SOIL HEALTH INDICATORS FOR SUSTAINABLE AGRICULTURE IN THE UNITED STATES AND MALAWI

By

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ABSTRACT

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Maintaining SH (SH) is critical for sustainable field crop production. The first step to understanding drivers is evaluating the effects of climate, soil edaphic properties, and management practices from an on-farm study across a regional scale on SH. Thus, the farmer participatory approach and statistical analysis were integrated to understand the SH drivers in the United States and Malawi. In summary, SH indicators were assessed in this study through two perspectives with various statistical models: 1) understand various viewpoints on SH assessment; and 2) integrating Bayesian statistical analysis, hierarchical cluster analysis, and principal component analysis to determine the drivers of SH and yield in Michigan, U.S. and the Central and Southern region of Malawi.

SH is assessed through soil physical, chemical, and biological properties. However, researchers used various minimum laboratory SH datasets, resulting in inconsistency in research studies. On-site SH evaluations recommended by extension educators were not always adopted by farmers. In Chapter 1, a Likert study was employed to understand farmers' views of common soil health indicators in Michigan. The results showed that the concept of SH assessment should be consistent and clear in research studies and extension education materials.

Soil degradation is the most challenging yield-limiting factor in Sub-Saharan Africa. Without the information of current soil carbon status, farmers do not have sufficient information for deciding the appropriate management practice. Malawi's rain-fed maize system is a representation of the rain-fed maize cropping system in East Africa. In Chapter 2, soil analyses were conducted on 1108 focal plots in Central and Southern Malawi to better understand the current total and labile soil carbon status. Bayesian statistical approaches were employed to evaluate environmental and management drivers for soil total and labile carbon on Malawi smallholder fields. Overall, clay content and the vegetative cover are positive drivers for soil total and labile carbon.

To better understand the SH across the regional scale in the Midwest United States, an on-farm study of 242 focal plots was conducted in Michigan. In Chapter 3, participatory monitoring and Bayesian linear regression models were used to investigate the impact of various drivers on SH indicators under a range of conditions in the state of Michigan. Location effects were observed, with each of the three regions differing in their climate, soil edaphic properties, and management practices. Overall, climate and soil edaphic properties were the dominant drivers of SH, management practices, which also play a critical role, especially in enhancing soil biological indicators.

When evaluating SH, multivariate statistical analysis is generally used due to the inherent correlation among the variables. In Chapter 4, hierarchical cluster analysis and principal component analysis were adopted to evaluate the 1) interrelationship of various SH indicators; and 2) drivers of the variation across focal plots and local clusters. Besides the high correlated SH indicators, independent variables provide valuable information. The key determinant of SH indicators is geographical clusters. Farmers' management practices should be site-specific and goal-oriented considering the tradeoff between residual nitrogen and soybean yield.

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CHAPTER 1

SOIL HEALTH ASSESSMENT TOOLS AND A MICHIGAN CASE STUDY

1.1 Introduction

Framed within their soil knowledge, farmers' management practices influence crop profit production, environmental quality, and human well-being. Soil health is used to enhance sustainable agricultural development (Kibblewhite et al., 2008). Soil health assessment refers to the measurements or evaluative processes of the different properties which make up soil health. It is vital for farmers to understand their field and adapt their practices to manage their specific sites.

The concept of soil health assessment in land management enables the integration of soil's physical, chemical, and biological attributes (Doran and Parkin, 1996; Andrews and Carroll, 2001). Traditionally, soil's physical and chemical properties have been focused on the most due to the development of tools and their relationship with agricultural performance (Haney et al., 2018). However, the adoption and development of a soil health framework and minimum dataset collected by different research groups have been inconsistent, posing a challenge to the assessment of soil health. Analytical soil tests in the commercial laboratory are the primary approach farmers use for assessing soil health. These commercial lab soil tests have been developed in the past twenty years and have become more comprehensive, especially in the improvement of the quick measurements of soil biological properties. Yet, there is a gap between the soil health framework in peer-reviewed scholarly articles and commercial soil test labs. The main causes of this disconnection are the cost, ease to measure, and ease to interpret.

On-site characterization is also a critical component of soil health assessment. Soil physical properties measurement, such as the soil surface resistance, can only be done on-site. The measurements farmers use to characterize their soils on-site have developed in the past century from visual and physical evaluation to assessment with digital aids (Doran, 2002; Bünemann et al., 2018). New technologies have grown rapidly and assist farmers in evaluating various soil properties, from detailed guidance on sampling and evaluation of individual indicators to providing an in-time response of the field conditions and management options. Still, there are disconnections between farmers' awareness of these tools and employing soil health assessments. In this chapter, we review the definition of soil health, various soil health assessment tools, and stakeholder involvement. Based on the gaps that we found in the literature review, we identify the importance of including farmers' perspectives in the development of soil health tools. Considering all the barriers Michigan farmers have identified during field days and individual interviews, we are trying to understand the challenges farmers have in using soil health assessment tools and how they view soil health indicators. To mimic the challenges, we conducted a case study and sampled from Michigan soybean farms, with various soil types in the field, and evaluated how different soil health assessments help in providing soil information. In addition, a Likert survey on soil health indicators was carried out for the focus group to better understand farmers' views and adoption.

1.2 Soil health Assessment

1.2.1 Soil health concept and definition

The term soil health originates from the underlying connection of soil to animal and human health, and the role of soil as a living biota (Warkentin, 1995). Soil health is defined as a synonym to the health of an organism. However, the concept of soil health is understood differently by scholars, which has resulted in various definitions of "soil health" in the literature. In addition, the soil health definition has been debated by scientists since the 1990s as it is ambiguous and hard to distinguish from "soil quality" which is a similar concept (Bünemann et al., 2018). Three major approaches to understanding the connection and distinctions of "soil health" and "soil quality" are: 1) soil health emphasizes the ecological attributes of soil health or the biological indicators that soil quality does not focus on (FAO., 2008); 2) soil health and soil quality are interchangeable and is a choice of preference (NRCS., 2012), and 3) soil health represents the section of dynamic soil quality properties (Moebius-Clune et al., 2016).

The definition of soil health, by the United Nations Food and Agricultural Organization (FAO), is a good example for the first approach: "Soil health is the capacity of soil to function as a living system, with ecosystem and land use boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and promote plant and animal health." (FAO., 2008) The FAO definition of soil health noted that soil health covers the function of soil provided to ecosystem services, such as the role of soil carbon in climate mitigation. Natural Resources and Conservation Service (NRCS) under the United States Department of Agriculture (USDA) defined soil health as "also referred to as soil quality, is defined as the continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans" (NRCS., 2012). Soil quality and soil health are viewed as "interchangeable" or "equivalent" in most cases as they are both used to depict soil properties and soil functions (Bennett and Cattle, 2013). It is commonly accepted in the majority of research studies. Soil quality and soil health are viewed as equivalent in many system reviews and meta-analysis papers of "soil health.". Some scientists argue that soil quality and soil health are preferred by scientists and farmers respectively. Moebius-Clune et al.,(2016) reviews that soil quality and soil health are interchangeable while the former one includes inherent and dynamic quality, the latter one only depicts the dynamic soil quality. Thus, soil health, is defined as "refers to soil properties that transform as a result of soil use and management over the human time scale." Still, this is quite ambiguous, it is hard to have a consistent understanding of the "human time scale".

Understanding the concept and definition of soil health is the first step for farmers to identify the tools that are beneficial to their specific goals. The lack of clarity in terms of the distinction between soil health and soil quality has contributed to the confusion of farmers' soil health knowledge and choices of assessment and tools. In addition, it also leads to an inconsistent assessment of soil health in scientific communities and commercial laboratories.

1.2.2 Overall review of indicators of soil health assessment

The indicators of soil health assessment are often chosen differently depending on the research studies. In most studies, soil health assessment adopts the same soil quality indicators or more

Table 1.1: Common soil health indicators used in research laboratory.

Categories	Indicators
Physical	Texture, penetration, infiltration, bulk density, water holding capacity, mean weight diameter, porosity
Chemical	Soil chemical composition (P, K, Mg, Ca, pH, CEC)
Biological	Organic Matter, Microbial biomass C and N, potentially mineralizable N, carbon mineralization, permanganate oxidizable carbon, soil protein, soil fauna, fungai, phospholipid fatty acids, enzyme activity, soil respiration.

newly developed soil biological indicators (Doran and Parkin, 1996; Haney et al., 2018). Soil biological properties are usually the focus of soil health assessment, such as active carbon and soil protein (Awale et al., 2017; Haney et al., 2018). This is due to the argument that the biological properties are towards depicting the relationship with ecosystem services and human health (Zhu and Meharg, 2015).

1.2.2.1 Soil health indicators and framework

Researchers attempted to quantify soil health by identifying and categorizing the soil health indicators (Doran and Parkin, 1996; Obade and Lal, 2016; Xue et al., 2019). The analytical approach is commonly employed to assess these soil health indicators. The soil health indicators are usually grouped into three categories, physical, chemical, and biological properties (Table 1.1). Building upon the analytical evaluation of single indicators, several evaluation frameworks are developed for different research and land-use purposes (Andrews and Carroll, 2001; Dominati et al., 2010; Adhikari and Hartemink, 2016; Vogel et al., 2018; Xue et al., 2019).

Andrews and Carroll (2001) framework is the foundation of the later developed Soil Management Assessment Framework (SMAF) (Bünemann et al., 2018). SMAF framework identified 81 potential soil health indicators and can be selected based on the objectives of research and management. Some researchers argue that studies following the SMAF framework lack sensitivity and generality (Xue et al., 2019). Thus, Xue et a., (2019) proposed a new soil health assessment approach based on the Meta-Analytic Hierarchy Process (Meta-AHP). Through the Meta-AHP approach, the soil health assessment can reach the desired sensitive and consistent level. The effectiveness of Meta-AHP was tested using a single, long-term organic farming experiment.

Although the minimum dataset identified from the Meta-AHP approach increased the sensitivity of the SH assessment, it did not consider the sensitivity of situations where farmers actually manage their field. As articulated, that is the one example of how the scientists' work is disconnected from real-world challenges, while theoretically, this research improved the process of identifying the minimum dataset for soil health assessment significantly.

1.2.2.2 Basic soil laboratory analyses and soil biological measurements

Soil chemical analysis consists primarily of extraction of nutrients in a weak acid or base and measurements of the nutrients extracted through colorimetric or related means (Haney et al., 2018). Chemical extractable nutrients have been calibrated extensively and are used widely as an indicator of plant-available nutrient supply (Rinot et al., 2019). The chemical composition test usually consists of soil organic matter, cation exchange capacity (CEC), nitrogen (N), potassium (K), phosphorus (P), pH, and the micronutrients. The chemical analyses of these common soil nutrients and minerals are already commercialized. Chemical tests, also known as the routine soil test, are the primary approach that farmers use for evaluation of soil nutrient status, one aspect of soil health.

Michigan soybean farmers have identified the soil routine test as the most common way to evaluate soil health. As discussed earlier in 2.2.1, the soil health test is not clear enough for farmers to identify the tools for their own needs and goals. Thus, farmers use the most well-developed common indicators of soil properties, the soil routine test, to quantify the nutrients and interpret them to relate to soil health.

The soil biological properties are a critical component of soil health (Bhowmik et al., 2016). Soil biological measurements can be found in every soil health assessment framework (Andrews and Carroll, 2001; Bünemann et al., 2018). The development of biological indicators is also usually the focus of soil health assessment, from active carbon to phospholipid fatty acids (PLFA)

(Culman et al., 2013; Mann et al., 2019). These biological measurements are widely adopted in the soil health studies as they are believed to present the dynamic soil properties and sensitivity to management practices (Culman et al., 2013; Plaza-Bonilla et al., 2014; Awale et al., 2017).

Permanganate oxidizable carbon (POXC) and carbon mineralization (Cmin) have been identified as simple measures of microbial activity (Awale et al., 2017). These cost-effective indicators are adapted and commercialized for farmers (Moebius-Clune et al., 2016). The Cornell soil health basic test includes a carbon indicator, which was soil carbon mineralization and just replaced by POXC in March 2020 (Soil Health Analysis Packages, 2020). Other soil biological measurements, such as PLFA and enzyme activity, are still not available for farmers due to the cost and the interpretation difficulty.

1.2.2.3 On-Site assessment and new technologies

On-site evaluation of soil health has a long history. Before the 1970s, farmers examined the soil health indicators, such as soil color and soil texture, visually or physically (by hand) in the field (Bünemann et al., 2018). This approach of on-site quick evaluation of field conditions is still used by farmers today. Soil color can reflect the mineral existence and abundance of humus; the latter is also viewed as an indicator for the soil fertility (Fan et al., 2017). Hand texture can give farmers a rough estimation of the sand, clay, and silt distribution in the soil. Soil texture is one of the most critical soil characterizations that site-specific management depends on. The visual soil examination and evaluation (VSEE) , which was initiated more than 30 years ago, has led to on-going collaboration on developing visual measures of soil properties (Ball et al., 2013). The development of visual evaluation of soil health also leads to the emerging new technologies that aim to benefit farmers.

New tools, spurred by the growth of digital technology, have been introduced to assist farmers to characterize soil on-site. There are several affordable handheld devices and free mobile apps that provide soil data for farmers. SoilWeb (USDA., 2019) is a mobile app that allows farmers to access real-time USDA-NRCS soil survey data based on the GPS locations. Land Potential Knowledge

System (LandPKS) offers a platform that connects to the global databases and different modules that guide users to examine the soil characterizations on-site (Herrick et al., 2016) which helps practitioners better understand their soil. The interactive mobile app LandPKS has elevated the level of on-site characterizations of soils for non-experts (Herrick et al., 2016; Wiesmeier et al., 2019). Through the in-app instructions, farmers can assess soil texture and color, which can later be used to estimate the soil infiltration, plant available water, and land capacity class. Besides, LandPKS assists farmers with making decisions about the sustainable management of soils with their input of site-specific information and the connected global databases (soils, climate, and topography). Yet, on-site soil organic matter needs to be estimated as the site characterization information generated from LandPKS can be improved with this information, notably the soil water holding capacity data generated by LandPKS depends in part on-site soil organic matter.

A quick on-site measure of soil organic matter is developed by using the estimation of soil organic carbon with adopting the spectroscopic method (Zimmermann et al., 2007). Spectroscopic methods of estimating soil organic carbon have been rapidly developing and introduced to be used in the field and the laboratory (Zimmermann et al., 2007; Wiesmeier et al., 2019). With consideration of soil texture data and near-infrared spectroscopy, researchers found the estimated soil organic carbon to have comparable accuracy (Wiesmeier et al., 2019). Still, we need to investigate how these affordable devices could help farmers interpret soil health.

1.2.3 Stakeholders

The research community is aware the importance of incorporating stakeholders' opinions on the soil health indicator choice through participatory on-farm studies (Liebig and Doran, 1999).Liebig and Doran (1999) are the pioneers in developing soil health assessments for farmers, practitioners, and land users. Their study revealed the importance of the incorporation of farmers' voices. However, the field tools for farmers were not well employed. Lambert et al., (2006) reported that less than 30% of farmers in the U.S. corn belt adopted the soil test, which is based on the data from the Agricultural Resource Management Survey, which is conducted every 5 years. Additionally, de

Bruyn and Andrews (2016) stated that the soil test can be less affordable for farmers if they choose to follow the required frequency and intensity for the purpose of soil health monitoring. The affordability of soil testing for farmers poses another challenge and implies the opportunity for a soil health scorecard or mobile app to be introduced. The Natural Resources Conservation Service (USDA, 1999) suggested two major principles for designing the soil health scorecard: (1) meet the local needs, and (2) developed by farmers and for farmers. We summarized the commonly used soil health indicators from 11 developed soil health scorecards (Table 1.2). These indicators represent a variety of soil properties and can be measured easily.

Table 1.2: The most listed 13 soil health indicators in 11 soil health scorecards in various states developed by the extensions.

Top 13 Indicators	Frequency in 11 soil health cards
Compaction	9
Runoff/Erosion	9
Earthworm	8
Infiltration	8
Roots	7
Crop residue	7
Color	6
Tilth/Friability Mellowness	6
Soil organic matter	5
Structure	4
Smell of soil	4
Respiration/Biological activity	4
Plant growth	4

Researchers developed surveys to understand the role of different stakeholder groups, such as how they understand soil health and what role different stakeholder play in developing the soil health assessment. In the report of soil health and resilience stakeholder survey by Booth et al., (2019), the three main stakeholder groups taken the survey are farmers (42%), researchers (30%), agricultural consultants (26%). Based on this survey, stakeholders' understanding of the soil health definition includes believing that "physical measurables" are mostly agreed upon and followed by "ability to sustain healthy plants, and animals." However, this survey report does not acknowledge the gaps between views from different stakeholder groups and the role they play in the developing phase. Through a short study through emails with scientists from eleven countries, Bunemann et al., (2018) identified that the leading role is taken by scientists in the development of soil health assessment.

Though farmers and agricultural consultants consist of a large component of people as end-users in the soil health assessment. Limited surveys have been used to understand farmers views of soil health indicators and how to improve the development of soil health assessment to fit their needs. Cornell Soil Health Test is the first commercialized systematic evaluation that thoroughly assesses the soil samples submitted by farmers. These soil health assessment kits are very-well developed with clear guidance for farmers' interpretation. Yet, these tests can be pricey for farmers.

1.3 Case Study in Michigan Perspective

1.3.1 Methods

1.3.1.1 Study Description

Thirty-five farmers were recruited in this research study through Michigan State University Extension (MSUE), southwest, central, and northeast Michigan in 2016 (Figure 1.1). Each farmer picked one or two soybean fields, which they identified as "Good" or "Bad." For each field, the USGS web of soil survey was used to identify three predominant soil types that cover at least 2 acres and labeled as a focal plot. The study includes 138 soybean focal plots. Soil sample and yield data were collected at the focal plot level, and the management practices data was collected based on the field level.

1.3.1.2 Soil sampling and analyses

For each focal plot, 20 soil cores were collected by a 2-in diameter soil probe and compiled to a soil sample. The soil was collected at the depth of 20 cm before planting, during mid-season, and at the time of harvesting. The soil samples were stored at -4 C before processing.

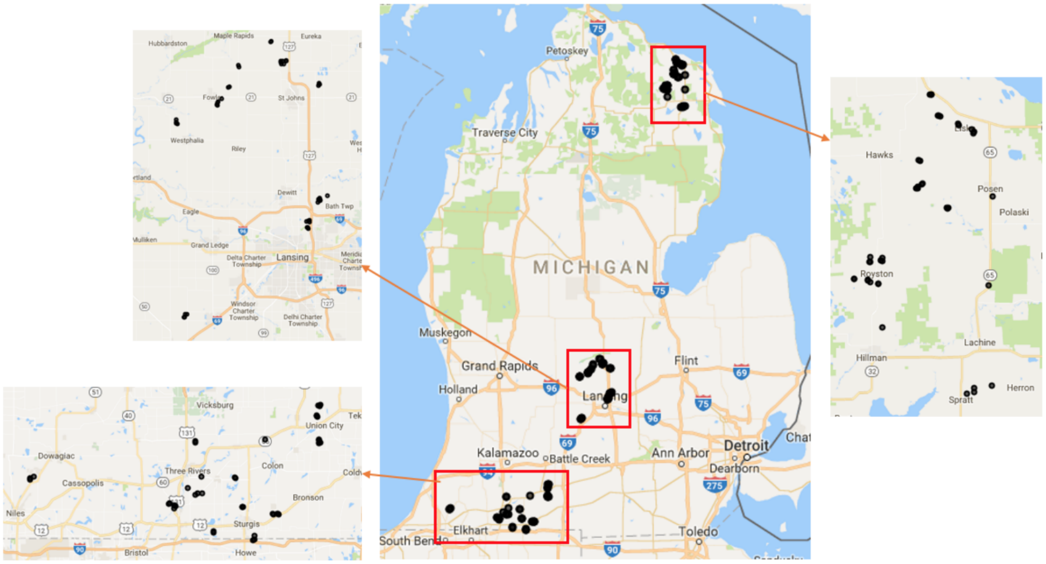
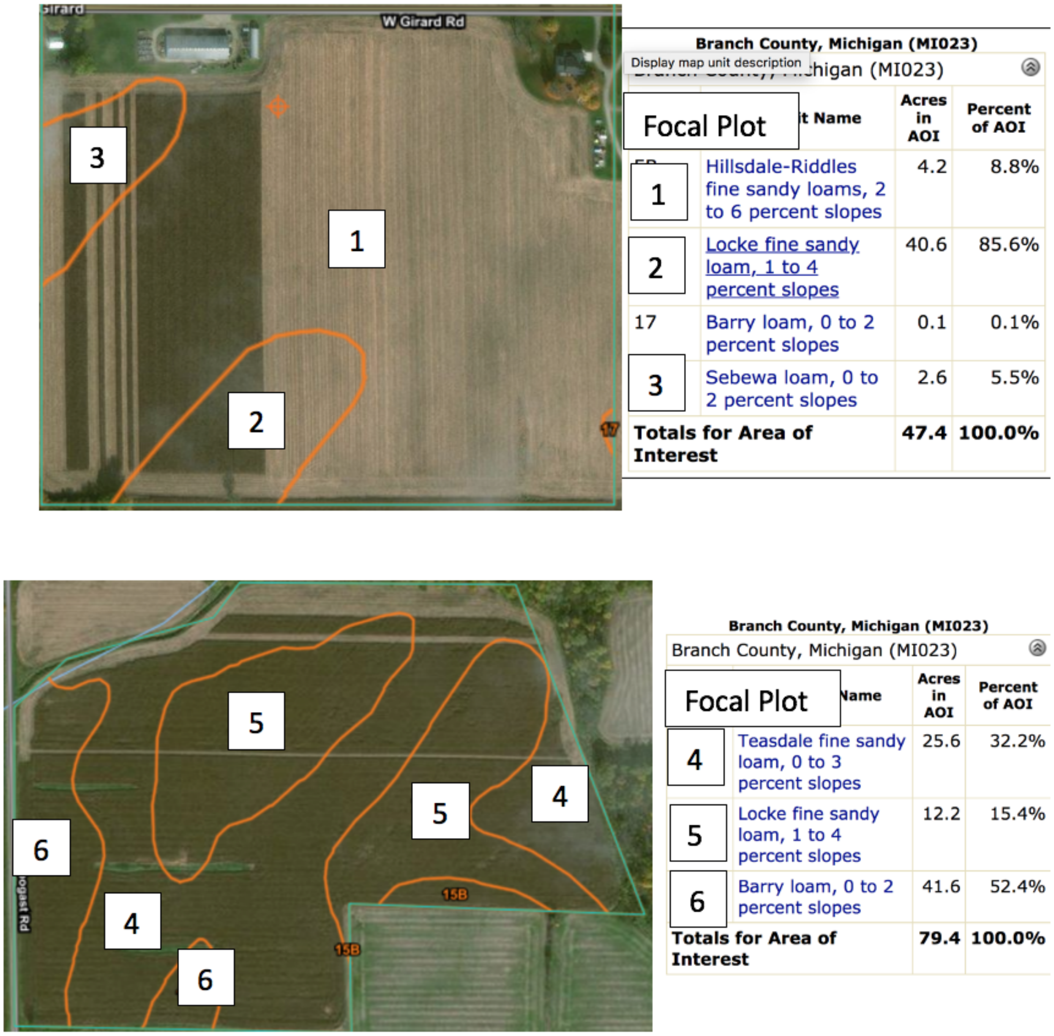


Figure 1.1: Focal plot sites in the case study

Table 1.3: Soil health indicators used in the case study.

Categories	Indicators
Soil Routine (e.g A&L Great Lakes)	Soil organic matter, P, K, Mg, Ca, pH, Buffer pH, CEC
Cornell Soil Health Basic Test	Soil organic matter, P, K, Mg, Ca, pH, Buffer pH, CEC, soil aggregate stability, active carbon, surface resistance, sub-surface resistance
Research Laboratory Tests	Soil organic matter, P, K, Mg, Ca, pH, Buffer pH, CEC, soil aggregate stability, active carbon, soil organic carbon, soil texture, carbon mineralization, potential mineralizable nitrogen.

Soil health indicators chosen from research laboratory analyses were tested in this study (Table 1.3). We also grouped them based on the 1) soil routine test, which was a common indicator for farmers, 2) Cornell Soil Health Basic Test, the most well-developed standard test; and 3) research laboratory test. The surface resistance and subsurface resistance are not tested in the Cornell soil health basic test, but the interpretation is provided based on farmer's readings of the penetrometer if they measure in the field.



Focal Plot	Map Unit Name	Acres in AOI	Percent of AOI
1	Hillsdale-Riddles fine sandy loams, 2 to 6 percent slopes	4.2	8.8%
2	Locke fine sandy loam, 1 to 4 percent slopes	40.6	85.6%
17	Barry loam, 0 to 2 percent slopes	0.1	0.1%
3	Sebewa loam, 0 to 2 percent slopes	2.6	5.5%
Totals for Area of Interest		47.4	100.0%

Focal Plot	Name	Acres in AOI	Percent of AOI
4	Teasdale fine sandy loam, 0 to 3 percent slopes	25.6	32.2%
5	Locke fine sandy loam, 1 to 4 percent slopes	12.2	15.4%
6	Barry loam, 0 to 2 percent slopes	41.6	52.4%
Totals for Area of Interest		79.4	100.0%

Figure 1.2: Site Map of the "Good" and "Bad " Fields

1.3.1.3 Study Site

All the fields in this study are from the same farmer, and every field was identified asas “Good” or “Bad.” The focal plot soil samples were collected based on the identified three dominant soil types (Figure 1.2). In the bad field, the soil types were scattered and the soil samples were collected randomly within the same soil type across the field. Thus, a total of 6 focal plots were used in this chapter.

1.3.1.4 Focus Group Likert Survey

We carried out a focus group Likert survey was carried out for a subset of farmers (n=15) to better understand farmers' views on the soil health indicators. Thus, we can improve the incorporation of farmers' views in developing soil health assessment. We summarized 14 common indicators that were recommended in various on-farm assessments by extension educators from different states. These indicators included soil-related and plant-related variables that reflect soil health conditions on a site. We developed a Likert survey based on these 14 indicators.. For each indicator, we asked farmers the following two questions: "Do you think it is a good indicator" and "Have you ever used it". The answer was recorded in a Likert system with five levels, which range from "Strongly agree" to "Strongly Disagree" and "Always" to "Never" for each question.

1.3.1.5 Statistical Analyses

The means of each soil health indicator tested in this study were calculated for each region as the benchmark. The variables were scaled using the center normalization R. We employed a radar chat to visualize the comparison of different For visualization, we used the Radar Chart. The focus group Likert survey was processed in the "Likert" package in R.

