

Article

Assessing Flood Susceptibility Using a Data-Driven, GIS-Based Frequency Ratio Model

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Abstract

Flooding is one of the major natural disasters that have a major impact on urban areas due to the increasing intensity of factors like extreme weather conditions, climate change, and unplanned urbanization. Considering Cook County, Illinois, the rapid development of the region, flat topography, and the induced rainfall extremes from climate change increase the potential risk of flooding when interacting with dense urban exposure and infrastructure. This study employed the Frequency Ratio (FR) model in a GIS environment to create a high-resolution flood susceptibility map of the county. The map was developed using 281 historical flood points collected from several authoritative sources, such as National Oceanic and Atmospheric Administration (NOAA) Storm Events Database records, Federal Emergency Management Agency (FEMA) Flood Insurance Study (FIS) and Flood Insurance Rate Map (FIRM)-based FIRMette products, and U.S. Geological Survey (USGS) flood-inundation studies. Thirteen conditioning factors, including land use, elevation, slope, soil drainage, rainfall, and distance to the stream, were used to calculate FR values and to develop the Flood Susceptibility Index (FSI). The resulting FSI was grouped into four susceptibility zones: low, medium, high, and very high. The findings indicated that more than 64% of Cook County has a high and very high risk of flood susceptibility, particularly in the vicinity of major river corridors. The model was validated using testing data with a 91.4% prediction accuracy, which also demonstrated the reliability and applicability of the FR model in the urban flood susceptibility assessment. The map serves as a valuable tool for risk-based urban planning and design of flood mitigation infrastructure in one of the most populated counties in the United States.

Keywords: flash flood; vulnerability; flood inventory; remote sensing; urban risk management



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1. Introduction

Floods are natural hydrological hazards that become disasters when their impacts affect human settlements, infrastructure, and socio-economic systems [1,2]. They have caused up to 40% of natural disasters and have an annual economic cost of more than \$40 billion [3,4]. Impervious surfaces, poor drainage systems, and extreme weather patterns due to climate change aggravate floods in urban areas [5–8]. The United States frequently experiences flooding, with the Midwest particularly vulnerable due to its rapidly expanding rivers and cities [9,10]. Cook County, Illinois, is a prime example of this problem,

particularly in the context of Chicago. Flooding in the area has caused billions of dollars in damage in the past few decades [11]. The flood in the Chicago area in 2013 was responsible for more than \$2.5 billion in damage to homes and businesses, and displaced thousands of people [12]. That event illustrated the need to assess risk beforehand.

Land-use planning requires the use of flood susceptibility mapping to mitigate disaster damage [13]. Flood susceptibility maps identify at-risk areas based on natural and anthropogenic factors and inform mitigation responses such as land use zoning or infrastructure upgrading [14–16]. Such maps can protect key infrastructure, such as transportation networks or utilities, in Cook County, which has over 90% developed land [17]. More reactive responses come at a higher cost and slower recovery [18].

Several approaches have been applied for flood susceptibility mapping, including GIS-based, machine learning [19], or statistical methods [14,20,21]. GIS-based methods such as Analytical Hierarchy Process (AHP) rely on experts to weight factors such as elevation or land use into risk indices [22,23]. AHP [24] has been applied in urban flood studies and takes a structured approach to decision-making but is susceptible to subjective bias [25]. Multi-Criteria Decision Analysis (MCDA) builds on this principle by incorporating multiple stakeholder input, a method applied in coastal cities, though it requires extensive data calibration [26]. Machine learning techniques such as Artificial Neural Networks (ANN) or Support Vector Machines (SVM) employ pattern recognition for flood prediction [27]. For example, ANNs have shown high accuracy in simulating non-linear flood relationships but require large datasets and computational resources [28,29]. Statistical methods like Weights of Evidence (WofE) and Frequency Ratio (FR) provide probabilistic frameworks with minimal assumptions [30–32]. WofE uses Bayesian statistics to quantify evidence of flood occurrence, making it useful in data-scarce areas [33,34]. However, the FR model represents a simple, objective, and interpretable weighing method that calculates the ratio of flood occurrences within a class factor to its areal proportion [35]. Similar studies have shown that FR remains valuable both as a standalone statistical approach and as a preprocessing step in hybrid models for susceptibility mapping [36,37]. Advantages of FR in urban applications are low required data, direct spatial correlation analysis, and ease of integration with GIS [38,39]. Unlike complex machine learning models, FR avoids overfitting and ensures factor contributions are directly visible, making it suitable for policy applications. Few flood susceptibility studies based on FR have been applied in the highly urbanized areas of the US, where urban drainage and glacial topography dominate [40,41].

Recent research further supports the strengths of FR [35,38,39,42]. The FR model is regarded as a highly accurate and reliable approach for hazard assessment, providing robust and predictive results, and is straightforward to implement in GIS environments [42]. As a bivariate statistical method, FR derives its weight directly from the presence of flood, ensuring objectivity and reproducibility. It is particularly valuable for areas where high-quality flood inventories are available, such as Cook County. Unlike knowledge-driven frameworks such as AHP, FR avoids subjective weighting by focusing on observed evidence.

Several case studies have shown FR's versatility. The FR model has been applied in various geographic conditions and hydrologic settings. It was satisfactorily applied in Jeddah, Saudi Arabia, to map flash flood-prone zones in a dense urban setting [43]. In New Cairo City, Egypt, FR was applied to prepare a flood susceptibility map with an Area Under the Curve (AUC) of ~0.90 and ~20% of the city falls in a very high-risk zone [38]. In the Indo-Bangladesh Barind region, FR yielded a high predictive accuracy with an AUC of 0.901 and was applied in a riverine floodplain setting [39]. FR was also combined with AHP to map flash flood susceptibility in mountainous terrain in the Chitral District, Pakistan, which shows FR is also applicable to complex hydrologic processes [44]. In the USA, the FR model has also proven valuable, with its use as a benchmark model for flood

susceptibility mapping in New Orleans, Louisiana [40]. Even in this flat, low-lying city, FR successfully identified high-risk neighborhoods based on environmental and infrastructural factors. While sophisticated machine learning models sometimes reached marginally higher accuracy, FR offered understandable outputs and was easier to communicate with planners and policymakers.

Compared to machine learning approaches like random forest or neural networks, FR offers a balance between predictive power, computational efficiency, and transparency. Complex models can overfit small datasets and produce results that are harder to interpret; FR defines factor–flood relationships and requires fewer resources. Even though the application of this model is rare in flood hazard mapping, the reliability and competitiveness of the model’s predictive ability have been satisfactorily demonstrated in landslide susceptibility mapping as a standalone technique and as a hybrid technique with sophisticated models such as ANN, SVM, Generalized Additive Models (GAM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) [36,45–49]. For Cook County, with diverse topography, mixed urban–suburban conditions, and well-documented flood history, FR’s simple, accurate, and interpretable results make it a suitable choice. Although flood risk assessment studies have been carried out in Cook County [11,17], this research utilizes a clear framework based on the FR model, incorporating a variety of GIS conditioning factors and a detailed flood inventory map to generate a detailed flood susceptibility map.

The emphasis of this research lies in the interpretation of the individual factors and the representation of anthropogenic flood processes, which are pertinent to urban planning and flood mitigation in a highly urbanized environment. Accordingly, the study focuses on the interpretability, data integration, and planning-oriented applicability of an established FR framework. Hence, this research attempts to address the following research question: How effectively can a clear framework based on the FR model, incorporating a variety of GIS conditioning factors and a detailed flood inventory map, be used to characterize and interpret flood susceptibility patterns influenced by anthropogenic and environmental processes in a highly urbanized environment such as Cook County, Illinois? The primary objectives of this paper are

1. To create a comprehensive and high-resolution flood susceptibility map for Cook County using integrated GIS and frequency ratio (FR) modeling techniques supported by a comprehensive, multi-source flood inventory.
2. To investigate, quantify and interpret spatial relationships between historical flood occurrences and a set of thirteen unique flood conditioning factors encompassing topography, hydrology, geology, soil characteristics, and land use.
3. To validate the generated flood susceptibility map using a dataset compiled from multiple authoritative sources for assessing predictive accuracy and reliability.

