. We summarized SPEI data in each county-year by calculating the mean of monthly SPEI values for the summer growing season months of May to August.

In addition to SPEI, we also retrieved drought data from The National Drought Mitigation Center (The National Drought Mitigation Center 2019c), which reports on a daily basis the percent area of each county that is at each level of their drought index: D0 (no drought) – D4 (severe drought). This drought index is a categorization based on the Palmer Drought Severity Index, Standardized Precipitation Index, soil and streamflow models, and local expert assessment/verification by USDA field agents (The National Drought Mitigation Center 2019b).

We then converted these coverage statistics to a daily Drought Severity Classification Index (DSCI), per the instructions of the US Drought Monitor website (The National Drought Mitigation Center 2019a). Briefly, DSCI is a weighted sum of the percent area of each county under each drought index level. We then subset daily DSCI data to the months of May to August, the months that are most crucial to maize growth and yield, and averaged them for each county-year across the study period. DSCI data were not used in our primary analyses but were instead used in a set of sensitivity analyses (Supplementary Information) to determine the relative importance of how drought is quantified on estimating the mitigating effect of soil organic matter on yields under drought.

2.1.3. Crop insurance data

The USDA Risk Management Agency collates a variety of data on the US crop insurance market on an annual basis, including total liabilities, total indemnities, and cause of loss. These data are available at the county-level via the USDA Southwest Climate Hub's AgRisk Viewer (Southwest Climate Hub 2018). We retrieved data on total liabilities and total indemnities in USD for maize due to loss by drought for the same set of counties for which we retrieved yield data. We then used these data to calculate loss cost (Reyes and Elias 2019), a unitless index based on the ratio of total indemnities to total liabilities in a given county-year. Loss cost implicitly accounts for differences in USD figures across years due to inflation, as well as differences across counties due to differences in total output and coverage patterns.

2.1.4. Soil data

To aggregate soil data for each county in our analysis we first identified those areas in each county that are primarily used for maize production. To do so, we used the "Corn Frequency" raster available at USDA NASS's CropScape portal, which reports how many years between 2008 – 2017 each pixel was used for maize production (Han et al. 2014). We then subset this raster to only those pixels in which maize was produced for 2 or more years to identify pixels from any field in which maize was grown with relative consistency but not opportunistically (e.g. in a high price year), while also eliminating non-crop areas. This subset of pixels was then used to generate a masking layer used in subsequent steps.

The gSSURGO database is spatially organized as a series of discrete polygons referred to as map units that are composed of different component soil series. Associated with each soil series is characterization data organized by pedological horizon, including soil texture, soil organic matter, and measures of soil biophysical characteristics. As such, we first used the *aqp* (Beaudette, Roudier, and Brown 2020) package in R to convert characterization data for each component soil series to a fixed depth increment of 0-30 cm to represent the typical rooting zone of maize. We then calculated a representative map unit value for each soil characteristic soil organic matter (%), clay content (%), H_3O^+ concentration (mol), cation exchange capacity (meq 100 g soil^{-1}), and available water capacity (%) by calculating a map unit mean weighted by the relative proportions of each component soil series in a map unit. We then converted the data to a raster format and used the masking layer described previously to remove soil data in each county from areas where maize is not consistently grown. Finally, we used these masked rasters to calculate county-level means for all soil properties we then used in our analyses.

2.1.5. Cropping system management

For the purposes of this study we did not include data on the rates of different cropping system management strategies or practices, such as mean fertilizer rate by county or incidence of conservation tillage by county. Such data are not available at the county level or on a timestep that would make them sufficiently useful for our analysis. For example, data on per area fertilizer use is available via USDA NASS only at the state level, and questions on implementation of conservation agriculture practices were only recently included in the agricultural census. Given these inconsistencies in data, we could not account for management effects with a fixed effect for each practice. Instead, we accounted for them by implementing a random effect for state (Section 2.2). We argue that since farms in the same state are generally more likely to implement fertilizer rates and management practices similar to other farms in their state than those out of their state, our model accounts to some degree for broad differences in management. Whereas direct estimation of the effect of different management practices would be preferable, sufficient data simply do not exist and use of current, sparser data could lead to flawed inference.

2.2. Data analysis

Initial data analysis demonstrated that the yield response to SPEI begins to saturate above SPEI values of 0, indicating that when the balance of precipitation and evapotranspiration is negative, yields drop below the typical yield potential of a given area. Additionally, we found that when

SPEI decreased (i.e. drought conditions became more severe) the impact of soil organic matter was greater on maize yield (Mg ha^{-1}), yield anomaly, and loss cost (Supplementary Information). As such, we chose to subset our data into different levels of drought severity based on SPEI and then analyze each subset to understand how the effect of soil organic matter on each outcome variable changed as drought severity changed. Drought severity thresholds were calculated based on the global mean and standard deviation of SPEI. Very severe drought was defined as greater than two standard deviations from the global mean (SPEI $\leq$ -1.02); severe drought as between one and two standard deviations from the mean (-1.02 < SPEI $\leq$ -0.46); moderate drought as between one standard deviation from the mean and the mean (-0.46 < SPEI $\leq$ 0.10); and normal conditions as greater than or equal to the mean (SPEI > 0.10).

Within each of these drought subsets we then fit a series of models wherein the dependent variable in these models was either yield (Mg ha^{-1}), yield anomaly, or loss cost. Independent variables across all models included soil organic matter, soil clay content, and soil H_3O^+ concentration. These variables were chosen by fitting a multivariate linear model with multiple potential independent variables then assessing variance inflation factors to eliminate spurious, highly collinear variables. We also included a random effect of state to account for possible impacts of geographic differences in management and production environment on model outcomes not accounted for in the data we collected. For yield and yield anomaly, linear mixed effects models including all possible interaction effects were fit using a restricted maximum likelihood approach in the *lme4* (Bates et al. 2020) package in R. For loss cost, a mixed effects Tobit regression model was fit using a Newton-Raphson maximization approach in the *censReg* (Henningsen 2020) package in R to account for the fact that loss cost was left censored at a value of 0. Prior to model fitting, all observations of each independent variable were standardized so that coefficient estimates would also be standardized. Data standardization was done by subtracting the mean of a given variable from each observation and then dividing that value by 2x the standard deviation of that variable (Gelman 2008).

Finally, we conducted a series of confirmatory path analyses to evaluate to what extent the impacts of soil organic matter on maize yields were mediated by their impacts on soil available water capacity and cation exchange capacity, a proxy variable for soil fertility, under both drought and normal conditions. First, we split data into those observations from normal SPEI years (SPEI > 0.10) and drought SPEI years (SPEI ≤ 0.10), and then calculated the mean yield (Mg ha^{-1}) for each county under either set of conditions. We then employed a piecewise structural equation modeling approach using the *piecewiseSEM* (Jon Lefcheck, Byrnes, and Grace 2019) package in R to fit models in which the effects of soil organic matter were either partially mediated or fully mediated by its effects on available water capacity and cation exchange capacity. Briefly, the fully mediated SEM was such that available water capacity and cation exchange capacity were modeled as functions of soil organic matter and yield was modeled as a function of available water capacity and cation exchange capacity. Whereas, in the partially mediated SEM, available water capacity and cation exchange capacity were modeled the same way, but soil organic matter was included as an additional independent variable for modeling yield. To determine the most parsimonious model, we compared models via an analysis of variance and on the basis of AIC/BIC scores. Coefficients were extracted from the final model and standardized to then assess whether or not effects of organic matter on yields under drought were mediated by its impacts on available water capacity and cation exchange capacity. An initial analysis with all data in either SPEI category indicated a negative relationship between cation exchange capacity and yields. When we manually inspected data we found that this result was the consequence of outlying cation exchange capacity values, defined as being two standard deviations greater than the mean (CEC $\geq$ 31.9), with extremely high clay content. As such, we removed these outliers for the final path analysis to better estimate effects on typical soils, but include results from a path analysis including these observations in Supplementary Information.

3. Results and Discussion:

3.1. Maize yields and yield anomalies

We found that across all county-years and possible weather conditions, soil organic matter content was a strong positive predictor of yield. Soil organic matter had a standardized marginal effect of 0.83 with a standard error of 0.04, meaning an increase of 1% soil organic matter was associated with an increase in yields of 0.83 ± 0.04 Mg ha^{-1}. This observed relationship between soil organic matter and yield is consistent with other studies which show yield increases are associated with higher levels of soil organic matter (Oldfield, Bradford, and Wood 2019). Our analysis extends these observations by showing that as drought conditions became more severe, the marginal effect of soil organic matter on yields increased (Figure 1; Table 1). For example, under moderate drought conditions ($-0.46 \leq$ SPEI < 0.12) an increase of 1% soil organic matter was associated with an increase in yields of 0.76 ± 0.07 Mg ha^{-1}, and under very severe drought conditions (SPEI < -1.02) a 2.2 ± 0.33 Mg ha^{-1} increase. Interaction effects of other soil properties with soil organic matter also emerged across the severe, moderate, and normal drought categories (Table 1). Sensitivity analyses of these interaction effects revealed that in many cases outlying observations were responsible for the interaction. When those outliers were removed, the size and significance of interaction effects and corresponding main effects were diminished

(Supplementary Information). However, interaction effects of soil organic matter and clay content were robust to outlier observations and indicated that the effect of soil organic matter on yields remained positive at higher levels of clay but was diminished relative to lower clay soils. This result is consistent with broad-scale studies which demonstrate the primary importance of clay on the water holding capacity of soils and the diminished impact of organic matter when clay is high (Minasny and McBratney 2018; Libohova et al. 2018). Nonetheless, our results show the effect of soil organic matter is still positive, regardless of clay content, and improves maize yields, and that soil organic matter was the only soil property that consistently buffered yields against drought conditions.

To more fully evaluate whether this greater relative yield advantage under drought is because soil organic matter protects against drought-induced yield losses, we also evaluated the relationship between soil organic matter and annual yield anomaly, the ratio of observed yield to expected yield estimated from long-term trends (Lu, Carbone, and Gao 2017). Under very severe drought conditions (SPEI < -1.01) an increase of 1% soil organic matter content was associated with a mitigation of yield losses of 12 $\pm$ 0.03%, under severe drought conditions ($-1.01 \leq$ SPEI < -0.46) this effect decreased to a 5 $\pm$ 0.01% mitigation, and under moderate drought ($-0.46 \leq$ SPEI < 0.10) the effect was non-significant (Table S2).

Further examination of yield anomaly data revealed that counties with lower soil organic matter content have high interannual variability, outperforming historical yield trends in favorable conditions but experiencing greater losses relative to historical trends under adverse conditions. Whereas counties with high soil organic matter have low interannual variability and consistently yield near expected yields based on historical trends, even under adverse drought conditions. For example, in counties with greater than 2.5% soil organic matter content, the mean of soil organic matter content across all counties in this study, the interquartile range for yield anomalies was 98% to 107% of expected yield under normal conditions and 91% to 104% under all drought conditions. By contrast, counties with lower than 2.5% soil organic matter ranged from 99% to 114% of expected yield under normal conditions and 82% to 104% under all drought conditions. This pattern is consistent with previous studies demonstrating that higher soil carbon is associated with lower long-term interannual yield variability (Pan, Smith, and Pan 2009; Williams et al. 2016). Our findings offer additional insight by demonstrating that those reductions in interannual variability are partly explained by the association of higher soil organic matter and lower yield losses under drought conditions.

