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Environmental and management drivers of soil health indicators on Michigan field crop farms

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ABSTRACT

Maintaining soil health is critical for sustainable field crop production. This on-farm study used participatory monitoring and employed a Bayesian linear regression model to investigate the impact of various drivers (i.e., climate, soil edaphic properties, management practices, cropping diversity, and tillage intensity) on soil health indicators. Over two years, we sampled 242 focal points in soybean fields on thirty-five farms across three regions in Michigan differing in climate, edaphic properties and management practices. Soils ranged from loam to sandy loam. Soil health indicators assessed included soil organic carbon (SOC), total soil nitrogen (TSN), permanganate oxidizable carbon (POXC), C mineralization (Cmin), potentially mineralizable nitrogen (PMN), phosphorus, calcium, soil surface and subsurface resistance, and wet aggregate stability (WAS). We observed location effects, with each of the three regions differing in their climate, soil edaphic properties, and management practices. We found that aridity and clay content are primary drivers of most soil health indicators. Specifically, crop diversity, irrespective of composition, was positively associated with Cmin and WAS. Tillage intensity was positively associated with PMN but negatively influenced POXC. Overall, we conclude that although climate and soil edaphic properties are the dominant drivers of soil health, management practices also play a critical role, especially when considering soil biological indicators.

1. Introduction

Given the vital role that soil plays within ecosystems and human life, it is important to assess soil health, especially on field crop farms that dominate agricultural landscapes in the US. Comprehensive soil health assessment relies on different measures, including multiple indicators across chemical, physical, and biological categories (Andrews et al., 2004; Bünemann et al., 2018; Doran and Parkin, 1996; Moebius-Clune et al., 2016; Nunes et al., 2021; Stockdale et al., 2019; Zuber et al., 2017). Soil organic carbon (SOC) is recognized as the most important indicator of soil health, as it affects soil structure, soil nutrients, and microbial activities (Wander, 2004). However, detecting changes in SOC associated with short-term management practices in cultivated fields is challenging (Mpeketula and Snapp, 2019). Permanganate oxidizable carbon (POXC) and carbon mineralization (Cmin) are emerging indicators used to assess soil health since they are 2–3 times more sensitive than SOC (Awale et al., 2013; Fine et al., 2017). Potentially mineralizable nitrogen (PMN) represents the largest N pool available for plant growth and is another useful measure of soil health and response to management. Available phosphorus (P) and calcium (Ca), wet aggregate stability (WAS), surface resistance (PEN15), and subsurface resistance (PEN45) are also common soil health indicators frequently discussed in the literature (Andrews and Carroll, 2001; Doran and Parkin, 1996; Zuber et al., 2017). Collectively, these simple and inexpensive indicators provide information regarding soil fertility, infiltration capacity, and aeration condition of crop fields (Bastida et al., 2008; Cardoso et al., 2013).

Soil health can be evaluated through scoring functions based on several emerging theoretical frameworks (Andrews et al., 2004; Moebius-Clune et al., 2016; Nunes et al., 2021). In general, three scoring

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functions are used: "more is better" for SOC, TSN, POXC, Cmin, PMN, and WAS; "less is better" for PEN15 and PEN45; and "mid-point optimal" for soil pH, available P, and Ca (Andrews et al., 2004; Moebius-Clune et al., 2016). Although unit-less scoring functions based on local knowledge can make soil health indicators easier to interpret and compare, they have generally included indicators based on their sensitivity to environmental conditions and management practices (Zuber et al., 2017). Emerging soil health frameworks have also highlighted the importance of assessing the effects of management practices on individual indicators under differing climate and soil edaphic conditions, which we emphasize in this study (Stockdale et al., 2019).

Environmental conditions and soil edaphic properties are the dominant determinants of SOC and other soil health indicators across various landscapes (Burke et al., 1989; Chaplot et al., 2010; Hontoria et al., 1999; Talmon et al., 2011). In terms of environmental conditions, temperature and aridity, in particular, can influence soil properties through weathering, decomposition, and biomass accumulation (Burke et al., 1989; Talmon et al., 2011). Yet, few published studies consider temperature and aridity when analyzing multiple soil health indicators. In addition, most research on the effects of aridity on soil properties focuses on semi-arid and arid systems (Delgado-Baquerizo et al., 2013; Jiao et al., 2016). Normalized difference vegetation index (NDVI), reflective of vegetative cover and biomass accumulation, is also a predictor used in models of spatial variation in SOC at multiple scales (Kunkel et al., 2011; Zhang et al., 2019). Yet, limited work evaluates NDVI as a driver of soil health in agroecosystems. Meanwhile, in terms of soil edaphic properties, soil clay content and soil pH also critically affect soil health indicators (Chaplot et al., 2010; Dlamini et al., 2016). Clay content, a key soil edaphic property, provides surface area for organo-mineral complexes and micro pits for ions (Six et al., 2002). Thus, clay content determines several soil chemical properties. Furthermore, soil clay content impacts soil structure, improving aeration and water infiltration (Fernández-Ugalde et al., 2013). Another key edaphic property is soil pH; a soil's acidity or alkalinity regulates the environment for ions and microbial activities and, thus, affects soil health indicators (Minasny et al., 2016; Turner and Blackwell, 2013).

While environmental and soil edaphic properties influence soil health indicators, the soil health of agroecosystems also depends on land management practices, including crop diversity and tillage intensity (Stockdale et al., 2019). In row crop systems, farmers generally plant a single species per season (Tiemann et al., 2015), meaning they increase temporal diversity versus spatial scale through a sequential rotation. McDaniel et al. (2014) found that crop diversity can improve soil quality through the above and below ground accumulation of biomass and through the functional diversity of microbial communities in a meta-analysis study. Tiemann et al. (2015) affirmed this notion that crop diversity sustains soil biological communities and improves soil organic matter in a 6-year Midwest biological station study. However, others have found otherwise. For example, Snapp et al. (2010) and Mpeketula and Snapp (2019) did not find that crop diversity benefitted SOC. Given these mixed findings, the impact of crop diversity on soil health indicators in field crop systems remains unclear.

Besides crop diversity, tillage is another critical management practice. Tillage disrupts soil structure and breaks down soil aggregates, which exposes soil's organic matter. In this way, tillage practices can influence soil's temperature, aeration, and water holding capacity and, in turn, further contribute to changes in microbial activity (Balota et al., 2004). Compared to conventional tillage (CNT), reduced tillage (RT) creates less disturbance and, thus, improves soil's physical properties and helps prevent soil loss through erosion (Huang et al., 2015; Kayan et al., 2017). However, RT practices do not always improve soil health (Bhowmik et al., 2016; Hurisso et al., 2014; Margenot et al., 2017; Wander and Bollero, 1999). For example, Wander and Bollero (1999) in an on-farm study found that PMN and SOC were lower in non-disturbed soils, and not significantly different in soils under no-till (NT) vs CNT. In addition, Hurisso et al. (2014) conducted a long-term field experiment that showed high PMN and other soil quality properties were associated with CNT, not RT. Greater understanding of local environmental context is needed to derive recommendations given the varied–and sometimes conflicting–results in terms of "best" management practices for soil health.

Considering the role of field crop systems in global food security, and the variations in climates, soil types, and farming practices under which they are produced, it is helpful to adopt a Farmer Participatory Research (FPR) approach that reflects real-world scenarios and contextualizes the observed effect of environmental factors and management practices on soil health indicators within specific farms and fields (Snapp et al., 2019). In this study, we employed the FPR approach and Bayesian statistics to test our hypotheses that 1) environmental and soil edaphic properties are the main drivers of soil health indicators across a geographical gradient; 2) crop diversity enhances soil biological indicators more than physical and chemical indicators; and 3) reducing tillage intensity can improve soil biological health indicators.

