Spatially representing biophysical and socio-cognitive aspects of vulnerability to climate change: A study of Midwestern farmers

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Abstract

Potential climate change-related impacts to agriculture in the Upper Midwest, pose serious economic and ecological risks to the U.S. and the global economy. Given the projected trend toward more extreme rainfall events in the Upper Midwest, it is important to note how such variation in rainfall can impact farm-level productivity and off-farm environmental sustainability. On a local level, farmers are at the forefront of responding to the impacts of climate change. Hence, it is important to understand how farmers' become more or less vulnerable to changes in the climate. A vulnerability index is a commonly used tool by researchers and practitioners for representing the geographical distribution of vulnerability in response to global change. Most vulnerability assessments measure objective adaptive capacity using secondary data estimated by governmental agencies. These assessments can potentially ignore people's subjective perceptions of changes in climate and extreme weather events and the extent to which people feel prepared to take necessary steps to cope and respond to the negative effects of climate change. This paper incorporates socio-cognitive aspects of vulnerability into a vulnerability assessment approach. Farmer-level vulnerability is calculated and spatial statistics are used to conduct small area (county) estimation with continuous areal data. The farmer and county-level 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.

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

1. INTRODUCTION

The Upper Midwestern United States is a global and national 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 droughts, floods, weeds, soil erosion and degradation of water quality.[(3)] These impacts on agriculture in the Upper Midwest, pose serious economic and ecological risks to the U.S. and the global economy.

One of the most striking observed and predicted climatic change for the Upper Midwest is an increase in heavy precipitation events.[(4–6)] Extreme precipitation events are described as events with more than four inches (101.6 millimeters) of rain.[(6)] Such events can pose serious economic and ecological challenges to farms' economic and environmental outcomes. For example, in the early growing season, extreme rain events can delay planting and increase farmers' economic risks. During the early growing season, the crop is not firmly established and heavy precipitation increases the risk of flooding and soil erosion.[(7,8)] Heavy rain events can also exacerbate off-farm environmental outcomes, such as an increase in the transportation of nitrogen, phosphorus and other nutrients into ground water, streams, and lakes.[(8)] 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.[(9,10)]

The production of corn and soybeans can result in less environmentally harmful farm and region-level impacts if farmers take necessary steps on their farm to reduce soil erosion and nitrate leaching into rivers and streams.[(11)] For example, farmers' use of agricultural best-management practices (BMPs), also known as conservation practices, can potentially mitigate nonpoint source pollution from agricultural lands and valuably contribute to on-farm ecosystem services such as reducing soil erosion and increasing crop yield.[(12)] Understanding the interactions between (1) farm-level environmental services, such as soil characteristics and use of conservation farming practices; (2)

biophysical stressors, such as extreme rainfall events, and (3) social outcomes, such as the farmers' access to financial resources, can in part explain the qualities or deficiencies that make a farm less or more vulnerable to a range of stressors related to climate change. A farm-level climate change vulnerability assessment can examine the degree to which a farm may be adversely affected by climate-related disturbances and the ability or inability of the farmer to cope with climate change-related stressors.

A climate change vulnerability assessment is a commonly used tool by researchers and practitioners for representing the geographical distribution of vulnerability in response to climate change(13). Assessments in the past have assessed climate change-related vulnerabilities for specific sectors, such as health(14) and agriculture(15), and in relation to natural hazards, such as floods(16) and heat(17). Previous studies have assessed vulnerability at different levels and scales(18) and for an array of multiple stressors.(19)

Most vulnerability assessments have measured objective adaptive capacity using secondary data collected by government agencies. These studies often assume that people and communities are likely to adapt to climate change if they have access to financial and technical resources and suitable institutional arrangements.(20,21) However, psychological barriers to adaptation can be more consequential for adaptation than physical resources such as access to financial and technical resources, especially if people systematically under- or over-estimate their own ability to adapt.(22) Perceived capacities are associated with people's perception of changes in climate and extreme weather events and the "extent to which they feel prepared to endure changes and take necessary steps to cope with them."(23) Self-efficacy or agency is a strong measure of individual's While extensive research on the relationships between objective adaptive capacity and vulnerability has been conducted in diverse contexts and among other populations, little rigorous, theoretically informed investigation has focused on farmers' perceived adaptive capacity and its association with their climate change-related vulnerability.

The objectives of this paper are to (1) incorporate socio-cognitive aspects of vulnerability into a vulnerability assessment approach and (2) construct reliable estimates of vulnerabilities for administrative areas with small sample sizes, such as the county.

Incorporating subjective measures of social wellbeing, such as self-efficacy or agency, into a vulnerability assessment can improve policy makers' understanding of the ability of a population to take suitable actions for adaptation.(24) A better understanding of the subjective dimensions of farmers' vulnerability can help policy makers develop targeted policies and regulations that promote environmental sustainability of natural resources while maintaining farmer livelihoods. County was chosen as the level for estimating vulnerability because this administrative area can be easily understood by decision-makers, both within and outside the realm of agriculture. This paper is organized as follows: it first discusses the evolution of climate change-related vulnerability assessments in the literature. It examines various rationales and approaches employed in conducting vulnerability assessments and situates this study's unique conception of vulnerability within that literature. Next, it presents a framework that defines vulnerability and its sub-components. The methods section presents 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, Simultaneous Autoregressive (SAR) and Conditional Autoregressive (CAR) models are used to spatially smooth county-level climate change vulnerability from farmer-level vulnerability scores. These models exploit auxiliary information from neighboring counties to find a vulnerability score estimate 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. The last part of the paper provides the discussion and concludes the study.

2 LITERATURE REVIEW:

2.1 Vulnerability frameworks in sustainability science literature

Vulnerability frameworks examine 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.(25) Vulnerability is the degree to which a system may be adversely affected by climate related disturbances and its inability to cope with them.[26] The SES literature defines social-ecological systems as groups of related parts that are nested and at multiple levels and “that provide essential services to society such as supply of food, fiber, energy and drinking water.”[27] 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 and response to climate change.[28] The development of the concept of vulnerability has advanced from a binary view that distinguishes between biophysical and social vulnerability, towards the attempt to synthesize multiple aspects of vulnerability across different scales. Understanding the evolution of the concept of vulnerability can explain why some aspects of human decision-making were included in the framework while other aspects were not.

