Web-Based Dynamic Flood Susceptibility Mapping: Leveraging Fuzzy Logic for Interactive Analysis

S M Samiul Islam[1,2 *] and Ibrahim Demir[3,4]

[1] IIHR Hydroscience and Engineering, University of Iowa, Iowa City, U.S.
[2] Civil and Environmental Engineering, University of Iowa, Iowa City, U.S.
[3] Department of River-Coastal Science and Eng, Tulane University, New Orleans, LA, USA
[4] ByWater Institute, Tulane University, New Orleans, LA, USA
[*] Corresponding author

Abstract

Flooding is one of the most frequent and devastating natural disasters, resulting in significant global social, environmental, and economic consequences. Performing comprehensive flood risk assessments is essential for comprehending community exposure and susceptibility to floods while facilitating the formulation of mitigation plans. This study presents a web-based framework for flood susceptibility mapping using fuzzy logic, providing dynamic, interactive, and accessible tools for flood risk analysis. Cedar Rapids, Iowa, was chosen as the research region because of its history of significant flooding, notably the catastrophic flood of 2008, and the accessibility of relevant records. The methodology combines physical and socio-economic data to assess flood vulnerability at community and property levels. The web application offers functionalities enabling users to view the impact of specific indicators, adjust their weights in real time, and monitor immediate developments in flood susceptibility maps. The platform also offers advanced query capabilities, allowing users to retrieve and download comprehensive data for additional study. Additional salient features comprise customized flood scenarios, interactive data displays, and accessibility for users without necessitating competence in Geographic Information Systems. The web-based approach markedly improves flood risk communication by providing an accessible interface for many stakeholders, including emergency managers, policymakers, and the general public. It facilitates educated decision-making for flood preparedness and mitigation, enhancing resilience in at-risk areas. The results highlight the potential to incorporate fuzzy logic into online tools to address conventional flood risk assessment issues, including computational intricacy and data constraints. The framework's scalable architecture enables adaptation to various natural hazards, enhancing overall catastrophe risk reduction initiatives.

Keywords: Flood vulnerability, Fuzzy logic, Web-based tool, Data Analytics, Flood risk assessment

1. Introduction

Flooding is one of the most destructive and recurrent natural hazards globally, inflicting extensive social, environmental, and economic damage (Jonkman, 2005; Vojinovic, 2015; Yesilkoy et al., 2024). Climate change, population growth, urban expansion, and aging infrastructure have exacerbated the frequency and severity of flood events (Quintero et al., 2018; Wilbanks et al., 2013; Yang et al., 2011). In the United States, flooding has been a pervasive issue, affecting nearly every region and causing average annual losses of $32.1 billion, a figure projected to escalate to $40.6 billion by 2050 due to accelerating climate risks and development in flood-prone areas (Alabbad, et al., 2024; Wing et al., 2022).

Understanding the effects of floods on infrastructure and communities and determining suitable mitigating measures to reduce negative consequences depends critically on flood vulnerability assessment (Alabbad & Demir, 2023; Espada et al., 2017). Examining the built environment's and population's exposure to flood disasters and its vulnerability reducing the general risk of flooding depends on flood control activities and floodplain management, which are part of effective flood risk management (Hyde, 2010; Koks et al., 2015). Eliminating flood risk is complex, given ongoing environmental and land use changes and limitations on data availability, computing resources, and modeling complexity (Li et al., 2023; Salman & Li, 2018; Ramirez et al., 2022).

Although most current studies focus on flood hazard mapping, there is an increasing need to prioritize distributing flood-related information, including exposure and vulnerability data (Hagemeier-Klose & Wagner, 2009; Tanir et al., 2024). Doing this may raise awareness of flood effects and provide stakeholders with the required understanding to assess mitigating strategies, risk communication and assist in wise decision-making (Bodoque et al., 2019; Islam and Demir, 2024; Mohanty et al., 2019).

Assessing vulnerability to floods is crucial for identifying the effects of flooding on infrastructure and communities, facilitating informed decision-making to alleviate these risks (Geekiyanage et al., 2020; Vamvakeridou-Lyroudia et al., 2020). It involves evaluating the physical and socio-economic vulnerability of communities to flood risks, offering insights into the infrastructure, demographics, and facilities that are most susceptible (Mansur et al., 2016; Rufat et al., 2015; Cikmaz et al., 2024). All these evaluations are essential for formulating floodplain management policies, prioritizing mitigation initiatives, and devising protective strategies to protect communities (Grant et al., 2024; Hyde, 2010). Traditional approaches for flood risk assessment encounter several problems, such as the requirement for specialist Geographic Information System (GIS) skills, restricted access to extensive computational resources and datasets, and the laborious nature of analysis (Jha et al., 2012; Salman & Li, 2018). These problems impede the accessibility and functionality of flood risk instruments for decision-makers and other stakeholders (Maskrey et al., 2022).

Although mapping of flooding hazards has been the subject of several studies, there is a growing demand for tools that incorporate flood vulnerability assessment and communicate this information to various stakeholders, including the general public, planners, and emergency management (Bakhtiari et al., 2024; Flax et al., 2002; Henstra et al., 2019). Effective quantification of flood vulnerability is crucial for enhancing awareness, promoting mitigation strategies, and aiding informed decision-making at both local and regional levels (da Silva et al., 2020; Mohanty et al., 2019; Alabbad et al., 2023). Web-based solutions have become efficient instruments for meeting these requirements, providing accessible platforms for visualizing environmental threats and involving non-expert users (Dixon et al., 2021; McGrath & others, 2023; Sit et al., 2021). By streamlining complex flood analysis procedures, these systems provide broader stakeholder access to flood information, enhancing community resilience and preparation (Demir & Beck, 2009; Holz et al., 2006).

Fluvial flooding is a pervasive and devastating natural hazard globally, causing billions of dollars in annual damage and displacing millions of people (Barrocu & Eslamian, 2022; Hudson, 2021). The United States is no exception to this trend, with communities across the nation facing increasing flood risks. The state of Iowa has been significantly impacted by flooding, with Cedar Rapids experiencing some of the most severe events (Tate et al., 2016; Villarini et al., 2020). Notably, in June 2008, the Cedar River crested at 31.12 feet, surpassing the previous record of 20 feet, and inundated approximately 10 square miles, or 14% of the city (Fung et al., 2021; Jacobs, 2018). This catastrophic event affected over 5,000 homes, displaced more than 18,000 residents, and caused an estimated $5.4 billion in damages, underscoring the region's critical need for comprehensive flood risk assessment and mitigation strategies (Birkett, 2014; Fung et al., 2021).

This study presents a web-based flood susceptibility mapping application using a fuzzy logic framework tailored explicitly for Cedar Rapids, Iowa. The system integrates physical and socio-economic indicators to evaluate flood vulnerability, enabling users to visualize the relative contributions of each indicator. Unique to this platform is its interactive functionality, allowing users to dynamically adjust the weight of individual indicators and observe real-time changes in flood susceptibility maps. Cedar Rapids serves as an ideal case study due to its history of severe flooding, particularly the 2008 disaster, the availability of relevant datasets, and the opportunity to address its unique flood challenges through advanced analytical tools. Furthermore, the application addresses the limitations of traditional flood risk tools by eliminating the need for GIS expertise and technical resources. Through its accessible web interface, the system democratizes flood risk analysis, making it available to diverse stakeholders, including the public, emergency managers, policymakers, and other stakeholders. Users can explore default scenarios and customized flood susceptibility results, retrieve detailed indicator data, and download results for further analysis, enhancing their utility for diverse use cases.

The research fills a critical gap in flood vulnerability communication by leveraging web-based technologies to make flood susceptibility information more accessible, customizable, and actionable. The remainder of this paper outlines the development and functionality of the web application, discusses its implementation in Cedar Rapids as a case study, and highlights the findings from the analysis. The study concludes with recommendations for future enhancements, including integrating additional datasets, scenario-based climate projections, and real-time flood monitoring capabilities to support decision-making and community resilience further.

2. Data and Methods

This research aims to create a generalized web-based flood susceptibility analysis and location identification framework. We posit that an integrated and open cyberinfrastructure and data management system are required to adapt the system for any region in the USA and to update the system with additional data resources. We used several physical parameters in the platform to detect the flood susceptible zones.

