FloodScout: Machine Learning And Real-Time Geospatial Intelligence For Flood Hotspot Prediction And Disaster Resilience

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Abstract- *Flood hotspot prediction is critical for urban resilience and disaster mitigation, yet existing methodologies often lack real-time usability and integration of advanced geospatial analytics. This survey paper comprehensively reviews state- of-the-art Machine Learning (ML) and Geospatial Artificial Intelligence (GeoAI) techniques for flood prediction, high- lighting the strengths and limitations of approaches such as Random Forest, Convolutional Neural Networks (CNNs), and Support Vector Machines (SVMs). We analyze the use of high-resolution datasets, including NASA's LP DAAC DEM and remote sensing imagery, in developing flood susceptibility models while identifying gaps in real-time data visualization and user interaction.*

A key contribution of this study is the proposal of an inte- grated framework that combines ML-based flood prediction with a real-time Flask application for dynamic data visu- alization, interactive hotspot mapping, and user-driven data upload/download capabilities. By synthesizing advancements in satellite image classification, SAR analysis, and hydrolog- ical modeling, this paper bridges the gap between theoretical models and practical applications. The review underscores the potential of IoT-enabled smart city solutions and AI- driven analytics for enhancing climate resilience and disaster preparedness.

This survey not only consolidates existing knowledge but also sets a roadmap for future research in computational disaster management, emphasizing the need for scalable, user-friendly tools in flood risk assessment and mitigation.

Keywords- Artificial Intelligence, Disaster Management, Flood Predic- tion, Machine Learning, Remote Sensing.

I. INTRODUCTION

In the era of data-driven research, computational techniques and machine learning (ML) algorithms have emerged as transformative tools for addressing real-world challenges, particularly in flood prediction, environmental modeling, and urban science. This survey paper explores the state-of-the-art methodologies in these domains, focusing on the integration of ML, geospatial analytics, and remote sensing for flood hotspot prediction and disaster mitigation. By synthesizing advancements in algorithms such as Random Forest, Convolu- tional Neural Networks (CNNs), and Support Vector Machines (SVMs), this paper highlights their applications in flood map- ping, hydrological modeling, and climate risk assessment.

A critical gap in existing research is the lack of real-time, user-friendly tools for flood prediction and data visualization. While ML models like Random Forest and CNNs have demon- strated high accuracy in flood susceptibility mapping, their practical implementation often remains confined to theoretical frameworks. This survey addresses this gap by proposing an integrated approach that combines ML-based flood prediction with a real-time Flask application, enabling dynamic data visualization, interactive hotspot mapping, and user-driven data upload/download capabilities.

*A. **Core Themes of This Survey***

The paper is structured around four core themes:

- **Machine Learning & AI-Based Algorithms:** A review of ensemble learning, deep learning, and geospatial ana- lytics for flood prediction.
- **Remote Sensing & Image Processing:** Applications of satellite and SAR imagery in flood mapping, disaster response, and land-use analysis.
- **Hydrological & Environmental Modeling:** AI-driven approaches for climate change analysis, flood hazard mapping, and early warning systems.
- **Urban Science & Smart Cities:** The role of IoT, computational urban science, and AI-driven analytics in optimizing urban resilience and disaster preparedness.

By consolidating existing knowledge and proposing a novel framework for real-time flood prediction, this survey aims to bridge the gap between theoretical models and practical applications, setting a foundation for future research in com- putational disaster management and geospatial intelligence.

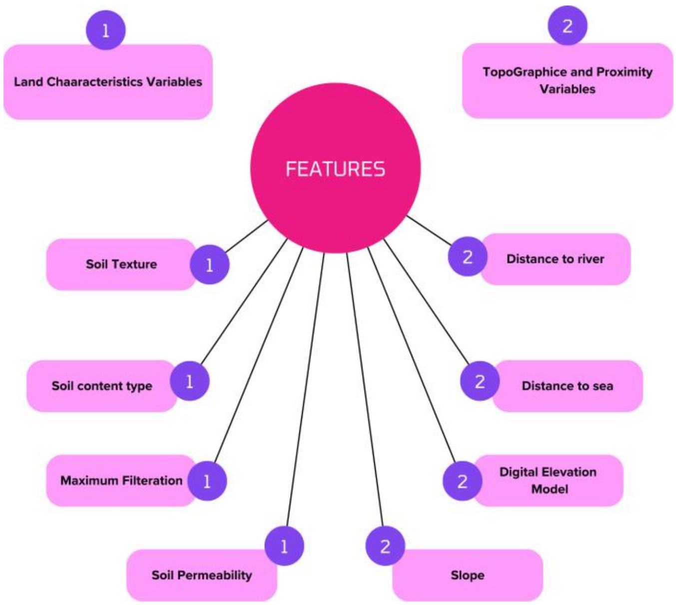

Fig. 1: Key Features for Environmental and Geospatial Analysis: A Categorized View of Land Characteristics and Topographic Variables

