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Department of Transportation

**A Framework for Rockfall Hazard
Analysis in PA**

FINAL REPORT

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**By Jonathan Hubler, Virginia Smith, EunSik Choi,
and Sarah Burghardt**

Villanova University

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16. Abstract Rockfalls pose significant safety and operational challenges for transportation systems. In Pennsylvania, damages and instabilities associated with rockfall have been documented along steep, exposed rock slopes adjacent to roadways, providing valuable opportunities to investigate the mechanisms and drivers of rockfall through continuous monitoring efforts. This research evaluates rockfall risk using two complementary approaches. The first approach involves LiDAR-based rockfall hazard analysis conducted at four sites—Riegelsville, Kintnersville, Narrows, and Fleecy Dale Road—using Rambo and CloudCompare software. Multiple LiDAR scans were collected to generate high-resolution point clouds, enabling detailed morphological assessment. Slope angles, Rockfall Activity Index (RAI) classifications, and RAI scores were evaluated at all sites. These high-resolution point clouds provide essential detail on rock surface morphology, which strongly influences rockfall hazard assessments and supports evaluation of overall hazard potential. The second approach applies machine learning techniques—Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)—to assess rockfall risk across Pennsylvania using weather-related predictors. Feature importance analysis indicated that precipitation intensity was the dominant driver of rockfall occurrence. Maximum precipitation volume was the top predictor in both models. This research presents a framework for identifying a rockfall-risk window that can be used to analyze historically high-risk counties in Pennsylvania and guide future rockfall hazard inspections. This framework supports proactive assessment of vulnerable rock slopes, thereby reducing potential hazards.					
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1. Introduction

Rockfalls pose significant risks to highway safety and infrastructure, particularly in regions with steep terrain or geological instability. These hazards not only threaten human safety but also disrupt transportation and incur substantial maintenance costs (Lato et al. 2012). Effective management and mitigation of rockfall hazards are therefore critical for maintaining road safety and infrastructure integrity. The mechanisms that cause rock mass detachment are primarily determined by the relationship between its geological structure, lithology, and slope configuration, as well as physical conditions and rock mass properties (Lato et al. 2012). Additionally, natural conditions, such as climate (Nissen et al. 2021; D’Amato et al. 2016; Macciotta et al. 2017), freeze-thaw (Weidner and Walton 2021), seismicity, and the presence of water can also greatly influence the stability of a rock mass. Recent advancements in geotechnical monitoring and data collection, notably through Light Detection and Ranging (LiDAR) technology, have revolutionized the ability to assess and manage these risks. LiDAR offers high-resolution data that significantly enhances the accuracy of rockfall modeling and risk assessment (Pradhan and Yusof 2017). PennDOT is interested in utilizing this technology to evaluate rockfall hazards and for improved asset management. The purpose of this report is to provide a framework for evaluating rockfall hazards in PA. Based on a comprehensive literature review, LiDAR data collection, and modeling framework, the Villanova University research team summarizes best practices for LiDAR scanning of rock slopes and provides a framework for assessing the risk of rock slopes in the Commonwealth of PA.

1.1 Objectives and Scope of Report

This report provides a comprehensive literature review that encompasses the state of the art (SOA) of research on the LiDAR scanning of rock slopes, generation of point clouds, and evaluating rockfall hazard. Additionally, this report provides the results from LiDAR scanning and hazard analysis for four rock slopes located in Pennsylvania’s District 6 as well as a modeling framework that considers drivers of rockfall and evaluates risk. The results from the literature review, the field testing, and modeling were compiled to provide practical recommendations on evaluation of rockfall hazard in the Commonwealth of PA.

1.2 Organization of the Report

The report is organized in the following manner:

- Chapter 2: This chapter provides background information on rockfall hazard and existing models used to evaluate the stability of rock slopes. Models used by state departments of transportation, such as the Rockfall Hazard Rating System are presented. The use of terrestrial laser scanning and application to models such as the Rockfall Activity Index are discussed. This chapter also provides background information on laser scanning (LiDAR) and focuses on available technologies for rock slope scanning, best practices for monitoring,

and data analysis. Typical ground-based scanner parameters are presented and data output via point clouds are shown. Optimized workflow for scanning and data analysis are discussed. Finally, this chapter identifies parameters that affect rockfall hazard, including geotechnical, climate related, and freeze-thaw. Literature showing scanning of rock slopes over time and change detection with seasonal variations are highlighted. A discussion of data uncertainties and limitations is also presented, highlighting conditions where laser scanning may or may not provide optimal results.

- Chapter 3: This chapter summarizes the data collection efforts at four rock slope sites located in PennDOT District 6-0. Best practices for LiDAR scanning and data analysis are presented and discussed. Point cloud data and results from modeling software (i.e., RAMBO) are presented and summarized.
- Chapter 4: This chapter presents a framework that applies machine learning techniques—Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)—to assess rockfall risk across Pennsylvania using weather-related predictors. Model assumptions, input variables, and performance are summarized and discussed.
- Chapter 5: This chapter concludes the findings of this report and provides details on the broader use of the results of this project.

2. Literature Review

This literature review is structured to first discuss existing rock stability models and their implementation. Volkwein et al. (2011) and Ferrari et al. (2016) provided a thorough analysis of both rockfall modeling and hazard zoning, along with an examination of protective measures. Next, the specific applications and best practices for LiDAR scanning of rock slopes will be discussed, followed by an analysis of critical parameters influencing rock stability. Finally, a summary will be provided of the data uncertainties and limitations inherent in using LiDAR technology.

2.1 Background on Existing Models

2.1.1 Historical Context & Evolution of Rock Stability Models

Ritchie (1963) carried out initial investigations into rockfall behavior, emphasizing the need for a method to predict the stability of rock cut surfaces. Ritchie's research focused on understanding the movement and trajectory of rocks and aimed to develop an analytical solution for rockfall based on the laws governing their motion (see Figure 1).

Following Ritchie's pioneering work, considerable advancements have been made in analyzing rockfall behavior, particularly in relation to highway projects. Studies encompass empirical investigations, physical simulations, and more recently, computer modeling techniques (Fanos and Pradhan 2019). While earlier research primarily relied on empirical methods, there has been a shift towards the widespread use of computer modeling over the past two decades.

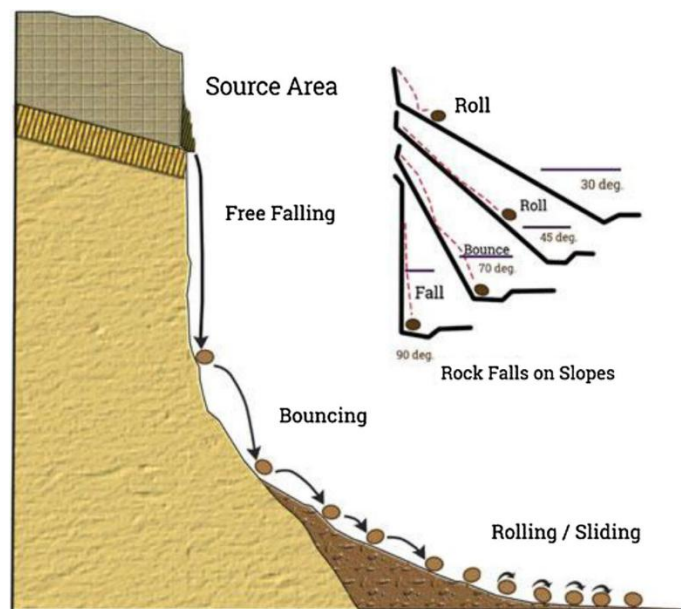


Figure 1. Rockfall typical process and motion modes related to slope angle (Ritchie 1963)

The assessment of rockfall hazards has evolved from reliance on field data and conventional mapping to the use of advanced remote-sensing technology and modeling tools. Initially, traditional slope stability analysis methods were predominantly based on empirical and limit equilibrium approaches, such as the widely utilized Bishop and Janbu's methods. These early models provided valuable insights into the factors influencing slope stability, including the material properties, slope geometry, and external loading conditions (Kemeny et al. 2011). Early models often relied on empirical or heuristic approaches to assess rockfall hazard. For example, the Rockfall Hazard Rating System (RHRS) developed by the Oregon Department of Transportation (ODOT) in 1984 provides a standardized method for evaluating the potential hazards posed by rock slopes along highways (Pierson 1992). This marked a significant milestone in the historical development of rockfall hazard assessments, laying the groundwork for subsequent models (Dunham et al. 2017). Similarly, the Evolving Rockfall Hazard Assessment (EHRA) and the Rockfall Risk Management (RoMa) approach offer qualitative and quantitative assessments, respectively, tailored to specific case studies (Mineo 2020).

Over time, the integration of terrestrial laser scanning (TLS) and airborne laser scanning (ALS) has paved the way for the development and refinement of advanced models aimed at identifying rockfall source areas and characterizing rockfall kinematic processes (Fanos and Pradhan 2019). These advancements have facilitated the development of more sophisticated models, such as the Rockfall Activity Index (RAI) introduced by Dunham et al. (2017). The RAI framework employs the quantitative and repeatable delineation of slope face areas into seven classes using surface slope inclination and roughness at varying scales, as shown in Table 1. RAI methodology represents a significant evolution in the field, leveraging high-resolution point-cloud-derived data and morphology-based approaches to provide more detailed and accurate assessments of rockfall hazards. Dunham et al. (2017) developed a framework to calculate yearly kinetic energy generated from rockfalls hitting a roadway at the base of a slope. It uses annual failure rates (Instability Rate) and average failure depths assigned to each RAI class on a 5 cm x 5 cm grid on the rock face. These rates and depths were based on lidar-based change detection data from two Alaska sites over one year (Dunham et al. 2017). Table 1 shows the preliminary estimated annual failure rates and average failure depths for each RAI class. The annual failure rate, average failure depth, and rock slope location are combined to estimate the average annual kinetic energy delivered to the base of the rock slope (Markus et al. 2023).

Olsen et al. (2015) successfully integrated the RAI framework into Rambo, a widely utilized commercial software package for LiDAR processing, change analysis, and rock-slope stability assessments. Figure 2 illustrates the RAI framework's output. The integration of these remote sensing technologies with slope stability models has contributed to the improved understanding and assessment of rock slope stability, enabling the detection of small-scale movements and changes in the rock mass that were previously challenging to capture (Kemeny et al. 2011).

Table 1. Original definitions of the 7 RAI classes and their preliminary estimated annual failure rates and average failure depths (Dunham et al. 2017)

RAI method morphological classes and associated failure mass depths and instability rates.

Morphological classification	Description	Estimated depth of failure mass (m) ^a	Instability rate (<i>r</i>) [%] ^b	Estimated typical range of instability rate (<i>r</i>) values ^c
Widely to moderately spaced discontinuous rock (<i>D_w</i>)	Intact blocks or fragments of rock separated by discontinuities typically spaced at ~30 cm or greater	0.3	0.71	0.4–3.0
Closely spaced discontinuous rock (<i>D_c</i>)	Intact blocks or fragments of rock separated by discontinuities typically spaced between ~10 cm and ~20 cm	0.2	0.34	0.2–2.0
Fragmented discontinuous rock (<i>D_f</i>)	Intact blocks or fragments of rock separated by discontinuities with a typical spacing of less than ~10 cm	0.1	0.18	0.1–1.0
Intact rock (<i>I</i>)	Rockmass with few or relatively minor discontinuities	0.05	0.1	0.02–0.3
Cantilevered overhang (<i>O_c</i>)	Overhanging rock whose lower portion is inclined at less than 120° [see Fig. 1]	0.5	1.98	1.0–5.0
Steep overhang (<i>O_s</i>)	Overhanging rock whose lower portion is inclined at greater (i.e., steeper) than 120° [see Fig. 1]	0.75	1.97	1.0–5.0
Talus (<i>T</i>) ^d	Mass wasting-derived rock fragments (debris) accumulated at the base of a slope, or along benches within a slope	0.025	0	0–0.4

^a Estimated depth of the failure mass is based on annual change detection data collected at the field study sites. The resulting failure volume for each 5-cm by 5-cm slope face cell is computed by multiplying the cell area (i.e., 25 cm²) by the estimated depth of the failure mass.

^b The instability rate *r* is computed as the fraction of the cells within a morphologic unit that failed (eroded) based on annual change detection data obtained at the field study sites in Alaska, USA.

^c The typical range of *r* values is estimated based on the authors' involvement with change detection studies at rock slope sites worldwide. The values vary based on a variety of factors including rock type, weathering, subsurface characteristics, and environmental conditions with lower bound values correspond to relatively stable conditions while upper bound values slopes that actively produce rockfall. Note that these values are associated with a high degree of variability and uncertainty.

^d The *r* value represents erosion and raveling of talus.

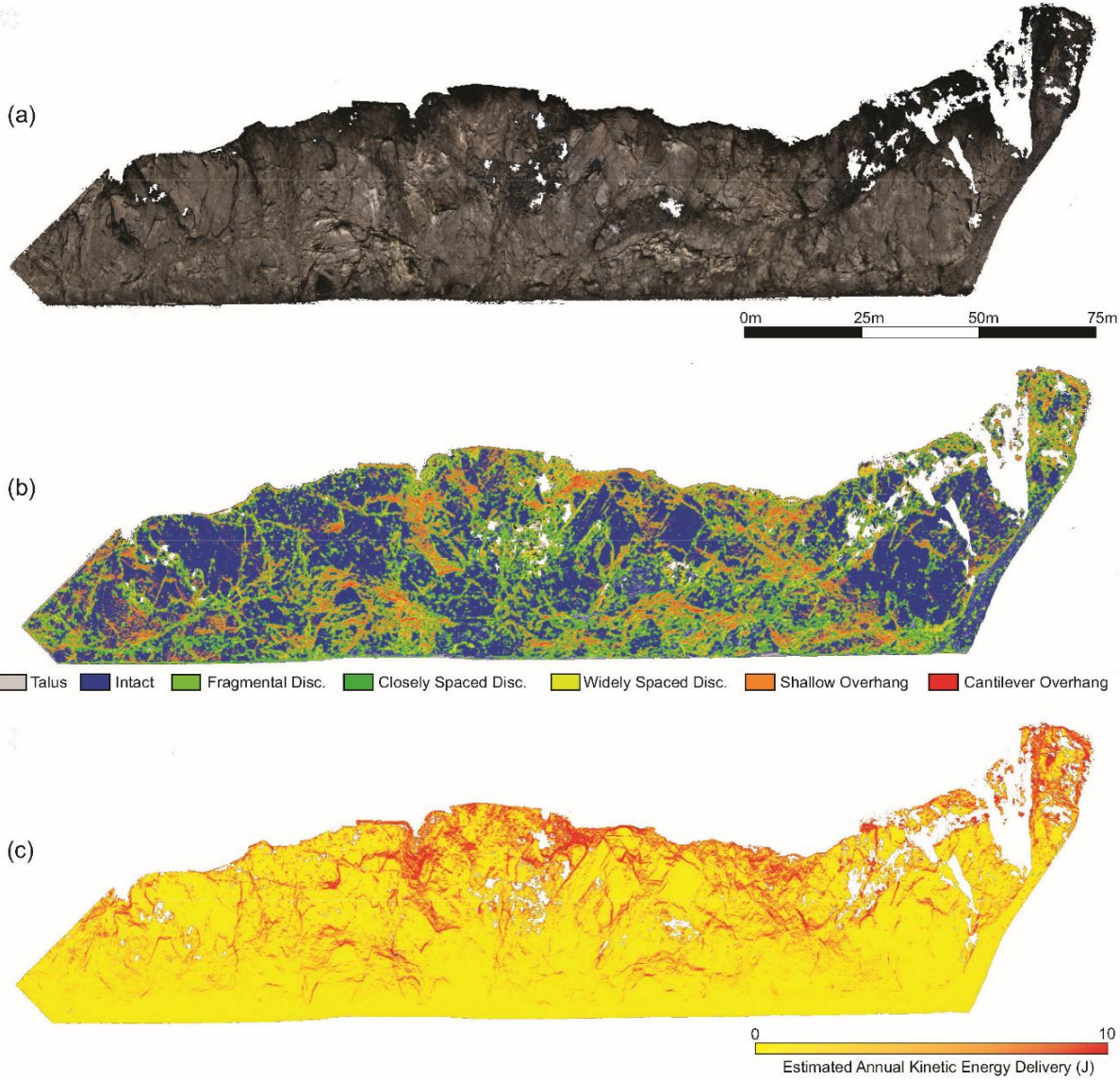


Figure 2. Example output of the RAI framework: (a) Lidar-based colored point cloud; (b) RAI classes assigned to the rock slope face; (c) Estimated annual kinetic energy delivery from each 5 cm by 5 cm cell in joules (data visualized using CloudCompare v2.11.3) (Markus et al. 2023).

Notably, the application of hybrid models based on machine learning techniques, Gaussian mixture models, and spatial modeling combined with the analytical hierarchy process (AHP) in a geographic information system (GIS) has significantly contributed to the enhancement of the accuracy and effectiveness of rock slope analysis (Fanos and Pradhan 2019). There has been a significant shift towards using GIS-based tools for a more rapid and cost-effective approach to assess rockfall hazards (Omran et al. 2021). The development of rock slope stability models reflects a progression towards more comprehensive, data-driven, and technology-integrated approaches to understanding and mitigating slope instability in mountainous or hilly regions.

2.1.2 Review of Existing Rockfall Stability Models

Rockfall analysis models are essential for assessing and mitigating the risks posed to transportation infrastructure. These models encompass a range of techniques from qualitative assessments to sophisticated 3D simulations (Ferrari et al. 2016; Crosta et al. 2015). On the quantitative side, high-resolution laser scanning data, such as LiDAR, facilitates comprehensive rockfall hazard assessments by enabling the identification of rockfall sources and the modeling of rockfall kinematics (Fanos and Pradhan 2019). Low-quality rock masses are traditionally assessed using rock-mass classification systems which depend on visual inspections and collection of generic data from the rock mass. These data are then entered into a classification scheme such as the RHRS, the Rock Mass Rating system (RMR), the Slope Mass Rating system (SMR), the Geological Strength Index (GSI), the Rockslope Deterioration Assessment (RDA), or Q-Slope Rating System. The results of these systems can be used to analyze the physical or empirical behavior of the rock mass, including rockfall hazard (Markus et al. 2023). One of the first models, the RHRS is based on parameters such as slope height, vehicle risk, geologic parameters, and movement per year, among others. These RHRS rating criteria is shown in Table 2.

Table 2. Rockfall Hazard Rating System Rating Criteria (Ferrari et al. 2016 based on Pierson, 1992)

Category	Rating criteria and scores			
	3 points	9 points	27 points	81 points
Slope height (ft)	25	50	75	100
Slope height (m)	7.6	15.2	22.9	30.5
Ditch effectiveness	Good catchment	Moderate catchment	Limited catchment	No catchment
Average vehicle risk	25 % of the time	50 % of the time	75 % of the time	100 % of the time
Percent of decision sight distance	Adequate, 100 % of low design value	Moderate, 80 % of low design value	Limited, 60 % of low design value	Very limited, 40 % of low design value
Paved road width (ft)	44	36	28	20
Paved road width (m)	13.4	11	8.5	6.1
Geologic character				
(a) Case 1				
Structural condition	Discontinuous joints, favorable orientation	Discontinuous joints, random orientation	Discontinuous joints, adverse orientation	Continuous joints, adverse orientation
Rock friction	Rough, irregular	Undulating	Planar	Clay infilling or slickensided
(b) Case 2				
Structural condition	Few erosion features	Occasional erosion features	Many erosion features	Major erosion features
Difference in erosional rates	Small difference	Moderate difference	Large difference	Extreme difference
Block size (ft)	1	2	3	4
Block size (m) or	0.3	0.6	0.9	1.2
Volume per event (Yd ³)	3	6	9	12
Volume per event (m ³)	2.3	4.6	6.9	9.2
Climate and presence of water on slope	Slow to moderate precipitation or no freezing periods or no water on slope	Moderate precipitation or short freezing periods or intermittent water on slope	High precipitation or long freezing periods or continual water on slope	High precipitation and long freezing periods or continual water on slope and long freezing period
Rockfall history	Few falls	Occasional falls	Many falls	Constant falls

Machine learning algorithms, including ensemble models like bagging neural networks (BBNN), have been employed to enhance the accuracy of rockfall source identification (Weidner et al. 2019). Moreover, 3D rockfall modeling integrated with GIS is used to derive rockfall trajectories and characteristics, which are crucial for hazard mapping and barrier design (Fanos and Pradhan 2019). The use of reliability concepts in risk mitigation methods allows for the classification of rockfall data and the modeling of occurrence probabilities, providing a quantitative measure of risk reduction through mitigation strategies (Lee et al. 2021). Additionally, the integration of fuzzy-AHP in spatial models offers a nuanced approach to rockfall hazard assessment, considering various rockfall characteristics and mitigation processes (Fanos et al. 2020).

The existing models for rockfall analysis related to transportation infrastructure protection range from qualitative rating systems to advanced quantitative simulations that incorporate machine learning and GIS integration (Fanos et al. 2020). These models are critical for identifying

hazardous areas, designing effective countermeasures, and ultimately safeguarding transportation corridors from rockfall incidents.

2.1.3 Implementation & Effectiveness of Existing Rockfall Stability Models

The implementation and effectiveness of rockfall hazard models vary across different geographical areas, including Pennsylvania and the broader United States. The literature indicates that rockfall hazard assessment methodologies are essential for identifying potential danger zones and informing mitigation strategies to protect infrastructure and human life (Ferrari et al. 2016). These methodologies often integrate high-resolution topographic data, such as LiDAR, and various modeling techniques to predict rockfall trajectories and impact areas (Fanos and Pradhan 2019; Fanos et al. 2020).

However, there are several parameters to consider. For instance, the effectiveness of rockfall hazard models can differ significantly depending on the terrain and slope characteristics. In areas with steep, convex slopes, some models show similar hazard values, while in less steep, concave slopes, the predicted hazards can vary considerably (Blahůt et al. 2013). Additionally, the sensitivity of hazard indices to the variables included in the models can influence the objectivity of the assessments (Crosta and Agliardi 2003).

Rockfall hazard models have been successfully implemented in various regions, however, their effectiveness is contingent upon the specific geological and topographical context of each area. The literature suggests that these models are valuable tools for risk management, but they must be carefully calibrated and validated against local conditions to ensure their reliability (Fanos and Pradhan 2019; Fanos et al. 2020). For Pennsylvania and the broader US, adopting and adapting these models to local geographies is crucial for accurate hazard assessment and the development of effective mitigation measures (Beckstrand et al. 2022). In PA, Jaime et al. (2008) used the Colorado Rockfall Simulation Program to develop guidance and suggestions on rock slope design for western PA slopes.

2.2 Laser Scanning

2.2.1 LiDAR Data Collection

Figure 3 shows the different categories of LiDAR data collection. LiDAR systems can be divided into two main categories: airborne and terrain/ground-based systems. Airborne acquisition allows for the rapid coverage of large areas, while terrain- or ground-based acquisition employs LiDAR mounted on a vehicle or on a device on the ground.

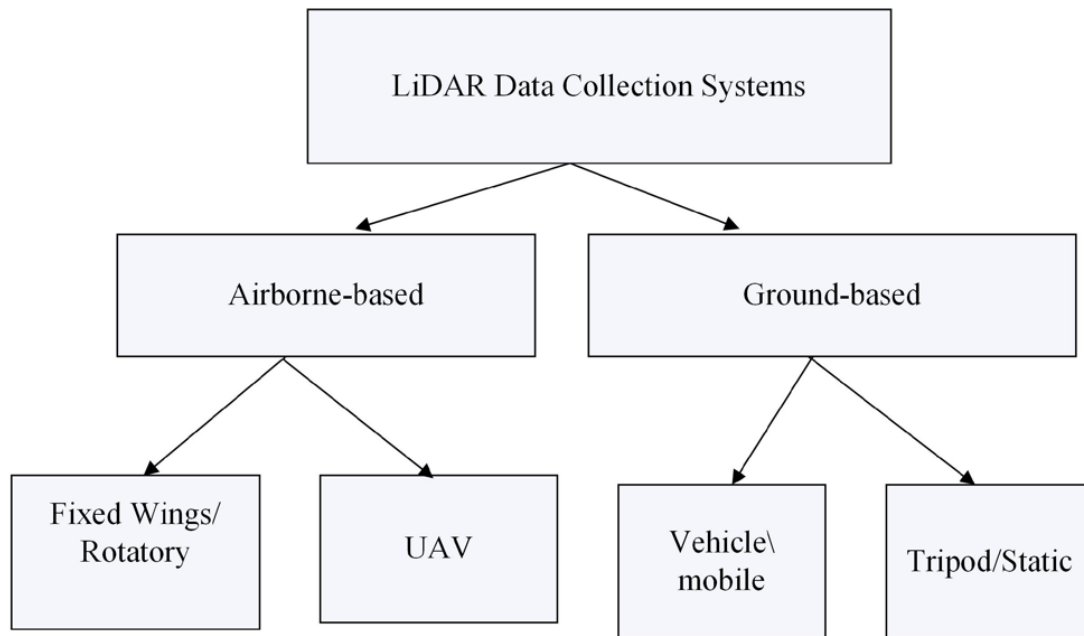


Figure 3. Different LiDAR data collection systems (Munir et al. 2023)

Airborne Laser Scanning (ALS) uses LiDAR measurements from an aircraft, such as a fixed-wing or rotary-wing aircraft or unmanned aerial vehicle (UAV), to acquire topographical data. Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) measurements provide information on the sensor's orientation, and the sensor generates data in the form of point clouds with coordinates (x, y, z). These coordinates and corresponding intensity values constitute a "point cloud". For example, the Leica ScanStation II (Fig. 4a), a time-of-flight scanner, can scan up to 300m at a top rate of 50,000 points per second. The Leica HDS6000 (Fig. 4b), a phase shift scanner, can scan up to 100m at a peak rate of 500,000 points per second. Both provide near-centimeter accuracy for single measurements, but accuracy improves significantly for modeled surfaces or specific conditions. Additionally, the ScanStation II features a built-in camera for adding optical color data to the point cloud (Norbert Maerz et al. 2015).



Figure 4. (a) Leica ScanStation II time of flight scanner with integrated optical camera; (b) Leica HDS 6000 phase shift scanner (adopted from Maerz et al., 2015).

Recent technological advancements in UAV components and battery technologies have increased the viability of UAV-based data collection for rockfall hazard assessments. The availability of lightweight sensor systems and development of UAV-related legislation have contributed to the commercial applicability of UAVs.

Terrestrial laser scanning uses ground-based remote sensing systems that can be mounted on static tripods (Terrestrial Laser Scanning, TLS) or vehicles (Mobile Laser Scanning, MLS), as shown in Figures 4-6. TLS scans closer to the targets than ALS systems, allowing for data collection with greater precision. However, MLS must travel on roads that do not always exist in regions without transportation infrastructure. After completing scans of a particular area, the tripod or vehicle is repositioned to scan from another angle or to capture data from a new location, enabling multiple scans of the same area from various angles, resulting in a more accurate and detailed depiction of the terrain (Farmakis et al. 2022). Typically, these scanners leverage opto-mechanical scanning methods (incorporating mirrors and prisms).

