

School of Mining Engineering



UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

**UTILISING INTERFEROMETRIC SYNTHETIC
APERTURE RADAR AND GROUND-BASED
RADAR DATA TO PREDICT TIME TO FAILURE
AND TO CALIBRATE NUMERICAL MODELS
ON AN OPENCAST COAL MINE**

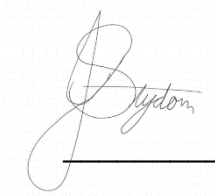
Jacques Strydom

A research thesis 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 in Engineering.

Johannesburg, 2022

DECLARATION

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A handwritten signature in black ink, appearing to read 'J. Lydon', is positioned above a horizontal line. The signature is written in a cursive style with a large initial 'J'.

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Date

ABSTRACT

Accurate time failure predictions and improved geotechnical certainty in an opencast mine will lead to tremendous safety and economical benefits. This study utilises interferometric synthetic aperture radar and ground-based radar data to conduct a back analysis on slope failures that have occurred in an opencast coal mine in South Africa. Time to failure predictions was done utilising the inverse velocity technique, while the effect of different data smoothing techniques on the accuracy of the failure predictions was evaluated. Additionally, ground-based radar data was used to calibrate a finite element numerical model to improve geotechnical certainty. Time to failure predictions based on satellite monitoring data was less accurate than predicted in the literature, but satisfactory results were obtained from ground-based radar data. This study confirms that displacement measurement from ground-based radars may be used to optimise the strength parameters of finite element numerical models. To improve the accuracy of time to failure predictions from satellite monitoring data, it was proposed that a satellite constellation with a shorter data acquisition time must be utilised. By having access to more frequent data acquisitions and by identifying the most active points within the failure zone of a slope, it is expected that the accuracy of the time to failure predictions can be improved.

DEDICATION

This project is dedicated to my wife, Johnel, who has supported and assisted me throughout my studies.

ACKNOWLEDGMENTS

I would like to thank my employers at Seriti New Vaal Colliery for their financial support and the opportunity to pursue my master's degree. To my supervisor, Ohveshlan Pillay, thank you for your guidance and the exceptional turn-around time when providing feedback. Last, but not least, thank you to Jason Pretorius from the SkyGeo team. Your continued assistance throughout the project was invaluable.

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LIST OF ACRONYMS

ACARP	Australian Coal Industry's Research Program
ESF	Exponential Smoothing Factor
FEM	Finite Element Method
InSAR	Interferometric Synthetic Aperture Radar
OOA	Onset of Acceleration
SAR	Synthetic Aperture Radar
SMA	Short-term Moving Average
SRF	Strength Reduction Factor

1 INTRODUCTION

1.1 Problem Statement

Slope monitoring and stability assessments are two of the main points of research and discussion in the field of rock mechanics. This is especially relevant in the opencast mining industry, as a significant economic and safety benefit may be gained from optimising slope angles and by prolonging mining activities underneath a potentially unstable slope (Carlà et al., 2017b). To safely achieve this, a comprehensive slope monitoring programme must be in place and geotechnical uncertainty must be minimised.

To predict the expected time to failure of a slope, displacement measurements on the slope are required. This study has attempted to utilise interferometric synthetic aperture radar (InSAR) and ground-based radar data for time to failure predictions and to minimise geotechnical uncertainty.

1.2 Justification for Research

New Vaal Colliery is situated in the Vaal Basin Coalfield in the Free State Province of South Africa. Due to the complexity of the geology, slope failures are a major risk to a mine. Therefore, slope monitoring and stability analysis are critical to ensure the safety of all personnel working in the mine. Slope monitoring is currently done using ground-based radars, drones and visual inspections, while stability analysis is done with a finite element method (FEM) numerical modelling package.

The monitoring sites for ground-based radars are prioritised, based on a consequence vs likelihood matrix which may be subjective, as it relies on the expertise of the onsite geotechnical engineer. The advantage of ground-based radars is their broad slope coverage area, near real-time slope deformation tracking and remote monitoring ability (Rose & Hungr, 2007; Dick et al., 2015). There is, however, a limitation in the ability of the ground-based radar to detect displacements above the slope crest (Carlà et al., 2018).

In opencast mines, the radar is also limited in the area of the slope that it is able to monitor effectively. While ground-based radars have proven to be highly successful as early warning systems for the detection of slope failures, it is not feasible to scan every slope on the mine due to the excessive pit lengths; thus, a regional monitoring system is required. Therefore, the integration of satellite monitoring was proposed to complement ground-based radar monitoring. Satellite monitoring enables the geotechnical engineer to proactively identify potentially unstable slopes to prioritise the deployment of ground-based radars.

To minimise production time lost and to improve safety, time to failure predictions were attempted from both satellite and ground-based radar data. Time to failure predictions were based on the inverse velocity method. The accuracy of time to failure predictions is heavily influenced by data noise and therefore the applied data smoothing technique was an important consideration. Two separate smoothing techniques were applied, namely the short-term moving average (SMA) and exponential smoothing factor (ESF).

The accuracy of numerical models relies on the quality and accuracy of the input parameters, namely geotechnical certainty. The input parameters for the properties of the low wall material that were utilised in the numerical models were based on research and no geotechnical tests were conducted on the mine. This work attempted to use the displacement measured by ground-based radars to calibrate the numerical models to improve confidence and reliability.

1.3 Sources of Data

InSAR and ground-based radar displacement measurements of historic slope failures that occurred at New Vaal Colliery were analysed for this study. InSAR data was obtained through an external service provider and ground-based data was collected on-site with Reutech's trailer-mounted MSR300 real aperture radar. Numerical modelling was done with Rocscience's RS2.

1.4 Structure of the Research Report

This report consists of five chapters which are summarised below.

Chapter 1 introduces the problem statement, study area, justification for the research, sources of the data and the structure of this report.

Chapter 2 consists of a comprehensive literature review. The focus was placed on the theory of the inverse velocity method and the different data smoothing techniques. Additionally, case studies that evaluated the accuracy of time to failure predictions and the integration of displacement measurements into FEM were reviewed.

Chapter 3 explains the research methodology followed for this study. The geological and geotechnical characteristics of the study area were discussed. The raw displacement data from both InSAR and ground-based radar for the specific failures were included in this section.

Chapter 4 consists of the results and discussion of the inverse velocity time to failure predictions and FEM calibration.

Chapter 5 summarises the findings and conclusion of the study, and addresses recommendations for further research.

2 LITERATURE REVIEW

2.1 Introduction

The devastating consequences of slope failures necessitate the proactive management of slope stability. Slope stability management involves the design, construction and monitoring of excavated slopes. To eliminate the potential loss of life and minimise the damage to equipment and production time losses in opencast mines, accurate time to failure predictions are required (Osasan & Stacey, 2014; Carlà et al., 2017a). To accurately predict the time to failure, a method is required to measure the location and rate of displacement on slopes. The combination of ground-based radar and InSAR monitoring proved to be highly effective in monitoring displacement on slopes to predict their expected time to failure (Paradella et al., 2015; Carlà et al., 2018).

During the design phase of rock slopes, a stability analysis is required to obtain a safety factor (SF) and probability of failure (POF) of the slope. This is done by conducting stability analysis with numerical modelling software (Kanda & Stacey, 2016). The material properties used in the numerical modelling software are usually obtained from laboratory tests and can be refined by conducting a probabilistic back analysis when a failure occurs (Mandal et al., 2017). Alternatively, ground-based radar data and InSAR data can be utilised to calibrate and refine sophisticated three-dimensional (3D) and two-dimensional (2D) numerical models (Woo et al., 2012; Escobar et al., 2013; McQuillan et al., 2020).

In the following sections, the utilisation of satellite InSAR and ground-based radars will be discussed to evaluate their ability to calibrate numerical models and to predict the time to failure of slopes on an opencast coal mine.

2.2 InSAR Satellite Monitoring

Radar technology has been used for more than 50 years, but it is only in the last decades that the hardware and software capabilities allowed for effective processing of the data to be utilised commercially (Paradella et al., 2015). The synthetic aperture radar (SAR) technique uses a broad fan beam to illuminate a specific target multiple times within the same scan. A phase value is measured for each pixel of the scanned image and by comparing phase differences of subsequent scans, it is possible to track deformation. Deformation can be accurately measured on a sub-millimetre scale.

InSAR has been used successfully for a variety of purposes related to mass movements such as landslide mapping, earthquake monitoring, volcanic deformation and tracking surface deformation rates (Berardino et al., 2003; Hooper et al., 2004; Raspini et al., 2017; Carlà et al., 2018).

2.2.1 Application of InSAR in surface mining

Satellite monitoring is becoming more relevant in the mining industry as it allows geotechnical engineers to detect surface deformation at relatively low costs without having to install in-situ instrumentation. Traditionally, satellite surface deformation mapping in the mining industry has focused on the monitoring of subsidence due to underground mining (Paradella et al., 2015). In recent years, the works of Paradella

et al. (2015), Carlà et al. (2018) and Leighton and Sullivan (2020) have all indicated the value of integrating satellite monitoring into opencast slope monitoring programmes. Until recently, it was considered that spaceborne monitoring systems could not yield information in the required systematic fashion to act as early warning systems for slope failures. However, Carla et al. (2019) reported that InSAR data of various slope failures indicated that there was an increase in the rate of slope movement in the time leading up to the failure which indicated that failure was imminent.

A study on an iron ore mine in the Carajás mineral province of Brazil proved that satellite monitoring could be integrated successfully into the slope monitoring programme of an opencast mine. InSAR was used effectively to monitor surface deformations, and it was noted that there was a good correlation between the displacement measured by InSAR and in-situ ground-based instrumentation (Paradella et al., 2015).

Similarly, the Grasberg Mine operated by PT Freeport Indonesia (PT-FI), has successfully incorporated InSAR into its geotechnical risk management system. InSAR is used to track the displacement of opencast slopes, access roads and deformation caused by block caving. InSAR at Grasberg Mine is considered complementary monitoring to visual inspections and ground-based radar monitoring. InSAR is used to detect the onset of ground movement to prioritise the deployment of ground-based radar systems (Leighton & Sullivan, 2020).

2.2.2 Limitations of InSAR

The long revisit time and the lack of regularity in acquisitions performed have been the main reasons why satellite monitoring is not used as an operational tool for landslide emergency management (Carlà et al., 2018). Furthermore, due to the setup of the satellite geometry and the fact that InSAR estimates displacement along the satellite line of sight, InSAR cannot measure horizontal ground movement accurately (Leighton & Sullivan, 2020). The orientation of the slope must also be considered as slopes striking East-West cannot be properly monitored by InSAR due to Sentinel-1 satellites moving in a North-South orbital plane.

Another factor to consider is coherence loss which occurs when the phase measurements in active mining areas are destroyed due to excavations and dumping during mining activities. Fortunately, this affects only the area that is being disturbed and only during the period of the mining activity. As the activities cease or move on, monitoring can continue. This will, however, result in data with gaps in time which will ultimately result in a time series with gaps in time. The data is still functional and useful if periods of disturbance do not dominate the dataset. Other causes of coherence loss are high soil moisture content, vegetation and high magnitudes of displacement (Leighton & Sullivan, 2020).

2.3 Ground-based Real Aperture Radar

Ground-based slope stability radars (SSRs) are based on differential interferometry obtained with real aperture radar (RAR). Instead of using SAR from a moving platform (satellite or plane), the SSR uses real aperture on a stationary platform positioned perpendicular to the area of interest. The ground-based radar scans a user-defined area of a slope and compares the phase measurements in each pixel with the first scan to determine the stability of the slope and the nature of the movement (Reeves et al., 2001). In Figure 1, the movement of a wedge failure is illustrated. In this example a wedge failure can be interpreted from the interference map. The advantage of ground-based radars is that they provide full area and real-time monitoring.

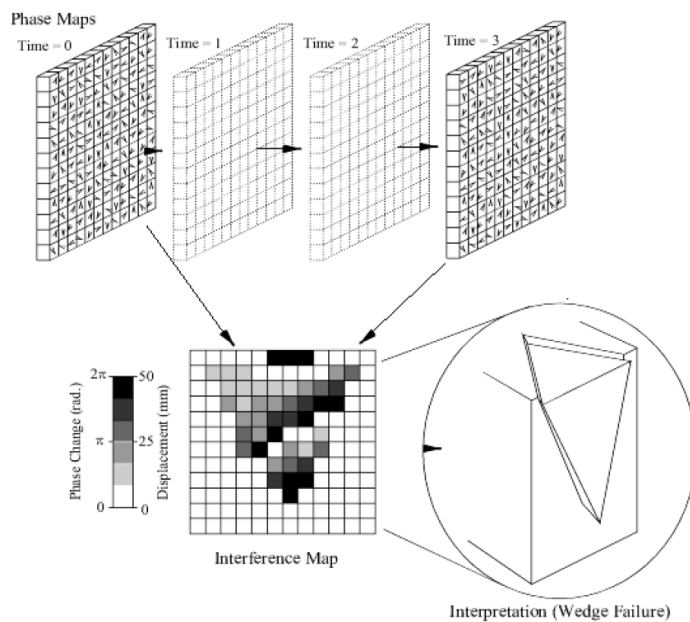


Figure 1: Differencing the phase of each pixel from two separate scans creating the deformation image (Reeves et al., 2001).

2.3.1 Ground-based radar application in the mining industry

The ability of SSRs to measure slope movement to sub-millimetre precision through a broad range of adverse weather conditions has made SSR highly popular in the mining industry. The high level of precision and broad area of slope coverage allow for a better understanding of the geomechanics of slope deformation. SSR systems have been utilised successfully in mines in Australia, Indonesia, South Africa, Chile and the United States of America. A case study of 70 rockfalls indicated that before every failure, the SSR recorded precursor “warning” movements. This technology brought about a radical change in opencast slope monitoring (Harries et al., 2006).

2.4 Inverse Velocity Technique

Various attempts have been made to develop methods to predict the expected time to failure of slopes. No single model is universally acceptable and the difference between the models depends on the adopted function (Osasan & Stacey, 2014). The most commonly used functions are the linear, exponential and power-law functions (Crosta & Agliardi, 2003).

The concept of the inverse velocity technique was developed by Teruki Fukuzono in 1985. The study was based on large-scale laboratory tests simulating rain-induced landslides in soil. The conditions simulated were considered to represent accelerated creep under gravity loading. When the inverse of the observed displacement rate (“inverse velocity”) was plotted against time, its values approached zero as velocity increased towards failure (Fukuzono, 1985).

Voight (1989) validated this theory and derived further expressions and proposed that the relation reflected a general physical law governing material failure under constant stress and temperature. Voight's material failure relation of tertiary creep under constant applied stress and temperature has been widely acknowledged in the slope failure prediction field. These empirical relations were based on the theory of damage accumulation and creep fracture due to stress corrosion and power-law lattice deformation (Voight, 1989; Cornelius & Scott, 1993).

The failure of a slope may be explained by a phase of progressive slope deformation (i.e., accelerating or tertiary creep) during which strain increments of the slope are observed in the power law in Equation 1.

$$\Omega^{-\alpha} \Omega - A = 0 \quad \text{Equation 1}$$

From Equation 1 the linear law relating inverse velocity and time are derived.

$$\Omega^{-1} = [A(1 - \alpha)(t - t_0) + \Omega_0^{1-\alpha}]^{1/(\alpha-1)} \quad \text{Equation 2}$$

where Ω is the measurable displacement, α and A are empirical constants, t is the time to failure and t_0 is the time. By linearly extrapolating the theoretical time of singularity in an inverse velocity versus time plot (i.e., $\alpha = 2$) (see *Figure 2*) the time to failure of the slope can be predicted (Fukuzono, 1985).

