Geo-Spatial Analysis of Built-Environment Exposure to Flooding: Iowa Case Study

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Abstract

Flooding is the most frequent type of natural disaster, inducing devastating damages at large and small spatial scales. Flood exposure analysis is a critical part of flood risk assessment. While most studies analyze the exposure elements separately, it is crucial to perform a multi-parameter exposure analysis and consider different types of flood zones to gain a comprehensive understanding of the impact and make informed mitigation decisions. This research analyzes the population, properties, and road networks exposed to the 100, 200, and 500-year flood events at the county level in the State of Iowa using geospatial analytics. We also proposed a flood exposure index at the county level using fuzzy overlay analysis to help find the most impacted county. During flooding, results indicate that the county-level percentage of displaced population, impacted properties, and road length can reach up to 46%, 41%, and 40%, respectively. We found that the most exposed buildings and roads are laid in residential areas. Also, 25% of the counties are designated as very high-exposure areas. This study can help many stakeholders identify vulnerable areas and ensure equitable distribution of investments and resources toward flood mitigation projects.

Keywords: flood exposure, geospatial analysis, floods, fuzzy overlay analysis

1. Introduction

The last two decades have witnessed a high number of flood disasters worldwide, resulting in overwhelming damage to people, infrastructure (Alabbad et al., 2023), and agriculture (Jongman et al., 2012; Yildirim and Demir, 2022; Davenport et al., 2021). Climate change, transforming natural landscapes for urban development purposes, and lack or detraction of flood hazard accounts when building a new environment have led to continuing and aggravating flood risk (Villarini & Zhang, 2020; Lehmann et al., 2015). From 2000 to 2020, the United States have experienced multiple flood events, with overall damages reaching or exceeding $1 billion per event (NCEI, 2022). Floods are responsible for not only economic losses, but also negative impacts on social well-being, health, and the environment. (Carroll et al., 2010; Oyinloye et al., 2013).

Flood risk can be quantified as a function of hazard, exposure, and vulnerability (Birkmann & Welle, 2015). Flood exposure analysis considers a key component of flood risk assessment. It encompasses identifying and aggregating exposure elements (e.g., population, infrastructure) located in the floodplain (UNISDR, 2016). The knowledge of flood exposure gives crucial information about the components and assets situated in flood-prone areas to decision-makers as a guideline for plans and actions (Carson et al., 2018) on preparedness, response, recovery, and mitigation (Tyler et al., 2019; Jha et al., 2013). The analysis requires identification of flood events (Haltas et al., 2021), comprehensive set of data on flood inundation maps, property footprints, population and demographics. While this is challenging for small communities with limited resources, data-driven approaches for generating inundation maps (Li et al., 2022; Li and Demir, 2022) provides an opportunity for reducing limitations.

A burgeoning interest in flood exposure research at different spatial scales has grown due to its importance in flood risk management. Researchers have investigated the exposure of the built environment to flooding at national scales for countries such as New Zealand (Paulik et al., 2020), Greece (Stefanidis et al., 2022), Canada (Chakraborty et al., 2021), and the United States (Tate et al., 2021; Qiang et al., 2017). At a watershed scale, Puno et al. (2021) analyzed the exposure of land use and land cover during six flood return periods. In addition, Hamidi et al. (2022) provide a social vulnerability assessment resulting from flood exposure in rural communities in Pakistan. Despite the valuable knowledge produced by earlier studies, the studies are generally constrained by a certain type of flood scenario or exposure element.

Flood risk indexes can provide a concise representation of the complex flood information and facilitate identifying the areas at high risk of flooding. Several studies have developed flood risk index derived from flood exposure analysis (Phongsapan et al., 2019; Quesada-Román, 2022; Calil et al., 2015). The Federal Emergency Management Agency (FEMA) has established the National Risk Index (NRI) to identify risk of 18 natural hazards including riverine flooding (FEMA, 2021) at the county and census tract levels. The NRI combines expected annual flood loss for buildings, population, agriculture, social vulnerability, and community resilience (Yildirim et al., 2022). For riverine flooding, the exposure analysis is limited to the area that intersects the 100-yr floodplain (1% annual chance) and does not include some of the critical infrastructure (i.e., roads and bridges). Also, when estimating the damage, NRI performs the analysis at the census block level with the assumption of evenly distributed building locations, which may result in over or under estimation of the economic losses (Alabbad et al., 2022).

State of Iowa lacks a large-scale comprehensive flood exposure assessment of the built environment, including rural and urban areas. Within the Iowa boundary, there has been relatively limited research on flood exposure analysis, focusing on buildings and road networks at small spatial scales (e.g., community) (Alabbad & Demir, 2022). This research aims to analyze building footprints, roads, bridges, and population during the 100, 200, and 500-yr riverine flood events at the county level for the entire State of Iowa. Also, we generated a flood risk index by combining the exposure assessment using fuzzy overlay analysis. In addition, we highlighted select factors that make some counties vulnerable to flooding. Insights from the study can be used to determine which locations should get priority attention for flood risk reduction investments and resources.

The rest of the paper is organized as follows. Section 2 provides details on flood exposure assessment methodology, including the flood exposure index. Research outcomes, along with the discussions, are shared in Section 3. The conclusion with future investigation is presented in Section 4.

2. Methodology

This study aims to analyze affected population, building footprints, road networks, and bridges during the 1%, 0.5%, and 0.2% annual flood probability for the State of Iowa to identify and rank vulnerable areas. While most studies utilize flood depth for flood risk assessment, many study areas lacks resources for generating a comprehensive flood depth map (Hu and Demir, 2021). It requires extensive data and computational resources, which may not be available for most communities (Li et al., 2023). Also, the assessment of the flood's impact goes beyond financial damages. Some of the impacts may aggravate the consequences.

For example, suppose a building is within the floodplain with low-risk index. Even though the flood depth is below the building foundation height, the life quality is affected with emotional stress due to inaccessibility and potential damage to the building. Furthermore, the flood might continue for an extended period (e.g., weeks or months), resulting in substantial relocation and cleaning expenses as well as contamination hazards. Regarding road networks, inundated edges can cause reduced accessibility to critical amenities (Alabbad et al., 2021). In this research, statewide inundation extent is available and utilized as the driver to assess flood exposure. Given the flood extent, we can cover a large spatial scale and determine the built environment at risk of flooding for better interventions for future flood events. Figure 1 shows the research components for flood exposure analysis.

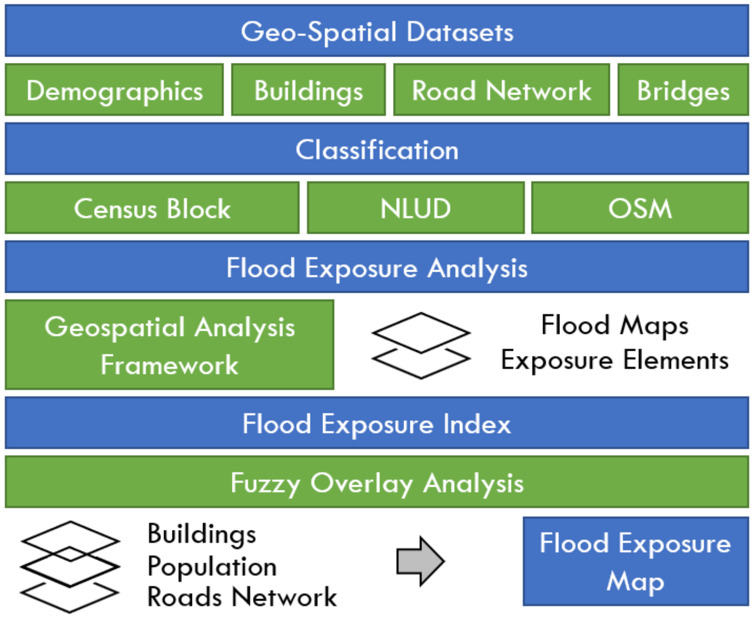

Figure 1: Overall workflow of the flood exposure assessment.