2. Materials and methods

2.1. Site description

This study was conducted on Michigan soybean (*Glycine max* (L.) Merr.) farms in 2016 and 2017 to investigate the influence of real-world environmental conditions and actual practices adopted by farmers on soil health indicators. Thirty-five farmers were recruited through Michigan State University Extension (MSUE), across Southwest, Central, and Northeast Michigan (Snapp et al., 2019). These study sites were located in 9 counties and represented a range of climate conditions (Fig. 1, Table 1). Each farmer picked one or two soybean fields to include in the study each year. For each field, Web Soil Survey (Web Soil Survey) was used to identify up to three predominant soil types that cover at least 2 acres, which were then labeled as focal plots. The study ultimately included 117 focal plots in 2016 and 125 focal plots in 2017. Dominant soil types in Southwest, Central, and Northeast Michigan focal plots were Oshtemo sandy loam, Capac loam, and Emmet sandy loam respectively. A full description of soil types across all the sampled plots are listed in Supplemental Table A1.

2.2. Management practices

For each field, a six-year history of management practices before the sampling year was established through a farmer survey supervised by the Michigan State University IRB board. Crop rotation was recorded, and a crop diversity index (CDI) was later calculated using the average number of crop species per year and total species across the six-year period (Eq. 1) following the approach in Tiemann et al. (2015). Notably, pasture and forage systems were counted as two species, since these systems are usually diverse with at least two species present within the system.

$$\mathrm{CDI} = \mathrm{S} \times \mathrm{A} \tag{1}$$

Where CDI is crop diversity index, S is the total species in 6 years prior to the soil sampling, A is average species per year. Thus, the CDI was used as a representation of temporal and spatial diversity. The species of crop and land use were summarized in Table A.2.

Tillage practice were documented through survey questions of tillage tool types and number of passes across the field. Then, tillage intensity was quantified for each field using a simplified version of the Soil Tillage Intensity Rating (STIR) formula from the NRCS RUSLE2 model (NRCS, 2008) and averaged over the years. The RUSLE2 formula assigns a unique intensity coefficient to each tillage tool. STIR coefficients were averaged across the range of possible values for each tool type because detailed information, such as tool set-up and working depth, was not available. Tillage intensity was thus calculated as Eq. 2.

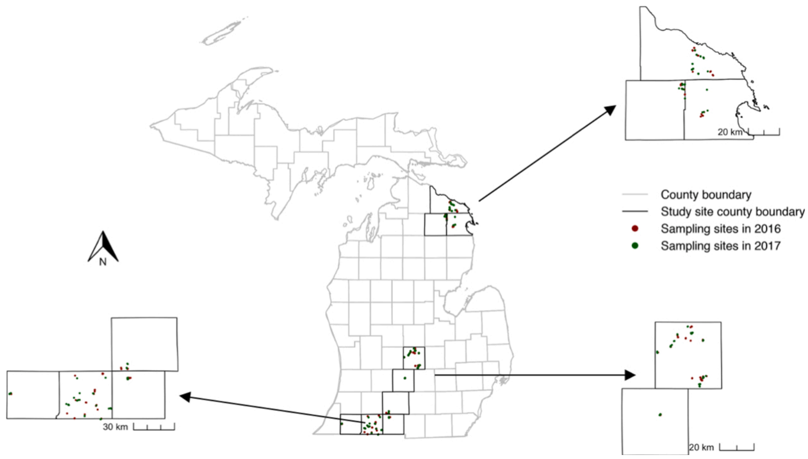


Fig. 1. Sampling Locations of 242 focal plots in three regions in Michigan.

Table 1
Mean of environmental properties, management index, and soil edaphic properties of focal plots (n = 242) per region. Letters compared across a row indicate differences by region at $p \leq 0.05$.

	Southwest (n = 74)	Central (n = 90)	Northeast (n = 78)
Latitude/ Longitude	41.93 °N/-85.47 °W	42.91 °N/-84.62 °W	45.23 °N/-83.82 °W
MAT	10.46 a	9.79 b	7.58 c
MAP	984.76 a	889.63 b	813.84 c
ARID	0.73 c	0.78 a	0.75 b
NDVI	0.19 b	0.22 a	0.21 a
Elevation	263.64 a	241.53 b	236.50 b
Slope	2.15	1.94	2.21
CDI	3.81 a	2.98 b	3.75 a
Tillage intensity	57.79 a	40.67 b	28.03 c
Clay	8.10 b	14.13 a	14.07 a
pH	6.52 b	6.60 b	7.28 a

MAT, mean annual temperature (C) from 2006 to 2015 or 2007–2016 based on the sampling year from MODIS11A2 at a resolution of 1 km; MAP, mean annual precipitation (mm) from 2006 to 2015 or 2007–2016 based on the sampling year from TerraClimate at a resolution of 4 km; NDVI, normal difference vegetation index, mean calculated from 2006 to 2015 or 2007–2016 based on the sampling year from LANDSAT band 3 and band 4 at a resolution of 30 m; Elevation, elevation (m) from STRM; Slope, slope (%) from STRM; CDI, crop diversity index; Clay, clay percentage (%). Means with different letter in each row indicate significant difference among the regions at $p \leq 0.05$.

$$\text{Avg.STIR} = C \times P / Y \tag{2}$$

Where Avg.STIR is the average annual tillage intensity, C is the average tillage tool coefficient, P is the number of passes reported in the management survey over the 6 years, and Y is the number of years. The system was categorized as NT when Avg.STIR is zero and categorized as CNT when Avg.STIR is above 80.

2.3. Soil sampling and analysis

2.3.1. Soil sampling

For each focal plot, 20 soil sub-samples were collected at the depth of 20 cm following a random zigzag pattern with a 5 cm diameter soil probe shortly before planting. The soil samples were stored at −4 °C before processing, sieved to 6 mm, and mixed until homogeneous. Soil penetration resistance was measured at 0−15 cm depth and 15−45 cm depth in situ using a hand-held penetrometer (Churchill Industries, Minneapolis, MN).

2.3.2. Soil properties

Soil pH, available phosphorus, exchangeable potassium, magnesium, calcium, and cation exchange capacity (CEC) were analyzed (A & L Great Lakes Laboratories, Fort Wayne, IN). Soil pH was determined in a 1:1 soil to water slurry. Available phosphorus and exchangeable cations were extracted according to Mehlich III (Mehlich, 1984), and analyzed by inductively-coupled plasma spectrometry through the mass spectrometer detection of elements. The data for exchangeable cations were correlated to and reported as a 1 N ammonium acetate extraction (McIntosh, 1969). Percent base saturation and CEC were calculated from exchangeable cations measurements. Soil texture and WAS were measured following the protocol described in Moebius-Clune et al. (2016) (Cornell Soil Health Lab, NY). Soil organic carbon (SOC) and total soil nitrogen were measured by dry combustion on a Costech ECS 4010 CHNSO Analyzer (Costech Analytical Technologies, Valencia, CA).

