

School of Mining Engineering



UNIVERSITY OF THE
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**UNRAVELLING THE PAST FOR A SAFER FUTURE:
HOW HISTORIC ROCK MASS CLASSIFICATION
DATA COMPARE WITH SLOPE PERFORMANCE
MONITORING DATA**

Mornè Pretorius

A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science.

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DECLARATION

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*“The scientific method is do whatever it takes-- whatever it takes--
to not fool yourself into thinking something is true that is not, or into
thinking that something is not true that is.”*

Neil deGrasse Tyson

ABSTRACT

This research investigates the correlation between empirically derived monitoring threshold values and actual slope monitoring data in open-pit mining, focusing on the Gamsberg Mine in South Africa. The study analyses two slope failure events within a schist layer. The goal was to quantitatively analyse available datasets to determine their relationship and evaluate whether empirical predictions can accurately forecast real-world rock mass behaviour in open pit slopes.

Rock mass classification data (RMR and GSI) from borehole logs were compared with real-time deformation measurements from slope stability radar. The methodology involved extracting relevant geotechnical data, calculating rock mass modulus and strain values, and comparing these with actual recorded deformations. Statistical analysis utilizing Z-tests and visual representations was employed to assess the correlation.

The study reveals a significant alignment between empirical predictions and actual measurements, with both events falling within one standard deviation of the empirical dataset's mean. This validates the utilization of empirical methods for initial deformation threshold estimations in slope stability monitoring.

The research underscores the importance of continuous calibration with site-specific data while validating empirical methods. It contributes to improving risk management and operational efficiency in open-pit mining by bridging the gap between theoretical models and real-world slope behaviour.

Future research should focus on expanding the sample size, investigating environmental factors, and integrating emerging technologies to enhance prediction accuracy. These steps will further refine the application of empirical methods in slope stability monitoring and improve overall mining safety and efficiency.

This study provides valuable insights into the practical application of empirical deformation thresholds in open-pit mining, offering a foundation for more accurate and reliable slope stability assessments. The findings have implications for

enhancing safety protocols, optimizing resource extraction and improving overall operational efficiency in the mining industry.

DEDICATION

To my beloved wife.

Your unwavering support has been the bedrock of our journey. This research report stands as a testament to your strength, patience and enduring belief in me. Just as rocks can withstand immense pressure, your love and encouragement have fortified me through every challenge.

Thank you for being my foundation and my inspiration.

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1 INTRODUCTION

1.1 Research Background and Context

The critical role of slope stability monitoring in open-pit mining operations has long been recognized by geotechnical engineers. This process involves the ongoing measurement and analysis of slope movements to anticipate potential failure events. Traditionally, rock mass classification systems have served as empirical tools for predicting slope stability. These systems categorize rock masses according to their physical and mechanical characteristics. Subsequently, this classification enables the estimation of parameters such as strain and deformation, which are measured during slope monitoring.

Modern advancements in monitoring technologies, such as robotic total stations and ground-based radars, offer real-time insights into slope movement, allowing immediate responses to deformation.

Slope stability monitoring in open-pit mining has been a critical aspect of mine safety and operational efficiency for several decades. The evolution of monitoring technologies and methodologies has been driven by the need for more accurate and real-time data to prevent catastrophic slope failures and to optimize mining operations. Early monitoring techniques relied heavily on manual observations and simple surveying tools, which were limited in their ability to detect subtle changes in the slope behaviour (Kaartinen et al., 2022).

As mining operations expand in scale and complexity, the demand for more sophisticated monitoring systems has increased. The advent of electronic distance measurement (EDM) instruments in the 1950s marked a significant milestone in slope-stability monitoring. This was followed by the introduction of global positioning systems (GPS) in the 1980s, which revolutionized the field by enabling precise, continuous measurements of slope movements. The 1990s and the 2000s saw the integration of remote sensing technologies such as LiDAR (light detection and ranging), radar and InSAR (interferometric synthetic aperture radar), which allowed for comprehensive, large-scale monitoring of entire pit walls.

More recently, the incorporation of artificial intelligence and machine learning algorithms has enhanced the ability to analyse and interpret vast amounts of monitoring data, leading to more accurate predictions of slope behaviour and potential failures.

This study aims to bridge the gap between historical and more recent approaches by examining the correlation between empirically determined threshold values and those derived from actual monitoring data.

1.2 Problem Statement

The primary problem addressed by this research is the potential discrepancy between the empirically determined deformation threshold values and those obtained through the back analysis of actual monitoring data. Although empirical methods provide a quick and cost-effective means of estimating deformation parameters, they may not always accurately reflect the complex behaviour of rock masses. In contrast, back-analysis of monitoring data offers a more precise assessment but requires extensive data collection and analysis.

This research specifically addresses the challenge of reconciling the discrepancies between empirical deformation thresholds, which tend to be conservative and the real-time deformation measurements obtained from advanced monitoring technologies at the Gamsberg Mine.

This research was conducted to determine whether a correlation exists in a case where both datasets (rock mass classification database and slope monitoring database) are present to determine the suitability and confidence levels of the threshold values.

1.3 Justification for Research

The significance of this study lies in its potential to improve the predictive accuracy of slope stability monitoring by correlating empirical deformation thresholds with the observed data. Enhanced accuracy in deformation thresholds could reduce operational risks by accurately predicting failures, support the development of more reliable Trigger Action Response Plans (TARPs) and contributing to more

effective slope management strategies. This study offers practical contributions to geotechnical engineering by proposing a methodology that combines traditional rock mass classification systems with modern monitoring techniques to enhance the safety and efficiency of mining operations.

1.4 Research Objectives

The objectives of this research were as follows:

- To analyse geotechnical data to establish empirical deformation thresholds for specific rock types at the Gamsberg Mine.
- To conduct a back-analysis of the slope stability monitoring data and determine the actual deformation values.
- To determine the statistical correlation between the empirical deformation thresholds and back-calculated deformation values.

1.5 Research Methods

This study adopted a mixed-method approach that integrates both empirical and observational methodologies to comprehensively evaluate deformation thresholds. The data for this research project was sourced from pre-existing databases. Data in the geotechnical database was collected from borehole core logging and laboratory tests, where rock mass characterization was performed.

The geotechnical database was populated by certified geologists who conducted the logging (Neufeld, 2008). A structured training program was implemented to ensure that geologists could accurately describe and record lithologies, and geotechnical data.

The borehole core was reconstructed in core boxes and placed on racks, where metre intervals were marked and the core orientation was verified using specialized tools. This ensured the reliability of the data for geotechnical and geological analyses.

The next step was to collect geotechnical data from the core. All logged parameters were documented and recorded. Specialized tools such as acoustic and optical televiewers were used and certified personnel conducted downhole

geophysical surveys to map the borehole trajectories and orientations. Optical and acoustic logging tools were also used to scan the holes.

Core photographs taken before sample selection served as visual references for structural and compositional analyses. Metadata, including depth and sample identifiers, were logged digitally for consistent records.

The final step in the process was to meticulously record the data, transfer it to spreadsheets and then verify the data. It was then incorporated into a central database, from which a final error-checking process were performed. The data for this study was extracted from the central database.

Data in the monitoring database were electronically captured using monitoring equipment (ground-based radars). The data recorded by ground-based radar were stored on a mobile computer or tablet before being transferred to a primary monitoring point (PMP). From this PMP, the data were transferred to a display in a manned control room from where the analysis is performed. At each point along the way, data were securely backed up and from the PMP it was shared electronically with a central database.

For this case study, data was recorded using a GroundProbe Slope Stability Radar XT (SSR XT). This type of radar, the SSR XT, is a 3-dimensionall real aperture radar, which has a maximum scan range of 3500 m whilst providing sub-millimetre accuracy.

Data from the geotechnical database was analysed to extract relevant information applicable to the rock types that make up the slope faces exposed in the pits. Data on previous failures was extracted from the database. From these two analysed datasets, visualization aids were created to visualize the data and draw conclusions. A non-parametric statistical approach was used to determine the correlations between the two datasets. By applying a quantitative analyses, this study ensures a robust comparison between empirical predictions and real-time measurements.

1.6 Sources of Data

The primary data for this study were sourced from the Gamsberg Mine's geotechnical and monitoring databases. The geotechnical database includes

borehole core logging results and rock mass properties, whereas the monitoring database comprises real-time data collected from robotic total stations and ground-based radar. These data provides a comprehensive understanding of rock behaviour across various geotechnical conditions within the mine, enabling detailed back analysis.

1.7 Research Validation

To validate the findings, a systematic approach was employed, which involved filtering data to focus on pertinent intersections, comparing deformation records with past failure information and conducting statistical analyses to verify the significance of the correlations. This validation protocol enhanced the reliability of the research conclusions and mitigated potential biases or limitations in the datasets.

1.8 Structure of the Research Report

The research report is structured into five chapters. Chapter 1 introduces the study's context, objectives and methodology. Chapter 2 reviews the relevant literature and foundational theories. Chapter 3 details the research methodology and Chapter 4 presents the findings of the data analysis. Chapter 5 concludes the study, offering research insights and recommendations for future research.

2 LITERATURE REVIEW

2.1 Introduction

This study investigates the relationship between rock mass classification systems and the data recorded by means of slope stability monitoring. This literature review will examine selected published research on various rock mass classification systems, the analysis of this data to extract specific parameters, slope stability monitoring techniques and data analysis.

2.2 Key Concepts, Theories and Studies

2.2.1 Rock Mass Classification Systems

Rock mass classification is a widely used system for evaluating the quality of rock mass in various geological engineering applications, including slope stability (Hoek, 2023). Some of the most common classification systems include Rock Mass Rating (RMR) (Bieniawski, 1973), Q-System (Barton et al., 1974) and the Geological Strength Index (GSI) (Hoek et al, 1992) . These systems allow engineers to assign numerical values to various aspects of a rock mass, including the strength, joint condition and spacing, which can then be used to estimate the stability of slopes and other geological features. Each classification system has its strengths and limitations.

2.2.1.1 The Rock Mass Rating System

The Rock Mass Rating (RMR) system, created by Bieniawski in 1973, is a geomechanical classification system for assessing rock mass conditions and providing support recommendations for excavations (Holland & Lorig, 1997). The Rock Mass Rating system is based on six parameters: strength of intact rock material, Rock Quality Designation (RQD), spacing of discontinuities, condition of discontinuities, groundwater conditions and an adjustment for discontinuity orientations (Jalalifar et al., 2014).

This system has undergone significant development and refinement over the past four decades since its introduction. This geomechanical classification system, initially designed to assess rock mass conditions and provide support

recommendations for excavations, has evolved into a versatile tool in various fields of rock engineering.

In 1979, Bieniawski published an updated version of the RMR system that incorporated more case histories and refined classification criteria (Bieniawski, 1979). This version, often referred to as RMR₇₉, has been widely adopted by the rock engineering community. Throughout the 1980s, the RMR system was applied in various fields, including hard rock mining, coal mining, rock slope stability assessments and foundation design for rock.

In 1989, Bieniawski introduced further modifications to the system, resulting in an RMR₈₉ version (Bieniawski, 1989). This update includes more precise definitions of the rating parameters and improved guidelines for support recommendations.

The 1990s saw the development of specialized adaptations of the RMR system. One notable example is the Slope Mass Rating (SMR) introduced by Romana (Romana, 1993). The Slope Mass Rating is a modification of RMR specifically tailored for rock slope stability assessment.

The latest version of the RMR₁₄ system was introduced by 2014 Celada et al. (2014). This update aimed to address some of the limitations of the previous versions while maintaining a strong correlation with the widely used RMR₈₉. The key features of RMR₁₄ include the following:

- Refined rating scales for some parameters
- Updated guidelines for support recommendations
- Improved consideration of anisotropic rock mass behaviour.

Recent research has focused on integrating the RMR system with other classification methods and advanced numerical modelling techniques. This integration aims to provide a more comprehensive rock mass characterization and support design.

Despite these developments, the RMR₈₉ version remains widely used in practice because of its simplicity and extensive case-history database. The RMR₈₉ system was used in this study.

Criticism of RMR₈₉ includes that it does not explicitly account for in situ stress conditions, which can significantly affect slope stability (Rehman et al., 2018). This limitation is particularly evident in highly stressed jointed rock masses where the actual support requirements may be heavier than those suggested by RMR₈₉ (Rehman et al., 2019). Additionally, RMR₈₉ incorporates Rock Quality Designation (RQD), which has been criticized for its inherent limitations and potential inconsistencies in assessments (Pells et al., 2017).

2.2.1.2 The Geological Strength Index

The Geological Strength Index (GSI) (Hoek et al. 1992) was developed in engineering rock mechanics to meet the need for reliable input data related to rock mass properties for designing tunnels, slopes and rock foundations (Marinos et al., 2005). It uses the geological character of rock material and the visual assessment of the mass it forms as direct inputs for the selecting parameters to predict rock mass strength and deformability (Marinos et al., 2005).

One of the key strengths of GSI is its ability to characterize difficult-to-describe rock masses, such as flysch and its geological reasoning, which allows adjustments to cover a wide range of rock masses and conditions (Marinos, 2017). It also enables a rock mass to be considered as a mechanical continuum without losing the influence of geology on its mechanical properties (Marinos et al., 2005). The GSI system is based on a careful engineering geology description of the rock mass encountered in engineering projects, which can be estimated from a visual examination of the rock mass exposed in outcrops (Zuo & Shen, 2020).

