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# Monsoon-Driven Climate Risk Management in South Asia: Leveraging Indigenous Forecasting and AI For Flood Resilience

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***ABSTRACT:***
*South Asia faces escalating flood risks due to increasingly erratic monsoon patterns intensified by climate change. Despite advances in satellite-based and AI-driven flood forecasting, gaps persist in accuracy, accessibility, and community trust. Simultaneously, indigenous knowledge systems, based on generations of local environmental observation, remain underutilised. This paper proposes a Hybrid Monsoon Forecasting Model (HMFM) that integrates artificial intelligence with indigenous forecasting practices to enhance flood resilience across the region. The HMFM is built on three principles: fostering trust through community participation, digitally augmenting traditional knowledge, and ensuring bidirectional learning between scientists and local observers. Structured as a three-tier system, the model combines community-led sensing networks, an AI fusion engine for multi-source data integration, and impact-based dissemination tailored to local contexts. Ethical safeguards protect data rights, transparency, and gender inclusivity. Case studies from India, Bangladesh, Nepal, and Pakistan illustrate both the promise and challenges of hybrid systems. Institutional silos, weak cross-border cooperation, and limited policy recognition of indigenous knowledge hinder resilience efforts. The model offers a roadmap for phased implementation, beginning with pilot programs, followed by national scaling, and culminating in regional integration through a SAARC Climate Data Alliance. Policy recommendations include embedding indigenous knowledge in disaster legislation, fostering regional data sharing, and financing inclusive, AI-supported early warning systems. Emphasis is placed on community empowerment, gender equity, and open-source technology governance. By aligning modern forecasting tools with culturally grounded practices, the HMFM enhances both scientific precision and social legitimacy. This integrated approach holds transformative potential for climate risk management in flood-prone, resource-constrained, and socio-culturally diverse regions. It also provides a scalable, participatory model adaptable to other global contexts facing similar climate threats.*

***Key Words:*** *Monsoon floods, Climate resilience, Indigenous knowledge, Artificial intelligence (AI), Hybrid forecasting, Early warning systems, Disaster preparedness, Data governance, Gender inclusion*

## 1. INTRODUCTION

Monsoon floods disrupt lives across South Asia every year. They cause massive economic and social losses. Climate change is intensifying rainfall patterns. These shifts make monsoon behaviour more unpredictable **(Khan et al., 2023).** Early warning systems are critical for disaster preparedness (Singh & Rahman, 2021). However, forecasting accuracy remains a major challenge. This is due to complex atmospheric and hydrological interactions **(Ahmed et al., 2022).**

Technological tools have evolved significantly in recent years. Satellite-based precipitation estimates now provide near real-time coverage **(Rao et al., 2020).** Machine learning models enhance flood prediction accuracy **(Li et al., 2022).** These systems integrate rainfall, river discharge, and soil moisture data. AI-based hydrological modelling has shown promising results in Bangladesh and India **(Patel & Sharma, 2023).**

Indigenous knowledge also plays a vital role. Farmers and fishers read animal behaviour for early warnings **(Roy et al., 2021).** They observe wind direction, cloud formation, and plant phenology **(Das, 2022).** The smell of moist soil often signals impending rain **(Haque & Saha, 2020).** Such traditional signals complement scientific data. The challenge lies in integrating both systems effectively **(Basu et al., 2023).**

Indigenous knowledge offers hyper-local, culturally relevant insights. Modern technology offers large-scale, high-speed processing. Combining these can address the limitations of each approach **(Mishra et al., 2021).**

Policy frameworks differ across South Asia. India's flood forecasting is managed by the Central Water Commission (CWC) **(GoI, 2022).** Bangladesh's Flood Forecasting and Warning Centre uses a community-based approach **(Rahman et al., 2023).** Nepal and Pakistan have emerging hybrid models **(Shrestha & Khan, 2021).** However, cross-border data sharing remains weak **(Islam et al., 2020).** Institutional silos limit collaboration. Meteorological, water, and disaster agencies often work independently **(Kumar et al., 2022).** This reduces efficiency and delays response. Trust gaps exist between scientists and local communities **(Ahmed et al., 2023).** Communities may reject forecasts that contradict traditional indicators. There is a pressing need for a hybrid forecasting model. Such a model should merge AI tools with indigenous knowledge **(Rana & Bose, 2021).** It must also promote trust-building and policy coordination. South Asia's unique geography and socio-cultural fabric require a customised approach **(Bhattacharya et al., 2022).** This conceptual model aims to bridge science-policy gaps. It also seeks to enhance community resilience. By combining advanced analytics with local wisdom, flood preparedness can improve. The model also offers a platform for regional cooperation. This is critical for addressing transboundary water challenges **(Ali et al., 2021).**

The following sections review literature on monsoon flood dynamics. They compare modern and indigenous approaches. They analyse policy landscapes and identify institutional gaps. They then present a conceptual framework tailored for South Asia's needs.