The concept of climate change vulnerability has its disciplinary roots in human geography and natural hazard research. Vulnerability frameworks borrow concepts from risk-hazard (RH) and pressure-and-release (PAR) models.[27] The RH approach assumes that all hazards are physical in nature. Only biophysical processes contribute to system vulnerability.[29] The RH model does not however recognize that people and nature reciprocally interact and form complex feedback loops.[29] As a result, the RH approach fails to highlight the importance of institutions, culture, and society in determining people’s and social groups’ climate change-related vulnerabilities.[30] The RH model has also been criticized for neglecting the capacity of people and social groups to moderate their vulnerabilities to natural hazards.[31]

The concept of vulnerability has evolved over time. Wisner et al.[32] are credited for the development of the pressure and release (PAR) model in disaster research. The PAR model considers risk to be a product of hazard and vulnerability. This model uses concepts from political economy to characterize vulnerability as a result of multi-scale social, political, and economic causes and conditions.[33–35] For example, in one application of this framework, Adger et al.[34] conceptualize social vulnerability to climate change as being dependent on the availability of resources and the ability of people and groups to access resources necessary for adaptation. The PAR model is an important approach to understanding the root causes of vulnerability and its multiple dimensions (social, environmental, political and economic).[36] However, the PAR model does not fully capture the dynamic interactions of social and biophysical vulnerability at different scales (25).

The Turner et al.[31] vulnerability framework is an important SES framework for analyzing how multiple environmental and social changes and location-specific hazards can exacerbate vulnerability for individuals and communities. In their seminal work, Turner et al.[31] responded to the criticism of the RH and PAR model by emphasizing that people and nature interact reciprocally, at different spatial and temporal scales, giving vulnerability an interactive and dynamic nature. Hence, vulnerability is not only influenced by climatic factors and weather extremes on nations, sectors, communities and individuals, but is also dependent on the role and capacities of heterogeneous institutional and socioeconomic contexts which may make some individuals or communities more or less vulnerable than others.[26]

Thus, recent conceptualizations of vulnerability to climate change posit that it is comprised of three components: exposure, sensitivity, and adaptive capacity.[25] Exposure is the likelihood of a system to experiencing hazard (e.g., an extreme rainfall event), while 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. The adaptive capacity is the ability of the system to cope, adapt, and respond to the negative effects of climate change. Hence, vulnerability is a function of the exposure and sensitivity to climate change mediated by the adaptive capacity of the system.[31,33,37]

2.2 From objective to subjective measures of adaptive capacity

Within the climate change literature, the concept of adaptive capacity has been defined in various ways. However, there is a consensus that adaptive capacity broadly includes three distinct, but related, parts: a resource system, the ability of individuals to access those resources, and the governance system that structures and mediates the management of resources and systems of access.[38] Factors such as access to resources (e.g., financial, technological, information) and infrastructure has been found to increase people's and social group's adaptive capacity.[21,37,39,40] These objective attributes define an important part of individuals' or communities' overall adaptive capacity.

While the literature on objective adaptive capacity (what an individual could do) has been growing within the sustainable science field, outside of it, much literature on decision making and behavior indicate that people's perceived capacities can be determinants of climate change-related adaptive behavior.(22,23,41) From a psychological perspective, socio-cognitive factors, such as "motivations" and "perceived abilities" are a core part of peoples' decision making.(22) Recent research has highlighted the need to distinguish between individuals' objective adaptive capacity (e.g. finances and institutional support) and their perceived or subjective adaptive capacity, or "judgements on how well individuals are expected to cope with negative events and developments".(41) The determinants of perceived adaptive capacity are "associated with…perception of the adequacy of available resources (e.g. financial, social) in allowing and aiding them to cope and adapt, and the extent to which people feel they are prepared to endure such changes or impacts and steps to cope with them".(23) Perceived adaptive capacity is an important step before people can decide whether to take an appropriate action in response to a climate change-related stimuli.(42)

In the case of climate change and agriculture, a farmer's (or farm's) degree of vulnerability to climate change can be highly dependent on factors such as geographic location, soil and water quality, and intensity of extreme rainfall events and/or drought. Equally important for reducing vulnerability are farmers' perceptions of their ability to cope to adapt to future climatic changes are important too. The following section develops a conceptual framework to evaluate Midwestern conventional farmers' vulnerability to climate change, in particular, to extreme rainfall events.

3. CONCEPTUAL FRAMEWORK

The conceptual framework proposed in this study describes vulnerability as composed of three farm (and farmer) level components: exposure, sensitivity, and perceived adaptive capacity. Farmers' exposure and sensitivity to extreme rainfall are mediated by their perceived adaptive capacity.

3.1 Exposure

In the Upper Midwest, the frequency of days with heavy precipitation has increased by almost 50% in the entire 20th century.[4] Heavy precipitation events are described as events with more than four inches (101.6 millimeters) of rain. Exposure is the likelihood of a farm experiencing an extreme rainfall event. Extreme rain events are among the most hazardous forms of climate change-related extremes that Midwestern farming faces. In the short term, extreme rains can damage crops through trauma and water logging; of greater concern is soil erosion and its long-term impacts on agricultural productivity. Climate observations and predictions depict an increase in heavy precipitation events for the Upper Midwest in the next 30 to 50 years.(4–6)

3.2 Sensitivity

A closely related concept to exposure is sensitivity, which refers to the likely magnitude of effect an extreme rainfall event will have on farm. The ways that corn and soybeans are produced can lead to greater or lesser magnitude of on- and off-farm ecological harm from extreme precipitation events, especially if farmers do not take necessary steps to protect the land and retain soils and nutrients.[11] Excessive sediment and nutrient export from corn-soybean producing agricultural lands is a significant driver of nonpoint source pollution loads,[9,10] and soil erosion reduces the productive capacity of the land over time. Agricultural best-management practices (BMPs), also known as conservation practices, can potentially mitigate nonpoint source pollution from agricultural lands and valuably contribute to ecosystem services such as reducing on-farm soil erosion.[12]

Sensitivity comprises the interaction between farmers' use of these conservation practices (social) and soil characteristics (biophysical/ecological) (see figure 1). Farmers can use various conservation farming practices to reduce nutrient and soil loss. In the Upper Midwest, three of the primary farm-level adaptive management strategies suitable for dealing with an increase in the frequency of extreme precipitation events are: (1) the enhancement of drainage systems (including drainage water management); (2) the minimization of tillage or disturbance of the soil; and, (3) the use of cover crops to maintain living ground cover after cash crops have been harvested.[8] A brief description of each practice is provided below.

Farm Drainage and Draining Water Management: Drainage tile systems are used to drain away excess water and transform poorly drained soils into productive croplands.[8] 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.[43] The impacts of drainage water management are spread unevenly across the region. Eastern and southern parts of the Corn Belt are more likely to reap the positive benefits of drainage water management (than the northern parts, such as Minnesota and South Dakota).[44]

Cover crops: Cover crops are "grown primarily for the purpose of protecting and improving soil between periods of regular crop production."[45] 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.[46,47]

No-Till: No-till is a farm 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."[8] Reduction in tillage or no-tillage has the potential to reduce soil erosion, increase soil porosity, and increase nutrient retention.[48] Benefits to soil properties from no-till farming can reduce the harmful impact of heavy precipitation events on the soil surface by improving retention of moisture for use by plants and reducing soil erosion.[8]

3.3 Perceived adaptive capacity

Perceived adaptive capacity describes farmers' self-assessments of their ability to respond to climate change and can be dependent upon farmers' perception of possessing an adequate and sustainable resource system and the ability to access resources needed to adapt. At the farm-level, farmers' perceived adaptive capacity can be influenced by 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 etc. 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. crop insurance program).