However, GSI systems have certain limitations. Its estimation is relatively subjective because of the lack of quantitative parameters, which makes it unsuitable for rock samples from drilled cores (Lin et al., 2014). To address this, some researchers have proposed modified methods for estimating GSI using more quantitative parameters (Lin et al., 2014). Additionally, GSI assumes that the rock mass is isotropic, which may not always be the case in real-world scenarios (Singh & Goel, 1999). The GSI can be derived through an empirical formula when Rock mass Rating data is available.

While GSI has proven to be an effective and reliable approach for predicting rock mass strength and designing excavations (Marinos, 2017), ongoing research continues to refine and improve the system. Efforts to quantify GSI parameters and adapt them to various rock types and engineering applications have demonstrated the importance and potential for further development in rock engineering (Morelli, 2018).

2.2.1.3 The Q - System

The Q-system of rock mass classification was originally proposed by Barton et al. (1974) at the Norwegian Geotechnical Institute (NGI) in 1974. The system is based on approximately 200 case histories of tunnels and caverns (Singh & Goel, 1999). This system has since been updated several times and is now based on 1,050 case records correlating the installed rock support to the observed Q-values.

The Q-system is primarily based on six parameters: Rock Quality Designation (RQD), joint set number, joint roughness, joint alteration, joint water reduction factor and stress reduction factor (Singh & Goel, 1999). It is particularly well suited for case studies of actual underground construction and is widely used in the mining industry for various applications, including ground support design, pillar strength estimation, fragmentation, rock mass strength and caveability assessment (Russo et al., 2022).

One of the advantages of the Q-system is its ability to provide both qualitative and quantitative indications of problems related to tunnel excavation and slope stability, as well as qualitative indications of the strength envelope and deformability of rock masses (Goel & Singh, 2011). Additionally, the Q-system has been found to correlate well with other rock mass classification systems, such as the Rock Mass Rating (RMR) system, allowing for more comprehensive rock mass characterization when multiple systems are used together (Díaz et al., 2021).

However, the Q-system has several limitations. It relies heavily on joint characteristics, which may be more applicable in regions with predominantly magmatic and high-grade metamorphic rocks such as Norway, but should be applied cautiously in areas with sedimentary, volcanic and strongly foliated rocks (Dimitrov, 2020). Furthermore, the system does not directly incorporate the uniaxial

compressive strength of the rock, which is considered an advantage in other classification systems, such as RMR (Dimitrov, 2020).

Another limitation of the Q system is its sensitivity to errors in data collection and interpretation. Common mistakes in assessing parameters such as joint counts, RQD and joint alteration can significantly impact the resulting Q-value and consequently, the geomechanical design (Russo et al., 2022). This highlights the importance of accurate data collection and interpretation when using the Q system.

Despite these limitations, Q-systems remain valuable tools for rock engineering classification. Its continued use and development, along with the integration of advanced technologies such as artificial intelligence and machine learning, demonstrate its ongoing relevance in the field (Saadati et al., 2024). The ability of the Q-system to provide practical guidance for rock support design and its adaptability to various geological conditions makes it an essential component of modern rock engineering practice.

2.2.1.4 Slope Stability Monitoring

Monitoring systems in open-pit mines have evolved with advancements in technology, allowing more accurate real-time measurements of slope deformation. Ground-based radar, Interferometric Synthetic Aperture Radar (InSAR) and laser scanning are widely used technologies that provide continuous monitoring and early warning of slope failures (Osasan & Afeni, 2010). Slope monitoring aims to detect slope movement at an early stage, allowing operators to take corrective action before a catastrophic failure occurs.

Slope stability radars (SSRs) are essential tools for monitoring and managing slope stability in open-pit mines. These ground-based radar systems provide near real-time displacement measurements over broad coverage areas, allowing geotechnical engineers to observe the spatial distribution of pit-wall movements and their progression over time (Dick, 2013). SSRs offer several advantages over the conventional monitoring methods.

- Real-time monitoring: SSRs provide continuous, near-real-time data on potential displacements and failures, enabling early warning systems for impending slope failures (Dick et al., 2015).
- Environmental resilience: Radar waves can penetrate rain, dust and smoke, providing reliable measurements 24 hours a day in challenging environmental conditions often encountered in mining operations (Kumar & Villuri, 2015).
- Integration capabilities: SSRs can be integrated with other monitoring techniques, such as surface measurement techniques at discrete points (total station/reflective prisms) and Differential Interferometric Synthetic Aperture Radar (DInSAR), to provide a comprehensive approach for slope stability monitoring (Paradella et al., 2015).
- Improved understanding of failure mechanisms: Case studies have demonstrated how SSR data contribute to understanding failure mechanisms, improving slope design and enhancing safety protocols (Harries et al., 2006).
- Risk management: SSRs are increasingly deployed as a preventive measure for hazards, particularly in managing rockfall risks in North American mines (Harries et al., 2009).
- Support for geotechnical modelling: SSR data can be integrated into geotechnical models, refining predictions of failure points and improving overall mine safety (Escobar et al., 2013).
- Automated prediction systems: SSR data can be used in automated prediction systems by employing methods, such as the inverse velocity method, to predict time-to-failure (Stacey & Osasan, 2014).

Recent advancements in SSR technology include wider coverage areas and improved detection of small-scale movement (Viviani et al., 2020). real aperture radar systems with improved reliability and adaptability for diverse geological conditions (Ding et al., 2024) and integration with satellite data, such as InSAR, for a more comprehensive view of slope conditions (Carlà et al., 2018).

2.2.1.5 Slope Stability Prediction Through Empirical Methods

Brox and Newcomen (2003) provided an influential study on utilizing strain criteria to predict high wall stability performance and established a formula for determining

deformation thresholds based on empirical data. Their research was instrumental in demonstrating how strain measurements can inform slope stability designs. The authors referenced the work of Zavodni (2001), who proposed that highwalls in open-pit mines could undergo a maximum strain of 0.6% to 1% before transitioning from regressive (self-stabilizing) movement to progressive (unstable) movement.

The Brox and Newcomen (2003) approach, focuses on utilizing strain criteria to predict high wall stability performance in open-pit mining. This approach can be described as follows:

- **Strain Definition:** The authors defined the high wall strain (ϵ) as a percentage, calculated by the formula $\epsilon = (\Delta x/H) \times 100\%$, where Δx represents the maximum deformation of the highwall and H denotes the total height of the wall.
- **Strain Direction:** The text does not explicitly specify the direction of strain measurement. However, based on the context, the authors consider the overall pit wall strain, measured as horizontal displacement at the crest of the high wall.
- **Threshold Strain Levels:** The approach proposes threshold strain levels for key stages of highwall stability which were, Tension Cracks $\geq 0.1\%$, Progressive Movement $\geq 0.6\%$, Imminent Failure/Collapse: $> 1.0\%$
- **Empirical Strain Criteria:** The authors postulate empirical highwall strain criteria based on trends observed in the highwall strain data from various case histories. These criteria relate the highwall strain to rock mass quality (RMR) and stability conditions.
- **Application:** This approach is intended as an additional means to assess the stability performance of open-pit high walls, complementing traditional methods based on displacement rates.
- **Factors Considered:** The method considers the rock mass quality, overall geometry of the open pit, high wall angle, overall depth and inferred instability mechanism.
- **Data Collection:** The approach relies on surface movement monitoring data, typically collected using survey-monitoring prisms.

The authors suggest that this strain criteria approach, in conjunction with the predictive numerical modelling of strains, may be beneficial for evaluating the proposed highwall modifications and pit expansions during open pit mine design and long-term planning.

Zavodni (2001) also suggested that strains greater than 1% could result in abrupt high wall instability or failure. These thresholds were based on field observations of multiple mining operations that exhibit time-dependent movements. Brox and Newcomen (2003) reviewed surface-movement monitoring data from a limited number of open-pit mining operations in North and South America. They correlated the observed strain data (measured using survey prisms) with actual high wall stability events, such as the onset of tension cracks, progressive movement and failures. These data allowed them to identify trends and refine the threshold strain values.

The empirical observations were used to validate the threshold strain levels proposed by Zavodni (2001). The specific case studies discussed in this work, such as the Smokey River Coal Mine and the Lornex Pit at Highland Valley Copper, provided real-world examples where the highwall strain was tracked over time and correlated with stages of instability.

In these case studies, movement data were analysed to determine the strain levels at key points: when tension cracks first appeared (approximately 0.1%), when movement became progressive (0.6%) and when failure occurred (strains over 1%).

The authors explained that surface movement monitoring, particularly using prism surveys, was critical in quantifying the total strain experienced by the high walls.

This monitoring data, combined with the rock mass quality (characterized using the RMR system), helped to derive and validate the threshold strain levels for various stages of high wall stability.

In summary, the strain levels were derived through a combination of previous research (Zavodni, 2001) and empirical observations from multiple case histories

in open-pit mines, where surface movement and high wall strain were carefully monitored and correlated with actual stability performance.

The following formula was published in the study:

$$\varepsilon = \Delta x / H$$

Equation 1

where:

ε = strain, presented as a percentage.

Δx = maximum deformation of the high wall

H = total height of the highwall

The study produced a chart as an output that related the different strain percentages calculated to the measured rock mass ratings. Figure 2-1 shows this chart and the strain percentages of the different case studies of wedge and planar failures evaluated.

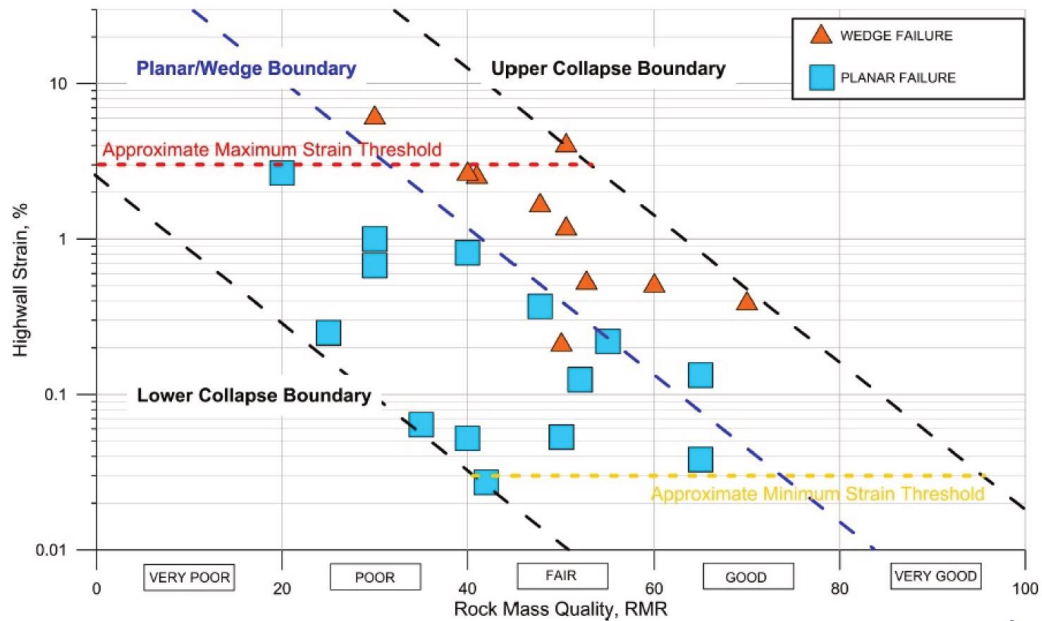


Figure 2-1 RMR versus pit wall strain for wedge and planar failures at collapse, after Brox & Newcomen (2003).

Newcomen and Dick (2016) built upon the study by Brox and Newcomen (2003), introducing several key updates in the strain-based approach for predicting pit wall failure. The first major update involved the use of an expanded dataset and refined definitions of failure. The initial study (Brox and Newcomen, 2003) was based on a limited dataset of 12 slope failures and included both complete and non-collapse failures.

In the updated study, the database was expanded to 48 slope failures, focusing only on cases of complete pit-wall collapse. This led to a more rigorous dataset, removing instances that did not result in full collapse. The updated dataset includes failures documented by Whittall et al. (2016).

Another update includes the refined strain thresholds. In the original publication, the strain threshold for collapse was set at 2%, with general guidance provided for various stages of pit-wall stability. In the 2016 update, the maximum strain threshold for collapse increased to 4%, reflecting findings from the expanded dataset. This was twice the previously suggested 2% strain threshold and four times the 1% threshold proposed by Zavodni (2001).

Furthermore, a clear separation of the failure mechanisms was achieved. In the original study, the failure mechanisms were broadly grouped, including wedge, planar, rock mass and toppling failures.

In the 2016 update, the study emphasized the need to differentiate the strain thresholds for different failure mechanisms. Separate analyses were conducted for planar and wedge failures versus rock mass and toppling failures with distinct strain ranges for each type of failure.

- Planar failures typically occurred at lower strains (0.03% to 3%).
- Wedge failures had strains up to 6%.
- Toppling failures exhibited the highest strain values (up to 15%).

An investigation into the correlation between strain and rock mass quality was also conducted. In the original study, there was a general understanding that rock mass quality (measured by RMR) influenced the strain-to-failure threshold. The work updated in 2016 included a refinement of the relationship between RMR and strain and the updated data confirmed that lower-quality rock masses can accommodate higher strains before failure. However, this correlation was complicated by the need to account for different failure modes, as rock mass failures showed surprising variability in the strain at collapse.