1.3.2 Results and Discussion

1.3.2.1 Information for farmers based on different choices of soil health.

Research laboratory soil health tests provide more information with extra indicators. Farmers in this project stated, "the soil analysis did at your lab (referring to the soil health analysis we did in an MSU lab) is much more comprehensive." The inconsistency of soil health tests leads to confusion for farmers. One farmer, who shipped out soil for tests at different locations, pointed out: "sometimes, soil testing labs give different results,". The extra soil health indicators that were tested are critical to show the soil functions to different ecosystem services. The indicators in the figures are also available at Cornell Soil Health test lab at a higher price. The soil properties in the "good" fields show less variation than the "bad" field.

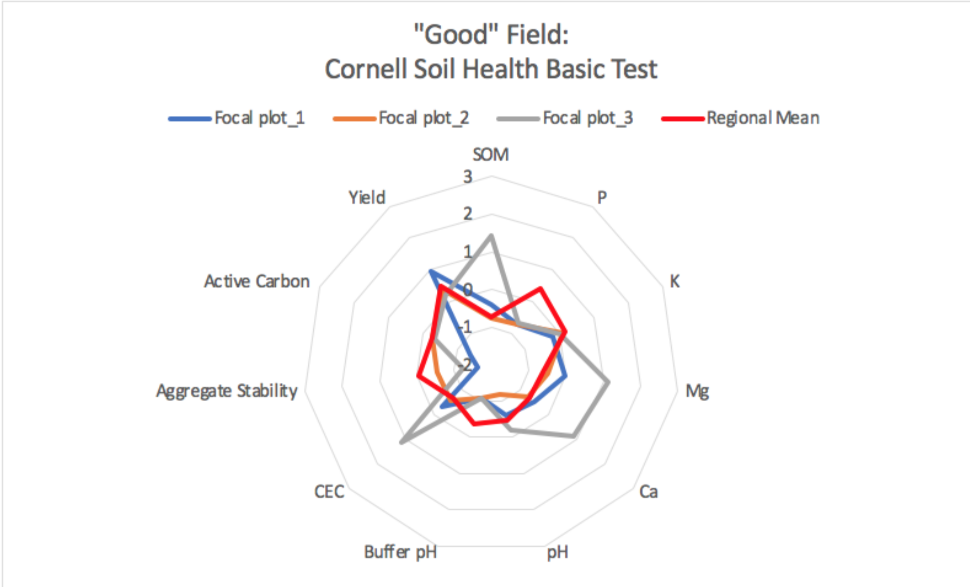
In general, both the Cornell soil health basic test and the research laboratory soil health test show the distinctions of the soil organic matter, chemical compositions, and the biological properties among focal plots for each field (Figure 1.3, Figure 1.4). In the "bad" field, there are more significant variations among the three focal plots. Active carbon, a frequently used soil health indicator, of all focal plots in the "bad" fields, is lower than the average. The low active carbon is usually linked to the available nutrient for crops. Only focal plot 4 in the "bad" field has a higher yield than the regional mean. Active carbon provides more information than SOM in the routine soil test for farmers to make site-specific management decisions. However, the active carbon (now identified as POXC in Cornell soil health basic test), needs to be better defined and explained for farmers to interpret.

In the "good" field the surface resistance and sub-surface resistance are both lower than the regional mean. In the "bad" field, focal plot-6 is significantly higher than the regional mean. Sub-surface resistance is identified as a key indicator of the yield in this project (DeDecker, 2019).Sub-surface resistance is a critical indicator that requires on-site assessment. The soil routine test does not provide the soil structure properties and underlying variations within a field. Thus, it is important to understand farmers' awareness of the accessible tools to do an on-site assessment.

Though farmers define the "good" or "bad" fields based on the previous yield, it is clear that the soil health test results of the "good" and "bad" fields are significantly different. In this case, the soil types in the "bad" field are scattered across the field and pose extra challenges in management. Improving consistency of soil health tests across research laboratories and commercial labs can better support farmers to do soil health tests and interpret the results.

1.3.2.2 Focus group survey

Farmers had positive responses in regards to valuing most of the 14 indicators as good indicators (Figure 1.5(a)). There were few neutral or negative opinions. Most indicators, except weed type



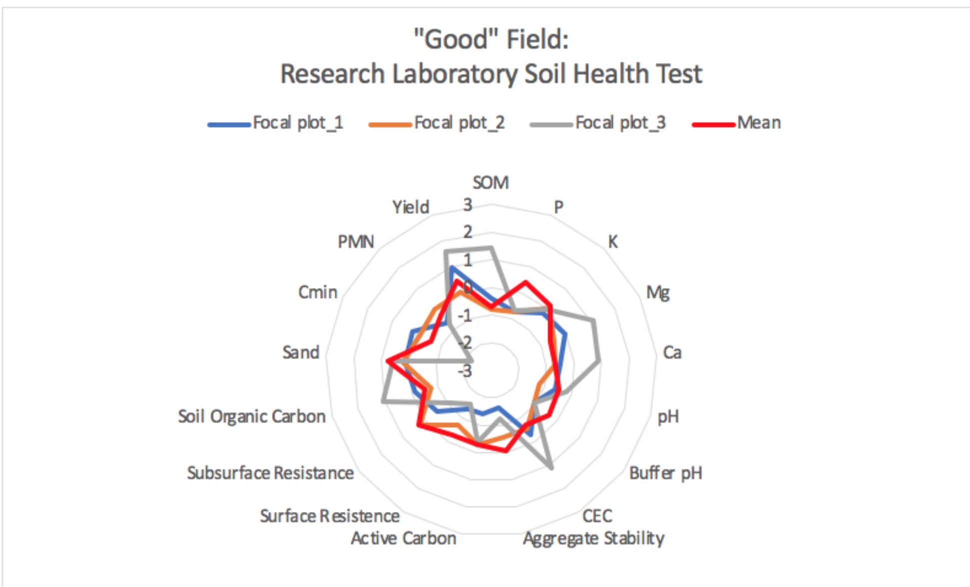
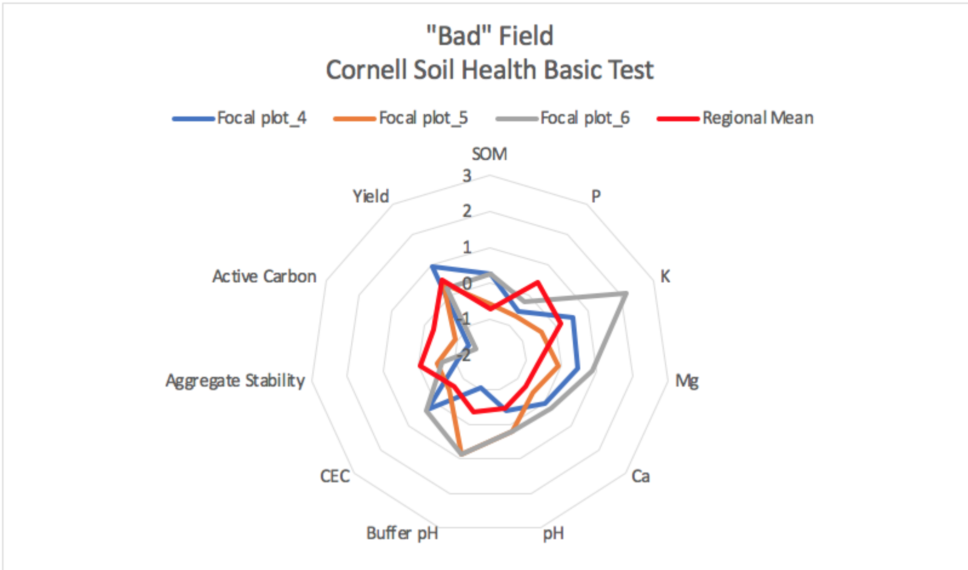


Figure 1.3: Soil health assessment of the example good fields focal plots.

present, tillage ease, and soil erosion, are recognized as good by more than 70% of Farmers responded significantly differently to the question "have you ever used it?" than they did to the question "do you think it is a good indicator" (Figure 1.5(b)). There is a gap between identifying these indicators as a good indicator and using them in the decision-making process. Most of the responses are neutral or even towards never. Crop yield stands out from all other indicators as a



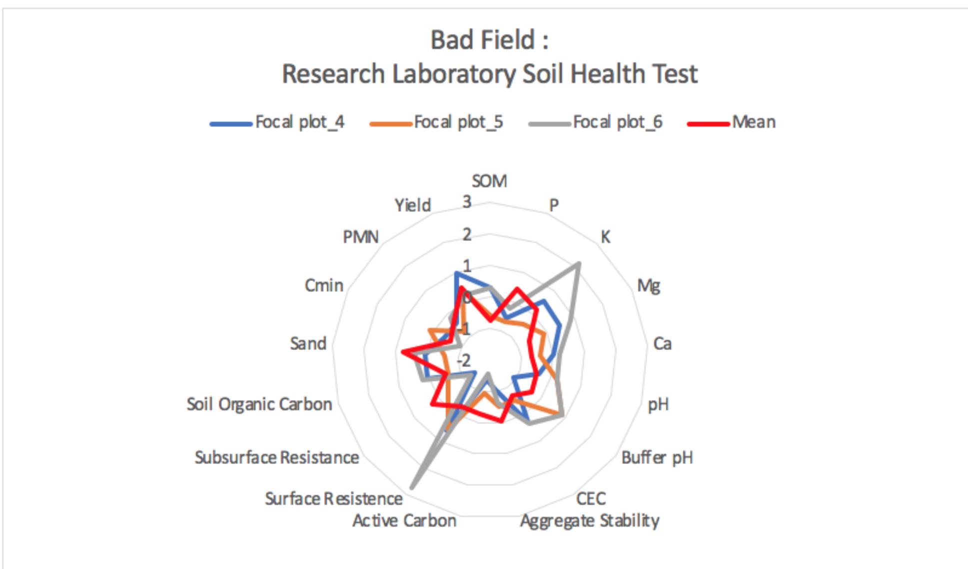
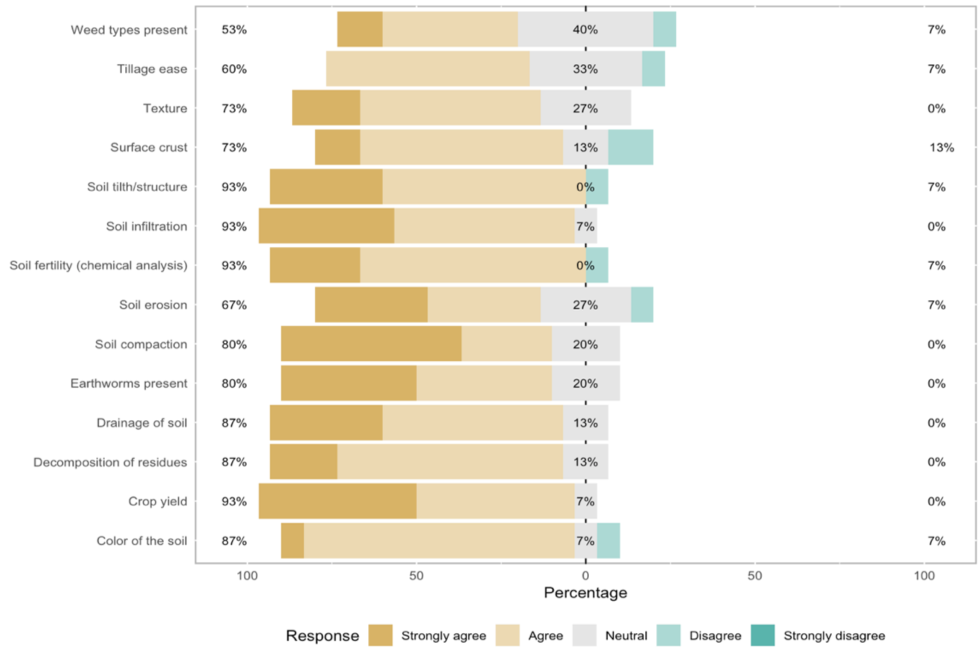


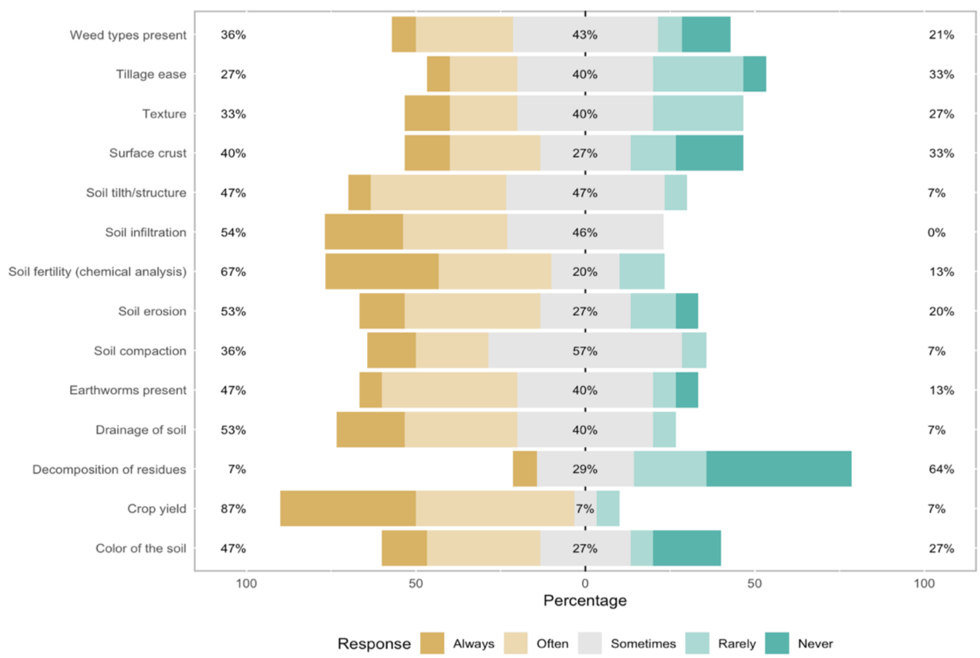
Figure 1.4: Soil health assessment of the example bad fields focal plots.

main-driver when farmers think about soil health. Though farmers have recognition of the weed type present as a good indicator, they still use it more than some other indicators, such as tillage ease and soil texture. Surprisingly, 87% of farmers view the decomposition of residues as a good indicator, while only 7% of farmers used it often.

One of the most popular soil health indicators on the scorecard, recommended from 6 out of 11 cards, is soil color (Table 1.2). In our collected data from a survey shared with Michigan farmers,



(a)



(b)

Figure 1.5: Likert study survey results

87% of farmers think soil color is a good indicator, while only 47% of farmers use it "often" and "always," and 20% of farmers have never used it before.

Soil color can reflect many soil properties and chemical processes which are not limited to organic matter and mineral composition (Fan et al., 2017., Lynn and Pearson., 2000). Identifying soil color is very simple and approachable; farmers can eyeball the difference in the soil and do not need to touch the soil. The example of an application disconnect in assessing soil color as a way to monitor soil health is not caused by the barriers in technology or affordability. Rather, we could enhance the educational program through extension programs to bridge the informational gap between researchers and farmers. Soil compaction, which can be measured through a penetrometer, is viewed by 80% farmers as a good indicator (agree or strongly agree). However, only 36% of the farmers used this often or always. The compaction measurements can only be tested in the field. Thus, it is important that farmers are aware of the method to measure and interpret the results.

These two figures show the gap between identifying soil health indicators and farmers' adoption of these indicators in the decision making process. It highlights the disconnections of farmers' views towards the value of indicators and actual use.

1.4 Conclusion

The development of soil health assessment has provided opportunities to support farmers in land management. However, the inconsistency in laboratory analyses and lack of well-developed field assessment poses challenges in cost-effective and easy to interpret soil health decision tools. The emerging new technologies highlight farmers' benefits towards site-characterization and in-time results. Including farmers in the early stage of developing field assessment tools can better fit their needs. Thus, stakeholders' perspectives should be identified at the beginning.

The highlight of this study is identifying the current gaps in the soil health assessment through literature and the focus group of Michigan soybean farmers. The stakeholder involvement is neglected in most of the soil health studies. The integration of stakeholder groups can improve the development of soil health assessment tools to fit the different needs.

1.5 Limitations

This study can be improved through three main aspects regarding. First of all, the application of new technologies can be adopted to evaluate the two fields in the case. The results of the application of new technologies, such as apps and handheld spectroscopy carbon scanner, can directly show what are the feedback and recommendations that are available for farmers. In addition, the results can be compared with the soil health indicators used in this paper. Second, parallel testing can be carried out with researchers and farmers to examine the same field using the on-site assessment aid, such as the soil health scorecard, to better understand the different perceptions and interpretations of soil health indicators. Last but not least, the Likert survey design did not investigate the reasons why farmers think the indicator is good and what are the barriers that prevent them from using the indicator.

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CHAPTER 2

A BAYESIAN APPROACH TO UNDERSTAND CONTROLS ON TOTAL AND LABILE SOIL CARBON IN EAST AFRICAN CULTIVATED SOIL

2.1 Abstract

Soil degradation on cultivated lands of Sub-Saharan African is a threat to food security. Even so, drivers of soil C total and labile pools are little understood for smallholder farms. Environment and edaphic drivers have been shown to influence soil C and N status, yet at multiple scales interactions with management practices are important, and remain largely unknown. We conducted an on-farm study of 1108 cultivated plots on smallholder farms in Malawi. Soil sample collection and analysis, crop yield monitoring and surveys of farmer practice were conducted, and linked to remote sense data on environmental and spectral factors. The farm plots were randomly chosen from seven sites, as representative of mid-altitude East African maize-based rain-fed production. Soil properties included the following ranges (mean values per site), soil clay (6.41% to 17.36%), pH (6.09 to 6.54), soil organic carbon (SOC) (6.31g C kg soil-1 to 16.17 g C kg soil-1), total soil nitrogen (0.42 g N kg soil-1 to 1.10 g N kg soil-1), and two labile soil C assays: permanganate oxidizable carbon (POXC) (291.5 mg C kg soil-1 to 504.5 mg C kg soil-1) and 24-h mineralizable C (Cmin) (28.71 mg C kg soil-1 to 65.34 mg C kg soil-1). Assessment of soil total and labile C drivers was conducted using Bayesian linear regression computed with 2 chains of 10, 000 iterations of the standard Gibbs sampler; the posterior distributions were used for determining the influential drivers for total and labile C variations. Overall, soil clay content is a strong predictor of SOC (0.479-0.517), TSN (0.475-0.555), POXC (0.139-0.266), and Cmin (0.125-0.223) at the 95% Bayesian credibility level from the Gibbs posterior samples. Vegetative cover, reflected by Normalized Difference Vegetation Index (NDVI), is also a dominant driver for SOC (0.234-0.329), TSN (0.276-0.368), POXC (0.163-0.285), and Cmin (0.249-0.38). Overall, of the management practices studied, crop diversity, residue incorporation and weed presence are all positive drivers

for total soil C and N, whereas fertilizer N is not. At both regional and local scales, labile soil C pools (as reflected by POXC and Cmin) are not consistently responsive to management. The drivers of SOC and TSN are highly consistent, a strong indication of statistical robustness. This contributes to our understanding of patterns of carbon pools in cultivated fields.

2.2 Introduction

Soil degradation is a critical problem for African countries in the tropics and subtropics where people heavily depend on agricultural production and often have limited resources or access to organic inputs (Tully et al., 2015). Smallholder farmers' cultivated lands in Africa contribute 90% of the food production (Wiggins and Keats, 2013). However, soil degradation with limited access to organic resources and the heterogeneous soil types of the smallholder farm less than 2 hectares create risks for regional food security (Mhango et al., 2013; Snapp et al., 1998). Malawi's agricultural production system is typical of the Sub-Saharan maize belt that stretches across East and Southern Africa, and increasingly in West Africa (Blackie et al., 2019). Malawi relies on rain-fed agriculture produced largely by hand cultivation on smallholder farms (Mhango et al., 2012). Yet, limited resources, soil depletion, and climatic risks pose challenges to Malawi's food security (Funk et al., 2008; Mungai et al., 2016; Snapp et al., 2018).

Soil organic carbon (SOC) is a critical component of smallholder farms because of its role in supporting soil structural stability and nutrients in addition to its other ecosystem functions (Mponela et al., 2020). In 1998, Snapp (1998) documented the status of soil on Malawian smallholder farms (generally sands and sandy loam) and concluded that SOC is sufficient for structural stability with a threshold concentration value of 8 g C kg soil-1. Mpeketula (2016), reporting an update of SOC in Malawi, observed depletion. Evaluating drivers of SOC change in smallholder farms requires understanding the impact of management practices. However, it is hard to detect how SOC responds to short-term management practices (Mpeketula and Snapp, 2019).

In recent years, researchers have used labile C measures as soil quality indicators to assess the influence of various management practices. This was because they found that labile C fractions are sensitive to the environment and management controls (Awale et al., 2013; Bongiorno et al., 2019; Culman et al., 2012; Culman et al., 2013). There is a strong theoretical understanding of soil-forming factors and the consequences for SOC pools (Wander, 2004). However, there are few studies of labile carbon pools across a climate gradient in tropical agricultural landscapes and overall limited understanding of carbon pools on smallholder farms in Africa (Murage et al., 2000; Ngwira et al., 2012). Chamberlin et al., (2021) stated that the low soil labile carbon in smallholder farms soils is a major barrier for further agriculture intensification strategies in Sub-Saharan Africa and produces complications for food security. The indicator of chemical labile SOC, permanganate oxidizable carbon (POXC), is viewed as a quick and affordable measure (Bongiorono et al., 2019) and the single best predictor for overall soil health (Fine et al., 2017). Biological labile SOC fraction measured through C mineralization (Cmin) indicates the potential availability of the labile fraction. Frost et al., (2019) stated that POXC and Cmin are two low cost soil C indicators that could potentially increase the measurements of soil health in tropical smallholder farm soils. Regional scale assessments of labile C across precipitation gradients are needed to understand the effects of environmental and management controls. There are some studies focused on the labile C variation across precipitation gradient (Fine et al., 2017; Mann et al., 2019; Nunes et al., 2021), while limited information on environmental and management controls in Malawian smallholder farm soils (Ngwira et al., 2012).

Environmental factors, including temperature and precipitation, are usually viewed as the dominant predictor of total and labile C at the regional level across landscapes, as they limit the biomass accumulation, weathering, and erosion (Burke et al., 1989; Hontoria et al., 1999; Johnson et al., 2011). Akpa et al,. (2016) evaluated several models to estimate SOC in Nigeria and found that soil type, climate, vegetation indices, and terrain attributes are important proxies. Researchers have found Normalized Difference Vegetation Index (NDVI), reflecting the vegetative cover, as a predictor for SOC at multiple temporal and spatial scales (Akpa et al., 2016; Kunkel et al., 2011, Page et al., 2013; Venter et al., 2021; Yang et al., 2020; Zhang et al., 2019). For cultivated fields, however, environmental factors are insufficient for understanding the SOC variation due to the importance of anthropogenic management (Calvo de Anta et al., 2020).

In Sub-Saharan Africa, farm practices that influence soil C are conditioned by the scarcity of organic resources. Crop residue retention can act as a mulch that provides physical protection to the surface layer, improves soil aggregate stability, and increases abundance of soil fauna. Thus, it has been widely promoted to benefit crop yield and long-term soil quality (Ghuman and Sur, 2001; Ngwira et al., 2013; TerAvest et al., 2015; Tittonell et al., 2015). However, limited crop residues are used as a soil amendment due to moderate crop growth and alternate uses, including the need for livestock feed, and fuel (Tittonell et al., 2015). There have been few smallholder farm studies that examine the impact of farmer practices on cultivated field SOC and Total Soil Nitrogen (TSN) at regional scale. Chivenge et al., (2011) pointed out that organic input is key to improving SOC on smallholder farms, particularly those on sandy soils. In the Dedza and Ntcheu districts in Malawi, crop residue retention is a widespread management practice used by farmers, although they also carry out burning of residues and removal for livestock feed (Mungai et al., 2016).

Another important farming practice besides crop residue retention, that influences soil carbon accrual is the biochemical diversity of residues. This is influenced by crop species choice and sole versus mixed cropping system arrangements. Spatial crop diversity, also referred to as intercropping, is a sustainable intensification practice that produces high grain yields per land area and, potentially, has soil fertility benefits (Snapp et al., 2010; TerAvest et al., 2015). A field study in China found that intercropping can specifically enhance soil C and N pools, relative to sole crop management (Cong et al., 2015). A crop species widely grown in East Africa, the pulse pigeonpea (Cajanus cajan L.), has recently been shown in a container experiment to enhance soil C within plant-mediated aggregates (Garland et al., 2017). There are few studies that consider how crop choice influences soil C at larger scales, which highlights the substantial research gap between the understanding of soil C determinants based on experimentation, and based on geospatial characterization.

However, challenges remain in terms of understanding long-term sustainability of intercropping and integrated crop management practices (Snapp et al., 2010; TerAvest et al., 2015). Management of all sources of diversity, including weeds, may influence organic residues' impact on soil properties. In the limited studies of weeds' ecosystem services, weeds have been found to have a positive effect on soil nutrients, although they often suppressing crop yield (Blaix et al., 2018). However, it is unknown if the role of weed presence alters soil C and N pools on Sub-Saharan smallholder farms. We know of no other study that quantifies the broad range of management practices implemented on smallholder fields, including crop diversity and weed presence, and that considers their influence on SOC and total soil N. Farmers in Malawi utilize both sole and intercrop management practices (Bezner Kerr et al., 2019; Mungai et al., 2016), providing an opportunity to evaluate soil C and N variation and the potential impact of management practices, within the context of tropical agroecosystems. As labile SOC pools are expected to be highly responsive to management, often more so than stable SOC (Culman et al., 2012; Ngwira et al., 2012), a further research gap addressed is that of predicting labile SOC patterns on these cultivated fields.

Thus, to better understand drivers for variation of stable and labile carbon pools, we integrated Bayesian analyses of statistical models to analyze the climate-induced and management-induced variables. The Bayesian approach fills the gap of identifying sensitive drivers as this method accommodates the domain specialist's expectation of uncertainty levels, as illustrated in a recent study utilizing Bayesian models to interpret maize yield predictors in an agricultural survey (Wang et al., 2019). The natural probabilistic interpretation of Bayesian outputs, aided by cutting-edge computational methods, is typically much more detailed than classical analyses, holding stronger predictive power, especially for datasets of moderate size (Dunson, 2001; Neufcourt et al., 2018), and it systematically avoids misinterpretations of p values (McShane and Gal, 2017; Wang et al., 2019).

The objectives of this study were to: 1) document current management practice and soil properties in Malawi smallholder farms; 2) evaluate the drivers that influence the stable and labile C and N pools; and 3) identify potential practices that increase SOC at the regional and local scale. We hypothesized that (i) labile C indicators would be more sensitive to management practices than SOC, and (ii) magnitude of environmental and management controls of SOC would vary at regional and local scales.

