Comparing Flood Models From Federal Emergency Management Agency (FEMA), First Street Foundation's Flood Factor, and a Multi-Criteria Decision Analysis (MCDA) to Evaluate Flood Risk in the Rouge River Watershed

by

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Abstract

Flooding in Southeastern Michigan is intensifying due to increasing temperatures, precipitation, and rapid urbanization. Such developments place an increasing number of people and capital at risk, which calls for public flood management as well as household level adaptation measures. Two models commonly used to understand flood risk and support flood management in the U.S. include: 1) Federal Emergency Management Agency (FEMA)'s flood zones and 2) First Street Foundation's Flood Factor model. FEMA's flood zones are mapped based on historical data, but they might not consider intense rainfall, a growing problem as the atmosphere warms. First Street Foundation's Flood Factor model integrates federal elevation, rainfall data and coastal flooding estimates from hurricanes, thus resulting in updated maps which show a vast increase in risk compared to official estimates. This study aims to compare the flood risk zones from FEMA's National Flood Hazard Layers and First Street Foundation's Flood Factor to analyze the percentage of properties at risk in the Rouge River Watershed of Southeast Michigan. Analyses identified almost a 2.5% and 5% increase in the number of parcels at risk in the 100-year and 500-year floodplain, respectively. This underestimated risk by FEMA represents almost 40% of the watershed population who might be unaware of the current and future flood risk. To further validate these additional at-risk parcels, a flood risk map of the watershed using a Multi-Criteria Decision Analysis (MCDA) model was created. This detailed comparative analysis involving two well-known flood models, along with this flood risk map, is a potential approach for improving flood management measures at a local or regional scale. This study can support climate adaptation

by informing flood risk reduction solutions such as green infrastructure, preservation of open space and improved stormwater drainage systems.

Chapter 1: Introduction

Flooding is the most frequent and costly natural disaster in the U.S. because it has an impact on public health, local and regional economies, and the environment. In the U.S., floods cause $7.96 billion in damages per year on average (Koen de Koninga, 2019). Flood risk is commonly defined as a combination of hazard, exposure, and vulnerability. Susceptibility to flood refers to the natural tendency to produce flood (Khosravi, 2016). Although flooding is inevitable, the assessment and management of future floods can be achieved through historical analyses and forecasting methods, and prediction. Trends of greater flooding over the course of the twentieth century have been observed by the statistical analyses of global historical flooding records (Milly, 2002). Studies have evaluated future flood risks analyzing trends using global climate models from such historical records (Xu, 2019). Annual precipitation has increased in the U.S. during the past century, with much of the increase driven by intensification of the heaviest rainfalls. This tendency towards more intense precipitation events is projected to continue in the future (Pryor, 2014). A significant increase in heavy precipitation events in the Midwest has also been documented since the 1920s which are likely due to spatial and temporal variations in sea surface temperatures (Angel, 1997). Studies utilizing historical precipitation data (1961-1990) and daily precipitation projections for the period 2000- 2099, show that 24-hour and 7-day extreme rainfall events are projected to double by the end of the next century in the Midwest (Wuebbles, 2004). More than half of the damages from the U.S. Billion Dollar disasters also occur due to flooding in the Midwest (Figure 1a.**;** Smith, 2021). Along with physical and socio-economic factors, these damages are sensitive to extreme precipitation, which has become more frequent in this region (Figure 1) (Diffenbaugh, 2021).

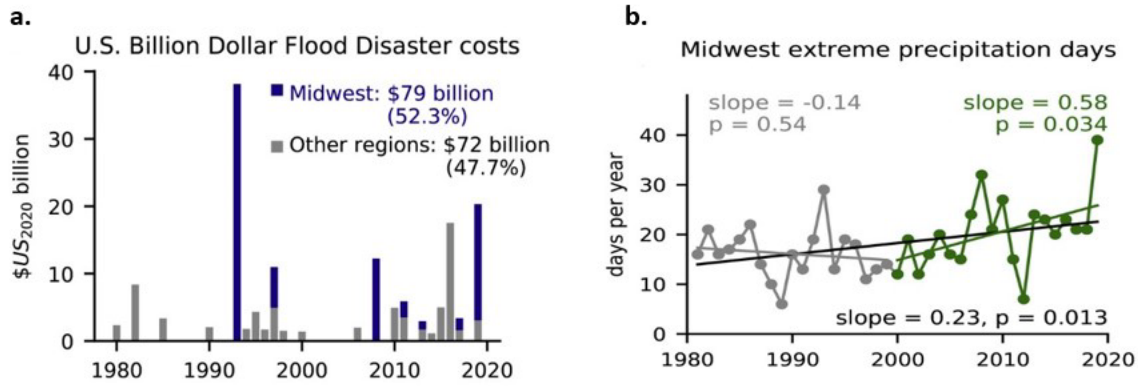


Figure 1: a. Annual damages from U.S. Billion Dollar Disaster Floods. Flood damage in Midwest shown in blue. b. Extreme precipitation days per year in the Midwest for overall (black), early (gray), and late (green) periods. (Davenport, 2021).

Flood damage accounts for a large proportion of the economic losses due to natural hazards in developed countries (Güneralp, 2015). A global assessment recently estimated that based on land use, the economic exposure to coastal and fluvial flooding could increase from $27 trillion in 2010 to $80 trillion in 2050 (Güneralp, 2015). According to the United States Geological Survey (USGS), “although the number of fatalities has declined due to improved early warning systems, economic losses continue to rise with increased urbanization in flood-hazard areas” (Water Resources, 2018). Flood losses are expected to increase, not only due to ongoing anthropogenic climate change (IPCC, 2014) but also due to socio-economic development (Röthlisberger, 2018). The increased intensity of rain events has contributed to $75 billion in flood-related damages in the U.S. between 1988 and 2017 (Sampson, 2021). According to the Intergovernmental Panel on Climate Change (IPCC) many of the global risks of climate change will be concentrated in urban areas (IPCC, 2014).

Many post-industrial cities like Detroit face a wide range of challenges including demographic change, financial and political neglect, and poor public service. With a median household income of $31,000, less than half the state median income, it is also one of the poorest large cities in the U.S. (Larson, 2021). Changes in frequency and intensity of rainfall patterns can therefore overwhelm aging infrastructure in such crippling environments and create multiple stormwater issues in the city and adjacent areas (Howell, 2019). Detroit has an almost flat topography and the city's natural drainage is split between the Detroit and Rouge rivers, though the natural tributaries were replaced with underground pipes prior to the 1960s. Sewage and water runoff run through a combined sewer system to discharge more than 58 million liters of treated and untreated sewage which eventually flows into Lake Erie (Michigan Department of Environment, Great Lakes, and Energy (EGLE), 2018). This combined system of rain runoff and sewage discharge can overwhelm the Detroit's treatment system causing sewage backflow into homes during large and extreme rain events (Steis Thorsby, 2020).

Asphalt and concrete-based "gray infrastructure" such as buildings, roads, and parking lots comprise majority of the urban growth in the U.S. (Brown, 2014). A larger amount of surface runoff is therefore generated owing to such types of urban expansion which leads to an increase in impervious surfaces. Stormwater drainage systems, including sewers, infiltration trenches, and detention basins, are used to remove runoff by controlling its flow rate and velocity. Water tends to accumulate on roadways, leading to potential damage to properties (e.g., houses, cars, and commercial activities) and other infrastructure, when drainage structures exceed their capacity. However, the increasing unpredictability of future weather risks suggests that even oversized infrastructure such as concrete levees, dams, retention basins, culverts and canals, may be vulnerable to future extreme rainfall that can far exceed existing design criteria (Kim, 2017).

Past attempts to estimate rainfall-driven flood risk across the U.S. either have incomplete coverage, coarse resolution, or use overly simplified models of the flooding process (Wing, 2018). Data from the study conducted by Wing et al., show that the total U.S. population exposed to significant flooding is 2.6 to 3.1 times higher than previous estimates, and that nearly 41 million Americans live within the 1% annual exceedance probability floodplain compared to only 13 million when calculated using Federal Emergency Management Agency (FEMA) flood maps. The growth of population and Gross Domestic Product (GDP) alone are expected to lead to significant future increases in flood exposure, and this change may be exacerbated in the future by climate change (Wing, 2018). Flood risk assessment is therefore an important tool to recognize various communities which are at risk of being exposed to flooding and can also help in the planning and implementation of mitigation techniques in flood vulnerable areas. In more recent decades, there has been a shift in the way in which disasters including from flooding are handled, from disaster management focused on relief and disaster preparedness to a more sustainable approach of avoiding and reducing the impacts of disaster, through developing communities' coping strategies to achieve resilience (Tunstall, 2009). Identification of flood-prone areas and preparation of susceptibility maps of flooding is an important tool to mitigate future flood damages. By identifying locations prone to flooding, strategies to facilitate quick response can be organized, therefore helping in decreasing the impact of possible flood events and providing means for early warning (Khosravi, 2016). However, national, and global-level assessments can undermine the spatial variability of climate change, land use and surface hydrology at smaller scales that are relevant for adaptation measures (Adger, 2005). Routing future climate data through smaller watershed-scale models can thus be a solution towards quantifying flood risk at a local or regional scale (Xu, 2019).

1.1 Historic Floods and Flooding in Southeast Michigan

Flooding in Southeastern Michigan has become more common with the shifts in weather patterns (Drawing Detroit, 2021). Even though flooding in Detroit has remained at the forefront, cities throughout southeastern Michigan like Grosse Pointe and Dearborn continue to be affected by the surge of storm events. In September 1986, the “Great Flood of 1986” was termed as one of the worst flood disasters in 50 years. This 500-year flood event reported rainfall averaging between 6 to 12 inches in central and lower southeast parts of Michigan, with certain isolated parts receiving up to 14 inches (Figure 2a.). The total damage was estimated between \$400 and \$500 million by the National Weather Service (Deedler, 2016) out of which around \$120 million was from crop damage due to the floods occurring near the harvest time.

Another historic rainfall event was recorded in August 2014 known as the “Metro Detroit Flood.” The hardest hit areas included Metro Detroit and surrounding communities, Flint, and the Saginaw Valley areas. Wayne, Southern Oakland, and Macomb counties experienced the worst flooding as 4 to 6 inches of rain fell over a 4-hour period (United States Flood Loss Report - Water Year 2014) (Figure 2b.,d.). The Rouge River in Detroit hit a flood stage of 17.51 feet which was the fifth highest recorded crest of this river. According to the United States Flood Loss Report – Water Year 2014, around 75,000 homes and businesses suffered damage, with over 3,000 suffering major damage. There was also damage to the roads and bridges, along with the city sewer pumps, which were overwhelmed by the torrential rainfall. This 500-year flood eventually exceeded the monetary damage of the 1986 floods, with up to $1.8 billion in flood damage (August 11, 2014 Historic Rainfall, n.d.) .

The June 2021 floods similarly affected areas of Detroit and surrounding Wayne, Oakland, and Macomb counties (Figure 2c.). This 500-year flood event recorded an average of 6 inches of rainfall in 24 hours, with some places like Dearborn receiving a record 7.5 inches compared to the 5.8 inches of rain in the flood event of August 2014 (Flood Response Summer 2021, n.d.). This historic flood event has led to the recognition of the importance of stormwater management for private and public development in the forty-eight communities of the Rouge River Watershed. Places like the Dearborn (Figure 2e.), with its proximity to the Detroit River, are most impacted during such intense rainfall events. Thus, regional corporations and local organizations may be required to identify such concerns and come up with regional and local solutions.

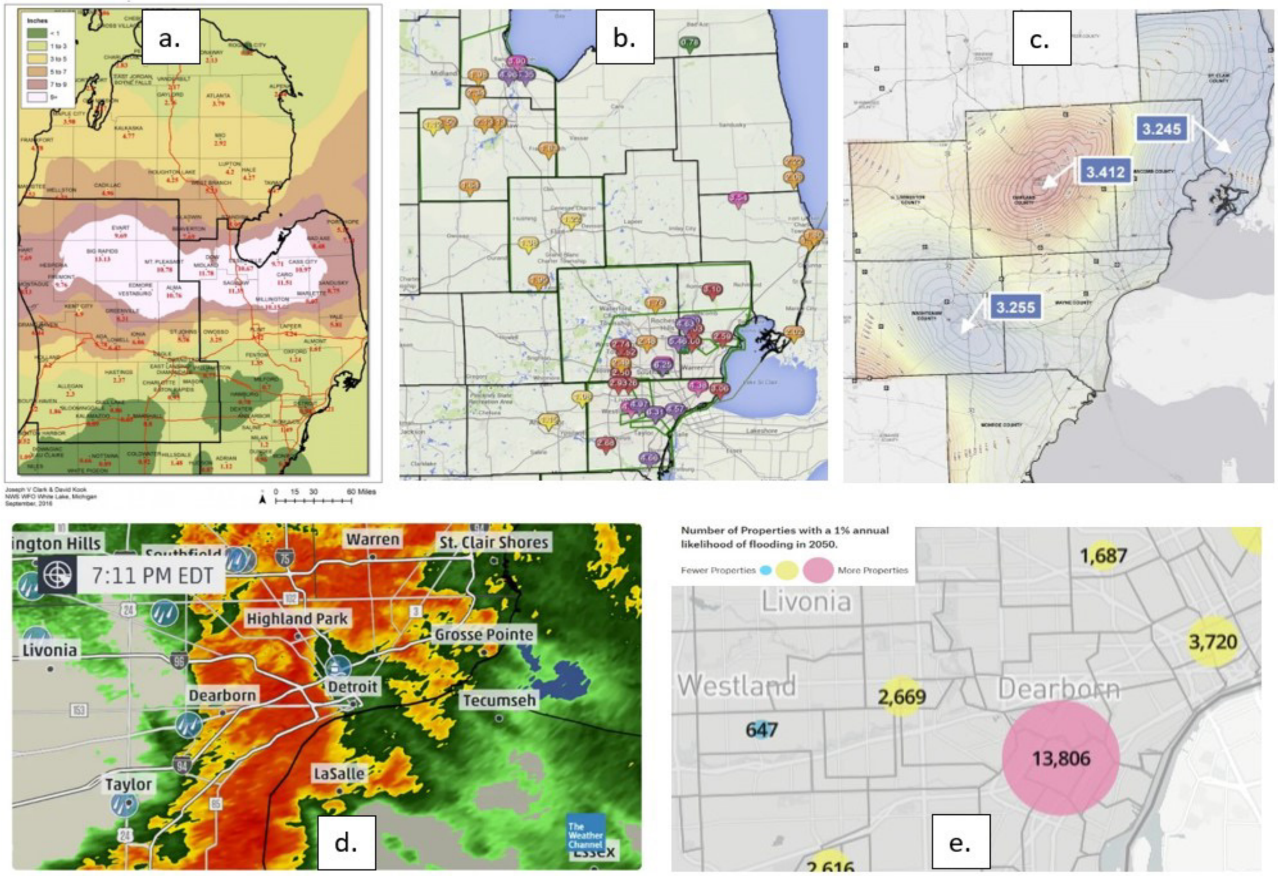


Figure 2: a. Extreme rainfall of September 1986, (Deedler, 2016); b. Flood Warnings in Metro Detroit, Flint, Saginaw during August 2014 floods c. Extreme average flooding in the SEMCOG region (SEMCOG, 2020) d. NEXRAD Doppler radar showing extremely heavy rainfall in Metro Detroit, August 2014, (Wiltgen, 2014) e. Properties at increased flood risk towards East Dearborn, (Matheny, 2020).

