Rethinking adaptive capacity: A study of Midwestern U.S. corn farmers

by

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ABSTRACT

Global climate change is one of the most significant challenges facing agriculture and society in the 21st century. In the Midwest, the projected trend toward more extreme rainfall has meant that farm-level responses are needed to maintain or increase crop yield and reduce soil erosion. On a local level, farmers are at the forefront of responding to environmental change. Thus, it is critical to understand their ability to take suitable actions for reducing risks and transforming agriculture to a more resilient system. Adaptive capacity is a term that is often used to describe farmers’ ability to access financial and technical resources. Although these are important attributes of farmers’ capacity, scholarship on human behavior has identified socio-cultural factors, such as perceived risk and capacity as strong predictors of farmers’ decision making. Therefore, our understanding of farmers’ true capacities is limited by our inability to comprehensively understand social and behavioral factors that influence their decisions to ignore, cope or adapt to climate change-related risks. In this dissertation, I attempt to address this gap by integrating social and behavioral theoretical frameworks and statistical modeling approaches to assess how variations in institutional and environmental conditions can influence farmers' adaptive capacity and their decision to use adaptive management practices.
CHAPTER 1. INTRODUCTION

The Upper Midwestern United States is a global leader in commodity crop production, including corn and soybean. This region produces one-third of the global corn supply and contributes a substantial amount of money to the national Gross Domestic Product (GDP). In 2015, $68 billion of corn and soybean was produced in this region (USDA-NASS, 2015). Climate change will cause agronomic and environmental impacts for corn and soybean crop production. Some of these impacts include a decrease in crop yield, increase in crop stressors due to extreme rain events, soil erosion, floods, droughts, and increase in weed, pest, and disease (Hatfield et al., 2014). The impacts of climate change on agriculture pose serious economic and ecological risks to Upper Midwestern agriculture and global commodity crop supply.

Projected trends toward more extreme rainfall events in the Upper Midwest can make agriculture more vulnerable via a reduction in short-term crop productivity and greater soil erosion and off-field nutrient losses across the region. On a farm level, farmers are at the frontline of responding to the impacts of climate change (McCarl, 2010). For example, farmers’ use of agricultural best management practices (BMPs), such as cover crops, can contribute to on-farm ecosystem services such as increasing crop yield and reducing soil erosion, and potentially mitigate nonpoint source pollution from agricultural lands (Kremen and Miles, 2012; Reimer et al., 2012). These is much concern whether farmers are using best management practices to make agriculture sufficiently resilient to changes in weather and climate (Walthall et al., 2012).
In the environmental change literature, adaptive capacity is an important social process for modulation of system resilience—defined as a system’s ability to respond to a shock and still maintain its general attributes, while also retaining capacity to evolve or transform to a more desirable state (Engle and Lemos, 2010; Nelson et al., 2007; Rockström et al., 2009). Adaptive capacity can be conceived of as comprising three components: a resource system; the ability of actors and social groups to access those resources; and, the institutions and structures that can influence whether actors manage natural resources effectively (Brown and Westaway, 2011).

Existing research often frames the likelihood that farmers will adapt to climate change as a function of objective capacity or material resources, such as access to finances and structures of governance (Engle and Lemos, 2010; Parry et al., 2007; Yohe and Tol, 2002). However, research on human behavior has noted that in addition to these objective attributes of adaptive capacity, behavioral factors are important for modulating actors' response to climate change (Grothmann and Patt, 2005; Moser et al., 2014). Perceived capacity—defined as the “extent to which [actors] feel prepared to endure changes and take necessary steps to cope with them” (Seara et al., 2016, p. 50)—is an important human cognitive characteristic that can influence actors’ pro-environmental behavior. Thus, it is important to understand the relationships between farmers’ objective and perceived measures of adaptive capacity. Examining this relationship can be especially important if farmers are systematically under- or over-estimating their ability to address the impacts of climate change. Moreover, simultaneously examining the objective and perceived
attributes of adaptive capacity may facilitate identification of culturally appropriate actions available to farmers for adapting to climate change.

Farmers’ responses to changes in weather and climate are dependent not only on their personal assessments of capacity, but also on the resources available through broader social, economic, and political systems that they operate within (Smit and Skinner, 2002). Contextual factors such as institutions and governance can importantly determine the ability of a social-ecological system to endure abrupt climatic changes (Agrawal, 2008; Berman et al., 2012; Dovers and Hezri, 2010; Engle, 2011; Ostrom, 2008). Institutions have been defined in the literature in many ways; one acceptable definition is that these are the “formal and informal rules and norms that govern actors, resources and their interactions in any given situation” (Eakin et al., 2016, p. 804). Previous research has found institutions to significantly mediate farmers’ objective capacity and perceived capacities by influencing their risk perceptions (Frank et al., 2011); intentions to change behavior (Grothmann and Patt, 2005), changes in conservation behavior (Prokopy et al., 2008) and their self-evaluation of capacity to adapt (Eakin et al., 2016). However, while these studies provide useful insights into analysis of institutional support and pro-environmental behavior, the environmental change literature is only beginning to address whether institutions can influence farmers’ use of adaptive management practices via changes in objective and perceived adaptive capacities (Eakin et al., 2016). An examination of the relationship among biophysical conditions, adaptive capacity, and institutional support can provide important indicators to develop risk management policies and programs that can influence farmers’ pro-environmental behavior.
The central objective of this dissertation is to contribute to agricultural sustainability by empirically examining the relationships among (1) farm-level environmental conditions, such as soil and slope characteristics; (2) biophysical stressors, such as extreme rain events, (3) socioeconomic, institutional, and behavioral attributes of adaptive capacity and (4) farmer adaptive responses to extreme rain events. These relationships are assessed to improve our understanding of farmers’ use of adaptive management practices that can enhance field-level or broader systemic resilience to climate change.

My dissertation research uses quantitative analysis, such as multilevel modeling approach, spatial statistics, and path analysis (mediation analysis) to develop a more thorough understanding of farmers’ use of adaptive management practices across the U.S. Corn Belt. I use primary data from a 2012 survey of corn and soybean farmers in 11 Midwestern states, and secondary data from Agriculture Census, the National Weather Service, and Natural Resource Conservation Service.

**Organization of Dissertation Chapters**

The dissertation is organized as follows. In Chapter 2, I evaluate the relationship among farmers’ faith in human exceptionalism, risk perceptions, perceived capacity, and support for climate change adaptation. I examined two dimensions of perceived capacity: (1) a paradigmatic type that is characterized as an abstract faith in human ingenuity and (2) farmers’ self-evaluation of their technical capacity to modulate climate change-related risks. Both dimensions are included in a path model that examines farmers’ attitudes toward adaptation.
In Chapter 3, I examine how farmers’ adaptive capacities—contextualized within institutional and environmental conditions—can influence their decision to use adaptive management practices. Two important dimensions of capacity are included in this chapter: objective attributes and structural or institutional factors. The objective was to evaluate the likelihood that Upper Midwestern corn farmers will adapt to extreme rain events—i.e., use suitable adaptive management practices (cover crops) on their farm. Adaptive action was examined vis-à-vis farmers’ (a) perceived capacity; (b) their material assets and entitlements; and (c) the institutional and environmental context in which adaptation occurs. Specifically, this study examines farmer use of cover crops, a soil and water conservation best management practice (BMP) that can be highly effective for reducing soil erosion and nutrient loss associated with extreme rain events as well as sequestering carbon and reducing the use of nitrogen. By modeling the interactions among watershed level institutional and environmental factors, and farmer level capacities, this study constitutes an important step in understanding the effects of perceived and objective attributes of adaptive capacity on the use of adaptive management practices. By comparing different dimensions of adaptive capacity and farmers’ use of cover crops, I provide a timely assessment for supporting specific dimensions of farmers’ capacities that can be beneficial for improving field and watershed-level soil and water quality.

In Chapter 4, I highlight the importance of understanding farmers’ perceived adaptive capacity by developing unique theoretical and methodological approaches to assess farm/farmer’s vulnerability to extreme rain events. As highlighted in
Chapter 2 and 3, many studies on adaptive capacity frame the likelihood that actors and communities will adapt to climate change as a function of access to financial and technical resources. Yet actors’ vulnerability can be modulated by other elements of adaptive capacity, such as how they assess their own capacity to cope or adapt to climatic risks. In this chapter, I include perceived adaptive capacity into a vulnerability assessment to evaluate the degree to which objective and perceived adaptive capacity can differentially modify farm/farmers’ vulnerability to extreme rain events. A better understanding of the relationships between objective and perceived measures of adaptive capacity in agriculture has implications for climate change policy and programs, especially if farmers are consistently under- or over-analyzing their ability to adapt to weather and climatic impacts. Moreover, examining the objective attributes of adaptive capacity in combination with the subjective measures of capacity facilitates identification of adaptation actions that are culturally suitable. In this chapter, we use spatial statistics to construct county level vulnerability estimates with perceived and objective dimensions of adaptive capacity.

Chapter 5 summarizes and concludes the dissertation. Overall, this dissertation empirically examines how biophysical stressors and socioeconomic, institutional, and behavioral attributes of adaptive capacity can influence farmers’ (1) attitude toward climate change adaptation, (2) ability to reduce vulnerability to extreme rain events, and (3) use adaptive management practices, such as cover crops. Finally, Appendix A provides a glossary of the key terms used in this dissertation.
References


CHAPTER 2. TECHNO-OPTIMISM AND FARMERS’ ATTITUDES TOWARD CLIMATE CHANGE ADAPTATION

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Maaz Gardezi¹ and J. Gordon Arbuckle²

Abstract

In industrialized societies, a dominant worldview speculates that human ingenuity, through improved science and technology, will ultimately provide remedies to most current and future adverse events, such as diseases, climate change, and poverty. Here we examine: (1) whether techno-optimism is found among Midwestern corn and soybean farmers and (2) how this blind faith in human ingenuity influences their support for climate change adaptation. By examining a survey of nearly 5000 conventional farmers in the Midwestern U.S., we found that greater techno-optimism can reduce farmers’ support for climate change adaptation and increase their propensity to express a preference to delay adaptation-related actions. This research can help extension educators to develop outreach programs that are sensitive to farmers’ views about the ability of science and technology to solve climate change-related issues. Such programs can also provide Corn Belt farmers with a balanced view about the limitations and possibilities of science and technology for solving climate change-related issues.

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Introduction

Climate change presents significant challenges to agriculture and society. It is affecting global and regional agricultural productivity now and predicts to continue impacting more severely in the future (Coumou and Rahmstorf, 2012; Hatfield et al., 2014). Farmers are at the frontiers of responding to the impacts of climate change on agriculture (Lal et al., 2011). Understanding the social and behavioral drivers of farmers’ attitudes toward climate change is crucial for increasing agriculture’s resilience to climate change. This study combines elements of the “Human Exemptionalism Paradigm (HEP)” (Catton and Dunlap, 1978; Dunlap and Catton, 1994; Foster, 2012) and the alternative agriculture—conventional agricultural (ACAP) paradigm (Beus and Dunlap, 1994, 1990a) frameworks with more recent cognitive factor approaches (Bubeck et al., 2012; Wachinger et al., 2013) to examine U.S. Corn Belt farmers’ attitudes toward climate change adaptation.

A major thread of environmental sociology theory posits that in industrialized societies, the “Human Exemptionalism Paradigm (HEP)” has become a dominant worldview (Catton and Dunlap, 1978). The main assumptions of the HEP include an assertion that humans are: (1) unique among other species on earth; (2) independent from the ecosystem that they inhabit, and (3) able to use technology to dominate over nature (Catton and Dunlap, 1978). The Human Exemptionalism Paradigm (HEP) implies natural resource limitlessness and expects social and technological developments to lead to perpetual progress. Confidence in science and technology is a core component of the HEP and Barry (2012) labels this attribute as “techno-optimism” or “belief in human technological abilities to solve
problems of unsustainability while minimizing or denying the need for large-scale social, economic and political transformation” (Barry, 2012). Techno-optimism is a belief that human ingenuity, through improved science and technology, will ultimately provide remedies to most current and future threats to human well-being, such as diseases and climate change (Foster, 2012).

Many of the elements of the HEP, such as domination over nature, exploitation of natural resources, and faith in human ingenuity, are central to the U.S. conventional agriculture paradigm (Beus and Dunlap, 1990a). In the last century, high-input, science-based capital intensive forms of agriculture, referred to as “conventional agriculture” contributed to substantial increases in yields, but have had impacts on the sustainability of farm income (Lobao and Meyer, 2001); well-being of farming communities (Lobao and Meyer, 2001); and on-farm and off-farm environmental degradation (Lowe et al., 1990). By the late 1980s these and other concerns had given rise to an environmental movement in U.S. agriculture, whose goal was to reduce the negative social and environmental impacts of farming that had been associated with conventional agriculture (Beus and Dunlap, 1990a). In contrast to the elements of the conventional agriculture paradigm, the alternative worldview stresses harmony between humans and non-human nature; inclusion of potential off-farm environmental impacts, and a critical approach toward examining science and technology’s utility in solving social and environmental challenges associated with agriculture (Beus and Dunlap, 1990a). Indeed, the alternative agriculture paradigm holds a diametrically different view of human ingenuity. It
recognizes that no matter how inventive humans may be, their science and
technology cannot completely reverse ecological degradation.

Previous research has demonstrated the relationship between farmers’
paradigmatic belief and pro-environmental behavior. For example, Beus and Dunlap
(1990) used surveys to examine the relationship between farmers’ adherence to
conventional or alternative paradigm and use of environmentally harmful production
practices. They found that endorsement of conventional agriculture worldview was
strongly associated with higher self-reported use of chemicals. Other research has
examined how techno-optimism can act as a barrier to farmers’ pro-environmental
behavior. For example, Dentzman et al. (2016) found that adherence to a techno-
optimist worldview could constrain U.S. farmers’ adoption of pro-environmental
behavior, such as their use of holistic weed management. Thus, techno-optimism
can be an important moderator of farmers’ pro-environmental behavior.

Another important thread of research has focused on cognitive factors, such
as risk perceptions and perceived capacity, as important for influencing actors’
support for pro-environmental behavior, including adaptation to climate change
(Moser et al., 2014). For example, perceived capacity—defined here as the “extent
to which [people] feel prepared to endure changes and take necessary steps to cope
with them” (Seara et al., 2016, p. 50)—has been found to influence actors’ decisions
about taking actions for managing risks (Moser et al., 2014). At the farm level,
farmers’ perceived capacity can be comprised of such factors as perceptions about
their financial and technical knowledge.
A concept that has been increasingly considered to be an important moderator of behavior is “decision delay.” Decision-delay is a common response to threats that may be well-known to people, but are perceived to pose no immediate risks (Anderson, 2003). This is a psychological phenomenon in which, rather than deciding on and preparing for risky scenarios ahead of time, people delay decisions and instead prefer to wait and see (McNeill et al. 2015). There are two steps of cognitive processes that explain why actors’ make decisions in relation to threat (Rogers, 1975). The first step is a risk or threat appraisal. In this stage, actors evaluate the “likelihood" and “severity” of the threat (Truelove et al., 2015, p. 86). If the risk is perceived to be high, in the second stage, people engage in “coping appraisal", which is an assessment of their personal capacity to respond to a threat (Bubeck et al., 2012). Both risk and coping appraisals are important for influencing personal action.

While extensive research on the relationships between perceived capacity and personal action has been conducted in diverse contexts, this research focuses rigorous, theoretically informed analysis on how farmers’ ideological dimensions of capacity (i.e., techno-optimism), beliefs about personal capacity (perceived capacity), and risk perception might influence their support for climate change adaptation. It is hypothesized that techno-optimism can be an ideological force that may hinder farmers from engaging in climate change adaptation, even when they perceive that the risks associated with climate change are serious. On one hand, farmers’ ought to continuously respond to the threats posed by climate change by planning, learning, and experimenting. On the other hand, adherence to an abstract
faith in human ingenuity to solve future challenges associated with climate change may reduce their ability to engage in adaptive management.

This paper examines how techno-optimism and perceived technical capacity may moderate farmers’ willingness to respond to the threats posed by climate change. We examine four research questions: (1) Does greater techno-optimism reduce farmers’ support for climate change adaptation?; (2) Does higher level of techno-optimism and perceived technical capacity reduce farmers’ support for adaptation?; (3) Does techno-optimism increase farmers’ propensity to delay adaptation-related decisions?; and, (4) Are farmers more likely to delay adaptation decisions if they have higher techno-optimism and greater perceived technical capacity? This paper is organized as follows: First, relevant literature is reviewed to examine four key concepts: techno-optimism, perceived technical capacity, risk perception, support for climate change adaptation, and decision-delay. Next, conceptual models are developed to frame the complex relationships between determinants of farmers’ climate change-related risk perception and support for climate change adaptation. The hypothesized relationships are empirically examined using a survey of almost 5000 conventional farmers from the Upper Midwestern U.S. Finally, the main findings of this research are presented and possibilities for future research on this subject are discussed.

**Literature Review**

**“Human Exemptionalism Paradigm” in conventional agriculture**

Many of the elements of the HEP, such as confidence in science and technology that drives faith in human ingenuity, are central to the U.S. conventional agriculture.
agriculture paradigm (Beus and Dunlap, 1990a). American agriculture in the first half of the 20th century went through tremendous technological change. Widely known as the “Green Revolution”, this era transformed farming from a labor-intensive to industrial or capital-intensive system of operation (Rasmussen, 1962). The widespread transitions to mechanization, advances in plant and animal breeding, and greater use of fertilizer and chemicals, has led to a dramatic increase in farm output and productivity (Dimitri et al., 2005). For example, between 1948 and 2011, the U.S. agricultural output grew at 1.49 percent per annum, driven mainly by growth in productivity and technology (Wang, 2013). The legacy of technological advancements during the Green Revolution and the resulting improvements in agricultural productivity is “…a source of national pride for many Americans, especially farmers, agricultural scientists, and politicians (Beus and Dunlap, 1990b, pp. 590–591).” Conventional farmers often highlight the strategic importance of technological advancements in solving challenges pertaining agriculture. For example, some research has documented perception among farmers that private seed and chemical companies will supply the next technological breakthrough to solve most problems related to drought, weed, pests and diseases (Dentzman et al., 2016).

Previous research has found a strong relationship between farmers’ paradigmatic belief and pro-environmental behavior. For example, Beus and Dunlap (1990) found evidence of a positive relationship between farmers’ adherence to human exemptionalism paradigm and use of production practices that were detrimental to the environment. They recommended that efforts should be made to
shift ideological focus of farmers from one that only targets productivity enhancements as its goal to one that also incorporates environmental concerns.

Other research has examined how techno-optimism can act as a barrier to farmers’ pro-environmental behavior. For example, Dentzman et al. (2016) used focus groups to examine whether farmers’ adherence to a techno-optimist worldview could constrain their adoption of pro-environmental behavior. They found that most farmers had faith in future technologies to provide adequate weed management, which made them less likely to use pro-environmental farming practices, such as holistic weed management. Thus, literature on U.S. farmers has found techno-optimism to moderate farmers’ pro-environmental behavior.

**Risk perception and trust in experts**

An important thread of research on human behavior has focused on risk perceptions as significant for influencing actors’ support for pro-environmental behavior, including adaptation to climate change (Grothmann and Patt, 2005; Moser et al., 2014). Risk perceptions are socially constructed and various factors such as past experiences of natural hazard, perceived capacity, and emotions can influence actors’ decisions about both the significance of risks and the willingness to take actions to cope, adapt or ignore such risks (Feldman et al., 2014; Weber and Stern, 2011). Farm-level research suggests that farmers who perceive climate change to be a threat to their farm enterprises are more likely to make adjustments to anticipate or react to changing conditions that may place the farm enterprise at risk (Arbuckle et al., 2013a; Morton et al., 2015). Although a positive relationship between risk perceptions and the willingness to take actions to cope, adapt or ignore
such risk is intuitive, scholars in the realm of natural hazard and climate change adaptation research have been perplexed by inconsistent findings. While some studies find a positive relationship between risk perceptions and behavioral change (Arbuckle et al., 2013a; Gramig et al., 2013), some studies do not (Hung et al., 2007), and still other research shows a negative correlation between the two (Jorgensen and Termansen, 2016; Lo, 2013).

