Evaluating the Flood Vulnerability of Urban Areas in Polk County, Iowa using Social-Ecological-Technological Framework

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Abstract
The escalating prominence of floods globally, with their catastrophic potential to inflict substantial losses in terms of both human lives and economic resources, underscores their significance. Particularly susceptible to flooding between May and July, the US Midwest faces heightened risks during this critical period, characterized by the highest average precipitation rates of the year. Flood vulnerability assessments furnish organizations with crucial insights into expected extreme events and strive to mitigate potential harm from these risks. The Social-Ecological-Technological (SETS) framework, a comprehensive flood vulnerability assessment method, highlights the significance of aligning natural, technological, and demographic systems to comprehend and effectively address the complexity of natural hazards, facilitating the achievement of optimal results. In this study, the relationship between the 500-year flood event and the SETS vulnerability indices formed by 18 selected parameters was examined for Polk County, Iowa. Moreover, linear regression and spatial autocorrelation analyses were conducted on vulnerability indices. The results indicated that the S-E-T vulnerability map, which is the combined effects of all social, ecological, and technological exposure, sensitivity, and adaptive capacity parameters considered, the areas most impacted to damage are identified as the highly populated downtown Des Moines, where urban development is concentrated along a highway (I-235) and large industrial buildings. When looking at all the vulnerability maps produced, the number of census block groups in the very high vulnerability class is low. However, in Polk County, it has been presented that there is strong spatial autocorrelation indicating that vulnerability index values are highly clustered. These findings will support sustainable approaches and stronger contextual solutions for city managers and practitioners that decrease the risks of flooding in Polk County communities.

Keywords: social-ecological-technological systems, flood risk, vulnerability, resilience, risk assessment, urban planning, GIS

1. Introduction

The catastrophic nature of floods and their potential to cause enormous losses in terms of both human lives and economic resources (Alabbad and Demir, 2022) have made them increasingly prominent on a worldwide scale in recent times (Saharia et al., 2017; Yildirim et al., 2022). According to the National Weather Service (2015), the concept of flood is briefly defined as a situation where a dry area is flooded by the rise of water in the waterbed, such as coastal areas, lakes, streams, or canals (Haltas et al., 2021). Extreme rainfall is a major cause of flooding and has become more common as global temperatures have increased (Huang et al., 2022). Due to rainfall events, floods can happen practically anywhere in the world in a matter of hours (flash flood) or days (flood), and their risks are rising in many parts of the world (Chang et al., 2019). One of the most affected countries by floods is the United States (Retchless et al., 2014; Li and Demir, 2022; Zhou et al., 2018).

According to the study conducted by Wing et al. (2018), by intersecting FEMA flood maps with the population data, over 13 million US population could be exposed to serious floods. According to the study, the calculated rate for flood exposure is 2.6-3.1 times higher than the estimates in previous years. Specifically, the Midwest region of the US is considered to be one of the regions where flood events are most common (Demir et al., 2022; Sit et al., 2021). The characteristics of extremely high precipitation in the late spring and summer months trigger this disaster. The period between May and July has the highest average precipitation rates in the Midwest and also the highest probability for flood events (Dirmeyer & Kinter III, 2010). Compounding the impacts of these events is the fact that agricultural production starts during the same time period (Islam et al., 2024; Tanir et al., 2024).

The critical component in managing flood risk is vulnerability assessment (Nasiri, 2016). It provides information about anticipated extreme events to organizations and helps to reduce the potential harm from these risks. It is crucial to evaluate not only the potential impacts of floods but also society's capacity to foresee, manage, and recover from such disasters (De Brito et al., 2018; Alabbad et al., 2023). Even though there are numerous methodologies to assess vulnerability, the indicator-based approach provides a clearer picture of overall flood vulnerability than other methods because it builds logical images that demonstrate the spatial distribution of vulnerability using integrated data from the physical, environmental, economic, and social domains (Nguyen et al., 2023; Yildirim et al., 2023). As a result of that, in the past decade, there has been a notable prevalence of adopting an indicator-based approach in assessing flood vulnerability (Chang et al., 2021; Alabbad et al., 2024).

Frameworks for analyzing social-ecological systems have been widely utilized in various research studies encompassing areas such as coastal systems (Lazzari et al., 2021), forest policy reforms (Rives et., 2012), marine management (Lauerburg et al., 2020) and coral reef fisheries (Cinner et al., 2013). Here, while some previous studies on vulnerability analysis considered social and ecological dimensions (Cikmaz et al., 2023), these studies did not sufficiently address indicators related to the technological domain. In other words, there are very few studies in the literature that combine these three, and their focus areas have a variety such as urban ecosystem services (McPhearson, 2022), flood exposure (Sauer, 2023), or metropolitan changes (Bixler et al., 2019). The study builds upon previous work done by Chang et al. (2021), which proposed a holistic approach to flood vulnerability assessment (Alabbad and Demir, 2024) by effectively integrating social, ecological, and technological factors for six US cities.

Climate change is considered one of the biggest challenges to global sustainability. The unpredictability of natural disasters, which is one of the outcomes of this reality, poses a great danger for living creatures on earth. Urban areas are particularly vulnerable to these events, human density, and increasingly complex and interdependent infrastructures (Beck et al., 2010). In this context, the SETS framework is an important tool in envisioning the future of urban areas as it sees cities as interconnected systems (Kim et al., 2021). Researchers and practitioners have developed the SETS framework to evaluate how infrastructure can be resilient, provide ecosystem services, improve social well-being, and use new technologies to benefit urban populations (Chester et al., 2015). SETS framework is presented in more detail in the section 2.2. However, it can be briefly mentioned that this framework combines areas such as social and equity issues, environmental quality and protection, and technical and engineering elements.

In this study, the potential flood events were compared with vulnerability maps produced using existing social, ecological, and technological parameters. Since a flood occurred in Polk County in a relatively recent period, this county was considered as a case study. Specifically, in 2018, there was a historic flood in Polk (National Weather Service, n.d.). Following this intense rainfall, numerous vehicles were stalled or swept away, and significant damage to several homes and individuals occurred. Although there has been some relevant research on flood analysis, prior research on Polk County's urban flood vulnerability assessment has mostly depended on socioeconomic factors. For instance, Dickey, K. A. (2017) investigated the relationship between social vulnerability and flood exposure over the years 1990–2014 using statistical and geographic approaches. To gain a greater understanding of the complex nature of urban flood vulnerability, this assessment focuses on a range of vulnerability factors, including exposure, sensitivity, and adaptive capacity. It is noteworthy that this study stands out in that it applies the SET framework to evaluate distinct and combined domains of vulnerability. Consequently, the findings will support sustainable approaches and stronger contextual solutions for city managers and practitioners that decrease the risks of flooding in Polk County communities.