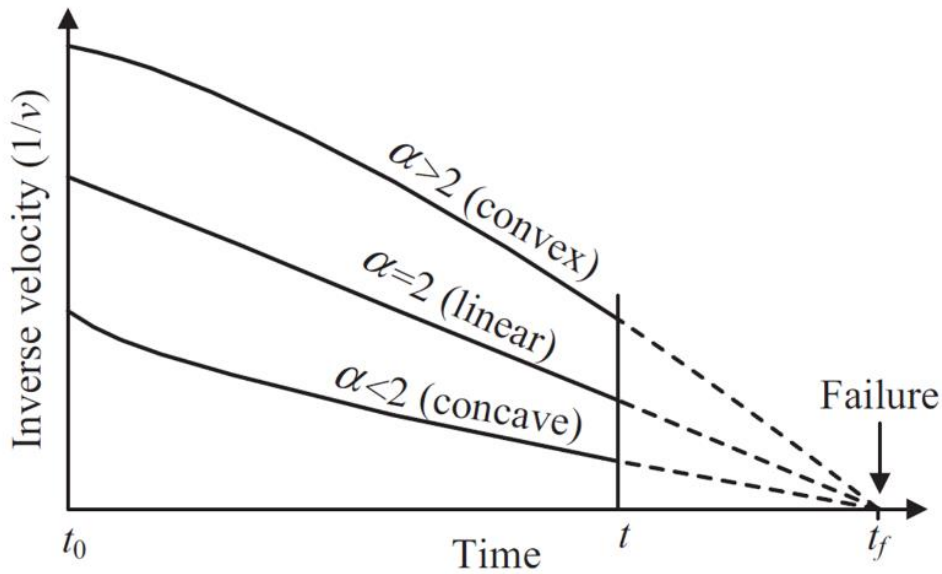


Figure 2: Inverse velocity versus time relationships (Fukuzono, 1985).

Fukuzono presented concave, convex and linear failure plots. Voight showed theoretically that under ductile conditions, accelerating creep under constant stress conditions in the soil, rock and other materials, the inverse velocity plot may be expected to be linear (Voight, 1989).

2.4.1 Variation of displacement rates

Fukuzono's experiments were based on idealised laboratory conditions which are not a true representation of slopes that exist in nature or the mining industry. Under typical field conditions, six types of variation of displacement velocity co-exist and interact (Rose & Hungr, 2007). These conditions are described in Table 1. These variations in displacement velocity are generally referred to as "noise".

Table 1: Variation of displacement rates preceding slope failures (Rose & Hungr, 2007).

Variation	Description
Measurement error and “random noise”	Optical refraction and daily temperature and pressure effects
Localised movement results in random, chaotic measurements.	Identify the failure mechanism of the main failure to disregard localised movement of isolated failures.
Periodic variation	Displacement rates are influenced by seasonal weather, mining activities etc.
Displacement rate trends	Linear displacement rate trends should be observable in the time leading up to the failure.
Trend changes	Linear inverse velocity trend plots can be used to predict the ductile failure of rock if there are no external influences on the failure process.
Brittle failure	The timing of brittle failures cannot be predicted with the inverse velocity technique.

These variations or the “noise” have a significant impact on the accuracy of the time to failure, T_f , and predictions. It is, therefore, crucial to process the velocity time series to remove as many of these variations as possible. This is referred to as data smoothing or noise filtering which is required to correctly identify the onset of acceleration (OOA) and trend updates (TU), and to improve the fit of the linear regression line (R^2). The OOA can be identified by the cross-over point between the short-term moving average trend line over the long-term moving average trend line. The linear fitting velocity data should only be applied from the OOA point (Carlà et al., 2017a).

The moving average and exponential smoothing algorithms are commonly used for noise clean-up and data smoothing (Carlà et al., 2017a). A short-term simple moving average (SMA), where the smoothed velocity, v_t , at a time, t , can be calculated with Equation 3.

$$v_t = \frac{v_t + v_{t-1} + \dots + v_{t-(n-1)}}{n} \quad \text{Equation 3}$$

where $n=3$.

A long-term simple smoothing average (LMA) can be calculated with Equation 4.

$$v_t = \frac{v_t + v_{t-1} + \dots + v_{t-(n-1)}}{n} \quad \text{Equation 4}$$

where $n=7$.

An exponential smoothing function (ESF) can be calculated with Equation 5.

$$v_t = \beta \cdot v_t + (1 - \beta) \cdot v_{t-1} \quad \text{Equation 5}$$

where the smoothing factor $\beta=0.5$.

The type and extent of data smoothing required are dependent on the frequency of data acquisition. High data acquisition rates require smoothing over longer periods and vice versa for low data acquisition rates.

Despite these limitations, the inverse velocity technique has been used successfully to predict time to failure in the mining industry. Examples specifically of ground-based radars and satellite monitoring are discussed in section 2.4.2.

2.4.2 Failure prediction in the mining industry

The inverse velocity technique has been applied successfully to InSAR and ground-based radar data to predict the time to failure (Osasan & Stacey, 2014; Dick et al., 2015; Carlà et al., 2017a; Carlà et al., 2018). This will be discussed in the following sections.

Failure prediction using ground-based radar

Osasan and Stacey (2014) developed an automatic slope failure prediction model that was based on the inverse velocity technique. Displacement data was recorded by ground-based radars. The prediction model proved to be effective in predicting the time to failure and providing adequate evacuation time. Two case studies were used to validate this model. The failure prediction model automatically identified the points that showed the most movements, commonly referred to as the most active radar points. This significantly improved the accuracy of the time to failure predictions.

The first case study was a failure that occurred in a copper mine. The failure occurred on 5 September 2008 at 21:11. The model predicted the time of the failure to be within three minutes of the actual failure time. The second case study was based on a highwall failure that occurred in a coal mine. The failure occurred on 13 March 2008.

The model accurately predicted the failure to be within four minutes of the actual failure time (Osasan & Stacey, 2014).

Similarly, the work of Dick et al. (2015) was based on eight major slope failures that occurred in opencast mines. Displacement data was captured by ground-based radars, while time to failure predictions were done by utilising the inverse velocity technique and slope gradient analysis methods. To compensate for the real-time data capturing of ground-based radars, they introduced two new terms, namely the *onset of acceleration* (OOA) and *trend update* (TU). By defining a TU point, older data may be discarded, resulting in more accurate time to failure predictions (Dick et al., 2015).

Figure 3 illustrates the OOA, TU and slope failure points.

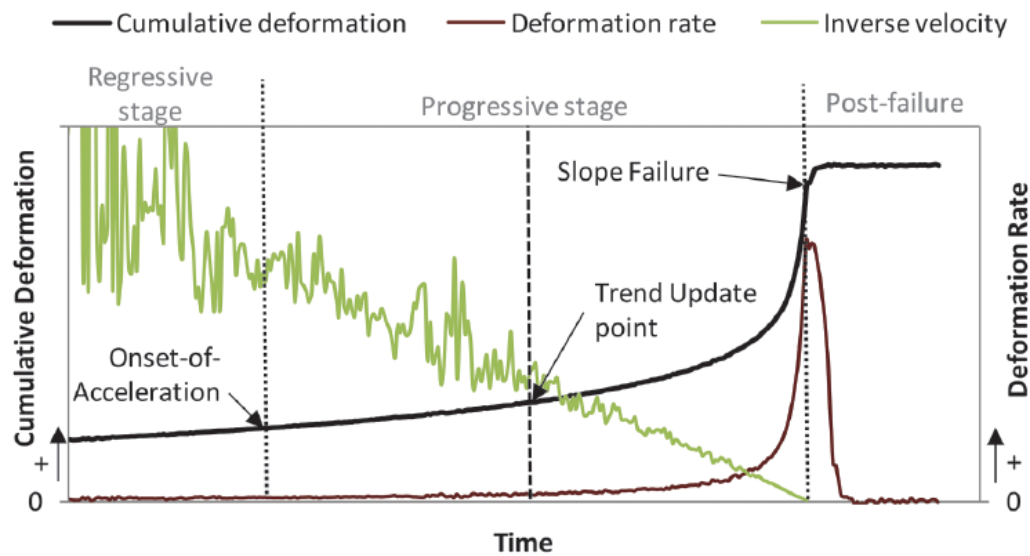


Figure 3: A theoretical cumulative deformation, deformation rate and inverse-velocity versus time plot illustrating the onset of acceleration, trend update point and slope failure (Dick et al., 2015).

Failure prediction using InSAR

The ability of InSAR to accurately predict time to failure and to identify the OOA of failing slopes was demonstrated by Carlà et al. (2019). A back analysis was conducted on a slope failure that occurred in an opencast copper mine on 17 November 2016. Twenty-eight InSAR images that were acquired between 19 February and 21 November 2016 on a revisited time of 12 days were used in the analysis (Carlà et al., 2019). The outline of the failure and monitoring points can be seen in *Figure 4*.

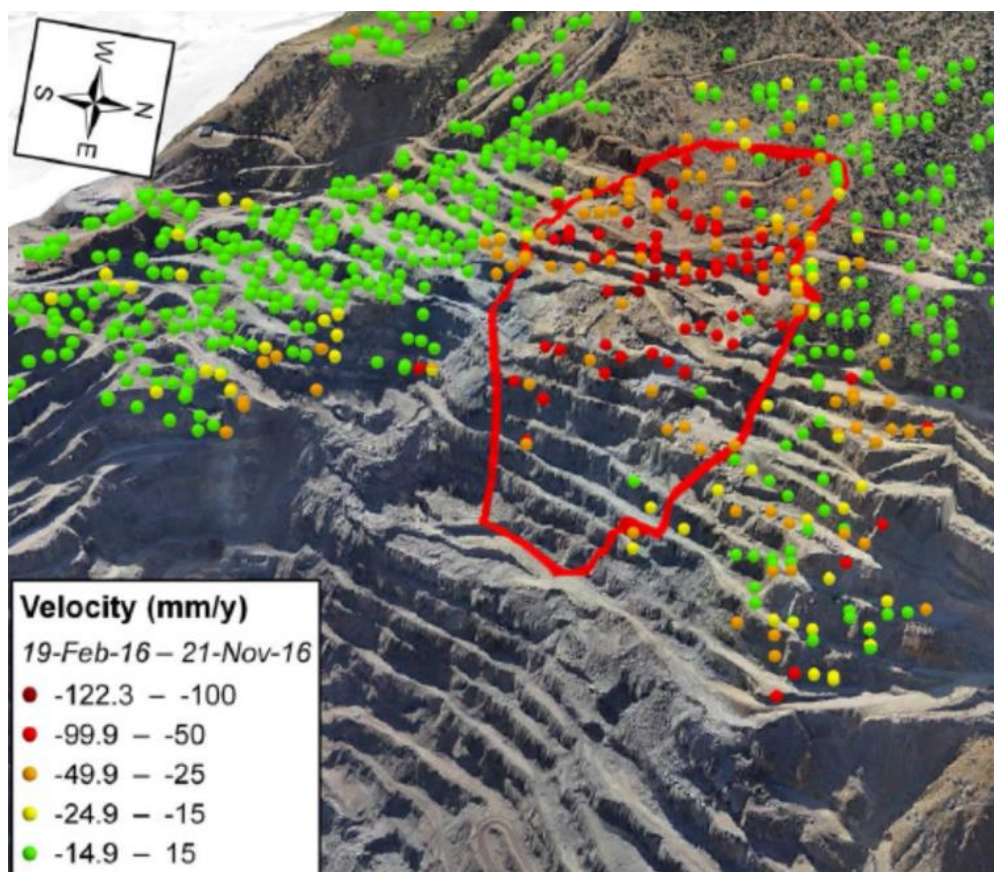


Figure 4: Satellite InSAR showing deformation in the days before the failure (Carlà et al., 2019).

A three-point moving average was used to smooth the data. To objectively identify the OOA from which each regression had to be predicted, the points preceding the failure that gave the highest R^2 were selected. This was typically four to seven points. The inverse velocity technique was applied to the displacement data and it was found that the failure could have been predicted within several hours of the actual failure time (Carlà et al., 2019).

2.5 Numerical Modelling

Even though three-dimensional (3D) numerical analysis software has been available commercially for nearly a decade, geotechnical engineers mainly conduct two-dimensional (2D) analysis despite its limitations. When deciding on utilising numerical modelling as part of the geotechnical design process, careful consideration should be given as to whether the design should be conducted in 2D or 3D. For example, a 2D analysis will be sufficient when a homogenous slope is analysed. On the other hand, for highly anisotropic rock masses with structures trending near parallel to the excavation, a 3D model will be necessary to conduct an accurate stability analysis (McQuillan et al., 2020).

Similarly, the benefits of progressing from limit equilibrium to finite element modelling should be considered carefully. For example, homogenous slopes with minimal intersecting structures may be analysed accurately with limit equilibrium models. In contrast, slopes with multiple weak structures and/or diverse material properties will benefit from finite element analysis (McQuillan et al., 2020).

When analysing the stability of highly anisotropic slopes, 3D models proved to be superior to 2D models in predicting accurate safety factors and slope behaviour (Bar & McQuillan, 2018). These same 3D models also allowed the direct importation of both ground-based radar and InSAR displacement data (McQuillan et al., 2020). The benefit of this is the ability to calibrate and validate the numerical model. This enables the geotechnical engineer to optimise designs as the confidence in the models is improved. Similarly, displacement data measured in 2D by ground-based radars have been used successfully to calibrate the displacement predicted by finite element models (Escobar et al., 2013; Silva et al., 2021). The combined use of 2D and 3D models is recommended to enable a better understanding of anisotropic rock mass behaviour and the impact of geological structure on slope stability (Bar & McQuillan, 2018).

In the following sections, three case studies using ground-based radar data and InSAR data to calibrate numerical models are discussed.

2.5.1 Case study 1: Ground-based radar data to calibrate 3D numerical models

Slope instability was detected with a ground-based radar in a 250 m deep gold mine in Papua New Guinea. The initial 3D limit equilibrium stability analysis indicated that the slope had an SF of 1.49 (refer to *Figure 5*).



Figure 5: Initial 3D limit equilibrium stability analysis indicating an SF of 1.49 (McQuillan et al., 2020).

The deformation was initiated by several days of excessive rainfall and deformation fluctuated with the rainfall events. The movement detected by the ground-based radar can be seen in *Figure 6*.

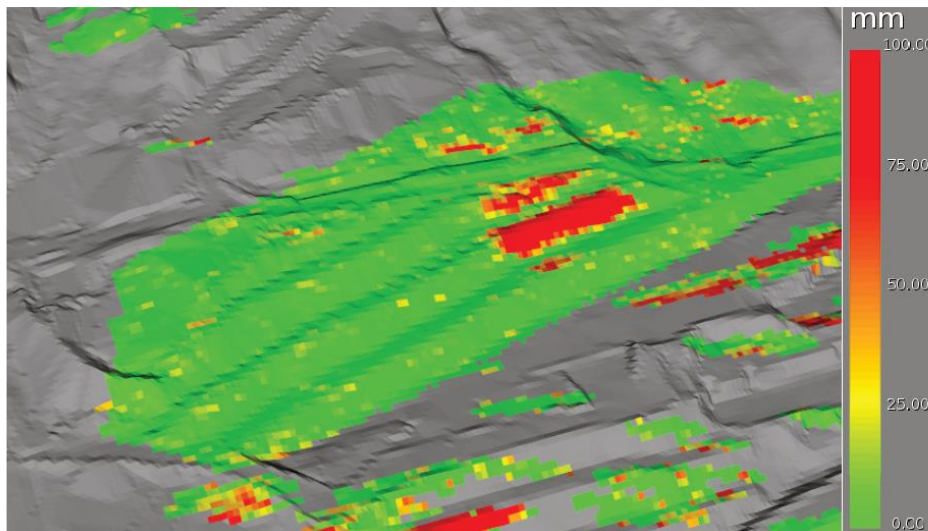


Figure 6: Slope deformation detected by the ground-based radar (McQuillan et al., 2020).

It was observed that cracks formed in the area directly above the failure zone and the failure mechanism was related to a low-angle, in-pit dipping fault. Porewater pressures recorded indicated that the slope was highly saturated. Refer to *Figure 7* for the slope stability models that reflect these conditions.

