TARGETING TILLAGE INTENSITY IN MICHIGAN SOYBEAN SYSTEMS: ON-FARM OBSERVATIONS AND MULTIVARIATE MODELING OF GROWER DECISION-MAKING WITH IMPLICATIONS FOR YIELD AND SOIL CARBON

BY

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DISSERTATION

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ABSTRACT

Soybean growers must balance multiple, sometimes competing, economic and environmental objectives when deciding what level of tillage intensity is appropriate for a given field. Research has shown that decreasing soil disturbance can reduce the cost of soybean production, but the effects of conservation tillage on the soil environment and soybean performance are elusively site-specific, making precise tillage recommendations difficult. Moreover, grower decision-making regarding tillage intensity is a socio-psychological process whereby an individual's attitude, beliefs, and social status augment their capacity for rational utility maximization. This study aims to illuminate how soybean growers in the State of Michigan select tillage technologies, and the effect of conservation tillage on key measures of agroecological performance in the field. Building on existing work in behavioral economics, human ecology, agricultural engineering, agronomy and soil science, it asks: What factors influence Michigan soybean growers' selection of tillage technologies, and how do selected tillage technologies interact with variation in management history and the extant biophysical environment to affect soybean yield and soil organic carbon as integrated measures of agroecological function?

In the context of three local 'learning communities' facilitated by Extension, thirty-five Michigan soybean growers were surveyed and on-farm observations of crop, soil and environmental variables collected from one hundred and thirty-three of their commercial soybean fields over a period of two growing seasons. Analysis of this large biophysical and social data set using a combination of behavioral, mixed and structural modeling demonstrated that the effects of a particular tillage system on soybean yield and soil carbon are indeed site-specific at the sub-field level, and that grower selection of tillage technologies is influenced by both economic and social factors. These results indicate that adapting tillage technologies to the environmental and social context in which they will be applied is critical to realizing the full potential of conservation tillage and its positive contributions to agricultural sustainability. On this basis, it is recommended that outreach promoting conservation tillage in Michigan target resource limited, experienced soybean growers with loose social network ties, and farms growing soybeans on poor quality soils in warmers areas of the State.

To my family, friends and colleagues for your kind support throughout the process of research and writing.

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CHAPTER 1: LITERATURE REVIEW

1.1 SOYBEAN PRODUCTION IN THE STATE OF MICHIGAN

Soybean (*Glycine max*) was domesticated in China and has been cultivated there since at least the eleventh century BC (Hymowitz, 1970). The crop was first introduced to North America in 1765 by Samuel Bowen near Savannah, Georgia, and was adopted by many farmers in the Eastern Corn Belt and South Central U.S. during the early twentieth century (Hymowitz and Shurtleff, 2005). Today, soybean is primarily cultivated between 35˚and 45˚N latitude, making the U.S. State of Michigan a somewhat marginal production environment at the northern extent of the crop's adapted range (41.5˚- 45.5˚N latitude in the Lower Peninsula) (Hymowitz, 1970). The exact year of soybean's introduction to Michigan is unclear, but the United States Department of Agriculture reported that 3,238 ha were planted in 1924, the first year that soybean acreage was recorded for the state. Henry Ford was an early promoter of soybeans in Michigan, conducting extensive research and outreach on the crop as a source of protein and oil for industrial uses during the 1930s and 40s (Smith, n.d.).

Soybean acreage has increased steadily in Michigan since the 1930s, and Michigan currently ranks 13th among soybean producing states. Michigan farmers planted around 931,000 hectares of soybean in 2018, which represented approximately 2.6% of the total U.S. soybean crop that year (USDA-NASS, 2018). Soybeans are commonly grown in rotation with corn, wheat, hay or specialty crops on a wide range of soils in the state. Michigan growers produced a state record mean soybean yield of 3.4 t/ha in 2016 (USDA-NASS, 2018). Since 1976, the Michigan Soybean Promotion Committee has directed the soybean checkoff program in Michigan, which levees 0.5% of the value of soybeans sold to support research and outreach benefitting the soybean industry, including a grant program that partially funded the research reported in this dissertation.

1.2 TILLAGE DEFINITIONS AND MEASUREMENT

Tillage is defined as mechanical modification of soil for the enhancement of crop production (ASAE, 2005). Tillage tools modify soil through a wide range of physical forces such as cutting, fracturing, milling, beating and inversion that alter soil structure. Tillage is usually motivated by the need for amendment incorporation, seedbed preparation, weed control, or residue management in field crop production, and specific tillage tools have been designed for each of these purposes. Yet according to Wander and Gruver (2008),

> "The outcome of soil:tool interactions varies with respect to both the characteristics of the tillage operation (i.e. action, depth and width of disturbance, timing) and the characteristics of the soil that is being tilled (i.e. texture, structure, moisture, plasticity)".

In other words, physical and biochemical processes in soil and resulting plant growth are not influenced *directly* by the tillage tool used, but instead *indirectly* by the soil environment created using (or not using) tillage (Carter, 1994; Havlin et al., 1990). A single tillage technology is capable of producing differing soil environments depending on how it interacts with extant soil and environmental conditions (Soane and Pidgeon, 1975).

Tillage systems are commonly categorized by the intensity of soil disturbance within four categories of no-till, conservation tillage, reduced tillage and conventional (a.k.a. intensive) tillage (ASAE, 2005). Tillage intensity has traditionally been judged based on the amount of crop residue remaining after all tillage and planting operations have been completed in a given cropping cycle, with < 15% residue cover defining conventional tillage, 15-30% reduced tillage, 30-70% conservation tillage, and >70% no-till (ASAE, 2005; Baker, 2004). However, residue yield and quality differences between crops contribute to error in such measurements, and there is a recognized need to further standardize tillage system definitions and measurement in the scientific community (Derpsch et al., 2011, 2014). A more direct method of quantifying soil disturbance called the Soil Tillage Intensity Rating (STIR) formula was developed as part of the Natural Resource Conservation Service Revised Universal Soil Loss Equation Version 2 (NRCS RUSLE2) model (USDA-NRCS, 2008, 2016; Widman, 2004). This formula assigns each tillage tool/operation a unique intensity coefficient and categorizes tillage systems based on their cumulative STIR score. According to Claassen et al. (2018), STIR more accurately characterizes tillage intensity as compared to residue cover methods, as it is a direct, continuous and cumulative measure.

1.3 TILLAGE AND SOIL PROPERTIES

Reducing soil disturbance in annual cropping systems has been recommended since the 1940s as a means of conserving the natural capital of soil and enhancing its ability to provide ecosystem services (Dominati et al., 2010; Faulkner, 1943; Whiteside and Smith, 1941). However, subsequent research has found the relationship between tillage intensity and soil properties to be elusively site specific, based on unique soil:tool interactions as discussed above (Baker et al., 2007; Derpsch et al., 2014). In some environments, conservation tillage appears to be capable of sequestering carbon in soils and generating improvements in physical, chemical and biological functioning important for crop production, such as enhanced aggregation, water holding capacity, microbial activity and nutrient cycling (Alvarez, 2005; Blanco-Canqui et al., 2013; Syswerda & Robertson, 2014). In other cases reducing soil disturbance appears to have a neutral or opposite effect on these critical processes (Abdalla et al., 2013; Govaerts et al., 2009; Lal, 2018; VandenBygaart, 2016).

The effect of tillage on important soil properties is largely dependent on how disturbance interacts with baseline environmental factors such as soil type and texture (Needelman et al., 1999), moisture (Cook and Trlica, 2016; Toliver et al., 2012) and temperature (Schimel et al, 1994). These same parameters also set limits on the extent of tillage effects, as in the phenomenon of carbon saturation in soils where additional C inputs and reduced disturbance fail to increase soil carbon levels above a certain threshold (Stewart et al., 2007).

The frequency and length of time that a particular tillage practice is maintained on a field further influences how soil properties and crops respond. Research suggests that the positive effects of conservation tillage and no-till on soil properties may require 4+ years to accrue (Rhoton, 2000). Similarly, crop yields respond most positively to multiple consecutive years of reduced soil disturbance (Pittlekow et al, 2015). Some studies suggest that even infrequent tillage can compromise gains in soil carbon and improvements in soil structure realized under long-term no-till (Grandy et al., 2006; Grandy and Robertson, 2006).

However, not all effects of reduced tillage are positive, with increased soil compaction, residue accumulation and pest pressure being common concerns (Vanhie et al., 2015). In some cases, periodic or low intensity tillage used strategically within a crop rotation may benefit crop production or environmental quality by addressing these limitations without compromising long-term soil health (Conant et al., 2007; Crawford et al., 2015; Quincke et al., 2007). Measurements of tillage intensity must therefore account for not only soil:tool interactions, but also patterns of disturbance across multiple years to accurately estimate effects of tillage.

1.4 TILLAGE AND SOYBEAN YIELD

Soybean is generally well adapted to conservation tillage and no-till production, with yields equivalent to conventional tillage on a global and national basis (DeFelice et al., 2006; Pittelkow et al., 2015). Producer adoption data indicates that no-till was in use on approximately 39% of U.S. soybean acreage by 2012, with another 31% managed using some form of conservation tillage other than no-till that year, outpacing conservation tillage adoption in corn, wheat and cotton (Claassen et al, 2018; Wade et al., 2015).

Yet, research has demonstrated that reduced tillage systems can compromise establishment and yield of soybean in cooler climates of the Upper Midwest, especially on poorly drained soils and where large amounts of crop residue are present at planting (DeFelice et al., 2006; Vanhie et al., 2015). In a regional meta-analysis of 43 soybean tillage experiments, DeFelice et al. (2006) found average yield penalties of 2.4-6.4% associated with no-till in the region. This may partially explain why growers in the Upper Midwest have lagged behind other regions of the U.S. in conservation tillage adoption (USDA-NASS, 2018, Wade et al., 2015). Only 60% of soybeans grown in the State of Michigan are planted using conservation tillage (including no-till), which is about 14% below the national average and roughly 37% below leading conservation tillage states like Kansas and Nebraska (Claassen et al, 2018; Wade et al., 2015).

Realizing the full potential of conservation tillage in states like Michigan will therefore require improved understanding of, and ability to predict, the outcome of soil:tool interactions with fine spatial resolution. Scientists made early attempts to classify soils by their adaptability to conservation tillage, based on texture, structure and drainage, but those efforts were limited in scope and uncertainty remains regarding which taxonomic characteristics should be included in classification models for accurate and efficient estimation of tillage response in a specific cropping system (Cannell et al., 1978,1994; Cosper, 1983).

Recent meta-analyses have begun to delineate where conservation tillage may be more or less advisable for Midwest soybean growers (DeFelice et al., 2006; Ogle et al., 2012; Pittelkow et al., 2015, Toliver et al., 2012). DeFelice et al. (2006) and Toliver et al. (2012) found that the yield penalties for no-till soybean were more likely at high latitudes in the northern tier of U.S. states and increased on poorly drained soils, but could be mitigated to some extent by crop rotation. Pittelkow et al. (2015) found that no-till reduced legume yields in humid environments, but crop rotation and maintaining continuous no-till for at least three years eliminated that risk. Ogle et al. (2012) found that soybean yields decreased on hydric soils under no-till, but also saw a benefit from maintaining no-till for multiple years.

Still, the limited number of published tillage trials has necessitated low spatial resolution for such meta-analyses, which lends little support to tillage decision-making at the field to sub-field scale. Long-term tillage system comparisons in the Upper Midwest offer more detailed insight into the mechanisms behind unique soil physical and biological changes induced by conservation tillage, but their results can only be reliably extended to similar management systems and micro-environments (Dick et al., 1991; Pederson and Lauer, 2003; Robertson et al., 2014).

1.5 TILLAGE DECISION-MAKING

Neoclassical economic theory suggests that human beings make choices that are expected to maximize utility, or the decision-maker's well-being (Edwards-Jones, 2006). Financial gain is often assumed to represent utility, and thus farmers are frequently represented as rational profit maximizers (Feder and Umali, 1993). From this theoretical position, economists have developed complex models of farmer decision-making that have significant power to predict decisions with strong business or financial components (Edwards-Jones, 2006; Feder and Umali, 1993). However, there is evidence that many farmers have developed a "post-productivist" self-identity, and other factors beyond financial status influence farming utility (Burton and Wilson, 2006). Therefore, many economic models break down when attempting to predict systems-level decisions where anticipated changes in utility are only partially related to finances.

Many factors, less quantifiable than finances, such as health, happiness, and morality can contribute to conceptions of human well-being. In addition, the rationality of human choice is augmented in several ways. Rationality could perhaps be better described as subjective or "bounded" rationality (Simon, 1990). Human choice occurs under uncertainty. Decisions are based upon limited information formulated into beliefs about the available options, which may be more or less correct. Because humans must base decisions on such limited information and because our analytic powers are also limited we tend to take short-cuts (Gintis, 2009).

First in any decision process, several possible choices are discarded in unconscious, or preattentive, processing based on assumptions regarding the system at hand. For example, a soybean grower may discard the idea of no-till if residue or manure management are their primary objective in tillage decision-making. Secondly, we develop and apply heuristic rules to guide decision-making under uncertainty, often based on past experience or referring to what the neighbors have chosen (Gintis, 2009). Decision-making does not take place in exclusive space where only the decision-maker and options resound. Decision-makers gather information not only from their own experience but also from the experiences of those around them, in a process termed social learning (Bandura, 1986). Social relationships also evoke cultural norms that may lead an individual to make seemingly irrational decisions (Gintis, 2009).

Many studies have sought to explain differences in producer adoption of conservation technologies (Knowler & Bradshaw, 2007; Reimer et al., 2012), and conservation tillage specifically (Bultena & Hoiberg, 1983; D'Emden et al., 2006, 2008; Rahm & Huffman, 1984; Wade et al., 2016). Efforts to account for farmers' tillage decision-making have largely been based on correlations between individual demographic, farm structure or socio-psychological variables and tillage behavior, frequently represented as discrete binary adoption of a practice like conservation tillage. Limitations of this approach are many. For example, tillage intensity often varies between crops or fields on an individual farm, and along a spectrum of soil disturbance intensity (ASAE, 2005; Morris et al., 2010). This means that individual farmers cannot be easily classified as adopters/nonadopters of any one tillage system with confidence.

Furthermore, few consistent socio-psychological and economic drivers of tillage behavior have been identified in the literature (Knowler & Bradshaw, 2006). Access to and quality of information, financial capacity, and being connected to agency or local networks of farmers appear to be among the more important factors explaining conservation tillage adoption, but findings differ among individual studies and agroecological systems (Baumgart-Getz et al., 2012). Burton (2004) argued that advances in socio-psychological theory, particularly the Theory of Planned Behavior (TPB) should be applied to behavioral studies in agriculture in order to more accurately represent the complex decision-making processes of farmers.

The TPB suggests that individual beliefs about a behavior or practice determine behavioral intention, which drives actual behavior within the limits of external controls like capital or environmental conditions (Ajzen, 1991; Ajzen and Driver, 1992). The intention of a farmer to engage in a behavior is determined by i) the degree to which this behavior is evaluated positively or negatively by the farmer (attitude), ii) the feeling of social pressure from others to perform or not perform the behavior (subjective norm) and iii) the subjective beliefs about the ease or difficulty of successfully performing the behavior (perceived behavioral control). The TPB has recently been applied to studies of CT adoption among farmers, demonstrating significant differences in calculated behavioral intention between adopters and non-adopters of reduced and non-inversion tillage (Bijttebier et al., 2018; Wauters et al., 2010). However, the TPB has not yet been applied to understanding farmers' tillage behavior along a more realistic continuous spectrum of tillage intensity.

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CHAPTER 2: SOCIAL AND ECONOMIC DETERMINENTS OF TILLAGE BEHAVIOR AMONG MICHIGAN SOYBEAN PRODUCERS

2.1 INTRODUCTION

Reducing soil disturbance in annual cropping systems has long been recommended as a means of conserving the natural capital of soil and enhancing its ability to provide ecosystem services (Dominati et al., 2010; Faulkner, 1943; Syswerda & Robertson, 2014; Whiteside and Smith, 1941). Conservation tillage (CT) has been associated with sequestration of carbon in soils and improvements in physical, chemical and biological functioning important for crop production (Alvarez, 2005; Blanco-Canqui et al., 2013). Today, increasing soil health on arable land is also invoked as a potential solution to some of humanity's greatest challenges, including global food security and climate change (Lal, 2004). Farmers have adopted conservation tillage (CT) technologies, including no-till, on 51% of U.S. cropland in an effort to lower their cost of production (Weersink et al., 1992) and simultaneously realize the benefits of improved soil health (USDA-NASS, 2018).

However, adoption of CT has been inconsistent, with implementation differing vastly across cropping systems and geographic regions. For example, CT was in use on approximately 70% of U.S. soybean acreage by 2012, making it the leading CT crop nationwide as compared to corn (~65%), wheat (~62%) and cotton (~40%) (Claassen et al, 2018). Some regions of the U.S. have almost completely converted soybean acres to CT. In a cluster of south central states known as the Prairie Gateway, CT is used on over 95% of soybean acres (Claassen et al, 2018). Despite long-term experiments in the Upper Midwest highlighting success with CT (e.g. Robertson et al., 2014), only 60% of soybeans grown in the region are planted using CT, which is about 14% below the national average and roughly 37% below leading CT states like Kansas and Nebraska (Claassen et al, 2018; Wade et al., 2014).

Many studies have sought to explain such differences in producer adoption of conservation technologies (Knowler & Bradshaw, 2007; Reimer et al., 2012), and CT specifically (Bultena & Hoiberg, 1983; D'Emden et al., 2006, 2008; Rahm & Huffman, 1984; Wade et al., 2016). Neoclassical economic theory suggests that people seek to maximize their own well-being or utility (Edwards-Jones, 2006). Financial gain is often assumed to represent an increase in utility, so farmers are frequently represented as rational profit maximizers (Feder and Umali, 1993). From this rationale, limited adoption of no-till in the Upper Midwest might easily be dismissed. Reduced tillage systems can compromise establishment and decrease yields of soybean by 2.4-6.4% at higher latitudes, which may in-turn reduce net profitability (DeFelice et al., 2006; Vanhie et al., 2015).

Yet, there is evidence that most farmers have developed a "post-productivist" self-identity (Burton and Wilson, 2006), and the rationality of farmer decision-making is augmented in several ways. Rationality could perhaps be better described as "bounded" rationality (Simon, 1990) constructed using limited information (Gintis, 2009) within influential social networks. Efforts to account for farmers' perspectives in tillage decision-making have largely been based on correlations between individual demographic, farm system or socio-psychological variables and tillage behavior, frequently represented as discrete binary adoption of a practice like CT. Limitations of this approach are many. For example, tillage intensity often varies between crops or fields on an individual farm, and along a spectrum of soil disturbance intensity (ASAE, 2005; Morris et al., 2010). This means that individual farmers cannot be easily classified as adopters/nonadopters of CT with confidence. Furthermore, few consistent socio-psychological and economic drivers of tillage behavior have been identified in the literature (Knowler & Bradshaw, 2006). Access to and quality of information, financial capacity, and being connected to agency or local networks of farmers appear to be among the more important factors explaining CT adoption, but findings differ among individual studies and agroecological systems (Baumgart-Getz et al., 2012).

