Closing the Last Mile: Field Evaluation of CAP-Driven Multi-Hazard Alerts

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Abstract: Last-mile disaster warnings in India increasingly depend on standardized public alerting, yet device-centric pilots often fail to convert forecasting advances into timely, actionable protection for outdoor and low-connectivity populations. This paper addresses the documented limitations and deployment gaps associated with the Bihar NITISH pendant by repositioning it within an SDG-aligned, data-driven early-warning and action ecosystem. A multi-layer framework is presented that (i) ingests real-time meteorological and hazard feeds, (ii) mitigates false alarms and missed alerts through an interpretable hybrid rules + ML risk tiering layer, (iii) operationalizes multi-channel delivery via a unified alert schema, and (iv) closes the last-mile usability gap through complementary endpoints, an app-based interface and an administrative dashboard for situational awareness, escalation, and compliance tracking. To strengthen evidence and accountability, a reproducible evaluation protocol is defined using CAP-anchored timestamps and device/app logs, reporting Probability of Detection (POD), False Alarm Ratio (FAR), missed-alert rate, lead-time distributions, and latency decomposition (platform, last-mile, and human acknowledgement) with percentile statistics. Inclusivity and governance safeguards multilingual prompts, audit trails, and equity checks, ensure that warnings remain actionable for diverse user groups and operational contexts. The proposed approach converts a single-endpoint pilot into a measurable, scalable, and policy - ready early-warning system capable of reliable operation under variable connectivity and real user routines.

Keywords: Disaster risk reduction; Common Alerting Protocol; Hybrid ML-rule systems; Multi-channel alerting; Low-connectivity populations; Evaluation metrics; SDG-aligned governance.

Introduction

Multi-hazard early warning systems are only beneficial if upstream forecasts are converted into effective protection at the last mile, especially for outdoor and low-connectivity communities. In the Indian context, standardized public alerting has a robust institutional foundation, but device-centric implementation might still be suboptimal in practice because of endpoint vulnerability, risk message inconsistency, and lack of operational auditability [1 - 3]. Early Warnings for All multi-stakeholder forum for Europe and Central Asia: Outcome report. This paper proposes a system-first approach to last-mile warning: an interpretable risk-tiering layer that integrates policy thresholds with lightweight learning, multi-endpoint dissemination through a mobile interface and wearable notification, and an administrative dashboard for situational awareness, escalation, and compliance analysis [4]. Digital transformation and early warning systems for saving lives: Background paper. International Telecommunication Union. The assessment is grounded in CAP time stamps and field-level data, reporting POD, FAR, missed alert rate, lead-time distribution, and percentile latency breakdown by platform, last-mile delivery, and human acknowledgement for multi-district implementation in Bihar[5 - 7]. Designing inclusive, accessible early warning systems: Good practices and entry points. Global Facility for Disaster Reduction and Recovery (GFDRR)[8 - 14].

Related work

More recent studies place the role of multi-hazard early warning systems as a fully-fledged service, consisting of risk knowledge, monitoring/forecasting, warning dissemination, and preparedness for response, and also identified the persistent issue of the "last mile" and inclusiveness in regions [5-8].

Recent developments have placed Multi-Hazard Early Warning Systems (MHEWS) as an end-to-end solution alongside Risk Knowledge, Monitoring/On The Sensing/Analytics, and IoT-enabled EWS Architecture and Constraints, as discussed in systematic surveys [9]. For short-lead time now casting, probabilistic predictions of thunderstorm hazards including lightning, hail, and heavy precipitation have referred to dl-based approaches [15 -19], and cross-region base lining is mentioned as part of pre-EW4All assessments [20 - 22].

The NITISH pendant has specific field-critical limitations, such as a fragile hardware model, a faulty charging system, low audibility, a lack of consistent risk signaling, and insufficient multi-hazard prompt sets, which make it a single point of failure in actual outdoor environments. The proposed research addresses these limitations by transitioning from a 'device-centric' approach to a 'system-centric' approach, which means an interpretable data-driven risk engine, a multi-endpoint delivery approach, mobile interface, wearable channel, authority dashboard, acknowledgement, and audit, which can actually lead to quantified reductions in failed alerts, false alarms, latency, etc.

Dataset and Methodology

The dataset will include three synchronized layers: (i) Official alert data: (ii) Environmental data: (iii) Delivery logs [24, 25].

