



North Central Texas
Council of Governments

Integrating Transportation and Stormwater Infrastructure

GIS-Based Approach for Flood Control Prioritization Mapping

June 2026



*This study was funded by the Texas Water Development Board and
Texas Department of Transportation.*



The GIS-based Multi-criteria Decision-making Approach for Flood Control Prioritization Mapping

Authors: Yufan Zhang, Ph.D., E.I.T (Texas A&M AgriLife), Fouad Jaber, Ph.D., P.E. (Texas A&M AgriLife)

1. Background

The Transportation and Stormwater Infrastructure (TSI) Study seeks to improve flood resilience across the West Study Area by integrating transportation, stormwater management, land use planning, and environmental considerations into a coordinated regional planning framework. As rapid urbanization and transportation system expansion continue throughout North Central Texas, communities face increasing flood risks that threaten transportation infrastructure, disrupt emergency access, degrade natural resources, and affect vulnerable populations. Because financial and land resources are limited, regional planning requires a systematic approach to identify where flood mitigation investments will provide the greatest overall benefit.

To support this objective, Texas A&M AgriLife team developed a GIS-based multi-criteria spatial analysis framework to evaluate flood susceptibility, flood vulnerability, and flood control priorities across the West Study Area. The framework integrates geological, hydrologic, environmental, transportation, and socioeconomic datasets to produce planning-level maps that identify areas where flood mitigation efforts are most needed. By considering both physical flood conditions and community vulnerability, the framework provides a comprehensive basis for prioritizing future flood mitigation investments.

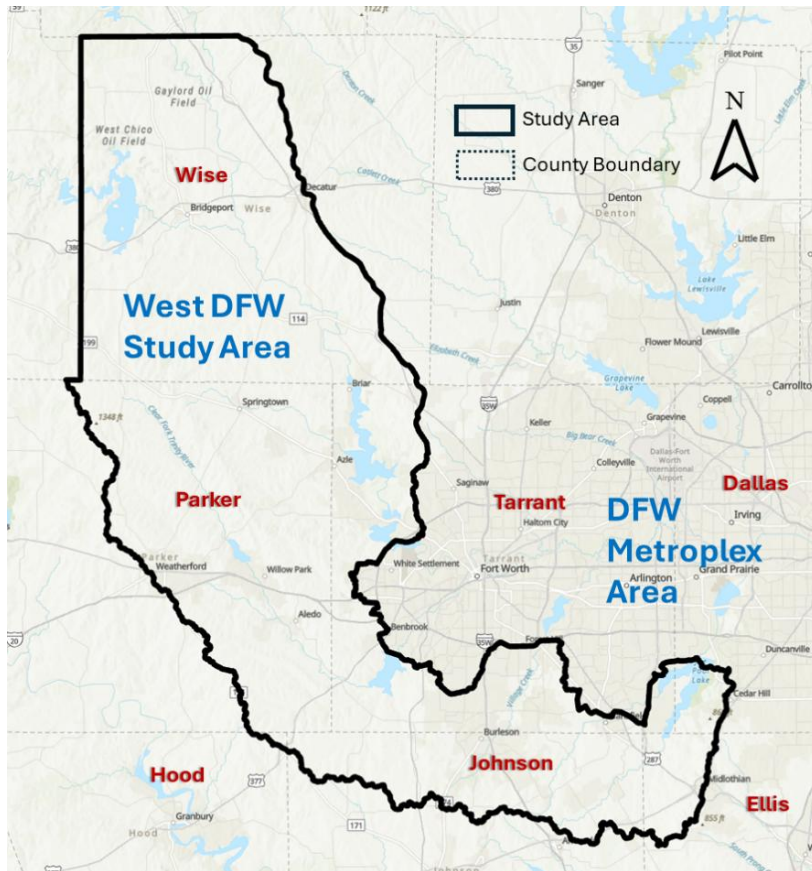
The resulting maps are intended to serve as regional decision-support tools rather than site-specific design products. They can be overlaid with additional GIS datasets, such as projected park improvements, roadway corridors, parking lots, medians, rights-of-way, publicly owned properties, or other implementation opportunity layers, to identify candidate locations where GSI and NBS practices are both needed and feasible. This integrated approach supports more informed planning by combining flood priority with implementation opportunity.

This document presents the complete methodology used to develop the GIS-based framework, including data acquisition, preprocessing, factor development, weighting procedures, and map generation. The methodology is designed to be transparent, repeatable, and transferable to other watersheds or regions with similar planning objectives. The resulting flood susceptibility, vulnerability, and prioritization maps

for the West Study Area are presented in the final section of this document and are intended to support future planning, project prioritization, and implementation of transportation and stormwater resilience strategies.

2. Study Area

An area northwest of the Dallas-Fort Worth (DFW) Metroplex located within the North Central Texas Council of Government (NCTCOG) boundary has been selected as the study area, deemed the West DFW Study Area. The West DFW Study Area (Fig. 1) consists of less developed land to the south, west, and northwest of the DFW Metroplex. The approximate population of the study area is 442, 171 (U.S. Census Bureau, 2018). The approximately 1,750-square-mile study area is bounded by county lines (between Wise County and Jack County to the west, and Wise County and Montague County to the north) as well as the Trinity River watershed boundaries to the south and southwest. The county boundaries also represent the NCTCOG boundaries, while other boundaries ensure that the study area considers only areas within the Trinity River Basin. The West study area includes portions of Dallas, Ellis, Hood, Johnson, Parker, Tarrant, and Wise Counties.

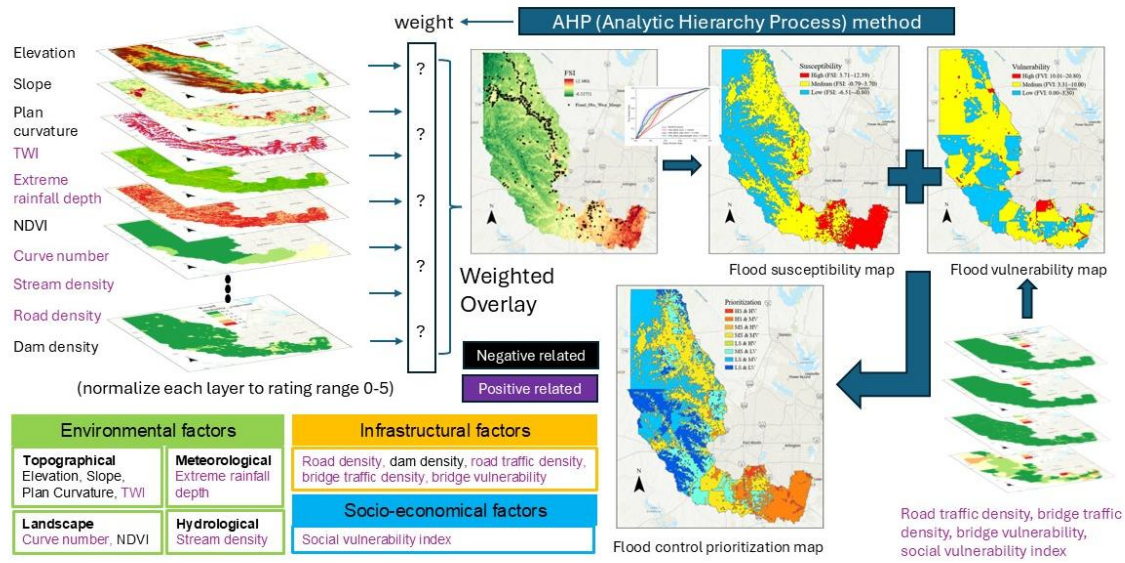


[Fig. 1 Study area]

The study area is upstream of the DFW Metroplex and is anticipated to experience urbanization and population growth, making it an ideal candidate for proactive regional stormwater management. Any increase in runoff or adverse effects from urbanization may cause or worsen flooding in communities in the DFW Metroplex along the Trinity River, notably Fort Worth, Arlington, Grand Prairie, and Dallas. Future conditions in the DFW Metroplex, including changes in frequency, duration, and intensity of storms, can present additional challenges for stormwater planning.

3. Methodology

The research methods and workflow in this study can be recapitulated in Figure 2 including a literature review summarizing and categorizing all the conditioning factors, GIS-based weighted overlay analysis, model validation, and consolidation of flood susceptibility and vulnerability.



[Fig. 2 Research workflow and methodology]

3.1. Conditioning Factors

After reviewing extensive, up-to-date literature (30 papers over the past 3 years, summarized in Table 1), ten conditioning factors that affect flood risk and vulnerability were selected: elevation, slope, plan curvature, topographic wetness index (TWI), extreme rainfall depth, curve number, normalized difference vegetation index (NDVI), stream density, road density, and social vulnerability index.

Table 1. Literature review on flood susceptibility mapping study

Authors/Year	Study area	Mapping approach	Conditioning factors
Alimi et al., 2022	Osogbo metro, Nigeria	MCDM: weighted overlay	Stream proximity, drainage density, elevation, slope, stream power index (SPI), topographic wetness index (TWI), normalized difference vegetation index (NDVI), land use/land cover (LULC)
Linh et al., 2022	Markazi, Iran	Machine learning: KNN, XGBoost, GA-XGBoost)	Altitude, aspect, slope, plan curvature, profile curvature, drainage density, distance from river, land use, lithology, distance from road, rainfall, SPI, TWI, distance from residential
Fang et al., 2022	Fujian, China	Machine learning: random forest (RF)	Distance to river, SPI, flow accumulation, stream transportation index (STI), stream order, aspect, plan curvature, profile curvature, slope, topographic position index (TPI), TWI, topographic roughness index (TRI), NDVI, normalized difference impervious surface index (NDISI), rainfall dynamic patterns index (RDPI)

