A CROSS-SCALE EXAMINATION OF HOW KNOWLEDGE AND THE PHYSICAL ENVIRONMENT INFLUENCE THE USE OF BEST MANAGEMENT PRACTICES IN US COMMODITY AGRICULTURE

By

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ABSTRACT

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While agriculture is of the utmost importance to human societies for its production of food and fiber (and increasingly fuel), it is also a source of environmental harm as a producer of nonpoint-source pollution to the air and water. Even though efforts to control agricultural nonpoint-source pollution have focused on encouraging farmers to voluntarily use practices that will better keep soil and nutrients on farms, agriculture remain a substantial source of water pollution in the US. This has led to continued efforts to better understand why farmers choose to use these best management practices (BMPs) so that incentives can be improved. Therefore, this dissertation focuses on farmer decision-making related to the use of soil, water, and nutrient conserving BMPs in row-crop agriculture in the US Midwest, with particular interest in the importance of the roles of knowledge and the biophysical environment. Conceptually, my dissertation is informed and organized by a theory of action, in which purposive individual actions cumulatively create system-level effects. This is done by analyzing data at the individual, county, and state scales as well as across-scales in three empirical chapters.

The first analysis uses qualitative interview data from 2014 with 151 Midwestern corn farmers in three states to explore the range and variation of the tillage practices in use, and to consider the reasons farmers give for their tillage decisions. The results show that farmers commonly use more than one style of tillage on their operation and base their tillage decisions on biophysical conditions, compatibility with other practices, and the relative savings and costs of

different tillage styles. The second analysis uses 2017 farmer survey data from four states (n=814) to compare the relative importance of a wide range of predictors of BMP use from the literature on the use of five BMPs: pre-sidedress nitrate tests (PSNTs), nutrient maps, variable rate nitrogen (N), variable rate phosphorus (P) or potassium (K), and cover crops. It also explores the use of practice knowledge as a predictor of BMP adoption that has been underutilized in previous research. The results show little overlap in the predictors of the five practices, even between those with similar characteristics. Two predictors in particular—the use of independent crop consultants as an information source and a general measure of practice knowledge—were found to be the most important influences across all five models. The third analysis considers the cumulative decisions of multiple farmers by using county and state data for the North Central region (1,042 counties) to examine the effects of conservation tillage, no-till and cover crops on county-level fertilizer use. The results show no significant total effects on fertilizer use by no-till, conservation tillage, or cover crops, though there is the potential for cover crops to increase fertilizer use.

The importance of the biophysical environment is a key finding of all three analyses, and different biophysical conditions can increase and decrease the use of BMPs. The differences in effects of both social and biophysical factors across BMPs has important implications for future research and suggests the need for specific measures of practices that include temporal and spatial variation, and the careful consideration of practices individually, rather than as groups of ostensibly related practices. Knowledge also shows promise as a variable of importance in practice use—both through knowledge of how to use or implement a practice, and through knowledge of environmental-systems that shape how farmers perceive and interpret their biophysical context.

Dedicated to my parents as a very small repayment
for all their love and support throughout the years.
And to JD, whose support, patience, and humor
have kept things real during this journey.
You are appreciated.

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KEY TO ABBREVIATIONS

AgCensus	Census of Agriculture
ANOVA	Analysis of Variance
BMP	Best Management Practice
CFI	Comparative Fit Index
CHANS	Couple Human and Natural Systems
CNH	Couple Natural and Human
CRP	Conservation Reserve Program
CSP	Conservation Stewardship Program
CTIC	Conservation Technology Information Center
EQIP	Environmental Quality Incentives Program
IA	Iowa
ICC	Intraclass Correlation Coefficient
IN	Indiana
K	Potassium
MI	Michigan
MIMIC	Multiple Indicators and Multiple Causes
MLR	Robust Maximum Likelihood
N	Nitrogen
NASS	National Agricultural Statistics Service
NRCS	Natural Resource Conservation Service
OLS	Ordinary Least Squares

P	Phosphorus
PBC	Perceived Behavioral Control
PSNT	Pre-Sidedress Nitrate Test
RAA	Reasoned Action Approach
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SEMLV	Structural Equation Modeling with Latent Variables
SES	Social-Ecological System
TLI	Tucker-Lewis Index
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
USDA	United States Department of Agriculture
WLSMV	Weighted Least Squares Means and Variance

CHAPTER 1: INTRODUCTION

While agriculture is of the utmost importance to human societies for its production of food and fiber (and increasingly fuel), it is also a source of environmental harm as a producer of non-point-source pollution to the air and water (Aneja, Schlesinger, and Erisman 2009; Carpenter et al. 1998; Drinkwater and Snapp 2007; Lal 1993; Robertson et al. 2013; Robertson and Vitousek 2009; Uri and Lewis 1998). Nutrients, nitrogen and phosphorus in particular, are vital to crop production but also create great environmental costs when they leave the farm and enter surrounding waterways where they contribute to eutrophication, algal blooms and hypoxia ("dead zones") (Blesh and Drinkwater 2013; Drinkwater and Snapp 2007; Hamilton 2015; Robertson and Vitousek 2009). Similarly, soil that washes off fields can impair surrounding water bodies through suspended soil particles that cloud the water and sediment accumulation at the bottom, and soil that is blown away by wind can impair air quality (Uri and Lewis 1998).

Concern over soil erosion in the US goes back to at least the Dust Bowl of the 1930s (Halcrow, Heady, and Cotner 1982), while concern over the off-farm effects of nutrient loss have only been of widespread concern since the 1970s (Drinkwater and Snapp 2007). Efforts to control both issues have focused on encouraging farmers to voluntarily use practices that will better maintain soil and nutrients on farms and thus benefit both farmers and society. While many farmers have changed their production practices in a variety of ways in response to these efforts, both nutrient loss and soil erosion from agriculture remain a source of pollution for water bodies in the US (EPA 2017). This has led to continued efforts to better understand why farmers choose to use these conservation or best management practices (BMPs) so that they can be better encouraged to use more of them on more of their land.

State-led efforts to reduce both soil and nutrient loss in the US have historically taken a voluntary approach through a number of federally supported conservation programs. The largest and oldest US conservation program is the Conservation Reserve Program (CRP), which pays farmers to either remove from cultivation or not start farming sensitive land. Working-land programs such as the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP) provide cost-share and resources for farmers with more specific management goals related to a range of topics (Reimer and Prokopy 2014).

Incentives for program participation have not typically exceeded making money available to farmers for setting aside land or to help in adopting a practice, and thus have been of limited effectiveness (Ribaudo 2015). The one exception is the Conservation Compliance provision, initiated in the 1985 Farm Bill, which requires that steps be taken to reduce erosion on land classed as highly erodible for the farmer to be eligible for commodity program payments (Arbuckle 2013). With the end of the commodity programs in the 2014 Farm Bill, Conservation Compliance for highly erodible land and wetlands is now required for eligibility for federal subsidies for crop insurance premiums among other things (NRCS n.d.).

My dissertation focuses on farmer decision-making related to the use of soil, water, and nutrient conserving BMPs in row-crop agriculture in the US Midwest. In it, I seek to better identify the variables that drive farmers' decisions to use or not use BMPs, with a particular interest on how the drivers may differ between practices, and to take a step towards considering how the use of BMPs influence other production decisions—in this case the degree of fertilizer use. The BMPs of interest in the analyses that follow are related to fertilizer rate and application methods, tillage practices, and the use of winter cover crops. These are all in-field practices that can have a direct impact on fertilizer use, fertilizer use efficiency, and ultimately nutrient loss from agriculture.

In my analyses I engage with and draw on the two most common conceptual approaches used in the literature to understand farmer decisions and behavior: the Theory of Planned Behavior/the Reasoned Action Approach (TPB/RAA), and the Diffusion of Innovations, or adoption-diffusion, model. I also specifically consider the role of knowledge and especially the biophysical environment in farmer decision-making, which represent two domains that, while not wholly absent from the approaches just mentioned, are extremely underutilized in the literature. In my analyses, I specifically work to integrate social and biophysical elements in the same analyses in a way that is rarely seen especially in the sociological literature. Conceptually, my dissertation is informed and organized by a theory of action, in which purposive individual actions all together create system-level effects. This is done by analyzing data at the individual scale as well as at the county and state scale, as appropriate, across my three empirical chapters.

WHY AGRICULTURE?

Agricultural systems sit right at the interface between society and the biophysical environment—they are rooted (literally) in chemical and ecological processes that exist independently of humans, and at the same time are highly "socialized" systems created by and for human purposes. As such agricultural systems are shaped by both "nature" and society, thus to understand the relationship between agriculture and society the biophysical world must also be considered (Carolan 2005; Dunlap and Martin 1983).

The "recognition of the fact that physical environments can influence (and in turn be influenced by) human societies and behavior" (Dunlap and Catton 1979:244) is the founding principle of environmental sociology. However, just how these reciprocal influences should be conceptualized and operationalized in research has often been a source of disagreement within the discipline—as an example, the social constructionist vs realist debate is/was at its core a disagreement over this question (see York and Dunlap 2011). The tendency thus far has been to take a biophysical problem as the context of a study, with the biophysical problem as an abstract outcome of the human activities being studied, but not to include biophysical problems or conditions as an influence on the human/social actions. This has resulted in research that retains social-social relationships as its primary interest.

Additionally, in spite of agriculture being one of the most immediate and tangible ways that societies interact with their biophysical environment (Dunlap and Martin 1983), agriculture has not generally been a topic of much interest to environmental sociology. Agriculture has been a common subject of rural sociologists, particularly those who study the sociology of agriculture though they have not always given as much attention to the biophysical context of agriculture as some have thought they should (Dunlap and Martin 1983). Natural resource sociologists and social scientists have perhaps given agriculture and its issues related to sustainability and resource conservation the most attention (Field, Luloff, and Krannich 2002), though largely in an applied way and, like environmental sociology, including environmental problems as the justification for a study but not incorporating them into the research question or design.

WAYS TO UNDERSTAND FARMER-DECISION MAKING

Two primary conceptual approaches have been used to explain farmers' adoption of BMPs: the adoption-diffusion model, and social-psychological theories in the Theory of Planned Behavior tradition. While both approaches have been used with apparent success to better understand the factors influencing farmers' decisions to use or not use BMPs, they are both, to different degrees, limited in how they account for the external social and biophysical factors that are the context in which farmers' make their management decisions. They both also have other limitations, which I discuss below.

Adoption-Diffusion Model

The adoption-diffusion model describes the process through which a new idea, technology, or practice (i.e., innovation) spreads through a social system, and is ultimately adopted (or not) by individuals over time (Rogers 2003). The study of innovation diffusion was originally developed independently in several social science fields in the first half of the twentieth century, including by rural sociologists to understand the spread and adoption of new agricultural technologies (Rogers 1958; Ruttan 1996; Ryan 1948; Ryan and Gross 1943). These traditions merged somewhat in the 1960s, through work by Katz and colleagues (Katz 1963; Katz, Levin, and Hamilton 1963), and that of Everett Rogers (Rogers 2003). Rogers, though not the creator of adoption-diffusion research[1], is perhaps the single person most associated with it, through his work in rural sociology and latter in communications (Rogers 2003).

Rogers (2003:5) describes diffusion as "the process in which an innovation is communicated through certain channels over time among the members of a social system." It is a macro process (as opposed to the micro-level adoption decision) that is heavily dependent on communication, and where the newness of the innovation and its effects creates uncertainty about the innovation (Rogers 2003). Over time the innovation is communicated to more people and uncertainty is reduced through greater information, sometimes resulting in the full adoption of the innovation in the population (Rogers 2003). The result of diffusion (and the adoption

[1] Rogers calls his model the Diffusion of Innovation Model.

process that results) makes it a form of social change, in that it can alter the structure and function of the social system (Rogers 2003).

As diffusion happens, individuals (or other decision-making entities) gain information about the innovation and ultimately decide to use it or not use it. The “innovation-decision process,” as described by Rogers (2003:14), “is essentially an information-seeking and information-processing activity in which an individual is motivated to reduce uncertainty about the advantages and disadvantages of the innovation.” Rogers (2003) breaks the innovation-decision process into five stages (Rogers 2003):

1) *Knowledge* of the innovation—existence of the innovation and how it works.
2) *Persuasion* of the usefulness/benefit or drawbacks of the innovation—formation of positive or negative attitudes about the innovation.
3) *Decision* to adopt or reject the innovation based on activities that provide additional information, such as using it on a trial basis.
4) *Implementation* of the innovation.
5) *Confirmation*, or reassessment, of the decision made based on additional information.

Rogers also describes five perceived attributes of innovations that influence how quickly the diffusion and adoption processes takes for a given innovation (Rogers 2003). These attributes are:

1) *Relative advantage* of the innovation over current options on any of a number of dimensions (e.g., economic, social, convenience, etc.)
2) *Compatibility* of the innovation with existing systems, beliefs and values.
3) *Complexity* of the innovation as it pertains to understanding how it works and how to use it.
4) *Trialability* of the innovation—being able to test it on a limited basis.
5) *Observability* of the innovation being in use and of its benefits.

Low levels of perceived complexity and high levels of the other attributes serve to accelerate the adoption-diffusion process.

The time it takes an individual to complete the innovation-decision process and start using an innovation is considered a measure of their “innovativeness,” and has been used to descriptively categorize individuals (Rogers 2003). If innovativeness is considered to be a personality trait it is expected to generally follow the normal distribution in a given population, and as such, adoption of an innovation also follows a generally normal distribution (Rogers 2003). This results in the “S-shaped curve of adoption” when the cumulative frequency of adopters over time is graphed, or a bell-shaped curve results if frequency of new adoption is graphed (Rogers 2003:272). Normality assumptions are based on full adoption, which often does not happen, so index measures of innovativeness are often used to avoid the technical difficulties of having non-exhaustive categories (Rogers 2003; Rollins 1993).

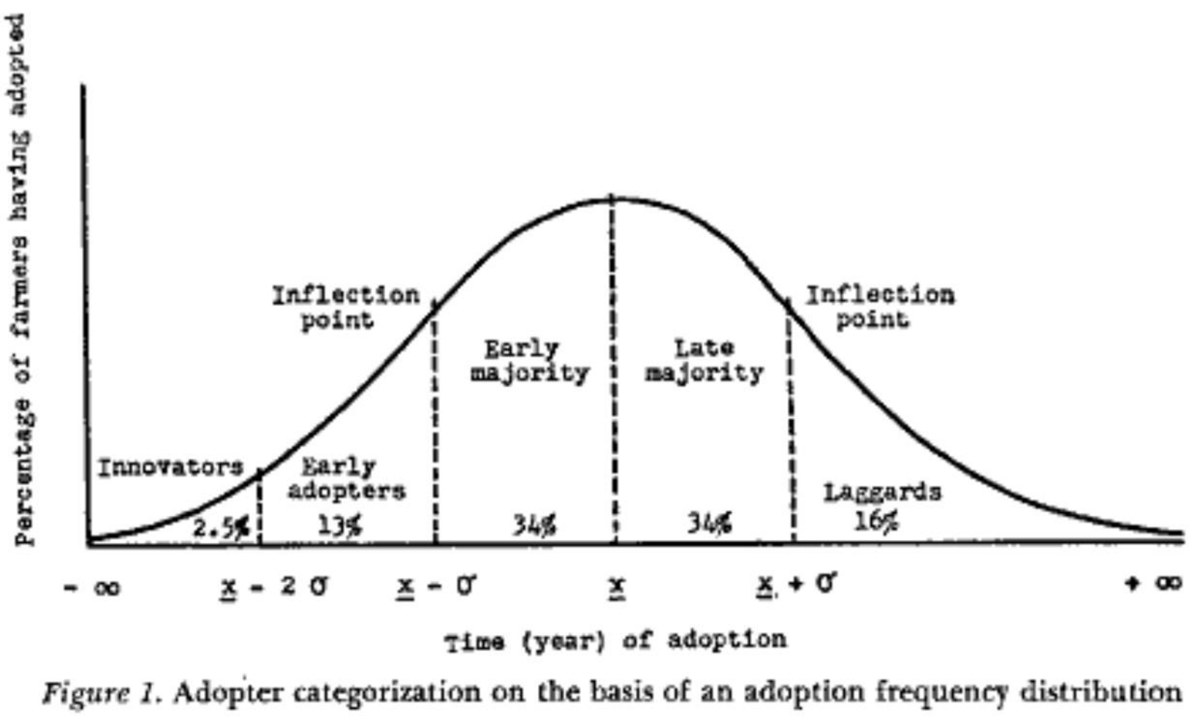


Figure 1.1. Adopter categorization on the basis of an adoption frequency distribution (Rogers 2003:351).

Rogers (2003) suggests making use of the normal properties of adoption rate by using standard deviation units from the mean to create five categories of innovation adopters: innovators, early adopters, early majority, late majority, and laggards, with early majority and late majority being the categories one standard deviation less than the mean and greater than the mean respectively (see Figure 1.1).

Use of the adoption-diffusion approach in rural sociology peaked in the late 1950s, but had declined dramatically by the early 1970s (Ruttan 1996). Ruttan (1996) suggests this decline can be explained by a shift in sociological perspectives of modernity and technology, in which new technologies could decrease autonomy and increase inequalities rather than being a liberator, coupled with a period of agricultural production surpluses that reduced concern with agricultural technology adoption. Other criticisms of the approach seem to be based more on how it has been applied, than critiques of the approach itself, such as a lack of engagement with sociological theory, and pro-innovation biases (Ruttan 1996). While the adoption-diffusion approach has been out of general favor in rural sociology for nearly 50 years, it has not disappeared entirely, and aspects of it, such as the qualities of innovations that influence adoption, are still commonly used and referenced (e.g., Reimer, Weinkauf, and Prokopy 2012; Weber and McCann 2015).

The adoption-diffusion model has certainly been considered as an explanation for conservation practices or BMPs, though not recently. The model has been challenged in its applicability to environmentally oriented practices (Pampel and van Es 1977), but has also been found to still be useful for understanding the adoption of these practices with appropriate adjustments for the purpose of the innovation being considered (Taylor and Miller 1978). The most recent form of the adoption-diffusion model (Rogers 2003) certainly is flexible enough to accommodate both economically and environmentally oriented practices if the purpose of the practice is accounted for and appropriate variables are used. For example, the relative advantage of a practice like vegetative buffers might reasonably be expected to lie more in the social realm (such as the farmers' personal identity, how they see themselves in their community, social and personal norms and values etc.) than a practice like precision fertilizer application that would have direct economic implications in the costs of adoption and the potential savings in more efficient fertilizer use.

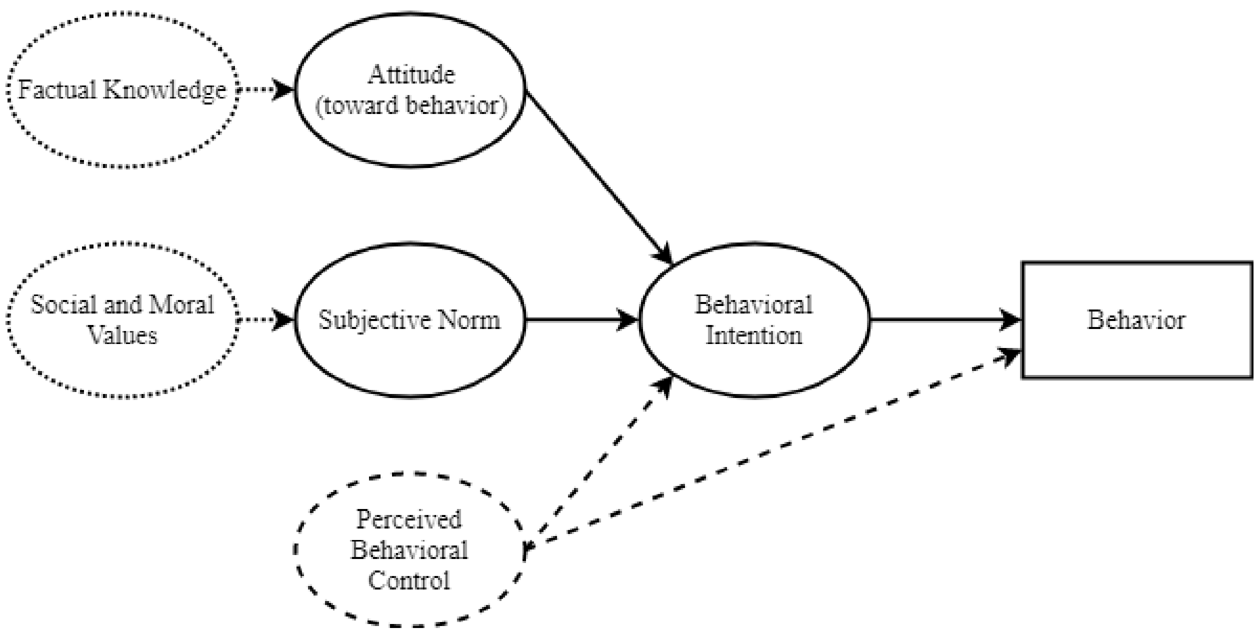
However, the adoption-diffusion model does have its flaws. A major challenge to fully utilizing the adoption-diffusion model for understanding BMP adoption is that the model is not easily operationalized empirically. The multi-scale nature of the model is one complicating factor, as the information networks and the diffusion process are conceptualized as macro or meso scale processes that are measured over time, while the five stages of the adoption decision take place at the individual level. This is further complicated by most farmer-level survey data being cross-sectional, and thus unsuitable for a true measure of adoption. In addition, there are the characteristics of the innovation that do not exist at either level, being properties of the innovation itself. It is important to note that the characteristics of a practice may have a subjective component at the individual level, especially for the relative advantage, compatibility, and complexity attributes.

Two obvious things that the adoption-diffusion model is missing are an explicit inclusion of the biophysical and the political-economic contexts in which the innovation is being considered. The biophysical context is especially important when considering agricultural practices since the outcome of their use (and its success or failure to achieve the expected or desired result) will depend at minimum on environmental conditions like the soil and climate in which it is being used. The political-economic context also potentially influences several aspects of the adoption-diffusion model, such as information sources, and the relative advantage of the innovation. The rise of large, integrated agricultural input suppliers that provide crop consulting services, and decreases in funding to agricultural extension has shifted to whom farmers turn for information away from extension and towards business affiliated consultants (Stuart et al. 2018), though the implications of this shift for what information farmers are receiving is not yet well understood. Similarly, the relative advantage of a practice would be expected to be influenced by factors such as crop prices, the availability of cost-sharing programs, and policies such as the Conservation Compliance provision discussed above.

Social Psychological Theories

With the adoption-diffusion model out of favor for studying agricultural decision-making, the TPB family of theories from social psychology has become a very common conceptual approach for understanding farmer adoption of conservation practices. This family consists of the theory of reasoned action (TRA), the theory of planned behavior (TPB), and the reasoned action approach (RAA) (Ajzen 1991; Fishbein and Ajzen 2015). The use of the TPB for understanding agricultural decisions started as early as the mid-1990s (Lynne et al. 1995) currently quite popular (Arbuckle and Roesch-McNally 2015; Borges, Tauer, and Lansink 2016; Van Hulst and Posthumus 2016; Price and Leviston 2014; Reimer et al. 2012; Werner et al. 2017).

The three theories in this family are related and began with the theory of reasoned action (TRA). In the TRA attitude towards the behavior and subjective norms—the perceived expectations of others–drive behavioral intention, in turn drives behavior (see Figure 1.2). The use of behavioral intention as a mediator between attitudes, norms and behavior is a distinguishing feature the TRA and the theories derived from it. The assumption is that intention leads to action, though there is evidence that this is not always the case in critical ways (Niles, Brown, and Dynes 2016). The theory of planned behavior (TPB) is an extension of the TRA that adds perceived behavioral control (PBC) as a predictor of behavioral intention and actual behavior (Madden et al. 1992 highlight the differences). Fishbein and Ajzen (2015:64) define PBC “as people’s perceptions of the degree to which they are capable of, or have control over, performing a given behavior.” This addition incorporates a contextual element to the theory and improves its predictive power, especially for behaviors that have greater actual or perceived external constraints (Ajzen 1991; Madden et al. 1992).



Solid line = typical Theory of Reasoned Action (TRA)

Solid line + dotted line = TRA with additional elements included by Kaiser, Wolfing, and Fuhrer (1999)

Solid line + dashed line = Theory of Planned Behavior

Figure 1.2. Conceptual diagram of the Theory of Reasoned Action and the Theory of Planned Behavior based on figures in Kaiser, Wölfing, and Fuhrer (1999:3) and Madden, Ellen, and Ajzen (1992:4).

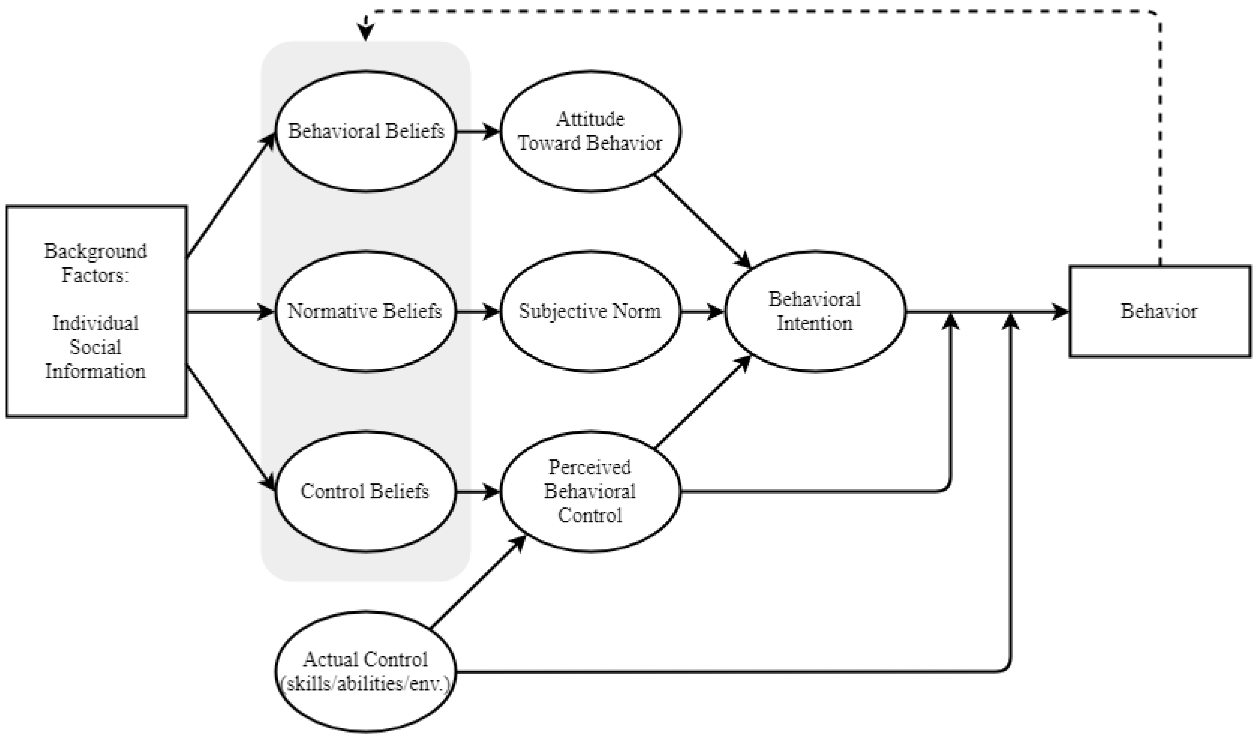


Figure 1.3. Conceptual diagram of the Reasoned Action Approach based on figure in Fishbein and Ajzen (2015:22).

The reasoned action approach (RAA) (see Figure 1.3) is the most recent incantation of this family of theories and extends the TPB by adding "individual," "social," and "information" background factors, along with a new tier of belief variables and an actual control variable (Fishbein and Ajzen 2015). The belief components underlie the attitude, subjective norms and perceived behavioral control variables, and typically measures of the different types of beliefs that are used to measure attitudes, subjective norms and perceived behavioral control using factor analysis (Fishbein and Ajzen 2015). Fishbein and Ajzen (2015:96, 223) formally describe beliefs "as the subjective probability that an object has a certain attribute" and more casually as "the information they [the person] have about a behavior." These beliefs can be formed through a range of experiences, education, and information sources, and can be short or long lasting, with the only conceptual requirement being that actions follow reasonably from beliefs, no matter how acurate or rational the beliefs may be (Fishbein and Ajzen 2015)[2].

Similar to the adoption-diffusion model, I see notable conceptual limitations in the TPB/RAA in that there is no conceptual location for political-economic or biophysical contexts[3] that may influence the decision process. Behavioral beliefs and PBC broadly might be able to accommodate some aspects of these contexts, such as beliefs in practice attributes and suitability, and adoption costs, but a closer look reveals these measures to be incompatible with the attitudes-measured-by-beliefs approach as discussed below, and with the theoretical conceptualization of PBC (Fishbein and Ajzen 2015), as whether costs constrain behavior is a complex and context specific condition that is heavily dependent on trade-offs and what alternatives are available. At best, the TPB/RAA offers indirect ways of incorporating political-economic or biophysical contexts that are entirely dependent on the individual's perceptions of them.

Of greater concern, is that the TPB/RAA does not account for the nature or characteristics of the behavior under investigation. More importantly, because the TPB/RAA was intended to predict the voluntary behavior of individuals in their everyday life, it may not be appropriate for studying farmers' decisions about their farming practices. The key distinction is that farming is a business, making it fundamentally different from use of public transportation

[2] "It is important to note that, within our reasoned action framework, we do *not* assume that people are rational but only that their actions follow reasonably from their beliefs. Given that beliefs are often based on information provided by others and on fallible inference processes, behavioral, normative, and control beliefs need not be veridical. They can be inaccurate, biased to conform with preconceptions or motives, or they may represent rationalizations, wishful thinking, or other irrational processes. Nevertheless, the beliefs people hold constitute the information they have about a behavior, and because they naively assume that their beliefs are valid . . . , they act upon them." (Fishbein and Ajzen 2015:223)

[3] The "background factors" as described by Fishbein and Ajzen (2015:24) are all specific to the individual and could include: "age, gender, ethnicity, socioeconomic status, education, nationality, religious affiliation, personality, mood, emotion, general attitudes and values, intelligence, group membership, past experiences, exposure to information, social support, and coping skills." Fishbein and Ajzen suggest that the selection of background factors can be guided by domain-specific theories.

(Heath and Gifford 2002), hotel choice (Han, Hsu, and Sheu 2010), hunting (Hrubes, Ajzen, and Daigle 2001), and the use of dual-flush toilets to save water (Lam 2006) as a few examples. For farmers to remain farmers they must remain profitable, so any decisions about the methods and tools they will use to farm must meet this basic standard. This is not to say that all or even most farmers are profit-maximizers, but their farming decisions have to at least not cost them too much money compared to what the decision will make them. This frequently places farmers in a situation where they *could* implement a given practice, but they have to decide if they *should* implement it, thereby greatly complicating the PBC portion of the TPB/RAA, and potentially curtailing the role of attitudes and norms in their decisions.

I also see empirical challenges with operationalizing the TPB/RAA, though these challenges are different than the ones for the adoption-diffusion model as the TPB/RAA already has a path model that is easily estimated through structural equation modeling (SEM). The main issue involves the potential conflict between the conceptualization and the common operationalization of beliefs and attitudes. Conceptually in the RAA beliefs are separate from and predict attitudes, but empirically it is most common to use beliefs as measures of attitudes in a latent variable. The measurement model of a latent variable uses the observed attitudes as endogenous variables that are predicted by the latent construct. In other words, the attitude predicts the beliefs, which is the opposite direction of the relationship as depicted in the RAA. This results in a model in which the belief variables have no direct or indirect effect on the behavior. It is possible to operationalize the model differently, as Borges, Tauer, and Lansink (2016) have done using a multi indicators and multiple causes (MIMIC) model[4], which maintains the directions of the causal relationships in the TPB/RAA, but this is not a common method.

[4] See Kline (2012) for more on MIMIC models.

OVERVIEW OF EMPIRCAL ANALYSES

This dissertation includes three empirical analyses. In the first analysis I use qualitative data and grounded theory to investigate farmers' tillage practices and the factors that influence their tillage choices. My primary purpose is to examine what tillage practices Midwestern corn farmers are using and why. The results that emerge on the ways farmers are tilling challenges the commonly used tillage categories, as I find that farmers' tillage practices are not easily assigned to the usual three or four categories. The results of the reasons farmers gave for why they till as they do calls into question the social-psychological theories that are commonly used in studies of farmer decision-making, as I find that the biophysical context, the needs of the operation, and practice compatibility were much more heavily referenced by farmers as reasons for their tillage choices than were attitudes or values related to the environment or the tillage practices themselves.

The second analysis is a quantitative analysis using structural equation modeling with latent variables that takes a broad approach to investigating the drivers of the use of five BMPs: pre-sidedress nitrate tests (PSNTs), nutrient maps, variable rate nitrogen (N), variable rate phosphorus (P) or potassium (K), and cover crops. The goal is to identify the common drivers of BMP use and assess their relative importance. It also explores the use of practice knowledge as a predictor of BMP use that has been underutilized in previous research. The results of this analysis show that these five practices have few drivers in common, even between practices that were expected to be similar. The relative importance of the significant variables suggests that the adoption-diffusion model may provide more predictive of farmers' use of these BMPs than the social-psychological theories, as information sources were found to be more important to practice use than attitudes.

The third analysis uses county and state data in a multilevel structural equation model to examine the scaled-up effects of many individual decisions relating to the rate of nitrogen fertilizer used in the presence of cover crops, conservation tillage and no-till. The retention of nutrients by these in-field practices means that they have the potential to reduce the amount of fertilizer that a farmer needs to apply to get a good crop, thereby saving farmers money and reducing non-point-source nutrient pollution from agriculture. However, it is not clear to just what extent farmers *actually do* reduce their fertilizer use when they adopt any of these practices. If farmers are not experiencing tangible savings from the use of these practices then it is likely that the present incentive system for their use is insufficient for encouraging their adoption. The analysis does not show any of the three practices to have a significant total effect on fertilizer use, but it does suggest that cover crops may have the potential to increase fertilizer use. Not only does this analysis scale up from the individual to better assess the cumulative effects of many individual actions at a scale where the effects are more visible, but it also includes a mixture of ecological and economic and non-economic social variables in a single model, which is novel in sociological studies.

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CHAPTER 2: MOVING BEYOND BASIC TILLAGE CATEGORIES IN MIDWEST ROW-CROP AGRICULTURE: AN EXPLORATORY ANALYSIS OF TILLAGE PRACTICES AND REASONS

Extensive research and outreach efforts have focused on encouraging farmers to use more conservation-oriented practices to reduce the environmental impacts of agriculture (Aneja, Schlesinger, and Erisman 2009; Carpenter et al. 1998). Therefore, there is also great interest in better understanding why farmers choose to use or not use these practices and what incentives can encourage their voluntary use (Baumgart-Getz, Prokopy, and Floress 2012; Knowler and Bradshaw 2007; Liu, Bruins, and Heberling 2018; Prokopy et al. 2008; Wauters and Mathijs 2014). The use of "conservation" tillage has long been a practice of interest in efforts to reduce soil erosion in US agriculture (Allmaras and Dowdy 1985; Halcrow, Heady, and Cotner 1982). However, the sociology of agriculture and the agriculturally oriented natural resource literature have long tended to oversimplify the ways that tillage is used and measured, particularly by ignoring the spatial and temporal aspects of tillage decisions (Reimer et al. 2014), though soil scientists are aware of the importance of crop rotation and soil type/qualities in the use of specific tillage practices (e.g., Reicosky and Allmaras 2003; Lal, Reicosky, and Hanson 2007).

The over simplification of farmers' tillage practices and decision-making process related to tillage has been exacerbated by the common division of tillage practices into three categories: "conventional" tillage, "conservation" or "reduced" tillage, and "no-till" and the use of binary measures of practice use/disuse, without consideration of duration, frequency, or area of use (Reimer et al. 2014). Furthermore, the use of these overly general categories of tillage mean that these binary measures may not be as accurate as desired. Reimer et al. (2014:57A) point out this problem:

> Conservation tillage, for example, can mean continuous no-till to one farmer, strip-till after soybeans (Glycine max [L.] Merr.) but not after corn (Zea mays L.) to another, and use of a chisel plow rather than moldboard plow to another. Such variance in meanings and behavior can lead to substantial measurement error associated with discrete, binary measures of adoption.

Categories are important and useful research tools, but too much aggregation can disguise important differences. Soil scientists Reicosky and Allmaras (2003) point out that terms like "conventional," "conservation" and "reduced" are all broad and relative, and often have different regional meanings. Additionally, as tillage practices have shifted in a more conservation direction over time (Lal et al. 2007), and with the advent of new tillage technology, the meanings of these terms will also have inevitably changed (Reicosky and Allmaras 2003)[5].

My primary purpose for this exploratory analysis using qualitative interview data is to examine what tillage practices Midwestern corn farmers are using and why. The results that emerge on the ways farmers are tilling challenges the commonly used tillage categories, as I find that farmers' tillage practices are not easily assigned to the usual three or four categories. The results of the reasons farmers gave for why they till as they do calls into question the social-psych theories that are commonly used in studies of farmer decision-making, as I find that the biophysical context, the needs of the operation, and practice compatibility were much more heavily referenced by farmers as reasons for their tillage choices than were attitudes or values related to the environment or the tillage practices themselves.

[5] "As new technology develops and new tillage and planting equipment become available, we should discontinue the use of the vague and nondescript terms of "conventional" and "conservation" terminology and provide explicit descriptions of equipment for tillage, residue management and planting. … An accurate description requires listing all operations in the system and should be the prime consideration in discussing various conservation tillage systems" (Reicosky and Allmaras 2003:77).

BACKGROUND ON TILLAGE

Tillage has long been an important agricultural practice. Reicosky and Allmaras (2003:76) describe tillage as “the mechanical manipulation of the soil and plant residue to prepare a seedbed where crop seeds are planted… [it] fragments soil, enhances the release of soil nutrients for crop growth, kills weeds, and modifies the circulation of water and air within the soil.” Early wooden hand tillage implements facilitated the rise of settled agriculture and their improvement into what we would recognize today as a “plow” that could be pulled by draft animals around 4000 to 6000 BC increased food production and supported the rise of urban-oriented civilizations in Mesopotamia (Lal et al. 2007). Further improvements over time included the use of metal plow shares and shaping the share to invert the soil, rather than just break and loosen it, the hallmark of the modern “moldboard” plow (Lal et al. 2007). As a result, the most common tillage practice in the US for several hundred years was moldboard plowing followed by “secondary” tillage, which breaks up the soil more finely, and levels and smooths the soil in preparation for planting (Belknap and Saupe 1988; Bultena and Hoiberg 1983; Reicosky and Allmaras 2003).

While soil erosion from plowing has been a concern for hundreds if not thousands of years, it took on new urgency in the US following the Dust Bowl of the 1930s and resulted in policies and programs to address it, such as the establishment of the Soil Erosion Service in 1933, and the passage of the Soil Conservation Act in 1935 (Lal et al. 2007; Rasmussen 1982). Addressing soil erosion meant addressing tillage practice, and led to the challenging of moldboard plowing and of plowing at all in favor of “conservation” tillage and “no-till” practices during the 1940s-1960s (Lal et al. 2007). New technologies facilitated this challenge of plowing, especially new herbicides that could replace tillage for weed management, and the development of implements for planting into untilled ground (Allmaras et al. 1998; Coughenour 2003; Lal et al. 2007; Reicosky and Allmaras 2003).

However, the use of moldboard plows nationally did not start to decrease until the 1970s (Bultena and Hoiberg 1983; Crosson 1981; Reicosky and Allmaras 2003). In the 1980s, continued concern over high rates of soil erosion (Crosson 1984) and relatively low rates of adoption of non-moldboard tillage led to a large body of research on the adoption process of "conservation tillage" by rural sociologists (Bultena and Hoiberg 1983; Dillman and Carlson 1982; Korsching et al. 1983; Napier, Thraen, and Gore 1984; Nowak 1987; Nowak and Korsching 1985; Warriner and Moul 1992) and agricultural economists (Belknap and Saupe 1988; Ervin and Ervin 1982; Gould, Saupe, and Richard 1989; Lee and Stewart 1983; Norris and Batie 1987; Rahm and Huffman 1984; Shortle and Miranowski 1986) during this decade.

Research during the 1980s mostly focused on the adoption of "conservation tillage" which was most commonly defined as any tillage system that did not involve the use of a moldboard plow (e.g., Belknap and Saupe 1988; Bultena and Hoiberg 1983). More broadly, "conservation tillage" has been defined as "a tillage system in which either crop residues are retained on or near the surface, or soil surface roughness is maintained, or both, to control soil erosion and to achieve good soil-water relations" (Allmaras and Dowdy 1985:197-198). However, a 30 percent remaining soil cover standard has been associated with "conservation" tillage since the 1980s (Allmaras and Dowdy 1985), and continues to be used by the Conservation Technology Information Center (CTIC, formerly the Conservation Tillage Information Center), with "reduced" tillage being defined as retaining 15-30 percent soil cover. These percentage soil cover standards have been regularly used in social research on tillage practice adoption (e.g., Reimer, Weinkauf, and Prokopy 2012; Vitale et al. 2011; Caswell et al.

2001). The retention of 30 percent or more residue can be achieved by a wide range of tillage methods from "one fall chisel with straight shanks, a shallow disking in the spring, a field cultivation and planting" to a full no-till system (NRCS 1992).

How "conservation tillage" is defined and operationalized is important because different environmental implications that result from the use of the range of practices that are often included in the "conservation tillage" category. For example, Kumar et al. (2014) compare soil organic carbon levels in drained and undrained field under no-till and chisel plowing on continuous corn in Ohio, and find significantly more SOC in the no-till plots compared to the chisel plowed plots after 18 years. Similarly, López-Fando and Pardo (2012:33) compare total nitrogen content and nitrogen stratification ratios between "no-tillage (NT), minimum tillage (18–22 cm depth) with chisel plow (MT), and conventional tillage (25–30 cm depth) with mouldboard plow (CT)" over 19 years of a chickpea-barley rotation in central Spain. They find significant differences between the no-tillage, minimum tillage and conventional tillage systems, with no-tillage having higher total nitrogen and nitrogen stratification than minimum tillage which in turn was higher than conventional tillage, and they conclude that these measures indicate better soil properties particularly under no-tillage as compared to minimum tillage and conventional tillage. Greater soil fertility, in the form of nitrogen and carbon content, resulting from tillage practices on the no-till end of the spectrum have the potential to help mitigate global climate change by storing carbon in the soil (Robertson et al. 2014; Robertson, Paul, and Harwood 2000; Uri and Bloodwirth 2000).

