

FLOOD RISK ASSESSMENT AND MANAGEMENT USING HYDROLOGICAL MODELING AND GIS TECHNIQUE

Engr. Omer Farooq^{*1}, Muhammad Naveed Khalil², Rana Saad Mahmood³, Ameer Jan⁴

^{*1}Department of Agriculture Engineering, MNS-University of Agriculture Multan

²National Centre of Excellence in Geology, University of Peshawar, Pakistan

³Department of Naval, Electrical, Electronic and Telecommunications Engineering, University of Genoa, Via all'Opera Pia 11, 16145 Genoa, Italy

⁴University of Makran

^{*1}omerf3333@gmail.com, ²geonaveed@uop.edu.pk, ³ranasaadm012@gmail.com, ⁴ameerjan@uomp.edu.pk

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Corresponding Author: *

Engr. Omer Farooq

Abstract

Floods represent one of the most destructive natural hazards globally, exacerbated by climate change, rapid urbanization, and hydrometeorological extremes. Effective flood risk assessment and management require the integration of hydrological modeling, hydraulic simulation, and Geographic Information Systems (GIS) to quantify hazard, exposure, and vulnerability. This study synthesizes advanced frameworks combining semi-distributed models (HEC-HMS, SWAT) for rainfall-runoff simulation with 2D hydraulic models (HEC-RAS) for inundation mapping, leveraging high-resolution DEMs, satellite precipitation products (GPM IMERG, CHIRPS), and derived indices such as the Topographic Wetness Index (TWI). Comparative analyses highlight the strengths of different modeling architectures: SWAT excels in long-term land-use impact assessment, while HEC-HMS performs well for event-based forecasting. Machine learning approaches (Random Forest, XGBoost, RiverMamba) enhance predictive accuracy and enable real-time forecasting in data-scarce regions. Case studies, including the 2022 Pakistan mega-flood in Balochistan, demonstrate how dam failures, inadequate infrastructure, and socio-economic vulnerability amplify impacts. Multi-criteria decision analysis (MCDA/AHP) and emerging technologies like BIM-GIS integration and opportunistic sensing further support proactive management through structural (levees, dams) and non-structural (early warning systems, zoning) measures. The review underscores the need for site-specific, hybrid modeling and participatory governance to build climate-resilient flood risk strategies.

1. INTRODUCTION

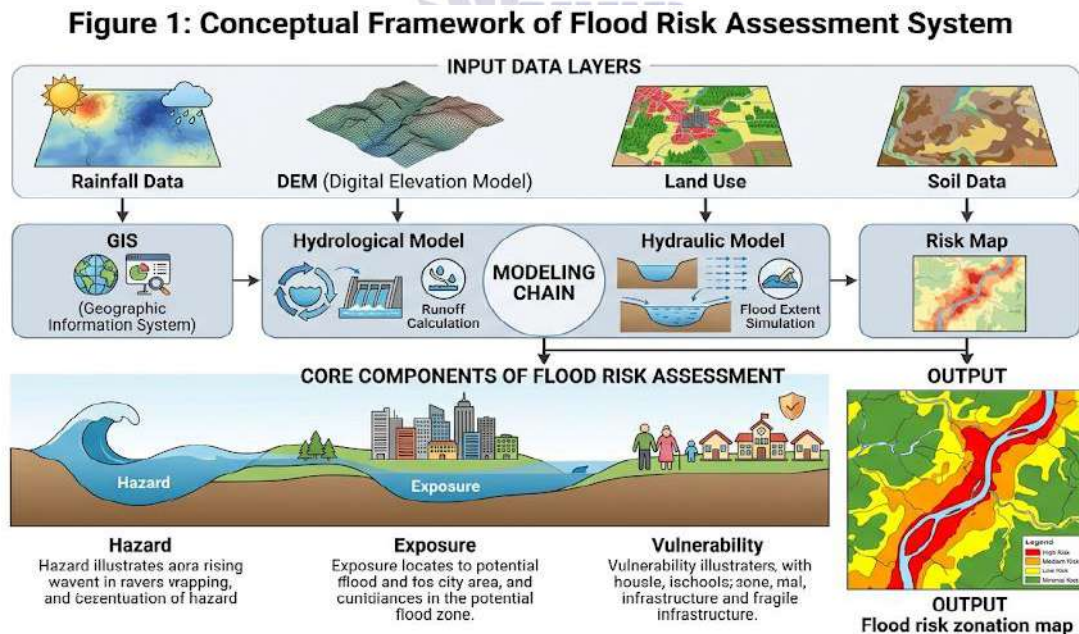
The global paradigm of disaster risk reduction has undergone a radical transformation in response to the increasing frequency and severity of hydrometeorological extremes (Winsemius et