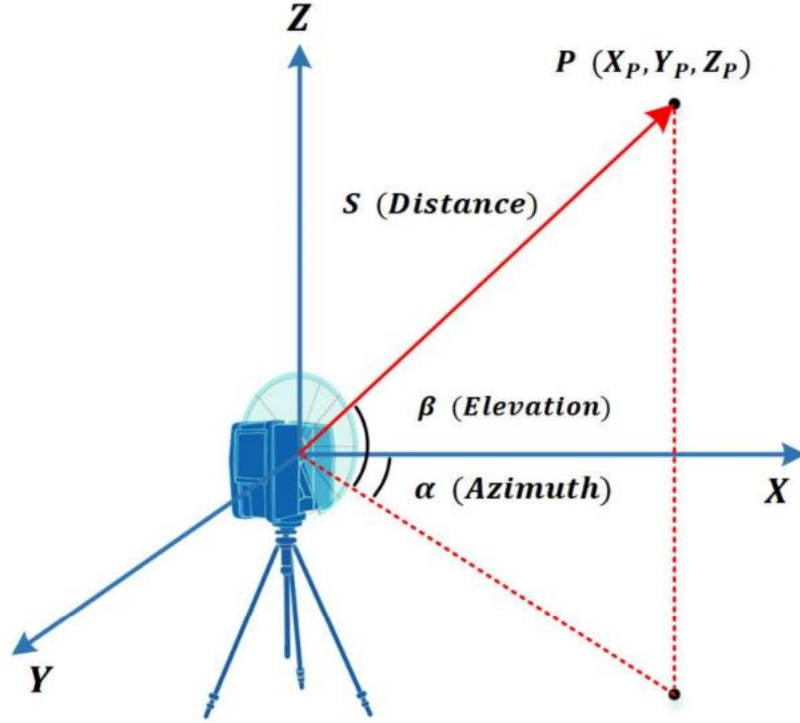


Figure 5. Example setup and measurements using ground-based Terrestrial Laser Scanner (Wu et al. 2022)

Table 3 outlines the distinctions between time-of-flight and phase shift scanners. Time-of-flight scanners cover a larger range, making them ideal for vast areas like highway slopes and cliffs. Conversely, phase shift scanners are better for smaller spaces, such as underground tunnels, due to their superior average data acquisition rate. While both scanners offer similar accuracy, phase shift scanners offer slightly higher accuracy. Both are portable, but phase shift scanners are lighter—largely because their batteries are built-in, while time-of-flight scanners often require an additional external battery (Kemeny and Turner 2008). LiDAR scanners have increased in use and therefore technology has developed rapidly over the past years. In Table 3 older scanners are listed on the left and newer scanners on the right.

Table 3. Specifications for a range of scanners (Kemeny & Turner 2008 and Wu et al. 2022).

<i>Scanner Type</i>						
<i>Parameter</i>	Optec ILRIS 3D	Leica (HDS6000)	Riegl (VZ-400i)	Topcon (GLS-2000)	Faro FocusS (150)	Z+F IMAGER (5016)
Type	Time-of-flight	Phase shift	Time-of-flight	Time-of-flight	Phase shift	Phase shift
Maximum Range (m)	1500m at 80% reflectivity	79m at 90% reflectivity	800	500	150	365
Scan Speed (pts/s)	2500	125,000	500,000	120,000	976,000	1,100,000
Ranging Accuracy	7mm @ 100m	4mm @ 25m	5mm @ 100m	3.5mm @ 150m	1mm @ 25m	1.6mm @ 100m

To obtain observations from the environment the 2D or 3D spatial information from the environment, the laser beam transmitted must be deflected. This deflection can occur using four types of mechanisms: Opto-mechanical, electromechanical, MEMS, and solid-state scanning (Roy et al. 2018).



Figure 6. Scanning rock slopes adjacent to highways with the Leica ScanStation; Point cloud is shown in the bottom right (Kenemy and Turner 2008).

2.2.2 LiDAR Monitoring Techniques

LiDAR technology has been increasingly utilized for rockfall monitoring, providing a means to accurately detect and analyze rockfall events. TLS provides a non-contact, high-resolution method for capturing detailed three-dimensional data of rock slopes, allowing for the characterization of discontinuity orientation, spacing, roughness, and other important information related to rock mass properties. In addition to rock mass characterization, TLS enables change detection through analysis of point clouds from successive scans of the same scene as demonstrated in the study by Kemeny et al. (2011). This capability has been applied to monitor rockfall events and assess movement over various time periods. For example, TLS was applied to assess rockfall hazards in mountainous regions, as demonstrated in a study along the Colorado State Highway 74 near the town of Morrison, Colorado, USA. This study highlighted the capability of LiDAR to detect rock slope changes and quantitatively document the impact of mitigation construction efforts on rockfall hazard with temporal scans revealing significant site-specific geological differences influencing rockfall volumes (Weidner et al. 2019). Detecting changes between two datasets recorded at different times can help identify active rockfall areas and provide useful data for analysis. Weidner and Walton (2021) applied LiDAR scanning techniques and point cloud comparison to evaluate rockfall over different time periods as shown in Figure 7. Common methods for tracking surface changes caused by geomorphic processes include the Digital Elevation Model of Difference (DoD), Cloud-to-Cloud (C2C), Cloud-to-Model (C2M), and Multiscale Model-to-Model Cloud Comparison (M3C2) (DiFrancesco et al. 2020). A commonly used software is CloudCompare, which has been used for alignment and comparison of point clouds from scans (e.g., by Weidner and Walton 2021 as shown in Figure 7).

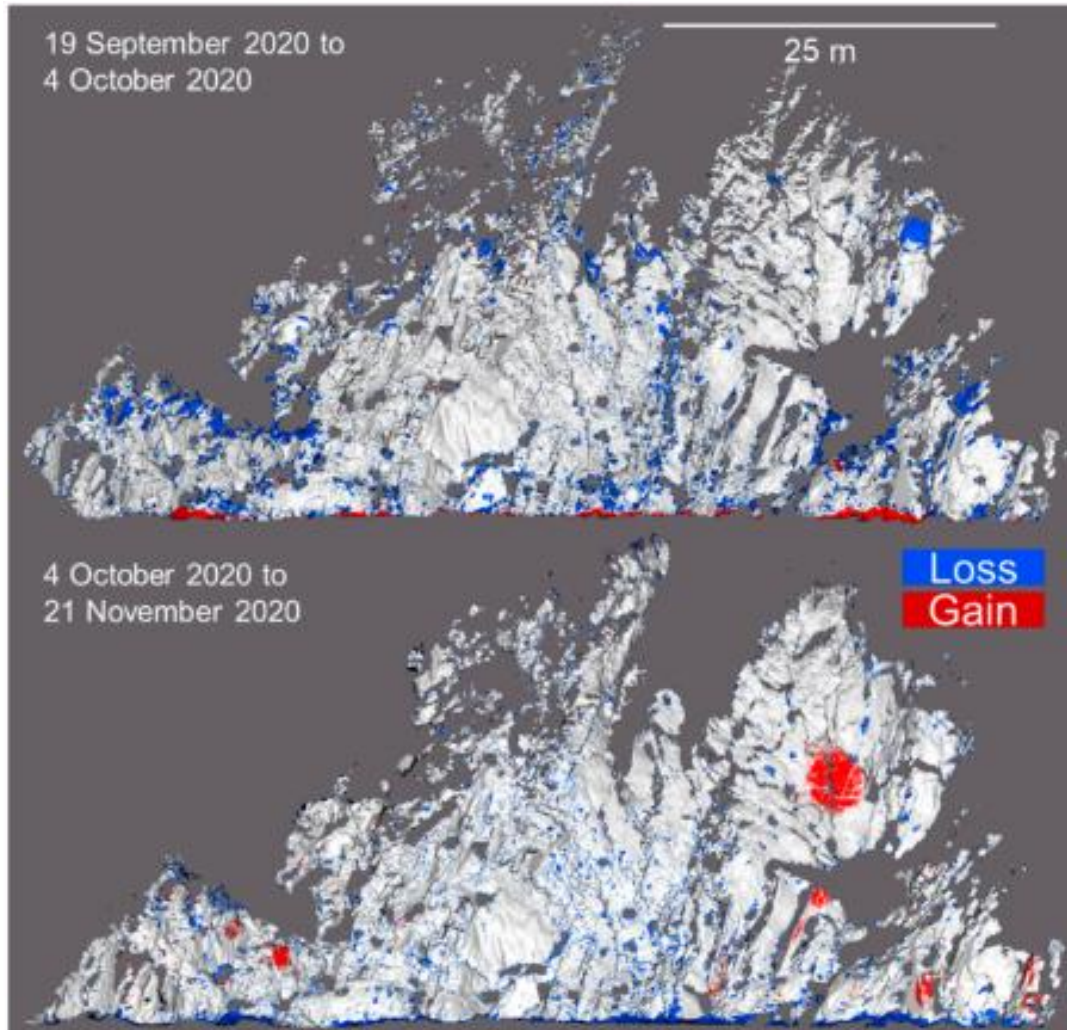


Figure 7. Point Clouds for a Rock Slope in Colorado monitored between September and November 2020. Gray points represent areas with change values less than 2 cm (Weidner and Walton 2021).

Additionally, the integration of LiDAR with artificial intelligence, specifically deep learning architectures like PointNet and PointNet++, has shown promise in automating the classification of rockfall events from 3D point cloud data, thereby enhancing rockfall risk management (Farmakis et al. 2022). Advancements in open-source point cloud processing algorithms have facilitated the creation of large digital rockfall databases, thereby increasing the accessibility and efficiency of TLS-based rockfall quantification (Weidner and Walton 2021). However, there are challenges in achieving generalization across different sites, suggesting that site-specific training of deep learning models is crucial for high-level performance in rockfall detection (Farmakis et al. 2022).

The technology's versatility is further underscored by its ability to generate a range of value-added products such as digital terrain models (DTMs), digital surface models (DSMs), and slope maps, which can be instrumental in rockfall analysis (Awange and Kiema 2019). In contrast to terrestrial photogrammetric techniques, which can lead to inaccurate data due to factors like vegetation and

wind, LiDAR offers a more reliable method for early detection of rockfall incidents, even at a small scale (Partsinevelos et al. 2015). Accurately classifying regions of interest in TLS data, particularly in the presence of vegetation, talus, and seasonal variations such as snow, remains a challenge. This necessitates the development of advanced classification techniques and automated workflows to enhance the efficiency and accuracy of the TLS-based monitoring of rock slopes (Weidner et al. 2019). The emergence of Multispectral LiDAR (MSL) systems also represents an advancement in the field, potentially offering enhanced capabilities for rockfall monitoring through the simultaneous acquisition of height and intensity information (Takhtkeshha et al. 2024).

2.2.3 LiDAR Best Practices

TLS has become a pivotal tool in the geometrical characterization of rock slopes, offering a remote sensing solution for inaccessible terrain (Francioni et al. 2015). The integration of LiDAR with applications such as Split-FX has been demonstrated to enhance the efficiency and safety of rock characterization, providing robust datasets for kinematic stability and rockfall hazard evaluations (Friede 2018). Split-FX software is specifically designed to extract geotechnical data from point clouds of exposed rock surfaces. This sophisticated tool includes several advanced features to streamline the analysis process. It automatically delineates fracture surfaces in a point cloud, determining their orientation, area, and roughness. Additionally, it plots fracture orientation on a stereonet, including both pole and contour plots. Users can select joint sets and perform statistical analysis on each set and delineate joint traces through both automatic and manual methods, which helps in determining joint spacing, length, and orientation. The software also enables tracing fractures on draped photos to establish more accurate fracture orientations. For assessing rock stability, it calculates rockfall volume and rate by subtracting two-point clouds and estimates a rockfall hazard rating directly from the point cloud data (Kemeny and Turner 2008).

The best practices for capturing high-quality point clouds in LiDAR scanning of rock slopes include the use of state-of-the-art monitoring workflows (see Figure 8) with semi-automated algorithms for alignment, change detection, clustering, and volume calculation (Weidner and Walton 2021). Additionally, the use of applications like Split-FX in conjunction with terrestrial LiDAR has been shown to result in robust datasets for kinematic stability and rockfall hazard evaluations, with validation of Split-FX-generated discontinuity orientations indicating insignificant variability compared to hand measurements (Friede 2018). It is also important to consider the use of different sensors and platforms, such as UAVs, which allow for accurate observation and 3D reconstruction of rock deposits, providing valuable input parameters for rockfall models.

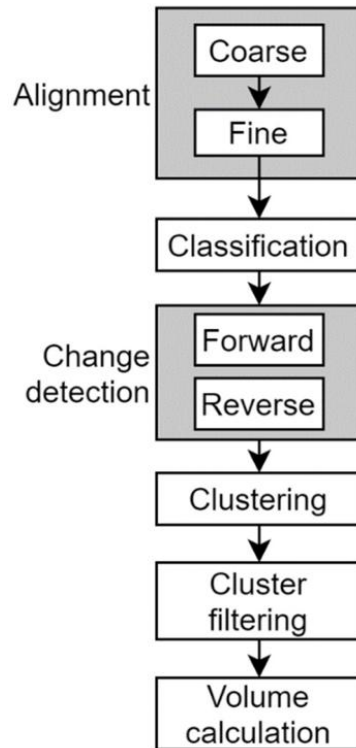


Figure 8. Workflow used to process TLS scans and calculate rockfall volumes (Weidner and Walton, 2021).

Advancements in structure-from-motion photogrammetry and oblique laser scanning have expanded the capabilities for high-resolution, remote assessment of rock slope hazards (Gauthier 2018). These tools and methods provide detailed and accurate characterization of rock slopes, which is essential for hazard assessment and the development of mitigation strategies. While LiDAR and photogrammetry are gaining traction, traditional rock mass classification systems like the slope mass rating (SMR) remain in use, often complemented by these newer remote sensing methods to improve the comprehensiveness of rock slope assessments (Salmanfarsi et al. 2019). In New Hampshire, for example, the integration of LiDAR with other geospatial datasets has been explored, although its application is limited by data acquisition costs (Disenhof 2018).

The use of unmanned aerial vehicles (UAVs) equipped with cameras for photogrammetry-based techniques has also been recognized as a cost-effective and accurate alternative for obtaining geotechnical data on steep rock faces. Similarly, the use of remotely piloted aircraft systems (RPAS) for terrain modeling has proven efficient in rockfall hazard assessment, emphasizing the value of remote sensing techniques in comparison to traditional TLS.

Regarding the number of scans and overlap, there is no specific number of scans or degree of overlap universally prescribed, as these can vary depending on the project requirements and the complexity of the rock slope being scanned. However, ensuring sufficient overlap between scans is crucial for accurate registration and comprehensive coverage of the rock face. Automated

registration methods, such as those based on edges detected using α -molecules, can support multi-platform datasets and perform better than traditional methods like ICP in some cases (Bolkas et al. 2021).

DiFrancesco et al. (2020) outlines a workflow for rockfall identification, involving automated data acquisition to rock slope deformation clustering using LiDAR data, as depicted in Figure 9. This process compares sequential 3D point clouds to identify negative changes or failures (shown in blue in Figure 9a). The analysis is then reversed to detect both the front and back surface of the dislodged volumes, leading to spatial clustering. Each change cluster (Figure 9d) signifies a distinct 3D point cloud dataset comprising the back and front surfaces of the affected volume (Farmakis et al. 2022).

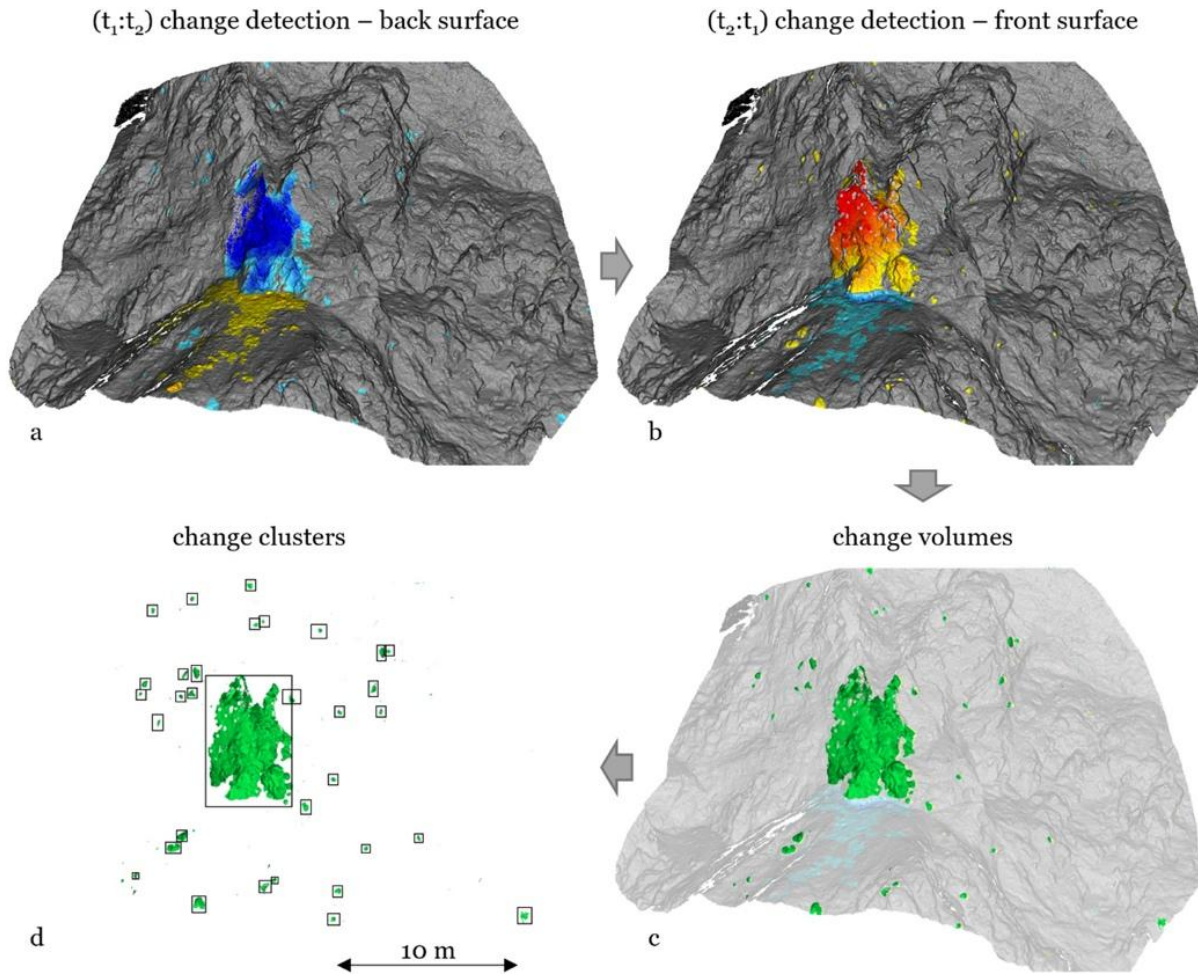


Figure 9. Deformation cluster identification process from change detection between time sequential LiDAR point clouds (Farmakis et al., 2022).

2.3 Drivers of Rockfall Hazard

2.3.1 Geotechnical Parameters Affecting Rock Stability

Rock stability is a critical factor for ensuring the safety and stability of slopes, rock cuts, and other geotechnical structures (Congress and Puppala 2021). Geotechnical parameters play a crucial role in rock stability models. The identification and discussion of critical geotechnical and spatial parameters affecting rock slope stability is a multifaceted issue that has been addressed by various studies. Geotechnical parameters such as the heterogeneity, anisotropy, and variability of rock mass properties are fundamental to slope stability analysis (Roy et al. 2018). The presence of joints and discontinuities within the rock mass significantly affects its mechanical characteristics and stress redistribution, which in turn influences the stability of rock slopes (Wang and Ni 2014). Spatial variability modeling of geotechnical parameters, including the extent of weathering and overburden pressure, is also crucial for a comprehensive stability assessment (Srivastava 2012).

When considering the methodologies used to assess these parameters, the use of geotechnical centrifuges to model rock slope failure mechanisms highlights the challenges in scaling and material representation. Additionally, the application of rock mass classification systems such as RMR, SMR, and GSI provides a method for assessing the stability of rock slopes, though these systems may not fully capture the complexity of spatial variability. The uncertainty of joint spatial distribution is another critical factor that can be addressed through reliability analysis methods, which consider the variability of joint geometric parameters and the randomness of joint locations (Zhang et al. 2023).

Rock slope stability is significantly influenced by a variety of geological and structural parameters. The strength characteristics of the rock, as well as the geometrical and strength properties of discontinuities such as joints and fractures, are crucial determinants of stability (Javan et al. 2015). Understanding these parameters and their interactions is vital for the design and implementation of effective stabilization measures and for ensuring the safety and sustainability of rock engineering projects. The presence of these discontinuities can weaken the intactness of the rock, altering its mechanical behavior and leading to stress redistribution within the rock mass (Wang and Ni 2014). Additionally, the size and configuration of rock blocks, which are delineated by these discontinuities, play a role in determining the failure modes of rock slopes (Li et al. 2005).

When comparing different analytical methods, the Discrete Element Method (DEM) and physical modeling can simulate various failure modes and provide results that align well with laboratory tests, whereas the Limit Equilibrium Method (LEM) may overestimate the factor of safety by not accounting for joint configurations (Li et al. 2005).

Dunham et al. (2017) identified the significance of morphological indices, such as local slope and roughness, as important geotechnical parameters for assessing rockfall hazards. These parameters were used to classify mass wasting processes acting on rock slopes and to map rockfall activity across slope faces. The RAI uses seven unique categories to examine different topographic and morphological patterns on rock slopes, each expected to show distinct erosion and mass-wasting

features. The RAI categorizes slope regions based on their inclination and roughness, allowing for a quantitative and repeatable classification into the seven RAI categories outlined in Table 1. Additionally, instability rates were also considered an important geotechnical parameter in the estimation of rockfall hazards using the Rockfall Activity Index (RAI) methodology.

2.3.2 Environmental and Climatic Parameters Affecting Rock Stability

Rockfalls can occur suddenly despite being the outcome of a protracted geological process influenced by tectonic activities and weathering (D'Amato et al. 2016). In addition to geotechnical parameters, environmental and climatic parameters play a significant role in rock stability models. These parameters include environmental factors such as rainfall and temperature. Rainfall and temperature have significant impacts on rock stability. Rainfall can induce pore pressure in a rock mass, reducing its effective strength and increasing its potential for failure. Temperature variations can also lead to thermal expansion and contraction, which can weaken the rock mass and increase its risk of instability. Furthermore, the influence of environmental parameters on rock stability can vary depending on the specific characteristics of the rock mass and the site conditions. For example, the presence of discontinuities in the rock mass, such as joints or faults, can create pathways for water infiltration and significantly affect the stability of rock slopes (Omran et al. 2021). Additional research has identified the primary trigger for rockfalls as the volume of precipitation on the day of the event. Moreover, moisture levels in the ground and freeze-thaw cycles occurring in preceding days also impact the likelihood of rockfall occurrence (Nissen et al. 2021).

The analysis of environmental parameters such as rainfall and temperature is critical in understanding their effects on rockfall hazard and slope stability. Rainfall, particularly its intensity and duration, has been identified as a significant factor influencing slope stability and the occurrence of landslides (Merat et al. 2019). Matsuoka (2019) indicates that heavy rainfalls in summer and early autumn can raise the moisture content of shallow bedrock, often triggering significant rockfalls. Although a specific threshold is not provided, the studies suggest that heavy rains are a critical factor. Similarly, Chen et al. (2023) discusses the multi-wing butterfly effects (MWBE) of climatic factors, including antecedent rainfall, in initiating catastrophic rockslides, though it does not quantify the amount of rainfall considered excessive.

Weidner and Walton (2021) drew conclusions regarding the time period for rockfall occurrence in relation to weather and seasonal factors. The findings suggested that rockfalls of the observed volume range were often conditioned for failure over relatively short antecedent periods, with triggering and conditioning periods being potentially several months to a year prior to the event. Additionally, it was noted that snowfall combined with freeze-thaw cycles and high-intensity rainstorms acted as conditioning and triggering factors responsible for rockfall events. The study shows that an increase in rockfall activity was consistent with an increase in precipitation in 2021 compared to 2020 (Figure 10). Precipitation in the form of both rain and snowfall increased, and this was matched with a corresponding increase in the number and total volume of rockfalls during those same months (Weidner and Walton 2021).

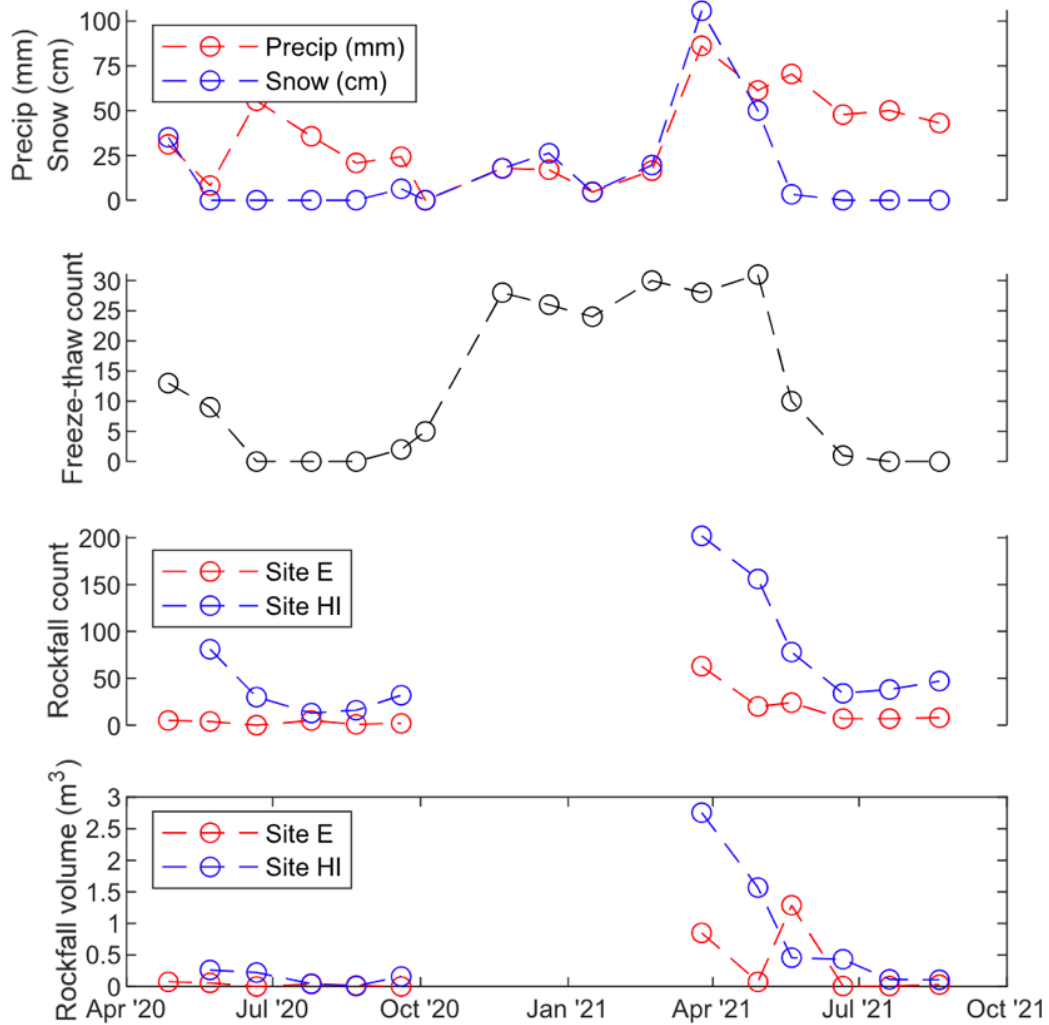


Figure 10. Plots of weather variables, including total precipitation (rain and/or melted snow), snow depth, and number of freeze-thaw cycles, with rockfall metrics per scanning period (Weidner and Walton, 2021).