1.2 Federal Emergency Management Agency (FEMA) Flood Data

Flood risk management using quantitative approaches has long been used, particularly with the mapping of flood hazards. FEMA maps are based on open-space conditions, flood-control works, development and historically available data. In the U.S., FEMA maintains and updates flood hazard data through the Flood Insurance Rate Maps (FIRMs). FEMA hosts the National Flood Hazard Layer (NFHL), a geospatial database that contains effective flood hazard data. They provide this flood hazard data to support the National Flood Insurance Program (NFIP) which provides flood insurance to help reduce the financial impact of floods. FIRMs show special flood hazard areas and risk premium zones in the form of official community maps. These are developed using historic meteorological data and from hydrological/hydraulic analyses and topographic surveys which delineate different flood risk zones. In each zone, the base flood elevations (BFE), which is the level to which the house is recommended to be elevated, is stated. The flood risk zones and BFEs, in turn, dictate design requirements and insurance pricing (Xian, 2015). FEMA has produced maps delineating the Special Flood Hazard Area (SFHA) for nearly all current coastal flood hazard areas in the U.S. Detailed estimates of the number of people exposed have been published along with the distribution of the exposure on a national level. Maps delineating fluvial (riverine) and pluvial (rainfall-driven) flooding, however, are only partially complete nationwide, and no comprehensive estimate of U.S. population exposure currently exists (Wing, 2018). Where they are available, FEMA flood maps are of varying age and levels of quality. They also have notably poor coverage of smaller catchments, which is a trait shared by many of the hazard maps that are used to inform risk calculations at global or continental scales. The flood hazard zones of FEMA also summarize notable flood risks within a study area and present the data within a map. Although FEMA redraws and updates the maps periodically, there are rising concerns that they underestimate flood risk.

The National Flood Insurance Reform Act of 1994 stated that FEMA should be reviewing and updating all their maps every 5 years. But based on a report by First Street Foundation (Kaminski, 2021), 75% of the maps are out of date and 11 % date back to the 1970's and 1980's. Most of the FEMA zones mapped in Southeast Michigan are 5 to 10 years old, with few parts dating back to more than 10 years (Figure 3). Part of the problem is keeping the maps up to date, which is not only costly and labor intensive, but also faces further complications as climate change alters the flood risk.

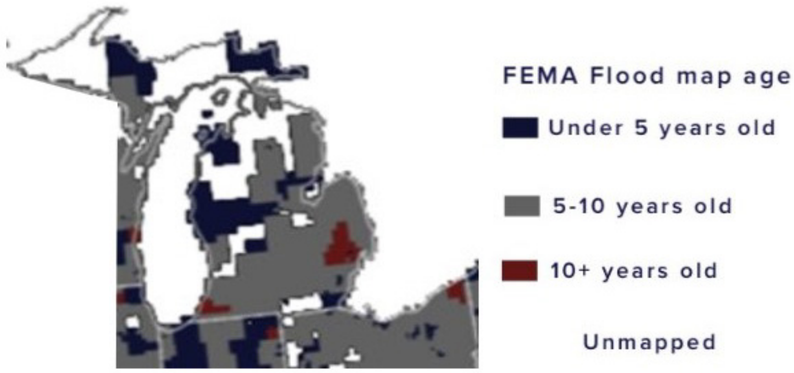


Figure 3: Age of FEMA maps in Michigan. Source: (Eby, 2019)

1.3 First Street Foundation's Flood Factor

The First Street Foundation is a non-profit research and technology group defining America's Flood Risk. There has been an urgent need for accurate, property-level, publicly available environmental risk information in the United States based on open source, peer reviewed science. In a mission to fill that need, First Street Foundation has built a team of leading modelers, researchers, and data scientists to develop the first comprehensive, publicly available risk models in the United States. It is a probabilistic model showing any location's risk of flooding from rain, rivers, tides, and storm surge. It also forecasts how flood risks will change over time due to changes in the environment. The model captures the likelihood of a flood occurring in a given year based on the location's historic and geographic information such as elevation, climate, proximity to water and adaptation measures. The model then analyzes select probabilities (0.2%, 1%, 10%, 20%, 50%) to create "hazard layers," which show where and how deep flooding could occur for each probability. Their flood model, called Flood Factor, uses federal elevation and rainfall data, and coastal flooding estimates from hurricanes. According to the Flood Factor model, a property's

Flood Factor is an indicator of its comprehensive flood risk, ranging from 1 (minimal) to 10 (extreme). The foundation then checks its results against a national database of flood claims and historic flood paths. This state-of-the-art flood model has been utilized for various studies by researchers and by businesses and government agencies to examine flood risk inequities to promote public safety and social equity (Flores, 2023), define flood risk for commercial and multi-unit residential buildings (Porter J. R., 2022) as well as community level flooding risk in the next 30 years (Porter J. R., 2021) .

The model covers the contiguous United States, including areas the FEMA has not yet mapped or updated in decades. When compared with the FEMA maps, the Flood Factor results show an increase in risk compared with FEMA estimates. According to The First National Flood Risk Assessment (First Street Foundation, 2020), the First Street Foundation Flood Model identifies around 1.7 times the number of properties as having substantial risk compared to the FEMA 1-in-100 Special Flood Hazard Areas (SFHA) designation. This equates to a total of 14.6 million properties across the country at substantial risk, of which 5.9 million properties and property owners are currently unaware of or underestimating the risk they face because they are not identified as being within the SFHA zone (Figure 4).

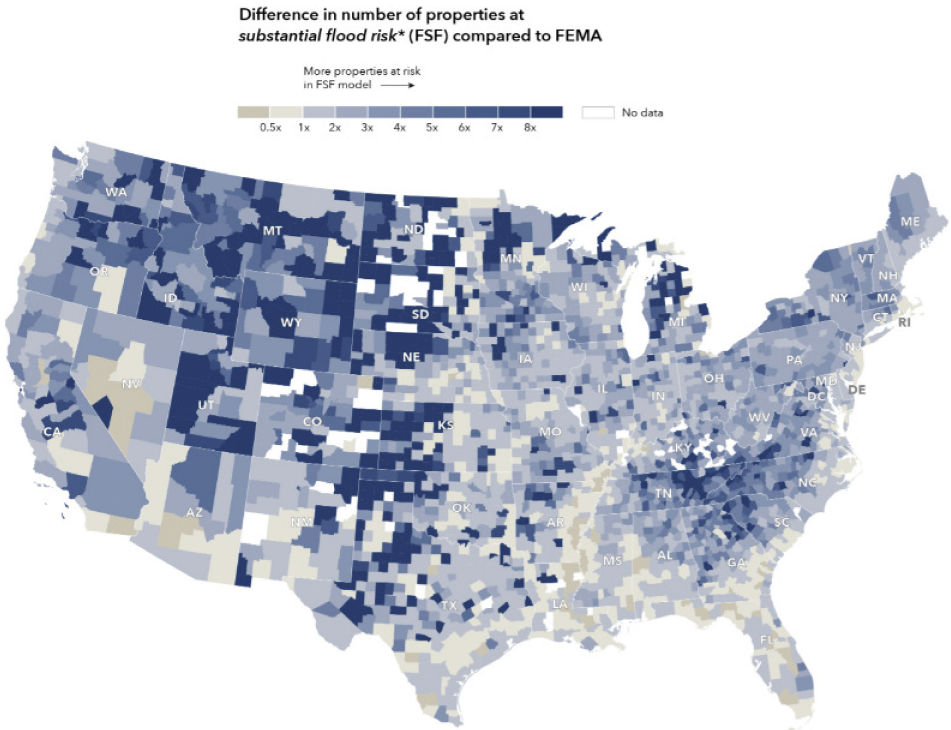


Figure 4: Difference in number of properties at substantial risk compared to FEMA (First Street Foundation, 2020).

1.4 Multi-Criteria Decision Analysis (MCDA)

New technologies and methodologies, such as Multi-Criteria Decision Analysis (MCDA), could be used to develop more detailed flood susceptibility maps that identify the areas with the highest exposure to flooding for Southeast Michigan. MCDA can structure decision problems by utilizing science-based approaches and schemes to form, assess and prioritize alternative decisions. The combination of GIS and MCDA can effectively and efficiently support the spatial decision-making process. It can be an optimal tool for land managers to assess flood risk and quantify the relationships between floods and their influencing factors. Recent decades have seen a major increase in the use of MCDA coupled with GIS. Kazakis (2015) assessed flood hazard areas at a regional scale in Greece using an index-based approach and Analytical Hierarchy Process (AHP) model. Finally, a comparison between the flood maps was produced and the historical events showed that the model was capable of flood hazard mapping. Similar approaches using Multi-Criteria Analysis by Stavropoulos (2020) and Nektarios N. Kourgialas (2011), use various factors to develop flood susceptibility and flood risk models to identify hazard prone areas and vulnerability. The weights in multi-criteria analysis are assigned to prioritize the relative importance of the different criteria. A fundamental factor in MCDA is that the weights are subjected to the judgment of the decision maker ensuring credibility. AHP is an effective multicriteria decision-making tool that can be used to set a systematic approach for evaluating and integrating the impacts of different factors, which include some levels for qualitative and quantitative information (Saaty T. L., 1990). The relative weight for each factor to be considered in this study can be estimated using the methods of AHP and pairwise comparison matrix. The comparative scale is a common methodology typically performed to analyze the comparison between various factors. The relative importance is measured between two factors based on a scale from 1 to 9, where 1 indicates the two factors are equally important while 9 reflects that one factor is much more important than another.

1.5 Objective

The objective of this thesis is twofold.

- Compare predicted flood extent from FEMA and First Street Foundation's Flood Factor to analyze the percentage of properties at risk and delineate the areas prone to flood risk in the Rouge River watershed.
- Developing a flood risk map using MCDA and AHP to estimate the overall flood risk of the watershed by identifying hazard layers.

Flood risk estimates from both models of FEMA and First Street Foundation as well as the flood risk map will be validated against each other to identify the extent of overlap of the high flood risk areas from these models. This comparison can identify parcels that have been over or underestimated by one or the other flood model. A thorough comparison will also recognize areas of concern consisting of parcels with increasing future risk that require immediate flood adaptation and mitigation measures. Highlighting such areas can be used as a guide not only to spread awareness among the population at high flood risk, but also for organizations looking to address the flooding conditions with risk reducing solutions. Improved stormwater pumps and drainage systems, construction of levees and dams, preservation of open spaces, marshes and wetlands are a few of the adaptation measures that can be implemented at a local level in reducing physical and financial flood risks.

1.6 Study Area

The Rouge River Watershed is located in southeastern Michigan and includes four sub watersheds (Figure 5). The boundaries of this watershed include the Main branch of the Rouge River, Upper Rouge River, Middle Rouge River, and Lower Rouge River. These branches total 126 miles of river. The Rouge River watershed drains 1206 square kilometers into the Detroit River and encompasses 48 communities, which are parts of three counties: Oakland, Washtenaw, and Wayne. It is a fan-shaped watershed with a maximum elevation of approximately 323 meters (above mean sea level [MSL]) in the northwestern portion and a minimum elevation of 192 meters feet above MSL at the point where the river discharges into the Detroit River. The stream patterns vary due to elevation changes and geologic characteristics from trellis to dendritic drainage patterns. The watershed contains the oldest and most heavily populated and industrialized area in southeast Michigan which has led to sediment and water contamination from industrial development and discharge, combined and sanitary sewer overflows (United States Environmental Protection Agency, 2022). Southeast Michigan Council of Governments (SEMCOG) projected that the continued urbanization would result in a 50% increase by 2020 and around 80% increase by 2050, in occupied land which will place continued stress on the watershed (Rogers, 2002) (Nowak, 2005).

