FLOOD MONITORING AND EARLY WARNING

PHASE 3

INTRODUCTION:

- ✓ Flooding is the most common natural hazard and results worldwide in the most damaging disasters. Recent studies associate the increasing frequency and severity of flood events with a change in land use (e.g., deforestation and urbanization) and climate. This particularly holds for the tropical Andes region, where complex hydro-meteorological conditions result in the occurrence of intense and patchy rainfall events.

- ✓ According to the flood generation mechanism, floods can be classified into long- and short-rain floods. A key for building resilience to short-rain floods is to anticipate in a timely way the event, in order to gain time for better preparedness. The response time between a rainfall event and its associated flood depends on the catchment properties and might vary from minutes to hours. In this study special attention is given to flash-floods, which are floods that develop less than 6 h after a heavy rainfall with little or no forecast lead time.

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- ✓ Flood anticipation can be achieved through the development of a flood early warning system (FEWS). FEWSs have proved to be cost-efficient solutions for life preservation, damage mitigation, and resilience enhancement. However, although crucial, flood forecasting remains a major challenge in mountainous regions due to the difficulty to effectively record the aerial distribution of precipitation due to the sparse density of the monitoring network and the absence of high-tech equipment by budget constraints.

- ✓ ML algorithms artificial neural networks (ANNs) , neuro-fuzzy, support vector machine (SVM), and support vector regression (SVR), were reported as effective for both short-term and long-term flood forecast.

Flood monitoring development part 1

1.Certainly! Developing a flood monitoring system typically involves several key steps:

2.Define Objectives: Determine the specific goals of the flood monitoring system, such as early warning, data collection, or flood risk assessment.

3.Data Collection: Gather data from various sources, including weather stations, river gauges, satellite imagery, and social media. Real-time data is crucial for monitoring and prediction.

4.Sensor Deployment: Install sensors and monitoring equipment in flood-prone areas. These can include water level sensors, rain gauges, and remote cameras.

5.Data Processing: Develop algorithms to process and analyze the collected data. This may involve real-time data processing and historical data analysis to identify trends and patterns.

6.Modeling and Prediction: Create predictive models to forecast potential floods based on the data collected. Machine learning and AI can be helpful in this step.

7.Alert System: Implement an alert system to notify authorities and the public when flood risk levels increase. This could include SMS alerts, mobile apps, and sirens.

8.GIS Integration: Use Geographic Information Systems (GIS) to map flood-prone areas and visualize data. This helps in decision-making and response planning.

9.Emergency Response Planning: Work with local authorities to develop flood response plans, taking into account the predicted flood events.

10.Testing and Validation: Rigorously test the system to ensure its accuracy and reliability. This may involve simulations and real-world testing.

11.Community Engagement: Educate and engage with the local community to ensure they understand the system and know how to respond to alerts.

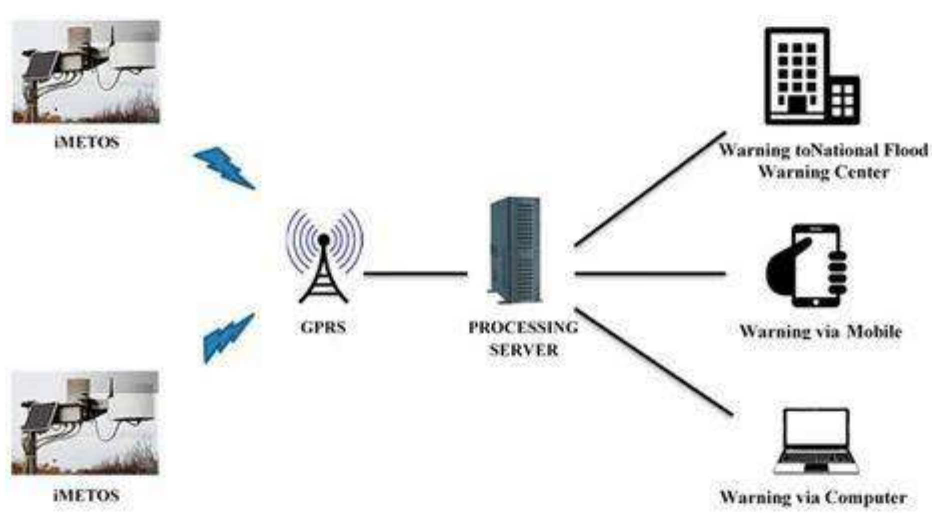
12.Continuous Improvement: Regularly update and improve the system based on feedback and new data.

