Social Vulnerability and Climate Risk Assessment for Agricultural Communities in The United States

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Abstract
Floods and droughts significantly affect agricultural activities and pose a threat to food security by subsequently reducing agricultural production. The impact of flood events is distributed disproportionately among agricultural communities based on their socio-economic fabric. Understanding climate-related hazards is critical for planning mitigation measures to secure vulnerable communities. This research presents a comprehensive risk evaluation methodology for assessing the combined risk of drought and flood hazards among agricultural communities in the United States. By integrating social vulnerability levels with drought and flood exposure data, the study identifies the most vulnerable agricultural communities individually, aiming to provide significant insights into the vulnerability of the agricultural community in the continental U.S. The research addresses a critical scientific gap through a nationwide social vulnerability assessment, evaluating expected annual losses for flood and drought hazards, and combining social vulnerability with expected annual losses. The analyses were conducted by adapting datasets and methodologies that are developed by federal institutions such as FEMA, USACE, and USDA. The study identified the 30 most socially vulnerable counties and assessed their exposure to drought and flooding, finding that Mendocino, Sonoma, Humboldt, El Dorado, Fresno, and Kern counties in California had the highest drought exposure and expected annual losses, with Humboldt (CA) and Montgomery (TX) having the highest combined risk.

Keywords: Flood, Drought, Social Vulnerability, Risk Quantification, Agricultural Communities

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1. Introduction

Hydrometeorological disasters have severely impacted agricultural activities over the past couple of decades (Sivakumar et al., 2005; Ye et al., 2014). Due to increasing catastrophic events, food security issues are receiving more attention from the scientific communities as a result of the effects of droughts and floods on agricultural activities in recent decades. According to the Food and Agriculture Organization (FAO), flooding alone is reported as the biggest underlying reason for crop production losses in the world (FAO, 2015). In many countries, floods also have a substantial impact on the fishing, farming, and forestry industries (Dewan, 2015; Meissner et al., 2013; Rubel and Kottek, 2010). Submergence of the crop causes complex abiotic stress, such as decreased light availability, oxygen depletion, and altered chemical properties of the soil. All of these physical and chemical changes can significantly reduce crop stand as well as crop growth and yield (Wang et al., 2022). In addition to floods, droughts are also a major risk factor for agricultural practices since they affect water availability and soil moisture as a result of a lack of rainfall (Leng et al., 2015; Islam et al., 2023). Numerous studies demonstrated the impact of drought events to crop yields around the globe (Cohen et al., 2021; Ray et al., 2018; Hamal et al., 2020).

Agricultural communities have an important role in food production, and understanding of the vulnerability of those communities is critical for evaluating food security (Sohail et al., 2022; Tanır et al., 2021a). In many countries, food security is in danger due to a growing number of hydrometeorological disasters (Prosekov and Ivanova, 2018). Extreme floods and prolonged drought events are deteriorating the existing food security problems, and some communities have limited resources to respond to these events (Workie et al., 2020). International organizations often provide mitigation grants and technical resources to help exposed areas before and after disasters (Ahmad and Ma, 2020; Tanır, 2021). However, the largest proportion of the aid is made for post-disaster events (United Nations, 2021). On the other hand, preparedness efforts generally result in reducing post-disaster expenses, which can be achieved by analyzing flood and drought history and future trends at the site (Chang et al., 2007).

Recent studies have shown that the frequency and magnitude of flood events are increasing due to the implications of climate change (Alfieri et al., 2017; Vousdoukas et al., 2018). Accelerated land use alterations, rapid urbanization, and underdeveloped drainage systems cause agricultural losses (Aich et al., 2016; Benito et al., 2010). Crop and livestock production are expected to be affected by more frequent floods in many regions of the world (IPCC, 2022). To reduce future losses, risk and vulnerability should be examined to develop flood response plans (Alabbad and Demir, 2022). Therefore, mitigation actions can be successfully implemented (Yildirim et al., 2022). In addition to damage reduction, several studies have presented the indirect benefits of mitigation efforts. Sustainable agriculture, diversification of the ecosystem, and enhanced resilience are addressed as the potential benefits of mitigation efforts by researchers (Johnson et al., 2020; Pudar et al., 2020). Designating the most vulnerable sites is the first step to starting such efforts to maximize mitigation benefits.

In the case of droughts, recent research reveals that drought conditions in many parts of the world may worsen as a result of global warming (Cook et al., 2015; Sun et al., 2019). Climate projections show that the severity and frequency of drought events are likely to increase due to climate change (Hagenlocher et al. 2019). People in rural areas are more susceptible to droughts because of their proximity to nature and reliance on agriculture (Savari et al. 2022). Thus, although there is uncertainty regarding future estimates, risk assessments are required to evaluate and reduce the negative consequences of drought events on agricultural activities (Hagenlocher et al. 2019). Addressing who is going to be affected to what degree is essential to reducing the potential risk of food security before a disaster (Savari et al. 2022). Therefore, the identification of disaster-prone regions is significant for responding to events in order to minimize their potential impact.

Successful identification of the most susceptible regions can lead to better mitigation planning and disaster management so that potential losses can be prevented in agricultural communities (Alabbad et al., 2022). Determining vulnerable locations is also essential for better allocation of mitigation resources (Yildirim and Demir, 2022). Socioeconomic parameters should be carefully evaluated to reflect the most accurate vulnerability of the communities (Tanır et al., 2021b). Flood and drought event datasets and social indicators can be evaluated as potential resources to establish data needs and prioritize parameters (Haltas et al., 2021; Cikmaz et al., 2022). This step should consider social equality to ensure that everyone has complete and equal access to meet their needs using distributed resources (Emrich et al., 2020). Thus, a fair allocation of support can be achieved while lowering the risk and vulnerability (Alabbad et al., 2023).

1.1. Importance of Equity in Vulnerability Assessment

Social vulnerability assessments are widely used tools to quantify both the physical and social dimensions of any risks (Adger, 2006; Tanir et al., 2021b). Several studies focused on the vulnerabilities of the agricultural communities under flood (Monterroso et al. 2014; Remo et al. 2016; Chen et al. 2019; Ahmadi et al. 2022) and drought events (Tran et al. 2021; Lottering et al. 2021; Savari et al. 2022; Mens et al. 2022). The spatial distribution of the social vulnerabilities is represented as a result of these studies to identify the most vulnerable agricultural areas among communities (Lottering et al., 2021). Some studies focus on different spatial scales (i.e., county, watershed) for regions like Potomac River Watershed (MD, VA, DC, PA) (Tanir et al. 2021a) or Iowa (Yildirim and Demir 2022). There are limited studies that focus on evaluating the flood and drought social vulnerability of agricultural communities in the entire U.S. Engström revealed drought vulnerability in the United States with integrated assessment by combining exposure index (drought frequency, population density, and protected waters as exposure index) with socio-economic (GDP per capita), preparedness (drought plan), and some physical (cattle, recreational lakes, irrigation, etc.) parameters (Engström et al. 2020).

Equity issues that underlie the disproportionate impacts of climate change on certain communities are needed to be addressed for social justice. Vulnerable communities, such as low-income and minority groups, may lack access to resources and social networks that can help them cope with and adapt to the impacts of climate change (Zografos et al., 2016). Similarly, these communities may have limited political power to influence policies and decision-making processes related to climate change. Equity issues need to be considered in climate vulnerability assessments to ensure that vulnerable communities are not further marginalized or excluded from decision-making processes related to climate change adaptation and mitigation (United Nations, 2022). This requires incorporating social vulnerability indicators, such as socioeconomic status, race and ethnicity, and language proficiency, into vulnerability assessments to better understand the underlying social and institutional factors that contribute to vulnerability. It also requires engaging with vulnerable communities to incorporate their perspectives and needs into decision-making processes related to climate change. By addressing equity issues in vulnerability assessments, decision-makers can work towards ensuring that climate change adaptation and mitigation efforts are inclusive and equitable for all communities.

1.2. Existing Methodologies for Vulnerability Indexing

Agricultural vulnerability indexes are used to assess the exposure of agricultural systems to different climate-related hazards and their capacity to cope with them. Existing indexes assess different aspects of vulnerability and can be used to inform decision-making and adaptation strategies. The Environmental Vulnerability Index (EVI) measures vulnerability of environment on a global scale by assessing social, economic, and ecological factors that contribute to vulnerability. The EVI includes an agricultural sub-index that evaluates the exposure of agricultural systems to climate hazards, such as drought and floods, as well as their adaptive capacity, which includes factors such as land-use policies and agricultural extension services (Kaly et al., 1999). Another agricultural vulnerability index is the Climate Change Vulnerability Index for Agriculture (CCVI-A), which assesses the vulnerability of agricultural systems to climate change. The CCVI-A includes indicators such as crop yield variability, irrigation potential, and access to financial resources (Edmonds et al., 2020).

In another study, Tanir et al. evaluate the spatiotemporal distribution of agricultural flood vulnerability in the Potomac River Watershed, by using socio-economic parameters such as the economic well-being of farmers, education level, age, social status, and access to information. Then, the study merges combined social vulnerability index with economic loss due to flood hazards to happen each day within the watershed to observe spatiotemporal agricultural flood vulnerability levels. The Agricultural Drought Vulnerability Index (ADVI) is a newly developed index that incorporates high-resolution satellite data to assess the vulnerability of agricultural systems to drought. The ADVI uses numerous indicators, including vegetation cover, soil moisture, and land-use patterns, to analyze the impact of agricultural systems on drought and their capacity to cope with it (Murthy et al., 2015). However, while current agricultural vulnerability indexes deliver useful information, they also have limitations, such as the lack of specificity for local contexts and the challenge of incorporating complex socioeconomic factors.

