ARTICLE

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Which management practices influence soil health in Midwest organic corn systems?

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Abstract

Fostering and maintaining soil health via holistic management is a central goal for most organic farmers. However, many questions remain regarding how different management practices influence soil health in farm fields. In this study, we used a mail-in soil survey to assess how organic management practices such as crop diversity, perennials in rotation, tillage, manure use, and subscription to soil cation balancing influence soil biochemical health indicators in certified organic corn (*Zea mays* L.) fields. Organic farmers ($n = 195$) from the eastern Corn Belt mailed in soil along with a completed management survey to a research lab for analysis. Soils were analyzed for mineralizable carbon (C), permanganate oxidizable carbon (POXC), soil protein, texture, and routine soil nutrient analyses. Soil texture had the largest influence on soil biochemical health indicators, underscoring the need to consider soil type with soil health assessments. Crop diversity was negatively correlated with mineralizable C, soil C, and soil nitrogen (N) ($r = -.19$ to $-.24$) at $p < .05$ when perennials were in the rotation. This was attributed to tillage frequency increasing with crop diversity across all soil types. The presence of a perennial in rotation influenced soil biochemical health indicators, except for total C. Additionally, mineralizable C significantly increased when perennials were left in rotation for longer periods of time. This study demonstrates the effectiveness of incorporating management survey data with soil biochemical health analyses. We conclude that a main management driver for improved soil biochemical health in organic corn production systems is to reduce tillage intensity and incorporate perennials.

1 | INTRODUCTION

Soil health has gained prominence in recent years due to evidence of positive influences on agronomic performance and ecosystem function (Culman et al., 2013; Hurisso et al., 2016; Wade et al., 2020). Soil health is especially important in the context of organic farming because producers rely heavily on cultural management practices and agroecosystem processes to provide crop nutrients and address common pest, weed, and disease problems (Reganold & Wachter, 2016). Yet, deep knowledge gaps persist in identifying which management practices are most effective for improving soil health on organic farms across the agricultural Midwest

Abbreviations: BCSR, base cation saturation ratios; OM, organic matter; POXC, permanganate oxidizable carbon.

(Lynch, 2014; Tully & McAskill, 2019). For instance, organic growers have a diverse toolbox of management practices, including crop rotational diversity, cover crops, and manure management that can be used to improve different aspects of soil health (Lynch, 2014). However, soil management practices designed to achieve different goals can often be counterproductive. For instance, organic farmers may implement cover crops and lengthen crop rotations to increase organic matter, but execute intensive mechanical tillage for weed control, which has negative impacts on soil health (Osterholz et al., 2020). More quantification of soil health indicators on organic farms is needed in order to truly understand the associated trade-offs in soil health.

Emerging soil health indicators allow for improved quantification of soil health because they have the ability to capture dynamic chemical, biological, and physical soil properties that are sensitive to recent changes in management (Culman et al., 2012; Hurisso et al., 2018; Moebius-Clune et al., 2016). In particular, soil biochemical health indicators have received heightened interest because of their ability to reflect different soil carbon (C) and nitrogen (N) processes. For example, permanganate oxidizable carbon (POXC) (Culman et al., 2012), mineralizable C (Hurisso et al., 2016), and soil protein (Hurisso et al., 2018; Moebius-Clune, et al., 2018; Roper et al., 2019) are three indicators that have all shown to be rapid and sensitive indicators that can reflect changes in management practices. These measures are listed as potential indicators by the NRCS (Stott, 2019) and are being evaluated in the Soil Health Institute's National Soil Health Assessment (https://soilhealthinstitute.org/soil-health-research; Fine et al., 2017; Mann et al., 2019; van Es & Karlen, 2019; Williams et al., 2020).

Large regional soil health datasets currently exist for the Mid-Atlantic, the upper Midwest (excluding Ohio), the Northeast, and across the state of Missouri where regional differences were measured using the comprehensive assessment of soil health framework (Fine et al., 2017; Zuber et al., 2020). Such datasets have provided key information on how chemical, physical, and biological health indicators correlate with one another and how such indicators are often dependent on textural groupings (Fine et al., 2017). A limitation of these existing regional soil surveys is that farmer management history is not included and thus it is challenging to assess how different management practices influence soil health indicators at a regional scale.

Despite the increased interest in soil health testing, there is a particular lack of data on many of these emerging indicators from working commercial organic farms, and a need to translate the results to better inform on-farm decision-making (O'Neill et al., 2021; Williams et al., 2020). For instance, in a study that examined farmer perceptions of soil health, Sprunger (2015) found that the three most common questions that farmers asked were: (a) What is a "good" value

Core Ideas

- Management and soil health trade-offs are evident in organic corn production.
- Soil health assessment needs to consider soil textural class.
- Tillage frequency increased with crop diversity, leading to reduced soil health.
- Subscription to soil cation balancing did not influence soil health.
- Perennials in rotation were associated with increased soil health.

for a given soil health indicator? (b) How do my soil health test values compare to other farms?, and (c) What management practices should I incorporate to improve soil health? A key way to address these types of farmer driven research questions is to build regionally relevant soil health databases that can provide information on the variability of soil health values across soil types and management systems under working farming conditions (Fine et al., 2017; Zuber et al., 2020).

Management practices that are implemented across farms in the United States are complex and multifaceted and are nearly impossible to replicate in experimental trials. For this reason, management impacts on soil health are typically quantified at the local scale using on-farm field observations (Collins et al., 2011; Gruver & Weil, 2007; Mann et al., 2019; Williams et al., 2020). Measuring soil health indicators on-farm can identify associations between the use of management practices and soil health outcomes under working farm conditions and across a wide range of soil types. For instance, soil texture often explains the largest amount of variation in soil health indicators, but specific management practices such as tillage frequency have also been shown to substantially alter biological soil health indicators across fields on an organic farm in Washington state (Collins et al., 2011). Moreover, a recent study assessing soil health on 20 farms in Sweden found that high crop diversity, low tillage intensity, and greater organic amendments led to increased soil health, as evidenced by greater aggregation, soil protein, and enhanced soil C (Williams et al., 2020). In general, examples of on-farm data collection are relatively rare in the published literature and those that exist tend to include a relatively small number of participant farms.

While these small-scale on-farm assessments provide important evidence about how management influences soil health at the farm or field scale, larger regionally calibrated datasets are needed to assess how specific soil management practices influence soil health indicators across different soil textures and regions. Soil health indicators are driven

by soil C and N pools, which strongly indicates that soil texture also needs to be considered when quantifying soil health (Fine et al., 2017; Franzluebbers & Poore, 2020). Yet, it is unknown the extent to which both texture and management drive soil health indicators on a regional basis. For instance, in the eastern Corn Belt, organic farmers apply a wide range of soil management practices in an effort to enhance soil health, which typically includes a combination of reducing soil disturbance, incorporating cover crops into the rotations, increasing crop diversity, and incorporating organic amendments to improve soil health (Brock, Jackson-Smith, Culman et al., 2021; Jarecki & Lal, 2003; Lynch, 2014; Tully & McAskill, 2019). Additionally, recent work has documented that the majority of organic corn (*Zea mays* L.) producers (55%) in the eastern Corn Belt subscribe to balancing base cation saturation ratios (BCSR) or a "soil balancing" philosophy and actively manage the soils to elevate Ca and reduce Mg base cation saturation percentages through the application of high-calcium limestone and gypsum (Brock, Jackson-Smith, Kumarappan et al., 2021). Despite the lack of scientific evidence that BCSR improves soil health and crop yields (Chaganti & Culman, 2017), it remains a core practice for many organic farmers who continue to self-report positive outcomes (Brock, Jackson-Smith, Kumarappan et al., 2021). Most organic farmers also use BCSR as one component of a broader soil balancing system which typically includes use of other soil health building management practices that can make it difficult to isolate the impacts of BCSR on perceived agronomic outcomes (Brock, Jackson-Smith, Culman, et al., 2021). A comprehensive assessment of how organic management influences soil health is needed on a regional scale.

Here we conducted a regional mail-in soil health survey consisting of 195 soil samples collected from organic corn fields across Michigan, Indiana, Ohio, and Pennsylvania in combination with a management survey to further understand how soil biochemical health indicators vary by soil type and organic management. The specific objectives of this study were to (a) evaluate distributions of soil biochemical health indicators on organic farms across major soil types of the eastern Corn Belt, (b) assess how various organic management practices influence key soil biochemical health indicators, and (c) determine to what extent farmer subscription to BCSR influences soil health in organic corn production.

