IBIS: A Community-Oriented Framework for Flood-Induced Bridge Vulnerability Assessment and Prioritization for Iowa

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Abstract
Floods are among the most frequent and damaging natural hazards, posing serious risks to transportation infrastructure and public safety. Bridges, as essential links in road and rail networks, are especially vulnerable, and their closures can trigger widespread disruption, economic losses, and reduced access to vital services. Effective flood-risk mitigation and emergency response require systems that integrate diverse data sources and deliver actionable information on infrastructure vulnerability and operational risk. Although several web platforms support asset management or flood forecasting, few provide an environment dedicated to bridge-specific vulnerability, where hazard data, structural characteristics, and operational factors can be examined together. The Iowa Bridge Information Service (IBIS) addresses this gap through a web-based framework that combines structural, spatial, and hydrological datasets to support flood-focused risk assessment for communities in Iowa. IBIS enables users to analyze bridge exposure through configurable filters, scenario-based flood overlays, and interactive tools such as heatmaps and statistical summaries. It applies multiple criteria decision-making techniques, including the Analytic Hierarchy Process (AHP), to evaluate vulnerability based on condition, traffic, detour length, and closure potential. County and watershed views allow assessment at policy-relevant and hydrologically meaningful scales. By combining data, analysis, and visualization in a single framework, IBIS provides a practical tool for maintenance planning, emergency preparedness, and resilience strategies for infrastructures generalizable to many flood-prone regions around the world.

Keywords: Flood Risk Assessment, Transportation Infrastructures, Web-Based Visualization, Information Systems, Decision Support

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1. Introduction

Floods are among the most destructive natural hazards worldwide, causing significant social and economic disruptions as well as loss of life (Adhikari et al., 2010). Their frequency and intensity have increased due to climate change, urbanization, and population growth (Sadler et al., 2017; Duran et al., 2024). Land-use changes and urban development have caused flood-prone areas to be more vulnerable, particularly riverbanks that have historically been occupied by communities (Douben, 2006). Floods can develop suddenly, catching communities off guard, and their effects may persist from days to weeks depending on terrain and drainage conditions (Duran et al., 2025a).

Their impacts are both direct, including structural damage and casualties, and indirect, such as disruptions to transportation of people and goods (Highfield & Brody, 2017). Hydrological and environmental factors like rainfall distribution, soil moisture, and land cover changes also affect flood frequency and severity (Lebbe et al., 2014; Sit et al., 2021b; Seo et al., 2019). In the late twentieth century, floods caused over 100,000 deaths and affected around 1.4 billion people (Jonkman, 2005). Moreover, economic losses have grown sharply in recent decades, with estimated annual flood damage rising from $6 billion in 2005 to projections exceeding $60 billion by 2050 (Rentschler et al., 2022), highlighting the need for proactive flood risk management measures (Mitchell, 2005).

Flooding is one of the most disruptive hazards for transportation systems, often cutting access to essential services such as hospitals and fire stations. Within this network, bridges play a particularly critical role, carrying roads and railways across rivers, valleys, and other obstacles (Dunbar, 1915; Schwantes, 1993). Bridges also support key societal and economic functions, including access to schools and workplaces, as well as the passage of utilities like electricity, water, gas, and communication lines (Pregnolato, 2018). Flood events frequently interrupt both road and bridge operations, disrupting daily travel, supply chains, and emergency response activities (Alabbad & Demir, 2024). Yet their strategic position makes them especially vulnerable to hydromechanical forces during floods, and resulting closures can lead to long detours, higher maintenance costs, and significant economic losses (Duran et al., 2025b). Unlike other floodplain structures, such as berms or levees, bridges and tunnels cannot easily be relocated or removed when flood risk increases (Seigel, 2021). Because of their essential role in sustaining mobility and the flow of goods, understanding flood-related risks to bridges is vital for improving resilience and ensuring continuity of critical services (Garlock et al., 2012; Wright et al., 2012).

Floods are the most financially devastating natural hazard in the United States, resulting in an average annual loss of $3.8 billion between 1980 and 2021 (Highfield & Brody, 2017; NOAA, 2021). Iowa, located in the Midwest, is particularly vulnerable to riverine flooding due to its topography and the presence of major rivers like the Mississippi and Missouri (Li et al., 2023). Over the past two decades, Iowa has repeatedly faced floods that have impacted its population, infrastructure, and agricultural sectors. Significant events include the 2008 flood, which affected over 40,000 people directly and caused an estimated $10 billion in damage (Zogg, 2014), and the 2019 floods, resulting in $1.6 billion in losses (Iowa.gov, 2019). Other major floods occurred in

1993, 2001, 2014, and 2016, demonstrating the frequency and severity of flood hazards in the state (Yildirim et al., 2022).

Alongside this high flood exposure, Iowa's bridge inventory further highlights infrastructure vulnerability. Bridge performance data from the Federal Highway Administration (1992–2024) reveals that Iowa consistently ranks among the top 10 states in terms of total bridges, yet it has experienced a persistently high proportion of poor-condition bridges, reaching the top rank between 2014 and 2023, reflecting that a significant share of its large bridge network is aging and may require prioritized maintenance. While the state has made progress in improving bridge conditions, the relative pace of improvement has fallen behind the other states. Together, the frequency and severity of floods and the high proportion of vulnerable bridges make Iowa an ideal case for studying flood-related infrastructure risks and for developing an interactive, data-driven platform for assessment and planning.

Web technologies have reshaped the way environmental and infrastructure information is gathered, processed, and communicated across disciplines (Yeşilköy et al., 2023). They allow data from remote sensing, weather networks, monitoring sensors, and predictive models to be combined efficiently, supporting real-time exploration of complex datasets to improve decision-making. Progress in WebGIS and cloud-based systems has broadened their role in flood-related studies, including risk and damage estimation (Haynes et al., 2018), geo-visual analytics (Sit et al., 2021a), and hydrologic tracking and visualization (Demir et al., 2009). Compared with traditional desktop GIS, modern web platforms use standard protocols and intuitive interfaces that help users focus on their objectives without the complexity or steep learning curve of specialized software (Simão et al., 2009). Through the involvement of online communities where scientists, decision-makers, and the public exchange insights, web-based systems foster transparency, encourage collaboration, and strengthen awareness and readiness for environmental and infrastructure issues (Mount et al., 2024).

While several web-based platforms offer support for bridge asset management or flood-related analysis, none provide a fully integrated environment focused specifically on bridge disaster vulnerability. The United States Long-Term Pavement Performance (LTPP) InfoBridge portal delivers extensive access to bridge inventories, inspection records, and performance trends, but it is primarily intended for static data and does not incorporate hazard or resilience analytics. Similarly, France's Programme National Ponts: Cartographie Publique (2024) provides registries and "health cards" for local bridges and retaining walls, but its function is largely limited to reporting and visualization without modeling disaster scenarios. In the flood domain, several recent applications demonstrate the potential of web technologies for improving accessibility and decision support.

Alabbad et al. (2023) developed a platform to estimate riverine flood damage, including impacts on properties, vehicles, businesses, and transportation infrastructure, using community- and property-level analyses. Complementing these efforts, Morsy et al. (2018) designed a cloud-based flood warning system using 2D hydrodynamic modeling to provide near real-time forecasts of infrastructure vulnerability. Despite these developments, there remains no publicly accessible system that synthesizes bridge inventory, condition, traffic characteristics, and environmental hazard data into a single, interactive platform for disaster preparedness and resilience planning.

The Iowa Bridge Information Service (IBIS) is a web-based platform developed to support flood-focused transportation risk assessment by combining structural, spatial, and hydrological data into a unified, interactive environment. The platform consolidates multiple decision-support tools, enabling users to explore flood scenarios, filter infrastructure attributes, and generate heatmaps that highlight areas of concentrated risk. County and watershed extents provide flexible geographic selection, while the statistics panel summarizes key indicators such as condition, traffic, age, and closure metrics to inform decision-making. Reflecting their extensive use in flood and infrastructure risk assessments, the platform employs multiple criteria decision-making techniques by (Papaioannou et al., 2015; Khosravi et al., 2019; Rincón et al., 2018; Xu et al., 2019). By integrating factors such as bridge condition, traffic, detour length, and flood closure, IBIS helps prioritize maintenance, mitigation, and emergency response efforts. In addition, the heatmap tool further reveals spatial clusters and patterns of vulnerability that might not be apparent from individual metrics alone. Lastly, users can export filtered and analyzed data for reporting, offline evaluation, or integration into broader resilience planning initiatives. This functionality is supported by IBIS's scalable and adaptable architecture, which allows the platform to be extended to other infrastructure systems and flood-resilience applications.

The remainder of this article explains the design and use of IBIS. The methodology details how structural, spatial, and hydrological datasets were gathered and linked through a modular system architecture, how counties and watersheds were chosen, and how transportation attributes were incorporated. It also describes the visualization layers, including flood maps and county analyses, as well as analytical tools such as statistical summaries, heatmap generation, and AHP-based scoring used to assess vulnerability. The results and discussion section presents case studies at county and watershed scales to demonstrate how these components work together for identifying at-risk assets and support planning, maintenance, and resilience. The conclusion summarizes the platform's contributions and its value for managing transportation systems exposed to flooding.

2. Methodology

This section outlines the methodological framework utilized to design and implement the IBIS platform. It presents how diverse datasets, analytical routines, and visualization tools were integrated into a single environment to evaluate infrastructure vulnerability and support decision-making. It contains a description of the data sources and preprocessing steps, the architecture that supports real-time analysis, and the workflows that connect analytical models with interactive visualization. Together, these elements demonstrate how IBIS translates heterogeneous inputs into a consistent environment.

