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Evaluating livelihood vulnerability of farming communities to winter storms in Iowa

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EVALUATING LIVELIHOOD VULNERABILITY OF FARMING COMMUNITIES

TO WINTER STORMS IN IOWA

An Abstract of a Thesis

Submitted

in Partial Fulfillment

of the Requirements for the Degree

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Yiyi Zhang

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ABSTRACT

Driven by unusually warm air in the Arctic, severe winter weather moves southward to mid-latitude areas, indicating the complexity in the ways that climate change may affect local weather extremes. The vulnerability of farming communities to climate risks and differential response capabilities have drawn much research attention. Winter storms are recognized as one of the common catastrophic events leading to agricultural damage and loss. However, research is notably lacking in understanding the consequences extreme winter weather could bring in farmer livelihood.

This study is concerned with the vulnerability patterns of farming communities shaped under varying climate and socio-physical conditions. Focusing on Iowa as a case study, this research determined indicators capable of differentiating households with unequal vulnerability to winter storms based on semi-structured interviews. Spatial analysis was incorporated to quantify spatial information (i.e. winter temperature variation, natural shelter, energy capacity and facility density) subject to data aggregation. Factor analysis was used to investigate the relationships between adaptive capacity indicators. It extracted three underlying factors that could determine adaptive capacity, namely, farming economic status, environmental institutional capital and innovative capital. The exposure, sensitivity, adaptive capacity and overall vulnerability were calculated for each county in Iowa. The output maps demonstrated high vulnerability in Southeast Iowa due to low farming economic status and innovative capital, and high vulnerability in Northwest Iowa due to high exposure and low

environmental institutional capital. The limitations in normalization and index development were also addressed and discussed.

To understand complex farmer decisions that lead to different outcomes in storm losses, a conceptual agent-based model was constructed in an attempt to examine geographically and temporally, the multiple reasons that drive the decisions and key pathways in the response-loss process. This study identified interacting entities and variables characterizing these entities under a simplified farmer decision-making process, with a view to decompose upscaled winter storm loss patterns. The future objective is to explore alternative policy scenarios that can improve farmer livelihoods and reduce vulnerability, thereby providing authorities with a compelling account for making better-informed decisions about land resource management.

This study provides significant findings that may inform resource management for enhancing farming communities' adaptive capacity to extreme winter weather. Increasing resilience of farming systems, especially pasture, to winter storms, includes investment in natural capital and enhancement of farming economic status. Further validation for the vulnerability pattern includes surveys investigating farmers' perceived vulnerability. Future suggestions on vulnerability assessment are to use factor analysis to examine framework-based vulnerability indicator systems through empirical vulnerability case studies at various levels (e.g. tract as the unit). Methodologies could be advanced in exploring complex non-climate scenarios combining ground survey for physical and socio-economical information.

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Entitled: Evaluating Livelihood Vulnerability of Farming Communities to Winter Storms in Iowa

has been approved as meeting the thesis requirement for the

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter provides the background of this study on vulnerability assessment, as well as research questions, goals and objectives, and significance. A summary of how this thesis is structured is presented at the end of this chapter.

1.2 Background

Climate change-related weather anomalies, such as extreme drought and intense rainfall, have been observed in recent years in places where people are highly vulnerable to the associated effects (Martens and Chang 2017). Vulnerability to climate change and differential capabilities associated with social, environmental, and spatial dynamics to respond in face of shocks have constantly drawn much research attention (Windfeld et al. 2019; Thomas et al. 2019; Martens and Chang 2017; McDowell, Ford, and Jones 2016; Reed et al. 2013; Taubenböck et al. 2008; Füssel and Klein 2006; Adger 2006; Gallopín 2006). Case studies include vulnerability to flooding (Nasiri et al. 2019; Owusu, Jakpa, and Awere 2016; Clark et al. 1998), urban vulnerability to extreme heat (Mushore et al. 2018; Uejio et al. 2011), agricultural production vulnerability to drought (Antwi-Agyei et al. 2012; Nettier et al. 2010; Wilhelmi and Wilhite 2002), and Tibetan pastoralists' vulnerability to severe snowstorm (Yeh et al. 2014).

Extreme winter weather in a warming world is found no longer distant and marginal in the Arctic. Polar cold air and anomalously cold extremes have moved south to mid-latitude areas, as a result of winter atmospheric circulation at high northern latitudes associated with Arctic sea ice loss (Cohen, Pfeiffer, and Francis 2018; Yao et al. 2017; Tang et al. 2013). An increasing trend in winter storm intensity and frequency has also been observed in the mid-latitude regions in the US (Figures 1 and 2) (Vose et al. 2014), while very few upward trends are found in most weather-related disasters after normalizing for changes in exposure (Bouwer 2019). These changes have implications for local people, especially those that historically rely on traditional agriculture (Andresen, Hilberg, and Kunkel 2012). The impact of winter storms on farm lands can involve a number of issues, including rendering traditional routines obsolete and wiping out crops (Kronik and Verner 2010), as well as damaging farm buildings due to heavy snow or ice accumulation. However, research is notably lacking in vulnerability of farm communities to increasing winter storm events, which is recognized as one of catastrophic events leading to agricultural damage and loss (Chodur et al. 2018).

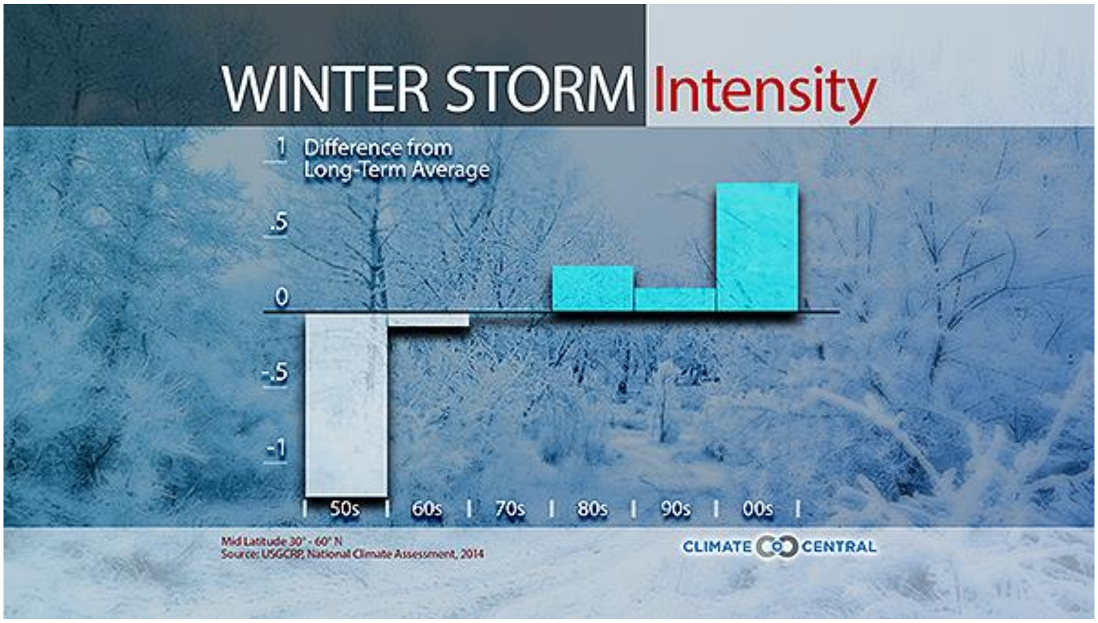

Figure 1 Mid-latitude National Winter Storm Intensity Since 1950

Source: Vose et al. 2014, “Monitoring and Understanding Changes in Extremes: Extratropical Storms, Winds, and Waves”, *Bulletin of the American Meteorological Society*, March 2014.

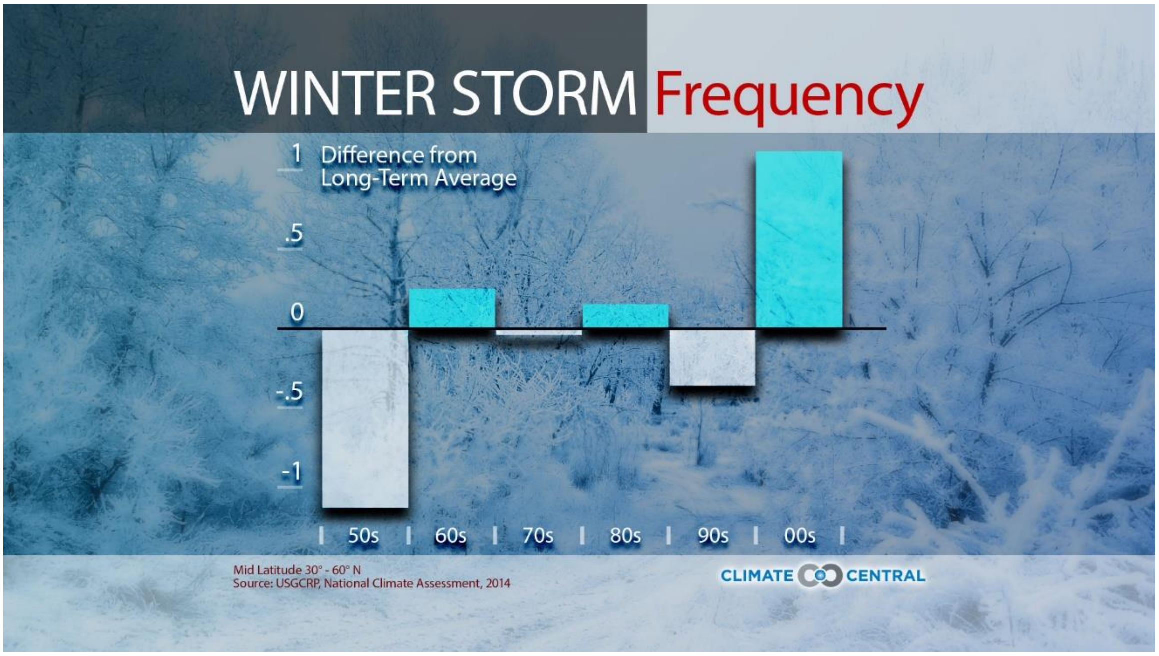

Figure 2 Mid-latitude National Winter Storm Frequency Since 1950

Source: Vose et al. 2014, "Monitoring and Understanding Changes in Extremes: Extratropical Storms, Winds, and Waves", *Bulletin of the American Meteorological Society*, March 2014.

There is little apparent consensus on a precise definition of vulnerability (Taubenböck et al. 2008; Gallopín 2006) and related theory is also split over how adaptation options are adopted. The vulnerability has been related to the degree to which a human social and ecological system will be affected by some forms of hazard (Reed et al. 2013; Turner et al. 2003). In particular, the vulnerability condition can be determined by physical, demographic, social, economic, environmental and political factors or processes which increase the susceptibility of a community to the impact of hazards taking the form of perturbations and stresses. Key parameters of vulnerability are the stress to which a system is exposed, its sensitivity and its adaptive capacity (Adger 2006).

The Sustainable Livelihoods Framework (SLF) is widely recognized as an effective approach to look at vulnerability and identify its elements. By using this framework, Reid and Vogel (2006) identified principal determinants shaping vulnerability as well as driving responses and adaptation to climate risks in South Africa. Hahn et al. (2009) pioneered the development of Livelihood Vulnerability Index (LVI) and recommended integration of local knowledge and information in empirical field settings when replicating the index. Vulnerability, often interchanged with livelihood vulnerability has been assessed in various settings with the adaptation of LVI. Although progress has been made regarding vulnerability assessment approaches and other formal methods (Pandey et al. 2017; Adu et al. 2017; Panthi et al. 2016; Ifejika Speranza, Wiesmann, and Rist 2014; Shah et al. 2013), mainstream literature still lacks a universally accepted measures of weather-related livelihood vulnerability. The lack of flexibility in inclusion or exclusion of location-specific indicators is a major reason. As McCarthy et al. (2001) asserted, methods and tools for vulnerability assessment combining component indicators should be tested. Therefore, this study seeks to sort out and test the indicators for winter storms vulnerability assessment, resting on the Sustainable Livelihood Framework (SLA).

It is acknowledged that vulnerability varies on small scales and even at the household level. This is because adaptive capacity, an integral consideration of vulnerability, can buffer the adverse impacts of stresses. Adaptive capacity to vulnerability manifests by adaptations employed to moderate stressful climatic extremes (Ford and Pearce 2010). Therefore, vulnerability is reduced when capacity is higher, which results from human deliberation and action. In a rural neighborhood, a farmer is a critical decision maker if agricultural lands are to be effectively managed to adapt to changing climate conditions (Arbuckle, Morton, and Hobbs 2013). Agents, understood as groups of population who deliberately interact with their surroundings – both the physical and social, are utilized in this study, to explore how farming households under diverse adaptive scenarios respond to winter storms to reduce potential loss. In order to illustrate what dominant factors influence household vulnerability to winter storms and decompose the adaptive process of farming households as agents, this study aims to conduct vulnerability assessment and construct a conceptual agent-based model, which has been used in simulating agent's response-loss process and assessing vulnerability to global environmental change (Liang, Scheffran, and Oßenbrügge 2015; Acosta-Michlik 2005).

1.3 Research Questions

This study is concerned with the patterns of winter storm vulnerability shaped by varying physical environments, weather conditions, as well as adaptation dynamics. To this end, this study works towards answering below research questions:

(1) What are the dominant winter storm characteristics and associated impacts on farming households?

(2) What are the patterns of winter storm vulnerability and its driving factors to that vulnerability?

(3) How to structure the agent-based model to simulate the dynamic process of households' responses to winter storms and economic loss?

1.4 Goal and Objectives, Research Significance

This study aims to investigate farming community vulnerability to winter storms in Iowa, which is very reliant on agriculture and has been experiencing extreme winter weather (Andresen et al. 2012). Specifically, the objectives are to:

(1) identify dominant factors contributing to the vulnerability of farming communities to winter storms and to develop an inclusive indicator system using interviews;

(2) identify underlying factors contributing to adaptive capacity using factor analysis;

(3) quantify and illustrate the stage of winter storm vulnerability, exposure, sensitivity, and adaptive capacity in Iowa;

(4) identify elements and address concepts related to farmer adaptive behavior for agent-based modeling.

Studying whether vulnerability of households in farming communities varies in relation to winter storms has implications in sustainable development of agriculture and rural livelihoods. Findings of this study are expected to bring several advantages:

(1) In supplementing the case studies and approaches to assessing vulnerability to extreme weather;

(2) In informing decision making on intervention strategies to minimize the consequences of extreme winter weather on community welfare, moving beyond understanding of phenomena to improving the human condition.

(3) In communicating an agent-based model as a useful instrument in climate vulnerability assessment by framing the dynamics in climate adaptation. At the scale of local communities, the simulation results would provide insights into households' behaviors and ensuing losses.

1.5 Thesis Framework

The remainder of this thesis is organized as follows. Chapter 2 presents theoretical concepts and framework, previous studies conducted to assess the vulnerability to climate-related weather, as well as the basis and foreground of the modeling approach. Chapter 3 incorporates the introduction of the scope of case study and presents research methods applied to achieve the objectives. Chapter 4 presents the results of the study, followed by more thorough discussions on the results presented in Chapter 5. Significant findings and conclusions are covered in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This literature review covers a range of topics pertaining to winter storms and their impacts in the rural context, as well as approaches to assessing climate vulnerability and adaptation.

2.2 The Impacts of Winter Storms on Farming Communities

Winter storms generally include storm events that occur at dangerously cold temperatures and accompanied by strong winds, freezing rain or sleet, heavy snowfall and other cold precipitation formations. Climate change has been observed to cause an increasing frequency of severe winter weather in mid-latitudes through the Arctic transitions from a relatively cold state to a warmer one (Cohen, Pfeiffer, and Francis 2018; Yao et al. 2017; Tang et al. 2013). Winter storms and their losses have been considered infrequent but produce consequential losses (Changnon, 2003). It was found that the US experienced increased occurrences between 1949-2000 in storm size and losses (Changnon and Changnon 2005). According to U.S. Natural Catastrophe Losses (Table 1), winter weather-related losses also increase steadily in recent years and no less costly than losses from floods. However, as one of the common catastrophic weather events, winter storms and their impacts are often overlooked and understudied.

Table 1 Natural Catastrophe Losses in The United States between 2014-2018

Estimated Overall Losses (US $ bn)	2014	2015	2016	2017	2018
Severe Thunderstorm	17	9.6	19	25.4	18.8
Winter Storms & Cold Waves	3.7	3.5	1.7	2.2	4.2
Flood, Flash Flood	1.8	1.1	15	0.4	2.6
Earthquake	0.75	Minor	Minor	Minor	0.5
Tropical Cyclone	0.095	0.06	7	123	30.4
Wildfire, Heat Waves, &Drought	1.7	1.9	1.2	14.3	25.4

Source: Data adapted from archived graphs by Munich Re and Property Claim Services, "Natural Catastrophe Losses in The United States", accessed November 11, 2019, from https://www.iii.org/graph-archive/96537.

Climate changes have great implications for people who historically rely on traditional agriculture (Andresen et al. 2012). In farming regions, severe winter storms such as unending snowfall and extremely low temperature can lead to structural damage, animal losses and milk production (Bunting 2019). Midwest is a major producer of vegetables, dairy and beef cattle, and pigs (Andresen, Hilberg, and Kunkel 2012). It is also a region that has experienced severe cold-air outbreaks and record numbers of snowstorms (Marinaro et al. 2015). Winter storms can keep farmers away from fieldwork or product delivery, and lead to crop damage or delays in planting. Ice cumulation of an inch or more could make travel hazardous and increase the potential of building damage, power outages and fuel shortages. Winter storms can also cause severe loss to livestock and wild game, with mounting daily loss to breeding animals (Knutson 1949). Farming communities are significantly exposed to negative consequences of the disastrous winter storms. Especially in some livestock farms, the climate risk can exacerbate the losses to farms that are simultaneously impacted by volatile feed costs and weak market conditions (Lawrence and Smith 2015).

Studies on the impacts of winter storms in rural settings are still limited, while some are found in discussing winter storm damage on forests (Schmidt et al. 2010; Seischab, Bernard, and Eberle 1993; Goebel and Deitschman 1967). There is a general lack of research focused on population in farming communities that are vulnerable to catastrophic winter weather.

2.3 Vulnerability to Climate Change and Winter Storm

The impacts of hazardous events are considered usually unevenly distributed among and within nations, regions, communities, and groups of individuals (Clark et al. 1998). For example, different severities of the same storm event can be observed in different parts of the country due to climate and non-climate factors including social-economics status and topographic characteristics. Vulnerable groups, especially natural resources dependent communities, are more likely to suffer from a disproportionate share of hazardous events (Shah et al. 2013; Shah 2011).

The vulnerability to climate change and differential response capabilities have drawn much research attention. It was not until 2001 third assessment report of the Intergovernmental Panel on Climate Change (IPCC), when the term “Vulnerability” was used in the assessment report title, although IPCC had produced assessments on climate change impacts, adaptation, and vulnerability since 1990. Changes in parameters of climate including temperature, precipitation and solar radiation are considered to affect human settlements and agricultural production (IPCC 1990). Rural households are more vulnerable because they rely heavily on climate-sensitive resources and activities. This "propensity or predisposition to be adversely affected" is the definition of vulnerability (IPCC 2012). It is an integrated measure of the expected magnitude of adverse effects of climate change to a system caused by a given level of certain external stressors (Füssel and Klein 2006; IPCC 2001b).

Many studies are focused on the vulnerability in rural contexts to thermal stress and summer precipitation rather than to winter weather, since global climate change is likely to take the form of the increasing frequency and severity in heat waves and milder winters (IPCC 2001a). Of these studies, vulnerability in coastal communities and drought or flood-prone regions account for the majority of topics (Uddin et al. 2019; Mushore et al. 2018; McDowell, Ford, and Jones 2016; Antwi-Agyei et al. 2012). Several studies also bring in novelties and methodological advances in approaches to assessing livelihood vulnerability to climate change in various sectors. Such as studies on the impacts of climate change on ski industry and fisheries, as well as studies using integrative or dynamic models to understand the compound social and physical vulnerability and interactions of climate change impacts (Pons-Pons et al. 2012; Hahn, Riederer, and Foster 2009; Acosta-Michlik and Espaldon 2008; Hunt, Kushneriuk, and Lester 2007; Clark et al. 1998). Research has also advanced considerably in vulnerability studies across multiple scales ranging from local level to macro level (Windfeld et al. 2019; Adu et al. 2017; Panthi et al. 2016; Uejio et al. 2011).

Numerous vulnerability studies have previously provided insights into the impacts of the multidimensional process of climate change and extreme weather. Location-specific modeling and empirical studies for vulnerability to long-term changes assists us in planning more plausible scenarios for adaptation. It also has to be noted that tangible impacts during short-term present-day extreme weather are not negligible. Places such as the Midwestern USA, with historical reliance on traditional agriculture, have seen significant losses and damages such as decreasing yields and commodity quality levels caused by extreme winter weather (Chodur et al. 2018; Andresen, Hilberg, and Kunkel 2012). The impact of winter storm can involve a number of issues in agriculture, to which households under different socioeconomic backgrounds and biophysical environments are likely to adapt in different ways. Current mainstream studies on climatic risks in rural contexts have not addressed on-farm losses from the short-term winter extreme weather, while some efforts are found in studies on pastoralists' vulnerability to snow storms under long-term climate change (Yeh et al. 2014). There is a need for theoretical and methodological advances in assessing the vulnerability of farming communities to winter storms.