The subsequent sections of this paper are structured as follows. Section 2 offers the research area information and details about the methodology of the social-ecological-technological systems framework. Section 3 presents the outcomes of the research with detailed discussions. Lastly, there is a conclusion section with potential future studies and limitations.

2. Methodology

2.1. Case Study

The presented study was conducted in Polk County, Iowa, United States. It is a county located in the central part of the state of Iowa. Based on the 2022 United States Census Bureau, the population was 493,378. This number makes it the most populous county in Iowa and contains almost 15% of the people in the state. Also, it is home to over 10 city municipalities. In terms of its total land area, it has 1482.5 square kilometers which is the 43rd largest county in Iowa. Largest city in the county is Des Moines, which is also the capital city of Iowa. Thus, Polk County is included in the Metropolitan Statistical Area. The elevation of the study area ranges from 228 m to 318 m above sea level (see Figure 1).

The county is bisected by the Des Moines River. It is the largest river flowing through Iowa. It rises in a glacial moraine in southwestern Minnesota and flows in a southeasterly direction across Iowa to the Mississippi River. One of the tributaries of the Des Moines River is the Fourmile Creek basin. In the time between June 30 and July 1, 2018, thunderstorms brought heavy rainfall to parts of Iowa. As a result, major flooding occurred following storm activity in the Four Mile Creek Basin in that time interval. The Des Moines metropolitan area received 5-10 inches of precipitation total in the northern half of Polk County, as a result of the largest recorded 24-hour precipitation total at a National Oceanic and Atmospheric Administration weather station (National Weather Service, n.d.). The estimated damage from the 2018 flood in Polk County was estimated to exceed \$15 million, of which \$970,000 was spent repairing road and bridge damage (O'Shea et al., 2021). Additionally, since multiple homes throughout much of Polk County were impacted by the heavy rain, the rest of the spending covered these home repairs. In summary, Polk County witnessed a large-scale flood throughout its history, and literature and news articles have focused on its physical and economic damage. This study analyzes which regions are more vulnerable by including social and technological factors.

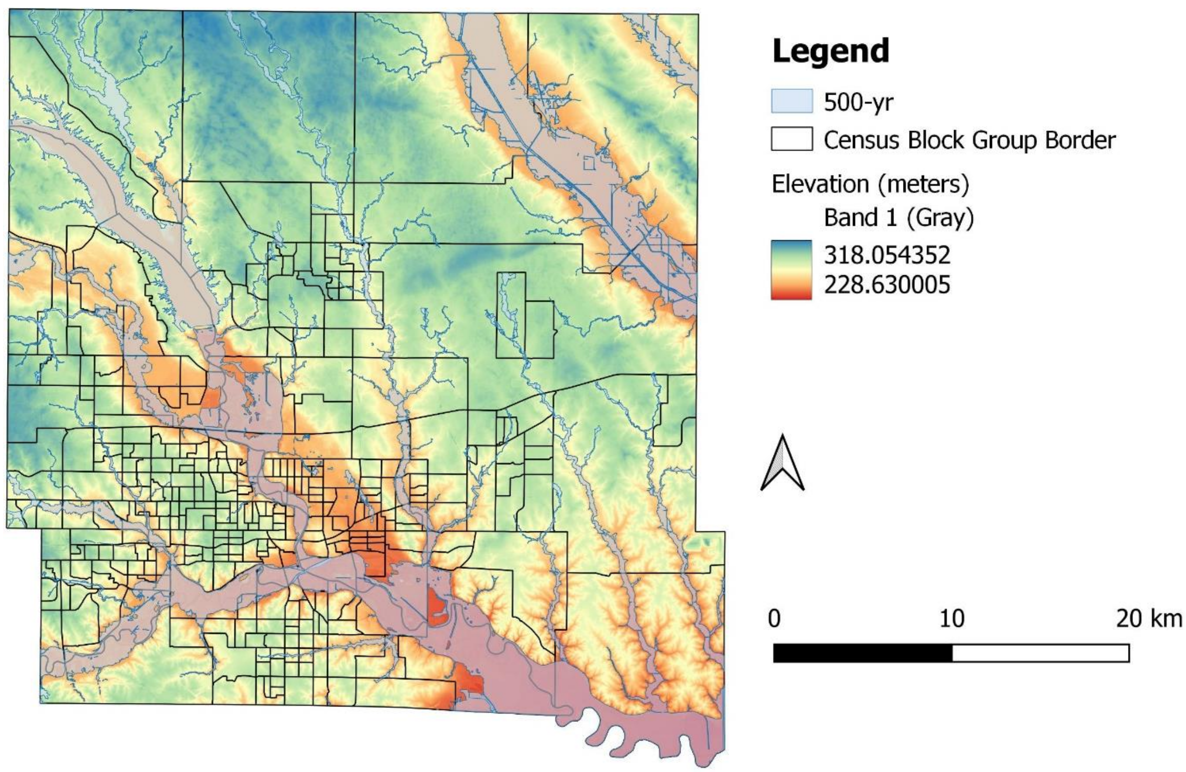

Figure 1. Census block groups in Polk County for a 500-year flood scenario.

2.2. SETS Framework

This study utilized the SETS vulnerability framework for Polk County. The SETS methodology was first developed by Chang et al. (2021) to evaluate vulnerability to urban floods. The SETS vulnerability framework integrates three aspects of vulnerability—namely, exposure, sensitivity, and adaptive capacity—across the domains of social, ecological, and technological that constitute urban context. Rather than complicating assessments, the method aims to address the inherent complexity of urban environments by simplifying and bringing them all together with the help of a structured framework. As shown in Figure 2, there are three domains and a total of six urban flood parameters within each domain. In one of each three vulnerability dimensions, two representative parameters were identified for exposure, sensitivity, and adaptive capacity. Social vulnerability parameters consist of population, age, gender, and tenant information. Ecological vulnerability parameters are slope, proximity to toxic release, land cover (barren land, green area, wetland), and productivity (NDVI). Technological vulnerability parameters represent the built environment (roads, built area, impervious surface, green infrastructure), and facilities (critical infrastructure, emergency centers). In total, 18 variables were used in light of data availability and the need to maintain consistency in the metrics, and the weight of each was treated equally. These parameters were carefully selected based on a review of the literature, especially referring to Chang et al. (2021), and Leta & Adugna (2023). Moreover, these parameters are visualized spatially as a census block group (CBG) scale. Therefore, small county cities such as German, Elkhart, or Runnels in Polk County did not show varying results in terms of flood vulnerability because they were confined to large CBGs.

