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Decontextualizing Landslide Early Warning Systems: A Review of Social Acceptance, Trust, and Institutional Capacity

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Abstract: For the past decades, landslide early warning systems (LEWS) have experienced a significant technological development which is characterised by improved rainfall threshold modelling, landslide susceptibility mapping, remote sensing and GIS technologies, hybrid intelligence systems and real time monitoring. Although landslide prediction accuracy has been shown to improve (Chen et al., 2020; Hong et al., 2018; Segoni et al., 2018), the effectiveness of landslide early warning systems is still a concern in many regions around the world. The review aims to summarize key research articles on landslide susceptibility and landslide early warning systems and reinterpret them from a perspective that emphasizes the importance of landslide early warning systems' acceptability, trust, and capacity (Achour & Pourghasemi, 2019; Arabameri et al., 2020). It points to a techno centric bias in the literature and suggests a socio-technical reconfiguration of Landslide Early Warning Systems (LEWS). It outlines an integrative analytical framework that draws on risk perception theory, institutional trust theory, disaster governance theories, and climate adaptation literatures. It ends with a structured research agenda for participatory co-production, explainable artificial intelligence, institution building, and equity-sensitive warning communication.

Keywords: Landslide Early Warning Systems, Institutional Capacity, Disaster Governance. GIS

I. Introduction

Landslides have been defined as a hydro-geomorphologic hazard that frequently occurs in mountainous areas around the world. The intensity of rainfall, which has been intensified by climate variability, has heightened the risk of slope instability (Gariano & Guzzetti, 2016). At the same time, human factors such as deforestation, the growth of settlements, and the construction of infrastructure have also amplified the risk of landslides. In response, scientific research has led to the improvement and development of better prediction technologies. The use of geographic information systems (GIS) in susceptibility mapping (Lee & Pradhan, 2007; Nefeslioglu et al., 2008), frequency ratio and weight-of-evidence modelling (Conoscenti et al., 2015), ensemble machine learning (Pham et al., 2018; Tien Bui et al., 2016), and deep learning (Hong et al., 2018) has led to better spatial hazard detection technologies. Rainfall threshold analysis has been used in providing temporal triggers for issuing landslide warnings (Segoni et al., 2018; Wang et al., 2015). Chang et al., 2021 highlighted that the adaption of remote sensing and technologies of InSAR has led to more real time landslide monitoring capabilities. Intrieri et al., 2013 however emphasised that sensor based infrastructures provide better automated alert systems. However, all these improvements, studies have shown that the landslide warning systems are lagging behind and that is attributed to social and institutional limitations rather than technical. This review seeks to bridge this gap by synthesizing landslide research and perspective of social acceptance, trust and institutional capacity.

II. EVOLUTION OF TECHNICAL FOUNDATIONS IN LEWS

2.1 Statistical and GIS-Based Approaches

The earlier susceptibility studies were carried out through logistic regression analysis and probabilistic modeling (Nefeslioglu et al., 2008), frequency ratio method (Lee & Pradhan, 2007), and weight-of-evidence techniques (Conoscenti et al., 2015). These techniques have provided the basis for spatial hazard zonation for LEWS. The evaluations indicate that there are inconsistencies in methodologies and standardized validation metrics (Yilmaz, 2009), but these models are essential in modern-day methods.

2.2 Rainfall Thresholds and Climate Dynamics

For landslide early warning systems, one of the key aspect is rainfall induced landslides. Real-time triggering of warnings for landslides has been achieved by the application of empirical intensity-duration thresholds (Segoni et al., 2018; Wang et al., 2015).

Gariano and Guzzetti (2016) highlight the increase in landslide occurrence under climate change scenarios. However, rainfall models tend to be specific to certain regions, and there has been a lack of consideration of the effect of communicating the thresholds to the public in technical standardizations.

2.3 Remote Sensing, Machine Learning and Hybrid Intelligence

The application of machine learning has greatly improved the predictive results. The Random Forest and Support Vector Machines have been found to have high accuracy in comparison to other statistical techniques (Pham et al., 2018; Chen et al., 2020). The application of hybrid intelligence techniques that incorporate multi-criteria decision techniques with machine learning has been found to improve robustness (Pourghasemi et al., 2017; Shirzadi et al., 2017). The superiority of hybrid intelligence techniques has been highlighted by Arabameri et al. (2020), but issues with interpretability have been identified. The ability of convolutional neural networks to detect nonlinear spatial relationships has been highlighted by Hong et al. (2018). However, issues with accessibility in resource-scarce regions have been identified. The application of satellite monitoring has been found to improve precision in landslide detection (Chang et al., 2021), while big data analysis has been found to improve precision in landslide detection (Huang et al., 2020). The application of sensor-based infrastructure has been found to improve landslide detection through the integration of rainfall and displacement sensors (Intrieri et al., 2013).

