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LANDSCAPE AND WATERSHED PROCESSES

Upper Midwest Climate Variations: Farmer Responses to Excess Water Risks

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Abstract

Persistent above average precipitation and runoff and associated increased sediment transfers from cultivated ecosystems to rivers and oceans are due to changes in climate and human action. The US Upper Midwest has experienced a 37% increase in precipitation (1958–2012), leading to increased crop damage from excess water and off-farm loss of soil and nutrients. Farmer adaptive management responses to changing weather patterns have potential to reduce crop losses and address degrading soil and water resources. This research used farmer survey (n = 4778) and climate data (1971–2011) to model influences of geophysical context, past weather, on-farm flood and saturated soils experiences, and risk and vulnerability perceptions on management practices. Seasonal precipitation varied across six Upper Midwest subregions and was significantly associated with variations in management. Increased warm-season precipitation (2007–2011) relative to the past 40 yr was positively associated with no-till, drainage, and increased planting on highly erodible land (HEL). Experience with saturated soils was significantly associated with increased use of drainage and less use of no-till, cover crops, and planting on HEL. Farmers in counties with a higher percentage of soils considered marginal for row crops were more likely to use no-till, cover crops, and plant on HEL. Respondents who sell corn through multiple markets were more likely to have planted cover crops and planted on HEL in 2011. This suggests that regional climate conditions may not well represent individual farmers' actual and perceived experiences with changing climate conditions. Accurate climate information downscaled to localized conditions has potential to influence specific adaptation strategies.

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Increased annual precipitation and heavy precipitation events are now observed and predicted to continue to characterize the US Midwest climate and have a direct influence on agriculture (Walthall et al., 2013; Hatfield et al., 2014). Variations in the hydrologic cycle marked by increased precipitation, runoff, and sediment transfers to rivers and oceans reflect increasing degradation of soil and water resources (Rossi et al., 2009; Collins et al., 2011). Land surface erosion from flowing water, saturated and ponded soils, and flooding have immediate and long-term implications for agricultural productive capacities and ecosystem functions associated with C cycling and water quality. The Third National Climate Assessment (NCA3) highlighted concern for "the current loss and degradation of critical agricultural soil and water assets," potential losses in future crop productivity in the United States, and the need for reactive and proactive adaptation strategies in response to changes in climate (Melillo et al., 2014, p. 46).

Cultivated ecosystems, in particular the major cereal crops corn or maize (*Zea mays* L.), rice (*Oryza sativa* L.), soybean [*Glycine max* (L.) Merr.], and wheat (*Triticum aestivum* L.), provide 75% of the world's caloric intake, with the United States producing one-third of the world's corn (USDA, 2014). In 2011, almost 63.9 million ha (158 million acres) of harvested grain corn and soybean generated US$101.5 billion in cash receipts for US agriculture (USDA, 2014), with 70% of these hectares located in the Upper Midwest. The corn–soybean rotation is the dominant corn-based system in this region; however, there are other corn-based systems such as corn after corn every year (continuous corn) and extended rotations of corn, soybean, and other crops on 3- or 4-yr cycles. Farmers' adaptive management decisions to adjust to changing climate conditions will affect the productivity of these cropping systems and have short- and long-term impacts on individual farmer livelihoods, local and US economies, and ecosystem conditions (Hatfield et al., 2014). Thus, there is a need to better understand how farmer experiences and their perceptions of risk associated with the timing, intensity, and amounts of rain and snow in their locale influence management decisions (Arbuckle et al., 2015; Walthall et al., 2013).

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Abbreviations: HEL, highly erodible land; NCA3, Third National Climate Assessment; NWS COOP, National Weather Service Cooperative Observer Program.

Intensive cultivation and low diversity of land use coupled with a changing climate has a number of unintended consequences on soil and water resources and long-term productivity (Blesh and Drinkwater, 2013; Segura et al., 2014). As the frequency and intensity of precipitation events continue to change (Karl et al., 2009), impacts of climate change on the agroecosystem of the Upper Midwest are becoming more visible to farmers, agricultural businesses, natural resource agencies, and environmental organizations with regional, national, and global interests. The challenge to agriculture is to find strategies that sustain and increase productivity while protecting ecosystem integrity (Blesh and Drinkwater, 2013).

Although the most robust climate change signals are global, farmer adaptive management responses are highly localized, based on personal experiences and perceptions of risks to their land and livelihood. Thus, climate change observations and predictions at large scales—globally, nationally, and even regionally—may have limited perceived or practical value and application to farmers' management decisions as they adapt their own enterprise. Farmer adaptation to climate change is fundamentally a set of adjustments in management practices based on short- and long-term production and conservation goals and perceptions of uncertainty and risk associated with changing conditions. The installation or enhancement of drainage systems, changing tillage practices, and adding a cover crop to a corn-based rotation are several of the adaptive management strategies that can be put in place to reduce the risks associated with flooding, saturated soils, ponding, and off-farm sediment and nutrient losses due to excess water. Planting highly erodible land (HEL) to cultivated crops can also be considered an adaptive response to changing climate and variable market conditions, which, however, from a soil erosion and water quality perspective, could be labeled "maladaptive."

In this study, we proposed that farmers' management decisions incorporate signals from local extreme events and long-term weather conditions and experiences with saturated soils, flooding, crop markets, and the biophysical aspects of their farmland. It follows that farm management adaptation probably varies across Upper Midwest watersheds in relation to differing climate and weather patterns. Farmers' management practices in 2011 were examined in light of a prior 5-yr wet period (2007–2011); their on-farm experiences with saturated soil, flooding, and erosion; perceptions of the risks associated with excess water concerns and corn markets; and the influence of their peers and other organizations controlling for hectares in crops, the percentage of land rented, heads of cattle and hogs, and education.

In this study, the overall and subregional climate patterns of the Upper Midwest of the past 5 yr were compared with the last 40 yr. Climate change implications were developed for the corn–soybean rotation and the suite of management practices available to farmers to better address the risk of excess water associated with potential crop and income losses and degradation of soil and water resources. The research design combined data from a 2012 random sample mail survey of 4778 farmers with climate and soil data. Structural equation models were then developed to test posited relationships among climate, geophysical context, on-farm experiences, perceived risk, and relationship influences associated with adaptive and maladaptive responses.

Materials and Methods

Study Context: Climate Patterns of the Upper Midwest

Climate is the distribution of weather with time. Many aspects of this distribution are associated with agricultural practices at local scales. The Intergovernmental Panel on Climate Change reports on world climate focuses on global trends and regional patterns where signals of temperature increase are most robust. They observed (Intergovernmental Panel on Climate Change, 2014, Ch. 26) that evidence of anthropogenic climatic influence on agriculture in North America is not clearly established but found that agriculture has substantial sensitivity to climate variability. Understanding of global Earth–human relationships requires attention to these large-scale trends. However, although global warming is projected to lead to increased daily-scale precipitation extremes affecting agriculture and water, it is very likely that locale-specific temperature and precipitation variations will emerge throughout North America (Intergovernmental Panel on Climate Change, 2014). Further, there is evidence that individual experiences with weather and climate are very local, and many adaptive solutions are applied locally (Rejesus et al., 2013). Thus, production planning and management decisions on individual fields and farms are most likely to be influenced by field-scale climate factors, while global-scale climate factors more likely to impact the prices farmers receive for their crops (NOAA, 2011).

Of interest to this study was the distribution of weather in the Upper Midwest, specifically the expected total precipitation during the growing season and the frequency of excessively wet seasons. Unusually wet seasons may impact agricultural practices differently, depending on the long-term climate and landscape. For example, relatively wet seasons in typically dry regions of the Upper Midwest may allow marginal lands to be pulled into crop production. On the other hand, relatively wet seasons in typically wet areas may be detrimental to crop production. Seasonal wetness also interacts with the frequency of heavy precipitation events, another important characteristic of the distribution of weather events. Warmer air can hold more water vapor than cooler air, and this extra moisture contributes to storm systems with heavier rainfall (Coumou and Rahmstorf, 2012; Melillo et al., 2014). This suggests that the 37% increase in very heavy precipitation documented in this region from 1958 to 2012 is likely to have influenced farmer perceptions of risk and adaptation strategies put in place to manage excess water (Melillo et al., 2014).