Existing agricultural vulnerability indexes extensively cover biophysical factors, such as climate, soil, and water availability; however, these indexes ignore social, economic, and political factors. To address these limitations, new indices are needed for the identification of vulnerable agricultural communities. The vulnerability of small-scale farmers to climate change may be influenced not only by their exposure to climate hazards but also by their access to resources, such as finance, technology, and markets, and their capacity to adapt to changing conditions (Gbetibouo and Ringler, 2009). Educational factors also play a significant role in the vulnerability of communities by affecting the accessibility of available resources (Muttarak and Lutz, 2014). Such demographic parameters are crucial to determining the level of vulnerability of communities. Therefore, developing a vulnerability index that embraces those parameters can pave the way for better vulnerability mapping. The development of a better social vulnerability index and its integration with physical hazard indicators will improve our understanding of spatial risk distribution. As a result of having both physical and social dimensions of risk, the selective targeting of the spatial allocation of mitigation measures on communities will be more robust, and mitigation activities will be planned more effectively (Cutter et al. 2003).

1.3. Proposed Study

This research proposes a comprehensive risk evaluation methodology for agricultural communities in the United States for both drought and flood hazards. The combined risk is assessed by merging social vulnerability levels with drought and flood exposure among communities to identify the most vulnerable agricultural communities individually. This study aims to provide significant insights on agricultural community vulnerability in the continental U.S. and investigate flood and drought exposure of the most vulnerable 30 counties. Due to the data collection and processing time, the study focuses on the 30 most vulnerable communities to understand the hydrometeorological disaster exposure on agriculturally vulnerable communities.

In the literature, urban populations are often selected as a focus area for vulnerability research. For instance, Tate et al. evaluated social vulnerability and the urban population's exposure to flooding by focusing on the social vulnerability of the entire population in the U.S. However, socioeconomic features that are specific to agricultural communities were not assessed. (Tate et al., 2021). Tanir et al. focused on only agricultural flood vulnerability in the Potomac River Watershed, but drought hazards were not included in the assessment (Tanir et al., 2021). The social vulnerability and resilience of farmers to climatic hazards, specifically drought and flooding, are underreported in the literature.

Therefore, this study aims to fill scientific gaps in the following areas: 1) investigating nationwide social vulnerability assessment for agricultural communities; 2) evaluating expected annual loss for flood and drought hazards; and 3) combining nationwide social vulnerability and expected annual loss for flood and drought hazards. The following section of the study describes the methodology that covers data sources, community vulnerability index development, and loss quantification of hydrometeorological events. The results section presents the key findings related to the quantified losses in terms of floods and droughts for the studied communities. Finally, the conclusion and any challenges encountered during the research will be discussed at the end.

2. Methodology

2.1. Data Life Cycle

The study utilized several datasets to conduct hydrometeorological disaster vulnerability analysis. Socio-economic parameters are employed to identify the most vulnerable agricultural communities in the United States. An extensive set of data is collected on agricultural information, census, and flood inundation maps for various spatial scales. The following subsections deliver more details about the obtained datasets.

Agricultural Information: Crop Data Layer (CDL), which is created annually by the United States Department of Agriculture (USDA), provides a high-resolution (30-meter) representation of cropland cover for the entire continental United States (USDA, 2023). Along with the agricultural land use data, price per unit (USDA, 2022a), crop yield (USDA, 2022b; USDA, 2022c; USDA, 2022d; USDA, 2022e; USU, 2022), harvest costs (USDA, 2022f), and government commodities (USDA, 2022g) are collected from the USDA for an accurate representation of quantified losses.

Census: The census information is collected from the US Census Bureau (Census Bureau, 2018) and USDA Census of Agriculture. Socioeconomic features of agricultural communities including gender, age, minority, net cash income, and access to information were obtained from Census of Agriculture while poverty level, percentage of population works in agriculture, fishing, and hunting, and percentage of the population have completed 12th grade were obtained from U.S Census Bureau.

Flood Inundation Maps: FEMA designated the Special Flood Hazard Area (SFHA) based on the 1-percent chance of a flood event. If the region is statistically at risk of being flooded with a 1% chance or more frequently, it is considered an SFHA. The study obtained flood risk inundation maps that were created by FEMA for the SFHA zone (FEMA, 2022). However, flood inundation maps are not available for some of the selected counties in the study. The maps were collected for 26 counties out of 30.

Drought Hazard: Drought hazards for agricultural areas were adapted from the National Risk Index calculated by FEMA, which is a baseline risk assessment for the U.S. in each county, and we utilized the methodology to estimate expected annual loss (EAL) (FEMA, 2023).

2.2.1. Socio-Economic Parameters

Socio-economic data were acquired from the Census of Agriculture (2017) of the United States Department of Agriculture National Agricultural Statistical Service (USDA, 2017) and the U.S. Census Bureau (2018). The Census of Agriculture is a comprehensive survey of the agriculture sector in the entire U.S. Information about the features of farms, ranches, and operators is gathered every five years in the Census of Agriculture. The most up-to-date data available at the time of this study, the 2017 census, was used. 13 different socio-economic parameters were considered representative in terms of indicating the social vulnerabilities of rural populations as a result of extensive literature research. Both data availability and the suitability of the parameters for the study were considered while determining the parameters. Socioeconomic parameters utilized in the SOVI are listed in Table 1. The United Census Bureau (2018) was used for parameters, such as the percentage of the population under the poverty level and the percentage of the population who have completed 12th grade. The county-level information was obtained from both data sources and analyzed on an individual county basis.

Table 1. Agricultural community vulnerability parameters (Tanir et al., 2021a)

Parameter Description	**Code/Data Sources/Effect on SOVI**
Percentage of female producers	F/USDA (2017)/(+)
Percentage of 65 years and older farmers	O/USDA (2017)/(+)
Percentage of farms with new and beginning producers (10 years less experience)	IE/USDA(2017)/(+)
Percentage of minority farmers	M/USDA(2017)/(+)
Average age of producers	AA/USDA(2017)/(+)
Total value of agricultural products sold	APS/USDA(2017)/(+)
Percentage of population works in agriculture, fishing, and hunting	PA/CENSUS(2017)/(+)
Percentage of population under poverty level	P/CENSUS(2018)/(+)
Percentage of farmers have internet connection	IA/USDA(2017)/(-)
Percentage of the population completed 12th grade	HE/CENSUS(2018)/(-)
Net cash income of farms	NCI/USDA(2017)/(-)
Percentage of farms with sales of $250.000 or more	X250K/USDA(2017)(-)
Acres of land in farms as percent of land area in acres	AL/USDA(2017)(-)

According to the vulnerability literature, the percentage of minority, older, inexperienced, farmers under the poverty level, and female producers increase the social vulnerability level of agricultural communities (Nelson et al. 2002; Brooks et al. 2005; Reid et al. 2007, Abdur Rashid Sarker et al. 2013; Monterrosso et al. 2014; Jose et al. 2017; Hoque et al. 2019; Fremstad and Paul, 2020; Tanir et al. 2021), while socio-economic parameters that enhance the resilience of farmers such as net cash income of farmers, internet connection, and higher education attainment decreases the total vulnerability level of farmers (Nelson et al. 2002; Ma et al. 2007; Abdur Rashid Sarker et al. 2013; Chauhan et al. 2020). It is assumed that some parameters used in the literature will not affect the vulnerability of farmers in the United States, since they are mostly used in developing or underdeveloped countries and the social dynamics of rural communities will differ among countries.

The correlations of SOVI parameters with each other were also evaluated (see Figure 1). The strong correlations were indicated by darker colors. The heatmap below illustrates that some parameters, such as the percentage of the population living below the poverty level and the percentage of farmers that have internet connections, are negatively correlated, whereas the average age and percentage of 65-year-old and older farmers are positively correlated with each other as expected. The lowest correlation was found between the total value of agricultural products sold and minority farmers, which is hard to logically relate. However, a logically reasonable negative correlation was found between the percentage of the population living below the poverty level, the percentage of the population who have completed the 12th grade, and the percentage of farmers who have an internet connection. Logical reasoning and comparisons were used as a control mechanism in terms of the compatibility and accuracy of the data, which will form the basis for future social vulnerability assessments.