2. Materials and Methods

2.1. Study Area

Cook County, located in northeastern Illinois, USA, spans approximately 2450 km² (945 square miles of landmass) and falls between latitudes 41°28′ N and 42°09′ N and longitudes 87°31′ W and 88°15′ W as shown in Figure 1. It covers 134 municipalities, with Chicago as the center, and is the second most populous county in the U.S. The county’s administrative divisions cover urban core areas, suburbs, and minimal rural pockets, with a population of roughly 5.2 million as of 2024, making its density exceed 5500 people per square mile in urban settings [11]. The climate is continentally humid, with hot summers and cold winters, with an average annual precipitation of 36.89 inches (937 mm). Precipitation peaks in the spring and summer (May–August) from thunderstorms, while winter precipitation includes snowpack that contributes to flooding. Recent trend anal-

ysis indicates intensification of extreme events; for instance, a 10–15% increase in heavy precipitation since the 1980s due to climate change [50].

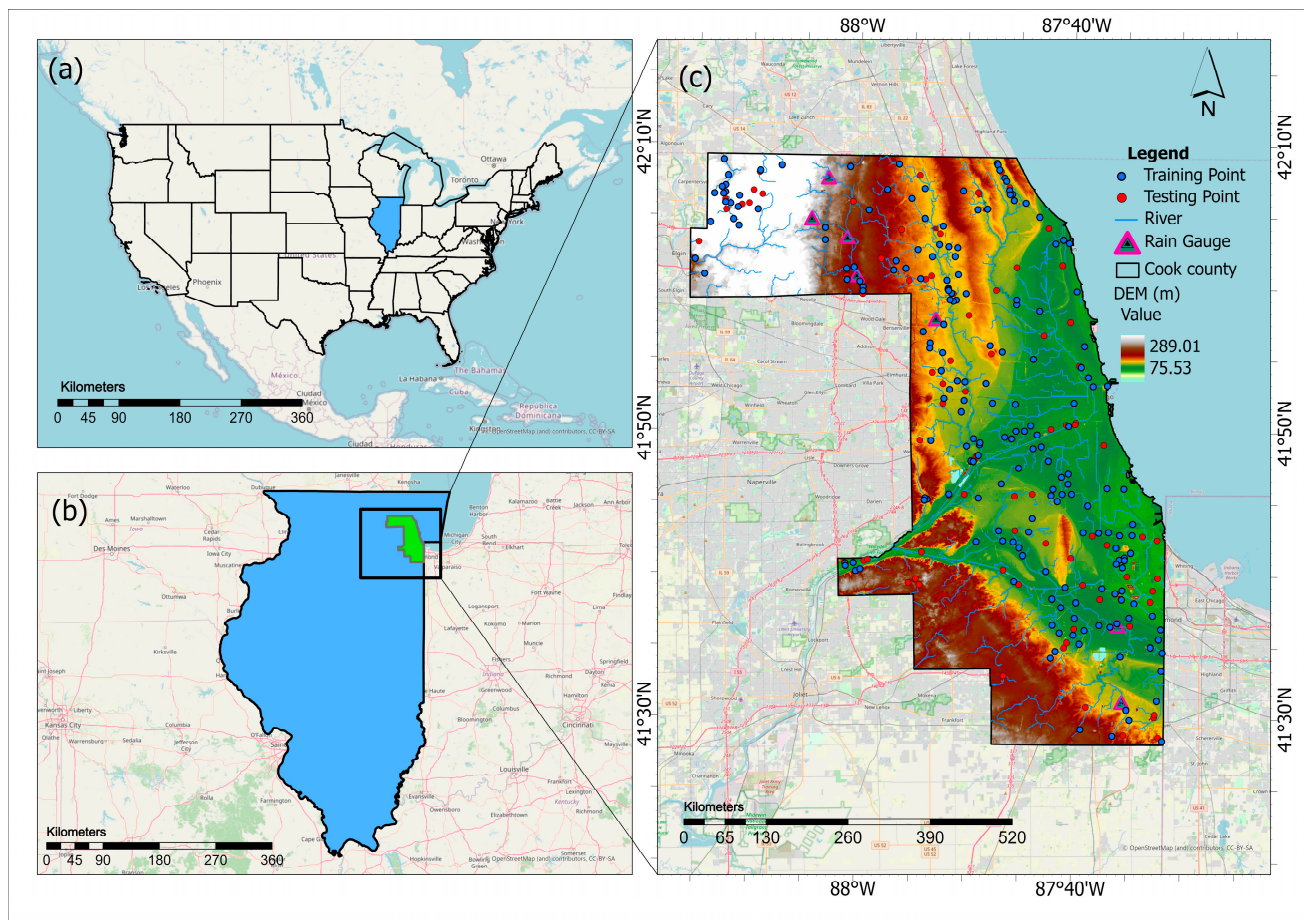


Figure 1. Study area map: (a) Location of the state of Illinois highlighted within the Contiguous United States; (b) Illinois map highlighting Cook County; (c) Spatial distribution of training and testing flood points, rivers, elevation and rain gauges in Cook County, Illinois.

Topographically, Cook County is predominantly flat, a legacy of Pleistocene glaciation. Geomorphologically, the county features moraines, lake plains, and outwash areas, which promote poor natural drainage. Lake Michigan borders the eastern side, affecting the local microclimate and serving as a flood outlet. Hydrologically, significant rivers such as the Chicago River (reversed for sanitation purposes), Des Plaines River, and Calumet River flow are part of the Mississippi and Great Lakes watersheds. The drainage network is dense in urban areas but altered by combined sewer systems, leading to overflow during heavy rains. Urbanization has increased impervious surfaces and reduced infiltration, increasing runoff. More than 90% of the land use consists of developed areas such as residential, commercial, and industrial, with fewer remnants of forest and wetland. The population density ranges from more than 20,000 per square mile in central Chicago to lower in the suburbs.

Historical floods have plagued Cook County, such as the 1986–1987 flood that overflowed the river and caused USD 62 million in damage [51] and the 2008 flood triggered by remnants of Hurricane Ike that affected 200,000 people and caused USD 100 million in damage [52]. The record 2013 rainfall caused widespread urban flooding and up to \$1 billion in losses in Cook County. The recent 2019–2020 flash floods have continued to elevate the vulnerability of the low-lying urban areas.

2.2. Data Sets

The study utilized multiple datasets for flood susceptibility mapping, detailed in Table 1. These include topographic, hydrological, soil, and land cover data from federal and county sources.

Table 1. Data, sources, spatial resolution, and temporal coverage for different flood-inducing factors.