2.3 Materials and Methods

2.3.1 Overall Site Description

Malawi (9°45'-17°16' S, 32°35'-35°24' E) is a landlocked country bordered by Tanzania, Zambia, and Mozambique, and occupies 118,484 km2 in Southeastern Africa. Malawi has an overall tropical climate and a sub-tropical climate at high latitude. The hot and wet season lasts from November to April, and the cool and dry season lasts from May to October. The mean annual temperature ranges from 18 °C to 27 °C, and the mean annual precipitation ranges from 725 mm to 2500 mm in Malawi. Maize is the dominant crop planted in the country and also contributes to the profit of smallholder farmers and to the main calories intake for households.

In 2016, seven Extension Planning Areas (EPAs) in Malawi were selected based on a range of agricultural potential and representing a variety of biophysical characterizations (Li et al., 2017; Mungai et al., 2016). Golomoti and Mtakataka EPAs are located adjacent to each other and were grouped into one study site that is referred to throughout as Golomoti. This resulted in seven EPAs being represented, located in Central and Southern Malawi (Figure 2.1). Linthipe was the only site classified as high agricultural potential (Mungai et al., 2016). Kandeu, Nsipe, Nyambi, and Nsanama were classified as medium agricultural potential sites. Golomoti and Mtubwi were classified as low agricultural potential sites. A total of 614 households from seven EPAs were randomly selected for the study, with farmers asked to select two plots per household where maize was commonly grown, as described previously (Burke et al., 2020). Soil classes of the focal plots were summarized in Table A1 based on the SoilGrids250m (Hengl et al., 2017).

2.3.2 Soil Fertility Panel Survey

A farm management practice survey of the 614 households and a soil survey of two plots per household (total 1108 plots) were carried out in September and October 2016. This survey was part of the Africa RISING Panel Survey project that documented, through a questionnaire, household socio-economic characteristics while also documenting plot management practices employed, and

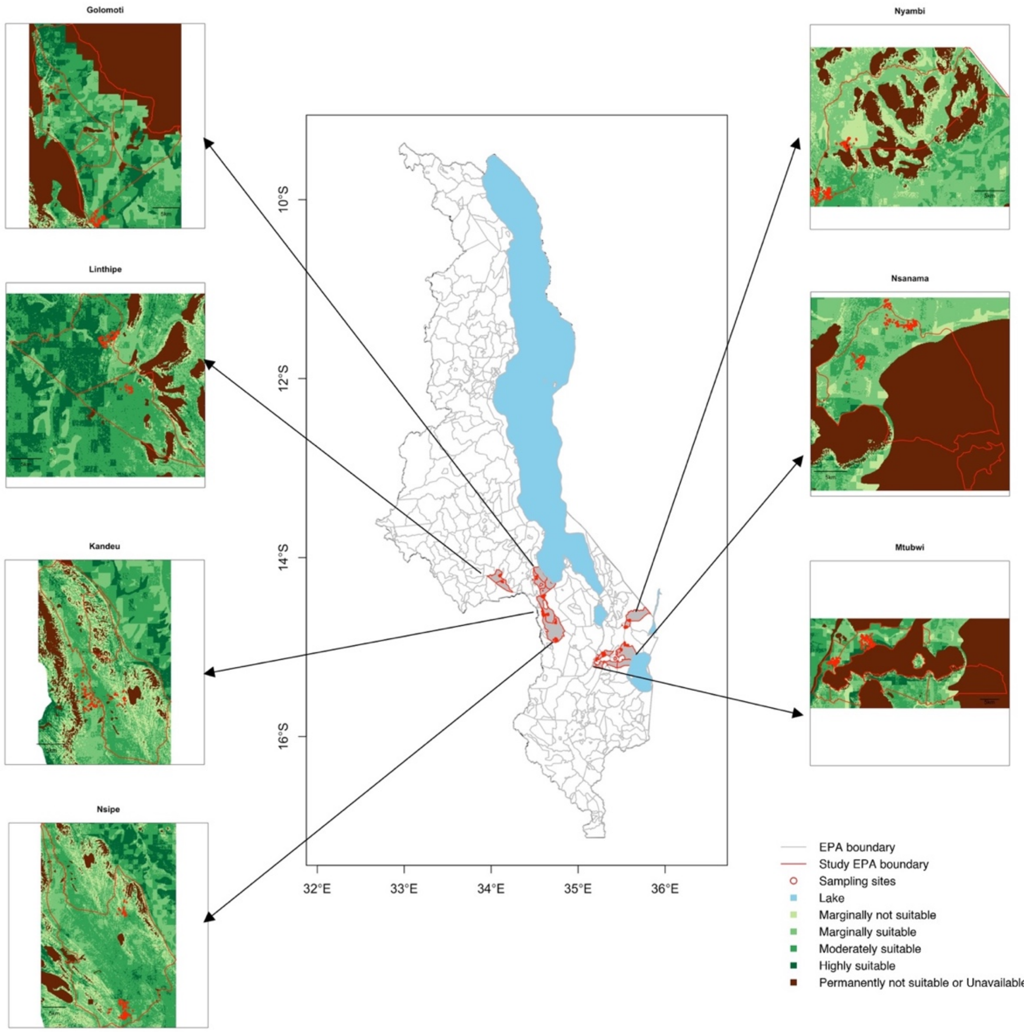


Figure 2.1: Location of farm sampling sites surveyed (n = 1108) and agricultural potential (Li et al., 2017) characteristics of Extension Planning Areas in Central and Southern Malawi.

rating of weed presence. Enumerators physically visited the plots with the farmer for the plot-specific questions, to enhance the quality of data by asking specifics about their plot management. The survey instrument and implementation protocols were supervised by MSU IRB Human Subjects Board, including following consent protocols, close supervision of enumerators by our research team, local language translations, and visual aids for specific questions.

Livestock variety and quantity were asked at the household level and then used to calculate household Tropical Livestock Units (TLUs) (Hockett and Richardson, 2018). For each household, a wealth score was calculated based on the asset indicators, employing the principal components analysis described in (Córdova, 2008).

The survey was conducted on two primary plots per household, which were rain-fed maize-based cropping systems. Most of the focal plot were under 2 acres and the mean of focal plot size per study site ranged from 0.45 to 0.83 ac. Enumerators were asked about the slope of the plot with a visual aid, the fertilizer use, manure, and compost use, residue management, crop diversity, and weed presence for the plots. The slope was assessed at each plot by categorized at four levels in the survey with a visual aid: nearly level, gentle, moderately steep, and steep. Nitrogen (N) rate in kg ha-1 of mineral fertilizer applied in each plot was calculated based on the type and application amount after converting from local units. Survey questions related to compost and manure use on study plots allowed farmers to answer regarding amounts and types of organic amendments based on local language terminology. Compost and manure amendments were further grouped into a single binary indicator of yes or no for data analysis due to the low application amount found in the explanatory analysis. Residue management was determined by categorizing the practices recorded into three groups: removal, burning, and incorporation. For assessing determinants of soil total and labile C, plot management data from the year of 2016 was used.

Crop diversity, the crop numbers per plot, was collected from 2016 in Central Malawi and 2017 in Southern Malawi. For assessing determinants of soil total and labile C, we used the crop diversity data collected around the time of the soil sampling exercise in the year of 2016. For Central Malawi, Golomoti, Linthip, Kandeu and Nsipe, 2016 data was used; for Southern Malawi, Nyambi, Nsanama, and Mtubwi, 2017 data was used (as 2016 data was not available). Data on weed presence at crop harvest was collected and used as an indicator of endogenous weediness of a plot. Enumerators were asked to rate weed cover at six random locations per plot, at four levels of weediness: zero weed presence, weeds cover soil equivalent to less than bare soil, equal to, or more of the area (photos were used to calibrate). The data were summarized into a range of 0 -18 to quantify weed intensity per plot.

2.3.3 Remote Sensing Data

Geographical coordinates of each plot were collected and used to obtain the remote sensing data of Mean Annual Temperature (MAT), Mean Annual Precipitation (MAP), Normalized Difference Vegetation Index (NDVI), and elevation. 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 from 2006 - 2016. Climate Hazards InfraRed Precipitation with Station (CHIRPS) database, recognized as the only comprehensive precipitation data source available for Malawi, was used to calculate the 10-year average precipitation from 2006 – 2016. Ten-year growing season NDVI from 2006 – 2016 were calculated based on the MODIS Vegetation Indices (MODIS13Q1). Elevation data was derived from Shuttle Radar Topography Mission (SRTM) Digital Elevation Model at 90 m resolution.

2.3.4 Soil Sampling and Analyses

Soil sampling was conducted in October, 2016, during the Malawian dry season before planting through a random sampling approach in each plot. The soil was sampled at 0-20 cm depth with a 5-cm diameter auger. The soil samples were mixed, air-dried, passed through a 2 mm sieve, and double-packaged before shipping to Michigan State University laboratory and analyzed for pH, texture, SOC, TSN, POXC, and Cmin.

Soil pH was measured in a one-to-two parts soil water solution with a standard pH meter. Textures of the samples were determined by the micro-pipette method described in (Burt et al., 1993). Soil organic carbon and total soil nitrogen were determined by dry combustion using Leco TruMac CN Analyzer (Leco Corporation, St. Joseph, MI). Permanganate Oxidizable Carbon was determined following the protocol by Culman et al., (2012) adjusted from Weil et al., (2003) with two analytical reps. 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 KMnO4 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. 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, 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 was determined using the rewetted method adjusted from Franzluebbers et al., (2000) and described in (Culman et al., 2013). 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 24 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 24 h CO_2 concentration.

2.3.5 Statistical analysis and data visualization

Fishers' Least Significant Difference (LSD) tests were used to assess the means of variables at EPAs at the 0.05 probability level with Bonferroni adjustment. The data was processed in the software R version 3.5.2. with agricolae package. Local village clusters were determined by the geographical locations of the sampling plot (Figure A2.1) Inverse Distance Weighting (IDW) interpolation map of SOC at village level was performed for six village clusters. Visualization of sampling locations and IDW maps were graphed in R.

A Bayesian approach was employed to determine drivers of SOC, TSN, POXC, and Cmin at the regional level (across all sites) and at the local level (village clusters). All the statistical analyses of Bayesian linear regression were performed in Python software version 3.6.5 with package PyMC3 package version 3.8. Prior distributions were set within classes of non-informative priors: standard normal distributions for the regression coefficients and the inverse-gamma distribution for each model's error term. Hyperparameters for these priors, particularly those determining distribution variances, were chosen according to the agronomists' prior interpretation of model uncertainty, in accordance with a systematic prior elicitation framework (Oakley and O'Hagan, 2019) two independent Monte Carlo Markov Chains (MCMC) were used as a way to check for adequate convergence with 10,000 iterations after burn-in with 500 samples, from a standard Gibbs sampler.

Equation (1) and equation (2) show the linear regression models used in the Bayesian framework in this study for regional scale and local scale, respectively:

$$Y_i = \alpha + X_i\beta + \sigma\epsilon_i \tag{2.1}$$

$$Y_{ij} = \alpha_i + X_{ij}\beta_j + \sigma\epsilon_i \tag{2.2}$$

where in equation (1): for each plot i, the vector Y_i is formed of the 4 possible responses SOC (g C kg soil-1), TSN (g N kg soil-1), POXC (mg C kg soil-1), and Cmin (mg C kg soil-1) of plot i; the vector α is the y-intercept; X is a design matrix that include all predictors (explanatory variables MAT, MAP, NVDI, slope, sand, pH, N rate from fertilizer, compost adoption, residue management, crop diversity, weed presence, and tropical livestock unit); β is the vector of regression coefficients; σ is a vector of standard deviations; and ϵ_i is a vector of Gaussian noise terms, assumed to be independent across all responses and all fields. In equation (2), the index j was introduced to the label the corresponding local village cluster; the same model structure was used for each village cluster as for the regional model of Eq. (1). For the data analysis, all variables in X and Y are standardized (their empirical means and standard deviations are computed across all i, and the variables are then scaled to result in variables with empirical mean = 0 and empirical standard deviation = 1). This allows an evaluation of the relative importance of each predictor in each model, by comparing the values of their corresponding β's directly, since all standardized variables are at the same dimensionless scale, in addition to determining whether each predictor is significant by checking that its posterior 95% credible interval does not contain the value 0. These two checks are facilitated by direct visual inspection of the so-called forest-plots produced by the Python package. The distance of a credible interval to 0 is an indication of its regressor's significance beyond the 95% credibility level, the size of its overlap with 0 is an indication of how nearly significant it might be. The distance of the middle of a significant credible interval to 0 (its β's posterior mean, indicated by a dot) is a way to measure the strength of a predictor.

The elevation was highly correlated with MAT and MAP (Table A2.2), and thus was not included in the Bayesian linear regression model analyses for climate and management. A relatively high correlation (R= - 0.69, p<0.05, Table A2.2) was found between the precipitation and temperature for the long-term 10-year average. While not necessarily of concern, such correlations can lead to collinearity problems in cases where both regressors are dominant predictors compared to other explanatory variables. This in turn can result in spurious conclusions if the regression with respect to one variable is not robust to omission of the other. It can also adversely affect the significance of less dominant predictors. In our study, robustness was an issue when omitting temperature as a predictor. Specifically, the results from models including both MAP and MAT, and MAP only showed that the model was not robust to the influence of MAP when MAP was present (Figure A2.2, Figure A2.3). Thus, only temperature was used in the model as a climatic indicator.

Robustness of the Bayesian linear regression was tested with reduced variables (Figure A2..4). With removal of three variables in the model, the results for the significance of drivers did not vary notably. Thus, the robustness of the model was confirmed to support our conclusion. We also tried classical, frequentist linear regression. We found that both methods draw the same conclusion and Bayesian is more robust. Thus, we decide to use the Bayesian approach.

2.4 Results

2.4.1 Site characterization and common management practices by EPA

2.4.1.1 The environmental context of the study sites

The average elevation of the plots in each EPA ranged from 515 to 1235 m above sea level. The Linthipe site had the highest elevation and Mtubwi site had the lowest elevation. The 10-year average MAP of the plots varied across the 7 EPAs and ranged from 782 to 978 mm (Table 2.1). Higher MAPs were observed for Nsipe site (978.30 mm), followed by Nyambi site (965.92 mm), and Linthipe site (959.54 mm) compared to all other sites. The lowest precipitation resided in the Golomoti EPA (782.21 mm). Golomoti (27.20 °C) and Mtubwi (27.17 °C) sites were identified as the two hottest environments and Nsipe (24.64 °C) and Linthipe sites (23.97 °C) were the two coolest sites based on the 10 year average MAT (Table 2.1). Long term NDVI of the 10 growing season from 2006-2016 was the highest at the Nsipe site (0.57) and the lowest at the Nsanama site (0.49) (Table 2.1).

Slopes of the plots from the collected survey with visual aid were mainly nearly level or gentle in (Table 2.1). Nsanama and Mtubwi site had no plots with steep slopes. The Golomoti EPA has the highest percentage of nearly level for the plots (57.82%), and it is the only one with nearly level as the most dominant slope. All other EPAs are dominated by the gentle slope (41.13% to 63.43%). Both Nyambi and Mtubwi had the highest percentage of gentle slope for the plots (63%). The percent of moderately steep slopes ranged from 2.67 % to 12.67%. Nsipe EPA has the highest number of moderately steep percentages (12.67%). The steep slope plots makes up 0% to 9% to the total. None of the plots in the two EPAs, Nsanama and Mtubwi, were located on steep slopes.

Table 2.1: Environmental properties based on remote sensing and observed slope of surveyed farms (n = 1108) on surveyed farms at seven sites (Extension Planning Areas, EPAs) in Central and Southern Malawi. Precipitation and temperature are mean of 10 years from 2006 - 2016. NDVI data is mean of growing season from 11/1-4/30 of 2006-2016. The range is based on the minimum and maximum value in that area. The letters indicate the Least Significant Difference (LSD) test category with one-way ANOVA test (comparison is across a row).

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 176	Nyambi	Nsanama	Mtubwi
Latitude	14.39 °S	14.22 °S	14.36°S	14.87°S	14.75 °S	14.99°S	15.10°S
Longitude	34.58°E	34.11°E	34.62°E	34.74°E	35.56°E	34.53°E	35.27°E
Elevation (m)	549.41e	1235.09a	908.43b	919.48b	817.84c	663.48d	514.85f
Precipitation (mean, mm)	782.21f	959.54b	939.91c	978.30a	965.92ab	858.49e	903.9d
Precipitation (range, mm)	754 1001	925 1048	912 989	937 1073	936 1001	850 891	844 1119
Temperature (mean, °C)	27.20a	23.97f	25.05d	24.64e	25.35c	26.23b	27.17a
Temperature (range, °C)	25.24 27.71	23.2 24.27	24.82 25.55	24.02 25.44	24.97 25.82	25.92 26.67	26.65 27.57
NDVI (mean)	0.54cd	0.53d	0.55bc	0.57a	0.52e	0.49f	0.53b
NDVI (range)	0.46 0.62	0.46 0.59	0.47 0.67	0.51 0.66	0.44 0.65	0.39 0.59	0.48 0.63
Slope							
Nearly Level (%)	57.82	36.37	39.01	36	23.43	46.52	28.41
Gentle (%)	30.61	58.33	41.13	48.67	63.43	50.8	63.07
Moderately steep (%)	10.88	3.79	11.35	12.67	11.43	2.67	8.52
Steep (%)	0.68	1.52	8.51	2.67	1.71		

2.4.1.2 Management practices by study sites

Overall, the range and intensify of farm management practices reported were consistent with an earlier survey of these farms, for the Central Malawi sites (Mungai et al., 2016). The only exception was compost use, which was substantially higher in this study (2016), at 46-60% of Central Malawi fields surveyed compared to 23 – 46% in a baseline survey conducted in this area in 2013. Across all 7 sites, 69 to 90% of the plots were fertilized (Table 2.2). Golomoti and Mtubwi both have the lowest percentage of plots with fertilizer use (69%). The average fertilizer N rate for each EPA was calculated based on the data from plots with fertilizer use. Fertilizer N rate was highest in the Nsipe (85 kg N ha-1) and the Linthipe (84 kg N ha-1), different from the two lowest sites of Mtubwi (54 kg N ha-1) and Nsanama (47 kg N ha-1). Compost application was moderately high, ranging from 36% to 60%, compared to fertilizer application which was high, ranging from 69% to 90% (Table 2.2). Crop management followed limited use of burning residues at 2 to 23%, and widespread use of intercrops (Table 2.2). Residue management of plots largely involved incorporation after crop harvest (71% - 93%), with burning residues being relatively high in only one location (Nyambi, at 23%). For the majority of plots, at least two crop species were grown. A wide range of crops per plot was observed in Central Malawi (1 to 5) compared to Southern Malawi (1 to 3). Linthipe had the highest numbers of crops per plot (3.18). A sole maize cropping system made up 0.57% to 18.37% of all plots, with few sole maize plots in Southern Malawi. Mean weed presence at all sites was above 9, equivalent to 50% coverage of the ground at harvest (Table 2.2). Nsanama (6) and Golomoti (6) had a low median weed presence, whereas Nsipe had the highest median weed presence (11). In each EPA studied, the majority of households had livestock, which ranged from 54.55% to 81.82% (Table 2.2). However, the number of livestock were very low, with a mean tropical livestock unit that ranged from 0.19 (Nsanama) to 0.93 (Kandeu).

Table 2.2: Farm management practices of plots (n = 1108) on surveyed farms at seven sites (Extension Planning Areas, EPAs) in Central and Southern Malawi. The letters indicate the Least Significant Difference (LSD) test category with one-way ANOVA test (comparison is across a row).

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
Wealth score	0.039 bc	-0.150c	0.331 a	0.243 ab	0.002 bc	0.249ab	-0.021c
Average plot size (acre)	0.63	0.45	0.68	0.49	0.62	0.59	0.83
Range of plot size (acre)	0.08-3.00	0.05-2.00	0.08-2.50	0.04-3.00	0.10-3.00	0.11-2.00	0.01-4.00
2016 Fertilizer Nitrogen							
Yes (%)	69	79	90	79	75	76	69
Mean at where applied (kg N ha-1)	64 abc	84a	81ab	85a	59abc	47c	54bc
Compost							
Yes (%)	46	56	60	49	39	45	36
Residue Management							
Incorporated (%)	81	89	93	92	71	92	81
Removal (%)	1	7	1	1	6	6	9
Burning (%)	18	4	6	7	23	2	10
Crop diversity							
Sole maize (%)	18.37	9.09	2.84	8.67	0.57	4.28	8.52
Range	1-5	1-5	1-5	1-5	1-3	1-3	1-3
No. per plot at when crop diversity > 1	2.53d	3.18a	3ab	2.83bc	2.88bc	2.73cd	2.67cd
Weeds (0-18)a							
Mean	9b	10ab	11a	11a	9b	7c	10ab
Median	6	8	10	11	7	6	9
Tropical Livestock Unit							
Yes (%)	76.87	81.82	66.67	81.33	68.57	64.17	54.55
Mean at when livestock present	0.63ab	0.46bc	0.93a	0.68ab	0.23c	0.19c	0.24c
Median	0.2	0.17	0.12	0.2	0.04	0.03	0.01
Max	6.6	2.6	9.33	6.5	1.22	1	1.55

[a] Observations of weed presence at crop harvest of 2017.

Table 2.3: Mean soil properties of plots (n = 1108) on surveyed farms at seven sites (Extension Planning Areas, EPAs) in Central and Southern Malawi. The letters indicate the LSD test category with one-tail ANOVA test (comparison is across a row).

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
pH	6.54a	6.09d	6.13cd	6.33bc	6.19bcd	6.33bc	6.34b
Texture							
Sand (%)	69.20bcd	58.64e	67.58cd	67.06d	72.53b	82.62a	70.69bc
Silt (%)	18.09bc	24.00a	17.27cd	17.72cd	15.80d	10.97e	19.91b
Clay (%)	12.71b	17.36a	15.14a	15.22a	11.67b	6.41d	9.41c
SOC (g C kg soil-1)	10.29c	16.17a	12.39b	12.25b	8.07d	6.31e	8.97cd
Coefficient of variation	0.5	0.47	0.44	0.41	0.43	0.54	0.55
Skewness	2.69	0.57	0.85	0.78	1.93	1.87	2.93
TSN (g N kg soil-1)	0.76cd	1.10a	0.86bc	0.90b	0.57e	0.42f	0.68d
Coefficient of variation	0.44	0.41	0.37	0.37	0.36	0.53	0.47
Skewness	2.97	0.56	0.78	0.56	1.34	1.67	3.18
C – N ratio	13.37cd	14.35b	14.09bc	13.56bcd	14.09bc	15.50a	12.91d
POXC (mg C kg soil-1)	386.9bc	504.5a	432.3abc	479.6a	369.3c	291.5d	446.7ab
Coefficient of variation	0.42	0.41	0.52	0.52	0.52	0.69	0.64
Skewness	0.65	0.49	0.61	1.19	2.01	2.41	1.72
C min (mg C kg soil-1)	52.76b	44.96c	56.99b	65.34a	28.71d	39.25c	40.73c
Coefficient of variation	0.43	0.37	0.41	0.4	0.44	0.52	0.4
Skewness	0.78	1.03	0.78	1	1.75	1.52	0.68

2.4.2 Characteristics of soil properties

Overall sites were slightly acid, with the highest pH at the hot and dry site of Golomoti (6.54) and the lowest at the cool and wet site of Linthipe (6.09) (Table 2.3). Linthipe also had the lowest percentage of sand (58.64%). Highest mean sand content was in Nsanama (82.62%), followed by Nyambi (72.53%) and Mtubwi (70.69%), the three sites located in Southern Malawi. Clay percentage means was highest in Linthipe (17.36%), followed by Nsipe (15.22%) and Kandeu (15.14%).

Mean of SOC and TSN ranged from 6.31 g C kg soil-1 to 16.17 g C kg soil-1, and 0.42 g N kg soil-1 to 1.10 g N kg soil-1, respectively (Table 2.3). Linthipe site had both the highest SOC (16.17 g C kg soil-1) and TSN (1.10 g C kg soil-1). The three sites with the highest sand percentage, Nyambi, Nsanama, and Mtubwi, also the three lowest SOC and TSN means. The mean C – N ratio was widest in Nsanama (15.50), the site that had the lowest SOC and TSN.

The mean POXC value was highest in Linthipe (504.52 mg C kg soil-1), and lowest in Nsanama (291.49 mg C kg soil-1). This followed the pattern observed for SOC and TSN. However, Mtubwi site with low SOC and TSN, had relatively high POXC. C mineralization value was highest in Nsipe site and lowest in Nyambi site, and generally followed the SOC status.

The two stable pools, SOC and TSN, were highly correlated at all study sites with Pearson' coefficient ranging from 0.92 to 0.98, with a significance level < 0.0001 (Table 2.4). Soil organic carbon was also correlated to POXC, with high Person' coefficient in three of the central sites, Golomoti, Linthipe and Kandeu. However, SOC was not significantly associated with the Cmin at two sites, Linthipe and Nyambi. The two labile factions, POXC and Cmin, were not correlated at the Nyambi and Mtubwi sites, whereas on other sites there was an association at low levels (0.19 to 0.47).

The regional analysis was conducted for all plots included in this study. Posterior results of the Bayesian regression analysis with 2 chains of 10, 000 iteration were shown in Fig.2. The dependent variable is at 95% Bayesian credibility if the interval of the drivers (blue line) resides on one side of the value zero. The posterior result lines show the range of 95% Bayesian credible intervals, where the two lines depict the credibility intervals for the two chains, as a convenient visual gauge of convergence of the regression's computational method.

Table 2.4: Pearson correlations between SOC, TSN, POXC, and Cmin by Extension Planning Areas in Central and Southern Malawi. Values with ***, **, and * indicate correlations are significant at the levels $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively.