Permanganate Oxidizable Carbon was determined following the protocol by Culman et al. (2012) adjusted from Weil et al. (2003). Two-and-a-half-gram soil samples were weighed and added to 50 mL centrifuge tubes with 2 mL of 0.2 mol L^{-1} $KMnO_4$ and 18 mL of deionized (DI) water. A batch of eight samples was run at each time as recommended in Culman et al. (2012). The centrifuge tube was shaken for exactly 2 min at 240 rpm and settled for exactly 10 min. Then, 0.5 mL of the supernatant was mixed with 49.5 mL of DI water, transferred to a 96-well plate, and the absorbance was read with the BioTek Synergy Microplate reader at the wavelength of 550 nm (BioTek Instruments Inc, Winooski, VT).

Water Filled Pore Space (WFPS) was determined for each soil type, classified based on the soil texture, with 5 replications through a gravimetric method adjusted from Haney and Haney (2010). Forty grams of soil were measured for volume, added to a 50 mL plastic beaker with drainage holes in the bottom, wetted by adding 30 mL DI water, mounted on a funnel in the 237 mL mason jar, and allowed to drain for 24 h. After 24 h, the wet soil sample was oven-dried at 105 °C for 24 h. Then, the WFPS for each soil type was calculated based on the wet soil weight, the oven-dried soil weight, and the volume. Carbon mineralization (Cmin) was determined using the rewetted method adjusted from Franzluebbers et al. (2000). Ten grams of air-dried soil samples were rewetted to 50 % WFPS based on the soil type in a 100 mL beaker and incubated for 72 h in a 237 mL mason jar at 24 °C in dark. The CO_2 concentration was measured by injecting 0.5 mL into LI−COR LI-820 infrared gas analyzer (LI−COR Biosciences, Lincoln, NE) at the time of sealing the jar and after 24 h. Carbon mineralization was then determined by difference of initial and 72 h CO_2 concentration.

Potentially mineralizable nitrogen (PMN) was determined on field moist soil samples adapted from the anaerobic incubation method (Drinkwater et al., 1996). Soil inorganic nitrogen at day 0 was determined by the nitrate and ammonium content extracted by 1 M potassium chloride through colorimetric approach. Ten grams of soil was added to 40 mL potassium chloride solution, shaken at 240 rpm for 1 h, settled for 1 h, and filtered through Whatman no. 42 filter paper. Next, 10 mL deionized water was added to 10 g of soils, purged with N_2 gas, incubated at 37 °C for 7 days, and removed for ammonium determination with 30 mL of 1.33 M potassium chloride. The difference of ammonium in day 0 and day 7 is the soil PMN.

2.4. Remote sensing data

National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST— MOD11A2) database was used to calculate the 10-year mean annual temperature at a resolution of 1 km from 2006 to 2015, and from 2007 to 2016 for focal plots sampled in the two years, respectively (Wan et al., 2015). Potential evapotranspiration and precipitation were extracted from TerraClimate (Abatzoglou et al., 2018) to calculate the 10-year average aridity index (ARID) at a resolution of 4 km from 2006 to 2015, and from 2007 to 2016 for focal plots sampled in the two years, respectively (Eq. 3). Ten-year growing season NDVI from 2006 to 2016 and from 2007 to 2017 were calculated based on the Landsat 7 database band 3 and band 4 at a resolution of 30 m (Eq. 4) (USGS, 2019). Elevation data was derived from NASA Shuttle Radar Topography Mission (SRTM) Digital Elevation Model at 30 m resolution (NASA JPL, 2013).

$$\text{Aridity Index} = \text{Potential evapotranspiration} / \text{Precipitation} \quad (3)$$

$$\text{NDVI} = (\text{Band } 4 - \text{Band } 3) / (\text{Band } 4 + \text{Band } 3) \quad (4)$$

2.5. Statistical analysis and data visualization

The data was processed in RStudio version 1.1.456 (Rstudio Team, 2021). Fishers' Least Significant Difference (LSD) tests were used to assess the means of variables at the three regions at the 0.05 probability level with Bonferroni adjustment using the *agricolae* package (de Mendiburu and Yaseen, 2020). Normality of residuals was tested through the Shapiro-Wilk test and homogeneity of variance was tested by Bartlett's test.

We performed Bayesian linear regression in Python 3.6.5 package *PyMC3* version 3.8 to assess the drivers of soil health indicators at the 90 % and 95 % credibility levels (Salvatier et al., 2016). This means that we provide credibility intervals for parameters at these levels of significance. Prior distributions were set within classes of conjugate priors: standard normal distributions for the regression coefficients and the inverse-gamma distribution for each model's error term. The prior variances for these distributions were taken to be fairly wide, to present relatively non-informative priors, allowing the Python package ample space for exploration. The generation of samples from the posterior densities, as performed in this package, was based on two independent Markov Chain Monte Carlo (MCMC) sequences of 10,000 iterations after burn-in with 500 iterations; the package uses the standard Gibbs sampler methodology.

Eq. (5) show the linear regression models used in the Bayesian framework in this study:

$$Y_{ij} = \alpha_j + \sum_k X_{ik}\beta_{kj} + \varepsilon_{ij} \quad (5)$$

where in Eq. (5): for each focal plot i, the response vector Y_{ij} is formed of the soil health indicators of interest (SOC, TSN, Available P, Available Ca, PEN15, PEN45, WAS, POXC, Cmin, PMN), the vector component α_j is the model's y-intercept for response j; X_{ik} is a design matrix that include all predictors (MAT, ARID, NDVI, CDI, TI, clay, and pH) in the vector X_i of response variables X_i for plot i; β is the vector of regression coefficients, so that β_{kj} is the regression coefficient of the kth explanatory variable in X as it relates to the jth response variable Y_j; and ε_{ij} is a matrix of Gaussian noise terms with mean 0 and variance 1, assumed to be independent across all responses and all focal plots.

3. Results

3.1. Environmental factors

Across all 242 focal plots, there was a consistent and significant location effect on the MAT and MAP (Table 1, Fig. 2). The long-term mean MAT for the southwest region was the highest (10.46 °C), followed by the central (9.79 °C), and then by the northeast region (7.58 °C). Our analysis of MAP data also showed the same pattern of the gradient from southwest to northeast. Yet, ARID was highest in the central (0.78) followed by north (0.75), and was lowest in the southwest (0.73). Noticeably, ARID was not related to any of the other environmental variables (Table A2). The southwest region also had the lowest NDVI compared to the central and northeast regions. The mean elevation per region ranged from 237 to 264 m; the southwest region had the highest average elevation compared to the other two regions. Slope was gentle across all regions (1.94 %–2.21 %). There were observed correlations among environmental variables as shown in Table A2. However, the majority of the correlation coefficients were low, except for MAP and MAT (R^2 = 0.87, p < 0.05). Thus, in our Bayesian linear regression model, we included MAT, ARID, and NDVI.