Data	Source of Data	Original Resolution	Temporal Coverage
Land Use/Land Change (LULC)	Multi-Resolution Land Characteristics Consortium (MRLC) [53]	30 m × 30 m	National LandCover Database (NLCD) 2023, Updates annually
Lithology	Illinois Geospatial Data Clearing House [54]	10 m × 10 m	2005 (Published Date)
Soil Drainage	Soil Survey Geographic Database (SSURGO) Downloader-Environmental Systems Research Institute (Esri) [55]	10 m × 10 m	December 2024 (Updates annually)
Soil Type	Same as Soil Drainage	10 m × 10 m	Same as Soil Drainage
Digital Elevation Model (DEM)	3DEP from the United States Geological Survey (USGS) [56]	1/3 Arc s	16 November 2021, 7 November 2024, and 8 March 2019 (Published Date)
Distance from the River	Derived from Digital Elevation Model	1/3 Arc s	Same as DEM
Slope	Derived from DEM	1/3 Arc s	Same as DEM
Rainfall	USGS Water Data for Nation [57]	Not Applicable	2011–2024 (Daily)
Topographic wetness index (TWI)	Derived from DEM	1/3 Arc s	Same as DEM
Aspect	Derived from DEM	1/3 Arc s	Same as DEM
Plan Curvature	Derived from DEM	1/3 Arc s	Same as DEM
Distance from Road	Topologically Integrated Geographic Encoding and Referencing system (TIGER) [58]	10 m × 10 m	25 September 2024 (Updates annually)
Drainage Density	Derived from river data	1/3 Arc s	Same as DEM

We resampled both raster-based datasets such as Digital Elevation Model (DEM) and Land Use/Land Cover (LULC) and vector-based datasets (including soil type, soil drainage, roads, and rivers) to a uniform spatial resolution of 10 m × 10 m and projected them to the North American Datum of 1983 (NAD83), Universal Transverse Mercator (UTM) Zone 16 North (N) coordinate system. This method allowed for the creation of consistent thematic layers, which were then reclassified and prepared for FR analysis. The DEM (1/3 arc-second) from the USGS 3D Elevation Program (3DEP) program (2019–2024) was used to derive topographic variables such as elevation, slope, aspect, plan curvature, and Topographic Wetness Index(TWI). Drainage density and distance from rivers were calculated from USGS hydrography data, while distance from roads was calculated from TIGER [58] (2024 version). LULC data were obtained from the MRLC [53] Consortium NLCD for the year 2023, lithology from the Illinois Geospatial Data Clearinghouse [54] representing 2005 conditions, and soil type and drainage from SSURGO [55] (2024 version). Daily rainfall data (2011–2024 period) from USGS Water Data for the Nation [57] were interpolated across the study area using Inverse Distance Weighting (IDW) method to generate continuous rainfall surfaces. All preprocessing, spatial analyses, and factor derivations were conducted in ArcGIS Pro 3.5.0 (Esri, Redlands, CA, USA) using Spatial Analyst and geoprocessing tools to ensure spatial alignment and thematic consistency of

all layers prior to FR computation. Figure 2 represents the schematic workflow used in this research.

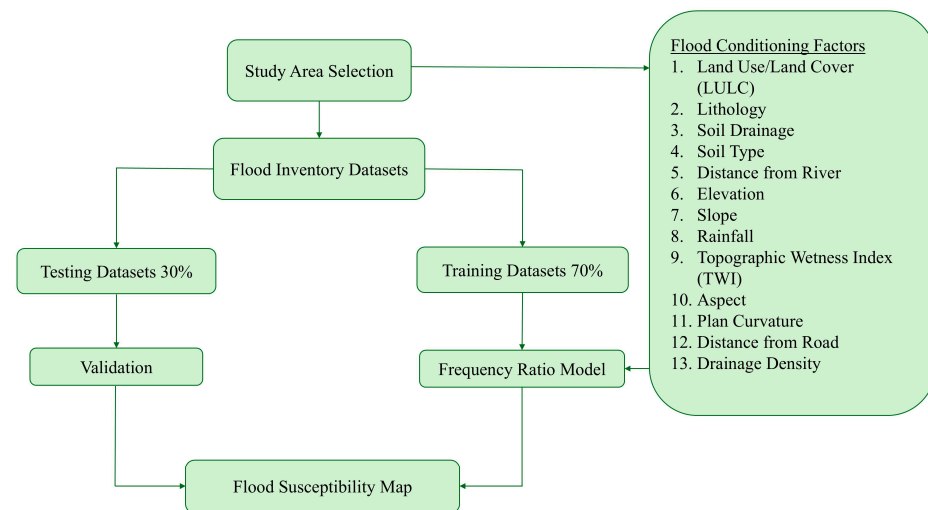


Figure 2. Frequency ratio-based flood susceptibility mapping workflow.

2.3. Flood Inventory Map

Flood inventory points are past historical flood events and the basis for developing data-driven flood susceptibility mapping using models such as the FR method [59]. In this study, a comprehensive flood inventory for Cook County, Illinois, was compiled from multiple authoritative sources, including National Oceanic and Atmospheric Administration (NOAA) Storm Events Bulk Data, Federal Emergency Management Agency (FEMA) Flood Insurance Study (FIS) reports and FIRMette products, and U.S. Geological Survey (USGS) flood-inundation studies. Together, these datasets document flood timing, flood occurrence at gauged and study-reach locations, peak stages and discharges, and mapped inundation extents for major flood events. The integration of these complementary data sources captures both riverine and urban flooding processes across the county, supporting a robust and reliable flood susceptibility analysis.

All identified flood locations were georeferenced and digitized within ArcGIS Pro 3.5.0. To facilitate model calibration and validation, the inventory was randomly partitioned using simple random sampling using Python 3.11.11 integrated in ArcGIS Pro to preserve spatial representativeness: 199 points (70%) were allocated to the training dataset for Frequency Ratio (FR) model development, while the remaining 82 points (30%) were reserved for testing and model performance evaluation [39,60–63]. Consistent with previous Frequency Ratio-based flood susceptibility studies conducted over large spatial extents [39,60,62,63], the adequacy of the 281 flood locations in this study lies in their spatial representativeness across diverse conditioning factors, making them sufficient to characterize flood susceptibility over the study area.

2.4. Flood Conditioning Factors

Thirteen environmental and anthropogenic variables were selected as flood conditioning factors based on their relevance to flood processes in Cook County and their frequent application in FR-based flood susceptibility mapping. These factors were chosen because they are the direct controls of the important flood generation mechanisms such as rainfall/runoff transformation, surface water accumulation, and floodplain connectivity under the physiographic and urbanized conditions. The relevance of each factor is discussed in the following subsections.

2.4.1. Land Use/Land Cover (LULC)

LULC is one of the most influential flood-conditioning factors because it directly impacts infiltration, evapotranspiration, and runoff generation. Areas with high impervious cover have low infiltration capacity and are more prone to rapid water accumulation, whereas wetlands and forests store and infiltrate water [64,65]. LULC data were obtained from the NLCD 2023 (MRLC Consortium) [53] at a 30 m resolution and resampled to 10 m. Categories include Open Water, Developed Open Space, Developed Low/Medium/High Intensity, Barren Land, Forest—Various Types, Shrub/Scrub, Grassland, Pasture/Hay, Cultivated Crops, Woody Wetlands, and Emergent Herbaceous Wetlands. For a heavily urbanized county like Cook, this factor provides a strong separation of high-risk zones from naturally resilient landscapes, and the final LULC layer is shown in Figure 3a.