Building on this work, Coetsee et al. (2020) further refined the empirical methods for determining strain threshold values for slope monitoring in open-pit mines. Their adaptation of Newcomen and Dick's (2016) criteria provided a method for using strain thresholds to develop TARP's in mining operations.

This study builds on established techniques for monitoring pit-slope stability, specifically referencing the method developed by Brox and Newcomen (2003). In this study, the authors rearranged the traditional strain criteria formula, commonly used for monitoring slope displacement, to better predict slope stability and movement transitions.

Newcomen and Dick's (2016) strategy involves calculating the strain. Coetsee et al. (2020) modified this formula by using algebraic principles, allowing deformation to be predicted based on pre-selected strain values and defined slope heights. This

adjustment helps provide proactive evaluations of the slope deformation history, making it easier to set alarms and monitor for potential instabilities in mining environments. The original formula was modified as follows:

$$\Delta x = \epsilon / H$$

Equation 2

The modification involved re-arranging the formula to obtain the deformation parameter (Δx), where a known strain and slope height is used as input.

This modified strain-based formula was applied to develop comprehensive TARPs, where displacement measurements served as proxies for strain. This approach provides guidelines for setting thresholds and alarms, facilitating timely responses to separate phases of slope instability, from initial deformation to collapse.

The study builds on the empirical data gathered from earlier works by Brox and Newcomen (2003), Newcomen and Dick (2016) and others, providing refined strain thresholds for various failure modes (e.g., planar, wedge, toppling) and rock mass qualities. This analysis is supported by case studies that illustrate the different instability types.

This study offers a more dynamic approach to assessing slope performance by integrating strain-based monitoring systems with real-time data, thereby enhancing the ability to track and respond to slope movements across the stages of pit life. This methodology has implications for improving safety and risk management in open-pit mining operations.

The authors presented an approach for using strain thresholds in slope stability TARP's for open-pit mines. Their method builds on previous work on strain criteria and incorporates them into a comprehensive TARP framework. The key aspects of their approach were as follows.

- Utilizing the strain criteria formula, they rearranged the traditional strain formula ($\epsilon = \Delta x / H$) to solve for displacement ($\Delta x = \epsilon \times H$), allowing them to

calculate indicative displacement values based on pre-selected strain percentages and slope heights.

- Incorporating empirical data, the authors draw on previous studies that provide strain percentages for different failure modes and rock mass qualities, using this information to inform their threshold selection.
- Considering movement stages, they integrated Sullivan's (2007) pit slope movement phases (elastic, creep, cracking and dislocation, collapse and post-failure deformation) into their TARP framework.
- By accounting for movement patterns, the approach considers various pre-failure, failure and post-failure movement patterns identified by Sullivan (2007), such as linear, bi-linear, stick-slip and accelerating patterns.
- The authors propose a TARP template that includes alert levels, movement stages, pit slope and movement pattern observations, strain percentages, calculated displacement thresholds, time windows and average velocity thresholds.
- This approach allows for customization based on site-specific conditions, back analysis of previous failures and ongoing monitoring data trends.
- The authors provide detailed recommendations for implementing and maintaining TARP, including setting area thresholds, interpreting data trends and adjusting alarm criteria as needed.

This approach aims to provide a more comprehensive and adaptable framework for monitoring and responding to slope instability in open-pit mines by integrating strain-based criteria with established movement patterns and stages to enhance early warning capabilities.

2.2.1.6 Correlating empirical and recorded data

Empirical methods have traditionally been used to determine the initial threshold values for monitoring purposes, particularly at the beginning of mining projects where no historical data are available. By using rock mass classification data, engineers can estimate key parameters such as deformation and rock mass strength (Moser et al., 2017). Although these methods are widely accepted, they can be prone to biases based on the quality and extent of the data collected during geotechnical investigations.

Once a mine has been in operation for some time, back analysis can be employed to refine the initial thresholds. This technique involves analysing historical deformation data and failure events to better understand the behaviour of the rock mass. According to Sharon and Eberhardt (2020), back analysis is one of the most reliable methods to confirm the validity of slope stability models, particularly when combined with continuous monitoring data.

Furthermore, slope stability monitoring is regarded as an industry best practice, not only for confirming slope designs but also as a key point of risk management for many mines (Osasan & Afeni, 2010; Dixon et al., 2011). A common practice is the use of back analysis of monitoring data to determine threshold values (Sharon & Eberhardt, 2020; Mulenga, et al., 2022).

A recent study by Mulenga et al. (2022) highlighted the importance of reconciling rockfall and slope safety-critical controls using real-time monitoring data. This study demonstrated that deformation thresholds determined through monitoring can provide more accurate predictions of slope performance than purely empirical methods.

A gap was identified in the literature, in that very few studies have investigated whether a correlation exists between these two types of datasets. Correlation was evaluated by gathering and visualizing the data, calculating the correlation coefficient, interpreting the results and finally performing a significance test. This study aims to contribute to the literature in this regard.

2.3 Key Debates and Controversies

The following were key debates highlighted from the literature:

- **Accuracy of Empirically Derived Thresholds:** A key debate in the literature revolves around the accuracy and reliability of empirically derived deformation thresholds. These thresholds were often based on theoretical models and assumptions made during the early project stages, which can lead to discrepancies between the predicted and actual slope behaviour. This issue is compounded by the variability in geological conditions within

a mining site, where rock mass properties can change significantly across different areas.

- **Bias in Empirical Data:** Several authors, including Basahel and Mitri (2017), have pointed out that empirical methods rely heavily on the experience of the engineer and quality of the data, which can introduce subjectivity into the process. Moreover, when the datasets used for empirical analysis were limited, the resulting deformation thresholds may not accurately reflect the real-world slope behaviour.
- **Reliability of Monitoring Systems:** While real-time slope monitoring is considered more accurate in predicting slope failures, there is still debate over the precision and timeliness of these systems, particularly in extreme conditions. For instance, radar-monitoring systems can be affected by adverse weather, leading to gaps in data (Osasan & Afeni, 2010).
- **Inconsistencies between Empirical and Real-World Data:** The disparity between the empirically derived and actual deformation thresholds remains an open question. Some studies, such as that of Dahiya et al. (2022), indicate that empirical methods can underestimate deformation, leading to conservative designs that may not be cost-effective. Conversely, empirical methods may overestimate stability in more complex geological environments, thereby increasing the risk of unforeseen slope failures.
- **Correlation Between Datasets:** Very few studies have focused on investigating whether empirical threshold values correlate with those obtained through back analysis and real-time monitoring. This is a key area that this study aims to address. Understanding this relationship could significantly impact the use of early-stage geotechnical models to inform slope stability monitoring practices.

The accuracy of empirically derived deformation threshold values is a key point of debate in literature. This stems from the fact that it may be susceptible to bias and depends heavily on the experience and expertise of the engineer performing the analysis, as well as the quality of the data used.

2.4 Chapter Summary

This literature review highlights the key theories and concepts surrounding slope stability monitoring and the use of rock-mass classification systems in open-pit

mining. Although empirical methods offer a practical starting point for determining deformation thresholds, their accuracy is often debated and the correlation between empirical data and real-time monitoring data has been underexplored. This chapter underscored the limitations of the empirical methods and the need for hybrid models that integrate real-time data. This study contributes to addressing these gaps by combining classification systems and monitoring for a refined approach to slope stability assessment.

3 RESEARCH METHODOLOGY

3.1 Introduction

This study uses a systematic approach to compare rock mass classification data from an existing database with slope performance monitoring data to examine whether the predictive data correlates with the actual recorded measurement. This section introduces the methodological framework used for the data comparison and analysis. It includes a description of the study area, research design, data collection process, validation process and analytical approaches used to meet the goals of the study.

3.2 Study Area

This research was conducted at an active open-pit zinc mine. This study focuses on Gamsberg Mine, a zinc mine in South Africa's Northern Cape province, between the towns of Pofadder and Aggeneys. The ore deposit is contained within an oval-shaped inselberg that rises approximately 220m above surrounding plains.

The Gamsberg deposit is hosted within the Bushmanland Group of the Namaqualand Metamorphic Complex. The rocks within this complex were subjected to polyphase deformation and medium-to high-grade metamorphism. Figure 3-1 shows the location of the Gamsberg Mine and Figure 3-2 shows the regional stratigraphic column of the area.



Figure 3-1. Location of the study area.

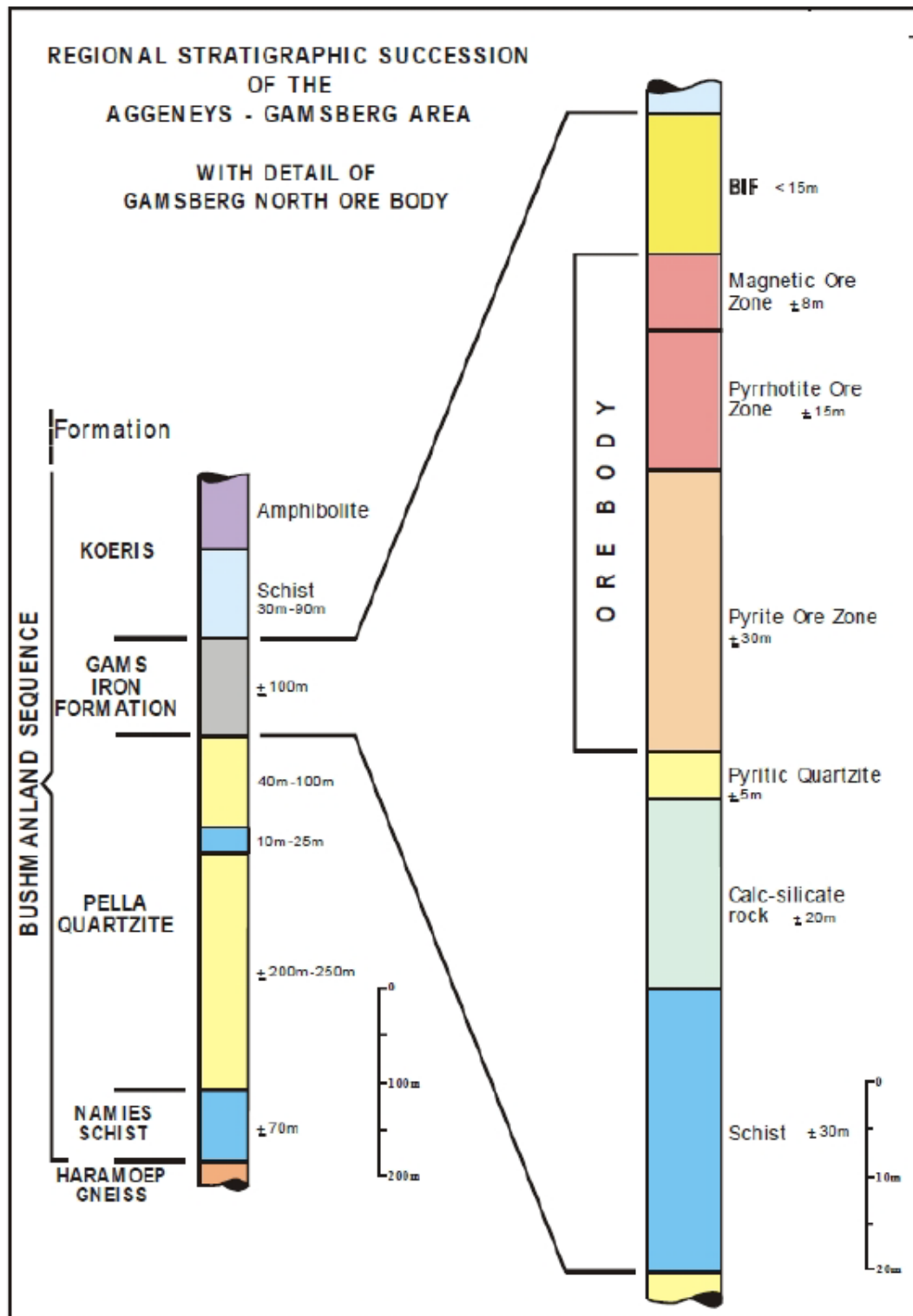


Figure 3-2. Typical regional stratigraphic column of the study area.

The Gamsberg deposit is structurally complex because of its high grade of metamorphism. Figure 3-3 shows the surface geological map and Figure 3-4 shows two cross-sections, highlighting the complexity.

