Spatially representing vulnerability to extreme rain events using Midwestern farmers' objective and perceived attributes of adaptive capacity

Maaz Gardezi*

J Gordon Arbuckle Jr

The affiliations and addresses:
Maaz Gardezi
004A Hansen Hall, Box 670A
Department of Sociology & Rural Studies
South Dakota State University
Brookings, SD 57007
maaz.gardezi@sdstate.edu

J Gordon Arbuckle Jr
303C East Hall
Iowa State University
Ames, IA 50011
Phone: 515-294- 1497
FAX: 515-294- 0592
arbuckle@iastate.edu

*corresponding author: Maaz Gardezi
maaz.gardezi@sdstate.edu
515-686-1594

Acknowledgments:
This research is part of a regional collaborative project supported by the USDA-NIFA, Award No. 2011-68002-30190, “Cropping Systems Coordinated Agricultural Project: Climate Change, Mitigation, and Adaptation in Corn-based Cropping Systems.” Project Web site: sustainablecorn.org.

Abstract

Potential climate change-related impacts to agriculture in the Upper Midwest pose serious economic and ecological risks to the U.S. and the global economy. On a local level, farmers are at the forefront of responding to the impacts of climate change. Hence, it is important to understand how farmers and their farm operations may be more or less vulnerable to changes in the climate. A vulnerability index is a tool commonly used by researchers and practitioners to represent the geographical distribution of vulnerability in response to global change. Most vulnerability assessments measure objective adaptive capacity using secondary data collected by governmental agencies. However, other scholarship on human behavior has noted that socio-cultural and cognitive factors, such as risk perceptions and perceived capacity, are consequential for modulating peoples' actual vulnerability. Thus, traditional assessments can potentially overlook people's subjective perceptions of changes in climate and extreme weather events and the extent to which people feel prepared to take necessary steps to cope and respond to the negative effects of climate change. This paper addresses this knowledge gap by: (1) incorporating perceived adaptive capacity into a vulnerability assessment; (2) using spatial smoothing to aggregate individual-level vulnerabilities to the county level, and (3) evaluating the relationships among different dimensions of adaptive capacity to examine whether perceived capacity should be integrated into vulnerability assessments. The result suggests that vulnerability assessments that rely only on objective measures might miss important socio-cognitive dimensions of capacity. Vulnerability indices and maps presented in this paper can inform engagement strategies for improving environmental sustainability in the region.

Keywords: climate change vulnerability, farmers, perceived adaptive capacity, spatial statistics

1. INTRODUCTION

The Upper Midwestern United States is a national and global leader in commodity crop production, mainly corn *(Zea mays)* and soybeans *(Glycine max)*. In 2015, approximately $68 billion of corn and soybeans was produced in this region.[(1)] This region also produces one-third of the global corn supply and one-quarter of its soybeans.[(2)] Current and predicted climate change-related impacts to corn and soybean crops include reduction in crop yield, higher crop stressors due to extreme rain events, soil erosion, droughts, floods, and weed and insect pests.[3] These impacts on agriculture in the Upper Midwest, pose serious economic and ecological risks to the U.S. and the global economy.

Extreme precipitation represents one of the greatest threats to agricultural productivity and environmental sustainability[4–6] Extreme precipitation is defined as an event with more than four inches (101.6 millimeters) of rain in a 24 hour period.[6] Such events can reduce the efficiency or total factor productivity (TFP) of agriculture.[7] For example, in the early growing season, extreme precipitation events can delay planting and increase farmers' economic risks. Before the crop canopy is established, extreme precipitation events increase the risk of soil erosion[8,9] and exacerbate negative off-farm environmental impacts, such as an increase in the transportation of nitrogen, phosphorus and other nutrients into ground water, streams, and lakes.[9] Excessive sediment and nutrient export from corn-soybean producing agricultural lands is a significant driver of nonpoint source pollution loads in the Mississippi River Basin and the Gulf of Mexico.[10,11] Thus, extreme precipitation events can not only hurt short-term crop productivity but also exacerbate soil erosion, off-field, and off-farm nutrient losses across the region.[9]

The US 3rd National Climate Assessment defines vulnerability as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes"[12, p. 672]. Vulnerability is a function of exposure, sensitivity, and adaptive capacity. In agriculture, farm-level vulnerability to extreme rain events can be determined by the interaction between (1) biophysical stressors or exposure, such as extreme rainfall events; (2) biophysical impacts or sensitivity, which are mediated by soil characteristics and use of adaptive management practices, and (3) adaptive capacity, such as availability and access to financial, technical, and institutional resources needed for facilitating adaptation. Assessing the exposure, sensitivity, and adaptive capacity at the farm-level can potentially help to explain the qualities or deficiencies that make a farm less or more at risk to a range of stressors related to extreme precipitation events.

In the environmental change literature, most vulnerability assessments have measured objective attributes of adaptive capacity using secondary data collected by government agencies. These studies often frame the likelihood that people and communities will adapt to climate change as a function of access to financial and technical resources and suitable institutional arrangements.[13,14] However, other scholarship on human behavior has noted that in addition to the objective attributes of adaptive capacity, socio-cultural and cognitive factors, such as risk perceptions and perceived capacity, are consequential for modulating peoples' actual vulnerability.[15,16] For example, perceived adaptive capacity (PAC)—defined as the "extent to which [people] feel prepared to endure changes and take necessary steps to cope with them" [17, p. 50]—has been found to influence peoples' decisions about both the significance of climatic risks and the willingness to take actions to cope, adapt or ignore such risks.[15,16] A better understanding of the relationships between objective and subjective measures of adaptive capacity in agriculture has implications for climate change policy and programs, especially if farmers are systematically under- or over-estimating their own ability to adapt to weather and climatic impacts. Moreover, examining the objective attributes of adaptive capacity in conjunction with the subjective measures of capacity may facilitate identification of culturally acceptable adaptation actions available to farmers.

The objectives of this study are to (1) incorporate perceived adaptive capacity into a vulnerability assessment, (2) use spatial smoothing to aggregate individual-level vulnerabilities to the county level, and (3) evaluate the relationships among different dimensions of adaptive capacity to examine the degree to which our measures of objective and perceived adaptive capacity correlate. We propose that this study, by incorporating measures of perceived adaptive capacity into a vulnerability assessment framework that typically employs only objective measures of capacity, will add to our understanding of farmers' proclivity to take suitable actions for adaptation and overall vulnerability.[18] A better understanding of the relationships between perceived and objective adaptive capacity may help to inform assessment of whether or not measures of perceived capacity should be integrated into vulnerability assessments.

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

2 LITERATURE REVIEW:

Global climate change is one of the most significant challenges facing agriculture in the 21st century. It is already affecting global and regional agricultural productivity with predicted impacts that will continue to increase in intensity and frequency.[3,19] Potential climatic and weather-related threats to agriculture represent threats to food security, livelihoods, and societal stability.[20,21] For example, limited availability of food, rising food prices, and limited access to food in 2007-2008 has been linked to political instability and regional conflict in 48 countries.[22] On a local level, farmers are at the forefront of responding to the impacts of climate change on agriculture.[23] Examining the dynamic interactions between climatic risks and social, economic, and institutional conditions, can highlight the qualities or deficiencies that make a farm/farmer more or less vulnerable to current and future climate change and variability.[24]

The third National Climate Assessment defines vulnerability as "The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes."[12, p. 672] In the environmental change and disaster studies literature, vulnerability is generally considered as a function of the likelihood and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity.[25–27] Exposure is the likelihood that a system will experience hazard. Sensitivity refers to the likely magnitude of effect that the hazard will have on a system. Thus, exposure is an external characteristic of a system, and sensitivity is an internal characteristic. Agricultural systems are human-dominated ecosystems, so the agriculture's vulnerability to climate change depends on both the biophysical effects of climate change but also on the responses taken by individuals and institutions to moderate those effects.[28,29]. These individual and social responses are dependent on adaptive capacity—the ability of the system to cope, adapt, and respond to the negative effects of climate change[25,30,31]. In the following section, we briefly highlight some of the current and potential changes in precipitation (exposure) and the impacts (sensitivity) of these changes on Midwestern U.S. agriculture.

