

## 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 damage 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 potentially exposed to the 100, 200, and 500-year flood events at the county level in the State of Iowa using geospatial analytics. We also propose 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 [1], and agriculture [2–4]. 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 [5, 6]. From 2000 to 2020, the United States have experienced multiple flood events, with overall damages reaching or exceeding \$1 billion per event [7]. Floods are responsible for not only economic losses, but also negative impacts on social well-being, health, and the environment [8, 9].

Flood risk can be quantified as a function of hazard, exposure, and vulnerability [10]. Flood exposure analysis is considered as a key component of flood risk assessment. It encompasses identifying and aggregating exposure elements (e.g., population, infrastructure) located in the floodplain [11]. At the same time, flood vulnerability refers to the degree to which an exposure element is susceptible to the adverse impacts (e.g., economic losses) of flooding. 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 [12] on preparedness, response, recovery, and mitigation [13, 14]. The analysis

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requires identification of flood events [15], 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 [16, 17] provide 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 [18], Greece [19], Canada [20], and the United States [21, 22]. At the watershed scale, Puno et al. [23] analyzed the exposure of land use and land cover during six flood return periods. In addition, Hamidi et al. [24] 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 [25–27]. The Federal Emergency Management Agency (FEMA) has established the National Risk Index (NRI) to identify the risk of 18 natural hazards including riverine flooding [28] at the county and census tract levels. The NRI combines expected annual flood loss for buildings, population, agriculture, social vulnerability, and community resilience [29]. 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 [1]. Furthermore, FEMA 100-year flood zones of many U.S. counties are either not currently mapped or are out of date [30], which creates a substantial barrier for local communities to understand flood risk and properly prepare for climate change's effects.

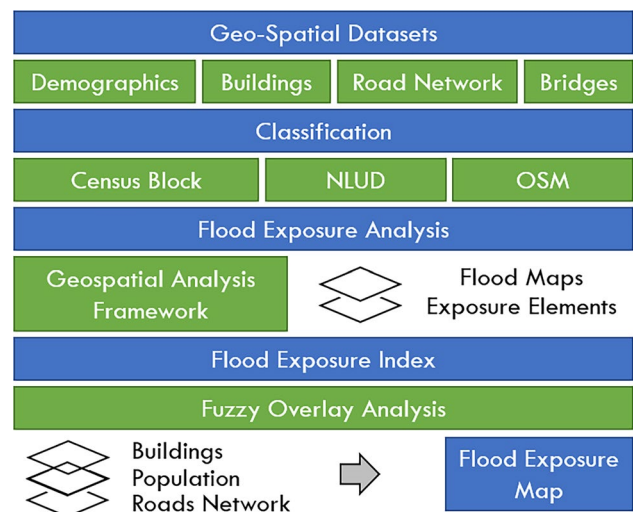
The state of Iowa lacks a large-scale comprehensive flood exposure assessment of the built environment, including rural and urban areas. Within the Iowa boundary, there has been relatively limited research on flood exposure analysis, focusing on buildings and road networks at small spatial scales (e.g., community) [31]. 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. We focused on the county scale since that's where most of local flood risk management decisions are decided [32]. 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 Sect. 3. The conclusion with future investigation is presented in Sect. 4.

## 2 Methodology

This study aims to analyze the 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 areas based on their level of exposure to floods. While most studies utilize flood depth for flood risk assessment, many study areas lack resources for generating a comprehensive flood depth map [33]. It requires extensive data and computational resources, which may not be available for most communities [34]. 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 [35]. 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.

**Fig. 1** Overall workflow of the flood exposure assessment



## 2.1 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 [36]. The maps are derived from hydrologic and hydraulic properties of basins and streams with high-resolution input data (e.g., 1 m 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>).

**Building Footprint** The Bing Maps project developed by Microsoft [37] 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).

**Demographics** The population data per census block was collected from HAZUS software (version 6.0) which is based on the 2020 U.S. Census Bureau [38]. The dataset contains population information, including sex, race, and income levels. The total census blocks within Iowa are 151,654.

**Transportation Network** 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 [39]. 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.

**Bridge Inventory** The bridge dataset is acquired from the Iowa Department of Transportation (last updated: 2020) [40] 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) [41] and OSM. The NLUD is a comprehensive 30 m-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 [42]. It is represented by polygon geometries and generated from daily updated OSM data.

## 2.2 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 (Eq. 1) [43]. The analysis considers the area-weighted approach to account for the variation in flood extent throughout a census block.

$$\text{Displaced population} = \sum \%A_i * T_i \quad (1)$$

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 [35]. A graph ( $G$ ) is described as  $G = (V, E)$ , where  $V$  is a collection of nodes connected by a set of edges ( $E$ ) [44]. 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.