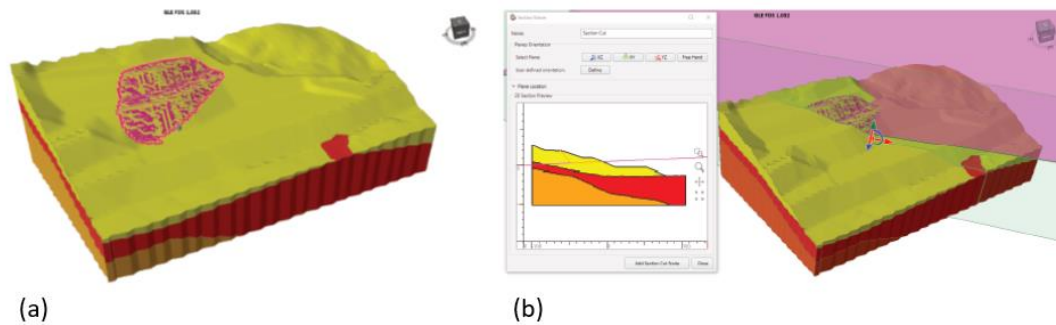


Figure 7: (a) Back-analysed 3D limit equilibrium analysis results, $SF=1.03$. (b) Back-analysed 3D limit equilibrium analysis results show sliding along the fault plane (McQuillan et al., 2020).

The deformation measurement recorded by the ground-based radar was superimposed over the 3D limit equilibrium slope analysis model and a good correlation was seen between the predicted slip surface and the actual measured slope movement (refer to Figure 8).

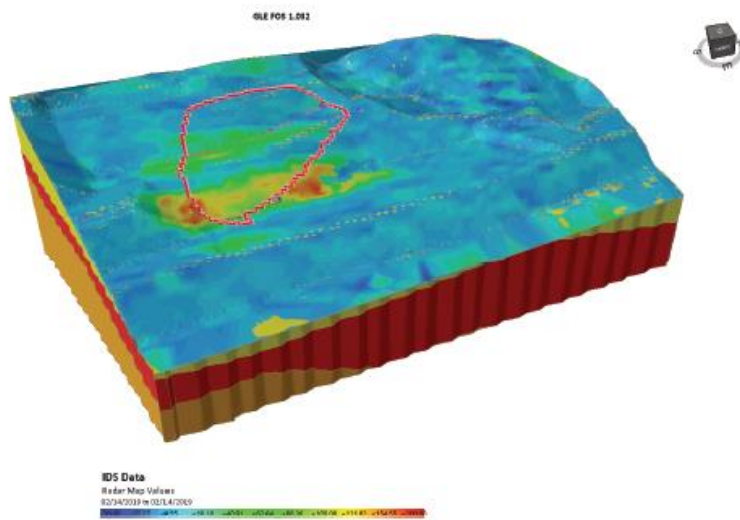


Figure 8: Ground-based radar monitoring data overlain over the excavated slope, showing a good correlation between modelled critical slip surface and the actual measured deformation (McQuillan et al., 2020).

This interoperability of 3D modelling results with monitoring data provides geotechnical engineers with the opportunity to back-analyse material properties and refine slope stability models (McQuillan et al., 2020).

2.5.2 Case study 2: InSAR monitoring data to calibrate numerical models

The Palabora copper mine is situated in the Limpopo province of South Africa. The opencast operation is approximately 800 m deep and 1900 m wide. The mine transitioned from an opencast operation to an underground block-caving operation in April 2001. Three years after the underground block caving had commenced, cracks were observed on the northwest wall of the pit. The cracks propagated over several months until the pit wall failed (Woo et al., 2012). The extent of the failure can be seen in Figure 9.



Figure 9: Slope failure at Palabora copper mine (Woo et al., 2012).

A 3D Fast Lagrangian Analysis of Continua (FLAC) numerical model was constructed to conduct a back analysis of the failure. The displacement predicted by the numerical model showed a good correlation with the actual displacement measured by InSAR data. This demonstrates the value of utilising InSAR to calibrate and validate complex 3D models (Woo et al., 2012).

2.5.3 Case study 3: Ground-based radar data to calibrate 2D limit equilibrium numerical models

A multi-bench failure occurred on an opencast iron ore mine in Brazil, situated in the geological domain of the Parauapebas and Carajas formations. The Parauapebas formations consist of basalts and diabases, while the Carajas formation contains ore in thick layers of jaspilites and lenses of haematite. The failure mode was

planar/circular and developed between the contact of friable haematite with high permeability and a mafic sill after a significant rainfall event (Silva et al., 2021).

Back analysis of the failure was done, using RS2 9.0, Finite Element Method (FEM) software developed by Rocscience, to calculate the stresses and displacement in the rock mass. The shear strength reduction (SSR) technique was used to identify the strength reduction factor (SRF). The critical SRF is considered as the point when the analysis fails to converge and the deformation rate increases (Silva et al., 2021).

The displacement predicted by the model was compared with the actual displacements measured by the ground-based radars. The input parameters of cohesion, friction angle, Poisson's ratio and Young's modulus were optimised with the help of a Python programming routine. These parameters were optimised until the measured and predicted displacement values were within 5% of each other (Silva et al., 2021).

Similarly, in the El Teniente Copper Mine in Chile, the slope monitoring data from ground-based real aperture radars were used to calibrate shear strength parameters (friction angle and cohesion) used in finite element models. In the Shear Strength Reduction (SSR) method, the material shear strengths are gradually reduced until the model does not converge anymore. At this point, the critical safety factor is reached and collapse occurs. In this case study, the rock mass strength parameters were adjusted until the displacement predicted by the FEM model matched the actual displacement measured by the ground-based radar (Escobar et al., 2013).

2.6 Discussion

The devastating impact of slope failures within the mining industry requires a proactive approach to prevent fatalities and minimise damages and production losses. By utilising ground-based radars and satellites to monitor slope movement, the occurrence of slope failures can be anticipated. By utilising monitoring data from ground-based radars, the expected time to failure can be predicted within minutes of the actual time of failure. Similarly, satellite monitoring data can be utilised to predict the time to failure of slopes within several hours. The accuracy of time to failure predictions based on the inverse velocity technique relies heavily on the quality of the monitoring data and the type of data smoothing conducted.

Numerical modelling software has been used extensively in the mining industry to assess the stability of proposed slope designs. The availability of actual displacement measured by ground-based radars and satellites has been used successfully to calibrate finite element numerical models. This is done by adjusting the strength parameters of the model until the predicted displacement matches the actual displacement measured directly before failure.

The integration of satellites, ground-based radar and numerical modelling may greatly improve the understanding of the rock mass behaviour and therefore improve safety and slope stability in mines.

3 RESEARCH METHODOLOGY

3.1 Introduction

Eleven historic slope failures were identified in the study area. Back analysis of the failures was conducted to evaluate the effectiveness of InSAR and ground-based radars to act as potential early warning systems and to predict the time to failure, utilising the inverse velocity technique. Additionally, the displacement measured by radar monitoring was compared to the displacement predicted by finite element models to calibrate the material properties used.

3.2 Study Area

The study was conducted on an operational opencast coal mine. The mine is situated in the Vereeniging-Sasolburg coalfield within the Cornelia sub-basin. The location of the mine and a typical stratigraphic profile of the mine are available in Figure 10. A description of the lithological units is available in Table 2.

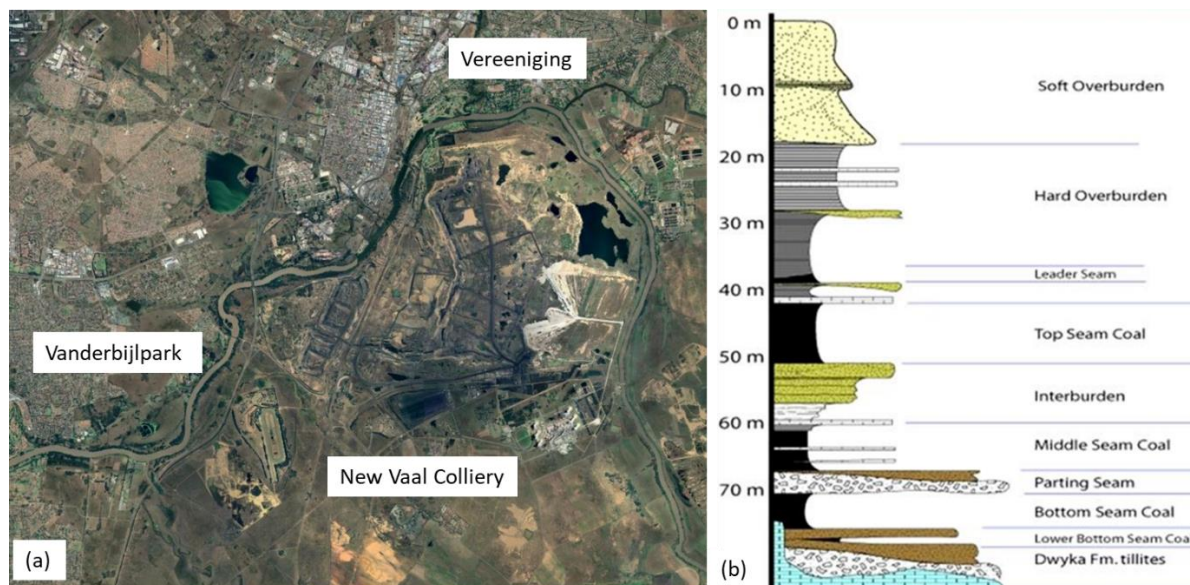


Figure 10: (a) Google earth image of the mine location and (b) a stratigraphic column of the study area.

Table 2: Summary of the different lithological units in the study area.

Lithological Unit	Description
Soft Overburden	This is a sequence of quaternary river alluvium and aeolian material, comprising mixed layers of semi-consolidated sandy and clayey soils, averaging a total thickness of approximately 20 m.
Hard Overburden	This is a sequence of the Ecca Group of which the Vryheid Formation shales and sandstones overlie the top seam coal. The average thickness of the hard overburden over the mining area is 7.5 m.
Top Seam Coal	Over large areas of the mine, the top seam is directly overlain by soft overburden sand where its upper portion has been partially eroded (in some areas the seam has been completely eroded) and may be slightly weathered. The top seam coal averages 8.7 m in thickness.

Interburden		This is an upward coarsening sequence, grading from a carbonaceous mudstone forming the middle seam roof, through shale and siltstone, to fine-grained micaceous sandstone forming the floor of the top seam. The interburden unit averages 11.6 m in thickness.
Middle Coal	Seam	The depth to the roof of the middle seam from the surface ranges from 20 m where the seam sub-outcrops beneath the soft overburden to a maximum of 66 m in the southern part of the lease area. This coal seam averages 7.4 m in thickness.
Parting		The parting typically consists of carbonaceous silty mudstone overlying a gritty sandstone bed. The typical parting averages approximately 2 m in thickness.
Bottom Coal	Seam	The depth to the roof varies from approximately 30 m where the seam sub-outcrops below the soft overburden to a maximum of about 80 m in the southern extremity of the lease area. This coal seam averages 5.9 m in thickness.
Dwyka		This is a sequence of interbedded shale, coal, sandstone, grit, conglomerate and tillite overlying massive tillites.
Dolomite		Throughout the area, the basement is composed of the dolomite of the Transvaal Supergroup. These are water-bearing sediments.

3.3 InSAR

Section 3.3 of this report addresses InSAR data acquisitions and data smoothing.

3.3.1 InSAR data acquisition

SkyGeo assisted with the back analysis of eleven historic slope failures at New Vaal Colliery, using InSAR to measure millimetre scale displacements. The data acquired originated from Sentinel-1 ascending orbital track T116 and descending orbital track T50. The satellite acquires new data over the same area, once every 12 days during each orbital repeat. This data is co-registered such that the data from different acquisitions, but the same orbital track, can be compared. Co-registration is the process performed to spatially align all acquisitions. The pixels contain both amplitude and phase information of the backscattered microwaves.

Temporal changes in amplitude may be caused by changes in the scattering characteristics of an object. Temporal changes in phase may be considered a combination of multiple factors, one of which being the physical change in distance between the satellite and the object. Persistent scatterer interferometry is the process used to correct the phase difference between acquisitions for orbital changes, flat-Earth phase, topography and atmosphere to attribute the remaining phase difference to a change in line-of-sight (LOS) distance.

The LOS displacement data was made available on an online viewer, displayed on either low-resolution satellite images or high-resolution digital elevation models supplied by New Vaal Colliery. The data was exported from the viewer into Microsoft Excel.

3.3.2 Inverse velocity plots and data smoothing

Two time to failure plots were done for every failure. The first plot was based on the average movement detected on all the radar points included within the failure boundary. Secondly, a cluster of highly active points within the failure boundary was manually identified to improve the failure prediction accuracy as proposed in the literature (Dick et al., 2015).

Data smoothing was done in Microsoft Excel using Equations 3 and 5. Inverse velocity plots were applied only from the OOA. As proposed in the literature, the OOA was identified by finding the points preceding the failure that gave the highest R^2 , typically four to seven points (Carlà et al., 2019).

3.4 Slope Failures

Table 3 contains a summary of eleven historic slope failures that have occurred between 17 March 2015 and 21 June 2021. Note that InSAR data was only available for five of the failures. No InSAR data was available for the failures that had occurred from 2015 to 2018. Ground-based radar data was available for three of the failures. No fatalities, injuries or damages occurred at any of the failures discussed in this report.

Table 3: Historic slope failures selected for the back-analysis

Date	Affected Slope	Failure Mechanism	InSAR Data Available	Radar Data Available
21-Jun-21	Highwall	Planar	Yes	No
30-Apr-21	Highwall	Circular	Yes	Yes
01-Jan-21	Highwall	Planar/Unravelling	Yes	Yes
08-Dec-20	Highwall	Planar/Unravelling	Yes	No
22-Oct-20	Highwall	Planar	Yes	No
01-Aug-18	Low wall	Circular	Yes	No
31-Mar-19	Highwall	Planar	No	No
31-Jul-18	Highwall	Planar	No	No
19-Jul-17	Highwall	Circular	No	No
18-Aug-16	Low wall	Circular	No	Yes
17-Mar-15	Highwall	Circular	No	No

3.4.1 Low wall failure, 18 August 2016

A low wall circular failure occurred on 18 August 2016. The low wall, which was placed by a dragline, consisted of a mixture of sand and blasted siltstone and shale; refer to Figure 11.



Figure 11: Ramp 19 low wall failure that occurred on 18 August 2016.

The synthetic map and trend plot of the displacement measured by the ground-based radar is available in Figure 12.

