Domain Understanding (Extension): AI-Based Flood Forecasting & Intelligent Decision Support for Flood Response

This section complements the previous *"Domain Understanding: Flood Forecasting & Decision-Making for Flood Response"* by focusing specifically on AI-based flood prediction, IoT-enabled early detection, and intelligent decision support systems (IDSS). It draws on recent work on machine learning, multi-criteria decision-making, digital twins, and group decision-making for floods and other emergencies.

1. Additional Key Terms for AI-Based Flood IDSS

- **Real-Time Urban Flood Forecasting (RTUFF):**
  Real-time flood forecasting in urban drainage systems focuses on predicting short-term water-level rise at critical nodes (e.g., manholes, pipes, inlets) using high-frequency rainfall and sensor data. Instead of simulating continuous time series, some newer approaches use event-based datasets and machine learning models to forecast water levels 1–3 hours ahead with higher accuracy and lower computational cost than traditional hydrodynamic models (Piadeh et al., 2023).

- **Early Warning System (EWS) with Machine Learning:**
  An EWS is a system that provides alerts before dangerous conditions occur, giving decision-makers time to respond. In urban flood management, ML-based EWSs replace or complement slow hydraulic models with trained neural networks that map rainfall inputs to predicted flooding at key locations. For example, the RAPIDS system uses a multi-output ANN to predict urban drainage flooding in near real-time, limited by the time of concentration and the availability of rainfall forecasts. (Duncan et al., 2013).

- **Group Decision Support System (GDSS):**
  A GDSS is a decision support system that explicitly supports **multiple decision-makers** and uses structured methods (e.g., ANP, VIKOR, BORDA voting) to aggregate preferences. In the context of flood early warning, a GDSS can combine criteria like rainfall, discharge, water level, embankment condition, and drainage status, and reconcile the preferences of government agencies and water managers into a single recommended warning level (Soebroto et al., 2024).

- **IoT-Based Flood Early Detection:**
  Internet of Things (IoT) flood systems use networks of inexpensive sensors (e.g.,

ultrasonic water-level sensors, water flow sensors, ombrometers, DHT22 humidity/temperature sensors) to monitor environmental variables in real time. Sensor data is sent to a backend, where a decision support system (often combined with methods like TOPSIS) assesses flood risk and issues alerts and recommended actions through a user interface and communication channels. (H et al., 2024)

- **Event-Based ML Modelling:**
  Rather than using full continuous time series, event-based modelling identifies rainfall–runoff events, builds event-focused datasets, and trains ML models (e.g., tree-based models, neural networks) to predict flood-related variables during those events. An event-based decision support algorithm for urban drainage has been shown to improve forecasting accuracy (e.g., ~50% reduction in RMSE and improved Nash–Sutcliffe efficiency), especially for 2–3 hour lead times.(Piadeh et al., 2023)
- **Multi-Criteria Decision-Making (MCDM) with AI:**
  MCDM techniques like AHP, TOPSIS, VIKOR, or ANP are used to rank or select actions when multiple criteria (e.g., cost, safety, sustainability, response time) are relevant. In flood damage management, ML models are used to estimate flood likelihood or intensity, and MCDM is then applied to prioritize strategies in pre-flood, during-flood, and post-flood stages (Zabihi et al., 2023)

- **Digital Twin for Urban Flood Management:**
  A **digital twin** is a virtual replica of a physical system (e.g., a city, river network, or drainage system) that is continuously updated with real-time data. In urban flood prevention, digital twins integrate meteorological data, sensor networks, social media, and hydrodynamic models to support monitoring, prediction, and scenario testing. Some recent frameworks implement digital twins over secure government intranets to ensure data privacy while enabling AI-driven analysis. (Fan et al., 2025)

