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GIS-enabled flood hazard assessment for enhancing early warning systems, land use regulation, and sustainable watershed management

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Abstract

Conventional flood hazard assessments often operate as static cartographic products, limiting their effectiveness for real-time warning, regulatory enforcement, and long-term watershed stewardship. As flood regimes become increasingly non-stationary due to climate-driven hydrological shifts and intensified land-use pressures, there is a growing need for assessment frameworks that move beyond descriptive mapping toward decision-oriented spatial intelligence. This study advances a GIS-enabled flood hazard assessment approach that explicitly links spatial analytics with early warning system design, land-use regulatory control, and sustainable watershed management objectives. The proposed framework integrates terrain-driven runoff dynamics, hydrological connectivity, and land-surface modification indicators to characterize flood hazard as a process rather than a fixed spatial condition. High-resolution digital elevation models, flow accumulation metrics, soil infiltration capacity, impervious surface expansion, and precipitation intensity thresholds are combined within a rule-based GIS modeling environment. Unlike traditional susceptibility mapping, the framework emphasizes threshold-sensitive hazard triggers that align with early warning activation, zoning compliance limits, and watershed response behavior. Application to flood-prone watersheds in the United States demonstrates how GIS-derived hazard intelligence can be translated into operational guidance across multiple governance domains. For early warning systems, spatially explicit hazard escalation zones are used to refine alert lead times and downstream impact forecasting. For land-use regulation, hazard thresholds are mapped to development control boundaries, enabling enforcement of floodplain setbacks and conditional permitting under variable hydrological states. For watershed management, the analysis identifies priority sub-catchments where land-cover interventions and restoration measures yield disproportionate reductions in flood propagation and peak discharge. By coupling hazard assessment with actionable decision thresholds, the study demonstrates how GIS can function as an integrative decision-support system rather than a passive analytical tool. The findings highlight the potential of GIS-enabled flood hazard assessment to synchronize early warning, regulatory planning, and watershed sustainability within a coherent spatial governance framework, supporting adaptive flood risk management under evolving environmental conditions.

Keywords: Flood hazard assessment; Geographic Information Systems; Early warning thresholds; Land-use regulation; Watershed hydrology; Spatial decision support

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1. Introduction to conceptual framing and research context

1.1. Flood Hazards as Dynamic Watershed Processes

Flood hazards are increasingly understood as dynamic watershed-scale processes rather than static spatial zones delineated by fixed boundaries [1]. Flooding emerges from the interaction of meteorological drivers, catchment characteristics, land-use patterns, and human infrastructure, all of which evolve over time and space [2]. As rainfall propagates through a watershed, runoff generation, flow concentration, and inundation extent vary temporally, producing flood impacts that shift rapidly across landscapes [3]. This spatiotemporal behavior challenges conventional representations of flood risk that rely on static floodplain delineations.

Non-stationarity in rainfall–runoff–land interactions further complicates flood hazard assessment [4]. Climate-driven changes in precipitation intensity, storm sequencing, and antecedent soil moisture conditions have altered hydrological response patterns in many U.S. watersheds [5]. Simultaneously, urban expansion, deforestation, and surface sealing have modified runoff pathways and reduced infiltration capacity, amplifying peak flows during extreme rainfall events [6]. These coupled climatic and anthropogenic changes violate the assumption of stationarity that underpins many legacy flood models.

Traditional hazard mapping approaches, often based on historical flood frequencies and fixed return periods, struggle to capture these evolving dynamics [7]. Such maps may underestimate risk in newly urbanized areas or fail to reflect compound flood drivers, including upstream land-use change and infrastructure failure [8]. As flood hazards become more dynamic and interconnected, there is a growing need for analytical frameworks that explicitly recognize floods as adaptive watershed processes rather than static hazards [9].

1.2. GIS and Machine Learning in Contemporary Flood Science

GIS has become a foundational tool in contemporary flood science due to its ability to couple spatial and hydrological information across multiple scales [3]. Through the integration of topography, drainage networks, land-use patterns, and infrastructure layers, GIS enables spatially explicit analysis of flood generation, propagation, and impact [4]. This spatial–hydrological coupling supports detailed representation of watershed behavior and localized flood exposure that cannot be achieved through non-spatial models alone [5].

Machine learning (ML) techniques have emerged as complementary tools for modeling nonlinear relationships within flood systems [6]. ML algorithms can capture complex interactions between rainfall intensity, antecedent conditions, land cover, and runoff response, often outperforming traditional statistical models in predictive accuracy [7]. These capabilities are particularly valuable for modeling rapid hazard escalation under extreme or compound events, where physical processes interact in non-linear ways.

However, ML models alone often lack spatial interpretability and governance relevance [8]. Hybrid GIS–ML frameworks address this limitation by embedding ML-driven predictions within spatial contexts, allowing hazard outputs to be mapped, interrogated, and linked to decision units [9]. Such integration is increasingly necessary for early warning systems, regulatory assessment, and infrastructure planning, where both predictive accuracy and spatial transparency are required to support timely and accountable decision-making [1].

1.3. Policy-Relevant Problem Statement

Despite advances in flood science, a persistent disconnect remains between hazard analysis and governance instruments in the United States [2]. Scientific insights into dynamic flood behavior are often not translated into planning regulations, infrastructure standards, or emergency protocols that reflect evolving risk conditions [3]. As a result, policy frameworks may rely on outdated hazard representations that underestimate exposure and vulnerability [7].

Early warning systems exemplify this gap. While many systems provide timely forecasts, they frequently lack spatial adaptability, offering limited differentiation between neighborhoods, infrastructure assets, or vulnerable populations [6]. This reduces their effectiveness for targeted evacuation, resource allocation, and emergency response [5].

Land-use regulation similarly lags behind hazard dynamics. Zoning decisions and development approvals are often based on static floodplain maps that fail to incorporate climate variability, upstream land-use change, or infrastructure stress [8]. This misalignment perpetuates exposure and undermines long-term resilience. Addressing these challenges requires analytical approaches that bridge flood science and policy by producing spatially explicit, decision-relevant vulnerability information [9].

1.4. Research Objectives and Contributions

This study aims to advance flood vulnerability assessment by framing flood hazards as dynamic watershed processes and integrating GIS-based spatial analytics with data-driven modeling approaches [1]. The research develops a spatially explicit vulnerability framework that aligns hazard dynamics with governance needs in the United States [4]. By producing policy-relevant vulnerability outputs, the study contributes tools to support adaptive land-use regulation, targeted emergency response, and resilience-oriented infrastructure planning under changing flood risk conditions [9].

2. Case study framework and watershed typology

2.1. Case Study Logic and Design

This study adopts a watershed-scale case study design to reflect the hydrological reality that flood processes operate across interconnected upstream–downstream systems rather than within administrative boundaries [6]. Watershed-scale analysis enables the integration of rainfall–runoff dynamics, land-use change, and infrastructure interactions within a coherent spatial unit, supporting more accurate representation of flood generation and propagation processes [7].

Case study selection was guided by three criteria. First, watersheds were required to exhibit recurrent flood events with documented historical impacts, ensuring empirical relevance and data availability [8]. Second, evidence of significant land-use pressure including urban expansion or floodplain encroachment was necessary to capture anthropogenic drivers of flood vulnerability [9]. Third, governance relevance was prioritized, selecting watersheds embedded within active planning, zoning, or emergency management frameworks where analytical outputs could inform real-world decision-making [10]. This logic supports comparative analysis across contrasting hydrological and socio-economic contexts while maintaining policy applicability [11].