2.1. Data Integration

IBIS integrates many authoritative and regional data sources to enable accurate, multi-layered analysis. These datasets come in different formats and are incorporated across multiple components of the platform. During preprocessing, each dataset is transformed and standardized as needed to ensure spatial and temporal consistency. The processed data are then stored on the server in an organized structure, where they can be accessed through spatiotemporal queries to support dynamic filtering and interactive visualization. Table 1 summarizes the data sources, their types and formats, and the specific ways they are used within the platform.

Table 1 presents the list of datasets that differ in both content and format but are harmonized during preprocessing to ensure spatial and temporal consistency. For instance, bridge metadata from the National Bridge Inventory (NBI) is ingested in coma separated values (CSV) format, which facilitates straightforward updating and supports attribute-based filtering and analysis within the platform. Bare-earth elevation data from the Department of Natural Resources (DNR) and Light Detection and Ranging (LiDAR) point clouds from GeoInformatics Training Research Education and Extension (GeoTREE) are processed to generate elevation models for flood depth estimation, while Federal Emergency Management Agency – National Flood Hazard Layers (FEMA NFHL) flood depths and flood extent layers support visual overlays at different scales.

Table 1. Data sources used in IBIS, including content type, format, and their role.

Source	Content	Format	Usage
FEMA NFHL	Flood depths and extends (2–500 year return periods)	Raster/Tile service	Visualizing flood extents, supporting inundation overlays and hazard analysis
Google Maps API	Road network and water bodies	Basemap	Providing geographic context, enabling road and water overlays
NBI / Iowa DOT	Bridge inventory and metadata (age, type, ADT, etc.)	CSV	Attribute filtering, statistical summaries, AHP/Fuzzy AHP scoring
LiDAR (GeoTREE)	Point cloud elevation data	.las	Creating high-resolution surface models for evaluating bridge deck elevation relative to terrain
DNR	Bare-earth elevation	Raster	Assessing bridge deck height and flood susceptibility
U.S. Census	Population data by county	Vector shapefile	Supporting demographic analysis and filtering for exposure assessment
USGS / Geodata	County and watershed boundaries	GeoJSON	Serving as spatial reference layers for mapping, selection, and filtering

Vector datasets from the United States Geological Survey (USGS) and the U.S. Census Bureau provide administrative boundaries and demographic layers, stored as shapefiles or Geographic JavaScript Object Notation (GeoJSON) to facilitate scalable filtering and base map integration. Together, these sources establish the foundation of the system, but their value comes from how they interact. County and watershed boundaries define the scope of analysis, demographic data gives context to the potential impacts, traffic attributes such as average daily traffic (ADT) and detour length illustrate the degree of exposure to disruption, structural characteristics like age and condition describe the physical state of bridges, and hazard layers from FEMA and LiDAR capture the flooding environment itself. By combining these dimensions into a single framework, the platform enables vulnerability to be assessed not as an isolated characteristic but as the product of infrastructure, network dependence, and environmental threats.

2.2. System Architecture

The platform is built to enable dynamic interaction with geospatial and bridge infrastructure datasets, allowing users to investigate flood risks, assess bridge vulnerability, and make informed decisions through configurable analysis tools. It combines client-side interactivity with server-side data handling and analytical processing, integrating diverse data sources, preprocessing routines, and computational modules to provide a responsive, visually driven decision-support environment. Broadly, the system architecture is composed of three main components: the frontend interface, the central server, and the analytical engine. The frontend, developed with HyperText Markup Language (HTML), Cascading Style Sheets (CSS), and JavaScript, utilizes The Google Maps API (Application Programming Interface) to deliver base maps, interactive heatmaps, flood overlays, and chart-based visualizations.

Users can dynamically filter infrastructure layers, explore spatial patterns, and export tailored datasets. The server hosts all data layers, icons, and CSV files, manages requests from the interface, and ensures timely updates, while PHP: Hypertext Preprocessor is utilized to integrate tabular datasets into the system with Structured Query Language (SQL) queries. Meanwhile, the analytical engine performs statistical calculations, implements multi-criteria decision frameworks such as AHP, and applies GIS-based logic to score and visualize bridge vulnerability in real time.

The platform transforms datasets into interactive visualizations, analytical outputs, and exportable summaries by utilizing a multi-channel data processing pipeline. Figure 1 illustrates that data is transmitted from a diverse array of sources and undergoes distinct processing pathways before ultimately converging at the server and being displayed in the web interface. Basically, the web interface sends user-driven requests to the server, which queries the database and analytical engine to retrieve filtered datasets, update overlays, and deliver real-time analytical outputs tailored to user selections.

On the input side, the system integrates authoritative datasets including National Bridge Inventory data, DNR bare-earth elevation, FEMA NFHL flood depths, GeoTREE LiDAR point clouds, and US Census demographic data, as well as spatial layers such as county and watershed boundaries. These datasets are first processed into consistent formats such as CSV, raster, shapefile, or GeoJSON, so they can be consolidated and prepared for analytical integration, GIS preprocessing, or direct geospatial application within the platform.

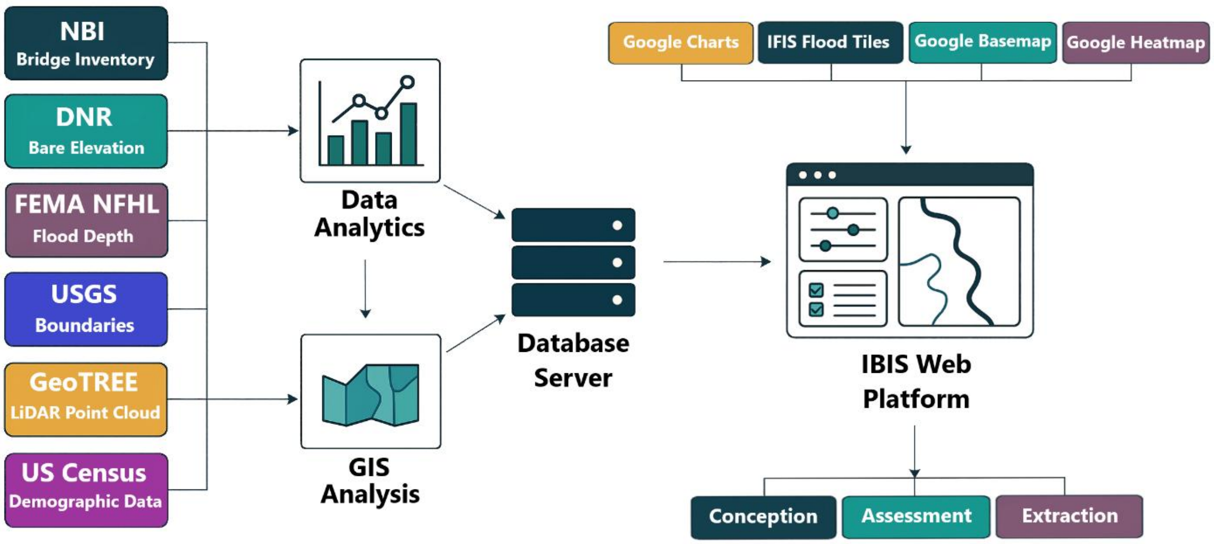


Figure 1. Schematic overview of IBIS architecture and major components, illustrating the integration of diverse data sources, preprocessing pipelines, analytical engines, and the web-based frontend interface.

Once acquired, datasets are processed through one of the assessment paths. Direct analytical integration is used for tabular or structured data such as bridge metadata and population statistics, which are analyzed to generate summaries, condition breakdowns, and AHP/Fuzzy AHP impact indices. These results are then made available for statistical panels, filters, and map overlays. Analysis via GIS preprocessing applies to datasets requiring spatial modeling, such as LiDAR-derived elevations or flood depth data. For these layers, geospatial computations such as bridge inundation evaluation that produce spatial overlays and impact maps and store for visualization. Combined analytic–GIS workflows occur when analytical outputs are fed into GIS layers for visualization, such as applying AHP or Fuzzy AHP scores to map-based overlays, enabling interactive filtering and spatial prioritization of infrastructure. Finally, direct GIS application is used for layers like flood maps or administrative boundaries, which are integrated as geospatial layers without additional preprocessing for immediate use in the interface.

All processed data are collected at the server, where they are organized with unique identifiers and linked with the analytical engine. At this stage, tabular, spatial, and combined datasets are treated as integrated inputs that can be used for real-time scoring, filtering, and visualization. The analytical engine carries out normalization routines, multi-criteria evaluations such as AHP and Fuzzy AHP, and vulnerability scoring, while also connecting these results to GIS layers. This arrangement ensures that when users apply filters, explore hazard layers, or engage assessment models, the system provides immediate and consistent outputs across all data types. The processed results are then delivered through the web interface, where several visualization modules work together.

Google Maps establishes the base for spatial orientation, Iowa Flood Information System (IFIS; Demir et al., 2018) tiles extend hazard context with dynamic flood extents, heatmaps highlight concentrations of exposure, and Google Charts render statistical outputs into interactive summaries. Within this environment, users can move fluidly between broad explorations of infrastructure patterns, detailed operational assessments such as vulnerability mapping and prioritization, and focused data extraction through filtered CSV exports. By combining computational processing with clear and accessible visualizations, the workflow of the platform brings diverse datasets into a unified decision-support system, strengthening the evaluation of bridge vulnerability and flood risk across both county and watershed scales.

2.3. Geographic Selection and Bridge Attributes

The IBIS platform is designed as a user-centered, interactive web environment, allowing users to explore, analyze, and interpret flood-related bridge vulnerabilities across Iowa. Its layout is structured into modular sections that provide access to both geographic layers and bridge-specific analytical tools. Users can explore the map using two interchangeable geographic layers: county boundaries and HUC-8 (Hydrologic Unit Code-8) watershed divisions. The county layer is suggested for bridge analysis because most bridges fall under county jurisdiction, making it the most policy-relevant and operationally meaningful scale for maintenance and emergency planning.