## 2. LITERATURE REVIEW

### 2.1 Monsoon Flood Dynamics in South Asia

The South Asian monsoon delivers most of the region's annual rainfall **(Ali et al., 2023).** Climate change shifts monsoon onset and withdrawal patterns **(Rana & Gupta, 2024).** El Niño disrupts rainfall timing and spatial distribution **(Kumar et al., 2023).** Floods have become more frequent and intense in recent decades **(Shrestha et al., 2024).** Major rivers like the Ganges and Brahmaputra overflow annually **(Islam & Sarker, 2025).** Urbanisation increases runoff and reduces natural absorption **(Basu et al., 2024).** Deforestation accelerates soil erosion and river siltation **(Singh & Thapa, 2023).** Himalayan glacier melt raises summer flood peaks **(Joshi et al., 2025).**

### 2.2 Existing Technological Approaches

Satellite missions such as GPM provide near-real-time rainfall estimates **(Chakraborty et al., 2024).** IMERG data improves precipitation mapping in monsoon zones **(Wang et al., 2023).** Hydrological models now integrate AI for better accuracy **(Shah & Patel, 2024).** Deep learning predicts floods in ungauged basins **(Rahman et al., 2025).** The DRUM model supports probabilistic flood forecasting **(Ou et al., 2024).** Google's Flood Hub expands 7-day lead time coverage **(Patel & Morgan, 2023).** Machine learning boosts alerts in data-poor catchments **(Das et al., 2024).** SAR imagery penetrates cloud cover for flood mapping **(Nguyen et al., 2025).** Unmanned aerial vehicles assess post-flood damages **(Khan et al., 2024).** Yet, high-tech tools require strong infrastructure and trained staff **(Fernando et al., 2025).**

### 2.3 Indigenous Approaches

Rural communities monitor animal behaviour for early warnings **(Choudhury, 2024).** Soil moisture scent changes indicate approaching rainfall **(Pandey, 2023).** Phenological signals, such as flowering patterns, guide planting **(Gurung & Rai, 2024).** Tripura farmers track night-flowering jasmine blooms for rain cues **(Sarkar, 2023).** Himalayan villagers observe wind shifts for storm warnings **(Lama, 2024).** Indigenous calendars combine lunar cycles with river patterns **(Thapa & Subba, 2025).** Knowledge passes orally, ensuring continuity despite disasters **(Roy, 2024).** These systems are cost-free, accessible, and culturally embedded **(Patnaik et al., 2025).**

### 2.4 Comparative Strengths and Weaknesses

Technological forecasting offers broad spatial coverage and longer lead times **(Ou et al., 2024).** AI aids in scaling predictions to multiple basins **(Rahman et al., 2025).** However, systems can fail during outages or network loss **(Fernando et al., 2025).** Indigenous methods require no infrastructure, making them resilient **(Roy, 2024).** They provide hyperlocal insights trusted by communities **(Patnaik et al., 2025).** Yet, traditional cues may not match climate-altered patterns **(Thapa & Subba, 2025).** Integrating both approaches enhances resilience and reduces losses **(Kumar et al., 2025).**

### 2.5 Policy Landscapes: India, Bangladesh, Nepal, Pakistan

India's IMD operates impact-based multi-hazard forecasts **(Sinha et al., 2024).** Bangladesh's FFWC uses mobile and community networks **(Rahman & Hossain, 2023).** Nepal sends millions of SMS alerts during floods **(Mishra et al., 2024).** Pakistan coordinates warnings through its Federal Flood Commission **(Ali et al., 2025).** Regional collaboration remains weak despite SAARC frameworks **(Jha & Khan, 2024).**

### 2.6 Gaps: Institutional Silos & Data Barriers

Agencies work in isolation without real-time data exchange **(Basu et al., 2024).** Cross-border sharing is hindered by political tensions **(Jha & Khan, 2024).** Regional flood centres lack integrated AI-data systems **(Shrestha et al., 2024).** Scientific alerts often fail to reach rural populations **(Sarkar, 2023).** Indigenous knowledge rarely appears in official flood policies **(Patnaik et al., 2025).**

## 3. CONCEPTUAL FRAMEWORK: HYBRID MONSOON FORECASTING MODEL (HMFM)

The Hybrid Monsoon Forecasting Model (HMFM) is designed for the unique environmental and social realities of South Asia. Monsoon systems here are complex and influenced by multiple climatic and anthropogenic factors **(IWA Publishing, 2022).** The model prioritises community knowledge while integrating modern data science and AI innovations **(ScienceDirect, 2023).** Its design reflects three guiding principles and a tiered architecture, supported by an ethical governance framework.