3.2. Crop insurance

Given the decrease in yield risk associated with greater levels of soil organic matter, we expected that lower yield risk would be reflected in crop insurance payouts to farmers. Specifically, we expected that counties with higher soil organic matter would have lower loss cost (Reyes and Elias 2019), a metric based on the ratio of total indemnities to total liabilities. Our results support this expectation, showing that soil organic matter is associated with reduced loss cost under drought conditions and that the marginal effect of soil organic matter increases as drought severity increases (Figure 2). Under very severe drought conditions (SPEI $\leq$ -1.02), an increase in soil organic matter of 1% was associated with a 36 $\pm$ 4.76% reduction in loss cost (Table S3). Similar to yield anomaly, though, this effect decreases sharply as SPEI approaches normal. Soil organic matter was associated with an 8.4 $\pm$ 1.41% reduction in loss cost under severe drought conditions (-1.02 < SPEI $\leq$ -0.46) and just a 4 $\pm$ 0.73% reduction under moderate drought (-0.46 < SPEI $\leq$ 0.10). Nevertheless, given the expectation of increasing frequency of severe droughts

(Hayhoe et al. 2010; Adams et al. 1990; Meehl et al. 2007), our results suggest that it would be strategic for rain-fed US agriculture to directly incorporate differences in soil properties into policy and insurance planning for yield resilience.

3.3. Path analyses

The fact that we found that soil organic matter appeared to impart such effective protection against yield losses under severe drought appears inconsistent with results from recent studies using large soil databases into how soil organic matter influences the plant available water capacity in soils. Briefly, the ability of soils to provide water to plants is often estimated as 'available water capacity', which typically is the difference in water content of saturated soil samples dried on pressure plates at -1500 kPa and -33 kPa (Cassel and Nielsen 2018; Soil Survey Staff 2015). These analyses have suggested that the net impact of soil organic matter on available water capacity is relatively modest and contingent on soil texture (Libohova et al. 2018; Minasny and McBratney 2018). To investigate potential discrepancies in conclusions between these past studies and our work, we performed a series of confirmatory path analyses (Jonathan Lefcheck 2019; Shipley 2009) to investigate the extent to which soil organic matter associations with yields under drought and non-drought conditions are related to its influence on available water capacity and cation exchange capacity, used here as a proxy measure of soil fertility. We found that soil organic matter was strongly associated with cation exchange capacity but only weakly associated with available water capacity, and under both drought and non-drought conditions, cation exchange capacity and available water capacity were positively associated with yields (Figure 3). However, our confirmatory path analysis also suggested that soil organic matter had an independent, unmediated positive effect on yields under both drought and non-drought conditions (Table S4).

These results confirm that soil organic matter has a positive influence on yields via its effects on available water capacity and soil fertility. But it also suggests that soil organic matter likely influences plant water availability and soil fertility in ways not captured by how those properties are commonly measured. Although our analyses cannot resolve these additional influences, we do know that soil organic matter affects other important soil biophysical properties, such as porosity, bulk density, and water infiltration (Franzluebbers 2002; Lado, Paz, and Ben-Hur 2004; Libohova et al. 2018; Boyle, Frankenberger, and Stolzy 1989). Favorable changes in all of these properties may increase the soil volume from which plants can draw water and may effectively increase the supply of water to plants between rain events. In addition, soil organic matter is also an important source of key nutrients for plant growth. Under drought conditions, water transpiration and radiation efficiency in maize plants increase with increasing nitrogen fertilizer use (Teixeira et al. 2014) and nitrogen fertilizer can be important for maintaining key metabolic functions and increasing yield (Zhang et al. 2007). Further work is required to ascertain whether soil organic matter has similar, nutrient-mediated effects under drought conditions.

3.4. Broader implications

Our analyses are based on subcontinental-scale variation in soil organic matter and yield outcomes. As such, they cannot be used to argue directly that field-scale increases in soil organic matter achieved through conservation agricultural practices such as cover-cropping or reduced tillage, will lead to the same level of meaningful yield protection under drought. More specifically, the demonstrated increases in soil organic matter such practices often achieve is smaller than the relative range of soil organic matter content represented in this study, and the magnitude of the effect of a soil organic matter demonstrated here may not be maintained at the field scale. Similarly, our results are specific to the ‘corn belt’ region of the US and we only examined the impact of soil organic matter under drought on maize. Much of this region comprises relatively high organic matter soils, and maize is a drought sensitive crop. Last, our results likely mask substantial variation in management practices (i.e. fertilizer regimes, tillage, cover crops, etc.) that could also impart resilience on rain-fed maize systems. Additional farm-scale evidence is required to understand whether increases in soil organic matter over time are associated with resilience to drought conditions at the farm scale, whether or not management practices can impart similar resilience, and whether or not these results are generalizable to other geographies, agro-ecological zones, and crops.

Nevertheless, our results do appear to have the potential to directly inform agricultural financing programs and policy in the US. At present, knowledge of risk is incorporated into US Federal Crop Insurance Programs (FCIP) only indirectly. Premiums are based on the Actual Production History (APH) of a given area and farm, and current policy dictates that APH be calculated based on a 10-year trend excluding years in which yield losses were extreme (Bryant and O’Connor 2017). While differences in soil organic matter and other biophysical limitations to resilience are arguably endogenous to these yield data, APH may become less predictive of risk under future climate scenarios where drought frequency is predicted to increase. It may therefore be more strategic for policy planning for agricultural resilience to explicitly consider differences in soil properties, such as organic matter levels, across counties. For instance, if maize yields in counties with low soil organic matter are particularly vulnerable to drought, it may make more sense to incentivize a transition to crops that are more appropriate to soil and predicted climate conditions in those counties, than to focus exclusively on economic protection through insurance.

Furthermore, while more extensive evidence is needed to understand if the trends we identified at the aggregate-level scale down to the farm, we argue that our findings generally support the notion that large-scale efforts to restore soil organic matter levels at regional/continental scales should improve the resilience of agricultural systems. Such a notion is key to soil health initiatives aimed at increasing agricultural resilience by rebuilding soil organic matter (Bradford et al. 2019) and initiatives such as 4 per Mille that argue the co-benefits of increased soil organic matter are an important additional incentive to advancing soil carbon sequestration (Lal 2016; Chenu et al. 2019).

4. Conclusions

Our analyses demonstrate that counties with higher mean soil organic matter content are associated with lower maize yield loss due to drought, that this relationship is strongest under severe drought conditions, and this increased yield protection translates to lower crop insurance payouts under drought conditions. Furthermore, we demonstrate that these impacts are not solely mediated through the impact of soil organic matter on conventional measures of plant available water, but likely occur through additional pathways that influence soil water supply and use by plants, which appear to collectively provide the yield protection benefits we document here. At least at the county level then for US rain-fed maize agriculture, soil organic matter content appears to be an important predictor of resilience to the type of drought conditions that are likely to occur more frequently under future climate scenarios. Further work should investigate whether similar benefits of soil organic matter for yield protection are afforded by agricultural managements that build organic matter in agricultural soils worldwide. In the interim, our analyses highlight the potential value of integrating soil information into resilience planning as agricultural outcomes become more uncertain with the increasing incidence and severity of extreme weather events.

Figures and Tables:

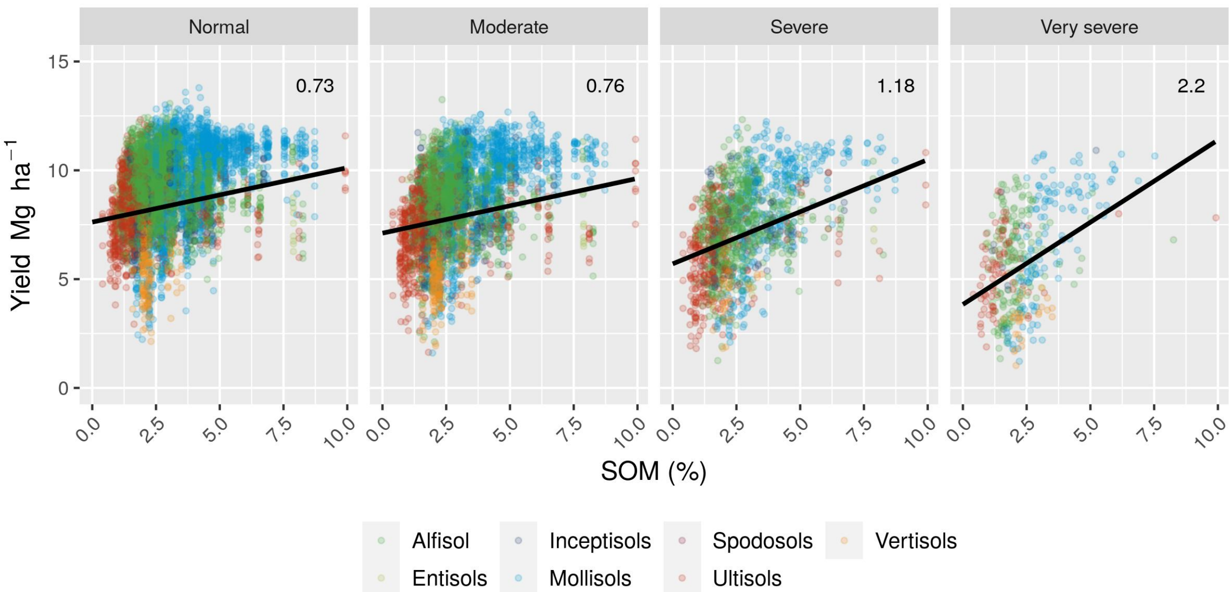


Figure 1. Maize yields increase with soil organic matter content (%), with the effect becoming more pronounced with increasing drought severity. Drought levels are based on the following ranges of Standardized Precipitation Evapotranspiration Index (SPEI): Very severe < -0.99; Severe ≥ -0.99 < -0.44; Moderate ≥ -0.44 < 0.12; Normal ≥ 0.12. Numbers on each panel represent the marginal effect of soil organic matter for the corresponding drought level and trendlines represent predicted yields based on that marginal effect.

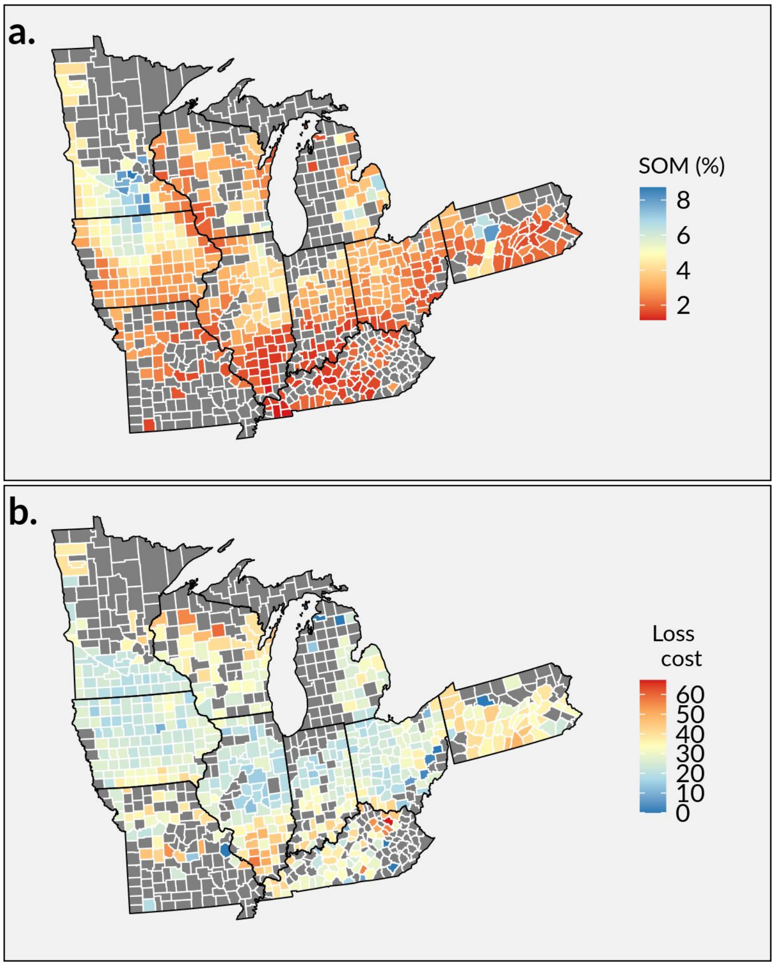


Figure 2. Higher levels of soil organic matter were associated with lower loss cost, the unitless ratio of crop insurance indemnities to liabilities, under drought conditions. Figure 2a is a map of mean soil organic matter content across counties (n=730) within a subset of states (PA, WI, MI, MN, IL, IN, IA, OH, MO, and KY) included in this study. Figure 2b is a map of mean loss cost under all drought conditions in those same counties. The marginal effect of soil organic matter on loss cost under all drought conditions is -6.47 (σ=0.84, p<0.001).