2.1 Exposure: Changes in precipitation for the Midwest

Exposure is the likelihood that a system will experience hazard.[12] Observed and projected changes in climate highlight that Midwestern U.S. is exposed to several climatic and weather-related changes, primarily driven by changes in temperature and precipitation. Of interest to this study is to examine agriculture's exposure to changes in precipitation. In the last century, there has been a 20% increase in annual precipitation in the U.S., much of which has been driven by an increase in extreme rain events—events with more than four inches (101.6 millimeters) of rain in a 24-hour period.[6] In the Midwest, the frequency of days with extreme rain events has increased by almost 50% in the entire 20th century.[4] There is seasonal variation in the observed trend, with 85% of extreme rain events occurring during the summer period (May-September). Projected changes in precipitation suggest that it is very likely that extreme rain events will continue to increase in the Midwest throughout the 21st century.[24]

Shifts in climatic conditions in the Midwest, such as changes in extreme precipitation events at important stages in crop development, pose risks of significant damages to crop productivity and environmental sustainability.[24] On an annual basis, extreme rain events can delay planting or cause waterlogging that reduces the efficiency or total factor productivity (TFP) of agriculture.[7] Extreme rains are also implicated in degradation of soil resources through erosion, which reduces the long-term productive capacity of agricultural lands.[8,9] Moreover, off-farm impacts, especially the transportation of nitrogen, phosphorus and/or other nutrients into ground water, streams, and lakes is also exacerbated greatly by extreme rain events.[9]

2.2 Sensitivity: Extreme rain events and adaptive practices

In the Upper Midwest, projected increases in extreme rain events pose a major threat to soil quality and agricultural productivity.[4–6] As discussed above, extreme precipitation events can reduce both annual and long-term crop productivity and exacerbate off-field, and off-farm nutrient losses across the region.[9] Thus, we examine sensitivity as the potential impacts of extreme rain events on farm-level soil erosion.[24]

Sensitivity, can be reduced if farmers implement adaptive management practices to protect the land and retain soils and nutrients.[32] Adaptive best management practices, also known as soil and water conservation practices, can potentially reduce soil erosion rates and loss of soil organic carbon and other important nutrients.[33] These management practices provide the farm/farmer an opportunity to modulate the sensitivities associated with extreme rain events. Sensitivity is the interaction between farmers' use of adaptive management practices (social) and soil characteristics (biophysical/ecological). Table I provides a brief description of the key adaptive management practices that we examine in this research.

Table I. Description of Adaptive Management Practices included in this study

Adaptive Management Practice	Description
Agricultural Drainage	Drainage tile systems are used to drain away excess water and transform poorly drained soils into productive croplands.[9] Drainage can directly benefit the soil structure and reduce soil erosion. However, research suggests that drainage can also increase the transfer rate of nitrate from fields to streams and rivers.[34]
Cover crops	Cover crops are "grown primarily for the purpose of protecting and improving soil between periods of regular crop production."[35] There are a number of ways in which cover crops can reduce the harmful impact of heavy precipitation events on Upper Midwestern corn-based cropping system. Cover crops can help farmers adapt to the impacts of climate change by (1) preventing soil erosion, (2) reducing the flow of nutrients, such as nitrate, from farms into streams and lakes, (3) improving water and nutrient cycling, (4) controlling pest and disease, and (5) improving field level soil organic carbon, soil structure, and soil carbon retention.[36,37]
No-Till	No-till is a farming practice that has the potential to protect soil erosion especially during extreme rain events. No-till is a form of tillage where the "soil is left undisturbed from harvest to planting except for strips up to ½ of the row width for planting the seed, with weed control accomplished with herbicides and methods other than tillage."[9, p. 814] Reduction in tillage or no-tillage has the potential to reduce soil erosion, increase soil porosity, and increase nutrient retention.[23] Benefits to soil properties from no-till farming can reduce the harmful impact of heavy precipitation events on the soil surface by reducing soil erosion.[9]

2.3 Objective attributes of adaptive capacity

In the environmental change literature, the term 'resilience' is defined as a system's ability of to respond to a shock and still maintain its general attributes, while also retaining capacity to evolve or transition to a more desirable state.[38,39] Adaptive capacity represents a primary social mechanism for regulation of system resilience.[40] Adaptive capacity includes three distinct, but related, parts: a resource system; the ability of individuals and communities to access those resources; and, the governance system that structures and mediates the management of resources and systems of access.[38] Recent research on adaptive capacity has highlighted various factors as determinants of adaptive capacity, including economic resources, technology, knowledge and skills, institutions, social capital, and infrastructure.[27,40,41]

In the context of adaptation in agricultural systems, studies have often focused on relationships between farmers' and farming communities' opportunities to cope, adapt, and respond to the negative effects of climate change and their access to financial resources, knowledge, and suitable institutional arrangements.[42,43] For example, Moser et al.[42] found that financial resources were the most significant determinant of Northeastern U.S. dairy farmers' adaptive capacity. Similarly, Swanson et al.[43] identified economic resources, technology, and knowledge to enhance the adaptive capacity of farmers and farm organizations in the Canadian agriculture sector. Most studies have examined external or objective dimensions of adaptive capacity, i.e., "the material and immaterial resources and the assets and entitlements that predetermine the decision options available to an actor at any point in time to cope with losses and to anticipate future harm".[44, p. 228] In this study, we examine some of the key objective attributes of adaptive capacity for Midwestern U.S. farmers. These include: (1) financial resources such as farm income, land size, and farm subsidies in the form of direct payments; (2) institutional resources, such as, opportunities to sell crops in multiple markets, and (3) technical resources, such as farmers' education levels and use of weather and climate-related decision support tools.

2.4 Perceived attributes of adaptive capacity

While most vulnerability assessments posit access to financial and technical resources and suitable institutional arrangements as the critical arbiters of adaptive capacity,[13,14] recent scholarship on social-ecological and psychological resilience has highlighted the importance of socio-cognitive factors, such as agency, as determinants of individuals' and communities' adaptive capacity to respond to environmental stressors.[15–17,45]. Agency refers to the ability of individuals to act freely and make independent choices.[45] At the individual level, agency can be influenced by personal beliefs and values; how people perceive risks and opportunities, and broader structural elements, which can either facilitate or serve as barriers to adaptation.[45] For example, at the individual level, farmers' perceived adaptive capacity in relation to climate change and variability can be composed of such factors as perceptions about their financial and technical knowledge, perceptions about the institutional environment, such as faith in crop insurance programs, and perceptions about their kinship and centrality in social networks. The determinants of perceived adaptive capacity can be local (e.g., the presence of a strong kinship network which has the potential to relieve stress) as well as broader socio-economic (e.g., a crop insurance program). Thus, perceived adaptive capacity describes the internal dimension of adaptive capacity, i.e., the individual's perception of the suitability of available resources (financial, technical, institutional, etc.) needed for facilitating adaptation.[15,17,29] It highlights the "…extent to which people feel they are prepared to endure changes or impacts and undertake steps to cope with them."[17]

Recent research on agricultural and ranching communities in the U.S.[29] and Australia[28] have used surveys and in-depth interviews to identify specific perceived dimensions of farmer's adaptive capacity. These include: perceived agency in terms of financial resources and technical skills (also referred to as *self-efficacy)*; perceptions of the extent to which people can utilize agency for learning and seeking new knowledge (*learning and knowledge seeking*); expectations that the institutional context, such as crop insurance programs can facilitate or buffer individuals from risk (*decision constraints*); and social networks that may help farmers in accessing and personalizing information regarding adaptation to climate change (*centrality in social networks*). On an individual level, farmers' perceived adaptive capacity is the perception of their ability to cope with change and withstand disturbances to their farm enterprise. It measures the confidence that farmers have in their ability to perform certain activities or implement a specific climatic risk mitigation action. Figure 1 summarizes the perceived and objective attributes of adaptive capacity commonly depicted in the climate change adaptation literature.