## 2.3 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 [45, 46]. Each exposure layer is converted to raster format and rescaled into 0 to 1 using fuzzy membership with setting the fuzzification algorithm to Large (Eq. 2) (adapted from [47]), 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 (adapted from [47]).

$$\mu(x) = \frac{1}{1 + (x/f2)^{-f1}} \quad (2)$$

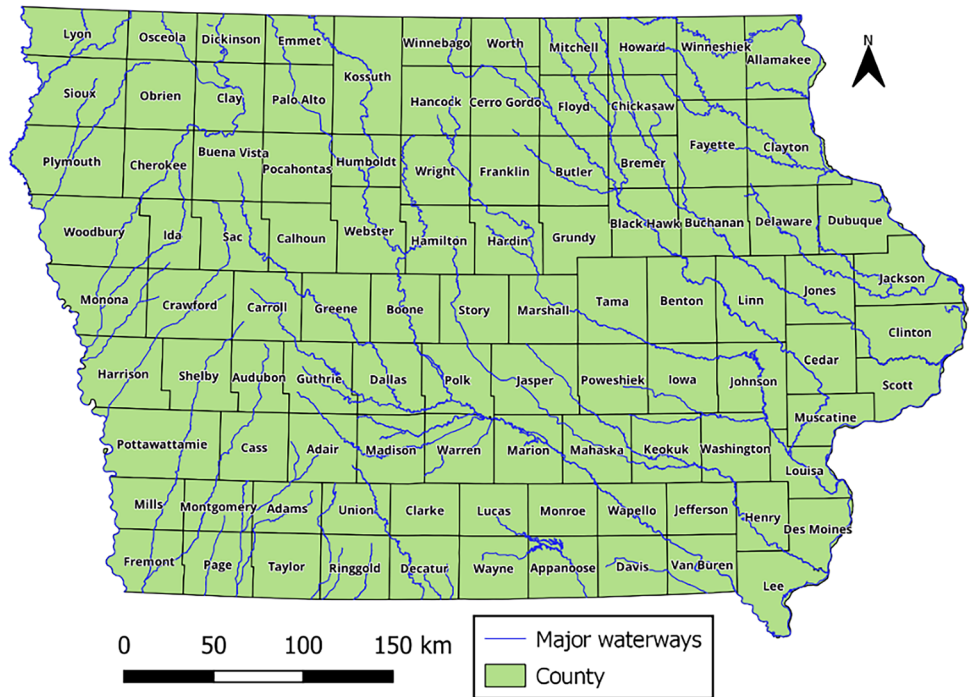
where the  $f1$  is the spread and  $f2$  is the midpoint.

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 [48, 49]. Using the fuzzy overlay tool in

**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

**Fig. 2** Iowa State counties labeled by county name



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 [50]. It is an algebraic product of the Fuzzy Product and Fuzzy Sum raised to the power of gamma (by default,  $\gamma=0.9$ ) (Eq. 3) (adapted from [47]). The range of fuzzy overlay values is redivided as an equal interval with five labels to reflect flood exposure status (Table 1).

$$\mu(x) = (\text{Fuzzy Sum})^\gamma * (\text{Fuzzy Product})^{1-\gamma} \tag{3}$$

### 2.4 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 2346 populated places and 99 counties (Fig. 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 [51].

**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	2189	111,092
200-yr	77,569	22,755	2618	142,745
500-yr	97,551	25,442	3132	180,402

### 3 Results and discussions

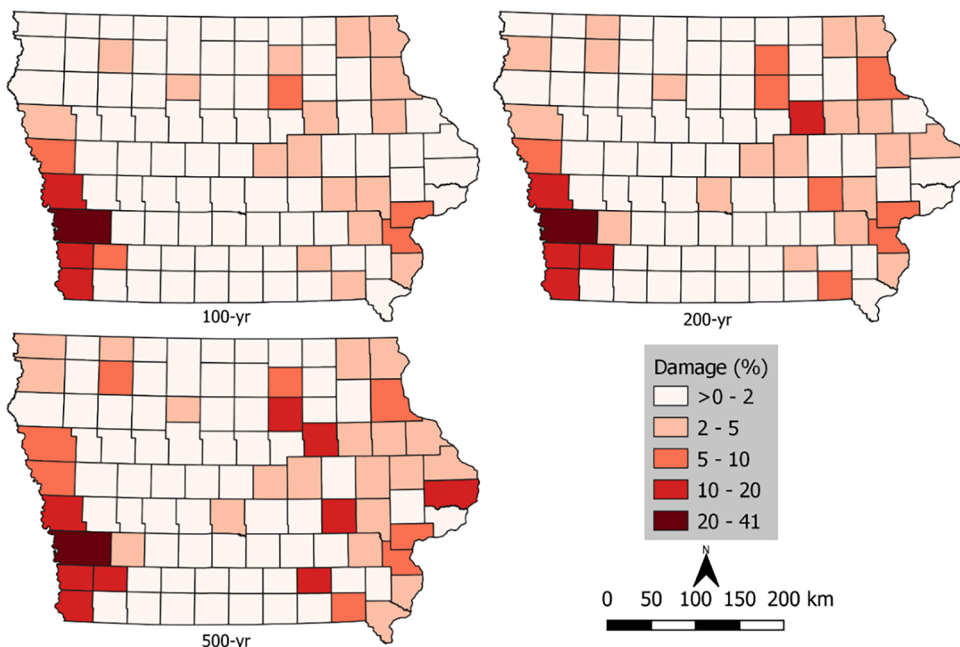
Table 2 shows a summary of Iowa State flood exposure components, including properties, roads, bridges, and population, during the 100, 200, and 500-yr flood scenarios. It indicates that the number of properties within the three floodplains can vary, with the proportion of properties within the floodplains reaching up to 5% for the 500-year scenario. Flooding can cut off the accessibility of roads and bridges with a total length of 25,442 and 3132 km, respectively. Also, more than 100,000 of the lowan 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.