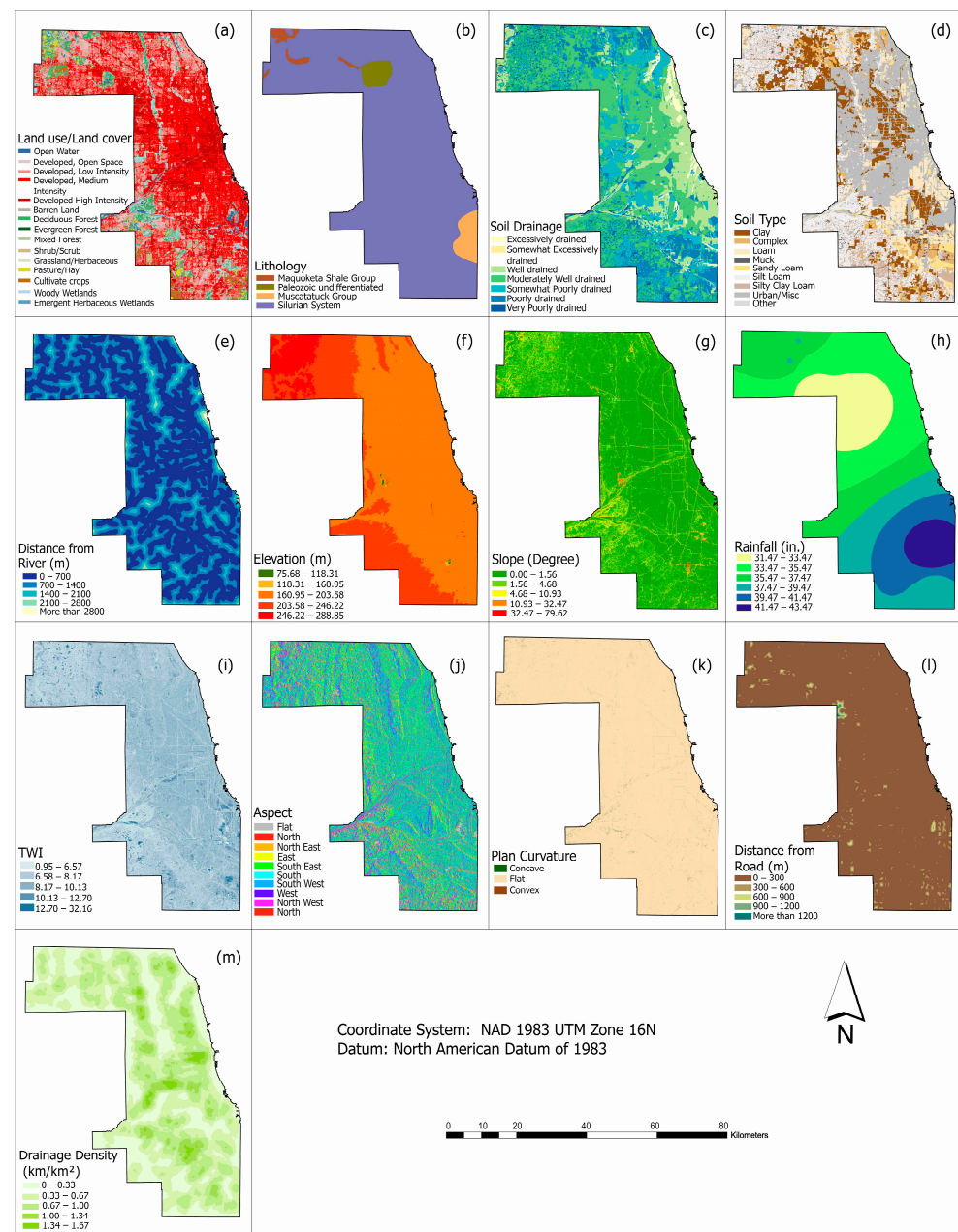


Figure 3. Parameters used for Frequency Ratio modelling: (a) Land use/land cover (LULC); (b) Lithology; (c) Soil drainage; (d) Soil type; (e) Distance from river; (f) Elevation; (g) Slope (degree); (h) Rainfall; (i) Topographic Wetness Index (TWI); (j) Aspect; (k) Plan curvature; (l) Distance from road; (m) Drainage Density.

2.4.2. Lithology

Lithology data from the Illinois Geospatial Data Clearinghouse were converted from vector to raster (10 m). Lithologic units were classified according to their capacity to transmit water and infiltrate rainfall. The lithologic classes identified in the study area include the Maquoketa Shale Group, Paleozoic undifferentiated, Muscatatuck Group, and Silurian System. Geological formations with low permeability, such as clay-rich glacial tills, drain poorly and result in higher runoff and surface water accumulation, whereas sandy or gravelly formations enable more drainage. In Cook County, which is situated atop glacially deposited sediments, variations in lithology are subtle but significant, influencing the speed at which rainfall translates into surface flow. Figure 3b illustrates the lithology map of the study area.

2.4.3. Soil Drainage

Soil drainage classes from SSURGO Esri Downloader were rasterized to 10 m. Soil drainage classes were obtained from the USDA NRCS SSURGO database by utilizing the Esri Living Atlas SSURGO Downloader, which provides map unit level attributes of the soils, including detailed field survey and laboratory analysis results. These classes reflect the inherent capacity of soils to transmit water. Poorly drained soils saturate and pond quickly, leading to greater runoff volume and duration, whereas well-drained soils can accommodate more infiltration before runoff begins [66]. In FR analysis, poorly drained soils consistently correspond to high susceptibility values. In Cook County, areas with poorly drained soil are often co-located with flat topography and developed land uses, generating conditions that prolong flooding following heavy rainfall. Figure 3c illustrates the soil drainage layer.

2.4.4. Soil Type

Soil texture and classification from SSURGO were derived similarly to the drainage layer. Though SSURGO is not a pedotransfer function, some of its hydric attribute values are actually derived by the NRCS from primary soil property values using well-established pedotransfer relationships, such as infiltration and water retention capacity. Differences in particle size (sand, silt, clay) affect infiltration rates and water retention capacity. Water retention capacity governs the partitioning of rainfall into infiltration and surface runoff and therefore represents a cornerstone control on flood generation in the study area. Clayey soils impede infiltration and more readily generate surface runoff, while sandy soils allow more drainage. In highly urbanized areas, even naturally well-drained soils may be functionally impermeable due to compaction and paving [67]. The inclusion of soil type in addition to drainage class enhances the FR model's capability to identify hydrologically sensitive zones. Figure 3d displays the spatial distribution of soil types.

2.4.5. Distance from River

Stream networks were derived from the DEM using a 0.32% flow accumulation threshold, a value developed to capture both main and secondary channels in Cook County's relatively low-relief landscape while maintaining realistic drainage connectivity. Euclidean distance from rivers was calculated to quantify proximity to primary drainage channels [68]. Flood probability typically decreases with increasing distance from rivers, as areas closer to watercourses are more exposed to overbank flooding and high water tables. In Cook County, this phenomenon is especially relevant for the Des Plaines, Calumet, and Chicago Rivers, where floodplains intersect with dense infrastructure and residential zones. The generated river-distance raster is provided in Figure 3e.

2.4.6. Elevation

Elevation data from the USGS 3DEP DEM were resampled to 10 m and classified into five equal-interval categories. Low-lying areas, particularly those near rivers and wetlands, are often more likely to flood given limited gravitational drainage [69]. Elevation also affects groundwater levels, with lower elevations more likely to have higher water tables. In the relatively flat terrain of Cook County, even slight variations in elevation can significantly influence flood behavior. The processed elevation classification is presented in Figure 3f.

2.4.7. Slope (Degree)

Slope was derived from the DEM and classified into five Natural Breaks categories. Flat or gently sloping areas slow runoff and encourage ponding, while steeper slopes promote rapid drainage [62]. In Cook County, low-slope areas are especially vulnerable to pluvial flooding when combined with high impervious surface coverage. This factor helps identify naturally well-drained upland areas from low-lying zones where water may pond after rain. Figure 3g illustrates the slope analysis results.

2.4.8. Rainfall

Daily rainfall records from USGS National Water Information system (NWIS) (2011–2024) [57] were interpolated using IDW to generate a continuous 10 m resolution surface. It is the most important factor for triggering flooding, and its spatial variability shapes flood distribution patterns. Localized storms, especially in the summer, can cause flash flooding in natural and urban drainage basins. Besides the quantity of rainfall, the rate of occurrence of rainfall is also significant in controlling flood generation in the study area. For example, short-period rainfall of high intensity can be greater than infiltration capacity, thus resulting in flash floods [70]. Precipitation gauges utilized for this analysis are presented in Table 2, and the resulting rainfall surface is shown in Figure 3h.

Table 2. USGS rain gauges with corresponding locations and Average annual rainfall.