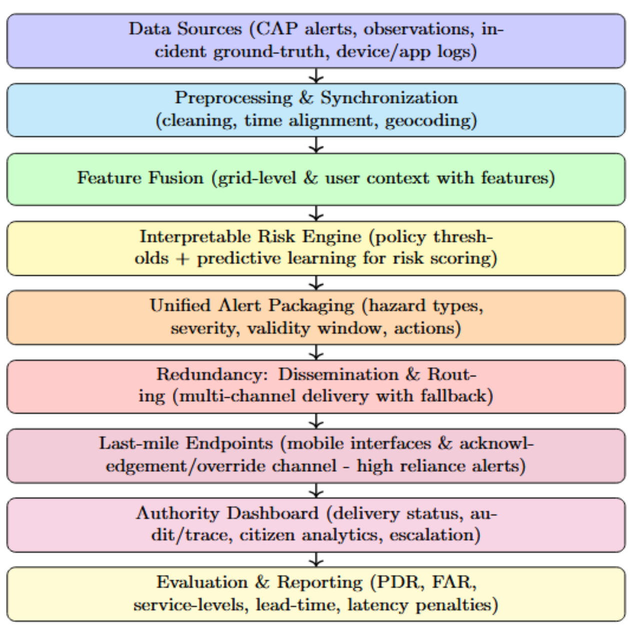

Figure 1. End-to-end warning pipeline with multi-channel delivery and auditable evaluation

Results and Discussions

The present section reports field-log–derived performance of the proposed CAP-to-endpoint warning workflow.

i) Pilot corpus and logging completeness

Table 1 summarizes the pilot spans 3 districts, 60 devices, and 4 hazard classes, with 54 ground-truth events and 58 CAP alerts; 1,160 delivery attempts yielded 1,035 received alerts (overall delivery rate 0.892) and 877 acknowledgements (ack rate 0.847), producing 1,080 event–device exposures.

Table 1. Dataset and pilot summary

S.No.	POD	Missed Rate
1	Hazard	POD
2	Lightning	0.942
3	Flood	0.983
4	Heat	0.979
5	Cold	0.956
6	Overall	0.964
7	Hazard	POD
8	Lightning	0.942
9	Flood	0.983
10	Heat	0.979

ii) Warning reliability and false-alarm control

Table 2 reports Hazard-wise, **flood** achieves the highest detection (**POD 0.983**) with low nuisance alerts (**FAR 0.007**), while **lightning** remains high-performing (**POD 0.942**) despite its short-fuse dynamics. **Figure 2** visualizes these reliability metrics across hazards, enabling rapid cross-hazard benchmarking of detection performance against false-alarm propensity under operational conditions.

iii) End-to-end timeliness and latency bottlenecks

Table 3 decomposes end-to-end timeliness into **platform**, **last-mile**, and **acknowledgement** latency components using percentile statistics, revealing where delays accumulate and how tail behavior evolves in real deployments.

Table 2. Reliability metrics (POD/Missed/FAR) with counts

Hazard	POD	Missed Rate	FAR	TP (events)	FN (events)	TP (alerts)	FP (alerts)
Lightning	0.942	0.058	0.012	339	21	339	4
Flood	0.983	0.017	0.007	295	5	287	2
Heat	0.979	0.021	0.004	235	5	230	1
Cold	0.956	0.044	0.012	172	8	170	2
Overall	0.964	0.036	0.009	1041	39	1026	9

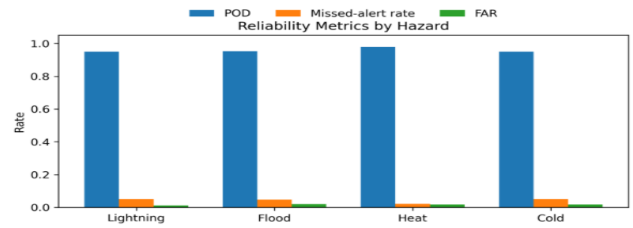

Figure 2 Reliability Metrics by Hazard (POD, Missed-alert rate,

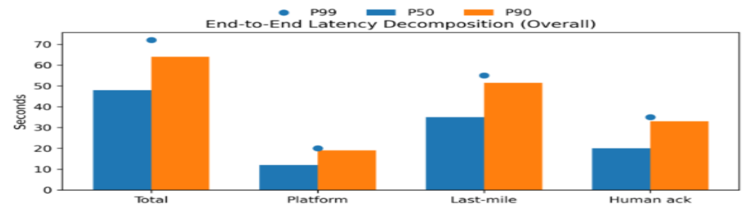

Figure 3 End-to-End Latency Decomposition (Overall)