Temperature fluctuations, especially freeze-thaw cycles, are also recognized as influential in rockfall frequency and magnitude (Birien and Gauthier 2023). Collins and Stock (2016) suggest that daily, seasonal, and annual temperature variations can drive cyclic and cumulative opening of fractures, particularly during the warmest times of the day and year. This implies that extreme fluctuations, especially high temperatures leading to solar heating of rock surfaces, can be significant in triggering rockfalls. Additionally, Matsuoka (2019) identifies short-term large thermal fluctuations as a contributing factor to submeter-scale rockfalls, mainly in winter, which are locally enhanced by freeze-thaw action.

Weather plays a significant role in triggering rockfalls, with various climatic conditions acting as both conditioning factors and triggers for rockfall events. Studies have shown that precipitation, freeze-thaw cycles, and temperature variations can significantly influence the stability of rock slopes, ultimately leading to the occurrence of rockfalls (Nissen et al. 2021; D’Amato et al. 2016; Macciotta et al. 2017; Weidner and Walton 2021). For example, freeze-thaw cycles can induce mechanical weathering, which weakens the structural integrity of rocks and increases the potential for detachment and subsequent rockfall. Similarly, intense, or prolonged rainfall events can saturate rock masses, leading to increased pore-water pressure and reduced shear strength, thereby enhancing the likelihood of slope failure and rockfall events. Additionally, the combination of weather factors, such as heavy rains following freeze-thaw cycles, can act synergistically to further destabilize rock slopes and trigger rockfalls. Understanding the complex interplay between weather variables and their role in rockfall triggers is crucial for mitigating rockfall hazards and developing effective risk-management strategies in mountainous areas.

2.3.4 Data Uncertainties and Limitation

Current methodologies for collecting data on rock slope stability exhibit several limitations. Traditional field methods, while indispensable for collecting detailed rock and discontinuity data, are often hindered by safety concerns, difficult terrain, and ongoing instability, which can prevent comprehensive data collection (Stead et al. 2019). Additionally, the subjective nature of some evaluation indices, such as intact rock strength and weathering degree, can introduce bias into stability assessments. Moreover, manual or semi-automated classification methods for layered rock slopes require significant human intervention and are not sufficiently automated for large-scale applications (Shang et al. 2023).

Understanding data uncertainties in LiDAR applications is crucial for interpreting results in rockfall hazard and slope stability assessments. The reliability of LiDAR data and subsequent analyses can be influenced by various factors, including the resolution of the data, the precision of the equipment, and the methods used for data processing. Data uncertainties stemming from noise and outliers within the raw LiDAR data necessitate pre-processing to ensure the generation of accurate DTMs and DSMs essential for rockfall hazard assessment. The variability in data quality, point density, and signal penetration in the presence of dense vegetation and adverse weather conditions introduces uncertainties. Challenges related to the differentiation of ground and non-ground points in LiDAR data necessitate the implementation of filtering algorithms to derive precise DTMs (Fanos and Pradhan 2019). Furthermore, the accuracy of LiDAR-derived Digital Elevation Models (DEMs) and DSMs can be affected by the density of LiDAR data points and interpolation algorithms utilized, potentially leading to the misrepresentation of subtle terrain features and small-scale rockfall events (Weidner and Walton 2021).

One significant limitation is the presence of occlusions and shadows in LiDAR point cloud data, particularly in rugged and vegetated terrains, which can result in incomplete coverage and inaccuracies in the representation of rock slopes. Contingent on the specific LiDAR system used, instrumental errors and calibration inaccuracies may also contribute to data uncertainties,

highlighting the importance of comprehensive data quality assessment and validation (Weidner and Walton 2021). While remote sensing techniques offer advantages in terms of safety and the ability to cover large areas, they cannot entirely replace the need for traditional field methods, which are crucial for obtaining certain types of data (Stead et al. 2019). The discrepancies in data, particularly with high values of geological strength index (GSI) and horizontal seismic acceleration coefficient (k_h), highlight the challenges in accurately predicting rock slope stability under seismic conditions (Roy et al. 2018). Addressing these limitations and uncertainties through advanced classification techniques, automated workflows, and the integration of machine-learning algorithms has become an essential focus of research in the field (Weidner et al. 2019).

While Friede et al. (2018) acknowledges the effectiveness of LiDAR in conjunction with the SplitFX application for rock characterization, it also points out the need to validate LiDAR-generated discontinuity orientations with hand measurements, demonstrating that there may be inherent uncertainties in LiDAR data that require cross-verification. Similarly, Lan et al. (2010) discusses the use of LiDAR for rockfall hazard assessment along Canadian railways, emphasizing the importance of calibrating LiDAR-based models with historical rockfall records to ensure accuracy.

2.4 Conclusions

Several conclusions can be made from the literature reviewed in this report. These conclusions are important because they will aid in guiding future work and model development for rockfall hazard assessment in PA. The conclusions from the literature reviewed are listed below:

- **Existing Models:** Several models exist for evaluating rockfall hazard. Low-quality rock masses are traditionally assessed using rock-mass classification systems which depend on visual inspections and collection of generic data from the rock mass. These data are then entered into a classification scheme such as the Rockfall Hazard Rating System (RHRS), which is based on parameters such as slope height, vehicle risk, geologic parameters, and movement per year, among others. The RHRS was initially adopted by the Oregon Department of Transportation and has since been used or adapted throughout the United States by other DOTs.
- **Laser Scanning:** LiDAR has increased in use due to technological advancements. LiDAR scanners can scan large slopes/areas in minutes, providing large datasets used to create 3D point clouds. These scanners have been used in studies to evaluate rock slope stability and hazard assessment, many of which scan slopes over time periods and compare point clouds for change detection. The Rockfall Activity Index (RAI) was developed to apply LiDAR scanning within a rockfall hazard evaluation index. Software is available to evaluate 3D point clouds, particularly for large scans (e.g., CloudCompare, Split-FX).

- **Drivers of Rockfall Hazard:** There are many competing parameters that may lead to rock slope instability and eventual rockfall, including geotechnical, environmental, and climatic. Material strength, roughness, and geologic characteristics can influence rock mass response under varying conditions. Studies have shown increased rockfall activity following precipitation and freeze-thaw cycles.

It is important to note that while LiDAR scanning has increased in use and been implemented in new rockfall hazard models, such as the RAI, there are data limitations and considerations. Data quality may be affected by vegetation and scan quality. Large datasets (i.e., 3D point clouds) can be created for large slopes or with repetitive scanning and this may lead to increased post-processing time for projects.

3. LiDAR Data Collection and Analysis

A landslide is defined as the downward movement of soil, rock, and organic matter under the force of gravity, often triggered by shifts in the Earth's surface and modifications of landforms (Delano and Wilshusen 2001). Landslides represent a significant geological hazard, causing damage to infrastructure and posing risks to human life. Based on mass movement characteristics, particle size, displacement volume, displacement velocity, and rupture shape, landslides can be classified into various types (Highland and Bobrowsky 2008). Rockfall is a type of landslide that describes the free fall of detached bedrock segments of any size from cliffs and steep slopes due to gravity and gradual cracking within the rock (Marija et al. 2022). Rockfall risk is influenced by environmental factors including freeze–thaw cycles, precipitation, and snowmelt; geological and morphological characteristics such as rock type and slope angle (Summa et al. 2015); and external influences such as proximity to roads and traffic flow (Wood and Jones 2025). Due to these complexities, estimating rockfall risk remains a challenge. However, recent methodological and technological advances have significantly improved risk assessment.

Rockfall occurrence is strongly influenced by geological and morphological factors. The tolerance for cracking varies with rock type, and several studies have examined parameters such as joint distribution, spacing, and discontinuity of rock segments (Zhang et al. 2023).

High resolution Light Detection and Ranging (LiDAR) technology has been extensively utilized for three dimensional modeling and data analysis. In LiDAR remote sensing, pulsed laser light is directed toward target objects. The collected data are represented as point clouds comprised of numerous data points, which accurately depict the terrain. These point clouds can be used to generate detailed terrain models, which are instrumental in analyzing rockfall risk.

Effectiveness of LiDAR scanning technology in geotechnical and geological applications has been demonstrated in numerous studies (Lato et al. 2012; Saroglou et al. 2018; Ambrosino et al. 2023; Wollenberg-Barron et al., 2024). Terrestrial Laser Scanning (TLS) and Unmanned Aerial Vehicle (UAV) platforms are among the commonly employed LiDAR acquisition methods. TLS systems, which are typically tripod-mounted, enable the capture of high resolution data over limited spatial extents. In contrast, UAV based LiDAR systems, when mounted on mobile platforms such as ground vehicles and aerial drones, facilitate coverage of larger area but generally yield lower resolution data relative to TLS.

LiDAR and point clouds offer many benefits; however, despite these advantages, the quality of LiDAR derived point clouds can vary significantly depending on environmental conditions. Inaccuracies in data acquisition can be introduced when precipitation interferes with laser pulses. Additionally, due to the linear nature of LiDAR scanning, obstructions such as streetlights, utility wires, and vegetation can block the laser path, resulting in shadow zones and incomplete data capture. To mitigate these limitations, LiDAR surveys are typically conducted from multiple

angles. Scans are also recommended to be performed during periods of minimal vegetation cover to optimize data quality and completeness.

3.1 LiDAR Scanning Locations

Damage and instability associated with rockfall have been reported from exposed, steep rock surfaces adjacent to roads in southeastern Pennsylvania, providing project sites to evaluate rockfall mechanisms through continuous monitoring coupled with climate data. Four sites—Riegelsville, Kintnersville, the Narrows, and Fleecy Dale Road—were selected to investigate rockfall hazard estimation for this project as shown in Figure 11. Riegelsville is situated along State Route 611, adjacent to the Delaware River; according to river gage records and maintenance logs, this area has experienced multiple floods. Based on the Pennsylvania Department of Conservation & Natural Resources, the bedrock here consists primarily of mafic gneiss and quartzite. Kintnersville is also located on State Route 611, the Narrows lies along River Road (Route 32), and Fleecy Dale Road is in Solebury Township. Based on data from the USGS National Cooperative Geologic Mapping Program (NCGMP), the rock types at each site have been identified as follows: the Riegelsville site consists partly of metamorphic rock from the Precambrian age and partly of sedimentary rock from the Cambrian age, while the Kintnersville and Narrows sites consist partly of alluvial sediment from the Pleistocene age and partly of sedimentary rock from the Triassic age.

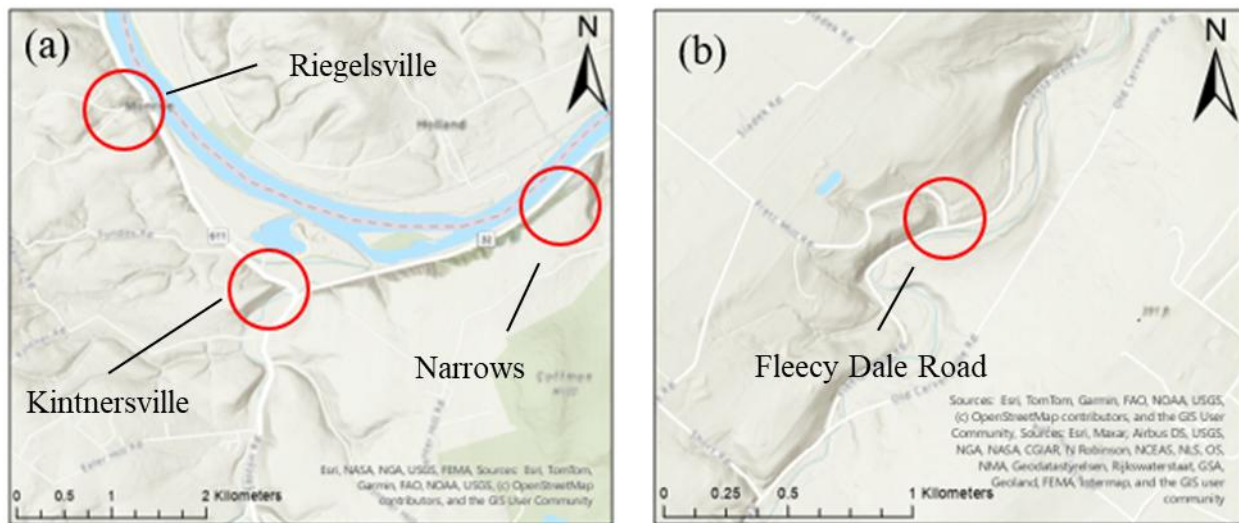


Figure 11. Site locations (a) Riegelsville, Kintnersville, and Narrows (b) Fleecy Dale Road

3.2 Methodology

3.2.1 Overview of LiDAR Scans and Equipment

To investigate the project sites, LiDAR scanning was conducted. The scans took place in April 2024, November 2024, February 2025, April 2025, and June 2025. A rockfall occurred at the Riegelsville site in December 2024. As shown in Figure 112, the event destroyed the fence and

deposited both large and small rock fragments onto the roadway. Although no injuries were reported, the incident posed significant hazards. Such rockfalls can produce steeper scarps, potentially exacerbating future instability. Therefore, it is recommended to compare the rock surfaces before and after the rockfall to assess morphological changes—such as slope steepness, crack development, and the volume of displaced material.

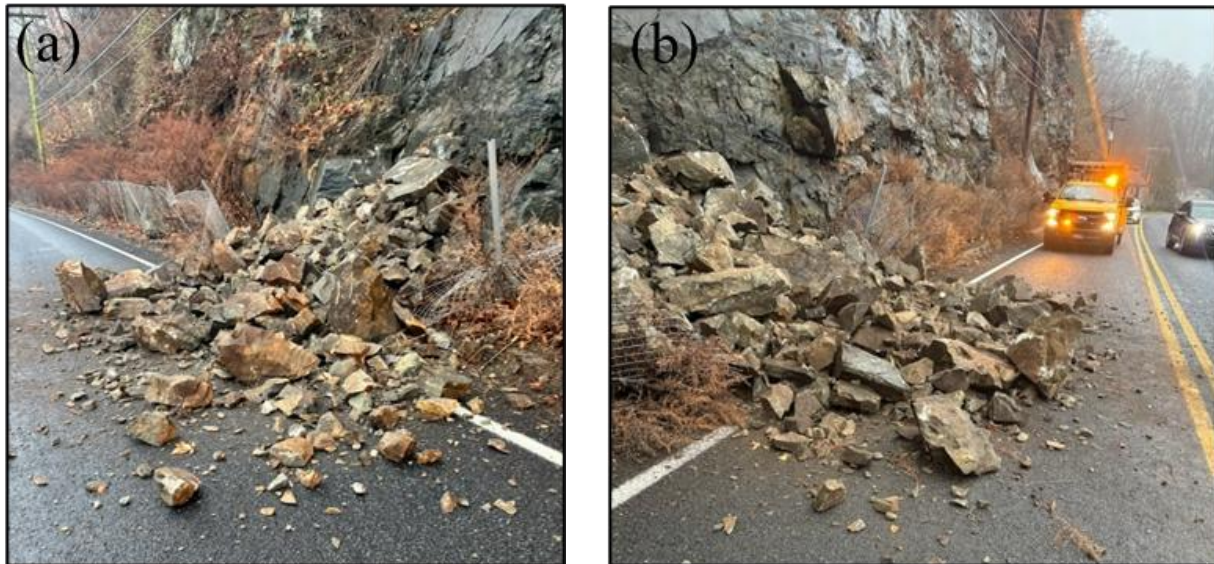


Figure 112. Photographs of the December 2024 rockfall at Riegelsville

For this study, a Leica RTC360 3D laser scanner was employed to acquire high-density LiDAR data as shown in Figure 113. The RTC360 is a high-speed scanner featuring an integrated HDR spherical imaging system and a visual-inertial system (VIS) for real-time registration. A scan with a spherical HDR image at 6 mm at 10 m resolution requires approximately 2 to 5 minutes, depending on the chosen resolution and filtering options.

A Leica GS18 GNSS RTK system—comprising a rover unit mounted atop the RTC360 and a fixed base station—was used to provide absolute positioning for the point-cloud data. GS18 offers tilt compensation, ensuring robust coordinate acquisition even on uneven terrain. To maximize baseline stability and minimize coordinate uncertainty, the base station was operated continuously for at least four hours prior to rover deployment. GNSS rover data collection began concurrently with each LiDAR scan and ceased upon scan completion. In instances where the scan area was partially obstructed by overhead cables, vegetation, or other occlusions, the rover maintained a minimum observation duration of 15 minutes. This interval ensures sufficient satellite constellations and base-to-rover link stability, thereby improving the precision of the derived coordinates.

The RTC360 permits three native scan-resolution settings—low, medium, and high—corresponding to nominal point accuracies of 5.3 mm at 40 m, 2.9 mm at 20 m, and 1.9 mm at 10

m, respectively. In environments with transient moving objects (e.g., vehicular traffic), activating the double-scan mode enables effective removal of such artifacts through scan-to-scan differencing. Scan duration increases with higher resolutions and double scanning, as illustrated in Figure 115.

The GS18 provides real-time status indicators for satellite fix quality, tilt compensation, RTK link status, Bluetooth connectivity, storage availability, battery level, and external power input. A flashing green RTK symbol denotes successful base-to-rover data transmission; while blinking or colored symbols indicate degraded link conditions. Proper initialization of both LiDAR and GNSS equipment, tailored to the site's environmental constraints, is essential for achieving survey-grade point clouds and georeferenced accuracy. For this project, the high-resolution, double-scan, and HDR options are enabled during LiDAR acquisition.

The CS20, which is the controller for the GS18, provides setting options for connection methods (Bluetooth or Internet) and for data-collection methods. For base-station setup, if a local GNSS station is used, it is recommended to select “over a known point”; otherwise, if it is creating own base station, it is recommended to select “over any point.” For this project, the base station is created for each site location, therefore, “over any point” option is used every time. To assess location accuracy, the number of satellites connected to the base and rover—and the corresponding resolution—appears at the top of the screen as shown in Figure 114.

For this project, the high-resolution, double-scan, and HDR options are enabled during LiDAR acquisition. For GNSS settings, “GS radio” is selected under the “Connect Using” menu, and “GS18 Pillar” is chosen for the Base Antenna. It is recommended to adjust the orientation of both rover and base antennas before beginning procedures (reception can improve in certain directions) then wait briefly to verify a stable connection. The base station should not be moved or adjusted during GNSS data collection.



Figure 113. Scan equipment (a) RTC 360 scanner with rover mounted on top (b) GS18 set up as a base station.

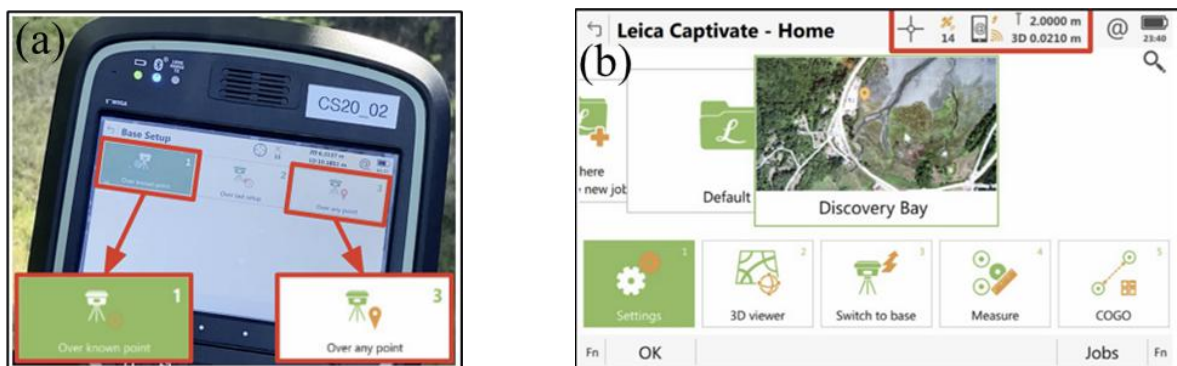


Figure 114. The CS20 controller's (a) base setup screen for configuring core parameters, and ("b) home screen displaying real time status and main controls.



Figure 115. (a) RTC360 scanner screen display showing scan settings (b) GS18 controller status.

3.2.2 Register LiDAR scans into Point Clouds

After completing the scanning procedure, the LiDAR point cloud data are extracted for registration. In this project, both Cyclone Register 360 and Cyclone CORE are used to register the point clouds. Cyclone Register 360 is applied first: once the scan setups are extracted, the data are imported into the software. As shown in Figure 116, Cyclone Register 360 links the individual scans and generates a bundled point cloud, allowing to adjust the alignment between scan setups and produce a cohesive, high-quality dataset. To refine this initial registration, both top and side views should be examined before finalizing the process. The alignment strength and overlap percentage of the bundle are then reported, as illustrated in Figure 116.

After initial registration in Cyclone Register 360, the point cloud data must be refined in Cyclone CORE to achieve higher resolution. The previously processed Cyclone Register 360 project file is imported into the site database. In the Registration screen, the “Unfinalized” icon is clicked to display the Constraints list. Initial registration is then performed by selecting the “Register” button at the top of the screen. Individual scan errors and overall group errors are automatically displayed beside each scan. If abnormal errors are detected or tighter alignment is required, the Visual Alignment tool can be used to specify corresponding points manually. Further improvement is obtained by modifying the Cloud Constraints parameters as follows: Max Iterations: 1000, Subsampling Percentage: 10 %, Maximum Search Distance: 0.2 m. After these parameters are set, the Optimize Cloud Alignment and Auto-Add Cloud Constraints tools are applied to minimize residual errors. Once the bundle is well aligned, scan locations are defined in Model Space. For each scan, a vertex is created at (0, 0, 0) and a registration label (S1, S2, etc.) is added. GNSS data are imported from a text file formatted with TargetID, Easting, Northing, and Height, using the same labels (S1, S2, etc.). The file is loaded into a ScanWorld, which is then designated as the Home ScanWorld. Auto-Add Constraints (Target ID only) is performed next, with the GNSS

weight set to 0.01 so that group errors remain minimally affected. The registration is then re-optimized, and Model Space is frozen, created, and opened for final review. For point cloud export, normals are deselected in the extraction options. The combined dataset is exported as an LAS file, while each individual scan setup is exported as an E57 file.

There are many tools for working with point-cloud data. After registration, the data are stored in LAS format, which offers great versatility but consumes significant storage that may be unnecessary for some applications. For example, ArcGIS Pro—used to convert point clouds into DEMs—requires LAS files, whereas CloudCompare—a popular point-cloud processing tool—supports the compressed LAZ format. To save storage space, LASTools can be used to convert LAS files to LAZ.

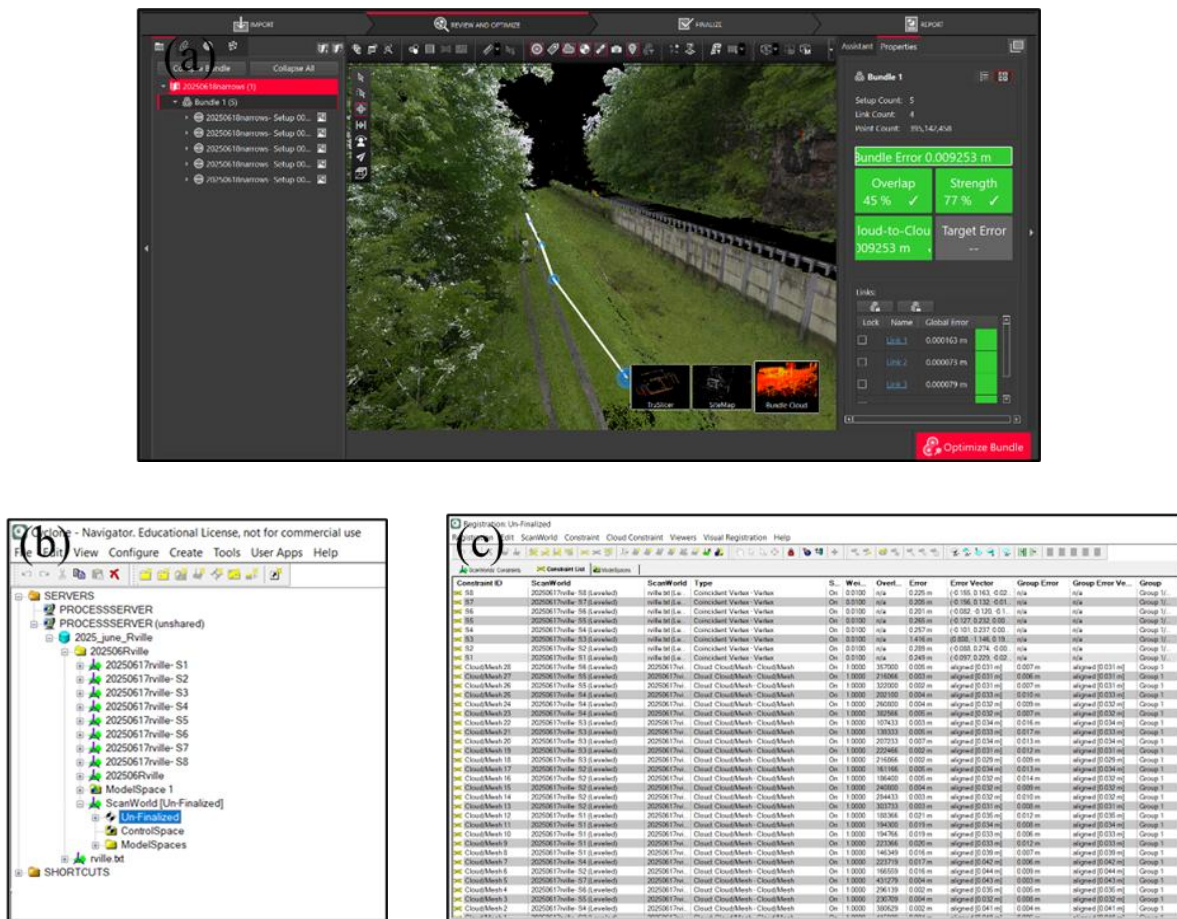


Figure 116. (a) Capture of the Cyclone Register 360 procedure (b) Cyclone core main screen (c) Cyclone core registration screen displayed after entering through the “unfinalized” icon.

