TOWARD RESILIENT COMMUNITIES – VULNERABILITY ASSESSMENTS OF COUPLED HUMAN AND NATURAL SYSTEMS

By

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ABSTRACT

Efforts to comprehend and assess social vulnerability amidst environmental hazard events are crucial for fostering adaptive and resilient communities, thereby mitigating risks posed to humans by environmental hazards. However, the intricate interactions between humans and environmental hazards give rise to highly interactive and complex systems, commonly known as coupled human and natural systems (CHANS), necessitating a nuanced approach for accurately assessing environmental and social vulnerability. This dissertation bridges a research gap and provides novel insights into social vulnerability within CHANS, such as understanding the dynamics that the behaviors of one stakeholder group can influence another stakeholder group in the system by affecting the environment, using Lake Erie's harmful algal blooms (HABs) as a case study.

This dissertation comprises three main chapters, each offering distinct perspectives. Chapter Two introduces a 5-theme hierarchical spatial framework for assessing social vulnerability to HABs at the county level. This framework not only generates a vulnerability index composed of socioeconomic, resource dependence, and spatial factors affecting vulnerability to HAB events but also provides a practical tool for policymakers and professionals to identify and prioritize communities for intervention. Chapter Three focuses on developing an integrated agent-based and multicriteria evaluation model aimed at simulating the dynamics in the system to pinpoint communities with high vulnerability. The agent-based section of the model simulates the CHANS from a bottom-up perspective to ensure the inclusion of interactions and dynamics, making the model more realistic and applicable. The model outputs are then used in the multicriteria evaluation section, which incorporates criteria representing the three pillars of social vulnerability factors suggested by the Intergovernmental Panel on Climate Change. In Chapter Four, sensitivity

and scenario analyses are conducted to scrutinize the model's behavior, introduced in Chapter Three, shedding light on contributing factors to community vulnerability and providing insights for future research and policy development.

This dissertation has identified high-vulnerability areas affected by Lake Erie HABs, offering significant insights into environmental and social vulnerability and thereby informing crucial policymaking recommendations. The studies yield three major findings: 1) The social vulnerability indices to harmful algal blooms, generated from both models in Chapters Two and Three, present clear spatial patterns; 2) The spatial distribution of the resulting indices, along with the social status of spatial units, provides valuable information to prioritize policy implementation, e.g., census tracts around the center of Lucas County, and inform targeted policies, e.g., focusing on alternative drinking water resource accessibility to enhance community resilience for most tracts in Wood County; and 3) Selected best management practices, such as cover crops, play a significant role in mitigating HAB severity in Lake Erie in the long run.

The intellectual merit of this dissertation is twofold. Methodologically, through the adaptive agent-based and multicriteria analysis framework, we advocate for increased focus on addressing the inherent multifaceted complexities of the vulnerability within CHANS. This includes understanding how the behaviors of one component in a system indirectly affect another component by influencing the severity of environmental hazard events, thereby enriching the research field of environmental social vulnerability. From the perspective of applied science, these studies yield insights crucial for guiding targeted community adaptation policies to lessen the negative societal impacts of HABs in Lake Erie and enhance community resilience in the study area by informing agricultural regulations to mitigate HAB severity in the lake and other aquatic systems prone to HABs.

This dissertation is dedicated to my grandparents,
Ms. Gongren Tang and Mr. Wenkai Sun

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1. CHAPTER 1: INTRODUCTION

1.1. Coupled human and natural systems and social vulnerability

The concept of coupled human and natural systems (CHANS) emerged about two decades ago to describe systems involving human behaviors and environmental events interacting with each other (Liu, Dietz, Carpenter, Folke, et al., 2007). CHANS framework is now widely used to study various environmental topics, such as environmental sustainability and land use change, which typically consists of complex interactions between human and environmental factors (Carter et al., 2014; J. Chen et al., 2015; Giuliani et al., 2016; Morzillo et al., 2014; Spies et al., 2014; Zhou, 2019). This widespread adoption is due to the framework's ability to address system complexities such as dynamics, heterogeneity, nonlinearity, and feedbacks – features that are challenging to assess using traditional study approaches (Liu, Dietz, Carpenter, Alberti, et al., 2007).

Environmental hazards can disturb the equilibrium within CHANS, affecting both human and environmental components. To effectively protect and support communities from disasters caused by environmental hazards, it is crucial to evaluate social vulnerability to identify the susceptible groups and target supportive policies (Raju et al., 2022). Social vulnerability, which encompasses socioeconomic and demographic factors reflecting community resilience, has become essential for evaluating a community's risk from environmental hazard events (Flanagan et al., 2011). However, questions remain regarding which factors to include when assessing social vulnerability, how to integrate the framework with a specific environmental context, and how to address the inherent spatiotemporal complexities.

The Intergovernmental Panel on Climate Change (IPCC) suggests three fundamental pillars of factors that affect social vulnerability: intrinsic sensitivity, referring to dependence on natural or economic resources; external exposure risk, denoting the likelihood of exposure to an event; and adaptive capacity, indicating the ability to adjust behaviors during or after an event to adapt or recover (McCarthy et al., 2001). These pillars provide a framework for selecting key factors influencing social vulnerability and allow for incorporating environmental events related to exposure risk and intrinsic sensitivity.

The social vulnerability index is a widely adopted metric for quantifying and assessing social vulnerability. Various indices have been developed for this purpose (CDC/ATSDR, 2022; Cutter et al., 2003). However, the criteria used in these indices are often highly correlated and tend to focus solely on socioeconomic factors without considering hazard-specific conditions (W. Chen et al., 2013; Finch et al., 2010). Moreover, due to their structure, these social vulnerability indices struggle to address the spatiotemporal dynamics of the factors contributing to vulnerability within CHANS.

1.2. Harmful algal blooms in Lake Erie

Lake Erie is susceptible to harmful algal blooms (HABs) for various reasons. Physically, it is relatively shallow and warm compared to the other Great Lakes. Socioeconomically, this lake is surrounded by areas predominantly used for agriculture. Currently, the issue of HABs in Lake Erie is significant, impacting the environment and the quality of life for residents (Lake Erie LaMP, 2011; National Centers For Coastal Ocean Science, 2022). Lake Erie is a drinking water source for over 11 million residents living in the contributing watersheds. At the same time, the occurrence and severity of HABs pose risks to the local economy by threatening the tourism and fishery industries, which generate profits exceeding $10 billion (NOAA, 2022; US EPA, 2022).

For nearly half a century, various governance actors and agencies operating at federal, state, regional, and international levels have made concerted efforts, albeit sometimes competing, to reduce nutrient loads into Lake Erie (Bitterman & Koliba, 2020; Kellogg, 1997; Lake Erie LaMP, 2011). In alignment with the objectives outlined in the 2012 Great Lakes Water Quality Agreement (GLWQA), both the U.S. and Canada have adopted a nutrient load reduction target of 40 percent by 2025 compared to the 2008 baseline loads (Valentine, 2012). Despite these efforts to mitigate HABs in Lake Erie, the severity is still moderate to high and fluctuates over the years (Figure 1.1). Therefore, this dissertation underscores the need for research on social vulnerability, focusing on how different groups of people are affected by HAB events in Lake Erie and on ongoing effects to mitigate HAB severity over the long term.

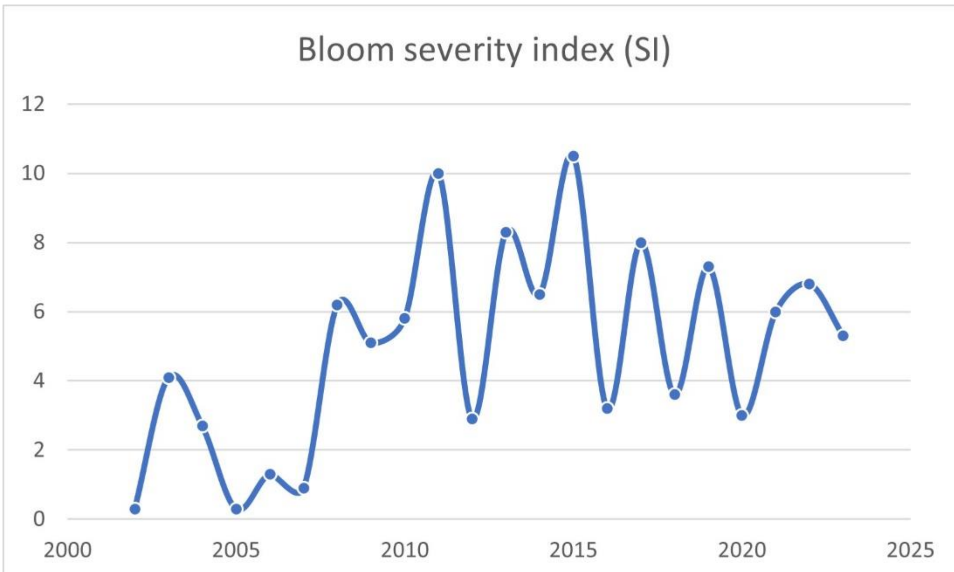

Figure 1.1 Western Lake Erie bloom severity from 2002 to 2023

1.3. Research objectives and dissertation framework

The overarching objective of this dissertation is to assess social vulnerability facing environmental hazard events in the complex CHANS. The results of this dissertation are expected to contribute to the understanding of the relationships and dynamic interactions between the social system (socioeconomic status and agricultural behaviors) and the natural system (HAB severity in an aquatic system). Additionally, this research aims to design a modeling framework that provides methodological insights into simulating the dynamic behaviors of CHANS from a process-based and bottom-up perspective and investigating social vulnerability through a thorough and concise assessment of relevant factors. Specifically, we ask three research questions:

1). "From a static perspective using existing socioeconomic datasets, which are the counties most vulnerable to Lake Erie HAB events in the south and west parts of Lake Erie Basin?"

2). "From a systemic coupled human and natural systems (CHANS) perspective considering stochastic, complexities and spatiotemporal dynamics, where are the most vulnerable regions to Lake Erie HAB events in Maumee River Basin?"

3). "According to the systemic model built to simulate the CHANS, how do different variables affect the resulting vulnerability index and contribute to the sensitivity of the model?"

We proceed through three steps to address these three questions in the following Chapters Two to Four as shown in Figure 1.2. In Chapter Two, we introduce a static (one time step) 5-theme hierarchical spatial HAB vulnerability index (HAB-VI) to evaluate the social vulnerability facing HAB events in Lake Erie. We apply the HAB-VI results to inform support for high-vulnerability communities. In Chapter Three, we develop an integrated agent-based model and multicriteria evaluation to ensure the inclusion of complexities and spatiotemporal dynamics in assessing social vulnerability to HABs. Monte Carlo-based uncertainty analyses are conducted in Chapters Two and Three to evaluate the model uncertainty and provide further suggestions for policymaking. Chapter Four features sensitivity analysis and scenario analysis based on the model developed in Chapter Three. These analyses offer insights into understanding vulnerability in a complex context by generating information about the most significant factor affecting the sensitivity of the model results when calculating vulnerability indices in different study area zones. Additionally, scenario analysis provides insights into policymaking by simulating the effectiveness of certain Best

Management Practices in agriculture. The results of these chapters can all help understand the behaviors of CHANS and how social vulnerability within this system varies across space and time.

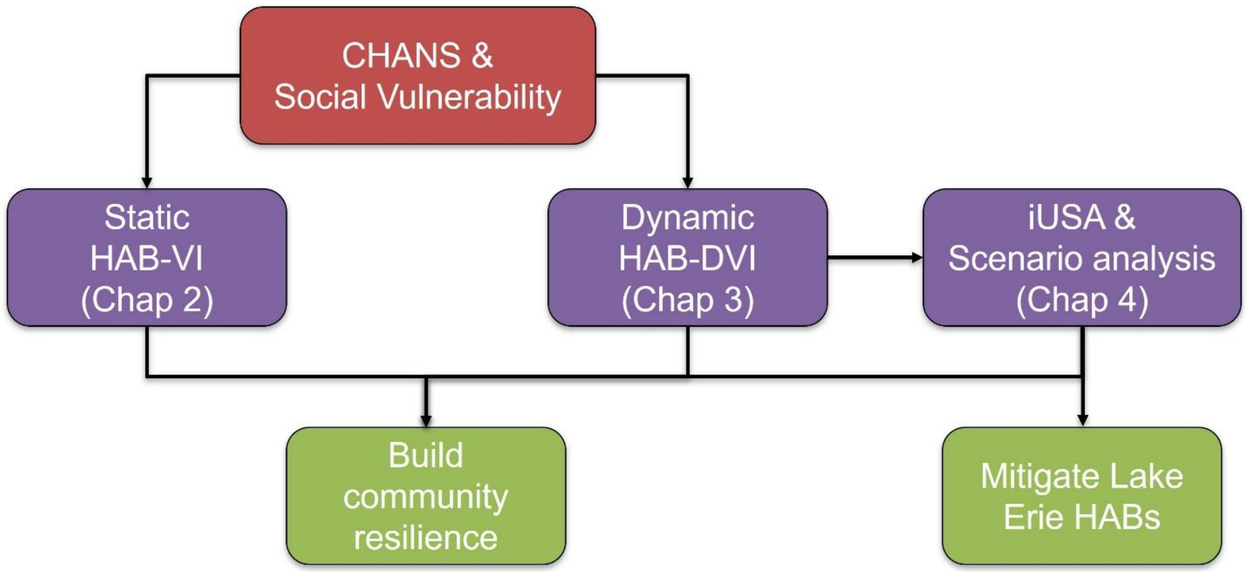

Figure 1.2 Dissertation framework: HAB: harmful algal blooms, VI – vulnerability index, DVI, dynamic vulnerability index, iUSA: integrated uncertainty and sensitivity analysis

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2. CHAPTER 2: DESIGN AND USE OF A SPATIAL HAB VULNERABILITY INDEX FOR INFORMING ENVIRONMENTAL POLICY AND ADVANCING ENVRIONMENTAL JUSTICE

Abstract

In recent decades, harmful algal blooms (HABs) have increased significantly in Lake Erie. The blooms can affect human health, aquatic ecosystems, and the local economy. The effects can vary across communities in the Lake Erie Basin due to local socioeconomic status and dependence on lake resources. Therefore, it is crucial to identify HAB-vulnerable populations and regions to adjust regional governance strategies and allocate resources for government support. This study introduces a 5-theme spatial HAB vulnerability index (HAB-VI) comprised of socioeconomic, resource dependence, and spatial factors affecting vulnerability to HAB events. Using a multi-factor hierarchical model, it also applies the index to evaluate the HAB-related vulnerabilities of 50 counties in the Lake Erie Basin. Uncertainty analysis is an essential step to assess the robustness of the model and the stability of the calculated indices. The research utilizes a Monte Carlo-based uncertainty analysis and visualizes the statistical results of the simulation runs to indicate the variability and reliability of the HAB-VI rankings. Comparing thematic maps of the generated HAB-VI rankings, indicators of local governance strength, and nonpoint nutrient loads provides further insights into prioritizing the regions for government support and building community resilience.

Keywords: Harmful Algal Blooms, Vulnerability Index, Uncertainty Analysis, Community Resilience, Environmental Justice, Lake Erie

2.1. Introduction

The intensity of harmful algal blooms (HABs) in Lake Erie has significantly increased in the past decades (National Centers For Coastal Ocean Science, 2022). Lake Erie is prone to HABs due to its physical characteristics and geographic location; it is the southernmost, smallest, and shallowest of the Great Lakes. However, these conditions are not the only reason for the increase in HABs. Most of the terrestrial area around the lake is urban or agricultural, and the massive amount of runoff makes the lake extremely nutrient-enriched. Such an optimal biological environment is very productive for microbes, including cyanobacteria, which cause blue-green algae blooms (CyanoHABs) like the event responsible for Toledo's 3-day water shutoff that affected more than half a million residents in 2014 (Lake Erie LaMP, 2011).

Lake Erie is a cross-border waterbody and comprises three basins surrounded by five US states (i.e., Michigan, Ohio, Indiana, Pennsylvania, and New York) and the province of Ontario in Canada. The lake provides drinking water for about eleven million people living in the watershed, which is approximately one-third of the total population of the Great Lakes basin. HABs have threatened the drinking water safety of these people living in Great Lakes cities. However, the impacts of algal blooms extend far beyond the drinking water crisis. Though some algal blooms are normal and necessary to aquatic ecosystems, blooms that cover large areas can block sunlight from reaching other organisms, deplete oxygen levels in the water, and negatively impact the aesthetic value of aquatic environments. More importantly, in cases of HABs such as blue-green algae blooms, toxic substances of the blooms are not only poisonous to human, but also lead to issues like fish die-offs and fisheries shutoffs (NOAA, 2022; R. S. Wilson et al., 2019). The excessive algal growth in Lake Erie can negatively affect the lake's critical tourism industry and world-class fishery, with more than $10 billion in economic profit (US EPA, 2022). However, all the detrimental consequences – health-wise, resource-wise, and economy-wise – are not equally allocated across all populations throughout the basin. Similar concerns about unequal vulnerability impact communities confronting algal blooms around the United States (Kourantidou et al., 2022) and the world (Glibert et al., 2014).

Environmental injustice arises when different communities are disproportionately exposed to environmental hazards and/or are denied fair treatment in aspects of environmental policy, including the allocation of amenities and resources (Brulle & Pellow, 2006; Downey, 2005; Mohai et al., 2009; US EPA, 2023). Studies show that structurally marginalized groups and people with lower incomes are more likely to be at higher risk for environmental hazards such as air pollution, extreme heat, and rising sea levels. For example, in the US, Black, Latinx, Asian, and Pacific Islander communities have a significantly higher risk of non-cancerogenic respiratory health issues caused by outdoor air pollution toxins (Alvarez, 2022). The southern New York State population, which has a higher proportion of non-native English speakers, is more likely to expose to and suffer from extreme heat events than upstate New York State residents (S. G. Nayak et al., 2018). Moreover, in the coastal areas of the US, it is more difficult for populations with lower property values to adapt to sea level change (Martinich et al., 2013).

Environmental injustice occurs when environmental issues are not dealt with in a fair and sustainable way that benefits all people. To achieve the goal of environmental justice, the first step is to determine the more vulnerable groups that need additional guidance and support and where they are located. Studies have shown that a community is more likely to suffer a more extensive loss due to an environmental hazard event if its individuals are more socially vulnerable (Barnett et al., 2008; Cutter et al., 2003; Flanagan et al., 2011). Therefore, the concept of social vulnerability, which covers socioeconomic and demographic factors that can reflect the resilience of communities, has been introduced to environmental research and has become an integral concept in evaluating a community's risk from environmental hazard events (Flanagan et al., 2011).

The Intergovernmental Panel on Climate Change (IPCC) suggests three essential components that affect vulnerability: intrinsic sensitivity, external exposure risk, and adaptive capacity (McCarthy et al., 2001). Intrinsic sensitivity refers to the dependence on natural or economic resources, or the system’s sensitivity responding to an event; external exposure risk is the chance of exposure to an event; and adaptive capacity describes the ability to adjust in an event to offset the impacts or recover from the hazard, and this capacity is usually related to socioeconomic status, such as wealth, infrastructure accessibility, information accessibility, etc. (Allison et al., 2009; McCarthy et al., 2001; O’Brien et al., 2004). Several studies followed this framework to break down vulnerability into these three components in case studies of environmental issues for targeting policy interventions, such as assessing fishery economy vulnerability of different countries under the impacts of climate change (Allison et al., 2009), and mapping agricultural communities’ vulnerability to climate change as well as globalization (O’Brien et al., 2004).

The social vulnerability index is a widely adopted metric that can be used to quantify and assess different groups’ vulnerability to various threats. Several indices have been developed and implemented in risk assessments and emergency management in recent years. For example, the Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry Social Vulnerability Index (CDC/ATSDR SVI) is among the most widely known vulnerability indices (https://www.atsdr.cdc.gov/placeandhealth/svi/index.html). The 2018 SVI separates 15 demographic and socioeconomic variables into four categories and ranks in each area under study with its percentile rank scores (CDC/ATSDR, 2022). It was initially developed to inform the mapping of CDC/ATSDR SVI in New Orleans using Hurricane Katrina's impact on the city and identify communities with low resilience capacity that need more support in post-disaster management (Flanagan et al., 2011). Recently, the index was applied in another hurricane research to evaluate the association between flood and emergency department visits in Texas before and after Hurricane Harvey (Ramesh et al., 2022). During the COVID-19 pandemic, Nayak et al. (2020) applied CDC/ATSDR SVI to examine the impact of social vulnerability using the county-level case incidence in the US and used both the index and COVID-19 case fatality rate to identify high-risk counties in the pandemic (A. Nayak et al., 2020). The index has also been applied to other health topics, such as heat-related health issues (Lehnert et al., 2020) and cardiovascular disease (Hong & Mainous, 2020).

The Hazard and Vulnerability Research Institute at the University of South Carolina developed another index (SoVI for Social Vulnerability Index). SoVI was initially constructed to measure the social vulnerability of US counties to environmental hazards. Twenty-nine socioeconomic variables are included in this additive index calculation (Cutter et al., 2003). SoVI has been applied to suggest post-hurricane management strategies for New Orleans (Finch et al., 2010) and identify flood-risk zones in Hampton Roads (Kleinosky et al., 2007). The index has also been adapted and applied to cases in other countries and areas, such as assessing social vulnerability to environmental hazards in Brazil (de Loyola Hummell et al., 2016), the Yangtze River Delta Region of China (Chen et al., 2013), and delineating natural risk zones in Greater Lisbon of Portugal (Guillard-Gonçalves et al., 2015).

While the social vulnerability indices have been applied to study various environmental hazards and events, they are uncommon in HAB studies until the recent decade (Broadwater et al., 2018; Delegrange et al., 2015; Glibert et al., 2014). However, most of these studies were focused on the vulnerability of ecosystems, and only a few discussed social aspects of vulnerability to HAB events. Social vulnerability was introduced to examine how HAB-triggered fishery closures affect fishing communities on the West Coast of the US (Moore et al., 2019). Unique challenges that indigenous communities face in HAB events were also analyzed through discussing the improvement opportunities in resilience and adaptation using the case study of the Quinault Indian Nation from a perspective of social vulnerability (Kourantidou et al., 2022). Such social vulnerability research only focused on a specific group of populations and did not generalize the indices to the whole coastal communities.

These social vulnerability indices (e.g., SVI, and SoVI) calculated with geospatial census data can provide more spatially explicit indicators of locations that may need more supportive policies to help with adaptation to HAB conditions. However, deciding where to implement regulatory policies, and how to improve the policy effectiveness to mitigate HAB environmental issues remain unanswered. An excess nutrient level in water is one of the necessary conditions for HABs. Therefore, nutrient loads, including total phosphorus (TP) and total nitrogen (TN), can be significant indicators reflecting the level that a specific area contributes to HABs issues in its nearby waterbody. This also makes nutrient load level an indicator to prioritized locations of regulatory governance. In addition to where to allocate governance efforts, geographic scale of governance is another critical point to consider for improving policy effectiveness. Decentralization has become popular in the governance of environmental issues, and has been believed to be effective for the incorporation of local knowledge, immediate interests, and mutual trust in local stakeholders (Larson et al., 2010; Lemos & Agrawal, 2006; Ostrom, 1990). However, studies also demonstrate that environmental externalities can weaken the advantages of decentralized governance. For instance, when pollution originates beyond the system being governed, decentralized governance is powerless to address local environmental impacts (Monogan et al., 2017; Ocampo-Diaz et al., 2022). As a result, such externalities also potentially lead to environmental injustice in terms of socially vulnerable communities having even less capacity to protect themselves from pollution that originates elsewhere. Therefore, the geographic scale of governance is a key concern to improve governance effectiveness, as well as pushing environmental justice in the governing process.

The framework of three components of vulnerability suggested by IPCC provides a qualitative metric and valuable direction to evaluate social vulnerability. At the same time, the application of social vulnerability indices is a functional approach to quantitatively assess vulnerabilities and offers a possibility to spatially address environmental injustice issues across certain research areas. Nevertheless, the review of existing studies points to some gaps in the literature. First, while the social vulnerability index has long been applied in environmental hazard studies, it has not been adopted to explore the effects of HAB events on aquatic ecosystems – and their beneficiaries – until recent years. In these recent studies, only specific groups of the population, e.g., fishery and indigenous communities, were examined (Kourantidou et al., 2022; Moore et al., 2019). Though disparities exist, HAB events can cause socioeconomic disruption to the whole population, which was not previously considered. Second, spatially-explicit aspects are rarely present in the existing studies. Akin to other natural hazard events, such as extreme heat, tornadoes, and earthquakes, where several adjacent counties are likely affected similarly by the event, the effects of HABs are dependent on the distance to the shoreline or bloom spots. Therefore, spatial factors in HAB effect studies warrant scrutiny. Third, though many studies were devoted to environmental policy or community recovery plans, very few have compared current governance situations with vulnerability. Existing environmental policy is also a pivotal point in evaluating environmental justice, as possible under governance, over governance, and informal governance can all exacerbate injustice (Amuzu, 2018; S. M. Wilson et al., 2010). Therefore, we suggest that a comprehensive and spatially-explicit analysis, which includes the present state of governance throughout the basin, is necessary to provide more efficient governance improvement recommendations.

This paper aims to assist policymakers in identifying and prioritizing regions for HAB-related policies while minimizing disturbance to local socioeconomic developments and assisting community resilience. To achieve this goal, we propose a modified social vulnerability index that accounts for spatial factors for populations facing HAB events.

We start by giving a general introduction to our research area's geographic and economic context (Section 2.2.1). Then, in Section 2.2.2, we describe the methods of improving CDC/ATSDR's SVI, organizing a 5-theme spatial HAB Vulnerability Index (HAB-VI). We adopt local total nutrient loads (TP and TN) as our indicator of HAB intensity and collect county-level agricultural policy and water management information to quantify policy strength. Finally, we present maps and comparisons of our calculated results of HAB-VI, nutrient contribution levels, and policy strengths (Section 2.3) and develop our policy recommendations (Section 2.4).

2.2. Materials and Methods

2.2.1. Study area

This study includes 50 counties in the Lake Erie Basin within Michigan, Ohio, and Indiana (Figure 2.1). Counties are an appropriate level of analysis in this watershed because they are responsible for governing water drainage, and often share water supplies across intra-county jurisdictions. We do, however, recognize that a finer level of analysis might highlight additional socio-economic contrast within counties. Counties in Pennsylvania, New York, and Ontario

(Canada) that are also parts of the Lake Erie Basin were excluded from this study because they are located on the eastern or northern side of Lake Erie, which are not historical hotspots of HAB events – or the agricultural runoff leading to such events – in the lake. Nine counties in Michigan and Ohio are located along the Lake Erie shoreline. The counties are significantly different in demographic and socioeconomic status. Metropolitan areas, e.g., Cleveland (Ohio), Detroit (Michigan), and Toledo (Ohio), dominate some counties, i.e., Cuyahoga County, Wayne County, and Lucas County respectively. Such counties tend to have higher population densities and a more diverse ethnic composition. Manufacturing, science, and technology industries share most of the economic sectors.

In contrast, the rest of the counties in this lake basin are dominated by agricultural land use and related industries (CDC/ATSDR, 2022; SSTI, 2019). In 2018, ~11,003,602 people lived across our study area, with around 14.5 percent in poverty (CDC/ATSDR, 2022). County-level social vulnerabilities calculated using the CDC/ATSDR's SVI based on general demographic factors vary across the watershed, with the index of most counties distributed over "low" to "moderate to high" levels (CDC/ATSDR, 2022). These data reveal that people's abilities to respond to hazardous events (e.g., HAB events) and adapt to anthropogenic events (e.g., drastic policy changes) are decidedly mixed.

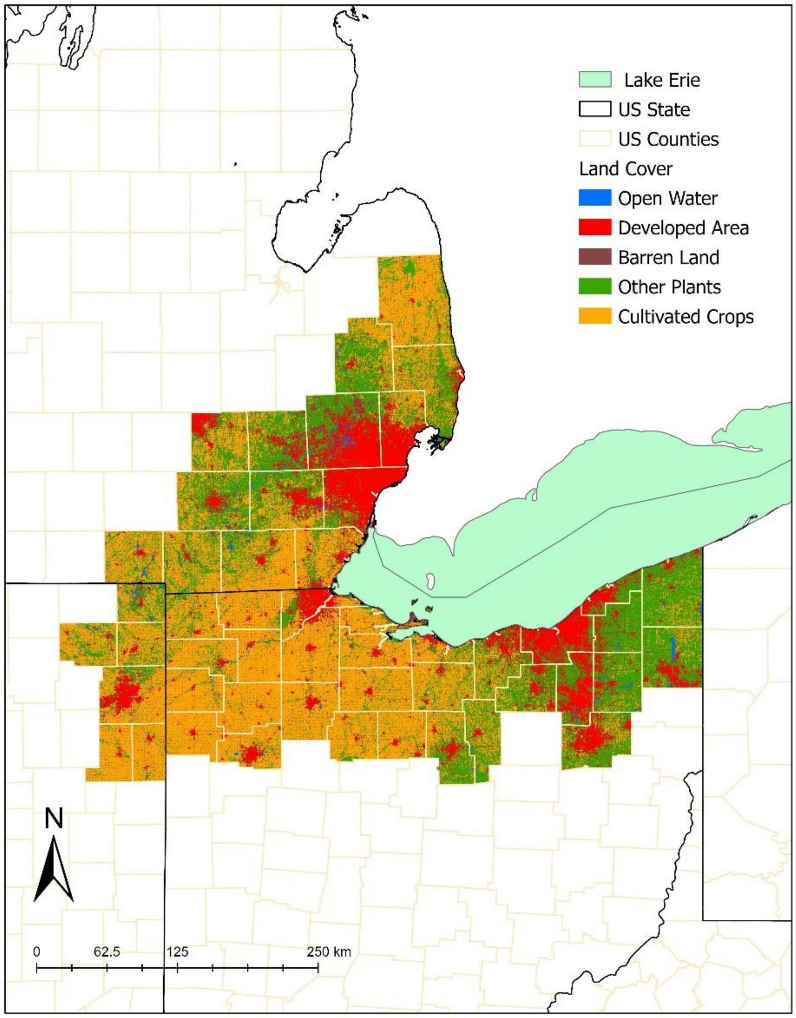


Figure 2.1 Study area

Due to the difference in location and economic industry status, the counties vary in their nutrient contributions to Lake Erie, as well as the level of impact they receive from HAB severity. On the other hand, factors most affected by HAB events are drinking water resources and economic income, which are highly related to the distances from counties to the lake. In other words, counties are more sensitive to HAB exposure when they depend on the lake for water supply or economic activity. Counties closer to the lake are more likely to be affected in aspects of drinking water resources and lake-dependent economic income, e.g., entertainment and fishery. This is because surface water resources closer to the lake tend to have similar water characteristics, such as nutrient level and water temperature, and their fishery and entertainment-related economic income are more likely to be directly related to Lake Erie.