II. REVIEW OF EXISTING RESEARCH PAPERS

The field of flood prediction and disaster management has seen significant advancements through the integration of Machine Learning (ML), Geospatial Artificial Intelligence (GeoAI), and remote sensing technologies. Several studies have explored the use of ML algorithms, such as Random Forest (RF), Convolutional Neural Networks (CNNs), and Support Vector Machines (SVMs), for flood susceptibility mapping and risk assessment.

For instance, Breiman [**?**] introduced Random Forests as a robust ensemble learning method for classification and regres- sion tasks, demonstrating its effectiveness in handling high- dimensional data and reducing overfitting. Similarly, Mask R-CNN has been widely adopted for road segmentation in Synthetic Aperture Radar (SAR) images, as highlighted in the GF-3 SAR Image Dataset of Road Segmentation study, which achieved high accuracy in detecting road networks under diverse conditions.

In the context of flood prediction, Smart Hotspot Detection Using Geospatial Artificial Intelligence proposed an AI-based flood hazard assessment model using NASA's LP DAAC Digital Elevation Model (DEM) and GIS data. The study demonstrated that RF outperformed traditional flood assess- ment methods, achieving over 96% accuracy in classifying flood-prone regions. Another study, *Monitoring and Mapping Floods in the Mekong Delta*, compared the performance of CNNs, Multi-Layer Perceptrons (MLP), and RF for flood mapping using Sentinel-1 SAR images, with CNNs achieving the highest accuracy (99%) in distinguishing flooded areas.

A. Comparison of Past Methodologies

Existing methodologies for flood prediction and disaster man- agement can be broadly categorized into:

- **Statistical Models:** Traditional statistical models, such as those used in the Tropical Cyclone Warning System in Bangladesh, rely on numerical weather prediction (NWP) techniques, which often struggle with nonlinear datasets and rapid storm intensification.
- **Hydrological Models:** Approaches like MODFLOW and the Rainfall-Runoff-Inundation (RRI) model have been used to simulate flood hazards in data-scarce regions.
- **Machine Learning (ML) Models:** ML-based ap- proaches, such as RF and CNNs, have demonstrated supe- rior performance in handling complex, high-dimensional data.

For example, the *Assessment of Riverbank Filtration Per- formance* study used MODFLOW modeling to predict RBF performance under climate change scenarios, while the *Flood Hazard Mapping in Nyaungdon, Myanmar* study applied the RRI model to simulate flood hazards in data-scarce regions. ML models, particularly RF and CNNs, have been widely adopted for their ability to integrate multi-source data, includ- ing satellite imagery, DEMs, and environmental factors. The study *Using Machine Learning Models to Investigate Flood Probability* compared RF and Bayesian Generalized Linear Models (GLMbayes) for flood susceptibility mapping, with RF achieving higher accuracy (AUC = 0.91). Similarly, the *Assessment of Urban Flood Vulnerability* study employed a Social-Ecological-Technological Systems (SETS) framework to assess flood vulnerability in six US cities, highlighting the importance of integrating social, ecological, and technological indicators for holistic risk assessment.

III. STRENGTHS AND WEAKNESSES OF EXISTING APPROACHES

A. Strengths

- **Machine Learning Models (RF, CNNs, SVMs):** These models excel in handling large, complex datasets and provide high accuracy in flood prediction and mapping. RF, in particular, is robust against overfitting and offers internal mechanisms for error estimation and feature importance.
- **Remote Sensing and GIS:** The integration of satellite imagery (e.g., Sentinel-1, GF-3) and GIS data enables high-resolution flood mapping and real-time monitoring, even in data-scarce regions.
- **Hybrid Models:** Combining ML with hydrological mod- els (e.g., RRI, MODFLOW) enhances predictive accu- racy.