3.2.3 Data Process Using CloudCompare

CloudCompare provides a wide range of useful point cloud processing and visualization tools, including change detection and volume calculation which are utilized in this study. It supports importing various file formats such as LAS, LAZ, and E57, which are the formats generated by the registration software. The software enables detailed investigation of point clouds in all directions and at multiple scales, supporting RGB data, scalar fields, and intensity values. For change detection between two point clouds, the Model-to-Model Cloud Comparison (M3C2) plugin was employed. According to Lague et al. (2013) and James et al. (2017), M3C2 computes a local surface normal for each core point, measures the average distance between the two clouds along that normal direction, and estimates positional uncertainty for each core point based on precision maps. This allows the method to determine distance uncertainty in the direction of the surface normal. This approach is particularly effective for change-detection on steep surfaces.

Prior to processing, the point cloud datasets were trimmed to the area of interest to improve computational efficiency; this was accomplished using the Segment tool in CloudCompare. Additionally, the point cloud files were converted from LAS to LAZ format to reduce storage requirements. As shown in Figure 117, distances between two point clouds were calculated by projecting points from cloud #1 onto cloud #2 using a cylindrical projection method (Lague et al., 2013). The normal and projection diameters were automatically estimated via the “Guess Parameters” function, and cloud #1 was designated as the source of core points. Preferred orientation options—X, Y, Z, barycenter, and origin—were selected based on the predominant direction of the rock surface. Although the choice of projection core points on clouds as an output option has minimal impact on the overall distance calculations, it can affect the distribution of negative and positive deviation values. Additionally, the 2.5D Volume tool was adopted to calculate the volumetric differences between two point clouds, enabling accurate estimation of the rockfall segment volume.

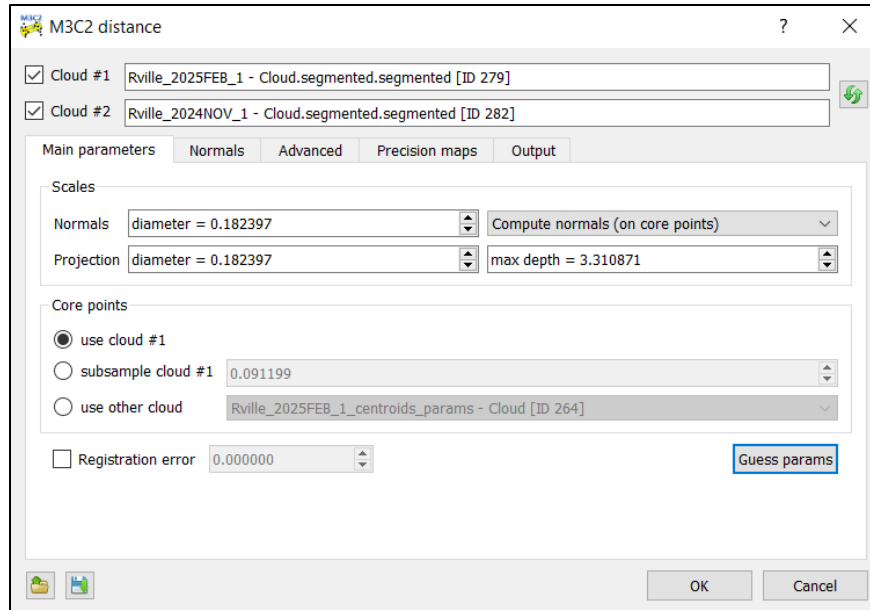


Figure 117. CloudCompare M3C2 plugin

3.2.4 Data Processing Using Rambo Software

Rambo (Rockfall Activity Morphological Big Data Optimizer) software was developed by Oregon State University and the University of Washington. For this project, Rambo software was utilized to conduct both morphological analysis and Rockfall Activity Index (RAI) analysis. The software is recognized for its robust capabilities in examining rock surfaces. A suite of tools is provided, including ground filtering, smoothing, hole filling, morphological analysis, RAI computation, change detection, and seismic analysis. The ground filtering tool is especially effective for removing vegetation from steep rock surfaces, as such vegetation can cast shadows and introduce errors into surface data analysis. Consequently, ground filtering tool is recommended in areas with substantial vegetation. However, its application can result in data voids and inappropriate smoothing of surfaces.

To address missing data, the hole filling tool is capable of interpolating using thin-plate splines (Olsen et al., 2015), with regularization parameters determining the accuracy of the interpolation. The morphological analysis tool accounts for crucial role in rockfall studies, enabling the calculation of slope angles, discontinuities, and surface roughness. A defining feature of the software is its RAI functionality. The RAI score was defined by Dunham et al. (2017) using parameters from Markus (2023). It represents a morphological classification based on failure depth, discontinuity attributes, and rock slope inclination. RAI classification has seven classes which are included: talus, intact, fragmented discontinuity, closely spaced discontinuity, widely spaced discontinuity, shallow overhang, and cantilever overhang (Dunham et al. 2017) and classification and definitions are provided in Table 4.

Table 4. Rockfall Activity Index Classification

Classification	Definition
1. Talus	Rock material that accumulates at the base of a rock slope
2. Intact	Rock mass with little discontinuity features
3. Fragmented discontinuity	Intact blocks within rock slope separated by discontinuities spaced 10cm or less
4. Closely spaced discontinuity	Discontinuity features spaced 10 to 20cm
5. Widely spaced discontinuity	Discontinuity features spaced 30 cm or greater
6. Shallow overhang	Overhanging rock with a ground facing side inclined 90 to 120 degrees
7. Cantilever overhang	Overhanging rock with ground facing side inclined 120 degrees or more

Accordingly, higher RAI scores imply greater risk associated with steeper slopes and elevated terrain. Therefore, higher classification levels suggest increased risk to rockfall. From each RAI class, the software computes an RAI score. The RAI score represents the kinetic energy of point cells based on their RAI classification and an assumed failure depth. The RAI score and mass are calculated as follows:

$$RAI\ Score = \sum_{i=1}^n \frac{1}{2} m_i v_i^2 AR_j \quad (1)$$

$$m = G_s \Delta^2 FD_j \quad (2)$$

Where n denotes the number of rock slope cells in 1m segment; i denotes cell number; AR denotes the activity rate; m denotes the mass; G denotes the specific gravity; FD denotes failure depth; and D^2 denotes cell dimensions (Dunham et al. 2017). Based on RAI score, the failure depth, rock mass, kinetic energy, and impact velocity can be evaluated, providing valuable insights into the magnitude of the rockfall.

Rambo uses a different change detection method: it computes orthogonal distances relative to an analysis plane for each cell and for each epoch, then identifies erosion and accretion areas (Olsen et al. 2015; Dunham et al. 2017).

Several key options are provided in Rambo to achieve more precise change detection. After the two point clouds have been imported via the DATA I/O interface, the Change Detection tool is selected from the main screen, and the available settings are automatically updated. To enhance accuracy, these settings should be adjusted appropriately. For steep rock surfaces, the “Work in Best Fit Plane of First Scan” option is recommended under DataProc. Specification of the cell size, function type, site code, and output filename is enabled by the control panel on the right side of the screen. In this project, a cell size of 0.05 m was chosen, and unique output names have been assigned for each analysis.

3.3 Results

3.3.1 April 2024

The first LiDAR scan of the site was conducted in April 2024. As shown in Figure 118, the rock surface is partially covered by vegetation. Front views of the rock surface point cloud data (Figure 118 b, d, and f) were generated by trimming the segments of interest from the complete dataset. Vegetation is rendered in white due to the HDR function's limited range and the shadowing effects of nearby obstacles. Using this point clouds data, ground filtering, hole filling, and RAI analysis were performed to evaluate the capabilities of Rambo software (Figure 119). Although most vegetation was removed by the ground-filtering function, empty holes were created and the surface was smoothed, which may influence subsequent analyses. In Figure 119, the purple points indicate areas where holes were filled automatically. The accuracy and extent of the hole filling vary depending on the chosen window settings. Optimal LiDAR scanning conditions will be achieved when redundant vegetation is absent. However, if scanning and surface analysis must be completed despite vegetation cover, ground filtering and hole filling in Rambo software can still be employed to assess rockfall hazard, even though the results will not be perfect.

RAI classification is determined based on failure depth, discontinuity attributes, and rock slope inclination. Therefore, it can be used as an indicator to represent rockfall hazard areas, allowing identification of the rock surface zones at the most risk to rockfall. The RAI classification system categorizes rock surfaces into seven distinct classes based on their structural and morphological characteristics as shown in Table 4. Figure 20 shows RAI classification for the three sites.

The RAI score represents kinetic energy in joules, calculated from assumed failure depth and RAI classification of rock segments. Therefore, potential rockfall damage can be evaluated using the RAI score, with higher values indicating greater rockfall magnitude due to steeper slopes and higher kinetic energy. The RAI score provides valuable insight into areas of high rockfall potential and associated damage by effectively identifying zones with elevated RAI values derived from kinetic energy characteristics. The RAI scores for the three sites are presented in Figure 21. From the scalar field of RAI scores, hazard areas can be delineated. By removing unnecessary elements above the rock surface and adjusting the scalar field scale, the most hazardous rock segment can be identified using this tool.



Figure 118. April 2024 scan results: (a) Riegelsville photograph; (b) Riegelsville point clouds; (c) Kintnersville photograph; (d) Kintnersville point clouds; (e) Narrows photograph; (f) Narrows point clouds

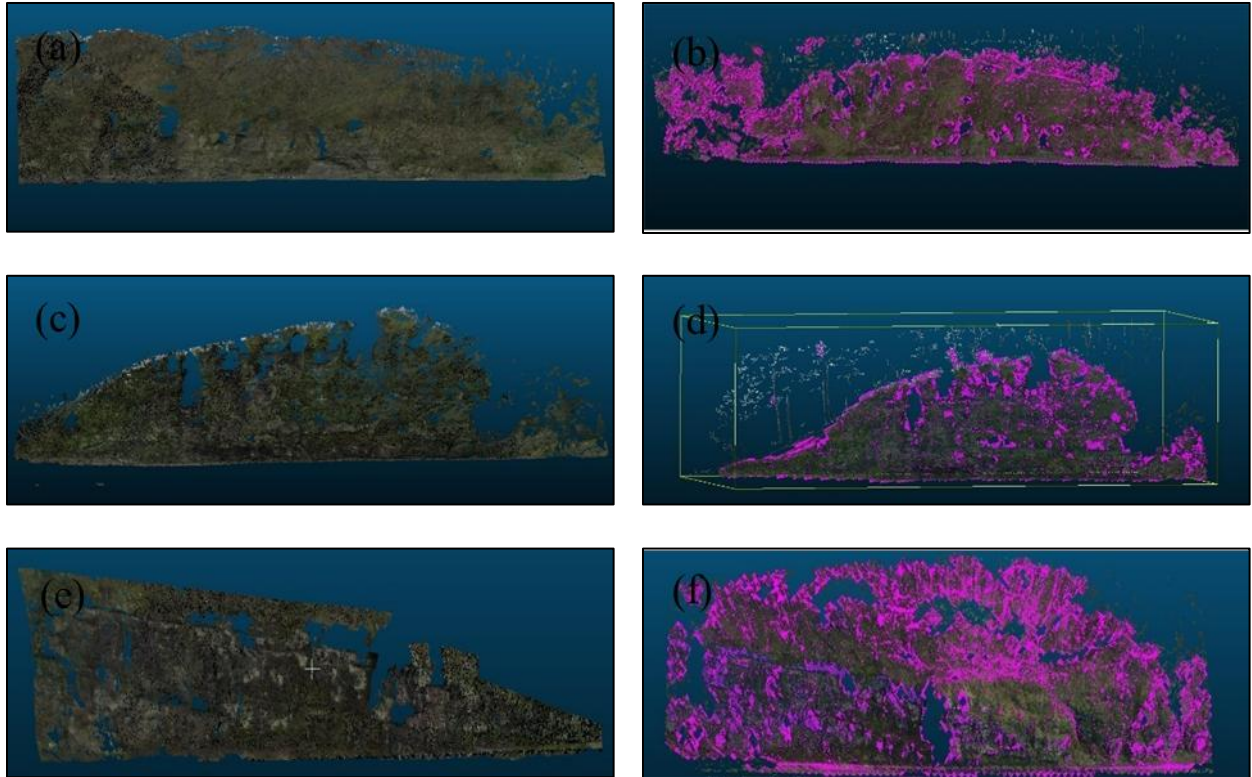


Figure 119. April 2024 scan processing: (a) Riegelsville ground filtering; (b) Riegelsville hole filling; (c) Kintnersville ground filtering; (d) Kintnersville hole filling; (e) Narrows ground filtering; (f) Narrows hole filling.

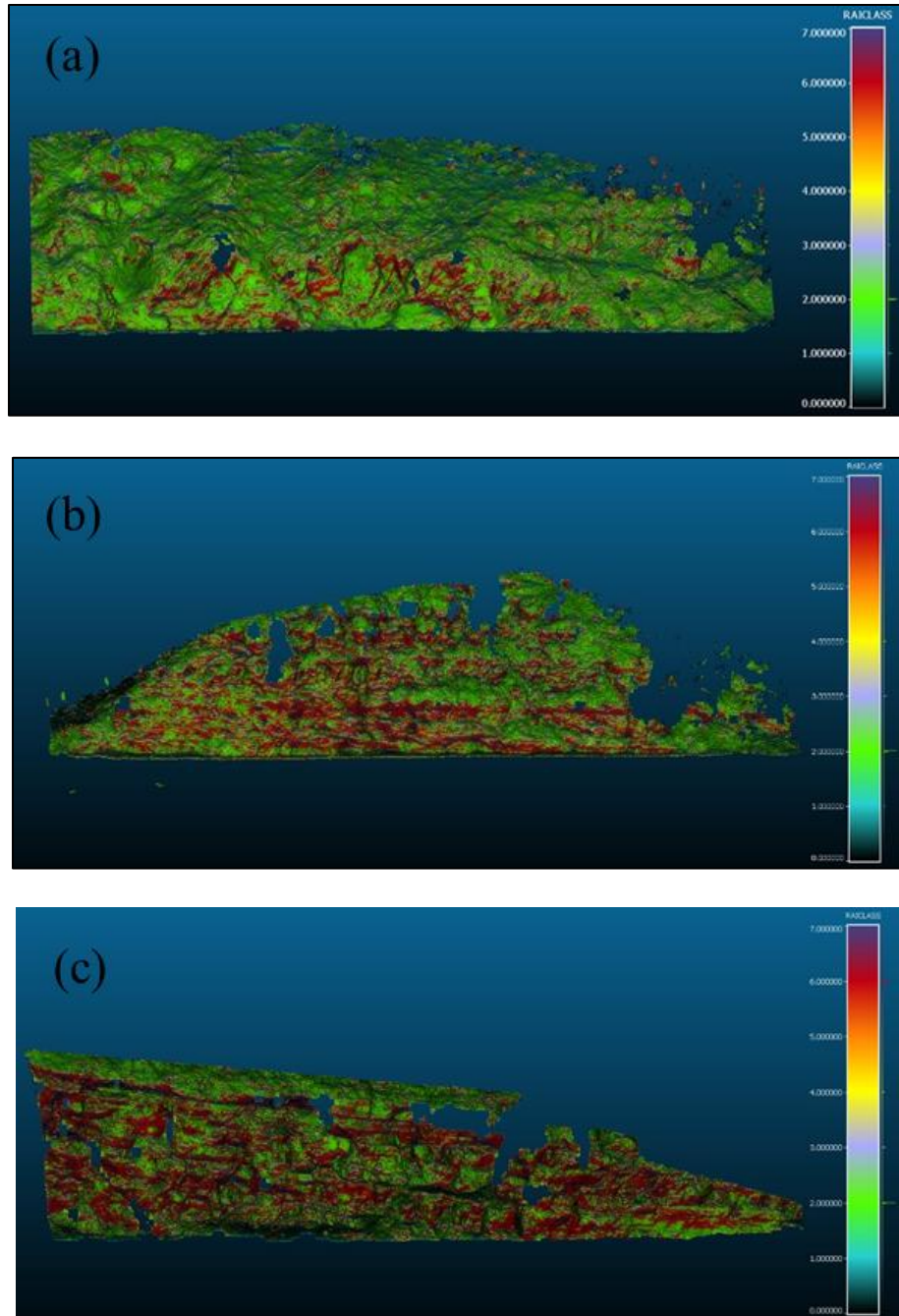


Figure 20. RAI classification results: (a) Riegelsville; (b) Kintnersville; (c) Narrows.

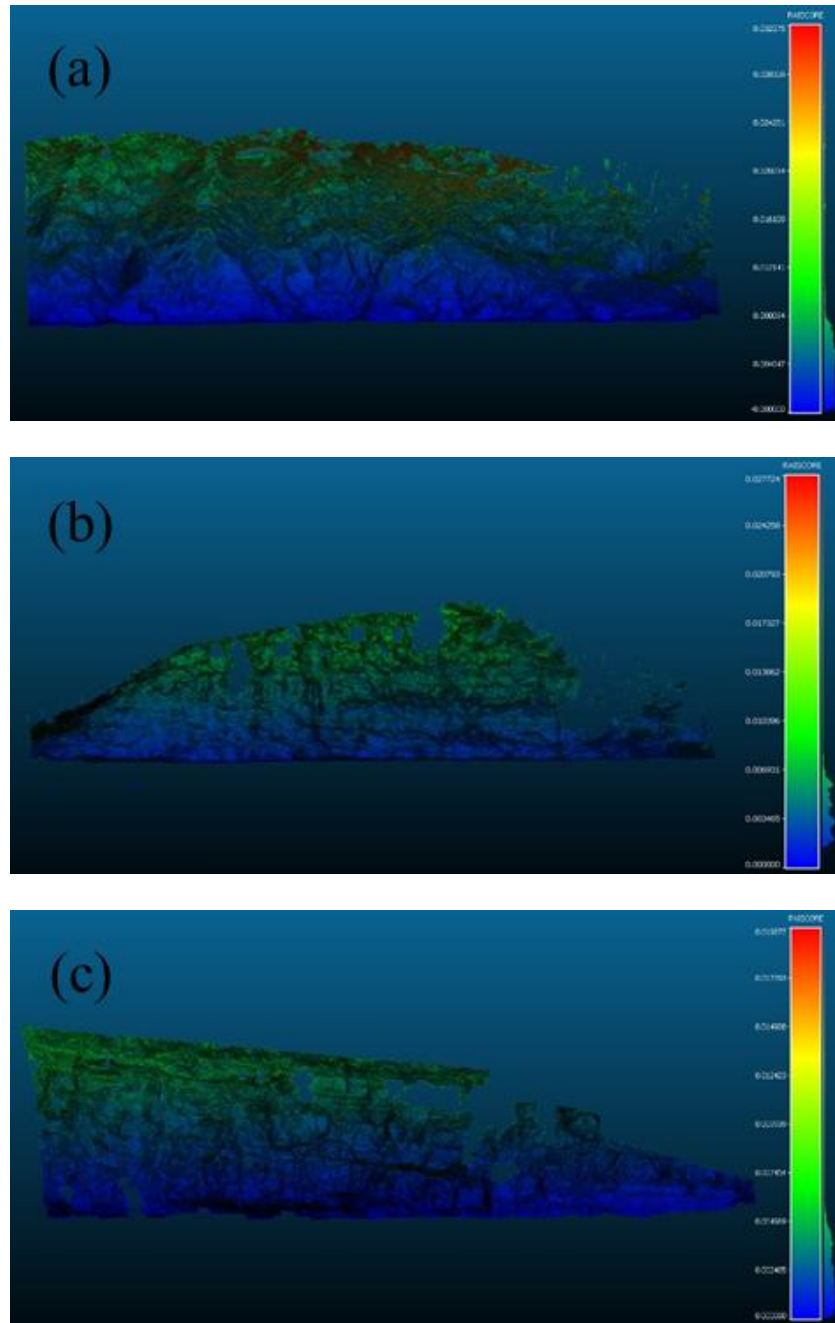


Figure 21. RAI score results: (a) Riegelsville; (b) Kintnersville; (c) Narrows.

3.3.2 November 2024

The second scan was conducted in November 2024. As shown in Figure 22, vegetation cover was noticeably reduced compared to the April scan, thereby facilitating data processing. LiDAR scanning of Fleecy Dale Road was performed in November rather than April 2024. Because the rock surface lay in close proximity to the road, capturing the entire face in a single pass proved difficult; accordingly, the two primary rock surfaces are presented in Figure 23. These surfaces

also exhibit distributions of overhang RAI classifications and segmented areas with elevated RAI scores relative to other rock faces at similar elevations.

Change detection analyses between April and November 2024 point clouds were conducted using Rambo software and are shown in Figure 24. Only minimal differences were detected, and these were attributable to vegetation. In Figure 24(d), change detection was repeated after applying ground filtering in Rambo; the removal of trees and most vegetation from the rock surface made comparison between datasets easier. However, this additional filtering may be unnecessary if vegetation does not significantly influence the results for both scans.



Figure 22. 2024 November Photograph: (a) Riegelsville; (b) Kintnersville; (c) Narrows; (d) Fleecy Dale Road.

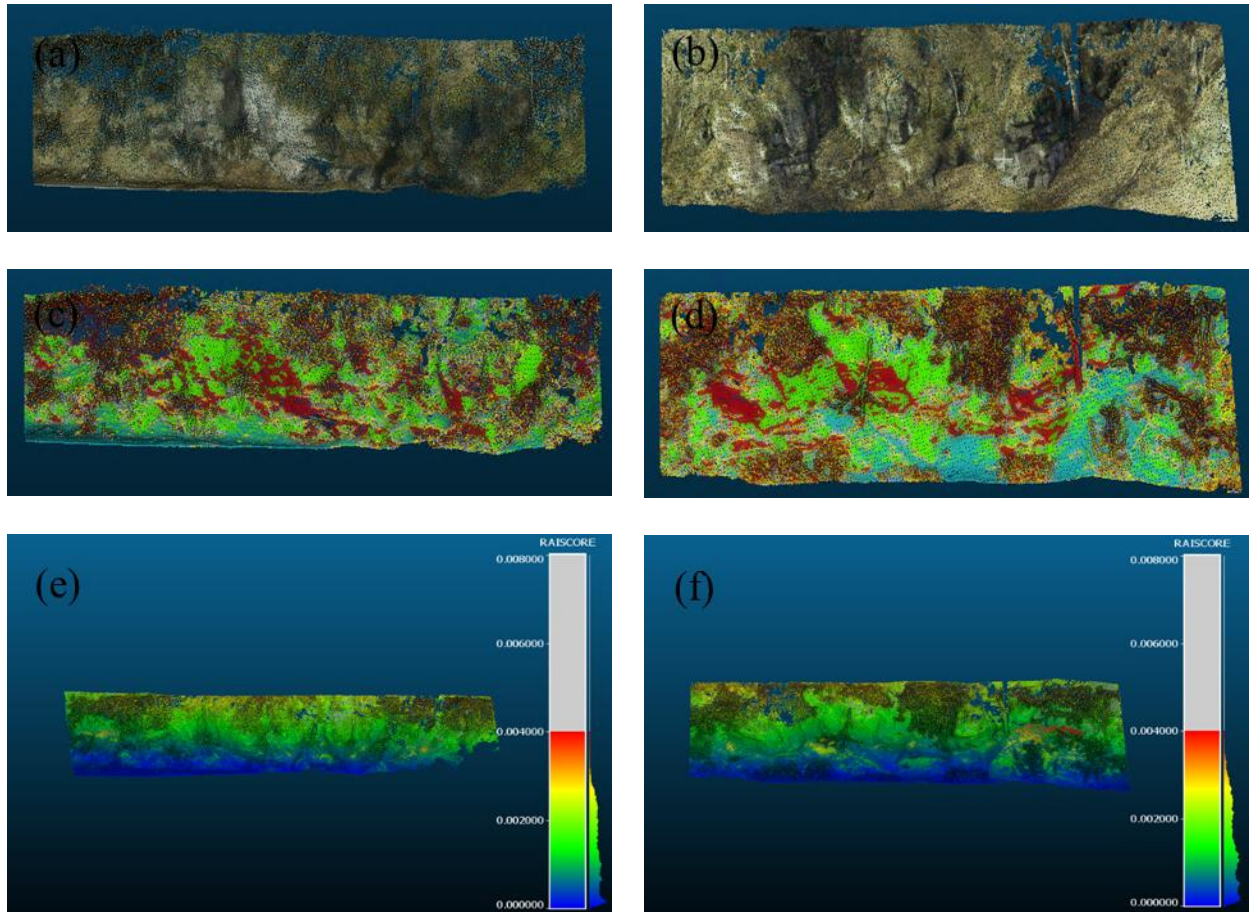


Figure 23. Fleecy Dale Road results: (a) front view of rock surface 1 (b) front view of rock surface 2 (c) RAI classification of rock surface 1 (d) RAI classification of rock surface 2 (e) RAI score of rock surface 1 (f) RAI score of rock surface 2.

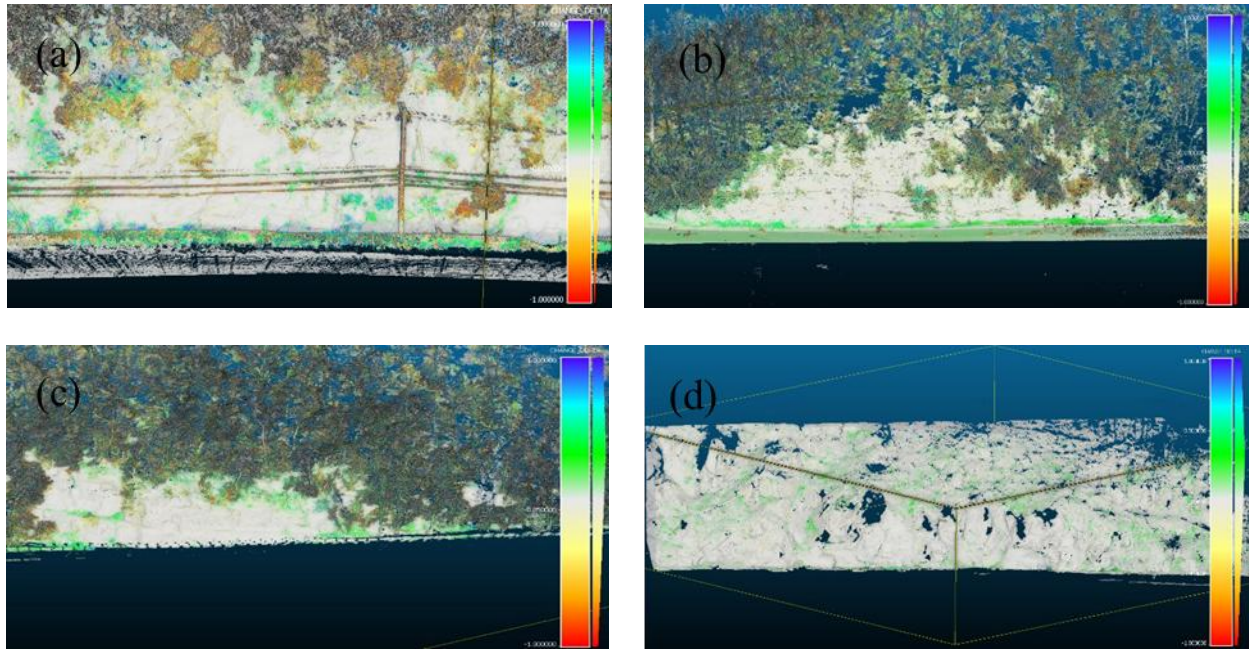


Figure 24. Change detection results: (a) Riegelsville; (b) Kintnersville; (c) Narrows; (d) Riegelsville with ground filtering.

