The Influence of Objective and Perceived Adaptive Capacity on Midwestern Farmers' Use of Cover Crops

MAAZ GARDEZI

Department of Sociology and Rural Studies, South Dakota State University, Brookings, South Dakota

J. GORDON ARBUCKLE

Department of Sociology, Iowa State University, Ames, Iowa

(Manuscript received 20 August 2018, in final form 15 May 2019)

ABSTRACT

Cover crops are grown between periods of regular crop production or planted into crops with the primary purpose of protecting and improving soil health. These crops possess several resilience-enhancing properties that are well suited to help farmers adapt to climate change. Through an ''adaptive capacities framework,'' we examine how farmers' adaptive capacities—contextualized within institutional and environmental conditions—can influence their decision to use cover crops. We use generalized linear mixed models (GLMMs) to examine the relative importance of (i) ''internal'' variables—farmers' perceived capacity to act; (ii) ''external'' or ''objective'' resources—assets and entitlements; and (iii) contextual variables—the institutional and environmental context within which adaptation occurs, as predictors of farmers' use of cover crops. Our results suggest that several objective and perceived adaptive capacities are positively associated with farmers' decisions to use cover crops, and formal institutions such as risk management subsidies are correlated with lower use of cover crops.

1. 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 agriculture in the U.S. Midwest, which contributes substantially to both the national economy and global crop availability (Hatfield et al. 2014). In the U.S. Midwest, increases in frequency and intensity of extreme rain events are identified as one of the most prominent biophysical changes due to climate change (Morton et al. 2015; Walthall et al. 2012). These events can pose serious risks to crop development, crop productivity, and ecological sustainability (Walthall et al. 2012). The U.S. agriculture system need to urgently respond to reduce vulnerabilities and improve resilience to climate change.

Cover crops are grown between periods of regular crop production or planted into crops with the primary purpose of protecting and improving soil health (Schnepf and Cox 2006). Several multifunctional and resilience-enhancing properties of cover crops are particularly well suited to help farmers adapt to extreme rain events (Arbuckle and Roesch-McNally 2015). Improvements in soil health, weed and pest control, and reductions in wind and water erosion are particularly suitable for farming in variable precipitation conditions (Snapp et al. 2005). Cover crops can improve nutrient retention in the field, which can decrease nutrient runoff during months with higher intensity of spring rain events and stop contaminants such as phosphorous and nitrogen from impacting ecosystems as distant as the Gulf of Mexico (Rabalais and Turner 2006; Scavia et al. 2017; Burnett et al. 2018). Some of these ecological benefits can improve farm's economic profitability. Improvements in crop yields, for instance, have been empirically observed within short to medium time periods after planting of cover crops (Delgado et al. 2007).

Although cover crops and their environmental and economic value have been demonstrated, adoption studies show limited use among farmers in the United States (Arbuckle and Roesch-McNally 2015; Burnett et al. 2018). Several social, economic, biophysical, and institutional factors are highlighted as barriers to farmers'

Corresponding author: Maaz Gardezi, maaz.gardezi@sdstate.edu

DOI: 10.1175/WCAS-D-18-0086.1

adoption of cover crops. These include extra costs of time, labor, seed, energy, equipment, and machinery needed for planting and killing cover crops; issues of compliance with crop insurance guidelines; and complex interactions between cover crops and weather and soil conditions (Dagel et al. 2014). How farmers perceive risks and benefits associated with cover crops and how confident they are in managing cover crops are important social and behavioral factors driving cover crops use and ultimately impacting the resilience of agricultural systems (Arbuckle and Roesch-McNally 2015; Burnett et al. 2018; Lee et al. 2018).

Adaptive capacity is a primary social process for modulation of system resilience and can be conceived of as composed of three interrelated parts: 1) a system of resources such as finances, 2) the capacity of people to access important resources, and 3) contextual factors such as institutional and governance systems that influence whether actors can feasibly access and manage resources (Brown and Westaway 2011). Previous research has often framed the likelihood that actors will make necessary changes in response to climate change as a function of objective capacity or material resources, such as access to finances, technology, knowledge, and infrastructure (IPCC 2007; Yohe and Tol 2002; Engle and Lemos 2010). Other scholarship on human behavior has found subjective attributes of adaptive capacity to be influential for moderating actors' response to climate change (Gardezi and Arbuckle 2017; 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)—is consequential not only for influencing actors' climatic risk perception but also their willingness to act to reduce such risks (Gardezi and Arbuckle 2019; Moser et al. 2014). This article examines how perceived and objective adaptive capacities can enable or constrain farmers' ability to adopt cover crops.

Contextual factors such as institutions play a vital role in determining the ability of a social–ecological system to manage risk associated with abrupt climatic and weather-related changes (Engle 2011; Agrawal 2010; Berman et al. 2012; Dovers and Hezri 2010). 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, such as risk management subsidies, can influence Midwest corn farmers' use of cover crops.

This article examines how farmers' perceived and objective adaptive capacities—contextualized within institutional and environmental conditions—can influence their decisions to use cover crops. We evaluate the relative importance of (i) "internal" variables—the perceived capacity; (ii) "external" or "objective" resources—the assets and entitlements; and (iii) the contextual variables—the institutional and environmental context in which adaptation occurs, as predictors of cover crops adoption.

2. Literature review

a. *Objective and perceived adaptive capacity*

Adaptive capacities illustrate important social, economic, and institutional mechanisms for allowing people and communities to respond to the potentially harmful socioclimatic impacts (Adger 2006; Smit et al. 2001; Turner et al. 2003). Objective adaptive capacity such as farm/farmer-level, managerial, technical, and economic resources can be important for farmers to cope or adapt to climate change. For example, 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). Technical knowledge about production practices with resilient-enhancing properties increased Canadian farmers' ability to diminish risks associated with climate change (Swanson et al. 2009).

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 including institutional and structural elements, 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, sociobehavioral factors, such as 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 adaptive capacity, i.e., the individual's perception of the suitability of available resources (financial, technical, institutional, etc.) needed for facilitating adaptation" (Gardezi and Arbuckle 2017, p. 5). In theory of planned behavior (TPB), Ajzen (1991) uses the term "perceived behavioral control" to suggest that an actor assesses his or her ability to perform an action and changes behavior accordingly. Perceived capacity serves as a mediator between intention to change behavior and actual behavior

(Niles et al. 2016) and perceived behavioral control has been found to positively correlate with higher adoption of cover crops among farmers (Arbuckle and Roesch-McNally 2015).