2 | METHODS

2.1 | Recruiting certified organic corn producers

In order to explore the link between organic farm management and soil health properties, we deployed a mixed methods approach to obtain soil samples and information about field management history from a large random sample of organic producers in the eastern Corn Belt. We built on a large mail survey of organic corn producers implemented in the spring of 2018 that was designed to document farm characteristics and detailed information about the use of various soil amendments and soil management practices on organic corn fields in 2017, as well as self-reported outcomes related to crop productivity, soil quality, and other agronomic outcomes. The survey sample included every organically certified corn grower listed on the USDA's certified Organic INTEGRITY Database in Michigan, Indiana, Ohio, and Pennsylvania ($n = 1,496$). The survey launched in February 2018 and utilized a modified Dillman approach that involved mailing surveys with prepaid return envelopes followed by reminder postcards in three waves over 3 mo (Dillman et al., 2014), and yielded a 57.4% response rate. Included with each survey was a postcard offering a free-soil health test that served as an incentive for filling out the survey. Survey respondents interested in receiving a free-soil health test returned the postcards. Once postcards were received, survey respondents were mailed a soil testing kit that included soil sampling instructions, a labeled plastic bag for the soil sample, a three-page supplemental management survey (Supplemental Information), and pre-paid return postage. We explicitly stated that soils would not be analyzed for a soil health test without a completed management survey. In total, 455 soil health packets were mailed out, and we received 195 soil samples with a completed management survey from 73 different counties from across Michigan, Indiana, Ohio, and Pennsylvania (Figure 1), resulting in a 43% response rate.

2.2 | Management survey

The management survey asked respondents to select a representative corn field and list every crop grown in the chosen field from 2014 to 2017, including any cover crops. We calculated crop diversity as the total number of crops in the rotation over a 4-yr period. Additionally, we coded the presence and absence of perennials and cover crops for the rotation as binary variables. Second, respondents were asked to complete a table to document the number of tillage passes per year for a given tillage type between 2014 and 2017. Here, we report the total number of tillage passes between 2014 and 2017. Third, we asked respondents to complete a table documenting soil amendment types (i.e., manure, compost, lime, gypsum, etc.) and rates that were applied to the selected field from 2014 to 2017. Accompanied with this table was a question regarding how farmers use BCSR to manage calcium/magnesium (Ca/Mg) ratios through the use of high-calcium limestone or gypsum (even if pH is in an optimal range). We explained that this is sometimes called soil balancing.
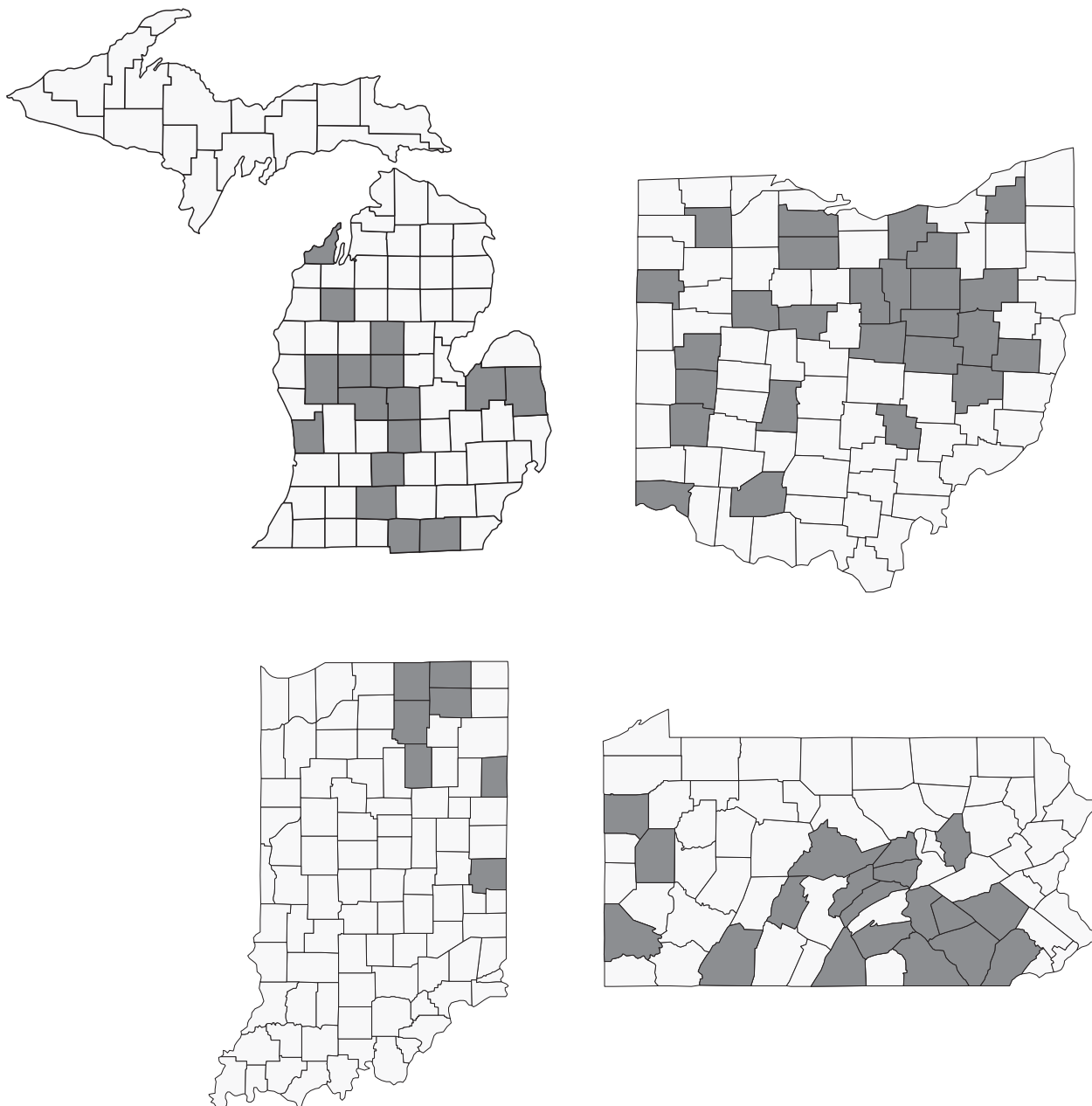
FIGURE 1 County representation of participant farms across the Eastern Corn Belt (Michigan, Indiana, Ohio, and Pennsylvania). In total, 195 farms across 73 counties (shaded) in the eastern Corn Belt region sent in soils via our mail-in survey

2.3 | Soil sampling instructions for farmers

Respondents were asked to select a sampling area of fewer than 2 ha (5 acres) and take 10 cores or slices to a depth of 20 cm. Next, we asked respondents to composite the 10 soil cores and mail the mass equivalent of 500–700 ml of soil to The Ohio State Soil Fertility lab along with a completed management survey. Soil samples for this study were taken during the growing season, post crop emergence.

2.4 | Laboratory analyses

Immediately after receiving soil samples in the mail, soils were oven-dried at 40 ˚C and ground <2 mm (Deiss, Culman, et al., 2020; Hurisso, Culman, et al, 2018). A portion of the soil sample was then sent to Spectrum Analytic Inc. where soils were analyzed for pH (1:1 water), soil organic matter (OM) via loss on ignition (Combs & Nathan, 1998), cation exchange capacity (estimated from cations; Warncke & Brown, 1998), and Mehlich-3 extractable nutrients

(Mehlich, 1984). Soils were analyzed for total soil C and soil N via a CHNS elemental analyzer. Lastly, we used the remaining soil to conduct soil biochemical health indicators, described below.

2.5 | Soil biochemical health indicators

Permanganate oxidizable C is based on a chemical oxidation of OM by a weak potassium (K) permanganate solution (Culman et al., 2012; Weil et al., 2003). Briefly, 2.5 g of air-dried soil were placed in 50-ml polypropylene centrifuge tubes. Each tube received 20 ml of 0.02 mol L^{-1} $KMnO_4$. The tubes were then shaken for exactly 2 min at 240 oscillations per minute and then sat undisturbed to ensure settling for exactly 10 min. After 10 min, 0.5 ml of the supernatant was transferred into a second 50-ml centrifuge tube containing 49.5 ml of deionized water. From this dilution, 200 µl from each sample was loaded into a 96-well plate. A spectrophotometer was used to read sample absorbance at 550 nm, and POXC (mg kg^{-1} soil) was calculated according to Weil et al. (2003).

Mineralizable C was determined via a 24 h mineralizable C assay that measures CO_2 respired from rewetted soils based on Franzluebbers et al. (2000), Haney et al. (2001), and Hurisso et al. (2016). Ten grams of air-dried soil were placed in 50-ml polypropylene centrifuge tubes and 3 ml of deionized water was added to each tube. Tubes were tightly capped with a lid fitted with a rubber septum. A time zero CO_2 reading was taken immediately after capping by injecting 0.5 ml of headspace air into a LI-820 infrared gas analyzer (LI-COR). Next, the centrifuge tubes were stored in the dark for 24 h at 25 °C. Following incubations for 24 h, a second CO_2 reading was taken following the same procedure. Short-term mineralizable C was determined as the difference between time zero and the 24 h CO_2 concentrations.