3.2. Management practice

Crop diversity indexes were lower in the Central region (2.98) compared to the Southwest and Northeast regions (3.75 and 3.81). The majority of the focal plots in the Central region had a CDI value lower than 4, as observed in the density plot in Fig. 3. In both the Southwest

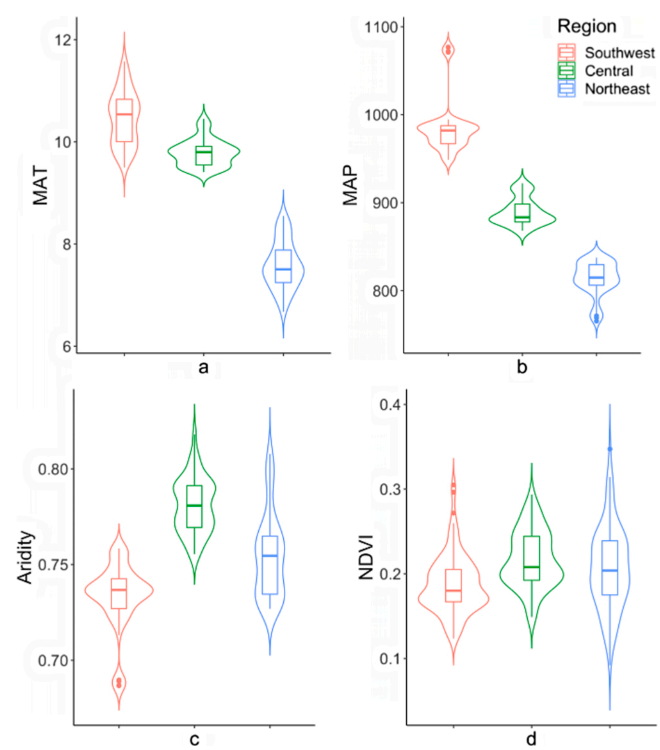


Fig. 2. Environmental factors (MAT, 10 year mean annual temperature; MAP, 10 year mean annual precipitation; Aridity, 10-year average aridity index; NDVI, normalized difference vegetation index) across three regions (n = 242).

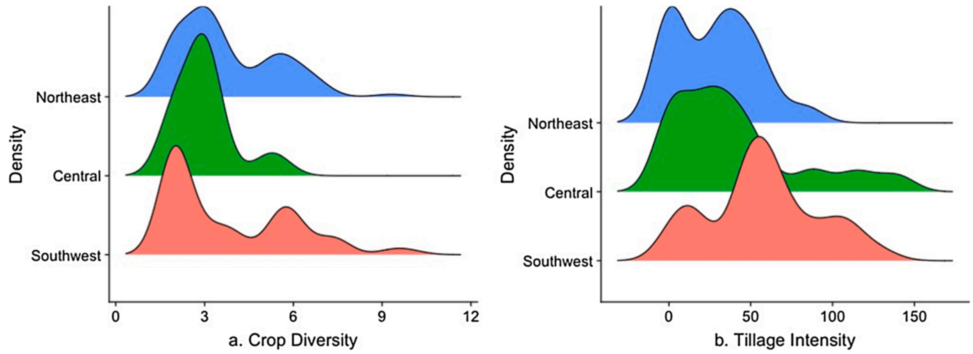


Fig. 3. Density plot of crop diversity index and tillage intensity across three regions (n = 242).

and Northeast regions, the distribution of CDI ranged from 2 to 10. Across all three regions, the most common crops were corn (*Zea mays* L.), soybean, cover crop, and wheat (*Triticum aestivum* L.) (Table A3). However, the frequency of corn, soybean, and wheat varied by region. In the Central region, corn, soybean, and wheat made up 91 % of all crops in 6 years, compared to 72 % in Northeast and 74 % in Southwest. Forage, potato (*Solanum tuberosum* L.) and dry beans added diversity to these other regions. There were no monocultures of continuous corn included in this study.

Tillage intensity across focal plots ranged from 0 to 143, where zero represents NT and a value of 80 or more represented CNT. Notably, focal plots were least intensely tilled in the Northeast (28) compared to the plots in the Central and Southwest regions (58 and 41, respectively). In the Northeast region, where MAT and MAP were both low compared to the other two regions, farmers used less intense tillage and more crop diversity. In the Southwest, where MAT and MAP were highest among the three regions, farmers used more conventional tillage compared to the Central and Northeast region (Fig. 3b). The highest use of NT was found in the Northeast region, followed by Central, while in the Southwest NT was half that of the Central region.

3.3. Soil properties

Our two soil edaphic indicators, clay content and soil pH showed location differences. Clay content average per region ranged from 8.10 % - 14.07 % (Table 1). The Southwest region (8.10 %) was less clayey compared to the other two regions (14.07 % and 14.13 %). Soil pH was generally neutral while ranging from 6.52 to 7.28 per region (Table 1). In this case, plots in the Northeast region showed the highest soil pH levels, indicating that this soil was neutral towards slightly alkaline. In contrast, with pH values of 6.52 and 6.60, soils in the Southwest and Central regions were slightly acidic.

In terms of the SOC and TSN pools, the Southwest region had the lowest values (Table 2). Other location patterns of soil chemical properties were not as consistent as SOC and TSN. For example, soil P and K were high in Southwest, whereas Mg and Ca were lowest (Table 2). Calcium and CEC followed the same pattern: highest in Northeast, followed by Central and Southwest region.

Surface penetration resistance per region ranged from 202.42–218.12 psi (Table 2). The variation by region was not significant at $p < 0.05$ level. However, PEN45 was more variable compared to PEN15, which was highest in the Southwest (489.16 psi), followed by Northeast (378.28 psi) and Central (302.25 psi). There was an increase of penetration resistance along the depth of sampling. The Central region had both the lowest PEN15 and WAS compared to the other two regions. Wet aggregate stability ranged from 33.29 % to 38.64 %. The Southwest region was lowest in all three biological indicators (PMN, POXC, and Cmin) among the three regions (Table 2). Carbon mineralization was less variable than PMN and POXC.

Soil clay content had a positive correlation with pH, SOC, TSN, Ca, PMN, POXC, and Cmin, as well as a negative correlation with P, PEN15, PEN45, indicating the influence of the soil edaphic properties on soil health indicators in all categories (Table 3). Yet, the negative relationship of soil clay content and PEN15 and PEN 45 showed that the high clay content did not contribute to increased penetration resistance. Similar to soil clay content, soil pH had the same pattern of correlation to those variables, except the PEN 45 (R^2= -0.11, NS). Though clay content and soil pH was correlated, the correlation coefficient was small ($R^2 = 0.34$). Therefore, we included both soil clay content and soil pH as edaphic indicators in the Bayesian linear regression analysis.

SOC and TSN were strongly correlated ($R^2 = 0.96$, $p < 0.01$). In addition, as a critical component of soil health, both SOC and TSN were correlated to all soil properties listed in the table (Table 3). Lower PEN15 and PEN45 were related to increased SOC (R^2 = -0.29, $p < 0.01$; R^2 = -0.23, $p < 0.01$) and TSN (R^2 = -0.29, $p < 0.01$; R^2 = -0.26, $p < 0.01$). Calcium content has a positive and high correlation coefficient with SOC ($R^2 = 0.78$, $p < 0.01$) and TSN ($R^2 = 0.70$, $p < 0.01$).

Soil physical properties, PEN15, PEN45, and WAS, were positively related to each other (Table 3). Among the three variable, PEN15 and PEN45 was most closely related ($R^2 = 0.45$, $p < 0.01$), followed by PEN45 and WAS ($R^2 = 0.26$, $p < 0.01$), then PEN15 and WAS ($R^2 = 0.13$, $p < 0.05$). All three soil physical variables were not correlated with soil biological indicators PMN and Cmin. In addition, WAS was correlated

Table 2
Mean soil properties of sampled focal plots per region (n = 242). Letters compared across a row indicate differences by region at p ≤ 0.05.