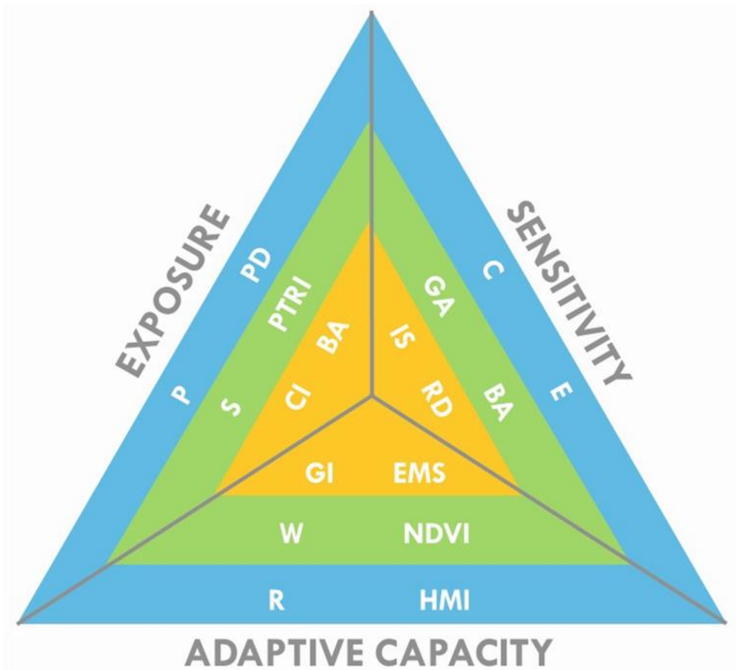

Figure 2. SETS flood vulnerability framework including selected 18 parameters shown with their abbreviations for each of three domains: social (blue), ecological (green), and technological (orange). [Figure adopted from Chang et al. (2021)]

2.3. Data Preparation

Analyses of SETS vulnerability involves a varying number of different sets of variables (Chang et al., 2021; Pallathadka et al., 2022), and there is no fixed definition for these variables (Sauer, 2023). The important point in the SETS framework is that all three areas are taken into account. It is noteworthy that the 18 indicators, which are used by Chang et al. (2021), have been utilized in flood vulnerability studies based on this method in recent years. In this study, 17 of these 18 data were taken as the basis. Combination of shape index and average patch size, which is one of the variables used by Chang et al., was replaced with the percentage of green area parameter due to data limitations in the study region. Since the green area is one of the parameters utilized recently in flood (Verma et al., 2020) or social-ecological (Afriyanie et al., 2020) studies, this variable was used for as replacement for the missing parameter.

Table 1. SETS flood vulnerability parameters, their abbreviations, and sources

Category	Parameter	Abbreviation	Source
Social Exposure	Population	P (+)	ACS 2022
	Population Density (# of people/area)	PD (+)	ACS 2022
	Children (% children < 5 years)	C (+)	ACS 2022

Social Sensitivity	Elderly (% people > 65 years)	E (+)	ACS 2022
Social Adaptive Capacity	Renters (% people who are renters)	R (-)	ACS 2022
	Household Median Income	HMI (+)	ACS 2022
Ecological Exposure	Slope (mean slope within the area)	S (-)	Derived from DEM
	Proximity parks to toxic release inventory (TRI) (nearest neighbor distance between centroids of parks and TRI)	PTRI (+)	US Environmental Protection Agency (EPA)
Ecological Sensitivity	Green Area (# of GA/area)	GA (-)	Derived from NLCD 2021 Land Cover
	Bare Soil (% bare soil within the area)	BS (+)	Derived from NLCD 2021 Land Cover
Ecological Adaptive Capacity	Wetland (% wetland within the area)	W (+)	US Fish & Wildlife Service
	Productivity based on normalized difference in vegetation index (NDVI) (mean NDVI within the area)	NDVI (+)	National Centers for Environmental Information
Technological Exposure	Critical Infrastructure (# of CI (e.g., wastewater treatment plants, public water supply facilities, power plants) within the area)	CI (+)	Iowa Geospatial Data & US Energy Information Administration (EIA)
	Building Area (% building area within the area)	BA (+)	QGIS QuickOSM Tool using OpenStreetMap data
Technological Sensitivity	Impervious Surface (mean % impervious surface within the area)	IS (+)	NLCD Impervious 2019
	Road Density (total lengths of roads/area)	RD (+)	QGIS QuickOSM Tool using OpenStreetMap data
Technological Adaptive Capacity	Green Infrastructure (total # GI/area)	GI (+)	City of Des Moines GIS Department
	Proximity to Emergency Management Services (hospitals, police departments, schools, fire, rescue departments) (nearest neighbor distance between centroids of areas and EMS)	EMS (-)	USGS National Structures Dataset (NSD) Iowa

(+) Standardized as there is a direct relationship between the parameter and urban flood vulnerability.
(-) Standardized as there is an inverse relationship between the parameter and urban flood vulnerability.
Note: It was treated differently for adaptive capacity parameters since they are dominators. Area refers to each census block group.

The SETS framework parameter dataset for Polk County was collected both from local authorities and open resources. For example, the green infrastructure data was acquired from the

City of Des Moines's GIS team. The other spatial data was obtained from the city's data portal or federal websites. In short, for each CBG, 18 datasets were obtained from multiple agencies to compute the socio-demographic, ecological, and infrastructure parameters. The social dataset had already been organized at the scale of the CBG. However, ecologic, and technologic parameters were first transferred into QGIS (version 3.20.1) and then arranged as CBG scales so that they could be appropriate for the analysis process. Table 1 lists 18 SETS flood vulnerability parameters, their abbreviations, and sources.

3. Methodology

3.1. Parameter Selection

Initially, raw data were standardized as percentages or densities because there was variability in CBG sizes across various urban areas in Polk County. Demographic data on children, elderly, women, and tenants were obtained as a percentage by dividing by the population of block group (BG) while some other data were converted to percentage or density by dividing by the population BG area. The derived parameter values were then normalized, where they were rescaled to a range between 0 and 1. Normalizing data entails adjusting the values of attributes to ensure they fall within the same numerical interval or scale, thereby equalizing their significance (Hossein Javaheri, 2008). There are three normalization techniques, namely z-score normalization, minimum-maximum normalization, and normalization by decimal scaling. In this research, the min-max rescaling formula was used. The formula is expressed as follows (Eq. 1):

$$V_{P\,(+)} = \frac{X_P - X_{Pmin}}{X_{Pmax} - X_{Pmin}} \quad \text{Eq. 1}$$

where V_P is the normalized value of a parameter, X_P is the original parameter value, X_{Pmin} and X_{Pmax} represent the minimum and maximum values of a specific parameter, respectively. On the other hand, for inversely related to urban flood vulnerability parameters (e.g., higher slope reduces flood vulnerability), the following formula was applied for standardization (Eq. 2).

$$V_{P\,(-)} = \frac{X_{Pmax} - X_P}{X_{Pmax} - X_{Pmin}} \quad \text{Eq. 2}$$

3.2. Vulnerability Scoring

After that, the normalized values for each parameter were used to determine the urban flood vulnerability score for each domain (social, ecological, technological) with the formula below (Eq. 3).