Increased precipitation in the Midwest in recent years has caused increased strain on the stormwater system. In 2018, Great Lakes Water Authority, which collects and treats most of the sewer from southeast Michigan, discharged 7,275 million liters of untreated sewage and 51,568 million liters of treated sewage, highlighting the need for additional stormwater management (Michigan EGLE, 2018). Because the sanitary sewer and the rainwater runoff use the same pipes, large rain events cause sewage backflow into houses if the system cannot handle high flows during storms (Steis Thorsby, 2020). A report from the Great Lakes Integrated Sciences and Assessments (GLISA, 2017) found annual precipitation in the region has increased by 14% since 1951, with the greatest increase happening in the winters and springs. The NOAA data from the National Centers for Environmental Information calculated 2016 to 2020 as the wettest five-year period in Great Lakes history (Climate at a Glance: Statewide Rankings, 2023). June 2021 was the 10th wettest month in Michigan history when an average of 4.9 inches fell on the state. Detroit recorded more than 6 inches in its historic June storm alone. According to First Street Foundation's Risk Factor for the state of Michigan, environmental changes can cause more 17.8 million properties to be at substantial risk by 2050 (First Street Foundation, 2021). This means Michigan could see a 4.2 % increase in the number of properties with risk of flooding. Thus, a flood risk assessment and flood susceptibility map for the different subsections of Rouge River Watershed can be a primary step towards minimizing flood hazards and optimizing flood adaptation measures in the region.

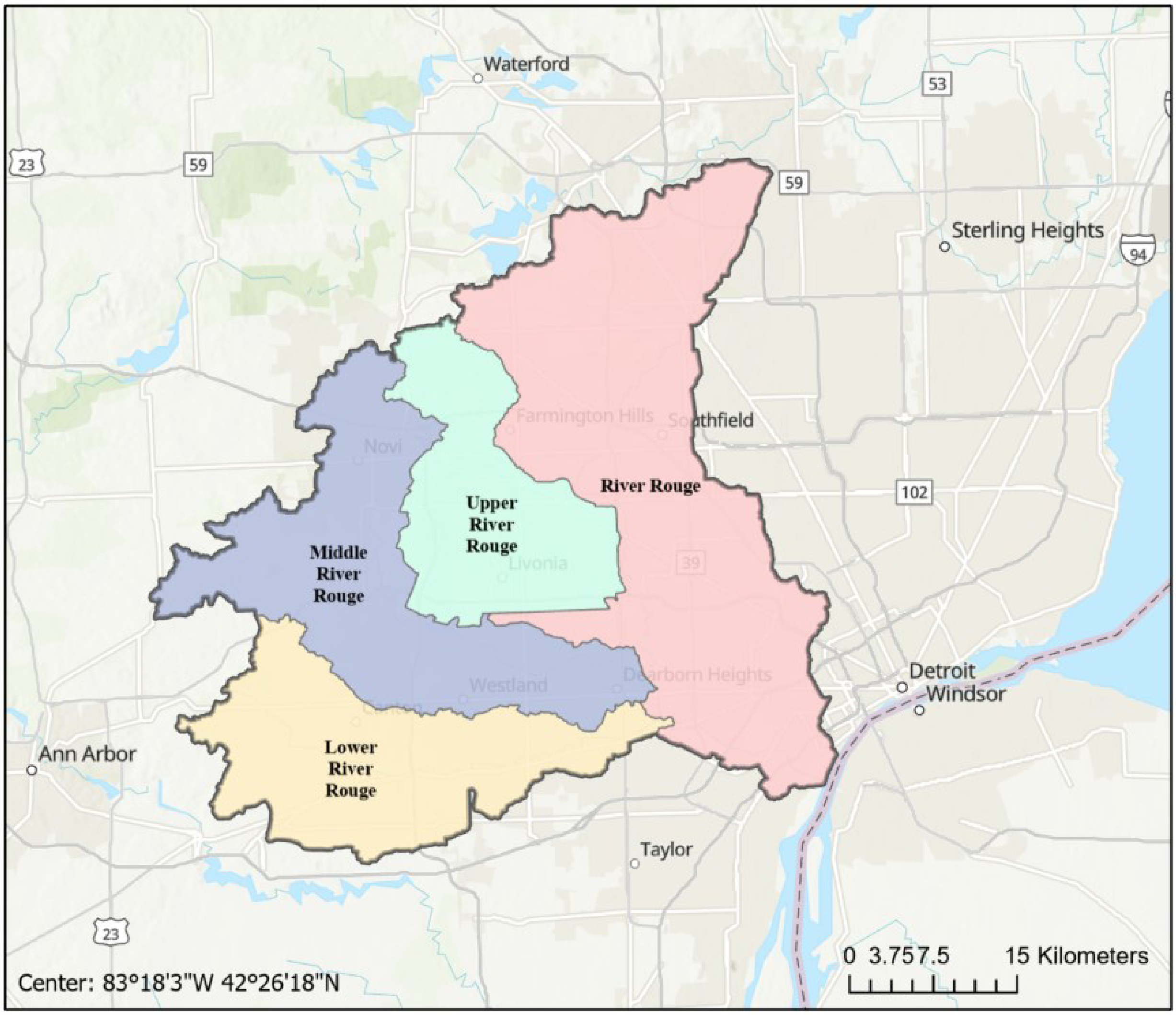


Figure 5: Rouge River Watershed with its sub watersheds.

Chapter 2: Methods

The methods for this study were divided into two parts. The parcels of land falling within the FEMA flood hazard layers and First Street Foundations high flood risk were compared. Then a Multi-Criteria-Decision-Analysis was conducted to visualize a more comprehensive flood risk for the study area.

2.1 Comparison of FEMA and First Street Flood Models

A comparison between the FEMA and First Street models revealed the differences between the percent properties at risk in the 100-year and 500-year floodplain within the study area.

2.1.1 *Parcels Under FEMA Flood Zones:*

The FEMA 100-year and 500-year floodplain data was obtained from the National Flood Hazard Layer (NFHL) available at the FEMA Map Service Centre. The NFHL is a geospatial database that contains effective flood hazard data. This data is divided into flood zones which FEMA has defined according to varying levels of flood risk, e.g., Moderate to Low-Risk Areas, High Risk Areas, and Undetermined Areas (Federal Emergency Management Agency, 2021) (Figure 12a.). Table 1 lists the FEMA flood zones used to determine flood risk in this study. The parcels of land which intersected with these flood zones were selected using ArcGIS Pro and the percentage of parcels falling under each of the flood zones (A, AE, and X) were summarized. To get a more detailed overview of the parcels at risk in the watershed, the percentage of parcels under each of the flood zones were calculated according to each of the four sub watersheds. The number of parcels in each of the flood zones, A, AE, and X was divided by the total number of parcels in each of the four sub watersheds to get an estimation of the at-risk parcels.

High Risk Areas	
Zone	Description
A	Areas with a 1% annual chance of flooding and a 26% chance of flooding over the life of a 30-year mortgage. Because detailed analyses are not performed for such areas; no depths or Base Flood Elevations (BFEs) are shown within these zones.
AE	Areas subject to inundation by the 1 % annual chance flood event determined by detailed methods. Base Flood Elevations (BFEs) are shown. Mandatory flood insurance purchase requirements and floodplain management standards apply.
Moderate Risk Areas	
Zone	Description
X (shaded)	Areas of moderate flood hazard between limits of the 1% annual chance floodplain and the 0.2% annual chance floodplain.

Table 1: Description of the FEMA Flood Zones (FEMA, 2020)

2.1.2 *Parcels Under First Street Foundation's (FSF) Model*

The Flood Factor data was accessed through the First Street Foundation's (FSF) Research Lab membership. Required parcel level data was requested directly from the organization which provided the ability to access flood risk data for research and analysis. The First Street Property Id is a point dataset containing the Flood Factor data, which indicates the comprehensive flood risk of each parcel and ranges from the values 1 to 10, where 1 represents minimal flooding and 10 represents extreme flooding (Figure 6) (First Street Foundation, n.d.). Parcel data from Wayne, Oakland and Macomb counties were derived from the respective county's GIS data. The Flood Factor point dataset was spatially joined to the parcel polygons to get a flood risk value for each land parcel in the study area. To compare FSF's flood risk against FEMA, Flood factor values representing 1 % chance of annual flooding (100-year floodplain) and 0.2 % chance of annual flooding (500-year floodplain) were selected (First Street Foundation, n.d.). According to FSF's Risk Factor, properties with "properties with 1% annual chance or at least a 26% chance of flooding over 30 years will have a Flood Factor of 4 or higher", so Flood factor values of 4 and greater than 4 were chosen to represent the 100-year floodplain. "Properties with 0.2 % annual chance or at least an 6% chance of flooding over 30 years will have a Flood Factor of 2 or higher", Flood Factor values of 2 and greater than 2 were chosen to represent the 500-year floodplain. The number of parcels exposed to these higher flood risk zones were identified in ArcGIS Pro and the at-risk parcels were summarized. Selecting by location, the data was analyzed for each of the four subsections of the watershed. The developed areas in the sub watersheds, subjected to high flood risk, were also delineated in ArcGIS Pro to evaluate the amount of developed land susceptible to flooding.

Figure 6: Flood intensity based on Flood Factor scores by FSF.

2.1.3 *Overlooked Parcels by FEMA and FSF*

FEMA has delineated the 100-year flood risk zones through Flood Insurance Rate Maps (FIRMs) as a basis of the national Flood Insurance Program (NFIP). They use these flood zones to delineate flood risk, regulate flood insurance premiums and inform floodplain management activities

(Flores, 2023). This program was established in 1968 which allowed businesses and homeowners to purchase flood insurance. However, these FIRMs are often outdated and fail to account for changes in the built environment and further increase flood losses (Wing O. E., 2017) (Patterson, 2009). Furthermore, large areal gaps in the FEMA FIRMs can exclude areas from risk identification and risk management processes in turn putting a large number of residents at an unknown risk. The at-risk parcels identified by FSF's Flood Factor data and the parcels falling under the 100-year FEMA flood zones were overlaid in ArcGIS Pro. The FSF-recognized parcels which fell outside the FEMA -delineated flood zones were then extracted. These parcels were then defined as the federally overlooked parcels (Flores, 2023). Certain parcels seemed to be overlooked by the FSF model as well, so similar methods were used to overlay the two models and extract the parcels falling outside the Flood Factor model.

2.2 Multi-Criteria-Decision-Analysis (MCDA) Model

In this study, the assessment of Rouge River watershed's susceptibility to flooding was the main objective for using a decision hierarchy. Flood risk assessment plays a crucial role in rainwater harvesting and flood mitigation. The MCDA model using Analytical Hierarchy Process (AHP) is one of the various approaches used to map flood risk (Radwan, 2019). This method of creating the flood risk map was divided into two main steps (Figure 7). First, six factors that affect the watershed's vulnerability to flooding were identified based on a thorough literature review (Danumah, 2016; Lyu, 2018; Radwan, 2019; Swain, 2020). These factors were then reclassified in ArcGIS Pro to form thematic maps. The factors contributing to the flood hazard of the study area are land use/land cover, rainfall, slope, drainage density, soil hydrology, and impervious surface. Second, a pairwise matrix (Figure 8) was used to assign weights to each of the six factors according to AHP (see 2.2.2 for explanations). Finally, a weighted overlay process was conducted in ArcGIS Pro to create the final flood risk map and identify the flood hazard areas in the study area. According to Nektarios N. Kourgialas, (2011) the hazardous areas cannot be estimated by considering the effect of each factor separately. The integration of all these factors were necessary to obtain the overall map of flood-hazard areas. Since all factors do not have the same degree of influence on the hazardous areas, a weighting approach, in which a different weight is assigned to each factor, was applied.

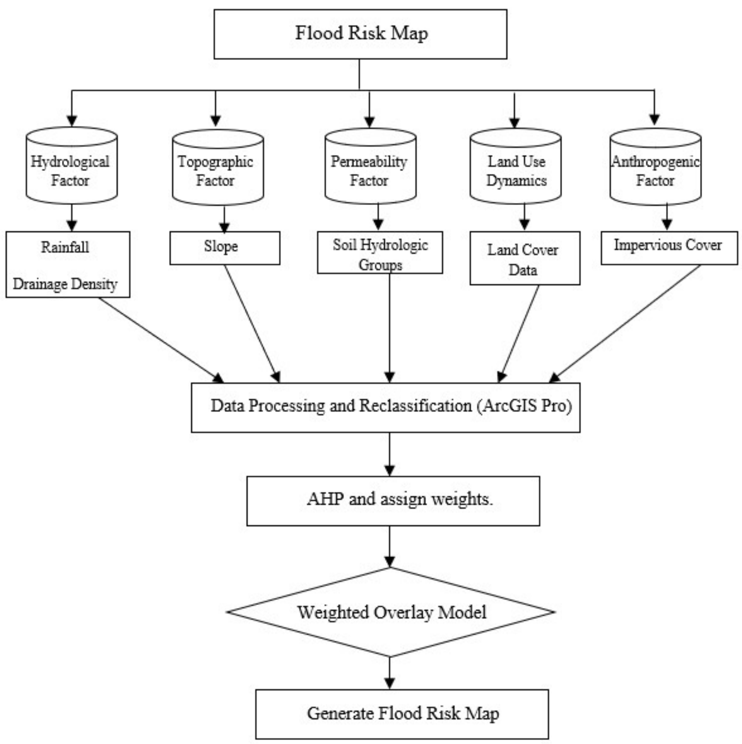


Figure 7: Schematic diagram of the methods used for mapping flood risk.

Matrix		Rainfall 1	Drainage Density 2	Slope 3	LULC 4	Soil Hydrolog 5	Impervious Surface 6	0 7	0 8	0 9	0 10	normalized principal Eigenvector
Rainfall	1	1	3	2	5	5	3	-	-	-	-	35.96%
Drainage Density	2	1/3	1	3	3	5	7	-	-	-	-	27.77%
Slope	3	1/2	1/3	1	3	5	5	-	-	-	-	18.41%
LULC	4	1/5	1/3	1/3	1	3	1	-	-	-	-	7.60%
Soil Hydrology	5	1/5	1/5	1/5	1/3	1	1	-	-	-	-	4.49%
Impervious Surface	6	1/3	1/7	1/5	1	1	1	-	-	-	-	5.77%
0	7	-	-	-	-	-	-	1	-	-	-	0.00%
0	8	-	-	-	-	-	-	-	1	-	-	0.00%
0	9	-	-	-	-	-	-	-	-	1	-	0.00%
0	10	-	-	-	-	-	-	-	-	-	1	0.00%

Figure 8: Pairwise comparison matrix and final weights for flood susceptibility criteria.