	Golomoti n = 147	Linthipe n = 132	Kandeu n = 141	Nsipe n = 150	Nyambi n = 175	Nsanama n = 187	Mtubwi n = 176
SOC (g C kg soil-1) and TSN (g N kg soil-1)	0.98***	0.98***	0.97***	0.96***	0.92***	0.96***	0.93***
SOC (g C kg soil-1) and POXC (mg C kg soil-1)	0.70***	0.86***	0.67***	0.31***	0.29***	0.43***	0.32***
SOC (g C kg soil-1) and Cmin (mg C kg soil-1)	0.36***	0.14	0.51***	0.40***	0.093	0.63***	0.51***
POXC (mg C kg soil-1) and Cmin (mg C kg soil-1)	0.37***	0.21*	0.47***	0.19*	0.026	0.27***	0.14

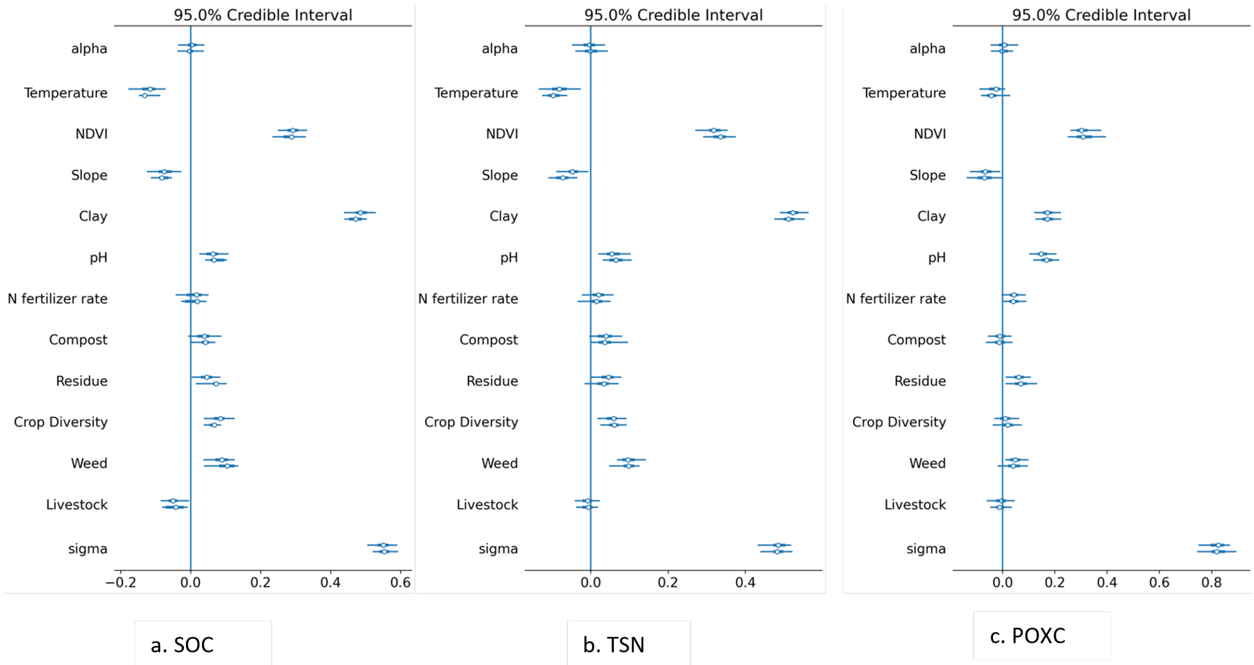


Figure 2.2: Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 95% credible intervals associated with drivers of SOC, TSN, POXC, and Cmin across all plots (n = 1108) in Central and Southern Malawi.

2.4.2.1 SOC and TSN

Across our study sites in Malawi, drivers of SOC and TSN showed a similar but not identical pattern (Figure 2.2a and Figure 2.2b). The dominant drivers were environmental and soil edaphic factors, including MAT, slope, NDVI, and clay content, where the latter two were highly positive drivers. The 10 year average MAT was negatively related to SOC and TSN, at medium magnitude (Figure 2.2a and Figure 2.2b, Table 2.4). Slope had a modest negative influence and soil pH had a modest positive association with SOC and TSN. Management practices' effects were identified, at small magnitude (Table 2.5). These included weed presence, which was a larger determinant for SOC than residue management and crop diversity. Instead of residue retention, compost was identified as a positive driver for TSN (Figure 2.2b). The number of tropical livestock units per household were found to be negatively associated with SOC.

Table 2.5: Bayesian statistics summary, significant variables are in bold with red indicate positive influence and black indicate negative influence. Values with * indicate 95% credible significant

	SOC		TSN	
	Mean (sd)	**95% Credible interval**	**Mean (sd)**	**95% Credible interval**
alpha	0.001(0.02)	[-0.036-(0.038)]	-0.002(0.022)	[-0.048-(0.037)]
Temperature	**-0.124(0.024)**	**[-0.172-(-0.086)]***	**-0.089(0.025)**	**[-0.13-(-0.04)]***
NDVI	**0.287(0.026)**	**[0.234-(0.329)]***	**0.326(0.024)**	**[0.276-(0.368)]***
Slope	**-0.078(0.023)**	**[-0.122-(-0.039)]***	**-0.059(0.024)**	**[-0.105-(-0.019)]***
Clay	**0.479(0.024)**	**[0.439-(0.517)]***	**0.518(0.022)**	**[0.475-(0.555)]***
pH	**0.067(0.023)**	**[0.03-(0.104)]***	**0.062(0.023)**	**[0.024-(0.104)]***
N fertilizer rate	0.01(0.024)	[-0.027-(0.056)]	0.018(0.023)	[-0.024-(0.061)]
Compost	0.039(0.023)	[-0.008-(0.081)]	**0.04(0.025)**	**[0.003-(0.093)]***
Residue	**0.058(0.025)**	**[0.015-(0.103)]***	0.037(0.023)	[-0.008-(0.075)]
Crop Diversity	**0.072(0.022)**	**[0.037-(0.115)]***	**0.057(0.019)**	**[0.021-(0.093)]***
Weed	**0.093(0.03)**	**[0.038-(0.136)]***	**0.097(0.022)**	**[0.06-(0.143)]***
Livestock	**-0.047(0.024)**	**[-0.082-(-0.006)]***	-0.009(0.017)	[-0.041-(0.019)]
sigma	0.552(0.022)	[0.509-(0.59)]	0.485(0.023)	[0.445-(0.528)]
	POXC		**Cmin**	
	Mean (sd)	**95% Credible interval**	**Mean (sd)**	**95% Credible interval**
alpha	0(0.025)	[-0.041-(0.046)]	0.003(0.026)	[-0.045-(0.052)]
Temperature	-0.036(0.037)	[-0.096-(0.029)]	-0.035(0.029)	[-0.084-(0.019)]
NDVI	**0.231(0.034)**	**[0.163-(0.285)]***	**0.309(0.036)**	**[0.249-(0.38)]***
Slope	-0.016(0.032)	[-0.07-(0.046)]	**-0.067(0.033)**	**[-0.126-(-0.003)]***
Clay	**0.189(0.033)**	**[0.139-(0.266)]***	**0.172(0.027)**	**[0.125-(0.223)]***
pH	**0.048(0.027)**	**[0.006-(0.104)]***	**0.161(0.028)**	**[0.117-(0.215)]***
N fertilizer rate	-0.028(0.032)	[-0.084-(0.032)]	**0.042(0.024)**	**[0.001-(0.092)]***
Compost	0.043(0.031)	[-0.007-(0.094)]	-0.012(0.026)	[-0.058-(0.034)]
Residue	0.018(0.027)	[-0.039-(0.059)]	**0.066(0.03)**	**[0.012-(0.122)]***
Crop Diversity	**0.074(0.029)**	**[0.009-(0.126)]***	0.015(0.028)	[-0.029-(0.07)]
Weed	0.035(0.032)	[-0.02-(0.09)]	0.045(0.028)	[-0.002-(0.096)]
Livestock	0.018(0.028)	[-0.036-(0.071)]	-0.006(0.027)	[-0.051-(0.04)]
sigma	0.877(0.038)	[0.81-(0.943)]	0.823(0.038)	[0.75-(0.881)]

2.4.2.2 Labile carbon

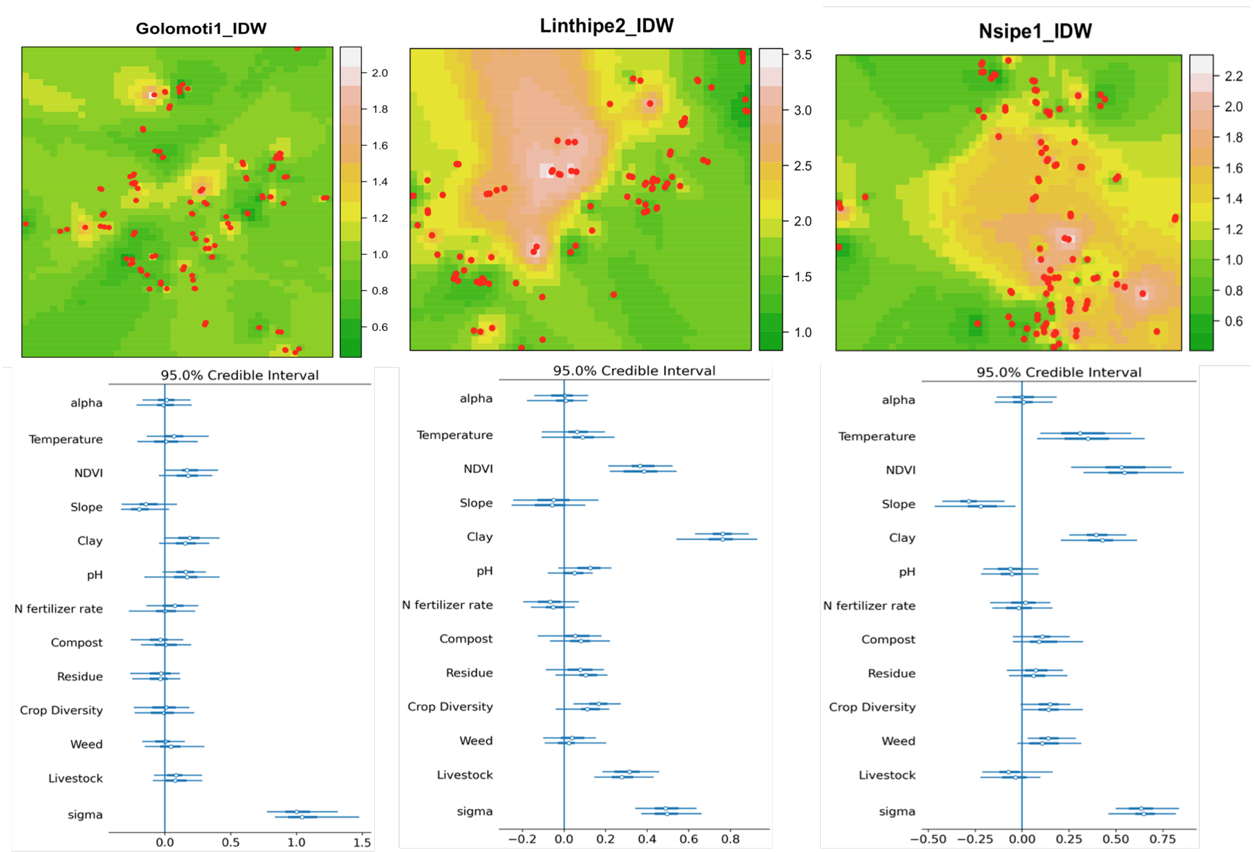
Main determinants of POXC were identified as NDVI and clay, which were also important determinants of SOC and TSN (Figure 2.2c). Soil pH was also significant at small magnitude. The only significant management practice indicator was crop diversity. However, environmental factors did not show an effect on POXC and only one management factor was influential, that of crop diversity.

Carbon mineralization was also not associated with the climatic indicator, MAT. Yet, C mineralization was more sensitive to drivers in the model compared to POXC (Figure 2.2d). Four environmental variables and two management indicators were determinants of Cmin. Similar to the stable C and N pools, NDVI, soil pH, and clay percentage were positively related to Cmin. The N rate from fertilizer application was found to be positively associated with Cmin, while no significance was shown for SOC, TSN, and POXC. Residue retention was also a positive driver for Cmin.

2.4.3 Local level drivers of soil properties

The climatic indicator, ten-year average MAT, was a dominant determinant of SOC at the regional level, and associated with SOC variations at three local sites (Figure 2.3 and Figure 2.4). Clay content and NDVI, showed markedly positive influences on SOC at several sites, and the magnitude was considerably larger than all other indicators in the local model.

At the Central Malawi sites, NDVI was a positive driver for SOC at varying magnitude for two local sites, but none of the management controls had shown influence on SOC except livestock ownership in the Linthipe cluster (Figure 2.3). At the Golomoti cluster, the low agricultural potential site, NDVI did not show any influence on SOC variation. Soil organic carbon in plots at the Linthipe village cluster was highest compared to other clusters. At the Linthipe cluster, three main determinants in the order of large to small magnitude are clay content, NDVI, and livestock. Compared to the Golomoti and Linthipe village clusters, plots in Nsipe had more steeper slopes (Table 2.1). Slope was identified as a negative determinant for SOC at Nsipe site. In addition, Nsipe site was identified as the coolest site in this study (Table 2.1), thus temperature was a positive

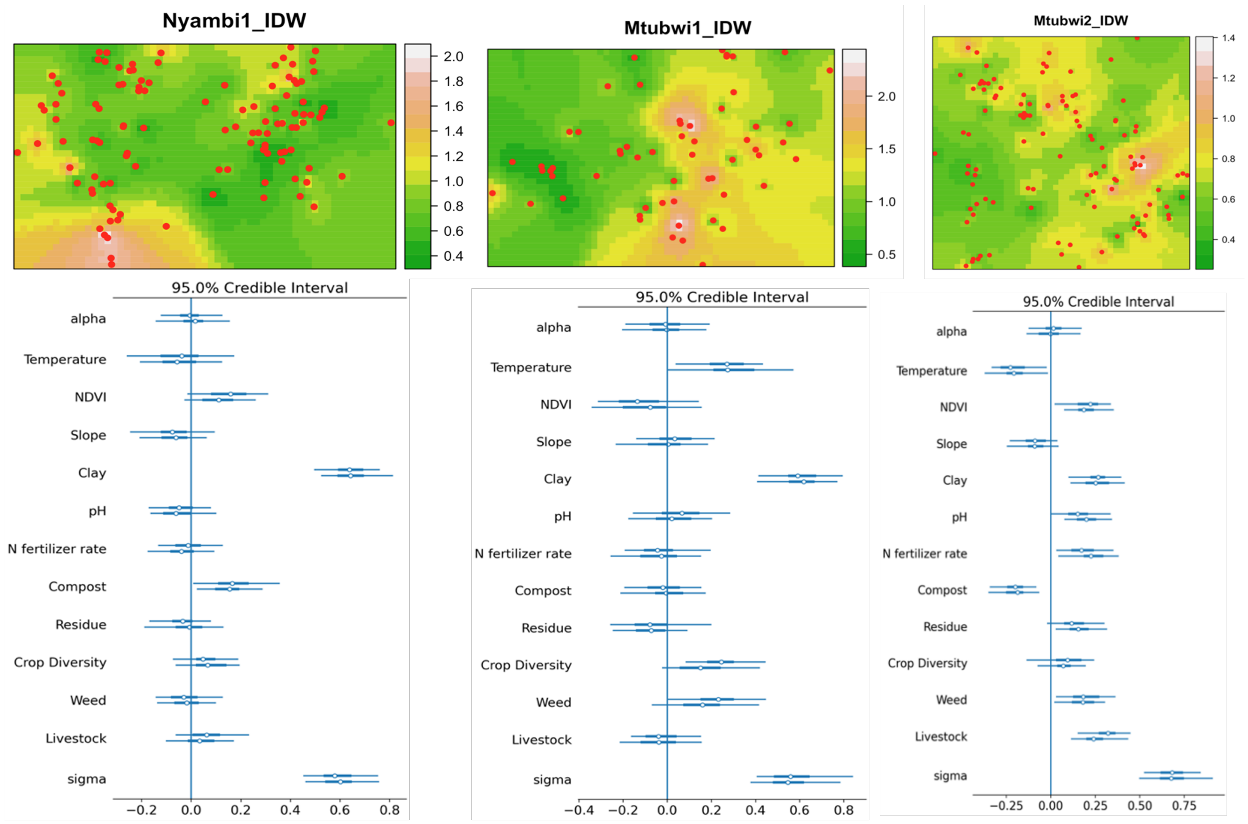


a. Golomoti village cluster b. Linthipe village cluster c. Nsipe village cluster

Figure 2.3: Inverse Distance Weighting (IDW) interpolation map of SOC and posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 95% credible intervals associated with drivers of SOC at three village clusters, Golomoti (n = 115), Linthipe (n = 96), and Nsipe (n = 112) in Central Malawi.

determinant for SOC beside NDVI and clay content. Crop diversity was also positively associated with SOC in Nsipe.

In Southern Malawi, a distinct positive effect of clay on SOC was found at all sites (Figure 2.4). Compost had a positive influence on SOC in Nyambi, where few plots were sole maize. Even within the same EPA, SOC spatial distribution in the cultivated field varied (Figure 2.4b and Figure 2.4c). The Mtubwi village cluster 1 had a higher SOC than the Mtubwi village cluster 2. At the low SOC village cluster, Mtubwi 2, several indicators had positive effects on SOC including clay content, fertilizer application, weed presence and livestock. The tropical livestock unit was found to be positively related to the highest SOC cluster in central Malawi and the lowest SOC cluster in



a. Nyambi village cluster

b. Mtubwi village cluster 1

c. Mtubwi village cluster 2

Figure 2.4: Inverse Distance Weighting (IDW) interpolation map of SOC and posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 95% credible intervals associated with drivers of SOC at three village clusters, Nyambi 1(n = 115), Mtubwi 1 (n = 61), and Mtubwi 2 (n = 115) in Southern Malawi

southern Malawi.

2.5 Discussion

2.5.1 Soil C and N

Overall, soil C status was low at the lakeshore site of Golomoti (10.29 g C kg soil-1) site and the Southern sites of Nyambi (8.07 g C kg soil-1), Nsanama (6.31 g C kg soil-1), and Mtubwi (8.97 g C kg soil-1). All of these had a high proportion of coarse soils, and often were hot sites as well. In contrast, at the coolest, mid-altitude site, Linthipe, soil C was 16.17 g C kg soil-1, and we note that this site was fine textured, with an average of 17.36 % clay. Low values of soil C and N for Malawi farmers' fields have been previously reported, such as a study with sites both north and south of our survey, at 6 to 7 g C kg soil-1 and 0.3 to 0.5 g N kg soil-1 (Kihara et al., 2016). On the other hand, the mean value of SOC (19.5 g C kg soil-1) in Nsipe reported by Mponela et al., (2020) was higher than our findings for Nsipe, a mean value of 12.25 g C kg soil-1. We note that the soil survey of Nsipe by Mponela and colleagues included non-cultivated natural sites as well as cultivated sites, which is expected to lead to a higher mean value overall.

The extent to which soil C values have changed over time is not possible to discern given the lack of archived soil samples. To put our data in perspective it is still interesting to consider that decades earlier, a study by (Snapp, 1998) reported values of SOC from hundreds of cultivated fields in Central Malawi (16 to 17 g C kg soil-1) that are substantially higher than our observations here from cultivated fields in the same region. Changes in soil C over two decades are reported in a longitudinal study in the Machinga district of Southern Malawi (which included three of our surveyed sites), and this was consistent with a decline in SOC having occurred specifically for intensively cultivated fields (Mpeketula, 2016).

There is limited data on thresholds for soil C, which poses a challenge to interpretation of the soil C status we observed. Literature summarized by Mponela et al. (2020) indicated critical limits of SOC for agricultural productivity that ranges from 5 to 20 g C kg soil-1. Burke et al. (2020) evaluated the SOC threshold from cultivated fields from our site locations and found that 9.4 g C kg soil-1 was the critical value in terms of a positive maize yield response to N fertilizer application. Based on these reports, the three EPA sites in Southern Malawi have degraded SOC status generally, with a poor potential to achieve positive yield response to fertilizer amendments. Overall TSN patterns followed that of SOC, and were generally low (using the threshold range of 0.8 to 1.2 g N kg soil-1 reported by Mponela and colleagues) across the seven EPAs (0.42 g N kg soil-1 to 1.10 g N kg soil-1). This suggests a major challenge in terms of providing sufficient macronutrients to crops, and is consistent with previous studies in Malawi (Kihara et al., 2016; Snapp, 1998).

Active C indicators such as POXC and Cmin provide further insights into soil C status and trends (Frost et al., 2019). Generally, a high correlation of these indicators was observed relative to SOC and TSN status. The exception was POXC levels in Southern Malawi at 291.5 mg C kg soil-1 to 446.7 mg C kg soil-1 , and a similar range to that observed in Central Malawi; this did not follow the low SOC levels in Southern Malawi (6.31 to 8.97 g C kg soil-1). The high turnover rate of POXC in Southern Malawi could be due to the (modestly) higher temperature range observed at these sites. Active carbon fractions may also be easily decomposed under high temperatures (Janzen et al., 1992), and lost through cultivation (Shang and Tiessen, 1997). We also note that sand fraction associated labile C is susceptible to oxidation and less stable compared to clay and silt (Shang and Tiessen, 1997), and we found high sand content in southern sites.

2.5.2 Environmental Factors

The surveyed smallholder farm sites with warmer temperatures were consistently associated with low soil organic C in this study (Figure 2.1). Soil C loss is biologically mediated, thus a rise in temperature is expected to be associated with rapid soil C loss due to high activity. Studies in the U.S. Central Plain Grassland found low SOC and TSN at sites with high annual temperatures (Burke et al., 1989). Indeed, the SOC to climate relationship is a vital component in most regional assessments of SOC (Burke et al., 1989; Calvo de Anta et al., 2020; Hontoria et al., 1999; Page et al., 2013). At the same time, variability in terms of climate is expected to be modest at a local scale. Not surprisingly, temperature was not always a significant driver of the SOC at individual sites. However, SOC was found to be positively related to temperature and NDVI at Nsipe, the coolest site; there could be high biomass accumulation within this area which had the highest NDVI mean value of 0.57 (Figure 2.3, Table 2.1).

The negative relationship of slope with SOC and TSN we observed has been found in other studies, due to processes associated with cultivated sloping lands, that of erosion and translocation of clay and silt particles (Negasa et al., 2017; Ottoy et al., 2017; Seibert et al., 2007). In a study conducted in Southern Ethiopia at smallholder farmers' managed land, SOC was found to be negatively influenced by the slope (Negasa et al., 2017).

Consistent with the literature, we found a markedly positive relationship of clay content and high soil organic carbon and nitrogen status (Burke et al., 1989; Meersmans et al., 2008; Tan et al., 2004). This was due to the large surface area and organo-mineral complexes associated with fine particle size (Chaplot et al., 2010; Six et al., 2002). This edaphic factor was a highly consistent positive driver of soil C and N pools, including labile pools POXC and Cmin. It was an important positive factor at almost all sites at the local scale, as well as at the regional scale. Soil pH was positive at varying magnitudes for the total C and N pool as well as labile C fractions. The positive relationship of soil pH and SOC in slightly acid soil was found earlier in forest soils in North America due to enhanced C stabilization through reduced mineral surface charges (Fissore et al., 2008).

The key role shown in our study for soil texture, as a determinant of labile as well as total C and N pools, has implications for both mapping and management recommendations. This is a novel finding as few studies have quantified active soil C patterns, at either regional or local scales. Overall, our findings are consistent with coarse textured soils, which requires specific and intensive management interventions if Cmin and POXC pools are to be maintained for productive agricultural soils (Culman et al., 2013).

2.5.3 Normalized Difference Vegetation Index

Vegetative cover, as reflected by NDVI values, has been found to be an important predictor of SOC and TSN (Kunkel et al., 2011; Page et al., 2013; Zhang et al., 2019). This is expected for natural areas where biomass inputs are a key determinant of SOC. However, cultivated soils are subjected to diverse management practices that influence decomposition as well as accrual processes, (e.g., soil disturbance, organic and inorganic amendments, and diversity of crops grown). Few studies of intensively cultivated lands have been conducted, and this is the first that we know of conducted at multiple scales for smallholder farms in the sub-humid tropics. The 10-year growing season average NDVI we used is a highly significant driver of both stable and labile C pools. This was observed at the regional scale and for SOC at three out of six sites at local scale. Kunkel et al., (2011) used the maximum monthly mean value of NDVI in a semi-arid watershed in the USA, and found it to be a highly significant predictor of SOC. They proposed a simple approach to estimate SOC and TSN based on potential insolation and maximum monthly mean value of NDVI, which explained most of the spatial variation across a region of forests and rangeland. In addition, NDVI values based on a range of time periods' have been identified as predictors of SOC in studies from Australia to China (Page et al., 2013; Zhang et al., 2019). One exception was a study by Gomez et al. (2008) where Hyperion NDVI data was not predictive of SOC measured by near infrared spectroscopy in a cotton field in semi-arid Australia.

2.5.4 Farm Management Factors

This is one of the first reports of management practices as drivers of soil C and N pools at multiple scales across a cultivated smallholder landscape. Over a 1000 farm plots are monitored in this project, where management practices were evaluated for effects on soil organic matter fractions at regional and local level. Overall, we found consistent evidence for biomass in the form of crop diversity and weed presence that had positive effects on SOC and TSN. POXC, on the other hand, was not influenced by management practices except crop diversity. This may be related to the existence of high sand fractions in the soil, which has previously been shown to be associated with low or variable POXC values (Plaza-Bonilla et al., 2014; Wade et al., 2020). Crop diversity is a key component of sustainable agricultural intensification, and several studies have recently pointed to a unique role for intercrops in soil C accrual (Cong et al., 2015; Garland et al., 2017; Powlson et al., 2016).

Residue retention through incorporation had positive associations with SOC and C mineralization in the regional level study. At local level, residue retention was not associated with SOC, this may be due to the modest size of the datasets at local levels which reduces the ability to detect drivers. Overall, the biological fraction Cmin appears to be sensitive to crop management, including crop residue use, more so than POXC. A previous study of conservation agriculture trials conducted on-farm in Malawi over multiple years provides experimentation evidence that crop residue retention can enhance Cmin (Ngwira et al., 2013). In our survey, farmer adoption of no-tillage was almost nil, so it was not possible to evaluate the effect of tillage, only the crop diversity aspect of conservation agriculture practices.

One of the challenges to promoting crop residue retention to build SOC is the high competition for this organic resource. It is often preferred to use crop stover as feed, rather than to retain to amend the soil (Tittonell et al., 2015; Valbuena et al., 2015). In Central Malawi, however, livestock ownership is low, and a survey in 2013 indicated that residues are generally retained, with incorporation of residues reported for three-quarters of plots either soon after crop harvest or within six months (Mungai et al., 2016). An important management practice of mixed cropping, which enhances residue biomass quantity and diversity of tissue types, is widely practiced in Malawi (Bezner Kerr et al., 2019; Wang et al., 2019). In our study, crop diversity (more than one crop per plot, grown as an intercrop) was found to be associated with enhanced SOC, TSN and POXC. Crop diversity primarily reflects the intensity of intercropping for maize, the dominant crop grown in Malawi (Silberg et al., 2017). This adds to growing evidence that biochemical diversity of residue tissues through crop diversity can positively influence soil organic matter fractions. Such processes may be influenced by quantity of belowground root biomass, but also enhanced retention of tissue N (Naab et al., 2017). Intercropping was specifically found to increase soil C higher than rotational diversity in a six year field experiment in China (Cong et al., 2015).

Weed presence is often considered as a negative factor in agriculture development, in terms of plant competition, and thus suppression of crop productivity. It has not, to our knowledge, been previously reported on in relationship to soil organic matter accrual at regional scale, at least for African cultivated fields (Bedada et al., 2014; Naab et al., 2017; Turmel et al., 2015). Weeds are a source of biomass above and belowground in field plots, and thus would be expected to generally enhance soil organic carbon (Arai et al., 2014). In addition, a recent review stated that weed presence can improve both available and total soil nitrogen through reducing erosion and increasing plant diversity (Blaix et al., 2018).