$$V_{domain} = \frac{E_1 + E_2 + S_1 + S_2}{AC_1 - AC_2} \quad \text{Eq. 3}$$

where E_1 is exposure parameter 1, E_2 is exposure parameter 2, S_1 is sensitivity parameter 1, S_2 is sensitivity parameter 2, AC_1 is adaptive capacity parameter 1, and AC_2 is adaptive capacity parameter 2. The composite social, ecological, and technological vulnerability scores are then normalized again. Lastly, the final normalized scores are used for generating a combination of these domains' vulnerability scores. The formulas are given below (Eq. 4-7).

$$V_{SE} = \frac{V_S + V_E}{2} \quad \text{Eq. 4}$$

$$V_{ET} = \frac{V_E + V_T}{2} \quad \text{Eq. 5}$$

$$V_{ST} = \frac{V_S + V_T}{2} \quad \text{Eq. 6}$$

$$V_{SET} = \frac{V_S + V_E + V_T}{3} \quad \text{Eq. 7}$$

After calculating the values of all possible permutations of the individual variables, they were transferred back to QGIS. A map was produced for each probability layer. In other words, seven different maps in total were produced: S, E, T, S-E, S-T, E-T, S-E-T. Vulnerability scores mapped according to natural breaks classification. These maps produced in the last stage were brought to the upper level with 500-year flood maps. Demographic information of the most vulnerable areas is also presented.

3.3. Statistical Analysis

Global Moran's I was applied in ArcGIS Pro obtain information about how the vulnerability indexes in the generated maps were geographically distributed throughout the whole. Moran's I value gives information about spatial autocorrelation. In this context, positive spatial autocorrelation happens when observations sharing similar values tend to be clustered together, whereas negative spatial autocorrelation arises when observations with dissimilar values tend to be dispersed (Moran, 1950). Moreover, Pearson’s correlation coefficient was used to examine whether or not the relation is statistically significant. As secondary analysis, a linear regression model was run using STATA software package. This analysis estimates the coefficients of the linear equation, involving one or more independent variables that best predict the value of the dependent variable. In our model, the dependent variable was the SET vulnerability index while the independent variables were all 18 parameters.

4. Results and Discussions

In this section, we discuss the study results present the regions in Polk County that are at risk in terms of social, ecological, and technological aspects. In order to better analyze the relationship of the produced maps with the existing flood risk, they were intersected with the 500-year flood map, so that it can be interpreted whether the areas with flood risk are particularly socially vulnerable. The delineation of flood hazard areas was acquired from the Iowa Flood Information System (IFIS, Demir and Krajewski, 2013). Iowa floodplain maps were created by analyzing hydrologic and hydraulic features of basins and streams, utilizing high-resolution input data such as a 1-meter digital elevation model, and employing MIKE FLOOD and HEC-RAS software. Despite the more frequent use of the 100-year floodplain, particularly in municipal regulatory planning, we used a 500-year floodplain map to include more extreme scenarios that is expected with changing climate regimes and land use practices. For instance, within the scope of unpredictable climate change scenarios, rainfall intensity can be expected to increase in the future, and as a result of this possibility, it could contribute to the expansion of regions susceptible to 100-year floods.

In Polk County, very high socially vulnerable BG occur mainly in the western part, but these sensitive areas are not clustered (Fig. 3). In other words, these very vulnerable areas are separate from each other. Nevertheless, when looking at the 500-year flood probabilities of the small-sized BG in that region, it is noteworthy that almost none of them will experience floods. Common reasons for their social vulnerability can be listed as having a population of more than 1000 people, having a high proportion of either rental tenants, elderly, or both. For the household median income information, the average income in Polk County was $78,827 according to 2022 Census data. While looking at the high and very highly vulnerable classes' median income, since their results are below the average, it can be said that it is an important criterion in the sensitivity results. On the other hand, it is interesting to note that BG with approximately 50% of the elderly population also have a much higher rate than the average Polk County income when the whole county's median income information is considered. However, if the percentage of both elderly and tenants is high, the average income drops significantly.