CONENT FOR PROJECT PHASE 3:

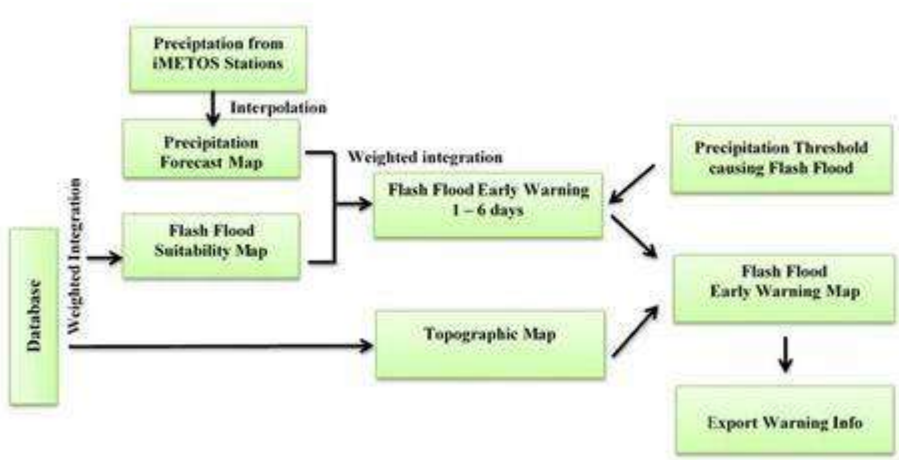
Consider incorporating predictive modeling and historical flood data to improve the accuracy of early warning.

The Theoretical Model in Flash Flood Warning:

The general principle of the model is that flash floods will only occur in locations with high potential risks and when rainfall exceeds the flood level.



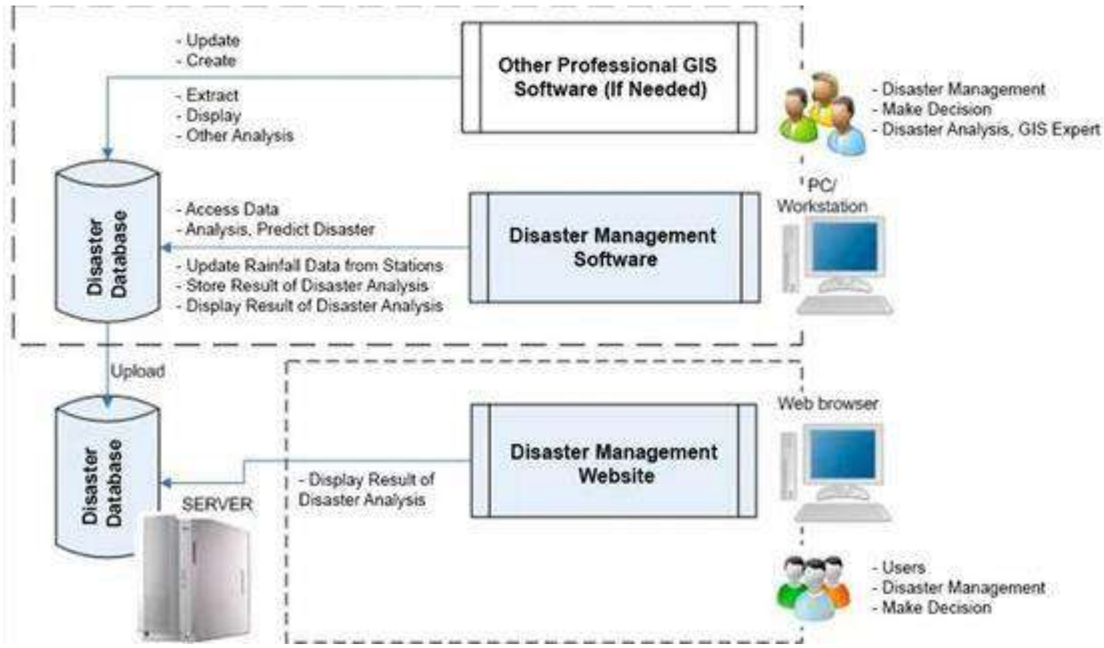
Model of information processing and integration



Workflow of the processing server for early flash flood warning

Structure of Flash Flood Warning System:

The rainfall forecast information processing for each iMETOS weather station system and integration with risk maps for flash flood early warning is done by webGIS. Accordingly, information is transferred to the website to provide flash flood warning information to users. The generalized model and key features of the system are shown in the below figure.

