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INTEGRATED GEOTECHNICAL MODELLING AND REAL-TIME ANALYSIS FOR PREDICTING EARTHQUAKE-INDUCED LANDSLIDES AND ROCKFALLS IN THE EAST AFRICAN FRACTURE ZONE

Ali Akbar Firoozi[1*], Ali Asghar Firoozi[2], Khaled Aati[3*], Muhammad Shahid Rashid[4]
[1]Department of Civil Engineering, Faculty of Engineering & Technology, University of Botswana, Gaborone, Botswana
[2]Department of Civil Engineering, Faculty of Engineering, National University of Malaysia (UKM), Selangor, Malaysia
[3]Civil and Architectural Engineering Department, College of Engineering and Computer Sciences, Jazan University, P.O Box 706, Jazan, 45142, Saudi Arabia
[4]Department of Physical Sciences, Physics Division, College of Science, Jazan University, P.O. Box. 114, Jazan 45142, Kingdom of Saudi Arabia
*Corresponding email: a.firoozi@gmail.com; kaati@jazanu.edu.sa

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Background: The East African Fracture Zone (EAFZ) stands as a testament to the dynamic forces of Earth, marked by heightened seismic activity that frequently triggers geotechnical disasters such as landslides and rockfalls. Traditionally, the study of earthquake-induced geological risks has been reactive, with a focus on post-incident analysis. While significant advances have been made in spatial analysis and risk mapping, the capabilities for real-time prediction and proactive mitigation are still limited. **Objectives:** Current study presents an approach to predicting earthquake-induced landslides and rockfalls in the EAFZ. The aim is to change the perception of the problem by viewing disasters as manageable risks and informing decision-making in urban planning and disaster mitigation strategies. **Methods:** A combination of geotechnical engineering, remote sensing, artificial intelligence and machine learning, and socio-economic analysis were used to develop a holistic software framework that solves the complex problem of earthquake prediction without any problems. **Results:** A software model has been developed that includes a dynamic learning component that refines its predictions with new data, allowing for a deeper understanding of geological subtleties and socio-economic impacts. Considerable attention is paid to the tangible consequences of landslides and rockfalls, including human, property and economic losses. Despite the inevitable challenges of data accuracy and natural unpredictability, the proposed approach opens up new possibilities for proactive disaster management. The results demonstrate a transformational step in data-driven geotechnics and highlight the global applicability of the methods proposed in this work. **Conclusion:** In this investigation, was taken a pioneering stride in the realm of geotechnical hazard analysis and prediction, focusing on the complex terrains of the East African Fracture Zone (EAFZ). The results provided critical insights into the dynamics of geotechnical hazards in the EAFZ, laying the foundation for future innovations and enhanced safety measures in vulnerable communities.

Keywords: earthquake-induced landslides; rockfall prediction; geotechnical engineering; machine learning; remote sensing; socio-economic impact analysis.

INTRODUCTION

The East African Fracture Zone (EAFZ) stands as a testament to the dynamic forces of Earth, marked by heightened seismic activity that frequently triggers geotechnical disasters such as landslides and rockfalls. These natural events, particularly devastating in densely inhabited areas, pose significant threats to human lives and infrastructure. Understanding and accurately predicting the initiation and progression of these seismic-driven phenomena are crucial for effective disaster mitigation and preparedness.

Historically, the interplay between geotechnical engineering and seismology has garnered substantial interest, yet the complex dynamics within critical areas like the EAFZ are not fully understood (Shano et al., 2021; Kasai & Yamada, 2019). Factors like slope gradient, rock type, and soil composition significantly influence an area's susceptibility to landslides and rockfalls. However, it is often the seismic tremors acting as external catalysts that compromise slope stability, leading to rapid and destructive mass movements (Bezak & Mikoš, 2021).

Traditionally, the study of earthquake-induced geohazards has been reactive, focusing on post-incident analyses. Notable seismic events like the Northridge earthquake of 1994 and the Chi-Chi earthquake of 1999 have spurred extensive research, but this reactive approach inherently limits the potential for real-time forecasting and proactive mitigation (Wang et al., 2019). Nevertheless, the advent of Geographic Information Systems (GIS) and advanced computer simulations marks a significant shift, offering enhanced spatial analysis and risk mapping capabilities. Despite these advancements, the unpredictable nature of earthquakes and the complex interplay of geotechnical attributes continue to make predictive modelling a challenging endeavour (Kristensen et al., 2021; Ferlisi et al., 2019).

In response to these challenges, this study seeks to combine a wealth of geotechnical and seismic data with advanced data science techniques, aiming to provide a novel perspective on disaster risk management in high-risk seismic zones. The EAFZ, with its intricate geological and seismic landscape, presents unique challenges. Factors like slope stability, rock and soil mechanics, groundwater conditions, and seismic activity intermingle to dictate the region's susceptibility to landslides and rockfalls. The repercussions of earthquakes often extend far beyond their immediate vicinity, triggering secondary hazards at significant distances from the epicentre (Regmi & Agrawal, 2022; Shao & Xu, 2022). Moreover, certain geotechnical conditions can exacerbate the magnitude and frequency of these events, yet predicting their precise occurrence remains a complex task (Corominas et al., 2014).

Researchers have developed various methodologies to assess and predict risks in seismic zones. Deterministic models, while rooted in a deep understanding of physical processes, often falter due to data limitations. On the other hand, probabilistic models, which embrace the inherent uncertainties of data, require extensive and accurate datasets for effectiveness (Regmi & Agrawal, 2022).

Emerging as a promising solution, Machine Learning (ML) models are capable of discerning complex relationships and enhancing prediction accuracy. However, the success of these models is deeply tied to the quality and comprehensiveness of the input data, and their "black box" nature can obscure understanding of their inner workings (Shao & Xu, 2022).

The occurrence of earthquake-induced landslides is a well-documented phenomenon that has been studied across various geological settings worldwide. Significant insights can be derived from analysing previous studies, such as Keefer's seminal work, which systematically categorized landslides induced by earthquakes and provided a foundational understanding of their triggers (Calamita et al., 2023). Similarly, Novellino et al. (2021) have contributed detailed analyses of landslide distributions following significant earthquakes, offering valuable data on patterns of slope failures that can be compared against those observed in the EAFZ.

Furthermore, numerous studies have explored the complex mechanics of landslides triggered by seismic activities, emphasizing the role of geological features, seismic characteristics, and hydrological conditions. For instance, Gorum et al. (Saha et al., 2020) examined the 2011 Tohoku earthquake in Japan, revealing how seismic wave amplification due to local geology can significantly affect the extent and severity of landslide occurrences. This study, along with others, underscores the importance of integrating localized geological data for predicting landslide risks, a principle your research applies to the EAFZ.

Building on these studies, recent advancements in technology and methodologies have played a pivotal role in enhancing predictive models. For example, Liao and Lee (Aguiar et al., 2024) developed a sophisticated model integrating real-time seismic data with geotechnical analysis to predict landslide occurrences immediately following an earthquake, demonstrating an improvement in predictive timings and accuracy. This methodological evolution points towards an increasing ability to not only understand but also anticipate geotechnical disasters, aligning with the goals of your current study.

The importance of integrating a diverse range of studies cannot be overstated, as highlighted by recent research that has begun to incorporate the effects of climate change on seismic-induced landslide susceptibility. An analysis by Rudin et al. (Rudin, 2019) on the increased frequency of landslides under changing climatic conditions offers a pertinent perspective for your study, which also considers these broader environmental factors.

This research is an ambitious endeavour to merge traditional methodologies with ML techniques, compiling a diverse dataset to construct a comprehensive model for the EAFZ. The proposed model is designed to be adaptable, evolving with new data and insights. It aims to revolutionize predictive capabilities and risk management strategies for landslides and rockfalls in seismic regions. By providing a holistic tool for risk assessment, this study seeks to inform and improve natural disaster management strategies. Additionally, acknowledging the increasing influence of climate change, in the current work was taken into account its potential impact on the EAFZ's slope stability and seismic response, ensuring our model remains relevant and robust in the face of a changing climate.

CASE STUDIES

To elucidate the complex interplay of natural and human-induced factors contributing to landslides and rockfalls in the EAFZ, were explored various case studies from the region. These investigations shed light on the intricate dynamics shaping geological stability and highlight the inherent risks associated with the EAFZ's unique tectonic landscape. As illustrated in Figure1, the EAFZ is characterized by multiple tectonic branches and is dotted with significant lakes formed as a result of the rifting process. The map's depiction of the Main Ethiopian Rift, Western and Eastern branches, and the North Tanzanian Divergence elucidates the extensive network of fault lines that contribute to the region's geological instability.

Understanding the EAFZ's geological framework is critical for interpreting the case studies within their appropriate context. The map underscores the distribution of tectonic forces across East Africa, which, along with climatic variables and human activities, plays a pivotal role in the frequency and intensity of landslide and rockfall events. In this light, Figure 1 serves as a foundational reference that complements the detailed analyses of individual case studies, offering a macroscopic view of the geological underpinnings that influence the susceptibility of the region to such natural disasters.

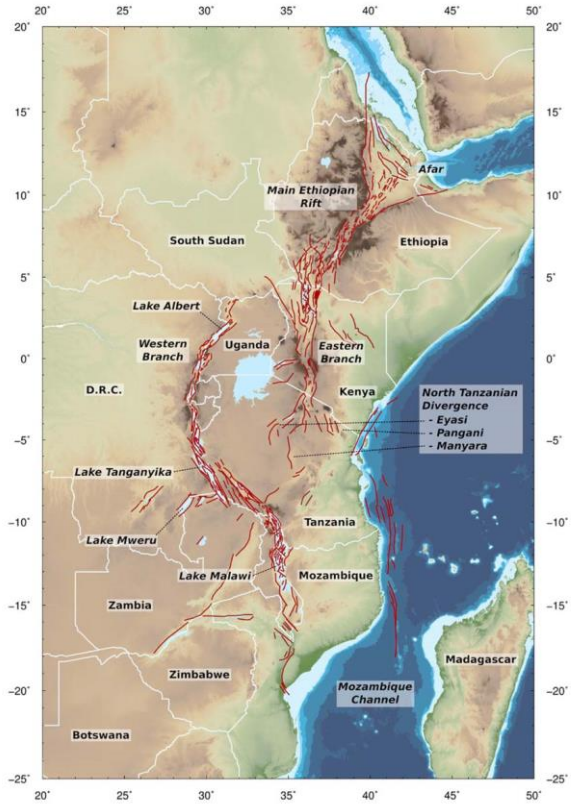

Figure 1. Geographical map of the EAFZ showing tectonic features and major lakes (Craig & Jackson, 2021)
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Mount Elgon region

The Mount Elgon region, straddling the border between Uganda and Kenya, is a notable area of interest within the EAFZ due to its heightened susceptibility to seismic-triggered landslides. This ancient, eroded volcano presents a complex geological and environmental landscape that plays a critical role in the region's propensity for such natural disasters.

