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Mathematical Modeling and Deep Learning for Early Prediction of Fluid Hazards in Mountain Communities

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Abstract

Mountain communities are increasingly exposed to rapidly evolving fluid hazards, including flash floods, rainfall-triggered debris flows, glacial lake outburst floods (GLOFs), and flood–landslide cascades. Their short response times, complex terrain, sparse observational networks, and changing hydro-climatic conditions limit the generalizability of conventional threshold-based warning systems. This study develops a hybrid research framework that integrates physically interpretable mathematical modeling with deep learning for the early prediction of fluid hazards in mountain environments, with particular relevance to Nepal. The proposed framework integrates rainfall, snow and glacier indicators, soil moisture, terrain attributes, river stage and discharge, surface deformation, and historical hazard observations. A rainfall–runoff and threshold-based component provides physical constraints, while LSTM and CNN-LSTM models capture nonlinear temporal and spatial relationships. A probabilistic decision layer then translates model outputs into actionable warning levels while explicitly representing predictive uncertainty. Model performance is evaluated using precision, recall, F1-score, false-alarm ratio, probability of detection, critical success index, lead time, and calibration. Evidence considered in the study indicates that LSTM models can outperform conceptual rainfall–runoff models in some mountainous catchments in Nepal, while community-based warning systems can substantially extend warning lead time when forecasts are effectively integrated with local response mechanisms. The study further identifies sensor limitations, domain shift, rare-event imbalance, communication failures, model interpretability, and institutional coordination as major implementation challenges. The proposed framework contributes an explainable and community-oriented architecture for data-scarce mountain regions by combining physical process representation, machine-learning-based hazard probability estimation, uncertainty communication, and locally meaningful warning dissemination. It provides a basis for developing next-generation early-warning systems in which mathematical models constrain prediction, machine learning updates hazard probabilities, and communities receive timely and actionable warnings.

Keywords: Deep Learning; Early Warning Systems; Fluid Hazards; Mountain Environments; Nepal Himalaya