2.4 Vulnerability Assessment Approaches and Sustainable Livelihood Framework

Previous studies conducted vulnerability assessments using diverse approaches to systematically examine the interactions between humans and their surroundings. The first and most widely used method to assess vulnerability is the IPCC framework, which provides a framework for analyzing key components determining the vulnerability to climate change in three dimensions: 1) exposure that characterizes the stressors and the entities under stress, 2) sensitivity that characterizes the first-order effects of the stresses, and the 3) capacity of the system to cope, adapt or recover from the effects of those conditions (Polsky, Neff, and Yarnal 2007; Smit and Wandel 2006; IPCC 2001b). This framework provides qualitative researchers with basis for framing problems. An eight-step methodological protocol was proposed by Schröter et al. (2005) to conduct vulnerability assessment. Ford et al. (Ford and Smit, 2004; Ford and Goldhar, 2012) have greatly advanced qualitative approaches to assessing vulnerability from local perspective and contributed to the characterization of exposure and adaptive capacity. Thereafter development of vulnerability assessment shifted the focus to quantitative-based studies. Quantitative approaches to assessing vulnerability are generally indicator-based and location- or case-specific (Nasiri et al. 2019; Panthi et al. 2016; Shah et al. 2013; C. E. Reid et al. 2009; Clark et al. 1998). These vulnerability studies have allowed more vulnerable areas and sectors to be covered.

There are several investigators and characterizations of vulnerability components that should be mentioned as they provided insights into holistic models for vulnerability assessment. Based on IPCC framework and Sustainable Livelihoods Framework (SLF), Hahn et al. (2009) developed the Livelihood vulnerability index (LVI). The LVI was among the first to categorize major indicators into contributing dimensions of vulnerability to assess livelihood vulnerability to climate change. This indicator system was further developed with the replacement and addition of some indicators to suit the local context and to be more relevant for target group. For example, Shah et al. (2013) introduced and modified indicators such as household dependence on hunting and fishing for food to emphasize the importance of fishing in coastal wetland context. Panthi et al. (2016) replaced average temperature and precipitation used in the climate variability component with climate-extreme duration as these were more relevant to the daily activities of livestock smallholders. There is also an increasing recognition of the linkage between vulnerability and livelihood capitals that constitute the SLF. Five forms of livelihood capitals were integrated into indices to measure vulnerability components (Pandey et al. 2017; Nelson et al. 2010; Gbetibouo, Ringler, and Hassan 2010). Table 2 compares in more detail the various indicator systems used in different case studies. Despite the commonality of some major indicators, such as, dependency ratio, various dissimilar measurements were also used to characterized vulnerability in the specific contexts, such as farm income that was not included in Hahn et al. (2009)'s LVI. What is also clear is the varying categorization of indicators at the major- and sub-component level. For example, Pandey et al. (2015)'s CVIW used crop diversification as adaptive capacity indicator, while Health component was considered to indicate sensitivity in Gbetibouo et al. (2010).

Table 2 Similar and Dissimilar Indicators Used in Case Studies on Climate Change Vulnerability

Index	Exposure components	Sensitivity components	Adaptive capacity components	Case study
Livelihood Vulnerability Index (LVI) by Hahn et al. (2009)	Natural disasters and climate variability • Frequency of events • Temperature deviation • Warning receiving	Health • Time to facility • Disease exposure • Family member illness Food • Crop saving • Family farm food dependence Water • Time to water source • Water storage	Socio-demographic profile • Dependency ratio • School attendance • Female headed households Livelihood strategies • Agricultural livelihood diversification Social networks • Receive: give ratio • Government assistance	Climate variability and change in Mozambique
Vulnerability Index (VI) by Gbetibouo et al. (2010)	• Extreme events • Temperature deviation	• Crop diversification* • Land degradation* * • Rural population density**	Human capital • Literacy rate Social capital • Farm organization* Financial capital • Farm income* Physical capital • Infrastructure	Climate change vulnerability in South African farming sector

Index	Exposure components	Sensitivity components	Adaptive capacity components	Case study
Vulnerability Index (VI) by Shah et al. (2013)	Natural disasters and climate variability • Temperature deviation • Extreme events • Household losses*	Health • Time to facility • Disease exposure • Family member illness Food • Crop diversification* • Family farm food dependence • Fish/hunting dependence** Water • Water storage	Socio-demographic profile • Dependency ratio • School attendance • Average age of female headed households* Livelihood strategies • Household income dependent on agriculture* • Livelihood diversification Social networks • Receive: give ratio • Government assistance	wetland communities in Trinidad and Tobago
Climate Vulnerability Index for Water (CVIW) by Pandey et al. (2015)	Natural resource access and scarcity** • Watershed potential • Water scarcity for agriculture Climate variability • Temperature • Water-related events** Climate impact • Change in water sources**	Health • Disease prevalence • Family member illness Water quality** • Mortality of flora Financial capital* • Decrease in agricultural products Food insufficiency* • Decrease in food production Water scarcity** • Scarcity of livestock water	Socio-demographic profile • Family decision** • Dependency ratio Livelihood • Change in livelihood strategies Cultivation practice* • New crop Water requirement** • Reduced water	Climate change vulnerability of water in Uttrakhand, India

Index	Exposure components	Sensitivity components	Adaptive capacity components	Case study
Livelihood Vulnerability Index (LVI) by Panthi (2016)	Natural disasters and climate variability • Extreme events • Event duration	Health • Time to facility • Disease exposure • Family member illness Food • Seed saving • Family farm food dependence Water • Time to water sources	Socio-demographic profile • Dependency ratio • School attendance • Female headed households Livelihood strategies • Livestock diversification** Social networks • Access to media** • Farm organization*	Agro-livestock smallholders around the Gandaki River Basin in Nepal
Climate Vulnerability Index (CVI) by Pandey et al. (2017)	Human capital • Farm Food sufficiency Social capital • Local crime* Financial capital • land loss* Physical capital • House and property loss* Natural capital • Problems accessing natural resources* • Decrease in crop production	Human capital • Family member illness Social capital • Access to daily information* Financial capital • Financial support from friends or relatives Physical capital • Low-lying land* Natural capital • Family farm food dependence • Natural disaster report*	Human capital • Dependency index • Profession diversity** Social capital • Receive and give indicators Financial capital • Government or NGO assistance Physical capital • Household with livestock** Natural capital • Cultivation practice* • Natural resource diversification**	Climate change vulnerability in Uttrakhand, India

*Indicators not included in the early LVI developed Hahn et al. (2009)

** Indicators selected exclusively to suit the specific context or not included in other listed studies

As shown in the Table 1, the Sustainable Livelihoods Framework has fundamentally influenced the composite of vulnerability indicators. The capital-based framework helps identify ways capital can be used to cope with problems in the short and long term. It views people as operating in the vulnerability context and identifies five core categories of capital (natural, physical, human, social and financial capital) upon which livelihoods are built (Department for International Development 1999; Carney 1998). Figure 3 demonstrates links between different factors affecting livelihoods in the context of vulnerability, referred to as the environment where people's livelihoods and availability of assets are affected by all types of external trends and shocks, including seasonality and climatic variability.

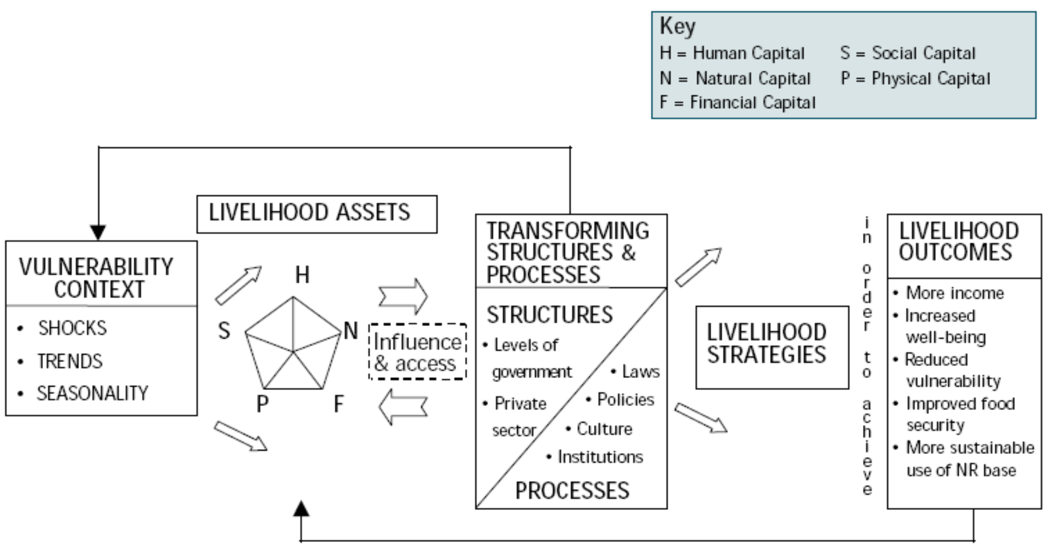

Figure 3 Sustainable Livelihoods Framework

Source: Department for International Development 1999, "DFID Sustainable Livelihoods Guidance Sheets", from http://www.livelihoodscentre.org/documents/20720/100145/Sustainable+livelihoods+guidance+sheets/8f35b59f-8207-43fc-8b99-df75d3000e86

Research attention has long been drawn to the examination of vulnerability to future climate-induced problems using SLF (Pandey et al. 2017; Sarker et al. 2019). Reed et al. (2013) provided several ways where SLF can be used in analyzing vulnerability to climate change and developed an integrated framework by combining widely used analytical frameworks including ecosystem services, diffusion theory, social learning, adaptive management and transitions management. Speranza et al. (2014) discussed the role of livelihood capitals in maintaining resilience to adverse consequences of change. Despite studies that have sought to estimate the level of livelihood vulnerability of agricultural communities to climate extremes such as flood and drought (Adu et al. 2017; Owusu, Jakpa, and Awere 2016), the common element indicating the vulnerability of farming communities to winter storms is a gap, found in many vulnerability analyses in the context of various sectors.

2.5 Agent-Based Simulation in Vulnerability Assessment

Vulnerability indicates the extent to which these assets, people and activities can suffer damage when a hazard occurs (Bouwer 2019). The vulnerability assessment approaches discussed above focus on overall socio-economic conditions of a society and areas by linking static indicators of human adaptive capacity and environmental exposure. It is acknowledged that these top-down approaches often fail to investigate the process through which adaptation measures are undertaken regarding specific climate conditions and local constraints (Smit and Wandel 2006; Windfeld et al. 2019). Adaptations to climate change are the adjustments of a system to moderate the impacts of climate change, to take advantages of new opportunities or to cope with the consequences

(Adger et al. 2003). It remains challenging to provide adequate information for the development of adaptation policy as vulnerable groups and communities are often merged into a larger unit in the majority of vulnerability analyses. Recognizing the complex human-environment dynamics and information needs of adaptation decision-makers (Füssel and Klein 2006), bottom-up approaches emerged to assesses vulnerability at individual or household scales (Hailegiorgis, Crooks, and Cioffi-Revilla 2018; Krömker, Eierdanz, and Stolberg 2008; Acosta-Michlik and Espaldon 2008) taking into account the adaptation process of people or groups affected by climate consequences. These studies addressed the complexity of human behavior against climate consequences and uncertainty using "fine-resolution" simulation models – agent-based models that integrate both biophysical and socioeconomic processes (Berger and Troost 2013).

Local stakeholders including farming households are in many cases agents of landscape change (Diniz et al. 2015). Agent-based models have been extensively used in modeling settlement and land-use change as a result of social and environmental processes. Such as the landscape structure change due to the processes of farm cessation, farm expansion and farm diversification (Valbuena et al. 2010). Agent-based models can also mimic emergent behaviors by simulating how individual interact with each other and adapt to changing conditions in a community such as water dynamics, snow cover decline and harvest shortfalls of climate change (Balbi et al. 2013; Naivinit et al. 2008; Berman et al. 2004). Coupling agent-based models with biophysical and climate models makes it possible to model which adaptation options are likely to be adopted where, and consequently how they may mitigate the effects of climate change (Reed et al. 2013).

Agent-based modelling illustrates how macro-level behavior can emerge from various types of rules which inform decisions at the local level. It has implications in clearer understanding of the original field data and scaling up of vulnerability assessment (Bharwani et al. 2005). Acosta-Michlik and Espaldon (2008) integrated indicator-based, profile-based and agent-based approach to identify vulnerable regions, construct farmer typologies and simulate the adaptive behavior of local people to global environmental change, significantly pushing forward vulnerability assessment. Agent-based model was also adopted to deal with the interaction between flood inundation and household responses, simulating agent's response-loss process (Liang, Scheffran, and Oßenbrügge 2015). While sufficiently complex social and ecological systems make it impossible to predict future vulnerability completely, current models greatly contribute to reducing uncertainties about what to do, when, and by who by deriving decision-rules from field-based data (Van Oel et al. 2019; Reed et al. 2013). To understand uncertainty is challenging and identified as one of promising area of research on differential vulnerability (Bouwer 2019; Thomas et al. 2019). Agent-based modeling is considered as a substantial policy experimentation vehicle as it can capture uncertainty sources of climatic and non-climatic scenarios. However, current ABM dealing with climate vulnerability and adaptation are far less accessible than traditional analytical models due to relatively ambiguous and incomplete descriptions (Grimm et al. 2006).

2.6 Summary of Literature Review

This literature review highlighted and analyzed current knowledge in relation to research questions concerning vulnerability to winter storms, vulnerability assessment methods, and adaptation dynamics. Knowledge gaps in assessing vulnerability to climatic risks in rural contexts were identified. Winter storms as one of the devastating natural disasters is far less discussed, especially their impacts on farms. Studies assessing vulnerability to climate change and extreme weather have advanced considerably in terms of the adopted indicator systems. These indicator systems developed previously for different vulnerability contexts were summarized. The Sustainable livelihoods framework (SLA) has been adopted to develop vulnerability indexes assessing the contribution to adaptation and hence vulnerability reduction. However, currently winter storm vulnerability index is a gap and the testing of SLA-based indicators is inadequate. There has also been very limited exploration of dynamic climate adaptation in farming communities. Despite capabilities in representing the dynamic and complex human-environment system, agent-based models dealing with climate vulnerability and adaptation are far less accessible than traditional analytical models.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter describes the study area including the physical environment, socioeconomic status and prominent characteristics. Approaches in data collection and data processing for indicator-based vulnerability assessment are presented. A conceptual agent-based model is constructed in an attempt to quantify on-farm storm loss at community-level with respect to climate scenarios, farmer behaviors and environment realities.

3.2 Study Area

The study area is Iowa, located in the Midwestern of the United States between 40°35’N-43°30’N latitude and 90°8’W-96°38’W longitude (Figure 4). It was declared that a total of 3,046,355 people lived in Iowa in 2010 and it is estimated as of 2019 the population in Iowa is 3.17 million (World Population Review 2019). Iowa maintains a diversified economy, with agriculture, manufacturing, biotechnology, finance and insurance services, and government services contributing substantially to its economy. The state comprises 35.7 million acres, with over 85 percent of the land farmed, and has long lead nationally in hog, egg, corn and soybean productions (Living History Farms n.d.). Metropolitan areas with a population of more than 100,000 include the capital city Des Moines in Polk County, Cedar Rapids in Linn County and Davenport in Scott County. There are 21 out of total 99 counties falling into metropolitan statistical areas in Iowa. County is chosen as the analytical scale in this study.

Iowa is located in the heart of blizzard-belt and experiences frigid winter temperatures as well as dramatic storms in the winter (Waite 1970). Average winters in the state have been known to drop well below freezing, even as low as below 6 °F (−14 °C) in Waterloo (US Travel Weather 2018) – the main study site of the research. Figure 5 shows continuous change of raw count of winter storm event over 20 years and the number of standard deviations (Z-score) each year's count to the average. There were more above-average event occurrences (Z-score﹥0) in recent time from 2007 to 2018, indicating a generally increasing trend in winter storm events in Iowa comparing with the earlier period (1995-2007). Figure 6 shows the storm occurrences of the top 15 counties with overall highest storm counts between 2010 and 2018. Several counties (from Ida to Osceola) experienced relatively uneventful winters during 2013-2016. However, winter storms hit more frequently in these counties in 2017. This indicates the complexity in the ways that climate change may affect local weather extremes.

Figure 4 Location of Study Area, State of Iowa, United States

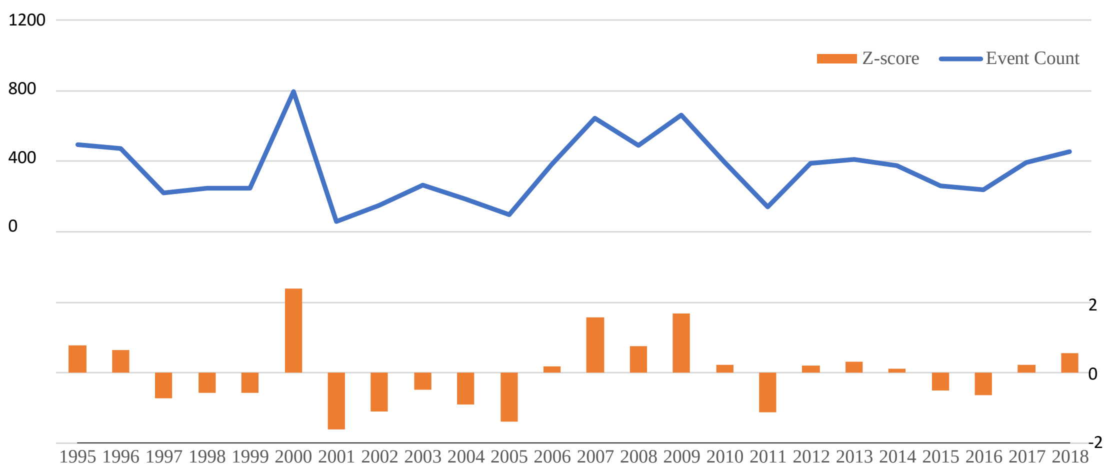

Figure 5 Winter Storm Event Count in Iowa between 1995 and 2018

Source: Data compiled from Storm Event Database by National Weather Service, from https://www.ncdc.noaa.gov/stormevents/choosedates.jsp?statefips=19%2CIOWA

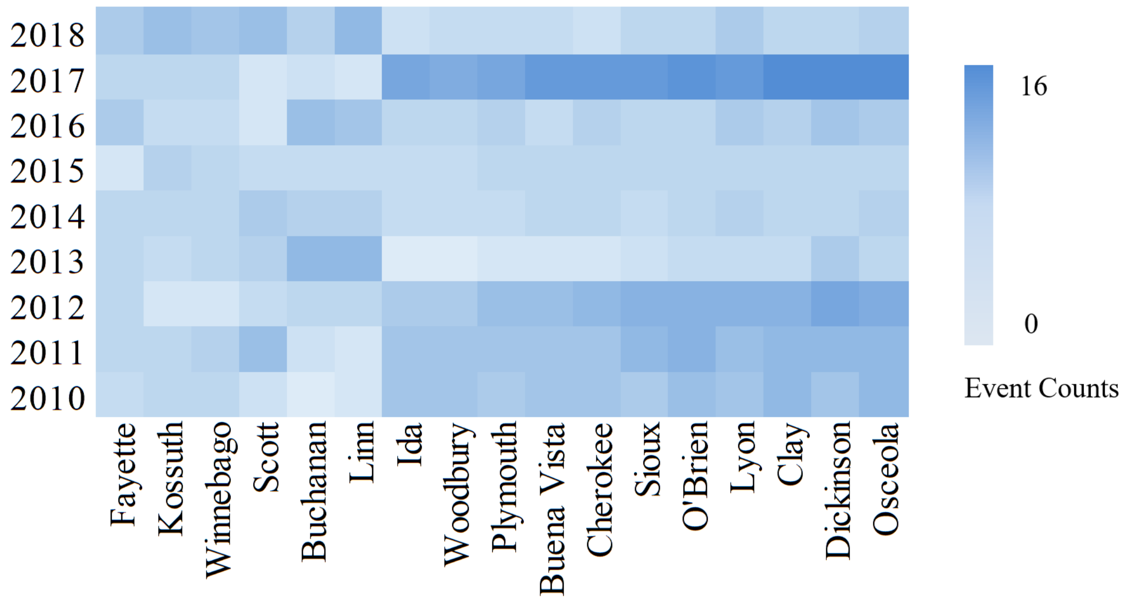

Figure 6 Winter Storm Event Raw Count and Z-score of Top 15 Counties with Highest Total Counts in Iowa between 2010 and 2018

Source: Data compiled from Storm Event Database by National Weather Service, from https://www.ncdc.noaa.gov/stormevents/choosedates.jsp?statefips=19%2CIOWA.

3.3 Semi-Structured Interview and Data Visualization

Semi-structured interviews were conducted in the January and February of 2019 in Black Hawk County and several other Iowa counties (Buchanan and Kossuth, and the southern Washington) in order to gain insights on farmers' winter storm experiences and response options with regard to winter storms. This information is helpful in the cross-validation of the relevant indicators differentiating households with unequal vulnerability and management decisions. During this phase, 14 farmers from a variety of farm settings (i.e. agricultural practicing methods and products) were selected using a purposive snowball sampling approach so that they can broadly represent the main types of farms and farmers for the study site. To probe into more information on farmers' perceptions and opinions and facilitate comparability, the varied farming status (active and non-active) and cultural background (Amish and non-Amish) were also taken into consideration. While the pilot study area did not cover the entire state, its geographic characteristics qualify it to provide supporting information on general issues and responses that farmers tend to have against the winter storms in Iowa.