LITERATURE REVIEW

Many of the 1980s studies on the adoption of “conservation” tillage as well as more recent ones have been reviewed in meta-analyses of the predictors of “best management” or “conservation practices” not limited to tillage (Baumgart-Getz et al. 2012; Knowler and Bradshaw 2007; Liu et al. 2018; Prokopy et al. 2008; Wauters and Mathijs 2014). However, these analyses find mixed or inconclusive results of predictors, even when potentially focused on tillage practices. For instance, Prokopy et al. (2008) include sub-analyses based on practice type, including one for “soil management” which is presumably some form of “conservation tillage,” though they do not define what they include in this category. They find that, only acres farmed is significant more often than it is not significant as a predictor of “soil management” practices. One reason for this lack of consistency may be the measurement error pointed out by Reimer et al. (2014).

Recent quantitative studies (Andrews et al. 2013; Ryan, Erickson, and De Young 2003; Vitale et al. 2011) on factors related the adoption/use of “conservation” tillage and no-till in the US have acknowledged the potential for multiple meanings of tillage practice terms, and some have made efforts to limit measurement error by providing respondents with definitions of the response categories. However, these studies, while recognizing that farmers use tillage in complex ways, limited their analyses to overly simple categories of tillage use (Andrews et al. 2013; Ryan et al. 2003; Vitale et al. 2011). These quantitative studies featured beliefs and attitudes but did not use any of the theories discussed in the introduction (Chapter 1).

Ryan, Erickson, and De Young (2003) considered the likelihood of farmers in a Michigan watershed adopting one of several specific practices, including no-till, along streams and drains in the future. They also considered farmers motivations for adopting these practices and considered six attitude and value-based variables (three of which are latent variables), though they did not draw explicitly on any specific theoretical approach. Twenty-seven percent of their respondents reported using "no-till farming to minimize soil erosion" and farmers rated no-till as the practice category they were most likely to adopt in the future (average score of 3.6 out of 5)[6]. However, the authors noted that "farmers may conceptualize no-till farming as a range of conservation tillage practices, such as minimum tillage" (Ryan, Erickson, and De Young 2003:28). They found that full time farmers were more likely to adopt no-till than part time farmers, and that attachment to their farm, intrinsic environmental motives, and the visual recognition of no-till were important factors in the reported likelihood of future no-till adoption.

Vitale et al. (2011) used a survey to study the adoption of three categories of tillage practices, conventional, reduced, and conservation tillage, among Oklahoma farmers. They took an atheoretical econometric approach that focused on the individual decision process and used three categories of "perception" variables related to conservation tillage: economic, agronomic, and other. The authors provided farmers with the CTIC definitions of each practice (see Figure 2.1). In their descriptives they differentiated between farmers who reported using only one type of tillage and those who reported using the type on at least 50 percent of their operation and one or more other tillage types on their remaining acres; 36.8 percent of their respondents fell into one of these groups or did not use any one type of tillage on a majority of their acres (calculated from authors descriptive table). However, in their regression models the authors only used the typical categories. Their results highlight the importance of farmer age, farm size, crop rotation, presence of livestock, perceptions of the benefits and costs of different tillage practices, and knowledge of conservation tillage practices in explaining farmers' dominant tillage type.

[6] The highest rated individual practice was "maintain a grassy buffer strip/filter strip" with average rating of 3.86, however the authors used factor analysis to group similar practices into categories. No-till was used as an individual item in their analysis as it did not fit into any calculated factor.

Table 2

Conservation Technology Information Center tillage classification system provided to producers on the survey instrument and used in this study.

Tillage practice	Definition
Conventional	Includes several tillage passes and leaves less than 15% of residue on soil surface after planting
Reduced	One to three full-width tillage passes and leaves 15% to 30% of residue on the soil surface after planting
Conservation	Minimum soil disturbance; practices that fall under no-till included strip-till, ridge-till, and vertical-till

Source: CTIC (2007).

Figure 2.1. Tillage definitions used by Vitale et al. (2011:252).

Figure 1

The instrument included the following tillage grid to allow farmers to indicate their tillage practices.

Please write the number of acres in your farming operation that were in each tillage category by crop type and year as defined below. This should include all land for which you actively made farm management decisions, including land you own and land you lease from others.

	2009			2010		
	Corn	Soybeans	Wheat	Corn	Soybeans	Wheat
No-till or strip-till (Leaving the soil undisturbed from harvest to planting, or for strip-till, disturbing less than 30% of the row width. Planting or drilling is in a narrow seedbed or slot created by disk openers.)						
Other conservation tillage (Leaving more than 30% residue on soil surface after planting using full-width tillage.)						
Conventional tillage (Leaving less than 30% residue on soil surface after planting. Includes moldboard plow, chisel plow, or rippers, followed by multiple secondary tillage trips.)						

Figure 2.2. Tillage definitions used by Andrews et al. (2013:504).

Andrews et al. (2013) asked a national sample of farmers about their tillage practices in 2009 and 2010 on three crops (see Figure 2.2) and reasons for using them as part of a survey on framing effects of conservation tillage on farmers' interest in using conservation tillage and in receiving more information about it. They considered four frames: a basic rationale that focuses on soil quality benefits and erosion reduction (the control frame), a profit frame that focuses on the money saving potential of conservation tillage, a carbon offset frame that focuses on the potential for getting carbon offset payments for using conservation tillage, and a payment for environmental benefits frame that focuses on the potential for payments for using conservation tillage based on the off-farm environmental benefits. How the benefits of a practice is presented or “framed” is expected to influence farmers’ attitudes towards the practice and in turn influence their likelihood of using it.

Nearly 50 percent of their respondents reported using a combination of tillage types (calculated from authors’ descriptives table). However, the authors combined their respondents into three categories: “conservation tillers” who only used conservation tillage and/or no-till, “combined tillers” who used all three types or a combination of no-till and conventional tillage, and “conventional tillers” who only use conventional tillage or a combination of conventional tillage and conservation tillage. They found that concerns over water quality, soil erosion, improving soil productivity, and lowering costs were important factors for the “conservation tillers” group who were using conservation tillage and/or no-till. In contrast, conventional tillers were highly concerned with high yields, soil compaction/drainage, and earlier plating windows. For the framing treatments, the authors found no significant differences between treatments in the whole sample; they did find that the profit frame significantly reduced “conventional tillers” interest in conservation tillage compared to the basic rationale. The authors hypothesized that this effect could be due to the profit frame highlighting financial considerations that these farmers do not believe can be achieved with conservation tillage, possibly due to local soil qualities and climatic conditions that make conservation tillage practices less advantageous.

Of particular interest to the present study are the small number of papers that use qualitative methods to better understand farmers’ use of different tillage practices. Two recent qualitative studies have been conducted in the US on conservation practices that included tillage (Reimer, Thompson, and Prokopy 2012; Reimer, Weinkauf, et al. 2012).

Reimer, Thompson, et al. (2012) use 32 semi-structured farmer interviews in an Indiana watershed to examine farmers awareness of environmental issues and attitudes towards conservation practices, as well as their current awareness and use of conservation practices. They defined "conservation tillage" as the use of 100 percent no-till practices on corn, since "nearly all" farmers interviewed were using no-till for their soybeans; 56 percent of their sample was found to practice "conservation tillage" as they defined it. They identified three attitude dimensions in their interview data: "farm as business," "[concern for] off-farm environment," and "stewardship." They found that the farm-as-business attitude was related with low use of conservation practices, while off-farm environmental concern and stewardship attitudes were associated with use of more conservation practices. Reimer, Thompson, et al. (2012) noted that

> the majority of farmers interviewed in this study were in a middle adopting group, adopting a few conservation practices but not expressing strong off-farm environmental, stewardship, or farm as business attitudes…. This group of farmers talked most extensively about the on-farm benefits and was aware of the indirect financial benefits of erosion control and soil nutrients that certain conservation practices brought. This group was most likely to adopt conservation tillage and grassed waterways where needed. (P. 36)

Reimer, Weinkauf, et al. (2012) use the same 32 interviews used in Reimer, Thompson, et al. (2012), as well as an additional 13 farmer interviews in a different Indiana watershed. They use the interviews to examine farmers' views on the "acceptability characteristics for each practice" (Reimer, Weinkauf, et al. 2012:121), drawing on the diffusion of innovations theory's five characteristics of innovations that relate to adoption or rejection of a practice along with the reasoned action approach. The authors recognize 8 types of tillage practices among their interview participants, including crop rotation-based differences, though their analysis just refers to "conservation tillage." About 66 percent of their sample reported using either no-till for soybeans and a different type of tillage for corn, or a combination of tillage types "based on sensitivity of the ground or compatibility with other practices" (Reimer, Weinkauf, et al. 2012:123). They found that soil conservation and input savings were the most important attributes reported that motivated farmers to use conservation tillage, while decreased yield, lack of perceived need, and uncertainty of effectiveness were the most important characteristics that deterred farmers from using conservation tillage.

METHODS

Overview

Interviews with corn farmers were conducted in 2014 as part of a National Science Foundation funded Couple Human and Natural Systems (CHANS) project examining nitrogen efficiency in Midwest corn production. A semi-structured interview guide was used that included questions on general farm characteristics and practices used, sources of information used, influence of crop insurance, conservation programs, private companies and other farmers on farming practices, and views on the environment and climate change. The interview guide had a particular interest in the use of nitrogen fertilizer on corn, and many of the questions were asked in this context.

Qualitative methods are particularly well suited to investigating exploratory research questions and gaining a detailed understanding of reasons and motivations. While theories and conceptual frameworks can be very useful research tools, there can also be benefit in collecting farmers' responses using open-ended questions. As such, qualitative methods are a good choice for approaching my research questions, which are: “what tillage practices do farmers use?” and “why do farmers till the way they do?” Tillage has not been a heavy focus of recent social science research, and the advance of tillage technology and demonstration of mixed tillage use in the literature suggests an exploratory analysis of tillage practices would be worthwhile. Why farmers till the way they do is also a topic that would clearly benefit from an exploratory analysis where farmers’ explanations for their actions could emerge. If the qualitative findings do not support the findings of the previous studies, or only do so in part, then the exploratory analysis will offer suggestions for additional angles of investigation, which can lead to further research questions, hypotheses and theory development.

Data Collection

The farmer interviews were conducted by three individuals between May and December 2014 in Iowa (IA), Indiana (IN) and Michigan (MI). Interviews lasted between 20 minutes and 3 hours, with a typical interview lasting about 45 minutes. A total of 154 interviews were conducted, with 53 in IA, 51in IN, and 50 in MI[7]. A small number (fewer than five total) of interviews were conducted by phone and/or not audio recorded; the rest were conducted in-person and were audio recorded with participant permission and subsequently transcribed verbatim. The interviews that were not recorded had notes written up immediately afterwards. The only requirement for inclusion in the sample was that the farmer be growing at least 100 acres of non-organic corn. The final sample of 152 farmers covered 27 percent of IA counties, 25 percent of IN counties, and 20 percent of MI counties[8].

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[7] Two Michigan participants did not meet the sample selection criteria so 48 Michigan interviews are used in the following analysis.

[8] Not all MI counties have extensive corn production, especially those in the northern part of the state, which is why the percent of counties covered in MI is lower than in the other states.

Farmer recruitment was done primarily through referrals from respective state University Extension personnel and through snowball sampling, though the portions varied by state. Table 2.1 shows the differences in participant recruitment methods by state. In IA, the extension source was through an extension-run program rather than direct referral by extension agents as was the case in IN and MI. In MI the participants recruited through "relevant organizations and programs" were all contacts made through the list of the Michigan Agriculture Environmental Assurance Program participants, while in IA it was through an email to the listserv of Practical Farmers of Iowa.

While snowball sampling can help achieve a more diverse sample, the heavy use of extension in the initial participant recruitment is likely to have skewed the sample towards farmers who extension personnel see as being exemplary farmers. This bias may have made the sample more environmentally aware and operationally efficient than is typical of the general farming population. All participants were white men ranging in age from 20s-70s. Female and racial minority farmers were not deliberately excluded from the sample, but due to the focus of the study no special effort was made to include them.

Table 2.1. Sample recruitment sources by state.

	Michigan	Iowa	Indiana
Number of interviews	50†	53	51
	% (#)	% (#)	% (#)
Extension	64.0 (32)	22.6 (12)	58.8 (30)
Snowball sampling	24.0 (12)	45.3 (24)	33.3 (17)
Other	12.0 (6)	32.1 (17)	7.8 (4)
County Soil and Water Conservation District	0.0 (0)	22.6 (12)	0.0 (0)
Field days and relevant events	0.0 (0)	3.8 (2)	0.0 (0)
Relevant organizations and programs	12.0 (6)	5.7 (3)	7.8 (4)

† Two Michigan participants did not meet the sample selection criteria so 48 Michigan interviews are used in the following analysis.

The sample is also skewed towards larger farms. Farm sizes in the sample ranged from 170 to 5,000 acres in IA, with an average size of 1,236 acres (average for the state was 347[9]), from 200 to 9,000 acres in IN, with an average size of 2,216 acres (average for the state was 253), and from 200 to 4,500 acres in MI, with an average farm size of 1,529 acres (average for the state was 193). The larger average farm size in the sample is likely the result of the 100-acre-minimum-corn selection criterion. This requirement automatically restricts the sample to farms greater than the median in MI and IN, and likely functionally does in IA as well (Table 2.2). Since this data is for total operation size, this means that the sample selection was restricted to the largest fifty-percent of farms. It is also plausible that larger farms are more likely to be growing corn.

Table 2.2. Mean and median farm size in acres per operation by state in 2012.

	Michigan	Iowa	Indiana
Mean farm size	191	345	251
Median farm size	60	136	57

Source: NASS Census of Agriculture.

Analysis

The analysis process used was based on Grounded Theory (Glaser and Strauss 1967) in the vein of Glaser's approach (Glaser 1978, 1992; Walker and Myrick 2006). Grounded theory is the process of developing a theoretical explanation of a social action, interaction or process that is grounded in the analysis of qualitative data (Creswell 2007). It is an inductive, rather than a deductive, process. Briefly, Glaser's approach involves two stages: "Substantive coding … is concerned with producing categories and their properties. Theoretical coding occurs at the

[9] Average farm sizes are for all farms (not corn specific) for the three states are for 2014 from a USDA survey. Data was collected from NASS.

conceptual level, weaving the substantive codes together into a hypothesis and theory" (Walker and Myrick 2006:550).

The initial substantive coding was done according to the questions on the interview guide. The responses analyzed in this paper were to the question: "How do you till and how does it affect your fertilizer decisions?" The question was alternatively asked in two parts: "How do you till?" and then after their response a follow up: "How does that affect your fertilizer decisions?" The analysis presented here began with coding the tillage question code by tillage tool. Given the large volume of data, even when only considering the tillage question code, the word search query in NVivo 11 (QSR) was used assist in locating all relevant passages. The terms till/tilling/tillage, plow/plowing and work/working were searched, and the relevant instances of them coded according to the tool/type mentioned. Each tool/type code was then searched for specifically to ensure that any instances that appeared without a form of till, plow or work were located.

Each tool/type code was then further coded to identify farmers who reported current use of the tool/type and mentions of past use, reasons for use, observations of use by others etc. The tool/type use codes were then further coded by sub-type, season of use, method of use, and/or extent of use as was appropriate for the tool/type. For example, use of harrows was coded for disk harrow use vs. non-disk harrow use, then disk harrow use was coded for use as primary tillage vs secondary tillage, and each of those was further coded for season of use, and method/purpose of use—e.g., based on rotation, or used on "as needed" basis.

The content coded to non-use tool/tillage codes as well as the tool/type specific codes related to method/purpose of the specific tool/tillage type were collected and substantively coded for reasons for tillage use, and then to pursue a more detailed set of reasons for each primary reason code. Finally, theoretical coding was used to group these reasons into the explanatory categories discussed in the results section.

Quantified results of tillage tool/type were based on the results of using the matrix query tool in NVivo 11. All tillage/type codes were expended as needed so that they overlapped, allowing for the use of multiple tools/types by a single farmer to be identified through matrix queries.

RESULTS

The first part of this section presents and briefly discusses the results of the substantive coding of tillage tools and tillage types, primarily using the quantified results in Tables 2.3 and 2.4. This portion of the analysis addresses my first research question: How are farmers tilling? My second research question is addressed by the theoretical codes that are discussed in the section on tillage decision factors. As it is not the purpose of this article to describe in detail the characteristics of the specific tillage tools and types, but rather to explore their overlap in use and the reasons for their use, only brief descriptions will be provided as needed. Readers are particularly referred to two publications: *Conservation Tillage Systems and Management* (MWPS 2000), and *Tillage* (John Deere 2007) for detailed descriptions, and images of the structure, performance, and options of the tillage tools and types discussed.

Table 2.3. Cross-tab comparison of instances of tillage tool/type overlap, as percent of 151 and number of respondents.

	Mold-board plow % (#)	Chisel plow % (#)	Ripper % (#)	Cultivator % (#)	Harrow % (#)	Soil finisher % (#)	Vertical tillage % (#)	Mulch till % (#)	Ridge till % (#)	Strip till % (#)	No-till % (#)	Cons. tillage % (#)	Conv. tillage % (#)
Primary tillage tools													
Moldboard plow	2.0 (3)	0.7 (1)	0.0 (0)	0.7 (1)	0.0 (0)	0.0 (0)	0.7 (1)	0.0 (0)	0.7 (1)	0.0 (0)	0.7 (1)	0.0 (0)	0.0 (0)
Chisel plow	0.7 (1)	19.2 (29)	3.3 (5)	5.3 (8)	4.0 (6)	3.3 (5)	2.0 (3)	0.0 (0)	0.0 (0)	0.0 (0)	12.6 (19)	4.6 (7)	1.3 (2)
Ripper	0.0 (0)	3.3 (5)	19.2 (29)	7.9 (12)	4.0 (6)	0.7 (1)	4.0 (6)	0.7 (1)	0.0 (0)	2.6 (4)	6.6 (10)	2.0 (3)	4.0 (6)
Secondary tillage tools													
Cultivator	0.7 (1)	5.3 (8)	7.9 (12)	17.9 (27)	4.0 (6)	1.3 (2)	2.0 (3)	0.7 (1)	0.7 (1)	0.7 (1)	7.3 (11)	2.0 (3)	3.3 (5)
Harrow	0.0 (0)	4.0 (6)	4.0 (6)	4.0 (6)	12.6 (19)	0.0 (0)	3.3 (5)	0.7 (1)	0.0 (0)	0.0 (0)	6.6 (10)	1.3 (2)	1.3 (2)
Soil finisher	0.0 (0)	3.3 (5)	0.7 (1)	1.3 (2)	0.0 (0)	5.3 (8)	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)	4.0 (6)	1.3 (2)	0.0 (0)
Tillage types													
Vertical tillage	0.7 (1)	2.0 (3)	4.0 (6)	2.0 (3)	3.3 (5)	0.0 (0)	15.2 (23)	0.0 (0)	0.0 (0)	0.7 (1)	6.6 (10)	2.6 (4)	0.0 (0)
Mulch till	0.0 (0)	0.0 (0)	0.7 (1)	0.7 (1)	0.7 (1)	0.0 (0)	0.0 (0)	1.3 (2)	0.0 (0)	0.0 (0)	0.7 (1)	0.0 (0)	0.7 (1)
Ridge till	0.7 (1)	0.0 (0)	0.0 (0)	0.7 (1)	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)	0.7 (1)	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)
Strip till	0.0 (0)	0.0 (0)	2.6 (4)	0.7 (1)	0.0 (0)	0.0 (0)	0.7 (7)	0.0 (0)	0.0 (0)	11.9 (18)	5.3 (8)	0.7 (1)	2.0 (3)
No-till	0.7 (1)	12.6 (19)	6.6 (10)	7.3 (11)	6.6 (10)	4.0 (6)	6.6 (10)	0.7 (1)	0.0 (0)	5.3 (8)	64.9 (98)	8.6 (13)	3.3 (5)
Cons. tillage	0.0 (0)	4.6 (7)	2.0 (3)	2.0 (3)	1.3 (2)	1.3 (2)	2.6 (4)	0.0 (0)	0.0 (0)	0.7 (1)	8.6 (13)	13.9 (21)	1.3 (2)
Conv. tillage	0.0 (0)	1.3 (2)	4.0 (6)	3.3 (5)	1.3 (2)	0.0 (0)	0.0 (0)	0.7 (1)	0.0 (0)	2.0 (3)	3.3 (5)	1.3 (2)	8.6 (13)

Table 2.4. Summary of tillage tool use and tillage type by state, as percent and number of respondents.

	Michigan	Iowa	Indiana
Number of interviews	48	53	51
	% (#)	% (#)	% (#)
Primary tillage tools			
Moldboard plow	2.1 (1)	1.9 (1)	2.0 (1)
Chisel plow	29.8 (14)	15.1 (8)	13.7 (7)
Ripper	27.7 (13)	17.0 (9)	13.7 (7)
Secondary tillage tools			
Cultivator	14.9 (7)	24.5 (13)	13.7 (7)
Harrow	21.3 (10)	7.5 (4)	9.8 (5)
Soil finisher	4.3 (2)	9.4 (5)	2.0 (1)
Tillage types			
Vertical tillage	17.0 (8)	11.3 (6)	17.6 (9)
Mulch till	2.1 (1)	1.9 (1)	0.0 (0)
Ridge till	0.0 (0)	1.9 (1)	0.0 (0)
Strip till	8.5 (4)	18.9 (10)	5.9 (3)
No-till	57.4 (27)	71.7 (38)	64.7 (33)
Conservation tillage	14.9 (7)	9.4 (5)	17.6 (9)
Conventional tillage	8.5 (4)	9.4 (5)	7.8 (4)

Primary Tillage Tools

> Primary tillage displaces and shatters the soil as it reduces soil strength and tends to bury and mix plant residues and fertilizers within the tilled zone. Primary tillage is more aggressive, deeper and leaves a rough surface relative to secondary tillage operations. Primary tillage tools are the moldboard plow, chisel plow and various types of combination disc-chisel-subsoil tools designed to disturb the soil to greater depths. However, depending on the features, options and operation of that implement, results of primary tillage will be different as soil conditions change. (Reicosky and Allmaras 2003:78-79)

As discussed above, the moldboard plow was long the go-to tillage implement of US farmers, but in the Corn Belt at least, this is no longer the case. Just three farmers, one in each state, mentioned that they use moldboard plows (Table 2.4) in some context. The IA and MI farmers indicated that they used it on a regular basis. All three farmers reported using other tillage types at other times or on other parts of their operation (Table 2.3).

Chisel plows and rippers are breaking and mixing tools[10], rather than an inverting type and appear to have replaced the moldboard plow for typical primary tillage in the Midwest. Overall, almost 20 percent of the farmers interviewed said they used chisel plows in some capacity, and almost 20 percent said they used rippers in some capacity (Table 2.3). MI farmers reported higher use of both chisel plows and rippers (30 percent and 28 percent respectively) compared to IA (15 percent and 17 percent respectively) and IN (14 percent for both types of implements) (Table 2.4). Almost 13 percent said they used chisel plows and no-till, and almost 7 percent reported use of rippers and no-till (Table 2.3). This overlap was often based on their crop rotation. Given the role of chisel plows and rippers as primary tillage tools, the overlap between their use and secondary tillage tools is as expected (Table 2.3).

Secondary Tillage Tools

> Secondary tillage varies widely with type and number of operations, penetration is nearly always shallower than with primary tillage tools. Secondary tillage provides additional soil breakup, levels and firms the soil, closes some air pockets and kills some weeds. Tillage equipment often associated with secondary tillage includes disk harrows, field cultivators, spring-tooth harrows, levelers, packers, and other types of finishing equipment. Interpreting tillage system results may be confusing or meaningless when little information about secondary tillage operations is available. (Reicosky and Allmaras 2003:79)

The following tools, field cultivators, harrows, and soil finishers, are considered secondary tillage implements and would typically be used after one of the primary tillage tools discussed above. However, some farmers described using them without first using primary tillage as part of a low-tillage system. These tools were sometimes used sequentially or as

[10] The main difference between these tools is the depth they penetrate the soil. Rippers (also called "subsoilers") run deeper (12-22 inches) than chisel plows (6-12 inches) and can break up compaction below the depth of other tillage tools (MWPS 2000). Both chisel plows and rippers can be designed to provide greater or lesser amounts of soil surface disturbance. Rippers were often mentioned in the form of disk rippers (8 percent of total sample).

substitutes for each other, as shown in the overlap of use, especially between field cultivators and harrows (Table 2.3).

Overall, field cultivators were used the most (18 percent), followed by harrows[11] (13 percent) and soil finishers (5 percent) (Table 2.3). Field cultivators appear to be most popular in IA (25 percent) and similarly less popular in MI (15 percent) and IN (14 percent), while harrows are more commonly used in MI (21 percent) than in IN (9 percent) or IA (8 percent) (Table 2.4). Soil finishers were more popular in IA (9 percent) than in MI (4 percent) or IN (2 percent) (Table 2.4).

Types of Tillage

The following terms refer to tillage types or styles based on function, rather than specific tools, though some like no-till, strip till and ridge tillage do need tools with specific capabilities. While there is certainly plenty of room for variation within the tillage tools discussed above (different names for the same tool, the use of different options on a tool that make it perform quite differently, etc.) there is even more room for vagueness when it comes to tillage styles, since they are not bound to a particular tillage tool even by name[12].

Vertical and mulch tillage. Vertical tillage appears to be a broad term without a firm definition (Kanicki 2014). It generally involves the use of an implement with vertical blades intended to cut up residue with minimal soil disturbance, though some have shallowly curved discs or wavy coulters that provide some soil lifting (Kanicki 2014). Mention of vertical tillage use was fairly even across the three states at 15 percent, 11 percent and 18 percent for MI, IA

[11] Almost 79 percent of harrow use was of a disk harrow, primarily as secondary tillage. When non-disk harrows were discussed they tended to be used in a first field pass context. The use of disk harrows was quite evenly split between use as primary and secondary tillage (10 farmers and 8 farmers respectively). As primary tillage, there were an even number of reports of fall vs. spring use (4 farmers each). The fall use was typically for residue management and the spring use was for planting preparation.

[12] The one exception to this might be ridge tillage, which, while not tied to a specific tool per se does require a tool with quite a specific function.

and IN respectively (Table 2.4). Of the 23 total farmers considered to use this method, 18 labeled their practice/implement as vertical tillage, and 5 were considered to use it based on the tool they mentioned using—4 of the 5 said they used a "turbo till," which is a trademarked name for an implement made by Great Plains that is billed as a vertical tillage tool. More mentions were made of using it in the spring, but fall use was also reported. There appears to be some overlap in tillage strategy with the harrows and cultivators in terms of timing and purpose of vertical tillage use, as well as with actual implement use.

Mulch tillage is potentially an even broader term than vertical tillage, being generally defined as any conservation tillage system that is not no-till, strip till or ridge till, either with the requirement of 30% soil surface cover remaining (Caswell et al. 2001; John Deere 2007) or without (MWPS 2000; NRCS 2012b). Only two farmers described their tillage practices as "mulch tillage," one in IA and one in MI (Table 2.4). The IA farmer described it as *"a conventional mulch tillage thing, we field cultivate in the spring and do a disk ripping in the fall."* The MI farmer simply said that he does *"mulch tillage on the soybeans to prepare for corn."*

Ridge till. Ridge tillage is a specific practice where ridges are formed in the field and the crop is planted into the ridge for multiple years in a row while leaving the residue in the valleys between the rows, and is considered a residue-retaining type of tillage (Caswell et al. 2001; Reicosky and Allmaras 2003). Three farmers reported using ridge tillage in the past, but only one IA farmer reported currently using the practice (Table 2.4).

Strip till. Strip till (also sometimes called "zone till") is often considered a form of no-till (CTIC 2002; NRCS 2012a) but is considered separately in this analysis as most farmers distinguished between strip till and no-till, as can be seen by the small overlap in Table 2.3. Strip till involves only tilling in strips across the field shortly before harvest, leaving the remaining portion of the field undisturbed (Reicosky and Allmaras 2003). The width of the allowed strip ranges up to 25 percent (Reicosky and Allmaras 2003) or 30 percent (CTIC 2002).

Overall, 11 percent of our respondents used strip till in some capacity[13] (Table 2.3). Nineteen percent of IA farmers mentioned using strip till compared to 6 percent of the MI and IN farmers (Table 2.4). Five percent of the sample noted using both strip till and no-till (Table 2.3). Some farmers blended the strip till/no-till distinction, either by using strip till and no-till at different points in their crop rotation, or by considering them as the same thing.

> *"I've been no till since 1994. Right now, I'm really happy with my system. Its taking some time and haven't been happy with it every year, this year I can be happy with how things have turned out…I work a 1/3 of the field. They're roughly 10 inch wide strips the whole way across the field and I plant right into those strips." IA07*

No-till. As previously mentioned, no-till can include strip tilling practices, but a more narrow concept of it is that the only soil disturbance is the opening of a narrow slot by equipment on the front of the planter or seed drill (MWPS 2000; NRCS 2012a). No-till has overlap with all other types of tillage except ridge till, which is incompatible by definition (Table 2.3). No-till of some version was reportedly used by 65 percent of the farmers interviewed, making it the most-used practice (Table 2.3). It was also the most used by state, with 72 percent of IA farmers and 57 percent and 65 percent of MI and IN farmers respectively using it (Table 2.4). Because of the variation described in the use of no-till by participants, however, no-till has been further divided into 4 categories: all no-till, mostly or nearly no-till, some or part no-till, and no-till in rotation.

The "all no-till" category is the use of 100 percent, or total no-till, or using no tillage. Farmers were still included in this group even if they mentioned specific exceptions in which

[13] There was a mix of reported fall and spring strip till.

they tilled in some way. These exceptions were related to smoothing the ground after installing tile drainage or manure spreading, or if they started farming new land that was not ready to be no-tilled. The “mostly or nearly no-till” category is farmers who did not claim to be completely no-till but indicated that they mostly were. This included all no-till on most but not all of their acres, or all no-till most years but not always. The “some or part no-till” category is farmers who indicated that they do no-till some years, or on some parts of their operation, but not as consistently as the previous group. The “no-till in rotation” category is farmers who indicated that they used no-till according to their crop rotation. Most commonly this was no-tilling soybeans into corn stubble, but some also reported no-tiling corn into soybean stubble or as part of a more varied crop rotation. The least common use of rotation-based no-till was between corn crops.

Table 2.5. No-till sub-categories by state and for total sample, as percent and number of respondents.

	Michigan	Iowa	Indiana	Total
Number of interviews	47	53	51	151
	% (#)	% (#)	% (#)	% (#)
All no-till	14.9 (7)	28.3 (15)	21.6 (11)	21.9 (33)
Mostly or nearly no-till	6.4 (3)	1.9 (1)	9.8 (5)	6.0 (9)
All no-till in rotation	17.0 (8)	24.5 (13)	19.6 (10)	20.5 (31)
No-till corn into bean stubble	2.1 (1)	15.1 (8)	0.0 (0)	6.0 (9)
No-till soy into corn stubble	14.9 (7)	11.3 (6)	19.6 (10)	15.2 (23)
No-till in other rotation	10.6 (5)	1.9 (1)	0.0 (0)	4.0 (6)
Some or part no-till	19.1 (9)	9.4 (5)	13.7 (7)	13.9 (21)
No-till is strip till	4.3 (2)	3.8 (2)	0.0 (0)	2.6 (4)
No-till is vertical till	2.1 (1)	1.9 (1)	3.9 (2)	2.6 (4)

Table 2.5 breaks down these four categories by state, and it also indicates the fuzziness between no-till and strip till and between no-till and vertical till. The use of total no-till is lower in MI than in IA and IN, and the use of no-till by crop rotation is higher in IA than in the other two states. The location of no-till in the rotation has some interesting state-level patterns. All of

the IN farmers who indicated using no-till in their rotation mentioned doing so between corn and soybeans, where the soybeans were no-tilled into the corn stubble. MI farmers mostly no-tilled soybeans into corn stubble as well, but there were several instances of using it in a non-corn-soy rotation. In contrast, IA farmers reported no-tilling corn into soybean stubble slightly more often than no-tilling soybeans into corn stubble.

The overlap between no-till and strip till and vertical till is relatively small. Some of this overlap likely comes some from the mixed definitions of no-till, and some from farmers who are transitioning between methods.

> *"I'm a not till farmer… on my first year corn I'm not doing any tillage at all. On my continuous corn, I'd guess you'd say I'm a vertical tiller, only one year. I just bought that machine." IA28*

> *"I no till everything. As much as I can with exception if we tile something or do something different or alter something, but other than that we no till or coulter till. Maybe its more of a strip till, cause we have three coulters in front of our corn planter to till a little bit of a strip. Its not necessarily slot planting on the corn planter and the bean planter is a more of no till thing and the wheat is actually a no till. Strip till and no till. However you want to." MI-40*

"Conservation" tillage. As mentioned previously, "conservation tillage" can include a wide variety of practices, so it is of interest to see what farmers consider it to be. Twenty-one farmers (7 MI, 5 IA, 9 IN) identified themselves as using either "conservation" or "minimum" tillage on their operation, in whole or in part (Table 2.6)[14]. The "conservation" tillage term was used less by farmers (4 farmers) than "minimum" tillage (18 farmers). There was no dramatic difference between states in the use of these terms, so they are considered together. Table 2.6 shows the overlap between farmers who identified themselves as using conservation or minimum tillage and their use of different implements and tillage types. Chisel plows and no-till had the most overlap. None of the farmers who referred to their tillage as either "minimum," or

[14] The coding for this topic was quite conservative and was only used for farmers who used the specific terms—references to "reducing" or "minimizing" tillage were not included.

"conservation," mentioned being completely or nearly no-till; they did report using no-till in their rotation, or on a portion of a crop or on a portion of their fields.

Table 2.6. Comparison of tillage tools/types used for conservation (or minimum) tillage and conventional tillage, as percent and number of respondents.

	Conservation tillage	Conventional tillage
Number using	21	13
	% (#)	% (#)
Michigan	33.3 (7)	30.8 (4)
Iowa	23.8 (5)	38.5 (5)
Indiana	42.9 (9)	30.8 (4)
Moldboard	0.0 (0)	0.0 (0)
Chisel plow	33.3 (7)	15.4 (2)
Ripper	14.3 (3)	46.2 (6)
Cultivator as primary tillage	9.5 (2)	15.4 (2)
Harrow as primary tillage	0.0 (0)	0.0 (0)
Finisher as primary tillage	9.5 (2)	0.0 (0)
Vertical tillage	19.0 (4)	0.0 (0)
Ridge till	0.0 (0)	0.0 (0)
Strip till	4.8 (1)	23.1 (3)
No-till	61.9 (13)	38.5 (5)
All no-till	0.0 (0)	0.0 (0)
Mostly or nearly no-till	0.0 (0)	0.0 (0)
All no-till in rotation	23.8 (5)	23.1 (3)
Some or part no-till	28.6 (6)	15.4 (2)
No-till is strip till	0.0 (0)	0.0 (0)
No-till is vertical till	9.5 (2)	0.0 (0)

"Conventional" tillage. Thirteen farmers, nearly evenly split by state, reported using what they called "conventional" tillage on all or part of their operation. One additional IA farmer referred to "full" tillage. Most of these farmers didn't elaborate on their tillage methods, but two said they chisel plowed, six said used a ripper, three used strip till and five used no-till (Table 2.6).

Tillage Decision Factors

While it is important to know *what* farmers are doing, it is also important to know *why* they are doing it. Three broad categories of influences on tillage practices emerged from the interviews: biophysical conditions, operational needs and compatibility, and operational savings and costs. For general reference, biophysical conditions were mentioned by about a third of the sample, topics related to operational needs and compatibility were also mentioned by about a third of the sample, and operational savings and costs were mentioned by about 15 percent of the sample. A handful of farmers mentioned personal values and preferences in relation to their use of no-till, but not frequently enough to be considered a major theme. Examples can be seen in Table 2.7 in the “Less tillage to improve soil” section and in Table 2.10 in the “Yield costs” section.

Biophysical conditions. Biophysical conditions centering around soil were by far the most mentioned influence on tillage decisions. However, there was not consistency in how some of these conditions influenced tillage decisions, such that apparently similar conditions led some farmers to till more and others to till less. Reducing soil erosion was consistently cited as a reason for less tillage—either no-till or strip till. Soil quality and texture influenced farmers to either till more or till less. Farmers felt like less tillage improved their soil quality, though none specifically gave this as a reason for why they reduced their tillage to begin with but rather reported it as a result. The texture of the soil was a primary reason given for use of more tillage or not using no-till at least on some areas or in certain parts of the rotation—farmers perceived their soil type as being incompatible with the successful use of no-till. Addressing soil compaction typically called for more tillage that was targeted to the problem areas, but some farmers discussed tilling less to avoid soil compaction.

Managing soil temperature and moisture was mentioned as reasons for both tilling more and tilling less. Less tillage was described as both retaining moisture as well as managing excess moisture. However, more tillage was said to be needed to dry and warm the soil in the spring, especially prior to planting corn. Extreme weather events were mentioned by a couple of farmers in relation to their tillage practices, with one specifically saying *"I think we're gonna get more rain more often. I believe that our climate is changing and we're having an effect on it. So… that's largely why I went to no till." IA09*. However, this was not a common sentiment.

Table 2.7. Examples of quotes pertaining to the biophysical conditions that influence farmers' tillage decisions.

<u>Less tillage to reduce soil erosion</u>

"the dirt running off the land is what we try to conserve." IA15 [strip till farmer]

"I think we're just going to have to get used to working with no till if we're gonna stay in this corn bean rotation. We're just losing too much soil." IA24

"We have some places that are really eroded over the years; it's one reason we went to no-till, to try to curb some of that." IN#36

"And especially in the spring when we get high winds; I've seen a lot of property change hands in the wind, the dust and dirt, and I don't lose it. Nope." MI-30 [mostly or nearly no-till]

<u>Less tillage to improve soil</u>

"And we no-till, we haven't worked any ground since '91, we went 100% no till, and what we've noticed over the years is our organic matter is up probably 2 to 2 ½ percentage points since then, and of course that's a lot more available nitrogen right there." IN#37

"now we have a deeper profile of a root zone to work with and I think we have much more volume of earth to hang onto what's there." IN#49 [a no-till/vertical tillage farmer]

"I don't think we use quite as much fertilizer because I think the soil is healthier. We're getting good microbial activity. And breaking down the left overs you might say. So we've had success that way with some of our soil… I just like no till, I think its better for the soil" MI-2

<u>More tillage due to soil texture</u>

"Our soils are really deep and black and fertile, so no till doesn't seem to work very well around here." IA63

"Our type of ground… No-till has been tried several times in our area and it just seems like everybody that… We've never tried it. We have no-tilled beans into corn ground that has not been tilled, that works half-way, well three-fourths way I'll say. But corn into bean ground no-till it just seems like it does not work in this area. A lot of it is the type of ground we've got I think." IN#13

"About every 3-4 years I like to rip it. Go in there, even when I no till, just trying to pick it up and drop it. Kinda loosens the soil up. I had some hills that were heavy clay and we couldn't get anything to grow on them since I was a kid and now I can have just as good of a crop on those hills as any other spot." MI-8 [farmer has been using no-till for several years]

<u>More tillage to reduce compaction</u>

"Yeah, we started no tilling in the early 90s and… Once in a while, maybe every… I'll take a wheat stubble field if it shows some compaction and I've got a ripper stripper that I'll run in the fall then when I plant corn I'll plant right on those same strips, and I don't do it every year but…" IN#41

"Well, I run primarily vertical tillage. Usually…I will use a chisel plow some, but predominately I'm probably on 75% of my acres I strictly use vertical tillage in the spring. If I'm trying to fight some compaction issues I'll chisel plow in the fall." MI-45

Table 2.7. (cont'd).

Less tillage to reduce compaction	
	"Before I started no tilling, it was a lot more variability in the yield, now it seems like its evened out a lot more… Seemed like we had a lot of compaction when we were doing tillage, so we had areas that were really bad. But that's evened out now. When we went to no till, we bought an inline ripper and I ripped everything 2 years in a row to try to relieve that compaction and that made a big difference and I think that's why we've been successful no tilling" IA48
	Our ground tends to be on the wet side, it's gummy, if you mess with it much deeper than that in the spring you bring nothing up the big old gummy balls of mud about like that, and they get harder'n a rock, and then it dries out and then you don't grow anything. So that's the reason we only scratch about that much in the spring, because if you go any deeper you've got mud, and you also start struggling with compaction. I mean, you don't compact it unless you try to pull something hard and deep; if you just drive over it it doesn't seem like it compacts it, but if you try to start pulling something and it makes the tractor work is when you start compacting. IN#13
Less tillage to manage moisture	
	"My opinion, and experts talk about this too, 80% of our yield is determined by the weather and we can't control that necessarily. We can do things to minimize the impact of the weather, you know, my opinion the no-till minimizes the impact of the weather." IN#12 [goes on to describe having more moisture in a dry year]
	"I have certain fields that just tend to be wet fields, and I tend to try to keep those no-tilled just so that they're a little easier to deal with." MI-7
	"I like no-till. And then in the fall if you get a wet year if you haven't worked it for several years the ground's nice and firm … You know, you get all the worm holes out there and they take the water" MI-36
More tillage to manage moisture	
	"I have kinda stayed away from the no till for the corn crop anyway because of some of the, those soils need to be dried and warm. And the bottom grounds tend to not, depending on planting dates and that type of thing." IA38
	"Last year was the first year its been a detriment to us. We were so so terribly wet and with strip till it seems like you always have to wait about 1 day more than the conventional, they were going in in really wet conditions with a field cultivator and that would dry it up enough that they could get in with a planter and we had to wait." IA19
	"And I don't strip till everything. I have some farms that aren't drained very well. Just haven't been brave enough to try the strip till on them yet." IA54
More tillage to increase soil temperature	
	"we do our low soils, we like to do some tillage because it helps them warm up. On the clay soils or sandy soils, there we'll no till some. One of the things that's been a concern is how cool we've been in the spring and actually have gone back to a little more tillage because of the cool spring because without the heat units the crop is off to a very slow start." IA10
	"I've tried no-tilling on our clay-loam soils, and some years it's okay, but you get the wrong year the soil doesn't warm-up and you're just… You start out behind the eight ball. So, by doing some tillage in the spring to prepare for corn planting it warms the soil up and it gives me more consistent yields." MI-33
	"The problem with no till in this area is we don't warm up in the spring enough and the crops don't come out of the ground." MI-34

Operational needs and compatibility. This theme focuses on the interplay between different crops and operations that take place on a field from one year to the next. It includes two sub-topics: crop rotation and residue management, and fertilizer application. As has previously been highlighted in the no-till section, many farmers till differently at different points in their crop rotation, and this is not limited to no-till. For example, among the farmers that elaborated on their chisel plow use, 12 percent reported chisel plowing according to their rotation, or in other words, following certain crops but not others. Most commonly mentioned was chisel plowing between corn crops or prior to planting corn. Some of this tillage variation based on crop rotation can also be seen in a couple of the quotes in Table 2.7 above.

