# Assessing Climate-Driven Flood Risk with the Community Resilience and Adaptation Spatial Infrastructure Database (CRASID) in Urban and Rural Great Lakes Settings"

Short title: CRASID in Urban and Rural Great Lakes Settings

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# Abstract

Climate change is intensifying flooding in the Great Lakes watershed, threatening critical infrastructure and limiting access to emergency health services. Existing U.S. flood risk tools, such as FEMA's Hazus and the National Risk Index, and newer models from the First Street Foundation, provide valuable coverage but often emphasize economic impacts while overlooking community-level vulnerabilities. To address this gap, we developed the Community Resilience and Adaptation Spatial Infrastructure Database (CRASID). The CRASID integrated tool combines flood risk, land use, emergency service accessibility, critical infrastructure, and sociodemographic indicators into a composite risk index. This study applies CRASID across six case study areas in the western Great Lakes—four overlapping areas in two urban metro areas (Cleveland, Detroit) and two non-overlapping rural areas—to assess model applicability and identify key drivers of flood-related risk. Statistical methods included three predictive models: principal components regression, backward stepwise regression, and boosted regression trees. The boosted regression trees model provided the strongest performance in predicting risk. Findings reveal that rural, floodplain-based communities with high concentrations of vulnerable populations are disproportionately at risk due to limited access to emergency services. While urban areas generally exhibit greater resilience, they also contain localized pockets of elevated vulnerability. These results underscore the importance of a community-centric approach, shifting focus away from primarily economic measures toward accessibility of critical services and locally relevant infrastructure. By highlighting where and for whom risks are most significant, CRASID offers policymakers and communities a novel framework for planning, adaptation, and resilience-building in the face of climate-driven flooding. This people-focused approach provides

actionable insights to enhance preparedness and protect public health across diverse Great Lakes communities.

# Introduction

Climate change is leading to an increase in the incidence of extreme weather globally, affecting both temperature and precipitation (1–7). These increases in temperature and precipitation are forecast to continue over the next century, according to global models (1). Global models show that half of the annual rainfall at any given location occurs over just 12 days. When these same models factor in climate change, this timing falls to six days each year (4). In the United States, the climate threat sequelae are increasing in not just intensity and frequency, but also in the patterns of climate stressors (8–12), including in the Midwest (1,4,7,11–13). Climate threats to communities are often multi-dimensional and stochastic, and are influenced by compound interactions (14). For example, flooding cannot be attributed solely to increased precipitation, but also to changes in infrastructure that impact rainwater runoff (1).

Within the Midwestern Great Lakes regions of the United States, changes in weather patterns have led to more severe storms, a higher likelihood of flooding, more frequent regional droughts, and an increase in days of extreme heat (15–18). Storms often bring increased precipitation, which leads to direct pluvial (ponding, standing water) flooding and to surface water networks exceeding their carrying capacity, so that fluvial (river, stream) waters flood onto adjacent land. (8,19,20). Around the Great Lakes, fluvial flooding may be exacerbated by seiches. Seiches form from a combination of strong winds and rapid changes in barometric pressure over partially or wholly enclosed bodies of water. Wind and pressure changes can move the water from one end (or side) of a lake to the other. When the wind stops, the water 'bounces back' or rebounds, only to be pushed forward again, creating an oscillation of high waves. In the Great Lakes, seiches increase localized flooding by pushing lake water up into the connected rivers and streams. (21–25).

## Flooding

Flood risk analysis is a complex task that requires accurate geologic, topographic, hydrologic, and environmental data fed into flood modeling software, such as HEC-RAS, HAZUS, or software developed by an organization, to predict where water will flow during a precipitation event (19,20,25–31) to create flood maps. Most flood risk analysis in the United States uses the historical flood maps generated or aggregated by the Federal Emergency Management Agency, which uses the Hazus Flood Loss Estimation Methodology (32). The Federal Emergency Management Agency flood maps are incomplete, and the Hazus methodology is poorly documented, with user guidance strongly encouraging the use of user-supplied depth grids (31–33). Other drawbacks to the Federal Emergency Management Agency flood maps, as well as many large-scale models, are the age and quality of the surveyed streams, poor coverage of small drainage areas, low-quality surface elevation data, and even simplified physics in the flood models (28). To address the drawbacks and issues in the Federal Emergency Management Agency's methods, companies such as Fathom Global and the First Street Foundation have begun using flood models built using a combination of satellite imagery, Light Detection and Ranging (LIDAR) point clouds, and machine learning algorithms to address this coverage gap, creating more detailed and comprehensive national-scale flood risk maps (20,34). Light Detection and Ranging typically uses near-infrared laser pulses to measure the distance between an aircraft and the ground with precision. From these laser pulses, professionals can create high-accuracy and precision digital elevation models of the Earth's surface (35).

People's lives are seriously impacted by flooding events, which cause economic losses and damage to critical infrastructure, in addition to temporary or permanent displacement (1). Flood events also affect human health by causing both mortality and morbidity. Flooding impacts human health in various ways, including limited access to necessary health services, which can be independent of or exacerbated by the storm and flooding. A lack of access to essential health services can further complicate these impacts. (1,2,36). This paper focuses on access to emergency health services as the risk focus in an analysis of flood risk associated with storm-induced flooding impacts on critical infrastructure.

## Critical infrastructure

Critical infrastructure supports our society and societal functions. National Critical Infrastructure is defined in the Critical Infrastructure Information Act (37). This act states that specific infrastructure sectors, such as telecommunications and energy, are critical to the nation's defense and security. These systems are considered so vital to the United States that should one or more become incapacitated or destroyed, their destruction could have a debilitating effect on a national scale, including impacting the safety, public health, and economy of the nation (38). The protection of these national critical infrastructures, as so defined, is the conjoined responsibility of the government, corporations, and Non-Governmental Organizations in a public-private partnership (37,39).

In the United States, the federal government defines, regulates, and sometimes administers critical infrastructure. However, in an emergency (such as storm-related flooding or other climate-induced disasters), federal, state, and municipal management or aid may be unavailable to individual households for hours, days, or even weeks. The Federal Emergency Management Agency recommends having an emergency kit that can last for 72 hours (40). From a climate emergency survival perspective, critical infrastructure, especially access to and from emergency services, needs to be redefined from a community-based perspective so that individual households can identify community-centric infrastructure vulnerabilities and plan adaptations to increase household-level climate emergency resilience.