Introduction

Integration of Artificial Intelligence, Numerical Methods, and Uncertainty Quantification in Decision-Making Systems The rapid development of artificial intelligence (AI), machine learning (ML), and computational methods has significantly transformed modern decision-making systems across engineering, healthcare, finance, and management domains. Recent research has focused on developing hybrid frameworks that combine analytical models, numerical techniques, and data-driven learning approaches to improve prediction accuracy, stability, and uncertainty management. Sahani et al. (2026) highlighted that complex management systems operating under uncertain environments require advanced mathematical frameworks capable of integrating stochastic modelling, machine learning algorithms, and robust decision mechanisms. Their work introduced a hybrid risk management approach incorporating fractional stochasticity, Wasserstein robustness, and rough-path neural filtering to address deep uncertainty in Nepalese management systems. The study demonstrated the importance of combining theoretical mathematical models with machine learning techniques to achieve reliable predictions and risk-aware decisions. The application of hybrid analytical–numerical–machine learning frameworks has also been explored for solving complex differential equations and improving computational stability. Sahani et al. (2026) developed a comprehensive framework integrating deterministic and stochastic differential equation methods with machine learning approaches. The research emphasized stability analysis, convergence evaluation, and uncertainty quantification as essential components for reliable computational modelling. By combining traditional mathematical solutions with learning-based approximations, such hybrid models overcome limitations associated with purely numerical approaches, particularly when dealing with nonlinear and uncertain systems. These findings suggest that interdisciplinary computational frameworks can provide more efficient solutions for complex real-world problems. Machine learning has also demonstrated significant potential in financial decision-making and risk management. Sahani et al. (2026) examined explainable machine learning methods for credit risk assessment and intelligent lending decisions in Nepalese cooperative banking systems. The study emphasized the importance of interpretability, transparency, and mathematical reliability when applying AI models in financial environments. Explainable AI approaches allow financial institutions to understand model predictions while maintaining accountability and reducing risks associated with automated decision-making. This research contributes to the growing literature on responsible AI adoption in financial systems, particularly in developing economies where risk management challenges are significant Beyond financial applications, hybrid computational architectures have been applied in healthcare and professional management systems. Sahani et al. (2026) proposed mathematical theories combining analytical, numerical, and machine learning models for improving decision-making, operational stability, and uncertainty quantification in dental practice management systems. Similarly, Sahani et al. (2026) explored biotechnology-driven catalysts within hybrid AI frameworks to support risk-aware decision-making and resource optimization in Nepalese management systems. These studies demonstrate that AI-based frameworks are increasingly becoming valuable tools for improving operational efficiency, forecasting risks, and optimizing resource allocation across healthcare-related sectors. In the broader healthcare management context, Sahani et al. (2026) developed a hybrid framework for health management, resource allocation, operational efficiency, and strategic decision-making in Nepal. The study emphasized predictive analytics and computational intelligence as essential tools for addressing challenges related to healthcare planning and resource distribution. By integrating numerical modelling with machine learning algorithms, such systems can improve forecasting accuracy and support evidence-based policy decisions. This approach is particularly relevant for developing countries where limited resources require optimized allocation strategies. Earlier research by Sahani (2024) examined the role of big data learning analytics and optimization algorithms in improving data-driven decision-making. The study identified major challenges associated with large-scale data processing, including computational complexity, algorithmic efficiency, and model optimization. The findings suggested that advanced learning algorithms combined with optimization techniques are necessary to extract meaningful patterns from large datasets. This foundation supports the development of modern AI systems capable of handling complex information environments. The integration of AI with traditional numerical methods has also been investigated in engineering applications. Sahani (2024) introduced an AI-enhanced finite element method (FEM) approach for structural analysis, demonstrating how machine learning can improve computational efficiency and predictive capability in engineering simulations. Similarly, Sahani (2023) explored numerical methods combined with IoT sensor data for structural health monitoring. The research highlighted the potential of integrating real-time sensor information with mathematical models to improve infrastructure monitoring, damage prediction, and maintenance planning. Machine learning has further been applied to improve numerical accuracy and computational prediction. Sahani et al. (2022) investigated the prediction of numerical integration errors using machine learning approaches. Their findings demonstrated that ML models can identify complex error patterns and improve the reliability of computational methods. This research represents an important step toward intelligent computational systems where machine learning assists traditional numerical techniques rather than replacing them entirely. Environmental modelling and differential equation applications have also benefited from AI integration. Sahani (2023) developed neural network surrogate models for weather prediction using numerical solutions of shallow water equations. The study demonstrated that neural networks can approximate complex physical processes while reducing computational costs. Such surrogate modelling approaches provide opportunities for faster simulations and improved forecasting in systems where traditional numerical computation is computationally expensive. Furthermore, Sahani and Sah (2024) investigated the integration of neural networks with numerical methods for solving nonlinear differential equations. The study showed that combining mathematical modelling with artificial intelligence can improve solution accuracy and computational efficiency for nonlinear problems. This approach reflects a broader research trend toward hybrid computational intelligence, where domain knowledge from mathematical models is combined with the adaptability of machine learning algorithms. Overall, existing literature demonstrates a clear movement toward hybrid analytical, numerical, and machine learning frameworks for solving complex problems under uncertainty. The reviewed studies indicate that AI alone is insufficient for many high-risk applications; instead, reliable decision-making requires integration with mathematical modelling, uncertainty quantification, and domain-specific knowledge. These hybrid approaches provide improved prediction, robustness, and interpretability across diverse fields including finance, healthcare, engineering, environmental modelling, and organizational management. Future research should continue exploring scalable, transparent, and ethically responsible AI frameworks capable of supporting complex decision-making environments, particularly in developing economies such as Nepal.

Mountain hazards are strongly controlled by the interaction of water, gravity, terrain and climate. In steep Himalayan catchments, a few hours of intense rainfall can generate rapid runoff, channel erosion, slope failure and debris-laden flows. Glacier retreat and changing snow conditions can additionally create or enlarge high-altitude lakes, while ice or rock avalanches can produce downstream flood waves. These processes may interact rather than occur independently. A rainfall event, for example, can saturate hillslopes, trigger landslides, block a river, and subsequently produce a secondary flood. The prediction problem is therefore inherently multiscale and nonlinear.

Nepal is a particularly important setting for this problem because settlements, roads, hydropower facilities and agricultural land occupy narrow valleys and steep slopes. Existing research demonstrates the value of community-based warning, rainfall thresholds, rainfall–runoff models, GIS-based susceptibility assessment and machine learning. Recent studies also show that LSTM models can simulate discharge effectively in steep Nepalese catchments and that rainfall thresholds can be integrated with hydrological modeling for early warning. However, no single model is sufficient for every hazard or every mountain basin.