County industry structure differences affect their TP load contribution to Lake Erie HAB events. Most counties in our study area that are not located along the lakeshore are agricultural land dominated by cultivated crops. Maumee River and Detroit River are Lake Erie's two biggest nutrient contributors. The two rivers contribute about 52 percent of TP load to Lake Erie, and nonpoint sources (NPS) in origin contribute 94 percent of the load to the Maumee River and 34 percent to the Detroit River in 2008 (GLWQA, 2015). Overall, NPS contributes to more than 50 percent of TP in Lake Erie (GLWQA, 2015), and fertilizer and manure are a major part of NPS sources. In recent decades after 1980s, on average, counties dominated by the agriculture industry have been bigger contributors to TP loads to Lake Erie than the rest.

On the other hand, the counties have varied levels of input effort in environmental policies to reduce their nutrient loads and mitigate Lake Erie HAB issues. As a part of the United States, the whole study area is required to fulfill the obligations and commitments under the U.S.-Canada Great Lakes Water Quality Agreement (GLWQA). Specifically, US EPA put forward a US Action Plan for Lake Erie, which sets TP reduction goals for priority tributaries and clarifies action strategies, including water management, nutrient management, and reducing agricultural sources. There are also several state-led efforts in approaching phosphorus reduction goals for Lake Erie. For example, all states in Lake Erie Basin endorsed a joint action plan developed by the Commission's Lake Erie Nutrient Target (LENT) Working Group and committed to following the ten proposed joint actions to achieve a 40 percent TP reduction target (US EPA, 2018). In addition, the Ohio Department of Agriculture (ODA) monitors agricultural nonpoint sources and educates farmers on fertilizer management, while Ohio EPA works with ODA on a stormwater management program.

Similarly, the Michigan Department of Environment, Great Lakes, and Energy (EGLE) is focused on P reduction goals through strategies such as stormwater management, fertilizing restrictions, and banning high phosphorus level detergent. Relatively, Indiana has fewer state-level regulatory policies. However, their efforts focus on ensuring compliance with fertilizer certification rules and attributing financial support to assist education and training on relevant environmental policies and actions. Most counties also have county-level environmental policies to help reduce their nutrient contribution to the lake. However, the 50 counties in our study area are varied in their policy orientation and strength. For example, Wood County in Ohio has a series of wastewater and fertilizing regulations, such as managing the amount, form, and timing of applying nutrients for plants, and the policies tend to be strict. Lucas County in Ohio, which is adjacent to Wood County, is focusing more on educational approaches that encourage the implementation of best management practices (BMPs), and the policies are mostly in a suggestive format. Thus, Lucas County’s policy strength is not as strict as that in Wood County. In contrast, there are also counties, such as Wyandot County in Ohio, where we did not find any specific regulations or management strategies to help manage water runoff or reduce nutrient load to the lake.

2.2.2. Methodology

2.2.2.1. HAB-VI

This research develops the HAB-VI as an extension to the CDC/ATSDR's SVI (CDC/ATSDR, 2022). On top of SVI's original 15 factors under four themes (i.e., socioeconomic status, household composition, and disability, minority status and language, and housing type and transportation), we add a theme of HAB impacts with two factors - local dependence on the lake-related economy, and local dependence on surface drinking water resources. With the 2-factor HAB impacts theme added, our 17- factor HAB-VI structure adapted from CDC/ATSDR's SVI (CDC/ATSDR, 2022) (Figure 2.2) is able to reflect the three components (i.e., intrinsic sensitivity, external exposure risk, and adaptive capacity) in the vulnerability framework suggested by IPCC (McCarthy et al., 2001). The four original themes in SVI, consisting of socioeconomic and demographic information, provide a proxy measurement of adaptive capacity, which describes residents' ability to adjust to a hazard event. Sensitivity under exposure to an environmental hazard refers to the degree that local systems would be impacted by a hazard, and this component is highly related to dependence on the impacted natural resource (in this case Lake Erie waters). Local dependence on lake-related economy and surface drinking water resources are two important indicators to measure sensitivity under exposures to the environmental hazard of HAB in our study (Allison et al., 2009; O'Brien et al., 2004). We used county-level GDP shares of fishing and service industries, e.g., accommodation and recreation, to indicate lake-related economic dependence (SSTI, 2019; US BEA, 2022) and the ratio of surface drinking water sources to alternative drinking water sources as an indicator of surface drinking water dependence (USGS, 2023). Both datasets were adjusted for proximity to Lake Erie (Figure 2.3) as the distance is a critical indicator to the level of local exposure risk to HABs in the lake (Allison et al., 2009).

The counties in our study area are located in the western side of Lake Erie Basin, the portion of the basin that is most affected by HABs. Though risks vary across the counties and degrade with distance to the lake, research shows that counties in the basin are all under exposure to HAB events of Lake Erie. For example, 88% of the 1.8 billion gallons of water used per day within the basin for public and domestic water supply is surface water drawn from Lake Erie and its surrounding waterbodies (Myers et al., 2000), which means the HAB events in Lake Erie affect the vast majority of population throughout the basin. In this situation, though counties far away from the lake have relatively lower exposure risk adjusted to the proximity compared to counites closer to the lake, their varied adaptive capacity and sensitivity to the hazard still function to balance or consolidate the differences in the component of exposure risk in our vulnerability framework. Moreover, there is no evidence showing any of the 17 factors in HAB-VI structure is playing a more significant role than others in quantifying and comparing social vulnerability. Therefore, in this study, we follow the CDC/ATSDR calculation rule for their SVI, and equally weigh our 17 factors in HAB-VI calculation.

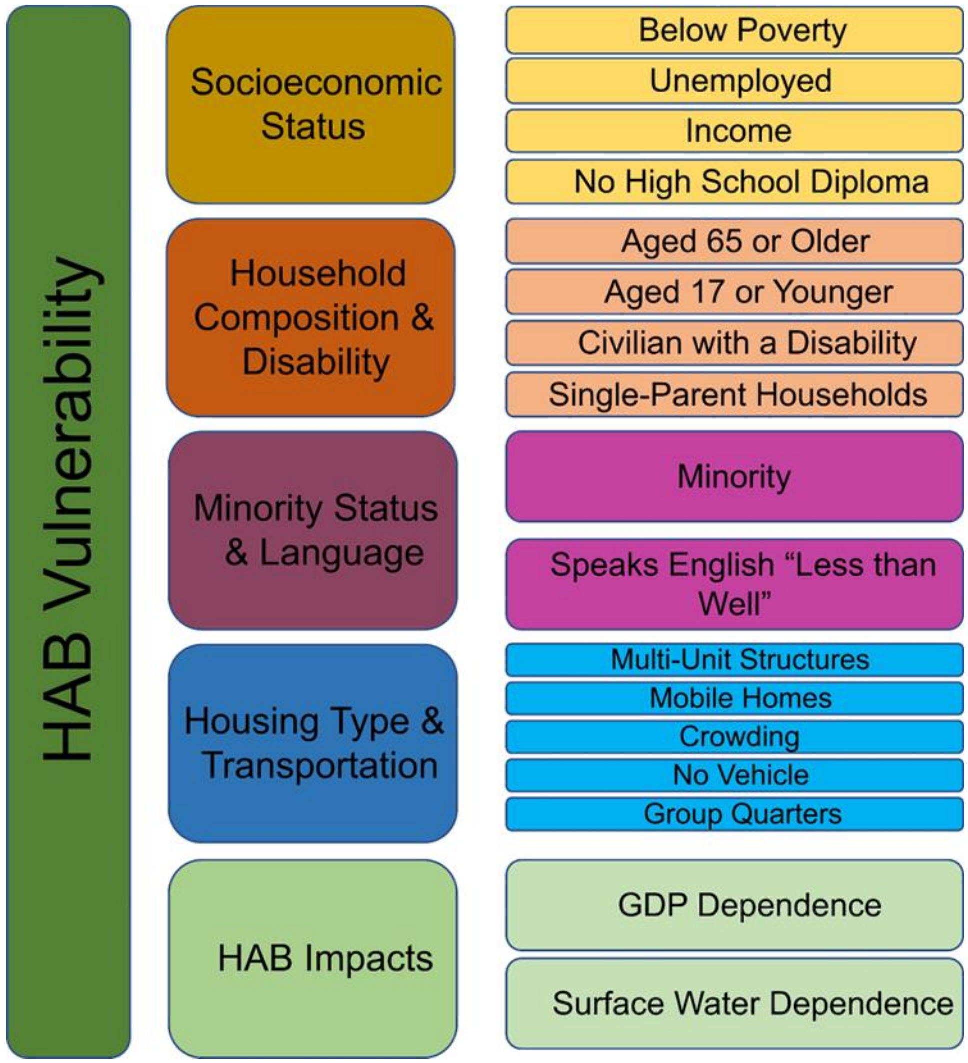


Figure 2.2 HAB-VI structure (adapted from CDC/ATSDR's 2018 SVI structure)

Similarly, the closer a county is to the lake, the more likely its surface water resources will be exposed to HAB contamination. Therefore, we suggest that the roles that the two HAB impact factors play in this index depend on the distance from a county's location to the lake shoreline. To add a weight based on the distance to the lake, we transform the original values according to the proximity-adjusted preferences (PAP) method (Ligmann-Zielinska & Jankowski, 2012) using a function defined as Equation (2.1),

$$IV_{iPAP} = IV_{iOri} \times \frac{d_{\mu}}{d_i} \qquad (2.1)$$

where IV_{iPAP} is the PAP-adjusted indicator values of lake-related GDP share or surface water resource ratio of county i, IV_{iOri} is the original indicator values of county i, d_i is the Euclidean distance from the center of county i to the nearest point of Lake Erie, and d_{μ} is the average Euclidean distance from all 50 county spatial centers to their nearest points of the lake shoreline. The original and PAP adjusted indicator values of lake-related GDP and surface water dependence are shown in Figure 2.3.

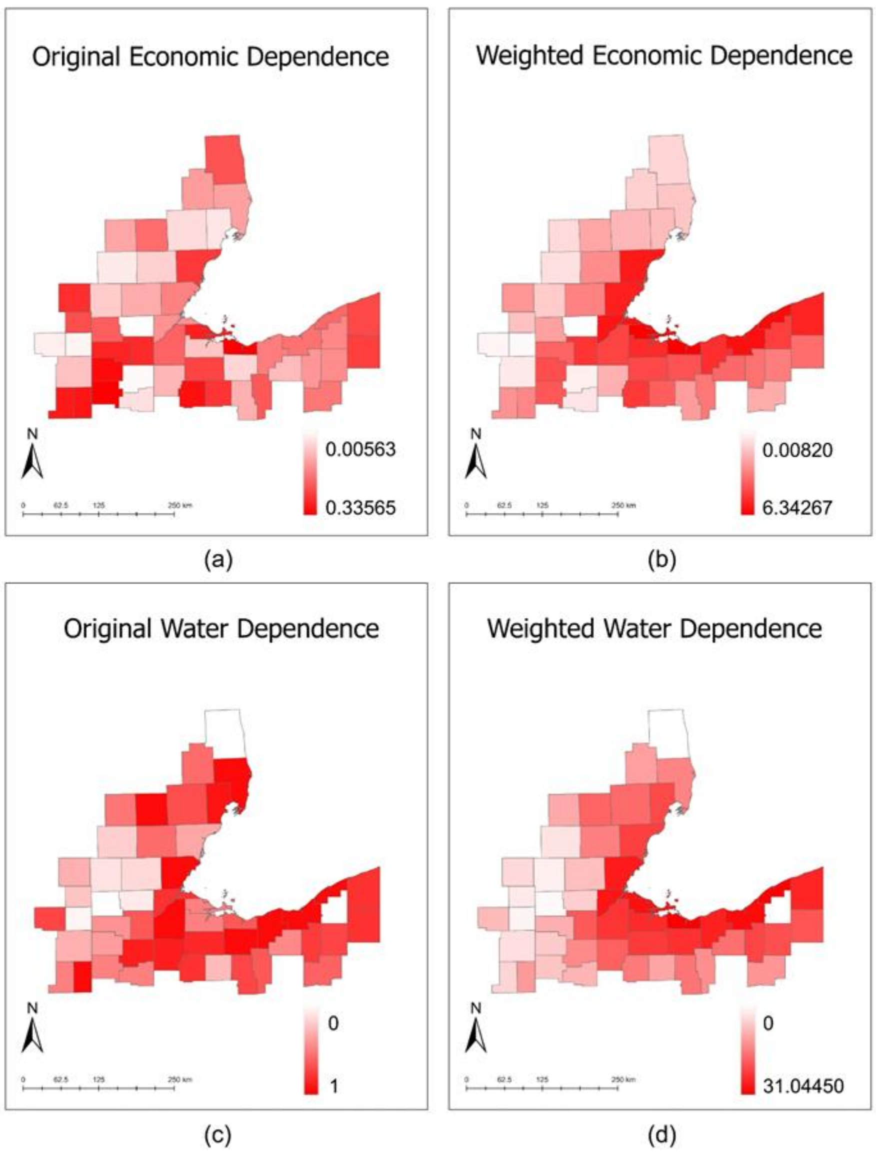


Figure 2.3 Comparisons of original and PAP-adjusted indicator values

To calculate HAB-VI, we use the original SVI's hierarchical ranking method (CDC/ATSDR, 2022). We applied percentile ranking to each of the 17 equally weighted factors. Each factor has a set of values presented in Equation (2.2)

$$I_{ij} = \{x_{ij1},\ x_{ij2},\ x_{ij3} \dots,\ x_{ij50}\} \qquad (2.2)$$

where I is a set of values for a particular factor, i denotes the i_{th} category of the HAB-VI structure (Figure 2.2), j means the j_{th} factor in that category, and x_{ijk} is the value of the j_{th} factor in the i_{th} category in the k_{th} county of our dataset.

We calculate the percentile ranking of the individual factor according to Equation (2.3)

$$PR_{ijk} = n(A)/(n(A) + n(R)) \qquad (2.3)$$

where, PR_{ijk} is the percentile ranking of the j_{th} factor in the i_{th} category of the k_{th} county of our dataset, $n(A)$ is the length of A as a subset of I_{ij} that contains all values that are smaller than x_{ijk}, and $n(R)$ is the length of A as a subset of I_{ij} that contains all values that are bigger than x_{ijk}.

Next, we aggregate the individual scores based on the theme categories into a theme score as follows:

$$I_i = \{\textstyle\sum_{j=1}^{m} PR_{ij1},\ \sum_{j=1}^{m} PR_{ij2},\ \sum_{j=1}^{m} PR_{ij3},\ \dots,\ \sum_{j=1}^{m} PR_{ij50}\} \qquad (2.4)$$

where m is the number of factors in category i, and conduct a second-level percentile ranking to each theme as shown in Equation (2.5):

$$PR_{ik} = n(A)/(n(A) + n(R)) \qquad (2.5)$$

where, PR_{ik} is the percentile ranking of the k_{th} value in I_i , $n(A)$ is the length of A as a subset of I_i that contains all values that are smaller than the k_{th} value, and $n(R)$ is the length of A as a subset of I_i that contains all values that are bigger than the k_{th} value.

Finally, we aggregate all five themes' percentile ranking scores:

$$I = \{\textstyle\sum_{i=1}^{5} PR_{i1},\ \sum_{i=1}^{5} PR_{i2},\ \sum_{i=1}^{5} PR_{i3},\ \dots,\ \sum_{i=1}^{5} PR_{i50}\} \qquad (2.6)$$

The calculated third-level percentile ranking provides an index for each county based on the sum of all theme scores:

$$PR_k = n(A)/(n(A) + n(R)) \quad (2.7)$$

where, $n(A)$ is the length of A as a subset of I that contains all values that are smaller than the k_{th} value, and $n(R)$ is the length of A as a subset of I that contains all values that are bigger than the k_{th} value.

2.2.2.2. Uncertainty analysis

Uncertainty analysis (UA) is an essential step to assess the reliability and express the inaccuracies of this multi-factor hierarchical vulnerability index and explain the calculated vulnerabilities (Ligmann-Zielinska & Jankowski, 2014; Macdonald & Strachan, 2001; Tate, 2012, 2013). This research conducts a Monte Carlo-based uncertainty analysis focusing on the uncertainty in the hierarchical index structure design (Tate, 2013) and visualizes the statistical results of the simulation runs to indicate the variability and reliability of the HAB-VI rankings. We generate 1000 different "on" and "off" combinations to the 17 individual factors in the HAB-VI structure to guide the UA calculations so that, for every index calculation, at least one of the 17 factors is excluded. For example, in one of the samples, the Unemployed factor in the Socioeconomic Status category and GDP Dependence in the HAB Impacts category are randomly set to "off, " meaning the two factors are excluded from this UA run. We then apply statistical analysis to the results of 1000 calculations.

2.2.2.3. Governance strength coding

We collected and researched governance data by searching for any legislation, programs, or informational websites regarding nonpoint source pollution at each level of government (i.e., national, state, and county level). We coded these nonpoint source pollution policies and programs to represent the strength of governance (i.e., the level of commitment required by actors in adhering to the rule) on a scale of zero to five, where zero is the lowest governance strength indicating that relevant policies and programs are nonexistent, and five means the strongest regulation in terms of stakeholder actions required for compliance. We adopted policy and program type, regulation objectives, supervisory approach, and actions to remain in compliance as criteria for score coding (Appendix).

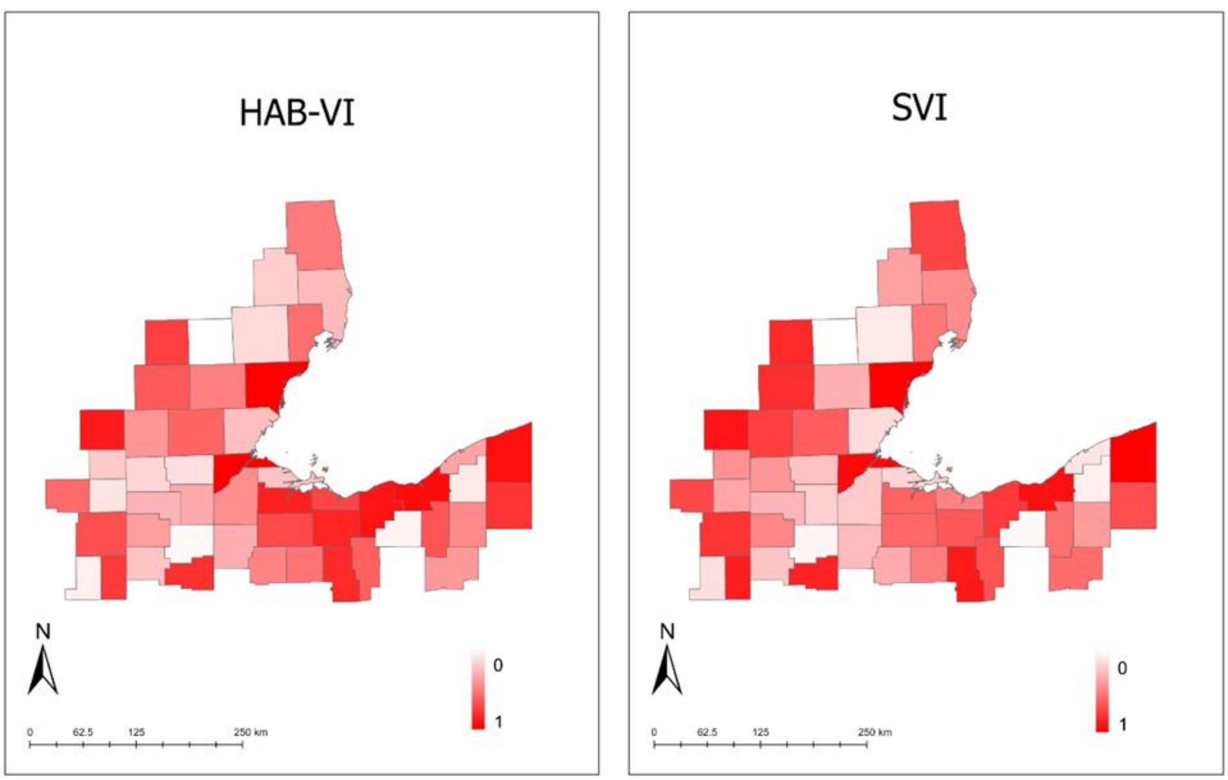
2.2.2.4. Thematic mapping and comparison

We created three thematic maps to provide information for further spatial comparative analysis. In addition to the HAB-VI and governance strength maps, we also generated a county-level nutrient load estimation map using 2017 county-level Nitrogen (N) and Phosphorus (P) input from fertilizer and manure on both farm and non-farm lands with data accessed from USGS (Falcone, 2021). The nutrient load map provides information about counties' estimated contribution level to the occurrence and severity of Lake Erie HAB events. This indicator points to the regulation aspect of policy design, especially on fertilizing and stormwater management. Compared with this nutrient load map, we use the HAB-VI map to identify counties in which more policy guidance and support may have the greatest impact on HAB generation. We propose that HAB-VI, nutrient contribution level, together with current policy situation, form the three pillars to support the decision process of policy design, policy effort allocation, and type of policy to be implemented. The combination of these two aspects contributes to a comprehensive targeted policy design.

2.3. Results

2.3.1. HAB-VI

As shown in Figure 2.4, there is a noticeable difference between the distributions of highly vulnerable counties from the two vulnerability index calculation methods, HAB-VI and SVI. For example, in the HAB-VI ranking shown in Figure 2.4 (a), high-vulnerability counties are more aggregated in Ohio adjacent to the southernmost boundary of Lake Erie. In contrast, high SVI counties shown in Figure 2.4 (b) are closer to the western border of our study area, with more inland counties in Michigan and Indiana (i.e., counties further from the lakeshore). While these differences are not surprising, they confirm that our HAB-VI calculation is indeed reflective of water-related activities and, hence, more geared towards assessing HAB vulnerability when compared to the original SVI.



(a) (b)

Figure 2.4 Comparison between HAB-VI and SVI results

We further use the equal interval method to divide HAB-VI and SVI results into three groups to represent high, medium, and low vulnerabilities. The number of counties in each state that are in the three levels of vulnerability is shown in Table 2.1.

For both Indiana and Michigan, more counties are categorized into higher levels of vulnerability using SVI compared to HAB-VI. In the six Indiana counties in our study area, for the SVI, 50% fall into high vulnerability, 33% into medium, and 17% into low. On the contrary, 33%, 17%, and 50% of Indiana counties are classified as high, medium, and low HAB-VI vulnerability. In Michigan, 43% counties have high SVI vulnerability, 29% medium, and 29% low, as opposed to 21%, 36%, and 43% using the HAB-VI. The situation is opposite for counties in the state of Ohio. Using SVI, 27% are considered high vulnerability, which is 13% less than using HAB-VI. Consequently, more counties in Ohio have medium or low SVI compared to HAB-VI.

Table 2.1 County vulnerability level distribution in HAB-VI and SVI

State	HAB-VI			SVI		
	High	Medium	Low	High	Medium	Low
Indiana	33%	17%	50%	50%	33%	17%
Michigan	21%	36%	43%	43%	29%	29%
Ohio	40%	30%	30%	27%	33%	40%

Comparing the difference in values between HAB-VI and SVI, some counties (e.g., Hillsdale, MI, and Wood, OH) are more affected by the HAB factors than others (e.g., Livingston, MI, and Putnam, OH). To identify if counties' rankings in vulnerability are positively or negatively affected by HAB factors, we generated Figure 2.5. Counties have higher HAB-VI than SVI are shown in red, which means that the HAB factors exacerbate counties' vulnerabilities in these counties. These counties are interpreted and presented as HAB-dominated. Other counties that have lower HAB-VI than SVI are illustrated in the figure as non-HAB-dominated counties. There is a noticeable spatial pattern in the HAB-VI impact map. The HAB-dominated counties are all in Michigan and Ohio; most tend to be closer to the lake. However, there are some outlier counties in this correlation, such as Van Wert and Defiance in Ohio.

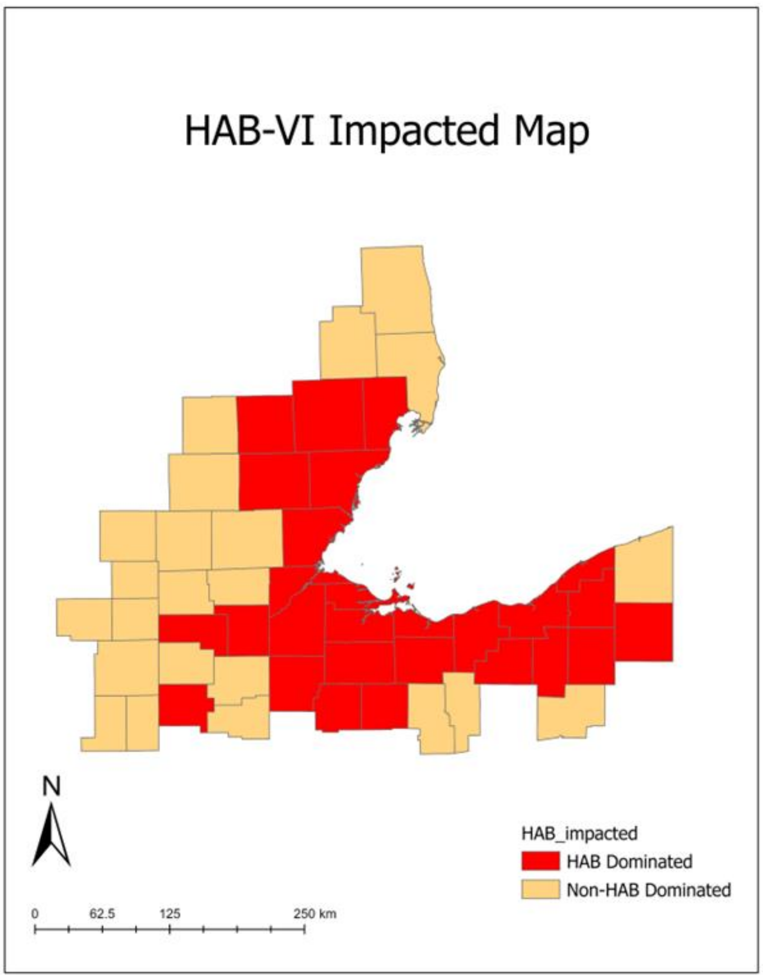


Figure 2.5 HAB-VI impacted map

2.3.2. Uncertainty analysis

We calculate average HAB-VI scores and their standard deviations for the 1000 UA runs for all 50 counties in our study area. The resulting maps are presented in Figure 2.6. A higher average indicates that a county is more vulnerable to Lake Erie HAB events, and a higher standard deviation means that a county has relatively fluctuating results over the 1000 UA calculations. The standard deviation values in all 50 counties are distributed from 0.02 to 0.19, which indicates that the average HAB-VI results are overall reliable. Still, the differences in average and standard deviation provide information about county-level HAB vulnerability and the robustness of the results. Therefore, we gathered and processed these data to create a robustness map (Figure 2.7).