Soil protein was measured to determine the size of the organically bound N pool in soils (Hurisso et al., 2018a). First, 3 g of air-dried soil and 24 ml of 20 mM sodium citrate (pH 7.0) were added to 50-ml glass extraction tubes. Samples were shaken at 180 strokes per minute for 5 min and then placed in the autoclave for 30 min at 121 °C and 1 atm. After cooling, the soil was re-suspended by shaking the tubes for 1 min at 180 strokes per minute. Next, 1.75 ml of the mixture was transferred to a 2-ml microcentrifuge tube and centrifuged at 10,000 × g for 3 min. Ten microliters of the clarified extract were transferred from the centrifuge tubes into a 96-well microplate for a standard colorimetric protein quantification assay (Thermo Pierce Bovine Serum Albumin (BSA) Protein Assay, Thermo Fischer Scientific). Two hundred microliters of a bicinchoninic acid (BCA) working reagent (Thermo Fischer Scientific) were added to each well of the microplate. The plate was then sealed and incubated on a heating plate for

60 min at 60 °C. Sample absorbance values were read using a spectrophotometric plate reader at 562 nm. The extractable protein content of the soil was calculated by multiplying the protein concentration of the extract by the volume of extractant used and dividing that product by the number of grams of soil used.

2.6 | Soil texture

Soil texture was estimated using diffuse reflectance infrared Fourier transform spectroscopy (mid-DRIFTS). Spectra were obtained with an X,Y Autosampler (Pike Technologies Inc.) coupled with a Nicolet iS50 spectrometer (Thermo Fisher Scientific Inc.) using soils sieved to <2 mm, potassium bromide (KBr) as background, 8 cm^{-1} resolution, 24 co-added scans, 4,000 to 700 cm^{-1} range, and four spectral replicates (Deiss, Culman, et al., 2020; Deiss, Margenot, Culman, et al., 2020). Support vector machines multivariate regression models (Deiss, Margenot, Demyan, et al., 2020) were trained using legacy data (733 samples) from the National Cooperative Soil Survey with soil texture determined by the pipette method (method 3A1, Burt, 2011). Root mean squared errors of independent validation sets (25% of dataset) were 3.03, 5.61, and 6.11%, for clay, silt, and sand, respectively. Soils were then classified into three soil textural groupings (coarse, medium, and fine) using the soil triangle method (Fine et al., 2017; Soil Survey Division Staff, 1993).

2.7 | Statistical analyses

All statistical analyses were conducted in R v. 4.2 (R Core Team, 2020). Analysis of variance was conducted on all soil biochemical health indicators using the agricolae V 1.3-3 package in R (de Mendiburur, 2020). Percent clay was added as a covariate structure to all models to help explain variation. However, the addition of percent clay as a covariate had no influence on statistical significance in the ANOVA output. A least significant difference test in agricolae was used for treatment mean comparisons. Significant differences were determined at $\alpha = .05$ and $\alpha = .1$. Correlations between soil health indicators and individual management practices were determined using the "pairs" function in R v. 4.2 (R Core Team, 2020). The "cor.test" function was used to determine the significance of the correlations at $\alpha = .05$ and $\alpha = .1$.

To assess which management practices had the greatest relative effect on each soil health indicator, linear mixed-effects models ("lme4" R package, Bates et al., 2015) were used. The most important experimental factors were categorized based on the size and direction of t values and the variability partitioning between factors and the textural classes was

determined based on the sum of squares. Crop diversity, cover-crop, perenniality, tillage, manure, and subscription to BCSR were included as continuous or categorical factors and textural classes were used as a random factor.

3 | RESULTS AND DISCUSSION

3.1 | Farm demographics and management practices

A total of 195 farmers participated in this mail-in soil survey. The total organic cropland managed by respondents varied across the dataset, with 64% farming between 10 and 100 ha (Table 1). Approximately 8% of farms were <10 ha, while 19% farms were 100–500 ha and 6% of farms more than 500 ha. Seventy-eight percent of survey respondents reported growing corn at least once in the 4-yr rotation (Table 1). Soybean [*Glycine max* (L.) Merr.] and wheat (*Triticum aestivum* L.) were much less common in the rotations with only 15 and 9% of survey respondents reported having grown them. Perennial crops, including alfalfa (*Medicago sativa* L.) and other hay crops, were grown by 76% of the survey respondents (Table 1). Thirteen percent of the respondents had perennials present for only 1 yr during the reported 4-yr rotation, while 63% reported growing perennials 2 or more years in the 4-yr rotation. Less than a quarter (24%) had an absence of perennials (Table 2).

More than half of the farmers from the soil management survey (58%) indicated that they subscribe to BCSR philosophy by actively managing Ca/Mg ratios, which suggests that BCSR is a common practice among organic corn growers in this four-state region. This result is consistent with findings from a larger survey of 850 organic farmers from this region (Brock, Jackson-Smith, Kumarappan, et al., 2021). A majority of the farms in our sample (87%) added some type of manure to their fields and 47% reported growing a cover crop at some point during the 4-yr rotation (Table 2). Farmers in the sample reported a wide range of different cover crops. Grasses including (cereal rye [*Secale cereale* L.], ryegrass [*Lolium perenne ssp. multiflorum.*], triticale[x Triticosecale], and oat [*Avena sativa* L.]) accounted for 52% of cover crops grown, while mixed cover crops and red clover (*Trifolium pratense* L.) accounted for 24 and 19%, respectively. A total of 5% of the cover crops were undisclosed in the management survey. While 53% of respondents did not report using cover crops, an overwhelming majority of those farmers (78%) reported growing some type of perennial crop during the 4-yr crop rotation. An overwhelming majority of respondents (92%) also implemented tillage at least once during the 4-yr rotation, which is unsurprising since organic farmers typically rely on tillage to control weeds (Lowry & Brainard, 2017).

TABLE 1 Key characteristics of participant farms and the fields sampled in this study (*n* = 195)

Organic cropland	Percentage of participant farms[a]	Row crops present at least once in 4-yr rotation	Percentage of participant farms	Perennial crop present in 4-yr rotation	Percentage of participant farms	Subscribe to BCSR?	Percentage of participant farms
ha	%		%		%		%
<10	8	Corn	78	None	24	Yes	58
10–50	33	Soybeans	15	1 yr	13	No	41
50–100	31	Wheat	9	2 yr+	63	na	<1
100–500	19						
500+	6						

Note. na, not applicable.

[a] Three percent of farms did not report farm size.

TABLE 2 Management practices prevalent across farms producing organic corn (n = 195) from 2014–2017 in Indiana, Michigan, Ohio, and Pennsylvania

Presence	Manure	Cover crops	Perennials in rotation	Tillage
			%	
Present	87	47	76	92
Absent	13	53	24	8
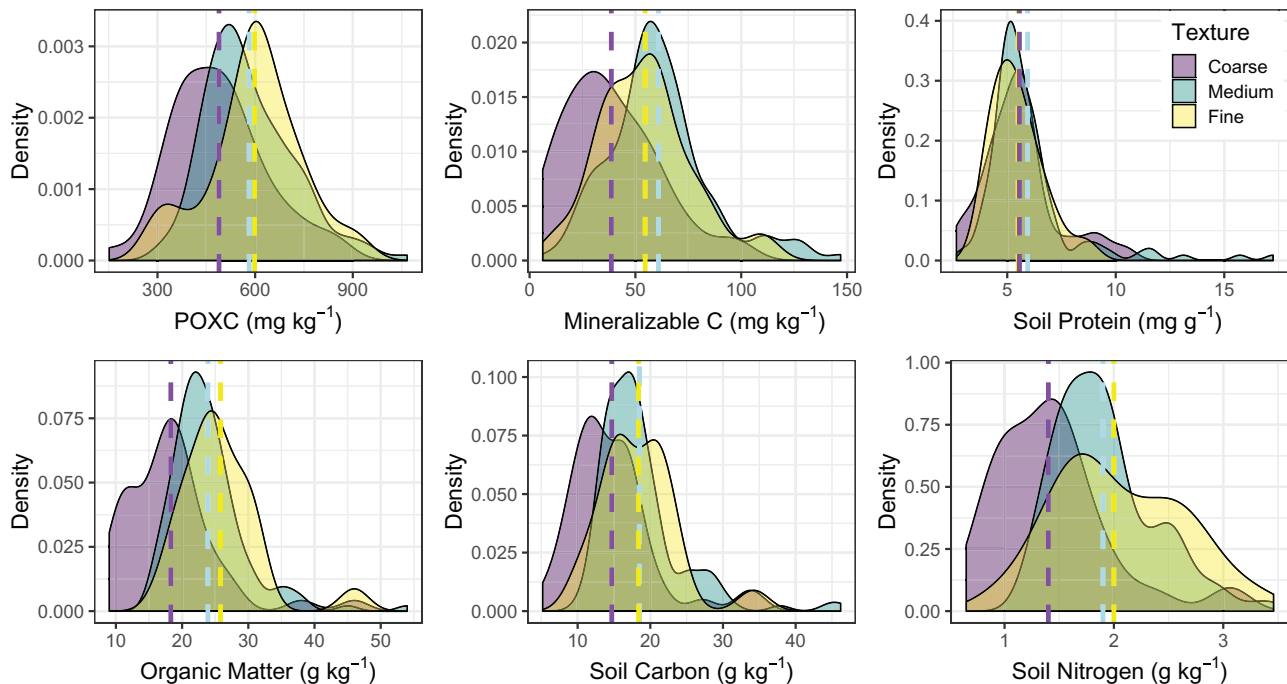
FIGURE 2 Density distributions of soil health indicators by texture class (coarse, medium, and fine). The y axis is the Gaussian probability density of a given soil health indicator and was determined using kernel density estimations