Ekmekcioğlu et al., 2022	AL, USA	Machine learning: RF, ET, Adaboost, XGBoost	Elevation, slope, aspect, plan curvature, profile curvature, drainage density, distance to river, curve number, rainfall, NDVI, TWI, TRI, STI, SPI
Mudashiru et al., 2022	Northeast Penang basin, Malaysia	MCDM: weighted overlay + AHP or fuzzy-AHP	Drainage density, elevation, land use, slope, rainfall, infiltration, TWI, time of concentration, flood depth, distance from inundated locations, distance from rivers, population, distance from roads/buildings
Deroliya et al., 2022	Lower Mahanadi river basin, India	Machine learning: decision tree, random forest, and gradient-boosted decision trees	Digital terrain model, elevation difference to the nearest stream, flow accumulation, multi-resolution valley bottom flatness index, topographic index, vertical distance to the nearest stream, local slope, plan curvature, profile curvature, convergence index, downslope index, tangential curvature, distance to the nearest stream
Edamo et al., 2022	Abela-Abaya floodplain, Ethiopia	MCDM: MABAC, TOPSIS, VIKOR, and SAW; Machine learning: NBT and NB	Elevation, LULC, soil, aspect, geomorphology, NDVI, rainfall, distance to river, TWI, STI, SPI, geology, curvature, flow accumulation, slope, flow direction
Pacetti et al., 2022	Florence, Italy	MCDM: weighted overlay	Impervious area, slope, hydrologic soil group, density of sewer system, social vulnerability index
Mousavi et al., 2022	Mohammad-Abad catchment, Iran	MCDM: TOPSIS; Machine learning: EBF and WoE	Elevation, slope, aspect, plan curvature, TWI, SPI, distance to river, drainage density, NDVI, geology, soil type, LULC
Kaiser et al., 2022	Bavaria region, Germany	Machine learning: RF, GBDT, CB	Elevation, slope, geographic coordinate, land use, sealing degree, heavy rain hours, distance to river, height above the nearest drainage, permeability of the upper aquifer, saturated hydraulic conductivity, landforms, elongation ratio, relief, melton number, length-area-relation, built-up area share, agricultural area share
Dutta et al., 2023	Dakshin Dinajpur, India	Bivariate statistical: SEI and WofE-IV	Rainfall, geomorphology, geology, soil, elevation, slope, curvature, flow direction, stream density, distance to road, distance to river, LULC, TWI, NDVI, NDWI
Addis, 2023	Upper Abay river basin, Ethiopia	Bivariate statistical: frequency ratio, information value model	Elevation, aspect, curvature, TWI, NDVI, distance to road, distance to river, soil texture, lithology, land use, rainfall
Saravanan et al., 2023	Idukki district, India	Machine learning: Adaboost, gradient boosting, XGB, CatBoost, SGB	Aspect, LULC, distance to road, distance to stream, geology, geomorphology, soil, elevation, SPI, STI, curvature, slope, TRI, TWI, NDVI, rain
Li et al., 2023	Chengdu, China	Statistical: NB	Elevation, aspect, slope, curvature, precipitation, land cover, normalized difference built-up index, fraction of vegetation cover, distance to rivers, population density
Ebrahimi et al., 2023	Zagros mountains, Iran	Machine learning: GLM, BRT, RF, SVM, MARS, MaxEnt	DEM, slope, TWI, distance to stream (vertical and horizontal), flow direction, flow accumulation, NDVI, precipitation
Chaulagain et al., 2023	Kathmandu metro, Nepal	MCDM: weighted overlay + AHP	Slope, elevation, drainage density, rainfall, LULC, distance from river
Mehrvan et al., 2023	Ahwaz, Iran	Machine learning: SVM	Altitude, slope, aspect, TWI, SPI, NDVI, distance to stream, curvature, rainfall, soil type, LULC
Razavi-Termeh et al., 2023	Sulaymaniyah, Iraq	Machine learning: RF, RF-GA, Bagging, Bagging-GA	Land cover, rainfall, altitude, distance to river, TWI, aspect, NDVI, geology, slope, SPI, plan curvature

Pradhan et al., 2023	Jinju Province, South Korea	Deep learning: CNN + SHAP	Elevation, land cover, topography, lithology, soil texture, soil depth, surface soil texture, deep soil texture, forest type, forest age, forest density, timber diameter
Lyu & Yin, 2023	The Guangdong-Hong Kong-Macau Greater Bay Area, China	Machine learning: RF, GBDT, XGBoost, CATBoost	Annual mean rainfall, annual mean rainfall days, annual mean wind speed, frequency of typhoon, elevation, slope, aspect, TWI, vegetation cover, river density, land use, population density, GDP, road density
Yadav et al., 2024	Mumbai, India	MCDM: weighted overlay + AHP	LULC, distance to water bodies, DEM, slope, drainage density, TWI, population density, temperature, soil type, rainfall
Jemai et al., 2024	Gabes catchment, Tunisia	MCDM: weighted overlay + AHP	Rainfall, slope, curvature, elevation, land cover, distance from river, drainage density, soil type
Chowdhury, 2024	Northeastern area, Bangladesh	Bivariate statistical: FR, WoE, CF, SE, IV	Elevation, slope, curvature, TWI, TRI, SPI, distance to stream, stream density, rainfall, physiography, aspect
Shah & Ai, 2024	Sindh province, Pakistan	Bivariate statistical: FR; MCDM: weighed overlay + AHP	Elevation, slope, aspect, curvature, TWI, LULC, NDVI, NDWI, rainfall, distance to road, distance to stream, drainage density, soil type, geological composition
Wahba et al., 2024	Ibaraki prefecture, Japan	Machine learning: RF	Elevation, slope, distance to stream, distance to road, distance to river, land cover, aspect, plan curvature, profile curvature, SPI, TWI
Widya et al., 2024	Cheongju, South Korea	Machine learning: SVR, BOOST, LSTM	Slope, aspect, LS factor, wind, exposition, TWI, plan curvature, NDWI, material, geology, soil drainage, soil depth, deep soil texture, surface soil texture, land use type, forest density
Danso et al., 2024	Sekondi-Takoradi, Ghana	MCDM: weighed overlay + AHP	Soil drainage profile, flow accumulation, drainage density, proximity to river, slope, land use/cover, NDVI
Amiri et al., 2024	Karkheh and Karun river basin, Iran	MCDM: weighed overlay + AHP	Elevation, curvature, slope, aspect, TWI, NDVI, land cover, geology, precipitation, distance to river, distance to town, distance to road
Liu et al., 2024	Houston/Dallas/New York, USA	Machine learning: RF, GBDT	Elevation, distance to the stream, impervious area, distance to the road, population density
Aloui et al., 2024	Qatar	MCDM: weighed overlay + AHP	Rainfall, elevation, slope, lineament density, drainage density, LULC, NDVI, soil type, lithology, stormwater drainage system density

In addition to the above conditioning factors, four factors (dam density, road traffic density, bridge traffic

density, and bridge vulnerability), which have rarely been used in previous studies, were introduced in

this study to better represent the vulnerability aspect and the purpose of protecting critical infrastructure

during extreme rainfall events. All the factors were classified in the following three categories:

environmental, infrastructural, and socio-economical. Within environmental factors, four sub-categories

(topographical, meteorological, landscape, and hydrological) were further identified. Detailed information

about data sources, data processing, and the relationship with flood risk and vulnerability are discussed in

the following paragraphs and summarized in Table 2 at the end of sub-section 3.1.

3.1.1. Environmental Factors

3.1.1.1. Topographical

Elevation: Elevation influences water flow, accumulation, and drainage patterns within a region. Areas with higher elevation are generally less susceptible to flooding due to their ability to facilitate runoff, directing water away from the surface. In contrast, low-lying regions, especially those near bodies of water or in floodplains, are more vulnerable to inundation, as they serve as natural collection points for surface water (Alrajhi et al., 2016; Dekongmen et al., 2024). In this study, the most recent available 1/3 arc-second digital elevation model (DEM) was acquired from The National Map (TNM) (USGS, 2025).

Slope: Slope determines the velocity, direction, and extent of surface water flow. Steeper slopes promote rapid runoff, reducing the likelihood of water accumulation and decreasing the probability of localized flooding in higher-gradient areas. Conversely, flatter slopes tend to impede water movement, encouraging water accumulation and prolonging inundation periods, particularly in areas with poor drainage infrastructure (Hallema et al., 2016; Negese et al., 2022; Al-Juaidi, 2023).

Plan Curvature: Plan curvature is perpendicular to the direction of the maximum slope of the land surface. It relates to the convergence and divergence of flow across the surface, and significantly influences water flow patterns and flood risk. A positive value of plan curvature indicates that the surface is laterally convex, which facilitates water dispersion and reduces flood susceptibility by directing runoff away from a specific area. Conversely, a negative plan curvature indicates that the surface is laterally concave, which tends to concentrate surface water flow, increasing the likelihood of water accumulation and flooding in these zones. A value of zero indicates that the surface is linear (Ghahraman et al., 2023; Esri Curvature function, 2025a).

Topographic Wetness Index (TWI): TWI quantifies the potential for water accumulation based on the interplay between slope and upstream contributing area. High TWI values indicate areas with low slopes and significant upstream water contribution, which are prone to saturation and flooding during rainfall events. Such zones often serve as natural collection points for surface runoff, making them more

vulnerable to prolonged inundation. Conversely, low TWI values, typically associated with steep slopes and limited contributing areas, correspond to regions with reduced flooding risk due to faster water drainage (Pourali et al., 2016; Blumenthal et al., 2018; Ali et al., 2019; Swain et al., 2020; Levien, 2022). The equation to calculate TWI in this study follows the original TWI formula (Equation 1) developed by Beven & Kirkby (1979).

$$TWI = \ln \frac{\alpha}{\tan \beta} \quad (1)$$

Where: α is upslope area (m^2m^{-1}), and β is the slope gradient (in degrees).

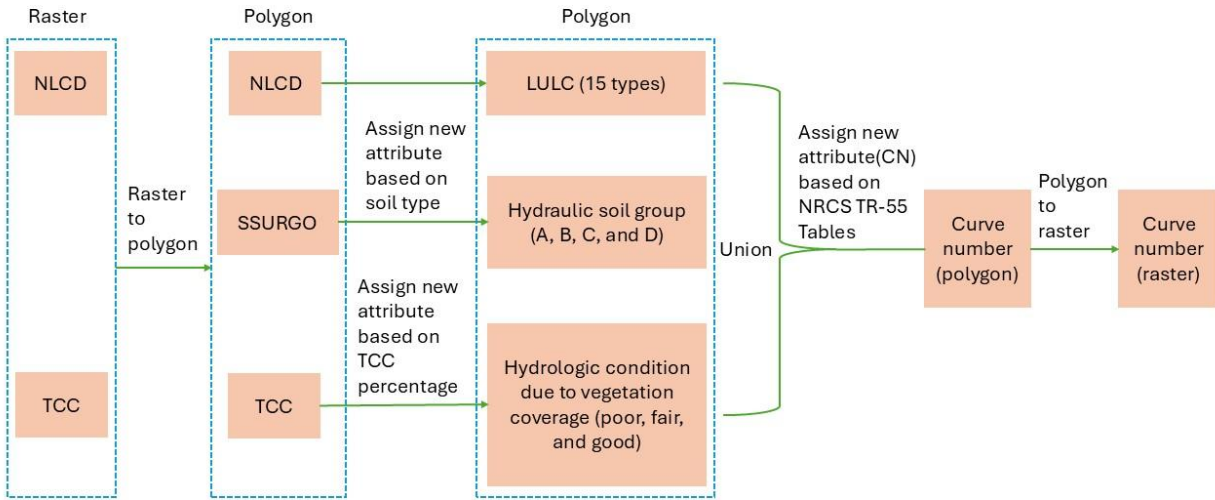
1.1.2. Meteorological

Extreme Rainfall Depth: Rainfall events are classified as "extreme" based on their recurrence intervals, such as a 50-year, 100-year, or 500-year storm (USGS, 2018). In this study, a 100-yr 24-hr rainfall event is considered extreme. The spatial distribution and intensity of extreme rainfall influence localized flood risks (Erhardt et al., 2022). To examine the variability of extreme rainfall depth (100-yr, 24-hr) within the study area, the gridded data in GIS compatible format was acquired from NOAA Atlas 14 precipitation frequency estimates (NOAA, 2025). The acquired Texas-scale dataset was then clipped to the extent of the study area.