Table 2.8. Examples of quotes pertaining to the crop rotation and residue management aspects of operational needs and practice compatibility features that influence farmers' tillage decisions.

Tillage in rotation and for residue management
"Generally, second year corn, we will till with a chisel plow or some kind of tillage. Just to handle the residue and what not." IA36
"Part of this vertical tillage and continuous corn is getting this tough crop mixed into the soil to get it breaking down faster." IA51
"We do some tillage on our corn stalks. Basically for residue management to deal with the corn stalks." IA63
"we're making a tillage pass in front of everything. Doing it to size residue, with the twin row corn, with the higher populations we've got a lot of residue, so we're doing it to size residue and to bury some residue and then for weed control and just to aerate and warm-up the soil." IN#45
Effects of newer corn varieties
"Now you're starting to see some tillage come back into soybeans more because of that darn residue with the corn. We're putting fungicides on which make it not deteriorate, the higher populations, the GMO corns, they did exactly what we wanted, we wanted a strong stalk to hold the plant up but that strong stalk doesn't break down. You almost need to break that stalk down so you can plant a good crop of soybeans next year." MI-18
"We got a tool they call vertical till that we go over the bean ground with and its mainly to break down the corn stalks. The corn stalks are greener and tougher now than they used to be. They bred that in to the seed." MI-41
"you get your soil so that it's kind of working, breaking down stuff, it was working good until the Bt corn came into practice, and then you can break that stuff down, and we never applied any nitrogen on the stalks or anything like that." MI-50
Tillage in relation to planting equipment
"Its [tillage] more to get the stand of the crop. We've got a no till drill and with these heavier corn stalks and stuff we were having an issue getting the stand that we want. Even in the wheat and I don't know why. We just feel its worth that [tillage] trip, we get a better stand." MI-26
"Corn we usually… we do a minimum till with the corn, just because the corn planter… We have some issues with our corn planter so we do a minimum till; we'll go in and run our finisher in front of it and just get the soil loosened up and stuff so we have a better… We feel we have a better seed rate." IN#48

At least some of the reason for tilling based on rotation is to handle the residue that remains from the previous crop. The higher volumes of residue from corn (versus that of soybeans for example) were most often cited as the focus of tillage for this purpose. Several farmers mentioned residue management being a bigger issue in recent years, with newer corn varieties having stronger stalks that take longer to break down. A few farmers also discussed residue management in relation to the operation of their planting equipment—needing to reduce the residue so their planting equipment would work better.

There are also certain timing aspects to tillage that are based on rotation since harvest times differ between crops. This creates more opportunity for additional operations in the fall after some crops rather than others. For example, wheat that is typically harvested in July in the study area, versus October for corn and soybeans (NASS 2010) (see IN#41 quote in Table 2.7).

Fertilizer application was the second sub-topic of the operational needs and compatibility theme. This has to do with the interaction between tillage practices and fertilizer practices, and how some fertilizer practices are incompatible with certain tillage practices, particularly no-till. The major issue was the desire to incorporate fertilizer into the soil through some sort of tillage, rather than leave them on the soil surface, though not all no-till farmers were concerned about it. This factor either put farmers off total no-till or pushed them to change or select their fertilizer practices to be compatible. As can be seen in the examples in Table 2.9, it was relatively common for farmers to switch from no-till to strip till in order to incorporate their applied nutrients. The use of anhydrous ammonia[15] as a nitrogen source was particularly mentioned as being incompatible with no-till, leading farmers to either not fully no-till or not use anhydrous ammonia.

The use of animal manure as a nutrient source was also mentioned as being a particular challenge with no-till, either through the injection process, the need to incorporate the manure if it has been spread on top of the soil, and/or the need to smooth the field following manure application and prior to planting. Manure is a resource but also a waste product and spreading manure on fields is a way to dispose of it, even if it is not optimal from a cropping standpoint.

[15] Anhydrous ammonia is a gas and has to be injected under the soil surface using a ripper-style shank.

Because it is so bulky, manure does not tend to be hauled very far, so it is not necessarily spread evenly across an operation's fields.

Table 2.9. Examples of quotes pertaining to the fertilizer application aspects of operational needs and practice compatibility features that influence farmers' tillage decisions.

Need for fertilizer incorporation

"Well, I actually switched to strip till because of the fertilizer management… When we went to straight no till, that P and K was just sitting on the surface. And people debate, about 50 percent say it doesn't matter. But I feel like you need to get it incorporated, so that's why I went to strip till. The strip till applicator actually injects that fertilizer about 4-6 inches deep, so I'm not spreading it on the surface anymore. So did tillage effect the way fertilizer, its probably the other way around, the way I fertilize effected how I wanted to do my tillage." IA06

"I didn't start out trying to go to strip tillage, my real goal was to get the fertilizer in the ground rather than lay it on top. And I did not like that fact that I was practically giving up the nitrogen that was in my MAP and DAP. That's practically free nitrogen. And if you're putting on 200 pounds an acre, that's 36 units at say 15 cents a unit, that's 15 dollars worth of nitrogen. Why not take advantage of it?" IA64

"when we started no tilling is when we started side dressing nitrogen, because historically my father had put all the nitrogen on with the local ag retailer, broadcast before we planted and we would work it in, and I just didn't feel like leaving 200 pound of N lying on top. And I never thought it was a good idea to put all the N in spring." IN#12

Anhydrous ammonia and no-till

"Minimum till. We're really not in a no-till situation; the anhydrous tracks pre-plant makes it tough to plant behind." IN#47

"Well, we don't use anhydrous for any purpose, and part of that is if you're going to no till I don't really want an anhydrous bar running through it prior. We primarily use 28…" IN#16

"…although they've got better equipment now, but that's why we got set up with 28 because pre-plant anhydrous and no-till doesn't work." IN#33

Manure use

For the strip tilling, does that encourage you towards manure use or away?

"Probably away. They're diabolically opposed based on the seasonality and the till, the strip till that goes in the bean stubble for residue management, that's a really nice way to do that, but obviously with the hog manure, between compaction and the way the hog manure is injected, strip till may not work with that very well." IA62

"We have all this manure to deal with, so no-till, just isn't a good fit if you have a lot of manure, because you've got to kinda work it in." IA23

"Where we have been able to no-till and avoid hauling manure on it definitely has an impact, but manure application just destroys a lot of the benefits… but we've got to spread manure around so…" MI-28

Operational savings and costs. The third major influence on tillage practice decisions is related to operational savings that come with less tillage in the form of time, labor, equipment, and/or fertilizer. The saving of time/labor was the most frequently and clearly articulated and came through fewer trips through the field and the ability to farm with fewer people. Fewer trips through the field also saves fuel and wear and tear on equipment. For some farmers less tillage was not their goal, but was an acceptable enough option when they ran out of time tilling all of their land with their preferred method. There was also the potential savings on fertilizer, either through strip tilling and restricting fertilizer application to the strips, or through improved soil quality and biological functions. However, some farmers mentioned that savings came at the cost of yield, or there were other disadvantages.

Table 2.10. Examples of quotes pertaining to the operational savings and costs that influence farmers' tillage decisions.

Time, labor, fuel and equipment savings

"A side benefit of going to no till is that I don't need to hire too many people. I can keep working my 82 year old father to death. There is a lot less trips across the fields. A lot less tractor time." IA09

"I mean we do do some no-tilling, you know, because you can't keep a field cultivator far enough ahead sometimes, so, you know, you may do 400 or 500 acres no-till." IN#38

"I'm probably leaning more towards no till. Some of my fields are getting further and further away. And just the time and the fuel costs. If I have a planter that is set up to do it, why not?" MI-10

How long have you been doing the minimum till?

"Oh, my dad and my grandpa started in 1980. Early. They were one of the first ones in the county to start, and really they started out of necessity because it was just two guys, and my dad was doing the same thing I'm doing now, he worked full-time down at General Motors and they just didn't have time to be working ground." MI-25

"We farmed 3000 acres when my dad was alive and we made some major changes [after he died] because it was just overwhelming, and we got rid of some of the less productive farms, and it was just my brother and I and we had a couple hired men and we went to no-till… I would never go back to conventional till; it's just made our lives so much simpler… We use to just go through an enormous amount of diesel fuel and cultivator shovels when you're out there working the ground, working the ground, working the ground, then you've gotta pick up stones, then you've got a clean out the ditches in the field; I mean, it just eliminated so much work it's phenomenal. I mean, you could farm two or three times more ground because you're not out there beating it all to death." MI-36

"I wanted to get to this no till stuff. We were starting out farming and I didn't want to go out and buy all this huge equipment." IA51

Fertilizer savings

"It [strip till] makes my fertilizer more efficient, it put it on right where the corn plant is gonna be." IA26

So you were saying you're strip tilling. Do you feel like that impacts nitrogen use compared to other forms of tilling that you might use or could use?

"Cuts it by a third, minimum. Everything's in the band where the crops going to use it." MI-35

"Well, low crop prices, you know, we've had a stretch where margins were very tight, so… But when I started strip tilling we cut fertilizer 40%, you know, because you weren't spreading 200 pounds of potash, you only needed 60 pounds in the band;" MI-35

"The no-till system… once it's established I think the nitrogen use is probably a little bit more efficient, there's a transitional period where it takes a little bit more nitrogen to feed that a little more biological system. For us we've been no-tilling for about 20 years and so with the exception of new farms that we pick up. We feel overall… I'm going to say probably that we're about 30 pounds less nitrogen required and that comes from the cycling of the stuff back from the biology that it seems to be that we're seeing there, compared to the kind of best guess we can get from guys around here on conventional systems." IN#18

Table 2.10. (cont'd).

Yield costs
"So, if we keep the soil in place, first and foremost, and the labor savings are a side benefit. But, I'm also leaving a little bit of money on the table by going to no till. If no till was the most profitable way to go, everybody would switch over in a season. As it is, hardly anybody switches over. Cause there is more money to be made, more yields to be had, planting that seed in freshly turned over black warm dirt, instead of unturned over soil that's had a crop on it. So, people are not streaming to no till, but they are gradually coming around." IA09
"And I realized I suffered some yield, but I'm a no tiller. Cause the earth will be hear a lot longer than I am. But we don't know, that's the philosophy that I'm farming with." IA53
"I've kinda been going back and forth whether to go back to tilling or not. You know, advantageous and disadvantages. You save fuel and stuff. For the most part, we've been fairly satisfied with the yields. It's kinda a pain…at the end, when you strip till you pick up a big chunk and its harder to keep your fields level. You need a finish tool." IN#3

DISCUSSION

Variation in Tillage Practices and Meanings

The results of this analysis show that there are several types of variation in tillage tool/type use among Midwestern farmers. The most obvious variation is in tillage tool/type use within a single farm: many farmers in the sample reported using multiple tillage tools/types, either consistently, based on soil type or crop rotation, or on an "as-needed" basis, such as to address soil compaction in specific places. The other type of variation is between farmers in the specifics of how tillage tools and types are used. This variation includes differences in how tools are set up—such as the size and shape of chisel plow and ripper shanks and the depths at which they are used—as well as what tools are used for different types of tillage. A prime example of variation in tillage tools and types this is whether chisel plows are an acceptable part of "minimum" tillage, with farmers expressing both views:

> *"We are minimum till; we try to… most everything gets chisel plowed in the fall but we leave a lot of residue on the top." MI-19*

> *"We're all minimal till. We don't chisel plow." MI-12*

The demonstrated variation in spatial and temporal dimensions of tillage use, as well as in the meanings of different tillage types, suggests that recent research has glossed over potentially important variation in tillage practices either by asking about tillage in too general a way and/or analyzing it in too general a way. Ryan, Erickson, and De Young (2003) recognize that they likely asked about the use of no-till in a way that potentially included a variety of actual practices. Vitale et al. (2011) and Andrews et al. (2013) do better by defining their categories, and in the case of Andrews et al. (2013) including differences in tillage by crop rotation in the question. However, neither Vitale et al. nor Andrews et al. seem to make use of the richness of their data as they collapse the variation into the typical categories. Reimer, Weinkauf et al. (2012) similarly recognize a more complex range of tillage practices, but did not seem to consider the meaning of this range—though their smaller sample size would have made this difficult.

There is an argument to be made for the relevance of general or collapsed categories of tillage practices—convenience, interest in relative versus absolute categories, the value of how farmers self-identify and their ostensible intention, the importance of what farmers do on the majority of their land etc. However, there are potentially important environmental differences between the use of practices within the common tillage categories, and the use of these common categories sets researchers up to ignore an interesting line of research on the significance of using multiple types of tillage.

The present analysis and previous studies (Andrews et al. 2013; Reimer, Weinkauf, et al. 2012; Vitale et al. 2011) indicate that many farmers do use multiple tillage practices on their farms, and the present analysis suggests several reasons why they might do so, such as soil qualities, crop rotation, compatibility with other practices etc. But why do all farmers not do this? The descriptives tables in Vitale et al. (2011), and Andrews et al. (2013) suggests that there could be some notable differences between farmers who use all one kind of tillage and those who use multiple types, which suggests an interesting line of future investigation. Are these farmers simply incomplete adopters who need more encouragement to complete the transition process to no-till? Or are these farmers actually the ideal? Are they the farmers with the skill, knowledge and equipment to tailor their practices to their crops, soil and weather conditions, such that they are flexible and resilient to a range of social, personal, economic and climate conditions?

Variation in Tillage Reasons

The results of this analysis suggest that biophysical conditions, operational needs and compatibility, and operational savings and costs are the dominant decision factors for tillage in Midwest corn agriculture. In contrast to the implied importance of attitudes and values in the use of social-psych theories to model farmer BMP decision-making, few farmers in the study mentioned values they hold as influencing, or at least being consistent with, their tillage practices. This suggests that farmers' environmental attitudes and values are not playing a conscious role in their tillage decisions. While the unconscious role that attitudes and values might play may be meaningful, my results suggest that additional logistical and biophysical factors should at least be considered in conjunction with them.

Vitale et al. (2011) and Reimer, Weinkauf et al. (2012) both consider perceived characteristics of conservation tillage and found them to be important positive and negative factors on practice use. They both find the perception that conservation tillage is good for reducing erosion and conserving soil as an important positive predictor, along with savings on inputs and labor, which is consistent with the findings of my analysis. Vitale et al. (2011) especially found soil type to be in important reason for not using conservation tillage, with soil type and trouble with soil compaction having negative influences on conservation tillage use. Similarly, Reimer, Weinkauf et al. (2012) found "lack of perceived need" as a reason for not adopting conservation tillage. These previous findings are also consistent with the results of my analysis and reinforce the importance of perceived practice characteristics and what Rogers (2003) calls the “relative advantage” and “compatibility” characteristics of tillage practices, where the practice being considered needs to be better in some way than the current practice (in this case, provides economic savings in some form), but also needs to be compatible with the existing system—in this case both the biophysical conditions as well as fertilizer application practices.

What is perhaps most surprising in my results, is that farmers reported different decisions to ostensibly the same soil conditions. This suggests that attitudes and values could possibly be influencing tillage decisions indirectly by influencing how farmers perceive their biophysical conditions, and how they prioritize different aspects of their operation (in other words, how do they define what they “can” and “cannot” do?). This is most apparent in Table 2.7, where soil compaction, and wet soils can either push farmers to till more or till less. This could be a case where the biophysical context is different enough to call for or make possible different responses, or it could be that farmers are in fact choosing to handle the same conditions in opposite ways. In either case, combined with the overall importance of soil qualities and conditions as a basis for tillage tool/type use, it suggests that researchers need to better consider the specific biophysical conditions in which a particular farmer is operating.

> *“It encouraged more of us to use no till. Especially planting soy beans back into corn. And then, we could see the variations from field to field, even doing the same practices with different soils. Some of my lighter soils I went stronger into no till and then some of my fields where I was like, I could soil condition index there better with corn on corn even with tillage. It kinda tuned us in to how different practices on different fields was appropriate. Since then, I’ve moved into more of a resiliency concept, how do we handle these extreme weather events and variations. And how do we prepare our land for that.” IA04*

Implications and Directions for Future Research

Future social research on tillage practices is advised to consider three elements. 1) When collecting data on tillage practices, design questions to capture, or at least not preclude, the use of multiple tillage tools/types on the farm at the same time, the variation in tillage by crop, and other forms of temporal and spatial variation in tillage. Assumptions should not be made on the consistency of tillage practices from year to year, or extrapolate the practices used on a single field to those used on the whole operation. 2) Incorporate research from other disciplines; such as by working with soil scientists to focus interview/survey questions on the specific characteristics of tillage practices that are most important from an environmental perspective—be it season of tillage, depth of tillage, use or non-use of specific tools, number of tillage passes etc. 3) Consider the significance of farmers using multiple types of tillage.

It is also worth noting that none of the farmers interviewed described their tillage practices in terms of the percentage of residue that remained—not for a specific tool or a type of tillage. This suggests that a common feature of tillage type definitions used on surveys may not be very helpful to farmers in accurately selecting the response category that reflects their tillage practices, even if the question were to be specific to a single field and year and thus removes the use of multiple tillage types from consideration. It seems likely farmers are categorizing their tillage practices when asked to do so based on broad conceptions of the practice and/or on the labels attached to the tillage tools they use, which may or may not match with definitions used on surveys.

A final note should be made on the limitations and advantages that result from the design of the present study. The largest limitation is that the question about tillage practices was very general and was often asked in conjunction with the interaction between tillage and fertilizer practices, resulting in many farmers focusing their responses on the later aspect and thus providing little detail on their tillage practices. The interviews were also focused on corn, so it is possible that many farmers only discussed their tillage on corn and did not mention how they till in other parts of their rotation. The result is that these interviews likely under-report farmers use of multiple tillage tools/types and their use in their crop rotation. The advantage of the general nature of how the tillage question was asked is that the reasons that farmers mentioned for their tillage practices were un-prompted (except for the fertilizer interaction and savings) and thus are expected to much more accurately represent the reasons that are most important to them.

CONCLUSION

This exploratory analysis had two research questions: How and why do Midwest farmers till? I find that how farmers till varies widely, with farmers utilizing a wide range of tillage tools and frequently use multiple tillage tools/types on different parts of their farm and at different times. Notably, the common tillage categories were found to contain great internal variation, especially in the case of no-till, which showed important temporal variation in its use that is rarely acknowledged in the literature. This intra-category variation poses a great challenge to the utility of the tillage categories currently in use in social science research as these categories are likely not measuring what the researchers think that they are, even when category definitions are provided, as spatial and temporal variation are rarely incorporated.

The reasons for tillage decisions that emerged as most important were soil conditions, operational compatibility, and savings, though not always in consistent directions. The inconsistency in farmers' tillage responses to soil conditions suggests the importance of 1) better understanding the soil conditions that farmers are actually dealing with so that their responses to soil conditions can be assessed, and 2) the biophysical knowledge and social constructions that farmers have that influence their perceptions of their soil conditions and what actions will lead desirable outcomes. This later point pushes beyond the capacity of the adoption-diffusion model and suggests the utility of adding a critical realism perspective to efforts to understand farmer decision-making (Carolan 2006). Critical realism assumes the existence of a tangible, biophysical reality but also acknowledges that there can be multiple meanings assigned to it, making possible multiple, and even conflicting, knowledge claims about the same ostensible reality (Carolan 2005).

The spatial and temporal variation in tillage practices reported, and the importance of the biophysical context in which the farmer is operating should be examined more systematically in future research. The exciting aspect of the diversity in tillage practices is that tillage is not a single binary decision, which leaves opportunity for experimentation and incremental change towards more sustainable farming practices. Better understanding why farmers use multiple types of tillage, can advise ways of encouraging farmers to take the first step and start using a practice on some of their fields and the potential to get farmers to use a given practice on a greater portion of their land. The work of soil scientists and those in related fields should be utilized to focus research efforts on the specific aspects of tillage practices that are most important environmentally.

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CHAPTER 3: DRIVERS OF THE USE OF FIVE BMPS IN MIDWEST ROW-CROP AGRICULTURE

The need for US commodity crop farmers to use increasing numbers of agricultural best management practices (BMPs) in order to reduce their effect on the surrounding environment has been well established (Holmes, Armanini, and Yates 2016; Lam, Schmalz, and Fohrer 2011; Liu et al. 2016; Sowa et al. 2016). At the same time, there has long been an interest in understanding the reasons farmers choose to use or not use these practices. In the last decade several meta-analyses have attempted to summarize the findings of this expansive research across practices and conceptual approaches (Baumgart-Getz, Prokopy, and Floress 2012; Knowler and Bradshaw 2007; Liu, Bruins, and Heberling 2018; Prokopy et al. 2008; Wauters and Mathijs 2014). However, there remains little agreement on what variables drive BMP use, and neither of the main conceptual approaches—the adoption-diffusion model and several social-psych theories, particularly those in the Theory of Planned Behavior (TPB) tradition—has emerged as a definitive winner. In addition, little research has been done that compares influential drivers across practices, though called for by Reimer et al. (2014).

This analysis takes an exploratory approach and compares the relative importance of a wide range of predictors of BMP use from the literature, using the meta-analyses as a guide, on the use of five specific BPMs: pre-sidedress nitrate tests (PSNTs), nutrient maps, variable rate nitrogen (N), variable rate phosphorus (P) or potassium (K), and cover crops. The goal is to identify the common drivers of BMP use and assess their relative importance. It also explores the use of practice knowledge as a predictor of BMP use that has been underutilized in previous research. Rather than being a meta-analysis like previous studies, this one uses data from a single four-state farmer survey.

APPROACHES TO UNDERSTANDING BMP ADOPTION/USE

Two main conceptual approaches have been used to explain farmers' use of BMPs: social-psychological theories, and the adoption-diffusion model. Over the years neither approach has displaced the other, though the adoption-diffusion model is not as popular for agricultural research as it once was (Ruttan 1996). This analysis does not take either approach as the a priori model to test, but rather includes variables commonly used in analyses based on both approaches in order to compare their relative importance along with common control variables. These two approaches also offer different ways to think about the role of knowledge in BMP use.

Social-Psychological Theories

One family of theories from social-psychology has become a very common conceptual approach for understanding farmer adoption of conservation practices. This family consists of the theory of reasoned action (TRA), the theory of planned behavior (TPB), and the reasoned action approach (RAA) (Ajzen 1991; Fishbein and Ajzen 2015). These three theories are related and began with the theory of reasoned action (TRA). In the TRA attitude towards the behavior and subjective norms—the perceived expectations of others–drive behavioral intention, in turn drives behavior. The use of behavioral intention as a mediator between attitudes, norms and behavior is a distinguishing feature the TRA and the theories derived from it. The theory of planned behavior (TPB) is an extension of the TRA that adds perceived behavioral control (PBC) as a predictor of behavioral intention and actual behavior (Madden et al. 1992 highlight the differences). This addition incorporates a contextual element to the theory and improves its predictive power, especially for behaviors that have greater actual or perceived external constraints (Ajzen 1991; Madden et al. 1992). The reasoned action approach (RAA) is the most recent incantation of this family of theories and extends the TPB by adding "individual," “social,” and “information” background factors, along with a new tier of belief variables and an actual control variable (Fishbein and Ajzen 2015). The belief components underlie the attitude, subjective norms and perceived behavioral control variables, and typically measures of the different types of beliefs that are used to measure attitudes, subjective norms and perceived behavioral control using factor analysis (Fishbein and Ajzen 2015).

Adoption-Diffusion Model

The adoption-diffusion model describes the process through which a new idea, technology, or practice (i.e., innovation) spreads through a social system, and is ultimately adopted (or not) by individuals over time (Rogers 2003). Originally developed in large part to understand the spread and adoption of new agricultural technologies (Rogers 1958; Ryan 1948; Ryan and Gross 1943), it has been applied to a wide range of topics and utilized by a number of different disciplinary fields, largely through the work of Everett Rogers (Rogers 2003).

Rogers (2003:5) describes diffusion as “the process in which an innovation is communicated through certain channels over time among the members of a social system.” It is a macro process (as opposed to the micro-level adoption decision) that is heavily dependent on communication, and where the newness of the innovation and its effects creates uncertainty about the innovation (Rogers 2003). Over time the innovation is communicated to more people and uncertainty is reduced through greater information, sometimes resulting in the full adoption of the innovation in the population (Rogers 2003). The result of diffusion (and the adoption process that results) makes it a form of social change, in that it can alter the structure and function of the social system (Rogers 2003).

As diffusion happens, individuals (or other decision-making entities) gain information about the innovation and ultimately decide to use it or not use it. The “innovation-decision process," as described by Rogers (2003:14), "is essentially an information-seeking and information-processing activity in which an individual is motivated to reduce uncertainty about the advantages and disadvantages of the innovation."

The Potential Importance of Knowledge

Knowledge is included implicitly and explicitly in the above discussed theories/models, but it is rarely included in empirical analyses. One potential reason for this is that "knowledge" can be referenced with a wide variety of other terms depending on how subjectively one is willing to consider it. If we are interested in what a participant "knows" then we must extend our concept of "knowledge" to include what researchers might typically term beliefs, awareness, and even perceptions, because we are interested in how the subject identifies the parameters of the world in which they operate (Carolan 2006).

"Factual knowledge" is included outright in the TRA, as described by Kaiser, Wölfing, and Fuhrer (1999), as the driver of attitude towards the behavior. Using a broad conceptualization of knowledge, the TPB has perceived behavior control in it, as does RAA along with knowledge as an information background factor and the three belief components, which are subjective knowledge measures.

The role of knowledge is more explicit in the adoption-diffusion model, where the spread of information through communication channels is a key aspect of the diffusion process and knowledge of the innovation is the first stage of the innovation-decision process. Rogers (2003) further breaks down knowledge of the innovation in to three types:

1) *Awareness-knowledge*, which is simply awareness that the innovation exists.
2) *How-to knowledge*, which is knowledge of how to correctly use and/or implement the innovation.

3) *Principles-knowledge*, which is knowledge of the systems and processes that underlay how the innovation works.

These types of knowledge, along with a couple other components of the adoption-diffusion model are notably similar to the four types of knowledge proposed by Kaiser and Fuhrer (2003) in the social-psych tradition. They posit that the role of knowledge in explaining ecological behaviors has been underestimated in past research because either education is used as a proxy for knowledge, different forms of knowledge are not considered simultaneously, and because knowledge is necessary but not sufficient for behavior, since other factors can constrain action even with sufficient knowledge. Kaiser and Fuhrer's (2003) four types of knowledge are:

1) *Declarative knowledge* is knowledge of environmental processes or how an environmental system works.

2) *Procedural knowledge* is knowledge of how to implement a behavior or achieve a particular goal.

3) *Effectiveness knowledge* is knowledge of the relative effectiveness of a given behavior to achieving the desired outcome.

4) *Social knowledge* is knowledge of social norms and expectations ("conventional social norms"), as well as personal, "moral social norms."

Figure 3.1 shows how Kaiser and Fuhrer incorporate their four types of knowledge into a version of the TPB. However, they leave out perceived behavioral control, though they mention the importance of external constraints on behavior even when sufficient knowledge is present in the text. Presumably, perceived behavioral control would predict intention and ecological behavior in their model, in keeping with their theoretical foundations in TPB.

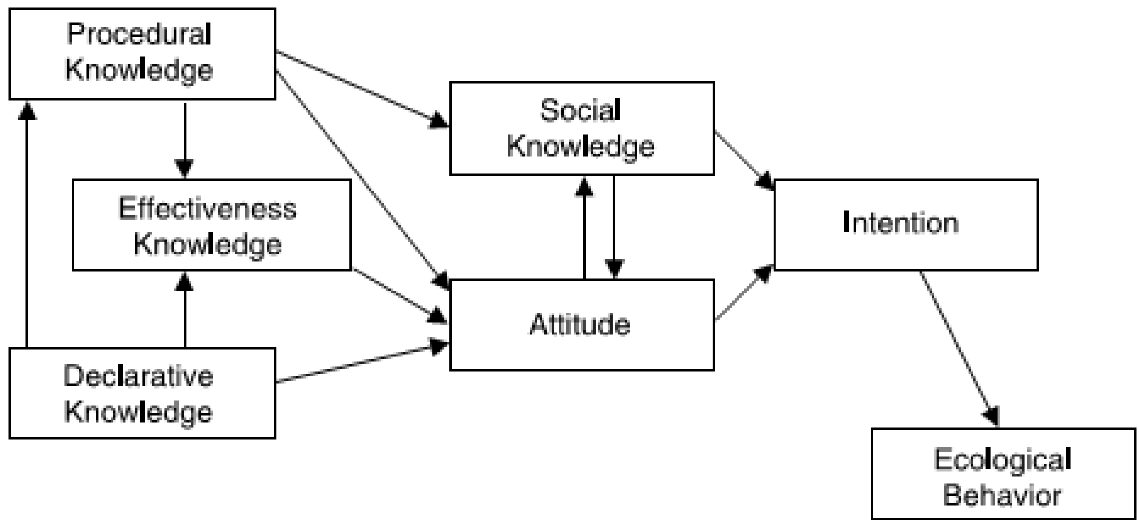

FIGURE 1. Knowledge's behavior-distal influence mediated by more behavior-proximal factors to affect ecological behavior.

Figure 3.1. Kaiser and Fuhrer's (2003:606) conceptual model of how know knowledge types influence each other and ultimately ecological behavior.

There are clear correlations between Rogers' principles-knowledge and Kaiser and Fuhrer's declarative knowledge, as well as between how-to knowledge and procedural knowledge. Kaiser and Fuhrer's effectiveness knowledge and social knowledge seem to both be included in Rogers' relative advantage component of perceived innovation attributes. The perceived innovation attributes are not discussed overtly as knowledge, but they do fit in the broad conceptualization of knowledge discussed above.

How knowledge has been operationalized and included in empirical analyses related to agriculture has varied, but the most common form is some type of awareness knowledge—awareness of problems (also called 'concern') and practices (e.g., Duff et al. 1992; Ervin and Ervin 1982; Napier, Thraen, and Gore 1984; Reimer and Prokopy 2012; Ulrich-Schad et al. 2017), and exposure to information, communication networks, and education (e.g., Duff et al. 1992; Dunn et al. 2016; Ervin and Ervin 1982; Napier et al. 1984; Ulrich-Schad et al. 2017). The variable categories used in the meta-analyses by Prokopy et al. (2008) and Baumgart-Getz et al. (2012), highlight the use of principles-knowledge or declarative knowledge, which describes their “cause” “consequences” and “knowledge” categories, while their “program” category is either awareness knowledge or perhaps procedural knowledge of conservation programs (see Table 3.2).

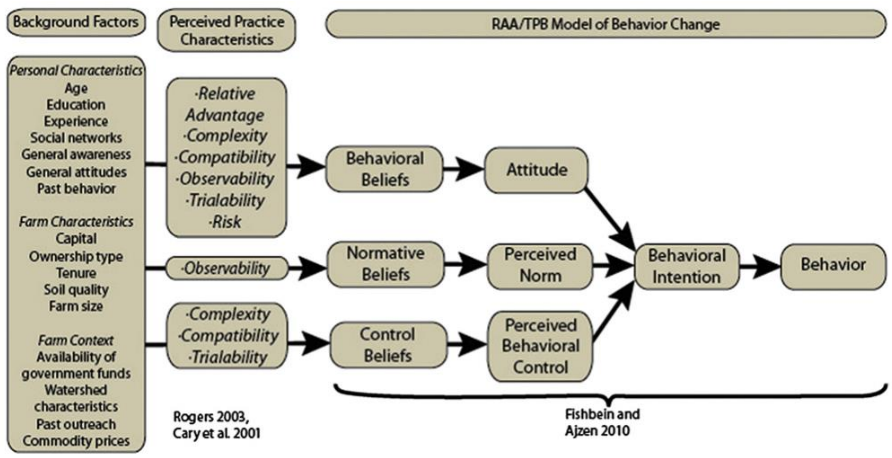

Fig. 1. Examining the role of practice characteristics in influencing the decision to adopt through the lens of the Theory of Planned Behavior/Reasoned Action Approach.

Figure 3.2. Combining perceived practice characteristics from the adoption-diffusion model with the Reasoned Action Approach by Reimer, Weinkauf, et al. (2012).

Knowledge of practice characteristics has also been used in empirical studies, drawing from the adoption-diffusion approach. Reimer, Weinkauf et al. (2012) merge the five perceived practice characteristics of Rogers (2003) with the RAA in their approach to understanding farmers’ reasons for adopting or not adopting best management practices in Indiana (see Figure 3.2). They find that relative advantage and compatibility of BMPs (or lack thereof) to be the most important practice characteristics motivating or discouraging practice adoption. Arbuckle and Roesch-McNally (2015) use this combined conceptual approach to study cover crop adoption in Iowa qualitatively and quantitatively. Similarly to Reimer, Weinkauf et al. (2012), Arbuckle and Roesch-McNally (2015) find variables related to the relative advantage and compatibility (or lack thereof) of cover crops to be important drivers of cover crop adoption or non-adoption.

Rogers' (2003:173) observed that "few diffusion investigations deal with how-to knowledge, although it must be a fundamental variable in the innovation-decision process," and an extensive search of the literature supports this. The only recent study I could find that considered how-to BMP knowledge was Vitale et al. (2011), who included a knowledge of conservation tillage practices measure in their survey of Oklahoma farmers. They found conservation tillage knowledge to have a significant, positive effect on the use of reduced tillage and conservation tillage and a significant, negative effect on the use of conventional tillage. Nowak and Korsching (1985) long ago recognized the importance of knowledge, learning and experience in the adoption practice, pointing to the example of farmers who had been using conservation tillage longer retained more crop residue than more recent adopters.

Table 3.1. Overview of conservation/best management practice adoption meta-analyses.

	Knowler and Bradshaw (2007)	Prokopy et al. (2008)	Baumgart-Getz, Prokopy and Floress (2012)	Wauters and Mathijs (2014)
Number of studies included	23	55	46 (published and unpublished)	38
Number of analyses included	31	at least 329	[not provided]	69
Type of analysis included	quantitative	quantitative with significant results at 0.05 level	quantitative with "enough information to calculate effect size"	quantitative
Number of predictor variables included (after reduction)	46	34	30	87
Year range of included studies	1984-2002	1982-2007	1982-2007	1982-2006
Study location	world-wide	US at multiple scales	US at multiple scales	developed country (most in US) at multiple scales
Outcome variable criteria	"farm-level adoption of a number of soil management and wider conservation practices consistent with conservation agriculture"	actual adoption of one or more practices expected to lead directly to water quality improvement	actual BMP adoption	use of soil conservation practices broadly defined, many on conservation tillage of some type
Method of analysis	vote-count	vote-count	mixed effects model using Hedges d	vote-count
Sub-analyses included:				
Practice / category	X	X		X
Analysis method	X	X		X
Predictor variable type			X	
Region	X			
Journal quality	X			

PREVIOUS RESEARCH ON DRIVERS OF BMP USE

As discussed above, the inclusion of knowledge, especially how-to or procedural knowledge, is ripe for further explanation, but is not expected to be the only factor of importance in predicting farmers' use/adoption of conservation and best management practices. Much of the more recent work on this topic, using both adoption-diffusion and social-psych approaches among others, has been analyzed in several recent meta-analyses (Baumgart-Getz et al. 2012; Knowler and Bradshaw 2007; Prokopy et al. 2008; Wauters and Mathijs 2014)[16]. However, the results of these analyses have found little consistency in sign and significance of the examined predictors. These analyses do provide a useful starting point for the present analysis though. These four meta-analyses (summarized in Table 3.1) include 23 to 55 studies from the early 1980s through the mid-2000s that used actual adoption (as opposed to intended adoption) of a range of BMPs as their dependent variables.

Knowler and Bradshaw (2007) include studies from all parts of the world, making it less directly applicable than the other three studies, while Prokopy et al. (2008) and Baumgart-Getz et al. (2012) restrict their sample to the US and Wauters and Mathijs (2014) limit theirs to studies of "developed" countries. Knowler and Bradshaw (2007), Prokopy et al. (2008), and Wauters and Mathijs (2014) all use vote-count methodology, while Baumgart-Getz et al. (2012) use a mixed effects model. This later analysis method provides effect sizes for the variables considered, while vote-count methodology counts the models for which a given variable has a significant positive effect, significant negative effect, or insignificant effect. The vote-count analyses find a definite overall trend towards insignificance, though some variables are more often significant than not. The more sophisticated mixed effect model finds a large portion of

[16] A very recent meta-analysis (Liu et al. 2018) is not included because they include studies that used program participation as the outcome of interest, making their results not directly comparable to the other studies referenced here.

variables with very small effect sizes and/or non-significant effects, but it allows for assessment of the relative importance/influence of different variables in a way that vote-count methods do not.

Connecting Variables and Theories

While there is overlap in the types of variables that are used to operationalize the theoretical approaches discussed above, the different approaches emphasize different categories of variables. The social-psych theories naturally call for variables that measure respondents' beliefs, attitudes and values as they relate to the environment, other entities, and the behavior in question (Baumgart-Getz et al. 2012; Prokopy et al. 2008). Beliefs, attitudes, and values are commonly measured as multi-item latent variables (see for example Price and Leviston 2014; Ulrich-Schad et al. 2017; Werner et al. 2017). While the adoption-diffusion model includes attitudes towards the practice as an important predictor of the adoption-decision process, it also focuses on the characteristics of the practice, and stresses the importance of education, and information sources (Nowak 1987; Nowak and Korsching 1985; Prokopy et al. 2008; Rogers 2003). Some, though not recently, have also operationalized farmers' innovativeness (Rollins 1993).

METHODS AND ANALYSIS

The goal of this analysis is to look for the common drivers of BMP use across the five practices considered, and to assess the relative importance of significant drivers. This analysis does not take either the adoption-diffusion model or any of the social-psych approaches as an a priori model to test, but rather includes variables commonly used in analyses based on both approaches in order to compare their relative importance along with common control variables. I use structural equation modeling with latent variables (SEMLV) with binary BMP use outcome variables, using 2017 farmer survey data from four states.

Sample

The data used comes from a 2017 survey of corn growers in Illinois, Indiana, Michigan, and Ohio. The questionnaire asked farmers about the 2016 growing season and included questions on their overall operation and cropping practices, specific practices used on their largest corn field, the frequency of their information source use and trust of those sources, their attitudes and values towards farming and the environment, and their demographic characteristics. Surveys were sent to 10,582 corn growers using a two-wave, modified Dillman (Dillman, Smyth, and Christian 2014) mailing procedure, with a response rate of 31 percent, of which 2289 surveys were at least partially filled out (22 percent useable response rate). After dropping cases with missing values on key variables, the working sample was 1958 cases. Case-wise deletion of missing values on independent variables was required by the analysis method, leaving a final sample of approximately 814 cases[17] (a few less on the dependent variables) (see Appendix A for details on data cleaning). The final sample response numbers by state are: IL = 282, IN = 212, MI = 114, OH = 256. As shown in Table 3.2, the sample contains more full-time farmers with larger farms than average. While this means that the sample is not representative of all farms in these states, it may be more representative of corn and soybean farms, and corn-soybean-wheat growing farms as these have larger average sizes. The farmers in this sample do represent those who can have the greatest environmental impact by using BMPs.

[17] There are fewer than 814 observations on some of the latent variable measures as noted in Table 3.5.

Table 3.2. Comparison between final sample (n=814) and 2012 Census of Agriculture on key demographic variables by state.

	2016 Survey--Final Sample				2012 Census of Agriculture†			
	IL	IN	MI	OH	IL	IN	MI	OH
Years farming	29.0	28.7	26.0	30.0	27.3	26.0	26.0	25.9
Age in years	58.2	57.0	55.3	58.9	57.8	55.8	57.6	56.8
Percent working X days off-farm								
0 days	54.8	59.1	58.7	54.1	42.4	35.5	41.3	36.7
1 to 49 days	18.6	13.1	15.6	13.9	9.4	7.6	7.9	8.1
50 to 99 days	3.4	4.0	3.7	4.1	4.0	3.4	4.0	3.8
100 to 199 days	8.0	6.6	4.6	9.4	7.3	7.9	8.1	7.9
200 or more days	15.2	17.2	17.4	18.4	36.9	45.5	38.7	43.5
Percent of household income from farming								
less than 25%	10.6	15.2	17.4	18.0	57.1	65.3	70.5	68.1
25 to 49%	17.9	15.7	11.0	23.8	10.1	9.5	7.8	9.6
50 to 74%	20.5	18.7	16.5	20.1	13.3	10.6	9.2	10.2
75 to 100%	51.0	50.5	55.0	38.1	19.6	14.6	12.4	12.1
Average cropland per farm	1192.1	1289.4	1515.6	935.0	351.3	257.7	171.7	167.3
Average acres of corn-soy operation*					591.8	497.5	336.6	331.4
Average acres of corn-soy-wheat operation*					684.1	567.6	423.0	385.8

†Data except for cropland for principle operator

*Only including farms that grow these crops

Variables

There are five outcome variables: use of pre-sidedress nitrate tests (PSNT), use of nutrient maps to inform fertilizer decisions, use of variable rate nitrogen (N), use of variable rate phosphorus (P) or potassium (K), and use of winter cover crops. PSNTs and nutrient maps are both decision aids for fertilizer applications, while the variable rate N and variable rate P or K are two examples of precision fertilizer application technology; cover crops represent a biological soil and nutrient management practice. The questions about these practices had five response categories[18], and the variables used were created by combining the “yes, regularly do this,” with the “yes, sometimes do this” responses into a binary variable reflecting current use of

[18] The three response categories that were not used are: “Used to, but no longer do,” “Never used, but might,” and “Never used, don’t want to.”

the practices[19]. The choice to use the collapsed, binary variables as opposed to the full range of responses was made based on my interest in actual practice use, rather than past use or possible future use.