- **AI-Driven Flood Risk Management (AI-FRM):**
  AI-FRM refers to the use of machine learning and deep learning to improve flood risk estimation, early detection, and decision-making. A large recent review shows that AI models can handle diverse data (satellite images, hydrological time series, weather forecasts) and provide accurate short-term flood risk estimates but face challenges such as data bias, interpretability, and also have computational demands.
- **Hybrid Rule-Based + Fuzzy Decision Support:**
  In other emergency domains (e.g., hospital triage), hybrid systems combine rule-based reasoning (IF–THEN rules derived from guidelines) with fuzzy logic to handle imprecise input variables. These systems convert narrative expert knowledge into machine-readable rules and use fuzzy classifiers to map vital signs to triage levels, achieving high accuracy and reducing misclassification. Similar hybrid approaches can inspire flood DSS design, especially where inputs (e.g., “high water level”, “rapidly rising”) are fuzzy. (Wang et al., 2025)

- **Integrated Flood Disaster DSS with Sustainable Implementation:**
  Some recent work proposes integrated decision support frameworks that combine data

collection, risk assessment, emergency planning, and long-term sustainability considerations (e.g., resilience, green infrastructure, community engagement). These highlight the need to balance immediate response with sustainable, long-term flood risk reduction. (William et al., 2024)

2. AI- and Data-Driven Forecasting Methods (Extension of Forecasting Overview)

Building on the earlier classification of data-driven, physics-based, and hybrid models, recent work refines what “data-driven” means in operational, real-time urban systems:

A. Machine Learning in Real-Time Urban Flood Forecasting

- Modern ML approaches (ANNs, tree-based models, event-based ML) are used as surrogate models for costly hydrodynamic simulations in urban drainage networks.
- Duncan et al. developed the RAPIDS EWS, where a multi-output ANN predicts flooding at key sewer nodes using observed rainfall time series, providing near real-time warnings. The model focuses only on “key nodes” identified as flood-prone, avoiding the need to simulate the entire network physically. (Duncan et al., 2013)
- Piadeh et al. propose an event-based ML framework: they detect rainfall events, create event-based datasets, and train ML models to predict water levels with longer lead times (2–3 hours) than traditional continuous models. Their framework significantly reduces errors and false alarms compared to baseline methods (Piadeh et al., 2023).

Implications for Flood-IDSS:

- Our system can realistically rely on compact ML models (e.g., Random Forest, Gradient Boosting, ANN) trained on event-based hydrometeorological data to predict a risk score per zone.
- We do not need to implement full hydrodynamic simulations inside the IDSS; instead, we can train ML surrogates or use external model outputs as inputs.

B. IoT-Enhanced Forecasting and Early Detection

- IoT-based systems combine multiple sensors (rainfall, water level, flow, temperature, humidity) connected to a cloud or local server.
- The early detection system by H et al. collects sensor data in real time, analyzes it, and uses a DSS (with TOPSIS) to assess risk and recommend actions for authorities, highlighting the importance of **user interfaces** that support monitoring and rapid decisions (H et al., 2024)

  Implications for Flood-IDSS:

- The project can assume an upstream “sensor layer” (actual or simulated) that streams data into our ML model.
- Our focus can be on processing these data streams into risk indices and feeding them to the rule-based allocation logic.

3. Decision & Resource Allocation Support in AI-Enabled Flood Systems

The previous documentation described rule-based, optimization, MCDM, and simulation-based decision-making. Recent literature refines these ideas for intelligent, AI-assisted DSS.

A. Group Decision Support for Flood Early Warning

Soebroto et al. (2024) propose a Group Decision Support System (GDSS) for flood hazard early warning. Their model:

