Landslide Early Warning Systems: Requirements and Solutions for Disaster Risk Reduction—India

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Abstract

Globally the prevalence of landslides has increased, impacting more than 4.8 million people between 1998 and 2017 and reported more than 18,000 casualties [UNDP]. The scenario has worsened dramatically, and it has become imperative to develop early warning systems to save human life. This demands the need for systems that could identify the potential of imminent landslides and disseminate the information related to landslide initiation in real-time. This would provide the opportunity to save lives. However, globally the research on reliable end-to-end systems for early warning of landslides is still in its nascent stage. Therefore, this paper explores in detail the requirements for developing systems for real-time monitoring, detection, and early warning of landslides. An integrated solution for building the real-time landslide monitoring and early warning system to provide community-scale disaster resilience is also proposed. This solution integrates multiple modules such as a heterogeneous sensor system, data storage and management, event detection framework, alert dissemination, and emergency communication system to address issues such as capturing dynamic variability, managing multi-scale voluminous datasets, extracting key triggering information regarding the onset of possible landslide, multilevel alert dissemination, and robust emergency communication among the stakeholders respectively. The paper also presents two case studies of real-time landslide early warning systems deployed in North-eastern Himalayas and Western Ghats of India. These case studies demonstrate the approaches utilized for risk assessment, risk analysis, risk evaluation, risk visualization, risk control, risk communication, and risk governance. The results from the deployed system in the case study areas demonstrate the capability of the IoT system to gather Spatio-temporal triggers for multiple types of landslides, detection and decision of specific scenarios, and the impact of real-time data on mitigating the imminent disaster.

Keywords

Landslide early warning systems (LEWS) • Disaster risk reduction (DRR) • Internet of things (IoT)

1 Introduction

Extreme and dynamic variability in weather patterns is leading to an unprecedented increase in natural hazards. Globally, from 2004 to 2016, there were 4862 distinct landslide events resulting in 55,997 reported deaths (Froude and Petley 2018). A recent study reported that more than 42% of the municipalities in Italy had been affected by landslides. (Franceschini et al. 2022). Asian Countries like China, India, Nepal, and Japan have experienced significant losses every year due to several catastrophic landslides. India also has a history of landslides combined with multiple hazards, leading to massive loss of human life (UNDP 2018). During the 2013 monsoon in Uttarakhand, 6000 people lost their lives during numerous landslides and extreme rainfall that led to flash flooding (Martha et al.

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2015). The North Indian states of Jammu and Kashmir, Himachal Pradesh, Sikkim, Assam of Himalayas ranges, and Peninsular states of Maharashtra, Karnataka, Tamil Nadu, and Kerala also suffer the loss of life and property every year, predominantly in the monsoon season (Geological Survey of India, https://www.gsi.gov.in). This clearly shows there is an increasing trend in landslides globally.

Furthermore, in the past four years, 2018–2021, India has experienced extreme rainfall in unpredicted pockets leading to multi-hazards such as floods, landslides, etc. (Ramesh et al. 2022). Most of the landslides in India are reported during the monsoon season. Furthermore, in recent years due to unprecedented extreme heavy rainfall events within a short duration, numerous catastrophic landslides have been experienced. The unpredictability of landslide events in space and time is leading to an increase in loss of life and its impact on the established infrastructure. This situation demands solutions that are capable of reducing landslide risk and increasing the community's resilience to landslides.

The state of Kerala, India, has reported more than 200 landslides in 2018. There were tragedies and incidents of catastrophic scale caused by the more than 65 landslides reported in 2019 (Manorama Online 2019); the events over Puthumala and Kavalappara also caused 81 deaths (Wadhawan et al. 2020). In 2021, the Pettimudi landslide event took place, claiming 66 lives (Achu et al. 2021). During the field visits and semi-structured interviews, it was observed that the time difference between landslide initiation and occurrence was about 8–10 h (Wadhawan et al. 2020). However, the community members did not receive any warnings and were not prepared enough to handle this disaster situation. This led to massive loss of lives, which could have been avoided. These incidents clearly demonstrate that landslides are becoming more and more life-threatening worldwide, and their impact could be reduced by developing integrated solutions that will provide landslide risk reduction and landslide resilience.

This research work details the challenges and requirements for building landslide early warning systems and their sub-systems. These events and their sequence of sub-events differ for different types of landslide classifications. This work also focuses on enhancing community-scale landslide resilience. Additionally, two case study scenarios from (i) tectonically active North Eastern Himalayas, and (ii) the structurally moderate dissected hills of Western Ghats are elaborated to unveil the complexity of building a landslide early warning system.

Section 2 details the review of the existing literature. Section 3 details the landslide dynamics related to different landslide types and their importance in early warning systems. It also discusses the requirements of the landslide risk management framework. Further, in Sect. 4, experiences from decade-long operational early warning systems in India are elaborated. The focus will be on the real-world deployments of such systems in India. Section 5 covers the (Internet of Things-Landslide Early Warning Systems) IoT LEWS Discussions based landslide early warning system in case study areas and the last Sect. 6, concludes by summarizing the early warning systems, which is an effective solution for Disaster Risk Reduction.

2 Literature Review

For Disaster Risk Reduction (DRR), several solutions have been proposed in the literature. However, there exists a trade-off among the costs of systems, range of coverage, time of forewarning, and reliability of systems. (Izumi and Shaw 2022). Moreover, the design and development of solutions for Disaster Risk Reduction vary according to the concept utilized, i.e., through community champions or technology. In technology-based solutions, the systems perform either based on remote sensing data (Orimoloye et al. 2021) or by utilizing the geophysical sensors for in-situ measurements (Abraham et al. 2020). Further, in-situ measurements are classified into hydrological and movement-based measurements. The community champions-based solution is explained in detail later. Both these systems have both advantages and disadvantages. In general, the community champions-based system lacks the accurate detection of the event, whilst the technology-based solutions lack effective communication of detected risk.

According to a recently published review on landslide early warning systems, there is a lack of information on past landslide incidents, inhibiting the refinement of models used in early warnings (Guzzetti et al. 2020). There is also a lack of literature on the systematic instrumentation of LEWS. However, there has been an increasing global interest in designing, developing, and deploying landslide early warning systems as a solution to disaster risk reduction (Guzzetti et al. 2020; Pecoraro et al. 2019). New geographical areas are being explored for the deployment of landslide early warning systems utilizing the application of geospatial technology and Web-GIS in order to save human lives by utilizing precipitation measurement as a key indicator for a regional level warning (Ahmed et al. 2020; Hidayat et al. 2019).

Site-specific monitoring using heterogeneous sensors such as rain gauges, moisture sensors, pore pressure sensors, inclinometers, and tiltmeters are detailed in the publications (Ramesh and Rangan 2014; Michoud et al. 2013; Gian et al. 2017; Thirugnanam et al. 2022). However, landslide detection and early warning demand long-term monitoring using these sensor systems. Most of the time, the spatial scale of monitoring required for landslide detection covers a very large area. This will lead to incurring a very high cost of deployment, operation, and maintenance. This makes it an impractical solution for some landslide-prone areas. The lifetime extension of these systems is highly challenging. Context-aware algorithms are applicable in extending the lifetime of such systems (Prabha et al. 2017; Tao 2020). Dixon et al. (2018) have proposed and prototyped a low-cost sensing using acoustic emission (AE) monitoring system. This system needs to be scaled and experimented with multiple sites having different types of landslide classifications. This solution needs to be further explored to understand its capability for early warning of landslides since the AE system lacks in deriving and mapping the multiple heterogeneous causative factors.

The recent literature covers the details of some of the relevant decision models for deriving rainfall thresholds, (Segoni et al. 2018; Harilal et al. 2019; Canavesi et al. 2020), pore pressure thresholds (Conrad et al. 2021; Thirugnanam et al. 2020), moisture thresholds (Orland et al. 2020) utilizing deep learning methods for forecasting the hydrologic response of hillslopes prone to landslides. Additionally, new attempts at utilizing soil moisture have given promising results with their own limitation after reaching the moisture saturation limit (Segoni et al. 2018; Wicki et al. 2020). However, none of these existing works have detailed a comprehensive decision model for early warning of landslides.

The review of selected recently published articles focused on the effectiveness and limitations of the landslide early warning systems. It briefly differentiates the research based on the landslide type, study area, types of sensors used, method for modeling, mode of data communication, and information dissemination capability. All these detailed analyses clearly show that existing landslide early warning systems need enhancements to incorporate the comprehensive needs for capturing the heterogeneous sensing to derive integrated decision models for forecasting imminent disasters and adaptively disseminate landslide early warnings to relevant stakeholders.

3 Landslide Dynamics and Requirements of LEWS

The most common categories of landslides detailed by Varnes (1978) include slides, flows, falls, topples, and spreads. However, each of these landslide types differs with respect to their causative factors or triggers and also with respect to the geological, morphological, hydrological, and meteorological conditions that lead to them. Therefore, one of the critical challenges in developing a LEWS is to identify and understand the distinct signals generated for different types of landslides. This would require in-depth knowledge of the different types of pre-events, failure mechanisms, and post-event spatial impacts for each type of landslide.

The proposed LEWS would require accurate capturing in real-time, the distinct signals generated due to pre-events, initiation of failure mechanism, and post-event scenario to provide an effective early warning to the at-risk, vulnerable community. This demands the identification of the sub-events involved in each type of landslide as well as the methodologies to timely collect those distinct signals accurately. Existing landslide-prone areas experience either single or multiple types of landslides at the same time. This demands the LEWS to capture the sub-events of multiple types of landslides for effectively delivering the location-specific landslide warnings. The key complexities lie in capturing location-specific causative or triggering signals based on the landslide type and developing context-aware decision models based on the interrelationship between the sub-events specific to each type of landslide.

Sensing and communication technologies, algorithms, and heterogeneous data analysis have to be designed and developed for deriving these decision models. The existing spatio-temporal relationship between these sub-events for specific landslide types needs to be uniquely knitted together for monitoring different types of landslides prevalent in specific landslide-prone areas. Table 1 details the landslide dynamics for major types of landslides prevalent in India. These landslide types include rock-topple, slide and fall, debris flow, debris slide, mudflow and slide, creep, and complex landslides. These have been analyzed for their precursor scenarios, failure mechanism, post-landslide scenario, sequence of sub-events, measurement techniques, and monitoring period.

For landslide detection, it is enough to identify the failure at its initiation point. However, when early warning of landslides is considered, it is necessary to detect the failure as well as to identify and monitor all the sub-events associated with the phenomena, including final deposition of the debris and sediments post landslide. Depending on the landslide type, debris rheology, and rate of movement, the location of sediment deposition will differ, thereby resulting in varying spatial impacts. Therefore, an efficient LEWS should be able to integrate multiple types of decision models for monitoring different types of landslides and deduce their final deposition areas as well. Based on the above factors, the risk levels will vary temporally as well as spatially and this demands the development of a metric of evaluation to map and assess these risk levels and identify the regions that can be impacted by these events in the future. Therefore the understanding of the real-time variability of landslide dynamics based on heterogeneous triggering factors, its spatial prevalence, and spatial impact on forecasted hazard zones need to be utilized to derive the lead time for effective landslide warning. Table 2 details the detection mechanism, decision model, expected temporal scale, and expected spatial scale for the key landslide types. These details need

Table 1 Landslide dynamics (part I) for major types of landslides prevalent in India

Landslide type	Precursor scenario	Failure mechanism	Post landslide scenario	Sequence of sub-events	Measurement techniques	Monitoring period
Rock:topple /slide/fall	Crack initiation, tree roots expansion, hanging rocks from clif, slanting electric poles etc. Increase in acoustic emissions (AEs) and micro-seismic activity	Crack initiation, crack propagation leading to rock failure, followed by rock–toppling, rock–sliding, rock-falling	Runout leading to road damages, infrastructure damages	(a) Crack initiation ⇒crack propagation⇒rock toppling (b) Crack initiation ⇒ crack propagation⇒ rock toppling⇒ rock sliding (c) Crack initiation⇒ rock rupture and collapse⇒ rock sliding (d) Crack initiation⇒ rock rupture and collapse⇒ rock fall	Geophone, crack meters, tiltmeters, extensometers, acoustic emission sensor, LiDAR scanning, time lapsed ground survey using drones cameras	Long term monitoring—multiple years
Debris flow	Tension cracks, flow of debris, seismic activity	Shearing sliding along the weak surface, rapid loss of strength	Depositing the mixed material at the mouth of debris flow gullies⇒often damming the main river ⇒formation of barrier lakes	(a) Shearing in the subsurface ⇒creation of tension cracks at the crown⇒rapid loss of strength⇒flow along the weak surfaces⇒formation of slurry⇒ moving very fast with relative movement between adjacent layers (b) Saturation⇒ loss of strength⇒ movement along the weak surface⇒ flow along the weak surfaces ⇒formation of slurry⇒ moving very fast with relative movement between adjacent layers (c) Seismic activity⇒ loss of strength⇒ movement along the weak surface⇒formation of slurry⇒ moving very fast with relative movement between adjacent layers	Rain gauge, moisture sensor, strain gauges, tiltmeters, geophone, accelerometers	Medium term monitoring — especially during monsoon period
Debris slide	Heavy rainfall, initiation of cracks followed by creation of slip zone, oversaturation of ground, rise in pore pressure	Unconsolidated soil deposits overlying highly fractured bedrock fails along the slip surface	Long runout	(a)Saturation⇒ loss of strength in the surficial deposits ⇒ movement along plane either bedrock/overburden interface or a surface ⇒ Rapid downward sliding and forward rolling of rock fragments	Rain Gauge, Moisture Sensor, Pore Pressure Transducer, Strain Gauges, Tiltmeters, Inclinometers, Geophone, Accelerometers	Medium to long term monitoring - especially during monsoon period