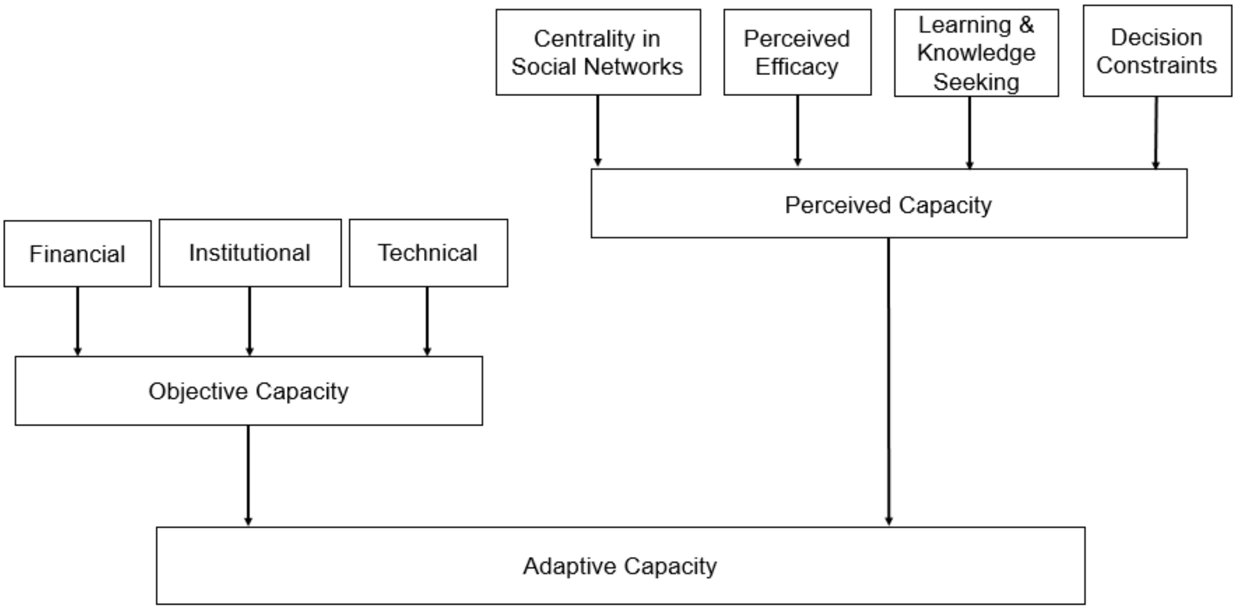

Fig 1. Objective and Perceived Attributes of Adaptive Capacity

2.5 Vulnerability framework

In section 2.1 and 2.2 we reviewed the concepts of exposure and sensitivity and their roles as dimensions of vulnerability. In section 2.3 and 2.4 we established that perceived adaptive capacity, in addition to objectively measured capacity, is also a potentially important mediator of adaptive action. In this section we outline a conceptual framework that brings these elements together in a vulnerability framework that is appropriate for the unique context of Midwestern agriculture.

Vulnerability frameworks generally outline the interactions between environmental services and social outcomes, in part to examine the qualities or deficiencies that make coupled human and natural systems (CHANS) or social-ecological systems (SES) more or less vulnerable to a range of social, economic, institutional and biophysical stressors.[46] In the last decade, use of vulnerability frameworks has become more common, primarily for recognizing the synergy or interdependency of the human and environmental subsystems in determining the vulnerability to and capacity to respond to climate change.[47] The conceptualization of vulnerability frameworks has advanced from solely examining the distribution of physical losses[48] to integrating biophysical and social, economic, and political drivers of vulnerability across space and time.[49,50]

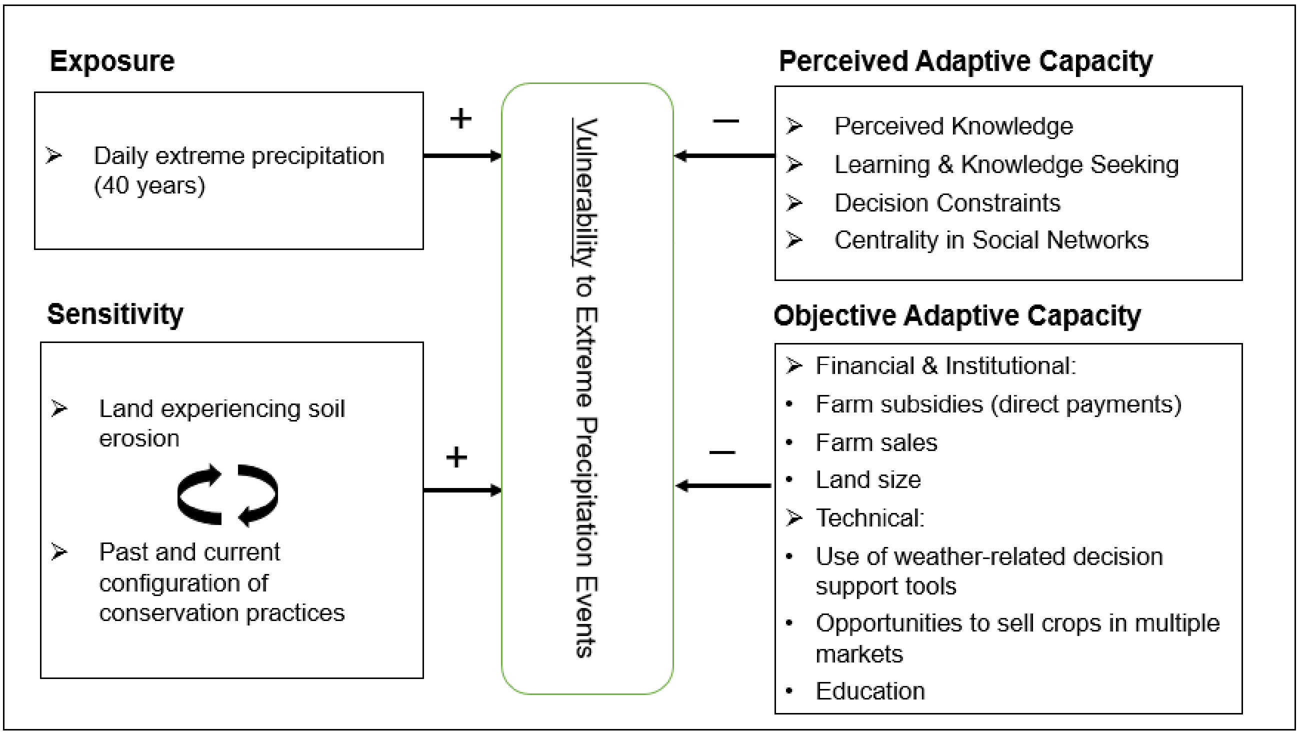

Fig 2. Vulnerability Framework for Midwestern Farmers

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

3 METHOD

3.1 Study Area & Data Collection

The study area comprises the Midwestern U.S. states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin (Fig 3). These 11 states are responsible for more than one-third of the global corn supply, represent nearly 65 percent of all corn acres and 55 percent of soybean acres in the U.S.[51] The climate of this region is continental with large seasonal differences in precipitation and temperature. Geographically, weather and climatic features vary from the west (warmer and drier) to east (cooler and wetter). Areas in the west can experience more recurrent summer drought than areas in the eastern and southeastern Midwest. There are regional variations in soil erosion potential due to complex multi-level interactions between geophysical properties and human activity.