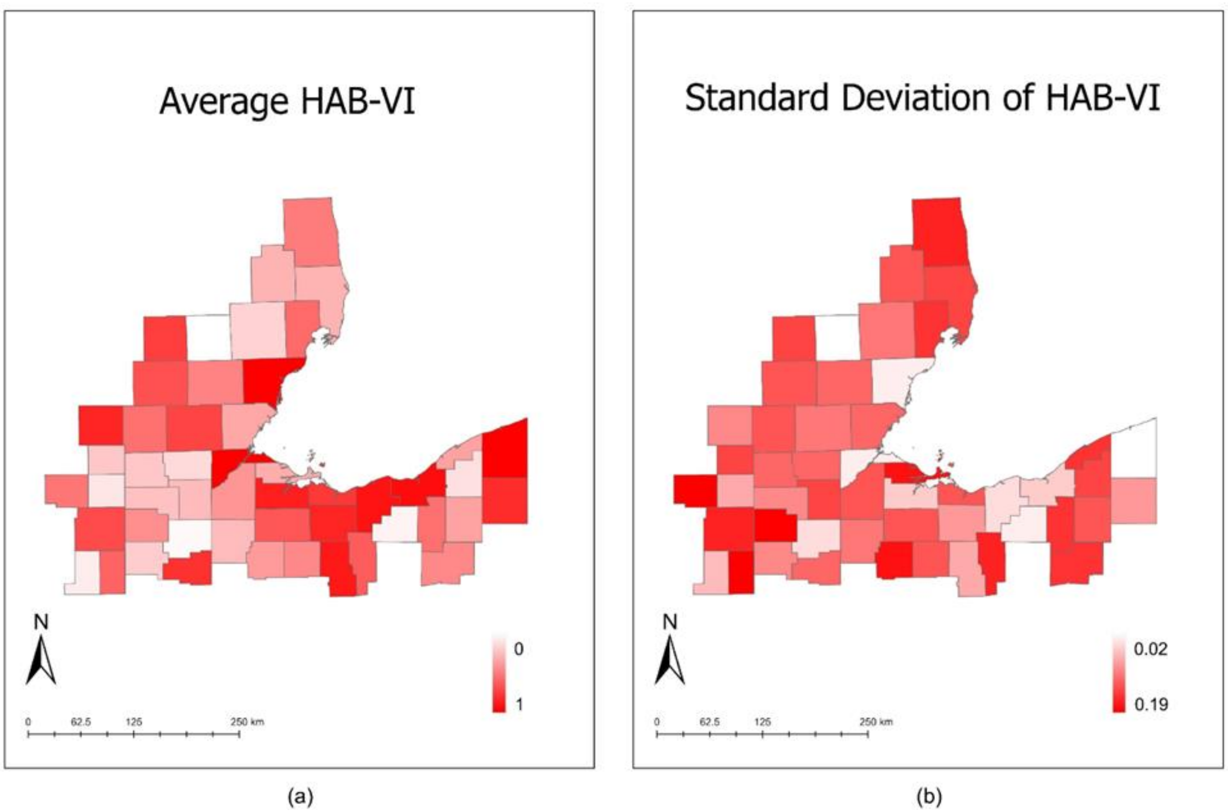


Figure 2.6 The average and standard deviation of 1000 UA calculations

We divide average (AVG) and standard deviation (STD) results into two groups using their natural break values to jointly categorize the scores into four groups. This method enables us to present the spatial distribution of uncertainty and the reliability of our HAB-VI results (Ligmann-Zielinska & Jankowski, 2014). The four categories and their indicative meanings in our result analysis are shown in Fig. 8. Counties with AVG higher than its breakpoint (i.e., 0.51) and STD smaller than its breakpoint (i.e., 0.09) are high-score robust counties (quadrant A), suggesting that these counties are highly likely to be vulnerable to HAB events. There are seven counties in this category, most located in Ohio along the Lake Erie shoreline, for example, Cuyahoga, Lorain, and Lucas. Eighteen counties are high-score volatile (quadrant B), with AVG and STD values higher than their breakpoints. STD values in this group are between 0.09 and 0.19, which means the results in UA runs are relatively stable but more variable than quadrant A. This result gives lower confidence in the stability of the HAB-VI scores. The robustness results also indicate stability in categorizing five counties as low HAB-VI (quadrant C). These counties show low HAB-VI, and the series of scores shows low variance. All other counties are in the category of low score volatile (quadrant D). They show low HAB-VI scores on AVG through the 1000 UA runs, and the variance in results indicates a relatively higher level of uncertainty. Consequently, these counties are more likely to fall into the higher AVG score group.

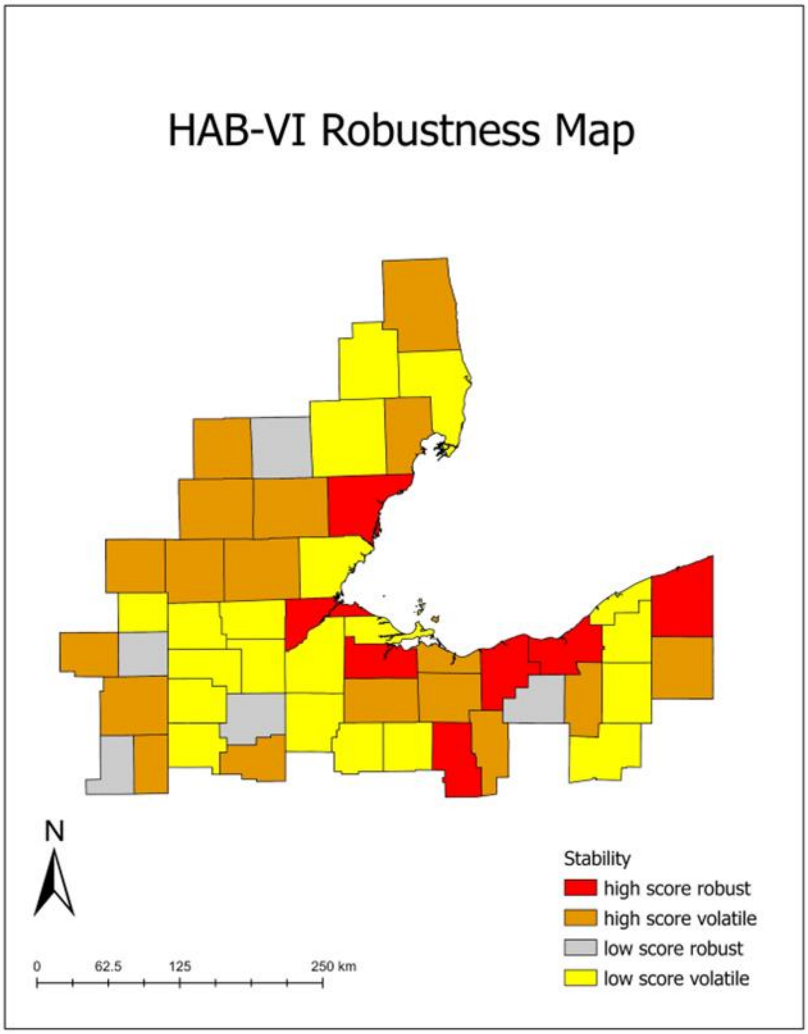


Figure 2.7 Results robustness map

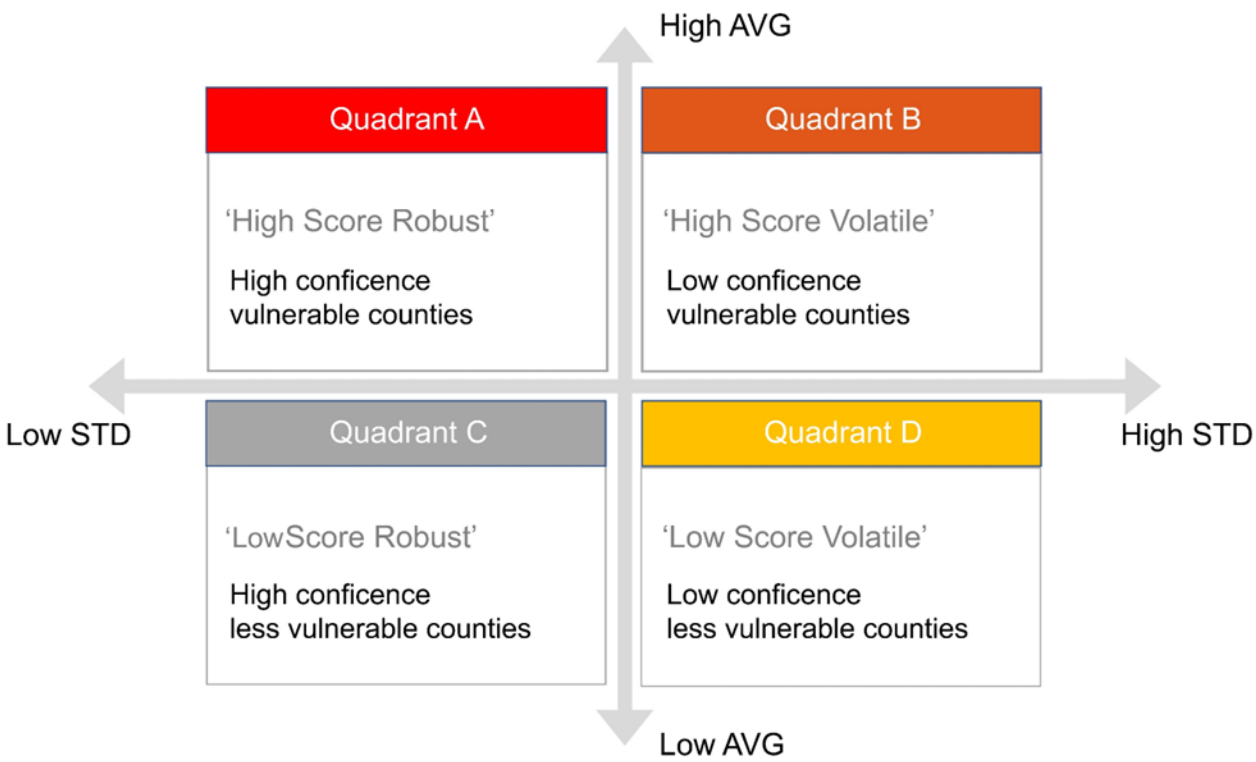


Figure 2.8 Aspects of UA robustness

2.3.3. Thematic maps of nutrient loads and governance strength

County-level total N and P loads are an important indicator of how human activities in each county influence the occurrence and severity of HAB events in Lake Erie. We adopt 2017 USGS county-level N and P input data from fertilizer and manure for farm and non-farm lands. Figure 2.9 illustrates the nutrient loads as estimations of their relative contributions to Lake Erie HABs (using an equal interval classification). Counties with more nutrient load tend to be located southwest of Lake Erie. Most of these are agricultural counties in Ohio and Indiana, such as Van Wert County in Ohio and Wells County in Indiana. Counties with less nutrient load surround the two largest metropolitan areas in our study area, i.e., Detroit and Cleveland.

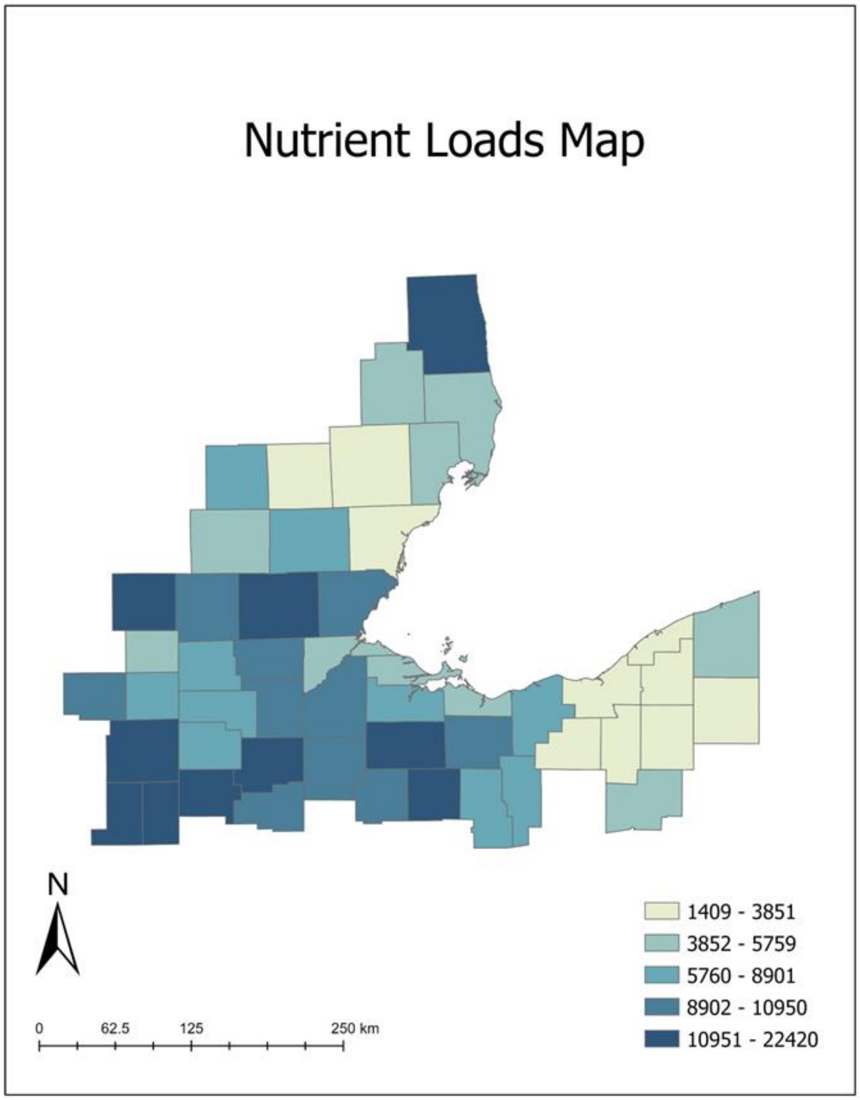


Figure 2.9 Nutrient contributions (unit: ton)

Using the policy data from official government websites and our governance strength coding design (Appendix), we generate Figure 2.10 to show each county's nonpoint source pollution and stormwater management policy strength. County-level environmental policy-making is relatively spatially independent; hence the strength levels are randomly scattered.

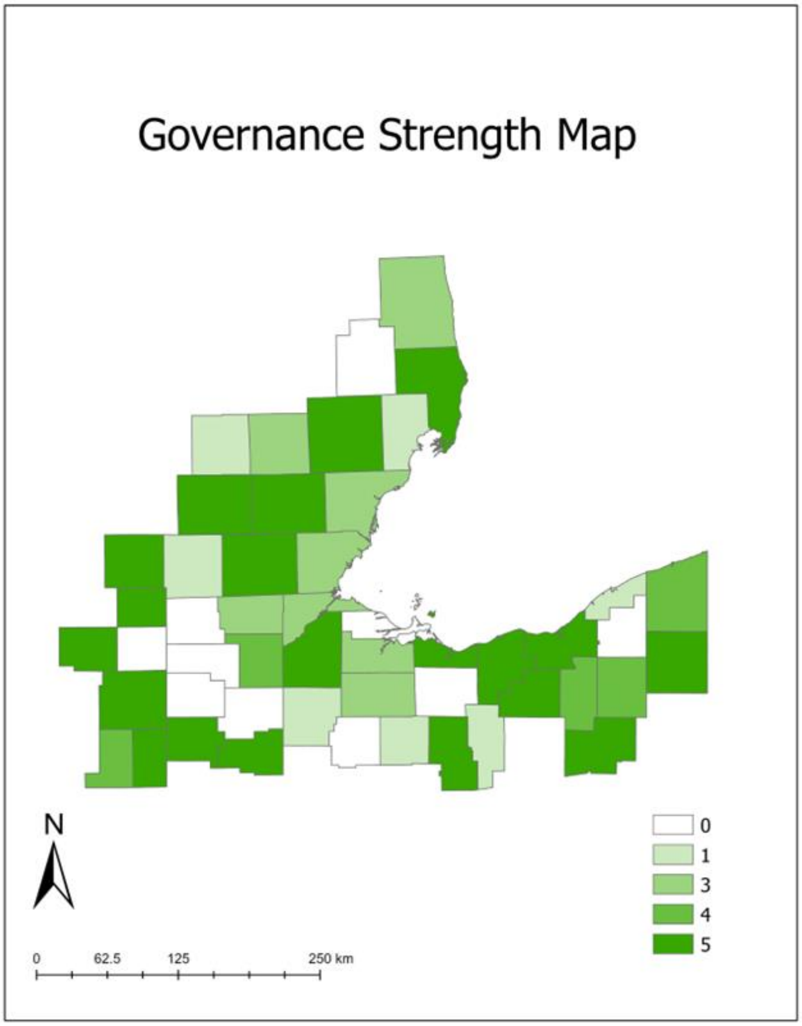


Figure 2.10 Governance strength

2.4. Discussion

This study extends a prior social vulnerability index designed by the CDC/ASTDR to evaluate the vulnerability of counties in the Lake Erie Basin to HAB events occurring in the lake. One contribution of this study is that it builds a new vulnerability index structure by adding an additional theme of spatial factors that are directly affected by and related to HAB events and adjusting the factors by their proximity to Lake Erie. This improvement equips our HAB-VI with spatial dependence on the lake and develops a variant of SVI to account for social issues related to HABs. This HAB-VI framework can be universally adapted to assess coastal communities' vulnerability facing HAB events. Currently, HABs have been a serious environmental issue threatening coastal residents worldwide. Severe events have been reported not only in Lake Erie or the Great Lakes, but also in every U.S. coastal state (NOAA, 2022). Severe and frequent blooms have also happened in Europe (e.g., Baltic Sea), Africa (e.g., Lake Victoria), and Asia (e.g., Taihu) (Conley et al., 2009; Paerl et al., 2011; Qin et al., 2010). HAB-VI is a suitable tool to provide insights and help these worldwide coastal communities to target and prioritize policy implementation, thus building resilience in these communities.

At the same time, the improvement in this index structure aligns with the framework of vulnerability suggested from IPCC with measurements accounting for sensitivity, risk exposure and adaptive capacities (McCarthy et al., 2001). The differences in spatial distribution of high vulnerability areas between SVI and HAB-VI shown in Figure 2.4 also shows how the weights of these three components impact this vulnerability framework in different areas. High HAB-VI counties have a propensity to be located close to the lake, indicating an overall tendency that vulnerability to HAB events is driven more by external exposure risk and sensitivity to the hazard events (potential threats and dependency on lake-related sources) than the internal socioeconomic component of adaptive capacity. There are also several high HAB-VI counties at the left border of our study area, where is far away from the lake. The spatial pattern, as well as the outliers, provides practical information for policy decision making (O'Brien et al., 2004). For example, for the high HAB-VI counties adjacent to the lake, policy should focus more on reducing their exposure risk and sensitivity, e.g., providing alternative water resources; whereas for the high HAB-VI counties off the lake, it is important to have policy addressing intrinsic adaptive capacities, e.g., improve socioeconomic status.

Applying a Monte Carlo-based uncertainty analysis in this research helps to evaluate our index's reliability and provides more information for policy recommendations (Najwer et al., 2023). From the four partitioned quadrants of the UA results (Figure 2.8), Quadrant A (high-score robust) includes areas of the most concern. Using the HAB-VI calculation and UA analysis, we can conclude that counties in Quadrant A are highly vulnerable to HAB events in Lake Erie. Seven counties fall into this quadrant (Wayne, MI; Lucas, OH; Sandusky, OH; Lorain, OH; Cuyahoga, OH; Ashtabula, OH; and Richland, OH). Six of these counties are along the lakeshore, except for Richland, OH, which is a little off the shore to the south. Six of them are in Ohio, and one is in Michigan. These counties call for the most attention for policy analysis, which is elaborated in the next section.

In contrast to Quadrant A, counties in Quadrant C are safe from HABs. The five counties in this quadrant are scattered across the states. On the other hand, counties in Quadrant B with high vulnerabilities are also more likely to score low for certain configurations of the index (the 'on/off' switch of factors in UA). Since the supportive management strategies that improve the HAB vulnerability status should first be assigned to counties with a relatively stable high HAB-VI score (i.e., counties in quadrant A), the 18 quadrant B counties become a lower priority if government resources are limited. However, since there is a possibility that these counties can also score high on HAB-VI, we recommend evaluating the HAB effects on these counties to suggest governance support if resources and fundings are sufficient.

Similarly, the 20 counties in Quadrant D could be disregarded because of their low average HAB-VI. However, they may also be considered pending resource availability (since the standard deviation values show higher fluctuations). We recommend that their policy priority is lower than Quadrant B, but regular and timely supervision is necessary. In sum, according to our UA, the prioritization of HAB management should focus on Quadrant A first, followed by Quadrant B and D. Finally, given their low robust HAB-VI scores, counties in Quadrant C can be disregarded.

UA as an analysis tool provides important information on prioritizing policy locations (Ligmann-Zielinska & Jankowski, 2014). On the other hand, the comparisons between the three thematic maps (i.e., HAB-VI, nutrient loads, and policy strength) as pillars for governance decision-making are a way to provide more specific policy recommendations in terms of management strategies (i.e., supportive or regulatory) based on more comprehensive information. The policy recommendation decision process applied in our research method is shown in Figure 2.11. Facing complicated environmental problems, our ultimate goal is to better balance the gains and losses between the environment, economy, and society through policy-making that considers multiple aspects (Doran et al., 2022; Hawkins et al., 2016). Integrating the results of HAB-VI and nutrient contribution in a scatter plot in the same coordinate system, some generalized information about governance strategies can be extracted (Figure 2.12). Overall, the closer a point is to the right end of x-axis (HAB-VI), the more the county is in need of government supports to decrease its vulnerability to HABs in Lake Erie, whereas the higher a point is at along y-axis (nutrient contribution), the higher requirement it has for regulatory policy to mitigate HAB events. Specifically, the four corners in this coordinate system indicate four potential governance scenarios. The upper left corner (high nutrient contribution and low HAB-VI) is an extreme endpoint with counties that require strict policy to mitigate, but have little incentive to advance such policy due to the lack of local impacts; the opposite located at the bottom left end of this coordinate system (low nutrient contribution and low HAB-VI) are counties where the government would not contribute much to the problem; the bottom right end (low nutrient contribution and high HAB-VI) is where government has little reason to regulate because of limited mitigation potential, but requires support to decrease their vulnerability to HAB events; the upper right corner (high nutrient contribution and high HAB-VI) consists of counties that need regulatory policies because of their high nutrient contributions, and also confront severe impacts of HABs and therefore have incentives for both regulatory and supportive interventions. The middle two scenarios – where vulnerability and contribution to the problem are mismatched warrant greater attention from the environmental justice perspective. In these counties, the mismatched incentives may lead to under- or over-regulation, with some vulnerable counties being impacted by externalities.

This policy decision making process can be demonstrated through the following example. Suppose nutrient load is the only factor to be considered in environmental policy-making in our Lake Erie HABs study. In that case, firm policies (e.g., raising fertilizing certificate fees or expanding fertilizing supervision control authorities) may significantly impact net income in the predominantly agricultural counties and thus ultimately worsen their vulnerability to various threats even if not to HABs specifically. On the other hand, these counties would then reduce the potential harm caused to other counties, and this contribution should be considered in the policy-making process from beyond the county. With our research method that combines multiple aspects, we can identify counties with relatively high nutrient loads that may also have high HAB-related vulnerability (both high score robust with higher confidence or high score volatile with relatively lower confidence). Their HAB-VI points to the fact that the counties may hardly be able to bear drastic increase in the strength of regulation, and need more supports to help them lower their risks to HAB events or improve the ability to recover from the damages, while simultaneously reducing their contribution to the threat. In other high nutrient load counties with low vulnerability, mitigation would benefit the wider region but is not incentivized. Therefore, considering the current governance strength data we collected, we propose that these counties apply stronger regulation (for those counties that have low current governance strength) or focus on providing educational or financial support to improve the high HAB-vulnerability situation (for those counties that have medium to high current governance strength). Otherwise, it is feasible to re-consider the governance scale to apply high-level governance to enhance local residents' willingness to adjust their pollution behaviors. One instance in this case is that Sandusky County in Ohio has a medium level estimated nutrient contribution, which warrants at least a medium regulation strength. The HAB-VI of this county falls in the high score robust quadrant, where our model gives a high confidence in the result that it is highly vulnerable to HAB events in Lake Erie. This second step suggests that some extension of governance is necessary, and supportive and educational policy are also required to address the county's concerns. In the final stage, we review the current governance strength result, which indicates that it currently has a low governance strength (strength score of 1) based on our evaluation scale. Therefore, we recommend that Sandusky County improve its policy implementation in the direction that is more focused on supportive policies. Based on the results about component relative weights in vulnerability framework for HAB-VI, exposure risk and sensitivity play a more significant role for Sandusky County, which is located near the lake. Therefore, relevant policies should assist residents in reducing their exposure risks and sensitivities in HAB events through providing alternative water supplies or income sources. Other than that, a higher level regulatory policy (e.g., state level) that enhances the trust and collaborations between neighbor counties, especially upstream counties, may also be effective in improving the low ability and willingness to alter their pollution behaviors (Michigan Department of Environment, Great Lakes, and Energy, 2018; Monogan et al., 2017). Such policies without intense strength, but emphasizing trust and collaborations could be surprisingly effective since they offer help to polluters instead of alienating them (Cartwright &

Hardie, 2012). Applying this decision process with theme comparisons enables policy makers to improve environmental governance, as well as alleviate or at least not worsen environmental injustice.

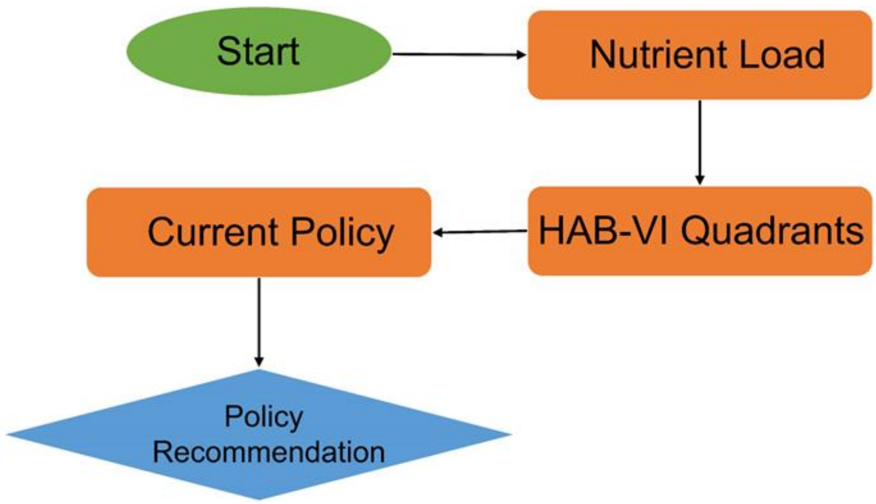


Figure 2.11 Policy recommendation decision process

As intended, when compared to the results of SVI, the HAB-VI result map shows a more apparent spatial pattern with highly vulnerable counties clustered along the lakeshore in the state of Ohio (Figure 2.4). At the same time, looking at the positive values of the HAB-VI – SVI difference in each county (Figure 2.5), we can observe HAB-related spatial clustering for most of the Ohio counties (21 out of 30). Consequently, for these counties, the HAB factors dominate the other four themes of socioeconomic factors (Figure 2.2). In Michigan, socioeconomic factors dominate social vulnerability in most counties (8 out of 14). The HAB factor-dominated counties all aggregate in the state's south, west of Lake Erie. Unlike counties in Ohio and Michigan, all six counties in Indiana have socioeconomic factors that play relatively more significant roles in vulnerabilities facing HAB events. According to the conceptual framework for vulnerability (Birkmann, 2006), the four socioeconomic factors in our HAB-VI structure indicate the internal aspect of vulnerability, which is the capacity to cope with, resist, and recover from the hazard.

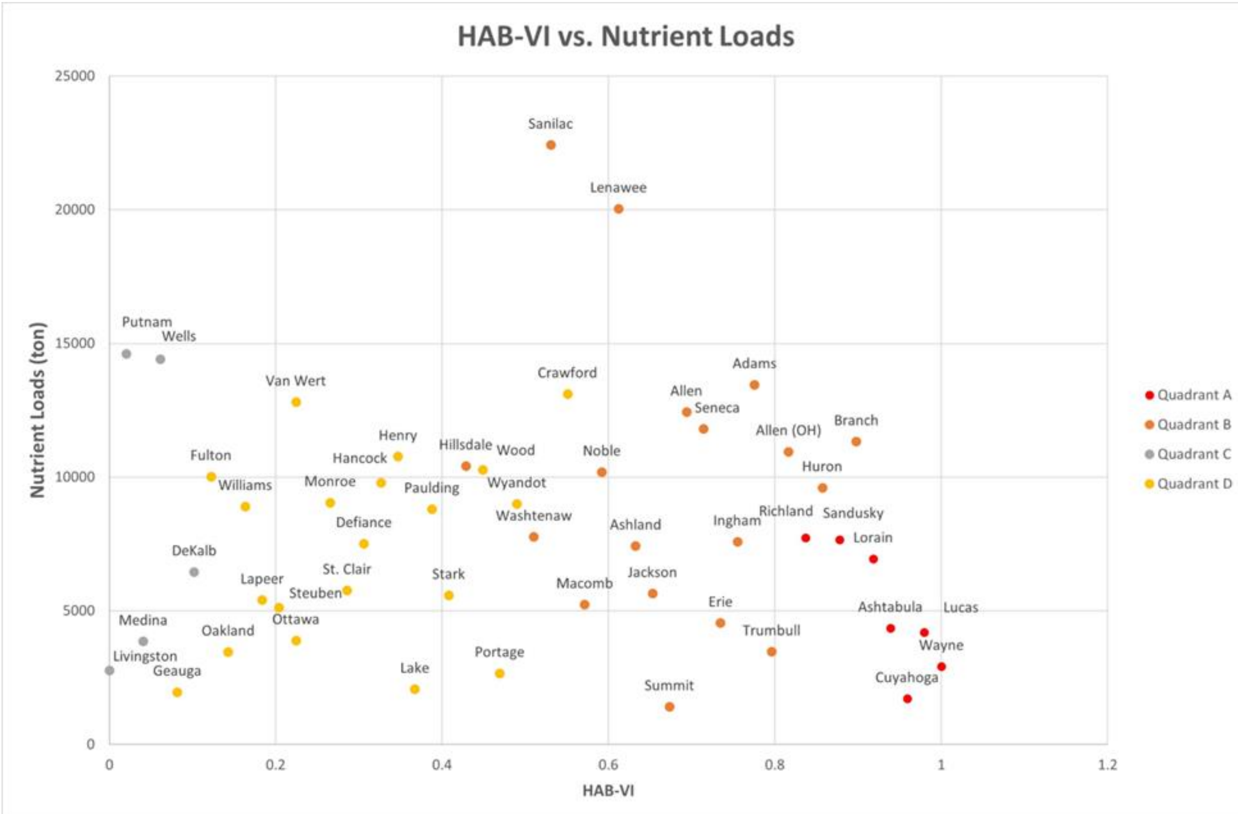


Figure 2.12 HAB-VI vs. nutrient contribution for governance strategy decision making

On the other hand, the HAB impact factor indicates the external side of vulnerability, which implies sensitivity to the risk, as well as proximity which heightens risk exposure. Overall, the high HAB-VI counties need more support to protect the residents from HAB hazard events (Cartwright & Hardie, 2012). The efforts to reduce their HAB vulnerability should include assisting in recovering after severe events and, more importantly, implementing preparedness policies and procedures. The comparative analysis between SVI and HAB-VI makes it possible to differentiate between HAB and non-HAB themes of the social vulnerability index. Local governments may extract useful information in specific ways, in terms of internal side of vulnerability (socioeconomic sections) or external side of vulnerability (exposure and sensitivity to the risk), to support their residents in the aspects they most need and the aspects that can help the most with higher marginal utility. For example, Erie County in Ohio is a high HAB-VI county with a relatively lower SVI score. Our data shows that the county's economy depends highly on Lake Erie's related recreational industries. Therefore, our results indicate that the county is very vulnerable to Lake Erie HAB events because if HABs happen, they will possibly drastically affect the county's and residents' income. With this information, local government could aim at assisting these recreational industries to make them more adaptive when confronting HAB events. Possible directions include expanding the diversity of their recreational attractions so that, if hazards occur, the recreational industry can refocus on income from other recreational activities. This information can also assist with implementation of Best Management Practices (BMPs) for farmers, as recent surveys suggest that environmental information can influence farmers' behavior over time (Doran et al., 2022).