3.2 │ Distributions of soil health indicators by texture

In total, this dataset included 195 samples that were separated into three textural classes, with 46 samples classified as coarse, 128 classified as medium, and 21 samples classified as fine. Distinct density distributions were visible by texture for mineralizable C, OM, POXC, soil C, and soil N, whereby fine- and medium-textured soils had greater mean values relative to coarse soils (Figure 2). These distinct differences were validated in Table 3, where fine- and medium-textured soils had significantly greater POXC, mineralizable C, OM, soil C, and soil N relative to the coarse-textured soils ($p < .05$). Permanganate oxidizable C followed a normal distribution by texture that was similar to OM distributions, which is consistent with findings reported by Fine et al. (2017). This trend also corroborates findings by Culman et al. (2012) and Hurisso et al. (2016) who report that POXC most closely resembles SOC which is heavily influenced by texture and mineralogical soil properties. Mineralizable C values were distinctly lower among the coarse soils, however, medium soils on average were no different than fine-textured soils (Figure 2). This result suggests that mineralizable C is less influenced by texture relative to the other soil biochemical health indicators. No difference in mineralizable C values between fine and medium soils is consistent with results reported by Fine et al. (2017). Soil protein distributions substantially overlapped by texture, revealing no statistical difference across the three textural classes (Figure 2, Table 3, Supplemental Table S1). Cation exchange capacity and Mehlich-3 extractable nutrients such as K, Ca, and manganese (Mn) also significantly varied by texture (Table 3 and Supplemental Table S1) and often were greater within the medium-textured soils. These findings underscore the fact that soil biochemical health indicators vary in relationship with soil texture and highlights the need to understand how both texture and management drive soil health indicators.

TABLE 3 Mean (standard error) values for measured soil properties across three textural classes. Different letters indicate statistically different values across a textural class for a given soil health indicator at $p < .05$

Soil health indicator	Fine	Medium	Coarse
POXC, mg kg^{-1}	598.5 (32) a	581.5 (12) a	489.0 (21.4) b
Soil protein, g kg^{-1}	5.50 (0.3)	5.94 (0.2)	5.56 (0.3)
Mineralizable carbon, mg kg^{-1}	54.6 (4.8) a	60.9 (2.1) a	38.6 (3.3) b
Organic matter, g kg^{-1}	25.8 (1.3) a	23.9 (0.5) a	18.3 (1.0) b
Soil carbon, g kg^{-1}	18.4 (1.2) a	18.5 (0.5) a	14.7 (0.9) b
Total nitrogen, g kg^{-1}	2.0 (0.1) a	1.9 (0.04) a	1.43 (0.08) b
pH	6.8 (0.1) a	6.6 (0.05) ab	6.5 (0.07) b
CEC, cmol$_c$ kg^{-1}	11.7 (1.0) a	10.4 (0.3) a	7.5 (0.5) b
Phosphorus, mg kg^1	88.1 (15)	78.3 (7.4)	104 (12.0)
Calcium, mg kg^{-1}	2162 (211) a	1817 (68) a	1324 (99) b
Potassium, mg kg^{-1}	157.1 (19) a	117 (5.2) b	105 (8.1) b
Sulfur, mg kg^{-1}	15.8 (1.4)	18.4 (1.2)	16.2 (0.99)
Magnesium, mg kg^{-1}	231.7 (36) ab	238.4 (11) a	171.5 (15.2) b
Iron, mg kg^{-1}	162.5 (13) a	177.8 (4.5) ab	195.2 (8.1) a
Manganese, mg kg^{-1}	67.6 (8.6) b	90.6 (4.2) a	52.7 (3.7) b
Zinc, mg kg^{-1}	4.2 (0.6)	5.04 (0.3)	5.0 (0.4)
Boron, mg kg^{-1}	0.59 (0.06)	0.62 (0.02)	0.54 (0.03)
Copper, mg kg^{-1}	2.81 (0.2) a	3.0 (0.2) a	1.59 (0.11) b
Sand, g kg^{-1}	170 (19) c	240 (9.0) b	710 (15.0) a
Silt, g kg^{-1}	520 (18) a	550 (9.0) a	210 (78) b
Clay, g kg^{-1}	310 (6.0) a	210 (4.0) b	80.0 (5.0) c

Note. POXC, permanganate oxidizable carbon; CEC, cation exchange capacity.

3.3 | The relative importance of texture vs. management on each soil biochemical health indicator

Linear mixed-effects models were used to identify which management practices were the most important experimental factors associated with each soil health indicator. In each model, the soil health indicator served as the response variable, while crop diversity, cover crop (yes/no), perenniality (number of years present in rotation), tillage frequency, manure (yes/no), and subscription to BCSR (yes/no) were included as continuous or categorical factors and textural class was used as a random factor. Fixed factors reflect the relative proportion of total variance caused by management, while the random factor demonstrates the relative proportion of variance caused by textural class (Table 4). Textural class was responsible for 60–95.6% of the variance across the different soil biochemical health indicators (Table 4). That said, the total variance explained by the models considering both random and fixed factors was generally low. Nevertheless, this reinforces the importance of distinguishing texture when quantifying soil health, especially on-farm, when farmers may

be managing numerous fields with different textural classes (O'Neill et al., 2021).

While soil texture explains much of the soil biochemical health outcomes, farmers, as well as the scientific community at large, are deeply interested in the role that management plays. Although management only accounted for 5.7–39.6% of the explained variance, factors were still ranked in order of relative importance for each soil biochemical health indicator (Table 4). The top three ranked management practices are reported in Table 4 along with level of significance. The most important factors for POXC were cover crops and manure, which were both significant at $p < .05$. Tillage was the most important factor for mineralizable C and significant at $p < .05$. Perenniality was also a significant driver of mineralizable C at $p < .05$. Perenniality was a top ranked factor for most variables, which demonstrates the key role that perennials have in driving soil health on organic farms (Tully & McAskill, 2019). Crop diversity was the most important factor for soil N, which can likely be explained by a greater number of legumes incorporated into more diverse crop rotations (Blesh, 2018). Manure appeared as a top ranked factor for all variables, which corroborates findings from Ozlu et al. (2019)

TABLE 4 Linear mixed-effects models and partitioning of variability between and experimental factors and textural classes to identify relative importance of each management practice to each soil health indicator. The top three most significant explanatory factors were maintained in the model

Variable	Factor[a]	t value and significant code[b]	Coefficient (std.)[c]	Relative proportion of total variance percentage		R^2 Total variance explained
				Fixed (Factors)[d]	Random (Textural classes)	
				%		%
POXC, mg kg⁻¹ [e]	Cover	2.7**	0.38	23.7	76.3	15.6
	Manure	2.0*	0.4			
	Perennial	−1.2	−0.09			
Mineralizable C, mg kg⁻¹	Tillage	−3.2**	−0.25	39.6	60.4	28.2
	Perennial	1.9•	0.14			
	Manure	1.8•	0.33			
Protein, g kg⁻¹ [f]	Manure	1.2	0.24	18.8	81.2	10.1
	Cover	1.1	0.16			
	Perennial	0.9	0.07			
Organic matter, g kg⁻¹	Cover	1.8•	0.25	4.4	95.6	20.8
	Perennial	−0.74	−0.05			
	Manure	0.84	0.17			
Total C, g kg⁻¹	Cover	1.5	0.27	17.6	82.4	16.1
	Manure	1.2	0.24			
	Crop diversity	−0.6	−0.06			
Total N, g kg⁻¹	Crop diversity	−1.8	−0.13	5.7	94.3	21.5
	Manure	1.5	0.3			
	Perennial	−1.0	−0.07			

[a]Experimental factors tested were number of crops, cover-crop, perennial time, tillage, manure, and soil balancing.

[b]p value significant code: .05. ** p value significant code: .01. *** p value significant code: .001.

[c]Standardized beta coefficient. Top ranked factors described in column.

[d]Top ranked factors described in column[a]. The top three most significant explanatory factors were maintained in the models.

[e]POXC, permanganate oxidizable carbon.

[f]Protein, soil protein.

who demonstrate that manure serves as an important driver of labile soil C pools and nutrient cycling. Cover crops appeared as the top predictor for OM and total C, which reinforces the importance of lengthening rotations and increasing C inputs via cover cropping (Jian et al., 2020; Kong & Six, 2010). Overall, each factor had a relatively low amount of variance explained, demonstrating the immense role that texture plays in driving soil biochemical health indicators. Top ranked management practices were also assessed for individual texture classes (Supplemental Table S2). The model demonstrates even more complexity with lower and sometimes negative R^2 values, depicting very poor exploratory power. This analysis underscores the complexity of quantifying soil health from 195 different farms in an effort to determine the impact of management practices on soil biochemical health indicators.