	Southwest (n = 74)	Central (n = 90)	Northeast (n = 78)
SOC	1.11 b	1.44 a	1.64 a
TSN	0.10 b	0.13 a	0.12 ab
C/N ratio	10.48 b	10.74 b	13.17 a
P	48.09 a	32.91 b	35.63 b
K	120.56 a	120.89 a	90.84 b
Mg	122.36 b	201.03 a	211.19 a
Ca	810.34 c	1091.85 b	1769.89 a
CEC	6.15 c	8.27 b	11.05 a
PEN15	215.74	218.12	202.42
PEN45	489.16 a	302.25 c	378.28 b
WAS	38.37 a	33.29 b	38.64 a
PMN	4.10 c	5.76 b	7.12 a
POXC	464.98 c	569.90 b	638.27 a
Cmin	65.23 b	87.03 a	86.05 a

SOC, soil organic carbon (%); TSN, total soil nitrogen (%); P, available phosphorus (mg kg^{-1}); K, extractable potassium (mg kg^{-1}); Mg, exchangeable magnesium (mg kg $^{-1}$); Ca, exchangeable calcium (mg kg^{-1}); CEC, cation exchange capacity; PEN15, penetration resistance at 0–15 cm depth (psi); PEN45, penetration resistance at 15–45 cm depth (psi); WAS, wet aggregate stability (g g^{-1}); PMN, potential mineralizable nitrogen (mg N kg^{-1} soil); POXC, permanganate oxidizable carbon (mg C kg^{-1} soil); Cmin, carbon mineralization (0–3 d; mg C kg $soil^{-1}$). Means with different letter in each row indicate significant difference among the regions at p ≤ 0.05.

Table 3
Pearson's correlation coefficients of soil edaphic properties and soil health indicators across all sampled focal plots (n = 242). Values with **, and * indicate correlations are significant at the levels p ≤ 0.01, and p ≤ 0.05, respectively.

	pH	SOC	TSN	P	Ca	PEN15	PEN45	WAS	PMN	POXC	Cmin
Clay	0.34**	0.31**	0.31**	−0.33**	0.55**	−0.21**	−0.41**	0.03	0.12*	0.31**	0.28**
pH		0.32**	0.2**	−0.23**	0.64**	−0.15*	−0.11	0.05	0.14*	0.27**	0.19**
SOC			0.96**	−0.18**	0.78**	−0.29**	−0.23**	0.19**	0.21**	0.47**	0.25**
TSN				−0.16*	0.7**	−0.29**	−0.26**	0.16*	0.17**	0.44**	0.27**
P					−0.31**	0.1	0.28**	0.04^{NS}	−0.03	−0.14*	−0.14*
Ca						−0.31**	−0.26**	0.15*	0.18**	0.48**	0.21**
PEN15							0.45**	0.13*	−0.04	−0.16*	−0.1
PEN45								0.26**	−0.11	−0.32**	−0.09
WAS									0.08	0.17**	0.04
PMN										0.18**	0.24**
POXC											0.1

SOC, soil organic carbon (%); TSN, total soil nitrogen (%); P, available phosphorus (mg kg^{-1}); K, extractable potassium (mg kg^{-1}); Mg, exchangeable magnesium (mg kg^{-1}); Ca, exchangeable calcium (mg kg^{-1}); CEC, cation exchange capacity; PEN15, penetration resistance at 0−15 cm depth (psi); PEN45, penetration resistance at 15−45 cm depth (psi); WAS, wet aggregate stability (g g^{-1}); PMN, potential mineralizable nitrogen (mg N kg^{-1} soil); POXC, permanganate oxidizable carbon (mg C kg^{-1} soil); Cmin, carbon mineralization (0–3 d; mg C kg $soil^{-1}$).

with the least amount of soil properties in the table compared to all other variables (Table 3).

Among the three biological indicators, POXC had the highest correlation coefficient with SOC ($R^2 = 0.47$, $p < 0.01$) and TSN ($R^2 = 0.47$, $p < 0.01$) compared to PMN ($R^2 = 0.21$, $p < 0.01$; $R^2 = 0.17$, $p < 0.01$) and Cmin ($R^2 = 0.25$, $p < 0.01$; $R^2 = 0.27$, $p < 0.01$). The two biological indicators based on nutrient mineralization, PMN and Cmin, were positively related at a low R2 ($R^2 = 0.24$, $p < 0.01$). In addition, PMN was also positively correlated with POXC ($R^2 = 0.18$, $p < 0.01$). However, the labile C indicators, POXC and Cmin, were not related ($R^2 = 0.1$).

3.4. Drivers of soil properties

3.4.1. Soil chemical properties

Aridity and soil edaphic properties were the main determinants for soil chemical properties, SOC, TSN, P, and Ca (Fig. 4). We observed aridity as a negative driver for all of the four soil chemical properties. Contrary to our hypothesis, the environmental factor MAT was not a determinant for SOC or TSN (Fig. 4). MAT was a negative driver for P and Ca (Fig. 4c, d). Although previous studies have used NDVI as a proxy for biomass accumulation and a predictor of regional level SOC, NDVI did not explain the three regions' SOC values. NDVI had a null to minimal negative influence on P. Clay and pH content had positive effects on SOC, TSN, and Ca; yet negative effects on soil P. The magnitude of clay and pH effect on Ca was larger than the magnitude of those two variables on SOC, TSN, and P. The management indicators, crop diversity and tillage intensity, did not have any effect on SOC, TSN, and Ca. Crop diversity index had a negative effect on the soil calcium content (Fig. 4d). The high CDI and high soil calcium content in the northeast region likely drive this relationship in our dataset (Table 2).

3.4.2. Soil biological properties

Though SOC and TSN did not respond to temperature variations, long term temperature showed a negative effect on POXC and PMN. Counter to the negative influence of aridity on SOC and TSN, aridity showed a positive effect on Cmin. In addition, NDVI was positively associated with Cmin and PMN. Clay content was a positive determinant for POXC and Cmin, which was consistent compared to the SOC and TSN (Fig. 5). Yet, neither clay nor soil pH had any impact on PMN.

Comparing the nil effects of management on SOC and TSN, we found effects of crop diversity and tillage on the labile C and N pools, which was reflected by the soil biological indicators, POXC, Cmin, and PMN (Fig. 5). Tillage intensity was a negative driver for POXC, indicating the reduced tillage intensity contributed to higher POXC (Fig. 5a). Crop diversity is a positive driver for both Cmin (at 95 % credible interval) and PMN (at 90 % credible interval). Surprisingly, tillage intensity was positively related to the PMN, RT can lead to lower PMN compared to conventional tillage systems.

3.4.3. Soil physical properties

Counter effects of ARID were found on soil physical properties: a positive effect of ARID was observed on PEN15, while negative effects of ARID was observed on PEN45 and WAS (Fig. 6). Consistent with POXC