A series of open-ended questions were asked in terms of the impacts of winter storms on farming and household coping responses (Table 3). Interview questions were designed to cover the topics involving sensitivity (Q1), exposure (Q2-4), and adaptive capacity (Q5, Q6). Questions 7 and 8 were designed to explore farmers' perceived vulnerability and the resilience which can reduce the initial outcome of a hazard event on capitals and minimize the loss (CAMP Alatoo 2013), while the resilience was not included in this study in calculating the overall vulnerability. Interviews for 8 main questions and 8 sub-questions took between 30 minutes to one hour to complete.

Table 3 Questions for Interviews with Farmers

Topic	Interview Questions
Household characteristics	Q1. What kind of agricultural products do you produce on your farm? How many acres?
Winter storms and impacts	Q2. Do you remember any severe winter storms that happened here last year? (e.g. heavy snow). Q3. Do you recall any impacts of them on the farm? What were the most significant impact? Q4. How do they affect your farm product and bottom line?
Winter storms adaptation	Q5. What did you do when your farm suffered from the winter storms? a. Did you received the warning information? Where was it from and how long was it before the event? b. What were your preparedness measures? c. What were your recovery actions after the events?
	Q6. What measures have the state or the county taken to addressing winter storms? How did the process work?
	Q7. What helped you reduce the risk and overcome the effects of these storms?
The end	Q8. Do you think you are more prone to be affected by the winter storms than farms around? Why? What can help you to mitigate this situation?

To ease the identification of key indicators, text visualization was performed using Tableau 2019 3.0 (https://www.tableau.com/). Interview recordings were first transcribed and compiled with written memos into a text document. Single-word labels were used as codes to represent the content in relation to the interested subjects based on the authors’ understanding of farmers’ responses. For example, “close up the barn and buildings” was coded as “buildings” to represent a means to prepare for winter storms. These words were imported in Tableau for visualization. A word cloud was generated to visualize the most frequently mentioned words regarding interview questions. A web application Carrot^2 (https://search.carrot2.org/#/web) was used to search online relevant articles using a keyword string “winter storm farm”. Search results were organized into hierarchical groups and visualized for a quick overview of most frequently mentioned topics related to the impacts of winter storms on farming.

3.4 Quantifying Integrated Vulnerability

3.4.1 Selection of Indicators

Potential regional and sectoral impacts of winter storm in Iowa together with the information on vulnerability and response options were gathered with the help of interview and face-to-face discussion with local farmers and farming experts. The integrated vulnerability is calculated based on the Intergovernmental Panel on Climate Change's definition of vulnerability understood as an aggregation of three components: exposure, sensitivity and adaptive capacity (IPCC 2001a; Gbetibouo, Ringler, and Hassan 2010). In this study, all indicators are thus categorized into three groups accordingly and are explained below:

3.4.1.1 Exposure The midwestern USA with historical reliance on traditional agriculture has seen significant losses and damages such as decreasing yields and commodity quality levels caused by extreme winter weather (Andresen, Hilberg, and Kunkel 2012). Farmers are exposed to extreme winter weather threatening animal health and power supplies, but not all farmers are equally vulnerable. Winter storms are unevenly distributed with an uncertain trend in event occurrences in recent years. This study selected two common indicators used in previous case studies on climate vulnerability to measure the differential exposure of Iowa's farming communities to winter storm (Hahn, Riederer, and Foster 2009; Shah et al. 2013):

Winter storm occurrences: a proxy of frequency of exposure. The incidence of storm events indicates the degree of households being exposed to winter storms.

Winter temperature deviation: represents the level of changes in daily mean weather conditions. A high deviation of average daily temperature during winter months indicates high inconsistency of temperature, leading to high exposure.

3.4.1.2 Sensitivity The sensitivity characterizes the first-order effects of the stresses (Polsky, Neff, and Yarnal 2007). The first-order impacts of winter storms come from affected on-farm structures and activities such as animal husbandry and building damage. Animal health can be threatened by low temperature and restrained freshwater access. Livestock farms are highly dependent on the climate conditions during the year and those operations make considerable efforts to prepare supplies, implement actions and recover in the face of winter storms. On the contrary, crop farms appear less sensitive during winter since crops have been harvested. It also has been observed that poorly constructed building may increase sensitivity to climate change (Thomas et al. 2019). To determine the sensitivity of farming communities to winter storms, these elements are incorporated into the indicator system:

Animal commodities sale: The more households depend on animal products, the more they are sensitive to winter storms due to animal illness.

Building age: Older buildings are more likely to suffer physical damage, so they are more sensitive to winter storms.

3.4.1.3 Adaptive Capacity A broad definition of adaptive capacity refers to the actions and adjustments undertaken to maintain the capacity to deal with stress induced by current and future external changes (Mearns and Norton 2009). Livelihood assets, encompassed in the Sustainable Livelihood Framework (SLF) was used in an indicator approach to characterize adaptative capacity (Egyir et al. 2015; Gbetibouo, Ringler, and Hassan 2010). People with more assets are less vulnerable and vice versa. Using the SLF, relevant information on socioeconomic status, specifically in terms of 5 types of livelihood capital, were identified as indicators to capture the adaptive capacity. Indicators to explain human capital included household size, education level and labor expense. Indicators related to natural capital included the coverage of natural shelter. Physical capital component included access to facilities, energy capacity, access to internet and feed expenses as indicators. Farm-related income was selected to indicate financial capital. Involvement in agricultural organization and government programs were related to social capital. Details of indicators selected to measure each capital are described below:

Natural capital: Farms that have timber as windbreaks are assumed more protected from wind, therefore they are less vulnerable. This has been concluded from interviews.

Financial capital: Poverty has been included as an vulnerability factor (Clark et al. 1998). It is assumed that households with lower income possess fewer assets such as equipment and appliances that can help with maintenance of buildings and animals.

Physical capital: the access to internet is included as through it the environment knowledge can be obtained to assist with decision-making (Thomas et al. 2019). With sufficient internet access, households can stay informed and are more likely to get benefit of new policies and plan. The access to infrastructure has been considered as a proxy indicator (Gbetibouo, Ringler, and Hassan 2010) for physical capital. More access to facilities or services can reduce the risk from winter storms. More access to power services can reduce the risk of power outage. Physical capital can also be represented by feed expense as a major storm loss is from animal death due to inadequate feed. Higher expense on purchasing feed indicates higher adaptive capacity.

Human capital: laborers are considered to make a positive impact on vulnerability reduction. The assumptions are: (i) the more family members can help work more efficiently during storms or recovery. (ii) The higher the expense on laborers, the lower the vulnerability. Education level is considered as a proxy indicator and it is assumed to increase the adaptive capacity by enhancing the access to information (Antwi-Agyei et al. 2012). The more skill and knowledge acquired, the more capable households are of emergency planning, recovery and decision-making.

Social capital: Social organizations can bolster adaptive capacity by enhancing social networks (Thomas et al. 2019). Households with membership in farm-related organizations are more likely to receive support or benefit from another professionals. Interview results also reveal the reduction of loss as a result of the registration of government programs. The higher the expense on government programs, the higher the adaptive capacity.

3.4.2 Secondary Data Collection and Standardization

Secondary data on winter storm events comes from the subset of storm event database for all counties in Iowa, event types include winter-related storms reported during winter months (Dec, Jan, Feb). Selected event types include blizzard, cold/wind chill, extreme cold/wind chill, frost/freeze, heavy snow, ice storm, strong wind, winter storm and winter weather. A Python script was created to batch calculate the Iowa Winter Storm Database consisting of the yearly winter storm event counts for Iowa counties.

Agricultural statistics including farm sale, internet operations, expenditures on feed, government programs and labor were retrieved from USDA web sites. Information on education level, poverty rate, household size and housing characteristics were collected from the US Census Bureau. GIS data containing information on power plants and facilities was obtained from EPA Facility Registry Service and Iowa Facility Explorer. This study also used a georeferenced, raster-formatted and cropland-specific land cover data layer retrieved from CropScape to identify pasture and tree cover in each county. Climate data was downloaded from PRISM which provides daily temperature values of recent years for this study. To obtain information on membership in agricultural organization, a request was submitted to contact on the organization website. This study used the best available data (e.g. Census statistics 2012) and the closet proxy data (e.g. Census housing characteristics 2012-2016) when the data of the same year was not available.

Taken together, 16 variables have been demonstrated in the literature and interview results to impact the vulnerability of Iowa farming sector to winter storms and for which county-level data were available as detailed below in Table 4.

Table 4 Indicator System for Winter Storm Vulnerability

Vulnerability component	Indicator	Definition	Measurement unit	Source
Exposure	Winter storm events	The incidents of winter-related storm events in December, January and February from 2010-2017	Number of winter storm events	NWS storm event database (National Centers for Environmental Information 2018)
	Winter temperature variance	The deviation of daily average winter temperature in December, January and February from 2010-2017	Celsius	PRISM (PRISM Climate Group 2004)
Sensitivity	Animal commodities sale	Annual income received from animal commodities sale/sales of all commodities from the entire farm	Percentage	USDA: Economics, Animal &Products 2012
	Building age	The percent of housing units built in 1939 or earlier of total units	Percentage	Census: Selected Housing Characteristics 2012-2016
Adaptive Capacity	Natural capital Natural shelter	The summed acreage of tree cover within the farmland that provide windbreaks to shield extreme winter weather such as heavy winds	Acre	(CropScape 2017)
	Financial capital Farm-related income	Household income earned by operating farm-related business	Dollar	USDA: Economics, Income 2012
	Poverty	Percent of population with incomes below the federally-defined poverty line	Percentage	Census: Poverty Status 2012

Vulnerability component	Indicator	Definition	Measurement unit	Source
	Physical Capital			
	Access to facilities	Summed density of facilities around each cell in a county	km^2	Iowa Facility Explorer
	Energy capacity	Summed density of energy produced around each cell in a county	kWh^2	EPA Facility Registry Service
	Access to internet	The sufficiency of internet operations	The number of internet operations	USDA: Demographics 2012
	Feed expense	The expenditure on purchasing feed	Dollar	USDA: Economics 2012
	Human Capital			
	Household size	Average number of population in a household	people	Census: Households And Families 2012
	Education level	Ratio of rural population completing college	percentage	Census: 2013-2017 American Community Survey 5-Year Estimates
	Labor expense	The expenditure for labor used in the production	Dollar	USDA: Economics 2012
	Social Capital			
	Membership in professional organization	Household that have membership with professional organizations	The number of membership in PFI (Practical Farmer of Iowa)	Provided by Practical Farmers of Iowa
	Government program expense	Payments made by agricultural producers participating in Farm Bill programs including commodity, price support, disaster assistance and conservation	Dollar	USDA: Economics 2012

The originally collected data were measures in a variety of units, such as -20°F for temperature and 100,000,000 dollars for farm income. They are not suitable for further statistical analysis due to the wide range of raw data measured at different scales. Consequently, before further analysis, they were normalized to standard scores (Z-scores) in SPSS, so that observation values for all indicators were in the common scale with an average of zero and standard deviation of one.

3.4.3 Spatial Analysis Using GIS

This study aims to conduct statistical analysis and quantify vulnerability using areal data aggregated from various datasets. In this study, continuous data (i.e. temperature and tree distribution) and point data (i.e. farming-related facilities and power plants) were processed and upscaled to county level using ArcGIS Pro.

The standard deviation of temperature was calculated using Cell Statistics. Daily average temperature rasters during winter months (December, January and February) were used as input to individually calculate yearly winter temperature standard deviation. Eight yearly standard deviation rasters as output represent the deviation daily average temperature in winter months of each year between 2010-2017. Finally, the average winter temperature standard deviation was computed using Cell Statistics with yearly standard deviation data as input.

Taking into account the distribution of power plants and the winter capacity they can produce, this study derived energy capacity by using the Kernel Density to calculate the density of power plant in the neighborhood with the population field set as winter capacity to weight the density. GIS data layer containing Iowa storm-related and farming facilities was generated by geocoding with facility address list obtained from Facility Explorer. Kernel Density was also used to calculate the density of facilities in the neighborhood. Temperature standard deviation, facility density and energy capacity density were finally aggregated at the census county level for all counties within Iowa using Zonal Statistics.

The distribution of timber and pasture was extracted individually by using Extract by Attributes to select trees and pasture from various land cover types. They were then converted to polygons and used for the tool Near to identify pastures endowed with windbreaks. A specified search radius of 200 feet was used in the tool Near based on the recommended distance of a proper tree windbreaks (Swistock 2017). A field NEAR_DIST was appended to the attribute table of pasture polygon. Finally, pasture polygons with windbreaks were extracted using Select tool to select polygon with NEAR_DIST set to "not equal to -1", which indicates that no windbreaks were found within the 200 feet radius around the corresponding pasture polygon. Selected pasture polygons were joined into Iowa counties using Spatial Join with Contains set for Match Options and Sum set for Merge Rule to generate area values of pasture polygons.

3.4.4 Factor Analysis

Principal component analysis (PCA) has been used and adapted in a large number of studies for reducing the dimensionality of large datasets and acknowledged as a useful tool in creating composite vulnerability indices (Jolliffe and Cadima 2016; Willis and Fitton 2016). Its application has also burgeoned in evaluating the vulnerability to extreme climates (Clark et al. 1998; C. E. Reid et al. 2009; Uddin et al. 2019). It is often confused with factor analysis which provides a formal way of defining what type of variation is relevant for the panel of data as a whole (Boivin and Ng 2006). In other words, factor analysis is a process to extract a smaller set of components (principal components) representing a specific theme based on the original larger dataset's characteristics (indicators' variations). What the extracted components represent is determined by the subsets of indicators that are highly correlated with these components. For example, in this study case, human capital is expected to be extracted as one of principal components and it is assumed to comprise human capital indicators as highly correlated indicators. In other words, education level, labor expense and household size are assumed to hold high correlation loadings. Indicators with lower loadings are deprioritized when calculating component scores. This study adopted factor analysis over PCA because factor analysis reveals the structure underlying selected indicators (e.g. relationships between selected indicators and livelihood capitals as hypothetical component), as PCA is often used to optimized the linear combination of variables based on users' arbitrary choice of the number of variables (e.g. create a composite that consider some of the indicators and weight them based on PCA-derived significance).

This study first calculated normalized values (Z-score) for all indicators to standardize scores of a range of measurements on the same scale for further analysis. Then the factor analysis was performed on the 12 adaptive capacity variables in SPSS (version 20) using PCA with a varimax rotation method to explore relevance of selected factors to livelihood capitals and to reconstruct the original adaptive capacity indicators using latent variables interpreted based on the subsets of indicators that were highly corelated with these components.

3.4.5 Vulnerability Calculating and Mapping

Having identified underlying factors, and their highly correlated indicators, adaptive capacity was calculated using factor scores on each of these components. Adaptive capacity scores including scores for individual indicators with high loadings (>0.8) and summed indicator scores for exposure and sensitivity were mapped onto a based map of counties for the state of Iowa. Bivariate maps were used to portray two sets of factor scores simultaneously for components comprising two indicators. The overall vulnerability of each county was estimated from the following:

Vulnerability = E + S – AC

where, E is exposure to winter storms, calculated by adding Z-scores for winter storm events and winter temperature variance. S is sensitivity calculated by adding Z-scores for building age and animal commodities sale. The adaptive capacity, AC, of regions to cope with winter storms is determined by livelihood capital proxy indicators. The adaptive capacity of each county is the summation of factor scores produced by Bartlett procedure that is advantageous in producing unbiased estimates and preserving univocity than the other refined methods (DiStefano, Zhu, and Mîndril 2009). The factor scores on adaptive capacity of each county are calculated by component weights, *w*s, factor coefficients, *e*s, and standardized observed scores *z* on indicator *i* as follows:

$$AC = w_1F_1 + w_2F_2 + \cdots + w_nF_n = \sum_{j=1}^{n}\sum_{i=1}^{k} w_j e_{kj} z_{ik}$$

3.5 Conceptual Framework of Agent-Based Modeling

3.5.1 Framework Overview

The methods described above were used to map vulnerability at the county scale for which the agricultural statistics and census data were available. However, it is acknowledged that vulnerability varies on small scales including community level and household level due to the climate process, environmental realities and human behavioral variability that is determined by the assets of a household, the correlation, frequency and timing, and severity of shocks, as well as the risk management instruments applied (Heitzmann, Canagarajah, and Siegel 2002). An agent-based model (ABM) is hence introduced to address these challenges of assessing vulnerability because it is capable of capturing the uncertainties and complexities of human-environment dynamics resulting in outcomes. For example, households take different actions dependent on livelihood capitals and quality and timing of warning information to cope with winter storms varying with locational attributes, leading to a range of storm losses. This study presents the first stage of evaluating the vulnerability to winter storms at the community scale with an agent-based model, for which a conceptual framework was constructed.

To model the community-level decision-making process and outcome, Structured Decision Making (SDM) is used as a guide to frame the problem of quantifying vulnerability. This ABM framework starts by asking what the objectives are, followed by presenting decision alternatives available to achieve the objectives. The last step is to create a model to encapsulate the relationships of various actions and outcomes. Vulnerability is typically expressed as the mean loss (or the full distribution of losses) for a given intensity of the hazard (Bouwer 2019). The objective in this model is to minimize the loss from winter storms through alternative farmer decisions that are summarized during the interviews. This conceptual framework emphasizes the creation of model that integrates weather conditions, agricultural conditions and farmer decision-making during different phases of winter storms. As shown in Figure 7, candidate decisions are considered to influence the state of storm impacts in order to achieve the objective, while these decisions may cause action cost or reduced assets.

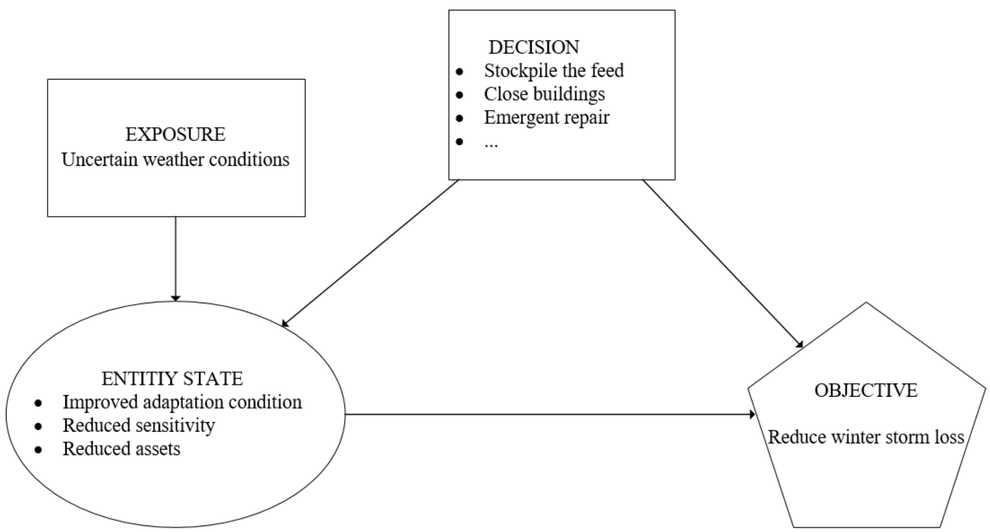

Figure 7 Schematic of Household Decision Making for Winter Storm Adaptation

Source: Adapted from the SDM Decision Diagram of Resource Decision Problem (Conroy and Peterson, 2013)

Drawing upon the standard protocol presented by Grimm et al. (2006) for describing agent-based models, this study outlines the overall structure of the community-level ABM following four standard components provided in the protocol: 1) Purpose, 2) entities, state variables and scales, 3) process overview and scheduling, 4) design concepts. This ABM is expected to be applied in farming communities that show differences in adaptive traits and geographical distribution. For example, communities with and without Amish concentrations may receive different storm damage patterns due to different adaptive behaviors.

This ABM is intended to present the winter storm losses of selected farming communities in Iowa by combining climate conditions, socio-economic and physical attributes of agent's environment, and by understanding adaptive behaviors to these changes. The purpose of this model is to demonstrate:

i) the spatiotemporal pattern of farmer decision-making for winter storm adaptation;

ii) the adaptation cost and total winter storm loss

An overview of this ABM is given in Figure 8 to demonstrate how this simulation can be achieved by linking vulnerability components and agent-based model elements.

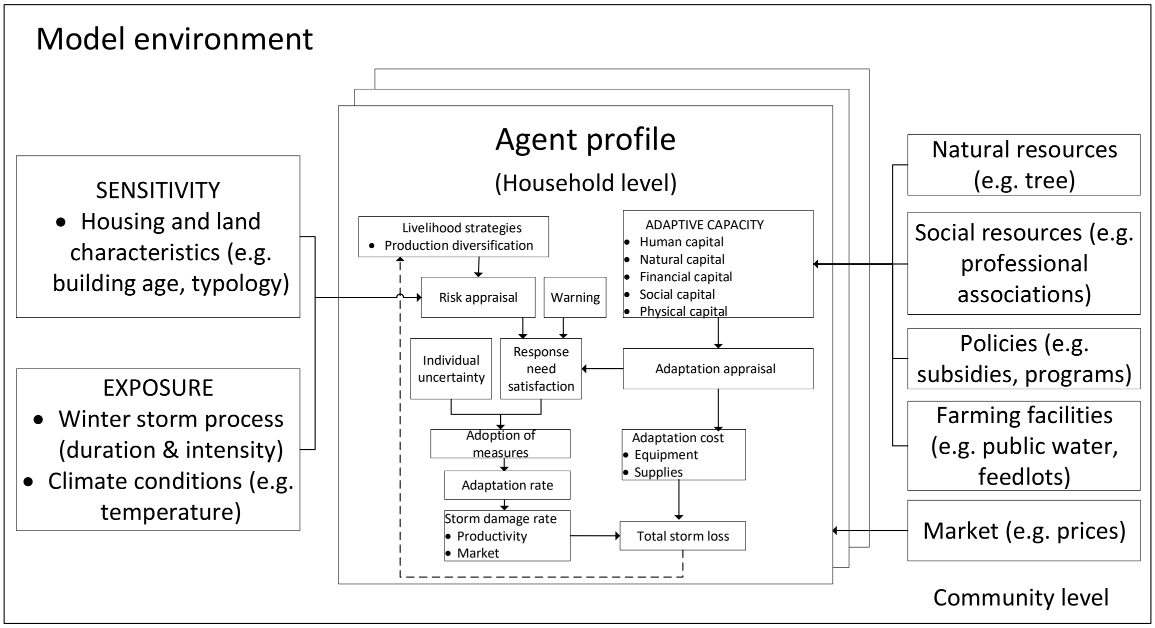

Figure 8 Framework of Community-Level ABM for Winter Storm Loss/Response Simulation

<u>3.5.2 Entities, State Variables, and Scales</u>

It is integral to define the entities in the model and describe state variables that characterize these entities. Despite the multiple factors considered to drive household decisions, this conceptual model only describes how the most important factors impact the patterns of winter storm loss in the most simplified scenarios. This ABM include three generic types of entities (Grimm et al. 2010): 1) agents at household/farm level, 2) ZIP code-based communities as the territories, and 3) climate process as overall environment. The spatial extent covers constituent ZIP code-based communities. The model is expected to run for winter months of a specified period. This conceptual model uses winter months (Dec, Jan, Feb) as the temporal extent.