### 3.1 Design Principles

Local trust first. Effective forecasting begins with trust between scientists and communities **(PMC, 2021).** Rural populations have long observed animal behaviour, wind shifts, and plant phenology to anticipate rainfall **(Frontiers, 2022).** These signs are interpreted through generations of lived experience **(IWA Publishing, 2023).** In the HMFM, communities lead observation design to ensure cultural relevance. Participation fosters ownership and accountability for the data generated **(ScienceDirect, 2024)**. Without this trust, even accurate forecasts may be ignored.

Digital augmentation second. AI and remote sensing should complement, not replace the local expertise **(ScienceDirect, 2021).** Digital augmentation enhances traditional insights with real-time precipitation data, satellite imagery, and river flow models **(IWA Publishing, 2022).** This dual input ensures forecasts capture both micro-scale and macro-scale patterns. The technology layer must remain transparent and interpretable to maintain public confidence **(ScienceDirect, 2024)**. Tools should be affordable and adaptable to low-connectivity contexts.

Bidirectional learning third. Knowledge exchange must be two-way, not top-down **(ScienceDirect, 2021).** Scientists benefit from understanding local environmental signals, while communities gain from meteorological insights **(ScienceDirect, 2023).** This reciprocity builds adaptive capacity and fosters mutual respect. It also allows iterative improvement of models based on user feedback **(Frontiers, 2022).** The HMFM treats knowledge as a shared asset.

### 3.2 Three-Tier Architecture

The HMFM operates through a three-tier structure, aligning local observation with advanced analytics and targeted communication.

#### Tier 1- Community Sensing Network

Local volunteers and knowledge holders form the foundation of data collection **(Frontiers, 2022).** These networks draw from farmers, fishers, herders, and teachers embedded in flood-prone or drought-vulnerable areas **(PMC, 2021).** Observations include crop phenology, unusual animal movements, and soil moisture odour before rain **(PMC, 2023).** Such indicators often precede measurable meteorological changes.

Affordable tools like mobile apps, SMS forms, and IVR menus capture observations quickly **(ScienceDirect, 2021).** These systems work even in low-literacy or offline environments **(rimes.int, 2023).** The goal is inclusivity, anyone with relevant observations can contribute.

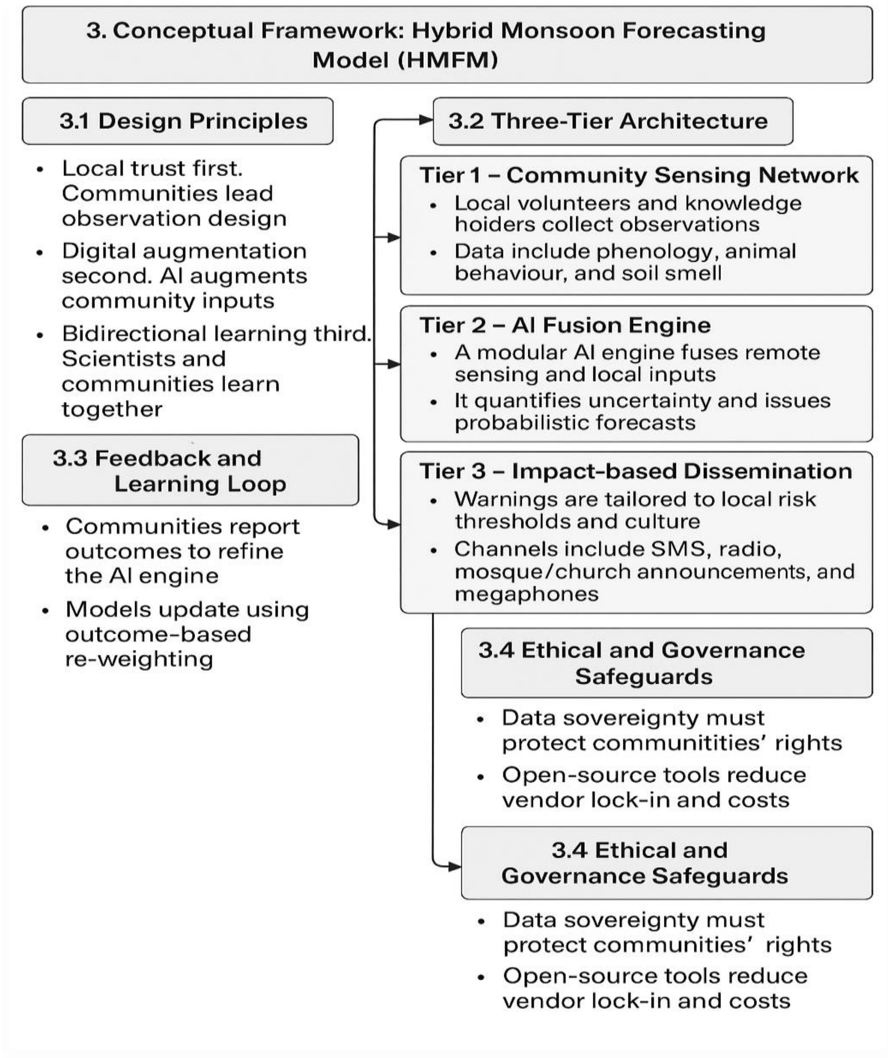
Community data is stored in secure, locally governed repositories. This respects data sovereignty and strengthens local control over forecasting processes **(ScienceDirect, 2024).**