## Local community resilience

The term resilience has been used for centuries and has slightly different definitions depending on the audience. Resilience is broadly defined as a system's ability to recover quickly from disruption. A more detailed definition, based on the National Academy of Sciences, includes the concepts of planning, absorbing, recovering, and adapting to disruptions, making risk an integral part of the definition of resilience (41–46). Resilience can be broken down into four phases in a linear analysis, or into three phases when the phenomenon is iterative. These phases include preparation and hardening, absorption of the stressor, accompanied by any immediate damage; recovery from the damage; and adaptation and transformation to ensure better preparation for the next similar stressor (21,47–49). These phases can be seen as a repeating or iterative cycle (47,50,51). This definition can be helpful in a broad range of applications, and is evident in the concepts of physical resilience, team resilience, biological and ecological resilience, economic resilience, social behaviors, and climate change resilience (41,43–45). Social or community resilience is the resilience concept applied to an individual or a community of individuals (46). As communities are composed of individual families and their members, shocks and stressors that directly affect families also affect the local community's structure and function. Therefore, protecting and enhancing the adaptability and resilience of individuals and families are essential to local community resilience. Since the associated support structures of communities are, effectively, the local community version of nationally embodied critical infrastructure, local community resilience analysis should incorporate local community-based critical infrastructure metrics (52). Local community resilience must enable the local community-based entities (individuals, families, groups) and their associated support structures to plan, absorb, recover, and adapt to disruptions that are already occurring and will continue to occur (53). The final adaptation step is crucial for enhancing future resilience, as catastrophic climate events, such as floods, have a lasting impact, whether visible or not (54). By adapting, we create a feedback loop that returns us to the beginning of the definition, making resilience an ongoing, iterative process.

## Community Resilience and Adaptation Spatial Infrastructure Database

Communities need a foundation to begin the four phases of resilience. Understanding how climate change-induced impacts affect individuals and families within communities is a complex problem (55). Planning for future resilience-related adaptations and minimizing vulnerability to disaster-related damage requires the ability to predict vulnerability and potential harm, especially when disasters develop quickly, as with flooding. CRASID was designed as a new tool for communities (currently, Western Great Lakes communities in the United States) and individuals to plan for and better understand the local community resilience factors that their specific spatial location's critical infrastructure is vulnerable to in the face of climate-driven hazards, such as flooding (52). The Community Resilience and Adaptation Spatial Infrastructure Database (CRASID) is a tool that combines metrics for floodplains, access to emergency services, community-centric critical infrastructure, land use, and vulnerable populations to create a new spatially integrated flood-related risk index. Here, we provide a proof-of-concept using the current CRASID database and its associated risk index. A proof of concept for a model can be evaluated by its applicability, or by how well it performs in cases similar to the original (56). The research questions asked are;

1) *Is CRASID applicable to local communities and individuals for risk and emergency planning?*

This will be assessed by comparing six different study areas within the spatial database. Four will reflect highly urban areas and are intentionally redundant to test whether watershed boundaries or approximate size are a better analytical frame. Two will reflect highly rural areas to assess the model implications of population density.

2) *What are the most critical factors driving the CRASID risk score in each of the six study areas?*

We will analyze the CRASID metrics to identify the most critical factors in predicting community-centric risk to emergency service access during flooding events.

# Data and methods

## Community Resilience and Adaptation Spatial Infrastructure Database (CRASID)

CRASID was initially developed to encompass portions of the western six states within the United States' Laurentian Great Lakes watershed (57). The database utilizes a buffered watershed boundary file from the United States Geological Survey's Watershed Boundary Dataset website (58). The watershed boundaries were extended by 40 km to include all spatial features that might extend outside the watershed (such as municipalities). A grid of five-kilometer vertex-to-vertex hexagons was generated and clipped to the watershed boundary feature, resulting in a tessellated grid of 22,178 hexagons, each uniquely identified by a twocharacter and two-digit identifier (59). Some feature layers were point locations, while others were based on census tracts or census block groups, or followed arbitrary boundaries (such as tribal lands). Others were created from satellite imagery (raster). ArcGIS Pro (60) was used to standardize the spatial feature layers within CRASID to develop indicators. Using the ArcGIS Pro Spatial Analysis Tools (60), the percentage of each polygon or raster, or the count of point locations, within each hexagon was calculated so that all indicators were standardized based on each hexagon's area. This approach resulted in a table with 22,178 rows — one for each hexagon — and a column for each of the 32 indicators. The metrics, submetric groupings, and individual indicators currently included in the CRASID risk score are listed in Table 1. The environmental metric represents the natural environment. In CRASID, this was further divided into two submetric groupings, flood risk and land use. Flood risk was defined as the percentage of each hexagon covered by each of the 100-year, 500-year, and 1000-year floodplains (derived from a combination of satellite imagery and machine learning) (61). Land cover was obtained from the Global Land Use/Land Cover with Sentinel 2 and Deep Learning project (62), hosted by Esri. The Global Land Use/Land Cover project identified eight distinct land cover types (derived from satellite imagery and machine learning) at 10-meter resolution across all landmasses on the planet. Therefore, the environmental metric can be thought of as the exposure (floodplains) and an effect modifier (land cover). The social metric represents the man-made features. CRASID divides the social metric into three submetric groupings: A Community-centric Critical Infrastructure, an Emergency Medical Services access, and a Vulnerable Populations grouping. The community-centric critical infrastructure indicators were pulled from the United States Homeland Infrastructure Foundation-Level Data website (62). The individual indicators included the number of child care centers, the amount of domestic well usage, the number of microwave towers, the number of mobile home parks, the number of nursing homes, the number of power plants, the number of power substations, the number of public or private schools, and the number of worship centers residing within each hexagon. The indicators that made up the emergency medical services access were generated by creating 15-minute drive-time road network service areas for each ambulance service, emergency operations center, fire department, hospital, and national shelter location, all obtained from the Homeland Infrastructure Foundation-Level Data website. Finally, the vulnerable populations indicators included the Centers for Disease Control and Prevention's Social Vulnerability Index, the United States Census Bureau's Resilience Index metrics for one and two risks, the United States Census Bureau's Resilience Index metric for three or more risks, and the percent of tribal land coverage (63,64). The social metric's indicators used in CRASID reflect a community-centric approach to defining a location's critical infrastructure. CRASID uses indicators that are more meaningful to individuals or communities, such as the number of schools or nursing homes in a given area, to define critical infrastructure, rather than relying on the dollar value of property.

**Table 1. Data features used in the Community Resilience and Adaptation Spatial Infrastructure Database.**

| Metric | Submetric grouping | Indicator |
|---|---|---|
| Environmental | Flood Risk | Percent 100-year fluvial flood coverage |
| | | Percent 100-year pluvial flood coverage |
| | | Percent 500-year fluvial flood coverage |
| | | Percent 500-year pluvial flood coverage |
| | | Percent 1000-year fluvial flood coverage |
| | | Percent 1000-year pluvial flood coverage |
| | Land Use | Percent Bare coverage |
| | | Percent Built coverage |
| | | Percent Crops coverage |
| | | Percent Grass coverage |
| | | Percent Scrub coverage |
| | | Percent Tree coverage |
| | | Percent Water coverage |
| | | Percent Wetlands coverage |
| Social | Critical Infrastructure | Child Care Center |
| | | Domestic wells usage |
| | | Microwave Tower |
| | | Mobile Home Parks |
| | | Nursing Homes |
| | | Power Plant |
| | | Power Substations |
| | | Public/Private Schools |
| | | Worship Centers |
| | Emergency Medical Services | Ambulance Service areas |
| | | EOC Service areas |
| | | Fire Department Service Areas |
| | | Hospital Service areas |
| | | National Shelter Service areas |
| | Vulnerable Populations | CDC Social Vulnerability Index coverage |
| | | Percent Tribal Land coverage |
| | | U.S. Census Bureau Resilience Index (1 and 2) |
| | | U.S. Census Bureau Resilience Index (3 or more) |

The indicators, submetric groupings, and metrics used in CRASID.