2.1. Data Sources

Precise and reliable information is essential for performing a comprehensive flood susceptibility examination (Islam & Demir, 2025; Zhao et al., 2020). Conventional techniques for identifying flood-prone regions can entail considerable ambiguity and uncertainty due to dependence on subjective human assessments (Mishra et al., 2022; Taubenböck et al., 2011). The results of this study use fuzzy set theory to systematically address the constraints posed by uncertainty and imprecision in decision-making processes. Fuzzy logic effectively captures intricate human preferences and judgments while minimizing error rates (Zadeh, 1965; Ahmed et al., 2018).

The parameters included in the fuzzy analytics process for flood susceptibility mapping are classified into two main categories: physical and socio-economic in this study. The physical parameters denote environmental and topographical characteristics that affect the probability and severity of floods, whereas the socio-economic elements denote human-related factors that enhance community vulnerability and resilience.

The physical factors encompass elevation, slope, land use/land cover (LULC), soil type, river drainage density, and road network density. Elevation and slope data were obtained from digital elevation models (DEMs) supplied by the Iowa Department of Natural Resources (2023) and processed to spatial resolutions of 30 x 30 meters and 5 × 5 meters, respectively. The drainage density of rivers and the road network density were computed utilizing vector datasets of hydrological and transportation networks from the USGS National Hydrography Dataset and U.S. Census Bureau TIGER/Line road shapefiles, which were processed into a high-resolution 5 × 5-meter grid to capture localized differences (USGS, 2023; U.S. Census Bureau, 2023). Soil categorization data was obtained from the Soil Survey Geographic Database (SSURGO) managed by the USDA, including a spatial resolution of 10 × 10 meters (USDA NRCS, 2023). Land use and land cover (LULC) data were sourced from the USDA's Cropland Data Layer (CDL), offering extensive coverage of land cover classifications at 30 × 30 meters resolution (USDA NASS, 2023).

Four essential socio-economic factors were identified: population density, the ratio of children and senior inhabitants, income level, and the number of renters. The data were obtained at the census block group level from the National Historical Geographic Information System (NHGIS) utilizing the American Community Survey (ACS, 2022). Incorporating these variables facilitates a detailed comprehension of the social risk landscape, essential in assessing flood impacts on communities. These physical and socio-economic facts collectively furnish a comprehensive foundation for flood vulnerability assessments. All parameters were standardized and included in the fuzzy logic framework, facilitating spatially explicit vulnerability evaluations across Cedar

Rapids. Table 1 presents an overview of these datasets, including their sources and geographic resolutions.:

Table 1: Summary of datasets with their sources and spatial resolutions.

Parameter Type	**Data / Parameters**	**Resolution**	**Data Sources**
Physical	Elevation	30 × 30 m	Iowa Department of Natural Resources (Iowa DNR, 2023)
	River Drainage Density	5 × 5 m	Generated using the river network data (Demir & Szczepanek, 2017)
	Soil Type	10 × 10 m	United States Department of Agriculture, Soil Survey Geographic Database (USDA, 2023)
	Land use (LULC)	30 × 30 m	United States Department of Agriculture, Crop Scape and Cropland Data Layer (NASS, 2023)
	Slope	5 × 5 m	Generated using DEM
	Road Network Density	5 × 5 m	Generated using the transportation network
Socio-economic	Population	Census Block Group	NHGIS (ACS, 2022)
	Children & Aged (>5 and >=65 years (>=65)	Census Block Group	NHGIS (ACS, 2022)
	Income rating	Census Block Group	NHGIS (ACS, 2022)
	Renters	Census Block Group	NHGIS (ACS, 2022)

2.1.1. Classification of Vulnerability and Weight Assignment

The same grid was used to resample all parameters to a five-by-five-meter grid data layer using ArcGIS. Each layer was classified into five flood risk classes after the data resampling, as illustrated in the following table. The classes are as follows: "1" is classified as very low, "2" is classified as low, "3" is classified as moderate, "4" is classified as high, and "5" is classified as very high. The weights of AHP were employed as parameters to generate geophysical-based risk maps and vulnerability maps, as various indicators contribute to flood risk in varying ways.

Table 2: Classification weight assignment of the parameters (Cikmaz et al., 2023).

	Parameters	**Unit**	**Classes of the Parameters**				
			1	**2**	**3**	**4**	**5**
Physical Vulnerability	Elevation	meter	269-284	254-269	239-254	224-239	209-224
	River drainage density	km / km^2	0-2.5	2.5-5	5-7.5	7.5-10	>10

	Soil type	-	clay loam, silty clay loam	silt loam, loam	sandy loam, complex, others	urban land complex	water bodies
	Land use	-	wetland	open space, forest	agricultural Cropland, vegetation	built-up area	water bodies
	Slope	degree	>15	8-15	4-8	2-4	0-2
Socio-economic Vulnerability	Population	-	0-50	50-200	200-350	350-500	500-1132
	Road network density	km / km^2	0-3	3-6	6-9	9-12	12-24
	Children & elderly population	-	0-5	5-50	50-100	100-200	200-449
	Renters	-	0-1	1-100	100-200	200-300	300-1100
	Income rating	-	1618-2670	1171-1618	892-1171	608-892	281-608

The following equation is used to calculate the magnitude of a convex fuzzy number derived from 'k' as another degree of possibility of fuzzy numbers:

$$V(S \geq S_1, S_2, \ldots S_k) = V(S \geq S_1) \text{ and } (S \geq S_2) \text{ and } \ldots \text{ and } (S \geq S_k) \quad \text{(Eq. 1)}$$

$$V = \min V(S \geq S_i),\ i = 1, 2, \ldots, k$$

Eq. (2) and (3) can be utilized to find the weight of factors (W′).

$$d'(A_i) = \min V(S_i \geq S_k), \text{ for } k = 1, 2, \ldots, n;\ k \neq i \quad \text{(Eq. 2)}$$

$$W' = (d'(A1), d'(A2), \ldots, d'(An)) \quad \text{(Eq. 3)}$$

Normalization of the final weight factor: In the final stage, the parameter weights are normalized to derive the non-fuzzy number, as illustrated in the corresponding Eq. 4:

$$W(A_i) = \frac{d'(A_i)}{\sum W'} \quad \text{(Eq. 4)}$$

While measuring flood susceptibility using the Fuzzy geospatial technique, the weights of each parameter are assigned based on their significance. The designated weights for each parameter were first obtained from Cikmaz et al. (2023), who employed a similar methodological approach in corresponding geographical regions. A slight modification was implemented to accommodate elevation and income categories since the geographical characteristics vary slightly to better align with the geographical context of this study (Table 3).

Table 3: Fuzzy judgment matrix for geophysical and socio-economic parameters.

	Elevation	**River Drainage Density**	**Soil Type**	**LULC**	**Slope**	**Child and Aged**	**Road Network Density**	**Population**	**Renters**	**Income Rating**
Elevation	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	(3, 4, 5)	(3, 4, 5)	(2, 3, 4)	(2, 3, 4)	(4, 5, 6)	(3, 4, 5)	(1, 1, 1)
River Drainage Density	(0.25, 0.33, 0.5)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(1, 2, 3)	(2, 3, 4)	(1, 1, 1)	(0.25, 0.33, 0.5)
Soil Type	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(1, 1, 1)	(1, 2, 3)	(1, 2, 3)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)
LULC	(0.2, 0.25, 0.33)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(0.5, 1, 2)	(0.33, 0.5, 1)	(0.5, 1, 2)	(1, 2, 3)	(0.33, 0.5, 1)	(0.33, 0.5, 1)
Slope	(0.2, 0.25, 0.33)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.5, 1, 2)	(1, 1, 1)	(0.5, 1, 2)	(1, 2, 3)	(1, 2, 3)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)
Child and Aged	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(1, 1, 1)	(1, 2, 3)	(0.5, 1, 2)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)	(0.5, 1, 2)	(0.33, 0.5, 1)
Road Network Density	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.5, 1, 2)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(1, 1, 1)	(2, 3, 4)	(0.33, 0.5, 1)	(0.33, 0.5, 1)
Population	(0.17, 0.2, 0.25)	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.33, 0.5, 1)	(0.25, 0.33, 0.5)	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.5, 1, 2)	(0.25, 0.33, 0.5)
Renters	(0.2, 0.25, 0.33)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)	(2, 3, 4)	(0.5, 1, 2)	(0.5, 1, 2)	(0.5, 1, 2)	(1, 1, 1)	(0.33, 0.5, 1)
Income Rating	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)	(2, 3, 4)	(1, 2, 3)	(2, 3, 4)	(4, 5, 6)	(1, 2, 3)	(1, 1, 1)

Table 4: Assigned weights of geophysical and socio-economic vulnerability parameters used in Fuzzy logic.