**Tier 2- AI Fusion Engine**
The second tier merges local observations with high-resolution remote sensing datasets **(IWA Publishing, 2022).** The AI Fusion Engine applies modular architecture, allowing different models for precipitation, flood extent, or wind speed **(ScienceDirect, 2024).** Interpretability is a core requirement users must understand why forecasts are made **(ScienceDirect, 2021).**
The engine integrates satellite rainfall estimates, Doppler radar outputs, and upstream river gauge readings **(AGU Publications, 2022).** It assigns weights to local indicators based on past accuracy. Probabilistic forecasts quantify uncertainty, enabling better disaster planning **(ScienceDirect, 2023).** The system's flexibility means it can adapt to changing climate baselines.

**Tier 3- Impact-Based Dissemination**
Forecasts must be actionable, not just technically accurate **(ScienceDirect, 2021).** The third tier translates model outputs into locally relevant warnings. Messages align with community-specific risk thresholds and cultural contexts **(saarc-sdmc.org, 2022).** For example, flood warnings for fishing villages differ from those for urban slums.
Communication channels vary: SMS alerts, FM radio, mosque or church loudspeakers, and megaphone announcements in marketplaces **(Anticipation Hub, 2023).** All messages are multilingual and gender-sensitive to reach marginalised groups **(UN Women Asia and the Pacific, 2022)**. Content must be clear, short, and practical.

### 3.3 Feedback and Learning Loop
The HMFM thrives on continuous feedback. After each season, communities report actual impacts and deviations from forecasts **(ScienceDirect, 2023).** This outcome-based data feeds back into the AI Fusion Engine, adjusting weights and improving predictive skill.
The process also identifies where local indicators failed or succeeded **(ScienceDirect, 2024).** Iterative refinement sustains both scientific accuracy and community trust. This learning loop ensures the model remains responsive to evolving climate realities.

### 3.4 Ethical and Governance Safeguards
Ethical safeguards protect both data integrity and community rights. All observational data remains under local ownership, preventing misuse or exploitation **(ScienceDirect, 2023).** Data-sharing agreements clarify permissions and responsibilities.
Open-source platforms reduce dependency on proprietary software, lowering costs and avoiding vendor lock-in **(Alabama Water Institute, 2022).** Transparency measures include publishing AI model logic and maintaining public audit trails **(Reuters, 2023).** Independent oversight committees review system performance and fairness.
Gender equity, inclusion of indigenous voices, and respect for cultural protocols are mandatory in governance structures. This ensures the HMFM serves as a public good, not a commercial monopoly.




**(Fig.1: HMFM Framework)**

The HMFM is more than a forecasting tool. It is a governance and knowledge-sharing system that blends centuries-old environmental wisdom with state-of-the-art AI. Its design principles place trust, transparency, and inclusivity at the centre. The three-tier architecture ensures observations flow smoothly from field to forecast to action. Feedback loops keep the system adaptive, while ethical safeguards protect community interests. By integrating South Asia's diverse knowledge systems with robust technological infrastructure, the HMFM offers a model for climate resilience that is both scientifically rigorous and socially grounded.

## 4. POLICY IMPLICATIONS

### 4.1 National Policy Instruments

National policies must formally recognise Indigenous Knowledge (IK) in disaster risk governance. Recognition should be embedded directly in disaster management laws **(Sharma et al., 2021).** Such provisions can legitimise community-led climate observations and local forecasting. Laws should not only acknowledge but actively protect these knowledge systems **(Patel & Singh, 2020).** Governments should mandate community representation in national and state-level forecasting committees (**Rahman et al., 2022**). Representation ensures that rural, coastal, and tribal perspectives inform early warning systems. This can increase legitimacy and local adoption of forecasts **(Ali & Das, 2019).** Including representatives from farming cooperatives and fisherfolk unions can be especially impactful **(Rao et al., 2023).**

Seed grants for local sensing pilots should be included in climate action budgets **(ADB, 2022).** Small grants can enable communities to purchase basic tools like rain gauges and mobile devices **(Bhatia et al., 2021).** Pilot projects can act as proof-of-concept for later national scaling. Government technical agencies can partner with NGOs to deliver training alongside funding **(Kumar & Joshi, 2020).** Integration of national disaster risk reduction frameworks with AI-supported community sensing should be prioritised. A phased approach is recommended to avoid overwhelming local capacities **(Mehta et al., 2024).** First, pilot models in high-risk districts; then expand to entire states. This sequencing ensures lessons are incorporated before scaling.