al., 2016). Flooding currently represents one of the most pervasive and destructive natural hazards, accounting for approximately 52% of all catastrophic events globally in 2021 alone (Mukhtar et al., 2024). With nearly 23% of the world's population roughly 1.3 billion individuals

directly exposed to significant flood depths, the necessity for robust, spatially explicit assessment frameworks has never been more urgent (Rentschler et al., 2022). This urgency is amplified by the accelerating drivers of climate change and rapid urbanization, which have complicated the traditional linear relationships between precipitation and runoff (Ajur & Al-Ghamdi, 2022). The contemporary approach to managing these risks relies on the sophisticated integration of Geographic Information Systems (GIS) with advanced hydrological and hydraulic modeling (Teng et al., 2017). This synthesis allows for the discretization of complex environmental variables into manageable spatial units, enabling a shift from reactive emergency response to proactive, adaptive management (Bubeck et al., 2012).

The conceptual foundation of modern flood risk assessment is rooted in the interplay between hazard, exposure, and vulnerability. Hazard is defined as the physical intensity and probability of a flooding event, typically quantified through

parameters such as depth, velocity, and return period (Haseeb et al., 2025). Exposure identifies the spatial intersection between these physical forces and human assets, including population centers, critical infrastructure, and agricultural lands (Ibrahim et al., 2024). Vulnerability, perhaps the most complex dimension, represents the susceptibility of these exposed elements to damage, influenced by socio-economic factors, building quality, and adaptive capacity (Cardona et al., 2012). By utilizing GIS as a central integration platform, researchers can now generate multidimensional risk maps that do not merely show where water will flow, but also predict the resulting economic and social disruptions (Sampson et al., 2015). Figure 1 conceptual framework illustrates the integrated structure of modern flood risk assessment systems. It combines hazard, exposure, and vulnerability components within a GIS-based modeling environment to generate spatial flood risk maps.



2. Theoretical Foundations of Geospatial Flood Modeling

The evolution of flood modeling has transitioned from empirical, site-specific observations to fully distributed, physics-based simulations that can

replicate the entire land phase of the hydrological cycle. At the heart of this transition is the Geographic Information System, which serves as both a repository for diverse datasets and a powerful analytical engine for spatial multi-

criteria analysis (Rentschler et al., 2022). In the GIS-integrated flood risk management framework, the landscape is treated as a dynamic system where topography, land use, soil properties, and climate interact in non-linear ways (Beyer et al., 2025).

One of the primary advantages of GIS-based modeling is the ability to define Hydrologic Response Units (HRUs). In semi-distributed models like the Soil and Water Assessment Tool (SWAT), HRUs represent unique combinations of land use, soil type, and slope within a sub-basin (Chathuranika et al., 2022). This level of discretization allows for a highly granular simulation of water balance components, including evapotranspiration, infiltration, and surface runoff. The mathematical representation of these processes often relies on the Soil Conservation Service (SCS) Curve Number (CN) method, which integrates land-cover characteristics with soil moisture conditions to estimate excess rainfall (Ahmad et al., 2025b).

Runoff Equation (Plain Text):

$$S = (25400 / CN) - 254$$

$$Q = ((P - Ia)^2) / ((P - Ia) + S)$$

In these equations, Q is the runoff, P is the rainfall, S is the potential maximum retention after runoff begins, and Ia is the initial abstraction, The spatial distribution of these CN values across a watershed is a core task of GIS preprocessing, involving the harmonization of diverse vector and raster layers (Crenganis et al., 2025).