Parameters	**Fuzzy Weight**
Elevation	0.22
River Drainage Density	0.21
Soil Type	0.20
Land use	0.20
Slope	0.17
Population	0.26
Road Network Density	0.22
Children & Elderly Population	0.20
Renters	0.18
Income Rating	0.14

2.2. Cyberinfrastructure Framework

Cyberinfrastructure framework of FloodRSS consists of two fundamental layers: the client-side user interface and the server-side application. The client-side interface enables users to access and view analysis and findings about flood susceptibility, allowing them to examine risky zones by adjusting parameter weights. This interface utilizes web technologies (HTML, CSS, JavaScript, and JS libraries) to facilitate user access to dynamic analysis interactively (Mozilla Developer Network, 2024). The server-side layer has four primary components: data, processing, mapping, and display. The data component comprises a geospatial database using PostgreSQL/PostGIS (PostgreSQL Global Development Group, 2024) and datasets from several agencies and organizations, including USDA, Iowa DNR, and NHGIS (USDA NASS, 2023; Iowa Department of Natural Resources, 2023; Manson et al., 2021).

We used Google Maps JavaScript API as our online mapping library (Google Developers, 2024). The visualization component depicts flood-prone areas for designated towns via fuzzy logic techniques implemented in JavaScript (Zadeh, 1965). We integrated query functions into PHP files on the server side and encoded geospatial outputs in GeoJSON format (Butler et al., 2016), subsequently linking them to the Google Maps JavaScript API. Users may download precise vulnerability-level data in CSV format for further analysis.

2.3. Data Acquisition

The FloodRSS system works on Microsoft SQL Server for data management. Using data migration scripts, we migrated all the FloodRSS system data from the MS SQL Server to the PostgreSQL server. We used GIS software systems like ArcGIS Pro and ArcMap to validate data migration. These systems can connect to the database and extract data to make it available for other servers. By connecting ArcGIS Pro to MS SQL, we extracted census block group shapefiles and transferred all geometric features to the PostgreSQL server using the PostGIS shapefile importer tool. Those layers store information about the census block group name, number, and all the ten indicators. By extracting these tables in the CSV (comma-separated values) format, we uploaded non-geometric tables to the PostgreSQL server. The raster data format was converted to the TIFF (tag image file) format, valid for query depth information. This script specified all user information (name and password, database properties, data projection, and coordinate system). We validated the accuracy of data migration using GIS and database tools (e.g., ArcGIS Pro and PGAdmin). Our team executed the same queries for each software package and compared the results visually.

2.4. Server-Side and Client-Side Components

The operational framework of the web-based flood vulnerability mapping system, illustrated in Figure 1, combines several data acquisition and integration layers, web application layer, and server-side application layer to provide interactive display and analysis. The framework starts with the acquisition of geographical and socio-economic datasets. Spatial data comprises elevation, river drainage density, soil classification, land use, and slope, whereas socio-economic data involves population statistics, road network density, demographics (children and the elderly), rental status, and income levels. These statistics represent the basis for evaluating flood susceptibility across multiple scales.

The web application layer functions as an interface between raw data and user interaction. This layer is developed with HTML, CSS, JavaScript, and the Leaflet library to provide an easy interface for visualizing flood vulnerability maps. It includes features such as zoom controls, scale bars, area-measuring tools, and geocoding capabilities to enhance user engagement. Data integration is achieved using JSON files that contain both spatial and non-spatial data, while Leaflet and jQuery methods dynamically manipulate these files for real-time display. Users can interactively examine flood susceptibility levels at group, community, or property scales and modify indicator values (0-10) using a scale bar to visualize variations in vulnerability. Additionally, the platform enables users to choose specific vulnerability maps—physical, socio-economic, or integrated flood scenarios—for comprehensive community-level analysis. Summary statistics, legends, and layer controls are available for enhanced insights.

The cyberinfrastructure/server architecture supports the system's functionality by managing data processing and analysis functions. This design, developed using PHP for server-side scripting and utilizing PostgreSQL and MySQL databases, comprises three fundamental components: data processing (Data Component), geospatial visualization (Mapping Component), and analytical insights (Analysis Component). The object database utilizes a Nested Set Model in PostgreSQL to manage hierarchical data structures effectively (Demir and Szczepanek, 2017). Distributed services are employed to guarantee scalability and performance over extensive datasets. It encompasses Distributed Data Services for processing unrefined data, Distributed Mapping Services for producing geographical maps, and Distributed Visualization Services for creating interactive results.

On the other hand, the client-side interface enables users to have an interactive platform that seamlessly integrates each process level effortlessly. The user interface allows users to modify indicators in real time to investigate flood vulnerability scenarios at different dimensions while providing access to extensive analyses related to block groups and summary data and visualization options. The system integrates geographical data analysis with socio-economic factors in a modular framework, providing practical insights on flood risk across various geographies. Figure 1 illustrates the integrated process for a web-based flood vulnerability mapping system.

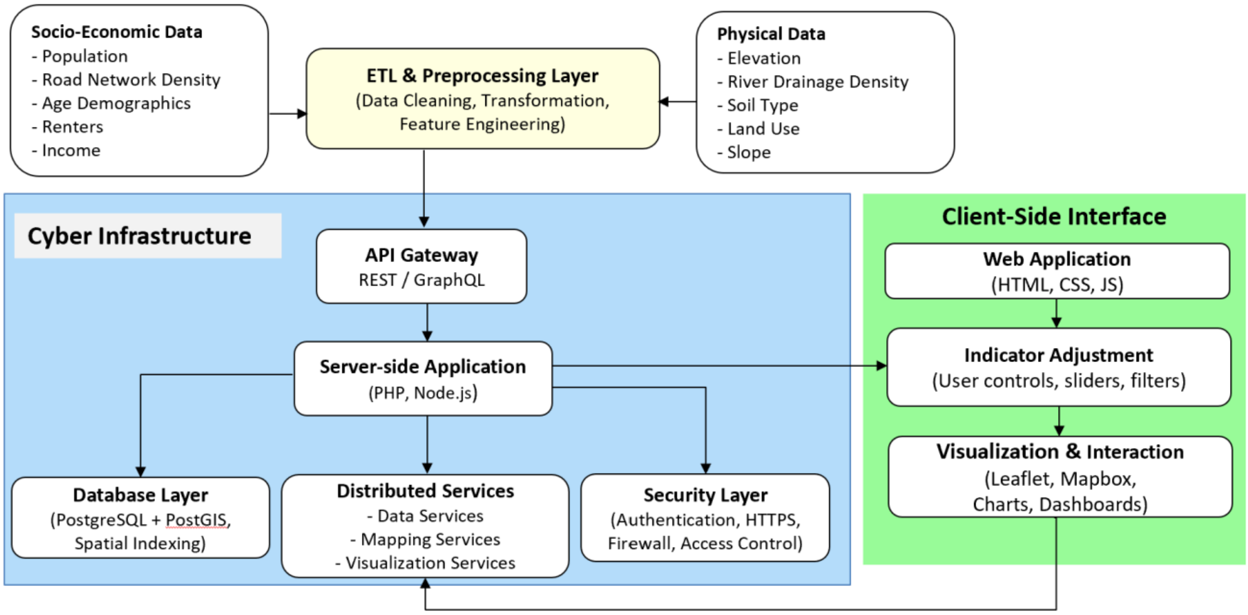


Figure 1: Integrated integration and Data workflow for a Web-based flood vulnerability mapping system.

2.5. Case Study

Iowa is located between two major river systems: the Mississippi River to the east and the Missouri River to the west. Alongside these boundary rivers, notable tributaries such as the Cedar and Iowa Rivers flow into the state's heartland, exacerbating Iowa's vulnerability to recurrent and intense flooding incidents. Iowa has experienced several flood catastrophes in the last fifty years, with the 2008 flood being particularly devastating in the state's history.

The 2008 flood significantly affected Cedar Rapids, Iowa's second-largest city. The Cedar River surpassed the 500-year flood threshold, inundating around 10 square miles, or about 14% of the city. Over 18,000 people were relocated, and more than 5,000 houses and businesses were impacted. The projected economic loss amounted to $5.4 billion, encompassing significant damage to public infrastructure, residential areas, and essential services (Fung et al., 2021). This incident underscored both the physical susceptibility of Cedar Rapids and also the socio-economic inequalities and infrastructural deficiencies that intensified the flood's effects.