This paper proposes a hybrid research architecture rather than claiming a completed operational predictor. The central idea is to combine the strengths of physical and data-driven approaches. Mathematical models encode conservation laws, catchment response and interpretable thresholds. Deep learning captures nonlinear temporal dependencies and interactions among heterogeneous observations. A decision layer then translates probabilistic forecasts into warning categories and community actions. Such an approach is consistent with the practical requirement that an early-warning system should be accurate enough to be useful, interpretable enough to trust, and robust enough to function when observations are incomplete.

Problem Statement and Research Questions

The core research problem is the early prediction of rapidly evolving fluid hazards under limited and heterogeneous observations. Traditional rainfall thresholds can be transparent but may produce false alarms when antecedent soil, snow or basin conditions differ. Purely data-driven models can learn complex patterns but may fail when an extreme event lies outside the training distribution. Mountain systems also suffer from missing sensors, disrupted communications and strong spatial variability.

Research questions

1. How can rainfall–runoff and threshold equations be combined with LSTM/CNN-LSTM models to improve early prediction of mountain fluid hazards?
2. Which variables provide the greatest predictive value at lead times of 1–24 hours?
3. How should rare-event imbalance and missing observations be handled without inflating apparent model performance?
4. How can uncertainty and model explanations be communicated to local disaster-management institutions and communities?
5. Which evaluation metrics best represent operational usefulness rather than only statistical accuracy?

Objectives

1. Develop a hybrid mathematical–deep-learning architecture for early prediction of flash floods, debris flows and related fluid hazards.
2. Define physically meaningful rainfall–runoff, antecedent-moisture and threshold features.
3. Design an LSTM/CNN-LSTM pipeline for nonlinear temporal and spatial prediction.
4. Develop a probabilistic warning index with uncertainty and explainability.
5. Establish a rigorous validation framework suitable for rare, high-impact events.
6. Propose an implementation pathway for mountain communities in Nepal.

Literature Review

Mathematical and hydrological modeling

Rainfall–runoff models convert precipitation and catchment state into streamflow. Conceptual models such as HEC-HMS are useful because their parameters have hydrological interpretations. In mountainous Nepal, recent comparative research reported that LSTM achieved stronger calibration performance than HEC-HMS and remained competitive during validation, illustrating the potential of deep learning for steep catchments. At the same time, conceptual models remain valuable for extrapolation, scenario testing and physical interpretation.

Deep learning for hydrological forecasting

LSTM networks are designed for sequential data and can retain information across time steps through gated memory. This is valuable where current discharge depends on rainfall accumulated over several hours or days. CNNs can extract local spatial patterns from gridded rainfall, terrain and satellite products, while CNN-LSTM combinations can represent both spatial and temporal dependencies. Recent work on explainable flash-flood prediction in mountainous watersheds has further emphasized the value of adding soil-moisture information and using SHAP-based interpretation.

Debris-flow and multi-hazard prediction

Debris-flow initiation is influenced by rainfall intensity, duration, antecedent wetness, sediment availability, slope and channel conditions. Recent deep-learning research has combined LSTM-type models with InSAR deformation observations to improve rainfall-induced debris-flow warnings. Nepal-specific research is also moving toward integrated susceptibility and early-warning systems using satellite rainfall, gauges and machine learning. These developments support a hybrid architecture in which deformation and rainfall are treated as complementary evidence rather than isolated predictors.

Community-based early warning

Forecast quality does not automatically produce disaster reduction. Warning must reach people, be understood, and be connected to pre-agreed action. Research in Nepal has shown that probabilistic forecasting and community-based warning can extend lead times, including an increase from approximately 2–3 hours to 7–8 hours in a Karnali application. This is an important design principle: the useful target is not simply higher model accuracy but more time for safe action.

Research gap

The literature suggests three gaps. First, many studies optimize one hazard or one data source, whereas mountain emergencies can cascade across floods, landslides and debris flows. Second, accuracy metrics are often reported without enough attention to calibration, false alarms, lead time and failure under missing data. Third, the final warning interface is frequently treated as separate from the prediction model. The proposed study addresses these gaps through hybrid modeling, uncertainty estimation, multi-hazard features and an explicit community decision layer.