USGS Site Number	Latitude (Degree)	Longitude (Degree)	Location (Station Name)	Average Annual Rainfall (Inches)
415755087525300	41.96528	−87.88139	O’Hare Airport at Chicago	31.47
420057088001700	42.01583	−88.00472	Busse Woods near Elk Grove Village	31.82
420453088043200	42.08139	−88.07556	Harper College at Palatine	37.59
413113087342201	41.52083	−87.59028	Near Chicago Heights	38.34
420745088025901	42.12917	−88.04972	Sundling Jr HS at Palatine	37.51
5530990	42.06000	−88.02000	Salt Creek At Rolling Meadows	33.62
5536290	41.61000	−87.59700	Little Calumet River at South Holland	43.47

2.4.9. Topographic Wetness Index (TWI)

TWI is a numerical measure of the likelihood that an area will accumulate water. It was derived from the DEM using the standard formula [71]:

$$TWI = \ln (\text{Specific Catchment Area} / \tan (\text{slope})) \quad (1)$$

where Specific Catchment Area = (Catchment Area/Unit Contour Length), Catchment Area = (Flow Accumulation Raster + 1) × (Area of each cell), and tan (slope) = (Slope Raster/100) + 0.001.

TWI indicates areas of potential water accumulation and soil saturation. High TWI values usually indicate depressions, riparian zones, and flat areas with a large upslope catchment. In Cook County's urban context, high-TWI zones are also likely to occur in poorly drained areas such as underpasses. The output TWI layer is displayed in Figure 3i.

2.4.10. Aspect

Aspect was derived from the DEM and classified into nine directional categories plus flat. The effect of aspect on flooding is indirect, but it gives an idea of how snowmelt, microclimate, and soil moisture are distributed [72]. When combined with other terrain attributes, it can define local runoff behavior in areas where seasonal variations have an impact on the control of flood patterns. The output aspect classification is displayed in Figure 3j.

2.4.11. Plan Curvature

The plan curvature from the DEM was classified as concave, convex, and flat [73]. Concave surfaces concentrate the runoff and increase the probability of flooding, while convex surfaces disperse water. This attribute complements slope and TWI by indicating micro-topography that influences water routing. The output plan curvature is displayed in Figure 3k.

2.4.12. Distance from Road

The road network from TIGER [58] (2024 version) was used to compute Euclidean distance from roads. Roads obstruct natural drainage, redirecting flows and creating artificial drainage paths. In densely built areas, roads are also a significant cause of hotspots for localized flooding due to limited stormwater capacity [74–76]. The output distribution of road distances is shown in Figure 3l.

2.4.13. Drainage Density

Drainage density was calculated from the DEM-derived stream network using the Line Density tool. Higher drainage density can indicate high conveyance of runoff, but could also indicate rapid flood response in impervious or steep areas [14]. In Cook County, drainage density reflects both natural channels and engineered drainage infrastructure. It can help to define the distribution of water during storm events (Figure 3m).

2.5. Frequency Ratio (FR) Model

The Frequency Ratio (FR) model is a well-established bivariate statistical approach that determines a probabilistic relationship between dependent and independent variables [33,77,78]. It is widely used as an effective method to map the susceptibility to flooding. It quantitatively evaluates the spatial relationship between historical flood locations (dependent variable) and a number of geo-environmental conditioning factors (independent variables—slope, elevation, land use, distance to rivers, etc.). The model is based on the comparison of the density of the number of flood occurrence events in a certain class of a factor of interest against the density of flood occurrence in the entire study area. The calculation is based on the ratio of the percentage of floods in a certain factor class over the percentage of the total area occupied by that class. The resultant value greater than 1 implies a strong positive relationship, which means that the particular factor class has a high probability of being flooded. However, a value less than 1 would signify a negative relationship. The frequency ratio (FR) for each class of factor is calculated using Equation (2) [38,60,79]:

$$FR = (E/F)/(M/L) \quad (2)$$

where E represents the number of flood pixels in a factor class, F is the total number of flood pixels in the entire study area, M is the number of pixels in the class area, and L is the total number of pixels in the study area.

To prepare an integrated flood susceptibility map, FR values calculated for each class of each conditioning factor are aggregated to a final Flood Susceptibility Index (FSI) for every pixel in the study area. The computation is done by summing the FR values of the specific class that the pixel belongs to for each factor, using Equation [33,80,81]:

$$FSI = \sum FR \quad (3)$$

Here, $\sum FR$ is the sum of all Frequency Ratio values for all the factors for a given pixel.

A higher FSI value implies higher susceptibility. Finally, the continuous FSI values were reclassified into four discrete susceptibility classes: low (6.96–9.00), medium (9.00–12.00), high (12.00–22.00), and very high (>22.00). This classification facilitates a clear interpretation of areas that are susceptible to flooding to some degree.

3. Results and Discussion

3.1. Conditioning Factor Analysis

The Frequency Ratio (FR) values for each conditioning factor and its subclasses are presented in Table 3, providing a quantitative measure of the spatial relationship between flood occurrences and environmental attributes. In the context of Cook County, a densely urbanized region with extensive impervious surfaces, altered drainage systems, and proximity to major water bodies like Lake Michigan and rivers such as Chicago and Des Plaines, these FR values reveal key drivers of urban flooding. The analysis highlights the dominance of anthropogenic factors, such as land use and infrastructure proximity, over natural topographic ones, aligning with patterns observed in other midwestern urban flood studies.

Table 3. Factors used for Flood Susceptibility mapping using the FR model.

Class Name	Subclass Name	Histogram	% of Histogram	Flood Numbers	Frequency Ratio
Land Use/Land Change	Open Water	364,428	1.471	38	12.985
	Developed, Open Space	2,514,069	10.145	19	0.941
	Developed, Low Intensity	5,626,620	22.706	40	0.885
	Developed, Medium Intensity	8,958,825	36.152	57	0.792
	Developed High Intensity	3,998,565	16.136	24	0.747
	Barren Land	99,513	0.402	1	1.251
	Deciduous Forest	1,255,824	5.068	10	0.992
	Evergreen Forest	918	0.004	0	0.000
	Mixed Forest	12,069	0.049	0	0.000
	Shrub/Scrub	98,568	0.398	0	0.000
	Grassland/Herbaceous	80,874	0.326	0	0.000
	Pasture/Hay	256,158	1.034	1	0.486
	Cultivate crops	431,217	1.740	2	0.578
	Woody Wetlands	860,364	3.472	5	0.724
	Emergent Herbaceous Wetlands	222,669	0.899	2	1.118
Lithology	Maquoketa Shale Group	360,190	1.454	4	1.383
	Paleozoic undifferentiated	539,577	2.177	9	2.077
	Muscatatuck Group	745,970	3.010	9	1.502
	Silurian System	23,134,507	93.359	177	0.953
Soil Drainage	Excessively drained	835,724	2.724	3	0.554
	Somewhat Excessively drained	33,537	0.109	0	0.000
	Well drained	5,076,183	16.543	55	1.671
	Moderately Well drained	12,787,870	41.676	66	0.796
	Somewhat Poorly drained	5,897,290	19.219	24	0.628
	Poorly drained	5,311,959	17.312	44	1.277
	Very Poorly drained	741,788	2.417	7	1.455

Table 3. Cont.