In a meta-study on actors’ risk perception of natural hazards, Wachinger et al. (2013) offer various explanations of why higher risk perception about natural hazard may not be associated with willingness to take actions to cope or adapt to such risks (Wachinger et al., 2013). One reason put forward is that actors may correctly evaluate the risk associated with a hazard, but rely on the support and expertise of authorities to take charge or respond to a hazardous situation. Thus, actors may trust experts in contemplation of reducing potential risks and improving potential benefits of present actions and future consequences.

Trust in experts can be defined as a “disposition willingly to rely on another person or entity to perform a given action or protect oneself or one’s interest in a given domain” (Nickel and Vaesen, 2012, p. 860). Applied decision theory posits that a rational decision-maker chooses to trust an expert after carefully quantifying risks and assessing the trustworthiness of the expert (Nickel and Vaesen, 2012). According to such reasoning, actors trust experts through a rational calculation of the latter’s knowledge, skills, experience, and intentions (Earle, 2010). However, scholars in the field of socio-cultural and cognitive studies argue that people’s trust in authority does not have to depend on an extensive calculation of the benefits and
costs of trusting experts. Most people do not have time, money, and knowledge, to conduct a rigorous risk assessment of the trust situation. Instead, people rely on their emotions, intelligence, and experience to guide their judgment about trusting experts (Hardin, 1991; Uslaner, 2008; Yamagishi, 2001). In its abstract form, trust can be considered as a way for people to increase their dependence on the ‘expert’ without consciously assessing the competence of the expert or the trust situation (Frederiksen, 2014).

In conventional agriculture, human ingenuity tends to be manufactured in sophisticated technologies such as commercial inputs, Global Positioning Systems (GPS) and genetics, etc. Following the general findings from previous research, it can be argued that in the absence of complete knowledge about the risks associated with climate change, conventional farmers’ attitude toward climate change adaptation can be guided by an abstract faith in technology (techno-optimism). This type of trust can be characterized as a “leap of faith” (Möllering, 2006) and may reduce farmers’ support for climate change adaptation.

**Perceived technical capacity**

In the realm of adaptation to climate change in agriculture, farmers’ perceived capacity is generally conceptualized as their personal beliefs as to whether they are able to adapt to climate change (i.e., they have sufficient knowledge, financial, and technical skills to make changes to their farming practices). For example, in a study of Sri Lankan farmers, Truelove et al. (2015) found that those farmers who felt capable of using climate-smart agriculture and perceived their adoption as necessary to reduce risks related to climate change were more likely to engage in
adaptive responses. Other studies have assessed the relationships between actors’ perceived capacity and various environmental behaviors, such as water conservation (Trumbo and O’Keefe, 2005), recycling behavior (Botetzagias et al., 2015; Cheung et al., 1999), health-related practices (Black and Babrow, 1991), and use of public transportation (Tikir and Lehmann, 2011). In general, these studies have found that higher perceived capacity can lead actors to more strongly support and practice environmental behavior. This paper examines how ideological dimensions of capacity (techno-optimism) and beliefs about personal capacity (perceived technical capacity) can moderate farmers’ willingness to respond to the threats posed by climate change.

**Decision-delay**

Previous studies have examined farmers’ decision to support adaptation as a dichotomous choice made by them, i.e. farmers either support or do not support taking adaptive measures on their farm. Yet, managed farming systems are complex and dynamic with unpredictability due to markets, policy, weather, and climate (Hess et al., 2012). Instead of being assertive in accepting or rejecting the use of adaptive management practices, farmers can be uncertain toward taking an action and may decide to wait and see. This psychological phenomenon has been described in the natural hazards literature as ‘Decision-delay’ and is associated with actors’ being fully aware of the threats posed by a natural hazard but still intending to delay risk-reduction action (Anderson, 2003).

Decision-delay is synonymous with uncertainty and Morton et al. (2017) recently examined some of the social and behavioral drivers of farmers’ uncertainty
about the impact of climate change on their farm operation. Findings from their research show that farmers’ uncertainty can be explained by the variation in beliefs held by them about the causes of climate change. We build upon this scholarship and advance our knowledge about how “decision-delay” can be influenced by broader ideological beliefs, such as farmers’ adherence to a techno-optimistic worldview.

**Conceptual Frameworks and Hypotheses**

This paper examines how ideological dimensions of capacity (techno-optimism) and beliefs about personal capacity (perceived technical capacity) can moderate farmers’ willingness to respond to the threats posed by climate change. In the previous section, we reviewed the concepts of risk perception and techno-optimism as predictors of farmers’ support for adaptation. We established that perceived technical capacity, in addition to techno-optimism, is also a potential mediator of support for adaptation. Drawing on the literature reviewed above, we develop two conceptual models. In the first model, we examine how two moderating variables; techno-optimism and perceived technical capacity, influences the strength of relationship between farmers’ risk perception and support for adaptation (Figure 1). The second model examines how the moderators modify the relationship between farmers’ climate change-related risk perception and their propensity toward decision-delay (Figure 2). Our models show that there are two types of capacities: farmers’ ideological dimensions of capacity (techno-optimism) and beliefs about personal capacity (perceived technical capacity). The interaction between the two moderators (techno-optimism and perceived technical capacity) can allow us to
examine whether there is a relationship between farmers’ adherence to a human exceptionalist ideology and perception of their personal technical capacity to support adaptation.

Figure 1: Multiple moderation model with ‘Support for Climate Change Adaptation’ as outcome variable (Model 1)

Figure 2: Multiple moderation model with ‘Decision-delay’ as outcome variable (Model 2)
Based on the literature reviewed above, for this study of Midwestern corn and soybean farmers, we propose the following hypotheses:

H1: Higher levels of techno-optimism will be associated with lower levels of support for climate change adaptation;

H2: Higher levels of techno-optimism and perceived technical capacity will weaken the relationship between risk perception and support for climate change adaptation;

H3: Higher levels of techno-optimism will be associated with greater decision-delay;

H4: Higher levels of techno-optimism and perceived technical capacity will weaken the relationship between risk perception and decision-delay.

**Method**

**Data collection**

The data in this research are from a February 2012 random sample survey of farmers stratified by 22 HUC6 watersheds in the Upper Midwestern U.S. (Arbuckle et al., 2013b). Appropriate human subjects research approvals were obtained under Iowa State University Institutional Review Board ID#10-599. The sample was drawn to ensure that it was representative of large-scale farmers in the region. Only farm operations with greater than 80 acres of corn production and gross farm revenue in excess of $100,000 were included in the sample frame. The survey was sent to over 18,000 farmers and 4,778 respondents replied, a response rate of 26%. Statistical tests for non-response bias showed no practical differences between respondents and non-respondents (Arbuckle et al., 2013b).
Measures

Each model employs one predictor variable, two moderator and control variables and a single outcome variable. Listwise deletion of cases with missing values on at least one variable reduced the sample size from 4,778 to 4,363 and 4,391 for model 1 and model 2, respectively. Cook’s D, leverage, and Mahalanobis distance criteria were used to assess for outlier respondents. Tests were conducted for multicollinearity, multivariate normality, and heteroscedasticity. Correlations between variables are in the range of 0.1 to 0.3, so they do not depict multicollinearity.

Outcome variables

There are two outcome variables, each measuring a unique attitude toward climate change adaptation. “Support for adaptation” consists of a single item that asked farmers to rate their agreement with the question: “I should take additional steps to protect the land I farm from increased weather variability” on a 5-point scale from strongly disagree (1) to strongly agree (5). The mean score on the support for adaptation item was 3.47 out of 5 (Table 1). The Likert-scale for the adaptation item were transformed into two categories (0 = “strongly disagreed, disagreed, uncertain” and 1 = “agreed or strongly agreed).

“Decision-delay” is measured through a single survey question that asked respondents to rate their agreement, on the same 5-point scale, with the statement: “There’s too much uncertainty about the impacts of climate change to justify changing my agricultural practices and strategies.” The mean score of 3.66 out of 5 on this question is evidence of sizeable agreement with the statement. We
constructed a dichotomous item for “Decision-delay” with 0 assigned to farmers who strongly disagreed, disagreed, or were uncertain and 1 who agreed or strongly agreed with the statements.

**Moderators**

This study uses two moderator variables. “Techno-optimism” is measured through a single item that asked respondents to rate their agreement with the statement, “climate change is not a big issue because human ingenuity will enable us to adapt to changes”, on a five-point scale from strongly disagree (1) to strongly agree (5). The mean score was 3.02 out of 5 on the techno-optimism item (Table 1). “Perceived technical capacity” is measured through a question that asked farmers to rate their agreement (on the same 5-point scale) with the statement, “I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation.” This question measures their assessment their farms’ capacity to withstand impacts of climate change.

**Predictor variable**

One predictor variable—“Perceived Risk”—is measured through a single question that was answered on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree): “My farm operation will likely be harmed by climate change.” This question measures respondents’ perception of threat associated with climate change. Farmer education and farm size were included as statistical controls.

<table>
<thead>
<tr>
<th>Table 1. Descriptive statistics for the variables in the analysis</th>
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<tr>
<td>Study Variables</td>
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<tr>
<td>Predictor:</td>
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<tr>
<td>Perceived Risk (PR)</td>
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We use a binary logistic regression to model farmers’: (1) support for adaptation and (2) propensity to delay adaptation decisions. Binary logistic regression is an appropriate method to use when a dependent variable is a dichotomous measure. This approach is often used to examine the relative importance of predictor variables on a binary outcome (Field, 2013). We conducted multiple moderation analysis to analyze the effect of moderators (‘techno-optimism’ and ‘perceived technical capacity’) on the responses of the outcome variables. This analysis was administered using a SPSS script developed by Hayes (2013). Moderation refers to a theoretical condition when strength of the relationship between a predictor variable and an outcome variable can be explained by their relationship to one or more moderating variables (Field, 2013). This script allows for simultaneous examination of multiple moderators and comparison of specific interaction effects. Following recent recommendations for testing moderation (Preacher and Hayes, 2008), we used 1,000 parametric bootstrap samples to obtain empirical standard errors and 95% bias-corrected confidence intervals with which to
assess the significance of estimates (Williams and Mackinnon, 2008). Parametric bootstrap confidence intervals generally perform better without requiring to make assumptions about the normality of the sampling distribution of the indirect effect (Hayes, 2013).

**Results**

Table 2 shows the results of the multiple moderator models that were specified in Model 1 (Figure 1) and Model 2 (Figure 2). The table reports logistic coefficients and standard errors. Statistical significance is illustrated using conventional asterisks on the coefficients. Model 1 examines both the main and interaction effects of Perceived Risk (PR) on Support for Adaptation (SA) through two moderators (TO and PTC). PR is the predictor, TO and PTC are moderators, and SA is the outcome variable. This moderation model allows us to consider each moderator’s unique influence on the relationship between PR and SA. The log odds estimates of model 1, their standard errors, and statistical significance (represented with an asterisk) are presented in Table 2. Overall, the model shows a coefficient of determination ($R^2$) of 0.05. The low $R^2$ is expected because of the relatively few predictor/moderator variables included in our model to explain farmers’ support for adaptation.

Model 1 can be divided into two types of effects: main and interaction effects. As shown in Table 2, with respect to the main effects, PR was positively associated with SA ($b=0.45$, $se=0.05$, $p<0.001$). With respect to the main effects from the moderators (TO and PTC) to SA, higher levels of TO was associated with lower levels of SA ($b=-0.13$, $se=0.04$, $p<0.001$). The relationship between PTC and SA
was not statistically significant (b=-0.09, se=0.04, p=0.81). These findings are consistent with Hypothesis H1 and lend support to claims regarding a positive relationship between PR and SA. Table 2 also shows three two-way interactions (TO-PR, TO-PTC, PR-PTC) and one three-way interaction (TO-PTC-PR) effects. We found a weakly significant interaction (TO-PTC) suggesting that the effect of perceived risk on support for adaptation is becoming weaker at higher levels of techno-optimism and perceived technical capacity (b=-0.06, se=0.04, p=0.09).

<table>
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<tr>
<th>Table 2. Logistic Regression with Interactions (log odds with standard errors)</th>
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<tr>
<td><strong>Outcome variables</strong></td>
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<tr>
<td><strong>Support for Adaptation (SA)</strong></td>
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<tr>
<td><strong>Decision-delay (DD)</strong></td>
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<td><strong>Model</strong></td>
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<td><strong>(1)</strong></td>
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<tr>
<td>Constant</td>
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<tr>
<td>Predictor:</td>
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<tr>
<td>Perceived Risk (PR)</td>
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<td>Moderators:</td>
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<tr>
<td>Techno-optimism (TO)</td>
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<tr>
<td>Perceived Technical Capacity (PTC)</td>
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<td>Interactions:</td>
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<td>PR X TO</td>
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<tr>
<td>PR X PTC</td>
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<td>TO X PTC</td>
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<td>PR X TO X PTC</td>
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<tr>
<td>Control variables:</td>
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<tr>
<td>Education</td>
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<td>Land Owned (acres)</td>
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<td>Fit Statistics</td>
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<td>Observations</td>
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<td>-2 Log Likelihood</td>
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<td>Nagelkerke-R²</td>
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Note: *p<0.1; **p<0.05; ***p<0.01

We graphically examine the conditional effect of risk perception on support for adaptation at low, average, and high values of the moderators (TO & PTC). Figure 3
illustrates risk perception on the x-axis and support for adaptation on the y-axis. Values on the x-axis represent one standard deviation below mean (low), mean value (average), and one standard deviation above mean (high) for the perceived risk survey item. Values on the y-axis show predicted probabilities of farmers self-reporting in favor of climate change adaptation—as opposed to against it. The graph shows that when TO is low (panel a), there is a significant positive relationship between PR and SA; at the mean value of TO (panel b) there is a weaker positive relationship between PR and SA, and this relationship weaken at higher levels of TO (panel c). Therefore, higher techno-optimism (TO) moderates the relationship between perceived risk (PR) and support for adaptation (SA). Figure 3 also shows the effect of PTC on support for adaptation. It shows that the relationship between PR and SA is weakest at the highest levels of PTC and TO (panel c). Thus, probability of supporting adaptation is at lowest level when farmers (1) do not perceive climate change to be a risk to their farming operation, (2) perceive higher level of technical capacity, and are (3) highly techno-optimistic. This interaction is prominent in panel c of figure 3, titled ‘High Techno-Optimism’, it is weakly statistically significant (Table 2) and does lend support to Hypothesis H2.
Figure 3: Interactions with Support for Adaptation as the outcome variable (values on the x-axis and for moderators represent one standard deviation below mean (low), mean value (average), and one standard deviation above mean (high) for the predictor and moderator items).

Whereas model 1 examined farmers’ support for adaptation as an outcome of their perceived risk (PR), model 2 takes a slightly different conceptual angle, with propensity to ‘decision-delay’ (DD) as an outcome of risk perception moderated by techno-optimism (TO) and perceived technical capacity (PTC). Table 3 shows the model results, including standard errors in parentheses. This model also allows investigation of the main and interaction effects of perceived risk (PR) on decision-delay (DD) while modeling a process where moderators (TO & PTC) influence this relationship (Hayes, 2013).

Model 2 (Table 3) is a multiple moderation model with two moderators (TO and PTC) representing three direct effects, three two-way interaction effects, and
one three-way interaction. As shown in Table 3, with respect to the main effects, climate change risk perception was negatively associated with the decision-delay (b=-0.25, se=0.05, p<0.001). With respect to the main effects from the moderators (TO & PTC) to DD, higher levels of TO were associated with higher levels of DD (b=0.45, se=0.04, p<0.001). The relationship between PTC and DD was statistically significant and positive (b=0.13, se=0.04, p=0.02). Therefore, higher level of perceived technical capacity is associated with greater decision-delay. These findings are consistent with Hypothesis H3. Table 3 also shows three two-way interactions (PR-TO, TO-PTC, PR-PTC) and one three-way interaction (PR-TO-PTC) effects. The two-way interaction, PR-TO, is statistically significant (b=-0.11, se=0.04, p=0.04), implying that the relationship between perceived risk (PR) and decision-delay (DD) is significantly (weakly) moderated by techno-optimism (TO).

Conditional effects are illustrated in figure 4. Figure 4 illustrates risk perception on the x-axis and decision-delay on the y-axis. Values on the x-axis represent one standard deviation below mean (low), mean value (average), and one standard deviation above mean (high) for the perceived risk survey item. Values on the y-axis show predicted probability of farmers’ responding either agree or strongly agree to the survey item that measured ‘decision-delay’. When techno-optimism is low (panel a) there is a negative relationship between risk perception and decision-delay. This negative relationship becomes stronger as levels of techno-optimism rise (panels b & c). Thus, higher levels of techno-optimism are associated with greater propensity to delay decisions associated with taking adaptive measures. Finally, and in support to Hypothesis H4, decision-delay is highest for those farmers who (1)
perceive low levels of climate change risk to their farming operation (low risk perception), (2) perceive higher levels of technical capacity, and are (3) highly techno-optimistic.

![Graph showing interactions with Decision-Delay as the outcome variable](image)

Figure 4: Interactions with Decision-Delay as the outcome variable (values on the x-axis represent one standard deviation below mean (low), mean value (average), and one standard deviation above mean (high) for the response and moderator items).

**Discussion and Conclusion**

In the last fifty years, a gradual decline in the number of small commercial farms and an increasingly homogenous commodity crop market has weakened Midwestern U.S. conventional farmers control over the price they receive when they choose to sell their crops (Macdonald et al., 2013). Therefore, farmers can only increase their profitability by producing and selling more crops in the market. Those who have been successful at improving their profits are ones who have aggressively adopted technology including commercial fertilizer, pesticides, and genetically
modified seed varieties. Indeed, many conventional farmers see the adoption of new technology as necessary for improving profitability and surviving a highly competitive commodity market.

Although extensive use of technology, such as synthetic inputs has allowed farmers to efficiently produce and sell more crops, some of these technologies have also been responsible for serious environmental problems associated with degradation of soil health and water quality. While outreach efforts are communicating and demonstrating to farmers the economic and environmental benefits of alternative or sustainable farming practices, recent research on farmer decision-making suggests that over time Midwestern corn farmers have become more skeptical about the efficacy of such practices to improve economic profitability and environmental quality (Morton et al., 2013). This raises concerns about the effectiveness of existing engagement strategies that communicate the benefits of adopting sustainable farm management practices to farmers.

In this study, we found that techno-optimistic farmers were less likely to indicate support for individual-level adaptation to climate change. An important implication of this finding is that effective outreach for adaptive management practices, such as soil and water conservation should be promoted from a techno-optimistic perspective. In other words, since many farmers attribute the use of new technology with higher crop productivity and profitability, outreach activities for soil and water conservation should highlight the technical aspects of sustainable farming practices to appeal to farmers’ techno-optimism. Communication with farmers should focus on the science of practices by highlighting their effectiveness. Outreach should
learn the principles of modern advertising (that many synthetic input manufacturers use) to communicate the science behind soil and water conservation practices.

Natural resource systems, such as farming, are highly complex, fraught with large uncertainties due to vagaries of weather and markets (Gunderson, 2015, 1999). Climate change is likely to create additional uncertainties related to farm management, such as deciding when to plant and harvest crops. Therefore, farmers’ ought to continuously respond to the threats posed by climate change by planning, learning, and experimenting. However, as identified in this study, farmers’ adherence to an abstract faith in human ingenuity to solve future challenges associated with climate change may reduce their willingness to support adaptation and increase their propensity to delay decisions pertaining to agricultural adaptation. For example, farmers could decide to wait and see whether research and development by public/private sector will develop the next needed technology to manage uncertainty associated with climate change. To deal with this unfettered faith in the capacity of humans to solve all social and environmental problems, we suggest that engagement strategies should highlight the limitations and possibilities of science and technology for addressing challenges of food security and environmental degradation.