2.2. Case Study A: Urbanized Watershed

The first case study focuses on a highly urbanized coastal watershed within the Houston metropolitan region, an area that has experienced repeated high-impact flood events over the past two decades [12]. Rapid population growth and expansive suburban development have transformed the watershed's hydrological response, with extensive increases in impervious surface cover significantly altering natural infiltration and runoff patterns [13]. These changes have reduced lag time between rainfall and peak discharge, contributing to frequent flash flooding during extreme precipitation events [8].

Hydrological alteration in the Houston region is further compounded by extensive channel modification and engineered drainage infrastructure designed to expedite stormwater conveyance [9]. While such interventions aim to reduce localized flooding, they often transfer flood risk downstream and amplify peak flows during large storm events [7]. The cumulative effect is a highly sensitive watershed where modest changes in rainfall intensity can produce disproportionate flood impacts across residential, commercial, and transportation networks [14].

The watershed's exposure profile includes dense residential development, major transportation corridors, petrochemical facilities, and critical public infrastructure [10]. Flood impacts in this context are therefore multi-dimensional, encompassing direct property damage, disruption of economic activity, public health risks, and long-term recovery challenges [6]. Socio-economic vulnerability is unevenly distributed, with lower-income neighborhoods frequently located in low-lying or poorly drained areas, reflecting historical zoning and housing market dynamics [11]. This case study provides a representative example of how urbanization, infrastructure design, and social inequality interact to shape flood vulnerability in major U.S. metropolitan regions [12].

2.3. Case Study B: Mixed-Use / Agricultural Watershed

The second case study examines a mixed-use watershed within a Midwestern river basin characterized by a combination of agricultural land use, small urban centers, and floodplain development [13]. Unlike the rapid-onset flash flooding observed in highly urbanized watersheds, flooding in this context is often associated with prolonged rainfall, snowmelt, and saturated soil conditions that produce widespread inundation [7].

Agricultural intensification has significantly altered watershed hydrology through drainage modification, soil compaction, and the loss of wetlands that historically moderated runoff [9]. Tile drainage systems, while improving agricultural productivity, accelerate water movement into river channels, increasing downstream flood peaks during extreme events [8]. Additionally, incremental floodplain encroachment for residential and commercial development has increased exposure in areas traditionally subject to periodic flooding [14].

Channel straightening and levee construction have further constrained natural flood storage, reducing the system's capacity to dissipate floodwaters [10]. As a result, flood impacts extend beyond agricultural losses to include damage to transportation infrastructure, small communities, and regional supply chains [6]. This case study illustrates how cumulative land-use decisions and hydrological modification can elevate flood vulnerability even in landscapes with lower population density [11].

2.4. Governance and Management Context

Both case study watersheds operate within multi-layered governance frameworks involving federal, state, and local institutions responsible for land-use regulation, flood warning, and watershed management [12]. Zoning ordinances and development controls are commonly informed by static floodplain maps, while early warning systems rely on regional forecasts with limited spatial differentiation [7]. Watershed management plans exist but are often advisory rather than regulatory, limiting enforcement capacity [9]. These governance characteristics provide an important context for evaluating how spatially explicit flood vulnerability analysis can enhance planning coherence, emergency preparedness, and adaptive risk management [14].

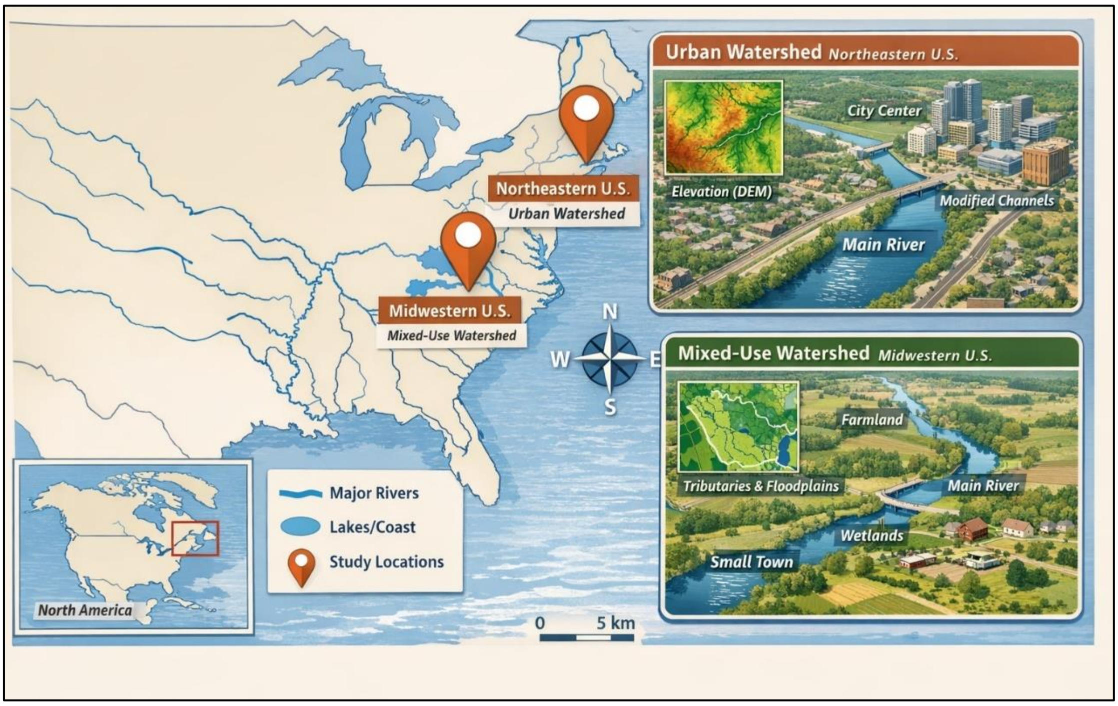

Figure 1 Case study watershed locations and hydrographic context

3. Data acquisition and GIS-based spatial conditioning

3.1. Hydrometeorological and Terrain Data

Hydrometeorological and terrain datasets form the foundation of spatial flood vulnerability assessment by characterizing the physical processes that govern runoff generation, flow routing, and inundation potential [12]. High-resolution Digital Elevation Models (DEMs) are particularly critical, as topography strongly controls surface drainage patterns, flow accumulation, and floodplain connectivity [13]. In this study, DEMs derived from LiDAR and United States Geological Survey (USGS) elevation products are used to represent terrain variability with sufficient precision to support watershed-scale analysis [14]. These datasets enable the derivation of slope, flow direction, and flow accumulation layers that underpin flood hazard modeling.

Rainfall data constitute the primary hydrometeorological driver of flood events and are essential for capturing spatiotemporal variability in precipitation intensity and duration [15]. This study integrates precipitation observations from the National Oceanic and Atmospheric Administration (NOAA), including gauge-based datasets and NEXRAD radar products, which provide high-frequency spatial coverage of storm systems [16]. Radar-derived rainfall estimates are particularly valuable for identifying localized extreme precipitation patterns that may not be captured by sparse ground stations, especially during convective storm events [12].

Stream network data provide the structural framework for understanding runoff convergence and flood propagation [17]. Hydrographic datasets derived from the National Hydrography Dataset (NHD) are used to delineate stream channels, drainage hierarchies, and watershed boundaries [14]. When combined with DEM-derived flow paths, these networks support the identification of areas susceptible to overbank flooding and backwater effects. Together, terrain, rainfall, and stream network datasets enable an integrated representation of watershed hydrology that is essential for spatially explicit flood vulnerability analysis [18].

3.2. Land-Use, Soil, and Surface Characteristics

Land-use, soil, and surface characteristics play a decisive role in shaping flood response by influencing infiltration, runoff generation, and surface roughness [13]. Impervious surface coverage is a key indicator of hydrological alteration, as paved and built-up areas reduce infiltration capacity and accelerate runoff during rainfall events [15]. In this study, imperviousness data are derived from national land-cover products, allowing for the spatial quantification of urbanization impacts across the study watersheds [16].