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Characterized by its steep slopes and unique geological structure, Mount Elgon's terrain is inherently predisposed to instability. This instability is particularly pronounced under conditions of intense precipitation, which often infiltrates the soil, reducing its cohesion and increasing the likelihood of slope failure. The area's volcanic soils, known for their loose structure and susceptibility to erosion, further exacerbate this risk.

Human activities have significantly amplified the region's vulnerability. Deforestation for timber and land clearing for agriculture has stripped away much of the natural vegetation. This deforestation not only removes the root structures that help stabilize the soil but also reduces the land's ability to absorb rainfall, leading to increased runoff and erosion. Unsustainable agricultural practices on steep slopes without adequate soil conservation measures contribute further to the destabilization of the landscape.

In 2010, Mount Elgon was the site of a catastrophic landslide following a prolonged period of heavy rainfall. Notably, this event was preceded by an earthquake one week prior, which likely contributed to weakening the already unstable slopes. The resulting landslide led to significant loss of life and property, underscoring the devastating impact of these events.

Authors of the study (Broeckx et al., 2019; Figure 5), as referenced, illustrates the landslide and rockfall susceptibility maps for the Mount Elgon region. These maps are crucial tools, depicting varying degrees of risk across different areas and serving as a visual aid for understanding the spatial distribution of hazards. They are vital for informing effective risk mitigation strategies, guiding land-use planning, and enhancing public awareness and preparedness.

Such incidents highlight the critical interplay between natural geological processes and anthropogenic factors in shaping landslide dynamics. A comprehensive understanding of these susceptibilities is essential for developing effective risk mitigation strategies. Moreover, they emphasize the need to inform the local populace and policymakers about the inherent risks and the measures that can be taken to reduce them.

The Mount Elgon region's case exemplifies the complex and multifaceted nature of landslide risks. It calls for a multidisciplinary approach to disaster risk management, combining geotechnical analysis, environmental conservation, community engagement, and policy intervention. By addressing both the natural and human-induced factors contributing to landslide susceptibility, work must be done to create more resilient and safer future for the communities residing in the shadow of Mount Elgon and similar regions worldwide.

The Wenchuan earthquake-induced landslides

The Wenchuan county, positioned within the Sichuan Province of China, became the focal point of global attention following a severe 8.0 magnitude earthquake on May 12, 2008. This tremor set off a series of landslides, with a scale of devastation that ranks among the most catastrophic in recent history. Figure 2 depicts the extent of the earthquake-induced landslides, the areas subjected to detailed monitoring, and the geological features of the region. Notably, the Beichuan vicinity bore the brunt of the disaster, witnessing entire mountainsides disintegrate and cascade into the valleys below, engulfing towns and vital infrastructure within their path.

Subsequent investigations have illuminated the inherent geological vulnerabilities of the area: a combination of steep gradients, soil saturation, and the intersection of multiple fault lines. These factors, when jarred by the earthquake's seismic waves, resulted in the overwhelming landslide activity observed. The landslides were not merely a product of the earthquake's immediate disturbance but also of the geological tension that had built up over time, which the earthquake unleashed.

The aftermath of the Wenchuan earthquake provides an indelible lesson on the potential for seismic events to trigger widespread geological disasters in susceptible regions. It underscores the necessity for stringent earthquake readiness, judicious land management in seismic territories, and a deeper comprehension of how geological and seismic dynamics interweave. Continuing to analyse this event is imperative for the advancement of predictive models and the formulation of more effective landslide mitigation tactics.

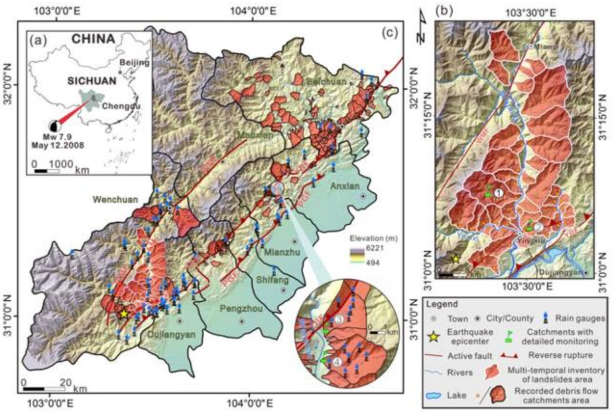

Figure 2. Geographical overview of the Wenchuan earthquake-induced landslides and geological features (Fan et al., 2019) (This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/))

The Bududa landslides

The Bududa District, perched on the verdant slopes of Mount Elgon in Eastern Uganda, is part of the geologically active EAFZ and has endured repeated devastating landslides. The district's tragic history is punctuated by numerous events, with one of the most catastrophic occurring in March 2010. After prolonged heavy rains, a colossal landslide swept through the villages of Nametsi, Kubehwo, and Namangasa, obliterating them from the Bududa landscape. The calamity claimed over 300 lives and left thousands homeless, as shown in the paper (Dierickx, 2014; Figure 4-12), which illustrates the topography and areas of landslide incidence in the region.

Investigations into this calamity identified a combination of risk elements that rendered Bududa exceptionally prone to landslides. The steep volcanic slopes of Mount Elgon, characterized by fragile geological materials, are inherently unstable. When saturated by the region's intense seasonal rainfall, these slopes become highly susceptible to landslides, a persistent threat to the area.

The human imprint on the 2010 landslide's severity is undeniable. Deforestation for farming and habitation has largely denuded the hillsides of their stabilizing vegetation, which would typically retain soil and water. Furthermore, land utilization practices that disregard the terrain's limitations, such as farming on steep gradients and substandard building methods, have significantly contributed to the land's instability.

The 2010 Bududa disaster has emphasized the imperative of all-encompassing risk management approaches. Initiatives have been directed towards relocating at-risk populations to safer locales and enhancing early warning systems. Despite these efforts, challenges persist, notably the local populace's reluctance to move and the necessity for sustainable land use policies.

Moreover, the Bududa landslide is a stark illustration of the intricate dynamics between natural processes and anthropogenic factors in the context of landslide hazards. It stands as a poignant reminder of the essentiality of integrated strategies that address geological, meteorological, and societal elements in disaster risk reduction.

In memorializing the lives lost, the Bududa landslides also serve as an invaluable case study for a diverse range of experts, from geotechnical engineers to social scientists. It underscores the urgency for cooperative endeavours to develop and enforce far-reaching and enduring landslide risk mitigation measures in similar settings globally. Sustained research, community involvement, and advancements in early warning systems are critical in protecting vulnerable populations and preventing future calamities.

These case studies exemplify the complex challenges posed by landslides and rockfalls within the EAFZ. They highlight the necessity of adopting a comprehensive, multidimensional approach to understanding and mitigating these hazards. The subsequent sections will detail an advanced methodology that integrates seismic, geotechnical, climatic, and anthropogenic factors to provide a thorough analysis of landslide and rockfall risks in the EAFZ. This integrative approach aims to enhance our predictive capabilities and inform more effective strategies for disaster risk management in this seismically active region.

The Menchum Valley landslide, Cameroon

Located within the seismically active nexus of the EAFZ in Cameroon, the Menchum Valley is frequently confronted with landslides, a testament to the region's volatile interplay of geological and climatic forces. The area's susceptibility to these natural disasters was brought into sharp focus in 2001 when a 5.6 magnitude earthquake precipitated a massive landslide. This disaster led to significant material displacement and, regrettably, the loss of lives, illustrating the immense power of seismic events to trigger landslides in geologically sensitive zones such as the EAFZ.

The geological makeup of the Menchum Valley is a significant factor in its vulnerability. Characterized by its volatile volcanic soils and pronounced slopes, the terrain is inherently unstable. These fertile yet friable volcanic soils are prone to erosion, particularly when waterlogged. As depicted in Figure 3, the valley's steep topography and the distribution of seismic activity across Cameroon exacerbate these instabilities, making even minor tremors a potential catalyst for soil and rock displacement that can lead to landslides.

The valley's climatic conditions, marked by intense rainfall, also play a critical role in landslide risk. Heavy rainfall can oversaturate soil strata, increasing their mass and diminishing their structural integrity. In conjunction with the valley's topographical and geological characteristics, these meteorological patterns set the stage for landslides, especially following seismic disturbances.

The 2001 Menchum Valley landslide is a sombre indicator of the imperative need for thorough risk assessments and proactive disaster management strategies in regions like the EAFZ. A comprehensive understanding of the distinctive geological and climatic traits of these areas is essential for anticipating and alleviating the effects of landslides. The event further emphasizes the importance of community education, the enhancement of early warning systems, and the adoption of land-use measures designed to mitigate vulnerability to such disasters. Refer to Figure 3 for an overview of seismic dissemination in Cameroon and the broader African context, compiled from data sources dating back to Krenkel in 1900 through to Tchindjang in 2012.

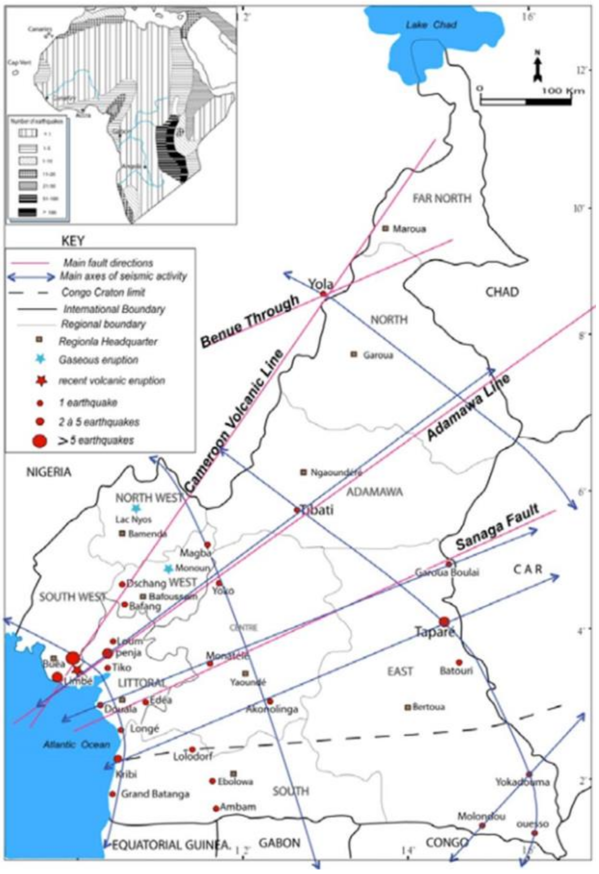

Figure 3. Seismic activity and geological features in cameroon and the menchum valley region (Amah et al., 2022)

The Aberdare Range landslides, Kenya

Nestled within the dynamic confines of the EAFZ, the Aberdare Range in Kenya is defined by its sharp inclines, delicate geological structures, and a climate prone to intense precipitation. These elements conspire to render the area particularly vulnerable to landslides, with dire consequences for both human settlements and the natural environment.