Multisectoral research on adaptive capacity and resilience in the United States (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 four key characteristics of farmers perceived adaptive capacity: 1) *perceived efficacy*, or the confidence that a farmer has in their self and in the resilience of their farm operation to mitigate risks [perceived efficacy is related to the concept of self-efficacy defined by Bandura (1978) as an assessment of one's capacity to accomplish a desired goal]; 2) *learning and knowledge seeking*, or the extent to which farmers can "use their agency for learning and seeking new knowledge (Gardezi and Arbuckle 2017, p. 5)"; 3) *centrality in social networks*, or how farmers view themselves in terms of membership and importance in social groups; and 4) *perceived adaptability*, or the desire to foster resiliency in social–ecological systems through learning and experimentation (Eakin et al. 2016; Marshall and Marshall 2007). These characteristics of perceived adaptive capacity are important drivers of farmers' willingness to implement appropriate protective measures on their farming operations, including taking necessary steps to reduce risks associated with climatic and nonclimatic hazards.

b. *Institutional support and adaptive behavior*

Contextual factors such as institutions and governance can play a vital role in determining the ability of a social–ecological system to withstand abrupt climatic and weather-related changes (Ostrom 2008; Engle 2011; Berman et al. 2012; Dovers and Hezri 2010). The U.S. federal government provides two forms of institutional support to protect farmers from volatility in crop production and profitability due to changes in weather and market prices: 1) farm subsidies such as government payments, including direct payments and countercyclical payments that are paid directly to farmers; and 2) Federal Crop Insurance Program (FCIP) administered by the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA), which includes crop and livestock insurance. Government payments were discontinued after 2012 but were valid when the survey for this study was conducted (2012). 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. 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 324 million acres in 2018 (USDA-RMA 1995, 2019).

In relation to adaptation in agricultural systems, risk management institutions can enable or impede farmers' ability to shift production practices for achieving greater resiliency (Blesh and Wolf 2014). At the time of writing this paper, crop insurance applications did not mandate farmers to include adaptive management plans as a prerequisite for benefit eligibility. Although eligibility for direct payments required farmers to control erosion on highly erodible land (HEL) (Arbuckle 2013), no provisions mandated farmers to implement climate risk management practices. Farm risk management subsidies can cause moral hazard or a "disincentive to reduce the damaging effects [of extreme heat events] (Annan and Schlenker 2015)." This may also be true for Midwest farmers and disincentivize their use of cover crops.

3. Methods

a. *Conceptual framework*

This paper examines several farm and watershed-level factors that are important for explaining farmers' adoption of cover crops. Figure 1 shows a multilevel conceptual model in which watershed-level environmental and institutional contexts and farm/farmer-level capacities influence farmers' use of cover crops. At level 1, field-level environmental conditions, adaptive capacities, and institutional factors (risk management subsidies) 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 cover crops.

Based on the literature reviewed, for this study of Midwestern corn and soybean farmers, this research proposes the following hypotheses:

H1: Perceived adaptive capacities are correlated with higher use of cover crops.
H2: Objective adaptive capacities are correlated with higher use of cover crops.
H3: Risk management subsidies (farm level) are correlated with lower use of cover crops.
H4: Observed extreme precipitation events are positively correlated with use of cover crops.

b. *Study region and data*

This study uses several sources of data. Primary data are from a random sample survey of upper Midwest corn

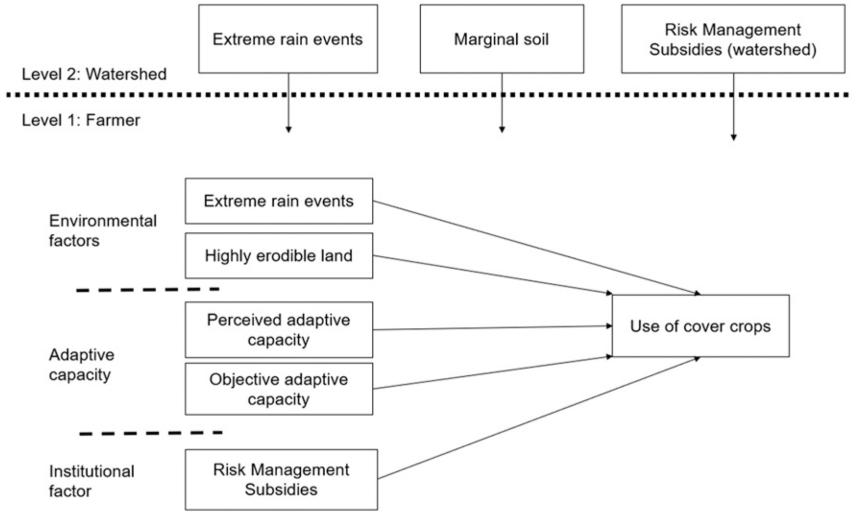

FIG. 1. Conceptual framework.

farmers that was stratified by 22 Hydrologic Unit Code 6 (HUC6) watersheds. These watersheds represent over half of all corn and soybean produced in the United States (Fig. 2). The survey was administered in February 2012 using a three-wave mailing process: 1) The survey was mailed to a sample frame of 18 813 corn farmers [the list was provided by the USDA National Agriculture Statistics Service (NASS)], followed by 2) a reminder postcard and 3) a final survey sent to nonresponders (Dillman 2011). The sample fame includes large-scale corn producers, defined as farmers that operate on a farm size larger than 80 acres and generated farm sales value that exceed \$100,000 yr^{-1}. A total of 4778 farmers responded to the mail survey, with an effective response rate of 26% using the American Association for Public Opinion Research (AAPOR) calculator.

Some survey questions had more than one missing response (Table 1). No survey variable had more than 10.83% of its values missing. We used the Little's test to examine if the survey data were missing completely at random (MCAR). We failed to reject the null hypothesis for the Little's test and concluded that the missing data were not MCAR. Thus, imputing missing values could produce more reliable and less biased estimates than removing them from the dataset through a list-wise deletion process. Multivariate imputations by chained equations (MICE) (van Buuren and Groothuis-Oudshoorn 2011) was implemented because neither of