The above mentioned meta-analyses were used as guides for the present analysis. The categories and sub-categories of Prokopy et al. (2008) and Baumgart-Getz et al. (2012) were combined (Table 3.3)[20], and the longer variable list from Wauters and Mathijs (2014) was used as examples of variables for each categories. These examples informed the selection and calculation of variables from those available to represent each sub-category in Table 3.3 as much as possible. This resulted in 53 independent variables, including two latent variables and two variables that are excluded from the analysis to serve as reference categories (see Table 3.4), representing 30 of the 39 sub-categories.

Two common variables were not included in the analysis for technical reasons though they were in the dataset: *age* and *operator gender*. *Age* was highly correlated with *farming experience* (> 0.75) so both could not be included without unacceptably high multicollinearity. Operator gender was left out due to the very small number of women in the overall sample (1.5 percent) and in the final sample (0.7 percent), which resulted in problematically low variation in the *operator gender* variable.

The independent variables used in this analysis are described in Table 3.4. To facilitate analysis and discussion, the variables have been re-organized into six categories, rather than the four shown in Table 3.3; this was done to group more similar variables together, in some cases based on the actual measures being used in the present analysis. Changes were made to all the

[19] This is a useful and simple measure, though it imperfectly reflects temporal variability in use and does not reflect the area on which the practice is used (spatial extent) at all.
[20] Many of the variable categories and definitions are the same between these two studies, which made combining them straightforward.

categories shown in Table 3.3, though the new “attitudes and values,” and “environmental awareness” categories are similar those of Prokopy et al. (2008) and Baumgart-Getz et al. (2012). The most substantial change was dividing the “capacity” variables into background factors, social farm characteristics, and information categories; the sub-category names are the same as in Table 3.3.

Table 3.3 Combined categories used in Prokopy et al. (2008) and Baumgart-Getz, Prokopy, and Floress (2012).

Categories and sub-category	Description
Capacity	
Acres / farm size	Number of acres farmed
Age	Farmer age
Capital	Measure of investment into farm (excluding acres)
Diversity	Measures that capture diversity of farm operation
Education	Farmer education
Extension Training	Subgroup of EDUCATION includes only extension training
Formal education	Subgroup of EDUCATION- includes only formal education
Farming experience	Years farming
Income	Measures of wealth such as income, crop value, etc.
Information	Access to and quality of information
Labor	Measures of increased labor available to the farm
Networking	Overall measure of networking capacity
Agency	Subgroup of NETWORKING: Connectivity to and familiarity with agency personnel and procedures
Business	Subgroup of NETWORKING: Measures of networking capacity in the agri-business sector
Local	Subgroup of NETWORKING: Interacts with neighboring farms as well as any grass roots organization
University Extension	Subgroup of NETWORKING: Exposure to a university extension office
Institutional / Ownership Type	Farm structure or organization measures e.g. individually owned versus corporate-owned farms
Tenure	Whether operator owns farmland
Attitudes	
Overall attitude	The attitude category as a whole
Adoption payments	Farmer receiving payments for participating in conservation programs
Environmental	Importance individual places on environmental quality
Profitability of practice	Farmer places financial gain as primary purpose of farm
Heritage	Farm will be taken over by a family member
Quality of environment	Farmer’s perception of the current quality of the environment
Regulatory	Farmer feels government can/should regulate agriculture

Table 3.3. (cont'd).

Risk	A measure of risk averseness
Scientific	Values scientific research
Environmental awareness	
Overall environmental awareness	The environmental awareness category as a whole
Cause	Understanding how agriculture can impact environmental quality
Consequences	Understanding the consequences of a degraded system
Knowledge	Knowledge of general terms or facts related to environmental quality
Program	Knowledge of nonpoint source programs or efforts
Farm characteristics	
Animal	Livestock or dairy operations
Grain	Primarily a grain farm
Operator gender	Primary operator is male
Other farm types	Other/unspecified type of farm
River	Farm located near a stream or in a river bottom
Slope	Fields are hilly or have steeper slopes
Soil quality	Measures of soil quality

Note: Sub-categories in italics are those which are not included in the present study. Age and gender were not used for technical reasons; the rest did not have relevant measures in the data used.

Some variables were not easily categorized, such as crop insurance use, which could reasonably go in the social farm characteristics category, but which was kept in the attitudes and values category as a measure of risk aversion. Similarly, participation in conservation programs, either in general or working land programs specifically, could be included in the attitudes and values category or the environmental awareness categories as they are in Table 3.3. However, they have been included in the social farm characteristics category for this analysis because farmers participate in conservation programs for a range of reasons and also use conservation practices without participating in a program (Reimer and Prokopy 2014); thus program participation does not inherently reflect a particular attitude, value or awareness.

Table 3.4. Variables used in analysis, their definition and scale, grouped by author-defined categories, and using sub-categories from the literature. All variables are for 2016.

Categories	Variable Name	Definition	Scale
Individual Characteristics			
Farming experience	Years farming	Years as primary farm decision-maker	Continuous
Education	Education level	Education level	Categorical with 4 ordered categories: 1 = less than high school, 4 = bachelor's degree or higher
	College ag courses	Took college courses in agriculture	Binary
Knowledge	Knowledge	Self-reported knowledge of practices for nutrient management and soil conservation	Categorical with 5 levels of knowledge: 1 = nothing at all, 5 = a great deal
Income	Value of sales	Gross value of farm products sold	Categorical with 4 ordered categories: 1 = less than $100,000, 4 = greater than $1 million
	Household income	Household adjusted gross income	Categorical with 6 ordered categories: 1 = less than $25,000, 6 = greater than $500,000
	Ag. income	Portion (%) of household gross adjusted income coming from farming	Categorical with 4 ordered categories: 1 = less than 25%, 4 = greater than 74%
Farm Characteristics—Physical			
Acres / farm size	Cropland area	Cropland planted in 1000 acres	Continuous
Diversity	Corn-soy ratio	Corn acres to soy acres ratio (from a3)	Continuous
Animal	Animal farm	Dairy production or other livestock (including poultry) account for more than 10% of farm revenue	Binary
Grain	Grain farm	Field or grain crops account for more than 10% of farm revenue	Binary
Other farm types	Other farm type	Something other than grain or livestock provides more than 10% of revenue—includes fruit, nut and vegetable crops, and flowers, ornamentals and live plants	Binary
Slope	Field slope	Slope of largest, owned corn field	Categorical with 4 ordered categories of slope: 1 = flat (0-2% average grade), 4 = severely hilly (10% or more average grade)

Table 3.4. (cont'd).

Soil quality	Soy yield	Average soy yield	Continuous
	Corn yield	Average corn yield	Continuous
	Loam	Main soil texture of largest, owned corn field is loam	Binary
	Clay	Main soil texture of largest, owned corn field is clay	Binary
	Clay-loam	Main soil texture of largest, owned corn field is clay-loam (reference)	Binary
	Silty-loam	Main soil texture of largest, owned corn field is silty-loam	Binary
	Sandy-loam	Main soil texture of largest, owned corn field is sandy-loam	Binary
	Other soil type	Main soil texture of largest, owned corn field is "other"—includes sand and silt textures	Binary
<u>Farm Characteristics—Social</u>			
Tenure	Cropland owned	Percent of operation cropland that respondent owns	Continuous
Labor	Days worked off farm	Days worked off farm	Categorical with 5 ordered categories: 1 = none, 5 = 200 days or more
	Number of employees	Number of family and non-family employees, not including the respondent	Continuous
Ownership Type/structure	Sole proprietorship	Sole proprietorship (reference)	Binary
	Partnership	Partnership	Binary
	LLC	Limited liability corporation	Binary
	S-corporation	Small corporation (subchapter S)	Binary
	C-corporation	Corporation (subchapter C)	Binary
	Other business structure	Other business structure--mostly combinations of the above	Binary
Program	Conservation program participation	Participate in any kind of conservation program	Binary
Adoption payments	Working land program participation	Participates in a working land program (EQIP or CSP)	Binary

Table 3.4. (cont'd).

Information			
Information access	Info index	Sum of frequency of use and level of trust for 9 info sources	Continuous
Networking	Associations info source	Frequency of use of growers associations and conferences as info source	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
Business	Chemical dealers info source	Frequency of use of chem dealers as info source	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
	Seed dealers info source	Frequency of use of seed dealers as info source	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
	Crop consultants info source	Frequency of use of independent consultants as info source	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
Local	Other farmers info source	Frequency of use of family and other farmers as info source	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
University Extension	Campus extension info source	Frequency of use of campus extension as info source	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
	Local extension info source	Frequency of use of local extension educators	Categorical with 5 levels of frequency: 1 = never, 5 = once a day
Attitudes and Values			
Importance of environment	Look after environment	Importance of looking after the environment	Categorical with 5 levels of importance: 1 = low, 5 = high
	Hunting and fishing environment	Importance of maintaining good hunting, fishing, hiking	Categorical with 5 levels of importance: 1 = low, 5 = high
Profitability of practice	Economic attitude	Economic attitude latent variable	Latent
	Wealth	Importance of building up wealth and family assets (used in latent variable)	Categorical with 5 levels of importance: 1 = low, 5 = high
	Profit	Importance of maximizing farm/company profit (used in latent variable)	Categorical with 5 levels of importance: 1 = low, 5 = high
	Income	Importance of earning a high income (used in latent variable)	Categorical with 5 levels of importance: 1 = low, 5 = high
Heritage	Passing on good land	Importance of passing on land in good condition	Categorical with 5 levels of importance: 1 = low, 5 = high
	Farming tradition	Importance of keeping family farming tradition alive	Categorical with 5 levels of importance: 1 = low, 5 = high
	Passing on farm	Child or other relative expected to take over farm after respondent retires	Binary

Table 3.4. (cont'd).

Risk	Debt aversion	Importance of minimizing debt	Categorical with 5 levels of importance: 1 = low, 5 = high
	Crop insurance use	Percent of corn and soy acres covered by crop insurance	Continuous
Environmental Awareness			
Cause	Concern ag. contributes to water problems	Concern agriculture contributes to water problems latent variable	Latent
	Groundwater contribution	Concern that agriculture contributes to groundwater contamination (used in latent variable)	Categorical with 5 levels of concern: 1 = low, 5 = high
	Algal bloom contribution	Concern that agriculture contributes to algal blooms in lakes (used in latent variable)	Categorical with 5 levels of concern: 1 = low, 5 = high
	Hypoxia contribution	Concern that agriculture contributes to hypoxia ("dead zones") in oceans (used in latent variable)	Categorical with 5 levels of concern: 1 = low, 5 = high
	Erosion contribution	Concern that agriculture contributes to soil erosion (used in latent variable)	Categorical with 5 levels of concern: 1 = low, 5 = high
Consequences	Erosion impacts	Concern about on-farm impacts from soil erosion	Categorical with 5 levels of concern: 1 = low, 5 = high
	Pest resistances impacts	Concern about on-farm impacts from weeds and insects developing resistance to pesticides	Categorical with 5 levels of concern: 1 = low, 5 = high
	Extreme weather impacts	Concern about on-farm impacts from droughts, floods, and other extreme weather events	Categorical with 5 levels of concern: 1 = low, 5 = high
	Warming impacts	Concern about on-farm impacts from warmer temperatures	Categorical with 5 levels of concern: 1 = low, 5 = high

Analysis

Structural equation modeling with latent variables was used for this analysis and was executed in Mplus8. A separate model was run for each of the five outcome variables using the same independent variables. Due to the use of binary outcome variables and categorical variables in the latent variables, a robust, diagonally weighted least squares, means and variance adjusted estimator (specifically the WLSMV estimator in Mplus8) was used. Due to the evidence of state-level differences for three of the five practice-use variables a “complex” analysis is specified in Mplus, which adjusts the standard errors and chi-square tests of model fit for clustering by state. See Appendix B for additional explanation and justification for these estimator and analysis type decisions.

Use of the WLSMV estimators results in estimated probit coefficients. The probit coefficients can be thought of as reflecting the rate of change in probability of practice use over different values of the variable, and significance indicates if the slope is significantly non-zero. The probit coefficients themselves do not indicate anything about the probability of practice use, but the probability of practice use can be calculated from the intercept[21], probit coefficients, and specified values for each variable using the following equation (Muthén, Muthén, and Asparouhov 2016) where F is the standard normal distribution function[22] (see Appendix B for more explanation):

$$P(u_i = 1 \mid x_i) = F(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i)$$

By calculating the probabilities of practice use at different values of a variable of interest while holding all other variables at a constant value the total effect of the variable on practice use

[21] The intercept for a binary outcome variable is the negative threshold value that Mplus reports. See Appendix B for more information about the meaning of threshold values with categorical outcomes and how the WLSMV estimator calculates them.

[22] A z score is calculated by the intercept, coefficients and specified variable values, then a left sided z table is used to determine the probability of $F(z)$—this is equal to the area under the curve to the left of the z value.

can be evaluated in a standardized way that is comparable across variables (Muthén et al. 2016). The "baseline" value used for each variable was the mean value for continuous variables (including latent variables) and the mode value for categorical variables, resulting in the probability of practice use by an "average" farmer. Due to the more meaningful interpretation of the probabilities versus the probit coefficients, the probabilities are the focus on the following section.

FINDINGS

General Approach to Results

Table 3.5 provides the descriptive statistics for the analysis sample, while tables 3.6, 3.7 and 3.8 present select probit results from the five models (see Appendix C for full probit results). Conceptually similar practices have been paired for sake of space and comparability, and only effects significant or marginally significant for at least one of the practices are included in these tables. PSNT and nutrient maps are paired because they are both decision support tools that are independent of the crop in a given year. Variable rate N and variable rate P or K are paired because they are both using similar technology. Cover crops is by itself since it is the most different from the other practices included, by virtue of being a practice that is not directly related to target crop production and requiring additional activities to the crop growing cycle to plant it in the fall and then kill it before planting the regular crop in the spring.

The sign of significant variables for all five practices are summarized in Table 3.9. One of the most notable results is the distinct lack of overlap in significant variables between the paired practices especially but also across all the models. In fact, of the fifty-three predictive variables in the models only one, use of *independent crop consultants as an info source*, is significant in all five models.

Table 3.5. Analysis descriptives (n = 814 unless otherwise noted).

	Mean	Mode	Std Dev	Minimum	Maximum
PSNT	0.182	0	0.386	0.000	1.000
Nutrient maps	0.833	1	0.373	0.000	1.000
Variable rate N	0.278	0	0.448	0.000	1.000
Variable rate P or K	0.643	1	0.480	0.000	1.000
Cover crops	0.355	0	0.479	0.000	1.000
<u>Individual Characteristics</u>					
Years farming	28.814	37	14.128	0.000	65.000
Education level	2.937	2	0.852	1.000	4.000
College ag courses	0.434	0	0.496	0.000	1.000
Knowledge	3.550	3	0.805	1.000	5.000
Value of sales	2.732	3	0.872	1.000	4.000
Household income	3.173	3	1.035	1.000	6.000
Ag. income	2.996	4	1.120	1.000	4.000
<u>Farm Characteristics—Physical</u>					
Cropland area	1.182	1	1.194	0.050	12.500
Corn-soy ratio	1.295	1	1.574	0.012	25.000
Animal farm	0.221	0	0.415	0.000	1.000
Grain farm	0.966	1	0.182	0.000	1.000
Other farm type	0.049	0	0.216	0.000	1.000
Field slope	1.483	1	0.646	1.000	4.000
Soy yield	58.825	55	9.082	20.000	82.000
Corn yield	179.712	170	34.492	56.250	270.000
Loam	0.053	0	0.224	0.000	1.000
Clay	0.076	0	0.265	0.000	1.000
Clay-loam	0.461	0	0.499	0.000	1.000
Silty-loam	0.200	0	0.400	0.000	1.000
Sandy-loam	0.140	0	0.347	0.000	1.000
Other soil type	0.070	0	0.255	0.000	1.000
<u>Farm Characteristics—Social</u>					
Cropland owned	42.552	0	33.640	0.000	100.000
Days worked off farm	2.138	1	1.554	1.000	5.000
Number of employees	1.373	0	4.227	0.000	68.000
Sole proprietorship	0.636	1	0.481	0.000	1.000
Partnership	0.087	0	0.282	0.000	1.000
LLC	0.128	0	0.334	0.000	1.000
S-corporation	0.064	0	0.245	0.000	1.000
C-corporation	0.076	0	0.265	0.000	1.000
Other business structure	0.009	0	0.092	0.000	1.000
Conservation program participation	0.420	0	0.494	0.000	1.000

Table 3.5. (cont'd).

Working land program participation	0.157	0	0.364	0.000	1.000
Information					
Info index	51.996	55	7.716	28.000	77.000
Associations info source	1.813	2	0.758	1.000	5.000
Chemical dealers info source	2.924	3	0.708	1.000	5.000
Seed dealers info source	2.802	3	0.747	1.000	5.000
Crop consultants info source	1.819	1	0.977	1.000	5.000
Other farmers info source	3.178	3	0.951	1.000	5.000
Campus extension info source	1.700	1	0.741	1.000	5.000
Local extension info source	1.736	2	0.675	1.000	4.000
Attitudes and Values					
Look after environment	4.290	4	0.742	1.000	5.000
Hunting and fishing environment	2.763	3	1.256	1.000	5.000
Economic attitude					
Income (n=813)	3.696	4	0.870	1.000	5.000
Wealth (n=812)	4.145	4	0.830	1.000	5.000
Profit	4.348	5	0.712	1.000	5.000
Passing on good land	4.576	5	0.693	1.000	5.000
Farming tradition	4.504	5	0.785	1.000	5.000
Passing on farm	0.764	1	0.425	0.000	1.000
Debt aversion	4.216	5	0.819	1.000	5.000
Crop insurance use	82.371	100	35.835	0.000	100.000
Environmental Awareness					
Concern ag. contributes to water problems					
Groundwater contribution (n=802)	3.608	4	1.058	1.000	5.000
Algal bloom contribution (n=803)	3.420	3	1.088	1.000	5.000
Hypoxia contribution (n=799)	3.185	3	1.192	1.000	5.000
Erosion contribution (n=805)	4.086	4	0.887	1.000	5.000
Erosion impacts	4.161	5	1.061	1.000	5.000
Pest resistances impacts	4.353	5	0.893	1.000	5.000
Extreme weather impacts	3.565	4	1.242	1.000	5.000
Warming impacts	3.061	3	1.210	1.000	5.000

Twelve variables were not significant for any of the practices: *years farming, ag income, grain farm, soy yield, clay soil type, other soil type, cropland owned, number of employees, s-corporation, c-corporation, campus extension info source*, and *hunting and fishing environment*. Five additional variables were only of marginal significance for any of the five practices: *college ag courses, sandy-loam soil, other business structure, passing on good land*, and *debt aversion*.

Table 3.6. Select probit regression coefficients and standard errors for PSNT and nutrient maps (n=814).

	PSNT	Nutrient maps
	Estimate (S.E.)	Estimate (S.E.)
Individual Characteristics		
Education level	-0.086 (0.112)	-0.084 (0.016)***
College ag courses	0.125 (0.070)^{t}	0.271 (0.141)^{t}
Knowledge	0.178 (0.222)	0.204 (0.097)*
Household income	0.083 (0.054)	0.060 (0.031)*
Farm Characteristics—Physical		
Other farm type	-0.458 (0.285)	-0.671 (0.298)*
Loam	-0.558 (0.149)***	0.265 (0.280)
Farm Characteristics—Social		
Partnership	0.310 (0.121)*	0.206 (0.374)
Other business structure	0.987 (0.584)^{t}	0.127 (1.008)
Information		
Seed dealers info source	0.035 (0.101)	-0.155 (0.072)*
Crop consultants info source	0.295 (0.037)***	0.174 (0.056)**
Local extension info source	0.067 (0.074)	-0.129 (0.054)*
Attitudes and Values		
Passing on good land	-0.091 (0.051)^{t}	-0.041 (0.040)
Farming tradition	0.290 (0.185)	-0.082 (0.034)*
Crop insurance use	0.000 (0.002)	0.003 (0.001)^{t}
Environmental Awareness		
Concern ag. contributes to water problems	0.060 (0.006)***	0.051 (0.015)***
Erosion impacts	0.094 (0.035)**	0.013 (0.077)
Warming impacts	-0.035 (0.075)	-0.098 (0.040)*
Intercept	-4.325 (1.351)**	-2.937 (0.695)***
R-Square	0.349 (0.073)***	0.371 (0.121)**
Chi-Square	679.695***	678.584***
RMSEA	0.033	0.033
CFI	0.839	0.839
TLI	0.812	0.812

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7. Select probit regression coefficients and standard errors for variable rate N and variable rate P or K (n=814).

	Variable rate N	Variable rate P or K
	Estimate (S.E.)	Estimate (S.E.)
Individual Characteristics		
Education level	0.034 (0.070)	-0.163 (0.094)[t]
Knowledge	0.123 (0.105)	0.244 (0.062)***
Value of sales	0.045 (0.068)	0.198 (0.077)*
Farm Characteristics—Physical		
Cropland area	0.156 (0.060)*	0.026 (0.102)
Other farm type	-0.415 (0.314)	-0.456 (0.260)[t]
Corn yield	0.004 (0.000)***	0.006 (0.003)*
Silty-loam	-0.375 (0.148)*	-0.100 (0.099)
Sandy-loam	0.091 (0.132)	0.328 (0.174)[t]
Farm Characteristics—Social		
Days worked off farm	0.000 (0.041)	-0.019 (0.006)**
LLC	0.306 (0.074)***	0.117 (0.118)
Conservation program participation	-0.029 (0.131)	0.279 (0.073)***
Working land program participation	0.236 (0.063)***	-0.108 (0.188)
Information		
Info index	0.011 (0.002)***	0.019 (0.021)
Chemical dealers info source	-0.013 (0.124)	0.226 (0.044)***
Crop consultants info source	0.134 (0.059)*	0.106 (0.039)**
Other farmers info source	0.018 (0.107)	-0.080 (0.037)*
Attitudes and Values		
Economic attitude	0.085 (0.035)*	0.008 (0.007)
Passing on farm	0.251 (0.082)**	0.070 (0.090)
Debt aversion	0.009 (0.054)	-0.144 (0.076)[t]
Crop insurance use	-0.001 (0.001)	0.003 (0.001)***
Environmental Awareness		
Extreme weather impacts	0.039 (0.012)**	0.002 (0.032)
Intercept	-2.878 (0.348)***	-2.758 (0.967)**
R-Square	0.237 (0.049)***	0.310 (0.028)***
Chi-Square	679.410***	677.040***
RMSEA	0.033	0.033
CFI	0.840	0.840
TLI	0.813	0.813

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8. Select probit regression coefficients and standard errors for cover crops (n=814).

	Cover crops
	Estimate (S.E.)
Individual Characteristics	
College ag courses	0.111 (0.064)^{t}
Knowledge	0.257 (0.088)**
Farm Characteristics—Physical	
Cropland area	-0.086 (0.044)^{t}
Corn-soy ratio	-0.035 (0.016)*
Animal farm	0.420 (0.164)*
Other farm type	0.338 (0.144)*
Field slope	0.065 (0.022)**
Corn yield	-0.006 (0.002)*
Silty-loam	-0.227 (0.048)***
Farm Characteristics—Social	
LLC	0.208 (0.059)***
Working land program participation	0.631 (0.127)***
Information	
Associations info source	0.136 (0.033)***
Crop consultants info source	0.129 (0.049)**
Local extension info source	0.292 (0.039)***
Attitudes and Values	
Look after environment	0.248 (0.097)*
Economic attitude	-0.126 (0.046)**
Environmental Awareness	
Concern ag. contributes to water problems	0.040 (0.024)^{t}
Erosion impacts	0.227 (0.017)***
Pest resistances impacts	-0.138 (0.051)**
Intercept	-2.726 (1.106)*
R-Square	0.338 (0.02)***
Chi-Square	681.087***
RMSEA	0.033
CFI	0.841
TLI	0.814

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9. Sign of significant variables in analyses.

	PSNT	Nutrient maps	Variable rate N	Variable rate P or K	Cover crops
Individual Characteristics					
Education level		-			
Knowledge		+		+	+
Value of sales				+	
Household income		+			
Farm Characteristics—Physical					
Cropland area			+		
Corn-soy ratio					-
Animal farm					+
Other farm type		-			+
Field slope					+
Corn yield			+	+	-
Loam	-				
Silty-loam			-		-
Farm Characteristics—Social					
Days worked off farm				-	
Partnership	+				
LLC			+		+
Conservation program participation				+	
Working land program participation			+		+

Table 3.9. (cont'd)

<u>Information</u>					
Info index			+		
Associations info source					+
Chemical dealers info source				+	
Seed dealers info source		-			
Crop consultants info source	+	+	+	+	+
Other farmers info source				-	
Local extension info source		-			+
<u>Attitudes and Values</u>					
Look after environment					+
Economic attitude			+		-
Farming tradition		-			
Passing on farm			+		
Crop insurance use				+	
<u>Environmental Awareness</u>					
Concern ag. contributes to water problems	+	+			
Erosion impacts	+				+
Pest resistances impacts					-
Extreme weather impacts			+		
Warming impacts		-			

+ indicates positive effect and significant at $p < 0.05$ or better

- indicates negative effect and significant at $p < 0.05$ or better

Figure 3.3 shows the predicted probability of practice use by an "average" farmer, that is, the probability of practice use when the mean or mode (for continuous and categorical variables respectively) of each variable is used in the equation discussed in the analysis section. These values represent the likelihood of a conceptually "average" of typical farmer using each practice, not the portion of the sample who reported using each practice (see Figure 3.5 in Appendix B for reported practice use by state).

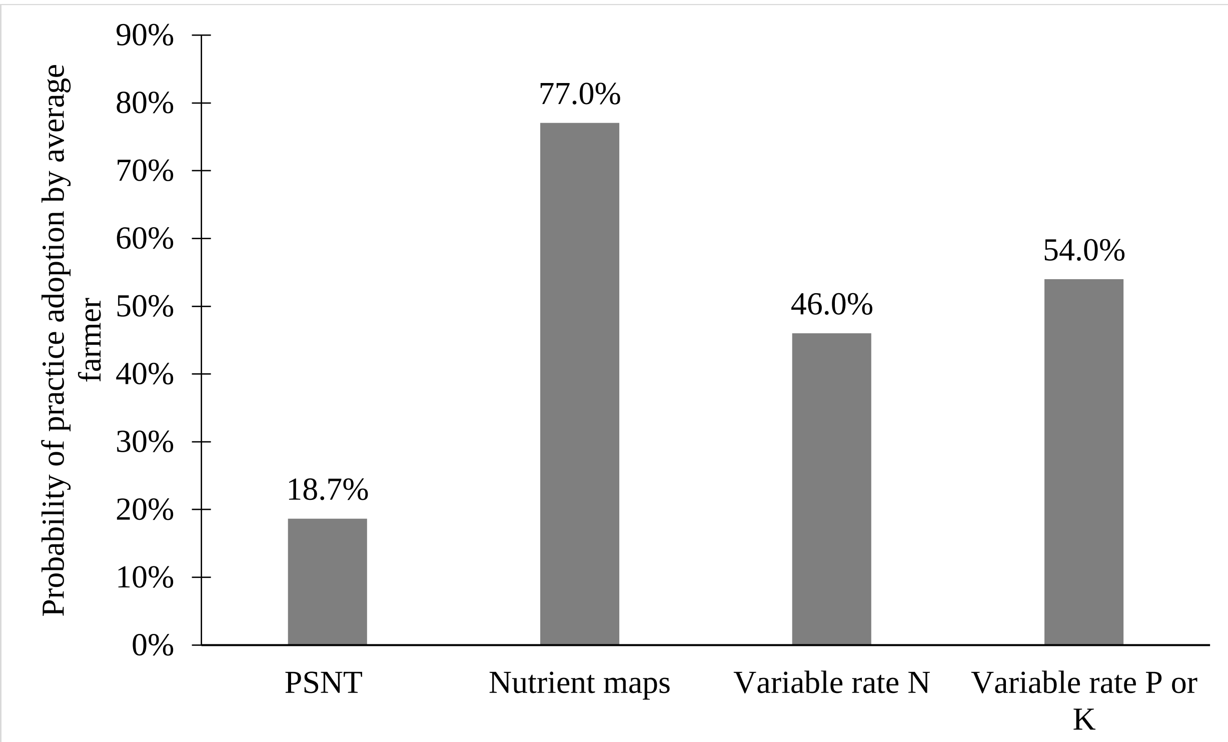

Figure 3.3. Probability of practice use by a typical farmer.

Results of PSNT Model

Five variables are found to be significant predictors of PSNT use. As shown by the probabilities in Table 3.10, farmers with *loam* soil type on their largest corn field were 11 percent less likely to use PSNTs than farmers with *clay-loam* soil type (reference category), and *partnerships* were 9 percent more likely to use PSNTs than *sole proprietorships* (reference category). The more frequent use of *independent crop consultants* as an information source is found to be a very important predictor of PSNT use, with farmers who report consulting with them on a daily basis found to be more than three times more likely to use PSNTs than farmers who never consult with them. Farmers with high *concern that agriculture contributes to water problems*, and those with high concern over *erosion impacts* on their farm are both more likely to use PSNT tests than farmers who have low concern on these variables, but only by 6 percent and 8 percent respectively.

Table 3.10. Total effects for significant variables on PSNT use in terms of probabilities with all other variables at average.

	Prob. at min (min value)	Prob. at max (max value)	Total effect
Farm Characteristics—Physical			
Loam (mode = 0)	18.7% (0)	7.4% (1)	-11.3%
Farm Characteristics—Social			
Partnership (mode = 0)	18.7% (0)	28.1% (1)	9.4%
Information			
Crop consultants info source (mode = 1)	18.7% (1)	61.4% (5)	42.7%
Environmental Awareness			
Concern ag. contributes to water problems (mean = 3.575)	14.7% (1)	20.9% (5)	6.2%
Erosion impacts (mode = 5)	10.2% (1)	18.7% (5)	8.5%

Note: Total effect is calculated as the probability at the variable's max value minus the probability at the variable's minimum value.

Results of Nutrient Map Model

Table 3.11 shows the total effects of the significant variables on nutrient map use. Farmers with higher levels of *education* are predicted to use nutrient maps less than their less educated counter-parts, with farmers with a bachelor’s degree or higher being about 8% less likely to use them than farmers with less than a high school degree. *Knowledge*, on the other hand has a positive effect on nutrient map use with a 25 percent total effect, and the second-largest probability at max at 87 percent predicted probability of nutrient map use. *Household income* has a positive if modest effect on nutrient map use with the difference between household incomes less than $25,000, and greater than $500,000 being only about 9 percent. *Other farm type*, those that generate more than 10 percent of their production value from something other than grain/field crop or livestock are predicted to be 24% less likely to use nutrient maps than farms not in this category.

Among the significant information sources, independent *crop consultants* are the only one with a positive effect on nutrient map use, while *seed dealers* and *local extension* have a negative effect. The difference in predicted probability of nutrient map use between farmers who use *seed dealers* as an information source daily, and those who never use them is about 19 percent. The difference for local extension is similar at 17 percent. The daily use of independent *crop consultants* versus non-use results in a 15 percent greater probability of nutrient map use. While this is not the largest total effect on nutrient map use, it notably produces the highest probability of use at 93 percent when all other variables are at their average.

Table 3.11. Total effects for significant variables on nutrient map use in terms of probabilities with all other variables at average.

	Prob. at min (min value)	Prob. at max (max value)	Total effect
Individual Characteristics			
Education level (mode = 2)	79.4% (1)	71.6% (4)	-7.8%
Knowledge (mode = 3)	62.9% (1)	87.5% (5)	24.6%
Household income (mode = 3)	73.2% (1)	82.1% (6)	8.9%
Farm Characteristics—Physical			
Other farm type (mode = 0)	77.0% (0)	52.8% (1)	-24.3%
Information			
Seed dealers info source (mode = 3)	85.3% (1)	66.6% (5)	-18.7%
Crop consultants info source (mode = 1)	77.0% (1)	92.5% (5)	15.5%
Local extension info source (mode = 2)	80.8% (1)	68.4% (4)	-12.3%
Attitudes and Values			
Farming tradition (5)	85.8% (1)	77.0% (5)	-8.7%
Environmental Awareness			
Concern ag. contributes to water problems (mean = 3.575)	72.9% (1)	79.1% (5)	6.2%
Warming impacts (mode = 3)	82.6% (1)	70.5% (5)	-12.1%

Note: Total effect is calculated as the probability at the variable's max value minus the probability at the variable's minimum value.

Farmers that feel it is important to *keep the family farming tradition alive* were 9 percent less likely to use nutrient maps than those that do not feel it is important to keep that tradition alive. Farmers with high *concern that agriculture contributes to water problems* were 6 percent more likely to use nutrient maps than those with low concern, but those with high concern that *warming* was impacting their farm were 12 percent less likely to use nutrient maps than those with low concern.

Results of Variable Rate N Model

Table 3.12 shows the significant total effects on the use of variable rate N technology. Farmers with larger farms and higher average corn yields are more likely to use variable rate N than those with smaller farms and lower average corn yields by about 22 percent. Farmers with *silty-loam* soil type on their largest corn field were 14 percent less likely to use variable rate than farmers with *clay-loam* soil type (reference category). Farmers with an *LLC* business structure were 12 percent more likely to use variable rate N than farmers in a sole proprietorship (reference category). Farmers who participated in a *working land conservation program* were 9 percent more likely to variable rate N than non-participants.

Farmers with a high information index value, those who use more information sources and who trust those sources more highly, are more likely to Nat a variable rate than those with low index scores. The difference in predicted probability of variable rate N use between farmers who use independent *crop consultants* as an information source on a daily basis, and those who never use is 21 percent. While this is not the variable with the largest total effect in the model, it is the variable that predicts that highest likelihood of variable rate N use at its max value (67 percent) when all other variables are at their average.

Farmers with a strong *economic attitude/orientation* are predicted to be 13 percent more likely to use variable rate N than those with a weak economic attitude. Farmers who expected to *pass on their farm* to a child or other relative were 10 percent more likely to use variable rate N than those who did not expect to pass on their farm. Farmers with high *concern over the impacts of extreme weather events* on their farm were 6 percent more likely to use variable rate N than those with low concern.

Table 3.12. Total effects for significant variables on variable rate N use in terms of probabilities with all other variables at average.

	Prob. at min (min value)	Prob. at max (max value)	Total effect
Farm Characteristics—Physical			
Cropland area (mean = 1.182)	39.0% (0.050) †	60.6% (3.569)	21.7%
Corn yield (mean = 179.712)	35.2% (110.727)	56.8% (248.696)	21.6%
Silty-loam (mode = 0)	46.0% (0)	31.6% (1)	-14.5%
Farm Characteristics—Social			
LLC (mode = 0)	46.0% (0)	57.9% (1)	11.9%
Working land program participation (mode = 0)	46.0% (0)	55.2% (1)	9.2%
Information			
Info index (mean = 51.996)	39.4% (36.564)	52.8% (67.429)	13.4%
Crop consultants info source (mode = 1)	46.0% (1)	66.6% (5)	20.6%
Attitudes and Values			
Economic attitude (mean = 4.063)	35.9% (1)	49.2% (5)	13.3%
Passing on farm (mode = 1)	36.3% (0)	46.0% (1)	9.7%
Environmental Awareness			
Extreme weather impacts (mode = 3)	41.3% (1)	47.6% (5)	6.3%

Note: Total effect is calculated as the probability at the variable's max value minus the probability at the variable's minimum value. For continuous variables the min and max values are two standard deviations below and above the mean respectively unless otherwise noted.
† The sample minimum is used because one standard deviation below the mean is less than the sample minimum.

Results of Variable Rate P or K Model

The significant total effects for the variable rate P or K model are shown in Table 3.13. The effect of high knowledge on variable rate P or K is 37 percent higher than having low *knowledge*. This is the largest magnitude total effect in this model, as well as producing the highest maximum probability at 72 percent. Farmers with *farm sales* greater than $1 million are predicted to be 23 percent more likely to use variable rate P or K than those with sales less than $100,000. Higher *average corn yields* were also related to more likely use of variable rate P or K. *Part time* farmers (those who worked off farm 200 days or more) were 3 percent less likely than full time farmers to use variable rate P or K. Participants in any kind of *conservation program* were 10 percent more likely to use variable rate P or K than non-program participant.

Table 3.13. Total effects for significant variables on variable rate P or K use in terms of probabilities with all other variables at average.

	Prob. at min (min value)	Prob. at max (max value)	Total effect
Individual Characteristics			
Knowledge (mode = 3)	34.8% (1)	71.9% (5)	37.1%
Value of sales (mode = 3)	38.2% (1)	61.4% (4)	23.2%
Farm Characteristics—Physical			
Corn yield (mean = 179.712)	37.5% (110.727)	69.5% (248.696)	32.1%
Farm Characteristics—Social			
Days worked off farm (mode = 1)	54.0% (1)	50.8% (5)	-3.2%
Conservation program participation (mode = 0)	54.0% (0)	64.4% (1)	10.5%
Information			
Chemical dealers info source (mode = 3)	35.9% (1)	70.1% (5)	34.1%
Crop consultants info source (mode = 1)	54.0% (1)	69.9% (5)	15.9%
Other farmers info source (mode = 3)	60.3% (1)	47.6% (5)	-12.7%
Attitudes and Values			
Crop insurance use (mean = 82.371)	45.2% (10.701)	56.0% (100.00) †	10.7%

Note: Total effect is calculated as the probability at the variable's max value minus the probability at the variable's minimum value. For continuous variables the min and max values are two standard deviations below and above the mean respectively unless otherwise noted.
† The sample maximum is used because one standard deviation above the mean is greater than the sample maximum.

Farmers who use *chemical dealers* as an information source on a daily basis are predicted to be 34 percent more likely to use variable rate P or K than farmers who never use chemical dealers, almost as large an effect as *knowledge*. Farmers with daily versus non-use of independent c*rop consultants* are predicted to be 16 percent more likely to use variable rate P or K, but farmers with daily use of *other farmers* as an information sources verses those who do not consult other farmers were 13 percent less likely to use variable rate P or K. Farmers with all of their corn and soy acres enrolled in *crop insurance* were 11 percent more likely to use variable rate P or K than those who did not use crop insurance.

Knowledge, corn yield, and chemical dealers as an information source have the three highest total effects in this model, and all three have similar probabilities of variable rate P or K at their max values. Independent crop consultants as an information source actually predicts a slightly higher probability of variable rate P or K use at its max value than does corn yield, in spite of having a total effect of about half the size.

Results of Cover Crop Model

Table 3.14 shows the significant total effects for the cover crop model. Farmers with a high level of knowledge are predicted to be 17 percent more likely to use cover crops than farmers with low knowledge. A high corn to soy ratio (i.e., farmer is growing mainly corn) is predicted to have a small negative effect on the probability of cover crop use. This variable is a measure of crop diversity, and cover crops are a type of crop diversity so this effect/relationship makes sense. Farmers having greater than 10 percent of farm revenue coming from livestock or from non-field crops or grain (e.g., other farm type), are also more likely to use cover crops by 9 percent and 7 percent respectively.

Farmers who have largest corn fields with a greater than 10 percent grade are about 4 percent more likely to use cover crops than farmers with flat largest corn fields. This suggests that at least some cover crop use is related to how sloped the farm is, assuming the largest corn field is generally indicative of the topography of the area/farm. Farmers with high average corn yields are less likely to use cover crops than those with lower average yields. Farms with silty-loam soil texture in the largest corn field are predicted to be 3 percent less likely to use cover crops than those with clay-loam as the dominant soil texture in the largest corn field. Having the farm structured as an LCC vs a sole proprietorship increased the predicted probability of using cover crops by 4 percent, while participation in a working lands conservation program increase cover crop use by an estimated 14 percent.

Table 3.14. Total effects for significant variables on cover crop use in terms of probabilities with all other variables at average.

	Prob. at min (min value)	Prob. at max (max value)	Total effect
Individual Characteristics			
Knowledge (mode = 3)	3.0% (1)	19.8% (5)	16.8%
Farm Characteristics—Physical			
Corn-soy ratio (mean = 1.295)	9.3% (0.012) †	6.9% (4.442)	-2.4%
Animal farm (mode = 0)	8.5% (0)	17.1% (1)	8.6%
Other farm type (mode = 0)	8.5% (0)	15.2% (1)	6.6%
Field slope (1)	8.5% (1)	12.1% (4)	3.6%
Corn yield (mean = 179.712)	17.1% (110.727)	3.8% (248.696)	-13.4%
Silty-loam (mode = 0)	8.5% (0)	5.6% (1)	-2.9%
Farm Characteristics—Social			
LLC (mode = 0)	8.5% (0)	12.3% (1)	3.8%
Working land program participation (mode = 0)	8.5% (0)	23.0% (1)	14.4%
Information			
Associations info source (mode = 2)	6.7% (1)	16.9% (5)	10.2%
Crop consultants info source (mode = 1)	8.5% (1)	19.8% (5)	11.2%
Local extension info source (mode = 2)	4.9% (1)	21.8% (4)	16.9%
Attitudes and Values			
Look after environment (mode = 4)	1.7% (1)	13.1% (5)	11.4%
Economic attitude (mean = 4.063)	16.4% (1)	6.8% (5)	-9.5%
Environmental Awareness			
Concern ag. contributes to water problems (mean = 3.575)	7.1% (1)	9.5% (5)	2.4%
Erosion impacts (mode = 5)	1.1% (1)	8.5% (5)	7.4%
Pest resistances impacts (mode = 5)	20.6% (1)	8.5% (5)	-12.1%

Note: Total effect is calculated as the probability at the variable's max value minus the probability at the variable's minimum value. For continuous variables the min and max values are two standard deviations below and above the mean respectively unless otherwise noted.
† The sample minimum is used because one standard deviation below the mean is less than the sample minimum.