3. Comparative Analysis of Hydrological Modeling Architectures

The selection of a hydrological model is a critical decision that depends on the specific objectives of the risk assessment, the scale of the watershed, and the availability of data. The research community frequently contrasts the performance of lumped, semi-distributed, and fully distributed models across different climatic zones and topographic settings (Samiev et al., 2025).

Table 1: Comparative Review of Hydrological Model Architectures and Applications

Model Identifier	Architecture Type	Primary Application Domain	Computation Effort
HEC-HMS	Lumped/Semi-distributed	Event-based flood forecasting (Chathuranika et al., 2022)	Low to Moderate
SWAT	Semi-distributed	Long-term land-use & climate impact (Chathuranika et al., 2022)	High
MIKE SHE	Fully distributed	Integrated surface-groundwater modeling (Aliye et al., 2020)	Very High
LISFLOOD	Gridded/Distributed	Large-scale floodplain risk assessment (Aliye et al., 2020)	Moderate
SWMM	Distributed/Urban	Urban drainage and stormwater management (Samiev et al., 2025)	Moderate

In tropical and humid watersheds, SWAT and HEC-HMS have both demonstrated robust performance in streamflow simulation. Comparative studies indicate that SWAT often excels at capturing high-flow events and long-term impacts of land-use changes due to its detailed representation of physical processes within HRUs (Arnold et al., 2012). Conversely, HEC-HMS is frequently cited for superior performance in simulating medium-flow conditions and providing rapid forecasts during emergency

scenarios (Feldman, 2000). In specific basins like the Katar River in Ethiopia, HEC-HMS has been shown to produce more satisfactory results than SWAT, with Nash-Sutcliffe Efficiency (NSE) values exceeding 0.73, compared to SWAT's 0.67. These discrepancies underscore that model performance is site-specific and sensitive to input parameter quality (Gassman et al., 2007).

4. Advanced Hydraulic Simulation and 2D Flood Routing

While hydrological models determine the volume of water generated from a storm event, hydraulic models are necessary to determine the spatial extent, depth, and velocity of the resulting inundation (Cook & Merwade, 2009). The coupling of HEC-HMS for rainfall-runoff simulation with HEC-RAS 2D for unsteady flow routing has emerged as a gold-standard workflow for producing basin-wide flood hazard maps (Quiroga et al., 2016).

The transition from 1D to 2D hydraulic modeling represents a significant leap in accuracy, particularly for complex floodplains where flow is not confined to a single direction. HEC-RAS 2D utilizes a flexible computational mesh that can follow terrain features and incorporate breaklines to represent levees, roads, and channel banks (Brunner, 2016). By solving the shallow water equations across this mesh, the model provides a detailed visualization of how floodwaters propagate, identifying areas of high-velocity "flash" flooding that pose the greatest risk to human life (Costabile et al., 2017).

Validation of these models is essential for ensuring their credibility. Traditional validation involves comparing simulated water levels against gauged observations (Hunter et al., 2007). However, in data-scarce regions, researchers turn to event-based validation using field evidence. In the Cagayan River Basin, a coupled HEC-HMS/HEC-RAS 2D framework was validated using 137 surveyed flood marks and community-reported data, achieving high statistical reliability represented by high R-squared values (Santillan et al., 2016).

5. Geospatial Data Acquisition and the Role of Remote Sensing

The "garbage in, garbage out" principle is particularly relevant in flood modeling. The spatial accuracy of a flood hazard map is fundamentally constrained by the resolution of the Digital Elevation Model (DEM) and the precision of the precipitation inputs (Ahmad et al., 2025b).

5.1. Topographic Analysis and DEM Refinement

DEMs provide essential data for watershed delineation, slope calculation, and flow accumulation. While global datasets like SRTM are widely used, they often lack the vertical accuracy required for detailed urban flood mapping (Aliye et al., 2020). Advanced studies leverage LiDAR-derived DEMs, which can capture micro-topographic features such as street gutters and building footprints (Elliot et al., 2025). Furthermore, the Topographic Wetness Index (TWI) is a critical derived metric that identifies areas where water is likely to accumulate based on local slope and contributing area (Rizwan et al., 2025).