The HUC-8 watershed layer, on the other hand, provides an alternative, hydrologically informed perspective, allowing users to evaluate flood risk and infrastructure vulnerability in terms of drainage patterns and river basin connectivity. Users can select layers through a dropdown menu or directly interact with the map. Additionally, a road network overlay can be turned on or off to provide contextual reference for the state's transportation infrastructure. This background layer symbolizes different road types, including highways, arterial roads, and local roads and it gives users a clearer sense of how bridges connect to different levels of the network. Beyond simple orientation, this helps users visually identify whether vulnerable bridges sit on critical corridors or on lower-capacity local roads.

Complementing the geographic layers, the Bridge Attributes module provides a flexible and interactive way to explore bridges. Users can dynamically filter bridges according to key characteristics and risk-related factors. This feature enables them to carry out analyses at both local and statewide scales. Age, ADT, and detour length are implemented as dual-handle sliders, allowing users to define specific intervals to highlight bridges that are older, carry higher traffic volumes, or have longer detour distances, which could indicate greater operational importance. Bridges can also be filtered by conditions (Good, Fair, or Poor), following NBI and Iowa DOT (Department of Transportation) inspection standards, to identify structurally deficient assets requiring prioritized maintenance.

Structure type filters allow selection of stringer/multi-beam, culvert, or slab designs, capturing vulnerabilities related to bridge form. Material filters (Steel, Concrete, or Prestressed Concrete) provide insight into durability and susceptibility to environmental stressors, while Class filters (Urban or Rural) reflect the bridge's role in connectivity and its potential impact on the transportation network. On the other hand, flood closure adds a scenario-based perspective of analysis. Using LiDAR-derived bridge deck elevations in combination with digital elevation model (DEM) based flood depths, IBIS determines functional status for 50-, 100-, and 500-year flood events. When floodwater exceeds the deck elevation at a bridge location, the structure is considered functionally closed, simulating conditions equivalent to a bridge failure for operational planning purposes (Duran et al., 2025a). This capability shifts analysis from static condition assessment to risk-informed evaluation of infrastructure continuity under varying flood magnitudes.

Individually, each of these attributes provides some insight into bridge characteristics and potential vulnerabilities. When examined in combination, however, they reveal relationships and correlations across the bridge network that may not be evident from any single parameter. For example, users can examine whether older bridges carry heavier traffic. They can also see if certain materials or structure types are more common in urban or rural areas. Detour lengths can be compared with bridge condition to identify patterns. When combined with flood closure data, users can determine which bridges are most likely to be affected under different flood scenarios. By focusing on these interconnections, IBIS supports a deeper, data-driven understanding of bridge inventory patterns and flood-related risks, informing targeted maintenance, resource allocation, and resilience planning. By integrating geographic selection with these multi-dimensional bridge filters, IBIS enables scenario-driven exploration of bridge vulnerabilities. Users can investigate infrastructure characteristics, flood exposure, and operational importance in combination, supporting targeted maintenance, resource allocation, and resilience planning without manually parsing large datasets.

2.4. Visualization Layers

IBIS presents data through interactive visualization layers, letting users explore bridge infrastructure and flood impacts across Iowa. These layers offer multiple perspectives on the transportation network, from administrative boundaries to flood scenarios, helping users spot patterns, compare regions, and focus on areas that may need targeted attention.

2.4.1. Flood Layers

IBIS incorporates flood inundation maps developed by the Iowa Flood Center (IFC), which provides scenario-based flood extents for return periods ranging from 2 years to 500 years. These layers allow users to visually explore the spatial reach of potential floods under varying magnitudes, helping identify which bridges and road segments are most vulnerable in different scenarios (Alabbad et al., 2025). The flood layers were generated through a comprehensive modeling process that combined LiDAR-derived DEMs with advanced tools such as HEC-RAS for statewide rivers and MIKE FLOOD for urban areas (Gilles et al., 2012). Streams with drainage areas greater than one square mile were modeled using LiDAR-based cross-sections, while urban simulations applied a coupled 1D–2D approach to represent both river channel flow and floodplain dynamics. After validation against historical flood events, including the 2008 Iowa flood, the modeled water surfaces were processed in GIS to delineate inundation polygons for multiple return periods (Giles et al., 2012). These polygons were cleaned, optimized for web delivery, and converted into Google Maps-compatible tile layers, which IBIS accesses directly through the IFIS service.

Flood layers are displayed to end users as semi-transparent overlays on a Google Maps basemap, emphasizing flood-risk areas while maintaining the geographic context. This feature turns complex flood models into an easy-to-use, interactive tool that allows users to compare flood extents across return periods and instantly evaluate which bridges or road networks intersect flood-prone zones. IBIS offers fast loading, complete statewide coverage, and seamless interaction by utilizing IFC's preprocessed flood tiles, eliminating the need for specialized GIS software and enabling planners, engineers, and decision-makers to access sophisticated flood modeling. These scenario-based layers serve as a standardized reference for assessing potential flood exposure, enabling users to consistently identify at-risk areas and make informed planning and management decisions.

2.4.2. County Analysis Layers

Bridges are primarily managed and maintained by county and state authorities, making the county level the most practical and policy-relevant scale for analysis. Organizing the data by county aligns with real-world administrative responsibilities, allowing local agencies to assess vulnerability and prioritize actions within their jurisdiction (Duran et al., 2025b). This framework ensures that the platform provides decision-makers who are responsible for emergency planning and infrastructure management with pertinent and actionable information. One of the core features of the platform, which is designed to assist users in comprehending the characteristics of bridge inventory and the performance of regional infrastructure under flooding conditions, is county-level visualization. Using a single GeoJSON dataset that contains all county attributes, the system dynamically generates thematic overlays based on user-selected metrics, such as bridge condition, average age, closure percentages, traffic disruption, or detour distances. Each overlay is styled dynamically with color gradients, transparency, and county labels, accompanied by a clear legend for interpretation. This dynamic approach offers a user-friendly method for comparing counties, identifying regions that are more susceptible to operational challenges during flooding, and emphasizing areas with a higher concentration of aging or structurally deficient bridges.

The overlays provide multiple perspectives on infrastructure to support informed decision-making. County summaries display baseline indicators such as population, total number of bridges, average bridge age, and the percentage of bridges rated as poor. These metrics help agencies prioritize maintenance by revealing where ageing or deficient structures coincide with large populations or extensive networks, indicating greater potential impact if failures occur. Flood closure layers provide the percentage and count of bridges likely to be closed under different return-period scenarios (50-, 100-, and 500-year floods). This allows planners to assess which counties face the highest disruption risk and prepare targeted mitigation strategies such as elevating vulnerable bridges or reinforcing approaches.

Traffic disruption layers illustrate both the total daily traffic affected and the average traffic per closed bridge. Planners can use these layers to visualize which counties face the greatest risk of disruption and plan targeted responses, like raising vulnerable bridges or strengthening approaches. High average traffic per bridge suggests a critical link in the transportation network that requires extra attention for resilience. Detour impact layers quantify the additional travel distance (in kilometers) caused by flood-related closures, presented as both total detour length and average per bridge. These metrics reveal the real-world economic and social costs of disruptions, helping agencies justify investments in redundancy or alternative routes. Impact zone layers then bring everything together, combining condition, hazard exposure, and operational importance into composite risk scores using AHP and Fuzzy AHP models. These scores integrate structural condition, hazard exposure, and operational importance, allowing decision-makers to identify high-priority regions for resilience investments rather than evaluating each metric in isolation.

2.5. Data Analytics

In this platform, data analytics refers to the systematic processing and interpretation of bridge, hazard, and demographic datasets to uncover meaningful patterns and relationships. Rather than concentrating on individual records, the analysis highlights aggregated characteristics, spatial distributions, and comparative indicators. This approach makes it possible to examine both descriptive attributes, such as material or structure categories, and modeled outcomes, including projected closures or impact indices. The subsections that follow describe the specific tools developed to support these analyses.

2.5.1. Statistical Analysis and Visualization

The statistics panel provides an interactive way for users to explore and interpret bridge-related data for any selected county or watershed. Instead of manually analyzing large datasets, users can view automated charts that summarize key characteristics and risk factors. This visual approach supports quick assessments of infrastructure conditions, traffic exposure, and vulnerability to flooding, allowing planners and decision-makers to make comparisons across regions and prioritize interventions more effectively.

The first set of visualizations focuses on basic infrastructure characteristics for the selected region. A pie chart showing the proportion of bridges in Good, Fair, or Poor condition provides an immediate sense of the region's maintenance needs and overall structural health. Additional charts display material composition, highlighting the prevalence of concrete, prestressed concrete, steel, and other materials, which is important for assessing durability and susceptibility to environmental stress. The panel also includes a chart on structure type, breaking down design forms such as stringer or multi-beam bridges, culverts, and slabs, offering insight into functional diversity and potential vulnerabilities. Another chart illustrates the distribution between rural and urban bridges, providing context on transportation significance and regional connectivity. Finally, a line chart plots the age distribution of bridges, accompanied by the average age for the selected area, enabling users to assess structural longevity and anticipate replacement or rehabilitation timelines.

The second group of visualizations incorporates outputs from the platform's impact assessment studies, integrating flood modeling and risk prioritization results. One bar chart displays the number of bridges projected to close under 50-, 100-, and 500-year flood scenarios, providing clear insight into regional vulnerability to extreme hydrologic events. Another chart quantifies the volume of traffic disrupted by such closures, emphasizing the transportation and economic implications of flooding on critical corridors. To support decision-making beyond simple counts, the panel also features histograms for both the AHP and Fuzzy AHP index distributions. These charts show how bridges rank based on multiple weighted criteria, such as traffic volume, detour availability, and structural condition, while the fuzzy approach accounts for uncertainty in expert judgment. Together, these analytics offer a robust prioritization framework for identifying high-risk, high-importance bridges under current and future hazard conditions.