3.4 | Management influences on soil biochemical health indicators

Analyses of variance was used to determine how different management practices influenced soil health indicators across the entire dataset ($n = 195$). Manure application did not have a significant effect on any of the soil health indicators ($p > .1$; Table 5, Supplemental Table S3), which is likely due to the small number of observations where manure was absent. However, most values trended higher on farms where manure was applied, which has been shown in other on-farm studies (Franzluebbers et al., 2020). High variability across the dataset, especially for POXC likely obscured any patterns of statistically different values for farms where manure was applied vs. when manure was absent. Additionally, we made no attempt to decipher differences in manure rates or sources, which could have also led to greater variability. Farms, where cover crops were absent, had significantly greater POXC and soil C relative to farms where cover crops were present (Table 5 and Supplemental Table S2). These contrast with meta-analyses and other on-station experiments, where cover crops have been shown to increase soil C (Jian et al., 2020; McDaniel et al., 2014). These trends are likely confounded by the fact that 78% of the farms that did not have a cover crop present, grew perennials for at least 1 yr of the 4-yr rotation. Perenniality significantly influenced mineralizable C ($p < .1$), where the presence of perennials (56.8 ±2.0 mg C kg^{-1}) had greater overall mineralizable C relative to farms where perennials were absent (49.7 ± 3.8 mg C kg^{-1}). Previous studies have reported greater mineralizable C under perennial cropping systems and attribute greater respiration rates to large and extensive root systems that significantly influence labile C pools (Sprunger & Robertson, 2018; Sprunger et al., 2020).

TABLE 5 Mean (standard error) values of soil properties by management practices including use of manure, cover crops, perennials in rotation within last 4 yr and subscription to base cation saturation ratios (BCSR). Different letters within treatment comparisons for a single indicator denote statistical significance at ($p < .1$) with clay as a covariate in the ANOVA Model. F statistics and p values in Supplemental Table S2

	POXC[a]	Mineralizable C	Protein[b]	Organic Matter	Soil C	Soil N	Soil Ca:Mg[c]
				(n = 195)			
	—mg C kg^{-1}—	—mg C kg^{-1}—	mg g^{-1}		—g kg^{-1} soil—		
Manure (+)	566.2 (11)	55.2 (2.0)	5.85 (0.2)	22.7 (1.0)	17.6 (0.5)	1.82 (0.4)	8.82 (0.7)
Manure (−)	531.1 (27)	53.9 (4.2)	5.49 (0.2)	22.8 (0.5)	17.2 (1.0)	1.77 (0.09)	8.31 (0.3)
Cover Crop (+)	538.7 (14) b	55.2 (2.7)	5.59 (0.2)	22.1 (0.6)	16.6 (0.5) b	1.78 (0.1)	9.12 (0.5)
Cover Crop (−)	581.5 (15) a	54.8 (2.4)	5.97 (0.2)	23.3 (0.7)	18.5 (0.6) a	1.84 (0.1)	8.43 (0.3)
Perennial (+)	555.8 (11)	56.8 (2.0) a	5.84 (0.2)	22.4 (0.5)	17.4 (0.5)	1.78 (0.04)	8.43 (0.6)
Perennial (−)	578.6 (24)	49.7 (3.8) b	5.67 (0.3)	23.7 (1.0)	18.2 (0.9)	1.90 (0.07)	8.86 (0.3)
BCSR (+)	564.0 (14)	54.3 (2.3)	5.91 (0.2)	23.1 (0.7)	17.7 (0.6)	1.83 (0.05)	9.00 (0.4)
BCSR (−)	561.0 (16)	56.6 (2.9)	5.69 (0.2)	22.5 (0.6)	17.5 (0.6)	1.81 (0.06)	8.45 (0.4)

[a]Permanganate Oxidizable Carbon (POXC).
[b]Soil Protein.
[c]Ratio of base saturation percentages of Mehlich-3 extractable soil calcium to magnesium.
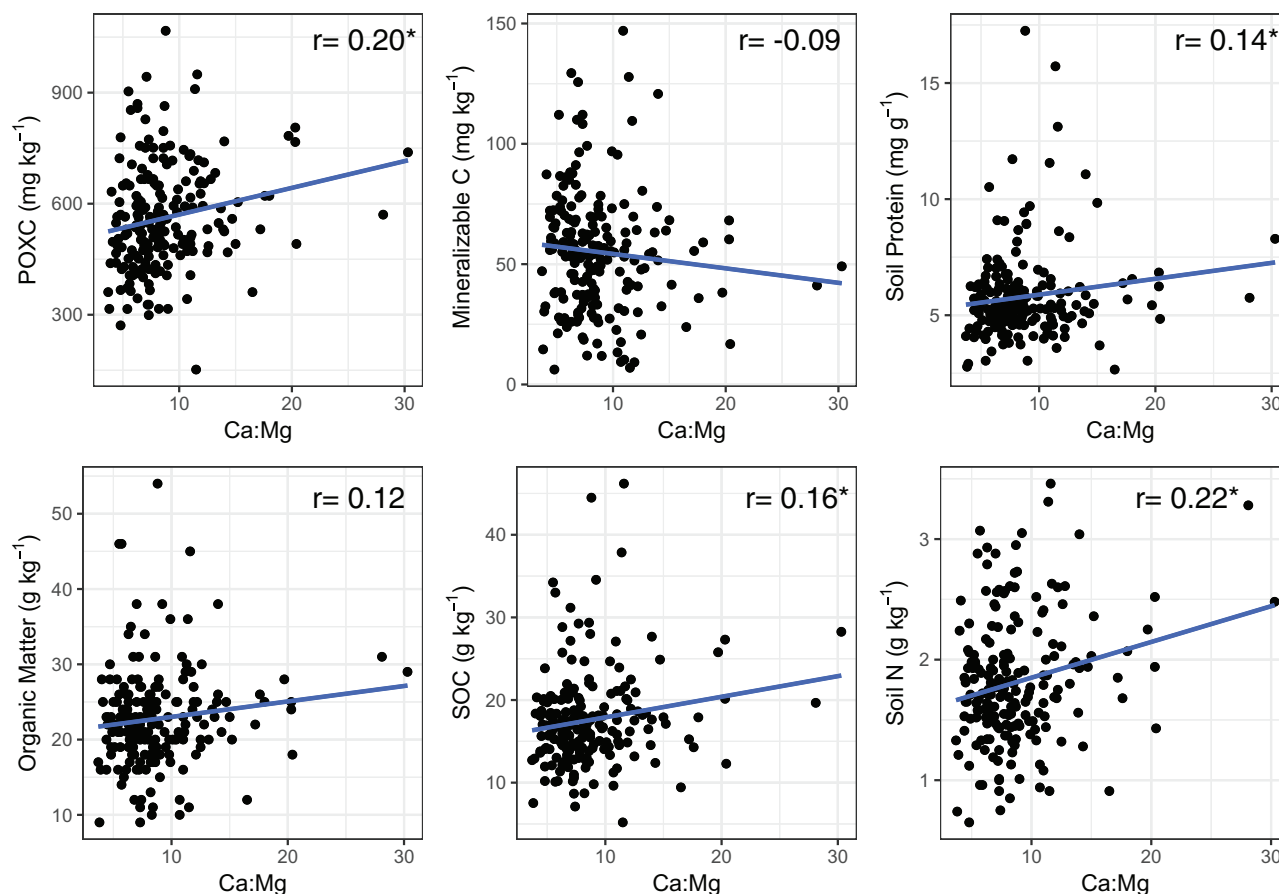
FIGURE 3 Relationship between soil health indicators and Ca/Mg ratios with least-squares trend line

We found no significant differences in soil health indicators between soils where farmers follow BCSR compared to where a BCSR approach was not used (Table 5 and Supplemental Table S2). Interestingly, subscription to BCSR had no influence on Ca/Mg ratios measured in the soils that were submitted for this study. However, two important caveats need to be considered, first, we do not have a strong sense of how long these farmers have been subscribing to BCSR and actively working to change Ca/Mg ratios (Brock, Jackson-Smith, Culman, et al., 2021; Brock, Jackson-Smith, Kumarappan, et al., 2021). Second, soils are highly buffered and altering Ca/Mg ratios can require time and heavy amendment application rates (see Chaganti et al., 2021), even when farmers are actively applying high-Ca limestone and gypsum. This again underscores the complexity of tracking one variable on working farms and some of the challenges of demonstrating the agronomic impact of subscription of BCSR practices. That said, we did find that these Ca/Mg ratios were positively correlated with each soil health indicator, with the exception of mineralizable C (Figure 3). Permanganate oxidizable C ($r = .2$), soil protein (0.14), soil C (0.16), and soil N ($r = .22$) all had positive relationships with Ca/Mg that were significant at $p < .05$. Organic matter ($r = .16$) was positively correlated with Ca/Mg and was marginally significant at $p < .1$.