(continued)

Table 1 (continued)

Landslide type	Precursor scenario	Failure mechanism	Post landslide scenario	Sequence of sub-events	Measurement techniques	Monitoring period
Mud: flow/slide	Heavy rainfall leading to super saturation of ground	After oversaturation the topsoil flows	Mud movement in the downstream, often arrested by road, break in slopes	(a) Saturation ⇒ oversaturation ⇒ cracks and ruptures at the soil layer⇒formation of mud slurry ⇒ moving very fast with relative movement between adjacent layers ⇒ traveling long distance along the drainage channel / gullies eroding the channel	Rain Gauge, Moisture Sensor, Accelerometers, Pore Pressure	Medium to long term monitoring - especially during monsoon period
Creep	Cracks on roads, buildings, Tilting of trees, oversaturation of ground, water seepage at new location, formation of new springs, water logging, rise in pore pressure, deformation	Weathered fragile rock overlaid by thick soil cover fails under influence of gravity, washing away fine particles leading with/without soil piping Creep movement can be continuous, seasonal or progressive	Slow movement of slide from deep weathering leading to surface signatures like cracks on roads, buildings, surface slides. After few years slides can also happen	(a) Slow surface movements⇒ gravitational deformation ⇒creates large disturbances in landscape morphology, such as scarps, counter-slope scarps⇒ Outflow of mudstones due to the lithostatic pressure⇒ progressive toppling of a rock mass leading to the catastrophic rock collapse along bedding planes	Measuring morpho-structures and tectonic features using Geomorphological mapping and time lapsed electrical resistivity tomography (ERT) Monitoring real-time pore pressure, ground vibration and ground inclination, for observing the changes in the subsurface	Long term monitoring
Complex landslides	Crack initiation, internal shear oversaturation, ground vibrations, tree roots expansion and slanting electric poles etc	Multiple factors including weathered regolith, excess rainfall leading to oversaturations, earthquake tremors	Debris movement in the downslope	(a) Oversaturation⇒ Slip zone formation⇒ failure along the slip zone (b) Rock fracturing⇒ debris slide (c) Creep⇒ subsidence⇒ debris slide, etc	Rain gauge, moisture sensor, pore pressure transducer, strain gauges, tiltmeters, inclinometers, geophone, accelerometers, ERT, Drone imaging	Medium to long term monitoring

Table 2 Landslide dynamics (part II) for major types of landslides prevalent in India

Landslide type	Detection mechanism	Decision models	Expected temporal scale	Expected spatial scale
Rock: topple/slide/fall	(a) GEOPHONE: multiple sensors capturing low-frequency ground vibration (5–10 Hz) signals for a specific duration, (b) CRACK METER: multiple sensors capture the increase in crack length (c) TILTMETERS: sensors capture the change in orientation of the unstable rock body (d) EXTENSOMETERS: multiple sensor captures the increase in movement of the unstable rock with reference to stable rock body (e) LiDAR: periodic point cloud data points for change detection (f) DRONE CAMERAS: periodic change detection	In all four scenarios of sub-events, the same decision model could be used for identifying crack initiation and propagation. However, the threshold for detecting rock toppling, rock sliding, and rock fall using various detection mechanisms will be different. The threshold values can be determined from the strength of the material, size of the unstable mass, structural properties of the rock,	Immediate to short duration	Site specific
Debris flow	(a) RAIN GAUGE: crossing rainfall thresholds, (b) STRAIN GAUGES: change in strain measurements beyond the threshold levels, (c) GEOPHONES: low frequency microseismic signal detection (d) ACCELEROMETERS: variations in ground acceleration	Rainfall thresholds, thresholds from various sensors can be used to derive the integrated decisions to early warn the scenario	Immediate to maximum of 15 days of antecedent condition	Regional/catchment scale, site specific
Debris slide	(a) RAIN GAUGE: crossing rainfall thresholds, (b) PORE PRESSURE: crossing pore pressure threshold, (c) STRAIN GAUGES: change in strain measurements beyond the threshold levels, (d) INCLINOMETERS: change in inclination beyond threshold levels. monitoring at slip zones (e) SLOPE STABILITY: factor of safety value moves below one, (f) GEOPHONES: low-frequency microseismic signal detection (g) ACCELEROMETER: detection of change in acceleration	Meteorological models: rainfalls thresholds, Hydrological models: pore pressure thresholds geological models: slope stability (Factor of Safety) can be used, signal processing models, forecast models	Short term to a maximum of 15 days of antecedent condition	Regional/catchment scale, site-specific
Mud: flow/slide	(a) RAIN GAUGE: crossing of rainfall threshold (b) SOIL MOISTURE: initial moisture conditions (c) PORE PRESSURE: saturation condition (d) ACOUSTIC: capturing variability in acoustic emission (e) VIBRATION/ACCELERATION: detection of ground acceleration	Rainfall threshold based models, movement, acoustic and signal processing based models. Derive integrated decision models based on the sub-events	Very short term to a few days of antecedent rainfall condition	Regional/catchment scale, site specific

(continued)

Table 2 (continued)

Landslide type	Detection mechanism	Decision models	Expected temporal scale	Expected spatial scale
Creep	(a) CRACKMETERS: increase in crack length (b) RAIN GAUGE: crossing rainfall thresholds, (c) PORE PRESSURE: crossing pore pressure threshold, (d) STRAIN GAUGES: change in strain measurements beyond the threshold levels, (e) INCLINOMETERS: change in inclination beyond threshold levels. monitoring at slip zones (f) ERT: periodic resistivity profiles for moisture changes (g) GEOMORPHIC CHANGES: ground survey to mark the cracks, subsidence etc (h) SAR interferometry: deformation monitoring	Rainfall threshold-based models, multiple thresholds for monitoring the rate of change of movement, after few years it crosses factor of safety and can fail	Multiple months to years	Site specific
Complex landslides	(a) Landslide hydrology plays important role in a complex landslide (b) Three-dimensional groundwater regime in both the short and long term needs to be captured	Meteorological models: rainfalls thresholds, hydrological models: pore pressure thresholds geological models: slope stability model can be used	Immediate to long-term	Site specific

to be integrated with the decision model of the LEWS for large-scale spatial monitoring of landslides since each of these events has a different time scale and diverse spatial scale of prevalence. This is essential for effective early warning of imminent landslides to save lives. However, this comprehensive approach is lacking in existing landslide monitoring and detection systems. This demands our existing traditional systems to be enhanced to derive landslide early warning. Therefore, this study is devised to explore and detail a few case studies of LEWS deployed in India for capturing multidimensional and multilevel landslide dynamics to effectively issue early warnings to the vulnerable population at risk.

4 Landslide Risk Management Framework

To achieve a real-time understanding and forecasting of the complex and unpredictable landslide phenomena, the key functionalities that need to be performed are compiled into an integrated landslide risk management framework, as illustrated in Fig. 3. The framework consists of three sections as follows.

(a) Risk Assessment
  1. Measure
  2. Monitor
  3. Knowledge Discovery, Event detection: Risk analysis
  4. Forecast Model, Artificial Intelligence Model: Risk evaluation

(b) Cost-Benefit Analysis
  1. Risk Visualization
  2. Early warning: Risk control
  3. Dynamic Model
  4. Artificial intelligence model
  5. Multiphase Decision model
  6. Multiscale Early Warning Model

(c) Risk Communication and Risk Governance
  1. Risk policy/protocol development
  2. Operations management
  3. Community engagement
  4. Capacity development
  5. Real-time communication
  6. Multiscale communication model
  7. Services and Alerts

To implement the above framework, we require a system with requirements as shown in Fig. 1. Such a system can bring community-level disaster resilience. These requirements can only be achieved through a multi-domain approach since a single domain is not capable of providing solutions to the challenges encountered in each and every area. Experts from the domains of climate science,

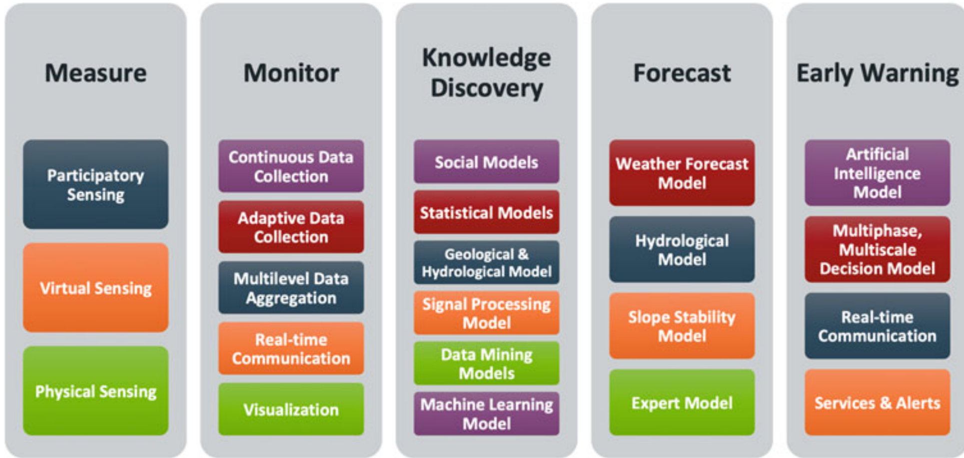


Fig. 1 Requirements for community level disaster resilience

geoscience, hydrology, engineering, data science, and social science, as well as community leaders, administrators, and community members, need to be involved to jointly design, develop, and deploy the solutions.

The complexity of landslide phenomena demands heterogeneous types of sensing to capture sub-events, unveiled through dynamic changes in multiple earth systems. Therefore it would require physical sensing of several events using sensors, where each sensor interacts with its surroundings to measure various environmental parameters. Participatory sensing by the community members is also very effective in capturing any anomaly, which could be a precursor. This is a community champions-based solution, where groups of individuals trained in physical landslide monitoring like measuring rainfall, new crack formation, old crack width tracking, open well water level tracking, etc., work as a group using social networking tools to detect the possibility of landslides and help the community to evacuate during disaster prone months of the year. Virtual sensing in landslide detection is another effective measurement tool to derive a few events based on the physical sensing of some other related parameters. This reduces the cost incurred for developing a direct sensing system and enhances the spatial and temporal coverage of sensing. The real-time measurement of causative factors and triggering mechanisms using physical sensors, participatory sensing approaches, and virtual sensing, need to be monitored either continuously or adaptively for each of the sub-events based on its domain characteristics. These data need to be aggregated in multiple levels based on the order of the sub-events and perform data visualization to extract inherent and useful knowledge for event detection.

Multilevel data aggregation, knowledge discovery, and event detection need to be utilized for risk analysis. However, the key challenge is that the different landslide classes differ in the temporal and spatial scale of prevalence. This demands the knowledge of landslide causative parameters, triggers, and causal relationship between the parameters, and dynamic thresholds. This knowledge will dynamically vary based on the context. Hence the sensing system needs to be

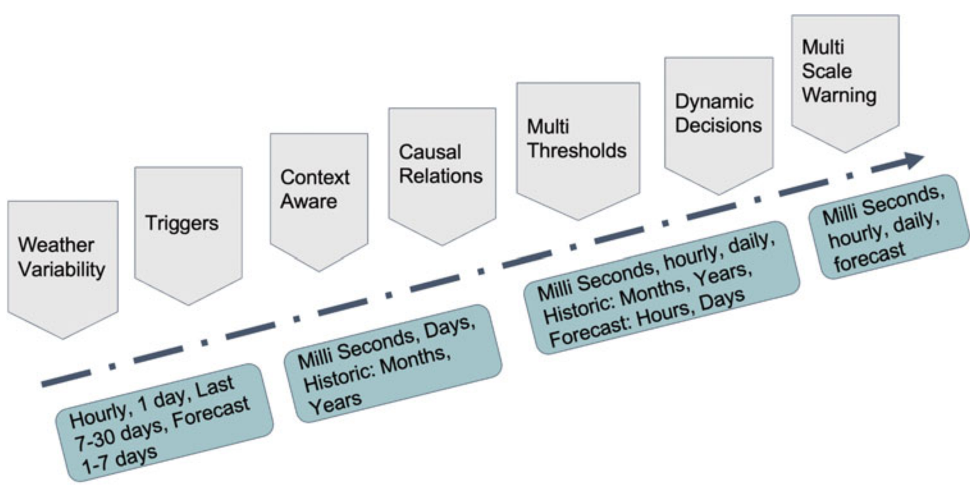


Fig. 2 Temporal variability in the landslide monitoring process

unique in capturing and processing the data on multiple scales to derive efficient landslide warnings. As Fig. 2 showcases, the temporal scale of monitoring and mapping of weather parameters, triggers, contexts, casual relationships, thresholds, decisions, and warnings differ. Therefore the sensing, processing, communication, and visualization system need to accommodate data collection, storage, and visualization in multiple time and spatial scales.

Specific to each of the landslide types and the characteristics of each of its sub-events, knowledge discovery and event detection need to be performed for real-time risk analysis. The knowledge discovery and event detection could be achieved using different models such as statistical, geological, hydrological, metrological, machine learning, and data analysis models. This derived knowledge will be utilized for risk evaluation by forecasting the events using existing and new models such as weather forecast models, hydrological models, slope instability models, and expert models. The output from these forecasting models will be utilized to provide early warning about the probable imminent landslides using artificial intelligence techniques, and multi-phase, multi-level decision models. The early warnings will be adaptively communicated in real-time using the different web and mobile app-based services.