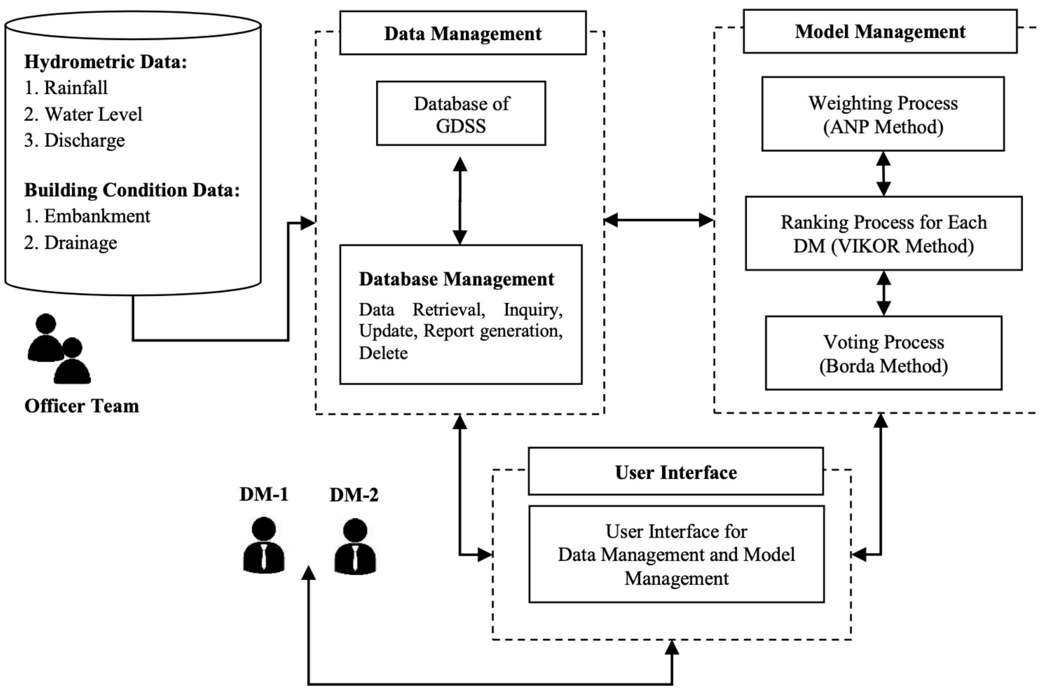


Figure 4. GDSS Architectural Model of Flood Warning

- Uses ANP (Analytical Network Process) to model interdependent criteria (rainfall, discharge, water level, embankment condition, drainage condition).
- Applies VIKOR to rank early-warning alternatives and BORDA voting to aggregate preferences from multiple decision-makers.
- Achieves high consistency and accuracy (e.g., Spearman correlation ~0.84, accuracy ≈ 86.7%).

Relevance for Flood-IDSS:

- Confirms that flood early warning is often a multi-criteria, multi-stakeholder decision.

- Suggests that our system should:
    - Support multiple roles (Administrator, Planner, Coordinator).
    - Make the decision logic transparent so different actors can agree on warnings and actions.

B. IoT + DSS for Operational Response

H et al. (2024) design an IoT-based flood early detection system integrated with a DSS:

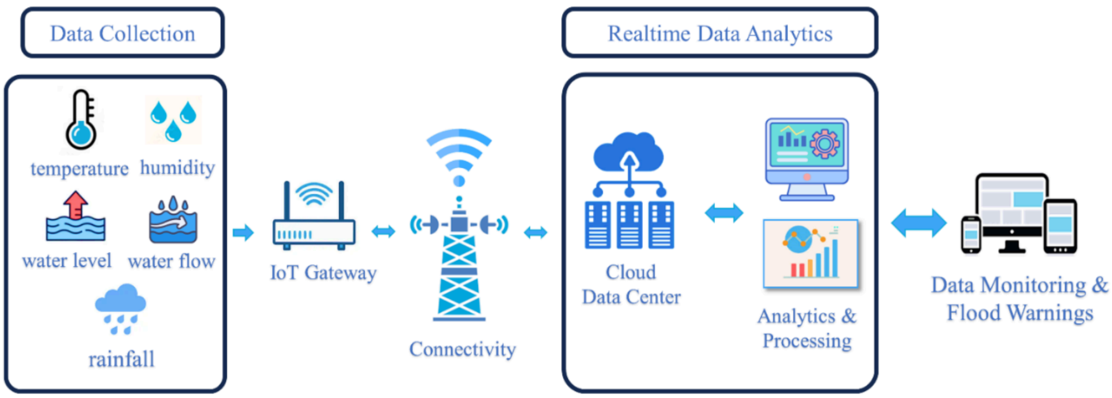


Figure 1. IoT Architecture design of flood detection systems

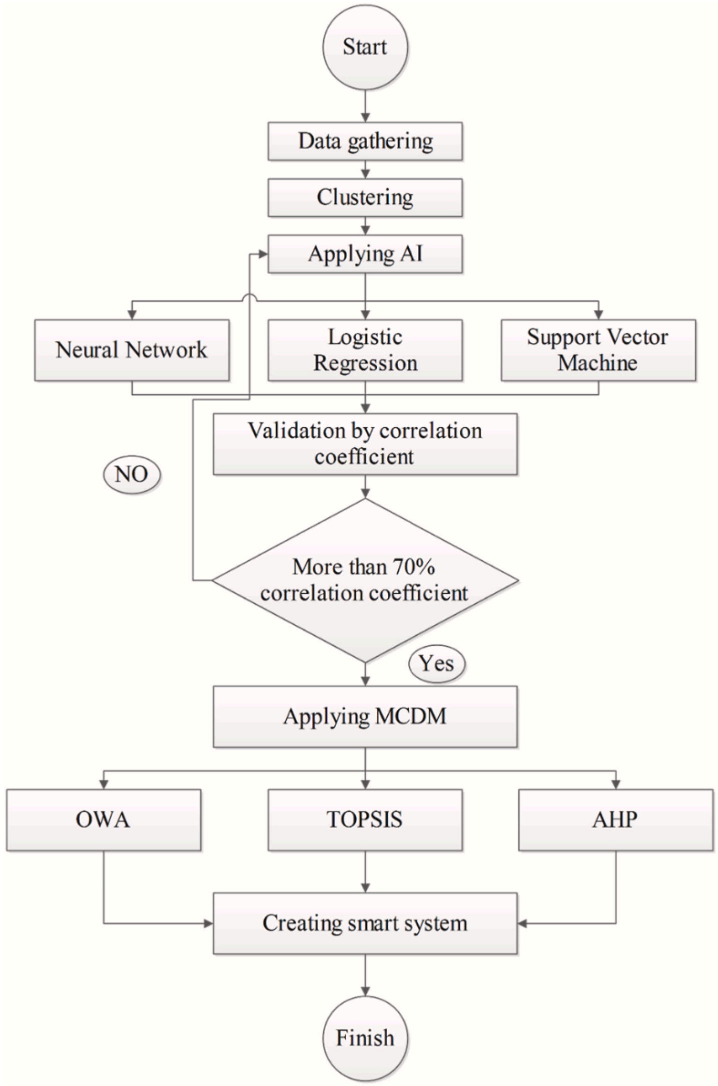
- Sensors continuously send data to the backend.
- The DSS processes data and applies decision logic (including TOPSIS) to:
    - Assess flood potential.
    - Provide **r**ecommended actions to authorities via a user interface.
- Emphasizes communication and participatory approaches to improve community response.

Relevance:

- Supports our choice to implement a backend API (`/predict`, `/allocate`) + Streamlit frontend to deliver decisions to human operators in real time.

C. AI + MCDM for Strategy Prioritization

Zabihi et al. (2023) propose a smart sustainable flood damage management system:



- Stage 1: Monitor and cluster rainfall/flood records using Ward's method.
- Stage 2: Apply Logistic Regression, ANN, and SVM to estimate flood occurrence based on rainfall and climate.
- Stage 3: Use MCDM (AHP, TOPSIS, OWA) to **prioritize strategies** across three phases:
  - Pre-Flood Activities (Pre-FA)
  - During Flood Activities (DFA)
  - Post-Flood Activities (Post-FA)
- Outputs ranked lists of strategies, helping decision-makers choose which actions to implement first under different scenarios.

Relevance:

- Suggests a way to rank response strategies (e.g., deploying pumps, closing roads, evacuating, protecting assets) based on multiple criteria.
- Even if our project does not fully implement AHP/TOPSIS, we can use a simplified weighted scoring inspired by MCDM.