The positive relationship between Ca/Mg and OM can be further explained by the role that Ca plays in cation bridging to mediate soil C stabilization (Rowley et al., 2018). Thus, it is possible that high OM levels drive Ca/Mg ratios more so than any type of subscription to BCSR. Ultimately, we know that a majority of organic growers in this study region subscribe to the philosophy of BCSR (Brock, Jackson-Smith, Kumarappan, et al., 2021), yet published experimental studies have been unable to show that manipulating Ca/Mg ratios positively influences soil health or agronomic performance (Chaganti & Culman, 2017). The lack of a significant link between use of BCSR amendments and measured soil Ca/Mg ratios in our sample suggests that adherence to a BCSR philosophy is an insufficient proxy for changes in soil base cation levels (and/or that farmers who have lower Ca/Mg ratios in their soils are more likely to subscribe to the approach).

3.5 | Management complexity in organic farming systems

Given that this dataset consists of farms that have implemented a wide range of management practices over a 4-yr period, these analyses needed to go beyond analysis of
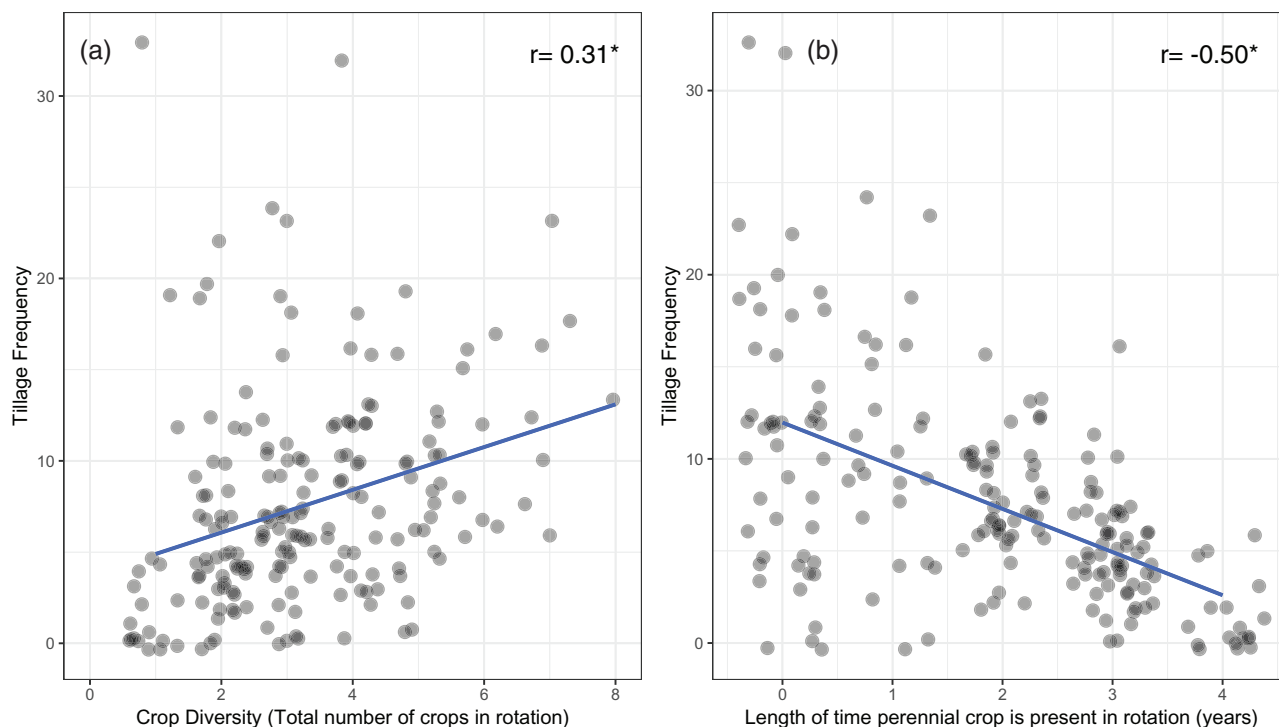
FIGURE 4 Relationship between (a) tillage frequency (number of tillage passes over 4-yr rotation) and crop diversity (total number of crops in 4-yr rotation) and (b) tillage frequency and the length of time that perennial crops were present in the rotation (years) with least-squares trend line

variance to fully explore the relationships amongst the various management practices in addition to the relationship between management practices and individual soil health indicators. For instance, a consistent critique of organic agriculture is that it heavily relies on tillage intensity for weed control, which has the potential to reduce soil health (Bhardwaj et al., 2011; Lowry & Brainard, 2017; Osterholz et al., 2020). Thus, we were particularly interested in understanding the relationship between tillage frequency and crop diversity in addition to tillage frequency and use of perennials (Figure 4). First, we used correlations to assess the relationship between tillage frequency (total number of passes in a 4-yr rotation) and total number of crops in a 4-yr rotation (i.e., crop diversity) (Figure 4a). We found a positive ($r = .31$) and significant ($p < .01$) correlation between tillage frequency and crop diversity (Figure 4a). This indicates that organic farmers are consistently implementing higher rates of tillage in order to grow a greater number of crops in the rotation. Given that 76% of farmers had some type of perennial crop in the rotation, it was also necessary to explore the relationship between tillage frequency and the length of time that perennials were present in a rotation. We found a strong negative relationship between tillage frequency and the length of time that perennials were present ($r = −.5$, $p < .0001$) (Figure 4b). This demonstrates that tillage frequency substantially drops when perennials are kept in the rotation for a longer period of time (Tully & McAskill, 2019; Williams et al., 2020).

Of the farms that only reported growing annual crops, corn–soy–wheat rotations were typically most common, while monoculture corn over the entire 4-yr period was extremely rare. Rotations that had more than four crops within a 4-yr period often had multiple different types of cover crops in the rotation and/or rotated organic corn with vegetable crops including green bean (*Phaseolus vulgaris* L.), kale (*Brassica oleracea var. sabellica*), and cabbage (*B. oleracea var. capitata*). Increasing the crop rotational diversity in this sense simply requires more tillage passages and likely explains the positive relationship with tillage frequency. In contrast, the inclusion of perennials resulted in reduced tillage frequency, which is noteworthy because 63% of participants reported having a perennial in the rotation for 2 or more years. For example, another common rotation reported in this study was 1 yr of corn, followed by 3 yr of alfalfa or another hay crop. The persistent presence of perennials in the rotation alleviates the need for tillage until another row-crop is planted (Weißhuhn et al., 2017).

This is one of the first studies in the peer reviewed literature to explore the relationship among tillage frequency, crop rotational diversity, and perenniality using information gathered via management surveys from organic corn growers. These findings highlight the complex patterns of farm management practices on working commercial operations that are difficult to replicate in experimental trials and the importance of collecting management data in conjunction with soil health quantification.
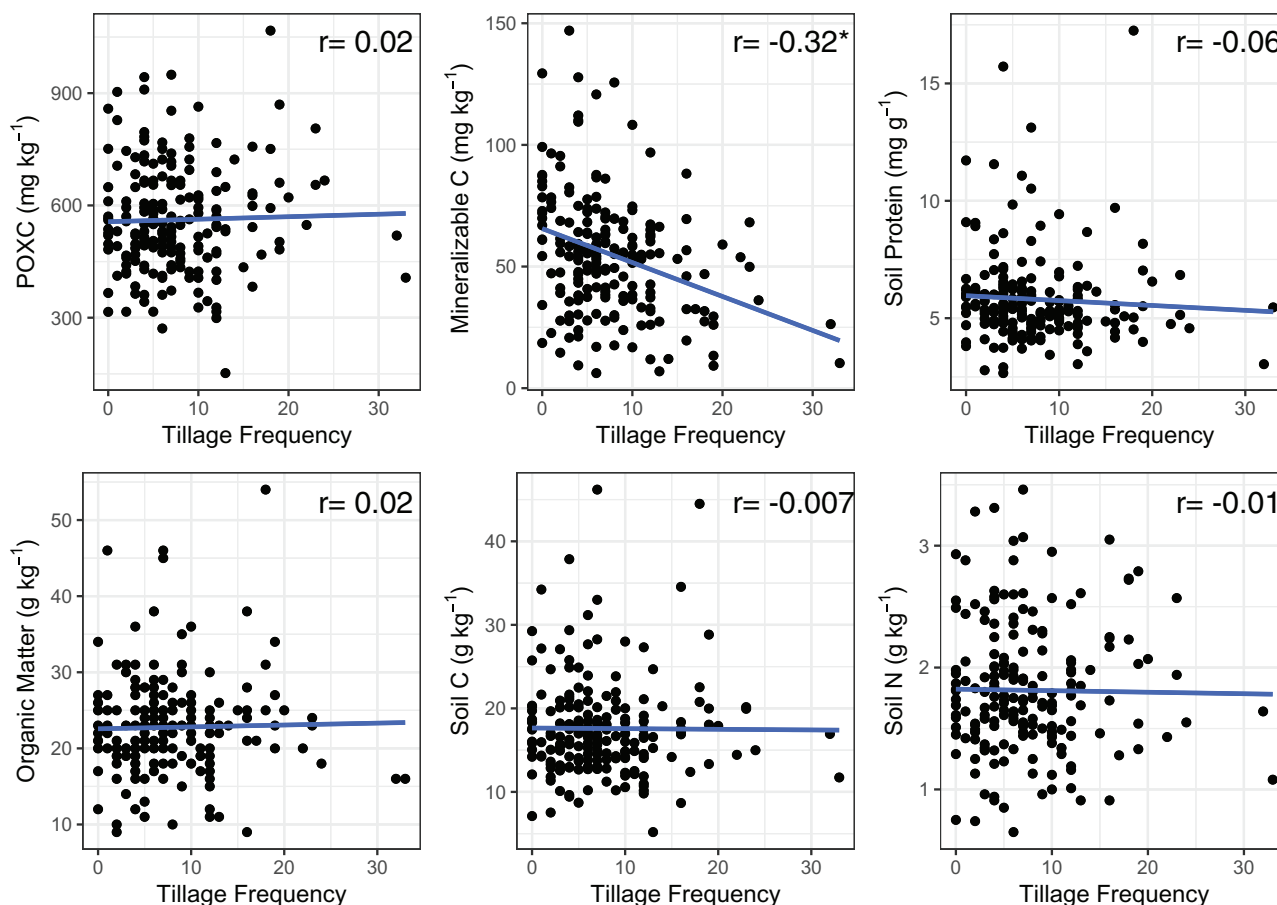
FIGURE 5 Relationship between soil health indicators and tillage frequency (number of tillage passes over 4-yr rotation) with least-squares trend line ($n = 195$)