The underlying dynamics resulting in landslides can be derived utilizing theoretical as well as data-driven models incorporating the real-time observations, historical data, and antecedent conditions of the triggering factors. This further leads to reliable forecasts of landslide initiation, incorporating meteorological, hydrological, and slope stability modeling systems along with advanced machine learning and artificial intelligence techniques. These forecasts will be utilized in a multi-phase, multi-level decision system in order to provide robust early warnings. Efficient web-based, as well as mobile app-based services, will enable the effective communication of these warnings in real-time. This process aids in providing warnings at regional, catchment, and site-specific scales. The visualization system further aids in the demonstration of the interrelations between the various heterogeneous parameters as well as their individual impact on landslide initiation.

Periodic cost-benefit analysis needs to be performed on such a system. This would require the deployment of continuous real-time visualization and risk control models. The visualization system should be equipped to deliver interrelationships between the spatio-temporal heterogeneous data collected from various sensing systems.

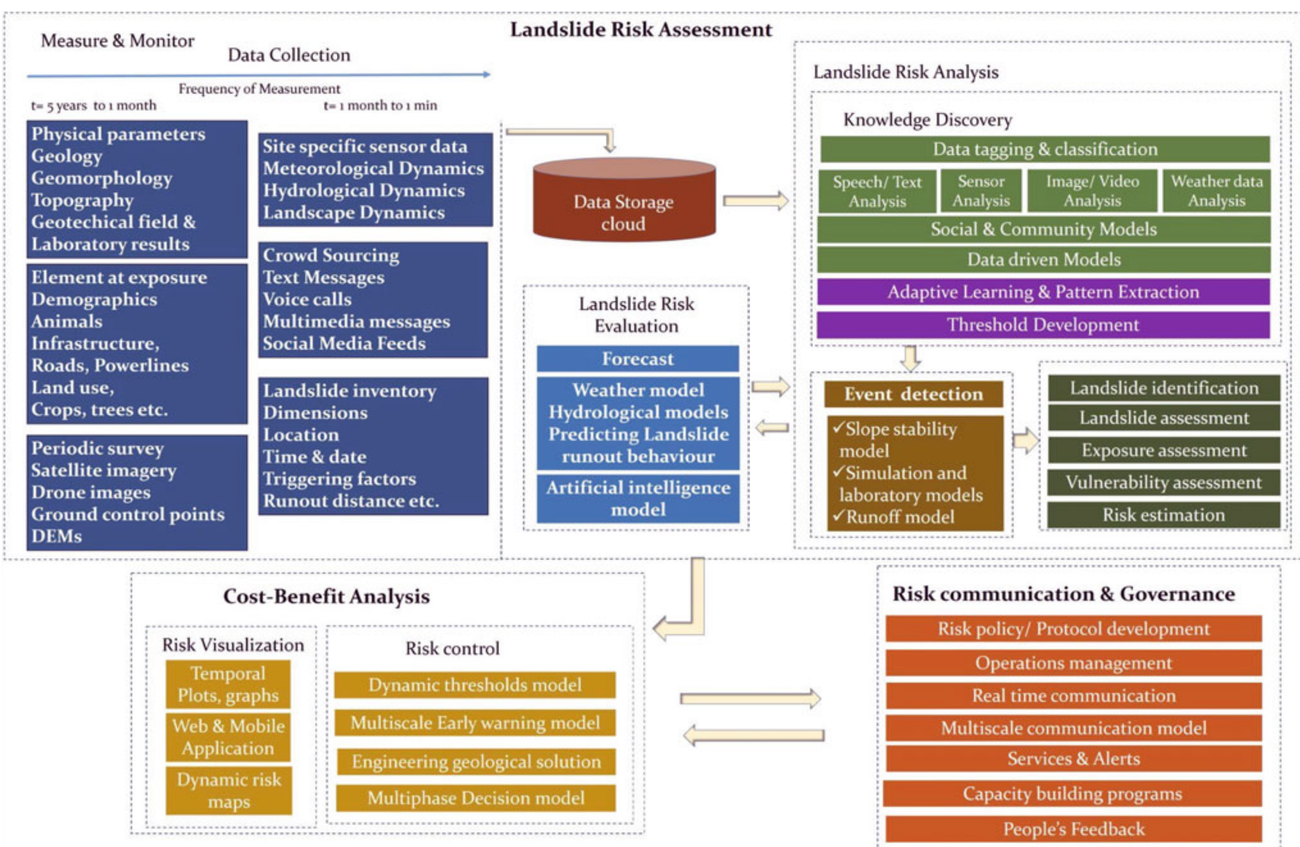


Fig. 3 Integrated landslide risk management framework

This will be utilized to elucidate the impacts due to individual parameters and their interrelationships on landslide initiation. Risk control demands the development of early warning models. This would require gathering an understanding of the dynamic variability of heterogeneous parameters, interrelationships, antecedent conditions, and their impact on landslide initiation. This knowledge could be utilized for developing machine learning-based models and artificial intelligence-based models to derive the thresholds and forecasts for single and multiple parameters. These models would be integrated based on the type of landslides prevalent in the deployment area, and the sequence of sub-events to derive the multiphase decision models. The output of the multiphase decision model will be utilized to derive the multiscale early warning model to produce warnings at regional, catchment, and site-specific scales.

In order to translate the outcomes of risk assessment and cost-benefit analysis, active risk communication, and an efficient risk governance mechanism are mandatory. Effective risk governance requires multi-level risk communication among the stakeholders such as scientists, research institutes, government bodies, local administration, non-profit organizations, and the community. To achieve this, specific risk policies or protocols need to be developed with the involvement of the stakeholders so that early warnings can be disseminated to the relevant stakeholders and local governance institutions in the expected region of landslide impact. The risk governance and risk communication are also dependent on end-to-end operations management, active community engagement, and integration of capacity development programs to equip the multi-stakeholders for operating and managing the LEWS.

The effectiveness of LEWS functionality is dependent on timely communication of real-time risk information and early warnings to relevant stakeholders. Multiscale communication models need to be developed to disseminate the risk levels to relevant stakeholders in specific landslide-prone areas. Additionally, this system needs to be adaptive to manage communication services during the dynamic scenarios of network and power outages. The real-time services and alerts need to be generated in local languages and disseminated using web services or mobile applications to reach a large number of stakeholders in the shortest time period.

Envisioning the need for a system integrated with the above requirements to provide an end-to-end solution for real-time landslide monitoring and early warning, a landslide risk management framework has been designed, as shown in Fig. 3. Multi-domain solutions such as IoT-based landslide early warning systems, social media analytics, community engagement, etc., are integrated to develop comprehensive solutions for landslide risk reduction and resilience building. Figure 3 depicts the landslide risk management framework and its sub-modules that could be utilized for developing landslide early warning systems for multiple landslide classifications.

5 Case Study: Real-World Deployment in India

The Himalayan region in North India and the Western Ghats in South India are major hotspots of landslides because of their ongoing tectonics and mass wasting processes, which are also accelerated due to anthropogenic activity (Martha et al. 2021). Therefore to observe and investigate these landslides with widely varying dynamics, one case study area has been chosen from each of the regions. These two case study areas are (i) Western Ghats region: Munnar, Idukki District, Kerala, (10° 5′ 26.56″ N; 77° 3′ 22.93″ E) (Ramesh and Vasudevan 2012) and (ii) North Eastern Himalayas region: Chandmari, Gangtok (Dist), Sikkim (27° 20′ 17.54″ N; 88° 37′ 22.78″ E) (Harilal et al. 2019) (see Fig. 4).

The first case study area, Munnar, being named after the confluence of three perennial rivers, lies in the Western Ghats. These are Precambrian mountains with Granitic bedrocks overlaid by a weathered regolith of aluminum-rich saprolites with variable thickness (GSI 2016). The mountain belts of Munnar are covered by tea estates, montane grasslands, shola forests, and urban areas which receive about 2470 mm of average rainfall annually (IMD, https://mausam.imd.gov.in/). These denudational hills see several landslides during the monsoon season resulting in the loss of lives and property (Ramesh and Vasudevan 2012). Rainfall is the major trigger for the landslides in this area and in the past 10 years, there have been more than 50, small and big landslides in less than 10 km^2 around Munnar (*Source* GSI 2018, 2020).

The second case study area, Chandmari comes under the main central thrust zone (MCT) of the Himalayas. Here the underlying lithology is weathered gneisses interbedded with mica-schists. This region receives more than 2500 mm of annual rainfall which makes it highly prone to landslides. The landslides here, and in the Himalayas in general, are induced by both rainfall and/or earthquakes. Therefore Chandmari is chosen as a representative case study area to learn about the dynamics of complex Himalayan landslides. Chandmari is an active landslide since the 1960s. It has been reactivated several times in the past with a huge landslide in 1968 and has experienced movements subsequently in 1984, 1997, 2007, and 2011. Recently during the monsoon periods of 2018–2022, several types of small and medium size landslides in the study area, Chandmari, have been observed as listed in Table 3. This mostly includes debris flow, shallow surface road-side slumps, rockfalls, mudslides, complex landslides, and deep-seated subsidences.

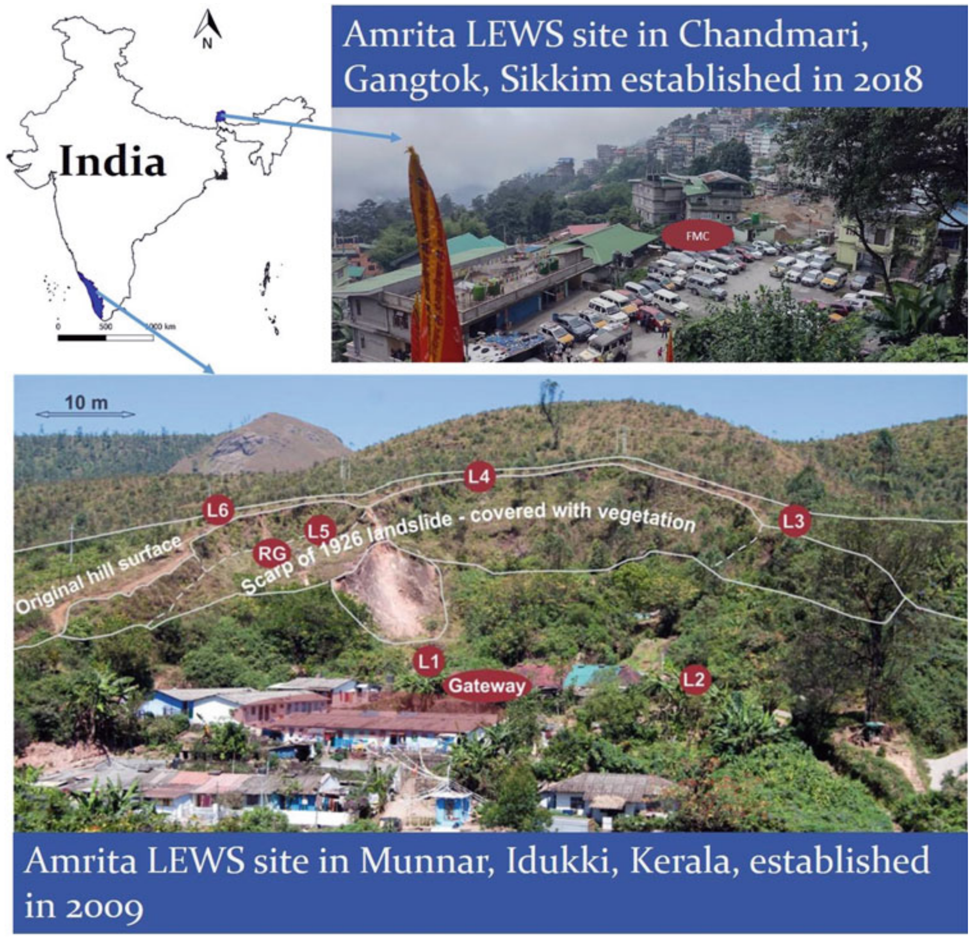


Fig. 4 Case study areas: the two Amrita-LEWS deployment sites

Additionally, anthropogenic activities such as unplanned construction, road widening, unscientific changes to land-use land cover, mining activities, heavy vehicular movement, seepage from sewages drains, etc., have accelerated the landslide activity in both the study areas (Kanungo et al. 2020). The architecture of buildings is also unique to both sites. In Munnar, there are buildings with mostly one to two stories whereas in Chandmari the buildings have three to six stories. These building practices are also influenced by the population density of both the sites; the population density of Chandmari is 1858 people per km^2 whereas at Munnar it is 170 people per km^2. In terms of seismic activity, Munnar lies in Zone III of Seismic maps whereas Sikkim comes under Zone IV, often experiencing micro tremors. Topsoil composition in Munnar is weathered granitic gneiss overlaid by red weathered saprolite (red colored soil where feldspars weathers to clay) whereas Chandmari has interbedded mica-schists in gneissic rock (sandy soil layers where mica minerals weathers to partially expansible clays such as illite and vermiculite).

In Chandmari the landslides are both rainfall-induced and earthquake-induced; whereas in Munnar the landslides are majorly rainfall-induced. The prominent types of landslides that occurred in Chandmari are rock falls, debris slides, and creep movement whereas debris-cum-earth slides, complex landslides with retrogative movement, are active in Munnar. The design, development, and deployment of IoT-based LEWS at both the case study areas are unique due to the distinctive landslide dynamics present at each of the case study sites, as explained above. Moreover, this affects each of the LEWS subsystem's design in different ways. For example, the selection of sensor/detection mechanism has to be performed in accordance with the landslide triggers of the area and the decision models deployed in servers also have to be tweaked, for detection of these triggers and for tracking the evolution of the sub-events associated with the landslide type for generating warnings.