Soil properties further condition flood behavior by controlling water storage and infiltration rates [17]. Soil infiltration capacity is represented using soil texture, hydrologic soil group, and permeability attributes obtained from national soil databases [18]. Areas dominated by low-permeability soils exhibit higher runoff potential, particularly under saturated conditions, increasing flood susceptibility even in the absence of extensive impervious cover [12].

Vegetation cover acts as a moderating influence on flood dynamics by enhancing interception, evapotranspiration, and soil stability [14]. Land-cover classifications are used to differentiate between forested areas, agricultural land, grasslands, and developed surfaces, each associated with distinct hydrological responses [19]. Changes in vegetation cover, whether due to urban expansion or agricultural intensification, can significantly alter watershed response to rainfall. By integrating land-use, soil, and surface characteristics, the analysis captures key anthropogenic and environmental drivers of flood vulnerability beyond purely hydrometeorological factors [15].

3.3. Flood Event and Hazard Reference Data

Historical flood event data provide essential reference points for validating spatial vulnerability patterns and contextualizing modeled hazard indicators [16]. Documented flood extents derived from satellite imagery, post-event surveys, and governmental reports are used to identify areas that have experienced past inundation [12]. These datasets help distinguish between theoretically vulnerable zones and locations with demonstrated flood impacts.

FEMA floodplain products, including Flood Insurance Rate Maps (FIRMs), are incorporated as standardized hazard references [17]. While these products are subject to known limitations, they remain widely used in land-use regulation, insurance determination, and risk communication [18]. Integrating FEMA floodplain boundaries with historical flood observations allows for comparative analysis between regulatory hazard representations and observed flood behavior [19]. This approach supports a more nuanced interpretation of flood risk and vulnerability within the study watersheds.

3.4. GIS Conditioning and Spatial Harmonization

Prior to analysis, all datasets undergo GIS conditioning to ensure spatial consistency and analytical compatibility [14]. This process includes reprojection to a common coordinate system, resampling to a uniform spatial resolution, and alignment of raster grids [15]. Vector datasets are topologically cleaned and spatially clipped to watershed boundaries to maintain analytical coherence [18]. These harmonization steps are essential for minimizing spatial bias and ensuring that multi-layer overlays accurately reflect underlying spatial relationships [19].

Table 1 Data sources, spatial resolution, and analytical role

Data Category	Data Source	Key Variables	Spatial Resolution	Analytical Role
Terrain / Topography	USGS LiDAR, National Elevation Dataset (NED)	Elevation, slope, flow direction, flow accumulation	1–10 m	Controls runoff pathways, flow convergence, and floodplain connectivity
Precipitation	NOAA rain gauges, NEXRAD radar	Rainfall intensity, duration, spatial distribution	1–4 km (radar), point (gauges)	Primary hydrometeorological driver for runoff generation
Hydrography	National Hydrography Dataset (NHD)	Stream networks, drainage hierarchy, watershed boundaries	Vector (1:24,000)	Defines flow routing, channel connectivity, and flood propagation paths
Land Use / Land Cover	National Land Cover Database (NLCD)	Urban extent, vegetation classes, agricultural land	30 m	Represents surface roughness, imperviousness, and land-use pressure
Impervious Surface	NLCD Impervious Surface Layer	Percent impervious cover	30 m	Anthropogenic runoff amplification indicator
Soil Characteristics	SSURGO / STATSGO	Soil texture, hydrologic soil group, infiltration capacity	10–30 m	Governs infiltration losses and saturation potential
Vegetation Cover	NLCD, remote sensing products	Canopy cover, vegetation type	30 m	Moderates evapotranspiration and surface runoff
Historical Flood Events	FEMA, satellite-derived flood extents	Observed inundation footprints	Variable	Flood / non-flood labeling and model validation
Regulatory Flood Zones	FEMA Flood Insurance Rate Maps (FIRMs)	100-year and 500-year floodplains	Vector	Regulatory benchmarking and exceedance analysis
Infrastructure & Built Assets	Local GIS portals, OpenStreetMap	Roads, bridges, critical facilities	Vector	Exposure assessment and impact interpretation

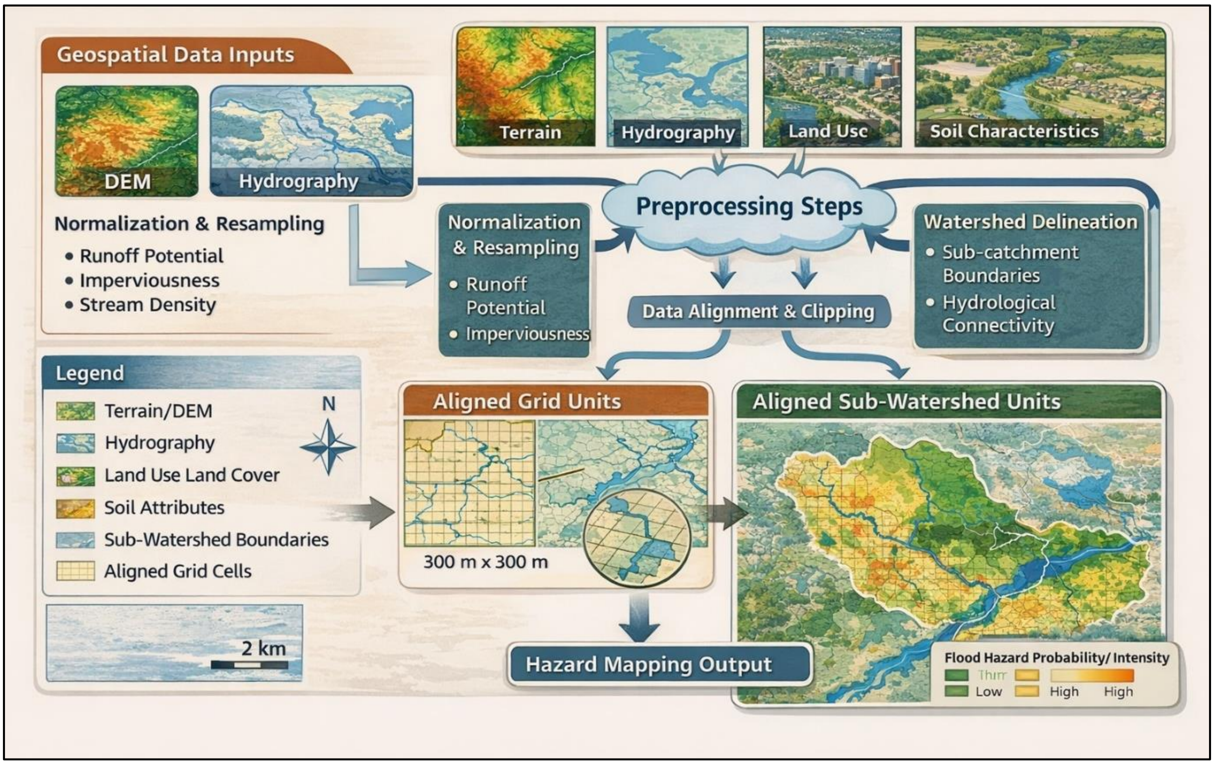

Figure 2 GIS conditioning and spatial alignment workflow

4. hazard feature engineering and process representation

4.1. Runoff Generation Indicators

Runoff generation represents a fundamental mechanism through which hydrometeorological forcing translates into flood hazard within a watershed [16]. At the spatial unit level, runoff is conceptualized as the residual of precipitation after accounting for losses due to infiltration and evapotranspiration, expressed as:

$$R_i = P_i - (I_i + ET_i) \qquad (1)$$

where R_i denotes runoff at spatial unit i, P_i represents precipitation input, I_i is infiltration, and ET_i corresponds to evapotranspiration [17]. This formulation reflects the water balance principle commonly applied in distributed hydrological modeling and provides a tractable indicator of flood-generating potential [18].