The management practices associated with high soil C status were all related to biomass, notably crop diversity, residue incorporation and weed presence. Taken together with the key determinant of NDVI, this is indicative of the need to pay close attention to biodiversity and management of organic inputs as SOC regulating factors in agricultural landscapes. Consistent with these findings, a meta-analysis of smallholder farm studies recently highlighted the role of legume intercrops in providing enhanced organic inputs belowground, relative to sole cropping, leading to modest but significant SOC accrual (Powlson et al., 2016). A recent review called for policies that support management of organic in conjunction with inorganic inputs, for sustainable intensification to be achieved in Africa (Jayne et al., 2019). Our findings are consistent with the need for agricultural policies and mapping of soil carbon efforts, that pay close attention to mixed cropping patterns and weed distribution as mediators of soil carbon accrual in cultivated fields.

2.6 Conclusion

Through integrating Bayesian statistical approach and on-farm study in Malawi cultivated fields, we found environmental and soil edaphic variables are determinants of labile soil C pools, as well as stable pools SOC and TSN. Soil clay content and NDVI are key determinants of soil C and N pools at both regional and local scales. The management variables that enhance biomass quantity and diversity were generally positively associated with soil C and N pools, as indicated by a consistently positive response to crop diversity, weed presence and residue retention. Inorganic nutrient amendment (fertilizer) was associated with enhanced C mineralization only, it had no benefits for other soil C pools. This has policy implications, as crop diversity should not be overlooked as a means to enhance soil C accrual, for mitigation and adaptation to climate change and sustainable soil management. Potential for soil quality benefits associated with weeds in resource-limited cropping systems in Sub-Saharan Africa is a related topic, one that may have been entirely overlooked. Overall, the benefits associated with enhancing the quality and quantity of organic resources on smallholder farms requires urgent attention, to reverse soil degradation in support of sustainable intensification.

APPENDIX

Table A2.1: Descriptive world reference base soil classes by study site.

Soil class	Golomoti (n = 147)	Linthipe (n = 132)	Kandeu (n = 141)	Nsipe (n = 150)	Nyambi (n = 175)	Nsanama (n = 187)	Mtubwi (n = 176)	Total (n = 1108)
Haplic Fluvisols	11					1		12
Haplic Lixisols	15			14	70	96	10	205
Haplic Luvisols	121	130	141	136	105	84	127	844
Haplic Gleysols		2						2
Haplic Arenosols						6		6
Haplic Planosols (Eutric)							14	14
Leptic Cambisols							14	14
Stagnic Luvisols							11	11

Table A2.2: Pearson correlations between 10 year mean annual temperature (°C), 10 year mean annual precipitation (mm), and elevation (m) for all surveyed plots in Central and Southern Malawi. Values with ***,**, and * indicate correlations are significant at the levels $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively.

	Ten-year Mean Annual Temperature (°C)	Ten-year Mean Annual Precipitation (mm)
Ten-year Mean Annual Precipitation (mm)	-0.69***	
Elevation (m)	-0.94***	0.61***

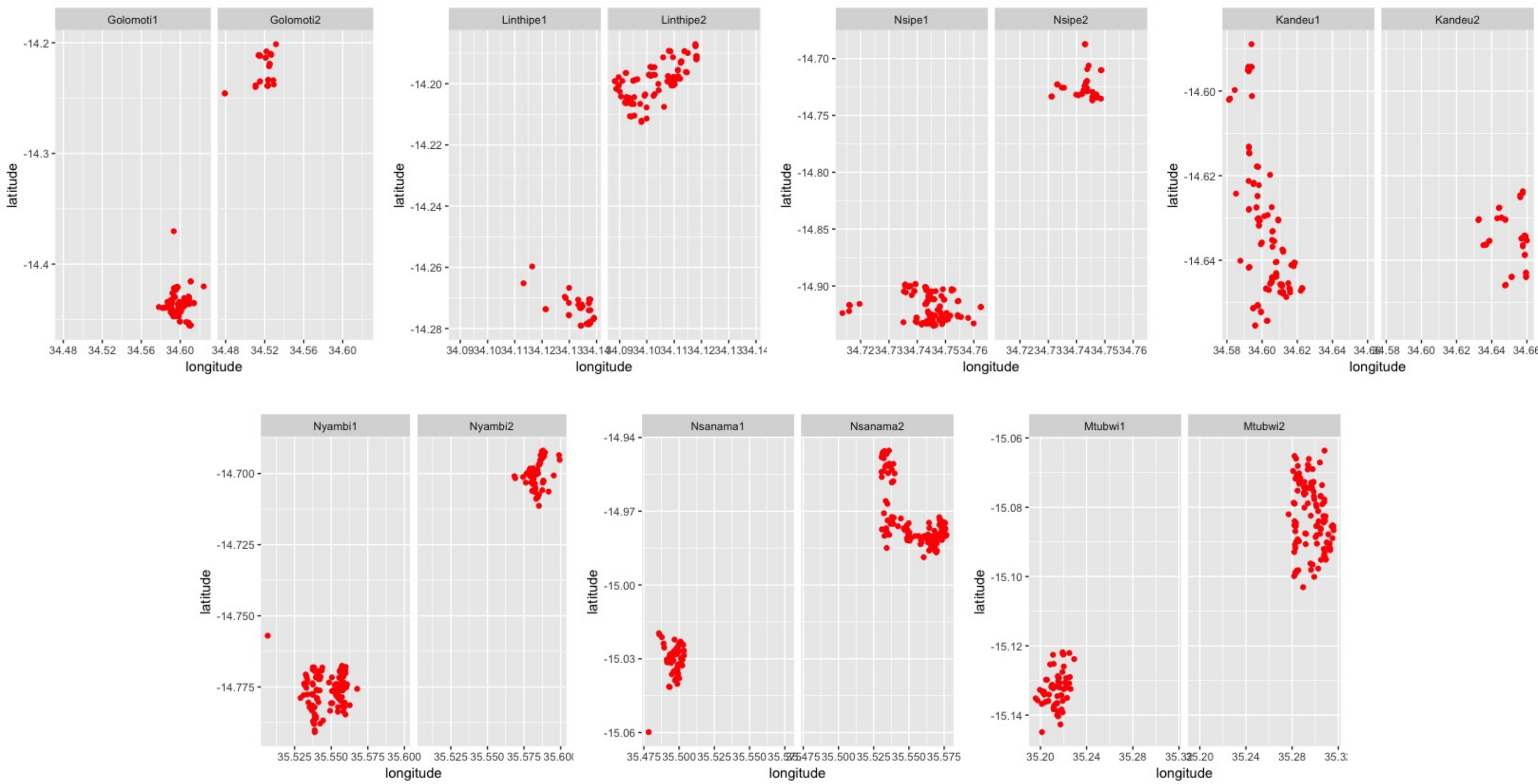
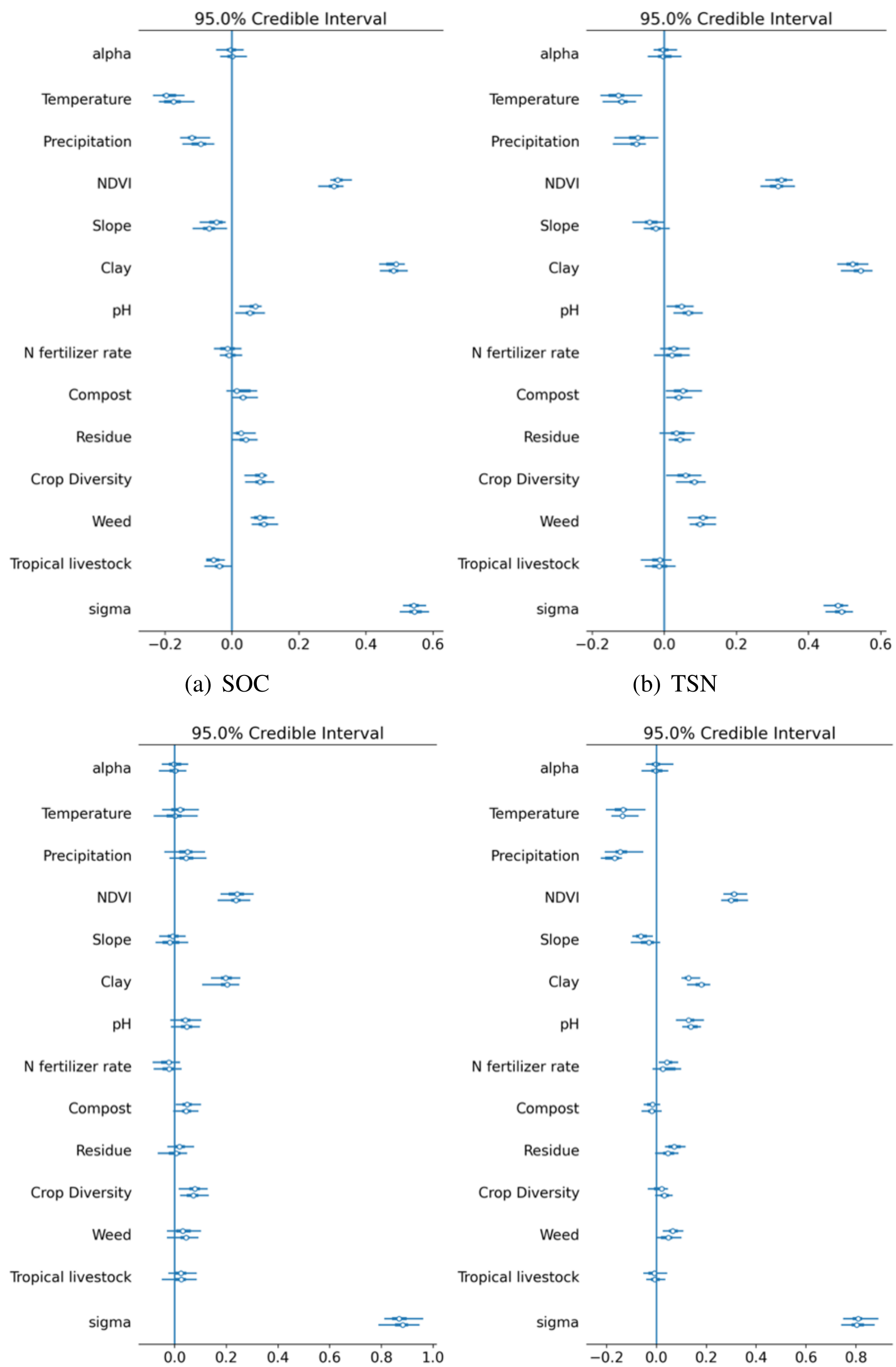


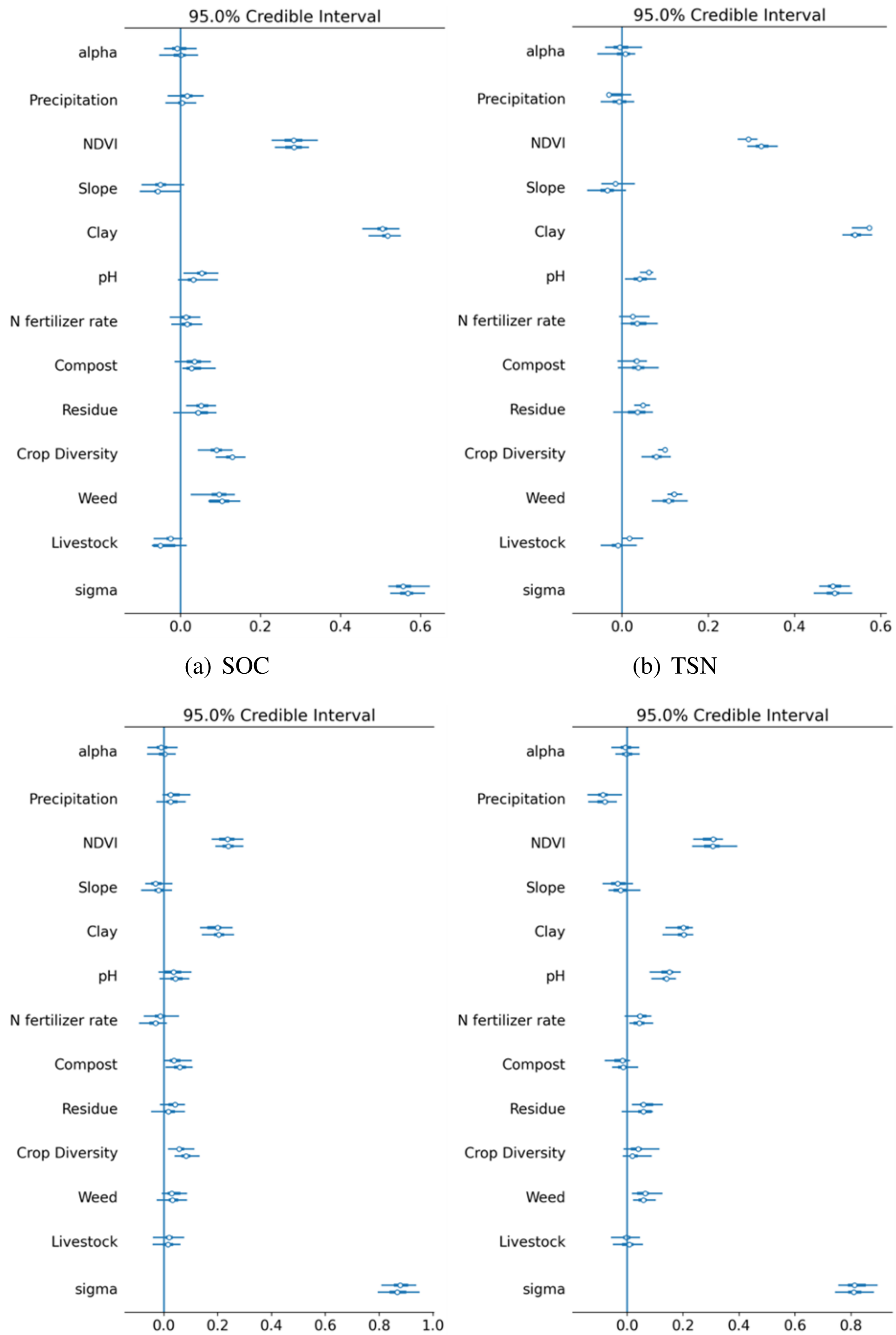
Figure A2.1: Village clusters used in the local level analysis determined by the sampling locations of surveyed plots in Central and Southern Malawi .



(a) SOC (b) TSN

(c) POXC (d) C min

Figure A2.2: Bayesian model with both temperature and precipitation as climatic drivers. Posterior results of Bayesian regression model with 2 chains of 10,000 iterations explicit the 95% credible intervals associated with drivers of SOC, TSN, POXC, and Cmin across all plots (n = 1108) in Central and Southern Malawi.



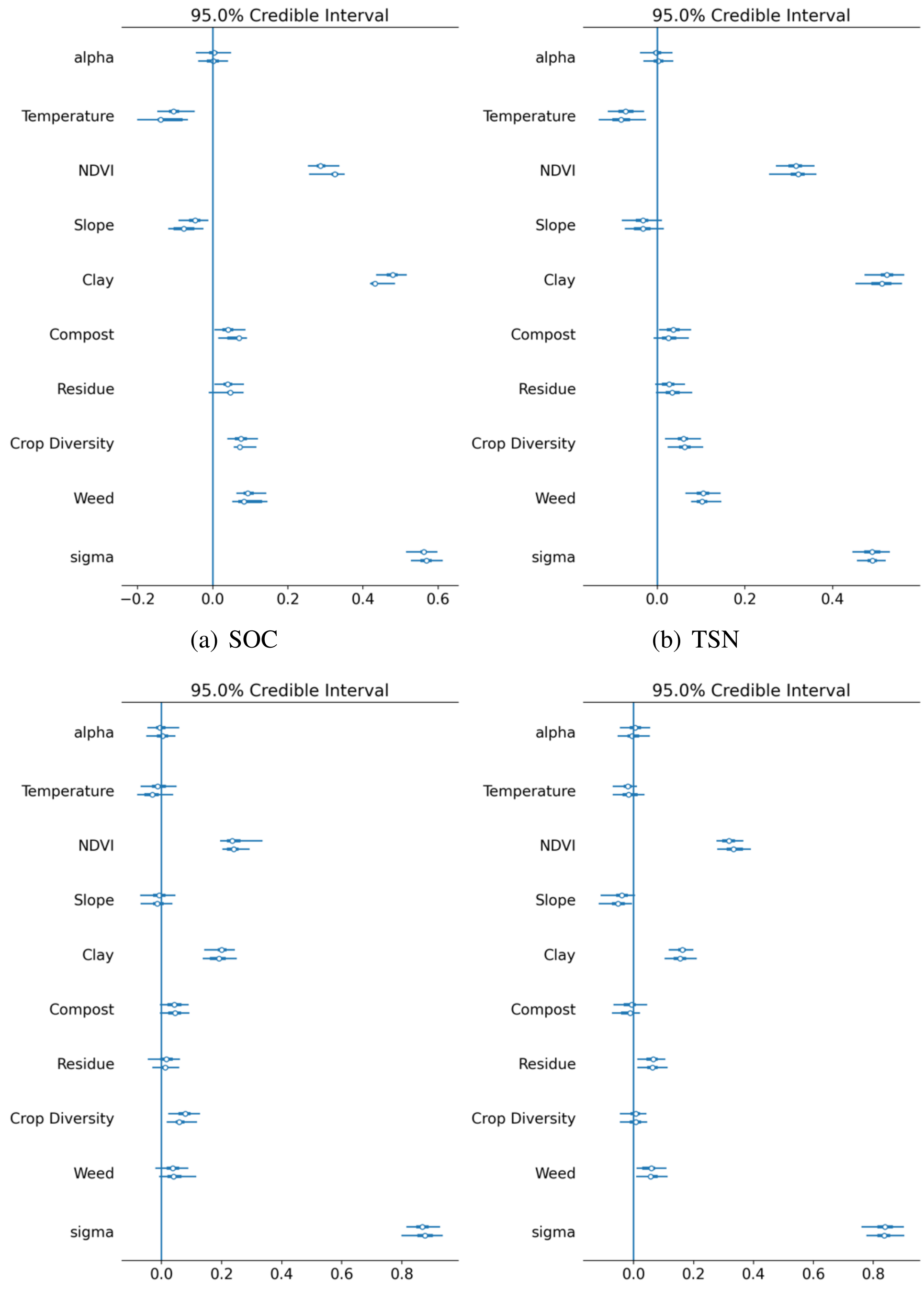
(a) SOC

(b) TSN

(c) POXC

(d) C min

Figure A2.3: Bayesian model with only precipitation as a climatic driver. Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 95% credible intervals associated with drivers of SOC, TSN, POXC, and Cmin across all plots (n = 1108) in Central and Southern Malawi.



(a) SOC (b) TSN (c) POXC (d) C min

Figure A2.4: Reduced model. Posterior results of Bayesian regression model with 2 chains of 10, 000 iterations explicit the 95% credible intervals associated with drivers of SOC, TSN, POXC, and Cmin across all plots (n = 1108) in Central and Southern Malawi.

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CHAPTER 3

ENVIRONMENTAL AND MANAGEMENT DRIVERS OF SOIL HEALTH INDICATORS ON MICHIGAN FIELD CROP FARMS

3.1 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

3.2 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 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 the 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. Tieman 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.

Table 3.1: 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/ 85.47	42.91/84.62	45.23/83.82
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 2006-2015 or 2007-2016 based on the sampling year from MODIS11A2 at a resolution of 1km; MAP, mean annual precipitation (mm) from 2006-2015 or 2007-2016 based on the sampling year from TerraClimate at a resolution of 4km; NDVI, normal difference vegetation index, mean calculated from 2006-2015 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 $p \geq 0.05$.

3.3 Materials and Methods

3.3.1 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 (Figure 3.1, Table 3.1). Each farmer picked one or two soybean fields to include in the study each year. For each field, Web Soil Survey (Soil Survey Staff, 2021) was used to identify up to three

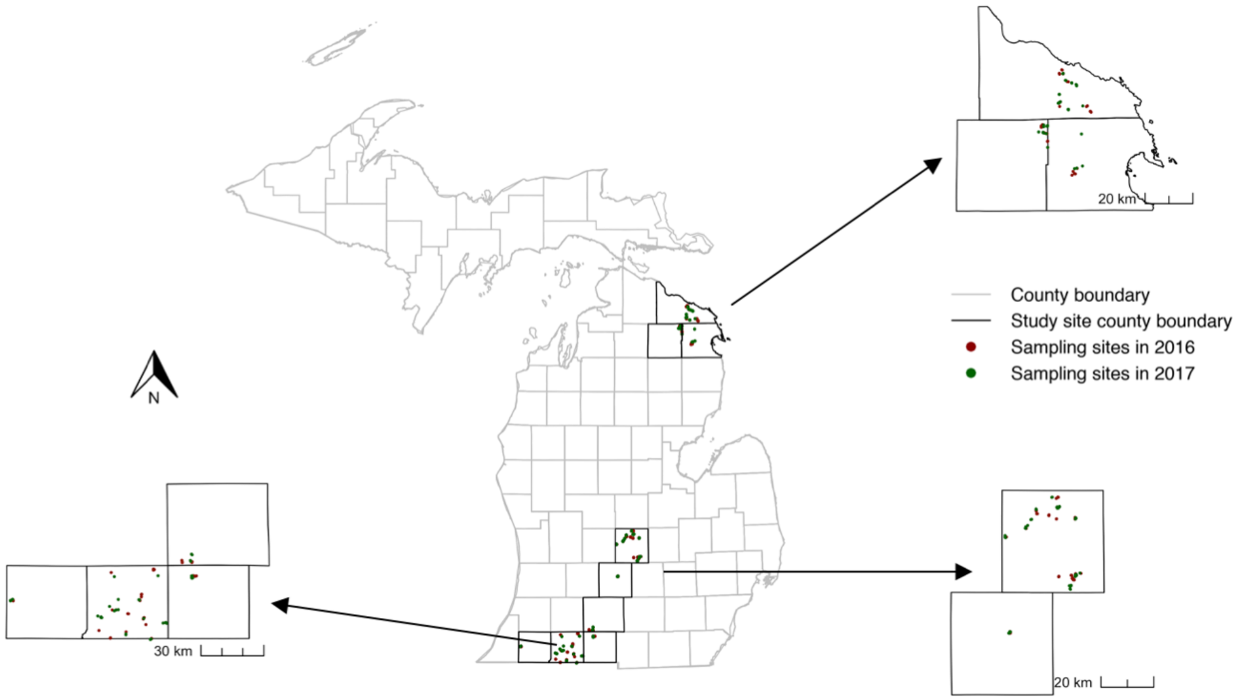


Figure 3.1: Sampling Locations of 242 focal plots in three regions in Michigan.

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 A3.1.

3.3.2 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.

$$\mathrm{CDI} = S \times A \tag{3.1}$$

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 A3.2.

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.

$$\text{Avg.STIR} = C \times P/Y \tag{3.2}$$

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.

3.3.3 Soil Sampling and Analysis

3.3.3.1 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 6mm, 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).

3.3.3.2 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 1N 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 KMnO4 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 N2 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.

3.3.4 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 - 2015, and from 2007-2016 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 – 2015, and from 2007-2016 for focal plots sampled in the two years, respectively (Eq. 3). Ten-year growing season NDVI from 2006 – 2016 and from 2007-2017 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).

$$\text{Aridity Index} = \text{Potential evapotranspiration}/\text{Precipitation} \tag{3.3}$$

$$\text{NDVI} = (\text{Band 4}\breve{}\text{Band 3})/(\text{Band 4} + \text{Band 3}) \tag{3.4}$$

3.3.5 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.

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

$$Y_{ij} = \alpha_j + \sum_k X_{ik}\beta_{kj} + \epsilon_{ij} \tag{3.5}$$

where in Eq.5: for each focal plot i, the response vector $Y_i j$ 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

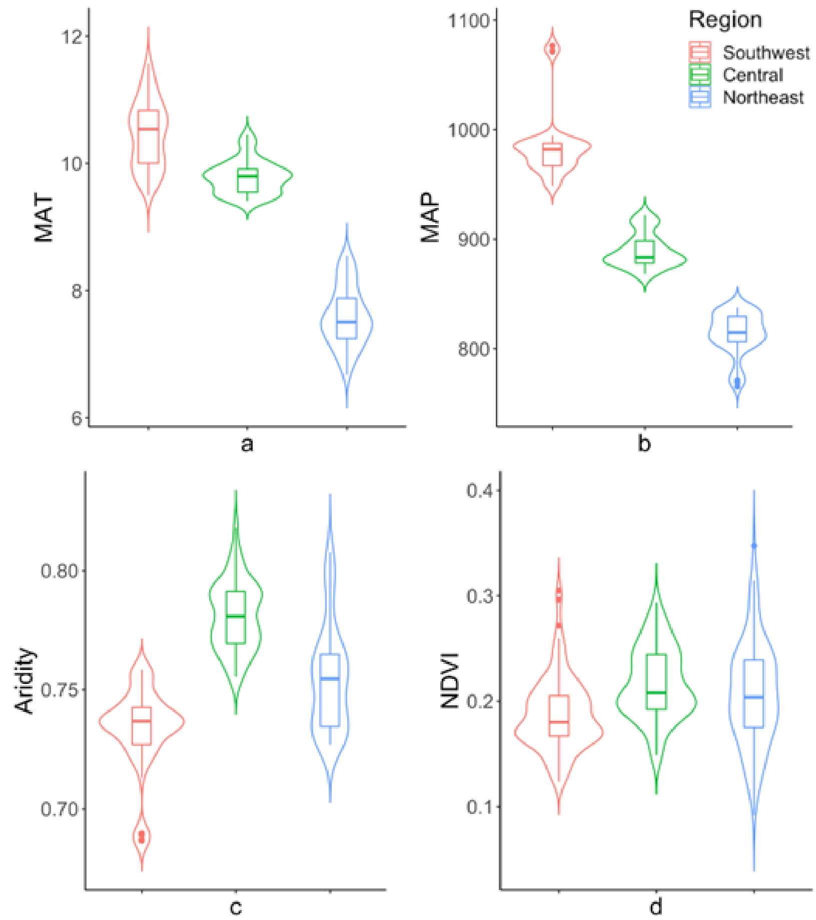


Figure 3.2: Environmental factors (MAT, 10 year mean annual temperature; MAP, 10 year mean annual precipitation; Aridity, 10-year average aridity index; NDVI, normalized difference vegetation index) across three regions (n = 242).

X_{ik} 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.

3.4 Results

3.4.1 Environmental factors

Across all 242 focal plots, there was a consistent and significant location effect on the MAT and MAP (Table 3.1, Figure 3.2). 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 A3.2). The southwest region also had the lowest NDVI compared to the central and northeast regions. The mean elevation per region ranged from 237 - 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 A3.2. 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.