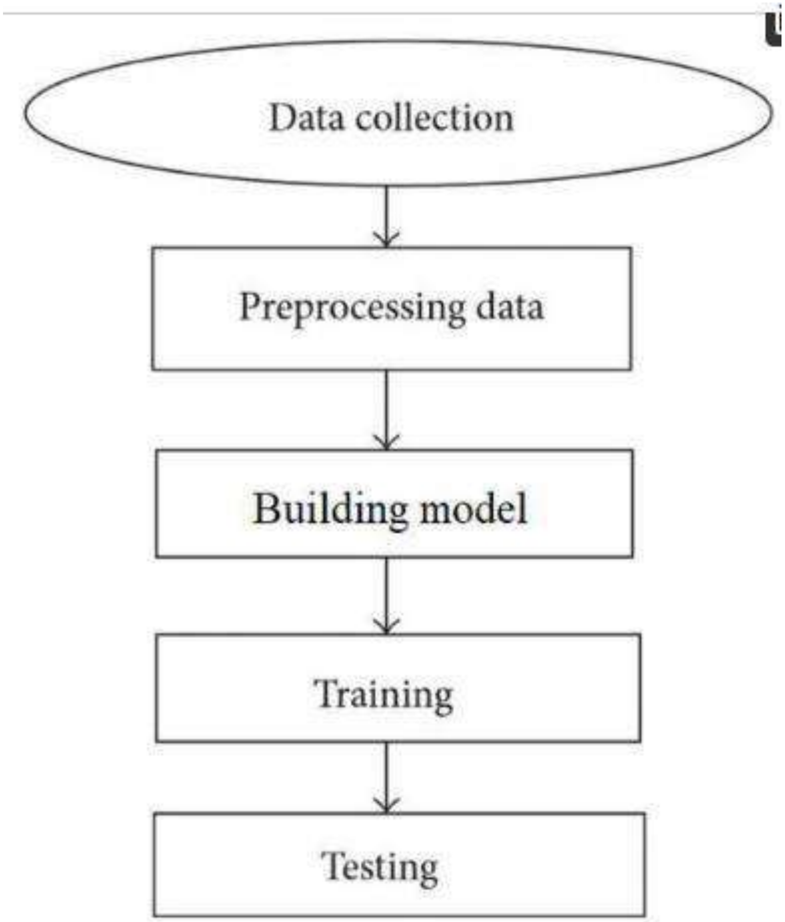


Generalized model and key features of flash flood warning software

This figure shows the completed resolutions for an early warning system for that study site. Input data, such as daily weather data (daily rainfall, daily temperature) and management documents, together with the hardware, have been analyzed, accessed, stored and displayed by disaster-management software. Using webGIS tools, information that is very useful for the decision will be displayed on the user interface. The residents can receive early-warning alerts via SMS message, streaming video and as electronic documents.

ML METHODES IN FLOOD PREDICTION:

For creating the ML prediction model, the historical records of flood events, in addition to real-time cumulative data of a number of rain gauges or other sensing devices for various return periods, are often used. The sources of the dataset are traditionally rainfall and water level, measured either by ground rain gauges, or relatively new remote-sensing technologies such as satellites, multisensor systems, and/or radars. Nevertheless, remote sensing is an attractive tool for capturing higher-resolution data in real time. In addition, the high resolution of weather radar observations often provides a more reliable dataset compared to rain gauges. Thus, building a prediction model based on a radar rainfall dataset was reported to provide higher accuracy in general .Whether using a radar-based dataset or ground gauges to create a prediction model, the historical dataset of hourly, daily, and/or monthly values is divided into individual sets to construct and evaluate the learning models. To do so, the individual sets of data undergo training, validation, verification, and testing. The principle behind the ML modeling workflow and the strategy for flood modeling are described in detail in the literature.The below figure represents the basic flow for building an ML model. The major ML algorithms applied to flood prediction include ANNs , neuro-fuzzy , adaptive neuro-fuzzy inference systems (ANFIS) , support vector machines (SVM), wavelet neural networks (WNN), and multilayer perceptron (MLP). In the following subsections, a brief description and background of these fundamental ML algorithms are presented.



ARIFICIAL NEURAL NETWORK(ANNS):

ANNs are efficient mathematical modeling systems with efficient parallel processing, enabling them to mimic the biological neural network using inter-connected neuron units.

Among all ML methods, ANNs are the most popular learning algorithms, known to be versatile and efficient in modeling complex flood processes with a high fault tolerance and accurate approximation . In comparison to traditional statistical models, the ANN approach was used for prediction with greater accuracy . ANN algorithms are the most popular for modeling flood prediction since their first usage in the 1990s. Instead of a catchment's physical characteristics, ANNs derive meaning from historical data. Thus, ANNs are considered as reliable data-driven tools for constructing black-box models of complex and nonlinear relationships of rainfall and flood, as well as river flow and discharge forecasting . Furthermore, a number of surveys (e.g., Reference) suggest ANN as one of the most suitable modeling techniques which provide an acceptable generalization ability and speed compared to most conventional models. References provided reviews on ANN applications in flood.