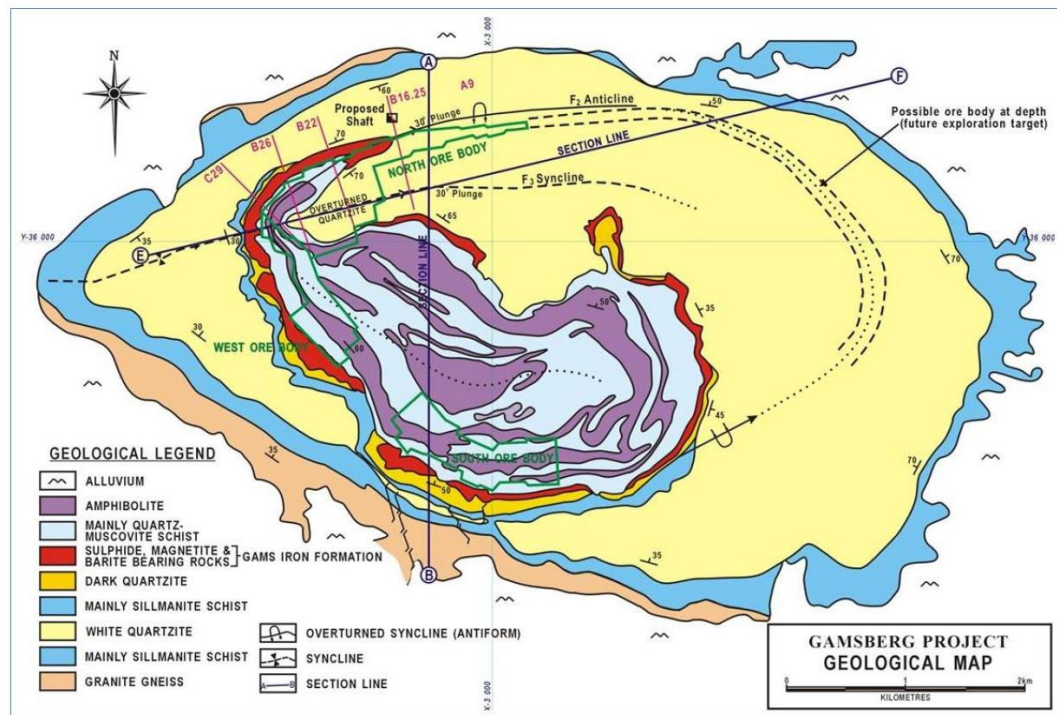


Figure 3-3. Surface geology of the study area

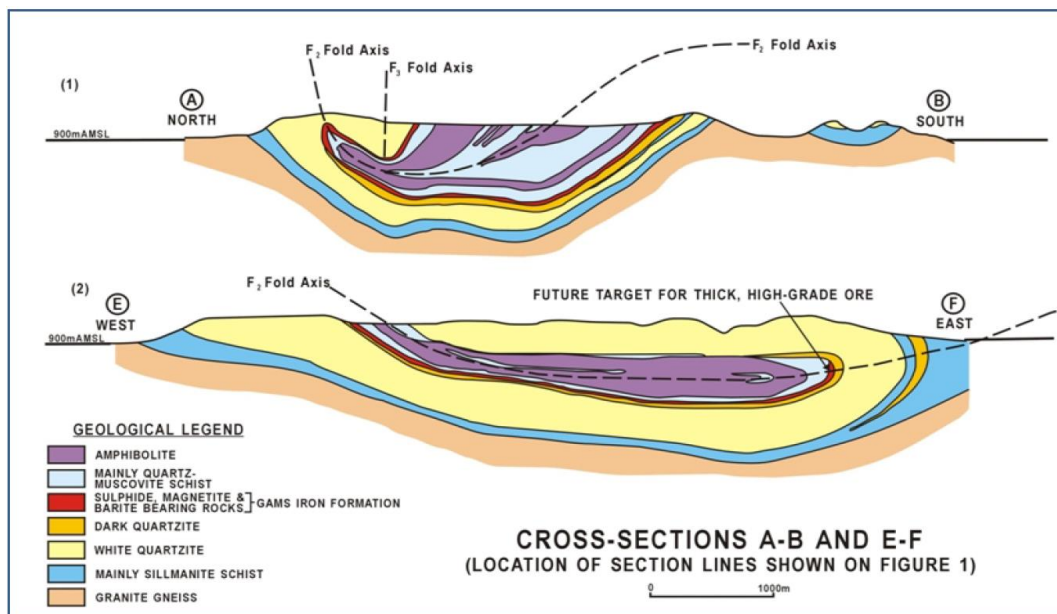


Figure 3-4. Cross sections of the geology for the study area.

From the cross-sections, an appreciation of the structural influences on the overall stability of the pit slopes can be observed. The importance of this study is the different rock types that are encompassed by these layers and the behaviour of the different rock types.

3.3 Research Design

The research design used a quantitative analysis, and further incorporated with a comparative observational study approach to compare the data. The goal was to quantitatively analyse both datasets – prepopulated rock mass classification data and actual slope performance monitoring data – to determine their relationship and evaluate whether empirical predictions can accurately forecast real-world rock mass behaviour in open-pit slopes. The quantitative analysis involved non-parametric statistical and visualization techniques to uncover the relationship between the datasets. The comparative observational study component allows for a detailed examination of how theoretical predictions align with real-world outcomes. This approach enabled the researcher to identify discrepancies between empirical models and actual slope behaviour, revealing limitations or areas for improvement in current predictive methodologies.

The primary objective of this research design is to assess the relationship between these two datasets and evaluate the predictive accuracy of empirical models in forecasting rock mass behaviour in open-pit slopes. By doing so, this study aims to bridge the gap between theoretical predictions and practical observations, potentially enhancing the reliability of slope stability assessments in open-pit mining operations. This study can lead to improved risk management strategies, more efficient mine planning and enhanced safety protocols in the mining industry.

3.4 Data Collection and Validation Process

The data collection process incorporated two primary sources of data:

1. Pre-populated rock mass classification database: This database contains historical data primarily collected through borehole core logging, downhole geophysics, field and laboratory tests. Key data points include the material

strength, fracture frequency, joint orientation and condition, rock mass classification and other geotechnical parameters.

2. Actual recorded monitoring data: This includes recorded deformation data gathered from slope monitoring equipment (Slope Stability Radar).

The data collection process was conducted in multiple phases. Initially, information was retrieved from the existing database to extract parameters associated with specific rock formations and geographical locations (specifically, the lithological units that comprise the slope surfaces in the region of interest). Figure 3-5 shows the locations of all the boreholes available for the study in relation to the pit outline.

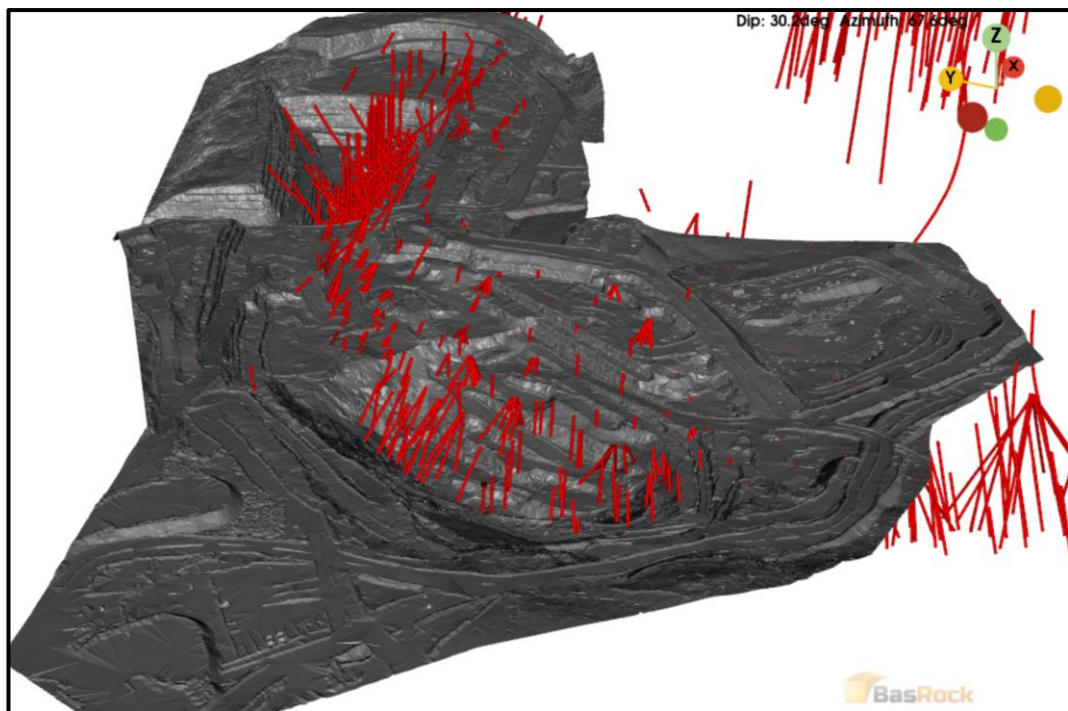


Figure 3-5. Borehole positions across the study area.

For the purposes of this study, data from two slope failure events were selected based on the selection criteria listed in Table 3-1.

Table 3-1. Selection criteria for slope failure events included in this study.

Event	Date	Pit and Location of Failure	Type of Failure	SSR Data Available	Geotechnical Logging & Rock Mass Classification Data Available	Lithological Unit	Selected for Study?
1	25/09/2022	West Pit – Western Wall	Planar	Yes	Yes	Schist	Yes
2	27/11/2023	West Pit – Northern Wall	Wedge	Yes	Yes	Schist	Yes
3	21/04/2021	East Pit – Southern Wall	Toppling Failure	No	Yes	Schist	No
4	06/06/2021	West Pit – Southern Wall		No	Yes	Planar	No

The Selection criteria required for this study were that SSR deformation data and RMR data were required. Thus, Events 1 and 2 were selected, which consisted of planar and wedge failures. Both failure events occurred within the schist layer. This means that data from the rock mass classification database for only the schist layer could be focused on.

Figure 3-6 shows the locations of events 1 and 2 plotted on a survey of the pit shell. The lithological layer (schist) in which the failures occurred is highlighted.

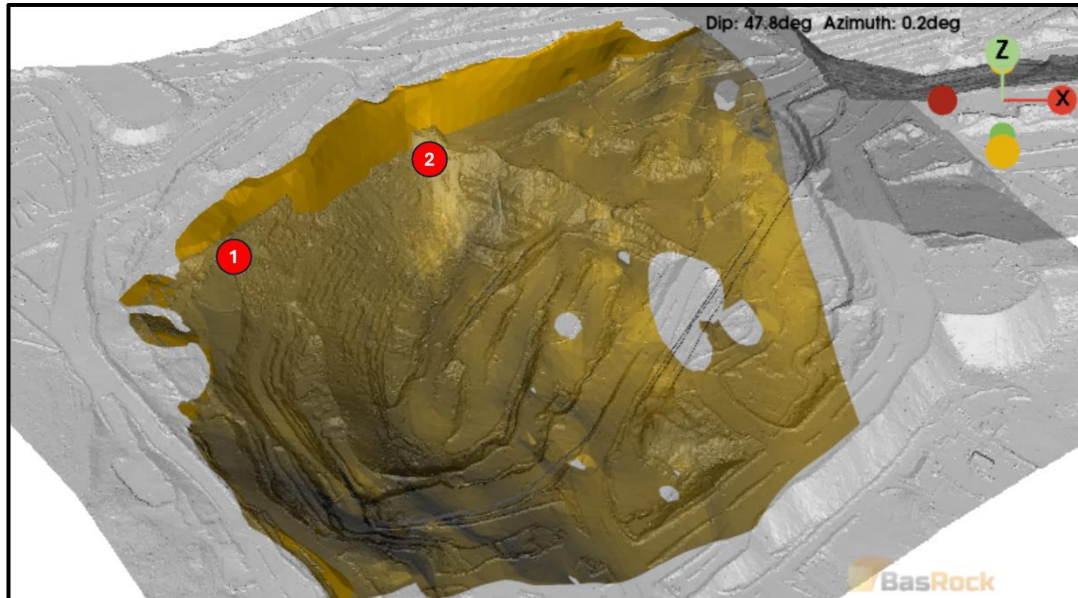


Figure 3-6. Location of failure events selected for this study.

To select only data applicable to the portion of the pit where events 1 and 2 occurred and within the relevant lithological layer only, borehole data that intersected the schist layer were selected. Figure 3-7 shows the boreholes available in the study area, from which a selection was made of boreholes that physically intersected the schist layer.

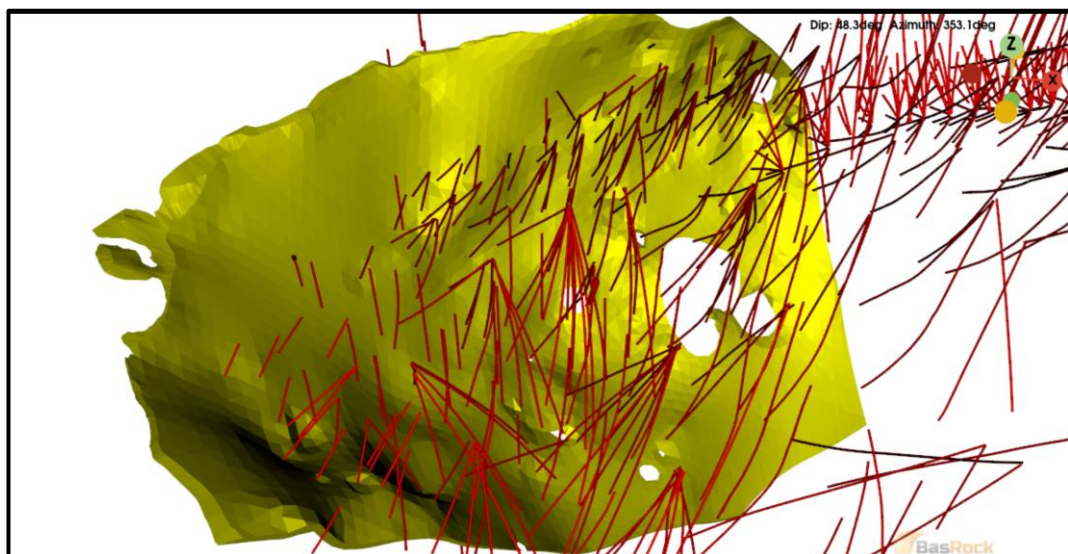


Figure 3-7. Borehole positions and directions in relation to the selected schist layer.