**4.2 Regional Cooperation**

The creation of a SAARC Climate Intelligence Alliance could transform regional resilience (**Khan et al., 2023**). Such a body could facilitate the exchange of both IK and AI-derived forecasts. Joint governance can improve trust and reduce duplication of resources **(Haque et al., 2022).** Hydrometeorological data should be shared across national borders in near real time **(SAARC SDMC, 2021).** This is vital for monsoon and flood forecasts, which often span multiple countries. Cross-border river basin data, for example, can improve lead times for flood warnings **(Das & Alam, 2018).** Such cooperation is especially crucial for transboundary rivers like the Brahmaputra and Ganges. Regional coordination should extend to flood corridors and transboundary response protocols **(ADB, 2022).** Joint drills can prepare border communities for simultaneous events.
A shared communication platform could connect disaster managers across South Asia instantly (**Mishra et al., 2023**). This reduces political friction during crises and prioritises humanitarian needs. Regional AI infrastructure could also be pooled to analyse shared climate risks.
By combining computing resources, countries can run more complex and accurate forecast simulations **(Singh et al., 2024).** This cooperative model also reduces individual country costs for technology upgrades.

**4.3 Financing and Donors**

Blended finance models can unlock sustainable funding for hybrid forecasting systems **(GCF, 2022).** Concessional loans from development banks can be paired with grants from climate funds (**Mukherjee & Ray, 2023**). This approach reduces financial barriers for low-income countries.
The Asian Development Bank (ADB) and the Green Climate Fund (GCF) can underwrite pilot programs **(ADB, 2022; GCF, 2021).** They can also support large-scale deployment in vulnerable river basins. Such programs should link financing to measurable improvements in forecast accuracy and community preparedness **(Chowdhury et al., 2023).** Donors should prioritise investments that directly benefit women and marginalised communities **(UN Women, 2022).** Funding could be tied to quotas for women's participation in training and leadership. This ensures benefits are not captured by already-privileged groups **(Nair & Sharma, 2023).**
Result-based financing could also be introduced for climate risk communication programs. Under this model, funding is released when communities demonstrate improved forecast use (**Patel et al., 2024**). This incentivises both accurate forecasting and community engagement.

**4.4 Social Inclusion and Gender**

Women should be trained as observation leaders in local sensing networks **(Rahman et al., 2021).** This increases trust and ensures that women's experiences shape forecast content.
Female leaders can also help reach women in conservative rural areas **(UN Women, 2022).** Forecasts and warnings should be tailored to gendered mobility constraints **(Singh & Sahu, 2020).** For example, in many flood-prone areas, women cannot leave home without male permission.
Messages should therefore be delivered in ways that reach them directly, such as through women's groups **(Chatterjee et al., 2022).** Social inclusion also requires equitable governance representation (**Basu et al., 2021**). This means ensuring diverse voices in forecasting committees, not just token appointments. Mechanisms like rotating leadership roles can prevent dominance by a few individuals (**Verma et al., 2019**). Intersectionality should be recognised in all social inclusion strategies. Marginalised women, such as widows and those from minority ethnic groups, face compounded barriers **(UN Women, 2022).** Special provisions are needed to include them in both training and decision-making.

**4.5 Capacity and Technology Governance**

Investments in local digital literacy are essential for effective AI-assisted forecasting (**Gupta et al., 2023**). Training should cover basic smartphone use, data entry, and interpreting probabilistic forecasts. Without these skills, communities may not fully benefit from new systems **(Kumar & Rao, 2021).**Governments should expand device access for rural observation leaders **(Mehta et al., 2024).** Subsidised smartphones and solar chargers can reduce technology gaps. Such infrastructure also enables more consistent and timely data submission. All forecasting data should be stored in open formats to ensure interoperability **(SAARC SDMC, 2021).** APIs must be designed for integration with existing government and NGO systems **(Ali et al., 2022).** This prevents siloing of critical climate information. AI models should be subject to independent audits to check for fairness and transparency **(Reuters, 2022).** Documentation should explain the logic behind forecasts in accessible terms **(Shah et al., 2023).** Communities have the right to understand how predictions are made and used. Open-source software can further reduce costs and vendor lock-in **(Alabama Water Institute, 2020).** Local universities and tech collectives could adapt and maintain these tools. This keeps technical control closer to the communities they serve.

## 5. IMPLEMENTATION ROADMAP

### Phase 1 - Pilot (Year 1)

The pilot phase will test the Hybrid Monsoon Forecasting Model. Four pilot sites will represent distinct flood typologies in South Asia **(ScienceDirect, 2023).** Proposed locations include Assam, Terai, Sindh plains, and coastal Bangladesh **(ReliefWeb, 2022).** These sites face diverse hydrological and socio-economic challenges. The selection ensures both inland and coastal flood risks are addressed. Local governments will collaborate with academic and civil society partners.