3.3.3 February 2025

A rockfall, shown in Figure 1125, was triggered in Riegelsville in December 2024. Large and small rock fragments were deposited onto the roadway and remained until they were cleared. Fortunately, no injuries were reported, although fences were damaged and considerable inconvenience was caused. A follow-up scan was performed in February 2025. In Figure 25, the red circle on the left delineates the original rockfall location, while the red circle on the right highlights small overhanging segments that appear to detach. Figure 25 (b) and (c) present before-and-after comparisons of the same rock surface area, clearly illustrating detached fragments. To examine the rockfall in greater detail, change-detection analyses were conducted in November 2024 and February 2025 point clouds using both CloudCompare and Rambo software. Identical zones of change were detected in the central rock face, where the primary rockfall occurred; at the slope base, which revealed removed vegetation, dismantled fences, and cleanup debris; and on adjacent surfaces, where minor discrepancies were attributed to snow-induced laser reflections (Figure 26).

A total rockfall volume of 6.74 m³ was calculated from Rambo software; the detached segments were predominantly classified as shallow overhang, encompassing 29486 analysis cells. These outcomes are sensitive to the chosen cell-size parameter—cell resolutions of 0.05 m and 0.01 m were adopted in this project to achieve high-resolution change detection.

Using the M3C2 plugin in CloudCompare, the output scale is determined by the projection scale (d) and the normal scale (D) parameters, which define the search cylinder used for point-cloud comparison. The normal scale corresponds to the diameter of the spherical neighborhood for normal calculation, and the projection scale corresponds to the diameter of the search cylinder. A

value of 0.207 m for both scales was determined by using the “Guess parameters” function, which automatically computes optimal values, and the preferred orientation was set to the +X axis.

Following the M3C2 process, clustering was performed to isolate the changed segments, and the clustered points were used to extract normal vectors and distance measurements as shown in Figure 27. Subsequently, the clustered points were projected onto one of the point clouds (or along any axis) to calculate volume. Alternatively, to obtain volume directly, the 2.5D volume tool was applied by selecting the two point clouds. To optimize computational efficiency, only the regions near the rockfall segments were trimmed and input into this tool. A volume of 7.4 m³ was obtained, with 97.3 % matching cells and an average of 7.9 neighbors per cell.

Slopes, RAI classifications, and RAI scores were compared to assess the impact of rockfall at the Riegelsville site. As shown in Figure 28, the segments affected by rockfall are indicated by the red-circled area. Originally, the rock surfaces exhibited slopes of approximately 130 degrees; following the rockfall event, the faces were reoriented inward, resulting in steeper inclinations and an expansion of the high-slope area. Consequently, both the RAI classification and RAI score were elevated, as illustrated in Figure 28. For the rockfall segments only, RAI scores were integrated as shown in Figure 29. Based on the failure depth and instability rate table from Dunham et al. (2017) and the RAI score equation (Eq.1), the rockfall segments exhibit an RAI score of 65kJ, and the rockfall segment reaches an impact velocity of 22.32km/h.

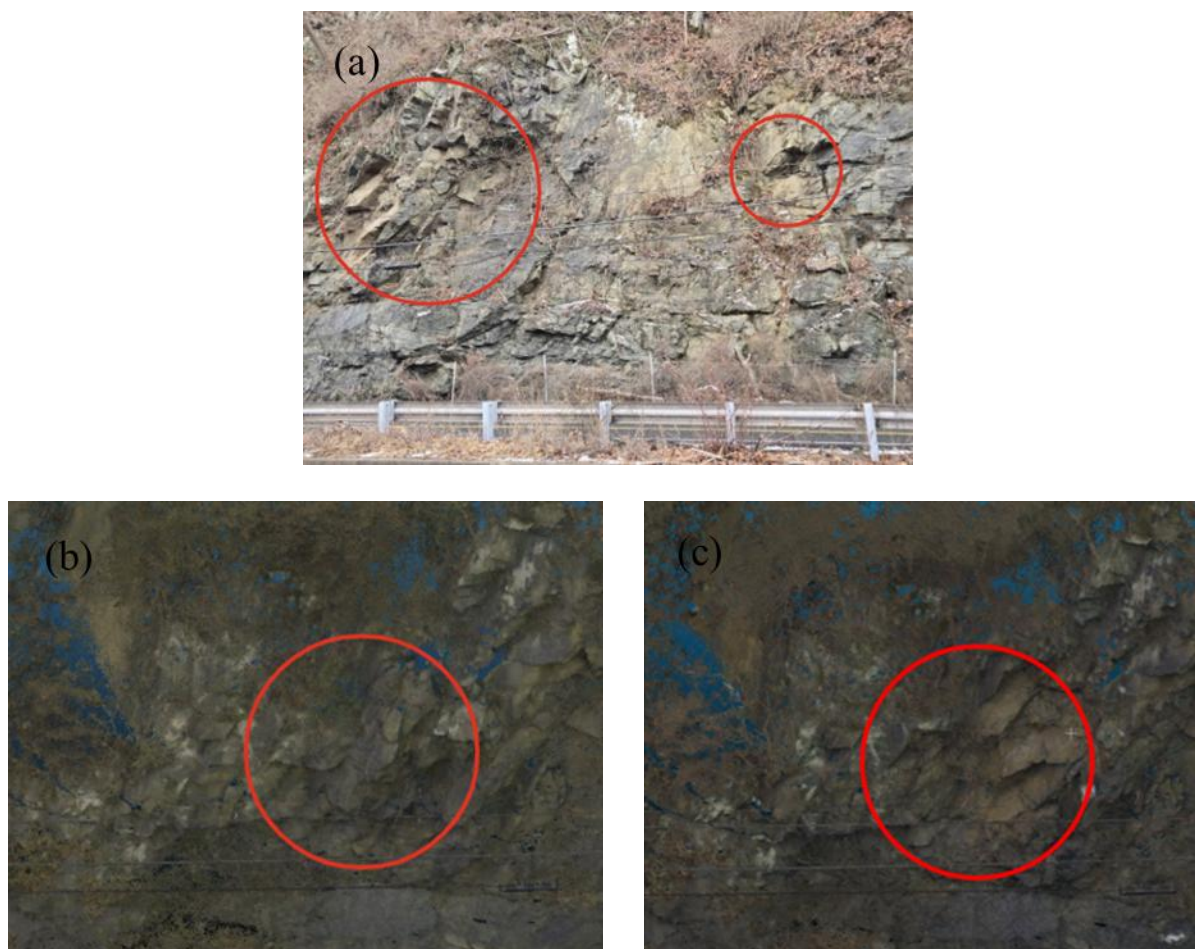


Figure 25. Front view of Riegelsville rock surface (a) Photograph in February 2025; (b) point clouds in November 2024; (c) point clouds in February 2025.

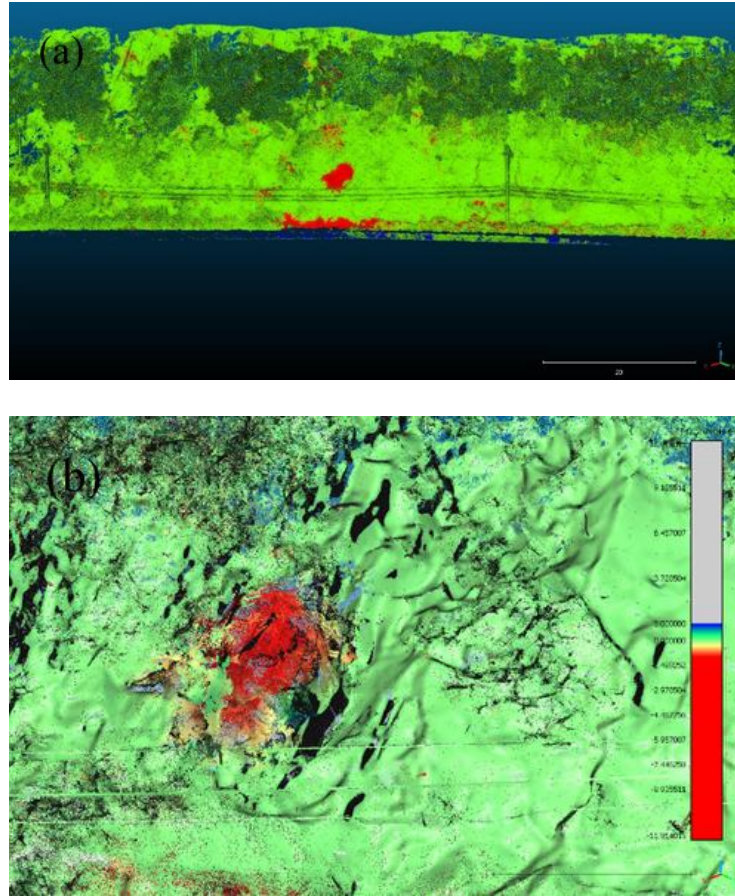


Figure 26. Change detection results obtained using (a) Rambo software and (b) CloudCompare software

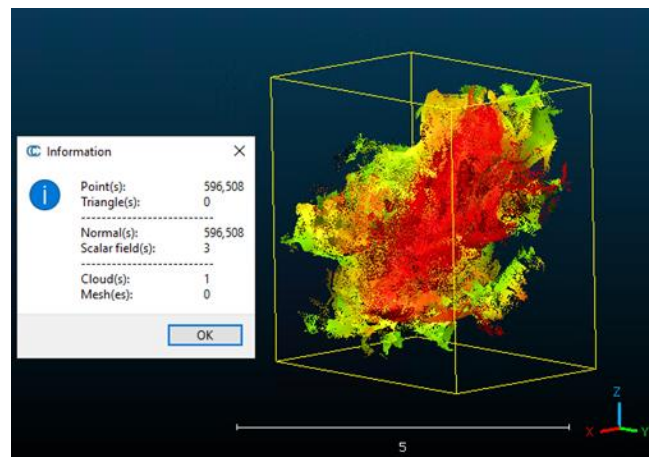
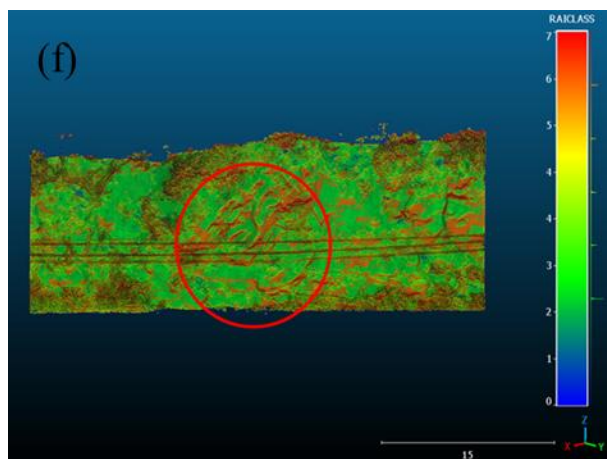
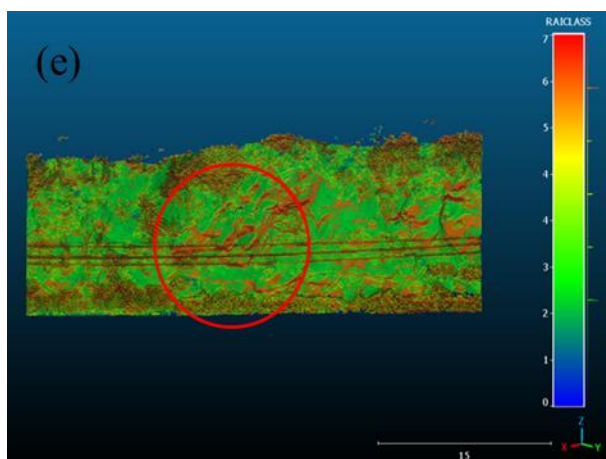
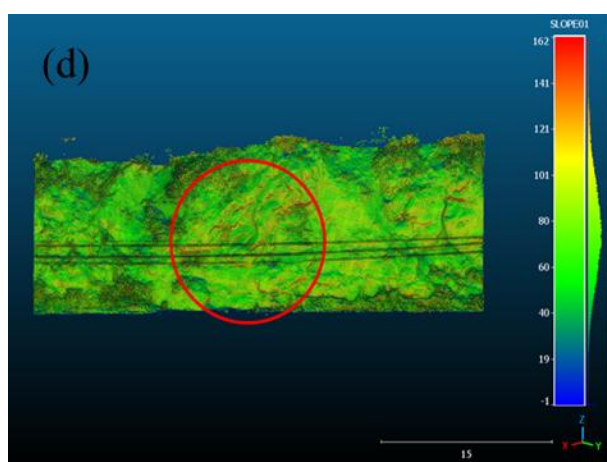
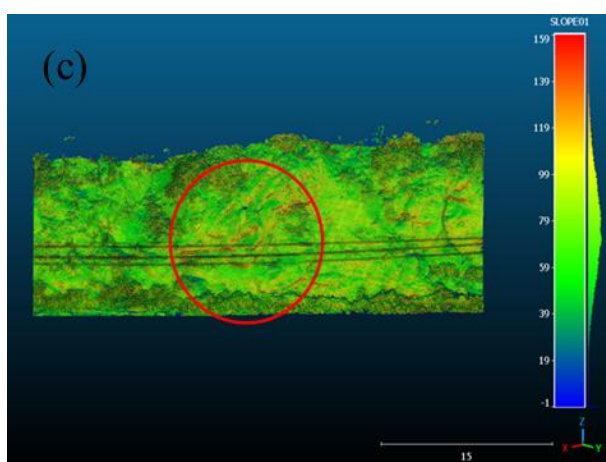
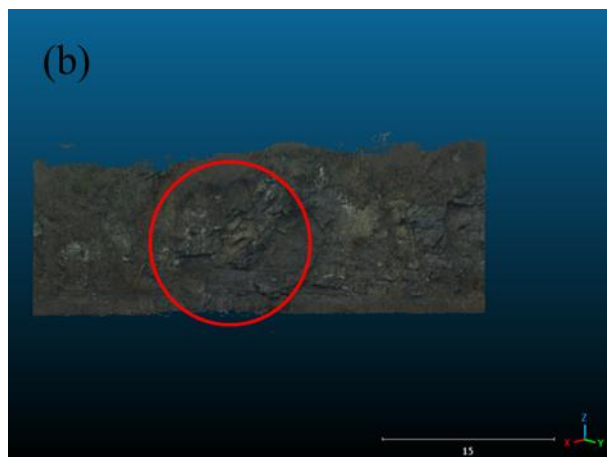
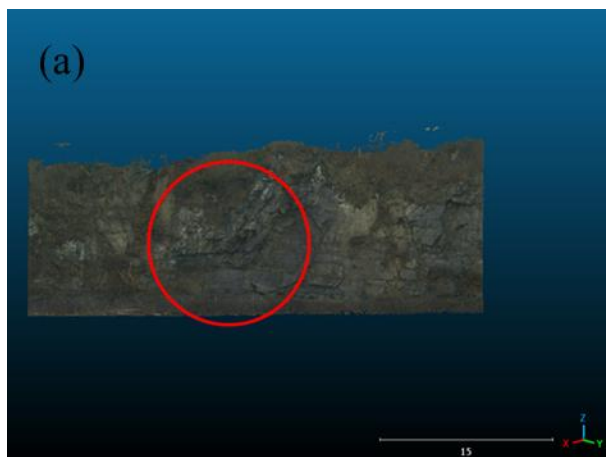


Figure 27. Rockfall segment identification



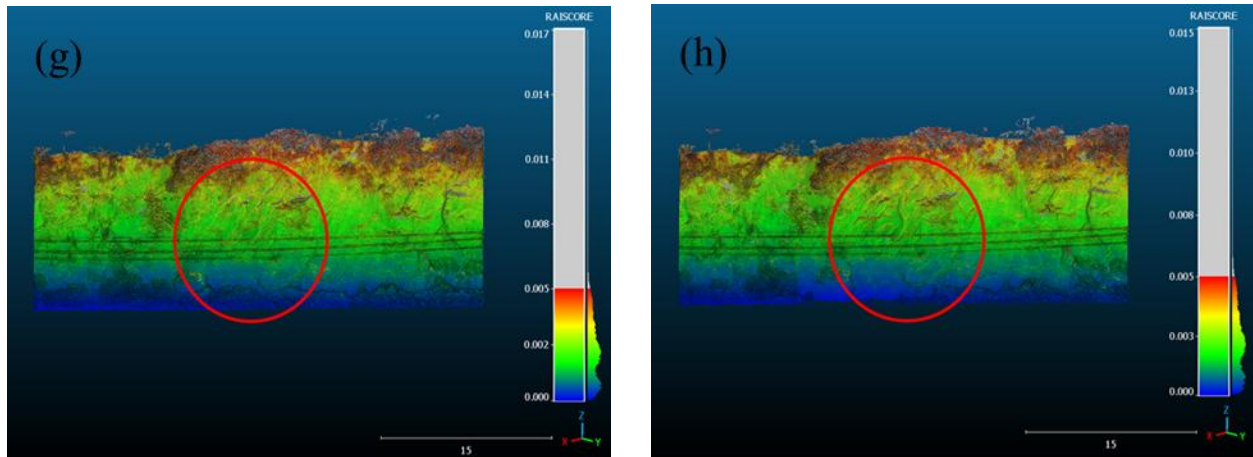


Figure 28. Riegelsville results comparison (a) RGB November; (b) RGB February; (c) Slope November; (d) Slope February; (e) RAI class November; (f) RAI class February; (g) RAI score November; (h) RAI score February.

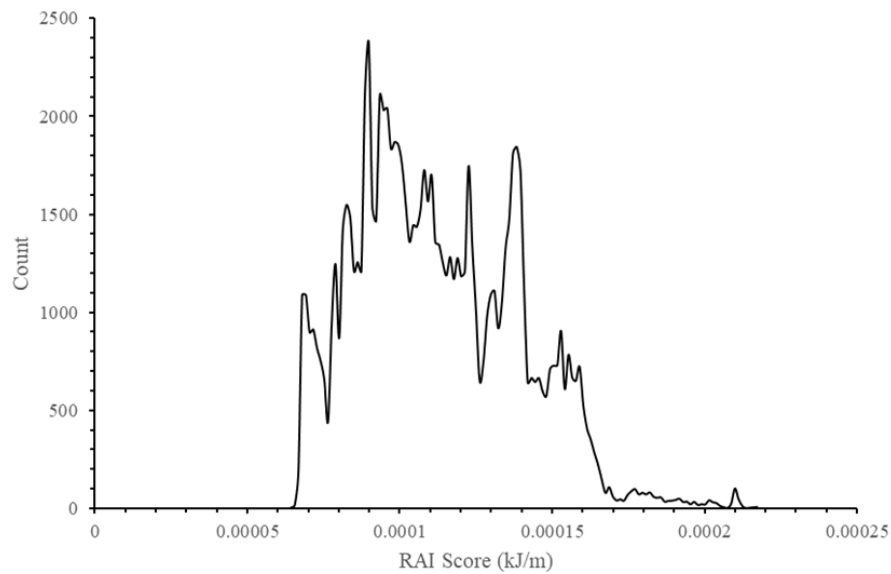


Figure 29. RAI score and number of points for each score of rockfall segments.

3.3.4 April 2025

LiDAR scanning was completed in April 2025 to maintain the regular monitoring interval. As shown in Figure 30, the April point clouds closely match the February dataset, with minimal vegetation obscuration of the rock surfaces. Change detection was conducted using CloudCompare and Rambo software; however, no significant alterations to the rock faces were identified, as illustrated in Figure 31. At the Fleecy Dale Road site, a notable elevation increase on the right side

of the model was observed compared to February—likely resulting from sediment accumulation between the two scan periods.



Figure 30. April 2025 photographs of the study sites: (a) Riegelsville; (b) Kintnersville; (c) Narrows; (d) Fleecy dale road.

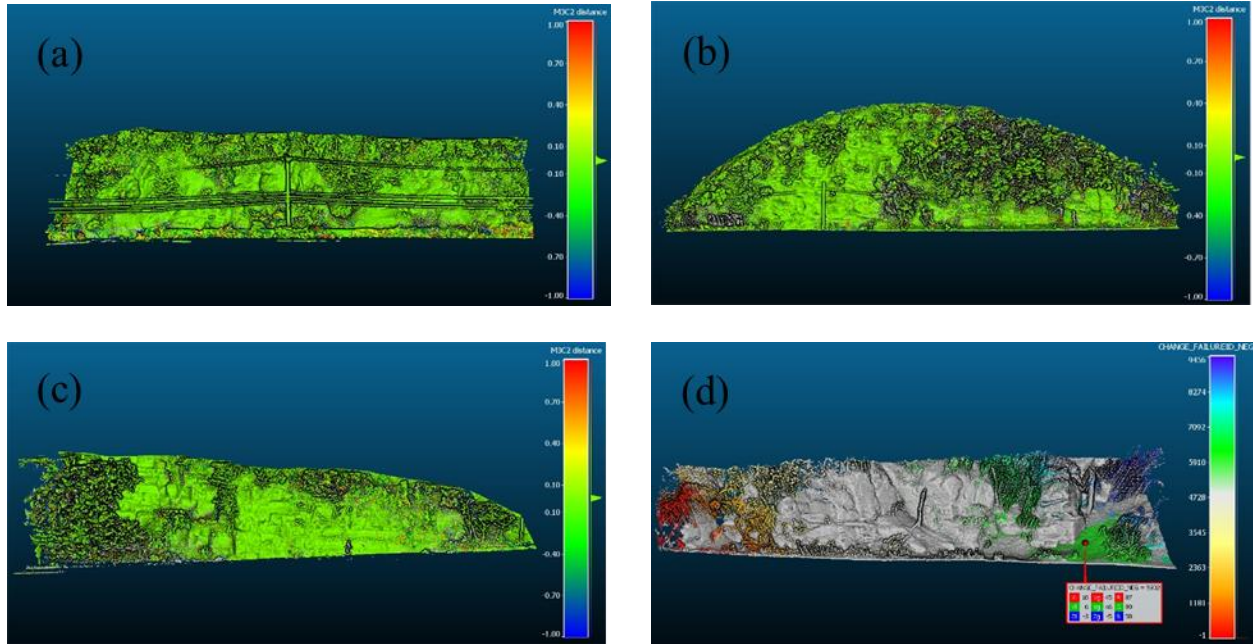


Figure 31. Change detection results comparing February 2025 and April 2025 at the study sites: (a) Riegelsville; (b) Kintnersville; (c) Narrows; (d) Fleecy dale road.

3.3.5 June 2025

The previously described scanning procedure was conducted in June 2025 to assess the effects of vegetation and weather conditions on point-cloud data processing. During the field survey, several issues were encountered due to extreme heat and dense vegetation. The scanner was suddenly shut down by overheating, which caused communication failures among the scans. In addition, dense vegetation, overhead power lines, and surrounding buildings obstructed the GNSS. Nonetheless, these issues did not significantly impair overall point-cloud registration. As shown in Figure 32, which presents photographs of the study sites, rock surfaces are largely obscured by vegetation, affecting analysis results. At the Fleecy Dale Road site, nearly all rock faces are covered, rendering surface scanning particularly challenging.

Figure 33 illustrates the results displayed as point clouds. Although only vegetation points were removed from the dataset, substantial residual vegetation continued to obscure the rock surfaces. To evaluate the performance of the Rambo software, ground-filtering tools were applied (Figure 33b). Partial vegetation removal was achieved, but complete clearance of plant cover from the rock faces was not possible. Furthermore, extensive vegetation cover produced large voids within the point clouds. For RAI classification analysis (Figure 33c), the best-fit rock surface was calculated, and residual vegetation points were inevitably included, complicating the identification of true rock-surface classes.

Change detection was also conducted to assess the function's accuracy (Figure 34). All colored facets represent vegetation growth since April 2025, and the widespread plant cover over the

rockfall has a significant impact on analytical outcomes. Segregating rock surfaces from vegetation within such point clouds remains challenging. Another approach involves applying a filter-by-value tool after change detection to isolate newly grown vegetation points; however, this method creates numerous empty holes that may compromise subsequent analyses due to inconsistent point-cloud density. For example, at the Riegelsville site, subsampled point clouds at 0.01 m resolution (used instead of 0.05 m for enhanced detail) contained approximately 4 million vegetation points and 4.8 million rock-surface points. As a result, nearly half of the points in the trimmed dataset represented vegetation for this scan.

At the Kintnersville site, approximately half of the rock surface was obscured by vegetation (Figure 33). The scanner was positioned in close proximity to the rock face, which restricted data acquisition to limited viewing angles and prevented capture of points hidden within the plant cover. Consequently, the ground-filtering algorithm was unable to remove vegetated sections effectively, resulting in extensive voids in the point cloud. As a result, noise was introduced into the RAI classification, and vegetation features appeared more prominently in the ground filtering and change-detection output.