Due to the severity and enduring effects of the 2008 flood, Cedar Rapids was chosen as the case study site to create and demonstrate the planned flood susceptibility web application. The tool combines the city's census block groups with physical and socio-economic information to evaluate flood susceptibility at a high spatial resolution. This micro-scale research facilitates the visualization and examination of community flood susceptibility patterns, offering essential insights for community-level planning and preparedness.

Comprehending the interplay among indicators, i.e., elevation, drainage density, population demographics, and economic levels in shaping flood vulnerability is essential for formulating tailored mitigation solutions. The research, centered on Cedar Rapids, illustrates the application's technological capabilities while highlighting the significance of utilizing historically affected areas in the real world to guide risk reduction initiatives. Figure 4 depicts the incorporation of Cedar Rapids into the flood vulnerability mapping system.

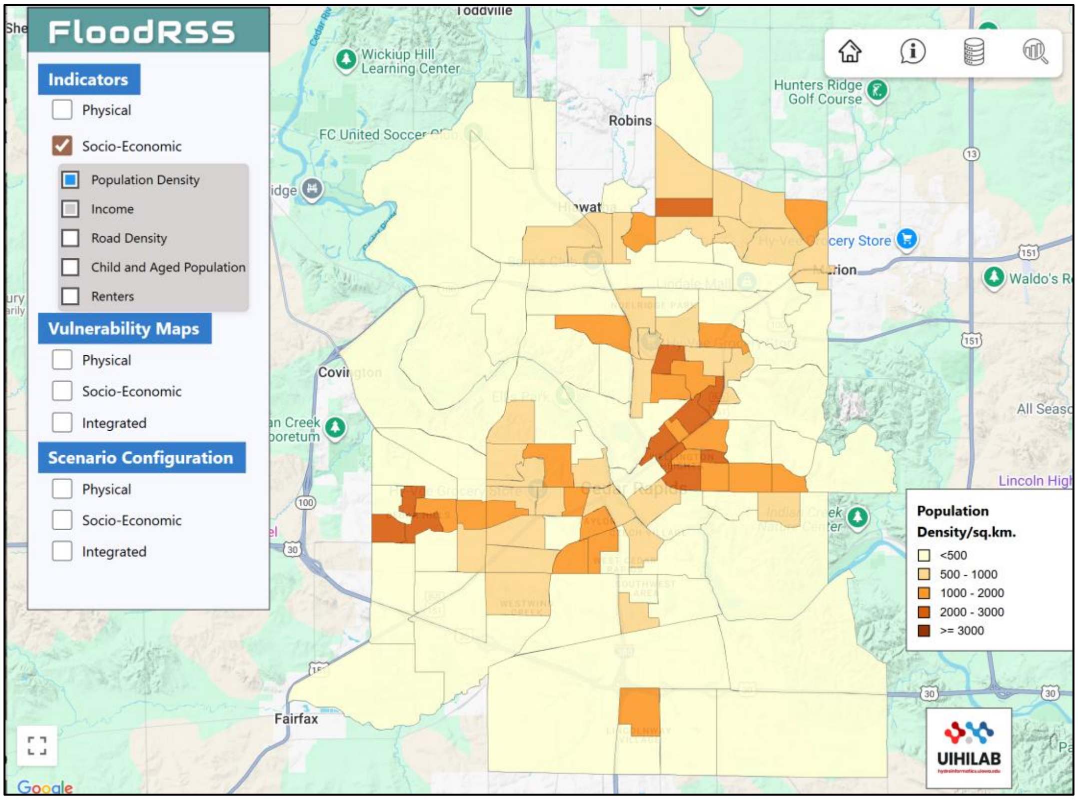
3. Results and Discussion

The web application provides a user-friendly platform to analyze and visualize flood vulnerability at varying spatial scales. The framework is named FloodRSS, which stands for Flood Resilience Support System and is accessible free of charge. The established framework allows thorough flood sensitivity analysis by combining physical and socio-economic factors influencing vulnerability at community and property levels. Using a flexible and interactive fuzzy logic-based approach, the system lets consumers evaluate the relative impact of important elements like elevation, drainage density, land use, slope, population demographics, income levels, and infrastructure distribution.

The findings are displayed via an easy-to-use web-based mapping environment constructed on the Leaflet JavaScript package. Using a familiar and dynamic map interface, the platform guarantees access to a broad spectrum of users independent of their technical experience or GIS knowledge. Users may evaluate thorough vulnerability classifications, change indicator weights, interactively explore several flood scenarios, and download pertinent data for additional study. Without sophisticated spatial analytics knowledge, the platform allows informed decision-making and community involvement in initiatives for flood risk reduction.

The system offers an extensive platform for examining the diverse effects of floods on residential and commercial buildings, census block groupings, and essential infrastructure, including transportation networks. The interactive interface, created with Leaflet and JavaScript, enables users to dynamically modify the weight of specific indicators on a scale from 0 to 10 and instantly observe the impact of these adjustments on flood susceptibility across geographical units. This adaptability facilitates scenario-based analysis that mirrors real-world intricacies and promotes user-directed inquiry. Flood vulnerability evaluations are conducted at community and property levels, providing specific and comprehensive information.

At the community level, users may model several flood scenarios, such as 100-year or 500-year events, specifically for areas inside Cedar Rapids. The tool presents spatial distributions of susceptibility, classifying them into vulnerability categories and offering corresponding summary data. This feature assists planners, emergency managers, and decision-makers in pinpointing high-risk areas and prioritizing measures. The platform integrates spatial datasets (e.g., elevation, slope, drainage density) with socio-economic data (e.g., population density, income levels, renter proportion) into a cohesive web-based environment, allowing non-expert users to perform significant analyses without specialized GIS expertise. The system's user-friendly design and immediate responsiveness provide access to flood risk information, improving stakeholder involvement and fostering informed community preparedness and planning.



FloodRSS

Indicators

☐ Physical

☑ Socio-Economic

- ☑ Population Density
- ☐ Income
- ☐ Road Density
- ☐ Child and Aged Population
- ☐ Renters

Vulnerability Maps

☐ Physical

☐ Socio-Economic

☐ Integrated

Scenario Configuration

☐ Physical

☐ Socio-Economic

☐ Integrated

Population Density/sq.km.