#### 3.1 Property exposure to flooding

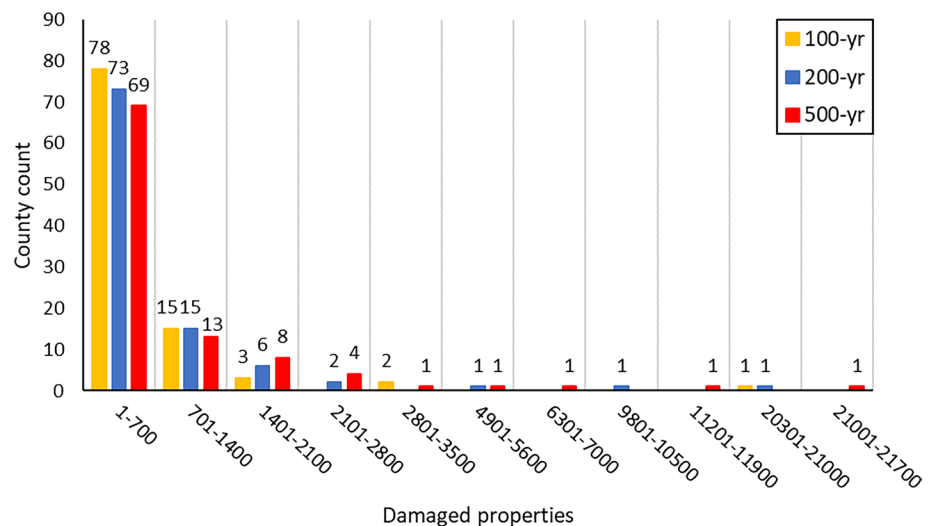
Within each county, we computed the properties exposed to flooding and extracted the county damage percentage (Fig. 3). The majority of counties have damage levels of up to 2%. However, some counties like Black Hawk will have a higher percentage of buildings residing in floodplain once they experience larger flood events. Pottawattamie, Mills, and Fremont counties, which are located along the Missouri River, recorded considerable impacted properties (10–40%) during the three flood scenarios. During the 100, 200, and 500-yr flood events, most counties expect up to 700 inundated properties (Fig. 4). Approximately 23% of Iowa counties have 701–2100 properties in the floodplain. Few counties will have up to 2800 properties laid on the floodplain, with Pottawattamie County being the most exposed area with 21,122 impacted 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

**Fig. 3** County-level property percentage located within the 100, 200, and 500-yr flood-plain



**Fig. 4** County count based on the number of impacted properties



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 [52], and support ethical decision-making frameworks [53]. Also, it emphasizes considering flood scenarios when zoning standards.

### 3.2 Displaced population

Once floodwater reaches structures, it can lead to people being displaced from their properties. In Fig. 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).

The potential actual population exposed to flooding for the top 20 impacted counties is represented in Fig. 6. For most counties, the displaced population is in the range of 100–5000. Given the total population, Pottawattamie County shows significant impact with similar displaced population numbers across the three flood scenarios, opposite of what happens in Woodbury, Story, Dubuque, despite the three counties having about the same total population. Clinton County also shows a noticeable increase in displaced population during the 500-year flood, possibly due to the county's existing flood defenses being designed for lower flood return period.

### 3.3 Road network exposure to flooding

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.

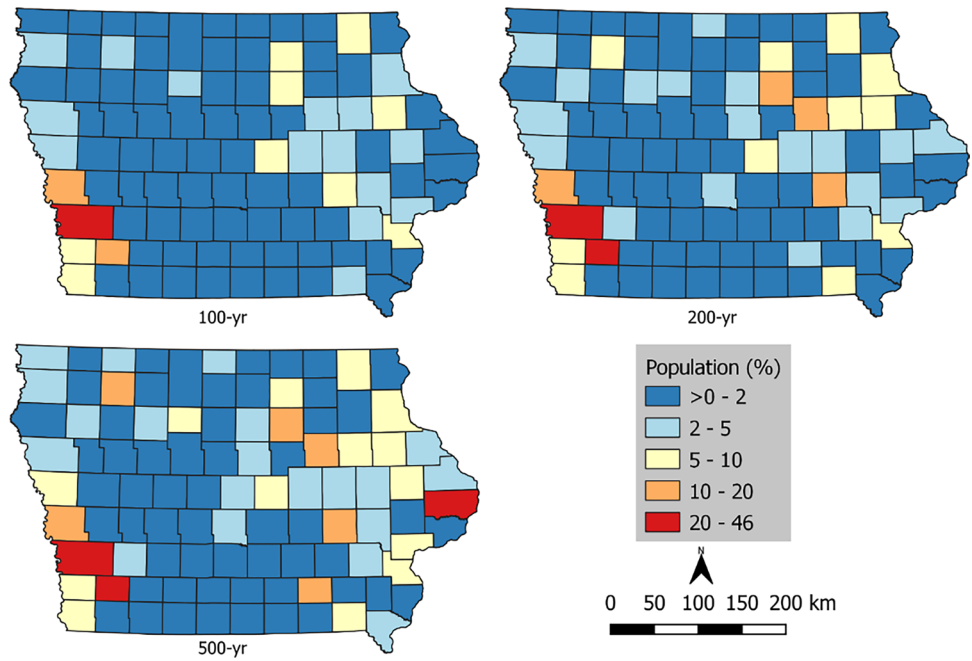
Bridges are crucial for connecting different regions in transportation network. Flooding, however, may cut off accessibility to the bridges and create isolated areas. In Iowa, the risk of bridge closures due to flooding affects all counties to some degree, with each facing varying levels of impact on bridge accessibility (Fig. 7). The highest length percentage of inaccessible bridges, ranging from 30 to 63%, was found in southwest 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 may reflect a higher density of road infrastructure in urban areas, suggesting potential disparities in infrastructure allocation between urban and rural regions.