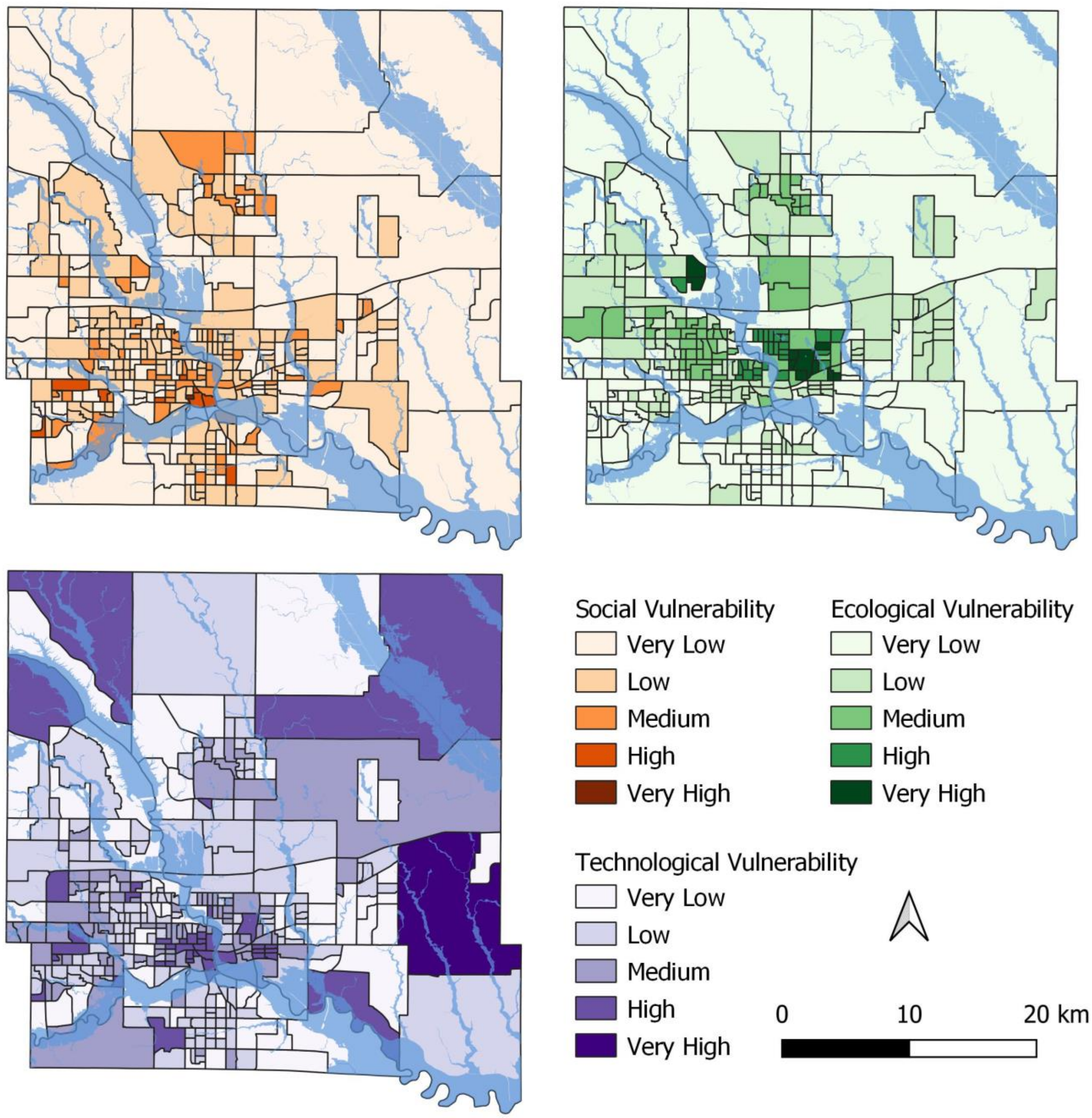

Figure 3. Equal Interval (Jenks) maps showing census block group-scale vulnerability of three domains to flooding for Polk County. (a) Social (S); (b) Ecological; (c) Technological.

Areas having over 0.25 flood vulnerability index and intersecting floodplains are medium-sized BGs in the south and east. More than 1,500 people live in the southern BG with about 50% renters and 30% elderly, whereas more than 2,500 people live in the eastern BG with about 30% renters and 10% kids. Both BGs have a similar household median income level of about $35,000. It is noted that even though there is a flood risk in these regions, it cannot be said that all of those BGs will be flooded, only some parts of them will be affected. In summary, high numbers of people, high percentages of renters and elderly, and low median income are the major contributors to the pattern of high social vulnerability.

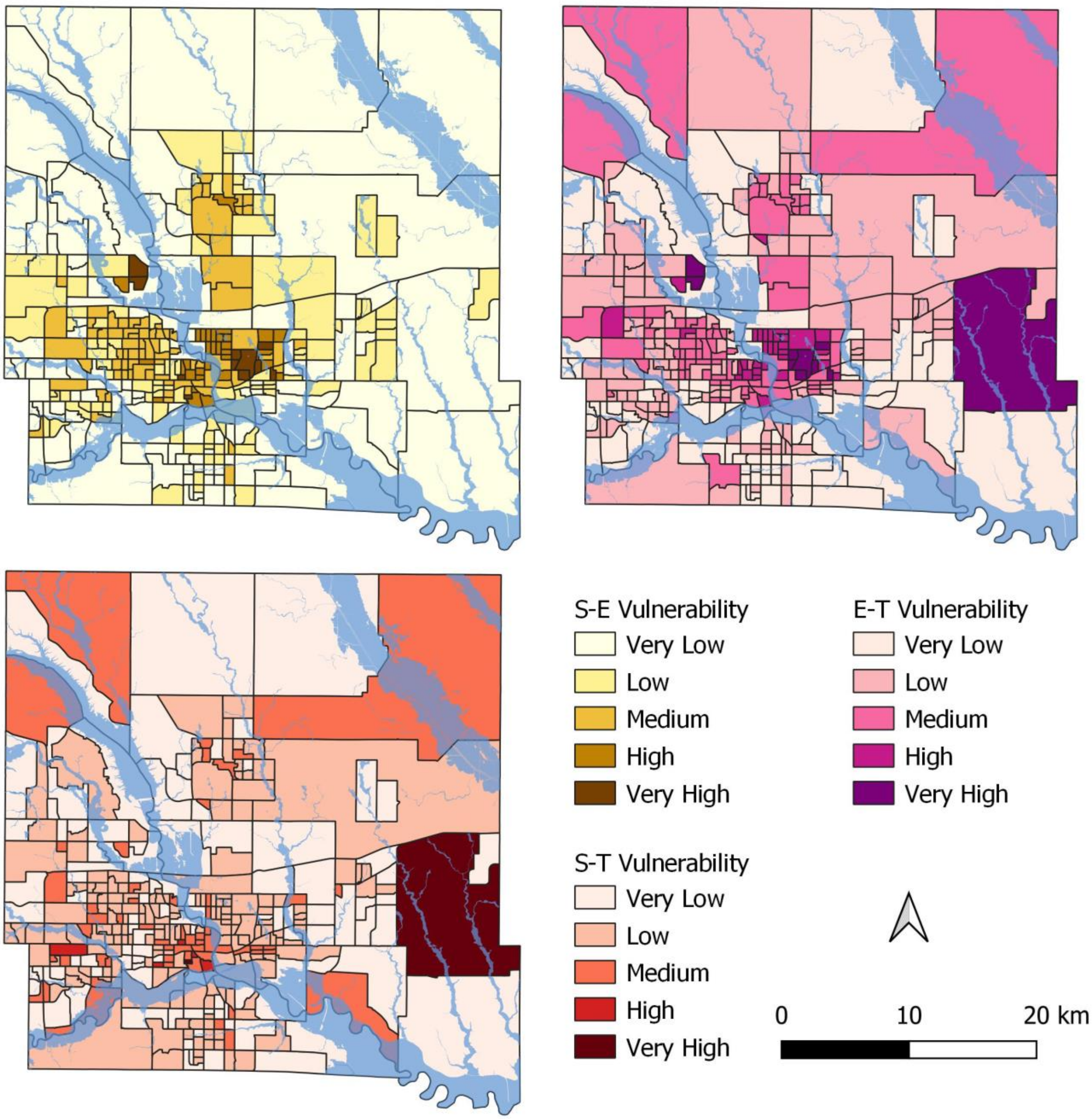

Figure 4. Combined vulnerability maps to flooding in Polk County. (a) Social-Ecological (S-E); (b) Ecological-Technological (ET); (c) Social-Technological (ST).

Areas with higher ecological vulnerability scores are located in the downtown of the city of Des Moines and highly urbanized areas (Fig. 3). However, it has been seen that the risk is higher in the northern part of the city center rather than in the majority of Des Moines downtown. When these BGs are examined in detail, they can be defined as places where mostly large structures are located, have fewer or no wetlands, and have low slope change. There are a total of 36 TRI facilities in Polk County, and they are concentrated near the Des Moines and Ankeny downtown areas. Additionally, ecologically vulnerable spaces are found in the western part which involves the Johnston city boundary, where it is relatively flat, and the percentage of impervious surface is relatively high. Nonetheless, it should be noted that although their ecological vulnerability scores are the highest, they do not fall under 500-year floodplain zones. It has been found BGs that have flood risk but have very low density and where agricultural production is generally carried out have low ecological vulnerability. The lower ecological vulnerability on the edges of the county borders seems to be driven by having wetlands as high as 40%, a higher productivity index, larger green areas, and lower percentages of bare soils.