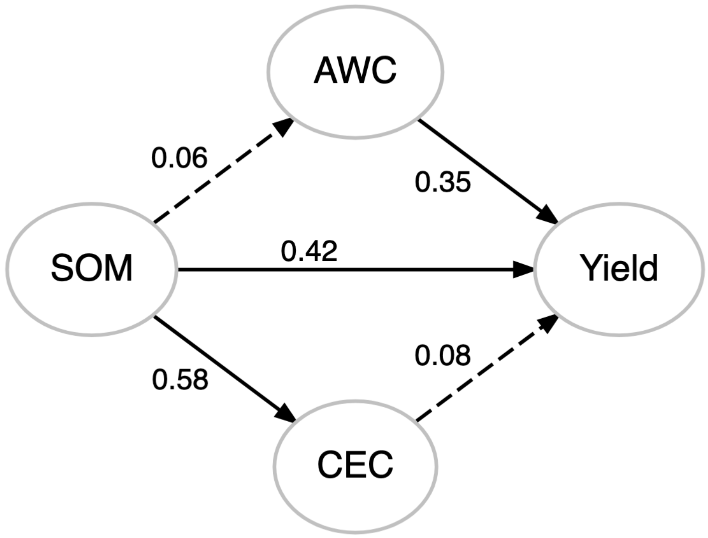


Figure 3. Increases in yield under drought associated with increasing soil organic matter appear only partially mediated by increases to soil available water capacity induced by higher soil organic matter. Figure 3 is a diagram of a structural equation model of best fit developed during a series of confirmatory pathway analyses. Numbers on each arrow represent standardized coefficients of the relationship between the variables connected, and the direction of arrows indicate variable dependence. Solid lines indicate statistically significant ($p \leq 0.05$) relationships and dotted lines indicate non-significant relationships.

Drought	Term	Coefficient	Std. error	p
Very severe	SOM	2.1976	0.3339	< 0.0001
	Clay	0.4999	0.3355	0.1371
	H_3O^+	0.5665	0.6013	0.3467
	SOM:Clay	0.6549	0.6312	0.3001
	SOM:H_3O^+	0.0426	0.9302	0.9635
	Clay:H_3O^+	1.0140	0.9089	0.2653
	SOM:Clay:H_3O^+	0.9120	1.6866	0.5890
Severe	SOM	1.1820	0.1270	< 0.0001
	Clay	-0.1776	0.1340	0.1852
	H_3O^+	-0.3637	0.1716	0.0342
	SOM:Clay	0.8457	0.2340	0.0003
	SOM:H_3O^+	-0.5317	0.2429	0.0288
	Clay:H_3O^+	-0.0274	0.2900	0.9249
	SOM:Clay:H_3O^+	-1.6099	0.5223	0.0021
Moderate	SOM	0.7616	0.0687	< 0.0001
	Clay	0.3132	0.0718	< 0.0001
	H_3O^+	-0.3794	0.0949	0.0001
	SOM:Clay	0.6793	0.1189	< 0.0001
	SOM:H_3O^+	-0.2837	0.1264	0.0249
	Clay:H_3O^+	-0.2869	0.1549	0.0640
	SOM:Clay:H_3O^+	-0.5372	0.2941	0.0678
Normal	SOM	0.7266	0.0514	< 0.0001
	Clay	0.2085	0.0577	0.0003
	H_3O^+	-0.5189	0.0856	< 0.0001
	SOM:Clay	0.5992	0.0985	< 0.0001
	SOM:H_3O^+	-0.1456	0.1219	0.2322
	Clay:H_3O^+	-0.2103	0.1445	0.1456
	SOM:Clay:H_3O^+	0.1430	0.2600	0.5822

Table 1. Results of linear mixed effects models across multiple levels of drought severity relating yield (Mg ha^{-1}) to soil organic matter (SOM, %), clay (%), and H_3O^+ concentration (mol). Coefficients for terms are standardized. Sample numbers for each drought level are as follows: Very severe, n=410; Severe, n= 1537; Moderate, n=3998; Normal, n=6431. Conditional coefficient of determination for each model is as follows: Very severe, R^2=0.53; Severe, R^2=0.45; Moderate, R^2=0.51; Normal, R^2=0.59.

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Supplementary Information:

Selection of independent variables

Since many soil properties predictive of crop yields are likely to be collinear with soil organic matter, inclusion of these properties as independent variables may reduce the accuracy of coefficient estimates for soil organic matter. As such, we performed an initial model specification analysis to determine a set of independent variables that would reduce collinearity. We fit a multivariate linear regression with yield (Mg ha^{-1}) as the dependent variable and no interaction effects. Independent variables included soil organic matter (%), soil clay content (%), soil H_3O^+ concentration (mol), and cation exchange capacity (meq 100g $soil^{-1}$). We then evaluated variance inflation factors to determine which independent variables could be removed to reduce multicollinearity. Cation exchange capacity had the highest variance inflation factor with a value of 4.6. We removed cation exchange capacity then fit the model again with the remaining three variables. Variance inflation factors remained within tolerance (1-2), so they were kept for use in further analyses.

Initial analyses and drought index sensitivity analysis

Prior to subsetting data into different ranges of drought severity, we fit an initial model to assess if soil organic matter interacted at all with the effect of drought conditions to affect yields. The dependent variable in these models was yield (Mg ha^{-1}) and the independent variables included soil organic matter (%), soil clay content (%), soil H_3O^+ concentration (mol), and mean standardized precipitation evapotranspiration index (SPEI) for the months of May to August. We also included a random effect of State to account for possible impacts of geographic differences in management and production environment on model outcomes not accounted for in the data we collected. In addition, we also developed a set of parallel models using the Drought Severity Classification Index (DSCI) to perform a sensitivity analysis to evaluate whether or not the interaction effects of soil properties with yield changed if drought was quantified in a different manner. Models including all possible interaction effects were fit using a restricted maximum likelihood approach in the lme4 (Bates et al 2020) package in R. Prior to model fitting, all observations of each independent variable were standardized so that coefficient estimates would also be standardized. Data standardization was done by subtracting the mean of a given variable from each observation and then dividing that value by 2x the standard deviation of that variable.

Results from the models using SPEI indicated that when SPEI decreased (i.e. drought conditions became more severe) the impact of soil organic matter was greater on maize yield (Mg ha-1) (Table S5). Sensitivity analyses confirmed that when DSCI was substituted for SPEI, directionality, significance, and relative magnitude of estimated coefficients remained largely the same (Table S6), as DSCI increased (drought conditions became more severe), the effect of soil organic matter on yields became more positive. To better understand the nature of this interaction effect, we then subset data to different ranges of drought severity for further analysis as described in the main text.

Analyses of interaction effects

While our primary interest was determining the main effect of soil organic matter on yields under variable drought conditions, several interaction effects with soil organic matter emerged for models in which yield or loss cost were the dependent variable. Here we document them and conduct a series of sensitivity analyses to understand why and how they emerged, and to demonstrate that the positive effects of soil organic matter on yields were robust across drought conditions and typical variation in soil properties.

For models in which yield (Mg ha^{-1}) was the dependent variable, which interaction effects emerged as statistically significant ($p < 0.05$) varied by drought category. For very severe drought, no interaction effects emerged; under severe and moderate drought two-way interaction effects emerged between soil organic matter and H_3O^+ concentration, soil organic matter and clay, as well as a three-way interaction effect between soil organic matter, clay, and H_3O^+ concentration; and under normal conditions, a two-way interaction between soil organic matter and clay emerged (Table S1). Matching significant interaction effects had the same direction and similar magnitude across drought levels.

Analysis of model residuals indicated that the interaction effect of soil organic matter and soil clay content is such that the positive effect of soil organic matter on yields diminishes as clay content diminishes. Multiple sensitivity analyses to test the sensitivity of this effect to observations on either end of the distribution of clay content did not substantially change coefficients or their p values. These sensitivity analyses indicate that this is a valid interaction effect and that organic matter has a more limited positive effect on yields in counties where clay content is limited.

The negative interaction effect of soil organic matter and H_3O^+ concentration is such that the positive effect of soil organic matter on yields is diminished as H_3O^+ concentration increases. This interaction effect appears to be primarily driven by observations from 6 counties with very high H_3O^+ concentration that are also high soil organic matter. When observations from these counties are removed, the interaction effect is rendered non-significant ($p=0.63$ at moderate drought). Removing these observations also rendered the three-way interaction effect of soil organic matter, clay, and H_3O^+ concentration non-significant ($p=0.76$ at moderate drought), as these same observations were also very high clay content.

For models in which loss cost was the dependent variable, negative two-way interaction effects emerged between soil organic matter and clay content, as well as between soil organic matter and H_3O^+ concentration at the severe and moderate drought levels; at the very severe drought level a negative three-way interaction effect between soil organic matter, clay, and H_3O^+ concentration (Table S3). The interaction effects between soil organic matter and clay content reflected the corresponding effects for yield discussed above. The mitigating (i.e. negative) effect of soil organic matter on loss cost diminished as clay content decreased, and sensitivity analyses indicate that this effect is robust against outliers.

The interaction effects between soil organic matter and H_3O^+ concentration did not reflect the corresponding effects from models in which yield was the dependent variable. As H_3O^+ concentration increases, the negative effect of soil organic matter on loss cost is made more strongly negative. Exploration of the residuals and the raw data indicated that this effect was due to a limited number of observations that had high H_3O^+ concentrations and high soil organic matter. At the severe drought level a very small number ($n=5$) of these observations also had a loss cost value of 0. When these observations were removed, the interaction effect was rendered non-significant ($p=0.72$). Similarly, at the moderate drought level a small number of observations ($n=29$) with both low clay and soil organic matter content that also had a loss cost of 0 appear to have been responsible for this interaction effect. Removing these observations rendered the effect non-significant ($p=0.93$). Given that this interaction effect was not robust to sensitivity analyses and was caused by opposite outlier cases at either drought level, it does not appear to be robust but is instead the result of anomalous observations.

Finally, the three-way interaction at the severe drought level is such that the negative effect of soil organic matter on loss cost becomes more strongly negative when soil clay content and H_3O^+ concentration increase. Evaluation of residuals and the data itself seem to indicate that this effect is largely the result of a small number of counties in Iowa that had normal yields, and thus low loss cost, despite bad weather conditions. These counties had low clay content and H_3O^+ concentrations in the lower quartile, producing the interaction effect we observed. Removing these observations (n=18) rendered the effect non-significant (p=0.13).