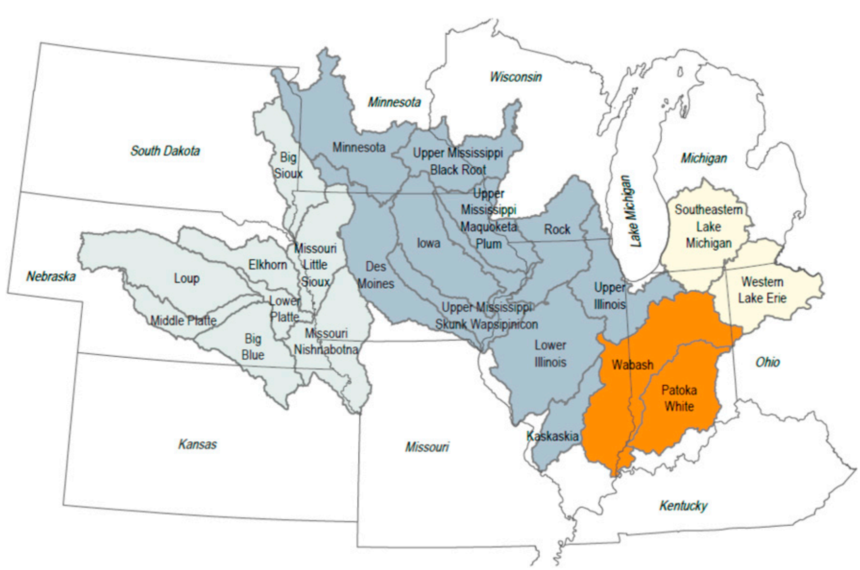

FIG. 2. Map of 22 HUC6 watersheds (study region).

TABLE 1. Percentage of missing values prior to imputation.

Components and statements	Percentage missing
Availability and accessibility of weather and climate-related decision-support tools (count)	10.38
In 2011, approximately what percentage of the land (owned and/or rented) you farmed was highly erodible land (HEL) that was planted to crops	7.76
Changing my practices to cope with increasing climate variability is important for the long-term success of my farm	6.50
It is important for farmers to adapt to climate change to ensure the long-term success of U.S. agriculture	6.34
I should take additional steps to protect the land I farm from increased weather variability	6.06
I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation	5.90
Farmers should take additional steps to protect farmland from increased weather variability	5.84
I consider myself to be a role model for other farmers	5.06
Extension staff, crop advisers, and others involved in agriculture tend to look to me for advice	4.92
Other farmers tend to look to me for advice	4.75
I am confident in my ability to apply weather forecasts and information in my crop-related decisions	4.67
I am willing to use seasonal climate forecasts to help me make decisions about agricultural practices	4.35
Education	1.42
Opportunities to sell crops in multiple markets (count)	0.38
Considering the farmland that you own and rent, are the following practices and strategies currently used: Cover crops?	0.00
Farm sales ($)	0.00
Number of markets corn produced for	0.00
Daily precipitation	0.00
Marginal soil	0.00
Farm subsidies (crop insurance)	0.00

the variables used in the study had more than 10% of values missing and list-wide deletion would not be suitable given that the data were not missing completely at random.

Our study proposes two levels of analysis so that farmers (level 1) are nested in watersheds (level 2). The 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) are related to farmers' use of cover crops. Biophysical conditions associated with water can be homogenous within each HUC6 watersheds; and, as an extension of reason 3, 4) there are substantial seasonal differences in precipitation across these watersheds.

TABLE 2. Summary statistics for response variable.

Scale and survey item	Mean	Std dev	No (%)	Yes (%)
Currently using the following practices on rented or owned land				
Cover crops (0 = no, 1 = yes)	0.21	0.43	77.96	21.78

c. *Variables included in the model*

1) OUTCOME VARIABLE

The outcome variable *Cover Crops* represents whether or not a farmer currently used cover crops on their owned or rented land. Table 2 shows the statistical description of the outcome variable. In our sample, 22% of farmers reported using cover crops on at least some of their owned or rented land. This percentage is higher than the national average. This may be because the sample consists of larger-scale annual row crop farmers. Cover crops are most suitable for and more heavily promoted among this population (Hamilton et al. 2017). It is important to recognize that this figure is the percentage of farmers, not the percentage of land, because farmers tend to use cover crops on only a portion of their cropland, the percentage of farmers using cover crops is consistently higher than the percentage of land in cover crops (National Agricultural Statistics Service 2014).

2) PREDICTOR VARIABLES

Level 1 variables: PAC consist of four 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 *Perceived Adaptability, Perceived Centrality in Social Network, Interested in Seeking Knowledge*, and *Perceived Efficacy* (see Table 3 for factor scores, eigenvalues, and reliability scores for each construct). Four survey items measured *Perceived Adaptability* (Table 4).

TABLE 3. Summary of perceived adaptive capacity types, factor loadings, and communalities (h^2), and reliability test (Cronbach alpha α) from exploratory factor analysis.

Item	Factor loading	h^2	α
Perceived adaptability			0.82
Farmers should take additional steps to protect farmland from increased weather variability	0.81	0.66	
I should take additional steps to protect the land I farm from increased weather variability	0.82	0.67	
It is important for farmers to adapt to climate change to ensure the long-term success of U.S. agriculture	0.62	0.38	
Changing my practices to cope with increasing climate variability is important for the long-term success of my farm	0.63	0.40	
Perceived centrality in social network			0.81
Other farmers look to me for advice	0.83	0.69	
I consider myself to be a role model for other farmers	0.80	0.64	
Extension staff, crop advisers, and other involved in agriculture tend to look to me for advice	0.68	0.46	
Interested in seeking knowledge			0.54
It is important for me to visit other farms to look at their practices	0.62	0.39	
I am willing to use seasonal climate forecasts to help me make decisions about agricultural practices	0.34	0.11	
It is important for me to visit other farms to look at their practices and strategies	0.66	0.44	
Perceived efficacy			0.63
I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation	0.90	0.80	
I have the financial capacity to deal with any weather-related threats to the viability of my farm operation	0.65	0.43	
I am confident in my ability to apply weather forecasts and information in my crop-related decisions	0.30	0.09	

These variables measured farmers' resolve to learn and experiment with new farming practices that might affect the overall resilience of their farm. Three survey items measured farmers' views about their social identify in social groups. These items were grouped together to create a construct titled *Perceived Centrality in Social Network* (Table 4). 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 new farming techniques 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.

The livelihood vulnerability index (Hahn et al. 2009) approach was used to normalize all four subcategories of perceived adaptive capacity on a numeric scale between zero and one. We expected that farmers with higher scores (closer to one) on perceived adaptive capacity items would be more likely to use cover crops. Table 4 shows the mean, standard deviation, and range of the four main categories of perceived adaptive capacity (factor scores are normalized). It also presents the frequencies and percentages of the subcategories that make up perceived adaptive capacity variables.

Four variables were included to measure farmers' objective adaptive capacity (OAC) (Table 5). 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 were 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—available for farmers to sell corn.

TABLE 4. Scale and survey items.