The agent at household level defines specific behavioral patterns of households in the selected communities in adaptation decision-making according to the assigned household characteristics and external conditions. The territory characterizes individual communities with attributes representing environment conditions and updates community storm loss patterns. It is represented by hypothetical ZIP Code-based farming communities set with attributes influencing the sensitivity and adaptive capacity to winter storm. The climate process updates weather conditions that drive agent decisions. There is no absolute concept of temporal extent as it can be specified by user. This study assumes required fine-level data (e.g. household survey data used to derive representative parameters, ZIP code-level demographic and socio-economic statistics) are available. Hypothetical state variables are listed in Table 5.

Table 5 Hypothetical State Variables and Implications

Entity	Variable	Description
Agent (household/farm level)	Location	Household location centered at an average area-farmland derived from land use layer and empirical data
	Animal sale	Total sale from livestock commodities
	Severity	Household storm severity calculated based on exposure and sensitivity
	Exposure	Household storm exposure calculated based on temperature deviation and storm probability
	Sensitivity	Household storm sensitivity determined by building age and animal sale
	Response cost	Investment for taking actions calculated based on exposure and sensitivity
	Cost threshold	Equivalent of adaptive capacity
	Damage rate	The rate of damage caused by events on livestock and building
	Warning probability	The probability of receiving storm warning
	Human capitals	
	Labor	Household size
	Education	Year of education of farm manager
	Financial capitals	
	Farm-related income	Household income earned by operating farm-related business

	Natural capitals	
	Proximity to windbreaks	The level of the distance to tree cover
	Physical capital	
	Access to farming facilities	The density of farming facilities
	Social capital	
	Membership	Membership with professional organizations
	Proximity to neighbors	The number of households within a specified neighborhood
	Total loss	Final total storm loss
Territory (community level)	Spatial extent	The extent of selected communities specified by ZIP code
	Initial numbers of households	The number of households distributed within the extent
	Tree cover distance	Euclidean distance to tree cover
	Building age	The proportion of housing units built in different time periods
	Household total loss list	List of households and their losses
	Probability of events	Calculated based on winter storm event counts
Climate process	Temperature variation	The level of changes in daily mean temperature
	Low temperature	Extreme low temperature observations

3.5.3 Process Overview and Scheduling

Agent, community and climate processes are built into this model. The households are randomly placed in the community farm lands and assigned with agent attributes. Figure 9 shows an example of household's response-loss process during winter storms. During each time step, hypothetical households as agents with different profiles follow different cognitive process to cope with winter storms based on the warning received, sensitivity and exposure. For example, when winter storm comes, the households have different chances of receiving the warning. Real-time temperature and temperature deviation are calculated and standardized. The level of exposure is updated at household level by adding up this calculated value and standardized community storm probability value. If household animal sale is not zero, the household starts to calculate its sensitivity level by adding up standardized building age level and animal sale level. The severity appraisal defines the following adaptation process and cost.

To keep this model relatively simple, there is no detailed cognitive process of households defined based on household typology. This model assumes the households take all the candidate measures to cope with winter storms. The adaptation cost rate is calculated based on the calculated severity. As exposures involving extreme events that may lie outside the coping range, or may exceed the adaptive capacity of the community (Smit and Wandel 2006), households are assumed to be unable to continue adaptation once the cost exceeds a threshold. The threshold is defined as the summation of the attribute values comprising of household adaptive capacity. The adaptation cost ends with this threshold if the calculated cost is greater than the adaptation threshold.

How much damage the winter storms bring to households depends on the damage rate. It is updated based on asset values and affordability of adaptation cost. Households failing to respond due to the lack of adaptive capacity are assigned higher damage rate, leading to higher damage loss. When the adaptation cost threshold is not activated, the damage loss is proportionate to standardized animal sale and house value.

In addition to capturing how these interactions lead to storm loss at household level, this model is also designed to summarize the losses of communities. Upon finishing adaptation process at agent level, the model updates the list of the total household losses. This allows for the comparison in aggregated losses, vulnerability and adaptive capacity at larger scales.

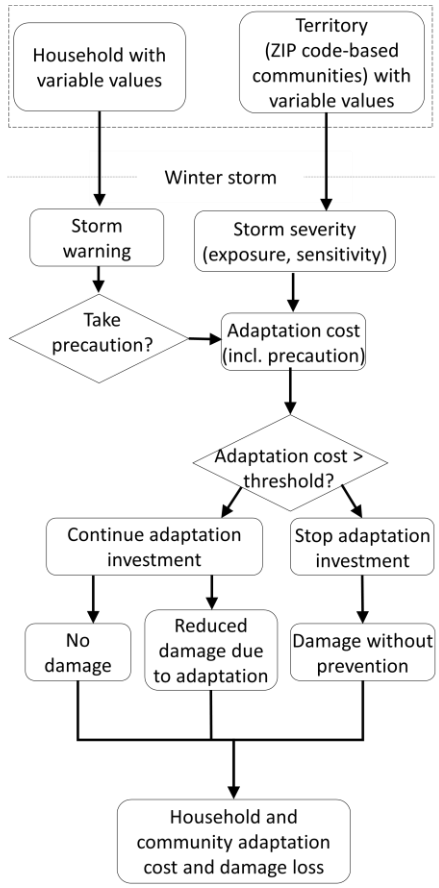

Figure 9 Hypothetical Agents' Winter Storm Response-loss Process

3.5.4 Design Concepts

The ODD update (Grimm et al. 2010) provides 11 design concepts for describing an agent-based model. They are Basic principles, Emergency, Adaptation, Objectives, Learning, Prediction, Sensing, Interaction, Stochasticity, Collective, Observation and Explanation. This proposed model considers 8 of these concepts and they are explained below:

Basic principles. This model is proposed to assess the vulnerability of farming communities to winter storm at household and community level. Related principles include Structured Decision Making (SDM), the expression of vulnerability and vulnerability assessment framework, as well as the possibility of exposures exceeding adaptive capacity (Smit and Wandel 2006). An explicit overall objective and alternative adaptation strategies linked to this objective are identified based on SDM. Using storm loss to indicate vulnerability makes the vulnerability quantifiable and measurable. Winter storm loss is hypothesized to be dependent on the factors indicating the vulnerability to winter storms.

Emergence. The emergent property of this model is household decisions on adopting adaptation measures. Decisions of households with different socio-economic backgrounds and locational attributes can jointly affect total winter storm loss. The behaviors are represented by combining empirical rules (e.g. damage rate) and dynamic adaptation efforts and outcome (e.g. varying adaptation cost depending on changes of climate, environment and household characteristics).

Adaptation. Household adaptation efforts are decided by comparing adaptation cost to adaptive capacity. When threshold (adaptive capacity) is activated there is no action, which can also be a choice in decision-making (Conroy and Peterson 2013). The household behavioral traits are also determined by the factors indicating the vulnerability to winter storms. These choices seek to increase the success of reducing storm loss as the objective through adjustment.

Objectives. Agents seek to minimize overall winter storm loss by taking actions that maximize the utility. The utility is measured by reduced damage rate with the consideration of affordability of response cost. Although adaptation process and corresponding cost are considered, there is no detailed ranking criteria used for alternative actions in current simplified model.

Learning. This model does not consider the potential of adaptive trait change. However, it is worth discussing the learning process of household and its associated impact on livelihood strategy transitions. For example, household memories in the storm loss from livestock commodities may lead to production diversification or agricultural practice changes.

Stochasticity. The pattern of settlements is drawn from empirical distributions to include spatial heterogeneity. The damage rate and the chances of receiving storm warning are simply assigned as ratios and probabilities. They can be derived based on the ground survey for information on household warning management and storm inventory.

Collective. Households are assumed to form networks that affect the social capital. These dynamic aggregations are generated by counting the number of households within a specified neighborhood.

Observation. Observations include graphical display of metrics capturing the characteristics of adaptation cost, storm loss, and multiple measures generated during the modeling. Another possible observation are dynamic visual elements displaying the real-time storm loss.

CHAPTER 4

RESULT

4.1 Introduction

This chapter provides an overview of farmers' perceived characteristics and associated impacts of winter storms, as well as, a summary of various storm response options to winter storms on different types of farms. Maps produced during spatial analysis and vulnerability quantification, as well as, factor analysis results are included and described in detail in this chapter.

4.2 Winter Storm Impacts on Farms and Household Responses

Table 6 shows the characteristics of farms with differences in farm types, geography, culture (Amish and non-Amish), status (active and non-active) and farm size. Interviewed farmers had lands farmed ranging from 0.25 to 500 acres. Of the 14 farms, 5 practiced mixed farming and 4 are livestock dominating. One farm was specialized in poultry production. Two crop farmers, one orchard farmer and one dairy producer were interviewed.

Table 6 Characteristics of Farms Interviewed

Household	Farm type	Farm size estimates (acres)	Products and activities	Remarks
1	Dairy	400	Cattle, milk, crops, feed, dairy, tour	
2	Mixed	100	Beef, calves, sheep, wool, chickens, guineas, lamb, crops, tour	
3	Mixed	80	Cows, pigs, chickens, feed, vegetables	
4	Crop	450	Crops	
5	Mixed	40	Horses, calves, crops, feed, craft	Amish
6	Livestock	500	Horses, calves, cow, hogs	Non-active
7	Livestock	200	Beef, cows	Non-active
8	Orchard	20	Orchard	Non-active
9	Mixed	150	Chickens, birds, crops	Amish
10	Livestock	100	Cattle, horse	Amish
11	Livestock	200	Pig, dog, sheep	
12	Poultry	0.25	Chickens	
13	Mixed	200	Cattle, crops	Non-active
14	Crop	250	Corn, bean	

Figure 10 shows a word cloud representing the frequency of labels coded for answers to all interview questions except for Question 1 concerning about the farm profiles. The 6 most frequent words mentioned are: animal (14), building (13), information (10), temperature (9), water (9), and feed (9). The word cloud demonstrates the importance of information and common concerns over animal health, building damage, water and feed shortage. Artificial windbreaks and tree cover were also widely mentioned by farmers. Ice and temperature appear to be among the main threats associated with winter storms.

Figure 10 Word Cloud Visualizing Frequency of Words Mentioned by Farmers

A cellular map (Figure 11) shows a summary of search results grouped by topic, revealing that livestock farms and power outage are most discussed on-farm issues during winter storms. Blizzard, extreme cold and strong wind are most mentioned severe winter-related weather.

Figure 11 Cellular Map Representing Searching Result Frequency

When asked about the most striking winter weather in experience, farmers expressed different views regarding specific agricultural operation. Retired farmers appear to have more recollections of specific severe winter storms, such as the blizzard in 1964 and the severe ice storm in 1988. With the reference to the named winter-related event types in the storm event database (National Centers for Environmental Information 2018) and detailed interview records, major winter storm types were identified: ice storm, extreme cold, blizzard, snowstorm, frost and strong wind, which can cause direct damage on buildings and power services. The impacts of winter storms on farms were summarized based on the farmers' perceptions and the review of theoretical and empirical literature (Table 7).

Table 7 Summary of Winter Storms Impacts

Winter storm type	General impacts
Extreme cold	Animal loss • Young animals (e.g. calves) are more susceptible to cold stress due to low body fat • Chicken eggs can freeze in the shells before they are collected • Animals are vulnerable to severe temperature variations Reduced productivity • Fodder (e.g. alfalfa) yield losses due to winter kill • Reduced dairy production due to affected animal health (e.g. frostbite threatens milk production) Reduced flowing water for animals • Broken pipes and frozen creeks Power outage • Extreme cold can knock out the heat and electricity due to equipment overload
Ice storm/Snow storm/ Blizzard	Animal loss • Drowning or missing of animals due to affected animal activities
Strong Wind	Building damage • Collapse or damage of farming structures and facilities

When asked about Farmers were all remarkably agreeable on the minimal impact of winter storms on crop farms. However, winter storms were thought to cause significant impact on animal health. Farmers felt constrained to keep buildings warm and prevent animals from winter diseases or egg loss up to 50 percent from being frozen. Better building structures and more labor force were needed to inspect the health condition of animals which are vulnerable to inconsistent or extremely low temperatures as well as feed shortage. This reflects the importance of the investment of a variety of capitals, such as human capital and financial capital. Natural capital also proved to be vital in adaptation to winter storms. One farmer noted, “I’ve got a nice row of trees out there as wind break that provides nice shade for animals. Windbreaks is very important on a farm.”

Social capital was found to play a notable role in reducing winter loss on farms as the more investment in government programs, the more benefits (e.g. livestock insurance, risk coverage) and information households are likely to receive. On the contrary, Amish farmers prefer to collectively help each other instead of claiming subsidies from government. Farm-related facilities such as feedlots were also considered useful in the face of severe winter weather as they provided assistance to risk management on farms, suggesting the positive significance of physical capital in mitigating winter storms.

In terms of household approaches to adaptation, a winter storm involved responses in these stages: i) before the winter storm, ii) during the winter storm, and iii) after winter storms (Figure 12). Farmers mostly agreed upon the importance of consciousness and devices for receiving storm forecast, with the exception of Amish farmers, who practice backbreaking agricultural methods and forgo using electronic devices and machinery. According to most farmers, “Preparation is the key”. Farmers have broad access to warning information including TV channel, radio station and smartphone apps. They check it on a regular basis (normally 2-3 times a day) and receive weather alerts a week ahead of storm hitting. Amish famers expressed strong belief in collective experience over forecast to assist with decision making. Alternatively, local weather line is accepted in a few Amish communities to prepare the farm for extreme weather. The increased need of feed and water resources as well as low or varying temperature are factors that hinder animal health. To be prepared for resource shortage and potential building damage, farmers stock up feed and reinforce buildings.

During a winter storm, livestock farmers face more challenges, such as navigating animals and keeping animal warm. They have to keep a close eye on animals’ needs and provide enough bedding and feed. Farm facilities with better structure experience less struggle in adapting while fabric and plastic buildings such as canvas barns and greenhouse require demanding work in building reinforcement and excessive attention to animal health and planting growth. A poultry farmer mentioned that he would have to “check the building four times a day”. Without heat and ventilation system in the buildings, some farmers had to “use spare heaters”.

A number of responses in terms of recovery measures involved after a severe winter storm vary among farmers from different backgrounds (Figure 12). As frequently mentioned during interviews, insurance is broadly noted during the interviews. As an essential element in the disaster recovery, insurance is used as an instrument to reduce a farm's storm loss. The coverage for the loss varies depending on the insurance scheme chosen by households. Instead of government assistance, community fund and mutual aid are used to support the recovery on Amish farms. Recovery activities also include snow blowing, repairment, accounting for inventory, evaluation and rethinking the way of dealing with storm. In terms of farmers' perceived vulnerability, there were hardly categorical answers due to varying farm size and farm type in the neighborhood.

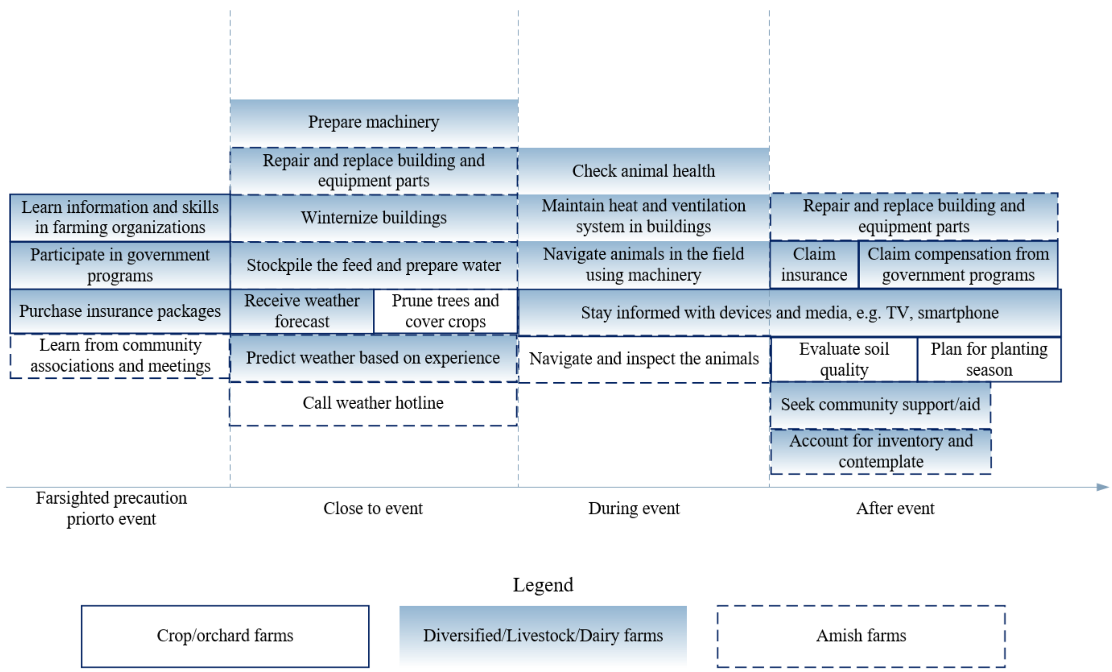

Figure 12 Adaptation Measures During Different Event Phases

4.3 Processing and Analysis for Spatial Data

Using cell statistics for daily temperature raster data, average standard deviation of daily mean temperature observations during 2010-2017 was calculated. Figure 13 shows in general the daily change of mean temperature for winter months (December, January, February) of different parts of Iowa. The temperature variation decreases significantly from mid-southern Iowa to northern Iowa. Density tool was used to generate a surface where each cell has a predicted value to indicate the likelihood of an event occurring. As shown in Figure 14, there are more areas with high density of winter energy capacity distributed in the southeast of Iowa. In the north of Iowa, northwestern Iowa in particular, there are more farming facilities built in the neighborhoods (Figure 15). These cells with high values are representations of locations more likely or easily to secure energy capacity and access facilities. The majority of land in Iowa appears to have much less denser winter energy capacity and facilities. Figure 16 shows the distribution of pasture and grass and the distance from these grazing areas to tree covers. These timberlands serve to break the force of wind and reduce building damage. Areas in yellow are pastures shaded more effectively with a required distance of 200 feet or lower to trees. There are more pastures in Iowa that appear to fail to meet this requirement.