Spatial variability in precipitation intensity and duration is captured using radar- and gauge-based rainfall surfaces, while infiltration capacity is approximated through soil texture and land-cover characteristics [19]. Evapotranspiration is incorporated as a moderating factor, reflecting vegetation cover and seasonal climatic conditions that influence water availability at the surface [16]. Areas characterized by high precipitation, low infiltration capacity, and limited evapotranspiration exhibit elevated runoff potential, increasing susceptibility to rapid surface flooding [20].

Importantly, runoff generation is treated as a spatially distributed indicator rather than a uniform watershed-average metric [21]. This allows for the identification of localized runoff hotspots driven by land-use change, soil sealing, or micro-topographic features. By integrating runoff indicators into a GIS environment, spatial contrasts in hydrological response can be explicitly mapped and linked to downstream hazard propagation [22]. This approach is particularly relevant in heterogeneous watersheds where flood impacts are driven by localized processes rather than basin-wide averages [23].

4.2. Flow Accumulation and Connectivity Metrics

While runoff generation defines the volume of excess surface water, flow accumulation and connectivity determine how this water is routed through the landscape toward channels and flood-prone zones [17]. Flow accumulation is derived from DEM-based flow direction models and quantifies the number of upstream cells contributing runoff to a given spatial location, expressed as:

$$FA(x) = \sum_{u \in U(x)} w_u \qquad (2)$$

where $FA(x)$is the flow accumulation at cell x, $U(x)$represents the set of upstream contributing cells, and $w_u$denotes weighting factors such as cell area or runoff potential [18].

High flow accumulation values indicate convergence zones where surface runoff concentrates, increasing the likelihood of channel overtopping and localized inundation [19]. When combined with runoff generation indicators, flow accumulation metrics help identify critical source–pathway–receptor linkages within the watershed [20]. Connectivity between hillslopes, drainage networks, and floodplains plays a decisive role in determining flood extent and severity [21].

In engineered landscapes, connectivity may be artificially enhanced through stormwater networks, culverts, and modified channels, accelerating runoff delivery to downstream locations [22]. GIS-based flow accumulation analysis provides a spatially explicit means of capturing both natural and anthropogenic connectivity patterns, supporting the identification of structural flood amplification pathways [23]. These metrics are therefore essential for understanding how localized runoff translates into broader flood impacts across the watershed [24].

4.3. Terrain-Controlled Hazard Amplification

Terrain characteristics exert a strong influence on flood hazard by controlling water movement, storage, and saturation dynamics [16]. One widely used indicator of terrain-controlled flood susceptibility is the Topographic Wetness Index (TWI), defined as:

$$TWI = \ln\left(\frac{A_s}{\tan\beta}\right) \qquad (3)$$

where $A_s$is the upslope contributing area per unit contour length and $\beta$is the local slope angle [17]. TWI captures the coupling between slope and drainage area, serving as a proxy for soil moisture accumulation and saturation likelihood [18].

Areas with high TWI values are predisposed to saturation excess runoff, particularly during prolonged rainfall events when soil storage capacity is exceeded [19]. In flood-prone landscapes, such zones often correspond to valley bottoms, riparian corridors, and low-gradient floodplains [20]. The spatial distribution of TWI therefore provides insight into terrain-driven hazard amplification mechanisms that operate independently of short-duration rainfall intensity [21].

Incorporating TWI into flood vulnerability modeling allows for the differentiation between rapid runoff-dominated flooding and saturation-driven inundation processes [22]. This distinction is critical for interpreting flood behavior across contrasting watershed contexts, such as urban flash flooding versus agricultural floodplain inundation [23]. GIS-based terrain analysis thus strengthens hazard representation by embedding physically meaningful controls on flood generation and persistence [24].

4.4. Anthropogenic Hazard Modifiers

Beyond natural terrain and hydrology, anthropogenic modifications significantly alter flood hazard dynamics [18]. The impervious surface ratio is used as a key indicator of urbanization, representing the proportion of land surface covered by impermeable materials such as roads, rooftops, and parking areas [19]. High imperviousness reduces infiltration and increases runoff volume and velocity, intensifying flood peaks [20].

A channel modification index is introduced to capture human alterations to natural drainage systems, including channelization, straightening, and lining [21]. While engineered channels may reduce localized flooding, they often increase downstream hazard by accelerating flow conveyance and reducing natural flood storage [22]. These anthropogenic modifiers are spatially encoded to reflect localized intervention intensity, enabling their interaction with natural hazard drivers to be explicitly modeled [23]. Including human-induced factors ensures that flood hazard assessment reflects real-world landscape transformations rather than idealized natural conditions [24].

4.5. Feature Normalization and Spatial Encoding

To enable multi-indicator integration, all hazard features are normalized using min–max scaling, expressed as:

$$X' = \frac{X - \min(X)}{\max(X) - \min(X)} \qquad (4)$$

where X' represents the normalized feature value [16]. Normalization ensures comparability across indicators with different units and magnitudes, preventing dominance by any single variable during aggregation [17].

Normalized features are spatially encoded as raster layers aligned to a common grid resolution, facilitating pixel-wise overlay and weighted combination [22]. This encoding supports both deterministic vulnerability modeling and downstream machine learning applications by providing standardized spatial inputs [23]. Feature normalization and encoding thus represent a critical bridge between raw geospatial data and analytical modeling, ensuring methodological robustness and reproducibility [24].

