ON THE DEEP-SEATED BEDROCK LANDSLIDE TRIGGERED BY THE 2018 HOKKAIDO EASTERN IBURI EARTHQUAKE: A CASE STUDY

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Introduction

The 2018 Hokkaido Eastern Iburi Earthquake, registering at a magnitude of 6.7 and striking at 3:08 on September 6th, prompted a significant number of landslides, resulting in a lot of casualties. While most slides occurred on tephra slopes and were shallow, there were instances of bedrock landslides, notably one in the Horonai area（referred to as the Horonai landslide in this study). This particular landslide exhibited translational movement, with materials shifting approximately 350 meters along a gently sloping bedding plane of about 6 degrees. Field examination revealed that the displaced materials suffered high-speed movement. To investigate the initiation and movement mechanisms of this landslide, we installed seismometers across the affected area to study the seismic response. Geological and geomorphological surveys were conducted on the landslide site, with soil samples taken from layers adjacent to the sliding surface. Subsequent undrained ring shear tests were performed on these samples to analyze their static and dynamic shear behavior. Based on the results, the initiation and movement mechenisms of this deep-seated bedrock landslide were discussed.

Horonai landslide and methods

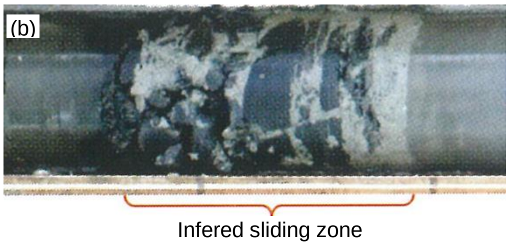

Figure 1. (a) view of Horonai landslide. ■: Power tower; □ : Former location of power tower (taken on October 18, 2018). (b) view of boring core at depth of around 75 m (Hayagawa et al., 2020)

Horonai landslide was the largest rockslide caused by the above mentioned earthquake. The bedrock around the landslide site consists of the Kemusi Formation, which includes siliceous to hard mudstone and glauconitic sandstone. The bedding planes at the landslide site dip approximately 10° towards the south to southeast. The landslide body is composed of interbedded sandstone and mudstone, predominantly muddy, with thin layers of calcareous concretions and tuffaceous sandstone. The landslide movement was translational with the sliding surface being formed along the bedding planes (Hayakawa et al., 2020). Additionally, the main block of the landslide body moved en masse while retaining the original rock structure. The landslide is about 1200 m in length and 400 m in width. The displaced mass traveled about 350 m along the slope, damming the river on the toe part and forming a large scale natural dam. The boring surveys revealed a crushed sandy layer (about 15 cm thick) around a depth of 75.15 to 75.30 m, which was inferred to be the sliding surface (Fig. 1b). Core observations near the sliding layer showed fractures in the upper soil layer, with sandy soil from the sliding layer intruding into these fractures. These phenomena suggest that during the earthquake, the tuffaceous sandstone near the sliding surface was crushed and liquefied, resulting in the rapid and long runout of the displaced mass. But why and how the shear failure along this layer had been triggered remain unclear. To clarify these questions, we conducted field surveys, collected soil samples from the sandstone and mudstone layers, and examined their shear behavior under different test conditions. We installed seismometers at different locations of the landslide, and then analyzed the possible coseismic response of the slope based on the recorded earthquake waves.

Results

As shown in Fig. 2a, the static shear tests showed that high pore-water pressure (PWP) could be built up within the sandy materials in saturated states, although in this test water leakage occurred during the undrained shearing. However, as shown in Fig. 2b, the sample taken from mudstone layer did not show significant buildup of PWP. It is noted that this test was conducted by applying the possible seismic shear loading during the main shock of the earthquake that was estimated by assuming an infinitely long slope of 6 degrees with a soil layer thickness of about 52 m, and by using the seismic wave data recorded at a nearby observation station during the main shock. Fig. 2b shows that although displacement occurred in the soil layer due to the application of dynamic shear stress, no continuous movement occurred in the soil layer after the seismic shear stress ended. Therefore, it is inferred that shear failure won't be triggered within the mudstone layer. Analysis on the seismic waves recorded the installed seismometers revealed that resonance during the main shock might have occurred, resulting in larger ground motion and then enabling the shear failure along the sandy layer of the bedrock.