Conceptual Framework

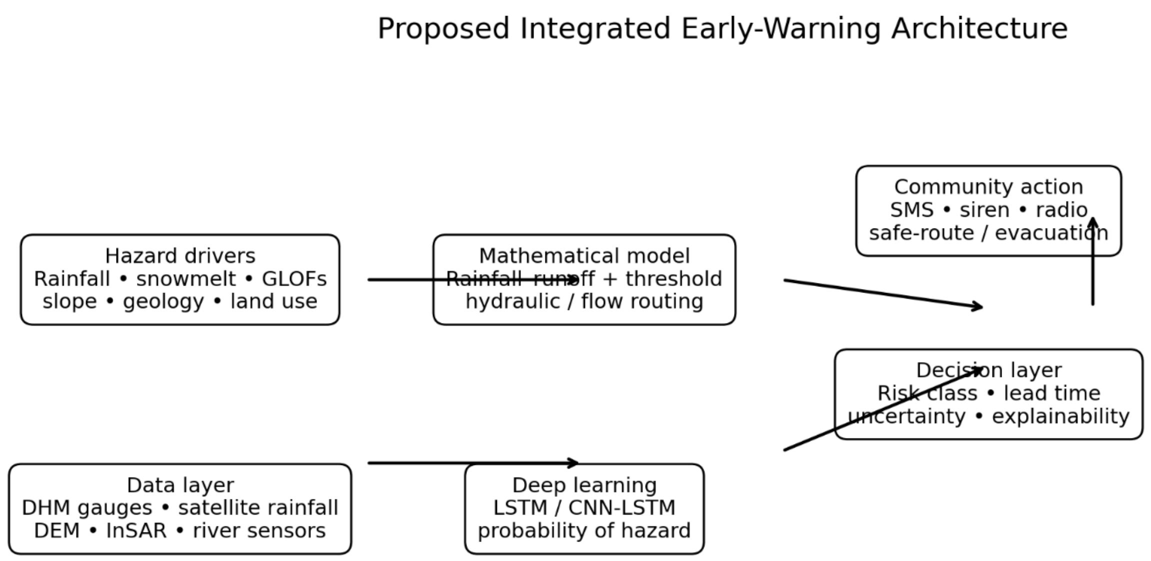

Figure 1. Proposed integrated architecture for mathematical and deep-learning early warning.

The framework has six linked layers: hazard drivers, data acquisition, mathematical modeling, deep learning, decision support and community action. The mathematical layer generates physically interpretable features such as runoff, soil-water storage, rainfall accumulation and threshold exceedance. The neural layer receives these features together with raw observations and learns residual or nonlinear relationships. The decision layer combines model probability, physical threshold status and uncertainty to determine a warning category.

Mathematical Modeling

Rainfall–runoff representation

A simplified continuous water-balance representation is

$$dS/dt = P(t) - Q(t) - ET(t) - L(t)$$

where S is catchment water storage, P is precipitation, Q is runoff/discharge, ET is evapotranspiration and L represents losses such as deep percolation. For an operational short-lead model, the equation can be discretized over an interval Δt. A nonlinear storage–discharge relationship can then be written as $Q = kS^\alpha$, where k and α are basin-response parameters.

The objective is not to reproduce every hydrological process, but to provide a stable physical backbone for machine learning.

Antecedent rainfall index

A useful predictor is an exponentially weighted antecedent rainfall index:

$$API_t = P_t + \lambda\, API_{(t-1)},\ \ 0 < \lambda < 1$$

Large API values represent wetter antecedent conditions. Combining API with short-duration rainfall intensity allows the model to distinguish a short storm falling on a dry basin from the same storm falling on an already saturated basin.

Rainfall threshold formulation

For landslide/debris-flow initiation, a generalized intensity–duration relation can be represented as $I = aD^{(-b)}$, where I is rainfall intensity, D is duration and a,b are estimated from historical events. Instead of treating the threshold as a rigid binary rule, the proposed system converts the distance from the threshold into a continuous feature. This allows machine learning to learn whether threshold exceedance has different meanings under different terrain and moisture conditions.

Flood-wave and flow routing

For channelized flood propagation, a simplified kinematic or diffusive-wave approximation can route predicted upstream discharge downstream. More detailed implementations can use the Saint-Venant equations when sufficient hydraulic information exists. The choice should reflect data availability: a computationally modest model is preferable to a sophisticated model that cannot be calibrated or maintained locally.