2.5. Limitations and Future Research

Inevitably, this study has some limitations. First, some datasets we applied are proxies for the factors in our model and analysis. However, they may not be the most accurate measures of the factors being addressed. For example, to calculate each county's economic dependence on lake-related industries, we use counties' GDP from industry sectors, including agriculture, fishing, entertainment, recreation, accommodation, and food services. However, there is no specific quantitative information on how these sectors contribute to the lake economy separately from other tourist attractions or other industrial strengths in the county. Our approximate representation of GDP dependence is based on several studies that demonstrated the adverse effects of HAB events on industrial sectors of agriculture, fishery, and recreation (Hoagland et al., 2002; Ritzman et al., 2018; Weir et al., 2022). In addition, to make the GDP dependence proxy more lake-related, we used the PAP spatial weighting method (section 2.2.2.1). Future data collection that directly quantifies the local lake-related GDP would increase the accuracy of our study results. On the other hand, outliers in the HAB-impacted map (Figure 2.5) is an indicator of some potential omitted variables in our HAB-VI structure that may affect the spatial pattern of the analysis result (Clarke, 2005).

Second, the small sample size of 50 counties can affect our research results in several ways. With a larger geographic extent, perhaps including other lakes that confront HAB events, it would be easier to assess the magnitude of spatial dependence of HAB-VI ranking. Similarly, a larger extent could result in more pronounced governance strength and nutrient contribution spatial patterns. Consequently, it would also be easier to differentiate between counties with high versus low policy intervention priorities. Finally, counties are relatively coarse spatial units in studies regarding social vulnerability and policy making. Higher resolution results (i.e., census tract) are available for most existing social vulnerability indices (e.g., SVI, SoVI). The county level resolution in our research was selected as a compromise based on data availability of nutrient loads, GDP, policy information, and water source. Higher resolution data layers would allow for identifying localized patches of nutrient contribution, vulnerability imparities and HAB-VI importance and, consequently, more spatially targeted interventions.

In the past several years, some datasets or tools that help to evaluate social features related to vulnerability have become available, such as the revised EJScreen tool developed by EPA (https://www.epa.gov/ejscreen) that helps to screen and map environmental justice, and CDC's PLACES dataset project (https://www.cdc.gov/places/index.html) that provides local health data. We would like to accommodate our HAB-VI in future work to be used as a complement to these datasets or tools for HAB specific assessments and services, such as enhancing environmental justice in HAB events, and improving community resilience facing HAB related health issues. Additionally, implementation science studies and community-based participatory research could enable us to better understand how county and municipal stakeholders are using the data to inform action and support adaptive capacity (Harley et al., 2020; Smit & Wandel, 2006; Vallury et al., 2022). Process-based studies would allow for explorations of the intrinsic dynamics in HAB events and HAB-related vulnerability assessments (Webster & Pavlovich, 2019). With such bottom-up research approaches, we would also be able to apply sensitivity analysis on this dynamic system of complexity to further determine which factors are playing more significant roles in local HAB vulnerabilities (Ligmann-Zielinska & Jankowski, 2014). This would be helpful to provide policy recommendations that are more targeted to unique local issues, especially for the areas that are not first tier policy prioritized.

2.6. Summary

In this study, we developed a vulnerability index that specifically helps to identify vulnerability levels facing HAB events. We calculated HAB-VI for 50 counties in Lake Erie Basin, and the uncertainty analysis applied on our HAB-VI results helped us to locate the prioritized counties for improvements in HAB-related environmental governance. Further, the comparisons between the results of county level nutrient loads, HAB-VI, and local governance strength provides more detailed information on the directions and strategies of governance improvement facing HAB issues in Lake Erie as well as vulnerability and environmental injustice. This research brings forth a new idea of extending vulnerability indices with data that can specifically (and spatially) delineate the societal impacts of natural hazard events (such as HABs) and assess vulnerabilities to such hazards. Identifying regions of high vulnerability is possible due to spatially-explicit uncertainty analysis, serving as a baseline for targeted policymaking.

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APPENDIX. GOVERNANCE STRENGTH CODING SCALE (AS OF JANUARY 2023)

0 = Policies and programs for this county or state are nonexistent; there is no indication of a policy/program in this jurisdiction

1 = There is no policy or program for this county or state, but there is some information available to the public about nonpoint source pollution and offering advice on small personal choices that one can make to limit personal output

2 = Voluntary program; represents a program that is voluntary to participate in to implement best management practices (BMPs) or other techniques to control nonpoint source pollution

3 = Weak nonpoint source regulation; established in the form of a set of goals or recommendations rather than strict regulatory policy

4 = Suggestive nonpoint source regulation; a policy using language like "should be implemented." These policies strongly suggest that targeted actors follow the recommended behaviors, but they do not mandate that the action "must be" taken or issue punishments for violation

5 = Strong nonpoint source regulation; a policy using language like "must be" or "shall be implemented/followed." These policies require private or public actors to take specific actions to remain in compliance

3. CHAPTER 3: A COUPLED AGENT-BASED – MULTICRITERIA MODEL TO SIMULATE SOCIAL VULNERABILITY TO HARMFUL ALGAL BLOOMS IN A COUPLED HUMAN AND NATURAL SYSTEM OF LAKE ERIE

Abstract

The concept of coupled human and natural systems (CHANS) features complex human-environment interactions and provides a holistic perspective to address questions in environmental science and policy studies. In this paper, we report on an integrated agent-based and multicriteria evaluation modeling framework to calculate social vulnerability and evaluate the risks of people facing disturbances. While accounting for CHANS dynamics, this framework aims to quantify and assess community vulnerability using spatially explicit model outputs. We applied Lake Erie's harmful algal blooms as our case study. We calculated a harmful algal bloom stochastic and spatially-explicit dynamic vulnerability index (HAB-DVI) to address the inherent dynamics in CHANS vulnerability. The model results show a spatially autocorrelated pattern in the distribution of HAB-DVI across the census tracts in our study area. The outcomes of uncertainty analysis on our HAB-DVI succinctly summarize the stochasticity in our model, inform policy decisions to support targeted communities, and provide insights to understand vulnerabilities in CHANS.

Keywords:

Social Vulnerability; Coupled Human and Natural Systems; Agent-Based Model; Multicriteria Evaluation; Harmful Algal Blooms; Lake Erie

3.1. Introduction

Coupled human and natural systems (CHANS) involve complex interactions between human behaviors and the environment (Liu, Dietz, Carpenter, Folke, et al., 2007). This framework features many complexities and dynamics, such as decision-making and spatial heterogeneity, nonlinearities, feedbacks between system components, emergent properties, etc., which are essential to describe the real-world interconnections between humans and the environment and provide a holistic perspective to understand complex systems (Liu et al., 2021). Such an integrative and interdisciplinary framework has spurred investigations into various contemporary challenges regarding human-nature interactions in recent decades and has proven instructive in addressing empirical issues such as landscape management (Chen et al., 2015; Spies et al., 2014), human-wildlife interactions (Carter et al., 2014; Morzillo et al., 2014), and resource sustainability (Giuliani et al., 2016; Zhou, 2019).

CHANS are susceptible to disturbances that can inflict harm to both human and environmental systems. Environmental hazards, being a form of natural disturbance, can pose varying degrees of risk to humans, depending on their vulnerabilities. “Disasters occur when hazards meet vulnerability” (Raju et al., 2022). The Sendai Framework for Disaster Risk Reduction (SFDRR) 2015-2030 has highlighted risk governance as a critical priority for mitigating potential harm to people or systems (UNDRR, 2015). Past disasters have underscored the inherent complexity and uncertainties in disaster risks, rendering risk governance a “wicked problem” that defies easy solutions (Head & Alford, 2015; Rittel & Webber, 1973). The underlying dynamics in social vulnerability and its interactions with natural hazard events are essential in amplifying the complexity and uncertainties in disaster risks (Cutter, 2018; De Ruiter & Van Loon, 2022; Drakes & Tate, 2022). Therefore, it is essential to quantify and assess social vulnerability to environmental hazards to effectively address complexity in risk governance and assist policymaking in managing CHANS.

Research on social vulnerability to natural hazard events has evolved its focus over time. Initially introduced to address environmental justice and sustainable development (Cutter et al., 1996; Hewitt, 2014), social vulnerability studies have engaged in a prolonged discourse regarding the interpretation, indicators, and assessment methods of social vulnerability (Cutter et al., 2003; Cutter & Finch, 2008; Flanagan et al., 2011; Tate, 2012). As a prominent measurement, the social vulnerability index has been widely employed to gauge communities' susceptibility to various hazards. Several indices, such as the Social Vulnerability Index (SoVI) designed by the Hazard and Vulnerability Research Institute at the University of South Carolina (Cutter et al., 2003), and the Center for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry Social Vulnerability Index (CDC/ATSDR SVI) (CDC/ATSDR, 2022b), have been developed and implemented in recent decades. Despite sharing common indicators like economic status and facility accessibility, each index holds distinct components and calculation methodologies (CDC/ATSDR, 2022b; Cutter et al., 2003).

On the other hand, contemporary research on vulnerability increasingly acknowledges the complexities inherent in the topic and has experienced a shift from defining vulnerability as a static concept towards exploring its dynamic nature and investigating how risk levels fluctuate across different communities and evolve in response to natural hazard events (Collins, 2008; Cutter et al., 2000; De Ruiter & Van Loon, 2022). Spatiotemporal dynamics in vulnerability can be identified from various perspectives. A critical factor is socioeconomic status fluctuations triggered by events like economic recession or temporal variations during a long-lasting natural hazard. For example, using the SoVI method to assess social vulnerability to natural hazards in Chile at three different time points, a recent study revealed heterogeneous and evolving vulnerability patterns attributable to spatial and temporal interactions among different SoVI elements (Bronfman et al., 2021). At the same time, unstable resource distribution during long-lasting hazard events makes a crucial contribution to the dynamic shifts. In pandemics like COVID-19, restricted resource accessibility due to quarantine or supply shortages exacerbated social vulnerability dynamics (Karaye & Horney, 2020). The compounded occurrence of consecutive disasters further amplifies dynamics by altering exposure risks across different population groups. For instance, individuals evacuated to public facilities during hazard events face heightened exposure risks to pandemics due to overcrowding (Gonzalo & Tiemroth, 2021). These findings stress the complex interactions of multiple components in the system, characterized by non-linear behaviors, spontaneous changes, and emergent patterns (Boccara, 2004; Ladyman et al., 2013). Consequently, traditional linear mathematical approaches, such as composite indices, may need to be revised to address the spatiotemporal dynamics and uncertainty inherent in CHANS. Despite the broad awareness, most studies tend to delineate the dynamics narratively or qualitatively or present statistical results without delving into the underlying driving forces behind changing outcomes of individual factors.

Discussion on these studies reveals two primary challenges confronting current research in assessing social vulnerability to environmental hazards: 1) how to define the specific indicators of vulnerability and 2) how to account for the dynamics of vulnerability. Therefore, this research endeavors to develop a framework to address these deficiencies. Our study is particularly interested in selecting indicators to succinctly yet comprehensively capture social vulnerability measurements and developing approaches to cover the inherent complexity of vulnerability within CHANS.

The Intergovernmental Panel on Climate Change (IPCC) suggests three fundamental systemic components that affect social vulnerability facing natural hazard events: intrinsic sensitivity, external risk of exposure, and adaptive capacity (McCarthy et al., 2001). Intrinsic sensitivity refers to the dependence on natural or economic resources or the system's susceptibility to event-induced impacts. External exposure to risk demotes the likelihood of exposure to an event. At the same time, adaptive capacity describes the ability to adjust or recover from hazards often linked to socioeconomic status, such as wealth, infrastructure accessibility, information accessibility, etc. (Allison et al., 2009; McCarthy et al., 2001; O'Brien et al., 2004). This tripartite structure underscores the need to consider a spectrum of social, economic, and political dimensions to assess social vulnerabilities. Naturally, these aspects may incorporate spatial or temporal perspectives, further amplifying the dynamics of long-term social vulnerability.

Over the last decades, there has been growing advocacy for employing system simulation methods, such as agent-based modeling (ABM), to address the complexity of "wicked problems." (An, 2012; Bonabeau, 2002; De Ruiter & Van Loon, 2022; Gilbert, 2020; Railsback & Grimm, 2019). ABM is a bottom-up simulation method that consists of a collection of autonomous decision-making entities with heterogeneous behaviors called agents situated in a spatial environment. Agents make decisions based on predefined behavior rules and their assessments of the timely situation related to other agents and the environment. The iterative interactions among agents, ongoing time steps, and changing environmental conditions emulate a real-world system. These dynamic interactions capture the non-linearity and spontaneity of complex systems, facilitating the depiction of emergent phenomena (Bonabeau, 2002; Grimm & Railsback, 2005; Ligmann-Zielinska & Jankowski, 2007). Moreover, ABM's capability to integrate geographic data for representing real-world spatial environments enhances its utility for empirical studies (Crooks

& Heppenstall, 2012). In short, ABMs have been recognized as one of the core tools in modeling CHANS.

Multicriteria evaluation (MCE), or multicriteria decision analysis (MCDA), has long been applied in geographic analysis to support decision-making processes such as location selection or spatial prioritization of decision alternatives (Atici et al., 2015; Jankowski, 1995; Karimi et al., 2019; Ligmann-Zielinska & Jankowski, 2014; Malczewski, 2006). This approach, known for its inclusivity of various evaluation preferences, facilitates the generation of suitability or prioritization scores. The general procedure of MCE usually involves defining quantifiable criteria, standardizing them, expressing preferences regarding their relative importance, and aggregating the preferences with standardized criterion values to derive a composite score (Ligmann-Zielinska & Jankowski, 2014). Although MCE has also been applied in recent studies to evaluate social vulnerability (Armaș & Gavriș, 2013; Fernandez et al., 2016), spatiotemporal stochastic factors are barely considered in the research.

This paper proposes a framework integrating ABM and MCE to evaluate social vulnerability due to natural disturbance within CHANS. This structure aims to capture the complexity and dynamics inherent in CHANS (using ABM) and generate a comprehensive vulnerability index encompassing a range of preferences (using MCE). Additionally, the framework is adaptable and can be tailored to assess social vulnerability in various hazard events.

In the subsequent sections, we introduce our study area's geographic and socioeconomic context, along with the questions arising therein. We then delineate our model design and implementation, followed by an uncertainty analysis to elucidate the model's behavior and supplement the vulnerability index results by identifying areas with different uncertainty levels.

Finally, within the context of our case study, we discuss how our vulnerability assessments can contribute to risk due to natural hazards and, more broadly, vulnerabilities in CHANS.

3.2. Study area and research questions

Lake Erie serves as a prominent freshwater body prone to harmful algal blooms (HABs), typically occurring annually from July to October (NOAA, 2022). The severity of HABs in Lake Erie stems from the lake's physical characteristics, geographic location, and socioeconomic status of its surrounding areas. Within the United States, Lake Erie is encircled by major agricultural states like Ohio, Michigan, and Indiana, leading to significant nutrient runoff that enriches the lake (Lake Erie LaMP, 2011). Providing drinking water for approximately eleven million people residing in the watershed, which constitutes roughly one-third of the total population of the Great Lakes basin, Lake Erie's excessive algal growth poses considerable challenges. Moreover, the proliferation of algae detrimentally impacts the lake's vital tourism industry and renowned fisheries, which collectively generate over $10 billion in economic revenue (US EPA, 2022). All the adverse consequences – health-wise, resource-wise, and economy-wise – are not evenly distributed across all populations throughout the basin (Gersony, 2022).

The Maumee River watershed is the primary tributary feeding into western Lake Erie, spanning parts of northwest Ohio, eastern Indiana, and southern Michigan. Encompassing approximately 21,540 km^2 of predominantly agricultural land, the river contributes around 30 percent of the annual total phosphorus (TP) load to Lake Erie, with over 90 percent of the load originating from nonpoint sources (NPS) (GLWQA, 2015). Census data indicate a total population of about 2 million across the Maumee River watershed, with most of the counties in the watershed exhibiting a poverty rate of around 10 percent. In contrast, a few counties have a significantly higher rate, nearing 18 percent (U.S. Census Bureau, 2022). This data reveals varied capacities among the watershed residents to respond to hazardous events such as HABs. These insights prompt intriguing research questions addressed in our model: Which communities are most vulnerable to Lake Erie HABs events, and where primarily do governments or environmental agencies allocate their resources to help build resilience in these communities and mitigate environmental injustice?

To investigate these questions, we selected 14 Ohio counties within or partially within the watershed, allowing for a geographically centered discussion on state and county-level policy recommendations. We refined our delineated areas separately for the agricultural and economic sub-models of our ABM. The agricultural sub-model encompasses census tracts within the entire 14-county region where agricultural land exceeds 50 percent based on the calculation using USGS's National Land Cover Database (NLCD) (USGS, 2016). Meanwhile, the economic sub-model includes all census tracts within the Toledo metropolitan area, the largest metropolitan area in the watershed, spanning Fulton, Lucas, and Wood counties. Figure 3.1 depicts an overview of the study area.

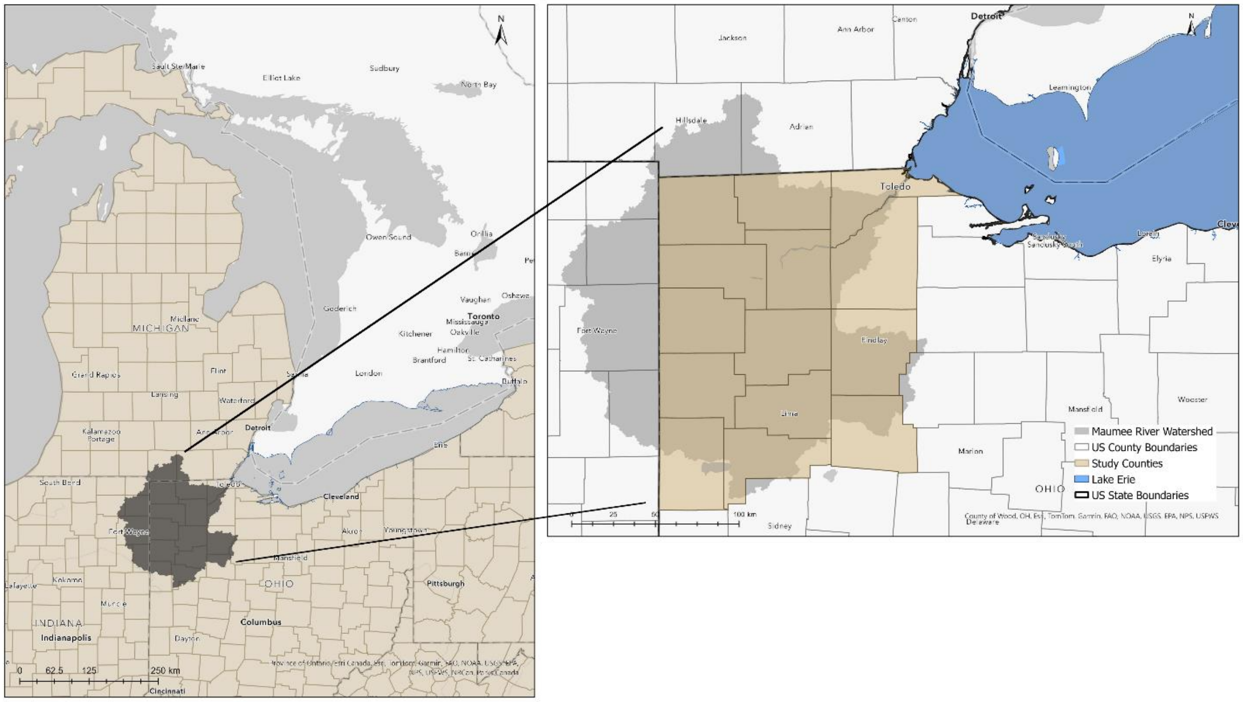

Figure 3.1 Study area

3.3. Methodology and Data

3.3.1. Agent-based Model

3.3.1.1. Conceptual Model

We developed an agent-based model named *Algae Vulnerability Simulation (AVUS)* using Python programming language (https://www.python.org/). AVUS aims to simulate the dynamics within the CHANS of HABs based on the decision-making processes of system actors, their interactions, and adaptations (Epstein, 2001). Like many previous studies employing ABM to explore CHANS, households are selected as the fundamental unit representing human decision-making (An et al., 2005; Vojnovic et al., 2020). The model comprises two sub-models: agricultural and economic and encompasses four major procedures: agricultural fertilization, projection of the HAB severity index for the year, imposition of negative impacts on residents, and incorporation of governance feedback on fertilization practices. The conceptual model is presented in Figure 3.2.

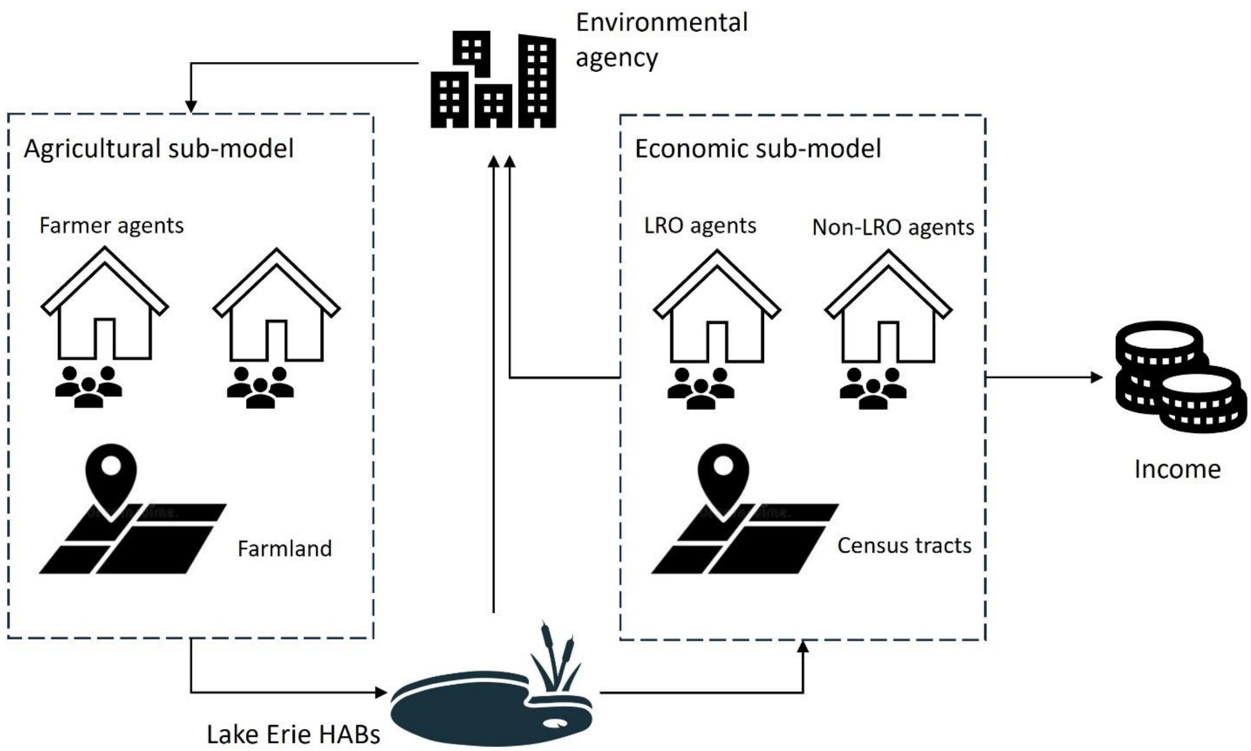

Figure 3.2 AVUS conceptual model

3.3.1.1. General Model Description

First, farmer household agents determine the amount of P_2O_5 fertilizer they apply annually. Surveys and studies suggest that US farmers typically base their fertilizer decisions on their experiences, economic considerations, and information obtained from fertilizer and seed dealers. While soil testing and recommendations from research studies have gained importance in recent years, evidence shows that most farmers tend to maintain their usual fertilization practices unless compelled by regulatory interventions or enticing incentives (Houser et al., 2019; Stuart et al., 2014). The initial fertilizer decisions fall within the recommended phosphorus input range for the farmlands for each farmer's household. Farmer agents generally adhere to their fertilization practices, making minor adjustments to the amount annually within a specified small range. However, if fertilizer regulations are in place for the year, they must modify their fertilizer amounts accordingly. Additionally, farmer agents may voluntarily participate in Best Management Practices (BMPs) in response to incentive programs – a topic researched in the next chapter.

Second, farmer agents' annual fertilizer inputs are aggregated to determine the total phosphorus potentially running off into Lake Erie, impacting the waterbody's nutrient level. While the 'fertilizer runoff – HAB occurrence' interconnectedness is complicated and understudied, nutrient runoff, temperature, and rainfall are widely recognized as significant factors influencing the occurrence of HABs (NOAA, 2022; Wells et al., 2020), and have been adopted as the decisive factors in previous HAB simulations (Webster & Pavlovich, 2019). AVUS uses these three factors to project the annual HAB severity index (SI).

Third, HAB events have been demonstrated to negatively affect the economic well-being of surrounding areas and residents, impacting tourism-related income, property values, and expenses incurred to cope with the hazardous events (Bingham et al., 2015; Bingham & Kinnell, 2021; Hartig, 2019). To emulate this relationship, the HABs SI directly influences the income fluctuations of metropolitan residents in the economic sub-model of AVUS. Within this sub-model, there are two types of economic agents: those involved in lake-related occupations (LRO agents) and those with other occupations (non-LRO agents). On average, LRO agents experience a higher economic impact from the severity of HAB than non-LRO agents. Additionally, all agents experience minor annual income fluctuations.

Finally, the model is equipped with the environmental agency agents who may propose fertilizer regulations based on the severity of the previous year's HABs or incentivize BMPs when aiming to reduce nutrient runoff and further mitigate HABs. These governance strategies serve as feedback in AVUS to the agricultural sub-model for adjusting fertilizer amounts. The environmental agency's decisions regarding the regulation of BMPs are influenced by their direct observation of HAB severity and the reflection of economic agents' environmental awareness due to HAB severity. BMPs and residents' environmental advocacy will be further explored in scenario analysis in the next chapter.

Through these four steps, the AVUS framework simplifies yet effectively forms an interaction and feedback loop representing the real-world dynamics in our CHANS under study. In this loop, individual agents' (both agricultural and economic) decisions aggregate and, along with natural factors, determine the severity of HABs in Lake Erie. The annual severity of HABs affects economic agents' awareness of this environmental issue (and, indirectly, exacerbates their financial situation) and pressures environmental management agencies to take action to mitigate the HABs. Agricultural regulations, which are well-recognized approaches to addressing aquatic environment issues, are implemented to influence agricultural agents' fertilizing behaviors, affecting nutrient input amounts in the next loop.

The direct output of AVUS is the individual income of economic agents. These simulation results are aggregated to determine the average income of each census tract in the economic sub-model, thereby serving as a spatiotemporal factor for the subsequent MCE procedure.

3.3.1.3. Agents and Environment of AVUS

In the agricultural sub-model, farmer agents represent agricultural households across the farmland of the 14 Ohio counties within the Maumee River Watershed. Each farmer agent is characterized by attributes such as a unique farmer agent ID, county location, distance from the farmland census tract to the nearest point of Lake Erie shoreline, farmland area, and fertilizer amount. Throughout the simulation, farmer agents engage in behaviors including determining fertilizer input, updating fertilizer input under normal conditions (i.e., no regulations), adjusting fertilizer input to comply with regulations, and modifying fertilizer input when participating in BMPs.

Within the economic sub-model, both LRO and non-LRO agents are distributed across the census tracts within the Toledo metropolitan area. These agents share attributes such as agent ID, annual income, distance from their census tract to the nearest point of Lake Erie shoreline, census tract ID, county ID, agent type, environmental awareness level, and the threshold for them to express environmental concerns. Their behaviors include updating annual income, adjusting awareness levels regarding HABs potential, and deciding whether to express concerns about the environmental issue. However, LRO and non-LRO agents are subject to different thresholds in their behavior rules and different distributions when the agents are parameterized.