3.1.1.3. Landscape

Curve Number (CN): CN is a widely used parameter in hydrological modeling that quantifies the potential for surface runoff based on land use, soil type (hydrologic soil group), and hydrologic condition (vegetation cover and antecedent soil moisture). Higher CN values indicate greater runoff potential, typically associated with urbanized areas or regions with impervious surfaces where infiltration is minimal. Conversely, lower CN values correspond to areas with permeable soil and vegetative cover, which promote water infiltration and reduce runoff. Changes in land use, such as deforestation or urban expansion, can significantly increase the CN value, altering the hydrological response of a watershed and exacerbating flood risk. On the other hand, the runoff mitigation strategies, such as green stormwater infrastructure implementation, could help reduce the negative impact of flooding (USDA, 1986; Garen &

Moore, 2005; Farran et al., 2021). In this study, three individual maps, land cover and land use (LULC), hydrologic soil group, and tree canopy cover (TCC), were consolidated to give each pixel required information to derive CN based on Natural Resources Conservation Service (NRCS) Technical Release-55 (TR-55) (USDA, 1986). The 2023 land cover product was retrieved as GIS compatible raster file from USGS as part of the Annual National Land Cover Database (NLCD). The dataset depicts the predominant thematic land cover class within the mapping year with respect to broad categories of artificial or natural surface cover (USGS 2023 Land Cover, 2024). Fifteen types of LULC were identified in the study area: open water, developed (open space), developed (low intensity), developed (medium intensity), developed (high intensity), barren land, deciduous forest, evergreen forest, mixed forest, shrub/scrub, grassland/herbaceous, pasture/hay, cultivated crops, woody wetlands, and emergent herbaceous wetlands. Soil type was downloaded as GIS compatible polygon shapefile from the Soil Survey Geographic Database (SSURGO) at Web Soil Survey (USDA-NRCS, 2024). The hydrologic soil group was developed as an additional attribute column based on the corresponding soil type names. The 2021 TCC dataset was obtained as a GIS compatible raster file from the USDA Forest Service, showing the tree canopy coverage in percentage (USDA Forest Service, 2023). The hydrologic condition was classified into three categories (poor, fair, and good) based on the thresholds defined in the NRCS TR-55 (USDA, 1986). Due to the data availability and uncertainty, antecedent soil moisture conditions were not applied in the process of CN determination in this study. A detailed GIS workflow regarding CN development is shown in Figure 3.



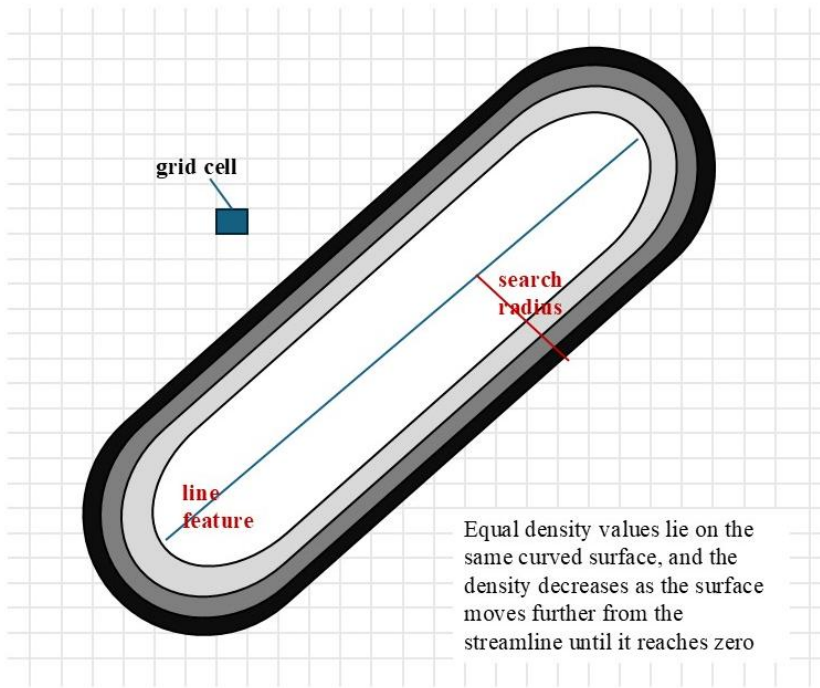
[Fig. 3 GIS workflow to develop curve number]

Normalized Difference Vegetation Index (NDVI): NDVI is a key indicator of vegetation health and density, which directly impacts flooding risk by influencing infiltration, runoff, and soil stability. Areas with high NDVI values, indicating dense and healthy vegetation, are generally less susceptible to flooding because vegetation enhances soil permeability, and reduces surface runoff. In contrast, areas with low NDVI values, such as barren or impervious surfaces, are more prone to flooding due to reduced infiltration capacity and increased runoff. Vegetation also plays a critical role in intercepting rainfall, delaying its impact on the ground, and reducing peak runoff rates (Saravanan et al., 2019; O’donohue, 2024). In this study, eVIIRS NDVI data (cell size: 375 m) from May 16-29, 2023, was retrieved as a GIS compatible raster file from USGS Earth Explorer (2025). This time period was chosen because most of the other datasets are in 2023 and May had the most rainfall in this study area, making it the most critical time (National Weather Service, 2025).

3.1.1.4. Hydrological

Stream Density: Stream density reflects the distance of a certain point to the nearby streams. High stream density, characterized by a greater number of streams within a region, often increases the risk of flooding because water from multiple sources converges, overwhelming the drainage capacity. Areas closer to

streams are particularly vulnerable, as they are directly affected by rising water levels during heavy rainfall or storm events. Conversely, regions farther from streams may experience less immediate flooding risk, but could still face inundation if runoff pathways are insufficiently managed (Pallard et al., 2009). Many previous studies (Edamo et al., 2022; Kaiser et al., 2022; Mudashiru et al., 2022; Ekmekcioğlu et al., 2022; Linh et al., 2022; Alimi et al., 2022; Chaulagain et al., 2023; Razavi-Termeh et al., 2023; Li et al., 2023; Addis, 2023; Dutta et al., 2023; Danso et al., 2024; Amiri et al., 2024) have employed the “Euclidean distance” method in ArcGIS Pro to analyze stream density for flood risk assessment. However, Euclidean distance only considers the closest stream to a point, disregarding the cumulative influence of multiple streams within the surrounding area. This limitation can lead to an incomplete understanding of how stream networks impact flood risk. In this study, a novel approach was used to account for variations in floodplain areas and their impacts on nearby neighborhoods based on different stream orders and “kernel density” function in ArcGIS Pro. Stream order was determined in ArcGIS Pro by developing flow direction and flow accumulation based on DEM data. Kernel Density provides a more comprehensive analysis by calculating the density of linear features (streams) within a specified neighborhood. This approach creates a smoothly curved surface over each streamline, where the density value is highest at the streamline and gradually decreases with distance, reaching zero at the defined search radius (Fig. 4). The total density at a given point is calculated by summing the contributions from all streams within the neighborhood. The kernel density concept, adapted from Silverman's quartic kernel function for point densities (Silverman, 1986), effectively represents the influence of stream networks on flood risk across a broader area.



[Fig. 4 Diminishing density values at curved surfaces (Adapted from Esri, 2025b)]

Two key parameters are critical for applying Kernel Density in this context:

- 1) *Search Radius*: This determines the extent of a stream's impact during flooding. In this study, varying search radius were assigned to different stream orders reflecting relative scales (from headwater to the ultimate convergence): order 1 (400m), order 2 (600m), order 3 (1000m), order 4 (1500m), order 5 (2000m), order 6 (2500m).
- 2) *Population Density*: This parameter measures the significance of a stream's impact on the surrounding area. For simplicity, all streams are assumed to have equal significance in this study, so population density is not considered.

3.1.2 Infrastructural Factors

Road Density: Road density shows the proximity of a certain point to the nearby transportation network.

Roads often alter natural hydrological patterns as they play a role in channelizing water flow and creating localized flooding due to the imperviousness, making them like another set of stream networks. High road density in urban areas is associated with increased impervious surfaces, which limit water infiltration and

lead to higher surface runoff during extreme rainfall events. Conversely, areas further from roads may experience less direct impact from runoff (Jones et al., 2000). The Kernel Density approach was also applied here to develop road density for this study. The transportation network data were sourced from the North Central Texas Council of Governments (NCTCOG) and the Texas Department of Transportation (TxDOT). NCTCOG's mobility plan provided the main road network, which generally chooses to include facilities in their travel demand model networks that are relevant to the model. This includes facilities that are important to regional travel like freeways, highways, and major arterials. However, it can also include some more minor facilities that connect to one or more of the polygonal Traffic Analysis Zones that the model uses. Most trips originate from one zone, traverse the network, and arrive at another zone. This means that any zone has to be adequately connected to the network to participate in the model, which is why some less significant facilities are excluded. To complement some of the missing county roads and local streets, TxDOT's comprehensive roadway inventory dataset was used. To account for the differences in impact range between main routes (NCTCOG dataset) and local routes (TxDOT dataset) due to variations in lane numbers and width, the road network was categorized into two groups: main roads (search radius of 2000 m) and local roads (search radius of 1000 m). No population density was applied in the kernel analysis, assuming equal significance for all roads in terms of road density.

Road Traffic Density: Road traffic density is closely linked to flood risk, as it reflects the intensity of transportation activity on a given road network, which in turn influences the vulnerability of infrastructure and nearby areas during flood events. High traffic density is often associated with major roads and highways that play critical roles in urban connectivity and emergency response during floods. However, these roads are also more prone to disruption due to their extensive usage and impervious surfaces, which increase surface runoff and exacerbate local flooding. Conversely, flooding in areas with high traffic density can lead to significant economic losses, impede evacuation efforts, and disrupt essential services (He et al., 2022). In this study, road traffic density was calculated using the same road network and Kernel Density approach. Traffic information for 2023 was obtained from the NCTCOG mobility plan, which

includes detailed data on Daily Vehicle Miles Traveled (DVMT) for various road segments. DVMT was used as the population density input in the kernel analysis to represent the relative significance of different roads based on their usage. To account for variations in the impact range between main routes and local routes, the analysis employed the following search radius: main roads (500 m) and local roads (250 m).

Dam Density: Dam density plays a crucial role in flood risk management by influencing water storage, flow regulation, and the downstream flooding potential. Under the assumption of well-maintenance, regions with high dam density often benefit from improved flood control, as dams can temporarily store excess water during heavy rainfall events and release it gradually to reduce peak flood discharge (Wurbs, 2021). In this study, the dam information was retrieved from the official website of the National Inventory of Dams (NID). Kernel density was utilized to develop dam density with a search radius of 2000 m and corresponding NID storage (maximum value of normal storage and maximum storage and accepted as the general storage of the dam) as population density.

Bridge Vulnerability: Bridge vulnerability is a critical factor in flood risk assessment, as it reflects the likelihood of a bridge being compromised during flood events and the consequential effect of being flooded. In this study, bridge GIS shapefile with locations and attribution was acquired from TxDOT. Bridge vulnerability was defined as the product of two attributes: historical significance (HIST_SIG) and appraisal rating for waterway adequacy (APPRSL_RTN_4). Historical significance considers the cultural, structural, or functional importance of the bridge, emphasizing the potential societal and economic impacts of its failure. The appraisal rating for waterway adequacy evaluates the bridge's capacity to handle water flow, accounting for the chance of overtopping the bridge deck or its approaches during extreme rainfall or flood conditions. Bridges with inadequate waterway openings are more susceptible to damage from high flows, debris accumulation, or overtopping, which can lead to structural failure and downstream flooding. Therefore, the lower the number of APPRSL_RTN_4, the higher frequency of flooding at this bridge. In this study, the specific rating table was provided as a supplementary material.

To make the correlation pattern align with historical significance (higher HIST_SIG leading to higher vulnerability), the appraisal rating for waterway adequacy used in this study was updated reversely as “10 - APPRSL_RTN_4”. Kernel density was applied to develop bridge vulnerability with a search radius of 1000 m and product of HIST_SIG and “10 - APPRSL_RTN_4” as population density to represent how vulnerable the bridge is in terms of flooding.

