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A NOVEL 3D GEOMORPHIC CHANGE DETECTION FRAMEWORK FOR LARGE-SCALE ACTIVE DUMP SLOPE USING MULTI-TEMPORAL IMAGERY

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Highlights:

- introduces a novel approach to mine dump slope stability assessment using UAV-based 3D photogrammetric reconstruction, point cloud analysis, change detection, and numerical modeling;
- achieves high precision in surface displacement detection through the use of high-resolution UAV data, involving 520 images and eight photogrammetric targets for accurate georeferencing;
- successfully applies a hybrid point cloud registration method, achieving the lowest RMS error, which is crucial for precise change detection analysis;
- identifies critical displacement zones and validates these findings through numerical modeling, resulting in FOS values of 1.107 indicating near-failure conditions;
- demonstrates the potential of this multi-modal approach for enhancing proactive slope management, offering a cost-effective solution for real-time monitoring across various geotechnical environments.

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Abstract. Slope stability of dumps in the mining industry is a critical issue due to frequent incidents involving loss of life, equipment damage, and operational disruptions. This study presents an innovative methodology integrating unmanned aerial vehicle (UAV)-based 3D photogrammetric reconstruction, point cloud analysis, change detection, and numerical modeling to assess slope stability. High-resolution data were acquired using a DJI drone. Geometric features were analyzed at multiple scales using advanced point cloud techniques. A key advancement was the implementation of a Hybrid registration approach that yielded the lowest RMS error (0.642), which ensures precise spatial alignment. Change detection analysis identified a maximum displacement of 31.13 m in the active dumping zone. Numerical modeling of the critical section with a Factor of Safety (FOS) of 1.107, confirming near-instability conditions. This multi-modal approach not only improves assessment precision but also promotes proactive slope management, offering broad applicability across various geotechnical contexts.

Keywords: mine dump slope, unmanned aerial vehicle (UAV), change detection analysis, 3D reconstruction, factor of safety (FOS), slope stability.

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1. Introduction

Slope instability of mine dump is one of the most important problems to be considered for successful surface mining as a huge quantity of overburden material is generated from the extraction process. It is very important to manage and deposit this material in a manner that minimizes the likelihood of slope failure being reduced to a minimum, since failures are responsible for hazardous conditions, operational delays, and substantial financial losses. All these are further compounded by the added variables, namely the height, gradient, composition of the dump and external influences such as weather conditions, and water infiltration.

Several dump slope failures have been reported in different parts of the world, causing catastrophic events that result in loss of human lives, in addition to costly operational breakdowns. Several cases of dump slope failure have also been reported in India (Dash, 2019), as depicted in Figure 1 below. The Rajmahal opencast mine, which collapsed in 2016 in India, was one of the most tragic mining disasters, resulting in the deaths of twenty-five people (Yadav et al., 2019). This incident has evidently pinpointed the critical importance of slope stability management and safety measures to avert occurrences that cost lives.

The rapid advancement of UAV technology has emerged in response to these challenges and in recent years, UAVs has advanced at an exceptional pace (Iqbal et al., 2023; Karam et al., 2022; Ollervides-Vazquez et al., 2023; Yordanov et al., 2023). UAVs with lightweight sensors are being used to provide low cost, short revisit intervals, effective data collection, and ease of use (Chen et al., 2015; Esposito et al., 2017; Rossi et al., 2017; Aasen et al., 2015; Dash et al., 2017; Tian et al., 2017). This technology has turned around the way data is collected in the mining industry by providing high-resolution aerial imagery and topographic information required for effective monitoring and analysis. When integrated with numerical modeling, UAV technology provides a complete approach to mine dump slope management.

In the processing of 3D data, the process of extracting geometric features is carried out as a step to assess datasets. This is a critical quality assessment of datasets, which can be applied from computer vision to urban planning. Geometric feature extraction allows for the identification and characterization of significant elements within point clouds that will inform further analysis and decision-making processes. However, noise, sparseness, irregular sampling, and other problems are always great in feature extraction, meaning that effective point cloud analysis needs to employ methods that are very robust. Some previous studies show the importance of features in point cloud analysis (Chehata et al., 2009; Mallet et al., 2011).

In the past few decades, automatic change detection has been a critical research area in remote sensing and photogrammetry, areas that have made significant contributions to urban monitoring and environmental science. Direct comparison and classification-based comparison are two ways of detecting changes in multi-temporal data and classifying objects such as buildings and plants for further analysis (A. Singh, 1989). For the purpose of identifying changes in land cover and buildings, recent research has made use of three-dimensional ground surface data obtained from terrestrial and aerial laser scanners (Abellán et al., 2011; Boehm et al., 2013; Jaboyedoff et al., 2012; Mineo et al., 2018; Ventura et al., 2011). LiDAR has been employed for the detection of alterations in significant water events (Boerner et al., 2019) and for forest surveillance (Polewski et al., 2015, 2017). Point clouds are extensively utilized for three-dimensional change detection, offering real-world data for diverse applications such as urban planning (Hebel et al., 2013), street view analysis (Gehrung et al., 2020), construction progress monitoring (Huang et al., 2022; Meyer et al., 2021), vegetation assessment (Hirt et al., 2021), and energy leak identification (Hoegner & Stilla, 2015). Progress in computer vision and machine learning has significantly enhanced 3D point cloud change detection (De Gélis et al., 2021; Ku et al., 2021; Tran et al., 2018; Stilla & Xu, 2023). The coupling of the change detection with numerical modeling can further enhance the visualization and understanding of these changes, ensuring higher safety and better management of mine dump slopes.

Numerical modeling has become an indispensable tool for the analysis of stability in mine dump slopes, which offers a comprehensive approach to better understand such complex interactions within the geological structure. Numerical models have the capability to give details of the stability factors and probable failure mechanisms by simulating the behavior of the materials. Among these, the Limit Equilibrium Method (LEM) remains a widely applied approach, effectively calculating the FOS by evaluating potential slip surfaces. Advanced methods such as finite element analysis (FEA) and discrete element modeling (DEM) also contribute to a more nuanced understanding of stress-strain responses and material interactions. In recent years, many extensive research works have investigated mine dump stability in static, dynamic, and rainfall conditions (Koner & Chakravarty, 2011, 2016), mechanisms of failure (Wang & Chen, 2017; Zhan et al., 2021), assessment of stability (Behera et al., 2016), and stabilization methods (Rai et al., 2012; Ranjan et al., 2017). Other works have been concerned with the probability analysis of dump failures(Kumar et al., 2023) and the determination of failure zones within dumps (Chand & Koner, 2023, 2024a).

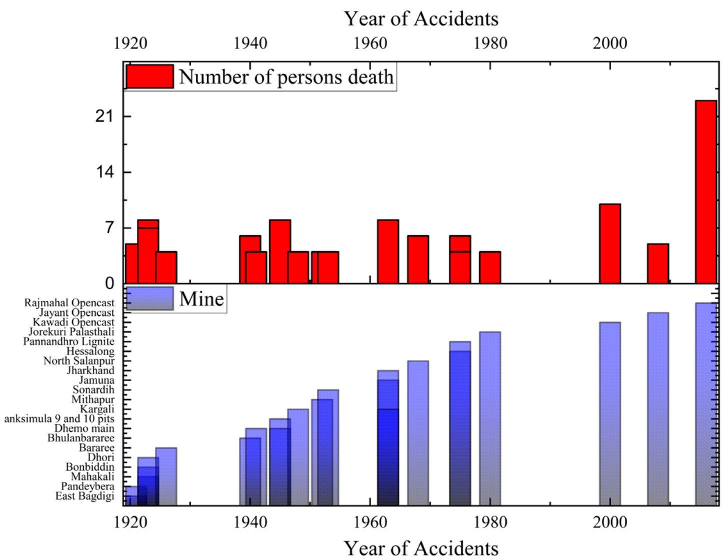


Figure 1. Accidents occurred in India from 1921 to 2016 (source: Dash, 2019)

In this study, an integrated approach of UAV-based 3D photogrammetric reconstruction, point cloud analysis, change detection, and numerical modelling were performed to assess the stability of a mine dump slope. High-resolution UAV imagery was used for a detailed point cloud analysis in assessing geometric features, and a hybrid approach for point cloud registration was implemented for change detection with high accuracy. The critical displacement zones were identified and validated by numerical modeling respectively, showing near-failure conditions. This multi-modal approach provides a robust framework for improving the assessment and proactive management of slopes.

2. Study area

The research was carried out in the Raniganj Coalfield of Eastern Coalfield Limited in Paschim Bardhaman district of West Bengal India as shown in Figure 2.

This location is close to important industrial hubs like Raniganj, Asansol, and Durgapur. It is one of the major mine operated by Eastern Coal Limited (ECL), having a land coverage of 24 km^2. The region has a tropical monsoon climate which is typified by hot summers and frigid winters. The average temperatures range from 42 °C during the summer to 6 °C during the winter (R. S. Singh & Ghosh, 2021). The average annual precipitation is 1450 mm. As of April 1, 2010, the mineable reserve is 141.90 million tons, with an expected lifespan of 46 years (Gautam et al., 2016). This area which is under the operation of ECL plays a crucial role in coal production (Chand & Koner, 2024b; Saha, 2019). The geological reserves in the area were estimated to be 807.97 million metric tons and with a minimum reserve of 214.98 million metric tons. The terrain within the mine is partitioned into many sections including active mining areas, locations for waste disposal, quarries filled with water, industrial infrastructure, road networks, and areas designated for vegetation.