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

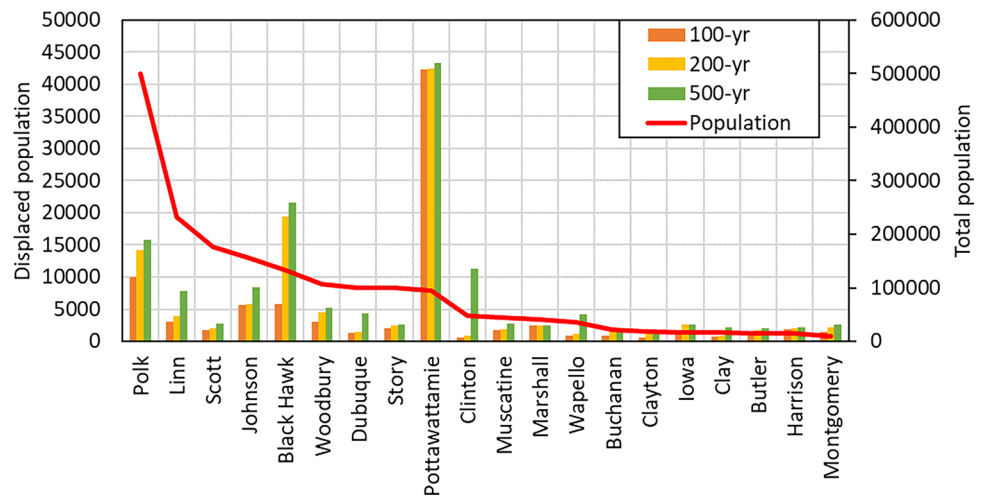
County	Residential			Production			Industrial			Commercial			Institutional			Total			
	100 yr	200 yr	500 yr	100 yr	200 yr	500 yr	100 yr	200 yr	500 yr	100 yr	200 yr	500 yr	100 yr	200 yr	500 yr	100 yr	200 yr	500 yr	
	Pottawattamie	18,542	18,611	18,914	423	438	469	511	511	511	544	459	461	481	150	150	154	20,618	20,710
Black Hawk	2043	8508	9473	406	483	545	241	515	549	549	113	318	352	3	11	12	2963	10,085	11,221
Clinton	135	208	5344	314	358	403	19	42	160	17	19	154	-	-	21	598	751	6355	
Polk	2176	3423	3785	67	79	86	593	710	732	316	316	503	550	13	18	21	3327	4927	5380
Linn	511	825	2336	78	111	140	96	109	188	139	154	283	6	6	17	913	1309	3094	
Woodbury	888	1317	1562	339	369	420	34	403	444	77	155	174	12	12	12	1390	2338	2707	
Wapello	478	591	1959	134	162	187	52	89	162	30	49	185	-	-	-	736	957	2578	
Harrison	1013	1028	1086	862	876	934	9	9	9	76	77	78	2	2	2	2094	2126	2269	
Muscatine	527	567	977	673	737	783	35	41	78	15	18	35	-	-	4	1460	1595	2122	
Dubuque	465	541	1329	53	74	92	65	85	212	37	43	204	-	-	-	730	885	2004	
Johnson	1054	1096	1370	134	154	184	94	102	153	98	101	140	8	8	28	1505	1581	2003	
Montgomery	821	1248	1463	39	47	53	13	13	15	28	60	111	3	8	12	964	1456	1751	
Scott	624	748	912	122	132	165	143	204	377	41	61	102	2	4	6	1089	1313	1735	
Butler	511	880	972	338	454	571	3	4	7	7	7	9	2	6	7	899	1407	1648	
Clayton	475	988	1141	166	215	256	3	6	8	31	47	54	2	4	6	763	1412	1628	
Iowa	566	1,191	1209	111	124	155	7	17	19	19	44	59	15	15	15	780	1483	1558	
Mills	688	693	765	504	509	525	24	24	43	62	62	66	-	-	-	1355	1367	1485	
Fremont	352	354	432	623	628	644	12	12	12	21	21	21	1	1	3	1090	1097	1201	
Clay	196	260	774	31	38	74	4	5	8	19	20	50	-	2	2	356	451	1058	
Monona	74	87	144	587	619	764	-	-	-	18	20	21	-	-	-	735	786	1007	