Burton (2004) argued that advances in socio-psychological theory, particularly the Theory of Planned Behavior (TPB) should be applied to behavioral studies in agriculture in order to more accurately represent the complex decision-making processes of farmers. The TPB suggests that individual beliefs about a behavior or practice determine behavioral intention, which drives actual behavior within the limits of external controls like capital or environmental conditions (Ajzen, 1991; Ajzen and Driver, 1992). The intention of a farmer to engage in a behavior is determined by i) the degree to which this behavior is evaluated positively or negatively by the farmer (attitude), ii) the feeling of social pressure from others to perform or not perform the behavior (subjective norm) and iii) the subjective beliefs about the ease or difficulty of successfully performing the behavior (perceived behavioral control) (Figure 2.1). The TPB has recently been applied to studies of CT adoption among farmers, demonstrating significant differences in calculated behavioral intention between adopters and non-adopters of reduced and non-inversion tillage (Bijttebier et al., 2018; Wauters et al., 2010). However, the TPB has not yet been applied to understanding farmers' tillage behavior along a more realistic continuous spectrum of tillage intensity.

In addition to the influence of attitude, subjective norms and perceived control captured by the TPB, there is increasing evidence that social connections within local networks influence farmer behavior, including their tillage practices (Baumgart-Getz et al., 2012; Ramirez, 2013;

Tessema et al., 2016). Farmers exhibit a strong preference for accessing information through personal experience and the experiences of other farmers (Eckert and Bell, 2006). Social interaction and information sharing among farmers in rural communities generates social capital that can influence individual behavior (Falk & Kilpatrick, 2000). Ingram (2010) noted that farmer experimentation with reduced tillage is enhanced and validated by social learning within communities of practice. Baumgart-Getz et al. (2012) found that interaction with neighboring farms and public agency personnel is positively correlated with adoption of best management practices like CT, while Tessema et al. (2016) showed that neighbor effect is a significant determinant of CT adoption.

Recognizing the combined influence of economic, socio-psychological and social network variables on tillage behavior, we sought to understand tillage intensity among Michigan soybean producers through application of the TPB and social network analysis. Our aim was to test the hypothesis that tillage intensity among this community is significantly influenced by farmers' subjective beliefs about CT technologies, which are partially dependent on their status within a farmer network. Using farmer survey data, we demonstrate that a continuous measure of tillage intensity can be accurately explained by modeling behavioral intention using a modified version of the TPB updated to include measures of social network centrality and engagement.

The remainder of the article is organized as follows. We first discuss our study area and sampling methodology targeting a constrained sample of Michigan soybean producers organized into three network groups. We then review analysis of the survey data using mixed models and social network mapping guided by the TPB and social network theory. This is followed by an outline of our study results and discussion of their contribution to the state of knowledge regarding the social aspects farmer behavior.

2.2 MATERIALS AND METHODS

2.2.1 Study Area and Sample

Our study focused on Michigan soybean producers participating in an on-farm observational tillage study coordinated by Michigan State University Extension (MSUE), known as the Jumpstarting Michigan Soybean Production Project (aka 'Jumpstart Project'). We recruited 33 commercial soybean growers in the spring of 2016, plus an additional two growers in 2017 to adjust for attrition. Participants farmed in one of three geographic target areas in the Lower Peninsula of Michigan, which we refer to here as the Northeast, Central and Southwest regions (Figure 2.2). Each target region included soybean fields distributed across 2-4 Michigan counties, and was associated with a local MSUE field crops educator on our research team. Most of the participating growers were recruited through, and had previously collaborated with, MSUE or other public agencies like Conservation Districts, which was likely a source of bias in our sample. However, this sampling approach also allowed us to test our hypothesis about the effects of established social networks on tillage behavior.

Each grower in the study supplied to our sampling population 1-3 fields planted to soybean in 2016, and 1-3 more in 2017. Fields were identified as "Good" or "Bad" as a form of sample stratification based on growers' experiential knowledge of historic soybean performance on-site. Six years of tillage history information was collected for each field using an initial written survey, including tillage tools used and number of passes (Appendix B). Cumulative tillage intensity was quantified for each field using a simplified version of the Soil Tillage

Intensity Rating (STIR) formula from the NRCS RUSLE2 model (USDA-NRCS, 2008, 2016; Widman, 2004). This formula assigns each tillage tool/operation a unique intensity coefficient and categorizes tillage systems based on their cumulative STIR score (Table 2.1). According to Claassen et al. (2018), STIR more accurately characterizes tillage intensity than residue cover methods used historically to categorize fields as conventional, conservation tillage or no-till. STIR coefficients were averaged across tool type because detailed information like the working depth of tillage tools was not available. Tillage intensity was thus calculated as STIR = Avg. Tillage Tool Coefficient * Number of Passes Reported. Resulting long-term STIR values ranged from 0 - 851.50.

2.2.2 Survey Design and Administration

A second survey instrument was designed to measure important demographic and socio-psychological variables, as well as network relationships among our farmer participants (Appendix B). The survey was customized for each of the three study regions (Northeast, Central, and Southwest) and began with a series of questions asking how well respondents knew each of the other growers in their region on a scale from 1 (Not at all) to 5 (Extremely well) to permit social network mapping. Respondents were also asked to rate the tillage intensity of other growers in their region on a scale from 1 (least intensive) to 5 (most intensive) as an objective measure of their knowledge of other growers' production practices.

The questionnaire continued to elicit responses to several Likert items related to the TPB on a scale from 1 (strongly disagree/extremely unlikely) to 7 (strongly agree/extremely likely). This included a) six questions measuring agreement with statements on various risks and benefits associated with reduced tillage in the literature to estimate respondents' attitude toward CT (e.g.

Further reducing tillage will…decrease the cost of soybean production); b) nine questions measuring agreement with statements on various barriers to CT adoption to estimate perceived behavioral control (e.g. How much do you agree or disagree that the following limits your ability to further reduce tillage on your farm? - Soil type constraints); c) seven questions measuring agreement with statements on various referents' opinion of CT (e.g. Do you believe that the following people/organizations agree-disagree that reduced tillage is a recommended practice for soybean production? - Jumpstart farmers within my region); and d) seven questions measuring respondents' inclination to follow the advice of the same referents, which were used to weight items C serving as an estimate of subjective norms regarding CT (e.g. If one of these parties were to recommend that you further reduce tillage for soybean production, how likely would it be that you would take their advice? - Jumpstart farmers within my region). Finally, respondents were asked to provide information on economic and demographic factors that might influence tillage intensity including their gender, age, education, annual household income, ethnicity, percentage of farm acres dedicated to soybeans, years of farming experience, percentage of owned vs. rented land, estimate dollars per acre spent on soil preparation and planting, whether or not a successor has been identified for the farm, and also their frequency of engagement with MSUE, the Jumpstart Project participants, and the Michigan Soybean Promotion Committee.

The survey was administered online via the Qualtrics software platform in March – May of 2018 targeting all 35 soybean growers participating in the Jumpstart project. An initial invitation to participate was made at regional grower meetings. Reminder emails were sent two weeks after each meeting. Growers that did not respond after an additional two weeks were contacted by phone with a follow-up request to complete the survey. This resulted in twenty-seven completed surveys, a 77% response rate. The twenty-seven responding growers included eight from the Northeast region, nine from the Central region and ten from the Southwest region who farmed a total of 98 fields in our on-farm sample, each with a different tillage history, which was treated as the effective sample size for analysis.

2.2.3 Statistical Analysis

Reliability of the TPB measurement scales for attitude, perceived behavioral control and subjective norm was assessed using Cronbach's alpha (Cronbach, 1951). Reliability was judged sufficient (threshold of alpha > 0.70) in all but our attitude scale. In that case, removal of one survey item measuring agreement with the statement that "Further reducing tillage will increase pest (weed, insect, or disease) pressure in soybeans" was required to increase alpha above the threshold. One attitude item gauging the effect of reducing tillage intensity on soybean yield had to be inversely coded to account for negative wording in the survey tool ("Further reducing tillage will decrease soybean yields").

Respondents' attitude, subjective norm and perceived behavioral control were then calculated as the mean of the related survey items to equally weight their potential influence on behavioral intention. Behavioral Intention (BI) was then calculated as:

$$(\mathrm{BI}) = \bar{X}a_{\mathrm{i}} + \bar{X}((s_{\mathrm{j}} * t_{\mathrm{j}})/7) - \bar{X}c_{\mathrm{k}}, \quad (1)$$

where $\bar{X}a_{\mathrm{i}}$ is the mean of survey items related to attitude, $\bar{X}((s_{\mathrm{j}} * t_{\mathrm{j}})/7)$ is the mean of individual referent scores multiplied by reported trust in those referents and divided by seven, and $\bar{X}c_{\mathrm{k}}$ is the mean of individual control items. The mean of control items was subtracted from the sum of attitude and subjective norm scores because our survey questionnaire framed them as barriers to reducing tillage with higher scores indicating greater barriers to adoption.

Linear mixed effects modeling (LME) was then applied to explain tillage intensity as a function of fixed behavioral intention, economic and demographic variables found to be significantly correlated with tillage behavior. Mathematically, our model can be identified as:

$$\text{(2)} \qquad \text{Tillage Intensity}_{ij} = \beta_{0j} - \beta_1 BI_{ij} + \beta_2 \chi_{ij} + \ldots + \beta_p \chi_{ij} + \mu_j + \varepsilon_{ij}$$

Our models included a nested random effects structure consisting of [region [field]] to account for our non-random sampling approach. LME models have several advantages over ordinary least squares regression models, particularly the ability to account for the inter-dependency common in on-farm observational data through the inclusion of nested random effects (Burger et al., 2012; Coe, 2002). This is accomplished by estimating parameters of a model of the covariance structure of the error, then using them to estimate the remaining parameters of the model with known variance. In this case, it allowed random shifts to the model intercept for each field within a region to account for differences in field history, like crop rotation, and also differences across regional social networks. Multi-model selection and inference was performed with a restricted maximum likelihood approach in the nlme package of R v3.5.3 (Pinheiro and Bates, 2004; R Development Core Team, 2019).

Social network mapping and analysis was performed using the igraph package of R v3.5.3 (R Development Core Team, 2019). Individual network maps were created for each of the three study regions by visualizing growers who indicated knowing one another as vertices (nodes) connected by edges (lines). Arrows were used to indicate the direction of relationships and edge thickness was weighted by how well one grower indicated knowing the other. Vertices were color coded according to growers' categorical tillage systems based on mean tillage intensity across all their fields. Network centrality scores were calculated for each grower, including hub, authority and degree scores. A grower's hub score measures the number of outward connections a grower indicated having in their network divided by the total number of possible outward connections. Authority score measures the number of inward connections a grower had based on others claiming to know them divided by the total possible, and degree scores are the sum of a grower's hub and authority score, measuring their total number of connections in the network. Network layout was based on Fruchterman-Reingold association index, which places nodes that share more connections in common closer together (Fruchterman & Reingold, 1991).

Finally, measures of network centrality and engagement were incorporated into a modified calculation of behavioral intention to determine if we could improve upon the traditional TPB model and its ability to predict tillage behavior. This was accomplished by multiplying a grower's hub score by seven, to make it equivalent to the other TPB model variables ranging from 1 to 7, then multiplying that value by a categorical rating of a grower's frequency of engagement with their social network through the Jumpstart project adjusted for scale, such that:

$$\text{Network connectivity} = (7(\text{HUB}))*\text{ENG}/5 \quad (3)$$

where HUB equals a growers hub score and ENG equals a categorical measure of network engagement frequency from 1 (never) to 5 (once a week). Because network connectivity proved to be positively correlated with tillage intensity in our analysis, a grower's calculated connectivity score was subtracted from their original behavioral intention value to generate a new network weighted behavioral intention score (BI_{net}). This modified BI value was subsequently used to predict tillage intensity in a new iteration of our final LME model.

2.3 RESULTS

Our sample was found to be representative of tillage practices for soybean across the state of Michigan and nationally, in that growers reported using CT on 64% of soybean fields during the study period (annual STIR 0-80 with no primary inversion tillage) and on 70% of study fields long-term (6 year cumulative STIR 0-480 with no primary inversion tillage). Average respondent ratings of TPB items are shown in Table 2.2. Agreement with attitude related items was much more pronounced than measures of subjective norms and behavioral controls. This suggests that respondents generally perceived significant advantages associated with reducing soil disturbance (positive attitude), but did not feel that farm system variables (behavioral controls) or social norms had much influence on their ability or willingness to reduce tillage intensity. Among the most agreed with attitude statements were the propositions that reducing tillage will reduce labor, reduce erosion and increase soil health. Potential barriers to CT adoption were generally rated low, although weather and climate, machinery availability and cost, crop rotation and manure management were noted as possible constraints by some. Referents viewed as most supportive of CT and trustworthy included MSU, other farmers participating in the Jumpstart project and the MI Soybean promotion committee.

Calculated behavioral intention (BI) scores not including our social network modification ranged from 3.61 to 12.51 and were negatively correlated with total tillage intensity as expected

(Pearson's $r = -0.271$, $P = 0.003$). A base LME model including BI as a single fixed effect and [region[field]] as nested random effects was significant ($F_{1,96} = 7.97$, $P = 0.006$), and explained a moderate amount of the variation in tillage intensity with a marginal R^2 (R^2m, fixed effects only) of 0.069 and conditional R^2 (R^2c, fixed and random effects) of 0.89. Economic and demographic variables that were significantly correlated with tillage intensity on a pairwise basis were then added to generate a global LME model explaining tillage intensity including farmer age, years of farming experience, attainment of a graduate degree, percentage of the farm planted to soybeans and annual household income. In this global model, BI ($F_{1,84} = 11.98$, $P = 0.0008$), income ($F_{6,84} = 5.20$, $P = 0.0001$) and years of experience ($F_{1,84} = 23.95$, $P < 0.0001$) were significantly correlated with tillage intensity, while age, attainment of a graduate degree and percentage of the farm planted to soybeans were not. A final reduced LME model including BI, income and farming experience was a significant improvement over the base model according to the likelihood ratio test and AIC, and explained a large proportion of the variation in tillage intensity (R^2m = 0.31, R^2c = 0.92) (Table 2.3).

Social network mapping generated three unique visualizations representing the Northeast, Central and Southwest regions (Figure 2.4). Overall network diameter for the Northeast region was 2, edge density was 0.82 and reciprocity was 0.91, suggesting that the Northeast growers were part of a close-knit network. Network diameter for the Central region was also 2, but edge density was 0.69 and reciprocity was 0.84, indicating that growers in this region were slightly less well connected. The Southwest region had the widest and least connected network with a diameter of 3, edge density of only 0.51 and reciprocity of 0.83.

Of the three available measures of network centrality (hub, authority and degree scores), hub score showed the strongest pairwise correlation with tillage intensity. Hub score was therefore combined with our categorical measure for frequency of engagement with other Jumpstart growers using the formula above to calculate a social network connectivity score for each grower. Because our analysis showed that this new measurement of network connectivity was positively correlated with tillage intensity (Pearson's $r = 0.42$, $P < 0.0001$) network connectivity was subtracted from our original BI values, generating new BI_{net} scores ranging from -0.22 to 11.27. BI_{net} was more strongly correlated with tillage intensity than our original measure of BI (Pearson's $r = -0.36$, $P = 0.0002$). Replace BI with BI_{net} in our reduced LME model improved the model significantly, reducing both the AIC and Log likelihood, and increasing the proportion of variation explained by the fixed effects ($R^2m = 0.35$, $R^2c = 0.93$). Table 2.3 compares our three successive LME models.

2.4 DISCUSSION

Our results support the hypothesis that the tillage behavior of Michigan soybean growers is influenced by a combination of social psychological, economic and control variables in line with the TPB. We also demonstrated that the TPB might be improved by incorporating measures of social network connectivity into the calculation of behavioral intention. While this analysis represents patterns of behavior among a small constrained sample of farmers, the patterns that emerged in our models are largely consistent with past research conducted at much larger scales (e.g. Baumgart-Getz et al., 2012).

The significant negative relationship between intention to reduce tillage intensity and tillage intensity behavior suggests that our items measuring farmers' attitudes, subjective norms, and perceived behavioral control over their tillage practice were robust. The positive relationship between household income and tillage intensity is supported by the literature in one sense because CT is recognized as a cost saving measure, which may not be necessary for growers with more disposable income (Weersink et al., 1992). However, income and capital are also frequently positively associated with adoption of conservation best practices, which seems to contradict our findings (Baumgart-Getz et al., 2012). Nevertheless, the role of financial capital as a strong external control on farmer behavior is widely recognized and was apparent in our study.

Farmer experience has shown inconsistent effects on adoption of conservation practices and CT specifically (Baumgart-Getz et al., 2012; Knowler & Bradshaw, 2006). On one hand, farmers experience often covaries with age, which suggests that older and more experienced farmers may have less time for, or interest in, innovation including adoption of new conservation practices. However, more experienced farmers may also be more skilled, well established, or face less risk when testing new practices, all which could encourage adoption of something like CT (Ingram, 2010). Our analysis showed a negative correlation between years of experience and tillage intensity, supporting the later conclusion.

The negative relationship between network connectivity and CT observed on our study contradicts past research showing that engagement in social networks, particularly those including like-minded experts or conservation practitioners, can facilitate CT adoption (Baumgart-Getz et al., 2012; Ingram, 2010; Ramirez, 2013; Tessema et al., 2016). We sought grower input to assist in interpreting this finding, which raised an intriguing point. Growers shared the perspective that being well-connected and visible in their network may at times increase the risk of innovation. For example, one grower who was also a former extension agent and quite prominent in his community told a story of trying no-till, which resulted in a crop failure due to uncontrolled weed pressure. He commented that he would never try no-till again because of the negative reaction from neighbors regarding his poor crop.

Innovation resistance, associated with network connectivity in this case, is an under studied phenomenon due to the strong pro-adoption bias present in most technology adoption research (Ram, 1987; Rogers, 2010). Many farmers demonstrate particularly risk-averse decision-making. Risk perceptions are socially constructed, which suggests that the strength of one's affiliation with a particular social network could easily influence risk perceptions (Wilkinson, 2001). Related to risk aversion is what Gintis (2009) called "time-inconsistency" in decision making, which can also bolster innovation resistance. Farmers tend to discount long-term risks, like soil degradation, and instead maximize short-term utility, as in tillage for weed control (Doohan et al. 2010). Performance uncertainty and perceived risk can further contribute to innovation resistance, and "major" or "discontinuous" innovations like CT threaten greater disruption of routine behavior, generating higher levels of perceived risk (Marra et al., 2003; Ram, 1987). A previous study showed that economic risk aversion among farmers was associated with delayed adoption of no-till in Michigan (Krause and Black, 1995). Weaker network ties may reduce the social risk of failure and are sometimes associated with greater capacity for creativity and innovation (Perry-Smith & Shalley, 2003).

2.5 CONCLUSION

Improved understanding of the many variables that influence farmers' tillage decisions can be used to target extension outreach for greater efficacy. Our study suggests that farmers with greater household income, more farming experience and weaker social network connectivity may be more likely to adopt CT technologies. In addition to these factors, accounting for farmers' subjective perspectives on the efficacy of CT (attitude), opinion of others regarding CT (subjective norm) and barriers to CT adoption is critical for the future success of outreach encouraging CT adoption.