Class Name	Subclass Name	Histogram	% of Histogram	Flood Numbers	Frequency Ratio
Soil Type	Clay	4,865,821	15.861	22	0.697
	Complex	1,624,512	5.295	10	0.949
	Loam	2,950,995	9.619	24	1.254
	Muck	282,128	0.920	2	1.093
	Sandy Loam	800,153	2.608	2	0.385
	Silt Loam	6,684,586	21.789	20	0.461
	Silty Clay Loam	3,507,948	11.435	23	1.011
	Urban/Misc	9,660,435	31.490	94	1.500
	Other	301,629	0.983	2	1.022
Distance from River (m)	0–700	14,507,006	58.557	159	1.364
	700–1400	7,698,002	31.073	35	0.566
	1400–2100	2,272,664	9.173	4	0.219
	2100–2800	270,681	1.093	1	0.460
	More than 2800	25,917	0.105	0	0.000
Elevation (m)	75.68–118.31	19,804	0.080	0	0.000
	118.31–160.95	20,636	0.083	0	0.000
	160.95–203.58	16,271,903	65.663	166	1.270
	203.58–246.22	6,784,024	27.376	25	0.459
	246.22–288.85	1,684,557	6.798	8	0.591
Slope (Degree)	0.00–1.56	17,517,167	70.767	151	1.072
	1.56–4.68	5,693,204	23.000	36	0.787
	4.68–10.93	1,271,477	5.137	12	1.174
	10.93–32.47	261,704	1.057	0	0.000
	32.47–79.62	9851	0.040	0	0.000
Rainfall (in.)	31.47–33.47	3,403,026	13.736	43	1.573
	33.47–35.47	7,135,182	28.801	51	0.890
	35.47–37.47	5,210,587	21.032	37	0.884
	37.47–39.47	4,250,991	17.159	25	0.732
	39.47–41.47	3,182,485	12.846	16	0.626
	41.47–43.47	1,591,994	6.426	27	2.111
Topographic wetness index	0.95–6.57	6,085,681	24.585	35	0.715
	6.58–8.17	9,776,132	39.494	49	0.623
	8.17–10.13	5,646,227	22.810	45	0.991
	10.13–12.70	2,561,634	10.349	51	2.476
	12.70–32.16	683,729	2.762	19	3.457
Aspect	Flat (–1)	219,132	0.885	27	15.326
	North (0.0–22.5 and 337.5–360.0)	1,347,848	5.445	5	0.461
	Northeast (22.50–67.50)	2,652,574	10.716	12	0.563
	East (67.5–112.5)	4,143,924	16.741	32	0.961
	Southeast (112.5–157.5)	3,526,490	14.246	25	0.882
	South (157.5–202.5)	3,829,480	15.471	34	1.104
	Southwest (202.5–247.5)	3,176,799	12.834	20	0.783
	West (247.5–292.5)	3,578,746	14.458	27	0.938
	Northwest (292.5–337.5)	2,278,410	9.204	17	0.928
Plan Curvature	Concave (–14.8––0.5)	210,451	0.849	2	1.183
	Flat (–0.5–0.5)	24,178,261	97.568	196	1.009
	Convex (0.5–14.8)	392,212	1.583	1	0.317
Distance from Road (m)	0–300	23,878,967	96.386	186	0.970
	300–600	748,997	3.023	8	1.330
	600–900	111,804	0.451	5	5.568
	900–1200	28,271	0.114	0	0.000
	More than 1200	6231	0.025	0	0.000
Drainage Density (km/km ²)	0.00–0.33	7,182,171	28.983	32	0.555
	0.33–0.67	8,949,084	36.113	67	0.932
	0.67–1.00	6,623,360	26.728	69	1.297
	1.00–1.34	1,691,088	6.824	28	2.062
	1.34–1.67	335,221	1.353	3	1.114

Starting with Land Use/Land Cover (LULC), this factor exhibits some of the most varied and influential FR values, reflecting the impact of human modification on hydrological processes. The subclass “Open Water” has the highest FR of 12.985, despite occupying only 1.471% of the area, as it accounts for 38 flood points. This strong correlation is expected, as open water bodies like rivers and lakes serve as natural flood conduits, exacerbating overflow during heavy precipitation in low-lying urban zones. In Cook County, this is particularly relevant along the Chicago River, where historical floods originated from riverine sources. Similarly, “Emergent Herbaceous Wetlands” shows an FR of 1.118, indicating moderate susceptibility due to their role in water retention but vulnerability to saturation. Urban development subclasses dominate the landscape, covering over 85% of the county. “Developed, Open Space” (FR 0.941) and “Developed, Low Intensity” (FR 0.885) have FR values close to 1, suggesting average risk, but their large areal coverage (10.145% and 22.706%, respectively) amplifies overall exposure. Higher intensity developments, such as “Developed, Medium Intensity” (FR 0.792) and “Developed, High Intensity” (FR 0.747), exhibit lower FR, likely because of engineered drainage in dense areas like downtown Chicago; however, these still contribute to flooding via impervious surface runoff. Natural vegetation subclasses like “Evergreen Forest” and “Shrub/Scrub” have FR of 0.000, indicating protective effects through infiltration, though their limited extent (0.004% and 0.398%) minimizes county-wide influence. As a relatively static conditioning factor, LULC reflects long-term land surface characteristics that control runoff generation and flow concentration. Overall, LULC underscores the spatial influence of urbanization patterns in Cook County on flood susceptibility, where impervious surfaces reduce permeability, channeling water into flood-prone channels, consistent with findings from similar urban flood mappings in the Midwest [11].

Lithology represents underlying geologic formations and demonstrates moderate variability in FR values [69]. The “Paleozoic undifferentiated” subclass has the highest FR of 2.077; however, it comprises only 2.177% of the area, as it has low permeability and is associated with 9 flood points. This Paleozoic formation is common in northern Cook County suburbs, which impedes infiltration and promotes surface runoff during storms [82]. The “Muscatatuck Group” and the “Maquoketa Shale Group,” with FR values of 1.502 and 1.383, are also over 1, indicative of their shale-rich composition, which restricts water percolation. The dominant “Silurian System” system covers over 93.359% of the area, with an FR value of 0.953, slightly less than 1, and is susceptible to flooding due to its dolomitic layers, which allow better drainage in less urbanized pockets. These patterns are consistent with Cook County’s glacial past, where thin soils over bedrock exacerbate flooding in developed areas.

Soil drainage and soil type help highlight subsurface factors. For soil drainage, the “well-drained” subclass had an FR of 1.671 (16.543% of area, associated with 55 floods), a higher risk than would be expected, possibly explained by its location in urban fringes where development overcomes natural advantages. The “Very Poorly Drained” and “Poorly Drained” subclasses combined comprise 19.729% of the total area and exhibit a strong relationship. Saturated soils in lowlands, such as around the Calumet region, prolong ponding times. Lower FR is seen in “Moderately Well Drained” with 0.796, demonstrating transitional behavior. Soil type complements this, as “Urban/Misc” has FR 1.500, occupies 31.490% of the area, and highlights anthropogenic soils in Chicago proper, where compaction and contamination reduce infiltration. “Loam” and “Muck” have FR over 1 and are common in areas of wetland remnants, while “Sandy Loam” provides protection with an FR of 0.385, reflecting its high permeability. The influence of anthropogenic soils in Cook County represents areas of amplified flood risk, different from rural Illinois, where natural soils dominate.

Proximity-based factors, such as distance from rivers and roads, show infrastructural vulnerabilities. For distance from river, the “<700 m” buffer has an FR of 1.364 (58.557% area, 159 floods), falling off sharply to 0.219 at 1400–2100 m, indicating riverine flooding along the Des Plaines and Chicago Rivers, where 70% of historic events occurred. Distances greater than 2800 m show FR 0.000, as uplands are free from direct overflow. The distance from the road reaches its peak at “600–900 m,” exhibiting a surprisingly high FR of 5.568. This high value is attributed to secondary flooding caused by overloaded storm drains near highways, a common occurrence in suburban Cook County. Closer ranges, 0–300 m, have an FR of 0.970, benefiting from engineered protections, and still pose risks.