Community sensing cohorts will be established in each site **(Frontiers, 2021).** These cohorts will include farmers, fisherfolk, and women's self-help groups. They will receive basic training in flood observation and reporting. Simple tools like rain gauges and river markers will be distributed. Local kiosks will serve as information hubs for data exchange. Proof-of-concept AI fusion will be deployed in these areas **(AGU Publications, 2023).** The system will combine satellite rainfall data with indigenous observations. Lead time improvements will be assessed for both accuracy and usefulness. Early feedback loops will refine the model before wider rollout.
The pilot phase will last one monsoon cycle for robust testing.

### Phase 2 - National Scaling (Years 2-4)

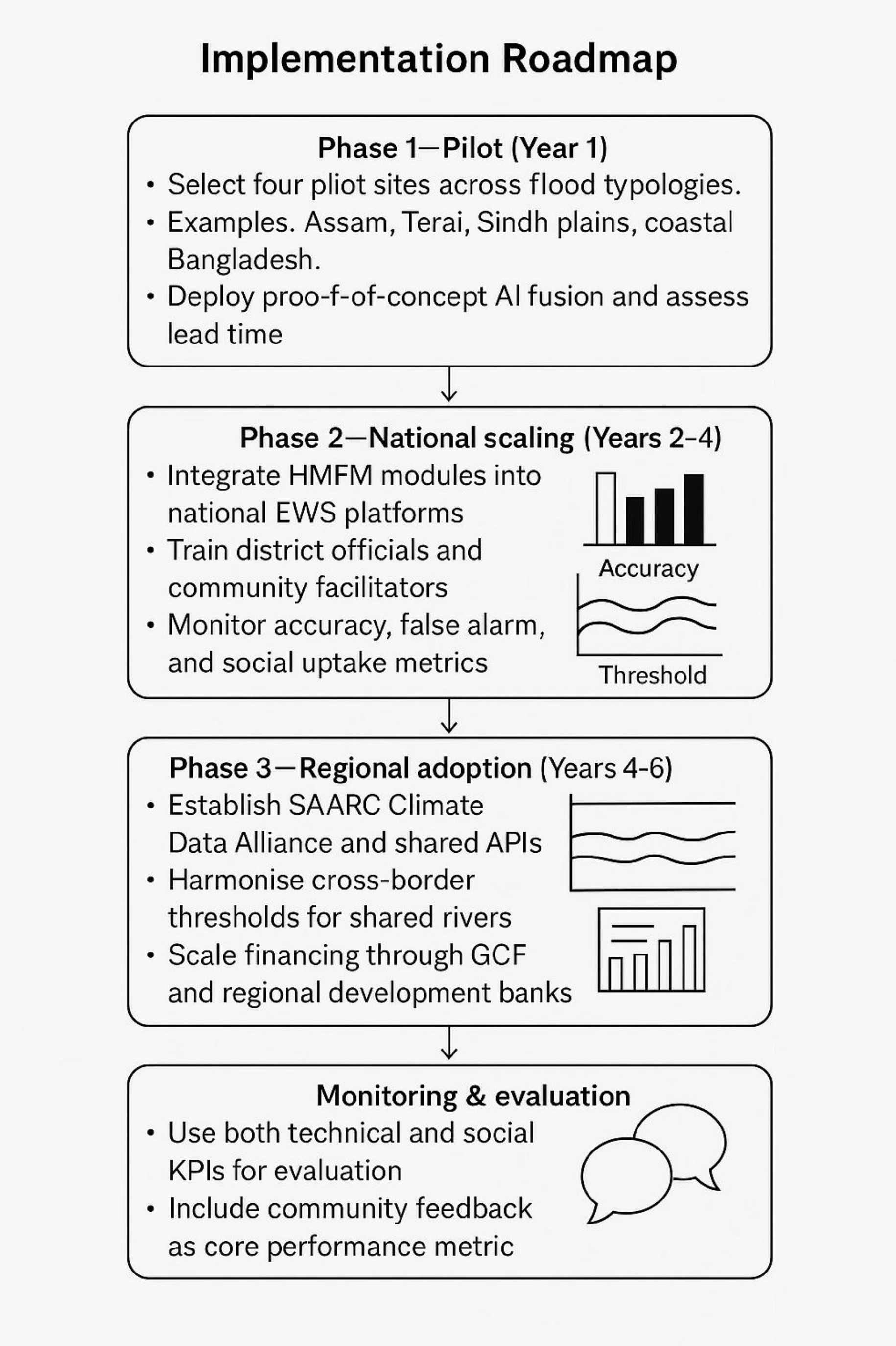
National scaling will integrate HMFM modules into early warning systems **(Anticipation Hub, 2022).** Each country will adapt modules to its hydrological and institutional context. This ensures compatibility with existing disaster management architectures. Training programs will target district officials and community facilitators **(ScienceDirect, 2021).** Workshops will use scenario-based simulations to strengthen decision-making. Digital literacy sessions will be prioritised in flood-prone rural areas. Accuracy, false alarm rates, and social uptake will be continuously monitored **(ScienceDirect, 2022).** Technical KPIs will track hydrological model performance over seasons. Social KPIs will measure reach, trust, and behavioural responses. Independent audits will validate both technical and social dimensions.