Structural equation model fitting

To determine the best, most parsimonious structural equation models for our confirmatory path analysis, we fit two candidate models for data from either drought or non-drought conditions in which the effect of soil organic matter on yields was either fully or partially mediated by its impacts on available water capacity and cation exchange capacity. We then compared these models for best fit based on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and an analysis of variance. In both cases, the model in which the effect of soil organic matter on yield was only partially mediated by its effects on available water capacity had lower AIC/BIC, and an analysis of variance indicated the partially mediated model was significantly different than the fully mediated model (Table S7). This initial analysis also resulted in a negative effect of cation exchange capacity on yields under both drought and non-drought conditions. As this result runs counter to previous evidence suggesting cation exchange capacity is an important positive predictor of yields, we manually inspected the data to find that this result was the consequence of outlying cation exchange capacity values that correlate to extremely high clay content. To make our confirmatory path analysis more representative of conventional, maize-growing soil types, we removed these observations (n=20) and then refit the structural equation models. The partially mediated model was again the better fitting model, and coefficients for soil organic matter and available water capacity's influence on yields remained similar, but cation exchange capacity's coefficient changed to become positive (Table S8).

Drought	Term	Coefficient	Std. error	p
Very severe	SOM	2.1976	0.3339	< 0.0001
	Clay	0.4999	0.3355	0.1371
	H_3O^+	0.5665	0.6013	0.3467
	SOM:Clay	0.6549	0.6312	0.3001
	SOM:H_3O^+	0.0426	0.9302	0.9635
	Clay:H_3O^+	1.0140	0.9089	0.2653
	SOM:Clay:H_3O^+	0.9120	1.6866	0.5890
Severe	SOM	1.1820	0.1270	< 0.0001
	Clay	-0.1776	0.1340	0.1852
	H_3O^+	-0.3637	0.1716	0.0342
	SOM:Clay	0.8457	0.2340	0.0003
	SOM:H_3O^+	-0.5317	0.2429	0.0288
	Clay:H_3O^+	-0.0274	0.2900	0.9249
	SOM:Clay:H_3O^+	-1.6099	0.5223	0.0021
Moderate	SOM	0.7616	0.0687	< 0.0001
	Clay	0.3132	0.0718	< 0.0001
	H_3O^+	-0.3794	0.0949	0.0001
	SOM:Clay	0.6793	0.1189	< 0.0001
	SOM:H_3O^+	-0.2837	0.1264	0.0249
	Clay:H_3O^+	-0.2869	0.1549	0.0640
	SOM:Clay:H_3O^+	-0.5372	0.2941	0.0678
Normal	SOM	0.7266	0.0514	< 0.0001
	Clay	0.2085	0.0577	0.0003
	H_3O^+	-0.5189	0.0856	< 0.0001
	SOM:Clay	0.5992	0.0985	< 0.0001
	SOM:H_3O^+	-0.1456	0.1219	0.2322
	Clay:H_3O^+	-0.2103	0.1445	0.1456
	SOM:Clay:H_3O^+	0.1430	0.2600	0.5822

Table S1: Results of linear mixed effects models across multiple levels of drought severity relating yield (Mg ha^{-1}) to soil organic matter (SOM, %), clay (%), and H_3O^+ concentration (mol). Coefficients for terms are standardized. Sample numbers for each drought level are as follows: Very severe, n=410; Severe, n= 1537; Moderate, n=3998; Normal, n=6431.

Drought	**Term**	**Coefficient**	**Std. error**	***p***
Very severe	SOM	0.1154	0.0362	0.0015
	Clay	0.0203	0.0358	0.5700
	H_3O^+	-0.0095	0.0650	0.8834
	SOM:Clay	-0.0246	0.0680	0.7184
	SOM:H_3O^+	-0.1604	0.1011	0.1135
	Clay:H_3O^+	-0.0607	0.0984	0.5376
	SOM:Clay:H_3O^+	-0.2421	0.1827	0.1858
Severe	SOM	0.0478	0.0135	0.0004
	Clay	-0.0304	0.0138	0.0287
	H_3O^+	0.0018	0.0188	0.9249
	SOM:Clay	0.0075	0.0258	0.7714
	SOM:H_3O^+	-0.0172	0.0272	0.5266
	Clay:H_3O^+	0.0365	0.0324	0.2600
	SOM:Clay:H_3O^+	-0.0934	0.0590	0.1139
Moderate	SOM	0.0016	0.0068	0.8150
	Clay	0.0155	0.0068	0.0230
	H_3O^+	0.0079	0.0096	0.4081
	SOM:Clay	0.0050	0.0123	0.6846
	SOM:H_3O^+	0.0045	0.0133	0.7366
	Clay:H_3O^+	0.0033	0.0161	0.8353
	SOM:Clay:H_3O^+	0.0273	0.0312	0.3803
Normal	SOM	-0.0261	0.0048	< 0.0001
	Clay	0.0016	0.0053	0.7605
	H_3O^+	-0.0058	0.0080	0.4678
	SOM:Clay	-0.0088	0.0093	0.3449
	SOM:H_3O^+	-0.0072	0.0116	0.5345
	Clay:H_3O^+	-0.0185	0.0137	0.1778
	SOM:Clay:H_3O^+	0.0104	0.0249	0.6749

Table S2: Results of linear mixed effects models across multiple levels of drought severity relating yield anomaly to soil organic matter (SOM, %), clay (%), and H_3O^+ concentration (mol). Coefficients for terms are standardized. Sample numbers for each drought level are as follows: Very severe, n=410; Severe, n= 1537; Moderate, n=3998; Normal, n=6431.

Drought	Term	Coefficient	Std. error	*p*
Very severe	SOM	-36.0966	4.7641	< 0.0001
	Clay	-17.8897	4.6736	0.0001
	H_3O^+	-32.0566	9.9484	0.0013
	SOM:Clay	-13.4321	9.5874	0.1612
	SOM:H_3O^+	-23.1025	15.2054	0.1287
	Clay:H_3O^+	-42.9249	13.4872	0.0015
	SOM:Clay:H_3O^+	-53.6069	24.4468	0.0283
Severe	SOM	-8.3689	1.4140	< 0.0001
	Clay	-1.3879	1.4720	0.3458
	H_3O^+	-5.5117	2.2093	0.0126
	SOM:Clay	-11.5867	2.7725	< 0.0001
	SOM:H_3O^+	-6.2995	3.0806	0.0409
	Clay:H_3O^+	-11.2259	3.7693	0.0029
	SOM:Clay:H_3O^+	0.9964	6.9334	0.8857
Moderate	SOM	-3.9536	0.7339	< 0.0001
	Clay	-0.7116	0.7060	0.3135
	H_3O^+	-4.3376	1.1342	0.0001
	SOM:Clay	-4.8935	1.3467	0.0003
	SOM:H_3O^+	0.9792	1.3513	0.4687
	Clay:H_3O^+	-7.4802	1.7291	< 0.0001
	SOM:Clay:H_3O^+	4.8528	3.6119	0.1791
Normal	SOM	-1.9504	1.3170	0.1386
	Clay	-0.4230	1.3886	0.7607
	H_3O^+	-8.7301	2.3950	0.0003
	SOM:Clay	3.4948	2.6662	0.1899
	SOM:H_3O^+	-0.9849	3.5804	0.7833
	Clay:H_3O^+	-7.4969	4.2564	0.0782
	SOM:Clay:H_3O^+	6.7002	8.1071	0.4086

Table S3: Results of mixed effects Tobit regression models across multiple levels of drought severity relating loss cost to soil organic matter (SOM, %), clay (%), and H_3O^+ concentration (mol). Coefficients for terms are standardized. Sample numbers for each drought level are as follows: Very severe, n=410; Severe, n= 1537; Moderate, n=3998; Normal, n=6431.

Drought	Model	Response	Predictor	Coefficient	Std. error	*p*
Drought	Partial	Yield	CEC	0.2007	0.0102	< 0.0001
		Yield	AWC	0.3253	0.0222	< 0.0001
		Yield	SOM	0.3979	0.0383	< 0.0001
		AWC	SOM	0.0557	0.0573	0.1332
		CEC	SOM	0.5848	0.1247	< 0.0001
	Full	Yield	CEC	0.4727	0.0087	< 0.0001
		Yield	AWC	0.2324	0.0233	< 0.0001
		AWC	SOM	0.0557	0.0573	0.1332
		CEC	SOM	0.5848	0.1247	< 0.0001
Normal	Partial	Yield	CEC	0.2044	0.0097	< 0.0001
		Yield	AWC	0.4085	0.0210	< 0.0001
		Yield	SOM	0.2337	0.0363	< 0.0001
		AWC	SOM	0.0557	0.0573	0.1332
		CEC	SOM	0.5848	0.1247	< 0.0001
	Full	Yield	CEC	0.3642	0.0078	< 0.0001
		Yield	AWC	0.3540	0.0208	< 0.0001
		AWC	SOM	0.0557	0.0573	0.1332
		CEC	SOM	0.5848	0.1247	< 0.0001

Table S4: Results of partially and fully mediated piecewise structural equation models under drought and non-drought conditions. SEMs relate the effect of soil organic matter (SOM, %) to yield (Mg ha^{-1}) via its impacts on available water capacity (AWC, %) and cation exchange capacity (CEC, meq 100 g $soil^{-1}$). Coefficients for terms are standardized. Models for the drought category include observations at all levels of drought severity (i.e. very severe, severe, moderate). To more accurately model typical soil types, observations with a CEC value greater than 31.92 meq 100 g $soil^{-1}$ were excluded. Sample numbers for each drought level are as follows: Drought, n=5740; Normal, n=6307. Model inputs were based on the mean value for each term at the county level.

Term	**Coefficient**	**Std error**	***p***
SPEI	1.1507	0.0325	< 0.0001
SOM	0.8316	0.0404	< 0.0001
H_3O^+	-0.4497	0.0613	< 0.0001
Clay	0.1992	0.0440	< 0.0001
SPEI:SOM	-0.6661	0.0659	< 0.0001
SPEI:H_3O^+	-0.1508	0.1070	0.1588
SOM:H_3O^+	-0.3258	0.0852	0.0001
SPEI:Clay	-0.1686	0.0647	0.0092
SOM:Clay	0.6487	0.0745	< 0.0001
H_3O^+:Clay	-0.2630	0.1029	0.0106
SPEI:SOM:H_3O^+	0.2498	0.1599	0.1182
SPEI:SOM:Clay	0.2117	0.1276	0.0972
SPEI:H_3O^+:Clay	-0.1153	0.1934	0.5512
SOM:H_3O^+:Clay	-0.4649	0.1881	0.0134
SPEI:SOM:H_3O^+:Clay	0.5682	0.3571	0.1115

Table S5: Results of linear mixed effects models relating yield (Mg ha^{-1}) to Standardized Precipitation Evapotranspiration Index (SPEI), soil organic matter (SOM, %), clay (%), and H_3O^+ concentration (mol). Coefficients for terms are standardized. Sample number was n=12,376.