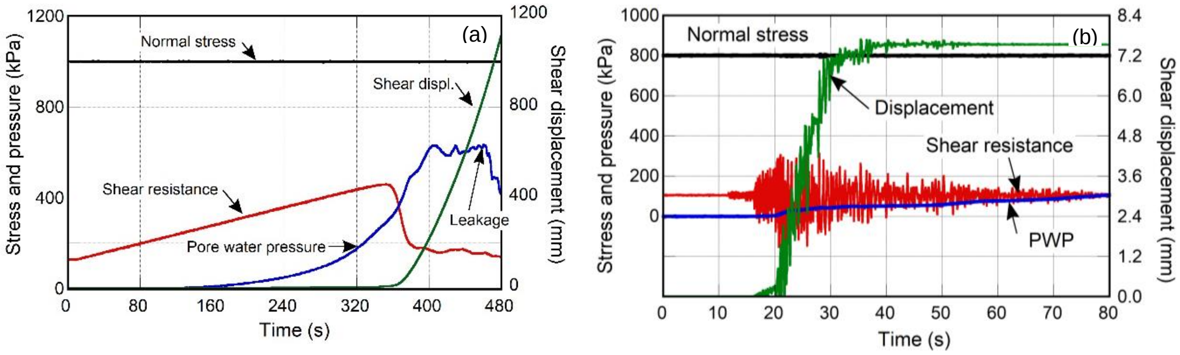

Figure 2. Undrained ring shear tests on samples taken from sandstone (a) and mudstone layers

Conclusion

During the 2018 Hokkaido Eastern Iburi earthquake, a large-scale rockslide occurred in the Hidaka Horokawa area, characterized by interbedded sandstone and mudstone formations. It is believed that this rockslide involved rapid and long-distance translational movement along a low-angle (about 6°) sliding surface parallel to bedding planes. The main block of the sliding mass had a thickness of about 80 m, and the slip plane was formed within the interbedded sandstone and mudstone layers, where liquefaction phenomena were observed. The resultss of shear tests revealed taht sandy layers in saturated state may suffer from buildup of high PWP and localized liquefaction phenomaon, and then enable the rapid long runout of dispaced landslide material. The soil layers along mudstone may not suffer from liquefaction behavior, although it has smaller peak shear strengh. Ground motion stronger than those recorded during the main shock in a nearby seismic station may occured in the landslide area, enabling the occurence of shear failure along the boundary between the sandstone and mudstone.

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POINT CLOUDS AND MACHINE LEARNING IN ROCK SLOPE MODELING

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Introduction

"When we open our eyes on a familiar scene, we form an immediate impression of recognizable objects, organized coherently in a spatial framework" (Treisman & Gelade 1980). This quote defines in simple terms the biological process of creating our "model" of the scene. This "model" is often the primary source of information that our cognitive perception relies on to develop intelligence. Today, with the available computational power and the ever-increasing level of digitization, the digital imitation of the biological "modelling" mechanisms is not only a very interesting and appealing exercise, but it is also achievable. Despite the practical challenges in replicating the biological sight-perception mechanisms in rock slope management, the process can be conceptualized as two distinct phases. The first phase translates into the transformation of reality to the "digital model" with the use of sensors to play the role of the eye and create computer-usable inputs. The second phase includes the evolution of the digital model to an "intelligent model". This involves processes for both the efficient representation of semantics and extraction of knowledge within digital rock slope replicas as well as the exploitation of the generated data to achieve autonomy and predictability (Figure 1).

Today in rock slope management we are able to leverage slope-scale point clouds utilizing various reality capture devices. These techniques provide large amounts of data that allow for site-specific digital modelling that would reliably represent the 3D complexity of a rock slope. This turn towards slope-scale knowledge extraction from point clouds signifies the conquest of the first phase in rock slope modelling evolution scheme (Figure 1). However, there is still the need to improve the capabilities of our models and achieve intelligence through automation. The analysis of these data is often limited to daunting time-consuming manual processing for the extraction of meaningful information to support the "intelligent model" phase. If we consider point clouds as digital reality assets, a whole new field of intelligent applications becomes available with the integration of Machine Learning (ML). The reflection to go from human-centered processes to autonomous data-driven workflows at slope-scale motivate our research to develop automation and Artificial Intelligence (AI) to speed-up inference processes.