2.1. Flood Exposure Assessment

This section describes the methods used to assess the impact of floods on several elements, including properties, population, road network, and flood exposure index. The evaluation is carried out at the county level utilizing a variety of spatial analytic tools, such as QGIS and ArcMap, as well as fuzzy logic-based methodologies.

Property Assessment: The number of properties located within a floodplain is calculated by intersecting the flood extent with the property layer. Buildings are represented as point geometry (centroid of the occupancy area), whereas the flood extent is depicted as a polygon. Using the intersection algorithm in the QGIS software (QGIS3.28), we have identified the flooded properties within different spatial boundaries that intersect with the flood extent layer. To investigate the most impacted occupancy type, each inundated property is given a class based on the land use dataset.

Population Assessment: In this analysis, we estimate the displaced population resulting from the 100, 200, and 500-yr flood scenarios at the county geographic scale. First, we extracted the population residing in the floodplain at the census block level as it is the smallest spatial scale the data is available. We overlap the flood extent over each census block to estimate the impacted area using the Overlay analysis tool in QGIS. If a census block is completely inundated, its entire population is assumed to be displaced. For partially flooded areas, we estimate the displaced population as a percentage of the inundated area multiplied by the population (Equation 1) (FEMA, 2022). The analysis considers the area-weighted approach to account for the variation in flood extent throughout a census block.

$$Displaced\ population = \sum \%A_i * T_i \qquad \text{Eq. 1}$$

where i belongs to a census block, A is the flood area, and T is the total population.

Road Network Assessment: Transportation network analysis has been facilitated by graph theory (Alabbad et al., 2021). A graph (G) is described as $G = (V, E)$, where V is a collection of nodes connected by a set of edges (E) (Gibbons et al., 1985). In this research, we have investigated the path length exposure during the 1%, 0.2%, and 0.5% chance of flooding. For non-bridge road segments, we extract the closed edges by overlapping the flood maps over the road networks using the intersection tool in QGIS. Once the road segment is partially or fully intersected with the flood extent, it is assumed to be closed. Bridges are analyzed in terms of accessibility due to the incomplete flood depth models within the study area, which hinder the calculation of flood depths at a certain bridge and the investigation of whether the bridge is inundated or not. Given that the bridge dataset is represented by point geometry, each bridge point is given a corresponding intersection edge to produce the bridge edges. In our analysis, if a bridge-edge completely connects with flooded roads, the bridge is considered inaccessible and closed. Then, we combine the inundated roads with inaccessible bridge edges to estimate the impacted road lengths, classify them (e.g., residential, motorway) and aggregate the results at the county level.

2.2. Flood Exposure Index

We used fuzzy logic approaches to blend exposure layers together and created a composite map, indicating the most impacted area from flooding. Fuzzy logic-based approaches are commonly used in flood risk assessment (Ziegelaar & Kuleshov, 2022; Cikmaz et al., 2022). Each exposure layer is converted to raster format and rescaled into 0 to 1 using fuzzy membership with setting the fuzzification algorithm to Large (Equation2), representing that the large values of the input raster have high membership closer to 1. By default, the midpoint input sets the median value of the input data, which is assigned a membership of 0.5. In our analysis, it is adjusted to be the average of exposure values over the study area to avoid biased fuzzification distribution. Another input parameter is spread, which controls how rapidly the fuzzy membership zone transits between 0 and 1. It sets to 5 by default.

$$\mu(x) = \frac{1}{1+(x/f2)^{-f1}} \qquad \text{Eq. 2 (adapted from Esri, n.d.)}$$

where the f1 is the spread and f2 is the midpoint.

After generating the fuzzy membership functions, the fuzzy overlay analysis is performed using ArcMap 10.8. Recent studies have utilized fuzzy overlay analysis for different applications (Hasanloo et al.,2019; Mallik et al., 2021). Using the fuzzy overlay tool in ArcMap, a multi-criteria overlay analysis can examine the likelihood that a phenomenon belongs to many sets. The fuzzy Gamma is used to combine the data based on set theory analysis, offering a mechanism to balance multiple input criteria to best represent suitability (Lewis et al., 2014). It is an algebraic product of the Fuzzy Product and Fuzzy Sum raised to the power of gamma (by default, γ =0.9) (Equation 3). The range of fuzzy overlay values is redivided as an equal interval with five labels to reflect flood exposure status (Table1).

$$\mu(x) = (FuzzySum)^{\gamma} * (FuzzyProduct)^{1-\gamma} \quad \text{Eq. 3 (adapted from Esri, n.d.)}$$

2.3. Case Study Region

The State of Iowa is located in the Midwestern United States and home to 3,255,566 people, according to 2020 U.S. census data, with 2,346 populated places and 99 counties (Figure 2). Mississippi and Missouri Rivers run on the eastern and western Iowa boundary, respectively. Most Iowa communities (e.g., Des Moines, Cedar Rapids) are located near major rivers (i.e., Des Moines, Cedar) and are vulnerable to inland flood events. Iowa is one of the top U.S. states at risk of flooding. In the last 30 years, each county in Iowa has experienced flooding, with total presidential flood disaster declarations of 951 (Iowa Flood Center, 2022).

Table 1: Fuzzy overlay categories.

Flood Index	**Fuzzy Range**
Very Low	< 0.20
Relatively Low	0.20 - 0.40
Relatively Moderate	0.40 - 0.60
Relatively High	0.60 - 0.80
Very High	0.80 - 1.00

2.4. Data Collection

We acquired a wide range of datasets from various sources to achieve the study's objectives, relying on publicly available data sources. This is particularly important since many communities may not have the resources to access costly data. Below, we describe each dataset utilized in this research, including information on its origin, content, and format. By utilizing these datasets, we aim to provide a comprehensive understanding of the impact of floods on various aspects of the built environment in Iowa, including building infrastructure, demographics, transportation networks, and land use patterns.

Flood Map Extent: Iowa Flood Center has worked on a statewide floodplain mapping project to generate flood extents for 2-, 5-, 10-, 25-, 50-, 100-, 200-, and 500-year return period scenarios (Gilles et al., 2012). The maps are derived from hydrologic and hydraulic properties of basins and streams with high-resolution input data (e.g., 1m digital elevation models) and produced using HEC-RAS software. The flood inundation maps are available at the Iowa Flood Information System (IFIS, https://ifis.iowafloodcenter.org).

<u>Building Footprint:</u> The Bing Maps project developed by Microsoft (2018) has released an open-source building footprint dataset for the entire United States. This collection includes 129,591,852 digitally created building footprints that were obtained from satellite images. It is available in GeoJson formats and represented as polygons. The total building footprints in Iowa are 2,074,904. We consider a footprint area larger than 40 square meters to avoid accounting for small structures (e.g., garage).