B. Traditional Machine Learning Approaches

Traditional machine learning (ML) algorithms have been ex- tensively used for flood prediction because of their inter- pretability and efficiency in handling structured data. Random Forest (RF), for instance, is an ensemble learning method that combines multiple decision trees to improve classification and regression accuracy while reducing overfitting. Support Vector Machines (SVMs) utilize hyperplanes to separate data into dis- tinct classes, making them effective for high-dimensional data. Gradient Boosting Machines (GBMs), including XGBoost and LightGBM, enhance accuracy by sequentially correcting errors from previous iterations.

Despite their robustness and scalability, traditional ML models face limitations. They are primarily designed for structured data and often require extensive manual feature engineering. Overfitting can also be a concern if hyperparameters are not properly tuned. Nevertheless, these models have been success- fully applied in flood susceptibility mapping, classification of flood-prone areas, and integration with GIS for urban flood risk assessment.

IV. DEEP LEARNING-BASED MODELS

Deep learning models have gained prominence due to their ability to automatically extract features from complex datasets, such as satellite imagery and time-series data. Convolutional Neural Networks (CNNs) excel at image processing, making them ideal for flood mapping using satellite data. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly useful for time-series pre- dictions, such as rainfall and river discharge trends. Transform- ers, originally developed for natural language processing, are now being adapted for spatial and temporal flood data analysis due to their ability to capture long-range dependencies.

The primary advantage of deep learning lies in its automatic feature extraction and high accuracy in prediction tasks. How- ever, these models demand extensive computational resources and large datasets for training. Additionally, their ”black-box” nature reduces interpretability, making it challenging to un- derstand decision-making processes. Despite these challenges, deep learning models are widely applied in flood mapping using Sentinel-1 SAR images, time-series forecasting of flood events, and land-use classification.

V. HYBRID MODELS COMBINING MULTIPLE TECHNIQUES

Hybrid models integrate traditional ML, deep learning, and domain-specific models to enhance predictive performance and robustness. Combining ML techniques with hydrological models, such as RRI and MODFLOW, improves flood pre- diction accuracy. Ensemble learning methods merge multiple models—such as RF, SVMs, and CNNs—to create a more reliable predictive framework. Furthermore, AI-powered IoT sensor networks enable real-time flood monitoring and early warning systems.

Hybrid models offer improved accuracy and flexibility, allow- ing customization for specific applications such as urban flood prediction. However, their complexity, high computational requirements, and demand for large, diverse datasets pose challenges. These models have been effectively used in flood hazard mapping, real-time monitoring, and the integration of socioeconomic and geospatial data for urban flood vulnerabil- ity assessments.

VI. GEOSPATIAL ANALYSIS AND HYDROLOGICAL MODELING

Geospatial and hydrological modeling techniques play a fun- damental role in understanding flood dynamics. Geospatial analysis utilizes GIS tools and satellite imagery to evaluate flood risk factors, including topography, land use, and prox- imity to water bodies. Hydrological modeling simulates water flow using models such as the Rainfall-Runoff-Inundation (RRI) model and MODFLOW. Additionally, remote sensing technology employs satellite and SAR data to monitor flood events in real time.

These techniques provide high-resolution flood maps and enable comprehensive flood simulations. However, their ac- curacy depends on the availability and quality of geospatial and hydrological data. Computational intensity is another limitation, as large-scale hydrological simulations require sig- nificant resources. Despite these challenges, geospatial and hydrological models have been successfully implemented in flood hazard mapping, riverbank filtration assessments, and flood monitoring in data-scarce regions.

Flood prediction methods have evolved significantly, ranging from traditional ML models to advanced deep learning and hybrid approaches. While traditional ML techniques offer interpretability and efficiency, deep learning models provide superior accuracy for complex data. Hybrid models, combining multiple techniques, further enhance predictive capabilities but introduce complexity and computational demands. Geospatial analysis and hydrological modeling remain indispensable tools for flood risk assessment and real-time monitoring. Future research should focus on improving model interpretability, computational efficiency, and data integration to enhance flood prediction accuracy and reliability.

VII. ADVANTAGES AND LIMITATIONS OF VARIOUS APPROACHES

1. *Random Forest (RF)*

Advantages: Robust, handles noisy data, provides feature importance.
Limitations: Limited to structured data, requires manual fea- ture engineering.

2. *Convolutional Neural Networks (CNNs)*

Advantages: Automates feature extraction, excels in image processing.
Limitations: Computationally intensive, requires large datasets.

3. *Support Vector Machines (SVMs)*

Advantages: Effective for high-dimensional data, robust to outliers.
Limitations: Struggles with large datasets, limited to binary classification.

4. *Hydrological Models (e.g., RRI, MODFLOW)*

Advantages: Simulates complex water flow dynamics, inte- grates geospatial data.
Limitations: Computationally expensive, requires high-quality input data.