A balanced view about the confines and opportunities of science and technology for solving climate change-related issues can help farmers make better evaluations of their perceived technical capacity. Contrary to previous research that has shown perceived capacity to positively influence actors’ support for adaptation (Esham and Garforth, 2013), we found that higher perceived technical capacity was
negatively related to support for adaptation and positively associated with decision-delay (Figure 5). Farmers’ who reported higher levels of perceived technical capacity to prepare for climate change were more likely to express uncertainty about adaptation decisions. Therefore, by developing communication strategies that explain both opportunities and limitations of adopting new technology, farmers’ can make more accurate assumptions about their own capacity to overcome challenges associated with climate change and variability.

We examined how the interaction effects between ideological dimensions of capacity (techno-optimism) and beliefs about personal capacity (perceived technical capacity) can moderate farmers’ willingness to respond to the threats posed by climate change. This study found that the combined effect of farmers’ techno-optimism and perceived technical capacity was associated with reduced support for adaptation (Figure 4) and greater decision-delay (Figure 6). Interestingly, these findings applied to farmers with low, average, and high levels of risk perception. In other words, even at higher levels of risk perception, farmers’ who perceived higher technical capacity and greater techno-optimism were (1) less likely to support adaptation (Figure 4) and (2) more likely to delay adaptation decisions (Figure 6). Thus, a key finding of this research is that while perceived risks are important indicators of farmers’ support for adaptation, they are filtered through other socio-cognitive dimensions of risk. These results suggest that a focus on risk perception, although an important complementary determinant of behavior, perhaps is not sufficient on its own. Therefore, engagement strategies need to consider how these mediating factors can play role in shaping adaptation-related behavior. Instead of
developing outreach efforts that focus only on educating farmers about risks, engagement strategies need to explain to farmers the technological limitations of different adaptation strategies. For example, the success of drought-resistant seeds depends greatly on biophysical and managerial factors, such as the availability and volatility of precipitation and the timing of planting seeds, respectively. Therefore, engagement strategies should highlight how biophysical conditions and management-related decisions can influence the success of farm-level adaptation to climate change.

This study assessed the influence of techno-optimism, perceived technical capacity, and risk perceptions on farmers’ attitudes toward climate change adaptation. We found that higher level of techno-optimism and perceived technical capacity can (1) reduce farmers’ support for climate change adaptation and (2) increase their propensity to express a preference to delay adaptation-related actions. The findings from this study advance our understanding of how social and cognitive factors influence farmers’ attitudes toward climate change adaptation. This study makes several contributions to our understanding of farmers and climate change. First, to the literature on environmental sociology, specifically to its understanding of human exemptionalism in conventional agriculture. Second, to natural hazard research by highlighting that actors may think of ‘experts’ in terms of abstract entities (Giddens, 1991) and not solely in terms of actual authorities, such as disaster relief and rehabilitation agencies (Bichard and Kazmierczak, 2012). Third, to the literature on farmers’ decision-making in uncertainty, specifically, as it relates to their willingness to support adaptation to climate change.
References


CHAPTER 3. CAN FARMERS’ ADAPTIVE CAPACITIES—CONTEXTUALIZED WITHIN INSTITUTIONAL AND ENVIRONMENTAL CONDITIONS—INFLUENCE THEIR DECISION TO USE ADAPTIVE MANAGEMENT PRACTICES?

*Modified from a paper to be submitted to Global Environmental Change*

Maaz Gardezi¹ and J. Gordon Arbuckle²

**Abstract**

In the Upper Midwest, the coupling effects of extreme rain events and intensive farming pose serious challenges to food security and environmental sustainability. On a farm level, farmers’ use of adaptive management practices, such as cover crops, is highly effective for improving crop yield and reducing soil erosion and nutrient loss. The objective of this article is to examine how farmers’ adaptive capacities—contextualized within institutional and environmental conditions—can influence their decision to use adaptive management techniques. We use Generalized linear mixed models (GLMMs) to examine the relative importance of (a) “internal” variables—the perceived capacity; (b) “external” or “objective” resources—the assets and entitlements; and (c) the contextual variables—the institutional and environmental context in which adaptation occurs, as predictors of adaptive action. Our results suggest that objective and perceived adaptive capacity can positively influence farmers’ decisions to use cover crops. However, risk management institutions, such as government subsidies (direct payments) can diminish the likelihood of farmers using cover crops. This study develops a novel theoretical

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approach to understanding farmer decision making that examines their objective and perceived capacities as determinants of pro-environmental action.

**Introduction**

Global climate change presents one of the most significant challenges to agriculture and society. Climate change will impact the economic and natural resource base of Midwestern agriculture, which contributes substantially to both the national economy and global crop availability (Hatfield et al., 2014). In the Upper Midwest, projected trends suggest an increase in extreme rainfall events. Such variation in rainfall can impact farm-level productivity and off-farm environmental sustainability. On a farm-level, farmers are at the frontline for responding to the impacts of climate change (McCarl, 2010). Thus, it is critical to examine capacities that can enable or constrain farmers’ ability to cope and adapt to the negative effects of climate change.

In the environmental change literature, adaptive capacity is a primary social process for modulation of system resilience—defined as a system’s ability to deal with shocks and still maintain its overall characteristics, while also retaining capacity to transform to a more desirable state (Engle and Lemos, 2010; Nelson et al., 2007; Rockström et al., 2009). Adaptive capacity can be conceived of as composed of three interrelated parts: a system of resources such as finances and institutions, the capacity of individuals and communities to access those resources; and, the contextual factors such as institutional and governance systems that influence whether actors can feasibly access and manage resources (Figure 1) (Brown and Westaway, 2011).
Previous research has often framed the likelihood that farmers will adapt to climate change as a function of objective capacity or material resources, such as access to finances, technology, knowledge and infrastructure (Engle and Lemos, 2010; Parry et al., 2007; Yohe and Tol, 2002). However, other scholarship on human behavior has noted that objective attributes of adaptive capacity, socio-cultural factors, such as risk perceptions and perceived capacity, are influential for moderating actors’ response to climate change (Grothmann and Patt, 2005; Moser et al., 2014). For example, perceived adaptive capacity (PAC)—defined as the “extent to which [actors] feel prepared to endure changes and take necessary steps to cope with them” (Seara et al., 2016, p. 50)—has been found to impact actors’ perception about climatic risks and their willingness to take actions to manage such risks (Grothmann and Patt, 2005; Moser et al., 2014).
Contextual factors such as institutions and governance play a vital role in determining the ability of a social-ecological system to manage risk associated with abrupt climatic and weather-related changes (Agrawal, 2008; Berman et al., 2012; Dovers and Hezri, 2010; Engle, 2011). Institutions are defined as the “formal and informal rules and norms that govern actors, resources and their interactions in any given situation” (Eakin et al., 2016, p. 804). Institutions have been found to influence not only farmers' objective attributes of capacity but also the perceived adaptive capacity (Eakin et al., 2016). Yet, it remains to be empirically examined whether risk-management institutions can influence Midwestern U.S. corn farmers’ use of adaptive management practices via changes in objective and perceived adaptive capacities. An examination of the relationship among institutional support and perceived adaptive capacity can improve the effectiveness of risk management programs by including program parameters that view farmers’ perceptions of risk and capacity as important determinant of their risk-reduction behavior.

Research in the social and behavioral sciences has shown that changes in biophysical conditions can influence actors’ adaptation decision making (Kasperson et al., 1988; Weber and Stern, 2011). A large body of literature has examined how past experiences with natural hazards can influence actors’ hazard coping and adaptation behavior (Wachinger et al., 2013). Actors make decisions in relation to threats in two steps: first, assess the magnitude of the threat and if the threat is considered serious, evaluate their capacity to respond to threat (Bubeck et al., 2012). Interaction of threat and coping appraisals influences actors’ decision to implement risk reduction behavior. Thus, farmers’ who feel capable of adapting to
climate change (perceived capacity) and perceive that extreme rain events pose a threat to their farm operation (risk perception) can be more willing to use adaptive management practices (Truelove et al., 2015).

The objective of this article is to examine how farmers’ adaptive capacities—contextualized within institutional and environmental conditions—can influence their decisions to use adaptive management practices. We evaluate the likelihood that Upper Midwestern corn farmers will adapt to extreme rain events—i.e., use suitable adaptive management practices on their farm, and examine the relative importance of (a) “internal” variables – the perceived capacity; (b) “external” or “objective” resources – the assets and entitlements; and (c) the contextual variables – the institutional and environmental context in which adaptation occurs, as predictors of adaptive action. Specifically, this study examines farmer use of cover crops, a highly effective climate change adaptation and mitigation strategy for reducing soil erosion and nutrient loss associated with extreme rain events, through the following research questions: (1) How does perceived adaptive capacity influence the relationship between observed changes in extreme rain events and farmers’ decision to use of cover crops? (2) Does higher perceived adaptive capacity increase the likelihood of farmers’ using cover crops? (3) Does higher objective capacity increase farmers’ use of cover crops? (4) How does higher perceived adaptive capacity influence the relationship between farm-level government payments and farmers’ use of adaptive management practices? (5) Does the variation of government payments across the 22 Upper Midwestern watersheds influence farmers’ use of adaptive management practice? Examining each question will allow us to understand how both individual-
level and contextual factors, such as institutional and environmental conditions, can influence farm-level support for adaptive management practices.

This paper is organized as follows: We first present a review of the related literature and discuss the shortcomings from the literature for understanding the role of adaptive capacity in influencing farmers’ use of adaptive management practices. Next, we present our study rationale, description of data, and methodological procedures. We present the results of our analysis. Next, we discuss the main results from the study and conclude with implications of this research for practice along with suggestions for future research.

**Literature Review**

**Extreme rain events and farm-level adaptation**

Observed and projected changes in climate suggest that Midwestern U.S. will continue to be exposed to changes in temperature, precipitation, and humidity (Hatfield et al., 2014; Walthall et al., 2012). Increase in frequency and intensity of extreme rain events are identified as one of the most prominent biophysical changes due to climate change. Extreme rains are defined as events with more than four inches of rain in a 24-hour period (Todey, 2014). These events can pose serious risks to crop development, crop productivity and ecological sustainability (Walthall et al., 2012). In this study, we are interested in examining agriculture’s susceptibility and farmers’ responses to changes in extreme precipitation.

Projected increases in extreme rain events pose a major threat to natural resource base and agricultural productivity in the Upper Midwestern U.S. (Arritt, 2016; Karl et al., 2009; Todey, 2014). To respond effectively to these climatic
changes, it is important for U.S. agriculture systems to modify existing systems to reduce vulnerabilities and improve resilience. Farm-level adaptation to climate change can include strategies, such as: (1) changes in farm production practices, including modifying crop rotations system; (2) using technology, such as drought-resistant crop varieties, and (3) practicing financial and risk management, such as utilizing government payments or farm subsidies to reduce financial losses due to unexpected changes in weather and markets.

At the farm level, adaptive management practices, many of which are also known as soil and water conservation practices, are important adaptation strategies that can provide the farm/farmer an opportunity to modulate the risks associated with extreme rain events. These practices can potentially reduce soil erosion rates and loss of soil organic carbon and other important nutrients (Reimer et al., 2012). In the Upper Midwest, three of the primary farm-level adaptive management practices suitable for dealing with an increase in the frequency of extreme rain events are: (1) the enhancement of drainage systems (including drainage water management); (2) the minimization of tillage or disturbances of the soil; and, (3) the use of cover crops to maintain living ground cover after cash crops have been harvested (Morton et al., 2015).

For this study, we focus solely on farmers’ use of cover crops as one of the most effective of many adaptive responses available to them. Cover crops are “grown primarily for the purpose of protecting and improving soil between periods of regular crop production.” (Kremen and Miles, 2012) They are perceived as an essential component of potential climate change adaptation and mitigation strategy.
(Arbuckle and Roesch-McNally, 2015). They can help farmers adapt to the impacts of climate change and extreme rain events by (1) preventing soil erosion, (2) reducing the flow of nutrients, such as nitrate, from farms into streams and lakes, (3) improving water and nutrient cycling, (4) controlling pest and disease, and (5) improving field level soil organic carbon, soil structure, and soil carbon retention (Kaspar et al., 2012; Kremen and Miles, 2012). As a mitigation strategy, some research suggests that cover crops can reduce greenhouse gas emissions (GHGs) through improvements in carbon sequestration and reduction in nitrogen use (Lal et al., 2011). Given these benefits of cover crops, it is important to examine the key factors that can explain farmers’ decisions regarding using this important adaptive management practices to cope and adapt to weather/climate-related risks.

**Climatic risks and adaptive behavior**

Past experiences with natural hazards can influence actors’ hazard coping and adaptation behavior (Wachinger et al., 2013). Empirical studies have examined the link between natural hazard-related events and how actors perceive such risks and found that personal experience with these events can increase or decrease their intention to change behavior (Lo, 2013). For example, Shao et al. (2014) and Hamilton and Keim (2009) examined the relationship between uncommon weather patterns and actors’ perception of climate change. These studies found that those who experienced increasing summer heat (Shao et al., 2014) and unusual winter warming (Hamilton and Keim, 2009) also perceived a greater threat from climate change.
Research in the U.S. agriculture sector has also found that spatial and temporal proximity to natural hazards can be an important driver of farmers’ perceived risk and their willingness to implement appropriate protective measures (Niles et al., 2013). These studies have examined how changes in weather and climate, such as drought (van Duinen et al., 2015) and excess water (Morton et al., 2015) can cause farmers to take necessary steps to reduce risks associated with these hazards. Farm-level research suggests that farmers who perceive climate change to be a threat to their farm enterprises are more likely to make adjustments to anticipate or react to changing conditions that may place the farm enterprise at risk (Arbuckle et al., 2013a; Morton et al., 2015). Observed changes in weather and climate, such as changes in frequency and volatility of extreme rain events can influence farmers’ behavior toward adjusting their farm management practices.

Research in the social and behavioral sciences has shown that there are two steps of cognitive processes that explain how actors make decisions in relation to threats (Rogers, 1975). The first step is a risk appraisal, where actors evaluate the possibility of the threat (Truelove et al., 2015). If the risk is assessed to be high, in the next stage, actors engage in “coping appraisal”, which is a self-evaluation of their capacity to respond to threat (Bubeck et al., 2012). Previous studies have found that it is the interaction of coping and threat evaluations that influences actors’ protection motivation, and results in their support for behavioral change. For example, Truelove et al. (2015) found that Sri Lankan paddy farmers who felt capable of using climate-smart farming practices and perceived these practices to reduce risks related to climate change, were more likely to engage in adaptive responses, i.e. planting a
new seed variety. Thus, farmers’ response to changes in weather and climate are dependent not only on observed changes in weather patterns, but also on their perceived capacity to implement appropriate risk-reduction measures.

**Adaptive capacity**

In the environmental change literature, adaptive capacity represents a key social, economic, and institutional mechanism for allowing actors to cope, adapt, and respond to the potentially harmful impacts of climate change (Adger, 2006; Smit et al., 2001; Turner et al., 2003). A large body of research has identified several types of material resources as important determinants of adaptive capacity (Moser et al., 2008; Swanson et al., 2009). For example, greater availability of financial resources significantly improved Northeastern U.S. dairy farmers’ adaptive capacity and allowed them to reduce risks associated with changes in weather and climate (Moser et al., 2008). Similarly, knowledge about production practices that could make farming more resilient to climate change increased Canadian farmers’ ability to diminish risks associated with climate change (Swanson et al., 2009). These studies have shown that at the farm/farmer-level, financial and economic resources can be important for farmers to cope or adapt to climate change.

In their seminal piece, Grothmann and Patt (2005) argued that existing research on adaptive capacity had theorized capacity primarily in relation to actors’ ability to acquire material resources, and that this conceptualization was overly simplistic and limiting. They proposed that while access to material resources, such as financial and technical resources, are important arbiters of adaptive capacity, cognitive factors, such as risk perceptions and perceived capacity, may also be
crucial for determining actors’ responses to environmental stressors, such as climate change and variability.

Perceived capacity describes the internal dimension of capacity, i.e., actors’ perceptions of the suitability of available resources including financial, technical, and institutional support needed for facilitating adaptation (Eakin et al., 2016; Grothmann and Patt, 2005; Seara et al., 2016). Multiple theories can help explain the role of perceived capacity in farmers’ climate change adaptation decision making. For example, the theory of planned behavior (TPB) uses the term “perceived behavioral control (PBC)” to define perceived capacity, i.e., the extent to which actors perceive the existence of factors that enable or impede adoption of a pro-environmental behavior. The theory of planned behavior (TPB) has been used to study the relationships between actors’ perceived capacity and various environmental behaviors, such as choosing: public over private transportation (Tikir and Lehmann 2011), conserving water (Trumbo and O’Keefe 2005), and using soil and water conservation practices such as cover crops (Arbuckle and Roesch-McNally, 2015). In general, these studies have found that higher perceived capacity can encourage actors to support and practice pro-environmental behavior. While previous research has added detailed insights on the relationships between actors’ perceived capacity and personal action, fewer studies have examined this relationship when decision making is complex and fraught with uncertainty, such as resulting from abrupt changes in climate and weather.

Multi-sectoral research on adaptive capacity and resilience in the U.S. (Eakin et al., 2016) and Australia (Marshall and Marshall, 2007) have examined the role of
perceived capacity in relation to actors’ decision making in uncertainty. This research has highlighted at least five key characteristics of farmers perceived adaptive capacity, which can promote adaptability through learning and experimentation. These are perceived efficacy, or the confidence that a farmer has in their ability to perform certain activities or implement a specific risk mitigation action; learning and knowledge seeking, the extent to which farmers can use their agency for learning and seeking new knowledge; decision constraints, the level of expectations about exogenous constraints; centrality in social networks, how farmers view themselves in terms of membership in social groups, and adaptive management, the desire to foster resiliency in social-ecological systems through learning and experimentation (Eakin et al., 2016; Marshall and Marshall, 2007). Elements of perceived adaptive capacity can be a useful indicator of actors’ intention to undertaken pro-environmental behavior. These dimensions can also form an integral part of actors’ strategy to improving resilience in agriculture (Marshall et al., 2012; Tschakert and Dietrich, 2010).

**Contextual factors: crop insurance and adaptation**

Contextual factors such as institutions and governance play a vital role in determining the ability of a social-ecological system to withstand abrupt climatic and weather-related changes (Berman et al., 2012; Dovers and Hezri, 2010; Engle, 2011; Ostrom, 2008). Institutions are defined as the “formal and informal rules and norms that govern actors, resources and their interactions in any given situation (Eakin et al., 2016, p. 804).” In relation to adaptation in U.S. Midwestern agricultural systems, institutions can constrain or enable farmers’ adaptive capacity. For
example, at the farm-level, economic incentives and availability of markets can either enable or impede farmers’ ability to shift production practices for achieving greater resiliency (Blesh and Wolf, 2014). In general, institutions involved in climate change adaptation (across various sectors) can range in characteristics from risk management and technological development to risk sharing and information dissemination (Engle and Lemos, 2010).

The U.S. federal government provides direct institutional support to protect farmers from volatility in crop production and profitability due to changes in weather and market prices. The government provides assistance to farmers to manage risk in two main ways: (1) farm subsidies such as government payments that are paid directly to farmers and (2) Federal Crop Insurance Program (FCIP) administered by the Risk Management Agency (RMA) of the United States Department of Agriculture (USDA). The goals of both government payments and FCIP are (1) to protect farmers’ income against crop failure and revenue loss and (2) maintain a stable supply of food, fuel, and fiber in the economy (RMA, 2017). In recent years, the FCIP program has gained significant popularity, with the total number of insured acres increasing from 100 million in 1989 to more than 297 million acres in 2015 (RMA, 2017).