Data were further extracted from the boreholes to focus only on the selected intervals that intersected the relevant schist layer. Figure 3-8 shows the methodology used to ensure that only the relevant intervals were selected.

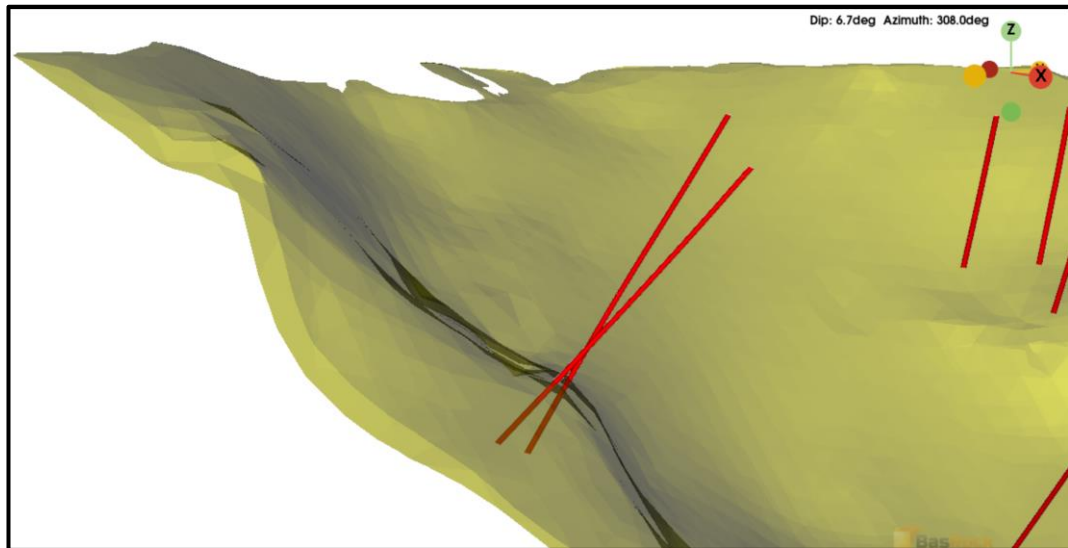


Figure 3-8. Verification of borehole intervals intersecting the schist layer.

The extraction criteria were used to select only variables directly applicable to rock mass behaviour and classification. Table 3-2 presents a sample of the extracted data. Appendix 1 lists the sample data extracted from the database.

Table 3-2. Sample of the extracted data from selected boreholes.

BH ID	Depth From	Depth to	Lith	RQD	ISRM Strength Code	RMR89	GSI	Q
GVD172	183.47	185.5	SCH	97	4.0	70	65	22
GVD185	99.5	101.2	SCH	52	4.0	59	54	8
GVD187	278.39	281.35	SCH	83	5.0	64	59	12
GVD187	281.35	284.35	SCH	97	5.0	70	65	26
GVD187	284.35	285.95	SCH	88	5.0	67	62	17
GVD190	210.8	212.55	SCH	97	5.0	75	70	43
GVD190	212.55	215.55	SCH	100	5.0	74	69	48
GVD190	215.55	218.55	SCH	100	5.0	73	68	45

From this data, the Rock Mass Rating (RMR) and Geological Strength Index (GSI) were extracted from all boreholes that intersect the specific schist layer. These data were grouped for further analysis to calculate the rock mass modulus and further strain calculations, from which the deformation values were calculated.

Building on the previous dataset, the rock strength database was used to extract the strength data for the applicable schist layer. A similar approach was adopted in that only the strength data from the relevant schist layer were analysed. The schist layer has the following strength properties:

- Uniaxial compressive strength (UCS): 103 MPa
- Poisson's Ratio: 0.24
- Elastic Modulus : 47.1 GPa

Finally, deformation data from two past failure events were extracted from the slope stability monitoring database. Figure 3-9 shows the typical deformation data extracted for a failure event from commercially available software used to analyse the data (Monitor IQ).



Figure 3-9. Typical deformation data (in millimetre) extracted from the slope monitoring database (GroundProbe).

A comparative analysis was employed to evaluate the relationship between actual measured data and empirically predicted values. A Z-test was utilized as the statistical method to determine whether there is a significant difference between the means of the two datasets. The Z-test is particularly useful in this context as it quantifies how far and in what direction a single data point deviates from the mean of a standardized distribution (Schober et al., 2021). By applying the Z-test, the correlation between the observed measurements and theoretical predictions can

could be assessed, thereby determining the accuracy and reliability of the empirical models.

3.5 Chapter Summary

This chapter describes the methodological steps in data extraction, monitoring and validation, ensuring a structured approach for correlating empirical and real-time deformation data in slope stability assessment.

4 ANALYSIS AND FINDINGS

4.1 Introduction

The results of the data analysis of the rock mass classifications and laboratory tests are discussed in Section 4.2 and the results of the slope stability monitoring data analysis are discussed in Section 4.3. A comparison and a final analysis of both datasets are presented in Section 4.4.

4.2 Rock Mass Classification and Laboratory Test Data Analysis

The data extracted from the two datasets, relating specifically to the schist layer, are summarized. Based on the analysis options selected from the literature, Bieniawski's (1989) Rock Mass Rating (RMR) and Hoek's Geological Strength Index (GSI). Table 4-1 presents the statistical summary of the values extracted from the database. Figure 4-1 shows a visual representation of the data, highlighting its spread. The full extracted data table is presented in Appendix 1.

Table 4-1. Summary of Rock Mass Classification Data

	RMR	GSI
Average	52	47
Standard Deviation	10.6	10.6
Minimum	32	27
Maximum	76	71
Number of Datapoints	152	152

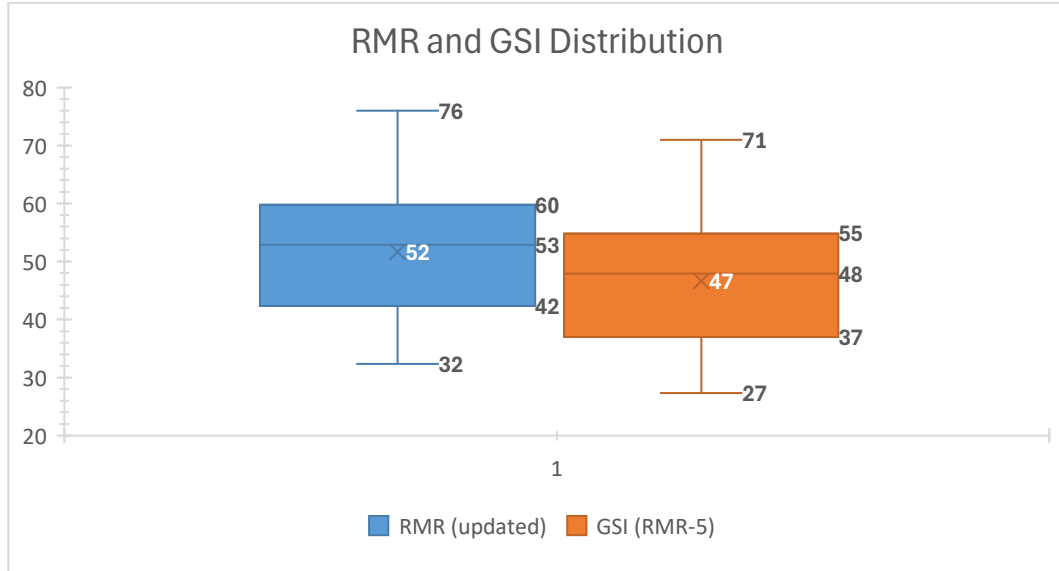


Figure 4-1. Comparison and Visualisation of RMR and GSI values for the schist layer on a Box Plot Graph.

Figure 4-1 illustrates the statistical distribution of the two datasets, highlighting the median, interquartile range (IQR), and potential outliers. The central line within each box represents the median value, while the edges of the box indicate the first and third quartiles. The whiskers extend to the minimum and maximum values within 1.5 times the IQR from the quartiles, and any points outside this range are considered outliers.

Using each individual RMR and GSI value, equations 3 and 4 were used to calculate the Rock Mass Modulus (E_{rm}):

$$E_{rm} = 10^{(RMR-10)/40}$$

Equation 3

where:

E_{rm} = Rock mass deformation modulus

RMR = Rock Mass Rating

$$E_{rm} = 0.33e^{0.064 \cdot GSI}$$

Equation 4

where:

E_{rm} = Rock mass deformation modulus

GSI = Geological Strength Index

From these calculations, a summary of the data is presented in Table 5 and the full list of the calculated values is presented in Appendix 2. Table 4-2 shows the data spread of the Rock Mass Modulus, calculated from the RMR and GSI values respectively.

Table 4-2. Summary of Rock Mass Modulus calculated values.

Erm from RMR		Erm from GSI	
Average	9.88		8.16
Standard Deviation	6.07		5.59
Minimum	2.72		1.90
Maximum	33.50		31.04

These calculations were used to determine the deformation modulus of the rock mass. Hooke's law was used to calculate the strain values from the rock mass modulus (Equation 5):

$$\varepsilon = \sigma/E$$

Equation 5

where:

E = Modulus of Elasticity. In this case Rock Mass Modulus

σ = stress (maximum stress; in this case, UCS)

ε = Strain

This calculation assumes that stress versus strain is linear, up to the moment of failure. Table 4-3 shows a summary of the calculated strain values and the full list of calculated values is provided in Appendix 2.

Table 4-3. Summary of Strain Values calculated from the RMR and GSI Rock Mass Modulus

Strain from Rock Mass Rating Values (mm/m)		Strain from Geological Strength Index Values (mm/m)
Average	14.90	19.57
Standard Deviation	8.83	12.82
Minimum	3.07	3.32
Maximum	37.93	54.21

The last step in the analysis was to use the approach of Coetsee et al. (2020) to calculate the deformation data (Equation 6):

$$\Delta x = \varepsilon/H$$

Equation 6

The values first calculated were based on the Rock Mass Rating and Geological Strength Index. For comparison, the same calculation was done for the actual recorded deformation data.

Table 4-4 lists the calculated deformation data from the strain values determined from the RMR and GSI. A full list of the calculated values is presented in Appendix 4.

Table 4-4. Calculated deformation values for Strain from RMR and GSI

	$\Delta x = \text{strain/slope height}$ RMR (mm)	$\Delta x = \text{strain/slope height}$ GSI (mm)
Mean	42	53
Standard Deviation	29	43
Minimum	10.25	11.06
Maximum	126.44	180.69

For these calculations, the strain is assumed to be surface strain and not the rock mass strain, as per Brox & Newcomen (2003). The strain direction, or Δx direction is normal to the failure surface and the slope height indicates the height of the anticipated failure and not the entire slope height (S Coetsee, personal communication, 06 November 2024).

The calculated deformation data were then used for comparison with the actual deformation data recorded.

4.3 Slope Stability Monitoring Data Analysis

As per the selection criteria, Events 1 and 2 were included in this study. For events 1 and 2, slope stability monitoring data were available.

Event 1 occurred on September 25, 2021. This was classified as a multiple bench scale (two benches of 15m each) planar failure. As per the mine's standard at the time, a ground-based slope stability radar (SSR) was used to monitor the high wall.

The deformation data leading up to failure were extracted from the slope monitoring database.

Figure 4-2 shows the typical data representation available from the commercially available software used to analyse the monitoring data.



Figure 4-2. Slope stability radar deformation data for Event1.

Event 2 occurred on November 27, 2023. This was classified as a multiple bench-scale wedge failure (two benches of 15m each). Figure 4-3 shows the data representation of this event.

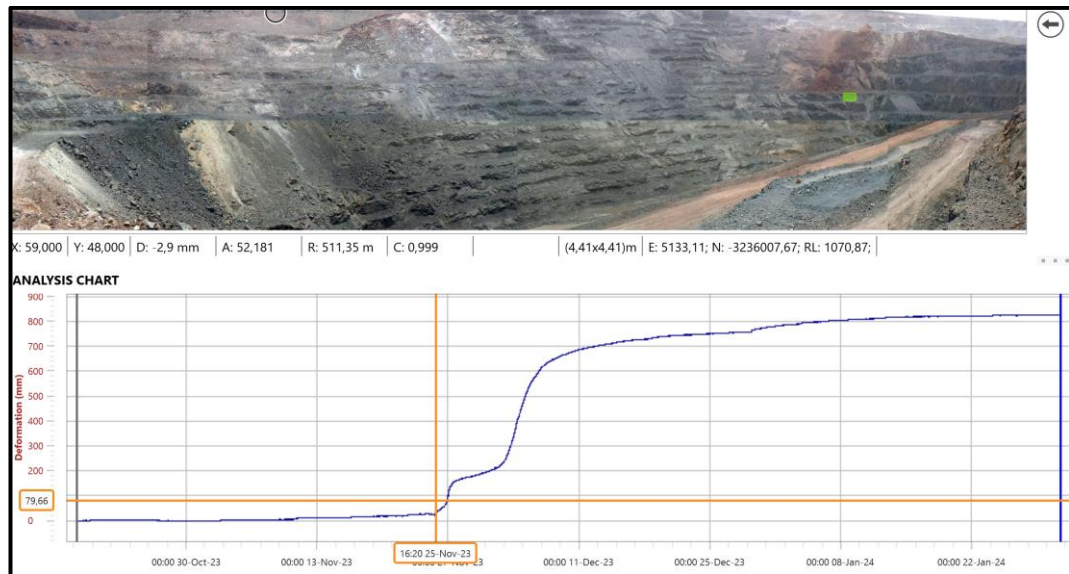


Figure 4-3. Slope Stability Radar Deformation Data Event 2.