Term	**Coefficient**	**Std error**	***p***
DSCI	-1.2245	0.0388	< 0.0001
SOM	0.8423	0.0407	< 0.0001
H_3O^+	-0.4235	0.0622	< 0.0001
Clay	0.2474	0.0443	< 0.0001
DSCI:SOM	0.4675	0.0760	< 0.0001
DSCI:H_3O^+	0.3370	0.1302	0.0096
SOM:H_3O^+	-0.1634	0.0857	0.0565
DSCI:Clay	0.2943	0.0663	< 0.0001
SOM:Clay	0.6290	0.0748	< 0.0001
H_3O^+:Clay	-0.1733	0.1029	0.0923
DSCI:SOM:H_3O^+	-0.2908	0.1942	0.1342
DSCI:SOM:Clay	-0.5208	0.1282	0.0001
DSCI:H_3O^+:Clay	0.1289	0.2005	0.5204
SOM:H_3O^+:Clay	-0.1827	0.1881	0.3316
DSCI:SOM:H_3O^+:Clay	-0.3559	0.3689	0.3347

Table S6: Results of linear mixed effects models relating yield (Mg ha^{-1}) to Drought Severity Classification Index (DSCI), soil organic matter (SOM, %), clay (%), and H_3O^+ concentration (mol). Coefficients for terms are standardized. Sample number was n=12,376.

Drought	**Model**	**AIC**	**BIC**	**Fisher C**	***p***
Drought	Full	343.85	389.75	323.85	---
	vs. Partial	219.4	269.89	197.4	< 0.01
Normal	Full	260.89	306.8	240.89	---
	vs. Partial	219.4	269.89	197.4	< 0.01

Table S7: Results of a fit comparison and analysis of variance for partially and fully mediated piecewise structural equation models under drought and non-drought conditions. SEMs relate the effect of soil organic matter (SOM, %) to yield (Mg ha^{-1}) via its impacts on available water capacity (AWC, %) and cation exchange capacity (CEC, meq 100 g $soil^{-1}$). Models for the drought category include observations at all levels of drought severity (i.e. very severe, severe, moderate). Sample numbers for each drought level are as follows: Drought, n=5945; Normal, n=6431. Model inputs were based on the mean value for each term at the county level.

Drought	Model	Response	Predictor	Coefficient	Std. error	*p*
Drought	Partial	Yield	CEC	-0.0752	0.0074	0.0155
		Yield	AWC	0.4465	0.0206	< 0.0001
		Yield	SOM	0.5282	0.0353	< 0.0001
		AWC	SOM	0.0677	0.0575	0.0642
		CEC	SOM	0.4522	0.1604	< 0.0001
	Full	Yield	CEC	0.1693	0.0078	< 0.0001
		Yield	AWC	0.4231	0.0244	< 0.0001
		AWC	SOM	0.0677	0.0575	0.0642
		CEC	SOM	0.4522	0.1604	< 0.0001
Normal	Partial	Yield	CEC	-0.1241	0.0071	0.0001
		Yield	AWC	0.5374	0.0198	< 0.0001
		Yield	SOM	0.3910	0.0340	< 0.0001
		AWC	SOM	0.0677	0.0575	0.0642
		CEC	SOM	0.4522	0.1604	< 0.0001
	Full	Yield	CEC	0.0569	0.0070	0.0745
		Yield	AWC	0.5201	0.0217	< 0.0001
		AWC	SOM	0.0677	0.0575	0.0642
		CEC	SOM	0.4522	0.1604	< 0.0001

Table S8: Results of partially and fully mediated piecewise structural equation models under drought and non-drought conditions. SEMs relate the effect of soil organic matter (SOM, %) to yield (Mg ha^{-1}) via its impacts on available water capacity (AWC, %) and cation exchange capacity (CEC, meq 100 g $soil^{-1}$). Coefficients for terms are standardized. Models for the drought category include observations at all levels of drought severity (i.e. very severe, severe, moderate). Sample numbers for each drought level are as follows: Drought, n=5945; Normal, n=6431. Model inputs were based on the mean value for each term at the county level.

Chapter 3: Testing the potential for a reduced-wavelength spectrophotometer to estimate soil carbon content at the point and field scales

Abstract

Proximal sensing methods for estimating soil carbon content on field collected samples have been proposed as a lower-cost, alternative method to standard laboratory methods that would enable the collection of data at higher spatial densities. Previous evidence suggests that such methods may have sufficient accuracy to do so, but most studies employ high-cost instruments (> 10,000 USD) that may not be accessible to practitioners in the field. We tested the capacity of the Our Sci Reflectomer, a low cost (< 500 USD) handheld spectrophotometer, to estimate soil carbon content on individual point-based samples across multiple grazing and rangeland sites in Wyoming, Montana, and New York, USA. We additionally simulated potential real-world applications of this tool for generating estimates of the distribution of soil carbon content at the field scale. We found that the accuracy of methods using this low-cost spectrophotometer to estimate soil carbon content on individual samples was highly variable but generally low ($R^2 < 0.5$; RMSE > 0.5) and sensitive to how representative training data were of a given site. Relatedly, simulated applications of these methods to real-world scenarios indicated that in order to accurately and consistently characterize field-level distribution characteristics of soil carbon content, a substantial amount of training data generated through laboratory testing is necessary, undermining any advantage gained through increased sampling. Our results indicate that the methods and tools we employed in this study likely have limited utility for assessing field carbon stocks with adequate statistical confidence. Other studies using more sophisticated VNIR instruments have generally achieved greater accuracy. But results from our best-performing models and sites were still within the range of other reported results, and many other studies are

based on large spectral libraries, whereas our analysis was limited to the site-level to represent potential real-world applications. As such, we suggest our research demonstrates the need for more deliberate testing of the use of proximal sensing methods for suggested field applications to assess their true usefulness. Furthermore, to make such low-cost proximal sensing methods most useful, adapting mid-infrared spectroscopy and building regional soil spectral libraries and corresponding methods for calibration transfer across instruments and geographies are necessary.

1. Introduction

The spatial variability of soil carbon content makes estimation of carbon stocks difficult at field and landscape scales. Numerous factors, including spatial variation in soil types, physical geography, and plant communities, dictate spatial patterns in accumulation of soil carbon and hence soil carbon content (Grunwald, Thompson, and Boettinger 2011; McBratney, Mendonça Santos, and Minasny 2003). These factors imply that efforts to map soil carbon must be correctly planned or large numbers of samples must be collected to estimate spatial variability of soil carbon with sufficient statistical confidence. Soil carbon content is typically measured in the laboratory using combustion analysis and gas chromatography/mass spectrometry (GCMS). These analyses provide highly accurate, per sample, soil carbon measurements, but involve substantial material and labor costs. Given the high analytical and labor costs of laboratory methods, spatially intensive sampling campaigns are generally cost-prohibitive.

Proximal sensing methods that employ visible/near-infrared (VNIR) or mid-infrared (MIR) spectrometry offer an approach to measuring soil carbon that is complementary to laboratory combustion analyses and potentially more affordable (McBratney, Minasny, and Viscarra Rossel 2006a; Angelopoulou et al. 2020; Nocita et al. 2015). As soil carbon content in like soils increases, soils absorb and reflect visible and infrared radiation differently. VNIR and MIR spectrometers can measure these spectral reflectance characteristics on bulk soil samples, and these data can then be used along with soil carbon content data from GCMS analyses to train models capable of estimating soil carbon content on further samples without the need for laboratory work. Research has demonstrated that these methods can achieve reasonable accuracy in soil carbon estimation with sufficient training data and adequate sample preparation, but they generally cannot achieve the same per-sample accuracy as GCMS (Gao et al., 2014; Minasny and McBratney, 2008; van Groenigen et al., 2003; Viscarra Rossel et al., 2006). However, compared to typical laboratory analysis, these methods are generally less labor-intensive, have near-zero material costs, and instrumentation is less expensive and less difficult to maintain/operate.

The suggested advantage, then, of proximal sensing tools is that they could allow users to collect lower accuracy data on soil carbon content at much higher spatial sampling rates to replace or complement lab-measured data (Nocita et al. 2015). With higher sampling rates, characterization of spatial variability in soil carbon content at the field-level with statistical confidence is potentially more achievable. Combining proximal sensing data with other sources of information predictive of soil carbon content, such as regional/national digital soil maps, remote sensing imagery, and elevation datasets, can further improve their accuracy and utility (Gomez, Viscarra Rossel, and McBratney 2008; Paul et al. 2019).

However, despite reducing per-sample costs, most spectrometers considered for use in proximal sensing of soils remain expensive (> 10,000 USD). Furthermore, past research has highlighted several barriers to expanding the use of such tools. For example, sufficiently large libraries of soil spectral data are necessary to train accurate estimation models (Viscarra Rossel et al. 2016; Reeves III 2010), and while efforts to create such libraries are underway at continental and regional scales, transferability of models across areas is not always possible (Minasny et al. 2009) and methods to aid in effective calibration transfer have only recently been developed (Padarian, Minasny, and McBratney 2019). These barriers limit the use of such methods by non-experts and suggest that in the short-term, proximal sensing will require calibration of models through at the local field scale with data acquired through laboratory analysis.

As part of the Quick Carbon research project developed at the Yale School of Environment, we tested the efficacy of the Our Sci Reflectometer (https://www.our-sci.net/reflectometer/; Ann Arbor, MI, USA), a simplified, inexpensive, and open-source field spectrometer to estimate soil carbon content at individual sample points and at the field scale (100 – 1000 ha) across multiple grassland and rangeland sites in the United States. At each site we collected spatially distributed sets of soil samples that were then analyzed for soil carbon content using conventional analytical laboratory approaches. We then tested the accuracy of a variety of modeling approaches using data from the reflectometer, geographic datasets, and digital soil maps to estimate soil carbon content of individual soil samples. Further, knowing that such modeling approaches were likely to be less accurate than conventional laboratory analysis on a per-sample basis but could potentially support higher sampling rates we wanted to investigate if this trade-off could allow for characterization of site-level distributions of soil carbon content at relatively lower effort. On a subset of sites, we tested the accuracy of estimates of site-level soil carbon distributions using models trained on a limited proportion of the collected samples. We then iteratively increased the proportion of samples in this subset to see if there was a threshold at which modeled estimates were consistently, statistically accurate as compared to a withheld test sample. This analysis was intended to simulate a real-world soil carbon monitoring scenario in which a limited budget is used for lab analysis and proximal sensing methods are then employed to gather more additional data points with the intention of increasing confidence in assessment of spatial variability at the field scale.

2. Methods

2.1. Field sites and sampling design

Samples and data used in this analysis were collected in 2016 and 2018 from 6 field sites. Sites included several working rangelands and grazing lands in the Northern Great Plains and one site in New England. We collected a total of 1302 complete samples across all sites. Total carbon concentrations of soil samples measured using elemental analysis ranged from 0.44% to 9.05%. Distributions of soil carbon content varied greatly across sites, but most followed a lognormal distribution with an extended right-hand tail (i.e. few, high carbon samples). Based on comparisons to digital soil maps, sites spanned a broad range of soil orders and suborders but most were dominated by soil types with minimal horizon development (i.e. Inceptisols, Entisols; Table 1).

Sample design varied across sites based on which year the site was sampled. For sites sampled in 2016, we sampled soils at a density of ~1 sample ha^{-1} based on a systematic radial transect sample pattern. Within each ranch we identified different parcels selected to represent different representative soil taxa, and within each parcel we established a series of anchor points at regular intervals. From these anchor points, we then set transects at 0, 72, 144, 216, and 288 degrees and collected samples at random distance intervals between 1–100 m along each transect until we met the boundary of the parcel. We sampled to a depth of 20 cm using a hammer probe with a 2 cm diameter and passed samples through a 4 mm sieve in the field at the point of collection.