Recent research has found at least five ways in which government payments and crop insurance programs can influence U.S. farmers’ land use management and response to climate change. First, government payments such as direct payments have been found to increase commodity specialization, such as an increase in acreage planted to continuous-corn (Broussard et al., 2012). Thus, direct payments
can influence farmers’ land use decisions in relation to cropland diversity, which can increase or decrease the level of off-farm environmental sustainability (Broussard et al., 2012). Second, subsidized crop insurance premiums can increase farmers’ expected revenue and thus incentivize faster conversion of grassland to crop production (Claassen, 2012). Expanding crop production to marginal land can increase soil erosion and water pollution at a regional-level (Claassen, 2012). Third, enrollment in crop insurance program has been found to encourage farmers to plant a less diverse portfolio of crops (Claassen et al., 2001, 2016; Claassen, 2012). For example, in a recent study of U.S. Corn Belt farmers, Claassen et al. 2001 found that higher utilization of crop insurance indemnities led to almost 4% increase in acreage planted to continuous corn, thereby reducing crop diversity. Fourth, and in relation to climate change adaptation, Annan and Schlenker 2015 found that participation in the federal crop insurance program reduced U.S. farmers’ engagement in farm-level adaptation to extreme heat events. They posit that crop insurance creates a moral hazard or a “disincentive to reduce the damaging effects [of extreme heat events] (Annan and Schlenker, 2015, p. 265).” Similarly, Hertel and Lobell 2014 argue that crop insurance can significantly delay farmers’ decision regarding investing in irrigation infrastructure to supplement for water supply during periods of water scarcity. Thus, institutional support from the government, such as government payments and crop insurance can influence farmers’ attitudes toward land use management, which in turn impact the economic and environmental impacts associated with crop production.
In relation to adaptation in agricultural systems, risk management institutions can either enable or impede farmers’ ability to shift production practices for achieving greater resiliency (Blesh and Wolf, 2014). Institutions have been found to influence not only farmers' objective attributes of capacity but also the perceived adaptive capacity, i.e. by influencing their risk perceptions (Eakin et al., 2016); intentions to change behavior (Grothmann and Patt, 2005), and their self-evaluation of capacity to adapt (Eakin et al., 2016). However, more empirical research is needed to examine how risk management institutions can encourage farmers’ use of adaptive management practices—especially those concerning soil and water conservation—through changes in their perceived dimensions of adaptive capacities.

Based on the reviewed literature, farmers’ adaptive response, i.e., their use of adaptive management practices, should be examined in relation to (a) “internal” variables—the perceived capacity; (b) “external” or “objective” capacity—the assets; and (c) the contextual variable—the institutional and environmental context in which adaptation occurs. Most studies on farmers' adaptation to climate change have exclusively focused on their objective attributes of adaptive capacity while ignoring the importance of perceived adaptive capacity in influencing their adaptive responses to climate change. We address this deficit by exploring the influence of environmental risks, objective and perceived adaptive capacity, and institutional conditions on farmers’ adaptive response to extreme rain events.
Methods

Conceptual framework

In the previous sections, we reviewed the interaction among the themes of biophysical conditions such as climate; the human conditions including perceived adaptive capacity, and institutional conditions, such as farm subsidies. First, we reviewed how risks associated with extreme rain events can be consequential to crop productivity and environmental sustainability. We found that observed changes in climate and weather can influence farmers’ adaptive responses to climate change. For example, farmers who perceived climate change to be a threat to their farm enterprises and felt capable of respond to it were more likely to adjust to changing conditions that may place the farm enterprise at risk.

Next, we reviewed the concept of adaptive capacity. We introduced two important attributes of adaptive capacity—objective and perceived adaptive capacity. It was established that farmers’ perceived adaptive capacity can influence their willingness to take actions to ignore, cope, or adapt to risks. Specifically, previous research had found positive relationship between perceived capacity and actors’ willingness to engage with risk-reduction behavior.

We also examined how farmers’ objective and perceived adaptive capacities are contextualized within an institutional context that can either enable or impede their response to climate change and variability. A review of the literature established that availability of government payments and enrollment in crop insurance programs can encourage U.S. farmers to (1) convert more grassland to
crop production; (2) diminish engagement in farm-level adaptation activities, and (3) favor a less diverse portfolio of crops.

Here we outline a conceptual framework that assembles these social and biophysical elements together in a conceptual model that facilitates the understanding of farmers’ use of an important adaptive management practice: cover crops. Figure 2 shows a multilevel conceptual model in which watershed-level (level 2) environmental and institutional contexts influence adaptive responses that farmers (level 1) undertake. At level 1, field-level environmental conditions, farmers’ adaptive capacity, and institutional factors (direct payments) are predicting farmers’ use of cover crops. There are multiple cross-level interactions (not shown in the figure) that highlight how institutional and environmental conditions at the watershed level can interact with farmers’ use of adaptive management practices.
Based on the literature reviewed, for this study of Midwestern corn and soybean farmers, this research proposes the following hypotheses:

H1: The relationship between extreme precipitation events and use of cover crops will be positive and stronger at higher levels of perceived adaptive capacity;

H2: Higher levels of perceived and objective adaptive capacity will predict greater likelihood of use of cover crops;

H3: Higher levels of (farm-level) farm subsidies will predict lower likelihood of cover crops use;

H4: Higher levels of (watershed-level) farm subsidies will predict lower use of cover crops;

H5: The effect of extreme precipitation events on use of cover crops will increase for farmers in watershed with more marginal land;

**Data and study region**

The study area comprises at least some of the Midwestern U.S. states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin (Figure 3). The study area watersheds are responsible for more than one-third of the global corn supply, represent nearly 65 percent of all corn acres and 55 percent of soybean acres in the U.S. (Arbuckle et al., 2013b). The climate of this region is continental with large seasonal differences in precipitation and temperature. Geographically, weather and climatic features vary from the west (warmer and drier) to east (cooler and wetter). Areas in the west can experience more recurrent summer drought than areas in the eastern and southeastern Midwest.
Primary data used in this study is from a February 2012 survey of corn and soybean farmers in 11 Midwestern states (Figure 3). The survey was mailed to a stratified random sample of farmers in a contiguous set of 22 watersheds (Arbuckle et al., 2013b). The USDA National Agricultural Statistics Service (NASS) Census of Agriculture’s master list, which is the most comprehensive and up-to-date list of US farmers was the sampling frame. Only farmers who grew at least 80 acres of corn and grossed farm sales value more than $100,000 per year were included in the mailing list. The survey was mailed by NASS to 18,707 eligible farmers. Completed surveys were received from 4,778 farmers for an effective response rate of 26%. Non-response bias checks compared respondent demographics to U.S. Census of Agriculture data, and no meaningful differences between respondents and non-respondents were observed (Arbuckle et al., 2013b). To maintain the privacy of respondents, the farm-level geospatial coordinates were not stored in the database. However, zip codes and county FIPS were used to identify farmers’ location in each watershed.

Our study proposes two levels of analysis so that farmers (level 1) are nested in watersheds (level 2). The Hydrological Unit Code 6 (HUC6) watersheds are selected as the higher-order unit (level 2) for several reasons: (1) farming systems are influenced by environmental conditions that can vary by hydrological unit; (2) the effects of climate change in the Upper Midwest are projected to be predominantly water-related; (3) we are interested in examining how changes in extreme precipitation (climatic) and soil conditions (environment) can influence farmers’ use of adaptive management practices. Biophysical conditions associated
with water can be homogenous within each HUC6 watersheds; and as an extension of point 3, and (4) there are substantial seasonal differences in precipitation across these watersheds.

![Map of 22 HUC6 Watersheds (Study Region)](image)

**Figure 3:** Map of 22 HUC6 Watersheds (Study Region)

**Missing data analysis**

A Multivariate Imputations by Chained Equations (MICE) was employed in the software R to impute missing values (van Buuren and Groothuis-Oudshoorn, 2011). MICE use Gibbs sampling to generate plausible values for missing data by examining the fundamental patterns in the data. The Predictive Mean Matching (PMM) method was used to help ensure that the imputed values were credible. The PMM method provides robust imputed values especially if the assumption of normality is violated for some of the imputed values (Schenker and Taylor, 1996). The percentage of missing values prior to imputation are shown in Table A (Appendix A). Overall, five datasets were imputed. The density of the imputed data
for all five datasets were compared with the density of the observed data (Figure B in Appendix B). This comparison highlighted that the density of the observed and imputed datasets for each variable are similar, i.e., we can assume that the missing values are missing at random and the imputation method generated plausible values for missing data.

**Variables included in the model**

**Outcome variable**

The outcome variable *Cover Crops* represents whether or not a farmer currently used cover crops on their owned or rented land. Table 1 shows the statistical description of the outcome variable. In our sample, 22% of farmers were using cover crops on at least some of their owned or rented land.

<table>
<thead>
<tr>
<th>Scale and Survey Item</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>No (%)</th>
<th>Yes (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Currently using the following practices on rented or owned land:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cover crops (0 = No, 1 = Yes)</td>
<td>0.21</td>
<td>0.43</td>
<td>77.96</td>
<td>21.78%</td>
</tr>
</tbody>
</table>

**Predictor variables**

The level 1 predictors include: (1) perceived adaptive capacity, including adaptive management, perceived centrality in social network, decision constraints, interested in seeking knowledge and perceived efficacy; (2) objective adaptive capacity, including farm sales, access to weather and climate-related decision support tools, number of agricultural enterprises (crop or livestock), and opportunities to sell crops in multiple markets; (3) environmental factors, including daily precipitation extremes, percentage of the land (owned and rented) that was
Highly Erodible (HEL) and planted to crops, and (4) institutional factors, including farm subsidies (direct payments).

Level 2 predictors include: (1) an environmental factor, including percent of marginal lands by watershed; (2) an institutional factor, government payments (excluding conservation and wetland reserve program payments) for each watershed, and (3) group means of level 1 variables. Reintroducing the group means at level 2 allow us to separately investigate the between-watershed and within-watershed effects of the predictors on the outcome variable.

**Level 1 variables:** Perceived adaptive capacity (PAC) consist of five subcategories, each constructed using an Exploratory Factor Analysis (EFA) technique. EFA is a commonly used statistical technique in the social sciences that can condense information from multiple items (survey, census etc.) into meaningful latent variables. EFA was applied to measure key concepts that can explain the various dimensions of perceived adaptive capacity, including **Adaptive Management**, **Perceived Centrality in Social Network**, **Decision Constraints**, **Interested in Seeking Knowledge** and **Perceived Efficacy**. Four survey items measured **Adaptive Management** (Table 2). These variables measured farmers’ resolve to learn and experiment with adaptive management practices, which might affect the overall resilience of their farm. Three survey items measured farmers’ views about their influence and membership in social groups. These items were grouped together to create a construct, **Perceived Centrality in Social Network** (Table 2). The **Decision Constraints** construct was developed using four survey questions, which included statements about farmers’ perceptions about the institutional environment, such as
crop insurance and informational availability. The survey item coding was reversed to measure the challenges associated with accessing resources available at the structural level. The *Interested in Seeking Knowledge* construct was created using three survey questions with statements inquiring about farmers’ willingness to proactively seek knowledge—by visiting other farmers—regarding farming methods and strategies. The *Perceived Efficacy* construct was created using three survey items that measured whether farmers believed that they possessed financial and technical resources to overcome field-level challenges associated with climate change. We adapted the method used in the Livelihood Vulnerability Index (Hahn et al., 2009) to normalize all five subcategories of perceived adaptive capacity on a numeric scale between zero and one. By adapting their approach, we calculated each category of perceived adaptive capacity as the ratio of the difference of the actual score and the minimum score in our sample of farmers, and the range of scores. As our conceptual framework suggests, we expected that farmers with higher scores (closer to one) on perceived adaptive capacity items would be more likely to use adaptive management practices. Table 2 shows the mean, standard deviation, and range of the five main categories of perceived adaptive capacity (factor scores are normalized). It also presents the frequencies and percentages of the subcategories that comprise of perceived adaptive capacity variables.

<table>
<thead>
<tr>
<th>Survey item</th>
<th>Mean</th>
<th>SD</th>
<th>Range</th>
<th>Strongly disagree (%)</th>
<th>Disagree (%)</th>
<th>Uncertain (%)</th>
<th>Agree (%)</th>
<th>Strongly Agree (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adaptive Management Farmers should take additional steps to protect farmland from increased weather variability</td>
<td>0.63</td>
<td>0.16</td>
<td>1</td>
<td>1.86</td>
<td>5.75</td>
<td>26.95</td>
<td>61.17</td>
<td>4.24</td>
</tr>
</tbody>
</table>
Table 2 continued

<p>| | | | | | |</p>
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<tr>
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<tbody>
<tr>
<td>I should take additional steps to protect the land I farm from increased weather variability</td>
<td>3.47</td>
<td>0.79</td>
<td>4</td>
<td>1.92</td>
<td>10.19</td>
</tr>
<tr>
<td>Profitable markets for small grains and other alternative crops should be developed to encourage diversified crop rotations</td>
<td>3.56</td>
<td>0.86</td>
<td>4</td>
<td>3.93</td>
<td>6.13</td>
</tr>
<tr>
<td>Changing my practices to cope with increasing climate variability is important for the long-term success of my farm</td>
<td>3.42</td>
<td>0.85</td>
<td>4</td>
<td>3.68</td>
<td>8.66</td>
</tr>
</tbody>
</table>

**Perceived Centrality in Social Network**

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<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Other farmers look to me for advice</td>
<td>2.92</td>
<td>0.79</td>
<td>4</td>
<td>3.10</td>
<td>25.70</td>
</tr>
<tr>
<td>I consider myself to be a role model for other farmers</td>
<td>2.95</td>
<td>0.81</td>
<td>4</td>
<td>3.37</td>
<td>24.09</td>
</tr>
<tr>
<td>Extension staff, crop advisers, and other involved in agriculture tend to look to me for advice</td>
<td>2.47</td>
<td>0.74</td>
<td>4</td>
<td>6.67</td>
<td>47.46</td>
</tr>
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</table>

**Decision Constraints**

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</thead>
<tbody>
<tr>
<td>I am concerned that available best management practice technologies are not effective enough to protect the land I farm from the impacts of climate change</td>
<td>3.67</td>
<td>0.80</td>
<td>4</td>
<td>4.29</td>
<td>23.17</td>
</tr>
<tr>
<td>There’s too much uncertainty about the impacts of climate change to justify changing my agricultural practices and strategies</td>
<td>2.89</td>
<td>0.79</td>
<td>4</td>
<td>4.33</td>
<td>17.12</td>
</tr>
<tr>
<td>Crop insurance and other programs will protect the viability of my farm operation regardless of weather (reversed)</td>
<td>2.96</td>
<td>0.91</td>
<td>4</td>
<td>3.14</td>
<td>28.59</td>
</tr>
<tr>
<td>Changes in weather patterns are hurting my farm operation</td>
<td>2.66</td>
<td>0.85</td>
<td>4</td>
<td>6.25</td>
<td>38.97</td>
</tr>
</tbody>
</table>

**Interested in Seeking Knowledge**

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</thead>
<tbody>
<tr>
<td>It is important for me to talk to other farmers about new farming practices and strategies</td>
<td>3.59</td>
<td>0.79</td>
<td>4</td>
<td>1.61</td>
<td>10.98</td>
</tr>
</tbody>
</table>
Four variables were included to measure farmers’ objective adaptive capacity (OAC) (Table 3). Two variables, total farm sales (Farm Sales) and number of farm enterprises (Farm Enterprises) were measured using data from the U.S. agricultural census. Total farm sales (Farm Sales) were used as a proxy for farmers’ economic capacity. A total count for the number of agricultural enterprises (Farm Enterprises), including hogs, cows, oats, hay, sorghum, barley, soybeans and corn were used to measure farmers’ potential capacity to diversify their crop portfolio to hedge against climate and market risks (Macdonald et al., 2013). Survey data was used to measure two additional attributes of objective capacity, including (1) farmers’ access to weather and climate-related decision support tools (Weather Tools) and (2) diversity of markets for corn (Market Diversity). The latter variable measures market diversification by summing the total number of corn-related markets—such
as commodity, ethanol, livestock, specialty, seed, and other—that farmers had the opportunity to produce corn for. For the Upper Midwestern U.S. farmers, market diversification has been positively correlated with greater use of adaptive management practices (Morton et al., 2015).

Table 3 Summary statistics for numeric predictors

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective Capacity:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm Sales ($)</td>
<td>457,000</td>
<td>653,461</td>
<td>100,000</td>
<td>20,060,000</td>
</tr>
<tr>
<td>Weather Tools¹</td>
<td>2.69</td>
<td>1.95</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Farm Enterprises²</td>
<td>3.90</td>
<td>1.60</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Market Diversity³</td>
<td>1.98</td>
<td>0.81</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td><strong>Environmental factors:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Precipitation (farm)</td>
<td>0.39</td>
<td>0.14</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>HEL (farm)</td>
<td>24.27</td>
<td>32.96</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Marginal Land (watershed)</td>
<td>0.17</td>
<td>0.16</td>
<td>0</td>
<td>0.97</td>
</tr>
<tr>
<td><strong>Institutional Capacity:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct Payments (farm)</td>
<td>12,770</td>
<td>13,247</td>
<td>0</td>
<td>160,000</td>
</tr>
<tr>
<td>Direct Payments (watershed)</td>
<td>1,284,000,000</td>
<td>432,270,000</td>
<td>225,400,000</td>
<td>2,274,000,000</td>
</tr>
</tbody>
</table>

1. Tools include: Crop disease forecast, Insect forecast, Evapotranspiration (ET) index, Growing degree day tools, Forage dry down index, Drought monitor/outlook and Satellite data/indices of water or soil nitrogen status.
2. Enterprises include: Hogs, Cows, Other Cattle, Corn, Soybeans, Oats, Hay (including Alfalfa), Sorghum, and Barley
3. Markets include: Commodity (sweetener, export, feed), Ethanol, Livestock-silage, speciality or organic, seed and other

Two variables were included in the model to examine the relationship between environmental factors and farmers’ use of adaptive management practices. Observed changes in extreme daily precipitation events (Daily Precipitation), defined as events registering in 99th percentile of daily precipitation for a given month for the record covering 1971-2011 (Loy et al., 2013). The data was obtained from Loy et al. (2013), who constructed various measures of extreme weather for the Upper Midwestern region from the National Weather Service (NWS) Cooperative Observer (COOP) data archive see Loy et al. (2013) for details on variable construction). Daily extreme precipitation values from the weather station nearest to the farm were assigned to each farmer in the survey. Table 3 provides a statistical description of daily extreme precipitation that we employed in this study. Another variable used in
this study to measure the environmental factors was the percentage of farmers’ land planted to crops in 2011 was highly erodible land (HEL). HEL is any land with high erosion properties. Farmers’ who produce crops on land identified as highly erodible are required to develop and implement a conservation plan (Conservation Compliance) that can reduce the propensity of soil erosion (Arbuckle, 2013).

One farm-level variable, farm direct payments (Direct Payments), was used to measure the institutional or structural dimension of farmers’ adaptive capacity. Farm direct payments was one of many farm subsidy programs available to farmers to reduce the yearly variation in agricultural production and farm profitability (Environmental Working Group, 2017). This government payment scheme was discontinued in 2014 (except for cotton producers) but was available to farmers in 2012 when the data for this study was collected. Direct payments were paid out to farmers each year based on the historic production of their land (base year is 1986). We chose direct payments as the measure of farmers’ institutional support because it provided farmers with additional income even during years when there was no loss in crop yield or farm revenue.

**Level 2 variables:** Our study proposes two levels of analysis so that farmers (level 1) are nested in 22 watersheds (level 2). For each watershed, we calculated an environmental variable, including soil conditions (Marginal Land) and a variable measuring institutional capacity: government payments (Government Payments). The data for the variable, marginal land, was obtained from Loy et al. (2013), who calculated the percent of non-irrigated marginal lands (by county) using the Soil Survey Geographic (SSURGO) database. The characteristics of soil were grouped
according to the USDA Natural Resources Conservation Service (NRCS) land capability classification system see Loy et al. (2013) for a detailed account of variable construction). The percentage of land designated as marginal land in each county were aggregated to the watershed level.