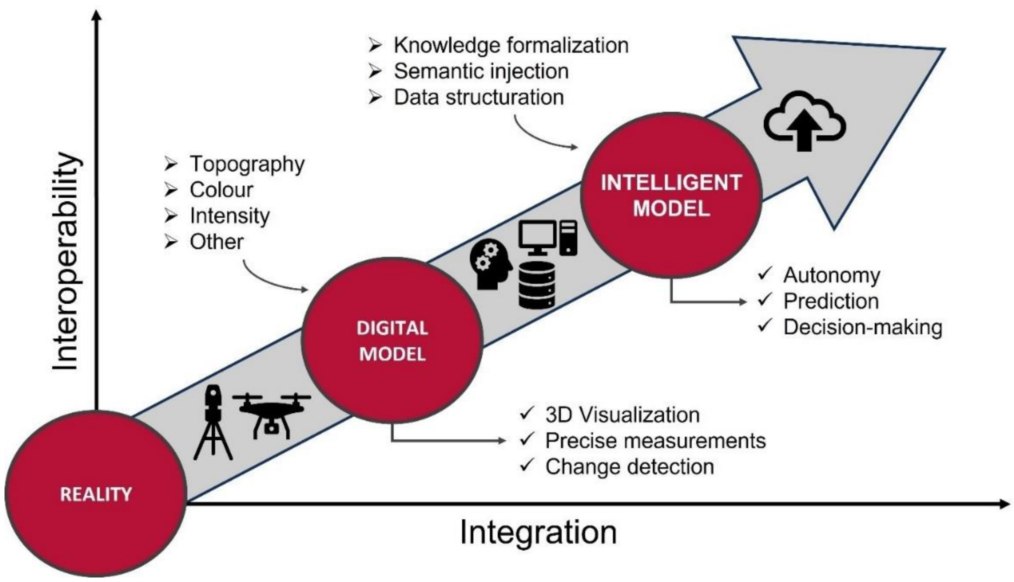

Figure 1. Schematic representation of the evolution of rock slope modelling through digital transformation and artificial intelligence.

Methods

In this work, we showcase ML integration into rockfall monitoring workflows for the development of AI able to automate data analysis and simulate processes as vision problems. We employ deep artificial neural network (ANN) architectures to tackle rockfall detection and slope-scale rockfall susceptibility modeling (RSM) based on long-term LiDAR-based monitoring data.

Deep neural network architectures for 3D point cloud learning are developed for rockfall detection based on a 5-year change detection database consisting of more than 8,000 rock slope clusters of identified change for training, with scanning intervals ranging from 5 days to 6 months. The models are tested on the 536 clusters from the two last data acquisitions to simulate the real monitoring situation and subsequently on the most frequent of the campaigns to increase the probability of working with single-event clusters.

We also explore the potential of simulating the conceptualization of slope-scale rockfall susceptibility modelling using computer power and AI. Three different types of 3D geometric learning neural networks are employed to interpret high-resolution digital observations capturing the rock slope evolution via long-term, LiDAR-based 3D differencing.

Results

The ML models are tested on real case examples from different rock slope settings in Canada and England and are successfully integrated into dynamic rockfall database population processes within the monitoring program. The best-performing rockfall detection model achieves an accuracy of about 89% and 84% on the last and shortest campaign, respectively. The optimized deep learning models are further evaluated on a geologically different rockfall database achieving almost 93% accuracy in a location where discrete geomorphologic features such as steep rock outcrops and erosion channels are present. Our novel slope-scale RSM apporoach leads to effective development of local susceptibility indicators from local geometry and learning from recent rockfall activity. The resultant models produce slope-wide rockfall susceptibility maps in high resolution, producing up to 75% agreement with validated occurrences.

Conclusions

The results indicate clear potential for our AI to develop engineering geological perception and learn from recent rockfall activity based on 3D computer vision. The study shows that although it is challenging to achieve generalization in rockfall detection, site-specific training of the proposed deep learning architecture can lead to high-level performance and support further advancements in rockfall risk management. Our novel approach shows that treating RSM as a vision problem enables AI-based, data-driven RSM at very high resolution. Our results imply that the DL models are able to develop a perception of rock slope geometry and the location of critical blocks, thereby imitating a field expert who deterministically assesses rockfall susceptibility in a qualitative manner based on their knowledge and experience but perhaps lacks empirical data to inform their analysis.

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EFFECTIVE ROCKFALL RISK MITIGATION TECHNIQUES BASED ON DIACHRONIC CLOSE-RANGE REMOTE SENSING DATASETS. CASE STUDY: KALYMNOS ISL. WORLD-RENOWNED CLIMBING TERRAIN (GREECE)

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Introduction

Kalymnos Island features extensive vertical limestone cliffs that span throughout the entire onshore area, establishing it as one of the world's premier locations for sports climbing. Drawing thousands of tourists and climbers annually, Kalymnos captivates with its unparalleled natural beauty and unique geomorphological relief. The absence of vegetation and the prevalence of large limestone vertical cliffs contribute to a distinctive geological setting, showcasing detached boulders throughout the island and positioning it as an ideal site for studying rockfall events worldwide. To investigate this peculiar geological landscape, contemporary close-range remote sensing techniques such as UAS images photogrammetric processing, terrestrial LiDAR point clouds, and high-resolution satellite imagery within a GIS platform are employed. This integrated approach facilitates the creation of detailed terrain models and enables the identification of spatial boulder distribution on the downslope areas of steep carbonate cliffs. Moreover, the diachronic study of the detected high-risk locations delineated the surface changes at the foot of the steep slopes where several back analyses were performed. Utilizing these quantitative techniques provides valuable information for designing protective measures for the stability of the slopes, highlighting the safe climbing routes for the athletes and the infrastructure at the cliff bases. Strategies involve anchoring individual rock blocks, removing unsafe rock masses, and implementing restraining nets or dynamic rockfall barriers at strategic locations along the route trail to mitigate risks effectively.

Methods

The methodology was based on the synergy of equipment in different working levels, depending on the type of the covered area and the scale of study, which varies at each location. Most of these sites are large and wide areas with numerous fallen boulders on the downslopes beneath the vertical cliffs, which needed to be mapped. In such cases, several planned UAS flights were conducted, and thousands of accurately georeferenced images were acquired, due to the use of Network RTK methods (Panagiotopoulou et al. 2020).