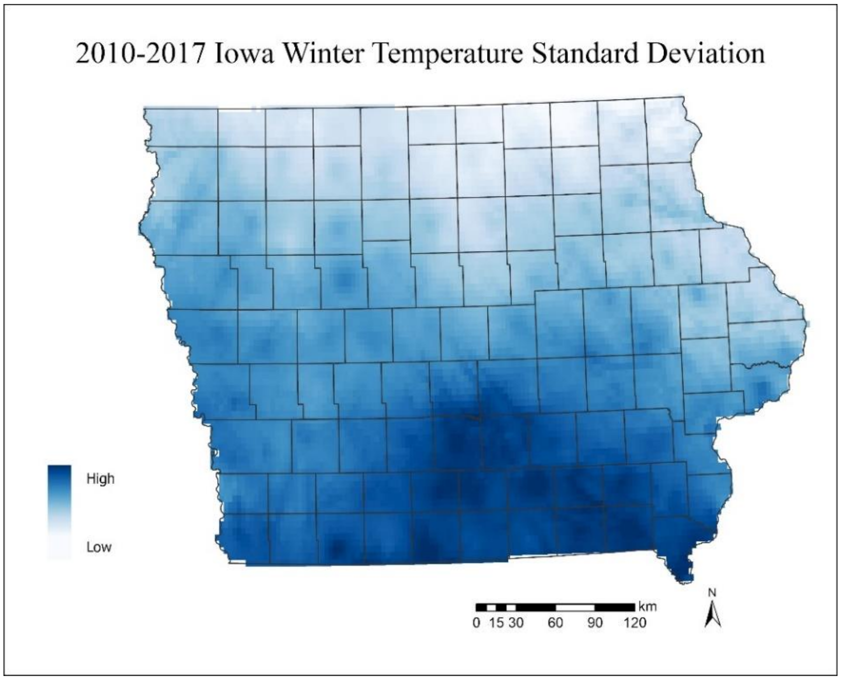

Figure 13 Standard Deviation of Daily Temperature during Winter Months

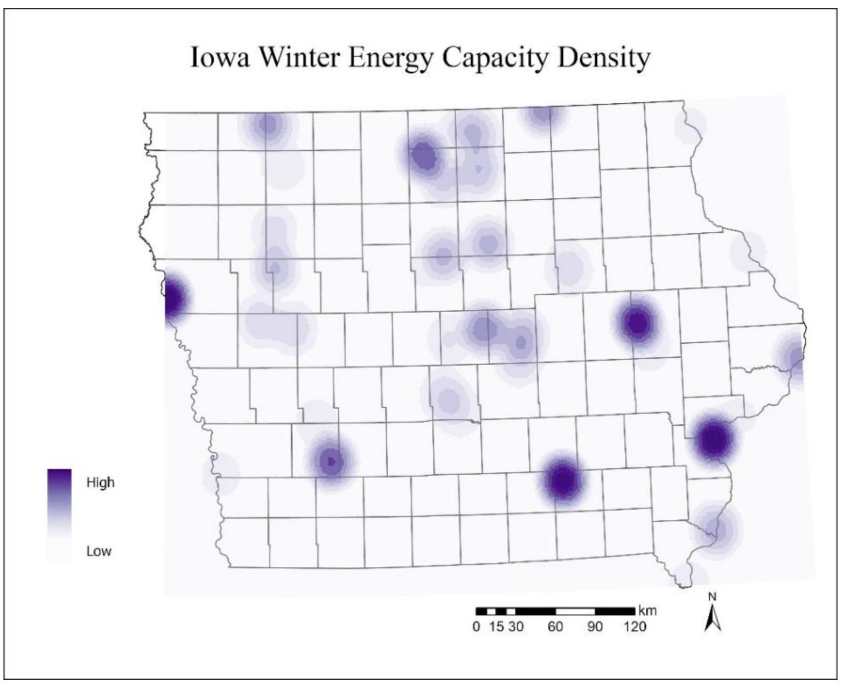

Figure 14 Density of Iowa Winter Energy Capacity

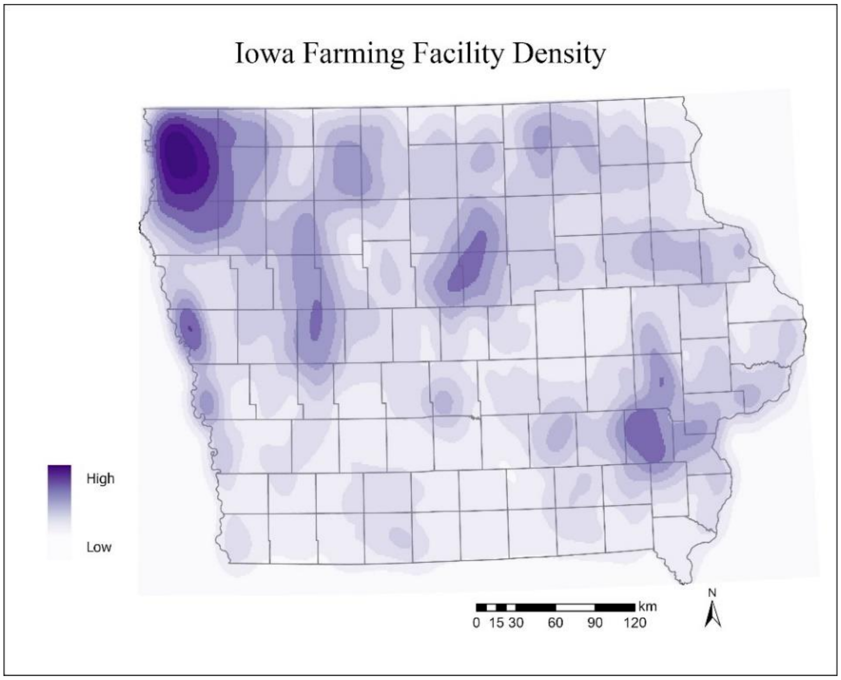

Figure 15 Density of Iowa Farming-Related Facility Density

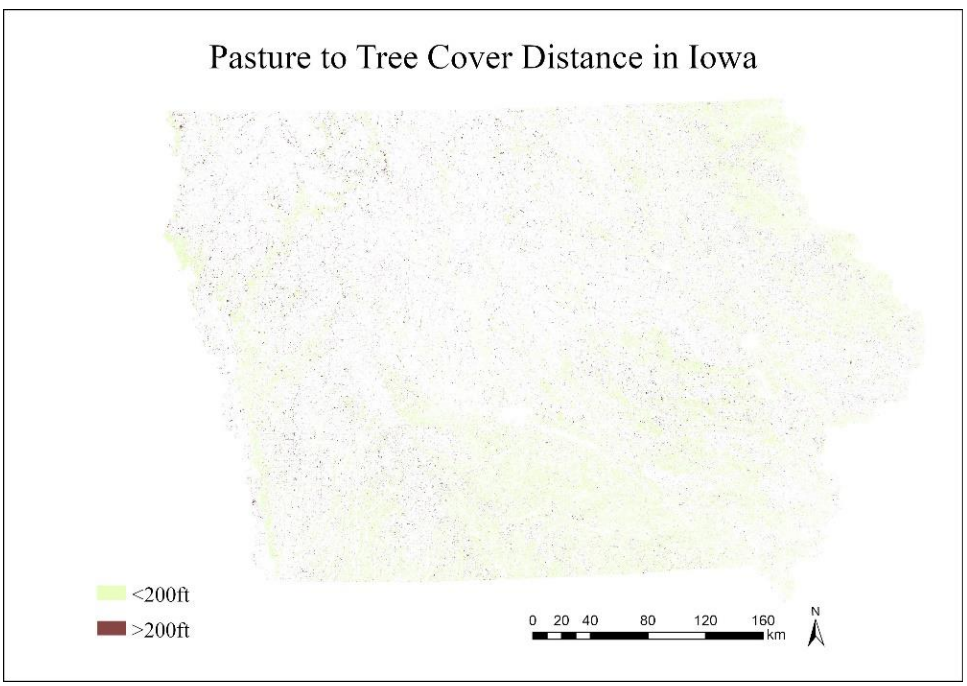

Figure 16 Distance of Pasture to Tree Cover

4.4 Factor Analysis for Adaptive Capacity Indicators

Factor analysis outputs included a correlation matrix, component coefficient score matrix, total variance explained and communities. Table 8 shows the pairwise correlations between 12 adaptive capacity variables. There are 29 out of 60 significantly correlated pairs with correlations ranging from -0.459 for farm income and natural shelter to 0.788 for farm income and labor expense. These interrelationships are suitable for factor analysis to extract principal components comprising highly correlated indicators. Table 9 shows each variable's variance that can be accounted for by the extracted factors, known as communalities. Four variables with low extraction values (lower than 0.7) were removed from further analysis: poverty, energy, internet operations and household size. Finally, 12 variables were reduced to 8 variables to make retained variables more statistically independent while the variability (i.e. variable's variance that can be explained by the principal components) was preserved as much as possible. Running factor analysis with remaining 8 variables, 3 components were yielded with 85.124% total variance explained (Table 10). These variables proved to be suitable for factor analysis as the KMO value (0.627) is greater than 0.6 and the Bartlett's Test (0.000) is statistically significant, indicating the sampling adequacy and high independency among variables. A scree plot (Figure 17) indicates that 4 is a marking point where further extraction of components is not recommended.

The loadings matrix in Table 11 shows the correlations of each indicator with the component. While the total variance could not be perfectly partitioned into 5 components that represent each of the 5 livelihood capitals, 7 of 8 indicators yielded loadings greater than 0.8 and three underlying factors could be reasonably interpreted based on salient indicators (loadings>0.8) and given inclusive themes. The first factor was interpreted as farming economic status regarding the heavily loaded indicators of labor expense, facilities and farm income. Natural shelter and government program were identified as the representation of environmental institutional capital to explain Factor 2. Factor 3 is highly correlated to membership count and education, considered to indicate innovative capital. Factors that accounted for the larger amount of total variance were considered to better predict adaptive capacity. This percentage (%Var) is used as factor weight to calculate the overall adaptive capacity. The coefficients for the linear combination of the variables shown in Table 11 indicate the relative weights of each variable in the factor and are often used for calculating factor scores (Grice 2001).

Table 8 Pearson’s Correlation Coefficients for Adaptive Capacity Variables

	InternetOp	Education	HHSize	PovertyRate	Membership Count	Facilities	EnergyCap	Natural Shelter	LaborExp	FeedExp	GOVExp	FarmIncome
InternetOp	1											
Education	$\mathbf{.313}^{**}$	1										
HHSize	.184	.179	1									
PovertyRate	$\mathbf{-.234}^{*}$	-.075	.002	1								
MembershipCount	.125	$\mathbf{.701}^{**}$	.094	.113	1							
Facilities	-.040	.105	.174	$\mathbf{-.316}^{**}$	-.056	1						
EnergyCap	-.077	.032	.091	.083	.103	-.018	1					
NaturalShelter	.102	-.021	.158	$\mathbf{.314}^{**}$	.054	$\mathbf{-.409}^{**}$	-.187	1				
LaborExp	$\mathbf{.282}^{**}$	$\mathbf{.259}^{**}$	$\mathbf{.234}^{*}$	$\mathbf{-.416}^{**}$	.164	$\mathbf{.637}^{**}$	-.102	-.174	1			
FeedExp	$\mathbf{.285}^{**}$	.169	$\mathbf{.391}^{**}$	-.158	.115	$\mathbf{.315}^{**}$	$\mathbf{-.218}^{*}$	$\mathbf{.439}^{**}$	$\mathbf{.648}^{**}$	1		
GOVExp	.064	-.144	-.007	$\mathbf{.344}^{**}$	-.053	$\mathbf{-.338}^{**}$	$\mathbf{-.203}^{*}$	$\mathbf{.788}^{**}$	$\mathbf{-.207}^{*}$	$\mathbf{.249}^{*}$	1	
FarmIncome	.083	.042	.101	$\mathbf{-.429}^{**}$	-.015	$\mathbf{.740}^{**}$	-.081	$\mathbf{-.459}^{**}$	$\mathbf{.812}^{**}$	$\mathbf{.332}^{**}$	$\mathbf{-.390}^{**}$	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 9 Communalities Representing Extraction Values for Adaptive Capacity Variables

Indicator	Extraction
NaturalShelter	**0.891**
LaborExp	**0.87**
FeedExp	**0.849**
FarmIncome	**0.84**
Education	**0.831**
GOVExp	**0.772**
Membership	**0.762**
Facilities	**0.745**
Poverty	0.574
EnergyCapacity	0.555
HHSize	0.555
InternetOp	0.496

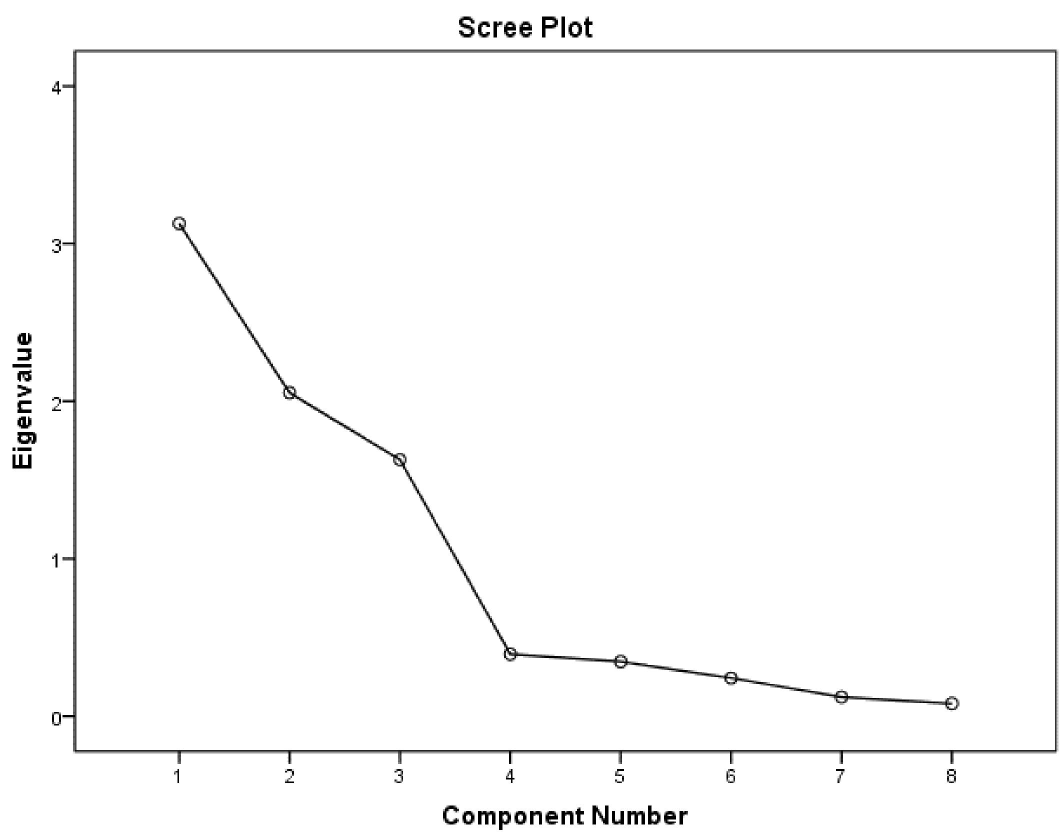

Figure 17 Scree Plot Indicating Threshold for Factor Retention

Table 10 Factor Loadings for Adaptive Capacity Variables

Variables	Livelihood capital themes		
	Component 1: Farming Economic Status	Component 2: Environmental Institutional Capital	Component 3: Innovative Capital
LaborExp	**0.930**	0.009	0.193
FarmIncome	**0.878**	-0.318	-0.047
Facilities	**0.810**	-0.294	-0.047
NaturalShelter	-0.189	**0.942**	0.043
GovExp	-0.205	**0.863**	-0.114
MembershipCount	-0.012	0.021	**0.922**
Education	0.110	-0.46	**0.914**
FeedExp	0.683	0.612	0.147
Variance explained (% Var)	35.611%	27.473%	22.4%
Cumulative variance explained	35.611%	63.084%	85.124%

Table 11 Component Score Coefficients for Adaptive Capacity Variables

Variables	Livelihood capital themes		
	Component 1: Farming Economic Status	Component 2: Environmental Institutional Capital	Component 3: Innovative Capital
LaborExp	0.332	-0.081	-0.077
FarmIncome	0.304	0.071	0.05
Facilities	0.28	-0.075	-0.074
NaturalShelter	0	0.428	0.015
GovExp	-0.002	0.394	-0.073
MembershipCount	-0.064	-0.013	0.534
Education	-0.023	-0.035	0.523
FeedExp	0.291	0.338	0.026

4.5 Maps of Exposure, Sensitivity, Adaptive Capacity and Vulnerability

4.5.1 Exposure

Exposure scores were calculated by summing standardized variable scores for temperature variation and winter storm event frequency. These variable scores were also classified into High, Medium and Low individually using natural break classification that minimize the within-level variances. These two 3-class single-variate maps were combined into a 3-class x 3-class bivariate map (left Figure 18) to show detailed contribution of indicators to the overall exposure. Figure 18 shows 9 combinations of the scoring of the two exposure factors simultaneously. The rates are above medium for both event frequency and temperature variation in west central and east central Iowa. Total exposure Z-scores were classified into 5 classes using Natural Break classification (right Figure 18). From Figure 18, it can be observed that the overall exposure rates are high in Northwest Iowa due to high event frequency and in Southeast Iowa due to high temperature variation. Central Iowa appears to have relatively moderate IPCC of winter storms and changes in temperature. North central and east central Iowa have slight changes in temperature, and these counties receive the smallest number of winter storms, leading to the overall low exposure. Allamakee is the only county that scores the lowest in both event count and temperature variation.

Considering the differential urban-rural residential and economic characteristics and the low resolution of data (e.g. census data) covering metropolitan areas may bias the pattern to underrepresent farming areas. Vulnerability component (i.e. exposure, sensitivity, adaptive capacity) scores for rural Iowa were also calculated and mapped onto a base map of rural Iowa. For winter storm exposure in Iowa, as is clear from the comparison of right Figure 18 and Figure 19, no pattern change is found after excluding metropolitan counties.

4.5.2 Sensitivity

Sensitivity indicator scores were calculated combining standardized variable scores for animal sale and building age. The bivariate sensitivity map (left Figure 20) illustrates the index scores of two attributed factors simultaneously. Counties peripheral to central Iowa tend to be more sensitive due to high percentage in animal sale of the total sales from all agricultural commodities. In central and east central Iowa, the counties are light colored, indicating low rate for building age and animal sale. This contributes to the notably least overall sensitivity for the Polk county and its surrounding counties. There are several counties (e.g. Union, Clayton) scoring high in both animal sale and building age, leading to their high overall sensitivity scores. From Figure 20, it is noted that highly sensitive counties (e.g. Clarke, Washington) do not necessarily have the highest rate for both indicators. Right Figure 20 and Figure 21 show that there is minor pattern change in sensitivity after excluding Iowa metropolitan counties.