3.4.2 Management Practice

Crop diversity indexes were lower in Central (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 inFigure 3.3 In both the Southwest 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 A3.3). 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 –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

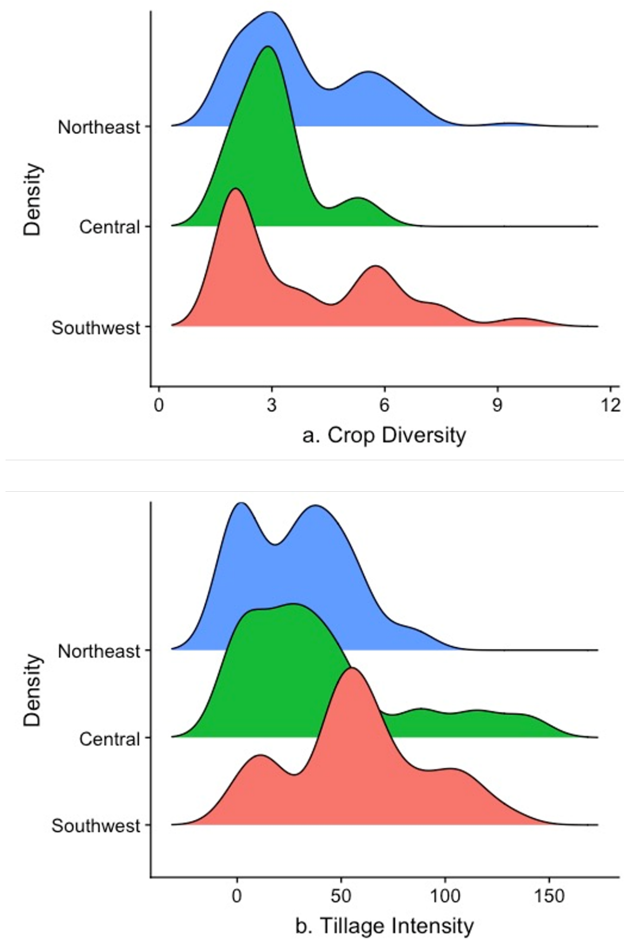


Figure 3.3: Density plot of crop diversity index and tillage intensity across three regions (n = 242).

used more conventional tillage compared to the Central and Northeast region (Figure 3.3b). 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.

3.4.3 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 3.1). 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 3.1). In this case, plots in the Northeast region showed the highest soil pH levels, indicating that this soil was neutral towards slightly alkaline. In

Table 3.2: Mean soil properties of sampled focal plots per region (n = 242). Letters compared across a row indicate differences by region at $p \leq 0.05$.

	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 $p \leq 0.05$.

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 3.2). 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 3.2). 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 to 218.12 psi (Table 3.2). 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 3.2). 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 3.3). 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 3.3). 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 3.3). 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 with the least amount of soil properties in the table compared to all other variables (Table 3.3).

Table 3.3: 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 $p \geq 0.01$, and $p \geq 0.05$, 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**	0.04NS	-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).

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 R^2 ($R^2 = 0.24, p < 0.01$). 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 ($R^2 = 0.1$).

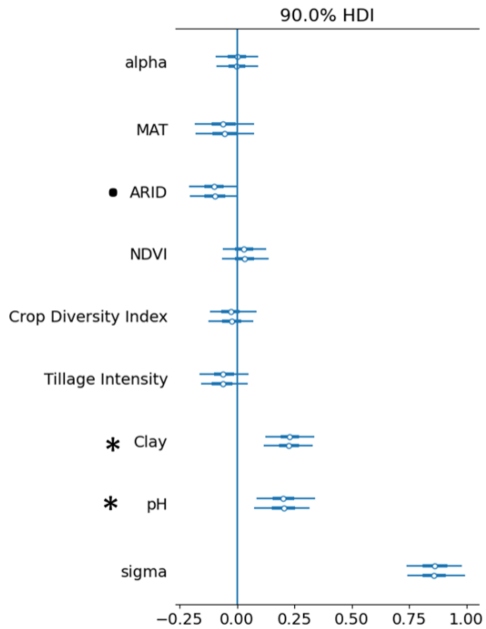
3.4.4 Drivers of soil properties

3.4.4.1 Soil chemical properties

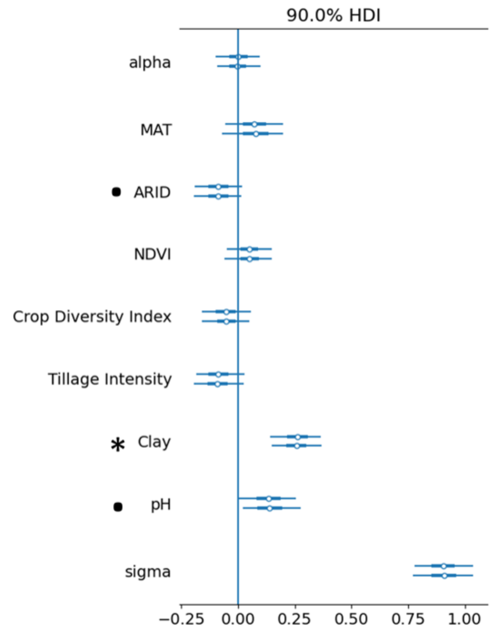
Aridity and soil edaphic properties were the main determinants for soil chemical properties, SOC, TSN, P, and Ca (Figure 3.4). We observed aridity as a negative driver for all of the four soil chemical properties. Contrary to our hypothesis, the environmental factor, MAT, was not a determinant for SOC or TSN (Figure 3.4). MAT was a negative driver for P and Ca (Figure 3.4c, Figure 3.4d). 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 (Figure 3.4d). The high CDI and high soil calcium content in the northeast region likely drive this relationship in our dataset (Table 3.2).

3.4.4.2 Soil biological properties

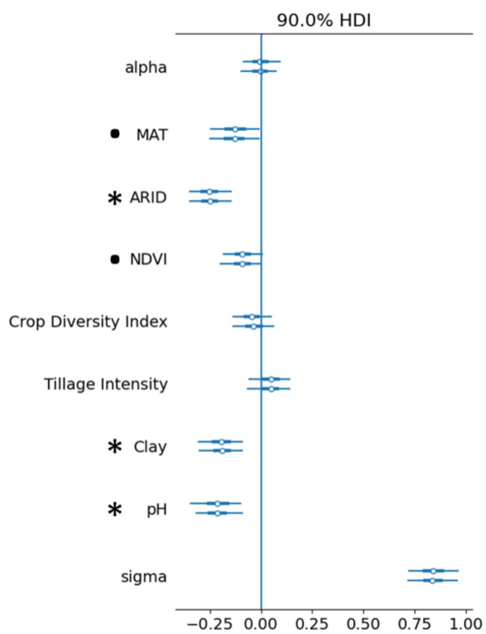
Though SOC and TSN did not respond to the temperature variations, long term temperature showed a negative effect on POXC and PMN. Counter to the negative influence of aridity on SOC and TSN,



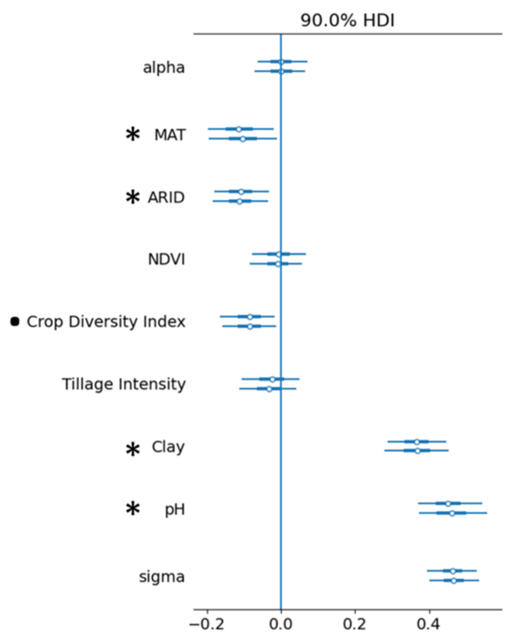
(a) SOC



(b) TSN

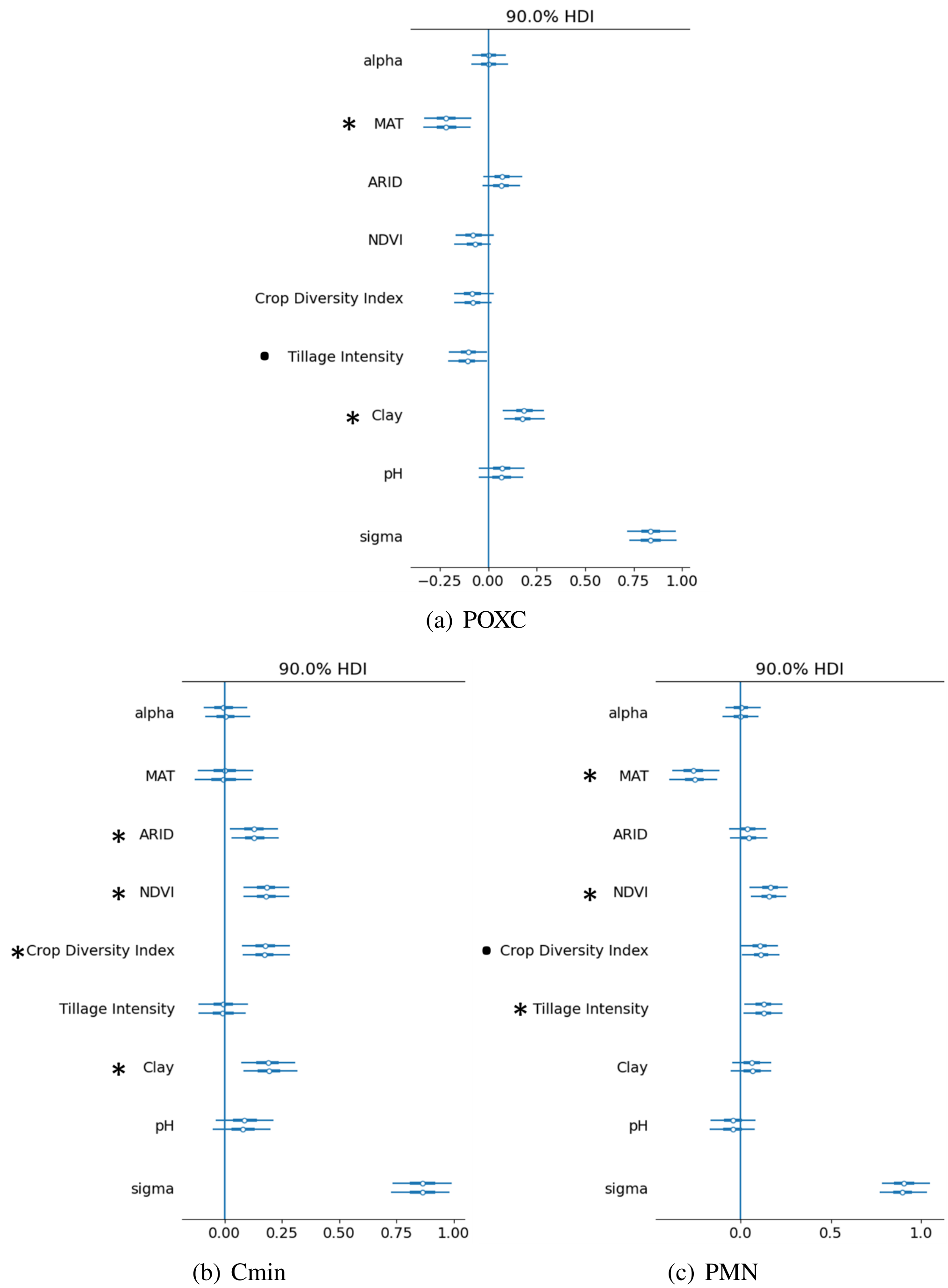


(c) P



(d) Ca

Figure 3.4: 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

Figure 3.5: 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.

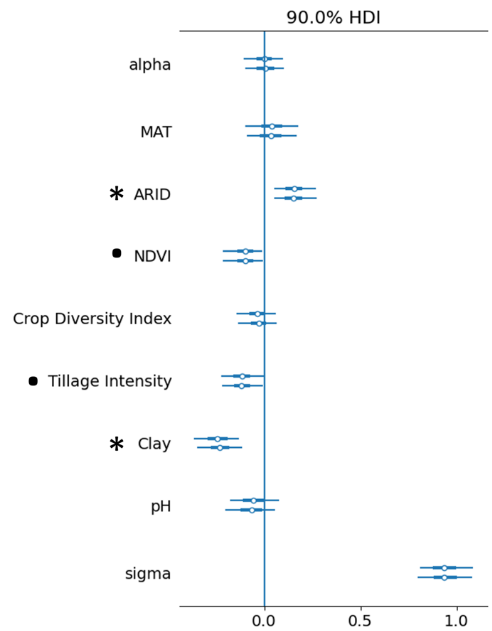
aridity showed a positive effect on Cmin. In addition, NDVI was positively associated with Cmin and PMN. Clay content was a positive determinant for POXC and Cmin, which was consistent compared to the SOC and TSN (Figure 3.5). Yet, neither clay nor soil pH had any impact on PMN.

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 (Figure 3.5). Tillage intensity was a negative driver for POXC, indicating the reduced tillage intensity contributed to higher POXC (Figure 3.5a). 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 lowerPMN compared to conventional tillage systems.

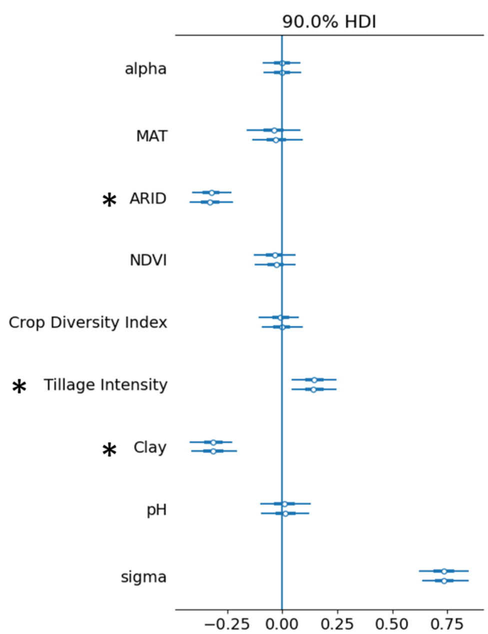
3.4.4.3 Soil physical properties

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 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 (Figure 3.4a). 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.

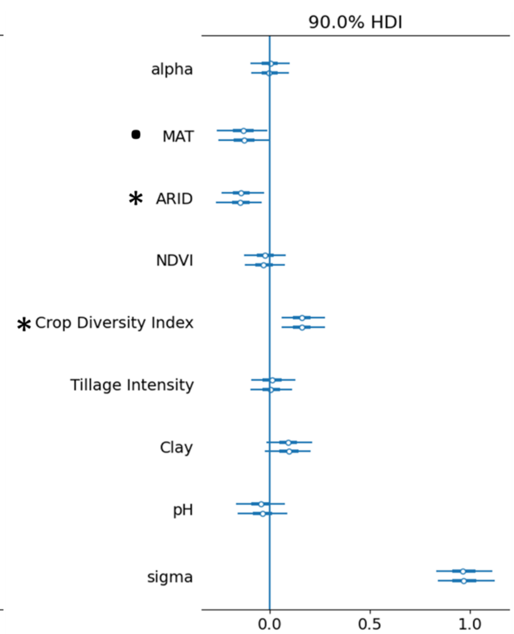
Management effects on soil physical properties were depth dependent (Figure 3.6). Tillage intensity was a negative determinant for PEN15 and positive determinant for PEN45. Reducing tillage intensity increases surface penetration resistance and decreases sub-surface resistance by limiting compaction. Crop diversity was also a positive determinant of WAS, which supports the positive impact of crop diversity on soil physical properties.



(a) PEN15



(b) PEN45



(c) WAS

Figure 3.6: 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.

3.5 Discussion

3.5.1 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 3.1). 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 3.2).

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 (Figure 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 A3.3). 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

(Figure 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.

3.5.2 Soil health properties

3.5.2.1 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 (Figure 3.5). 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 (Fernandex-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 (Figure 3.4). The soil pH of our sites ranged from 5.3 to 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.

3.5.2.2 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 (Figure 3.4 & Figure 3.5). 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 (Figure 3.5). 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) .

3.5.2.3 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 (Figure 3.5). 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 (Figure 3.5). 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.

3.6 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.

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APPENDIX

Table A3.1: Soil types of the focal plots (n = 242).

Soil Types	Frequency	Soil Types	Frequency
Algonquin Silt Loam	1	Hillsdale Sandy Loam	2
Algonquin-Richter Complex	1	Iosco Loamy Sand	1
Algonquin-Springport Complex	1	Kalamazoo Loam	1
Alstad Loam	1	Kibbie Loam	1
Annalake Loamy Fine Sand	1	Klacking Loamy Sand	1
Barry Loam	2	Krakow Flaggy Fine Sandy Loam	1
Blount Loam	2	Locke Fine Sandy Loam	2
Bowers Silt Loam	1	Marlette Loam	2
Boyer Complex	1	Matherton Loam	1
Boyer Loamy Sand	2	Melita Loamy Samd	1
Boyer Sandy Loam	1	Metamora-Capac Sandy Loams	2
Brady Sandy Loam	1	Negwegon Silt Loam	1
Bronson Sandy Loam	2	Oakville fine Sand	1
Capac Loam	2	Omena Fine Sandy Loam	1
Capac-Marlette Loams	2	Onaway Fine Sandy Loam	1
Cheboygan Loamy Sand	1	Oshtemo Sandy Loam	2
Cohoctah Loam	1	Ossineke Fine Sandy Loam	1
Coruna Sandy Loam	1	Owosso Sandy Loam	1
Crosier Loam	1	Owosso-Marlette Sandy Loams	2
Dry corners	1	Parkhill Loam	2
Elmdale Sandy Loam	1	Richter Loamy Fine Sand	1
Elston Sandy Loam	1	Richter-Algonquin Complex	1
Emmet Sandy Loam	1	Schoolcraft Loam	2
Gilford Sandy Loam	1	Sebewa Loam	2
Gladwin Loamy Sand	1	Shipshe Sandy Loam	1
Granby Sandy Loam	1	Sims Silty Clay Loam	2
Hagensville Fine Sandy Loam	1	Slade Loam	1
Hagensville Sandy Loam	1	Spinks Loamy Sand	2
Hatmaker Loam	1	Springport Silt Loam	1
Hessel Loam	1	Teasdale Fine Sandy Loam	2
Hillsadle-Riddles Fine Sandy Loam	1	Wasepi Sandy Loam	2

Table A3.2: Pearson's correlation coefficients among environmental variables 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.

	MAP	ARID	NDVI	Elevation	Slope
MAT	0.87**	-0.12NS	-0.19**	0.42**	-0.06NS
MAP		-0.52	-0.19**	0.44**	-0.02NS
ARID			0.14*	-0.14*	-0.04NS
NDVI				-0.36**	-0.09NS
Elevation					0.07NS

MAT, mean annual temperature (C) from 2006-2015 or 2007-2016 based on the sampling year from MODIS11A2 at a resolution of 1km; MAP, mean annual precipitation (mm) from 2006-2015 or 2007-2016 based on the sampling year from GRIDMET at a resolution 4km; NDVI, normal difference vegetation index, mean calculated from 2006-2015 or 2007-2016 based on the sampling year from LANDSAT band 4 and band 5 at a resolution of 30; Elevation, elevation (m) from STRM; Slope, slope (%) from STRM.

Table A3.3: Crop diversity frequencies by region

Overall		Southwest		Central		Northeast	
Crop	Frequency (%)	Crop	Frequency (%)	Crop	Frequency (%)	Crop	Frequency (%)
Soybean	41.18	Corn	36.5	Soybean	44.51	Soybean	44.16
Corn	28.77	Soybean	36.15	Corn	33.24	Wheat	14.35
Cover Crop	12.41	Cover crop	23.07	Wheat	13.12	Corn	13.56
Wheat	9.05	Wheat	1.66	Cover crop	7.99	Forage	11.2
Other Forage	3.26	Pasture	0.71	Fallow	0.57	Alfalfa	7.41
Alfalfa	2.16	Rye	0.71	Radish	0.57	Cover crop	3.15
Pasture	0.78	Potato	0.71			Pasture	1.74
Potato	0.74	Green Bean	0.24			Potato	1.58
Dry Bean	0.41	Snapbean	0.24			Dry Beans	1.42
Sunflower	0.32					Sun flower	1.1
Rye	0.28					Oats	0.32
Fallow	0.18						
Radish	0.18						
Green Bean	0.09						
Oats	0.09						
Snap beans	0.09						

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CHAPTER 4

SOYBEAN YIELD AND SOIL HEALTH TRADEOFFS WITH TILLAGE INTENSITY IN MICHIGAN

4.1 Abstract

Soil health in fields crop farms is linked to various ecosystem functions, including crop production and the environment. However, there are few on-farm soil health studies that evaluate the common soil chemical, physical, and biological indicators and the tradeoff of agricultural and environmental performance. The objective of this study was to assess the interrelationships of various soil health indicators, crop production, and potential environmental risks under different climatic and management conditions. We adopted a farm participatory approach to conduct an on-farm study with 202 focal plots in Michigan, USA. Multivariate analysis, including hierarchical cluster analysis and principal component analysis, was employed to identify the driver of similarity and variation across all focal plots at a regional scale. We incorporated six short-term and long-term climatic and environmental factors; sixteen soil chemical, physical, and biological properties; one measurement of after-harvest residual nitrogen; and the soybean yield in the analysis. Our results showed that climatic factors contribute to most variation across the focal plots. Intense tillage practice leads to high soybean yield and low residual nitrogen. The tradeoff effect identified in this study requires further investigation of the impact of different management in balancing soil health, agronomic performance, and environmental cost.

4.2 Introduction

Soil health has been a widely discussed topic in agricultural studies as it provides multi ecosystem services that are closely related to global sustainability (Doran, 2002). While soil health by definition should involve measurements that reflect the functions of various ecosystem services, agroecosystem studies mainly focus on the primary service, productivity (Bünemann et al., 2018;

Doran and Parkin, 1996; Kibblewhite et al., 2008). Soil health assessment is recommended to be linked to capacity and functions, both crop production and environment (Arshad and Martin, 2002; Bhardwaj et al., 2011). Andrews et al., (2002) pointed out that soil health assessment would be substantially improved through including environmental endpoints evaluation. However, soil residual nitrogen reflects the environmental function that is rarely used in the soil health measurements (Moebius-Clune et al., 2016).

Instead of directly referring to specific functions, soil health is directly measured and presented in the soil physical, biological, and chemical categories (Andrews et al., 2004; Doran and Parkin, 1996; Moebius-Clune et al., 2016). The most common adopted soil health measurement is the soil chemical properties. Nunes et al., (2019) stated that both soil physical and biological indicators need to be included while making management guidelines. Due to the large numbers of variables of soil health indicators, multivariate analysis is recommended as an effective approach and is widely adopted in soil health studies (Bhardwaj et al., 2011; Mann et al., 2019; Rottler et al., 2017; Wander and Bollero, 1999; Zuber et al., 2017). Principal component analysis (PCA) is employed for evaluating the sensitivity of the soil health indicators through interpreting the accountability of variance across the study sites (Wander and Bollero, 1999; Zuber et al., 2017). Hierarchical cluster analysis is another multivariate approach that exhibits the characteristics by grouping the site similarities (Seaton et al., 2020; Sena et al., 2002).

However, previously soil health assessment studies are primarily conducted on research stations (Caudle et al., 2020; Congreves et al., 2015; Wulanningtyas et al., 2021; Xue et al., 2019; Zuber et al., 2017). Only a modest number of soil health studies adopt the on-farm trials, and even less considered the sub-regional differences across the latitudinal and longitudinal gradient (Mann et al., 2019; Wander and Bollero, 1999). Thus, there is a unique opportunity to address this gap and evaluate at this scale on-farm management and the climatic factors. There have been valuable regional soil health analyses that have provided insights into the environmental factors (Rottler et al., 2019). However, the main goals of on-farm soil health in literature focused on evaluating the management effects on various soil physical, chemical, and biological properties. There are limited soil health studies that include environmental functions as endpoints.

Climatic factors, including long-term and growing season temperature and precipitation, influence multiple soil properties (Burke et al., 1989; Hontoria et al., 1999; Rottler et al., 2017). For example, soil organic carbon (SOC) provides biological and physical foundations for soil health and is expected to be higher with substantial precipitation and cooler temperature at regional analysis (Burke et al., 1989; Hontoria et al., 1999; Johnson et al., 2011). The climatic factors are dominant drivers of soil health parameters as they limit biomass accumulation, weathering, and erosion. Rottler et al., (2019) in a regional on-farm soil health study identified that climate is the primary driver of the difference in soil health. The challenges of expanding the latitudinal and longitudinal scale of soil health assessment and evaluation of the management practice effect limited most soil health studies within the defined crop or environment scenarios (Arshad and Martin, 2002).

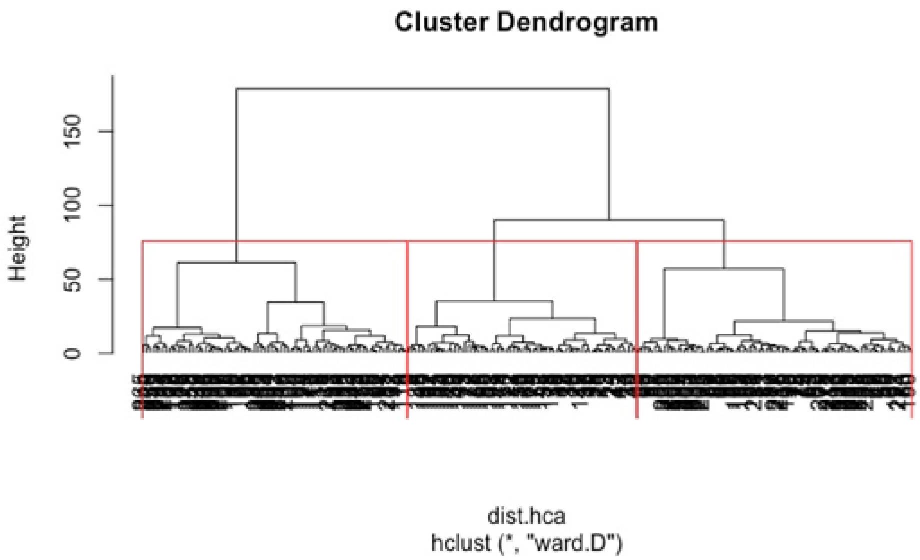
Tillage and crop diversity are two main management practices that researchers attempted to assess for improving sustainability. Common approaches to evaluate the impact of management practice on soil health are 1) multivariate analysis with the interpretation of a given score, and 2) the effects of management practices on individual indicators (Congreves et al., 2015; Martínez et al., 2017; Zuber et al., 2017). The no-tillage (NT), reduced tillage (RT), and high crop diversity is viewed as conservation practice that can improve soil health conditions while reducing environmental costs. Congreves et al., (2015) used Ontario Soil Health Assessment (OSHA) to evaluate the impact of long-term tillage and observed a higher OSHA score under NT. Wander and Bollero (1999) observed improved soil physical and biological properties under the NT system in an on-farm study. Martínez et al., (2017) in a long-term study found NT practice has high N mineralization potential, yet not linked to the high N uptake. Another benefit of NT in the N dynamic is the buffer effect against the intensified rainfall on N loss (Hess et al., 2020).Yet, NT and RT are not always associated with better soil health and crop production compared to CT (Hurisso et al., 2014). Hurisso et al., (2014) found the potential mineralizable C was at a level across different tillage practices assessed in a dryland agricultural study. Crop diversity in agricultural sites is even harder to evaluate due to variation in crop rotation types, prenniallity, and compositions of the crop residues. Congreves et al., (2015) argued that crop type is more influential in enhancing soil health compared to cropping diversity. Mpeketula and Snapp, (2019) in a long-term Michigan study found that the soil aggregate stability was positively associated with crop rotational diversity while SOC was not influenced. In addition, the biomass accumulation of a high crop diversity system did not always associated with high-yield compared to the corn monoculture (Finney et al., 2016).