At specific locations where larger scale observations needed to be made, such as cliffs which are used for sports climbing, the point clouds were generated by using terrestrial LiDAR equipment. Several bases were established for covering the entire cliff from different angles, as the roughness is generally quite high and the 'shadow' effect during the data acquisition could produce holes within the datasets (Vassilakis and Konsolaki, 2022). The bundling of the point clouds acquired from the different bases, was made possible since the proposed methodology includes the establishment of a dense network of Ground Control Points, which were measured with RTK-GNSS equipment for gaining actual coordinates. After merging the partial scans and combining them into a single point cloud, the methodology continues with further processing including filtering and noisy points removal. Moreover, the final product is combined with the point cloud that was generated after the photogrammetric processing.

The same procedure is repeated either once a year, before the climbing season starts or after extreme weather events or earthquakes with nearby epicentres. The multitemporal datasets are co-registered and compared with each other, with several algorithms such as M3C2, C2C DoD etc. (Bernard et al. 2021) and we were able to point out locations where several safety measures should be taken, either by constructing them or by removing rock blocks that were about to fall, potentially after the next catastrophic event. The methodology is completed by exporting the results into file formats that can be imported in several geotechnical or discontinuity recognition software for further interpretation.

Results

The results and the produced 3D models were utilized to determine areas susceptible to different failure types. The assessment of rock stability at several climbing sites by combining innovatively high-accuracy equipment, sophisticated techniques, and research methods could lead to hazard identification in great detail. Additionally, the results may be seriously considered by the local authorities for the maintenance and/or re-design the climbing routes, as well as for certifying them as “safe climbing”.

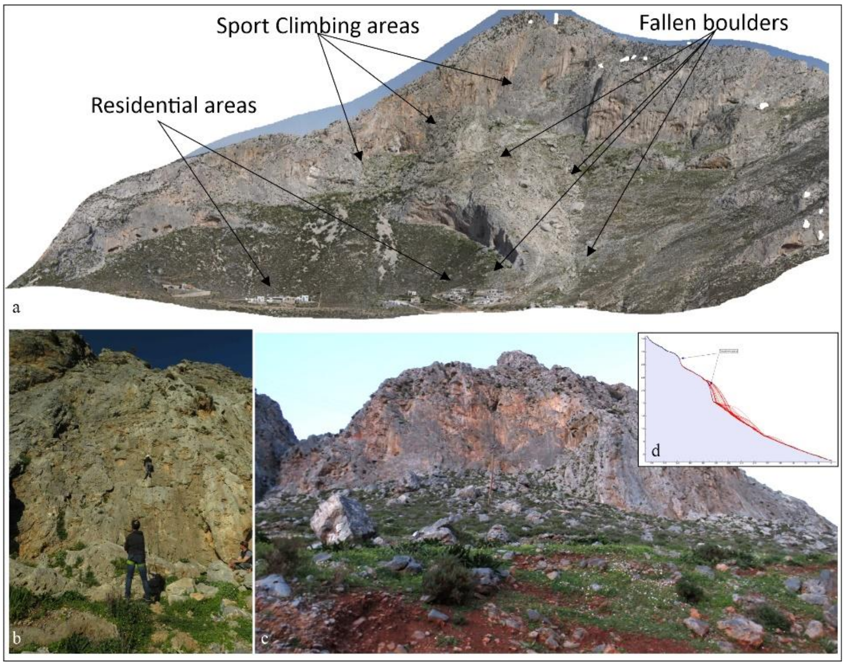

Figure 1. (a) A very typical part of Kalymnos Isl. as visualized after the photogrammetry processing of UAV images. The methodology involves TLS equipment to be used for the data acquisition at high risk climbing sites (b), whereas UAS image acquisition is suggested for wider areas where rockfalling is a continous phenomenon (c). The point cloud data are used for detailed topography cross section, which are imported into rockfalling simulation software (d).

Conclusion

The highly accurate products, including detailed elevation models and ortho-geo-referenced images, are the valuable outcomes of these kinds of workflows. It is widely accepted that the sophisticated simulation software, used for designing safety measures, needs as highly accurate input data as possible. Therefore these close-range remote sensing methodologies are ideal for producing such datasets.

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UNVEILING COASTAL CLIFF VULNERABILITIES BY INTEGRATING LIDAR, UAS, AND AI TECHNOLOGIES. CASE STUDY: NAVAGIO SHIPWRECK BEACH, ZAKYNTHOS (GREECE)

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Introduction

Coastal cliffs are one of the cases of steep terrains naturally vulnerable to a range of erosional processes, with rockfalls emerging as one of the most prevalent and hazardous. Although predicting rockfall occurrences remains challenging due to multi-faceted triggering factors such as extreme weather events, seismic activity, erosion, and human actions, technological advancements offer promising avenues for developing more robust and effective risk assessment methodologies. Light Detection and Ranging (LiDAR), photogrammetry from Unmanned Aerial System images, and satellite imagery, coupled with the evolution of artificial intelligence, have revolutionized the field of rockfall assessment by enabling precise detection and quantification of 3D topographic changes, offering insights into rockfall dynamics (Abellán, A., et al. 2010).