Topographic Wetness Index Equation (Plain Text):

$$TWI = \text{natural log} (\text{upslope contributing area} / \text{tangent of slope gradient})$$

Regions with high TWI values are inherently more susceptible to flooding, making this index a valuable screening tool (Zahli, 2026).

5.2. Satellite-Based Precipitation and Climate Data

In many regions, the lack of a dense rain gauge network presents a significant barrier to accurate modeling. Satellite-based precipitation products (SPPs) have bridged this gap by providing high-frequency, global coverage of rainfall events (Chidi et al., 2025).

Table 2: Comparative Analysis of Global Satellite-Based Precipitation Products

SPP Dataset	Spatial Resolution	Key Strengths	Identified Limitations
GPM IMERG	0.1 degree	Superior daily accuracy; stable spatial performance (Chidi et al., 2025)	Can underestimate intense monsoon pulses
TRMM 3B42	0.25 degree	Long historical record; reliable for tropical basins (Chidi et al., 2025)	Lower spatial resolution than GPM
CHIRPS	0.05 degree	Excellent for humid regions and seasonal trends (Chidi et al., 2025)	Less effective for flash floods
MSWEP	0.1 degree	High consistency with gauge observations (Chidi et al., 2025)	Complex merging algorithm

Research in mountainous watersheds has shown that while SPPs like GPM and TRMM fit annual observations well, they tend to overestimate light rainfall and underestimate heavy, short-duration events. This bias is particularly pronounced in alpine regions where topography influences cloud formation (Kron, 2005).

6. Machine Learning and AI: The Data-Driven Frontier

The computational intensity of traditional physics-based models has led to the emergence of machine learning (ML) as a powerful alternative for flood forecasting. ML algorithms are adept at identifying complex, non-linear relationships within large datasets without the need for explicit physical equations (Neelz & Pender, 2013).

6.1. Algorithms and Predictive Performance

Models such as Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN) are now routinely integrated into GIS workflows. For instance, in Indus Kohistan, Pakistan, a synergistic approach combining RF and XGBoost for hazard mapping with the Best-Worst Method (BWM) for vulnerability assessment has proven highly effective. These models process a diverse array of inputs, including slope, lithology, and distance to river, to classify land into risk categories (Ahmad et al., 2025a).

The accuracy of these data-driven models is often validated using Receiver Operating Characteristic (ROC) curves. Studies have reported prediction rates as high as 90.3% when utilizing hybrid

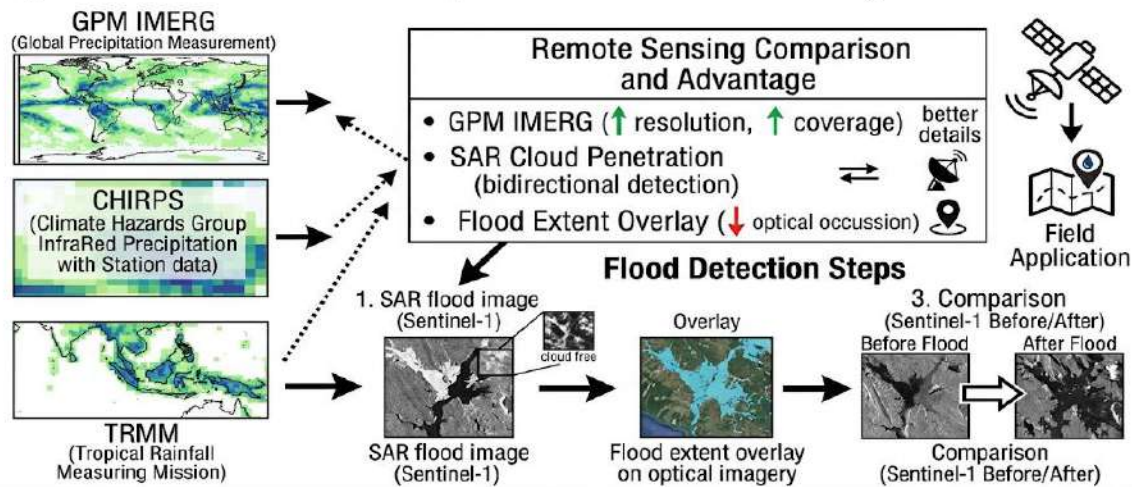
models that integrate fuzzy membership values with convolutional neural networks. This level of precision is comparable to traditional numerical modeling while requiring significantly less computation time once the model is trained (Samiev et al., 2025).