MULTILAYER PRECEPTION(MLP):

The vast majority of ANN models for flood prediction are often trained with a BPNN. While BPNNs are today widely used in this realm, the MLP—an advanced representation of ANNs—recently gained popularity. The MLP is a class of FFNN which utilizes the supervised learning of BP for training the network of interconnected nodes of multiple layers. Simplicity, nonlinear activation, and a high number of layers are characteristics of the MLP. Due to these characteristics, the model was widely used in flood prediction and other complex hydrogeological models. In an assessment of ANN classes used in flood modeling, MLP models were reported to be more efficient with better generalization ability. Nevertheless, the MLP is generally found to be more difficult to optimize . Back-percolation learning algorithms are used to individually calculate the propagation error in hidden network nodes for a more advanced modeling approach.

Here, it is worth mentioning that the MLP, more than any other variation of ANNs (e.g., FFNN, BPNN, and FNN), gained popularity among hydrologists. Furthermore, due to the vast number of case studies using the standard form of MLP, it diverged from regular ANNs. In addition, the authors of articles in the realm of flood prediction using the MLP refer to their models as MLP models. From this perspective, we decided to devote a separate section to the MLP.

1.Data Acquisition Layer:

- Sensor Network: Deploy a network of sensors such as rain gauges, river gauges, weather stations, and water level sensors to collect real-time data on rainfall, river levels, and weather conditions.
- Remote Sensing: Utilize satellite imagery and remote sensing technology to monitor large geographic areas and detect changes in water levels and weather patterns.

2.Data Transmission Layer:

- Telemetry Systems: Use telemetry systems to transmit data from sensors to a central data collection point. This can include wired and wireless communication methods.
- Data Aggregation: Aggregate data from various sensors and sources to provide a comprehensive view of the current conditions.

3.Data Processing Layer:

- Real-Time Data Processing: Implement real-time data processing algorithms to continuously analyze incoming data streams, identify anomalies, and trigger alarms if necessary.
- Data Validation: Validate and quality-check incoming data to filter out erroneous or unreliable measurements.
- Historical Data Integration: Incorporate historical data to identify trends and patterns over time, aiding in flood prediction.

4.Modeling and Prediction Layer:

- Hydrological Models: Develop hydrological models that consider factors like rainfall, soil saturation, and river basin characteristics to predict potential flooding events.
- Machine Learning Algorithms: Utilize machine learning algorithms to improve the accuracy of flood predictions and adapt to changing conditions.

5.Alert and Communication Layer:

- Alert Generation: Generate alerts based on the output of predictive models and real-time data. These alerts may be classified into different levels of flood risk.
- Communication Channels: Establish multiple communication channels for disseminating alerts, including SMS, mobile apps, sirens, and social media.

5.Data Visualization and Reporting Layer:

- Geographic Information Systems (GIS): Utilize GIS to create maps that display flood-prone areas, real-time data, and predicted flood extents.
- Reporting Tools: Develop reporting tools to provide detailed information to emergency responders and the public.

6.Community Engagement Layer:

- Education and Outreach: Engage with the community to educate them about the system, the significance of alerts, and evacuation procedures.
- Feedback Mechanism: Establish a feedback mechanism for the community to report local conditions and issues.

7.Emergency Response Layer:

- Integration with Emergency Services: Ensure that the system is tightly integrated with local emergency services, allowing for swift and coordinated response to flood events.
- A multilayer reception approach in flood monitoring enhances the system's ability to detect and predict floods accurately and disseminate timely alerts, thus minimizing the potential damage and loss of life associated with flooding events

CONCLUSION:

The current state of ML modeling for flood prediction is quite young and in the early stage of advancement. For future work, conducting a survey on spatial flood prediction using machine learning models is highly encouraged. This important aspect of flood prediction was excluded from our paper due to the nature of modeling methodologies and the datasets used in predicting the location of floods. Nevertheless, the recent advancements in machine learning models for spatial flood analysis revolutionized this particular realm of flood forecasting, which requires separate investigation. In conclusion, developing a flood monitoring system is a complex but essential endeavor to mitigate the risks associated with flooding. It involves defining clear objectives, collecting and processing data, predictive modeling, implementing alert systems, and engaging with the community. By continuously improving the system and working closely with local authorities and communities, we can enhance preparedness and response to floods, ultimately reducing their impact on lives and property. Additionally, advancements in technology, such as AI and real-time data processing, are making flood monitoring systems more effective and accurate in providing early warnings and aiding in disaster management