2.6 TABLES AND FIGURES

Tillage operation	STIR[1]
No tillage	0
Double-disk opener planter	2.4
Strip till - coulter, 5" depth, 8" berm	7.7
Strip till - shank, 7" depth, 10" berm	15
Tandem disk, light finishing	19
Vertical till	20
Field cultivator, 6- to 12-inch sweeps	23
Tandem disk	32-39
Ripper	33
Chisel, twisted shovel or sweeps	42-49
Moldboard plow	55-65

[1]STIR values range from 1 - 200; lower scores indicate less soil disturbance.

Table 2.1. An example of STIR coefficients associated with particular tillage practices in the RUSLE2 model, adapted from USDA-NRCS, 2008.

Attitude Mean	**Reduce cost**	**Reduce labor**	**Reduce erosion**	**Reduce soybean yield**	**Increase soil health**				
5.60	5.85	6.26	6.15	3.78	5.96				
Control Mean	**Soil type**	**Manure**	**Equipment**	**Weather**	**Growing season length**	**Labor Avail.**	**Crop rotation**	**Financial capital**	**Knowledge**
2.21	2.33	2.35	2.48	2.48	2.04	2.11	2.37	2.04	1.73
Subjective Norm Mean	**Jumpstart farmers**	**Other farmers**	**Michigan State Univ.**	**Agribusiness**	**Landlords**	**General public**	**MI Soybean Promotion Committee**		
3.57	4.07	3.22	4.60	3.53	3.20	2.51	3.82		

Table 2.2. Mean grower responses to TPB items on a scale from 1 (strongly disagree) to 7 (strongly agree) that reducing tillage intensity a) will…, b) is constrained by…, and c) is recommended by… Attitude item "increase pests" was removed to improve index reliability and "reduce soybean yield" was reverse coded. Behavioral control items were framed as potential barriers to adoption of conservation tillage.

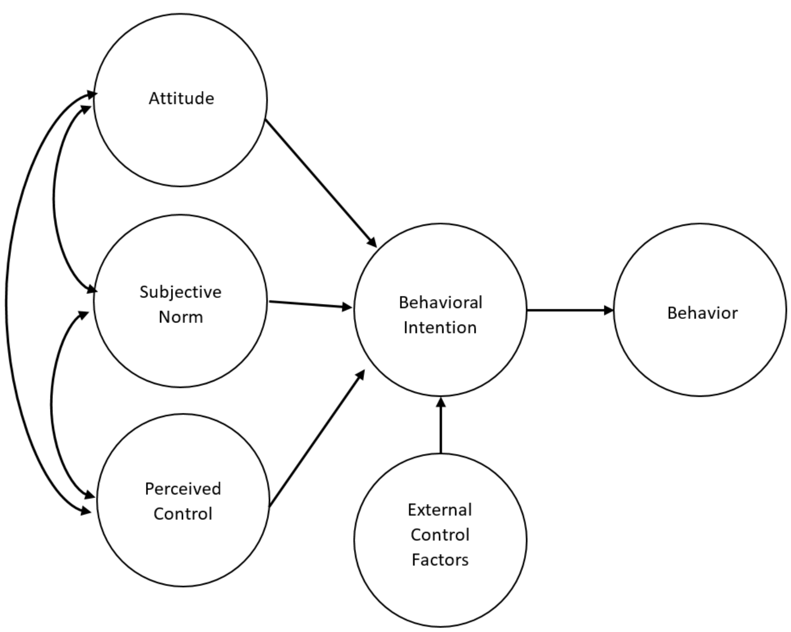

Figure 2.1. Representation of Ajzen's (1991) Theory of Planned Behavior. Adapted from Eagly and Chaiken (1993, p. 187).

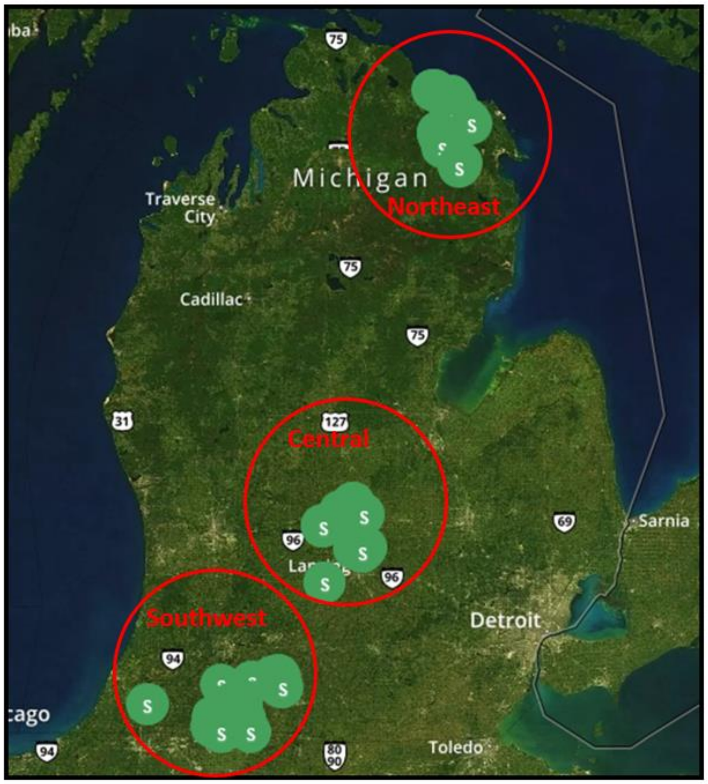

Figure 2.2. A map of Michigan showing study soybean field (S) locations on the farms in Northeast, Central and Southwest Lower Michigan.

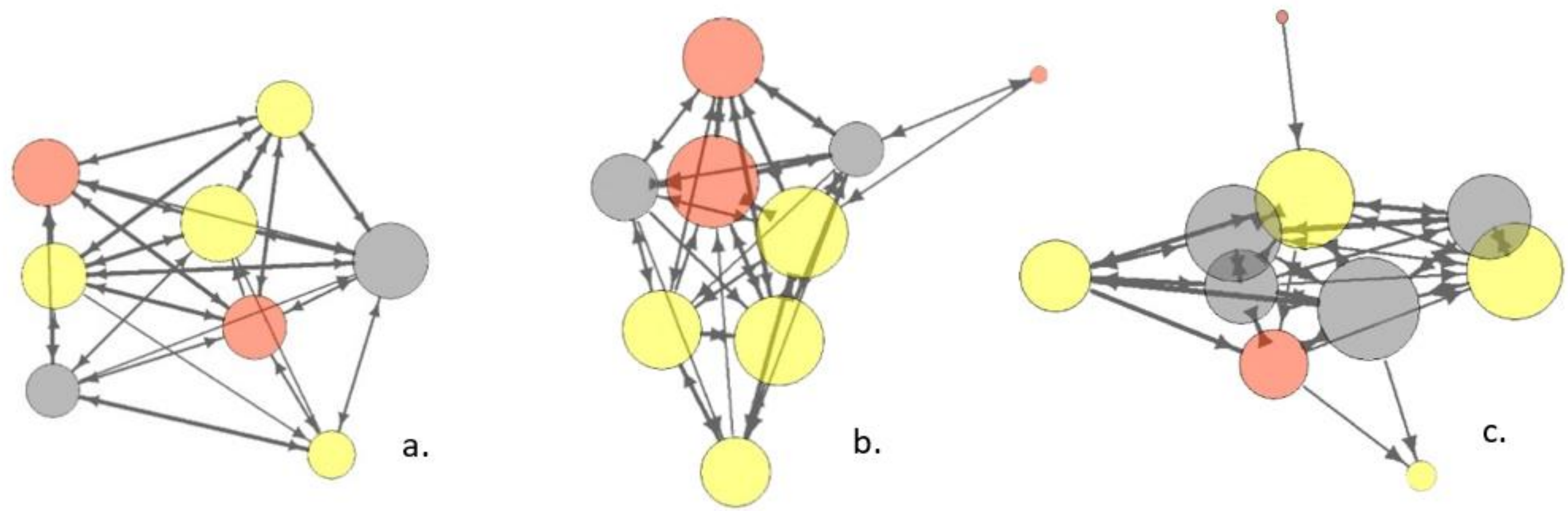

Figure 2.3. Social network maps of the Northeast (a), Central (b) and Southwest regional networks. Vertex color represents mean tillage intensity where red = no-till, gold = conservation tillage and grey = conventional tillage. Vertex size is weighted by authority score, and edge thickness is weighted by the reported strength of relationships. Network layout is based on the Fruchterman-Reingold association index.

	Model 1			Model 2			Model 3		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	461.35	293.14 – 629.55	**<0.001**	271.77	-11.11 – 554.64	0.072	161.85	-94.88 – 418.57	0.236
Behavioral Int.	-28.11	-47.59 – -8.63	**0.006**	-22.03	-40.08 – -3.99	**0.023**			
Income 3				184.89	-75.87 – 445.66	0.183	197.44	-52.92 – 447.79	0.139
Income 4				291.55	28.50 – 554.61	**0.039**	323.48	68.46 – 578.50	**0.018**
Income 5				256.97	-4.96 – 518.89	0.067	264.14	11.49 – 516.79	0.051
Income 6				184.57	-78.56 – 447.70	0.187	235.71	-20.18 – 491.60	0.085
Income 7				147.69	-131.20 – 426.58	0.319	182.14	-87.82 – 452.09	0.205
Income 9				445.31	185.06 – 705.57	**0.002**	458.47	207.23 – 709.72	**0.001**
Years of Experience				-3.16	-5.59 – -0.73	**0.016**	-2.61	-4.99 – -0.24	**0.040**
Behavioral Int. Network							-22.46	-34.53 – -10.39	**0.001**
Observations	98			98			98		
AIC	1329.549			1314.188			1307.243		
R^2_m	0.069			0.313			0.352		
R^2_c	0.894			0.920			0.926		

Table 2.3. Comparison of three LME models explaining tillage intensity as a function of behavioral intention (Model 1), behavioral intention plus income and years of experience (Model 2), and behavioral intention network plus income and year of experience (Model 3).

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CHAPTER 3: A TEMPERATURE DEPENDENT YIELD PENALITY FOR NO-TILL SOYBEANS IN MICHIGAN

3.1 INTRODUCTION

Many U.S. soybean producers have adopted conservation tillage technologies over the last 30 years in an effort to lower their cost of production (Weersink et al., 1992) and simultaneously realize the benefits of improved soil health (Alvarez, 2005; Blanco-Canqui et al., 2013; Hammerbeck et al. 2012; Syswerda and Robertson, 2014). Soybean is generally well adapted to conservation tillage and no-till production, with yields equivalent to conventional tillage on a global and national basis (DeFelice et al., 2006; Pittelkow et al., 2015). Producer adoption data indicates that no-till was in use on approximately 39% of U.S. soybean acreage by 2012, with another 31% managed using some form of conservation tillage other than no-till that year, outpacing conservation tillage adoption in corn, wheat and cotton (Claassen et al, 2018; Wade et al., 2015).

However, accumulating research and farmer experience have demonstrated that reduced tillage systems *can* compromise establishment and yield of soybean in cooler climates of the Upper Midwest, especially on poorly drained soils and where large amounts of crop residue are present at planting (DeFelice et al., 2006; Vanhie et al., 2015). In a regional meta-analysis of 43 soybean tillage experiments, DeFelice et al. (2006) found average yield penalties of 2.4-6.4% associated with no-till in the region. This may partially explain why growers in the Upper Midwest have lagged behind other regions of the U.S. in conservation tillage adoption (USDA-NASS, 2018, Wade et al., 2015). Only 60% of soybeans grown in states like Michigan are planted using conservation tillage (including no-till), which is about 14% below the national average and roughly 37% below leading conservation tillage states like Kansas and Nebraska (Claassen et al, 2018; Wade et al., 2015). In some Midwest States, growers that had adopted conservation tillage are now reverting from the practice, increasing soil disturbance on their farms to close perceived soybean yield gaps and also address new challenges like herbicide resistant weeds (Jussaume & Ervin, 2016; Reicosky et al., 2011; USDA ARMS, 2012; Vanhie et al., 2015).

Such geographic variability in conservation tillage adoption and outcomes might be expected, as research has demonstrated that biochemical processes in soil and resulting plant growth are influenced not by the tillage tool used, but by the soil environment created (Carter, 1994; Havlin et al., 1990). A single tillage tool is capable of producing differing soil environments depending on how it interacts with extant soil and environmental conditions (Soane and Pidgeon, 1975). Two of the primary effects of soil disturbance are warming and drying, which can create very different soil environments that are more or less favorable for crop growth depending on baseline moisture and temperature prior to tillage. This highlights the site-specific nature of tillage outcomes and suggests that tillage technologies must be further adapted to the environment(s) and cropping systems of the Upper Midwest to optimize profitability and sustainability (Lal, 2015; Luo & Sun, 2010; Venterea et al., 2006).

Scientists made early attempts to classify soils by their adaptability to conservation tillage, based on texture, structure and drainage, but those efforts were limited in scope and uncertainty remains regarding which taxonomic characteristics should be included in classification models for accurate and efficient estimation of tillage response in a specific cropping system (Cannell et al., 1978,1994; Cosper, 1983). Recent meta-analyses have begun to delineate where conservation tillage may be more or less advisable for Midwest soybean growers

(DeFelice et al., 2006; Ogle et al., 2012; Pittelkow et al., 2015, Toliver et al., 2012). DeFelice et al. (2006) and Toliver et al. (2012) found that the yield penalties for no-till soybean were more likely at high latitudes in the northern tier of U.S. states and increased on poorly drained soils, but could be mitigated to some extent by crop rotation. Pittelkow et al. (2015) found that no-till reduced legume yields in humid environments, but crop rotation and maintaining continuous no-till for at least three years eliminated that risk. Ogle et al. (2012) found that soybean yields decreased on hydric soils under no-till, but also saw a benefit from maintaining no-till for multiple years. Still, the limited number of published tillage trials has necessitated low spatial resolution for such meta-analyses, which lends little support to tillage decision-making at the field to sub-field scale. Long-term tillage system comparisons in the Upper Midwest offer more detailed insight into the mechanisms behind unique soil physical and biological changes induced by conservation tillage, but we posit that their results can only be reliably extended to similar management systems and micro-environments (Dick et al., 1991; Pederson and Lauer, 2003; Robertson et al., 2014).

Realizing the full potential of conservation tillage in a state like Michigan will therefore depend on advancing our understanding of, and ability to predict, what level of tillage intensity is optimal across gradients of several interrelated environmental variables. This requires documentation of both long-term management history and current sub-field variability in environmental conditions and crop response across a large geographic area. On-farm participatory research has been used successfully to address similar questions about site-specific management X environment interactions in agriculture by leveraging commercial farms to capture the necessary data and also facilitating iterative co-learning among farmers and researchers through direct interaction (Drinkwater, 2002; Snapp & DeDecker, in-press).

Recognizing the opportunity to improve conservation tillage adoption and outcomes in the Upper Midwest and similar environments, we sought to compare soybean yield under different long-term tillage regimes in the State of Michigan and identify key environmental factors that affect soybean yield under no-till in Michigan. Our aim was to test the hypotheses 1) conservation tillage is associated with lower soybean yields, and 2) that the relationship between tillage intensity and soybean yield is context dependent at the sub-field level, based on the site-specific interaction of tillage and soil properties. Using on-farm observations and producer management data, we demonstrate that no-till does generally result in lower soybean yields in Michigan, and this negative effect on yield can be mitigated by either increasing soil disturbance or by targeted application of no-till in warmer locations, on low organic matter soils, and in delayed planting scenarios.

3.2 MATERIALS AND METHODS

3.2.1 Experimental Design

Michigan farmers plant nearly 931,000 ha of soybean (2.6% of U.S. soybean crop) in rotation with corn, wheat, and sometimes hay or specialty crops. Soybeans are grown on a wide range of Alfisols and Spodosols, primarily in the state's Lower Peninsula from 41.5 - 45.5 degrees N latitude using the entire breadth of commercially available tillage/no-till tools. We therefore assumed that on-farm tillage outcomes, based on soil-tool interactions, would be highly variable. To account for this diversity, we conducted an observational study on a sample of commercial soybean fields in Michigan during the 2016-17 cropping years. Field history data was collected using a grower survey. Long-term tillage intensity was thus quantified and fields categorized by tillage system (no-till, conservation, conventional). Direct observations of multiple plant, soil and weather covariates were made at the sub-field level. Data reduction and mining techniques were subsequently applied to identify important environmental and management variables associated with differences in soybean yield in no-till systems.

We recruited 33 commercial soybean growers in the spring of 2016, plus an additional two growers in 2017 to adjust for attrition. Participants farmed in one of three geographic target areas in the Lower Peninsula of Michigan, which we refer to here as the Northeast, Central and Southwest regions (Figure 2.2). Each target region included fields distributed across 2-4 Michigan counties, and was associated with a local MSU Extension field crops educator on our research team. Most of the growers had previously collaborated with MSU Extension or other public agencies like Conservation Districts, which was likely a source of bias in our sample.

Each grower in the study supplied to our sampling population 1-3 fields planted to soybean in 2016, and 1-3 more in 2017. Fields were identified as "Good" or "Bad" as a form of sample stratification based on growers' experiential knowledge of historic soybean performance on-site. Six years of management history information was collected for each field using a written survey (Appendix B). Field histories included crop rotation, tillage tools and number of passes, plant date, variety, row spacing and seeding rate information, as well as a binary (Y/N) record of irrigation, cover crop and manure use.

To account for intra-field variation, fields were sub-divided by predominant soil types into $\leq$ 3 zones, each at least 0.81 ha in size. Soil zones nested within fields were considered our experimental unit (n=273), and three 3.35 M^2 quadrats were randomly established in each soil zone shortly after soybean planting to replicate crop observations. Soil penetration resistance at 0-15 cm and 15-45 cm deep, ¼ m^2 residue cover images and zone-wide aggregate soil samples (20-30 1.27 cm diameter cores ~20 cm deep) were collected within one week after planting. At maturity, soybean plants were clipped from sampling quadrats and grain threshed using a research scale bundle thresher. Grain weight, moisture and test weight were recorded at harvest.

Soil samples were stored at 4˚C, sieved through a 6mm sieve and divided into three subsamples. One batch of soil subsamples was dried at 35 ˚C, pulverized to fine powder with a shatterbox mill 8515 (SPEX) and analyzed for total organic carbon by dry combustion in a CHNS analyzer at A & L Great Lakes Lab to gauge baseline soil health status (Nelson and Sommers, 1996). Cornell University Soil Health Lab analyzed a second batch of subsamples to quantify surface texture in an effort to confirm *a priori* soil classifications and also quantify inherent differences in site potential (Kettler et al., 2001). We analyzed the final batch of soil subsamples for permanganate oxidizable carbon (POXC) (Culman et al., 2012), potentially mineralizable nitrogen (PMN) (Drinkwater et al., 1996; Gugino et al., 2009), and carbon mineralization (Franzluebbers et al., 1996, 2000) to measure the short-term effects of soil disturbance on C and N cycling.