Bridge Traffic Density: High bridge traffic density often indicates significant reliance on these structures for connectivity, making them particularly vulnerable during flood events. Flooding can compromise bridge stability, leading to disruptions in traffic flow, economic losses, and challenges in emergency response and evacuation efforts. Additionally, bridges with high traffic density are more likely to experience stress and wear, increasing their susceptibility to damage during extreme weather conditions (Pregnotato et al., 2022). To develop bridge traffic density, the kernel density method was employed using the Daily Vehicle Miles Traveled (DVMT) as the population density. The DVMT was calculated as equation (2):

$$DVMT = ADT * Structure Length \quad (2)$$

where ADT represents the Average Daily Traffic, and Structure Length is the length of the bridge. The search radius for kernel density analysis was classified based on structure length to account for varying scales of impact. The following classifications were used: structure length ≤ 50 ft (search radius of 25 ft), structure length ≤ 100 ft (search radius of 50 ft), structure length ≤ 200 ft (search radius of 150 ft), structure length ≤ 600 ft (search radius of 400 ft), structure length < 1000 ft (search radius of 800 ft), structure length ≤ 2000 ft (search radius of 1500 ft), structure length ≤ 3000 ft (search radius of 2500 ft), structure length > 3000 ft: (search radius of 8520 ft).

3.1.3 Socio-Economic Factors

Social Vulnerability Index (SVI): Social Vulnerability Index (SVI), jointly developed by the U.S. Centers for Disease Control and Prevention (CDC) and Agency for Toxic Substances and Disease Registry (ATSDR), is a widely used tool for assessing community-level vulnerability to hazards, including floods.

The CDC/ATSDR SVI includes 15 variables grouped into four key themes: socioeconomic status (e.g., income, poverty, education), household composition and disability (e.g., elderly, children, disability status), minority status and language (e.g., racial and ethnic minorities, limited English proficiency), and housing and transportation (e.g., housing type, vehicle access). These variables provide a comprehensive picture of a community's ability to prepare for, respond to, and recover from flooding events (ATSDR, 2024). In this study, the CDC/ATSDR SVI was integrated into the framework to highlight areas where populations may face heightened challenges during flood events. Communities with high SVI scores are often disproportionately affected by floods due to limited access to emergency services, inadequate infrastructure, and economic constraints.

Table 2. Data sources, processing and relation to flooding

Factors	Category	Data sources	Year	Processing	Relation to flooding	Cell size (m × m)
Elevation (DEM)	Topographical	USGS TNM	2021	Direct download	Negative	10×10
Slope		DEM-derived	-	Slope	Negative	10×10
Plan curvature		DEM-derived	-	Curvature	Negative	10×10
TWI		DEM-derived	-	Flow direction, flow accumulation	Positive	10×10
Extreme rainfall depth	Meteorological	NOAA Atlas 14	-	Direct download	Positive	366×366
CN	Landscape	USGS NLCD, SSURGO, USDA Forest Service	2023, 2023, 2021	Union	Positive	366×366
NDVI		USGS Earth Explorer	2023	Direct download	Negative	366×366
Stream density	Hydrological	DEM-derived	-	Stream order, Kernel density	Positive	374×374
Road density	Infrastructural	NCTCOG, TxDOT	2023	Kernel density	Positive	420×420
Road traffic density		NCTCOG, TxDOT	2023	Kernel density	Positive	420×420
Dam density		NID	2024	Kernel density	Negative	435×435
Bridge vulnerability		TxDOT	2024	Kernel density	Positive	420×420
Bridge traffic density		TxDOT	2024	Kernel density	Positive	420×420
SVI	Socio-economic	CDC/ATSDR	2022	Direct download	Positive	457×457

3.2 Factor Weight Determination

The Analytic Hierarchy Process (AHP) (Saaty, 1977; 1980). was employed to determine the relative importance of each conditioning factor in developing the Flood Susceptibility Map (FSM) and Flood Vulnerability Map (FVM). AHP is a structured decision-making approach that systematically assigns weights to multiple criteria based on expert judgment, which is originally used in marketing-related problems before being adapted for use in other fields, such as engineering, social science, and environmental science (Wind & Saaty, 1980; Subramanian & Ramanathan, 2012; Belay et al., 2022; Theilig et al., 2024). In the context of mapping, Souissi et al. (2019) applied AHP method to weight eight factors relating to flood susceptibility in southeastern Tunisia. Roy et al. (2024) used AHP method to determine the weight for each thematic layer used to develop ground water potential zones West Bengal, India. Although diagnostic functionality is provided to ensure that the comparison evaluations among all pairs is logically consistent (Saaty, 2008), the subjectivity and uncertainty of using AHP method still exist by forcing decision-makers into exact values, which may not accurately reflect their nuanced or uncertain preferences (Toth & Vacik, 2018). Still, AHP has been widely used in natural hazards (e.g. landslide, and flooding) susceptibility mapping (Mudashiru et al., 2022; Chaulagain et al., 2023; Yadav et al., 2024; Jemai et al., 2024; Shah & Ai, 2024; Danso et al., 2024; Amiri et al., 2024; Aloui et al., 2024). Therefore, we used AHP for simplicity in this study. Eight individuals from different types of agencies (academia, local government, federal government, consulting firm, and local water district) specializing in civil engineering, hydrology, flood risk management, and urban planning participated in a pairwise comparison process, evaluating the significance of each factor relative to the others. The Saaty scale (Table 3) was used to quantify these comparisons, assigning values from 1 (equal importance) to 9 (extreme importance). The pairwise comparisons were synthesized into a consistency matrix (Table 4), and the consistency index (CI) and consistency ratio (CR) were calculated to ensure logical consistency in judgments based on formula (3)~(4) and the corresponding value of random index (RI) in Table 5. If the CR exceeded the acceptable threshold (0.1), adjustments were made to improve consistency. The final normalized weights derived from the AHP process were applied to each factor, ensuring an objective and

balanced integration of environmental, infrastructural, and socio-economic variables into the FSM and FVM.

Table 3. Saaty scale for pairwise comparison in AHP

The scale of relative importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

Table 4. Synthesized comparison matrix

FSM						FVM		
factor	TP	MT	LS	HD	IF	factor	SE	IF
TP	1	1.781250	3.270833	4.041667	2.895833	SE	1	0.340426
MT	0.561404	1	3	4.392857	2.413690	IF	2.93750	1
LS	0.305732	0.333333	1	2.892857	0.440367	SUM	3.93750	1.340426
HD	0.247423	0.227642	0.345679	1	0.488017			
IF	0.345324	0.414303	2.270833	2.049107	1			
SUM	2.459882	3.756529	9.887346	14.37649	7.237908			

TP = Topographic, MT = Meteorological, LS = Landscape, HD = Hydrological, IF = Infrastructural, SE = Socio-economic

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3)$$

Where: CI is the consistency index; n is the number of conditioning factors/criteria; λ_{max} is the maximum eigenvalue of the comparison matrix.

$$CR = \frac{CI}{RI} \quad (4)$$

Table 5. Random index (RI) values for consistency check

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

3.3 Flood Mapping

3.3.1 Flood susceptibility mapping

Factors involved in flood susceptibility mapping include: topographical (elevation, slope, plan curvature, TWI), meteorological (extreme rainfall depth), landscape (CN, NDVI), hydrological (stream density), and infrastructural (road density, dam density).

3.3.1.1 Normalization

To develop the Flood Susceptibility Map (FSM), the Flood Susceptibility Index (FSI) was applied. FSI represents the linear integration of all conditioning factors weighed according to their respective importance (weighted overlay), as illustrated in Equation (5). Same linear integration approach was applied in extensive previous studies (Alimi et al., 2022; Pacetti et al., 2022; Chaulagain et al., 2023; Yadav et al., 2024; Jemai et al., 2024; Shah & Ai, 2024; Danso et al., 2024; Amiri et al., 2024; Aloui et al., 2024):

$$FSI = \pm(\text{rating of factor } A) * (\text{weight of factor } A) \pm (\text{rating of factor } B) * (\text{weight of factor } B) \pm \dots \pm (\text{rating of factor } Z) * (\text{weight of factor } Z) \quad (5)$$

The addition will be applied if the factor is positively related to FSI, which means the higher factor value leads to the higher flood susceptibility. Conversely, the subtraction will be used in equation (5) if the factor is negatively related to FSI (Pacetti et al., 2022). The symbol “ $\pm$ ” is used to indicate that the variable can be either positive or negative. The relation information has been provided in Table 2. The factor weights were determined using the AHP, as described in the previous section. A key challenge in applying this formula is assigning an appropriate rating to each factor. The traditional approach involves standardization, where raster values are classified into discrete classes, and each class is assigned a numerical rating based on its influence on flooding (Aloui et al., 2024; Danso et al., 2024; Chaulagain et al., 2023; Alimi et al., 2022; Mudashiru et al., 2022; Mousavi et al., 2022). For example, a Digital Elevation Model (DEM) dataset ranging from 0 to 500 m could be classified into five categories (e.g., 0–100 m, 100–200 m, 200–300 m, 300–400 m, and 400–500 m), with ratings assigned from 5 to 1 to reflect higher flood susceptibility in lower elevations. However, this classification process is highly subjective, as the selection of threshold values and rating scales (e.g., 1–5 or 1–10) can vary significantly, potentially affecting the final flood susceptibility results. To be specific, as the most common used classification

method, “Jenks natural breaks” determines the threshold values depending on the distribution of the factor data. In other words, the thresholds will be changing as more data gets involved, which brings the trouble to keep consistency especially when it comes to future scenario analysis. Additionally, this traditional discrete classification diminishes the distinction within each class and can easily separate two close values into two different classes and give them two rating numbers as the threshold cuts them off. This could hurt the continuity of the data and propagate errors.

To overcome these limitations, this study employs an approach to normalize each conditioning factor based on Equation (6):

$$y = y_{min} + (y_{max} - y_{min}) * \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

Where x is the initial data value, x_{min} and x_{max} are the minimum and maximum of the initial dataset, y is the data value after normalization, y_{min} and y_{max} are the minimum and maximum of the rescaled dataset. In this study, $y_{min} = 0$, $y_{max} = 5$.

This normalization method proportionally adjusts the dataset to a standardized 0–5 scale without arbitrary classification. By converting all factor values into a dimensionless scale, this approach ensures consistency and continuity in factor rating and enhances comparability across different study areas, mitigating the influence of data distribution.

3.3.1.2 Validation

In this study, the FSM was validated against observed flood inventory data using a Receiver Operating Characteristic (ROC) curve and calculating the Area Under the Curve (AUC). The ROC curve evaluates the model's ability to distinguish between flooded and non-flooded areas, while the AUC provides a quantitative measure of the overall accuracy, with higher values indicating better performance. The flood inventory map was developed by importing geospatial information (longitude and latitude) of observed/reported flooded spots provided by the North Central Texas Council of Government (NCTCOG), Tarrant Regional Water District (TRWD), Texas Geographic Information Office (TxGIO)

DataHub (Low water crossing), and NOAA Storm Events Database (flood & flash flood). Other than TRWD dataset, others are publicly accessible. TRWD data were extracted from aerial photographs.

3.3.2 Flood vulnerability mapping

Factors used in flood vulnerability mapping include: infrastructural (road traffic density, bridge traffic density, bridge vulnerability), and socio-economic (SVI). Normalization was also applied to these factors alongside the AHP-derived weights to develop flood vulnerability index (FVI) and a comprehensive flood vulnerability map. No validation was conducted for vulnerability mapping in this study.

3.3.3. Flood control prioritization mapping

The Flood Control Prioritization Map (FCPM) was developed by integrating the Flood Susceptibility Map (FSM) and the Flood Vulnerability Map (FVM) using the Union tool in ArcGIS. Both FSM and FVM were categorized into three classes—high, moderate, and low—based on their respective indices (FSI and FVI). By performing a Union operation, the FCPM was created with nine unique categories, representing all possible combinations of flood susceptibility and vulnerability levels.