The measured deformation data for Event 1 was 22.84 mm and for Event 2 69.79 mm. As per Brox and Newcomen (2003), deformation data were used to calculate the strain percentage. The result of this analysis is shown in Table 4-5.

Table 4-5. Strain percentages calculated from actual measurements.

Strain % From Actual Measurement – Planar Failure	Strain % From Actual Measurement – Wedge Failure
0.03%	0.03%

4.4 Data Comparison and Test For Correlation

The analysis compared the actual measured deformation data with empirically determined predictions using statistical methods and visual representations. Firstly, the empirical data was input into a histogram, to determine the distribution. Figure 4-4 shows this histogram, showing that a normal distribution is applicable, evident by the bell-shaped curve of the data.

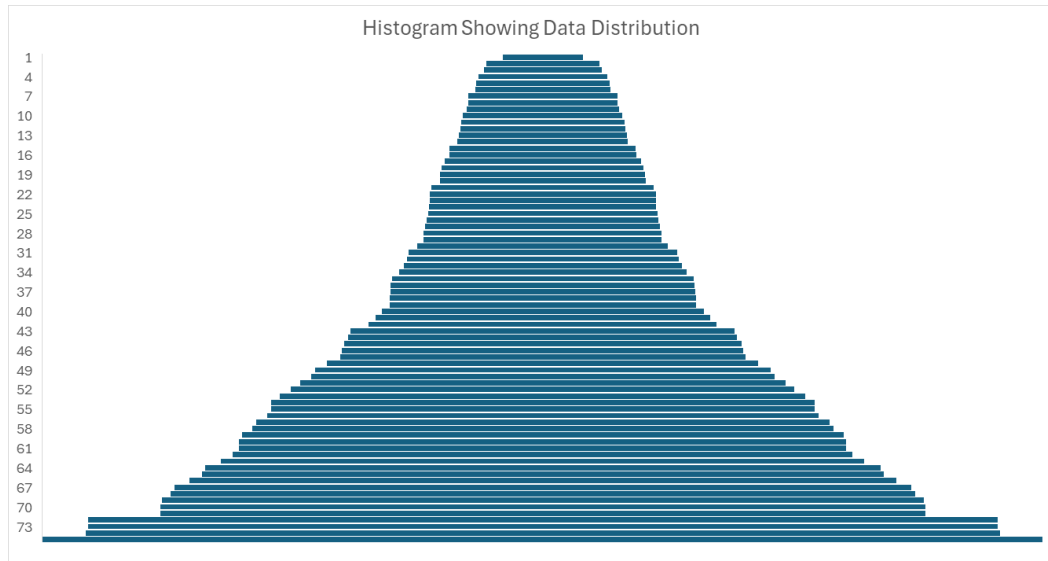


Figure 4-4. Histogram showing normally distributed empirical data

To assess the correlation between the two datasets, a Z-test was conducted to evaluate the relationship between the actual measurements and empirically predicted values. A Z-score quantifies how far and in what direction a single data point deviates from the mean of a standardized distribution, measured in units of standard deviation.

The process of conducting a Z-Test begins with formulating the null hypothesis (H_0), which assumes no significant difference, and the alternative hypothesis (H_a), which assumes a significant difference. The significance level (α) is typically set at 0.05, representing a 5% risk of concluding that a difference exists when there is no actual difference.

Next, the Z-score is calculated, and the critical value is then obtained from the standard normal distribution table corresponding to the chosen significance level. The following equation is used to calculate the Z Score:

$$Z = \frac{x - \mu}{\sigma / \sqrt{n}}$$

Equation 7

Where:

$\bar{x}$ = sample mean (in this case the actual measurement)

μ = population mean (in this case the mean of the empirical dataset)

σ = population standard deviation (in this case the standard deviation of the empirical dataset)

n = sample size (in this case not explicitly included in the calculation ,as it is implicitly used in the calculation of the mean)

For a two-tailed test at $\alpha = 0.05$, the critical values are ± 1.96 . The calculated Z-score is then compared to the critical value. If the absolute value of the Z-score exceeds the critical value, the null hypothesis is rejected, indicating a significant difference between the means. If the null hypothesis is not rejected, it suggests no significant difference between the means

For Event 1, the Z-test yielded a score of -0.91. In this study, a Z-score of -0.91 indicates that the observed value is 0.91 standard deviations below the mean. Negative Z-scores reflect values below the mean, while positive Z-scores represent values above the mean. This further indicates that the null hypotheses is accepted.

A Z-score of -0.91 places the observed value 0.91 standard deviations below the mean of the distribution. Referring to the Z-distribution table, this corresponds to a cumulative probability of 18.19%, meaning the observed value is greater than approximately 18.19% of the distribution.

Given that it lies within one standard deviation of the mean ($-1 \leq Z \leq 1$), the measured value can be considered a good fit to the empirical dataset. Figure 4-5 shows a visual representation of the Z value distribution on a standard, normal distribution chart.

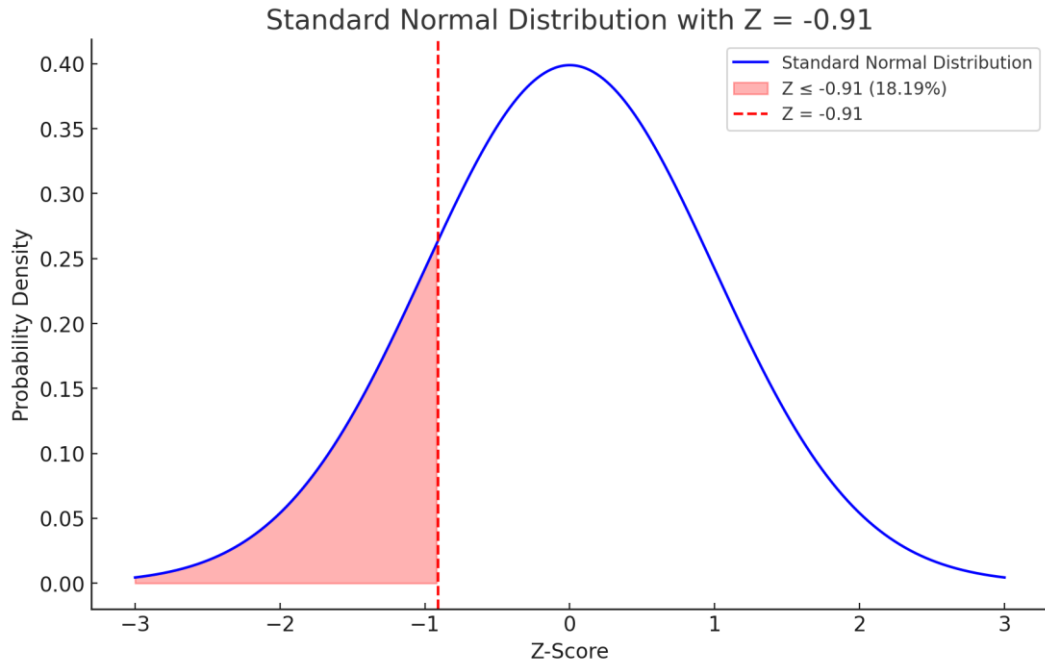


Figure 4-5. Visual representation of the Z-Value distribution for Event 1.

The data used to calculate this Z value was specifically related to that of Event 2, and Equation 7 as described earlier was used. Appendix 3 tables the different data values for Event 1 and Event 2 used in these calculations. For Event 2, the Z-test yielded a score of 0.68. In this study, a Z-score of 0.68 indicates that the observed value is 0.68 standard deviations above the mean. The Z-score places the observed value 0.68 standard deviations above the mean of the distribution. Referring to the Z-distribution table, this corresponds to a cumulative probability of 75.17%, meaning approximately 75.17% of the values in the distribution were below this point. Conversely, 24.83% of the values were above it. Given that it lies within one standard deviation of the mean ($-1 \leq Z \leq 1$), the measured value can be considered a good fit to the empirical dataset. Figure 4-6 shows a visual representation of the Z value distribution on a standard, normal distribution chart.

As a visual comparison, both Z Scores are presented on a distribution graph in Figure 4-7.

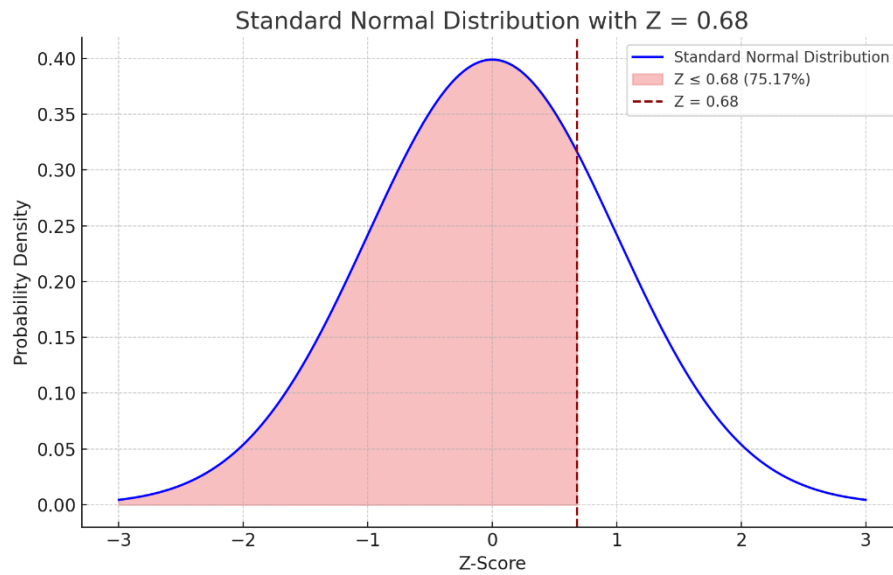


Figure 4-6. Visual representation of the Z-Value distribution for Event 2.

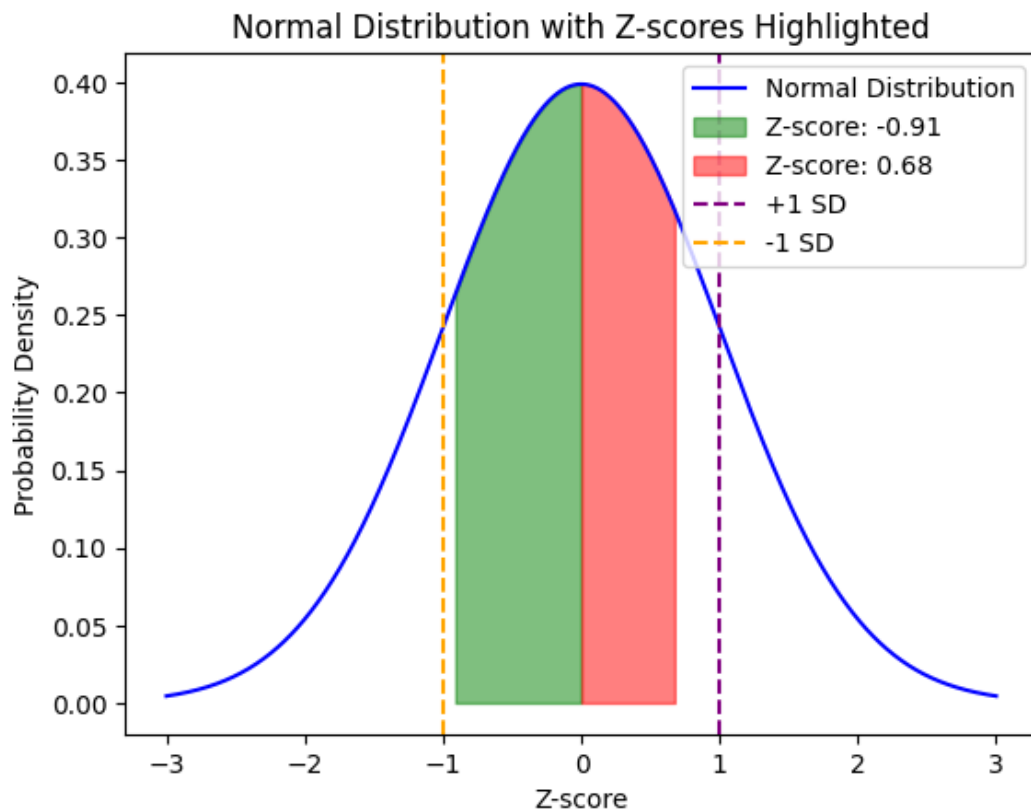


Figure 4-7. Visual representation of the actual measurements for Event 1 and Event 2 in comparison with the empirical data.

Figure 4-7 shows the following:

- Data distribution of the empirical data (blue line),
- The Z-Score of -0.91 for Event 1 (Green shaded area below distribution),
- The Z-Score of 0.68 for Event 2 (Red shaded area below distribution),
- The standard deviation from the mean.

From this graph, it can be seen that both Z-scores fall within 1 standard deviation of the mean. This means that for both Event 1 and Event 2, the Null Hypothesis is accepted (significance value of 0.05).

To complement the statistical analysis, the data were also visualized to provide a more intuitive understanding of the relationship between the empirical predictions and recorded values. This visual representation allows for a clear comparison of the range of empirically predicted data with actual observed values. Figure 4-8 illustrates this comparison for Event 1 and Event 2 with the empirical data.