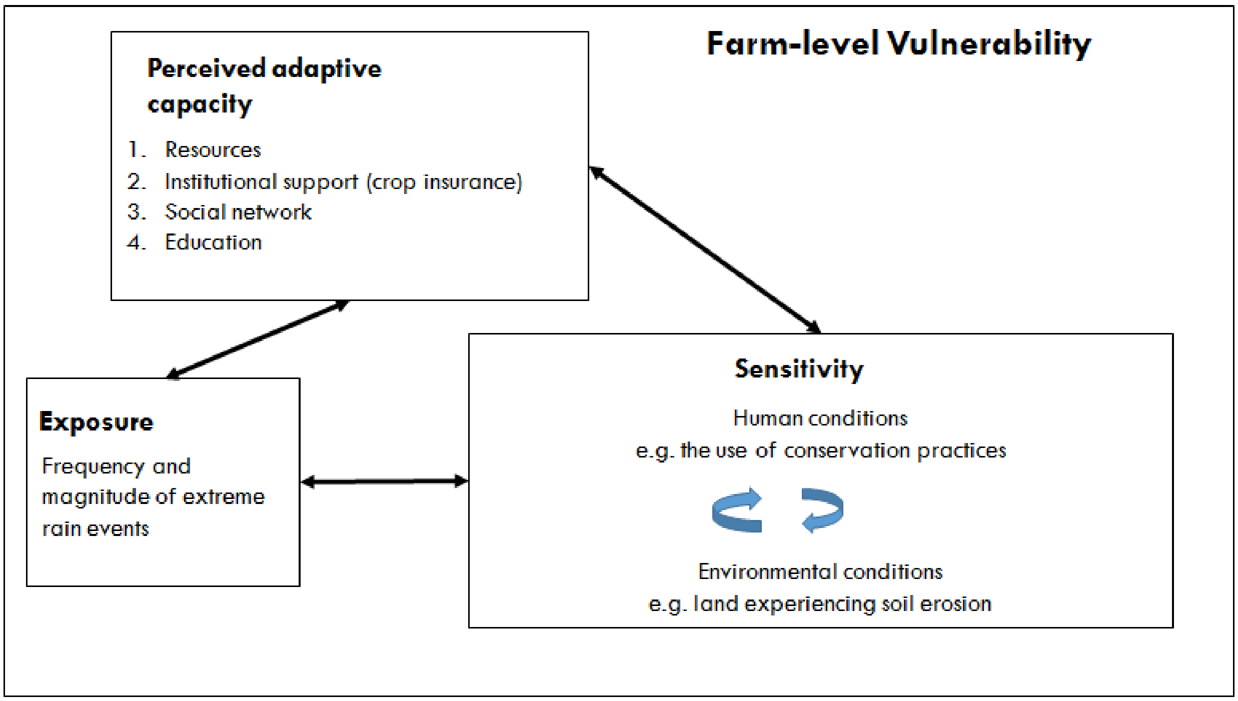

Figure 1: Vulnerability framework

Figure 1 illustrates the vulnerability framework used in this study. Vulnerability comprises of three components: exposure, sensitivity, and perceived adaptive capacity. The framework highlights the interaction between the sub-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). A farm's (or farmer's) sensitivity to heavy rain events can be mediated by their use of on-farm conservation practices. Perceived adaptive capacity, a third component of vulnerability can influence farmers' sensitivity, by influencing their use and choice of adaptive management practices. The vulnerability framework presented here aims to highlight the complex interactions between exposure, sensitivity, and perceived adaptive capacity.

4 METHOD:

4.1 Study Area

The study area comprises of the 11 Midwestern states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin (Figure 2). 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.(49) 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 landscape, with higher soil erosion occurring in some parts of the region.

Figure 2: Map of US & Study Region

4.2 Data collection and variables included in the analysis

Primary data used in this study is from a February 2012 survey of farmers stratified across 22 HUC6 watersheds in the Upper Midwestern U.S.(49) The sampling approach was designed to select farmers who produced a substantial proportion of corn and soybean in the Midwestern U.S. To ensure that the sample was representative of farmers who produced large quantities of corn, only farm operations with greater than 80 acres of corn production and farm value sales in excess of $100,000 were included in the sample frame. The survey was sent to over 18,000 farmers and the analysis in this study utilizes the data from all 4,778 respondents, a response rate of 26%. Statistical tests for non-response bias detected no meaningful differences between respondents and non-respondents.[49] 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. Table I provides a description of variables in the survey that were employed in this study.

Table I Survey items and response format used in the study.

Items	**Response format**
Do any creeks, streams, or rivers run through or along any of the land you farm?	0 = *No,* 1 = *Yes*
In 2011, approximately what percentage of the land (owned and/or rented) you farmed was…	
Artificially drained through tile or other methods	%
Reduced tillage (e.g., strip, ridge tillage)	%
No-till	%
Planted to cover crops	%
Percent of non-irrigated marginal lands by county	%
Given what you believe to be true about the potential impacts of climate change on agriculture in the Corn Belt, please provide your opinions on the following statements.	
I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation	*1 = strongly disagree, 5 = strongly agree*
I have the financial capacity to deal with any weather-related threats to the viability of my farm operation	*1 = strongly disagree, 5 = strongly agree*
I am confident in my ability to apply weather forecasts and information in my crop related decisions	*1 = strongly disagree, 5 = strongly agree*
Crop insurance and other programs will protect the viability of my farm operation regardless of weather	*1 = strongly disagree, 5 = strongly agree*

Please indicate your level of agreement with each of the following statements.	
Other farmers tend to look to me for advice	*1 = strongly disagree, 5 = strongly agree*
I consider myself to be a role model for other farmers	
Extension staff, crop advisers, and others involved in agriculture tend to look to me for advice	*1 = strongly disagree, 5 = strongly agree*
What is your highest level of education?	*1 = some formal education, 6 = graduate degree*

Weather variables were obtained from Loy et al.[(50)], who constructed weather variables for the Upper Midwestern region from the National Weather Service (NWS) Cooperative Observer (COOP) data archive. This archive includes daily values of minimum and maximum temperature, and precipitation recorded in the United States. Data is for the historical record covering 1971-2011. Loy et al.[(50)] constructed seasonal precipitation as the total precipitation for April 1 through September 30. They computed an empirical cumulative distribution function (CDF) to yield a percentile rank for each year (in total 41 years). Next, they computed the percentile rank for a year. A value of 50% in this dataset is the median seasonal precipitation. This paper includes deviation from this median value as a measure of change in seasonal precipitation.