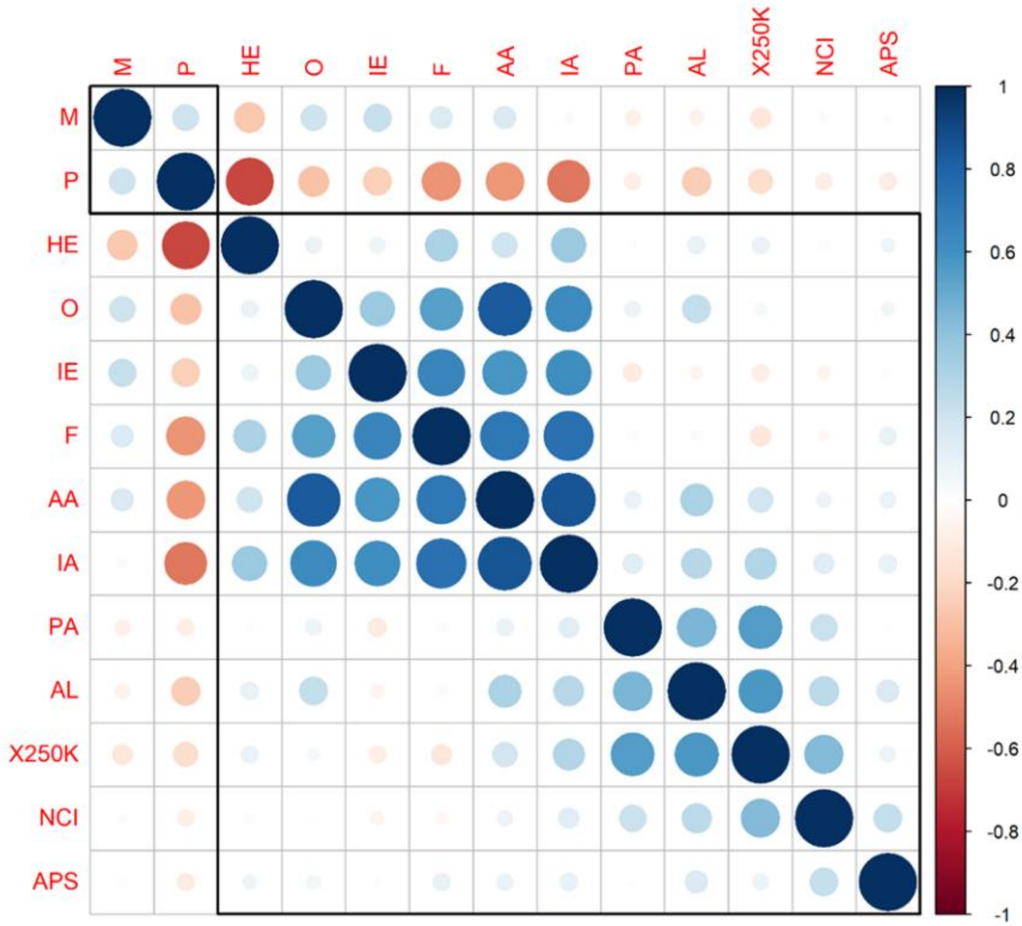

Figure 1. Correlation of social vulnerability parameters with each other

2.2.2. Drought Parameters

Drought risk was evaluated using the National Risk Index (NRI), which indicates the risk of communities in all counties of the U.S. across 18 different hazard types, including drought. The method was introduced by the federal government and widely accepted by decision-makers in the US. Then, we enabled the collected datasets for risk quantification to specifically evaluate drought hazard. The expected annual loss, which is the product of drought annualized frequency, exposure, and historic loss ratio (HLR), was used to define drought exposure on agricultural practices within the scope of this study (Zuzak et al., 2022).

The results of the NRI were not utilized directly in this study since social vulnerability parameters in NRI are defined to express the vulnerabilities and resilience of entire population.

However, in this study, adapted parameters that specifically define both the resilience and social vulnerability of agricultural communities were utilized in the generation of SOVI. Thus, the SOVI was calculated based on the features of agricultural communities and then combined with expected annual losses in agriculture due to drought from NRI (NDMC, 2018; Zuzak et al., 2022). Then, SOVI and expected annual loss were combined with a bivariate evaluation, as represented in Figure 2.

2.2.3. Flood Risk Parameters

Flood risk is evaluated by utilizing FEMA flood inundation maps and the AGDAM damage model, which was created by the U.S. Army Corps of Engineers. In this study, we only considered 100-year flood inundation maps due to limited access to other scenarios. In general, average annualized loss is computed by using multiple flood scenarios such as 2, 5, 10, 25, 50, 100, 200, and 500-year flood scenarios, but this study provides the analysis for 100-year flood event scenarios. Because the analyzed scenario is designated as SFHA by FEMA, risk quantification is still significant to understand the potential crop vulnerability. The AGDAM model allows estimating direct crop loss based on the crop pricing information and inundation area. The AGDAM model is one of the most notable agricultural flood loss estimation models that take flood duration and growing time into account (Yildirim and Demir, 2022). The model estimates the loss for a scenario using the following equation (USACE, 1985):

$$L_s = A(p \cdot Y - H) \cdot R(t) \cdot D(t) \qquad \text{Eq. 1}$$

where "A" stands for the inundated agricultural area, "p" is the unit price of the crop (price per bushel), "Y" is the crop yield (bushels per acre), "H" is the harvest cost ($ per acre), "D" is crop loss at the "t" day, and "R" is a crop loss modifier based on the duration of the flood. The unique loss function for each crop type indicates crop loss for a given time of year and flood duration modifier. In this investigation, losses based on crop growth are estimated at three distinct times of the year. As previously mentioned, USDA reports are adopted as primary resources for our analysis. The required agricultural information is collected for each studied county.

2.2. Risk Quantification

In Figure 2, a detailed workflow for the agricultural community vulnerability index is provided. In the following sections, more information is given about utilized datasets and adapted methodologies. As depicted in Figure 2, three main indexes (Agricultural Drought Exposure, Agricultural Community Social Vulnerability Index, and Agricultural Flood Exposure Index) were evaluated and utilized to assess the agricultural community Drought/Flood Vulnerability Index among all counties in the U.S. Firstly, the 30 most vulnerable counties in the U.S. were identified based on the SOVI that utilized the parameters in Table 1, and then drought and flood exposure were evaluated. For drought exposure, expected annual loss (EAL) values for each county were obtained from the FEMA National Risk Index, while flood exposure values were calculated using

FEMA inundation maps for a 100-year return period and the AGDAM Loss Model. Then, both exposure values and FSOVI were evaluated together (bivariate evaluation) to identify FD(F)VI.

2.2.1. Social Vulnerability Index

Social vulnerability of agricultural communities is determined not only to capture risk definition entirely with the inclusion of social perspective but also to develop operational strategies before disasters. Figure 2 presents the methods used to quantify the Social Vulnerability Index (SOVI). 13 different socioeconomic factors (Table 1) were combined to define the overall vulnerability levels of agricultural communities with the statistical procedure Principal Component Analysis (PCA). After implementing PCA, the combined SOVI was calculated via the equation below. Parameters that have a positive and negative impact on vulnerability were calculated separately and then combined. The impacts of parameters on combined SOVI were listed in Table 1. After combining SOVI values, all SOVI values are normalized and represented by Natural Jenks Classification using ArcGIS. Red colors in the SOVI map represent more vulnerable farmers in the indicated county.

$$SOVI(+) = PCA_1(+) * W_{PCA_1}(+) + PCA_2(+) * W_{PCA_2}(+) + \cdots + PCA_8(+) * W_{PCA_8}(+) \qquad \text{Eq. 2}$$

$$SOVI(-) = PCA_1(-) * W_{PCA_1}(-) + PCA_2(-) * W_{PCA_2}(\pm) + \cdots + PCA_8(-) * W_{PCA_8}(-) \qquad \text{Eq. 3}$$

$$SOVI = SOVI(+) - SOVI(-) \qquad \text{Eq. 4}$$

2.2.2. Principal Component Analysis

The principal component analysis (PCA) is a factor reduction method that enables researchers to capture the linear combinations that accurately represent the information from a large group of variables (Monterroso et al., 2014; Kong et al., 2017; Bucherie et al., 2022). It is considered as a matrix factorization method based on the covariance of the entire dataset (Abson et al. 2012). Many studies in vulnerability assessment have utilized PCA (Cutter 1996; Rygel et al. 2006; Oxfam America 2009; Chakraborty et al. 2020; Medina et al. 2020).

In addition, PCA is one of the most widely used tools for quantifying vulnerability, according to a systematic review study that evaluates the validity of social vulnerability assessment methods (Fatemi et al. 2017). The PCA method is the most efficient way to avoid the disadvantages of the unit difference between parameters, which is a common problem in vulnerability assessments since different parameters with different units have been utilized (Rygel et al. 2006; Abson et al. 2012; Tanir et al. 2021). PCA offers several advantages in the case of the aggregation of spatially explicit, presumably incommensurable variables (Abson et al. 2012).

Each principal component (PC) contains information from the combination of original variables. The higher-order principal components describe more of the data's overall variation than any individual original variable. Except for the lower-order PCs, PCs reduce the data's dimensionality (number of variables) while minimizing information loss. PCA provides a method for transitioning from a large set of individual indicators to a limited number of composites, unitless indices (PCs). In addition, it reduces the trade-off between information richness and communicability (Abson et al. 2012).

Prior to performing the PCA procedure, some statistical tests, such as Bartlett's Test of Sphericity and Kaiser-Meyer Olkin (KMO) measures of sampling adequacy, must be performed to determine if the dataset is suitable for the procedure (Chakraborty et al., 2020; Tanir et al., 2021). All tests were performed using RStudio packages such as Factoextra, FactoMiner, REdaS, Bartlett.test, and KMO. A visual assessment was used after the PCA procedure to decide how many PCs will be utilized in the assessment. The common consensus in literature is that the representation of the information by more than 70% is enough to claim that original variability has been represented with the PCs (Cutter et al. 2003; Chakraborty et al. 2020; Tanir et al. 2021).