Daily versus non-use of associations, independent crop consultants, and local extension as information sources had total positive effects on cover crop use of 10 percent, 11 percent, and 17 percent respectively. Farmers who feel that looking after the environment is very important are predicted to be 11 percent more likely to use cover crops than farmers who feel it has low importance, while having a high economic attitude predicts a 10 percent lower probability of cover crop use than a low economic attitude. High concern that agriculture contributes to water problems and high concern over erosion impacts on the farm both predict higher likelihood of cover crop use than low levels of concern, by 2 percent and 7 percent respectively. Farmers who are highly concerned about the impacts of pest resistance to pesticides on their farm are predicted to be 12 percent less likely to use cover crops than those who are not concerned about pest resistance. This represents a key practice trait deterring farmers from using the practice, as cover crops are often killed with herbicides in the spring prior to planting the main crop especially if no-till is also being use.

Additional comparative insight across predictors can be gained by graphing probabilities across variable value gradients, and variables on the same scale can be graphed together to visually demonstrate the dynamics at play between minimum and maximum probability, and total effect. An example of this is given in Figure 3.4 where we can see the important influence that local extension can have on cover crop use, even though its total effect is only slightly larger than that of knowledge. Independent crop consultants have a smaller total effect than knowledge, but they have the same predicted probability of cover crop use at their max values. These differences occur because the normal distribution function is S-shaped, and thus the slope (and curve) of the predicted probabilities depends on the where on that S-curve the variable is being measured (Muthén et al. 2016).

This graph also clearly shows which variables have the most potential to increase cover crop use, and which are “maxed out” so to speak. Because the majority of farmers already have a high level of concern over erosion impacts on their farm, there is little if any room for increasing concern to change the likelihood that they will use cover crops. In contrast, these results suggest that increasing the frequency of contact with local extension, increasing the use of independent crop consultants, and increasing knowledge have the potential to increase the likelihood of cover crop use. Even increasing contact with local extension from once a year to once a month has the potential to increase the probability of cover crop use by more than 5%.

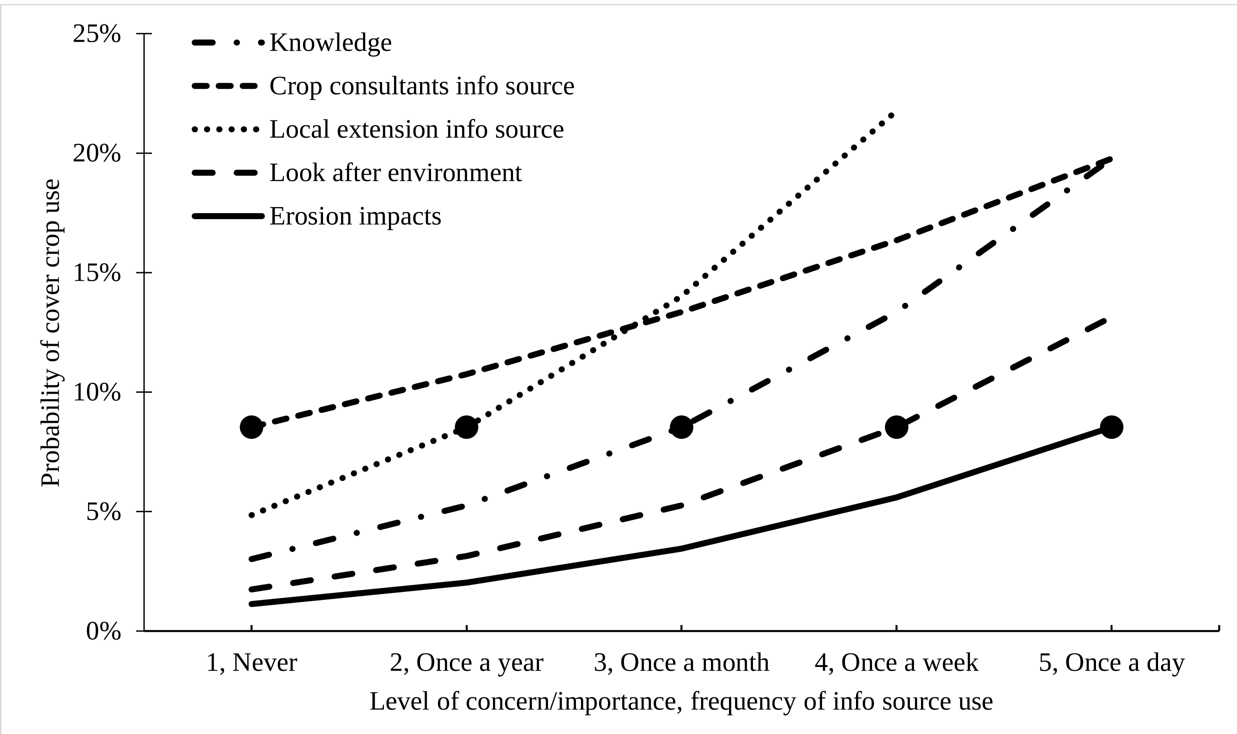

Figure 3.4. Graphical depiction of the predicted probabilities of select variables on cover crop use across a range of values.
Note: The points on the lines indicate the mode value of the respective variables.

DISCUSSION

Independent Crop Consultants

As previously mentioned, the use of independent crop consultants as an information source is the only variable that is significant in all five models of practice use; it also has a positive effect on the use of all five practices. Figure 3.5. shows the graphed predicted probabilities of the five practices across the frequency of use of independent crop consultants. Here we can see the effect of the more than 40 percent total effect of independent crop consultants on PSNT use, with the effect on the other practices ranging between 10 percent and 20 percent.

This shows that while the use of independent crop consultants has the potential to increase the use of all five practices, it is expected to be most effective at increasing the use of PSNTs based on its large total effect. The question then remains, why do some farmers choose to use independent crop consultants, and how can their use be increased? Stuart et al. (2018) do not consider the use of independent crop consultants specifically in their analysis of information source use in relation to nitrogen fertilizer, but they find from qualitative analyses that lack of trust in consultants associated with seed or fertilizer suppliers appears to be a reason that some farmers do not use those consultants, or do not put much weight in what they say. It is possible that for some farmers, the added cost of hiring an independent crop consultant is a worthwhile alternative to these other sources. Cost might be a factor in deterring the use of independent crop consultants, or farmers may have sufficient trust in the specific retail affiliated consultants they use, as found by Stuart et al. (2018), to not feel the need to hire an independent consultant.

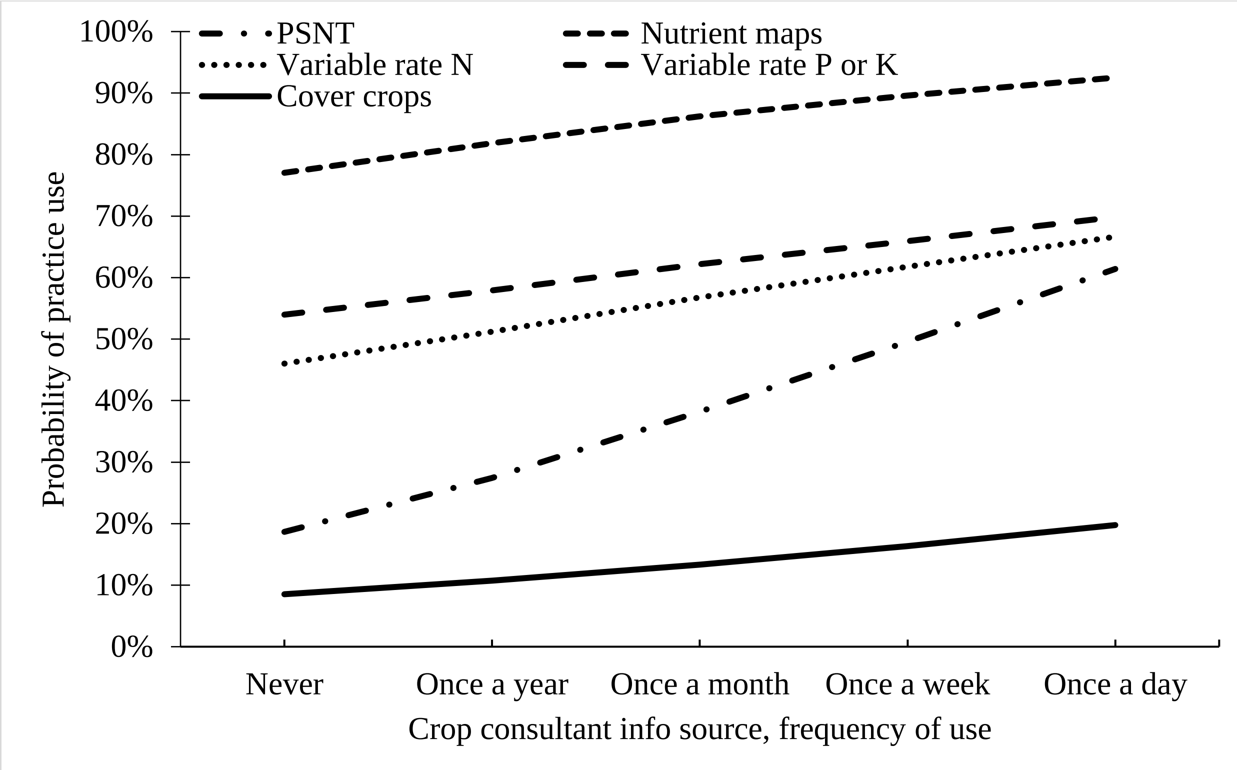

Figure 3.5. Graphical depiction of the probability of using BMPs at different frequencies of use of independent crop consultants as an information source, with all other variables at the average response level.

Knowledge

Self-reported knowledge on nutrient management and soil conservation practices was positive and significant for three of the five practices: nutrient maps, variable rate P or K and cover crops. In Figure 3.6, we can see the effect of knowledge level on practice use for all five practices, and how the slopes of the practices that are significantly influenced by knowledge are steeper than those of the other practices. We can also see the larger total effect that knowledge has on variable rate P or K (37 percent), compared to nutrient maps (25 percent) and cover crops (17 percent). These large total effects and relatively high predicted probabilities at the max, make knowledge one of the most important variables in the analysis. These results suggest that even the non-specific measure of knowledge used in this analysis is an important contributor to the use of at least some practices and should be investigated further.

The use of a non-practice specific measure of knowledge in this analysis may be the reason that the knowledge variable is not significant in all the models. If farmers associate some practices more strongly with "nutrient management and soil conservation practices" than others, then a lack of association wouldn't be surprising. Using practice-specific measures of "how-to" or "procedural" knowledge is an important next step in this line of research and would be expected to have positive and significant effects on the use of the given practice. Vitale et al. (2011) find this to be the case with conservation tillage, where understanding of conservation tillage practices had a positive and significant effect on the use of both conservation tillage and reduced tillage, and a negative and significant effect on the use of conventional tillage.

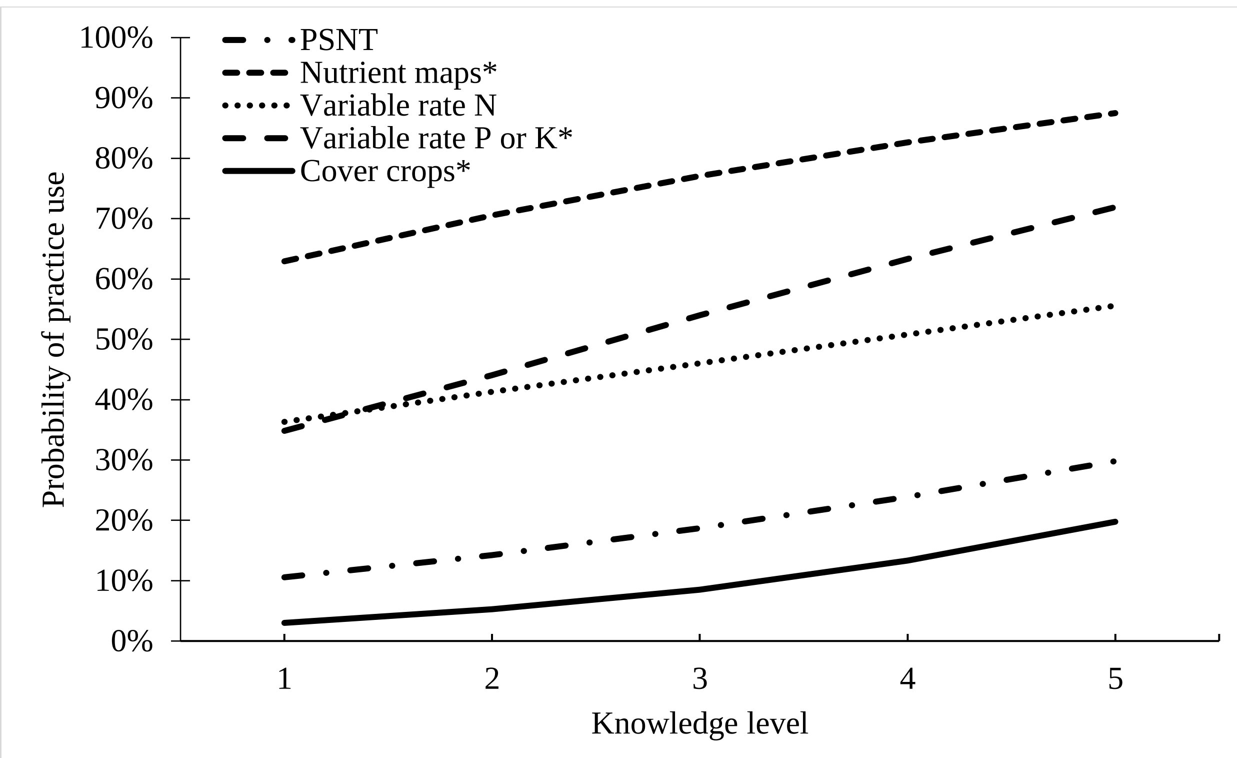

Figure 3.6. Graphical depiction of the probability of using BMPs at the five reported levels of knowledge, with all other variables at the average response level.
Note: Asterisks (*) indicates the models in which knowledge has a significant effect.

While using practice-specific measures of knowledge is a clear next step, so is better understanding what leads to knowledge creation/acquisition. Education, experience and use of and trust in specific information sources are obvious candidates as important predictors of practice knowledge. However, these may be practice specific and/or have a complex relationship due to the low levels of correlation (< 0.5) found between knowledge, education and information source use in the present data (see Table 3.20 in Appendix C). Future modeling with more specific data can investigate this further.

Corn Yield

Average corn yield is a significant positive predictor of variable rate N, and variable rate P or K, and a significant negative predictor of cover crop use (Figure 3.7). It is among the most important predictors for the use of variable rate nutrients in terms of total effect size and predicted probability at the max value, though it is of relatively minor importance for cover crop use. Corn yield is included in the model as a measure of soil quality, and as such is not a measure that has potential for encouraging practice use. There is also the potential for variable rate nutrient use to be influencing corn yield, either directly or as an indicator of general attentiveness of the operator. Future examination of this dynamic would benefit from additional data on the soil type and quality of the farm (not just the largest field) and the inclusion of data on fertilizer rate and the use of other management practices.

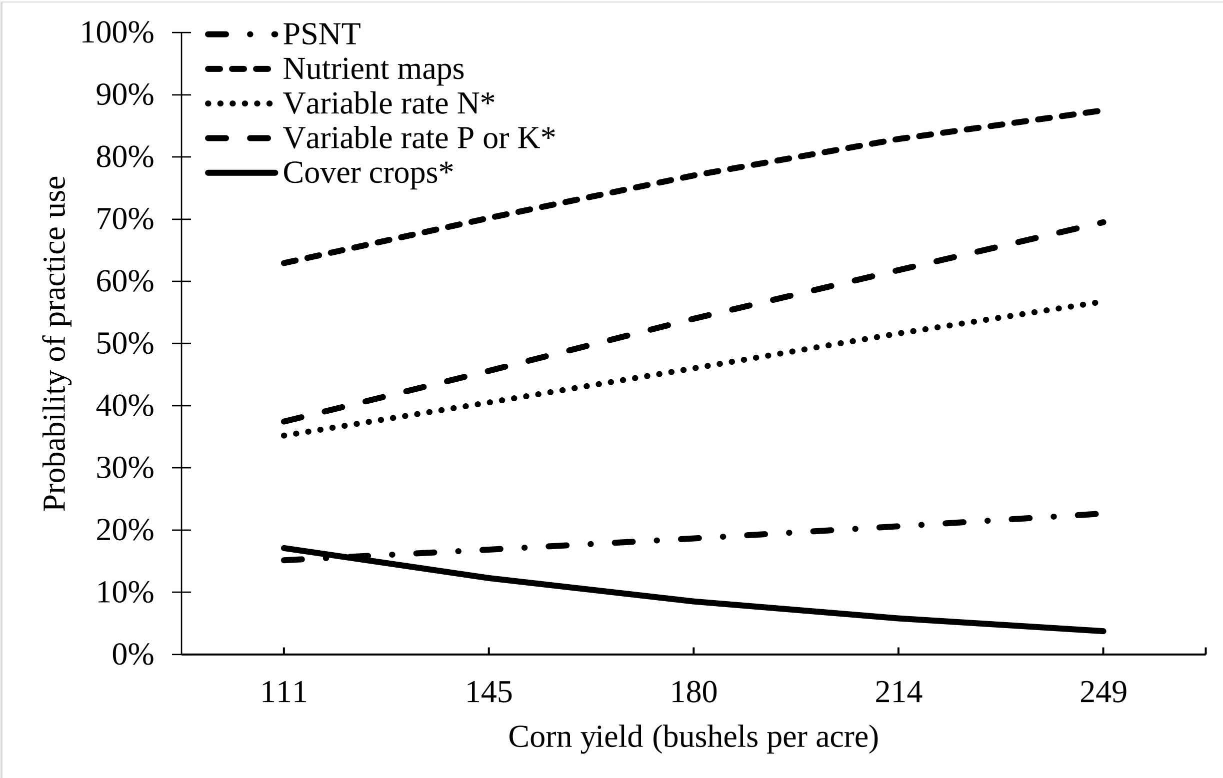

Figure 3.7. Graphical depiction of the probability of using BMPs at the mean average corn yield, and at one and two standard deviations below and above the mean.
Note: Asterisks (*) indicates the models in which corn yield has a significant effect.

Similarities Between Practices

As previously mentioned and as is clearly apparent in Table 3.9, there is remarkably little overlap in variable significance across the practice models, and especially between the practices that were expected to be the most similar. The only variables that are significant for both PSNT and nutrient map use are the use of independent crop consultants as is discussed above, and concern that agriculture contributes to water problems, which has a positive effect on both of about 6 percent. Variable rate N and variable rate P or K only have corn yield in common besides independent crop consultant use as previously discussed, though corn yield has a positive effect on both practices.

Variable rate N has more variables in common with cover crops than with variable rate P or K. Being organized as an LLC instead of a sole proprietorship and participation in a working land conservation program both increase the likelihood of both variable rate N and cover crops. The effect of working land conservation programs on the use of both practices is not surprising since these are both practices that would be supported by such programs, though it is interesting that it did not have a significant effect on PSNT use. It is possible that the reduction in personal liability of the LLC business structure encourages farmers to take more risk in the purchase of new equipment in the case of variable rate N and in the new use of cover crops, which can take time to return benefits. It is interesting that the working land programs, which are intended to help reduce the risk of practice adoption, do not appear to do so enough to remove the significant effect of being an LLC. The total effect of being an LLC is larger than that of working land program participation for variable rate N (12 percent versus 9 percent), but the reverse is true for cover crops, where the total effect of being an LLC is quite small (4 percent) while the effect of working lands programs is notably larger (14 percent).

Having a dominantly silty-loam soil texture on the largest 2016 corn field compared to a clay-loam texture had a negative effect on the use of both variable rate N and cover crops. This might also be an indication of similarity between these practices, but it could also be spurious given that the whole farm may not share that dominant soil type. More knowledge of soil properties by the researcher would be necessary to hypothesize on the reasons for the negative effect of silty-loam on variable rate N and cover crops, and the negative effect of loam on PSNT use. The fact that any of the soil texture of the largest 2016 corn field variables is significant in any of the models suggests that soil texture is a potentially relevant variable for some practices and might be worth investigating with more precise data. This could be done at the field level with detailed enough field-level data, or possibly at the farm level using remote sensing data to determine soil type and variability across a region that could be assigned to a farm.

There are a few other variables that have a significant effect on more than one practice. Other farm type and use of local extension as an information source both have a negative effect on nutrient map use but a positive effect on cover crop use. The effect of other farm type (i.e., those having more than 10 percent of their revenue generated by neither field/grain crops nor livestock) on nutrient map and cover crop use is not immediately apparent, though it could be related to the (in)compatibility of these practices with their production practices. The effect of local extension on nutrient map and cover crop use would appear to be from local extension not promoting or supporting the use of nutrient maps while promoting or supporting the use of cover crops. Lastly, concern over erosion impacts on the farm is positively significant on the use of both PSNTs and cover crops. The relation between erosion and the use of cover crops is clear, but the connection between erosion and PSNT use requires further investigation.

Finally, a few other variables are interesting in their lack of significance, since they are staple variables for this type of analysis. For example, farming experience, and cropland owned are not significant in any of the models, education level is only significant for nutrient maps, but has a negative effect on their use, and cropland area is only significant for variable rate N. Some of these variables were significant in smaller models but became insignificant when additional variables were added. Since most analysis of predictors of BMPs use many fewer variables than the present one, it is perhaps not so surprising that some common control variables are not significant.

CONCLUSION

The goal of this analysis was to look for the common drivers of BMP use across the five practices considered, and to assess the relative importance of significant drivers. The results showed that these five practices have few drivers in common, even between practices that seemed to be similar. The use of independent crop consultants was the only variable of the 53 used in the model that had a significant effect on the use of all five practices. Practice knowledge and average corn yield each had significant effects on three of the five practices. These three variables were also consistently among the most important for predicting the use of each practice when considering both the total effect size and the probability of practice use at the maximum value of each variable.

The first conclusion of these results is that there are no “families” or “types” or BMPs that share a common set of predictors. Without additional empirical testing we should not assume that any or all BMPs are meaningfully similar, and we should treat them separately in future analyses. This is goes against Reimer et al.’s (2014:58A) suggestion that “one approach might be to compare the significant drivers (or overall predictive power) of multivariate adoption models across categories of practices that share certain characteristics.” There are many dimensions in which practices could share characteristics, and the present analysis shows that these similarities may not be easily apparent—I find variable rate N and cover crops to be the most similar (and this is a relative measure as they only share three variables with the same sign in addition to independent crop consultant use), perhaps due to similarities in amount of cost and risk involved, rather than the pairs that seemed most similar based on the purpose of the practice, or pairs suggested by nutrient or practice timing. At the very least the formation of such categories should come with empirical support.

This conclusion is supported by the lack of consistent variable effects in the meta-analyses of BMP adoption studies (Baumgart-Getz et al. 2012; Prokopy et al. 2008; Wauters and Mathijs 2014) that consider all types of BMPs together. Prokopy et al. (2008) also include analyses broken down by general practice categories such as “soil management,” “nutrient management,” and “pest management,” which shows some potential trends in variables effects, but nearly all are not significant more than they are significant, suggesting that a fruitful avenue of future research could be meta-analyses of specific practices.

The differences in significant predictors between the five practices could be due to differences between nutrients and timing of practice, as well as type of practice. For example, PSNTs and variable rate N are both nitrogen specific practices that would be used during the growing season, though they are different types of practices (decision aid vs application technology). Nutrient maps are based on soil tests that are done in the fall and would typically be used to inform P application placement, which is also done in the fall, though these practices are also of different types (decision aid vs application technology). The five practices considered in this analysis each have a unique combination of these three dimensions (practice type, nutrient, and season) that helps explain the lack of overlap in significant predictors.

The second conclusion is that the larger effect sizes of knowledge and independent crop consultants on the probability of practice use, especially compared to the effect sizes of the significant attitudes and value variables and environmental awareness variables, suggests that the adoption-diffusion model may provide more predictive power in predicting farmers’ use of BMPs compared to the social-psych theories. This is not to say that attitudes, values and awareness are not important, but this analysis finds them to be substantively less important in a relative sense than knowledge, information sources and corn yield. This is at least partly due to the already quite high levels of environmental attitudes, and awareness reported by farmers in the sample, which leaves little room for these variables to increase the probability of practice use beyond the current level, all else being equal. In contrast, the low use of independent crop consultants and modest average levels of knowledge reported provides greater potential for increasing practice use by increasing knowledge, and the use of independent crop consultants. This suggests that while analyses that focus on the role of attitudes and environmental awareness in BMP use are not incorrect, they may be missing important predictive variables from their models such as information sources, knowledge, and biophysical context.

The adoption-diffusion model depends heavily on the transmission of information about innovations, and from this analysis we can see that it matters from whom farmers are receiving information. The large positive effects of both knowledge and the use of independent crop consultants suggests that there may be a relationship between the use of independent crop consultants and farmers' knowledge of the practices, but also that some practices may be more dependent on knowledge than others. In the latter case it is possible that independent crop consultants are in some way directly facilitating the implementation of the practice, possibly why they are so important for the use of PSNTs. The relationships between information sources, practice knowledge, and practice use, warrant greater and more nuanced investigation to see how these relationships are similar or different across BMPs.

While the present analysis highlights the important differences between the predictors of the use of different practices, and indicates the value of considering them individually, this in no way means that multiple practices should not be considered in combination. The use of multiple BMPs simultaneously has important environmental implications (Holmes et al. 2016; Lam et al. 2011; Liu et al. 2016; Sowa et al. 2016), and little social research has been done on how the use of one BMP may lead to, facilitate or enhance the use of another (Weber and McCann (2015) are a notable example). For example, there is no reason for a farmer to use PSNTs if they do not intend to sidedress any of their nitrogen, but they very well might sidesdress nitrogen without using PSNTs. Arguably the use of both practices together would be the most effective at applying the optimal amount of nitrogen to the crop. It is these types of combined practice use that would be very interesting and useful to pursue.

Future research could consider: 1) alternative measures of BMP use that better account for the spatial and temporal patterns of use, 2) practice specific measures of knowledge, 3) predictors of knowledge creation for different practices, 4) interaction effects of predictors on BMP use, 5) effects of the use of one BMP on another, and 6) the relative fit and explanatory power of the adoption-diffusion model compared to social-psych theories, using the same dataset and multiple BMPs—is the use of some practices better predicted by one approach vs the other?

APPENDICES

APPENDIX A: Data Cleaning and Variable Calculation

Cleaning

```
if f3=1924 then delete; *remarkably long time farming;
if state='NA' then delete; *one respondent removed all identifying survey info;

*a4 outliers;
if a4_corn_low=4030 then delete;
if a4_corn_avg=4355 then delete;
if a4_corn_high=4482 then delete;
```

Some questions were coded with missing values as zero. These variables were set to missing when all parts of the question were zero.

```
**recoding "other" write in responses so not double counted when added;
***decided to put contract livestock into a7e--important part being livestock on the farm;
if a7f_desc = '32 acres alfalfa' then a7a = 1 and a7f = 0;
if a7f_desc = 'Alfalfa and Timothy Hay' then a7a = 1 and a7f = 0;
if a7f_desc = 'Beef Cows 18 HD' then a7e = 1 and a7f = 0;
if a7f_desc = 'Christmas Trees' then a7c = 1 and a7f = 0;
if a7f_desc = 'Contract Pullets' then a7e = 1 and a7f = 0;
if a7f_desc = 'Custom dairy heifer raising' then a7e = 1 and a7f = 0;
if a7f_desc = 'Fish' then a7e = 1 and a7f = 0;
if a7f_desc = 'Hay' then a7a = 1 and a7f = 0;
if a7f_desc = 'Hay Alfalfa/ Grass' then a7a = 1 and a7f = 0;
if a7f_desc = 'Haylage (73 Acres Alfafa)' then a7a = 1 and a7f = 0;
if a7f_desc = 'I custom raise hiefens for another person' then a7 = 1 and a7f = 0;
if a7f_desc = 'Layers' then a7e = 1 and a7f = 0;
if a7f_desc = 'Organic Spelt' then a7a = 1 and a7f = 0;
if a7f_desc = 'Processing Pumpkins' then a7b = 1 and a7f = 0;
if a7f_desc = 'Seed Corn' then a7a = 1 and a7f = 0;
if a7f_desc = 'Seed Production' then a7a = 1 and a7f = 0;
if a7f_desc = 'Seed corn' then a7a = 1 and a7f = 0;
if a7f_desc = 'Tobacco' then a7a = 1 and a7f = 0;
if a7f_desc = 'alfalfa' then a7a = 1 and a7f = 0;
if a7f_desc = 'alfalfa hay' then a7a = 1 and a7f = 0;
if a7f_desc = 'alfalfa sales' then a7a = 1 and a7f = 0;
if a7f_desc = 'contract canning crop' then a7b = 1 and a7f = 0;
if a7f_desc = 'corn & soybean' then a7a = 1 and a7f = 0;
if a7f_desc = 'corn & soybeans' then a7a = 1 and a7f = 0;
if a7f_desc = 'corn and beans' then a7a = 1 and a7f = 0;
if a7f_desc = 'corn+soybeans' then a7a = 1 and a7f = 0;
if a7f_desc = 'corn,beans,wheat' then a7a = 1 and a7f = 0;
if a7f_desc = 'cull cows and calves' then a7e = 1 and a7f = 0;
if a7f_desc = 'eggs' then a7e = 1 and a7f = 0;
if a7f_desc = 'greenhouse bedding' then a7c = 1 and a7f = 0;
```

```
if a7f_desc = 'hal-alf' then a7a = 1 and a7f = 0; *assuming should be 'hay-alf';
if a7f_desc = 'hay' then a7a = 1 and a7f = 0;
if a7f_desc = 'hay + straw' then a7a = 1 and a7f = 0;
if a7f_desc = 'hay&straw' then a7a = 1 and a7f = 0;
if a7f_desc = 'popcorn' then a7a = 1 and a7f = 0;
if a7f_desc = 'rent hay' then a7a = 1;
if a7f_desc = 'seed corn' then a7a = 1 and a7f = 0;
if a7f_desc = 'seed wheat' then a7a = 1 and a7f = 0;
if a7f_desc = 'soybeans' then a7a = 1 and a7f = 0;
if a7f_desc = 'soybeans=corn' then a7a = 1 and a7f = 0;
if a7f_desc = 'straw bales sales' then a7a = 1 and a7f = 0;
if a7f_desc = 'timothy hay clover hay' then a7a = 1 and a7f = 0;
if a7f_desc = 'tobacco' then a7a = 1 and a7f = 0;
if a7f_desc = 'turkeys' then a7e = 1 and a7f = 0;

*a10--scale 1-6;
**recodeing 6 responses that fit in listed categories;
***only a few clearly seem to be in a listed category;
if a10_desc = 'Owner' then a10=1;
if a10_desc = 'just me' then a10=1;
```

Outcome variables

PSNT

```
if c1a in (4 5) then c1a_use2=1; else c1a_use2=0;
if c1a=. then c1a_use2=.;
```

Nutrient maps

```
if c1d in (4 5) then c1d_use2=1; else c1d_use2=0;
if c1d=. then c1d_use2=.;
```

Variable rate N

```
if c1b in (4 5) then c1b_use2=1; else c1b_use2=0;
if c1b=. then c1b_use2=.;
```

Variable rate P or K

```
if c1c in (4 5) then c1c_use2=1; else c1c_use2=0;
if c1c=. then c1c_use2=.;
```

Cover crops

```
if c1k in (4 5) then c1k_use2=1; else c1k_use2=0;
if c1k=. then c1k_use2=.;
```

Individual Characteristics

Years farming

```
yrsfrm=2017-f3;
```

Education level

```
f4;
```

College ag courses

```
f5_rc=f5;
```

```
if f5=. then f5_rc=0;
if f4=. then f5_rc=.;
if f5=0 and f4=. then f5_rc=0; *one respondent didn't answer f4 but did answer f5 so
        putting that response back in;
```
Knowledge
```
c2;
```
Value of sales
```
f9;
```
Household income
```
f10;
```
Ag. income
```
f11;
```

Farm Characteristics—Physical

Cropland area
```
crop2size=(a3_corn+a3_soy+a3_wheat+a3_other)/1000;
```
Corn-soy ratio
```
corn_soy=a3_corn/a3_soy;
```
Animal farm
```
if a7d=1 then animal=1; else animal=0;
if a7e=1 then animal=1;
if a7d=. then animal=.;
if a7e=. then animal=.;
```
Grain farm
```
a7a;
```
Other farm type
```
if a7b=1 then frm_oth=1; else frm_oth=0;
if a7c=1 then frm_oth=1;
if a7f=1 then frm_oth=1;
if a7b=. then frm_oth=.;
if a7c=. then frm_oth=.;
if a7f=. then frm_oth=.;
```
Field slope
```
b6;
```
Soy yield
```
a4_soy_avg; *renamed soy_avg;
```
Corn yield
```
a4_corn_avg; *renamed corn_avg;
```
Loam
```
if b7=3 then loam=1; else loam=0;
if b7=. then loam=.;
```
Clay
```
if b7=4 then clay=1; else clay=0;
if b7=. then clay=.;
```
Clay-loam
```
if b7=5 then clay_loam=1; else clay_loam=0;
```

```
    if b7=. then clay_loam=.;
Silty-loam
    if b7=6 then silty_loam=1; else silty_loam=0;
    if b7=. then silty_loam=.;
Sandy-loam
    if b7=7 then sandy_loam=1; else sandy_loam=0;
    if b7=. then sandy_loam=.;
Other soil type
    if b7=1 then sand=1; else sand=0;
    if b7=. then sand=.;
    if b7=2 then silt=1; else silt=0;
    if b7=. then silt=.;
    if b7=8 then soil_other=1; else soil_other=0;
    if b7=. then soil_other=.;
    oth_soil=soil_other+sand+silt;
```

Farm Characteristics—Social

```
Cropland owned
    crpown_pc=(a2_crop_own/(a2_crop_own+a2_crop_in))*100;
Days worked off farm
    f8;
Number of employees
    employ=a8a+a8b;
Sole proprietorship
    if a10=1 then sole_prop=1; else sole_prop=0;
    if a10=. then sole_prop=.;
Partnership
    if a10=2 then partnshp=1; else partnshp=0;
    if a10=. then partnshp=.;
LLC
    if a10=3 then llc=1; else llc=0;
    if a10=. then llc=.;
S-corporation
    if a10=4 then s_corp=1; else s_corp=0;
    if a10=. then s_corp=.;
C-corporation
    if a10=5 then c_corp=1; else c_corp=0;
    if a10=. then c_corp=.;
Other business structure
    if a10=6 then other_bs=1; else other_bs=0;
    if a10=. then other_bs=.;
Conservation program participation
    a5;
Working land program participation
    if a5a>0 then wrkldprg=1; else wrkldprg=0;
    if a5a=. then wrkldprg=.;
```

Information

Info index

    info_tot=d1cedu+d1tedu+d1ccamp+d1tcam+d1cchem+d1tchem+d1cseed+d1tseed+d1cin
        d+d1tind+d1cfam+d1tfam+d1cmag+d1tmag+d1cweb+d1tweb+d1cass+d1tass;

Associations info source

    d1cass;

Chemical dealers info source

    d1cchem;

Seed dealers info source

    d1cseed;

Crop consultants info source

    d1cind;

Other farmers info source

    d1cfam;

Campus extension info source

    d1ccamp;

Local extension info source

    d1cedu;

Attitudes and Values

Look after environment

    d2envi;

Hunting and fishing environment

    d2hunt;

Economic attitude

    ECON_AT BY d2inco d2weal d2prof;

Income

    d2inco;

Wealth

    d2weal;

Profit

    d2prof;

Passing on good land

    d2land;

Farming tradition

    d2trad;

Passing on farm

    f7;

Debt aversion

    d2debt;

Crop insurance use

    crop_ins=(a6/(a3_corn+a3_soy))*100;
    if crop_ins>100 then crop_ins=100;

*274 cases had crop insurance use over 100% suggesting they didn't read the question correctly and put all crop insurance acres, rather than just those for corn and soy, so I capped the values at 100 if they were larger than that;

Environmental Awareness

Concern ag. contributes to water problems
WATERCON BY e1ccont e1calga e1chypo e1csoil;
e1calga WITH e1chypo;
Groundwater contribution
e1ccont;
Algal bloom contribution
e1calga;
Hypoxia contribution
e1chypo;
Erosion contribution
e1csoil;
Erosion impacts
e1fsoil;
Pest resistances impacts
e1fresi;
Extreme weather impacts
e1fextr;
Warming impacts
e1fwarm;

APPENDIX B: Modeling Decisions

Estimator Choice

The choice of estimator was driven by the binary nature of the outcome variables of interest. In addition, the measures of the two latent exogenous variables are categorical with five response options. I had two options for estimators: maximum likelihood and categorical least squares.

Maximum likelihood (ML)—often with robust standard errors (MLR)—is a full-information estimator and probably the most common estimator in SEM. ML(R) can be used with binary or categorical outcomes as the robustness correction adjusts for the non-normality of the categorical variable to make it compatible with the ML assumptions that apply to continuous variables (Li 2016; Rhemtulla, Brosseau-Liard, and Savalei 2012). This estimator uses the observed variable with a probit or logit link function to estimate the relationships between the specified variables (Rhemtulla et al. 2012).

The alternative estimator is some form of limited information, categorical least squares (LS) estimator (usually weighted) that assumes a continuous latent variable underlying the categorical variable—threshold values are calculated that relate the values of the latent variable to the categories in the observed variable, and the latent variable is used in the rest of the model estimates (Li 2016; Rhemtulla et al. 2012). These estimators can also have robustness corrections, but these corrections are to adjust for using limited instead of full information rather than for data being non-normal as it is for ML(R) (Li 2016; Rhemtulla et al. 2012).

In this analysis I use a robust, diagonally weighted least squares, means and variance adjusted estimator (specifically the WLSMV estimator in Mplus8). There are several reasons for using a limited information, categorical LS estimator, even though it is less common.

1. More recent weighted LS estimators perform better than older versions (Beauducel and Herzberg 2006; Li 2016).

2. Simulation studies have found categorical LS estimators to perform as well or better than ML estimators under a range of model conditions (Bandalos 2014; Beauducel and Herzberg 2006; Li 2016; Rhemtulla et al. 2012).

3. Weighted LS estimators, by being limited information, are less computationally intensive than ML(R), especially with large models (Muthén and Muthén 2017).

4. Though LS estimators are less efficient by virtue of being limited information, this has not been found to a problem in practice (Rhemtulla et al. 2012).

5. By using the underlying latent variables weighted LS estimators have additional benefits when computing more complex models, like models with categorical mediators, such as allowing for the estimation of indirect and total effects, and standardized effects, which can't be done with ML(R), allowing for more comparisons between the results of different models (Muthén and Muthén 2017).

Simulation studies of confirmatory factor analysis (CFA) models have found diagonally weighted LS to perform better than ML (Beauducel and Herzberg 2006), and MLR (Bandalos 2014; Li 2016), especially for binary outcomes (Beauducel and Herzberg 2006), as well as with model misspecification, as long as both sample size was sufficiently large and the data was not excessively asymmetric (Bandalos 2014; Li 2016). Bandalos (2014) and Li (2016) also consider the effects of different estimators on structural coefficients between latent variables with categorical measures, and they find that diagonally weighted LS performs at least as well as ML or MLR in most conditions. With a larger number of response categories, the differences between estimators diminished (Li 2016; Rhemtulla et al. 2012).

While none of these studies examine the effects of estimators on estimates between two observed variables (I was not able to find any studies that did this), these findings are still relevant for my observed outcome variable, at least for the relationship between it and my latent exogenous variables, since these are very similar to CFA dynamics. They are also relevant for the estimation of my exogenous latent variables themselves.

Given my large sample size[23] and not excessively skewed endogenous variables[24] (see Table 3.15) there may not be a critical need for the WLSMV estimator, but it is conceptually the more appropriate choice and the simulation studies do not suggest that I face conditions where it would perform poorly.

Table 3.15. Skewness and kurtosis for endogenous variables.

	Number of response categories	N	Skewness	Kurtosis
PSNT	2	814	1.653	0.734
Nutrient maps	2	814	-1.788	1.201
Variable rate N	2	814	0.995	-1.013
Variable rate P or K	2	814	-0.596	-1.649
Cover crops	2	814	0.607	-1.636
Income	5	813	-0.226	-0.191
Wealth	5	812	-0.886	0.911
Profit	5	814	-0.844	0.357
Groundwater contribution	5	802	-0.454	-0.321
Algal bloom contribution	5	803	-0.361	-0.428
Hypoxia contribution	5	799	-0.246	-0.765
Erosion contribution	5	805	-0.886	0.726

Calculating Probabilities Using the WLSMV Estimator

The WLSMV estimator uses a probit link function and thus estimates probit coefficients. However, if the outcome is considered to be the underlying latent variable then the coefficient can be treated as a linear coefficient—this is relevant for the discussion of standardized results below.

[23] Sample sizes in the simulation studies ranged from 100 to 1,000, putting mine in the 'large' category.
[24] In considering asymmetry in my endogenous observed variables, my variables fall in the low nonnormality category used by Bandalos (2014) by having skew smaller than ±2.4 and kurtosis less than ±3.8.

Probabilities of y =1 can be calculated from the intercept[25], probit coefficients, and specified values for each variable using the following equation where *F* is the standard normal distribution function (Muthén, Muthén, and Asparouhov 2016:222-223).

$$P(u_i = 1 \mid x_i) = F(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i)$$

Using the above equation, a *z* score is calculated, then a left sided *z* table is used to determine the probability of *F(z)*—this is equal to the area under the curve to the left of the *z* value. Probabilities can be calculated from probit coefficients the same way whether the observed variable or the underlying latent variable is used *if* the residual variance is fixed at 1, which is typical for probit regression (Muthén, Muthén, and Asparouhov 2016:224-226). In cases where there is more than one categorical dependent variable, such as a mediation model, then the residual variance must be included in the probability calculation:

$$P(u_i = 1 \mid x_i) = F[(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i)/\sqrt{residual\ variance}]$$

If there is more than one mediator the formula is more complex (see Nguyen et al. 2016).