Daily precipitation extreme values were computed as the 99th percentile of daily precipitation for a given month.[(50)] These percentiles are computed for each station and for each month. This paper includes the proportion of days that exceeded the 99th percentile for the record covering 1971-2011. The precipitation values from the weather station nearest to the farm were assigned to each farmer in the survey.

The percent of non-irrigated marginal lands by county were obtained from Loy et al.[(50)] They calculated this percentage by using the USDA Natural Resources Conservation Service (NRCS) land capability classification system. This classification characterizes the land based on its soil capability and ability to grow crops and pasture plants. Loy et al.[(50)] obtained soil data for each county from the Soil Survey Geographic (SSURGO) database. They computed the percent of marginal lands for each county by summing the capability acreages for classes that depict marginal soil (for each county) and creating a proportion of all acres in the county. This paper used the percent of non-irrigated marginal lands by county to measure farmers' ecological sensitivity.

4.3 Measuring exposure, perceived sensitivity and perceived adaptive capacity

Prior to index construction, maximum likelihood (ML) data imputation was employed to impute missing variables. This method uses maximum likelihood to estimate missing data simultaneously by examining the underlying patterns in the data. The advantage of using ML imputation is that it uses all information in the data (without deleting any cases) and produces estimates that are statistically efficient, consistent, and unbiased.

4.3.1 Exposure

Three items were used to assess farmers' exposure: (1) proximity to a creek, stream, or river; (2) daily precipitation extremes, and (3) seasonal precipitation extremes. This paper used an exploratory factor analysis (EFA) with oblique rotation to condense information from these variables into a single variable measuring exposure. Factor scores were estimated in Mplus and factor loadings, eigenvalue, and communalities are reported in Table II. As can be seen from Table II, factor loading and communalities were low for the survey item that measured proximity to a creek, stream, or river. However, a one factor solution was chosen for its suitability in interpreting results and for incorporating survey item and secondary data that measured farmers' exposure. Formally, factor scores for farmers' exposure were estimated using the following equation:

$$F_{ze} = X_{ze}C \qquad \text{Equation (1)}$$

Where:

F_{ze} is a matrix of standardized factor scores for exposure

$X_{ze}$is a matrix of standardized observed scores for exposure (z-scores)

C is a matrix of factor score weights

The z-scores for exposure were normalized by this equation:

$$F_{ze_i} = \frac{F_{ze_i} - F_{ze_{min}}}{F_{ze_{max}} - F_{ze_{min}}} \qquad \text{Equation (2)}$$

Where F_{ze_i} denotes the standardized factor score for exposure for farmer i

Table II | Summary of factor loadings and communalities from principal axis factor analysis for exposure (oblique rotation, 1 factor solution)

Exposure	**Factor loading**	***h^2***
River	.16	.03
Seasonal precipitation	.66	.45
Daily precipitation extreme	.77	.60
Eigenvalue	2.83	
RMSEA	.24	
CFI	.78	

Notes. h^2 = communality

4.3.2 Sensitivity

Latent Profile Analysis (LPA) 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.[(51)] 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. In this study, a LPA is used to assign farmers to discrete profiles based on five items: (1) one item that measures the characteristics of soil in farmers' county and (2) four items that measure the maximum percentage of land on which farmers' self-reported to use conservation practices (drainage, reduced and no-till farming, and cover crops). This study used a LPA instead of a traditional Latent Class Analysis (LCA) because the observed indicators were continuous (instead of categorical).

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

$$y = \Lambda\eta + \varepsilon \qquad \text{Equation (3)}$$

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

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. A five-profile model (P = 5) provided the least BIC and a statistically significant Lo-Mendell-Rubin LR test. Model comparisons and model fit with fewer profiles are provided in Table III.

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 *p* = .00	2496 *p* = .00	2164 *p* = .00	1310 *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 five latent profiles were suitable for interpreting farmers' sensitivity. Profile 1 made up 47% of the farmer population and contains farmers' who were least sensitive. These farmers had low potential for soil erosion and were using a moderate level of conservation practices on their farm. Profile 2 made up farmers who had moderate potential for soil erosion, but had invested in high level of conservation practices to reduce erosion and improve crop productivity. Profile 2 constituted 1.9% of the population. Profile 3 made up the moderately sensitive profile of farmers. These farmers had medium potential for soil erosion and moderately used conservation practices on their farm. Farmers in this profile constituted 6.7% of the population. Profile 4 made up 38.7% of the population. Farmers in profile 4 had medium potential for soil erosion and had limited use of conservation practices. Profile 5 made up the most sensitive profile of farmers. These farmers had high potential for soil erosion and limited to no-use of conservation practices on their farm. Farmers in this profile represented 5.6% of the population. These five latent profiles constitute an ordinal scale (1-5) with 1 representing least sensitive and 5 representing most sensitive farmers. The five latent profiles were normalized using the following equation:

$$F_{se_i} = \frac{F_{se_i} - F_{se_{min}}}{F_{se_{max}} - F_{se_{min}}} \qquad \text{Equation (4)}$$

Where F_{se_i} denotes the standardized sensitivity score for sensitivity for farmer i

4.3.3 Perceived adaptive capacity:

Eight items were used to assess farmers' perceived adaptive capacity (Table IV). An exploratory factor analysis (EFA) with oblique rotation was used to condense information from these variables into a single variable measuring perceived adaptive capacity. As can be seen from Table IV, factor loading and communalities were not high for all items and a two factor solution could have been more appropriate. However, a one factor solution was chosen for its suitability in interpreting results and for incorporating a variety of survey items that measured farmers' perceived adaptive capacity. The z-scores derived from EFA were normalized by the following equation:

$$F_{pac_i} = \frac{F_{pac_i} - F_{pac_{min}}}{F_{pac_{max}} - F_{pac_{min}}} \qquad \text{Equation (6)}$$

Where F_{pcc_i} denotes the standardized factor score for adaptive capacity for farmer i

Table IV | Summary of factor loadings, and communalities from principal axis factor analysis for perceived adaptive capacity (oblique rotation, 1 factor solution)

Perceived adaptive capacity	**Factor loading**	***h*^{2}**
Other farmers tend to look to me for advice	.27	.07
I consider myself to be a role model for other farmers	.85	.72
Extension staff, crop advisers, and others involved in agriculture tend to look to me for advice	.82	.67
I have the knowledge and technical skill to deal with any weather-related threats to the viability of my farm operation	.61	.37
I have the financial capacity to deal with any weather-related threats to the viability of my farm operation	.56	.08
I am confident in my ability to apply weather forecasts and information in my crop related decisions	.29	