- ☐ <500
- 🟨 500 - 1000
- 🟧 1000 - 2000
- 🟧 2000 - 3000
- 🟫 >= 3000

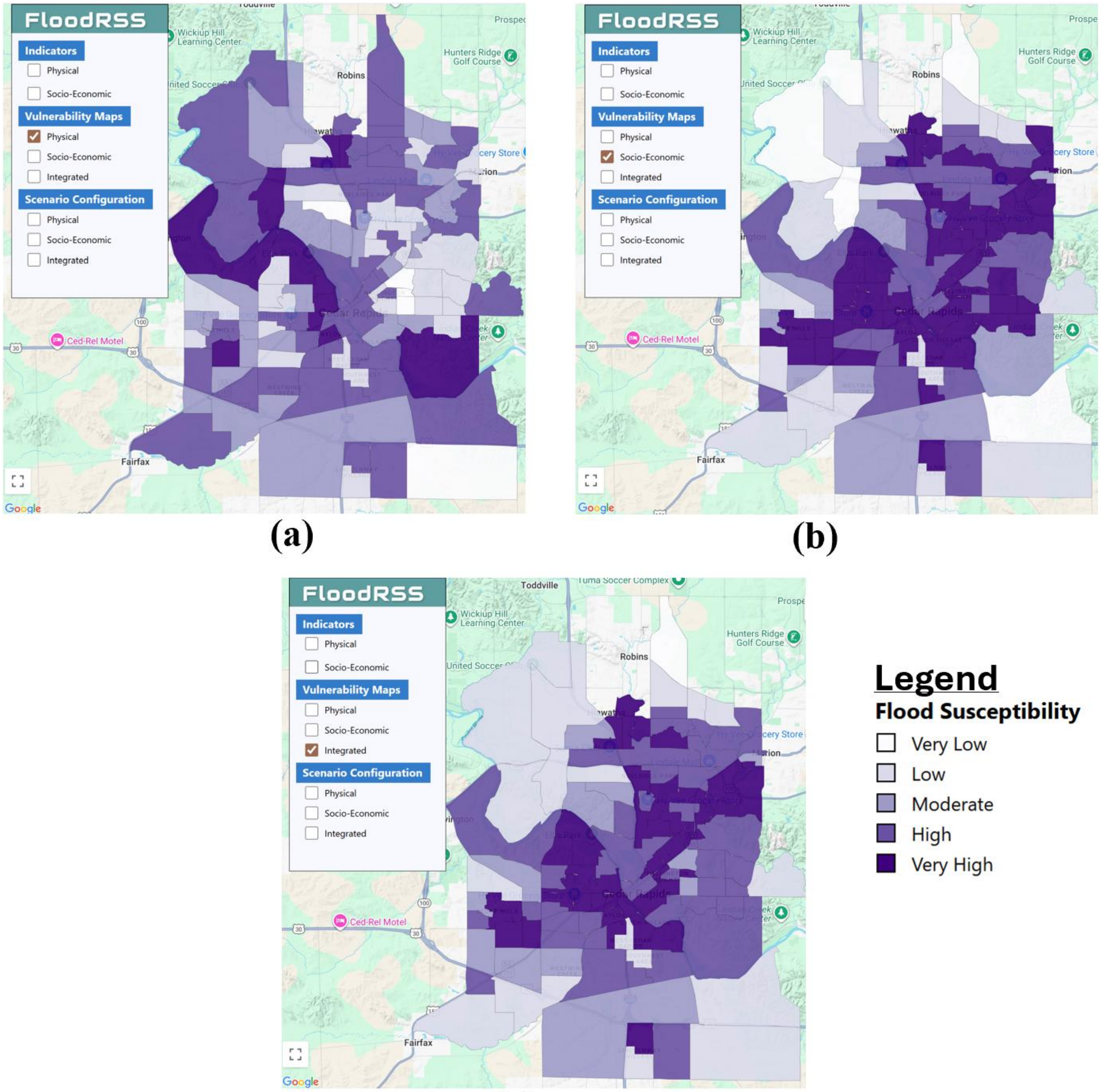
Figure 2: Landing page for the FloodRSS (showing 'population density' under socio-economic indicators).

The web-based application integrates robust query, database, and geospatial analytics capabilities to provide a user-driven examination of flood susceptibility data. Users can select and get census block groupings according to established vulnerability classifications—from very low to very high—or inquire about specific characteristics of individual blocks. Each query yields a complete dataset with all 10 flood vulnerability indicators for the designated block groupings. The data outputs are accessible for download in CSV format, providing a significant resource for academics, planners, and policymakers who need high-resolution data for analysis, modeling, or integration with external decision-support systems. The system has many user-centric features aimed at improving accessibility and encouraging autonomous interaction with the platform. A "Help" option is prominently located in the interface, offering sequential instructions on system operations. This part functions as a comprehensive user manual, enabling those lacking technical GIS or spatial data analysis expertise to navigate the platform effortlessly.

Furthermore, the "About" section provides a comprehensive discussion of the fuzzy logic approach that underpins the susceptibility estimates and links to pertinent research articles. It fosters transparency in the analytical framework and encourages users to examine the scientific literature underpinning the system's design and implementation. These attributes collectively provide the platform with a technical instrument for flood susceptibility evaluation and an instructional and decision-support resource that connects intricate geospatial analysis with accessible, user-oriented insights.

3.1. Default Weight Vulnerability

In the first stage of flood susceptibility, default weight values were allocated to each indicator based on published literature. The weight method utilized in this study was derived from the research of Cikmaz et al. (2023), which provides a robust framework for determining the relative significance of both physical and socio-economic flood susceptibility variables. The chosen indicators—ten in total—were classified into two categories: physical (e.g., elevation, slope, drainage density, land use, soil type, and road network density) and socio-economic (e.g., population density, proportion of children and old, income rating, and percentage of renters). The associated weights are already mentioned in Table 3.



(a)

(b)

(c)

Figure 3: Three types (a: Physical, b: Socio-economic, and c: Combined) of flood vulnerability maps using default fuzzy weight.

The algorithm produced flood susceptibility maps for Cedar Rapids utilizing these default weights inside two analytical frameworks. The initial set of maps illustrated vulnerability through distinct indicator groups—physical and socio-economic—offering insights into the separate contributions of each category to flood risk. These maps illustrate geographical patterns of flood susceptibility resulting from environmental exposure or demographic vulnerability. In practical situations, flood danger rarely originates from a single source. Physical and socio-economic variables interact and exacerbate each other, affecting the probability of floods and their consequences on human systems. A composite flood vulnerability map was constructed to illustrate this intricacy. This map combines both indicator categories utilizing the standard fuzzy logic weights, providing a comprehensive perspective on overall susceptibility across the city of Cedar Rapids region.

The "default weights" establish a baseline for comprehending the overall vulnerability environment and serve as a reference for comparing user-defined weight modifications accessible via the interactive platform. This allows both technical professionals and non-specialist users to examine how changes in the effect of various variables may affect susceptibility results and guide customized mitigation actions.

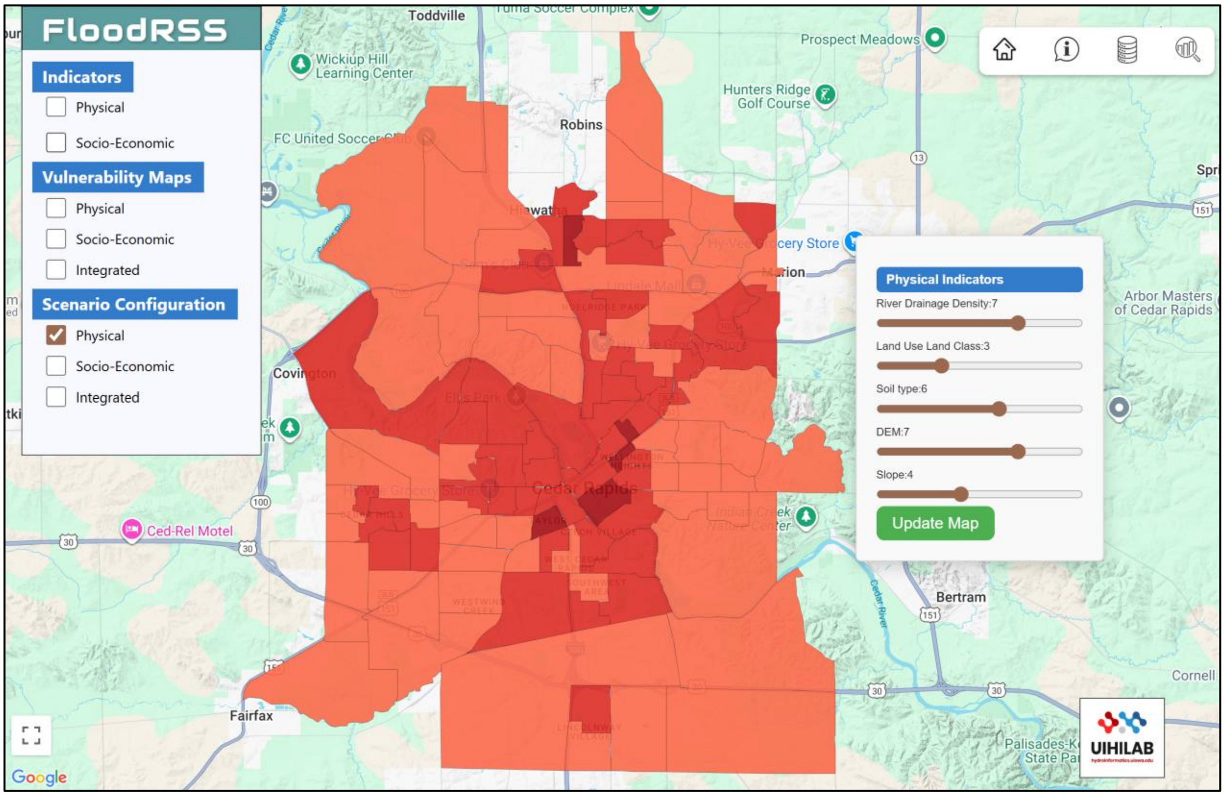
3.2. User Analytics

The web-based flood susceptibility platform's interactive section facilitates default and user-initiated analyses via a dynamic user interface. The system employs a fuzzy logic framework to facilitate real-time flood vulnerability assessments at the community and property levels. Users may see susceptibility outcomes based on default indicator weights or personalize the study by modifying the weight of specific physical and socio-economic markers using a simple slider interface. These modifications enable users to model "what-if" scenarios and evaluate the impact of various combinations of indicator weights on overall vulnerability ratings.