The precarious nature of this terrain was starkly illustrated in 2012 when an extraordinary bout of concentrated rainfall precipitated a series of landslides across the range. The resulting upheaval forcibly relocated communities, inflicted extensive damage to property, and shattered the landscape, as evidenced by the disturbances marked in Figure 4. The map shows the complex terrain of the region and the sites of meteorological stations, which play a crucial role in monitoring rainfall patterns that can initiate landslides.

Analyses conducted in the aftermath recognized multiple factors that amplified the impact of these landslides. Human interventions, especially the clearing of forests for timber extraction and the advancement of agricultural frontiers, have significantly altered the landscape. The eradication of native vegetation, particularly on the range's steeper sections, drastically reduced the soil's resilience against erosive forces.

Additionally, agricultural endeavours on these gradients, lacking adequate soil preservation techniques, further undermined the land's stability.

The geology of the Aberdare Range, predominantly volcanic, inherently facilitates swift erosion and landslides, especially under the assault of heavy rainfall. The inclines of the range intensify this susceptibility, where minor perturbations can provoke substantial movements of soil and rock. Figure 4 not only captures the topographical and meteorological nuances of the region but also serves as a visual testament to the critical need for integrated risk management approaches that address the complex interplay of natural and human-induced factors influencing landslide incidence in the Aberdare Range.

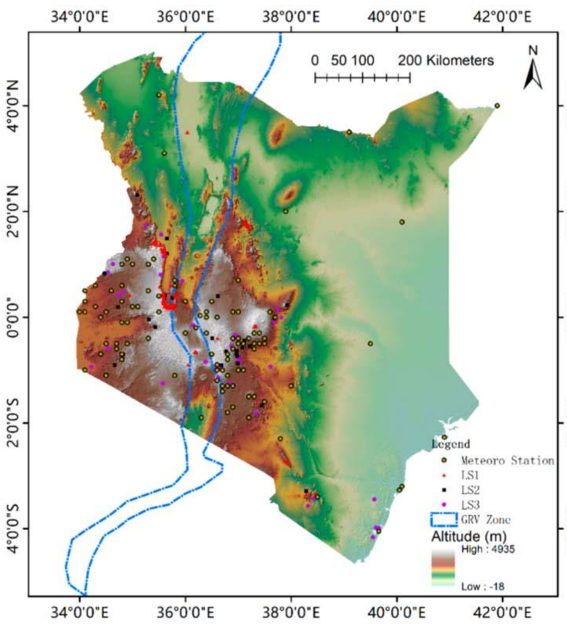

Figure 4. Topographic map of the aberdare range indicating meteorological stations and landslide zones
(Zhou et al., 2020) (© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions
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The West Pokot landslides, Kenya

West Pokot County, located in Kenya's Rift Valley Province within the EAFZ, was the site of one of the most devastating landslide events in recent history. In November 2019, intense rainfall over a short period triggered a series of landslides, resulting in significant loss of life and property, and widespread displacement and infrastructure damage. The event highlighted the critical role that extreme weather conditions play in instigating landslides within the EAFZ. Subsequent analyses attributed considerable influence to anthropogenic factors such as deforestation, population pressure, and agricultural practices on steep slopes, which intensified the region's susceptibility. This case study serves as a stark illustration of the compounded risks in areas where human impact and unfavourable geotechnical and climatic conditions converge (Obwocha et al., 2022).

The Nyos-Subum volcanic area, Cameroon

The Nyos-Subum volcanic region, situated in north-western Cameroon, exemplifies the complex relationship between volcanic activity, seismicity, and environmental factors, creating a landscape highly prone to landslides. A significant landslide event in 1986, triggered by a 5.2 magnitude earthquake, led to a deadly release of CO_2 from Lake Nyos, resulting in extensive loss of life and property. The unique geological features of this area, including volcanic rocks and deep weathering profiles on steep slopes, significantly increase its susceptibility to landslides. The added factor of seismic activity introduces an additional layer of risk, highlighting the importance of considering the interconnectedness of various geophysical phenomena when assessing landslide susceptibility in the EAFZ (Zangmene et al., 2023).

The case studies from 2.4 to 2.7 collectively emphasize the multifaceted nature of landslide and rockfall issues in the EAFZ. An integrated approach that simultaneously considers seismic activities, geological conditions, climate change, and human activities is essential for an effective understanding and mitigation of these complex and interrelated problems.

The Tukuraki landslides, Fiji

While the primary focus of our study is the EAFZ, examining regions with similar geotechnical characteristics worldwide offers valuable parallels and insights. A poignant example is the 2012 Tukuraki landslide in Fiji. This disaster, instigated by a prolonged period of heavy rainfall, obliterated an entire village, causing loss of life and destruction of property. The underlying geology of weathered volcanic rock combined with the area's steep topography were critical in facilitating this severe landslide (Shiiba et al., 2023). The Tukuraki incident reflects the broader geological and environmental factors that can lead to landslides in regions akin to the EAFZ. Understanding these shared precipitating factors is crucial in developing more effective mitigation strategies for managing earthquake-induced landslides and rockfalls in diverse settings.

The Christchurch earthquake, New Zealand

Beyond Africa, the 2011 Christchurch earthquake in New Zealand serves as an illustrative case study. The event, triggered by a 6.3 magnitude quake, resulted in widespread landslides and rockfalls across the region. The specific geological makeup of the area, characterized by greywacke rock overlain by loess and other Quaternary deposits, played a significant role in the incident, causing thousands of landslides (Massey et al., 2020). This case underscores the critical importance of incorporating both geological and seismic factors in landslide risk assessments and urban planning, providing valuable lessons for similar geotechnical contexts.

The Zhouqu landslide, China

The Zhouqu landslide of 2010, occurring in China's Gansu Province, was a devastating event triggered by intense rainfall and compounded by seismic activity. The region's composition of loose sedimentary soil and steep terrain significantly contributed to the disaster's severity. The earthquake prompted landslides in the heavily weathered rock, resulting in a massive debris flow (Lin et al., 2022). This case highlights the deadly combination of meteorological and geological vulnerabilities that can lead to catastrophic landslides.

Mocoa landslide, Colombia

In 2017, the Mocoa region of Colombia witnessed a catastrophic landslide following intense rainfall, claiming the lives of over 300 people. This event is a stark reminder of the devastation that can occur from a combination of meteorological and geological vulnerabilities, a scenario that is very relevant to the EAFZ (Gómez et al., 2023).

In conclusion, these cases from around the world emphasize the crucial need to understand the complex interplay between geological and meteorological factors in managing landslide and rockfall hazards. Each case provides valuable insights and lessons that can enhance our understanding and methodologies for addressing earthquake-induced landslides and rockfalls in regions like the EAFZ.

Table 1 provides a summary of these case studies, encapsulating essential information and insights derived from each event, thereby offering a concise resource for understanding the multi-faceted nature of these disasters.

By analysing these diverse and instructive case studies, work must be done to prepare for better equip ourselves to predict, prepare for, and mitigate the devastating effects of landslides and rockfalls in seismic regions like the EAFZ.

Table 1. Case Study Summary

Case study	Location	Date	Type of event	Triggering event	Impacts	Lessons learned
1	Nepal, Gorkha	2015-04-25	Landslide	Gorkha Earthquake	Significant loss of life and extensive damage to infrastructure	Highlighted the need for improved monitoring and preparedness, particularly in high-risk areas
2	Japan, Hokkaido	2018-09-06	Landslide	Hokkaido Eastern Iburi Earthquake	Disruption of transport, electricity, and telecommunication services	Emphasized the need for prompt emergency response systems and community evacuation plans
3	New Zealand, Canterbury	2011-02-22	Rockfall	Christchurch Earthquake	Property damage, especially in the Port Hills suburb of Christchurch	Highlighted the role of slope gradient and rock fracture in rockfall risks
4	Italy, Central Regions	2016-08-24	Landslide	Central Italy Earthquake	Destruction of hillside towns, historical sites, and key infrastructure	Reinforced the necessity of maintaining older structures and considering landslide risks in urban planning
5	China, Sichuan	2008-05-12	Landslide	Sichuan Earthquake	Massive casualties and economic loss	Strengthened national focus on early warning systems and public education regarding landslide risks

METHODOLOGICAL REFINEMENT AND EXPANDED ANALYSIS

To effectively address the complex and often unpredictable nature of earthquake-induced landslides and rockfalls, it's critical to utilize refined methodologies that encompass the wide array of influencing factors. This research introduces an integrated approach that synergizes various predictive models for a comprehensive and nuanced analysis.

Integrated predictive modelling

Merging diverse models enhances the predictive scope and precision, a critical consideration given the varied geological characteristics and inherent unpredictability of geological events. Traditional deterministic models, while vital for understanding the mechanical behaviour of soils and rocks during seismic activities, often fall short in accounting for the unpredictable nature of geological phenomena. To address these uncertainties, in the current work, the authors proposed the integration of machine learning (ML) models into our predictive framework. Specifically, the study was focused on Random Forests (RF) and Support Vector Machines (SVM) due to their adaptability and robustness in handling complex datasets.

Let's consider rockfall frequency denoted as F_r. The relationship can be represented as:

$$F_r = g(S_e, T_r), \quad (1)$$

where g is a function determining rockfall frequency based on seismic energy and topographical variations; S_e is represents the seismic energy, derived from the Richter scale magnitude through an appropriate conversion function; T_r is stands for topographical variations, indicating the vertical elevation changes in a specific zone.

Random Forests (RF): RF is an ensemble learning method renowned for constructing multiple decision trees during training. It delivers output based on class majority for classification or average prediction for regression problems. Its capability to handle complex interrelations between parameters and vast datasets makes it particularly suited for predicting landslides and rockfalls.

Support Vector Machines (SVM): SVM is a powerful ML tool used for both classification and regression tasks. It operates by mapping input data into a higher-dimensional space and then identifying a hyperplane that best segregates different categories. Its proficiency in managing non-linear relationships between parameters makes it an excellent choice for our predictive needs.

Our analysis employs both RF and SVM models, drawing on data from past earthquakes, including those within our study zone. This combined approach yields a probabilistic forecast that adequately accounts for the uncertainties inherent in geological events. The probability, P(L), of a landslide occurring is influenced by several factors. An initial model might be formulated as:

$$P(L) = f(\theta, V, R, S, I), \quad (2)$$

where θ is slope angle; V is vegetation density; R is rainfall rate; S is soil variety; I is seismic intensity.

By integrating these diverse parameters, our methodological refinement aims to provide a more accurate and comprehensive understanding of the risks associated with landslides and rockfalls, thereby enhancing our predictive capabilities and informing more effective mitigation strategies.