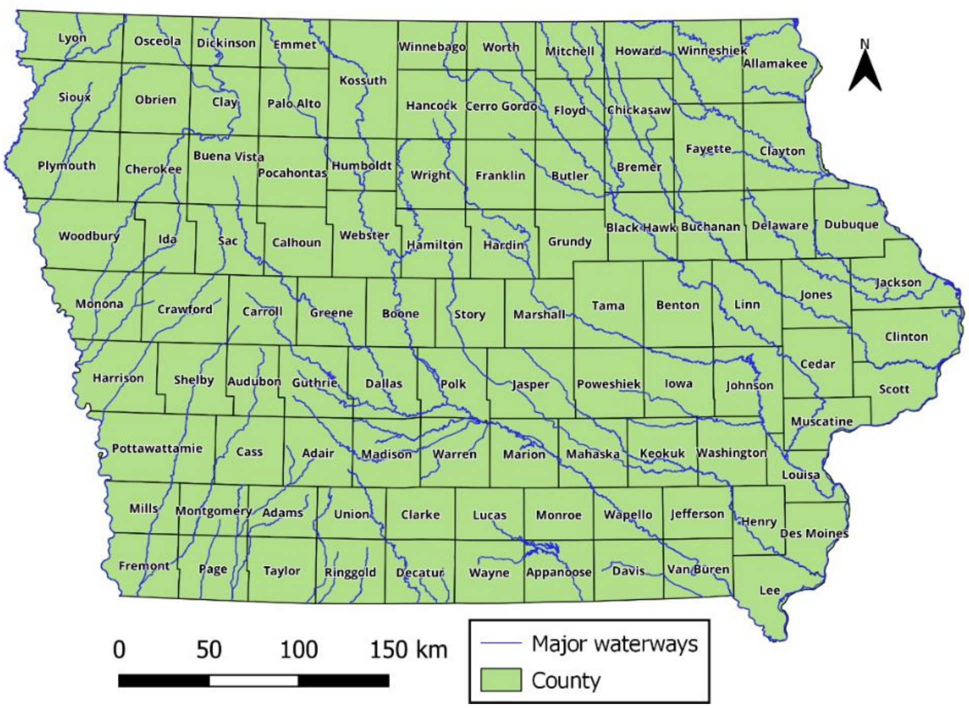

Figure 2: Iowa State counties labeled by county name.

<u>Demographics:</u> The population data per census block was collected from HAZUS software (version 6.0) which is based on the 2020 U.S. Census Bureau. The dataset contains population information, including sex, race, and income levels. The total census blocks within Iowa are 151,654.

<u>Transportation Network:</u> Road networks are shared freely by the OpenStreetMap (OSM) project. The dataset contains edges and nodes where the edge represents a road segment, and the node point represents the start/end point of the road segment. For the entire U.S., it can be downloaded from relevant study (Boing, 2017). Each edge has information such as class (e.g., residential, primary) and number of lanes. There are 356,159 edges and 247,452 nodes inside the Iowa border.

<u>Bridge Inventory:</u> The bridge dataset is acquired from the Iowa Department of Transportation (last updated: 2020) and available in a point-geometry layer. In Iowa, there are 24,006 bridges and culverts.

Land Use: Property classification (e.g., residential, commercial) has been performed using the National Land Use Dataset (NLUD) (Theobald, 2014) and OSM. The NLUD is a comprehensive 30m-resolution dataset for the conterminous United States, containing 79 land use classes. It is developed through spatial analysis of multiple spatial datasets, including land cover from satellite imagery. The OSM land use dataset, including urban and agricultural classification can be downloaded from (Geofabrik, 2020). It is represented by polygon geometries and generated from daily updated OSM data.

3. Results and Discussions

Table 2 shows overall Iowa flood exposure components during the 100, 200, and 500-yr flood scenarios. We found that up to 5 % of Iowa properties are at risk of flooding. Flooding can cut off the accessibility of roads and bridges with a total length of 22,442 and 3,132 km, respectively. Also, more than 100,000 of the Iowan population are threatened to being displaced during flooding. The following detailed outcomes are aggregated at the county level. We focus on calculating the ratio of exposed elements to the total amount of elements in each county. This implies that both large and small counties have been given equal consideration.

Table 2: State-wide summary of elements exposed to flooding.

Scenarios	Properties	Roads (km)	Bridges (km)	Population
No flood	1,983,047	191,987	26,218	3,255,566
100-yr	59,500	20,555	2,189	111,092
200-yr	77,569	22,755	2,618	142,745
500-yr	97,551	25,442	3,132	180,402

3.1. Property Damage

Within each county, we computed the properties exposed to flooding and extracted the county damage percentage (Figure 3). The majority of counties have damage levels of up to 2%. However, some counties like Black Hawk will have a higher damage percentage once they experience larger flood events. Pottawattamie, Mills, and Fremont counties, which are located along the Missouri River, recorded considerable damage (10 – 40%) during the three flood scenarios. During the 100, 200, and 500-yr flood events, most counties expect up to 700 damaged properties (Figure 4). Approximately 23% of Iowa counties have 701- 2100 properties in the floodplain. Few counties will have up to 2,800 in property damage, with Pottawattamie County being the most vulnerable with 21,122 damaged properties.

Table 3 reveals the occupancy types for the most flood-exposed properties. We have used the NLUD and OSM dataset to assign a class to each impacted property. OSM land use dataset has missing classifications for some areas. Also, it is found that some properties are located in areas classified as water and transportation using the NLUD. Table 3 shows the most impacted classes during the three flood scenarios for the top impacted counties. Results indicate that the residential properties are the most affected occupancy type. Institutions (e.g., fire and police stations) seem to be the less vulnerable class; however, they become very important during flooding for emergency response. This analysis can help decision-makers protect exposed areas by implementing mitigation measures (e.g., levee, retrofitting structures) or enforcing new policies (Teague et al., 2021), and support ethical decision-making frameworks (Ewing and Demir, 2021). Also, it emphasizes considering flood scenarios when zoning standards.

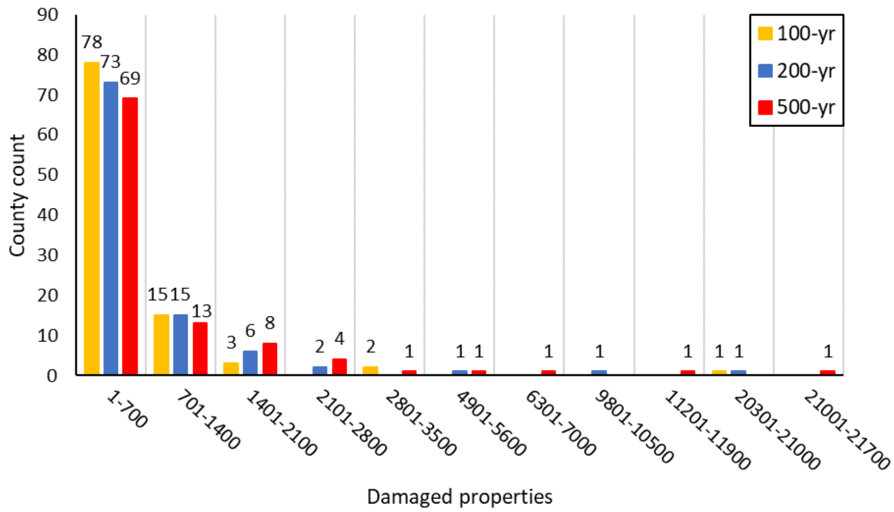

Figure 4: Distribution of property damage count per county.