The data for Government Payments was obtained from 2012 Census of Agriculture’s data browser. Government payments category in the Agriculture Census consist of all federal farm programs which make payments directly to the farm operators. Thus, it provides a holistic view of institutional support available at the watershed level. Government payments comprise of farm subsidy programs such as direct payments, loan deficiency payments, disaster payments, as well as conservation programs such as the Conservation Reserve Program (CRP) and Wetland Reserve Program (WRP). We excluded CRP and WRP from the government payments to make them comparable to our level 1 variable for institutional support (direct payments). The total of government payments for each county was computed and aggregated for all 22 watersheds. We used the county FIPS and HUC6 codes to merge the farmer-level data with level-2 variables. Merging data at multiple levels can pose statistical complications, such as the error terms of farmers’ responses nested within the same watershed are no longer independent of one another. A multilevel model was a suitable approach to model such hierarchical data structure and fulfill the basic assumptions of regression analysis.
Regression analysis

Generalized linear mixed models (GLMMs) combine two commonly used statistical frameworks in social and natural science research: (1) linear mixed effects modeling for examining random effects and (2) dealing with dichotomous outcome variables using exponential family of distributions (Bolker et al., 2009). Several GLMMs were constructed to investigate the relationship between environmental factors, adaptive capacity, institutional factors and farmers’ use of cover crops. We constructed three models each with farmers at the first level and HUC6 watersheds at the second level. All models tested for random intercepts between watersheds. Random slopes were not included because there was little variance remaining in the final model. Model 1 is the null model with only a varying intercept across all watersheds. Model 2 and include all predictors, and Model 3 adds the interaction terms.

The outcome variable, use of cover crops in watershed, is a proportion—the number of farmers who either use or do not use cover crops. We use a logit function (logit(x)=ln[x/(1-x)]) as the link function. The observed proportion of farmers using cover crops $i$ in a watershed $j$ is given by $P_{ij}$. 
The logit\((P_{ij})\) has an approximate normal distribution and we use a linear regression equation at the farmer level to specify a simplistic model with one intercept and one farmer-level explanatory variable:

\[
\text{logit}(P_{ij}) = B_{0j} + B_{1}X_{ij} \quad \text{Equation 1}
\]

Equation 1 shows that the intercept is assumed to vary across watersheds and the coefficient for the slope is fixed. This variation in intercept is modeled by the watershed-level variable \(Z_j\) as follows:

\[
B_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \quad \text{Equation 2}
\]

\[
B_{1j} = \gamma_{10} + u_{1j} \quad \text{Equation 3}
\]

We could substitute Equation 2 and 3 into 1, and re-write it as a single-equation:

\[
\text{logit}(P_{ij}) = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + u_{0j} + u_{1j} + \gamma_{10}X_{ij} \quad \text{Equation 4}
\]

For GLMMs it can be difficult to find ML estimates without integrating the likelihoods for all random effects-a process that can be computationally expensive (Bolker et al., 2009). Therefore, we computed the Maximum Likelihood (ML) estimates of equation 4 by using a Gauss-Hermite quadrature (GHQ) approximation approach. We choose a GHQ approach because it balances the need for computational speed and accuracy. For example, GHQ approach is also more accurate than Laplace approximation. A Bayesian framework using Markov Chain Monte Carlo (MCMC) technique could have been advantageous if there were at least three or more random factors to be estimated in our models (our GLMMs only have one random effect) (Bolker et al., 2009).
Testing the ex-ante assumptions of GLMMs

Prior to fitting the GLMMs, we examined the predictor variables for multicollinearity. A correlation matrix shown in Appendix C suggests that the highest correlation found among the predictors was 0.45. Thus, multicollinearity is not a matter of concern in our study (we also tested multicollinearity using a variance inflation factor (VIF) and found similar results). All level 1 variables were centered-within-context (CWC) and standardized. CWC includes rescaling variables by subtracting the group (watershed) mean. These group means were then reintroduced at level 2.

We also specified the covariance structure, i.e. described the form of the variance-covariance matrix for our GLMMs. We used an unstructured covariance structure so that covariances are assumed to be random (Field, 2013). We examined the distribution of predictor variables at each level of our binary outcome variable (Appendix A). The distributions seem normal and symmetric, except for farm sales and direct payments, which had skewed distributions. These variables were transformed (logarithmic).

The intra-class correlation coefficient (ICC) or $\rho$ measures the proportion of variance explained by the higher-order unit, in this case the 22 watersheds. The ICC can be measured by various methods (Snijders and Bosker, 1999). We used the commonly used formula:

$$\rho = \frac{\tau_{11}}{\tau_{11} + \sigma^2}$$

Equation 5

$\tau_{11}$ is the amount of variance attributed to watershed differences or variance between groups. The $\sigma^2$ is attributed to the farmer-level variation. It explains the
within watershed variation. The computed value of $\rho$ is 0.24 so 24 percent of the variance in farmers’ use of cover crops can be attributed to watershed level conditions, which suggests that a GLMM is an appropriate method for assessing the hierarchical structure of the data. We used a parametric bootstrap approach to create standardized residuals of the fitted models. Transformed residuals are then tested for fulfilling the ex-post assumptions of GLMMs.

**Results**

Table 4 presents results of three GLMMs predicting farmers’ use of cover crops. Model 1 is the null model that uses random intercepts for watersheds; Model 2 includes random intercepts and predictors representing environmental factors, adaptive capacity, and institutional factors. Model 3 includes random intercepts, predictors, and adds three interaction terms. The fixed effects are presented as odds ratios with standard errors in the parenthesis. The random effects are presented as variance between watersheds $\tau_{11}$ and ICC. We did not include random slopes between the watersheds since there was little variance remaining to be explained in the final model.

We will be interpreting the results of Model 2 as it has the lowest log likelihood value, AIC, and DIC among all three models. To confirm our results, we used a Likelihood Ratio Test (Chi-square test) to examine whether Model 2 fitted better than other models and confirmed that Model 2 fits better than Model 3 (the value of Chi-square is weakly significant for Model 3). We also calculated the Tjur’s Coefficient of Discrimination or Tjur’s D (Tjur, 2009). This is an alternative approach to other Pseudo-R-squared values such as Nakelkerke’s R2 or Cox-Snell R2 when
the model is a generalized linear mixed model (Tjur, 2009). The values of Tjur’s D for Model 1 & 2 are 0.05 and 0.13, respectively. Therefore, the explained variance increases by a small percentage after inclusion of farmer and watershed level predictors.

**Fixed effects**

Using the random intercepts model with predictors (Model 2), we found a few level 1 predictors to statistically explain farmers’ use of cover crops (Table 4). For perceived attributes of adaptive capacity, we found that a single standard deviation increase in farmers’ perceived centrality in social networks (Social Network) improves the odds of using cover crops by 13% (Exp(B)=1.13, p<0.01). An increase in one standard deviation in farmers’ perceived decision constraints (Perceived Decision Constraints) increases the odds of using cover crops by 9% (Exp(B)=1.09, p<0.05). A single standard deviation increase in farmers’ interest in seeking knowledge (Seeking Knowledge) is associated with an increase in the odds of using cover crops by 8%, however this association was weakly significant (Exp(B)=1.08, p<0.1).

For objective capacity predictors, our results show that one standard deviation increase in farm sales (Farm Sales) is associated with 17% increase in the odds of farmers’ using cover crops. The direction of relationship with farmers’ use of cover crops is very similar for other predictors of objective capacity, such as Weather Tools (14%) and Market Diversity (8%). Notably, the single largest predictor of farmers’ use of cover crops is the number of farm enterprises (Farm Enterprises), i.e. crop and livestock diversification. A one standard deviation increase in the
number of farm enterprises is associated with 72% increase in the odds of using cover crops.

For the institutional factors, we found a significant relationship between farm-level direct payments and farmers’ use of cover crops. A one standard deviation increase in Direct Payments is associated with 12% reduction in the odds of farmers’ using cover crops. We examined this relationship in detail by illustrating the predicted probabilities of using cover crops at different levels of farm-level direct payments (Figure 4). The figure shows that the predicted probabilities of using cover crops range from 15% to 35% for this sample of farmers. Thus, our results suggest empirical support for hypothesis H3: farmers receiving more direct payments from the government are less likely to use cover crops.

Figure 4: Predicted probabilities of using cover crops at varying levels of direct payments

We were interested in examining how institutional factors at the watershed level, such as government payments, might influence farmer’s use of cover crops. Although the sum of government payments at each watershed did not significantly predict farmers’ use of cover crops, figure 5 below suggests a negative but statistically insignificant relationship between the variables. The predicted probabilities decrease from over 20% to 15% across the range of government payments for all watersheds.
Table 4. Multilevel Logistic Regression of Farmers' use of Cover Crops
(Odds ratios with standard errors)

<table>
<thead>
<tr>
<th>Models</th>
<th>Random intercepts (RIs) only</th>
<th>RIs with level 1 and 2 predictors</th>
<th>RIs with interaction terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1: Farmers</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.25*** (1.13)</td>
<td>0.23*** (1.13)</td>
<td>0.23*** (1.07)</td>
</tr>
<tr>
<td>Environmental factors:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Precipitation</td>
<td>0.98 (1.04)</td>
<td>0.98 (1.05)</td>
<td></td>
</tr>
<tr>
<td>HEL</td>
<td>1.06 (1.04)</td>
<td>1.06 (1.04)</td>
<td></td>
</tr>
<tr>
<td>Objective Capacity:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm Sales (log)</td>
<td>1.17*** (1.04)</td>
<td>1.18*** (1.05)</td>
<td></td>
</tr>
<tr>
<td>Weather Tools</td>
<td>1.14*** (1.04)</td>
<td>1.14*** (1.04)</td>
<td></td>
</tr>
<tr>
<td>Diversity of Markets</td>
<td>1.08** (1.04)</td>
<td>1.08** (1.04)</td>
<td></td>
</tr>
<tr>
<td>Farm Enterprises</td>
<td>1.72** (1.04)</td>
<td>1.73** (1.04)</td>
<td></td>
</tr>
<tr>
<td>Perceived Capacity:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adaptive Management</td>
<td>0.99 (1.04)</td>
<td>0.99 (1.04)</td>
<td></td>
</tr>
<tr>
<td>Social Network</td>
<td>1.13*** (1.04)</td>
<td>1.12*** (1.04)</td>
<td></td>
</tr>
<tr>
<td>Decision Constraints</td>
<td>1.09** (1.04)</td>
<td>1.09** (1.04)</td>
<td></td>
</tr>
<tr>
<td>Seeking Knowledge</td>
<td>1.08 (1.05)</td>
<td>1.08 (1.05)</td>
<td></td>
</tr>
<tr>
<td>Perceived Efficacy</td>
<td>0.99 (1.04)</td>
<td>0.99 (1.04)</td>
<td></td>
</tr>
<tr>
<td>Institutional factor:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct Payments</td>
<td>0.88*** (1.12)</td>
<td>0.87*** (1.12)</td>
<td></td>
</tr>
<tr>
<td>Level 2: Watershed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reintroducing means:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm Sales (log)</td>
<td>1.14 (1.12)</td>
<td>1.14 (1.12)</td>
<td></td>
</tr>
<tr>
<td>Weather Tools</td>
<td>0.78* (1.16)</td>
<td>0.78* (1.16)</td>
<td></td>
</tr>
<tr>
<td>Market Diversity</td>
<td>0.89 (1.12)</td>
<td>0.90 (1.12)</td>
<td></td>
</tr>
<tr>
<td>Farm Enterprises</td>
<td>1.44*** (1.17)</td>
<td>1.43*** (1.36)</td>
<td></td>
</tr>
<tr>
<td>Environmental factors:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Precipitation (watershed mean)</td>
<td>1.13* (1.11)</td>
<td>1.13* (1.11)</td>
<td></td>
</tr>
<tr>
<td>Marginal Land</td>
<td>0.95 (1.15)</td>
<td>0.96 (1.15)</td>
<td></td>
</tr>
<tr>
<td>Institutional factors:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Government Payments</td>
<td>0.91 (1.09)</td>
<td>0.91 (1.09)</td>
<td></td>
</tr>
<tr>
<td>Interactions</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HEL (farmer) X Direct Payments (farmer)</td>
<td>0.92** (1.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adaptive Management (farmer) X Direct Payments (farmer)</td>
<td>1.01 (1.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Precipitation (farmer) X Perceived Efficacy (farmer)</td>
<td>0.96 (1.03)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Precipitation (farmer) X Marginal Land (watershed)</td>
<td>0.99 (1.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fit Statistics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,766</td>
<td>4,766</td>
<td>4,766</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2,399.70</td>
<td>-2,215.78</td>
<td>-2,221.44</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>4,803.40</td>
<td>4,475.60</td>
<td>4,474.90</td>
</tr>
<tr>
<td>Deviance Inf. Crit.</td>
<td>4726.00</td>
<td>4,341.30</td>
<td>4,334.10</td>
</tr>
<tr>
<td>$\chi^2$/df</td>
<td>-</td>
<td>367.85*** (20)</td>
<td>6.68* (3)</td>
</tr>
<tr>
<td>Pseudo-$R^2$ (Tjur's D)</td>
<td>0.05</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>Interclass correlation (ICC)</td>
<td>0.24</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>$\tau_{11}$ (variance of watershed intercepts)</td>
<td>0.32</td>
<td>0.09</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Note:
* $p<0.1$; ** $p<0.05$; *** $p<0.01$

1Government payments excluding conservation reserve program (CRP) and wetlands reserve program (WRP)
Figure 5: Predicted probabilities of using cover crops at varying levels of government payments (watershed level)

For the environmental factors, we did not find a significant relationship between farm-level observed changes in daily extreme precipitation and farmers’ use of cover crops. However, we found a weakly significant association between watershed-level observed precipitation extreme and farmers’ use of cover crops. We plotted the predicted probabilities of this relationship (Figure 6). The figure below illustrates that predicted probabilities of using cover crops increase from 15% to 25% across the full range of watershed-level observed extreme precipitation. Farmers’ in watersheds with higher observed change in extreme precipitation are more likely to use cover crops. This relationship is only weakly significant.
Figure 6: Predicted probabilities of using cover crops at varying levels of daily extreme precipitation events (watershed mean)

**Random effects**

Figure 7 illustrates the variation in the random effects by showing the mode and the conditional variances for each watershed. It shows that Western Lake Erie ($\gamma = 0.57$) and Missouri-Nishnabotna ($\gamma = -0.47$) watersheds have the highest and lowest intercepts, respectively. Since all predictors are centered within context, the value of the intercepts can be interpreted as the odds of using cover crops in each watershed when all predictors are at their mean value. Therefore, for this sample of farmers, those farming in Western Lake Erie watershed are on average more likely to use cover crops than those in the Missouri-Nishnabotna watershed.
Discussion

This study examined possible influences of adaptive capacity and environmental and institutional conditions on farmers' adoption of cover crops. We found that farmers' perception of their capacity to adapt can be an important predictor of their use of cover crops. This evidence supports the claim made by previous research regarding cover crop adoption (Arbuckle and Roesch-McNally, 2015) and attitude toward climate change adaptation (Burnham and Ma, 2017; Grothmann and Patt, 2005).

We studied multiple dimensions of farmers' perceived adaptive capacity. Our results suggest that perceived decision constraints are positively and significantly
related to farmers' use of cover crops. Our results support findings of previous studies that have found farmers' perceptions of constraints (exogenous) associated with biophysical stressors, such as drought (van Duinen et al., 2015) and excess water (Morton et al., 2015) to increase their willingness to take necessary steps to reduce risks associated with these hazards.

Our study suggests that farmers’ centrality in social network—a measure of their relative positioning with the social structure—can influence their adaptive response to climate change. We found that farmers’ who perceive themselves to be central in their social group are more likely to use cover crops. This result supports previous research on farmer adoption of adaptive management practices that have found that social networks can influence farmers’ pro-environmental behavior (Floress et al., 2011) and response to adaptive management of resources (Bodin et al., 2006). We also found that farmers’ desire to seek knowledge can increase their use of cover crops. This study corroborates findings from previous research in the U.S. and Australia, which have found that farmers’ attitude toward seeking new knowledge is a key attribute for achieving greater resilience in agriculture (Eakin et al., 2016; Marshall and Marshall, 2007).

In terms of institutional factors influencing farmers’ use of cover crops, we found that formal institutions such as direct payments are likely to impede farmer’s decision to use cover crops. We found that the effect of receiving direct payments on farmers’ land use decisions are comparable to them obtaining crop insurance indemnities. Both are sources of additional revenue. Our study’s results are consistent with findings from other studies (Annan and Schlenker, 2015; Babcock,
2014; Falco et al., 2014) who found that crop insurance can create a disincentive for the farmer to take necessary adaptive measures on their farm because of the additional revenue protection provided by these programs. We examined the interaction effect between direct payments and farmers planting crops on highly erodible land. We found that farmers are less likely to use cover crops if they have received (1) direct payments and (2) plant on highly erodible land. Our finding supports results from previous studies that have attributed farmers’ enrollment in subsidized crop insurance programs with an increase in conversion rate of non-cropland to cropland (Claassen, 2012; Hertel and Lobell, 2014). Overall, we found that risk management institutions such as direct payments can influence farmers’ land use decisions, with potential negative economic and environmental consequences.

We also examined how objective dimensions of adaptive capacity can influence farmers’ adoption of cover crops. We found that more crop and livestock diversification increases farmers’ use of cover crops, which supports findings from earlier research that found a positive relationship between crop and livestock diversification and adoption of adaptive management practices (Knutson et al., 2011; Singer et al., 2007). We also found that material resources had an influence on farmers’ use of cover crops. These results concur with recent studies that have identified farm revenue (Prokopy et al., 2008), weather and climate information (Lemos et al., 2014), and availability of various markets for selling corn (Morton et al., 2015) as important predictors of farmers’ adaptive response.
Conclusion

Our study contributed to understanding how biophysical stressors, perceived and objective characteristics of adaptive capacity and institutional conditions may enhance or impede farmers’ use of cover crops. We presented a comprehensive model that reconciled farmer agency with structural risks and capacities. Results of this study are believed to be directly applicable in the policy-making domain as many plans and policies are designed and implemented at multiple levels: farm and watersheds. At the farm level, we identified several farmer specific variables, including perceptions of capacity and objective or material sources of capacity which can predict farmers’ pro-environmental behavior. At the watershed level, we examined whether regional changes in soil and weather (extreme rain) and institutional conditions such as government payments could impact farmers’ adaptive responses.

Overall both levels of analysis provided some results to instigate interesting policy discussion on increasing adaptive management practices in the Upper Midwest. For example, our study shows that farm subsidies can impede farmers’ use of adaptive management practices. Therefore, it is important to inquire whether government payments and crop insurance can also encourage farmers to implement practices that are beneficial for soil health and water quality? How can rules be made for crop insurance or government payments that encourage farmers to use soil and water conservation practices? In our view, farm subsidies provide an excellent opportunity to connect financial incentives with pro-environmental behavior. However, currently farm subsidies are creating barriers to conservation.
One reason is that the United States Department of Agriculture (USDA) guidelines for crop insurance eligibility requires farmers to manage cover crops through extensive “termination guidelines”. This extra layer of compliance with procedures can increase the managerial complexity for farmers to integrate cover crops into existing cropping system.

A Midwestern conventional farmer recently drafted an opinion piece on the potential role of crop insurance to encourage farmers’ use of conservation practices. He wrote: “There’s a powerful opportunity for crop insurance to encourage conservation practices. Right now, farmers and the government split the cost of crop insurance premiums. What if the government paid a larger share to farmers who practice conservation? If my crop insurance agent offered me a lower crop insurance premium because I plant cover crops, I’d definitely try to plant cover crops every year. I’m sure my neighbors would say the same.” (Peterson, 2016) Farm subsidies programs have made payments to farmers proportional to their use of conservation practices. More research is needed to examine which programs have been successful and what have been the social, economic, and behavioral reasons behind their success. Our study provides the building blocks for future research that can use perceived and objective adaptive capacities to understand how certain farm subsidies programs can help achieve conservation goals.