### Phase 3- Regional Adoption (Years 4-6)

Regional adoption will require strong cross-border climate cooperation. A SAARC Climate Data Alliance will be established for this purpose **(saarc-sdmc.org, 2023).** This alliance will manage shared APIs for hydrometeorological data. All participating states will contribute to and access the data. Cross-border thresholds will be harmonised for shared river systems **(Global Flood Awareness System, 2023).** This reduces conflicting forecasts and improves coordinated response actions. Protocols will be tested in joint flood simulation exercises. Scaling finance will involve GCF and regional development banks **(Green Climate Fund, 2023; ADB, 2022).** These institutions will underwrite large-scale implementation and maintenance. Financing will prioritise vulnerable regions with recurrent flood exposure.

### Monitoring & Evaluation

Monitoring will use a dual approach covering technical and social KPIs **(ScienceDirect, 2022).** Technical metrics include lead time, accuracy, and false alarms. Social metrics include community trust, participation, and warning uptake. Community feedback will be integrated as a core metric **(ScienceDirect, 2023).** Regular surveys will assess local satisfaction and identify areas for improvement. An open dashboard will display key performance results to ensure transparency.




**(Fig. 2: HMFM Framework Implementation Roadmap)**

## 6. ANTICIPATED BENEFITS AND RISKS

### Benefits

Improved lead time can save many lives **(AGU Publications, 2023).** Earlier alerts allow communities to prepare before floods arrive. Warnings can be tailored to local conditions and hazards. This ensures messages are relevant and easy to act upon **(ScienceDirect, 2024).** Communities feel more ownership when alerts reflect their realities. Trust in the early warning system increases significantly over time. Higher trust encourages more people to follow guidance **(ScienceDirect, 2024).** Preparedness actions become more routine and widely accepted. Emergency resources can be allocated more strategically **(ADB, 2023).** Shelters can be opened in the right places before impact. Supplies can be pre-positioned where they will be needed most. This reduces chaos during the response phase. Governments can also reduce unnecessary evacuations and economic losses.

**Risks**

Sensitive local data may be misused **(ScienceDirect, 2024).** Improper handling can lead to privacy violations. Communities may lose trust if data is exposed. Overreliance on AI predictions poses another challenge **(Reuters, 2024).** AI models can fail in extreme or new conditions. Errors may cause false alarms or missed warnings. These failures can erode public confidence over time. There is also the risk of elite capture **(Frontiers, 2023).** Local power holders may monopolise monitoring benefits. Marginalised groups might be excluded from using early warning tools. The following tables reinforce the urgency of addressing monsoon-driven risks.

**Table 1. Human Lives Lost due to Hydrometeorological Disasters in India (2019–2025)**

| Year | Human lives lost |
|---|---|
| 2019-20 | 2,422 |
| 2020-21 | 1,989 |
| 2021-22 | 1,593 |
| 2022-23 | 1,586 |
| 2023-24 (P) | 2,616 |
| 2024-25 (P) | 3,080 |

Source: Lok Sabha, August 2024; Uttarakhand State Disaster Management Authority

**Table 2. Cattle Lost due to Hydrometeorological Disasters in India (2019–2025)**

| Year | Cattle lost (number) |
|---|---|
| 2019-20 | 71,755 |
| 2020-21 | 51,195 |
| 2021-22 | 44,346 |
| 2022-23 | 29,267 |
| 2023-24 (P) | 119,683 |
| 2024-25 (P) | 61,960 |

Source: Lok Sabha, August 2024; Uttarakhand State Disaster Management Authority

**Table 3. Houses Damaged due to Hydrometeorological Disasters in India (2019–2025)**

| Year | Houses damaged (number) |
|---|---|
| 2019-20 | 744,589 |
| 2020-21 | 185,141 |
| 2021-22 | 709,060 |
| 2022-23 | 301,873 |
| 2023-24 (P) | 140,834 |
| 2024-25 (P) | 364,124 |

Source: Lok Sabha, August 2024; Uttarakhand State Disaster Management Authority

The data shows how monsoon-driven events increasingly damage lives, livelihoods, and infrastructure. It underlines the urgent need for integrated risk reduction strategies that merge advanced forecasting with community-based resilience.