Assessing the Nestedness of the Data

Besides the model decisions based on the binary nature of the outcome variable, the potential for nestedness in the data drove many modeling decisions. When data is nested or clustered the OLS assumption of independence among observations is violated, and analyses that do not treat the data as clustered will tend to underestimate the standard errors, resulting in higher rates of type 1 errors (Bell and Jones 2015). Since the survey data used was collected in four states there is the potential for there to be significant clustering of respondents by state—that is, respondents from a given state may be more like each other than they are like farmers

[25] The intercept for a binary outcome variable is the negative threshold value that Mplus reports.

from the other states. Examining the data for evidence of clustering is the key next step in determining how the model should be specified.

The first step of assessing clustering is to run a one-way ANOVA model that divides the variance in the variable between levels, and to calculate the intraclass correlation coefficient (ICC), which is the between variance divided by the total variance, effectively providing the portion/percent of the variance that exists at the between level/level 2 (Snijders and Bosker 2012). Table 3.15 presents the ICCs and design effects for the full sample and the final sample using the WLSMV estimator with the variable specified as categorical, and for the full sample using MLR with the variable specified as continuous. When the variable is defined as categorical, regardless of what estimator is used, Mplus does not allow variances on the within level, thus making the between variances reported from these models suspect (none are significant). Therefore, I also present the results using MLR with the variable specified as continuous, to include the within level variance. The null model could not be computed for PSNT and variable rate N when using MLR for the final sample, due to the estimated between covariance matric not being positive definite.

Design effect[26] is included because there is no established threshold rule for ICC size, and even small ICCs can indicate important clustering with large cluster size (Snijders and Bosker 2012). The design effect, as a function of average cluster size and ICC, provides a way to evaluate the significance of the ICC based on cluster size (Lai and Kwok 2015). Lai and Kwok (2015) find that the 'rule of thumb of being able to ignore clustering if the design effect is less than two is reasonable under certain conditions[27]. All but two of the design effects in Table 3.15

[26] Design effect = 1 + (average cluster size – 1) x ICC (Lai and Kwok 2015)
[27] When "(a) the cluster size … is at least 10, (b) the relations between level 1 predictors and the outcome are constant (i.e., no random coefficients are present), and (c) the predictors are group-mean centered" (Lai and Kwok 2015:434)

are substantially larger than 2, suggesting that there is important clustering in the data, at least for nutrient maps, variable rate P or K, and cover crops.

Table 3.16. ICC comparison by sample and estimator.

	PSNT	Nutrient maps	Variable rate N	Variable rate P or K	Cover crops
Final sample					
sample size	814	814	814	814	814
average cluster size	203.5	203.5	203.5	203.5	203.5
Full sample					
sample size	2007	2113	2061	2117	2098
average cluster size	501.8	528.3	515.3	529.3	524.5
WLSMV final sample					
ICC	0.000	0.039	0.000	0.025	0.054
Design Effect	1.000	8.898	1.000	6.0625	11.935
WLSMV full sample					
ICC	0.009	0.008	0.007	0.011	0.074
Design Effect	5.507	5.218	4.600	6.811	39.739

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The conclusions from Table 3.16 are that there appears to be significant clustering for three of the five practices. For PSNT and variable rate N, the clustering appears to be less significant: the ICCs are zero for the final sample resulting in design effects of one, and these are the only two practices that do not have even marginally significant between level variances in the MLR model. This conclusion is also supported by considering the graphs of practice use by state (see Figure 3.8), which shows significant state-level differences as tested by logistic regression[28] (see Table 3.17) for nutrient maps, variable rate P or K, and cover crops, but not PSNT and variable rate N.

[28] Logistic regression used since ANOVA is inappropriate for binary variables.

Table 3.17. Wald Chi-square for joint test of logistic regression for state differences in practice use using final sample (n=814).

	Degrees of Freedom	PSNT	Nutrient maps	Variable rate N	Variable rate P or K	Cover crops
State	3	2.474	17.274***	3.733	16.235**	33.692***

t p < 0.1, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001

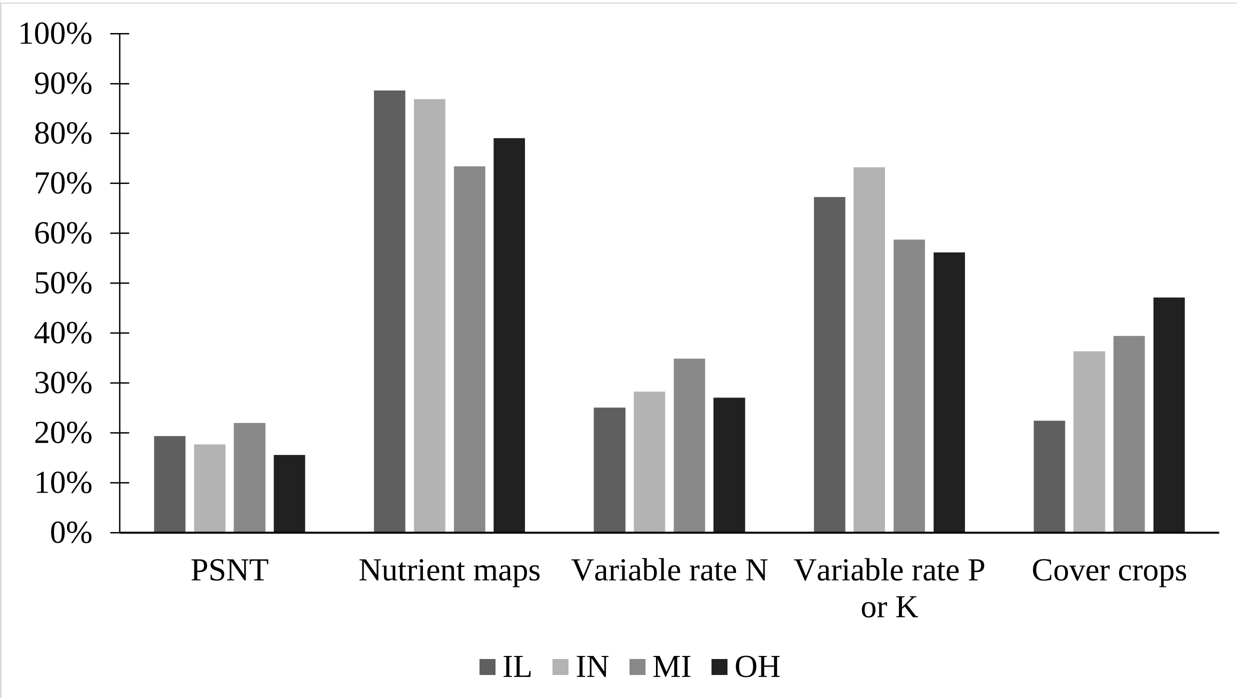

Figure 3.8. Practice use by state for final sample.

Snijders and Bosker (2012) also suggest checking for group-by-covariate interaction effects, as clustering can manifest in relation to covariates. The presence of significant interaction terms for all five practices across a sample of covariates (using logistic regression given the inappropriateness of ANOVA for binary variables and the challenges of ANCOVA with binary outcomes) suggests that there are important group differences in the presence of covariates for all of the practices (see Table 3.18). Given the presence of group-by-covariate interactions and design effects >2 for the full sample, clustering is considered to be an important consideration for all five practices considered. This assumption also facilitates comparisons across models, as it justifies using the same model specification.

However, given the small number of clusters (there are only four) specifying a multilevel model is problematic and can produce downwardly biased standard errors for both coefficients and variances, though the coefficients and variances themselves have been found to be unbiased (Lai and Kwok 2015; Maas and Hox 2005). Use of the COMPLEX analysis type in Mplus8 should avoid this problem by adjusting the standard errors and chi-square test of model fit for clustering but without modeling the clustering as a multilevel model would (Muthén and Muthén 2017).

Table 3.18. Wald Chi-square for joint test of logistic regression for group-by-covariate interactions for select variables using final sample (n=814).

	Degrees of Freedom	PSNT	Nutrient maps	Variable rate N	Variable rate P or K	Cover crops
State	3	1.255	12.173**	0.632	1.013	14.546**
Average corn yield	1	8.182**	31.273***	15.908***	42.957***	0.050
Average corn yield x State	3	1.624	12.358**	1.640	1.376	12.863**
State	3	1.172	3.637	1.057	1.141	17.190***
Average soy yield	1	4.920*	25.969***	11.021***	36.116***	0.471
Average soy yield x State	3	1.598	3.660	2.075	1.680	17.629***
State	3	2.248	6.059	5.912	6.135	26.578***
Corn-soy ratio	1	0.006	4.430*	1.625	0.641	1.184
Corn-soy ratio x State	3	2.744	5.357	3.602	8.803*	2.639
State	3	3.628	15.836**	3.581	9.314*	16.841***
Percent cropland owned	1	4.672*	15.462***	3.702^{t}	7.429**	3.664^{t}
Percent cropland owned x State	3	2.634	11.490**	2.718	1.372	4.143
State	3	17.795***	4.687	15.116**	1.159	1.426
Importance of looking after environment	1	20.674***	3.592^{t}	2.979^{t}	5.960*	23.756***
Importance of looking after environment x State	3	19.186***	4.006	14.255**	2.527	2.031
State	3	8.250*	3.869	7.636^{t}	2.405	6.976^{t}
Knowledge of practices	1	26.530***	33.181***	24.247***	37.176***	28.406***
Knowledge of practices x State	3	9.396*	1.901	8.520*	0.677	2.551

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX C: Additional Results

A Note on R^2 with Binary Outcomes

The R-square values produced for the models are a bit different than the R-square for a regression model with a continuous variables, because, for binary outcomes, the R-square is based on the liner underlying latent variable and does not "involve a freely estimated residual variance" (Muthén et al. 2016:227).

> The proportion of variance explained is determined by the slope parameter alone which also describes the strength of relationship between *x* and *u*. Viewed from a probability curve perspective it is the steepness of a curve…that summarizes the situation: the flatter the curve, the lower the value of the slope, the lower the R^2, and the higher the fixed residual variance relative to the total *u** variance. (Muthén et al. 2016:227)

For a binary outcome $R^2 = \gamma^2 V(x) / (\gamma^2 V(x) + c)$

The variance is $V(u^*) = \gamma^2 V(x) + c$ where c =1 for probit regression

Additional Descriptives

Table 3.19. Tolerance and variance inflation factor (VIF) for exogenous analysis variables (n=814).

	Tolerance	VIF
Individual Characteristics		
Years farming	0.785	1.274
Education level	0.580	1.724
College ag courses	0.594	1.685
Knowledge	0.770	1.299
Value of sales	0.422	2.372
Household income	0.792	1.262
Ag. income	0.607	1.647
Farm Characteristics—Physical		
Cropland area	0.399	2.509
Corn-soy ratio	0.873	1.146
Animal farm	0.827	1.209
Grain farm	0.635	1.576
Other farm type	0.641	1.561
Field slope	0.893	1.120

Table 3.19. (cont'd).

Soy yield	0.514	1.944
Corn yield	0.491	2.035
Loam	0.856	1.169
Clay	0.851	1.176
Silty-loam	0.787	1.270
Sandy-loam	0.824	1.213
Other soil type	0.858	1.166
Farm Characteristics—Social		
Cropland owned	0.842	1.188
Days worked off farm	0.556	1.798
Number of employees	0.711	1.406
Partnership	0.823	1.215
LLC	0.788	1.270
S-corporation	0.882	1.134
C-corporation	0.823	1.215
Other business structure	0.939	1.065
Conservation program participation	0.681	1.468
Working land program participation	0.671	1.491
Information		
Info index	0.362	2.765
Associations info source	0.689	1.451
Chemical dealers info source	0.522	1.915
Seed dealers info source	0.526	1.902
Crop consultants info source	0.757	1.320
Other farmers info source	0.668	1.497
Campus extension info source	0.556	1.798
Local extension info source	0.573	1.746
Attitudes and Values		
Look after environment	0.695	1.439
Hunting and fishing environment	0.785	1.274
Passing on good land	0.786	1.272
Farming tradition	0.673	1.487
Passing on farm	0.713	1.402
Debt aversion	0.856	1.169
Crop insurance use	0.858	1.166
Environmental Awareness		
Erosion impacts	0.577	1.734
Pest resistances impacts	0.600	1.667
Extreme weather impacts	0.488	2.051
Warming impacts	0.488	2.050

Table 3.20. Select Pearson correlation coefficients for exogenous variables where correlation coefficient is < -0.5 or > 0.5 (n = 814).

	Ed. level	Value of sales	Ag. income	Grain farm	Soy yield	Conservation program participation	Chemical dealers info source	Campus extension info source	Erosion impacts	Extreme weather impacts
College ag courses	0.580***									
Cropland area		0.645***								
Other farm type				-0.518***						
Corn yield					0.651***					
Days worked off farm			-0.553***							
Working land program participation						0.507***				
Seed dealers info source							0.621***			
Local extension info source								0.584***		
Pest resistances impacts									0.568***	
Warming impacts										0.681***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Measurement Model Results

Table 3.21 Average and range of measurement model results across the five practice analyses.

	Probit		Standardized		R-square	
	Average coefficient (min - max)	Average standard error (min - max)	Average coefficient (min - max)	Average standard error (min - max)	Average coefficient (min - max)	Average standard error (min - max)
Economic attitude						
Income	1	0	0.8178	0.0084	0.669	0.014
	(1.000 - 1.000)	(0.000 - 0.000)	(0.812 - 0.822)	(0.008 - 0.009)	(0.659 - 0.676)	(0.012 - 0.014)
Wealth	0.6988	0.0436	0.7044	0.015	0.496	0.021
	(0.681 - 0.724)	(0.042 - 0.045)	(0.701 - 0.709)	(0.015 - 0.015)	(0.491 - 0.503)	(0.021 - 0.021)
Profit	0.627	0.079	0.665	0.037	0.442	0.049
	(0.613 - 0.648)	(0.077 - 0.080)	(0.663 - 0.669)	(0.036 - 0.037)	(0.439 - 0.448)	(0.048 - 0.049)
Concern ag. contributes to water problems						
Groundwater contribution	1.000	0.000	0.918	0.017	0.843	0.031
	(1.000 - 1.000)	(0.000 - 0.000)	(0.917 - 0.919)	(0.016 - 0.017)	(0.841 - 0.844)	(0.030 - 0.032)
Algal bloom contribution	0.511	0.081	0.763	0.015	0.583	0.023
	(0.508 - 0.514)	(0.077 - 0.082)	(0.763 - 0.764)	(0.014 - 0.015)	(0.582 - 0.583)	(0.022 - 0.023)
	0.394	0.048	0.673	0.007	0.454	0.009
Hypoxia contribution	(0.392 - 0.395)	(0.046 - 0.048)	(0.673 - 0.674)	(0.007 - 0.007)	(0.453 - 0.455)	(0.009 - 0.010)
Erosion contribution	0.401	0.056	0.680	0.016	0.462	0.022
	(0.399 - 0.403)	(0.053 - 0.057)	(0.679 - 0.681)	(0.016 - 0.016)	(0.461 - 0.463)	(0.022 - 0.022)

Note: All factors are significant at < 0.001

Full Probit Regression Results

Table 3.22. Probit regression coefficients and standard errors for PSNT and nutrient maps (n=814).

	PSNT	Nutrient maps
	Estimate (S.E.)	Estimate (S.E.)
Individual Characteristics		
Years farming	0.004 (0.005)	-0.001 (0.007)
Education level	-0.086 (0.112)	-0.084 (0.016)***
College ag courses	0.125 (0.070)^{t}	0.271 (0.141)^{t}
Knowledge	0.178 (0.222)	0.204 (0.097)*
Value of sales	-0.065 (0.128)	0.149 (0.131)
Household income	0.083 (0.054)	0.060 (0.031)*
Ag. income	0.039 (0.049)	0.008 (0.034)
Farm Characteristics—Physical		
Cropland area	0.041 (0.083)	-0.097 (0.192)
Corn-soy ratio	0.050 (0.047)	0.021 (0.052)
Animal farm	-0.114 (0.306)	-0.038 (0.145)
Grain farm	-0.197 (0.437)	-0.093 (0.559)
Other farm type	-0.458 (0.285)	-0.671 (0.298)*
Field slope	-0.165 (0.127)	0.050 (0.190)
Soy yield	0.000 (0.008)	0.010 (0.006)
Corn yield	0.002 (0.002)	0.006 (0.008)
Loam	-0.558 (0.149)***	0.265 (0.280)
Clay	0.079 (0.100)	0.153 (0.124)
Silty-loam	-0.319 (0.216)	-0.026 (0.126)
Sandy-loam	0.101 (0.272)	0.135 (0.232)
Other soil type	-0.120 (0.256)	0.529 (0.418)
Farm Characteristics—Social		
Cropland owned	-0.002 (0.002)	-0.003 (0.005)
Days worked off farm	0.013 (0.025)	0.015 (0.068)
Number of employees	0.005 (0.026)	0.028 (0.109)
Partnership	0.31 (0.121)*	0.206 (0.374)
LLC	-0.025 (0.077)	0.08 (0.0970)
S-corporation	-0.126 (0.465)	-0.109 (0.378)
C-corporation	0.001 (0.318)	-0.035 (0.480)
Other business structure	0.987 (0.584)^{t}	0.127 (1.008)
Conservation program participation	0.053 (0.235)	0.277 (0.192)
Working land program participation	0.290 (0.201)	0.056 (0.194)

Table 3.22. (cont'd).

<u>Information</u>		
Info index	-0.005 (0.004)	0.021 (0.025)
Associations info source	0.161 (0.176)	0.064 (0.066)
Chemical dealers info source	0.143 (0.155)	0.171 (0.232)
Seed dealers info source	0.035 (0.101)	-0.155 (0.072)*
Crop consultants info source	0.295 (0.037)***	0.174 (0.056)**
Other farmers info source	0.018 (0.041)	0.033 (0.093)
Campus extension info source	0.017 (0.086)	0.109 (0.078)
Local extension info source	0.067 (0.074)	-0.129 (0.054)*
<u>Attitudes and Values</u>		
Look after environment	0.217 (0.271)	-0.014 (0.121)
Hunting and fishing environment	0.007 (0.053)	-0.001 (0.060)
Economic attitude	0.052 (0.070)	-0.003 (0.024)
Passing on good land	-0.091 (0.051)^t	-0.041 (0.040)
Farming tradition	0.290 (0.185)	-0.082 (0.034)*
Passing on farm	0.046 (0.145)	0.015 (0.153)
Debt aversion	-0.107 (0.100)	-0.056 (0.078)
Crop insurance use	0.000 (0.002)	0.003 (0.001)^t
<u>Environmental Awareness</u>		
Concern ag. contributes to water problems	0.060 (0.006)***	0.051 (0.015)***
Erosion impacts	0.094 (0.035)**	0.013 (0.077)
Pest resistances impacts	-0.084 (0.055)	0.091 (0.098)
Extreme weather impacts	-0.040 (0.026)	0.011 (0.054)
Warming impacts	-0.035 (0.075)	-0.098 (0.040)*
Intercept	-4.325 (1.351)**	-2.937 (0.695)***
R-Square	0.349 (0.073)***	0.371 (0.121)**
Chi-Square	679.695***	678.584***
RMSEA	0.033	0.033
CFI	0.839	0.839
TLI	0.812	0.812

t p < 0.1, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001

Table 3.23. Probit regression coefficients and standard errors for variable rate N and variable rate P or K (n=814).

	Variable rate N	Variable rate P or K
	Estimate (S.E.)	Estimate (S.E.)
Individual Characteristics		
Years farming	0.001 (0.003)	0.000 (0.007)
Education level	0.034 (0.070)	-0.163 (0.094)^{t}
College ag courses	-0.187 (0.171)	0.130 (0.165)
Knowledge	0.123 (0.105)	0.244 (0.062)***
Value of sales	0.045 (0.068)	0.198 (0.077)*
Household income	0.019 (0.071)	0.004 (0.064)
Ag. income	-0.093 (0.057)	-0.062 (0.041)
Farm Characteristics—Physical		
Cropland area	0.156 (0.060)*	0.026 (0.102)
Corn-soy ratio	-0.002 (0.051)	-0.009 (0.107)
Animal farm	-0.231 (0.169)	-0.132 (0.110)
Grain farm	-0.040 (0.298)	-0.119 (0.144)
Other farm type	-0.415 (0.314)	-0.456 (0.260)^{t}
Field slope	-0.063 (0.097)	0.023 (0.080)
Soy yield	0.002 (0.009)	0.010 (0.010)
Corn yield	0.004 (0.000)***	0.006 (0.003)*
Loam	0.030 (0.233)	0.217 (0.150)
Clay	-0.173 (0.124)	-0.261 (0.241)
Silty-loam	-0.375 (0.148)*	-0.100 (0.099)
Sandy-loam	0.091 (0.132)	0.328 (0.174)^{t}
Other soil type	-0.213 (0.157)	0.242 (0.329)
Farm Characteristics—Social		
Cropland owned	0.000 (0.002)	0.000 (0.001)
Days worked off farm	0.000 (0.041)	-0.019 (0.006)**
Number of employees	0.001 (0.025)	-0.007 (0.010)
Partnership	-0.014 (0.367)	-0.127 (0.160)
LLC	0.306 (0.074)***	0.117 (0.118)
S-corporation	0.064 (0.100)	-0.087 (0.209)
C-corporation	-0.050 (0.169)	-0.030 (0.187)
Other business structure	-0.403 (0.869)	-0.077 (0.456)
Conservation program participation	-0.029 (0.131)	0.279 (0.073)***
Working land program participation	0.236 (0.063)***	-0.108 (0.188)

Table 3.23. (cont'd).

Information		
Info index	0.011 (0.002)***	0.019 (0.021)
Associations info source	0.051 (0.094)	-0.121 (0.112)
Chemical dealers info source	-0.013 (0.124)	0.226 (0.044)***
Seed dealers info source	0.072 (0.122)	-0.087 (0.081)
Crop consultants info source	0.134 (0.059)*	0.106 (0.039)**
Other farmers info source	0.018 (0.107)	-0.080 (0.037)*
Campus extension info source	-0.108 (0.079)	0.044 (0.082)
Local extension info source	0.157 (0.124)	-0.059 (0.059)
Attitudes and Values		
Look after environment	0.004 (0.161)	0.035 (0.106)
Hunting and fishing environment	-0.037 (0.031)	-0.002 (0.018)
Economic attitude	0.085 (0.035)*	0.008 (0.007)
Passing on good land	-0.048 (0.030)	-0.132 (0.106)
Farming tradition	-0.001 (0.050)	-0.010 (0.081)
Passing on farm	0.251 (0.082)**	0.070 (0.090)
Debt aversion	0.009 (0.054)	-0.144 (0.076)^{t}
Crop insurance use	-0.001 (0.001)	0.003 (0.001)***
Environmental Awareness		
Concern ag. contributes to water problems	-0.001 (0.021)	0.022 (0.013)
Erosion impacts	0.060 (0.056)	0.029 (0.071)
Pest resistances impacts	-0.027 (0.108)	0.057 (0.084)
Extreme weather impacts	0.039 (0.012)**	0.002 (0.032)
Warming impacts	-0.069 (0.096)	0.001 (0.019)
Intercept	-2.878 (0.348)***	-2.758 (0.967)**
R-Square	0.237 (0.049)***	0.310 (0.028)***
Chi-Square	679.410***	677.040***
RMSEA	0.033	0.033
CFI	0.840	0.840
TLI	0.813	0.813

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.24. Probit regression coefficients and standard errors for cover crops (n=814).

	Cover crops
	Estimate (S.E.)
Individual Characteristics	
Years farming	0.002 (0.006)
Education level	0.042 (0.071)
College ag courses	0.111 (0.064)^{t}
Knowledge	0.257 (0.088)**
Value of sales	0.031 (0.038)
Household income	0.038 (0.048)
Ag. income	0.041 (0.074)
Farm Characteristics—Physical	
Cropland area	-0.086 (0.044)^{t}
Corn-soy ratio	-0.035 (0.016)*
Animal farm	0.420 (0.164)*
Grain farm	0.130 (0.286)
Other farm type	0.338 (0.144)*
Field slope	0.065 (0.022)**
Soy yield	-0.003 (0.010)
Corn yield	-0.006 (0.002)*
Loam	0.091 (0.140)
Clay	0.112 (0.132)
Silty-loam	-0.227 (0.048)***
Sandy-loam	0.040 (0.105)
Other soil type	0.343 (0.245)
Farm Characteristics—Social	
Cropland owned	-0.001 (0.002)
Days worked off farm	0.003 (0.071)
Number of employees	-0.005 (0.018)
Partnership	0.144 (0.128)
LLC	0.208 (0.059)***
S-corporation	-0.062 (0.225)
C-corporation	0.166 (0.231)
Other business structure	0.287 (0.843)
Conservation program participation	0.122 (0.101)
Working land program participation	0.631 (0.127)***

Table 3.24. (cont'd).

<u>Information</u>	
Info index	-0.009 (0.010)
Associations info source	0.136 (0.033)***
Chemical dealers info source	-0.001 (0.067)
Seed dealers info source	-0.072 (0.071)
Crop consultants info source	0.129 (0.049)**
Other farmers info source	0.074 (0.050)
Campus extension info source	-0.060 (0.079)
Local extension info source	0.292 (0.039)***
<u>Attitudes and Values</u>	
Look after environment	0.248 (0.097)*
Hunting and fishing environment	0.025 (0.078)
Economic attitude	-0.126 (0.046)**
Passing on good land	0.082 (0.069)
Farming tradition	-0.040 (0.074)
Passing on farm	0.125 (0.108)
Debt aversion	-0.034 (0.042)
Crop insurance use	-0.002 (0.001)
<u>Environmental Awareness</u>	
Concern ag. contributes to water problems	0.040 (0.024)^{t}
Erosion impacts	0.227 (0.017)***
Pest resistances impacts	-0.138 (0.051)**
Extreme weather impacts	0.010 (0.024)
Warming impacts	-0.105 (0.064)
Intercept	-2.726 (1.106)*
R-Square	0.338 (0.020)***
Chi-Square	681.087***
RMSEA	0.033
CFI	0.841
TLI	0.814

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standardized Results

Standardized results are included to satisfy expectations for the presentation of regression results. However, standardization is of little usefulness when dealing with probit results, and especially with probabilities, as the probability effect of a given variable is highly dependent on the range of possible values the variable can take and the average variable value as is discussed in the chapter. This means that the standardized coefficients are no more useful in comparing the relative effects of different variables than the unstandardized coefficients; one still has to consider the value range for the variable, the size of the coefficient/slope, and the variable average. The reason for this is that the standardization is done on the latent variable underlying the observed binary variable, not on the binary variable itself; the standardized value would still need to be related to the binary outcome via the threshold values. As Muthén, Muthén, and Asparouhov (2016) explain it:

> Although the need for comparing effects of covariates having different metrics may arise, it should be emphasized that these are effects in the metric of the standardized u*. In contrast, the effects on the probability of $u = 1$ vary depending on where along the x-axis it is evaluated…. With two or more covariates, standardization refers to partial regression coefficients where the effect on the u probability depends on the location of the combination of covariates. This complicates the comparison of standardized coefficients. A possible solution is instead to study the change in probability as one covariate changes around a value of importance while holding the other covariates fixed at values of importance. (P. 227-228)

In the below results binary variables were standardized based on the x variable changing from 0 to 1 (the STDY command in Mplus), while the rest of the variables were standardized based on a one standard deviation change in the x variable (STDYX command in Mplus), as is recommended by Muthén, Muthén, and Asparouhov (2016).

Table 3.25. Standardized regression coefficients and standard errors for PSNT and nutrient maps (n=814).

	PSNT	Nutrient maps
	Estimate (S.E.)	Estimate (S.E.)
Individual Characteristics		
Years farming	0.050 (0.056)	-0.011 (0.073)
Education level	-0.059 (0.075)	-0.057 (0.013)***
College ag courses	0.101 (0.055)ƚ	0.215 (0.101)*
Knowledge	0.115 (0.141)	0.130 (0.057)*
Value of sales	-0.046 (0.090)	0.103 (0.097)
Household income	0.069 (0.043)	0.049 (0.029)ƚ
Ag. income	0.035 (0.042)	0.007 (0.031)
Farm Characteristics—Physical		
Cropland area	0.039 (0.080)	-0.092 (0.178)
Corn-soy ratio	0.063 (0.057)	0.027 (0.064)
Animal farm	-0.092 (0.243)	-0.030 (0.113)
Grain farm	-0.159 (0.361)	-0.074 (0.444)
Other farm type	-0.369 (0.232)	-0.532 (0.241)*
Field slope	-0.086 (0.069)	0.026 (0.097)
Soy yield	0.002 (0.056)	0.071 (0.053)
Corn yield	0.048 (0.046)	0.178 (0.199)
Loam	-0.450 (0.140)**	0.210 (0.211)
Clay	0.064 (0.082)	0.121 (0.092)
Silty-loam	-0.257 (0.171)	-0.021 (0.101)
Sandy-loam	0.081 (0.222)	0.107 (0.179)
Other soil type	-0.097 (0.209)	0.420 (0.337)
Farm Characteristics—Social		
Cropland owned	-0.046 (0.056)	-0.091 (0.122)
Days worked off farm	0.016 (0.031)	0.019 (0.082)
Number of employees	0.016 (0.088)	0.095 (0.358)
Partnership	0.250 (0.091)**	0.163 (0.286)
LLC	-0.020 (0.063)	0.064 (0.076)
S-corporation	-0.101 (0.377)	-0.086 (0.308)
C-corporation	0.001 (0.256)	-0.028 (0.379)
Other business structure	0.796 (0.498)	0.101 (0.805)
Conservation program participation	0.043 (0.191)	0.220 (0.149)
Working land program participation	0.234 (0.155)	0.045 (0.158)

Table 3.25. (cont'd).

Information		
Info index	-0.030 (0.022)	0.128 (0.166)
Associations info source	0.098 (0.109)	0.039 (0.041)
Chemical dealers info source	0.082 (0.085)	0.096 (0.122)
Seed dealers info source	0.021 (0.061)	-0.092 (0.040)*
Crop consultants info source	0.233 (0.019)***	0.135 (0.055)*
Other farmers info source	0.013 (0.031)	0.025 (0.068)
Campus extension info source	0.010 (0.052)	0.064 (0.043)
Local extension info source	0.037 (0.042)	-0.069 (0.031)*
Attitudes and Values		
Look after environment	0.130 (0.157)	-0.008 (0.072)
Hunting and fishing environment	0.007 (0.054)	-0.001 (0.059)
Economic attitude	0.060 (0.079)	-0.004 (0.028)
Passing on good land	-0.051 (0.030)^t	-0.022 (0.024)
Farming tradition	0.184 (0.111)^t	-0.051 (0.016)**
Passing on farm	0.037 (0.117)	0.012 (0.121)
Debt aversion	-0.071 (0.064)	-0.036 (0.048)
Crop insurance use	-0.005 (0.069)	0.073 (0.037)*
Environmental Awareness		
Concern ag. contributes to water problems	0.112 (0.019)***	0.094 (0.013)***
Erosion impacts	0.080 (0.027)**	0.011 (0.066)
Pest resistances impacts	-0.061 (0.037)	0.064 (0.071)
Extreme weather impacts	-0.040 (0.028)	0.011 (0.054)
Warming impacts	-0.034 (0.073)	-0.094 (0.042)*
Intercept	-3.489 (0.903)***	-2.329 (0.591)***
R-Square	0.349 (0.073)***	0.371 (0.121)**
Chi-Square	679.695***	678.584***
RMSEA	0.033	0.033
CFI	0.839	0.839
TLI	0.812	0.812

t p < 0.1, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001
Note: Binary variable standardization is based on a change from 0 to 1, rather than a one standard deviation change as is used for the non-binary variables.

Table 3.26. Standardized regression coefficients and standard errors for variable rate N and variable rate P or K (n=814).

	Variable rate N	Variable rate P or K
	Estimate (S.E.)	Estimate (S.E.)
Individual Characteristics		
Years farming	0.012 (0.035)	-0.002 (0.077)
Education level	0.025 (0.052)	-0.116 (0.068)^{t}
College ag courses	-0.164 (0.147)	0.108 (0.138)
Knowledge	0.086 (0.073)	0.164 (0.044)***
Value of sales	0.034 (0.052)	0.143 (0.056)*
Household income	0.018 (0.063)	0.004 (0.055)
Ag. income	-0.091 (0.053)^{t}	-0.058 (0.039)
Farm Characteristics—Physical		
Cropland area	0.163 (0.064)*	0.026 (0.101)
Corn-soy ratio	-0.003 (0.070)	-0.011 (0.139)
Animal farm	-0.202 (0.151)	-0.110 (0.091)
Grain farm	-0.035 (0.261)	-0.099 (0.118)
Other farm type	-0.363 (0.265)	-0.379 (0.214)^{t}
Field slope	-0.035 (0.054)	0.012 (0.043)
Soy yield	0.016 (0.073)	0.076 (0.076)
Corn yield	0.110 (0.013)***	0.178 (0.077)*
Loam	0.026 (0.203)	0.180 (0.122)
Clay	-0.152 (0.105)	-0.217 (0.196)
Silty-loam	-0.328 (0.134)*	-0.083 (0.081)
Sandy-loam	0.080 (0.113)	0.272 (0.148)^{t}
Other soil type	-0.186 (0.137)	0.201 (0.277)
Farm Characteristics—Social		
Cropland owned	-0.002 (0.064)	0.005 (0.028)
Days worked off farm	0.000 (0.055)	-0.025 (0.008)**
Number of employees	0.004 (0.093)	-0.024 (0.035)
Partnership	-0.012 (0.321)	-0.106 (0.133)
LLC	0.268 (0.060)***	0.097 (0.098)
S-corporation	0.056 (0.086)	-0.072 (0.173)
C-corporation	-0.044 (0.148)	-0.025 (0.155)
Other business structure	-0.352 (0.768)	-0.064 (0.380)
Conservation program participation	-0.026 (0.115)	0.232 (0.065)***
Working land program participation	0.206 (0.053)***	-0.089 (0.156)

Table 3.26. (cont'd).

<u>Information</u>		
Info index	0.074 (0.011)***	0.122 (0.129)
Associations info source	0.034 (0.062)	-0.076 (0.070)
Chemical dealers info source	-0.008 (0.077)	0.133 (0.028)***
Seed dealers info source	0.047 (0.078)	-0.054 (0.050)
Crop consultants info source	0.114 (0.048)*	0.086 (0.03)**
Other farmers info source	0.015 (0.089)	-0.064 (0.03)*
Campus extension info source	-0.070 (0.050)	0.027 (0.051)
Local extension info source	0.093 (0.074)	-0.033 (0.033)
<u>Attitudes and Values</u>		
Look after environment	0.002 (0.104)	0.022 (0.066)
Hunting and fishing environment	-0.040 (0.035)	-0.003 (0.018)
Economic attitude	0.105 (0.045)*	0.009 (0.007)
Passing on good land	-0.029 (0.019)	-0.076 (0.061)
Farming tradition	-0.001 (0.034)	-0.006 (0.053)
Passing on farm	0.220 (0.065)**	0.058 (0.076)
Debt aversion	0.006 (0.039)	-0.098 (0.051)*t*
Crop insurance use	-0.038 (0.044)	0.102 (0.029)***
<u>Environmental Awareness</u>		
Concern ag. contributes to water problems	-0.003 (0.043)	0.042 (0.028)
Erosion impacts	0.055 (0.053)	0.025 (0.062)
Pest resistances impacts	-0.021 (0.084)	0.042 (0.062)
Extreme weather impacts	0.043 (0.013)**	0.002 (0.033)
Warming impacts	-0.073 (0.103)	0.001 (0.019)
Intercept	-2.514 (0.323)***	-2.292 (0.779)**
R-Square	0.237 (0.049)***	0.31 (0.028)***
Chi-Square	679.410***	677.040***
RMSEA	0.033	0.033
CFI	0.840	0.840
TLI	0.813	0.813

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Binary variable standardization is based on a change from 0 to 1, rather than a one standard deviation change as is used for the non-binary variables.

Table 3.27. Standardized regression coefficients and standard errors for cover crops (n=814).

	Cover crops
	Estimate (S.E.)
<u>Individual Characteristics</u>	
Years farming	0.020 (0.069)
Education level	0.029 (0.049)
College ag courses	0.090 (0.053)[t]
Knowledge	0.168 (0.059)**
Value of sales	0.022 (0.027)
Household income	0.032 (0.040)
Ag. income	0.037 (0.067)
<u>Farm Characteristics—Physical</u>	
Cropland area	-0.084 (0.044)[t]
Corn-soy ratio	-0.045 (0.021)*
Animal farm	0.342 (0.130)**
Grain farm	0.106 (0.234)
Other farm type	0.275 (0.120)*
Field slope	0.034 (0.012)**
Soy yield	-0.021 (0.074)
Corn yield	-0.155 (0.060)*
Loam	0.074 (0.114)
Clay	0.091 (0.109)
Silty-loam	-0.185 (0.042)***
Sandy-loam	0.033 (0.086)
Other soil type	0.279 (0.201)
<u>Farm Characteristics—Social</u>	
Cropland owned	-0.040 (0.043)
Days worked off farm	0.004 (0.090)
Number of employees	-0.017 (0.063)
Partnership	0.117 (0.105)
LLC	0.169 (0.048)***
S-corporation	-0.050 (0.183)
C-corporation	0.135 (0.189)
Other business structure	0.234 (0.685)
Conservation program participation	0.099 (0.083)
Working land program participation	0.513 (0.099)***

Table 3.27. (cont'd).

<u>Information</u>	
Info index	-0.054 (0.064)
Associations info source	0.084 (0.021)***
Chemical dealers info source	0.000 (0.038)
Seed dealers info source	-0.044 (0.044)
Crop consultants info source	0.102 (0.040)*
Other farmers info source	0.057 (0.039)
Campus extension info source	-0.036 (0.047)
Local extension info source	0.160 (0.021)***
<u>Attitudes and Values</u>	
Look after environment	0.150 (0.058)*
Hunting and fishing environment	0.026 (0.080)
Economic attitude	-0.142 (0.050)**
Passing on good land	0.046 (0.039)
Farming tradition	-0.026 (0.048)
Passing on farm	0.102 (0.088)
Debt aversion	-0.022 (0.028)
Crop insurance use	-0.056 (0.039)
<u>Environmental Awareness</u>	
Concern ag. contributes to water problems	0.075 (0.047)
Erosion impacts	0.196 (0.017)***
Pest resistances impacts	-0.100 (0.038)**
Extreme weather impacts	0.010 (0.024)
Warming impacts	-0.104 (0.063)^{t}
Intercept	-2.218 (0.896)*
R-Square	0.338 (0.020)***
Chi-Square	681.087***
RMSEA	0.033
CFI	0.841
TLI	0.814

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Binary variable standardization is based on a change from 0 to 1, rather than a one standard deviation change as is used for the non-binary variables.

APPENDIX D: Mplus Code

ICC Code

Using WLSMV estimator with binary variable

```
USEVARIABLES ARE c1a_use2;
   MISSING ARE ALL (-99);
   CATEGORICAL ARE c1a_use2;
   CLUSTER IS stateansi;
ANALYSIS:
   ESTIMATOR=WLSMV;
   TYPE IS TWOLEVEL;
MODEL:
   %WITHIN%
   %BETWEEN%
```

Using MLR estimator with continuous variable

```
USEVARIABLES ARE c1a_use2;
   MISSING ARE ALL (-99);
   CLUSTER IS stateansi;
ANALYSIS:
   ESTIMATOR=MLR;
   TYPE IS TWOLEVEL;
MODEL:
   %WITHIN%
   %BETWEEN%
```

Model Code

```
*example using c1d_use2;
*these models are called _final7_v6 in my dissertation folder for each practice;

DATA:
   FILE IS "C:\Users\rchdenny\Dropbox\Riva's Dissertation\mplus\mplus8.dat";
   NOBSERVATIONS ARE 814;
VARIABLE: !variable names in NAMES ARE section must match the order of the variables in
         the dataset, in USEVARIABLES ARE they can be in any order;
   NAMES ARE a5 a7a b6 c2 d1cedu d1ccamp d1cchem d1cseed d1cind d1cfam d1cass d2debt
         d2weal d2inco d2hunt d2envi d2prof d2land d2trad e1fsoil e1fresi e1fextr e1fwarm
         e1ccont e1calga e1chypo e1csoil f4 f7 f8 f9 f10 f11 stateansi IL IN MI OH crpown_pc
         crop2size corn_soy av_corn av_soy wrkldprg crop_ins animal frm_oth employ sole_prop
         partnshp llc s_corp c_corp other_bs loam clay clay_loam silty_loam sandy_loam oth_soil
         info_tot f5_rc yrsfrm c1a_use2 c1b_use2 c1c_use2 c1d_use2 c1e_use2 c1k_use2;
   USEVARIABLES ARE c1d_use2 yrsfrm f4 f5_rc c2 f9 f10 f11 crop2size corn_soy animal
         a7a frm_oth b6  av_soy av_corn loam clay silty_loam sandy_loam oth_soil crpown_pc f8
         employ partnshp llc s_corp c_corp other_bs a5 wrkldprg info_tot d1cass d1cchem
```

```
        d1cseed d1cind d1cfam d1ccamp d1cedu d2envi d2hunt d2weal d2prof d2inco d2land
        d2trad f7 d2debt crop_ins e1ccont e1calga e1chypo e1csoil e1fsoil e1fresi e1fextr
        e1fwarm;
   MISSING ARE ALL (-99);
   CATEGORICAL ARE c1d_use2 e1ccont e1calga e1chypo e1csoil d2weal d2prof d2inco;
   CLUSTER IS stateansi;
ANALYSIS:
   ESTIMATOR = WLMSV;
   ITERATIONS = 1000;
   CONVERGENCE = .00005;
   TYPE IS COMPLEX; !this accounts for the clustering of the data in the standard errors;
   PARAMETERIZATION = THETA;
MODEL:
   ECON_AT BY d2inco d2weal d2prof;
   WATERCON BY e1ccont e1calga e1chypo e1csoil;
   e1calga WITH e1chypo;
   c1d_use2 ON yrsfrm f4 f5_rc c2 f9 f10 f11 crop2size corn_soy animal a7a frm_oth b6  av_soy
        av_corn loam clay silty_loam sandy_loam oth_soil crpown_pc f8 employ partnshp llc
        s_corp c_corp other_bs a5 wrkldprg info_tot d1cass d1cchem d1cseed d1cind d1cfam
        d1ccamp d1cedu d2envi d2hunt ECON_AT d2land d2trad f7 d2debt crop_ins
        WATERCON e1fsoil e1fresi e1fextr e1fwarm;
   c1d_use2@1; !fixes variance to 1;
OUTPUT:
   STDY;
   STDYX;
   TECH4;
```

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CHAPTER 4: QUESTIONING THE FERTILIZER SAVINGS INCENTIVE FOR BMP ADOPTION IN THE NORTH CENTRAL REGION

Agriculture is of the utmost importance to human societies for its production of food and fiber (and increasingly fuel), but it is also a source of environmental harm as a producer of non-point-source pollution to the air and water (Aneja, Schlesinger, and Erisman 2009; Carpenter et al. 1998; Drinkwater and Snapp 2007; Lal 1993; Robertson et al. 2013; Robertson and Vitousek 2009; Uri and Lewis 1998). Nutrients like nitrogen (N) and phosphorus (P) are vital to crop production but also create great environmental costs when they leave the farm and enter surrounding waterways or the atmosphere, where they contribute to eutrophication and hypoxia ("dead zones") and global climate change respectively (Blesh and Drinkwater 2013; Robertson and Vitousek 2009).