2.2.1 *Data Processing and Classification:*

Remote sensing data was used to create thematic maps of the six factors for the proposed study area. The general topographic surveying and mapping of the landscape features within the Rouge River Watershed were derived from a digital elevation model (DEM) of 1 meter resolution to define the slope of the watershed (U.S. Geological Survey, 2019). Surface runoff being dependent on the watershed relief, the layer was reclassified with areas close to the lowest values of the slopes having higher values and in turn higher flood risk (Figure 10 A).

The National Land Cover Database (NLCD) 2019 groups land use and land cover (LULC) into 20 classes including vegetation type, development density and agricultural use, areas of water, ice, snow, and barren lands. Depending on the type of land use, this factor can increase or decrease the soil infiltration that impacts on the surface runoff rate (Figure 10 B). Some of the LULC categories were combined to be more meaningful in this study. All categories labeled "developed" were aggregated into one class "Developed", and all categories labeled "Forest" were aggregated into one class. Similarly, "wetland" categories were aggregated as well as cultivated Crops (Figure 9).

The drainage density is an important morphometric parameter and reveals the impact of land use, terrain, and soil texture in the watershed (Horton, 1932). It is calculated as a proportion of the total stream lengths in the watershed per unit area of the watershed. The DEM raster layer was used to develop the thematic map of the study area's drainage density. After filling the DEM using the 'Fill' tool in ArcGIS Pro, the flow direction was determined along with the flow accumulation and flow conditions. Then the total stream lengths were calculated along with the total basin area to create the final map. Low drainage density values indicate high permeable soils which support thick vegetation (Abdelkareem, 2017). In contrast, high drainage density values indicate soils with low permeability which leads to impermeable subsurface materials and sparse vegetation (Radwan, 2019). This layer was therefore reclassified with higher values of drainage density demonstrating high flood risk and lower values of drainage density indicating lower flood risk in the study area (Figure 10 C).

Higher precipitation rates increase the probability of flooding in high flood-risk areas (Swain, 2020). The annual rainfall data for the past 30 years (1991 to 2021) was accessed from the Climate Research Unit gridded Time Series (CRU TS) dataset which is a widely used climate dataset on a 0.5° latitude by 0.5° longitude grid over all land domains excluding Antarctica (Harris, 2020). The data is derived by interpolating monthly climate anomalies from a network of weather stations observations (mm/month). The collected rainfall data for the study area was then reclassified to represent areas recording highest rainfall values as high flood-risk zones and areas recording low values of rainfall as low flood risk zones (Figure 10 D).

Soil infiltration heavily depends on the geologic substrate. High infiltration rates reduce the surface runoff and results in floods as well as flash floods. The hydrologic soil groups of the study area were accessed from the Web Soil Survey of the United States Department of Agriculture (USDA) (Staff, 2019). They were further classified according to the classes (A-D) which are based on the intake and transmission of water under conditions of maximum yearly wetness, bare soil surface and maximum swelling of expansive clays. The soil groups also estimate the runoff potential and the water infiltration capacities of the soil. Dual hydrologic soil groups were regrouped to represent Group D since of them are placed under group 'D' based on the presence of a water table within 60 centimeters (USDA Natural Resources Conservation Service, 2007). The data was reclassified to represent the A and B hydrologic groups as areas with high infiltration and in turn pertaining to low flood-risk. Areas with hydrologic groups C and D were classified as areas with high flood risk potential due to the soil's low infiltration capacity (Figure 10 E).

Urbanization increases regional impervious surface area, which generally reduces hydrologic response time and therefore increases flood risk (Feng, 2021). Areas prone to flood risk due to urbanization are related not only to overall impervious surface area percentage but also to the spatial distribution of impervious surface coverage. With similar average impervious surface area percentage, land use with spatial variation may aggravate flash flood conditions more intensely compared to spatially uniform land use distribution. The NLCD 2019 impervious surface data was used to map the percent impervious cover in the study area. The layer was then reclassified assigning the buildings, land cover changes and non-road impervious surfaces as high flood-risk prone areas (Figure 10 F).

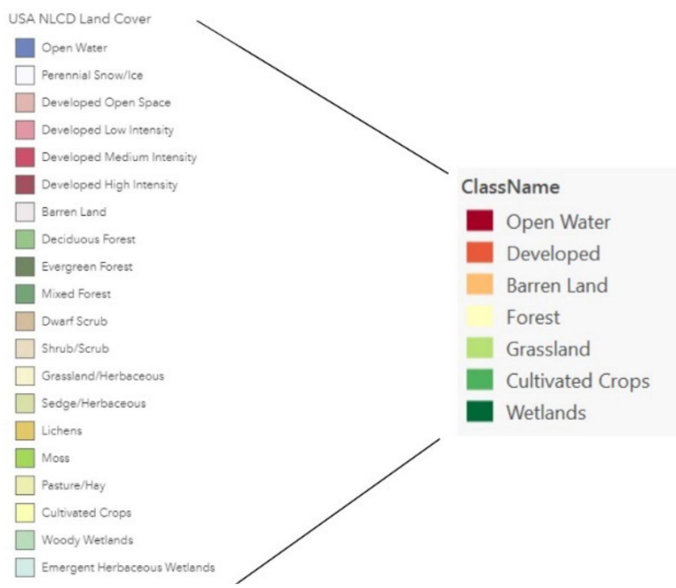


Figure 9: Reclassification of Land Cover categories of The NLCD data.

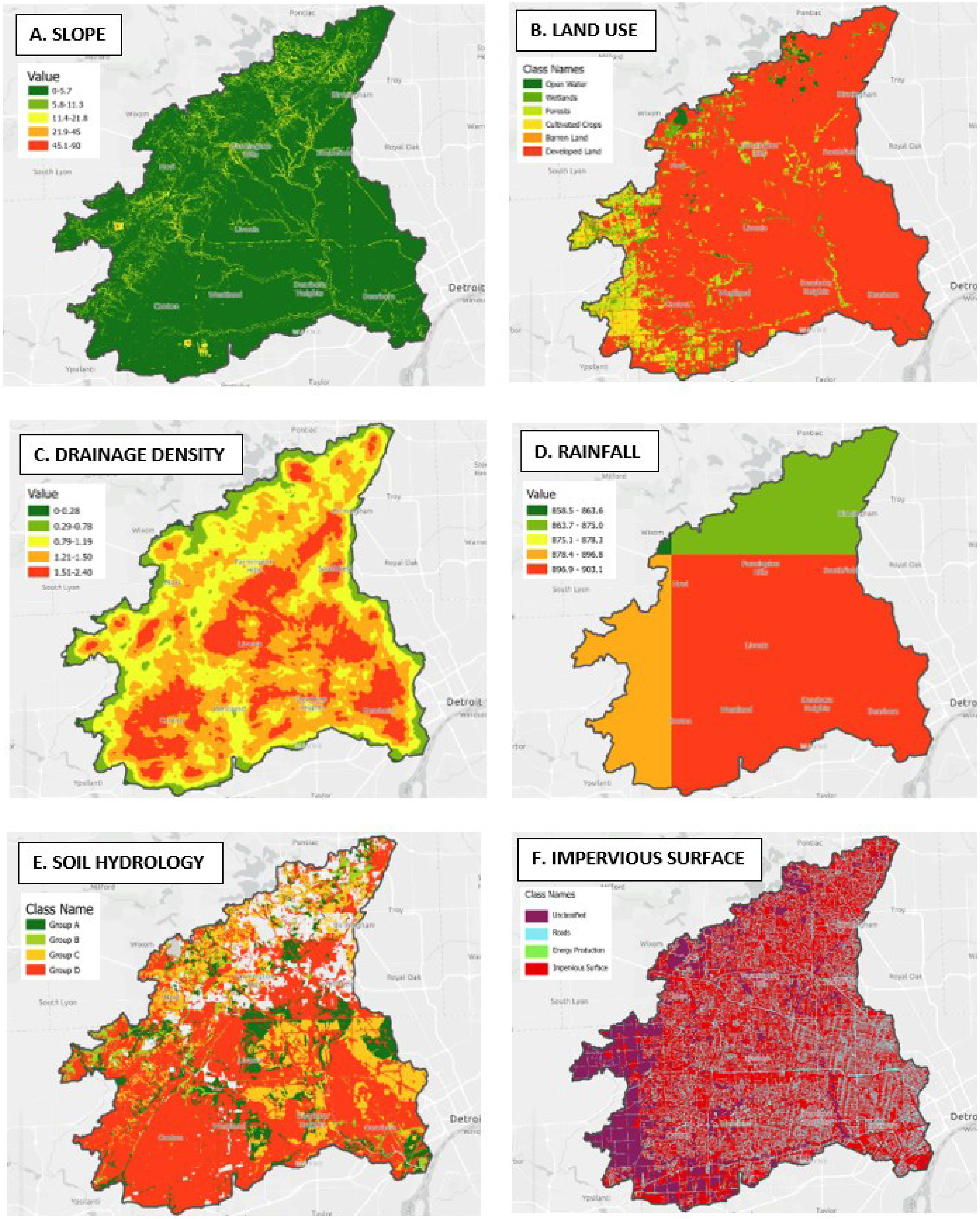


Figure 10: Thematic maps to identify areas at the risk of flooding.

2.2.2 *Analytical Hierarchy Process and Weighted Overlay Model*

AHP is an effective multicriteria decision-making tool that can be used to set a systematic approach for evaluating and integrating the impacts of different factors, which include some levels for qualitative and quantitative information (Saaty, 1990). Relative weight for each factor considered in this study was estimated using the methods of AHP and a pairwise comparison matrix. The comparative scale (Table 2) is a common methodology typically performed to analyze comparison between various factors (Saaty, 2003). The relative importance is measured between two factors based on a scale from 1 to 9, where 1 indicates the two factors are equally important while 9 reflects that one factor is much more important than another. A consistency ratio (CR) is computed to check the differences between the pairwise comparisons and the reliability of the measured weights. The consistency ratio should be < 0.1 to be accepted; otherwise, it is important to check subjective judgments and recalculate the weights (Saaty, 2001).

Weights for this study were assigned using a freely available AHP Excel template (Goepel, 2013) which allowed for multiple inputs with individual and consolidated outputs for decision makers. The excel template was made available for download on the Business Performance Management Singapore website. Six factors identified in this study were then compared using the comparative scale, and each factor was rated and evaluated against every other factor by assigning a relative dominant value between 1 and 9 (Kayastha, 2013) (Table 2). A pairwise matrix was then developed after assessing the relative weights of these factors for the watershed's flood risk vulnerability assessment (Figure 8). From the calculated pairwise matrix, the weightage of each layer contributing to the watershed's vulnerability to flood risk was derived.

These assigned weights were then used for analysis using the weighted overlay method (Figure 11). The determination of factors, the development of weightage for each, and the ranking of the weights were based on a synthesis of similar studies which were conducted to investigate possible factors and their impacts on the flood risk. According to the judgment of experts and literature reviews in this field (Danumah, 2016; Lyu, 2018; Radwan, 2019; Swain, 2020), in addition to the data available and required for the study area, each factor was categorized into sub-categories. Then, each sub-category was specified for a suitability rating value from 1 to 9, where 1 meant least importance of a class and 9 meant most importance of a class in the watershed vulnerability analysis (Table 3). Each of these six factors were then overlayed using the "Weighted Overlay" tool in ArcGIS Pro based on these suitability ratings. In this method each calibrated factor (Xi) was multiplied by its respective weight percentage (W_i). The summation of all the factors then gave us the final flood risk map of the study area following the equation (Gemitzi, 2006):

$$S = \sum w_i \, x_i$$

where S is Final flood risk map, w_i is the weight of a factor 'i' (percentage) and x_i is the rate of factor 'i' according to the range of the criterion values. Figure 19 depicts the final flood risk map of the study area which includes into five classes (very low, low, moderate, high, and very high) of flood risk.

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgement slightly favour one activity over another
5	Strong importance	Experience and judgement strongly favour one activity over another.
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6,8	For compromise between the above values	Sometimes one needs to interpolate a compromise judgement numerically because there is no good word to

Table 2: Judgement scale and definitions for pairwise comparison.

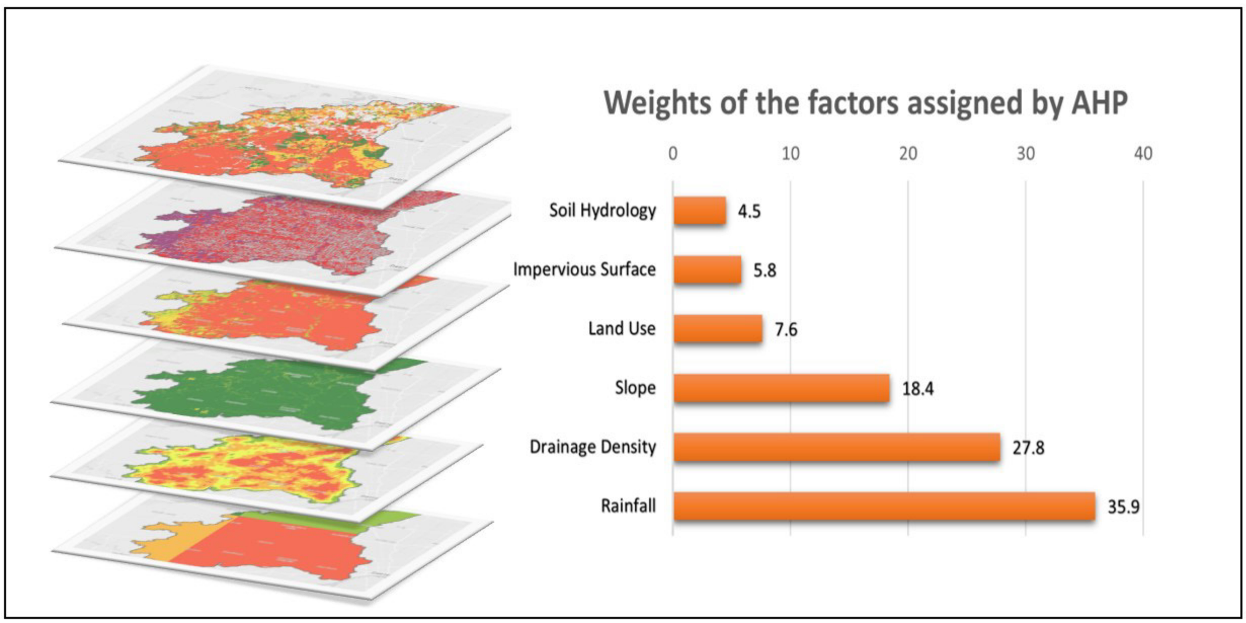


Figure 11: Weights assigned to each factor for the weighted overlay model.