Short-term (fall-spring of soybean year) and long-term (six-year cumulative) tillage intensity was quantified for each experimental unit using a simplified version of the STIR formula from the NRCS RUSLE2 model (USDA-NRCS, 2008, 2016; Widman, 2004). This formula assigns each tillage tool/operation a unique intensity coefficient and categorizes tillage systems based on their cumulative STIR score. According to Claassen et al. (2018), STIR more accurately characterizes the continuous spectrum of tillage intensity than residue cover methods used historically to categorize tillage systems. STIR coefficients were averaged across tool type because detailed information like the working depth of tillage tools was not available. Tillage intensity was thus calculated as STIR = Avg. Tillage Tool Coefficient * Number of Passes Reported. Resulting short-term STIR values ranged from 0 -120.69 and long-term STIR values ranged from 0 - 851.50. Fields were further classified into one of three categorical tillage systems based on their long-term STIR value. The U.S. Dept. of Agriculture Natural Resource Conservation Service (USDA-NRCS) classifies conservation tillage as an annual STIR score < 80 with no primary inversion tillage (USDA-NRCS, 2016). We therefore classified fields with long-term STIR values < 30 as no-till, fields with STIR values 30 – 480 and no primary inversion tillage as Conservation Tillage, and fields with primary inversion tillage or STIR values > 480 were classified as Conventional Tillage (USDA-NRCS, 2008, 2016; Widman, 2004).

Our analysis focused on yield gap, rather than raw yield, as the dependent variable to account for differences in soybean yield potential based on environment, soybean genetics, etc. across the state and between tillage systems. Soybean yield gap was calculated in two ways for each observation; yield gap (YG) as the percent difference between zone yield and farmer attainable yield potential within each region (highest observed zone yield within each region) for the purpose of comparisons across tillage systems, and yield gap-tillage (YG_T) as the percent difference between zone yield and farmer attainable yield potential within each tillage system by region (highest observed zone yield within each tillage system, by region) for the purpose of comparisons within tillage systems (Rattalino Edreira, et al., 2017; van Ittersum et al., 2013). The maximum yield numbers used to calculate yield gap were observed in dryland culture, and should therefore be interpreted as a water limited yield potential, except in the case of the Southwest Region where irrigation capacity was nearly ubiquitous.

3.2.2 Statistical Analysis

Statistical analyses were conducted within RStudio: Integrated Development Environment for R (RStudio, Inc., 2016). Hierarchical linear mixed effects (LME) models were developed first to explain YG as a function of tillage system statewide. The models included tillage system as the sole fixed effect, plus a nested random effects structure consisting of [year [field [zone]]] to account for our observational study design (R Development Core Team, 2019). LME models have several advantages over ordinary least squares regression models, particularly the ability to account for the inter-dependency common in on-farm observational data through the inclusion of nested random effects (Burger et al., 2012; Coe, 2002). This is accomplished by estimating parameters of a model of the covariance structure of the error, then using them to estimate the remaining parameters of the model with known variance. In this case, it allowed random shifts to the model intercept for each [year [field [zone]]] to account for baseline differences in soybean yield potential due to soil quality, weather variability or management history other than tillage. Multi-model selection and inference was performed with a restricted maximum likelihood approach in the nlme package of R v3.5.3 (Pinheiro and Bates, 2004).

Principal Components Analysis (PCA) was then used to model covariances and reduce dimensionality in our large set of potential independent variables that could interact with no-till to influence soybean yield (Yeater & Villamil, 2018). Twenty normalized location (latitude and longitude), soil (percent sand, silt and clay, aggregate stability, surface and subsurface resistance, available water capacity, percent organic matter, total and labile organic carbon, total organic nitrogen P, K, Mg, Ca and Cation exchange capacity) and weather (precipitation and growing degree day accumulation) variables were included in the analysis. Normalization was achieved by first centering the data, subtracting variable means from each observation. Then scaling was applied by dividing each centered observation by the variable's standard deviation. PCA generated a set of twenty linearly uncorrelated principal components ordered by the proportion of variance in the original datasets that they each explained. Principal components (PCs) can be considered as latent variables (conceptual; represented as factors), demonstrating the interaction of important covariates and nature of their combined influence on a dependent variable. This was useful in our case to address significant collinearity among our many independent variables, which is common in soils and ecology data (Harrison et al., 2018).

In an effort to understand the influence of our environmental PCs on yield gap, no-till cases were first sorted by yield gap (YG_T) to identify those in the upper vs. lower terciles as examples of the least and most successful no-till cases in a given region. Logistic regression was then applied to measure the probability of cases being in the upper vs. lower tercile of yield gap based upon PC values and complementary management practices (Peng et al., 2002). Principal components were selected for inclusion in the logistic regression models based on their relationship to the binary response variable (upper/lower tercile of yield gap) using a forward stepwise method and conditional likelihood-ratio tests to select between nested models (Aguilera et al., 2006). This method emphasizes the relationship between PCs and the dependent variable in model development, whereas it is otherwise common to use only the first few PCs that explain a large proportion of the variance in a dataset, independent of the dependent variable of interest.

First, the correlation between individual PCs and binary yield gap was tested using single logistic models and likelihood-ratio tests comparing their performance to the null model. PCs significantly correlated with yield gap were subsequently added to a multiple logistic regression model in a stepwise fashion until further additions failed to improve the model. The same approach was used to further expand our multiple logistic regression model by adding complementary management variables that might interact with environmental conditions (represented by PCs) to better explain binary yield gap (rotational diversity, previous crop, soil residue cover, planting date, planting population, row spacing, and seed treatment). A final model that minimized residual deviance and AIC was selected for no-till systems, including two PCs and one complimentary management variable. Heavily weighted independent variables were extracted from each of the PCs included in our model, and partial correlations between the independent variables and YG_T were calculated to understand their individual contributions to yield gap in Michigan no-till systems.

3.3 RESULTS

3.3.1 Sample Description

The 136 soybean fields in our original sample ranged from 2.06-52.53 ha in size (16.46 ha avg.) and captured 2,238.36 total hectares, or approximately 0.12% of Michigan's soybean crop in a given year. Each field contained 1-3 primary soil types (2.00 avg.), which were managed homogeneously at the field scale by producers using a range of long-term no-till (17.36%), conservation (56.23%) and conventional (26.41%) tillage practices, as defined above. Short-term tillage practices (disturbance in the fall-spring prior to soybean planting) in our sample reflected trends reported elsewhere for the Midwest, with 45.66% of soybeans no-till planted into undisturbed soil, 13.96% following low intensity conservation tillage, and 40.38% planted following a two or three pass conventional tillage system (USDA-NASS, 2018; Wade et al., 2014). This contrast suggested that short-term tillage practices used for soybean are not necessarily indicative of average tillage intensity across a crop rotation at longer time intervals, which led us to believe that our cumulative STIR metric would be a more relevant independent variable when considering the effect of tillage on the soil environment and soybean yield.

3.3.2 Weather and Yield Trends

The 2016 and 2017 growing seasons were somewhat abnormal in Michigan. This was evident in the state's mean soybean yields for those years, and also in mean soybean yields across our sample. Michigan farmers produced a record average soybean yield of 3.40 t/ha statewide in 2016, and yields averaged 3.42 t/ha in our sample. Planting was delayed slightly by wet spring weather that year, but soybeans were still planted by May 22nd on average. Growing degree day (GDD base 10˚C) accumulation was well above normal during the 2016 growing season, which paired with below normal precipitation May-July, caused drought stress in soybeans statewide. Drought stress persisted in the Northeast region through harvest in 2016, and the crop suffered from the 7.5-10 cm precipitation deficit. However, timely rainfall in the Southern Lower Peninsula during August rescued the crop there, resulting in mostly excellent yields for growers in our Central and Southwest regions.

Conversely, Michigan's average soybean yield was only 2.86 t/ha in 2017, or 2.95 t/ha in our sample. 2017 soybean yields tied 2014 as the lowest statewide average since 2009. Planting occurred three days earlier than 2016 on average (May 19th). GDD accumulation was near normal statewide, but dry weather once again plagued the Central and Southwest Regions. Drought stress worsened there as the season progressed, and like the Northeast Region in 2016, many parts of the Central and Southwest Regions were 7.5-10 cm below normal rainfall at harvest time. This led to soybean yields that were 0.87 t/ha less than 2017 on average across the Southern Lower Peninsula. Conditions in the Northeast Region were quite the opposite during

2017, with 2.5-5 cm above normal precipitation May-Aug. and more hours of rainfall than usual. White mold was widespread in the crop due to the persistent moisture, but soybean yields in our Northeast region were near to slightly above average in 2017.

3.3.3 Statewide Tillage Performance

Tillage system classification by long-term tillage intensity (STIR) identified 44 no-till cases with a mean tillage intensity of zero, yield of 2.69 t/ha and yield gap (YG) of 47.16% (5.86-83.59%), 149 conservation tillage cases with a mean tillage intensity of 203.42, yield of 3.26 t/ha and yield gap of 38.01% (0-73.07%), and 69 conventional tillage cases with a mean tillage intensity of 516.99, yield of 3.44 t/ha and yield gap of 38.02% (13.57-69.42%). The most parsimonious linear mixed effects model explaining yield gap (YG) as a function of tillage system showed a significant difference between no-till and tilled systems, with conservation tillage and conventional tillage reducing yield gap by 7.79% and 8.17% respectively as compared with no-till ($F_{2,125}$ = 2.39, P=0.096) (Figure 3.1). This result is only slightly higher than previous estimates of yield gap for no-till in the Upper Midwest documented in the literature (DeFelice et al., 2006), and supports a general recommendation of using moderate intensity conservation tillage practices to maximize soybean yield in Michigan. Mean yield gap for no-till was near 50% in both 2016 and 2017, and tillage was most effective at reducing yield gap when yield potential was higher overall in 2016. The marginal R^2 for our final LME model (R^2m, fixed effects only) was 0.03, and the overall conditional R^2 for the model (R^2c, fixed and random effects) was 0.95.

Despite this result, we recognized that a blanket recommendation of conservation tillage for soybeans in Michigan would be an oversimplification, ignoring the fact that no-till has produced competitive soybean yields in previous Michigan studies (Robertson et al., 2014) and also some of the individual cases in our sample. Furthermore, no-till may offer important economic and soil conservation benefits independent of yield effects (Dominati et al., 2010; Syswerda & Robertson, 2014). These points encouraged us to parse out management by environment interactions to identify where no-till systems may be more or less successful in Michigan. This process began with isolation of no-till cases in our sample and removal of cases in the middle tercile of yield gap for no-till systems, which left 29 cases with a mean tillage intensity of zero, yield of 2.71 t/ha and yield gap of 47.32% (0-83.58%).

3.3.4 No-till Performance across Environments

Principal components analysis of the remaining no-till soybean cases, followed by multi-model selection from a candidate pool of logistic regression analyses, initially identified three PCs (1, 2 and 16) that were significant predictors of case membership in either the upper or lower tercile of yield gap. PCs 1 and 2 together explained 63.83% of the variance in our no-till data set, with PC 16 adding only 0.083% more. PC 16 was also redundant in its representation of soil texture, AWC and GDD accumulation, similar to PC 2. For these reasons, PCs 1 and 2 were selected for inclusion in our multiple logistic regression model (Table 3.1). A variable loading threshold of 0.28 was used to identify influential variables comprising each PC in an effort to understand which location, soil and weather factors are most important for no-till performance in Michigan.

PC1 was representative of soil carbon and moisture status, and positively correlated with yield gap ($Z=2.01$, $P=0.04$). Significant loading was observed from soil organic matter concentration, cation exchange capacity (CEC), calcium, labile (POXC) and total organic carbon, as well as precipitation. Loadings were positive for all of these variables, except precipitation, suggesting that higher soil organic matter and carbon levels are associated with greater yield gaps under no-till production. Precipitation was conversely associated with lower yield gaps, which might be expected in dry years, such as those experienced in most of Michigan during our study.

PC2 was largely representative of soil texture and temperature, and negatively correlated with yield gap ($Z=-2.62$, $P=0.009$). Significant loading was observed from soil texture (percent sand, silt and clay), AWC, site latitude and GDD accumulation. Loadings were positive for percent silt, clay, AWC and GDD accumulation, suggesting that fine textured, wet soils and warmer locations may result in lower yield gaps for no-till soybeans. Loadings were negative for latitude and percent sand in soils, indicating that yield gaps in no-till increase at high latitudes and on coarse textured soils.

Only one management variable, planting date (DOY), significantly improved the predictive power of our logistic regression model. Plant date was negatively correlated with yield gap, suggesting that delayed planting might interact with environmental conditions to improve soybean yield in a no-till system. Our final model including PCs 1, 2 and planting date had a residual deviance of 19.63 on 25 degrees of freedom and AIC of 27.63, achieving 89.66% correct classification of cases as being from the upper vs. lower tercile of yield gap in no-till systems (Table 3.2).

Figure 3.2 demonstrates how PC 1, PC 2 and plant date interacted to influence the probability of case membership in either the upper (1) or lower tercile (0) of yield gap for no-till. At the earliest plant dates, only sites with relatively low soil carbon (PC1), fine texture or high temperature (PC2) had a lower probability of being in the upper tercile of yield gap (high no-till yields). At median plant dates, either a relatively low value for PC 1 or a high value for PC 2 could significantly decrease the probability of a significant yield penalty for no-till soybean. At the latest plant dates, most no-till cases yielded competitively, regardless of soil characteristics.

Partial correlation of key independent variables in our logistic regression model were calculated to futher examine covariance relationships among the variables highlighted by PCA (Table 3.3). GDD accumulation was negatively correlated with yield gap when controlling for both plant date and soil quality (texture and carbon represented here by CEC). Plant date (DOY) was also negativly correlated with yield gap when controlling for soil quality and GDD accumulation, although the relationship was weaker and less significant (b=-0.21, P=0.18). Soil quality, represented here by soil CEC, had no discernable relationship with yield gap independent of GDD accumulation and plant date. However, there was significant correlation between both GDD acumulation and CEC, and also GDD and plant date, showing that soils tended to be of lower quality in warmer locations and that no-till planting occurred earlier in warmer locations, which could be expected. These results suggest that yield gap in no-till systems was primarily driven by temperature in our study, with no-till performing better in warmer locations.

3.4 DISCUSSION

Our objective was to examine how tillage intensity interacts with environmental conditions to affect soybean yield in the State of Michigan, and we hypothesized that this relationship would be site-specific at the sub-field level. Our finding that no-till is generally associated with yield reductions for soybean across the state is supported by previous research, as is our result suggesting that the performance of no-till is site-specific based on the interaction of temperature, soil quality and plant date (DeFelice et al., 2006; Ogle et al., 2012; Pittelkow et al., 2015, Toliver et al., 2012). Yield of no-till soybeans decreased significantly under low air and soil temperatures at high latitudes, consistent with other studies in the Upper Midwest (DeFelice et al., 2006; Vanhie et al., 2015). Tillage can help to warm soil prior to planting, which may be important for timely planting, stand establishment and rapid early growth in soybeans, all of which can ultimately affect yield (Malhi and O'Sullivan, 1990; Moraru and Rusu, 2012, Shen et al., 2018).

The positive association between fine soil texture, higher water holding capacity and no-till yields in our PCA and logistic regression analysis was somewhat unexpected based on previous research showing poor performance of no-till on clay soils that tend to stay wet (Cannell et al., 1978; Cosper, 1983; DeFelice et al., 2006; Ogle et al., 2012, West et al., 1996; Yin and Al-Kaisi, 2004). However, this result aligns with other research showing significant year to year variation in the effect of soil type, where no-till can benefit soybeans through improved soil moisture retention in a dry year, but lead to yield reductions in wet years, particularly on soils with inherently poor drainage (Cook and Trlica, 2016; Toliver et al., 2012).

Two of three geographic regions in our study, Central and Southwest, were abnormally dry in both 2016 and 2017. The Northeast region was abnormally dry in 2016 and wet in 2017. Overall, one would expect fine soil texture and greater water holding capacity to benefit soybean growth in such dry conditions. In contrast, the increased water holding capacity commonly associated with reduced tillage systems did not produce an overall yield advantage for no-till, even in these abnormally dry years. No-till yields *were* more stable than yields in tilled systems across the two years of our study, albeit significantly lower. Irrigation and artificial drainage are two factors that may confound our understanding of the relationship between soil texture, moisture and no-till in this study. 29 of the 133 soybean fields in this study (21.8%) were irrigated, all of them located in the Southwest region on naturally well drained soils. We failed to collect information on artificial drainage at our study sites. However, Sugg (2007) reported that Branch County in our Southwest region has 4-8% of the total county area with subsurface drainage, while Clinton County in our Central region has subsurface drainage in 17-27% of the total county area. All other counties in our study area were reported to have only 0-3% of their total area under subsurface drainage

Our most surprising result was the negative association between soil organic carbon (SOC) and no-till performance in our PCA and logistic regression analysis, which was consistent across site-years. Other attempts to categorize soils based on adaptability to no-till have focused on soil texture rather than SOC (Cannell et al., 1978,1994; Cosper, 1983). SOC is generally associated with improvements in physical, chemical and biological functioning of soils important for crop production, with high SOC levels increasing crop yields (Alvarez, 2005; Blanco-Canqui et al., 2013). Based on the partial correlations in Table 3.3, our opposite finding of lower soybean yields in no-till systems with high SOC may have been an artifact of the relationship between temperature (GDD accumulation, latitude) and soil quality in our data set, where soils at high latitudes tended to have more carbon. Accumulation and decomposition of SOC are driven by C inputs and placement, temperature, moisture and structural dynamics in soils (Derpsch et al., 2014; Lal, 2018). The rate of SOC turnover has been linked to soil processes that are important for crop yield, such as nitrogen mineralization (Franzluebbers et al., 1995; Vanhie et al., 2015; Watts et al., 2010).

Schimel et al. (1994) showed that SOC storage capacity and turnover times are greater in locations with lower mean temperature, such as Northern Michigan. Changes in soil physical properties induced by tillage may have a reduced effect on SOC where cool temperatures limit microbial degradation of newly exposed SOC (Franzluebbers & Arshad, 1996; Roberts and Chan, 1990; Trumbore et al., 1996). Tillage may therefore be an important tool for improving crop yields by increasing soil temperature and thus enhancing SOC cycling in cooler regions of Michigan (Franzluebbers et al., 1995; Trumbore et al., 1996). In our Northeast region, CT with a mean long-term STIR score of 208, or 35 annually (equivalent to one pass with a disc), was all that was required to significantly reduce soybean yield gap. Despite this moderate level of disturbance, CT soils in the Northeast averaged 1.64% SOC compared to 1.60% in long-term no-till fields.

Finally, our finding that delayed planting may off-set environmental risks to improve no-till soybean yields was intriguing. Across all tillage systems, delayed planting tends to reduce soybean yield regardless of environment, although this negative effect may be slightly less pronounced in the Midwest vs. the southern U.S. (Egli and Cornelius, 2009). While the idea that delayed planting may help to overcome temperature limitations in no-till is supported by our analysis, most other research has failed to demonstrate significant interactions between tillage system and plant date directly influencing soybean yield in such a way that might support a recommendation of delaying planting in no-till systems (Elmore, 1990; Lueschen et al., 1992; Oplinger and Philbrook, 1992; Perez-Bidegain et al., 2007). However, the influence of planting date on stand establishment, with later planting improving stand in no-till systems, is widely accepted (Oplinger and Philbrook, 1992; Vyn et al., 1998). Therefore, it is likely that the positive effect of delayed planting on yield under no-till in our logistic regression model was related to improved stand establishment. This conclusion is supported by the positive correlation of plant date (DOY) and stand establishment in our no-till sample, showing that delayed planting had a positive effect on stand establishment in no-till systems (P=0.065).