Fig 3. Map of US & Study Region

Primary data used in this study is from a February 2012 survey of corn and soybean farmers in 11 Midwestern states (Fig 3). The survey was mailed to a stratified random sample of farmers in a contiguous set of 22 watersheds.[51] The USDA National Agricultural Statistics Service (NASS) Census of Agriculture's master list, which is the most comprehensive and up-to-date list of US farmers was the sampling frame. Only farmers who grew at least 80 acres of corn and grossed farm sales value in excess of $100,000 per year were included in the mailing list. The survey was mailed by NASS to 18,707 eligible farmers. Completed surveys were received from 4,778 farmers for an effective response rate of 26%. Non-response bias checks compared respondent demographics to U.S. Census of Agriculture data, and no meaningful differences between respondents and non-respondents were observed.[51] To maintain the privacy of respondents, the farm-level geospatial coordinates were not stored in the database. However, zip codes and county FIPS were used to identify farmers' location. The survey measured farmers' climate change-related risk perceptions, use of conservation practices, past experiences with climate change-related hazard, beliefs about climate change and other sociodemographic features.

Prior to index construction, a Multivariate Imputations by Chained Equations (MICE) was employed in the software R to impute missing values.[52] MICE uses Gibbs sampling to generate plausible values for missing data by examining the underlying patterns in the data. The Predictive Mean Matching (PMM) method was used to help ensure that the imputed values were credible. The PMM method provides robust imputed values especially if the assumption of normality is violated for some of the imputed values.[53] The percentage of missing values prior to imputation are shown in Table A (Appendix A). Overall, 5 datasets were imputed. The density of the imputed data for all 5 datasets were compared with the density of the observed data (Figure A in Appendix). This comparison highlighted that the density of the observed and imputed datasets for each variable are similar, i.e., we can assume that the missing values are missing at random and the imputation method generated plausible values for missing data.

3.2 Measuring components of vulnerability

3.2.1 Exposure to extreme precipitation events

Farmers' experience of extreme precipitation events was measured as number of days that they had experience extreme precipitation events, defined as events registering in 99th percentile of daily precipitation for a given month for the record covering 1971-2011.[(54)] The data was obtained from Loy et al.[(54)], who constructed various measures of extreme weather for the Upper Midwestern region from the National Weather Service (NWS) Cooperative Observer (COOP) data archive (see Loy et al.[(54)] for details on variable construction). Daily extreme precipitation values from the weather station nearest to the farm were assigned to each farmer in the survey. Table II provides a statistical description of daily extreme precipitation that we employed in this study.

3.2.2 Sensitivity

We used two items to measure farm-level sensitivity to extreme precipitation events. The first item measured the percent of land designated as "marginal lands" in each county to represent the local soil characteristics. The data to measure soil characteristics were obtained from Loy et al.[(54)], who calculated the percent of non-irrigated marginal lands (by county) using the Soil Survey Geographic (SSURGO) database. The characteristics of soil were grouped according to the USDA Natural Resources Conservation Service (NRCS) land capability classification system (see Loy et al.[(54)] for a detailed account of variable construction). The second item used for measuring sensitivity was the maximum percentage of land on which farmers' self-reported to use adaptive management practices. Four farm-level adaptive management practices were included in our analysis: drainage, reduced and no-till farming, and cover crops. Justification for the including these practices in our analysis is provided in Table I. Table II provides a statistical description of the two items that we employed in this study to measure sensitivity.

Table II. Exposure and Sensitivity

Components & Statements	Mean	Std. Dev	Range
Exposure (Daily precipitation extremes)	0.39	0.14	1
Sensitivity			
In 2011, approximately what percentage of the land (owned and/or rented) you farmed was…			

• Artificially drained through tile or other methods	49.09	40.01	100
• Reduced tillage (e.g., strip, ridge tillage)	32.63	39.8	100
• No-till	37.2	38.74	100
• Planted to cover crops	6.38	16.45	100
Percent of non-irrigated marginal lands by county	0.17	0.16	0.97

The Latent Profile Analysis (LPA) technique was employed to estimate profiles of farmers' sensitivity. LPA is a probability-based clustering technique that aims to explain the relationships observed in multivariate data by grouping cases according to an unobserved variable.[55] In this study, LPA is used to assign farmers to discrete profiles based on (1) the characteristics of soil in the farmers' county and (2) farmer's self-reported use of adaptive management practices on their farm. The LPA assumes that the population is comprised of a mixture of P different profiles of survey respondents with each profile having separate response distributions for each observed item.

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

$$y = \Lambda\eta + \varepsilon \qquad \text{Equation (1)}$$

Where,

y is a vector of observed indicator variables

Λ is a matrix of classification probabilities

η is a vector of classification profiles

ε is a vector of classification errors

Table III. Summary of Latent Profile Analysis for Profiles 2 – 5

	2 Profiles	3 Profiles	4 Profiles	5 Profiles
AIC	177397	174863	173369	171414
BIC	177500	175005	173550	171634
Entropy	.994	.918	. 915	.920
	2 *vs* 1profile	3 *vs* 2 profiles	4 *vs* 3 profiles	5 *vs* 4 profiles
Lo Mendell Rubin	3980	2496	2164	1310
	p = .00	*p* = .00	*p* = .00	*p* = .00
Number of farmers in each profile	P1= 4526 P2= 252	P1= 2361 P2= 2184 P3=233	P1=2301 P2=1952 P3= 302 P4= 223	P1=269 P2=2234 P3=1859 P4=321 P5=92

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

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

3.2.3 Objective adaptive capacity:

We selected six items to assess farmers' objective adaptive capacity. Following Swanson et al.[43] the items measure two dimensions of objective adaptive capacity: (1) financial and institutional capacity and (2) technical capacity. Farm sales, land size, and farm subsidies were associated with farmers' financial and institutional capacity. Availability and accessibility of weather and climate-related decision support tools, opportunities to sell crops in multiple markets, and farmers' education represented farmers' technical capacity. Factor analysis was used to condense information from these six items into two indices, each representing a single component of objective adaptive capacity (Table IV). Both components of objective adaptive capacity were then averaged to create a single index representing farmers' overall objective adaptive capacity. We adapted the method used in the Livelihood Vulnerability Index[56] to normalize the objective capacity index. By adapting their approach, we calculated the objective capacity index as the ratio of the difference of the actual objective capacity and the minimum objective capacity in our sample of farmers, and the range of objective capacity (Fig 5 in the results section).

TABLE IV. Objective Adaptive Capacity

Components	Statement	Mean	Std. Dev	Range	Factor weight
Financial & Institutional Capacity	Farm Sales ($)	457000	653461	20060000	0.95
	Land size (Acres)	429	469	10150	0.83
	Farm subsidies (direct payments) ($)	12760	62120	16000	0.74

Technical Capacity	Availability and accessibility of weather and climate-related decision support tools	2.69	1.95	8	0.47
	Opportunities to sell crops in multiple markets	1.98	0.81	6	0.41
	Education	3.26	1.32	5	0.23

3.2.4 Perceived adaptive capacity:

We selected 13 items that corresponded to the four perceived dimensions of adaptive capacity: *self-efficacy*; *learning and knowledge seeking*; *decisions constraints*, and *centrality in social networks* (some outlined by Marshall et al.[28] and Eakin et al.[29]). Factor analysis with varimax rotation was used to condense information into these four components of perceived adaptive capacity (Table V). Since decision constraints are likely to reduce farmers' perceived capacity, factor scores for *decision constraints* were subtracted from the other three components of perceived adaptive capacity. The perceived adaptive capacity index was also normalized and the scores were distributed on a continuous scale between 0 and 1 (Fig 5 in the results section).