Factor	Weightage (%)	Sub- Criteria	Rating
Rainfall (mm)	35.96	858-863	2
		864-875	3
		876- 883	5
		884-894	7
		895-903	9
Drainage Density (Per square kilometer)	27.77	0-0.27	2
		0.28-0.77	4
		0.78-1.19	6
		1.20-1.50	7
		1.51-2.39	9
Slope	18.41	3.43-7.71	9
		7.72-11.3	6
		11.4-21.8	4
		21.9-45.1	3
		45.2-90.1	2
Land Use	7.6	Open Water	1
		Wetlands	2
		Forests	3
		Crops	3
		Barren Land	6
		Developed Land	9
Soil Hydrologic Groups	4.5	Group A	1
		Group B	4
		Group C	7
		Group D	9
Impervious Surface	5.8	Unclassified layer	1
		Primary/Secondary/ Tertiary Roads	6
		Well pads/Energy Production	5
		Buildings/Non-Roads/ Impervious surfaces	9

Table 3: Relative weights and suitability ratings for the six factors.

Chapter 3: Results

3.1 FEMA vs First Street Foundation (FSF) Flood Models

3.1.1 *FEMA*

The FEMA flood zones were found to buffer the Rouge River and its tributaries for most parts of the study area. The A, AE and X zones accounted for around 6% of the total parcels of the watershed. The A and AE zones making up the 100-year floodplain consisted of around 3.3% of the parcels and the remaining fell under the X or the 500-year floodplain (Figure 12).

3.1.2 *FSF*

The FSF model can determine the likelihood of a flood reaching a minimum depth in a given year, known as an annual flood likelihood. A property's annual flood likelihood for a specific depth in 15 or 30 years may differ from its annual likelihood this year because of changes in the environment. The Flood Factor score, which indicates a property's flood risk, increases as the 30-year cumulative flood likelihood increases, or as the projected depth of flooding increases. Properties with a higher Flood Factor are either more likely to flood, are more likely to experience high floods, or both. Based on the First Street Foundation's data, 3% of the parcels in the Rouge River Watershed were found to not have a Flood Factor score. This likely translates to the fact that in case of a flood event, the parcels with no Flood Factor or a Flood Factor score of 1 should not show any flood water reaching the building outline. While it is still possible for properties with a Flood Factor of 1 (minimal) to flood, these properties have a less than 0.2% chance of flood water reaching the building in every analyzed year (First Street Foundation, n.d.).

Ninety-five percent of the Rouge River Watershed had parcels with a Flood Factor score, of which approximately 89% had a score of 1 (i.e., minimal flood risk). Almost 8% of the parcels of the watershed had a Flood Factor score higher than 2 which identifies increasing risk of flooding. According to the Flood Factor model, properties with at least a 6% chance of flooding over 30 years will have a Flood Factor of 2 or higher and properties with at least a 26% chance of flooding over 30 years will have a Flood Factor of 4 or higher. Four percent of the watershed also shows parcels with a Flood Factor of greater than or equal to 5 (Figure 13b**.**). Properties with at least an 80% chance of flooding over 30 years will have a Flood Factor of 5 or higher and at least a 99% chance of flooding over 30 years will have a Flood Factor of 6 or higher (First Street Foundation, n.d.). The map (Figure 13a.) of the study area shows the spatial distribution of the parcels at risk of flooding according to the FSF model with Flood Factors ranging from 2 to 10.

3.1.3 *FEMA vs. FSF*

Comparing the number of parcels within the FEMA Flood Zones and the parcels with flood factors corresponding to the 100 year and 500-year flooding, First Street Foundation identifies a higher percentage of at-risk parcels in the Rouge River Watershed (Figure 14). Almost 2.5% of additional parcels were found at-risk in the 100-year floodplain identified by FSF, with a 26% chance of flooding over a period of 30 years. The 500-year floodplain identified by FSF saw an almost 5% increase in the at-risk parcels with a minimum of 6% of flooding over the next 30 years (Figure 15).

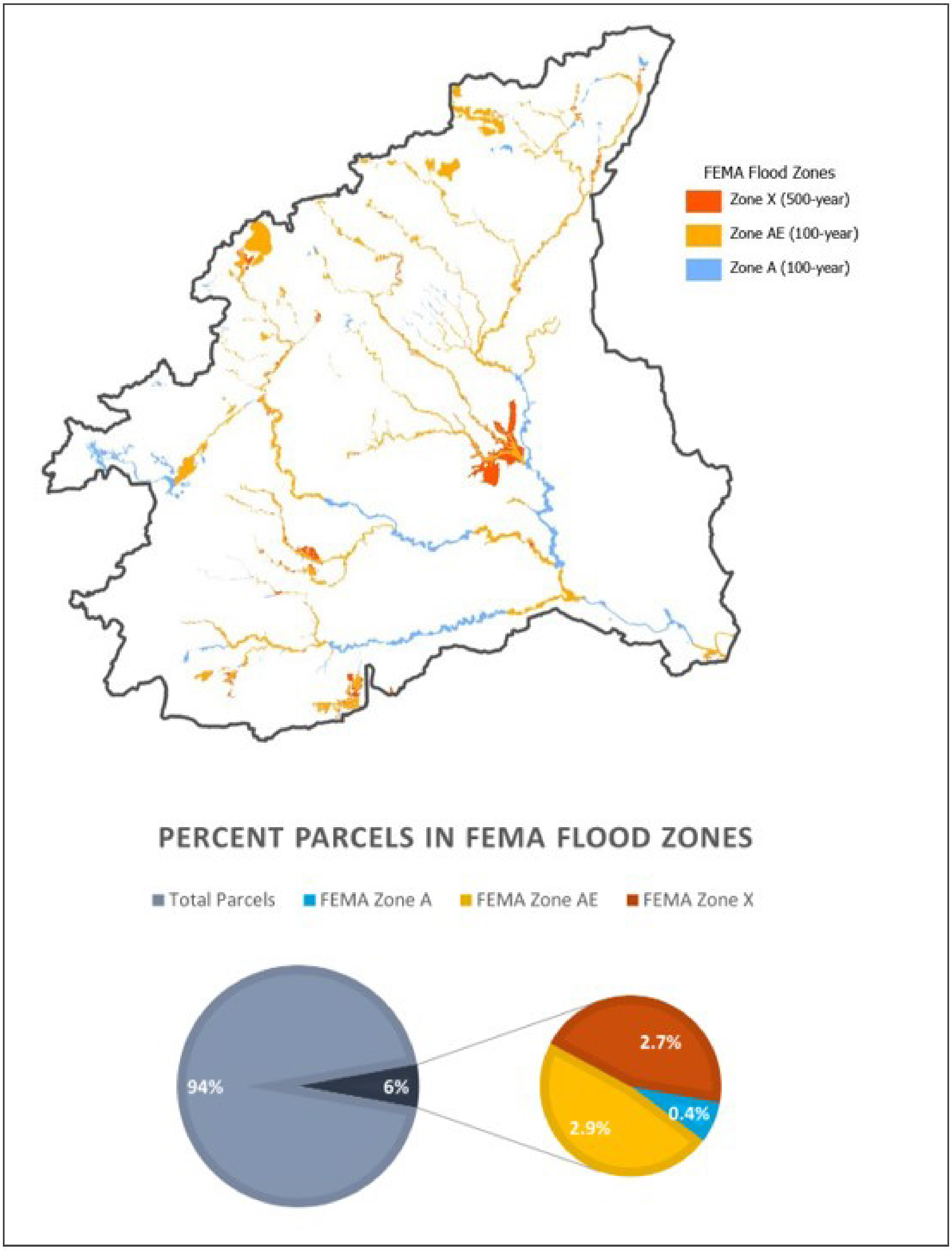


Figure 12: a. 100-year and 500-year Flood Zones of FEMA (Above); b. Percentage of parcels in the FEMA Flood Zones.

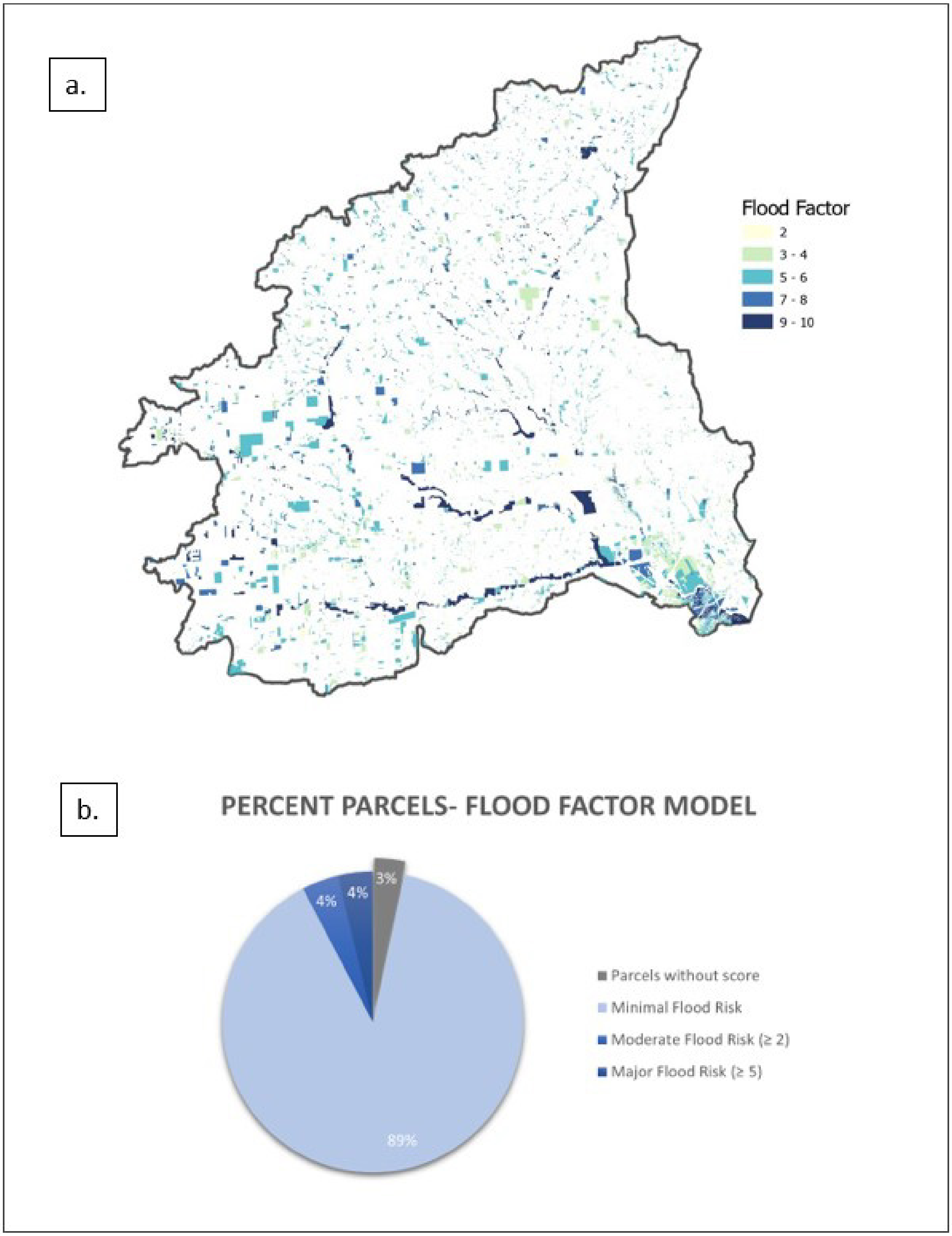


Figure 13: a. Parcels with Flood Factor score between 2 to 10; b. Percentage of Parcels with different flood factor scores.