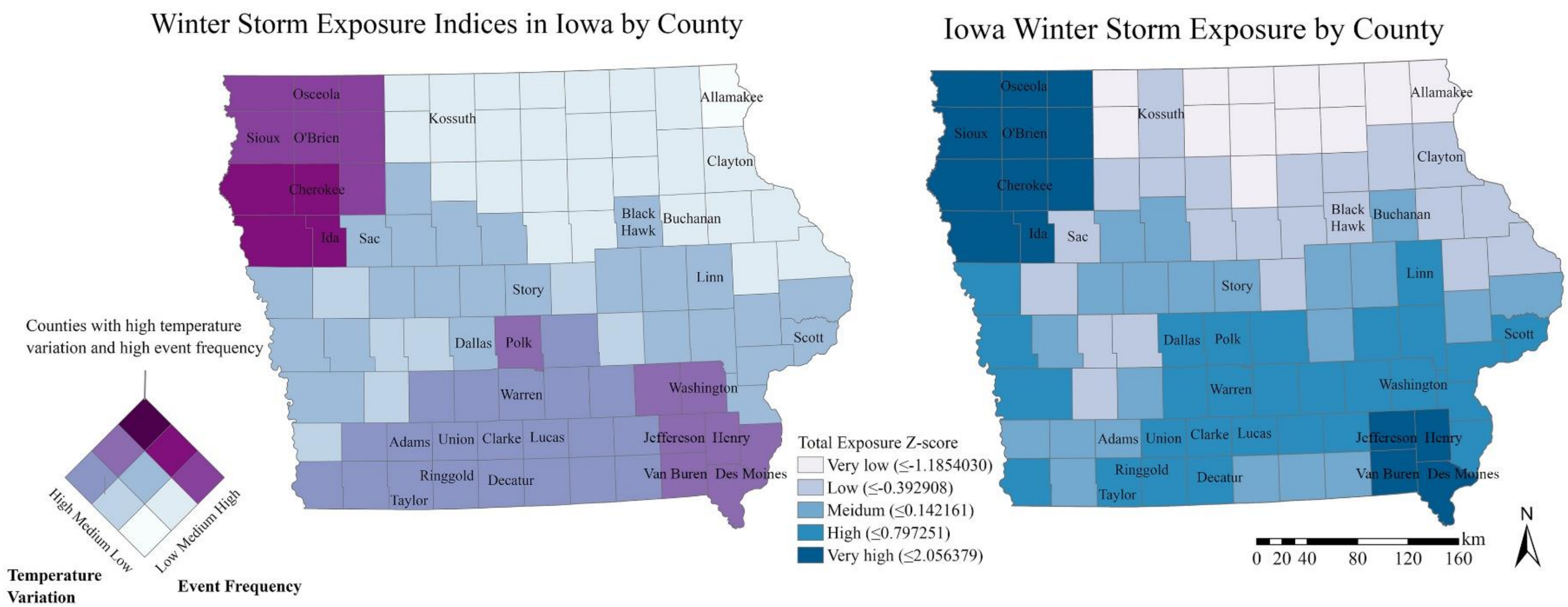

Figure 18 Index Scores of Winter Storm Exposure in All Iowa Counties

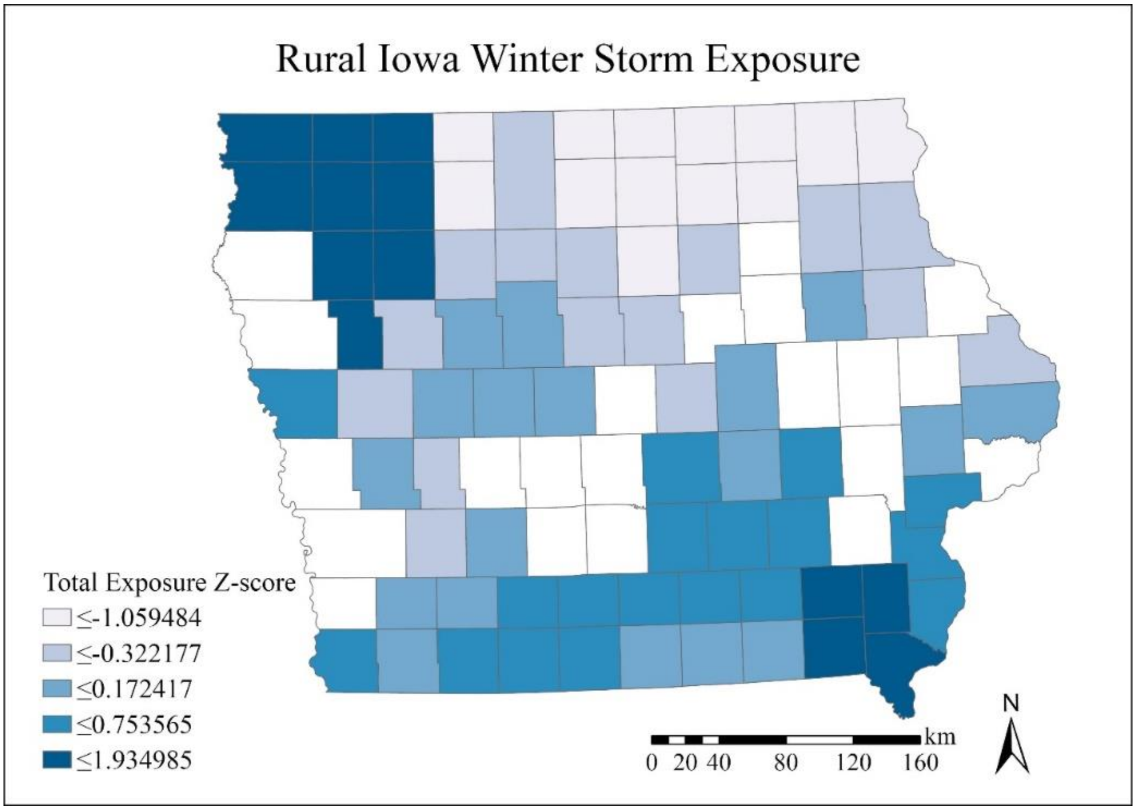

Figure 19 Index Scores of Winter Storm Exposure in Rural Iowa

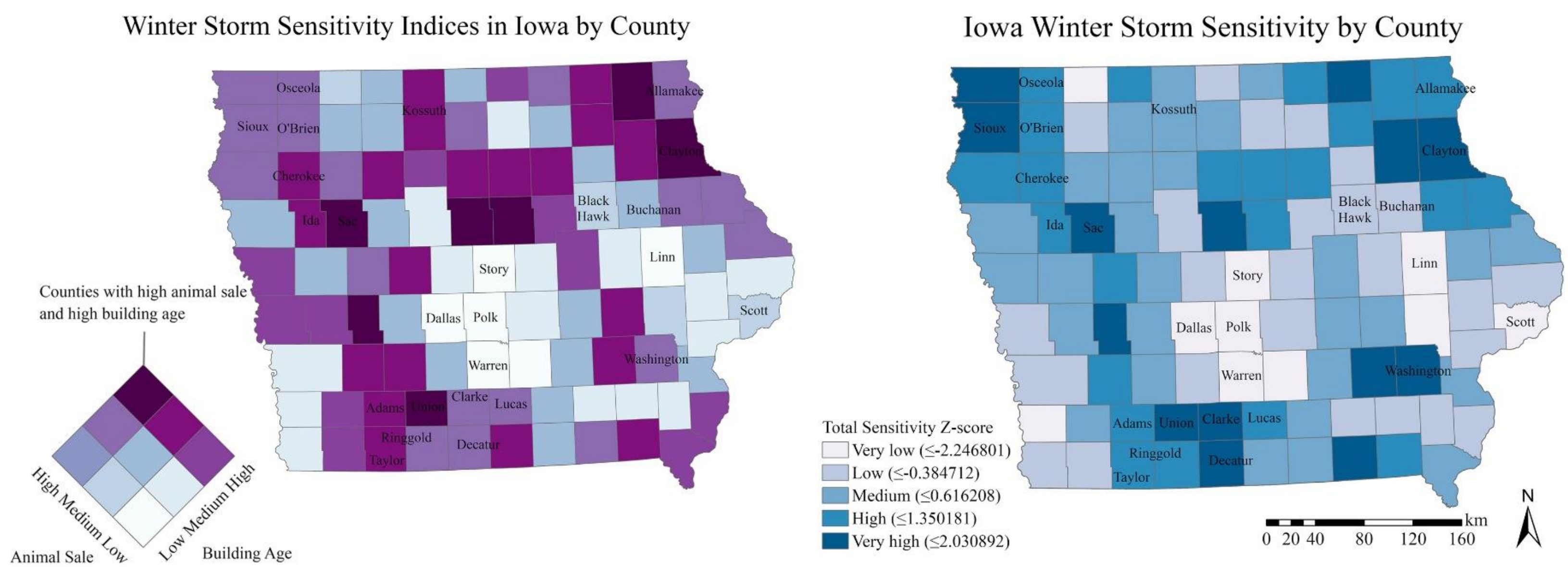

Figure 20 Index Scores of Winter Storm Sensitivity in All Iowa Counties

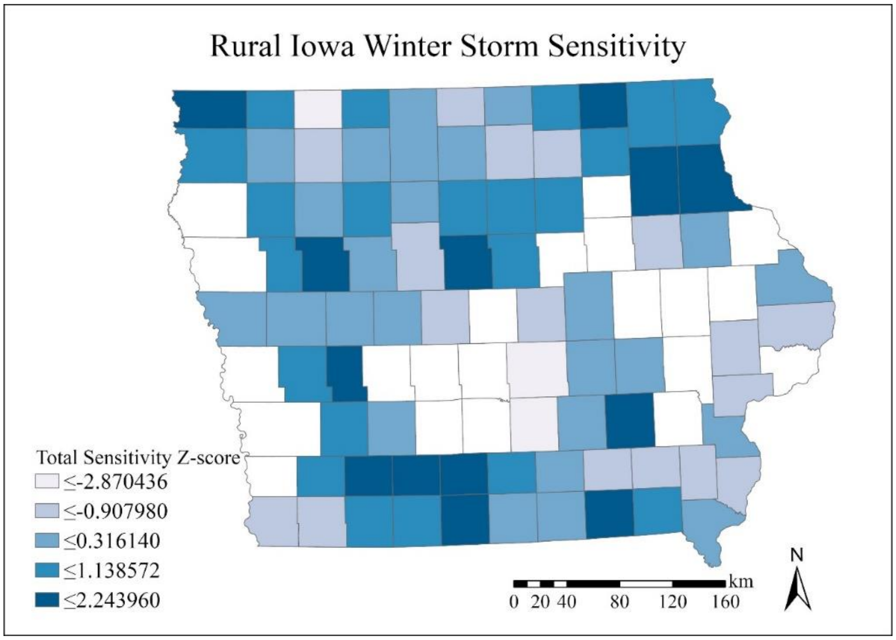

Figure 21 Index Scores of Winter Storm Sensitivity in Rural Iowa

<u>4.5.3 Adaptive Capacity</u>

Adaptive capacity scores were calculated using factor loadings, variance explained and coefficients from factor analysis. Individual factor scores and overall adaptive capacity scores were mapped onto a base map of all counties for the state of Iowa. Z-scores were classified into 5 classes using Natural Break classification. Figures 21-23 are maps of factor scores on farming economic status, environmental institutional capital and innovative capital with Z-scores for highly correlated indicators.

Figure 21 shows that counties with low farming economic status lie in the southernmost counties of Iowa with the same pattern for labor expense, farm-related income and facilities. In contrast, rates are generally high for farm-related income and facilities in Northwest Iowa. Labor expense appears to be higher in northeast Iowa. Sioux is the only county that has the highest scores for all these indicators. As expected, metropolitan regions (e.g. Polk and Washington County) have lowest rates for farming economic status due to urban development and low farming related investment. Few pattern changes are found for farming economic status after excluding metropolitan counties, comparing top left Figure 22 and Figure 23.

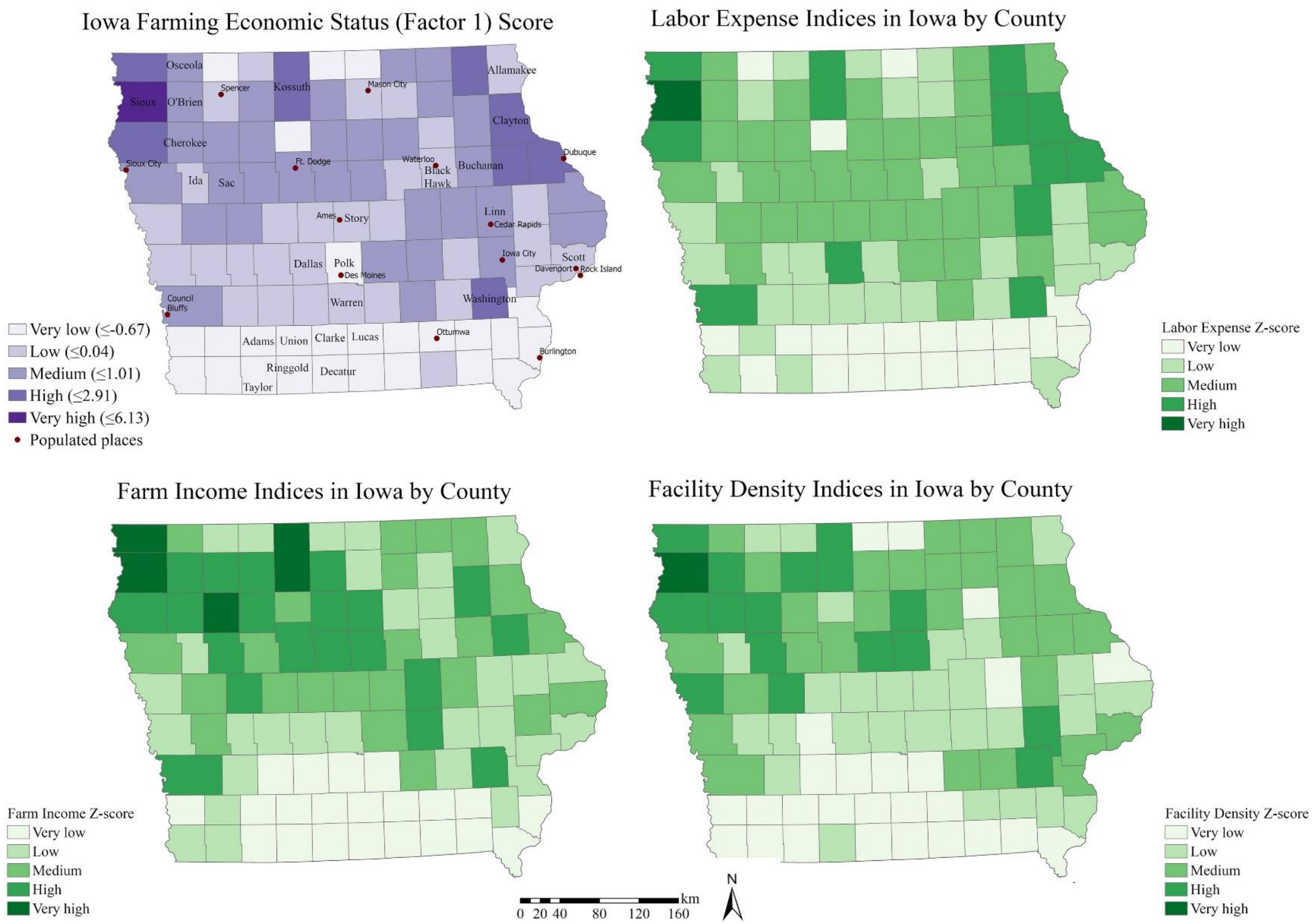

Figure 22 Factor Scores on Farming Economic Status in All Iowa Counties

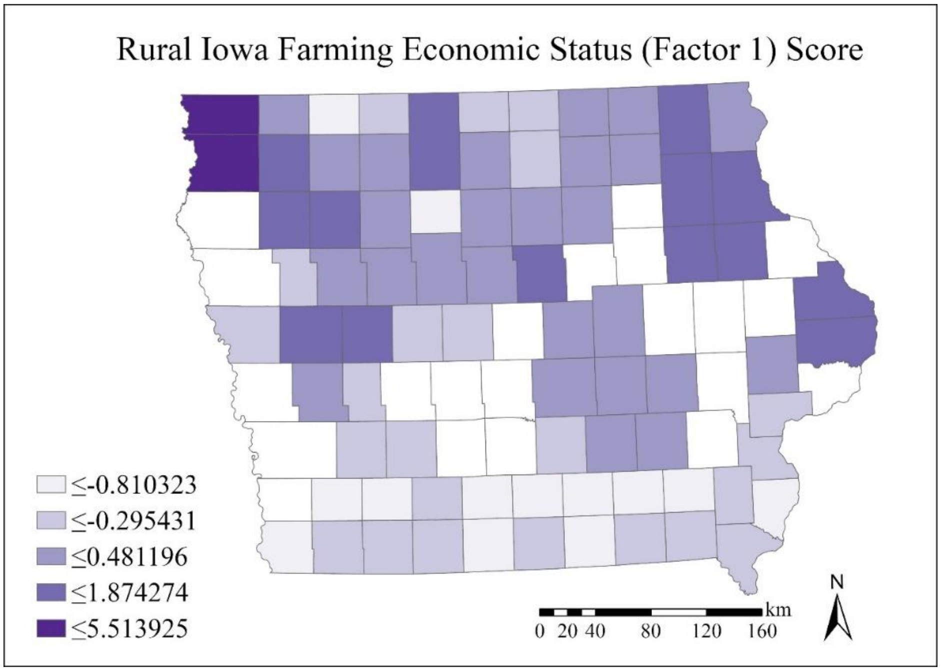

Figure 23 Factor Scores on Farming Economic Status in Rural Iowa

Figure 24 shows that natural shelter is significantly limited around northwestern Iowa as opposed to southern and northeastern parts of Iowa, where more tree cover can serve as windbreaks. Similarly, northwestern Iowa has less government expense than southern and northeastern Iowa. As shown in Figure 25, after removing metropolitan counties from calculating factor score on environmental institutional capital, there is a clearer divide between northwest and southeast Iowa.

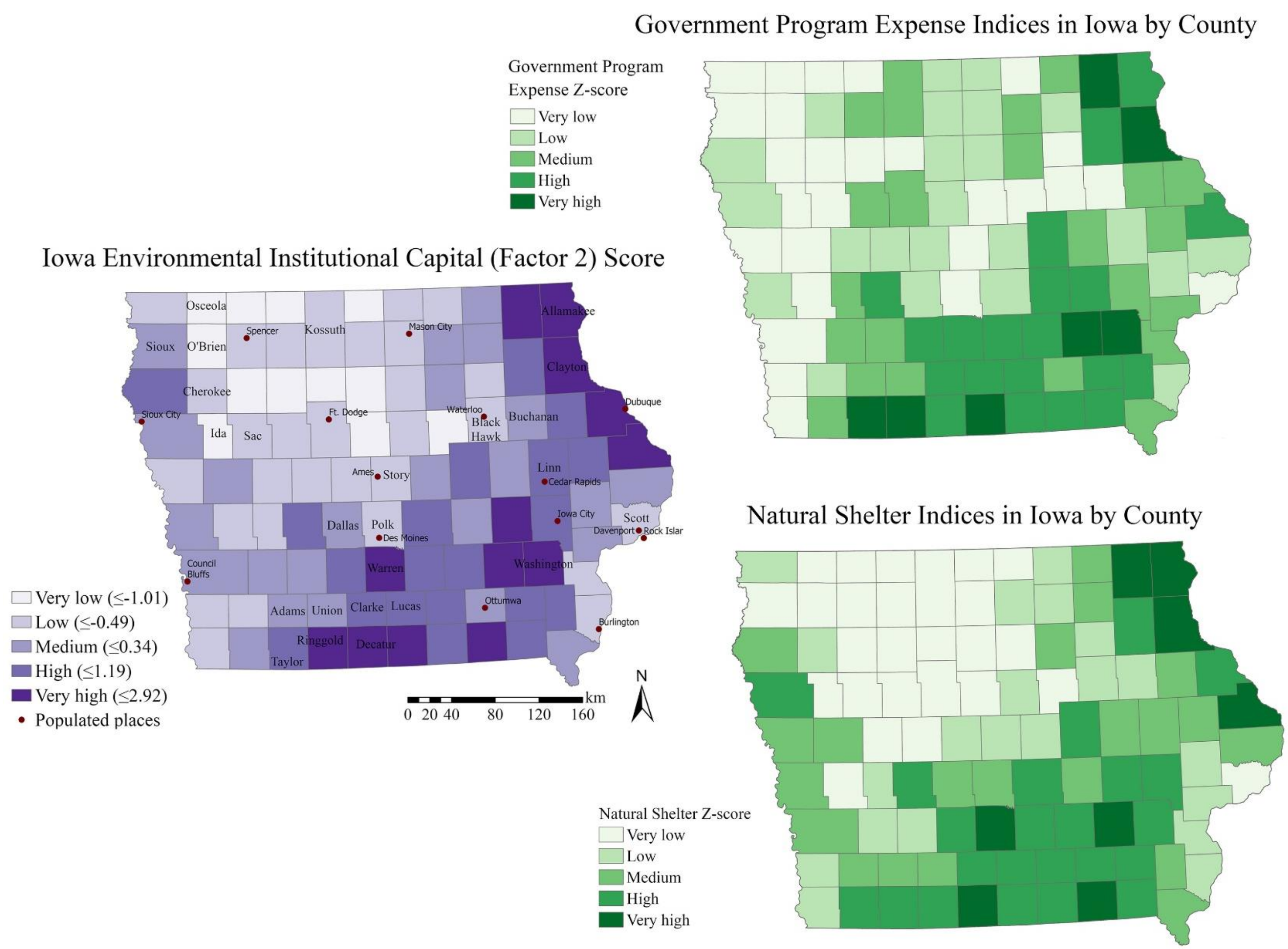

Figure 24 Factor Scores on Environmental Institutional Capital in All Iowa Counties

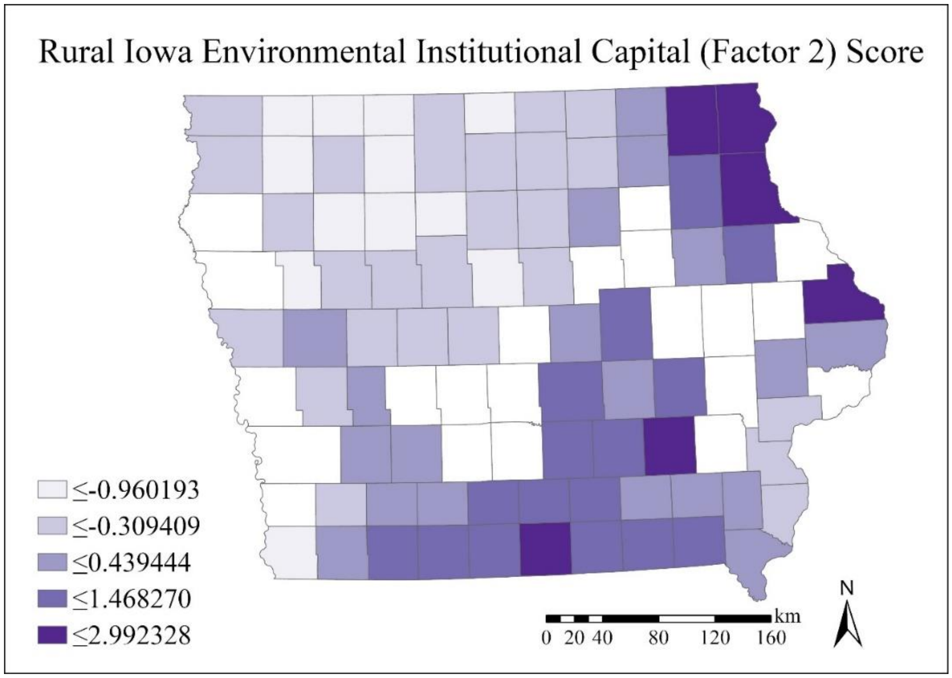

Figure 25 Factor Scores on Environmental Institutional Capital in Rural Iowa

Figure 26 shows innovative capital concentrated in central Iowa metropolitan areas. Similar pattern is found in farming organization membership. Southeastern Iowa has low rates for both education and membership, contributing to overall low innovative capital. As shown in Figure 27, innovative capital rates are higher in rural counties, especially in Northwest Iowa, when factor score is not calculated for metropolitan areas.