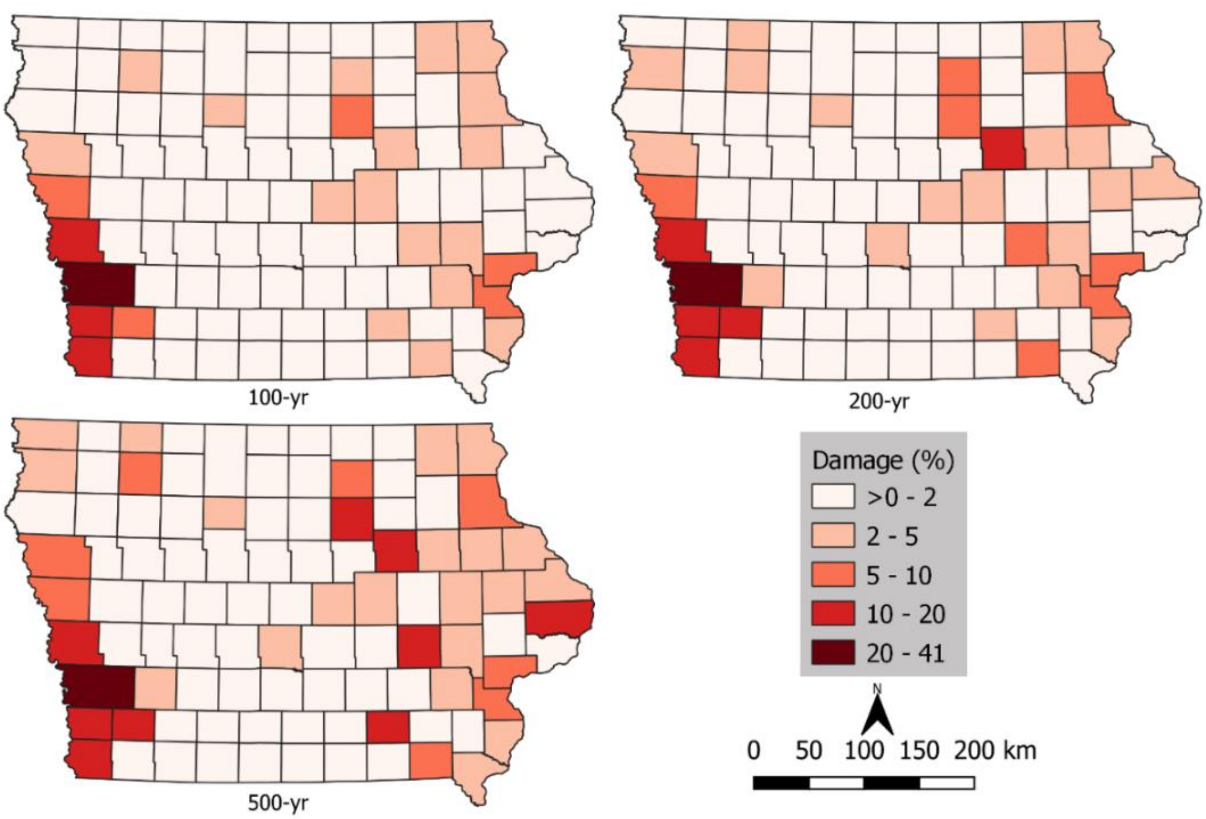

Figure 3: The percentage of property damage per county.

Table 3: The most impacted property classes for counties with more than 1,000 damaged properties during the 500-yr flood sorted by total damaged properties.

County	Residential			Production			Industrial			Commercial			Institutional			Total		
	100yr	200yr	500yr	100yr	200yr	500yr	100yr	200yr	500yr	100yr	200yr	500yr	100yr	200yr	500yr	100yr	200yr	500yr
Pottawattamie	18,542	18,611	18,914	423	438	469	511	511	544	459	461	481	150	150	154	20,618	20,710	21,122
Black Hawk	2,043	8,508	9,473	406	483	545	241	515	549	113	318	352	3	11	12	2,963	10,085	11,221
Clinton	135	208	5,344	314	358	403	19	42	160	17	19	154	-	-	21	598	751	6,355
Polk	2,176	3,423	3,785	67	79	86	593	710	732	316	503	550	13	18	21	3,327	4,927	5,380
Linn	511	825	2,336	78	111	140	96	109	188	139	154	283	6	6	17	913	1,309	3,094
Woodbury	888	1,317	1,562	339	369	420	34	403	444	77	155	174	12	12	12	1,390	2,338	2,707
Wapello	478	591	1,959	134	162	187	52	89	162	30	49	185	-	-	-	736	957	2,578
Harrison	1,013	1,028	1,086	862	876	934	9	9	9	76	77	78	2	2	2	2,094	2,126	2,269
Muscatine	527	567	977	673	737	783	35	41	78	15	18	35	-	4	4	1,460	1,595	2,122
Dubuque	465	541	1,329	53	74	92	65	85	212	37	43	204	-	-	-	730	885	2,004
Johnson	1,054	1,096	1,370	134	154	184	94	102	153	98	101	140	8	8	28	1,505	1,581	2,003
Montgomery	821	1,248	1,463	39	47	53	13	13	15	28	60	111	3	8	12	964	1,456	1,751
Scott	624	748	912	122	132	165	143	204	377	41	61	102	2	4	6	1,089	1,313	1,735
Butler	511	880	972	338	454	571	3	4	7	7	7	9	2	6	7	899	1,407	1,648
Clayton	475	988	1,141	166	215	256	3	6	8	31	47	54	2	4	6	763	1,412	1,628
Iowa	566	1,191	1,209	111	124	155	7	17	19	19	44	59	15	15	15	780	1,483	1,558
Mills	688	693	765	504	509	525	24	24	43	62	62	66	-	-	-	1,355	1,367	1,485
Fremont	352	354	432	623	628	644	12	12	12	21	21	21	1	1	3	1,090	1,097	1,201
Clay	196	260	774	31	38	74	4	5	8	19	20	50	-	2	2	356	451	1,058
Monona	74	87	144	587	619	764	-	-	-	18	20	21	-	-	-	735	786	1,007

3.2. Displaced Population

Once floodwater reaches structures, it can lead to people being displaced from their properties. In Figure 5, the percentage of the displaced population is calculated for each county during the 100, 200, and 500-yr flood events. Our analysis shows that at least 2% of the county's inhabitants can experience evacuation during floods. Some counties like Clinton and Montgomery can encounter a significant impact in the exposed population during the studied flood events. Pottawattamie County is the most impacted area during the three flood scenarios with displaced population ranging from 20 to 46%. This investigation can give insights into what may be required to accommodate the displaced population (e.g., the number of evacuation centers).