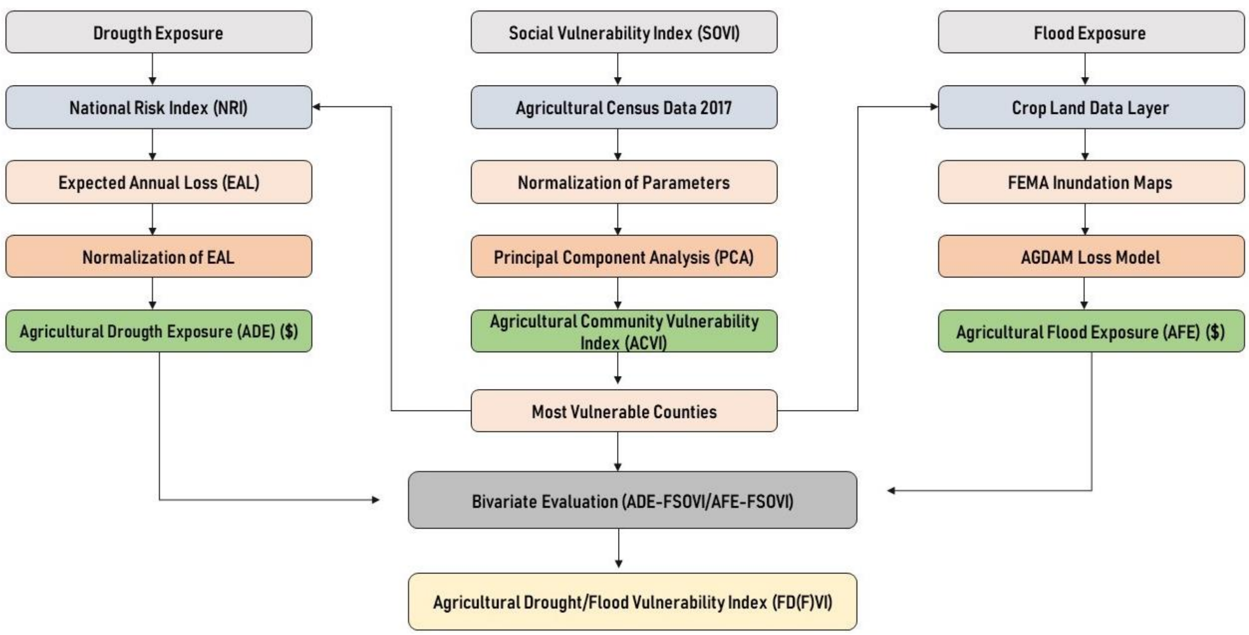

Figure 2. Agricultural community vulnerability indexing procedure.

2.3. Flood and Drought Vulnerability Assessment

Initially, the study identified 30 counties in the United States with the highest social vulnerability, and then proceeded to assess their risks to flood and drought using separate methods. The procedure is illustrated in Figure 2. For the drought vulnerability assessment, data from FEMA's National Risk Index and expected annualized loss methodology values were employed to evaluate drought hazards in each county. The hazard index was normalized to allow for the combination of the hazard index with the Social Vulnerability Index (SOVI). On the other hand, the Flood Vulnerability Assessment involved the combination of 100-year return period flood inundation maps with crop data layers to assess hazard loss on major crops in each county (see Figure 2).

To observe the relationship between social vulnerability and hazard exposure, the study utilized the bivariate mapping technique. This technique allowed for the combination of Expected Annual Loss (EAL) and 100-year flood loss data, which were spatially distributed using quantiles within ArcGIS. The highest quantiles, representing very high exposure levels (V) to drought and flood hazards, were classified using the same color scheme as the SOVI map, thus indicating their spatial distribution. Finally, the study combined the SOVI and exposure levels, incorporating geospatial layers that captured both the physical and social dimensions of risk.

3. Results

3.1. Agricultural Community Vulnerability Assessment

Based on the spatial distribution of social vulnerability levels among agricultural communities (Figure 3), it can be deduced that communities are generally more vulnerable in southern states than they are in northern states. Particularly, counties in the West South Central, Pacific, South Atlantic, and East South-Central regions have high or very high vulnerability levels. Most agricultural communities have low or very low vulnerability levels in the Midwest states. The share of the state's labor force contribution by farmers is highest in the Midwest states, which means that the total size of the agricultural business is significant. The size of the agricultural sector in those regions indicates the ability of the local farmers to economically withstand and absorb potential shocks (Ma et al. 2007).

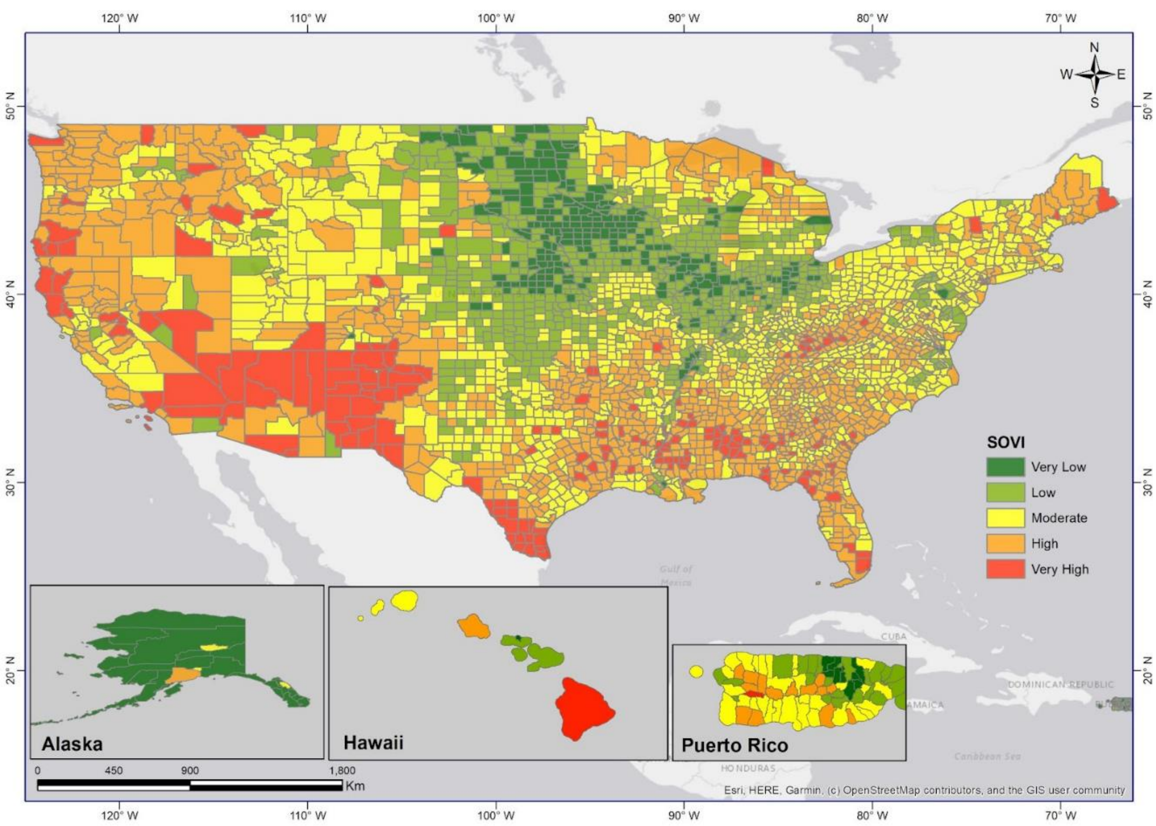

Figure 3. The spatial distribution of agricultural community vulnerability in the U.S.

Similarly, counties in the northern part of the South Atlantic, Mid-Atlantic, Alaska, and New England have lower vulnerability levels. The main reason for the heterogeneous distribution is the spatially differentiated socio-economic characteristics of the agricultural communities in the U.S. For instance, parameters that increase the level of vulnerability, including the percentage of minority farmers, the population under the poverty level, and older farmers, are higher in southern states. On the other hand, socio-economic features that decrease the vulnerability of farmers, such as the percentage of farmers who have an internet connection, higher educational attainment, net cash income of farmers, and percentage of farms with sales of $250.000 or more, are higher in Midwest states.

Figure 4 demonstrates the ratio of counties to the total number of counties based on vulnerability levels. It is indicated that farmers in more than half of the counties in New Mexico and Arizona are very vulnerable (Figure 4). In addition, it is striking that 93% of Arizona's counties are determined to be highly or very highly vulnerable. The analysis also shows the vast majority of communities in Arizona are less resilient to any shock compared to communities that have average socioeconomic vulnerability levels in the U.S. Similar to Figure 3, geographic patterns illustrate that agricultural communities in counties located in the southern states have higher levels of vulnerability. The least socially vulnerable counties were concentrated in Connecticut, Alaska, DC, Delaware, Illinois, Iowa, Kansas, Maryland, Minnesota, Nebraska, Ohio, Pennsylvania, and West Virginia (Figure 4), which are mainly located in the northern part of the country (Figure 3). In particular, most agricultural communities in North Dakota have very low levels of SOVI. Therefore, it is fair to claim that the consequences of any natural hazard will be unevenly distributed between the northern and southern parts of the country (Yoon D.K., 2012).