Methods

There are many methods applied, considering the advancing study of rockfalls. DEM of Difference (DoD) (Li et al., 2024), Adaptive Cloud-to-Cloud (AC2C) (Huang et al., 2022) and Multiscale Model-to-Model Cloud Comparison (M3C2) (Lague et al., 2013) are some of the most utilized and consistent methods for 3D change detection analyses. The latter as the most insighted has various applications in estimating changes in a 3D spatial environment (DiFrancesco et al.,2020). In relation to the other methods, M3C2 is a direct 3D point cloud comparison, that computes 3D distances along the normal direction of the topographic surface, allowing better capture of subtle changes on steep surfaces (Bernard et al., 2021).

The “U” shaped vertical cliffs of “Navagio” shipwreck in Zakynthos, Greece were chosen as case study for applying the above-mentioned methodology. In a time-frame of three years (2020-2023), multiple UAS surveys and a TLS survey (in 2023) have been carried out, providing us valuable data for the detection of possibly loosened rocks. During the UAS surveys we managed to succeed the high precision Direct Georeferencing (DG), taking advantage of the Network Real Time Kinematics, which does not necessarily require Ground Control Points (GCPs). Moreover, we enhanced the methodology by using the Post Processing Kinematics (PPK) approach, including GNSS permanent station’s RINEX data within the procedure, along with the establishment of pseudo GCPs succeeding a perfect co-registration of the datasets (<5mm).

After the co-registration, we applied the M3C2 algorithm by isolating patches of significant topographic change using the statistical model accounting for point cloud roughness, density, and registration error (Figure 1). The efficiency of this workflow was tested by comparing a UAS and a TLS survey of the same day.

Results

In total, three simulations were performed by applying the M3C2 algorithm: (P1) a UAS-UAS comparison of 2020 – 2023 surveys, (P2) a UAS-TLS comparison of 2020 – 2023 surveys, and (P3) a UAS-TLS comparison of the same period (July 2023). P1 and P2 were registered by Gaussian noise with mean 0 and a standard deviation of 0.04 m and 0.12 m respectively. The point cloud was divided in three segments as the orientation changes significantly. The final spatial level of detection (LoD) based on our data process was 0.2 m meaning all features larger than this LoD are recognizable and valid. The P3 simulation served as a validation procedure, leveraging the high accuracy and detail of the TLS data to verify the UAS change detection analysis.

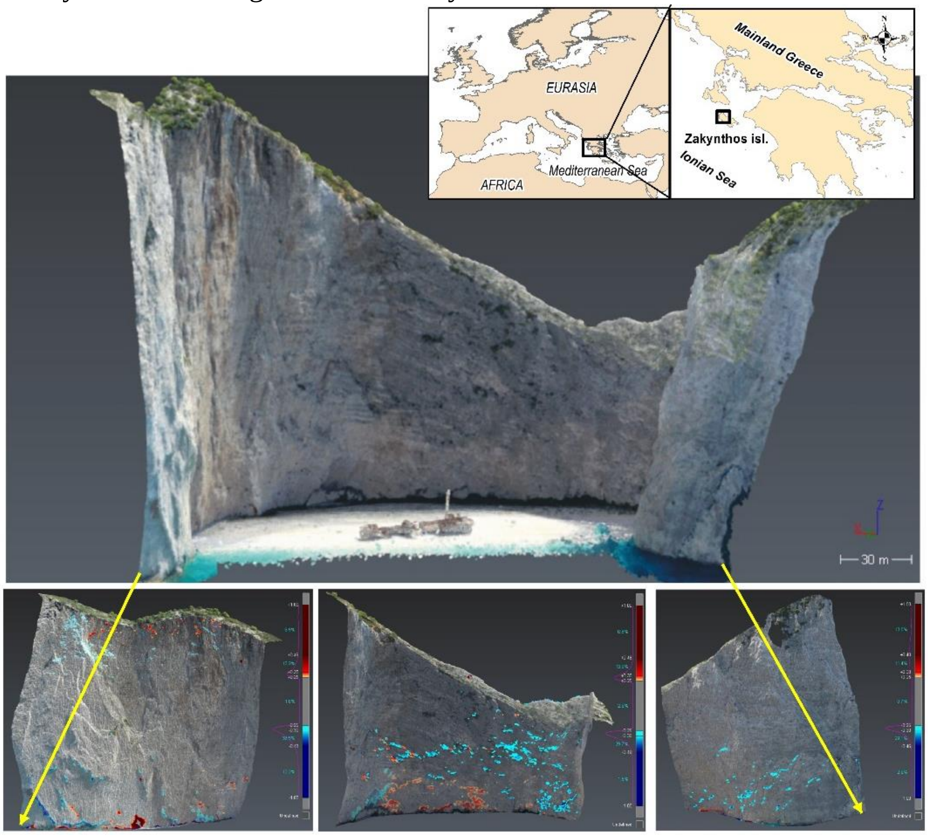

Figure 1. The results of the processing of the Navagio beach cliff with the M3C2 algorithm. The color scale shows the calculated 3D changes, with blue areas indicating erosional areas whereas red areas indicating depositional areas. The bottom row figures represent the three segments.