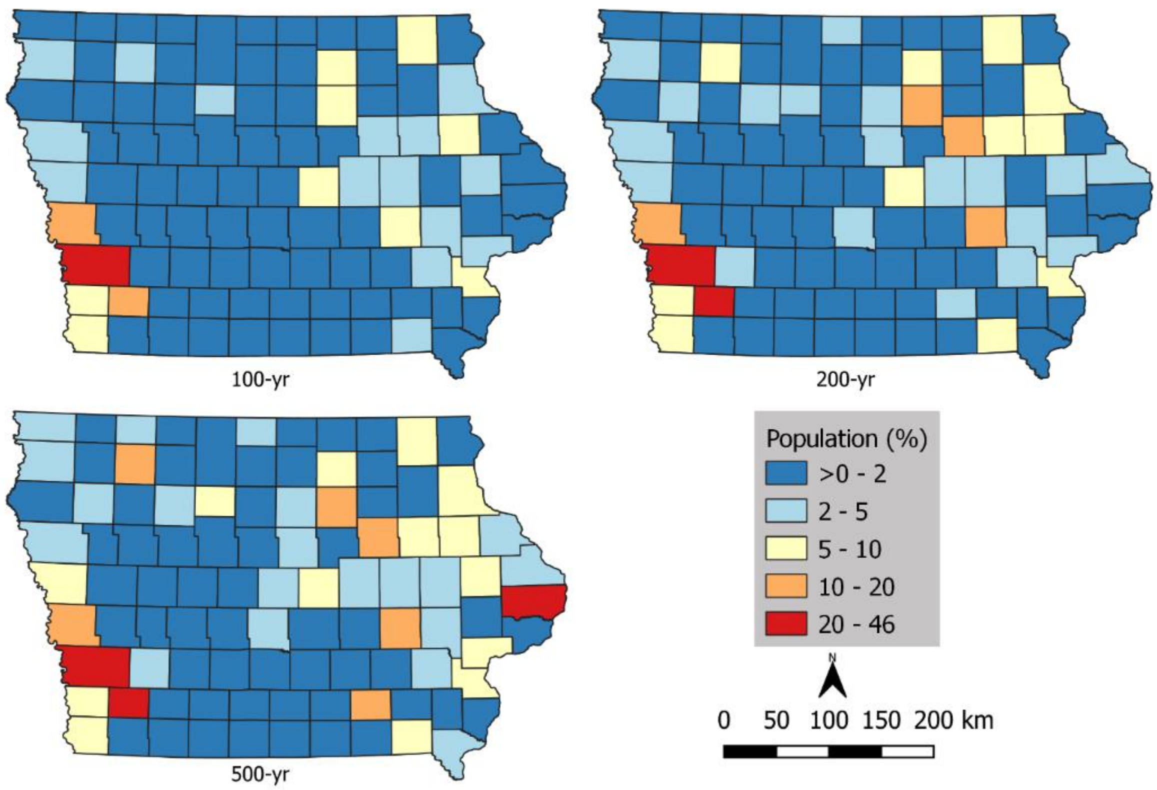

Figure 5: The percentage of displaced population per county.

The potential actual population exposed to flooding for the top 20 impacted counties is represented in Figure 6. For most counties, the displaced population is in the range of 100 – 5,000. Given the total population, Pottawattamie County shows significant impact with a similar number during the three flood scenarios, opposite of what has been seen for similar counties (e.g., Woodbury, Story, Dubuque). Also, Clinton County will experience a noticed shift in displaced population during the 500-year flood, possibly due to the county's existing flood defenses being designed for low flood probability. Furthermore, Polk, the county with the largest population in our dataset, appears to be less vulnerable to the displaced population.

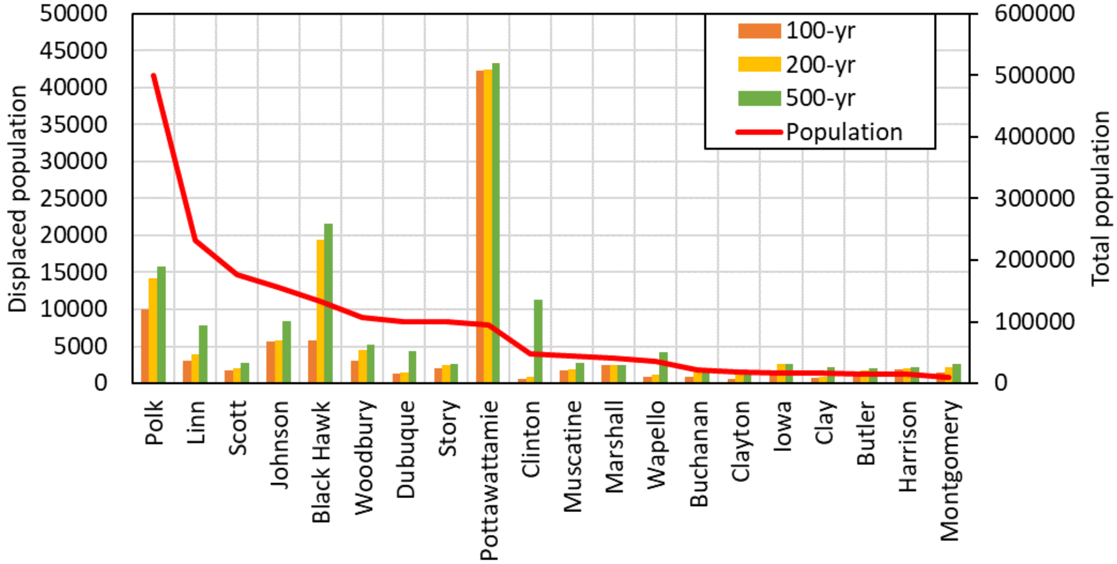

Figure 6: Displaced population for top 20 counties sorted by county total population.

3.3. Road Network Damage

Road networks are analyzed with respect to the road length instead of the road segment count to reduce underestimation of the impacts. For instance, some counties may lose up to 100 road segments with the impacted road length smaller than counties with a road segment count of 50. Additionally, the length of the road is a major factor in estimating road reconstruction. Bridges are crucial for connecting different regions in transportation network. Flooding, however, may cut off accessibility to the bridges and create isolated areas. In Iowa, each county can lose access to bridges up to 10% of their total bridge length during flooding (Figure 7). The highest length percentage of inaccessible bridges, ranging from 30 to 63%, was found in the lower left side of Iowa, along with Muscatine County on the eastern border. In comparison to other counties, the percentage for counties with large cities, such as Des Moines and Cedar Rapids, is small, which might be interpreted as less attention being paid to areas with smaller cities.

The percentage of damaged road length, including the inaccessible bridge, is shown in Figure 8. Counties along the lower western border show major losses in terms of road length exceeding 20% during the 100, 200, and 500-yr flood events. Also, it has been noticed that the percentage for most counties located in the middle fluctuated between 1 to 20%. Moreover, some counties like Johnson have the same lost percentage during the three flood scenarios, and others like Black Hawk show a noticeable change between flood events. Even though the percentage is considered low for some counties, it might reflect significant impacts (e.g., losing accessibility to essential services). Figure 9 illustrates how the number of counties might alter depending on the flood scenario and impact based on road length range. We found that 13 counties can experience a less-than-100 km reduction in the length of their roads. The majority of counties are susceptible to losing between 100 and 300 km of their road networks during flooding. Also, few counties can have an inaccessible road length from 700 to 1,100 km. The mitigation costs (e.g., elevate a road) can be estimated roughly with the use of this analysis.