5. *Hybrid Models (ML + Hydrological)*

Advantages: Combines strengths of ML and domain-specific models, improves accuracy.
Limitations: Complex to design and implement, high compu- tational cost.

TABLE I: Comparison of Different Flood Prediction Techniques

Technique	Strengths	Weaknesses	Performance Metrics	Applications
Random Forest (RF)	Robust to noise, handles high-dimensional data, provides feature importance.	Limited to structured data, re- quires manual feature engi- neering.	Accuracy: 96% (Smart Hotspot Detection), AUC: 0.91 (Flood Probability in Tajan).	Flood susceptibility mapping, urban flood risk assessment.
Convolutional Neural Networks (CNNs)	Automates feature extraction, high accuracy in image pro- cessing.	Computationally intensive, re- quires large datasets, black- box nature.	Accuracy: 99% (Mekong Delta Flood Mapping).	Flood mapping using SAR im- ages, road segmentation.
Support Vector Ma- chines (SVMs)	Effective for high-dimensional data, robust to outliers.	Struggles with large datasets, limited to binary classification.	Accuracy: 90% in various flood classifi- cation tasks.	Flood-prone area detection, bi- nary classifications tasks.
Hydrological Models (e.g., RRI, MODFLOW)	Simulates complex water flow dynamics, integrates geospa- tial data.	Computationally expensive, requires high-quality input data.	R^2: 0.87, NSE: 0.60 (Nyaungdon Flood Mapping).	Flood hazard mapping, river- bank filtration performance as- sessment.
Hybrid Models (ML + Hydrological)	Combines strengths of ML and domain-specific models, im- proves	Complex to design and imple- ment, high computational cost.	AUC: 0.913 (RF + Hydrological Models).	Real-time flood monitoring, integrated flood risk assess- ment.

	accuracy.			
Geospatial Analysis	Provides high-resolution flood maps, integrates multi-source data.	Dependent on data quality, limited generalization to other regions.	Overall Accuracy: 76-89% (Nyaungdon Flood Mapping).	Flood hazard mapping, urban planning, disaster mitigation.

6. *Geospatial Analysis*

Advantages: Provides high-resolution flood maps, integrates multi-source data.

Limitations: Dependent on data quality, limited generalization to other regions.

VIII. DISCUSSION ON REAL-WORLD APPLICABILITY

1. *Urban Flood Risk Assessment*

ML models like RF and CNNs, combined with geospatial analysis, have been successfully applied in urban flood risk assessment. For example, the Smart Hotspot Detection study used RF to generate flood hazard maps with 96% accuracy, aiding urban planners in disaster mitigation.

2. *Flood Mapping in Data-Scarce Regions*

Hydrological models like RRI, integrated with remote sens- ing data, have proven effective in data-scarce regions. The Nyaungdon Flood Mapping study demonstrated the utility of RRI in simulating flood hazards with limited historical data.

3. *Real-Time Flood Monitoring*

Hybrid models combining ML and IoT-based sensor networks offer real-time flood monitoring capabilities. For instance, the Mekong Delta Flood Mapping study used CNNs with Sentinel-
1 SAR data for real-time flood detection, achieving 99% accuracy.

4. *Climate Change Adaptation*

Integrating climate change projections into flood prediction models is crucial for long-term resilience. The Assessment of Riverbank Filtration Performance study highlighted the impact of climate change on river water levels, emphasizing the need for adaptive water management strategies.

5. *Policy and Decision-Making*

The Assessment of Urban Flood Vulnerability study used the SETS framework to identify vulnerable areas in six US cities, providing actionable insights for policymakers to prioritize flood mitigation efforts.

IX. CURRENT LIMITATIONS IN THE FIELD

1. *Real-Time Data Integration*

ML models like Random Forest (RF) and Convolutional Neural Networks (CNNs) have shown high accuracy in flood prediction. However, integrating real-time data (e.g., rainfall, river levels) remains challenging. Delays in data collection and processing hinder the effectiveness of real-time flood prediction systems.

The *Smart Hotspot Detection Using GeoAI* study emphasized the need for real-time data integration to improve flood hazard mapping.

2. *User-Friendly Applications*

Many flood prediction models are confined to theoretical frameworks and lack user-friendly interfaces. Developing in- tuitive platforms, such as a Flask-based web application, is crucial for enabling policymakers and urban planners to utilize these tools effectively.