Tradeoffs among soil health, crop production functions, and environmental function is observed in previous ecosystem literature (Agomoh et al., 2020; Greer et al., 2020). Greer et al., (2020) evaluated both the crop production and environment services as a result of reduced, standard, and high input management in the Illinois soybean cropping system. The high input management has a higher soybean yield compared to the reduced input with NT. However, the high-input system also introduces the issue of high N leaching, an environmental concern. In another North American study, Agomohh et al., (2020) found that high crop diversity is associated with increased wheat yield while diminishing soil health. There is clearly more research needed in trade-off effects in soil health properties, yield, and the environment. The purpose of this study was to evaluate the interrelationships of environmental factors, soil properties, and the management of field crop farms at a sub-regional level. We hypothesized that 1) environmental conditions be primary drivers of soil health, 2) high crop diversity and reduced tillage will be management factors positively associated with soil health, and 3) productivity and environmental soil health properties will vary in distinct ways, and not necessarily be positively related.

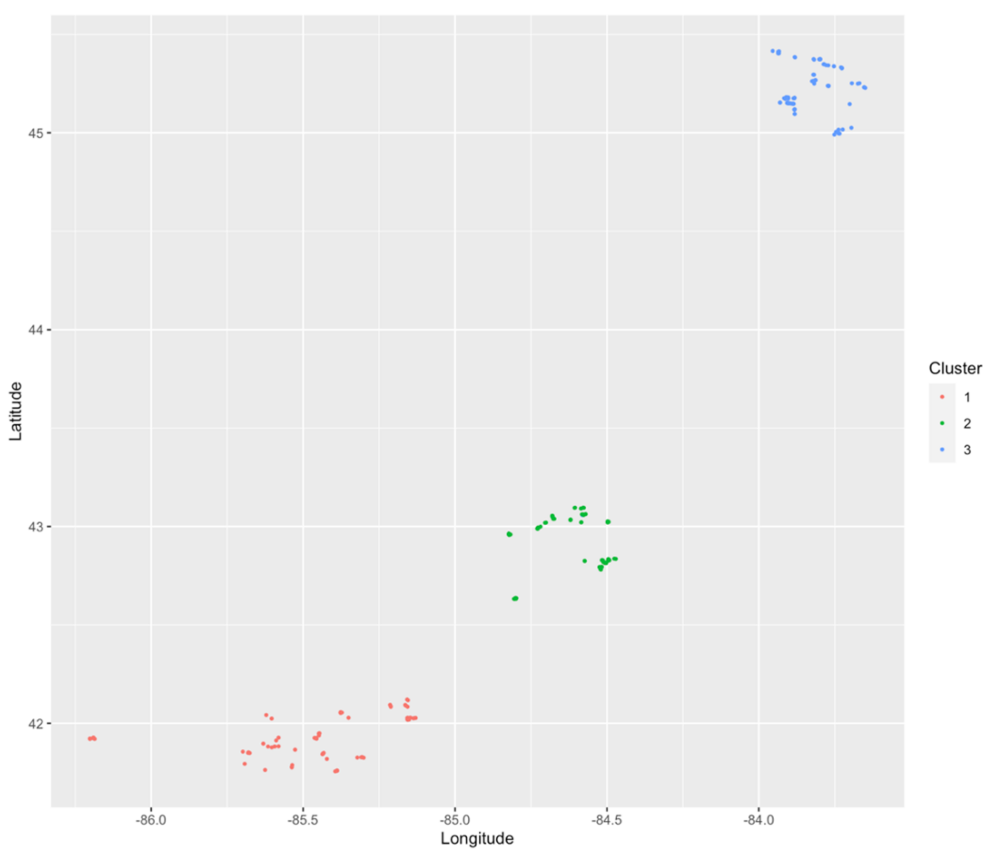
4.3 Materials and Methods

4.3.1 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; Tu et al., 2021). These study sites were located in 9 counties and represented a range of



(a)



(b)

Figure 4.1: (a) Dendrograms obtained by hierarchical cluster analysis for 202 focal plots; (b) location of each cluster.

climate conditions (Figure 4.1, Table 4.1). Each farmer picked one or two soybean fields to include in the study each year. For each field, Web Soil Survey (Soil Survey Staff, 2021) 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 97 focal plots in 2016 and 105 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.

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) followed the description 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.

$$\mathrm{CDI} = S \times A \tag{4.1}$$

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 focal plots with CDI value above 4 is defined as high diversity; others are defined as low diversity.

Tillage practices 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 tool type because lack of detailed information, such as the tillage working depth was not available. Tillage intensity was thus calculated as Eq.2.

$$\mathrm{Avg.STIR} = C \times P/Y \tag{4.2}$$

where Avg.STIR is the average annual quantitatively 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. In this study, we refer Avg.STIR = 0 as NT, Avg.STIR < 80 as RT, and the Avg.STIR ≥ 80 as conventional tillage (CT).

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 - 2015, and from 2007-2016 for focal plots sampled in the two years, respectively (Wan et al., 2015). Precipitation were extracted from TerraClimate (Abatzoglou et al., 2018) at a resolution of 4 km from 2006 – 2015, and from 2007-2016 for focal plots sampled in the two years, respectively. Elevation data was derived from NASA Shuttle Radar Topography Mission (SRTM) Digital Elevation Model at 30 m resolution (NASA JPL, 2013).

4.3.2 Soil Analyses

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 6mm, 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).

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 1N 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 KMnO4 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 the 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.

Inorganic nitrogen (Nin) and residual nitrogen (Nres) were measured 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. Potentially mineralizable nitrogen (PMN) was determined on field moist soil samples adapted from the anaerobic incubation method (Drinkwater et al., 1996). In addition to Nin determined at day 0, 10 mL deionized water was added to 10 g of soils, purged with N2 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.

4.3.3 Agronomic Performance

We established three 3.35 M2 quadrats in each focal plot shortly after soybean planting. The quadrats were used for crop sampling and measurement of soybean yield at the harvest. At maturity, soybean plants were collected from sampling quadrats and grain weight, moisture and test weight were recorded for yield calculation.

4.3.4 Statistical Analyses

Statistical analyses were conducted in RStudio version 1.1.456 (RStudio Team, 2021). Hierarchical Cluster Analysis (HCA) was used as the first step to characterize the similarity of the focal plots' features. Clustering methods are used to classify objects, characterized by the values of a set of variables, into groups. As one of the widely used unsupervised models, HCA was adopted in soil science studies to identify the natural cluster with the visualization through dendrograms (Sena et al., 2002; Seaton et al., 2020). The HCA was computed with the hclust function in R based on Ward's criteria (Murtagh and Legendre, 2011).

Principal component analysis (PCA) was conducted for three purposes: (1) reduce the dimensionality of the dataset; (2) identify the main contributor of the variance; and (3) evaluate the sensitivity of various soil health indicators. We considered both long- and short- term environmental factors, various soil properties, agronomic performance, and management practices. First, we computed a primary PCA that included all variables to interpret the variance contribution from different categories. Secondly, we computed a final PCA that focused on the soil health indicators. The PCA was conducted with the Rfunction prcomp.

4.4 Results

4.4.1 Site Characterization

We grouped the focal plots into three clusters based on a dendrogram, which was drawn from long and short-term climate factors as well as soil properties (Figure 4.1a). Three clusters were a reasonable choice because of the balance of within-cluster variance and the number of clusters. Through the visualization of the geographical locations of the focal plots and cluster information (Figure 4.1b), we found that the clusters grouped by HCA were identical to our regional groups (Southwest, Central, and Northeast). The agreement between the HCA clusters and the geographical regions indicated that the variability associated with soils at the farm level is less than the variability at the regional level. Geographical location is the dominant determinant of focal plot similarity. Due to the consistency of HCA clusters and the geographical locations, the analysis proceeded using these three study sites (Southwest, Central, and Northeast).

The southwest site was characterized as warm and wet, because it had the highest average for temperature and growing season precipitation (long-term and short-term): MAP (983.87 mm), MAT (10.44 ° C), GDD (2564.91), GRprecip (512.54 mm), and GRtemp (19.46 ° C) (Table 4.1). In contrast, the cool and dry Northeast site had the lowest temperature, a growing degree average that was almost 3° C less than the Southwest. In addition, the Northest site also had the lowest precipitation, on average 170 mm less than the Southwest. The Central site is relatively warm and dry as the GRtemp was similar to the Southwest site (slightly cooler), and the GRprecip did not vary much from the Northeast site. Overall, there is a temperature trend across the latitude gradients as the MAT, GDD, and GRtemp all decrease as latitude increases.

Soil physical properties varied by regions as well (Table 4.1). Southwest sites had predominantly coarse soil, with low average clay content (8.40%), whereas the sites in the Central and Northeast respectively had average clay content of 14.17% and 15.47%. The Northeast site had low surface soil penetration resistance, PEN15, compared to the Southwest and Central sites. However, the subsurface soil penetration resistance did not follow the same pattern: compared to the Southwest

Table 4.1: Descriptive statistics of the environment, soil properties, residual nitrogen, yield, and tillage intensity of the three regions.

		Southwest (n = 59)	Central (n = 78)	Northeast (n = 65)
Environment	Elevation (m)	265	239.55	234.85
	Slope (%)	2.21	1.92	2.13
	MAP (mm)	983.87	891.4	812.95
	MAT (° C)	10.44	9.78	7.56
	GDD	2564.91	2471.35	2060.63
	GRprecip (mm)	512.54	444.64	436.77
	GRtemp (° C)	19.46	19.21	16.28
Soil physical properties	Clay (%)	8.4	14.17	15.47
	PEN15 (psi)	218.76	216.28	189.79
	PEN45 (psi)	487.83	302.44	361.67
	WAS (g g-1)	38.24	33.61	38.23
Soil chemical properties	SOC (g C kg soil -1)	10.2	13.8	17.1
	TSN (g N kg soil -1)	1	1.3	1.3
	P (mg kg-1)	43.14	33.21	27.51
	K (mg kg-1)	121.31	120.59	92.62
	Mg (mg kg-1)	127.03	201.15	236.54
	Ca (mg kg-1)	747.46	1054.49	1958.46
	CEC	5.89	8.1	12.15
	pH	6.54	6.59	7.4
	Nin (mg N kg-1 soil)	9.19	10.08	11.67
Soil biological properties	PMN (mg N kg-1 soil)	3.78	5.88	6.67
	POXC (mg C kg-1 soil)	466.5	555.61	655.29
	Cmin (0-3 d; mg C kg soil-1)	67.68	85.68	87.84
Residual Nitrogen	Nres (mg N kg-1 soil)	13.59	17.14	15.96
Yield	Yield (Mg ha-1)	3.66	3.55	2.4
Management practice	Tillage	58.36	42.79	31.22
	Crop Diversity (Low; % in the region)	68	87	66
	Crop Diversity (High; % in the region)	32	13	34

MAP, 10 yr mean annual precipitation; MAT, 10 yr mean annual temperature; GDD, growing degree days; GRprecip, growing season precipitation; GRtemp, growing season temperature; PEN15, penetration resistance at 0-15 cm depth; PEN45, penetration resistance at 15-45 cm depth; WAS, wet aggregate stability; SOC, soil organic carbon; TSN, total soil nitrogen; P, available phosphorus; K, extractable potassium; Mg, exchangeable magnesium; Ca, exchangeable calcium; CEC, cation exchange capacity; PMN, potential mineralizable nitrogen; POXC, permanganate oxidizable carbon; Cmin, carbon mineralization; Nres, residual nitrogen.

and Northeast, the Central site had the lowest PEN45 compared to the Southwest and Northeast sites. Similarly, the Central site also had the lower WAS than the Southwest and Northeast sites. For many soil biological and chemical properties (6 out of 9 variables), the Northeast site had the highest value compared to the other two sites, including SOC, Mg, Ca, CEC (12.15), pH (7.40), and Nin (11.67 mg N kg-1 soil). In addition, the Northeast site had the lowest P (27.51 mg kg-1) and K (92.62 mg kg-1). The Northeast site had relatively low total soil N, compared to high average SOC values, as TSN (1.3 g N kg soil -1) was the same as the average TSN level observed in the Central sites. The Southwest and Central sites were at similar levels for available K (121.31 mg kg-1 and 120.59 mg kg-1) and soil pH (6.54 and 6.59). The Southwest site was different from the Northeast site for all soil chemical properties, while the Central site overlapped with the Northeast for several edaphic properties.

The three soil biological properties, PMN, POXC, and Cmin generally increased with increased latitude across the state (Table 4.1). The Southwest site had the lowest PMN, POXC, and Cmin levels. The Northeast site was high in PMN, POXC, and Cmin. Residual nitrogen was highest in the Central site, similar to the Northeast site, and almost 4 mg N kg-1 soil higher than the Southwest site. In contrast, the soybean yield was highest in the Southwest site, followed by the Central site, and one-third lower at the Northeast site.

Field cropping system and management practices - allowing the calculation of a tillage index - were assessed in a survey that recorded a six year history, by field. Intensity of tilling on average was highest in the Southwest site (58.36), followed by the Central site (42.79), and lowest at the Northeast site (31.22) which had a large proportion of no-till fields. The Northeast site not only had the lowest tillage intensity, it also had the highest percentage of high crop diversity (34 %) based on the previous 6 year survey data. Southwest sites had a similar presence of crop diversity (32 %), and the Central site was the lowest. The focal plots represented a variety of Michigan field crop systems. In general, the dominant crops were corn and soybean. The high crop diversity was generally due to the incorporation of cover crop or perennials.

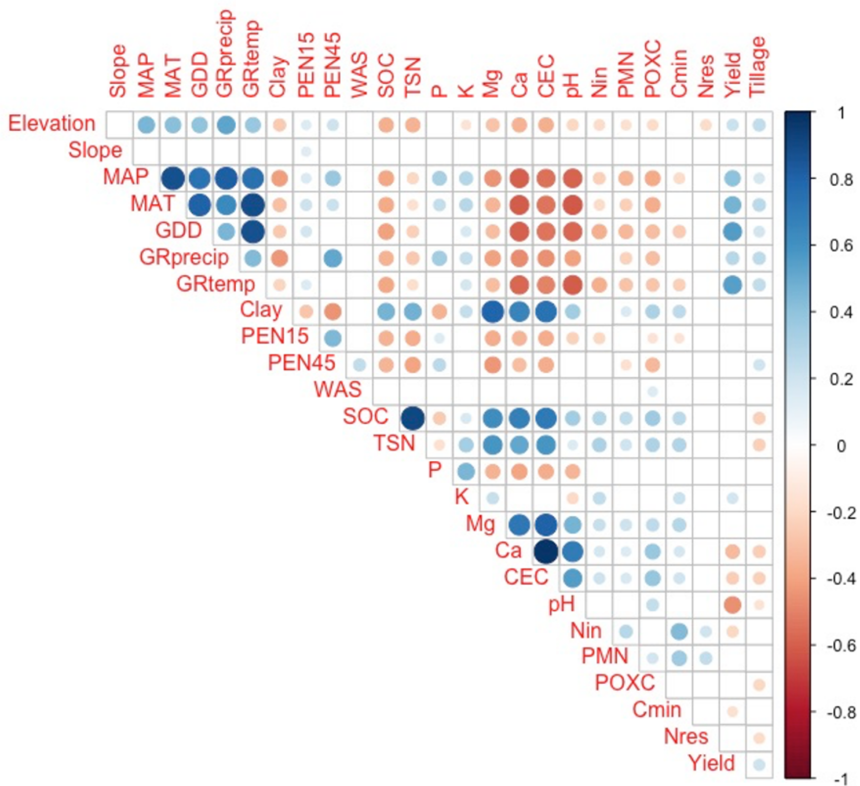


Figure 4.2: Visualization of a correlation matrix showing coefficients between management and environmental factors, and soil properties. Circles indicate significant ($p < 0.05$) correlations with positive relationships in blue and negative relationships in red. The degree of shading indicates the strength of the correlations

4.4.2 Correlation

We did a correlation analysis to explore the relationships among the environment, soil properties, agronomic performance, and management (Figure 4.2). We observed a significant correlation among the variables. There were strong correlations between the elevation and the short- and long-term precipitation and temperatures. Slope, as an environmental indicator, did not correlate with any other environment variables (Figure 4.2). The long-term precipitation and temperature were significantly associated with various variables: negatively associated with the clay, SOC, TSN, Mg, Ca, CEC, pH, Nin, PMN, POXC; and positively related to PEN15, PEN45, P, K, Yield, and Tillage (Figure 4.2). The majority of the soil variables, particularly, soil chemical properties were negatively associated with high precipitation and temperature. The high precipitation and temperature might not only lead to a crop production increase, but also the soil weathering and loss of nutrients.

Clay was negatively associated with PEN15, PEN45, and P; and positively correlated with SOC, TSN, Mg, Ca, CEC, pH, PMN, POXC, and Cmin. Surprisingly, soil clay was not significantly associated with WAS, residual N, or yield. The influence of clay on soil residual nitrogen or yield might be indirect from clays' interaction with other soil variables. Both surface and subsurface penetration resistances were negatively associated with SOC, TSN, Mg, Ca, CEC, and POXC. However, the relationships of surface and subsurface penetration resistance to other variables were not consistent. To be specific, PEN15 was also negatively linked to soil pH, Nin, and Cmin while PEN45 did not have a significant relationship to any of these variables. In contrast, PEN45 was positively linked with WAS and tillage while negatively associated with PMN. The last soil physical property, WAS, was only significantly linked to two variables PEN45 and POXC.

In general, soil chemical properties were positively linked to each other for the majority of the variables (SOC, TSN, Mg, Ca, CEC, pH, and Nin). Yet, some of the chemical properties, including available P and K showed different patterns. Available P was negatively linked to SOC, TSN, Mg, Ca, CEC, pH while positively linked to K. Though available K was positively associated with available P, these two variables did not share the same pattern. Available K was positively associated with SOC, TSN, Mg, Nin, Cmin, and yield, while negatively associated with pH.

The soil biological indicator PMN was positively associated with POXC and Cmin. However, Cmin and POXC were not significantly related. The three biological properties were positively associated with the soil chemical variables, including SOC, TSN, Mg, Ca, and CEC. Cmin was positively associated with available K while PMN and POXC did not show a significant relationship. POXC was the only soil biological variable that was positively linked with soil pH. The two mineralization indicators, PMN and Cmin, were both positively associated with Nin.

The residual nitrogen, Nres, reflected the soil N condition after harvest. Yet, it did not show

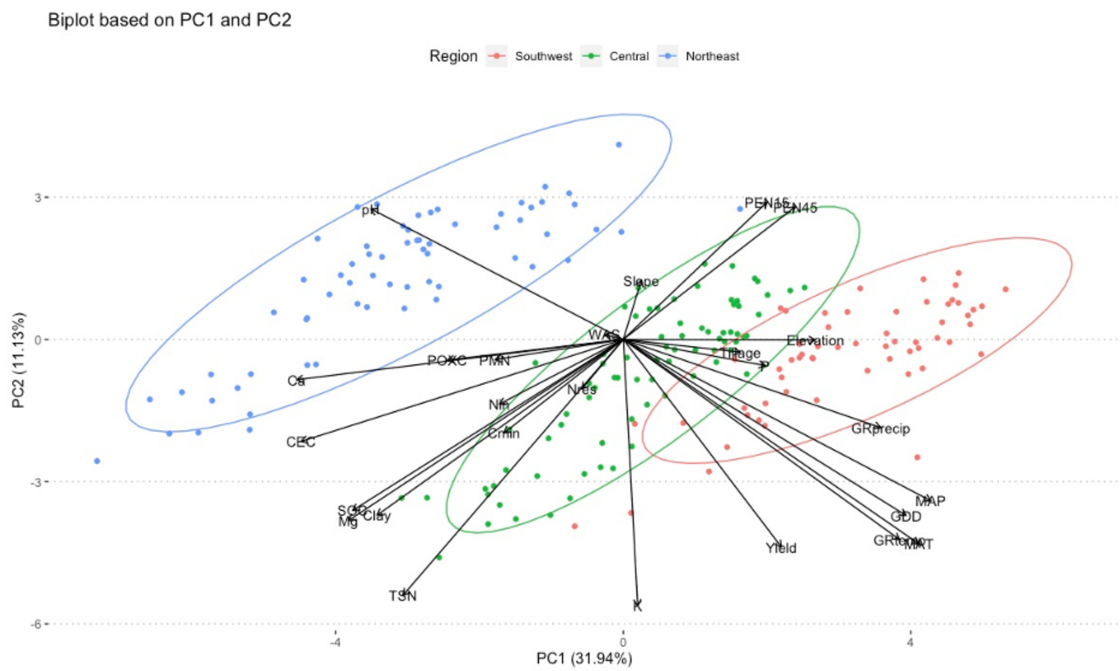


Figure 4.3: Biplot of 26 environmental, soil properties, and management variables for 202 focal plots (PC1 and PC2). The color shows the region of the focal plots.

any significant relationship with the growing seasons' environment variables (GDD, GRprecip, GRtemp). Residual nitrogen was positively linked with the Nin and PMN, while being negatively associated with elevation and tillage.

The soybean yield was positively associated with many environmental factors including long-term and short-term precipitation and temperature. The soybean yield was also significantly associated with several soil chemical properties (K, Ca, CEC, pH, and Nin), whereas K was the only one that had a positive relationship. Interestingly, the tillage intensity was positively associated with yield.

Noticeably, the correlation showed that the relationships among the variables did not indicate causality. We have observed significant correlations among various variables (Figure 4.2). These correlations suggested that PCA is a reasonable method to reduce the dimensionality and allowed exploration of the variance among properties associated with the focal plots.

Table 4.2: Principal component analysis of soil health indicators with eigenvalues and proportion of variability explained for the first seven principal components (PC) with eigenvalues > 1. Loadings greater than 0.23 are bolded.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigenvalue	8.3	2.89	2.08	1.54	1.42	1.18	1.14	1
Proportion	0.32	0.11	0.08	0.06	0.05	0.05	0.04	0.04
Cumulative variance	0.32	0.43	0.51	0.57	0.62	0.67	0.71	0.75
Environment								
Elevation	0.18	0	0.17	-0.17	**0.39**	-0.1	0.21	0.24
Slope	0.02	0.08	0.09	-0.13	-0.19	-0.16	**0.55**	**0.5**
MAP	**0.29**	**-0.23**	-0.03	-0.16	-0.01	0.09	0.1	0.05
MAT	**0.27**	**-0.29**	0.03	-0.01	0.05	0.01	0.12	-0.05
GDD	**0.26**	**-0.25**	0.2	0.04	-0.06	-0.05	0.01	-0.1
GRprecip	**0.24**	-0.12	-0.17	**-0.31**	0.19	0.09	0.08	0.19
GRtemp	**0.26**	**-0.28**	0.22	0.08	-0.02	-0.04	0.02	-0.07
Soil Physical Parameters								
Clay	**-0.23**	**-0.25**	0.17	-0.05	0.02	-0.03	0.14	-0.22
PEN15	0.13	0.19	-0.08	-0.12	**-0.26**	**-0.23**	**0.25**	**-0.34**
PEN45	0.16	0.19	**-0.27**	**-0.41**	0.03	-0.05	0.09	-0.24
WAS	-0.02	0.01	-0.13	**-0.41**	-0.13	**-0.55**	-0.2	-0.11
Soil Chemical Parameters								
SOC	**-0.25**	**-0.24**	-0.04	-0.13	-0.04	-0.03	-0.1	0.1
TSN	-0.2	**-0.36**	-0.06	-0.06	-0.09	0.01	-0.09	0.14
P	0.13	-0.04	**-0.4**	0	**-0.28**	0.21	-0.22	0.1
K	0.01	**-0.37**	**-0.32**	-0.18	-0.22	0.1	0.04	-0.07
Mg	**-0.25**	**-0.25**	0.1	-0.11	0.11	0.01	0.09	-0.19
Ca	**-0.3**	-0.06	0.1	-0.22	0.02	0.08	0.09	-0.09
CEC	**-0.3**	-0.14	0.1	-0.19	0	0.06	0.09	-0.1
pH	**-0.23**	0.18	0.1	-0.22	0.13	0.14	0.1	-0.06
Soil Biological Parameters								
Nin	-0.11	-0.09	**-0.43**	0.14	0.21	0.16	0.14	0.15
PMN	-0.12	-0.03	**-0.26**	**0.3**	0.19	**-0.49**	-0.08	0
POXC	-0.16	-0.03	0.08	-0.03	**-0.25**	**-0.34**	-0.1	**0.44**
Cmin	-0.11	-0.13	**-0.33**	0.08	**0.35**	-0.12	0.2	0.05
Residual Nitrogen								
Nres	-0.04	-0.07	-0.14	**0.36**	-0.14	-0.15	**0.52**	**-0.27**
Agronomic Performance								
Yield	0.15	**-0.29**	0.15	0.13	-0.05	-0.22	-0.13	0.01
Management								
Tillage	0.11	-0.02	0.02	-0.08	**0.48**	-0.2	-0.19	-0.1

4.4.3 PCA analysis

We used 26 variables from environmental, soil properties, agronomic performance, and management practice to understand the drivers of variance among the focal plots (Table 4.2). In this general analysis, we found the long and short term climatic variables and soil edaphic physical and chemical properties made up 32% variability in the dataset. In the first principal component (PC1), positive loadings were MAP, MAT, GDD, GRprecip, and GRtemp; while the negative loadings were clay, SOC, Mg, Ca, CEC, and pH. The variables with high positive loadings of PC1 were generally related to the geographical locations of the focal plots. The variables with negative loadings of PC1 were mostly soil edaphic properties that were subtle to farm managements, except the soil pH. The biplot of the 26 variable PCA (Figure 4.3) showed a clear separation of regions. The PCA result also agreed with the HCA that the geographical location contributed to most of the variance in the dataset.