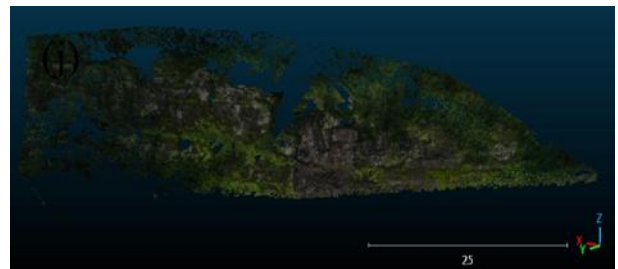
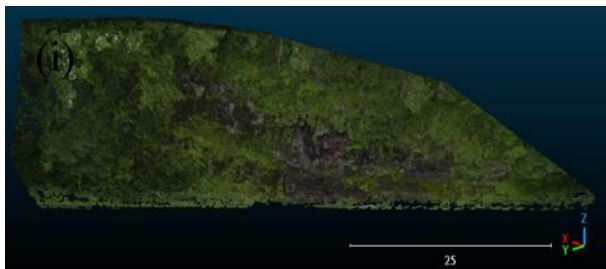
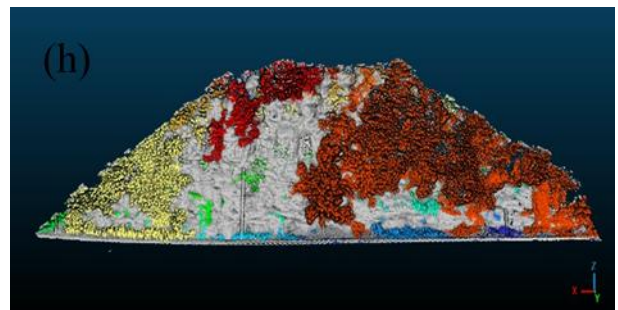
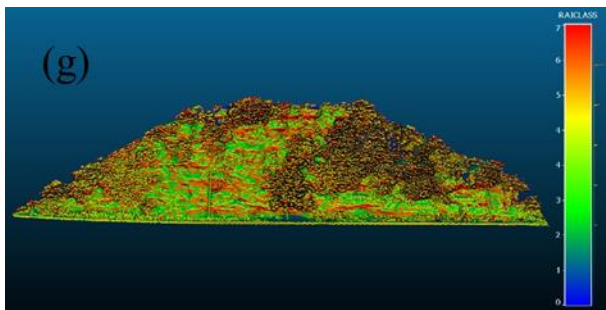
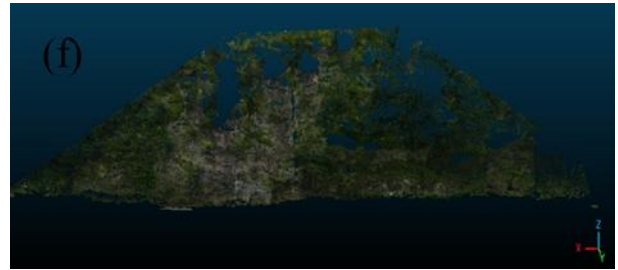
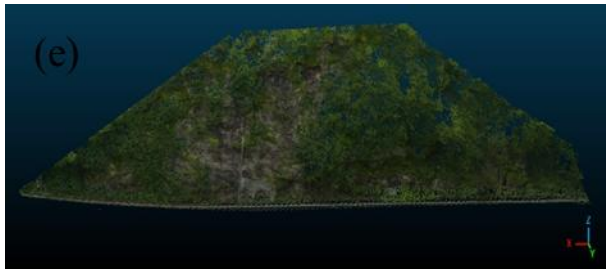
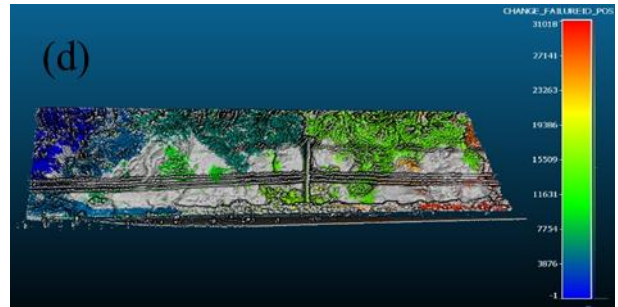
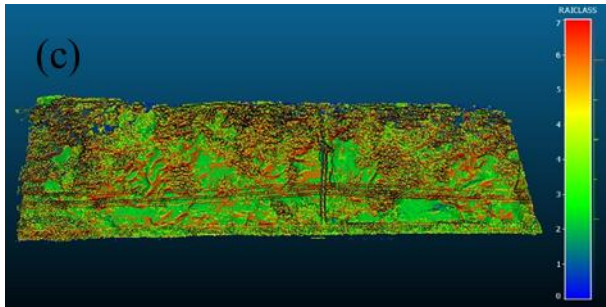
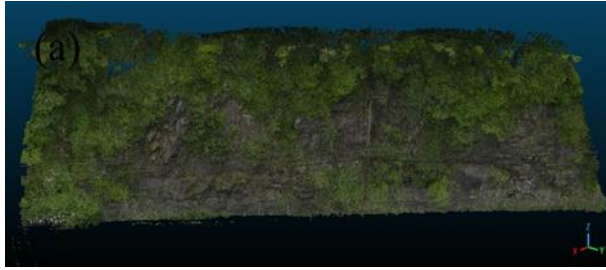
At the Narrows site, extensive vegetation coverage was observed in both the photographs and point-cloud data. The left side of the rock face was completely obscured by plant growth relative to the April survey, and the remainder of the surface was partially covered. The same processing workflow was applied at this location. As with the other sites, partial vegetation removal was achieved using Rambo's ground filtering tool, but complete clearance was not attained. Notably, change detection failed to identify newly grown vegetation adhering to the rock surface, in contrast to the successful detections made at the other locations even with small cell size.

At the Fleecy Dale Road site, vegetation cover was greatest among all study locations. As shown in Figure 33, the entire rock surface was obscured by vegetation. During ground filtering, only minimal separation of rock and vegetation points was achieved, and no continuous rock-surface segments could be delineated.

To assess the negative impact of vegetation cover, change detection was performed on the November 2024 and June 2025 scans at the Riegelsville site. As shown in Figure 34, rock segments affected by rockfall were detected by Rambo software. It reports the volume of the changed segments as 6.79 m³, which represents only minor errors. The M3C2 tool in CloudCompare likewise identified the same rockfall segments.



Figure 32. June 2025 scanning results of photograph at study sites (a) Riegelsville; (b) Kintnersville; (c) Narrows; (d) Fleecy dale road.



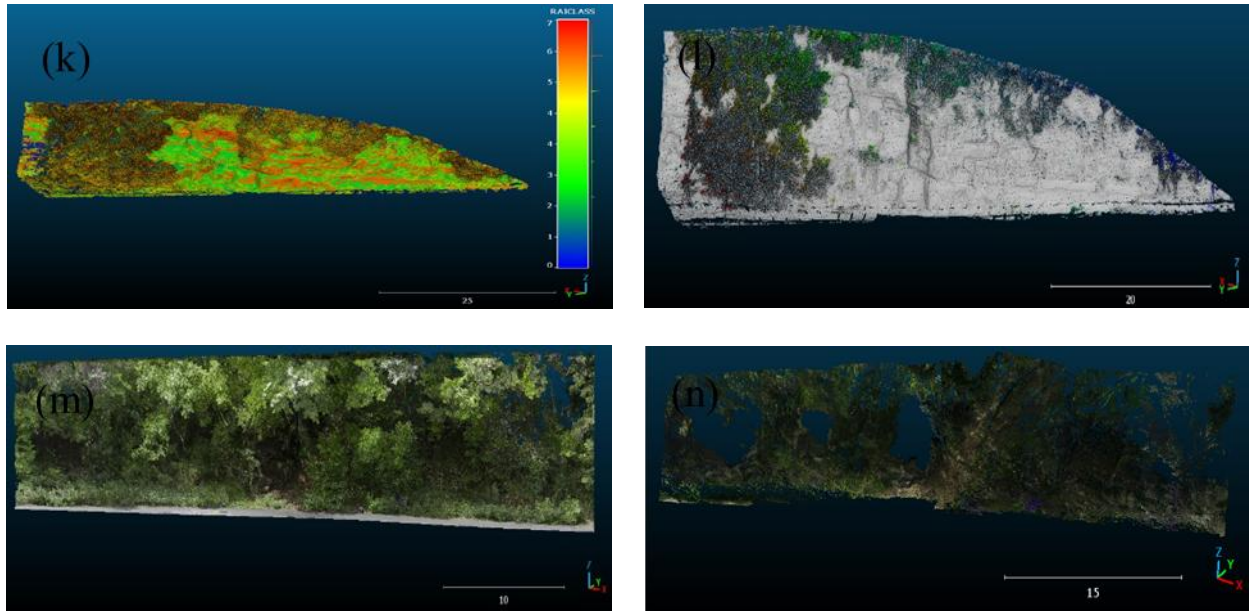


Figure 33. Scanning results from June 2025, for Riegelsville (a-d), Kintnersville (e-h), Narrows (i-l), and Fleecy Dale Road(m-n); (a) point cloud front view; (b) ground filtering; (c) RAI classification; (d) change detection; (e) point cloud front view; (f) ground filtering; (g) RAI classification; (h) change detection; (i) point cloud front view; (j) ground filtering; (k) RAI classification; (l) change detection; for Narrows; (m) point clouds front view; (n) ground filtering.

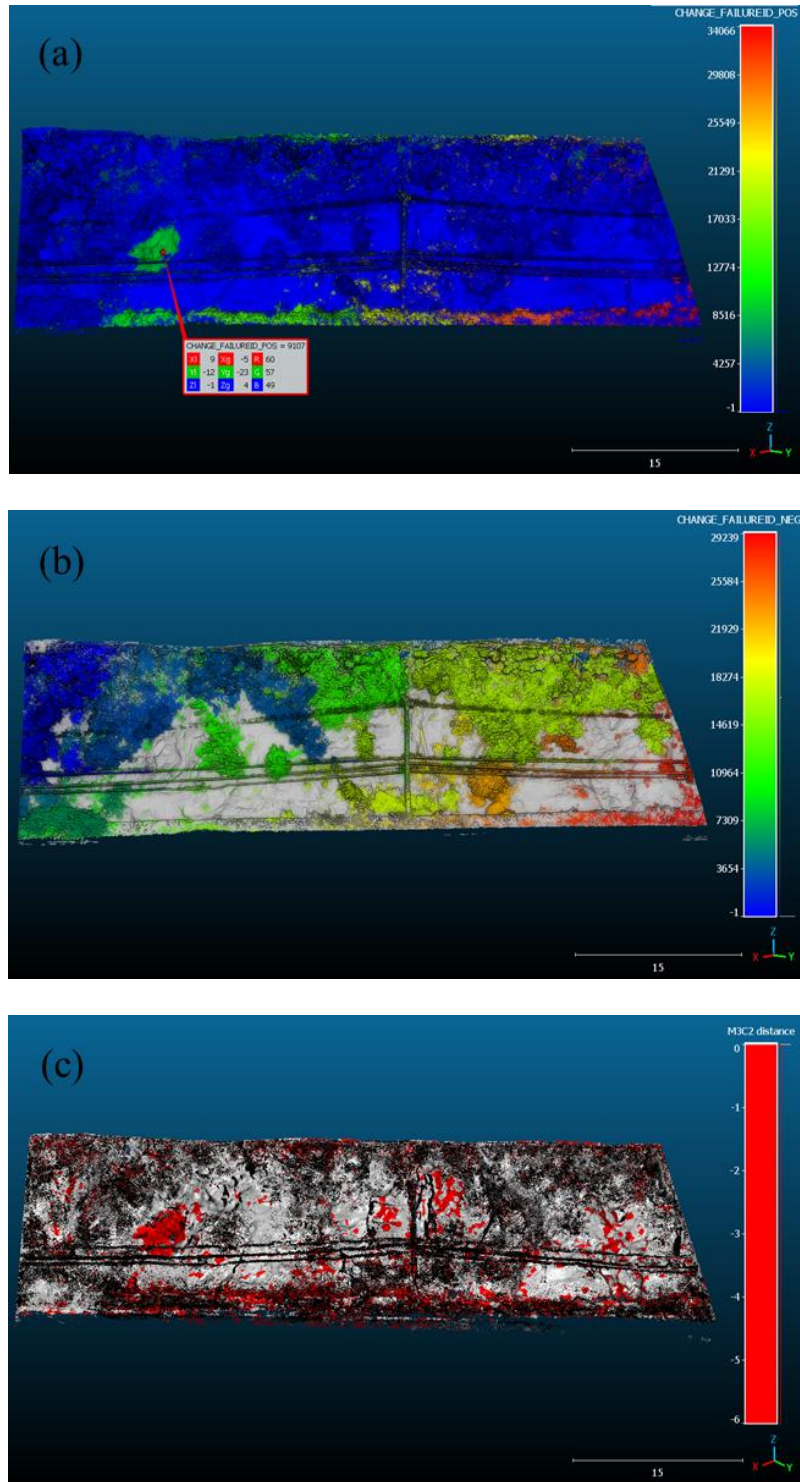


Figure 34. Change detection results at Riegelsville site: (a) rock changes detected by Rambo Software; (b) vegetation changes detected by Rambo software; (c) M3C2 tool result obtained using CloudCompare software.

3.4 Discussion

Multiple LiDAR scans were conducted at rockfall prone sites and analyzed using point clouds generated with CloudCompare and Rambo software. In April 2024, vegetation partially obscured the rock surfaces, interfering with analysis. To address this, the ground filtering function was applied. Although most vegetation was removed by the ground-filtering function, empty holes were created and the surface was smoothed, which may influence subsequent analyses. In Figure 119, the purple points indicate areas where holes were filled automatically. The accuracy and extent of the hole filling vary depending on the chosen window settings. Optimal LiDAR scanning conditions will be achieved when redundant vegetation is absent. However, if scanning and surface analysis must be completed despite vegetation cover, ground filtering and hole filling in Rambo software can still be employed to assess rockfall hazard.

As RAI classification increases, the likelihood of rockfall and the potential for damage are also increased. As shown in Figure 20 at all three sites, high RAI classes were observed for the rock surfaces. Although RAI classification serves as a useful tool for identifying areas with steep slopes and discontinuities—features commonly associated with rockfall—it does not fully capture the underlying causes of rockfall due to complexity of the process. Therefore, even though it provides valuable information, it should not be used as an absolute index for hazard assessment.

Based on field investigations, the risk of rockfall activity was identified in the Riegelsville and Narrows areas, as fractures, steep slopes, and fragmented strata were observed on the rock surfaces. In contrast, the Kintnersville area was depicted as solid and stable in photographs, despite being assigned a high RAI classification.

In November 2024, the vegetation had visibly decreased compared to the April 2024 scan. After applying the ground filtering function, the removal of trees and most vegetation from the rock surface made comparison between datasets easier. One issue to be addressed when conducting change detection is the coordinate alignment between two point clouds. Initially, the point cloud datasets should be checked in CloudCompare to confirm that they occupy the same spatial location. Even if identical coordinates are assigned in Cyclone and both datasets appear co-located in Haz mapper and ArcGIS Pro, misalignments can still be observed in CloudCompare. In such cases, change detection using CloudCompare or Rambo may yield no significant differences. Registration of both completed point clouds—on which change detection will be performed—in Cyclone 360 and Cyclone Core can serve as one of the mitigation methods.

A rockfall, shown in Figure 112, was triggered in Riegelsville in December 2024 and a follow-up scan was performed in February 2025. Based on the change detection between the November 2024 and February 2025 scans, the rockfall segment was identified. Rambo computed the rockfall volume as 6.74 m^3 while CloudCompare computed it as 7.4 m^3 . Although Rambo and CloudCompare employ different methods, both produced consistent and robust results. Change detection in Rambo was performed using the best fit plane setting with 1 cm resolution.

CloudCompare's change detection results were supported by 97.3% matching cells and an average of 7.9 neighbors per cell.

The "Matching cells" metric in the 2.5D volume calculation represents the percentage of grid cells in which the height difference between two point clouds falls within a predefined tolerance, with higher values indicating better correspondence and more accurate volume estimation. The "Average neighbors per cell" metric indicates grid density; values above seven suggest a suitable grid step size and sufficient point coverage for accurate surface representation, whereas lower values may reveal holes or missing data due to an excessively small step size. Therefore, the selection of an appropriate cell size and empty-cell option (either leaving cells empty or integrating them) is critical for obtaining reliable results.

As shown in the Figure 28, the slope and RAI class increased after the rockfall, indicating that the slope became steeper following the event. The steepening slope may contribute to elevated rockfall hazards. The integrated RAI score for this rockfall is 65 kJ and estimated impact velocity under a free fall assumption is 22.32 km/h . Although rockfall typically involves bouncing and rolling rather than pure free falling, this estimate provides useful intuition regarding the magnitude of the rockfall. The RAI score represents kinetic energy in joules, calculated from assumed failure depth and RAI classification of rock segments. Therefore, potential rockfall damage can be evaluated using the RAI score, with higher values indicating greater rockfall magnitude due to steeper slopes and higher kinetic energy. Although the RAI score does not directly indicate the probability of rockfall occurrence, zones with high rockfall potential and associated damage are effectively identified based on kinetic energy characteristics.

In April 2025, a regular monitoring LiDAR scan was conducted. The detected changes were identified as vegetation and no significant changes were observed on the rock surfaces. The June 2025 scan was significantly affected by weather conditions and vegetation. Due to the extreme heat, the scanner shut down unexpectedly, and vegetation, overhead power lines, and thermal inference obstructed the GNSS connection. This resulted in weak signals and reduced connectivity between the rover, base station, and satellites compared with the previous survey. Overlap between setups was also diminished by vegetation shadows, weakening linkage strength and introducing alignment errors. Although these issues did not significantly impair overall point-cloud registration, they did affect subsequent analyses.

At Fleecy Dale Road, most of the rock surfaces were covered by dense vegetation. This vegetation created significant shadowing and prevented reliable detection of the underlying rock surfaces, complicating the identification of RAI classes. Although multi-angle LiDAR scanning can sometimes capture portions of the rock surface beneath vegetation, the limited scanning geometry at Fleecy Dale Road and Kintnersville restricted this capability. As a result, the ground-filtering process produced large voids where vegetation could not be distinguished from the rock surface.

In contrast, the Riegelsville site had approximately 15 m of stand-off distance and sufficient open space to conduct scans from multiple angles. This improved geometry allowed CloudCompare and

Rambo to better separate vegetation from rock surfaces. The Narrows site also offered adequate space and scanning angles; however, the vegetation was extensive enough that the software still struggled to reliably differentiate vegetation from the underlying rock, leading to incomplete surface identification. Consequently, the ground-filtering algorithm was unable to remove vegetated sections effectively, resulting in extensive voids in the point cloud. As a result, noise was introduced into the RAI classification, and vegetation features appeared more prominently in the ground filtering and change-detection output.

This limited discrimination is attributed to both the dense canopy and the scanner's close proximity to the rock face, which constrained capture of subsurface points at varying angles. Although rock-surface points beneath the vegetation can generally be classified and removed using CloudCompare or Rambo software when captured, the excessive midsummer growth and limitation of scan during the June 2025 survey impeded effective differentiation of vegetation and bedrock, thus reducing analytical accuracy.

3.5 Conclusions

LiDAR-based rockfall hazard analysis was performed at Riegelsville, Kintnersville, Narrows, and Fleecy Dale Road sites using Rambo and CloudCompare software. Multiple scans were acquired to generate high-resolution point clouds. The scan datasets were registered in Cyclone 360 and Cyclone Core, and the resulting point clouds were used for subsequent analyses.

As part of the morphological assessment, slope angles, rockfall activity index (RAI) classifications, and RAI scores were evaluated at all sites. Steep rock faces were identified at every location and classified as overhangs according to the RAI classification. Certain rock segments exhibited elevated RAI scores, indicating steep surfaces with high potential kinetic energy.

A rockfall event occurred at the Riegelsville site in December 2024. This segment originally displayed high RAI values, and the rockfall increased the extent of the area characterized by elevated RAI. Although steep slopes were present elsewhere, only the Riegelsville location experienced failure. Based on field investigations, the risk of rockfall activity was identified in the Riegelsville and Narrows areas, as fractures, steep slopes, and fragmented strata were observed on the rock surfaces. In contrast, the Kintnersville area was depicted as solid and stable in photographs, despite being assigned a high RAI classification.

Change detection analyses were conducted for the Riegelsville site before and after December 2024 rockfall using both Rambo Software and CloudCompare. Volume estimates were 6.7 m³ by Rambo and 7.4 m³ by CloudCompare. In Rambo, the adjustable parameters of change detection tool govern calculation accuracy. In CloudCompare, the M3C2 distance and clustering tools define the rockfall cluster, and the 2.5D volume calculation computes the volumetric difference between point clouds. The RAI score for rockfall segments is 65 *kJ* and estimated impact velocity under a free fall assumption is 22.32 *km/h*. Although rockfall typically involves bouncing and rolling rather than pure free falling, this estimate provides useful insights into rockfall magnitude.

To assess the influence of vegetation, scans were repeated in June 2025, revealing that dense foliage introduced noise and obscured rock surfaces. At Riegelsville and Narrows, scans from multiple angles and distances captured sufficient sub-canopy points to permit reliable morphological analysis. In contrast, noise levels at Kintnersville and Fleecy Dale Road impeded surface estimation. A comparison between November 2024 and June 2025 datasets showed that Rambo could still estimate rockfall volumes at Riegelsville—owing to partial canopy penetration—whereas CloudCompare was unable to compute volumes due to empty cells and vegetation interference.

In conclusion, high-resolution point clouds enable detailed quantification of rock surface morphology, which strongly influences rockfall hazard assessments. Therefore, they provided essential input for evaluating overall hazard potential.

4. Modeling Framework

In rockfall risk assessments, weather conditions are recognized as a critical factor (Pratt et al. 2019). Moisture within rock pores and cracks generates internal pressure through ice crystallization, a process that depends on rock type characteristics and freeze-thaw cycles (Deprez et al. 2020). Consequently, accelerated hazards are induced by recurrent freeze-thaw events and precipitation. Surface weathering and erosion of rock faces are exacerbated by heavy rainfall, thereby increasing the vulnerability of rock slopes (Birien and Gauthier 2023). Additionally, snowmelt also plays a pivotal role in rockfall initiation by enhancing freeze-thaw cycling and introducing additional moisture into the rock mass (Mourey et al. 2022). Accordingly, areas with frequent rockfall occurrences are observed to experience higher event rates during the spring season. Therefore, investigating weather data patterns can provide valuable clues for predicting rockfall frequency and associated hazards. Numerous studies have examined the relationship between weather conditions and rockfall occurrence.

However, determining the timing of rockfall events remains challenging because of the complex nature of rockfall processes and the spatial variability of weather conditions. Previous research has considered various weather-related factors, such as the number of freeze-thaw cycles, precipitation events, and specific temperature thresholds. In this project, multiple weather factors are analyzed to explain rockfall occurrences in Pennsylvania using machine learning techniques. Recent studies have increasingly attempted to predict rockfall risk using ML techniques. ML enables systems to learn from data, identify patterns, and make predictions or decisions (Wen et al. 2022). Among the advances in ML, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) have been widely adopted as effective classifiers for rockfall risk mapping (Li et al. 2022).

Tree-based algorithms make decisions by mapping out different choices and possible outcomes in a tree-like structure, as shown in the Figure 35. The process begins at the root node, where a question is asked. Branches represent the flow of decisions, and leaf nodes are the endpoints where final predictions or classifications are made. Because this structure resembles a tree, the model is called a decision tree. RF and XGBoost differ fundamentally in how they build predictive models. RF employs a bagging strategy in which decision trees are trained independently on bootstrap samples of the training data, and the ensemble prediction is obtained by averaging or voting across trees (Dietterich 2000). By contrast, XGBoost implements a boosting strategy in which models are trained sequentially; each new model concentrates on correcting the errors of the ensemble accumulated thus far, producing a strong learner through additive optimization (Li et al. 2022).

Because RF and XGBoost employ different learning strategies, each has distinct strengths and limitations, and many researchers have therefore compared both methods for rockfall probability mapping. However, rockfall events are rare, which makes it challenging to create risk maps from limited data. Therefore, this study focuses on estimating the probability of rockfall in Pennsylvania using ML techniques, based on data of past rockfall events that have caused infrastructure damage

(e.g., roads) and posed threats to human safety in order to provide insights into historical trends, support early warning of rockfall hazards, and prioritize infrastructure asset management and maintenance.

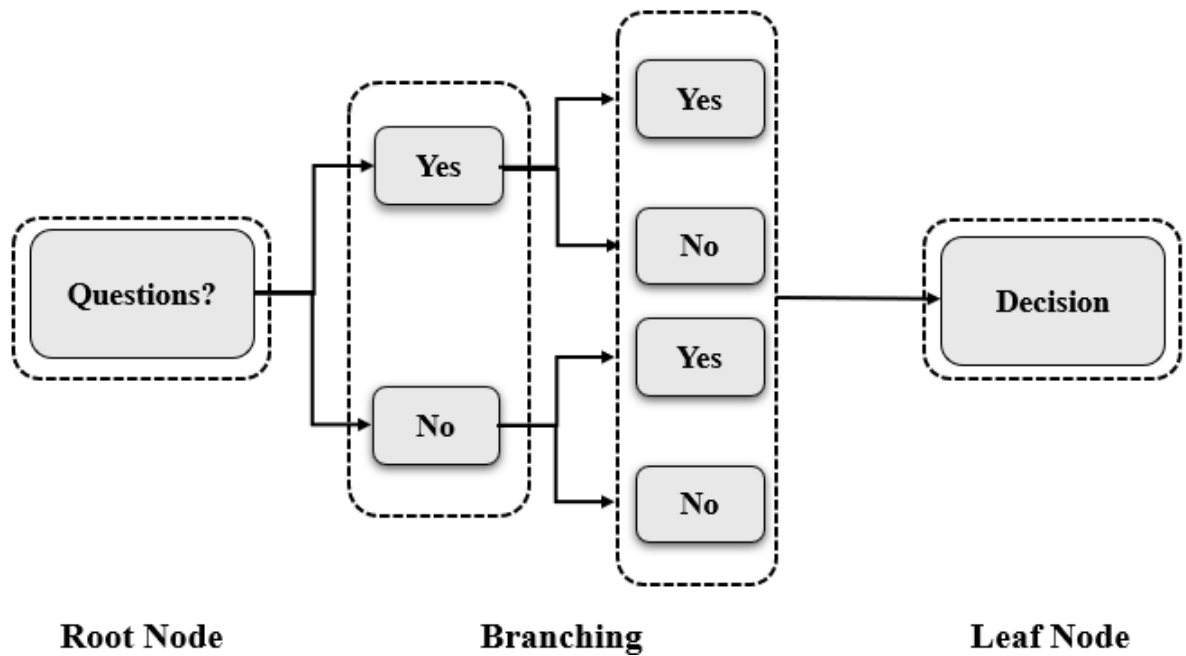


Figure 35. Example structure of tree-based algorithms.

4.1 Data Description

Pennsylvania has experienced numerous rockfall due to its climatic and morphological characteristics. In this study, only rockfall events that have caused damage or have been officially reported by institutions are considered. Rockfall inventory data were obtained from the Cooperative Open Online Landslide Repository (Belair et al. 2022) and from Pennsylvania Department of Transportation (PennDOT), where the records were classified as transportation project points. These providers presented landslide inventories, from which only rockfall events were filtered and utilized in this study.