6 IoT Based Landslide Early Warning System in Case Study Areas

The Amrita's IoT-based LEWSs have been deployed and operational 24/7 in the two sites namely Munnar, Western Ghats and Chandmari, North Eastern Himalayas as depicted in Fig. 4. The LEWSs at both the sites consist of several

Table 3 Details the different types of landslide occurred in the study areas

Study area	Types of landslides	Location of landslide	Date of slide	Activity
Chandmari	Rockslide	Near Dep 1, 2 mile JN road	16 June 2022	Active
	Rockfall	Near Dep 5	Aug 2019	Suspended
	Debris flow	Below Dep 5	1997, 2005, 2018	Reactivated
	Debris slide	Above Dep 8	Aug 2019	Active
	MudSlide	Below Enchey Monastery	26 June 2022	Suspended
	Deep seated Subsidence/ creep	Near petrol pump near Dep 7, on the JN road above Dep 3, above Dep 1 (crown region)	Aug 2018, July 2019, Aug 2020, July 2021, June 2022	Active
	Complex landslides	Chandamri Hill	Recorded since 1984–2022	Active
	Channel wash	JN road along the drainges between Dep 1 and Dep 3	Aug 2019, 16th June 2022, 28th June 2022	Suspended
	Anthropogenic landslides	Below Enchey Monastery	28th June 2022	Active
Munnar and Devikulam villages	Debris cum earth slides	Nalathani road	2018	Suspended
	Deep seated complex landslide	Govt college Munnar	2018, 2019	Active
	Channel wash	Near Devikulam Hospital	Aug 2018	Inactive
	Rock falls	Gap road	Every monsoon 2018–2022	Active
	Mudslide	Behind Sarvana Bhavan, Munnar town	2018	Inactive
	Creep slide	Near Dep 4, Anthonior colony	2013–2022	Active
	Debris cum earth Slides	Behind SBI, Devikulam	Aug 2018	Active
	Debris cum earth Slides	Behind Brothers house, Devikulam	Aug 2018	Active
	Debris flow with long runout	Pettimudi landslide, Munnar	Aug 2020	Suspended

Deep Earth Probes (DEPs) installed below ground that can sense the various geophysical parameters and their dynamics. These DEPs are connected to above-ground, state-of-the-art embedded systems, heterogeneous communication systems, and smart algorithms to make them Intelligent Wireless Probes (IWPs). These IWPs constitute the edge nodes and are integrated within an IoT framework across the case study site and into the decision models in the cloud servers.

The pilot system of Munnar was deployed from January to March 2008, and the full-scale system from January to June 2009. Currently, the whole area consists of 20 Deep Earth Probes integrated with approximately 150 geophysical sensors connected to 20 wireless sensor nodes. At Chandmari in Sikkim, 11 potential locations for deployment of DEP were identified after detailed investigations. The pilot deployment was completed in 2015 and included three pore pressure sensors, two inclinometers, three 3-axis geophones, and one weather station to monitor the area. The full deployment was completed in 2018, with the area consisting of 11 IWPs with around 200 geophysical sensors.

Indeed for effective early warning of landslides, the IoT-based LEWS should integrate features such as multi-parameter sensing, adaptive scalability with respect to the dynamic contexts, heterogeneous coverage in sensing and networking, remote configuration, dynamically acquiring the sensing data based on the context, a scalable resilient communication network for handling heterogeneous upstream and downstream data transfer in harsh environments, spatial knowledge absorption, multiple level decisions based on both real-time and historic heterogeneous sensor data, and information dissemination to different stakeholders such as students, researchers, citizens, administrators, policymakers etc. Therefore, the subsystems need to be integrated with features such as heterogeneity, flexibility, adaptability, and scalability for autonomous information generation. Considering all the above parameters Amrita LEWS has been developed and is designed for continuous monitoring and warning of landslides.

The unique features of the Amrita LEWS are summarized below:

1. Real-time risk assessment is performed by measuring and monitoring of multi-domain parameters using a dynamic IoT platform, crowd sourced- landslide tracker (Hariharan et al. 2021) and Amritakripa app (Guntha et al. 2020; Guntha and Vinodini Ramesh 2021) and Social media data collection (Phengsuwan et al. 2019) as opposed to traditional static maps. The dynamic platform of Amrita LEWS captures:
   (a) Meteorological dynamics: Rainfall, Temperature, Humidity, Wind speed and direction. Both Chandmari and Munnar have different climatic regimes. One is Himalayan tropical, temperate, and alpine climatic conditions with several snow-capped mountains and glaciers but the other is Western Ghats climate where heavy rainfall varies from 935 ± 185.33 to 1794 ± 247 mm. Rainfall patterns of both regions differ and thus rainfall threshold also varies both at regional and site-specific scales.
   (b) Hydrogeological dynamics: Volumetric water content from moisture sensor, hydraulic pressure, groundwater level, and soil temperature from piezometers.
   (c) Geophysical dynamics: Three components of ground velocity data from three axis geophones, Time-varying three-dimensional resistivity profiles from electrical resistivity tomography (ERT), (Ramesh 2017; Vinodini Ramesh et al. 2017).
   (d) Landscape dynamics: Movements along two axes from inclinometers, strain gauges, and tilt meters
   (e) Social dynamics: Response of community data from Twitter feeds and participatory sensing approaches such as mobile apps which include text, audio, video, maps, and lat-long information.
2. Risk analysis is performed by knowledge discovery by initiating continuous learning of dynamic behaviors and interrelationships between multiple heterogeneous parameters for identifying Precursor scenarios, understanding Failure Mechanisms, forecasting Post Landslide scenarios, and identifying Reinitiating mechanisms (Ramesh 2014).
3. Risk analysis is enhanced by integrating event detection modules through heterogeneous Models such as rainfall threshold (Prabha et al. 2017) Hydrological models, slope stability and IoT edge analytics (Kumar et al. 2020).
4. Risk evaluation is performed by forecasting and early warning through machine learning and artificial intelligence-based models (Hemalatha et al. 2019) to predict the pore pressure variability and factor of safety of the hill.
5. Cost-benefit analysis is performed by utilizing “Amrita Drishti”, a web-based visualization software integrated with decision models for spatio-temporal data analysis, deriving interrelationships, and multi-level thresholds for causative and triggering parameters
6. Enhancing the reliability of detection and early warning using heterogeneous detection models (Harilal et al. 2019; Thirugnanam et al. 2020) and integration of multi-domain parameters, for reducing false alarms.
7. Multi-phase decision models developed based on the expected sub-events for each type of landslides
8. Multi-scale early warnings utilizing the knowledge discovered from real-time heterogeneous data and historic data have been developed
9. Real-time risk communication and risk governance through participatory DRR approach and mobile applications (Amritanand et al. 2020) to adaptively disseminate context and location-aware information to relevant stakeholders
10. In-person multi-level multi-phase community engagements performed during pre-monsoon time period
11. Training provided for empowering the community Monitoring social dynamics related to rain, flood, members to map the triggers, causative factors, and real-time sub-events using the landslide tracker mobile application for achieving enhanced risk governance and risk communication to relevant stakeholders and landslides from automated tweet collection, event detection, and providing situational awareness of the real-world conditions from tweets and online news.

7 Uniqueness of LEWS: Munnar and Chandmari

Case Study Area 1: Munnar, Western Ghats

The key landslide types prevalent in Munnar are debris-cum-earth slides, complex landslides with retrogrative movement, creep landslides, and debris flow. Most of them are triggered by long-duration medium/heavy rainfall, changes in LULC, and anthropogenic activities. The material type and heavy rainfall cause increased pore pressure leading to landslide initiation as shown in Fig. 5.

Based on the triggering mechanisms, the material type, and the major geological, hydrological, and meteorological features the key parameters that need to be measured by LEWS are selected. The key sub-event group is rainfall leading to water infiltration, and saturation of the material, which results in increased pore pressure leading to failure of the slope. This failure mechanism could initiate landslide types such as flow or slide or creep, based on the localized geomorphology. Therefore the risk assessment demands measurement and monitoring of Deep Earth Probe (DEP) integrated with sensors such as rain gauges, moisture sensors, pore pressure transducers, strain gauges, tiltmeters, etc. The slip surface activity of landslides in the Western Ghats is much lower in comparison to the Himalayas and hence strain gauges are good at detection of activity in comparison to inclinometers. The frequency of monitoring by each type of sensor will depend on the characteristics of (a) weather pattern to decide on rain gauge sampling rate, (b) water infiltration rate to decide on moisture sensor sampling rate, (c) water flow lines and soil layer properties to decide the pore pressure sampling rate, (d) strength of soil or rock materials in the deployment field and its geological structure to decide the rate for sampling strain gauge, tiltmeter, etc. This knowledge will provide the opportunity to finalize the dynamic temporal scale monitoring for the heterogeneous parameters. The monitoring of spatial variability of sensing parameters will be dependent on the sensing systems coverage and variability of parameters with respect to its domain, rainfall rate, and soil or rock properties. Based on these variabilities, the risk analysis is performed either in the edge node or in the cloud. The DEP integrated with the IoT system for edge analytics, real-time communication, and powering the whole system is known as the intelligent wireless probe (IWP), as shown in Fig. 6.

Risk analysis is performed through spatiotemporal analysis of single parameters for a long duration, deriving interrelationship among the parameters using data analysis or machine learning, and integrated multistage analysis for the heterogeneous parameters to derive the progression of sub-events using data analysis, machine learning and artificial intelligence approaches. This provides the opportunity for knowledge discovery and acts as the impetus for forecasting selected parameters and thus deriving the early warning models.

Over the years the rainfall patterns in the region have been drastically varying. The key rainfall data for more than ten years and the landslide event details are utilized in developing the Amrita Regional Rainfall Threshold Model and Amrita Site Specific Rainfall Threshold Model for Munnar. An integrated decision model using both real-time data and historic data is utilized to compare multiple models such as Caine, Amrita Model, and Innes Model (Harilal et al. 2019) for both real-time and antecedent rainfall scenarios. Based on this integrated model, both regional and site-specific warnings are provided for multi-stakeholders in Munnar. This will contribute to risk evaluation and risk control.

The unique soil properties in the Munnar region can lead to high pore pressure during extended periods of rainfall leading to landslides, hence pore pressure data collection by the detection mechanism in LEWS is very important. It is highly beneficial for risk evaluation and risk control if the