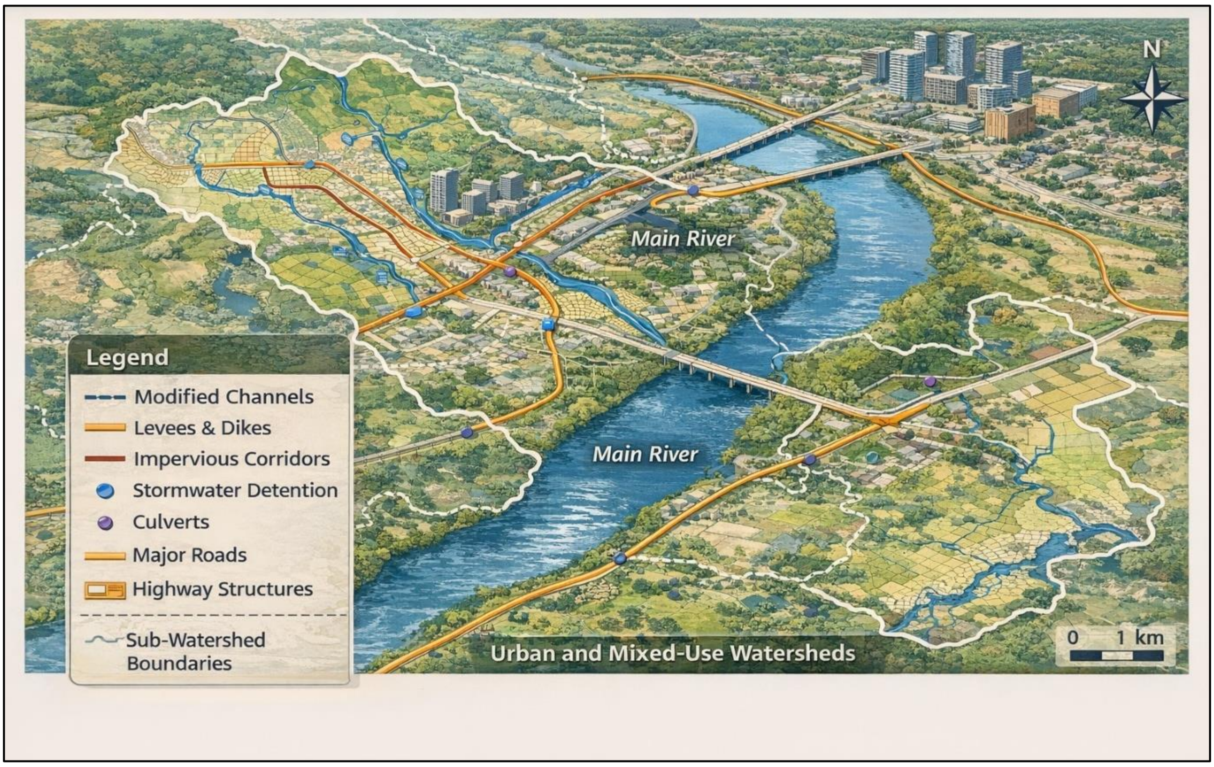

Figure 3 Spatial distribution of engineered hazard features

5. Machine learning–based flood hazard modeling

5.1. Hazard Prediction Formulation

Flood hazard prediction in this study is formulated as a supervised learning problem in which hazard intensity or probability is modeled as a function of multiple spatially distributed predictors derived from hydrological, terrain, and anthropogenic indicators [22]. The general formulation is expressed as:

$$H = f(X_1, X_2, \dots, X_n) \qquad (5)$$

where H represents flood hazard intensity or the probability of flood occurrence, and $X_1, X_2, \dots, X_n$ denote normalized predictor variables such as runoff potential, flow accumulation, terrain wetness, imperviousness, and channel modification indices [23]. This formulation allows the model to capture nonlinear interactions among predictors that are difficult to represent using traditional rule-based or linear approaches [24].

Rather than assuming explicit physical relationships, the function $f(\cdot)$ is learned from data, enabling adaptive representation of complex flood-generating processes under heterogeneous landscape and climatic conditions [25]. Framing hazard prediction in this manner supports probabilistic interpretation, facilitating integration with vulnerability assessment and decision-support frameworks [26].

5.2. Spatial Sampling and Label Construction

Accurate hazard prediction depends on robust spatial sampling and reliable label construction [27]. In this study, spatial units are defined using a regular grid overlaid on each watershed, complemented by sub-watershed aggregation units to capture hydrological coherence [22]. Grid-based sampling enables high-resolution spatial learning, while sub-watershed units support interpretation at management-relevant scales [23].

Flood and non-flood labels are constructed using historical flood extent data derived from observed inundation footprints, satellite imagery, and post-event records [24]. Spatial units intersecting documented flood extents during reference events are labeled as flood-positive, while units outside these extents are labeled as non-flood [25]. To reduce noise, temporal filtering is applied to ensure that labels correspond to periods of significant hydrometeorological forcing rather than isolated anomalies [26].

Class imbalance, common in flood datasets due to the relatively small proportion of flooded areas, is explicitly addressed through stratified sampling [27]. This ensures adequate representation of both flood and non-flood classes during model training while preserving the spatial structure of the data [28]. Careful spatial labeling and sampling are essential for preventing biased hazard predictions and ensuring generalizability across watershed contexts [29].

5.3. Training, Validation, and Testing Strategy

The dataset is partitioned into training, validation, and testing subsets using a 70–15–15 split, a configuration widely adopted in spatial machine learning to balance model learning, hyperparameter tuning, and unbiased performance evaluation [22]. However, random sampling alone is insufficient in spatial contexts due to spatial autocorrelation, which can lead to information leakage and overly optimistic accuracy estimates [23].

To address this challenge, a spatial blocking strategy is employed in which contiguous spatial regions are assigned entirely to a single subset [24]. This approach ensures that training, validation, and testing data are spatially independent, providing a more realistic assessment of model performance under real-world deployment conditions [25]. Spatial blocks are defined based on sub-watershed boundaries and hydrological connectivity, preserving internal coherence while enforcing separation across subsets [26].

The validation set is used for hyperparameter optimization and early stopping, while the test set is reserved exclusively for final performance evaluation [27]. Model performance is assessed using metrics appropriate for probabilistic hazard prediction, including accuracy, recall, and area under the receiver operating characteristic curve [28]. This training strategy strengthens the robustness and credibility of hazard predictions, particularly when models are transferred across spatially heterogeneous environments [29].

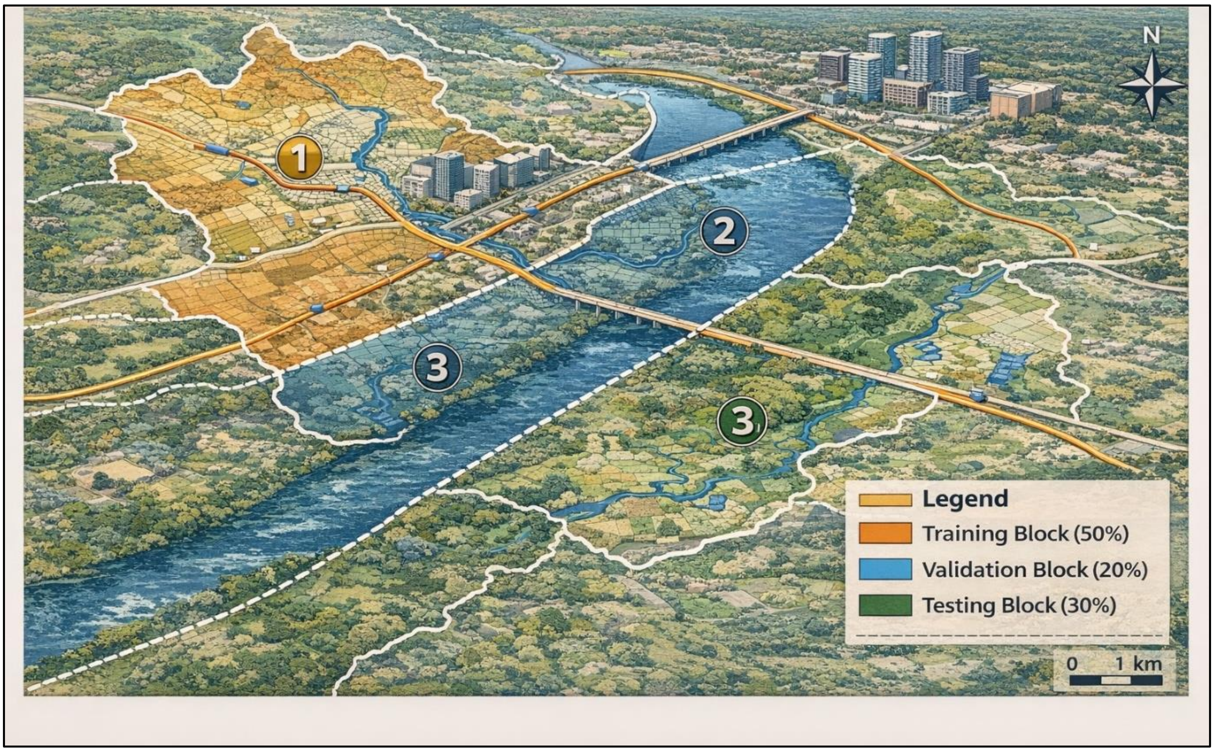

Figure 4 Spatial data partitioning scheme for training, validation, and testing

5.4. Model Training Phase

Two ensemble learning algorithms are employed for flood hazard prediction: Random Forest (RF) and Gradient Boosted Trees (GBT). These methods are well suited to spatial hazard modeling due to their ability to capture nonlinear relationships, handle mixed data types, and accommodate complex feature interactions [22].