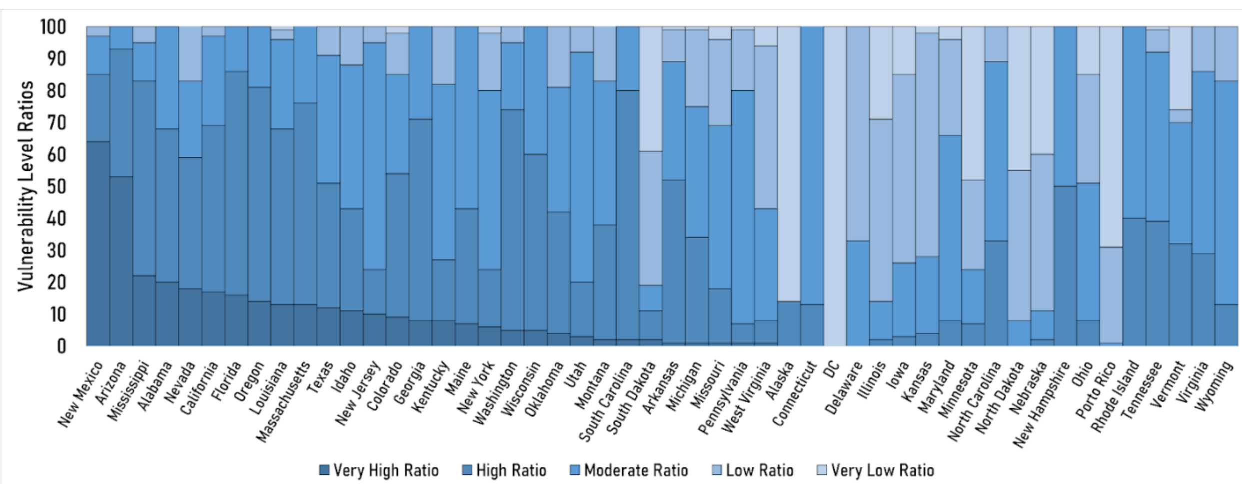

Figure 4. Distribution of SOVI level ratios among counties in the U.S.

As a result of the social vulnerability assessment conducted by PCA, the 30 counties with the highest vulnerability ratings across the country were determined. Later, these counties were normalized between 0 and 10 and ranked according to their scores. Among these 30 counties with the highest vulnerability, 10 show the highest vulnerability and 0 show the lowest. The fact that these top 30 counties are from 10 different states shows that high social vulnerability was found in one-fifth of the states in the country. Even though it was stated that agricultural communities in southern states are more vulnerable, the results reveal that 50% of the states are from the west and Midwest regions. The SOVI assessment found that the three counties with the highest degree of vulnerability were in the state of Texas. The study discovered that the majority of counties with the highest vulnerability level were from the southern states (TX, AZ, and NC) and California.

Table 2. Agricultural community vulnerability scores for the 30 most vulnerable communities

County/State	**Vulnerability Score**
Parker, TX	10
Harrison, TX	9.71
Hamilton, TX	9.46
Weld, CO	9.45
Marion, OR	9.41
Harvey, KS	9.39
Humboldt, CA	9.36
Shelby, TX	9.29
Montgomery, TX	9.25
Cass, TX	9.24
Saline, KS	9.24
Sonoma, CA	9.16
Kern, CA	9.16
Yavapai, AZ	9.13
Sedgwick, KS	9.12
Fresno, CA	9.09
Austin, TX	9.07
Stephens, OK	9.07
El Dorado, CA	9.07
Guadalupe, TX	9.06
Washington, KS	9.05
Mendocino, CA	9.04
Lamar, TX	9.02
Lancaster, NE	9.02
Johnston, NC	9.01
Gem, ID	9.01
Hunt, TX	9.01
Los Angeles, CA	9.00
Dawson, TX	9.00
Graham, KS	9.00

3.2. Drought Assessment

The expected annual loss values for the 30 most vulnerable countries in the U.S. are listed in Table 3. As Table 3 illustrates, Sonoma (CA) has the highest expected annual agricultural loss of approximately 57 million dollars. Gem (ID), Shelby (TX), and Hamilton (TX) have experienced less loss than the rest of the counties due to drought. Similar to SOVI, strong regional differences were found across the most vulnerable counties in terms of EAL. For instance, 95 million dollars of EAL have occurred in California from a total of approximately 100 million dollars, which is 95% of the total EAL occurring in the 30 most vulnerable counties.

In the analysis of the IPCC report, which investigates the regions where the likelihood of agricultural drought has intensified due to climate change, it was concluded with medium confidence that the probability of encountering agricultural drought has increased, primarily in West North America, encompassing California, consistent with NRI results (IPCC, 2022). Figure 5 illustrates that Sonoma County had by far the highest expected annual loss value and a high number of producers. Upon further analysis of the overall distribution, Fresno County emerged with the highest number of producers. Evaluating the expected annual loss per producer value, Sonoma County was found to have the highest level at approximately $8,600. The counties in California (Sonoma, Mendocino, Fresno, and Humboldt) have the highest expected annual loss per producer. In addition, Gem County ($0.61) exhibited the smallest expected annual loss per producer value.

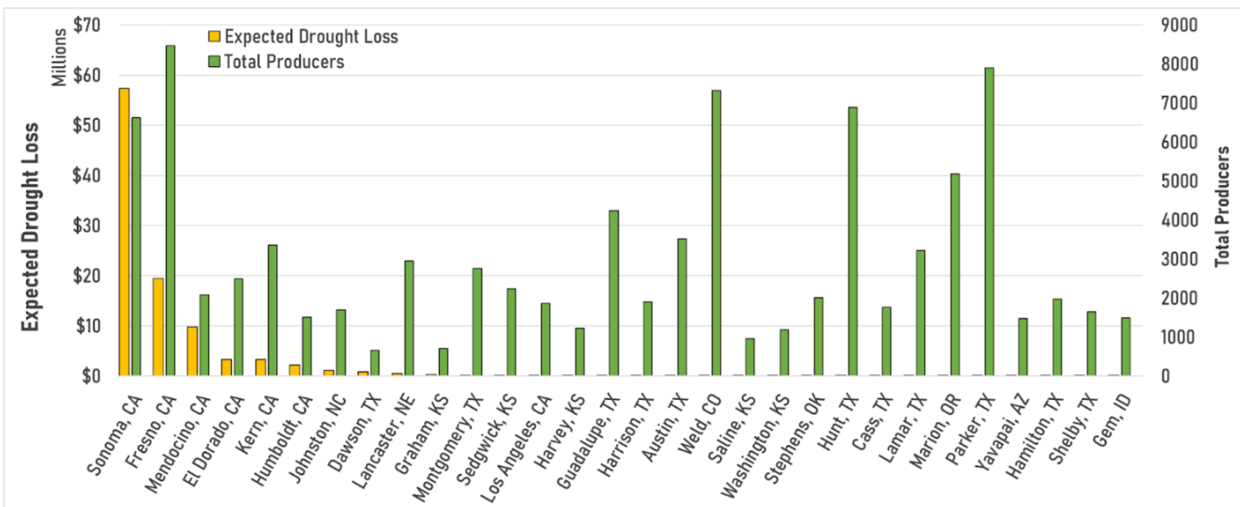

Figure 5. Expected annual loss and number of farmers

Table 3. Expected annualized losses due to droughts.

County/State	Expected Annual Loss
Parker, TX	$10,000
Harrison, TX	$74,000
Hamilton, TX	$4,000
Weld, CO	$56,000
Marion, OR	$12,000
Harvey, KS	$118,000
Humboldt, CA	$2,162,000
Shelby, TX	$3,000
Montgomery, TX	$168,000
Cass, TX	$26,000
Saline, KS	$47,000
Sonoma, CA	$57,294,000
Kern, CA	$3,287,000
Yavapai, AZ	$10,000
Sedgwick, KS	$165,000
Fresno, CA	$19,475,000
Austin, TX	$68,000
Stephens, OK	$32,000
El Dorado, CA	$3,300,000
Guadalupe, TX	$88,000
Washington, KS	$47,000
Mendocino, CA	$9,762,000
Lamar, TX	$18,000
Lancaster, NE	$532,000
Johnston, NC	$1,156,000
Gem, ID	$900
Hunt, TX	$27,000
Los Angeles, CA	$142,000
Dawson, TX	$905,000
Graham, KS	$285,000

Using the agricultural drought vulnerability assessment method, the expected annual loss (EAL) from agricultural drought exposure was spatially assessed. Figure 6 demonstrates the spatial distribution of EAL and SOVI in the right and left panels, respectively. The top counties having the largest drought exposure were identified as Mendocino, Sonoma, Humboldt, El Dorado, Fresno, and Kern, all of which are located in California. Considering the fact that the western part of the U.S. experiences more severe drought (Engström et al., 2020; Yesilkoy et al., 2023) and is more agriculturally active (Pathak et al., 2018; USDA/NASS 2022 State Agriculture Overview for California, 2022), it is likely that the counties located in the western part of the U.S. have a larger expected annual loss, according to literature (Engström et al., 2020).

In a study conducted in California that aimed to quantify climate, crop, land use, and socioeconomic vulnerability in the entire state, the south of California was more vulnerable than the north of the state (Pathak et al., 2018). Owing to inherent disparities encompassing dissimilarities in the parameters employed as well as the scale and scope of the undertaken investigation, articulating a distinct distribution pertaining exclusively to California within the purview of our study is unattainable. In addition, a substantial portion of counties in Texas and Oklahoma indicate lower EAL values in Drought Exposure Index analysis.