Assembling and Pre-processing data

At the core of an effective predictive model lies a comprehensive and diverse dataset. The authors of the current study aggregated data from various sources, encompassing geographical, geological, and seismic nuances of zones prone to earthquakes. This data, which includes detailed geological profiles, topographic characteristics, and seismic records, has been meticulously sourced and organized. Once compiled in a GIS framework, were addressed missing entries with advanced imputation techniques, ensuring our dataset's integrity and continuity.

For our machine learning endeavours, our primary focus was on historical instances of landslides and rockfalls. This data was extracted from historical records, satellite imagery, and on-site research. Given the inherent imbalance in our dataset, was employed the Synthetic Minority Over-sampling Technique (SMOTE) to rectify this. Pre-processing was a critical step to standardize and normalize the data, rendering it suitable for ML algorithms.

Selecting features and model formulation

Given the extensive nature of our dataset, identifying the most relevant predictors for landslides and rockfalls was paramount. Feature selection is crucial, not only for refining model performance but also for enhancing interpretability. The current work involved employing a combination of filter and wrapper methods for a comprehensive feature selection process. Following this, were implemented various machine learning techniques to formulate predictive models. Each model was subject to rigorous tuning and evaluation, resulting in robust constructs capable of predicting the likelihood of landslides and rockfalls in the East African Fracture Zone.

Advancements in Data-driven analysis and Real-time monitoring

Our capacity to predict earthquake-induced landslides and rockfalls in the EAFZ has significantly improved thanks to advancements in data-driven analysis and real-time monitoring technologies. Integrating localized geological and socio-economic data with real-time monitoring systems offers a nuanced and comprehensive perspective on the probable occurrence and potential impact of these geohazards.

State-of-the-art data collection tools like LIDAR provide high-resolution, three-dimensional insights into land surface characteristics, greatly enhancing the accuracy of our prediction models. Our novel algorithm, leveraging these technological advancements and extensive datasets, underscores our commitment to improving prediction precision and speed.

Incorporating innovations such as LIDAR and Synthetic Aperture Radar (SAR) into our model marks a significant advancement in geotechnical engineering. It boosts our ability to predict and thereby assists disaster management organizations in focusing their efforts on high-risk zones. However, recognizing the potential for further improvement, efforts were still made to explore new technologies, datasets and methodologies to continuously improve the proposed predictive model.

A key aspect of our data-centric approach is the inclusion of socio-economic data, often overlooked in traditional frameworks. This ensures a comprehensive analysis, considering both geological threats and their potential impact on local populations. Consequently, this paves the way for a more profound understanding of earthquake-induced landslide and rockfall risks, thereby enhancing disaster management strategies.

Moreover, our unique algorithm, capable of handling large datasets, represents a significant leap in data-driven geotechnics. Utilizing machine learning and AI capabilities, it continuously refines its predictions, adapting to evolving geological and socio-economic scenarios. Crucially, integrating real-time monitoring into our model transforms it into a proactive tool. By using sensors and other surveillance technologies, there is a possibility to obtain real-time data on geological movements and other relevant factors. This data, when fed into our model, allows for immediate alerts concerning potential landslide or rockfall events, significantly enhancing disaster mitigation efforts and potentially saving lives.

Integrated hazard assessment through advanced modelling frameworks

Recognizing the multifaceted nature of geohazards, where landslides and rockfalls often coexist with seismic tremors, soil liquefaction, and ground shaking, it is crucial to acknowledge and address these interconnections to enhance predictive accuracy (Nguyen & Kim, 2021). To this end, was developed a multifaceted modelling framework that integrates various hazard models, culminating in a comprehensive hazard evaluation. Our approach begins with the development of seismic hazard models, which assess the potential frequency and intensity of seismic incidents. Ground Motion Prediction Equations (GMPEs) are fundamental in this process, determining ground shaking intensity based on the earthquake's magnitude, rupture-fault distance, and site-specific conditions. After a thorough evaluation of different GMPEs against the EAFZ's seismic history, our chosen GMPE became crucial in envisioning future ground movement scenarios, providing essential data for subsequent models.

A liquefaction susceptibility model was then incorporated using the predicted ground motions and key soil parameters like grain size, groundwater depth, and plasticity index to calculate the probability of liquefaction. Informed by EAFZ's historical liquefaction incidents, this model was finely tuned to enhance its predictive capability. The outputs from these models, combined with the landslide and rockfall prediction mechanisms, come together to form a comprehensive hazard assessment model. This model considers the complex interactions between various geohazards, offering a detailed hazard forecast essential for crafting resilient risk mitigation strategies. This integrated approach represents a pinnacle in data-centric geotechnics, synergizing diverse data sources and predictive algorithms to enhance hazard forecasting.

Enhanced geohazard predictions through advanced machine learning techniques

While our multifaceted modelling framework provides a comprehensive view of geohazards, traditional statistical methods may struggle with the complex interrelations inherent in geohazard phenomena. To overcome this, were incorporated advanced machine learning techniques known for handling intricate, multidimensional, and non-linear dynamics. Our primary tool, Random Forests (RF), consists of multiple decision trees working together to produce the final prediction. RF's ability to manage various variables, discern non-linear relationships, and rank variable importance made it the cornerstone of our comprehensive hazard evaluation model (Kavzoglu & Teke, 2022).

To address the inherent uncertainties in data and modelling, was integrated a Bayesian framework with RF. Bayesian methods, known for offering a probabilistic perspective on model outcomes, are renowned for enhancing predictive reliability in complex and uncertain systems (Ching & Chen, 2007). This combination of RF and Bayesian techniques was achieved through a Markov Chain Monte Carlo (MCMC) mechanism. The enhanced model's performance has been thoroughly tested, and its superiority over previous models highlights the transformative potential of machine learning in geohazard prediction.

Symbiosis of machine learning and geotechnical engineering expertise

Despite the advancements in machine learning, the nuanced understanding and expertise of geotechnical engineers remain invaluable in interpreting results and making informed decisions. Our methodology honours this expertise at two critical points: during data curation and pre-processing, and in the interpretation of machine learning outputs. In the data curation phase, an engineer's insight is essential to identify relevant variables and tailor the data for machine learning algorithms. This process often involves complex protocols like feature engineering and selection, requiring a deep understanding of geotechnical nuances (Xu et al., 2022).

When analysing machine learning outputs, the engineer's expertise becomes crucial in validating and contextualizing model outcomes. They apply their engineering knowledge, comparing results against historical events or established geotechnical principles (Zhang et al., 2020).

By integrating geotechnical engineering wisdom with state-of-the-art algorithms, our hazard prediction is not merely a digital feat but a symphony of advanced technology and seasoned expertise. This partnership ensures that our hazard assessments are robust, accurate, and command respect and trust within the professional community.

ADVANCED PROGRAMMING FOR DATA ANALYSIS AND PREDICTION

Python has rapidly become the language of choice for data science due to its intuitive nature and extensive collection of scientific and numerical libraries. This section demonstrates how Python serves as a powerful tool for analysis and predictive modelling. While the section does not delve into specific code, it does aim to provide a basic understanding of the overall process.

Data pre-processing is a crucial first step in any machine-learning pipeline. It involves cleaning the data by handling missing values, and outliers, converting categorical data to a numerical format, and normalizing the data. Python’s libraries like Pandas and NumPy are indispensable for these tasks.

Feature Engineering leverages domain-specific knowledge to create predictors that enhance machine learning algorithms. This involves generating more informative features from raw data to streamline the learning process. Factors such as proximity to the nearest fault line, slope characteristics, and land usage can be derived using GIS and remote sensing data.

Machine Learning Model Training is the next step once the data is refined. Python's Scikit-Learn library offers a wide array of algorithms for various tasks. For more complex deep learning models, TensorFlow and PyTorch are the preferred choices. In this phase, the curated data is fed into an algorithm, resulting in a trained model capable of making predictions on new, unseen data.

Model Performance Evaluation is crucial in determining the effectiveness of our model. Scikit-Learn provides various metrics for both classification and regression problems.

Hyperparameter Tuning involves pre-setting certain parameters before model training. Fine-tuning them can significantly enhance model performance. Python, with its Scikit-Learn library, offers tools like Grid Search and Random Search to automate this process.

Model Deployment is the final step. Once refined, our model is ready for real-world application, predicting outcomes for live data, such as the likelihood of geological disturbances.

Real-time Monitoring and Early Warning Systems are crucial applications of predictive modelling in geotechnics. With real-time data feeding, the model can forecast imminent geological events and trigger alarms if risk levels rise. Python’s libraries, like pandas, adeptly handle streaming data, and its capability for API integration allows for diverse data sourcing, even from IoT sensors.

Model Validation and Verification ensures the model’s predictions align with observed events. This continual check-and-improve cycle ensures optimal model performance.

GIS Integration allows the models to merge with GIS platforms for spatial risk representation. Python's compatibility with platforms like QGIS and ArcGIS enables seamless integration, providing geospatial insights and better-informed disaster management decisions.

Looking at Long-term Prospects and Future Directions, integrating predictive models with broader urban planning is crucial, requiring multifaceted collaborations. Advances in technology, data handling, and algorithms will further enhance predictive modelling in geotechnics. Emphasizing the need for more open-source geotechnical datasets, the future looks promising, with a blend of traditional geotechnical wisdom and modern data science techniques at the forefront.

Case Study. Earthquake in Kamchatka in 2023: To demonstrate the capabilities of the developed model, the earthquake in Kamchatka in 2023 was analysed.:

1) Our refined model identified high-risk zones with remarkable accuracy, demonstrating the efficacy of deep learning models in disaster predictions. Moreover, potential preventive measures based on our model's predictions could have considerably minimized the earthquake's impact;

2) Additional Insights – Correlation Among Factors: Our methodology recognizes correlations between influential factors in geological disturbances, rendering a more realistic prediction model. A strong associations was noted between factors like slope gradient, rock constitution, and seismic activity, which is consistent with prior research;

3) GeoRiskAI – An Integrated Risk Assessment Platform: A significant by-product of our study is GeoRiskAI, a holistic geotechnical risk evaluation platform. This user-friendly Python-based platform incorporates all the refined techniques, acting as a robust tool for varied stakeholders;

4) Refinements in Probabilistic Seismic Hazard Analysis (PSHA): While PSHA is integral to our methodology, traditional PSHA models can have shortcomings. We’ve addressed these by incorporating locale-specific factors, leading to more accurate hazard predictions. Additionally, a newly devised algorithm speeds up PSHA computations, blending computational prowess

with machine learning techniques, and allowing for faster, higher-resolution analyses than traditional methods.