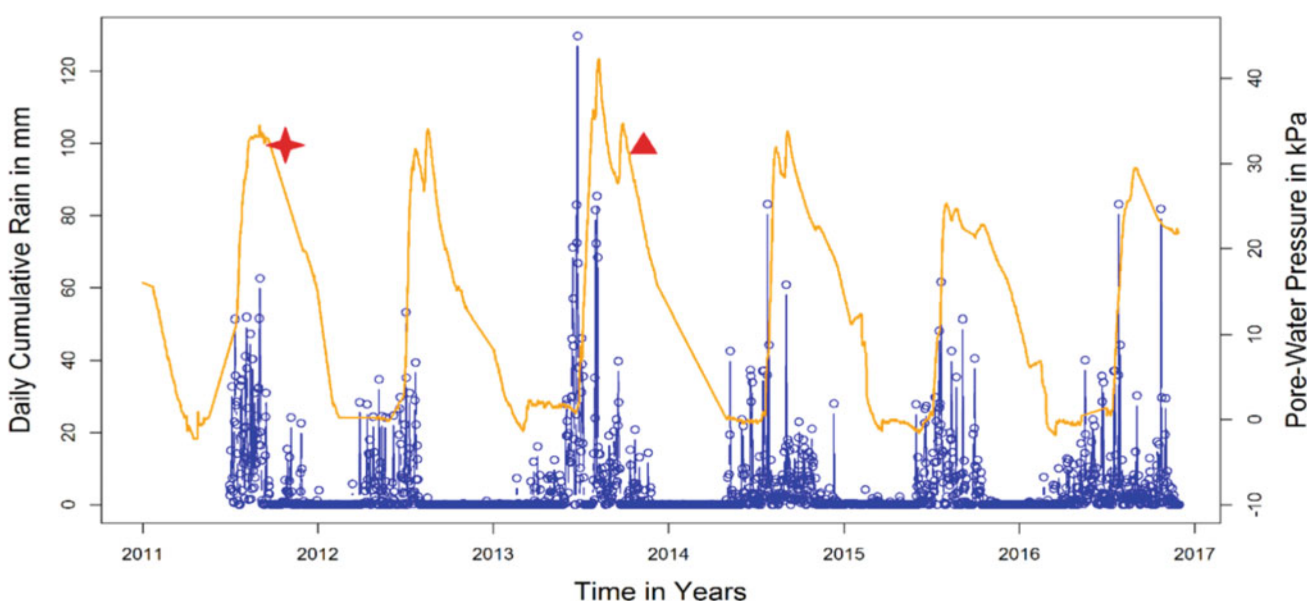


Fig. 5 Interrelationships of triggering factors and temporal variability

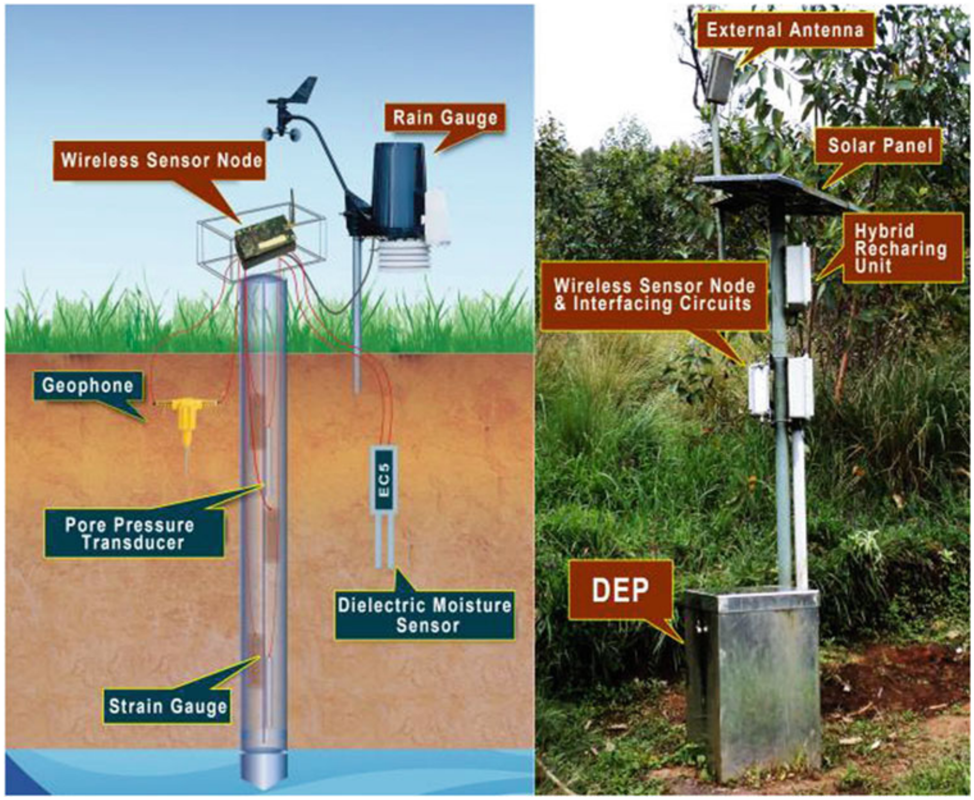


Fig. 6 Intelligent Wireless Probe with Edge Computation (Ramesh et al. 2014)

LEWS can forecast the pore pressure based on the real-time and antecedent rainfall conditions and soil properties of the specific location. The work detailed in Hemalatha et al. 2019, showcases the approaches used for nowcasting and forecasting the pore pressure and factor of safety values for the Munnar region using support vector regression methodology, as shown in Fig. 7. Support vector regression methodology is an adaptive learning methodology that takes into account the historic data and real-time data for learning and forecasts the futuristic condition of the slope 24 h ahead of time. The algorithm is designed in such a manner that even when real-time data from the field is not available due to any unforeseen reasons, the algorithm takes into account the rainfall forecast information from the Indian Meteorological Department to forecast the futuristic condition of the slope, thereby ensuring the reliability of the system. The forecasted futuristic conditions of the slope are utilized for risk evaluation and risk control. This approach is intended for enhancing the reliability of LEWS and provides extra lead-time for early warning.

The risk communication is integrated to perform automatically through the "Amrita Drishti" web platform to all stakeholders. However, based on the suggestion provided by Kerala State Disaster Management Authority (KSDMA), the initial communication will be sent to the secretary of KSDMA, the District collector, and Sub-district collector of the LEWS deployment location. KSDMA and District Government officials work with the local administration to implement the risk governance. In addition, has created a vast network of youngsters, women, and community members to inclusively work with Amrita and disseminate timely information. The team has also created a WhatsApp group named "Munnar community 4 DRR" for effective exchange of relevant information from multiple groups to enhance community-level disaster resilience.

Case Study Area 2: Chandmari, Eastern Himalayas

The key landslide types prevalent in Chandmari are triggered by short-duration heavy rainfall, seismic activity, high surface runoff, erosion, change in LULC, etc. Therefore in LEWS, the key parameters for observation are selected accordingly to detect these events and their subevents. In the Himalayas, geophones are key components of the detection mechanism, as seismic activity is very high and can lead to landslides with unique sub-events. Creep movement and subsidence along the slip surface of the slide is also commonly seen leading to landslide sub-events that require inclinometers and geophones to measure the slip surface activity and ground velocity. The pore pressure build-up and excessive pore pressure triggered landslides are much less in the selected case study area, possibly due to the presence of internal cracks leading to high drain out rates. Moreover, the design and maintenance of the subsystem are also complex due to the harsh operational conditions. For example, the

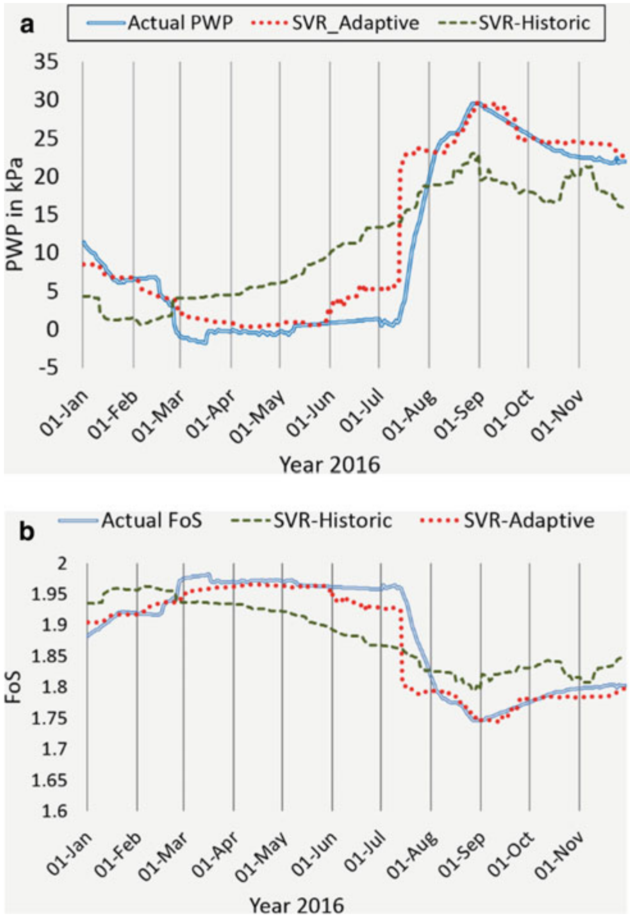


Fig. 7 Forecasting pore pressure. Forecasting factor of safety

thick vegetative cover introduces challenges for the operation of wireless communication and solar power systems. The wireless signal attenuation is very high in these conditions, requiring us to use heterogeneous communication architecture for better reliability. The challenges introduced by vegetation cover over solar panels have also led us to use a heterogeneous power system drawing power from multiple power sources.

Chandmari study area (32 ha) demonstrates the real-time risk analysis, risk evaluation, and risk control for multiple types of landslides (Fig. 8). The deployment area contains 11 Deep Earth Probes (DEP) integrated with heterogeneous sensors such as rain gauges, weather stations, moisture sensors, pore pressure sensors, strain gauges, inclinometers, and geophones.

The location of DEP 1 is more prominent for rock falls and rock slides, DEP 2 is more prominent for deep-seated landslides, DEP 3 is prominent for creep movements, DEP 4 creep movement, DEP 5 is prominent for debris flow and debris slide, DEP 6 is prominent for creep movements, DEP 7 is more prominent for subsidence cum complex movement, DEP 8 has shown debris slide, DEP 9 is relativity stable DEP 10 is more prominent for creep movements and debris flow or debris slide. Additionally, mudslides are also experienced within 1 km of the deployment area. The integrated IoT system deployed in each of these locations is fine-tuned to capture the causative factors, triggers, and the context using heterogeneous sensors. The thresholds of the decision models

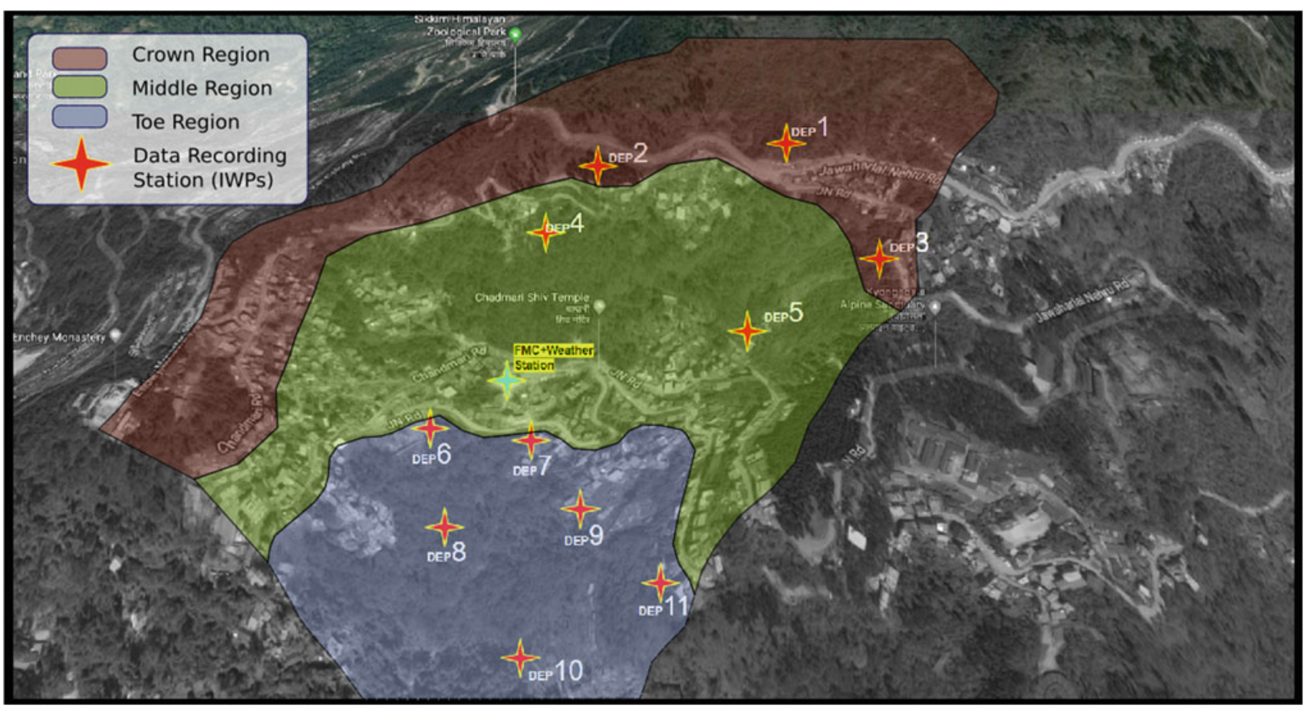


Fig. 8 Satellite view of Chandmari site, Sikkim (courtesy Google Maps)

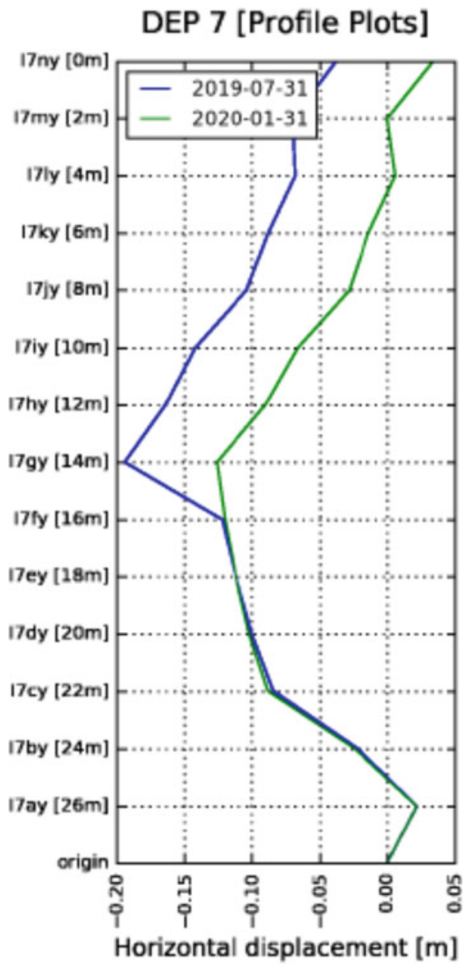


Fig. 9 Inclinometer data from Chandmari: detection of movements from 14 m beneath the earth

also differ due to the way the slopes react to the hydro-meteorological inputs. The integrated decision model for the whole deployment area had to integrate the models required for detecting the subevents of each landslide type. The decision model for Munnar is different from that of Chandmari as the sub-event types are different in both regions.

The risk assessment for the Chandmari case study area demands measurement and monitoring of Deep Earth Probe (DEP) integrated with sensors such as rain gauge, moisture sensor, pore pressure transducer, strain gauges, inclinometers, geophones, etc. The data analysis, knowledge discovery and event detection using these multiple parameters provide the opportunity to derive real-time risk assessment. Figure 9 displays the inclinometer data from DEP 7 Sikkim showing considerable movements, indicating displacement along slip zones.

Figure 10 displays the microseismic activity in DEP 1 captured by the geophones. These microseismic activities indicate the cracks' initiation and propagation leading to rock fall at about 7:30 am on 17th June 2020 about 100 m from DEP 1. These indications are further analyzed for undertaking propagation of movement within the subsurface and dynamically varying risks in the crown, middle and bottom part of the hill slope.