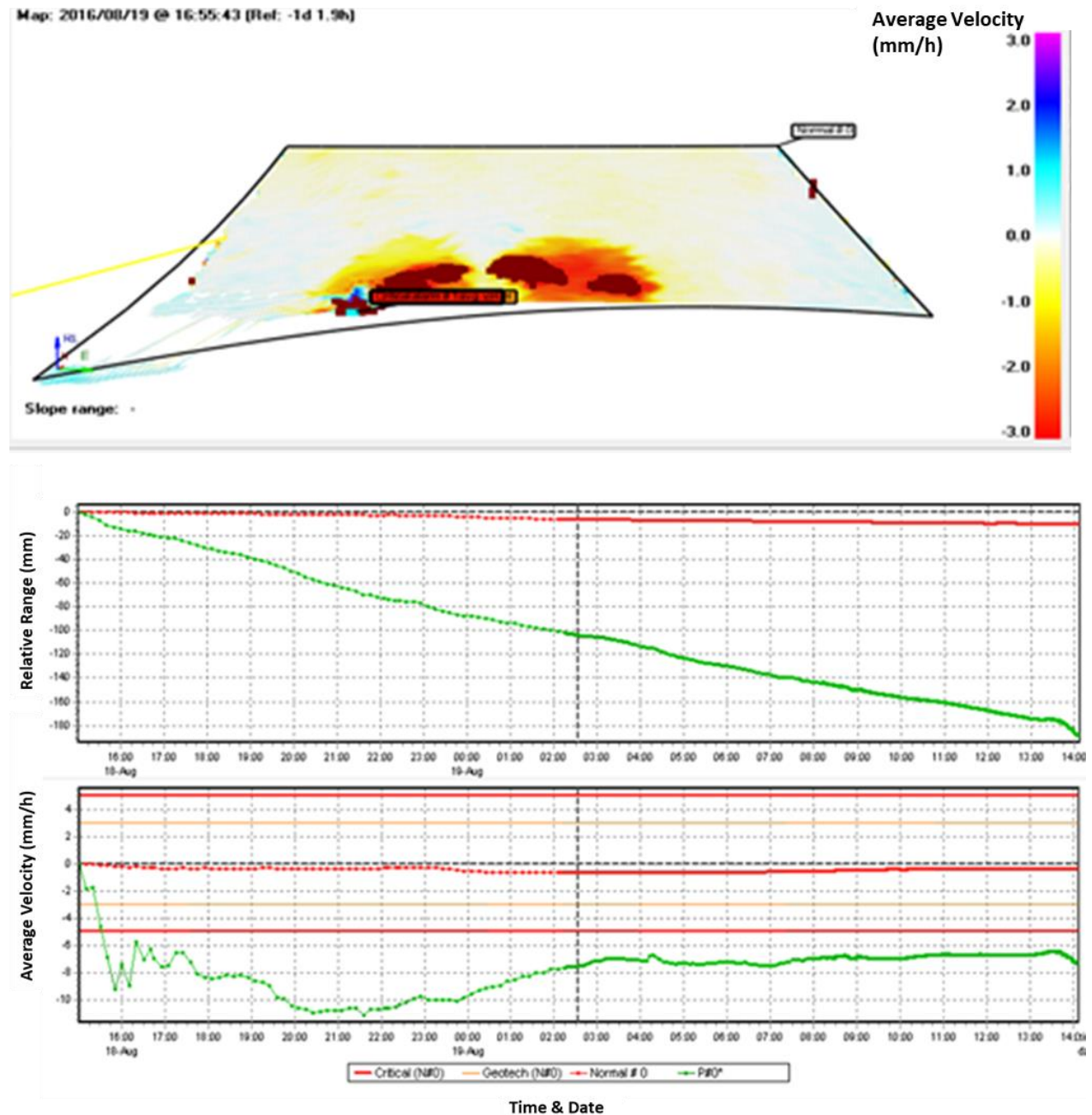


Figure 12: Synthetic map and average velocity and relative range trend plots of the slope movement of the low wall failure that occurred on 18 August 2016.

The synthetic map and movement trend plot in Figure 12 confirms that the failure occurred at the bottom of the slope and that the maximum movement recorded directly before the failure occurred was approximately 16 mm.

3.4.2 Low wall failure, 30 March 2019

A low wall circular failure occurred in Ramp 20 on 30 March 2019. The low wall, which was placed by a dragline, consisted of a mixture of sand and blasted siltstone and shale; refer to Figure 13.



Figure 13: Ramp 20 low wall failure that occurred on 30 March 2019.

A total of 13 radar points, over 14 measurements were analysed. The measured LOS displacement can be seen in Figure 14.

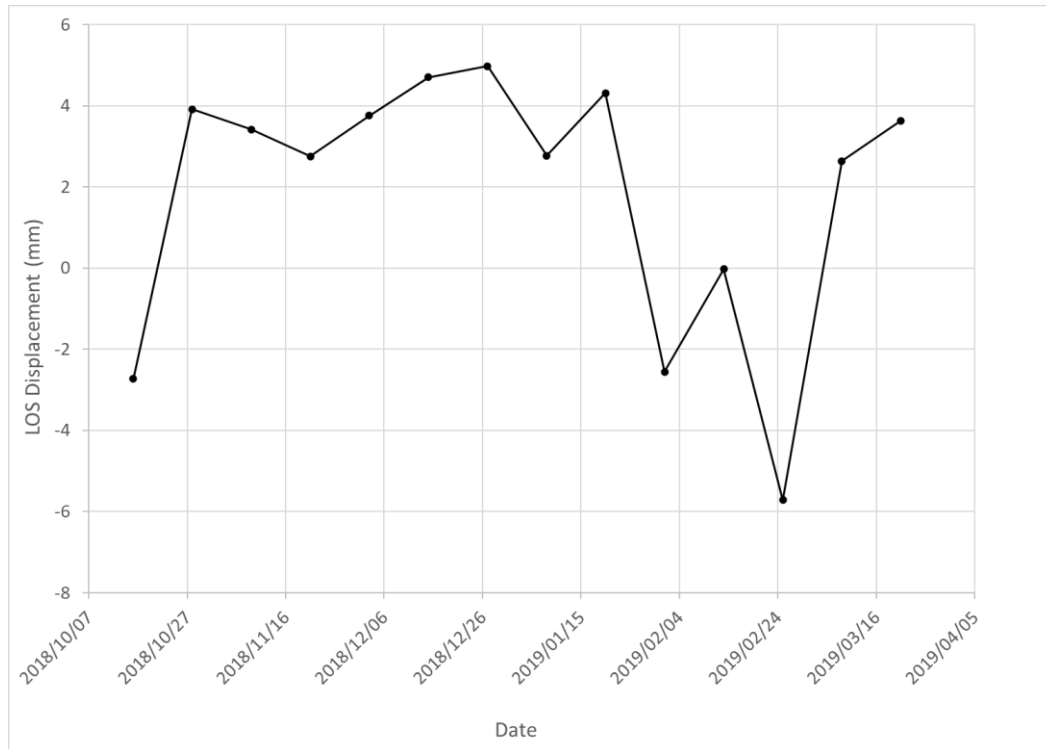


Figure 14: LOS displacement measured at the failure position between 7 October 2018 and 21 March 2019 by the Sentinel-1 satellite.

Take note that the measured displacement fluctuated between positive and negative displacement. This indicates that the recorded movement was both towards and away from the satellite, with positive displacement indicating movement towards the satellite.

3.4.3 Highwall failure, 22 October 2020

A multi-bench highwall failure occurred in Ramp 2-4 on 22 October 2020. The slope height was 62 m and consisted of sand, siltstone and shale; refer to Figure 15.



Figure 15: Ramp 2-4 highwall failure on 22 October 2020.

A pinnacle and fault plane were visible on the highwall. Take note of the relatively intact interburden. The sand layer is approximately 20 m thick. The measured LOS displacement can be seen in Figure 16.

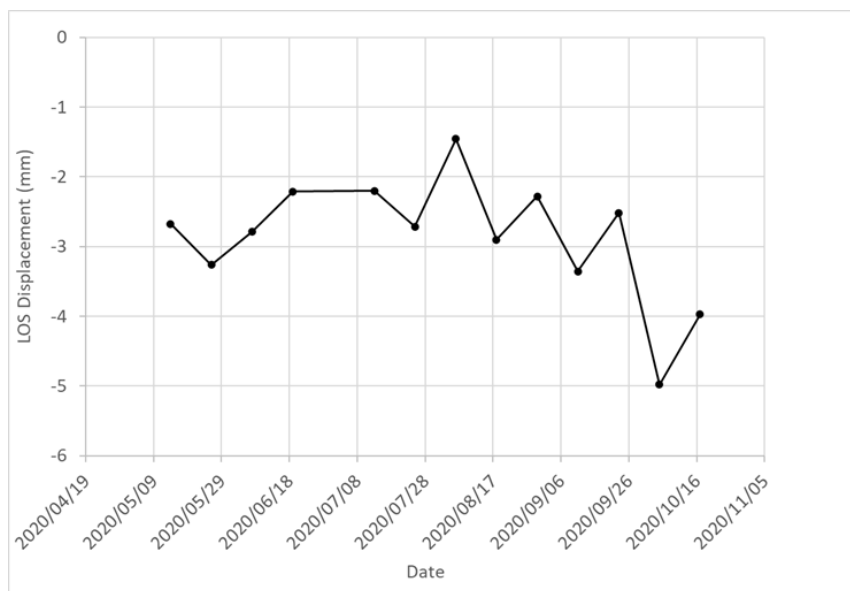


Figure 16: LOS displacement measured at the failure position between 4 April 2019 and 16 October 2020 by the Sentinel-1 satellite.

A total of 68 radar points over 13 measurements were analysed. Despite the fluctuating displacement measurements, the overall movement indicates movement away from the satellite.

3.4.4 Highwall failure, 8 December 2020

On 8 December 2020, a second failure occurred on the interburden of the highwall failure discussed in section 3.4.3; refer to Figure 17. The area was monitored with a ground-based radar at the time of the failure and discussed in section 3.4.3 of this report. The interburden is approximately 12 m thick. Take note that the interburden bench did not fail completely.



Figure 17: A second interburden failure that took place on the highwall of Ramp 2-4.

A total of 11 radar points were analysed. The measured LOS displacement can be seen in Figure 18.

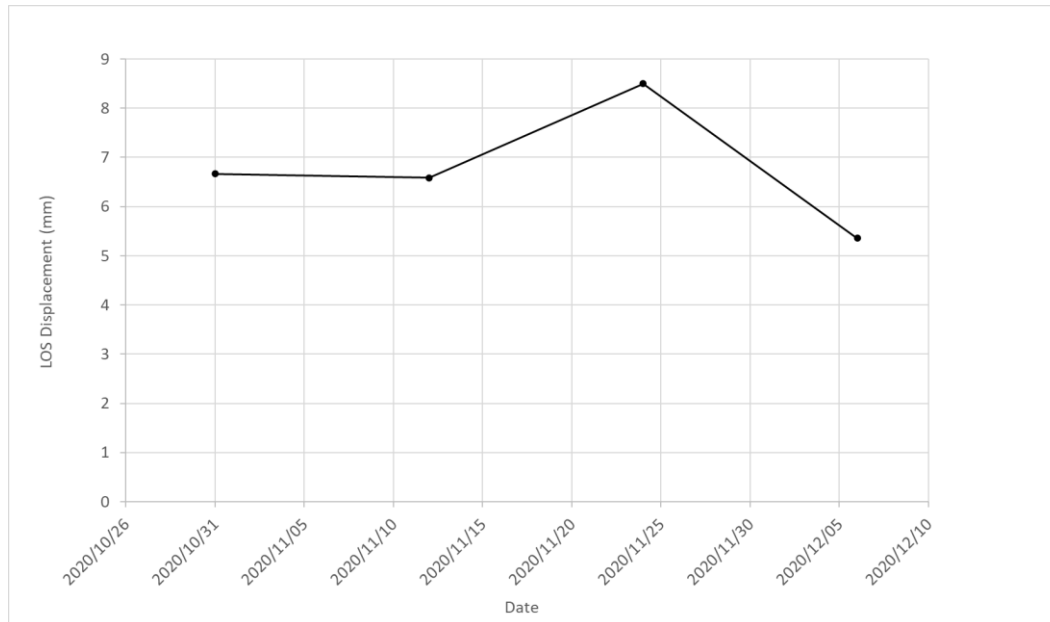


Figure 18: LOS displacement measured at the failure position between 26 October 2020 and 6 December 2020 by the Sentinel-1 satellite.

Take note that only four measurements were taken after the initial failure on 22 October 2020 and the secondary failure on 8 December 2020.

3.4.5 Highwall failure, 1 January 2021

On 1 January 2021, a third failure occurred on the interburden of the highwall failure discussed in section 3.4.3 of this report (refer to Figure 19). The interburden was approximately 12 m thick in this area. The area was monitored with a ground-based radar at the time of the failure. Refer to section 3.4.3 of this report.



Figure 19: Complete interburden failure of the highwall in Ramp 2-4.



Figure 20: Drone image of the complete interburden failure of the highwall in Ramp 2-4.

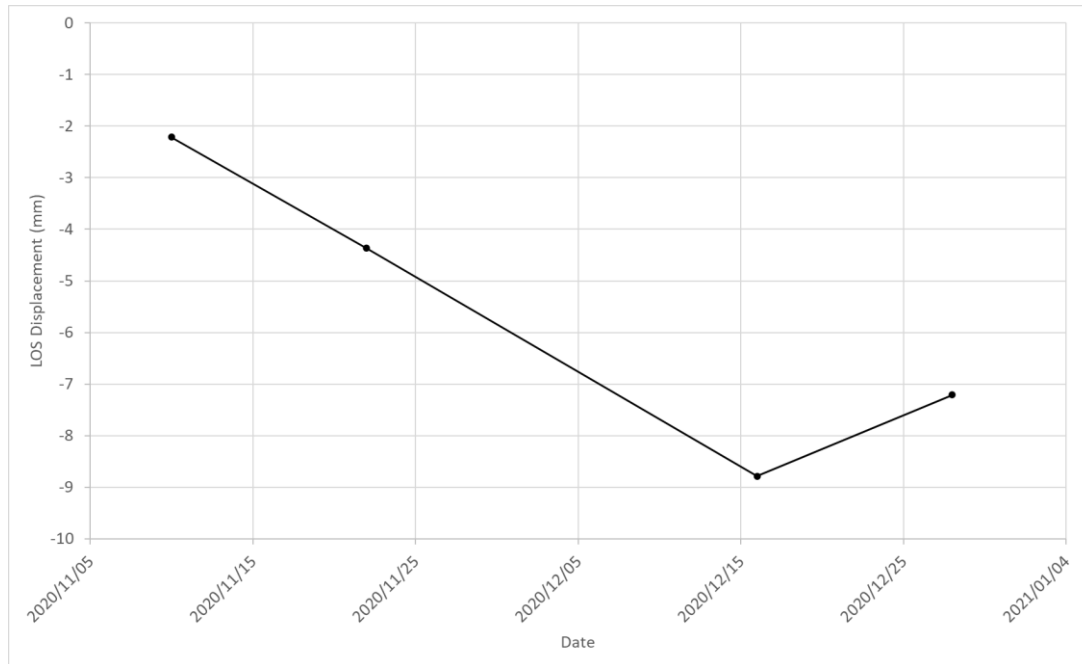


Figure 21: LOS displacement measured at the failure position between 10 November 2020 and 28 December 2020 by the Sentinel-1 satellite.

A total of 19 radar points were analysed. The measured LOS displacement can be seen in Figure 21. The failure that occurred on the exposed interburden on 8 December 2020 was ignored, as no significant displacement was recorded during the failure by the satellites.

3.4.6 Sand highwall failure, 30 April 2021

On 30 April 2021, a circular failure occurred on the sand highwall of Ramp 7 (refer to Figure 22). The sand is approximately 20 m thick.

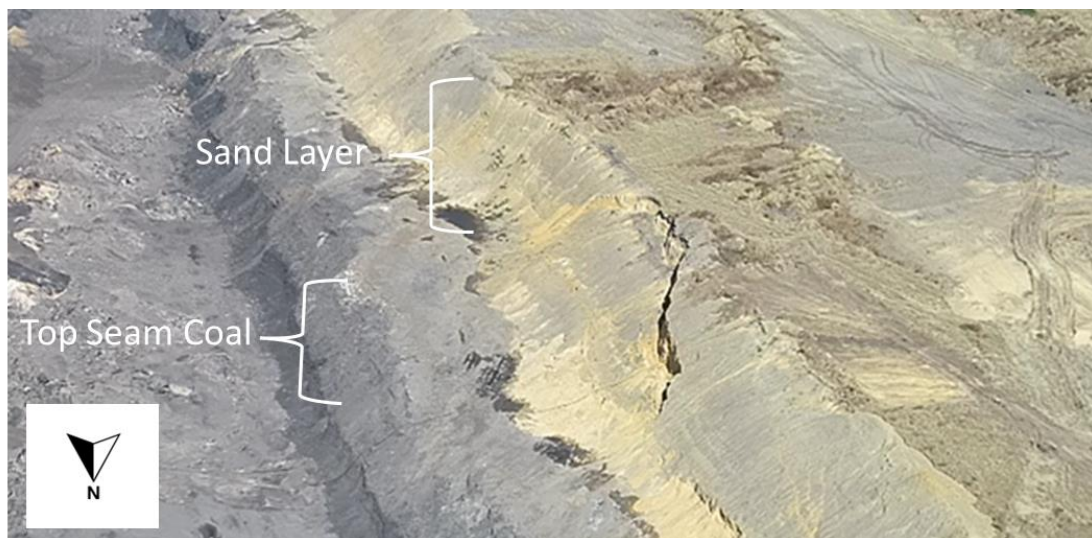


Figure 22: Ramp 7 sand highwall circular failure.