Three characteristics—expected seasonal precipitation, excessive seasonal wetness, and frequency of heavy precipitation events—are summarized locally across the Upper Midwest in Fig. 1 to 3. Seasonal and daily extremes during the 5-yr period 2007 to 2011 were assessed in the context of a historical record covering 1971 to 2011 at 521 National Weather Service Cooperative Observer Network (NWS COOP) stations. Warm-season precipitation totals, defined as the total precipitation between 1 April and 30 September, were computed at each station. At a selected station, the seasonal total for each year in the record was ranked from 1/41 (lowest seasonal total) to 41/41 (highest seasonal total), and these rankings were converted to percentile ranks. The median warm-season precipitation is the

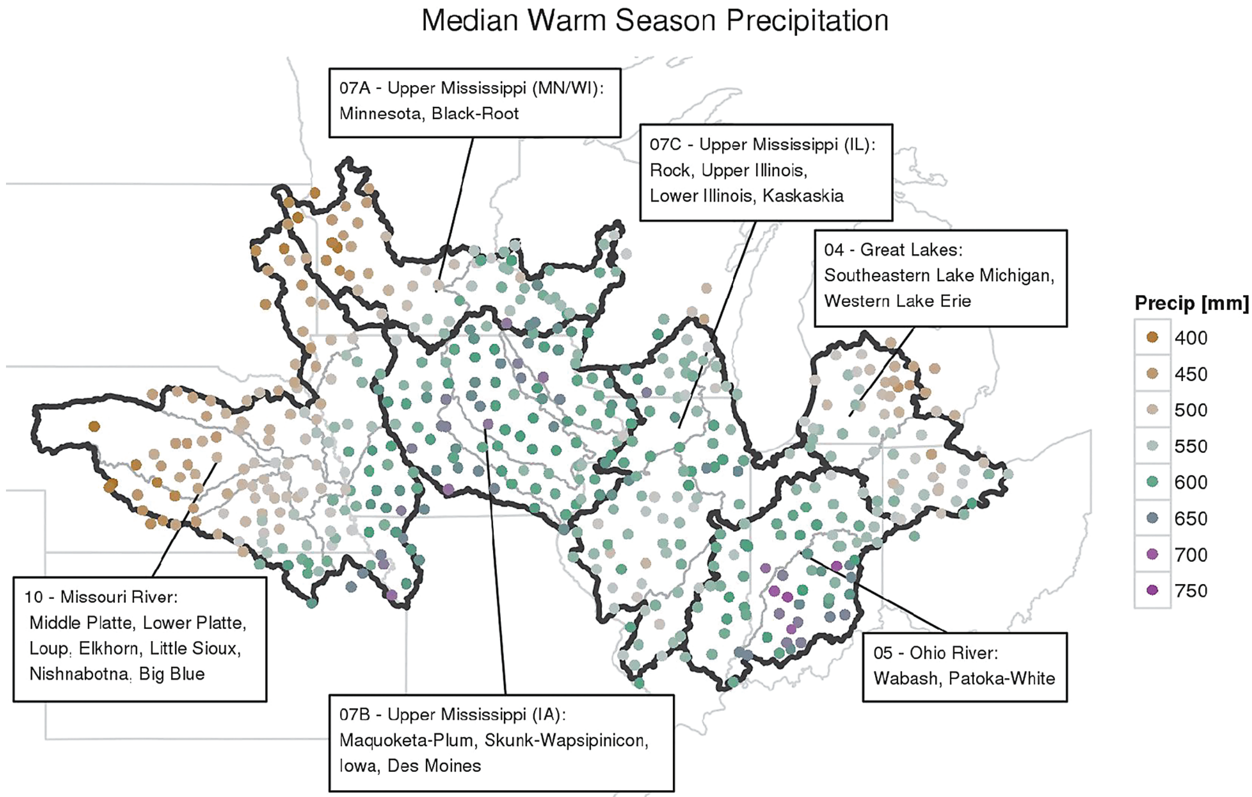

Fig. 1. Median warm-season precipitation from the historical record at National Weather Service Cooperative Observer Program stations. Warm-season precipitation is defined as the total precipitation from 1 April to 30 September. The reported value is the median of these yearly totals from 1971 to 2011.

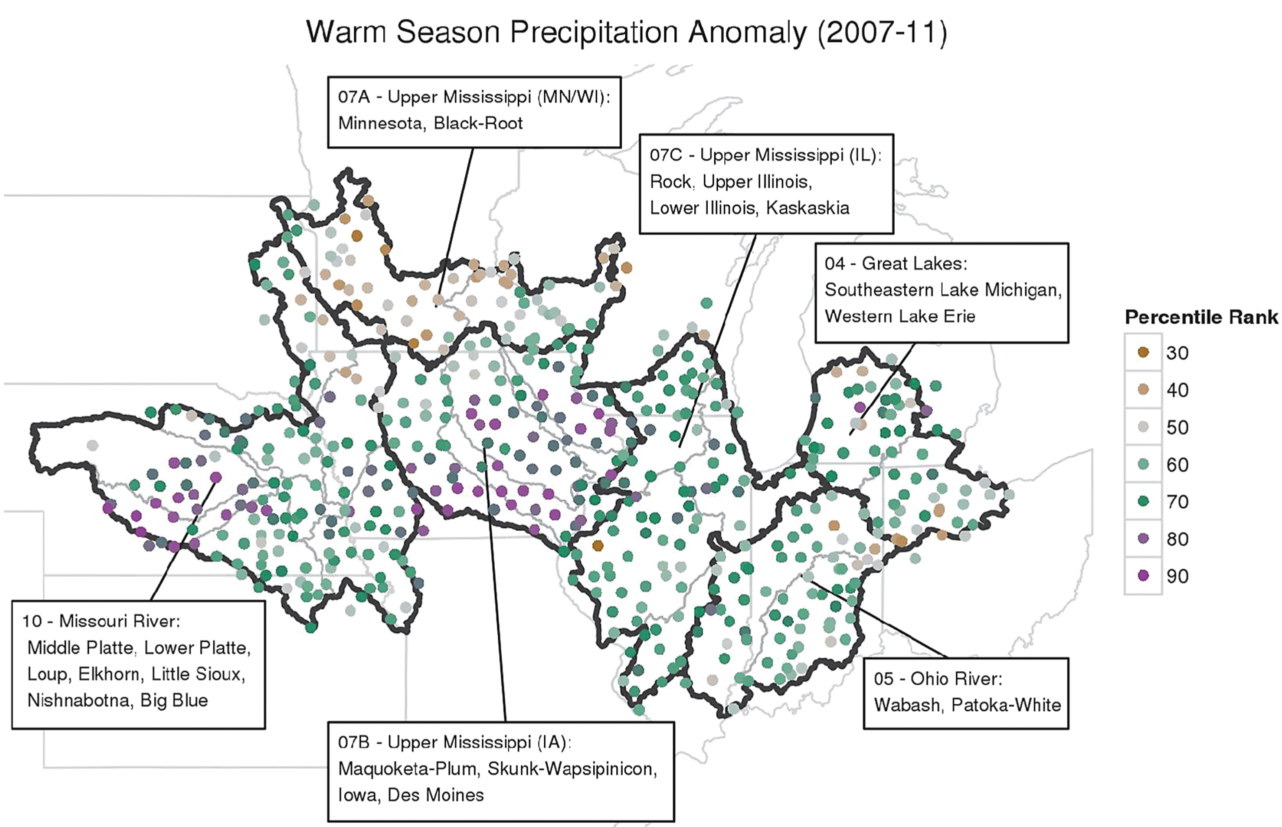

Fig. 2. Warm-season precipitation anomaly for 2007 to 2011 at National Weather Service Cooperative Observer Program stations. The reported values are the average percentile rank of April to September precipitation within the historical record for the 5-yr period.

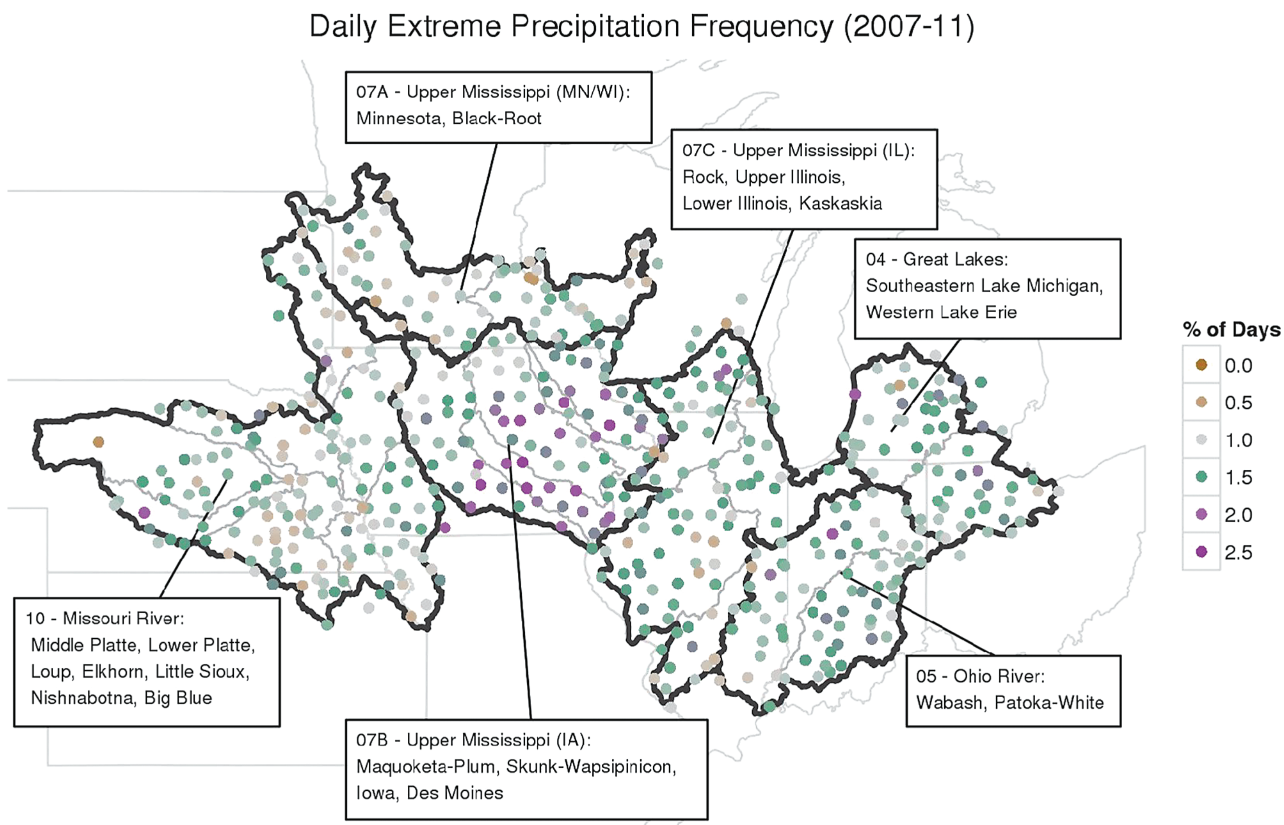

Fig. 3. Frequency of extreme heavy daily precipitation, represented as the percentage of days with daily totals exceeding the 99th percentile, at National Weather Service Cooperative Observer Program stations.

precipitation amount corresponding to a percentile rank of 50% and quantifies the expected seasonal precipitation for a location. These median precipitation totals are displayed in Fig. 1. The Corn Belt is situated in a northwest to southeast gradient in median seasonal precipitation, with farmers in southwestern Minnesota and eastern Nebraska expecting <500 mm during the warm season while southern Indiana receives >700 mm during half of all growing seasons.