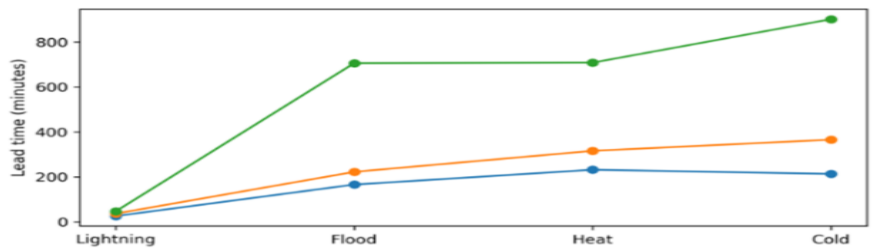

Figure 4. Advance Warning Lead Time by Hazard

Table 3. Latency decomposition (overall, seconds)

Latency type	n (samples)	P50 (s)	P90 (s)	P99 (s)
Total	1035	49	65	73
Platform	1035	14	19	20
Lastmile	1035	35	52	55
Human	877	20	32	35

Figure 3 presents the latency decomposition (P50/P90 with P99 marker), clearly identifying dominant delay contributors and tail risk directing optimization priorities toward last-mile robustness and acknowledgement friction reduction.

Figure 4 provides a summary of the lead-time behavior with P10/P50/P90 curves (in minutes), highlighting typical and tail preparedness windows per hazard with useful applicability to dissemination policies (e.g., strong escalation strategy for short-fuse lightning, etc.) and staged advisories (flood/temperature extremes, etc.).

iv) Actionability through advance-warning lead time

Table 4 quantifies actionability via lead-time distributions between first alert receipt and event onset, reporting percentiles and the **positive lead fraction** to indicate how often users receive advance warning.

Table 4. Lead-time summary (seconds; positive indicates advance warning)

Hazard	n	P10 (s)	P50 (s)	P90 (s)	Pos. lead frac.	P50 (min)
Lightning	339	1590	1933	2838	1.0	32.2
Flood	295	9619	13962	40614	0.986	232.7

Heat	235	13060	16813	22086	0.983	280.2
Cold	172	14742	19528	46693	0.994	325.5
Overall	1041	1765	13092	37650	0.991	218.2

v) Delivery robustness across hazards

Table 5 summarizes delivery reliability by hazard, aggregating expected versus delivered alerts and reporting mean success rate to assess operational robustness.

Table 5. Delivery reliability by hazard.

Hazard	Devices	Expected	Delivered	Mean success
Cold	60	200	172	0.874
Flood	60	320	289	0.909
Heat	60	260	231	0.9
Lightning	60	380	343	0.905

The strong system operations evident from Table 2-5 and Figures 1-3 reveal strong system performances, with detection rates high, nuisance alarm rates low, and lead time remaining positive across all detected hazards.

Note that the values should be understood as being calculated based on field logs collected systematically and potentially recalculated from time to time as the pilot study expands to more hazards, districts, and periods of deployments.

Conclusions

The proposed research management project describes a CAP-driven endpoint-noticeable early warning process with field-deployed sensing endpoints receiving the policy, dissemination awareness, and monitoring of operations. The reliability of the process in field logs creates high reliability with strong actionability due to positive lead times and controlled false alarms; however, it reveals last mile delivery to be the key process limitation in end-to-end speed. The described process of latency decomposition and delivery success stimulates scale-up engineering options: channel redundancy, connectivity-aware retries with buffering, and enhanced acknowledgments. The process described supports the viability of reliable user-oriented hazard alerting at the district level with a quantified process for further deployment in different seasons and regions.