**Fig. 5** Percentage of displaced population per county



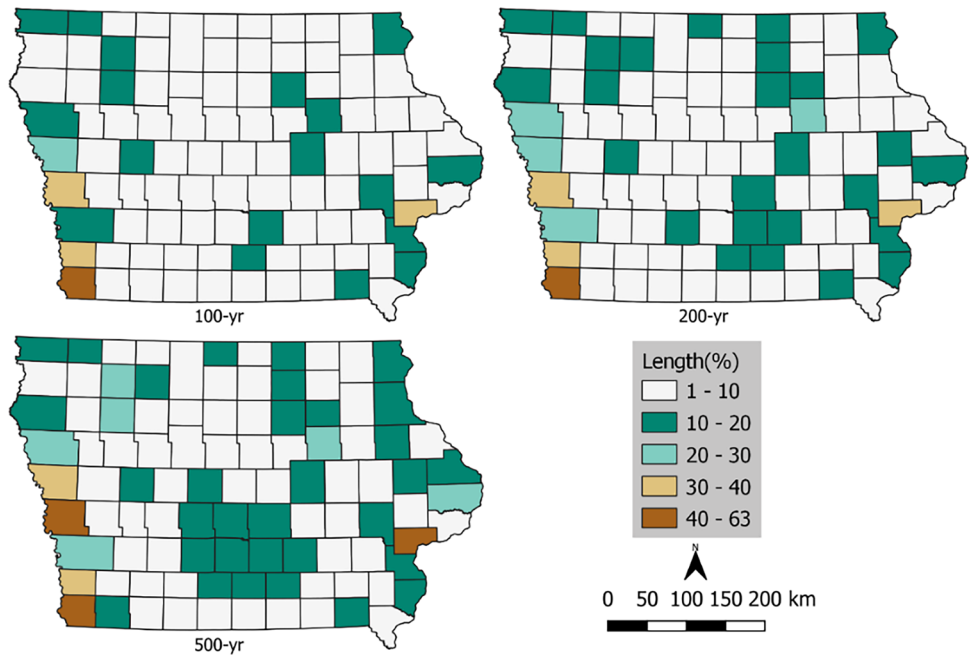
**Fig. 6** Displaced population for top 20 counties sorted by county total population



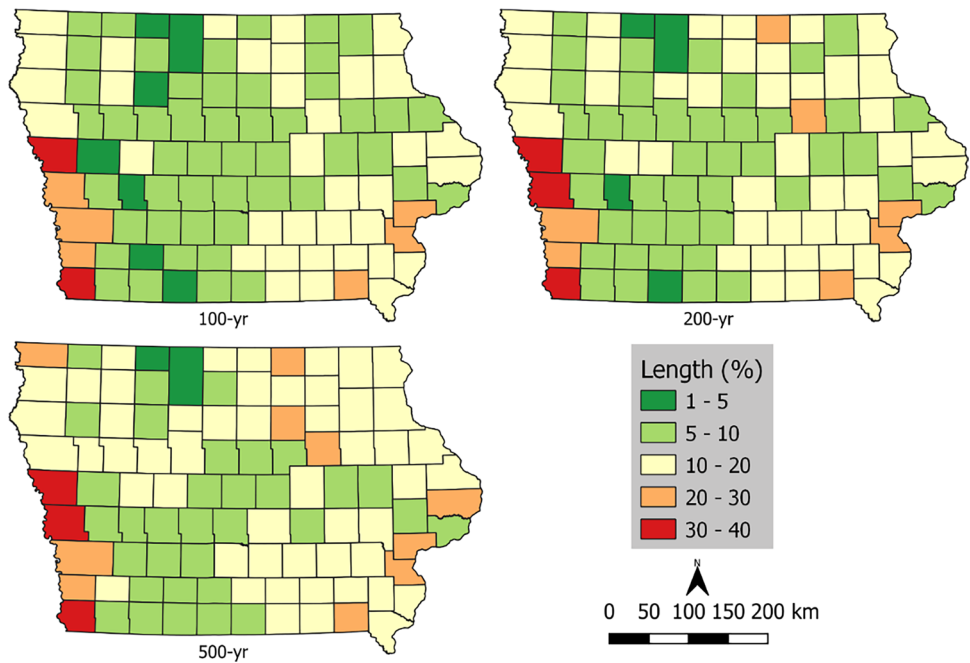
The percentage of damaged road length, including the inaccessible bridge, is shown in Fig. 8. Counties along the lower western border show the potential for major losses in terms of road length exceeding 20% during the 100, 200, and 500-yr flood events. Also, it is possible to see that for most counties in central Iowa the percentage is within 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). In Fig. 9 we classified counties based on flooded road length and flood scenario. Our analysis reveals that in 5 counties, the length of inundated roads remains consistently within 100 km across various scenarios. The majority of counties are susceptible to losing between 100 and 300 km of their road networks during flooding. Also, five counties can have an inaccessible road length from 700 to 1100 km. The mitigation costs (e.g., elevating a road) can be estimated roughly with the use of this analysis.

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. The concentration of residential roads in flood-prone areas highlights a broader urban planning issue, as entire residential areas may have been developed in these zones rather than just individual roads near waterways. Consequently, the challenge extends beyond road infrastructure to encompass entire residential communities, significantly complicating emergency activities such as evacuation.