For sites sampled in 2018, soil sampling points were selected through a stratified random sampling procedure with the Google Earth Engine web application Stratifi (Bettigole 2021). This web app first retrieves data on vegetative productivity (Landsat 8 derived indices; 30 m resolution), topography/slope/aspect (National Elevation Dataset; 10 m resolution), and soil properties (gSSURGO 30 m resolution) within a pre-defined study from the Google Earth Engine data catalog ("Earth Engine Data Catalog" 2022). It uses an unsupervised hierarchical clustering algorithm, WEKA X-Means (Witten et al. 2016), to select an optimal number of strata based on these input layers and then generates those strata by assigning each pixel (30 m resolution) to a stratum, optimizing for likeness across input data. Stratifi then chooses a series of random sampling sites based on the desired sampling density and the relative size of each stratum. At each point we collected soil at two depth increments 0-15 cm and 15-30 cm using a battery-operated drill, auger bit, and custom sample collection device. This device was designed with depth stops to ensure soil was collected at the correct depth increments. In cases where this approach was inadequate given soil wetness or loose soil structure, we used a push probe with a 2 cm diameter instead. For the purposes of this analysis, we chose to only use data from the 0-15 cm increment.

2.2. Sample processing and analysis

Field-collected samples were left to air dry until they could be shipped or returned to the lab. Once in the lab, we dried all soil samples to constant mass in ovens at 60°C, and homogenized them in a SPEX Sample Prep ball mill (Metuchen, NJ, USA) or manually with a rolling pin. We then collected visible/near-infrared reflectance data on each sample using the Our Sci Reflectometer ("Our Sci - Reflectometer" 2021). This device is a highly simplified, low cost (<$500) spectroscopy instrument that employs a series of LEDs and photoreceptors to measure sample reflectance at a select series of wavelengths: 370, 395, 420, 530, 605, 650, 730, 850, 880, and 940 nm. A soil sample is placed in front of the optical window inside a glass petri dish. The

LEDs then flash in sequence and the photoreceptors record reflectance measurements simultaneously in a companion smartphone app. To control for instrument drift over repeated measurements, we also scanned a “black/white” standard card at the beginning of each session in the lab to standardize measurements to a 0-100 scale. Corrected reflectance measurements were then converted to an absorbance scale using the following formula.

$$Absorbance = \log_{10} \frac{1}{reflectance}$$

We also analyzed each sample for carbon and nitrogen content using standard laboratory techniques. We analyzed samples collected in 2016 at the Yale Stable Isotope Center on a Costech *Elemental Analyzer* (Valencia, CA, USA) attached to a Thermo DeltaPlus Advantage Isotope Mass Spectrometer (Waltham, MA, USA). Samples collected in 2018 were analyzed at Ward Labs (Kearney, NE, USA) on a LECO TruMac Analyzer (St. Joseph, MI, USA).

2.3. Data processing

We recorded the coordinates of each sample location in the field, allowing us to later retrieve data from digital soil maps and other geostatistical sources for all sample points for use in model development. We focused on collecting data types that would add predictive power to our models for estimating soil carbon content, including data on soil texture and soil chemical properties from SoilGrids, normalized differential vegetation index (NDVI), and topographic data (Table 2).

SoilGrids is a global, 250m resolution dataset on soil properties generated using a machine learning process trained on several continental and national level soil inventories (Hengl, Jesus, et al. 2017; Hengl et al. 2014). Data were retrieved from SoilGrids for every sample point via their RESTful API using the GSIF package (Hengl, Kempen, et al. 2017) in R v. 4.0.3 (R Core Team 2020).

NDVI was calculated as the normalized difference between band 8 (NIR, 835.1 nm) and band 4 (red, 664.5 nm) of the Sentinel 2 Multi-spectral Instrument dataset from the European Space Agency. To calculate NDVI at each sampling point, we retrieved Level 1-C Sentinel 2 reflectance data for a bounding box containing the entire sampling area using the *ee* package (Gorelick 2021) in Python to access the Google Earth Engine data catalog (Google 2021b). Data were retrieved for all available dates from January 1, 2019 to December 31, 2019. Images for each date were then cloud-masked using the QA60 band from Sentinel 2 for the corresponding date to identify and remove all pixels obscured by clouds or cirrus clouds. Finally, a 'greenest pixel' composite image of the study area was created by selecting the highest NDVI value across the date range for each pixel. Specific NDVI values for each sample point were then extracted from this composite image by overlaying point coordinates and finding the corresponding NDVI value.

Topographic data was similarly retrieved for each point by accessing the Google Earth Engine data catalog with the *ee* package in Python. Using the same bounding box, we retrieved elevation data from the USGS National Elevation Dataset for the entire study area (Google 2021c). Slope was then derived from elevation data using the Google Earth Engine *ee.terrain.products* function (Google 2021a). Specific values of elevation, slope, and aspect were then extracted for each sample point by overlaying the coordinates on each final image.

2.4. Accuracy of soil carbon estimation

For each site we then developed models to estimate soil carbon content using two different approaches: 1.) using just absorbance data from the Our Sci Reflectometer, herein referred to as “reflectance only” models, and 2.) using absorbance data from the Our Sci Reflectometer in combination with data extracted for each point from the digital soil maps and geostatistical datasets described above in Section 2.3, herein referred to as “combination” models. Models were calibrated using soil carbon data content from elemental analysis as the dependent variable. All models were developed in R v. 4.0.3 (R Core Team 2020). We used a Random Forest approach and developed models using the ‘caret’ package (Wing et al. 2018). Random Forest is a machine learning ensemble method that is well-suited for building non-linear predictive models with multiple, colinear independent variables. We used a grid search to select model parameters, and employed a 5-fold cross-validation to tune hyperparemeters and select the best model.

For each model type, 80% of samples from each site were randomly partitioned to create a training dataset for the model, while the remaining 20% were partitioned for testing model predictions. The data were randomly partitioned this way 100 times to bootstrap each modeling approach and assess the distribution of possible model outcomes depending on training data. In addition, we used a similar iterative 80/20 approach in which we used a conditioned Latin hypercube sampling (cLHS) algorithm (Minasny and McBratney 2006) provided in the R package ‘cLHS’ (Roudier et al. 2021) to select training data based on the independent variables of the model. Conditioned Latin hypercube sampling is a stratified random data selection procedure that uses a multi-dimensional set of covariates to identify a subset of *n* points from a sample population (*N*) that is optimally representative of the distribution and correlation of those covariates. This approach was intended to optimize spread in the indepdendent variables and thereby enhance the accuracy of estimation models.

Model fit was evaluated for all iterations of each combination of model type and training data selection procedure by comparing laboratory measures of soil carbon content with modeled estimates of soil carbon content in the withheld test data and calculating root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) based on those comparisons.

2.5. Estimating distributions of soil carbon at the field scale

Since spectrometry methods have higher measurement error than typical laboratory methods on a per sample basis but lower labor and material costs, a suggested use for such methods is assessment of spatial variability in soil carbon content at the field scale at reduced cost. The logic behind this suggested use is that while individual estimates may be inaccurate, estimates of the distribution of soil carbon content at the field scale (100-1000 ha) may still be sufficiently accurate in aggregate to estimate field carbon stocks or make inferences about management with statistical confidence. We simulated this suggested application for our combination modeling approach described in 2.3.1 at the two sites with the greatest per-sample estimation accuracy, SB and SR, to assess if they could accurately capture characteristics of field-scale soil carbon content distributions. We additionally sought to base this analysis on potential real-world constraints to more accurately understand if such approaches truly reduce sampling effort as compared to conventional lab analysis, or if the need for sufficient training data obviates any possible reduction of effort and cost savings. Lastly, to account for the possible impact of training data on estimates and to account for measurement error inherent in the approach we used a Monte Carlo-Markov Chain (MCMC) approach to simulate and test a more complete range of possible outcomes.

At each site, we iteratively sub-sampled the full dataset using an increasing proportion of the total number of samples collected at the site, starting with just 10% of samples and increasing up to 50% of samples at 10% increments. This approach was used to simulate a potential real-world scenario in which a limited budget is available for laboratory analysis, so a subset of samples is analyzed in the lab to train a site-specific model for estimating carbon at other points in the same field. Sample subsets were selected using the cLHS algorithm (Roudier et al. 2021) with digital soil map and remote sensing data corresponding to each point to attempt to ensure the sub-sample was representative of the total population. This training data selection process was repeated 100 times at each level of sampling proportion (n = 8) for both sites (n = 2) for a total of 1000 iterations.

For each of these iterations we built a combination model similar to those described in Section 2.3.1 that included data for each point from the reflectometer, geostatistical data sources, and digital soil maps, but instead, models were fit using a Quantile Regression Forest (QRF) approach as implemented in the 'quantregForest' package in R (Meinshausen 2017). QRF is an extension of Random Forests that allows for easy estimation of posterior predictive distributions on individual points (Meinshausen 2006). Models were then used to estimate 95% prediction intervals on the posterior predictive distribution of carbon content for all collected sample points. We then iteratively resampled this distribution for each point 100 times to bootstrap a set of 100 samples of the field-level population based on each of the 1000 estimation models. This approach was employed to account for estimation error in our assessment of methods instead of simply relying on the mean estimate of the model for each point.

Each bootstrapped sample of estimated soil carbon content values was then combined with laboratory values from the training dataset, and this combined sample was then compared to an independent, randomly selected test sample of actual soil carbon content values as determined by lab analysis from the same site with *n* equal to 50% of the total number of points. We compared these samples using the following procedures:

1. Two-sample Student's t-test: We performed this test using the *t.test* function in the 'stats' package in R (R Core Team 2021) to determine if the means of either sample are significantly different from one another. When the *p* value was greater than 0.05, we considered that an indication that sample means were not significantly different and the test was passed.
2. Two-sample Kolmogorov-Smirnov test: We performed this test using the *ks.test* function in the 'stats' package in R (R Core Team 2021) to determine if either sample was drawn from the same probability distribution function. As opposed to a Student's t-test, the KS test allows to make inferences as to how well distributions match instead of just how well means match. When the *p* value was greater than 0.05, we considered that an indication that the samples were drawn from the same population distribution function and the test was passed.
3. Confidence interval comparison: For each sample we generated 95% confidence intervals for estimated soil carbon content using the following formula: $\mu_i \pm (1.96 \times SE_i)$, where μ_i is the sample mean and SE_i is the standard error of estimated carbon for the i^{th} sample, and 1.96 is the z-score corresponding to a 95% confidence interval. This interval was then compared to intervals using ± 5% and ± 10% margin of error around the mean actual soil carbon content for the i^{th}

sample. When the 95% confidence interval for estimated soil carbon fell within the margin of error, we considered that a pass of the test.

We then aggregated test results for each sampling proportion level (10%-50%) at each site by calculating the frequency with which each test was passed as per the criteria outlined above. If for a given site and sampling proportion level, the test was passed in ≥95 % of iterations, we concluded that soil carbon estimation using a combination modeling approach was robust to variation in training data and model error and could pass the corresponding test consistently.

3. Results and discussion

3.1 Estimation accuracy at individual points

Accuracy of soil carbon estimates at individual sample points using absorbance only models from the reflectometer varied widely across sites (Table 3). For most sites, average mean absolute error (MAE) and root mean squared error (RMSE) on test samples across all iterations were between 0.5 and 1. Coefficient of determination (R^2) of estimated soil carbon as compared to actual measured soil carbon was highly variable across sites but generally remained low as models tended to underestimate carbon on samples in the upper tail of a site's distribution and overestimated those in the lower tail (Figure 1).

Including additional data from digital soil maps, NDVI data, and data on physical geography (e.g. slope) improved the accuracy of models across nearly all sites, as did applying a conditioned Latin hypercube sampling (cLHS) selection algorithm to training data to ensure they were sufficiently representative of variability in soil properties (Table 3). In particular, these approaches helped to improve prediction accuracy at the tails of the distributions for each site, increasing correlation coefficients (Figure 1). This finding is consistent with studies of other ‘multi-sensor’ studies in which local collected soil proximal sensing data was combined with remote sensing or digital soil map data to enhance predictions (Cobo et al. 2010; Paul et al. 2019; Gomez, Viscarra Rossel, and McBratney 2008). At two sites, TS and PF, prediction accuracy was poor and estimates skewed strongly towards the mean carbon content value of the site regardless of modeling approach.