Individual CRASID indicators were normalized using percentile ranking. Submetric groupings were then grouped and averaged together based on an adaptation of the CalEnviroScreen (65) model. The five submetric groupings (Critical Infrastructure, Emergency Medical Services, Environmental Land Use, Flood Risk, Vulnerable Populations) were then combined to create two metrics (Social and Environmental). These two metrics were percentile-ranked and multiplied together to form a risk index score. The risk score was then percentile-ranked before all of the data was mapped back to the original hexagons (57). The metrics and risk index score were then mapped in ArcGIS using a quartile symbology to facilitate easier visualization. A flowchart outlining the overall data processing approach is shown in Fig 1.

**Fig 1. Data standardization and normalization**. This flowchart was adapted from Ashby and Henshel (2025).

## Study areas

The 22,178 hexagons in CRASID cover an area of 360,226 square kilometers in the western Great Lakes, as shown in Fig 2 (grey shaded area). This extensive database makes a diverse sociodemographic backdrop for study, ranging from densely populated urban areas to sparsely populated tribal areas. We analyze six study areas within CRASID to determine their applicability, predictive strength, and driving factors. Three study areas (two urban and one rural) were selected to match the watersheds. Three study areas (two urban and one rural) were chosen to approximately match the number of hexagons in the study area, while still aligning with governance boundaries. The two urban regions (Cleveland, Detroit) were incorporated into both the watershed and the municipal-size-based study areas to assess which approach (watershed versus approximate size-based mapping) would be more effective in the future. The rural areas were not well aligned with governance boundaries and were then selected to be comparable based on population density and the inclusion of tribal areas.

**Fig 2. Study areas.** The western Great Lakes watershed (in grey), highlighting the six study areas. Municipal areas are shaded in orange (greater Cleveland area), purple (greater Detroit area), and green (rural area). Watershed areas are shaded in blue (Greater Cleveland), pink (Greater Detroit), and red (rural areas).

## Statistical analysis

### Applicability

The applicability of CRASID to local communities and individuals for risk and emergency planning was explored using violin plots, distribution skew, and Tukey Honest Significant Differences groupings for each composite metric across the six study areas. Violin plots combine a box-and-whisker plot within a distribution plot. Violin plots help visualize the full distribution and where the quartile breaks fall within the data. This makes violin plots helpful in comparing the different study areas and identifying similarities and differences. The skew values for each distribution were added to numerically reinforce what the violin plots showed numerically, allowing easier comparison across the composite metrics. A distribution with a skew value greater than one is considered highly skewed. Finally, Analysis of Variance was performed to obtain the Tukey Honest Significant Differences groupings. The Tukey Honest Significant Differences test compares the distribution of each study area to those of the others in a pairwise fashion. Study areas that are not significantly different from each other are assigned the same letter. Using the Tukey Honest Significant Differences test quantifies and more effectively separates distributions that are more closely related than visual inspection alone. All applicability testing was done using the R statistical package (66).

## Analytical models

We tested three analytical models for determining the critical factors driving the CRASID risk score within each study area: principal components analysis with regression, backward stepwise linear regression, and boosted regression trees machine learning algorithm. The outputs of the three models were compared using both Pearson's correlation and Root Mean Squared Error. The Pearson correlation is a linear measure of the relationship between the actual and predicted values. Pearson's correlation uses covariance and standard deviation to produce a normalized metric. This standardization ensures that the Pearson correlation coefficient will always lie between -1 and 1, with values closer to the extremes indicating stronger correlation (67). The Root Mean Square Error is commonly used as a goodness-of-fit measure, indicating how far off predictions are from the actual values. Rather than a line through the data cloud representing the least error, such as used in R-squared analysis, the Root Mean Square Error uses a line of perfect prediction. This makes Root Mean Square Error helpful in comparing different models, as the results are expressed in the same units as the dependent variable (68). The smaller the Root Mean Square Error score for a model, the better its performance. Both Pearson's correlation and Root Mean Square Error were used to evaluate the outputs of the three analytical models: principal components analysis with regression, backward stepwise linear regression, and a boosted regression trees machine learning algorithm.

Principal Components Analysis is a standard unsupervised method for reducing a large number of variables in a dataset while still explaining a high level of variability within the data.

When dealing with a large number of interrelated variables, principal components can be used to condense them into a few key elements that still account for most of the original variation. Each Principal Components Analysis dimension is a linear combination of all of the features in the data, many of which are correlated, or even highly correlated. Using Principal Components Analysis, we can thus reduce the number of variables needed to explain the data (69) satisfactorily. Since CRASID contains both standardized and normalized variables, the percentile-ranked values in CRASID were used for Principal Components Analysis and Principal Components Regression. The 'prcomp' function in R was used (69,70). For the regression portion of the model, the dependent variable was the risk score percentile, and the same CRASID standardized variables used in the Principal Components Analysis portion served as explanatory variables. Since the variables were already scaled, the scale component was set to FALSE. Validation was set to use a standard 10-fold cross-validation (71). The 'sample' function split the data into training (80%) and validation sets (20%). Finally, the model was run using the 'pcr' and 'predict' functions. The predictions were then compared with the training set using Root Mean Square Error and Spearman's correlation (72).

Stepwise linear regression is another standard method for reducing the number of least useful predictors in a dataset. Backward stepwise linear regression begins with all variables in the least squares model and, one by one, removes those that are least useful. This form of regression can be more desirable when there are many variables to consider (71). Stepwise linear regression was performed in R using the same standardized variables as in the Principal Components Analysis model, with the risk score percentile as the dependent variable for each of the six study areas. Validation was set to use a standard 10-fold cross-validation. The 'sample' function split the data into training (80%) and validation (20%) sets, and the model was trained and evaluated using the ‘train’ and ‘predict’ functions. The method component was set to use the Akaike Information Criterion. The Akaike Information Criterion is commonly used as a metric within models like this to balance fit and simplicity in the model's predictions (70,71,73,74).