The percentile rank of warm-season precipitation can also quantify the extent of relatively wet or dry conditions during recent growing seasons. Figure 2 presents the excessive seasonal wetness patterns across the region using the average of the percentile ranks during the 5-yr period of 2007 to 2011. This map highlights local areas that have experienced relatively wet or dry conditions during the 5-yr period. The prevalence of values >50% reflects the widespread pattern of unusually wet conditions leading up to 2011.

Daily precipitation extremes were also assessed using the NWS COOP archive. The 99th percentile of daily precipitation totals was computed for each month from April to September at each location. The extreme heavy daily precipitation patterns are as important to agricultural management practices as the changes in average precipitation. It is these "gully washers" that have significant consequences for soil erosion and crop losses. Our third weather and climate map is the percentage of days from 2007 to 2011 for which precipitation exceeded the 99th percentile (Fig. 3). Many locations experienced extremes on at least 1% of days, which is the expectation. Several watersheds in Iowa experienced more than twice as many heavy rainfall events as expected. These events are locally remembered as the floods of 2008, 2009, and 2010, which caused considerable damage to urban and rural places (Olson, 2009; Olson et al., 2011).

Excess Water Impacts on Corn-Based Cropping Systems

Changes in the seasonal distribution of precipitation, along with precipitation increases and more extreme rainfall events, have a number of implications for corn-based cropping systems of the Upper Midwest. Plant vegetative and reproductive development is sensitive to the timing and availability of water. Excessive rain during the spring planting season can delay planting, causing risks to productivity and profitability for the corn crop (Hatfield et al., 2011). Seed germination is influenced by moisture, temperature, and seed–soil contact. The corn seed will absorb water until it has 30 to 35% moisture at germination when it begins its growth; however, seeds exposed to prolonged cool, wet conditions germinate and develop slowly and are likely to result in an injured plant or die (Abendroth et al., 2011). Flooding in the early growing season is associated with anoxia, increases to susceptibility to root disease, increases in soil compaction due to the use of heavy farm equipment on wet soils, soil erosion and runoff, and off-field and -farm leaching of N, P, and other nutrients into ground and surface waters (Hatfield et al., 2011).

Prolonged flooding (24–48 h) or intense rain during early vegetative stages can lead to distortion and stunting with excessive tillering or complete lack of ear and tassel formation (Mueller and Sisson, 2013). Changes in moisture and timing of precipitation have been found to be associated with overwintering and increased seed production of weeds, altering the competition between invasive weeds and corn-based cropping systems and subsequently affecting productivity (Patterson, 1995; Bradley and Mustard, 2005; Hatfield et al., 2011). Further, as the soil becomes saturated, it is less able to maintain infiltration rates high enough to absorb high-intensity rainfall events, leading to runoff, soil erosion, and loss of N, P, and other production inputs. The corn–soybean rotation is known to be a leaky system, with N leaching into surface waters. Mississippi River Basin grain farming has been identified as a primary cause of hypoxia in the Gulf of Mexico as a result of off-farm nutrient losses (Qi et al., 2011; Blesh and Drinkwater, 2013).

There are a number of adaptive (and maladaptive) management strategies that farmers of corn-based systems have put in place to assure high yields and profitability under excess water conditions while responding to soil erosion and water quality concerns. These include (i) the addition and enhancement of farm drainage systems, (ii) conversion to no-till, and (iii) the use of cover crops. A fourth strategy has been to expand planting into HEL. Key drivers of this strategy have been the expiration of 10- to 15-yr contracts for hectarage enrolled in the Conservation Reserve Program, low corn carryover stocks in the United States, and grain price volatility associated with increased weather variability (NOAA, 2011; Stabbe, 2013).

Farmer Adaptation Strategies

Farm Drainage

Subsurface tile drainage is used to transform poorly drained soils into productive cropland and provides economic benefits through removal of excess water from the soil column; this results in decreased surface water runoff and reduced soil erosion and loss of P attached to eroding soils (Sugg, 2007). Farm drainage is a routine practice, with more than a third of cultivated areas in the Midwest and more than three-quarters of Illinois and Iowa cropland tile drained (Power et al., 2000; Nangia et al., 2010). Much of the drainage in the Upper Midwest occurs in the spring and early summer. Although drainage can reduce soil erosion and protect soil structure by reducing compaction from equipment traffic, there is increasing evidence that subsurface drainage can accelerate the transfer of NO_3–N from fields to streams and rivers in the Mississippi River Basin and ultimately the Gulf of Mexico (Qi et al., 2011; Kaspar et al., 2012).

No-Till

No-till is a practice that provides substantial protection from the erosive effects of rainfall and the movement of water across farm fields. No-till is a form of reduced tillage where the soil is left undisturbed from harvest to planting except for strips up to 1/3 of the row width for planting the seed, with weed control accomplished with herbicides and methods other than tillage (Coughenour, 2003). Any tillage practice compared with sod, pasture, and grasslands leads to changes in soil characteristics and the loss of soil organic C (SOC) storage and retention (Olson, 2010). However, a reduction in tillage in cultivated systems reduces soil erosion and nutrient and sediment losses to proximate waterways and retains more organic matter and SOC (Horowitz et al., 2010). Poor soil structure and erosion are major causes of soil degradation, weak plant growth, and loss of crop productivity (Wang et al., 1985; Lal et al., 2004).

Variations in soil organic matter are directly associated with differences in the soil's capacity to store water (Hudson, 1994; Jiang et al., 2008). One measure of soil degradation is a decrease in the soil water holding capacity as a result of reduced SOC (Hatfield and Morton, 2013). Changes in soil properties can increase or reduce the impact of intense rainfall events on the soil surface and affect the amount of water absorbed and stored and soil erosion that occurs (Hatfield and Morton, 2013). Soil aggregates under no-till management are more stable when exposed to rainfall because increased soil organic matter reduces breakdown of the soil structure, thus increasing resistance to erosion when exposed to raindrops during rainfall events (Hatfield and Morton, 2013).

Cover Crops

Cover crops are plants grown to cover the soil between harvest and before the establishment of crops such as corn and soybean the following growing season (Arbuckle and Ferrell, 2012). Cover crops have the potential to mitigate the effects of excess precipitation by (i) preventing erosion, (ii) retaining C and improving soil structure, (iii) scavenging N, thereby reducing NO_3 leaching into drainage ditches and waterways, (iv) improving soil permeability and increasing water infiltration and aeration, (v) suppressing weeds and thereby maintaining or boosting crop yields, and (vi) reducing greenhouse gas emissions (Kladivko et al., 2004; Strock et al., 2004; Hillel and Rosenzweig, 2011; Kaspar et al., 2012; Midwest Cover Crops Council, 2012). Soils without vegetation or crop residue are exposed to surface sealing and soil crusting from raindrops, which consolidate the surface layers and change the soil properties (Hatfield and Morton, 2013). After the soil surface seals, erosive forces increase sheet and rill erosion and off-field N loss under heavy rainfall (Hatfield and Morton, 2013). The biomass of a cover crop acts as a barrier between the soil surface and the flow of water, allowing infiltration into the soil profile rather than runoff. Cover crops used in conjunction with tile drainage have been found to reduce the average annual flow of NO_3 concentration (Strock et al., 2004; Qi and Helmers, 2010).

Planting on Highly Erodible Lands

Both grassland and cropland used for agricultural purposes offer direct economic returns to the land owner. Topography, soil characteristics, climate patterns (changes in wetness or droughtiness), and local and global markets influence land use functions and values (Hatfield and Morton, 2013). In recent years, volatile weather events and increased demand for biofuel feedstocks has removed the buffer of excess grain production capacity, lowered carryover of grain stocks, and led to a doubling of corn and soybean prices (NOAA, 2011; Wright and Wimberly, 2013). As a result, cropland has provided a higher direct economic value to landowners and accelerated conversion of grassland to cropland in the US Corn Belt (Claassen et al., 2011; Wright and Wimberly, 2013). While grasslands have lower direct cash value, they are less susceptible to soil erosion and sediment runoff and receive lower levels of fertilizer applications, which can translate into less nutrient runoff to water, thereby providing a higher level of offsite and indirect benefits downstream (Claassen et al., 2011).