Conclusion

This study applies cutting-edge methodologies that enhance our understanding of slope stability and monitoring in tectonically active coastal areas. The presented approach can be a useful, efficient and transferable tool that can significantly benefit risk-mitigation efforts for the design of protection measures by expanding applications to other sites with similar geological and geomorphological properties worldwide.

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ADVANCING LANDSLIDE MAPPING: INTEGRATING MACHINE LEARNING AND OBJECT-BASED ANALYSIS WITH UAV-DERIVED DATA

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Introduction

We find ourselves in an ever-evolving environment, where the past fifty years have marked a pivotal moment in scientific thinking. This shift is particularly evident in the scientific approach to analyzing natural-induced hazards. Geohazards annually contribute significantly to loss of life and property, with mass movements standing out as widespread occurrences globally. The study of extreme events and their repercussions on landscape stability is a critical area in environmental research. In this paper, we showcase the advancements in the integration of Artificial Intelligence (AI) and Remote Sensing (RS) for improved landslide assessments, leveraging developments in Earth Observation (EO) data analysis. We highlight the application of Object-Based Image Analysis (OBIA), which have not traditionally been tailored for landslide studies but have proven effective in this context. The framework enables the translation of complex real-world landslide scenarios into analyzable objects through segmentation algorithms, applying subsequent classifications via rule-based or advanced Machine Learning (ML) algorithms. We demonstrate how ML has the potential to revolutionize geoscience data analysis and address major societal concerns presented by landslide hazards by tapping into the vast reserves of geoscience data. ML algorithms, particularly Random Forest (RF), integrated into an Object-Based Image Analysis (OBIA) workflow, demonstrated adaptability for sub-zone landslide mapping on a local scale. Given the increasing frequency of extreme meteorological events driven by climate change, the integration of UAV datasets, Structure from Motion (SfM), and advancements in OBIA and AI can respond effectively by enabling precise and accurate analysis of landslide and rockfall failures. Our results affirm that rotational landslides and their thematic sub-zones were adequately recognized and mapped through the ML procedure.

Methods

Understanding the large deviations in landslide mechanisms is of paramount importance for providing long-term landslide mitigation in a region. However, this task is challenging and quite poorly addressed in the literature because landslide failures are often highly variable in space and time due to their stochastic and episodic characteristics. While engineering geological assessment is a fundamental task in landslide characterization, unstable slopes can pose a high level of risk to geoscientists employing traditional field reconnaissance (landslide mapping, discontinuity measurements, Schmidt hammer test, etc.) due to difficult accessibility and safety concerns. In addition to the exploitation of an optimal data collection and analysis procedure for landslide characterization, the presented study also addressed methodological questions related to the reproducibility and efficiency of the developed object-based workflows (figure 1) for different landslide scenarios, considering the sensitivity of the selected attributes (morphometric, spectral, contextual, and spatial) (Karantanellis et al., 2021).

The two created dataset structures were processed distinctly following the same workflow for segmentation and classification during object-based analysis. Two major challenges exist in the OBIA process: first, the determination of optimal parameters for image segmentation, and second, the selection of suitable features and thresholds for classification. Consequently, the selection of appropriate segmentation parameters is a challenging task, and they are often estimated subjectively through trial and error. Several studies have proposed automated approaches for objectively estimating the scale parameter (SP) value for multi-resolution segmentation (MRS). The Estimation of Scale Parameter 2 (ESP 2) (Drăguţ et al., 2014) was employed to identify statistically relevant object levels for a set of input layers by evaluating the relative changes in local variance for a predefined scale spectrum. Second, trial and error tests based on expert's prior site knowledge have been explored on both input structures ("RGB" and "RGB+DSM").