By combining structural summaries with advanced impact and risk indicators, the statistics panel transforms raw data into actionable intelligence. Users can compare counties or watersheds, visualize how flooding affects infrastructure systems, and identify where investments will have the greatest impact. This integration of ready data with modeled assessments ensures that the platform serves not only as an informational tool but also as a decision-support system for engineers, planners, and emergency managers.

2.5.2. Kernel Density Estimation and Visualization

The heatmap tool provides a flexible way to visualize spatial patterns of bridge attributes, enabling users to explore areas of concentration or intensity for selected parameters such as bridge age, traffic volume, or detour length. The visualization is produced using Kernel Density Estimation (KDE), which converts discrete points into a continuous surface, emphasizing areas where the selected attributes are spatially clustered (Silverman, 1986; Diggle, 1985, 1990). In this platform, a Gaussian kernel is applied, providing a smooth, continuous density representation without incorporating additional weights. The 2D Gaussian Kernel function is expressed as Equation 9.

$$K(u) = \frac{1}{2\pi} \exp\left(-\frac{u^2}{2}\right) \qquad \text{Eq. 1}$$

In equation 9, K(u) represents the Gaussian Kernel closeness function, where u is the normalized distance between the Kernel center and the point being evaluated, calculated as u=d/h, where d is the spatial distance between a bridge and the Kernel center, and h (the radius or bandwidth) controls the smoothness of the algorithm. The Gaussian kernel generates a continuous density surface from discrete bridge locations by assigning a higher weight to nearby points and gradually decreasing its influence as distance increases. Our heatmap analysis tool utilizes this Kernel function in an interactive environment, and it allows users to adjust the radius (h) and intensity, modify the color scheme, and apply bridge attribute filters to refine the data visualization. The visualization dynamically updates, including automatic adjustment when the map is zoomed to maintain appropriate resolution and clarity. The tool transforms bridge data into a continuous spatial landscape by integrating Gaussian smoothing with these interactive controls. This landscape reveals patterns and clusters that may have been overlooked, highlights areas of potential vulnerability or high bridge concentration, allows exploration of different scenarios and "what-if" conditions, and provides an intuitive overview of spatial trends. This enables stakeholders to identify critical regions, anticipate resource needs, and support data-driven decisions without recalculating the underlying dataset.

2.5.3. Analytic Hierarchy Process (AHP) Analysis

AHP is a widely used multi-criteria decision-making (MCDM) method that quantifies the relative importance of multiple factors in complex decisions under uncertainty. The method breaks down a complex MCDM problem into a hierarchical structure, evaluates the relative significance of various decision criteria, compares alternatives based on each criterion, and establishes an overall priority and ranking for the decision options (Wang et al., 2008). In bridge vulnerability assessment, AHP provides a structured framework for translating expert judgment or user preferences into quantitative weights, which can then be applied to rank bridges by overall vulnerability (Saaty, 1987; Yang et al., 2013). Within our platform, this process is implemented in an interactive and customizable environment where users define evaluation criteria, arrange them hierarchically, and adjust pairwise comparisons in real time. Rather than relying on fixed weights or predefined hierarchies, users select the parameters of interest and compare them using Saaty's 1–9 scale—where 1 indicates equal importance and 9 denotes that one criterion is considered extremely more important than another (Putra et al., 2018). Reciprocal values are automatically calculated, forming the pairwise comparison matrix:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \qquad \text{Eq. 2}$$

with $a_{ii} = 1$ and $a_{ij} = \frac{1}{a_{ji}}$. Once the pairwise matrix is constructed, the results are normalized using Equations 4 and 5, ensuring that each parameter's weight is proportionally represented for subsequent calculations.

$$b_{ij} = \frac{a_i}{\sum_{i=1}^{n} a_{ij}} \qquad \text{Eq. 3}$$

$$A = \begin{pmatrix} b_{11} & b_{12} & \ldots & b_{1m} \\ b_{21} & b_{22} & \ldots & b_{2m} \\ b_{n1} & b_{n2} & \ldots & b_{nm} \end{pmatrix} \qquad \text{Eq. 4}$$

The weight of each parameter is obtained by averaging each row in the normalized pairwise comparison matrix, as described in Equation 6, where "n" denotes the total number of factors.

$$W_i = \frac{\sum_{i=1}^{n} b_{ij}}{n}; \text{ where } \sum_{i=1}^{n} W_i = 1 \qquad \text{Eq. 5}$$

The consistency ratio (CR) is calculated by comparing the consistency index with a random index.

$$CI = \frac{\lambda_{max} - n}{n - 1}; \; CR = \frac{\text{Consistency Index (CI)}}{\text{Random Index (RI)}} \qquad \text{Eq. 6,7}$$

In Equation 7, λ_{max} is the largest Eigenvalue from the pairwise matrix, and RI is the Random Index for a matrix of size n (Saaty, 1980; Malczewski, 1999). Having CR value below 0.1 indicates that the data is nearly fully consistent and considered acceptable (Saaty, 1987). Once weights are finalized, they are applied to the selected bridge attributes to calculate a composite bridge vulnerability index. The resulting scores are displayed on the map with color-coded icons, highlighting high, medium, and low vulnerability tiers according to their relative rankings. As illustrated in Figure 2, the system allows adjustments to criteria or pairwise comparisons at any time, with scores and visualizations updating dynamically.

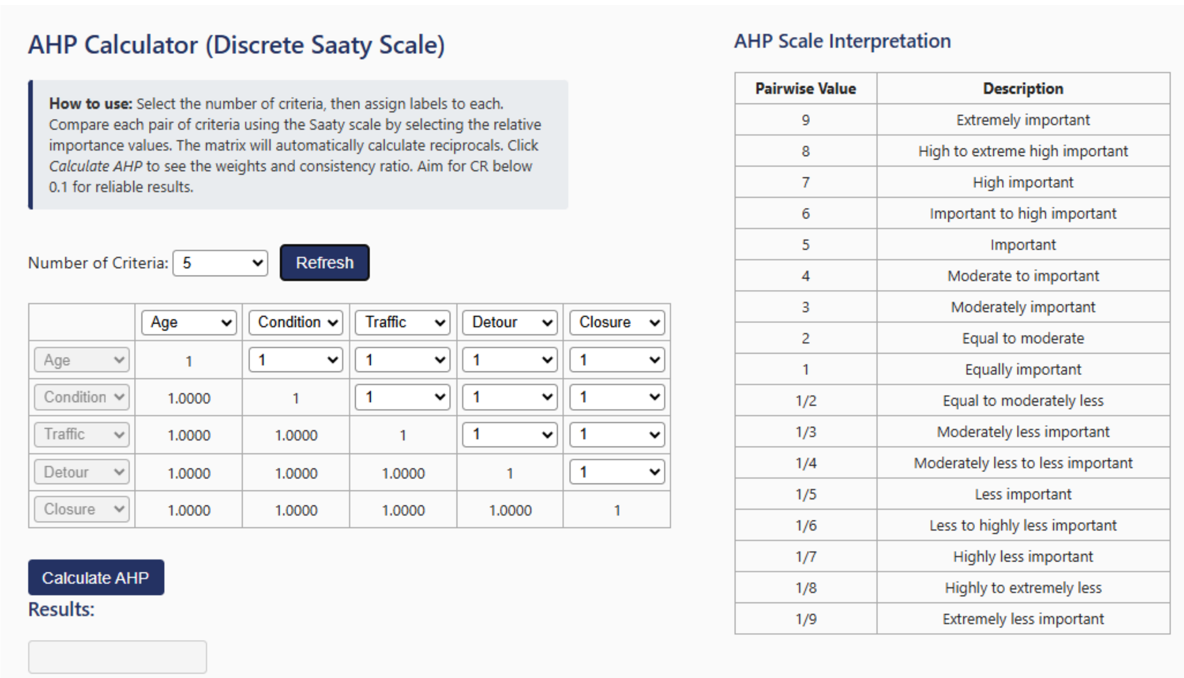


Figure 2. User interface of the AHP calculator within IBIS, showing interactive matrix input, reciprocal value auto-calculation, and real-time computation of weights for bridge vulnerability assessment.

In addition to custom weight configurations, our suggested index calculations are also available for comparison or further evaluation. Results can be exported as CSV for external use or integration. While the platform could be extended to support Fuzzy AHP for situations with greater uncertainty, the current implementation relies on standard AHP. This is because all judgments are provided directly by the user, so the variability and uncertainty that Fuzzy AHP addresses are already represented in user-defined pairwise comparisons. Standard AHP therefore sufficiently captures the relative importance of criteria and integrates directly with the dynamic vulnerability scoring and visualization framework.

IBIS has also an export feature that allows users to extract the dataset that is currently being displayed and filtered directly from the platform. The exported file contains all the relevant bridge attributes, such as its location, age, daily traffic, detour length, condition score, structure type, material, functional class, flood exposure, and hydrologic unit identifiers like the HUC-8 watershed ID. When the AHP analysis tool is applied, it also includes the calculated weights for each parameter and the overall bridge vulnerability scores. This allows users to review and compare the prioritization results without having to log in to the platform. Our approach promotes transparency, enables further offline analysis, supports reporting and documentation, and ensures that both raw and analyzed data can be seamlessly integrated into broader decision-making workflows.