D. Digital Twin-Based AI-Assisted Flood Prevention

Fan et al. (2025) propose an AI-assisted urban flood prevention framework using a digital twin and multi-dimensional data fusion over a secure government intranet:

- Fuses real-time sensor data, meteorological data, and social media into a city-level digital twin.
- Uses AI models and hydrodynamic simulations within a secure intranet to:
    - Enhance flood prediction accuracy.
    - Support decision-making and emergency response.
- Demonstrates implementation in Hebi City, showing improved response efficiency.

Relevance:

- Reinforces the idea that Flood-IDSS should be able to integrate heterogeneous data and may later evolve towards a more complete digital twin architecture.
- The security and governance aspects (using an intranet) are important for real-world deployment.

4. AI-Driven Flood Risk Management: Opportunities and Challenges

Wang et al. (2025) provide a broad review of AI-driven approaches to flood risk management:

- **Benefits of AI/ML/DL:**
    - Can process large and complex datasets (satellite imagery, hydrological data, real-time weather).
    - Provide more accurate real-time risk estimates.
    - Support adaptive, short-term flood risk management across different types of floods (pluvial, fluvial, coastal, compound).
- **Main challenges:**
    - Data bias (e.g., lack of extreme flood events in historical data).
    - Interpretability (black-box models reduce trust among stakeholders).
    - Computational resources (especially for large-scale 2D simulations).
    - Difficulty in generalizing across regions with very different socio-economic and physical conditions.

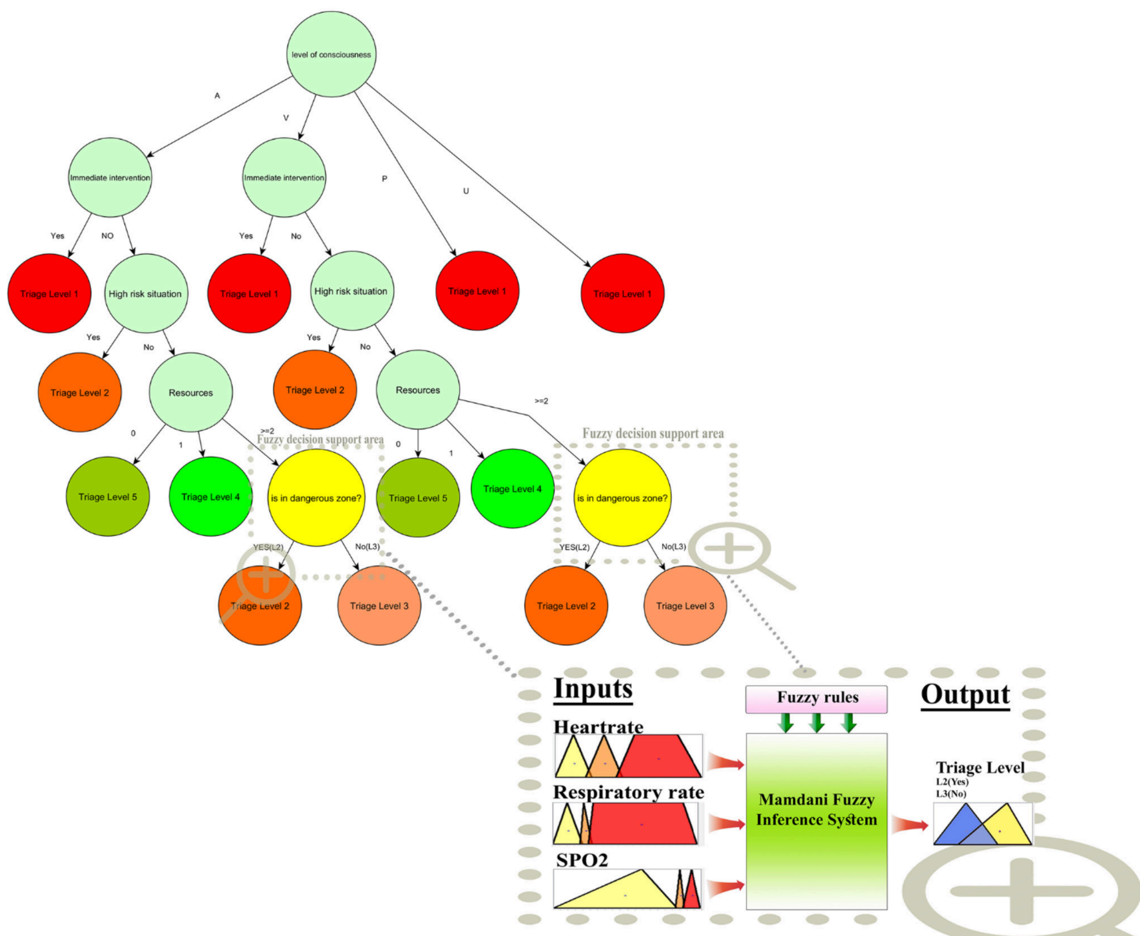
Implications for Flood-IDSS:

- Supports the choice to keep ML as a supporting component, not the only decision-maker.
- Justifies a hybrid AI + rule-based approach, where:

  - ML models generate a risk score or probability.
  - Transparent rules translate those scores into risk levels and actions.
- Underlines the need to expose risk classes (e.g., Low/Medium/High/Extreme) rather than raw scores.

5. Hybrid Rule-Based & Fuzzy Logic Approaches (Inspiration from Emergency Triage)

While not flood-specific, Dehghani Soufi et al. (2018) present a hybrid DSS for emergency triage, combining rule-based reasoning (RBR) and fuzzy logic:



- RBR encodes guidelines (Emergency Severity Index) as IF–THEN rules to decide triage level.
- Fuzzy logic handles imprecise input data (e.g., vital signs) by mapping to linguistic variables (e.g., “high heart rate”, “low blood pressure”).
- The system achieves very high accuracy (~99%) and significantly reduces mis-triage and documentation errors.

Relevance to Flood-IDSS:

- Shows a pattern we can reuse:
    - Convert narrative expert knowledge (e.g., emergency plans, thresholds) into rules.
    - Use fuzzy logic or simple thresholds to handle noisy inputs (e.g., water levels, rainfall intensity, rate-of-rise).
- Suggests that even with imperfect AI predictions, a well-designed rule layer can deliver consistent and auditable decisions.

6. Guidance for Building Our Flood-IDSS (Based on These Studies)

Combining your teammate's domain understanding with these additional articles, we can refine the design guidelines for Flood-IDSS:

A. Architecture

- **Data Layer:**
    - Inputs: rainfall, water level, IoT sensor data, forecasts, GIS layers, basic infrastructure and population data.
    - Inspired by IoT and digital twin systems.
- **Model Layer:**
    - Event-based ML models for flood risk prediction in each zone (e.g., using approaches similar to RAPIDS and event-based RTUFF).
    - Optional MCDM-inspired scoring for strategy prioritization.
- **Knowledge / Rule Base:**
    - Rule sets that:
        - Translate ML risk scores into discrete risk levels.
        - Prioritize zones with critical infrastructure and vulnerable populations.
        - Trigger dynamic reallocation rules as conditions change.
    - Possibly extended with fuzzy logic for more nuanced thresholds.
- **User Interface:**
    - Dashboards for roles (Administrator, Planner, Coordinator) displaying:
        - Risk maps.
        - Alerts.
        - Suggested resource allocations and recommended actions.
    - Trends and event-based summaries (e.g., active flood events, predicted peak times).

B. ML → Risk → Rules

1. **Predict**:
    - ML model outputs a risk indicator for each zone.
2. **Classify**:
    - Map indicator to risk levels (e.g., Low / Medium / High / Extreme) using thresholds calibrated on historical events.
3. **Prioritize**:

    - Compute a simple priority score combining risk level, critical infrastructure presence, and exposure (inspired by AI+MCDM literature).
4. **Allocate**:
    - Apply rules such as:
        - “IF risk = Extreme AND hospital in zone THEN allocate rescue teams + pumps.”
        - “IF risk = High AND high population density THEN deploy barriers + send warning messages.”
5. **Iterate**:
    - Update predictions and rules as new data arrives (IoT feeds, updated rainfall) to support dynamic reallocation.

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