Knowledge discovery and event detection are very key modules for risk analysis and risk evaluation. For Chandmari, the impact of rainfall intensity on landslide triggering is studied in detail. Daily rainfall observations from the India Meteorological Department (IMD), from six stations of Sikkim, namely Gangtok, Mangan, Namathang, Maziar, Dentam, and Damthang, during the period 1990–2017 and the rainfall observations from our R-LEWS in Chandmari from 2015 onwards were utilized to derive regional rainfall threshold and site-specific rainfall Threshold. For this work, an intensity–duration (I–D)-based regional rainfall threshold for Sikkim state (Fig. 11) is derived as $I = 43.26\ D - 0.78$ (I = rainfall intensity in mm/day and D = duration in days) for the rainfall-triggered landslides, and a site-specific rainfall threshold for Gangtok area is derived as $I = 100\ D - 0.92$ (Fig. 12) (Harilal et al. 2019). Along with this, the influence of antecedent rainfall in landslide initiation is explored by considering the daily, 3-day, 5-day, 7-day, and 20-day cumulative rainfall values associated with landslides. The proposed threshold equations will aid in enhancing the real-time landslide early warning system (R-LEWS) being developed for Sikkim and will act as the first level regional and site-specific warning for the Chandmari region. Figures 11 and 12 showcases the implementation of the Amrita Regional Rainfall Threshold Model and Amrita Site Specific Rainfall Threshold Model in "Amrita Drishti"—a web-based platform respectively. Figure 13 shows a 7 days threshold crossed during 2021 in Chandmari and a comparison of three different types of thresholds. It compares and indicates how different models are utilized for generating early warnings for different types of landslides.

The LEWS at both the case study sites have been enhanced by the integration of an event-specific detection mechanism and corresponding response protocols. Each landslide event is thus sub-divided into a sequence of sub-events inside the LEWS as mentioned in Table 1. This knowledge of sub-events is generated based on learnings from the past landslide activity in the study area. The whole landslide process is therefore modeled as an evolution from one sub-event to another sub-event, from initiation to slope failure.

The detection mechanism as mentioned in Table 1 helps in capturing the dynamics of the signal from the geophysical sensors. The detection mechanism consists of heterogeneous sensors such as Meteorological, Hydrological, and other Geophysical sensors. Thresholds exist for each of the measured parameters such as rainfall or movement rate and for derived parameters such as slope factor of safety.

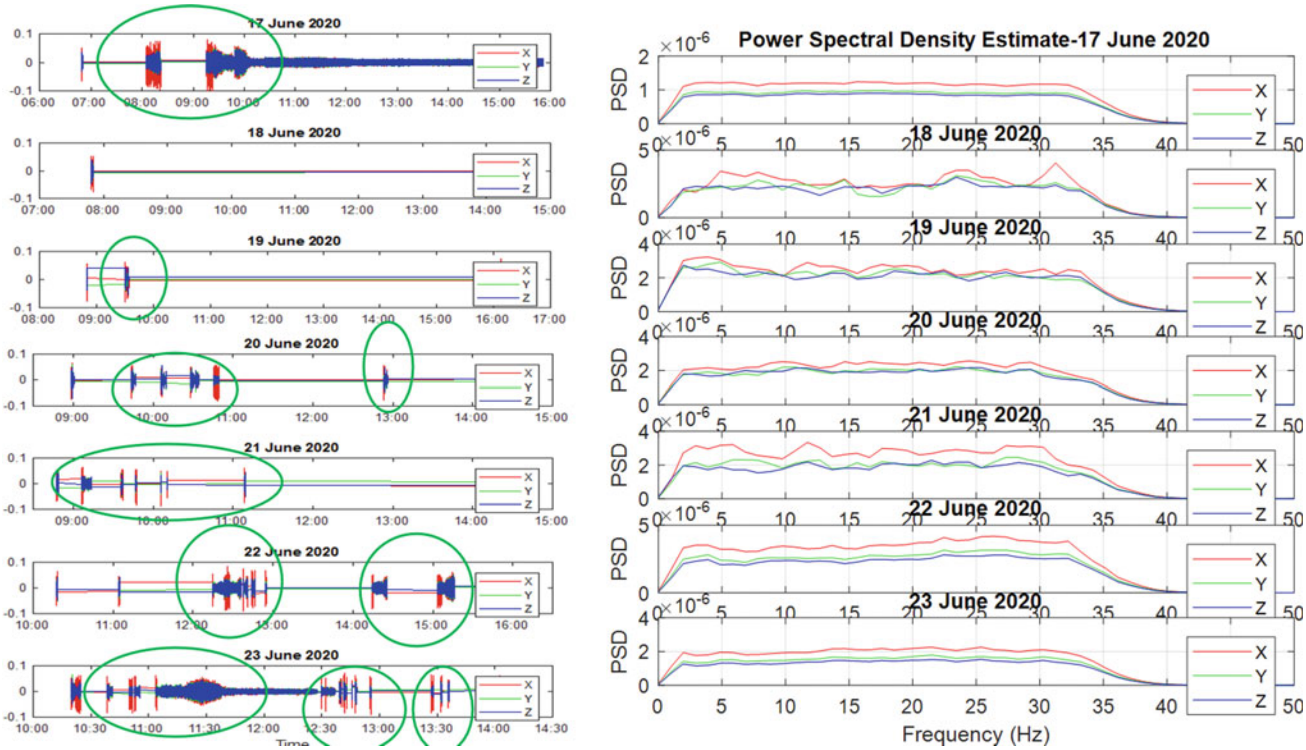


Fig. 10 Geophone data from Chandmari—micro seismic activity detection

The real-time data is collected from all the DEPS and stored into data servers for further processing. In order to increase the reliability of the LEWS and increase the available lead time for warning, edge processing based algorithms are also deployed on the IWPs and these also increase the reliability of the system.

In comparison to other LEWS globally, the LEWS deployed in both the case study sites monitor the sub-events of a landslide and pinpoint the evolution of the subevents. For example, Munnar has more prominently debris cum earth slides with head ward retreat movement owing to large soil thickness and extremely heavy rainfall. The sequence of events for such slides is saturation leading to loss of strength in the surficial deposits. After prolonged rainfall the movement along the plane either bedrock/overburden interface or a surface gets initiated which turns to rapid downward sliding and forward rolling of rock fragments within a few minutes. Whereas in Sikkim the terrain is more rocky with both rainfall and seismic tremors resulting to rock-cum debis falls. The sequence of events for such slides as detailed in Table 1, starts with crack initiation which over time progresses to crack propagation finally leading to rock toppling, rock sliding and rock fall. Although both in Munnar and Sikkim, several other types of landslides are prevalent at different locations as detailed in Table 3 and for each of them a combination of sequence of events needs to be captured.

The decision model is selected based on the sub-event type being encountered by the LEWS, this increases the reliability of the overall early warning system, as the detection algorithms are dealing with individual sub-events. In addition to this, the decision model outputs four levels of warnings based on the current status in the evolution of the landslide process. The four level warning generated by the system is shown in Fig. 14.

Based on the above shown four-level early warning system, the LEWS has generated warnings for Munnar sites in the year 2009, 2011, 2013, 2018, 2019, 2020, 2021 and 2022 and for Chandmari site in the year 2022. And these warnings have been relayed to various stakeholders for the purpose of evacuation (Fig. 16).

Risk control and mitigation could be initiated from the continuous measurement data. For example in Chandmari, the output from the inclinometer sensors has been selected by Sikkim State Disaster Management Authority to initiate mitigation activities near DEP6, DEP7 and DEP8. The output of the movement sensor (inclinometer) (Fig. 8) in the Chandmari site is used to map the downslope vulnerable areas associated with the landslide. The total volume of the unstable sliding mass was calculated as roughly 7×105 m^3. This entire unstable mass is also measured to be moving in the north 195° East [S15E] direction as per the sensor data. For calculating the mass of the unstable material, mean density for underlying material, biotite granite

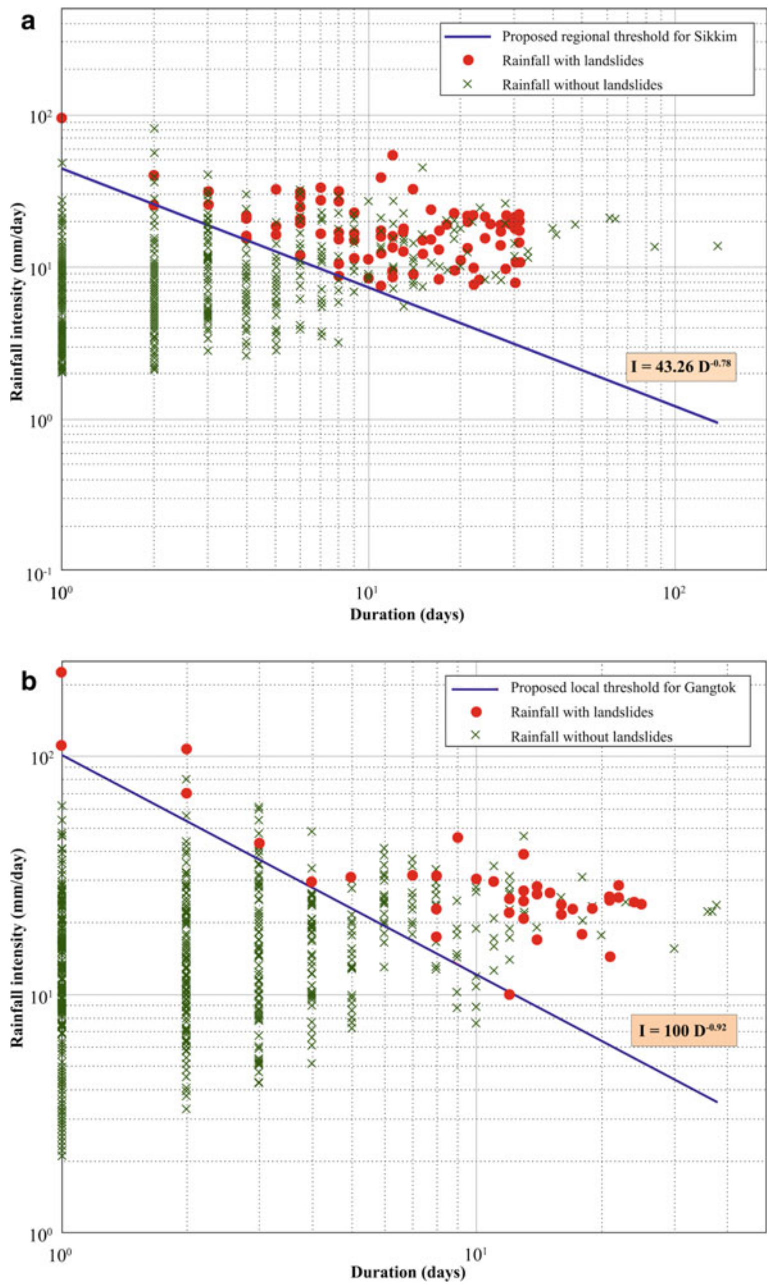


Fig. 11 Sikkim—Amrita regional rainfall threshold model. Implementation of Amrita regional rainfall threshold model in "Amrita Drishti"—web based platform

gneiss (1.65 gm/cm3) is used for rough estimates. The mass of the material is approximately 1.155 million tons. This indicates if a landslide is initiated 1.155 million tons of material will fall on individuals living on the downslope. The various elements at risk as a result of this movement are fuel stations, roads connecting the Gangtok Town to Nathula Pass, Numerous Human settlements, Schools and a Tourist Parking lot. With the calculated affected/ destabilized soil mass, the stability of the slope/vertical cut could be estimated and retaining structures could be built suiting the needs.

The risk control, communication and governance at Chandmari site is explained below. Figure 15 shows the rainfall thresholds were crossed on 28th July 2022 followed by initiation of six small landslides in the Chandmari.