3. Results and Discussion

To illustrate the capabilities of the IBIS, we present a case study instead of a purely descriptive overview. This approach allows us to show how the platform functions in practice, highlighting how different analytical tools, visualization layers, and filtering options work together to reveal patterns in bridge vulnerability and flood exposure. The case study guides the workflow from broad, statewide perspectives down to local insights, illustrating both methodology and practical interpretation. We start by examining county-scale visualizations and the statistics to provide context on demographic and infrastructure distributions. County overlays for population and bridge count establish a baseline across Iowa State to identify areas where many bridges support dense populations. These initial observations prepare the way for more detailed analyses, allowing users to see how IBIS can identify high-priority regions, detect clusters of vulnerable bridges, and support multi-criteria decision-making. By presenting this concrete example, we show not only the functionality of IBIS but also how stakeholders can use the platform to gain actionable insights.

3.1. Case Study

As can be seen in Figure 3, Polk and Linn emerge as possible candidates because both concentrate high populations and large bridge inventory, making them critical for studying potential flood-related disruption and for showcasing IBIS features.

As shown in the statistics panel in Figure 4, Linn County emerges as the strongest candidate for a case study because it combines a large and varied bridge inventory with characteristics that stand apart from the overall state profile. While Iowa contains a high proportion of older and structurally deficient bridges, Linn County's network is generally in better condition, with most bridges rated good and only a small share considered poor. The county also has a diverse mix of structure types and designs, nearly half of which are multi-beam or slab configurations, typical in urban areas and particularly vulnerable to flooding at approach roads.

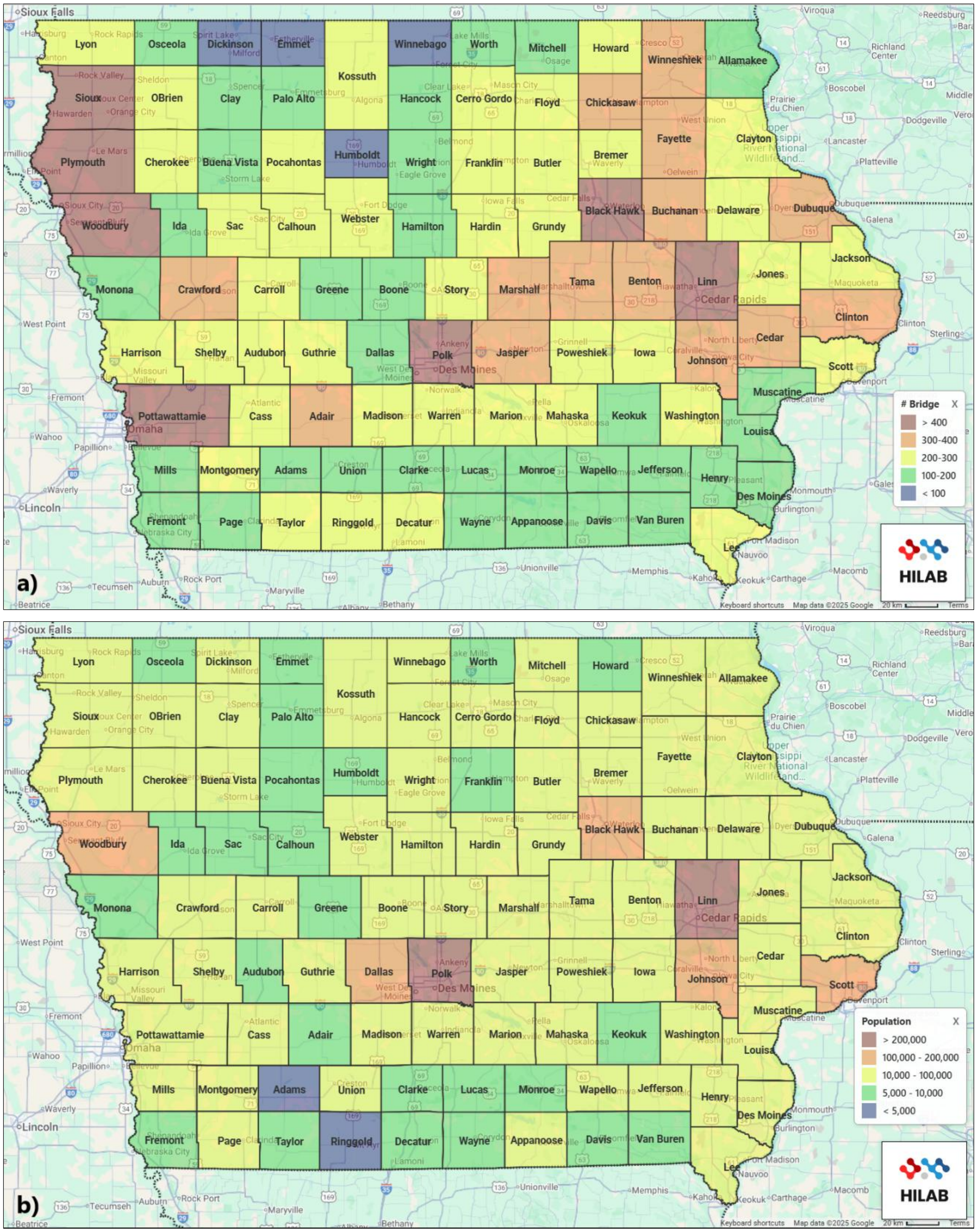
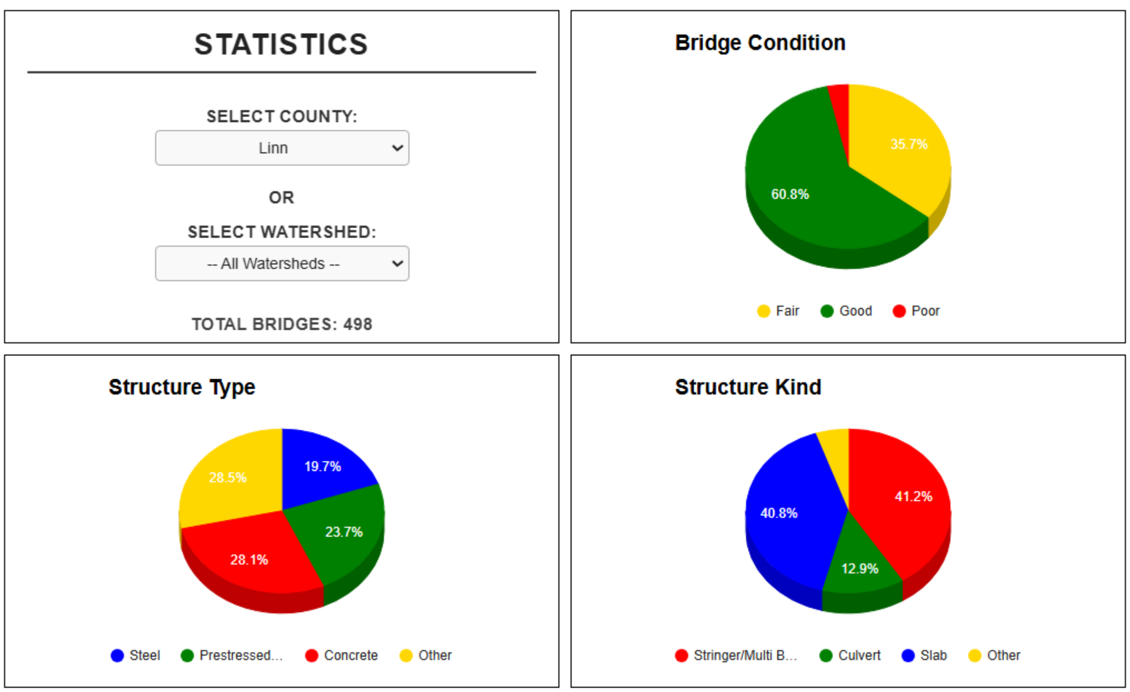


Figure 3. County-level analysis layers in Iowa showing (a) bridge inventory and (b) population distribution as semi-transparent color-gradient overlays.

Unlike the state, where rural bridges dominate, Linn County has an almost even balance of urban and rural bridges, so closures here would disrupt both neighborhood access and regional traffic. Traffic demand is also higher than the state average, meaning that detours caused by flooding would produce more significant delays and ripple effects. Taken together, Linn County has better conditions overall, but higher traffic exposure and localized flood risk. Taken together, Linn County has better overall bridge conditions but experiences higher traffic exposure and localized flood risk, including potential overtopping and temporary closures during major events. These conditions, coupled with the county's strong institutional capacity to implement improvements, make it an ideal setting to demonstrate how IBIS integrates structural, hydraulic, and operational factors in prioritizing bridge resilience.

Historically, Linn County experienced severe impacts during the 2008 Cedar River flood, when the river crested nearly 20 feet above flood stage and inundated much of downtown Cedar Rapids, disrupting transportation corridors and urban mobility (Zogg, 2014). This past event points out the county's susceptibility to flooding and provides relevant context for the case study. The system uses a three-color scheme, represented by condition, to show all bridges within the chosen case area: green (good), yellow (fair), and red (poor). This choice is deliberate: condition ratings aggregate major structural evaluations (deck, superstructure, substructure, culvert, channel, and channel protection) and are reported using standardized inspection protocols, providing a comprehensive, inspector-calibrated snapshot rather than a narrow single-component indicator (Iowa DOT, 2015).