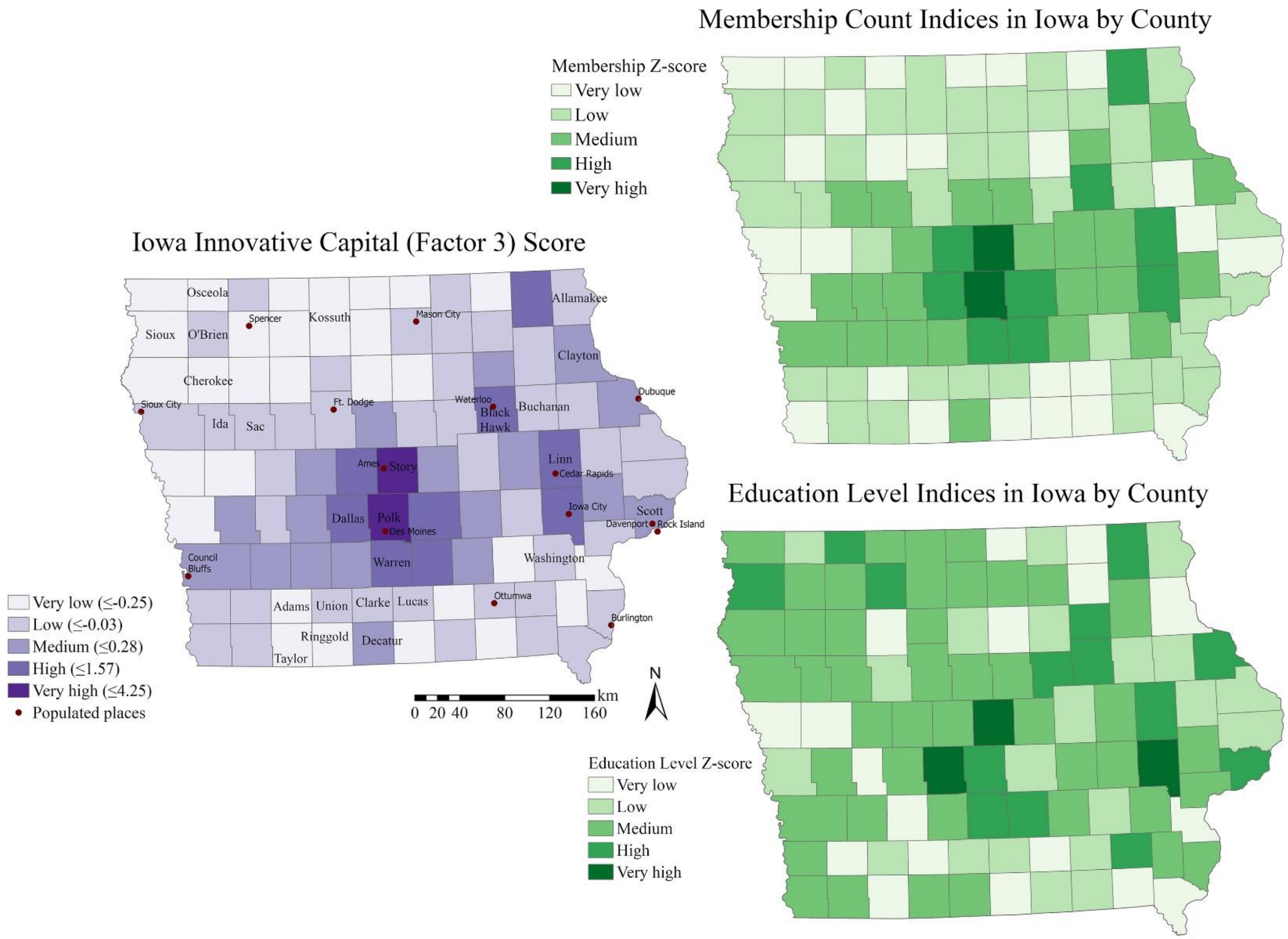

Figure 26 Factor Scores on Innovative Capital in All Iowa Counties

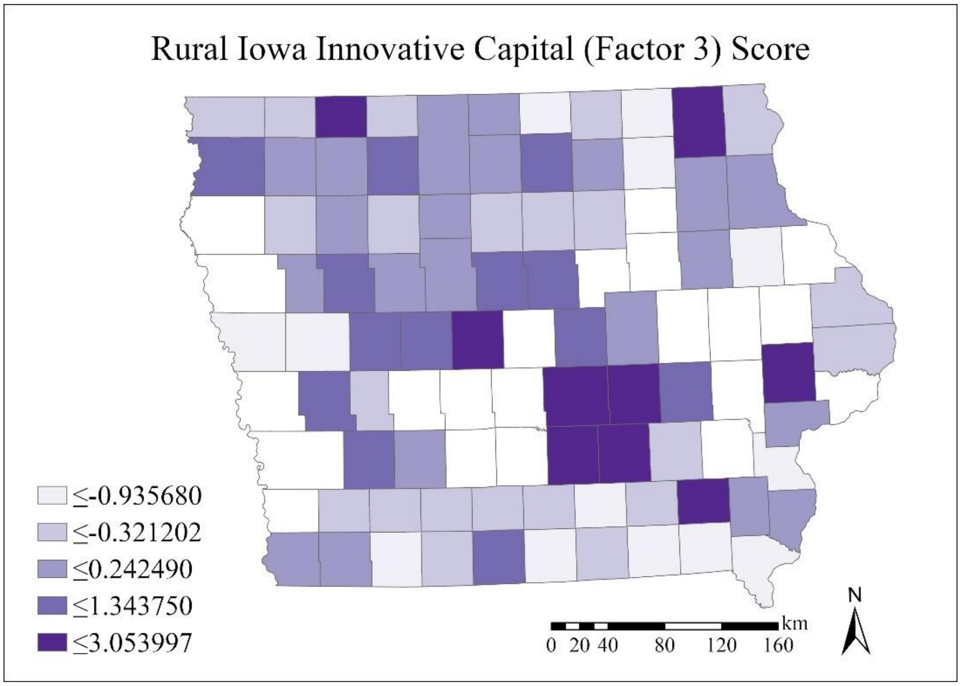

Figure 27 Factor Scores on Innovative Capital in Rural Iowa

Figure 28 shows the overall index scores for adaptive capacity. Counties with higher adaptive capacity are found in the central Iowa and northeastern margins. Adaptive capacity is low in most northwestern counties in Iowa. Figure 29 shows an obvious cluster of higher rates for adaptive capacity after excluding metropolitan areas.

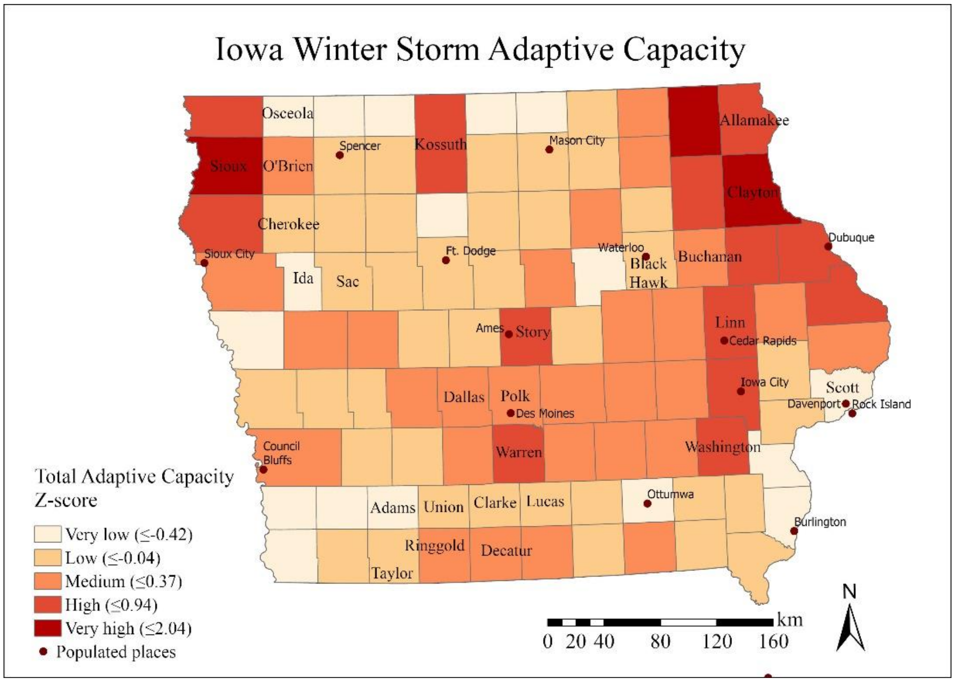

Figure 28 Overall Adaptive Capacity in All Iowa Counties

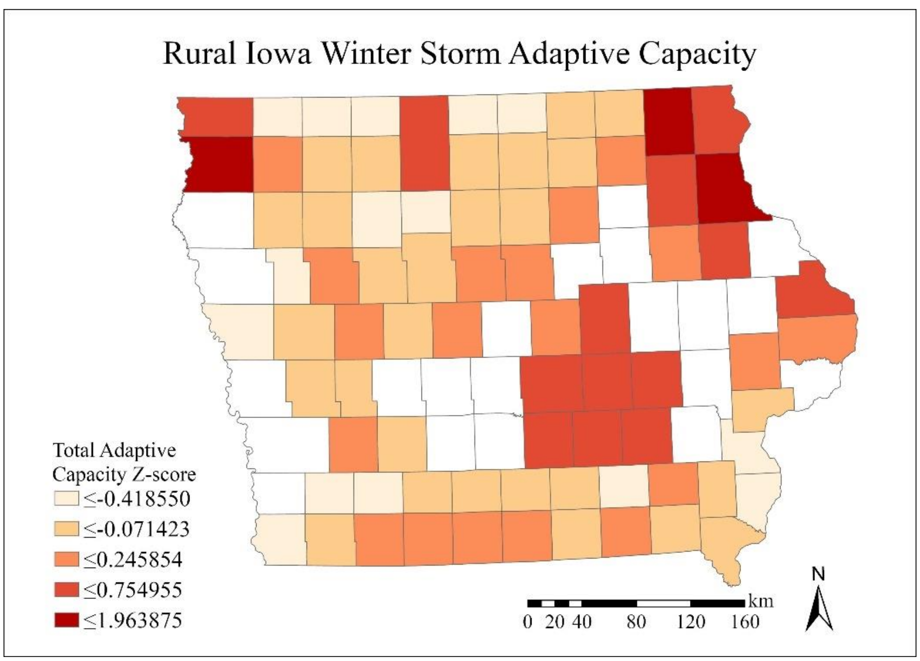

Figure 29 Overall Winter Storm Adaptive Capacity in Rural Iowa

<u>4.5.4 Vulnerability</u>

Figure 30 demonstrates the overall vulnerability for all Iowa counties calculated using overall exposure, sensitivity adaptive capacity scores. Southern counties such as Adams and Union are remarkably vulnerable to winter storms. The vulnerability is lower in the central and northeastern Iowa. Central Iowa especially Polk and its adjacent metropolitan areas are least vulnerable to the winter storms. Overall, highly vulnerable counties lie in West Iowa with the most vulnerable counties clustered in the Northwest and Southeast. After excluding metropolitan areas, vulnerability is still notably high in the northwest and southern margins of Iowa, with lower rates found in northeast Iowa and central Iowa comparing Figures 30 and 31.

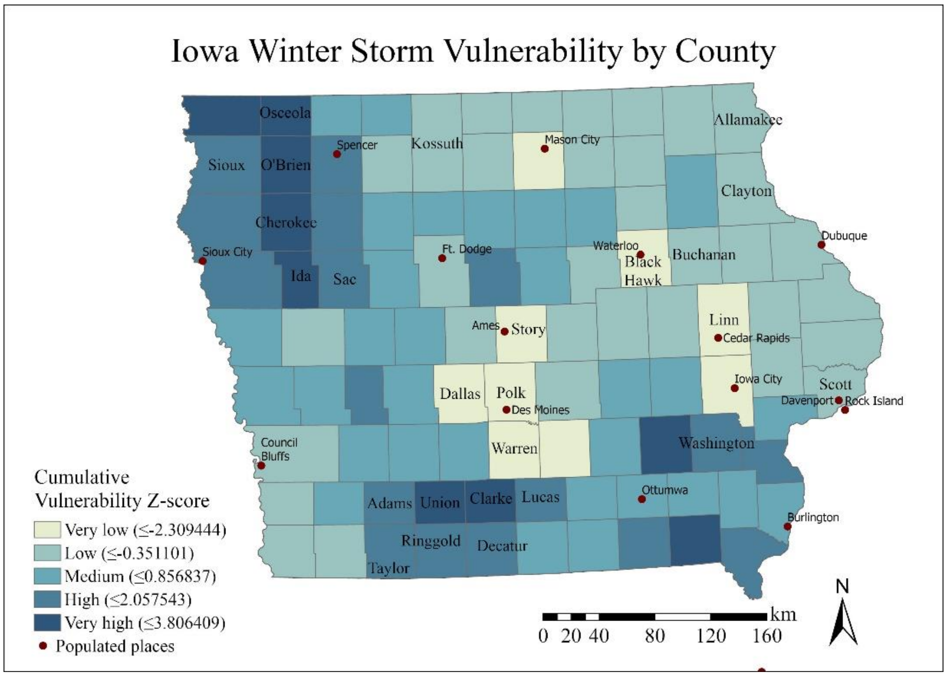

Figure 30 Overall Winter Storm Vulnerability in All Iowa Counties

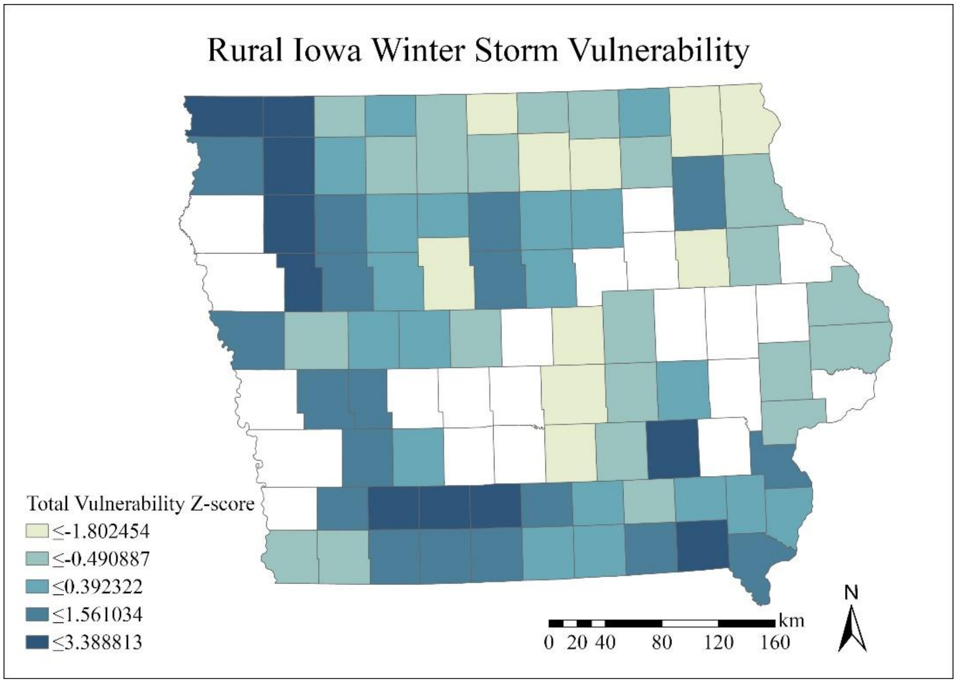

Figure 31 Overall Winter Storm Vulnerability in Rural Iowa

CHAPTER 5

DISCUSSION

5.1 Introduction

This chapter digs into research results including interview results, factor analysis results and vulnerability maps. Research methods included qualitative analysis, an indicator-based approach and a conceptual agent-based model all of which will be discussed. It is hoped this study can also provide insights into policy making in reducing vulnerability to climate risks at the end.

5.2 Analysis for Interview Results

This study first addressed the characteristics of winter storm-induced impacts in the agricultural context through semi-structured interviews to obtain farmers' narrated perceptions. This step was important because the interviews with stakeholders and subject matter experts can provide necessary information and knowledge in the local context (Polsky, Neff, and Yarnal 2007). In this study, conversations were interpreted based on the investigator's understanding and coded as labels for visualizing interview content. This process can produce subjectivity and a cross-validation with computer-assisted coding such as MaxQDA (Walpole et al. 2017) is needed to ensure the reliability of the extracted information.

During interviews, few current farmers recalled specific severe winter storm events. Interestingly, retired farmers or more experienced farmers appeared to have more memories about certain winter storms that happened at some time in the last century. A possible reason could be the increasing frequency of winter storm events have obscured farmers' perceptions of the severity of winter storm events. In addition to specific winter storm types identified as disastrous in farming, farmers repeatedly mentioned hazardous climate events such as flood, tornado, snowmelt runoff and other sources of extreme precipitation that could damage farms and paralyze the production. Crop farms are more vulnerable to changing precipitation in growing season than the influence of winter-related extremes. However, these farms' management for following growing season can be impacted severely by snowmelt runoff in late winter or early spring. This unique event was not included in the measures of event count and associated factors due to the definition of winter storm, time period set for this study and data availability, while it is a winter-related event acknowledged to add stress on crop growth. To improve the understanding of the vulnerability of farming communities to winter-related extremes, further studies are needed on the variability in winter extreme precipitation such as snowmelt flow and its impacts. There is no lack of successful investigation of winter precipitation variability, but very limited are focused on farming settings (Rudd, Kay, and Bell 2019; Dong, Leung, and Song 2018; Neukom et al. 2010).

Although the climate variability and the indicator of temperature deviation is taken into consideration in most vulnerability case studies, its impacts are not well discussed. In this study, sudden temperature change has proven to be one of farmers' concerns over animal health. This short-term uncertainty appears to add more stress to the adverse effects that long-term climate change brings. The mechanism of this rapid temperature change is far less discussed than mainstream climate issues on decadal or slow temperature change (Bathiany et al. 2018; Cassou et al. 2018).

An interesting finding throughout all the interviews was that two farmers from the same Amish community who are both diversified in agricultural production expressed different attitudes towards the impacts of winter storms. One of the farmers was more proactively prepared for winter storms than was the other farmer who had not noticed significant impacts induced by winter storms. A possible explanation for this difference could be the awareness in possibility of reducing loss through preparedness. The proactive farmer quoted that “An ounce of prevention is worth a pound of cure”, suggesting that farmers who are more prepared may be more resourceful in options to avoid or reduce the costs for recovery.

During these semi-structured interviews, several unmeasurable factors were found to exacerbate or alleviate the vulnerability of farms to climate extremes, such as unpredictable changes in the market and temporary community support. To approach a holistic assessment for vulnerability to climate extremes or climate change, different sources of vulnerability and the linkage between risks brought about by these sources need to be clearly identified. It is challenging because it involves considerable interdisciplinary work to conduct a full accounting of causality of multidimensional vulnerability origins at multiple scales. Another challenge in gathering farmers’ climate is inadequate recollection attributable to the influence of near-term conditions (CAMP Alatoo 2013). It was common that recollection of winter storms is short during interviews and group discussions, and it is often heavily influenced by near-term mild winter weather. To ensure the adequacy and accuracy of information on time- or status-sensitive cases, investigators need foresee the external influencers.

5.3 Factor Analysis for Adaptive Capacity Variables

Prior to calculating the integrated vulnerability, factor analysis was used to reduce the dimensionality of adaptive capacity indicators and explore underlying factors. The scree plot recommended extracting no more than 4 components and only 3 factors were eventually extracted. This meant that selected indicators from 5 dimensions could hardly fall into 5 components representing 5 types of livelihood capitals but could be grouped to represent 3 dimensions. This dimension reduction may be because of the interrelations between livelihood capitals and it can be explained by factor loadings. It was noted that government expense yielded high loading in the second component and was significantly correlated natural capital. It is possible to consider it as an independent capital - political capital, which is not originally in the sustainable livelihood framework, but has been used in Central Asia climate risk assessment (CAMP Alatoo 2013). Previous study has based on Sustainable Livelihoods Framework and qualitative approach to categorize resilience indicators into reduced dimensions defined as a function of livelihood capitals (Sadik and Rahman 2009). Factor analysis shows promise in testing framework-based index quantitatively as it can identify the structure of dataset and subsets of variables as representing a specific dimension.

Of the three extracted primary components of adaptive capacity, the first factor accounted for most of the variance. Therefore, farming economic status can be considered to project adaptive capacity most accurately. This may because economic resources can facilitate preparation and recovery, making economic condition a major determinant of adaptive capacity (Smit and Pilifosova 2003). The second component “environmental institutional capital” seemed to indicate institutional effort in enhancing environment services. For example, Conservation Reserve Program (CRP) provides cost-sharing for tree planting on highly erodible row crop and pasture land through general or continuous funding. The third component was highly related to education and organization membership. There was also a strong correlation found between membership counts and education, indicating that counties with higher education level are likely to be more active in associating with agricultural organizations. Human and social capital are considered to affect innovative performance (Veenendaal, van Velzen, and Looise 2014), therefore innovative capital was reasoned as the theme for the third component.

Factor analysis is useful in identifying subsets of variables as representing a specific theme. It demonstrated the complexity and subjectivity in quantifying adaptive capacity. The classification and interpretation of primary components and underlying indicators, as well as, the summation for the overall adaptive capacity were tentative and subject to investigator’s decision-making. It would be helpful to include more indictors and examine the performance of different methods and various weighting criteria through comparing resultant patterns statistically and spatially. For example, Willis and Fitton (2016) examined different weighting approaches in social vulnerability classification. A cross-examination can provide more evidence when identifying vulnerable population, increasing the accountability of the results.

In addition to recognizing the uncertainty resulting from the adoption of indices, uncertain adaptive capacity is shown when it is examined at a larger scale. Despite many equally plausible models or frameworks in explaining the vulnerability varying from place to place, we often fail to hold the frequently mentioned factors accountable as these models are not capable of capturing the manifold population characteristics in specific place or explaining adaptation dynamics. For example, response rates may vary from community to community due to effectiveness of warning information received by households. We cannot ignore the changing context and adopt the same strategy in an area which was treated as a point. The collective behavior of a group or community may make a significant difference at a larger scale. To effectively assess the household adaptive capacity, more research efforts are expected in theoretical studies on human behavior and decision-making, qualitative analysis for local knowledge and transitioning to computer modelling.

5.4 Vulnerability of Farming Communities to Winter Storms in Iowa

The overall vulnerability map shows that in general, southern and northwestern parts of Iowa are more vulnerable to winter storms. Northeastern Iowa shows significantly high exposure to winter storms, consistent with the northeast’s long history of severe winter storms and blizzards (Waite 1970). It is also noted that northwestern quarter of Iowa is low in environmental institutional capital, with poorly dispersed natural shelter and low expense on government programs. In contrast, southeastern areas have high scores for both government program expense and natural shelter. This may be because the long-standing large tracts of wetlands concentrated in the northwest and north central parts of Iowa provided rich farm land for growing intensive crops. The increase of monocultures and decrease of livestock pastures in northwest could lead to the destruction of windbreaks. Patchwork of small, diversified fields that once was common remains in southeastern Iowa (Iowa Association of Naturalists 1998). However, southern Iowa also shows high vulnerability, perhaps because much of the land area in southern Iowa is used for perennial pastures (Florine et al. 2006), leading to high sensitivity. Smallholdings with low farming economic status can also explain the high vulnerability in Southeast Iowa.