Survey item	Mean	Std dev	Range	Strongly disagree (%)	Disagree (%)	Uncertain (%)	Agree (%)	Strongly Agree (%)
Perceived adaptability	0.63	0.16	0–1					
Farmers should take additional steps to protect farmland from increased weather variability	3.60	0.74	0–4	1.86	5.75	26.95	61.17	4.24
I should take additional steps to protect the land I farm from increased weather variability	3.47	0.79	0–4	1.92	10.19	29.95	54.54	3.39
It is important for farmers to adapt to climate change to ensure the long-term success of U.S. agriculture	3.55	0.87	0–4	4.12	6.25	26.45	56.19	6.96
Changing my practices to cope with increasing climate variability is important for the long-term success of my farm	3.42	0.85	0–4	3.68	8.66	34.82	48.05	4.77
Perceived centrality in social network	0.45	0.17	0–1					
Other farmers look to me for advice	2.92	0.79	0–4	3.10	25.70	48.34	21.78	1.06
I consider myself to be a role model for other farmers	2.95	0.81	0–4	3.37	24.09	48.16	22.92	1.46
Extension staff, crop advisers, and other involved in agriculture tend to look to me for advice	2.47	0.74	0–4	6.67	47.46	38.44	6.95	0.46
Interested in seeking knowledge	0.59	0.16	0–1					
It is important for me to talk to other farmers about new farming practices and strategies	3.59	0.79	0–4	1.61	10.98	18.18	65.24	3.97
I am willing to use seasonal climate forecasts to help me make decisions about agricultural practices	3.14	0.82	0–4	3.62	16.24	44.01	35.08	1.05
It is important for me to visit other farms to look at their practices and strategies	3.31	0.88	0–4	2.51	18.77	25.93	50.59	2.19
Perceived efficacy	0.59	0.19	0–1					
I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation	3.36	0.86	0–4	3.78	9.14	39.10	42.80	5.17
I have the financial capacity to deal with any weather-related threats to the viability of my farm operation	3.25	0.93	0–4	5.23	13.29	36.98	39.55	4.93
I am confident in my ability to apply weather forecasts and information in my crop-related decisions	3.58	0.70	0–4	1.21	6.36	28.17	61.74	2.51

For the upper Midwest U.S. farmers, market diversification has been positively correlated with greater use of adaptive management practices, including cover crops (Morton et al. 2015).

Two variables were included in the model to examine the relationship between environmental factors and farmers' use of cover crops. Daily precipitation is measured by examining the extreme daily rainfall values (99th percentile) for the time period of 1971–2011. The data for this period were obtained from the National Weather Service (NWS) Cooperative Observer (COOP) archive and was assigned to each farm according to its nearest weather station (Loy et al. 2013). Another variable used in this study to measure the environmental factors was the percentage of farmers' land planted to crops in 2011 was 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

TABLE 5. Summary statistics for numeric predictors.

Variables	Mean	Std dev	Min	Max
Objective capacity				
Farm sales ($)	457,000	653,461	100,000	20,060,000
Weather tools[a]	2.69	1.95	0	8
Farm enterprises[b]	3.90	1.60	1	9
Market diversity[c]	1.98	0.81	1	6
Environmental factors				
Daily precipitation (farm)	0.39	0.14	0	1
HEL (farm)	24.27	32.96	0	100
Marginal land (watershed)	0.17	0.16	0	0.97
Institutional capacity				
Risk management subsidies (farm, $)	13,188	16,154	0	226,000
Risk management subsidies (watershed, $)	1,284,000,000	432,270,000	225,400,000	2,274,000,000

[a] Tools include crop disease forecast, insect forecast, evapotranspiration index, growing degree-day tools, forage dry-down index, drought monitor/outlook, and satellite data/indices of water or soil nitrogen status.
[b] Enterprises include hogs, cows, other cattle, corn, soybeans, oats, hay (including alfalfa), sorghum, and barley.
[c] Markets include commodity (sweetener, export, feed), ethanol, livestock silage, speciality or organic, seed, and other.

(Arbuckle 2013). Table 5 provides a statistical description of abovementioned environmental factors.

Farm direct payments, countercyclical payments, and crop and livestock insurance (*Risk Management Subsidies*) were 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. 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 were 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: risk management subsidies (*Risk Management Subsidies–watershed*). The data for the variable, *Marginal Land*, are constructed using the Soil Survey Geographic (SSURGO) database. This database provides the percent of marginal land for each administrative county in the United States. The intensity of marginal land was characterized according to the USDA Natural Resources Conservation Service (NRCS) land capability classification system (Loy et al. 2013).

The data for *Risk Management Subsidies–watershed* were obtained from 2012 census of agriculture's data browser. Government payments category in the agriculture census consist of all federal farm programs that make payments directly to the farm operators. Thus, it provides a holistic view of institutional support available at the watershed level. Government payments are made up of farm subsidy programs such as direct payments, loan deficiency payments, and 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 (*Risk Management Subsidies*). 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.

d. Regression analysis

Farm characteristics and farmers' responses to survey questions are nested within shared hydrological conditions prevailing at the watershed level. Thus, we used a generalized linear mixed model (GLMM) to simultaneously analyze two levels of data: farm and farmer-level data (level 1) and biophysical conditions for each watershed (level 2). 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 includes 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 $\{\text{logit}(x) = \ln[x/(1-x)]\}$ 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:

$$\text{logit}(P_{ij}) = \beta_{0j} + B_1 X_{ij}. \tag{1}$$

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:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j}, \tag{2}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}. \tag{3}$$

We could substitute Eqs. (2) and (3) into Eq. (1), and rewrite it as a single equation:

$$\text{logit}(P_{ij}) = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{01} Z_j + u_{0j} + u_{1j} + \gamma_{10} X_{ij}. \tag{4}$$

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 Eq. (4) by using a Gauss–Hermite quadrature (GHQ) approximation approach (Bolker et al. 2009).

Prior to fitting the GLMMs, 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, that is, 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. The distributions seem normal and symmetric, except for *Farm Sales* and *Risk Management Subsidies*, which had skewed distributions. These variables were transformed (logarithmic).

The intraclass correlation coefficient (ICC) or ρ 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

$$\rho = \frac{\tau_{11}}{\tau_{11} + \sigma^2}, \tag{5}$$

where τ_{11} is the amount of variance attributed to watershed differences or variance between groups. The σ^2 is attributed to the farmer-level variation. It explains the within-watershed variation. The computed value of ρ is 0.24, so 24% 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.