In addition to these sub-model agents, AVUS also includes two global agents. The first is the HAB agent, representing the occurrence and severity of HABs each year. Its attributes include data from farmer agents, temperature, rainfall, and HAB severity for each year. The HAB agent calculates HAB severity using aggregated nutrient amounts from farmer agents combined with temperature and rainfall data. The other global agent represents environmental agencies responsible for proposing regulations or BMPs. These agencies collect concerns from LRO and non-LRO agents as input for policy decisions. Their attributes include information on all economic agents, thresholds for regulatory decisions, and regulated fertilizer amounts. Figure 3.3 illustrates the attributes and behaviors of agents using a Unified Modeling Language (UML) diagram.

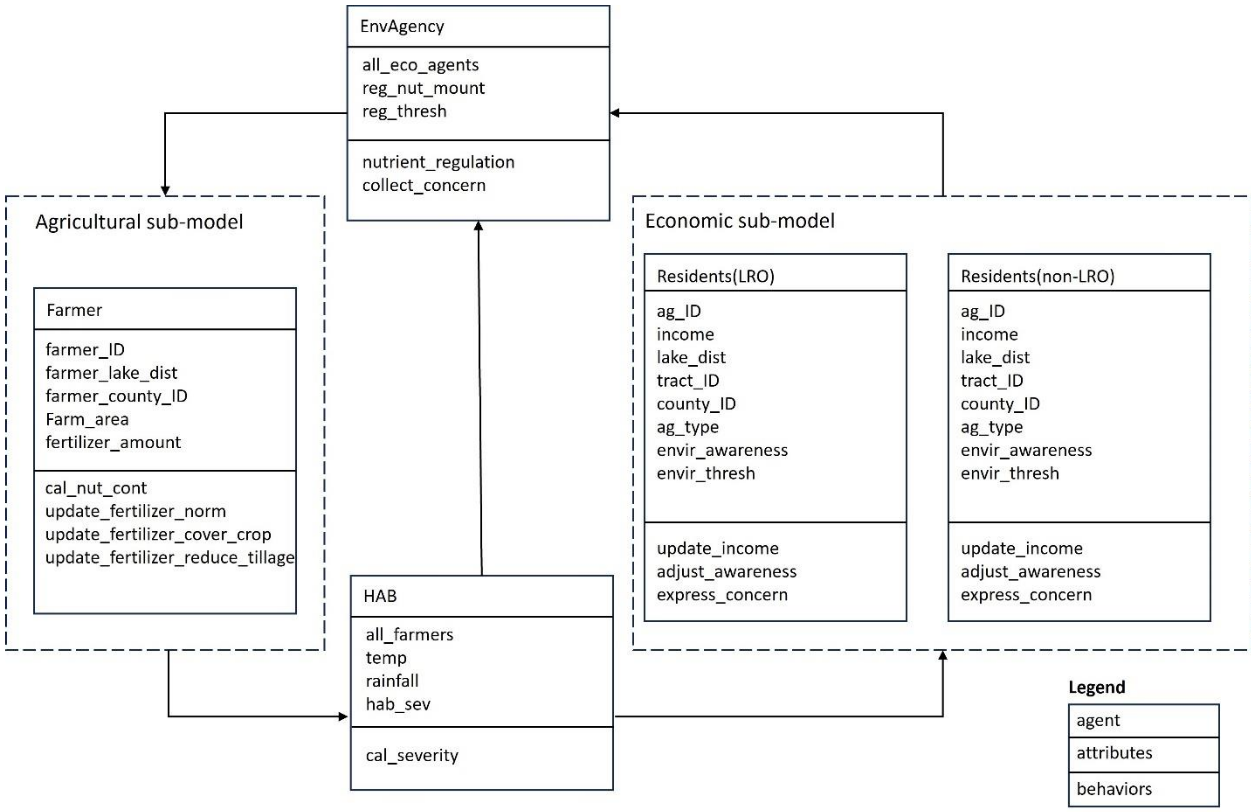

Figure 3.3 UML of AVUS agent attributes and behaviors

3.3.1.4. Data and AVUS parameterization

Vector data for all census tracts in the 14 counties within the Maumee River Watershed in Ohio was acquired from the Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry (CDC/ATSDR) (CDC/ATSDR, 2022a). The shapefile for the agricultural sub-model was tailored to include only census tracts predominantly comprised of agricultural land, defined as having agricultural land covering more than 50 percent of the area. The land use classification was determined using the 30-meter spatial resolution land cover map from the USGS's National Land Cover Database (NLCD) for 2016 (USGS, 2016). Following this selection process, 115 census tracts were retained for the agricultural sub-model. In contrast, all census tracts within the Toledo metropolitan area were included in the economic sub-model, except for two occupied by universities, which lacked socioeconomic data. This resulted in a total of 117 census tracts for the economic sub-model.

Socioeconomic data, including the number of households in each economic census tract and the mean and median household incomes, are sourced from the United States Census Bureau for 2020 (https://www.census.gov/). Distances from the census tracts to Lake Erie are calculated from the centroid of each tract to the nearest point of the lake shoreline. The proportion of LRO agents in each metropolitan area county, along with their median income, were retrieved from DATA USA (https://datausa.io/). Industries classified as LRO include arts, entertainment, recreation, accommodations, and food services.

Agricultural data, such as the number of farming households in each county categorized by different sizes of farmland, were obtained from the 2017 National Agricultural Statistics Service by the United States Department of Agriculture (USDA) (https://www.nass.usda.gov/). The fertilizer input amounts for farmer agents are estimated based on the recommended P_2O_5 amounts outlined in the Ohio Agronomy Guide (Barker et al., 2018). To ensure computational efficiency, we halved the number of households for each agent type in every census tract.

We further gathered pertinent data to assess how annual HAB severity is influenced by nutrient runoff, temperature, and rainfall. Specifically, we obtained Lake Erie's average water temperature from July to October, the typical bloom season, from NOAA CoastWatch (https://coastwatch.noaa.gov/cwn/index.html). Additionally, we acquired average observed rainfall data from seven precipitation gauge stations in the Maumee River Watershed through NOAA/NCEI Climate Data Online (https://www.ncei.noaa.gov/cdo-web/). For the Western Lake Erie cyanobacterial bloom severity index (SI), we sourced data from NCCOS/NOAA (National Centers For Coastal Ocean Science, 2022). These datasets all spanned from 2002 to 2016. To estimate the total P_2O_5 tonnage potentially contributing to HAB severity, we utilized data from IPNI's Nutrient Use Geographic Information System (NuGIS) for the U.S. (https://nugis.tfi.org/).

We aggregated yearly P_2O_5 amounts impacting HAB severity using a distance decay function transformation, as presented by Equation (3.1):

$$P_{trans_{total}} = \sum_{i=1}^{n} {P_i}/{D_i^2} \qquad (3.1)$$

where, $P_{trans_{total}}$ denotes the aggregated P_2O_5 amount after transformation, n signifies the number of counties in this aggregation process, P_i represents the P_2O_5 from the i-th county, and D_i indicates the distance from the centroid of the i-th county to the lake in kilometers. This equation is also applied in the simulations to put a distance-affected adjustment on our individual P_2O_5 inputs from farmer agents. We used distance decay rather than Euclidean distance to simulate the significantly higher contribution of agricultural runoff from near-shoreline farmland compared to areas further away.

Next, we employed SciPy optimization (Vugrin et al., 2007) to derive a nonlinear fitted function using the HAB severity index as the dependent variable and the following three independent variables – fertilizer, temperature, and rainfall. The resulting function is depicted as follows:

$$SI = 1.0587 \times 10^{-4} \times P_{trans_{total}} + 3.8936 \times 10^{-1} \times temp + 6.9766 \times 10^{-3} \times rainfall - 15.8398 \qquad (3.2)$$

where, $P_{trans_{total}}$ is the aggregated amount of P_2O_5 in metric tons, temp represents the average water temperature in Celsius, and rainfall indicates the calculated rainfall amount in millimeters.

We utilized average bloom season water temperature data from 1995 to 2023 and rainfall data from 2002 to 2023 from PRISM as distribution references to generate the temperature and rainfall samples in AVUS. Table 3.1 outlines all input parameters for AVUS and their corresponding probabilities, along with household agent parameters. The model is conducted in one year's time steps to simulate the process.

Table 3.1 Parameters to sample agents and their respective probabilities (U: continuous uniform, T: continuous triangular, WRC: weighted random choices, t: census tract, x: agent)

Input Factor	Definition and Units	Distribution
Farmland area	Farmland area for each agricultural household (ac)	U = (1, 10) U = (10, 50) U = (50, 70) U = (70, 100) U = (100, 140) U = (140, 180) U = (180, 220) U = (220, 260) U = (260, 500) U = (500, 1000) U = (1000, 2000) U = (2000, 4000)
Fertilizer input amount	P_2O_5 input per acre of land (lb)	U = (5, 40)
Non-LRO income	Annual income of non-LRO agents	T = (0, $median_t$, $mean_t \times 2$)
LRO income	Annual income of LRO agents	WRC = ((0,$median_t, mean_t \times 2$), $LROCount_t$, P) where,P=$e^{-0.5\times\left(\frac{\lvert Income_x - median_{tLRO}\rvert}{\sigma}\right)^2}$
Environmental awareness	LRO and non-LRO agents	U = (0, 0.5)
Environmental threshold	LRO and non-LRO agent's threshold to express environmental concern	U = (0.7, 0.9)
HAB threshold	HAB severity levels where agents start to react	(3, 5, 7)
Temperature	Water temperature (℃)	U = (19, 23)
Rainfall	Rainfall amount (mm)	U = (700, 1401)

3.3.2. Multicriteria Evaluation for Social Vulnerability Assessment

In this study, we employed MCE to consolidate the spatial heterogeneity within our study area, ultimately generating a social vulnerability index for communities facing HAB events over time. The index is referred to as HAB-DVI for HAB Dynamic Vulnerability Index. Drawing from the IPCC framework (McCarthy et al., 2001). We utilize three critical pillars of social vulnerability: *adaptive capacity*, *intrinsic sensitivity*, and *exposure risk*, as the foundation for selecting criteria in our MCE approach.

To operationalize these three pillars, we approximated them as follows. First, we employed income, a critical indicator of economic status, to represent a community's adaptive capacity. Income directly impacts various socioeconomic factors such as housing and transportation and serves as a proxy for the community’s economic resilience. The income criterion data is derived from the average income of each census tract simulated over time – the outcome of the ABM described above. As such, it constitutes the dynamic element of our framework.

Next, we utilized alternative drinking water resource status to reflect intrinsic sensitivity, as defined by the IPCC. In the context of HAB events, surface water resources are particularly vulnerable and can become scarce. To gauge this dependence, we employed the ratio of surface drinking water sources to alternative drinking water sources as an indicator (Zhang et al., 2024). County-level data on water resource dependency were obtained from USGS (USGS, 2023).

Lastly, we utilized the distance to Lake Erie to represent the exposure risk to HAB hazard events. Proximity to the lakeshore is a proxy for the likelihood of residents being affected by HAB events. Communities closer to the lakeshore face higher exposure risks, impacting factors such as employment, income, and access to water resources.

Three key steps characterize a typical MCE process: criteria standardization, expressing preferences (weights), and aggregating the weighted standardized criteria (Ligmann-Zielinska & Jankowski, 2014). We start with shifting raw values measured on different scales for the three criteria using a linear scale transformation into a common scale ranging from 0-1. In this scale, zero denotes the absence of the factor's effect on vulnerability, intermediary values signify varying impact levels, and represents the maximum influence of the factor on vulnerability (Fernandez et al., 2016; Malczewski, 1999).

The income and distance criteria are considered cost criteria, where lower raw values contribute to higher HAB-DVI. For these criteria, the transformation is expressed as follows:

$$x'_{ij} = \frac{x_j^{min}}{x_{ij}} \qquad (3.3)$$

Where x'_{ij} represents the standardized score for the i-th census tract and the j-th criterion, x_{ij} is the raw value, and x_j^{max} is the maximum score for the j-th criterion. Conversely, the surface water dependency criterion operates as a benefit criterion, where higher raw values correlate with higher HAB-DVI scores. For this criterion, the transformation function is given by Equation (3.4):

$$x'_{ij} = \frac{x_{ij}}{x_j^{max}} \qquad (3.4)$$

where x_j^{min} is the minimum score for the j-th criterion.

We then applied Ordered Weighted Averaging (OWA) as the decision-making rule for expressing preferences and aggregating operators in our MCE. OWA incorporates the concept of order weights, representing the positional weight of each criterion in ranking all criteria by importance. The order weights are considered in addition to criterion weights in this approach to manage the level of risk-taking in decision-making processes (Fernandez et al., 2016; Malczewski, 1999; Zabihi et al., 2019). To calculate the order weights, we first arrange the criteria in descending order of their standardized values and sort their criterion weights accordingly. For $n > 1$, the order weights are computed using Equation. (3.5):

$$OW_n = \left(\sum_{i=1}^{n} CW_i\right)^{\alpha} - \left(\sum_{i=1}^{n-1} CW_i\right)^{\alpha} \qquad (3.5)$$

when $n = 1$:

$$OW_n = \left(\sum_{i=1}^{n} CW_i\right)^{\alpha} \qquad (3.6)$$

where OW_n represents the order weight of the n-th criterion, CW_i is the criterion weight of the reordered i-th criterion, and α is a fuzzy quantifier defined using a fuzzy linguistic quantifier approach (Meng et al., 2011). The quantifier reflects the preference for risk-taking in decision-making: a lower quantifier value ($\alpha \geq 0$) indicates a more risk-taking strategy, where one criterion is enough to satisfy the decision-maker. Contrarily, a higher value indicates a more risk-averse approach, which requires that most-to-all criteria are satisfied. When α =1, the decision rule aligns with the weighted linear combination representing no risk. We employed α values of 0.5 (optimistic), 1 (neutral), and 2 (pessimistic) in our study to represent different risk level. We selected OWA as the aggregation function for the vulnerability index calculation because social vulnerability is a societal concept imbued with subjectivity of risk perception. Depending on the level of compensation between the three variables (one-many-all) we can directly incorporate this risk perception in the stochastic index calculation.

Subsequently, we aggregated the order weights with our weighted standardized criterion values to compute the HAB-DVI separately for each census tract. The aggregation function is shown as follows:

$$DVI_j = \sum_{i=1}^{n}\left(OW_{nj} \times OV_{nj}\right) \qquad (3.7)$$

Where OW_{nj} is the order weight of the n-th criterion after ranking for the j-th census tract, and OW_{nj} stands for of the value of the n-th criterion after the ranking. We assigned criterion weights of 0.25, 0.25, and 0.5 to distance, surface water dependency, and income, respectively, based on expert and stakeholder opinions and the real-world impact of income on other economic factors and its role in mitigating the influence of the other two criteria. The overall framework combining ABM and MCE for HAB-DVI assessment is illustrated in Figure 3.4.

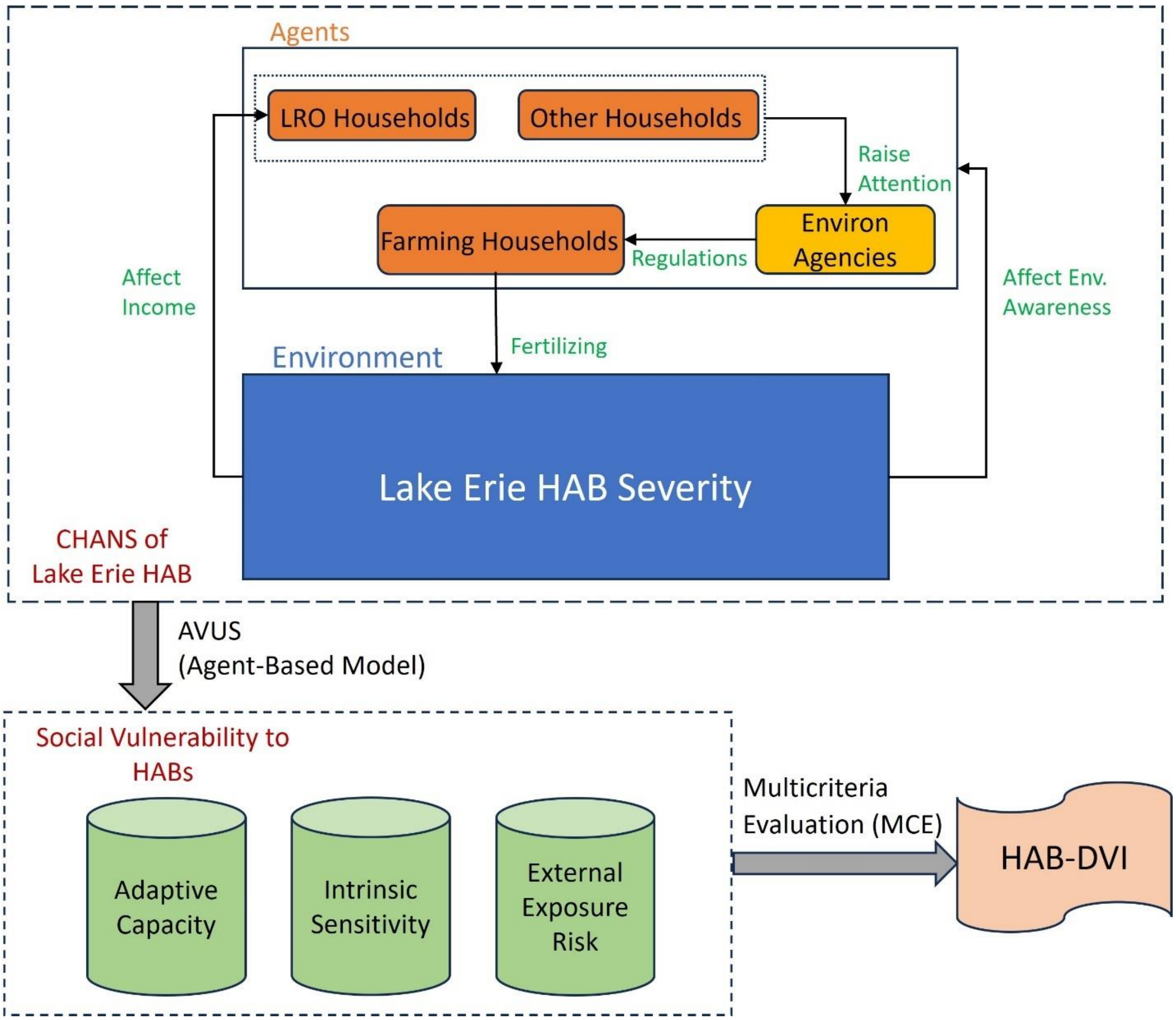

Figure 3.4 HAB-DVI evaluation framework integrating ABM and MCE

3.3.3. Uncertainty Analysis

Uncertainty analysis (UA) is a crucial step in assessing the reliability of stochastic model outcomes (Ligmann-Zielinska & Jankowski, 2014; Tate, 2012). We performed UA by resampling and repeating the ABM simulation for 50 individual runs, with each simulation spanning 20 years to gather the results of final year income for each census tract in the economic sub-model. These dynamic incomes, along with the corresponding distance to the lake and surface water dependency variables, were then integrated into the MCE to conduct Monte Carlo-based UA (Tate, 2013; Zhang et al., 2024). Our UA focuses on capturing uncertainty stemming from the inherent randomness in

ABM simulations and the design of the HAB-DVI calculation (i.e., level of risk). Additionally, we conduct statistical analysis and visualization to illustrate the variability and reliability of the HAB-DVI results.

3.4. Results

3.4.1. HAB-DVI

Figure 3.5 illustrates the HAB-DVI generated by our model averaged over 50 runs. Employing natural breaks to classify our results, we categorize the index into five vulnerability levels: very low, low, moderate, high, and very high. A descriptive breakdown of these categories across the three counties in our study area is presented in Table 3.2.

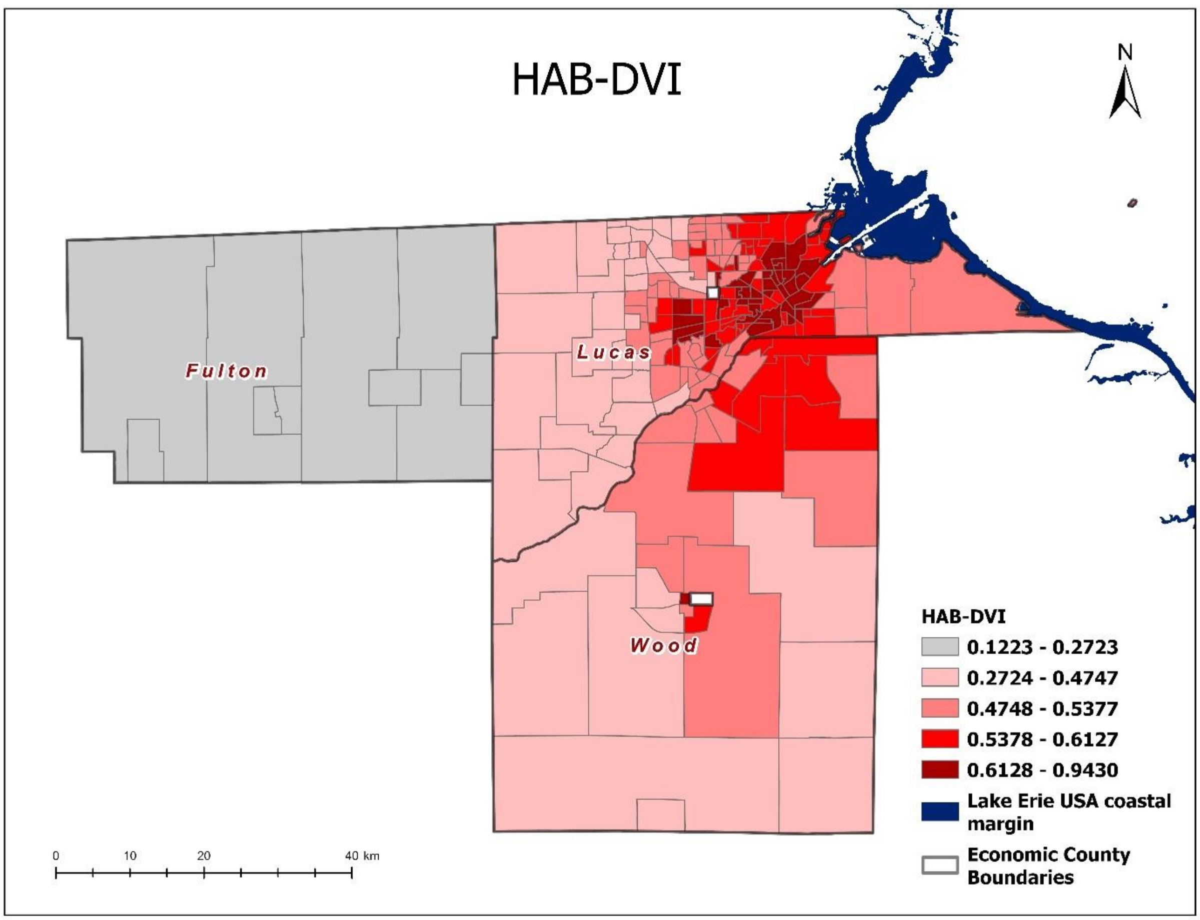

Figure 3.5 HAB-DVI results

All ten census tracts within Fulton County, situated on the western side of the study area, fall into the category of very low HAB-DVI, comprising the entirety of this category. In Wood County, located in the southeastern area, one census tract is classified as very high, but the county predominantly hosts low, moderate, and high HAB-DVI tracts. Tracts in the low, moderate, and high categories are distributed almost evenly throughout Wood County. Spatially, one high HAB-DVI tract and the sole very high tract are adjacent to each other near the county's centroid. Close to them is a tract occupied by a university that lacks data for this study. Other highly vulnerable tracts are in close proximity to the border with Lucas County. In Lucas County, the number of tracts in categories ranging from low to very high is relatively balanced, with moderate and high levels slightly more prevalent. Tracts with moderate to very high levels cluster on the eastern side of the county, and the 94 tracts classified as high and very high HAB-DVI are concentrated around the county center.

Table 3.2 Descriptive distribution of HAB-DVI results

	Very low	**Low**	**Moderate**	**High**	**Very high**	**Total**
Fulton	10	0	0	0	0	10
Lucas	0	34	49	45	39	167
Wood	0	10	11	8	1	30
Total	10	44	60	53	40	207

3.4.2. Uncertainty Analysis

Apart from calculating the average HAB-DVI scores, we also computed their standard deviations for the 50 simulation runs. The resulting maps are depicted in Figures 3.6. A higher standard deviation provides information about the fluctuating outcomes across the simulation runs. We classified the standard deviation into five categories to present the UA results. Standard deviation values range from 0.0067 to 0.1729, indicating overall stability in the HAB-DVI results across the simulation runs.

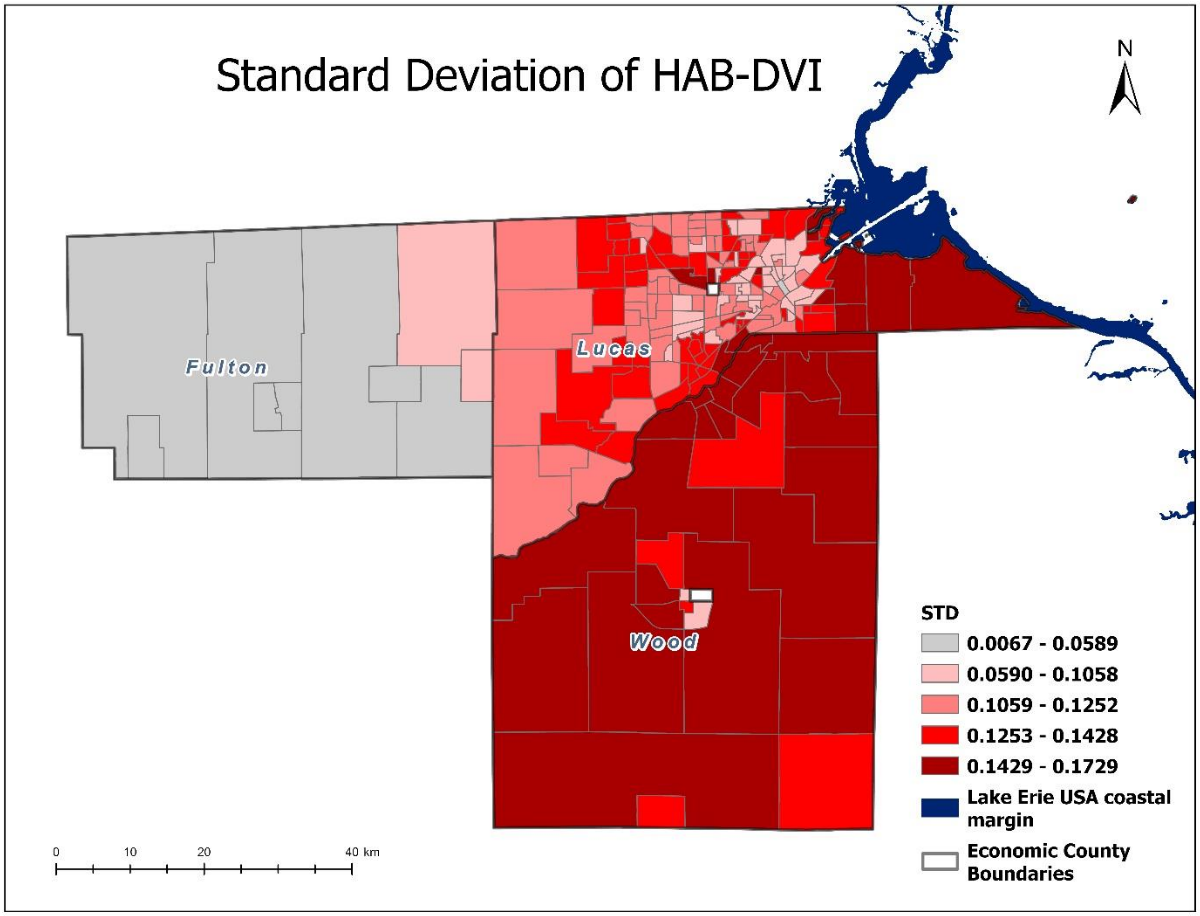

Figure 3.6 Standard deviation results

Drawing upon the robustness assessment methodology employed in prior research (Ligmann-Zielinska & Jankowski, 2014; Zhang et al., 2024), we categorize the average and standard deviation results into two classes, each using their natural breakpoints. This division yields four groups to illustrate the robustness of our findings. The robustness map, along with the four groups, is shown in Figure 3.7.