Future research should examine the reasons why farmers in some watersheds are more likely to use adaptive management practices, such as cover crops. Are variations in biophysical conditions across watersheds, such as the length of the growing season influencing greater use of cover crops in some watersheds?
or outreach and engagement efforts in some watersheds are contributing more toward farmers’ use of cover crops? Empirical examination of these questions can answer questions pertaining to the importance of meso-level engagement efforts and structural policies for encouraging farmers to use more adaptive management practices.

References


Arritt, R., 2016. Climate Change in the Corn Belt. Resilient Agric.


### APPENDIX A. PERCENTAGE OF MISSING PRIOR TO IMPUTATION

**TABLE A.** Percentage of Missing Values Prior to Imputation

<table>
<thead>
<tr>
<th>Components, Sub-Components, and Statements</th>
<th>Missing %</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>In 2011, approximately what percentage of the land (owned and/or rented) you farmed was…</em></td>
<td></td>
</tr>
<tr>
<td>• Artificially drained through tile or other methods</td>
<td>5.15</td>
</tr>
<tr>
<td>• Reduced tillage (e.g., strip, ridge tillage)</td>
<td>10.44</td>
</tr>
<tr>
<td>• No-till</td>
<td>7.14</td>
</tr>
<tr>
<td>• Planted to cover crops</td>
<td>10.15</td>
</tr>
<tr>
<td>Farm subsidies (direct payments) ($)</td>
<td>12.49</td>
</tr>
<tr>
<td>Availability and accessibility of weather and climate-related decision support tools (Count)</td>
<td>10.38</td>
</tr>
<tr>
<td>Opportunities to sell crops in multiple markets (Count)</td>
<td>0.38</td>
</tr>
<tr>
<td>Education</td>
<td>1.42</td>
</tr>
<tr>
<td>I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation</td>
<td>5.90</td>
</tr>
<tr>
<td>I have the financial capacity to deal with any weather-related threats to the viability of my farm operation</td>
<td>6.32</td>
</tr>
<tr>
<td>I am confident in my ability to apply weather forecasts and information in my crop related decisions</td>
<td>4.67</td>
</tr>
<tr>
<td>It is important for me to talk to other farmers about new farming practices and strategies</td>
<td>4.58</td>
</tr>
<tr>
<td>I am willing to use seasonal climate forecasts to help me make decisions about agricultural practices</td>
<td>4.35</td>
</tr>
<tr>
<td>It is important for me to visit other farms to look at their practices and strategies</td>
<td>4.48</td>
</tr>
<tr>
<td>I am concerned that available best management practice technologies are not effective enough to protect the land I farm from the impacts of climate change</td>
<td>6.84</td>
</tr>
<tr>
<td>There’s too much uncertainty about the impacts of climate change to justify changing my agricultural practices and strategies</td>
<td>5.90</td>
</tr>
<tr>
<td>Crop insurance and other programs will protect the viability of my farm operation regardless of weather (reversed)</td>
<td>6.40</td>
</tr>
<tr>
<td>Changes in weather patterns are hurting my farm operation</td>
<td>5.88</td>
</tr>
<tr>
<td>Other farmers tend to look to me for advice</td>
<td>4.75</td>
</tr>
<tr>
<td>I consider myself to be a role model for other farmers</td>
<td>5.06</td>
</tr>
<tr>
<td>Extension staff, crop advisers, and others involved in agriculture tend to look to me for advice</td>
<td>4.92</td>
</tr>
</tbody>
</table>
Figure B: Imputed dataset is illustrated in magenta while the density of the observed data is showed in blue.
APPENDIX C. CORRELATION PLOT

Figure C: Correlation Plot
CHAPTER 4. SPATIALLY REPRESENTING VULNERABILITY TO EXTREME RAIN EVENTS USING MIDWESTERN FARMERS’ OBJECTIVE AND PERCEIVED ATTRIBUTES OF ADAPTIVE CAPACITY

Modified from a paper submitted to Risk Analysis

Maaz Gardezi¹ and J. Gordon Arbuckle²

Abstract

Potential climate change-related impacts to agriculture in the Upper Midwest pose serious economic and ecological risks to the U.S. and the global economy. Given the projected trend toward more extreme rainfall events in the Upper Midwest, it is important to recognize that such variation in rainfall can impact farm-level productivity and off-farm environmental sustainability. On a local level, farmers are at the forefront of responding to the impacts of climate change. Hence, it is important to understand how farmers and their farm operations may be more or less vulnerable to changes in the climate. A vulnerability index is a tool commonly used by researchers and practitioners to represent the geographical distribution of vulnerability in response to global change. Most vulnerability assessments measure objective adaptive capacity using secondary data collected by governmental agencies. These assessments can potentially overlook people’s subjective perceptions of changes in climate and extreme weather events and the extent to which people feel prepared to take necessary steps to cope and respond to the negative effects of climate change. This paper incorporates socio-cognitive aspects of adaptive capacity into a vulnerability assessment approach. Farmer-level vulnerability is calculated and spatial statistics

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are used to conduct small area (county) estimation with continuous areal data. The farmer and county-level vulnerability indices presented in this paper can be useful to meet the information needs of a diversity of decision makers such as farmers, agricultural educators, and policy makers.

Introduction

The Upper Midwestern United States is a national and global leader in commodity crop production, mainly corn (*Zea mays*) and soybeans (*Glycine max*). In 2015, approximately $68 billion of corn and soybeans was produced in this region (USDA-NASS, 2015). This region also produces one-third of the global corn supply and one-quarter of its soybeans (FAOSTAT, 2015). Current and predicted climate change-related impacts to corn and soybean crops include reduction in crop yield, higher crop stressors due to extreme rain events, soil erosion, droughts, floods, and weed and insect pests (Hatfield et al., 2014). These impacts on agriculture in the Upper Midwest, pose serious economic and ecological risks to the U.S. and the global economy.

Extreme precipitation represents one of the greatest threats to agricultural productivity and environmental sustainability (Arritt, 2016; Karl et al., 2009; Todey, 2014). Extreme precipitation is defined as an event with more than four inches (101.6 millimeters) of rain in a 24 hour period (Todey, 2014). Such events can reduce the efficiency or total factor productivity (TFP) of agriculture (Liang et al., 2017). For example, in the early growing season, extreme precipitation events can delay planting and increase farmers’ economic risks. Before the crop canopy is established, extreme precipitation events increase the risk of soil erosion (Abendroth et al., 2011; Morton et
al., 2015) and exacerbate negative off-farm environmental impacts, such as an increase in the transportation of nitrogen, phosphorus and other nutrients into ground water, streams, and lakes (Morton et al., 2015). Excessive sediment and nutrient export from corn-soybean producing agricultural lands is a significant driver of nonpoint source pollution loads in the Mississippi River Basin and the Gulf of Mexico (Mitsch et al., 2001; Rabalais, 2006). Thus, extreme precipitation events can not only hurt short-term crop productivity but also exacerbate soil erosion, off-field, and off-farm nutrient losses across the region (Morton et al., 2015).

The US 3rd National Climate Assessment defines vulnerability as “the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes (Bierbaum et al., 2014, p. 672).” Vulnerability is a function of exposure, sensitivity, and adaptive capacity. In agriculture, farm-level vulnerability to extreme rain events can be determined by the interaction between (1) biophysical stressors or exposure, such as extreme rainfall events; (2) biophysical impacts or sensitivity, which are mediated by soil characteristics and use of adaptive management practices, and (3) adaptive capacity, such as availability and access to financial, technical, and institutional resources needed for facilitating adaptation. Assessing the exposure, sensitivity, and adaptive capacity at the farm-level can potentially help to explain the qualities or deficiencies that make a farm less or more at risk to a range of stressors related to extreme precipitation events.

In the environmental change literature, most vulnerability assessments have measured objective attributes of adaptive capacity using secondary data collected by
government agencies. These studies often frame the likelihood that people and communities will adapt to climate change as a function of access to financial and technical resources and suitable institutional arrangements (Adger, 2003; Berkes and Jolly, 2002). However, other scholarship on human behavior has noted that in addition to the objective attributes of adaptive capacity, socio-cultural and cognitive factors, such as risk perceptions and perceived capacity, are consequential for modulating peoples' actual vulnerability (Grothmann and Patt, 2005; Moser et al., 2014). For example, perceived adaptive capacity (PAC)—defined as the “extent to which [people] feel prepared to endure changes and take necessary steps to cope with them” (Seara et al., 2016, p. 50)—has been found to influence peoples' decisions about both the significance of climatic risks and the willingness to take actions to cope, adapt or ignore such risks (Grothmann and Patt, 2005; Moser et al., 2014). A better understanding of the relationships between objective and subjective measures of adaptive capacity in agriculture has implications for climate change policy and programs, especially if farmers are systematically under- or over-estimating their own ability to adapt to weather and climatic impacts. Moreover, examining the objective attributes of adaptive capacity in conjunction with the subjective measures of capacity may facilitate identification of culturally acceptable adaptation actions available to farmers.

The objectives of this study are to (1) incorporate perceived adaptive capacity into a vulnerability assessment, (2) use spatial smoothing to aggregate individual-level vulnerabilities to the county level, and (3) evaluate the degree to which objective and perceived adaptive capacity align or misalign. We propose that this study adds value
to existing research on farmers’ vulnerability in three ways: (1) incorporating subjective measures of capacity into a vulnerability assessment can improve understanding of the farmers’ perceived ability to take suitable actions for adaptation (Hicks et al., 2016); (2) if there is misalignment between objective and subjective measures of adaptive capacity, such findings could point to ways that government agencies might include questions about farmers’ perceived capacity in large-scale surveys, such as the agriculture census; and (3) disaggregating farmers’ adaptive capacity can highlight how objective measures of adaptive capacity alone often inadequately capture these complex behavioral processes.

We organize the paper as follows: we first summarize the literature on exposure, sensitivity, and adaptive capacity in the context of Upper Midwestern agricultural systems. We examine various rationales and approaches employed in understanding adaptive capacity and present a framework that situates this study’s conception of perceived adaptive capacity within that literature. In the methods section, we present the study region, the list of measures used in the construction of farmer-level vulnerability index, and justification for choosing the administrative region—county—as the scale for mapping vulnerabilities. Next, we report the results of Conditional Autoregressive (CAR) modeling employed to spatially smooth county-level climate change vulnerability from farmer-level vulnerability scores. This model exploits auxiliary information from neighboring counties and estimates a farmer vulnerability score for each Upper Midwestern county in the study sample. The farmer-level and county-level spatially smoothed vulnerability indices produced in this paper can be useful to meet the information needs of a diversity of decision makers such as
farmers, agricultural educators, agencies, and policy makers. Finally, we discuss the main findings and conclude by suggesting possibilities for future research on this subject.

**Literature Review**

Global climate change is one of the most significant challenges facing agriculture in the 21st century. It is already affecting global and regional agricultural productivity with predicted impacts that will continue to increase in intensity and frequency (Coumou and Rahmstorf, 2012; Hatfield et al., 2014). Potential climatic and weather-related threats to agriculture represent threats to food security, livelihoods, and societal stability (Howden et al., 2007; McCarl, 2010). For example, limited availability of food, rising food prices, and limited access to food in 2007-2008 has been linked to political instability and regional conflict in 48 countries (Brinkman and Hendrix, 2011). On a local level, farmers are at the forefront of responding to the impacts of climate change on agriculture (Lal et al., 2011). Examining the dynamic interactions between climatic risks and social, economic, and institutional conditions, can highlight the qualities or deficiencies that make a farm/farmer more or less vulnerable to current and future climate change and variability (Walthall et al., 2012).

In the environmental change and disaster studies literature, vulnerability is generally considered as a function of the likelihood and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (Adger, 2006; Brooks et al., 2005; Parry et al., 2007). Exposure is the likelihood that a system will experience hazard. Sensitivity refers to the likely magnitude of effect that the hazard will have on a system. Thus, exposure is an external characteristic of a system, and
sensitivity is an internal characteristic. Agricultural systems are human-dominated ecosystems, so the agriculture’s vulnerability to climate change depends on both the biophysical effects of climate change but also on the responses taken by individuals and institutions to moderate those effects (Eakin et al., 2016; Marshall and Marshall, 2007). These individual and social responses are dependent on adaptive capacity—the ability of the system to cope, adapt, and respond to the negative effects of climate change (Adger, 2006; Smit et al., 2001; Turner et al., 2003). In the following section, we briefly highlight some of the current and potential changes in precipitation (exposure) and the impacts (sensitivity) of these changes on Midwestern U.S. agriculture.

**Exposure: Changes in precipitation for the Midwest**

Exposure is the likelihood that a system will experience hazard (Bierbaum et al., 2014). Observed and projected changes in climate highlight that Midwestern U.S. is exposed to several climatic and weather-related changes, primarily driven by changes in temperature and precipitation. Of interest to this study is to examine agriculture’s exposure to changes in precipitation. In the last century, there has been a 20% increase in annual precipitation in the U.S., much of which has been driven by an increase in extreme rain events—events with more than four inches (101.6 millimeters) of rain in a 24-hour period (Todey, 2014). In the Midwest, the frequency of days with extreme rain events has increased by almost 50% in the entire 20th century (Arritt, 2016). There is seasonal variation in the observed trend, with 85% of extreme rain events occurring during the summer period (May-September). Projected
changes in precipitation suggest that it is very likely that extreme rain events will continue to increase in the Midwest throughout the 21st century (Walthall et al., 2012).

Shifts in climatic conditions in the Midwest, such as changes in extreme precipitation events at important stages in crop development, pose risks of significant damages to crop productivity and environmental sustainability (Walthall et al., 2012). On an annual basis, extreme rain events can delay planting or cause waterlogging that reduces the efficiency or total factor productivity (TFP) of agriculture (Liang et al., 2017). Extreme rains are also implicated in degradation of soil resources through erosion, which reduces the long-term productive capacity of agricultural lands (Abendroth et al., 2011; Morton et al., 2015). Off-farm impacts, especially the transportation of nitrogen, phosphorus and/or other nutrients into ground water, streams, and lakes is also exacerbated greatly by extreme rain events (Morton et al., 2015).

**Sensitivity: Extreme rain events and adaptive practices**

In the Upper Midwest, projected increases in extreme rain events pose a major threat to soil quality and agricultural productivity (Arritt, 2016; Karl et al., 2009; Todey, 2014). As discussed above, extreme precipitation events can reduce both annual and long-term crop productivity and exacerbate off-field, and off-farm nutrient losses across the region (Morton et al., 2015). Thus, we examine sensitivity as the potential impacts of extreme rain events on farm-level soil erosion (Walthall et al., 2012).

Sensitivity can be reduced if farmers implement adaptive management practices to protect the land and retain soils and nutrients (Arbuckle Jr. et al., 2011). Adaptive best management practices, also known as soil and water conservation
practices, can potentially reduce soil erosion rates and loss of soil organic carbon and other important nutrients (Reimer et al., 2012). These management practices provide the farm/farmer an opportunity to modulate the sensitivities associated with extreme rain events. Sensitivity is the interaction between farmers’ use of adaptive management practices (social) and soil characteristics (biophysical/ecological). Table I provides a brief description of the key adaptive management practices that we examine in this research.

**Table 1.** Description of Adaptive Management Practices included in this study

<table>
<thead>
<tr>
<th>Adaptive Management Practice</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Agricultural Drainage</strong></td>
<td>Drainage tile systems are used to drain away excess water and transform poorly drained soils into productive croplands. (Morton et al., 2015) Drainage can directly benefit the soil structure and reduce soil erosion. However, research suggests that drainage can also increase the transfer rate of nitrate from fields to streams and rivers. (Qi et al., 2011)</td>
</tr>
<tr>
<td><strong>Cover crops</strong></td>
<td>Cover crops are “grown primarily for the purpose of protecting and improving soil between periods of regular crop production.” (Schnepf and Cox, 2006) There are a number of ways in which cover crops can reduce the harmful impact of heavy precipitation events on Upper Midwestern corn-based cropping system. Cover crops can help farmers adapt to the impacts of climate change by (1) preventing soil erosion, (2) reducing the flow of nutrients, such as nitrate, from farms into streams and lakes, (3) improving water and nutrient cycling, (4) controlling pest and disease, and (5) improving field level soil organic carbon, soil structure, and soil carbon retention. (Kaspar et al., 2012; Kremen and Miles, 2012)</td>
</tr>
<tr>
<td><strong>No-Till</strong></td>
<td>No-till is a farming practice that has the potential to protect soil erosion especially during extreme rain events. No-till is a form of tillage where the “soil is left undisturbed from harvest to planting except for strips up to ½ of the row width for planting the seed, with weed control accomplished with herbicides and methods other than tillage.” (Morton et al., 2015, p. 814)</td>
</tr>
</tbody>
</table>
Table 1 continued

| Reduction in tillage or no-tillage has the potential to reduce soil erosion, increase soil porosity, and increase nutrient retention. (Lal et al., 2011) Benefits to soil properties from no-till farming can reduce the harmful impact of heavy precipitation events on the soil surface by reducing soil erosion. (Morton et al., 2015) |

**Objective attributes of adaptive capacity**

In the environmental change literature, the term ‘resilience’ is defined as a system’s ability to respond to a shock and still maintain its general attributes, while also retaining capacity to evolve or transition to a more desirable state (Nelson et al., 2007; Rockström et al., 2009). Adaptive capacity represents a primary social mechanism for regulation of system resilience (Engle and Lemos, 2010). Adaptive capacity includes three distinct, but related, parts: a resource system; the ability of individuals and communities to access those resources; and, the governance system that structures and mediates the management of resources and systems of access (Nelson et al., 2007). Recent research on adaptive capacity has highlighted various factors as determinants of adaptive capacity, including economic resources, technology, knowledge and skills, institutions, social capital, and infrastructure. (Engle and Lemos, 2010; Parry et al., 2007; Yohe and Tol, 2002).

In the context of adaptation in agricultural systems, studies have often focused on relationships between farmers’ and farming communities’ opportunities to cope, adapt, and respond to the negative effects of climate change and their access to financial resources, knowledge, and suitable institutional arrangements (Moser et al., 2008; Swanson et al., 2009). For example, Moser et al. (2008) found that financial resources were the most significant determinant of Northeastern U.S. dairy farmers’
adaptive capacity. Similarly, Swanson et al. (2009) identified economic resources, technology, and knowledge to enhance the adaptive capacity of farmers and farm organizations in the Canadian agriculture sector. Most studies have examined external or objective dimensions of adaptive capacity, i.e., “the material and immaterial resources and the assets and entitlements that predetermine the decision options available to an actor at any point in time to cope with losses and to anticipate future harm (Eakin, 2014, p. 228).” In this study, we examine some of the key objective attributes of adaptive capacity for Midwestern U.S. farmers. These include: (1) financial resources such as farm income, land size, and farm subsidies in the form of direct payments; (2) institutional resources, such as, opportunities to sell crops in multiple markets, and (3) technical resources, such as farmers’ education levels and use of weather and climate-related decision support tools.

**Perceived attributes of adaptive capacity**

While most vulnerability assessments posit access to financial and technical resources and suitable institutional arrangements as the critical arbiters of adaptive capacity (Adger, 2003; Berkes and Jolly, 2002), recent scholarship on socio-ecological and psychological resilience has highlighted the importance of socio-cognitive factors, such as agency, as determinants of individuals’ and communities’ adaptive capacity to respond to environmental stressors (Brown and Westaway, 2011; Grothmann and Patt, 2005; Moser et al., 2014; Seara et al., 2016). Agency refers to the ability of individuals to act freely and make independent choices (Brown and Westaway, 2011). At the individual level, agency can be influenced by personal beliefs and values; how people perceive risks and opportunities, and broader structural
elements, which can either facilitate or serve as barriers to adaptation (Brown and Westaway, 2011). For example, at the individual level, farmers’ perceived adaptive capacity in relation to climate change and variability can be composed of such factors as perceptions about their financial and technical knowledge, perceptions about the institutional environment, such as faith in crop insurance programs, and perceptions about their kinship and centrality in social networks. The determinants of perceived adaptive capacity can be local (e.g., the presence of a strong kinship network which has the potential to relieve stress) as well as broader socio-economic (e.g., a crop insurance program). Thus, perceived adaptive capacity describes the internal dimension of adaptive capacity, i.e., the individual’s perception of the suitability of available resources (financial, technical, institutional, etc.) needed for facilitating adaptation (Eakin et al., 2016; Grothmann and Patt, 2005; Seara et al., 2016). It highlights the “…extent to which people feel they are prepared to endure changes or impacts and undertake steps to cope with them (Seara et al., 2016).”