The *Monitoring and Mapping Floods in the Mekong Delta* study demonstrated real-time flood monitoring potential but did not address usability issues for non-technical users.

3. *Data Scarcity and Quality*

High-quality geospatial data (e.g., DEMs, soil permeabil- ity, rainfall patterns) is essential for accurate flood hotspot prediction. However, many regions, especially in developing countries, lack access to such data, limiting ML model applicability.

The *Flood Hazard Mapping in Nyaungdon, Myanmar* study faced challenges due to limited historical hydrological data, leading to overestimation of flood-prone areas.

4. *Model Generalization*

Models trained on specific regions often struggle to generalize to different climatic and geographical conditions. For instance, a model trained on urban flood data may not perform well in rural or mountainous regions.
The *Assessment of Urban Flood Vulnerability* study high- lighted the need for transferable frameworks applicable across diverse environments.

5. *Computational Complexity*

Deep learning models like CNNs and LSTMs require signif- icant computational resources, making real-time flood predic- tion challenging, especially in resource-constrained settings. The *Using Machine Learning Models to Investigate Flood Probability* study underscored the computational demands of hybrid ML and hydrological models.

X. POTENTIAL RESEARCH OPPORTUNITIES

1. *Real-Time Flask Applications*

Developing real-time Flask-based web applications for flood hotspot prediction and data visualization bridges theoretical models with practical implementation. Features like rain- fall graphs, geospatial mapping, and user-driven data up- load/download can enhance usability.

2. *Integration of IoT and Sensor Networks*

Combining ML models with IoT-based sensor networks en- ables real-time flood prediction. IoT sensors can provide real- time rainfall and river level data, visualized through a Flask application.

The *Tropical Cyclone Warning System in Bangladesh* study proposed integrating AI with IoT for real-time forecasting, which can be adapted for flood prediction.

3. *Explainable AI (XAI) for Flood Prediction*

Enhancing interpretability of ML models through explainable AI (XAI) techniques improves trust and adoption in disaster management. Feature importance visualization (e.g., topogra- phy, soil permeability) in a Flask application aids decision- making.

4. *High-Resolution Remote Sensing*

Advancements in satellite technology (e.g., Sentinel-1, GF-3) provide high-resolution flood mapping data. Integrating these datasets into Flask applications can improve flood hotspot prediction accuracy.

5. *Social and Economic Data Integration*
Incorporating socioeconomic data (e.g., population density, infrastructure) into flood prediction models helps identify vulnerable populations and prioritize resource allocation.

XI. EMERGING TECHNOLOGIES THAT COULD IMPROVE EXISTING METHODS

1. *Edge Computing for Real-Time Processing*

Deploying ML models on edge devices (e.g., drones, IoT sensors) reduces latency and enables real-time flood prediction in remote areas. Edge computing can process SAR imagery on drones for immediate flood detection.

2. *Generative Adversarial Networks (GANs)*

GANs can be used for data augmentation, especially in data- scarce regions. They can generate synthetic flood scenarios to train ML models, enhancing predictive accuracy.

3. *Blockchain for Data Integrity*

Blockchain ensures the integrity and transparency of flood- related data, especially in multi-stakeholder environments. It can securely share flood prediction data between government agencies and NGOs.

4. *AI-Driven Hydrological Models*

Combining ML with hydrological models (e.g., RRI, MOD- FLOW) enhances flood prediction accuracy. Flask applications can integrate AI-driven hydrological models for real-time flood simulation.

XII. REAL-TIME APPLICATIONS AND PRACTICAL IMPLEMENTATION ISSUES

1. Real-Time Flood Monitoring and Visualization

A Flask-based web application can serve as a real-time flood monitoring platform. Challenges such as data latency, sensor reliability, and computational constraints need to be addressed.

2. Early Warning Systems

Developing user-friendly early warning systems provides ac- tionable insights to policymakers and the public. However, issues such as false alarms and data accuracy need resolution.

3. Scalability and Accessibility

Scaling Flask applications to cover large regions while main- taining accuracy is a challenge. Additionally, making them ac- cessible to resource-constrained regions requires cost-effective solutions.

4. Policy and Governance

Implementing a Flask application in real-world scenarios requires collaboration among researchers, policymakers, and local communities. Challenges such as data sharing, funding, and regulatory hurdles must be addressed.