A total of nine radar points were analysed. The measured LOS displacement can be seen in Figure 23.

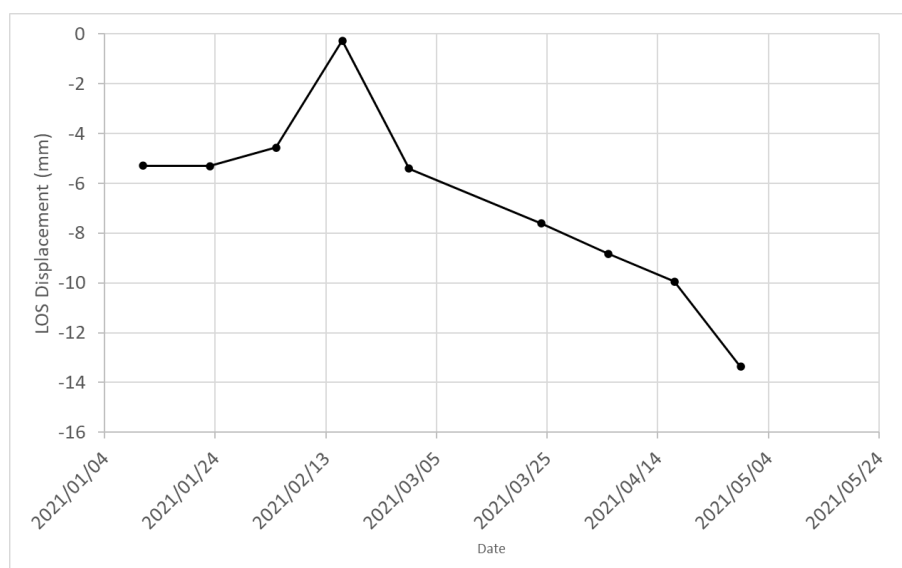


Figure 23: LOS displacement measured at the failure position between 4 January 2021 and 29 April 2021 by the Sentinel-1 satellite.

From 13 February 2021, a clear acceleration of the slope away from the satellite can be observed.

3.4.7 Highwall failure, 21 June 2021

A multi-bench highwall failure occurred on the Ramp 2-4 highwall on 21 June 2021 ; refer to Figure 24. Activated fault planes were visible after blasting and the failure occurred as the dragline removed the interburden, unconfining the highwall.

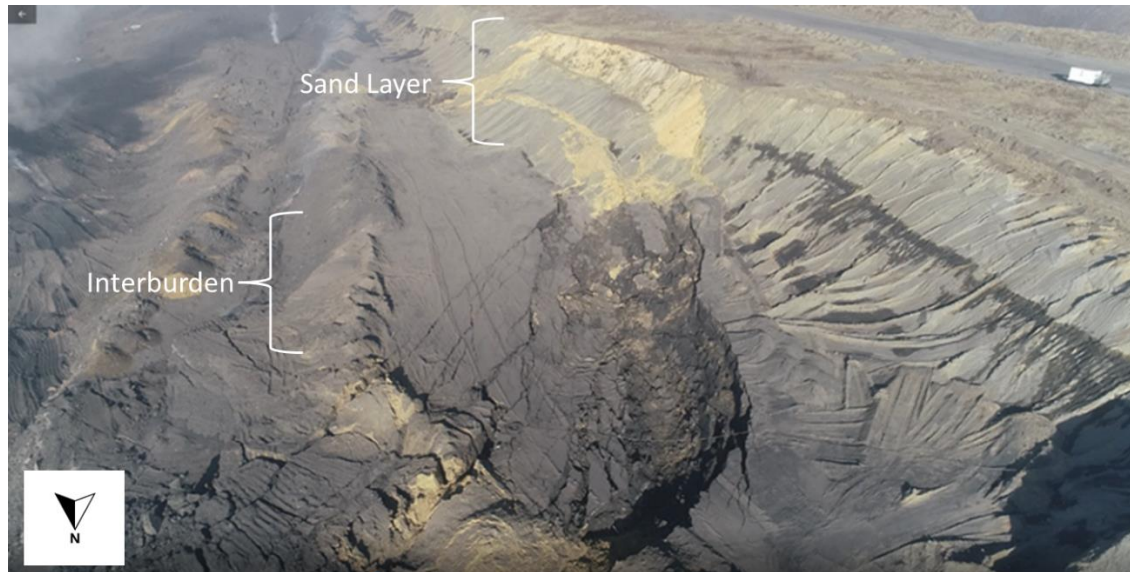


Figure 24: Ramp 2-4 highwall failure, 21 June 2021.

A total of 113 radar points were analysed. The measured LOS displacement can be seen in Figure 25.

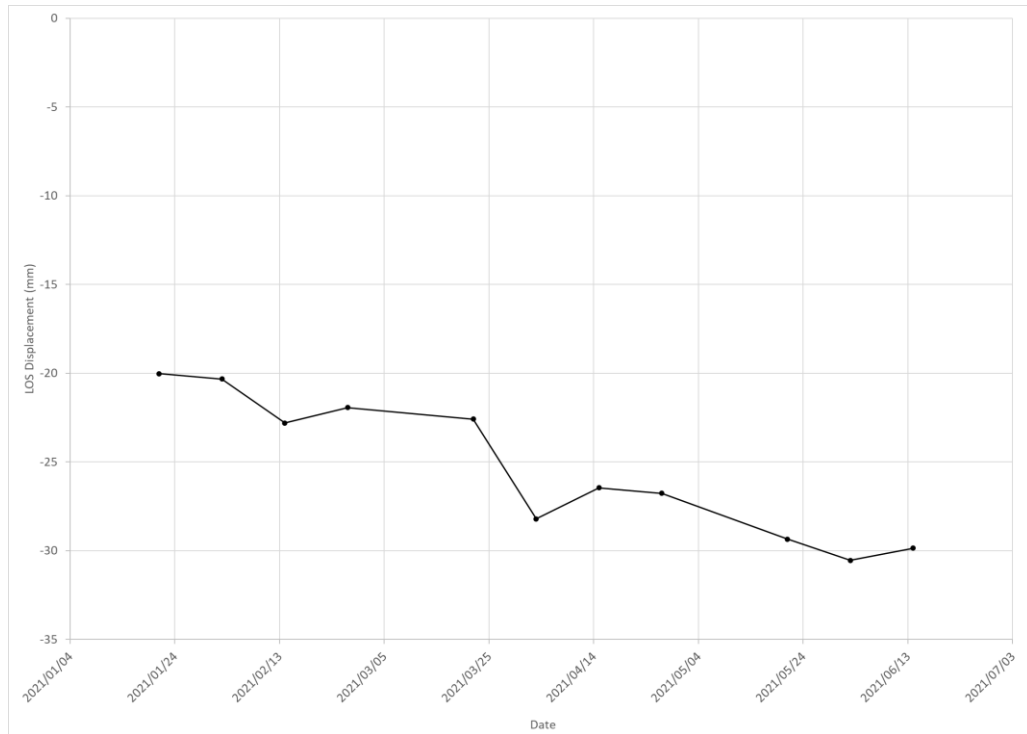


Figure 25: LOS displacement measured at the failure position from 21 January 2021 to 14 June 2021 by the Sentinel-1 satellite.

Take note of the gradual movement away from the satellite in the months leading up to the failure.

3.5 Ground-Based Radar Monitoring: Inverse Velocity

After the highwall failure discussed in section 3.4.3 of this report had occurred, a ground-based radar was deployed to monitor the highwall. On 8 December 2020 and 1 January 2021, the interburden highwall failed. The movement was recorded by the ground-based radar and can be seen in Figure 26.

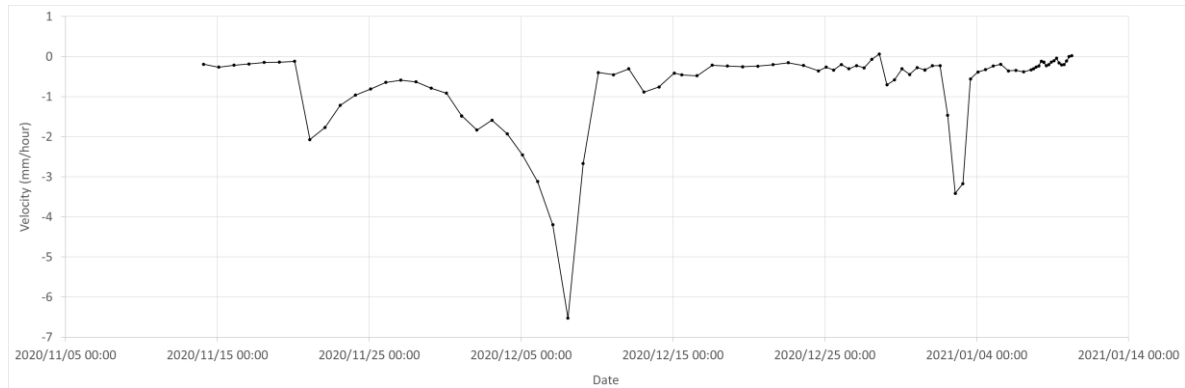


Figure 26: Ground-based radar of the interburden failures that occurred on 8 December 2020 and 1 January 2021 respectively.

Take note of the increase in acceleration measured on 6 December 2020 and 1 January 2021.

3.6 Ground-based Radar Monitoring: Finite Element Model Calibration

The ground-based radar dataset for the low wall failure discussed in section 3.4.1 was used to calibrate the material properties of the numerical models. The Mohr-Coulomb failure criterion was used and the material considered as perfectly plastic. RS2 9.0 (Rocscience) software was used to calculate the stresses and displacement of the slope to identify the strength reduction factor (SRF).

For the initial models, material properties based on ACARP research were used. The rock mass strength parameters were adjusted until the displacement predicted by the FEM model was within 5% of the actual displacement measured by the ground-based radar, directly before failure occurred, as done in literature (Escobar et al., 2013; Silva et al., 2021).

3.7 Rainfall Data

The mine is located in a summer rainfall region with an average rainfall of 740 mm per year (Banda et al., 2021). The graph in Figure 27 indicates that the highest rainfall occurs in January, February and December.

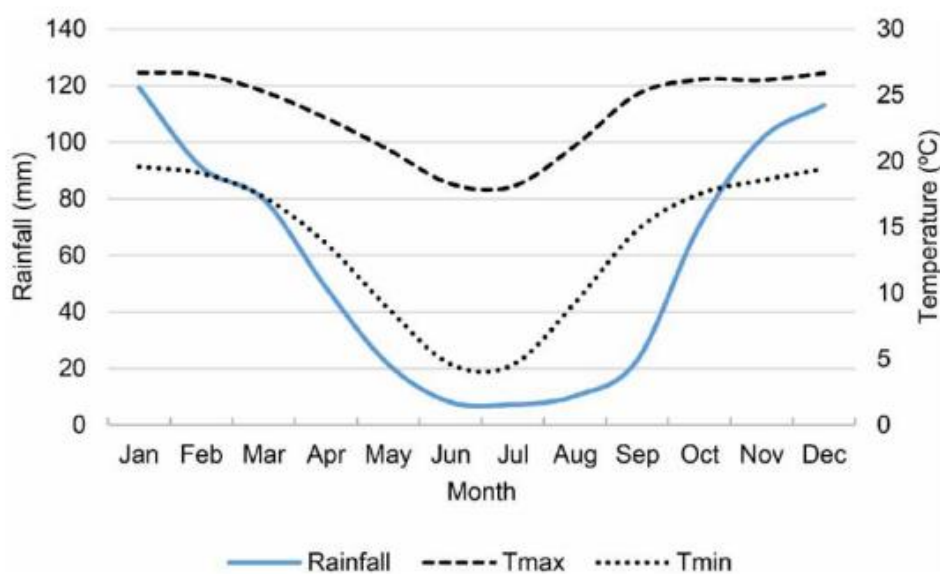


Figure 27: Rainfall and temperature data for the Vereeniging district (Banda et al., 2021).

The measured rainfall for the months in which the failures occurred discussed in this report is available in Figure 28 to Figure 32.

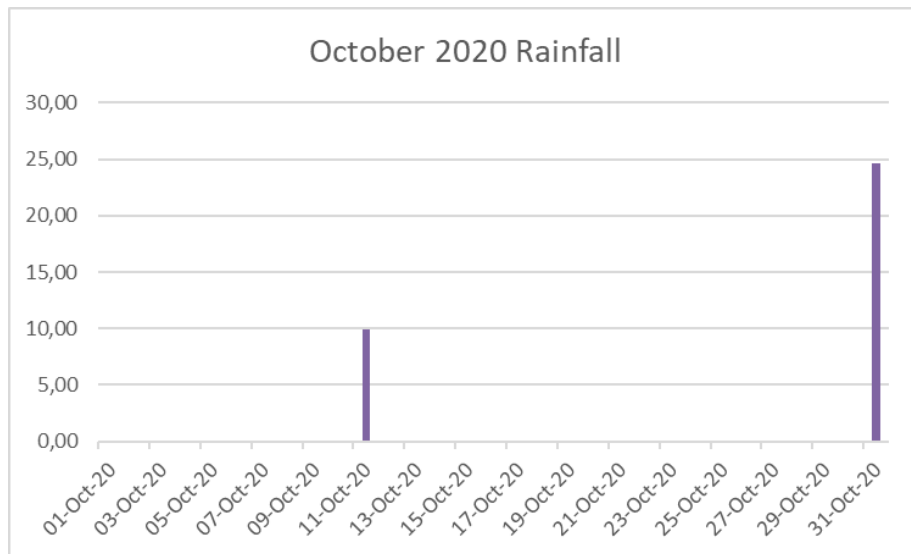


Figure 28: Rainfall measured on New Vaal Colliery in October 2020.

The total rainfall for the month of October was 34.5 mm.

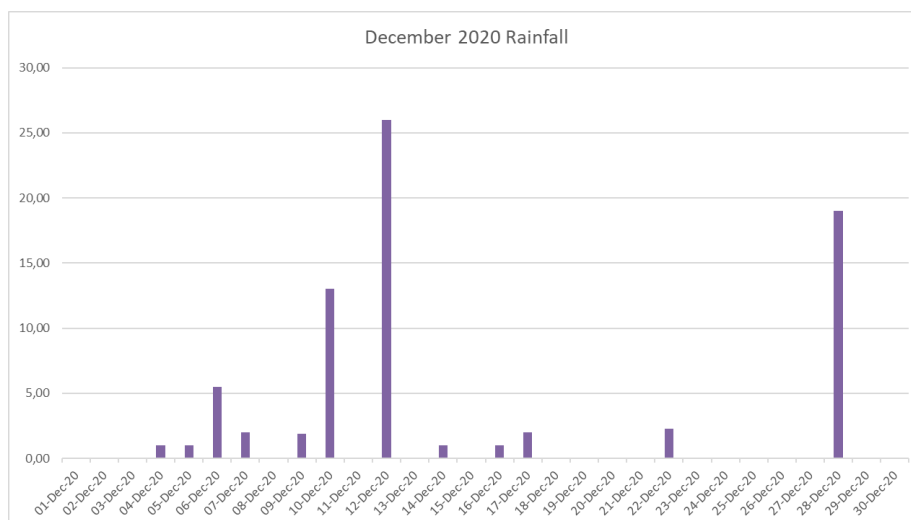


Figure 29: Rainfall measured on New Vaal Colliery in December 2020.

The total rainfall for the month of December was 75.7 mm.

Significant rainfall events that occurred in December 2020 included an excess of 25 mm on 12 December 2020 and 18 mm on 28 December 2020.