The term *highly erodible land*, a legal designation determined by the NRCS, refers to land with soils highly susceptible to erosion by wind or water, the two primary causes of land degradation (Farm Service Agency, 2007; Blanco-Canqui and Lal, 2010, p. 2). Much HEL has long and steep slopes, with soils susceptible to erosion and increased vulnerability to high rates of runoff during heavy rains. High grain prices provide a strong market signal and in the western Corn Belt have accelerated the rate of conversion of highly erodible grassland into row crop production at a rate of 1.0 to 5.4% annually (Wright and Wimberly, 2013). The 2012 Census of Agriculture estimated that farmland in the Conservation Reserve Program and the Wetlands Reserve Program declined from 15.6 million to 11.1 million ha between 2007 and 2012 (National Agricultural Statistics Service, 2014). The Environmental Working Group estimates that a total of 2.1 million ha of previously uncultivated HEL was planted with row crops, primarily wheat and corn, between 2009 and 2012 (Cox and Rundquist, 2013).

This trend suggests that expanding row crop production into HEL is a maladaptive response to plentiful rain, with possible short-term economic benefits but long-term negative water and soil consequences. Combined, the increased frequency of extreme precipitation and land use change have made Midwest farmlands and specific watersheds more vulnerable to soil erosion, sediment-laden runoff containing excess N and P, and increased crop damage from excessive water.

Study Design

This study explored the relationships of actual local soil and climate conditions, farmer perceptions and experiences with excess water, and adaptive responses to better understand how farmers are responding to these events and how the variations across Upper Midwest watersheds relate to adaptation practices on the landscape. Specifically, we examined the adaptive and maladaptive management responses associated with (i) geophysical contexts, (ii) past weather patterns, (iii) on-farm experiences with flooding, saturated soils and water ponding, increased loss of nutrients, more variable weather, and increased erosion, (iv) relationship influences of public and private farm groups and individuals, and (v) perceptions of risk and vulnerability associated with concerns about too much water and diversity of grain markets. Structural equation models were developed to understand these relationships using a suite of management practices: drainage, no-till, cover crops, and increased planting on HEL.

Our analysis focused on a suite of four adaptive practices as dependent variables. A 2012 USDA CSCAP-U2U jointly administered stratified random sample mail survey was completed by 4778 farmers with at least US$100,000 in gross sales and a minimum of 32 ha of corn production in 22 Hydrologic Unit Code 6 Upper Midwest watersheds (for survey details, see Supplemental Materials). The survey included a question set that asked farmers to estimate what percentage of the land that they farmed in 2011 (owned and/or rented) was (i) artificially drained through tile or other methods, (ii) managed by no-till, (iii) planted to cover crops, and (iv) highly erodible land that was planted to crops. We combined values from owned and rented land by computing the maximum of the two percentages reported for owned and rented land for each of the four practices.

Explanatory Variables

Our modeling objective was to characterize the relationships among these adaptive practices and between them and several explanatory variables. We grouped our explanatory variables into six conceptual categories. Two predictors characterized the geophysical context: proximity to a creek, stream, or river and soil capability classification. Proximity to a creek, stream, or river was self-reported on the survey, and the soil capability variable was constructed as the proportion of unirrigated land classified in Soil Capability Classes 4 to 8 according to the NRCS classification system, as mapped in each respondent's county. The NRCS soil capability classification system (Classes 1–8) uses the land's ability to grow crops as a metric to evaluate soil suitability for specific uses (Hatfield and Morton, 2013). Class 1 is best suited for growing a wide range of crops and Class 8 is considered unsuitable for growing crops. Classes 2 and 3 have moderate to severe limitations that reduce the choice of plants that can be grown and require special conservation practices to assure crop productivity. Soils classified in Classes 4 to 8 are considered marginal, with substantive limitations on their productive capacities for row crops, and require careful management. Both variables characterize the landscape and may be related to the adoption of our practices of interest.

Climate and weather, especially precipitation, may also relate to adaptive management practices. Long-term average precipitation can influence the need for drainage, and unusual weather events at a variety of time scales, from daily to seasonal, may relate to the timing of planting and harvest as well as root establishment and plant growth and development. We utilized the three weather and climate variables defined above (Fig. 1–3) constructed from daily precipitation records from the NWS COOP network. Each survey respondent was matched to the closest NWS COOP station to provide individual-level weather and climate data on median warm-season precipitation, warm-season precipitation anomaly (percentile rank), and daily extreme precipitation frequency. The average distance from the closest NWS COOP station to a respondent's zip code was 14.3 km.

We are particularly interested in the interaction between weather and climate, given the unusually wet seasons of 2007 to 2011 leading up to the CSCAP-U2U survey. Excessive rainfall over areas that have relatively wet climates (e.g., Illinois and Indiana) may influence management practices differently than unusually wet conditions over areas that have relatively dry climates (e.g., Nebraska). To investigate this further, we grouped the surveyed watersheds into six subregions. Watersheds were grouped according to water resource regions (Hydrologic Unit Code 2), with two watersheds in the Great Lakes region, two watersheds in the Ohio region, 10 watersheds in the Upper Mississippi region, and eight watersheds in the Missouri region. The watersheds in the Upper Mississippi region were further divided into three subregions, with watersheds primarily in Iowa making up one subregion, those in Illinois making up another subregion, and the two remaining watersheds in Minnesota and Wisconsin making up a third subregion. The subregions are depicted in Fig. 1 to 3.

The next set of variables measured farmers' self-reported "on-farm" experience with weather extremes. Two dichotomous variables (0 = no, 1 = yes) measured whether within the previous 5 yr farmers had experienced four phenomena on the land they farm. These were: “problems with saturated soils or ponding” or “significant flooding (stream/river).” Two other variables were reported on a five-point scale ranging from strongly disagree (1) to strongly agree (5). Respondents reported their level of agreement that during the past 5 yr at least some of their land had experienced significant soil erosion or they had noticed more variable or unusual weather on their farm.

Two predictor variables represented aspects of perceived risk and may be related to implementation of adaptive practices. One perceived risk variable measured the diversity of farmers’ corn markets as a simple count of the number of options respondents chose when asked for which markets they produce corn. Respondents were asked to select all that applied from a list of six options: (i) commodity (sweetener, export, feed), (ii) ethanol, (iii) livestock (silage), (iv) specialty or value-added including organic, (v), seed, and (vi) other. The other perceived risk variable was a factor score from a factor analysis of five items related to concerns about excess water (see Supplemental Materials). The five items measured concerns about increased flooding, more frequent extreme rains, saturated soils and ponded water, loss of nutrients into waterways, and soil erosion on a four-point scale (not concerned, slightly concerned, concerned, very concerned).

Farmers’ implementation of adaptive management practices may be influenced by input from other people and organizations, so we incorporated five predictors that measured relationship influence. These measures were factor scores from a factor analysis on eight survey items (see Supplemental Materials). One factor measured the overall influence of all actors, and the remaining factors measured the influence of specific types of actors. These are public agriculture (NRCS, soil and water conservation office, state climatologist, university extension, and state department of agriculture), farm organizations, agriculture peers (other farmers), and private agriculture (seed dealers and farm chemical dealers).

We also incorporated several control variables, including the level of education, total cropland, proportion of land rented, total cattle, and total hogs. Figure 4 provides a conceptual diagram of the relationships among the explanatory variables and adaptive practices.

Modeling Approach

The response variables are reported as percentages, with high frequencies of 0 and 100% (Table 1). This discrete–continuous mixture motivated a tobit-type model for the responses (Amemiya 1984). Let $y_{i,j}$ represent the response for the ith subject for the jth practice. We connected an unobserved continuous random variable $y_{i,j}{}^*$ with each response, and these variables are related according to

$$y_{i,j} = \begin{cases} 0\% & \text{if } y_{i,j}{}^* \leq 0 \\ y_{i,j}{}^* \times 100\% & \text{if } 0 < y_{i,j}{}^* < 1 \\ 100\% & \text{if } y_{i,j}{}^* \geq 1 \end{cases}$$

We then used a multivariate multiple regression model on the unobserved continuous variables:

$$y_{i,j}{}^* = \mathbf{x}_i'\boldsymbol{\beta}_j + \varepsilon_{i,j}$$

The same set of predictors $\mathbf{x}_i'$ was used for each of the four response variables, but each response variable had its own vector of coefficients $\boldsymbol{\beta}_j$. The error terms for each subject followed a multivariate normal distribution:

$$\boldsymbol{\varepsilon}_i = \left[\varepsilon_{i,1}, \varepsilon_{i,2}, \varepsilon_{i,3}, \varepsilon_{i,4}\right]'$$
$$\boldsymbol{\varepsilon}_i \sim \text{MVN}\left(\mathbf{0}, \boldsymbol{\Sigma}\right)$$

The vector of predictors, $\mathbf{x}_i'$, included an intercept and the 26 variables outlined above. In the multivariate regression model, each subregion had a unique intercept as well as its own coefficients for seasonal precipitation percentile rank, frequency of extreme daily precipitation, and the interaction between these two weather variables.

Bayesian Inference

We performed a Bayesian analysis for the multivariate response regression model outlined above. Bayesian analysis requires that prior distributions be specified for all model parameters, which included the regression coefficients, $\boldsymbol{\beta}_j$, and the covariance matrix of the error terms, $\boldsymbol{\Sigma}$. We specified diffuse Gaussian priors for the regression coefficients and developed priors for the standard deviations and correlation matrix of the error terms using the approach of Barnard et al. (2000).