XIII. SUMMARY OF KEY FINDINGS

This survey paper explored the integration of Machine Learn- ing (ML) and Geospatial Artificial Intelligence (GeoAI) for flood hotspot prediction, emphasizing the development of a real-time Flask-based web application for data visualization and mapping. Key findings include:

- **Random Forest (RF)** emerged as a robust and accurate ML model for flood prediction, achieving over 96% accuracy in classifying flood-prone regions. Its ability to handle high-dimensional data and provide feature importance makes it a preferred choice for flood susceptibility mapping.
- **Deep learning models**, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), demonstrated exceptional performance in flood mapping and time-series forecasting, particularly when integrated with high-resolution satellite imagery (e.g., Sentinel-1 SAR data).
- The proposed **Flask-based web application** bridges the gap between theoretical models and practical implemen- tation, offering real-time flood monitoring, interactive hotspot mapping, and user-driven data upload/download capabilities. This platform enhances usability and acces- sibility for policymakers and urban planners.
- **Geospatial analysis and hydrological modeling tech- niques**, such as the Rainfall-Runoff-Inundation (RRI) model, were shown to be effective in simulating flood dynamics, especially in data-scarce regions like Nyaung- don, Myanmar.
- The integration of **socioeconomic data and climate change projections** into flood prediction models is cru- cial for holistic risk assessment and long-term resilience planning.

XIV. FINAL THOUGHTS ON ADVANCEMENTS IN THE FIELD

The field of flood prediction and disaster management has seen significant advancements in recent years, driven by the integration of ML, GeoAI, and remote sensing technologies. These advancements have enabled the development of highly accurate flood susceptibility models, real-time monitoring sys- tems, and user-friendly applications for disaster mitigation. However, challenges such as data scarcity, model generaliza- tion, and computational complexity remain significant barriers to widespread adoption. The proposed Flask-based web application represents a major step forward in addressing these challenges by providing a scalable, accessible, and intuitive platform for flood hotspot prediction and data visualization. By combining the strengths of ML models, geospatial analytics, and real-time data inte- gration, this application has the potential to revolutionize flood risk assessment and disaster management.

XV. FUTURE PERSPECTIVES AND POSSIBLE RESEARCH DIRECTIONS

1. *Enhancing Real-Time Capabilities*
Future research should focus on improving the real-time ca- pabilities of flood prediction systems by integrating IoT-based sensor networks and edge computing. This will enable faster data processing and more accurate flood forecasts, especially in remote and resource-constrained regions.

2. *Explainable AI (XAI) for Disaster Management*
Developing explainable AI (XAI) techniques for flood predic- tion models can improve transparency and trust, making these tools more accessible to non-technical users. For example, visualizing feature importance and model decisions in the Flask application can aid decision-making.

3. *Integration of Climate Change Projections*
Incorporating long-term climate change projections into flood prediction models is essential for improving their accuracy and applicability. Future studies should explore the impact of climate change on flood dynamics and integrate these insights into real-time monitoring systems.

4. *Scalable and Transferable Models*
Developing scalable and transferable models that can be ap- plied across diverse geographical and climatic conditions is a key research direction. For example, pre-

trained deep learning models could be fine-tuned for specific regions with limited data.

5. *User-Friendly Applications for Policymakers*
Future work should focus on creating user-friendly applica- tions that enable policymakers and urban planners to utilize flood prediction tools effectively. The Flask application can serve as a prototype for developing similar platforms for other disaster management scenarios.

6. *Integration of Socioeconomic Data*
Incorporating socioeconomic data into flood prediction mod- els can help identify vulnerable populations and prioritize resource allocation. For example, the Flask application can visualize flood risk maps overlaid with socioeconomic indica- tors, enabling targeted interventions.

7. *Nature-Based Solutions for Flood Mitigation*
Research on integrating nature-based solutions (e.g., wet- lands, urban green spaces) into flood mitigation strategies can enhance urban resilience. The Flask application can be extended to include tools for evaluating the effectiveness of these solutions.

8. *Blockchain for Data Integrity*
Exploring the use of blockchain technology for ensuring the integrity and transparency of flood-related data is a promising research direction. This can improve data sharing and collab- oration between stakeholders.

XVI. CLOSING REMARKS

The integration of ML, GeoAI, and real-time data visualization has the potential to transform flood prediction and disaster management. By addressing current limitations and exploring emerging technologies, researchers can develop more accurate, scalable, and accessible tools for mitigating flood risks. The proposed Flask-based web application represents a significant step forward in this direction, offering a practical solution for real-time flood monitoring and decision-making. As the field continues to evolve, collaboration between researchers, policymakers, and local communities will be essential for achieving sustainable and resilient flood management systems.

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