3.5 CONCLUSION

In summary, our study found a general yield penalty for no-till soybeans in Michigan, which persisted even after a mimimun of six years without disturbance. No-till performed especially poorly in cool environments at high latitudes and on high organic matter soils. Contrary to previous research, fine soil texture and high water holding capacity improved no-till soybean yield in our study, likely because our observations were made in abnormally dry years. Delayed planting helped to buffer environmental risks facing no-till soybeans, likely by allowing soil to warm-up, which improved stand establishment.

These results suggest that long-term no-till may not be advisable for maximizing soybean yield in Michigan, and certainly should not be implemented in the coldest areas of the state. Of course, the 7.79% and 8.17% yield increase associated with conservation and conventional tillage respectively in our study must be weighed against the added costs of labor, machinery, and fuel assocaited with tillage. A survey of custom farming rates administered by MSU Extension found that tillage operations cost $21.99-$51.65 per hectare including machine, power unit and labor costs, depending on the tool used (Stein and Battel, 2018). Using an average soybean yield of 3.36 t/ha, an 8% yield increase achieved through conservation tillage translates to a 0.269 t/ha (4 bu/a) difference. Assuming a soybean price of $331 per tonne, this yield increase would generate $89.04 per hectare, which more than covers the cost of conservation tillage. Growers must also consider the enviromental risk of degrading long-term soil health with tillage, which we address for this data set in Chapter 4.

It is important to note that only moderately intensive or intermittent tillage was necessary to significantly reduce mean soybean yield gap across all environments in our analysis. Finding the least costly conservation tillage options may be a strategy to maximize profitability in Michgian soybean systems, even if tillage occurs at a different point in the crop rotation (i.e. tilling soybean residue prior to corn planting). In the warmest areas of the Southern Lower Peninsula, and on poor quality soils, long-term no-till is likely a competitive option for balancing profitability and soil conservation objectives.

3.6 TABLES AND FIGURES

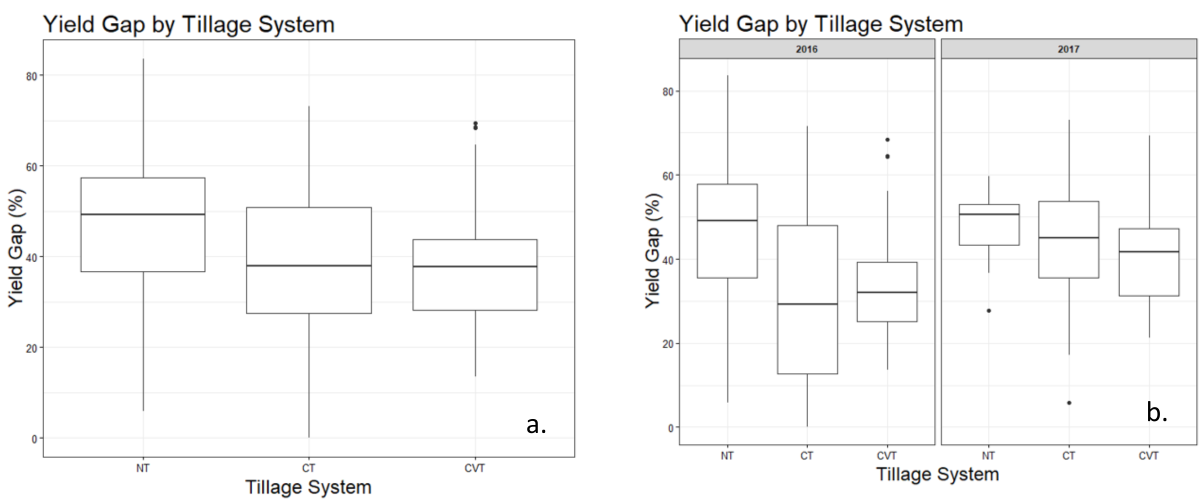

Figure 3.1. Yield gap by tillage system (a), and tillage system within year (b), showing significantly lower yield gaps associated with Conservation Tillage (CT) and Conventional Tillage (CVT) as compared to No-till (NT).

	PC 1	PC 2
Latitude	0.219065180	**-0.324966060**
Longitude	0.261957268	-0.248606542
Growing degree days	-0.212005148	**0.301984528**
Precipitation	**-0.278287156**	0.099523908
Surface resistance	-0.109130606	-0.048447282
Subsurface resistance	-0.200241281	-0.194978404
Sand	-0.206595501	**-0.343322960**
Silt	0.206497047	**0.320058044**
Clay	0.174879359	**0.346083216**
Aggregate stability	-0.003220603	-0.153758633
Avail. water capacity	0.204666724	**0.333464021**
Organic matter	**0.315620371**	-0.057275833
Total organic carbon	**0.279804152**	-0.156240290
Labile organic carbon	**0.282995281**	-0.095919299
Total nitrogen	0.252850693	-0.029441194
Phosphorus	-0.069078762	-0.269541241
Potassium	-0.105415917	0.170490503
Magnesium	0.137581232	0.263772045
Calcium	**0.310369445**	-0.084050802
Cation exchange capacity	**0.313241004**	0.009409077

Table 3.1. Principal components one and two showing significant variable loadings (>2.8) in bold and shaded.

Predictor	**β**	**SE β**	**Wald's $\chi 2$**	**df**	**P**	**Marginal effects**	**95% C.I.**
Constant	56.11	29.47	3.6	1	0.057	NA	NA
PC 1	0.46	0.23	4.0	1	0.045	0.114	0.09 − 1.04
PC 2	-0.97	0.37	6.9	1	0.009	-0.241	-1.92 − -0.39
Plant Date	-0.39	0.21	3.6	1	0.057	-0.098	-0.92 − -0.09
Test			**$\chi 2$**	**df**	**P**		
Likelihood ratio test			20.54	3	<0.001		
Wald test			9.6	4	0.048		
Hosmer & Lemeshow			2.04	2	0.359		

Table 3.2. Logistic regression model showing the significant effect of PC 1, PC 2 and plant date on the probability of no-till cases being in the upper tercile of yield gap (YG_T)

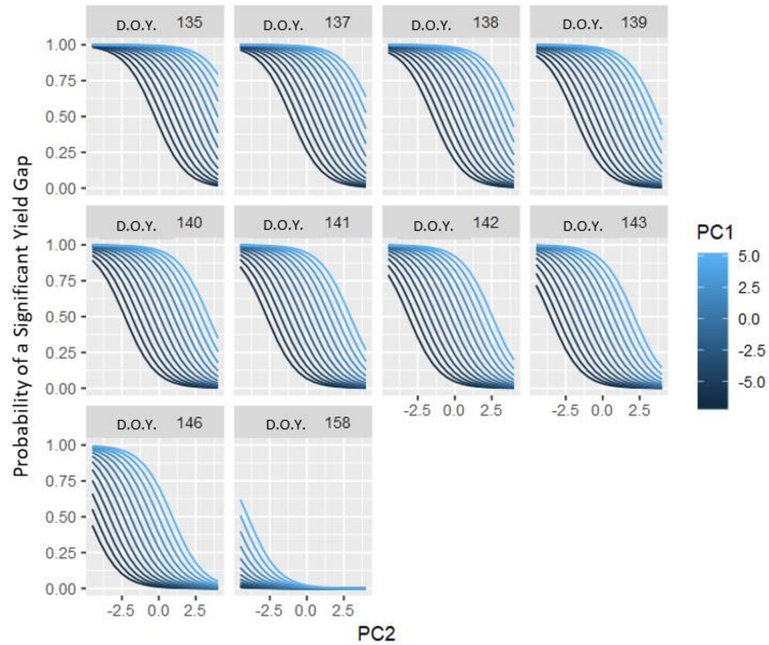

Figure 3.2. Logistic regression curves showing the interaction of PC 1, PC 2 and plant date day of year (DOY) influencing the probability of a significant yield gap in no-till soybeans across Michigan.

Variable 1	**Variable 2**	**Variable 3**	**Variable 4**	$r_{12,34}$	$r_{13,24}$	$r_{14,23}$	r_{23}	r_{34}	r_{24}
Yield gap-tillage	Soil CEC	GDD	Plant Date	0.04	-0.48***	-0.21	-0.30*	-0.38**	0.02

Table 3.3. Partial correlations of variables highlighted by PCA and logistic regression as important for predicting yield gap in no-till soybeans. $R_{12,34}$ represents the partial correlation of Variable 1 and Variable 2 controlling for Variable 3 and 4. Asterisks indicate relationships with P < 0.05 (*), 0.01 (**) and 0.001 (***).

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CHAPTER 4: THE INDIRECT INFLUENCE OF TILLAGE ON SOIL ORGANIC CARBON IN MICHIGAN SOYBEAN SYSTEMS

4.1 INTRODUCTION

Reducing soil disturbance in annual cropping systems has long been recommended as a means of sequestering carbon in soils to increase their natural capital and ability to provide ecosystem services (Dominati et al., 2010; Faulkner, 1943; Syswerda & Robertson, 2014; Whiteside and Smith, 1941). Today, conservation tillage (CT) is often claimed to increase carbon in soils categorically (Lal et al., 2004) and increasing soil organic carbon (SOC) on arable land is invoked as a potential solution to some of humanity's greatest challenges, including global food security and climate change (Lal, 2004). Farmers have adopted conservation tillage (CT) technologies, including no-till, on 51% of U.S. cropland based on these claims, seeking to lower their cost of production (Weersink et al., 1992) and simultaneously realize the benefits of accruing SOC (Blanco-Canqui et al., 2013; USDA-NASS, 2018).

However, research has shown the relationship between tillage intensity and SOC dynamics to be inconsistent and site specific (Baker et al., 2007; Derpsch et al., 2014). In some environments, CT is capable of reducing CO_2 efflux and increasing SOC stocks, while in other cases CT appears to have a neutral or opposite effect on these processes (Abdalla et al., 2013; Govaerts et al., 2009; Lal, 2018; VandenBygaart, 2016). The effect of CT on crop yields is also site-specific, with CT producing equal or higher yields relative to conventional tillage in certain environments and cropping systems, but significantly less in others (DeFelice et al., 2006; Pittelkow et al., 2015a; 2015b). Aside from the economic implications of yield differences, the effect of CT on crop productivity and biomass yield can indirectly influence SOC outcomes, which further complicates assessments of CT as a soil carbon stewardship practice (Lal, 2015; Venterea et al., 2006).

Observed variability in SOC outcomes related to CT is not surprising. It has been demonstrated that biochemical processes in soil and resulting plant growth are influenced not by the tillage tool used, but by the soil environment created (Carter, 1994; Havlin et al., 1990). A single tillage tool is capable of producing differing soil environments depending on how it interacts with extant soil and environmental conditions (Soane and Pidgeon, 1975). For example, there is growing evidence that tillage and soil texture interact to influence aggregation, which can alter SOC cycling in agricultural fields (Beare et al., 1994). It only follows that CT technologies must be adapted to specific environments and cropping systems, or may not be appropriate at all in some cases, when maximizing SOC accumulation is the stated objective (Lai, 1989; Lal, 2015; Luo & Sun, 2010; Venterea et al., 2006).

Although soybean occupied nearly 36.1 M hectares of U.S. cropland in 2017, with CT in use on approximately 70% of that acreage (more than any other crop), limited information is available regarding how specific environmental conditions influence the effect of CT on SOC in soybean production systems (Claassen et al., 2018; USDA-NASS, 2018). Some studies have concluded that CT may not significantly increase SOC in soybean systems due to lower biomass yield and rapid decomposition of soybean residues relative to other crops like corn (Havlin et al., 1990; Huggins et al., 2007; West & Post, 2002). For example, Havlin et al. (1990) found that no-till did not increase SOC in a soybean-soybean rotation, but did increase SOC by 5% in a sorghum-soybean rotation and by 14% in a sorghum-sorghum rotation. Conversely, other studies have found that differences in below ground net primary productivity, the timing and level of root turnover/exudates, tendency to foster the formation of soil aggregates, and changes in microbial communities associated with legumes can help to increase SOC (Drinkwater et al., 1998; Puget & Drinkwater, 2001). Soil physical properties like texture, moisture and temperature are likely important mediating factors in this relationship, and may explain the divergent results of research on the topic. Fine textured, wet and cool soils have greater capacity to physically and chemically protect SOC from mineralization when disturbed (Balesdent et al., 2000; Needleman et al., 1999, Wander and Bollero, 1999).

Michigan farmers plant nearly 931,000 hectares of soybean on a wide range of sand - silty clay loam soils using the entire breadth of commercially available tillage/no-till tools (USDA-NASS, 2018). Soybean production in the state occurs along a gradient from farms in the southern Lower Peninsula that closely resemble intensive corn-soybean systems of the U.S. Corn Belt, to more extensive systems in the marginal environment of Northern Michigan where a short growing season limits soybean yield potential and encourages greater cropping systems diversity. In this study, we sought to understand the influence of tillage intensity on SOC status in Michigan soybeans by quantifying how unique biophysical environments interact with farmer tillage practices to mediate SOC dynamics. Our aim was to test the hypothesis that the relationship between tillage intensity and SOC is context dependent, based on the site-specific interaction of tillage and soil physical properties.

4.2 MATERIALS AND METHODS

4.2.1 Experimental Design

Research investigating the influence of tillage intensity on SOC must explicitly document how tillage practices interact with soil biophysical factors to generate robust recommendations (e.g. Huggins et al., 2007). One approach to achieving this involves intensive, long-term experimentation under controlled conditions at a small number of locations (Syswerda & Robertson, 2014; Shrestha et al., 2015). However, the results of such studies may only be reliably applied to similar environments, which limits their relevance and impact. Another approach gaining popularity uses extensive sets of on-farm observations to capture real-world variability in tillage intensity and site conditions, then applies multivariate statistical techniques to quantify the interaction of important variables (Blanco-Canqui & Lal, 2008; Wander and Bollero, 1999; Xu et al., 2016). This serves to elucidate systems level relationships, which can be subsequently tested under controlled conditions for verification purposes (Drinkwater, 2002).

We assumed that on-farm tillage outcomes, based on soil-tool interactions, would be highly variable in Michigan. To account for this diversity, we conducted an observational study on a sample of commercial soybean fields during the 2016-17 cropping years. We recruited 33 Michigan soybean growers in the spring of 2016, plus an additional two growers in 2017 to adjust for attrition. Each grower in the study supplied to our sampling population 1-3 fields planted to soybean in 2016, and 1-3 more in 2017. Fields were identified as “Good” or “Bad” as a form of sample stratification based on growers’ experiential knowledge of historic soybean performance on-site. To account for intra-field variation, fields were sub-divided by predominant soil types into ≤ 3 zones, each at least two acres in size. Soil zones nested within fields were considered our experimental unit (n=261).

Fifteen soil penetration resistance measurements at 0-15 cm and 15-46 cm in depth and aggregate soil samples (20-30 1.27 cm cores, 20 cm deep) were collected randomly within each experimental unit within one week after planting. Cumulative growing degree days (GDD, base 10 C) between planting and harvest were obtained for each field from the nearest MSU or

NOAA weather station to account for local temperature differences. Soil samples were stored at 4˚C, sieved through a 6mm sieve and divided into three subsamples.

One batch of soil subsamples was dried at 35 ˚C, pulverized to fine powder with a shatterbox mill 8515 (SPEX) and analyzed for total organic carbon by dry combustion in a CHNS analyzer at A & L Great Lakes Lab (Nelson and Sommers, 1996). Cornell University Soil Health Lab analyzed a second batch of subsamples to quantify surface texture (Kettler et al., 2001) and wet aggregate stability (Moebius-Clune et al., 2011). We analyzed the final batch of soil subsamples for permanganate oxidizable carbon (POXC) (Culman et al., 2012). Briefly, 2.5 g of air-dried soil was shaken with KMnO4 for exactly 2 min at 240 oscillations per minute on an oscillating shaker. After allowing to settle exactly 10 min, 0.5 mL of the supernatant were transferred, diluted and an aliquot loaded into a 96-well plate containing a set of replicated internal standards, a soil standard and laboratory reference samples. Sample absorbance was read at 550 nm with a SpectraMax M5 microplate reader using SoftMax Pro software (Version 5.4.1, Molecular devices, Sunnyvale, CA).

Six years of tillage history information was collected for each field from the primary operator using a written survey instrument approved by the Michigan State University and University of Illinois Institutional Review Boards, including tillage tools used and the number of passes made (Appendix B). Cumulative tillage intensity was quantified at the field scale using a simplified version of the Soil Tillage Intensity Rating (STIR) formula from the NRCS RUSLE2 model (USDA-NRCS, 2008, 2016; Widman, 2004). This formula assigns each tillage tool/operation a unique intensity coefficient and categorizes tillage systems based on their cumulative STIR score. According to Claassen et al. (2018), STIR offers a more accurate continuous measure of tillage intensity than residue cover methods used historically, mainly because residue cover after planting is dependent on residue yield and quality from the proceeding crop. In this case, STIR coefficients were averaged across tool type because detailed information like the working depth of tillage tools was not available. Tillage intensity was thus calculated as STIR = Avg. Tillage Tool Coefficient * Number of Passes Reported. Resulting long-term STIR values ranged from 0 - 851.50.

4.2.2 Statistical Analysis

Our approach to analyzing this dataset involved a three step process designed to answer our question about the relationship between tillage intensity and SOC in Michigan soybean systems, while also accounting for the variation and error inherent in our on-farm observations. We began with hierarchical linear mixed effects (LME) modeling as a means of investigating linear correlation between the variables of interest (Pinheiro and Bates, 2004). Our second step involved integrating principal components analysis (PCA) and LME models to control for covariation among independent soil variables (Yeater & Villamil, 2018). Lastly, we used structural equation modeling (SEM) to map the patterns of variation and covariation in our dataset at the statewide and sub-state level while incorporating latent soil factors (Smith et al., 2014). Statistical analyses were conducted within RStudio: Integrated Development Environment for R (RStudio, Inc., 2019).

LME models were developed to explain total and labile SOC as a function of fixed effects including tillage intensity (STIR), soil physical properties, GDD and their interaction terms. The models also included a nested random effects structure consisting of [year [field [zone]]] to account for our observational study design (R Development Core Team, 2019). LME models have several advantages over OLS regression models, particularly the ability to account for the inter-dependency common in on-farm observational data through the inclusion of nested random effects (Burger et al., 2012; Coe, 2002). This is accomplished by estimating parameters of a model of the covariance structure of the error, then using them to estimate the remaining parameters of the model with known variance. In this case, it allowed random shifts to the model intercept for each soil zone within a field to account for baseline differences in SOC due to inherent soil quality. One drawback of LME models is their sensitivity to collinearity among independent variables, which is common in soils data (Harrison et al., 2018). To account for this, we applied PCA to transform our soil physical variables into a set of linearly uncorrelated principal components, then developed a second set of LME models using principal component (PC) values as independent variables along with tillage intensity and GDD to explain SOC. In both cases, whether using the raw soils data or principal components, multi-model selection and inference was performed with a restricted maximum likelihood approach in the nlme package of R v3.5.3 (Pinheiro and Bates, 2004).