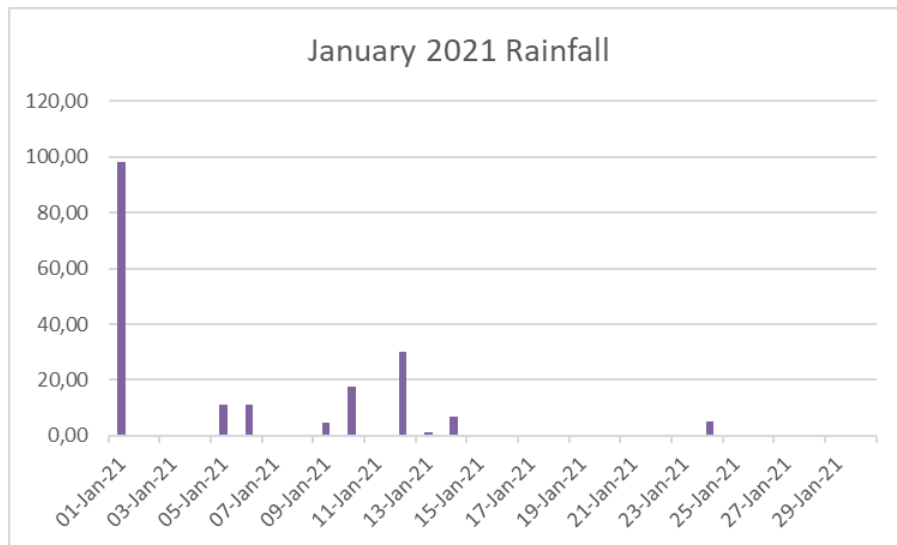


Figure 30: Rainfall measured on New Vaal Colliery in January 2021.

The total rainfall for the month of January was 185.5 mm. On the night of 31 December 2020 and the morning of 1 January 2021, 99 mm of rain was measured.

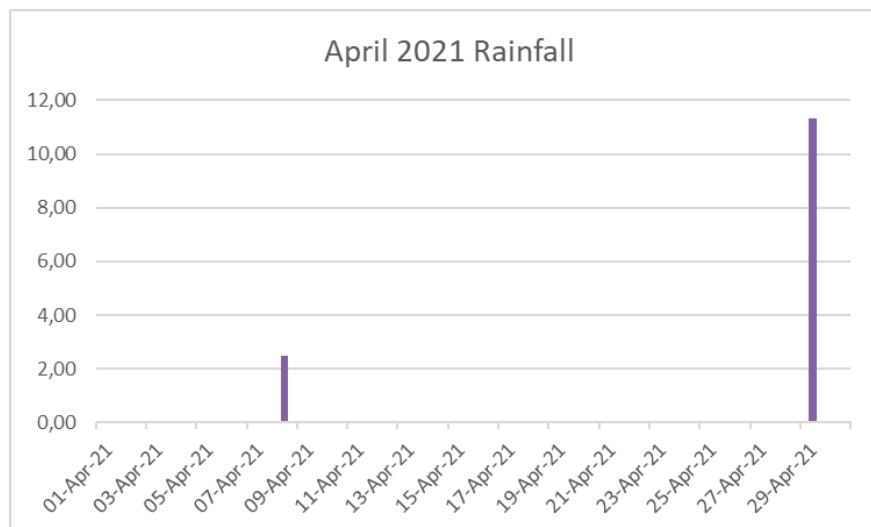


Figure 31: Rainfall measured on New Vaal Colliery in April 2021.

The total rainfall for the month of April was 13.8 mm.

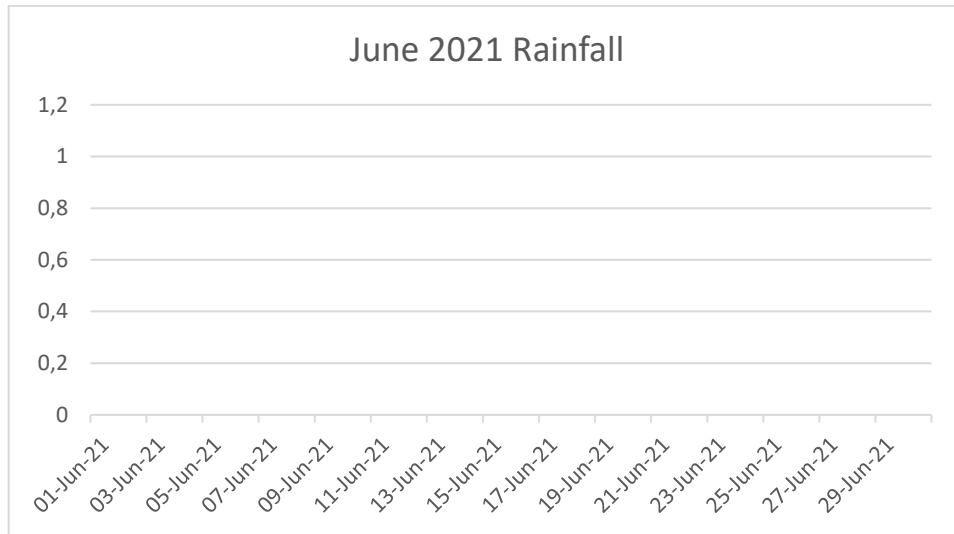


Figure 32: No rainfall recorded in June 2021.

The rainfall measured at New Vaal Colliery were correlated with displacement measured by both InSAR and ground-based radar to determine whether it contributed to the failure. It can be noted that with the exception of June 2021, rainfall occurred in every month preceding the failures discussed in this report.

4 RESULTS AND DISCUSSION

The results obtained from the inverse velocity time to failure predictions are discussed in section 4.1 and the numerical modelling results are discussed in section 4.2.

4.1 Inverse Velocity Predictions

The accuracy of inverse velocity time to failure predictions is extremely variable, and relies significantly on both measurement noise and the data smoothing technique that have been applied. As predicted by literature, the inverse velocity plots were especially sensitive to the influence of noise when working with low velocities (Carlà et al., 2017a).

When evaluating the time to failure predictions, based on InSAR data with a low data acquisition time, it is important to keep in mind that a significant percentage of the overall slope displacement occurs in the final hours before the failure. A clear correlation was observed between the accuracy of the failure prediction and the closer the last measurement was taken before the failure.

The size of the failure also has a significant influence on the length of the pre-failure deformation phase. Larger failures tend to show longer phases of precursor deformation (Carlà et al., 2017a). In general, slope failures in coal mines are significantly smaller in size compared to landslides and slope failures in massive opencast mines.

The linear fit of the regression line is an indication of the quality of the data, and a R^2 value of between 0,7 to 0,9 is considered to be of sufficient quality for the predictions

(Osasan & Stacey, 2014). Due to the excessive noise in the data, numerous failure predictions could not satisfy this requirement and were, therefore, excluded when the averages of the failure accuracies and regression line values were calculated.

As proposed in the literature, the inverse velocity predictions were based on the last four to seven measurements taken before the failure, depending on what resulted in the highest R^2 value.

4.1.1 Low wall failure, 30 March 2019

The velocity for all the radar points, as well as the most active radar points was plotted against time before failure. Refer to Figure 33 and Figure 34.

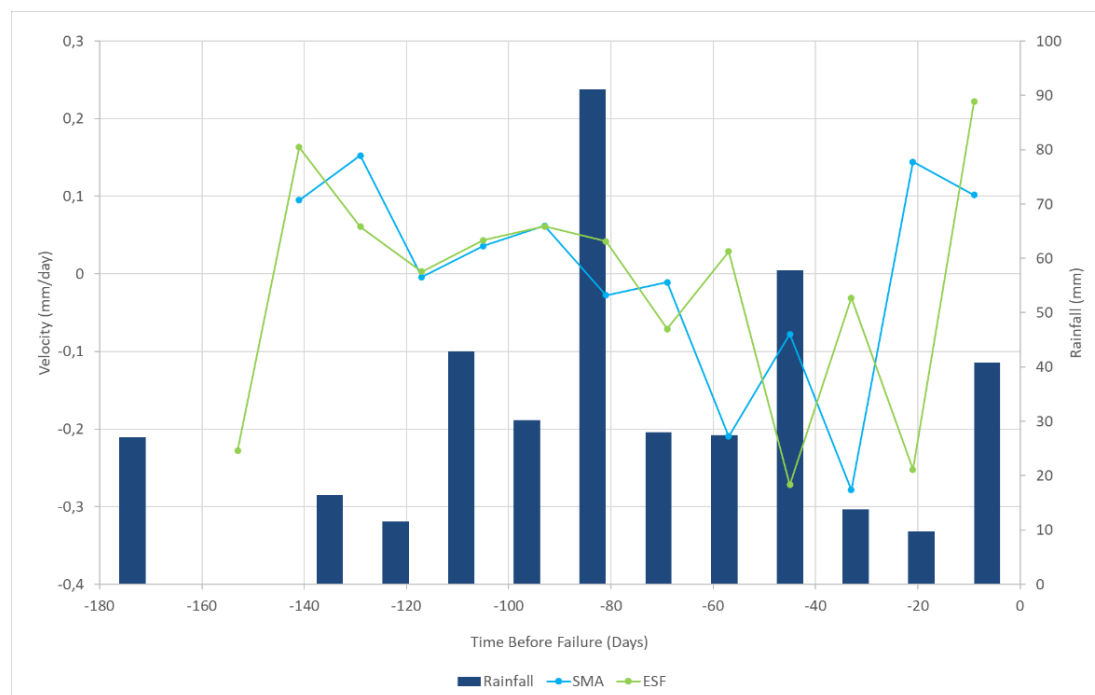


Figure 33: Slope velocity and rainfall for all the radar points included within the failure on 30 March 2019.

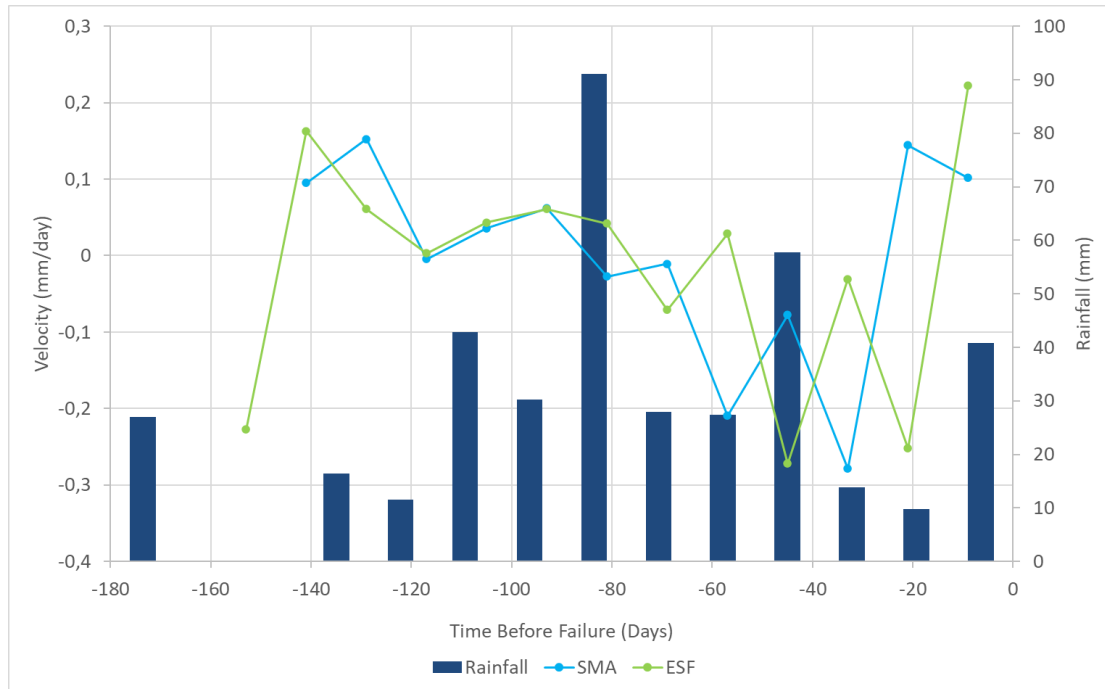


Figure 34: Slope velocity and rainfall for the most active radar points included within the failure area on 30 March 2019.

It was observed that the velocity of the radar points showed acceleration towards and away from the satellite between respective measurements. These fluctuations could be due to atmospheric interferences, resulting in inaccurate measurements which are commonly referred to as “noise” (Carlà et al., 2017a). Despite these fluctuations, both datasets showed a slight increase in acceleration after 91 mm of rain had fallen approximately 81 days before the failure occurred.

The high level of noise resulted in very poor regression line values, leading to unreliable data for failure predictions. The inverse velocity plot for the low wall failure that occurred on 30 March 2019 can be seen in Figure 35.

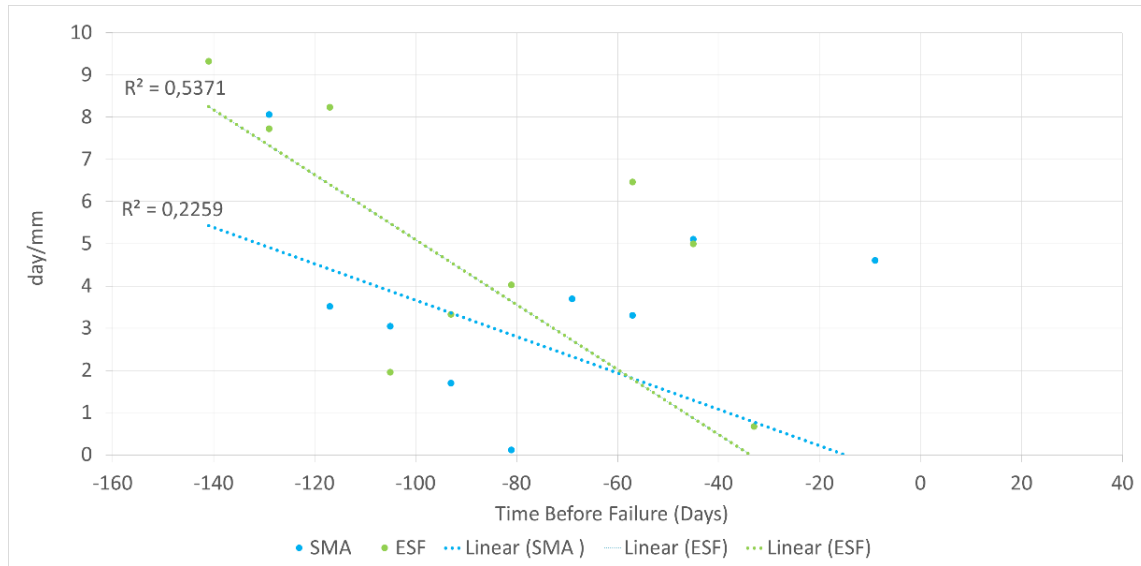


Figure 35: Inverse velocity plots for the low wall failure on 30 March 2019.

The predicted failure dates for the SMA and ESF were 14,94 days and 33,71 days before the failure respectively. The R^2 values for the SMA and ESF were 0.23 and 0.54 respectively, which indicated that the fit of the data was of insufficient quality to use for time to failure predictions. A total of 13 displacement measurements from 13 radar points were analysed for the failure prediction. The last measurement was taken nine days before the failure.

The prediction based on the ESF was less accurate as this method produces forecasts where the weighted averages of the most recent observations exponentially increase, and the last two measurements showed acceleration towards the satellite, against the trend of acceleration away from the satellite.

The predicted failure dates, based on the most active point, for the SMA and ESF were 15,36 days and 17,49 days before the failure respectively (refer to Figure 36).