3.4 Future Scenarios

Future scenarios are essential to account for changes in factors over time, which may alter the flood-prone area patterns. Considering future trends helps with proactive flood risk management. In this study, the following five factors were considered in future analysis.

Future CN: As previously introduced, the CN is influenced by land use type, soil hydraulic group, and tree canopy percentage. In this study, the soil hydraulic group and tree canopy percentage are assumed to be constant over time, at least until the near future (Year 2045). However, land use patterns are dynamic and difficult to predict with certainty. To address this, projected impervious area changes provided by the North Central Texas Council of Governments (NCTCOG) for Year 2045 are incorporated. This serves as a basis for estimating future CN values. To develop the projected CN:

- For areas where the land use/land cover (LULC) classification falls under "22 – Developed, Low Intensity," "23 – Developed, Medium Intensity," or "24 – Developed, High Intensity," the future CN is derived based on the projected impervious percentage for Year 2045.
- For areas where the LULC is not classified as 22, 23, or 24, we used a 20% threshold to differentiate areas experiencing negligible land-use change from areas undergoing substantial urbanization. The 20% threshold aligns with literature identifying imperviousness levels change as indicative of watershed hydrologic regime shifts (Schueler, 1994; Arnold, Jr & Gibbons, 1996; Mitchell et al., 2003; Lhomme et al., 2004; Easton et al., 2007; Elga et al., 2015; Miller & Hess, 2017)):
 - If the change in impervious area between 2023 and 2045 is less than or equal to 20%, the future CN remains the same as the current CN.
 - If the change in the impervious area is greater than 20%, the area is assumed to undergo significant urbanization or residential development. In this case, the future CN is assigned based on the projected impervious percentage for Year 2045, referencing CN values for urban/residential districts in the CN Table.

Future Extreme Rainfall Depth: Based on Delta Method, a multiplier was applied to the current extreme rainfall depth (100-yr, 24-hr) to represent the research projection which shows the intensity of extreme rainfall events is getting greater while the near future annual total precipitation is likely to remain at the same level as now (Tefera et al., 2024). A multiplier of 1.05 was chosen in the study area based on several previous studies (Villarini et al., 2013; Easterling et al., 2017; Nielsen-Gammon et al., 2021)

Future Road Density: Transportation network of 2045 due to urban development and expansion was obtained from NCTCOG. Only changes in those main transportation corridors (e.g. state highways) were considered because the NCTCOG Mobility Plan neglects those local streets and most of county roads. Same as the current condition, kernel density analysis was used to develop the future (Year 2045) road density pattern.

Future Road Traffic Density: Projected changes in traffic levels in 2045 were provided by TxDOT and NCTCOG. Kernel density was applied to develop future road traffic density in 2045.

Future Bridge Traffic Density: Anticipated usage of bridges in 2045 was acquired from TxDOT. The Kernel density approach was used to develop the future (year 2045) bridge traffic density.

The projected data for these factors were integrated into the existing framework to develop updated flood susceptibility and vulnerability patterns to reflect future scenarios, furtherly to examine the shifts in flood control prioritization.

4. Results

4.1 Conditioning Factor weight

After the calculation based on Tables 4 and 5 and equations (3) and (4), CR for FSM and FVM are 0.04 and 0, respectively, which are both smaller than the threshold (0.1). Therefore, the pairwise comparison (Table 4) is consistent and can be used to determine the factor weights through matrix normalization (Table 6). The final weight for each individual factor is listed in Table 7 considering each factor has equal contribution in each category.

Table 6. Comparison matrix normalization and factor weight calculations

FSM							FVM			
factor	TP	MT	LS	HD	IF	weight	factor	SE	IF	weight
TP	0.41	0.47	0.33	0.28	0.40	0.38	SE	0.25	0.25	0.25
MT	0.23	0.27	0.30	0.31	0.33	0.29	IF	0.75	0.75	0.75
LS	0.12	0.09	0.10	0.20	0.06	0.11	SUM	1	1	1
HD	0.10	0.06	0.04	0.07	0.07	0.07				
IF	0.14	0.11	0.23	0.14	0.14	0.15				
SUM	1	1	1	1	1	1				

TP = Topographic, MT = Meteorological, LS = Landscape, HD = Hydrological, IF = Infrastructural, SE = Socio-economic

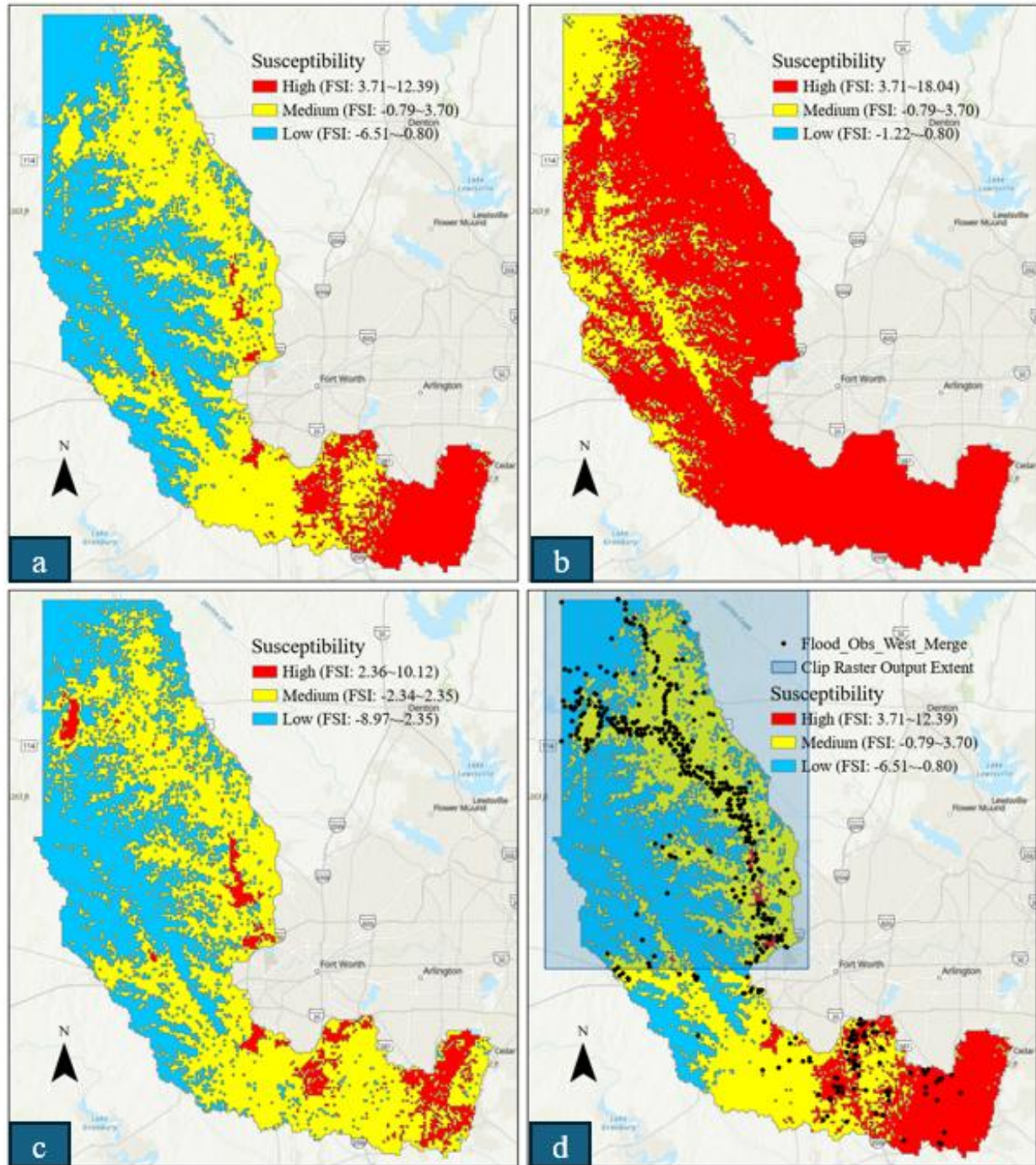
Table 7. Conditioning factor weight

FSM		FVM	
Elevation	0.95	Road traffic density	2.5
Slope	0.95	Bridge vulnerability	2.5

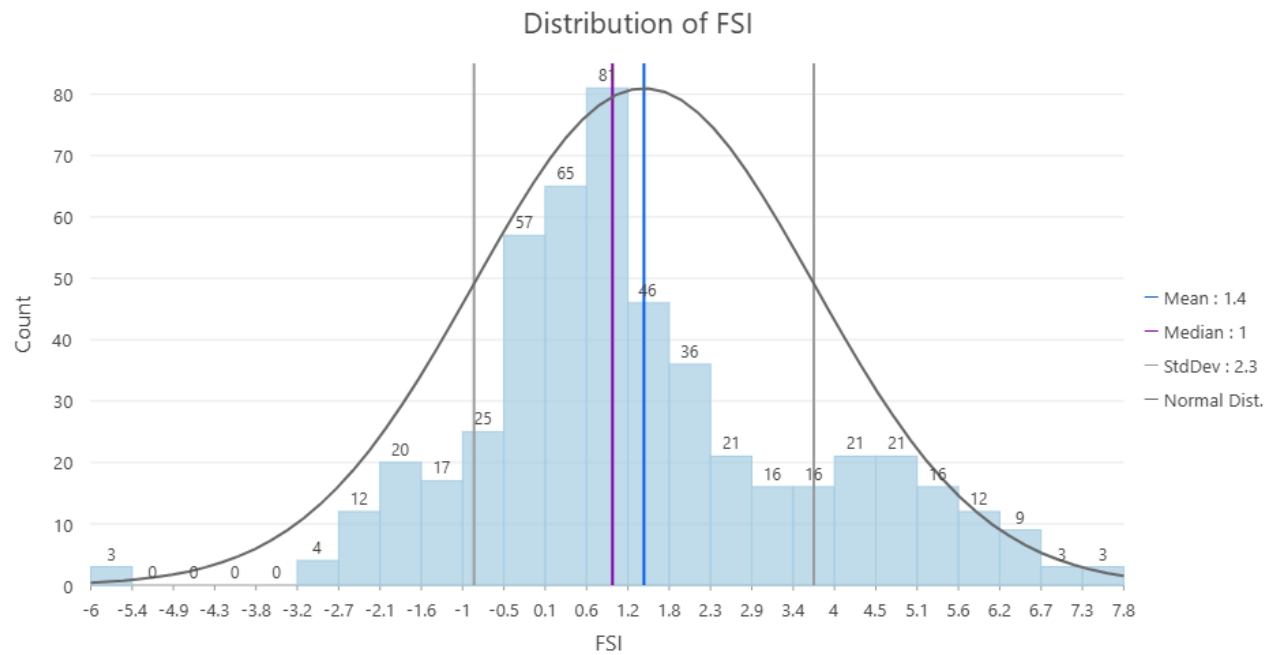
Plan curvature	0.95	Bridge traffic density	2.5
TWI	0.95	SVI	2.5
Extreme rainfall depth	2.90	Sum	10
CN	0.55		
NDVI	0.55		
Stream density	0.70		
Road density	0.75		
Dam density	0.75		
Sum	10		