Daily weather data, provided by the PRISM Climate Group, were organized seasonally from 2010 to 2024 and the parameters are calculated. The input variables from processed weather data include number of days of precipitation (N of ppt), number of days of freeze-thaw cycles (N of FT), number of days of freeze-thaw with precipitation (N of FT with ppt), number of days of temperature which is identified to effectively cause crack (N of cracking), average seasonal precipitation volume (average ppt vol), total precipitation volume (total ppt vol), maximum precipitation volume (max ppt vol), number of days of precipitation for week before (N of ppt season before), and number of days of freeze-thaw for season before (N of FT season before).

Days with precipitation exceeding 0 mm were counted as precipitation events (N of ppt). Freeze-thaw events (N of FT) were defined as days when the minimum temperature fell below 0°C and the maximum temperature rose above 0°C. FT events accompanied by precipitation (N of FT with ppt) were recorded when precipitation occurred on the same day as an FT cycle or on the preceding day, accounting for residual moisture in soil, vegetation, and rock (Kim et al. 2023). Cracking days (N of cracking) were identified when temperatures ranged between -8 °C and -3 °C, the interval in which rock cracks typically initiate (Deprez et al. 2020). Average, total, and maximum precipitation volumes were calculated over each study interval.

4.2 Methodology

4.2.1 Method

The overview of the rockfall hazard assessment is shown in Figure 37. Only weather parameters are considered as input variables (X) and rockfall occurrence is considered as target variables (Y) in machine learning techniques. XGBoost and RF are implemented using Python codes through Google Colab tool which provides the online coding service. The landslide data is organized using the ArcGIS Pro software and after filtering the rockfall, it is sorted by county and date to correspond to weather conditions.

4.2.2 Organize Weather Parameters

Weather parameters were calculated seasonally from March 2010 through November 2024 using daily weather conditions. The rockfall events that cause damage are recorded as data along with corresponding weather conditions from these open data sources. For example, as shown in Table 5, Allegheny County experienced rockfall events between 2010-03-01 and 2010-06-01 which

correspond to the spring season. Therefore, the rockfall indicator is recorded as 1. If a county did not experience rockfall events during the specified time periods, it was recorded as 0. However, because the method uses a classification model that requires binary input (0 or 1), multiple rockfalls occurring within the same time period were recorded as 1, rather than 5 or 6. Weather parameters are calculated over one seasonal time period. Thirty-six seasonal rockfall events were observed across Pennsylvania counties during this period (i.e., March 2010 to November 2024).

Table 5. Example of input data

County	Date Begin	Date End	Season	Rockfall
Allegheny	2010-03-01	2010-06-01	Spring	1
Allegheny	2010-06-01	2010-09-01	Summer	0
Allegheny	2010-09-01	2010-12-01	Fall	1
Allegheny	2010-12-01	2011-03-01	Winter	0

In this study, a machine learning classifier was used that requires binary input data. Consequently, even if a county experienced multiple rockfall events during the specified time periods, it was still assigned a value of 1, which creates a highly imbalanced dataset. Furthermore, western Pennsylvania has reported more landslide and rockfall than other regions due to its morphological characteristics. After organizing the data instances, the distribution of positive instances for corresponding counties and seasons are represented in Figure 36. As a result, model performance may be diminished and cause overfitting because only weather-related parameters are considered in this study. Due to limitations in data collection, a highly imbalanced dataset was compiled, and the data distribution remains uneven. This dataset does not capture all rockfall occurrences in Pennsylvania that caused damage to humans between 2010 and 2024, indicating that some rockfall events were not reported in the database.

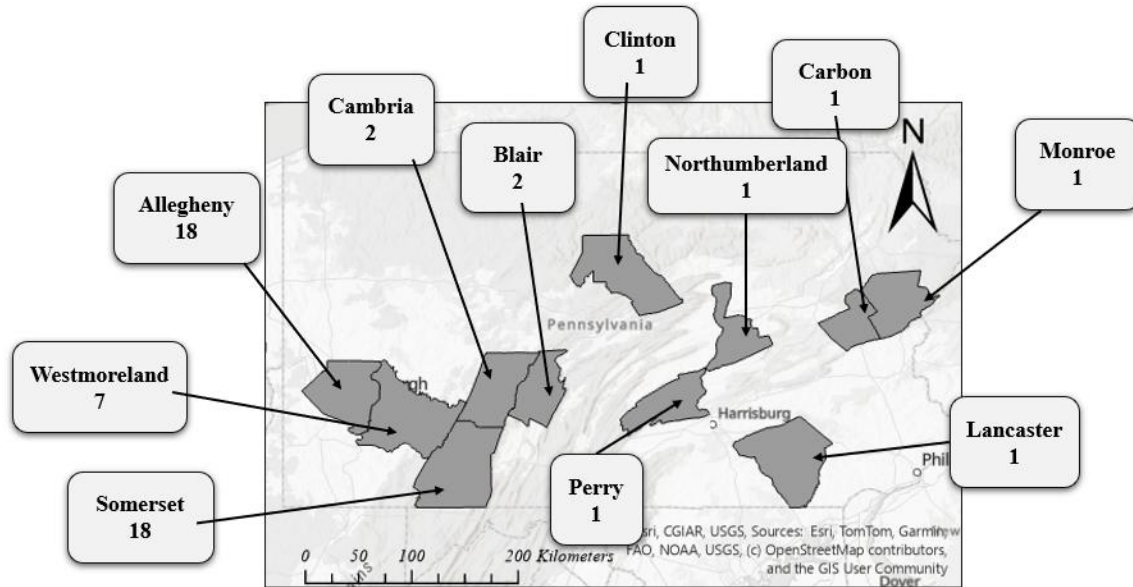


Figure 36. Distribution of positive instances across Pennsylvania

4.2.3 Process Data using RF and XGBoost

Based on rockfall events and the weather parameters, RF and XGBoost classifiers were employed to predict rockfall probability using Python. RF and XGBoost are complex algorithms whose behavior is influenced by hyperparameters. By optimizing these hyperparameters, model performance for predicting rockfall probability can be improved. For XGBoost, the hyperparameter optimized in this study includes the learning rate, maximum depth, number of estimators, column subsampling ratio, and row subsampling ratio. For the RF model, the tuned hyperparameters include the splitting criterion, maximum tree depth, minimum number of samples required to split an internal node, minimum number of subsamples required at a leaf node, number of features considered at each split, class weighting scheme, and number of trees. The dataset is highly imbalanced, containing 3917 negative samples and 36 positive samples which are rockfall occurrences. Thus, there are 36 seasons with rockfalls and 3917 non-rockfall seasons across the counties during 2010 to 2024 period. To mitigate this imbalance, class weights were applied and stratified k-fold cross-validation was used. Cross-validation splits the data into multiple subsets, trains the model on folds and validates it on the held-out folds, and then averages the results to produce a more robust performance estimate. Stratified k-fold preserves class proportions in each fold, which is important when the positive class is rare and helps produce consistent results across runs. As shown in Figure 38, the dataset is split into 60% training, 20% validation, and 20% testing. Therefore, a total of 36 positive samples were split into 22 for training, 7 for validation, and 7 for testing, while 3,917 negative samples were split into 2,351 for training, 783 for validation, and 783 for testing. The model is first trained on the training set, then evaluated and fine-tuned using the validation set. Finally, the model's performance is assessed on the untouched test set. This helps

prevent data leakage, ensures consistent results, and reduces the impact of dataset imbalance. The model code can be accessed in Python file.

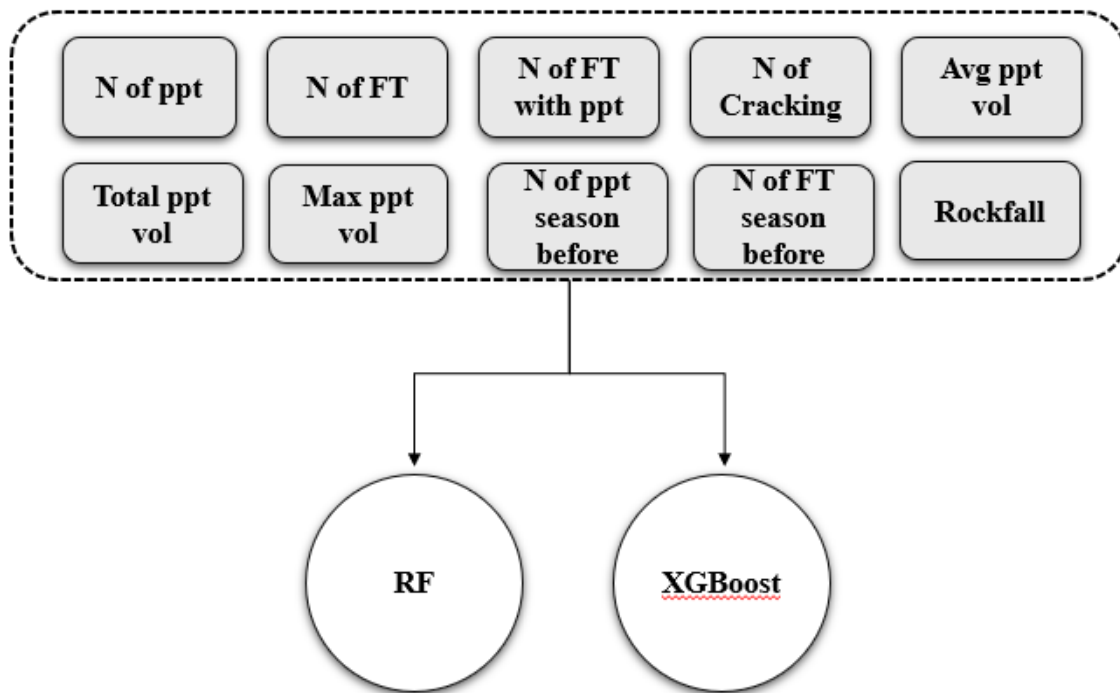


Figure 37. Overview of the rockfall hazard assessment using Random Forest and XGBoost.

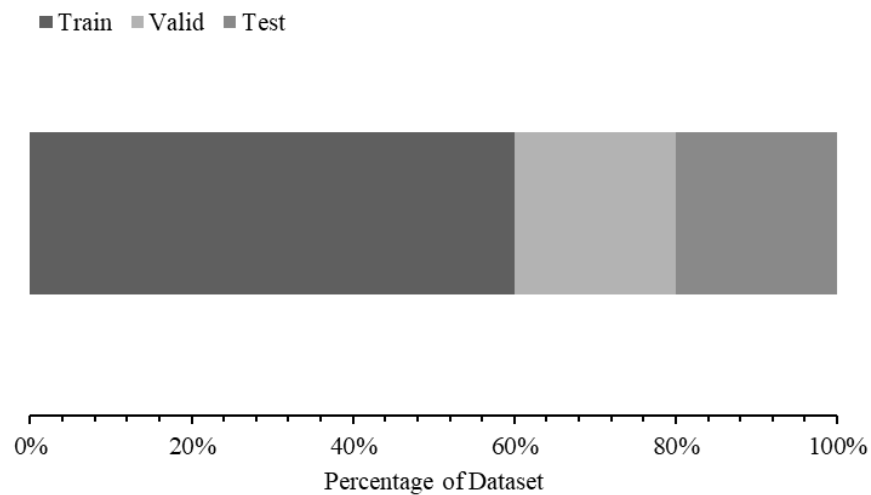


Figure 38. Principle of cross validation.

These enhanced machine-learning models were constructed to estimate the probability of rockfall from meteorological input parameters and recorded rockfall events using Python. Because rockfall occurrence is binary, classifier function is formulated. XGBoost and RF employ different strategies

to aggregate results from individual trees through boosting and bagging procedures, respectively, however, both models estimate probabilities using a logistic function, as implemented through the “predict_proba” method in scikit-learn. The input features, consisting of weather parameters in this study, are represented as x_i , and rockfall occurrence (Y) is defined as a binary variable with values of 0 or 1. Accordingly, a multivariate linear function z is defined as:

$$z = \left(\sum_{i=1}^n \omega_i x_i \right) + b \quad (3)$$

Where ω_i denotes the weights or coefficients with i th input feature and b represents the bias term. Therefore,

$$z = \omega X + b \quad (4)$$

The probability of rockfall occurrence is then obtained by applying the sigmoid function and the probability of logistic function is finalized as:

$$p(x) = \frac{1}{1 + e^{-\omega X + b}} \quad (5)$$

Through this procedure, XGBoost and RF derived rockfall probabilities for the period from 2010 to 2024.

4.2.4 Create Rockfall Risk Map

The machine learning framework produced seasonal probability estimates of rockfall occurrence for each county in Pennsylvania. To visualize these results, ArcGIS Pro software was employed. County boundary polygons were obtained from the USGS open data repository (Belair et al. 2022). Between March 1, 2010, and December 1, 2024, each county was represented by 59 seasonal datasets. Consequently, the county boundary polygons were duplicated 59 times, with each copy assigned a distinct identifier. These polygons were subsequently consolidated using the Merge tool, resulting in a merged dataset containing 59 records per county.

To integrate weather variables and calculated rockfall probabilities, the Join function was applied. The attribute table of the merged county boundaries was first sorted by county name, and the OBJECTID field was duplicated into the rockfall probability dataset prepared in Microsoft Excel. This probability dataset was then imported into ArcGIS Pro, and this operation successfully linked the rockfall probability table to the merged polygon dataset.

For temporal visualization, symbology was configured using Graduated Colors, with rockfall probability specified as the display field. The temporal filter was enabled by selecting the option to filter layer content based on attribute values, thereby allowing visibility to be controlled through the time slider. This configuration enabled dynamic representation of rockfall risk across counties, with probabilities displayed according to the selected temporal interval.

4.2.5 Further Methods to Mitigate Data Imbalance

Due to limitations in rockfall event data collection, this study utilizes an imbalanced dataset. To mitigate this imbalance and prevent data leakage, class weighting and k-fold cross-validation were

applied. However, because the dataset remains highly imbalanced, additional mitigation strategies were explored to evaluate whether they can further improve model performance. K-means clustering and SMOTE (Synthetic Minority Over-sampling Technique) are widely adopted to mitigate imbalance datasets (Zoumpekias et al. 2021).

The first method applied was K-means clustering. Clustering techniques group similar data instances into clusters based on their characteristics without using labeled data (Yen and Lee 2009). The algorithm begins by randomly selecting k initial centroids, assigning each point to the nearest centroid, and iteratively recalculating the centroid of each cluster by averaging the points within it until the clusters stabilize. The K-means++ algorithm is an improved version of K-means. Instead of selecting all initial centroids randomly, it selects the first centroid at random and then chooses subsequent centroids from the remaining data points with probability proportional to the squared distance from the nearest existing centroid.

The second method applied was SMOTE. SMOTE is an oversampling technique that increases the minority class (Chawla et al. 2002). It selects minority class samples, identifies their nearest neighbors, and generates synthetic instances between them. While SMOTE can improve model performance and mitigate class imbalance, it may also amplify noise and increase the risk of overfitting.

Clustering and SMOTE methods were applied only to the training dataset to ensure that the split datasets were not processed with different clustering structures or data standards. Therefore, K-means, K-means++, and SMOTE combined with K-means++ were applied in this study to evaluate whether these methods can further improve model performance.

4.3 Results

Hyperparameter tuning was implemented for each model. For XGBoost, 1,800 combinations were tested to identify the best parameters. The optimal XGBoost hyperparameter values were identified as follows: learning rate of 0.02, maximum tree depth of 3, number of estimators of 1,000, column subsampling ratio of 0.25, and row subsampling ratio of 0.5. Model tuning was performed using Stratified K-fold cross-validation with four folds ($K = 4$). For the Random Forest model, a total of 25,200 hyperparameter combinations were evaluated using RandomizedSearchCV with 200 iterations and Stratified K-fold cross-validation ($K = 4$). The selected hyperparameters included number of estimators of 50, a maximum tree depth of 12, a minimum of 15 samples required to split an internal node, a minimum of 1 sample per leaf node, a feature subsampling ratio of 0.7, the entropy-based splitting criterion, and balanced class weights.

To interpret the model performance, two key metrics are evaluated: the Area Under the ROC Curve (AUC) and Average Precision (AP). AP summarizes the precision–recall curve as the weighted mean of precision achieved at each threshold, where the increase in recall from the previous threshold is used as the weighting factor. In this study, AP was computed using the `average_precision_score` function in scikit-learn:

$$AP = \sum_n (R_n - R_{n-1})P_n \quad (6)$$

The area under the receiver operating characteristic curve (ROC AUC) quantifies the model's discriminative ability based on prediction scores and was calculated using the “roc_auc_score” function in scikit-learn. As shown in Table 6, the AUC for XGBoost is 0.68 and the AUC for RF is 0.65. The AP for XGBoost is 0.17 and the AP for RF is 0.16. The total instances were randomly split into 60% training, 20% validation, and 20% test datasets, as shown in Figure 38. The final results were obtained from the tuned model evaluated on the test dataset, which includes 783 negative samples out of 3,917 negative samples and 7 positive samples out of 36 positive samples. For more details about the results, confusion matrixes are shown in Figure 39 and 40. The confusion matrix is a 2x2 array that compares predicted values with actual values. In the case of XGBoost, the model predicted 11 positive rockfall cases, but only 1 was an actual rockfall event. This means that there were 10 false positives and 1 true positive. False positive means that the model predicted a rockfall to occur, but no rockfall did occur. Additionally, the model incorrectly predicted 6 actual rockfall events as negative which is no rockfall and resulted in 6 false negatives. The precision is calculated as true positive divided by sum of true positive and false positive, the recall is calculated as true positive divided by sum of false negative and true positive. For the Random Forest results, the model predicted 428 false positives and 6 true positives, missing 1 actual rockfall which is false negative. Although it produced more false alarms, it successfully captured more rockfall events. As a result, Random Forest has lower precision than XGBoost due to the high number of false positives, but it has higher recall because it identified more true positives.

Table 6. AUC and AP results.

	Results
Total instances	3953
Seasonal County Rockfall	36
XGBoost_AUC	0.68
XGBoost_AP	0.177
RF_AUC	0.65
RF_AP	0.16

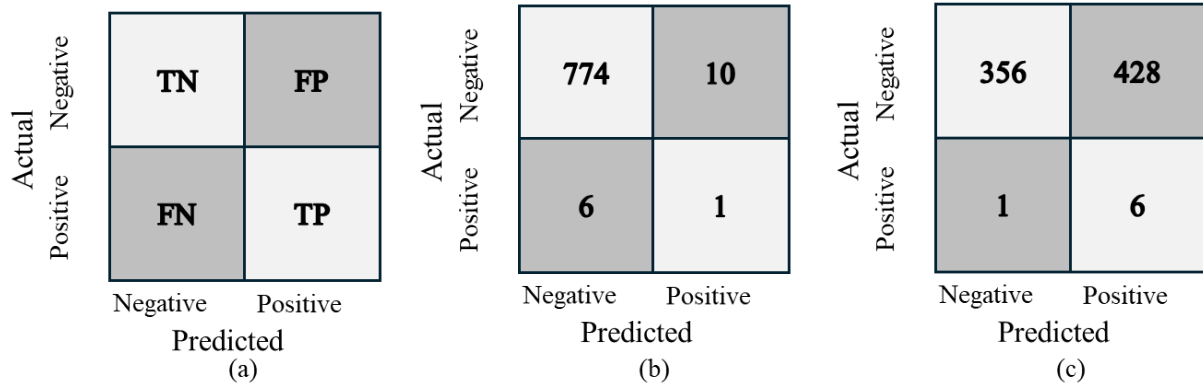


Figure 39. (a) Basic form of confusion matrix; (b) XGBoost confusion matrix result; (c) Random Forest confusion matrix result.

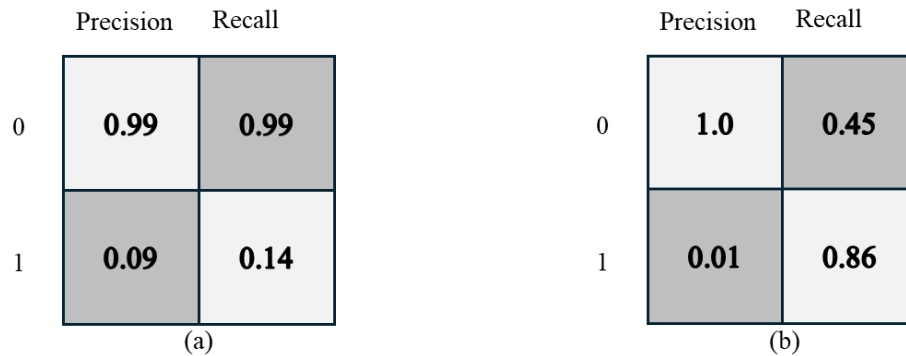


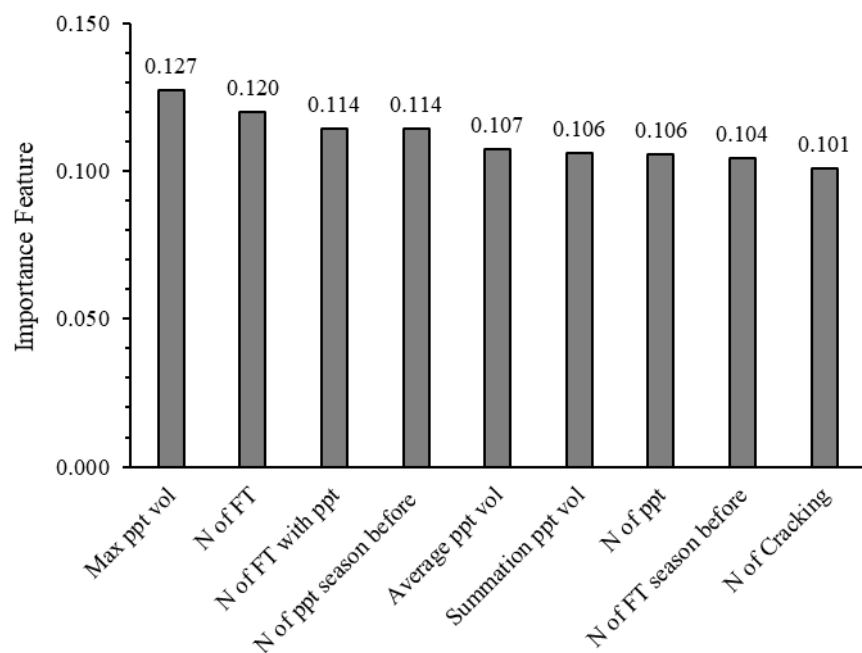
Figure 40. Precision-Recall results: (a) XGBoost; (b) Random Forest.

Importance feature refers to the relative significance of each variable to the model's predictions. As shown in Figure 41, for the XGBoost model, the most important variable is maximum precipitation volume, followed by the number of freeze-thaw events, number of freeze-thaw events with precipitation and so on. For the Random Forest model, maximum precipitation volume is also the most important followed by the number of precipitation events from the previous season, number of freeze-thaw events with precipitation and so on.

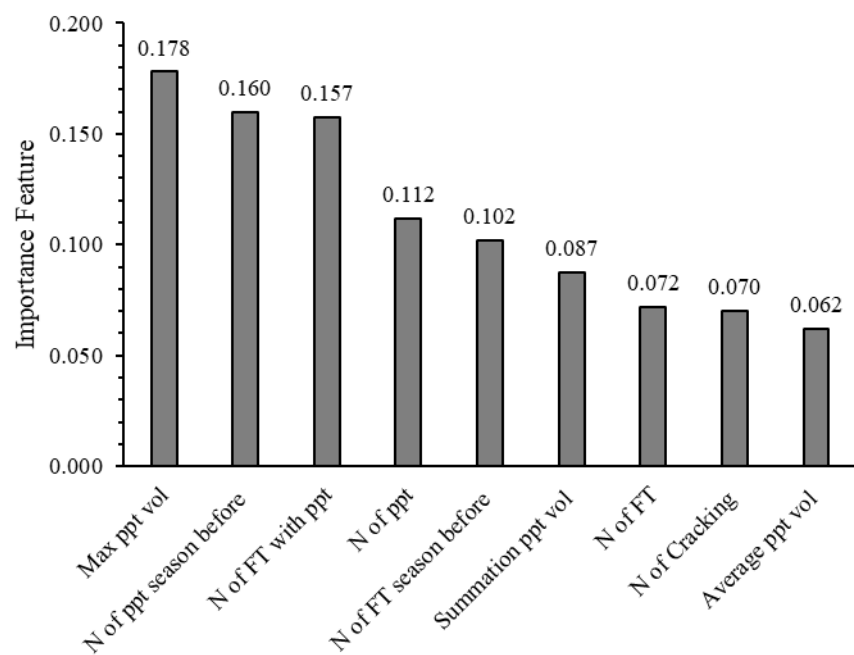
Correlation between variables is exhibited in Figure 42. A correlation value greater than 0.8 indicates a strong relationship between variables. Although tree-based machine learning models are generally not affected by multicollinearity, meaning that correlated features do not significantly impact performance metrics such as AUC, AP, precision, or recall, the impact of removing these variables are explored. As shown in the figure, the number of freeze-thaw events with precipitation are highly correlated with the number of freeze-thaw events. Similarly, average precipitation volume and total precipitation volume show strong correlation. Additionally, the number of cracking temperature days defined as days with temperatures between -3°C and -8°C is correlated with freeze-thaw variables. After removing these correlated features, the updated

importance feature is displayed in Figure 43. For the XGBoost model, maximum precipitation volume remains the most important feature. For the Random Forest model, the number of precipitation events from the previous season becomes the most important.

Finally, rockfall risk probability maps were generated for the period from 2010 to 2024. As shown in Figure 45, most predicted probabilities are distributed below 1%. Probabilities exceeding 10% account for 16.2% in the XGBoost model and 9.1% in the Random Forest model. For example, Figure 44 illustrates the rockfall risk maps in 2023 produced by each model. The results of seasonal rockfall probability maps can be accessed in ArcGIS Pro file.



(a)



(b)

Figure 41. Importance feature results: (a) XGBoost; (b) Random Forest.