For incorporating the comprehensive needs of end-to-end community disaster resilience, an adaptive and integrated approach is proposed. This approach has been developed and enhanced through the decade-long involvement in disaster management in the Munnar region and is also being implemented in Sikkim since 2018 in collaboration with state disaster management and Indian Meteorological

Fig. 12 Sikkim—Amrita site specific rainfall. Implementation of Amrita site specific rainfall threshold model in "Amrita Drishti"—web-based platform

Department (IMD). The adaptive integrated community disaster resilience solutions implemented in the case study area are detailed as follows (Fig. 17). For enhancing the preparedness development of crowdsourced applications, social media based awareness programs, IoT systems for monitoring have been implemented. In order to equip the rescue and response team, we developed Amrita Kripa Mobile app, 24/7 call centers, prepared and trained field volunteers during the 2018–2019 Kerala Multihazards. To optimize the response based on early warnings from the

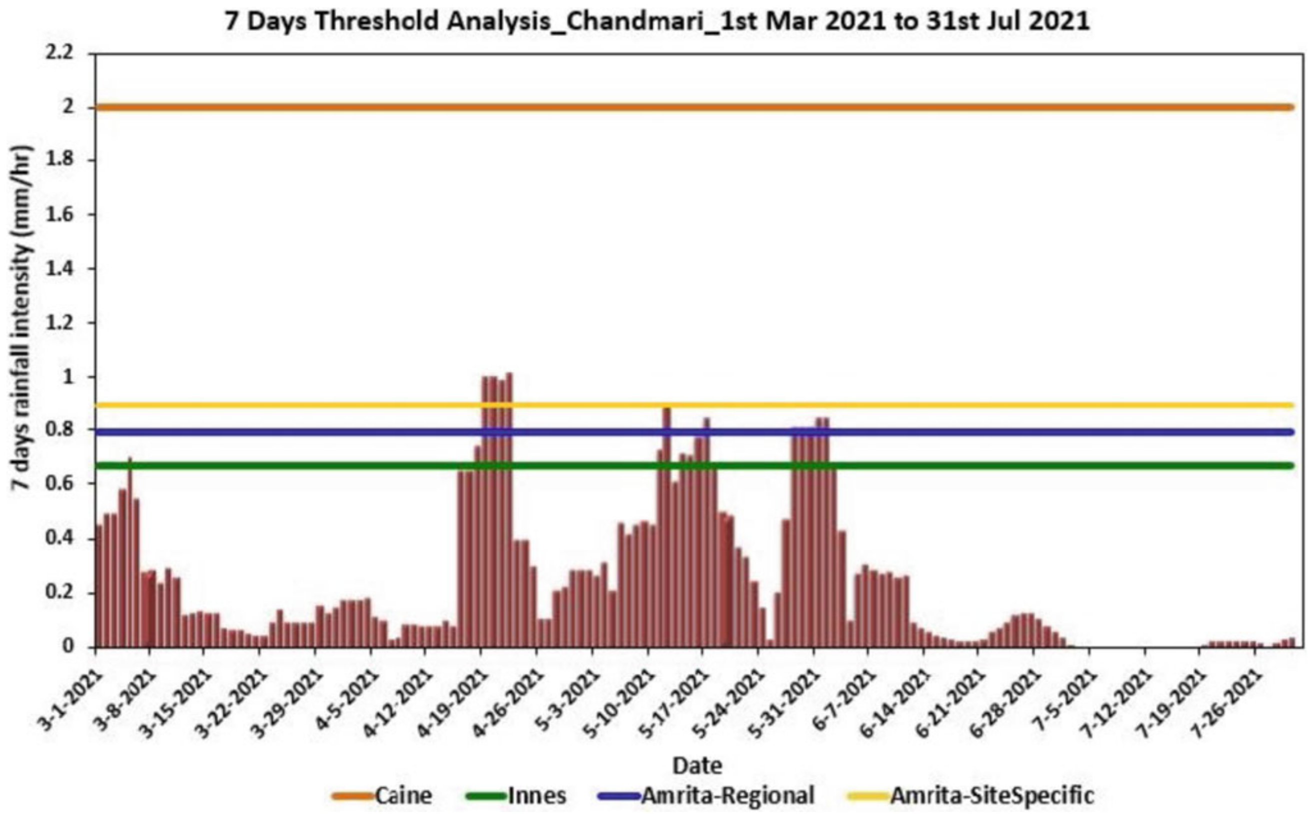
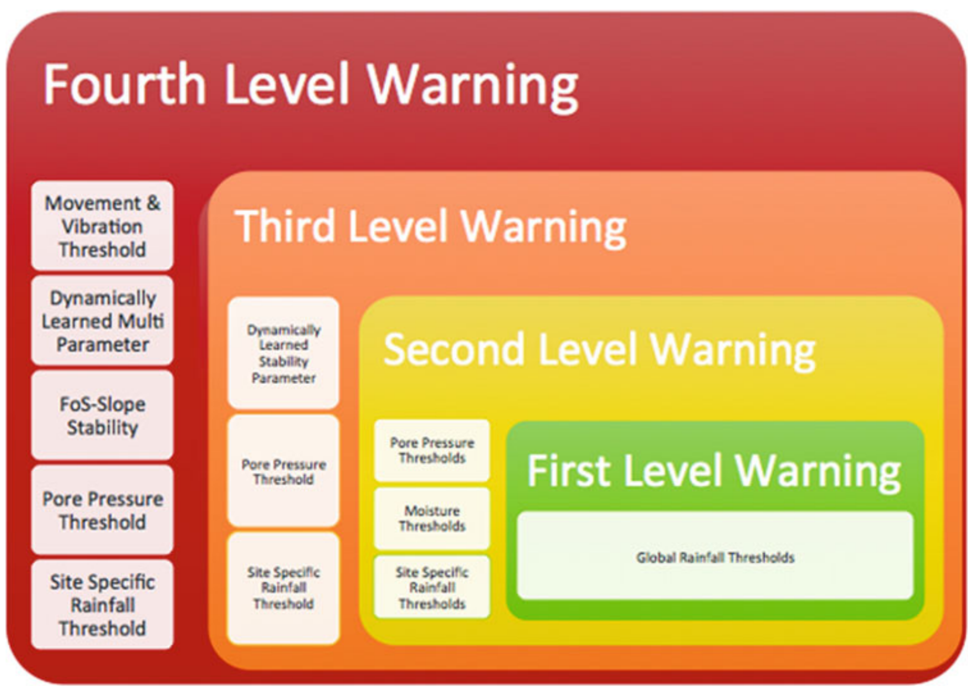


Fig. 13 Rainfall threshold and comparison of models: 7 days threshold crossed during 2021 in Chandmari

Fig. 14 Multi level warning: integration of heterogeneous spatio temporal data and intelligent knowledge management



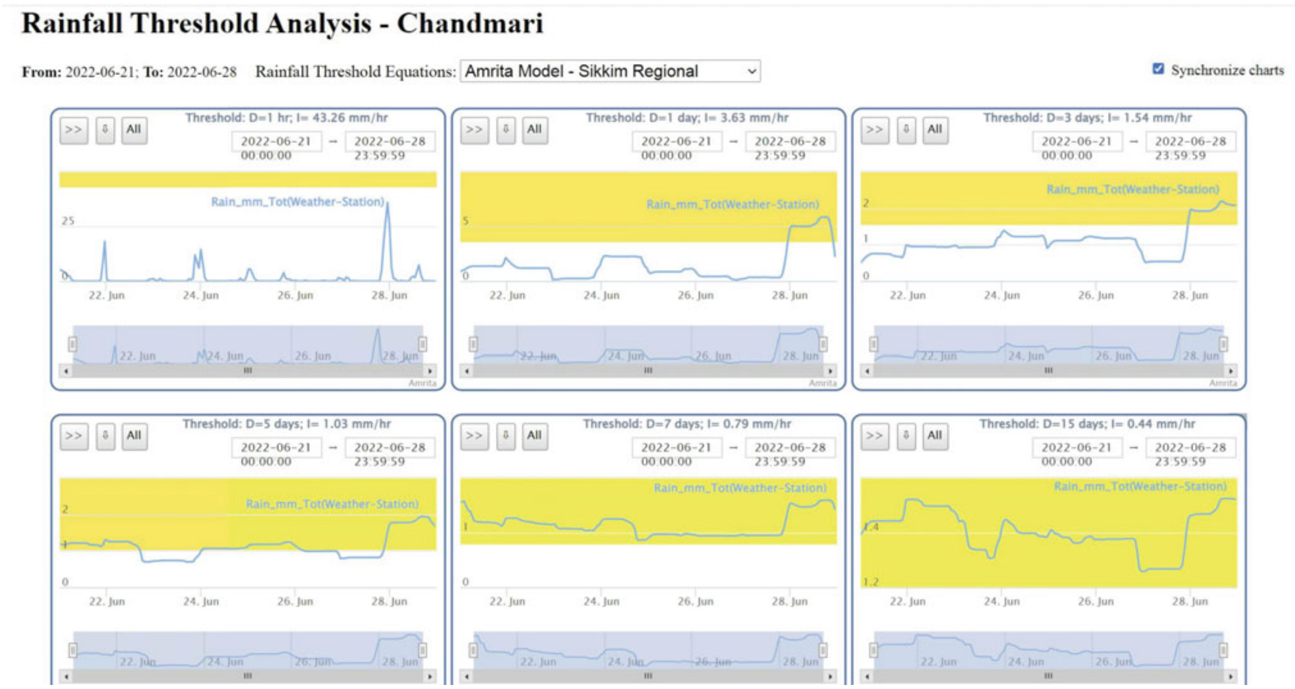


Fig. 15 Regional and site specific rainfall threshold crossed on 28th July 2022. Six landslides got initiated within 24 h of the issuing of warning in Chandmari area

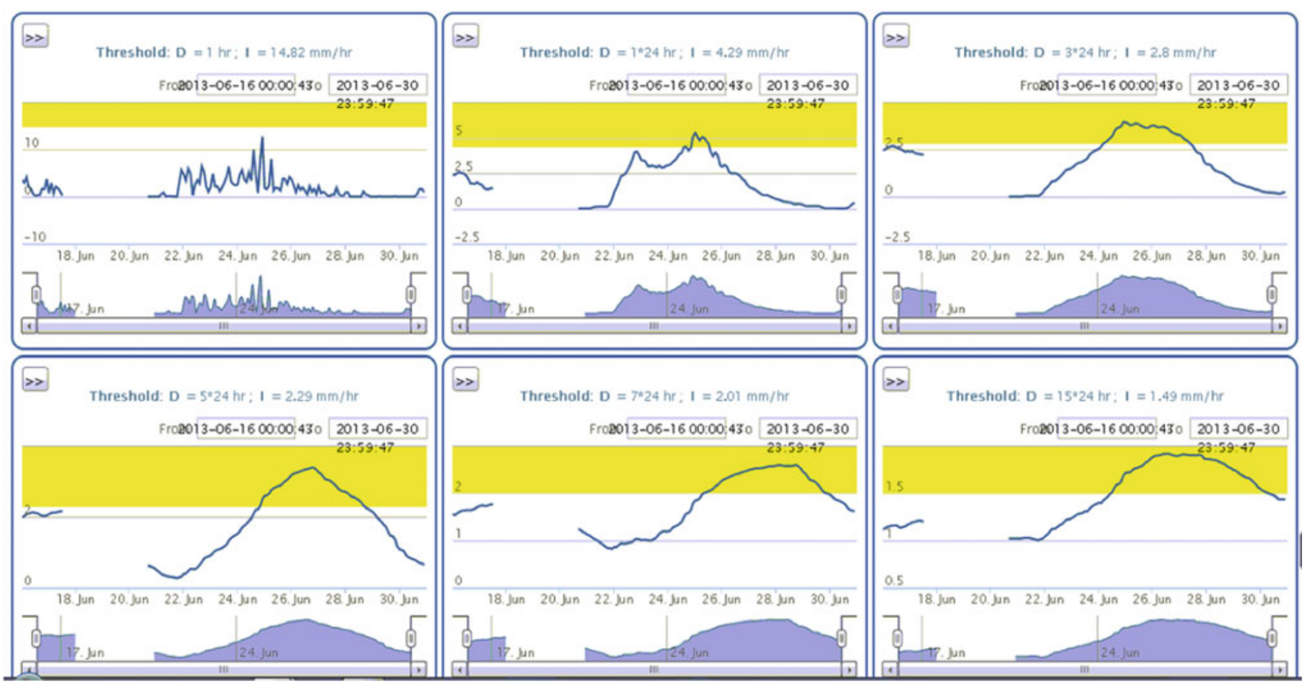


Fig. 16 Sample screenshot of a first level warning based on rainfall thresholds

Fig. 17 Snapshot of Kerala flood 2018 efforts to facilitate the rescue and relief operations: Amrita Kripa rescue app

LEWS, multi-level risk communication using mobile applications and early warning using social media were developed.

Furthermore, in LEWS design, we explored enhancing reliability, reducing false alarms through multi domain integration, reducing the cost of deployment and maintenance through bringing in the participatory approaches. In the year 2018 in Munnar, the automatic integrated decision model was used by LEWS and three effective warnings were issued on 12 July 2018, 15 July 2018, 9 Aug 2018. Based on these warnings the district administration and tahsildar evacuated the community members to safe places. During the initial phase of these monsoon periods, the Amrita IoT system was able to clearly convey that regional thresholds have crossed however site-specific thresholds have not. Based on these instructions from the LEWS, the community in the case study area stayed back in their home, trusting Amrita's warning. As these warnings were later validated by the absence of landslides in study site, the reliability of the warnings and the communities trust on these warnings from the LEWS has increased. The Amrita IoT systems capability to predict the regional landslides and denied the possibility of initiation of site specific landslides is highly appreciated by the community as this provides site specific warnings with higher reliability avoiding the need for unnecessary preparedness/evacuation based on regional warnings alone. The heavy downpour on 6 Aug 2020, initiated a regional warning and second level warning. These are communicated to KSDMA and its screenshot is shown in Fig. 18.

Further to increase the reliability of warnings, risk governance through capacity building and community participation has been initiated. As a first step, the community has been trained in measuring rainfall and updating these measurements via crowdsourcing platforms such as mobile apps and WhatsApp to derive better rainfall thresholds, which act as the first level community-wise warning for that region and enhances the risk perception of the community.

Therefore, by integrating all the components the early warning system has a comprehensive set of submodules to ensure the reliability of the landslide early warning as shown in Fig. 20. The key submodules include such as site characteristics, inputs from landslide laboratory, modeling and simulation, sensor system, algorithms, communication system, software system, dynamic learning and multilevel warning system. This clearly demonstrates that landslide risk reduction would be required to solve multi scale needs through a multipronged approach by utilizing transdisciplinary capabilities and community empowerment as shown in Fig. 21.

Extending landslide risk reduction to multihazard disaster risk reduction, the key solutions that has been developed and utilized are: (a) vulnerability mapping, (b) geotechnical analysis, (c) real-time monitoring of multihazards, (d) Multiscale decision models and early warning, (e) community resilience programs using social media. These integrated comprehensive solutions will enhance the capability to provide multihazard disaster risk reduction (Fig. 19).

Requirements and solutions discussed in this paper are summarized below.