4.2 Flood Susceptibility Map

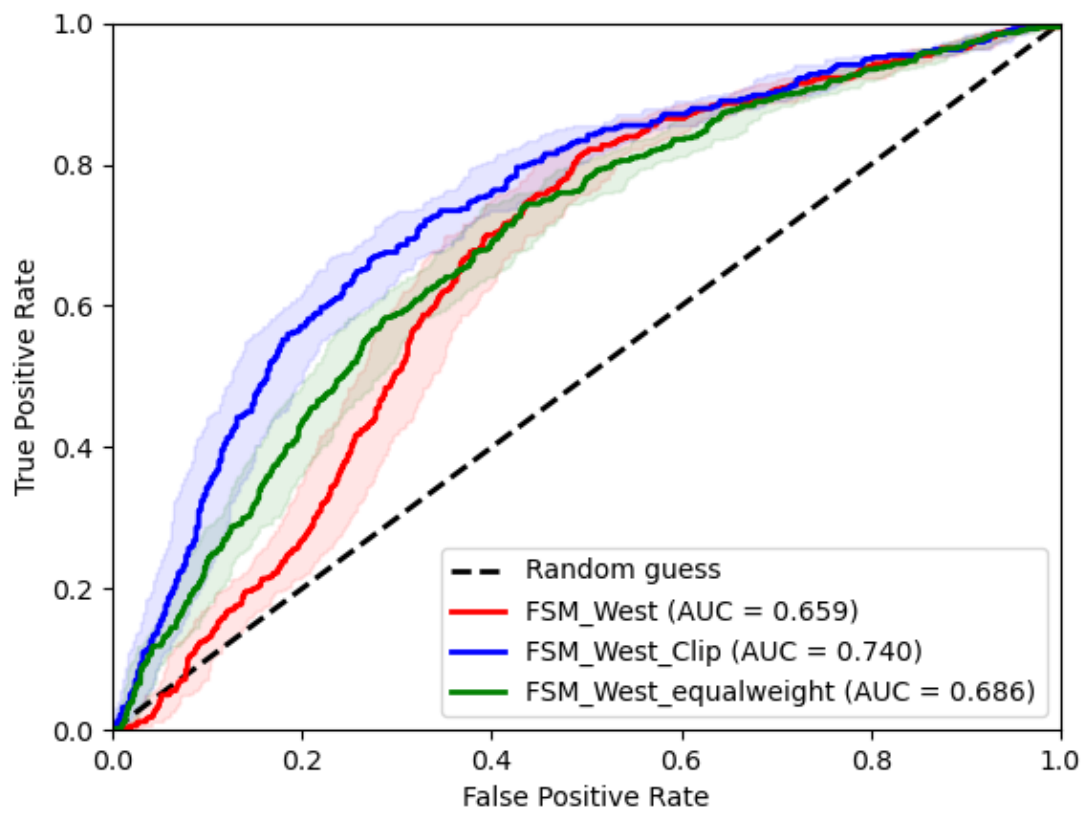
The final flood susceptibility maps (current and future version), the outcome of stacking all the susceptibility-related maps, are shown as Fig. 5a and 5b. The threshold (-0.80 and 3.70) to separate flood susceptibility categories (Low, Medium, High) was determined by inspecting the data distribution of flood susceptibility index (FSI) for all observed flooded spots (Fig. 6). The ROC curves and AUC values are presented in Fig. 7. Other than the aforementioned model, a model with equal factor weight (Fig. 5c) and a model with smaller study area focusing on the clustered flooded points (Fig. 5d), are both examined. Map layers for each individual conditioning factor are attached as supplementary materials.



[Fig. 5 FSM (a: current condition with different factor weights; b: future condition with different factor weights; c: current condition with equal factor weights; d: clipped Fig. 5(a) with observed flooded spots)]



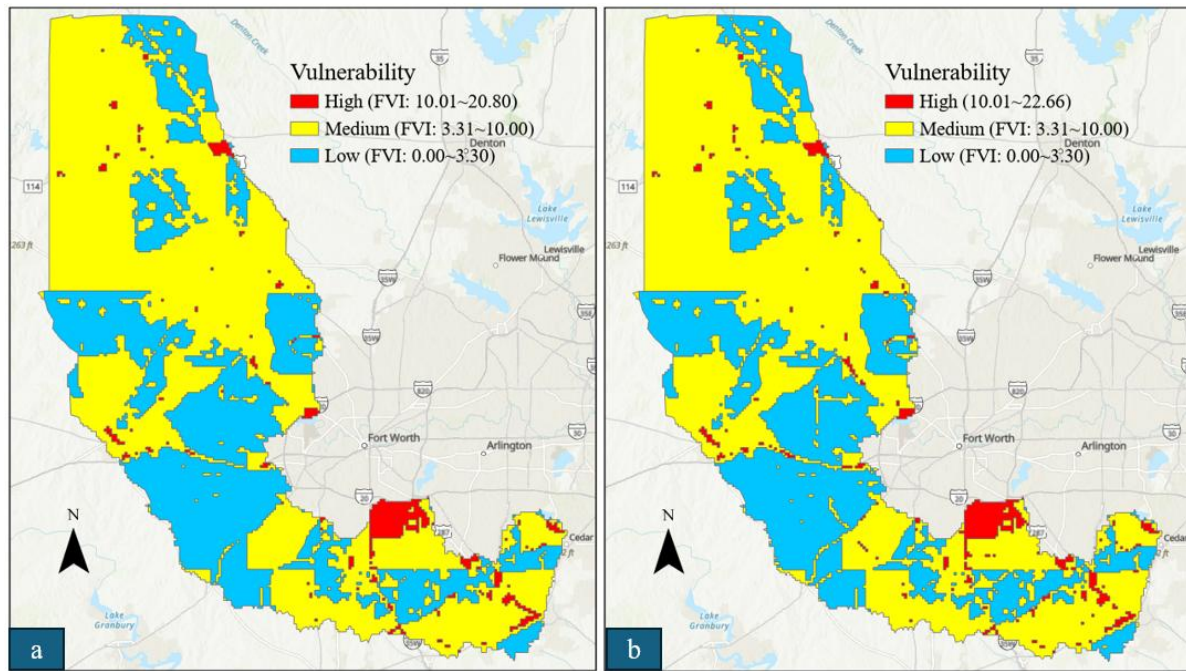
[Fig. 6 Distribution of FSI]



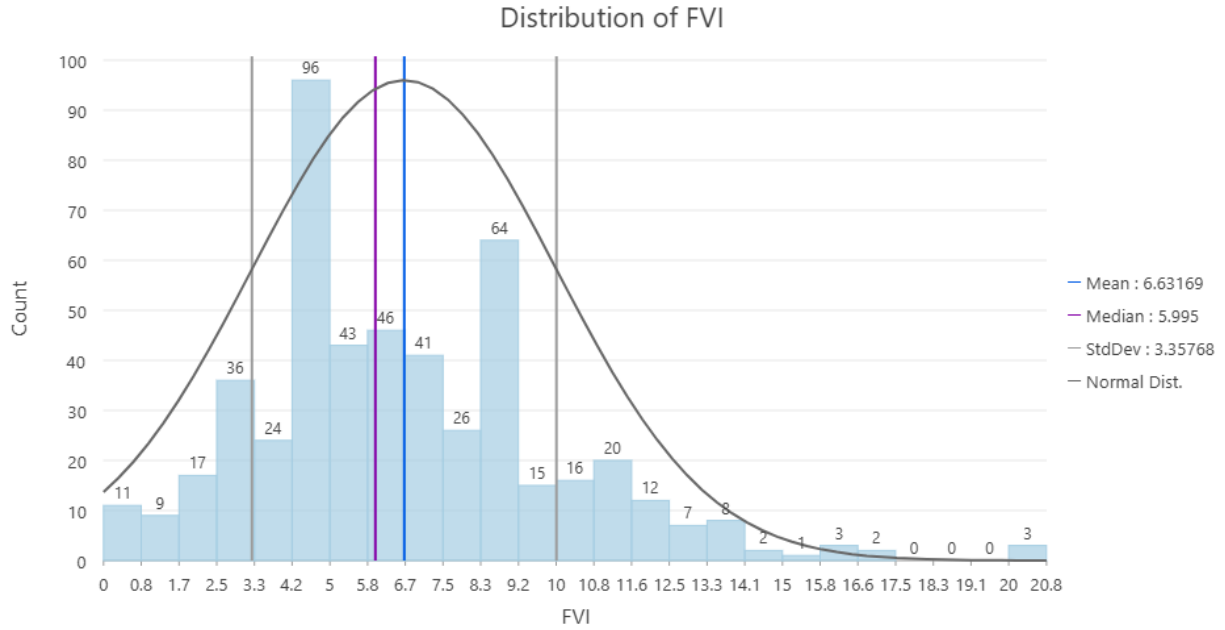
[Fig. 7 ROC curves and AUC values]

4.3 Flood Vulnerability Map

The final flood vulnerability maps (current and future version), which are the overlay of all the vulnerability-related maps, are shown as Fig. 8a and 8b. The individual vulnerability-related layers were attached as supplementary materials. Fig. 9 shows the distribution of flood vulnerability index (FVI) associated with all the observed flooded spots, which was used to distinguish the flood vulnerability categories (High, Medium, Low) in the stacking model.



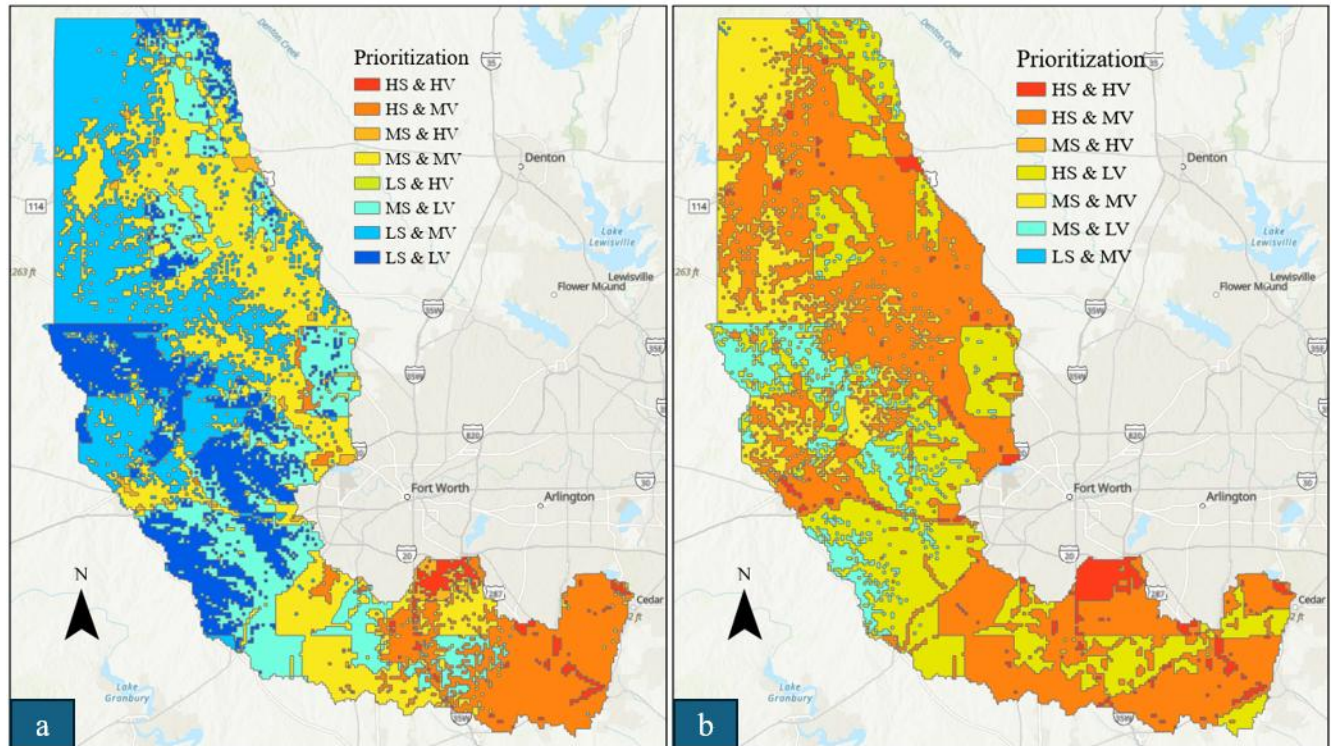
[Fig. 8 FVM (a: current condition; b: future condition)]



[Fig. 9 Distribution of FVI]

4.4 Flood Control Prioritization Map

Fig. 10a and 10b show flood control prioritization maps (current and future version), identifying regions with different levels of combined flood susceptibility and vulnerability. The redder areas represent the communities with higher combined flood susceptibility and vulnerability, which determines them and their upstream areas as a higher priority to be considered as flood control measures are implemented. The bluer the region represents areas that are less susceptible and vulnerable to flooding. They are assigned lower priority for control measure consideration.