We then modelled covariance and regression relationships among tillage, soil and weather variables using SEM. SEM is a multivariate statistical modelling method that is descended from path analysis; in that, it explicitly considers the covariance and variance relationships (causal pathways) among variables in a multiple regression. It extends upon the path analysis frame-work by including latent (conceptual; represented as factors) variables, in addition to manifest (directly measured) variables (Smith et al., 2014). By accounting for covariance relationships among the exogenous variables in the model, in addition to their relationships to the dependent variable of interest, SEMs allow the analyst to weigh the relative importance of indirect and direct causal pathways between independent and dependent variables. Candidate SEMs included both latent (conceptual factors) and manifest (directly measured) variables for some soil physical properties, but only manifest variables for tillage intensity and GDD. Model selection to identify the most parsimonious models was based on goodness of fit between the modelled and observed covariance matrices when adjusted for sample size (χ^2 / df < 5), maximization of incremental fit indices (TLI and CFI), and minimization of model residuals (RMSEA and RSMR) (Hooper et al., 2008). To further investigate the mediating effect of temperature on the relationship between tillage and labile SOC, we also developed separate SEM models for each of the three sub-state regions in our study (Northeast, Central and Southwest Michigan). SEM models were implemented in the lavaan package of R v3.5.3. (R Development Core Team, 2019).

4.3 RESULTS

Model selection indicated that the most parsimonious linear mixed effects model for explaining sub field-scale variation in total SOC contained only main effects for tillage intensity, soil percent silt plus clay, wet aggregate stability, surface resistance and growing degree day accumulation (Table 4.1a). Percent silt plus clay ($F_{1,122} = 22.66$, $P < 0.0001$), aggregate stability ($F_{1,122} = 12.89$, $P = 0.0005$), surface resistance ($F_{1,122} = -4.63$, $P < 0.0001$) and growing degree day accumulation ($F_{1,122} = 8.19$, $P = 0.005$), but not tillage intensity ($F_{1,122} = 3.58$, $P = 0.06$), showed significant main effects on total SOC. Total SOC ranged from 0.31% to 4.73%, and was higher on soils with high clay, high aggregate stability, low surface penetration resistance, and also in cool locations. The overall marginal R^2 for the total SOC model (R^2m, fixed effects only) was 0.26, and the overall conditional R^2 for the model (R^2c, fixed and random effects) was 0.99.

Model selection indicated that the most parsimonious linear mixed effects model for explaining sub field-scale variation in labile SOC (POXC) also contained main effects for tillage intensity, soil percent silt plus clay, wet aggregate stability, surface resistance and growing degree day accumulation (Table 4.1b). Percent silt plus clay ($F_{1,122} = 20.13$, $P < 0.0001$), aggregate stability ($F_{1,122} = 12.61$, $P = 0.0005$), surface resistance ($F_{1,122} = 6.98$, $P = 0.009$), growing degree day accumulation ($F_{1,122} = 17.21$, $P = 0.0001$), and tillage intensity ($F_{1,122} = 6.02$, $P = 0.016$), showed significant main effects on labile SOC. Labile SOC ranged from 123.52 to 1136.76 mg C kg^{-1}, and like total SOC was higher on soils with more clay, greater aggregate stability, lower surface penetration resistance, and in cooler locations. Unlike total SOC, labile SOC was loosely correlated with tillage intensity, decreasing as tillage intensity increased. R^2m for the labile SOC model was 0.22, and R^2c was 0.94.

Our initial analysis indicated pairwise correlations between soil physical variables ranging from r = -0.114 (surface resistance and aggregate stability) to r = 0.180 (silt plus clay and surface resistance), which can be problematic because those predictors explain some of the same variance in the response variable, and their effects cannot be estimated independently (Harrison et al., 2018). PCA was therefore applied as a means of controlling covariation between our soil physical variables, including percent sand, silt and clay, wet aggregate stability, surface resistance and subsurface resistance. The first wo PCs together explained 74.4% of the variance in our data set. A loading threshold of 0.45 was used to identify important variables contributing to each PC. PC1 captured soil texture, including significant loadings for percent sand, silt and clay. PC2 showed significant loadings for the remaining soil variables, making it representative of soil aggregation and structure (Table 4.2).

We incorporated PC1 and PC2 as linearly uncorrelated independent variables in a new set of LME models explaining total and labile SOC (Table 4.3). Model selection indicated that the most parsimonious linear mixed effects model for explaining sub field-scale variation in total

SOC contained only main effects for PC1, PC2, tillage intensity and growing degree day accumulation. PC1 (soil texture) ($F_{1,123}$ = 40.39, P < 0.001) and growing degree day accumulation ($F_{1,123}$ = 11.55, P < 0.001), but not PC2 (soil structure) ($F_{1,123}$ = 0.39, P = 0.53) or tillage intensity ($F_{1,122}$ = 1.83, P = 0.18), showed significant main effects on total SOC. R^2m for the total SOC model was 0.18, and R^2c was 0.99. Similarly, model selection indicated that the most parsimonious linear mixed effects model for explaining sub field-scale variation in labile SOC also contained only main effects for tillage intensity, PC1, PC2 and growing degree day accumulation. PC1 (soil texture) ($F_{1,123}$ = 26.96, P < 0.0001), growing degree day accumulation ($F_{1,123}$ = 20.19, P < 0.0001), and tillage intensity ($F_{1,122}$ = 4.33, P < 0.039) showed significant main effects on labile SOC, but PC2 (soil structure) ($F_{1,123}$ = 0.44, P = 0.51) did not. R^2m for the labile SOC model was 0.19, and R^2c was 0.94.

While tillage intensity did have a marginally significant relationship with labile SOC, results of our LME analysis suggest that SOC is highly variable across sites in Michigan, and that SOC is more strongly associated with soil physical properties, particularly texture and temperature, than tillage intensity. Although the importance of soil physical properties for predicting SOC is well supported in the literature (Burke et al., 1989; Rasmussen et al., 2018), our inability to identify significant interactions effects between tillage intensity and soil physical properties in either the LME or PCA-LME models encouraged us to investigate whether SEM might provide a more complete picture of the variance-covariance structure in our data set, and thus further illuminate the relationship between tillage intensity and SOC in Michigan soybean systems.

The most parsimonious SEM models for both total and labile SOC included tillage intensity, GDD and soil aggregate stability as manifest variables, as well as latent variables representing fine soil texture measured as percent silt and clay, and soil hardness measured as surface and subsurface penetration resistance (Figures 4.1 and 4.2). Our SEM models explained a modest, but significant, amount of the statewide variation in total (22%) and labile SOC (25%). GDD accumulation had a substantial negative association with SOC levels in both models, reflecting the temperature dependence of SOC cycling based on changes in microbial activity (Roberts and Chan, 1990; Trumbore et al., 1996). Aggregate stability had a highly significant positive association with both total and labile SOC, highlighting how SOC can be physically protected from microbial degradation within soil macroaggregates (Buyanovsky et al., 1994; Kravchenko et al., 2015). Fine soil texture had a significant positive association with total SOC, but its association with labile SOC was non-significant, which aligns with the documented ability of silt and clay to protect processed SOC through physical and chemical stabilization respectively (Buyanovsky et al., 1994).

The relationship between soil hardness and SOC was strongly negative in both SEMs. Soil hardness (penetration resistance) is usually correlated with bulk density and/or doughtiness (Vaz et al., 2001). Dense, compacted soils have less pore space to accommodate air, water and biology, while dry soils simply lack water to support microbial communities and plant growth. Both of these conditions can limit plant biomass production and carbon sequestration in soils (Brevik et al., 2002). Soil hardness also showed significant covariation with soil texture and aggregate stability in our models, where fine texture decreased penetration resistance and stable aggregates increased soil resistance.

Tillage intensity did not have a significant direct association with either total or labile SOC. Rather, the association of tillage with SOC was indirect and mediated by interactions with the soil physical variables in our models including texture, hardness and temperature. Tillage intensity covaried with fine soil texture, but we assume that this relationship represented fewer opportunities for tillage on fine textured soils based on moisture differences rather than an effect of tillage on soil texture. Greater tillage intensity was associated with hard soils, which were in turn relatively low in SOC. Tillage intensity also positively covaried with GDD in our SEM models, which could be interpreted in two ways. On one hand, a warmer or longer growing season offers more opportunities for tillage operations. If GDD is alternatively assumed to be a proxy for soil temperature, tillage is known to increase soil temperature, which can hasten SOC degradation (Trumbore et al., 1996).

4.4 DISCUSSION

We sought to understand the influence of tillage intensity on SOC status in Michigan soybean production systems and hypothesized that the relationship between tillage intensity and SOC is context dependent, based on the site-specific interaction of tillage and soil physical properties. Our LME models were only able to detect a marginally significant effect of tillage intensity on labile SOC and did not support our hypothesis of tillage by soil type interactions, suggesting that SOC content was largely driven by differences in soil texture and temperature across the sites in our sample. However, our SEM results indicate that the relationship between tillage intensity and SOC in Michigan soybeans is indeed significant, though mediated by edaphic and climatic factors including soil texture, structure and temperature.

Soil texture, aggregation and hardness were the most significant drivers of SOC in our analysis, and the effect of tillage on SOC occurred through interaction with these soil physical properties (Figure 4.3). Where soils have capacity for physical and chemical protection of SOC due to fine texture and well developed aggregation, SOC levels tend to be high (Balesdent et al., 2000; Buyanovsky et al., 1994; Kravchenko et al., 2015). This has been shown in a long-term experiment in Michigan, with a soybean-corn rotation sequence, where practices associated with ~20% gain in soil aggregation showed similar accrual in SOC over a decade (Mpeketula and Snapp, 2019).

The effect of increasing tillage intensity on SOC is also soil texture and structure dependent, with some studies finding that fine textured soils tend to lose more SOC when disturbed relative to coarse soils (Arshad et al., 1999; Franzluebber and Arshad, 1996), and other research suggesting that texture may influence C stratification in disturbed soils, but not overall SOC content (Needelman et al., 1999). SOC increased linearly with silt plus clay content in our soil samples, but the difference in SOC between conventional and no-till systems was similar across soil types (~29%). Yet, this may have been an artifact of our sample containing mostly coarse textured soils. Mechanical disturbance can reduce soil density temporarily, but also destabilizes soil structure, which can contribute to compaction and hardness long-term (McGarry, 2003). As noted above, compacted soils resulting from intensive tillage are often low in SOC.

Temperature had a significant negative association with SOC in our study, with our Northeast region showing a greater capacity to accrue and maintain SOC relative to the Central and Southwest regions (Figure 4.4). Changes in soil physical properties induced by tillage may have a limited effect on SOC where cool temperatures limit microbial degradation of newly exposed SOC (Roberts and Chan, 1990; Trumbore et al., 1996). Roberts and Chan (1990) found that lowering soil temperature to 10˚C reduced CO2 efflux following soil disturbance in a simulation study, resulting in a nonsignificant difference in C loss between their disturbed and control samples. Franzluebbers and Arshad, (1996) found tillage treatments had little effect on

SOC in Northern Alberta and British Colombia where cold temperatures and aridity limited SOC turnover. Similarly, there are examples of conventionally tilled high latitude sites in our sample that rank in the top tercile of labile POXC statewide, likely due in part to the lower average temperature at those locations, which can commonly be below 10˚C when tillage operations are completed in late fall or early spring.

Shimel et al. (1994) quantified the effect of soil texture, temperature and residue quality on SOC content and turnover time on a global scale. They determined that natural variation in each of these parameters could result in an approximate difference of 1,000-2,000 g m^{-2}, or ~40%, in SOC, which is at least equivalent to the 30-40% difference in SOC observed between different tillage systems in the literature and in our study. They also noted that the effect of texture differences on SOC was accentuated in cool environments, with cool temperatures doubling the difference in SOC residence time across the range of soil textures. This could help to explain the prominent relationship between soil texture and SOC in our analysis of Michigan soybean systems where cool temperatures may be an important limiting factor in SOC dynamics.

Limitations of our study design include 1) single post "treatment" measurements of soil properties with no baseline SOC data, 2) the limited amount of time accounted for by our management history data, six years, and 3) the lack of direct accounting for soil moisture, temperature or carbon inputs in the form of plant biomass, manure, etc. Our on-farm observational study design unfortunately precluded any baseline measurements of soil properties. While it could be argued that the six years of tillage history captured is our study may not be enough time to accumulate appreciable differences in total SOC, labile POXC is known to be more sensitive to management within timeframes similar to what we captured in this study, indicating that our models of labile SOC should be reliable (Culman et al., 2012). We attempted to use available data on the number of manure applications over the six-year survey period, single year soybean yields and crop residue cover as estimations of carbon inputs that may interact with tillage intensity to influence SOC in our models. However, none of these candidate variables showed any consistent relationship with the other model parameters.

4.5 CONCLUSION

While many studies have supported the assertion that limiting soil disturbance can reduce or reverse SOC loss, the universal value of CT as a SOC stewardship practice is often oversimplified and overstated (Baker et al., 2007; VandenBygaart, 2016). The agroecological context within which CT is applied ultimately influences SOC outcomes. Therefore, improved understanding of how tillage intensity interacts with unique soil environments and cropping systems is necessary to permit more precise application of CT technologies. This is especially true where adoption of CT may involve trade-offs, such as reduced crop yields, in pursuit of sequestering SOC to enhance soil health or mitigate climate change (Lal, 2015; Pittlekow et al, 2015b; Venterea et al., 2006).

This study is unique in that it provides quantitative systems-level insights into the relationship between tillage and SOC under on-farm conditions. While the results are not absolutely definitive, they highlight important relationships with relevance to real world agricultural systems, and are complementary to conventional factorial experiments and long-term studies using simulated/representative agroecosystems. (Drinkwater, 2002; Kravchenko et al., 2017). For example, our finding that temperature may mediate the effect of tillage on SOC could not be easily observed in a single location experiment, regardless of how long it was maintained.

Yet, it is apparent that this knowledge is critical to improving the relevance and accuracy of tillage recommendations across differing environments, even within a single state.

Based on our results, efforts to increase SOC in Michigan soybean systems should focus on CT practices that limit degradation of soil macroaggregates and overall structure to protect extant SOC, while also maintaining soybean and rotational crop yields to maximize C inputs to soil. Sites in Michigan that are cooler and fine textured soils likely have greater capacity to accrue and protect SOC, and may be prone to yield reductions when managed under CT. For this reason, moderately intensive conservation tillage may be advisable in those environments to optimize SOC management. However, in southern Michigan, or on coarse textured soils, no-till would likely be necessary to maintain or increase SOC in soybean production systems.

4.6 TABLES AND FIGURES

	Total Soil Carbon			**Labile Soil Carbon**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	2.39	1.30 – 3.48	**<0.001**	1037.37	721.40 – 1353.34	**<0.001**
Silt + Clay (%)	0.01	0.01 – 0.02	**<0.001**	1.87	0.36 – 3.38	**0.017**
Aggregate Stability	0.02	0.01 – 0.02	**<0.001**	3.54	1.49 – 5.60	**0.001**
Surface Resistance	-0.00	-0.00 – -0.00	**<0.001**	-0.45	-0.79 – -0.10	**0.013**
Tillage Intensity	-0.00	-0.00 – 0.00	0.173	-0.10	-0.24 – 0.03	0.122
GDD	-0.00	-0.00 – -0.00	**0.005**	-0.24	-0.35 – -0.13	**<0.001**
Observations	251			251		
AIC	582.812			3355.886		
log-Likelihood	-281.406			-1667.943		
R^2_m	0.26			0.22		
R^2_c	0.99			0.94		

Table 4.1. Linear mixed effects models including raw soil physical variables to explain total and labile soil organic carbon.

Variables	PC1	PC2
Surface resistance	-0.21323561	**0.5516737**
Sub-surface resistance	-0.35367815	**0.4642200**
Aggregate stability	-0.05285841	**0.6008435**
Percent sand	**-0.54209911**	-0.2041973
Percent silt	**0.51872026**	0.1879331
Percent clay	**0.51352331**	0.2052501

Table 4.2. Principal components analysis results showing significant loadings (bold text and highlighted) for soil texture variables in PC1 and structure variables in PC2.

	Total Soil Carbon			Labile Soil Carbon		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	3.10	2.16 – 4.04	**<0.001**	1192.67	921.37 – 1463.97	**<0.001**
PC1 (soil texture)	-0.15	-0.21 – -0.09	**<0.001**	-27.13	-42.00 – -12.26	**0.001**
PC2 (soil structure)	0.01	-0.08 – 0.10	0.827	1.00	-21.08 – 23.08	0.929
Tillage Intensity	-0.00	-0.00 – 0.00	0.443	-0.08	-0.21 – 0.05	0.247
GDD	-0.00	-0.00 – -0.00	**0.001**	-0.26	-0.37 – -0.14	**<0.001**
Observations	251			251		
AIC	606.385			3364.738		
log-Likelihood	-294.192			-1673.369		
R^2_m	0.18			0.19		
R^2_c	0.99			0.94		

Table 4.3. Linear mixed effects models including principal components to explain soil organic carbon

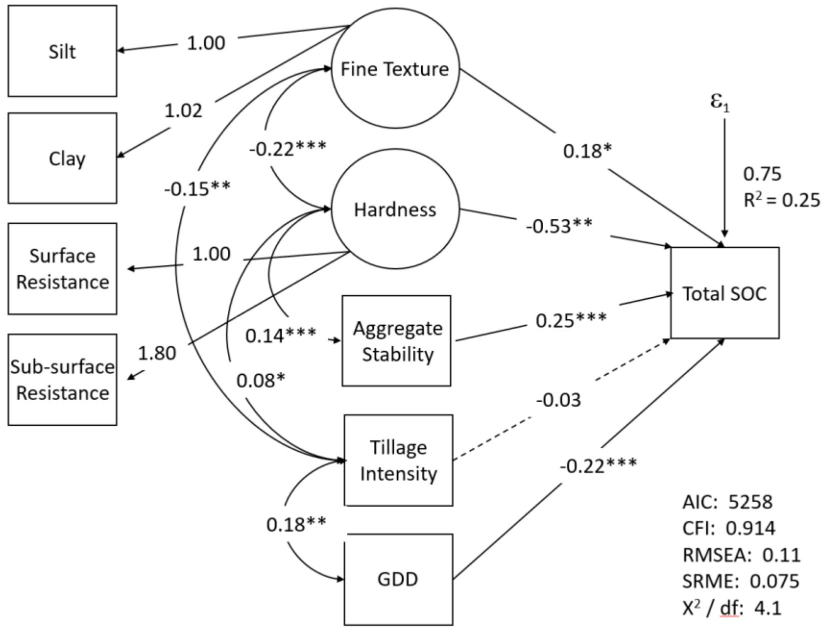

Figure 4.1. Structural equation model explaining total soil organic carbon. Asterisks indicate relationships with P < 0.05 (*), 0.01 (**) and 0.001 (***).