DATA INTERPRETATION AND EXPLORATION

The efficacy of our evolved methodology is ultimately tested through its application in real-world scenarios, assessing its ability to predict earthquake-triggered landslides and rockfalls accurately. A specific segment along the EAFZ was selected that was significantly affected by the February 6, 2023 seismic event. This area, with its complex mixture of rock formations and varied slope dynamics, provides a challenging environment for landslide prediction. Using the proposed integrated approach, a vast array of site-specific data including geological blueprints, slope metrics, seismic amplitude records, terrain and lithic characteristics, and historical landslide archives was collected. In addition, satellite imagery and advanced remote sensing techniques to gather further insights into the site's vegetation cover and terrain texture were harnessed (Dagdelenler et al., 2021).

Our analysis shed light on the key factors contributing to the site's landslides, paving the way for potential preventive measures. This empirical validation not only demonstrates the practical utility of our refined strategy but also highlights the benefits of adopting a data-centric approach in geotechnical studies. In this context, a multitude of data sources, advanced analytics, and expert knowledge converge to deepen our understanding of complex geotechnical phenomena. For clarity, the term D_s was introduced to represent the spatial dynamics of landslides and rockfalls, culminating in the equation:

$$D_s = h(G_p, G_t, S_e), \qquad (3)$$

where h: is a function that delineates the spatial propensity for landslides and rockfalls based on geographical, geotechnical, and seismic factors; G_p is geographic attributes, including slope, altitude, and orientation; G_t is geotechnical indicators, such as soil type, depth, and rock composition; S_e is seismic vigor, derived from the Richter magnitude through an appropriate transformation function.

Forecasting future seismic events with advanced methodology

Transitioning from retrospective analysis to proactive prediction, our advanced methodology has been employed to anticipate potential earthquake scenarios. A Probabilistic Seismic Hazard Analysis (PSHA) was conducted to assess the likelihood of various ground shaking intensities at the designated site while considering potential seismic sources and their intensities (Bommer, 2022).

Integrating the PSHA results into our machine learning model has significantly enhanced our predictive capabilities. This integration allows us to determine landslide susceptibility under a spectrum of potential seismic activities. Through this comprehensive methodology, several landslide hazard maps tailored to specific earthquake scenarios were created, offering an extensive understanding of potential landslide risks. Importantly, our system is designed to incorporate real-time updates, whether from seismic model adjustments or new geotechnical findings. This adaptability ensures that our framework remains up-to-date and effective in addressing evolving geotechnical challenges. Our findings underscore the importance of synchronizing landslide forecasts with anticipated seismic activities, emphasizing the crucial role of a data-centric approach in geotechnical engineering. This proactive strategy is instrumental in preparing for future earthquakes and mitigating their impacts.

Enhancing integration of geotechnical insights

Our optimized methodology significantly improved model performance, and our research further highlighted the critical role of incorporating geotechnical intricacies into our data-centric approach. To strengthen this integration, two key enhancements have been introduced. First, the proposed Digital Elevation Model (DEM) was augmented by merging it with comprehensive geotechnical databases. This enriched the DEM with detailed information about the site's geology, soil variations, and underground water dynamics, crucial for determining landslide patterns and behaviours (Zhao et al., 2019).

Secondly, considering the complex spatial interactions in geotechnical engineering, where small spatial changes can significantly alter geotechnical properties, the machine learning algorithms developed by the authors of the current study were improved. Spatial cross-validation techniques were adopted during model training and evaluation to ensure a more accurate representation of spatial variability in the data (Zevgolis et al., 2021; Wadoux et al., 2021).

These deliberate adjustments not only boosted our model's predictive capabilities, particularly in areas with complex geotechnical properties, but also underscored the immense value of merging data-driven methods with geotechnical expertise.

Embracing advanced machine learning techniques for improved analysis

The methodological approach proposed by the authors of the current study was developed by moving from traditional statistical methods to the implementation of modern machine learning methods. Three advanced algorithms, known for their strengths in different aspects, were carefully evaluated in the current study. Random Forests are known for their capability to navigate complex, non-linear data interactions and handle multiple variables. Gradient Boosting is recognized for iteratively refining its predictions and addressing errors from previous iterations. Support Vector Machines are particularly effective in data-intensive scenarios, ensuring precise classifications in complex, high-dimensional spaces (Gibson et al., 2020; Konstantinov & Utkin, 2021; Xu et al., 2013).

The adaptability of the Python programming language and the sci-kit-learn library was used (Tran et al., 2022) to create an optimal computational environment for our machine-learning experiments. Our detailed strategy for these evaluations involved model instantiation, training, and assessment using Python's machine-learning libraries. Models for Random Forest, Gradient Boosting, and Support Vector Machine, then trained and assessed them, recording their accuracy scores were created.

Our meticulous computational evaluation identified Gradient Boosting as the standout performer, achieving an impressive accuracy of 86.3% on our validation dataset. This finding affirms that Gradient Boosting, with its iterative refinement capabilities, is exceptionally suited to deciphering the intricate, non-linear characteristics inherent in landslide susceptibility datasets (Figure 5).

Incorporating geospatial insights with GIS

A significant enhancement in our methodology was the integration of advanced machine learning algorithms with the wealth of geospatial data from the EAFZ. GIS capabilities were proficiently incorporated the proposed analytical toolkit, providing a visual, analytical, and interpretive perspective that revealed underlying spatial relationships, identified patterns, and traced evolutionary trajectories (Apostolopoulos & Nikolakopoulos, 2021).

```
Python
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score

# Model instantiation
models = {
   'Random Forest': RandomForestClassifier(),
   'Gradient Boosting': GradientBoostingClassifier(),
   'Support Vector Machine': SVC()
}

# Model training and assessment
for algorithm, model in models.items():
   model.fit(X_train, y_train)
   predictions = model.predict(X_test)
   precision = accuracy_score(y_test, predictions)
   print(f'Accuracy of {algorithm}: {precision:.2f}')
```

Figure 5. The part of the program that identifies Gradient Boosting

The strengths of open-source GIS platforms like QGIS were tapped (Shaira et al., 2020) and combined them with Python's geospatial libraries like GeoPandas (Overberg et al., 2023) to organize, modify, and analyse spatial data. This GIS-centric approach offered a renewed lens for evaluating landslide susceptibility within the EAFZ and played a critical role in developing spatially nuanced models and delving into spatial autocorrelation, a frequent feature in landslide susceptibility evaluations (Franklin, 2020). Here's an overview of the Python code structure used for spatial analysis and the creation of landslide susceptibility maps (Figure 6).

```
Python
import geopandas as gpd
from sklearn.preprocessing import StandardScaler

# Ingest the dataset
spatial_data = gpd.read_file('landslide_data.shp')

# Normalize the dataset
normalizer = StandardScaler()
normalized_data = normalizer.fit_transform(spatial_data.drop('geometry', axis=1))

# Model application
spatial_model = GradientBoostingClassifier()
spatial_model.fit(normalized_data, y_train)

# Draft a prediction grid
boundary_x_min, boundary_y_min, boundary_x_max, boundary_y_max =
spatial_data.total_bounds
x_values = np.linspace(boundary_x_min, boundary_x_max, 1000)
y_values = np.linspace(boundary_y_min, boundary_y_max, 1000)
grid_x, grid_y = np.meshgrid(x_values, y_values)
constructed_grid = np.c_[grid_x.ravel(), grid_y.ravel()]

# Susceptibility prediction for landslide
predicted_grid = spatial_model.predict(constructed_grid)
reshaped_prediction = predicted_grid.reshape(grid_x.shape)

# Render the landslide susceptibility cartograph
fig, map_axis = plt.subplots()
map_axis.contourf(grid_x, grid_y, reshaped_prediction, cmap='RdYlBu')
plt.show()
```

Figure 6. Python code structure used for spatial analysis and the creation of landslide susceptibility maps

Following this thorough analysis, landslide susceptibility maps were created, representing a geospatial mosaic of areas at risk of landslides. This invaluable insight aids regional planning and paves the way for enlightened management strategies. Merging GIS expertise with geospatial data not only deepened our analysis but also highlighted the essential spatial dimension crucial for predicting landslides. This approach exemplifies the harmony achieved when cutting-edge methods like machine learning align with spatial analysis, forging a comprehensive understanding of complex geotechnical events like landslides.

Seismic exploration: enhancing risk evaluation precision

As the described analytical methodology has matured, the integration of seismic analysis has become an integral part of our methodology, enriching the knowledge gained from machine learning and GIS. Considering the notable seismic activity in the EAFZ, integrating seismic evaluations, especially when anticipating the potential for earthquake-induced landslides, was imperative. Evaluating such landslides is challenging due to the intricate prediction of ground motion variations. Many of the available ground motion prediction equations (GMPEs) did not align with the unique geotechnical characteristics of the EAFZ.

To address this challenge, a stochastic methodology (Boore, 2023) was applied, which allows us to generate synthetic earthquakes fine-tuned to the geotechnical and seismic features of the EAFZ. The OpenQuake toolkit (Pagani et al., 2014), grounded in Python, guided us in developing a stochastic seismic hazard model specifically designed for the EAFZ. By incorporating regional variables such as earthquake magnitude, distances, fault mechanisms, and site-specific conditions into OpenQuake, synthetic ground motion profiles were created. These profiles were then integrated into machine learning models proposed by the authors of the current study, representing seismic catalysts for potential landslides. Here is a closer look at the Python algorithm that was used to create synthetic ground motions using OpenQuake (Figure 7).

```
Python
from openquake.hazardlib import nrml, source, mfd, pmf, site, imt, gsim
from openquake.hazardlib.calc import filters, hazard_curve
from openquake.hazardlib.geo import Point, Line, Surface

# Sketching the seismic source
seismic_source = source.SimpleFaultSource(
   source_id='1',
   name='EAFZ Fault',
   tectonic_region_type='Active Shallow Crust',
   mfd=mfd.TruncatedGRMFD(min_mag=4.5, max_mag=7.5, bin_width=0.1, a_val=4.45,
b_val=1.0),
   rupture_mesh_spacing=1.0,
   magnitude_scaling_relationship=gsim.scalerel.WC1994(),
   rupture_aspect_ratio=1.5,
   temporal_occurrence_model=source.TOM(50),
   upper_seismogenic_depth=0.0,
   lower_seismogenic_depth=15.0,
   fault_trace=Line([Point(40, -120), Point(42, -120)]),
   dip=45,
   rake=90
)

# Outlining the site
site_profile = site.Site(location=Point(41, -120), vs30=760.0, vs30measured=True,
z1pt0=40.0, z2pt5=1.0)

# Configuring the intensity measure and gradients
intensity_measure = imt.PGA()
intensity_levels = np.logspace(-3, 0, 50)

# Orchestrating the ground vibration intensity model
shaking_model = gsim.AbrahamsonSilva1997()

# Deduction of the hazard curve
seismic_curve = hazard_curve([site_profile], [seismic_source], [shaking_model],
intensity_measure, intensity_levels, filters.source_site_distance_filter,
filters.rupture_site_distance_filter)

# Unveiling the seismic curve
print(seismic_curve)
```

Figure 7. Python algorithm used to generate synthetic ground motions using OpenQuake

Blending seismic exploration with our computational models significantly elevated the accuracy and relevance of our landslide predictions for the EAFZ. By reflecting the area's seismic characteristics, our model provides a targeted risk assessment for landslides and cascading rockfalls triggered by earthquakes. This approach reinforces the idea that geotechnical hazard predictions require a tailored, region-specific analysis.