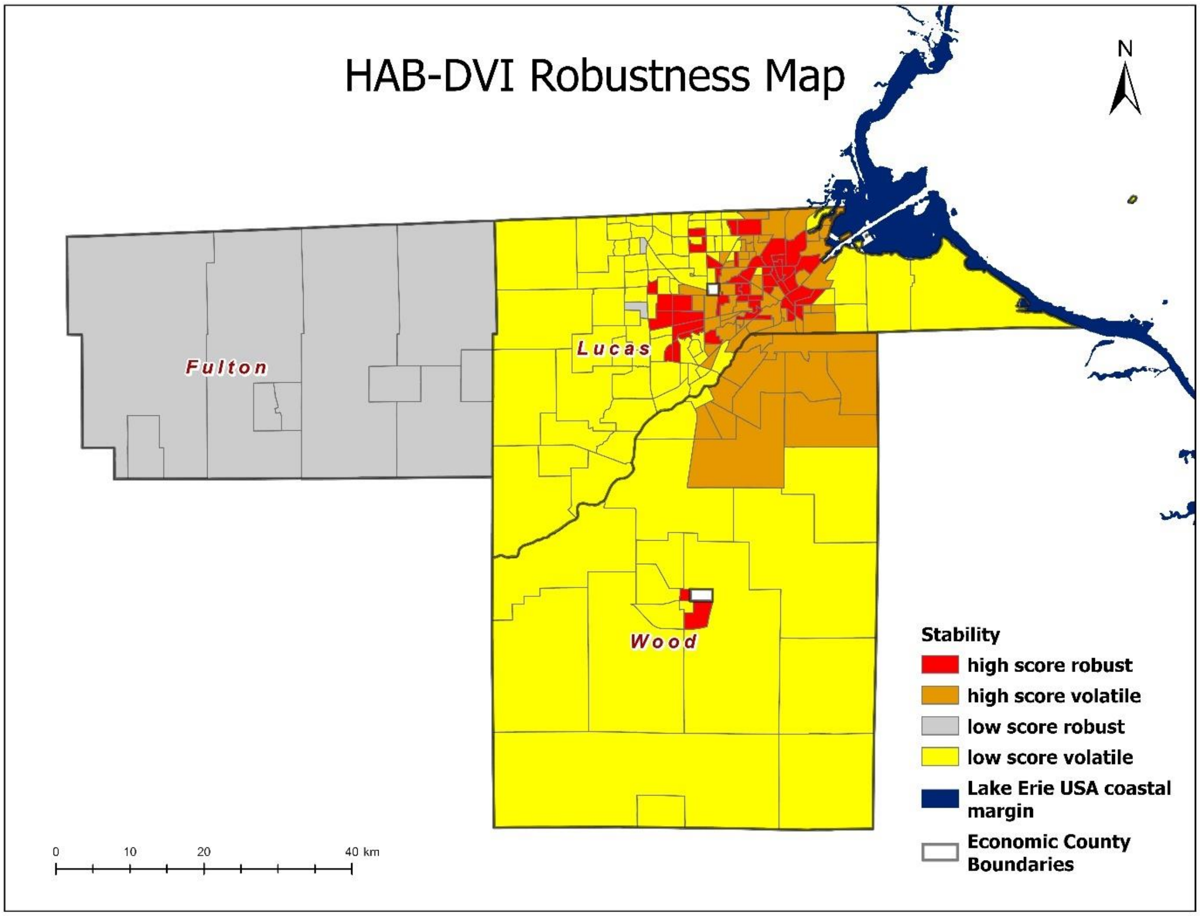

Figure 3.7 Robustness map

Census tracts with higher average values and lower standard deviations than the natural breakpoints of the two variables, specifically 0.5220 and 0.1098, are designated as high-score robust tracts. These tracts are likely highly vulnerable to HAB events. Except for two tracts in Wood County, all other high-score robust tracts are concentrated around the center of Lucas County. Meanwhile, all census tracts in Fulton County are categorized as low-score robust due to their lower average HAB-DVI scores and low standard deviation, suggesting minimal vulnerability to Lake Erie HAB events. Two additional tracts in Lucas County are also included in this category. Most tracts spanning the lower half of Wood County and around the left and right borders of Lucas County are considered low-score volatile. While they have lower average HAB-DVI scores, indicating lower susceptibility to HAB events, the standard deviation scores highlight significant uncertainty. Census tracts with both higher average and standard deviation values are primarily located around the center of Lucas County or neighboring areas across the border in Wood County. These tracts demonstrate relatively higher vulnerabilities, yet the model outcomes reflect heightened uncertainty, classifying them as higher-score volatile tracts.

3.5. Discussion

Environmental scientists have long called for academic attention and empirical studies to identify populations susceptible to environmental hazards and provide targeted solutions for hazard adaptation and community resilience (Djalante & Thomalla, 2011; Elms, 2015; UNDRR, 2015). This research tries to address this calling in the context of Lake Erie HAB events. Our integrated ABM-MCE model generates HAB-DVI scores for census tracts in the three counties of the Toledo metropolitan area, revealing a clear spatial pattern in the resulting scores. All census tracts in Fulton County exhibit very low HAB-DVI scores, with the UA indicating high confidence in these results. Consequently, prioritizing supportive policies to assist in building community resilience to HAB events in Lake Erie may be of lower priority for the entire county. Conversely, our UA results robustly indicate that the most susceptible tracts cluster around the center of Lucas County, with most of the group demonstrating very high HAB-DVI scores. Previous census data highlight this clustered area's predominance of census tracts with high population density and poverty rates (CDC/ATSDR, 2022a; U.S. Census Bureau, 2022). Moreover, being closer to the lake increases residents' exposure risk to HAB events, which is compounded by heavy reliance on surface water resources. Most residents lack alternative water sources if HABs contaminate their drinking water. These tracts warrant policymakers' attention when prioritizing government support. Unfortunately, many of these high-score robust DVI tracts experience weaknesses across all three pillars affecting vulnerability, necessitating policymakers to adopt comprehensive approaches addressing these factors to bolster community resilience. Tracts falling into the other two categories -- high score volatile and low score volatile -- could be secondary considerations for resource allocation when enhancing adaptive measures to HAB events. However, the relatively high uncertainty in the UA results underscores the importance for government or environmental agencies to closely monitor the status of these communities, especially the high score volatile tracts, to prevent potential severe disaster consequences caused by HAB events.

In addition to providing policy prioritization suggestions, the results also offer a systemic perspective for revisiting the management resource allocation strategies, considering the dynamics within the system, like the yearly variation of the application of fertilizer, the seasonal occurrence of HABs, or varying weather. Insights into the social vulnerability facing Lake Erie HAB events may contribute to proposing risk management strategies and building resilient communities within lake CHANS. The proposed ABM-MCE framework identifies geographic regions of high-risk management concerns by proposing and evaluating the causes of HABs, predicting their occurrences and the resulting social responses, followed by simulating interventions to mitigate the negative impacts and prepare for potential future hazards.

In the context of this integrated model, the amount of agricultural P_2O_5 input is a significant factor affecting the occurrence and severity of HABs, and this factor, along with temperature and rainfall levels, determines the HAB severity each year. In AVUS, the annual total P_2O_5 input is aggregated as a collective value by simulating the farming household's independent adaptive fertilizing behavior. This bottom-up method is more realistic than homogeneously representing agents' decisions by averaging out historical statistical data, as it ensures heterogeneity of decision-making driven by different values, spontaneity of choices, and bounded rationality (limited access to information either due to ignorance or biases), which are typical behavioral patterns for stakeholders in the real world (Manson, 2006; Simon, 1990). At the same time, the model simulates a process that encompasses the entire disaster management cycle, covering the bottom-up dynamics with all elements in the model (agricultural decisions, HAB severity, social vulnerability, and environmental adaptation policies) interacting with each other in CHANS, as well as the complexities caused by consecutive hazard events inherent in social vulnerability (Cutter, 2018; De Ruiter & Van Loon, 2022; Liu, Dietz, Carpenter, Alberti, et al., 2007). The framework generates continuous presentations of each component within the system, such as HAB severity and HAB-DVI, on a yearly basis. This provides valuable information for adaptive management, which is essential in the CHANS context, to dynamically reallocate resources (e.g., every year) based on ever-changing social and environmental conditions. Additionally, the results of prioritized policy intervention regions, based on stochastic outputs, generally reveal patterns indicating their specific risk components, corresponding to the three-pillar structure of social vulnerability. This understanding aids in comprehending environmental social vulnerability components and offers critical policymaking information tailored to the specific needs of different vulnerable communities. A more in-depth discussion on policy interpretation is provided in the next chapter.

Additionally, the integrated ABM-MCE framework significantly contributes to developing methodologies for studying environmental social vulnerability within CHANS. This framework successfully addresses the key features emphasized in the literature, like exploring the complexity within social vulnerability assessments and advocating for including dynamic factors (Cutter et al., 2000; De Ruiter & Van Loon, 2022). ABM has been proven to represent dynamics in social processes effectively (Crooks & Heppenstall, 2012; Ligmann-Zielinska & Jankowski, 2007).

However, only some efforts have focused on developing a framework incorporating dynamics for assessing social vulnerabilities.

Our integrated ABM-MCE addresses this deficiency in several ways. First, our agent-based AVUS model simulates temporally varying agricultural fertilizer input from farmers in the whole Maumee River Watershed. This, in turn, contributes to the volatility of residents' income, a key factor in vulnerability assessment. Second, we adopt the IPCC's three pillars to represent social vulnerability, providing a holistic inclusion of factors while avoiding potential double counting of effects. For example, existing vulnerability assessment tools often include correlated economic indicators such as income, housing, and transportation (Armaș & Gavriș, 2013; CDC/ATSDR, 2022a; Guillard-Gonçalves et al., 2015) while exposure risk indicators are commonly neglected. Third, our MCE approach aggregates the selected indicators into a composite score accounting for subjective risk perception. Finally, the integrated framework is versatile and can be applied in various contexts of environmental hazards. Existing social vulnerability indices are generic and insufficient to evaluate vulnerability in hazard events (Fernandez et al., 2016; O'Brien et al., 2004), making our framework significant as it offers an environmental perspective and enables policy recommendations specifically for environmental governance.

Social vulnerability to environmental hazards is a crucial factor in CHANS (Hagenlocher et al., 2018; Zarghami & Dumrak, 2021), influencing how various components are affected by disturbances and how the system dynamics unfold. By simulating interactions between agricultural agents, economic agents, and the lake environment, our agent-based model demonstrates the complexities and dynamics in a CHANS of Lake Erie HAB events. Furthermore, by measuring the HAB-DVI, this study provides a social vulnerability perspective to understand mechanisms in

CHANS. It offers insights to support interventions and enhance community resilience to environmental hazards.

3.6. Limitations and Future Research

The data utilized in our study are primarily sourced from publicly available online databases. Therefore, specific datasets may have inaccuracies, necessitating approximations to address the factors under examination. For example, the surface water dependency data, used to represent the intrinsic sensitivity pillar of vulnerability in our MCE, relied on USGS water resource data at the county level (USGS, 2023). This implies that all census tracts within the same county share the same surface water dependency value, potentially impacting the accuracy of our HAB-DVI results. Similarly, the lack of specific survey data on farmers' fertilization preferences and practices in the Maumee River Watershed or the state of Ohio prompted us to use the recommended range of P_2O_5 input amounts outlined in the Ohio Agronomy Guide to parameterize our agents (Barker et al., 2018). Although we validated the data with estimated historical data on P_2O_5 utilization (https://nugis.tfi.org/), it may not fully capture Ohio farmers' fertilization behaviors. Therefore, future surveys or on-site fieldwork to gather specific data for parameterizing our model would enhance the accuracy of this Lake Erie HABs case study.

While our study presents an integrated model framework for evaluating social vulnerability to specific environmental hazard events within the context of CHANS, we have yet to explore how different variables in our ABM may influence our vulnerability index results. Investigating the impacts of these variables on our model results can offer insights into the underlying mechanisms within CHANS and enable more targeted policy recommendations to address heterogeneous issues of individual communities. Sensitivity analysis is one way to gain insight into the mechanisms of the integrated model. Consequently, we will conduct a Sobol sensitivity analysis (Ligmann-

Zielinska & Jankowski, 2014; Nossent et al., 2011) to explore the influence of variables on our HAB-DVI results and integrate these findings to inform further policy suggestions in subsequent studies.

3.7. Summary

In this study, we introduced an integrated ABM-MCE framework to assess social vulnerability to environmental hazard events within the context of CHANS. This approach allows for quantifying and examining social vulnerability while accommodating the complexity and dynamics inherent in both CHANS and social vulnerability. We applied this framework to a case study involving a tightly interconnected system comprising farmers, metropolitan residents, and the lake environment to evaluate the vulnerability of neighboring communities to Lake Erie HAB events. The resulting HAB-DVI reveals that communities with high vulnerability are clustered around the center of Lucas County. By combining these findings with the results of uncertainty analysis, the study points to areas of high vulnerability. It provides confidence assessments to further inform targeted policymaking efforts to enhance community adaptability and resilience to cope with Lake Erie HAB issues.

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4. CHAPTER 4: AN APPLICATION OF SPATIALLY-EXPLICIT UNCERTAINTY AND SENSITIVITY ANALYSIS IN A SOCIAL VULNERBAILITY MULTICRITERIA EVALUATION MODEL

Abstract

Integrated uncertainty and sensitivity analyses (iUSA) are crucial in assessing model robustness and are often employed in multicriteria evaluation (MCE) models studying land use suitability. This research adopts the iUSA method in an integrated agent-based model (ABM) and MCE simulation framework to investigate dynamics in a coupled human and natural system (CHANS) involving agricultural practices, harmful algal blooms (HABs), environmental hazard effects on residents, and the actions by environmental agencies. The model assesses a spatially explicit social vulnerability index for residents in different census tracts facing Lake Erie HAB events. The resulting dynamic vulnerability indices and the iUSA outcomes provide valuable information for policymakers to prioritize high-vulnerability areas and offer targeted assistance to communities with specific needs to address their vulnerability. Scenario analysis conducted on the ABM sub-model of the integrated framework provides evidence to advocate the promotion of cover crops in Ohio agriculture. It offers suggestions for enhancing the adoption rate of cover crop practices.

Keywords:

Sensitivity analysis; multicriteria evaluation; agent-based model; harmful algal blooms; social vulnerability

4.1. Introduction

Multicriteria evaluation (MCE), or multicriteria decision analysis (MCDA), has long been one of the best-known tools to support decision-making processes. Its widespread application in location selection or spatial prioritizing stems from its capacity to incorporate geographic information and involve spatial criteria in the evaluation process (Atici et al., 2015; Karimi et al., 2019; Ligmann-Zielinska & Jankowski, 2014). This flexibility has led to MCE's recent utilization in assessing social vulnerability based on spatial heterogeneity (Armaș & Gavriș, 2013; Fernandez et al., 2016). The MCE process typically entails selecting a set of quantifiable criteria, standardizing them to ensure comparability, establishing preferences to denote their relative importance, and aggregating these preferences with standardized criterion values to generate an evaluation score (Ligmann-Zielinska & Jankowski, 2014; Malczewski, 1999).

Within the MCE framework, a notable source of uncertainty lies in expressing the relative preferences for each criterion. Various methods, including ranking, rating, pairwise comparison, and trade-off analysis, have been developed to estimate criterion weights (Malczewski, 1999). While these methods vary in accuracy and ease of implementation, they all remain inherently subjective, susceptible to differing stakeholder perspectives, and potentially constrained by limited information or varying levels of awareness. Additionally, uncertainty may also permeate other aspects of MCE, such as the selection and measurement of criteria. Hence, it becomes imperative to evaluate the inherent uncertainty in MCE models.

Uncertainty analysis is intended to measure the variability of a model's outcomes in light of uncertainties in its inputs. In contrast, sensitivity analysis aims at discerning the contributions of these inputs to the variability of outcomes and identifying key drivers of the model behavior or simulated systems. Often conducted concurrently, these two techniques form a synthetic approach known as integrated uncertainty and sensitivity analysis (iUSA) (H. Chen et al., 2011; Ligmann-Zielinska & Jankowski, 2008). This approach finds utility across various model types, including empirical agent-based models exploring uncertainties in simulated residential development, impacts of agricultural policy interventions, and landscape fragmentation (Ligmann-Zielinska, 2013; Ligmann-Zielinska & Sun, 2010; Schouten et al., 2014; Ten Broeke et al., 2016). Moreover, the method has also been employed to understand the uncertainties in system dynamics models concerning topics like pollution management (Wang et al., 2012). Similarly, iUSA has gained traction within the MCE context, offering insights into inherent model uncertainties. Recent studies have integrated iUSA with MCE to address empirical issues such as river catchment management and land suitability evaluation (Benke & Pelizaro, 2010; H. Chen et al., 2011; Ligmann-Zielinska & Jankowski, 2014).

Conduction of iUSA typically involves screening through predefined value ranges for model input variables, executing the model for each combination of variable values, and observing the corresponding changes in model outputs (Delgado & Sendra, 2004). Various approaches have been proposed to facilitate this iUSA process. One-Factor-At-A-Time (OAT) is among the most commonly used methods due to its intuitive nature and implementation simplicity. OAT involves varying one variable at a time while keeping all others fixed at their nominal values (Saltelli et al., 2006). While straightforward, OAT may suffer from arbitrary changes in variable magnitudes, failing to comprehensively and accurately reflect outcome variability. Additionally, OAT might overlook interactions between the variables, particularly in complex models with high uncertainty and interactive components (Saltelli & Annoni, 2010). Variance-based global sensitivity analysis (GSA) offers an alternative to OAT, aiming to address its limitations. As a global method (Saltelli et al., 2008), variance-based GSA explores the entire range of input conditions rather than relying on arbitrary selections, as in OAT. Moreover, it considers the interaction effects among input components by calculating two sensitivity indices: a first-order index (S), representing the individual contribution of each input component to model output variability, and a total effect index (ST), which takes into consideration both the individual contribution of each input component and its interactions with other components in the model (Ligmann-Zielinska & Jankowski, 2014).

To effectively support an MCE in addressing empirical studies within a geographic context, such as location suitability or spatial vulnerability assessments, an iUSA method must be capable of operating in a spatially explicit manner, as underscored by recent research (Y. Chen et al., 2010; Ligmann-Zielinska et al., 2024). Variance-based GSA can be adapted to fit this spatial context by mapping weight sensitivities (Feick & Hall, 2004), considering spatial heterogeneity in criteria values that contribute to the outcome variability (Rinner & Heppleston, 2006), and utilizing relative distance relationships to adjust the criteria weights (Ligmann-Zielinska & Jankowski, 2012) to name a few. Therefore, this approach allows for investigating uncertainties in MCE models within their unique spatial framework.

Furthermore, we contend that insights gleaned from appropriate iUSA methods applied in spatially explicit MCEs can offer valuable interpretations of the real-world systems under examination, thereby informing pertinent problem-solving endeavors. Specifically, spatial iUSA identifies heterogeneous significant factors for each spatial unit that influence the system's behavior simulated by MCE. Consequently, the results can aid in policy formulation or resource prioritization based on the distinct influential variables across different spatial units, thereby enhancing understanding and decision-making in complex systems. For example, previous research employing spatial iUSA has demonstrated its viability in guiding decision recommendations for the allocation of suitable habitat areas (Ligmann-Zielinska & Jankowski, 2014), identifying regions with varying levels of geodiversity (Ligmann-Zielinska et al., 2024), analyzing land-use change and urban growth (Şalap-Ayça et al., 2018), and revealing uncertainty factors in soil and water assessments (Koo et al., 2020).

Scenario analysis is another widely used approach to assist policy design in empirical studies, especially integrated with simulations. The approach typically involves designing hypothetical scenarios, adjusting the baseline model according to the scenario design, simulating the scenarios based on the model assumptions and variable frameworks, and exploring the potential impacts on the simulated system or factors under examination. A parameter (set) in each scenario is set to specific constant values, reflecting conditions under which this particular alternative "reality" manifests itself. Due to the nature of this approach to explore future hypothetical situations, it has been commonly employed in environmental policy studies to inform future policy designs. It has been applied in environmental policy study topics such as agricultural irrigation, land use change and urbanization, and emission regulations (Riesgo & Gómez-Limón, 2006; Wu et al., 2011; Yang et al., 2018).

In this study, we apply spatial iUSA and scenario analysis within an integrated framework combining agent-based modeling (ABM) and MCE. This integrated ABM-MCE framework is tailored to investigate the dynamics of a complex coupled human and natural system (CHANS) encompassing farming, harmful algal blooms (HABs), and economic systems. We focus on assessing the dynamic vulnerability index reflecting residents exposed to HAB events (HAB-DVI) and applying it in the Lake Erie context. Further details regarding the model framework can be found in Chapter Two of this dissertation. Our objectives are twofold as we conduct iUSA and scenario analysis on this integrated model. Firstly, we aim to address uncertainties in our HAB-

DVI results and elucidate how the criteria within our spatially explicit MCE influence HAB-DVI variability. Secondly, we explore the efficacy of various hypothetical policy designs in mitigating local community vulnerability to HAB events, thereby enhancing community resilience in the face of natural hazards and potentially reducing the severity of HABs in Lake Erie, thus shedding light on the dynamics within this simulated CHANS.

Key questions we seek to address in this research include identifying factors in our MCE that contribute most to the uncertainty of HAB-DVI results for each spatial unit (census tract) and, based on the HAB-DVI and sensitivity analysis results, recognizing actionable measures that can be implemented by government or environmental agencies that consider the unique needs of communities in building resilience to HAB events, and, therefore address environmental injustice. Furthermore, this research aims to identify potential policies to support highly vulnerable communities, fostering improvements in the simulated system's socioeconomic (vulnerability) and environmental (HAB severity) aspects.

In the subsequent sections of this chapter, we outline our methodological approach, including details of iUSA and policy scenarios, and elucidate how these methodologies are implemented in our ABM-MCE framework. We then present our analyses' findings, showcasing the inherent uncertainty inherent in our model, delineating the spatially heterogeneous contributors to this uncertainty, and examining the potential efficacy of hypothetical policy designs in ameliorating community vulnerability. Lastly, we discuss how the results derived from iUSA and scenario analysis can inform regulatory measures, incentive structures, and the formulation of supportive policies in our case study. Concurrently, we will explore how these insights contribute to understanding the complexity and dynamics within the CHANS.

4.2. Methodology

4.2.1. iUSA

4.2.1.1. Sampling and Monte Carlo simulation

Criteria weights typically represent a significant aspect of subjective components, encapsulating uncertainties in MCE models. In our study, we aim to focus on the individual influence of each criterion in our ABM-MCE model on the calculation of HAB-DVI, which also serves as an indicator of each pillar of social vulnerability (McCarthy et al., 2001). Therefore, the results of these analyses are expected to inform policy recommendations in this empirical case study. Specifically, the three pillars of social vulnerability, as suggested by the Intergovernmental Panel on Climate Change (IPCC), are *adaptive capacity, intrinsic sensitivity, and exposure risk*. We used income, a critical indicator of economic status, to represent a community's adaptive capacity; alternative drinking water resources to indicate intrinsic sensitivity, reflecting the level of dependency on surface water resources; and distance to Lake Erie to measure the exposure risk to HAB events. To achieve the goal of identifying the influence of each criterion, we employ the weighted linear combination (WLC) method for MCE aggregation (Malczewski, 1999). Each criterion is assigned a fixed weight per simulation, reflecting its relative importance in determining the evaluation outcomes. The aggregation process involves multiplying each criterion value by its corresponding weight and summing the results, as shown in Equation (4.1):

$$DVI_j = \sum_{i=1}^{n} w_{ij} \times c_{ij} \qquad (4.1)$$

Where DVI_j is the HAB-DVI value for the j-th census tract, w_{ij} is the weight of the i-th criterion in the j-th census tract, c_{ij} is the corresponding value of this criterion, and n is the total number of criteria in the MCE (Malczewski, 1999).

The iUSA process involves sampling the input variables under examination, specifically criteria weights in our study, to address model uncertainty. We utilize Sobol sampling, a quasi-random sampling method renowned for efficiently sampling inputs across the entire input range space, making it particularly suited for variance-based GSA (Saltelli, 2002; Saltelli et al., 2010). We start the sampling process by employing percent point functions (PPF) to select distributions and generate two independent lists, A_{NK}, and B_{NK}, each containing N weight sample sets for the K (in our case, three) examined criteria. Subsequently, radial samples are generated using these two lists by substituting one weight in sample set A_{NK} by a value from sample set B_{NK} each time, resulting in $K + 2$ radials per run for Sobol samples, where 2 stands for the two independent lists. Specifically, $N \times 2$ runs are necessary for the two original sample sets, and $N \times 2$ simulations are need for the sample sets with substituted weight values (Saltelli et al., 2010). Ultimately, the Monto Carlo MCE simulations yield a 3-dimensional array in the shape of $N \times (K + 2) \times j$, where N is the number of runs, $K + 2$ represents radials, and j indicates the number of census tracts in our model (Ligmann-Zielinska & Jankowski, 2014; Saltelli et al., 2010).

4.2.1.2. Uncertainty analysis

We conduct Monte Carlo simulation runs based on a sample size of $N = 131{,}072$ $(2\text{^}17)$, as generated in the Sobol sampling procedure. This sample size is chosen to ensure it is large enough to cover the entire range of the input variables and to produce a sufficiently large number of model realizations, thereby comprehensively representing the model outcomes. A sub-set of the 3-dimensional array generated from the Monte Carlo simulation, which represents all weight combinations in one of the two N arrays and then summarized to provide the mean and standard deviation of the MCE output maps. This indicates the resulting average vulnerability index for each census tract in the study area and the variability of the model output.

4.2.1.3. Sensitivity analysis

The 3-dimensional array generated from the Monte Carlo simulation is used in the sensitivity analysis to generate first-order (S) and total-effect (ST) index maps to illustrate how different criterion weights influence HAB-DVI results in different census tracts in our study area. This spatially explicit iUSA can provide information on the difference in importance of the criterion in each census tract and can assist policy recommendations that account for the spatial heterogeneity of the decision criteria. The overall workflow of iUSA is presented in Figure 4.1.

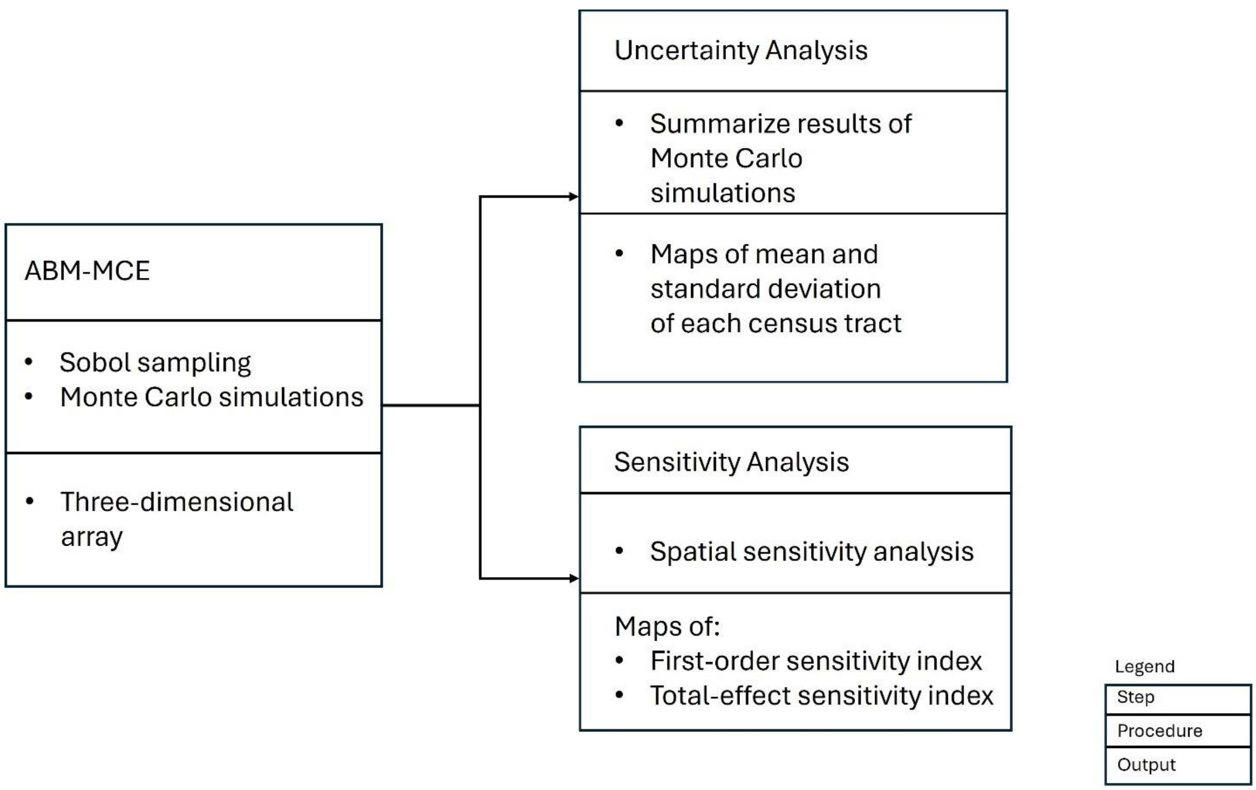

Figure 4.1 Overview of iUSA workflow

4.2.2. Scenarios

This study explores fertilizer regulation policy effectiveness and their implementation strategies for mitigating HAB severity. We formulated three policy scenarios based on the baseline ABM-MCE. Since the complexities and dynamics of the CHANS related to HABs in our integrated model are simulated in the ABM section of the model, adjustments are made to variables and parameters in AVUS (Chapter Three) to simulate these policy scenarios.

In the first policy scenario, we introduce a behavioral aspect for economic agents to reflect their environmental concerns regarding HABs in Lake Erie. Economic agents' environmental awareness can escalate when they perceive the severity of HAB events exceeding their tolerance level (for non-LRO agents) or when their income from lake-related activities diminishes due to severe HAB events (for LRO agents). If their collective environmental awareness surpasses pre-defined thresholds prompting action, government or environmental agencies may be forced to take action to address the HAB issue in Lake Erie. Consequently, policymakers might strengthen regulations on fertilizer usage among agricultural agents. This scenario aims to simulate a simple democratic policy-making process and assess how this behavioral addition impacts the dynamics within our simulated CHANS, potentially improving vulnerability conditions for economic agents across different spatial units.