Recent research on agricultural and ranching communities in the U.S. (Eakin et al., 2016) and Australia (Marshall and Marshall, 2007) have used surveys and in-depth interviews to identify specific perceived dimensions of farmer’s adaptive capacity. These include: perceived agency in terms of financial resources and technical skills (also referred to as self-efficacy); perceptions of the extent to which people can utilize agency for learning and seeking new knowledge (learning and knowledge seeking); expectations that the institutional context, such as crop insurance programs can facilitate or buffer individuals from risk (decision constraints); and social networks that may help farmers in accessing and personalizing information
regarding adaptation to climate change (centrality in social networks). On an individual level, farmers’ perceived adaptive capacity is the perception of their ability to cope with change and withstand disturbances to their farm enterprise. It measures the confidence that farmers have in their ability to perform certain activities or implement a specific climatic risk mitigation action. Figure 1 summarizes the perceived and objective attributes of adaptive capacity commonly depicted in the climate change adaptation literature.

![Diagram of Objective and Perceived Attributes of Adaptive Capacity]

**Figure 1.** Objective and Perceived Attributes of Adaptive Capacity

**Vulnerability framework**

In the sections above, we reviewed the concepts of exposure and sensitivity and their roles as dimensions of vulnerability. We established that perceived adaptive capacity, in addition to objectively measured capacity, is also a potentially
important mediator of adaptive action. In this section, we outline a conceptual framework that brings these elements together in a vulnerability framework that is appropriate for the unique context of Midwestern agriculture.

Vulnerability frameworks generally outline the interactions between environmental services and social outcomes, in part to examine the qualities or deficiencies that make coupled human and natural systems (CHANS) or social-ecological systems (SES) more or less vulnerable to a range of social, economic, institutional and biophysical stressors (Turner, 2010). In the last decade, use of vulnerability frameworks has become more common, primarily for recognizing the synergy or interdependency of the human and environmental subsystems in determining the vulnerability to and capacity to respond to climate change (Dow et al., 2013). The conceptualization of vulnerability frameworks has advanced from solely examining the distribution of physical losses (Hafner-Burton and Montgomery, 2006) to integrating biophysical and social, economic, and political drivers of vulnerability across space and time (Cutter, 2006; Preston et al., 2011).
Figure 2. Vulnerability Framework for Midwestern Farmers

Figure 2 illustrates the vulnerability framework developed for this study, showing how vulnerability is comprised of the four components: exposure, sensitivity, perceived and objective adaptive capacity. The framework highlights the direction of relationships between these four components and the overall vulnerability to extreme precipitation events. For example, farmland with a higher exposure and sensitivity will be more vulnerable to the impacts of extreme rain events. The framework also illustrates adaptive capacity as a primary social mechanism for reducing vulnerability. For example, a farm’s (or farmer’s) vulnerability to extreme precipitation can be mediated by their perceived and objective attributes of adaptive capacity.
Method

Study area & data collection

The study area comprises areas of the Midwestern U.S. states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin (Figure 3). These 11 states are responsible for more than one-third of the global corn supply, represent nearly 65 percent of all corn acres and 55 percent of soybean acres in the U.S. (Arbuckle et al., 2013b) The climate of this region is continental with large seasonal differences in precipitation and temperature. Geographically, weather and climatic features vary from the west (warmer and drier) to east (cooler and wetter). Areas in the west can experience more recurrent summer drought than areas in the eastern and southeastern Midwest. There are regional variations in soil erosion potential due to complex multi-level interactions between geophysical properties and human activity.

Figure 3. Map of US & Study Region
Primary data used in this study is from a February 2012 survey of corn and soybean farmers in 11 Midwestern states (Fig 3). The survey was mailed to a stratified random sample of farmers in a contiguous set of 22 watersheds. (Arbuckle et al., 2013b) The USDA National Agricultural Statistics Service (NASS) Census of Agriculture’s master list, which is the most comprehensive and up-to-date list of US farmers was the sampling frame. Only farmers who grew at least 80 acres of corn and grossed farm sales value in excess of $100,000 per year were included in the mailing list. The survey was mailed by NASS to 18,707 eligible farmers. Completed surveys were received from 4,778 farmers for an effective response rate of 26%. Non-response bias checks compared respondent demographics to U.S. Census of Agriculture data, and no meaningful differences between respondents and non-respondents were observed (Arbuckle et al., 2013b). To maintain the privacy of respondents, the farm-level geospatial coordinates were not stored in the database. However, zip codes and county FIPS were used to identify farmers’ location. The survey measured farmers’ climate change-related risk perceptions, use of conservation practices, past experiences with climate change-related hazard, beliefs about climate change and other sociodemographic features.

Prior to index construction, a Multivariate Imputations by Chained Equations (MICE) was employed in the software R to impute missing values (van Buuren and Groothuis-Oudshoorn, 2011). MICE uses Gibbs sampling to generate plausible values for missing data by examining the underlying patterns in the data.
**Measuring components of vulnerability**

**Exposure to extreme precipitation events**

Farmers’ experience of extreme precipitation events was measured as number of days that they had experience extreme precipitation events, defined as events registering in 99th percentile of daily precipitation for a given month for the record covering 1971-2011 (Loy et al., 2013). The data was obtained from Loy et al. (2013), who constructed various measures of extreme weather for the Upper Midwestern region from the National Weather Service (NWS) Cooperative Observer (COOP) data archive (see Loy et al. (2013) for details on variable construction). Daily extreme precipitation values from the weather station nearest to the farm were assigned to each farmer in the survey. Table II provides a statistical description of daily extreme precipitation that we employed in this study.

**Sensitivity**

We used two items to measure farm-level sensitivity to extreme precipitation events. The first item measured the percent of land designated as “marginal lands” in each county to represent the local soil characteristics. The data to measure soil characteristics were obtained from Loy et al. (2013), who calculated the percent of non-irrigated marginal lands (by county) using the Soil Survey Geographic (SSURGO) database. The characteristics of soil were grouped according to the USDA Natural Resources Conservation Service (NRCS) land capability classification system (see Loy et al., 2013) for a detailed account of variable construction). The second item used for measuring sensitivity was the maximum percentage of land on which farmers’ self-reported to use adaptive management practices. Four farm-level adaptive
management practices were included in our analysis: drainage, reduced and no-till farming, and cover crops. Justification for the including these practices in our analysis is provided in Table I. Table II provides a statistical description of the two items that we employed in this study to measure sensitivity.

<table>
<thead>
<tr>
<th>Components &amp; Statements</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure (Daily precipitation extremes)</td>
<td>0.39</td>
<td>0.14</td>
<td>1</td>
</tr>
<tr>
<td>Sensitivity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In 2011, approximately what percentage of the land (owned and/or rented) you farmed was…</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Artificially drained through tile or other methods</td>
<td>49.09</td>
<td>40.01</td>
<td>100</td>
</tr>
<tr>
<td>• Reduced tillage (e.g., strip, ridge tillage)</td>
<td>32.63</td>
<td>39.8</td>
<td>100</td>
</tr>
<tr>
<td>• No-till</td>
<td>37.2</td>
<td>38.74</td>
<td>100</td>
</tr>
<tr>
<td>• Planted to cover crops</td>
<td>6.38</td>
<td>16.45</td>
<td>100</td>
</tr>
<tr>
<td>Percent of non-irrigated marginal lands by county</td>
<td>0.17</td>
<td>0.16</td>
<td>0.97</td>
</tr>
</tbody>
</table>

The Latent Profile Analysis (LPA) technique was employed to estimate profiles of farmers’ sensitivity. LPA is a probability-based clustering technique that aims to explain the relationships observed in multivariate data by grouping cases according to an unobserved variable (Vermunt and Magidson, 2003). In this study, LPA is used to assign farmers to discrete profiles based on (1) the characteristics of soil in the farmers’ county and (2) farmer's self-reported use of adaptive management practices on their farm. The LPA assumes that the population is comprised of a mixture of P different profiles of survey respondents with each profile having separate response distributions for each observed item.
Table 3. Summary of Latent Profile Analysis for Profiles 2 – 5

<table>
<thead>
<tr>
<th></th>
<th>2 Profiles</th>
<th>3 Profiles</th>
<th>4 Profiles</th>
<th>5 Profiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>177397</td>
<td>174863</td>
<td>173369</td>
<td>171414</td>
</tr>
<tr>
<td>BIC</td>
<td>177500</td>
<td>175005</td>
<td>173550</td>
<td>171634</td>
</tr>
<tr>
<td>Entropy</td>
<td>.994</td>
<td>.918</td>
<td>.915</td>
<td>.920</td>
</tr>
<tr>
<td>Lo Mendell Rubin</td>
<td>3980</td>
<td>2496</td>
<td>2164</td>
<td>1310</td>
</tr>
<tr>
<td></td>
<td>p = .00</td>
<td>p = .00</td>
<td>p = .00</td>
<td>p = .00</td>
</tr>
<tr>
<td>Number of farmers in each profile</td>
<td>P1= 4526</td>
<td>P1= 2361</td>
<td>P1=2301</td>
<td>P1=269</td>
</tr>
<tr>
<td></td>
<td>P2= 252</td>
<td>P2= 2184</td>
<td>P2=1952</td>
<td>P2=2234</td>
</tr>
<tr>
<td></td>
<td></td>
<td>P3=233</td>
<td>P3= 302</td>
<td>P3=1859</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P4= 223</td>
<td>P4=321</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>P5=92</td>
</tr>
</tbody>
</table>

Formally, the LPA model was generated by a mixture distribution:

\[ y = \Lambda \eta + \varepsilon \]  

Equation (1)

Where,

- \( y \) is a vector of observed indicator variables
- \( \Lambda \) is a matrix of classification probabilities
- \( \eta \) is a vector of classification profiles
- \( \varepsilon \) is a vector of classification errors

The LPA model was estimated using Mplus software. Overall model fit was assessed with information criteria such as the Bayesian Information Criterion (BIC) and the Lo-Mendell-Rubin adjusted likelihood ratio test. Model comparisons and model fit with fewer profiles are provided in Table 3. A five-profile model (\( P = 5 \)) provided the least BIC and a statistically significant Lo-Mendell-Rubin LR test and was chosen as suitable for interpreting farmers’ sensitivity. In this model, profile 1 made up 5.62% of the sample and consisted of farmers who were either currently using most of adaptive management practices on their farm or had used these management
practices in the past (management practices were identified in Table I). This group of farmers also had farmland with the lowest potential for soil erosion (as measured by the land capability classification system). Thus, a combination of low potential of soil erosion and high use of on-farm adaptive management practices allowed us to assign farmers (farms) in Profile 1 as least sensitive to extreme precipitation events.

Profile 2 consists of farmers whose farmland had low-to-moderate potential for soil erosion. These farmers were using most of the desirable adaptive management practices. Thus, farmers in profile 2 were low-to-moderately sensitive to extreme rain events and constituted 46.75% of the sample. Similarly, farmers whose farmland had medium potential for soil erosion and who were moderately using adaptive management practices on their farm were in profile 3. Farmers in this profile constituted 38.9% of the sample. Profile 4 made up 6.71% of the sample. Farmers in profile 4 had medium-to-high potential for soil erosion and had limited-to-no use of adaptive management practices. Lastly, profile 5 farmers and farms were most sensitive and represented 1.92% of the sample. These five latent profiles constitute an ordinal scale (1-5) with Profile 1 representing least sensitive and Profile 5 representing most sensitive farmers. The descriptive statistics for sensitivity are shown in Table VI in the results section.

Objective adaptive capacity

We selected six items to assess farmers’ objective adaptive capacity. Following Swanson et al., (2009) the items measure two dimensions of objective adaptive capacity: (1) financial and institutional capacity and (2) technical capacity. Farm sales, land size, and farm subsidies were associated with farmers’ financial and institutional
capacity. Availability and accessibility of weather and climate-related decision support tools, opportunities to sell crops in multiple markets, and farmers’ education represented farmers’ technical capacity. Factor analysis was used to condense information from these six items into two indices, each representing a single component of objective adaptive capacity (Table IV). Both components of objective adaptive capacity were then averaged to create a single index representing farmers’ overall objective adaptive capacity. We adapted the method used in the Livelihood Vulnerability Index (Hahn et al., 2009) to normalize the objective capacity index. By adapting their approach, we calculated the objective capacity index as the ratio of the difference of the actual objective capacity and the minimum objective capacity in our sample of farmers, and the range of objective capacity (Fig 5 in the results section).

**Table 4. Objective Adaptive Capacity**

<table>
<thead>
<tr>
<th>Components</th>
<th>Statement</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Range</th>
<th>Factor weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial &amp; Institutional Capacity</td>
<td>Farm Sales ($)</td>
<td>457000</td>
<td>653461</td>
<td>20060000</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Land size (Acres)</td>
<td>429</td>
<td>469</td>
<td>10150</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>Farm subsidies (direct payments) ($)</td>
<td>12760</td>
<td>62120</td>
<td>16000</td>
<td>0.74</td>
</tr>
<tr>
<td>Technical Capacity</td>
<td>Availability and accessibility of weather and climate-related decision support tools</td>
<td>2.69</td>
<td>1.95</td>
<td>8</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>Opportunities to sell crops in multiple markets</td>
<td>1.98</td>
<td>0.81</td>
<td>6</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>Education</td>
<td>3.26</td>
<td>1.32</td>
<td>5</td>
<td>0.23</td>
</tr>
</tbody>
</table>

**Perceived adaptive capacity**

We selected 13 items that corresponded to the four perceived dimensions of adaptive capacity: *self-efficacy; learning and knowledge seeking; decisions constraints*, and *centrality in social networks* (some outlined by Marshall and Marshall
Factor analysis with varimax rotation was used to condense information into these four components of perceived adaptive capacity (Table V). Since decision constraints are likely to reduce farmers’ perceived capacity, factor scores for decision constraints were subtracted from the other three components of perceived adaptive capacity. The perceived adaptive capacity index was also normalized and the scores were distributed on a continuous scale between 0 and 1 (Fig 5 in the results section).

<table>
<thead>
<tr>
<th>TABLE 5. Perceived Adaptive Capacity</th>
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</thead>
<tbody>
<tr>
<td>Componen</td>
</tr>
<tr>
<td>Self- efficacy</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Learning &amp; knowledge seeking</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Decision constraints</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Centrality in social networks</td>
</tr>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>
**Vulnerability Index**

The 3rd National Climate Assessment defines vulnerability as a “function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (Bierbaum et al., 2014).” Thus, climate change vulnerability is the sum of exposure and sensitivity mediated by the system’s adaptive capacity. We used this definition of vulnerability and adapted it for the context of examining Midwestern farmers’ vulnerability to extreme rain events. We constructed two vulnerability indices: (1) an index that incorporated objective attributes of farmers’ adaptive capacity and (2) a vulnerability index that included farmers’ perceived attributes of adaptive capacity. We calculated these indices separately to demonstrate the added value of incorporating farmers’ perceived adaptive capacity into a vulnerability assessment. Finally, all indices were normalized and the distributions of farmer/farm vulnerability were aligned to a normal distribution (Fig 6 in the results section).

**Aggregating farmers’ vulnerability scores in each county**

For agricultural and climate policy makers and planners it is important to spatially locate the distribution of vulnerabilities to provide policy recommendations for targeted farm, county, and watershed-level adaptation. However, it can be challenging to map farmers' vulnerabilities to climate change without having the geospatial coordinates of their farms. In this situation, one possible solution is to use spatial statistics to construct vulnerability estimates for small areas, such as counties. Our choice of county as the focal geographic unit was based on the following considerations: (1) institutional processes including many policies and decisions are
made at the county level, such as crop insurance indemnities and disaster relief; 2) related to the consideration above, results at this aggregate level can be directly applicable in the policy-making domain; and 3) numerous county-level variables are available from secondary data sources such as the Census and NASS, and these can be included in future research to explain variations in farmers’ vulnerabilities to extreme rain events (or similar threats).

Preparing data for estimating county-level vulnerability scores

First, an average vulnerability score was calculated for each county by summing vulnerability scores of all respondents in county $j$ and then dividing it by the number of respondents in that county. One issue with using average county vulnerability scores is that these are calculated for unequal number of farmers in each county. Figure 4 shows the variation in the number of respondents in each county included in the study area. It illustrates that sample size in each county varies from as low as 1 to as high as 50.
To compensate the wide variation displayed among counties, this paper uses an approximation technique to calculate the county-level simple random sample variance. The approximation consists of three steps: 1) the variance among all residents is calculated; 2) the sample variance of the county mean is obtained by dividing overall variance by total number of residents in each county; 3) the first two steps are repeated for each county so that an approximate county-level simple random sample variance was calculated. Intuitively, this approximation ensures that counties with fewer survey respondents have larger sampling variances.

Spatial smoothing vulnerability scores using a Conditional Autoregressive (CAR) model

Next, a Conditional Autoregressive (CAR) model was estimated. A CAR model is appropriate for situations with first order dependency or relatively local spatial autocorrelation. CAR model assumes that the state of a particular area is influenced by its neighbors. Formally, the CAR model can be written as:

$$Y_i | Y_{-i} = X_i \beta + \sum_{j=1}^{N} c_{ij} (Y_j - X_j \beta) + \nu_i$$  \hspace{1cm} \text{Equation 2}$$

Where $Y_{-i}$ is treated as having fixed values when specifying the distribution of $Y_i$. The variance of Y is specified as:

$$\text{Var}[Y] = (I - C)^{-1} \sum \nu$$  \hspace{1cm} \text{Equation 3}$$

For a valid variance-covariance matrix, two constraints must be set on the parameters of the model: (1) the value of $\rho$ cannot be very large, (2) $C$ must be symmetric, so that $c_{ij}=c_{ji}$.

First, suitable neighbors for each county were identified by specifying a queen neighbor structure, i.e., counties sharing a boundary point were taken as neighbors
(Bivand et al., 2013). A queen neighbor structure was selected for ensuring that each county was assigned at least one neighbor. This neighboring structure ensured that the prediction for a county will also include contributions from at least one spatial neighbor. On average, there are almost 5 neighboring links for every county. After establishing the set of neighbors, spatial weights were assigned to each neighbor relationship. Binary weights were assigned to ensure that the structure can define symmetry needed for estimating a CAR model. A binary weight structure assigns weight of 1 to each neighbor and 0 to non-neighbor relationship. Thus, binary weights differentiate the influence of observations—those with many neighbors are more influential compared to those with few neighbors.

Prior to specifying the CAR models, Moran’s I was also calculated to test the null hypothesis that no spatial correlation existed among county-level vulnerability scores. This study used queen neighbors with row-standardized weights to estimate the Moran’s I. The equation for estimating the Moran’s I (eq. 4) is given below:

\[
I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]

Equation 4

Where, \(y_i\) is the ith county score, \(y_j\) is the jth county score, \(\bar{y}\) is the overall mean of the study area and \(w_{ij}\) represents the spatial weight between county i and j.

Results

Results of the farm/farmer-level analysis

Table 6 summarizes the distribution of the computed values of farmers’ exposure, sensitivity, perceived adaptive capacity and objective adaptive capacity. Two overall vulnerability scores that are made up of the preceding components are also summarized. The components of vulnerability are normalized so they represent
relative measures for our sample of farmers. For example, exposure has a mean value of 0.39, a standard deviation of 0.14 and a maximum value of 1 (normalized scores). Farmers whose exposure values are closer to the maximum value of 1 are relatively more exposed to extreme rain events than those whose exposure values are nearer to the lower bound of the range. Relative values of measures of vulnerability are useful for examining the distribution of vulnerability for our sample of farmers across the Midwestern U.S.