This dual approach of statistical testing and visual representation offers a comprehensive view of how well the empirical predictions align with actual measurements, enabling a more thorough interpretation of the deformation data for both events.

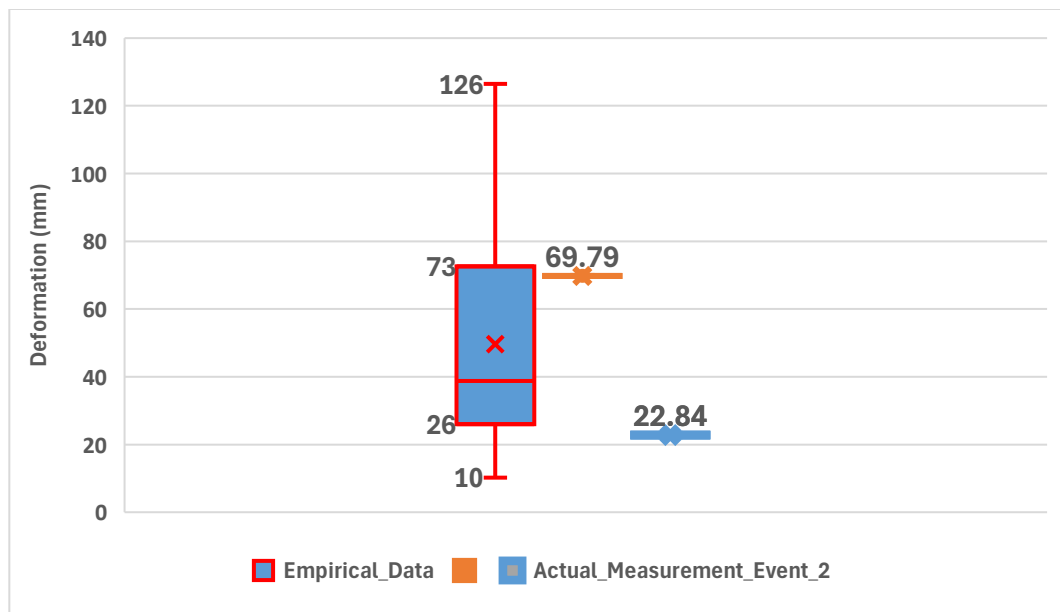


Figure 4-8. Visual representation of the actual measurements for Event 1 and Event 2 in comparison with the empirical data.

Further analysis was performed, where the deformation data recorded were converted back to strain, as per the work of Newcomen and Brox (2003). Using the original chart produced in their study, where the rock mass rating data were plotted against the pit wall strain at failure, both Event 1 and Event 2 data were plotted. By plotting the results, it can be seen that both events plot well within the range (upper and lower collapse boundary) for planar failures, as compared to the

original work of Newcomen and Brox (2003). Figure 4-9 shows the two case studies evaluated in this research project, plotted on the original chart of Newcomen and Brox (2003).

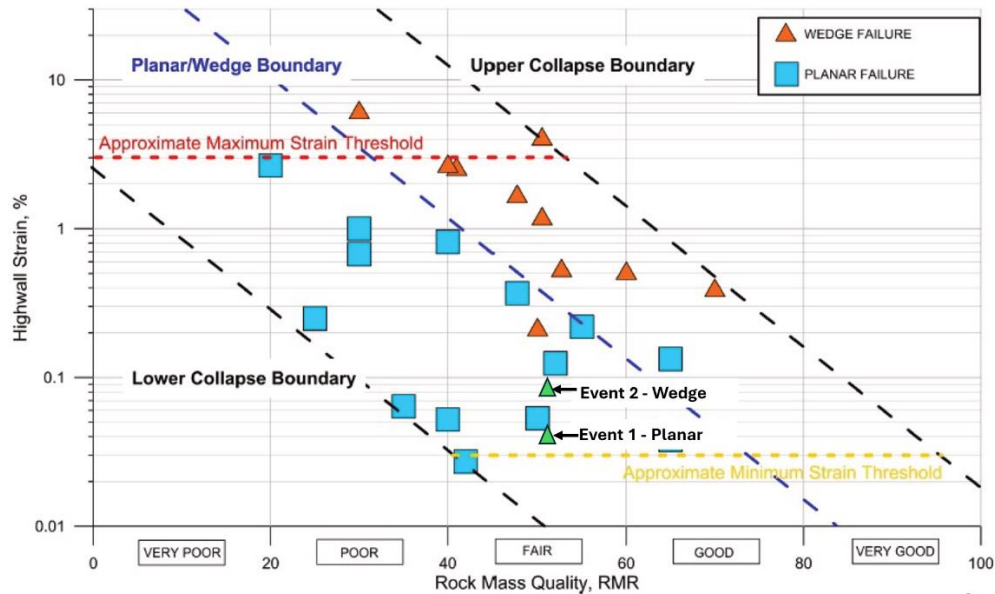


Figure 4-9. Strain and RMR data for Event 1 and Event 2 plotted against the original published work of Newcomen & Brox (2003).

4.5 Chapter Summary

Chapter 4 presents a comparative analysis of actual measured deformation data against empirically determined predictions using statistical methods and visual representations. Results indicate a significant correlation between empirical and real-time deformation values. The findings validate the use of combined datasets to enhance slope stability predictions for open-pit mines.

The study revealed that the recorded deformation data falls within one standard deviation of the empirical dataset's mean value. This indicates a good fit of the data.

The recorded displacement value for Event 1 (Z-score of -0.91) indicates that the actual value is slightly less than the average value predicted by the empirical

dataset. This indicates that the slope may become unstable before the average empirical deformation is reached.

In comparison Event 2 (Z-score of 0.68) shows that the recorded displacement for a wedge failure is slightly more than the average value of the empirical dataset. Comparing the empirical deformation values with actual recorded values show that in the two particular cases there is very good correlation. Consistent values indicate that the empirical model is reliable for predicting slope stability within the limitations of this .

This study demonstrates the value of combining statistical analysis with visual representation for interpreting deformation data. This dual approach provides a more comprehensive understanding of slope behaviour and can help identify patterns or anomalies that may not be apparent through either method alone.

This study has the following direct implications for the Gamsberg Mine:

- In terms of risk management, the findings suggest that the mine's geotechnical engineers can use actual recorded deformation values to plot against the empirically determined values. If a variation of more than one standard deviation is recorded, further analysis is required.
- In terms of monitoring protocols: There is a clear need for continuous, real-time monitoring systems to complement empirical predictions.
- Furthermore, this study highlights the importance of calibrating empirical models for site-specific conditions. Mining operations should regularly update their geotechnical models based on the observed data to improve prediction accuracy.
- Finally, this study suggests that in cases where a detailed geotechnical model is available, deformation threshold values for slope monitoring can be determined empirically with reasonable accuracy. This is not only important for the Gamsberg Mine but can be transferred to the broader mining industry as well.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter concludes the study by summarizing the research findings, contributions, limitations and recommendations for future work to enhance slope stability assessments.

5.2 Summary of Chapters

This report is structured across five key chapters, each addressing the aspects of rock classification, slope monitoring and comparative data analysis. The summarized findings reinforce the study's objectives of bridging empirical and real-time data to improve stability predictions.

5.3 Research Observations

The research revealed that empirical deformation threshold values, if based on a quality geotechnical database can be used to set slope stability monitoring threshold values within a relative degree of accuracy at the onset of a mining project. This shows that there is a good correlation between the two datasets used and that empirical predictions can forecast real-world rock mass behaviour in open pit slopes.

5.3.1 Key findings and observations

Based on the analysis presented in Section 4, the following conclusions can be drawn:

- The empirical predictions showed degrees of accuracy within one standard deviation of the actual measured deformation data.
- Event 1 demonstrated a slight negative deviation from the predictions, as evidenced by a Z-score of -0.91. A negative value shows the observation lies below the mean value. This relates to a more than 95% confidence level, as the corresponding Z score would be ± 1.96 .

- Event 2 demonstrated a slight positive deviation from the predictions, as evidenced by a Z-score of 0.68. A positive value shows the observation lies above the mean value. This relates to a more than 95% confidence level, as the corresponding Z score would be ± 1.96 .
- The use of Z-tests provides a quantitative measure of the correlation between empirical predictions and actual measurements.
- The findings suggest empirical predictions may be useful and that this could accurately reflect real-world deformation events.
- These results highlight the importance of comparing empirical models with actual measurements to validate and improve the predictive capabilities of deformation studies.
- This analysis provides a foundation for refining existing empirical models and developing novel approaches to enhance the accuracy of deformation predictions.

5.4 Research Limitations

Based on the outcomes of study, the following key research limitations were observed:

- Limited sample size: This study focused on only two slope failure events that met the selection criteria. The small sample size may limit the generalizability of the findings.
- Restricted geological context: The analysis was confined to failures that occurred within a single lithological unit (schist layer). This narrow focus may not capture the full range of rock mass behaviours across different geological settings.
- Data availability constraints: Some potentially relevant slope failure events were excluded from the study because of a lack of SSR data or geotechnical logging data. Selective inclusion could have introduced bias into the results.
- Reliance on preexisting databases: The study relied on prepopulated databases, which may have inherent limitations in terms of data quality, completeness, or consistency.

- Technological limitations: The accuracy of slope monitoring equipment (e.g., ground-based radar) may be affected by environmental factors, potentially introducing errors in the deformation data. Additional monitoring data, such as prisms installed on the high wall prior to failure, could overcome these limitations.
- Focus on specific failure types: This study primarily examined planar and wedge failures, potentially overlooking other failure mechanisms.
- Empirical method limitations: This research acknowledges potential biases in empirically derived thresholds, which were dependent on the quality of data and engineer expertise.

5.5 Recommendations

Based on the outcomes of the research, the following recommendations are made:

- Expand the sample size: Include a larger number of failure events across diverse geological settings to enhance the generalizability of the findings.
- Conduct long-term trend analysis: Examine long-term deformation trends and their correlation with empirical predictions to potentially elucidate patterns not discernible in short-term studies.
- Develop a system for real-time analysis of monitoring data to expeditiously identify deviations from predicted behaviour and facilitate prompt response to potential instabilities.
- Study environmental factors: Investigate the influence of environmental factors (e.g., precipitation and temperature fluctuations) on the relationship between empirical predictions and actual deformation behaviour.
- Compare prediction methods: Conduct comparative studies on the accuracy of various prediction methods (empirical, numerical and probabilistic) across different geological settings to identify the most reliable approaches for specific conditions.
- Optimize thresholds: Develop optimized site-specific deformation thresholds that balance safety considerations with operational efficiency.
- Analyse failure mechanisms: Conduct comprehensive studies of different failure mechanisms (rock mass failures, planar, wedge, toppling, circular

and non-circular) and their relationship to empirical predictions to develop more accurate modelling techniques.

- Integrate emerging technologies: Investigate the potential integration of emerging technologies (e.g., satellite-based InSAR and drone-based photogrammetry) with ground-based monitoring to enhance prediction accuracy and coverage.

5.6 Recommendations for Future Research Work

The following recommendations and considerations for future research were derived based on the outcomes of this study:

- Influence of Environmental Factors: Further research should explore how environmental factors (e.g., rainfall and temperature fluctuations) affect the relationship between empirical predictions and actual deformation behaviour.
- Comparative Analysis of Prediction Methods: Conduct studies comparing the accuracy of various prediction methods (empirical, numerical and probabilistic) across different geological settings to identify the most reliable approaches for specific conditions.
- Failure Mechanism Analysis: In-depth studies of different failure mechanisms (rock mass failures, planar, wedge and toppling) and their relationship to empirical predictions could lead to more accurate modelling techniques.
- Investigate the potential of machine-learning algorithms to improve deformation predictions.
- Conduct in-depth studies on the relationship between different failure mechanisms and empirical predictions.
- Research the integration of satellite-based InSAR and drone-based photogrammetry with ground-based monitoring.
- Develop methods to optimize site-specific deformation thresholds that balance safety with operational efficiency.
- Explore long-term deformation trends and their correlation with empirical predictions to identify patterns not visible in short-term studies.