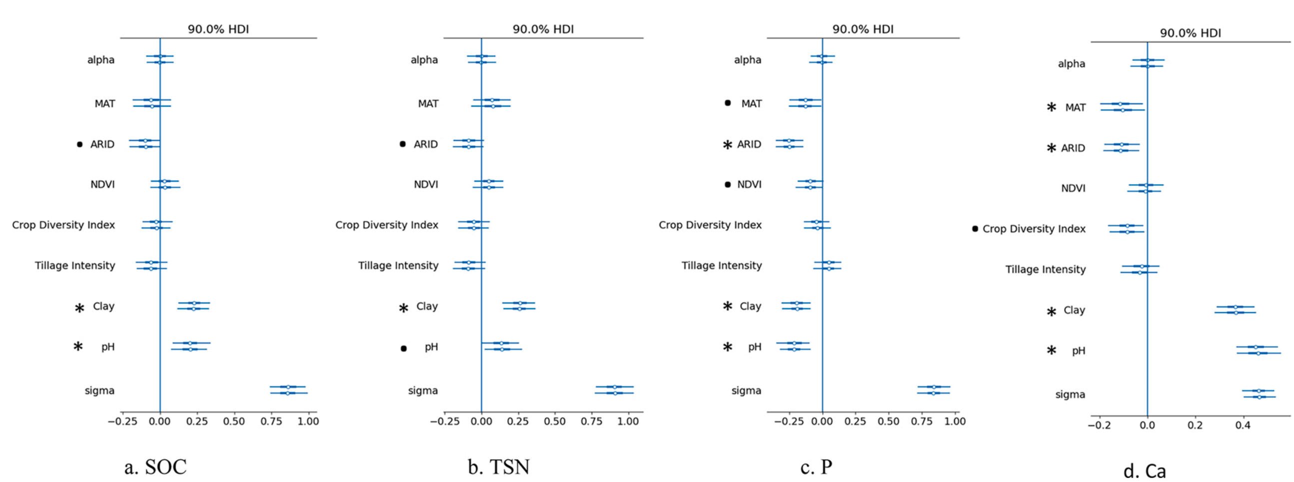
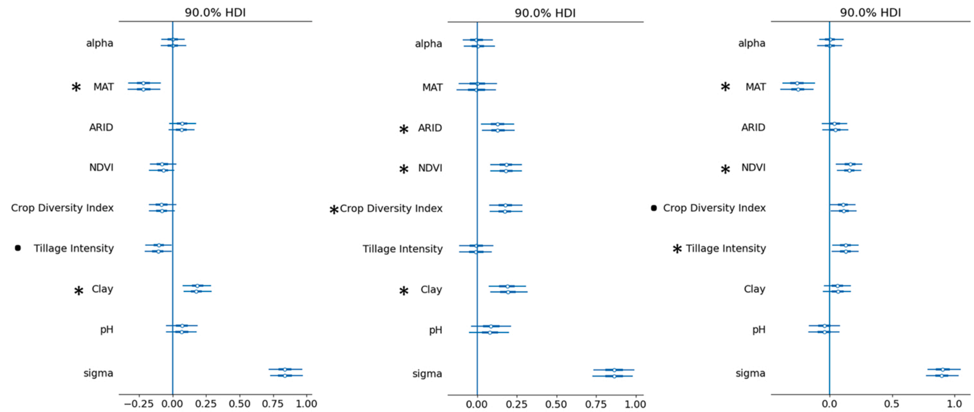
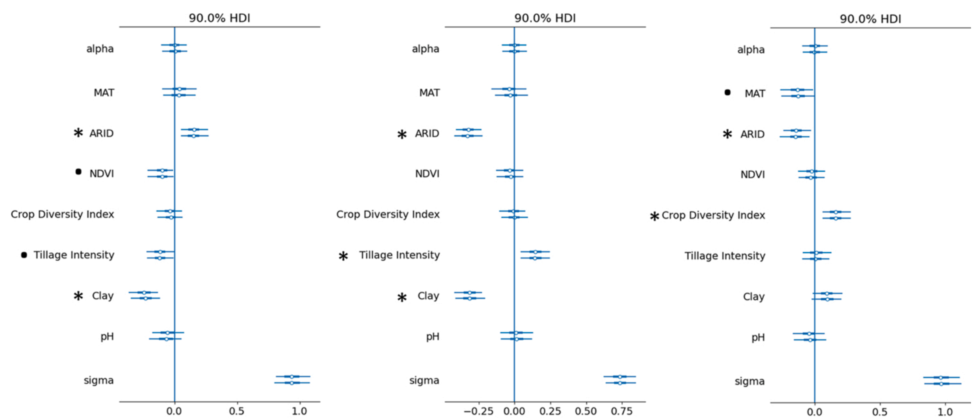


Fig. 4. Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 90 % credible intervals associated with drivers of SOC, TSN, P, and Ca across all plots (n = 242). Values with •, * indicates significance at 90 % credible interval and 95 % credible interval.



a. POXC b. Cmin c. PMN

Fig. 5. Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 90 % credible intervals associated with drivers of POXC, Cmin, and PMN across all plots (n = 242). Values with •, * indicates significance at 90 % credible interval and 95 % credible interval.



a. PEN15 b. PEN45 c. WAS

Fig. 6. Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 90 % credible intervals associated with drivers of PEN15, PEN45, and WAS across all plots (n = 242). Values with •, * indicates significance at 90 % credible interval and 95 % credible interval.

and PMN, MAT had a negative impact on WAS. We also found an inverse relationship between NDVI and PEN15, which suggested less compaction leading to more accumulation of biomass. Penetration resistance at both 0−15 cm and 15−45 cm depth was negatively related to soil clay content (Fig. 4a). Clay content was the only consistent driver for PEN15 and PEN45. Unlike PEN15 and PEN45, soil clay content did not show any impact on WAS.

Management effects on soil physical properties were depth dependent (Fig. 6). Tillage intensity was a negative determinant for PEN15 and positive determinant for PEN45. Reducing tillage intensity increases surface penetration resistance and decreases sub-surface resistance by limiting compaction. Crop diversity was also a positive determinant of WAS, which supports the positive impact of crop diversity on soil physical properties.

4. Discussion

4.1. Michigan sites

Across Michigan, location of focal plots was a key factor determining climate and soil edaphic properties, whereas farm management practices overlapped across regions. The Southwest region has a generally conducive plant growth environment for Michigan, with high MAT and long growing days. The Central region has an intermediate growth environment, whereas the Northeast region has generally cold conditions, with moderate precipitation (Table 1). For example, it can be challenging to predict which conditions are conducive to soybean production as above 20 °C is associated with suppressed soybean yield in Nebraska, but the opposite effect is seen in neighboring Minnesota (Mourtzinis et al., 2015; Wilhelm and Wortmann, 2004). Soil properties vary as well by location, with coarse textured sites common in the Southwest and alkaline sites with high calcium common in the Northeast (Table 2).

Conservation practices on field crop farms vary widely across the USA, including adoption of NT, reduced tillage and cover crops (Wade et al., 2015). Wade et al. (2015) grouped Michigan with other North Central states in their study of conservation practices, a scale of analysis which overlooks variations within a region, and in our case, within a state or farm. We found that mean tillage intensity was lowest in Northeast Michigan, with a clumped distribution, whereas tillage intensity was low for about half of Central Michigan producers, with a long tail that included a substantial minority using intensive tillage (Fig. 3).

Crop diversity patterns were also highly variable, with relatively simple rotational sequences dominated by corn and soybean in Central Michigan, and a wide range of cropping system practices at the other locations (Table A3). Northeast Michigan cropping systems stood out in terms of the presence of pasture and hay crops. Similarly, a study by Aguilar et al. (2015) found that Michigan's Northeast region has a high crop diversity index. The Northeast had both high crop diversity and the largest proportion of NT fields. The Southwest also had high crop diversity, due to high frequency of cover crop use, as well as the highest rate of tillage intensity among all regions (Fig. 3). This variable use of practices stands in contrast to studies that have shown a positive relationship between crop diversity and uptake of conservation tillage (Aguilar et al., 2015; Prokopy et al., 2019). Other studies have found that mean temperature is often positively associated with use of CT (Wade et al., 2016; Wade and Claassen, 2017). Our study highlights the variability in adoption of conservation practices that can occur within one state, where a marked gradient in mean temperature is not associated clearly with adoption of reduced tillage.