Probabilistic hazard index

Let p_f, p_d and p_g denote predicted probabilities of flash flood, debris flow and GLOF-related flow respectively. A composite hazard probability can be expressed as

$$P(H) = 1 - \Pi_j\, [1 - w_j\, p_j]$$

where w_j are calibrated dependence weights. In practice, dependence among hazards should be modeled carefully; the expression is a design starting point rather than a universal probability law. A warning level can then be determined from calibrated probability intervals together with physical threshold status and expected lead time.

Deep Learning Model Design

Input variables

Candidate inputs include hourly rainfall, cumulative rainfall over 1/3/6/12/24/72 hours, temperature, snow-cover indicators, soil moisture, river stage, discharge, upstream water level, DEM-derived elevation and slope, curvature, flow accumulation, land cover, lithology, distance to river, InSAR deformation, glacier/lake indicators and recent hazard observations. The feature set should be adapted to the target basin rather than assuming all variables are available everywhere.

LSTM architecture

For a time sequence x_t, the LSTM updates its cell state using input, forget and output gates. The network can receive a rolling window of observations, for example the preceding 24–72 hourly records, and output the probability of a hazard within the next h hours. A multi-horizon model can produce $p(t+1)$, $p(t+3)$, $p(t+6)$, $p(t+12)$ and $p(t+24)$, allowing emergency managers to distinguish imminent from developing risk.

CNN-LSTM extension

When rainfall radar, satellite precipitation or gridded soil-moisture data are available, CNN layers can encode spatial patterns before LSTM layers model their temporal evolution. This is especially relevant for mountain basins where storm position relative to steep tributaries may matter as much as basin-average rainfall.

Hybrid loss function

A practical training objective can combine classification loss, regression loss and a physics penalty:

$$L = L_{class} + \beta L_{flow} + \gamma L_{physics}$$

L_{class} penalizes incorrect hazard probabilities, L_{flow} penalizes discharge prediction error, and $L_{physics}$ penalizes violations of selected physical relationships. β and γ are tuned through validation. This strategy can reduce physically implausible predictions without forcing the neural network to exactly reproduce a simplified hydrological model.

Data Architecture and Preprocessing

Data sources

A Nepal-oriented implementation can integrate observations from the Department of Hydrology and Meteorology, local river gauges, rain gauges, satellite precipitation products, digital elevation models, optical satellite imagery, InSAR, glacier/lake inventories, community reports and historical disaster databases. The strongest operational architecture is redundant: if a river sensor fails during a flood, satellite rainfall, upstream gauges or community observations should still provide partial evidence.

Quality control

- Detect impossible values and sensor spikes.
- Apply temporal consistency checks and duplicate detection.
- Use physically informed gap filling only for short gaps; preserve missingness indicators.
- Synchronize all variables to a common time step.
- Normalize continuous inputs using training-period statistics only.
- Document sensor changes, relocation and calibration history.

Rare-event imbalance

Extreme hazards are rare relative to non-hazard periods. Random train/test splitting can therefore produce misleadingly high accuracy. The proposed design uses event-based splits, class-weighted losses or focal loss, careful negative sampling and metrics such as precision–recall, F1 and critical success index. All observations belonging to an event should remain in the same temporal fold to prevent information leakage.

Training and Validation Strategy

A robust experiment should use chronological or event-based validation. For example, earlier monsoon seasons can be used for training, an intermediate period for validation and the most recent independent seasons for testing. Cross-basin testing is even more demanding: train on several basins and test on a basin not used for optimization. This evaluates generalization rather than memorization of local sensor signatures.

Evaluation metrics

For binary prediction, precision = TP/(TP+FP), recall = TP/(TP+FN), and F1 = 2PR/(P+R). Operational flood forecasting should additionally report probability of detection, false-alarm ratio, critical success index, Brier score and reliability diagrams. For discharge prediction, RMSE, MAE and Nash–Sutcliffe efficiency can be used. Most importantly, report the distribution of warning lead times and the number of missed high-consequence events.