Crop insurance and other programs will protect the viability of my farm operation regardless of weather	.21	.05
What is your highest level of education	.69	.48
Eigenvalue	2.83	
RMSEA	.24	
CFI	.78	

Notes. h^2 = communality

4.3.4 Vulnerability Index

The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as a function of people's exposure and sensitivity to extreme rainfall mediated by their adaptive capacity. Vulnerability index (VI) = (exposure + sensitivity) – perceived adaptive capacity.

$$VI_i = F_{ze_i} + F_{se_i} - F_{pac_i} \qquad \text{Equation (7)}$$

Normalizing vulnerability index, so that the vulnerabilities are between 0 and 1:

$$VI_i = \frac{VI_i - VI_{min}}{VI_{max} - VI_{min}} \qquad \text{Equation (8)}$$

As can be seen from Figure 3, the distribution of farmers' vulnerability scores is normally distributed. The mean vulnerability score is .39, mean exposure score is .29, average sensitivity is .27 and mean perceived adaptive capacity is .47 (Table V). The descriptive statistics for all items that measure vulnerability, exposure, sensitivity and perceived adaptive capacity are provided in Table V.

Table V | Descriptive statistics for the variables in the analysis

N = 4778	Min	Max	Mean	SD
Vulnerability Index	0	1	.39	.14
Exposure	0	1	.29	.19
River	0	1	.76	.42
Seasonal precipitation	.05	1	.56	.26
Daily precipitation	0	.03	.01	.01
Sensitivity	0	1	.27	.29

Drainage management (%)	0	100	49.1	39.34
Reduced tillage (%)	0	100	32.63	37.81
No-till (%)	0	100	36.11	38.29
Planted to cover crops (%)	0	100	6.64	16.17
Marginal soil	0	.97	.17	.16
Perceived adaptive capacity	0	1	0.47	.13
Perceived knowledge & technical skills	1	5	3.36	.84
Perceived financial capacity	1	5	3.25	.90
Perceived confidence in using weather forecasts	1	5	3.03	.69
Perceived institutional support (crop insurance)	1	5	3.58	.88
Perceived importance in social network	1	5	2.92	.77
Role model for other farmers	1	5	2.95	.79
Role model for extension agents	1	5	2.47	.73
Education	1	5	3.26	1.31

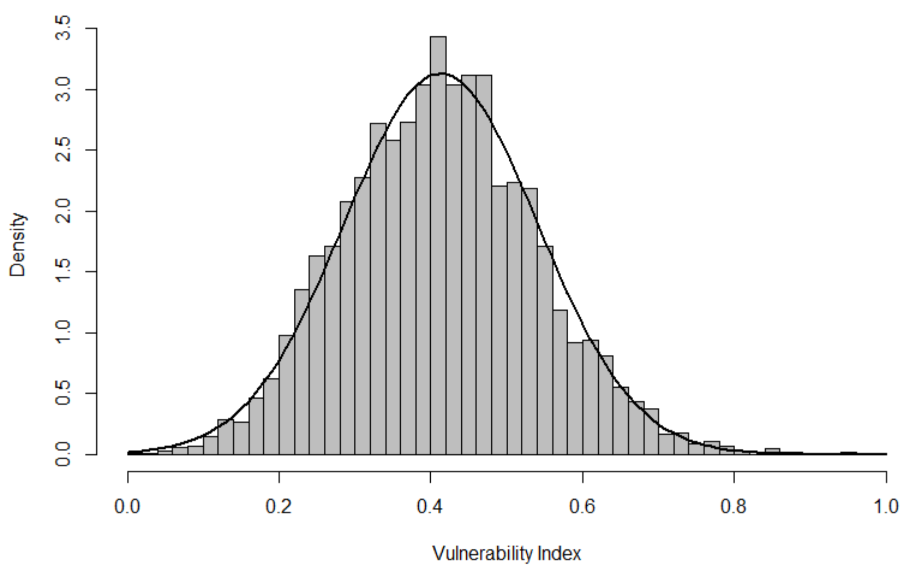

Figure 3: Distribution of Climate Change Vulnerability Scores

4.4 Aggregating farmers' vulnerability scores for 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 geospatial information about their farm. In this situation, one possible solution is to use spatial statistics to construct reliable vulnerability estimates for small areas, such as counties.

Prior to conducting a small area estimation, it is important of choose an appropriate spatial scale. The county level was selected for several reasons: (1) Upper Midwestern counties are relatively homogeneous in area in comparison to zip codes; (2) social and economic processes, such as crop insurance and disaster relief are organized at the county level; (3) farmers' street addresses are not available and it is not possible to identify their exact spatial location. Using county as the unit of analysis can be useful to make reasonable estimation of farmers' location; 4) a sufficiently large number of variables are available from secondary data sources such as the Census and Agricultural Census and these can be included in future research, and (6) the administrative level county is easily understood by decision-makers, both within and outside the realm of agriculture. Based on these reasons, county was chosen as the unit of analysis for small area estimation.

4.4.1 Preparing data for estimating county-level vulnerability scores

First, an average vulnerability score was calculated for each county by averaging the county's farmers' scores. One issue with this approach is that the average county vulnerability score is based on an unequal sample of farms/farmers. For example, figure 4 shows two box-plots depicting the variation in farmers' vulnerability scores between counties in the state of Ohio (top) and Iowa (bottom). These plots illustrate that there is considerable variation in vulnerability scores and sample size, both within and between counties in the state of Ohio and Iowa.

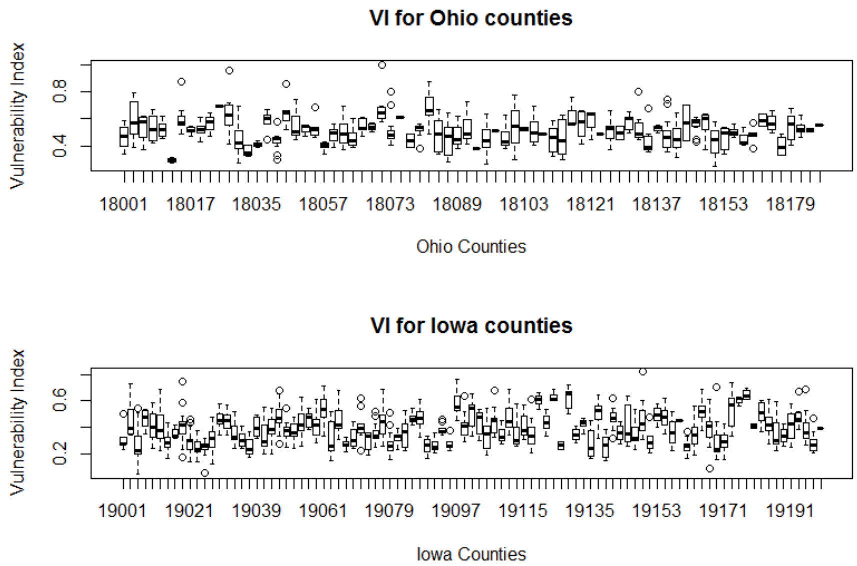

Figure 4: Vulnerability Index (VI) for farmers in counties in Ohio (top) and Iowa (Bottom)

This paper used an approximation to find the county-level simple random sample variance. This was done in three steps: (1) the variance among all farmers was calculated and was called 'V'; (2) The simple random sample variance of the county mean was found by dividing V by the number of farmer respondents for that county; and, (3) steps 1 and 2 were repeated for each county and a county-level simple random sample variance was computed. Hence, counties with fewer farmer respondents had a larger sampling variance.