3.6 | Tillage impacts on soil health in organic corn production

When exploring the relationship between tillage frequency and soil health indicators, mineralizable C had the most negative correlation ($r = -.32$), which was significant at $p < .01$ (Figure 5). In contrast, we found no relationship between tillage frequency and the rest of the soil biochemical health indicators (Figure 5). Hurissio et al. (2016) documented that tillage has a much greater influence on mineralizable C compared to POXC. Thus, it is not surprising that mineralizable C had the most negative relationship with tillage compared to the other soil health indicators in this dataset. Numerous studies have documented that tillage reduces overall soil health by releasing greater amounts of CO_2 emissions, disrupting soil aggregates, and creating less structured soil food webs (Fiorini et al., 2018; Grandy & Robertson, 2006; Melland et al., 2016). However, these findings are typically dichotomous comparisons of no-till vs. plow tillage in long-term trials. In reality, tillage on commercial farms is more complex because of the wide range of tillage practices that are implemented

(Williams et al., 2020). For instance, Mann et al. (2019) found that tillage intensity was negatively correlated with MinC across farmer fields in Canada and positively responded to mixed perennial–annual systems. While this study did not attempt to differentiate tillage type, it does corroborate findings found in Mann et al. (2019) and demonstrates how soil health changes with tillage frequency using on-farm data and how tillage frequency is largely dependent on crop rotation and perenniality (Figure 4).

3.7 | Crop diversity, perenniality, and soil health

We found that each soil health indicator had a slightly negative relationship with crop rotational diversity over a 4-yr period (Figure 6). These findings are a departure from the literature as previous studies have generally reported positive relationships between increased crop diversity and soil nutrient pools (McDaniel et al., 2014; Tiemann et al., 2015). However, a decrease in soil health with increased crop
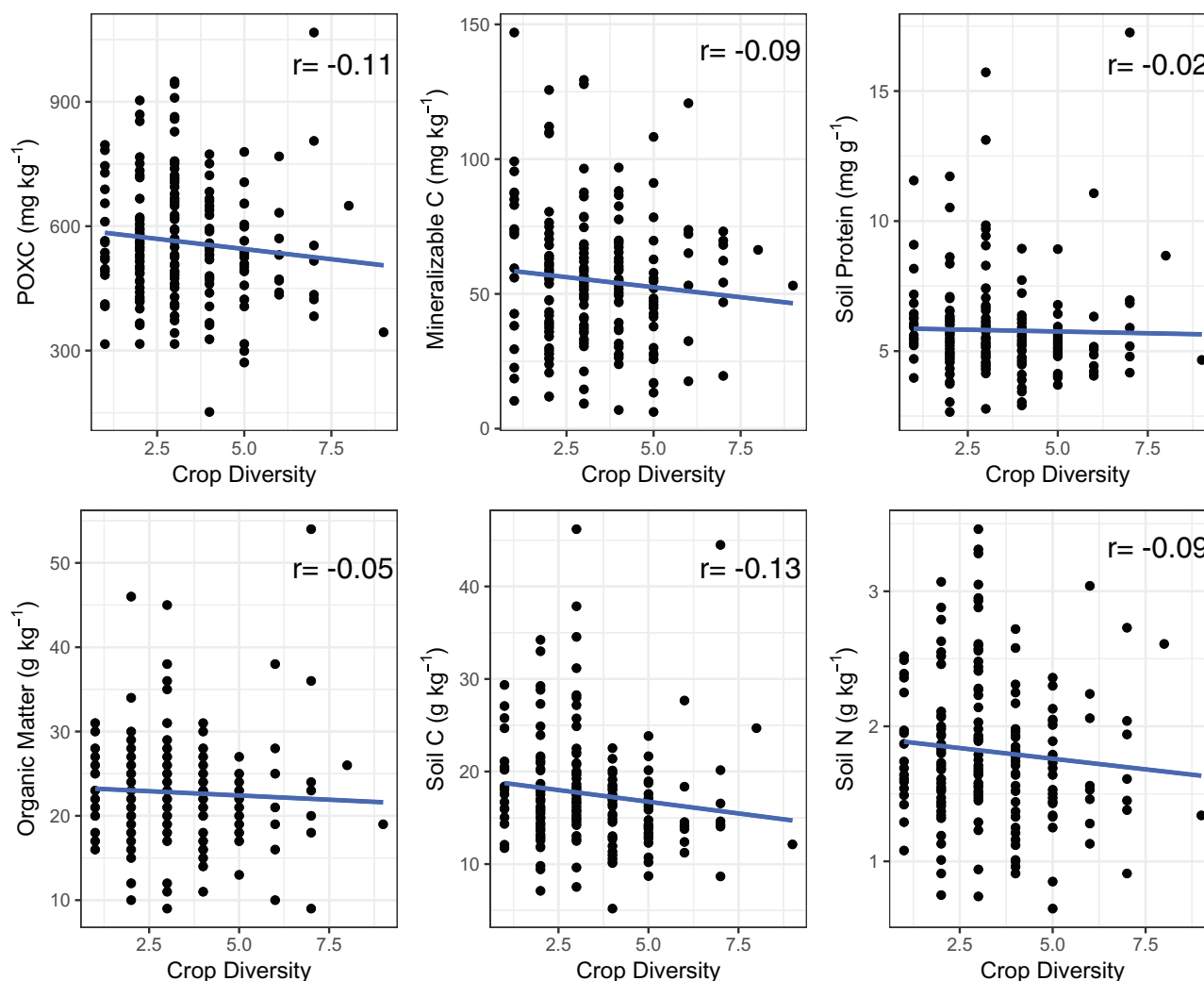
FIGURE 6 Relationship between soil health indicators and crop diversity (total number of crops in 4-yr rotation) with least-squares trend line (n = 195)

diversity is not surprising, given that we observed a significant positive correlation between crop diversity and tillage. That said, not all soil health indicators had a negative relationship with increased tillage, which suggests the relationship among tillage, crop diversity, and soil health is more nuanced. Lack of response to an increase in tillage frequency could also have to do with the sensitivity of each indicator (Hurisso et al., 2016). For instance, mineralizable C has been shown to be more responsive to recent changes in management relative to POXC, which reflects a more processed pool of C (Culman et al., 2012; O'Neill et al., 2021; Sprunger et al., 2020).

To better understand the interconnectedness of tillage, crop diversity, and soil health, we correlated crop diversity with soil health indicators again, only this time denoted where perennials were present or absent (Figure 7). This analysis revealed that crop diversity continued to have a negative relationship with soil health indicators when perennials were present in the rotation. For instance, mineralizable C ($r = -.24$), soil C ($r = -.19$), and soil N ($r = -.18$) all

had statistically significant negative correlations ($p < .05$) with perennials present, as noted by the solid best fit lines (Figure 7). Permanganate oxidizable C, soil protein, and OM also had negative correlations but were not significant at $p > .05$. Most noteworthy was the positive relationship between crop diversity and the majority of the soil health indicators, when perennials were absent (Figure 7), which aligns with a previous assessment of the benefits of crop diversity (McDaniel et al., 2014). Mineralizable C ($r = .1$), soil protein ($r = .2$), OM ($r = .04$), and soil N ($r = .1$) were all positively correlated with crop diversity, though none were statistically significant ($p > .1$). Although not statistically significant ($p > .1$), POXC and soil C remained negatively correlated with crop diversity when perennials were absent (Figure 7).