Bayesian inference is based on the posterior distribution for the parameters given the observed data and combines the prior distribution with the likelihood. In this case, the posterior distribution was not available analytically, so simulation was used to sample from the posterior distribution of the parameters. We used Markov chain Monte Carlo (MCMC) methods, specifically a Gibbs sampler, to sample successively from the individual parameters’ conditional posterior distributions (Gelman et al., 2004). The Gibbs sampler includes updates of the unobserved continuous variables $y_{i,j}{}^*$, which results in more efficient posterior sampling. Further details on prior distributions and the MCMC procedure can be found in the Supplemental Materials.

In addition to summarizing posterior distributions, we provided measures of explained variability for this model using the approach from Gelman and Pardoe (2006). In our modeling we used the approach to quantify the proportion of variability in the unobserved variables $y_{i,j}{}^*$ explained by the conditional relationship with the predictors and the other unobserved variables, $y^*_{i,j'}, j' \neq j$.

Missing Data

We imputed values for missing covariates using a modeling strategy informed by the conceptual model outlined in Fig. 4. Raghunathan et al. (2001) outlined a strategy for imputation using a sequence of regression models in a Bayesian framework. Imputation includes sampling from the posterior predictive distribution for the missing values. The missing value model included a multivariate probit model for the four on-farm experience variables, with the control, climate and weather, and geophysical context variables as predictors. In addition, a multivariate normal population model was developed for the collection of predictors because some control and on-farm experience variables were missing as well.

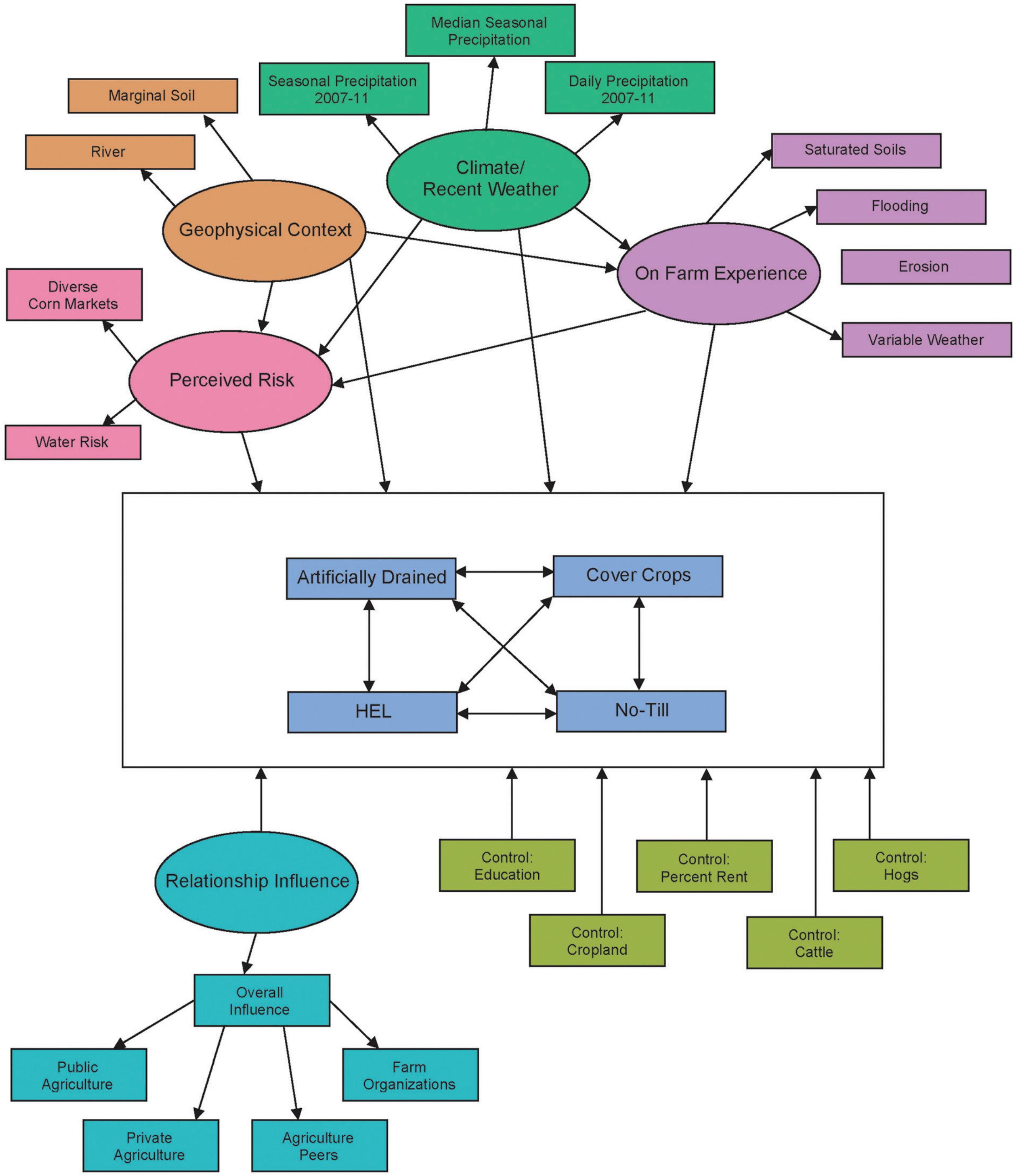

Fig. 4. Structural diagram for a multivariate response model (HEL is highly-erodible land).

A Bayesian analysis was implemented for the missing data model, and any missing values were sampled from their posterior predictive distribution (see Supplemental Materials). These sampled values were imputed for use in the Bayesian analysis of the multivariate tobit model. The relationship influence factors, perceived risk, and climate and weather variables were completely observed.

Table 1. Summary statistics for response variables. Respondents reported a percentage for each practice. Percentages have been collapsed into five groups, with the percentage of respondents in each group reported. For example, a value of 9.0 in the 41–59% column indicates 9% of respondents reported that between 41 and 59% of land is artificially drained.

Practice	Mean	SD	0%	1–40%	41–59%	60–99%	100%
Artificially drained through tile or other methods	49.3	40.0	22.9	22.7	9.0	22.8	22.6
No-till	37.5	38.8	38.3	18.5	15.3	9.9	18.0
Planted to cover crops	6.4	16.5	73.3	21.8	2.6	1.1	1.2
Highly erodible land that was planted to crops	24.5	33.1	41.0	34.0	6.5	10.9	7.6

Results

Table 1 summarizes the reported percentages and means for the response variables. Almost 75% of respondents reported that at least some cropland they farmed was artificially drained, and 23% reported that 100% of their land was drained. Artificial drainage is the most commonly used of the four adaptive practices. Just over 60% of respondents reported using no-till on at least some of their land, with 18% reporting use on 100% of their land. More than one-fourth of the sample reported using cover crops, with most of those planting cover crops on 40% or less of their land. Nearly 60% of farmers surveyed reported planting at least some HEL to crops.

Tables 2 and 3 summarize the covariates used in the multivariate regression models. Nearly three-fourths of respondents reported experience with saturated soils, and a majority agreed or strongly agreed that they had noticed more variable or unusual weather on their farms. About one-fourth of the sample agreed or strongly agreed that they had experienced significant soil erosion. As noted previously (Fig. 2), most locations saw five particularly wet years from 2007 to 2011, with the average warm-season anomaly precipitation percentile rank being 0.64. An average of 1.3% of days saw precipitation exceeding the 99th percentile (extreme precipitation frequency 2007–2011). The distribution for the diverse corn market variable indicates that more than half of the respondents produced corn for at least two different markets.

Model Findings

Table 4 presents the posterior means for the standardized multivariate tobit model coefficients along with the Gelman and

Table 2. Summary statistics for numeric predictors.

Variable	Mean	SD	Q1	Median	Q3
Extreme precipitation frequency 2007–2011, %	1.3	0.3	1.1	1.3	1.5
Warm-season precipitation anomaly 2007–2011, %	64	11	57	65	72
Median warm-season precipitation, mm	561	56	521	569	605
Marginal soil (proportion)	0.17	0.16	0.05	0.13	0.23
Diverse corn markets, no.	2.0	0.8	1	2	3
Cropland, ha	320	320	140	230	400
Proportion of rented land	0.53	0.34	0.25	0.57	0.83
Cattle, no.	80	390	0	0	60
Hogs, no.	70	710	0	0	0

Table 3. Percentage distributions for categorical predictors.

Variable	Category	Distribution
		%
River		
Do any creeks, streams, or rivers run through or along any of the land you farm?	0–No	24.5
	1–Yes	75.5
Saturated soils		
During the past 5 yr, have you had problems with saturated soils on any of the land you farm?	0–No	26.0
	1–Yes	74.0
Flooding		
During the past 5 yr, have you experienced significant flooding (stream/river) on any of the land you farm?	0–No	63.0
	1–Yes	37.0
Erosion		
At least some of the land I farm has experienced significant soil erosion during the last 5 yr.	1– Strongly Disagree	12.2
	2– Disagree	48.5
	3– Uncertain	12.8
	4– Agree	23.6
	5– Strongly Agree	2.9
Variable weather		
In the past 5 yr, I have noticed more variable/unusual weather on my farm.	1– Strongly Disagree	2.2
	2– Disagree	20.5
	3– Uncertain	20.0
	4– Agree	49.8
	5– Strongly Agree	7.5
Education		
What is your highest level of education?	1– Less than high school	2.0
	2– High school graduate/GED	38.8
	3– Some college	18.3
	4– 2-yr college/technical degree	16.1
	5– 4-yr college degree	20.8
	6– Graduate degree (MS, MD, PhD)	4.0

Table 4. Summary of standardized coefficients for multivariate regression model coefficients. Posterior means are reported.