TABLE V. Perceived Adaptive Capacity

Components	Statement	Mean	Std. Dev	Range	Factor weight
Self-efficacy	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	4	0.89
	I have the financial capacity to deal with any weather-related threats to the viability of my farm operation	3.25	0.93	4	0.66
	I am confident in my ability to apply weather forecasts and information in my crop related decisions	3.58	0.70	4	0.31
Learning & knowledge seeking	It is important for me to talk to other farmers about new farming practices and strategies	3.59	0.79	4	0.61
	It is important for me to visit other farms to look at their practices and strategies	3.31	0.88	4	0.67
	I am willing to use seasonal climate forecasts to help me make decisions about agricultural practices	3.14	0.82	4	0.34
Decision constraints	My farm operation will likely be harmed by climate change	2.97	0.79	4	0.76
	I am concerned that available best management practice technologies are not effective enough to protect the land I farm from the impacts of climate change	3.67	0.80	4	0.63
	Changes in weather patterns are hurting my farm operation	2.66	0.85	4	0.54
	Crop insurance and other programs will protect the viability of my farm operation regardless of weather (reversed)	2.96	0.91	4	0.13
Centrality in	Other farmers tend to look to me for advice	2.92	0.79	4	0.83

social networks	I consider myself to be a role model for other farmers	2.95	0.81	4	0.79
	Extension staff, crop advisers, and others involved in agriculture tend to look to me for advice	2.47	0.74	4	0.68

3.2.5 Vulnerability Index

The 3rd National Climate Assessment defines vulnerability as a "function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity."[(12)] Thus, climate change vulnerability is the sum of exposure and sensitivity mediated by the system's adaptive capacity. We used this definition of vulnerability and adapted it for the context of examining Midwestern farmers' vulnerability to extreme rain events. We constructed two vulnerability indices: (1) an index that incorporated objective attributes of farmers' adaptive capacity and (2) a vulnerability index that included farmers' perceived attributes of adaptive capacity. We calculated these indices separately to demonstrate the added value of incorporating farmers' perceived adaptive capacity into a vulnerability assessment. Finally, all indices were normalized and the distributions of farmer/farm vulnerability were aligned to a normal distribution (Fig 6 in the results section).

3.3 Aggregating farmers' vulnerability scores in each county

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

NASS, and these can be included in future research to explain variations in farmers' vulnerabilities to extreme rain events (or similar threats).

3.3.1 Preparing data for estimating county-level vulnerability scores

First, an average vulnerability score was calculated for each county by summing vulnerability scores of all respondents in county *j* and then dividing it by the number of respondents in that county. One issue with using average county vulnerability scores is that these are calculated for unequal number of farmers in each county. Figure 4 shows the variation in the number of respondents in each county included in the study area. It illustrates that sample size in each county varies from as low as 1 to as high as 50.

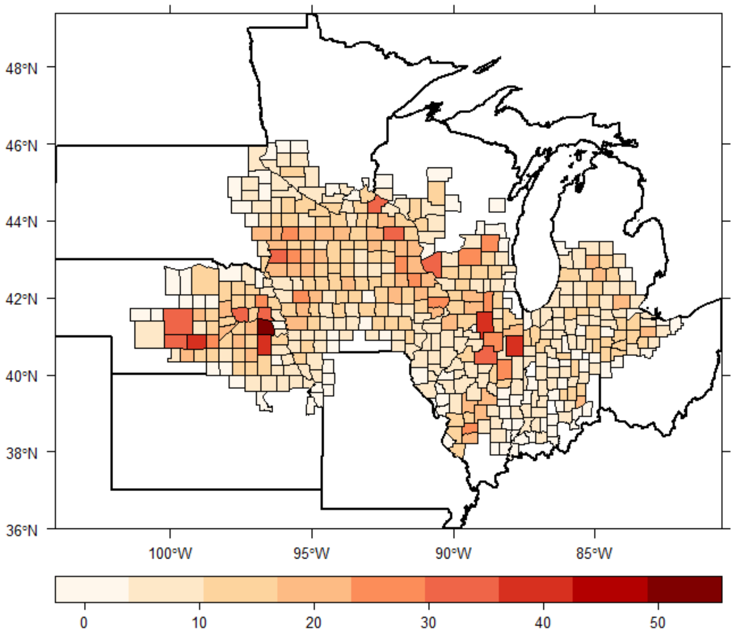

Fig 4. Sample Size

To compensate the wide variation displayed among counties, this paper uses an approximation technique to calculate the county-level simple random sample variance. The approximation consists of three steps: 1) the variance among all residents is calculated; 2) the sample variance of the county mean is obtained by dividing overall variance by total number of residents in each county; 3) the first two steps are repeated for each county so that an approximate county-level simple random sample variance was calculated. Intuitively, this approximation ensures that counties with fewer survey respondents have larger sampling variances.

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

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

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

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

$$\mathrm{Var}[Y] = (I - C)^{-1} \sum v \qquad \text{Equation 3}$$

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

First, suitable neighbors for each county were identified by specifying a queen neighbor structure, i.e., counties sharing a boundary point were taken as neighbors.[57] A queen neighbor structure was selected for ensuring that each county was assigned at least one neighbor. This neighboring structure ensured that the prediction for a county will also include contributions from at least one spatial neighbor. On average, there are almost 5 neighboring links for every county. After establishing the set of neighbors, spatial weights were assigned to each neighbor relationship. Binary weights were assigned to ensure that the structure can define symmetry needed for estimating a CAR model. A binary weight structure assigns weight of 1 to each neighbor and 0 to non-neighbor relationship. Thus, binary weights differentiate the influence of observations—those with many neighbors are more influential compared to those with few neighbors.

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

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})} \qquad \text{Equation 4}$$

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

4. RESULTS

4.1 Results of the farm/farmer-level analysis

An objective of this study is to evaluate the relationships among various dimensions of perceived adaptive capacity, such as *self-efficacy, learning & knowledge seeking, decision constraints, and centrality in social networks* and the more formally used and validated measures of objective capacity, such as *technical*, *financial*, and *institutional capacity.* To examine these associations, we calculated correlation between the various dimensions of perceived and objective adaptive capacity. Table VI shows that, for the most part, the measures of perceived and objective capacity are weakly correlated.

TABLE VI. Association of Perceived Capacity Indicators with Objective Adaptive Capacity

Correlation (factor scores)	Financial & Institutional Capacity	Technical Capacity
Self-efficacy	0.06*	0.10*
Learning & knowledge seeking	0.01	0.26*
Decision constraints	-0.04*	0.01
Centrality in social networks	0.17*	0.24*

* significant at the 0.01 level

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

TABLE VII. Farm/Farmer-level estimates of vulnerability and its components

Vulnerability and its components	Mean	Std. Dev	Range
Exposure	0.39	0.14	1
Sensitivity	0.40	0.19	1
Perceived adaptive capacity	0.49	0.12	1
Objective adaptive capacity	0.41	0.15	1
Vulnerability with perceived adaptive capacity	0.48	0.13	1
Vulnerability with objective adaptive capacity	0.47	0.14	1

4.3 Results of the county-level analysis

Figure 5 graphs the Moran's I for county-level vulnerability indices using (1) perceived adaptive capacity (I = .40) and (2) objective adaptive capacity (I = .43). The results of the Moran plot suggest that neighboring counties have similar vulnerability values, i.e., the pattern is clustered. A Monte-Carlo estimate of the p-value is calculated to ensure consistency in results and spatial autocorrelation is confirmed in this dataset.

