AI-Powered Flood Risk Assessment for Gilgit-Baltistan Using Multi-Source Satellite Data and Machine Learning

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This is a non-peer-reviewed preprint submitted to EarthArXiv. The paper is currently under preparation for journal submission.

Abstract

Flood disasters are intensifying worldwide due to climate change, with mountainous regions among the most vulnerable yet least studied. This paper presents an AI-powered flood risk assessment framework for Gilgit-Baltistan, Pakistan, a high-mountain region prone to flash floods and glacial lake outburst floods (GLOFs). Multi-source satellite datasets—including CHIRPS precipitation, JRC Global Surface Water occurrence, ERA5-Land soil moisture, SRTM elevation, and MODIS land surface temperature—were integrated within Google Earth Engine and analyzed using a Random Forest classifier. District-level risk classes (high, medium, low) were derived using historical flood records and validated through Leave-One-Out Cross-Validation, achieving 88.9% accuracy. Results consistently identified Astore, Diamer, and Nagar as high-risk districts, with precipitation and water occurrence as dominant predictors. Unlike many flood studies in lowland regions, elevation and slope were secondary yet important drivers in this mountainous context. The study demonstrates that even with limited ground data, satellite-driven AI models can deliver actionable insights for disaster management. The framework is scalable to other mountain regions globally and provides a step toward operational early warning and climate adaptation systems.

Keywords: Flood risk; Gilgit-Baltistan; Random Forest; Google Earth Engine; Remote sensing; Climate adaptation; Mountain hazards

1. Introduction

Floods are the most frequent and destructive natural disasters worldwide, causing loss of lives, infrastructure, and livelihoods. According to the UN Office for Disaster Risk Reduction, climate change is intensifying both the frequency and magnitude of flood events across regions ranging from South Asia to Europe and Africa. Recent advances in satellite Earth observation and artificial intelligence (AI) provide powerful tools for flood risk mapping, enabling large-scale monitoring where ground-based hydrological data are sparse. Despite this progress, mountainous regions such as the Himalayas and Karakoram remain underrepresented in global flood risk studies, even though they are among the most climate-vulnerable landscapes due to steep terrain, rapid hydrological changes, and glacier-related hazards.

This study addresses this gap by developing a satellite-driven, AI-based flood risk assessment for Gilgit-Baltistan, Pakistan. Unlike many existing studies that focus on lowland or urban regions, our framework integrates multi-source datasets to classify flood risk at the district level in a high-mountain context. By combining CHIRPS precipitation, JRC Global Surface Water occurrence, ERA5-Land soil moisture, SRTM elevation, and MODIS land surface temperature with a Random Forest classifier, we test whether machine learning can produce reliable results even with a small sample size (nine districts). The contribution of this study lies not only in its regional relevance but also in demonstrating a scalable and transferable framework for other data-scarce mountainous regions worldwide.

2. Methodology

2.1 Study Area

Gilgit-Baltistan (34.80°N, 76.19°E) spans nine districts, with elevations ranging from 1,000 to 8,000 m. The region is prone to flash floods, GLOFs, and heavy rainfall events, making it a high-priority area for flood risk assessment.

2.2 Data Sources and Feature Engineering

Dynamic datasets covering January 2024–June 2025 were processed in Google Earth Engine. Metrics included seasonal maxima, temporal means, and anomalies. District-level zonal statistics were computed for each feature.

Feature	Description	Dataset	Aggregation
precip_max	Maximum daily precipitation	CHIRPS	Max (2024–2025)
precip_mean	Mean daily precipitation	CHIRPS	Mean (2024–2025)
precip_anomaly	Deviation from 10-year max	CHIRPS	Derived
precip_var	Variance of daily precipitation	CHIRPS	Variance (2024–2025)
water_occurrence	Water presence probability	JRC	Static (1984–2023)

soil_moisture_max	Max daily soil water content	ERA5-Land	Max (2024–2025)
soil_moisture_mean	Mean soil water content	ERA5-Land	Mean (2024–2025)
elevation_mean	Mean elevation	SRTM	Static
elevation_min	Minimum elevation	SRTM	Static
slope_mean	Mean slope	SRTM	Static
lst_mean	Mean land surface temperature	MODIS	Mean (2024–2025)

2.3 Machine Learning Model

A Random Forest classifier was implemented via Google Earth Engine's machine learning library. The model used 100 decision trees with default hyperparameters. Districts were labeled high, medium, or low risk based on historical flood records from the Gilgit-Baltistan Disaster Management Authority (GBDMA). Validation was performed using Leave-One-Out Cross-Validation (LOOCV).

3. Results

3.1 District Risk Classification

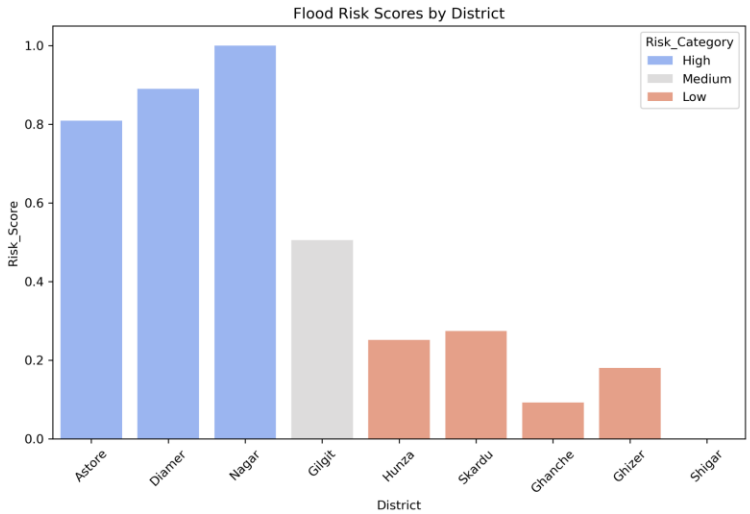
District	Risk Score	Risk Category
Astore	0.809	High
Diamer	0.890	High
Nagar	1.000	High
Gilgit	0.505	Medium
Hunza	0.251	Low
Skardu	0.274	Low
Ghanche	0.092	Low
Ghizer	0.180	Low
Shigar	0.000	Low

3.2 Model Validation

The LOOCV process yielded an average accuracy of 88.9%, confirming the model's robustness despite limited sample size.