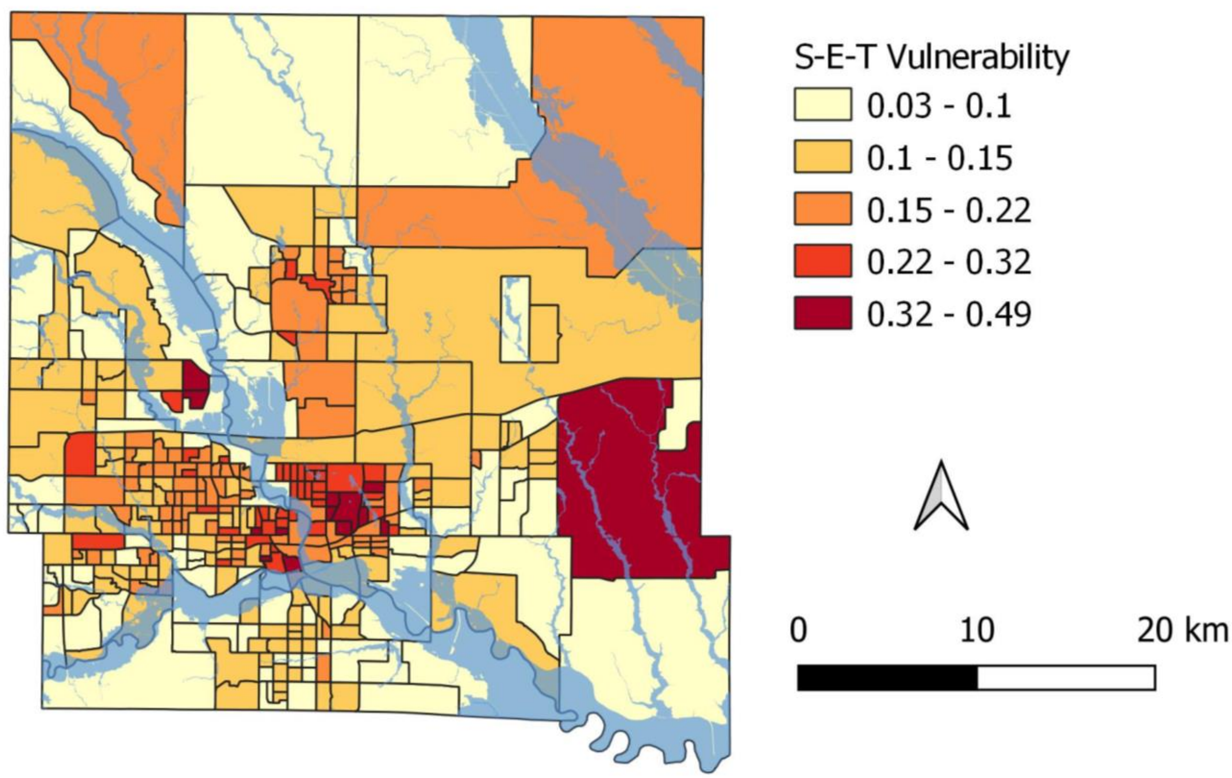

Figure 5. Social-ecological-technological (SET) vulnerability map to flooding in Polk County based on census block group scale.

In Polk County, the distribution of technological vulnerability results forms a completely different pattern compared to the distribution of social and ecological vulnerability (Fig. 3). When looking at Des Moines downtown, it can be interpreted that primary drivers of technological vulnerability are closely related to urbanized land use parameters. Particularly, the combined effects of both exposure and sensitivity parameters, such as the percentage of impervious surface, which varies between approximately 50%-80%, and building and road density, largely contribute to the high technological vulnerability class in the city center. However, on the other hand, the population BG with the highest technological fragility index appears in the eastern part, which mostly covers agricultural areas. The main reason for this is that it has adaptive capacity parameters.

Other peripheral areas, especially northwestern and northeastern edges also appear vulnerable because of the same reason. These BGs have limited availability of green infrastructure systems, and their centroid points are far away from any nearby emergency centers. Even though approximately 98% of the over 200 designated emergency centers are not located in floodplains for protection purposes, many sensitive areas require rapid connection to such facilities. Furthermore, it should be indicated that these large BGs include critical infrastructures (i.e., water/wastewater treatment plant facilities, public water supply facilities, and power plants) within their limits. To sum up, technological vulnerability seems to be related to a higher percentage of impervious surface cover, a high number of water facilities and power plants, and higher building and street density in Polk.

Figure 4 illustrates the combination of S-E, E-T, and S-T maps, respectively. The pattern of combined S-E and E-T vulnerability in Polk is similar due to ecological parameters. Higher vulnerability areas are clustered around the Interstate 235 (I-235) highway, and they include the railway transfer zone. Even though only a small part of them overlaps with the 500-year floodplain, they can be defined as areas that will be affected by floods. When analyzing the median household income level in the clustered area where more than 5000 people reside, it stands out that the income level of each BG is lower than the average county's income level. Another striking point is that the BG on the east side has the highest vulnerability in S-T while it has the lowest vulnerability in S-E. This BG is also the highest in combined S-T analysis. Apart from that, another BG, whose vulnerability is high, intersects the flooding area, and it is located in Des Moines downtown. Considering the demographic characteristics, it is noteworthy that 60% of the people living in this BG are tenants. Moreover, it includes two farmer's markets, which is key for the local economy, food systems, and communities.

Figure 5 reveals the combined compound effects of all social, ecological, and technological exposure, sensitivity, and adaptive capacity parameters considered in this study. In Polk, from this figure, S-E-T vulnerability areas are generally clustered in downtown Des Moines, where urban development is concentrated along a highway (I-235) and large industrial buildings. From a detailed domain perspective, firstly, exposure impacts vulnerability to flooding due to high numbers of people (S), low slope variation (E), and the presence of several water-related facilities (T), especially in downtown Des Moines. Secondly, as a sensitivity domain, the vulnerability exists in a high percentage of elderly (S), sparse green areas (E), and relatively high impervious surfaces and road densities (T). Thirdly, in terms of adaptation capacity, in the city center, low-income households (S) and scarcely any wetlands (E), while considering the peripheral areas of the county, the high percentage of tenants, and the long distances to access emergency centers (T) make these areas vulnerable to floods.