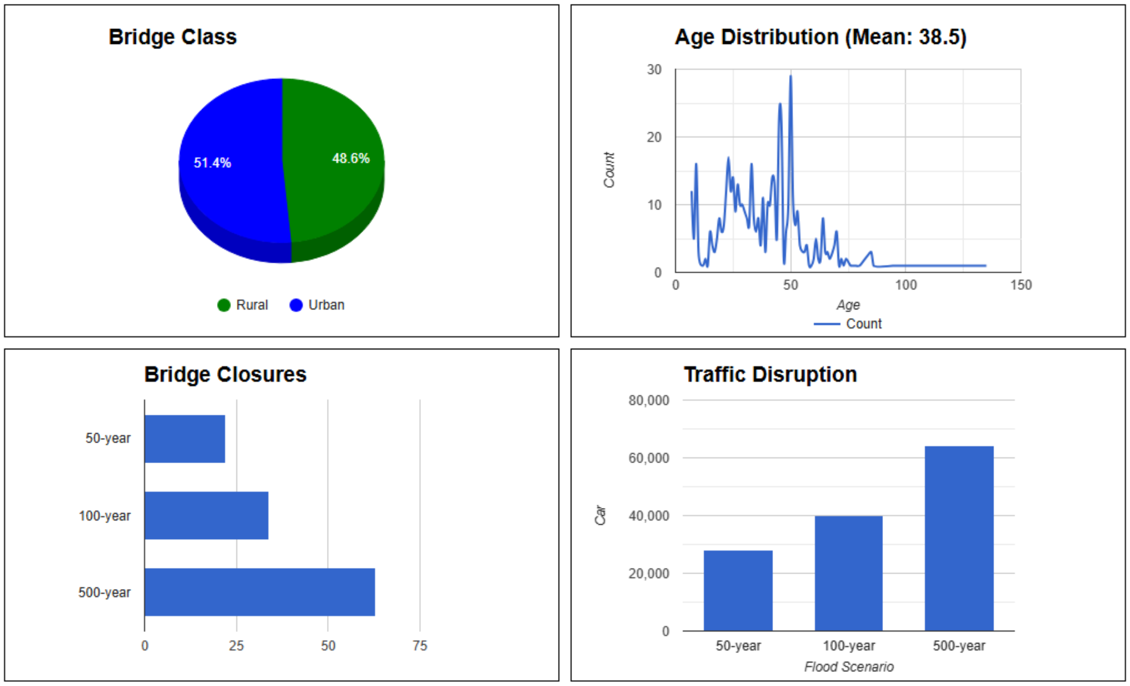


Figure 4. Summary statistics for the bridge inventory in Linn County, including condition, structure type, structure kind, and bridge class (pie charts), age distribution (line chart), and bridge closures and traffic disruptions (bar charts).

Figure 5 illustrates how bridge-level visualization can be integrated with contextual layers, such as the 500-year flood extent and the road network, revealing not only where inundation intersects dense corridors but also that the flood footprint extends into the city center and covers critical road segments, shows that even urban areas within Linn County remain highly susceptible to flooding.

By portraying spatial clustering, the heatmap tool offers an additional perspective. As can be obtained from Figure 6, the Cedar Rapids core and the I-380 corridor stand out as hotspots of bridge density and activity. This is not only a reflection of urban growth patterns but also an indicator of where disruptions would cascade through multiple corridors simultaneously. Adjusting the radius changes how each bridge's influence spreads on the map: smaller radii highlight precise clusters, while larger radii smooth local peaks into broader patterns, emphasizing regional concentrations of vulnerability or exposure. Additionally, users can apply filters to focus on specific subsets of bridges such as age, traffic, condition, or detour length, and change the perspective of the analysis and reveal patterns that might be masked in the full dataset. In this way, the heatmap extends beyond simple visualization of bridge counts, it allows practitioners to explore spatial clustering at multiple scales and across different attribute-driven scenarios. By scanning broad areas and isolating such clusters, agencies can identify zones where a limited set of targeted actions, such as retrofitting a few key crossings or strengthening local detour networks, would yield system-wide resilience benefits.

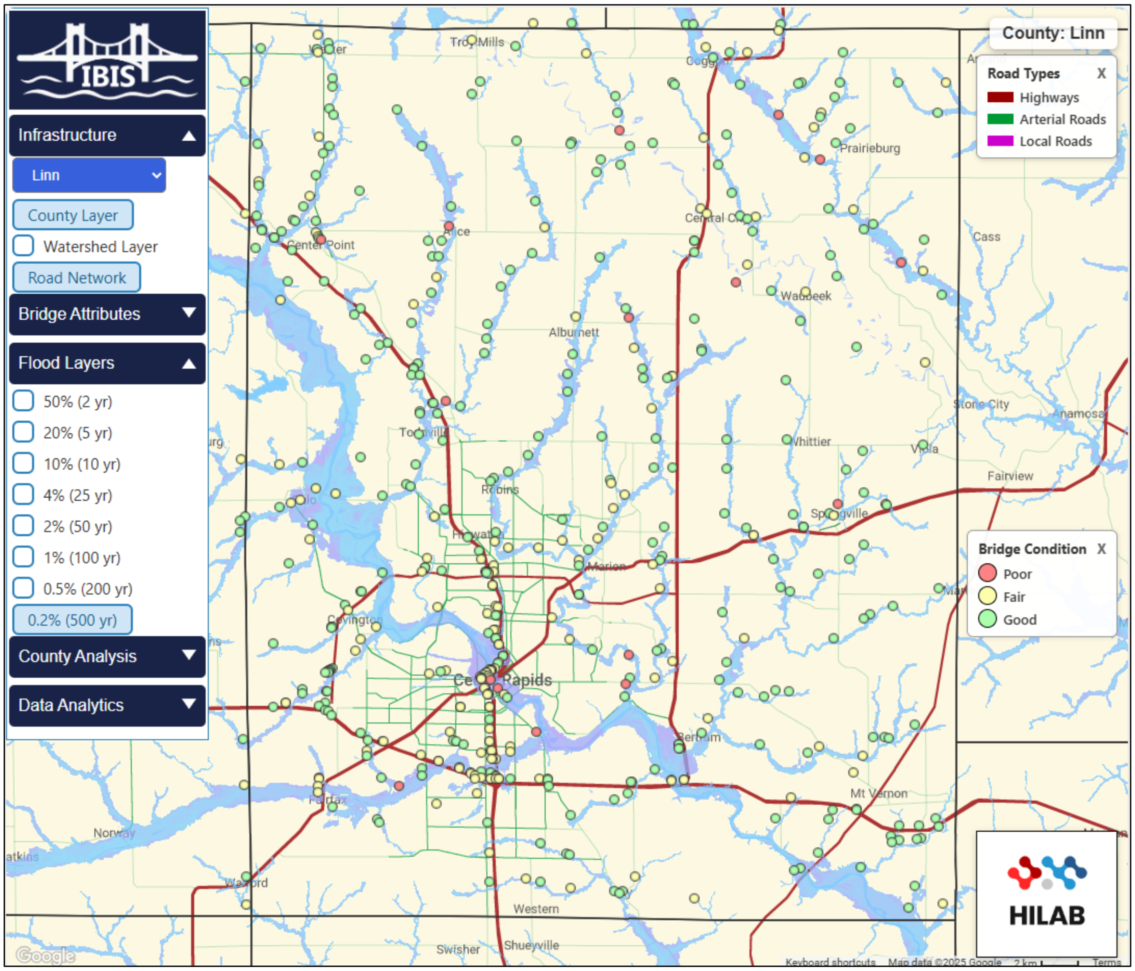


Figure 5. IBIS case study for Linn County showing the 500-year flood layer with bridge inventory and road network overlays.

For this case study, we demonstrate the AHP functionality using a combination of parameter weights that capture both bridge vulnerability and traffic disruption. Bridge condition and age are included as structural parameters because of their correlation and their ability to represent overall structural integrity. Traffic impacts are addressed through ADT, the average number of vehicles passing over a bridge each day across a full year (Huntsinger, 2022), and detour length, which measures the additional travel distance imposed when a bridge is closed (US DOT, 1995). Flood-related closure is incorporated as a single ordinal parameter ranging from 0 (open in all scenarios) to 3 (closed in all scenarios).

Within the hierarchy, closure is emphasized as the most critical factor because it directly governs accessibility and traffic flow during flood events. ADT and detour length are assigned equal importance, reflecting the combined significance of traffic demand and rerouting burdens, while condition and age serve as structural performance indicators secondary to the immediate effects of closure. By prioritizing parameters in this way, the case study demonstrates how AHP can guide practical decision-making for flood risk management and bridge safety within IBIS.

Users can select pairwise values within the Hierarchy Analysis interface, as shown in Figure 7, and the system automatically computes the consistency index and generates weights that can then be applied to normalized attributes with a single action.