Boosted Regression Trees is a supervised ensemble of two machine learning methods. One method uses recursive splitting of the explanatory variables in relation to the dependent variable (called regression trees), and the second method adaptively combines many simple ‘learners’ into a strong predictive learner with high performance (called boosting) (75–77). The Boosted Regression Trees analysis was conducted in R using a set of Boosted Regression Trees-specific functions developed by Elith et al. (2008) (76). The CRASID standardized variables and the risk score percentile were used as the explanatory and dependent variables, respectively. Validation was set to use a standard 10-fold cross-validation. The ‘sample’ function split the data into training (80%) and validation (20%) sets, and a model was trained and evaluated using the ‘train’ and ‘predict’ functions. Within the Boosted Regression Trees models, the family component was set to ‘Bernoulli’, tree complexity was set to 5, learning rate was set to 0.004, and bagging fraction was set to 0.75. The predictions were then compared with the training set using Root Mean Square Error and Spearman's correlation (75,76). This was repeated for the entire western US Great Lakes watershed and each of the six study areas.

# Results

## Applicability

The violin plots for each composite metric and the risk percentile score for each of the six study areas are shown in Fig 3. The n-value underneath each study area name on the x-axis refers to the number of hexagons for that area. The skew value is listed below the number of hexagons. Above each distribution is the Tukey Honest Significant Differences grouping letter.

**Fig 3. Violin plots for each composite metric and the risk percentile score.** The n-value underneath each study area name refers to the number of hexagons comprising that area, followed by the skew value. The Tukey Honest Significant Differences grouping letter is listed above each distribution.

## Analytical model comparison

The most important factors driving the risk score in CRASID were analyzed using each of the three models (principal components analysis with regression, backward stepwise linear regression, and boosted regression trees machine learning algorithm). The Root Mean Squared Error (RMSE) and Pearson correlation results for each model by study area are shown in Table 2, with the best-fitting model highlighted in bold. The same results from Table 2 are presented as radar graphs in Fig 4. For the Root Mean Squared Error results, the closer to the center of the graph, the smaller and therefore better the Root Mean Squared Error score for that model. The Pearson correlation radar graph is the opposite: the rings farther from the center indicate higher correlation values.

**Table 2. RMSE and Pearson correlation scores.**

| | RMSE | | | Correlation | | |
|---|---|---|---|---|---|---|
| **Area** | **PCR** | **SLR** | **BRT** | **PCR** | **SLR** | **BRT** |
| Great Lakes watershed | 0.141 | 0.12 | **0.05** | 0.89 | 0.93 | **0.98** |
| Cleveland municipal | 0.175 | 0.09 | **0.06** | 0.83 | 0.93 | **0.98** |
| Cleveland watershed | 0.176 | 0.14 | **0.08** | 0.83 | 0.91 | **0.94** |

| | | | | | | |
|---|---|---|---|---|---|---|
| Detroit municipal | 0.134 | 0.07 | **0.06** | 0.9 | 0.95 | **0.96** |
| Detroit watershed | 0.173 | 0.08 | **0.07** | 0.83 | 0.9 | **0.92** |
| Rural municipal | 0.14 | 0.08 | **0.05** | 0.89 | 0.97 | **0.98** |
| Rural watershed | 0.155 | **0.07** | 0.08 | 0.87 | **0.98** | 0.97 |

**RMSE and Pearson correlation results**. The best model fit is highlighted in bold.

**Fig 4. Radar plots of Table 2 results.** For the Root Mean Squared Error plot (above left), the closer to the center of the graph, the better the model. In the Pearson correlation plot (above right), the farther from the center, the higher the correlation value.

## Critical factors

The results of the Root Mean Squared Error and correlation analyses indicate that the boosted regression trees model was the best overall fitting model. While backward stepwise linear regression performed better in the rural watershed, the improvement was only marginal compared to the boosted regression trees model. Therefore, the boosted regression trees model was selected as the preferred model. The most influential factors for the boosted regression trees model are shown in Fig 5.

**Fig 5. Most influential factors for the boosted regression trees model.** The larger the area, the greater the relative influence of that variable.

# Discussion

Climate change has intensified the frequency, severity, and patterns of extreme weather events worldwide (1), with notable regional effects in the Midwestern Great Lakes region of the United States (78). These changes, especially increases in precipitation and temperature, amplify the risk of compound and stochastic hazards, such as flooding, which in turn threaten critical infrastructure and public health. To our knowledge, this project is the first human health-oriented risk assessment of climate change as a stressor in the Great Lakes watershed, focusing on risks associated with access to emergency services. The CRASID database and risk assessment use social vulnerability and a unique community-centric critical infrastructure metric as influencing factors. We found that vulnerable populations living in highly rural, floodplain areas are at greater risk than similarly situated urban populations in most urban floodplain areas when they need to seek out or be sought out by emergency services. While the impact on rural, vulnerable populations is a theme across the findings, some subpopulations within larger municipalities also have high-risk rankings. Thus, greater urbanization does not guarantee greater access to emergency services that could be vital to community members during weather emergencies and floods.

The need for communities to better understand their risk and resilience in these weather-related emergencies has spurred the development of risk models. One of the first and most referenced national flood risk models is the U.S. FEMA National Risk Index. The National Risk Index uses highly accurate terrain measurements, surveyed river channels, stream gauge data, and flood protection measures to calculate its riverine flood component. The National Risk Index is considered a gold standard in inundation modeling. While considered a gold standard, the National Risk Index does have some drawbacks; not all areas have been assessed for flood risk (missing data), it is based only on the 100-year (and sometimes on the 500-year) floodplains, does not take pluvial flooding into account (which is one of the flood stressors that is changing most in recent years), can take time to update after recent flooding and keep updated, and is not a balanced assessment. In saying it is not a balanced assessment, the combination of missing data and an urban bias due to economic weighting leads to money, policy, and resources being unevenly distributed. The uneven distribution disproportionately affects rural and tribal areas, perpetuating inequity (19,28,79,80). Therefore, as climate variability and precipitation extremes continue to worsen, the NRI becomes less and less applicable yet remains the common standard for policy and decision-making.

The National Risk Index calculates risk using a function that divides a social vulnerability metric by a community resilience metric, and then multiplies the result by the expected annual loss metric (80). Both the social vulnerability and the community resilience metrics are strongly influenced by (incorporate indicators related to) population density. The use of an expected annual loss metric also makes the National Risk Index more focused on the economic impact of natural hazards rather than on the direct effect of flooding on people. The NRI comprises 18 individual hazard types, but utilizes an "Inclusion Threshold" based on state disaster plans to determine whether a particular hazard should be included in the analysis (80). If at least 25 of the 50 state disaster plans included one of the 18 hazards, or if it was deemed by the FEMA committee to be a regionally significant hazard, then it was included in the National Risk Index (80). Given these drawbacks and its methodology, the National Risk Index significantly underestimates the risk to rural areas and warrants re-evaluation.