Predictors	Adaptive management practices			
	Artificial drainage	No-till	Cover crops	Plant HEL†
Geophysical context				
River	0.051***	0.089***	0.015	0.105***
Marginal soil	−0.373***	0.149***	0.140***	0.158***
On-farm experience				
Saturated soils	0.082***	−0.055***	−0.046*	−0.075***
Flooding	−0.039**	−0.013	0.064**	−0.029
Erosion	−0.034*	0.028	0.004	0.159***
Variable weather	0.015	−0.001	0.032	−0.032
Perceived risk				
Water risk	0.029	−0.004	0.012	0.032
Diverse corn markets	−0.001	0.028	0.086***	0.049**
Relationship influence				
Overall influence	0.010	0.043**	0.010	−0.006
Public agriculture	−0.005	0.033*	0.025	0.002
Private agriculture	0.004	−0.012	−0.066***	0.023
Farm organizations	0.012	−0.004	−0.002	−0.003
Agriculture peers	0.002	0.006	0.008	−0.017
Control				
Education	0.045***	0.053***	−0.013	−0.009
Cropland	−0.005	−0.014	−0.033	0.013
Percent rent	0.042**	0.029	−0.117***	−0.009
Cattle	−0.042**	−0.022	0.098***	0.033*
Hogs	0.038**	−0.010	−0.027	0.030*
Other adaptive practices				
Artificial drainage		−0.002	−0.089***	−0.064**
No-till	−0.002		0.103***	0.322***
Cover crops	−0.057***	0.082***		0.078***
Plant HEL	−0.049**	0.308***	0.093***	
Climate				
Median warm-season precipitation	0.167***	0.157***	0.027	0.142***
Daily extreme precipitation frequency				
Great Lakes	0.036**	0.025	0.007	−0.027
Ohio	0.021	−0.004	0.023	−0.005
Upper Mississippi (IL)	−0.020	−0.004	−0.016	0.004
Upper Mississippi (IA)	−0.010	0.005	−0.006	0.018
Upper Mississippi (MN/WI)	0.035**	−0.009	−0.004	−0.011
Missouri	0.061***	−0.034	0.022	−0.027
Warm-season precipitation anomaly				
Great Lakes	−0.043***	−0.034*	−0.010	0.024
Ohio	−0.038**	−0.011	−0.052**	−0.036*
Upper Mississippi (IL)	−0.020	−0.020	−0.019	0.021
Upper Mississippi (IA)	0.004	0.139***	0.035	0.125***
Upper Mississippi (MN/WI)	−0.073***	0.045*	0.018	0.021
Missouri	−0.126***	0.100***	−0.020	0.075***
Daily × seasonal				
Great Lakes	−0.003	−0.010	0.002	0.008
Ohio	0.009	−0.006	−0.009	−0.002
Upper Mississippi (IL)	−0.009	−0.001	−0.036*	0.018
Upper Mississippi (IA)	0.007	0.022	0.008	0.007
Upper Mississippi (MN/WI)	−0.003	−0.004	0.002	0.010
Missouri	−0.001	−0.069***	0.003	−0.065***
Error variance	0.281	0.483	0.184	0.234
Gelman–Pardoe R^2	0.451	0.318	0.144	0.288

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

† HEL, highly erodible land.

Pardoe (2006) measures of explained variability. Overall, climate and weather, geophysical context, and on-farm experience tended to be significant predictors of the adaptive practices. In addition, the adaptive practices were significantly associated with each other. Relationship influence factors were generally not significant predictors, and perceived risk had different relationships for different practices.

Median warm-season precipitation was positively associated with the percentage of land that is artificially drained; climatologically, wetter areas are more extensively drained. Drainage is less prevalent in areas with a larger proportion of marginal soils. Drainage was also significantly related to the on-farm experience predictors, having positive relationships with proximity to a river or stream and experience with saturated soils, while having negative relationships with experience with river flooding and erosion. There were regional differences in the relationships between drainage and the frequency of daily extreme precipitation. No relationship was evident in Illinois, Iowa, and southern Indiana (Ohio basin), while a positive association was found in the northern (Great Lakes and Upper Mississippi basins) and western (Missouri basin) parts of the Corn Belt.

The predicted percentage of land in no-till increased with increasing median warm-season precipitation and proportion of marginal soils. Proximity to a river or stream was positively associated with the use of no-till, while a negative association was present for experience with saturated soils. Once again, relatively wet conditions in the western Corn Belt watersheds in the Missouri and Upper Mississippi basins predicted greater use of no-till, but the opposite relationship was found in the Great Lakes region. Two relationship influence factors, the overall influence and public agriculture, showed modest positive association with the percentage of land in no-till.

The model for cover crops accounted for the least explained variability among the four practices, but several predictors were significant. Climate had minimal association with cover crop use, with the exception of a negative relationship in the Ohio basin for warm-season precipitation anomaly. Experience with flooding predicted additional use of cover crops, while experience with saturated soils predicted reduced use of cover crops. The number of corn market outlets used was positively associated with land in cover crops. Farmers who reported a stronger decision-making influence from private agriculture entities (seed and chemical dealers) had lower expected cover crop use.

The percentage of HEL planted to crops was positively associated with the proportion of marginal soils and median warm-season precipitation. Positive relationships also existed with proximity to a river or stream and experience with significant soil erosion. As the number of total markets for corn increased, the expected percentage of HEL planted increased. Regional differences were present in the relationship between HEL and warm-season precipitation anomalies for the previous 5 yr. Parts of the western Corn Belt that were relatively wetter coincide with additional HEL planted to crops, and locations in the Ohio River basin that were relatively wetter had less predicted HEL planted to crops. Cropping of HEL was also strongly related to the other adaptive practices: drainage (negative), no-till (positive), and cover crops (positive).

Discussion

The timing, amount, and intensity of precipitation during the growing season can have large effects on the capacity of a crop to establish, grow and develop, and reach its full grain yield potential. Excess water on the landscape not only can compromise crop productivity but also influences soil erosion, off-field and off-farm nutrient losses, and degraded conditions across the landscape (Segura et al., 2014). Although our models are complex, with a variety of nuances that will need continued exploration, there are three key findings that inform our understanding of factors that influence Midwestern farmers' adaptation to changing conditions. First, warm-season precipitation varies across the six subregions of the Upper Midwest (2007–2011) and is significantly associated with variations in agricultural management practices. Second, increased wetness in the last 5 yr relative to the past 40 yr (warm-season precipitation anomaly) and median warm-season precipitation when linked to farmer practices (drainage, no-till, cover crops, and planting crops on HEL) reveal differential responses associated with geographic location (subregion), personal experiences with saturated soils and flooding, marginality of soils, and diversification of corn markets. Excessive precipitation can be problematic for traditionally wet parts of the eastern Corn Belt, but wetter conditions make the traditionally drier west more suitable for production.

Third, practices are significantly related to each other. Increased planting on HEL is associated with increased use of no-till and cover crops. This may partially be explained by NRCS requirements that when 50 acres (20 ha) or one third or more of the total field acreage are identified as highly erodible, a conservation plan must be in place to substantially reduce soil erosion projected to occur from the cropping use to retain eligibility for government benefit programs (such as USDA programs for crop insurance, marketing loans, and disaster assistance [Farm Service Agency, 2007]). No-till and cover crops are two conservation practices that have some capacity to mitigate runoff and soil loss on steep slopes. Part of the complementariness of these practices may be the different time scales associated with the capacity to manage excess water (e.g., drainage, long; cover crops and HEL, short).

Our results show that many Upper Midwest corn farmers use a suite of practices to help them better address management issues associated with too much water on the landscape. Farmers consider risks and uncertainties associated with future weather conditions on a daily basis. "As such, farmers have experience in dealing with climate variability and uncertainty, but increases in ranges of variability have the potential to put farms' adaptive capacities to the test, creating substantial challenges" (Crane et al., 2011, p. 180). This suggests that as increased climate variability becomes more visible, farmers will continue to explore how to develop resilient management systems that have the flexibility to serve multifunctional goals of crop productivity while addressing soil and water resource integrity. Although widespread awareness and discussions about climate change as a root cause have been limited in the farm community, adaptation to protect farm investments is occurring (NOAA, 2011; Rejesus et al., 2013). The NCA3 confirms our findings that agriculture has been adapting to recent climate changes (Hatfield et al., 2014). Analysis of climate change in the first half of the 21st century suggests that adaptation strategies may be effective in the near term to reduce threats to food security (Takle et al., 2013). However, the NCA3 urges accelerated innovation and adaptation to offset future increasing variability and uncertainty in climate conditions.

Our findings suggest that generalized regional climate conditions may not well represent individual localized farmers' actual and perceived experiences with excess precipitation. Farmer responses to local climate signals of increasing seasonal precipitation with time vary considerably by geography and the specific practice. There is a need for increased localized understanding of climate patterns and how farmers incorporate actual climate conditions and perceived experiences about excess precipitation into management decisions. The four adaptive strategies presented here are only some of the combinations of practices and innovations available to farmers. More accurate downscaled climate information and detailed local forecasts beyond 3- to 5-d projections could help farmers better develop an expanded suite of short- and long-term adaptive management strategies in response to changing precipitation patterns.