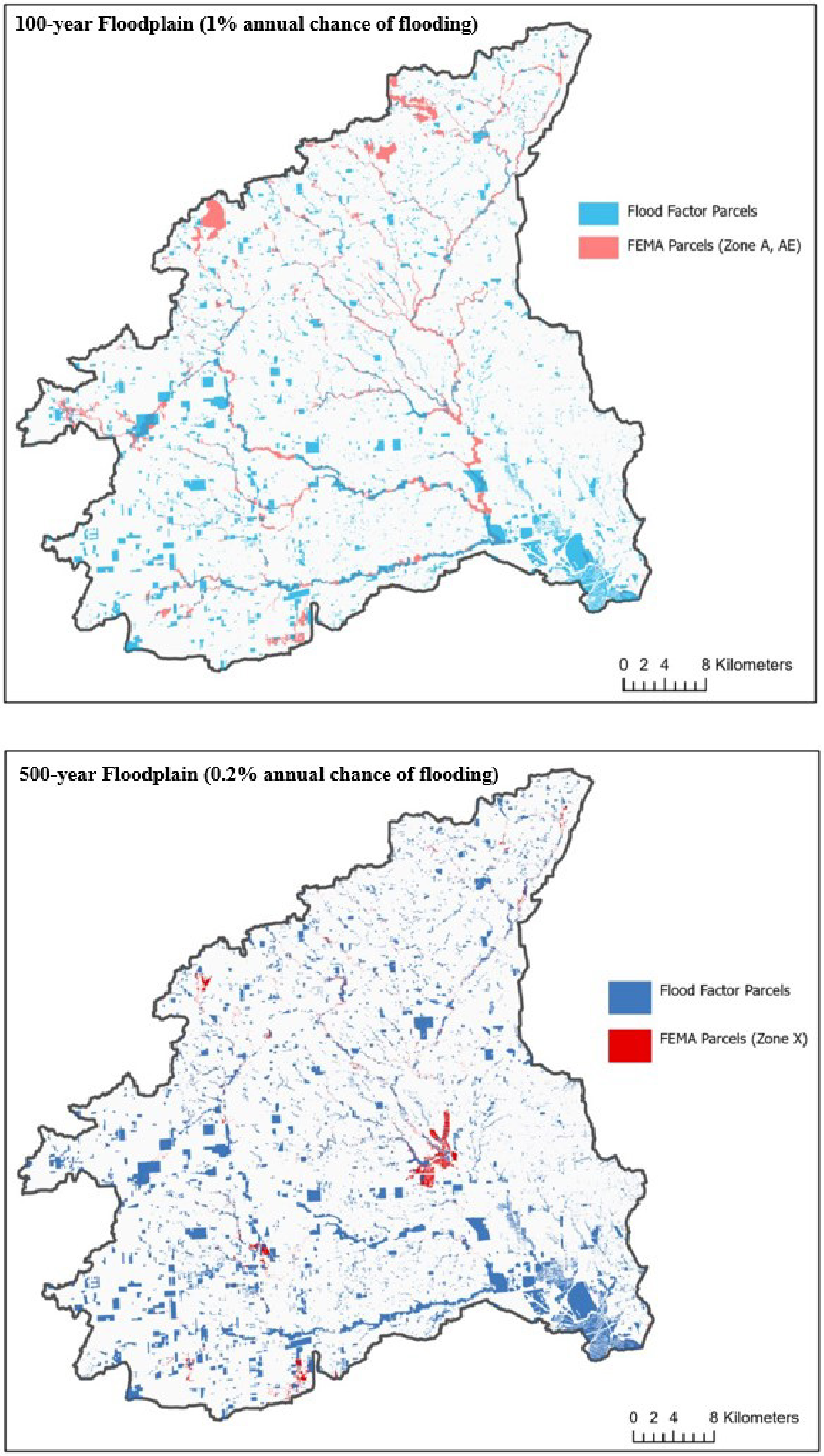


Figure 14: Comparison of parcels in the FEMA flood zones and with corresponding Flood Factor scores.

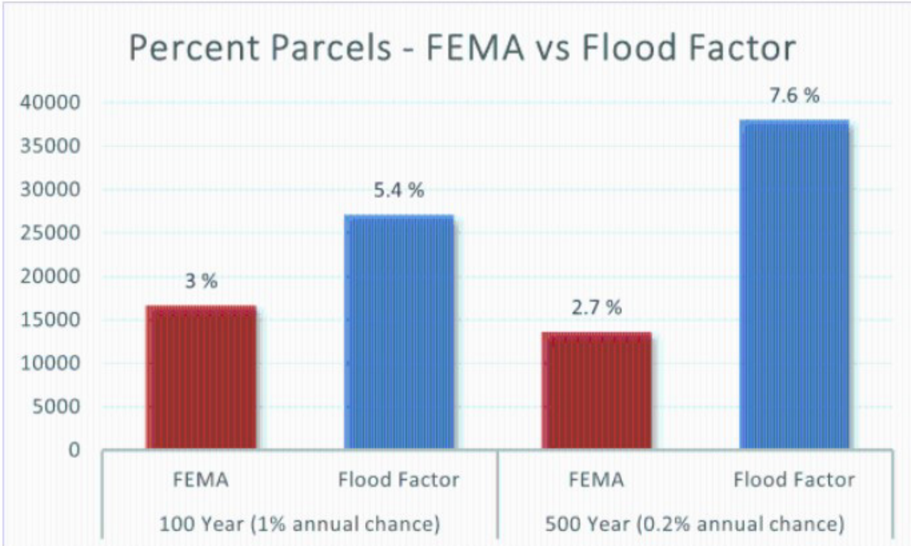
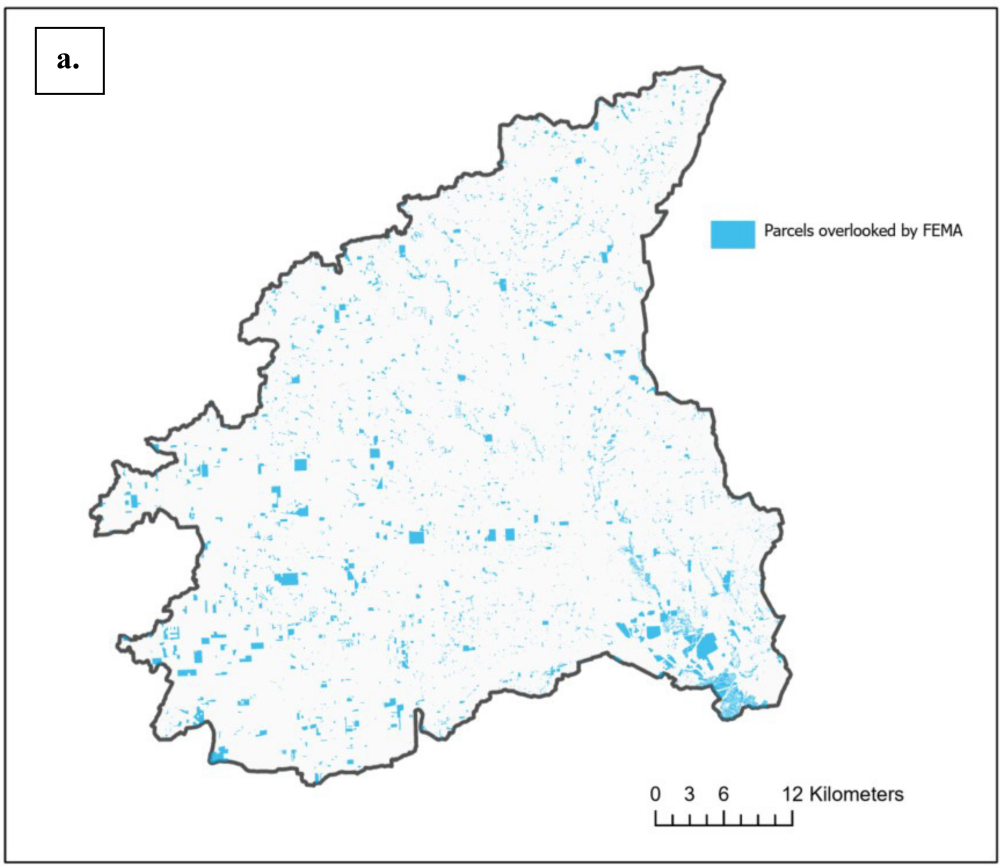


Figure 15: Bar chart showing the increased flood risk identified by FSF's model.

3.2 Overlooked Parcels by FEMA and FSF

Around 89% of the at-risk parcels identified by the FSF model constitute the federally overlooked 100-year FEMA flood zone. These parcels fall outside the boundaries of the federally recognized FEMA's Special Flood Hazard Area (SFHA) which are identified on the Flood Insurance Rate Map (FIRM). These parcels therefore stand the chance of not qualifying for suitable flood insurance if the areas are to be inundated by a flood event having a 1 % chance of being equaled or exceeded in any given year. Figure 16a. shows the spatial distribution of these federally overlooked lands, which are mostly concentrated in the southeastern and western parts of the watershed. Similarly, around 93 % of FSF's at-risk parcels in the 500-year floodplain constitute the federally overlooked flood zone. Since the 100-year floodplain is at a higher flood risk than the 500-year floodplain, a more detailed study of the land use of these federally overlooked parcels was conducted. Analyzing the land use of these overlooked parcels showed that almost 85% of these parcels comprised developed areas in highly populated areas of the watershed. The remaining areas comprised mostly forests and wetlands (Figure 17). The FSF flood model also overlooked certain parcels which were a part of the FEMA 100-year floodplain (Figure 16b.**).** Around 30% of the parcels that represented the FEMA 100-year flood zone were not identified by the FSF flood model. Looking closely at the land use of these parcels, around 35% of these parcels belonged to developed areas. The remaining parcels comprised mostly of water bodies, forests, and wetlands (Figure 17).



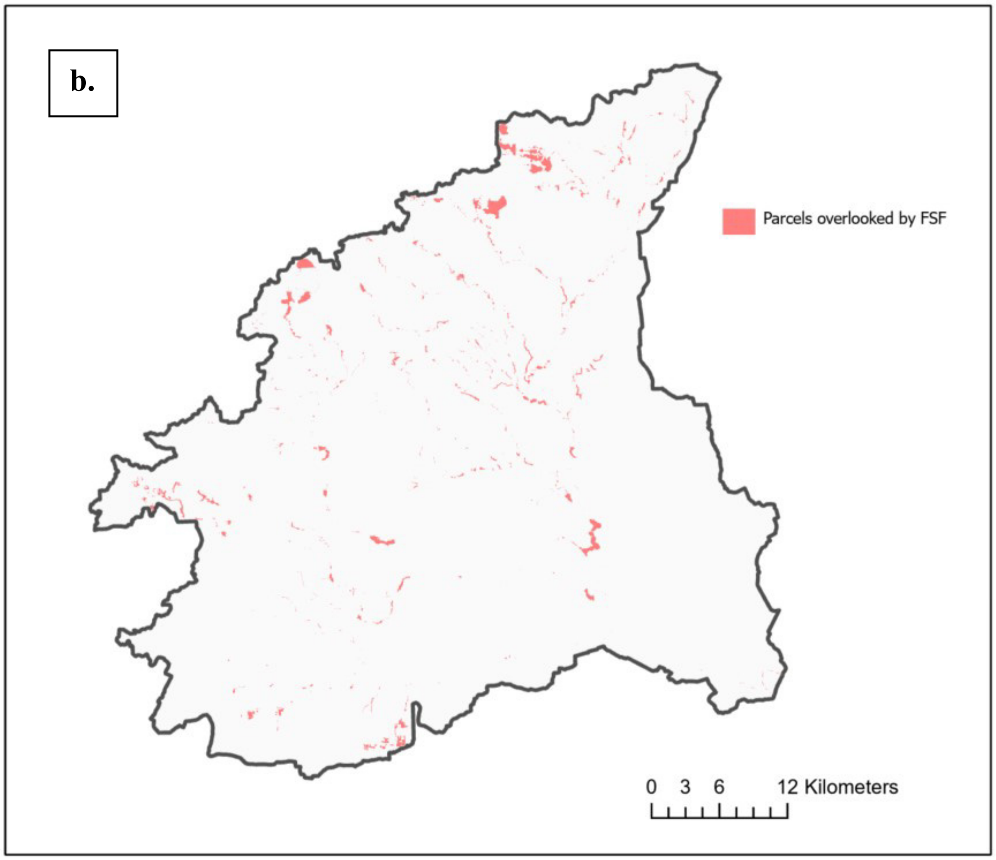


Figure 16: a. Federally (FEMA) overlooked parcels and b. parcels overlooked by FSF.

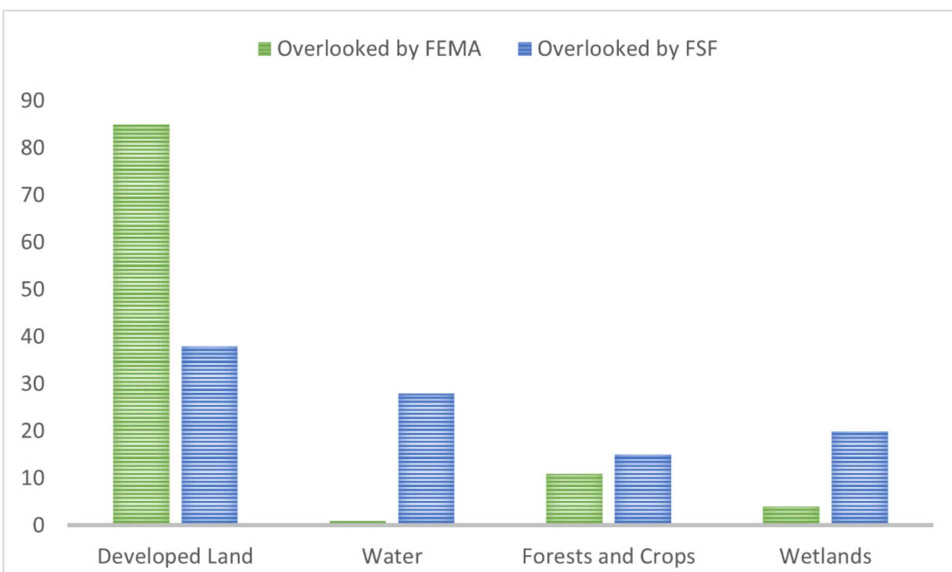


Figure 17: Land Use characteristics of the overlooked parcels.