The second scenario builds upon the first, maintaining the democratic policy-making process. However, policymakers promote agricultural Best Management Practices (BMPs) instead of reinforcing fertilizer amount regulations. BMPs are designed to address environmental concerns and enhance environmental sustainability. Practices such as planting cover crops and adopting reduced or no-till farming techniques are widely recognized BMPs that aid in reducing water erosion and improving water quality (United States Department of Agriculture, 2020). While reduced tillage or no-till practices generally entail fewer field operations and lower financial costs for farmers, adopting cover crops may require additional operations and higher financial investments in seeds, tools, and herbicides (Wallander et al., 2021).

Despite the benefits of cover crops in reducing nutrient runoff from fields by an estimated 50-60 percent on average (Blanco-Canqui, 2018; Sustainable Agriculture Research and Education, 2017; Yeo et al., 2014), their adoption rates vary widely across different states in the US. Maryland, for instance, exhibited the highest adoption rate of around 33 percent in 2017, with a significant upward trend. Conversely, Midwest states in the Great Lakes region demonstrate relatively lower to moderate adoption rates. Specifically in Ohio, the adoption rate of cover crops was approximately eight percent in 2017, with a growth rate of around three percent from 2012 to 2017 (United States Department of Agriculture, 2020; Wallander et al., 2021).

Recognizing the benefits of cover crop adoption, our second scenario proposes that when residents' strong opinions regarding the severity of HABs surpass a threshold prompting environmental agency intervention, incentives will be offered to promote the adoption of cover crops. Agricultural agents will then have the opportunity to accept these incentives and implement cover crop practices on part of their land.

The third scenario aligns with the principles of the second scenario but suggests a more robust governmental initiative to achieve a higher adoption rate of cover crops. This could involve implementing measures such as increasing cover crop adoption incentives or introducing educational programs. Agricultural agents are more likely to adopt this practice in this situation. The parameterization for both scenarios is detailed in Table 4.1.

Table 4.1 Parameterization for scenario analysis

Input Factor	Definition and Units	Factor Value		
		Policy Scenario One	Policy Scenario Two	Policy Scenario Three
Environmental concern probability	The probability that individual environmental concern is expressed and noticed by the government agency	0.33	0.33	0.33
Agent voice threshold	The threshold that agencies respond to the advocacy of actions	Number of economic agents/3	Number of economic agents/3	Number of economic agents/3
Reinforced regulation amount	The amount of fertilizer regulated in addition to the baseline amount (lb)	Baseline regulated amount − 5	N/A	N/A
Adoption rate	The opportunity that farmers adopt cover crop	N/A	0.2	0.5
Adoption area	The area of adoption when agricultural agents decide to practice cover crop (ac)	N/A	Individual farmland area/2	Individual farmland area/2
Nutrient reduction rate	The reduction rate of P_2O_5 in runoff	N/A	50%	50%

4.3. Results

4.3.1. HAB-DVI

Figure 4.2 illustrates the average HAB-DVI from the Monte Carlo simulation conducted using our integrated ABM-MCE baseline model. Utilizing natural breaks to classify our results, we organize the index into five vulnerability levels: very low, low, moderate, high, and very high. Table 4.2 provides a descriptive breakdown of these categories across the three counties within our study area.

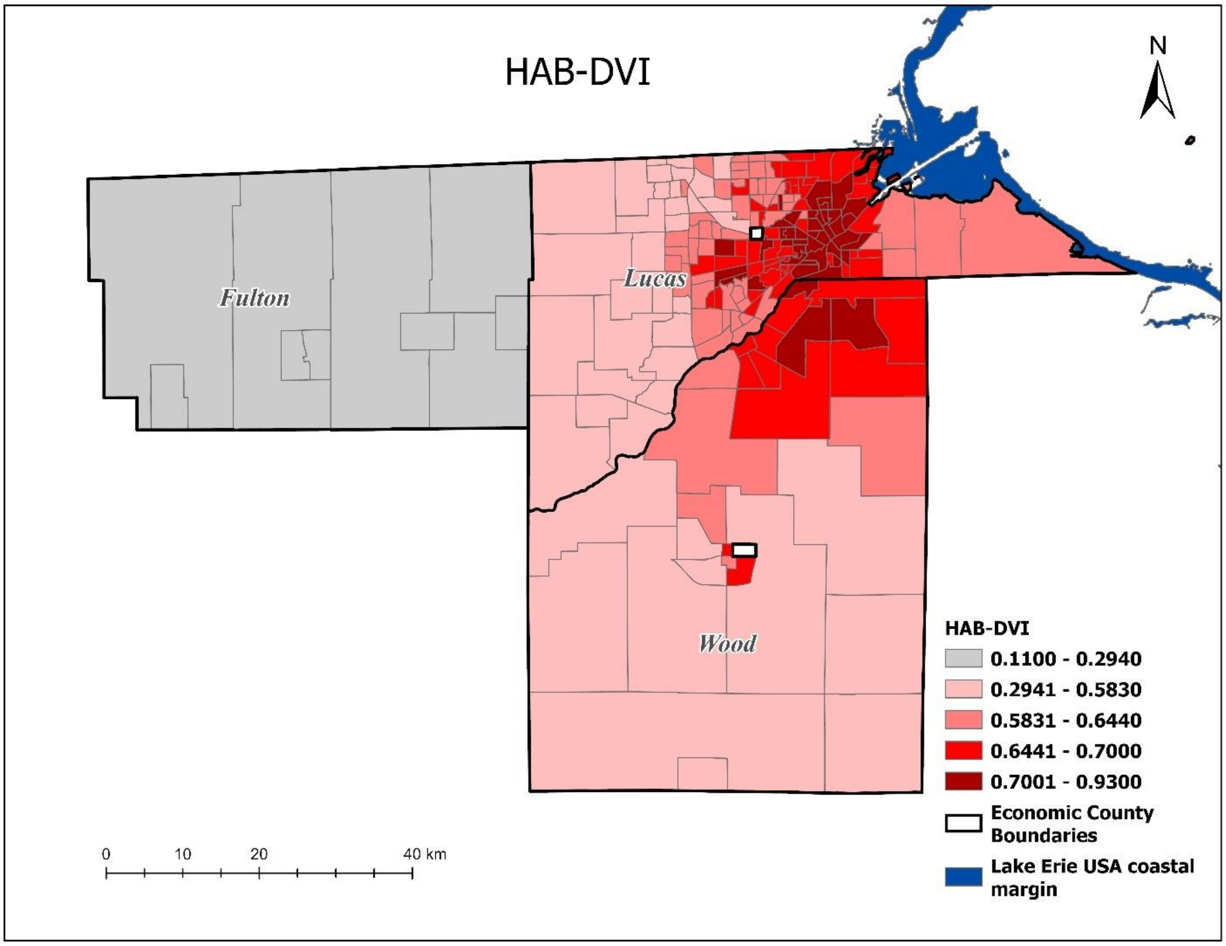

Figure 4.2 HAB-DVI results of the baseline model

All ten census tracts within Fulton County, situated on the west part of the study area, fall into the very low HAB-DVI tract category, comprising the entirety of this category. Moving to Wood County, situated in the lower right section of the map, three census tracts are designated as very high. At the same time, five are classified as moderate, with the county primarily hosting tracts categorized as low and high HAB-DVI. Spatially, most of the high and very high HAB-DVI tracts are concentrated near the border with Lucas County, with two exceptions adjacent to each other near the county’s centroid. A tract occupied by a university lacks data for this study in this vicinity. In Lucas County, approximately one-third of the tracts fall within the moderate HAB-DVI category, representing the highest count across all classifications. Thirty tracts are categorized as low HAB-DVI. Concurrently, the county holds about half of the tracts classified as high and very high. Notably, 85 tracts are classified as high and very high HAB-DVI and clustered around the county center.

Table 4.2 Descriptive distribution of HAB-DVI results in the baseline model

	Very low	Low	Moderate	High	Very high	Total
Fulton	10	0	0	0	0	10
Lucas	0	30	52	45	40	167
Wood	0	11	5	11	3	30
Total	10	41	57	56	43	207

4.3.2. Uncertainty analysis

We calculate the standard deviation (STD) for the HAB-DVI scores derived from the Monte Carlo simulation runs using Sobol sampling within our ABM-MCE model. The resulting map depicts the STD's spatial heterogeneity across the entire study area, as illustrated in Figure 4.3. A higher standard deviation indicates greater variability in Lake Erie HAB event vulnerability scores across the simulation runs.

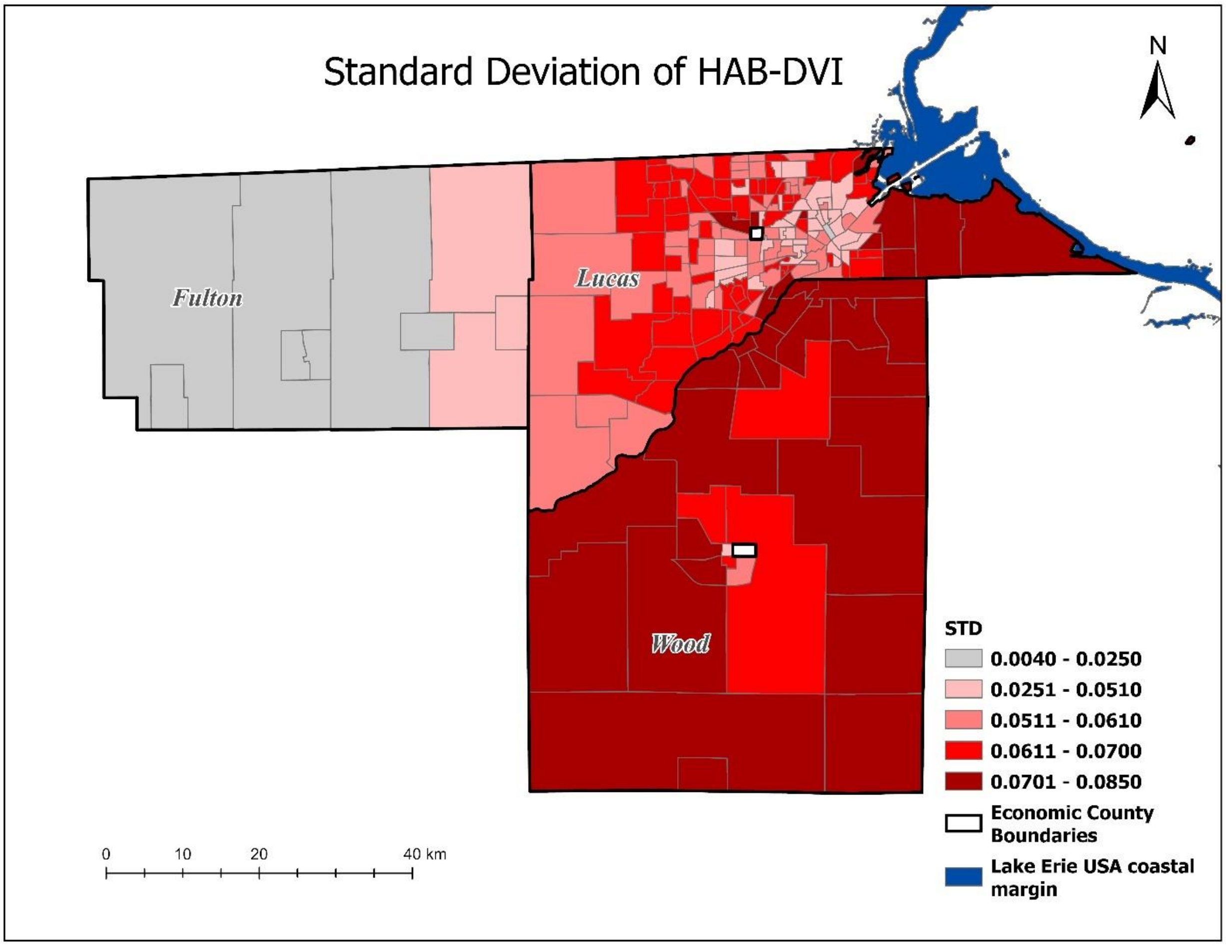

Figure 4.3 Standard deviation resulting from uncertainty analysis

Similar to the classification of HAB-DVI results, we categorize the STD results into five categories to present the UA results. The spatial distribution of standard deviation also exhibits clear patterns. In Fulton County, all census tracts display very low to low STDs. The three tracts categorized as low are clustered near the border with Lucas County. Conversely, the majority of tracts in Wood County exhibit very high STDs, while in Lucas County, most tracts show low to moderate variability in their HAB-DVI results.

When analyzed in tandem, average HAB-DVI and STD results demonstrate comparable spatial clustering trends. Therefore, to analyze both spatial results concurrently, we employ the quadrant classification method utilized in previous chapters (Ligmann-Zielinska & Jankowski, 2014; Zhang et al., 2024). This method categorizes the average scores of HAB-DVI and STD results into two classes, each using its natural breakpoints. This results in groups that illustrate the robustness of our model outcomes, i.e., high score robust, high score volatile, low score robust, and low score volatile. The robustness map is presented in Figure 4.4.

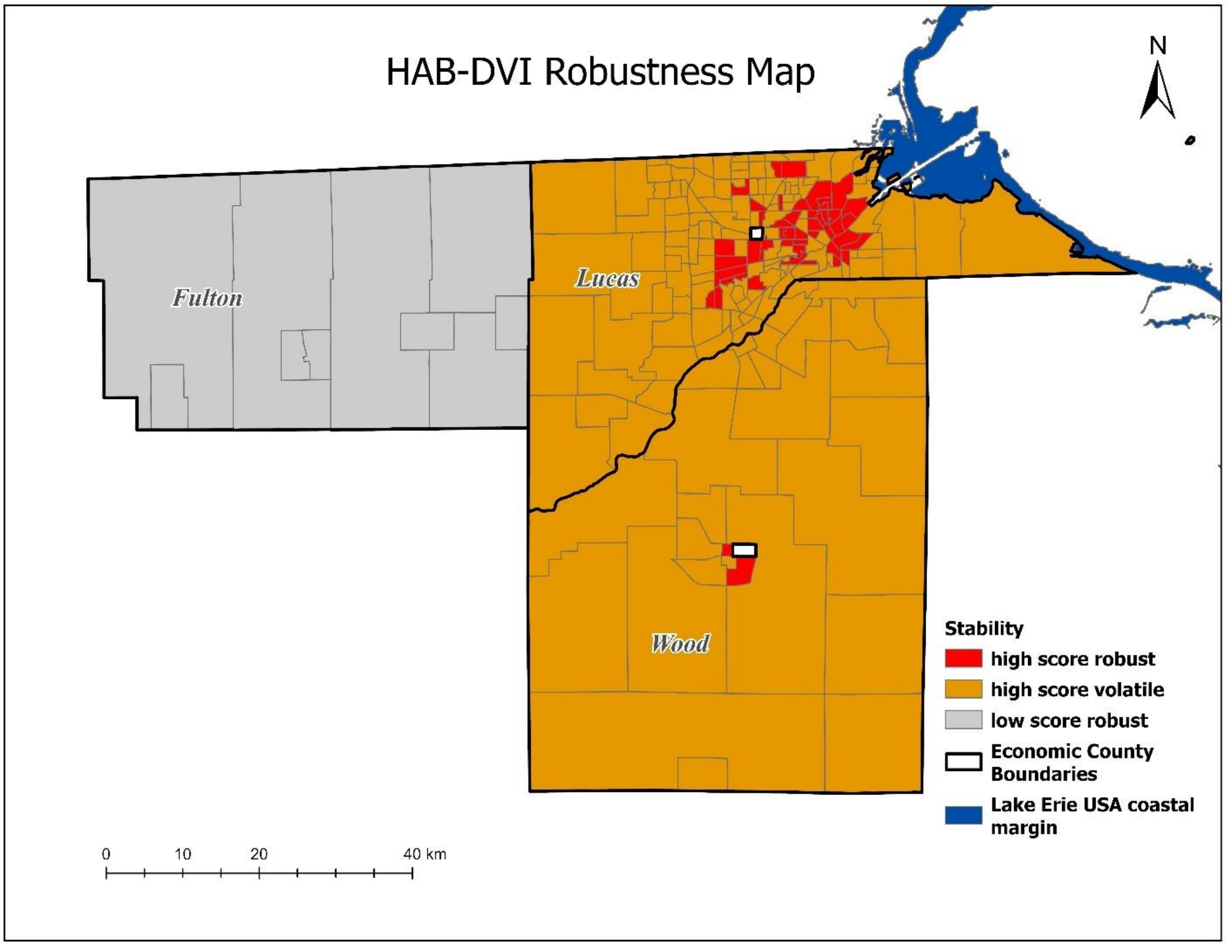

Figure 4.4 HAB-DVI robustness map

The natural breakpoints for HAB-DVI and STD are determined to be 0.053 and 0.294, respectively. The value set of HAB-DVI and STD breakpoints predominantly categorizes the majority of census tracts into the high-score volatile class, indicating susceptibility to Lake Erie HAB events, with significant uncertainty in the outcomes. All ten tracts in Fulton County are classified as low-score robust, comprising the entirety of this category. Tracts classified as high-score robust are primarily concentrated in two areas surrounding the spatial centers of Lucas and Wood County, suggesting a high likelihood of vulnerability to HAB events in Lake Erie. Interestingly, no census tract falls into the category of low score volatile.

4.3.3. Sensitivity analysis

The sensitivity analysis examines the weights of three criteria in our ABM-MCE model, each representing a pillar in the system of social vulnerability. The analysis reveals minimal interaction effects for all variables, with values below 0.02. Consequently, the first-order sensitivity index (S) adequately reflects model sensitivity to each variable. The distribution of S across the entire study area for each criterion weight is presented in Figure 4.5.

Census tracts exhibiting the highest sensitivity to distance weight are exclusively situated in Fulton County. For other tracts, distance weight sensitivity generally correlates with proximity to the lakeshore – tracts closer to the lakeshore tend to have higher sensitivity indices, with a few exceptions located at the south of Wood County. Tracts with the highest surface water dependency weight are predominantly found in Wood County. Tracts near the border between Lucas and Fulton County generally exhibit moderate to high sensitivity levels, while tracts closer to the lakeshore in Lucas County demonstrate the lowest sensitivity to this criterion weight. Most tracts in Lucas County display very high sensitivity to income weight. Wood County exhibits an even distribution in this criterion weight sensitivity, with a spatial pattern indicating higher sensitivity indices closer to the border with Lucas County. Conversely, most tracts in Fulton County show very low sensitivity to this weight.

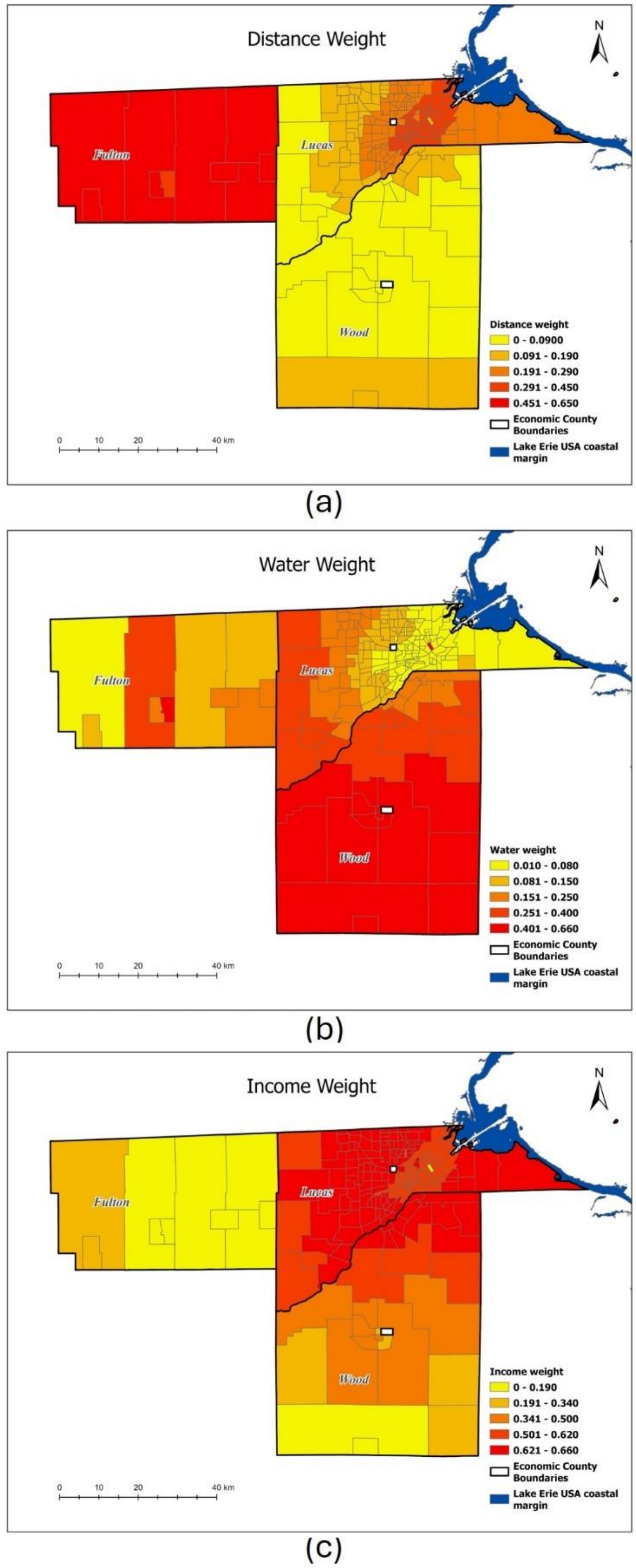

Figure 4.5 First-order sensitivity index for distance weight (a), water weight (b), and income weight (c)

4.3.4. Scenario analysis

The HAB-DVI computed in this study is based on an MCE model, which requires standardizing all criterion values. Consequently, our vulnerability index results does not indicate absolute values, but rather be rank-based values that are highly correlated with the criterion values of each census tract in the study area. Since the criterion values in our model are either real-world one-time-point empirical data or simulated based on samples derived from one-time-point empirical data that do not exhibit any extreme probability distributions, the rank-based vulnerability index resulting from this model is not expected to undergo significant changes over a 20-year simulation period. Indeed, after running the integrated ABM-MCE model, the resulting HAB-DVI across different policy scenarios confirms this expectation, with only minor differences. Therefore, we evaluate the differences in these HAB CHANS across scenarios by analyzing HAB severity in our ABM over the years through the simulation runs. Like the baseline model, we resample our agents and conduct 50 ABM simulations for each policy scenario. Each simulation spans 20-year steps and generates a HAB severity index (SI) for each step. We then summarize the variability of SI results over the 20 years in each simulation to account for the fluctuations in HAB severity over time for each scenario.

Additionally, to estimate how HAB severity changes over time from a broader temporal perspective, particularly examining the HAB situation before and after the implementation of cover crop incentives in the second and third scenarios, we divide the HAB SI results for each year of simulation into two time spans and compare the average of each period. In both scenarios two and three, cover crop incentive actions typically commence around the seventh to the tenth step, with a 20-year average reflected in the eighth step. Therefore, we designate step eight as the dividing point for each simulation. Step eight is also applied to divide the results for scenario one to maintain consistency.

The SIs' STD for each scenario is calculated for each time step to represent the overall conditions of HAB severity stability or fluctuation over the 20-year simulation time. We then summarize the results by averaging the STDs in the 50 simulations to mitigate the effects of extreme runs. The STDs for three scenarios are presented in Table 4.3.

Table 4.3 Average of STDs for policy scenarios

	Scenario1	**Scenario2**	**Scenario3**
Average of STDs	1.64	1.50	1.58

In scenario one, the overall standard deviation is the highest, slightly surpassing scenario three and substantially exceeding scenario two. This suggests that the fluctuation in SI results across the 50 simulations over time is the most pronounced in scenario one. Conversely, scenario two exhibits the most stability in the SI results, while scenario three falls in between the other two scenarios in terms of stability.

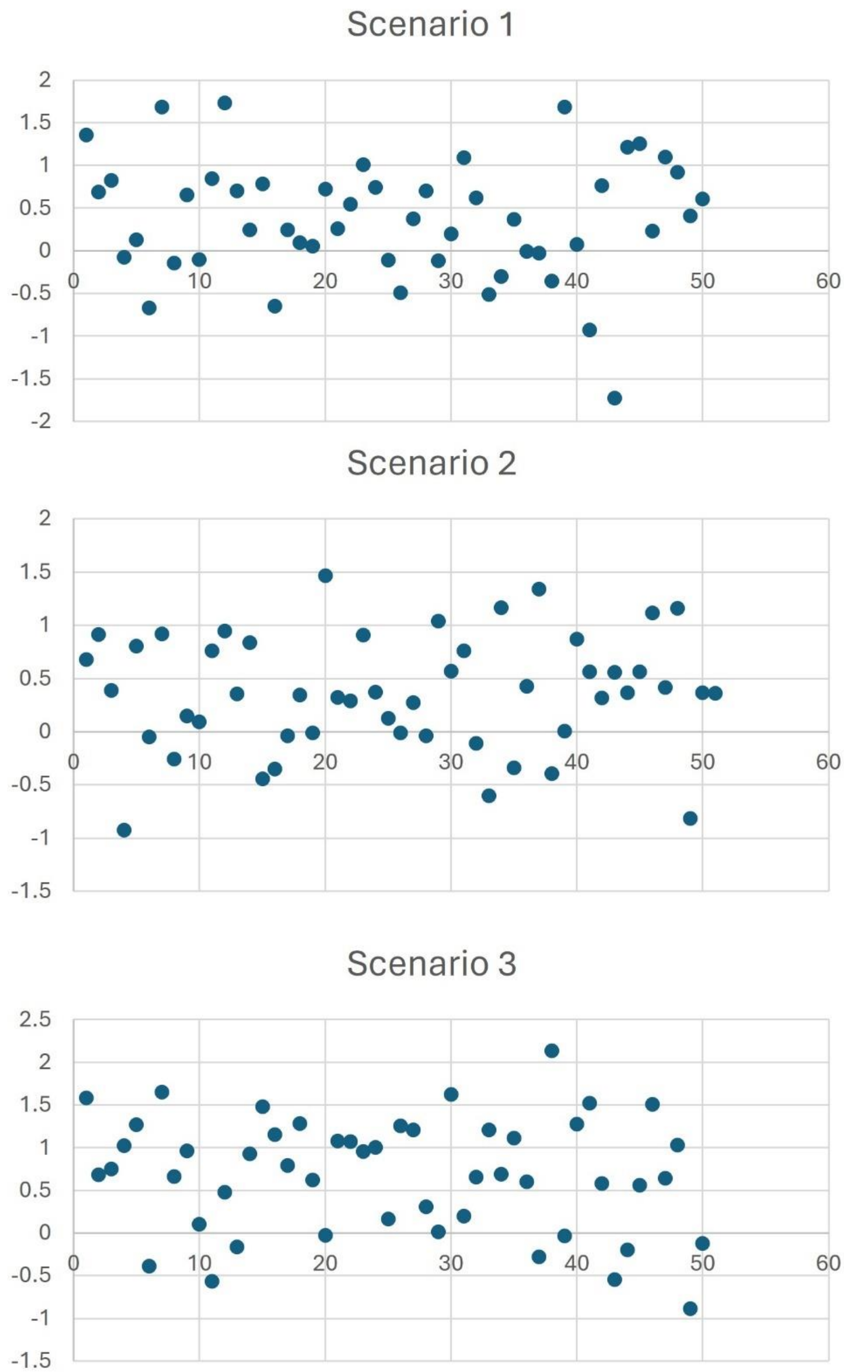

Figure 4.6 Average SI differences pre- and post- step eight for 50 simulations for three scenarios

Figure 4.6 illustrates the difference in averaged SIs before and after the division step set for the scenarios. Scenarios one and two display a similar distribution in the number of difference values above or below zero, with scenario two values clustering more closely around the x-axis.

This consistency with the standard deviation results suggests that scenario two yields relatively stable SI results over time. In contrast, scenario 3 shows most points above zero, indicating that the pre-eighth step average SI is significantly higher than and post-eighth step average SI across the 50 simulations. This result reveals that cover crop promotion policy simulated in scenario three positively mitigates HAB severity over the years. We discuss the effectiveness of the scenarios in the following section.

4.4. Discussion

The HAB-DVI result map reveals a distinct spatial pattern. Generally, census tracts that are most susceptible to Lake Erie HAB events cluster near the lakeshore around the center of Lucas County and the border between Lucas and Wood County. Conversely, census tracts least vulnerable to HAB hazards are predominantly located in Fulton County. By referring to the robustness map, which combines the HAB-DVI results with the STD, we can evaluate the level of uncertainty of the index in each census tract. Specifically, census tracts clustering around the spatial center of Lucas County, with two additional tracts at the center of Wood County, are highly likely to be most vulnerable to HAB events. In contrast, census tracts in Fulton County exhibit low susceptibility with confidence.

These findings suggest that governments should prioritize the high-score robust areas in policymaking to support targeted communities to enhance their adaptation abilities and build resilience after hazard events, especially when resources are limited. In contrast, census tracts in Fulton County pose low risks for HAB events and serve as a buffer zone for supportive policymaking. With limited resources to allocate, governments can safely consider other areas before addressing these tracts. Additionally, tracts categorized as high-score volatile with relatively high uncertainty in their vulnerability may present high susceptibility to HAB but with less confidence. Therefore, policymakers should closely monitor economic and social conditions during HAB and be prepared to support these areas as secondary priority zones.

On the other hand, the sensitivity analysis of the spatial MCE model exploring environmental social vulnerability has played a significant role in the application of this research to guide policy suggestions. The analysis distributes uncertainties in results for each census tract in our study area among the three criteria in our MCE model. To clearly identify the most important variable contributing to result uncertainty in each census tract, we rank the sensitivity scores for each tract and determine the factor that dominates the other factors, as presented in Figure 4.7. The dominant criterion weights across the study area exhibit a clear spatial pattern, with each criterion weight showing a relatively even spatial sensitivity distribution.