3. Materials and methodology

This study presented a four-stage systematic approach to assessing the slope of the mine dump as shown in Figure 3. Each stage is progressive and builds upon the data acquired in the preceding step, enabling a comprehensive analysis of slope structural stability over time.

The first stage was the creation of a high-resolution 3D model of the mine dump slope using imagery captured from a UAV. The second stage involves the assessment of the generated point cloud for extracting essential topographic and geomorphologic details. In the third stage, the change detection of the mine dump slope with displacement analysis. The fourth stage involved numerical modeling of the mine dump slope based on the details extracted through 3D reconstruction and analysis of change detection.

3.1. 3D model generation

3.1.1. Images and GCPs acquisition

Image acquisition from UAVs is a sensitive process influenced by multiple factors that are fundamental to the quality and efficiency of data collection. Amongst those factors, flight planning is one of the most important factors to ensure optimal image acquisition. These plans describe the trajectory, altitude and speed of the UAV, which directly impact the control and resolution of the acquired images (Nex & Remondino, 2014).

During the image acquisition from UAV as shown in Figure 4, the image is significantly influenced by many factors such as the time of day, sun angle, and seasonal fluctuations. A meticulous plan is essential with a comprehensive understanding of these factors. The images are acquired in this work using UAV in a grid pattern as shown in Figure 5b. The percentage of overlapping plays a very important role during image acquisition, which

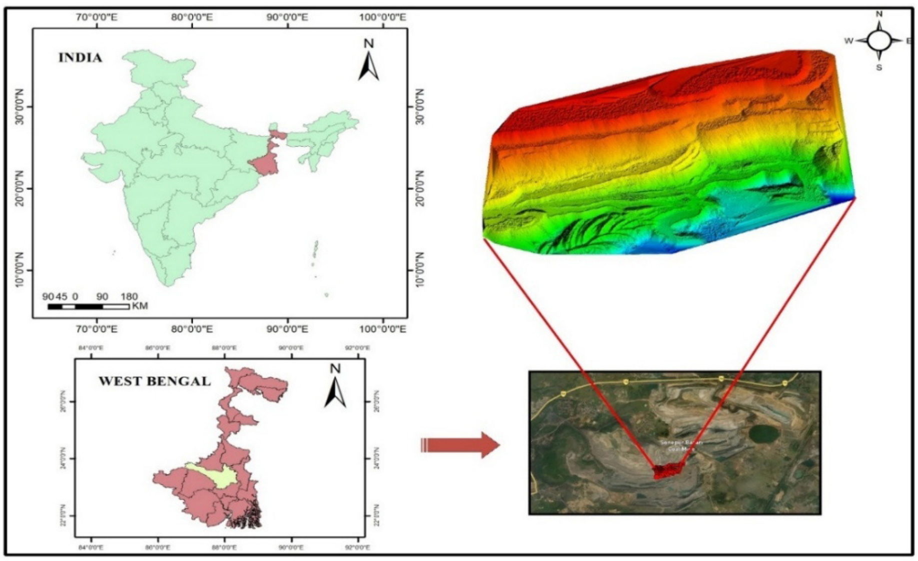


Figure 2. Study area in Raniganj coalfield

ensure comprehensive coverage and redundancy in captured imagery, which enhance the accuracy and reliability of subsequent data processing in an analysis (Mankar & Koner, 2023a, 2023b). The UAV survey was conducted at an altitude of 120 m between 11 a.m. and 1 p.m. to maintain consistent illumination and reduce shadow affect. An image overlap of 70% (forward) and 60% (side) was considered, resulting in a Ground Sampling Distance (GSD) of 5.17 cm. Total 8 number of photogrammetric targets were used as GCPs and surveyed using a Total Station to achieve sub-centimeter georeferencing accuracy. Photogrammetric reconstruction using structure from motion (SfM) and multi-view stereo (MVS) algorithms yielded 39,071,219 densified points with an average density of 41.08 points/m^3. A reprojection error of <0.4 pixels were maintained, and noise filtering was applied to ensure model precision.

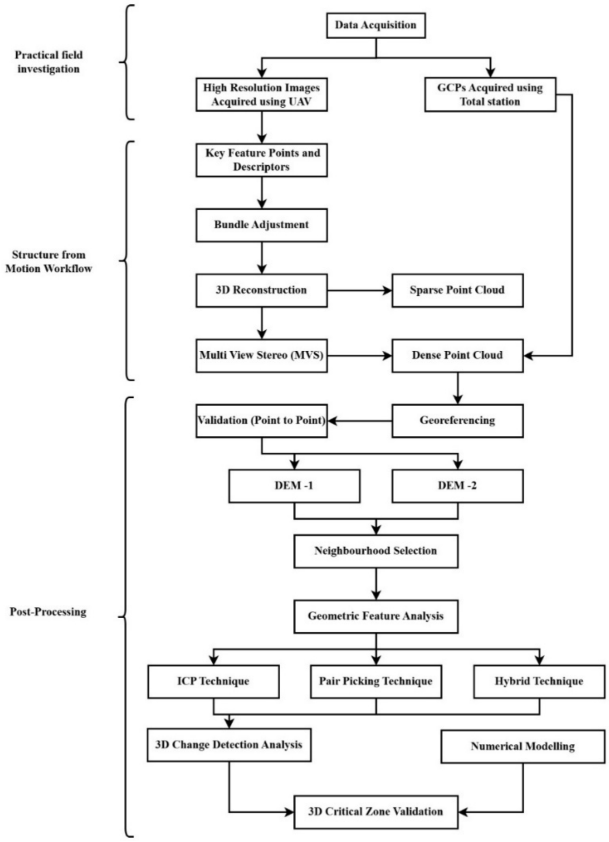


Figure 3. Workflow of 3D change detection and numerical modelling

GCPs acquisition was done simultaneously with the image acquisition process to increase the accuracy of the 3D reconstructed model by georeferencing, as presented in Figure 5a. A total number of 8 GCPs were placed within the area of interest to give spatial reference points for aligning and geolocating the acquired imagery with high accuracy. These GCPs were marked using photogrammetric targets, ensuring their visibility and precise identification in aerial images. Inclusion of GCPs into the workflow of image acquisition enables geometric distortion due to varying terrain, camera lens imperfection, and UAV flight dynamics to be properly corrected during the processing of the data. Attention to the acquisition of GCPs strengthens the integrity and precision of the acquired data, while solid spatial analysis can also be achieved (Ren et al., 2020).

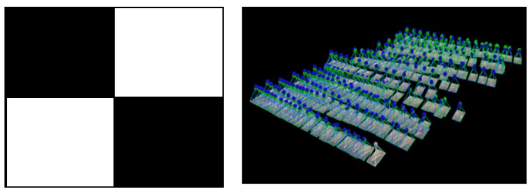
3.1.2. 3D reconstruction of mine dump slope

Following image acquisition, the high-resolution images were imported into photogrammetry software Pix4D Mapper for further processing and analysis. A total of 520 images were imported into the photogrammetric software to generate accurate 3D models and orthomosaic of the surveyed area. To ensure spatial consistency and compatibility with geospatial standards, the coordinate system was set to WGS 84, one of the widely used reference systems based on the Earth's ellipsoid. This standardized coordinate framework facilitates seamless integration with other geospatial data sources and enables precise georeferencing.

Figure 4. High-resolution images acquired using UAV

For the 3D reconstruction process, the Structure from Motion (SFM) algorithm was employed. SfM generates 3D models from a set of overlapping 2D images as shown in Figure 6. SfM is a photogrammetric method that relies on two key principles: binocular vision, and the varying perspective of an object as it moves or is observed from different positions (Koenderink & van Doorn, 1991).

SfM is advantageous over the traditional photogrammetry with three merits: it can automatically detect and match features between images of different scales, angles, and orientations (Figure 7), it solves the necessary equations without any data of camera positions or ground



a) b)

Figure 5. UAV-based photogrammetric data acquisition framework: a) photogrammetric targets; b) UAV flying pattern

control points, although such information will reinforce the process, and automatic camera setting calibrations or refinements can be done during processing (Iglhaut et al., 2019; Westoby et al., 2012). Initially, the algorithm generated a sparse point cloud from the imported images, capturing key feature points and their corresponding camera positions. Subsequently a dense point cloud was generated, refining the spatial detail by densely reconstructing the scene from multiple image viewpoints. This comprehensive point cloud representation forms the foundation for creating a detailed 3D model of the mine dump area as shown in Figure 8.

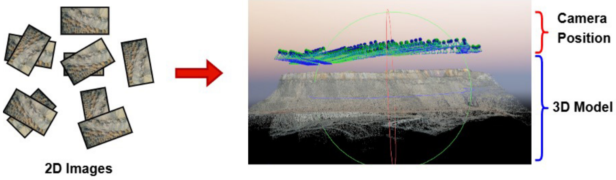


Figure 6. 3D reconstruction from 2D aerial images

Following the point cloud generation, the 3D model underwent georeferencing using the 8 GCPs previously laid out in the area of interest. By correlating the GCPs' known geographic coordinates with their corresponding positions in the reconstructed 3D model and a precise alignment between the model and real-world coordinates was achieved. This georeferencing process ensures the spatial accuracy and reliability of the 3D model, enabling meaningful spatial analysis and integration with other geospatial datasets.