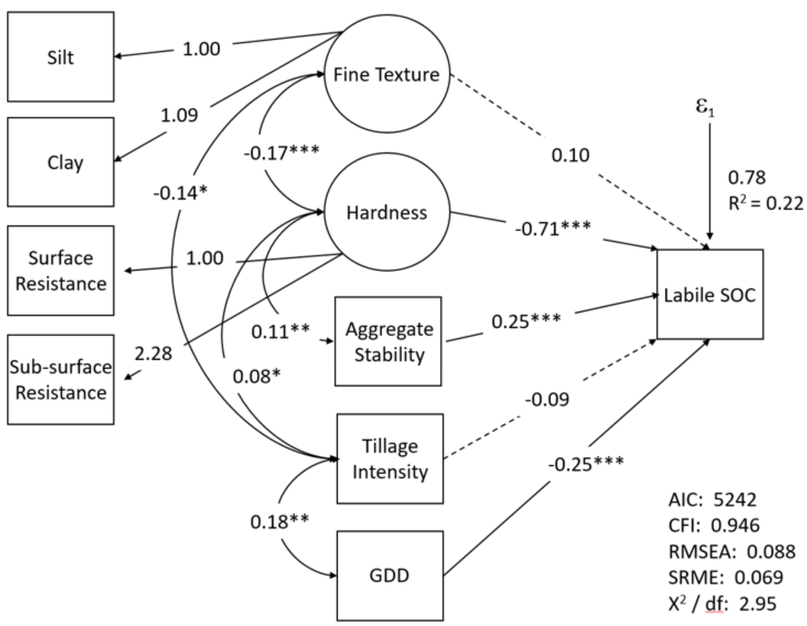

Figure 4.2. Structural equation model explaining labile soil organic carbon. Asterisks indicate relationships with P < 0.05 (*), 0.01 (**) and 0.001 (***).

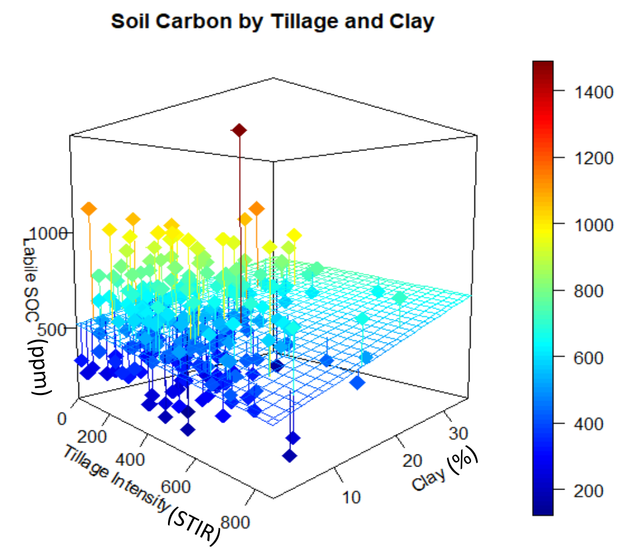

Figure 4.3. Labile soil organic carbon by tillage intensity and soil percent clay in Michigan

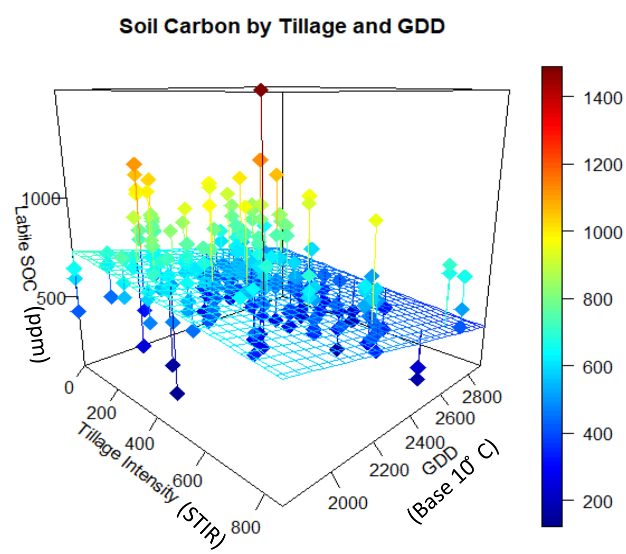

Figure 4.4. Labile soil organic carbon by tillage intensity and growing degree days (GDD)

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CHAPTER 5: GENERAL CONCLUSION

We sought to understand how soybean growers in the State of Michigan select tillage technologies, and the effect of conservation tillage on key measures of agroecological performance in the field. The results reported here support our hypotheses that grower tillage behavior is socially motivated, and that tillage effects on soybean yield and soil carbon are site specific at the field to sub-field level. Our study offers two primary contributions to the literature including a) advances in application of integrated, quantitative methods to answer a systems-level question using observational on-farm data, b) documentation of site-specific tillage X environment interactions across both environmental and spatial gradients that can be used to inform precision tillage recommendations in Michigan soybeans.

Previous field research has frequently tested tillage systems as a prescribed suite of representative operations applied in a handful of site-years. This approach fails to account for the context dependency and cumulative effects of mechanical soil disturbance over time. Long-term tillage studies can capture system-level effects, but are often still constrained to a few locations that may not be representative of agroecological conditions elsewhere. Meta analyses are able to identify trends in tillage effects across environments, but the low spatial density of past independent experiments and methodological differences in how tillage treatments are applied, what covariates are measured, and how outcomes are measured make comparisons difficult. In addition, tillage intensity is too often discussed in value-laden, categorical terms in outreach and education on the subject, ignoring the diversity and dynamic nature of tillage systems used by commercial farmers.

These traditional limitations have resulted in a body of tillage research and education that offers little specific guidance for growers regarding how to target tillage and thus achieve production and soil conservation objectives within the context of unique farm systems. Directly quantifying tillage intensity and tillage effects on working farms over extended periods of time, as accomplished in this study, is critical to improving both clarity and consistency in tillage research and the reliability of extension tillage recommendations. We demonstrated here a suite of multivariate statistical tools that permit robust analysis of the noisy data resulting from on-farm observations. Data reduction and mining techniques can be used to effectively map the complex web of interactions between important variables in these agroecosystems. Methods like linear mixed effects and structural equation modeling make the dependencies common in on-farm data explicit, and effectively leverage covariation rather than treating it as a liability.

Furthermore, using participatory research approaches to collect on-farm data enhances social learning and the relevance of research outcomes for both researchers and farmers by adapting research questions, methods, analysis and interpretation to real world problems. Place-based and spatially explicit on-farm methods help research embrace and quantify the variability that farmers face every day. Generating new knowledge in the context of grower networks can help researchers account for the way that social relationships, risk and trust influence tillage or other agricultural practices. In this way, participatory on-farm research may provide a model for shoring-up trust in science and ensuring relevance in extension work by rooting agriculture research and extension directly in the needs of communities and their unique capacities for learning and adaptation.

Our results indicate that adapting tillage technologies to the environmental and social context in which they will be applied is necessary to help growers realize the full potential of conservation tillage and its positive contributions to agricultural sustainability. We found that growers' tillage decision-making is driven by a combination of socio-psychological and economic factors, with social networks setting the stage for tillage behavior by delineating what practices are recommended and accepted within a particular community. On this basis, we recommend that outreach promoting conservation tillage in Michigan target resource limited, experienced soybean growers with loose social network ties that may soften the social risk of innovation. Recruiting these specific audiences may prove challenging, but extension programming can certainly highlight the cost-saving and technical aspects of a fine-tuned conservation tillage system to better reach potential adopters.

Previous research has produced contradictory results regarding the implications of various tillage systems for soybean yield. These inconsistencies can be explained by the limitations common to tillage research noted above. Using a novel research approach, we found that long-term no-till was associated with significantly higher yield gaps in Michigan soybeans, but only moderate or intermittent soil disturbance was necessary to improve soybean yields. No-till performed best in the relatively warm climate of southern Michigan and on low organic matter soils. Our results suggest that increasing soil disturbance (i.e. conservation or zone tillage) in northern Michigan, and on high organic matter soils, may help to maximize soybean yield and profitability with minimal risk to soil health.

An important next step is to empirically verify the relationships we highlight in a controlled experiment(s) specifically designed for this purpose. Still, this work provides much needed preliminary guidance for extension workers and others offering tillage recommendations to growers in Michigan. It serves to refute the overly simplistic message that reducing soil disturbance is equally feasible for all growers, and will always result in healthier soil and healthier crops regardless of context. While not entirely definitive, we have identified important interactions and potential mechanisms that can help practitioners better predict where conservation tillage is more likely to be adopted and also enhance agricultural sustainability. In that way, it brings us one step closer to a future where tillage intensity can be targeted with the same precision that fertilizer and pesticide applications are today, enhancing outcomes for growers and society at large.

APPENDIX A: IRB LETTERS

UNIVERSITY OF ILLINOIS
AT URBANA-CHAMPAIGN

Office of the Vice Chancellor for Research

Office for the Protection of Research Subjects
528 East Green Street
Suite 203
Champaign, IL 61820

01/28/2015

Adam Davis
Crop Sciences
N-319 Turner Hall
M/C 046

RE: *Northeast Michigan Soil Fertility Survey*
IRB Protocol Number: 15538

EXPIRATION DATE: January 27, 2018

Dear Dr. Davis:

Thank you for submitting the completed IRB application form for your project entitled *Northeast Michigan Soil Fertility Survey*. Your project was assigned Institutional Review Board (IRB) Protocol Number 15538 and reviewed. It has been determined that the research activities described in this application meet the criteria for exemption at 45CFR46.101(b)(2).

This determination of exemption only applies to the research study as submitted. Please note that additional modifications to your project need to be submitted to the IRB for review and exemption determination or approval before the modifications are initiated.

We appreciate your conscientious adherence to the requirements of human subjects research. If you have any questions about the IRB process, or if you need assistance at any time, please feel free to contact me at the OPRS office, or visit our website at http://www.irb.illinois.edu.

Sincerely,

Rose StClair

Rose St. Clair, BA
Assistant Human Subjects Research Specialist, Office for the Protection of Research Subjects

c: James DeDecker

telephone (217) 333-2670 • *fax* (217) 333-0405 • *email* IRB@illinois.edu

MICHIGAN STATE UNIVERSITY

Initial IRB Application Determination *Exempt*

March 2, 2015

To: Sieglinde Snapp
A-576 Plant and Soil Science Building
MSU

Re: **IRB# x15-152e** Category: Exempt 2
Approval Date: March 2, 2015

Title: Northeast Michigan Soil Fertility Survey

The Institutional Review Board has completed their review of your project. I am pleased to advise you that **your project has been deemed as exempt** in accordance with federal regulations.

The IRB has found that your research project meets the criteria for exempt status and the criteria for the protection of human subjects in exempt research. **Under our exempt policy the Principal Investigator assumes the responsibilities for the protection of human subjects** in this project as outlined in the assurance letter and exempt educational material. The IRB office has received your signed assurance for exempt research. A copy of this signed agreement is appended for your information and records.

Renewals: Exempt protocols do not need to be renewed. If the project is completed, please submit an *Application for Permanent Closure*.

Revisions: Exempt protocols do not require revisions. However, if changes are made to a protocol that may no longer meet the exempt criteria, a new initial application will be required.

Problems: If issues should arise during the conduct of the research, such as unanticipated problems, adverse events, or any problem that may increase the risk to the human subjects and change the category of review, notify the IRB office promptly. Any complaints from participants regarding the risk and benefits of the project must be reported to the IRB.

Follow-up: If your exempt project is not completed and closed after three years, the IRB office will contact you regarding the status of the project and to verify that no changes have occurred that may affect exempt status.

Please use the IRB number listed above on any forms submitted which relate to this project, or on any correspondence with the IRB office.

Good luck in your research. If we can be of further assistance, please contact us at 517-355-2180 or via email at IRB@msu.edu. Thank you for your cooperation.

Sincerely,

H. McGee

Harry McGee, MPH
SIRB Chair

c: James DeDecker

Office of Regulatory Affairs
Human Research Protection Programs

Biomedical & Health Institutional Review Board (BIRB)

Community Research Institutional Review Board (CRIRB)

Social Science Behavioral/Education Institutional Review Board (SIRB)

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APPENDIX B: SURVEY INSTRUMENTS

TillageNetworks

Start of Block: Intro

Thank you for participating in this study. The following contains information about the study and your rights as a research participant. Project Title: Tillage Networks: Farmer Perceptions and Peer Groups Driving Tillage Decisions

Investigators: Trey Malone, Ph.D., Michigan State University, and James DeDecker, Michigan State University Extension

Purpose: This is a web-based survey designed to track preferences and sentiments regarding tillage practices for soybean production. Procedures: Proceeding with the following web-based survey indicates your consent to participate in this study. There are 24 questions asking about possible motivations and constraints that influence your tillage system. The survey will take about **15 minutes to complete**.

Risks of Participation: The risks associated with this study are minimal. The risks are not greater than those ordinarily encountered in daily life. Moreover, you may stop the survey at any time.

Benefits: Your completion of this survey will assist researchers in developing evidence-based tillage recommendations that may improve productivity, profitability and sustainability for Michigan soybean growers. Confidentiality: The data will be stored by the principal investigators. Although the data will be saved for future research, the information obtained from it will only be released in analytical summaries in which no individual's answers can be identified or linked to said individual.
Contacts: If you have any questions or concerns about this project, please contact Dr. Trey Malone, tmalone@msu.edu.

Participant Rights: Your participation in this research is voluntary. You may discontinue the survey at any time without reprisal or penalty. Consent: I have read and fully understand the consent form. I understand that my participation is voluntary. By clicking below, I am indicating that I freely and voluntarily agree to participate in this study. I also acknowledge that I am at least 18 years of age.

The project investigators recommend that you print a copy of this consent page for your records before you begin.

End of Block: Intro

Start of Block: Sort

Q 1. In which region of Michigan do you farm?

- Central (1)
- Southwest (2)
- Northeast (3)

End of Block: Sort

Start of Block: SW

Q 2.1. How well do you know each of the following growers?

	Extremely well (1)	Very well (2)	Moderately well (3)	Slightly (4)	Not at all (5)	Click here if this is you (6)
Max Benne (1)	○	○	○	○	○	○
Dave Girton (2)	○	○	○	○	○	○
Wally Hekter (3)	○	○	○	○	○	○
Jerry Jones (4)	○	○	○	○	○	○
Sam Korn (5)	○	○	○	○	○	○
Tom Krull (6)	○	○	○	○	○	○
Darin LaBar (7)	○	○	○	○	○	○
Henry and Ricardo Miller (8)	○	○	○	○	○	○
Dave Mumby (9)	○	○	○	○	○	○
Larry Walton (10)	○	○	○	○	○	○
Herb Miller (11)	○	○	○	○	○	○

Page Break

Q 2.2. On a scale of one to five where one is the least intensive and five is the most intensive, how would you categorize tillage practices used by each of the following growers?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Max Benne (1)	○	○	○	○	○
Dave Girton (2)	○	○	○	○	○
Wally Hekter (3)	○	○	○	○	○
Jerry Jones (4)	○	○	○	○	○
Sam Korn (5)	○	○	○	○	○
Tom Krull (6)	○	○	○	○	○
Darin LaBar (7)	○	○	○	○	○
Henry and Ricardo Miller (8)	○	○	○	○	○
Dave Mumby (9)	○	○	○	○	○
Larry Walton (10)	○	○	○	○	○
Herb Miller (11)	○	○	○	○	○

End of Block: SW

Start of Block: NE

Q 3.1. How well do you know each of the following growers?

	Extremely well (1)	Very well (2)	Moderately well (3)	Slightly (4)	Not at all (5)	Click here if this is you (6)
Todd Ableidinger (1)						
Mike Brandt (2)						
James Delekta (3)						
Robert Erke (4)						
Noel Hardies (5)						
Tyler Idalski (6)						
Julian Pilarski (7)						
Waylon Smolinski (8)						
Christopher Tulgestka (9)						
Clifford Wilk (10)						
Gerard Wozniak (11)						
Jason Pilarski (12)						
John Chappa (13)						
Ed Ciarkowski (14)						

Q 3.2. On a scale of one to five where one is the least intensive and five is the most intensive, how would you categorize tillage practices used by each of the following growers?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Todd Ableidinger (1)	○	○	○	○	○
Mike Brandt (2)	○	○	○	○	○
James Delekta (3)	○	○	○	○	○
Robert Erke (4)	○	○	○	○	○
Noel Hardies (5)	○	○	○	○	○
Tyler Idalski (6)	○	○	○	○	○
Julian Pilarski (7)	○	○	○	○	○
Waylon Smolinski (8)	○	○	○	○	○
Christopher Tulgestka (9)	○	○	○	○	○
Clifford Wilk (10)	○	○	○	○	○
Gerard Wozniak (11)	○	○	○	○	○
Jason Pilarski (12)	○	○	○	○	○
John Chappa (13)	○	○	○	○	○
Ed Ciarkowski (14)	○	○	○	○	○

End of Block: NE

Start of Block: Central

Q 4.1. How well do you know each of the following growers?

	Extremely well (1)	Very well (2)	Moderately well (3)	Slightly (4)	Not at all (5)	Click here if this is you (6)
Dan Fedewa (1)	○	○	○	○	○	○
Bob Feldpausch (2)	○	○	○	○	○	○
David Motz (3)	○	○	○	○	○	○
Robert Reese (4)	○	○	○	○	○	○
David Seeger (5)	○	○	○	○	○	○
Donald Sisung (6)	○	○	○	○	○	○
Lee Thelen (7)	○	○	○	○	○	○
Paul Upright (8)	○	○	○	○	○	○
Joe Woodruff (9)	○	○	○	○	○	○
Pat Zeeb (10)	○	○	○	○	○	○

Page Break

Q 4.2. On a scale of one to five where one is the least intensive and five is the most intensive, how would you categorize tillage practices used by each of the following growers?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Dan Fedewa (1)	○	○	○	○	○
Bob Feldpausch (2)	○	○	○	○	○
David Motz (3)	○	○	○	○	○
Robert Reese (4)	○	○	○	○	○
David Seeger (5)	○	○	○	○	○
Donald Sisung (6)	○	○	○	○	○
Lee Thelen (7)	○	○	○	○	○
Paul Upright (8)	○	○	○	○	○
Joe Woodruff (9)	○	○	○	○	○
Pat Zeeb (10)	○	○	○	○	○

End of Block: Central

Start of Block: Tillage_Perceptions

Q 5. How much do you agree or disagree with the following statements. Further reducing tillage on my farm would...

	Strongly agree (1)	Agree (2)	Somewhat agree (3)	Neither agree nor disagree (4)	Somewhat disagree (5)	Disagree (6)	Strongly disagree (7)
Decrease the cost of soybean production (1)	○	○	○	○	○	○	○
Decrease labor needs for soybean production (2)	○	○	○	○	○	○	○
Decrease soil erosion (3)	○	○	○	○	○	○	○
Decrease soybean yields (4)	○	○	○	○	○	○	○
Increase soil health (5)	○	○	○	○	○	○	○
Increase pest (weed, insect, or disease) pressure in soybeans (6)	○	○	○	○	○	○	○

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Q 6. How much do you agree or disagree that the following limits your ability to further reduce tillage on your farm?

	A great deal (1)	A lot (2)	A moderate amount (3)	A little (4)	None at all (5)
Soil type constraints (1)	○	○	○	○	○
Manure management constraints (2)	○	○	○	○	○
Machinery availability and cost (3)	○	○	○	○	○
Weather and climate constraints (4)	○	○	○	○	○
Growing season length (5)	○	○	○	○	○
Labor availability (6)	○	○	○	○	○
Crop rotation constraints (7)	○	○	○	○	○
Limited financial resources (8)	○	○	○	○	○
Limited technical knowledge (9)	○	○	○	○	○

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Q 7. Do you believe that the following people/organizations agree-disagree that reduced tillage is a recommended practice for soybean production?