Distance weight drives the score uncertainty for most tracts in Fulton County, with one exception showing a dominant factor of surface water dependency weight. Note, however, that since tracts in Fulton County demonstrate low STD, variance-based decomposition results are less valuable (with low variance, there is little to decompose). Therefore, the dominant map of Fulton County plays a minor role in directing policymaking.

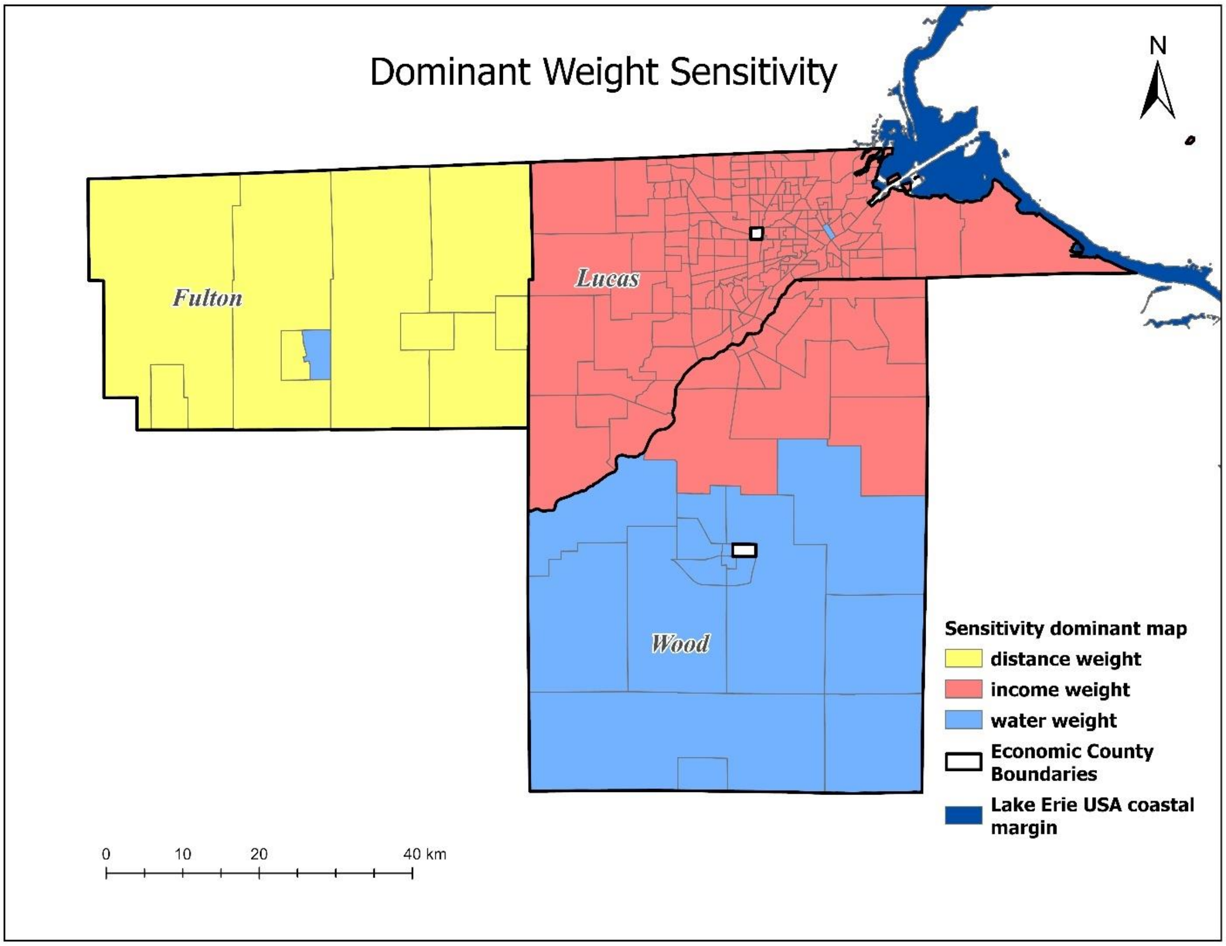

Figure 4.7 Dominant weight sensitivity map

On the other hand, except for one tract dominated by surface water dependency, all other tracts in Lucas County and those located at the northeast section of Wood County are dominated by the income criterion. In contrast, tracts in the south section of Wood County are predominantly influenced by surface water dependency. This outcome aligns with empirical observations indicating that many census tracts in this area, especially those closer to the center of Lucas County and Lake Erie, have relatively lower average incomes (CDC/ATSDR, 2022). Lucas County tends to have sufficient substitute groundwater sources, whereas most areas in Wood County are solely dependent on surface drinking water sources (USGS, 2023). Hence, unsurprisingly, the results of sensitivity analysis indicate high surface water dependency in most tracts in the south part of Wood County.

The results can inform HAB-related supportive policymaking. For example, when considering providing support to the communities prioritized for assistance in mitigating vulnerability to Lake Erie HAB events, like the vast majority in Lucas County and the North East communities in Wood County, focusing on economic support may be the most effective. Conversely, for tracts in the south section of Wood County, it would be more significant to provide facilities to address their drinking water needs.

While the simulation and sensitivity analysis results guide adaptation supportive policies to address the social vulnerability aspect in this complex system, the scenario analysis results reveal how agricultural regulation policies can mitigate HAB severity, addressing the natural aspect in this simulated CHANS. Each scenario represents an environmental policy designed to address the environmental issue, and from the perspective of CHANS framework, it acts as an external intervention to disrupt the system's equilibrium which might further deteriorate the environmental condition. The model demonstrates the interactions among components within a CHANS, helpful for understanding the system, and more importantly, examining the efficacy of specific policies. In our case study, overall, the current adoption rate of cover crop, at around eight percent, contributes to stabilizing HAB severity at a moderate to severe level (Wittkofsky, 2023), consistent with our scenario two results. However, this adoption rate does not effectively mitigate the severity level over time, as the average severity indices before and after the practice promotion program do not show a significant difference. Conversely, if the adoption rate increases to 25 to 30 percent of farmland, as seen in states that effectively promote cover crop practices, such as Maryland (Wallander et al., 2021), overall HAB severity will present a downward trend after the program is implemented as revealed by Figure 4.6 for scenario three. This suggests that promoting cover crop practices and increasing the adoption rate can effectively address nutrient runoff and its contribution to the HAB issue in Lake Erie.

These findings align with previous studies that advocate establishing long-term targets for cover crop adoption, ranging from 20 million acres by 2020 to 100 million acres by 2025 (Hamilton et al., 2017). However, considering the financial burden and requirements for farmers to adopt cover crops (Wallander et al., 2021), we suggest governments consider increasing incentives to support farmers' cover crop adoption or promoting educational programs to enhance farmers' awareness of environmental issues and the benefits of adopting cover crops. Another potentially effective approach is targeting farms that have already adopted cover crops to increase their area of land dedicated to more cover crops, thereby reducing the overall adoption costs. Spatially, these regulations can be more effective when focusing on agriculturally dominated areas like census tracts, as shown in Figure 4.8.

Combining the policy implications on adaptation-supportive management discussed in this chapter and in the two previous studies, as well as agricultural regulations, we offer further discussions on specific areas based on their distinct agricultural and socioeconomic status, which can point to more complex policymaking circumstances. For example, Fulton County is a significant nutrient contributor to Lake Erie with medium-to-high levels of nutrient load as shown in Chapter Two (Figure 2.9). This signals to environmental policymakers that actions on HAB mitigation are necessary in this area. However, the results of both Chapters Three and Four indicate that census tracts across the county are not susceptible to, and face low risks from, HAB events in Lake Erie, which means mitigating HAB severity would not directly benefit the residents of the county. Consequently, local governments and residents lack motivation to allocate government resources or incur regulatory costs, such as implementing incentives for adopting cover crops, to address this environmental issue. Conversely, Lucas County is not a major nutrient contributor affecting HAB severity, but most tracts in this county suffer from poor socioeconomic status, resulting in high vulnerability to HAB events. This disparity raises issues of environmental injustice, as Lucas County residents, being downstream lake resource consumers, are the environmentally marginalized communities bearing a disproportionate share of negative environmental impacts (Mohai et al., 2009; US EPA, 2023).

We argue that multi-scale governance and implementing interventions at the most appropriate scales are essential to address this environmental justice issue. First, spontaneous actions are typically the main approaches to achieve adaptations (Adger, 2001), and smaller-scale interventions can be effective in encouraging these spontaneous actions. For example, community-based educational programs in the high-vulnerability census tracts around the center of Lucas County can help residents understand how the water issue affects their health and quality of life, know where to obtain resources and support during HAB hazard events, and raise awareness about the environmental justice issue they are facing. These programs can effectively reduce residents' responding time when hazards occur, thereby decreasing the harm they experience. At the same time, if the programs successfully build collective awareness of this environmental justice issue, residents can act to stimulate responsive governance from higher-level governments, such as county or state authorities, which can offer further support to these communities (Webster & Pavlovich, 2019). This process can create positive feedback to build adaptation capacity and community resilience for these high-vulnerability census tracts.

On the other hand, larger-scale governance usually has a broader vision of the issue across space and can set overarching goals based on it. For instance, even though the government of

Fulton County may not be motivated to address the HAB or environmental justice issue, the state government of Ohio may be able to hear the voices from the community-educated high-vulnerability residents and respond to their advocacy by implementing regulations on agricultural practices in nutrient-contributing areas like Fulton County. Similarly, federal level or international environmental agencies can set goals and coordinate efforts to mitigate the HAB issue, distributing nutrient loading reduction targets and incentivizing local governments to take regulatory actions. This approach aligns with current national and international efforts, such as Clean Water Act of 1972 and the Great Lakes Water Quality Agreement.

Additionally, higher-level government can be an appropriate source to directly address environmental injustice or HAB vulnerability issues through economic interventions. For example, the results of this study indicate that the extreme high-vulnerability communities located around the center of Lucas County would benefit from government allocation of resources to mitigate their HAB vulnerability sensitive negative factors, such as economic status, thereby reducing these residents' risks from HAB events and build community resilience. However, local government has tried to improve the economic status of low-income residents, but this long-standing issue remains. Local government programs, such as Lucas County's Prevention, Retention and Contingency Program (https://co.lucas.oh.us/913/Prevention-Retention-and-Contingency-Pro), have been assisting families in overcoming poverty. If the local government cannot mitigate the economic issues that contribute to HAB vulnerability in central Lucas communities, they cannot fully address this vulnerability issue. In this situation, higher-level governments or agencies can play a significant role by imposing charges on parties responsible for nutrient loads, such as farmers or fertilizer companies in upstream areas, and distributing these payments to support programs for downstream high-vulnerability communities. This approach can contribute to vulnerability reduction and environmental injustice mitigation in this CHANS of Lake Erie HABs.

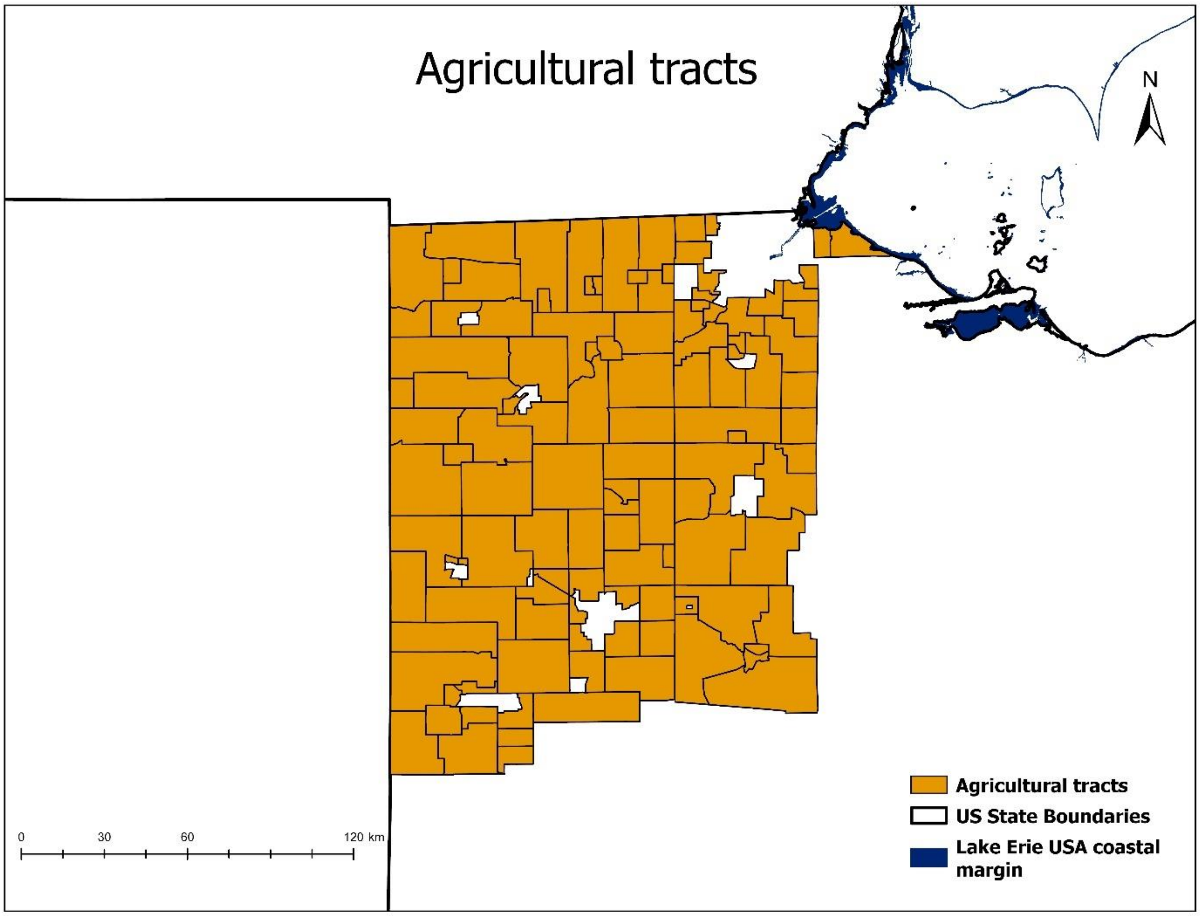

Figure 4.8 Agricultural tracts

Methodologically, this study demonstrates the utilization of a Monte Carlo-based simulation built upon Sobol sampling and the model's iUSA process to assess environmental social vulnerability to Lake Erie HAB events. While this approach has been applied in determining land use suitability in previous studies (Ligmann-Zielinska, 2013), this research marks the first instance of adopting this method to evaluate spatially explicit social vulnerability indices. By applying this method to environmental vulnerability studies, we highlight the usefulness of iUSA results in understanding the complexity of social vulnerability, exploring significant contributing factors that affect the HAB-DVI results in each spatial unit of our model, and providing policy recommendations. The application of this method in our study justifies the utilization of iUSA by exploring and examining the model. It also provides information on the drivers of change in the system and their significant implications from an applied perspective. Moreover, the scenario analysis in this study delves into the efficacy of adopting cover crops, a widely recognized beneficial agricultural activity that has not been sufficiently adopted in practice in Ohio. In short, our analyses may offer insights into understanding this practice's influence on mitigating Lake Erie HAB severity in the long run and suggesting government attention be directed towards its promotion.

4.5. Limitations and Future Research

As mentioned in Chapter Two, the lack of high-quality empirical data constrains the accuracy of the results of this study. Specifically, this chapter shows the disadvantage of spatially coarse empirical data in the dominant weight sensitivity map. We mainly attribute the relatively smooth surface of the dominant weight map to the lack of more specific drinking water source data. While the current results provide some insight into policy support when assisting vulnerable communities exposed to HABs, the results could be more specific if the water resource datasets matched the resolution of census tracts. Collecting more detailed empirical data could enhance this study's capacity to provide more specific and accurate information assisting policy design.

While exploring the weights of the three pillar criteria in social vulnerability that contribute to the HAB-DVI is the specific aim of this research, exploring the effects of additional variables, such as criteria values and MCE aggregation function, would provide more insight into the specifics of social vulnerability in terms of the variability of criteria values in each spatial unit, and the limitation of MCE results from the function choice. This limitation is partially due to computational costs and data availability. For the next step of this study, we propose integrating more variable effects in the HAB-DVI (Equation 1), like alternative layers reflecting adaptive capacity in vulnerability structure, to examine how different operationalizations of this pillar affect the uncertainty of the vulnerability index.

There is still ample opportunity to expand the model to provide a broader range of policy suggestions. First, in addition to agricultural regulation and incentive policies evaluated in current scenarios, more actions can be simulated as external forces affecting the dynamics in the system and potentially benefiting the agents or environment. For example, *could adaptation policies that help build community resilience ultimately play a positive role in mitigating HAB severity after the complex interactions in the CHANS? How does the scale of governance impact this issue?* Besides simulating a state-level regulation in this chapter, future studies will also implement different actions at various governance scales, such as federal and local, to examine their effectiveness and efficiency in addressing environmental and social vulnerability issues. The question of governance scale leads to another question: *What is the most suitable scale for specific policies, or what are the feasible policies for a specific governance scale that ensure that stakeholders are not overwhelmed by their costs or deprived of rights?* Addressing these questions has the potential to support policymaking in evaluating who supports or opposes the implementation of specific policies and evaluating the extent to which those policies might be blocked from being enacted. This part of the work requires more fieldwork and in-depth interviews.

Lastly, the scenario analysis could be augmented by using a more comprehensive model development that accounts for the viewpoints of different stakeholders – an aspect that is of particular importance in any social system study. For example, a policy scenario simulating a participatory policymaking process can be designed and implemented in this model. The scenario can involve a more complex policymaking process where specific actions are taken to ensure stakeholders, such as lake-related occupants and farmers, have their voices and opinions heard by the policymakers.

4.6. Summary

This chapter demonstrates the use of a Monte Carlo-based simulation built upon Sobol sampling and the model's iUSA process to assess environmental social vulnerability to Lake Erie HAB events (HAB-DVI). The results of this study identify census tracts with high HAB-DVI, aiding in prioritizing supportive financial resource allocation to help build communities' adaptation abilities and resilience in Lake Erie HAB events. The sensitivity analysis results of this study further delve into these vulnerabilities by identifying drivers of HAB-DVI across geographic locations (figure 4.7). Finally, the scenario analysis examines the dynamics in the CHANS of HABs involving the agricultural behaviors of farmers and their impacts on residents affected by the HAB events. It provides agricultural policy suggestions to mitigate HAB severity through interventions in farmers' behaviors that change the dynamics of this system.

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5. CHAPTER 5: DISSERTATION SUMMARY

5.1. Main research conclusions

This dissertation delves into the realm of environmental hazards, which are common and potentially high-consequence disturbances to the equilibrium of coupled human and natural systems (CHANS), rendering communities vulnerable to these events. The study's pivotal aim is to develop a robust research framework that seamlessly integrates the stochasticity, complexity, and dynamics inherent in CHANS vulnerability. This framework is not just a tool but a significant step towards assessing a spatially explicit social vulnerability for communities within CHANS. Its implementation will aid in prioritizing supportive policies to enhance community adaptability and resilience, a crucial aspect in the face of environmental hazards.

As CHANS for our case study, we took the harmful algal blooms (HABs) occurring in Lake Erie, the agricultural contributors to HABs, and the people affected by these events. We evaluated the social vulnerability of different communities facing Lake Erie HABs to comprehend the dynamics in this system and inform environmental policymaking. The real-world implications of this research are significant, as it can help in the formulation of targeted policies and strategies to mitigate the impact of HABs on communities, thereby enhancing their resilience and adaptability. Specifically, we investigated three aspects of this environmental-social vulnerability topic:

1). "From a static perspective using existing socioeconomic datasets, which are the counties most vulnerable to Lake Erie HAB events in the south and west parts of Lake Erie Basin?"

2). "From a systemic coupled human and natural systems (CHANS) perspective considering stochastic, complexities and spatiotemporal dynamics, where are the most vulnerable regions to Lake Erie HAB events in Maumee River Basin?"

3). "According to the systemic model built to simulate the CHANS, how do different variables affect the resulting vulnerability index and contribute to the sensitivity of the model?"

Research question #1 was addressed in Chapter Two, where we introduced a 5-theme spatial HAB vulnerability index (HAB-VI). This index comprises socioeconomic, resource dependence, and spatial factors affecting vulnerability to HAB events. Using a multi-factor hierarchical model, which enhances the CDC/ATSDR's Social Vulnerability Index (SVI) by extending indicators and thematic dimensions, we applied the index to evaluate the HAB-related vulnerabilities of 50 counties in the Lake Erie Basin. We also conducted a Monte Carlo-based uncertainty analysis and compared thematic maps to gain further insights into prioritizing regions for government support and community resilience.

Based on this study, we conclude with three main points. First, the identified high-vulnerability counties exhibiting a spatial pattern primarily aggregated in Ohio, adjacent to the southernmost boundary of Lake Erie. This finding offered valuable information for prioritizing supportive policies for local governments. Second, the uncertainty analysis yields a robustness map for our HAB-VI results, categorizing the study area into four segments and providing additional insights for policy prioritization. For example, while certain areas may not be prioritized based solely on their average HAB-Vi results, the uncertainty of the model suggests that some counties in these areas may require closer attention due to their highly possibly changing socioeconomic conditions during and after HAB events. Third, the comparison of thematic maps informs policymaking regarding management strategies. By integrating nutrient contribution levels and current policy strength with the HAB-VI, some areas with high contributions may not be suitable for environmental policy reinforcement due to their high vulnerability or existing regulation strength.

Research question #2 was investigated in Chapter Three by building an integrated agent-based model (ABM: AVUS) and multicriteria evaluation (MCE) to simulate a CHANS involving agricultural, economic, and governance systems. The Ordered Weighted Averaging (OWA) aggregated MCE model generated results in a stochastic and spatially explicit dynamic vulnerability index (HAB-DVI), reflecting the susceptibility of each census tract in the Toledo Metropolitan Area to Lake Erie HAB events. A Monte Carlo-based uncertainty analysis was further employed to provide policy prioritization suggestions.

This chapter yielded three main conclusions. First, the HAB-DVI results revealed a clear spatial pattern, with most high-vulnerability census tracts clustered around the center of Lucas County and the border between Lucas and Wood Counties close to Lake Erie. In contrast, low susceptibility tracts are aggregated in Fulton County. Second, the robustness map generated from uncertainty analysis indicates high confidence in most of the very high and very low vulnerability census tracts. However, most of the Wood and Lucas Counties tracts exhibited relatively high uncertainty. Therefore, we recommend monitoring most parts of this study area except for Fulton County, with certain tracts in the center of Lucas and Wood County identified as high-priority zones for community supportive policies or practices, such as putting more efforts in identifying low-income households, providing job opportunities, and guaranteed income programs. Specific aspects of support are discussed later in Chapter Four. Lastly, the integrated ABM-MCE framework effectively simulates the CHANS regarding environmental hazard disturbances and focuses on social vulnerability. By modeling the dynamics of CHANS, the chapter proposes a tool for evaluating the uncertainties of alternative future scenarios – a topic of the final - fourth chapter. In short, the framework can investigate various environmental hazards and provide adaptable policy recommendations.

Chapter Four conducted an integrated uncertainty and sensitivity analysis (iUSA) and scenario analysis on the ABM-MCE model framework to address question #3. We employed Monte Carlo simulation based on Sobol sampling on the MCE model to investigate how weights of the three vulnerability pillar criteria – distance (exposure risk), surface water dependency (intrinsic sensitivity), and income (adaptive capacity) – affect the variability of the outcome HAB-DVI. Additionally, three policy scenarios were designed and applied to AVUS to simulate the changes in dynamics of the CHANS and thereby estimate how the proposed policies can affect the severity of Lake Erie HAB events in the long run.

Two conclusions were drawn from the iUSA in this study. First, income weights predominantly influenced the sensitivity of HAB-DVI results in Lucas County and the North side of Wood County, which is adjacent to the border with Lucas County. On the other hand, the South side of Wood County primarily exhibited surface water dependency as the dominant variable affecting model sensitivity. This information is constructive for supportive policymaking targeted to these two areas. Specifically, areas dominated by income as the diver of HAB severity may require more economic support to cope with these disturbances while providing substitute drinking water facilities or focusing on improving communities' drinking water accessibility can be crucial for census tracts in South Wood County. Additionally, the scenario analysis also indicates that cover crop implementation is an effective practice to mitigate HAB severity in Lake Erie. Considering the costs of cover crop adoption, government should place efforts in promoting this practice and adjust incentive levels to encourage the implementations.

5.2. Intellectual merit

Methodologically, this dissertation develops a novel framework integrating ABM and MCE to explore environmental and social vulnerability within CHANS. This approach presents a state-of-the-art method for studying social vulnerability as one of the major characteristics of CHANS. First, CHANS involve complex interactions between human and environmental systems, which are inherently dynamic (Liu et al., 2007). To provide effective environmental policy recommendations targeting natural or social systems, it is crucial to employ approaches that can address these complexities (An et al., 2005, 2014, 2021). Hence, policy suggestions derived from such simulations are based on the dynamic nature of these systems. From the social vulnerability perspective, complexity and spatiotemporal dynamics are also significant features. Various dynamic factors within CHANS influence social vulnerability (De Ruiter & Van Loon, 2022; Drakes & Tate, 2022).

This study unitized agent-based modeling – a tool that has been used to model CHANS complexity (An, 2012; Chen et al., 2023; Nazir & Olabisi, 2015; Yang et al., 2022). Also, since environmental and social vulnerability must be measurable to inform policymaking, we employed a multicriteria evaluation that produces composite indicators accounting for multiple facets of the target system. Hence, this study develops the first ABM-MCE integrated framework to address CHANS's environmental and social vulnerability. This framework is particularly suited for evaluating vulnerability in CHANS, as the ABM simulates interactions and dynamics within these systems, generating spatiotemporal results that indicate significant factors for calculating a follow-up vulnerability index. In short, the proposed framework provides a robust method for policy-relevant analysis.

This dissertation also contributes to applied environmental science in studying social vulnerability within CHANS from multiple perspectives. First, the vulnerability indices calculated in this dissertation (HAB-VI in Chapter 2 and HAB-DVI in Chapters 3 and 4) are spatially explicit, allowing for delineating regions of high versus low social vulnerability (Armaș & Gavriș, 2013;

Cutter & Finch, 2008; Guillard-Gonçalves et al., 2015; Lehnert et al., 2020). In addition to addressing spatial heterogeneity, this dissertation also incorporates spatial features of vulnerability by adjusting the factors impacting or being affected by HAB events (specifically nutrient contribution and economic impacts on local income) through proximity-adjusted preferences (Ligmann-Zielinska & Jankowski, 2012). By integrating these adjustments and emphasizing the distance effect, the model simulates vulnerability that more accurately represents the spatial susceptibility distribution in real-world scenarios.

From the perspective of environmental policymaking, this dissertation provides empirically-based information to guide policies to support local community resilience and regulate agricultural fertilizer inputs, specifically in the context of Lake Erie HAB events and surrounding agricultural and economic systems. While previous studies have emphasized the importance of researching social vulnerability to environmental hazard events (Alvarez, 2022; Martinich et al., 2013; Nayak et al., 2018) None have explicitly focused on the Lake Erie HABs system. This study addresses this gap and provides suggestions on prioritizing areas for supportive policies. It also examines the importance of each criterion contributing to the vulnerability results, providing deeper insights into understanding HAB vulnerability from a systemic perspective. This enables policymakers to allocate resources more effectively and enhance community resilience.

Lastly, this research evaluated how selected Best Management Practices (BMPs) reduce the severity of HABs. Specifically, the coupled model tested cover crops BMP in Ohio that have been shown to reduce the nutrient levels in runoff (Blanco-Canqui, 2018; Hamilton et al., 2017). Through scenario analysis, this research tests the effectiveness of cover crop implementation in mitigating HAB severity and calls for policy efforts to promote this practice.

5.3. Limitations and future work

The data utilized in this dissertation are primarily sourced from public databases. Since the data are not specifically tailored for this study, some datasets require approximations that may inaccurately measure the selected system characteristics. For example, surface water dependency, used as a vulnerability indicator in Chapter 2 and as a pillar criterion in Chapter 3, is estimated based on the county-level ratio of surface drinking water sources to groundwater sources. This estimation excludes other possible drinking water sources, such as private wells. Additionally, the data are not detailed enough to accurately represent drinking water sources in each census tract, as other sources are not included. Another instance is the parameterization of the agents in AVUS. The aggregated fertilizer application level, estimated from historical data, may not accurately represent the fertilizing behavior of Ohio farmers. These data issues could affect the results of this study. Therefore, fieldwork, including surveys on farmers' behaviors and water accessibility, and especially participatory modeling, would help improve the accuracy of the conclusions from this study and provide more targeted policy recommendations to address the issues of importance to local communities.

While the spatiotemporal dynamics inherent in vulnerability within CHANS are adequately addressed in the integrated ABM-MCE framework, our results did not investigate the evolution trends of some focal factors, such as annual HAB severity and HAB-DVI. We plan to expand the simulations by looking into the temporal changes in model runs to reveal any potential emergent trends. Additionally, exploring how compounding hazard events affect this CHANS is another promising direction. The occurrence of different types of hazards adds more complexities to this framework and is an important topic in studying environmental and social vulnerability in a complex context. *For example, after years of Lake Erie HAB events, how would the occurrence of* *a pandemic compound the dynamics in the system and stress the adaptive capacity of different communities?* Similar topics warrant further investigation in future work.

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