4. Results

Table 6 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 (ORs) with standard errors (SEs) in the parentheses. The random effects are presented as variance between watersheds τ_{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, Akaike information criterion (AIC), and deviance information criterion (DIC)

TABLE 6. Multilevel logistic regression of farmers' use of cover crops. Values indicate odds ratios, with standard errors in parentheses unless otherwise indicated. "RI" is random intercept. Asterisks indicate p values: **, $p < 0.05$; ***, $p < 0.01$.

	Model 1 (RIs only)	Model 2 (RIs with level 1 and 2 predictors)	Model 3 (RIs with interaction terms)
Level 1: Farmers			
Constant	0.25*** (1.13)	0.23*** (1.13)	0.23*** (1.07)
Environmental factors			
Daily precipitation		0.98 (1.04)	0.98 (1.05)
HEL		1.06 (1.04)	1.06 (1.04)
Objective capacity			
Farm sales (log)		1.17*** (1.04)	1.18*** (1.05)
Weather tools		1.14*** (1.04)	1.14*** (1.04)
Market diversity		1.08** (1.04)	1.08** (1.04)
Farm enterprises		1.72*** (1.04)	1.73*** (1.04)
Perceived capacity			
Perceived adaptability		0.99 (1.04)	0.99 (1.04)
Social network		1.13*** (1.04)	1.12*** (1.04)
Seeking knowledge		1.08 (1.05)	1.08 (1.05)
Perceived efficacy		0.99 (1.04)	0.99 (1.04)
Institutional factor			
Risk management subsidies		0.87*** (1.12)	0.87*** (1.12)
Level 2: Watershed			
Reintroducing means			
Farm sales (log)		1.14 (1.12)	1.14 (1.12)
Weather tools		0.78** (1.16)	0.78** (1.16)
Market diversity		0.89 (1.12)	0.90 (1.12)
Farm enterprises		1.44** (1.17)	1.43** (1.36)
Environmental factors			
Daily precipitation (watershed mean)		1.13 (1.11)	1.13 (1.11)
Marginal land		0.95 (1.15)	0.96 (1.15)
Institutional factors			
Risk management subsidies[a]		0.91 (1.09)	0.91 (1.09)
Interactions			
HEL (farmer) × risk management subsidies (farmer)			0.93 (1.04)
Perceived adaptability (farmer) × risk management subsidies (farmer)			1.01 (1.04)
Daily precipitation (farmer) × perceived efficacy (farmer)			0.98 (1.03)
Daily precipitation (farmer) × marginal land (watershed)			1.02 (1.05)
Fit Statistics			
Observations	4773	4773	4773
Log likelihood	−2399.70	−2226.8	−2224.00
AIC	4803.40	4495.70	4497.90
DIC	4726.00	4364.70	4359.10
χ^2 (degrees of freedom)	—	356.84*** (19)	5.78 (4)
Pseudo-R^2 (Tjur's D)	0.05	0.13	0.13
ICC	0.24	0.08	0.09
σ^2	1.00	1.00	1.00
τ_{11}	0.32	0.09	0.09

[a] Excluding conservation reserve program and wetlands reserve program.

among all three models. To confirm our results, we used a likelihood ratio test (chi-squared 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 squared 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^2 values such as Nakelkerke's R^2 or Cox–Snell R^2 when the model is a generalized linear mixed model (Tjur 2009). The values of Tjur's D for models 1 and 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 6). 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% (OR = 1.13, SE = 1.04, p = 0.00). We did not find statistically significant relationships for other three perceived capacity predictors: *Perceived Adaptability*, *Seeking Knowledge*, and *Perceived Efficacy*.

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 (OR = 1.17, SE = 1.04, p = 0.00). The direction of relationship with farmers' use of cover crops is very similar for other predictors of objective capacity, such as *Weather Tools* (14%) (OR = 1.14, SE = 1.04, p = 0.01) and *Market Diversity* (8%) (OR = 1.08, SE = 1.04, p = 0.04). Notably, the single largest predictor of farmers' use of cover crops is the number of farm enterprises (*Farm Enterprises*), that is, 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 (OR = 1.72, SE = 1.04, p = 0.00).

For the institutional factors, we found a significant relationship between farm-level risk management subsidies and farmers' use of cover crops. An increase of one standard deviation in *Risk Management Subsidies* is associated with 13% reduction in the odds of farmers' using cover crops (OR = 0.87, SE = 1.12, p = 0.00). We examined this relationship in detail by illustrating the predicted probabilities of using cover crops at different levels of farm-level risk management subsidies. Figure 3 shows that the predicted probabilities of using cover crops range from 15% to 35% for this sample of farmers.

We were interested in examining how institutional factors, such as risk management subsidies at the watershed level, might influence farmer' use of cover crops. Although the sum of risk management subsidies at each watershed did not significantly predict farmers' use of cover crops, Fig. 4 shows 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.

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 (OR = 0.98, SE = 1.04, p = 0.75).

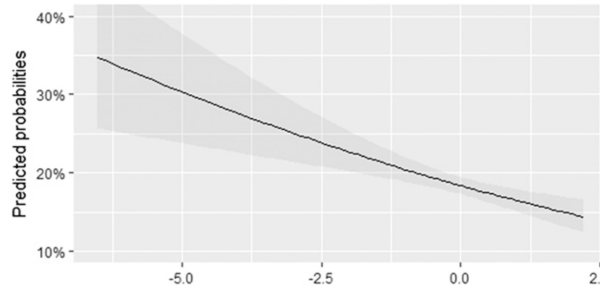

FIG. 3. Predicted probabilities of using cover crops at varying levels of risk management subsidies received by farmer. The horizontal axis shows the standardized U.S. dollar amount of risk management subsidies received by farmers in the study sample. Zero denotes the mean amount for the sample of farmers. Values above and below the mean are represented as standard deviations.

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 (Fig. 5). The plot 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.

5. 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 farmers' centrality in social network—a measure of their relative positioning with the social structure—is correlated with higher cover crop adoption. 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 conservation practices that have found that social networks are positively correlated with farmers' proenvironmental behavior (Floress et al. 2011) and response to adaptive management of natural resources (Bodin et al. 2006).

In terms of institutional factors influencing farmers' use of cover crops, we found that formal institutions

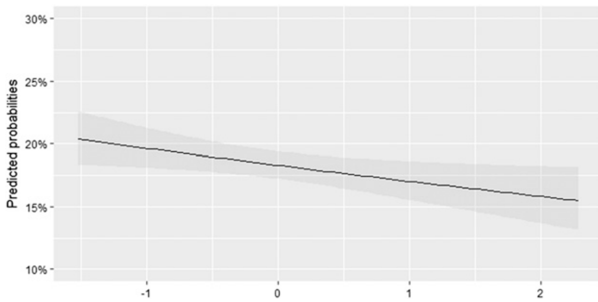

FIG. 4. Predicted probabilities of using cover crops at varying levels of government payments (watershed level). The horizontal axis shows the standardized U.S. dollar amount of risk management subsidies received by farmers in the study sample aggregated for the watershed. Zero denotes the mean amount for the sample of farmers. Values above and below the mean are represented as standard deviations.