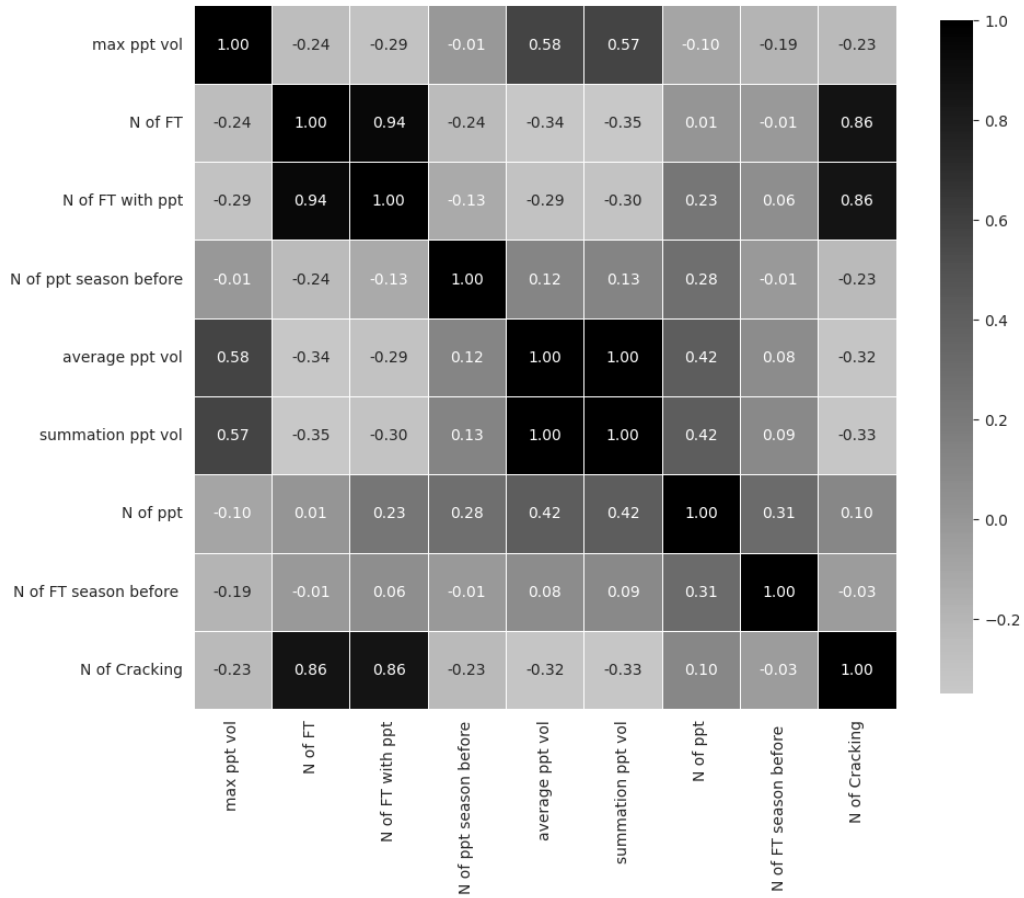


Figure 42. Correlation between variables.

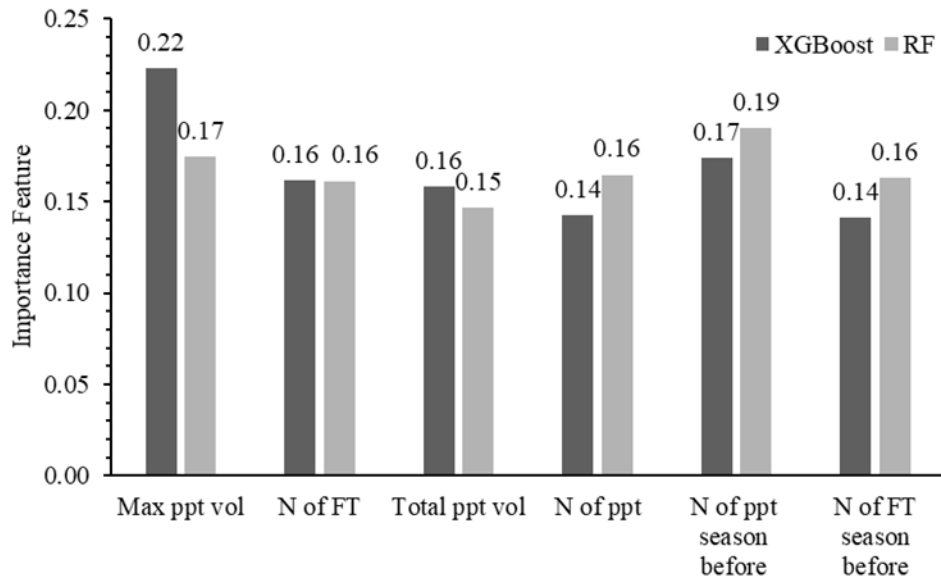


Figure 43. Importance features after removing correlated variables.

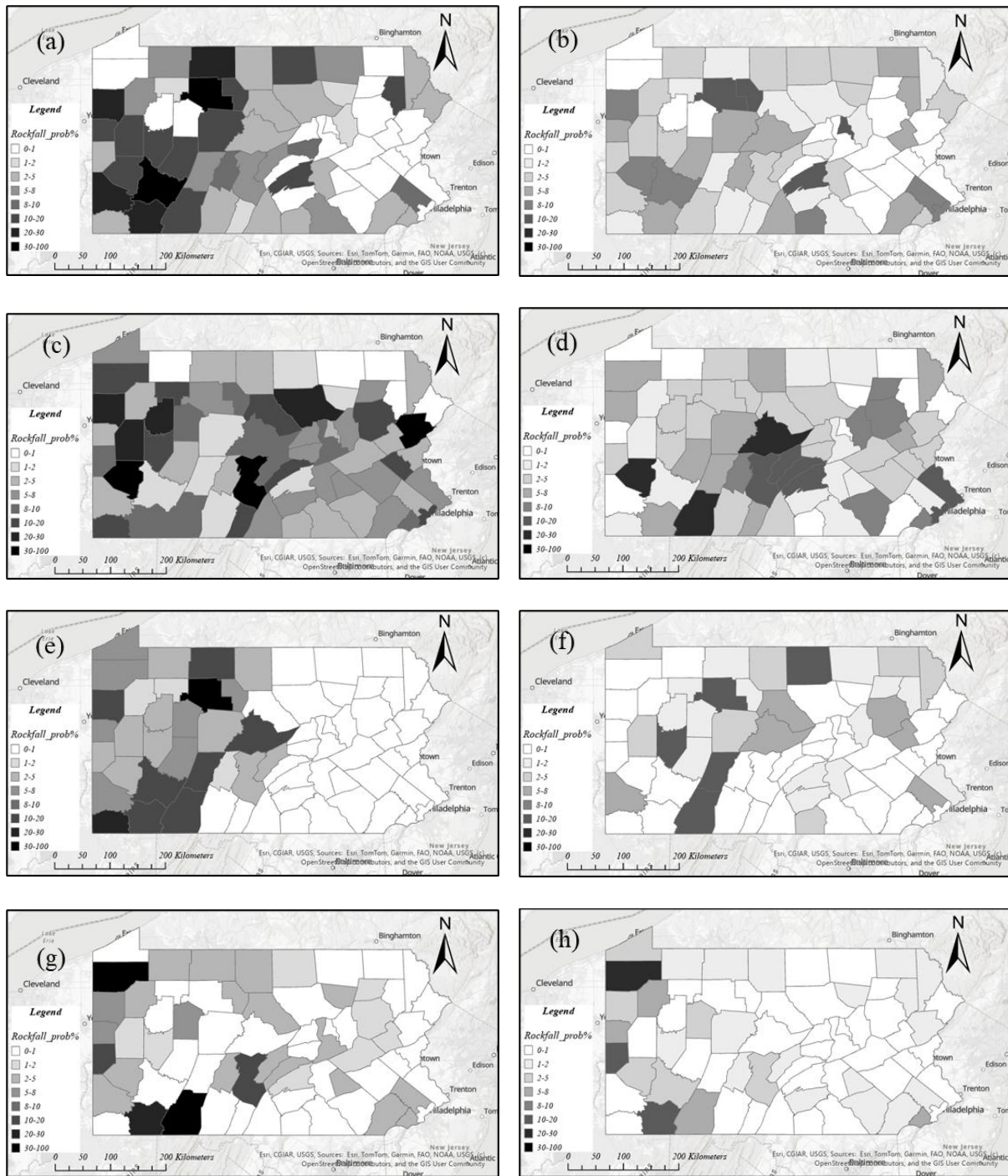


Figure 44. Rockfall risk maps: (a) XGBoost from 2023-03-01 to 2023-06-01; (b) RF from 2023-03-01 to 2023-06-01; (c) XGBoost from 2023-06-01 to 2023-09-01; (d) RF from 2023-06-01 to 2023-09-01; (e) XGBoost from 2023-09-01 to 2023-12-01; (f) RF from 2023-09-01 to 2023-12-01; (g) XGBoost from 2023-12-01 to 2024-03-01; (h) RF from 2023-12-01 to 2024-03-01.

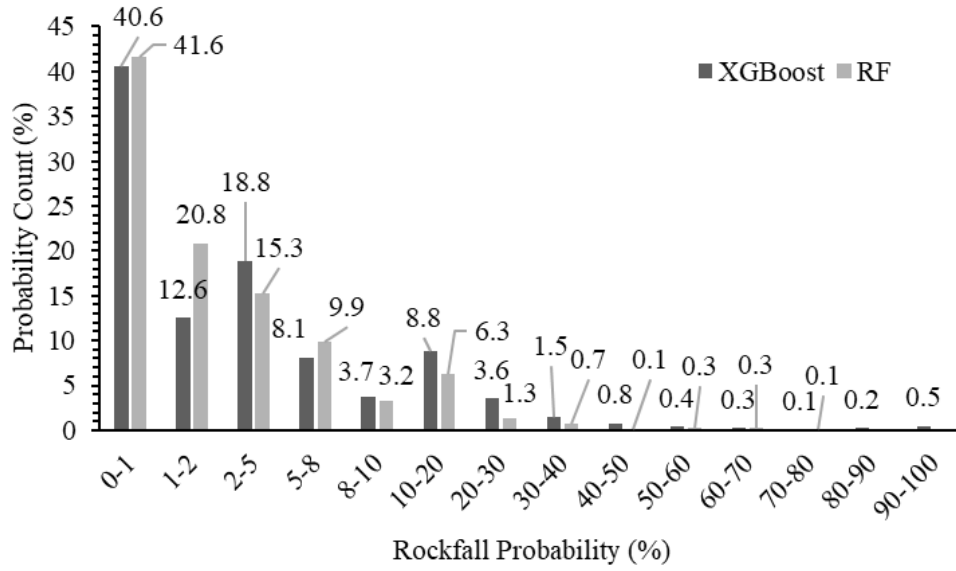


Figure 45. Summary of rockfall probability results.

To assess whether the clustering and SMOTE methods improve model performance, these approaches are applied in this study. Figure 46 illustrates the number of clusters produced by K-means++ clustering method and by the SMOTE with K-means++ clustering method.

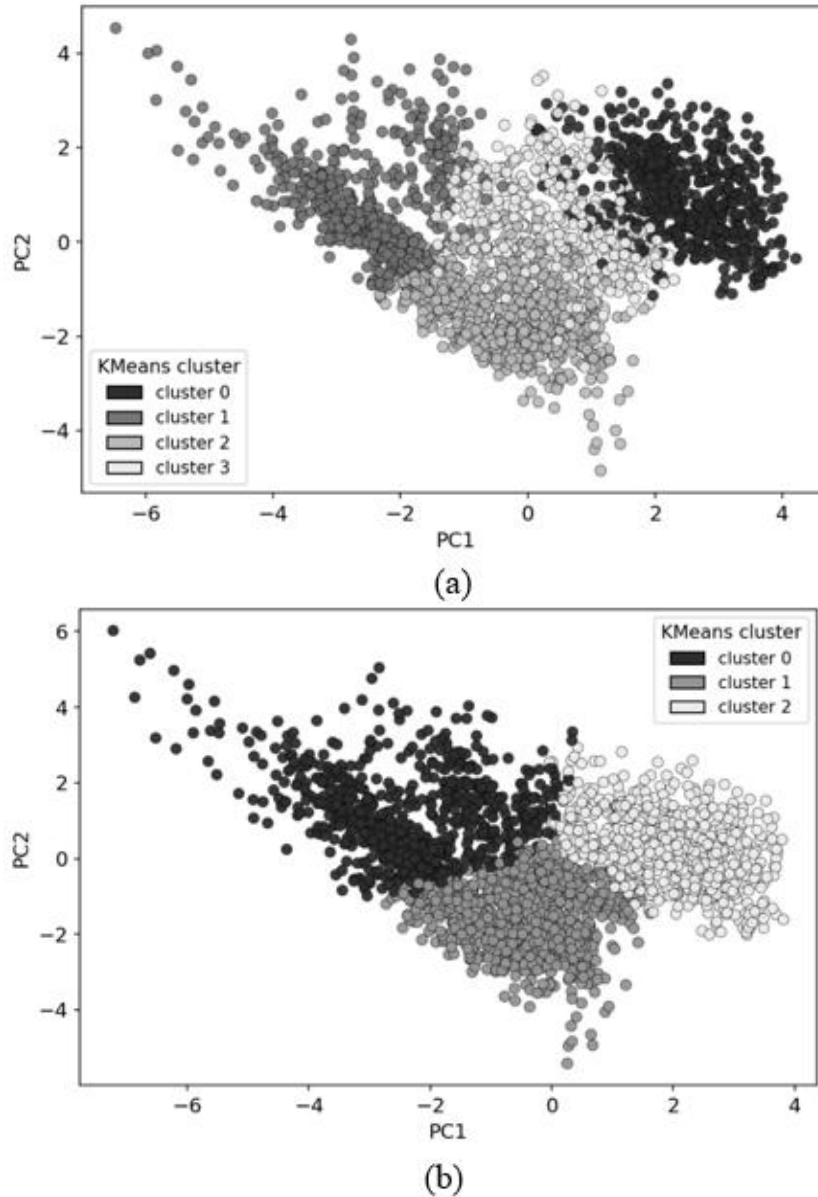


Figure 46. Cluster results: (a) K-means++ clustering; (b) SMOTE with K-means++ clustering.

The number of clusters is determined based on the input parameter; however, the Silhouette Score can assist in selecting an appropriate value. The Silhouette Score evaluates the quality of clustering by measuring the similarity of each data point to its assigned cluster relative to other clusters. A score close to 1 indicates well-separated, well-matched clusters, whereas a score close to -1 indicates poor clustering. Using this metric, iterative testing was performed to identify the optimal number of clusters for this model. The K-means++ method identified four clusters, while the SMOTE with K-means++ method identified three clusters.

As shown in Table 7 and Figure 47, the clustering and SMOTE methods influenced the model results. The K-means clustering and SMOTE approaches did not improve performance; instead,

they reduced overall accuracy. The K-means++ method increased the AUC but decreased the AP value.

Table 7. Comparison of AUC and AP results among the original method, K-means method, and SMOTE method.

	AUC	AP
XGBoost_Original	0.68	0.177
XGBoost_K-means	0.46	0.03
XGBoost_K-means++	0.69	0.06
XGBoost_SMOTE with K-means++	0.61	0.06
RF_Original	0.65	0.16
RF_K-means	0.58	0.09
RF_K-means++	0.66	0.09
RF_SMOTE with K-means++	0.59	0.08

Figure 47 provides a more detailed view of the results and can be compared with the original confusion matrix shown in Figure 39. Compared with the original model performance, the clustering methods produced results that differed in the opposite direction from the original approach. For the XGBoost model, which originally produced few false positives and true negatives, the K-means++ and SMOTE with K-means++ methods resulted in more false positives and more true positives. In contrast, the original RF model produced many false positives and true positives, whereas the clustering methods reduced both false positives and true positives.

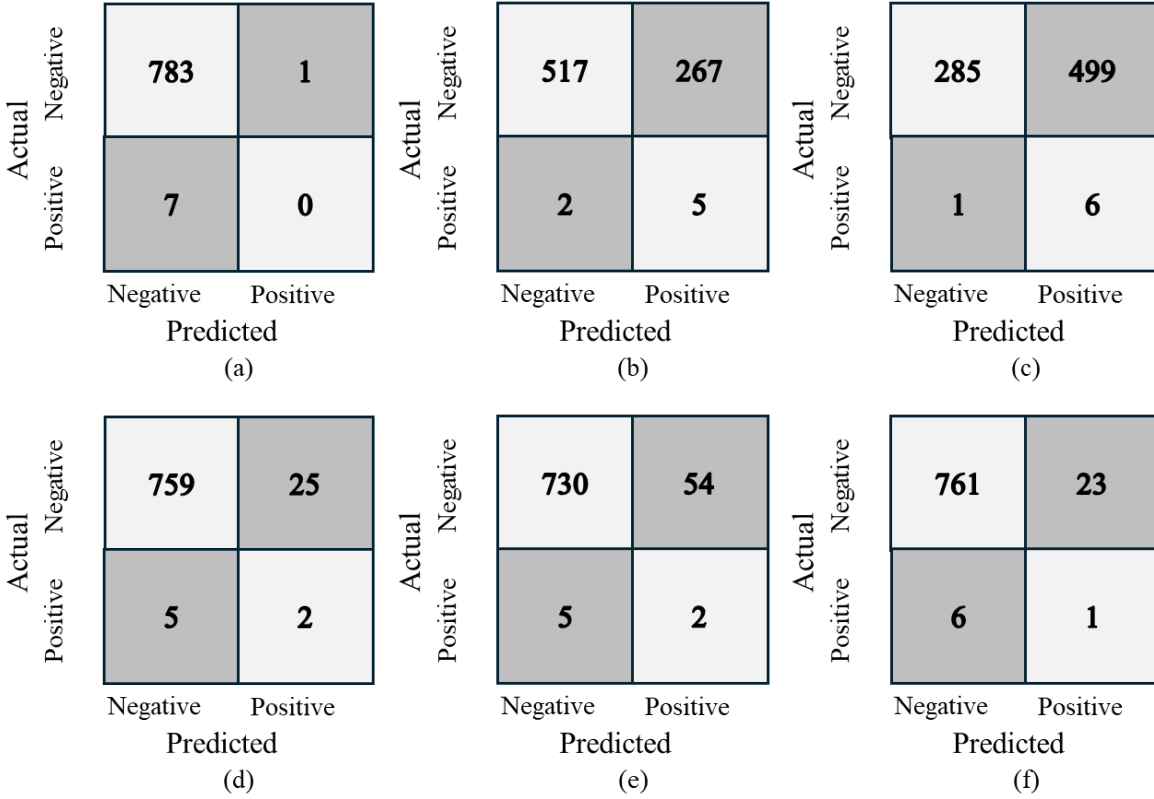


Figure 47. Confusion matrix results: (a) XGBoost with K-means; (b) XGBoost with K-means++; (c) XGBoost with SMOTE and K-means++; (d) RF with K-means; € RF with K-means++; (f) RF with SMOTE and K-means++.

4.4 Discussion

Predicting rockfall occurrence and preventing associated damage remain significant challenges. Various studies have been conducted to estimate rockfall hazards (Bravo-López et al. 2025; Conforti et al. 2014; Makonyo and Zahor 2023). This study provides valuable insight into predicting rockfall risk across Pennsylvania using machine learning techniques. Weather factors such as freeze–thaw cycles and precipitation are among the most significant influences contributing to rockfall. Therefore, in this study, weather data are analyzed to determine rockfall hazards.

For the machine learning approaches, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) were adopted and their performance compared. To interpret model performance, the Area Under the Curve (AUC), Average Precision (AP), and confusion matrix were assessed. AUC measures how well the model distinguishes between classes 0 and 1. The Receiver Operating Characteristic (ROC) curve plots classifier performance in terms of true positives versus false positives, and the AUC quantifies the model’s ability to correctly discriminate between classes regardless of the decision threshold. An AUC of 1.0 indicates perfect classification, whereas an

AUC of 0.5 suggests performance equivalent to random guessing, such as flipping a coin. According to Yesilnacar (2005), AUC values in the ranges of 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9, and 0.9–1.0 can be classified as poor, fair, good, very good, and excellent, respectively. The second metric, Average Precision (AP), represents the area under the precision–recall curve. Precision reflects the proportion of predicted positives that are correct, while recall measures the proportion of actual positives that are successfully identified. AP is high only when both precision and recall are high; if either metric is low, AP also tends to be low. AUC and AP results are shown in Table 6. AUC and AP may not follow general performance standards when evaluating models trained on highly imbalanced datasets, particularly those dominated by negative instances (Richardson et al. 2024; Saito and Rehmsmeier 2015). In such imbalanced datasets, AP values tend to be low because AP is highly sensitive to the prevalence of the positive class. Owing to the different approaches used to compute these metrics, AUC remains generally unaffected by changes in class imbalance, whereas AP varies substantially with the positive-to-negative class ratio. Consequently, AP is useful for comparing models across datasets with different positive-class prevalences; however, it is not appropriate to assess model performance using AP alone. In contrast, the AUC values of 0.68 and 0.65 obtained for the XGBoost and RF models, respectively, indicate fair discriminative performance, which should be interpreted in the context of the underlying class imbalance. Therefore, model performance should be evaluated using multiple complementary metrics.

Comparing the confusion matrix results provides insight into model performance and preferences for this analysis. The final models include 783 negative samples out of 3,917 negative samples and 7 positive samples out of 36 positive samples. XGBoost predicted 10 false positives, 1 true positive, and 6 false negatives, whereas RF predicted 428 false positives, 6 true positives, and 1 false negative. Therefore, in this analysis, XGBoost tends to enhance the precision of the model, while RF prioritizes recall. For rockfall analysis, if missing a rockfall event is costly, recall should be prioritized; if false alarms are costly, precision should remain significant. Accordingly, the RF model, which produced more false alarms but successfully captured more rockfall events, offers a more suitable trajectory for providing a rockfall risk window.

Weather conditions were processed into different parameters to investigate their impact on rockfall occurrence. Feature importance indicates the relative contribution of each predictor to the model's predictions. As shown in Figure 41, XGBoost and RF emphasize different aspects of feature importance. Maximum precipitation volume ranked first in both models, suggesting that precipitation intensity is a primary driver of rockfall occurrence. The number of freeze–thaw days ranked second in the XGBoost model but seventh in the RF model. In XGBoost, most features exhibit similar importance values; by contrast, in the RF model the most influential predictors are maximum precipitation, the number of precipitation seasons prior, and the number of freeze–thaw days with precipitation—these variables show substantially higher importance than the others and therefore exert a slightly greater effect on rockfall occurrence.

Figure 44 displays an example of seasonal rockfall risk maps across Pennsylvania. By examining seasonal rockfall risk in ArcGIS Pro, the analysis provides valuable insights into historically

high-risk counties and seasons, supporting proactive inspection of rock slopes in those areas. In addition, based on the weather parameters analyzed in this study, the feature-importance results offer useful guidance for anticipating rockfall-prone seasons.

For further analysis aimed at improving the imbalanced dataset, K-means clustering and SMOTE methods were applied. However, these methods did not improve the AUC or AP values, which are the primary indicators of model performance. In addition, compared with the original RF and XGBoost models, the clustering-based approaches produced results that moved in the opposite direction of the original models rather than enhancing or stabilizing the imbalance characteristics, as shown in Figure 47. The original XGBoost model captured only 10 false positives and 1 true positive, whereas the K-means++ and SMOTE with K-means++ methods resulted in increased numbers of both false positives and true positives. When comparing XGBoost with SMOTE and K-means++ to the original RF model, the original RF model achieved higher AUC and AP values and produced fewer false positives. For the RF model with clustering, fewer false positives and true positives were captured; however, the original XGBoost model still produced fewer positive predictions than the RF model with SMOTE and K-means++. Overall, these findings indicate that although clustering and SMOTE are widely used techniques for addressing class imbalance, they did not mitigate the imbalance in this dataset and instead introduced overfitting and amplified noise.

4.5 Conclusions

This study applied machine learning techniques, specifically Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), to evaluate rockfall risk across Pennsylvania using weather-related parameters. Model performance was evaluated using AUC, AP, and the confusion matrix. XGBoost achieved an AUC of 0.68 and an AP of 0.16, while RF achieved an AUC of 0.65 and an AP of 0.16. Despite the extremely imbalanced dataset, this model produces meaningful results for generating rockfall risk models.

The confusion matrix offers important insight into the logical preferences of each model. XGBoost reduced false alarms, resulting in higher precision compared to RF, while RF successfully captured more true positives, yielding higher recall despite generating a larger number of false positives. For machine learning applications, prioritizing precision or recall depends on the objective of the analysis. In this case, RF demonstrates a more suitable trajectory, as its strength lies in capturing more rockfall events even though it produces more false positives.

Importance features analysis indicates that precipitation intensity is the dominant driver of rockfall occurrence: maximum precipitation volume was the top predictor in both XGBoost and RF models. XGBoost yields more uniformly distributed importance values while the Random Forest highlights a small subset of predictors (maximum precipitation, the number of prior precipitation seasons, and freeze–thaw days with precipitation) with relatively greater influence. These findings imply that, beyond peak precipitation, antecedent seasonal precipitation and freeze–thaw interactions deserve particular attention when modelling rockfall risk.

In conclusion, this research presents a framework for identifying a rockfall-risk window, which can be used to analyze historically high-risk counties in Pennsylvania and to guide future rockfall hazard inspections. Both machine learning models were constructed robustly, demonstrating different strengths, and they provide meaningful outcomes for monitoring rockfall-prone counties. This approach enables proactive inspection of rock slopes in vulnerable areas, thereby reducing potential hazards.

5. Conclusions

Rockfalls pose significant safety and operational challenges for transportation systems. In Pennsylvania, damages and instabilities associated with rockfall have been documented along steep, exposed rock slopes adjacent to roadways, providing valuable opportunities to investigate the mechanisms and drivers of rockfall through continuous monitoring. This research evaluated rockfall risk using two complementary approaches.

The first approach involved LiDAR-based rockfall hazard analysis conducted at four sites—Riegelsville, Kintnersville, Narrows, and Fleecy Dale Road—using Rambo and CloudCompare software. Multiple LiDAR scans were collected to generate high-resolution point clouds, enabling detailed morphological assessment. Slope angles, Rockfall Activity Index (RAI) classifications, and RAI scores were evaluated at all sites. A rockfall event occurred at the Riegelsville site in December 2024; the affected segment previously exhibited high RAI values, and the event expanded the area characterized by elevated RAI. The estimated rockfall volumes were 6.7 m³ using Rambo and 7.4 m³ using CloudCompare. The corresponding RAI score for the failed segments was 65 kJ, and the estimated impact velocity under a free-fall assumption was 22.32 km/h. These high-resolution point clouds provide essential detail on rock surface morphology, which strongly influences rockfall hazard assessments and supports evaluation of overall hazard potential.

The second approach applied machine learning techniques—Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)—to assess rockfall risk across Pennsylvania using weather-related predictors. Model performance was evaluated using area under curve (AUC), average precision (AP), and confusion matrices. XGBoost achieved an AUC of 0.68 and an AP of 0.16, while RF achieved an AUC of 0.65 and an AP of 0.16. XGBoost reduced false alarms and demonstrated higher precision, whereas RF captured more true positives, resulting in higher recall despite generating more false positives. Feature importance analysis indicates that precipitation intensity is the dominant driver of rockfall occurrence; maximum precipitation volume was the top predictor in both models. XGBoost produced a more uniform distribution of feature importance, while RF emphasized a smaller subset of influential predictors, including maximum precipitation, the number of prior precipitation seasons, and freeze–thaw days with precipitation.

In conclusion, this research presents a framework for identifying a rockfall-risk window that can be used to analyze historically high-risk counties in Pennsylvania and guide future rockfall hazard inspections. This framework supports proactive assessment of vulnerable rock slopes, thereby reducing potential hazards.

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