(i) Real-time risk assessment through physical sensing using IoT platform
(ii) Threshold models for decision making from sub-events leading to a landslide
(iii) Machine learning and Artificial Intelligence based models to forecast the futuristic conditions of the slope.
(iv) Factor of Safety models to understand the dynamic variations in slope stability conditions
(v) Multi-level early warning models to provide site-specific and regional warnings.
(vi) Community awareness program to create awareness about landslides in the community and encourage the community to participate in collecting data related to landslides and multi-hazards
(vii) Participatory sensing approaches involving the community through Landslide Tracker mobile app to report landslides and other precursor events.
(viii) Amrita Kripa app to provide rescue and relief during a disaster

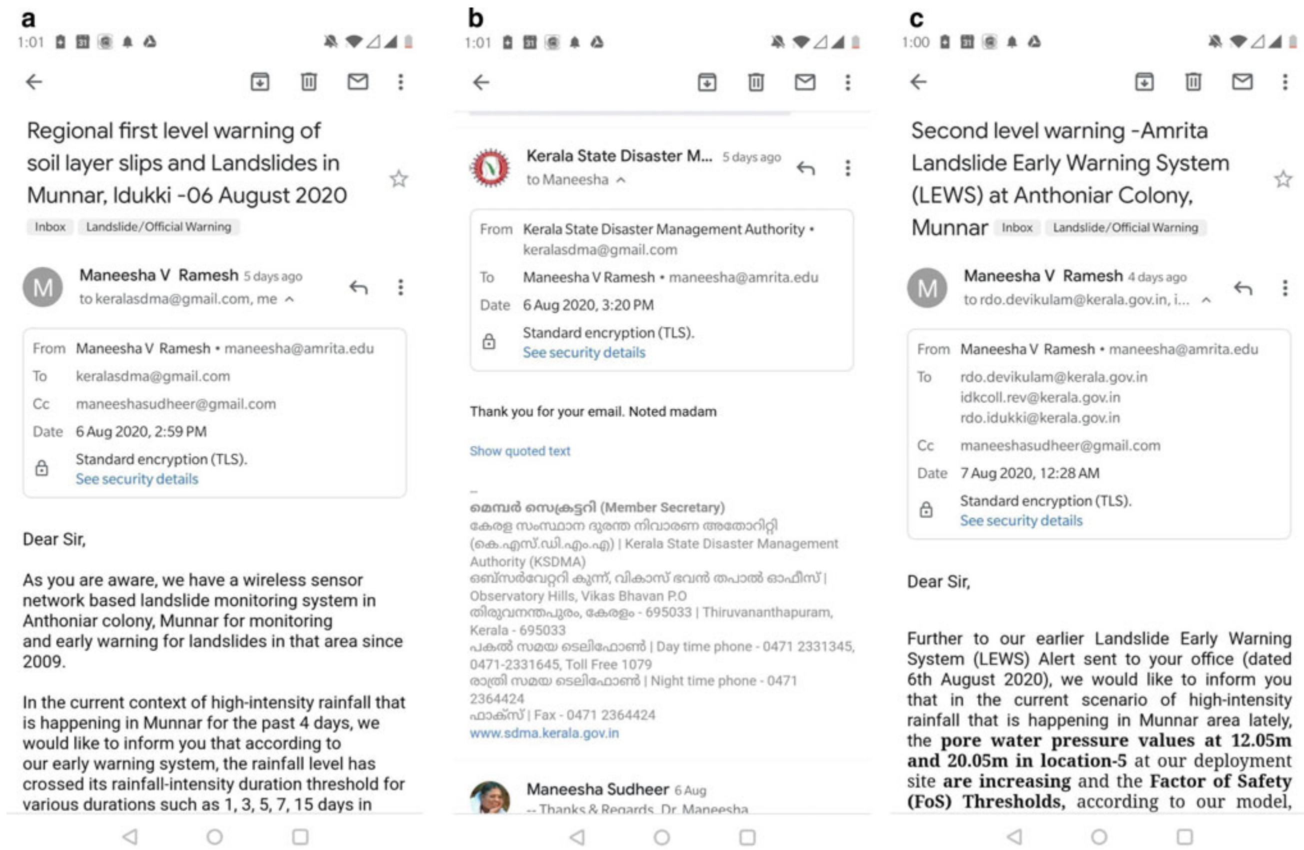


Fig. 18 Regional first level warning. Reply from the KSDMA. Second level warning

(ix) Social models for understanding the ground reality and people's reaction to disaster through social media data analytics.
(x) Twitter data-based automatic event detection, tracking and providing situational awareness models.

To facilitate disaster preparedness and response, specific solutions for the following areas to enhance the existing system are given below:

1. Strengthening activity in the existing volunteer group in Munnar, extending to other landslide-prone areas and facilitating them through community engagements and awareness programs for preparing the community to face future disasters
2. Conducting pre and post monsoon medical camps and providing ICU Ambulance facility during the time of monsoon
3. Providing a copy of LEWS alerts issued to the State government to the community through WhatsApp and facilitating relief and rescue operations through volunteer groups.
4. Facilitating Communication during the rough climate by providing radio-based communication devices
5. Further development of Amrita Kripa App to coordinate and facilitate the relief and rescue operations
6. Suggesting suitable mitigation measures for wherever possible
7. Providing alternative places for their stay after a landslide has destroyed their homes

There is still a long way to go. Also since the areas prone to landslides are quite large and it is challenging to cover the entire area with limited resources. However, the proposed integrated approach detailed in the present paper provides a feasible workflow to achieve this (Fig. 22).

8 Conclusion

The current study is intended to unveil the requirements for landslide risk reduction and design a comprehensive landslide risk management framework. Using this framework, IoT solutions have been proposed. The IoT system for

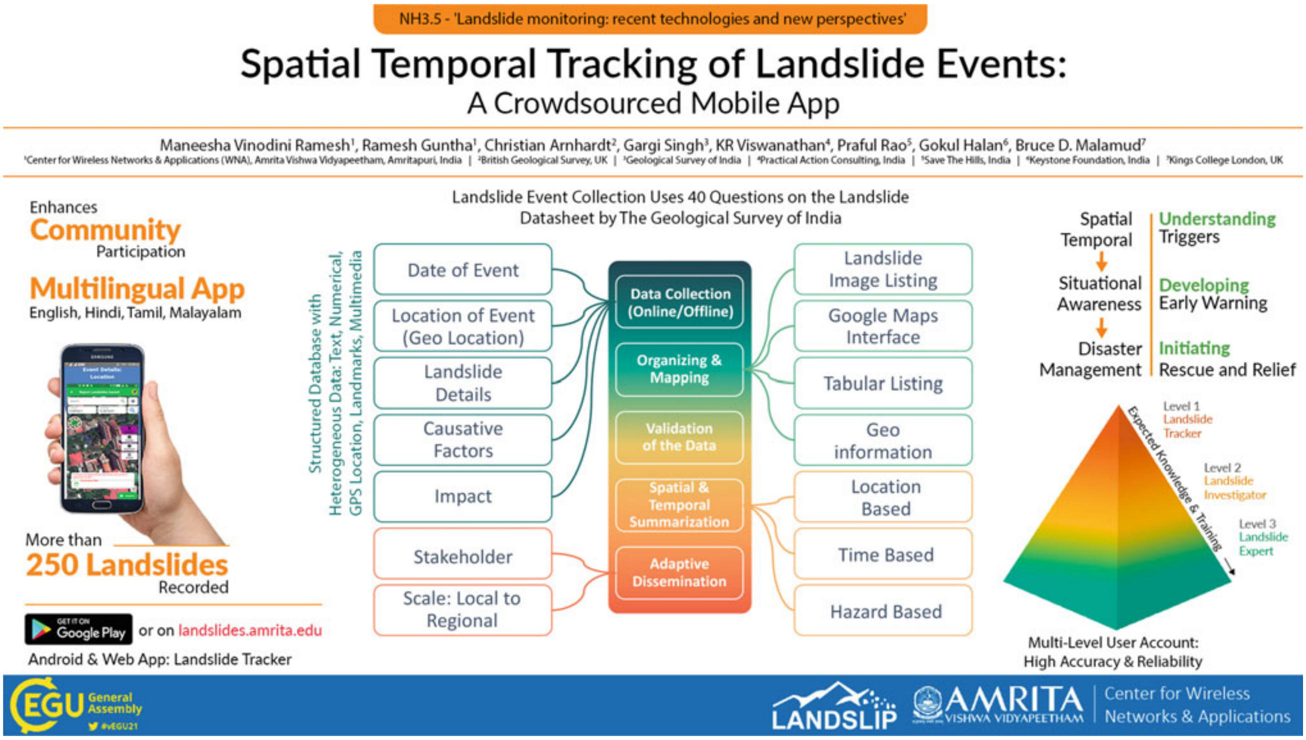


Fig. 19 Landslide tracker: a crowdsourced mobile application

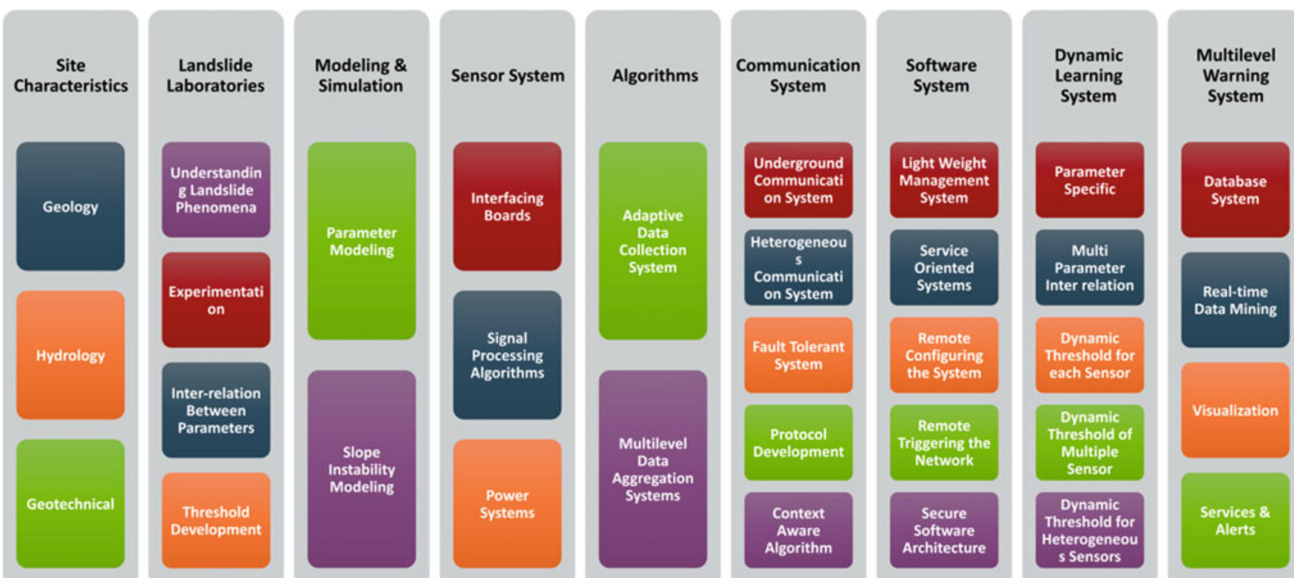


Fig. 20 Comprehensive landslide early warning system

landslide early warning systems deployed at North Eastern Himalayas and Western Ghats has been elaborated. It elaborated the decade-long experience of establishing an end-to-end system for landslide disaster risk reduction. An adaptable and integrated method is suggested for combining the entire requirements of end-to-end community disaster resilience in Amrita-LEWS. Landslide disaster risk reduction is continuously enhanced over a decade-long involvement in Munnar through various means such as threshold models, machine learning models, social models, community

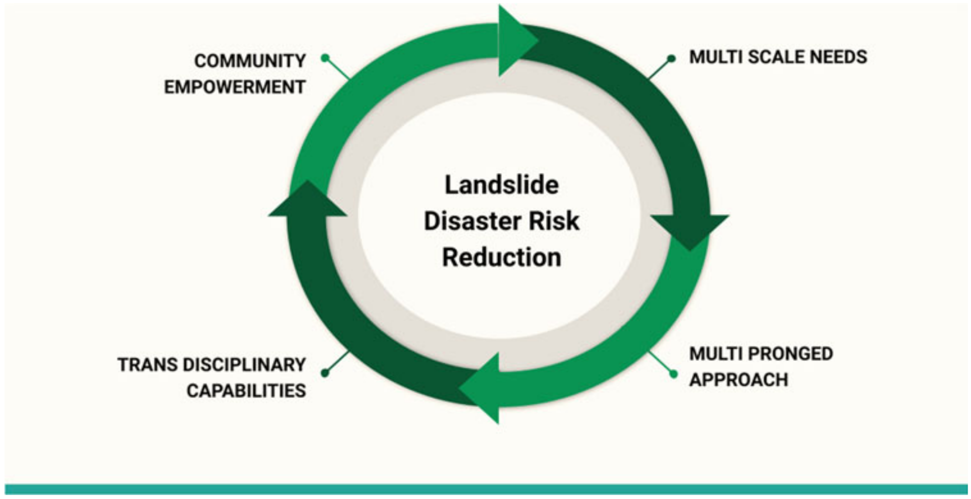


Fig. 21 Landslide risk reduction

Fig. 22 Multihazard disaster risk reduction: approaches and solutions

engagement, Landslide Tracker app and Amrita Kripa app. Amrita-LEWS is replicated in Sikkim region with customization for the terrain conditions there.

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