Topographic factors include elevation, slope, TWI, aspect, and plan curvature. Elevation at the “160–203 m” class (FR 1.270, 65.663% of area) dominates susceptibility, indicative of Cook County’s flat glacial plains, where minor depressions hold water. Higher elevations (>246 m) have an FR of 0.591, offering relief. Slope, the class 4.68–10.93°, has an FR of 1.174, indicative of moderate inclines that channel runoff inefficiently in urban settings. A flat “<1.561°” class has an FR of 1.072, promoting ponding. TWI, a proxy for wetness, reaches peak FR at “>12.696” with a value of 3.457, indicating saturated zones in floodplains. Aspect at “Flat” (FR 15.326) exhibits the strongest correlation, as directionless terrain lacks drainage gradients. Plan Curvature’s “Concave” (FR 1.183) funnels water, enhancing risk in valleys.

Rainfall and drainage density address hydrological inputs. Rainfall in southern gauges, such as in South Holland, measures “41.47–43.47 inches” (FR 2.111) and corresponds to areas that drive susceptibility to convective storms. Drainage density, a class of “1.00–1.34 km/km²” (FR 2.062), represents ideal channel efficiency for flooding in urban watersheds.

Urban factors like LULC and road proximity dominated the ranking, appropriate for Cook County’s 90% conversion to imperviousness, where imperviousness trumps natural topography. This result contrasts with rural studies emphasizing slope [61,83], highlighting the need for urban-specific strategies.

3.2. Flood Susceptibility Map

The Flood susceptibility index (FSI) map was generated from summing each of the 13 conditioning factors’ FR values at each pixel, producing a continuous susceptibility surface from as low as 6.96 to over 22.00. This FSI was reclassified into four classes: low, medium, high, and very high [79,81]. The resulting flood susceptibility map (FSM) is depicted in Figure 4 and illustrates a spatial overview of vulnerability in Cook County. Table 4 presents the classes’ FR ranges, areas in km², and percentages of the total study area (~2475 km²). High and very high classes combined cover 63.977%, highlighting the widespread risk in this urbanized Midwest County, where development intensifies natural hazards.

Table 4. Spatial distribution of flood susceptibility categories within the study area.

Flood Susceptibility	Range of FR Value	Area in Sq.km	% Area
Low	6.96–9.00	7.584	0.306
Medium	9.00–12.00	884.001	35.717
High	12.00–22.00	1544.354	62.397
Very High	More than 22.00	39.108	1.580

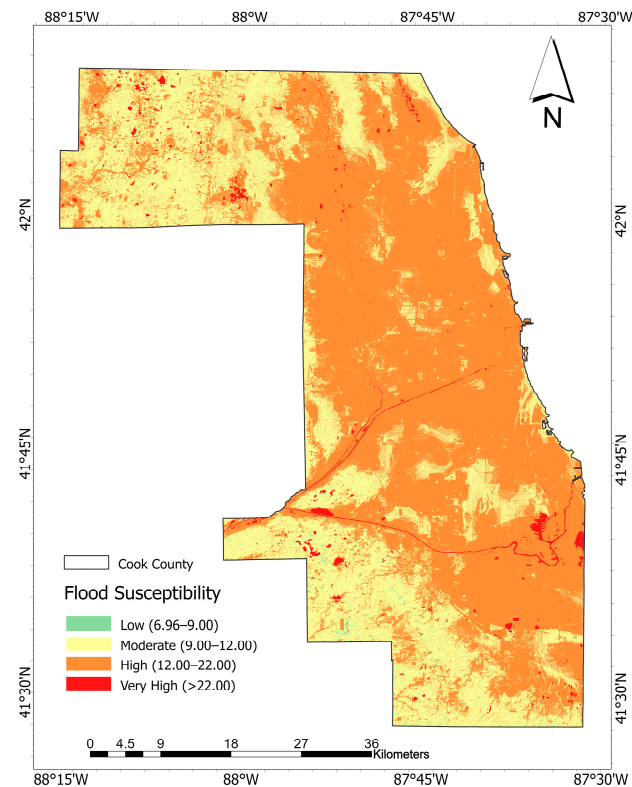


Figure 4. Flood susceptibility map of Cook County, Illinois, classified into four zones: low, moderate, high, and very high susceptibility.

The low susceptibility class (FR 6.96–9.00, 7.584 km²) overlaps with uplands; favorable conditions such as higher elevations (e.g., >246 m, FR 0.591), steep slopes (e.g., >10.929°, FR 0.000), and distances from rivers > 2800 m (FR 0.000). In Cook County, this classification includes the western hills in Barrington, acting as natural buffers where minimal historic flooding has occurred.

The medium class (FR 9.00–12.00, 884.001 km², 35.717%) spans the suburban transitions such as Schaumburg and Mount Prospect. This is derived from moderate FRs in medium-intensity development (0.792), loamy soils (1.254), and mid-range rainfall (0.890–0.884). These regions feature occasional urban flooding events, such as in 2023 in Berwyn, based on Chicago Metropolitan Agency for Planning (CMAP) reports [84].

The high class (FR 12.00–22.00, 1544.354 km², 62.397%) dominates, representing urban lowlands in the Chicago and Des Plaines Rivers, Uptown, and Alsip. Driven by FRs such as river proximity (<700 m, 1.364), high TWI (>12.696, 3.457), and flat aspects (15.326), the resulting susceptibility pattern broadly corresponds with flood-prone areas delineated in CMAP's regional planning datasets. The 2013 flood (USD 2.5 billion damage) affected these zones most, particularly Austin, where sewer overflows occur. The First Street Foundation calculates higher risks in these zones than official maps.

The very high class (FR > 22.00, 39.108 km², 1.580%) designates hotspots in southern Chicago, such as Calumet City. The highest FRs from open water (12.985), extreme rainfall (2.111), and dense drainage (2.062) combine to form a high risk. These overlap with Greenprint priorities, where a 2023 storm created catastrophes in Austin's low tracts (160–203 m, 1.270) [85,86]. Center for Neighborhood Technology (CNT) maps show flood recurrence in these tracts, affecting disadvantaged communities [87,88].

The FSM suggests Cook County drainage problems where more than 90% of high zones' imperviousness overstrains infrastructure, triggered by storms like remnants of 2008 Ike. High-risk dominance (62.4%) outstrips FEMA's 0.3% estimate using climate models.

This justifies green infrastructure in very high zones, zoning in high zones for 5.2 million residents, and the 2019 Hazard Mitigation Plan zoning [11,89].

3.3. Model Validation

The reliability and predictive power of the FR approach for mapping flood susceptibility in Cook County should be assessed through model validation. This research employed a zonal overlay validation approach—a standard GIS-based technique whereby independent testing data is overlaid on a classified FSI map to determine how well the model captures known flood events [79]. In this study, ArcGIS software was used to spatially intersect the 82 testing flood points with the four susceptibility classes (low, medium, high, and very high). The method quantifies testing points in each class, with a robust model expected to assign most points to high/very high zones, reflecting areas modeled as likely to experience flooding. Training points were also used to calculate the success rate (199 points, 70%) by overlaying them on the map to provide an internal measure of fit [62,90]. Table 5 summarizes the distribution across classes of both datasets and the associated accuracy metrics generated.

Table 5. Calculation of prediction accuracy and success rate for flood susceptibility mapping.

S. No.	Susceptibility Class	Verification (30% Flood Points)	Accurate (High to Very High Class)	Prediction Accuracy	Training (70% Flood Points)	Success (High to Very High Class)	Success Rate
1	Low	0			0		
2	Medium	7	75	0.914 or 91.4%	15	184	0.924 or 92.4%
3	High	53			145		
4	Very High	22			39		
Total		82			199		

Validation results indicate that the model is performing well. For the testing data, the distribution is 0 points in the low class, 7 in the medium, 53 in the high, and 22 in the very high, for a total of 82 points. The prediction accuracy, measuring the percentage of testing points correctly classified in the high-to-very-high-susceptibility zones, is 91.4 percent (75 of 82 points, 53 high + 22 very high). This indicates that the FR model identifies flood-prone areas well in advance of test data availability while minimizing false negatives in critical urban areas. Likewise, the success rate, based on the training points, is 92.4 percent (184 out of 199 points in the high-to-very-high classes: 145 high + 39 very high).