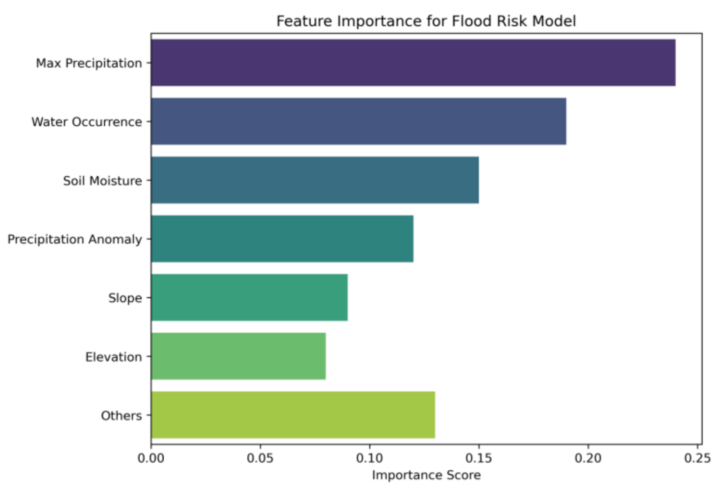
3.3 Figures

Figure 1.



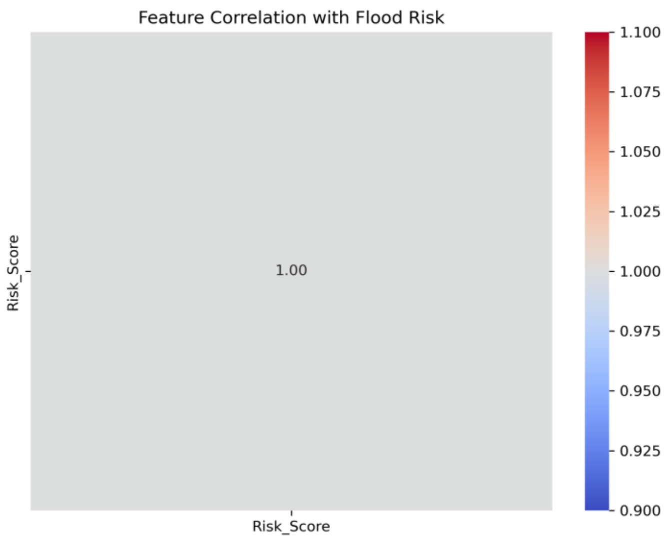
Bar chart of district-level flood risk scores (0–1). Astore, Diamer, and Nagar are high risk; Gilgit is medium; Hunza, Skardu, Ghanche, Ghizer, and Shigar are low risk.

Figure 2.



Feature importance plot showing maximum precipitation (24%) and water occurrence (19%) as the leading predictors.

Figure 3.



Correlation heat map illustrating relationships between predictors and flood risk score.

4. Discussion

The findings highlight precipitation and water occurrence as dominant drivers of flood risk, consistent with earlier studies. High-risk districts align with historical flood hotspots, validating the model. Despite strong accuracy, the small sample size (n=9) restricts generalizability. Perfect classification scores in some districts may reflect overfitting. Expanding the framework to pixel or watershed level would improve robustness. Integrating socio-economic variables would further enhance operational application.

5. Conclusion

This research developed and validated an AI-powered flood risk assessment framework for Gilgit-Baltistan using multi-source satellite data and a Random Forest classifier. The model achieved 88.9% accuracy, identifying precipitation and water occurrence as dominant predictors, and consistently classified Astore, Diamer, and Nagar as high-risk districts. Importantly, the study shows that even in contexts of limited ground observations, machine learning combined with Earth observation datasets can provide robust flood risk information. While district-level results are valuable for disaster management authorities, future work should scale the framework to finer spatial levels, integrate socio-economic exposure, and incorporate real-time precipitation forecasts for operational flood early warning. Beyond Gilgit-Baltistan, the approach is transferable to other mountainous regions worldwide, offering a low-cost, data-driven pathway to strengthen climate adaptation and disaster resilience.

Statements

Author Contributions: Conceptualization, Z.A.; Methodology, Z.A.; Data Curation, Z.A.; Writing—Original Draft Preparation, Z.A.; Writing—Review & Editing, Z.A.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used in this study (CHIRPS, JRC Global Surface Water, ERA5-Land, SRTM, and MODIS) are publicly available through Google Earth Engine. Processed data are available on request from the corresponding author.

Conflicts of Interest: The author declares no conflict of interest.

Acknowledgments

The author acknowledges Google Earth Engine for data access, the Pakistan Meteorological Department, and the Gilgit-Baltistan Disaster Management Authority for providing records. Appreciation is extended to colleagues and family for their support.

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