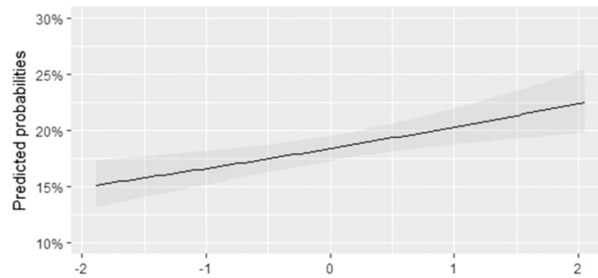

FIG. 5. Predicted probabilities of using cover crops at varying levels of daily extreme precipitation events (watershed mean). The horizontal axis shows the standardized daily extreme precipitation levels for all farmers in their respective HUC6 watersheds. Zero denotes the mean extreme precipitation amount (watershed) for the sample of farmers. Values above and below the mean are represented as standard deviations.

such as risk management subsidies are correlated with lower use of cover crops. We found that the effect of receiving risk management subsidies on farmers' land-use decisions are comparable to them obtaining crop insurance indemnities. Both are sources of additional revenue. Our results are consistent with findings from other studies (Annan and Schlenker 2015; Babcock 2013; Di Falco et al. 2014) that found 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. Overall, we found that risk management subsidies, including direct payments, countercyclical payments, and crop and livestock insurance, are negatively related to farmers' use of cover crops.

We also examined how objective dimensions of adaptive capacity are associated with farmers' adoption of cover crops. We found that more crop and livestock diversification was positively correlated with farmers' use of cover crops, which supports findings from earlier research that found a positive relationship between crop and livestock diversification and adoption of conservation practices (Knutson et al. 2011; Singer et al. 2007). We also found that material resources are correlated with less 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.

6. Conclusions

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 that can predict farmers' proenvironmental 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 results to instigate policy discussion on increasing cover crops use in the upper Midwest. For example, our study shows that farm subsidies may impede farmers' use of cover crops. Therefore, it is important to consider how government payments and crop insurance might be designed to encourage farmers to implement practices that are beneficial for soil health and water quality. How can rules be made for crop insurance or other government payments that incentivize farmers to use soil and water conservation practices? In our view, farm subsidies provide an excellent opportunity to connect financial incentives with proenvironmental behavior, yet our research indicates that farm subsidies may serve as barriers to conservation. One example is that the U.S. Department of Agriculture (USDA) guidelines for crop insurance eligibility requires farmers to manage cover crops through extensive "termination guidelines." This 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). This farmer's recommendation is echoed in the policy positions of major environmental groups such as the Environmental Working Group and the Union of Concerned Scientists (Union of Concerned Scientists 2017). Farm subsidies programs could be made more beneficial for soil and water conservation if payments to farmers were linked to their use of conservation practices. 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? Given that some watersheds have received more attention and resources in recent years, such as Saginaw Bay (Eanes et al. 2019) and western Lake Erie (Burnett et al. 2018), are these outreach and engagement efforts in such watersheds contributing more toward farmers' use of cover crops? Empirical examination of these questions can evaluate the importance of mesolevel engagement efforts and structural policies for encouraging farmers to use more cover crops.

Acknowledgments. This research is part of a collaborative project supported by the USDA–NIFA, Award 2011-68002-30190, "Cropping Systems Coordinated Agricultural Project: Climate Change, Mitigation, and Adaptation in Corn-based Cropping Systems" (project website: sustainablecorn.org). We thank the anonymous reviewers whose comments and suggestions helped improve and clarify this manuscript.

REFERENCES

Adger, N., 2006: Vulnerability. *Global Environ. Change*, **16**, 268–281, https://doi.org/10.1016/j.gloenvcha.2006.02.006.

Agrawal, A., 2010: Local institutions and adaptation to climate change. *Social Dimensions of Climate Change: Equity and Vulnerability in a Warming World*, R. Mearns and A. Norton, Eds., World Bank, 175–197.

Ajzen, I., 1991: The theory of planned behavior. *Organ. Behav. Hum. Decis. Processes*, **50**, 179–211, https://doi.org/10.1016/0749-5978(91)90020-T.

Annan, F., and W. Schlenker, 2015: Federal crop insurance and the disincentive to adapt to extreme heat. *Amer. Econ. Rev.*, **105**, 262–266, https://doi.org/10.1257/aer.p20151031.

Arbuckle, J. G., 2013: Farmer support for extending conservation compliance beyond soil erosion: Evidence from Iowa. *J. Soil Water Conserv.*, **68**, 99–109, https://doi.org/10.2489/jswc.68.2.99.

——, and G. Roesch-McNally, 2015: Cover crop adoption in Iowa: The role of perceived practice characteristics. *J. Soil Water Conserv.*, **70**, 418–429, https://doi.org/10.2489/jswc.70.6.418.

Babcock, B. A., 2013: Taxpayers, crop insurance, and the drought of 2012. Environmental Working Group, 19 pp., https://static.ewg.org/pdf/2013babcock_cropInsurance_drought.pdf.

Bandura, A., 1978: Self-efficacy: Toward a unifying theory of behavioral change. *Adv. Behav. Res. Ther.*, **1**, 139–161, https://doi.org/10.1016/0146-6402(78)90002-4

Berman, R., C. Quinn, and J. Paavola, 2012: The role of institutions in the transformation of coping capacity to sustainable adaptive capacity. *Environ. Dev.*, **2**, 86–100, https://doi.org/10.1016/j.envdev.2012.03.017.

Blesh, J., and S. A. Wolf, 2014: Transitions to agroecological farming systems in the Mississippi River Basin: Toward an integrated socioecological analysis. *Agric. Hum. Values*, **31**, 621–635, https://doi.org/10.1007/s10460-014-9517-3.

Bodin, Ö., B. I. Crona, and H. Ernstson, 2006: Social networks in natural resource management: What is there to learn from a structural perspective? *Ecol. Soc.*, **11**, r2, http://www.ecologyandsociety.org/vol11/iss2/resp2/.

Bolker, B. M., M. E. Brooks, C. J. Clark, S. W. Geange, J. R. Poulsen, M. H. H. Stevens, and J.-S. S. White, 2009: Generalized linear mixed models: A practical guide for ecology and evolution. *Trends Ecol. Evol.*, **24**, 127–135, https://doi.org/10.1016/j.tree.2008.10.008.