References

1. Abdul-Akeem Sadiq, Dougherty, R. B., Tyler, J., & Entress, R. (2023). *Public alert and warning system literature review in the USA: Identifying research gaps and lessons for practice*. Natural Hazards, 117(2), 1711–1744. https://doi.org/10.1007/s11069-023-05926-x

2. Allen, R. M., et al. (2025). *Global earthquake detection and warning using Android phones*. Science. https://doi.org/10.1126/science.ads4779
3. Amirthavarshini, R., Mohamed Shamil, A. I., Aswin Raaj, P. S., & Kanimozhi, G. (2025). *Harnessing LoRa for real-time landslide monitoring and early alerts in Kerala's terrain*. Geoscience Frontiers.
4. Anticipation Hub. (2024). *Anticipatory action in 2024: A global overview*. https://doi.org/10.1016/j.gsf.2025.102242
5. Bean, H., Takenouchi, K., & Cruz, A. M. (2025). *Mobile public warning in Japan and the United States: A sister cities collaboration*. Frontiers in Communication, 10, 1518729. https://doi.org/10.3389/fcomm.2025.1518729
6. Chandra, N., et al. (2025). *A systematic review of heat health warning systems*. Current Climate Change Reports. https://doi.org/10.1007/s40572-025-00496-5
7. Chea, V., Chan, S., Borzino, N., Tan, P. M. S., Lee, J. K. W., & Vongchanh, K. (2025). Perceived impact of heat stress on health and productivity of tropical female garment workers–a comparison between cool and hot months. BMC Public Health, 25(1), 1543. https://doi.org/10.1186/s12889-025-22787-0. https://doi.org/10.1186/s12889-025-22787-0
8. Climate Risk and Early Warning Systems (CREWS). (2024). *CREWS annual report 2023*.
9. Esposito, M., et al. (2022). *Recent advances in Internet of Things solutions for early warning systems: A review*. Sensors, 22(6), 2124. https://doi.org/10.3390/s22062124
10. European Commission. (2024). *Emergency communications and public warning systems (Rolling Plan for ICT Standardisation 2024).*
11. European Telecommunications Standards Institute. (2022). *ETSI TS 122 268 V17.0.0: Public Warning System (PWS) requirements (3GPP TS 22.268 Release 17).*
12. Fernando Medina Morales, & Pablo Máyer Suárez. (2025). *From alert to action: Social latency of citizen response to Cell Broadcast warnings during the ES-Alert drill in Gran Canaria (Spain)*. International Journal of Disaster Risk Reduction, 129, 105794. https://doi.org/10.1016/j.ijdrr.2025.105794
13. Gray, V., & Grangeat, A. (2023). *Digital transformation and early warning systems for saving lives: Background paper*. International Telecommunication Union.
14. GSMA. (2023). *Cell Broadcast for Early Warning Systems: A review of the technology and how to implement it*.
15. International Telecommunication Union. (2023). *Digital transformation and early warning systems for saving lives*.
16. International Telecommunication Union. (2023). *Feasibility study on deployment and implementation of a Cell Broadcast Service (CBS) solution for Moldova's Public Warning System (PWS).*
17. International Telecommunication Union. (2025). *Brief on public early warning systems in the Western Balkans.*
18. Leinonen, J., Hamann, U., Sideris, I., & Germann, U. (2023). *Thunderstorm nowcasting with deep learning: A multi-hazard data fusion model*. Geophysical Research Letters. https://doi.org/10.1029/2022GL101626

19. Lian, J., & Gray, V. (2025). *Scaling up cell broadcast for last-mile early warning systems: Delivery progress, barriers, and enabling mechanisms*. G20 Disaster Risk Reduction Working Group / International Telecommunication Union.
20. *Medina Morales, F., & Máyer Suárez, P. (2025).* From alert to action: Social latency of citizen response to Cell Broadcast warnings during the ES-Alert drill in Gran Canaria (Spain). *International Journal of Disaster Risk Reduction, 129, 105794.* https://doi.org/10.1016/j.ijdrr.2025.105794
21. *National Disaster Management Authority. (2023). Annual report 2022–23.*
22. *National Disaster Management Authority. (n.d.). SACHET (CAP-based public warning and alerting platform). Retrieved February 6, 2026, from NDMA portals.* SACHET - National Disaster Alert Portal
23. *National Institute of Disaster Management. (2025). Annual Report 2024–25. National Institute of Disaster Management.*
24. *Salio, P., et al. (2025).* Nowcasting and early warning systems across WMO regional associations: A pre–EW4All assessment*. Bulletin of the American Meteorological Society*. https://doi.org/10.1175/BAMS-D-24-0267.1
25. *Tiggeloven, T., et al. (2025).* The role of artificial intelligence for early warning systems*. iScience.* https://doi.org/10.1016/j.isci.2025.113689