As said by a farmer who diversified his products into crops and income sources into tourism, “I think the secret to successful farming is to have a diverse operation. If you put all marbles in one basket you cannot pick up from different things if something goes wrong.”. For both northwest and Southeast Iowa, diversification is a common recommendation for reducing climate vulnerability and developing sustainable agriculture. Institutional efforts such as incentives for diversification and tree planting are expected for the northwest to increase resilience. There is a need for enhancing innovative capital and farming economic status in the Southeast. Innovation livelihood strategies such as diversifying income into other sources (e.g. tourism) may be helpful for economic development in the Southeast.

Climate exposure can be changed by population growth (Bouwer 2019), and storm impacts are likely to be worse in populous area than where the population is less dense (Changnon and Changnon 2005). However, Polk and Linn – two of the most populous counties rated least vulnerable to winter storms, whilst these counties have relatively high exposure. This means that climate-induced losses are not necessarily tied to population as they may vary depending on the specific disaster or sector. For example, it is reasonable that vulnerability and on-farm losses are low in metropolitan counties such as Polk and Linn, because of their industry-oriented economies. But from Figure 32 comparing calculated vulnerability level with factual on-farm total loss data, it is noted that metropolitan county Story had farm loss above average (Z-score>0) with significantly low vulnerability. This suggests it is important to understand where most losses come from and how identified and unidentified factors can add or reduce the losses. Although area plot is generally used for time series data visualization, it can also provide a quick comparison of the fitness between calculated vulnerability and farm loss over the counties. Figure 32 also shows that several counties (e.g. Ida, Sioux, Monora, Win Winneshiek) have actual loss well matched with predicted vulnerability. This means the selected indicators for winter storm vulnerability may also be used to evaluate general loss. On the other hand, counties that are low in actual loss but high in winter storm vulnerability may be more resilient to harsh winter, such as Van Buren county.

Certainly, the calculated vulnerability cannot fully explain the losses due to the specific vulnerability focus and aggregation for loss data. However, it can be visibly and statistically unified with the ground truth. The gaps between aggregated data analysis results and real-world data can be bridged by vulnerability assessment at different level. Future research would include coupling questionnaires estimating farm losses and assessing farmers' vulnerability perceptions. It also remains not clear if the vulnerability patterns will look similar when focusing on other weather-related events. To address the gap between our assumptions and the fact, multiscale (e.g. spatial, temporal) studies are needed to improve our understanding of what works to reduce the loss.

This study did not restrict study area to community level due to the data availability, instead countywide vulnerability was calculated and mapped to illustrate where is more vulnerable to winter storms and why. We can glean the information on how likely the counties' farming communities are to be adversely impacted from vulnerability patterns across all parts of Iowa state. However, the inclusion of metropolitan areas may underrepresent rural characteristics. This research addressed potential bias from coarsened data by examining the pattern change after excluding non-rural counties. Exposure pattern remained the same and few significant pattern changes were found for sensitivity. The patterns of adaptive capacity and its factors "farming economic status" and "innovative capitals" were biased due largely to the low resolution of census data. For example, high education level and membership count concentrated in central urban area may stretch the data range, overshadowing the innovative capital in counties with more farmland. On the other hand, data for climate variability used in this study (i.e. storm event count and temperature variation) seemed to maintain the exposure pattern. Figure 33 compares the patterns for indicator scores normalized using difference methods and there are rate changes found for several counties, although slight difference is found for the pattern as a whole. This has implications for the choice of coarsened data and normalization approach in vulnerability assessment.

To calculate the overall vulnerability, this study simply merged index scores of sub-components that makes up major components. An alternative formula developed by

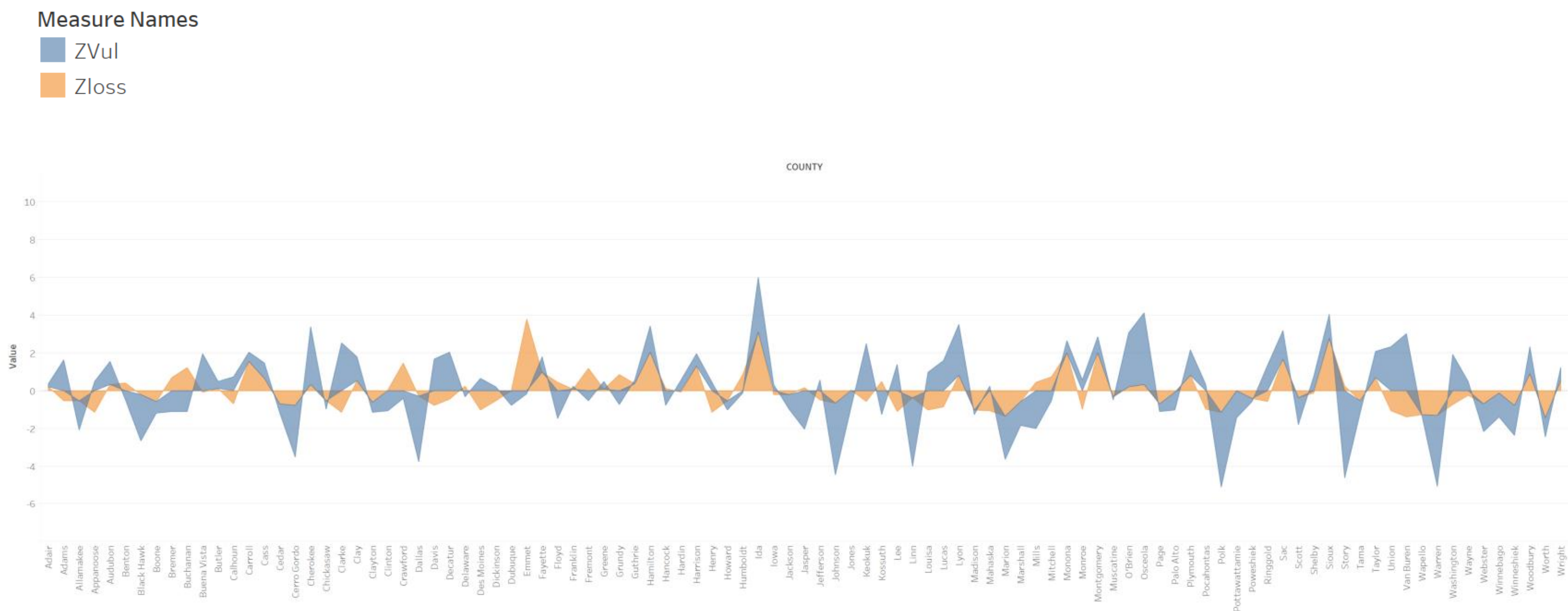

Figure 32 Area Plot for Vulnerability Z-scores and Farm Loss Z-scores

Source: Data plotted using Tableau with Z-scores for vulnerability and actual farm loss on y-axis against equally spaced intervals of Iowa counties. Data for farm loss from Iowa county-level economics by USDA. Retrieved from https://quickstats.nass.usda.gov/results/7E214D15-CFBA-37DA-8E1E-757AD282A45A

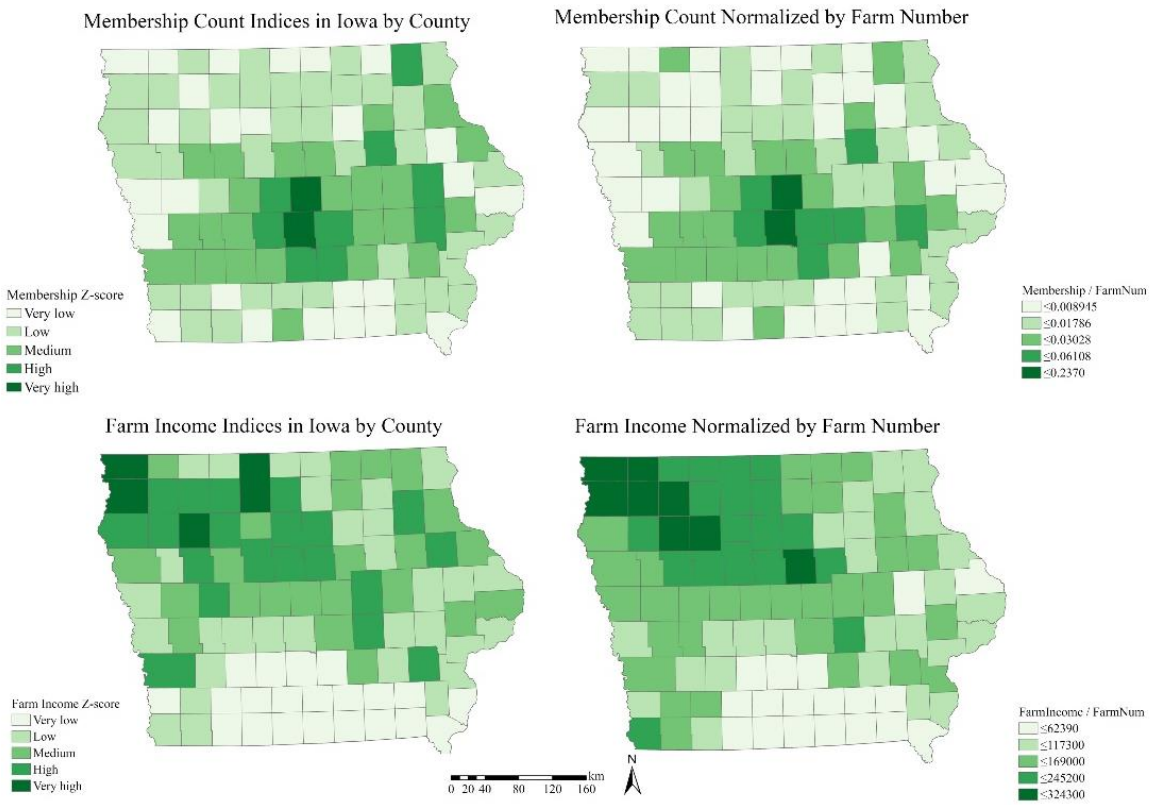

Figure 33 Maps of Indicator Scores based on Different Normalization Methods

Hahn, Riederer, and Foster (2009) calculated index scores for major components considering the weight and the number of indicators, resulting in overall vulnerability ranging from -1 to 1. There needs to be more effort in developing a plausible index to measure winter losses, with emphasis on selecting indicators and normalizing for livestock farming and exposure. For example, in Antwi-Agyei et al. (2012), a crop yield sensitivity index and an exposure index were developed to calculate the vulnerability to drought. The number of extreme days, such as average number of days with maximum temperature greater than 90 percentile (Panthi et al. 2016), was considered as indicating exposure. The number of consecutive cold days may be used to measure the exposure to winter storms in future studies.

Regarding the indicators selected for sensitivity component, building age may be limited in indicating the capability of a building to withstand extreme winter storms as uncertainty exists in where a winter storm event may cause damage or disruption. A ground survey may need to be incorporated to further validate the potential of building collapse or damage considering associated factors. Current winter storm model (CoreLogic 2015) has been developed to predict structural damage taking into account relevant indicators, such as snow depth, snow and ice thickness and wind speed. It is possible to incorporate this precision winter damage model in agricultural setting to assess winter storm vulnerability. However, to achieve this more knowledge is needed in engineering, agriculture and climate science. It was asserted that we do not necessarily need detailed knowledge in climate change to study vulnerability (Keskitalo 2012). It may not hold true as interdisciplinary studies increasingly requires collaboration that unifies social science and hard science to provide a more compelling account for the global change and vulnerability patterns.

5.5 Implication for Agent-based Modelling for Climate Adaptation

A conceptual model designed for addressing the adaptation dynamics in farming communities in face of winter storms was described. As discussed in this chapter, there are a great deal of uncertainties in winter storm formation and adaptation process that relates to constantly changing weather conditions and varying farmer decisions as well as regional characteristics. Multi-agent systems can therefore serve as a bridge between farm-level and regional-level model analysis (Berger and Troost 2013). It can also address the limitation of the summation of indicator scores that cannot capture interconnectedness of these indicators and present vulnerability with temporal changes.

The simplified conceptual model also addressed the acknowledged challenge in communicating agent-based models that are often used to simulate human-environment interactions (Grimm et al. 2006). Current agent-based models dealing with adaptation are often hard to read and far less accessible than traditional analytical models due to relatively ambiguous and incomplete descriptions. This study demonstrated a formalized way of connecting climate risk and rural livelihoods. A simplified conceptual model was established that allows a replication in assessing the dynamics of response-loss processes under climate risks. It is hoped that this vehicle could be more accessible to researchers assessing complexities in climate adaptation but lacking an explicit or adjustable framework. Framing the dynamic storm loss-response process also shed light on the future data collection and survey design for generating realistic agents. High-resolution land use and property maps may be helpful for the creation of a realistic spatial data structure. Rural household surveys and agricultural census data provide the basis for the generation of agent populations (Berger and Troost 2013). For example, to appropriately classify agent populations with differential cognitive process of taking actions that vary depending on the characteristics of households, information on candidate adaptation measures and farm profiles is needed from household survey and interviews to extract the rules. Survey data has also been used to parameterize an agent-based model for the diffusion of soil conservation efforts (Van Oel et al. 2019).

Overall, approaches to evaluate future dimensions of vulnerability tend to aggregate local characteristics to the regional level (Windfeld et al. 2019). There is a need for methodological advances for vulnerability and strategy analysis that not only capture dynamics of global change but also represent community specificity. Location-specific assessments would contribute towards improving our understanding of future vulnerability under projected climate change, adaptation processes that involve aggregate groups behaviors, as well as, policy impact pathways. The realization of this model beyond this thesis is expected to improve our understanding of the adaptation behavior, changing climate and environmental realities at temporal and spatial scale, thereby providing valuable information on what works to mitigate negative impacts and what could be neglected.

5.6 Policy Implications for Decision-Making

Vulnerability assessment has implications in supporting decision-making in the allocation of resources services. Vulnerability and policy decisions are interconnected. Policies are designed to offset the above-average negative impacts as a result of original above-average vulnerability. An informed decision relies on an integrated vulnerability investigation. This study addresses climate issues often missed by current mainstream studies, investigating the impacts of winter storms on farming communities that experience long and harsh winter. Through calculating the exposure, sensitivity, adaptive capacity, and vulnerability to winter storms for Iowa counties, mitigation or intervention priorities are revealed for counties prone to receive higher winter farm loss.

Decisions can be made through the approaches in relation to capital enhancement, such as incentive programs or services encouraging farmers planting trees in places in lack of natural windbreaks. Figure 34 shows the distribution of the nursery professionals around the state providing guidance to livestock farmers who want to plant trees and shrubs (Coalition to Support Iowa's Farmers n.d.). Limited participating nurseries were found in northeast Iowa where natural capital is also distinctively less than elsewhere in Iowa. Future efforts could focus on engaging more participants in places in greater need. Along with investment in natural capital, efforts can be made in enhancing household farming economic status and innovative capital, such as through subsidies and facilities to offset the negative impacts of poverty. For example, financial support may be conducive to alleviating the likely suffering in southern Iowa with low farm income. In light of sensitivity, counties that highly rely on livestock farming deserve more attention. However, making sensible decisions requires detailed information about multidimensional benefits and costs. For example, downscaled data is needed to determine where to construct the natural shelter or facilities and to what extent would minimize the cost and maximize the benefits for areas of greatest need or population who lose the most due to the storms.

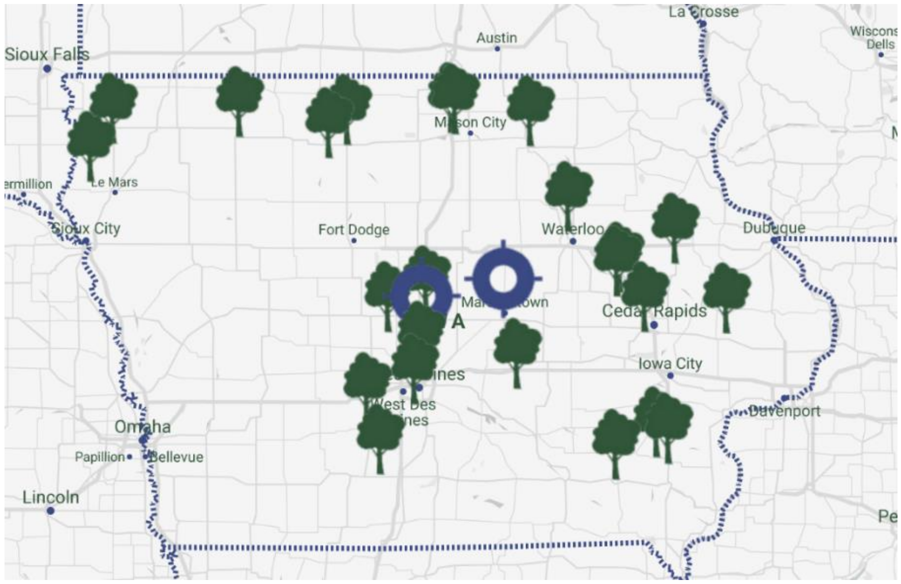

Figure 34 Participating Nurseries for Green Farmstead Partner Program. Search Tool by Coalition to Support Iowa's Farmers, "Green Farmstead Partner Program", https://www.supportfarmers.com/green-farmstead-partner-program/.

According to interviewed farmers' emphasis on preparation, enhancing warning coverage and accuracy in severity and timing is important in increasing preparedness and reducing the devastating outcomes attributable to mis-issued warning (Erik 2019). What is also important to understand in climate adaptation is social learning, which has been extensively discussed and included in agent-based models to address uncertainty and collective behavior (Van Oel et al. 2019; Hailegiorgis, Crooks, and Cioffi-Revilla 2018). It is important to understand the role of knowledge sharing in household decision-making and identify effective pathways of social learning. For example, a farmer can have memories about economic loss caused by climate events. This can potentially influence his decisions on whether to diversify agricultural production, which is recognized as a common adaptation to increase the sustainability (Doll, Petersen, and Bode 2017).

Another example could be simulating the social influence among community members (Van Oel et al. 2019). The process of knowledge sharing, collective behaviors and uncertainties have great implications in identifying interventions that can minimize the losses from climate risks.

The results of this study and the conceptual agent-based model show there are multiple reasons and pathways resulting in varying vulnerability scenarios. The ultimate goal of utilizing ABM is to inform public decisions by providing a compelling account visually. There is always need for understanding the existing dynamics of adaptation before projects are initiated (Ziervogel, Bharwani, and Downing 2006). With the help of dynamic simulation combining empirical data and behavioral theories, the what, when and how to adapt will become clearer and more precise.

CHAPTER 6

CONCLUSION

Winter storms are the second-most frequent catastrophe in the Midwest and tend to create non-negligible impacts on farming communities that highly rely on climatic-sensitive resources and activities. However, few examples of studies were found to assess the vulnerability to winter storms in the rural context. This study identified both of climatic and non-climatic indicators for winter storms vulnerability assessment by analyzing the previous vulnerability case studies and interview results. Factor analysis was used to identify underlying factors impacting adaptive capacity and calculate index scores. An array of maps was generated to inform the stage of vulnerability, exposure, sensitivity and adaptive capacity. Recognizing the limitations of data analysis for aggregated data and the complexities inherent to human-environment systems, a conceptual agent-based model was established in an attempt to examine geographically and temporally the multiple reasons that drive the decisions and key pathways in the response-loss process. These research findings could contribute to the understanding of the role of vulnerability components in a specific setting and to framing climate adaptation dynamics.

This study revealed the characteristics of winter storms and the associated impacts on farms based on interviews with 14 farmers. Major types of winter storms such as extreme cold, ice storm, and strong wind can cause direct and indirect impacts on farming, especially farms with animals. There were in total 12 adaptive capacity indicators, 2 sensitivity indicator and 2 exposure indicators selected for quantifying vulnerability. Factor analysis extracted 3 components to indicate adaptive capacity: 1) farming economic status highly correlated to labor expense, farm income and facilities, 2) environmental institutional capital highly correlated to government program expense and natural shelter, and 3) innovative capital highly correlated to education and organization membership. Among these factors, farming economic status was considered to indicate adaptive capacity most accurately. More empirical studies, at different scales, are needed to evaluate the suitability of using the Sustainability Livelihood Framework to determine indicators. Factor analysis shows great potential in testing such a framework-based indicator system.

Vulnerability component scores were calculated and mapped. Southern Iowa showed low adaptive capacity due to low farming economic status but with high environmental institutional capital. Despite high farming economic status, Northwest Iowa showed significantly low environmental institutional capital and high exposure rates, contributing to the overall high vulnerability in this region. Northeast Iowa were comparatively low in vulnerability as a result of low exposure and high adaptive capacity. Vulnerability maps could be helpful when analyzed with auxiliary data, such as actual loss data, maps of vulnerability to other weather-related events, and other census statistics.

The limitations in normalization and index development were addressed and discussed. In Iowa, low resolution of data covering metropolitan areas did not seem to make a significant difference in sensitivity patterns. No pattern change was found for exposure after excluding metropolitan counties. However, rural characteristics of adaptive capacity tended to be underrepresented when including metropolitan areas.

To address the limitations inherent to the indicator-based vulnerability assessment approaches that tend to aggregate local characteristics to the regional level and often fail to capture interconnectedness of indicators. An explicit agent-based model was conceptualized by determining entities and their variables interacting during winter storms and designing household's response-loss process. Future studies are expected to focus on ground survey for physical and socio-economical information to generate realistic agent populations and extract decision rules to parameterize the processes for agent-based models. Overall, vulnerability assessments have proved to have great implications in designing appropriate adaptation and mitigation policies targeted towards climate extremes and the associated impacts on populations with high reliance on agriculture for their livelihoods.

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