First Street Technology, Inc. has developed a suite of modernized models that, for the first time, incorporates climate change considerations into hazard analysis at both national and global scales. In contrast to the National Risk Index, which integrates flood, drought, extreme heat, and other factors directly into the risk model, First Street has developed separate models for each hazard (8). The First Street Flood Model addresses some of the limitations and drawbacks of the National Risk Index by including pluvial flooding, or the ponding of water due to rainfall, as well as fluvial (river and waterbody) and coastal flooding (19,81). The First Street Flood Model takes advantage of LIDAR-derived topography from the United States Geological Survey's 3DEP program. First, the First Street Flood Model combines 3DEP topography with multiple data sources. The First Street Flood Model, therefore, achieves an accuracy of 3 meters, even in areas with complex topography or dense infrastructure (81). Using this method has allowed First Street to build high-resolution, national-scale flood inundation maps for use in their models. The hazard maps are accurate to the parcel level, allowing individual homes and buildings to be assigned scores. By evaluating risk at the building level, they have overcome the drawback of using U.S. Census tracts as the aggregation unit. U.S. Census tracts change every 10 years and are based on street centerlines, making it more challenging to conduct longitudinal studies. Similar to the National Risk Index, the First Street Flood Model has incorporated the National Levee Database. The National Levee Database is necessary to accurately determine flood inundation in the context of human interventions. Adding the National Levee Database data makes the First Street Flood Model superior to the National Risk Index, as it has the same quality topographic feature set as the National Risk Index, but covers the entire United States. One of the most significant drawbacks to both the National Risk Index and the First Street Flood Model is their focus on economics. Both models heavily weigh the economic cost of floods on buildings and infrastructure. While useful for high-level recovery cost planning, economic impact is much less helpful to small communities and individuals who need emergency and escape route planning before or during an extreme flood event.

To address some of the limitations of the National Risk Index and First Street methods, the *Community Resilience and Adaptation Spatial Infrastructure Database* (CRASID) was developed (52). CRASID utilizes the same raw flood inundation data as the First Street Flood Model and includes sociodemographic data similar to that of the National Risk Index, as well as similar environmental factors and some critical infrastructure. The notable differences between CRASID and other tools include how data is aggregated, the choice of infrastructure, and access to emergency services. CRASID uses a tessellated mesh of 5 km hexagons spanning the entire watershed, with vertices spaced 5 km apart. By aggregating all variables to these hexagons, we reduce the variability of census tracts or cadastral parcels. The size of the hexagons was also chosen to help visualize travel on foot in an emergency, when an individual or family may need to escape or seek medical attention. Using hexagons also conveys a sense of directionality through their sides. Visualizing the general direction of escape is easier with a standardized mesh, such as a hexagonal one. CRASID also differs from the National Risk Index and First Street in the choice of critical infrastructure features. The CRASID database employs a unique approach, utilizing local community resilience factors rather than the more typical federal-level factors. These local community resilience factors examine what a person or family would consider necessary in an emergency. Taking a community-centric approach makes the CRASID database more people-centric and less economic-centric. In an emergency, when people may be injured or need shelter, knowing where emergency services are concentrated and how far they can reach quickly can make a significant difference. From a policy perspective, knowing where services are lacking, such as in highly rural areas, can inform planners where resilience measures may be needed. By focusing on the individual and community aspects of flood hazards, and by centering the analysis on emergency health service accessibility and community-centric critical infrastructure, the CRASID framework offers a novel, spatially resolved approach to evaluating and enhancing local community resilience to climate-driven flooding.

The purpose of CRASID is to be used as a tool for communities and individuals to plan for and better understand their vulnerability (57). From escape planning before or during an emergency to repurposing floodplain areas to increase resilience, the use of CRASID enables us to understand a community's vulnerability drivers better. One of the outcomes of this study is to hopefully stimulate discussions among communities and policymakers on how they can collaborate to mitigate the impact of climate change-induced flooding. As seen frequently with hurricane events and dam breaches, flooding can affect anyone, regardless of social status. Those most vulnerable and sensitive, however, are at greater risk due to lower resilience and limited capacity to adapt to the physical, economic, and health and safety effects of such events. Such local community-centric critical infrastructure-focused risk assessments, available within a visualization tool, will better enable information-centric adaptation decision-making by communities and governments, helping individuals, families, and communities increase resilience in the face of floods and other anthropogenic climate change stressors. CRASID shifts the focus away from purely economic metrics toward more human-centered ones. These metrics highlight who and where people are most affected in an extreme flood event. Vulnerable populations, such as people living on tribal reservations, are at greater risk due to their increased reliance on the land. Events such as flooding can contaminate areas where wild edibles are gathered (82–84). At the same time, these maps show that overlapping service areas contribute to increased resilience in highly urban areas, in stark contrast to the low resilience of the rural regions. However, we found ‘pockets’ of metropolitan areas with very low resiliency and greater risk, even within larger municipal regions.

Like all risk indexes, the CRASID model has several limitations. Unlike the FEMA National Risk Index and the First Street Flood Model, CRASID only covers the western part of the Great Lakes watershed. The original funding source and available computing resources determined the extent of the watershed. Future developments of the CRASID database include a state-by-state analysis. This would make the risk scores even more relevant to state-level policymakers, while also reducing computing resource needs.

The CRASID database uses a tessellated hexagonal mesh to standardize the different feature layers. Using hexagons means that every point in the study area can be compared to every other point. The limitation lies in how the hexagons are created. It is tough to recreate the same hexagon overlay when expanding the original area. Getting around this limitation could be achieved by using a more standardized, global hexagonal mesh, such as the Uber ride-sharing service’s H3 project (59,85). Using a standardized hexagon layer would make the CRASID database more reproducible at different scales.

Another limitation was the use of power plant and power substation locations as a proxy for power infrastructure (86). Using the density of power line networks, while computationally intensive, would reduce this limitation. Power line networks are similar to road networks: higher density means greater resilience.

The use of 15-minute access times to calculate emergency service areas could be improved by using multiple buffers with different time steps. Generating the 15-minute access times was the most significant computational limitation of the CRASID database. This would require a high-performance computing platform. Once the computational limitations are overcome, it could be helpful for emergency planners to have multiple buffers at different time steps to plan emergency routes and shelters more effectively.

Future directions for research include adding the impact of different climate change models on flooding in the Great Lakes watershed. Running 'what-if' scenarios would enable communities to plan for future events under varying levels of uncertainty. Additionally, incorporating feedback from focus groups, further risk factors (e.g., leaking underground storage containers) could be identified to gain a more comprehensive understanding of the factors driving risk. This would allow communities to include risks specific to their location. Another direction of research includes adapting the CRASID database to a Bayesian Network. Using a Bayesian Network approach, compared to the current method of calculating risk metrics for CRASID and the National Risk Index, would enable both forward and backward prediction, making it useful for what-if scenarios. The CRASID database also utilized risk indicators from both the Centers for Disease Control and Prevention's Social Vulnerability Index and the U.S. Census Bureau's Resilience Index. By associating the CRASID hexagon identifiers with the Centers for Disease Control and Prevention and U.S. Census databases, deeper analyses can be conducted, including household earnings, the number of children, and more. Finally, adding a population density per hexagon indicator might allow rates to be calculated and specific adjustments to be made, making the implications between highly rural and highly urban areas more understandable.