6.2. Real-Time Forecasting with AI: RiverMamba and Beyond

The next generation of flood forecasting is represented by models like RiverMamba, which utilizes a novel AI architecture to process temporal and spatial environmental data more efficiently than previous deep learning models. RiverMamba can evaluate data on soil moisture, temperature, and flow velocity to predict river discharges six days in advance (Dwarakish & Ganasri, 2015). This capability is transformative for regions with incomplete measurement series, as the model can "learn" from both physics-based global systems and local environmental observations (Shams Eddin et al., 2025).

7. Monitoring and Mapping in Challenging Environments

Satellite remote sensing remains the primary tool for near real-time flood monitoring, but its effectiveness varies significantly depending on the sensor type (Chidi et al., 2025). Satellite-based precipitation products and radar remote sensing have significantly improved flood monitoring in data-scarce regions. The figure 2 compares rainfall estimation datasets and demonstrates how SAR imagery enables flood detection even under cloud cover.

Figure 2: Satellite-Based Precipitation and Remote Sensing Flood Detection

7.1. SAR vs. Optical Sensors

Synthetic Aperture Radar (SAR), such as the Sentinel-1 mission, is the preferred tool for flood mapping during storm events because its microwave signals can penetrate clouds. Optical sensors are often blinded by the cloud cover that accompanies extreme rainfall. However, SAR-based flood mapping in arid regions is challenging because dry sand and water both produce low radar backscatter (Yamazaki, 2026). Technical innovation has addressed this through the fusion of SAR amplitude and coherence data. Coherence measures phase stability; while land surfaces change slowly, water surfaces typically lose coherence completely. Studies in Pakistan and Iran have shown that fusing these two layers can improve flood mapping accuracy in arid regions by approximately 50% (Tibebe et al., 2019).

8. Case Study: The 2022 Pakistan Mega-Flood and Balochistan Dynamics

The catastrophic floods that struck Pakistan in 2022 provide a sobering case study. Triggered by a monsoon season that delivered up to 800% of normal rainfall in some regions, the floods affected over 33 million people and damaged nearly 2 million homes (NDMA, 2022).

8.1. Drivers and Impacts in Balochistan

In Balochistan, the disaster was amplified by the failure of aging infrastructure. Analysis revealed that 80-85% of the economic losses in Balochistan were directly attributable to the failure of 177 check dams. These dams were not engineered to handle the massive volumes of runoff generated by the 2022 monsoon (Rizwan et al., 2025).

Table 3: Regional Flood Drivers and Impacts during the 2022 Mega-Flood

Basin/Region	Peak Discharge (2022 Estimate)	Primary Damage Driver	Key Vulnerability
Pishin Lora Basin	> 5,000 cumecs (Ahmad et al., 2025b)	Dam breach/overflow	Non-perennial streams
Quetta Valley	Urban inundation	Inadequate urban drainage	Rapid urbanization (Elliot et al., 2025)
Hunza-Nagar	Glacial Lake Outbursts (GLOF)	Heatwave-induced melt + monsoon	High-altitude terrain

Hydrological modeling of the Pishin Lora Basin using HEC-HMS has shown that runoff volumes during wet years often exceed the holding capacities of small dams by orders of magnitude (Cardona et al., 2012). For example, the Bostan Dam was shown to have high water potential, leading to a critical mismatch between infrastructure and the environment. This suggests that in the absence of scientific planning, human interventions can exacerbate disaster impacts (Ibrahim et al., 2024).

8.2. Socio-Economic Vulnerability and Perception

Risk assessment has increasingly incorporated social dimensions. In Gwadar, findings indicated a strong correlation between housing quality, income level, and perceived risk, with informal settlements in low-lying areas facing the highest exposure. This highlights a growing "vulnerability gap" where marginalized populations are forced into the most hazardous locations due to rapid, unplanned expansion (Sindhushree et al., 2025).