4.2. Soil health properties

4.2.1. Environment and edaphic factors

We evaluated drivers of soil health indicators, including chemical, biological and physical properties. Among environmental and soil edaphic properties, MAT, NDVI, and soil pH had modest effects on soil health indicators, whereas aridity and soil clay content were key determinants. Limited studies evaluate management practices on soil health across environmental gradients (Morrow et al., 2017; Rottler et al., 2019). In particular, there appears to be no other published research on the effect of environment, soil edaphic factors, and management practices on soil health, specifically within the Midwestern United States. In a study conducted in the Pacific Northwest on a dryland cropping system, Morrow et al. (2017) observed that MAT and MAP influence soil's organic matter more than tillage practices and crop diversity. In a study conducted across the Southern Great Plains region of the United States, Rottler et al. (2019) reported similar findings, uncovering that climate affects soil health more so than management practices. Our results confirm that environmental and soil edaphic factors, especially aridity and soil clay content, are dominant drivers of soil health in Michigan. However, we also found that management practices influence certain indicators, namely Cmin was positively associated with CDI. Although we used different soil health indicators than both Morrow et al. and Rottler et al., our results still make clear that environment and soil edaphic factors drive soil health far more than management practices.

Temperature can influence soil health indicators given its effects on the freeze and thaw cycle, decomposition rate, and biomass production from crops (Johnson et al., 2011; Rottler et al., 2019). Generally, there is a negative association between temperature and SOC and TSN due to decreased decomposition rates at lower temperatures shielding stable SOC and TSN pools from mineralization (Burke et al., 1989; Johnson et al., 2011; Morrow et al., 2017). This finding has been shown for a wide range of land uses at the regional level in the United States. from rangelands and cultivated lands in the Central Plain Grassland as observed by Burke et al. (1989) to the high altitude state of Alaska as described by Johnson et al. (2011). Yet, we observed no discernable effect of MAT on SOC or TSN across the fields included in this study. This finding may be due to the scale of our study, which focused on a gradient across the State of Michigan, rather than broad geographics areas as in the cases of both Burket et al.'s (1989) and Johnson et al.'s (2011) studies. In line with our findings, two studies conducted in the Loess Plateau region of China found that MAT did not drive spatial variation in cultivated fields' SOC or TSN values (Liu et al., 2011, 2013). In contrast to SOC and TSN, POXC and PMN were soil health indicators affected by temperature variation on Michigan farms. More specifically, we found a negative relationship between MAT and both POXC and PMN, which suggests that farms in the warmest region of Michigan (the Southwest region in this study) need to pay close attention to organic inputs in order to build labile C and N pools.

Aridity is a critical determinant of all soil health indicators investigated in this study, except for POXC and PMN. Specifically, aridity was negatively associated with SOC, TSN, Ca, P, PEN45, and WAS, and positively associated with Cmin and PEN15. Such findings on the significant effect of aridity on soil health are expected; research has long documented aridity's impact on soil's physical conditions and biological activities, given its relationship to water availability and geochemical processes (Delgado-Baquerizo et al., 2013). However, most research, to date, on the influence of aridity on soil health indicators has focused on arid or semi-arid lands (Delgado-Baquerizo et al., 2013; Jiao et al., 2016; Wang et al., 2014). Our results confirm that increased aridity poses challenges to soil health in the U.S. Midwest cultivated lands – a comparatively more humid environment than those previously studied. Additionally, the negative influence of aridity on SOC and TSN aligns with previous studies showing how low water availability can limit plant growth and biomass accumulation (Delgado-Baquerizo et al., 2013; Jiao et al., 2016). However, our finding of the negative relationship between aridity and available P countered previous research, specifically Delgado-Baquerizo et al.'s (2013) global dryland study and Jiao et al.'s (2016) regional grassland study in Inner Mongolia, China. Jiao et al. (2016) found that aridity did not affect available P. In contrast, Delgado-Baquerizo et al. (2013) observed a positive relationship between available P and aridity. Aridity may play a stronger role in physical weathering than in biological solubilization processes that influence available P. Thus, in drylands, physical weathering may increase available P. In addition, we found that aridity contributes mostly to soil's physical processes, only observing its effect on one biological characteristic—Cmin. Specifically, aridity had a positive relationship with Cmin (Fig. 5). This result counters the findings of a large-scale study conducted in Mediterranean and desert systems, which found that aridity was negatively associated with soil CO_2 respiration (Talmon et al., 2011).

Vegetative cover, as indicated by NDVI, had clear positive effects on two biological indicators — Cmin and PMN. NDVI from satellite remote sensing reflects plant growth and biomass accumulation and, thus, is used to predict SOC and TSN at multiple scales (Kunkel et al., 2011; Zhang et al., 2019). Furthermore, in managed field crop systems, NDVI determined by canopy measurements is a promising proxy for in-season N management (Fabbri et al., 2020; Po et al., 2010; Solari et al., 2008). Our study is the first to investigate remote-sensing NDVI as a driver for soil labile C and N fractions in cultivated lands. The positive relationship between NDVI and both soil labile C and N pools is due to the high return of biomass from these fields.

In addition to aridity, soil clay content was another dominant driver influencing soil health on Michigan fields. Soil clay content positively influences most soil health indicators, including SOC, TSN, Ca, POXC and Cmin, and negatively impacts available P, PEN15, and PEN45. The large surface area and high organo-mineral complexes of clay support SOC stabilization (Chaplot et al., 2010; Fernández-Ugalde et al., 2013; Swanepoel et al., 2018). Thus, clay content acts as a cementing medium that binds soil nutrients and contributes to the development of aggregates, which further stabilize soil C (Fernández-Ugalde et al., 2013; Mpeketula and Snapp, 2019). Unexpectedly, clay content was not a driver of WAS; this may be related to the role of crop residue quality on WAS in field crop farms. Although soil compaction can be an issue on fine-textured soils (Nunes et al., 2015), we observed low penetration resistance under high soil clay content. Accordingly then, there might be an interaction effect between clay content and tillage practices on soil compaction, meaning that soil texture is not the only limiting factor for WAS in managed fields.

Soil pH regulates many soil properties and is a critical driver of soil nutrients in agroecosystems (Robson, 1989; Penn and Camberato, 2019). Affirming this understanding, our results showed that soil pH influences the four soil chemical indicators (Fig. 4). The soil pH of our sites ranged from 5.3–8.0, meaning the soil we studied was slightly acid. Under these slightly acidic conditions, the SOC and TSN pool were more degraded–a finding Dlamini et al. (2016) previously noted in their meta-analysis of SOC in semi-arid soils. Our results also support that soil pH increases SOC and TSN. As Ca is a base-forming cation, the positive association between SOC and pH was expected. P availability is expected to be low in either highly acid or highly alkaline fields (Penn and Camberato, 2019). Though our sites are mostly within the range of neutral to slightly acid, we found that P decreased with soil pH.

4.2.2. Crop diversity

In terms of crop diversity (CDI), our study included 242 focal plots with 91 crop combinations over six years. Crop species directly influence the quality and quantity of residues and, thus, belowground biota, soil pores, and carbon accrual processes (Kravchenko et al., 2019; McDaniel et al., 2014). The literature shows mixed findings in terms of the effect of crop rotational diversity on SOC and TSN. In a meta-analysis, McDaniel et al. (2014) pointed out that rotated fields had significantly higher SOC values than monoculture fields. In contrast, SOC and TSN levels in monoculture corn fields were not significantly different from rotational diversified corn fields (Zuber et al., 2015). Furthermore, it is difficult to detect the effects of crop diversity on SOC and TSN in the context of an on-farm study due to underlying edaphic factors, namely texture. We observed no influence of crop diversity on SOC or TSN in this study, likely because clay content and pH varied markedly across the three studied regions in Michigan.