Table 2 contains summary information about the high and very high-class BGs of the SETS vulnerability map which intersects with the 500-year flood risk. This summary information includes the number of people, median household income, the percentages of renters, kids, elderly, and people who do not have a vehicle, the poverty index, and city names. Additionally, information on which other vulnerability maps each BG intersects with is included in this table. BGs with very high vulnerability indexes are specified using bold. All of these in this group are located in the Des Moines area. However, this result is ordinary since the city with the largest developed surface area in Polk County is Des Moines. Nevertheless, it is noteworthy that the poverty level and tenant population of the BG which has the greatest population in this group, are high. It can also be interpreted that the population without access to a vehicle has the highest percentage compared to the other BGs in the table, so this group of households will be the most disadvantaged group when any emergency occurs. Similar BGs should be identified, and strong infrastructures and policies against flood risk should be created for these regions. This table summarizes information that can be used as a reference, especially for public institutions in Polk County. A more detailed summary table, that is, the BGs where the high and very high classes of all maps intersect with floods, can be found in Table 5 in the appendix section.

Table 2. Summary information for census block groups of high and very high vulnerability classes intersected with the 500-year flood in the SET map.

# P	$ HMI	% R	% C	% E	% No vehicle	Poverty Index*	Place	S	E	T	S-E	E-T	S-T	S-E-T
2,964	**52,474**	**63**	**1.2**	**13.3**	**24.2**	**16**	**Des Moines**	**X**			**X**	**X**	**X**	**X**
461	63,178	80.3	0	30.4	8.7	66	West Des Moines	X					X	X
1,364	42,225	73	0	7.8	24.2	16	Des Moines	X			X			X
583	N/A	26.8	7.4	15.1	23.5	8	Des Moines		X		X	X		X
764	18,036	19.1	3.4	4.6	14.4	14	Des Moines					X		X
1,246	53,589	7.1	11.3	12	11.9	13	Des Moines		X		X	X		X
857	52,589	14.8	6.1	3	4.2	71	Des Moines		X		X	X		X
1,284	52,949	0.5	5.1	10.6	4.2	71	Des Moines		X		X	X		X
1,275	**62,564**	**14.4**	**7.9**	**20.2**	**14.8**	**86**	**Des Moines**		**X**		**X**	**X**		**X**
1,221	60,625	5.7	9.1	6.2	4.2	71	Des Moines		X		X	X		X
689	71,316	4.5	2.5	15.8	6.6	41	Des Moines		X		X	X		X
755	71,607	17.6	4.5	38.1	6.6	41	Des Moines		X		X	X		X
678	**49,250**	**13.4**	**0**	**18.9**	**6.6**	**41**	**Des Moines**		**X**		**X**	**X**		**X**
725	47,135	9.4	7.2	8.8	4.2	71	Des Moines		X		X	X		X
801	41,500	11.2	6.6	7.7	6.6	24	Des Moines		X		X	X		X
1,035	60,239	15.6	3.9	6.1	6.6	24	Des Moines		X		X	X		X
338	**45,556**	**4.4**	**7.1**	**8.9**	**3.6**	**38**	**Des Moines**		**X**		**X**	**X**		**X**
1,391	**136,169**	**0.1**	**5.2**	**13.4**	**6.5**	**62**	**N/A**			**X**		**X**	**X**	**X**
2,083	75,179	15.8	11.3	22.2	2.6	73	Ankeny				X			X
1,309	55,699	17.3	12.8	8.9	3.6	38	Des Moines					X		X

*The data is exported from the poverty index by census tract. The lesser score means the higher the exposure to poverty in a neighborhood.

The linear regression analysis aimed to understand the factors influencing the Social-Ecological-Technological (SET) flood vulnerability index, employing 18 distinct parameters as independent variables. In that model, the dependent variable and independent variables are identified with SET index and normalized values for 18 indicators, respectively. Table 3 shows the correlation coefficients of the 18 parameters used and whether they are statistically significant or not. Among 18 parameters, 13 of them affect the SET index. While interpreting these 13 parameters, for the social domain, the index exhibits a negative correlation with the percentage of renters and households' median income, suggesting that areas with larger renter populations with low-income people may experience lower vulnerability. Positive correlations are observed with the population density, percentage of children, elderly people, and median household income, indicating that regions with dense populations especially with children and elderly residents, and lower household incomes tend to have heightened vulnerability.

In the ecological domain, vulnerability is positively correlated with slope, proximity of parks to toxic release inventory, and green area density, implying that areas with steeper slopes, closer potentially hazardous parks, and denser green areas are more susceptible to flood vulnerability. Conversely, negative correlations with the percentage of wetland areas, and the NDVI suggest that regions with more wetland areas, and lower vegetation indices are associated with decreased vulnerability. Within the technological domain, vulnerability shows positive correlations with the number of critical infrastructures and road density, indicating that areas with more critical infrastructure and greater road density are more vulnerable to floods. On the other side, there is a negative correlation with proximity to emergency management services, suggesting that long distances to emergency management services are associated with reduced vulnerability.

Table 3. Correlation coefficient values for 18 parameters

Domains	Parameters
Social	P (-0.0002), PD* (0.1), C* (0.06), E* (0.07), R* (-0.07), MI** (-0.04)
Ecological	S* (0.06), PTRI* (0.08), GA** (0.06), BS (-0.007), W* (-0.15), NDVI* (-0.32)
Technological	CI* (0.13), BA (0.04), IS (0.04), RD* (0.12), GID (-0.15), EMS* (-0.13)

*Correlation is statistically significant at the 0.01 level.
**Significant at the 0.05 level.

The coefficients of some parameters (i.e. slope, green density, NDVI, EMS) attract attention because they do not exactly match the expected nature of flood vulnerability. The reason may be that the relationships between certain parameters and flood vulnerability may be influenced by complex interactions with other variables not included in the analysis. To better understand the reasons behind unexpected correlation coefficients, it might be necessary to conduct further analysis, such as sensitivity analysis. However, in this study, once it was found out which parameters were statistically significant or not contributing to flood risk in Polk County, no further analysis was conducted. Overall, these findings underscore the multifaceted system of flood vulnerability, influenced by social, ecological, and technological factors, highlighting the importance of integrated strategies for mitigating flood risk, and enhancing resilience.

Table 4. Moran's I value for three domains and combined maps.

	S	E	T	S - E	E - T	S - T	S - E - T
Moran's I Values	0.06* (clustered)	0.26* (clustered)	-0.04* (dispersed)	0.24* (clustered)	0.22* (clustered)	0.03* (clustered)	0.21* (clustered)

* Statistically significant at the 0.01 and 0.05 level.

Moran's I value for each generated seven maps is demonstrated in Table 4. From this table, it can be interpreted that there is strong spatial autocorrelation in all vulnerability maps. Except only for a technological vulnerability map, all data have positively spatially correlated in Polk County, showing clustered patterns. Although Moran's index of technological vulnerability is statistically significant, there is a dispersed spatial pattern. Moran's I is a correlation coefficient that measures the overall spatial autocorrelation of the dataset and gives multidimensional and multidirectional information; consequently, even though various results do not appear when looking at the maps produced, thanks to this analysis, it has been shown that the areas with high flood vulnerability levels in Polk County are strongly clustered.