Efforts to reduce non-point-source nutrient pollution from agriculture have long focused on getting farmers to voluntarily adopt a range of best management practices (BMPs) either in the field to help retain nutrients or outside of fields to intercept nutrients. The retention of nutrients by in-field practices means that they have the potential to reduce the amount of fertilizer that a farmer needs to apply to get a good crop (Robertson and Vitousek 2009), thereby saving farmers money and reducing non-point-source nutrient pollution from agriculture. These nutrient savings are commonly assumed to act as an incentive for farmers to use these in-field practices and as an off-set for adoption costs, thus reducing the need for outside, particularly monetary, incentives (Odum 1984; Robertson and Harwood 2013; Robertson and Vitousek 2009). However, it is not clear to just what extent farmers *actually do* reduce their fertilizer use when they adopt any of these practices. If farmers are not experiencing tangible savings from the use of these practices, then it is likely that the present incentive system for their use is insufficient for encouraging their adoption.

The present study examines the effects of three in-field practices (cover crops, conservation tillage, and no-till) on fertilizer use in the North Central Region of the US using county and state-level data. The use of this type of aggregated data, rather than farm-level or field-level data, represents an important move towards considering the overall environmental effects of agriculture and BMPs. While it is important to understand the farm-level dynamics surrounding fertilizer and BMP use, larger scale data lets us evaluate the cumulative effects of the agricultural practices of individual farmers. In this case: are enough farmers reducing their fertilizer use on their farms by a large enough amount when they use these BMPs to all together have a measurable effect on the environment?

The use of aggregated data also moves the analysis in a different direction than the theoretical approaches commonly used to explain the drivers of BMP adoption: the Theory of Planned Behavior and related theories (Ajzen 1991; Fishbein and Ajzen 2015), and the Diffusion of Innovations Model (Rogers 2003). Variables these approaches have in common, such as attitudes towards a practice and personal values, are not easily attainable at the county level. Rather, biophysical characteristics become important contextual variables for the individual decisions that are aggregated, and important controls for county differences over a multi-state area. A coupled natural and human systems approach is used instead to inform the model design, which includes both social and biophysical variables.

BACKGROUND

Fertilizer and BMPs

As previously mentioned, the use of large amounts of concentrated chemical fertilizers, a hallmark of contemporary agriculture in much of the "developed world," has greatly increased crop yields, but has also exacerbated the environmental problems from non-point source nutrient pollution (Robertson and Vitousek 2009). Nitrogen (N), and Phosphorus (P) are two of the most important nutrients that plants need and are the two nutrients that contribute most to non-point source nutrient pollution from agriculture, making them the focus of most nutrient management efforts (Kleinman et al. 2011; Robertson and Vitousek 2009). Nitrogen in particular is a critical nutrient in determining corn grain yields (Mahama et al. 2016), and its many, highly mobile forms make it especially challenging to manage (Robertson and Groffman 2015; Robertson and Vitousek 2009).

To maximize profit and minimize environmental harm farmers are currently being encouraged to apply fertilizer of all kinds according to the 4R's: right time, right place, right source, and right rate (Bruulsema, Lemunyon, and Herz 2009; Roberts and Johnston 2015; Snyder 2017). Applying fertilizer at the right time means applying it in accordance with the seasonal needs of the crop to ensure that the nutrients are available when the crop needs it and to reduce loss; this can include applying fertilizer in the spring instead of the fall, applying it during or after planting, or applying it multiple times. The right place means applying nutrients as close as possible to the plants' roots, and particularly under the soil surface. The right source of nutrients refers to the formulation or product used, and particularly for N can include using a slow release product or a nitrification inhibitor (Snyder 2017). The right rate refers to applying the correct amount of the product to meet but not exceed crop needs, which is facilitated by the use of decision-aids like soil or plant tissue tests that indicate the amount of nutrients available and variable rate technology. Some of these, primarily technology-based, practices serve more than one purpose, like slow-release products that relate to source and timing, and variable rate that relates to place and rate. Due to the interconnectedness of the 4Rs, changes to one means that the others should be re-assessed and also perhaps changed accordingly (Bruulsema et al. 2009).

In addition to the 4R BMPs discussed above, which are primarily technology-based, biologically-based practices function by supporting and enhancing the composition of, and biological functions in, the soil to increase nutrient availability and at the same time reduce nutrient losses (Blesh and Drinkwater 2013; Drinkwater and Snapp 2007; Robertson et al. 2014; Robertson and Vitousek 2009). These practices include crop rotation, off-season cover crops, and reduced/conservation tillage or no-till, which all have the potential to increase the amount of organic matter in the soil, which in turn has an important function in retaining nitrogen and phosphorus and making them available to later crops (Blesh and Drinkwater 2013; Drinkwater and Snapp 2007; Robertson and Vitousek 2009; Vandermeer 2011).

Diverse, multi-year crop rotations, particularly those that include legumes, have been shown to increase grain yields over time and to produce high yields with lower external N inputs (Coulter et al. 2011; Osterholz, Liebman, and Castellano 2018; Stanger and Lauer 2008), as well as reduce N losses (Gardner and Drinkwater 2009). Cover crops, non-harvested crops grown between the harvest and planting of cash-crops, not only provide crop rotation benefits, but they also add the benefit of living soil cover during the time that the field would otherwise be bare. The cover crop takes up available N remaining in the field after the cash crop is harvested, thus preventing it from being washed out of the soil over the winter; when the cover crop is killed prior to planting the next cash-crop the N remains in the field and is slowly released as the cover crop residue decomposes (Robertson and Vitousek 2009). Similarly to diverse crop rotations, cover crops have been shown to reduce if not fully replace the need for additions N inputs (Doane et al. 2009; Mahama et al. 2016; Robertson and Vitousek 2009). In addition, the soil cover provided by living or dead cover crops also helps reduce soil erosion (Dabney, Delgado, and Reeves 2001), and thus retain P (Gentry et al. 2007; Yuan et al. 2018).

Conservation tillage and no-till represent additional in-field practices[29] that can retain nutrients and thus reduce the amount of additional nutrients that need to be applied. Conservation tillage is typically defined as leaving at least 30 percent residue cover on the soil after planting (CTIC 2002) often through the use of a non-inversion plows or harrows (see Chapter 2). No-till involves the minimal disturbance of the soil surface and crop residue between harvest and planting (CTIC 2002)[30]. Conservation tillage and no-till have long been shown to reduce soil erosion by increasing soil surface roughness and retaining more crop residue on the soil surface (Allmaras, Unger, and Wilkins 1985). Reducing soil erosion is a key mechanism for reducing P loss, though dissolved P can also be lost through tile drainage (Gentry et al. 2007; Yuan et al. 2018). Conservation tillage and no-till have also been shown to increase soil organic carbon, which increases the amount of N that can be stored in the soil (Grandy et al. 2006; Mazzoncini et al. 2011), at least in the upper soil layers (Dolan et al. 2006; Du, Ren, and Hu 2010). Conservation tillage and no-till can have additional soil benefits related to soil properties, including better water infiltration and retention, and larger and more diverse microbial communities that also contribute to soil fertility (Busari et al. 2015; Robertson et al. 2014).

[29] There is also a significant technological aspect to tillage, but the primary feature that relates to nutrient retention is based in the soil qualities that result, rather than the direct effect of the specific tool.
[30] A related practice commonly called "strip-till" is often included in the no-till category, where strips of up to one-third of the row width may be disturbed to facilitate planting and fertilizer application (CTIC 2002; NRCS 2012).

The cost of implementing BMPs is a potential barrier to their use. Conservation tillage and no-till offer direct savings through reduced fuel use and equipment wear, in addition to soil and nutrient benefits, though these benefits are not always clear enough to farmers to entice them to use those practices (Andrews et al. 2013). However, cover crops have the up-front cost of the seed, as well as adding an additional activities and management to plant and kill them (Plastina et al. 2018; Robertson and Vitousek 2009; Singer, Nusser, and Alf 2007) and farmers have been found to be uncertain about the benefits they may gain from using them (Arbuckle and Roesch-McNally 2015). The high potential costs, both up-front and indirect, especially for cover crops but also for conservation tillage and no-till, combined with uncertainty in benefits indicates the importance of having an accurate understanding of the benefits that these practices may or may not provide to farmers in the form of fertilizer savings.

While the use of 4R practices and biological in-field BMPs have been a common topic of inquiry in the BMP adoption literature, the actual rates of fertilizer application are rarely considered as an outcome variable of interest (Houser et al., *in preparation*). This is an important omission from the body of BMP adoption literature, as fertilizer rate is just as important (economically and environmentally) as the other 4Rs and is highly related to non-point-source nutrient loss from agriculture (Ribaudo et al. 2011). The key assumption is that farmers want to use these tools to reduce their fertilizer rate, but this assumption has not been systematically tested.

Weber and McCann (2015:392) report: “Previous 2001 and 2005 ARMS data showed that corn farmers who use soil testing *can* reduce overall commercial fertilizer application compared with nonadopters … *If* N soil testing similarly reduced N applications in excess of crop needs, this would improve water quality” (italics added). They do not, however, discuss whether farmers actually *do* reduce their nitrogen applications when using soil testing. Henke (2006) reports that very few California vegetable growers even adopted a quick test for nitrogen that was demonstrated to allow for reductions in fertilizer without reducing yields, let alone actually reduced their fertilizer application because of it. However, Reimer, Thompson, et al. (2012) report reduced input costs as a motivating factor for conservation adoption in their study of an Indiana watershed, suggesting that at least some farmers do adjust their fertilizer use as a result of using conservation practices.

The question of whether or not BMPs reduce actual fertilizer use is an important one since an assumption of cost reduction is highly involved in assumptions of farmer motivations for practice adoption, and thus what other incentives might be needed to encourage a farmer to adopt them. The potentially false assumption is that farmers will save money on fertilizer when they use conservation practices and that these savings will substantially offset the cost of adopting the practice (Odum 1984; Robertson and Harwood 2013; Robertson and Vitousek 2009), thereby assuming a reduction in the incentive needed. To be clear, agronomically the conservation practices do reduce fertilizer needs, but the question is how much do farmers believe this to be true and to what extent does that offset their perceived need for applying extra fertilizer.

Coupled Natural and Human Systems

A coupled human and natural system (CHANS), also often called a social-ecological system (SES), is most basically a "systems in which human and natural components interact" (Liu, Dietz, Carpenter, Folke, et al. 2007:639). While the two terms have somewhat different origins and disciplinary tendencies, the common defining characteristics of both are reciprocal effects and relationships across time and space, and the terms are frequently used interchangeably (An and López-Carr 2012; Liu, Dietz, Carpenter, Alberti, et al. 2007; Liu, Dietz, Carpenter, Folke, et al. 2007). In studies that take this broadly defined CHANS/SES approach (henceforth referred to a coupled natural and human [CNH] system), the researcher(s) bring ecological variables into the heart of the study, especially allowing them to influence social actions and systems, either as exogenous variables or as endogenous variables as part of a feedback loop (see Figure 4.1). So far, few researchers have explicitly taken a CNH approach to understanding BMP use in industrialized agriculture, though Stuart et al. (2015) have made the case for doing so, and other studies have incorporated social and biophysical factors as drivers of human actions without referring to CHANS and without considering feedback effects (Blesh and Wolf 2014; Duff et al. 1992; Halbrendt et al. 2014; Houser, Stuart, and Carolan 2017; Stonehouse 1996).

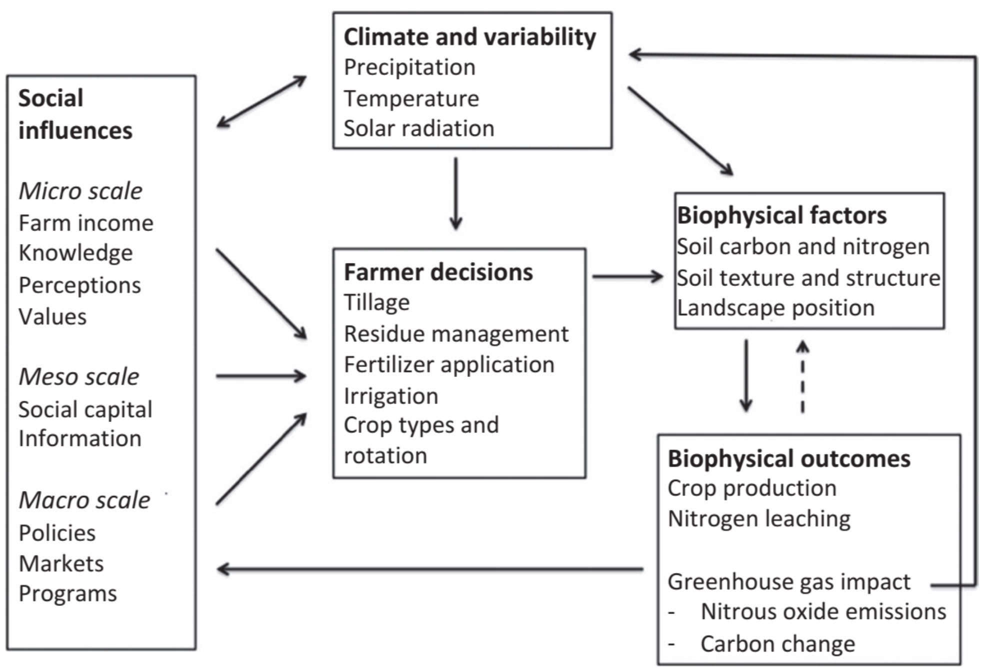

Figure 1. The coupled natural and human nitrogen cycle in agriculture.

Figure 4.1. Diagram of feedback of CHN feedback in an agricultural system from Stuart et al. (2015:573).

For example Duff et al. (1992) and Stonehouse (1996) conceptualize a linked cultural and biophysical system where individual farmers and their farms are embedded in cultural and institutional settings and regional biophysical settings respectively. Stonehouse, more than Duff et al., conceptualizes farmer decision making as being dynamically embedded in this larger setting and as being both influenced by and influencing this larger context, that is, he recognizes the presence of feedbacks. Neither study makes any attempt to empirically test the conceptual models. More recently, Halbrendt et al. (2014), Blesh and Wolf (2014), and Houser et al. (2017) have also integrated social and biophysical factors in empirical studies, using mental models and qualitative interviews respectively. All three consider how the biophysical context of the agricultural system of interest influences farmers' perceptions and farming practices.

In the present study, I follow this tradition, but use a quantitative analysis. I include the environmental context in which farmers are operating and making decisions as an important control for their fertilizer use—both directly and indirectly through influencing corn yield.

RESEARCH PROBLEM AND QUESTIONS

The core question of this research is: Does the use of BMPs reduce fertilizer use? Anecdotally there are examples of this happening (Reimer, Thompson, et al. 2012), but it does not appear to have been studied systematically, so it is unclear how common or widespread this result is. More specifically: Are enough farmers reducing their fertilizer use enough for it to show up at a great-than-farm-size scale? The implications of this question are two-fold: 1) are the fertilizer reductions great enough to function as an incentive for farmers to adopt the practice and/or offset the cost of adoption?, and 2) are the fertilizer reductions enough to reduce nutrient loads to local waterbodies?

Fertilizer rate is an important aspect of the potential for nutrient losses from agricultural fields to local waterbodies, but has rarely been the outcome of interest in analyses (Houser et al. *in preparation*). Reducing fertilizer rates to just meet crop needs is an important method of reducing nutrient losses to the environment and can potentially be done without reducing crop yields (Davis et al. 2000; Hoben et al. 2011; McSwiney and Robertson 2005; Moriasi et al. 2013; Rocha, Roebeling, and Rial-Rivas 2015; Teshager et al. 2017).

Much agricultural research is done at the farmer scale, and this seems to be particularly true of research on the adoption of soil and water conservation practices where a focus on attitudes as explanations for conservation practice adoption or conservation program participation is common (cf. Arbuckle et al. 2013; Arbuckle and Roesch-McNally 2015; A. Reimer and Prokopy 2014; Reimer, Thompson, et al. 2012; Reimer, Weinkauf, et al. 2012; Roesch-McNally, Gordon Arbuckle, and Tyndall 2017). However, the individual scale of these studies limits their usefulness when it comes to understanding the potential for these practices to have an effect at larger scales such as watersheds. While the decisions to adopt one or more conservation practices and how much fertilizer to apply are individual decisions this analysis is at the county-level. There are two reasons for the choice of scale used: 1) data availability, and 2) interest in the prevalence and potential impact of the phenomena. Using county level data allows for a large geographic sample, and to study the cumulative patterns of farmer management decisions to see if reducing fertilizer due to adopting a conservation practice happens often enough to be detected at the county level.

If conservation practice use is not found to be significantly related to fertilizer use at the county-level, then it is unlikely that the conservation practices considered are having a significant impact in reducing the overall nutrient loss from agriculture at a watershed scale at their current rate of use. An insignificant result would not necessarily indicate a lack of relationship between the conservation practices and fertilizer use. County-level data cannot tell us what is happening at the individual-level—for example we cannot distinguish between farmers not reducing their fertilizer use when using the conservation practices, and farmers substantially reducing their fertilizer use when using the conservation practices but doing so on too small a portion of the acres in the county to have a significant effect on the county total.

METHODS AND ANALYSIS

Data and sample

The data for this analysis come from the 2012 Census of Agriculture ("AgCensus" hereafter) and from the PRISM Climate Group at Oregon State University (http://prism.oregonstate.edu) as further described below. The 2012 AgCensus is the first one to included questions on specific conservation practices, providing national data on the number of farms using each practice, as well as the number of acres under each one. These much more specific measures are an important step forward in the study of conservation practice adoption and use by being more specific than a simple binary of adopt or did not adopt that ignores the extensiveness of practice use; a step that was called for by Reimer et al. (2014).

The sample used is the counties of the twelve North Central US states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. Thirteen counties had to be excluded from the analysis due to either a lack of fertilized cropland or missing data[31], leaving a final sample of 1,042 counties.

In its reporting of the AgCensus, NASS withholds values in situations where the variable value is too close to the value of a specific operation (NASS 2012a). These missing, but not truly

[31] See Appendix C for description of the excluded counties and descriptive statistics by state.

missing, values were replaced in the exogenous variables using the agriculture district[32] mean for that variable (see Appendix A for details). In the one case where there were no observations for an agriculture district, the average of the counties immediately adjacent to the agriculture district were used instead (see Appendix A for details).

Variables

Outcome Variables. The main outcome variable of interest, average fertilizer use, is measured in dollars spent on fertilizer, including lime and soil conditioners per acre of fertilized cropland. The use of this dollar-based proxy is necessitated by the nature of the data available, and the complexity inherent in the large number of fertilizer products available containing different combinations and concentrations of nutrients.

Independent Variables. The key independent variables in this analysis are the use of conservation tillage, no-till and cover crops, operationalized in this analysis as the proportion of cropland acres where each practice was used[33]. Conservation tillage is defined in the AgCensus as leaving at least 30 percent residue cover (NASS 2012c) and excludes no-till (NASS 2012b). No-till is described as "using no-till or minimum till" (NASS 2012a:B-13). Cover crops are "a crop planted primarily to manage soil fertility, soil quality, water, weeds, pests, diseases, or wildlife" (NASS 2012a:B-13), and do not include acres enrolled in the Conservation Reserve Program (CRP).

[32] Agriculture districts are sub-state designations made by USDA NASS. There are 9 agriculture districts in each state in the sample (https://www.nass.usda.gov/Charts_and_Maps/Crops_County/boundary_maps/indexgif.php).
[33] This formulation of independent variables as ratios was necessitated by the need to control for differences in total county size and more importantly the total area of farmland and cropland in each county without the introduction of the extreme multicollinearity that would result from including even one of these area measures as an independent variable along with total acres or counts.

Nineteen county-level control variables are included in the analysis and include farmer and farm characteristics, crop choice, and climate characteristics; all are group-mean centered[34]. The included variables were selected based on variables available in the AgCensus, literature on practice adoption, and agronomic principles. The farmer and farm characteristics are *average years of farming experience*, the portion of farmers who farm full time (*full time famer ratio*), *median farm size*, the ratio of rented county farmland to total county farmland (*rented land ratio*), the ratio of county acres under crop insurance to total county cropland acres (*crop insurance acres ratio*), and the ratio of irrigated county acres to total county cropland acres (*irrigated acres ratio*). Experience, farming full time, farm size, and amount of rented land are all common controls for BMP adoption analyses (Baumgart-Getz, Prokopy, and Floress 2012; Kara, Ribaudo, and Johansson 2008; Prokopy et al. 2008; Wauters and Mathijs 2014). Insurance and irrigation use are less common variables but both represent aspects of risk tolerance (Baumgart-Getz et al. 2012; Prokopy et al. 2008; Wauters and Mathijs 2014), and irrigation is an important aspect of growing conditions in conjunction with precipitation. *Average farmland value* is included as a measure of soil quality that is expected to have a positive effect on both corn yield and fertilizer spending, as high-quality soils have higher potential yields but only with sufficient fertilization.

Because fertilization varies by crop (Kara et al. 2008; Wade, Claassen, and Wallander 2015), and some crops and livestock can contribute to soil fertility and thus influence fertilizer use (Robertson and Vitousek 2009), I include crop and livestock variables in the form of ratios of county cropland where they were grown and density of animals. *Corn acres ratio* is the

[34] Corn yield is not centered because it is an endogenous variable, but controlling for state average corn yield (by including path between state corn yield and county fertilizer use) produces the same effect—effectively partitioning the effect of corn yield on fertilizer use between the county and the state (Bell and Jones 2015). See Appendix C for explanation of centering decisions.

proportion of cropland acres that was harvested for corn grain, and is considered on its own given that corn is a very common crop in the region and is given high rates of N fertilizer (Ribaudo et al. 2011). The *legume acres ratio* is the ratio of county acres in a legume, either soy beans or alfalfa, and is included as a control for fertilizer use, because legumes can contribute nitrogen to the cropping system (Robertson and Vitousek 2009) and because legume crops are an indication of a more diverse crop rotation, which can improve yield and reduce fertilizer needs (Coulter et al. 2011; Osterholz et al. 2018; Stanger and Lauer 2008). Three livestock variables, operationalized as density of animals, are included to control for manure use that could replace purchased fertilizers (Robertson and Vitousek 2009). The livestock variables are the average number of animals per acre of county cropland for poultry, including broilers, layers, and turkeys (*poultry density*), cattle, including beef cattle on feed and dairy cattle (*cattle density*), and hogs (*hog density*). The different kinds of animals are considered separately, since the volume and composition of manure varies by animal type.

Lastly, three climate variables are included to control for the normal[35] climatic conditions across the region and the effects of the 2012 drought. The normals are used because they represent the typical growing conditions. The *normal annual corn growing degree days*[36] is the number in thousands for the county, the *normal growing season precipitation* (April-September) is the normal precipitation in inches for the county, and the *2012 growing season precipitation* is the April-September 2012 precipitation for the county.

[35] The "normal" is the 30-year average. For this analysis normals were calculated from daily temperature and precipitation data from 1982-2011, in accordance with NOAA description at https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/climate-normals/1981-2010-normals-data. See Appendix A for more detail.
[36] Corn growing degree days are a measure of the accumulated heat units in the temperature range in which plant growth occurs. For corn this temperature range is 50 °F to 86 °F (https://ndawn.ndsu.nodak.edu/help-corn-growing-degree-days.html). See Appendix A for more detail.

At the state level, average fertilizer use in dollars per acre is used as a control for county-level fertilizer use, and state average corn grain yield in bushels per acre is used as a control for county-level corn yield. Both the state-level variables are grand-mean centered as is standard in multilevel models (Enders and Tofighi 2007)[37].

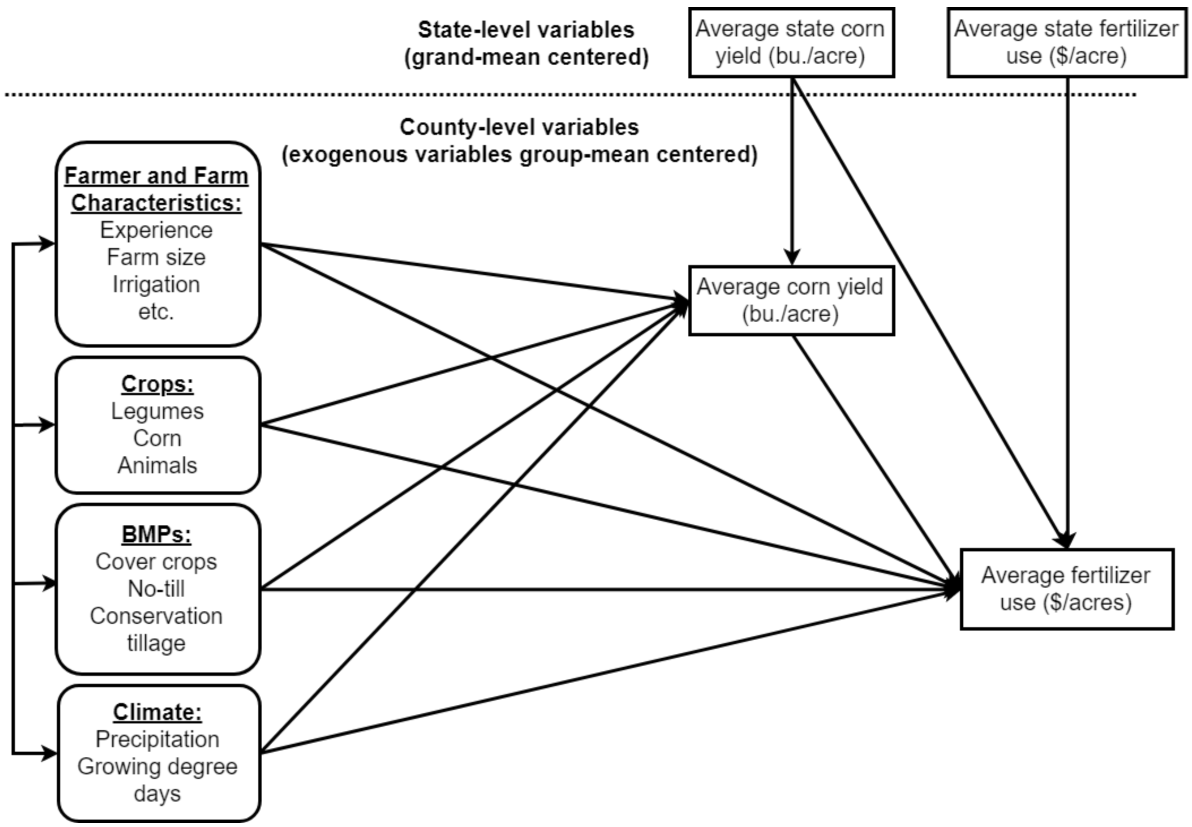

Figure 4.2. Conceptual Multilevel SEM diagram of fertilizer use.

Mediating variable. The mediating variable is *average corn yield* in bushels per acre. This variable, as a mediator, functions as both an outcome and an independent variable in the model. Expected yield is a guide that farmers use when determining how much fertilizer to apply. Corn yield is expected to be highly driven by soil quality, which is measured by the *average farmland value*. While corn yield is measured for the 2012 growing season, it is used in the model as a measure of the typical yield expected and which is thus the basis for the fertilizer

[37] See Appendix C for explanation of centering decisions.

used. The growing season precipitation for 2012 is used as a control for corn yield to account for the effects of the 2012 drought that affected much of the study area.

Analysis

For this analysis I use a multilevel, random intercept, structural equation model (SEM) with county-level and state-level data. The state-level data is included in the intercept portion of the county-level equations. The key feature of a multilevel model is that it can include multiple random effects and accommodate data that includes variables at multiple levels (i.e., it is grouped or nested in a hierarchy) and not only control for but explain the variation that exists at those levels. Failing to account for the nested structure of one's data and simply using an OLS model to analyze it typically results in underestimated standard errors, which increases the likelihood of type-1 errors (Bell and Jones 2015). The essential feature of nested, grouped or hierarchical data is that the observations are not all independent of each other; in other words, some are more alike than others. In the present case the grouping is related to counties sharing a state context (Jones and Duncan 1998). In this model, the multilevel features of the model that relate to the data structure are combined with the features of a structural equation model (SEM) to handle the specification of the desired conceptual relationships.

SEM uses multiple, simultaneously estimated regression models and partitions variance among the different parts of the model. A notable feature of SEM is that it developed in-part from path modeling (Schumacker and Lomax 2010), so it has an integral visual element that makes it unique within the family of regression analysis. As the name suggests, SEM has a structural element and can accommodate multiple relationships between multiple variables including indirect effects, and reciprocal and feedback relationships, which makes it particularly well suited to modeling CNH systems as well as agricultural systems where many variables are related to each other. SEM has not been used much to study agriculture or CNH systems, though its value for the latter purpose has been recognized (Fan et al. 2016; Marquart-Pyatt, Jorgenson, and Hamilton 2015), as well as its use as a communication tool in interdisciplinary research groups (Smith et al. 2014). SEM has also been recognized as being useful for modeling ecological systems (Fan et al. 2016; Grace et al. 2010).

The effect of conservation practices on fertilizer use is the key outcome of interest, but the model includes corn yield as a mediator. The model also includes biophysical climate data among the control variables of corn yield and fertilizer use. Restricting the sample to corn-heavy states simplifies the analysis as the use of conservation practices and nitrogen fertilizer use and practices, especially rate and timing, are highly crop specific (Ribaudo et al. 2011; Ribaudo, Livingston, and Williamson 2012; Wade et al. 2015).

RESULTS AND DISCUSSION

Table 4.1 provides the descriptive statistics for the sample used in the analysis (see Table 4.5 in Appendix C. for select descriptives by state). Of particular interest in Table 4.1 are the average use of BMPs. On average, conservation tillage is used on 22 percent of cropland acres in a county but ranges up to just over 50 percent at the maximum. No-till has an even higher average rate of use at 28 percent, with a maximum close to 80 percent. Cover crops are only used on 3 percent of cropland acres on average, and 32 percent at most. Crop rotation is indicated by the distribution of crops grown, and a balanced corn-soy rotation appears to be quite common on average as indicated by the equal corn and legume acres ratios (32 percent).

Table 4.1. Uncentered descriptive statistics for analysis variables (n=1042 unless otherwise noted).

	Mean	Std Dev	Minimum	Maximum
<u>Outcome Variables</u>				
Average fertilizer use ($/acre) a	122.994	44.118	33.214	784.530
Average corn yield (bu./acre) b	103.479	39.112	14.000	193.722
<u>Farmer and Farm Characteristics</u>				
Rented land ratio	0.446	0.136	0.035	0.821
Average farmland value ($1000/acre)	3.868	2.057	0.420	17.113
Tile acres ratio	0.189	0.233	0.000	0.844
Full-time farmer ratio	0.510	0.096	0.249	0.838
Average years of farming experience	26.827	1.917	18.000	33.700
Median farm size	229.014	325.380	2.000	3900.000
Irrigated acres ratio	0.067	0.141	0.000	0.875
Crop insurance acres ratio	0.617	0.221	0.000	2.253
<u>Crops</u>				
Corn acres ratio	0.315	0.181	0.000	0.771
Legume acres ratio	0.321	0.133	0.001	0.638
Poultry density	1.589	8.782	0.000	193.220
Cattle density	0.054	0.063	0.000	0.343
Hog density	0.194	0.345	0.000	3.730
<u>BMPs</u>				
Conservation tillage ratio	0.221	0.114	0.000	0.512
No-till ratio	0.277	0.185	0.000	0.787
Cover crops ratio	0.026	0.029	0.000	0.318
<u>Climate</u>				
Normal growing season precipitation	21.622	3.851	10.506	30.396
2012 growing season precipitation	16.042	4.202	3.540	32.960
Normal annual growing degree days (in 1000s)	3362.570	663.122	1853.850	4993.650
<u>State-level Variables</u>				
Average state fertilizer use ($/acre)	121.721	24.870	72.346	150.198
Average state corn yield (bu./acre)	111.382	24.586	68.545	156.041

Notes:

a. n=1008

b. n=1014

Results are presented in Table 4.2, organized by endogenous variable. The unstandardized coefficients of the ratio variables can be meaningfully interpreted by considering a tenth of a unit change (i.e., a 10 percent change in area) in the independent variable ratio and in the outcome variable unit. For example, a 0.1 unit increase in the irrigated acres ratio in a county is associated with a 12.3 bushel per acre higher average corn yields.

Average corn yield is significantly and positively predicted by the average farmland value, the cattle density, the irrigated acres ratio, and the tile acres ratio, which are all consistent with expectations. Higher value land produces more corn, while ensuring sufficient water through irrigation and sufficient drainage through tile drainage also contributes to higher corn yields. Interestingly, cattle density is associated with higher corn yields, while hog density is associated with lower corn yields, though this could reflect the growing conditions where hog vs cattle production is favored. Cover crops are significantly associated with lower corn yields, though it should not be presumed that cover crops cause lower corn yields as they may be being grown more in areas that have more challenging growing conditions and thus lower corn yields to start with. Tillage practices did not have a significant effect on corn yield. The average state corn yield is a significant and positive predictor of county corn yield as is expected.

Table 4.2. Direct effect coefficients and standard errors from multilevel structural equation model with random intercepts for 12 states, 2012 (n=1042).

	Coefficient (S.E.)	Standardized Coefficient	R2
Average corn yield (bu./acre) ←			0.439
Average farmland value ($1000/acre)	2.885 (1.395)*	0.130 (0.062)*	
Average years of farming experience	0.629 (0.545)	0.035 (0.030)	
Cattle density	70.701 (35.494)*	0.112 (0.053)*	
Conservation tillage ratio	20.494 (15.496)	0.065 (0.048)	
Cover crops ratio	-124.364 (49.378)*	-0.096 (0.038)*	
Full-time farmer ratio	29.096 (19.007)	0.073 (0.051)	
Hog density	-3.607 (1.18)**	-0.033 (0.010)**	
Irrigated acres ratio	123.495 (24.67)***	0.409 (0.068)***	
Legume acres ratio	-3.922 (16.759)	-0.014 (0.061)	
Normal annual growing degree days	-0.012 (0.009)	-0.109 (0.080)	
No-till ratio	-23.016 (14.962)	-0.111 (0.075)	
Poultry density	0.000 (0.071)	0.000 (0.020)	
Tile acres ratio	53.609 (15.053)***	0.287 (0.075)***	
2012 growing season precipitation	0.506 (0.554)	0.053 (0.058)	
Residual variance (within)	531.025 (51.897)***	0.561 (0.048)***	

Table 4.2. (cont'd).

State-level effects			0.953
Average state corn yield (bu./acre)	0.989 (0.040)***	0.976 (0.014)***	
Intercept	104.398 (1.651)***	4.396 (0.868)***	
Residual variance (between)	26.437 (11.975)*	0.047 (0.028)^{t}	
Average fertilizer use ($/acres) ←			0.342
Average corn yield (bu./acre)	0.385 (0.078)***	0.321 (0.072)***	
Average farmland value ($1000/acre)	13.235 (7.347)^{t}	0.498 (0.194)*	
Average years of farming experience	1.474 (1.154)	0.068 (0.044)	
Cattle density	-97.07 (49.332)*	-0.129 (0.057)*	
Conservation tillage ratio	-27.929 (18.517)	-0.074 (0.048)	
Corn acres ratio	-1.828 (43.490)	-0.006 (0.148)	
Cover crops ratio	219.191 (106.027)*	0.142 (0.066)*	
Crop insurance acres ratio	-0.108 (13.874)	0.000 (0.064)	
Full-time farmer ratio	-21.743 (29.799)	-0.046 (0.059)	
Hog density	-5.396 (4.009)	-0.042 (0.026)	
Legume acres ratio	-53.518 (20.512)**	-0.163 (0.068)	
Median farm size	0.009 (0.006)	0.063 (0.044)	
Normal annual growing degree days	0.022 (0.009)*	0.168 (0.071)*	
Normal growing season precipitation	1.567 (0.966)	0.099 (0.075)	
No-till ratio	-26.011 (14.376)^{t}	-0.105 (0.067)	
Poultry density	0.107 (0.086)	0.025 (0.023)	
Rented land ratio	-94.080 (43.533)*	-0.276 (0.091)**	
Residual variance (within)	895.957 (294.11)**	0.658 (0.041)***	
State-level effects			0.926
Average state fertilizer use ($/acre)	0.956 (0.066)***	1.007 (0.057)***	
Average state corn yield (bu./acre)	-0.194 (0.080)*	-0.185 (0.093)*	
Intercept	119.765 (2.225)***	4.868 (0.956)***	
Residual variance (between)	44.724 (24.553)^{t}	0.074 (0.052)	
Chi-square	13.567		
Chi-square p-value	0.139		
Root mean square error (RMSEA)	0.022		
Comparative fit index (CFI)	0.980		
Tucker-Lewis index (TLI)	0.901		

t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Estimator used is maximum likelihood estimation with robust standard errors in Mplus8. County-level exogenous variables are group-mean centered; state-level variables are grand-mean centered.

Because the model includes a mediator, the interpretation of the fertilizer use coefficients (the direct effects) only provides part of the story, so I discuss these results briefly before discussing the total effects on fertilizer use. Average county-level fertilizer use is significantly predicted by average county corn yield, cattle density, cover crop ratio, legume ratio, normal annual growing degree days, and the rented land ratio. Average corn yield, cover crops, and normal annual growing degree days are all positively and significantly associated with county fertilizer use, while cattle density, legume ratio, and the rented land ratio are all negatively and significantly associated with county fertilizer use. Average farmland value and the ratio of no-till acres are marginally significant with average farmland value having a positive effect and no-till having a negative effect. County-level fertilizer use is also positively predicted by the average state fertilizer use.

The effect of state corn yield on county-level fertilizer use is included in the model to partition the effect of corn yield on fertilizer use between the county and the state levels, since the county corn yield variable cannot be centered like the exogenous variables in the model, and it is the difference between the county-level and state-level effects of corn yield on county fertilizer use (Bell and Jones 2015). The effect of the state corn yield on county fertilizer use can be calculated in this case by adding the county-level corn yield effect (0.385) and the state corn yield coefficient (-0.194) resulting in the actual effect of state corn yield on county fertilizer use being 0.191.

Because it is a two-level model, variation in the outcome variables exists at both levels. The model explains 43.9 percent of the observed county-level variation in county-level corn yields. 37.5 percent of the variation in the corn yield data exists at the state-level[38] and the R^2 value for the state-level effects describes the portion of that variation that is explained by the state-level variables. In this case 95.3 percent of the 37.5 percent of variation in county corn yield is explained by the average state corn yield. The model explains 34.2 percent of the observed county-level variation in county-level fertilizer use. The ICC for fertilizer use is 0.326,

[38] This measure is the intraclass correlation coefficient (ICC).

so the state-level predictors explain 92.6 percent of the 32.6 percent of variation in county fertilizer that is at the state level. Over-all model fit is very good with a non-significant chi-square, an RMSEA that is smaller than 0.05, and a CFI that is larger than 0.95, while the TLI is larger than 0.9 (West, Taylor, and Wu 2012).

Given the mediating position of corn yield in the model, the direct effects on county fertilizer use given in Table 4.2 are of limited use, so the standardized total effects that combine the direct effect on fertilizer use with the indirect effect on fertilizer use that works through corn yield are presented in Table 4.3. The results show that use of conservation tillage has no significant total effect on fertilizer use, while cover crops and no-till have only a marginally significant total effect on fertilizer use. For cover crops the positive direct effect on fertilizer use is off-set by the negative effect on corn yield. The negative direction of the total effect of no-till on fertilizer use is the direction that the agronomic findings suggest should be there though and thus weakly supports the assumption that no-till can save farmers money, not only through saved time and fuel from less tillage but also through fertilizer use. However, the positive effect direction of cover crops on fertilizer use, does not lend any support to the assumption that cover crops can save farmers money on fertilizer.

Among the control variables, average corn yield, average farmland value, the irrigated acres ratio, and the tile acres ratio all have significant and positive total effects on fertilizer use. The effects of corn yield and farmland value are consistent with expectations. The effects of irrigation and tile were less expected as they are coming entirely through their effect on corn yield, as their directs effects on fertilizer use were not included in the model. The total effects of farming experience, and normal annual corn growing degree days are positive but marginally significant.

Table 4.3. Standardized, county-level, total effects on fertilizer use per acre.