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APPENDIX 1. Extracted drill-hole database

BH ID	Depth From	Depth to	Lith	RQD	Weathering	ISRM Strength Code	RMR ₉₀	GSi	Qcm	Qtm	Q	N'	Faults	Weighted Fracture Jv	Estimated Intact UCS (Mpa)	Estimated Rock Mass UCS (Mpa)	RMR (updated) Incl Groundwater	GSi _{90mm-30}
GVD172	183.47	185.5	SCH	97	2	4.0	70	65	19	0.5	22	109		6	90	19	67	62
GVD172	185.5	185.66	SCH	100	2	4.0	72	67	20	0.6	84	431		0	90	20	72	67
GVD172	242.79	245.5	SCH	89	2	4.0	63	58	15	0.3	11	51		8	90	15	62	57
GVD172	245.5	248.5	SCH	89	2	4.0	65	60	16	0.3	13	61		11	90	16	64	59
GVD172	248.5	251.5	SCH	100	2	4.0	69	64	19	0.5	20	101		7	90	19	66	61
GVD172	251.5	252.4	SCH	100	2	4.0	70	65	19	0.5	21	104		6	90	19	66	61
GVD172	255.71	257.5	SCH	96	2	4.0	66	61	17	0.4	19	95		5	90	17	64	59
GVD172	257.5	260.5	SCH	97	2	4.0	67	62	17	0.4	18	88		6	90	17	65	60
GVD172	260.5	262.58	SCH	81	2	4.0	63	58	15	0.3	9	42		17	90	15	61	56
GVD172	277.07	277.5	SCH	85	2	4.0	65	60	16	0.3	19	92		2	90	16	65	60
GVD172	277.5	278.5	SCH	100	2	4.0	68	63	18	0.4	21	105		6	90	18	66	61
GVD185	20.01	20.34	SCH	91	2	3.0	68	63	8	0.2	69	353		0	40	8	67	62
GVD185	20.34	21.65	SCH	85	2	3.0	64	59	7	0.1	17	81		2	40	7	62	57
GVD185	21.65	23.31	SCH	78	2	3.0	60	55	6	0.1	7	34		8	40	6	58	53
GVD185	23.31	24	SCH	35	2	3.0	51	46	4	0.0	4	16		6	40	4	50	45
GVD185	24	26.2	SCH	65	2	3.0	58	53	5	0.1	4	18		19	40	5	54	49
GVD185	26.2	29.2	SCH	65	2	3.0	58	53	6	0.1	5	22		11	40	6	55	50
GVD185	29.2	32.2	SCH	38	3	3.0	47	42	4	0.0	2	5		29	40	4	45	40
GVD185	32.2	32.66	SCH	98	2	3.0	65	60	7	0.1	12	58		15	40	7	60	55
GVD185	87.29	89.2	SCH	73	3	4.0	57	52	12	0.1	5	22		20	90	12	57	52
GVD185	89.2	92.2	SCH	41	3	4.0	52	47	10	0.1	4	14		17	90	10	52	47
GVD185	92.2	95.2	SCH	48	3	4.0	53	48	11	0.1	4	17		15	90	11	53	48
GVD185	95.2	95.35	SCH	0	3	4.0	39	34	6	0.0	1	4	1	67	90	6	40	35
GVD185	99.5	101.2	SCH	52	2	4.0	59	54	13	0.2	8	38		6	90	13	58	53
GVD185	104.31	104.89	SCH	28	3	4.0	45	40	7	0.0	2	8		37	90	7	46	41
GVD185	107.74	110	SCH	68	2	4.0	61	56	14	0.2	10	45		5	90	14	60	55
GVD187	278.39	281.35	SCH	83	2	5.0	64	59	28	0.5	12	56		22	160	28	65	60
GVD187	281.35	284.35	SCH	97	2	5.0	70	65	34	0.9	26	131		7	160	34	70	65
GVD187	284.35	285.95	SCH	88	2	5.0	67	62	30	0.7	17	85		13	160	30	68	63
GVD190	0	1.14	SCH	66	4	2.0	52	47	1	0.0	35	177		0	10	1	54	49
GVD190	1.14	2.73	SCH	100	4	2.0	60	55	2	0.0	12	55		2	10	2	57	52
GVD190	2.73	4	SCH	88	3	3.0	62	57	6	0.1	52	265		0	40	6	64	59
GVD190	4	5.64	SCH	91	3	3.0	65	60	7	0.1	15	70		2	40	7	63	58
GVD190	5.64	7	SCH	95	3	3.0	63	58	7	0.1	13	61		3	40	7	61	56
GVD190	7	8.6	SCH	94	3	3.0	62	57	6	0.1	11	49		4	40	6	60	55
GVD190	8.6	10	SCH	100	3	3.0	65	60	7	0.1	10	46		8	40	7	60	55
GVD190	10	11.7	SCH	82	3	3.0	58	53	5	0.1	7	30		7	40	5	56	51
GVD190	11.7	13.79	SCH	42	3	3.0	50	45	4	0.0	10	47		1	40	4	52	47
GVD190	16.21	17.3	SCH	89	3	4.0	60	55	14	0.2	10	45		5	90	14	61	56
GVD190	21.97	23.55	SCH	37	3	4.0	51	46	10	0.1	15	75		1	90	10	56	51
GVD190	23.55	26.55	SCH	70	3	4.0	58	53	12	0.2	9	39		4	90	12	59	54
GVD190	26.55	29.55	SCH	77	3	4.0	60	55	14	0.2	9	41		6	90	14	60	55
GVD190	29.55	32.55	SCH	89	3	4.0	61	56	14	0.2	18	88		2	90	14	63	58
GVD190	32.55	33.2	SCH	77	3	4.0	61	56	14	0.2	50	252		0	90	14	65	60
GVD190	210.8	212.55	SCH	97	2	5.0	75	70	40	1.4	43	219		5	160	40	73	68
GVD190	212.55	215.55	SCH	100	2	5.0	74	69	39	1.3	48	241		2	160	39	74	69
GVD190	215.55	218.55	SCH	100	2	5.0	73	68	36	1.1	45	226		2	160	36	73	68
GVD190	218.55	220.74	SCH	99	2	5.0	74	69	39	1.3	42	212		3	160	39	73	68
GVD190	237.69	239.55	SCH	100	2	4.0	71	66	20	0.6	46	235		1	90	20	71	66
GVD190	239.55	242.55	SCH	94	2	4.0	69	64	19	0.5	45	230		1	90	19	71	66
GVD190	242.55	245.55	SCH	95	2	4.0	67	62	17	0.4	18	90		4	90	17	65	60
GVD190	245.55	248.55	SCH	97	2	4.0	69	64	18	0.4	24	121		3	90	18	67	62
GVD190	248.55	251.55	SCH	97	2	4.0	70	65	19	0.5	21	102		8	90	19	66	61
GVD190	251.55	253.47	SCH	94	2	4.0	66	61	17	0.4	14	70	1	11	90	17	64	59

**APPENDIX 2. Calculated Rock Mass Modulus (E_{rm})
from RMR and GSI data and Calculated Strain for each**

Rock Mass Modulus from Rock Mass Rating Values	Rock Mass Modulus from Geological Strength Index Values	Strain From Rock Mass Modulus based on Rock Mass Ratings	Strain From Rock Mass Modulus based on Geological Strength Index
13.78	11.57	7.47	8.91
13.19	11.02	7.81	9.35
4.47	3.30	23.06	31.17
4.47	3.30	23.06	31.17
4.73	3.52	21.77	29.24
6.76	5.24	15.24	19.67
3.55	2.56	29.03	40.26
4.66	3.47	22.08	29.70
11.93	9.85	8.63	10.46
16.10	13.75	6.40	7.49
16.51	14.13	6.24	7.29
11.99	9.91	8.59	10.40
8.98	7.18	11.47	14.34
2.99	2.11	34.50	48.78
4.99	3.74	20.63	27.54
3.68	2.67	27.95	38.61
6.98	5.43	14.76	18.98
3.56	2.57	28.92	40.09
6.82	5.29	15.10	19.47
4.99	3.74	20.65	27.57
6.29	4.84	16.37	21.30
8.85	7.07	11.64	14.57
16.43	14.06	6.27	7.33
19.98	17.48	5.15	5.89
7.79	6.14	13.22	16.78
11.54	9.49	8.92	10.85
9.96	8.06	10.34	12.77
13.39	11.20	7.69	9.20
23.90	21.33	4.31	4.83
20.18	17.67	5.10	5.83
20.99	18.46	4.91	5.58
15.89	13.55	6.48	7.60
11.38	9.34	9.05	11.02
11.68	9.62	8.82	10.70
5.16	3.88	19.95	26.54
8.88	7.10	11.59	14.51

18.10	15.66	5.69	6.58
3.98	2.91	25.87	35.42
3.65	2.64	28.25	39.06
2.97	2.10	34.70	49.10
4.22	3.10	24.43	33.23
4.51	3.34	22.83	30.82
8.10	6.41	12.71	16.08
9.44	7.59	10.91	13.57
14.51	12.24	7.10	8.41
22.87	20.31	4.50	5.07
5.85	4.46	17.59	23.07
2.72	1.90	37.93	54.21
4.02	2.94	25.65	35.08
3.84	2.79	26.85	36.91
7.06	5.50	14.58	18.73
9.73	7.85	10.59	13.11
14.44	12.18	7.13	8.45
18.10	15.66	5.69	6.58
8.86	7.07	11.63	14.56
10.08	8.17	10.22	12.61
12.17	10.07	8.46	10.23
5.39	4.07	19.12	25.31
8.41	6.68	12.24	15.42
11.39	9.35	9.04	11.01
4.38	3.23	23.53	31.87
13.15	10.98	7.83	9.38
6.68	5.17	15.41	19.91
5.96	4.55	17.29	22.63
4.92	3.68	20.94	28.01
5.59	4.24	18.42	24.28
11.98	9.90	8.60	10.40
16.96	14.56	6.07	7.07
3.55	2.56	29.03	40.26
33.50	31.04	3.07	3.32
11.79	9.72	8.74	10.59
17.72	15.29	5.81	6.74
8.92	7.13	11.55	14.45
10.81	8.82	9.53	11.67
2.99	2.11	34.50	48.78

APPENDIX 3. Strain calculations form Rock Mass Modulus

Empirically determined Displacement Value (mm)	Event 1 - Actual Measurement (mm)	Event 2 - Actual Measurement (mm)
24.91	22.84	69.79
26.02	22.84	69.79
76.86	22.84	69.79
76.86	22.84	69.79
72.56	22.84	69.79
50.79	22.84	69.79
96.76	22.84	69.79
73.60	22.84	69.79
28.78	22.84	69.79
21.32	22.84	69.79
20.80	22.84	69.79
28.63	22.84	69.79
38.24	22.84	69.79
115.00	22.84	69.79
68.77	22.84	69.79
93.18	22.84	69.79
49.20	22.84	69.79
96.39	22.84	69.79
50.34	22.84	69.79
68.82	22.84	69.79
54.57	22.84	69.79
38.79	22.84	69.79
20.90	22.84	69.79
17.18	22.84	69.79
44.05	22.84	69.79
29.75	22.84	69.79
34.46	22.84	69.79
25.65	22.84	69.79
14.36	22.84	69.79
17.01	22.84	69.79
16.36	22.84	69.79
21.61	22.84	69.79
30.18	22.84	69.79
29.39	22.84	69.79
66.50	22.84	69.79
38.64	22.84	69.79
18.97	22.84	69.79

86.24	22.84	69.79
94.16	22.84	69.79
115.68	22.84	69.79
81.42	22.84	69.79
76.10	22.84	69.79
42.37	22.84	69.79
36.38	22.84	69.79
23.67	22.84	69.79
15.01	22.84	69.79
58.64	22.84	69.79
126.44	22.84	69.79
85.49	22.84	69.79
89.49	22.84	69.79
48.61	22.84	69.79
35.28	22.84	69.79
23.77	22.84	69.79
18.96	22.84	69.79
38.77	22.84	69.79
34.06	22.84	69.79
28.21	22.84	69.79
63.74	22.84	69.79
40.81	22.84	69.79
30.15	22.84	69.79
78.42	22.84	69.79
26.10	22.84	69.79
51.37	22.84	69.79
57.64	22.84	69.79
69.81	22.84	69.79
61.41	22.84	69.79
28.65	22.84	69.79
20.25	22.84	69.79
96.76	22.84	69.79
10.25	22.84	69.79
29.12	22.84	69.79
19.38	22.84	69.79
38.50	22.84	69.79
31.77	22.84	69.79
115.00	22.84	69.79

Mean Displacement of Empirical Data (mm)	49.65
Standard Deviation of the mean (mm)	29.23
Z Score of Event 1	-0.918

Strain % from Actual Measurement - Event 1	0.03%
Z Score of Event 2	0.68
Strain % from Actual Measurement - Event 2	0.09%

APPENDIX 4. Deformation data calculated from Strain

Delta x = strain/slope height RMR	Delta x = strain/slope height GSI	Delta x = strain/slope height RMR	Delta x = strain/slope height GSI	Delta x = strain/slope height RMR	Delta x = strain/slope height GSI
24.9	29.69	49.2	63.27	30.2	36.75
26.0	31.16	96.4	133.62	29.4	35.68
76.9	103.89	50.3	64.90	86.2	118.08
76.9	103.89	68.8	91.89	94.2	130.20
72.6	97.45	54.6	70.99	115.7	163.68
50.8	65.55	38.8	48.58	81.4	110.76
96.8	134.20	20.9	24.42	76.1	102.75
73.6	99.00	17.2	19.64	42.4	53.58
28.8	34.85	44.1	55.95	36.4	45.23
21.3	24.97	29.7	36.16	23.7	28.04
20.8	24.29	34.5	42.58	15.0	16.90
28.6	34.65	25.6	30.66	58.6	76.90
38.2	47.81	14.4	16.10	126.4	180.69
115.0	162.61	17.0	19.43	85.5	116.94
68.8	91.80	16.4	18.60	89.5	123.03
93.2	128.68	21.6	25.35	48.6	62.42

Delta x = strain/slope height RMR	Delta x = strain/slope height GSI	Delta x = strain/slope height RMR	Delta x = strain/slope height GSI	Delta x = strain/slope height RMR	Delta x = strain/slope height GSI
66.5	88.45	51.4	66.38	26.1	31.27
38.6	48.37	57.6	75.44	115.0	162.61
19.0	21.93	69.8	93.35	30.1	36.70
35.3	43.72	61.4	80.95	78.4	106.24
23.8	28.18	28.7	34.68	38.5	48.17
19.0	21.92	20.2	23.58	31.8	38.91
38.8	48.55	96.8	134.20	40.8	51.39
34.1	42.03	10.2	11.06	19.4	22.46
28.2	34.09	29.1	35.31	63.7	84.37