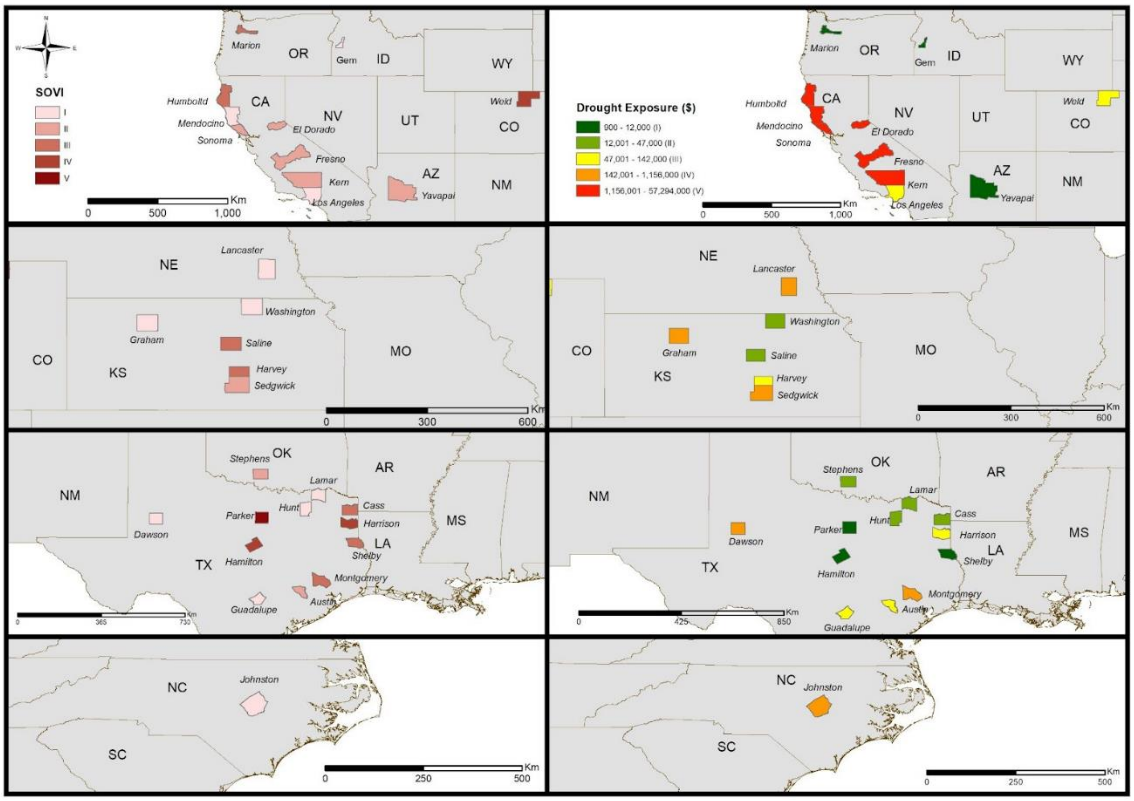

Figure 6. Drought Exposure and SOVI levels among most vulnerable counties

3.3. Flood Assessment

Direct flood impact is examined for the selected counties, considering the special flood hazard area (SFHA), which is designed by FEMA for regions within the 100-year flood zone. The inundation area is estimated at each of the land use data to quantify at-risk areas and potential monetary losses. In figure 7, inundation area by land use is provided for each county to understand what specific land use types are in the 100-year risk zone. More than half of the studied sites have a substantial risk of crop losses due to flooding. The regions with the highest exposure are close to large streams or water bodies, with the exception of Dawson, Texas.

Despite Dawson being located in an arid area, agricultural activities are being practiced over 40% of the 100-year flood zone. This may be an indicator that the county may be prone to flash flooding given the geographical features of the region (i.e., arid, low-lying). The inundated crop land area is estimated to be particularly high for Midwestern communities such as Kansas and Nebraska. Although vulnerability indexes for the selected communities are higher than in other regions, some of the studied sites have low flood exposure in Texas, California, and North Carolina. Croplands are not within the 100-year flood zone for these communities; however, these regions are prone to drought, as shown in Table 3 above.

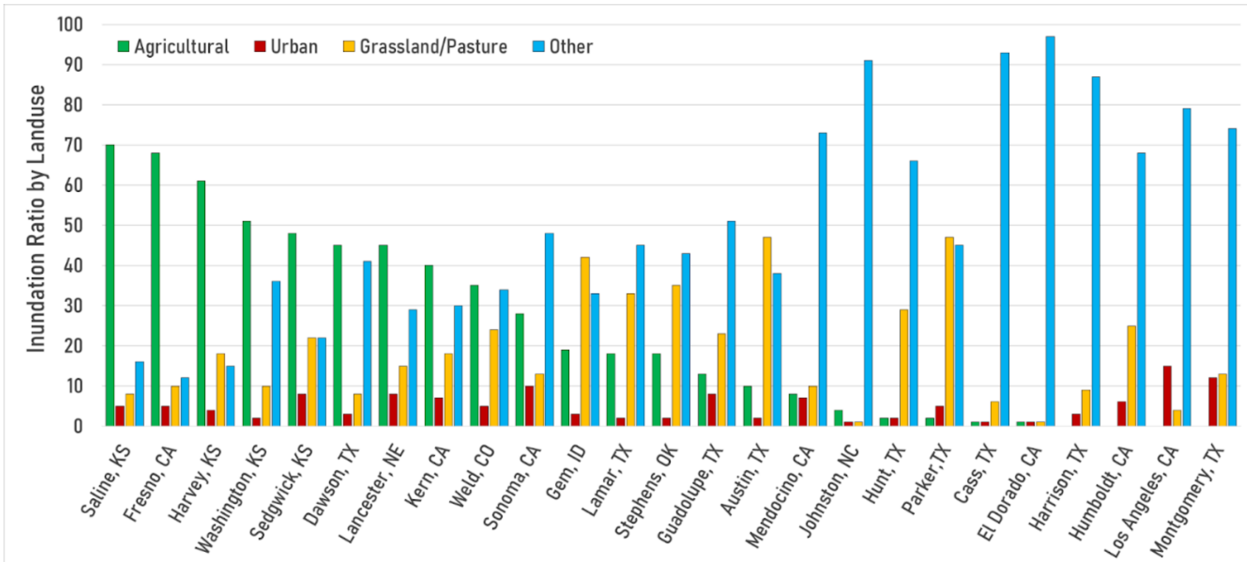

Figure 7. Inundation area ratios by distinct land uses

In Table 4, we provide the estimated monetary losses from crop damage due to flooding. We also present the flood map availability for the studied regions. Four of the selected communities had no publicly available flood maps at FEMA at the time the study was conducted. While some flood maps are relatively new, some regions have over 10-year-old flood maps. Particularly in Texas, the flood maps are older than others, and the majority of the missing flood information was from the same state. Because the selected communities are in the top 30 most vulnerable counties, recent flood risk products are essential to address existing vulnerabilities and take action against flooding. Also, up-to-date flood maps are critical to reflect vulnerable regions considering frequent land alterations.

Our results show that over $1 billion in crop damage is estimated in all studied counties within the 100-year flood zone. Because the adopted damage quantification model (AGDAM) only estimates direct damage, overall loss is very likely to be higher considering indirect losses (i.e., market disruption, unemployment, and insurance premiums). Quantified losses are found to be greater, particularly for California counties such as Kern, Fresno, and Sonoma, due to large-scale agricultural practices, the diversity of the impacted crop types, and higher market value crops. Our analysis reveals 14 distinct crop types are impacted in California, which is higher than any other selected site. Some of these crop types include almonds, pistachios, tomatoes, grapes, wheat, alfalfa, garlic, onions, and walnuts. On the contrary, the diversity of the impacted crops is limited in the Midwestern counties. Primarily, corn, soybeans, and wheat are the major crop types that are impacted in the Midwest (Saline, Sedgwick, Harvey, and Lancaster). We also found that flood damage has no impact on agricultural lands in some of the Texas and California counties. The underlying reason is that those regions are either highly urbanized or arid lands; therefore, flooding has no impact in these communities.

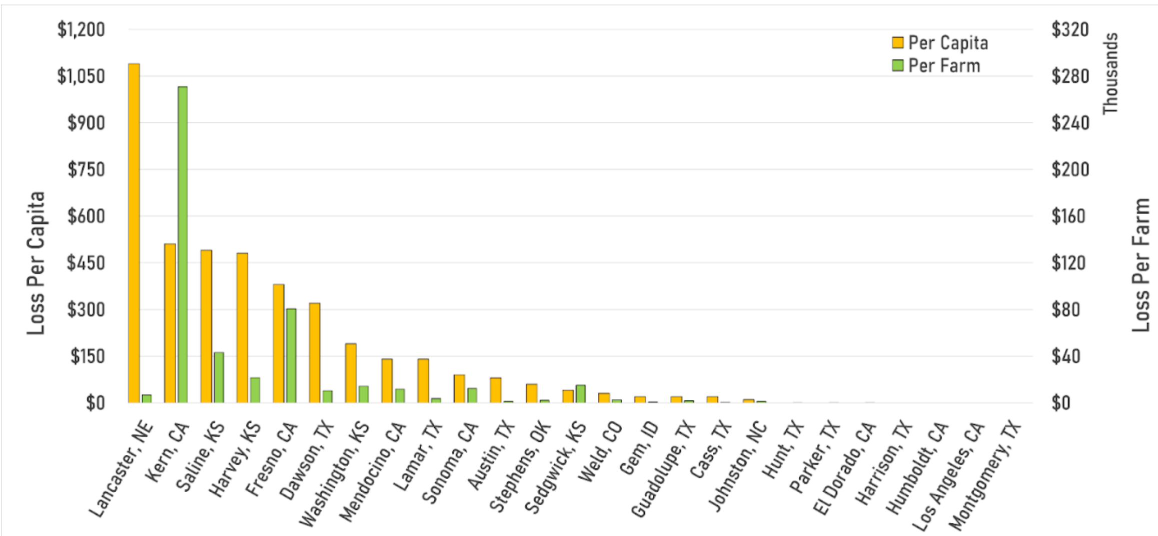

Figure 8. Quantified flood losses per capita and per farm in the studied region

Quantified crop losses per capita and per farm are illustrated in Figure 8 for the selected sites in the study. The figure helps to understand regions where the agricultural community is specifically impacted. In Lancaster, Nebraska, crop loss per capita is greater than in other regions; however, crop loss per farm is significantly lower. While the loss per capita is estimated at just over a thousand US dollars, the estimated loss per farmer is nearly seven thousand US dollars. This is a strong indicator that small-scale individual farmers are particularly impacted. Similar to Lancaster, individual farms are impacted in some of the Kansas and Texas counties, as shown in Figure 8. On the contrary, larger farms are especially impacted in California counties such as Kern and Fresno. The estimated loss per farm is substantially and proportionally higher than the loss per capita in other US counties. The estimated loss per capita is almost negligible for the remaining counties, as is the loss per farm.