	Coefficient (S.E.)
Average corn yield (bu./acre)	0.321 (0.072)***
Average farmland value ($1000/acre)	0.539 (0.190)**
Average years of farming experience	0.079 (0.042)^t
Cattle density	-0.092 (0.050)^t
Conservation tillage ratio	-0.053 (0.051)
Corn acres ratio	-0.006 (0.148)
Cover crops ratio	0.111 (0.063)^t
Crop insurance acres ratio	0.000 (0.064)
Full-time farmer ratio	-0.022 (0.062)
Hog density	-0.052 (0.024)*
Irrigated acres ratio	0.131 (0.031)***
Legume acres ratio	-0.168 (0.063)**
Median farm size	0.063 (0.044)
Normal annual corn growing degree days	0.133 (0.080)^t
Normal growing season precipitation	0.099 (0.075)
No-till ratio	-0.141 (0.075)^t
Poultry density	0.025 (0.028)
Rented land ratio	-0.276 (0.091)**
Tile acres ratio	0.092 (0.034)**
2012 growing season precipitation	0.017 (0.019)

t p < 0.1, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001
Note: Estimator used is maximum likelihood estimation with robust standard errors in Mplus8. All variables listed are effectively group-mean centered.

Hog density, legume ratio and rented land all have negative total effects on fertilizer use. That the legume ration decreases fertilizer spending is consistent with the agronomic literature on crop rotations and leguminous properties. Interestingly the total effect of hog density is negative and significant, while the negative effect of cattle density on fertilizer use is balanced by its positive effect on corn yield which in turn is related to increased fertilizer spending, resulting in cattle density having a non-significant total effect. A similar situation occurs for cover crops, where the positive direct effect on fertilizer use is off-set by the negative effect on corn yield to result in a marginally significant total effect on fertilizer use. Higher proportions of rented land have a negative and significant total effect on fertilizer use, which is generally consistent with Prokopy et al. (2008), but inconsistent with Baumgart-Getz et al. (2012), though these studies are based on general BMP use, in which fertilizer rate is not typically included. Based on unpublished interviews I expect that this negative effect is the result of farmers not wanting to “build up” the land they rent through higher fertilizer applications.

The lack of significant total effect of conservation tillage, no-till and cover crops, is not as expected, but important lessons can still be learned from this analysis. The big one is the potential, indicated by the significant direct effects and the marginally significant total effects, for cover crops to increase fertilizer use. Dunn et al. (2016) reported that farmers in their national 2013 survey thought that costs of cover crops and their reduction in yield in the following cash crop were “somewhat limits” to the adoption of cover crops in their area. It is possible that in order to try to avoid reductions in the following crop that farmers are tending to apply more fertilizer than they otherwise would. Even a slight inclination by farmers to apply more fertilizer when using cover crops would have large implications for not only the actual but perceived costs of using cover crops and with that the incentives needed to effectively promote their use for their other benefits.

CONCLUSION

The primary goal of this analysis was to see if greater use of three BMPs was related to a decrease in the use of fertilizer at the county-level. However, I found no significant reduction in fertilizer use as a result of more prevalent use of either of the three practices. As previously mentioned, because this is an analysis of county-level averages care should be taken not to extend these findings to the individual-level (an ecological fallacy). As such, while the result is a bit disappointing from a sustainable agriculture standpoint, it does not rule-out the practices having a fertilizer reducing effect at the individual farm-level. Care should also be taken not to over interpret the implication of causal effects in the model. For instance, while conservation practices precede both yield and fertilizer use in this model, this does not mean that the use of these conservation practices *causes* a reduction in yield, since we do not know what yield was prior to the use of the practices; it may be that farmers are more likely to use cover crops and no-till on lower yielding fields where they are trying to maximize yield by applying relatively more fertilizer.

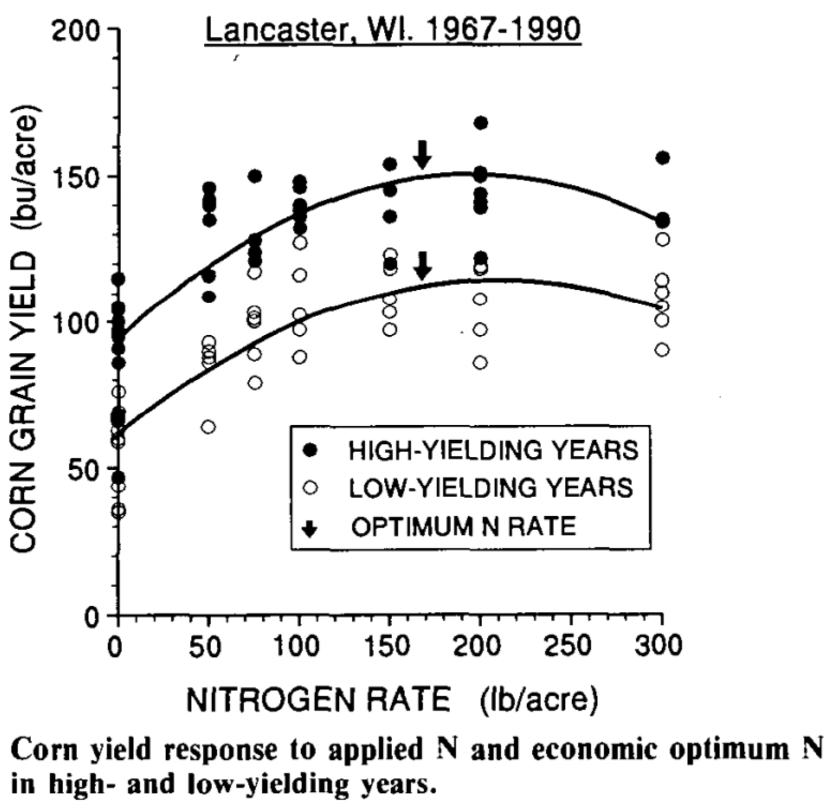

Figure 4.3. Yield response graph (Vanotti and Bundy 1994:184).

The size of the effect of corn yield on fertilizer use is relatively small, which may be due to fertilizer and yield having a non-linear relationship, combined with average county fertilizer use falling near the optimum amount by virtue of being an average. At the arrows in the yield response curve in Figure 4.3, the slope of the yield to input graph is relatively shallow, and a

0.385 unit relationship seems very reasonable. In addition, the fertilizer use variable is not corn specific, thus diffusing some of the potential effect.

Water is clearly a key piece of yield and fertilizer use, with normal growing season precipitation, irrigation and tile drainage all having important effects on fertilizer use. Irrigation and tile both have substantial positive effects on corn yield that carry through to significant total effects on fertilizer. Tile lines are a major way that both N and P leave fields, so it is notable that tile is associated with greater fertilizer spending and suggests that there might be a positive feedback between fertilizer use and tile drainage. The 2012 growing season precipitation is an important control for the effects of the 2012 drought, but the effects appear to be spotty given the lack of significant effect on county average corn yield in 2012 even controlling for irrigation.

Future work along the lines of this analysis would be benefited by more precise data—such as fertilizer use on corn rather than general fertilizer use—and additional waves of data at the county level. The release of the 2017 AgCensus data in early 2019 will make it possible to consider temporal variation in addition to the spatial variation considered in this analysis. Using farmer survey data (either from a private survey or the USDA Agricultural Resource Management Survey [ARMS]) to consider the relationships from this model at the farmer-level would also be an avenue for future work, as would scaling up further to the watershed scale, where measures of water quality could be included as an outcome of interest to see how conservation practices and fertilizer use affect water quality singularly and together and how water quality might feedback to influence the use of conservation practices.

The county-level used in this analysis could also be used to model the drivers of the three conservation practices. I attempted to incorporate the three conservation practices as mediators in the current model of fertilizer use but given the number of variables available there were not enough degrees of freedom to estimate that large a number of parameters. The contexts that relate to the wider spread use of the practices could be estimated separately or as a seemingly unrelated regression model with the three practice-use ratio variables as correlated outcomes.

The effect of corn yield on fertilizer use raises some questions of order and causality. The relationship between corn yield and fertilizer is potentially complicated by having a reciprocal effect, since logically yield is a function of fertilizer use. In this model yield is being used as a proxy for expected yield, and thus as a predictor of fertilizer use. However, a non-recursive model with reciprocal effects between corn yield and fertilizer use was considered to see if the effect in the model was being suppressed by a negative effect going in the opposite direction. The effect from fertilizer use to corn yield was negative but not significant, suggesting that the relationship between these variables used in the model is appropriate.

In sum, the use of conservation tillage, no-till and cover crops does not appear to have an effect on fertilizer use at the county-level, while corn yield, land value, hog density, irrigation crop rotation, (i.e. use of legumes), rented land, and tile drainage all have a significant effect on fertilizer use. Farmers' use and management of nutrients like nitrogen have very real environmental impacts (hypoxia, climate change) and very real money is spent trying to minimize these impacts. Not only does this analysis scale up from the individual to better assess the cumulative effects of many individual actions at a scale where the effects are more visible, but it also includes a mixture of ecological and economic and non-economic social factors. The combining of all of these types of variables in one analysis is novel in sociological studies, but is in keeping with calls for more integrated research on social-ecological systems and soil and water conservation behaviors (Liu, Dietz, Carpenter, Alberti, et al. 2007; Reimer et al. 2014; Stuart et al. 2015) as well as a few recent studies that have integrated social and ecological elements in one study (Blesh and Wolf 2014; Halbrendt et al. 2014). This analysis provides an important step toward both better integration of social and biophysical systems, from a sociological stand-point, and also better understanding how conservation practices can play a role in reducing the environmental impact of US agriculture.

APPENDICES

APPENDIX A: Variable Calculations

Replacing Missing Values

For exogenous variables for which NASS had withheld values I replaced them using the agriculture district[39] average. The process involved calculating agriculture district averages from the county data, calculating the ratio variables I use with the agriculture district averages, and then using the agriculture district ratios to replace the missing values in the county-level ratio variables. It is important that I use the ratio values in the replacement processes, rather than the counts, to avoid scale miss-matches resulting from counties of different sizes.

I first calculated the agriculture district averages from the county data:

```
proc sort data=yy; by agdist; run;
proc summary data=yy; *means by ag district to replace missing values;
var agdist farmland_12a corngrain_12b corngrain_12a cropland_12a
alfalfa_12a soy_12a cropins_12a covcrop_12a constill_12a
rentpartown_12a tenant_12a irrig_12a notill_12a hogs_12c catfeed_12c
dairy_12c broilers_12c
layers_12c turkeys_12c fertcrop_12a fert_12d tile_12a income_12df;
by agdist;
output out=adm_vars
     mean(agdist farmland_12a corngrain_12b corngrain_12a cropland_12a
alfalfa_12a soy_12a cropins_12a covcrop_12a constill_12a
rentpartown_12a tenant_12a irrig_12a notill_12a hogs_12c catfeed_12c
dairy_12c broilers_12c
layers_12c turkeys_12c fertcrop_12a fert_12d tile_12a income_12df)
     =agdist adm_farmland adm_corn_b adm_corn_a adm_cropland
adm_alfalfa adm_soy adm_cropins adm_covcrop adm_constill
adm_rentpartown adm_tenant adm_irrig adm_notill adm_hogs adm_cat
adm_dairy adm_broil
adm_lay adm_turk adm_fertcrop adm_fert adm_tile adm_income;
run;
```

Then I used those averages to calculate the agriculture district ratios for the variables I needed to replace:

```
*calculate agdist averages for ratios that need to be replaced;
data adm_r; set add;
adm_alfalfa_r=adm_alfalfa/adm_cropland;
adm_constill_r=adm_constill/adm_cropland;
adm_corn_r=adm_corn_a/adm_cropland;
adm_covcrop_r=adm_covcrop/adm_cropland;
adm_cropins_r=adm_cropins/adm_cropland;
adm_soy_r=adm_soy/adm_cropland;
adm_rentpartown_r=adm_rentpartown/adm_farmland;
adm_tenant_r=adm_tenant/adm_farmland;
adm_irrig_r=adm_irrig/adm_cropland;
```

[39] Agriculture districts are sub-state designations made by USDA NASS. There are 9 agriculture districts in each state in the sample (https://www.nass.usda.gov/Charts_and_Maps/Crops_County/boundary_maps/indexgif.php).

```
adm_notill_r=adm_notill/adm_cropland;
adm_hogs_r=adm_hogs/adm_cropland;
adm_dairy_r=adm_dairy/adm_cropland;
adm_cat_r=adm_cat/adm_cropland;
adm_broil_r=adm_broil/adm_cropland;
adm_lay_r=adm_lay/adm_cropland;
adm_turk_r=adm_turk/adm_cropland;
adm_tile_r=adm_tile/adm_cropland;
run;
```

One district was missing dairy cattle data for all the counties in the district, so I calculated the average for the district from the surrounding counties. All other agriculture districts had data from at least two counties for each variable.

```
proc means data=ratios; *calculating an alternate dairy ratio average
for agdist 3820 which is missing observation on that variable for all
counties. These 9 counties are adjacent to agdist 3820.
Calculated mean for the 7 of these that are non-missing is 0.00009523;
var dairy_12r; where fips in (38075 38101 38055 38083 38103 38027
38063 38071 38095)
and dairy_12r~=.; run;
data fill1; set ratios; *dropping a couple variables left over from
calculating agdist means and replacing missing agdist with
alternatively calculated value;
drop _TYPE_ _FREQ_;
if agdist=3820 then adm_dairy_r=0.00009523;
run;
```

I calculated the ratios for the county-level variables:

```
*calculate county level ratio variables;
data ratios; set adm_r;
constill_12r=constill_12a/cropland_12a;
corngrain_12ba=corngrain_12b/corngrain_12a;
corngrain_12r=corngrain_12a/cropland_12a;
covcrop_12r=covcrop_12a/cropland_12a;
cropins_12r=cropins_12a/cropland_12a;
cropland_12r=cropland_12a/county_12a;
csp_12df=csp_12d/csp_12f;
csp_12da1=csp_12d/cropland_12a;
csp_12da2=csp_12d/farmland_12a;
eqip_12df=eqip_12d/eqip_12f;
eqip_12da1=eqip_12d/cropland_12a;
eqip_12da2=eqip_12d/farmland_12a;
farmland_12r=farmland_12a/county_12a;
fert_12da=fert_12d/fertcrop_12a;
fertcrop_12af=fertcrop_12a/fertcrop_12f;
fertcrop_12r=fertcrop_12a/cropland_12a;
fullowner_12r=fullowner_12a/farmland_12a;
fulltime_12r=fulltime_12f/farms_12c;
irrig_12r=irrig_12a/cropland_12a;
```

```
notill_12r=notill_12a/cropland_12a;
rentpartown_12r=rentpartown_12a/farmland_12a;
tenant_12r=tenant_12a/farmland_12a;
soy_12r=soy_12a/cropland_12a;
alfalfa_12r=alfalfa_12a/cropland_12a;
tile_12r=tile_12a/cropland_12a;
broilers_12r=broilers_12c/cropland_12a;
layers_12r=layers_12c/cropland_12a;
turkeys_12r=turkeys_12c/cropland_12a;
cat_12r=catfeed_12c/cropland_12a;
dairy_12r=dairy_12c/cropland_12a;
hogs_12r=hogs_12c/cropland_12a;
run;
```

Then I replaced the missing county data in the ratio variables with the agriculture district average ratios:

```
*replacing missing values with agdist average;
data fill2; set fill1;
corngrain_r=input(corngrain_12r,best32.);
if corngrain_12r=. then corngrain_r=adm_corn_r;
soy_r=input(soy_12r,best32.);
if soy_12r=. then soy_r=adm_soy_r;
alfalfa_r=input(alfalfa_12r,best32.);
if alfalfa_12r=. then alfalfa_r=adm_alfalfa_r;
cropins_r=input(cropins_12r,best32.);
if cropins_12r=. then cropins_r=adm_cropins_r;
covcrop_r=input(covcrop_12r,best32.);
if covcrop_12r=. then covcrop_r=adm_covcrop_r;
constill_r=input(constill_12r,best32.);
if constill_12r=. then constill_r=adm_constill_r;
rentpartown_r=input(rentpartown_12r,best32.);
if rentpartown_12r=. then rentpartown_r=adm_rentpartown_r;
tenant_r=input(tenant_12r,best32.);
if tenant_12r=. then tenant_r=adm_tenant_r;
irrig_r=input(irrig_12r,best32.);
if irrig_12r=. then irrig_r=adm_irrig_r;
notill_r=input(notill_12r,best32.);
if notill_12r=. then notill_r=adm_notill_r;
hogs_r=input(hogs_12r,best32.);
if hogs_12r=. then hogs_r=adm_hogs_r;
catfeed_r=input(catfeed_12r,best32.);
if catfeed_12r=. then catfeed_r=adm_cat_r;
dairy_r=input(dairy_12r,best32.);
if dairy_12r=. then dairy_r=adm_dairy_r;
broilers_r=input(broilers_12r,best32.);
if broilers_12r=. then broilers_r=adm_broil_r;
layers_r=input(layers_12r,best32.);
if layers_12r=. then layers_r=adm_lay_r;
turkeys_r=input(turkeys_12r,best32.);
if turkeys_12r=. then turkeys_r=adm_turk_r;
tile_r=input(tile_12r,best32.);
```

```
if tile_12r=. then tile_r=adm_tile_r;
income_df=input(income_12df,best32.);
if income_12df=.d then income_df=adm_income;
run;
```

I created the combined variables in a separate data step:

```
poultry_r=broilers_r+layers_r+turkeys_r;
rented_r=rentpartown_r+tenant_r;
cattle_r=catfeed_r+dairy_r;
legume_r=soy_r+alfalfa_r;
```

Calculation of Normal Precipitation and Corn Growing Degree Days

30-year normals (e.g., averages) were calculated from daily from daily temperature and precipitation data from 1982-2011, in accordance with NOAA description at https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/climate-normals/1981-2010-normals-data.

For precipitation this was done by calculating the total precipitation for each of the 360 months, and then taking the average for each month of the year (e.g., the average of the 30 June totals) to get the normal precipitation for each month of the year. These normal totals for April through September were then added together to get the normal growing season precipitation.

For corn growing degree days (GDD) the same process as above was followed except that prior to finding the total for each of the 360 months the corn GDD were calculated for each day according to the following formula and rules (https://ndawn.ndsu.nodak.edu/help-corn-growing-degree-days.html):

Daily Corn GDD (°F) = [(Daily Max Temp °F + Daily Min Temp °F) / 2] - 50 °F

If the daily max and/or min temperature was < 50 °F it was set equal to 50 °F, and if the daily max temperature > 86 °F, it was set equal to 86 °F.

APPENDIX B: Centering Analysis Variables

There are two ways to center a variable: group mean centering and grand mean centering. Group-mean centering (also called centering within clusters) is what its name suggests—centering the variable around the mean for each group. Grand-mean centering is centering the variable around the mean for all the observations of that type—for instance the average farm size across all the counties sampled. Level-2 variables (e.g., state-level variables) can be grand mean centered or left in their raw form.

The decision to center level-2 variables depends on the nature of the variable and is for ease of interpretation as it is in OLS regressions (Enders and Tofighi 2007). In this case, grand-mean centering the state-level variables is helpful because while having zero fertilizer use or zero corn grain yield can conceptually exist it does not in practice, thus the average is more interesting.

Centering level-1 (e.g., county-level) variables has more important model implications than centering at level-2. Group-mean centering level-1 variables serves to separate the within-group effects from the between group effects by removing the between group variation from the data, and thus removing correlation between the level-1 variables and the level-2 variables (Enders and Tofighi 2007). This results in level-1 coefficients that only include level-1 effects, thus making their interpretation more precise when the level-1 effects are of primary interest, as they are in this analysis (Enders and Tofighi 2007). The removal of between-level correlation is critical in random-slope models, where this lack of correlation is an important assumption (Enders and Tofighi 2007). Group-mean centering level-1 variables means that the model results are interpreted as follows (Enders and Tofighi 2007):

- Intercept is the average unadjusted cluster mean—ie the average intercept of all the clusters

- Slope is pooled within-cluster level-1 regression coefficient (ie the average slope of all the group slopes)—in this case since model has fixed slope it is the same for all the groups
- Intercept variance is the variance of the unadjusted cluster means

APPENDIX C: Extra Sample Descriptives

Table 4.4. Counties excluded from analysis due to low amount of agriculture or withheld data.

County	State	FIPS	Corn bushels	Corn acres	Fertilizer dollars	Fertilized acres	Notes
Cook	IL	17031	375456	WH	765000	WH	County contains majority of metro Chicago
DuPage	IL	17043	WH	WH	499000	WH	County contain west Chicago suburbs
Keweenaw	MI	26083	0	0	0	0	County in the Upper Peninsula
Iron	MI	26071	0	0	473000	WH	County in the Upper Peninsula
Luce	MI	26095	0	0	WH	1023	County in the Upper Peninsula
Ontonagon	MI	26131	WH	31	72000	WH	County in the Upper Peninsula
Schoolcraft	MI	26153	WH	WH	91000	WH	County in the Upper Peninsula
Cook	MN	27031	0	0	1000	WH	Most of county is in Superior National Forest
Lake	MN	27075	0	0	9000	WH	Most of county is in Superior National Forest or Finland State Forest
St. Louis City	MO	29510	0	0	0	0	County is metro St. Louis
Grant	NE	31075	0	0	WH	WH	
Hooker	NE	31091	0	0	WH	1560	
Menominee	WI	55078	0	0	0	0	County essentially coterminous with Menominee Indian Reservation

WH = Withheld (by NASS)

Table 4.5. State-level averages for analysis variables.

	IL	IN	IA	KS	MI	MN	MO	NE	ND	OH	SD	WI
Outcome Variables												
Average fertilizer use ($/acre)	134	150	135	74	147	133	124	113	72	141	90	128
Average corn yield (bu./acre)	102	99	134	85	131	156	69	131	117	120	91	120
Farmer and Farm Characteristics												
Rented land ratio	0.6	0.5	0.5	0.5	0.4	0.4	0.3	0.4	0.5	0.4	0.4	0.3
Av. farmland value ($1000/acre)	6	5	6	2	4	4	3	2	1	5	2	4
Tile acres ratio	0.4	0.5	0.5	0.0	0.3	0.3	0.1	0.0	0.0	0.5	0.0	0.1
Full-time farmer ratio	0.5	0.4	0.5	0.5	0.5	0.5	0.4	0.6	0.6	0.4	0.6	0.5
Average years of farming experience	27	26	28	27	26	28	26	27	28	26	27	26
Median farm size	100	57	136	200	60	142	120	280	480	69	337	96
Irrigated acres ratio	0.02	0.03	0.01	0.10	0.08	0.02	0.08	0.38	0.01	0.00	0.02	0.04
Crop insurance acres ratio	0.74	0.67	0.80	0.63	0.53	0.75	0.51	0.72	0.76	0.60	0.82	0.50
Crops												
Corn acres ratio	0.52	0.48	0.52	0.14	0.31	0.39	0.22	0.42	0.13	0.34	0.28	0.33
Legume ratio	0.39	0.43	0.38	0.15	0.34	0.36	0.36	0.27	0.22	0.46	0.32	0.28
Poultry density	0.19	2.51	1.91	0.01	1.61	1.42	2.22	0.23	0.01	3.05	0.11	1.15
Cattle density	0.01	0.02	0.06	0.05	0.05	0.04	0.01	0.06	0.00	0.03	0.01	0.11
Hog density	0.17	0.25	0.67	0.04	0.11	0.29	0.10	0.07	0.00	0.15	0.03	0.02
BMPs												
Conservation tillage ratio	0.32	0.24	0.33	0.21	0.23	0.28	0.18	0.23	0.23	0.22	0.18	0.26
No-till ratio	0.25	0.39	0.26	0.37	0.20	0.04	0.26	0.43	0.29	0.40	0.37	0.18
Cover crops ratio	0.01	0.05	0.01	0.01	0.06	0.02	0.03	0.02	0.01	0.03	0.01	0.06
Climate												
Normal growing season precipitation	23	24	25	21	20	21	26	19	14	23	17	22
2012 growing season precipitation	17	18	16	14	17	19	18	11	11	19	13	18
Normal annual growing degree days (in 1000s)	4	4	3	4	3	3	4	3	2	3	3	3

Note: The data presented here (except for the climate variables) are the state-level values from the AgCensus, not an average of the county-level data used in the analysis.

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CHAPTER 5: CONCLUSION

In the preceding three analyses I examine how farmers till and the major factors that influence their tillage decisions, the range of predictors of the use of cover crops and four nutrient management BMPs, and the aggregated effects of tillage, and cover crops on fertilizer use. While these analyses have been written up as separate papers for purposes of the dissertation, there are several ways that the findings intersect and several overall conclusions that can be drawn.

MEASURES AND RESEARCH METHODS

One of the other general conclusions that can be drawn from my analyses is the importance of how BMP use is measured. This should involve not just the incorporation of temporal and spatial variability, which is particularly important for practices like tillage and cover crops, but how practices are defined and grouped. The first analysis clearly demonstrates, with the number of versions of no-till found, just how important it is to consider the temporal and spatial use of a practice as well as clearly define the parameters of the practice of interest. This is not to pretend that doing so is easy. Indeed, a practice like tillage presents a substantial challenge given the number of dimensions that need to be considered. However, it is clear that the current method of using three or four categories provides at best a cursory representation of the actual practices being used and as a result much inconsistency is likely to exist in the data of such summary categories. The second analysis further demonstrates the potential trouble with using practice categories. The lack of overlap in significant variables across the practices, even ones like variable rate nitrogen (N) and variable rate phosphorus (P) or potassium (K), indicates that the meaningful features that could define a class of practices may not be readily apparent. There is certainly great utility in using categories to simplify analyses, but it would seem that researchers in the social sciences have not yet spent enough time empirically establishing those categories for agricultural BMPs.

This conclusion is not to disparage previous or current research, but rather to push us all to do more and to do it better. There are reasons why BMP use data has been collected as it has, and there are still useful things to be learned from analyzing it. Indeed, as an example, I fail to follow my own advice in my second and third analyses by using binary practice use measures in my second analysis and the same tillage categories in the third analysis that I call out in the first. Mostly this use is because the data had already been collected, as is often the case. I have, however, done my best to reduce the worst of the effects of these measurement issues. For example, spatial variation in the four nutrient management practices I consider in the second analysis should be relatively low, thereby making the use of the binary measures less problematic than it is for cover crops. Using aggregated data in the third analysis potentially smooths out some of the variation in the overly general tillage categories used by the US AgCensus, making it reasonable to think that on average they indicate a relative position along the tillage continuum.

KNOWLEDGE AND THE BIOPYISCAL ENVIRONMENT

The inclusion of the biophysical environment was a secondary goal of all three analyses, and the importance of it is a key finding, especially in the first two analyses. Soil qualities and conditions are an important aspect of farmers' tillage decisions and also an influence on the use of PSNTs, variable rate N and cover crops. The biophysical context is a notable omission from both the adoption-diffusion model as well as the TPB/RAA though it potentially influences the appropriateness and function of BMPs and therefore their use. However, the finding of different tillage decisions in response to ostensibly the same environmental conditions in the first analysis demonstrates a challenge to incorporating biophysical variables into social analyses: Are the environmental conditions the farmers are responding to actually the same? If they are then why are farmers responding differently? Do the farmers have the same understandings of how different tillage approaches work or are their differing responses based on different knowledge and expectations of the practices? How important then is the perception vs. the "reality"? These questions raise the possibility of the existence of substantial differences in how farmers perceive both their biophysical conditions and the practices themselves.

The environmental implications of only considering farmers' perceptions can be considerable. If two farmers in the same farming conditions perceive their conditions differently so that one thinks it is important to use conservation tillage to reduce erosion and the other does not think it is needed because the land is pretty flat, then the two farmers are both acting consistently with their perceptions but the environmental outcomes will be quite different. The TPB/RAA is fully based on the importance of individual perceptions that may or may not be accurate (Fishbein and Ajzen 2015), especially through the behavioral beliefs and perceived behavioral control (PBC) components, which make it poorly suited for connecting the social and the ecological, since it is unknown what signals farmers actually received from their environmental contexts and thus how similar or dissimilar their perceptions are. With this approach the environmental context remains a social idea, which can limit our ability to connect social and environmental conditions, understand the causal paths that create environmental problems and conduct research that can contribute to finding solutions to those problems.

In contrast, the adoption-diffusion model perhaps does not include the importance of perceptions enough, especially in the knowledge and persuasion steps of the innovation-decision process and in the relative advantage and compatibility innovation attributes. The innovation attributes are conceptualized as inherent characteristics of the innovation, meaning there is no conceptual space for these attributes to differ between farmers. The lack of conceptual interaction between the knowledge and persuasion decision steps, and the practice characteristics in the adoption-diffusion model is an additional limitation to those discussed in the introduction chapter. Critical realism (Carolan 2005) offers a conceptual framework for integrating the “real” and perceived and for connecting the adoption-diffusion decision process to the innovation attributes.

Knowledge was of particular interest at the outset of these analyses, though it is only explicitly examined in the second analysis. In this analysis it is found to be an important predictor of the use of nutrient maps, variable rate P or K and cover crops, in spite of being a non-practice-specific measure. Knowledge of how to use or implement a practice is a basic threshold necessary for practice use (at least successful practice use). However, as is discussed in Chapter 3, there are conceptualized to be multiple types of knowledge, of which technical knowledge of the how-to variety is but one. Of particular interest is what Rogers’ *principles-knowledge* and Kaiser and Fuhrer’s *declarative knowledge*—knowledge of how the environmental system and the practice work. In the context of the present analyses, this might include knowledge of the nitrogen cycle, soil physics and chemistry, and crop physiology, and is hypothesized to be extremely important in providing farmers with an understanding of how and why a given practice works. Not only would this knowledge be very helpful in successfully implementing the practice in the farmer’s specific conditions, but it would also help in adapting to changing conditions.

Conceptually this system-type of knowledge goes beyond both education and information. Though education and information can contribute to the acquisition of system knowledge they are not equivalent to it. The potential importance of system knowledge in the agricultural context is that it includes aspects that cannot be observed directly, such as nitrogen in its elemental form, and thus connects the biophysical world with the social world. The less a process can be observed directly the more room exists for multiple social meanings and explanations to be attached to it, and thus for multiple actions seem appropriate (Carolan 2004, 2006). This type of relationship between the biophysical and social through knowledge can be understood through the lens of critical realism. Rosa (1998) and Carolan (2004) both offer very similar looking and compatible, but apparently independently developed[40], conceptual frameworks for understanding of the interaction between social and biophysical components.

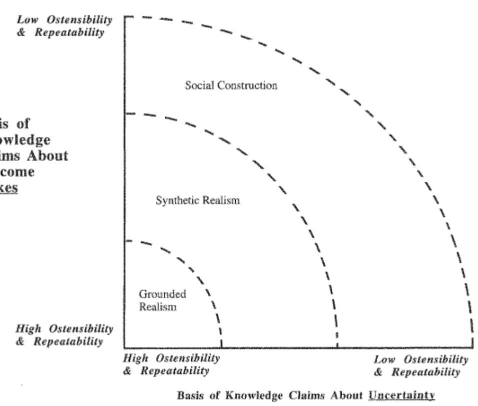

Fig. 3. The realism–constructivism continuum of knowledge claims about risk. Note: Because the diagram compresses four variables – ostensibility, repeatability, uncertainty and outcome stakes – into two dimensions, the orientation of the axes is high to low, rather than the typical orientation.

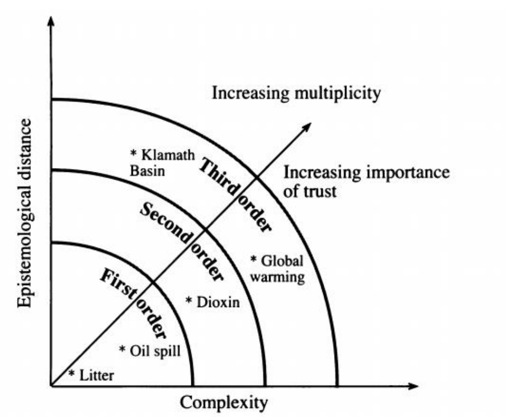

FIGURE 2. The rising salience of trust as epistemological distance and complexity increase

Figure 5.1. Conceptual diagrams from Rosa (1998:35) on left and Carolan (2004:515) on right.

Rosa developed his framework (shown on the left in Figure 5.1) in the context of studying and understanding risk in the face of meta-theoretical debates in the sociology of risk. He takes a position of ontological realism but recognizes and incorporates the potential

[40] Carolan does not cite Rosa's 1998 article.

usefulness of constructivist insights into his model. He does this by including epistemological hierarchicalism with his ontological realism (what he acronyms to OREH). What he means by epistemological hierarchicalism is that while all knowledge claims are potentially fallible, not "all knowledge claims are equally fallible" (Rosa 1998:34). His method of determining where a knowledge claim falls in the hierarchy is to ask where it falls in its measures of "ostensibility" and "repeatability" or "O&R." "Ostensibility" is the degree to which observations align while "repeatability" is the degree to which repeated observations align. In Figure 5.1 above, Rosa places claims with high O&R in the corner of the axis and with these claims being highest in the epistemological hierarchy and thus being most appropriately understood by a "grounded realist" approach. On the other hand, claims with low O&R are at the other end of the scale and are best understood using a social constructivist approach. Claims between the two extremes easily take a middle approach, i.e., critical realism, or what Rosa calls "synthetic realism."

Carolan takes an ultimately similar but slightly different approach. He suspends belief in a single realist ontology not because he thinks that a physical reality doesn't exist but because he recognizes that some environmental problems are more epistemologically distant and complex than others, and asks "What if multiple knowledges reflect not only varying positions but, in certain situations, a multiple ontology?" (Carolan 2004:498). Thus, he proposes that the more epistemologically distant and complex a phenomenon is the harder it is for us to know about it and the more ontologically fuzzy it is. He organizes the degree of fuzziness in his diagram of ontological orders (shown on the right in Figure 5.1). First order phenomena, like litter, are ones that are epistemologically closest to us—we can assess them with our own physical senses. Second order phenomena, like dioxin and nitrogen, area a step removed from our own senses; we can identify clearly what they are, but we need to use tools to measure or "see" them. Third order phenomena, like global climate change, cannot be "seen" in their entirety, even with tools; we can only know them by observing other things (like temperature, size of ice caps etc.) that we then "translate" "into" the phenomena itself. Carolan (2004:505) says that this translation causes a shift (even if a small one) in our reality "because the object itself has shifted." Not surprisingly, Carolan posits that at higher ontological orders trust in information and its sources becomes more important to hold together the complexity, and navigate the increased potential for multiple "realities."

If we were to lay Rosa and Carolan's diagrams on top of each other we can easily see how similar and compatible they are. Ostensibility is highly related to epistemological distance—things that are easily observed are epistemologically closer and thus observations are more likely to be in agreement. Similarly, complex and epistemologically distant things are harder to observe and measurements are less likely to be repeatable, as differences in timing, place, instrument etc. are more likely to produce a variety of results. Agreement on these more complex and distant phenomena are therefore going to require more trust in those producing the results and the processes they use. Additionally, while realism certainly still applies to complex and epistemologically distant phenomena, the increased multiplicity that arises at higher ontological levels makes social constructions surrounding those empirical observations of greater political and research interest. As Carolan (2004:513) puts it: "if reality is social—and thus multiple—than it is also political" and we have seen this play out clearly in the case of global climate change where different groups have created different (and often political) narratives about the existence and potential impact of climate change and have expressed a lack of trust of the scientific observations that have been made of it (see for example: McCright and Dunlap 2003; McCright 2007; Steel, Lach, and Satyal 2006; Zehr 2000). Agricultural nitrogen would likely fall somewhere in the middle of these models—it is not overly complex in that it can be fully measured, but it also cannot be observed directly, being only "visible" through a chemical test or plant growth—including algae in local water bodies.

In relation to farmer decision-making, these critical realist frameworks and the idea of "epistemological distance" helps contextualize several of the notable results of my analyses and suggests future research directions. One is the potential for farmers to respond differently to the same biophysical situation, as was found in the tillage analysis, indicates either that the biophysical situations are not in fact the same, and/or that as seemingly tangible as soil is it still has enough ontological distance to complicate the relationship between the biophysical conditions and the farmers' actions. More detailed data on farm conditions, such as researcher conducted soil tests and geospatial data, that can be coupled with more detailed information from farmers on how they till and what they are trying to accomplish with their tillage, would help tease out the sources of this variation.

Second, the importance of information sources in Chapter 3 relates well to the need for greater trust in information sources that comes with greater epistemological distance. While I did not include trust in information sources in the analysis explicitly, the frequency of use should be related to both trust and mode of access (Stuart et al. 2018). The association of specific information sources with specific practices suggests that something beyond a general trust in the source is at play, which bears further investigation.

Third, critical realism provides opportunity for developing an alternative approach to thinking about the relationship between attitudes, knowledge and action than that proposed by the TPB/RAA. The adoption-diffusion model, while certainly including the importance of trust and communication could likely benefit by being considered within an explicitly critical realist framework as well.

Lastly, epistemological distance is an important aspect to keep in mind when considering coupled natural and human (CNH) systems, and especially modeling feedbacks within them between the biophysical and social components. The critical realist approach suggests that these feedbacks will only be as good as the social system (or its relevant segment given the topic) is at recognizing the effects that society is having on the environment. Thus, the dominant narrative about the environment will mediate the feedback, rather than there being a direct relationship between environmental conditions. A very simplified example of this is shown in Figure 5.2 part B, where water quality influence the social narrative that in turn influences water policy to address it, rather than being conceptualized as having a more directed reciprocal relationship (part A.).

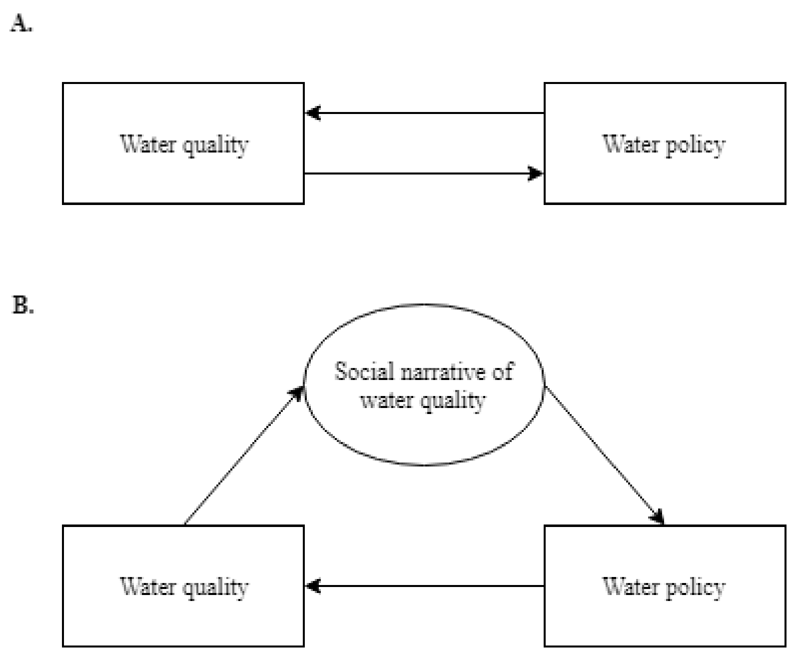

Figure 5.2. Simple example of realist (part A.) versus critical realist (part B.) approach to CNH feedback model.

PLANS FOR FUTURE RESEARCH

My plans for future research extend beyond what I suggest in the analysis chapters and includes dividing several of the chapters into multiple papers that will be a suitable length for publication in academic journals.

Tillage

My first analysis chapter will be divided into two parts. One that covers the variation in the ways that farmers are tilling and the implications for tillage categories, and one that covers the reasons farmers gave for why they till the way they do. Extensions of this research could use survey data to tease out tillage variation using a larger number of observations as well as more representative and systematic data. Potential research questions include: How common is the use of multiple practices? Are farmers who use multiple practices different from those who use only one type? Does it depend on which combinations of tillage types a farmer uses? A mixed methods approach using the interviews data could be very helpful in interpreting the results of the quantitative analyses.

Given the measurement challenges discussed above, I think that it would be profitable to compare the results of the tillage questions asked on the four farmer surveys I have been involved with to date and compare how the questions have been formulated. This type of analysis could reveal aspects that are consistent across samples and measures and provide guidance in the design of future surveys on tillage.

In the longer term, I would like to work with soil scientists to better understand the measurable biophysical context in which farmers are tilling and the tillage features that have the most important environmental implications. In other words, can we narrow the number of tillage facets that we need to measure to focus on those that matter the most? For example, how critical is the distinction between no-till and strip till environmentally, or is it the season of the tillage that matters more?

BMP Adoption

The second analysis will be divided into at least two journal articles. The nutrient management practices and the lack of consistency in their predictors will be one article. The drivers of cover crops will be another article—one that could use a step-wise regression model to look at the different categories of predictors separately before considering them all together, and one that could also interaction effects between select variables. A possible third article could focus on the probabilities of practice use and could utilize more of the response categories that were collected on the survey—including both adoption and non-adoption as possible outcomes.

Future work could consider the combinations in which practices are used, and the use of one practice to predict another. This could potentially lead to the creation of practice categories that have an empirical basis and that may not be based on practice function, but on some other aspect of compatibility, such as practice timing. This data could also be used for a preliminary comparison of the predictive power of the adoption-diffusion model vs. the TPB/RAA, as I believe that there is the need for a critical look at the appropriateness of the TPB/RAA for farmer decision-making and the potential for a useful revival of the adoption-diffusion model. I also am looking forward to using more recent survey data to consider the effects of practice-specific measure of knowledge, and the relationships between knowledge, education, experience, information sources and practice use in an analysis that could be a step towards incorporating a critical realist approach to understanding practice adoption.

Fertilizer Use

The third analysis will not be divided. Future extensions of this analysis could include the use of non-recursive models that consider the reciprocal effects between corn yield and fertilizer use. The 2017 AgCensus data (to be released in 2019) will make possible a longitudinal examination of cover crops, conservation tillage and no-till. Watershed scale models (facilitated by data integration using GIS software) could allow for the inclusion of a true feedback loop between water quality and practice use in the CNH tradition. Further developments along these lines would be greatly facilitated by more specific data at the county and watershed scale (like fertilizer spending on corn acres specifically)—which might be available from NASS by special tabulation or other arrangement.

As I have discussed above, I plan to continue the work that I have started in my dissertation in a number of ways. I am particularly interested in investigating the relationships between agricultural decisions and the biophysical environment, and in developing innovative modeling strategies that integrate social and biophysical data. In doing so, I plan to utilize geographic information system (GIS) tools and agent-based modeling alongside regression-based models.

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