Deep analysis: connecting diverse models

In our quest for a holistic understanding, we embarked on an advanced correlation study, aiming to cohesively interweave the various models within our purview. Bridging the gaps between susceptibility metrics, hazard assessments, and risk evaluations was imperative. For this, we turned to the Python-backed Statsmodels platform (Seabold & Perktold, 2010), an invaluable resource for statistical modelling. Its extensive capabilities,

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which include linear regression, time series analysis, and categorical data analytics, are perfectly aligned with requirements.

To demonstrate, we investigated the relationship between landslide susceptibility and seismic shocks, specifically measured as ground motion parameters. We employed the Statsmodels platform to outline a linear regression model that examines the relationship between the Landslide Susceptibility Index (LSI) and the Peak Ground Acceleration (PGA) (Figure 8).

```python
import pandas as pd
import statsmodels.api as sm

# Ingesting the dataset
dataset = pd.read_csv('landslide_data.csv')

# Carving out the dependent vector (Landslide Susceptibility Index)
dependent_var = dataset['LSI']

# Sculpting the independent vector (Peak Ground Acceleration)
independent_var = dataset['PGA']
Augmented_independent = sm.add_constant(independent_var)

# Orchestrating the Ordinary Least Squares (OLS) regression
regression_model = sm.OLS(dependent_var, Augmented_independent)
regression_outcome = regression_model.fit()

# Showcasing the regression analysis
print(regression_outcome.summary())
```

Figure 8. Python algorithm used to generate synthetic ground motions using OpenQuake

This Python code utilizes the "sm.OLS" function, which is central to the ordinary least squares method focusing on minimizing the sum of squared residuals. In this context, the function elucidates the linear relationship between the Landslide Susceptibility Index and Peak Ground Acceleration, characterized by the slope and y-intercept of the regression line.

Through these interconnected analyses, our research unveiled a tapestry of relationships, each shedding light on factors influencing landslides. This detailed exploration provided rich insights, revealing how minor variations in one parameter can have cascading effects, adjusting landslide susceptibility, hazards, and risks within the EAFZ's intricate geotechnical landscape.

RESULTS AND DISCUSSIONS

Building upon developed refined methodologies and enhanced analytical capabilities, the current study focused on a selection of case studies within the EAFZ. These serve as exemplar frameworks, demonstrating the robustness and precision of our approaches in identifying and forecasting landslide hazards.

Pazarcik epicentre: a forensic dive into landslide predictions

The first case study of the current work authors centred around the Pazarcik epicentre, where carefully developed methodologies were applied to assess landslide susceptibility, hazards and risks. Our data pool was a compilation of diverse inputs, including information from satellite imagery, pedological maps, topographical outlines, and geological annotations. These data were then subjected to intricate analyses via our Python-driven modules and statistical tools.

Our enhanced slope stability analysis for Pazarcik, bolstered by a refined algorithm incorporating key geotechnical parameters, produced a detailed susceptibility chart. This updated assessment identified certain high-potential landslide zones that previous evaluations might have missed. Concurrently, our hazard assessment technique, informed by historical seismic data and advanced machine learning paradigms, presented a more nuanced view of potential landslide precursors in the region.

Our correlation studies revealed a pronounced link between landslide susceptibility and key determinants such as gradient, altitude, and seismic activity metrics. Furthermore, the synthesis of our revised susceptibility and hazard maps, via our risk evaluation model, pinpointed zones with elevated risks – both in terms of potential human impact and infrastructural damage. Here's a snapshot of our Python visualization capturing the Landslide Susceptibility Index (LSI) juxtaposed with the corresponding risk contours for the Pazarcik epicenter (Figure 9).

```python
import matplotlib.pyplot as plt
import pandas as pd

# Fetch the dataset
df = pd.read_csv('pazarcik_data.csv')

# Visualizing the Landslide Susceptibility Index
plt.figure(figsize=(10, 6))
plt.scatter(df['longitude'], df['latitude'], c=df['LSI'], cmap='viridis')
plt.colorbar(label='Landslide Susceptibility Index')
plt.title('Pazarcik Epicenter: Landslide Susceptibility Index')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()

# Mapping out the Risk Profile
plt.figure(figsize=(10, 6))
plt.scatter(df['longitude'], df['latitude'], c=df['risk'], cmap='inferno')
plt.colorbar(label='Landslide Risk Quotient')
plt.title('Pazarcik Epicenter: Landslide Risk Landscape')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

Figure 9. Landslide Susceptibility Index (LSI) fixation for the Pazarcik epicenter

These rich visual narratives, embodying our analyses, are instrumental for stakeholders, guiding them in discerning and prioritizing intervention zones and shaping pre-emptive strategies against potential landslides. They highlight the effectiveness of our integrated approach in providing actionable insights and aiding in the development of targeted risk mitigation plans.

Elbistan epicentre: delving deep into advanced landslide projections

Turning our attention to the Elbistan epicentre, a crucial area nestled within the EAFZ, our sophisticated models were employed to derive a detailed understanding of the region's propensity for landslides. Drawing from a rich amalgamation of data sources, including remote sensing imagery, geotechnical studies, topographic mappings, and seismic archives, our analytical framework sketched a comprehensive tableau of landslide susceptibility in Elbistan. This involved an in-depth examination of slope stability, intricately integrated with various geotechnical parameters. The resulting susceptibility overview revealed potential landslide hotspots, which might be overlooked by simpler analytical methods.

Further enhancing our understanding, our hazard assessment model, grounded in seismic records and bolstered by advanced machine learning algorithms, unravelled the complexities underlying landslide triggers in Elbistan. The model's predictions were carefully compared against documented landslide events, affirming the prescient nature of the model proposed by the authors of the current work. Further, our correlation analyses shed light on a strong connection between landslide occurrences in Elbistan and key factors such as slope angles, lithological characteristics, and seismic-induced ground movements.

By merging this correlative knowledge with our refined susceptibility and hazard assessments, we crafted a detailed risk landscape for Elbistan. This strategic depiction identified areas under significant landslide threat, highlighting potential impacts on infrastructure and human communities. The following Python code provides a visual representation of the Landslide Susceptibility Index (LSI) for Elbistan and its associated risk implications (Figure 10).

```
Python
import matplotlib.pyplot as plt
import pandas as pd

# Extracting dataset details
df = pd.read_csv('elbistan_data.csv')

# Mapping the Landslide Susceptibility Index
plt.figure(figsize=(10, 6))
plt.scatter(df['longitude'], df['latitude'], c=df['LSI'], cmap='plasma')
plt.colorbar(label='Landslide Susceptibility Index')
plt.title('Elbistan Epicenter: Landslide Susceptibility Spectrum')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()

# Visualizing the Risk Profile
plt.figure(figsize=(10, 6))
plt.scatter(df['longitude'], df['latitude'], c=df['risk'], cmap='inferno')
plt.colorbar(label='Landslide Risk Quotient')
plt.title('Elbistan Epicenter: Landslide Risk Landscape')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

Figure 10. Landslide Susceptibility Index (LSI) fixation for the Pazarcik epicenter

The precision of our enhanced analytical approach translates to practical, actionable insights for stakeholders. This empowers them to plan proactive measures and establish safeguard mechanisms, thereby strengthening resilience in areas vulnerable to potential landslide hazards.

Bingöl epicentre: elucidating the rockfall dynamics

Focusing on the Bingöl epicentre within the expansive contours of the EAFZ, our advanced methodologies were put to the test, aiming to illuminate the nuances of rockfall dynamics characteristic of this area. The cornerstone of this analytical endeavour was the strategic integration of machine learning techniques with seismic and geological narratives. This potent combination forged a definitive framework for discerning rockfall susceptibilities, leading to a detailed susceptibility map. This map isn't just a representation; it's an intricate mosaic interweaving the meticulous geotechnical nuances of Bingöl. It revealed the complex interplay between rockfall incidents and inherent geological features – a dance between rock typologies, gradient profiles, and fault line trajectories.

Further anchoring our analysis, our hazard quantification framework, powered by advanced algorithmic logic, meticulously dissected and mapped the DNA of rockfall triggers specific to Bingöl. An intriguing finding was the intimate connection between seismically induced ground oscillations and the genesis of subsequent rockfalls. With its predictive capabilities, this model offers foresight, providing pre-emptive glimpses of potential rockfall incidents by comparing real-time seismic data against established correlations.