The system utilizes contemporary web technologies, such as Leaflet for mapping and JavaScript for functionality, to present susceptibility findings, usually in a matter of seconds. Upon users adjusting indicator values and commencing the computation, revised flood susceptibility outcomes are immediately presented on the map, illustrated by a color gradient that differentiates vulnerability levels from very low to very high. A built-in caption facilitates user interpretation of classifications, while spatial trends are depicted across census block groupings for comprehensive geographic knowledge. It features a sophisticated query mechanism that allows users to select census block groups based on certain vulnerability levels or other indicator thresholds, facilitating comprehensive examination. The data supplied is comprehensive, encompassing values for all 10 contributing indicators, and is available for download as CSV files for subsequent statistical or GIS analysis. This capability especially benefits academics, planners, and policymakers aiming to incorporate localized vulnerability data into comprehensive flood management systems.

In addition, the system features a "Display Statistics" module that visualizes analytical summaries, including the distribution of susceptibility levels across the research region and the average value of indicators by class. Interactive charts enable the examination of correlations between socio-economic characteristics (e.g., rental percentages or median income) and flood vulnerability, offering valuable information for focused resilience design. Furthermore, the program provides functionalities for user assistance to enhance accessibility. The support section offers practical instructions, while the about section elucidates the foundational fuzzy logic approach and references pertinent literature, improving transparency and user comprehension.

The interface is designed for scalability and extensibility. The design facilitates the incorporation of future modules, including flood return period scenarios, damage estimation algorithms, or supplementary indicators from national datasets such as the U.S. Census. While the existing depth–damage functions rely on generic models, future advancements may incorporate locally calibrated damage functions particularly designed for Cedar Rapids. This will provide enhanced accuracy in assessing possible structural and content-related flood losses. Integrating raster-based inputs, spatial characteristics, and user-centric analytics inside a unified decision-support system highlights the platform's ability to provide sophisticated flood risk modeling and visualization without necessitating technical GIS proficiency. Consequently, emergency managers, urban planners, and community stakeholders possess a readily available, scientifically validated instrument for evaluating and alleviating flood risk in susceptible metropolitan areas.



FloodRSS

Indicators
☐ Physical
☐ Socio-Economic

Vulnerability Maps
☐ Physical
☐ Socio-Economic
☐ Integrated

Scenario Configuration
☑ Physical
☐ Socio-Economic
☐ Integrated

Physical Indicators
River Drainage Density:7
Land Use Land Class:3
Soil type:6
DEM:7
Slope:4
Update Map

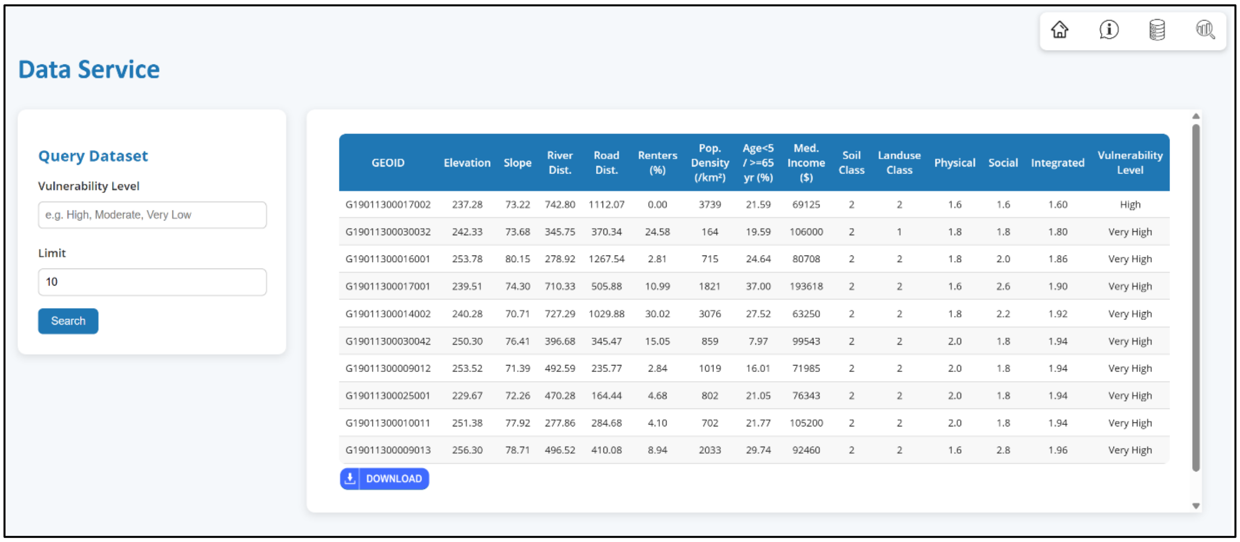
Figure 4: Customized flood vulnerability analysis at user analytics component.

3.3. Data Exploration and Statistical Visualization Tools

The web-based application features real-time flood susceptibility mapping, sophisticated capabilities for data exploration, and statistical visualization to improve user involvement and facilitate comprehensive research. These tools—utilized via the Data Service and Statistical Information tabs—enable users to interact with the foundational datasets and analyze patterns across several vulnerability indicators at the census block group level.

The Data Service tab offers users a configurable interface to access the flood susceptibility database. Users may filter data according to established vulnerability tiers (e.g., very low, low, moderate, high, very high) and specify the number of census block groups to retrieve. The query generates a comprehensive table that includes all 10 vulnerability indicators for each block group, including elevation, slope, distances to rivers and roads, population density, proportion of renters, age distribution (children and older adults), soil type, land use, and median income. These features enable users to analyze the factors leading to the designated vulnerability categorization. A built-in tool allows users to export data for additional analysis, modeling, or integration into external systems, providing significant utility for academic researchers, urban planners, and policy analysts.

The Statistical Information tab enhances the data service by showing consolidated findings across vulnerability categories. Users may choose any of the 10 indicators from a dropdown menu, which will cause the program to present an interactive bar chart comparing average indicator values across all five vulnerability levels. Selecting the "Renters" indication presents a graphic illustrating the average percentage of renters across each risk group, emphasizing societal trends in flood sensitivity. These statistical summaries help users in identifying systematic inequities and prioritizing targeted solutions for the most vulnerable communities.



Data Service

Query Dataset

Vulnerability Level: e.g. High, Moderate, Very Low

Limit: 10

GEOID	Elevation	Slope	River Dist.	Road Dist.	Renters (%)	Pop. Density (/km²)	Age<5 / >=65 yr (%)	Med. Income ($)	Soil Class	Landuse Class	Physical	Social	Integrated	Vulnerability Level
G19011300017002	237.28	73.22	742.80	1112.07	0.00	3739	21.59	69125	2	2	1.6	1.6	1.60	High
G19011300030032	242.33	73.68	345.75	370.34	24.58	164	19.59	106000	2	1	1.8	1.8	1.80	Very High
G19011300016001	253.78	80.15	278.92	1267.54	2.81	715	24.64	80708	2	2	1.8	2.0	1.86	Very High
G19011300017001	239.51	74.30	710.33	505.88	10.99	1821	37.00	193618	2	2	1.6	2.6	1.90	Very High
G19011300014002	240.28	70.71	727.29	1029.88	30.02	3076	27.52	63250	2	2	1.8	2.2	1.92	Very High
G19011300030042	250.30	76.41	396.68	345.47	15.05	859	7.97	99543	2	2	2.0	1.8	1.94	Very High
G19011300009012	253.52	71.39	492.59	235.77	2.84	1019	16.01	71985	2	2	2.0	1.8	1.94	Very High
G19011300025001	229.67	72.26	470.28	164.44	4.68	802	21.05	76343	2	2	2.0	1.8	1.94	Very High
G19011300010011	251.38	77.92	277.86	284.68	4.10	702	21.77	105200	2	2	2.0	1.8	1.94	Very High
G19011300009013	256.30	78.71	496.52	410.08	8.94	2033	29.74	92460	2	2	1.6	2.8	1.96	Very High

Figure 5: Figure 5: Data download option as CSV format.