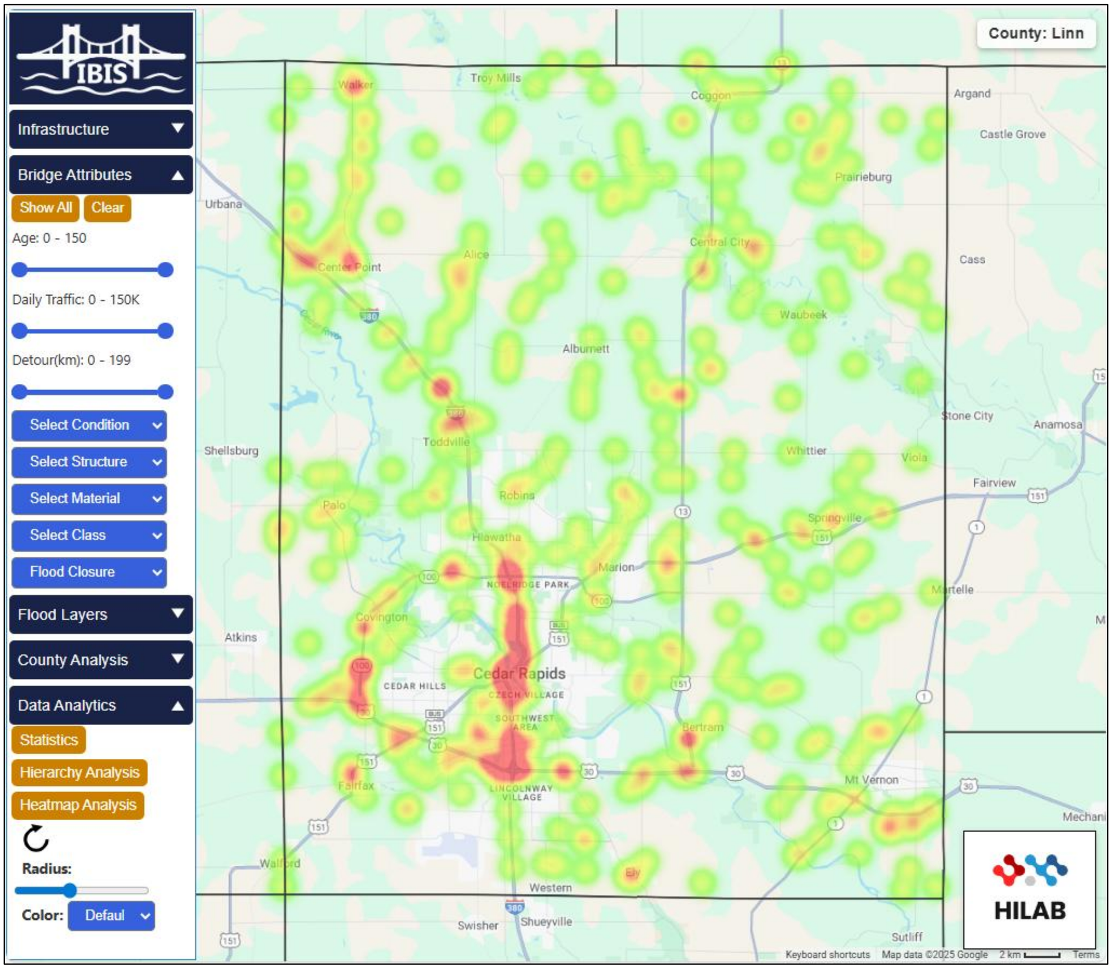


Figure 6. Heatmap visualization of bridges in Linn County based on IBIS analysis, showing spatial cumulation of bridges using color gradients to highlight areas with higher concentrations of infrastructure.

IBIS dynamically updates the map symbology to classify bridges into three categories (top, middle, and bottom third) based on their weighted scores, ensuring consistent comparison across different geographies, as demonstrated in Figure 8. Users can also export both the weights and the weighted scores for further analysis, maintaining congruence between assumptions and results. The weighted map for Linn emphasizes the highest-priority set, which are bridges along major routes near the urban core. These locations are where flood susceptibility intersects with high volumes and limited rerouting options. The color scheme is chosen to make these patterns guide attention to corridors, where proactive inspection, drainage improvements, or design upgrades would mitigate outsized disruption.

IBIS also supports exporting the visualized results so users can preserve exactly what they see (filters, geography, and current weights) in a CSV for client-side work. When further review is needed, users can visualize the full statewide inventory (bridge attributes such as id, location age, daily traffic, type, and the platform's ready analyses including inundation, AHP, and Fuzzy AHP impact indices) and export those as well. Heatmaps, filters, and the AHP tool scale seamlessly, so the same workflow used in Linn can be repeated across other counties without reconfiguration. Although the case study is presented at the county scale, the analysis is equally repeatable at the watershed scale. Watersheds align with hydrologic processes, making them especially relevant for flood-specific questions such as upstream–downstream propagation, cumulative impacts, and coordination across jurisdictions.

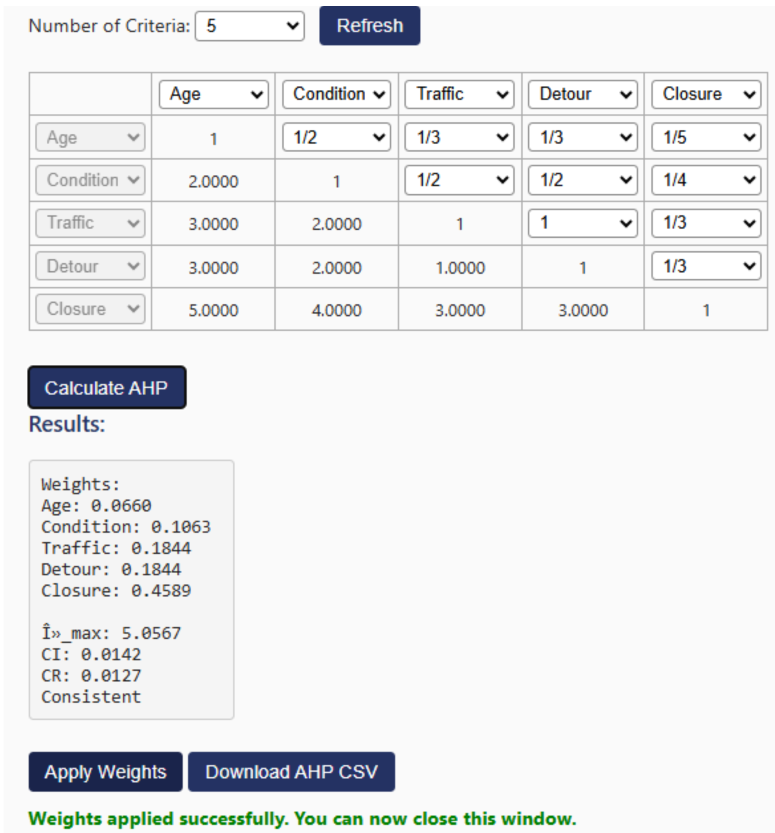


Figure 7. AHP pairwise comparison matrix and the resulting criterion weights for the Linn County case study, illustrating the relative importance of bridge attributes in the multi-criteria assessment within IBIS.

In watershed mode, IBIS provides the same map layers, statistics, heatmaps, and AHP tools, enabling users to frame problems by natural drainage boundaries when that perspective is more informative. The importance of watershed framing is well established in prior research: Sheridan et al. (2005) linked road traffic intensity to sediment delivery across catchments and Shorshani et al. (2014) showed how traffic emissions contribute to stormwater contamination in urban basins. Together, these studies show that environmental, hydrologic, and infrastructure factors are deeply interconnected within drainage systems, making watershed perspectives an essential addition to decision-support tools like IBIS.

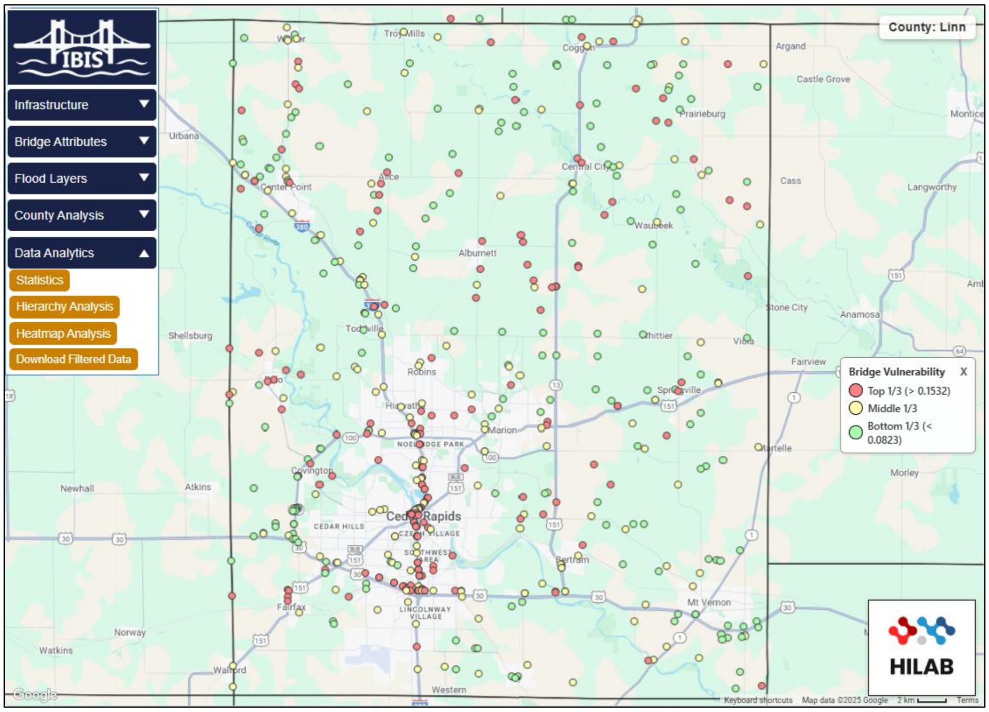


Figure 8. Spatial distribution of AHP-weighted bridge vulnerability in Linn County, showing bridges color-coded according to their calculated vulnerability scores to highlight relative differences across the county.

As can be seen in Figure 9, The West Fork Cedar watershed example demonstrates this functionality in practice. Bridge points are displayed alongside the 100-year flood extent to highlight exposure, while AHP scores provide drainage-based prioritization of vulnerable structures. The heatmap reveals spatial concentrations of bridges with higher criticality, and the statistics panel adds contextual information through charts of bridge condition, structure type, and bridge kind. These illustrations highlight how IBIS enables users to analyze vulnerability and system performance holistically within hydrologic boundaries, providing a richer and more actionable understanding than county-scale summaries alone.

Overall, the Linn County and West Fork Cedar watershed examples show how IBIS can be applied across different spatial frames to highlight vulnerability patterns and prioritize bridges under flood scenarios. By combining condition, traffic, and closure data with visualization and decision tools, the platform has the capacity to adapt to both jurisdictional and hydrologic perspectives, providing a clear demonstration of its practical utility.