	Strongly agree (1)	Agree (2)	Somewhat agree (3)	Neither agree nor disagree (4)	Somewhat disagree (5)	Disagree (6)	Strongly disagree (7)
Jumpstart farmers within my region (1)	○	○	○	○	○	○	○
Other farmers generally (2)	○	○	○	○	○	○	○
MSU Extension (3)	○	○	○	○	○	○	○
Agribusiness professionals I work with (4)	○	○	○	○	○	○	○
My landlords (5)	○	○	○	○	○	○	○
The general public (6)	○	○	○	○	○	○	○

Page Break

Q 8. If one of these parties were to recommend that you further reduce tillage for soybean production, how likely would it be that you would take their advice?

	Extremely likely (1)	Moderately likely (2)	Slightly likely (3)	Neither likely nor unlikely (4)	Slightly unlikely (5)	Moderately unlikely (6)	Extremely unlikely (7)	Not possible; I am already 100% no-till (8)
Jumpstart farmers within my region (1)	○	○	○	○	○	○	○	○
Other farmers generally (2)	○	○	○	○	○	○	○	○
MSU Extension (3)	○	○	○	○	○	○	○	○
Agribusiness professionals I work with (4)	○	○	○	○	○	○	○	○
My landlords (5)	○	○	○	○	○	○	○	○
The general public (6)	○	○	○	○	○	○	○	○

Page Break

Q 9. Please share your thoughts on tillage practices for soybean production in the space provided.

____

End of Block: Tillage_Perceptions

Start of Block: Demographics

We would now like to ask you a few questions about yourself.

Q 10. What is your gender?

- ◯ Male (1)
- ◯ Female (2)
- ◯ Other (3)

Q 11. What is your current age?

- ◯ 18-24 (1)
- ◯ 25-34 (2)
- ◯ 35-44 (3)
- ◯ 45-54 (4)
- ◯ 55-64 (5)
- ◯ 65 or older (6)

Q 12. Have you obtained a Bachelor's degree from a university or college?

- Yes (1)
- No (2)

Q 13. Have you obtained a graduate degree such as an M.S., M.A., M.B.A., Ph.D., M.D., D.D.S., or J.D.?

- Yes (1)
- No (2)

Q 14. What was your approximate annual household income before taxes in 2017?

- Less than $20,000 (1)
- $20,000 to $39,999 (2)
- $40,000 to $59,999 (3)
- $60,000 to $79,999 (4)
- $80,000 to $99,999 (5)
- $100,000 to $119,999 (6)
- $120,000 to $139,999 (7)
- $140,000 to $159,999 (8)
- $160,000 or more (9)

Q 15. What race or ethnicity do you consider yourself?

- ○ White (1)
- ○ Black or African American (2)
- ○ Hispanic (3)
- ○ American Indian (4)
- ○ Asian (5)
- ○ Native Hawaiian or Other Pacific Islander (6)
- ○ Other (7)
- ○ Prefer not to indicate (8)

Q 16. On what percentage of your farm acreage do you grow soybeans?

	0 10 20 30 40 50 60 70 80 90 100
Percent of Soybeans (1)	

Q 17. How many years of farming experience do you have?

	0 7 14 21 28 35 42 49 56 63 70
Years experience (1)	

Q 18. What is your ratio of owned to rented land? The percent must total 100%.
Percent owned : _______ (1)
Percent rented : _______ (2)
Total : ________

Q 19. Please estimate the dollars per acre you spend on soil prep and planting for soybeans?

____

Q 20. Do you have a successor identified for your farm?

- ○ Definitely yes (1)
- ○ Probably yes (2)
- ○ Might or might not (3)
- ○ Probably not (4)
- ○ Definitely not (5)

Q 21. Do you apply a significant amount of manure on your farm?

- ○ Yes (1)
- ○ No (2)

Q 22. Do you feel you have enough labor available?

- ○ Definitely yes (1)
- ○ Probably yes (2)
- ○ Might or might not (3)
- ○ Probably not (4)
- ○ Definitely not (5)

Q 23. How often have you been engaged with the following groups over the last two years?

	Once a week (1)	Once a month (2)	Once every six months (3)	Once a year (4)	Less than once a year (5)	Never (6)
MSU Extention (1)	○	○	○	○	○	○
MSU Jumpstart Project (2)	○	○	○	○	○	○
Michigan Soybean Promotion Committee (3)	○	○	○	○	○	○

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Q 24. Thank you for completing this survey. We would like to give you a pocket knife as a token of our appreciation. Please choose which logo you would like to have placed on the knife.

○ MSU Extension (1)

○ Michigan Soybean Promotion Committee (2)

End of Block: Demographics

Dear Jumpstart Collaborator:

This is a friendly reminder to please respond to our survey at your earliest convenience. The Jumpstarting Michigan Soybean Production project is designed to improve our understanding of current tillage and other related management practices (i.e. crop rotation, residue shredding or chopping, cover crops, etc.) with direct implications for soybean stand establishment, yield and soil health. Participation is voluntary, however our goal is to collect field-specific information about inputs, management practices and crop performance from 60-100 fields per year to be able to generate meaningful results (more fields will produce better recommendations). **Please complete the enclosed survey to provide all of the requested information 2010-2016 for your two fields that were planted to soybeans in 2016 and included in the Jumpstart study, one with a history of high crop yields (good) and the other low yielding (bad).** Do your best to complete the entire survey as accurately as possible, particularly those questions regarding your tillage practices. The information you provide will be kept confidential, combined with information from other producers and used to develop decision support tools for field specific tillage recommendations. There are no known risks associated with participating in this study.

Contact James DeDecker, MSU Extension educator by phone at 989-225-3221 or by email at dedecke5@msu.edu if you have any questions. **Please return the completed form as soon as possible to James DeDecker at dedecke5@msu.edu or 106 E. Huron Ave., Suite C; Rogers City, MI 49779.**

Thank You!

Survey Form Explanation and Recommendations

- **Producer name and mailing address:** Please provide this information as it will be enable us to follow-up in years 2 and 3. Your information will be kept confidential.
- **Crop:** Please indicate the cash crop and any cover crops grown that year, or “fallow” as appropriate.
- **Field location:** This information is essential to retrieving soil and weather data for your fields. The options for providing field locations are provided below:
  - Legal land description with the field boundaries identified in the diagram
  - GPS coordinates for the center of each field
  - Provide the county, nearest intersection and indicate the field location relative to the intersection
- **Dryland or irrigated and field size:** Indicate if irrigation was run in the field that year. Please indicate the total number of acres in each field.
- **Inches of irrigation water:** Please indicate the total amount of irrigation water applied to the field each year.
- **Planting date:** Do not include fields where planting was not completed within a couple of days.
- **Variety name (company and variety name):** Please try to provide this information if possible. At a minimum, please list the maturity group.
- **Seeding rate:** Please list the actual seeding rate in seeds dropped per acre.

- **Row spacing:** Please indicate your row spacing for each crop/year. For twin rows, list the distance between the two twin rows first and then the distance between the center of the twin rows and the adjacent set of twin rows. For example: 7.5" twins, 30" centers.
- **Seed treatment:** Please indicate yes or no. If a seed treatment was applied, please be as specific as possible. If you don't remember the specific product(s), contact your seed supplier. If you can't provide product names, please list the categories (insecticide **I**, fungicide **F**, nematicide **N** or Rhizobia inoculant **R**).
- **Any (non-starter) fertilizer applied after the prior crop (rate and timing):** Do not report starter fertilizer here. Only report nutrients applied after harvesting the previous crop. Please report the pounds per acre of the actual nutrients (N, S, Zn, Mn, Mg, B, K_2O and P_2O_5 not the fertilizer. For example, if you applied 150 lbs. of 0-0-60 per acre, please report 90 lbs. of actual K_2O per acre. Please report the date of all nutrient applications.
- **Any starter fertilizer (yes/no) and nutrients applied:** If a starter was applied, please indicate placement (2x2 or in-furrow) and nutrients applied. Application rates are not required.
- **Lime (L) and Manure (M) and timing:** Only report lime and manure applications made after harvesting the previous crop. Please indicate the year and month for any lime and manure applications. Application rates are optional.
- **Herbicide Program (pre-emergence or post-emergence or both):** Please indicate application timing (pre, post or both). Product names and application rates are not needed.
- **Any in-season fungicide (F) and/or insecticide (I) (yes/no):** Please indicate if a foliar fungicide **(F),** foliar insecticide **(I)** or both was applied. Product names and rates are not necessary.
- **Soybean Cyst Nematodes (SCN yes/no or I don't know):** Only answer "Yes" or "No" if the field has been tested for SCN. If the field has not been tested for SCN, please answer "I don't know".
- **Any significant yield loss due to other factors (insects, diseases, weeds, frost, hail, flooding, and lodging):** Please report yield losses due to any of these problems only if the problem occurred in at least 1/3 of the area in the field and the yield loss exceeded 5%.
- **Average crop yield:** Please indicate the average yield for each year adjusted for moisture.
- **Tillage after crop, before next crop:** Indicate any tillage that occurred between harvest of the current crop and planting of the next crop. If your specific tillage practice is not listed on the form, please write your practice on the form. Please list the number of passes, month and year for all tillage operations.
- **Residue left, harvested or grazed:** Please indicate if crop residue was left on the field, harvested or grazed.

Please provide information for the **historically high yielding (good)** field on your farm that was **planted to soybeans in 2016 and included in the Jumpstart Project**. If you have questions, contact James DeDecker (Phone: 989-225-3221 / e-mail: dedecke5@msu.edu).

An EXAMPLE is shown in the first column.

Year: Crop	EXAMPLE: Corn	2010:_______	2011:_______	2012:_______	2013:_______
Specify field location by Section: Township: Range. → Please sketch-in the boundaries of your field location within the Section →	NE ¼ 25 : 20N : 26W NW 1/4 NE 1/4 SW 1/4 SE 1/4	_____ :____:___ NW1/4 NE1/4 SW1/4 SE1/4	NA	NA	NA
OR GPS coordinates of field center: OR County & field location relative to Rd Intersection:	41.678, -100.257 Saunders Co, SW of Rd 11 & N		NA	NA	NA
Dryland? OR Pivot, Gravity? Indicate field size (acres)	Dryland (90 ac)				
Total Inches of Irrigation Applied to crop?	(ignore if dryland)				
Planting Date in this FIELD (Month/Day/Year):	5/15/2014				
Variety Name (Brand & Number):	Pioneer P93M11				
Seeding Rate (seeds/ac):	125,000				
Row spacing (inches):	30				
Seed Treated (Yes/No)? What Brand Name Product(s)?	Yes (Cruiser-Max)				
Any (non-starter) fertilizer after prior crop? Specify rate (pounds NUTRIENT/ac) and timing (month-year)	P_2O_5: 70 | K_2O: 30 Other: S (11 lbs) Time: March-2014	P_2O_5: | K_2O: Other: Time:	P_2O_5: | K_2O: Other: Time:	P_2O_5: | K_2O: Other: Time:	P_2O_5: | K_2O: Other: Time:
Any STARTER fertilizer (Yes/No)? If Yes, specify nutrients	Yes (N, P, Zn)				
Any Lime (L) or Manure (M)? If yes, specify timing (mm-yy)	M (Nov-2013)				
PRE- or POST-emergence herbicide program or BOTH?	Both				
Any in-season foliar fungicide (F) / insecticide (I)?	F and I				
Soy Cyst Nematodes (Yes/No/I don't know)?	No				
Any significant yield loss due to Insects, Diseases, Weeds, Frost, Hail, Flood, Lodging? Specify problem	Frost (Sept-2014)				
AVERAGE CROP YIELD (bushels/acre) for this FIELD:	60				
Residue left, harvested or grazed?	Grazed				
All tillage after crop, before next crop? No-Till (NT); Ridge (RT); Strip (ST); Disk (D); Chisel (C); Vertical (V); Field Cultivator (FC); Harrow(H) – Indicate # of passes and timing (month-year)	D X2 (March-2014)				

Year: Crop	EXAMPLE: Corn	2014:_______	2015:_______	2016: Soybean
Specify field location by <u>Section</u>: <u>Township</u>: <u>Range</u>. →	<u>NE ¼ 25 : 20N : 26W</u>	NA	NA	NA
Please <u>sketch-in the boundaries of your field</u> location within the <u>Section</u> →	NW 1/4, NE 1/4, SW 1/4, SE 1/4			
OR GPS coordinates of field center: OR County & field location relative to Rd Intersection:	41.678, -100.257 Saunders Co, SW of Rd 11 & N	NA	NA	NA
<u>Dryland</u>? <u>OR</u> Pivot, Gravity? Indicate field size (acres)	Dryland (90 ac)			
Total Inches of Irrigation Applied to crop?	(ignore if dryland)			
Planting Date in this FIELD (Month/Day/Year):	5/15/2014			
Variety Name (Brand & Number):	Pioneer P93M11			
Seeding Rate (seeds/ac):	125,000			
Row spacing (inches):	30			
Seed Treated (Yes/No)? What Brand Name Product(s)?	Yes (Cruiser-Max)			
Any (non-starter) fertilizer after prior crop? Specify rate (pounds NUTRIENT/ac) and timing (month-year)	P_2O_5: 70 | K_2O: 30	P_2O_5: | K_2O:	P_2O_5: | K_2O:	P_2O_5: | K_2O:
	Other: S (11 lbs)	Other:	Other:	Other:
	Time: March-2014	Time:	Time:	Time:
Any STARTER fertilizer (Yes/No)? If Yes, specify nutrients	Yes (N, P, Zn)			
Any Lime (L) or Manure (M)? If yes, specify timing (mm-yy)	M (Nov-2013)			
PRE- or POST-emergence herbicide program or BOTH?	Both			
Any in-season foliar fungicide (F) / insecticide (I)?	F and I			
Soy Cyst Nematodes (Yes/No/I don't know)?	No			
Any significant yield loss due to Insects, Diseases, Weeds, Frost, Hail, Flood, Lodging? Specify problem	Frost (Sept-2014)			
AVERAGE CROP YIELD (bushels/acre) <u>for this FIELD</u>:	60			
Residue left, harvested or grazed?	Grazed			
All tillage after crop, before next crop? No-Till (NT); Ridge (RT); Strip (ST); Disk (D); Chisel (C); Vertical (V); Field Cultivator (FC); Harrow(H) – Indicate # of passes and timing (month-year)	D X2 (March-2014)			

Please provide information for the **historically low yielding (bad)** field on your farm that was **planted to soybeans in 2016 and included in the Jumpstart Project**. If you have questions, contact James DeDecker (Phone: 989-225-3221 / e-mail: dedecke5@msu.edu).

An EXAMPLE is shown in the first column.

Year: Crop	EXAMPLE: Corn	2010:_______	2011:_______	2012:_______	2013:_______
Specify field location by Section: Township: Range. → Please sketch-in the boundaries of your field location within the Section →	NE ¼ 25 : 20N : 26W NW 1/4 NE 1/4 SW 1/4 SE 1/4	_____ :____:___ NW1/4 NE1/4 SW1/4 SE1/4	NA	NA	NA
OR GPS coordinates of field center: OR County & field location relative to Rd Intersection:	41.678, -100.257 Saunders Co, SW of Rd 11 & N		NA	NA	NA
Dryland? OR Pivot, Gravity? Indicate field size (acres)	Dryland (90 ac)				
Total Inches of Irrigation Applied to crop?	(ignore if dryland)				
Planting Date in this FIELD (Month/Day/Year):	5/15/2014				
Variety Name (Brand & Number):	Pioneer P93M11				
Seeding Rate (seeds/ac):	125,000				
Row spacing (inches):	30				
Seed Treated (Yes/No)? What Brand Name Product(s)?	Yes (Cruiser-Max)				
Any (non-starter) fertilizer after prior crop? Specify rate (pounds NUTRIENT/ac) and timing (month-year)	P_2O_5: 70 | K_2O: 30 Other: S (11 lbs) Time: March-2014	P_2O_5: | K_2O: Other: Time:	P_2O_5: | K_2O: Other: Time:	P_2O_5: | K_2O: Other: Time:	P_2O_5: | K_2O: Other: Time:
Any STARTER fertilizer (Yes/No)? If Yes, specify nutrients	Yes (N, P, Zn)				
Any Lime (L) or Manure (M)? If yes, specify timing (mm-yy)	M (Nov-2013)				
PRE- or POST-emergence herbicide program or BOTH?	Both				
Any in-season foliar fungicide (F) / insecticide (I)?	F and I				
Soy Cyst Nematodes (Yes/No/I don't know)?	No				
Any significant yield loss due to Insects, Diseases, Weeds, Frost, Hail, Flood, Lodging? Specify problem	Frost (Sept-2014)				
AVERAGE CROP YIELD (bushels/acre) for this FIELD:	60				
Residue left, harvested or grazed?	Grazed				
All tillage after crop, before next crop? No-Till (NT); Ridge (RT); Strip (ST); Disk (D); Chisel (C); Vertical (V); Field Cultivator (FC); Harrow(H) – Indicate # of passes and timing (month-year)	D X2 (March-2014)				

Year: Crop	EXAMPLE: Corn	2014:_______	2015:_______	2016: Soybean
Specify field location by <u>Section</u>: <u>Township</u>: <u>Range</u>. → Please <u>sketch-in the boundaries of your field</u> location within the <u>Section</u> →	<u>NE ¼ 25 : 20N : 26W</u> NW 1/4 NE 1/4 SW 1/4 SE 1/4	NA	NA	NA
OR GPS coordinates of field center: OR County & field location relative to Rd Intersection:	41.678, -100.257 Saunders Co, SW of Rd 11 & N	NA	NA	NA
<u>Dryland</u>? <u>OR</u> Pivot, Gravity? Indicate field size (acres)	Dryland (90 ac)			
Total Inches of Irrigation Applied to crop?	(ignore if dryland)			
Planting Date in this FIELD (Month/Day/Year):	5/15/2014			
Variety Name (Brand & Number):	Pioneer P93M11			
Seeding Rate (seeds/ac):	125,000			
Row spacing (inches):	30			
Seed Treated (Yes/No)? What Brand Name Product(s)?	Yes (Cruiser-Max)			
Any (non-starter) fertilizer after prior crop? Specify rate (pounds NUTRIENT/ac) and timing (month-year)	P_2O_5: 70 K_2O: 30 Other: S (11 lbs) Time: March-2014	P_2O_5: K_2O: Other: Time:	P_2O_5: K_2O: Other: Time:	P_2O_5: K_2O: Other: Time:
Any STARTER fertilizer (Yes/No)? If Yes, specify nutrients	Yes (N, P, Zn)			
Any Lime (L) or Manure (M)? If yes, specify timing (mm-yy)	M (Nov-2013)			
PRE- or POST-emergence herbicide program or BOTH?	Both			
Any in-season foliar fungicide (F) / insecticide (I)?	F and I			
Soy Cyst Nematodes (Yes/No/I don't know)?	No			
Any significant yield loss due to Insects, Diseases, Weeds, Frost, Hail, Flood, Lodging? Specify problem	Frost (Sept-2014)			
AVERAGE CROP YIELD (bushels/acre) <u>for this FIELD</u>:	60			
Residue left, harvested or grazed?	Grazed			
All tillage after crop, before next crop? No-Till (NT); Ridge (RT); Strip (ST); Disk (D); Chisel (C); Vertical (V); Field Cultivator (FC); Harrow(H) – Indicate # of passes and timing (month-year)	D X2 (March-2014)			