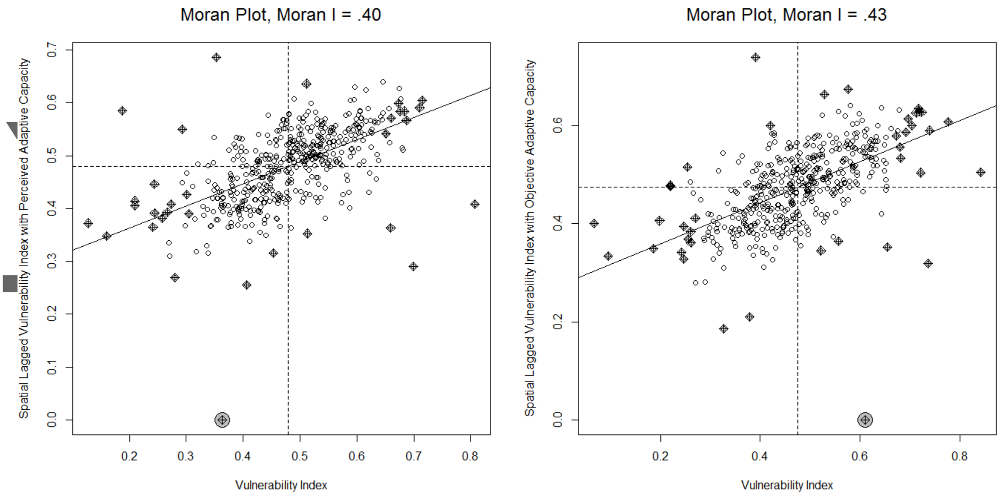

Fig 5. Moran plots for vulnerability index with perceived adaptive capacity (left), vulnerability index with objective adaptive capacity (right)

Figure 6 illustrates the county-level vulnerability scores obtained after spatial smoothing average vulnerability score in each county. The smoothed values of county-level vulnerability are the sum of non-spatial and spatial fitted values, including contributions from spatial neighbors. Vulnerability scores computed using perceived capacity and objective capacity are shown in left and right panel of figure 6, respectively. Darker shaded areas represent higher vulnerability than lighter shaded areas. The map illustrates that vulnerability is geographically heterogeneous, with it being relatively greater for counties in Iowa. Vulnerability is also increasing toward the Eastern regions of the Upper Midwest.

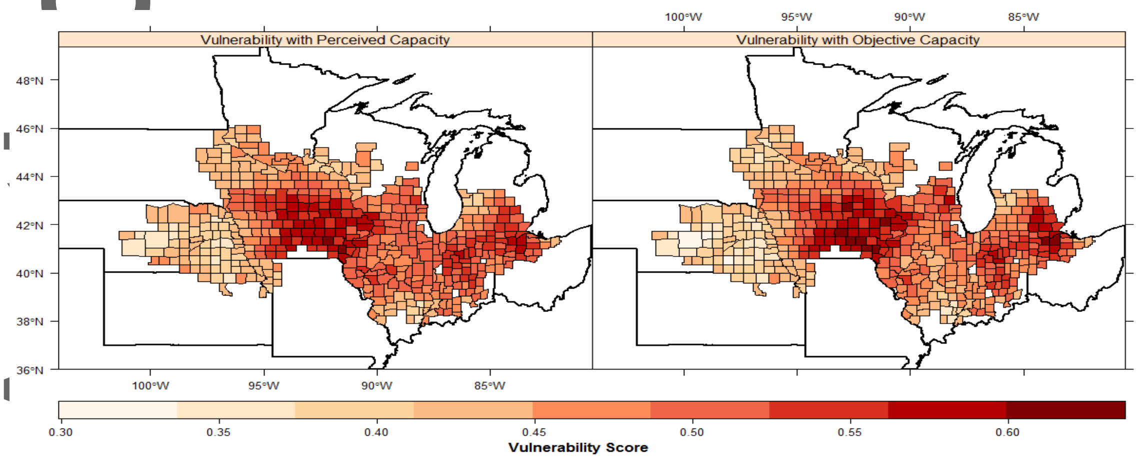

Fig 6. County-level vulnerability with perceived adaptive capacity (left), vulnerability with objective adaptive capacity (right) smoothed with CAR model

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

TABLE VIII. Smoothed estimates of county-level vulnerability

Component	Mean	Std. Dev	Range
Vulnerability with perceived adaptive capacity	0.48	0.05	0.27
Vulnerability with objective adaptive capacity	0.47	0.06	0.29

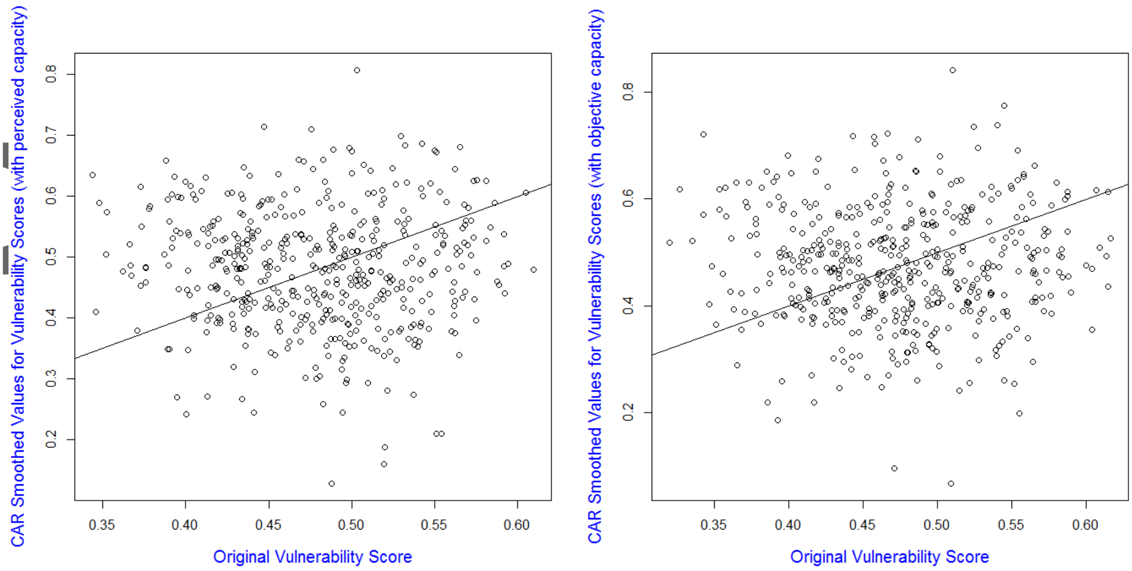

Fig 7. Raw vs Spatially Smoothed values for vulnerability with (1) perceived adaptive capacity (left) and (2) objective adaptive capacity (right)

5. DISCUSSION & CONCLUSION

Our study implemented a socio-behavioral view of farmers’ adaptive capacity that acknowledges their perception of risk and agency to reduce vulnerability related to climate change. We examined farmers' objective attributes of capacity in conjunction with their perceived adaptive capacity to improve the knowledge base on whether perceived capacity should be integrated into vulnerability assessments. We found that our estimates of farmers' perceived adaptive capacity were weakly correlated with the objective attributes of capacity (Table VI). This result suggests that the indicators of perceived and objective capacity are measuring distinct dimensions of adaptive capacity. Given that the previous studies have shown perceived capacity to be a predictor of adaptive action, this result suggests that vulnerability assessments that rely only on objective measures might miss important dimensions of capacity. In other words, if the measures of perceived and objective adaptive capacity had been highly correlated, we might conclude that the objective measures are suitable indicators for use in vulnerability frameworks. Since they are weakly correlated, this result may suggest that vulnerability frameworks should include indicators of perceived capacity. This finding is unique because on their own, objective attributes of adaptive capacity may inadequately capture these complex socio-cultural and behavioral processes associated with adaptation to climate change.