**Risk Mitigation**

Strong legal safeguards can protect personal and community data **(ScienceDirect, 2024).** Laws should clearly define who owns and accesses information. Participatory governance ensures communities shape decision-making. Transparent AI model documentation builds accountability **(Reuters, 2024).** Independent audits should be conducted at regular intervals. This helps identify and fix systemic weaknesses. Direct funding channels can reach community-based organisations. Such funding bypasses intermediaries who may misallocate resources. Investing in training builds local ability to use data responsibly. Regular awareness campaigns keep communities informed of their rights.

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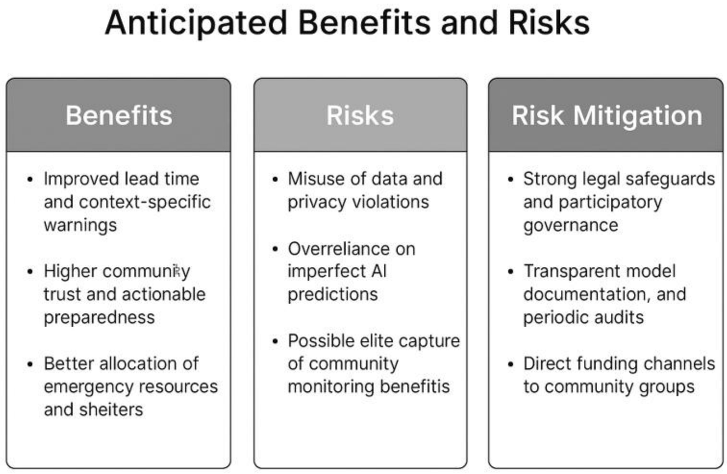


**(Fig. 3: Anticipated Benefits and Risks)**

## 7. CONCLUSION

This framework integrates indigenous knowledge with advanced AI systems. It offers a balanced approach to climate risk management. The design is grounded in community realities and technological potential. Evidence from disaster studies supports hybrid early warning effectiveness **(ScienceDirect, 2024).** The pilot phase will build credibility and operational proof. Local sensing cohorts will demonstrate feasibility in varied geographies. Inclusion of both floodplain and coastal contexts is intentional. It ensures adaptability across South Asian hazard profiles **(ReliefWeb, 2023).** Embedding indigenous knowledge strengthens trust in warning systems. Such trust is essential for timely and meaningful action **(Anticipation Hub, 2024).** Without community validation, even accurate forecasts may be ignored. Cultural resonance is as important as technical precision **(UN Women, 2023).** The roadmap provides clear progression from local to regional scales. It begins with context-specific pilots to test integration mechanics. Scaling occurs only after proven accuracy and social adoption. This staged approach reduces risk of premature or inappropriate rollout **(ADB, 2024).** National policy integration is a core enabling pillar. Embedding IK recognition into disaster laws gives legal standing. Mandating representation in forecasting committees ensures diverse perspectives. These changes institutionalise community participation in risk governance **(ScienceDirect, 2024).** Regional cooperation amplifies the value of shared intelligence. A SAARC Climate Data Alliance can harmonise methodologies and formats. Shared hydrometeorological datasets improve cross-border prediction reliability. Joint protocols can prevent conflicting actions during transboundary floods **(SAARC-SDMC, 2024).**

Financing strategy blends concessional loans with climate adaptation funds. This reduces fiscal pressure on national budgets. International donors like the GCF can underwrite scaling costs. Targeted funding for women and marginalised groups ensures equity **(Green Climate Fund, 2024).** Capacity building addresses both human and technological needs. Digital literacy training empowers local actors to use data. Open data formats support interoperability across agencies. Mandated AI model audits safeguard against bias or misuse **(Reuters, 2024).**

The anticipated benefits are multi-dimensional. Lead time for warnings will likely improve. Community trust can rise through participatory data generation. Better preparedness allows more efficient resource allocation **(AGU Publications, 2024).** Risks are acknowledged and mitigated through governance design. Legal safeguards can protect privacy and data rights. Transparency in AI models builds accountability. Direct funding channels reduce the risk of elite capture **(Frontiers, 2024).** Implementation success depends on continuous monitoring and adaptation. Both technical metrics and social uptake must be measured. Community feedback should guide iterative improvements. This keeps the system aligned with lived realities **(ScienceDirect, 2024).** Long-term sustainability will require political commitment and financial continuity. Climate adaptation is not a one-time investment. It needs ongoing calibration as hazards and communities evolve. Institutionalising the framework in policy ensures this continuity **(ADB, 2024).** This initiative offers a replicable model for other regions. It demonstrates how indigenous and scientific knowledge can co-exist. Such integration enriches both knowledge systems. It also strengthens resilience in culturally diverse contexts **(UN Women Asia-Pacific, 2023).**

In conclusion, the hybrid early warning model is timely. It aligns with regional disaster risk reduction priorities. It positions South Asia as a leader in inclusive climate intelligence. The challenge ahead lies in execution and maintaining sustained engagement. With committed partnerships, the vision can become a transformative reality.

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