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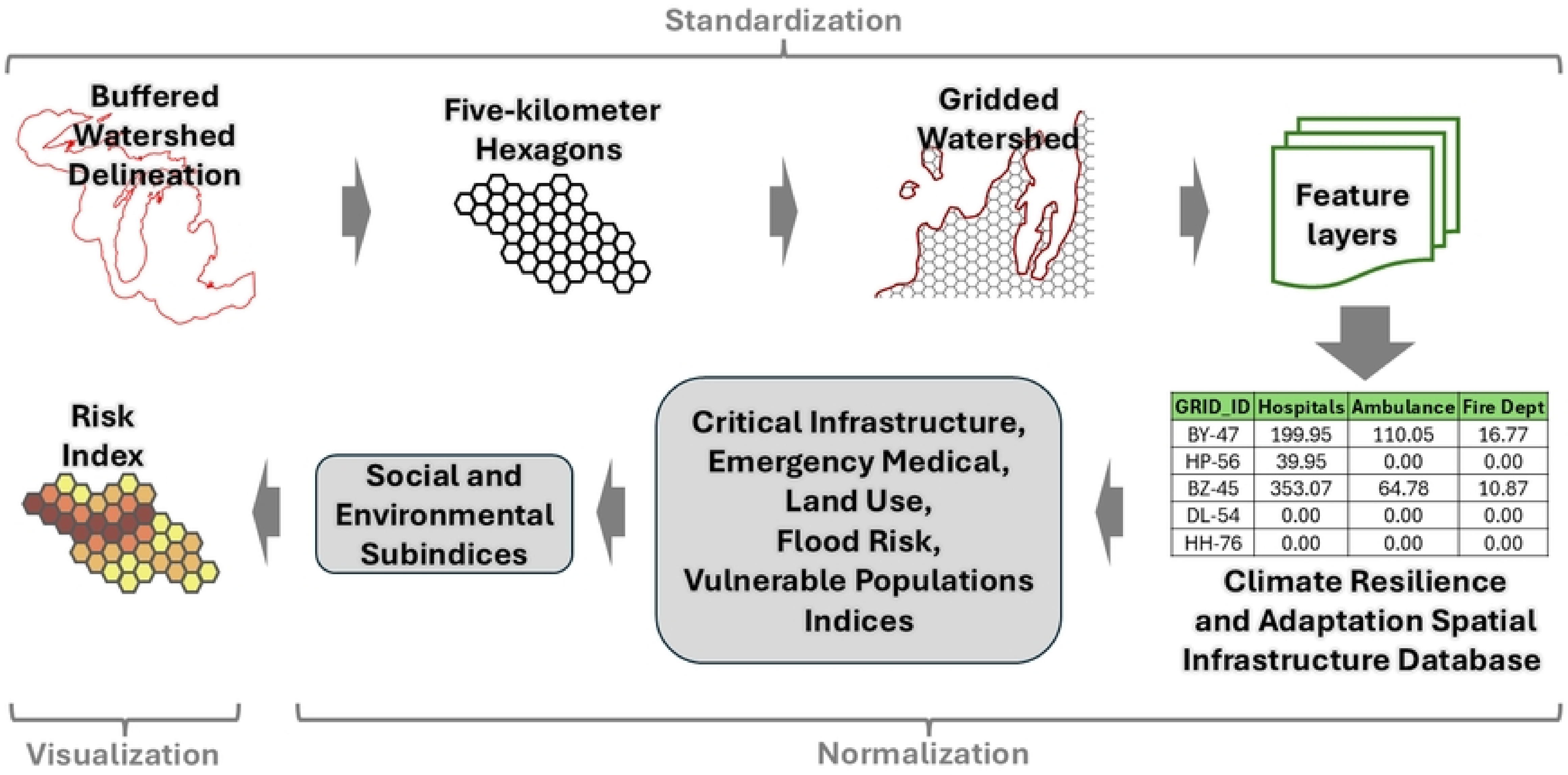
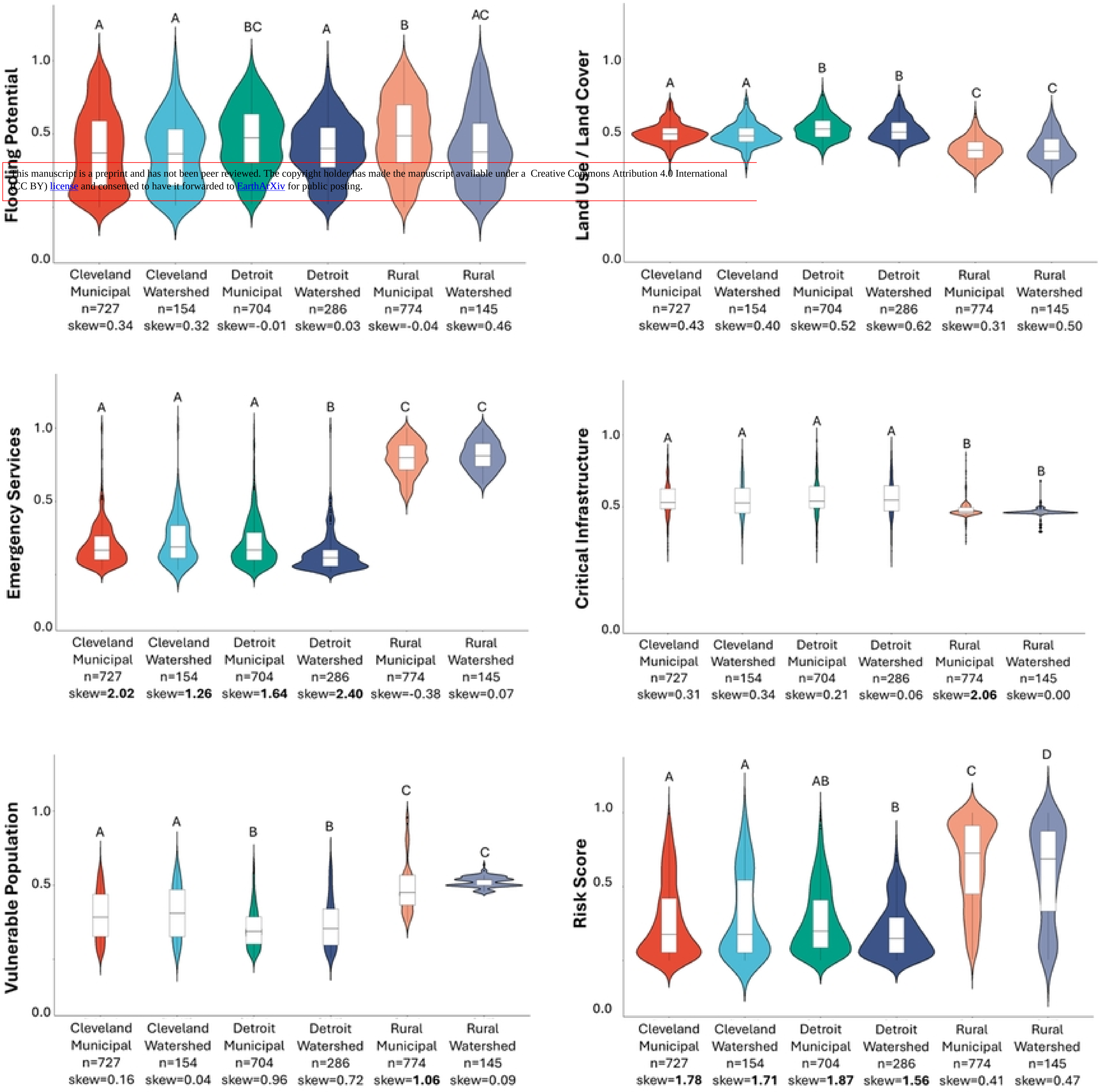