<table>
<thead>
<tr>
<th>Vulnerability and its components</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure</td>
<td>0.39</td>
<td>0.14</td>
<td>1</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.40</td>
<td>0.19</td>
<td>1</td>
</tr>
<tr>
<td>Perceived adaptive capacity</td>
<td>0.49</td>
<td>0.12</td>
<td>1</td>
</tr>
<tr>
<td>Objective adaptive capacity</td>
<td>0.41</td>
<td>0.15</td>
<td>1</td>
</tr>
<tr>
<td>Vulnerability with perceived adaptive capacity</td>
<td>0.48</td>
<td>0.13</td>
<td>1</td>
</tr>
<tr>
<td>Vulnerability with objective adaptive capacity</td>
<td>0.47</td>
<td>0.14</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 5 shows that farmers’ perceived capacity and their objective attributes of adaptive capacity do not align. Perceived adaptive capacity is represented by the dotted red curve and is greater than objective adaptive capacity (black curve) for most farmers in the sample. Thus, farmers in our sample appear to be systematically overestimating their capacity. In other words, their self-reported or perceived capacity is greater than what can be inferred about them based on available secondary data measuring their financial, technical, and institutional capacity (using agriculture census).
Figure 5. Examining the difference between farmers’ perceived and objective adaptive capacity

Figure 6. Examining the difference between vulnerability scores using perceived and objective adaptive capacity

We also examined how the misalignment in farmers’ perceived and objective capacity might impact their vulnerability scores. Figure 6 illustrates no difference between vulnerability scores computed using farmers’ perceived (red dotted curve) and objective capacity (black curve). Thus, incorporating exposure and sensitivity
reduced the computed differences between farmers’ vulnerability with perceived and objective adaptive capacity scores.

**Results of the county-level analysis**

Figure 7 graphs the Moran’s I for county-level vulnerability indices using (1) perceived adaptive capacity (I = .40) and (2) objective adaptive capacity (I = .43). The results of the Moran plot suggest that neighboring counties have similar vulnerability values, i.e., the pattern is clustered. A Monte-Carlo estimate of the p-value is calculated to ensure consistency in results and spatial autocorrelation is confirmed in this dataset.

![Moran plots for vulnerability index with perceived adaptive capacity (left), vulnerability index with objective adaptive capacity (right)](image)

**Figure 7.** Moran plots for vulnerability index with perceived adaptive capacity (left), vulnerability index with objective adaptive capacity (right)

Figure 8 illustrates the county-level vulnerability scores obtained after spatial smoothing average vulnerability score in each county. The smoothed values of county-level vulnerability are the sum of non-spatial and spatial fitted values, including contributions from spatial neighbors. Vulnerability scores computed using
perceived capacity and objective capacity are shown in left and right panel of figure 8, respectively. Darker shaded areas represent higher vulnerability than lighter shaded areas. The map illustrates that vulnerability is geographically heterogeneous, with it being relatively greater for counties in Iowa. Vulnerability is also increasing toward the Eastern regions of the Upper Midwest.

![Map of vulnerability scores]

**Figure 8.** County-level vulnerability with perceived adaptive capacity (left), vulnerability with objective adaptive capacity (right) smoothed with CAR model

Table 7 shows the descriptive statistics for the estimated values of county-level vulnerability. As was anticipated from spatial smoothing, the range of county-level vulnerability scores is narrower than the range of scores earlier computed for farmer-level vulnerability. Figure 9 illustrates the comparison of the raw values of $Y_i$ with the spatially smoothed values. It illustrates that vulnerability scores that are above the average are “pulled down” by smoothing, while points that are below the average are “pulled up”.

![Comparison of raw and smoothed vulnerability values]
**TABLE 7.** Smoothed estimates of county-level vulnerability

<table>
<thead>
<tr>
<th>Component</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vulnerability with perceived adaptive capacity</td>
<td>0.48</td>
<td>0.05</td>
<td>0.27</td>
</tr>
<tr>
<td>Vulnerability with objective adaptive capacity</td>
<td>0.47</td>
<td>0.06</td>
<td>0.29</td>
</tr>
</tbody>
</table>

**Discussion and Conclusion**

Our study implemented a socio-behavioral view of farmers’ adaptive capacity that acknowledges their perception of risk and agency to reduce vulnerability related to climate change. We examined farmers’ objective attributes of capacity in conjunction with their perceived adaptive capacity. We found that our estimates of farmers’ perceived adaptive capacity were systematically higher than the objective attributes of capacity. Thus, farmers in our sample may perceive higher levels of confidence in their ability to prepare for challenges associated with climate change.
This finding is unique because it is often difficult to understand attitudes such as self-confidence by only assessing objective attributes of adaptive capacity.

The primary implication of our findings is that vulnerability assessments should take farmers’ perceived attributes of capacity into account. While objective attributes of capacity, such as financial and technical resources, may be important for adaptation, this research suggests that understanding of perceived adaptive capacity is also necessary for evaluation of farmers’ overall adaptability. In other words, the culturally acceptable levels of actions that the farmer is willing to take for climate change adaptation may depend on both objective and perceived adaptive capacity. Our results suggest that farmers in the Midwestern U.S. may perceive that they can overcome most threats associated with climate change, even when they don’t possess adequate levels of resources to make structural or managerial changes to their farm operation. In addition, objective attributes of adaptive capacity may inadequately capture these complex socio-cultural and behavioral processes associated with adaptation to climate change. Thus, our findings suggest that perceived aspects of adaptive capacity should be considered in conjunction with objective measures when assessing farmers’ vulnerability to climate change.

Our results may be of interest to policy makers and extension educators. Such stakeholders could look to our county-level estimates of vulnerability to inform engagement strategies for improving environmental sustainability in the region. These agencies can use the result of this research to engage more effectively with farmers. For example, we have identified counties in the Midwestern U.S. that are
vulnerable to extreme rain events. Extension educators could use our maps to target their communication strategies toward these regions.

The results of this research also point to potential shortcomings in official data collection. If, as our results suggest, farmers’ perceived adaptive capacity is greater than their actual, objective capacity to adapt to climate change, this could have substantial ramifications for the agricultural sector as policy and programs seek to increase adaptive capacity. Although our approach has limitations, primarily associated with sparseness of data, the results suggest that government agencies and other data collection organizations might consider including questions about agency, risk perceptions, and perceived capacity in large-scale surveys, such as the agriculture census. Such questions may improve our understanding of the complex behavioral processes influencing farmers’ (and other groups’) decisions to cope, adapt or ignore climate change-related risks.

One limitation of our research is that we are examining vulnerability as a linear combination of exposure, sensitivity, and adaptive capacity (perceived or objective). Future research might examine interactions between the components of vulnerability. For example, farmland with a higher potential for soil erosion (sensitivity) may be more drastically harmed by frequent and extreme rainfall events (exposure). Similarly, a farm's (or farmer's) sensitivity to heavy rain events can be mediated by their objective attributes of capacity, such as the amount of crop insurance available to them. An in-depth examination of vulnerability should highlight the complex interactions between exposure, sensitivity, and adaptive capacity.
Moreover, as importantly highlighted in this study, there is a need to disaggregate adaptive capacity to study both its perceived and objective dimensions.

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CHAPTER 5. GENERAL DISCUSSION

This dissertation highlights the importance of social and behavioral drivers in determining farmers’ attitudinal and behavioral support for using adaptive management practices. We were able to highlight an important lacuna in existing research on agricultural adaptation to climate change: farmers’ perceived capacity can be consequential for their climate change decision making. Various dimensions of perceived capacity were assessed, including (1) ideological, (2) perceived efficacy, and (3) perceived effectiveness of exogenous factors such as institutional support. Each chapter examined some aspect of the overall adaptive capacity and evaluated its effectiveness for policy making and outreach.

In chapter 2, we wanted to study whether an abstract faith in human ingenuity, often characterized in conventional agriculture by greater confidence in science and technology, could encourage or impede farmers’ support for adaptation. We identified this worldview as “techno-optimism.” In the Midwestern U.S. agriculture, adoption of technology, such as synthetic inputs and genetically modified seeds have enabled Midwestern farmers to increase their profitability in a commodity crop market where farmers are price-taker (they cannot influence price by their supply). Most farmers increase their farm profitability through enhancements in crop yield and by expanding to more acres of crop land—often requiring aggressive adoption of new technology. We wanted to examine whether greater dependence on technology is causing higher levels of “techno-optimism” among conventional farmers and influencing their support for climate change adaptation.
We identified two dimensions of perceived capacity: (1) ideological or “techno-optimism” and (2) personal belief about capacity or perceived efficacy. The path models empirically found that both types of capacity (ideological and personal) could diminish farmers’ support for adaptation and cause them delay decisions regarding adaptation. The results from this study suggest that outreach activities should focus on the scientific and technological properties of adaptive management practices. This might make such management practices more attractive to conventional farmers’ who hold a techno-optimistic worldview.

In chapter 3, we introduced additional characteristics of perceived adaptive capacity, including centrality in social networks, decision constraints, and learning and experimenting. We found that these dimensions of capacity were as much important as the material resources needed by farmers for using adaptive management practices. We also studied whether institutional conditions, such as government payments and direct payments could encourage farmers to use more soil and water conservation practices, such as cover crops. Our study found that instead of supporting farmers to engage in adaptation, farm subsidies can diminish farmers’ adoption of cover crops. This finding suggests the need to closely examine the role of government support in influencing farmers’ use of adaptive management practices.

In chapter 4, we found three very interesting findings. First, farmers’ perceived adaptive capacity were systematically higher than their material or objective adaptive capacity. This means that if we were to only include objective indicators of capacity, our results would have overestimated farmers' vulnerability. It
also implied that farmers may be less prepared to manage risks than what they perceive. Second, by including perceived attributed of capacity we could understand the culturally acceptable levels of adaptive actions that farmers were willing to undertake. In other words, there is a need to explain this mismatch between perceived and objective attributes of capacity. We suggest that future research should identify whether the socioeconomic and demographic trends in Midwestern counties could explain why some farmers are over-or under-estimating their capacity. Finally, we did not settle with computing farmer level score of vulnerabilities. Instead, we aggregated farmer scores to county level. Our estimates of county level vulnerability can be useful for agencies that are trying to engage more effectively with farmers. We found evidence of a misalignment between objective and perceived capacity at the country level and propose that government agencies can include questions about farmers’ perceived capacity in large-scale surveys, such as the agriculture census to adequately capture these complex behavioral processes.
APPENDIX GLOSSARY OF KEY TERMS

**Coupled human-natural systems**: Coupled human-natural systems or social-ecological systems (SES) are groups of related social and environmental parts that are nested at multiple levels and “that provide essential services to society such as supply of food, fiber, energy, and drinking water (Binder et al., 2013, p. 26).” Human and environmental systems can be established at multiple scales as a nested set of arrangements from the local scale through regional and national and so forth (Damm, 2010).

**Human systems**: The human systems include a range of interconnected actors and institutions, such as people, societal processes, organizations, and networks (Binder et al., 2013). These actors and institutions operate at multiple scales i.e. they interact with other social and ecological systems at the individual, community, sub-national, national and international scales. For example, in agriculture, the social or human scale can range from the farmer to his or her social network.

**Natural systems**: The natural systems include the various biotic and abiotic components of the environment that interact with one another at multiple geographical and temporal scales (Damm, 2010). In the case of agriculture, the environmental scale can range from a single plant to the existence of large ecological community of plants and animals.

**Risk**: Risk represents a potential negative consequence that may arise from some process, activity, or event (Cox and Thompson, 2015). Risks are usually evaluated in relation to some reference values, such as protecting livelihoods, human health, environmental and social sustainability. For example, the Risk Management
Agency (RMA) of the United States Department of Agriculture (USDA) defines risk as the consequential effect on farm income volatility from ecological and market-driven events (USDA, 2011). Thus, risk is usually defined in relation to some unfavorable consequences, where consequences are often viewed within the context of protecting some individual and societal values (Cox and Thompson, 2015).

Uncertainty: Uncertainty is often defined in a probabilistic sense to explain a decision-maker’s knowledge about the future consequences of an activity (Blau, 1964; Frederiksen, 2014). Uncertainty is frequently a result of incomplete or imperfect knowledge available to decision makers about a possible risky event (Taylor, 2003).

Decision-maker: Decision-makers are defined as individuals who are actively involved in “management of an establishment” (Slovic, 2000, p. 1). Thus, decision maker is used synonymously with ‘farmer’ or ‘farm manager’.

Establishment: Establishment is defined as a unique areal entity, such as a farm that serves a distinct purpose.

Event: Event is a specified change of the state from the normal. Such as an extreme precipitation event.

Extreme precipitation events: Extreme precipitation events are described as events with more than four inches (101.6 millimeters) of rain in a 24-hour period (Todey, 2014).

Exposure: Exposure is broadly defined as the physically defined climate-related hazard to a system (Brooks et al., 2005). In relation to the impact of climate change on conventional agriculture in the Upper Midwest, one measure of exposure is the likelihood of the farm enterprise experiencing an extreme precipitation event. In
the Upper Midwestern U.S., extreme rain events are among the most hazardous forms of climate change-related weather extremes affecting conventional farming (Morton et al. 2015). In this region, the frequency of days with heavy precipitation has increased by almost 50% in the entire 20th century (Arritt, 2016). Moreover, climate observations and predictions depict an increase in heavy precipitation events for the Upper Midwest in the next 30 to 50 years (Arritt, 2016; Karl et al., 2009; Todey, 2014).

**Sensitivity**: Sensitivity is the vulnerability component that describes the internal state of the system. The Intergovernmental Panel on Climate Change (IPCC) defines sensitivity as the “degree to which a system is affected, either adversely or beneficially, by climate-related stimuli” (McCarthy et al., 2001, p. 6). Sensitivity is generally conceptualized as the mutual interaction between the human condition and the environmental condition (Turner et al., 2003). The human condition includes a range of actors and institutions, such as people, societal processes, and decisions. The environmental condition includes the various biotic and abiotic components that interact with one another at a given place. Sensitivity emerges from the iterative interactions between the human and environmental conditions. In the case of climate change and conventional agriculture in the Upper Midwest, one measure of sensitivity is the likely magnitude of effect an extreme rainfall event will have on the farm enterprise.

**Adaptive capacity**: The Intergovernmental Panel on Climate Change (IPCC) defines adaptive capacity as the “ability of a system to adjust to climate change to moderate potential damages, to take advantage of opportunities, or to cope with the consequences” (IPCC 2007). Adaptive capacity represents the main social
mechanisms for reducing vulnerability and regulation system resilience (Engle and Lemos, 2010). It includes three distinct, but related, parts: a resource system, the ability of individuals to access those resources, and the governance system that structures and mediates the management of resources and systems of access (Nelson et al., 2007). In the case of climate change and agriculture, farmers’ adaptive capacity is their ability to cope, adapt, and respond to the negative effects of climate change.

**Vulnerability**: Vulnerability is a function of the exposure and sensitivity to climate change as well as the adaptive capacity of social-ecological systems to cope and adapt to climate change (Adger, 2006; Brooks et al., 2005; Parry et al., 2007). In relation to climate change and conventional agriculture, vulnerability is dependent both on the farm-level risks associated with climate change as well as the adaptive capacities of decision-makers (i.e. farmers) to mediate these risks.

**Resilience**: Resilience is the ability of social-ecological systems to cope, adapt and respond to change (Folke, 2006). Some properties of resilient socio-ecological systems include, adaptability, flexibility and preparedness for change and uncertainty (Eakin et al., 2016; Gunderson, 1999; Hughes et al., 2005). Specifically, three system characteristics are at the core of resilience theory: (1) the amount of disturbance a system can absorb while retaining its original structure and function, (2) the capability of the system to self-organize, and (3) the degree to which the system can build the capacity for adaptation and learning (Carpenter and Gunderson, 2001; Folke, 2006; Holling, 1973).

**Objective adaptive capacity**: Objective adaptive capacity focuses on the external dimensions of adaptive capacity, i.e. “the material and immaterial resources
and the assets and entitlements that predetermine the decision options available to an actor at any point in time to cope with losses and to anticipate future harm” (Eakin, 2014, p. 228). Thus, objective adaptive capacity links individuals or societies ability to adapt to change with the overall availability of financial, technical, and institutional resources. Studies that investigate and model the interaction between the social and the ecological systems often assume that individuals will have more opportunities to cope, adapt, and respond to the negative effects of climate change if they have adequate access to financial resources, knowledge, and suitable institutional arrangements (Adger, 2003; Smit and Wandel, 2006).

**Perceived adaptive capacity:** Perceived adaptive capacity is the internal dimension of adaptive capacity, i.e. the individual’s perception of the suitability of available resources (financial, technical, institutional, etc) needed for facilitating adaptation (Eakin et al., 2016; Grothmann and Patt, 2005; Seara et al., 2016). In other words, perceived adaptive capacity highlights “…the extent to which people feel they are prepared to endure changes or impacts and undertake steps to cope with them” (Seara et al., 2016).

**Perceived technical capacity:** Perceived technical capacity describes farmers’ self-assessments of their technical abilities to respond to climate change and can be dependent upon farmers’ perception of possessing an adequate and accessible technological and knowledge system.

**Risk perceptions:** Risk perceptions are a person’s subjective judgement or appraisal of risk (SRA Glossary), i.e. it is how risk and uncertainty are perceived. Risk perceptions are socially constructed and various factors such as past experiences of
natural hazard, self-efficacy, and emotions can influence peoples' decisions about both the significance of risks and the willingness to take actions to cope, adapt or ignore such risks (Feldman et al., 2014; Weber and Stern, 2011).

**Intention to Adapt:** Attitudes are defined as the “degree to which a person has favorable or unfavorable evaluation or appraisal of the behavior in question” (Ajzen, 1991, p. 10). Attitudes are often assessed directly in relation to a specific behavior. For example, in the case of farmers’ conservation practice adoption, pro-environmental attitudes have been found to be important predictors of behavioral intentions (Prokopy et al., 2008). Similarly, farmers' intention to adapt to climate change is indicative of adaptive behavior (Arbuckle et al., 2013a; Hyland et al., 2015).

**Decision-delay:** ‘Decision-delay’ is a common response to threats that may be well-known to people, but are perceived to pose no immediate risks (Anderson, 2003). This is a psychological phenomenon in which, rather than deciding on and preparing for risky scenarios ahead of time, people delay decisions and instead prefer to wait and see (McNeill et al. 2015).

**Techno-optimism:** In modern industrialized societies, techno-optimism is the dominant common sense belief that the less beneficial legacies of the capitalist economic growth model, such as over-production, social inequality, and environmental degradation, can be solved or eliminated through greater technological innovation. Barry (2012) defines techno-optimism as “an exaggerated and unwarranted belief in human technological abilities to solve problems of unsustainability while minimizing or denying the need for large-scale social, economic and political transformation” (Barry, 2012, p. 108). Techno-optimists have unlimited
confidence or faith in human ingenuity, including the ability of science and technology to solve socio-environmental problems, such as using geoengineering technologies as solutions to climate change (Hulme, 2014). Thus, techno-optimism is a belief that technological innovation can by itself lead to a sustainable society or world.

**Trust (expert):** Trust in experts can be defined as a “disposition willingly to rely on another person or entity to perform a given action or protect oneself or one’s interest in a given domain” (Nickel and Vaesen, 2012, p. 860). Applied decision theory posits that a rational decision-maker chooses to trust an expert after carefully quantifying risks and assessing the trustworthiness of the expert (Nickel and Vaesen, 2012). According to such reasoning, actors trust experts through a rational calculation of the latter's knowledge, skills, experience, and intentions (Earle, 2010). However, scholars in the field of socio-cultural and cognitive studies argue that people’s trust in authority does not have to depend on an extensive calculation of the benefits and costs of trusting experts. Most people do not have time, money, and knowledge, to conduct a rigorous risk assessment of the trust situation. Instead, people rely on their emotions, intelligence, and experience to guide their judgment about trusting experts (Hardin, 1991; Uslaner, 2008; Yamagishi, 2001).

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