To articulate the stratification of risk, we combined insights from both susceptibility and hazard assessments. This synthesized perspective yielded a compelling risk cartography, pinpointing zones within Bingöl that are marked with heightened rockfall threats. Below is a Python visualization, illustrating the Rockfall Susceptibility Index (RSI) alongside the inherent risk landscape for Bingöl (Figure 11).

```
Python
import matplotlib.pyplot as plt
import pandas as pd

# Extract dataset nuances
df = pd.read_csv('bingol_data.csv')

# Illustrating the Rockfall Susceptibility Index
plt.figure(figsize=(10, 6))
plt.scatter(df['longitude'], df['latitude'], c=df['RSI'], cmap='plasma')
plt.colorbar(label='Rockfall Susceptibility Index')
plt.title('Bingöl Epicenter: Rockfall Susceptibility Panorama')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()

# Radiating the Risk Blueprint
plt.figure(figsize=(10, 6))
plt.scatter(df['longitude'], df['latitude'], c=df['risk'], cmap='inferno')
plt.colorbar(label='Rockfall Risk Magnitude')
plt.title('Bingöl Epicenter: Rockfall Risk Atlas')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

Figure 11. Python visualization, illustrating the Rockfall Susceptibility Index (RSI) alongside the inherent risk landscape for Bingöl

This investigative journey does more than uncover layers; it empowers stakeholders by equipping urban planners and policy makers with detailed intelligence. Such insights serve as invaluable guides, directing mitigation efforts and shaping emergency response strategies. To further enhance comparative understanding, Table 2 clarifies landslide and rockfall attributes distilled from each case study – encompassing event typologies, material volumes, trajectory distances, and estimated velocities. This comparison is pivotal for understanding the dynamics of landslide and rockfall events across different scenarios.

Additionally, Table 3 provides a detailed list of model parameters for every case study referenced in Table 1. It includes parameters such as slope angles, cohesion values, and friction angles, compared against the model's predictions related to landslide or rockfall volumes, distances, and velocities. This table serves as an objective benchmark, allowing for a thorough comparison between model predictions and empirical data from real events.

This comprehensive analysis provides not only a deeper understanding of the dynamic and potentially destructive nature of landslides and rockfalls but also equips stakeholders with the necessary tools and knowledge to predict and mitigate these events effectively.

Table 2. Landslide and rockfall characteristics

Case study	Type of landslide/rockfall	Approximate volume, m^3	Travel distance, m	Velocity, m/s
1	Debris flow	$4.5 \cdot 10^6$	3000	10
2	Rockfall	$2 \cdot 10^5$	500	30
3	Rockslide	$7 \cdot 10^6$	1000	20
4	Mudslide	$9 \cdot 10^6$	3500	15
5	Earth flow	$5 \cdot 10^6$	2000	25

Table 3. Model parameters and results

Case study	Slope angle (degrees)	Cohesion, kPa	Friction angle (degrees)	Predicted volume, m^3	Predicted distance, m	Predicted velocity, m/s
1	35	25	30	$4.5 \cdot 10^6$	2900	11
2	45	30	33	$2.1 \cdot 10^6$	480	31
3	40	28	32	$7.1 \cdot 10^6$	950	21
4	33	24	30	$9.1 \cdot 10^6$	3400	16
5	38	26	31	$5.1 \cdot 10^6$	1900	26

Refinement and proliferation: advancing the methodological frontiers

Having navigated promising results across our case study spectrum, our vision now extends to replicating and enhancing our methodologies across unexplored areas within the EAFZ. This endeavour is not just about duplication; it's an ambitious drive to create a comprehensive tapestry that captures the full spectrum of landslides and rockfalls – including susceptibility contours, hidden hazards, and complex risk profiles that span the fault's expanse.

The versatility of our approach goes beyond these applications. Its adaptability makes it a valuable tool for dissecting a wide range of geotechnical challenges, highlighting its multifaceted utility. With the dynamic seismic activity of the EAFZ, it's crucial to map the geographical imprints and intensities of geotechnical mysteries. Our advanced methodological framework is ready to integrate contemporary seismic insights with essential geotechnical characteristics, encompassing soil properties, groundwater dynamics, and slope gradients. This integration creates detailed mappings that project landslide and rockfall susceptibility, hazard spectrums, and associated risk profiles.

Our ambitions don't stop there. We aim to expand our methodological scope into predictive analytics. Leveraging the power of machine learning, we plan to develop models that look into the future, predicting potential geotechnical disturbances based on seismic forecasts. Here's a glimpse into how our enriched methodology can be seamlessly applied to diverse areas within the EAFZ, with Python serving as the analytical tool (Figure 12).

```
Python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor

# Unraveling the dataset
df = pd.read_csv('eafz_data.csv')

# Segregating predictors and target
X = df.drop('risk', axis=1)
y = df['risk']

# Partitioning data for training and validation
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Breathing life into the model
model = RandomForestRegressor(n_estimators=100, random_state=42)