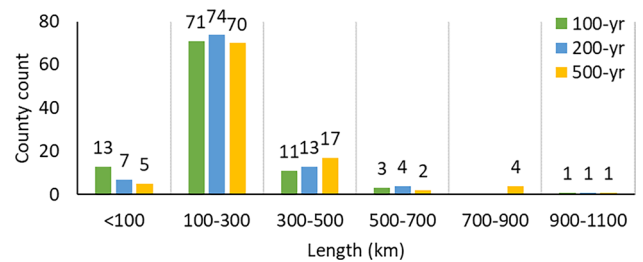
**Fig. 7** Percentage of inaccessible bridge edge per county



**Fig. 8** Percentage of road length impacted per county



**Fig. 9** County count based on total impacted length



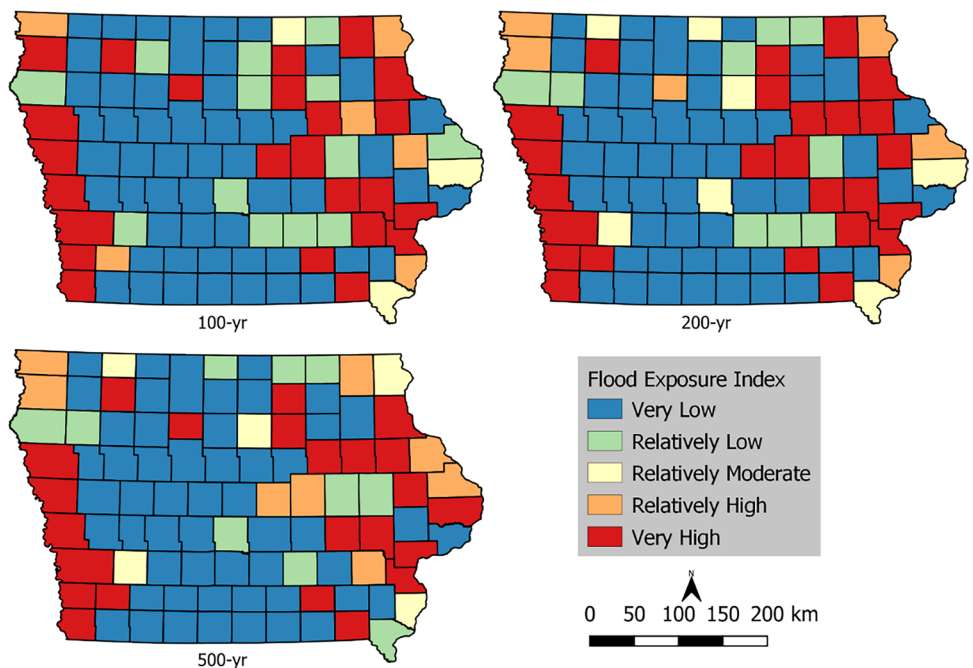
**Table 4** Top 20 counties based on impacted road length (km) sorted by the total length

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	1052
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

**Fig. 10** Flood exposure index for overlay layers (population, properties, and roads)



**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

**Table 6** Selected counties for flood exposure comparison

County	Flood Index	Population	Area (km <sup>2</sup> )	Levee (km)	Elevation Mean (m)	Poverty (%)	Floodplain (km <sup>2</sup> )		
							100-yr	200-yr	500-yr
Pottawattamie	High	94,351	2484	170	359	12.3	415	432	454
Dallas	Low	103,255	1532	8.6	303	5.3	147	154	160
Clay	High	16,717	1483	8	419	9.4	200	207	221
Madison	Low	17,332	1456	–	325	7.4	117	122	128

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 Fig. 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.

We noticed that the county could receive a lower or higher index as the exposure layer changes under flooding. For example, Lee County, located in Southeast Iowa, is “relatively moderate” under the 100 and 200-yr 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. This finding 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. Also, the proposed index is significant since flood exposure is often assessed separately (e.g., property damage), failing to capture multiple exposure layers together. 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 conducted a correlation analysis using the Pandas Python library to assess the geospatial correspondence between the exposure layers (building footprints, population, roads) and the flood exposure index. The analysis aimed to understand the degree to which the spatial distribution of exposure elements aligns with the flood exposure index at the county level (see Table 5 for correlation coefficients).

Across all three flood scenarios, positive correlations were observed between the exposure layers and the flood index map. Specifically, the building footprints and displaced population exhibited correlation coefficients exceeding 0.9, indicating a high degree of alignment with the flood exposure index. These results suggest that areas with higher concentrations of buildings and population tend to experience higher flood exposure, as reflected in the flood index map. However, the correlation coefficients for road networks ranged from 0.70 to 0.72, indicating a slightly weaker but still significant association with the flood exposure index. This implies that road networks also contribute to flood risk but may exhibit some variability in their geospatial relationship compared to building footprints and population distribution. The correlation analysis provides valuable insights into the alignment between exposure layers and the flood exposure index, enhancing our understanding of flood risk assessment at the county level.