Overall, these trends demonstrate that perenniality drives soil biochemical health in these organic farming systems, whereby the longer a perennial is left in a rotation, the better it is for soil biochemical health. Contrastingly, reduced
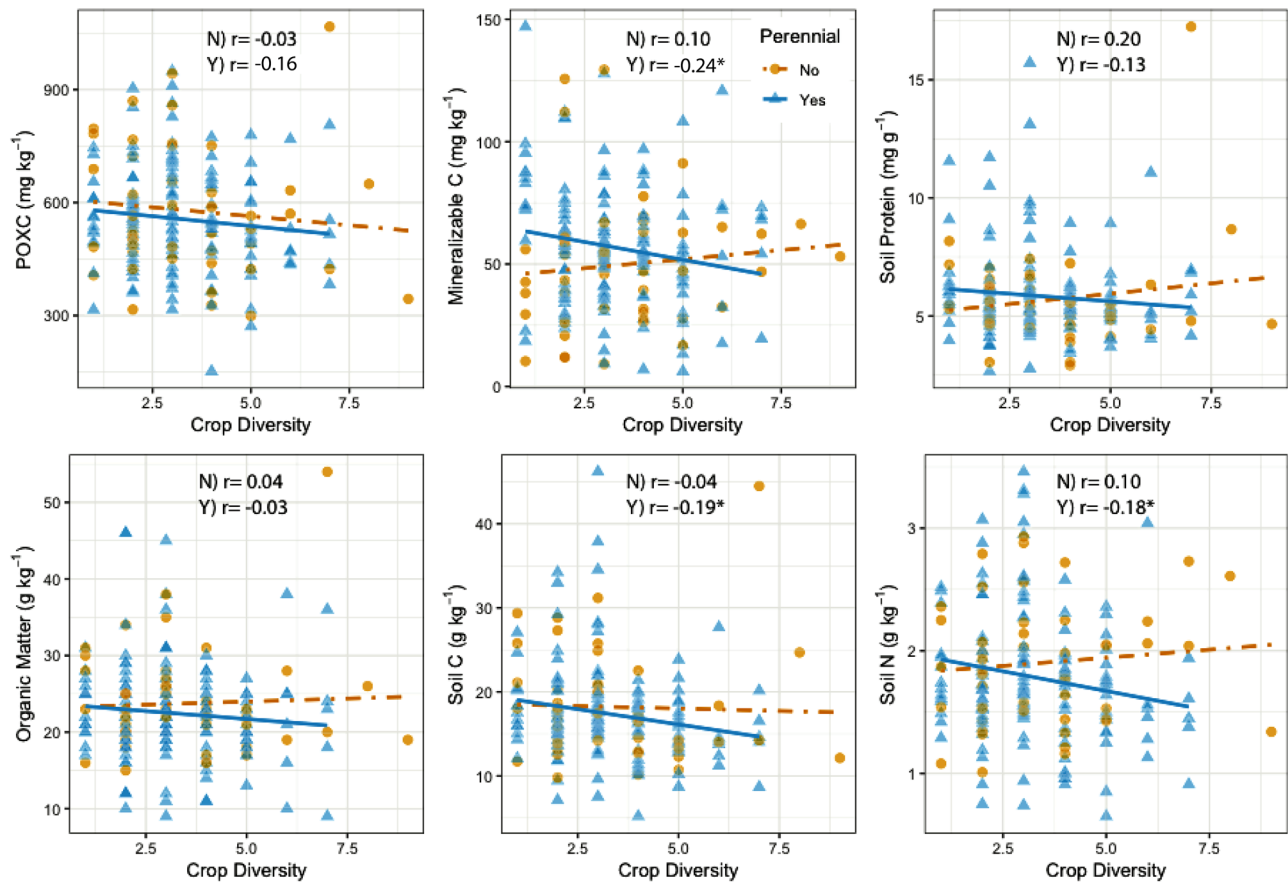
FIGURE 7 Relationship between soil health indicators and crop diversity (total number of crops in 4-yr rotation) delineating where perennials are present or absent in 4-yr rotation. Triangular blue dots reflect farms that included perennials in the rotation and the solid blue line is the associated linear trendline. Circular gold dots reflect farms where perennials were not included in the rotations and the dotted gold line is the associated linear trendline. Asterisks reflect significant correlations

perenniality is associated with an increase in the number of annual crops grown within a 4-yr period. This generally led to greater tillage frequency, likely leading to reductions in nutrient levels. For example, Figure 8 demonstrates that mineralizable C significantly increases when perennials are left in the rotation for a greater number of years. The importance of including perennials in crop rotations for enhanced soil biochemical health has been documented by multiple studies (Congreves et al., 2015; Ernst & Siri-Prieto, 2009; King & Blesh, 2018). Perennial crops are efficient at improving soil health over time because of greater belowground C inputs and consistent year-round ground cover, which reduces disturbance relative to annual cropping systems (Nunes et al., 2020; Sprunger & Robertson, 2018; Syswerda et al., 2011). Consistent with these findings, perennials are also able to increase labile soil C pools as they age (Szymanski et al., 2019). These results highlight the important caveats that need to be considered when seeking to increase crop diversity for enhanced soil health. Most noteworthy is that organic farmers need to be mindful of tillage frequency.
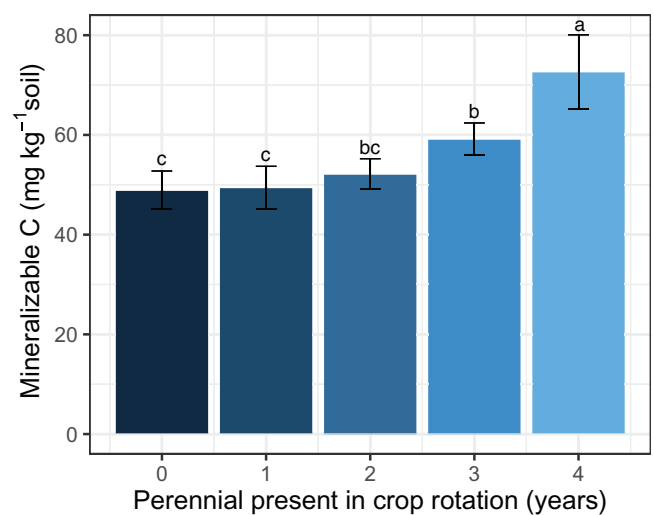

FIGURE 8 Mineralizable C values averaged across farms ($n = 195$) where perennials were absent (0 yr) or present for a certain number of years within the 4-yr rotation). Bars reflect means and error bars represent standard errors of the mean. Bars with different lower-case letters are statistically different from one another at $p < .1$

3.8 | Benefits and limitations of mail-in soil surveys

This project highlights the effectiveness of using mail-in soil health surveys to assess how management influences soil health at a regional scale. The ability to merge quantitative management survey data with biophysical soil health test data is novel and should be conducted in future regional soil health surveys. The approach allowed us to disentangle the complexity of on-farm soil management by considering how multiple management practices influence soil biochemical health, which is often impossible to replicate in on-station experiments (Williams et al., 2020). This approach also provides empirically grounded benchmarks that allow individual organic farmers to understand how soil health test values compare to other farms with similar soil types across the four-state region. The limitations of mail-in soil health surveys are that we were only provided one-snapshot in time for each field which could mask variation in soil health indicators over the course of a growing season (Culman et al., 2013). Other limitations include relying on farmers to sample soil consistently. We provided detailed instructions but have no way to verify that soil samples were collected in compliance with these instructions. Furthermore, the survey data relied on farmer self-reporting management behaviors. Finally, there may be other management factors that we did not ask about and other soil variables that were not measured that could be important in this context. That said, we feel that the benefits of mail-in soil health surveys largely outweigh the limitations and expect that these types of studies will be a highly valued tool in assessing soil health on-farm.

4 | CONCLUSIONS

This study is the first to examine management impacts on soil health indicators using a mail-in soil health survey merged with soil health test results for a large sample of farms across the eastern Corn Belt. These findings demonstrate the complexity of on-farm management behaviors and how these combine to impact soil biochemical health outcomes in organic farming systems. Based on these findings, we reject the notion that simply increasing crop diversity is beneficial for soil biochemical health in an organic farming context, where tillage disturbance is prevalent and positively linked to crop diversity. In this study, crop diversity was associated with declines in soil biochemical health, especially when perennials were present in the rotation. Perenniality seemed to have the strongest influence on soil health indicators likely because of the association with reduced soil disturbance and year-round soil C inputs. While subscription to a BCSR management philosophy was not associated with an increase in

soil health indicators, the relationship between Ca/Mg and soil health indicators was generally positive, suggesting that applying high-Ca limestone and gypsum to influence base cation saturation could be an effective way to build OM pools and soil biochemical health. Most importantly, building soil health in organic farming systems requires incorporating perennial crops and reducing tillage frequency to minimize soil disturbance.

CONFLICT OF INTEREST
The authors declare no conflict of interest.

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SUPPORTING INFORMATION

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