3.2. Geometric feature extraction analysis

The dense point cloud generated in Pix4D Mapper is then utilized to evaluate geometric characteristics using Principal Component Analysis (PCA) on the open-source platform Cloud Compare. Geometric features are assessed to analyze the statistical properties of the point cloud by extracting eigenvectors and their corresponding eigenvalues through principal component analysis (PCA). These eigenvectors and eigenvalues offer insights into the local geometry of the point cloud, particularly when considered alongside other input parameters such as neighborhood radius. They provide a wealth of significant statistical information including omni-variance, surface variation, roughness, and surface density etc.

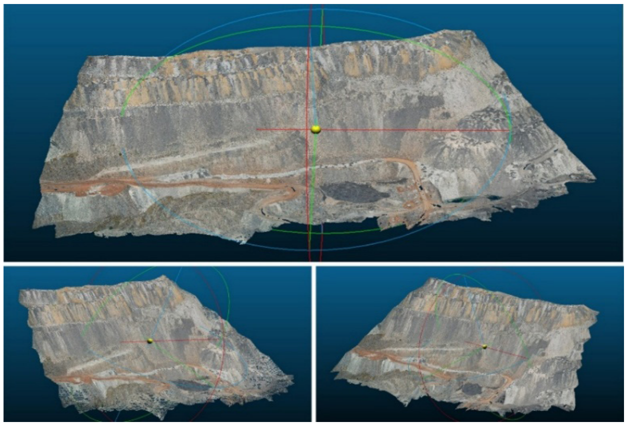


Figure 8. 3D reconstructed model of dump slope

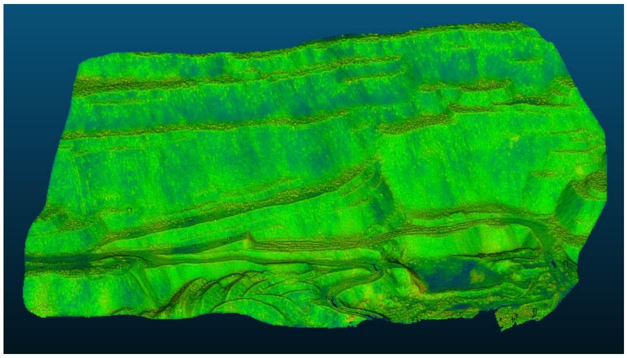


Figure 9. Omni-variance map of dump slope

3.2.1. Omni-variance

Omni-variance is a statistical measure used in 3D point cloud analysis to assess the geometric features of spatial data by describing the distribution of points in the neighborhood as shown in Figure 9. It integrates the eigenvalues obtained from the covariance matrix of the points, hence providing information on the dimensionality and structure of the analyzed region. The omni-variance is a frequently utilized geometric attribute or characteristic that characterizes the three-dimensional local structure surrounding a point of interest.

$$O_\lambda = \left(\lambda_1 * \lambda_2 * \lambda_3\right)^{\frac{1}{3}}, \tag{1}$$

where λ_1, λ_2 and λ_3 correspond to eigenvalues, with $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$, estimated from the neighborhood around each point.

The eigenvalues (λ_1, λ_2, and λ_3) in Equation (1) are calculated from the 3D covariance matrix, also referred to

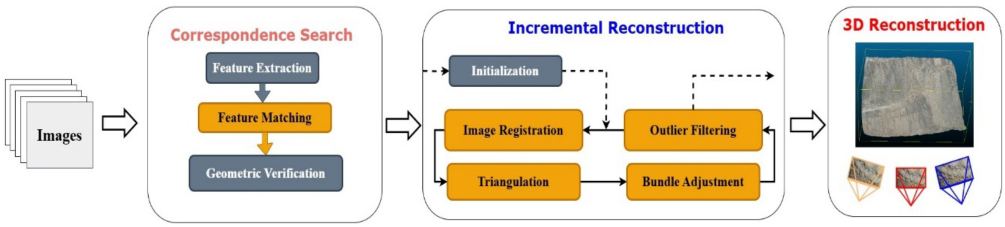


Figure 7. SfM pipeline

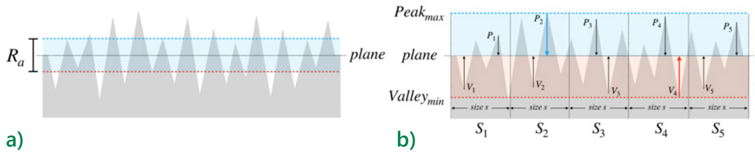


Figure 10. Surface profile: a) the value of the parameter R_a; b) dividing the surface into parts to compute R_a (source: Tonietto et al., 2019)

as the 3D structure tensor. The 3D covariance matrix is derived using the 3D coordinates of the point. Low values are typically associated with points that have been sampled on flat surfaces, such as rooftops of buildings. On the other hand, surfaces with high O_λ values are characterized by their roughness, such as ridge lines and areas with vegetation.

3.2.2. Roughness

A three-dimensional point cloud's surface irregularity or unevenness is denoted by its roughness as shown in Figure 10. It quantifies the depth or elevation variation across the surface. The degree of point spacing would be more uniform on a finer surface, while it would be more variable on a rougher surface (Figure 11).

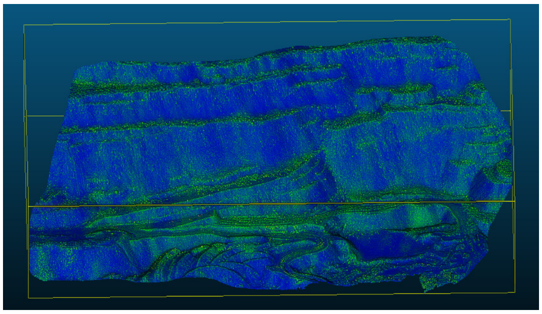


Figure 11. Roughness map of dump slope

The primary roughness parameters consist of the average roughness (R_a) and the root-mean-square roughness (R_q) (Santos & Júlio, 2013; Tonietto et al., 2019). These metrics assess the mean standard deviation of the elevations (low points and high points) in a surface profile to calculate the level of roughness. Prior to calculating these values, it is essential to calculate the fitting plane for the points obtained from the surface. By analyzing the plane coefficients, one can ascertain the elevation of a peak or valley by assessing the vertical coordinate of each point in the cloud.

The average roughness R_a, is given by:

$$R_a \approx \frac{1}{n}\sum_{i=1}^{n}\left|Z_i\right|, \tag{2}$$

where Z_i is the height coordinate of the current point

The root-mean-square roughness (R_q), is defined as:

$$R_q \approx \sqrt{\frac{1}{n}\sum_{i=1}^{n}Z_i^2}. \tag{3}$$

3.2.3. Eigenentropy

Eigenentropy is a statistical measure in 3D point cloud analysis used to quantify the complexity or randomness of point distributions within a local neighborhood as shown in Figure 12. It is derived from the eigenvalues of the covariance matrix of the points, reflecting the distribution of spatial variance along principal axes. Eigenentropy is calculated using the normalized eigenvalues as inputs to an entropy function, offering a scalar value that captures the degree of anisotropy or isotropy in the point cloud.

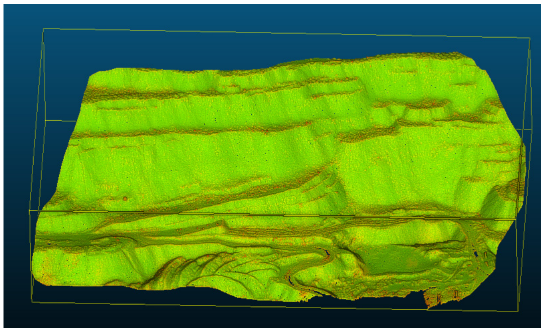


Figure 12. Eigenentropy map of dump slope

3.2.4. Surface variation

Surface variation in 3D point clouds measures the extent of local roughness or undulation in the scanned surface (Figure 13). This is a fundamental geometric characteristic utilized in diverse applications including terrain analysis, structural monitoring, item recognition, and change detection. Surface variation is especially valuable for describing features in geospatial and geotechnical research, including the evaluation of slope stability and the identification of morphological alterations in dump slopes. The surface variation can be deduced from the eigenvalues of the 3D structure tensor. This heuristic search, with an important increase of C, allows us to estimate the critical size of the neighborhood and then choose a k value accordingly.

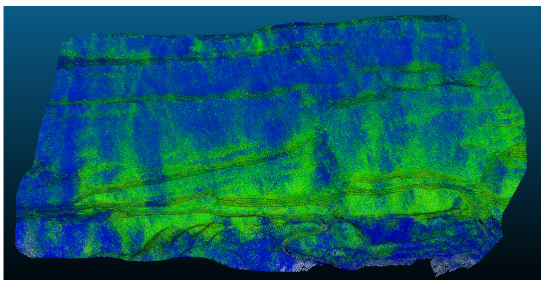


Figure 13. Surface variation map of dump slope

$$C_\lambda = \frac{e_3}{e_1 + e_2 + e_3}, \tag{4}$$

where C_λ = Surface variation, e_1 = Largest eigenvalue indicating the direction of maximum variation in the data, e_2 = Second eigenvalue representing the intermediate level of variation, e_3 = Smallest eigenvalue representing the direction of minimum variation.

3.2.5. Surface density

In the context of a 3D point cloud, surface density refers to the distribution of points across surfaces in a dataset to provide information with regards to the detailed insight about how points are laid out. This is one of the most important metrics that quantify concentration. It helps in differentiating between areas where points are spread with high density on surfaces from other areas that have them sparsely spread over the same surface as shown in Figure 14.