Our results may be of interest to policy makers and extension educators. Such stakeholders could look to our county-level estimates of vulnerability to inform engagement strategies for improving environmental sustainability in the region. These agencies can use the result of this research to engage more effectively with farmers. For example, we have identified counties in the Midwestern U.S. that are vulnerable to extreme rain events. Extension educators could use our maps to target their communication strategies toward these regions (Figure 6). While previous studies on vulnerability to climate change in the Midwestern U.S. have focused primarily on mapping changes in projected corn and soybean yield changes [58,59], this is the first study to (1) examine vulnerability to extreme rain events using both perceived and objective indicators of capacity and (2) map these vulnerabilities for a large part of the Upper Midwestern U.S. Future research should examine how this study's vulnerability indicators (county-level) compare to measures of vulnerability (e.g. yield gap) found in other studies.

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

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

References:

1. USDA-NASS. Quick-Stats. 2015.

2. FAOSTAT. Crop Production Database. Food and Agriculture Organization Statistics Division. 2015.

3. Hatfield J, Takle G, Grotjahn R, Holden P, Izaurralde RC, Mader T, Marshall E, Liverman D. Agriculture. Pp. 150–174 in Climate Change Impacts in the United States: The Third National Climate Assessment. 2014.

4. Arritt R. Climate change in the Corn Belt. Resilient Agriculture, 2016.

5. Karl TR, Melillo JM, Peterson TC. Global Climate Change Impacts in the

United States. Cambridge UK: Cambridge Universitiy Press, 2009.

6. Todey D. Climate Change impacts in the Corn Belt. Resilient Agriculture, 2014:8–9.

7. Liang X-Z, Wu Y, Chambers RG, Schmoldt DL, Gao W, Liu C, Liu Y-A, Sun C, Kennedy JA. Determining climate effects on US total agricultural productivity. Proceedings of the National Academy of Sciences, 2017:201615922.

8. Abendroth LJ, Elmore RW, Boyer M., Marlay SK. Corn Growth and Development., Iowa State Univ. Extension, Publication# PMR-1009, 2011.

9. Morton LW, Hobbs J, Arbuckle JG, Loy A. Upper midwest climate variations: farmer responses to excess water risks. Journal of Environmental Quality, 2015; 44(3):810–22.

10. Mitsch WJ, Day JW, Gilliam JW, Groffman PM, Hey DL, Randall GW, Wang N. Reducing Nitrogen loading to the Gulf of Mexico from the Mississippi River Basin: strategies to counter a persistent ecological problem. BioScience, 2001; 51(5):373–388.

11. Rabalais NN. Oxygen depletion in the gulf of Mexico adjacent to the Mississippi river. Gayana (Concepción), 2006; 70:225–245.

12. Bierbaum R, Lee A, Smith J, Blair M, Carter LM, Chapin FS, Fleming P, Ruffo S, McNeeley S, Stults M, Verduzco L, Seyller E. Ch. 28: Adaptation. Climate change impacts in the United States: The Third National Climate Assessment, 2014:670–706.

13. Berkes F, Jolly D. Adapting to climate change: Social-ecological resilience in a Canadian western arctic community. Ecology and Society, 2002; 5(2).

14. Adger WN. Social aspects of adaptive capacity. Climate change, adaptive capacity and development, 2003:29–50.

15. Grothmann T, Patt A. Adaptive capacity and human cognition: The process of individual adaptation to climate change. Global Environmental Change, 2005; 15(3):199–213.

16. Moser C, Stauffacher M, Blumer YB, Scholz RW. From risk to vulnerability: the role of perceived adaptive capacity for the acceptance of contested infrastructure. Journal of Risk Research, 2014; 9877(June 2014):1–15.

17. Seara T, Clay PM, Colburn LL. Perceived adaptive capacity and natural disasters: A fisheries case study. Global Environmental Change, 2016; 38:49–57.

18. Hicks CC, Levine A, Agrawal A, Basurto X, Breslow SJ, Carothers C, Charnley S, Coulthard S, Dolsak N, Donatuto J, Garcia-Quijano C, Mascia MB, Norman K, Poe MR, Satterfield T, et al. Engage key social concepts for sustainability. Science, 2016; 352(6281):38–40.

19. Coumou D, Rahmstorf S. A decade of weather extremes. Nature Climate Change, 2012; 2(7):491–496.

20. Howden SM, Soussana J-F, Tubiello FN, Chhetri N, Dunlop M, Meinke H. Adapting agriculture to climate change. Proceedings of the National Academy of Sciences, 2007; 104(50):19691–19696.

21. McCarl BA. Analysis of climate change implications for agriculture and forestry: An interdisciplinary effort. Climatic Change, 2010; 100(1):119–124.

22. Brinkman H, Hendrix CS. Food insecurity and violent conflict: causes , consequences , and addressing the challenges. Challenges, 2011; (July):1–28.

23. Lal R, Delgado J a., Groffman PM, Millar N, Dell C, Rotz A. Management to mitigate and adapt to climate change. Journal of Soil and Water Conservation, 2011; 66(4):276–285.

24. Walthall CL, Hatfield J, Backlund P, Lengnick L, Marshall E, Walsh M, Adkins S, Aillery M, Ainsworth EA, Ammann C, Anderson CJ, Bartomeus I, Baumgard LH, Booker F, Bradley B, et al. Climate Change and Agriculture: Effects and Adaptation. Washington, DC., 2012.

25. Adger WN. Vulnerability. Global Environmental Change, 2006; 16(3):268–281.

26. Brooks N, Adger WN, Kelly PM. The determinants of vulnerability and adaptive

capacity at the national level and the implications for adaptation. Global Environmental Change, 2005; 15(2):151–163.

27. Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE. IPCC, 2007: Summary for Policymakers. Pp. 7–22 in Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution ofWorking Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. 2007.

28. Marshall NA, Marshall PA. Conceptualizing and operationalizing social resilience within commercial fisheries in northern Australia. Ecology and Society, 2007; 12(1), 1. [online] URL: http://www.ecologyandsociety.org/vol12/iss1/art1/

29. Eakin H, York A, Aggarwal R, Waters S, Welch J, Rubiños C, Smith-Heisters S, Bausch C, Anderies JM. Cognitive and institutional influences on farmers' adaptive capacity: insights into barriers and opportunities for transformative change in central Arizona. Regional Environmental Change, 2016; 16(3):801–814.

30. Smit B, Pilifosova O, Burton I, Challenger B, Huq S, Klein RJT, Yohe G, Adger WN, Downing T, Harvey E, Kane S, Parry M, Skinner M, Smith J, Wandel J. Adaptation to Climate Change in the Context of Sustainable Development and Equity. Pp. 879–906 in Climate Change 2001: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. 2001.

31. Turner BL, Kasperson RE, Matson PA, McCarthy JJ, Corell RW, Christensen L, Eckley N, Kasperson JX, Luers A, Martello ML, Polsky C, Pulsipher A, Schiller A. A framework for vulnerability analysis in sustainability science. Proc Natl Acad Sci U S A, 2003; 100(14):8074–8079.

32. Arbuckle Jr. JG, Helmers M, Liebman M, Schulte L. From Vulnerability to Resiliency: Iowa Agriculture in the Age of Biorenewables. Report, Iowa State University, 2011.

33. Reimer AP, Weinkauf DK, Prokopy LS. The influence of perceptions of practice characteristics: An examination of agricultural best management

practice adoption in two indiana watersheds. Journal of Rural Studies, 2012; 28(1):118–128.

34. Qi Z, Helmers MJ, Christianson RD, Pederson CH. Nitrate-nitrogen losses through subsurface drainage under various agricultural land covers. Journal of Environmental Quality, 2011; 40(5):1578–85.