[Fig. 10 FCPM (a: current condition; b: future condition)]

References

- Addis, A. (2023). GIS – based flood susceptibility mapping using frequency ratio and information value models in upper Abay river basin, Ethiopia. *Nat. Hazards Res.*, 3(2), 247–256. <https://doi.org/10.1016/j.nhres.2023.02.003>
- Ali, S. A., Khatun, R., Ahmad, A. and Ahmad, S. (2019). Application of GIS-based analytic hierarchy process and frequency ratio model to flood vulnerable mapping and risk area estimation at Sundarban region, India. *Model. Earth Syst. Env.*, 5, 1083–1102. <https://doi.org/10.1007/s40808-019-00593-z>.
- Alimi, S. A., Andongma, T. W., Ogungbade, O., ..., & Muhammed, Q. O. (2022). Flood vulnerable zones mapping using geospatial techniques: Case study of Osogbo Metropolis, Nigeria. *Egypt. J. Remote Sens. Space Sci.* 25(3), 841–850. <https://doi.org/10.1016/j.ejrs.2022.08.003>
- Al-Juaidi, A.E.M. (2023). The interaction of topographic slope with various geo-environmental flood-causing factors on flood prediction and susceptibility mapping. *Environ. Sci. Pollut. Res.* 30, 59327–59348. <https://doi.org/10.1007/s11356-023-26616-y>
- Aloui, S., Zghibi, A., Mazzoni, A., Elomri, A., & Al-Ansari, T. (2024). Identifying suitable zones for integrated aquifer recharge and flood control in arid Qatar using GIS-based multi-criteria decision-making. *Groundw. Sustain. Dev.*, 25. <https://doi.org/10.1016/j.gsd.2024.101137>
- Alrajhi, M., Khan, M., Khan, M.A., & Alobeid, A. (2016). Influence of DEM in Watershed Management for Flood Zonation Mapping. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLI-B8, 2016 XXIII ISPRS Congress, 12–19 July 2016, Prague, Czech Republic.
- Amiri, A., Soltani, K., Ebtehaj, I., & Bonakdari, H. (2024). A novel machine learning tool for current and future flood susceptibility mapping by integrating remote sensing and geographic information systems. *J. Hydrol.*, 632. <https://doi.org/10.1016/j.jhydrol.2024.130936>
- Arnold Jr, C. L. & Gibbons, C. J. (1996). Impervious Surface Coverage: The Emergence of a Key Environmental Indicator. *J. Am. Plan. Assoc.*, 62, pp. 243-258
- ATSDR (Agency for Toxic Substances and Disease Registry). Social Vulnerability Index. Retrieved on December 10, 2024, from https://www.atsdr.cdc.gov/place-health/php/svi/index.html?utm_source=chatgpt.com
- Belay, S., Goedert, J., Woldeesenbet, A., & Rokooei, S. (2022). AHP based multi criteria decision analysis of success factors to enhance decision making in infrastructure construction projects. *Cogent Engineering*, 9(1). <https://doi.org/10.1080/23311916.2022.2043996>
- Beven, K. J. and Kirkby, M. J. (1979). A physically based, variable contributing area model of basin hydrology. *Hydrol. Sci. J.*, 24, 43–69. <https://doi.org/10.1080/02626667909491834>
- Blumenthal, B., Haas, J. and Andersson, J. O. (2018). A GIS-based multivariate approach to identify flood damage affecting factors. *Nat. Hazards Earth Syst. Sci. Discuss.* <http://dx.doi.org/10.5194/nhess-2018-286>

- Bunmi Mudashiru, R., Sabtu, N., Abdullah, R., Saleh, A., & Abustan, I. (2022). Optimality of flood influencing factors for flood hazard mapping: An evaluation of two multi-criteria decision-making methods. *J. Hydrol.*, 612. <https://doi.org/10.1016/j.jhydrol.2022.128055>
- Chaulagain, D., Ram Rimal, P., Ngando, S. N., Nsafon, B. E. K., Suh, D., & Huh, J. S. (2023). Flood susceptibility mapping of Kathmandu metropolitan city using GIS-based multi-criteria decision analysis. *Ecol. Indic.*, 154. <https://doi.org/10.1016/j.ecolind.2023.110653>
- Chowdhury, M. S. (2024). Flash flood susceptibility mapping of north-east depression of Bangladesh using different GIS based bivariate statistical models. *Watershed Ecol. Environ.*, 6, 26–40. <https://doi.org/10.1016/j.wsee.2023.12.002>
- Danso, S. Y., Ma, Y., Osman, A., & Addo, I. Y. (2024). Integrating multi-criteria analysis and geospatial applications for mapping flood hazards in Sekondi-Takoradi Metropolis, Ghana. *J. African Earth Sci.*, 209. <https://doi.org/10.1016/j.jafrearsci.2023.105102>
- Dekongmen, B.W., Kabo-bah, A.T., Anornu, G.K., ..., Sunkari, E.D.. (2024). Delineation of flood risk terrains and rainfall visualisation in the North Western part of Ghana. *Model. Earth Syst. Env.*, 10, 4567–4594. <https://doi.org/10.1007/s40808-024-02041-z>
- Deroliya, P., Ghosh, M., Mohanty, M. P., Ghosh, S., Rao, K. H. V. D., & Karmakar, S. (2022). A novel flood risk mapping approach with machine learning considering geomorphic and socio-economic vulnerability dimensions. *Sci. Total Environ.* 851. <https://doi.org/10.1016/j.scitotenv.2022.158002>
- Dutta, M., Saha, S., Saikh, N. I., Sarkar, D., & Mondal, P. (2023). Application of bivariate approaches for flood susceptibility mapping: a district level study in Eastern India. *HydroResearch*, 6, 108–121. <https://doi.org/10.1016/j.hydres.2023.02.004>
- Easterling, D.R., Kunkel, K.E., Arnold, J.R., ..., & Wehner, M.F. (2017) Precipitation change in the United States. In: Climate Science Special Report: Fourth National Climate Assessment, Volume I. U.S. Global Change Research Program, Washington, DC, USA, pp. 207-230, doi: 10.7930/J0H993CC
- Easton, Z. M., Gérard-Merchant, P., Walter, M. T., Petrovic, A. M., & Steenhuis, T. S. (2007). Hydrologic assessment of an urban variable source watershed in the northeast United States. *Water Resour. Res.*, 43 (3) (2007), p. W03413
- Ebrahimi, E., Araújo, M. B., & Naimi, B. (2023). Flood susceptibility mapping to improve models of species distributions. *Ecol. Indic.*, 157. <https://doi.org/10.1016/j.ecolind.2023.111250>
- Edamo, M. L., Ukumo, T. Y., Lohani, T. K., ..., & Abdi, D. M. (2022). A comparative assessment of multi-criteria decision-making analysis and machine learning methods for flood susceptibility mapping and socio-economic impacts on flood risk in Abela-Abaya floodplain of Ethiopia. *Environ. Chall.*, 9. <https://doi.org/10.1016/j.envc.2022.100629>
- Ekmekcioğlu, Ö., Koc, K., Özger, M., & Işık, Z. (2022). Exploring the additional value of class imbalance distributions on interpretable flash flood susceptibility prediction in the Black Warrior River basin, Alabama, United States. *J. Hydrol.*, 610. <https://doi.org/10.1016/j.jhydrol.2022.127877>

- Elga, S. Jan, B., & Okke, B. (2015). Hydrological modelling of urbanized catchments: A review and future directions. *J. Hydrol.*, Vol 529, pp 62-81
- Erhardt, R.J., Boudreault, M., Carozza, D.A. & Yu, K. (2022). Climate, Spatial Dependence, and Flood Risk: A U.S. Case Study. Casualty Actuarial Society. Retrieved from https://www.casact.org/sites/default/files/2022-12/RP_ClimateSpatialDependence_FloodRisk.pdf
- Esri. (2025a). Curvature function. Retrieved on Jan 14, 2025, from: <https://pro.arcgis.com/en/pro-app/latest/help/analysis/raster-functions/curvature-function.htm>
- Esri. (2025b). How Kernel Density works. Retrieved on Jan 18, 2025, from <https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm>
- Fang, L., Huang, J., Cai, J., & Nitivattananon, V. (2022). Hybrid approach for flood susceptibility assessment in a flood-prone mountainous catchment in China. *J. Hydrol.*, 612. <https://doi.org/10.1016/j.jhydrol.2022.128091>
- Farran, M.M., Elfeki, A., Elhag, M., & Chaabani, A. (2021) A comparative study of the estimation methods for NRCS curve number of natural arid basins and the impact on flash flood predications. *Arab. J. Geosci.* 14, 121. <https://doi.org/10.1007/s12517-020-06341-3>
- Garen, D.C. & Moore, D.S. (2005). Curve number hydrology in water quality modeling: Uses, abuses, and future directions. *JAWRA*. 41(2):377-388
- Ghahraman, K., Nagy, B., & Nooshin, F.N. (2023). Flood-Prone Zones of Meandering Rivers: Machine Learning Approach and Considering the Role of Morphology (Kashkan River, Western Iran). *Geosciences*, 13(9), 267. <https://doi.org/10.3390/geosciences13090267>
- Hallema, D.W., Moussa, R., Sun, G., & McNulty, S.G. (2016). Surface storm flow prediction on hillslopes based on topography and hydrologic connectivity. *Ecol Process.* 5, 13. <https://doi.org/10.1186/s13717-016-0057-1>
- He, Y., Rentschler, J., Avner, P., Gao, J., Yue, X., & Radke, J. (2022). Mobility and Resilience : A Global Assessment of Flood Impacts on Road Transportation Networks. Policy Research Working Paper. 10049. World Bank. Retrieved from https://blogs.worldbank.org/en/developmenttalk/mobility-and-resilience-global-assessment-flood-impacts-urban-road-networks?utm_source=chatgpt.com
- Jemai, S., Belkendil, A., Kallel, A., & Ayadi, I. (2024). Assessment of flood risk using Hierarchical Analysis Process method and Remote Sensing systems through arid catchment in southeastern Tunisia. *J. Arid Environ.*, 222. <https://doi.org/10.1016/j.jaridenv.2024.105150>
- Jones, J. A., Swanson, F. J., Wemple, B. C., & Snyder, K. U. (2000). Effects of Roads on Hydrology, Geomorphology, and Disturbance Patches in Stream Networks. *Conserv. Biol.*, 14(1), 76–85. <http://www.jstor.org/stable/2641906>
- Kaiser, M., Günnemann, S., & Disse, M. (2022). Regional-scale prediction of pluvial and flash flood susceptible areas using tree-based classifiers. *J. Hydrol.*, 612. <https://doi.org/10.1016/j.jhydrol.2022.128088>