Brown, K., and E. Westaway, 2011: Agency, capacity, and resilience to environmental change: Lessons from human development, well-being, and disasters. *Annu. Rev. Environ. Resour.*, **36**, 321–342, https://doi.org/10.1146/annurev-environ-052610-092905.

Burnett, E., R. S. Wilson, A. Heeren, and J. Martin, 2018: Farmer adoption of cover crops in the western Lake Erie basin. *J. Soil Water Conserv.*, **73**, 143–155, https://doi.org/10.2489/jswc.73.2.143.

Burnham, M., and Z. Ma, 2017: Climate change adaptation: factors influencing Chinese smallholder farmers' perceived self-efficacy and adaptation intent. *Reg. Environ. Change*, **17**, 171–186, https://doi.org/10.1007/s10113-016-0975-6.

Claassen, R., 2012: The future of environmental compliance incentives in U.S. Agriculture: The role of commodity, conservation, and crop insurance programs. Economic Information Bull. 94, 18 pp., https://www.ers.usda.gov/webdocs/publications/44666/16471_eib94_2_.pdf?v=0.

Dagel, K. J., S. L. Osborne, and T. E. Schumacher, 2014: Improving soybean performance in the northern Great Plains through the use of cover crops. *Commun. Soil Sci. Plant Anal.*, **45**, 1369–1384, https://doi.org/10.1080/00103624.2014.884108.

Delgado, J. A., M. A. Dillon, R. T. Sparks, and S. Y. C. Essah, 2007: A decade of advances in cover crops. *J. Soil Water Conserv.*, **62**, 110–117.

Di Falco, S., F. Adinolfi, M. Bozzola, and F. Capitanio, 2014: Crop insurance as a strategy for adapting to climate change. *J. Agric. Econ.*, **65**, 485–504, https://doi.org/10.1111/1477-9552.12053.

Dillman, D. A., 2011: *Mail and Internet Surveys: The Tailored Design Method—2007 Update with New Internet, Visual, and Mixed-Mode Guide*. John Wiley & Sons, 523 pp.

Dovers, S. R., and A. A. Hezri, 2010: Institutions and policy processes: The means to the ends of adaptation. *Wiley Interdiscip. Rev.: Climate Change*, **1**, 212–231, https://doi.org/10.1002/wcc.29.

Eakin, H., and Coauthors, 2016: Cognitive and institutional influences on farmers' adaptive capacity: Insights into barriers and opportunities for transformative change in central Arizona. *Reg. Environ. Change*, **16**, 801–814, https://doi.org/10.1007/s10113-015-0789-y.

Eanes, F. R., and Coauthors, 2019: Crop advisers as conservation intermediaries: Perceptions and policy implications for relying on nontraditional partners to increase U.S. farmers' adoption of soil and water conservation practices. *Land Use Policy*, **81**, 360–370, https://doi.org/10.1016/j.landusepol.2018.10.054.

Engle, N. L., 2011: Adaptive capacity and its assessment. *Global Environ. Change*, **21**, 647–656, https://doi.org/10.1016/j.gloenvcha.2011.01.019.

——, and M. C. Lemos, 2010: Unpacking governance: Building adaptive capacity to climate change of river basins in Brazil. *Global Environ. Change*, **20**, 4–13, https://doi.org/10.1016/j.gloenvcha.2009.07.001.

Field, A., 2013: *Discovering Statistics: Using IBM SPSS Statistics*. Sage, 496 pp.

Floress, K., L. S. Prokopy, and S. B. Allred, 2011: It's who you know: Social capital, social networks, and watershed groups. *Soc. Nat. Resour.*, **24**, 871–886, https://doi.org/10.1080/08941920903493926.

Gardezi, M., and J. G. Arbuckle, 2017: Spatially representing vulnerability to extreme rain events using midwestern farmers' objective and perceived attributes of adaptive capacity. *Risk Anal.*, **39**, 17–34, https://doi.org/10.1111/risa.12943.

——, and ——, 2019: Techno-optimism and farmers' attitudes toward climate change adaptation. *Environ. Behav.*, https://doi.org/10.1177/0013916518793482, in press.

Grothmann, T., and A. Patt, 2005: Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Global Environ. Change*, **15**, 199–213, https://doi.org/10.1016/j.gloenvcha.2005.01.002.

Hahn, M. B., A. M. Riederer, and S. O. Foster, 2009: The livelihood vulnerability index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Global Environ. Change*, **19**, 74–88, https://doi.org/10.1016/j.gloenvcha.2008.11.002.

Hamilton, A. V., D. A. Mortensen, and M. K. Allen, 2017: The state of the cover crop nation and how to set realistic future goals for the popular conservation practice. *J. Soil Water Conserv.*, **72**, 111A–115A, https://doi.org/10.2489/jswc.72.5.111A.

Hatfield, J., G. Takle, R. Grotjahn, P. Holden, R. C. Izaurralde, T. Mader, E. Marshall, and D. Liverman, 2014: Agriculture. *Climate Change Impacts in the United States: The Third National Climate Assessment*, U.S. Global Change Research Program, 150–174.

IPCC, 2007: Summary for policymakers. *Climate Change 2007: Impacts, Adaptation and Vulnerability*, S. Solomon et al., Eds., Cambridge University Press, 7–22.

Knutson, C. L., T. Haigh, M. J. Hayes, M. Widhalm, J. Nothwehr, M. Kleinschmidt, and L. Graf, 2011: Farmer perceptions of sustainable agriculture practices and drought risk reduction in Nebraska, USA. *Renewable Agric. Food Syst.*, **26**, 255–266, https://doi.org/10.1017/S174217051100010X.

Lee, D., J. G. Arbuckle, Z. Zhu, and L. Nowatzke, 2018: Conditional causal mediation analysis of factors associated with cover crop adoption in Iowa, USA. *Water Resour. Res.*, **54**, 9566–9584, https://doi.org/10.1029/2017WR022385.

Lemos, M. C., Y. J. Lo, C. Kirchhoff, and T. Haigh, 2014: Crop advisors as climate information brokers: Building the capacity of us farmers to adapt to climate change. *Climate Risk Manage.*, **4**, 32–42, https://doi.org/10.1016/j.crm.2014.08.001.

Loy, A., and Coauthors, 2013: Farmer perspectives on agriculture and weather variability in the Corn Belt: A statistical atlas. USDA, 115 pp.