These strong validation results can be further understood by examining how the selected conditioning factors contribute positively or negatively to flood prediction. The high prediction accuracy (91.4%) and success rate (92.4%) of the FR model result from the deliberate selection of conditioning factors that explicitly represent the dominant physical and anthropogenic mechanisms controlling flood occurrence in Cook County. Land use/land cover, soil type, and soil drainage were included to capture variations in imperviousness, infiltration capacity, and surface runoff generation. Accordingly, urban and miscellaneous soil types (FR = 1.500), poorly and very poorly drained soils (FR = 1.277–1.455), and open water bodies (FR = 12.985) show positive contributions to flood prediction by promoting rapid runoff and prolonged water retention, whereas natural vegetation and well-drained soils contribute negatively due to enhanced infiltration and storage capacity.

Lithology was included in the model to simulate the effect of subsurface permeability and geological control on infiltration processes. Low permeability lithologies have FR > 1, signifying positive contributions due to the restriction of percolation and the promotion of surface runoff, while high permeability lithologies have negative contributions due to the promotion of subsurface drainage. Topographic variables, including elevation, slope, aspect, plan curvature, and the topographic wetness index, were included in the model

to simulate the potential for water accumulation and the efficiency of surface drainage. Flat areas (FR = 15.326), high TWI (FR = 3.457), concave areas, and low-lying areas have positive contributions due to the promotion of water accumulation, while high slopes and high elevations have negative contributions due to the surface runoff.

Hydrological proximity and connectivity indicators, such as distance to rivers, drainage density, and proximity to roads, were also included to assess exposure to riverine flooding and disruptions to flow as a result of infrastructure. The proximity to rivers (FR = 1.364), higher drainage density (FR = 2.062), and intermediate values of distance to roads all have a positive contribution since these areas are more hydraulically connected, have a higher concentration of channels, or have obstruction to natural drainage channels. Areas far removed from rivers and infrastructure have a negative contribution since their reduced connectivity limits their exposure to flooding. Rainfall was identified as a primary cause of flooding events, and higher rainfall classes up to a maximum value of FR = 2.111 have a positive contribution since they generate enough rainfall to initiate flooding events, while lower rainfall classes have a negative contribution. These individual mechanisms help to distinguish areas conducive to flooding and areas not conducive to flooding, thereby improving the ability of the FR model to identify flood-prone areas and explaining the strong validation results.

These high accuracy rates confirm the FR model's suitability for urban environments like Cook County, where complex interactions between factors such as impervious land use and river proximity dominate flood dynamics. Compared to similar studies, this aligns with FR applications in Chennai (95.6% prediction) [79] and with findings in urban New Cairo, Egypt, where FR yielded AUC ~ 0.90 [38].

3.4. Limitations of the Frequency Ratio (FR) Model and Contribution of the Study

The whole process of understanding and using the Frequency Ratio (FR) model for the purpose of mapping flood susceptibility revealed the limitations that are characteristic of the statistical methods used in flood susceptibility mapping (FSM). The FR method establishes the relationship between the historical records of floods in the study area and the individual conditioning factors, but it does not simulate the flood processes in the catchment area. Therefore, the flood susceptibility map derived using the FR method is based on relative flood-prone areas in the catchment, not the dynamic flood processes in the catchment. In addition, the FR method requires historical records of floods in the catchment for the estimation of weights for the conditioning factors and validating the results derived using the model, making the accuracy of the results dependent on the accuracy of the records used in the process [91]. The FR model analyzes the conditioning factors in isolation, making the interaction between the factors not explicitly addressed in the model.

Within this context, the present study contributes by applying the FR approach in a clear, systematic, and transparent manner [92] for flood susceptibility mapping in Cook County. The study integrates a comprehensive set of hydrologically and anthropogenically relevant conditioning factors and emphasizes interpretation of results based on the positive and negative contributions of these factors to flood susceptibility. By relating flood-promoting (FR > 1) and flood-limiting (FR < 1) subclasses to observed flood patterns, the study enhances the interpretability of FR-based outcomes. Overall, the proposed framework supports the effective use of the FR method as a practical tool for preliminary flood susceptibility assessment and spatial planning in urban environments.

3.5. Flood Management Implications

The flood susceptibility map identifies high and very high flood risk zones covering 64% of Cook County land area, primarily along riverine corridors such as the Chicago, Des Plaines, and Calumet Rivers. These areas include urban lowlands in Chicago's South Side and suburbs such as Alsip and Calumet City and expose well over 3 million residents to recurrent flooding, particularly in economically disenfranchised communities that are home to 87% of historical claims (2007–2016) made by communities of color [87]. Critical infrastructure, including O'Hare International Airport and major transportation systems, is at increased risk, with more than 200,000 properties exposed to major or severe risk in the next 30 years. These risks, unmitigated, could result in annual economic losses of over USD 10 billion, factoring in property damage, business disruptions, and recovery costs, and echoing the USD 2.5 billion impact of the 2013 flood [12,93] and recent USD 12 billion federal disaster relief funds.

Structural measures are needed to curtail immediate risks. Combined sewer system improvements, as proposed in the Multi-Jurisdictional Hazard Mitigation Plan (MJ-HMP) for Cook County, prevent overflow during heavy rains. Bioswales and permeable pavements [94] in urban high FR zones with open water (FR 12.985) and poor drainage promote infiltration. Retention basins near the Des Plaines River and extended storm sewer upgrades, financed by USD 20 million county programs [95], could intercept stormwater and limit flash flooding. Levees and flood-control structures in very high zones, such as the Calumet floodplain, reduce riverine overflows and match Metropolitan Water Reclamation District projects.

Complementary non-structural measures augment structural measures to encourage long-term resilience. Zoning enactment with high susceptibility areas, including floodplain map updates, prevents development in vulnerable tracts. Building code updates requiring flood elevation and inspection of valves in sewer traps minimize basement flooding. Public awareness campaigns, including RainReady programs, inform residents on flood history and preparedness. Emergency plans should integrate the susceptibility map for targeted evacuations and allocate resources.

Overall, integrating this FR-based map into Cook County's MJ-HMP would bolster resilient planning, prioritizing green infrastructure and equity-focused investments [86] to address disparities in flood-impacted areas.

4. Conclusions

This study demonstrates the application of a GIS-based FR model to create a high-resolution flood susceptibility map for Cook County, Illinois, using 13 environmental and infrastructural conditioning factors. The FR model proved to be a simple yet powerful spatial modeling technique able to quantify flood risk patterns across the urbanized Midwest landscape. The final FSI map shows that nearly 64% of the county is within the high–very high susceptibility zones, which are concentrated along the Chicago, Des Plaines, and Calumet River corridors, as well as other low-lying suburban and urban areas.

Model performance using a train–test split (70/30) yielded a prediction accuracy of 91.4% and a training success rate of 92.4%. Results support the FR model's ability to identify high-risk flood zones using only a historical record of flood locations and a set of spatially distributed environmental variables. The most influential conditioning factors for flooding in Cook County included proximity to rivers and roads, high TWI, flat areas, and impervious land use, highlighting the urban-driven nature of flood risk in Cook County.

Beyond its predictive capability, the FR method is transparent, interpretable, and computationally efficient for policy-driven applications, such as municipal zoning, floodplain regulation, and green infrastructure prioritization. The resulting FSI map could be

used as input to an MJ-HMP to better inform risk reduction plans for underserved or flood-vulnerable communities.

Future research could further improve this modeling framework by using linked rainfall-runoff simulations, socioeconomic vulnerability metrics, and climate change scenarios. This study contributes to the growing body of literature on the utility of FR-based mapping for risk-informed urban planning and equitable flood resilience in major U.S. counties.

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