Researchers need to take seriously farmers' skills and capacity to adapt to erratic and variable circumstances in the short and long term (Crane et al., 2011). Timescales of adoption vary among practices, and there are important relationships among practices that need to be better understood if farmers are to successfully adapt their agroecosystems.

Conclusion

While global to continental climate projections offer a rule of thumb that wet areas will get wetter and dry areas drier, the Upper Midwest has a climatological gradient between wet and dry areas with substantial uncertainty as to which local areas will experience wetness and drought seasonally and across years. Localized growing season precipitation patterns are critical to seedling growth, rooting depth, and pollination and seem to be an important factor in how farmers perceive risk and prepare for extreme wet conditions. An unanswered question is, can farmers learn, experiment, and adapt quickly enough to effectively maintain their livelihoods as climate circumstances increasingly change? The NCA3 refers to adaptation as "actions to prepare for and adjust to new conditions, thereby reducing harm or taking advantage of new opportunities" (Melillo et al., 2014, p. 10). The strategies farmers put in place to manage future excess water on their fields and farms will affect the short- and long-term capacity of agriculture to be productive and assure the integrity of essential soil and water resources.

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Supplemental Material

Upper Midwest Climate Variations: Farmer Responses to Excess Water Risks

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CSCAP-U2U Survey

The survey data used in this study come from a February 2012 survey of farmers stratified across 22 HUC6 watersheds in the Corn Belt (Arbuckle et al., 2013b). Watersheds were selected according to a number of factors, primarily overall corn production. The target population was the largest producers, with sample selection limited to operations with at least 32.4 hectares (80 acres) of corn production and at least $100,000 in gross sales. The survey was sent to over 18,000 producers, and the analysis in this study utilizes the data from all 4,778 respondents, a response rate of 26%. The survey was conducted as part of a partnership between the Climate and Corn-based Cropping Systems Coordinated Agricultural Project (CSCAP, www.sustainablecorn.org) and the Useful to Usable (U2U) project (www.AgClimate4U.org). Loy et al. (2013) provide details of the survey methodology and many of the variables used in this study.

Latent Factors as Predictors

Some of the socioeconomic predictors used in the multivariate tobit model involve latent factors, and the details of the factor analysis used in their construction are presented here. The latent factors, their measurement variables and estimated loadings are presented in Supplemental Table S1. One perceived risk predictor is a latent factor that quantifies each subject's perceived risk related to excess water and is measured by survey items that asked respondents' level of concern about increased flooding, more frequent extreme rains, saturated soils, soil erosion, and nutrient loss. The other set of latent factors aim to quantify influence on decision-making from social relationships. This is a two-level factor model, with an overall influence factor that is measured by four specific influence factors. These specific influences, which are public agriculture, private agriculture, ag peers, and farm organizations, are then measured by several survey items that asked respondents about the level of influence of various actors on their management decisions. Estimation is performed through a Bayesian analysis for confirmatory factor analysis with ordinal response variables (Arbuckle et al., 2013a). The posterior mean factor scores are used as predictors in the multivariate tobit regression model.

Missing Data Model

We adopt a model-based strategy for imputation of missing predictors. The model for imputation is motivated by the conceptual framework in Figure 4. In particular, on-farm experience may be influenced by weather and climate as well as geophysical context. Therefore the covariates used to predict agricultural practices are divided into two groups, termed exogenous predictors and endogenous predictors (Supplemental Table S2). The J_α exogenous predictors for subject i are assembled into a vector $\mathbf{x}_{i,\alpha}$, with a similarly-defined vector $\mathbf{x}_{i,\beta}$ for the endogenous predictors. Then the model for imputation, adapted from Raghunathan et al. (2001), consists of a multivariate model for $\mathbf{x}_{i,\alpha}$ and a multivariate regression for the conditional distribution, $\mathbf{x}_{i,\beta} \mid \mathbf{x}_{i,\alpha}$. The exogenous predictors include the geophysical context, climate and weather, and control variables. The on-farm experience variables make up the endogenous predictors. The perceived risk predictors discussed in the factor analysis development have been constructed to have complete information for all subjects and are not included in the missing variable model.

Multivariate normal models for the two components of the missing variable model would be a convenient option, but the individual variables have very different marginal behavior, including a combination of discrete and continuous distributions. We therefore assume that the marginal distribution of an individual predictor, $x_{i,j}$ for subject i and variable j, can be represented as a transformation from an unobserved continuous random variable $x^*_{i,j}$ according to

$$x_{i,j} = F_j^{-1}\left(\Phi(x^*_{i,j})\right),$$

where Φ is the Gaussian cumulative distribution function (CDF) and F_j^{-1} is a quantile function, or inverse CDF, for predictor j. The multivariate regression model is then defined in terms of the unobserved continuous variables $x^*_{i,j}$,

$$\begin{aligned}
&\mathbf{x}^*_{i,\alpha} \sim \mathrm{N}\left(\boldsymbol{\mu}_\alpha, \boldsymbol{\Sigma}_\alpha\right),\\
&\mathbf{x}^*_{i,\beta} = \boldsymbol{\gamma}_0 + \boldsymbol{\Gamma}\mathbf{x}^*_{i,\alpha} + \boldsymbol{\delta}_i,\\
&\boldsymbol{\delta}_i \sim \mathrm{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_\beta\right).
\end{aligned}$$

The parameters to be estimated include the exogenous population mean vector $\boldsymbol{\mu}_\alpha$ and covariance matrix $\boldsymbol{\Sigma}_\alpha$, along with the regression intercepts $\boldsymbol{\gamma}_0$ and coefficient matrix $\boldsymbol{\Gamma}$, as well as the error covariance $\boldsymbol{\Sigma}_\beta$. In addition the forms for the quantile functions must also be specified and their parameters estimated.

Since several of the predictors of interest in the CSCAP-U2U data set are discrete ordered random variables, the quantile functions take the form of a step function defined by the K_j possible values for $x_{i,j}$. For example, there are two distinct values for proximity to a river and five distinct values for experiences with soil erosion and extreme weather. This approach is also adopted for the continuous variables by specifying a small set of discrete values across each variable's possible range.

Then the model for the unobserved continuous variables $x_{i,j}^{*}$ is

$$x_{i,j} = \begin{cases} X_j^{(1)}, & \text{if } x_{i,j}^{*} \le \lambda_j^{(1)}, \\ X_j^{(2)} & \text{if } \lambda_j^{(1)} < x_{i,j}^{*} \le \lambda_j^{(2)}, \\ \ldots & \\ X_j^{(K_j)} & x_{i,j}^{*} > \lambda_j^{(K_j)}. \end{cases}$$

The parameters $\lambda_j^{(k)}, k = 1, \ldots K_j$, are unknown and estimated for each variable as part of the estimation procedure for the missing data model. These parameters reflect the relative frequencies of each of the possible discrete values $X_j^{(k)}$. Supplemental Table S1 outlines the minimum discrete value $X_j^{(1)}$ and the maximum discrete value $X_j^{(K_j)}$ possible for each variable. Finally, if $x_{i,j}$ can assume multiple values between $X_j^{(k-1)}$ and $X_j^{(k)}$, and the unobserved variable falls in the appropriate range $\lambda_j^{(k-1)} < x_{i,j}^{*} \le \lambda_j^{(k)}$, then the actual realized value $x_{i,j}$ is assumed to be uniformly distributed between $X_j^{(k-1)}$ and $X_j^{(k)}$. This definition requires an additional lower bound $X_j^{(0)}$ be defined. This behavior occurs for exogenous predictors cropland, percent rent, total cattle, and total hogs. However, this is only the case for nonzero values as the missing data model does allow for zero values for these variables with a certain probability, consistent with that in the population.

Model-based imputation allows missing data to be simulated from the missing data model, but model parameters first need to be estimated. We perform both tasks in a Bayesian framework, using a strategy similar to the sequences of regression models used by Raghunathan et al. (2001). After collapsing the set of parameters to be estimated into a vector $\boldsymbol{\theta}$, Bayesian inference uses the posterior distribution of the parameters given the data,

$$p(\boldsymbol{\theta} \mid \mathbf{X}) \propto \pi(\boldsymbol{\theta})\ f(\mathbf{X}_\beta \mid \mathbf{X}_\alpha, \boldsymbol{\theta})\ f(\mathbf{X}_\alpha \mid \boldsymbol{\theta}),$$

which requires the specification of a prior distribution $\pi(\boldsymbol{\theta})$. We utilize diffuse multivariate normal prior distributions for the population mean vector $\boldsymbol{\mu}_\alpha$, regression intercepts $\boldsymbol{\gamma}_0$, and regression coefficients $\boldsymbol{\Gamma}$. The covariance matrices are parameterized as

$$\begin{aligned}\boldsymbol{\Sigma}_\alpha &= [\mathrm{diag}(\mathbf{S}_\alpha)]\mathbf{R}_\alpha[\mathrm{diag}(\mathbf{S}_\alpha)],\\ \boldsymbol{\Sigma}_\beta &= [\mathrm{diag}(\mathbf{S}_\beta)]\mathbf{R}_\beta[\mathrm{diag}(\mathbf{S}_\beta)],\end{aligned}$$

where $\mathrm{diag}(\mathbf{S}_\alpha)$ is a diagonal matrix of standard deviations and $\mathbf{R}_\alpha$ is a correlation matrix. We then specify independent uniform prior distributions for each of the standard deviations and a uniform prior on the space of positive definite matrices for $\mathbf{R}_\alpha$ and $\mathbf{R}_\beta$ (Barnard et al., 2000).