Both features are effortlessly incorporated into the user interface and available without requiring prior GIS expertise. Their incorporation enhances the analytical rigor of the system while preserving its accessibility for lay audiences. The platform enables users to investigate, comprehend, and respond to localized flood vulnerability data by integrating granular data access with easy visualization. This systematic approach to data engagement conforms to open data standards and facilitates transparent decision-making. Moreover, it enables opportunities for future improvements, such as the incorporation of time-series data, longitudinal analyses, or API access for other applications. The data exploration and visualization capabilities are essential in enhancing the platform's effectiveness as a comprehensive flood risk decision-support system.

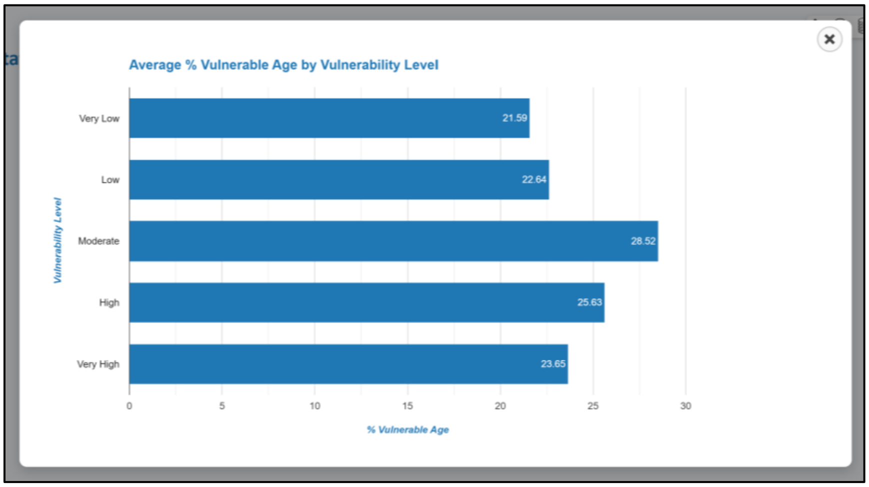


Figure 6: Statistical insights on different variables.

4. Conclusion

Evaluating flood susceptibility is essential for understanding the factors that influence flood risk and guiding evidence-based mitigation and adaptation measures. This study presents a web-based flood susceptibility mapping system developed using a fuzzy logic framework, particularly tailored for Cedar Rapids, Iowa, an urban region historically affected by severe flooding episodes. The system facilitates exploration, visualization, and interaction with flood susceptibility data by combining physical and socio-economic variables in a dynamic and accessible format. A notable characteristic of the platform is its capacity to enable users to modify indicator weights in real-time, helping decision-makers, emergency managers, and the general public analyze customized flood risk scenarios at both community and property levels.

The proposed program addresses several restrictions often linked to flood risk modeling—such as the necessity for technical GIS expertise or access to high-performance computing—by providing a streamlined yet analytically sound online interface. Utilizing the Data Service and Statistical Information modules, users may query census block groups according to vulnerability levels, analyze the raw values of all contributing indicators, and download the data for subsequent offline study. This feature improves transparency and facilitates informed decision-making for community planning, policy formulation, and resource distribution. The ability to provide real-time susceptibility maps with color-coded categories boosts public awareness, facilitates risk communication, and encourages interaction among diverse user groups.

Notwithstanding the system's capabilities, numerous shortcomings persist. The standard indicator weightings and susceptibility connections are broad and may not adequately represent the distinct environmental, infrastructural, and demographic attributes of Cedar Rapids. Consequently, the following platform versions should include localized datasets, community-specific harm functions, and context-sensitive adjustments of fuzzy logic parameters to enhance accuracy. Furthermore, the existing model fails to incorporate specific dynamic flood features, such as water velocity, flood duration, or the cascade consequences of infrastructure collapse.

Enhancing the analytical methodology to incorporate scenario-based climate projections and real-time river forecasts would provide further value. These skills might guide immediate reaction strategies—such as transferring cars or household items before an event—and long-term resilience planning. Additional improvements may encompass creating evacuation route planning tools, incorporating alerts and early warning systems, and expanding the platform to provide multi-hazard analysis for many catastrophe types, including earthquakes, wildfires, and excessive heat. This research illustrates the capability of scalable, web-based apps to convert intricate flood vulnerability assessments into functional tools that connect technical analysis with community-level initiatives. The platform enhances community resilience, promotes participatory planning, and fortifies disaster preparedness in flood-prone areas by rendering flood risk information understandable and accessible to diverse stakeholders.

5. References

Alabbad, Y., Mount, J., Campbell, A. M., & Demir, I. (2024). A web-based decision support framework for optimizing road network accessibility and emergency facility allocation during flooding. Urban Informatics, 3(1), 10.

Alabbad, Y., & Demir, I. (2023). Geo-Spatial Analysis of Built-Environment Exposure to Flooding: Iowa Case Study. EarthArxiv, 5157.

Alabbad, Y., Yildirim, E., & Demir, I. (2023). A web-based analytical urban flood damage and loss estimation framework. Environmental Modelling & Software, 163, 105670.

Bakhtiari, V., Piadeh, F., Chen, A. S., & Behzadian, K. (2024). Stakeholder analysis in the application of cutting-edge digital visualisation technologies for urban flood risk management: A critical review. Expert Systems with Applications, 236, 121426.

Barrocu, G., & Eslamian, S. (2022). Geomorphology and flooding. In Flood handbook (pp. 23-54). CRC Press.

Birkett, K. (2014). Cedar Rapids: Building Community while Recovering from a Devastating Flood. Nat'l Civic Rev., 103, 33.

Bodoque, J. M., Díez-Herrero, A., Amérigo, M., García, J. A., & Olcina, J. (2019). Enhancing flash flood risk perception and awareness of mitigation actions through risk communication: A pre-post survey design. Journal of Hydrology, 568, 769-779.

Butler, H., Daly, M., Haas, J., & Schaub, T. (2016). The GeoJSON Format (RFC 7946). Internet Engineering Task Force. https://www.rfc-editor.org/rfc/rfc7946

Cikmaz, B. A., Yildirim, E., & Demir, I. (2023). Flood susceptibility mapping using fuzzy analytical hierarchy process for cedar rapids, iowa. International Journal of River Basin Management, 1–24.

Cikmaz, A. B., Mount, J., & Demir, I. (2024). Evaluating the Flood Vulnerability of Urban Areas in Polk County, Iowa using Social-Ecological-Technological Framework. EarthArxiv, 7375.

https://doi.org/10.31223/X5Z10F

da Silva, L. B. L., Alencar, M. H., & de Almeida, A. T. (2020). Multidimensional flood risk management under climate changes: Bibliometric analysis, trends and strategic guidelines for decision-making in urban dynamics. International Journal of Disaster Risk Reduction, 50, 101865.

Demir, I., & Beck, M. B. (2009). GWIS: a prototype information system for Georgia watersheds. Georgia Water Resources Conference: Regional Water Management Opportunities, UGA, Athens, GA, U.S.

Demir, I., & Szczepanek, R. (2017). Optimization of river network representation data models for web-based systems. *Earth and Space Science*, *4*(6), 336-347.

Dixon, B., Johns, R., & Fernandez, A. (2021). The role of crowdsourced data, participatory decision-making and mapping of flood related events. Applied Geography, 128, 102393.

Espada, R., Apan, A., & McDougall, K. (2017). Vulnerability assessment of urban community and critical infrastructures for integrated flood risk management and climate adaptation strategies. International Journal of Disaster Resilience in the Built Environment, 8(4), 375–411.

Flax, L. K., Jackson, R. W., & Stein, D. N. (2002). Community vulnerability assessment tool methodology. Natural Hazards Review, 3(4), 163–176.

Fung, J. F., Helgeson, J. F., Webb, D. H., O'Fallon, C. M., & Cutler, H. (2021). Does resilience yield dividends? Co-benefits of investing in increased resilience in Cedar Rapids. Economic Systems Research, 33(3), 336–362.

Geekiyanage, D., Fernando, T., & Keraminiyage, K. (2020). Assessing the state of the art in community engagement for participatory decision-making in disaster risk-sensitive urban development. International Journal of Disaster Risk Reduction, 51, 101847.

Google Developers. (2024). Google Maps JavaScript API documentation. https://developers.google.com/maps/documentation/javascript/

Grant, C. A., Alabbad, Y., Yildirim, E., & Demir, I. (2024). Comprehensive Assessment of Flood Risk and Vulnerability for Essential Facilities: Iowa Case Study. Urban Science, 8(3), 145.