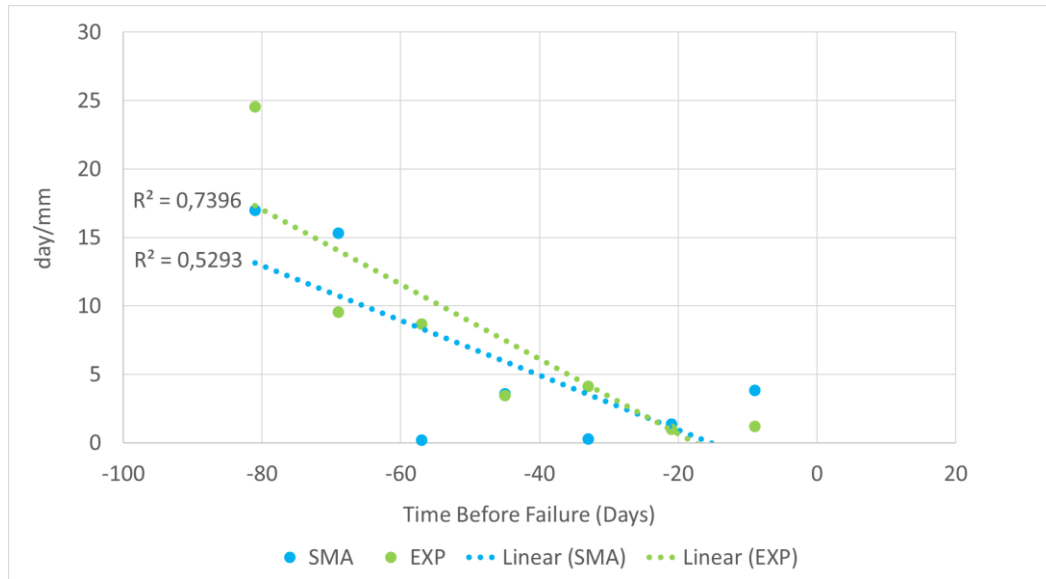


Figure 36: Inverse velocity plots for the low all failure on 30 March 2019, based on the most active points within the failed area.

The R^2 values for the SMA and ESF improved, and were 0.52 and 0.74 respectively. A total of seven displacement measurements from two radar points were analysed for the failure prediction. The last measurement was taken nine days before the failure.

From the four failure predictions done, only the prediction based on the most active points where the ESF had been applied, could be used. This prediction was still 17,49 days before the actual failure, an impractical margin of error in a high production environment. Despite the excessive noise and inaccurate failure predictions, the slope acceleration observed after continuous rain was considered sufficient evidence that the rain had been a contributing factor to the failure, refer to Figure 33 and Figure 34.

4.1.2 Highwall failure, 22 October 2020

The velocity for all the radar points included within the failed area can be seen in Figure 37.

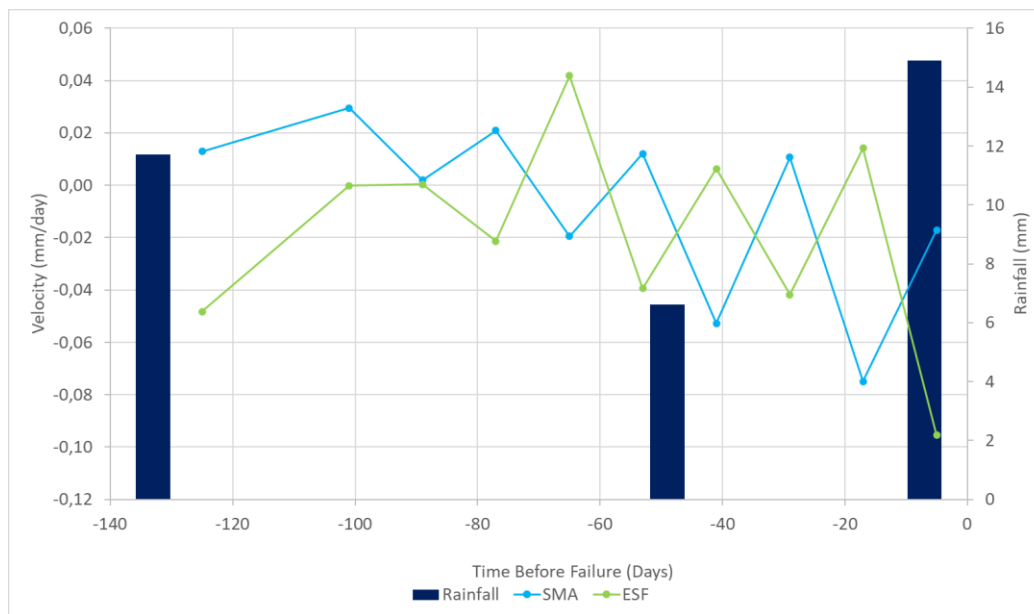


Figure 37: Average daily slope velocity and rainfall for all the radar points included within the failure on 22 October 2020.

From the graph in Figure 37, it can be observed that the radar points accelerated both away and towards the satellite in the days leading up to the failure, similar to the failure discussed in section 4.1.1 of this report. These fluctuating measurements could have been due to the influence of blasting activities resulting in heave, the influence of vegetation cover or noise due to atmospheric disturbances. No clear correlation was observed between slope acceleration and rainfall events.

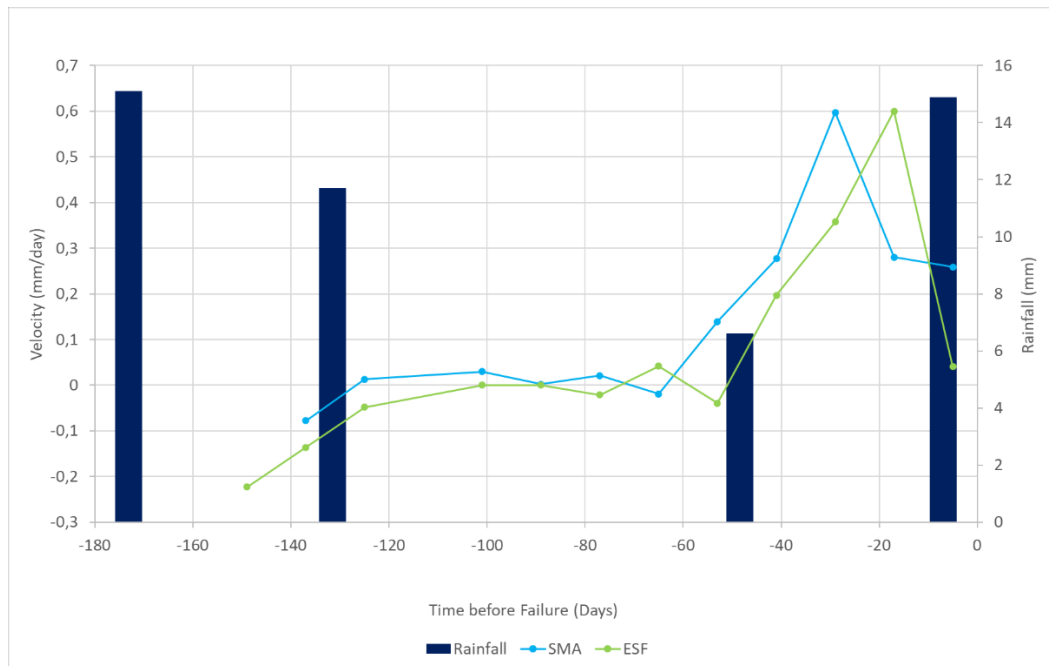


Figure 38: Slope velocity and rainfall for the most active radar points included within the failure area on 22 October 2020.

From the graph in Figure 38, it was observed that the most active radar points showed less noise and a clear increase in velocity towards the satellite from approximately 60 days before the failure. The last and second-last measurements, however, showed acceleration away from the satellite.

The inverse velocity plot for the highwall failure on 22 October 2020 can be seen in Figure 39.

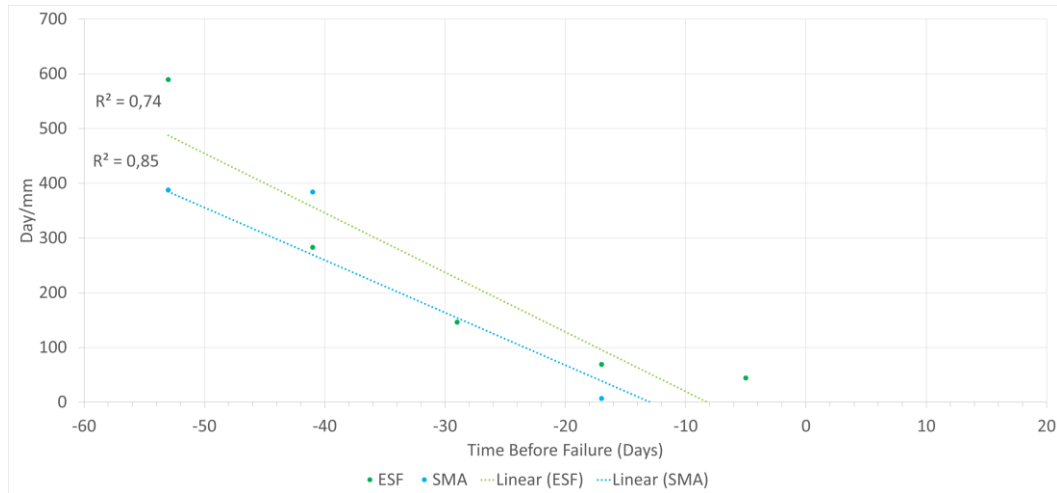


Figure 39: Inverse velocity plots for the highwall failure on 22 October 2020.

The predicted failure dates for the SMA and ESF were 12,95 days and 8,18 days before the failure date respectively. The R^2 values for the SMA and ESF were 0.74 and 0.85 respectively. A total of eight displacement measurements from 68 radar points were analysed for the failure prediction. The last measurement was taken five days before the failure.

The predicted failure dates, based on the most active points for the SMA and ESF, were 5,37 days and 13,86 days before the failure respectively (refer to Figure 40).

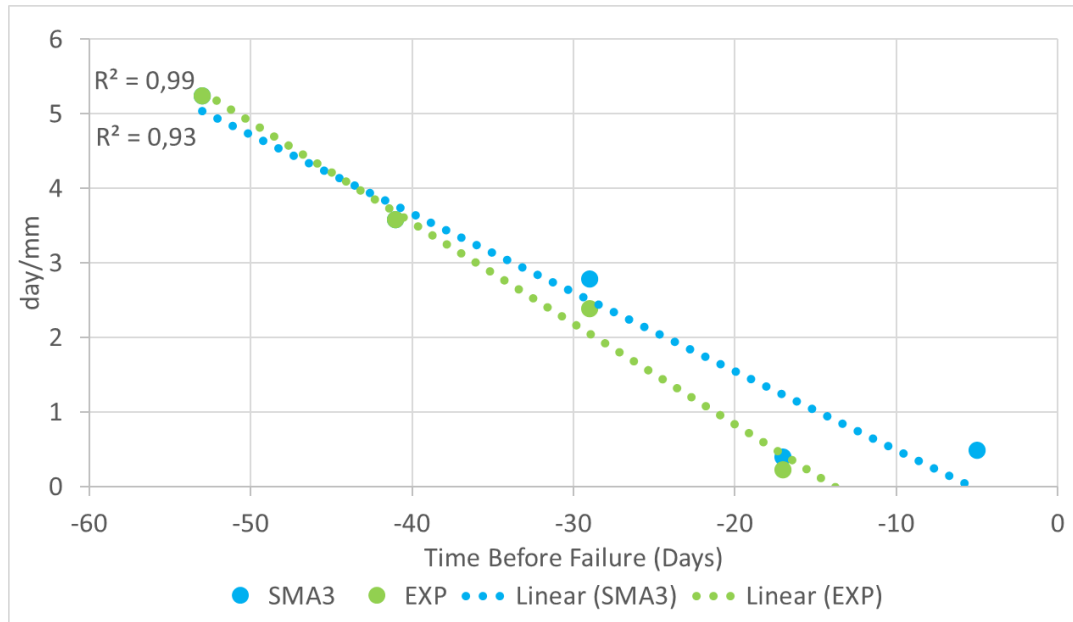


Figure 40: Inverse velocity plots for the highwall failure on 22 October 2020, based on the most active points only.

The R^2 values for the SMA and ESF were 0.94 and 0.99 respectively. A total of five displacement measurements from a cluster of three radar points were analysed for the failure prediction. The last measurement was taken five days before the failure.

The accuracy of the prediction improved for the SMA but decreased for the ESF. This was due to the last point showing acceleration away from the satellite which had a greater impact on the ESF prediction accuracy.

4.1.3 Highwall failure, 8 December 2020

Due to the limited data acquisitions that were obtained between 22 October 2020 and 8 December 2020 and the fact that the failure was limited to the vertical interburden face, time to failure predictions were not possible from the satellite data. This

emphasised the limitation of InSAR as a primary tool for slope monitoring and its ability to capture small-scale, near-instantaneous failures.

In Figure 41, the velocity of the radar points between 31 October 2020 and 6 December 2020 can be seen. Take note that the slope showed a decrease in movement as the rainfall decreased. The measurements were taken on the interburden that had failed.

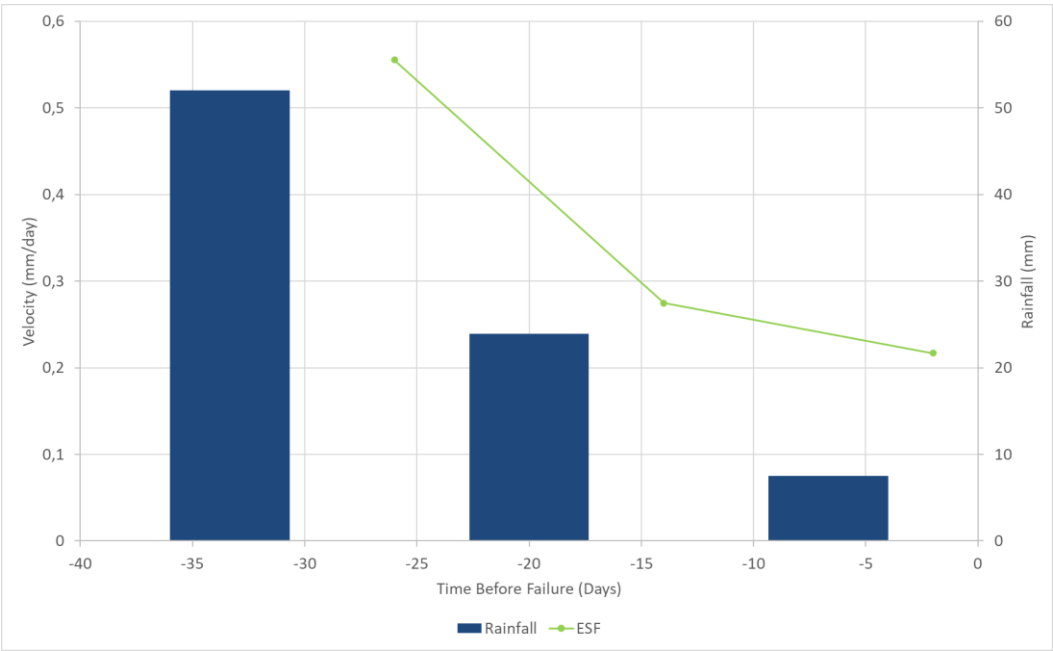


Figure 41: Average daily slope velocity and rainfall for all the radar points included within the failure on 8 December 2020.