Uncertainty and calibration

A warning system should not present an overconfident probability. Ensemble models, Monte Carlo dropout, quantile prediction or conformal prediction can be used to estimate uncertainty. Calibration should be evaluated independently of discrimination. A model that ranks events well but systematically reports 0.9 probabilities for events occurring only 0.6 of the time is not operationally reliable.

Explainability

SHAP values, permutation importance and sensitivity experiments can identify whether rainfall accumulation, soil moisture, deformation or discharge dominates a warning. Explainability should be used as a diagnostic tool, not as proof of causality. Physical consistency checks remain necessary.

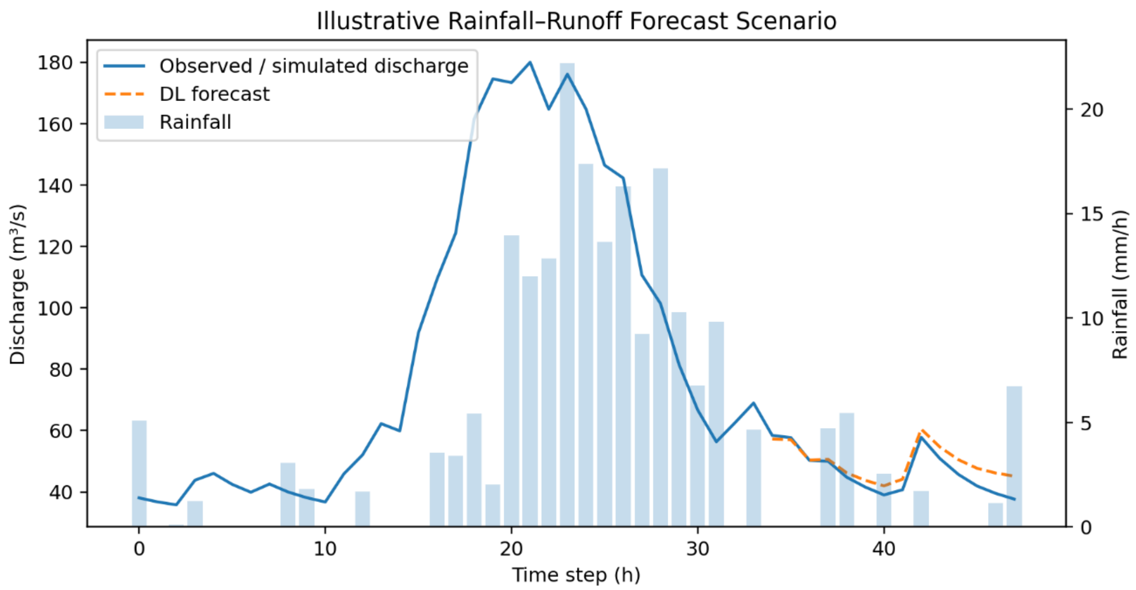

Figure 2. Illustrative rainfall–runoff forecasting scenario; values are synthetic and are included to explain the proposed evaluation workflow.

Proposed Experimental Design

The research can be implemented in four phases. Phase I establishes a multi-hazard event catalogue for selected mountain basins and aligns hydrometeorological, terrain and remote-sensing variables. Phase II develops baseline rainfall-threshold, persistence, conceptual rainfall–runoff and tree-based machine-learning models. Phase III trains LSTM and CNN-LSTM models and then develops a hybrid model using mathematical outputs as features and/or constraints. Phase IV evaluates operational performance, uncertainty, missing-data resilience and community usability.

Baseline models

• Persistence / climatological baseline

• Rainfall intensity–duration threshold

• Conceptual rainfall–runoff model

• Random Forest / XGBoost

• LSTM

• CNN-LSTM

• Hybrid physics-informed LSTM

Ablation experiments

To determine what actually improves performance, remove one data group at a time: rainfall, antecedent rainfall, soil moisture, terrain, discharge, deformation and glacier/lake indicators. Compare full and reduced models at multiple lead times. This provides a more defensible interpretation than simply reporting the best model.