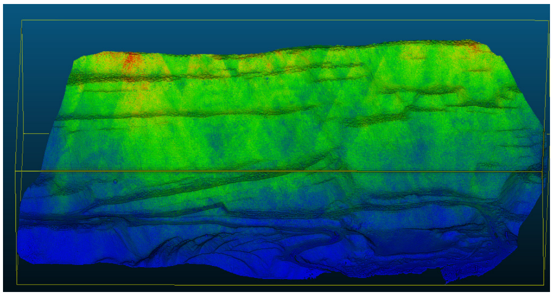


Figure 14. Surface density map of dump slope

Density in 3D point clouds is one of the most important measures to reveal the complicated structure of spatial information enclosed in the volumetric data representation. By carefully investigating the surface distribution of points, this measure uncovers the hidden structure of objects or scenes represented in a point cloud.

The areas of high surface density contain many points. These typically signify the locations in the point cloud where fine detail, sharp edges, and complicated geometry exist. Such regions often contribute to substantial features or main parts of the captured environment and thus are crucial for many applications, like object recognition or precise modeling. Even more to the contrary, low surface density values represent the points that are distributed in far less dense manners, forming surfaces that are considerably smoother, or lacking in considerable structural intricacy. Although low-density areas may appear less useful initially, they are crucial in demarcating borders, establishing volumes, and emphasizing overall spatial relationships within the point cloud collection.

3.3. Numerical modelling and geotechnical investigation

3.3.1. 3D Numerical modelling

Numerical modeling integrated with advanced technologies such as UAV and state-of-the-art software like Slide 3D has considerably enhanced the capability of better prediction, understanding, and mitigation of potential hazards in the field of geotechnical engineering and slope stability analysis. In this paper, high-resolution terrain data captured by UAV were used to prepare a detailed 3D model that has provided a precise and comprehensive representation of the study area as shown in Figure 15. The DEM, which serves as the basis for subsequent numerical modeling analysis. The detailed 3D representation of the mine dump slope allows a more realistic simulation of the geological conditions. Figure 15 shows the realistic 3D model of mine dump slope.

LEM was used in assessing the stability of dump slope and which divides the slope of the waste dump into a series of slices or blocks to analyze the forces acting on each slice or block to arrive at the overall

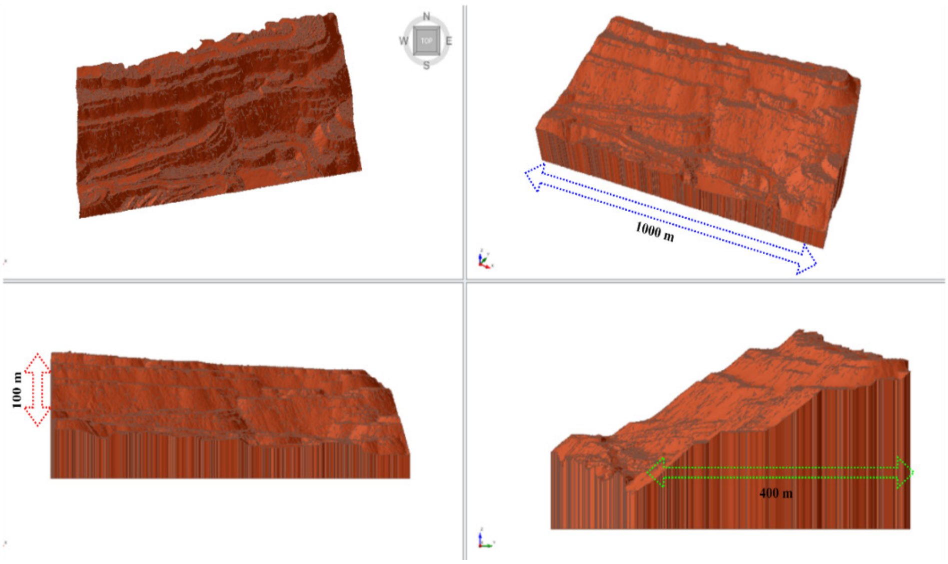


Figure 15. 3D realistic model of dump slope for stability analysis

stability of the slope. The main metric derived from this method is the factor of safety, calculated as the ratio of resisting forces to driving forces acting upon the slope. An FOS value greater than one indicates a stable slope condition and whereas a value less than one signifies potential failure and instability. This extensive analysis gives a great deal of insight into the conditions and factors responsible for slope instability and thus leads to the development of effective mitigation and remediation strategies. The FOS calculations and detailed slope stability analyses were performed in Slide 3D, a powerful and specialized software tool.

3.3.2. Geotechnical test

In numerical modelling, parameters obtained from geotechnical investigation play a very vital role for the assessment of dump slope stability. In the study, a number of laboratory tests were conducted on dump material (or overburden material), which includes compaction test, pycnometer test, and triaxial test to measure key geotechnical parameters: density (kg/m^3), friction angle (°) and cohesion (kPa). These geotechnical parameters are essential for better understanding the behaviour of dump material and Table 1 shows the parameters calculated from laboratory tests.

Table 1. Geotechnical parameters of dump material obtained from laboratory tests

S. No	Properties	Value
1.	Unit Weight (kN/m^3)	18
2.	Cohesion (kPa)	50
3.	Friction Angle (°)	25.55

3.4. Change detection analysis

Stability and safety are two critical aspects of mine dump slopes, having a direct influence on both the environmental footprint and the efficiency of the operation. Dump slopes are influenced with time due to various natural or anthropogenic factors, which may result in significant changes in their geometry and mechanical properties. For reliable and timely detection of these changes are crucial for accurate risk assessment, optimization dump manage strategies and maintenance this mining site sustainable in the long term.

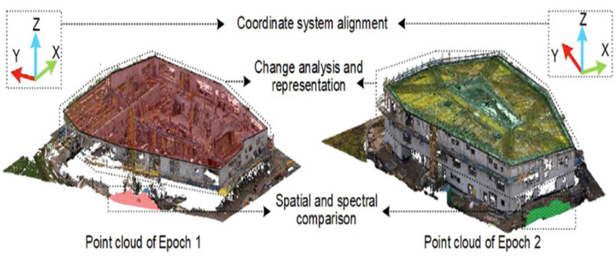


Figure 16. Fundamental operations for three-dimensional change detection with point clouds (source: Stilla & Xu, 2023)

In surface mining industry the monitoring of mine dump slope using change detection techniques is an essential part of the assessment of slopes. This approach allows for the identification of subtle slope variations by comparing time-series dataset as shown in Figure 16. Recent advancements in remote sensing techniques, mainly due to the use of UAV equipped with sensors have significantly increased the accuracy and proficiency of change detection methods. These technologies allow for spatial data to be collected over the mine dump slopes in closer detail, leading to improved site monitoring and slope stability assessments.

3.4.1. Registration approaches

The process of change detection includes a number of extremely important stages, one of which is the registration of point clouds. For facilitating direct comparison, this operation requires the alignment of several datasets inside a single coordinate system as shown in Figure 17. Accurate registration is crucial as even little misalignments between datasets can result in substantial inaccuracies in identifying and measuring changes. Aligning on complicated, uneven surfaces such as mine dump slopes, which often suffer from topographic differences and probable deformation, and may complicate the process of alignment. This research adopted three techniques for point cloud registration to assure precision before the change detection analysis.

ICP is an approach that iteratively updates the position and orientation between point clouds to minimize their distance between points. The performance of ICP appears sensitive to initial alignment, and ICP may converge to only a local minimum when there is large misalignment or when large regions of similar characteristics exist in point clouds.

Firstly, the ICP algorithm aligns two datasets by iteratively constructing a rigid-body transformation matrix using point-to-point correspondences. It initially identifies the source data points (Q) that correlate to the points in a target set (P), computes a proper transformation matrix used for alignment, and repeats this in an iterative way until the root mean square distance of the aligned datasets becomes smaller than a preset threshold.

$$dRMS\left(P^*,Q^*\right)=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\parallel p_i-q_j \parallel)^2} < \sigma,\left(1\le j\le m\right), \quad (5)$$

where q_j is the corresponding point in source cloud matched with P_i in target cloud. The number of points in datasets P and Q are denoted by n and m respectively and σ is the threshold that the minimum distance allowed between the two sets of data. ICP establishes the error function dRMS to assess convergence.

In the picking approach, the corresponding points are selected by hand in datasets to guide the registration process. This method major dependence is on human

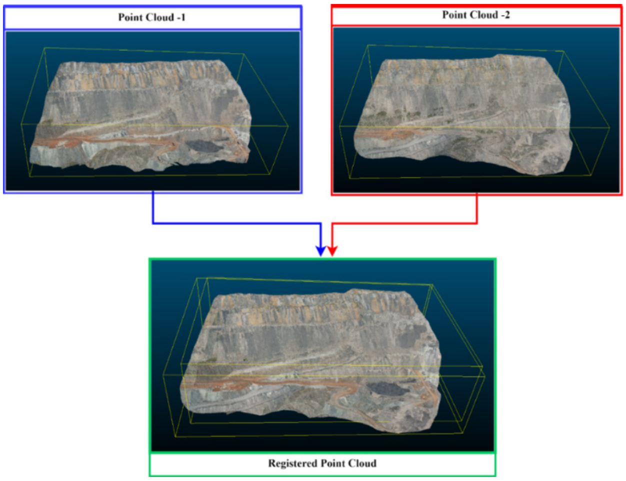


Figure 17. Workflow of point cloud registration

judgment to identify some of the distinct features in the point clouds, such as boulders or hill crests. Such pairs are carefully chosen as reference points, and a very high accuracy of registration can be achieved. However, Pair Picking tends to be very labor-intensive and prone to human error, especially over areas that lack distinct landmarks or have less distinguishable features in the terrain.