Random Forest constructs an ensemble of decision trees using bootstrap sampling and random feature selection, reducing variance and improving generalization [23]. Each tree independently predicts flood hazard, and the final prediction is obtained through aggregation. Gradient Boosted Trees, by contrast, build trees sequentially, with each new tree correcting errors made by previous ones, allowing for finer-grained modeling of complex patterns [24].

For ensemble prediction, the hazard estimate is expressed as:

$$\widehat{H} = \frac{1}{T}\sum_{t=1}^{T} h_t\,(X) \qquad (6)$$

where $\widehat{H}$is the predicted hazard, $h_t(X)$represents the prediction of the t-th tree, and $T$is the total number of trees [25]. Hyperparameters such as tree depth, learning rate, and number of estimators are optimized using the validation dataset [26].

Feature importance metrics are extracted to evaluate the relative contribution of hydrological, terrain, and anthropogenic predictors [27]. This supports interpretability and aligns model outputs with physical understanding of flood processes, enhancing trust in predictive results [28]. Training both RF and GBT models enables comparative assessment of predictive performance and stability across watershed types [29].

5.5. Model Selection and Stability Checks

Final model selection is based on a combination of predictive performance, spatial consistency, and robustness to sampling variability [22]. Performance metrics are evaluated across spatial blocks to ensure that selected models generalize beyond localized training conditions [23]. Stability checks include repeated training with alternative spatial partitions and perturbation of input features to assess sensitivity [24].

Model predictions are further examined for spatial coherence, ensuring that hazard patterns align with known hydrological pathways rather than exhibiting isolated artifacts [25]. Consistency between Random Forest and Gradient Boosted Tree outputs is used as an additional validation criterion [26]. Models demonstrating stable performance across metrics, partitions, and watershed contexts are selected for downstream vulnerability integration and policy-relevant analysis [27–29].

6. Model evaluation, uncertainty, and standards comparison

6.1. Statistical Performance Metrics

Quantitative evaluation of flood hazard prediction models is essential for assessing their reliability, interpretability, and suitability for decision support [27]. This study employs multiple statistical performance metrics, with particular emphasis on error-based measures that capture the magnitude of deviation between observed and predicted flood hazard outcomes [28]. The primary metric used to evaluate overall predictive accuracy is the Root Mean Square Error (RMSE), defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_i - \widehat{H}_i)^2} \qquad (7)$$

where $H_i$represents the observed flood hazard value at spatial unit i, $\widehat{H}_i$denotes the corresponding model prediction, and $n$is the total number of evaluated spatial units [29]. RMSE penalizes large errors more strongly than small errors, making it particularly useful for identifying models that produce extreme misestimations in high-risk zones [30].

RMSE values are computed separately for training, validation, and testing datasets to assess model generalization under spatial blocking constraints [31]. Lower RMSE values on independent test data indicate robust predictive performance across heterogeneous watershed conditions [27]. However, RMSE alone does not reveal directional bias or spatial clustering of errors, necessitating complementary evaluation metrics and spatial diagnostics [32]. As such, RMSE is interpreted alongside bias measures and spatial uncertainty analyses to provide a comprehensive assessment of model performance [33].

6.2. Mean Deviation and Bias Characterization

While RMSE captures the magnitude of prediction errors, it does not indicate whether a model systematically overpredicts or underpredicts flood hazard [28]. To address this limitation, mean deviation (MD) is calculated as an indicator of directional bias:

$$MD = \frac{1}{n}\sum_{i=1}^{n}(H_i - \widehat{H}_i) \qquad (8)$$

Positive MD values indicate systematic underprediction of flood hazard, whereas negative values reflect overprediction [29]. Bias characterization is particularly important in flood risk applications, where underestimation of hazard intensity can lead to inadequate preparedness and increased exposure [30].

Mean deviation is evaluated across spatial units and aggregated by land-use class and watershed sub-region to identify patterns of systematic bias [31]. For example, consistent underprediction in highly urbanized zones may suggest insufficient representation of impervious surface effects or drainage connectivity [32]. Conversely, overprediction in agricultural floodplains may indicate conservative model behavior driven by terrain or soil indicators [33].

By explicitly quantifying bias, MD analysis supports model refinement and transparent communication of uncertainty to decision-makers [27]. Bias-aware interpretation is essential when model outputs are used to inform regulatory or emergency planning contexts, where asymmetric consequences of under- and overestimation must be carefully managed [28].

6.3. Spatial Error and Uncertainty Mapping

Beyond global statistics, spatially explicit error and uncertainty mapping provides critical insight into where and why model predictions deviate from observed flood behavior [29]. Error surfaces are generated by mapping residuals (H_i −

$\hat{H}_i$) across the study area, enabling visualization of localized over- and under-prediction patterns [30]. These maps reveal whether prediction errors cluster along specific terrain features, land-use types, or hydrological pathways [31].

Uncertainty is further characterized through the construction of confidence zones derived from ensemble variability and prediction consistency [32]. Areas exhibiting low inter-model variance and low residual error are classified as high-confidence zones, while regions with high variance or persistent bias are flagged as uncertain [33]. Such spatial differentiation supports risk-informed decision-making by distinguishing between robust hazard estimates and areas requiring cautious interpretation.

Spatial uncertainty mapping is particularly valuable for emergency response and infrastructure planning, where localized confidence in hazard predictions influences prioritization [27]. By embedding uncertainty diagnostics directly into spatial outputs, the analysis moves beyond single-value predictions toward more transparent and accountable hazard communication [28].

6.4. Benchmarking Against Regulatory Standards

To assess policy relevance, model-predicted flood hazard outputs are benchmarked against existing regulatory standards and hazard representations commonly used in the United States [29]. FEMA Flood Insurance Rate Maps (FIRMs) serve as the primary regulatory reference, delineating Special Flood Hazard Areas based on historical hydrological modeling and fixed return periods [30]. These maps are widely used for land-use regulation, insurance determination, and infrastructure design, despite acknowledged limitations under changing climate and land-use conditions [31].

Predicted hazard zones derived from the machine learning models are overlaid with FEMA floodplains to evaluate spatial agreement and divergence [32]. Areas where predicted hazard exceeds FEMA-designated zones are identified as regulatory exceedance zones, indicating potential underestimation of risk in existing regulatory frameworks [33]. Conversely, regions where FEMA zones extend beyond model-predicted hazard areas are examined to assess potential over-conservatism or changing flood dynamics [27].

Benchmarking is further extended to design storm thresholds commonly used in infrastructure planning, such as 100-year and 500-year rainfall events [28]. Model outputs are evaluated for their ability to capture hazard intensification under extreme precipitation scenarios that exceed historical design assumptions [29]. This comparative analysis highlights the extent to which data-driven, spatially adaptive hazard modeling can complement or challenge static regulatory standards.

By systematically benchmarking predictive outputs against regulatory baselines, the study demonstrates how machine learning–enhanced flood hazard models can inform adaptive zoning, updated design criteria, and more responsive risk governance [30–33].