III. SOCIAL ACCEPTANCE OF LANDSLIDE EARLY WARNING SYSTEMS

Social acceptance is defined as the public's acceptance of trust and comprehension of warning information, and acting on it. Studies technically assume rational response behaviour. However, studies on risk perception have shown that response behaviour is socially constructed. Both Reichenbach et al. (2018) and Dikshit et al. (2020) recognize the need for an integrated response but do not discuss response behaviour. False alarms can damage public trust, and under warning can damage institutional trust. Socioeconomic status, disaster experience, and livelihood dependency can affect decision-making on response behaviour. The information presented must be relevant to local circumstances to gain public acceptance

IV. INSTITUTIONAL CAPACITY AND GOVERNANCE STRUCTURES

Institutional capacity refers to financial support, manpower, data-sharing conventions, and legal authority. LEWS, no matter how technologically successful, can fail in a fragmented governance setting. Pradhan and Lee (2010) discuss the issue of GIS integration, but there is no mention of coordination between agencies. Kavzoglu et al. (2014) discuss issues related to spatial resolution but neglect implementation issues. Intrieri et al. (2013) discuss issues related to deployment in rural environments. LEWS implementation demands vertical integration (from national to local levels) and horizontal integration (meteorology, geology, emergency management). Without funding support and institutional ownership, technology can rapidly deteriorate

V. TRUST, TRANSPARENCY, AND ALGORITHMIC GOVERNANCE

LEWS using machine learning techniques raise concerns related to their explainability. Hybrid and deep learning models function as opaque “black boxes.” Such models may not be trusted for decision-making related to issuing evacuation orders. (Arabameri et al., 2020; Hong et al., 2018). Institutional actors may hesitate to base evacuation orders on models lacking interpretability. Trust can be developed through procedural transparency, communication, and accountability. Moreover, public trust can be achieved not only through prediction accuracy but also through the institution's credibility. The development of Explainable AI frameworks and participatory validation processes could also be beneficial.

VI. INTEGRATING RISK PERCEPTION AND DISASTER GOVERNANCE THEORY

Risk Perception Theory focuses on cognitive biases, cultural aspects, and experiential knowledge, which influence response behaviour. Institutional Trust Theory indicates that perceived competence and fairness influence compliance. Disaster governance theories highlight aspects such as coordination, decentralization, and management complexities. The application of the theories in LEWS research extends the depth of analysis beyond purely technical parameters.

VII. SOCIO-TECHNICAL FRAMEWORK FOR LEWS

An integrated framework for Landslide Early Warning Systems (LEWS) should have different technical, institutional, and social components to be effective in terms of accuracy and usability. To begin with, technical soundness in terms of integrating different statistical models, machine learning techniques, and hybrid predictive models should be considered to enhance landslide prediction accuracy. Next, to account for the dynamic changes in climate, climate adaptability should be integrated into landslide warning systems through dynamic recalibration mechanisms to account for changes in rainfall patterns and extreme weather occurrences. In addition, to enhance the effectiveness of landslide warning systems, strengthening institutional capacity in terms of data management and funding should be considered to improve the operation and maintenance of landslide warning systems. Finally, to improve communication with landslide-prone communities in terms of landslide warnings and consequent actions, participatory communication strategies should be considered in landslide warning systems. In this case, it is important to integrate explainable algorithmic techniques to improve stakeholders’ trust in landslide warnings generated by complex algorithmic techniques.

Moreover, the dissemination of warnings should also be sensitive from an equity perspective, ensuring that marginalized groups, remote populations, or digitally excluded groups are not left out. Approaches such as Participatory GIS can greatly improve the effectiveness of the warnings. Interdisciplinary collaboration is therefore critical for the development of socially embedded warning systems. However, one of the most critical challenges that have characterized the development of LEWS initiatives is the tendency of the systems to focus more on the use of technology than on the development of trust with the local population or the institutional capacities of the local government. In this respect, it can therefore be argued that the most advanced of the warning systems may not have the desired impact unless the challenges of governance, local knowledge, or socio-economic inequalities are addressed.

VIII. FUTURE DIRECTIONS FOR STRENGTHENING LEWS

Strengthening Landslide Early Warning Systems requires a more holistic shift from technology-centric approaches to more socially embedded and institutionally responsive approaches. There should be more focus on understanding how communities actually comply with landslide early warnings, which makes longitudinal assessments of warning compliance important. Another important aspect of landslide early warning systems is institutional capacity, which remains a critical concern since the effectiveness of landslide early warning systems often depends on the coordination, preparedness, and responsiveness of local administrative structures. Another way of enhancing landslide early warning systems relevance to communities is by integrating social vulnerability indicators into landslide susceptibility models, which will not only focus on landslide exposure but also on response capacities. Another important aspect of landslide early warning systems in the near future will be the need to develop algorithmic transparency frameworks, especially in machine learning and hybrid predictive models, to enhance trust among landslide early warning systems' stakeholders. Another way of enhancing landslide early warning systems' relevance to landslide-prone communities will be to strengthen community-based landslide monitoring initiatives**.** From a practical viewpoint, it has been noted that a better response to warning systems is achieved when communities are involved and participate in data collection and communication processes, rather than remaining passive responders to technical warnings. Finally, there is a need to mainstream climate change adaptation into landslide early warning systems because changing rainfall patterns and extreme weather occurrences are gradually modifying landslide susceptibility in mountainous regions.

IX. CONCLUSION

It can be stated that Landslide Early Warning Systems (LEWS) have developed significantly with the enhancement of geospatial technology, remote sensing, and predictive models. However, it has been identified through this review that the sophistication of technology alone is not sufficient for the effectiveness of the warning systems in reducing landslide-related hazards. The effectiveness of the Landslide Early Warning Systems depends on the degree of acceptance by the people, the trust that the public places in the warning systems, and the institutional capacity of the agencies that are involved in the dissemination of the warnings. Most of the existing landslide early warning systems have been identified as techno centric, ignoring the socio-political factors that influence the acceptance of the warnings.

Hence, for their effectiveness, it is essential to recontextualize Landslide Early Warning System as socio technical systems within a broader governance structure and societal context.. For example, the incorporation of participatory components, transparent communication strategies, and institutionalized collaboration can be helpful for improving the overall credibility of warning information, among other aspects. Conclusion: The gap between technology and society is essential for ensuring that landslide early warning systems can be effectively used for risk reduction and building resilience in landslide-prone regions of the world.

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