Imputation of missing values can naturally be incorporated into the Bayesian inference via the posterior predictive distribution. The vector of observed covariates, $\mathbf{x}_{i,obs}$, for subject i informs the posterior predictive distribution for the subject's vector of missing covariates, $\mathbf{x}_{i,miss}$, through the relation

$$p(\mathbf{x}_{i,miss} \mid \mathbf{x}_{i,obs}) = \int f(\mathbf{x}_{i,miss} \mid \boldsymbol{\theta}, \mathbf{x}_{i,obs})\, p(\boldsymbol{\theta} \mid \mathbf{X})\, d\boldsymbol{\theta}.$$

Ultimately we are interested in the impact of the uncertainty due to the missing covariates on inference in the multivariate tobit model for adaptive agricultural practices. This is accomplished by generating random samples from this posterior predictive distribution and incorporating these samples in the estimation for the multivariate tobit model. The posterior predictive distribution is not available in closed form, so sampling is performed with Markov Chain Monte Carlo

(MCMC) methods (Gelman et al., 2004). Specifically, a Gibbs sampler is used to sample from two key conditional distributions at each iteration of the algorithm.

1. Sample from the posterior distribution of the model parameters, $p(\boldsymbol{\theta} \mid \mathbf{X})$, given both missing and observed covariates.
2. Sample from the conditional posterior predictive distribution for the missing covariates, $p(\mathbf{x}_{i,miss} \mid \mathbf{x}_{i,obs}, \boldsymbol{\theta})$, for each subject with missing data.

The marginal posterior predictive distribution is ultimately sampled through several thousand iterations of the MCMC procedure. These sampled values of the missing covariates are saved for use in the multivariate tobit model.

Bayesian Analysis of Tobit Regression Model

The multivariate tobit regression model (Amemiya, 1984) connects an unobserved continuous random variable $y^*_{i,j}$ with each response, $y_{i,j}$, which represents the reported percentage of land in use for practice *j* by subject *i*. The multivariate regression model is

$$y^*_{i,j} = \boldsymbol{x}'_i \boldsymbol{\beta}_j + \varepsilon_{i,j} .$$

As with the model for missing covariates, we perform a Bayesian analysis for the multivariate tobit model. The Bayesian analysis requires that prior distributions be specified for all model parameters, which include the regression coefficients $\boldsymbol{\beta}_j$ and the covariance matrix of the error terms $\boldsymbol{\Sigma}$. We specify diffuse Gaussian priors for the regression coefficients and develop priors for the standard deviations and correlation matrix of the error terms using the approach of Barnard et al. (2000), similar to the missing covariate model. In this approach the covariance matrix is decomposed as

$$\boldsymbol{\Sigma} = [\mathrm{diag}(\mathbf{S})]\mathbf{R}[\mathrm{diag}(\mathbf{S})],$$

where diag(**S)** is a diagonal matrix of standard deviations and **R** is a correlation matrix. We then specify independent uniform prior distributions for each of the standard deviations and a uniform prior on the space of positive definite matrices for **R**.

A Gibbs sampler is used to generate samples from the posterior distribution through successive sampling from several conditional distributions. This procedure incorporates the sampling of missing covariates from their posterior predictive distribution. The conditional sampling steps at each iteration of the Gibbs algorithm proceed as follows.

1. Sample the missing covariates from the posterior predictive distribution defined in the missing covariate model. These samples can be generated offline, but there is a unique set of sampled missing values for each iteration of the current algorithm.
2. Sample from the conditional posterior distribution of the error correlation matrix, $p(\mathbf{R} \mid \mathbf{X}, \mathbf{Y}^*, \mathbf{S}, \mathbf{B})$. A random-walk Metropolis-Hastings (MH) step is used to sample from this distribution (Gelman et al., 2004).
3. Sample from the conditional posterior distribution of the error standard deviations, $p(\mathbf{S} \mid \mathbf{X}, \mathbf{Y}^*, \mathbf{R}, \mathbf{B})$ with a MH step.
4. Sample from the conditional posterior distribution of the regression coefficients, $p(\mathbf{B} \mid \mathbf{X}, \mathbf{Y}^*, \mathbf{R}, \mathbf{S})$. With a multivariate Gaussian prior for **B**, the conditional posterior is also multivariate Gaussian and can be sampled directly.
5. Sample from the conditional posterior distributions for each of the unobserved continuous variables, $p(y^*_{i,j} \mid \mathbf{y}_i, \mathbf{y}^*_i, \mathbf{X}, \mathbf{R}, \mathbf{S})$. This is a truncated Gaussian

distribution with a range that depends on the value of $y_{i,j}$, and samples can be drawn by inverting the Gaussian CDF. This posterior can also be sampled for any $y^*_{i,j}$ with a corresponding $y_{i,j}$ that is missing. In this case, the conditional posterior is simply Gaussian.

The MCMC procedure also allows the computation of Gelman and Pardoe's (2006) measure of explained variability. The measure is

$$R_j^2 = 1 - \frac{\mathrm{E}\left(\left(y^*_{i,j} - \hat{y}^*_{i,j}\right)^2\right)}{\mathrm{E}\left(\left(y^*_{i,j} - \bar{y}^*_j\right)^2\right)},$$

where E represents the posterior mean, which can be the Monte Carlo mean from the posterior simulation. The conditional means $\hat{y}^*_{i,j}$ are defined by the regression coefficients and the other other unobserved variables $y^*_{i,j'}, j' \neq j$. This conditional mean can be computed from the marginal distribution of $\mathbf{y}^*_i$ using techniques outlined in Cressie and Wikle (2011).

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Supplemental Table S1. Survey items used in factor analysis for relationship influence and excess water risk variables. Posterior means and 95% credible intervals for standardized factor loadings are also included.

Factor/Variable	Standardized Loadings	
	Posterior Mean	95% Credible Interval
Overall Influence[1]		
Public Agriculture	0.828	(0.799, 0.856)
Farm Organizations	0.921	(0.890, 0.952)
Ag Peers	0.524	(0.483, 0.563)
Private Agriculture	0.428	(0.390, 0.465)
Public Agriculture[2]		
NRCS	0.669	(0.645, 0.693)
State Climatologist	0.786	(0.766, 0.805)
University Extension	0.808	(0.789, 0.825)
State Department of Agriculture	0.794	(0.774, 0.813)
Farm Organizations[2]		
Farm Organizations	0.896	(0.889, 0.903)
Ag Peers[2]		
Other Farmers	0.862	(0.851, 0.871)
Private Agriculture[2]		
Seed Dealers	0.904	(0.866, 0.940)
Chemical Dealers	0.878	(0.843, 0.917)
Excess Water Risks[3]		
Increased Flooding	0.704	(0.680, 0.726)
More Frequent Extreme Rains	0.842	(0.825, 0.857)
Saturated Soils and Ponded Water	0.901	(0.886, 0.916)
Loss of Nutrients	0.707	(0.682, 0.731)
Increased Soil Erosion	0.656	(0.629, 0.683)

[1]The overall influence factor is measured by four latent factors.

[2]The measurement variables for public agriculture, farm organizations, ag peers, and private agriculture correspond to survey items that asked, “Please indicate how influential the following groups and individuals are when you make decisions about agricultural practices and strategies.” Response options were no contact, no influence, slight influence, moderate influence, or strong influence.

[3]The measurement variables for excess water risks correspond to survey items that asked, “How concerned are you about the following potential problems for your farm operation?” Response options were not concerned, slightly concerned, concerned, or very concerned.

Supplemental Table S2. Covariate groups for missing data model. The percentage of missing values for the full sample (n=4,778) is reported for each variable. Characteristics of the quantile functions in the missing data model are summarized in the final three columns.

Exogenous Covariates $\mathbf{x}_\alpha$	Percent Missing	Min Value $X_j^{(0)}$ or $X_j^{(1)}$	Max Value $X_j^{(K_j)}$	Categories K_j
Median Seasonal Precipitation	0.0	457.2 mm	762.0 mm	8
Seasonal Precipitation Percentile Rank	0.0	0.0 %	100.0 %	7
Daily Extreme Precipitation Frequency	0.0	0.0 %	2.5 %	6
River	3.9	0 (No)	1 (Yes)	2
Marginal Soil	0.0	0.0 %	100.0 %	6
Education	1.4	1 (Less than High School)	6 (Graduate Degree)	6
Cropland	0.0	0 ha	4,047 ha	8
Percent Rent	1.3	0.0 %	100.0 %	6
Cattle	0.0	0	5,000	3
Hogs	0.0	0	10,000	3
Endogenous Covariates $\mathbf{x}_\beta$	**Percent Missing**	**Min Value $X_j^{(1)}$**	**Max Value $X_j^{(K_j)}$**	**Categories K_j**
Saturated Soils	1.6	0 (No)	1 (Yes)	2
Flooding	2.0	0 (No)	1 (Yes)	2
Erosion	4.4	1 (Strongly Disagree	5 (Strongly Agree)	5
Variable Weather	4.1	1 (Strongly Disagree)	5 (Strongly Agree)	5