Standardization
Buffered Watershed Delineation
Five-kilometer Hexagons
Gridded Watershed
Feature layers
GRID_ID | Hospitals | Ambulance | Fire Dept
BY-47 | 199.95 | 110.05 | 16.77
HP-56 | 39.95 | 0.00 | 0.00
BZ-45 | 353.07 | 64.78 | 10.87
DL-54 | 0.00 | 0.00 | 0.00
HH-76 | 0.00 | 0.00 | 0.00
Climate Resilience and Adaptation Spatial Infrastructure Database
Critical Infrastructure, Emergency Medical, Land Use, Flood Risk, Vulnerable Populations Indices
Social and Environmental Subindices
Risk Index
Visualization
Normalization

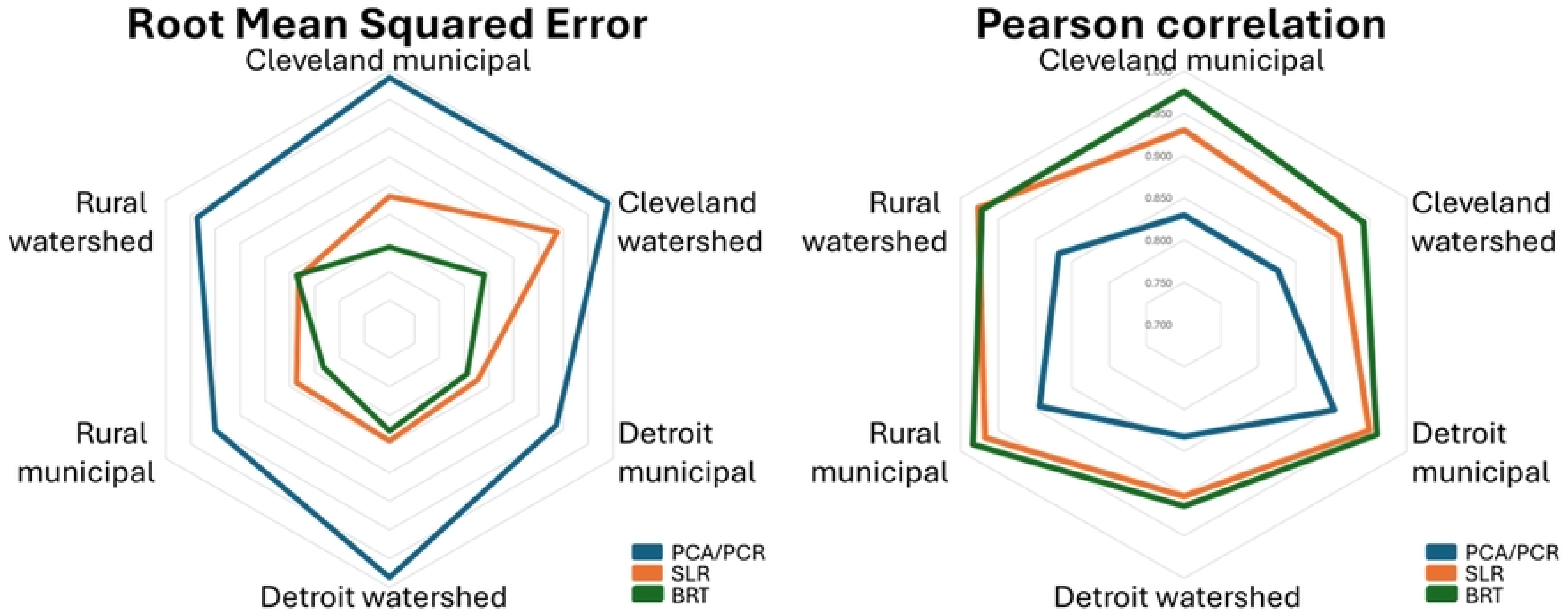
Figure


Study areas
Cleveland Municipal
Cleveland Watershed
Detroit Municipal
Detroit Watershed
Rural 'Municipal'
Rural Watershed
Kilometers
0 60 120 240
Map author: Jeffrey Ashby, MPH 2024
N
Detroit
Cleveland
Thunder Bay
Minneapolis
Milwaukee
Chicago
Madison
Grand Rapids
Sault Ste Marie
Sudbury
Sarnia
London
Hamilton
Toronto
Barrie
Pittsburgh
Columbus
Minnesota
Lake Superior