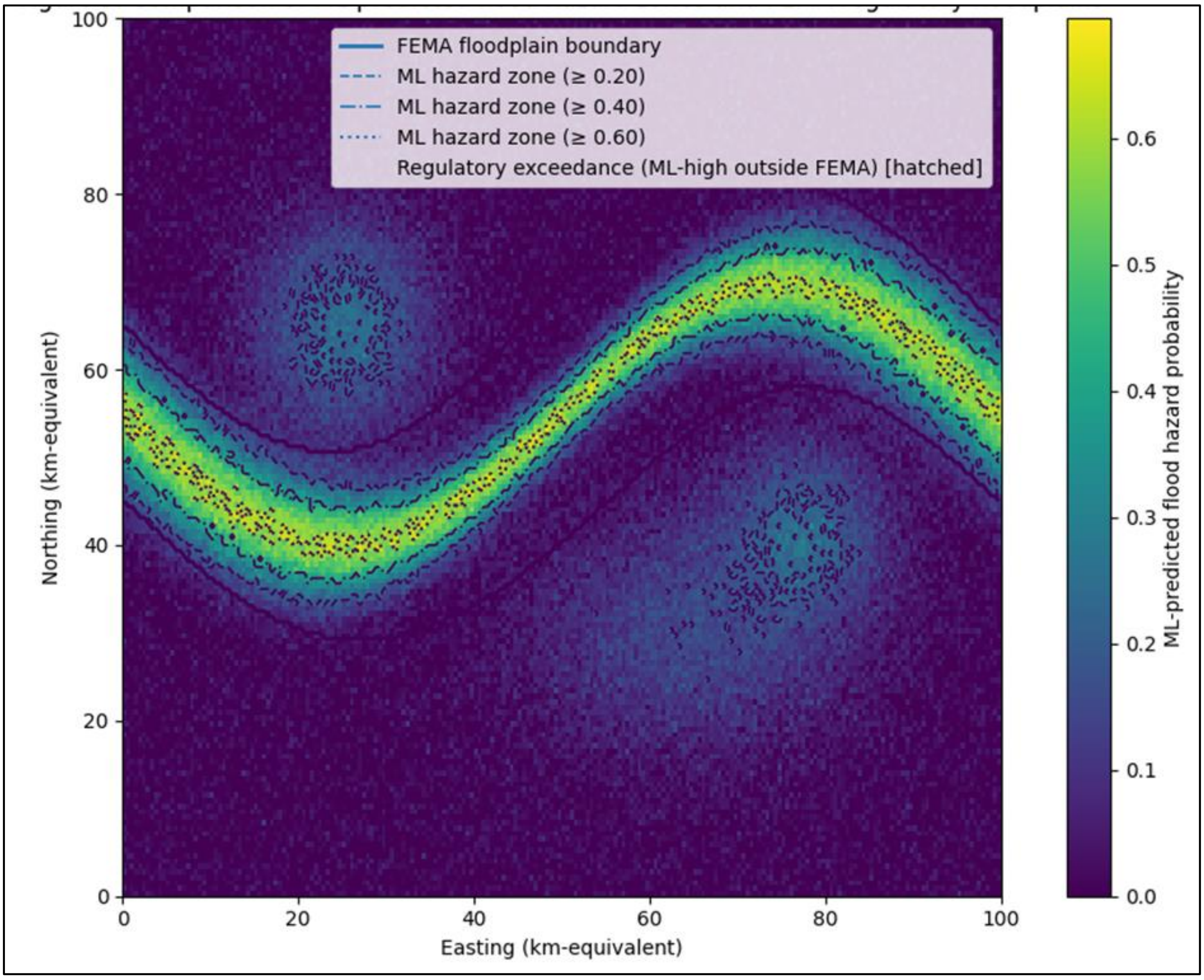

Figure 5 Comparison of ML-predicted flood hazard zones and FEMA regulatory floodplains

7. Translating hazard intelligence into decision systems

7.1. Early Warning System Enhancement

Advanced flood hazard prediction outputs provide a critical opportunity to enhance early warning systems by shifting from coarse, region-wide alerts to spatially differentiated, risk-sensitive warning mechanisms [31]. In this study, model-derived hazard probabilities are translated into threshold-triggered hazard escalation zones, enabling graduated warning levels that reflect localized flood intensity and likelihood rather than uniform administrative boundaries [32]. Such zonation allows emergency managers to issue targeted alerts for high-risk neighborhoods, infrastructure corridors, and vulnerable populations before flood impacts fully materialize.

Thresholds are defined based on hazard probability distributions and validated against historical flood outcomes, ensuring that warning triggers correspond to meaningful risk levels [33]. This approach improves lead time and situational awareness, particularly in rapidly evolving flood scenarios such as flash flooding in urban watersheds [34]. Spatially explicit escalation zones also support differentiated response actions, ranging from monitoring advisories to mandatory evacuations, depending on projected hazard severity.

By embedding predictive hazard intelligence within early warning systems, authorities can reduce false alarms in low-risk areas while prioritizing resources where flood impacts are most likely [31]. This enhancement strengthens public trust in warning systems and supports more effective emergency response coordination under increasingly dynamic flood conditions [35].

7.2. Land-Use Regulation and Zoning Control

Flood hazard modeling outputs have direct implications for land-use regulation and zoning control, particularly in regions experiencing rapid development pressure [32]. Traditional zoning frameworks often rely on static floodplain delineations that fail to reflect evolving hydrological and climatic conditions [33]. In contrast, spatially adaptive hazard maps enable the designation of conditional development zones, where land-use permissions are contingent on projected flood risk rather than historical boundaries [34].

Conditional zoning allows for differentiated regulatory responses, such as restricting high-density development in zones with elevated hazard probability while permitting low-impact or flood-resilient land uses [31]. Dynamic floodplain buffers can also be established by expanding or contracting regulatory setback distances based on modeled hazard intensity under different rainfall or land-use scenarios [35]. This flexibility supports proactive risk reduction while accommodating uncertainty and future change.

Integrating predictive hazard intelligence into zoning decisions enhances the alignment between hazard science and governance instruments [32]. It also supports equitable planning by identifying areas where vulnerable communities face disproportionate risk, enabling targeted regulatory protection and investment [33]. Such adaptive zoning frameworks represent a critical step toward long-term flood resilience in the face of non-stationary risk drivers [34].

7.3. Watershed Management and Intervention Targeting

At the watershed scale, flood hazard predictions support more strategic and cost-effective management interventions by identifying priority sub-catchments that disproportionately contribute to downstream risk [31]. These areas are characterized by high runoff generation, strong flow connectivity, or significant anthropogenic modification, making them leverage points for intervention [32]. Targeting management actions at these locations can yield outsized reductions in overall flood hazard.

Nature-based solutions, such as wetland restoration, riparian buffer enhancement, and floodplain reconnection, are particularly well suited for deployment in high-priority sub-catchments [33]. By increasing natural water storage and slowing runoff pathways, these interventions complement engineered infrastructure while delivering co-benefits for ecosystem health and water quality [34]. Spatial hazard analysis enables these solutions to be sited where they are most likely to reduce flood peaks and volumes.

Linking hazard classes to predefined management actions supports transparent and accountable decision-making [35]. By aligning modeled risk levels with intervention strategies, watershed managers can prioritize investments, monitor outcomes, and adapt strategies over time. This evidence-based targeting strengthens the effectiveness of watershed planning under increasing flood uncertainty [31].

Table 2 Flood hazard classes and corresponding management actions

Flood Hazard Class	Hazard Probability / Intensity Range	Typical Spatial Characteristics	Primary Management Actions	Responsible Planning / Response Instruments
Very Low	Minimal or negligible hazard	Upland areas, well-drained soils, low connectivity	Routine monitoring; standard development controls	Local land-use plans; baseline infrastructure standards
Low	Low probability or shallow inundation	Peripheral floodplain zones; moderate slopes	Flood-aware building codes; surface drainage maintenance	Zoning ordinances; municipal engineering guidelines
Moderate	Periodic or localized flooding	Transitional zones near drainage pathways	Conditional development; flood-resilient construction; enhanced drainage	Development permits; stormwater management plans
High	Frequent or high-intensity flooding	High flow accumulation zones; urban corridors	Development restrictions; infrastructure retrofitting; evacuation planning	Floodplain management programs; emergency operations plans

Very High	Persistent or extreme flood hazard	Active floodplains; low-lying urban or riparian areas	No-build zoning; property buyouts; nature-based solutions	FEMA mitigation programs; watershed restoration plans
Critical	Severe hazard with cascading impacts	Dense urban or critical infrastructure zones	Mandatory evacuation; asset protection; real-time warning activation	Emergency declarations; real-time early warning systems

8. Cross-case synthesis and comparative insights

8.1. Urban vs Mixed-Use Watershed Dynamics

The comparative analysis of urban and mixed-use watersheds reveals distinct flood hazard dynamics shaped by contrasting land-use patterns, hydrological modification, and governance contexts [27]. In highly urbanized watersheds, flood behavior is dominated by rapid runoff generation, short response times, and strong hydraulic connectivity created by impervious surfaces and engineered drainage networks [28]. These conditions amplify flash flooding, where small increases in rainfall intensity can produce disproportionate hazard escalation [29]. Model outputs for urban watersheds show tightly clustered high-hazard zones aligned with transportation corridors, dense residential areas, and modified channels, reflecting the spatial concentration of exposure and sensitivity [30].