4.4.2 Spatial smoothing vulnerability scores using Spatial Autoregressive (SAR) and Conditional Autoregressive (CAR) models

This paper used a Spatial Autoregressive (SAR) model and a Conditional Autoregressive (CAR) model to spatially smooth county-level vulnerability. These scores were estimated by using a maximum likelihood estimation technique. The analysis was conducted using the statistical software R.

First, suitable neighbors for each county were found by specifying a queen neighbor structure. On average there were 5.6 neighboring links for every county (Fig 5).

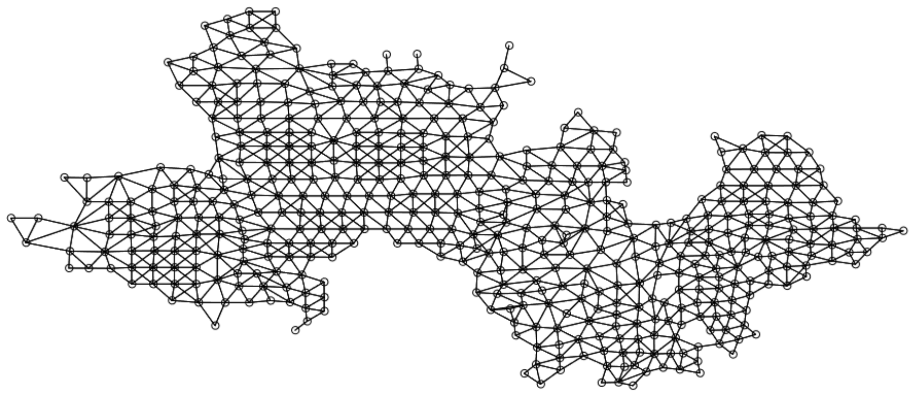

Figure 5: Queen Neighbors

After establishing the set of neighbors, spatial weights were assigned to each neighbor relationship. Two types of weights were specified: (1) Row standardized, where the "weights for links originating at areas with few neighbors are larger than those originating at areas with many neighbors (52)", and (2) Binary weights, which adds weight of 1 for each neighbor and 0 for non-neighbor relationship. The former is used to ensure that weights are asymmetric, which is essential for specifying a SAR model and the latter weight structure is used to define symmetry to estimate a CAR model.

Prior to specifying SAR and CAR models, a test was conducted for spatial association between counties. This study used queen neighbors with row-standardized weights to estimate the Moran's I. The Moran's I tests the null hypothesis of no spatial association between vulnerability scores for counties. The equation for estimating the Moran's I (eq. 9) is given below:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})} \qquad \text{Equation 9}$$

$\bar{y}$ is the mean of the variable of interest and w_{ij} represents the spatial weight.

As shown in Figure 6, the computed value of Moran's I = 0.50 and the p-value is <0.001. This suggests that counties with a higher vulnerability score tend to be surrounded by counties that also have a higher vulnerability score, and vice versa.

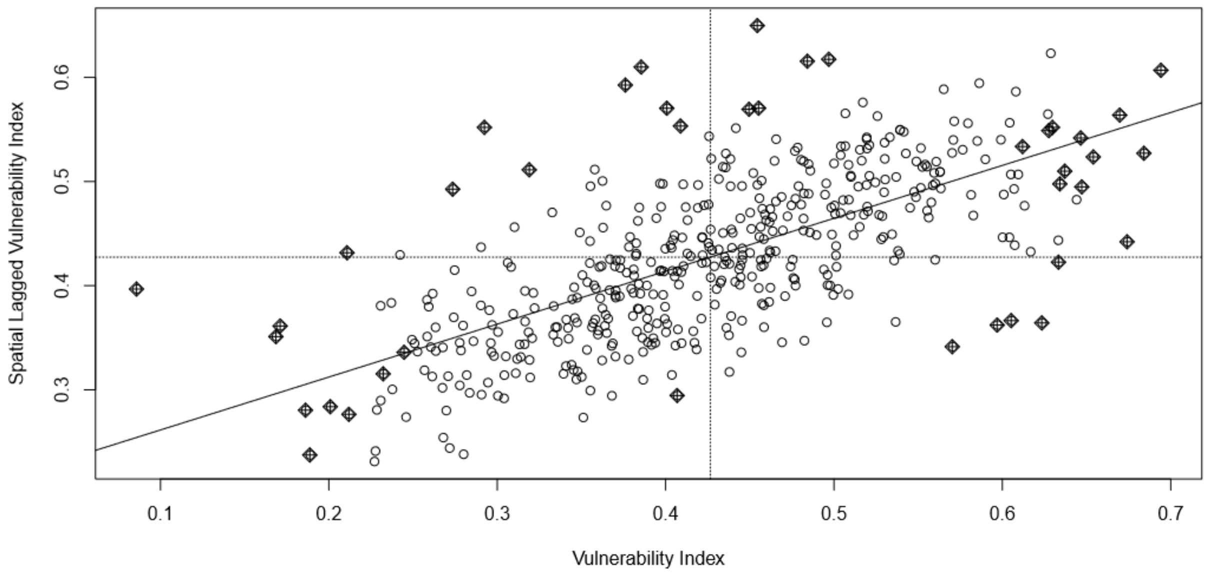

Figure 6: Moran Plot, Moran I = .50

Next, a spatial autoregressive model (SAR) was estimated. The SAR model allowed e_i to depend on error values in neighboring counties. The error terms were modeled in this form:

$$e_i = \sum_{i=1}^{m} b_{ij} e_i + \nu(s_i) \qquad \text{Equation 10}$$

Here, e_i represented the residual errors, where e_i ~ N(0, σ_e^2). The b_{ij} were the elements of the spatial dependence matrix expressing dependence among counties. $\nu(s_i)$ was an independent random disturbance for each county, where e_i ~ N(0, σ_ν^2). The error terms can also be expressed as:

$$Y = X^T\beta + B(Y - X^T\beta) + \nu(s_i) \qquad \text{Equation 11}$$

According to Bivand[(52)], this model can be re-written by using B in equation 11 as $B = \rho W$, where ρ is a spatial autocorrelation parameter and $W$is a matrix representing spatial dependence. Therefore equation 11 can be rewritten as:

$$Y = X^T\beta + \rho W(Y - X^T\beta) + \nu(s_i) \qquad \text{Equation 12}$$

Where $X^T\beta$ is the non-spatial trend component and $\rho W(Y - X^T\beta)$ is the spatial component. For conducting spatial smoothing, this study expresses $X^T\beta =$ μ, where μ is the global constant mean. The variance of Y can be written as:

$$\mathrm{Var}[Y] = \sigma^2(I - \rho W)^{-1}(I - \rho W^T)^{-1} \quad \text{Equation 13}$$

Equations 12 and 13 are estimated using maximum likelihood estimation technique in R.