This hybrid approach integrated the strengths and weaknesses of ICP and Pair Picking, as it was determined that each technique has its own advantages and disadvantages. In this combined approach, manually picked point pairs will be used to give a strong initial alignment that would reduce the risk of ICP converging on an incorrect solution. After the initial alignment is built, further registration fine-tuning has been done using ICP since it is an iterative algorithm. This hybrid method works to maximize the precision of manual Pair Picking as well as the speed of ICP, and it will result in more accurate point cloud alignments that are considerably more reliable. These three registration techniques are employed to ensure that point clouds are properly aligned, which is crucial for minimizing errors in the subsequent change detection analysis. So, the selection of the right approach in point cloud registration is meticulous, thereby forming the basis for monitoring changes in the stability and structural integrity of mine dump slopes, which are often subject to continuous and unpredictable shifts over time.

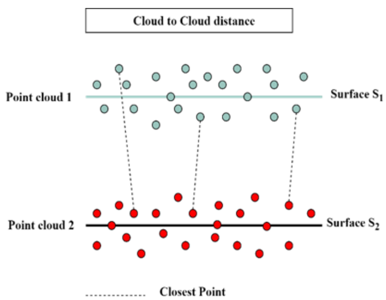


Figure 18. Cloud to Cloud (C2C) approach

3.4.2. Change detection techniques

After the registration, the change detection analysis was performed using the C2C method. The C2C technique is one of the most straightforward methods for change detection. The distance between the corresponding points in two-point clouds is calculated by this technique to estimate changes over time are shown in Figure 18. The effectiveness of the C2C analysis is that even slight changes over the whole surface are well captured, delivering a view of their magnitudes and distribution in great detail. On the other hand, its accuracy largely depends on the density and quality of the point clouds, being computationally intensive for large datasets.

4. Result

In this study, a detailed analysis of geometric features and deformation patterns of the dump slope was performed by integrating point cloud feature analysis, change detection techniques, and numerical modeling. High-resolution ground data were captured from UAV derived point clouds before and after selected key events that influenced the slope. A geometric characteristic were analyzed first, then the change detection analysis for the displacements across the slopes, and numerical modeling was conducted in order to assess the stability of the critical zones identified with change detection analyses.

4.1. Point cloud feature analysis

Point cloud features such as omni-variance, roughness, surface density, and surface variation were analyzed to compare geometric properties between the pre- and post-event point clouds.

4.1.1. Omni variance

The comparison between the two-point cloud plots shows a uniform distribution trend of omni variances observed as the neighborhood changes as shown in Figure 19. At smaller scales (n = 0.5 and n = 1.0), both Point Cloud-1 and Point Cloud-2 exhibit a narrow range of concentrations. It shows that at smaller scales, both point cloud geometric structures exhibit uniformity and minimum variation in them.

As the neighborhood size increases (n = 1.5 and n = 2.0), distributions widen in breadth. Widenings are indicative of larger and increasingly complex geometric structures. Omni variance histograms reveal that locality of variation in each of the neighborhood scales is captured, with larger scales representing more complex structures. Trends in both point clouds were similar in terms of neighborhood scales.

4.1.2. Roughness

Both the point cloud roughness distribution reveals similar trends. At small scales (n = 0.5 and n = 1.0), both Point Cloud-1 and Point Cloud-2 exhibit concentrated roughness distributions, indicating fine-scale localized topography with minimal surface irregularities as shown in Figure 20.

As the neighborhood expands in size (n = 1.5 and n = 2.0), roughness distributions become broader, with larger-scale fluctuations in the ground. This broadening represents the complex detail in terms of shape, for larger neighborhoods span larger parts of the surface, including larger amplitude abnormalities. Point Cloud-1 and Point Cloud-2 both have similar roughness behaviour.

4.1.3. Eigenentropy

The Eigenentropy plots for Point Cloud-1 and Point Cloud-2 reveal both uniformity and variation in shape at a variety of scales (n). At small scales (n = 0.5 and n = 1.0), Eigenentropy distributions cluster closely together, indicative of high uniformity and limited directional variation in the terrain. These scales capture localized, orderly shape structures.

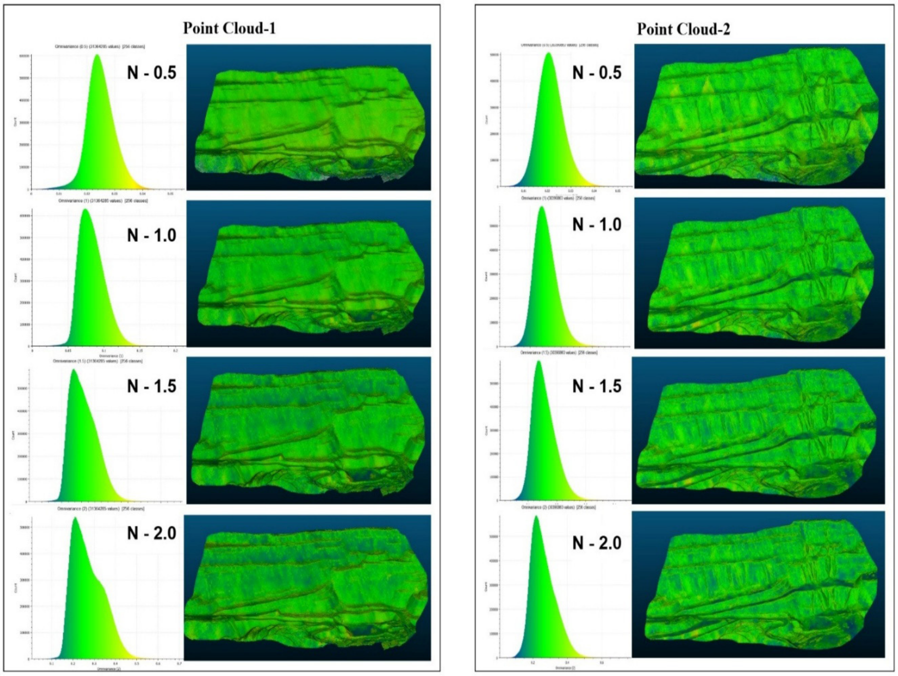


Figure 19. Omni variance plots between point clouds with different neighborhood

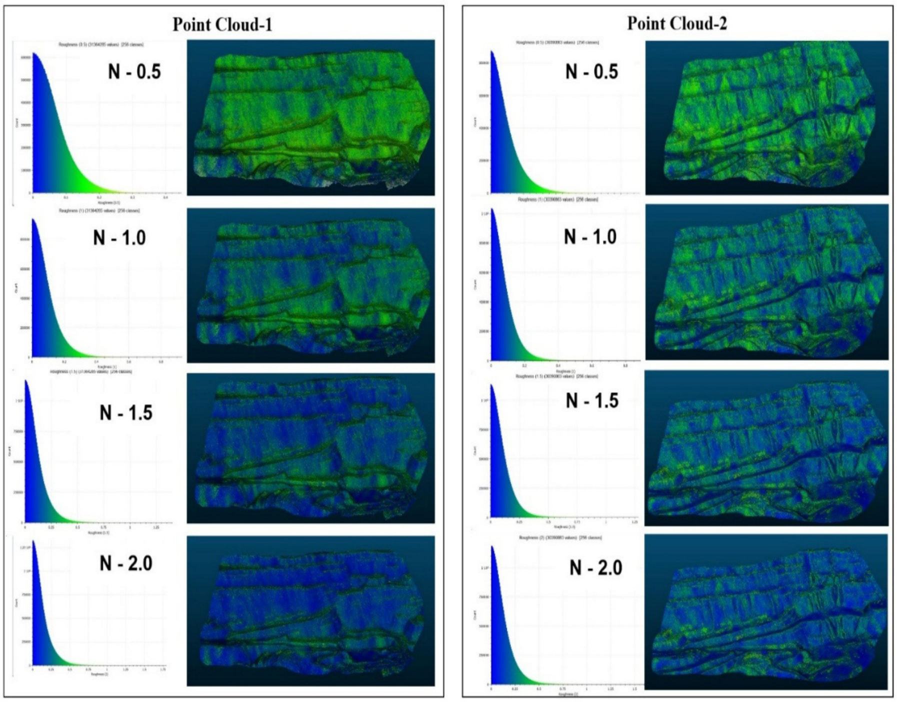


Figure 20. Roughness plots between point clouds with different neighborhood

As the neighborhood expands in size (n = 1.5 and n = 2.0), distributions become somewhat broader, indicative of integration of a broader range of structural components in the environment. Figure 21 reveals larger neighborhoods enclose larger geometric variances with equivalent patterns in both point clouds.

The consistency observed between Point Cloud-1 and Point Cloud-2 demonstrates eigenentropy's effectiveness in describing directional uniformity in terms of a sound metric. Analysis in this case reveals eigenentropy's scale-dependent nature, with localized uniformity at small scales and larger scales defining larger geometric structures, as depicted in Figure 21.