Angelopoulu et al. (2020) conducted an exhaustive review of literature on estimation of soil carbon via VNIR methods and reported a broad range in outcomes with some studies reporting poor accuracy and high bias ($R2 < 0.5$; RMSE > 1%) and others reporting high accuracy and minimal bias ($R2 > 0.8$; RMSE < 0.01%). Results from the best-performing models and sites in our study were on the lower end of the accuracy range indicated by this review. But their comparability with these other studies is notable given that most other studies used more sophisticated spectrometers. Results from the worst-performing models and sites in our study were substantially less accurate.

One possible explanation of weak performance is high sensitivity to training datasets. Iterative random selection of training datasets at each site led to considerable range in accuracy outcomes within sites as represented by the standard deviations of accuracy metrics across all 100 train/test iterations (Table 3). This pattern indicates that the methods we tested were highly sensitive to selection of the training dataset and how well it represented true variability in soil properties at a given site. Improvement of model performance when training data were selected using the cLHS algorithm further supports this finding. The need for optimal calibration datasets has been studied previously (Ramirez-Lopez et al. 2014a), and our results confirm this finding.

As well, despite being considerably less expensive than alternative devices, limiting the Our Sci Reflectometer’s range to select VNIR wavelengths may create substantive trade-offs in terms of accuracy. Several recent studies have indicated that visible/near-infrared (VNIR) spectroscopy alone for estimation of soil carbon content is limited and that data on reflectance of samples further in the NIR range and into the mid-infrared range of the spectrum provides higher accuracy estimates (Johnson et al. 2019; Riedel et al. 2018; Hutengs et al. 2019; Sanderman, Savage, and Dangal 2020; Dangal et al. 2019a). These ranges likely provide greater accuracy as functional groups frequently found in organic carbon compounds that largely comprise soil carbon produce a greater, more distinct signal in them, particularly the MIR. Expanding the range of the Our Sci Reflectometer to be capable of measuring reflectance further into the infrared range, potentially including the MIR range, could be an essential next step to improving accuracy.

Finally, while some soil samples likely included appreciable inorganic carbon content particularly at sites in WY and MT, budget limitations meant we were unable to measure inorganic carbon on samples to determine if it was indeed reducing accuracy by contaminating the reflectance signal of organic carbon compounds. Similarly, soils at some of the worst-performing sites included soil types with parent materials with strong visible color signals (e.g. red sandstone at RC) that we expect would have reduced overall site accuracy. While we weren't able to directly test the impacts of such factors on our results, if they did indeed decrease accuracy, we note that such an impact suggests the tools we tested may be less generalizable across the broad range of soil conditions most real-world users would be likely to encounter.

3.2. Accuracy at the field-level

In simulated real-world scenarios based on equivalent effort, estimates of the distribution of soil carbon content at the field scale using combination models were little improved as compared to traditional lab methods, despite enabling the collection of greater numbers of samples. After propagating measurement uncertainty through MCMC simulation, combination models at the SB and SR sites were not capable of producing samples with 95% confidence intervals that were consistently (> 95% of iterations) within a 5% margin of error of withheld test samples, regardless of how much training data were used to calibrate the model. The same was true for producing 95% confidence intervals within a 10% margin of error at the SB site, but at the SR site, models produced samples within a 10% margin of error when 30% or more of data were used to calibrate the model (Table 4). By comparison, we calculated that relatively fewer samples were necessary to achieve the same level of accuracy using laboratory data alone given statistics on the mean and standard deviation at each site (SB: 5% - 141, 10% - 35; SR: 5% - 194, 10% - 49).

Furthermore, Kolmogorov-Smirnov tests indicated that combination models were not capable of consistently characterizing distributions of soil carbon content in a statistically robust manner until substantial amounts of data were dedicated to training models (Table 4). Performance on Student's t-tests were better, with SB passing a 90% threshold with 20% of data dedicated to model training and SR at 30% of data dedicated to model training. However, again by comparison, using just lab data from the training dataset these tests were consistently passed at low sampling rates, indicating that selection of samples using a procedure such as cLHS may be adequate for reducing sampling costs/effort. This result is consistent with other work demonstrating such model-based sampling design approaches can produce representative samples at relatively lower effort than unbiased, designs (Minasny and McBratney 2006; Malone, Minansy, and Brungard 2019; de Gruijter et al. 2016). This pattern additionally indicates that the addition of proximal soil sensing based estimates reduced statistical confidence because of the introduction of measurements with high error.

However, we note that similar studies using more sophisticated, but also more expensive, instrumentation have realized greater success. Paul et al. (2019) found that mid-infrared spectroscopy (MIRs) could enhance mapping of multiple soil properties, including soil organic matter, on a 54 hectare field in Vancouver, BC, Canada by enabling researchers to collect samples at greater spatial densities than sampling efforts that relied on laboratory analysis alone at equivalent effort/cost. Cobo et al. (2010) similarly found that combining MIRs with geostatistical mapping methods supported rapid, cost-effective assessment of the spatial variability of multiple soil properties at the landscape scale (730 – 1360 ha) in multiple villages in Tanzania. Finally, Mirzaeitalarposhti et al. (2017) demonstrated that such approaches were effective at the regional level in southwest Germany and Vågen et al. (2016) demonstrated their utility at the continental scale in sub-Saharan Africa. Nonetheless, our results indicate that when estimation accuracy at the point level is limited, that error propagates to the field scale in a measurable way.

4. Conclusions

Using a simplified handheld spectrometer to measure soil reflectance at a select number of wavelengths, we were able to estimate soil carbon content for soil samples spanning a range of soil types, but results varied widely across sites and prediction was particularly poor at the tails of distributions as modeled estimates tended to skew towards site means. Including additional information easily acquired from publicly available digital soil maps and geostatistical datasets and ensuring that model training data were well stratified to represent variability and correlation of independent variables further improved accuracy, particularly at the tails of a site's possible distribution of soil carbon values. However, at some field sites, accuracy remained limited, regardless of modeling approach or training data selection.

In simulated real-world scenarios at the SB and SR sites where a fraction of samples were used to train an estimation model that was then used across a sample of other points, estimation of soil carbon via methods that employed the reflectometer in combination with data from geostatistical sources and digital soil maps (combination models) did not consistently result in samples that were statistically similar to the true distribution of soil carbon content as determined via laboratory analysis on the same sample.

Our results suggest that the methods and instruments tested in this study likely have limited utility for measuring soil carbon at the point scale and are sensitive to site conditions and selection of training data. Nonetheless, results from our best-performing models and sites were within the accuracy range indicated by other studies of VNIR spectroscopy for soil carbon estimation, albeit on the lower end, even though the device we tested was considerably less sophisticated than instrumentation used in other studies (Angelopoulou et al. 2020; McCarty et al. 2002). As such, we suggest the results of our analysis simulating real-world applications still have useful implications for continued testing of proximal soil sensing methods.

The promise of enabling the collection of greater numbers of samples is often cited as a possible advantage of proximal soil sensing and a reason to employ such methods (Alex B. McBratney, Minasny, and Viscarra Rossel 2006b). Despite documented trade-offs in terms of accuracy and sensitivity to model calibration procedures and training data, the suggestion is that characterization of soil carbon distributions at larger spatial scales can be achieved at lower cost. This advantage is of particular interest to participants in nascent agricultural carbon markets, as most current accounting protocols primarily require characterization of site-level carbon stocks for estimation of change in those stocks over time rather than accurate, precise measurement at the point scale (“Soil Enrichment Protocol” 2021; “Verra - VM0042 Methodology for Improved Agricultural Land Management, v1.0” 2021). Furthermore, such projects are likely to be conducted over multiple fields in aggregate and monitoring of soil carbon is potentially cost-constrained.

However, our results indicate that when measurement error and potential sensitivities of models to training data and field-scale variability are considered, the suggested advantage of enabling collection of more samples may be obviated by the need to collect more and better laboratory data in-field. In other words, to achieve sufficient accuracy to have statistical confidence in data collected through proximal soil sensing methods, users of such methods must collect so much training/testing data via lab analysis that no real reduction of effort is achieved. However, other studies focused on testing the application of more sophisticated, accurate proximal sensing tools (e.g. MIR spectrometry) at field scales or greater did achieve better results, demonstrating a possible sampling advantage of proximal soil sensing (Brodský et al. 2013; Paul et al. 2019).

As proximal soil sensing methods gain greater acceptance and use, generalized approaches for testing their accuracy will be necessary to supporting robust use in real-world scenarios. Most importantly, full accounting of measurement error and its impacts on inferences made with such tools is necessary to ensure that users do not draw spurious conclusions. Similarly, research exploring the scales, agricultural systems, and monitoring scenarios for which these tools are most well-suited is lacking and represents an important new direction for future research.

We suggest that for low-cost proximal sensing methods, such as those we tested here, to achieve their suggested value in reducing sampling costs and supporting rapid data collection at scale, continued development of instruments with the intent of improving accuracy and efforts to develop libraries of soil spectroscopy data for cross-site model development are key. Without these improvements, more extensive laboratory analysis of samples on-site is necessary to achieve sufficient accuracy for soil carbon estimates that support statistically robust monitoring.

Several studies indicate that MIR spectroscopy is likely a superior method for estimation of soil carbon content as reflectance/absorbance data from such instruments can be more directly tied to organic compounds that comprise soil carbon (Soriano Disla et al. 2014; Reeves 2010; Dangal et al. 2019b). Although such instruments appear to be less widely adopted given their greater expense and limited portability relative to VNIR instruments, they may be a more viable tool for reducing the cost of soil sampling efforts, and compared to traditional laboratory analytical methods they are likely to still have lower per-sample costs.

Research has demonstrated that with sufficient regional data, models capable of accurately predicting soil carbon content can be applied at more local scales that reduce the need for additional laboratory analysis and support use of proximal sensing methods to map carbon (Cobo et al. 2010; Paul et al. 2019). Furthermore, other research has demonstrated and our research confirms that stratified sampling algorithms can help identify an optimal set of samples for model training at the local scale (Minasny and McBratney 2006; Ramirez-Lopez et al. 2014b). These studies and several others suggest that development of extensive soil spectral libraries could make proximal sensing tools most useful in real-world applications, and several efforts are underway to build such libraries for public use. However, challenges still remain for making such libraries practical for the implementation of proximal sensing methods related to understanding how information from such large libraries can be useful at the field scale (Padarian, Minasny, and McBratney 2019) and if/how models developed at one site or region can be successfully transferred to new sites and regions (Minasny et al. 2009; Dangal and Sanderman 2020).

While proximal soil sensing tools may still prove useful for reducing the burden of soil carbon monitoring efforts at scale, our study exemplifies the need for proper accounting of measurement error, sensitivity to training data, and constraining tests to real-world conditions to earnestly assess their usefulness. Furthermore, our results highlight that efforts to produce extremely low-cost, portable sensors, such as the one employed here, may make trade-offs in terms of accuracy too substantial for them to be useful in carbon monitoring scenarios. Instead, more expensive, but more accurate instrumentation may still be necessary. Low-cost tools may still provide utility in other applications (e.g. rapid mapping, pre-sampling, change detection over long time periods), particularly when previous training data are available, but we were unable to test such applications. Coordination of effort to create procedures for testing proximal sensing tools and continued development of standardized training datasets and calibration transfer procedures will be essential to helping realize the suggested usefulness of proximal soil sensing methods.