- Levien, J. (2022). Topographic Wetness Index (TWI) Application for Predictive Flood Risk Mapping using GIS Technology. Geographical Information Systems AS.430.601.81.SU22. Johns Hopkins University.
- Lhomme, J., Bouvier, C., & Perrin, J.-L. (2004). Applying a GIS-based geomorphological routing model in urban catchments. *J. Hydrol.*, 299 (3–4), pp. 203-216
- Li, Y., Osei, F. B., Hu, T., & Stein, A. (2023). Urban flood susceptibility mapping based on social media data in Chengdu city, China. *Sustainable Cities and Society*, 88. <https://doi.org/10.1016/j.scs.2022.104307>
- Lyu, H. M., & Yin, Z. Y. (2023). Flood susceptibility prediction using tree-based machine learning models in the GBA. *Sustain. Cities Soc.*, 97. <https://doi.org/10.1016/j.scs.2023.104744>
- Mehravar, S., Razavi-Termeh, S. V., Moghimi, A., Ranjgar, B., Foroughnia, F., & Amani, M. (2023). Flood susceptibility mapping using multi-temporal SAR imagery and novel integration of nature-inspired algorithms into support vector regression. *J. Hydrol.*, 617. <https://doi.org/10.1016/j.jhydrol.2023.129100>
- Miller, J. D., & Hess, T. (2017). Urbanisation impacts on storm runoff along a rural-urban gradient. *J. Hydrol.*, Vol 552, pp 474-489
- Mitchell, V. G., McMahon, T.A., & Mein, R. G. (2003). Components of the total water balance of an urban catchment. *Environ. Manage.*, 32 (6) (2003), pp. 735-746
- Mousavi, S. M., Ataie-Ashtiani, B., & Hosseini, S. M. (2022). Comparison of statistical and MCDM approaches for flood susceptibility mapping in northern Iran. *J. Hydrol.*, 612. <https://doi.org/10.1016/j.jhydrol.2022.128072>
- National Weather Service. DFW - Monthly and Annual Precipitation. Retrieved on Jan 15, 2025, from https://www.weather.gov/fwd/dmoprecip?utm_source=chatgpt.com
- Negese, A., Worku, D., Shitaye, A., & Getnet, H. (2022). Potential flood-prone area identification and mapping using GIS-based multi-criteria decision-making and analytical hierarchy process in Dega Damot district, northwestern Ethiopia. *Appl. Water Sci.* 12, 255. <https://doi.org/10.1007/s13201-022-01772-7>
- Nielsen-Gammon, J., Holman, S., Buley, A., Jorgensen, S., Escobedo, J., Ott, C., Dedrick, J., & Van Fleet, A. (2021): Assessment of Historic and Future Trends of Extreme Weather in Texas, 1900-2036: 2021 Update. Document OSC-202101, Office of the State Climatologist, Texas A&M University, College Station, 44 pp.
- NOAA Atlas 14 Precipitation Frequency Estimates in GIS Compatible Format. Retrieved on Jan 15, 2025, from https://hdsc.nws.noaa.gov/pfds/pfds_gis.html
- O'donohue, D. (2024). Understanding NDVI: The Normalized Difference Vegetation Index. Retrieved from https://mapscaping.com/understanding-ndvi-the-normalized-difference-vegetation-index/?utm_source=chatgpt.com
- Pacetti, T., Cioli, S., Castelli, G., Bresci, E., Pampaloni, M., Pileggi, T., & Caporali, E. (2022). Planning Nature Based Solutions against urban pluvial flooding in heritage cities: A spatial multi criteria approach for the city of Florence (Italy). *J. Hydrol. Reg. Stud.*, 41. <https://doi.org/10.1016/j.ejrh.2022.101081>

- Pallard, B., Castellarin, A., & Montannari, A. (2009). Links between drainage density and flood statistics. *Hydrol. Earth Syst. Sci.*, 13, 1019–1029.
- Pourali, S.H., Arrowsmith, C., Chrisman, N., Matkan, A.A., Mitchell, D. (2016). Topography Wetness Index Application in Flood-Risk-Based Land Use Planning. *Appl. Spatial Analysis* 9, 39–54. <https://doi.org/10.1007/s12061-014-9130-2>
- Pradhan, B., Lee, S., Dikshit, A., & Kim, H. (2023). Spatial flood susceptibility mapping using an explainable artificial intelligence (XAI) model. *Geoscience Front.* Vol. 14, Issue 6, 101625.
- Pregolato, M., Winter, A. O., Mascarenas, D., Sen, A. D., Bates, P., & Motley, M. R. (2022). Assessing flooding impact to riverine bridges: an integrated analysis, *Nat. Hazards Earth Syst. Sci.*, 22, 1559–1576, <https://doi.org/10.5194/nhess-22-1559-2022>.
- Razavi-Termeh, S. V., Sadeghi-Niaraki, A., Seo, M. B., & Choi, S. M. (2023). Application of genetic algorithm in optimization parallel ensemble-based machine learning algorithms to flood susceptibility mapping using radar satellite imagery. *Sci. Total Environ.*, 873. <https://doi.org/10.1016/j.scitotenv.2023.162285>
- Roy, D., Barman, S., Mandal, G., ..., Mandal, D. K. (2024). Extracting of prospective groundwater potential zones using remote sensing data, GIS, and multi-criteria decision-making approach in the Sub-Himalayan Dooars region of West Bengal, India. *Appl Water Sci* 14, 72. <https://doi.org/10.1007/s13201-024-02124-3>
- Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures, *Journal of Mathematical Psychology* 15, 234–81
- Saaty, T. L. (1980). *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*”, McGraw-Hill
- Saaty, T. L. (2008). Decision making with the analytic hierarchy process’, *Int. J. Services Sciences*, Vol. 1, No. 1, pp.83–98.
- Sabzevari, T., & Noroozpour, S. (2014). Effects of hillslope geometry on surface and subsurface flows. *Hydrogeol. J.* 22, 1593–1604. <https://doi.org/10.1007/s10040-014-1149-6>
- Saravanan, S., Abijith, D., Reddy, N. M., KSS, P., Janardhanam, N., Sathiyamurthi, S., & Sivakumar, V. (2023). Flood susceptibility mapping using machine learning boosting algorithms techniques in Idukki district of Kerala India. *Urban Clim.*, 49. <https://doi.org/10.1016/j.uclim.2023.101503>
- Saravanan, S., Jegankumar, R., Selvaraj, A., Jennifer J., J., Parthasarathy, K.S.S. (2019). Utility of Landsat Data for Assessing Mangrove Degradation in Muthupet Lagoon, South India. *Coastal Zone Management*. <https://doi.org/10.1016/B978-0-12-814350-6.00020-3>
- Schueler, T. (1994). The Importance of Imperviousness. *Watershed Protection Techniques* Vol. 1, No. 3
- Shah, S. A., & Ai, S. (2024). Flood susceptibility mapping contributes to disaster risk reduction: A case study in Sindh, Pakistan. *Int. J. Disaster Risk Reduct.*, 108. <https://doi.org/10.1016/j.ijdr.2024.104503>

- Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. New York: Chapman and Hall.
- Souissi, D., Zouhri, L., Hammami, S., Msaddek, M. H., Zghibi, A., & Dlala, M. (2019). GIS-based MCDM – AHP modeling for flood susceptibility mapping of arid areas, southeastern Tunisia. *Geocarto International*, 35(9), 991–1017. <https://doi.org/10.1080/10106049.2019.1566405>
- Subramanian, N. & Ramanathan, R. (2012). A review of applications of Analytic Hierarchy Process in operations management. *Int. J. Prod. Econ.* Vol 138, Issue 2, pp: 215-241
- Swain, K.C., Singha, C. & Nayak, L. (2020). Flood Susceptibility Mapping through the GIS AHP Technique Using the Cloud. *ISPRS International Journal of Geo-Information*, 9(12), 720. <https://doi.org/10.3390/ijgi9120720>.
- Theilig, K., Lourenço, B., Reitberger, R. & Lang, W. (2024). Life cycle assessment and multi-criteria decision-making for sustainable building parts: criteria, methods, and application. *Int J Life Cycle Assess* 29, 1965–1991. <https://doi.org/10.1007/s11367-024-02331-9>
- Thi Thuy Linh, N., Pandey, M., Janizadeh, S., Sankar Bhunia, G., Norouzi, A., Ali, S., Bao Pham, Q., Tran Anh, D., & Ahmadi, K. (2022). Flood susceptibility modeling based on new hybrid intelligence model: Optimization of XGboost model using GA metaheuristic algorithm. *Adv. Space Res.*, 69(9), 3301–3318. <https://doi.org/10.1016/j.asr.2022.02.027>
- Toth, W. & Vacik, H. (2018). A comprehensive uncertainty analysis of the analytic hierarchy process methodology applied in the context of environmental decision making. *J Multi-Crit Decis Anal.* 25:142–161
- U.S. Census Bureau. (2018). “American Community Survey.” <https://www.census.gov/programs-surveys/acs>.
- United States Department of Agriculture (1986). *Urban hydrology for small watersheds*. Technical Release 55 (TR-55) (Second ed.). Natural Resources Conservation Service, Conservation Engineering Division.
- USDA Forest Service. (2023). Tree canopy cover datasets. Retrieved on Jan 15, 2025, from <https://www.mrlc.gov/data>
- USDA-NRCS. (2024). SSURGO Dataset. Retrieved on Jan 15, 2025, from <https://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx>
- USGS 2023 Land Cover. (2024). Annual National Land Cover Database (NLCD). Retrieved on Jan 15, 2025 from <https://www.mrlc.gov/data>
- USGS Earth Explorer. Retrieved on Jan 15, 2025 from <https://earthexplorer.usgs.gov/>
- USGS. (2018). Floods and Recurrence Intervals. Retrieved from https://www.usgs.gov/special-topics/water-science-school/science/floods-and-recurrence-intervals?utm_source=chatgpt.com
- USGS (2025). The National MAP. Retrieved on Jan 15, 2025 from <https://www.usgs.gov/programs/national-geospatial-program/national-map>

- Wahba, M., Essam, R., El-Rawy, M., Al-Arifi, N., Abdalla, F., & Elsadek, W. M. (2024). Forecasting of flash flood susceptibility mapping using random forest regression model and geographic information systems. *Heliyon*, 10(13), e33982. <https://doi.org/10.1016/j.heliyon.2024.e33982>
- Widya, L. K., Rezaie, F., Lee, W., Lee, C. W., Nurwatik, N., & Lee, S. (2024). Flood susceptibility mapping of Cheongju, South Korea based on the integration of environmental factors using various machine learning approaches. *J. Environ. Manage.*, 364. <https://doi.org/10.1016/j.jenvman.2024.121291>
- Wind, Y. & Saaty, T. L. (1980). Marketing Applications of the Analytic Hierarchy Process. *Management Science*. 26(7):641-658. DOI: 10.1287/mnsc.26.7.641
- Wurbs, R. A. (2021). Storage and regulation of river flows by dams and reservoirs. *Texas Water Journal*. 12(1):10-29. Available from: <https://doi.org/10.21423/twj.v12i1.7106>.
- Yadav, N., Wu, J., Banerjee, A., Pathak, S., Garg, R. D., & Yao, S. (2024). Climate uncertainty and vulnerability of urban flooding associated with regional risk using multi-criteria analysis in Mumbai, India. *Environ. Res.*, 244. <https://doi.org/10.1016/j.envres.2023.117962>