9. Integrated Management: Structural and Non-Structural Paradigms

Managing flood risk requires a balance between structural engineering and non-structural interventions. While large-scale levees remain essential, they can create a false sense of security and lead to catastrophic "levee effects" when they fail (Teng et al., 2017).

9.1. Non-Structural Measures and Policy Frameworks

Non-structural measures, including early warning systems (EWS) and zoning regulations, are often more adaptive to climate uncertainty. Pakistan's Multi-Hazard EWS Plan emphasizes establishing robust dissemination systems. However, challenges remain, including weak governance and a lack of real-time telemetry data in remote regions (NDMA, 2022).

9.2. The Role of MCDA and AHP in Priority Setting

Decision-makers use Multi-Criteria Decision Analysis (MCDA) to prioritize interventions. The

Analytic Hierarchy Process (AHP) allows experts to assign weights to different risk factors such as rainfall intensity and elevation to identify critical zones. In Larkana, AHP analysis revealed that over 60% of the area was at "high risk," primarily due to proximity to the Indus River (Bubeck et al., 2012).

10. Emerging Technologies: BIM-GIS Integration and Opportunistic Sensing

A novel approach in Quetta involves the integration of Building Information Modeling (BIM) with GIS. While GIS is excellent for large-scale hazard mapping, BIM provides detailed building-specific information, such as floor heights (Rentschler et al., 2022). By combining these, researchers can estimate non-structural damage costs with high precision. In Quetta, simulations showed that incorporating flood-resistant materials could reduce repair costs by 30-50% (Elliot et al., 2025).

For data-scarce regions, the use of "opportunistic" data gathered from non-traditional sensors such as Commercial Microwave Links (CMLs) and smart vehicles offers a revolutionary way to enhance monitoring. Real-time streaming platforms like Apache Kafka enable the continuous ingestion of this "big data," ensuring that forecasting models stay updated during dynamic disaster scenarios (Ahmad et al., 2025a).

11. Strategic Challenges and Global Perspectives

Despite significant technological advancements, a gap remains in methodologies and data availability between developed and developing nations. This is particularly evident in Africa and parts of South America, where a lack of long-term records hinders model calibration (Tabish & Syed, 2025). To address this, future research must prioritize ecosystem-based adaptation and participatory governance, ensuring communities at risk are included in decision-making (Beyer et al., 2025).

12. Conclusion

Flood risk assessment and management have evolved from reactive, empirical approaches to proactive, data-driven frameworks that integrate

hydrological modeling, advanced hydraulic simulation, GIS, remote sensing, and machine learning. The synergistic use of models such as HEC-HMS/SWAT for runoff generation and HEC-RAS 2D for detailed inundation mapping enables accurate prediction of flood extent, depth, velocity, and associated hazards, while accounting for complex interactions among topography, land use, soil, and climate. Satellite-based precipitation products and high-resolution DEMs overcome data limitations in many regions, and indices like the Topographic Wetness Index provide valuable screening tools for susceptibility. Emerging AI techniques, including Random Forest, XGBoost, and RiverMamba, offer efficient alternatives or complements to physics-based models, particularly for real-time forecasting and handling non-linear relationships. The 2022 Pakistan mega-flood, especially in Balochistan, illustrates how infrastructure failures, rapid urbanization, and socio-economic vulnerabilities can dramatically amplify impacts, highlighting the critical need for balanced structural (dams, levees) and non-structural (early warning systems, land-use zoning, community participation) measures. Multi-criteria decision analysis and technologies such as BIM-GIS integration further enhance prioritization and damage estimation. To address persistent gaps in developing countries, future efforts must focus on improving model calibration with local data, incorporating climate change projections, strengthening institutional coordination, and promoting ecosystem-based adaptation. Ultimately, a holistic, integrated approach combining cutting-edge modeling with inclusive governance will be essential to reduce flood-related losses, enhance resilience, and support sustainable development in flood-prone regions worldwide.

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