Figures and tables:

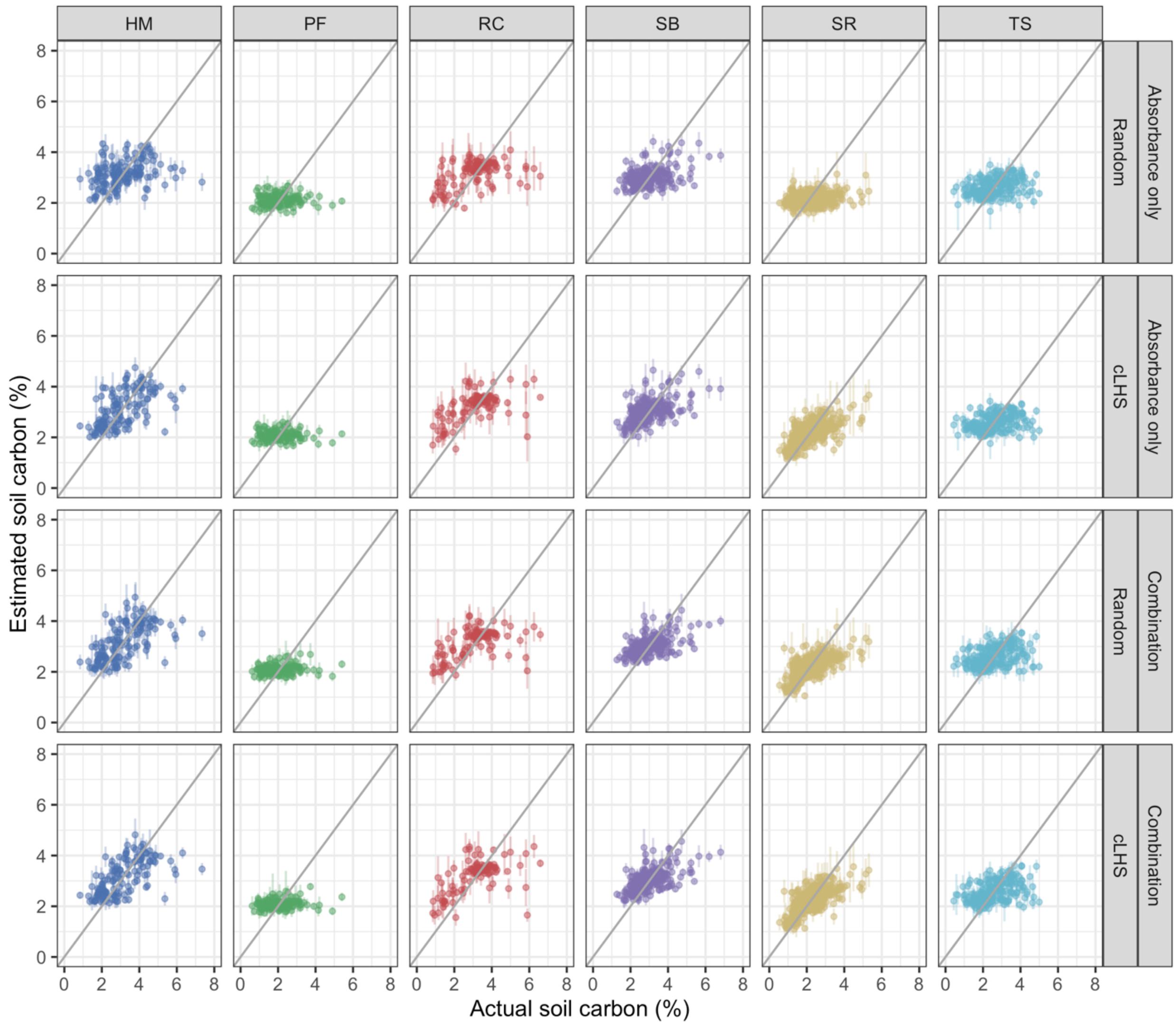

Figure 1. Comparison of actual soil carbon content (%) and estimated soil carbon content (%) from models trained using OurSci Reflectometer (absorbance only) and models trained using absorbance data and data retrieved from digital soil maps and geostatistical datasets (combination). Models were trained for each site using 80% of the dataset, and the remaining 20% was used to test model predictions. This process was repeated 100 times for each site using either random selection of training data or a cLHS algorithm implemented on model independent variables to select training data. Panel columns correspond to different study sites, and rows correspond to different combinations of modeling approach and training data selection. Dots represent the mean estimated soil carbon content across 100 modeling iterations. Bars represent the mean ± 2 standard deviations of the estimated soil carbon content across 100 modeling iterations.

State	Site	n	Mean soil carbon (%)	Dominant soil order	Location
MT	PF	123	1.87	Entisols	44.9907, -106.4229
	SR	456	2.06	Entisols	47.5047, -110.0081
NY	SB	237	2.47	Inceptisols	41.1032, -73.8332
WY	HM	137	3.15	Aridisols	44.6825, -109.0664
	RC	135	3.16	Entisols	42.6324, -108.6471
	TS	214	2.59	Mollisols	43.9913, -107.2405

Table 1. Location information, total samples collected, and descriptive soil information for all study sites.

Source	Category	Property
SoilGrids	Soil chemical properties	Organic carbon (%)
		pH
		Cation exchange capacity
	Soil texture	Sand (%)
		Silt (%)
		Clay (%)
Sentinel-2	Plant properties	Normalized differential vegetation index (NDVI)
USGS National Elevation Dataset	Topography	Slope

Table 2. Remote sensing, digital soil map, and geostatistical data used in development of ‘combination’ models.

	Random selection of training data						cLHS selection of training data					
	Absorbance only			Combination			Absorbance only			Combination		
location	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
HM	1.12 (0.18)	0.85 (0.12)	0.13 (0.1)	0.96 (0.17)	0.73 (0.11)	0.36 (0.13)	0.91 (0.15)	0.7 (0.11)	0.33 (0.13)	0.89 (0.15)	0.7 (0.1)	0.41 (0.13)
PF	0.87 (0.15)	0.68 (0.1)	0.02 (0.03)	0.83 (0.16)	0.66 (0.11)	0.07 (0.08)	0.96 (0.15)	0.74 (0.1)	0.03 (0.05)	0.95 (0.15)	0.74 (0.1)	0.09 (0.09)
RC	1.16 (0.26)	0.81 (0.15)	0.2 (0.13)	1.14 (0.29)	0.78 (0.14)	0.25 (0.18)	1.03 (0.33)	0.74 (0.16)	0.3 (0.18)	0.97 (0.3)	0.68 (0.15)	0.36 (0.18)
SB	0.86 (0.14)	0.63 (0.07)	0.14 (0.1)	0.79 (0.15)	0.57 (0.07)	0.27 (0.13)	0.78 (0.17)	0.55 (0.07)	0.22 (0.12)	0.75 (0.17)	0.53 (0.07)	0.26 (0.12)
SR	0.75 (0.06)	0.59 (0.04)	0.05 (0.05)	0.56 (0.06)	0.41 (0.04)	0.46 (0.08)	0.58 (0.06)	0.44 (0.04)	0.44 (0.09)	0.53 (0.06)	0.38 (0.04)	0.54 (0.07)
TS	0.85 (0.1)	0.66 (0.08)	0.14 (0.09)	0.83 (0.11)	0.63 (0.08)	0.18 (0.1)	0.88 (0.1)	0.68 (0.08)	0.14 (0.09)	0.84 (0.09)	0.61 (0.07)	0.21 (0.09)

Table 3. Accuracy statistics for soil carbon estimation models trained with just absorbance data from the OurSci Reflectometer (absorbance only) and models trained using absorbance data and data retrieved from digital soil maps and geostatistical datasets (combination). Models were trained for each site using 80% of the dataset, and the remaining 20% was used to test model predictions. Training data were selected using either a random selection algorithm or using cLHS on independent variables. This process was repeated 100 times for each site. Figures provided in each table cell represent the mean of the corresponding metric across all 100 iterations, and figures in the parentheses of each cell represent the standard deviation of the corresponding metric across all 100 iterations.

		Probability of 95% CI w/in specified margin of error		Probability of passing specified statistical test	
Location	Proportion to training	5% ME	10% ME	KS test	Student's t
SB	10 %	9.43 %	60.66 %	36.77 %	73.19 %
	20 %	16.38 %	80.92 %	69.96 %	90.7 %
	30 %	17.81 %	84.32 %	80.84 %	91 %
	40 %	22.65 %	89.89 %	87.69 %	90.85 %
	50 %	29.77 %	92.45 %	88.01 %	92.58 %
SR	10 %	15.14 %	75.96 %	42.48 %	80.34 %
	20 %	25.92 %	85.15 %	68.37 %	84.01 %
	30 %	32.75 %	93.74 %	76.01 %	90.4 %
	40 %	42.12 %	99.47 %	89.68 %	96.96 %

Table 4. Probability at two sites that combination models will produce a sample of with 95% confidence intervals within a 5% or 10% margin of error of a withheld test dataset with increasing proportions of the total dataset dedicated to model training, and/or pass specified statistical tests. Probabilities are based on the frequency with which individual bootstrapped samples (n = 10000) produced an estimate within the specified margin of error or passed the specified statistical test (i.e. $p > 0.05$, indicating no statistical difference between samples). Bootstrapped samples were generated using a MCMC process to account for prediction uncertainty and sensitivity of the method to training data.

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Concluding Remarks:

Claims that increasing soil carbon is a "win-win" for agriculture have been poorly supported to date by evidence and anecdotal claims. Here I synthesize quantitative evidence to support claims that increasing soil carbon stocks does indeed lead to improvements in the resilience of agricultural systems by improving soil water infiltration dynamics and protecting yields under drought conditions. I believe this evidence suggests that action to increase soil carbon in agricultural systems can indeed provide benefit to farmers and potentially greater food security under projected future climate conditions.

As efforts to support such action develop, such as through emerging markets for soil carbon offsets, accessible tools for monitoring of outcomes will support and enhance such efforts. My research here also tested one such tool combining soil spectroscopy with digital soil mapping approaches. Results indicates that despite some promise and the potential to reduce costs, further development seems necessary. Most importantly, while conversations around such emerging tools often suggest that new tools do not need to achieve accuracy on par with standard laboratory techniques, my research reveals that reduced accuracy can strongly impact the accuracy of more spatially explicit estimates of soil carbon and that requirements for training datasets for such methods are substantial enough that the necessary site-level laboratory analysis may undermine their potential to reduce effort and costs.

Based on my research I suggest the following direction for future research and action:

1. Continue to develop policy and market mechanisms to support famers in transitioning to improved agricultural practices that sequester soil carbon. Climate mitigation and adaptation outcomes appear to be achievable by increasing soil carbon, so corresponding social/policy tools could accelerate success.

2. Continue research that better quantifies adaptation outcomes at the field scale. At the field scale, variation in soil carbon content is lower and potential increases to soil carbon are not of the same magnitude as differences in soil carbon content seen at regional scales. As such, adaptation outcomes and improvements to resilience may be more muted than the results described in Chapter 2, so more local research is key to extending our understanding.
3. Continue to improve soil spectroscopy and digital soil mapping tools with an explicit focus on application. To date, much research in this area has been done in a manner that does not provide direct insight into proposed field applications. Accuracy/bias of new measurement tools and their sensitivity to training data appear to have strong impacts on their efficacy as compared to more traditional laboratory analysis methods with much lower measurement error. As such tools develop, better testing in real-world monitoring scenarios, such as those that are likely to emerge in nascent soil carbon market projects, will be necessary.