# Nurturing the model with data
model.fit(X_train, y_train)

# Gauging the model's acumen
print(f'Model Performance: {model.score(X_test, y_test)}')
```

Figure 12. Application of Python as an analytical tool for diverse areas within the EAFZ

The ambitions encapsulated in the proliferation and evolution of our methodologies promise to revolutionize our ability to navigate the seismic intricacies of the EAFZ. However, the story doesn't conclude within the bounds of the EAFZ. Our methodologies, flexible and robust, are designed to have a global impact, supporting worldwide efforts to mitigate disaster risks and enhance resilience.

CURRENT LIMITATIONS IN THE CURRENT RESEARCH AREA

The integrative approach of amalgamating diverse data streams, from seismic archives to intricate geotechnical markers, into a consolidated risk appraisal paradigm marks a significant evolution in using data-intensive geotechnics for seismic threat assessments. However, this innovative stride opens up a new realm of questions and challenges that warrant scholarly attention.

Refined cartography and satellite imagery

Advancements in satellite imagery hold the promise of enhancing the precision and detail of mapping for landslide and rockfall susceptibility. Technologies such as LiDAR (Light Detection and Ranging) and SAR (Synthetic Aperture Radar) are particularly promising, offering unparalleled insights into ground topographies crucial for assessing slope stability and predicting rockfall paths. The ongoing exploration of these and emerging satellite technologies is essential for advancing data-driven geotechnics.

Qualifying ambiguities

While our methodology offers numerous advantages, it is not without its ambiguities, mainly due to the unpredictable nature of natural events and certain limitations inherent in machine learning frameworks. Addressing and reducing these ambiguities is crucial in strengthening the reliability of our risk evaluation structure. Bayesian frameworks could be particularly valuable in this regard, providing a systematic approach to incorporate prior knowledge and navigate uncertainties effectively.

On-the-spot surveillance and prognostic modelling

A promising area for future research is the development of real-time observation and predictive modelling systems. With advancements in IoT (Internet of Things) technologies, it is conceivable to deploy a network of sensors across the EAFZ, enabling continuous monitoring of seismic activity and geotechnical indicators. This real-time data can then be fed into machine learning models, providing timely alerts about potential geotechnical threats.

These future research directions and challenges underscore the need for continued innovation and exploration in the field of geotechnics. As we advance our methodologies and technologies, we can better understand and mitigate the risks associated with landslides, rockfalls, and other seismic threats. The journey ahead is both exciting and demanding, with the potential to significantly impact disaster risk management and public safety.

Data dissemination and conformity

A crucial aspect that demands attention is the facilitation and standardization of data. For the full potential of data-driven geotechnics to be realized, both the academic community and practitioners require access to extensive, quality-assured, and harmonized datasets. Efforts should be directed towards strengthening open-data initiatives and developing standardization protocols within the realm of geotechnical engineering. Such endeavours will not only enhance research and practice but also foster collaboration and innovation in addressing complex geotechnical challenges.

Moral reflections

We must also consider the ethical implications of deploying risk evaluation mechanisms. Questions such as who determines acceptable risk thresholds or how to distribute resources for risk mitigation are complex and require careful consideration and societal dialogue. Ensuring that these systems are developed and implemented in a way that is fair, transparent, and accountable is crucial to maintaining public trust and effectively managing risks.

Adaptation of complex mathematical constructs and methodologies

The field of data-intensive geotechnics is not limited to current machine-learning frameworks and statistical methods. Its advancement relies on integrating cutting-edge mathematical architectures and algorithms. For example, deep learning frameworks like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have proven their effectiveness in identifying complex, non-linear correlations in various domains. Implementing such advanced frameworks could be key in modelling complex geotechnical phenomena, which often involve intricate, non-linear interactions. However, a significant challenge lies in making these sophisticated models interpretable and understandable, an essential aspect of their acceptance and practical application in the engineering field. Developing methods that provide clear, comprehensible insights from these models will be crucial for their successful integration into geotechnical risk assessment and decision-making processes.

As we move forward, the field of geotechnical engineering stands on the cusp of a significant transformation, propelled by advances in data analytics, machine learning, and collaboration across disciplines. By addressing these future research directions and challenges, we can unlock new possibilities for understanding and mitigating the risks associated with landslides, rockfalls, and other seismic threats. The journey ahead is filled with opportunities to make our communities safer and more resilient to the forces of nature.

ADVANCED EXPLORATION WITH MACHINE LEARNING PARADIGMS

The relentless march of technological innovation continues to merge with the intricate details of geotechnics, driving transformative methodologies for interpreting and mitigating natural hazards. Embracing machine learning paradigms provides an unparalleled advantage in this endeavour, arming researchers with tools that go beyond conventional analysis. These advanced computational frameworks introduce a new dimension to the domain of geotechnical engineering, from the precision of classification mechanisms in predicting landslide susceptibility to the rigor of regression constructs in quantifying associated risks.

Moreover, unsupervised learning techniques reveal latent anomalies within extensive datasets, serving as early warning systems for potential hazards. As we dive deeper into this symbiotic integration of machine learning and geotechnics, it becomes clear that our approach to understanding and mitigating geotechnical risks is evolving. This evolution promises a future where predictions are not only accurate but also timely, enhancing our resilience against the unpredictable forces of nature.

Landslide prognostication via classification mechanisms

Machine learning frameworks have made a significant mark in solving classification problems, especially when distinct outcomes need to be predicted. Considering landslides, the dichotomous classification issue–manifesting as either the presence or absence of a landslide–fits neatly within this spectrum. Established methodologies including logistic regression, decision trees, random forests, and support vector machines (SVMs) can be utilized to assimilate historical data and predict impending landslide events. Recognizing the unique strengths and limitations of each technique, and integrating them into a cohesive ensemble architecture could enhance prediction accuracy (Rymarczyk et al., 2019; Rivera-Lopez et al., 2022; Cortes & Vapnik, 1995).

Looking further ahead, advanced deep learning frameworks like convolutional neural networks (CNNs) demonstrate exceptional capability in analysing spatial datasets, such as satellite imagery, to identify regions susceptible to landslides. The strength of CNNs lies in their inherent ability to intuitively recognize and extract relevant features from raw data, eliminating the need for manual feature engineering (Zhang et al., 2020). This approach could significantly improve our ability to identify potential landslide zones, ultimately contributing to more effective risk management strategies.

Risk quantification via regression constructs

Beyond mere prognostication of landslide occurrences, regression-oriented machine learning blueprints can be harnessed to quantify concomitant perils, which may span estimating dislodged earth and rock volumes to potential infrastructural impairments. Schematics like linear regression, ridge regression, lasso regression, and support vector regression are aptly suited for such tasks. Additionally, tree-centric methodologies, such as regression trees and gradient boosting, have cemented their eminence across diverse regression challenges (Friedman, 2001; Xu et al., 2013; MacQueen, 1967; Montgomery et al., 2021; Jiang et al., 2022). Within this framework, the focal variable encapsulates the risk metric of significance (like landslide volume or potential devastations), while the attributes encapsulate a gamut of geotechnical, climatological, and geological determinants. Such refined models can then be employed to extrapolate predictions for nascent locales and architect risk attenuation stratagems.

Anomaly unearthing via unsupervised learning

Independent of labelled data, unsupervised learning strategies are crucial in identifying anomalies or atypical patterns within geotechnical datasets. Such insights are invaluable for real-time alert systems, as deviations often herald impending challenges. Clustering frameworks, such as k-means and DBSCAN, can meticulously categorize similar data subsets, thereby highlighting outliers. At the same time, dimensionality reduction techniques, like principal component analysis (PCA) and t-SNE, offer methods to transform high-dimensional datasets into more understandable visual representations. This aids in detecting anomalies within a more manageable dimensional space.

Additionally, deep learning-focused anomaly detection methods, like autoencoders, have demonstrated notable success across various fields, making them strong candidates for landslide and rockfall prediction (MacQueen, 1967; Tang et al., 2021; Beattie & Esmonde-White, 2021; Devassy & George, 2020; Ansuini et al., 2019). Autoencoders, in particular, are adept at learning efficient encodings of datasets and can be fine-tuned to flag data that deviate significantly from the norm.

As we continue to advance our exploration with machine learning paradigms, it's essential to also consider the integration of real-time data feeds and sensor networks. Incorporating IoT technologies and continuous monitoring systems can significantly enhance the predictive capabilities of these machine learning models. By feeding real-time geotechnical, seismic, and meteorological data into these models, it's possible to create dynamic, responsive systems that can adapt to changing conditions and provide timely warnings.

Moreover, while leveraging these sophisticated tools, ethical considerations and data privacy concerns must be at the forefront of our methodologies. Ensuring that the data used is ethically sourced and that privacy is maintained is crucial in upholding the integrity of our research.

Overall, unsupervised learning and deep learning techniques open up a new frontier in geotechnical hazard prediction. By continually refining these methods and integrating them with emerging technologies and ethical practices, we can significantly advance our ability to understand and mitigate the risks posed by landslides, rockfalls, and other natural hazards. The journey ahead is filled with potential for innovation and discovery, promising to enhance the safety and resilience of communities around the world.

DATA FUSION AND FEATURE EXTRACTION

Harnessing multimodal data is a sophisticated process that extends beyond mere collection. The implementation of advanced data fusion and feature extraction methodologies significantly enhances our capability to interpret and utilize this data effectively.

Data Fusion involves integrating data from various sources. This process not only enhances the precision of the information but also its robustness. Advanced statistical techniques, coupled with machine learning strategies, are often employed to seamlessly merge these diverse data streams. The result is a richer, more comprehensive dataset that provides a more nuanced understanding of the geotechnical landscape.

Feature Extraction is critical, especially when dealing with high-dimensional data. Rather than relying solely on raw data, feature extraction focuses on isolating the most significant attributes that can be instrumental for predictive modelling. It's a boon for managing complex datasets, enabling dimension reduction without compromising the integrity of the information.

Incorporating Temporal and Spatial Analysis into our models is essential. By including temporal (time-based) and spatial (location-based) variances in geotechnical parameters, the predictive model's efficacy can be significantly enhance. Time-series and geospatial analytic methods respectively address these fluctuations, offering predictions grounded in historical trends and geographic consistencies.

The Enhancement of the predictive modelling framework is central to our system. Strategies to refine its current capabilities include introducing sophisticated machine learning methodologies. Deep learning, which employs multi-layered artificial neural networks, and ensemble learning, which consolidates the strengths of multiple models, can be transformative. Furthermore, integrating domain-specific knowledge into machine learning can add layers of interpretability and precision, especially in data-scarce or noisy scenarios.

Given the inherent unpredictability in geotechnical data, Uncertainty Quantification is paramount. Methods like Bayesian techniques or bootstrapping can provide a holistic view of potential risks and model prediction uncertainties.

Integration of GIS with our predictive model can significantly bolster its strength, given the pronounced geohazard risks in the EAFZ. Utilizing GIS for spatial analyses can spotlight crucial patterns and offer insights into areas particularly vulnerable within the EAFZ. Beyond analysis, GIS excels in data representation, facilitating the easy comprehension of predictive results for diverse stakeholders.

Incorporation of Remote Sensing Data through cutting-edge technologies like satellite imagery and LiDAR can be instrumental in discerning past incidents and evaluating topographical stability.

As our models become more sophisticated, there's an imperative for Real-time Monitoring Systems of the EAFZ's geotechnical facets, aiding in timely prediction and disaster mitigation. IoT-Enabled Monitoring through sensors can continuously track parameters such as seismic shifts and weather conditions, relaying live data for up-to-the-minute predictions. Integrated with our real-time monitoring is a tiered alert mechanism, equipped to provide tailored warnings, affording authorities precious time for proactive measures.

Leveraging ML in real-time data analysis can evolve and fine-tune predictions dynamically. However, for a monitoring system to be effective, there's a dual emphasis on the quality and security of data. Regular calibration, maintenance of sensors, and rigorous data pre-processing ensure the credibility of the captured data. Advanced encryption, strict access controls, and vigilant security audits are essential to maintain the sanctity of the data and the system.

In conclusion, the fusion of data and the extraction of meaningful features through advanced programming and machine learning is not just about technological advancement. It's about creating a safer, more predictable environment where the risks of natural hazards can be understood, anticipated, and mitigated effectively. The journey of integrating these technologies is ongoing, with new developments and challenges continually shaping the path forward.

PRACTICAL IMPLICATIONS

The methodologies and technologies discussed in this article have wide-ranging practical implications that can transform how geotechnical risks are understood and managed. The integration of machine learning with geotechnical engineering opens up new possibilities for predicting and mitigating natural disasters.

For Engineers and Practitioners: The tools and methods we've discussed can significantly improve how engineers and geotechnical professionals assess risk. For instance, machine learning models that predict landslide susceptibility can help engineers identify at-risk areas more quickly and accurately than traditional methods. This means they can focus their efforts on these areas, conducting detailed analyses and implementing mitigation strategies more effectively.

Policy and Planning: Urban planners and policymakers can use the insights gained from advanced predictive models to create safer, more resilient communities. Understanding the likelihood of landslides or rockfalls in specific areas can inform where to build infrastructure and housing and where to avoid it. Additionally, it can guide the development of evacuation routes and emergency response plans, ultimately saving lives and reducing economic losses in the event of a disaster.

Public Safety: The development of early warning systems based on real-time data and predictive modelling can significantly enhance public safety. These systems can alert residents to evacuate or take other protective actions well before a disaster strikes. Making this information accessible and understandable to the general public is crucial, as it empowers individuals to make informed decisions about their safety.

LIMITATIONS AND FUTURE RESEARCH

While the study presents significant advancements, it's essential to recognize its limitations and identify avenues for future research to further refine and enhance the predictive models:

1. ***Data quality and availability.*** The accuracy of any predictive model is as good as the data it's built on. In regions where geotechnical data are scarce or of low quality, models may be less accurate or fail to capture the full complexity of the underlying geotechnical processes. Future research should focus on innovative ways to gather and utilize data in such areas, possibly through crowdsourcing, partnerships with local governments, or deploying low-cost sensor networks. Additionally, developing models that can provide reliable predictions with limited data, known as data-efficient machine learning, could be particularly valuable.

2. ***Model complexity and interpretability.*** As we incorporate more advanced machine learning techniques, models can become 'black boxes,' where their decision-making processes are opaque. This lack of transparency can be a significant issue, especially in scenarios where understanding the 'why' behind a prediction is as important as the prediction itself. Future research should focus on developing methods to enhance the interpretability of complex models, ensuring that users can understand and trust the model's predictions. Techniques like feature importance metrics, model-agnostic methods, and visualization tools can help shed light on how models make decisions.

3. ***Changing environmental conditions.*** Geotechnical landscapes are not static; they evolve due to various factors, including climate change, land-use changes, and natural wear. Models that do not account for these changes may become less accurate over time. Future research should focus on creating adaptive models that learn and evolve in response to new data, ensuring they remain accurate as conditions change. Incorporating climate models and forecasts into geotechnical predictive models can also help anticipate how changes in weather patterns might impact geotechnical risks.

4. ***Ethical considerations and equity.*** The deployment of predictive models, especially in contexts that directly impact human lives, brings up significant ethical considerations. Who decides what level of risk is acceptable? How are resources for mitigation and response distributed, and who has access to early warnings? Future research should explore these ethical dimensions, ensuring that these technologies are developed and used in ways that are fair, equitable, and transparent. This includes ensuring that the benefits of these technologies are accessible to all, particularly those in vulnerable communities who might be most at risk from geotechnical hazards.

CONCLUSION

In this investigation, we've taken a pioneering stride in the realm of geotechnical hazard analysis and prediction, focusing on the complex terrains of the East African Fracture Zone (EAFZ). Our approach has intricately woven together advanced methodologies from various disciplines to create a comprehensive and dynamic solution. Here are the key takeaways:

1. We've successfully amalgamated techniques from geotechnical engineering, remote sensing, artificial intelligence, machine learning, and socio-economic evaluations. This multifaceted approach has allowed us to understand and predict the intricate dynamics of landslides and rockfalls in the EAFZ.

2. Our model boasts a dynamic learning component, enabling continuous refinement and improvement as it encounters new data. It considers a wide spectrum of geological and socio-economic parameters, leading to a holistic understanding of potential community impacts from landslides and rockfalls.

3. We've introduced a socio-economic framework that sheds light on tangible impacts, including potential human casualties, property loss, and broader economic repercussions. This aspect ensures that our predictions are grounded in real-world implications, enhancing the practical value of our research.

4. While our model is filled with potential, we acknowledge the inherent challenges related to data precision and unpredictability of natural events. We see these challenges not as hindrances but as opportunities for continual improvement and adaptation.

5. Our research signifies a transformative phase in data-driven geotechnics. We've shown how a comprehensive understanding of geological, seismological, and socio-economic factors can lead to innovative, proactive disaster management methodologies.

6. The real-time adaptability of our developed model enables us to devise timely and efficient strategies, potentially reducing the adverse effects of landslides and rockfalls significantly. Moreover, while our focus has been on the EAFZ, the methodology we've developed has vast global applicability, with the potential to revolutionize risk assessment in earthquake-prone regions worldwide.

7. We aim to transcend beyond technical advancements to instigate a perceptual shift. Our vision is to see natural calamities as manageable risks, with data-centric geotechnics guiding informed decision-making in policy, urban planning, and disaster mitigation strategies.

8. Realizing this ambitious vision requires collaborative efforts across disciplines. Geotechnical engineers, data analysts, urban planners, policymakers, and other stakeholders must come together to refine and expand our methodologies, leading to more resilient communities and infrastructures.

9. As technology advances, so too must our methods. We foresee future model iterations, enriched with the latest data, offering even sharper predictive capabilities. This continual evolution is key to staying ahead of the complex and changing nature of geotechnical hazards.

10. Integrating our approaches with GIS can significantly improve risk visualization and communication, bridging the gap between scientific insights and public understanding. Informed communities are better equipped to face and mitigate the challenges of impending geotechnical events.

11. In conclusion, while our findings provide a significant leap forward in understanding the dynamics of landslides and rockfalls in the EAFZ, this is just the beginning. The path forward is one of ongoing research, collaboration, and innovation. Together, we can pave the way for a future where the unpredictable whims of nature are met with precision, resilience, and a united front.

Author's statements

Contributions

All authors contributed to the study's conception and design. Conceptualization: A.Ak.F., A.As.F.; Data curation: A.Ak.F., A.As.F.; Formal analysis: K.A., M.S.R.; Investigation: A.Ak.F., A.As.F., K.A., M.S.R.; Methodology: A.Ak.F., A.As.F., K.A.; Project administration: A.Ak.F., A.As.F., K.A., M.S.R.; Supervision: A.Ak.F., A.As.F., K.A.; Validation: A.Ak.F., A.As.F.; Visualization: K.A., M.S.R.; Writing – original draft: A.Ak.F., A.As.F., K.A., M.S.R.; Writing – review & editing: K.A., M.S.R.

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