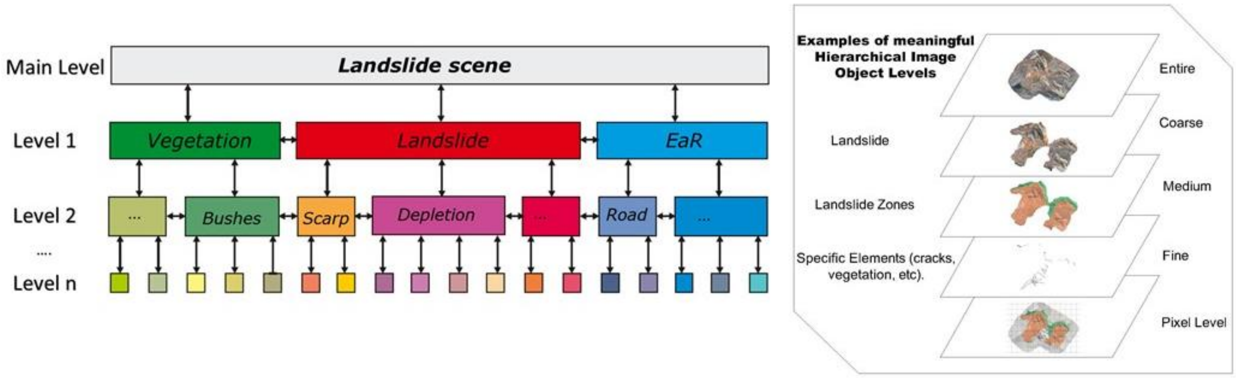

Figure 1. Object-based hierarchical landslide levels for segmenting and classifying datasets.

Results

The combination of object-based analysis and knowledge-based classification provided a robust framework for landslide classification, as it enabled the extraction of both spectral semantic and spatial features, allowing for a more comprehensive characterization of the landslide sites. This comprehensive approach contributes to a more accurate and detailed understanding of the landslide phenomena, improving the overall quality of the classification results. To assess the transferability of the developed workflow, the most efficient classification configuration determined from the previous tests (input data structure: RGB+DSM, SP: 100, and shape/color weight: 0.6) was applied to another landslide, which constitutes a similar failure in the wider region under the same landslide characteristics as the previous one (geological, lithological, failure type). The test site is a landslide failure that occurred in an open-pit mine of coal in northern Greece. Transferability is critical in image classification, and it was conducted to test its efficiency in the proposed study. To ensure consistency in the implementation approach, the study applied identical object features and processes for both segmentation and classification. Considering the extracted F1 metrics, the RF model for the RGB+DSM structure illustrated the best classification agreement.

Conclusion

Landslide phenomena represent natural scenes of complex and heterogeneous character. Such natural processes can be better understood by analyzing them with OBIA as this approach mimics the way how humans recognize patterns. In conclusion, this study employed a novel approach for landslide classification using OBIA and ML techniques. The selection of an appropriate method, i.e. an expert-based or ML approach, depends on the availability of training data and the scope of the study. Expert-based methods are more flexible and adaptive for site-specific landslide mapping than ML, which requires a large amount of training data. This suggests that the knowledge-based approach can be applied to similar failure mechanisms. By using OBIA for site-specific landslide assessment, sub-zones of rotational landslides could be effectively identified with high precision. A limitation is the need for prior knowledge of the site under investigation to optimally adapt the ruleset. Future research should focus on improving automated sub-zone classification for different landslide types. In addition, the integration of deep learning and OBIA for landslide susceptibility mapping using UAV datasets is highly proposed for future consideration.

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ENVIRONMENTAL SEISMOLOGY WITH AI

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Introduction

A seasonal climate, frequent typhoon and high earthquake activity links to interaction between the evolution of mountain landscape and the physical/chemical erosion processes is an important scientific issue in Global, especially for the active orogenic belt region. Recently, the environmental seismology has been widely applied to study the surface processes, such as landslide, debris flow, rockfalls and fluvial processes, which would be helpful to clarify the aforementioned scientific issue. This study presents four topics about the environmental seismology using AI algorithms: (1) Rapid coseismic landslide susceptibility assessment using Newmark analysis and decision-tree (DT) algorithm, (2) An automatic machine-learning classifier using riverine seismic signals: flooding, debris flooding and debris flow, (3) Seismic classifier by deep neural network (DNN) for early warning of post-failure landslides and (4) A wavelet scattering network using seismic records of a single station for roadside rockfall recognition. Aforementioned studies not only provide a better understanding of earth surface processes in the context of climatic and tectonic forcing but also reduce the social impact of of geohazards.

Methods

Decision Tree (DT, Ahmadi et al., 2018) algorithms is a supervised machine-learning model with simplicity, flexibility and high interpretability, which are adopted to train two DT models: coseismic landslide susceptibility model and a classifier of water-and-sediment events. Five features (peak ground acceleration, peak ground velocity, epicentral distance, source-to-station azimuth, strike) and two labels (YES: landslide, NO: non-landslide) for coseismic landslide model. For clarifying water-and-sediment events (FD: flooding, DFD: debris flow flooding, DF: debris flow), peak value of power spectral density and signal-to-noise ration are crucial parameters for source recognition.

In case of DNN model for early warning of post-failure landslides, VGG16 architecture (Simonyan and Zisserman, 2015), which comprising 16 convolution layers and 3 dense layers, was used. 224 × 224 pixel RGB images are created by combining two 112 × 224 RGB single-station spectrogram as model inputs. The convolutional layers used a fixed filter size of 3 × 3 pixels with a stride of 1 pixel. Spatial pooling was performed using max pooling with a 2 × 2 pixel window and a stride of 2. We replaced the flattened layer with global average pooling. A softmax activation function is used for the final layer, while all other layers used the rectified linear unit (ReLU) activation function. For training, we set the epoch to 150, batch size to 128, learning rate to 0.001, and stochastic gradient descent (SGD) as the optimizer.