5. Conclusion

This study examined the association between several flood vulnerability maps produced using the Social-Ecological-Technological (SETS) framework and the future 500-year flood probability for Polk County, and linear regression and spatial autocorrelation analyses were performed using all produced indexes and maps. In the compilation of all generated maps, it cannot be definitively asserted that every high-risk block groups, characterized by a heightened vulnerability index, will be submerged. Rather, the analysis suggests that only specific segments within these areas are projected to be impacted. The results of the S-E-T vulnerability map, which is the combined effects of all social, ecological, and technological exposure, are presented with sensitivity and adaptive capacity parameters.

The areas most impacted by damage are identified as the highly populated downtown Des Moines, where urban development is concentrated along a highway (I-235) and large industrial buildings. Also, while assessing the vulnerability maps produced, even though the number of CBGs in the high and very high vulnerability class is low, vulnerability to flooding across SET domains exhibits a clustered distribution pattern according to global Moran's I. Additionally, spatial correlations between combined vulnerabilities (S-E, E-T, S-T) were identified, suggesting opportunities for enhancing flood mitigation efforts across multiple domains. These findings offer valuable insights for devising more efficient strategies, especially for local authorizations, to reduce flood vulnerability in Polk County and other urban areas confronting comparable issues.

The methodology follows a comprehensive framework that incorporates S-E-T domains. However, various challenges have been encountered that may impose some limitations on data collection and analysis. Since many communities cannot afford expensive data sources, the research relies on easily accessible and publicly available data, so one of the 18 parameters used in previous studies (combination of shape index and average patch size) was replaced with another parameter (green area) due to a lack of data. In terms of analysis, vulnerability indicators should be further developed with consultation and participation of city practitioners and other stakeholders because the distributions of SETS vulnerability to flooding or other hazards will vary greatly depending on which indicators or geographic locations are considered for analysis.

Furthermore, the method calculates all vulnerability parameters using equal weights. However it should be considered that some indicators could be more or less effective than others in real world scenarios, so variable weights could be evaluated during calculations. Additionally, unexpected correlation coefficients emerged in the linear regression analysis; therefore, additional analyses (e.g. sensitivity analysis, diagnostic checks for model assumptions, or exploration of potential confounding variables) would be helpful to better understand the reasons behind this behavior.

For future analyses, the methodology used in this research could be examined in detail across various geographic regions and at different scales, such as city or census block, with more recent data sets to capture how flood risk varies within different areas and help implement effective flood risk reduction strategies. Additionally, the parameters can be expanded by thoroughly studying the factors that make each geographic area more vulnerable to flooding and discussing them with city stakeholders. Nevertheless, this study emphasizes the importance of utilizing the SETS framework to assess flood vulnerability in urban settings like Des Moines. Moreover, the current analysis, using publicly available data, offers clues for developers of plans and policies for vulnerable areas to assess vulnerability to future floods and prevent economic and social losses from flooding.

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Appendix

Table 5. Summary information for census block groups of high and very high vulnerability classes intersected with the 500-year flood in all vulnerability maps.

# P	$ HMI	% R	% C	% E	% No vehicle	Poverty Index	Place	S	E	T	S-E	E-T	S-T	S-E-T
2,964	**52,474**	**63**	**1.2**	**13.3**	**24.2**	**16**	**Des Moines**	**X**			**X**	**X**	**X**	**X**
1,580	30,699	48.7	2.3	31.8	19.2	48	Des Moines	X						
461	63,178	80.3	0	30.4	8.7	66	West Des Moines	X					X	X
1,364	42,225	73	0	7.8	24.2	16	Des Moines	X			X			X
583	N/A	26.8	7.4	15.1	23.5	8	Des Moines		X		X	X		X
764	18,036	19.1	3.4	4.6	14.4	14	Des Moines					X		X
1,246	53,589	7.1	11.3	12	11.9	13	Des Moines		X		X	X		X
1,031	49,013	8.6	6.5	31.1	15.1	17	Des Moines		X		X			
857	52,589	14.8	6.1	3	4.2	71	Des Moines		X		X	X		X
1,284	52,949	0.5	5.1	10.6	4.2	71	Des Moines		X		X	X		X
1,275	**62,564**	**14.4**	**7.9**	**20.2**	**14.8**	**86**	**Des Moines**		**X**		**X**	**X**		**X**
1,221	60,625	5.7	9.1	6.2	4.2	71	Des Moines		X		X	X		X
689	71,316	4.5	2.5	15.8	6.6	41	Des Moines		X		X	X		X
755	71,607	17.6	4.5	38.1	6.6	41	Des Moines		X		X	X		X
678	**49,250**	**13.4**	**0**	**18.9**	**6.6**	**41**	**Des Moines**		**X**		**X**	**X**		**X**
725	47,135	9.4	7.2	8.8	4.2	71	Des Moines		X		X	X		X
801	41,500	11.2	6.6	7.7	6.6	24	Des Moines		X		X	X		X
1,035	60,239	15.6	3.9	6.1	6.6	24	Des Moines		X		X	X		X
338	**45,556**	**4.4**	**7.1**	**8.9**	**3.6**	**38**	**Des Moines**		**X**		**X**	**X**		**X**
1,479	66,750	62.5	0	0	6.1	16	Des Moines			X				
835	108,224	49.7	2.6	0	24.2	16	Des Moines			X				
2,964	52,474	63	1.2	13.3	24.2	16	Des Moines			X				
2,786	148,929	2.6	5.3	18.5	1.9	98	Polk City			X				
1,742	135,417	0	1.6	9.5	1.9	98	N/A			X				
1,391	**136,169**	**0.1**	**5.2**	**13.4**	**6.5**	**62**	**N/A**			**X**		**X**	**X**	**X**
2,755	181,281	1.1	8.6	13.6	1.1	81	Ankeny			X				
1,035	60,239	15.6	3.9	6.1	6.6	24	Des Moines			X				
1,662	109,176	1.2	7.3	14.6	0	76	Pleasant Hill			X				
1,587	117,750	13.7	6.4	21.4	6.5	98	Clive			X				
1,150	71,597	7.1	8.7	7.6	1.3	48	West Des Moines			X				
461	63,178	80.3	0	30.4	8.7	66	West Des Moines			X				
1,103	N/A	27	5.7	23.4	23.5	8	Des Moines			X				
882	57,202	59	7.8	0	24.2	16	Des Moines			X				
338	45,556	4.4	7.1	8.9	3.6	38	Des Moines			X				
2,083	75,179	15.8	11.3	22.2	2.6	73	Ankeny				X			X
1,309	55,699	17.3	12.8	8.9	3.6	38	Des Moines					X		X