3.3 Flooding by Sub Watersheds

To get a more detailed overview of the risk and intensity of flooding in the study area, the number of parcels at high flood risk under both FEMA and First Street Foundation's flood model was estimated separately for all four sub watersheds of the Rouge. From Figure 18 and Table 4, the Main Rouge River sub watershed shows the highest number of parcels that are exposed to flood risk with around 7% in the 100-year floodplain where FSF identifies more parcels than FEMA. There is also a substantial increase in the at-risk parcels by around 7% in the 500-year floodplain where predictably FSF identifies more parcels at-risk than FEMA. However, the Upper Rouge River sub watershed shows a significant number of parcels lying in the 100-year and 500-year floodplain, more than any other areas of the watershed. These additional parcels are seen to be identified by the FEMA flood zones but not by the FSF model. Most of these additional parcels identified by FEMA

Even though Flood Factor identifies a higher number of at-risk parcels in the watershed, a lot of parcels identified by First Street Foundation's data falls outside the designated FEMA flood zones. First Street mostly identifies this additional data due to using current climate data and precipitation data as a stand-alone risk. These parcels outside the FEMA zones therefore represent homeowners that have been unaware of and underestimated the current risk. To get further estimations and more detailed comparisons of areas with flood susceptibility the Multi-Criteria Decision Analysis (MCDA) model was applied.

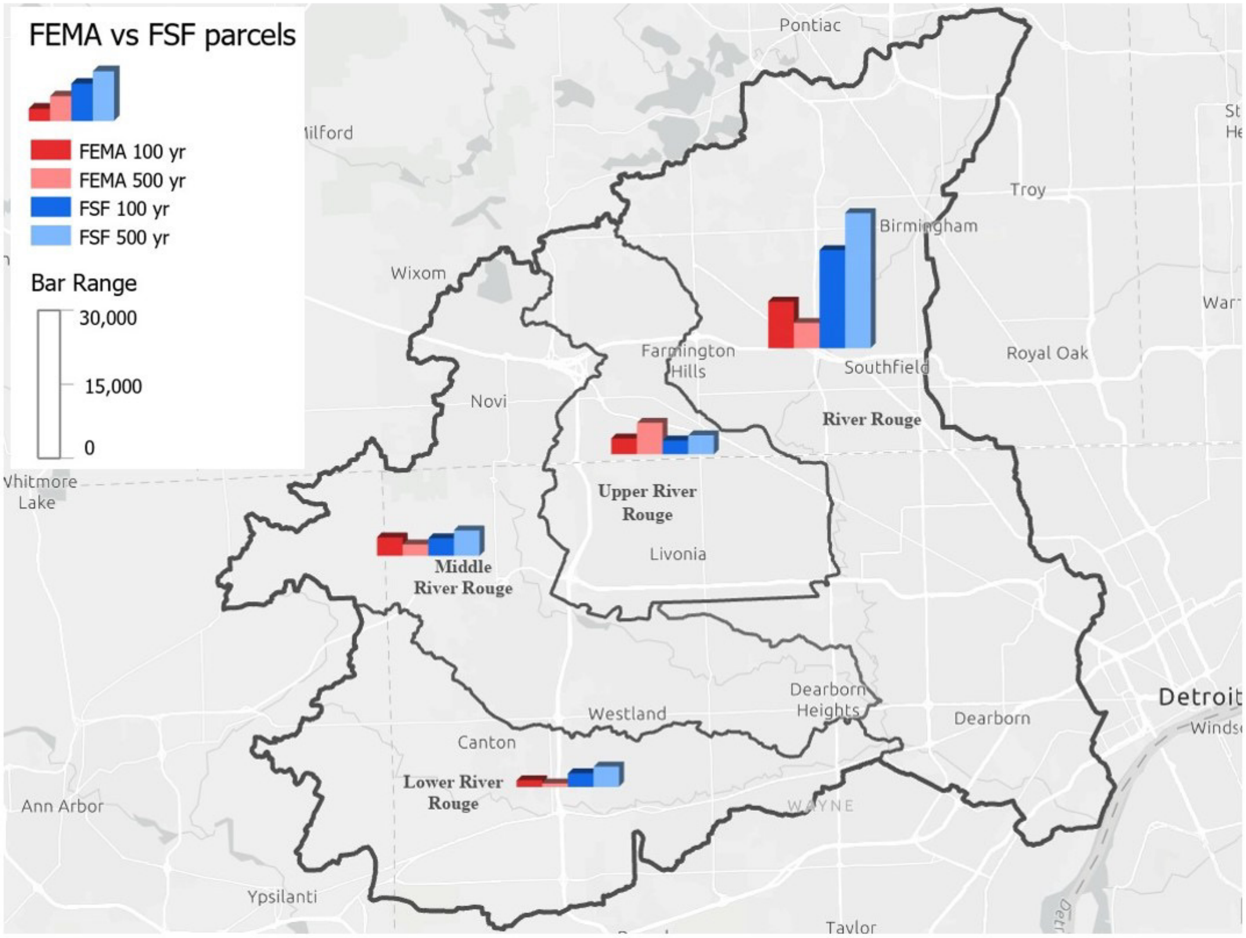


Figure 18: Comparing flood risk identified by FEMA and FSF in each sub watershed of the study area.

Rouge Sub watersheds	Percentage of Parcels			
	FEMA 100 yr.	FEMA 500 yr.	FSF 100 yr.	FSF 500 yr.
Main Rouge	3.2	1.7	6.7	9.2
Middle Rouge	3.9	2.4	3.7	5.5
Upper Rouge	4.3	8.7	3.8	5.2
Lower Rouge	1.9	1.0	3.9	5.8

Table 4: Percentage of parcels at risk flooding based on both the FEMA and FSF model.

3.4 Flood Risk Mapping

The final flood risk obtained highlighted five levels of flood risk (Figure 19): very low, low, moderate, high, and very high flood risk. The very low and low classes cover around 12% of the parcels in the study area including parts of Rochester Hills, Farmington Hills, and Wixom. These are essentially areas with high slopes, low precipitation amounts and low drainage density, majorly consisting of forests, wetlands, water bodies and less developed areas. Moderate risk areas account for around 15% of the watershed but are close to areas with high and very high flood risk and comprise mostly of low and medium intensity developed areas. The very high flood risk class identifies at least 25% of the parcels in the study area to be at extreme flood risk, of which around 99% are highly developed land. More than 50% of the parcels in the study area are also at high flood risk which also includes majority of the developed land and few parcels of forest area and barren lands. Almost all of the high flood risk areas are dominated by lower slopes, high drainage density, significantly higher amount of rainfall and 'C' or 'D' soil groups with low infiltration capacities. Increased development and uncontrolled urbanization plays a key role in addition to population density, flatter slopes, and heavy rainfall to the aggravating risk of flooding.

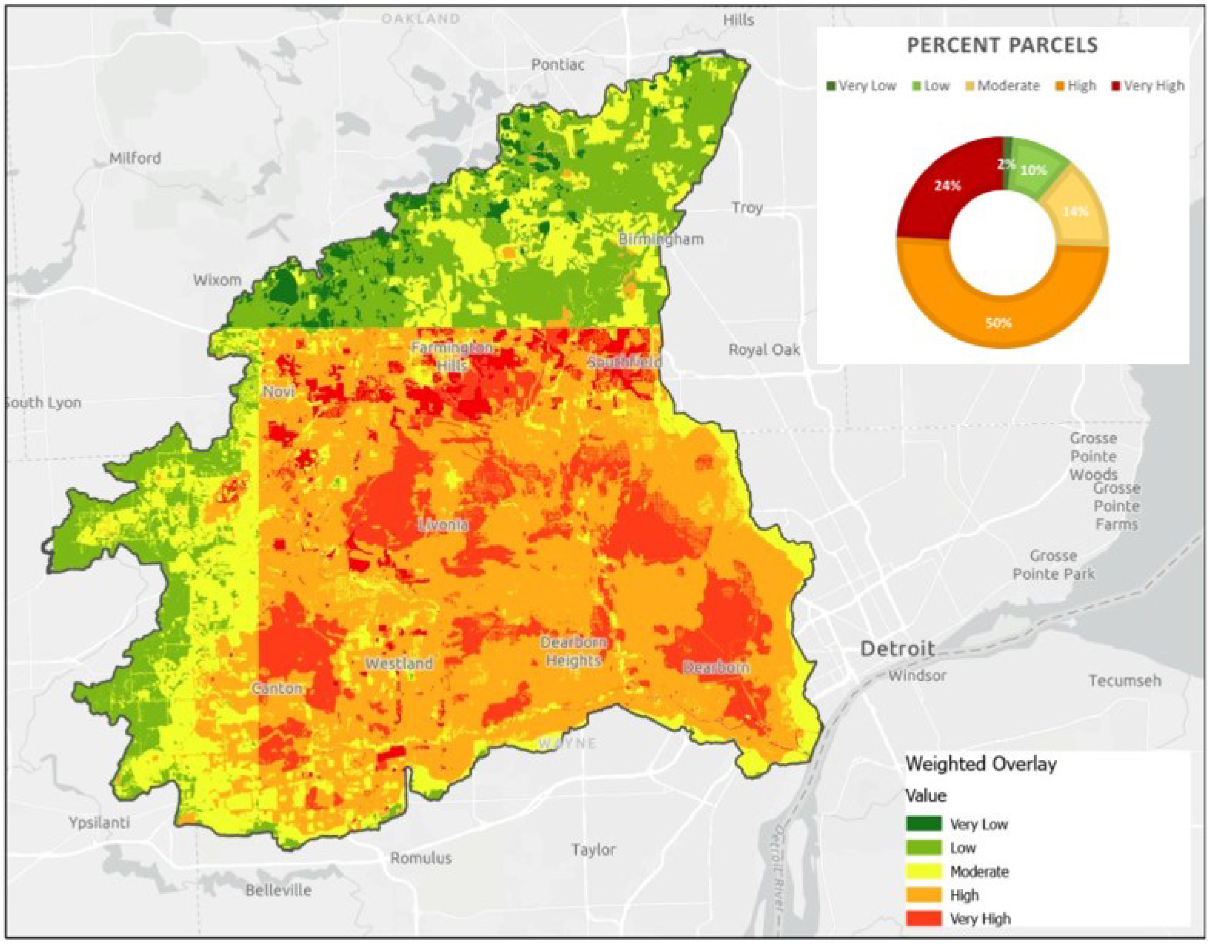


Figure 19: Final Flood Risk Map of the study area generated from the weighted overlay method.

3.5 Validation of the MCDA Model Against FEMA and FSF Flood Models

The various classes of flood risk in the final flood risk map were compared with the FEMA and the First Street Foundation's flood models. High and very high flood risk areas showed an overlap with more than 85% of the parcels with a flood factor of 5 to 10. These are the areas of major to extreme flood risk where parcels with a Flood Factor or 6 or higher have almost a 47% chance of at least 1 inch of floodwater reaching their homes (First Street Foundation, n.d.). More than 50% of both 100-year and 500-year FEMA floodplain also intersected with the identified high flood risk areas of the map. Parcels having moderate flood factor scores of 3 and 4 saw almost 70% of the parcels comprising of moderate flood risk but also consisted of a substantial amount of high flood risk areas. Around 40% of the FEMA flood zones were found to have intersected with these moderate risk areas. A significant number of parcels with a high flood factor rating were found in areas recognized as moderate or low risk areas by the MCDA model. Similarly, very high-risk areas identified by the MCDA model were found intersecting with parcels having minimal flood factor values and residing outside the FEMA 100-year and 500-year flood zones.

Chapter 4: Discussion

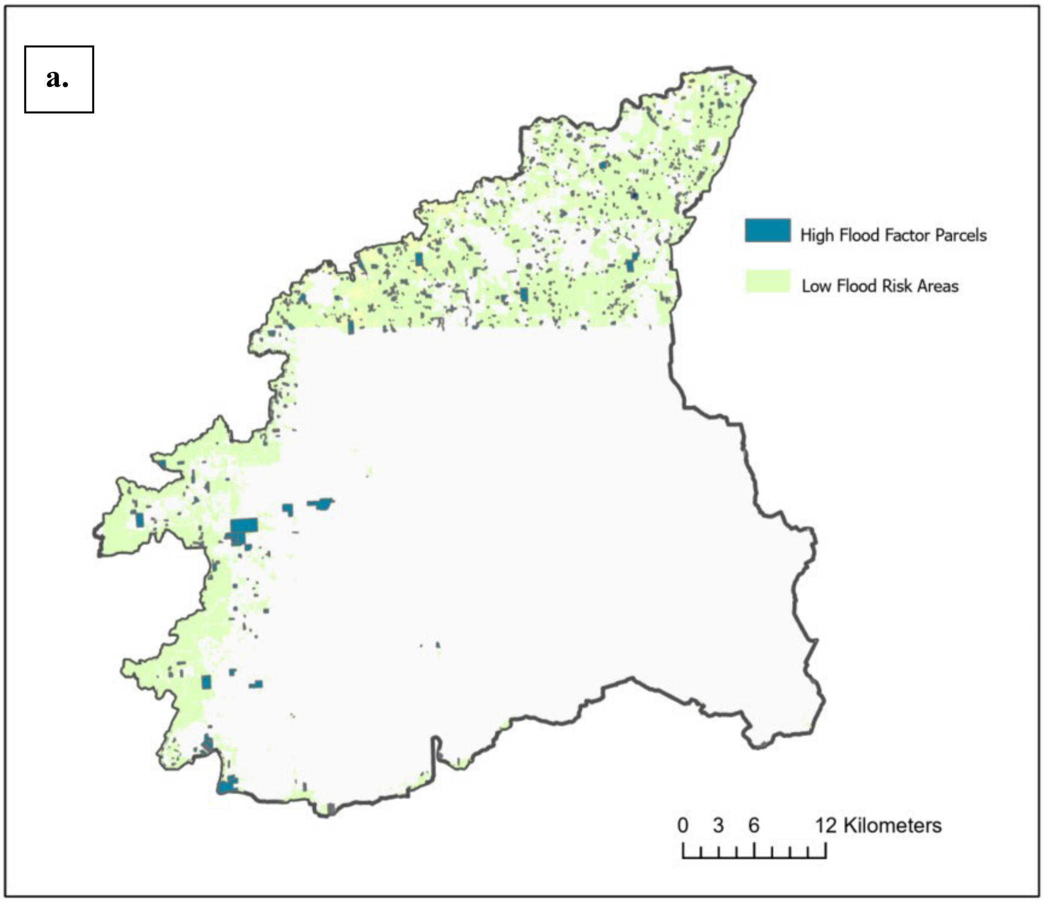
In response to the first objective of the study, the First Street Foundation's Flood Factor Model identifies a higher and increased amount of flood risk in the Rouge River Watershed. When compared with the FEMA flood zones, the Flood Factor model identifies an additional 2.5% of at-risk in the 100-year flood plain and an additional 5% of at-risk parcels in the 500-year flood plain. Moreover, utilizing the U.S. Census Redistricting Blocks (U.S. Census Bureau, 2021) data, the study identified that almost half a million people lived at risk to 100-year flooding outside the FEMA -delineated flood zone. This accounts for at least 40 percent of the total population of the watershed. This alarmingly large amount of at-risk population is being overlooked mostly because of the government's reliance on a largely incomplete and historical data dependent flood model as the foundation for the assessment of flood risk, mitigation, and policymaking nationwide (Flores, 2023).