Table 4. Estimated direct crop losses and flood map data availability for the studied sites.

County	100-year Loss	Flood Map Availability	Flood Map Year
Kern, CA	$468,666,000	Yes	10/21/2021
Fresno, CA	$383,990,000	Yes	01/20/2016
Sonoma, CA	$44,289,000	Yes	07/19/2022
Saline, KS	$26,291,000	Yes	04/18/2018
Sedgwick, KS	$20,468,000	Yes	12/22/2016
Harvey, KS	$16,176,000	Yes	08/04/2014
Mendocino, CA	$13,039,000	Yes	07/18/2017
Lancaster, NE	$11,899,000	Yes	04/16/2013
Weld, CO	$10,318,000	Yes	01/20/2016
Washington, KS	$9,926,000	Yes	11/18/2015
Lamar, TX	$6,860,000	Yes	08/16/2011
Guadalupe, TX	$4,315,000	Yes	12/30/2020
Dawson, TX	$4,010,000	Yes	02/04/2011
Stephens, OK	$2,571,000	Yes	09/29/2010
Austin, TX	$2,384,000	Yes	10/18/2019
Johnston, NC	$1,204,000	Yes	07/19/2022
Cass, TX	$578,000	Yes	04/03/2012
Gem, ID	$490,000	Yes	08/24/2021
Hunt, TX	$431,000	Yes	01/06/2012
Parker, TX	$236,000	Yes	04/05/2019
El Dorado, CA	$176,000	Yes	04/05/2019
Humboldt, CA	$0	Yes	06/21/2017
Los Angeles, CA	$0	Yes	06/02/2021
Montgomery, TX	$0	Yes	08/18/2014
Harrison, TX	$0	Yes	09/03/2014
Hamilton, TX	N/A	No	N/A
Shelby, TX	N/A	No	N/A
Graham, KS	N/A	No	N/A
Marion, OR	N/A	No	N/A
Yavapai, AZ	N/A	No	N/A

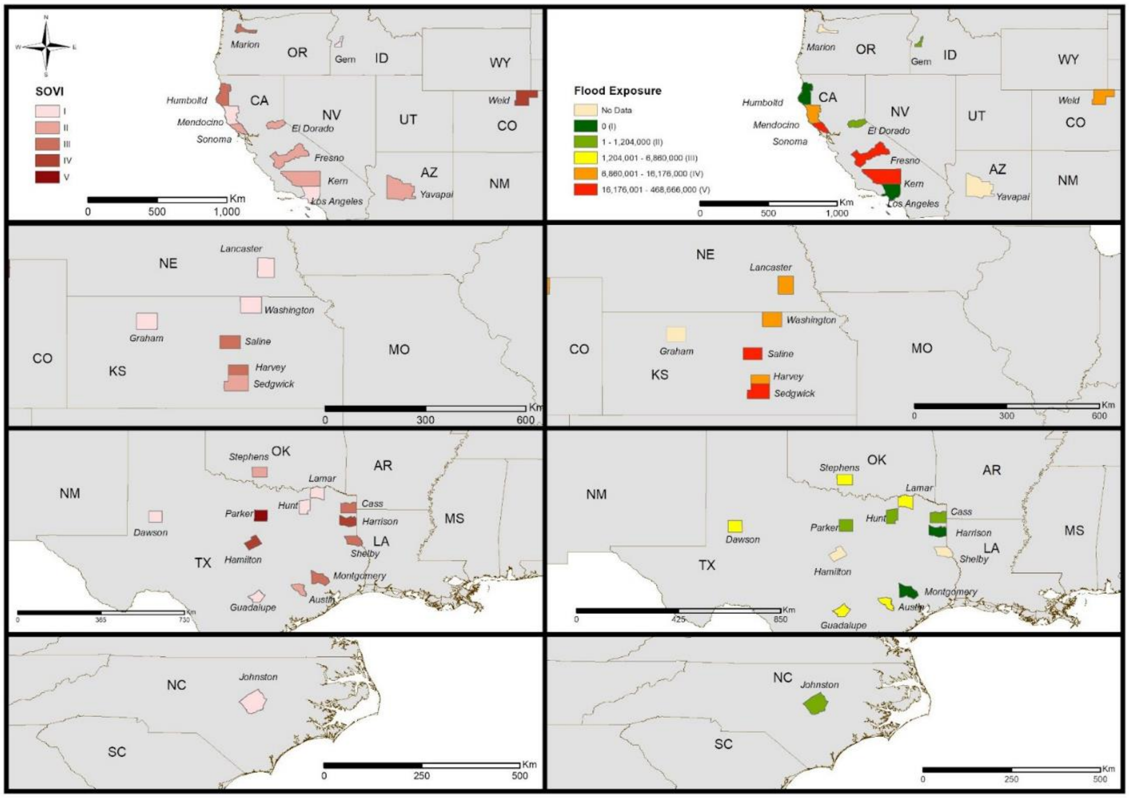

Figure 9. Flood Exposure and SOVI levels among most vulnerable counties

In Figure 9, we demonstrate the spatial distribution of the SOVI (left) and the quantified agricultural flood losses (right). The majority of the vulnerable counties are located in the Midwestern region, which has large streams such as the Smoky Hill, Saline, and Kansas Rivers. However, Lancaster has several small creeks that are contributing to major flooding in the counties rather than having a major stream. Considering the higher social vulnerability of the region, the overall vulnerability of these communities is significantly higher than other regions. Some of the California counties are also prone to agricultural flood losses; however, their social vulnerability indexes are relatively lower than those of Midwestern counties.

3.4 Flood and Drought Assessment

The primary goal of this research is to identify areas with high social vulnerability as well as high exposure to drought and flooding separately. Therefore, exposure and social vulnerability indexes were combined. The high spots (where SOVI (IV-V) and exposure (IV-V)) were illustrated as dark red. As the exposure and vulnerability scores decrease, the colors on the map transition from a dark red to lighter colors, indicating a reduction in combined risk. Table 5 shows the SOVI and exposure index values for each county. The results of the drought vulnerability assessment demonstrate a more dispersed pattern of vulnerability compared to the flood vulnerability assessment. The pattern of high vulnerability appeared in almost each section on the left panel of Figure 10. On the right panel of Figure 10, the spatial distribution of the flood vulnerability assessment shows, however, that the majority of the highly vulnerable agricultural communities were in the West and Midwest**.**

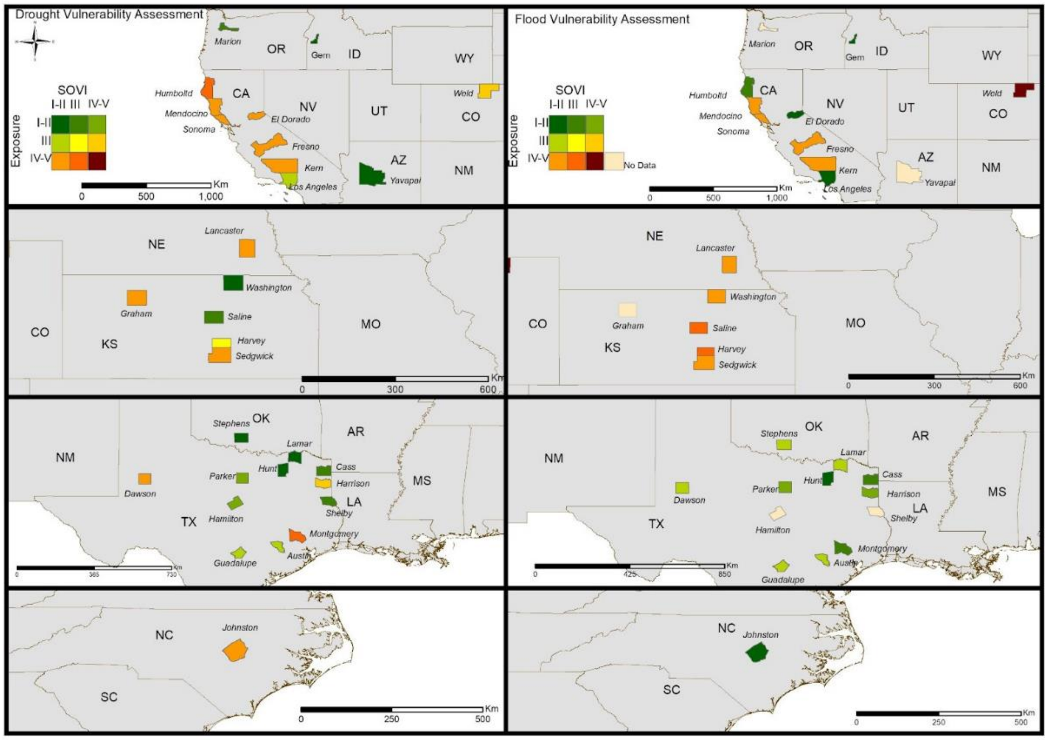

Figure 10. Combined figure to show bivariate analysis of drought and flood farmers vulnerability