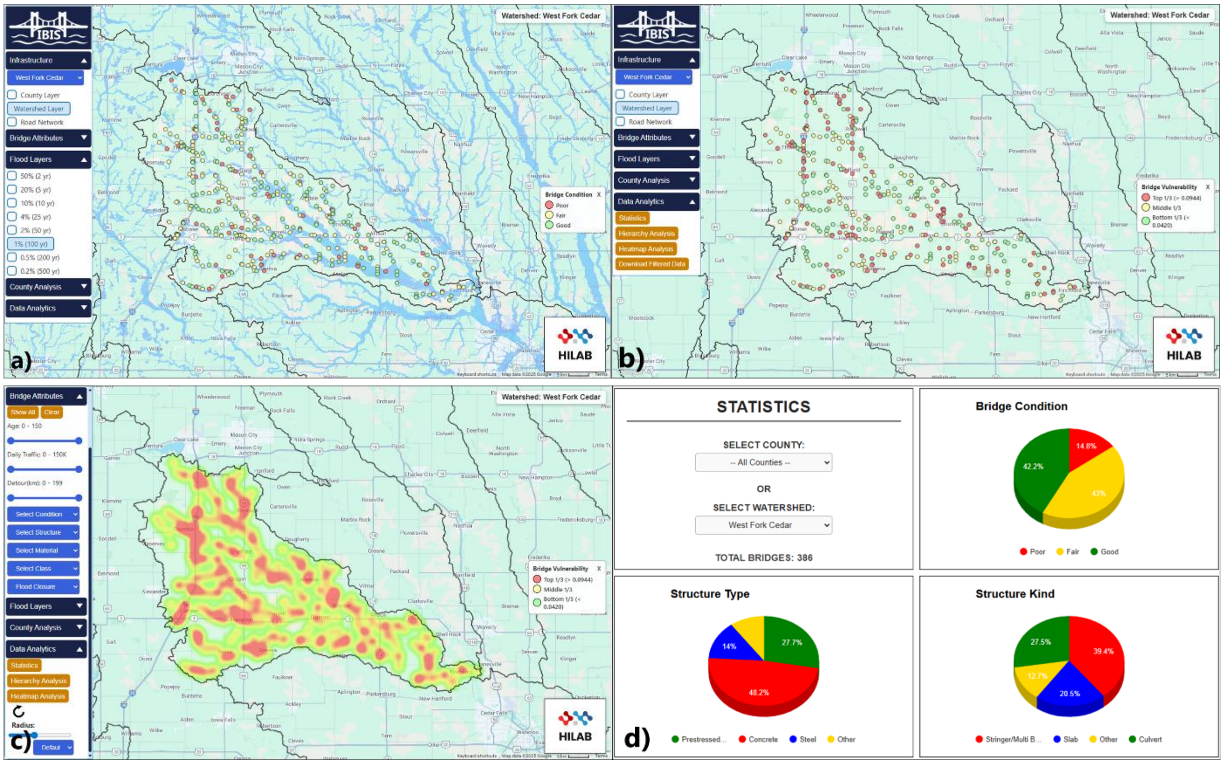


Figure 9. West Fork Cedar watershed case study: (a) bridge inventory with 100-year flood layer, (b) AHP-based vulnerability visualization, (c) heatmap of bridge vulnerability, and (d) summary statistics for the bridge inventory.

3.2. Discussion

The IBIS tool demonstrates major advantages in transparency, usability, and adaptability, making it an effective tool for flood-related bridge risk assessment. One of its main advantages is that it is completely user-controlled, enabling stakeholders to specify parameter weights using the integrated AHP functionality and see immediately how these decisions affect thematic maps and bridge rankings. This interactive weighting works seamlessly with other tools, such as attribute filtering and visualization components, creating a smooth and cohesive user experience where changes in one panel automatically update across the interface. Complementing this, the heatmap tool provides an additional perspective by showing spatial concentrations of bridges. For instance, in Linn County case study, the Cedar Rapids core and the I-380 corridor emerge as clear clusters of bridge locations, and users can dynamically adjust the heatmap by changing which attributes are visualized, modifying intensity, or altering the color scheme to explore different patterns. Combined with exportable outputs, the platform enables users to analyze bridge vulnerability, traffic disruption, and detour impacts, while producing ready-to-use datasets for reporting, planning, or further analysis.

Despite these strengths, certain limitations remain that shape how the platform should be interpreted and applied. Currently, IBIS relies on static flood scenarios rather than real-time hydraulic modeling or live gauge data. This situation constrains its ability of immediate disaster response. Similarly, the accuracy of inundation mapping depends on the resolution and alignment of DEM and floodplain datasets, meaning that localized inaccuracies could influence bridge-level vulnerability estimates. Another limitation is the absence of real-time or crowd-sourced inputs, such as updated traffic conditions, or sensor-based monitoring, which would enhance operational awareness during evolving events. These gaps do not lessen the platform's utility for planning and long-term prioritization. Instead, they highlight opportunities for future integration of dynamic datasets to improve predictive and adaptive capabilities.

From the point of view of stakeholders, the platform offers an extensive range of benefits in multiple areas. For example, DOT engineers, county planners, and emergency managers could leverage the platform to evaluate infrastructure vulnerabilities, assess potential impacts of historical or hypothetical flood events, prioritize maintenance and replacement strategies, and enhance preparedness for emergency situations. By integrating structural conditions, traffic, detour lengths, and flood exposure, the platform enables a comprehensive assessment of bridges, allowing users to determine which resilience measures should be addressed first.

Local planners can utilize IBIS outputs for pre-disaster mitigation funding, such as FEMA's Building Resilient Infrastructure and Communities (BRIC) program, which provides competitive grants to support hazard mitigation projects that reduce disaster risks (Mendelsohn et al., 2021), using transparent scoring to justify investment in critical corridors. Researchers benefit from customizable design, which allows experimentation with alternative metrics, scoring hierarchies, and flood scenarios. Importantly, IBIS is not limited to bridge analysis; its modular structure provides a framework adaptable to other infrastructure types, making it a versatile tool for resilience planning in transportation systems. By combining intuitive visualization with decision-support functionality, the platform bridges the gap between technical analysis and actionable policy guidance, offering a robust foundation for data-driven flood risk management.

4. Conclusion

IBIS introduces a unique integration of spatial visualization, decision-support modeling, and interactive filtering into a single environment, making it more than a traditional mapping or data analysis tool. What makes our platform different is its focus on transparency, flexibility, and user control. Stakeholders can actively guide the analysis rather than just view the results. This makes the platform useful not only for evaluating bridge vulnerability but also for broader infrastructure resilience, providing a framework that can be applied to other decision-support systems.

At its core, IBIS demonstrates how complex datasets such as bridge inventories, flood extents, traffic information, and structural attributes can be synthesized into an accessible, user-friendly interface. This design allows users to explore the data and gain insights more easily. The platform includes customized weighting through AHP, dynamic map overlays, and interactive tools like heatmaps. These features reflect the realities of decision-making, where trade-offs and competing priorities must be evaluated transparently and carefully. The county- and watershed-based organization grounds the platform in operational practice, aligning with how transportation assets are managed, while the ability to visualize flood layers, road networks, and structural conditions in combination underscores the interconnectedness of infrastructure vulnerability. These design choices bridge the gap between technical data and the practical needs of planners, engineers, and emergency managers. The result is advanced analytics presented in a way that is both rigorous and approachable.

Overall, IBIS advances the assessment of flood-related infrastructure risks by demonstrating how interactive, user-driven tools can transform static datasets into actionable insights. While the current implementation is powerful for scenario planning and long-term prioritization, it will extend its capabilities with real-time data integration, including streamflow and traffic, mobile-responsive design, crowd-sourced hazard reporting, advanced export options, and predictive modeling such as machine learning for scour assessment. Future versions could integrate forecasted stage heights or crest levels, enabling dynamic probability assessment of bridge closures or route disruptions, which would provide near-term risk information for users. Additionally, Artificial Intelligence (AI) driven reporting and storytelling, where artificial intelligence generates contextual summaries from the analyzed or visualized data, will further support users by clarifying results, streamlining interpretation, communicating findings, and enabling evidence-based decisions efficiently. Together, these enhancements will increase the platform's practical value, helping IBIS develop into a more comprehensive decision-support system that strengthens resilience planning for bridges and other critical infrastructure.

5. Software Availability

Name: Iowa Bridge Information System (IBIS)
Developers: Ege Duran
Contact Information: ege-duran@uiowa.edu
Date First Available: 2026
Software Required: Web browser (Google Chrome, Firefox, or equivalent)
Programming Languages: JavaScript, HTML, CSS, PHP
Platform Access: https://hydrointelligence.github.io/apps/ibis/
Platform: Web-based application
Availability and Cost: The platform is freely accessible
Documentation: All necessary usage instructions, interactive controls, and methodological explanations are embedded within the web interface
Data Access: Bridge, flood, and ancillary datasets are retrieved and processed within the platform from publicly available sources

6. Data Availability

The Iowa Bridge Information System (IBIS) visualizes and analyzes bridge infrastructure and flood hazard information derived from publicly available, authoritative sources. The platform does not provide direct data download functionality; instead, it presents preprocessed and aggregated datasets for interactive visualization and decision support. The data sources visualized within the platform are listed below.

Bridge inventory data are obtained from the Iowa Department of Transportation (Iowa DOT) open data portal, which provides National Bridge Inventory (NBI)–based records including bridge location, condition ratings, age, structure type, material, functional class, average daily traffic (ADT), and related attributes: https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm

Flood hazard data consist of scenario-based flood inundation extent tiles for multiple return periods (2–500 years), provided by the Iowa Flood Center (IFC) through the Iowa Flood Information System (IFIS). These layers represent modeled flood extents and are visualized as map tiles; flood depth values are not displayed in the platform: https://www.iowafloodcenter.org

Administrative boundary data, including county boundaries and HUC-8 watershed divisions, are obtained from Iowa Geodata and U.S. Geological Survey (USGS) repositories and are used for spatial selection, aggregation, and visualization: https://geodata.iowa.gov - https://www.usgs.gov

Population data used for contextual exposure analysis were obtained from the U.S. Census Bureau's 2020 Census datasets: https://data.census.gov

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