The FEMA zones and the Flood Factor are independent risk assessments. FEMA captures the risk from a single 1-in-100 or 1-in-500-year flood event from storm surge and overflowing rivers and streams, and also most importantly it determines flood risk on the community level. In contrast, the Flood Factor model estimates flood risk on a property-level and the model accounts for flood risk due to high-intensity rainfall as well as changing climate conditions (Risk Factor, n.d.). This difference in scale of assessing flood risk can be the main factor why Flood Factor identifies more nuanced and property-specific flood risk compared to the 'in-or-out' binary floodplain analysis from FEMA maps. Flood risk identified by Flood Factor can also vary for a variety of reasons. In the case of vacant lots or where building information is unavailable the risk of flooding is analyzed against the center of the property. Such minor differences between similar buildings, including personal adaptation measures taken by the homeowners can lead to differences in the flood factor (Risk Factor, n.d.). Additionally, the model also considers 'grey' and 'green' infrastructure and adaptation projects affecting flow of water and flooding to get a more accurate flood risk (First Street Foundation, 2020). These can be the main reasons why some parcels identified in the FEMA flood zones in this study, have been overlooked by FSF'S model. Eighty-five percent of the parcels overlooked by FEMA were part of highly developed regions of the watershed, whereas the Flood Factor model overlooked parcels in areas covered majorly in forests, crops, wetlands, and water bodies. That being said, the Flood Factor data is also known to be the most powerful dataset when used in conjunction with the FEMA flood maps as well as other state or local flood risk resources. Using this model complementary to the FEMA flood maps can be beneficial not only in identifying and mitigating flood risk but can also be used for building and permitting purposes (First Street Foundation, 2020). This study can therefore be considered as a case study to calculate and estimate increased flood risk in any highly urbanized watershed like the Rouge River Watershed, across the country. The Flood Factor model further identifies and analyzes the economic impact of these underestimated at-risk parcels on a national level. The potential damage and flood risk in many parts of the country is being underestimated based on current understandings of flood risk. This is concerning since the insurance premiums in the market are priced based on these understandings by estimating the property-level average annual loss (First Street Foundation, 2021). This puts homeowners, prospective buyers, renters, and cities at risk about which insurance should be purchased, potential dangers, and what sorts of development should be restricted (Oakford, 2022). Therefore, identifying the at-risk parcels outside FEMA's designated Special Flood Hazard Areas

(SFHA), can reveal a vast economic risk associated with flooding. FEMA's new Risk Rating 2.0 calculates premiums based on specific characteristics of individual properties and also incorporates a broader range of flood frequencies such as pluvial flooding, Great Lakes flooding, flooding in leveed areas and coastal erosion outside the coastal flood zone (Horn, 2022). However, further research in these areas can demonstrate the extent of information asymmetries on flood risk and how they can contribute to financial and personal risk to property owners (First Street Foundation, 2021).

In terms of the second objective of this study, a multi-criteria analysis (AHP) was adopted which facilitated multi-source data combinations to constitute a flood risk map of the Rouge River watershed. The method was based on physical, hydrogeological, and anthropogenic parameters such as slope, drainage density, rainfall, land use, soil hydrology and impervious surface cover. Based on various previous studies, the use of a weighted approach for each of these parameters to generate areas of high flood susceptibility in a GIS environment proved to be an efficient method to gauge the overall flood risk of the watershed (Danumah, 2016). However, normalization and assigning weights were important factors in reducing bias and uncertainty in the final weighted risk model. The subjective nature of choosing the value of the weights for each parameter based on expert and personal judgements might result in an inaccurate model. But, based on Saaty's (Saaty T. L., 1990) consistency ratio test of judgments, this inaccuracy was reduced. A consistency ratio threshold of less than 10% is necessary to make a coherent judgement. A 7% consistency ratio achieved for this study proved that the judgements used in this study could be considered mostly coherent. However, a lesser value would have been preferred for a more accurate and consistent model which could be improved by dividing the chosen flood risk parameters into hazard factors and vulnerability factors. Furthermore, inclusion of parameters such as NDVI, population density, storm drainage system and urban structure types (Danumah, 2016); (Radwan, 2019); (Swain, 2020) could give us a more refined and detailed overlook at the flood risk of the study area. Such an in-depth model might have also been useful to understand the explanations behind certain discrepancies observed during the validation of the MCDA model in this study. The existence of a significant number of parcels with high flood factor in low flood risk areas and parcels with minimal flood factor in high flood risk areas were identified. Based on understandings from First Street Foundation's (FSF) methodology (First Street Foundation, 2020), the Flood Factor model considers the uncertainty of the future climate along with the current climate by using projections from twenty-one Global Climate Models, which could not be included in the MCDA model used in this study. Based on this process which includes possible future risks along with carbon emission scenarios and historical period analysis of thirty years, it is highly possible that the high flood factor parcels recognized in the low-risk regions showcases impending flood risk in the coming years. Locations of such regions (Figure 20 a.) can therefore be used for possible local adaptation measures along with identifying flood mitigation projects and storm drainage system limitations. The Flood Factor model has also included various adaptations and modifications by human activity which impact the flow of water and in turn flooding. This can therefore result in the parcels occurring in the high flood-risk areas to have low flood factors (Figure 20 b.). The FSF has incorporated an extensive database of 'grey and green infrastructure and adaptation projects. Infrastructure solutions like levees, flood control channels and pump stations make up the 'grey' adaptations whereas 'green' infrastructure consist of wetland restoration, retention basins, creek rehabilitation projects and floodable open space to contribute to flood reduction. The adoption of such green infrastructure projects in Southeast Michigan can lead to significant ecological benefits by preserving river-floodplain ecosystems as well as serve a large economic potential by saving hundreds of millions of dollars in flood losses. Hybrid solutions, utilizing both green and grey infrastructure are also proving to be the most cost-effective and resilient infrastructure systems. Examples of hybrid solutions such as utilizing a mangrove conservation and a levee can become important flood mitigation measures as incidences of flooding increase. Detroit's recent initiative to transform vacant lots into green spaces is a particularly noteworthy project that can result in a reduction of stormwater discharge by approximately 100,000 gallons during large storms (Dauer, 2020).

Overall, the comparison of two well-known flood models along with the flood risk map using an MCDA technique can be used as a simple and executable method to identify the risk of flooding at a parcel level in any vulnerable area. Determining location of parcels at high flood risk can further help government agencies as well as local non-profit organizations to use a targeted approach at developing restoration plans and mitigation practices, especially in a highly urbanized and impaired watersheds like the Rouge River Watershed.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High Flood Factor Parcels
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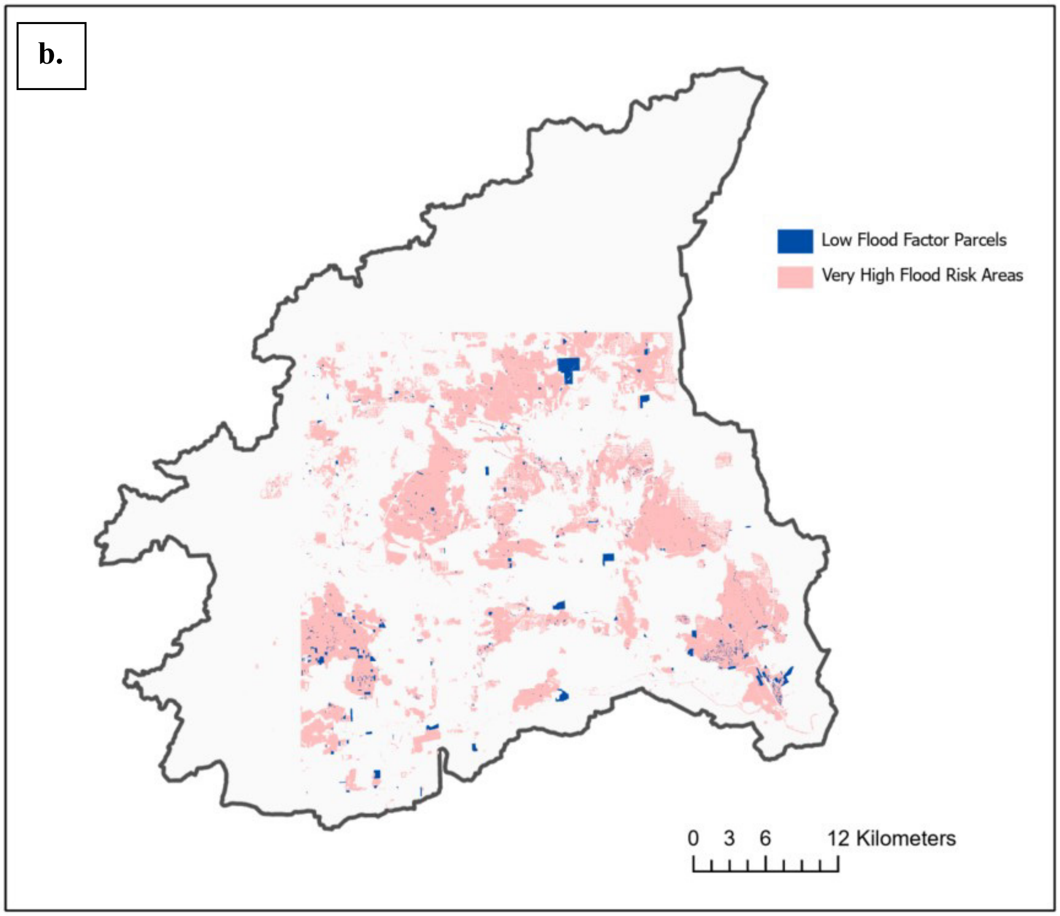

Figure 20: a. Parcels with High Flood Factor scores in Low-risk areas identified by MCDA; b. Parcels with Low Flood Factor scores in Very High Flood Risk areas identified by MCDA.

Chapter 5: Conclusion

In this study, an integrated approach was taken to assess the flood risk of the Rouge River Watershed by comparing two well-known flood models and a multi-criteria-decision-analysis technique. The objective was to utilize the data from FEMA, which is a federally funded flood model, and Flood Factor, a more detail-oriented model by the non-profit organization, First Street Foundation, to gauge the over or underestimation of flood risk in the study area. The impact of our changing climate, more intense rainfall and increasing urban development provides the need to develop more robust and detailed risk assessments, especially in a highly impaired watershed like the Rouge. The analyses conducted in this research conceivably revealed an additional 2.5% and 5% parcels at risk of a 100-year and 500-year flood respectively. These parcels are currently being overlooked in terms of flood risk and account for around half the study area's population thus proving the underestimation by FEMA's flood model. Moreover, these unidentified parcels that are being overlooked by FEMA's 100-year flood zones are not 'mandated for protection' through the National Flood Insurance Program (NFIP) and lack the investments in flood protection received by these FEMA-delineated 100-year flood zones (Flores, 2023). Approximately 13 million U.S. residents have been identified by FEMA to reside in 100-year flood zones, however First Street Foundation's analysis has identified approximately 41 million residents (Wing, 2018). Hence, effective, and unbiased flood protection, along with accurate flood risk mapping, is needed more than ever. The simultaneous use of both the FEMA and FSF's flood model can be one approach of a more accurate flood risk estimation and mapping in areas prone to increased flooding. Flood susceptible zone mapping can be considered as one of the most constructive methods to assess the flood risk of a vulnerable area (Swain, 2020). The generation of a flood risk map using MCDA was therefore advantageous to estimate the overall hazard-prone regions of the study area. This technique also used various previous studies and expert judgments to show that combined effects of factors such as rainfall, soil hydrology, slope, land use and drainage density, play a significant role in flooding. Additionally, using Saaty's AHP technique, every flood dependent factor was given the highest suitability ranking and weightage to create areas of high flood susceptibility. The resulting map indicated that almost 50% of the watershed was at high flood risk.

Analyses from this study can be used to assist stakeholders, planners, and decision-makers to create potential anticipatory measures and suitable infrastructure for flood risk management. Such maps can also be used for better land use planning and proper supervision of the flood-prone regions in turn ensuring sustainable socio-economic development (Danumah, 2016; Swain, 2020). Further development of the methodology used in this study can be applied by including high resolution satellite imagery of flood hazards as well as information on mitigation and adaptation projects to generate more precise flood risk maps for the overlooked (Porter, 2021). Overall, special attention should be given to the high-risk areas based on increasing population density and local needs. Monitoring should also be undertaken in the medium to low-risk areas to prevent or minimize any imminent flooding as a result of a changing climate.

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