35. Schnepf M, Cox C. Environmental Benefits of Conservation on Cropland: The Status of Our Knowledge. Ankeny, IA: Soil and Water Conservation Society, 2006.

36. Kremen C, Miles A. Ecosystem services in biologically diversified versus conventional farming systems: Benefits, externalities, and trade-offs. Ecology and Society, 2012; 17(4), 40. http://dx.doi.org/10.5751/ES-05035-170440

37. Kaspar TC, Jaynes DB, Parkin TB, Moorman TB, Singer JW. Effectiveness of oat and rye cover crops in reducing nitrate losses in drainage water. Agricultural Water Management, 2012; 110:25–33.

38. Nelson DR, Adger WN, Brown K. Adaptation to environmental change: contributions of a resilience framework. Annual Review of Environment and Resources, 2007; 32(1):395–419.

39. Rockström J, Steffen W, Noone K, Persson Å, Chapin FS, Lambin E, Lenton TM, Scheffer M, Folke C, Schellnhuber HJ, Nykvist B, de Wit CA, Hughes T, van der Leeuw S, Rodhe H, et al. Planetary boundaries: Exploring the safe operating space for humanity. Ecology and Society, 2009; 14(2), Art 32

40. Engle NL, Lemos MC. Unpacking governance: Building adaptive capacity to climate change of river basins in Brazil. Global Environmental Change, 2010; 20(1):4–13.

41. Yohe G, Tol RSJ. Indicators for social and economic coping capacity F moving toward a working definition of adaptive capacity. Global Environmental Change, 2002; 12:25–40.

42. Moser SC, Kasperson RE, Yohe G, Agyeman J. Adaptation to climate change in the Northeast United States: Opportunities, processes, constraints.

Mitigation and Adaptation Strategies for Global Change, 2008; 13(5–6):643–659.

43. Swanson DA, Hiley JC, Venema HD, R. Grosshans. 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, Winnipeg, Manitoba, Canada. 2009:31.

44. Eakin H. The "turn to capacity"in vulnerability researchitle. Applied Studies in Climate Adaptation, 2014:225–230.

45. Brown K, Westaway E. Agency, Capacity, and Resilience to Environmental Change: Lessons from human development, well-being, and disasters. Annual Review of Environment and Resources, 2011; 36(1):321–342.

46. Turner BL. Vulnerability and resilience: Coalescing or paralleling approaches for sustainability science? Global Environmental Change, 2010; 20(4):570–576.

47. Dow K, Berkhout F, Preston BL. Limits to adaptation to climate change: A risk approach. Current Opinion in Environmental Sustainability, 2013; 5(3–4):384–391.

48. Hafner-Burton EM, Montgomery AH. Power positions: international organizations, social networks, and conflict. The Journal of Conflict Resolution, 2006; 50(1):3–27.

49. Cutter SL. Moral Hazard, Social Catastrophe: The changing face of vulnerability along the hurricane coasts. The ANNALS of the American Academy of Political and Social Science, 2006; 604(1):102–112.

50. Preston BL, Yuen EJ, Westaway RM. Putting vulnerability to climate change on the map: A review of approaches, benefits, and risks. Sustainability Science, 2011; 6(2):177–202.

51. Arbuckle JG, Prokopy LS, Haigh T, Hobbs J, Knoot T, Knutson C, Loy A, Mase AS, McGuire J, Morton LW, Tyndall J, Widhalm M. Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the

Midwestern United States. Climatic Change, 2013; 117(4):943–950.

52. van Buuren S, Groothuis-Oudshoorn K. Multivariate imputation by chained equations in R. Journal of Statistical Software, 2011; 45(3):1–67.

53. Schenker N, Taylor. JM. Partially parametric techniques for multiple imputation. Computational Statistics & Data Analysis, 1996; 22(4):425–446.

54. Loy A, Hobbs J, Arbuckle Jr JG, Morton LW, Prokopy LS, Haigh, T., ... & Tyndall J. Farmer Perspectives on Agriculture and Weather Variability in the Corn Belt: A Statistical Atlas, 2013.

55. Vermunt J, Magidson J. Latent class models for classiffication. Computational Statistics & Data Analysis, 2003; 41:531–537.

56. Hahn MB, Riederer AM, Foster SO. The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change-A case study in Mozambique. Global Environmental Change, 2009; 19(1):74–88.

57. Bivand RS, Pebesma EJ, Gómez-Rubio V. Applied Spatial Data Analysis with R., 2013.

58. Hatfield JL, Wright-Morton L, Hall B. Vulnerability of grain crops and croplands in the Midwest to climatic variability and adaptation strategies. Climatic Change, 2017.

59. Lobell DB, Roberts MJ, Schlenker W, Braun N, Little BB, Rejesus RM, Hammer GL. Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. Science, 2014; 344(6183):516–519.

Appendix

TABLE A. Percentage of Missing Values Prior to Imputation

Components, Sub-Components, and Statements	**Missing %**
In 2011, approximately what percentage of the land (owned and/or rented) you farmed was…	
• Artificially drained through tile or other methods	5.15
• Reduced tillage (e.g., strip, ridge tillage)	10.44

• No-till	7.14
• Planted to cover crops	10.15
Farm subsidies (direct payments) ($)	12.49
Availability and accessibility of weather and climate-related decision support tools (Count)	10.38
Opportunities to sell crops in multiple markets (Count)	0.38
Education	1.42
I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation	5.90
I have the financial capacity to deal with any weather-related threats to the viability of my farm operation	6.32
I am confident in my ability to apply weather forecasts and information in my crop related decisions	4.67
It is important for me to talk to other farmers about new farming practices and strategies	4.58
I am willing to use seasonal climate forecasts to help me make decisions about agricultural practices	4.35
It is important for me to visit other farms to look at their practices and strategies	4.48
I am concerned that available best management practice technologies are not effective enough to protect the land I farm from the impacts of climate change	6.84
There's too much uncertainty about the impacts of climate change to justify changing my agricultural practices and strategies	5.90
Crop insurance and other programs will protect the viability of my farm operation regardless of weather (reversed)	6.40
Changes in weather patterns are hurting my farm operation	5.88
Other farmers tend to look to me for advice	4.75
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

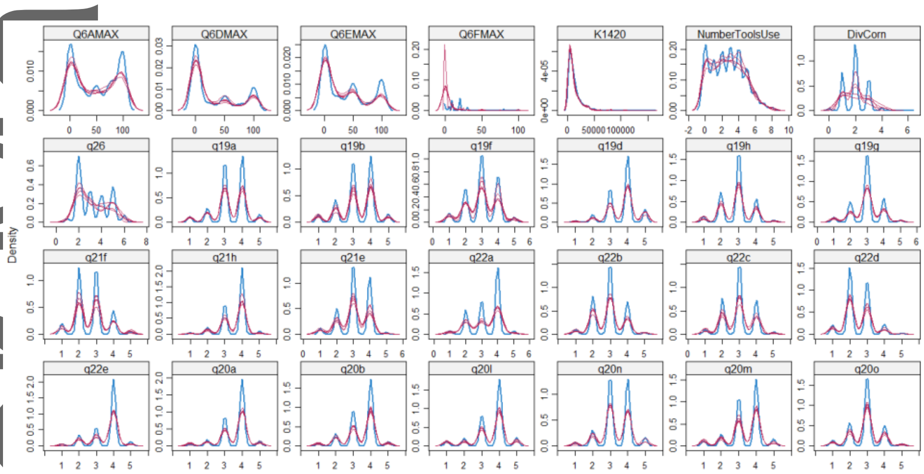

Figure A: Imputed dataset is illustrated in magenta while the density of the observed data is showed in blue