While SAR model is suitable where there are second order dependency or a more global spatial autocorrelation, a Conditional Autoregressive Model (CAR) is more 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 and not neighbors of neighbors, etc. Formally, the CAR model can be written as:

$$Y_i|\, Y_{-i} = X_i\beta + \sum_{j=1}^{N} c_{ij}\left(Y_j - X_j\beta\right) + \nu_i \qquad \text{Equation 14}$$

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

$$\mathrm{Var}[Y] = (I - C)^{-1}\textstyle\sum v \qquad \text{Equation 15}$$

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}. To fulfill the second constraint, the study used binary weights that ensured symmetry in the neighboring structure.

Figure 6 illustrates the county-level vulnerability score found after spatial smoothing using a SAR model. The map depicts regional clusters of vulnerability. The value of ρ or the spatial autocorrelation parameter is 0.67 with a significant value of the likelihood ratio test i.e. $p<0.001$. The statistically significant value of ρ suggests that there is a significant spatial correlation in the residuals. The Akaike Information Criterion (AIC) is used to compare the fit of the SAR and CAR models. The AICs of the SAR and CAR models were -992 and -993, respectively. The AICs of the SAR and CAR models with a linear trend were -1008 and -1004, respectively. Therefore, both CAR and SAR models with a linear trend give a better model fit statistic than the same model without a linear model. Figure 6 shows a map of vulnerabilities for Upper Midwestern counties, spatially smoothed using SAR model. The map illustrates that vulnerability is geographically heterogeneous, with it increasing toward the Eastern regions of the Upper Midwest. Table VI shows the descriptive statistics for the estimated values of vulnerability. The smoothed values of vulnerability are the sum of non-spatial and spatial fitted values, including contributions from spatial neighbors.

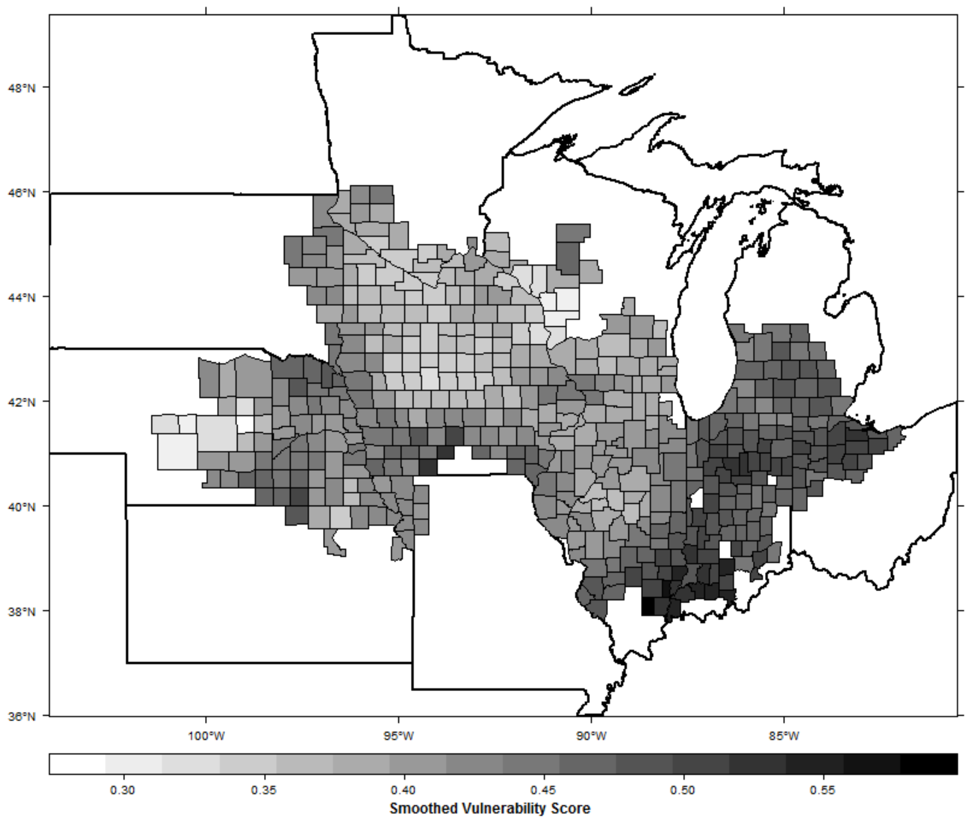

Figure 6: County-level vulnerability smoothed with SAR model

Table VI | Descriptive statistics for the smoothed estimates of vulnerability, exposure, sensitivity and perceived adaptive capacity

	SAR estimates				**CAR estimates**			
	Min	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**
Vulnerability Index	.29	.57	.43	.05	.23	.58	.43	.07
Exposure	.10	.63	.32	.19	-.05	.73	.32	.14
Sensitivity	.16	.53	.38	.05	-.01	.53	.38	.07
Perceived adaptive capacity	.46	.48	0.46	.002	.45	.48	.46	.004

Figure 7 illustrates the spatial representation of the sub-components of vulnerability: exposure, sensitivity, and perceived adaptive capacity. Darker shaded areas represent higher vulnerability than lighter shaded areas. As can be seen from Figure 7, there are geographical differences in county-level exposure (top-left) and sensitivity (top-right). Interestingly, the spatially smoothed values of perceived adaptive capacity (bottom-left) suggest that on average, the county-level smoothed score for perceived adaptive capacity were close to the average vulnerability. This suggests that on average farmers' in most Midwestern counties perceive themselves to be moderately prepared to cope with present and future impacts of climate change.