4.1.4. Surface variation

The surface variation feature analysis between Point Cloud-1 and Point Cloud-2 provides insights into geometric complexity across multiple neighborhood scales (n) as shown in Figure 22. At smaller scales (n = 0.5 and n = 1.0), distributions are sharply peaked, suggesting minimal variation in the surface and uniformity in terms of geometric properties. These scales capture localized feature with little structural irregularity. As the neighborhood extends (n = 1.5 and n = 2.0), the distributions become flatter, depicting a larger range of variations in the surface. This transition corresponds to larger and more complex topog-

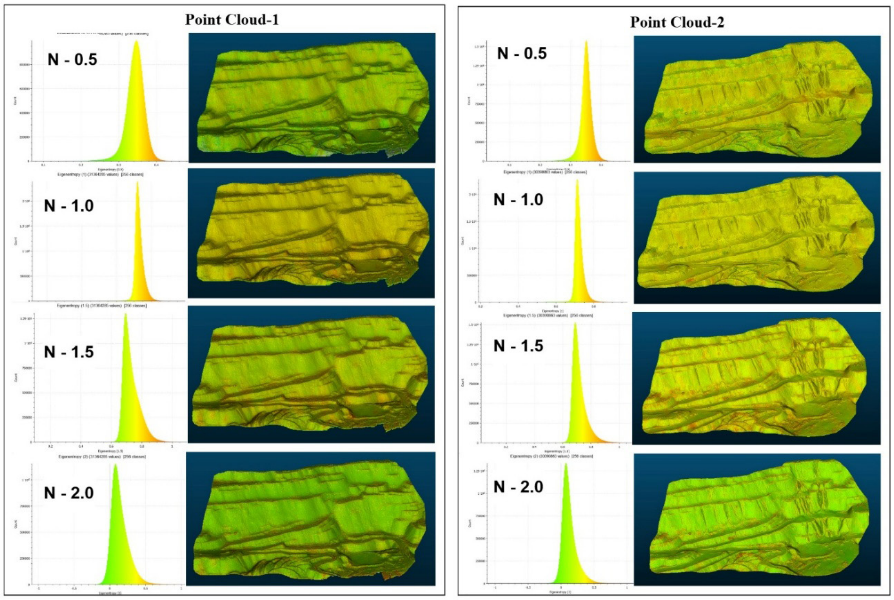


Figure 21. Eigenentropy plots between point clouds with different neighborhood

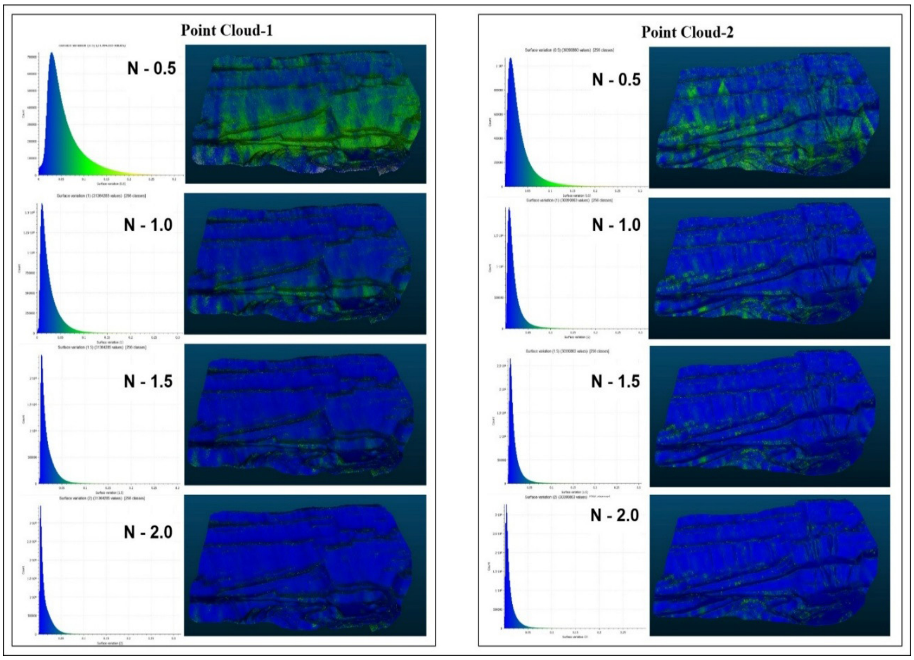


Figure 22. Surface variance plots between point clouds with different neighborhood

raphy, with modelled representations having increased variation in surface shape at these scales.

The consistent trends observed in both point clouds validate the high robustness of the surface variation metric in characterizing terrain complexity. Smaller scales effectively work in resolving fine-scale variation, and larger scales effectively work in resolving larger-scale variation. The results validate the scale-dependent nature of surface variation, as shown in the Figure 22.

4.1.5. Surface density

The surface density analysis for Point Cloud-1 and Point Cloud-2 highlights the influence of varying neighborhood sizes (n) in characterizing the spatial distribution of this feature. At smaller scales (n = 0.5 and n = 1.0), the distributions of surface density are sharply peaked, representing high local uniformity and reduced variation in density values. Scales work effectively in extracting fine surface details as shown in Figure 23.

As the neighborhood expands in size (n = 1.5 and n = 2.0), distributions become flatter and more scattered. That transition reflects incorporation of larger-scale structures and larger variation in structure at the surface. Consequent visualization reveals density at the surface transitioning from concentrated in small structures to encompassing larger, complex geometric structures. Most noticeably, both Point Cloud-1 and Point Cloud-2 exhibit similar trends in density transition at scales, confirming such a feature can effectively record variation in structure at a surface.

The analysis of omni variance, roughness, density, and variation at the surface reveals the scale-dependent nature of Point Cloud-1 and Point Cloud-2 feature character. Furthermore, a multi-scale neighborhood analysis (n = 0.5 – 2.0) was applied to capture both fine-scale roughness and large-scale morphological variations, ensuring comprehensive representation of terrain complexity and deformation characteristics across spatial scales. The consistent trends across both point clouds validate the robustness of these metrics, emphasizing their effectiveness in balancing detailed and large-scale terrain analysis.

4.2. Change detection assessment

Accurate registration of point clouds is the cornerstone of reliable 3D change detection, particularly in UAV-based terrain analysis. High accuracy in aligning pre-event and post-event datasets is critical for capturing even minor deformations, allowing for meaningful interpretation of spatial variation. High accuracy in registration, nevertheless, tends to be challenging with regard to misalignment generated through variation in data collection environments, point density, and terrain difficulty.

To address such a challenge, three techniques for registration, namely ICP (Iterative Closest Point), Pair Picking, and a Hybrid technique, were considered in this work. All three techniques were measured in terms of Root Mean Square (RMS) error, transformation parameters, and efficiency in terms of alignment. ICP, a purely automated algorithm, generated an RMS value of 6.9586, indicative of high misalignment. Pair Picking generated a RMS value of 1.80761, with high translation mismatches. The Hybrid approach, combining the strength of both techniques, performed best, with a minimum value for RMS, at 0.642454, and best-fit for change detection analysis. RMS errors for all approaches are shown in Table 2.

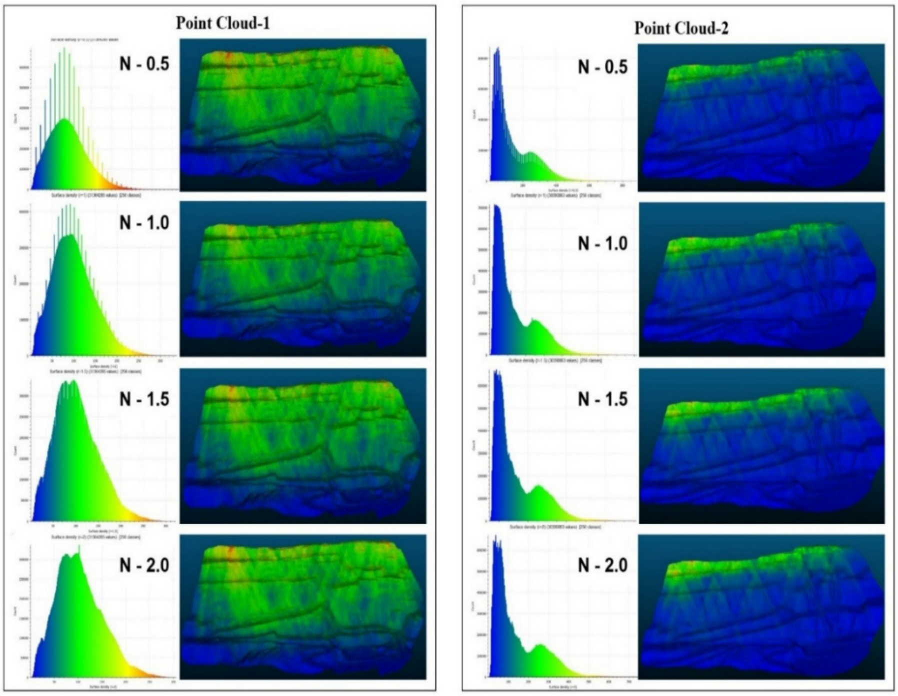


Figure 23. Surface density plots between point clouds with different neighborhoods

Table 2. RMS errors of different registration approaches

Method	RMS error	Translation X	Translation Y	Translation Z	Rotation matrix
ICP	6.9586	–4.002	–26.036	–2.542	1.000, –0.014, 0.008
Hybrid	0.642454	–28.32	–4.484	0.745	1.000, 0.006, –0.005
Pair Picking	1.80761	–997.625	–15.337	92.532	1.000, –0.007, 0.008

With the Hybrid registration method achieving the highest alignment accuracy, it was selected as the optimal approach for change detection analysis. To evaluate spatial variations over time, the C2C method was applied, identifying a maximum displacement of 31.13 meters across the study area. This analysis highlighted two critical zones of significant change within the dump slope.