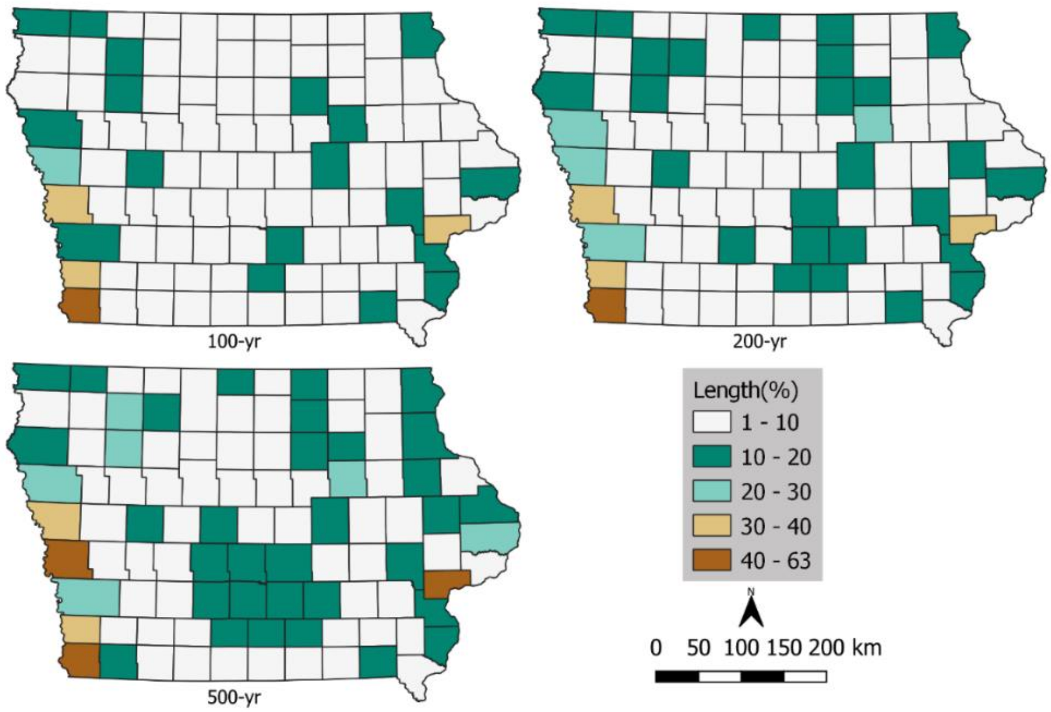

Figure 7: The percentage of inaccessible bridge edge per county.

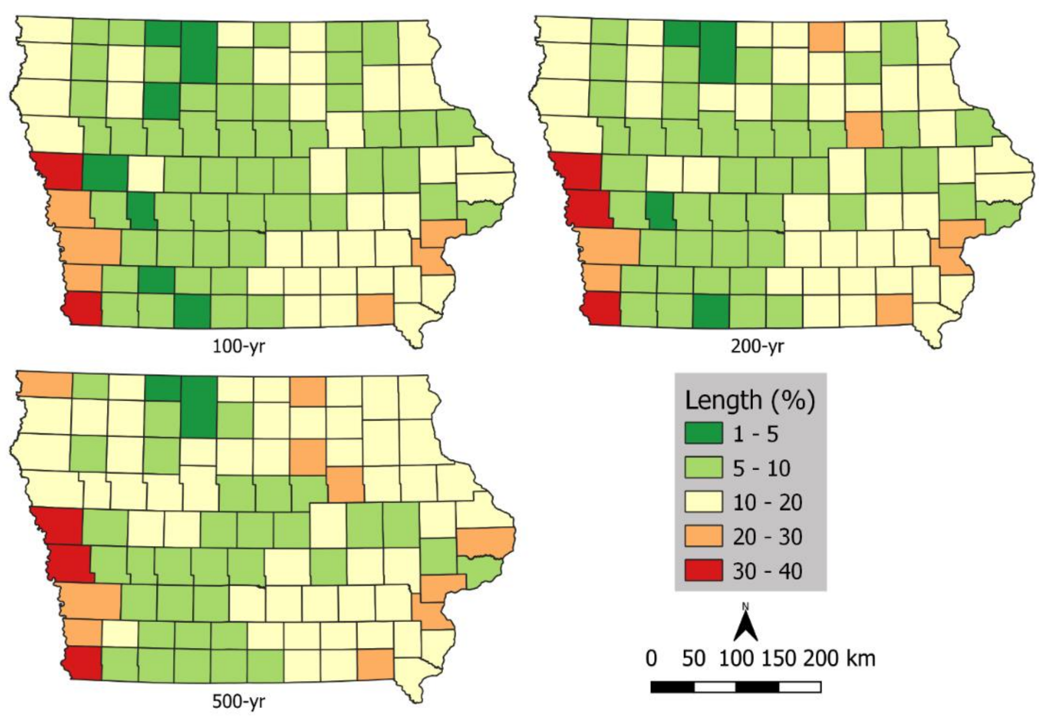

Figure 8: The percentage of road length damage per county.

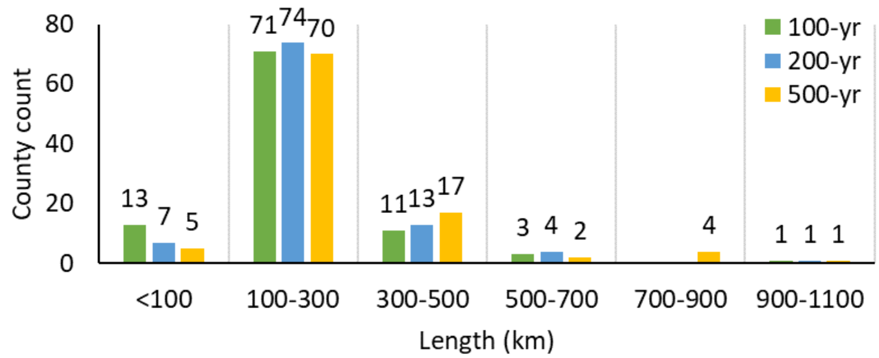

Figure 9: County count based on total impacted length.

In Table 4, the total length of each impacted road class is estimated during the 100, 200, and 500-yr floods. Among the top 20 impacted counties, the residential class is the highest road length type with a range of 211-658 km, while the trunk class appears the less vulnerable to flooding. This may indicate that routes within residential area lack account for flood scenarios, or they might be built near waterways. Also, residential roads that are under water may make it difficult for individuals to evacuate.

Table 4: Top 20 counties based on impacted road length (km) sorted by the total length.