To better understand the variability of focal plot due to soil properties, we focused on the soil physical, chemical, and biological parameters as well as residual nitrogen and agronomic performance (Table 4.3). We used residual nitrogen and soybean yield in the soil health PCA analysis because both of the two variables reflect soil ecosystem functions. In addition, farmers use the yield as an indicator to evaluate the resilience of the cropping system. The first PC explained 32% variability of the dataset, which included large magnitude variables such as clay, SOC, TSN, Mg, Ca, and CEC. These variables can be grouped into soil edaphic properties that could be reluctant to farming practices. The second PC accounted for 11% of the variability of the dataset. High loading variables on PC2 include P (-0.39), K (-0.51) , pH (0.35), Nin (-0.35), and Cmin (-0.31). Different from PC1, the variables with high loadings for PC2 were more sensitive to management practices. According to the biplot, the Northeast site had the largest variation in both PC1 and PC2 (Figure 4.4a) while the Central site had the least variation in PC1 and the Southwest region had the least variation in PC2. Though there was no clear separation of the three sites in the biplot of PC1 and PC2, the Northeast site did have more focal plots with low PC1 scores compared to the Central and the Southwest site. There was no clear separation in the tillage groups (Figure

Table 4.3: Principal component analysis of soil health indicators with eigenvalues and proportion of variability explained for the first seven principal components (PC) with eigenvalues>1. Loadings greater than 0.3 or smaller than -0.3 are bolded.

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	5.83	2.07	1.54	1.42	1.14	1.01
Proportion	0.32	0.11	0.09	0.08	0.06	0.06
Cumulative variance	0.32	0.44	0.52	0.6	0.67	0.72
Soil Physical Parameters						
Clay	**-0.32**	0	-0.17	0.06	-0.05	**0.32**
PEN15	0.2	0.04	0.24	0.25	0.13	**0.4**
PEN45	0.22	-0.02	**0.38**	**0.35**	-0.05	0.17
WAS	-0.02	-0.04	0.22	**0.51**	**0.5**	-0.09
Soil Chemical Parameters						
SOC	**-0.34**	-0.11	-0.03	0.14	0.07	-0.18
TSN	**-0.31**	-0.24	-0.14	0.12	0.02	-0.18
P	0.17	**-0.39**	0.03	0.19	-0.24	-0.11
K	-0.06	**-0.51**	-0.08	**0.36**	-0.23	0.18
Mg	**-0.36**	-0.02	-0.07	0.06	-0.09	0.19
Ca	**-0.37**	0.18	0.08	0.12	-0.08	0.12
CEC	**-0.38**	0.1	0	0.12	-0.07	0.15
pH	-0.24	**0.35**	0.28	0.03	-0.17	0.02
Nin	-0.14	**-0.35**	**0.33**	-0.23	-0.2	-0.14
Soil Biological Parameters						
PMN	-0.13	-0.22	0.24	-0.28	**0.49**	-0.08
POXC	-0.19	0.06	-0.08	0.13	**0.41**	-0.22
Cmin	-0.15	**-0.31**	**0.34**	-0.19	-0.03	-0.08
Residual Nitrogen						
Nres	-0.05	-0.18	0.1	**-0.35**	0.25	**0.64**
Agronomic Performance						
Soybean Yield	0.1	-0.23	**-0.55**	0.02	0.22	0.16

PEN15, penetration resistance at 0-15 cm depth; PEN45, penetration resistance at 15-45 cm depth; WAS, wet aggregate stability; SOC, soil organic carbon; TSN, total soil nitrogen; P, available phosphorus; K, extractable potassium; Mg, exchangeable magnesium; Ca, exchangeable calcium; CEC, cation exchange capacity; PMN, potential mineralizable nitrogen; POXC, permanganate oxidizable carbon; Cmin, carbon mineralization; Nres, residual nitrogen.

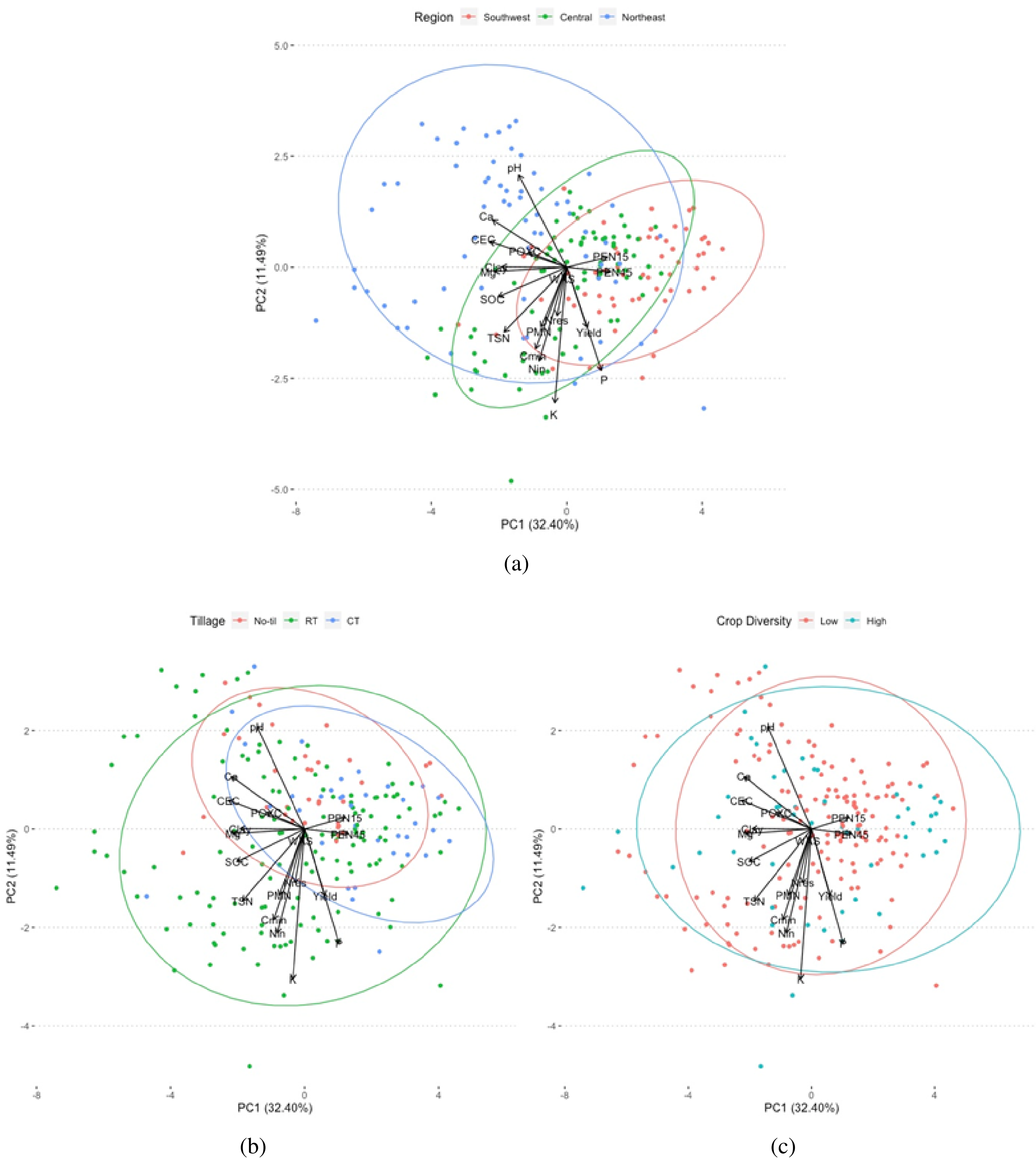


Figure 4.4: Biplot of 18 variables and 202 focal plots (PC1 and PC2): (a), the color shows the region of the focal plots; (b) the color shows the tillage practice of the focal plots; (c) the color shows the crop diversity of the focal plots.

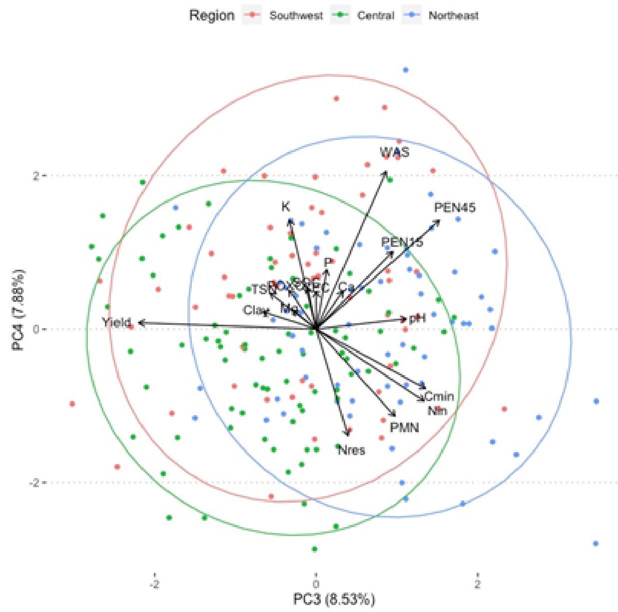
4.4b). The RT plots had the largest variation in PC1 and PC2 compared to the NT and CT plots, which was due to the larger numbers of the RT plots in this study. The NT plot had slightly lower PC1 and higher PC2 scores than CT plots. The biplot of the low and high crop diversity focal plots were overlapped and no specific pattern was observed (Figure 4.4c).

The third PC explained 9% of the variation with loading positively with PEN45, Nin, Cmin, and positively with soybean yield (Table 4.3). The fourth PC explained 8% of the variation with loading positively with PEN45, WAS, K, and negatively with residual N. In the biplot, we observed the soybean yield as a strong determinant of PC3, while Nres was a negative determinant of PC4 (Figure 4.5a). The PC3 and PC4 did not separate the region clusters (Figure 4.5a). However, there was a clear difference of the variation pattern in the tillage practice and crop diversity group (Fig 5b). The CT focal plots had high variation in PC4 while NT and RT plots had high variations in PC3. The high diversity plot had high variation in PC4. However, the low diversity plot and high diversity plot had similar variations in PC3.

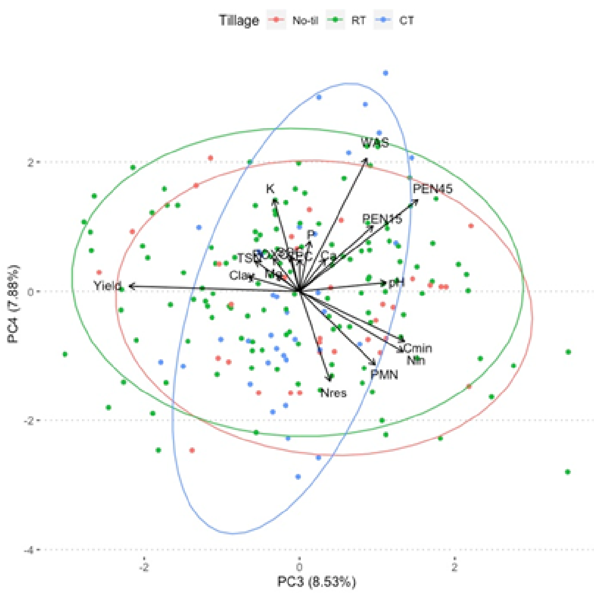
4.5 Discussion

4.5.1 Site characterization

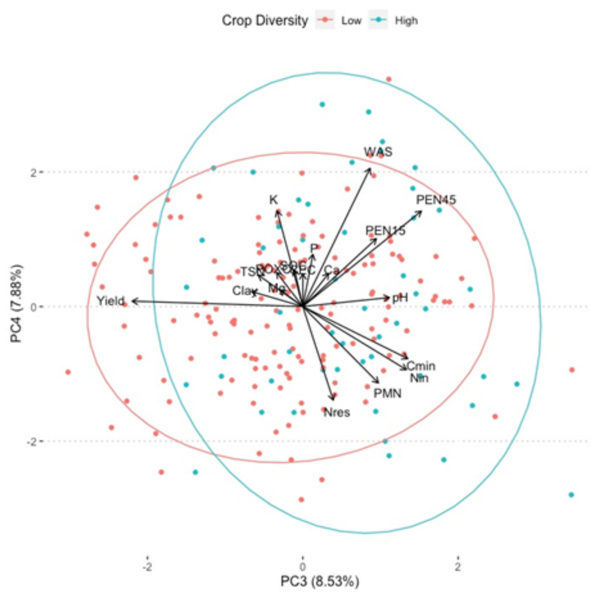
Climatic factors were the dominant contributors to the variation observed with focal plot soil and plant properties in this study. This is not surprising as there are marked gradients in temperature, and rainfall, across the state of Michigan. Similar observations have been reported in several regional studies across a single state or several states (Mann et al., 2019; Rottler et al., 2019). Rottler et al., (2019) in an U.S. southern great plains regional study evaluated both environmental and agricultural management effect on soil health. With the data from three southern state, Rottler et al., (2019) concluded the climatic factors are dominant drivers of soil health variations across the regional scale. Variation between three geographical clusters was much larger than variation within clusters or at the farm level. Soil genesis theory proposed by Jenny (1941) pointed out that soil-forming is a function of climate, organisms, topography, parent material, and time. Thus, variations in climate and other factors are expected to lead to soil heterogeneity. Our study confirmed this



(a)



(b)



(c)

Figure 4.5: Biplot of 18 variables and 202 focal plots (PC3 and PC4): (a), the color shows the region of the focal plots; (b) the color shows the tillage practice of the focal plots; (c) the color shows the crop diversity of the focal plots.

viewpoint as the cluster groups by HCA were identical to the three geographical locations. Previous studies have used soil health frameworks with soil scoring functions that were built upon inherent site-specific factors (Andrews et al., 2004; Moebius-Clune et al., 2016; Nunes et al., 2021). Our results highlight the importance of locality, namely that soil health assessment requires attention to context. This is supported by previous studies that show the importance of setting realistic goals by location and by management objectives (Haddaway et al., 2017; Rottler et al., 2019). Realistic management goals do require understanding of the local climatic conditions and soil properties.

4.5.2 Soil health indicators

Clay is a key determinant of the majority of the soil health indicators investigated in this study. The positive relationship between clay and soil organic matter has been observed in many previous studies (Burke et al., 1989; Fine et al., 2017; Rottler et al., 2019). Soil texture is a common soil health indicator included in various soil health frameworks (Andrews et al., 2004; Moebius-Clune et al., 2016; Nunes et al., 2021). The soil physical parameter WAS, on the other hand, was not closely related to texture or SOC. Interestingly this measure of soil structure was associated with properties likely to be influenced by field management practices: PEN45 and POXC. Two of these parameters -WAS and PEN45 - are generally not measured in on-farm studies (Rottler et al., 2019; Wander and Bollero, 1999) . Yet, we have found that WAS and PEN45 account for considerable variation across the focal plots. Similar findings were observed by Zuber et al., (2017) and Fine et al., (2017) that WAS contributes substantially to variation, as shown by the PC loadings calculated using multivariate PCA. However, soil physical properties are generally tested in commercial labs nor as popular as the soil chemical nutrient packages.

Soil chemical parameters provide insights into available nutrient supply, and are a base for recommendations to improve agronomic performance. Consistent with our findings, other multivariate analysis studies have shown soil chemical parameters to contribute substantially to variation, as indicated by high loadings in the primary two PCs (Fine et al., 2017; Mann et al., 2019; Zuber et al., 2017). The correlation among soil chemical parameters also implied that high fertility plots are generally high in each nutrient. As we observed soil chemical parameters were generally correlated with climate and environment factors, this implies that inherent site-specific variations accounted in large part for field soil fertility status. Yet, as each nutrient element provides specific functions for crops, the individual test of soil chemical parameters is still needed.

Residual inorganic nitrogen subsequent to crop harvest is an indicator of potential N loss through leaching. This is an ecosystem disservice that has been studied previously and associated with water quality regulation (Al-Kaisi and Licht, 2004; Drury et al., 2011; Sainju et al., 2017; Varvel and Peterson, 1990). At the same time, Nres is not widely used as an indicator of soil health. Instead, nitrate-leaching is measured through leachate and the inverse of the nitrate-leaching has been included in assessments as a N conservation health indicator (Snapp et al., 2010). Sampling timing may also play a role in why it is often overlooked, as Nres is sampled after harvest, generally in the fall, which requires investment in additional sampling beyond a pre-plant soil collection which is widely used for soil health evaluations (Moebius-Clune et al., 2016).

Our finding of a positive relationship between Nres and Nin and PMN implies potential leaching concerns in soybean systems where N availability in the spring is sufficient to support early rapid growth. Similarly, Varvel and Peterson (1990) found that the high N application leads to high residual soil nitrate in the continuous corn and sorghum system. In our soybean cropping system, there was nil N fertilizer application at the beginning of the growing season. Thus, the baseline Nin indicates the potential residual nitrogen within the system after harvest. For the soybean system, evaluation of Nin and PMN will benefit the understanding of the N dynamics in the system. We also observed a negative relationship between tillage intensity and Nres. This is the first study we are aware of to evaluate this relationship, at this spatial scale. Al-Kaisi and Licht, (2004) assessed the residual N in a corn cropping system in two Iowa research demonstration farms with three different tillage systems. Counter to our findings of low tillage intensity associated with high residual nitrogen, Al-Kaisi and Licht, (2004) found NT and strip-tillage have lower residual N compared to fall chisel plow tillage after two years of corn and soybean rotation. In our study, the Nres was measured after the soybean growing season, which implies the legume system has different N dynamics.

Reduced disturbance of soil, through practicing NT or RT, has been recommended as good management practices in corn-based rotations, as studies in United States and Canada show that farmers can reduce nitrogen loss and maintain yields (Jayasundara et al., 2007; Singh et al., 2018). Our findings raised questions regarding these recommendations, as there appeared to be tradeoffs between soybean yield and late season inorganic N, at least at some sites. Thus, our study expands on previous experimentation which was conducted primarily on well-managed research stations, to evaluate these relationships across a hundred or more field sites. This can provide valuable insight. Indeed, a recent study in SW Michigan compared crop management at plot, field and farm scale and found that performance at plot scale was often not predictive of field or farm scale (Kravchenko et al., 2017). In our case, there does appear to be high variation in soybean yield, associated with reduced tillage, and interacting with the site. This requires more investigation, and suggests the need for recommendations that are location specific or soil type specific.

Yield is often evaluated as a dependent variable of soil health. However, it is also used as a soil health indicator in soil health scorecards (Romig et al., 1994). We include soybean yield as a soil health indicator as it reflects the provisioning service of soil. The high correlation of soybean yield with the short- and long-term climate factors from remote sensing data and several soil parameters implied a potential yield predicting model with satellite. Khaki et al., (2021) used remote-sensing data for soybean yield prediction. The inclusion of soil chemical parameters can improve yield prediction. Surprisingly, we did not find a correlation of soybean yield with soil physical parameters. Tillage practice in this study is positively associated with soybean yield, which supports the findings in a Midwest soybean study by Greer et al., (2020) that high input leads to high yield. Noticeably, the warm and wet Southwest site also had the highest tillage intensity compared to the other two sites.

4.5.3 Variations

When evaluating the accountability of the variation across focal plots from soil health indicators, PCA is generally used (Congreves et al., 2015; Fine et al., 2017; Mann et al., 2019; Sena et al., 2002; Wander and Bollero, 1999; Zuber et al., 2017). The PC1 from our PCA results (Clay, SOC, TSN, Mg, Ca, and CEC) can be categorized as soil edaphic properties and are reluctant to manage practice changes. The PC2 (P, K, pH, Nin, and Cmin) is a group of more dynamic soil parameters that can be adjusted with management practices based on recommendations. The implication of these findings is that the dominant driver of the variation might be influenced by the inherent site-specific condition, while the second-largest variation PC could be improved with proper recommendation. The Nin and Cmin are two active soil health indicators that reflect the available N and C while PEN45 indicated the structural support from the deep depth. All of these indicators and soybean yield are in the PC3, another main contributor to the variance. However, only a couple of these variables are used in the PCA in previous research studies (Wander and Bollero, 1999; Zuber et al., 2017).

4.5.4 Management

We did not observe clear separation or patterns associated with crop diversity. The composition of cropping system patterns was complex, including forage, cover crop, and a wide range of field crops not limited to corn, soybean, wheat, alfalfa, potation, and dry bean. Grouping as high and low diversity cropping systems may have been insufficient to capture the wide range of plant types and combinations. At the same time, our findings that crop diversity had minimal effect on variability of crop yield and soil properties is consistent with a few other studies that evaluated tillage practice and crop diversity, where the former was more influential (Snapp et al; 2010; Zuber et al., 2017).

In contrast to crop diversity, tillage management was associated with high variability soil health properties. The intense tillage of conventional practice was generally associated with low Nres values, and with large variation in PC4 (Nres). Further, fields under reduced tillage (NT and CT) showed high variations in PC3 (yield). There appears to be a trade-off between soybean yield and potential N loss through leaching, as indicated by Nres. Farmer use of NT and RT is a means to stabilize residual N and thus mitigate environmental concerns with this potential N loss pathway; however this management was associated with some risk of variable soybean yield. This is consistent with an earlier analysis of this same Michigan on-farm data set, where a yield tradeoff was observed with reduced tillage (DeDecker et al., 2019).

4.6 Conclusion

We used two multivariate methods in this study, HCA and PCA. Both of these two methods confirmed that geographical clusters across a regional scale is the key determinant of soil health indicators. Recommendation for farming management practices should be made based on site-specific conditions. Residual nitrogen is an informative soil health indicator regarding the soil regulating function, which was determined by the available N rather than short-term temperature and precipitation. Soybean yield increased with tillage intensity in the soybean cropping system while SOC decreased. Thus, tradeoff of soybean yield and long-term SOC accrual need to be taken into consideration for management practice recommendations.

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CHAPTER 5

CONCLUSIONS

In this dissertation, I contribute to the understanding of soil health in four aspects 1) the current gap in laboratory analysis, commercial services, and farmers actual adoption of soil health assessment; 2) documentation of stable and labile carbon and nitrogen pool in Malawi and analysis of the main drivers of the variation; 3) investigation of the dominant contributor of individual soil health indicators in Michigan; and 4) multivariate analysis of the interrelationship of the soil health indicators in Michigan. From the Midwest United States to Malawi, I conducted soil analyses of over a thousand on-farm focal plots and revealed the drivers of various soil health indicators through real-world scenarios.

The development of sensitive laboratory soil health indicators added to the understanding of soil biological properties. Yet, farmers as end-users did not always have access to the whole soil health assessment package and mostly used the chemical package. Through a Likert survey, I identified the gap of awareness and the actual use of on-site soil health measurements. The on-site assessment tools provide new opportunities for farmers to do field characterization and monitoring.

I have documented the current labile and stable C and N pools in the tropic country of Malawi. It is the first study that investigates the labile carbon pool at the regional scale in Malawi. The analysis of environmental and management practices influence on the soil labile and stable C at regional and local scales provide further insights to understand the cause of the labile and stable C variations. The organic resource, including weeds, can improve soil C. In addition, the vegetative cover is potentially a useful indicator for predicting soil C at both regional and local scales.

The on-farm study that sampled across Michigan field crop farms evaluated the drivers of various soil health indicators individually. The environment factor, aridity, and soil clay content are the dominant drivers of a variety of soil health indicators. Crop diversity, regardless of the specific rotation types, was associated with better water aggregate stability. Intense tillage practice was associated with high PMN while did not lead to improved POXC. Thus, I need to consider the tradeoff effect on various soil health indicators while applying intense tillage.

Beyond investigation of drivers of individual soil health indicators, multivariate analysis is another common approach used in soil health research studies due to the intercorrelations among the variables. I employed hierarchical cluster analysis and principal component analysis and conclude that 1) geographical locations were the key determinant of the focal plot similarities, 2) soil edaphic properties (a few common soil health indicators in chemical package) explained most of the variations across the focal plots, and 3) intense tillage leads to low residual nitrogen and high yield.

My study brought insights for understanding soil health from different perspectives and future soil health on-farm trial research studies.

Lessons for policy and practice

Facing climate change – mitigation and adaptation

Climate change is happening now, and includes an increase in extreme weather events. This poses challenges for agricultural systems as crop growth and soil health rely on weather stabilities. An intense weather event, such as intense rainfall, can lead to crop failure during the growing season and soil erosion. The increasing temperature is also threatening the soil organic carbon in agricultural systems as shown in this dissertation. The soil loss will damage the resilience of agricultural systems. While I highlighted the dominant drivers of soil health as climate and soil edaphic properties, I do identify the contribution of management practice to soil health.

Soil management is viewed as one option for climate change mitigation in agricultural systems through carbon sequestration. In real-world scenarios, carbon sequestration in the agricultural system can be very complicated and involve large uncertainties. Management practices, such as increasing organic resources, can positively contribute to soil organic carbon in semi-arid Malawi. Through appropriate management, improved soil health should act as a medium to buffer the crop response to climate change. For example, soil physical properties influence water infiltration leading to variation of water content and nutrient cycling. Under extreme weather activities, management variation in different cropping systems is the key for soil health and resilience of the system. Increasing crop diversity has shown the potential to improve soil biological properties. In addition, the cropping system with high diversity can be more resilient to climate and pest risks, which can contribute to a stable and continuous biomass or residue return to the field.

Valuing soil health begins with measurements

The 2018 Farm bill has included the soil test in the Environmental Quality Incentive Program (EQIP). Soil health measurements are the critical first step for farmers to characterize their fields and evaluate the resilience of their fields. However, through my interaction with farmers in Michigan, there is still a need to deliver soil health assessment tools and technologies. For example, since 1995, the development of soil health scorecards in various states aims to build a useful tool with the rule of farmers and for farmers. However, few farmers were aware of such tools. Through participatory research, I included the end user in the process of identifying the problem, which helped me to understand the actual use and the need for soil health assessment tools. Laboratory analysis of soil health for farmers needs to be well interpreted and a reminder of keeping the consistency of the same lab.

Farmer participatory research in soil health

Participatory approaches are helpful for agricultural research and development in many ways, including being used to identify problems that deliver innovative solutions for new soil health assessment tools and technologies. In this dissertation, I adopted the farmer participatory research to document the actual adoption of various farm management practices and how farmers use soil health measurements for an on-site assessment. My study is an example that the participatory approach is a feasible and useful method in soil health studies. Through surveys and sampling on farmers' fields, I had direct interaction with farmers, which helped me to understand their socio-economic conditions and the land history.

Soil health management is impacted by the local context, including government policy. For example, in Malawi, the Government of Malawi has promoted the National Extension Policy to improve farmer's training. My study as a part of the Africa Research in sustainable intensification for next-generation (Africa RISING) has shown the potential of incorporating farmers in research to improve understanding of soil health. Continuous efforts will be needed to introduce the concept of soil health and innovative assessment tools for farmers under climate change. Chapter 2 as part of the Africa RISING panel study focused on continuous visits to smallholder farmers' fields and kept records of the management practice over years. These results are valuable resources for extension and policymakers in terms of maintaining soil health. The incorporation of organic resources in the maize field provides an opportunity to increase soil organic carbon. In this study, farmer participatory research approach implemented the local knowledge of drivers for soil health.