Accurate change analysis revealed two specific high-displacement regions in the dump slope. In-depth analysis provides valuable insights into the combined influence of geologic instability and anthropogenetic activities in controlling terrain deformation. Section-2 has experienced high displacement, and its cause was predominantly construction of a new haul road as shown in Figure 24. Road construction involved processes such as grading, compaction, and excavation, and these processes played a critical role in altering initial topography, and localized motions in the dump slope followed. The alteration of surface geometry and reorientation of materials initiated a notable change in slope configuration, resulting in observable variations in elevation and displacement.

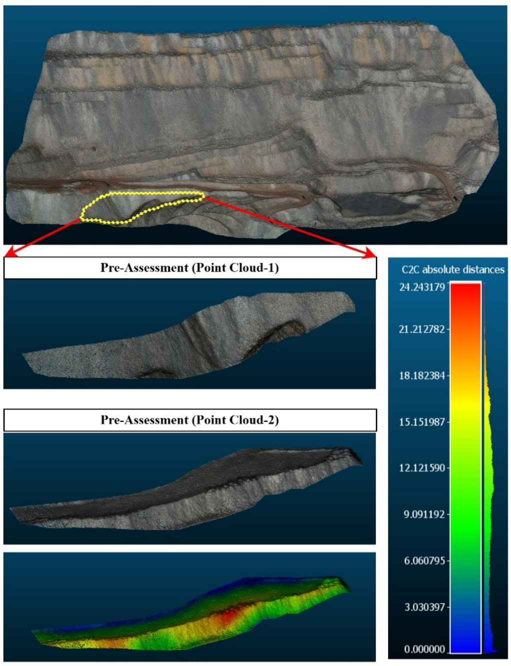


Figure 24. Section-2 showing the displacement zone of the dump slope

Section-1, the second critical zone, exhibited displacement trends primarily associated with geomechanical, and continuous active dumping operations as shown in Figure 25. Unlike the first zone, in which motion was triggered from an external source, this section's movement was influenced by both geomechanical instability and continuous material deposition. Active nature of the dump played a significant role in contributing towards acceleration of motion in the slope, with new overburden materials added periodically to the present dump surface. Progressive overburden loading through continuous deposition added overburden weight, redistributed overburden stress, and deformation in the slope. Besides, weathering processes and infiltration of water could have contributed towards weakening of materials, and increased susceptibility towards failure. Mass movement susceptibility in this zone is high, and real-time observation and proactive stabilizations will become critical to mitigate future hazards.

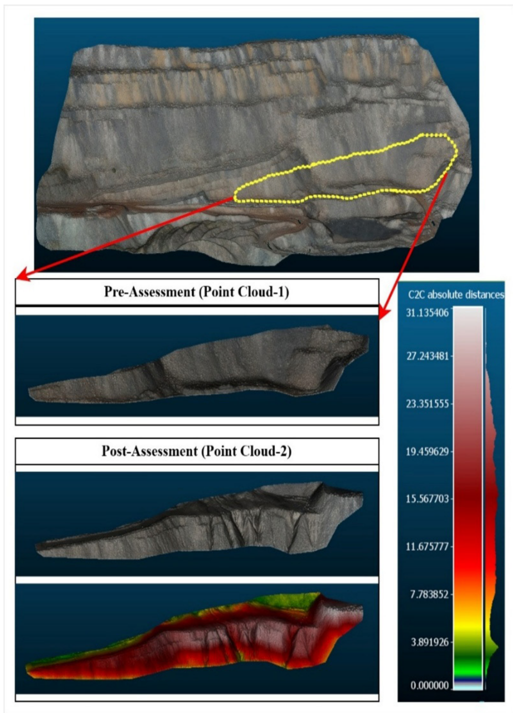


Figure 25. Section-1 showing the displacement zone of the dump slope

Figure 26 provides a general visualization of the critical displacement zones, depicting intensity and distribution of ground deformations. C2C technique precisely captured intensity and direction trends of displacement, offering useful information regarding structural behaviour. These findings emphasize the importance of proactive monitoring, optimized dumping strategies, and slope reinforcement measures to enhance long-term stability in active mining environments.

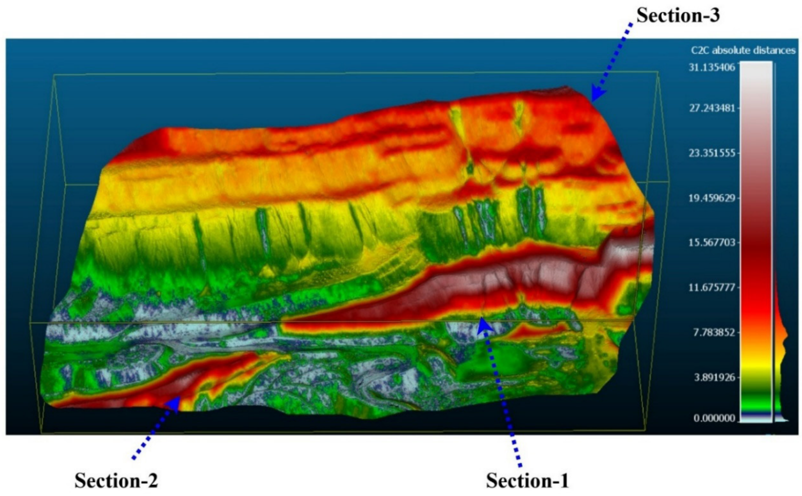


Figure 26. Displacement patterns and deformation zones of the mine dump slope

4.3. Numerical modeling analysis

To further investigate the potential risk, numerical modeling was conducted using the LEM. This method provided an in-depth analysis of the slope stability, simulating the behaviour of the mine dump slope. The focus of the analysis was to determine whether the area showing major displacements (section-1) corresponded to the critical zone where failure might initiate.

Numerical modeling using LEM was conducted to assess the stability of this zone. The results from the analysis provided the following Factors of Safety of 1.107 as shown in Figure 27. This yielded relatively low FOS values, indicating that the slope is close to instability, especially in the critical zone identified by the change detection analysis. The alignment of the critical zone with the observed area of major displacement confirms the accuracy of the UAV-based analysis in identifying potentially unstable areas.

5. Discussion

5.1. UAV-driven point cloud registration analysis for mine dump slope

The results of this study have identified that UAV technology integration into a change detection and numerical modeling workflow provides a number of crucial benefits. First, the high-resolution data captured through UAVs enable the detailed and accurate mapping of surface displacements on the mine dump slope, and, the level of detail is often unattainable through traditional monitoring methods.

The hybrid registration approach was adopted as it integrates the automated precision of ICP with the manual control of Pair Picking, effectively reducing transformation and misalignment errors caused by uneven terrain and variable point densities. The hybrid method combines the strengths of both, achieving the lowest RMS error (0.642), thereby ensuring accurate alignment crucial for reliable change detection. Figure 28 clearly indicates that the Hybrid method is the most effective for point cloud

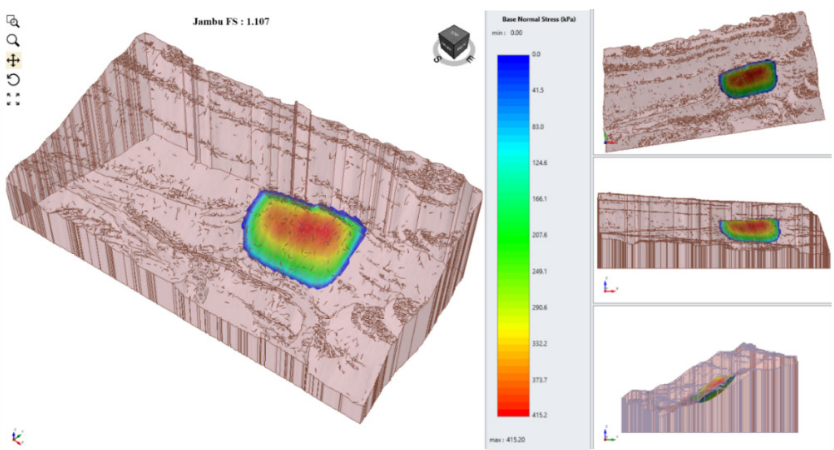


Figure 27. 3D Numerical model with a critical zone of interest

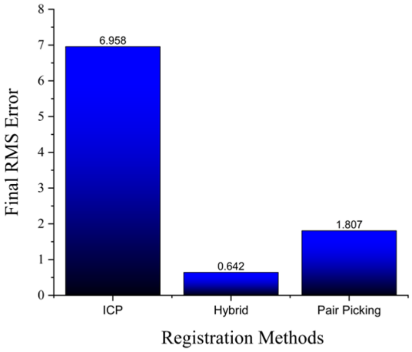


Figure 28. RMS error of registration methods

alignment since it produces the lowest error in RMS, making it the most effective means of accurate registration.

The success of the hybrid registration method in reducing errors underscores its capability to analyze complex terrains. In general, UAV technology, combined with advanced registration (hybrid registration) and change detection techniques, worked effectively in detecting significant changes in the dump slope, providing valuable insights for proactive slope management and stability assessments.

At the time of point cloud registration using the ICP–based change detection, prominent spatial misalignments were observed between the pre- and post-trigger point clouds, as shown in Figure 29. Misalignments are clearly visible in specific areas, where the point cloud data failed to converge as accurately as expected. This could be due to factors such as variations in point cloud density, non-uniform surface textures, or the complexity of the modelled terrain.

5.2. Analyzing spatial correlation of displacement and critical zones

The change detection analysis, which identified the displacement zones through UAV-generated point cloud data, was confirmed by numerical modeling. The FOS values of 1.107 highlight the fact that the slope is nearing the point of failure, particularly in the area of major displacement.