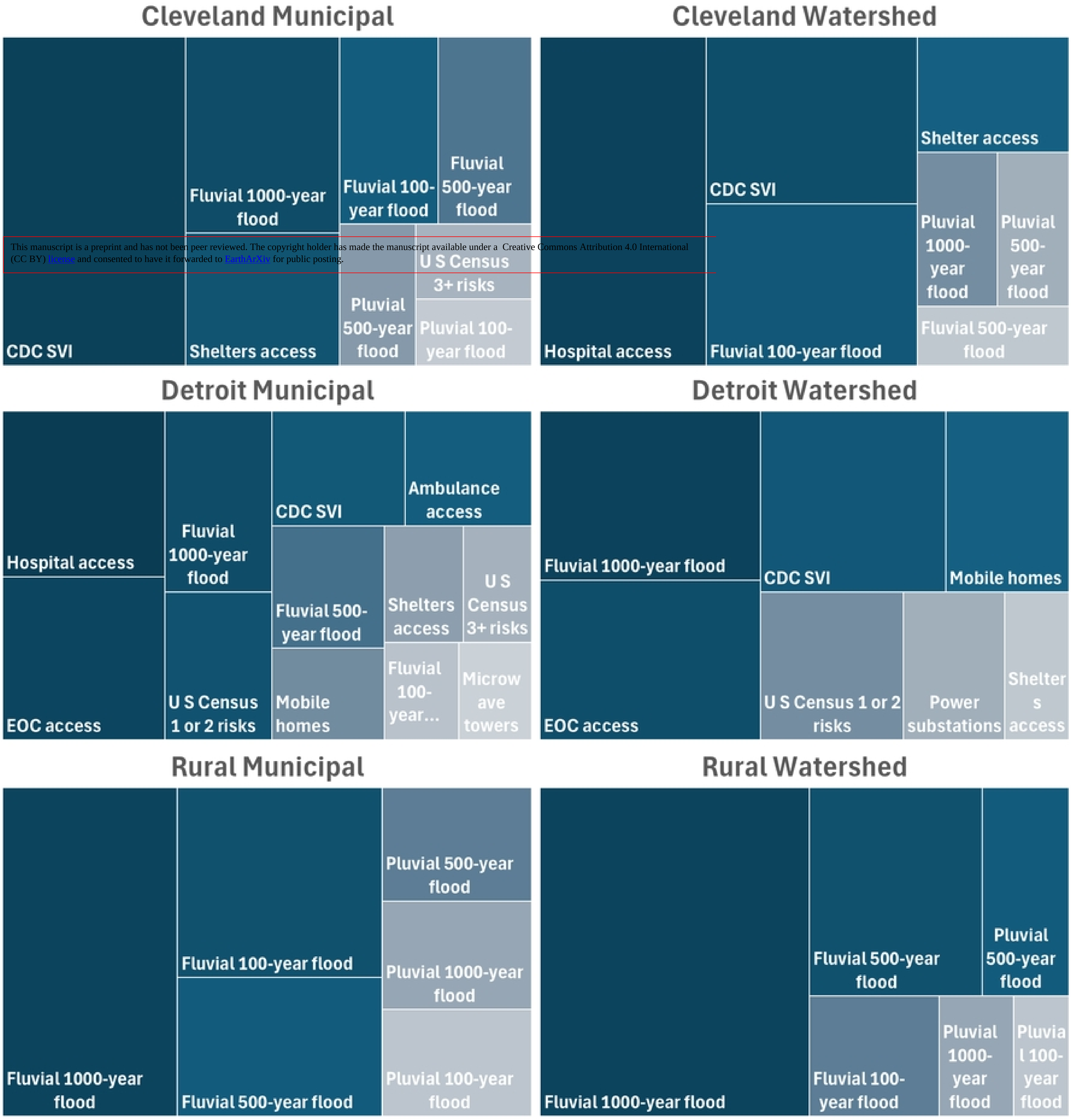
Figure


Flooding Potential
A
A
BC
A
B
AC
1.0
0.5
0.0
Cleveland Municipal n=727 skew=0.34
Cleveland Watershed n=154 skew=0.32
Detroit Municipal n=704 skew=-0.01
Detroit Watershed n=286 skew=0.03
Rural Municipal n=774 skew=-0.04
Rural Watershed n=145 skew=0.46
Land Use / Land Cover
A
A
B
B
C
C
1.0
0.5
0.0
Cleveland Municipal n=727 skew=0.43
Cleveland Watershed n=154 skew=0.40
Detroit Municipal n=704 skew=0.52
Detroit Watershed n=286 skew=0.62
Rural Municipal n=774 skew=0.31
Rural Watershed n=145 skew=0.50
Emergency Services
A
A
A
B
C
C
1.0
0.5
0.0
Cleveland Municipal n=727 skew=**2.02**
Cleveland Watershed n=154 skew=**1.26**
Detroit Municipal n=704 skew=**1.64**
Detroit Watershed n=286 skew=**2.40**
Rural Municipal n=774 skew=-0.38
Rural Watershed n=145 skew=0.07
Critical Infrastructure
A
A
A
A
B
B
1.0
0.5
0.0
Cleveland Municipal n=727 skew=0.31
Cleveland Watershed n=154 skew=0.34
Detroit Municipal n=704 skew=0.21
Detroit Watershed n=286 skew=0.06
Rural Municipal n=774 skew=**2.06**
Rural Watershed n=145 skew=0.00
Vulnerable Population
A
A
B
B
C
C
1.0
0.5
0.0
Cleveland Municipal n=727 skew=0.16
Cleveland Watershed n=154 skew=0.04
Detroit Municipal n=704 skew=0.96
Detroit Watershed n=286 skew=0.72
Rural Municipal n=774 skew=**1.06**
Rural Watershed n=145 skew=0.09
Risk Score
A
A
AB
B
C
D
1.0
0.5
0.0
Cleveland Municipal n=727 skew=**1.78**
Cleveland Watershed n=154 skew=**1.71**
Detroit Municipal n=704 skew=**1.87**
Detroit Watershed n=286 skew=**1.56**
Rural Municipal n=774 skew=0.41
Rural Watershed n=145 skew=0.47

Figure


Root Mean Squared Error
Cleveland municipal
Cleveland watershed
Detroit municipal
Detroit watershed
Rural municipal
Rural watershed
PCA/PCR
SLR
BRT
Pearson correlation
Cleveland municipal
Cleveland watershed
Detroit municipal
Detroit watershed
Rural municipal
Rural watershed
0.900
0.850
0.800
0.750
0.700
PCA/PCR
SLR
BRT

Figure


Cleveland Municipal
CDC SVI
Fluvial 1000-year flood
Shelters access
Fluvial 100-year flood
Fluvial 500-year flood
U S Census 3+ risks
Pluvial 500-year flood
Pluvial 100-year flood
Cleveland Watershed
Hospital access
CDC SVI
Fluvial 100-year flood
Shelter access
Pluvial 1000-year flood
Pluvial 500-year flood
Fluvial 500-year flood
Detroit Municipal
Hospital access
EOC access
Fluvial 1000-year flood
U S Census 1 or 2 risks
CDC SVI
Ambulance access
Fluvial 500-year flood
Mobile homes
Shelters access
U S Census 3+ risks
Fluvial 100-year...
Microwave towers
Detroit Watershed
Fluvial 1000-year flood
EOC access
CDC SVI
Mobile homes
U S Census 1 or 2 risks
Power substations
Shelters access
Rural Municipal
Fluvial 1000-year flood
Fluvial 100-year flood
Fluvial 500-year flood
Pluvial 500-year flood
Pluvial 1000-year flood
Pluvial 100-year flood
Rural Watershed
Fluvial 1000-year flood
Fluvial 500-year flood
Pluvial 500-year flood
Fluvial 100-year flood
Pluvial 1000-year flood
Pluvial 100-year flood


Figure