### 3.5 Differential flood exposure investigation

Due to the differential flood exposure among the analyzed counties, it is essential to highlight why some counties are at higher risk of floods than others. We used the digital elevation model [54], distance to stream [55], levee [56], poverty rate [57], and city boundary [40] 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 potential relationship regarding flood exposure (Table 6). The floodplain extent appears larger for counties with high flood index. As

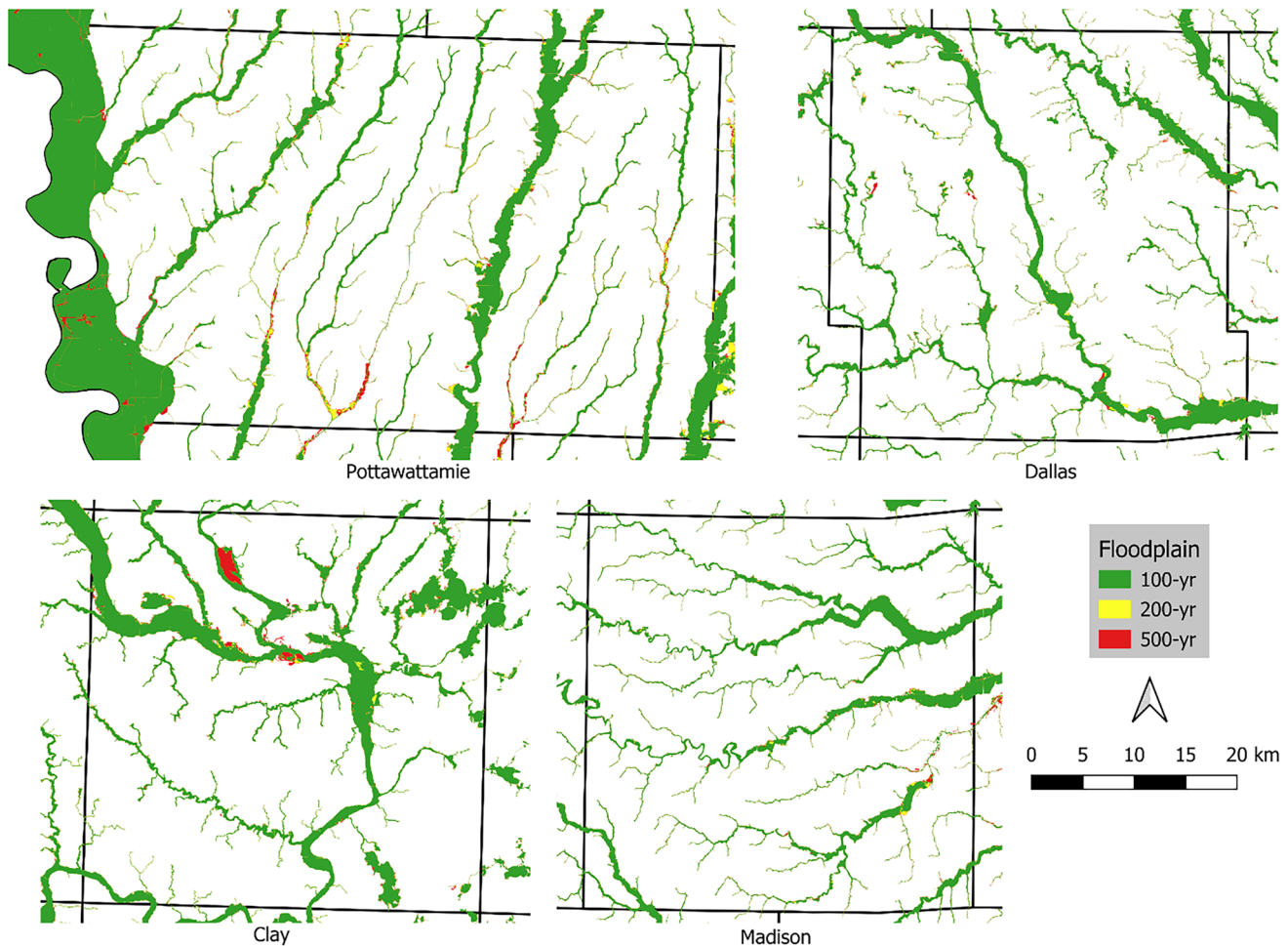


Fig. 11 Flood inundation maps for the selected counties

depicted in Fig. 11, the incremental increase in flood extent between the 100-yr, 200-yr, and 500-yr scenarios is not disproportionately large. This suggests a relatively consistent pattern of flood risk distribution across these counties, despite variations in size, population, and flood index. 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 a substantial association between poverty and flood exposure.

Figure 12 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 mean distance between a flooded property and its closest stream 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 km. However, further efforts are necessary to improve and update the levees to lower the area's exposure level to flooding. The likelihood and extent of flooding are crucial criteria to consider when developing new areas, and selecting a suitable location for new development is essential to avoid a variety of adverse impacts and related costs.