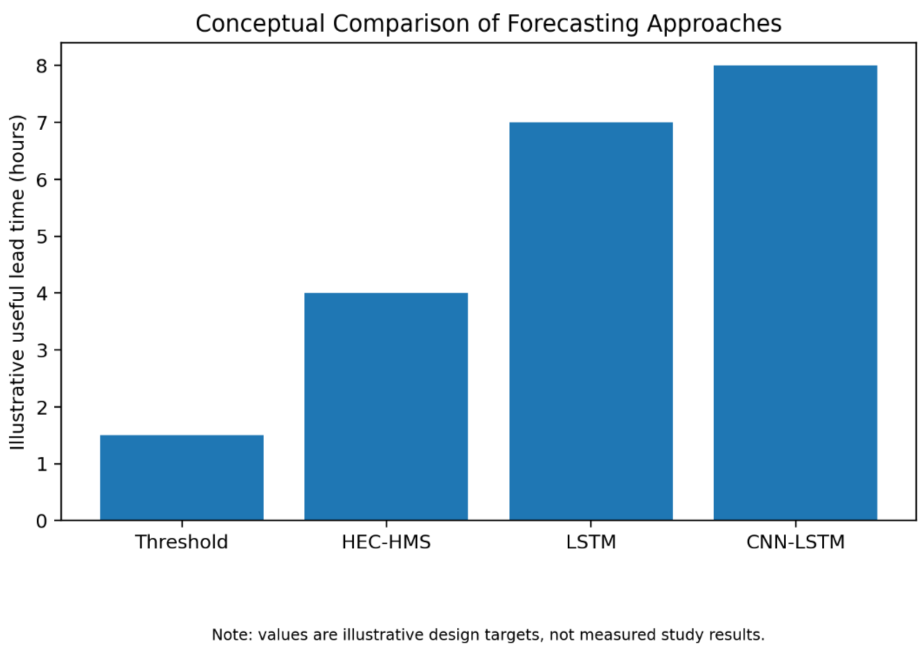

Figure 3. Illustrative comparison of forecasting approaches. Values are design targets only and are not empirical findings.

Expected Results and Interpretation

The expected outcome is that the hybrid model will outperform simple threshold and persistence baselines during complex events, particularly where antecedent moisture and spatial storm structure matter. LSTM should be most useful for sequential rainfall–runoff behavior, while CNN-LSTM is expected to be advantageous where gridded spatial data are available. Mathematical features should improve interpretability and potentially stabilize predictions during moderate data gaps.

However, the expected result should not be interpreted as a guarantee that deep learning will always outperform physical models. Recent Nepal evidence shows that model performance depends strongly on basin, dataset size and validation period; a 2026 landslide study, for example, found Random Forest and boosting approaches stronger than several deep-learning models in one Nepalese setting. This reinforces the need for comparative baselines and local validation rather than assuming that deeper networks are automatically better.

Application to Mountain Communities in Nepal

An operational warning chain should begin with sensors and data services, proceed through automated quality control and forecasting, and end with a small number of understandable actions. For example: Green = normal monitoring; Yellow = heightened readiness; Orange = prepare to evacuate and protect assets; Red = immediate evacuation to predefined safe areas. Exact thresholds must be co-designed with local authorities and validated against historical events.

Community engagement should occur before deployment. Residents can identify flood marks, safe routes, communication dead zones, vulnerable bridges and trusted messengers. Local observations can also become model inputs through structured mobile or radio reports. Redundant communications—SMS, sirens, radio, public address systems and local volunteers—are particularly important because the hazard itself can damage electricity and cellular infrastructure.

Institutional architecture

A practical Nepal implementation would require coordination among hydrometeorological agencies, disaster-management authorities, municipalities/rural municipalities, universities, telecommunications providers and communities. Data-sharing agreements should specify ownership, latency, quality control and responsibilities during system failure. Cross-border information is also important for transboundary glacier and river systems.

Challenges and Limitations

• Data scarcity: high-altitude basins have few long, reliable records.

- Nonstationarity: climate change and land-use change can alter rainfall–runoff relationships.
- Extreme-event scarcity: the most dangerous events are precisely the least represented in training data.
- Domain shift: a model trained in one basin may not transfer to another without adaptation.
- Sensor failure: floods and landslides can destroy gauges and communication infrastructure.
- False alarms: frequent warnings can cause communities to ignore future alerts.
- Interpretability: a high-performing black-box model may be difficult to trust for high-consequence decisions.
- Computational constraints: remote institutions may require lightweight edge or cloud architectures.
- Ethical and governance issues: automated warnings must have clear human accountability.