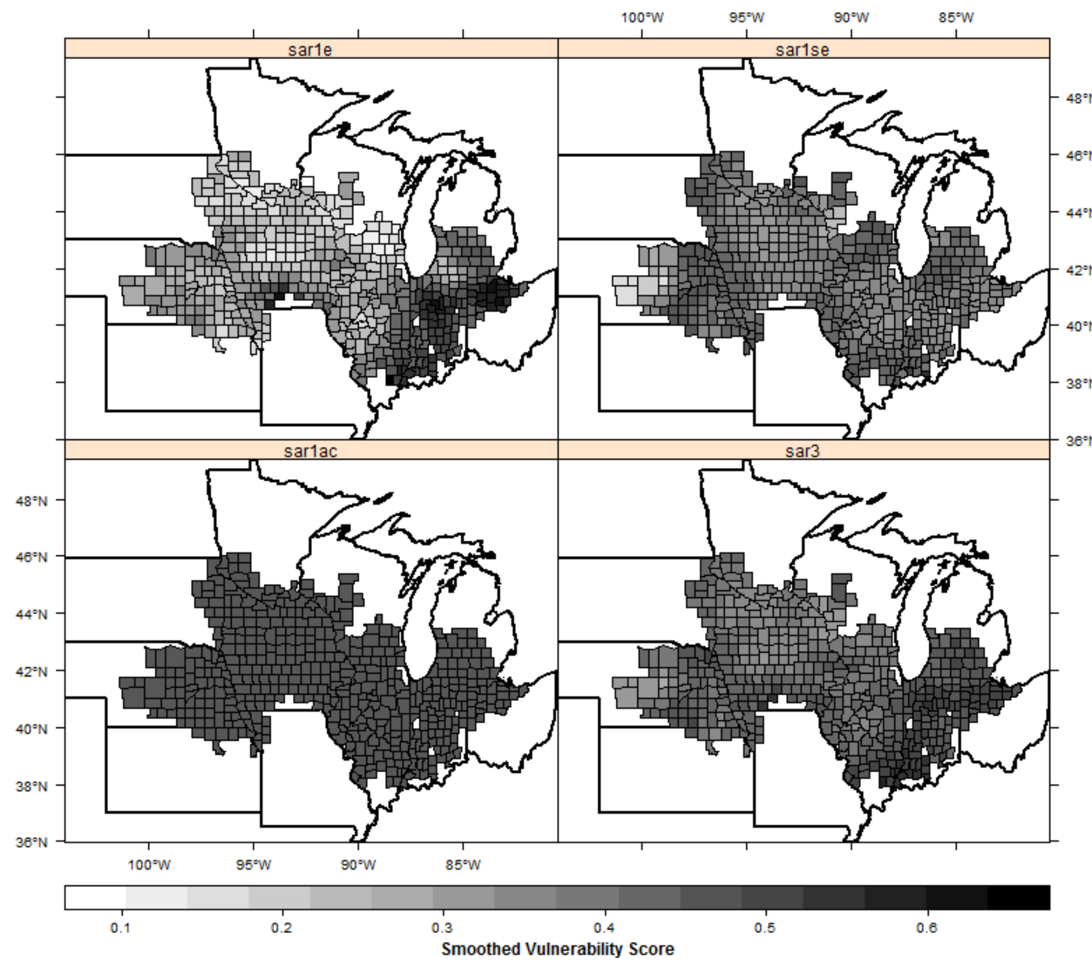

Figure 7: County-level exposure (top-left), sensitivity (top-right), perceived adaptive capacity (bottom-left), and vulnerability (bottom-right) smoothed with SAR model

5. DISCUSSION & CONCLUSION

Extension educators and agriculture policy makers are interested in spatially locating the distribution of farmers' vulnerabilities to climate change. They are interested in finding individual-level vulnerability in a given region. However, equally important for policy and planning purpose is to identify vulnerability in small administrative areas, such as at the county level. Focusing on small areas, such as counties in Midwestern U.S. can assist in the development of targeted policies and programs at the nexus of climate change, environmental conservation, and agriculture. This study estimated vulnerability indices for farmers as well as for administrative counties using both socio-cognitive (perceived adaptive capacity) and biophysical measures (exposure and sensitivity). Policy makers and extension educators can use these multi-level and multidimensional indices to develop 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, this research can identify places (counties) and individuals (farmers) that are vulnerable to extreme rain events and target their communication strategies toward these regions and people. Another application of the results from this study is to combine the results from both the county and farmer level indices. Combining the vulnerability scores can locate four (and potentially more) types of farmers-county categories: (1) low farmer vulnerability and low county vulnerability score, (2) low farmer and high county vulnerability score, (3) high farmer and low county vulnerability score and (4) high farmer and high county level vulnerability score. This configuration of farmer-county vulnerability scores would help outreach efforts to target farmers who can serve as role models and others who need most assistance. Therefore, the results from this research can help examine the interaction between place-specific (county) and farmer-level (farmer) vulnerability to form valuable strategies for farmer engagement.

Examining the interaction between farmer/county level exposure, sensitivity, and perceived adaptive capacity can also provide valuable lessons for engagement and communication. For example, the spatially smoothed county values of perceived adaptive capacity suggest that many farmers feel confident in their ability to face challenges posed by climate change. For policy makers and extension educators, it is important to note that when estimating vulnerability and communicating their findings they should account for farmers' level of self-efficacy. This research provides potential measures at the county level that can be used by government statistical agencies to corroborate their county-level objective measures.

One limitation of this research is that it is comprehensively relying on farmers' perception of their abilities to adapt to climate change as measure of their adaptive capacity. Future research should be looking at combining objective and perceived measures of adaptive capacity to improve estimation of vulnerability to improve this assessment. Overall, this research attempts to use biophysical and social indicators (both subjective and objective) to measure regional variation in vulnerability. The study found that There are regional variations in landscape, with higher potential for soil erosion in some parts of the region. However, there are few socio-cognitive differences between farmers within and between each county. This analysis used secondary data from the weather stations and primary data from survey of farmers' to map county-level climate change-related vulnerabilities. The spatial analysis, using a CAR and SAR model, suggests an Easting trend i.e. vulnerability increase in the East-West direction. Counties (average of farmers' vulnerabilities) in Indiana tend to be more vulnerable than other counties in the East, for example in Upper Iowa. There is also some degree of North-South trend i.e. northern counties of the Upper Midwest are less vulnerable than the southern counties. Lastly, there is spatial correlation with neighboring counties, even after accounting for a linear trend. Therefore, spatial neighbors have a great influence on other neighboring counties. Future research that looks at climate change vulnerability can improve their findings by incorporating spatial autocorrelation in their analysis.

This paper seeks to advance methodologies for assessing the vulnerability of Midwestern farmers to climate change. Specifically, it is argued that conventional measures of adaptive capacity in vulnerability assessments, which rely on 'objective' indicators such as income, fail to account for how social-psychological factors may facilitate or limit farmer's capacity to cope with extreme rain events.

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