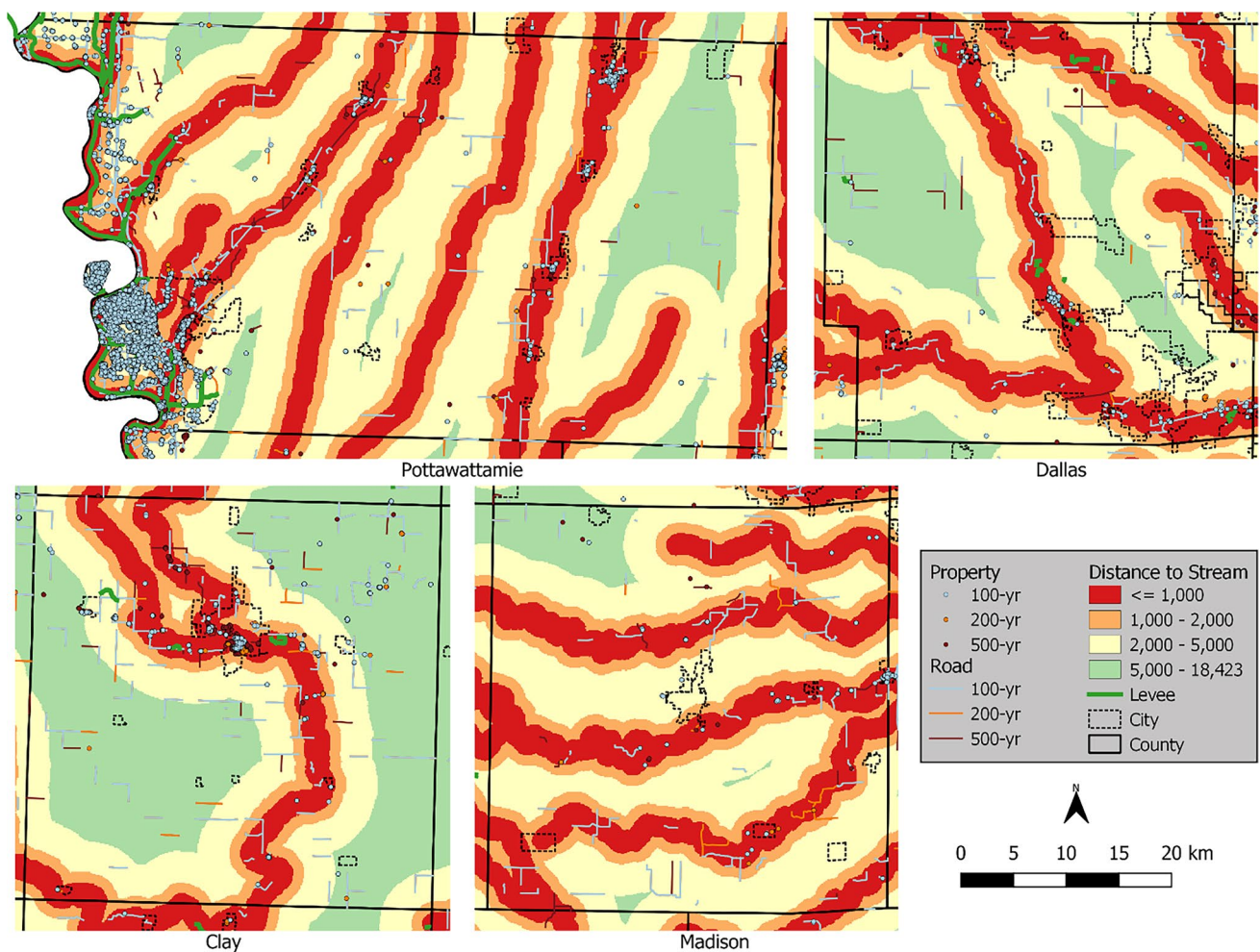


Fig. 12 Representation of impacted properties and roads, distance to streams, levee, and city boundary for the selected counties

### 4 Conclusion

This study presents a comprehensive county-level analysis of flood exposure elements, including population, properties, and road networks across Iowa counties, focusing on the 1%, 0.5%, and 0.2% annual flood probabilities. Our findings show that the impact of the floods on the Iowa counties varied. For instance, in counties like Pottawattamie, our study identifies over 40,000 residents located within the surveyed floodplains, whereas in counties such as Story, with a comparable total population, the number of displaced residents does not exceed 5,000. Residential properties are the most impacted class across the studied counties. Moreover, many counties experience reductions in road lengths ranging from 100 to 300 km due to flood inundation. By combining the exposure layers into a single map using fuzzy overlay analysis to establish a flood exposure index, our analysis reveals that more than 20 counties are designated as “very high” flood exposure areas. This integrated approach allows for a comprehensive assessment of flood risk, synthesizing various data layers to provide a nuanced understanding of vulnerability. These findings have practical implications for flood mitigation planning and strategies, prioritizing interventions in counties with higher flood exposure.

Large-scale analysis encounters challenges regarding data collection and analysis, which may introduce some limitations to our research. This study relies on publicly accessible data as many communities cannot afford pricey data resources. However, our analysis 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. Furthermore, some buildings analyzed in this

study are situated on land-use cells classified as transportation network or water, indicating the need for further refinement to improve the resolution of the land-use product.

For further analysis, the methods employed in this research can be scaled to 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 (e.g., flood controls, land use policies) [58, 59] at different scales. Additionally, integrating additional built environments (e.g., agriculture, railways) with analyzed elements in this study can enhance the overall evaluation of flood risk. Finally, expanding the scope of this research to include statistical analysis [60] of the factors contributing to high flood exposure can provide valuable insights for future flood risk management efforts.

**Author contributions** Y.A.: Conceptualization, Data preparation, Formal analysis, Investigation, Writing—Original Draft. I.D.: Validation, Investigation, Supervision, Writing—Review & Editing.

**Data availability** All data used during the study is provided within the manuscript.

## Declarations

**Competing interests** The authors declare no competing interests.

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