Finally, a scattering network (Seydoux et al., 2020) performs convolution and pooling on the three-component seismic records to extract multiscale wavelet scattering coefficients. For feature extract, the pricipal components analysis (PCA) is used. Subsequently, we cluster the primary features using unsupervised learning algorithm of K-means. Cluster events are eathquake, rockfall and background noise.

Results

Figure 1 shows two DT models for coseismic landslide and water-and-sediment events, which result the accuracy rate larger than 0.8. Results of the PCA decomposition for primary and secondary features and

K-means clustering of six events are shown in Figure 2.

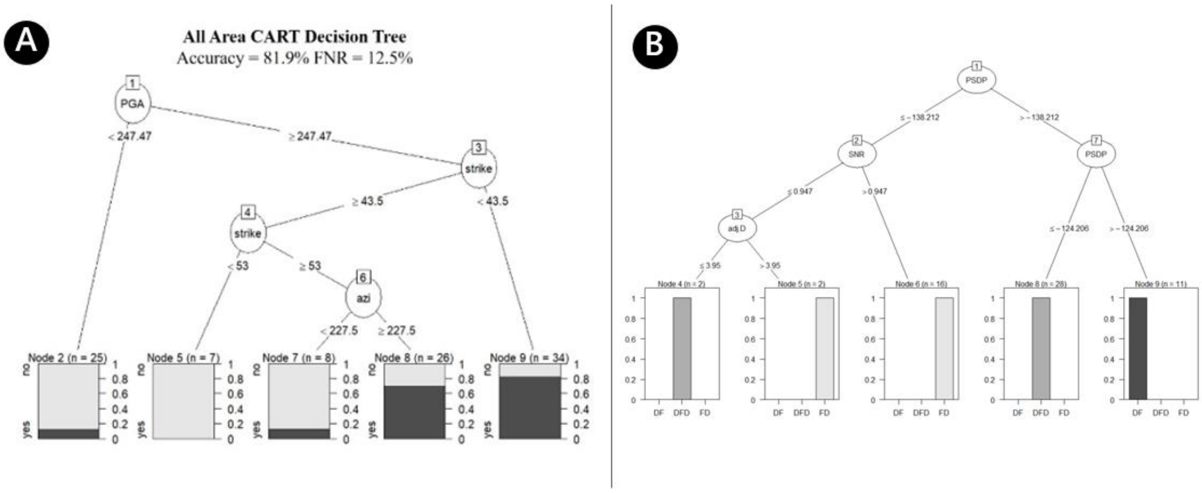

Figure 1. Resulted DT models of (A) coseismic landslide and (B) water-and-sediment events.

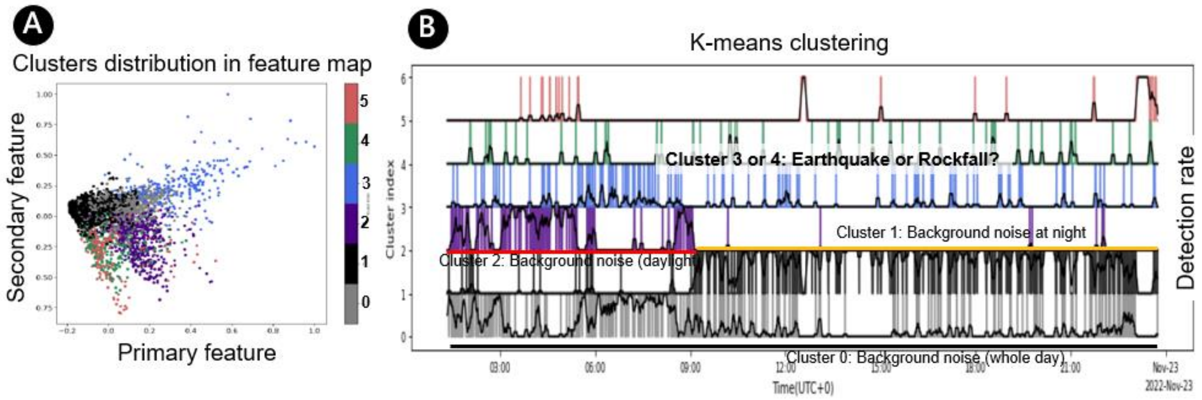

Figure 2. (A) Map of primary and secondary features based on scattering coefficients. (B) K-means result obtained from one-day single seismic station with detection rate for each of the 6 clusters.

Conclusion

Both of supervised and unsupervised machine-learning algorithms applied this study can provide information such as seismic source identification and coseismic landslide prediction, which would be very helpful for geohazard early warning and monitoring system.

References

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