Crop diversity was a positive driver for three of the soil health indicators in our study—Cmin, PMN, and WAS (Figs. 4 & 5). In our study, inclusions of cover crop, pasture, and forage led to higher CDI in field crop farms regardless of species composition and perenniality. Our results confirm previous research on Cmin's responsiveness to management practices (Balota et al., 2004; Culman et al., 2013). Observations from a number of field crop experiments in the Upper Midwest are consistent, finding that plant residue diversity positively affects soil microbial communities and soil respiration (Jilling et al., 2020; Tiemann et al., 2015). Carbon mineralization and PMN were correlated in previous studies, as both are biologically mediated processes (Franzluebbers et al., 2000). Culman et al. (2013) observed higher Cmin and PMN under corn-soybean-wheat rotation than continuous corn. Similarly, Balota et al. (2004) pointed out that Cmin and PMN are higher under rotations with soybean due to the lower C: N ratio of soybean residue compared to corn. Diederich et al. (2019) in a long-term study found that perennial cropping systems had significantly higher POXC. Noticeably, crop diversity did not contribute to higher POXC in our study, which aligns with the results of Culman et al. (2013) showing that crop rotational diversity is more influential on Cmin than POXC, with the latter being more responsive to stabilized C inputs (Fig. 5). Also, our study focused on annual field crops systems, and did not include many cases of perennial crops maintained for multiple years.

Aggregate stability status was significantly higher on fields with a diverse crop history, which supports Mann et al. (2019) findings of high WAS in grass and mixed perennial-annual systems. Long-term field experimentation has provided evidence that soil aggregate stability benefits from cover crops and rotational diversity, as the biochemical diversity of residues and diverse root system architectures enhance/-support soil biological processes (Kravchenko et al., 2019; Mpeketula and Snapp, 2019; Tiemann et al., 2015). Unsurprisingly, we found that fields with high crop diversity, generally including cover crops, had high aggregate stability. However, not all studies have found a positive association between soil stabilization and cover crop diversity. Specifically, Snapp and Surapur (2018) have found that winter rye cover does not have a detectable effect on aggregate stability. Nevertheless, Tiemann et al. (2015) stated that diversity in field crop systems, regardless of the composition of specific cover crops, is beneficial to soil aggregate stability. A contribution of our study is sampling realistic rotational sequences in the Upper Midwest to show that crop diversity (regardless of species composition and perenniality) benefits soil structural stability, and microbially mediated soil C and N (indicated by Cmin and PMN).

4.2.3. Tillage intensity

Tillage intensity was associated with reduced POXC, enhanced PMN, and a depth dependent effect on penetration resistance, but had no effect on SOC and TSN in this study. SOC status has been observed to be enhanced under RT in a long-term corn-soybean wheat experiment in southwest Michigan (Grandy and Robertson, 2007), and in a decadal wheat study in China (Chen et al., 2019). Yet, the interaction of SOC and tillage intensity can be highly variable (Margenot et al., 2017; Wander and Bollero, 1999; Wulanningtyas et al., 2021). Soil depth also matters in studies of SOC response to management, as shown in a soybean experiment where NT was associated with SOC accrual only in the top 0–2.5 cm, whereas deeper in the soil SOC was not altered (Wulanningtyas et al., 2021). We considered only the surface soil at 0–20 cm, within which management effects can be more challenging to detect. This undetectable effect of tillage on SOC is in agreement with a pioneering on-farm soil health study conducted in a neighboring Midwest state (Wander and Bollero, 1999), which did show higher SOC in non-disturbed soil outside of fields, but no difference in agricultural fields with a history of NT vs CT.

Whereas stable carbon pools are generally slow to respond to management and challenging to detect changes in, we expected tillage intensity to influence soil biological indicators, such as POXC and Cmin. In a Midwest silty clay soil, Awale et al. (2013) found that POXC is less sensitive to tillage effects than Cmin. However, we found that tillage intensity was a driver for variation in POXC, but not Cmin (Fig. 5). Greater POXC under RT confirms previous studies that evaluated the tillage influence on POXC under various environments, cropping systems, and soil textures (Awale et al., 2013; Chen et al., 2019; Lewis et al., 2011). High tillage intensity leads to the breakdown of soil macroaggregates and elevated oxidization (Chen et al., 2009). POXC was higher in shallow tillage and NT systems than CT in an 11 year long-term winter wheat monoculture system on a loam in Loess Plateau of China (Chen et al., 2009). Similarly, under two silt loam soils, POXC was greater under RT compared to NT in a 3-year field experiment in Florida in a cover crop - soybean - corn system that is transitioning to organic systems (Lewis et al., 2011). In a diverse 6-year cropping system in North Dakota with soybean-corn-sugar beet, POXC values were larger under strip-till and NT than CT (Awale et al., 2013).

Tillage intensity was associated with moderate enhancement of PMN across the Michigan field sites (Fig. 5). As the most critical fraction of N for crop growth, PMN is regulated by factors, such as the water content and temperature, which can be altered by tillage through physical disturbance. Consistent with our finding, a winter wheat study that evaluated the effect of 60-year tillage practice showed that PMN was higher under conventional tillage than NT (Hurisso et al., 2014). This may be related to enhanced mineralization activity associated with a high level of disturbance, due to increased temperature (Drury et al., 1999). We presented the real-world 6-year tillage choices by farmers, which showed the disturbance in the field can contribute to releasing of the N pool for crop growth. Yet, this positive influence of tillage intensity is counter to previous long-term studies that showed greater PMN under RT than CT (Martínez et al., 2017; Sharifi et al., 2008). The effect of tillage intensity on PMN may be important for performance of legume crops like soybean that are generally not fertilized with supplemental nitrogen and left to rely on fixation and mineralization.

We observed higher compaction under lower tillage intensity at the surface (PEN15). Similar results were observed in other Midwest states, such as an on-farm study by Wander and Bollero (1999) in Illinois and a field experiment by Burgos Hernández et al. (2019) in Ohio. Since the plow layer is at 20–25 cm depth, the penetration resistance for 0–15 cm under RT is high due to lack of disturbance (Nunes et al., 2020). We confirm that high tillage intensity was associated with high compaction deeper in the soil (PEN45), which supports Burgos Hernández et al. (2019) and Nunes et al. (2020) that tillage practice hardened soils below the plow layer.

The variability in tillage operations might be another concern or limitation of this study. Differences in tillage depth or other details might restrain detection of soil health effects from specific tillage operations. Still, we hope to emphasize the value of our on-farm research approach that captures real-world variability, allowing us to consider the context within which farmers make decisions regarding tillage intensity and conservation practices more broadly.

5. Conclusion

Our on-farm study reflected real-world scenarios associated with Michigan field crop production and evaluated soil health as influenced by various environmental conditions, crop rotation sequences, and tillage intensity. The experiment confirmed that aridity and clay content are the dominant drivers for a wide range soil health metrics. Six-year management histories represented a variety of crop rotation sequences and showed the benefits of high crop diversity, including enhanced soil biological and physical properties (Cmin, PMN, and WAS). Increasing crop diversity irrespective of composition, is a promising approach to improve soil health for a wide range of environmental conditions and field crop systems. We note that crop diversity was the only factor that enhanced water aggregate stability. However, tillage effects on soil health were less clear, as intense tillage was associated with low POXC and high PMN. Although reduced tillage was associated with gains in POXC pools in the topsoil and alleviated soil compaction at lower depths; it did not contribute to available soil N. Thus, the adoption of tillage type depends on field management goals. Clearly, further investigation of tillage practices is needed to determine long-term sustainability and potential trade-offs between active C, available N, and ultimately, crop yield.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.still.2021.105146.

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