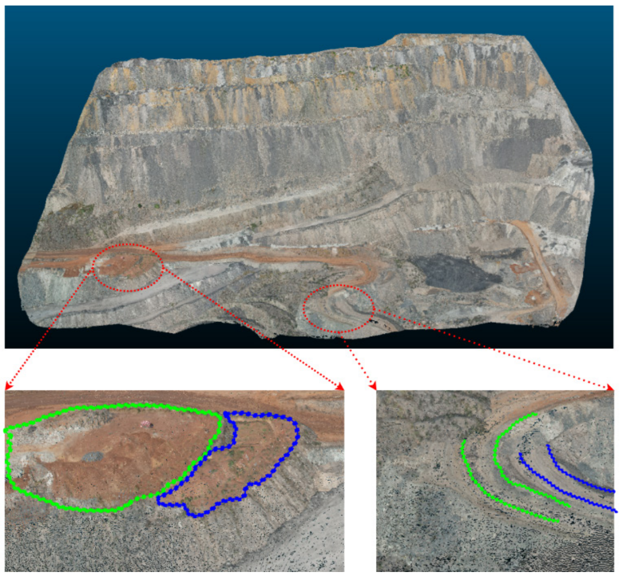


Figure 29. Misalignment of dump area in ICP method

The results demonstrate that the use of UAVs for change detection is not just limited to surface mapping but can also enhance the accuracy of numerical modeling. The fidelity of the numerical models improves with high-resolution input data derived by UAV and, therefore, higher reliability of forecasting regarding slope stability. The close alignment between the areas of detected displacement and the critical failure zone identified through LEM analysis suggests that UAV technology can play a pivotal role in early-warning systems for slope failures.

Additionally, Figure 30 illustrates the spatial correlation between the substantial displacements identified using change detection analysis and the crucial zone established by numerical modeling. It thus offers strong evidence that UAV-based monitoring is very reliable in the identification of risk areas, with the integration of its results with numerical analysis likely to significantly enhance the accuracy of slope stability predictions.

This work demonstrates the synergy of combining UAV-based change detection and numerical modelling methods. UAVs provide a rapid, cost-effective, and highly accurate means to detect surface changes, while numerical modelling carries out the analysis for stability and safety regarding the slope. The integrated use of UAV data with numerical models provides a thorough framework for the assessment and management of the mine dump slope, hence contributing to safer mining operations.

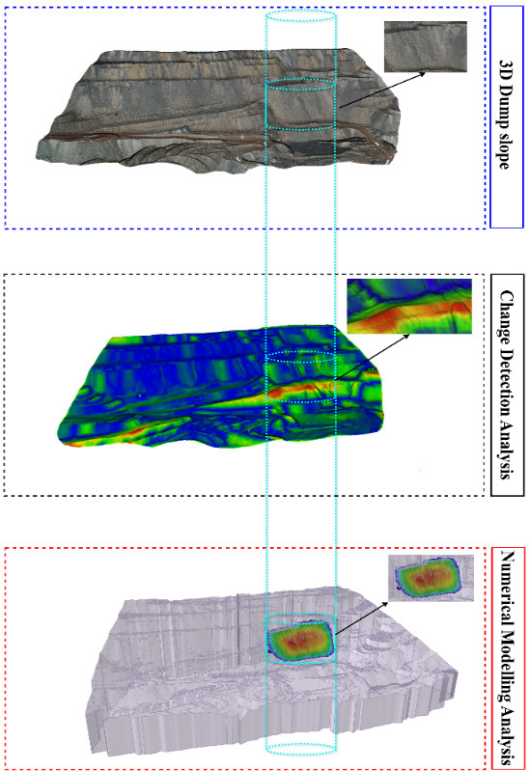


Figure 30. Spatial correlation map showing the overlap between instability zones delineated from numerical modeling and displacement regions derived from change detection analysis

5.3. Comparative analysis of mine dump slopes

The current work expands traditional failure zone mapping and calculation of Factor of Safety (FOS) through integration of UAV-based photogrammetry, hybrid registration, C2C algorithm change mapping, and numerical modeling for critical zone mapping. All such studies in the past (Table 3), including studies performed by (Chand & Koner, 2023; Yang et al., 2024, 2025; Igwe & Chukwu, 2019, Layek et al., 2022), have focused specifically on failure zone mapping and calculation of FOS through a variety of numerical and geotechnical approaches. More recent research, however, reflects a shift toward digitally enabled and high-resolution geotechnical monitoring. Ansari et al. (2025) employed a coupled analytical–numerical framework to evaluate seismic sensitivity of Himalayan tunnels using P-wave dynamics, highlighting the value of integrated modeling for infrastructure resilience in complex terrains. Malik and Koner (2024) introduced a cloud-based, real-time deformation monitoring system for large open-pit mine slopes, demonstrating the effectiveness of continuous sensing for early-warning and hazard mitigation. In accordance with these recent developments, the current study integrates UAV-derived 3D photogrammetry with numerical modeling to attain spatially detailed and near-real-time assessment of dump-slope stability, thereby enhancing existing methodologies in geotechnical monitoring and hazard evaluation.

The findings of this study have profound implications for the advancement of slope stability assessments in mining operations. By integrating UAV-based 3D photogrammetry, point cloud analysis, and change detection with numerical modeling, this research provides a cutting-edge solution for the early detection of slope instability. The high-resolution UAV data allows the identification of displacement zones with unmatched precision. Advanced hybrid registration techniques and high-resolution data enable a reliable understanding of surface dynamics, providing new perspectives for improved slope management strategies.

The successful application of the hybrid registration method enhances change detection accuracy and demonstrates its potential for treating complex and hazardous terrains. This method, alongside UAV technology, can be adapted across various geotechnical environments, including mine dumps, tailings dams, and other high-risk areas.

The toolset developed through this research will offer mining operations, in practical terms, an effective toolset for cost-efficient monitoring. Moreover, UAV technology will be integrated with modern geotechnical risk management, henceforth allowing mining companies to take a proactive approach towards preventing catastrophic failures by refining safety protocols and ensuring sustainability in mining activities.

7. Conclusions and future research

This work proves that the integration of UAV-based 3D photogrammetric reconstruction, geometric feature analysis, and change detection with numerical modeling can indeed be transformative for the assessment of slope stability in mine dumps. It underlines how high-resolution data provided by UAVs plays a critical role in defining displacement zones with a high degree of accuracy in comparison with traditional methods. The successful implementation of the Hybrid point cloud registration method and its contribution to precise change detection further reinforce the value of this approach.

UAV-derived data strongly correlates with the results of numerical modeling, underlining the efficiency

Table 3. Comparison of Past studies on mine dump slope

Authors	Key area	Key criteria	Methodology
Current study	Change detection in mine dump slopes	Geometric feature analysis, Failure zones and displacement analysis using 3D point clouds	UAV-based Photogrammetry, Hybrid Registration, Geometric analysis, change detection using C2C algorithm, and numerical modeling for Critical Zone identification
Chand and Koner (2023)	Internal mine dump stability	3D numerical modeling for failure zone identification	UAV photogrammetry, 3D Limit Equilibrium Method (LEM), and Factor of Safety (FOS) analysis
Yang et al. (2024)	Steep waste dump slope stability	Stability evaluation of iron ore waste dumps under multiple conditions	Direct shear tests, GEO-SLOPE stability analysis, Particle Flow Code (PFC) simulations
Igwe and Chukwu (2019)	Mine tailing dump stability	Geotechnical assessment and slope failure analysis	Slope stability modeling using GeoStudio, material composition analysis, and FOS calculations
Yang et al. (2025)	Slope stability in Ziluoyi iron ore mine	Slope failure mechanisms and modeling under multiple loading conditions	Hoek-Brown and Mohr-Coulomb criteria, Morgenstern-Price method, and Geo-Slope software
Layek et al. (2022)	Seismic and rainfall effects on dump slopes	Influence of rainfall and earthquakes on dump stability	UAV-based 3D modeling, GIS mapping, numerical simulations (FEM), and safety factor analysis

of drone technology as a reliable tool in early-warning systems for slope failure detection. The paper represents an integrated approach to proactive slope management that will contribute to safer, more sustainable mining operations through the integration of modern technologies based on UAV-based data acquisition and numerical modeling. As UAV technology continues to evolve, its application in slope stability assessments will likely become even more robust, allowing for real-time monitoring and more frequent data updates, and this will improve not only the ability to anticipate and mitigate slope failures but also contribute to wider goals of sustainable mining by enabling safer and less environmentally injurious practices that ensure better long-term stability of mine sites.

This comprehensive UAV-based framework shows wide applicability beyond the present case study and can be implemented well for slope stability analysis in other civil and mining applications, such as waste dump monitoring, embankment inspection, and landslide hazard analysis and mapping. The fusion of 3D photogrammetry, hybrid registration, and numerical modeling provides a scalable and repeatable approach for the early identification of instability. Future research needs to emphasize the integration of real-time UAV imagery with automated feature analysis and machine-learning methods for the purpose of continuous monitoring and predictive stability analysis. Overall, this research provides a practical, data-oriented paradigm that closes the gap between remote sensing and geotechnical modeling for sustainable slope management.

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Author contributions

Writing, visualization, validation, methodology, data analysis, investigation of result and review-editing – Amit Kumar Mankar. Review and supervision – Radhakanta Koner.

Disclosure statement

The authors declared that they have no conflicts of interest related to this work.

Data availability

The data used in this study are confidential and cannot be shared.

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