County	Residential			Motorway			Tertiary			Secondary			Trunk			Primary			Total Length		
	100	200	500	100	200	500	100	200	500	100	200	500	100	200	500	100	200	500	100	200	500
Pottawattamie	599	619	658	155	155	169	128	129	138	52	55	66	13	13	13	5	5	8	953	976	1,052
Monona	512	516	574	-	-	8	80	81	91	60	62	62	-	-	-	26	26	33	678	684	768
Harrison	479	501	542	54	54	61	52	52	59	12	12	14	-	-	-	39	39	44	636	658	722
Black Hawk	249	398	433	62	82	89	80	114	129	17	29	30	6	11	11	13	25	26	428	659	719
Fremont	448	460	485	87	87	87	97	100	109	-	-	-	9	9	9	13	13	14	653	668	703
Woodbury	256	295	329	14	18	19	51	57	66	50	61	67	5	6	7	28	37	48	404	474	535
Clinton	281	297	412	-	-	-	47	49	63	-	-	-	1	1	8	16	20	28	345	366	511
Mills	254	272	286	46	46	48	48	50	56	16	16	19	15	15	17	5	5	6	384	404	431
Muscatine	271	288	328	-	-	-	28	28	34	5	5	5	2	2	16	37	41	43	344	364	426
Polk	209	239	264	17	17	21	53	55	56	50	59	60	4	4	4	8	12	13	340	386	419
Johnson	238	251	275	16	16	16	60	62	73	8	13	18	-	-	-	9	10	16	331	352	397
Clayton	281	311	345	-	-	-	16	19	25	2	4	4	-	-	-	7	12	12	306	345	386
Butler	251	289	328	-	-	-	20	27	33	-	-	-	-	-	-	14	19	20	285	335	380
Plymouth	209	227	253	-	-	-	32	32	35	22	25	27	28	36	41	9	9	17	300	329	373
Sioux	218	234	252	3	3	3	37	41	42	26	27	36	4	4	6	14	14	15	300	321	354
Lyon	262	274	282	-	-	-	53	57	58	2	4	4	-	-	-	8	8	9	326	343	354
Linn	167	202	244	8	8	13	28	33	38	16	19	26	-	-	7	5	5	10	224	266	337
Louisa	272	272	293	-	-	-	19	19	27	13	13	13	-	-	-	3	3	4	306	306	336
Mitchell	251	268	282	-	-	-	32	32	36	-	-	-	-	-	-	3	3	3	286	303	321
Clay	211	231	274	-	-	-	9	9	13	17	17	19	1	3	4	2	3	4	240	263	314

3.4. Flood Exposure Analysis

We generated a flood exposure index for the study area during the 100, 200, and 500-yr flood events using fuzzy overlay analysis. The exposure index map is the result of combining impacted property, population, and road network layers scaled throughout the state. We used the percentage of exposure generated from the previous analysis as input values. Using this methodology, we conducted an equal-footing analysis of small and large counties. Resulted fuzzy values are divided into equal size ranges to assign exposure index. As can be seen in Figure 10, up to 25 counties are classified "very high", Notably, most appear to be geographically concentrated along the Missouri River, as well as in the eastern region of Iowa. On the other hand, more than 40 counties classified "very low". The rest of the counties are either relatively low, relatively moderate, or relatively high.

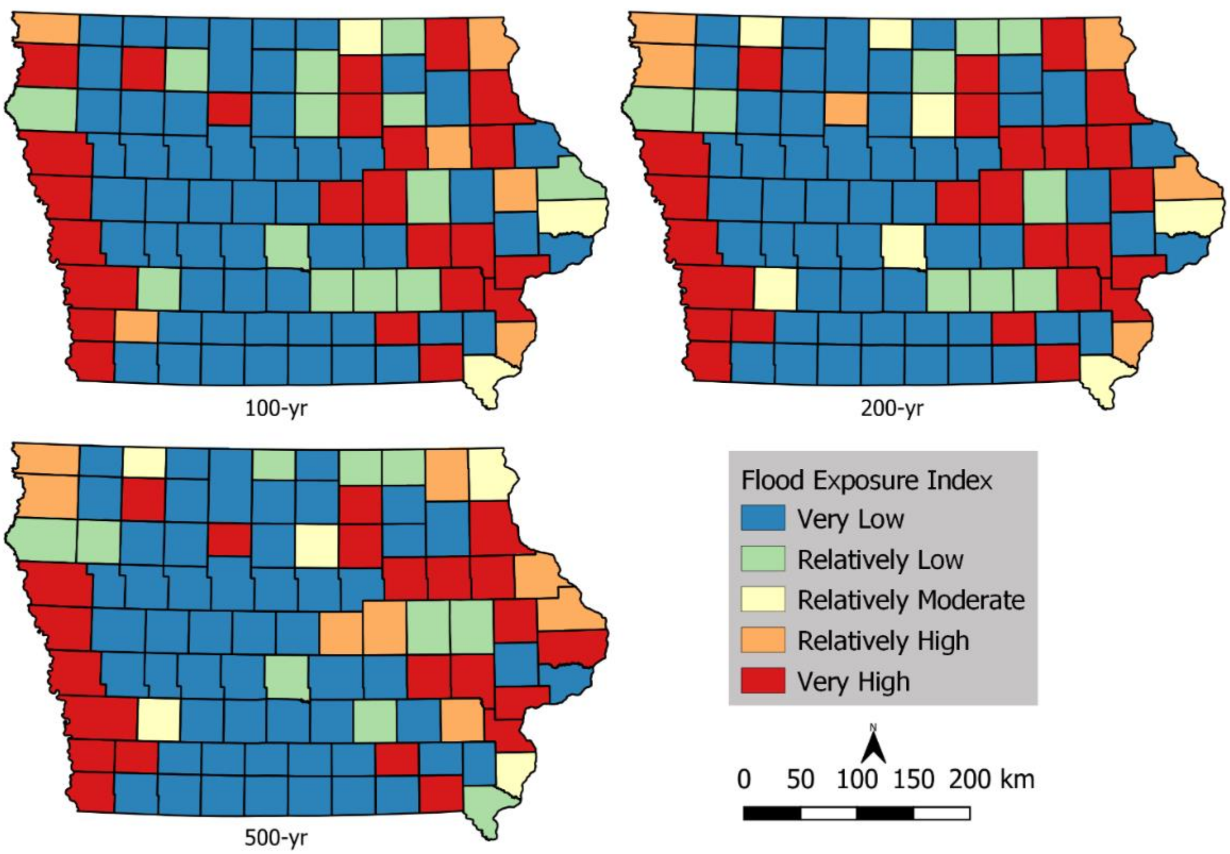

Figure 10: Flood exposure index for overlay layers (population, properties, and roads).

It has been noticed that the county can receive a lower or higher index as the exposure layer changes under flooding. For example, Lee County, located in the lower right corner, is "relatively moderate" under the 100 and 200 flood events but "relatively low" during the 500-yr flooding. This is mainly due to the significantly increased flood exposure experienced by other counties during the 500-year flood event, which impacts the index values of neighboring counties. The findings are significant since flood exposure is often assessed separately (e.g., property damage), failing to capture multiple exposure layers together. Also, it points out the way to consider different flood scenarios, as usually the assessment is limited to a certain flood extent (i.e., 100-yr flood), which may result in misleading decisions when evaluating flood risk. This index can be used to create plans and strategies to minimize exposure to flooding and help drive financial support to the most impacted counties.

We analyzed the correlation using the Panda python library between the exposure layers and the flood exposure index to understand the strength and direction of the relationship (Table 5). Among the three flood scenarios, all layers are positively correlated with the flood index map, with building footprints and population (> 0.9) being the strongest and roads (0.70-0.72) showing the lowest. This indicates that the building footprint and displaced population maps are quite comparable to the flood index map.

Table 5: Similarity correlation analysis.

Flood	Footprint	Population	Roads
100-yr	0.94	0.91	0.70
200-yr	0.94	0.92	0.71
500-yr	0.95	0.94	0.72

3.5. Differential Flood Exposure

Due to the differential flood exposure among the analyzed counties, it is essential to highlight why some counties are at high risk of floods than others. We used the digital elevation model (Iowa Geodata, 2022), distance to stream (USGS, 2022), levee (IFIS, n.d.), poverty rate (US Census Bureau, 2022), and city boundary (Iowa DOT, 2020) to carry out the analysis. We have selected two large counties (Pottawattamie, Dallas) and relatively small ones (Clay, Madison) with different flood indexes to understand the relationship between flood exposure (Table 6). The floodplain extent looks positively linked with high flood index counties. Given the elevation-mean of each county, the topographic surface seems not significantly associated with flood exposure as low-elevation counties have a low flood exposure index. Also, we found that Pottawattamie and Clay have a percentage of persons in poverty higher than Dallas and Madison, which may indicate that strong correlation of poverty on vulnerability to floods.