In none of the counties, the highest values of drought exposure and social vulnerability indexes coincided. Thus, counties where the highest exposure and social vulnerability values coincide were identified as being at the highest risk in terms of drought. High index values of social vulnerability and counties with moderate drought exposure are located in California (Humboldt) and Texas (Montgomery). High social vulnerability values were observed in these areas, primarily attributed to their socio-economic characteristics, including high percentages of female and older farmers, a very low percentage of farms with sales of $250.000 or more, and a low percentage of farms with net cash income. Weld County (CO) stands out with the highest vulnerability and flood exposure rating among all the counties, with a $10,318,000 100-year flood loss. Weld County (CO) emerged as the most socially vulnerable due to a higher proportion of females, inexperienced farmers, and a population living below the poverty level.

Almost all counties located in the east and south were found to be at low risk due to low exposure levels. In flood vulnerability assessment, Midwestern counties are specifically under higher exposure, such as Lancaster (NE), Washington (KS), Saline (KS), Harvey (KS), and Sedgwick (KS). On the other hand, we found that some of the counties have considerably high exposure to both floods and droughts in California, such as Kern, Fresno, Sonoma, and Mendocino. Considering their high agricultural productivity, hazard reduction efforts are significant for these communities to ensure high food production. The need for the highlighted region is also acknowledged by recent research (Ward et al., 2020; Pathak et al., 2018)

Table 5. Scores for SOVI, drought exposure, drought vulnerability index, flood exposure, and flood vulnerability indexes

County/ State	SOVI	FDE	FDVI	FFE	FFVI
Parker, TX	High (V)	Low (I)	L-H (I-V)	Low (II)	L-H(II-V)
Harrison, TX	High (IV)	Moderate(III)	M-H(III-IV)	Low (I)	L-H(I-IV)
Hamilton, TX	High (IV)	Low (I)	L-H (I-IV)	Low (I)	L-H(I-IV)
Weld, CO	High (IV)	Moderate(III)	M-H(III-IV)	High (IV)	H-H(IV-IV)
Marion, OR	Moderate(III)	Low (I)	L-M(I-III)	Low (I)	L-M(I-III)
Harvey, KS	Moderate(III)	Moderate(III)	M-M(III-III)	High (IV)	H-M(IV-III)
Humboldt, CA	Moderate(III)	High (V)	H-M(V-III)	Low (I)	L-M(I-III)
Shelby, TX	Moderate(III)	Low (I)	L-M(I-III)	Low (I)	L-M(I-III)
Montgomery, TX	Moderate(III)	High (IV)	H-M(IV-III)	Low (I)	L-M(III-I)
Cass, TX	Moderate(III)	Low (II)	L-M(II-III)	Low (II)	M-L(III-II)
Saline, KS	Moderate(III)	Low (II)	L-M(II-III)	High (V)	H-M(V-III)
Sonoma, CA	Low (II)	High (V)	H-L(V-II)	High (V)	H-L(V-II)
Kern, CA	Low (II)	High (V)	H-L(V-II)	High (V)	H-L(V-II)
Yavapai, AZ	Low (II)	Low (I)	L-L(I-II)	Low (I)	L-L(I-II)
Sedgwick, KS	Low (II)	High (IV)	H-L(IV-II)	High (V)	H-L(V-II)
Fresno, CA	Low (II)	High (V)	H-L(V-II)	High (V)	H-L(V-II)
Austin, TX	Low (II)	Moderate(III)	M-L(III-II)	Moderate(III)	M-M(III-III)
Stephens, OK	Low (II)	Low (II)	L-L(II-II)	Moderate(III)	M-L(III-II)
El Dorado	Low (II)	High (V)	H-L(V-II)	Low (II)	L-L(II-II)
Guadalupe, TX	Low (I)	Moderate(III)	M-L(III-I)	Moderate(III)	M-L(III-I)
Washington, KS	Low (I)	Low (II)	L-L(II-I)	High (IV)	H-L(IV-I)
Mendocino, CA	Low (I)	High (V)	H-L(V-I)	High (IV)	H-L(IV-I)
Lamar, TX	Low (I)	Low (II)	L-L(II-I)	Moderate(III)	M-L(III-I)
Lancaster, NE	Low (I)	High (IV)	H-L(IV-I)	High (IV)	H-L(IV-I)
Johnston, NC	Low (I)	High (IV)	H-L(IV-I)	Low (II)	L-L(II-I)
Gem, ID	Low (I)	Low (I)	L-L(I-I)	Low (II)	L-L(II-I)
Hunt, TX	Low (I)	Low (II)	L-L(II-I)	Low (II)	L-L(II-I)
Los Angeles, CA	Low (I)	Moderate(III)	M-L (III-I)	Low (I)	L-L(I-I)
Dawson, TX	Low (I)	High (IV)	H-L(IV-I)	Moderate(III)	M-L(III-I)
Graham, KS	Low (I)	High (IV)	H-L(IV-I)	Low (I)	L-L(I-I)

4. Conclusion

The study provides an easy and convenient methodology that can enable researchers to combine both social and physical dimensions of risks. The Social Vulnerability Index (SOVI), flood hazards, and drought hazards were combined separately to identify both dimensions of risks. The analysis of SOVI results shows geographical variability in social vulnerability between the northern and southern parts of the U.S. due to differences in the social fabric of farmers. Parker

County, located in Texas, has been identified as the most vulnerable county due to its high percentage of female and older farmers, as well as a substantial proportion of farmers living below the poverty level. Additionally, the county exhibits low levels of income derived from agricultural activities. Results of the SOVI assessment depicts that socioeconomic factors in farmers influence the degree of severity of impacts of meteorological natural hazards such as drought and flood, which is consistent with related literature.

In this study, the 30 counties with the highest social vulnerability were identified to examine their exposure to drought and flooding and conduct a combined risk analysis. Subsequently, the exposure values for drought and flooding were assessed separately and merged with social vulnerability. The Expected Annual Loss (EAL) values for drought in agricultural areas, as calculated by the National Risk Index (NRI), were used for the 30 most vulnerable counties. Using the agricultural drought vulnerability assessment method, drought exposure was spatially assessed using EAL. The analysis showed that Mendocino, Sonoma, Humboldt, El Dorado, Fresno, and Kern counties in California had the highest drought exposure and expected annual losses. This is consistent with previous literature indicating that the western part of the U.S., known for more severe drought conditions and agricultural activity, tends to have larger expected annual losses. The counties with the highest level of risk were found to be Humboldt (CA) and Montgomery (TX) when exposure and vulnerability values were combined.

The research examined the direct impact of flooding on selected counties in terms of flood hazard areas, inundation areas, and potential monetary losses. The findings indicate that more than half of the studied sites are at substantial risk of crop losses due to flooding, with the highest exposure occurring near large streams or water bodies. Surprisingly, Dawson, Texas, an arid region, also experiences significant agricultural activities within the 100-year flood zone, suggesting the possibility of flash flooding due to the region's geographical features. The Midwest, particularly Kansas and Nebraska, shows a particularly high area of inundated crop land. While vulnerability indexes are higher in the selected communities, some regions in Texas, California, and North Carolina have low flood exposure due to their location outside the 100-year flood zone. The estimated crop damage due to flooding amounts to over $1 billion in all studied counties within the flood zone, with California counties experiencing the greatest losses due to large-scale agricultural practices and a diverse range of impacted crops. Conversely, the Midwest is primarily impacted in terms of major crop types such as corn, soybeans, and wheat. The study emphasizes the importance of up-to-date flood maps, as some regions have outdated maps or lack publicly available flood information. It is worth noting that the estimated losses only consider direct damage and do not account for indirect losses such as market disruption and unemployment. Additionally, the analysis reveals that crop losses per capita and per farm vary across regions, indicating that small-scale individual farmers are particularly impacted in some areas while larger farms face substantial losses in others.

The proposed methodology can be replicated in other countries or at other scales by utilizing similar datasets to identify vulnerable agricultural communities. However, accessibility of the flood inundation maps can be challenging due to the required expertise and long processing time which can be tackled with data driven flood map generation approaches (Li and Demir, 2022). In this research, 100-year flood extents were the only accessible dataset for the studied regions. A detailed assessment generally requires multiple flood scenarios (i.e., 2-, 5-, 10-, 25-, 50-, 100-, 200-, and 500-year) so that results can indicate an expected annual loss to present an existing risk for the studied community. Therefore, more accurate flood reduction planning can be achieved. Mitigation and adaptation efforts should not only focus on the physical damage but also the social fabric of farmers, and all efforts should be tailored to the root causes of vulnerabilities. The study's findings identify specific locations throughout the country that require additional efforts in terms of adaptation and mitigation to flood and drought hazards so that resiliency of these communities can be improved.

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