In contrast, mixed-use watersheds exhibit flood dynamics driven by cumulative upstream processes rather than rapid local runoff [31]. Agricultural drainage modification, floodplain encroachment, and channelization increase downstream flood volumes over longer durations, producing widespread inundation rather than localized flash events [32]. Hazard patterns in these watersheds are more spatially diffuse, with high-risk zones extending along riparian corridors and low-gradient floodplains [33]. These differences underscore the importance of context-sensitive hazard modeling, as uniform assumptions about flood behavior can obscure critical drivers of risk across watershed types [34]. The comparative findings reinforce the need for flexible, spatially adaptive flood assessment approaches capable of capturing both rapid-onset and slow-onset flood processes [35].

8.2 Transferability of GIS–ML Hazard Framework

The GIS–ML hazard framework developed in this study demonstrates strong potential for transferability across diverse watershed contexts, provided that local data availability and governance needs are adequately addressed [27]. The modular structure of the framework separating data conditioning, feature engineering, model training, and policy translation supports adaptation to different spatial scales, climatic regimes, and land-use configurations [28]. By relying on widely available geospatial datasets and generalizable machine learning algorithms, the approach avoids dependence on highly specialized or region-specific inputs [29].

Transferability is further enhanced by the use of spatial blocking and validation strategies that explicitly test model generalization beyond local training conditions [30]. This reduces the risk of overfitting to site-specific patterns and supports deployment in data-scarce or rapidly changing environments [31]. However, successful transfer requires recalibration of model inputs, thresholds, and governance interpretations to reflect local hydrological processes and regulatory contexts [32].

The framework's emphasis on interpretability through feature importance analysis, spatial error mapping, and regulatory benchmarking facilitates stakeholder engagement and policy uptake across jurisdictions [33]. As flood risk becomes increasingly non-stationary, transferable GIS–ML approaches offer a scalable pathway for enhancing flood preparedness and resilience planning across regions facing diverse but interconnected flood challenges [34,36].

9. Discussion

9.1. Scientific Contributions to Flood Hazard Modeling

This study advances flood hazard modeling by integrating GIS-based spatial analytics with machine learning techniques to capture the dynamic, non-linear nature of flood-generating processes [37]. Unlike traditional flood models that rely on static assumptions or single-factor hazard representations, the proposed framework explicitly incorporates terrain controls, hydrological connectivity, and anthropogenic modification within a unified predictive structure [28]. This integration enables more realistic representation of flood behavior across heterogeneous landscapes and land-use contexts [38].

A key scientific contribution lies in the spatial treatment of hazard prediction as a learning problem constrained by hydrological logic and spatial independence [39]. The use of spatial blocking, ensemble learning, and uncertainty mapping addresses long-standing challenges related to spatial autocorrelation and model overconfidence in environmental prediction [31]. Additionally, the framework bridges physical process understanding with data-driven adaptability, allowing hazard estimation to evolve as new data become available [40].

By embedding error diagnostics and regulatory benchmarking within the modeling workflow, the study contributes to the growing body of research emphasizing transparency and interpretability in applied hazard science [37]. These methodological advances support the development of flood models that are not only accurate but also decision-relevant and scientifically defensible under conditions of climatic and land-use change [34,38].

9.2. Governance and Policy Implications

The findings highlight a persistent gap between advances in flood hazard science and the governance instruments used to manage flood risk [39]. Static floodplain maps and fixed design standards struggle to accommodate the dynamic hazard patterns revealed through GIS–ML modeling [40]. By providing spatially explicit, probabilistic hazard outputs, the framework supports more adaptive approaches to zoning, infrastructure planning, and emergency management [41].

Policy implications include the potential to redefine regulatory flood boundaries as dynamic risk zones, update design storm assumptions, and prioritize investments based on forward-looking hazard intelligence [42]. Importantly, the integration of uncertainty information enables policymakers to distinguish between high-confidence risk areas and zones requiring precautionary planning. These capabilities support more equitable and resilient flood governance in an era of increasing hydrological uncertainty [43].

9.3. Limitations and Assumptions

Despite its strengths, the study is subject to several limitations. The modeling framework relies on the quality and resolution of available geospatial and flood event data, which may vary across regions and introduce uncertainty [44]. Assumptions related to indicator selection, normalization, and weighting may influence hazard predictions, particularly in data-scarce contexts [38]. Additionally, machine learning models infer relationships from historical patterns, which may not fully capture unprecedented future conditions [45].

The framework also simplifies complex hydrological processes into proxy indicators, potentially omitting fine-scale dynamics such as subsurface flow or infrastructure failure modes [46]. While spatial blocking mitigates overfitting, transferability still requires local validation and contextual calibration [47]. These limitations highlight the importance of continuous model refinement, integration with physical modeling, and cautious interpretation when applying predictive hazard outputs to high-stakes policy decisions [48].

10. Conclusion and future directions

This study demonstrates that flood hazard is best understood as a dynamic, spatially distributed process shaped by the interaction of hydrometeorological forcing, terrain structure, land-use change, and human intervention. By integrating GIS-based spatial analytics with machine learning techniques, the research moves beyond static floodplain representations toward a more adaptive and evidence-driven understanding of flood risk. The results show that hazard intensity and spatial extent vary significantly across watershed types, underscoring the limitations of one-size-fits-all flood assessment and management approaches.

Key findings highlight the contrasting dynamics between highly urbanized and mixed-use watersheds. In urban settings, flood hazard is dominated by rapid runoff generation, strong hydraulic connectivity, and engineered drainage networks that amplify flash flooding. In mixed-use and agricultural watersheds, hazard emerges through cumulative upstream processes, floodplain modification, and prolonged saturation, leading to extensive but slower-onset inundation. These differences reinforce the importance of watershed-scale analysis and context-sensitive modeling in accurately characterizing flood risk.

The case studies further demonstrate the value of spatially explicit hazard prediction for informing real-world decisions. By identifying localized hazard escalation zones, priority sub-catchments, and regulatory exceedance areas, the framework provides actionable insights for early warning systems, land-use regulation, and watershed management. Importantly, the integration of uncertainty and bias diagnostics enhances transparency and supports more accountable use of predictive outputs in policy and planning contexts.

Looking forward, the methodological framework developed in this study provides a clear pathway toward real-time operational flood hazard systems. Advances in near-real-time rainfall observation, remote sensing, and sensor networks create opportunities to continuously update hazard predictions as conditions evolve. Coupling these data streams with automated GIS conditioning and trained machine learning models would enable dynamic hazard mapping, threshold-based alerts, and adaptive decision support at fine spatial scales.

Such operational systems have the potential to transform flood risk management from a reactive, map-driven practice into a proactive, intelligence-driven process. By aligning hazard science with governance needs and technological capabilities, future flood management strategies can better anticipate emerging risks, allocate resources more effectively, and enhance community resilience under increasing climatic and land-use uncertainty.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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