Table 6: Selected counties for flood exposure comparison.

County	Flood Index	Population	Area (km^2)	Levee (km)	Elevation Mean (m)	Poverty (%)	Floodplain (km^2)		
							100-yr	200-yr	500-yr
Pottawattamie	High	94,351	2,484	170	359	12.3	415	432	454
Dallas	Low	103,255	1,532	8.6	303	5.3	147	154	160
Clay	High	16,717	1,483	8	419	9.4	200	207	221
Madison	Low	17,332	1,456	-	325	7.4	117	122	128

Figure 11 presents city boundaries, proximity distance to streams, levees, and flooded properties and roads within the selected counties. The observation reveals that the major cities in Pottawattamie and Clay counties are spatially concentrated in close proximity to waterways in contrast to those in Dallas and Madison counties. This geographic clustering of cities near waterways increases their exposure to flood hazards. The distance mean from the flooded properties to the closest streams for Pottawattamie and Clay falls within a range of 1200 – 1800 m, whereas for Dallas and Madison counties, this distance is limited to 400-800 m. In Pottawattamie, most of the inundated roads are situated within a distance range of 1000-5000 m, while the corresponding range for Dallas, Clay, and Madison is less than 1000 m. Indeed, impacted buildings and roads in Pottawattamie appear far from water bodies but at high risk of flooding, which may be attributed to inefficient flood structural protections and deficient city planning. Also, the levee dataset indicates that Pottawattamie County has constructed levees spanning 170 kilometers. However, further efforts are necessary to improve and update the levees to lower the area's exposure level to flooding. Flooding is a crucial consideration when developing new areas since it helps avoid a wide variety of adverse impacts (e.g., levee construction costs, property damage).

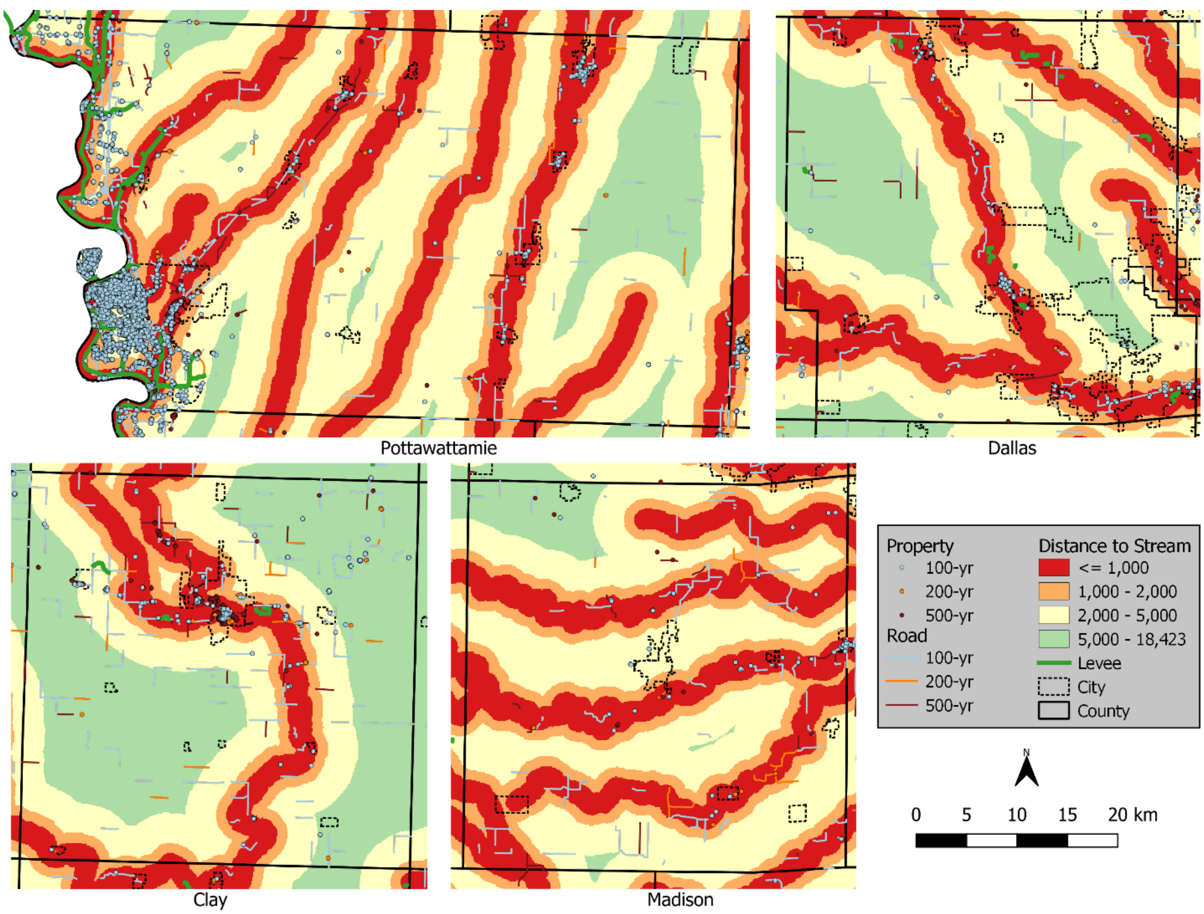

Figure 11: Impacted County spatial layout.

4. Conclusion

This study has presented a county-level comprehensive analysis of the exposure elements (population, properties, and road networks) during the 1%, 0.5%, and 0.2% annual flood probabilities. We combine the exposure layers into a single map to determine the most affected county. Our findings show that the impact of the floods on the Iowa counties varied. More than 10,000 population are residing within the floodplain in some counties. Most counties can experience inundated properties and road lengths of up to 700 and 300 km, respectively. Our analysis reveals that more than 20 counties are designated as "very high" flood exposure areas. This research identifies susceptible locations to flooding that may be utilized to develop plans and strategies (e.g., investigate mitigation measures) to avoid economic losses and improve community resilience to flooding.

Large-scale analysis encounters challenges regarding data collection and analysis, which may introduce some limitations. This research relies on publicly accessible data as many communities cannot afford pricey data resources. It lacks to capture the vulnerability assessment associated with exposed elements (i.e., economic losses) which requires additional flood components (e.g., flood depth) and occupancy characteristics (e.g., foundation height) that are not available within the study area. Some of the studied buildings are in transit and water land, indicating that more work is needed to improve the land use product resolution.

For further analysis, the methods used in this research can be scaled at various geographic boundaries (e.g., watersheds, communities) to capture how flood risk changes within and across different areas and help implement the most effective flood risk mitigation strategies (Yildirim and Demir, 2021) at different scales (e.g., flood controls, land use policies). Integrating additional built environment exposure (e.g., agriculture, railways) with analyzed elements in this study can enhance the overall evaluation of flood risk. This research can be extended to look deeply into the factors that lead to making areas more vulnerable to flooding.

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