MacDonald, J. M., P. Korb, and R. A. Hoppe, 2013: Farm size and the organization of U.S. crop farming. USDA Economic Research Rep. 152, 61 pp., https://www.ers.usda.gov/webdocs/publications/45108/39359_err152.pdf.

Marshall, N. A., and P. A. Marshall, 2007: Conceptualizing and operationalizing social resilience within commercial fisheries in northern Australia. *Ecol. Soc.*, **12**, http://www.ecologyandsociety.org/vol12/iss1/art1/.

Morton, L. W., J. Hobbs, J. G. Arbuckle, and A. Loy, 2015: Upper Midwest climate variations: Farmer responses to excess water risks. *J. Environ. Qual.*, **44**, 810–822, https://doi.org/10.2134/jeq2014.08.0352.

Moser, C., M. Stauffacher, Y. B. Blumer, and R. W. Scholz, 2014: From risk to vulnerability: The role of perceived adaptive capacity for the acceptance of contested infrastructure. *J. Risk Res.*, **18**, 622–636, https://doi.org/10.1080/13669877.2014.910687.

Moser, S. C., R. E. Kasperson, G. Yohe, and J. Agyeman, 2008: Adaptation to climate change in the northeast United States: Opportunities, processes, constraints. *Mitig. Adapt. Strategies Global Change*, **13**, 643–659, https://doi.org/10.1007/s11027-007-9132-3.

National Agricultural Statistics Service, 2014: 2012 census of agriculture. USDA, https://www.nass.usda.gov/Publications/AgCensus/2012/#full_report.

Niles, M. T., M. Brown, and R. Dynes, 2016: Farmer's intended and actual adoption of climate change mitigation and adaptation strategies. *Climatic Change*, **135**, 277–295, https://doi.org/10.1007/s10584-015-1558-0.

Ostrom, E., 2008: Institutions and the environment. *Econ. Aff.*, **28**, 24–31, https://doi.org/10.1111/j.1468-0270.2008.00840.x.

Peterson, M., 2016: Let's improve soil and water quality with crop insurance. *Des Moines Register*, December, https://www.desmoinesregister.com/story/opinion/columnists/iowa-view/2016/12/19/lets-improve-soil-and-water-quality-crop-insurance/95597654/.

Prokopy, L. S., K. Floress, D. Klotthor-Weinkauf, and a. Baumgart-Getz, 2008: Determinants of agricultural best management practice adoption: Evidence from the literature. *J. Soil Water Conserv.*, **63**, 300–311, https://doi.org/10.2489/jswc.63.5.300.

Rabalais, N. N., and R. E. Turner, 2006: Oxygen depletion in the Gulf of Mexico adjacent to the Mississippi River. *Past and Present Water Column Anoxia*, L. Neretin, Ed., Vol. 64, Nato Science Series IV: Earth and Environmental Sciences, Springer, 225–245.

Scavia, D., and Coauthors, 2017: Multiple models guide strategies for agricultural nutrient reductions. *Front. Ecol. Environ.*, **15**, 126–132, https://doi.org/10.1002/fee.1472.

Schnepf, M., and C. Cox, Eds., 2006: *Environmental Benefits of Conservation on Cropland: The Status of Our Knowledge*. Soil and Water Conservation Society, 326 pp.

Seara, T., P. M. Clay, and L. L. Colburn, 2016: Perceived adaptive capacity and natural disasters: A fisheries case study.

Global Environ. Change, **38**, 49–57, https://doi.org/10.1016/j.gloenvcha.2016.01.006.

Singer, J. W., S. M. Nusser, and C. J. Alf, 2007: Are cover crops being used in the US corn belt? *J. Soil Water Conserv.*, **62**, 353–358.

Smit, B., and Coauthors, 2001: Adaptation to climate change in the context of sustainable development and equity. *Climate Change 2001: Impacts, Adaptation and Vulnerability*, J. J. McCarthy et al., Eds., Cambridge University Press, 879–906.

Snapp, S. S., S. M. Swinton, R. Labarta, D. Mutch, J. R. Black, R. Leep, J. Nyiraneza, and K. O'Neil, 2005: Evaluating cover crops for benefits, costs and performance within cropping system niches. *Agron. J.*, **97**, 322–332, https://doi.org/10.2134/agronj2005.0322.

Snijders, T. A. B., and R. J. Bosker, 1999: *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. Sage, 266 pp.

Swanson, D. A., J. C. Hiley, H. D. Venema, and R. Grosshans, 2009: Indicators of adaptive capacity to climate change for agriculture in the prairie region of Canada: Comparison with field observations. Working Paper for the Prairie Climate Resilience Project, 31 pp., https://www.iisd.org/sites/default/files/publications/pcr_adaptive_cap_ag.pdf.

Tjur, T., 2009: Coefficients of determination in logistic regression models—A new proposal: The coefficient of discrimination. *Amer. Stat.*, **63**, 366–372, https://doi.org/10.1198/tast.2009.08210.

Turner, B. L., and Coauthors, 2003: A framework for vulnerability analysis in sustainability science. *Proc. Natl. Acad. Sci. USA*, **100**, 8074–8079, https://doi.org/10.1073/pnas.1231335100.

Union of Concerned Scientists, 2017: Rotating crops, turning profits: How diversified farming systems can help farmers while protecting soil and preventing pollution. UCSUSA, 16 pp., https://www.ucsusa.org/sites/default/files/attach/2017/05/rotating-crops-report-ucs-2017.pdf.

USDA-RMA, 1995. Summary of Business Report for 1989 through 1995. U.S. Department of Agriculture, Risk Management Agency, 1 p., https://www3.rma.usda.gov/apps/sob/current_week/sobrpt1989-1995.pdf.

——, 2019. Summary of Business Report for 2016 through 2019. Department of Agriculture, Risk Management Agency, 2 pp., https://www3.rma.usda.gov/apps/sob/current_week/sobrpt2016-2019.pdf.

van Buuren, S., and K. Groothuis-Oudshoorn, 2011: mice: Multivariate imputation by chained equations in R. *J. Stat. Software*, **45**, 1–67, https://doi.org/10.18637/jss.v045.i03.

Walthall, C. L., and Coauthors, 2012: Climate change and agriculture: Effects and adaptation. Climate Change Program Office Tech. Bull. 1935, 186 pp., https://www.usda.gov/oce/climate_change/effects_2012/CC%20and%20Agriculture%20Report%20(02-04-2013)b.pdf.

Yohe, G., and R. S. J. Tol, 2002: Indicators for social and economic coping capacity—Moving toward a working definition of adaptive capacity. *Global Environ. Change*, **12**, 25–40, https://doi.org/10.1016/S0959-3780(01)00026-7.