Discussion

The central methodological argument is that mountain hazard prediction should be treated as a decision problem under uncertainty rather than as a single regression task. The mathematical component provides a physically meaningful state estimate; the neural component learns nonlinear residual behavior; the uncertainty layer describes confidence; and the community layer determines action. This division of responsibilities reduces the temptation to treat a single accuracy score as the definition of success.

Recent evidence reinforces this position. Community-based forecasting in Nepal has demonstrated that useful lead time can be increased through data-based forecasting. Recent Nepal studies have integrated satellite rainfall with susceptibility and early-warning methods.

Research on rainfall-induced debris flow has shown the value of combining deformation and rainfall with recurrent neural networks. Together, these findings support an integrated rather than model-isolated approach.

The system should also be designed around failure. During an extreme event, missing data are not an edge case—they are plausible. A robust warning system should degrade gracefully, using simpler thresholds or upstream observations when the deep-learning service is unavailable. This creates a hierarchy of warning modes: full hybrid model, reduced model with missing-data handling, physical threshold mode, and manual/community observation mode.

Conclusion

This paper presents a hybrid framework for mathematical modeling and deep learning to support early prediction of fluid hazards in mountain communities, with Nepal as a principal application context. The proposed architecture integrates rainfall–runoff equations, antecedent rainfall indices, hazard thresholds, hydraulic concepts, LSTM/CNN-LSTM models, uncertainty estimation and community-centered decision rules. The framework is designed to address the specific difficulties of Himalayan forecasting: rapid response times, heterogeneous hazards, sparse sensors, complex terrain and evolving hydro-climatic conditions.

The recommended research pathway is comparative and evidence-driven. Physical thresholds and conceptual models should establish transparent baselines. Deep learning should be tested against these baselines using event-based validation, rare-event metrics, calibration and lead-time analysis. Hybrid physics-informed models should then be evaluated for whether they improve generalization and operational reliability. Finally, the forecasting output should be connected to community-defined actions and redundant communication channels. The ultimate measure of success is not simply a lower prediction error; it is whether the system gives people credible warning early enough to reduce loss of life and disruption.

For Nepal, the most promising next step is a pilot multi-basin dataset combining DHM observations, satellite rainfall, DEM-derived terrain variables, river discharge, soil moisture and selected remote-sensing indicators. Such a dataset would allow reproducible comparison of threshold, hydrological, machine-learning and deep-learning models. With careful governance and community participation, the resulting system could form a scientific basis for more adaptive, explainable and resilient mountain early-warning services.

Recommendations for Future Research

- Establish standardized multi-hazard event databases linking rainfall, discharge, landslide/debris-flow observations and impacts.
- Develop basin-specific and cross-basin transfer-learning experiments.
- Investigate physics-informed neural networks and differentiable rainfall–runoff components.
- Develop missing-data and sensor-failure benchmarks using realistic outage simulations.
- Use probabilistic forecasting and calibration as mandatory operational metrics.
- Test low-bandwidth deployment and edge inference for remote communities.
- Co-design warning thresholds and evacuation actions with local communities.
- Create open evaluation protocols so that future models can be compared fairly.

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Appendix A. Proposed Operational Pseudocode

1. Acquire rainfall, river, soil-moisture, terrain and remote-sensing observations.
2. Perform automated quality control and attach missing-data flags.
3. Calculate rainfall accumulation, API, physical thresholds and hydrological state variables.
4. Generate baseline discharge/threshold predictions.
5. Feed the rolling multivariate sequence into LSTM/CNN-LSTM.
6. Combine model probabilities with physical indicators.
7. Estimate predictive uncertainty and calibrate probabilities.
8. Assign warning level using pre-agreed thresholds and expected lead time.
9. Send redundant alerts through institutional and community channels.
10. Log forecasts, observations, decisions and outcomes for continual model evaluation.

Appendix B. Suggested Minimum Dataset

Variable	Minimum temporal scale	Purpose	Preferred source
Rainfall	Hourly	Storm intensity and accumulation	DHM gauge + satellite
River stage/discharge	15–60 min	Hydrological response	River gauges
Soil moisture	Hourly/daily	Antecedent wetness	In situ + satellite
DEM / slope	Static	Terrain control	DEM
Surface deformation	6–24 h or available	Slope instability evidence	InSAR
Glacier/lake indicators	Daily/weekly	GLOF context	Satellite + inventories
Hazard labels	Event time	Training target	DHM/local reports/disaster records