Hagemeier-Klose, M., & Wagner, K. (2009). Evaluation of flood hazard maps in print and web mapping services as information tools in flood risk communication. Natural hazards and earth system sciences, 9(2), 563-574.

Henstra, D., Minano, A., & Thistlethwaite, J. (2019). Communicating disaster risk? An evaluation of the availability and quality of flood maps. Natural Hazards and Earth System Sciences, 19(1), 313–323.

Holz, K.-P., Hildebrandt, G., & Weber, L. (2006). Concept for a web-based information system for flood management. Natural Hazards, 38, 121–140.

Hudson, P. F. (2021). Flooding and Management of Large Fluvial Lowlands: A global environmental perspective. Cambridge University Press.

Hyde, J. (2010). Flood control and the growth machine in Des Moines. Cities in the 21st Century, 2(1), 5.

Iowa Department of Natural Resources. (2023). Iowa Geospatial Data Resources.

https://www.iowadnr.gov/Environment/Geology-Minerals

Iowa Department of Natural Resources. (2023). Iowa LiDAR digital elevation models (DEMs) [Raster dataset]. https://geodata.iowa.gov/

Islam, S. S., & Demir, I. (2024). A Novel Methodology for Enhancing Flood Risk Communication: The Nines of Safety. EarthArxiv, 6539. https://doi.org/10.31223/X58H5Z

Islam, S. S., & Demir, I. (2025). Comparative Analysis of Flood Risk Zoning and Susceptibility Assessment for the Western Corn Belt Plains using Geospatial Techniques. EarthArxiv, 8957. https://doi.org/10.31223/X5072K

Jacobs, J. W. (2018). Cedar Rapids Flood Risk Management: A Case Study in Disaster Recovery.

Jha, A. K., Bloch, R., & Lamond, J. (2012). Cities and flooding: a guide to integrated urban flood risk management for the 21st century. World Bank Publications.

Jonkman, S. N. (2005). Global perspectives on loss of human life caused by floods. Natural Hazards, 34(2), 151–175.

Koks, E. E., Jongman, B., Husby, T. G., & Botzen, W. J. W. (2015). Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. Environmental Science & Policy, 47, 42–52.

Li, Z., Duque, F. Q., Grout, T., Bates, B., & Demir, I. (2023). Comparative analysis of performance and mechanisms of flood inundation map generation using Height Above Nearest Drainage. Environmental Modelling & Software, 159, 105565.

Manson, S., Schroeder, J., Riper, D. V., & Ruggles, S. (2021). IPUMS National Historical Geographic Information System: Version 17.0 [Database]. University of Minnesota. https://www.nhgis.org

Mansur, A. V, Brond'izio, E. S., Roy, S., Hetrick, S., Vogt, N. D., & Newton, A. (2016). An assessment of urban vulnerability in the Amazon Delta and Estuary: a multi-criterion index of flood exposure, socio-economic conditions and infrastructure. Sustainability Science, 11, 625–643.

Maskrey, S. A., Mount, N. J., & Thorne, C. R. (2022). Doing flood risk modelling differently: Evaluating the potential for participatory techniques to broaden flood risk management decision-making. Journal of Flood Risk Management, 15(1), e12757.

McGrath, H., & others. (2023). Web-based flood risk assessment-rapid, user-friendly tools leveraging open data.

Mishra, A., Mukherjee, S., Merz, B., Singh, V. P., Wright, D. B., Villarini, G., ... & Stedinger, J. R. (2022). An overview of flood concepts, challenges, and future directions. Journal of hydrologic engineering, 27(6), 03122001.

Mohanty, M. P., Karmakar, S., & Ghosh, S. (2019). WEBFRIS: A web based flood information system for enhanced resilience through risk awareness. 11th World Congress on Water Resources and Environment: Managing Water Resources for a Sustainable Future-EWRA 2019. Proceedings.

Mozilla Developer Network. (2024). Web technology documentation (HTML, CSS, JavaScript). https://developer.mozilla.org/

PostgreSQL Global Development Group. (2024). PostgreSQL: The world's most advanced open-source database. https://www.postgresql.org/

Quintero, F., Mantilla, R., Anderson, C., Claman, D., & Krajewski, W. (2018). Assessment of changes in flood frequency due to the effects of climate change: Implications for engineering design. Hydrology, 5(1), 19.

Ramirez, C. E., Sermet, Y., Molkenthin, F., & Demir, I. (2022). HydroLang: An open-source web-based programming framework for hydrological sciences. *Environmental Modelling & Software*, *157*, 105525.

Rufat, S., Tate, E., Burton, C. G., & Maroof, A. S. (2015). Social vulnerability to floods: Review of case studies and implications for measurement. International Journal of Disaster Risk Reduction, 14, 470–486. https://doi.org/https://doi.org/10.1016/j.ijdrr.2015.09.013

Salman, A. M., & Li, Y. (2018). Flood risk assessment, future trend modeling, and risk communication: a review of ongoing research. Natural Hazards Review, 19(3), 4018011.

Tanir, T., Yildirim, E., Ferreira, C. M., & Demir, I. (2024). Social vulnerability and climate risk assessment for agricultural communities in the United States. Science of The Total Environment, 908, 168346.

Taubenböck, H., Wurm, M., Netzband, M., Zwenzner, H., Roth, A., Rahman, A., & Dech, S. (2011). Flood risks in urbanized areas–multi-sensoral approaches using remotely sensed data for risk assessment. Natural Hazards and Earth System Sciences, 11(2), 431-444.

Tate, E., Strong, A., Kraus, T., & Xiong, H. (2016). Flood recovery and property acquisition in Cedar Rapids, Iowa. Natural Hazards, 80, 2055–2079.

USGS. (2023). National Hydrography Dataset (NHD) [Vector data]. U.S. Geological Survey. https://www.usgs.gov/national-hydrography.

U.S. Census Bureau. (2023). TIGER/Line Shapefiles: Roads [Vector data]. U.S. Department of Commerce. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html

USDA NRCS. (2023). Soil Survey Geographic (SSURGO) Database [Raster and vector data]. U.S. Department of Agriculture, Natural Resources Conservation Service. https://www.nrcs.usda.gov/resources/data-and-reports/ssurgo

USDA NASS. (2023). Cropland Data Layer (CDL) [Raster data]. U.S. Department of Agriculture, National Agricultural Statistics Service. https://nassgeodata.gmu.edu/CropScape/

Vamvakeridou-Lyroudia, L. S., Chen, A. S., Khoury, M., Gibson, M. J., Kostaridis, A., Stewart, D., Wood, M., Djordjevic, S., & Savic, D. A. (2020). Assessing and visualising hazard impacts to enhance the resilience of Critical Infrastructures to urban flooding. Science of the Total Environment, 707, 136078.

Villarini, G., Zhang, W., Quintero, F., Krajewski, W. F., & Vecchi, G. A. (2020). Attribution of the impacts of the 2008 flooding in Cedar Rapids (Iowa) to anthropogenic forcing. Environmental Research Letters, 15(11), 114057.

Vojinovic, Z. (2015). Flood risk: the holistic perspective. IWA Publishing.

Wilbanks, T., Fernandez, S., Backus, G., Garcia, P., Jonietz, K., Kirshen, P., Savonis, M., Solecki, W., Toole, L., & others. (2013). Climate change and infrastructure, urban systems. An d Vulnerabilities: Technical Report for the U.S. Department of Energy in Support o f the National Climate Assessment, Springer.

Wing, O. E. J., Lehman, W., Bates, P. D., Sampson, C. C., Quinn, N., Smith, A. M., Neal, J. C., Porter, J. R., & Kousky, C. (2022). Inequitable patterns of U.S. flood risk in the Anthropocene. Nature Climate Change, 12(2), 156–162.

Yang, M., Qian, X., Zhang, Y., Sheng, J., Shen, D., & Ge, Y. (2011). Spatial multicriteria decision analysis of flood risks in aging-dam management in China: A framework and case study. International Journal of Environmental Research and Public Health, 8(5), 1368–1387.

Yeşilköy, S., Baydaroglu, O., Singh, N., Sermet, Y., & Demir, I. (2024). A contemporary systematic review of Cyberinfrastructure Systems and Applications for Flood and Drought Data Analytics and Communication. Environmental Research Communications.

Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zhao, G., Pang, B., Xu, Z., Peng, D., & Zuo, D. (2020). Urban flood susceptibility assessment based on convolutional neural networks. Journal of Hydrology, 590, 125235.