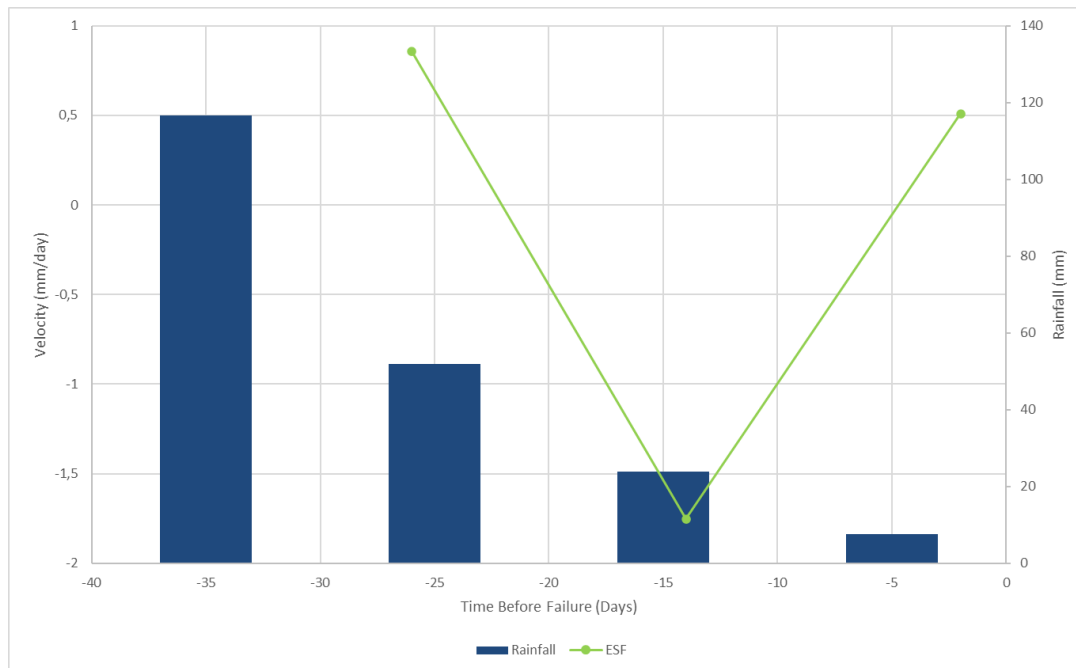


Figure 42: Daily slope velocity and rainfall for all the most active radar points situated on the interburden that failed on 8 December 2020.

The time to failure plot in Figure 43, based on ground-based radar data, predicts a failure time to be 1,58 days after the failure.

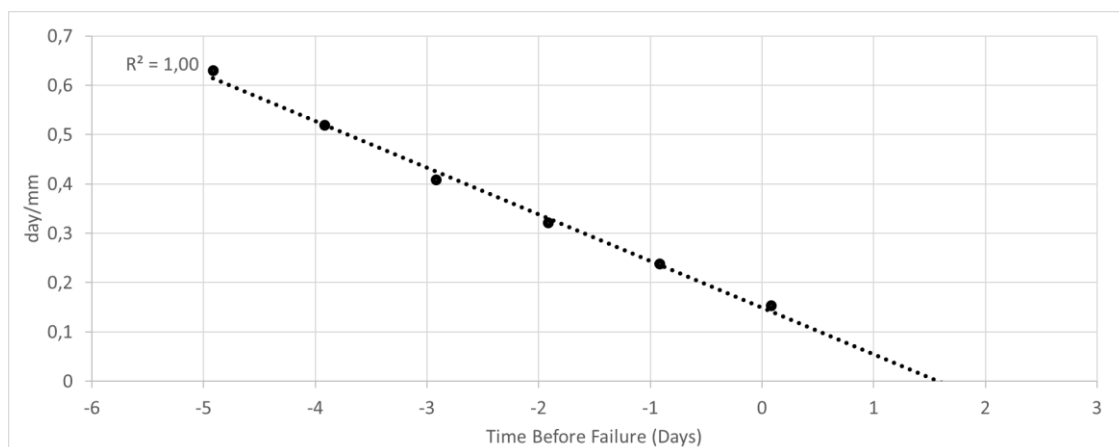


Figure 43: Inverse velocity plots for the highwall failure that occurred on 8 December 2020, based on ground-based radar data.

The R^2 value of the regression line was 1. This failure prediction was less accurate than expected from ground-based radars, as this prediction was based on the movement recorded over the whole slope. The accuracy of the prediction was also compromised when the data was exported from the ground-based radar, since it only exported the movement in 12-hour intervals, based on the 12-hour time window selected. The accuracy of this prediction might have been improved by identifying the most active points for time to failure predictions and applying the data over a shorter time window. Despite the inaccuracy of the time to failure prediction, the ground-based radar was still effective in identifying the increase in slope velocity to trigger the evacuation of the area.

4.1.4 Highwall failure, 1 January 2021

In the graph of Figure 44, Figure 41 the velocity of the radar points between 31 October 2020 and 28 December 2020 can be seen. Take note that the failure that had occurred on the interburden on 6 December was ignored and data from before this failure was included.

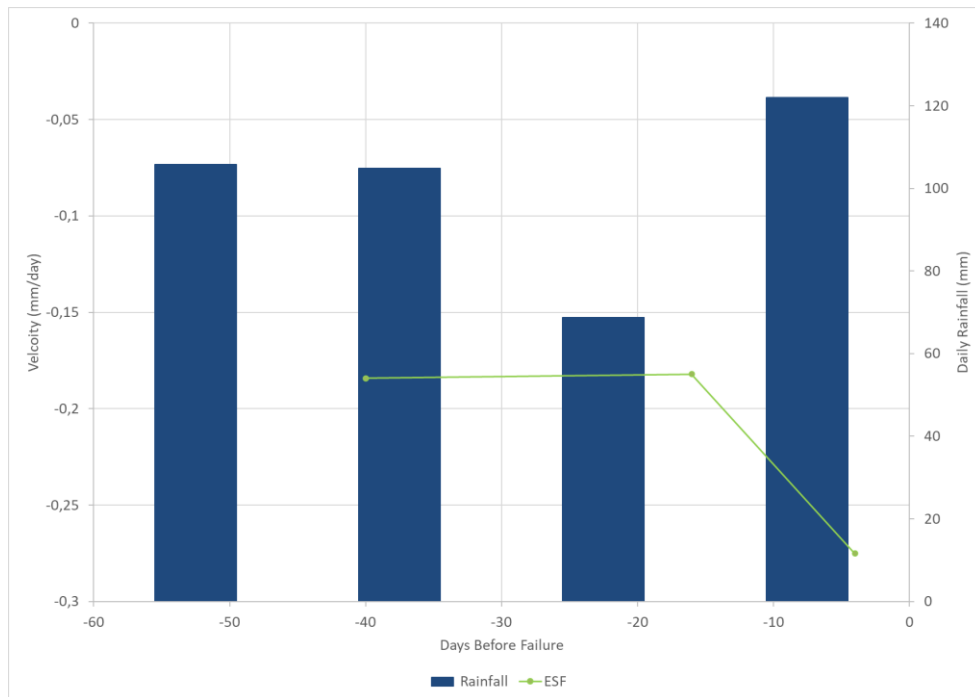


Figure 44: Average daily slope velocity and rainfall for all radar points included within the failure on 1 January 2021.

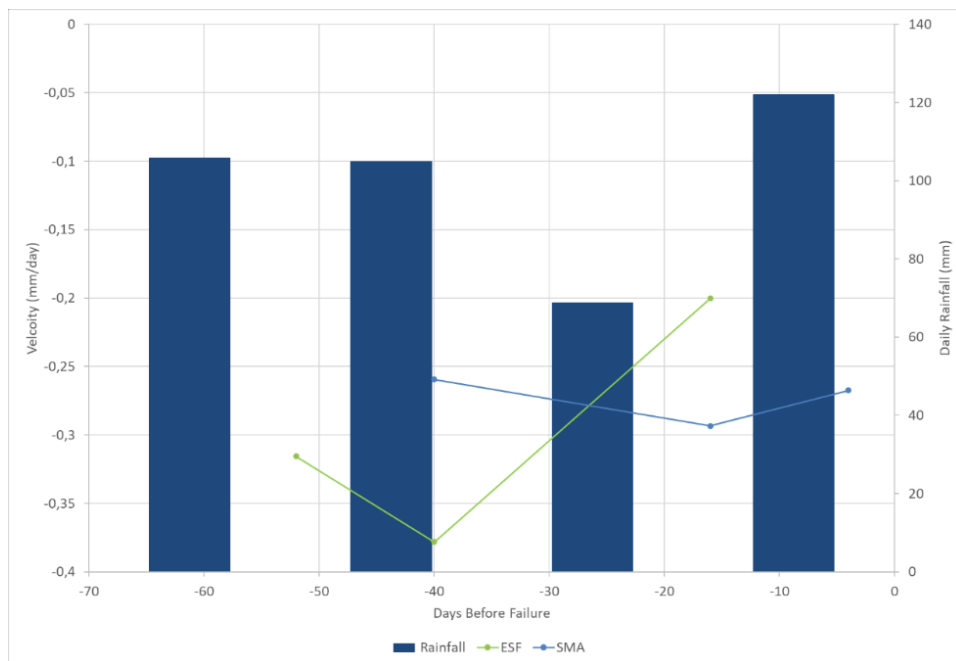


Figure 45: Daily slope velocity and rainfall for all the most active radar points for the failure on 1 January 2021.

The inverse velocity plot for the highwall failure that occurred on 1 January 2021 can be seen in Figure 46.

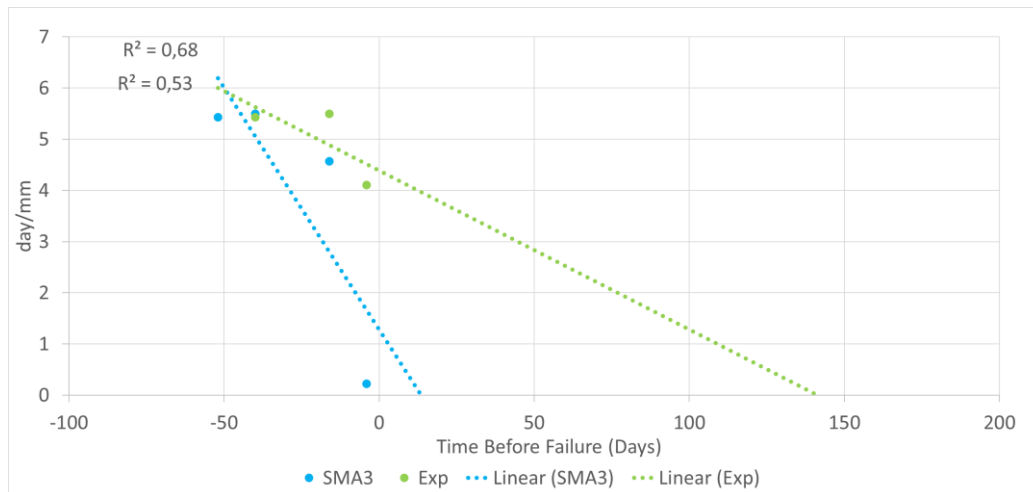


Figure 46: Inverse velocity plots for the highwall failure on 1 January 2021.

The predicted failure dates for the SMA and ESF were 13,57 days and 141,10 days after the failure date respectively. The R^2 values for the SMA and ESF were 0.68 and 0.53 respectively. A total of four displacement measurements, based on 19 radar points, were analysed. The last measurement was taken three days before the failure.

The predicted failure dates, based on the most active points for the SMA and ESF, were 5,77 days and 60,91 days after the failure respectively; refer to Figure 47.

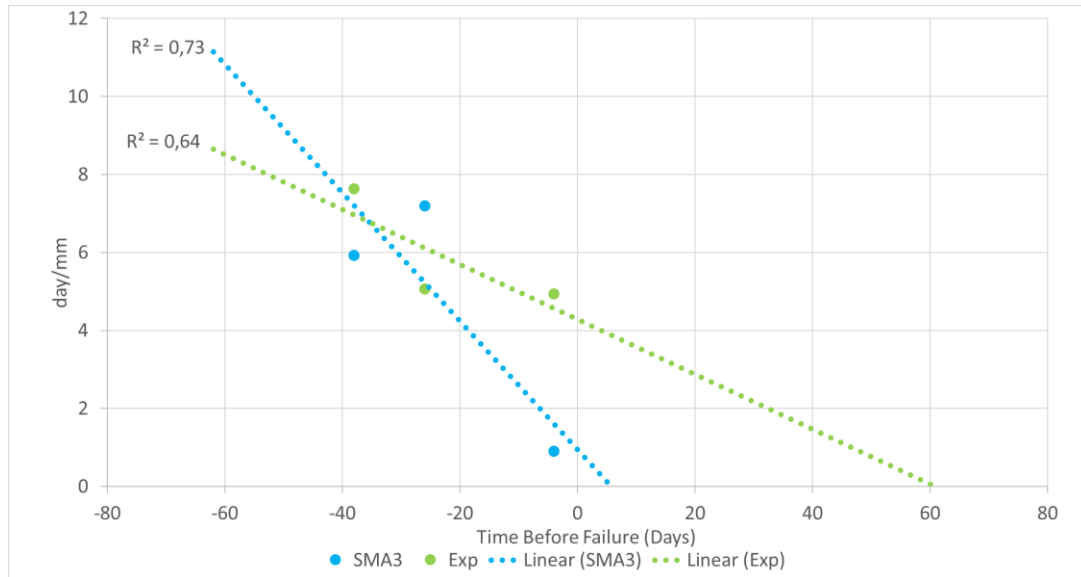


Figure 47: Predicted failure date based on the most active points contained within the failure boundary.

The R^2 values for the SMA and ESF were 0.73 and 0.64 respectively. A total of five displacement measurements from two radar points were analysed for the failure prediction. The last measurement was taken three days before the failure.

The excessive rainfall, 99 mm within one night, triggered a near-instantaneous failure of the slope. Therefore, limited pre-cursor movement was identified by the satellite, resulting in highly inaccurate time to failure predictions from the satellite data. The instantaneous nature of the failure was also confirmed by the ground-based radar, refer to Figure 26.

The time to failure plot in Figure 48, based on ground-based radar data, was inconclusive due to the lack of pre-cursor movement. No OOA was identified from the monitoring data, as the failure occurred instantaneously.

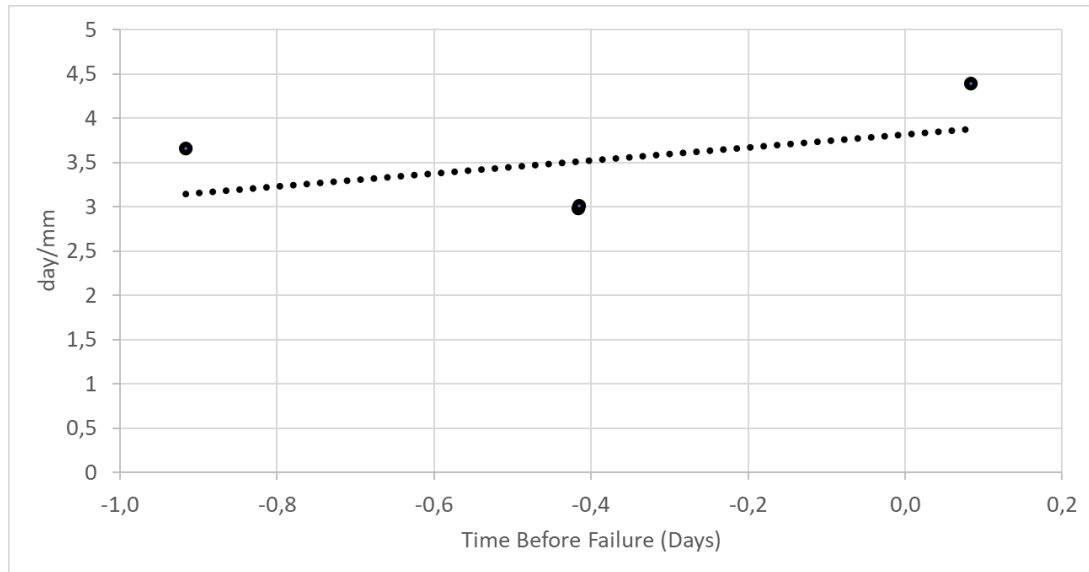


Figure 48: Inverse velocity plots for the highwall failure on 1 January 2021, based on ground-based radar data.

4.1.5 Sand highwall failure, 30 April 2021

The velocity for all the radar points included within the failed area can be seen in Figure 49. Approximately 60 days before the failure, the slope showed acceleration away from the satellite.

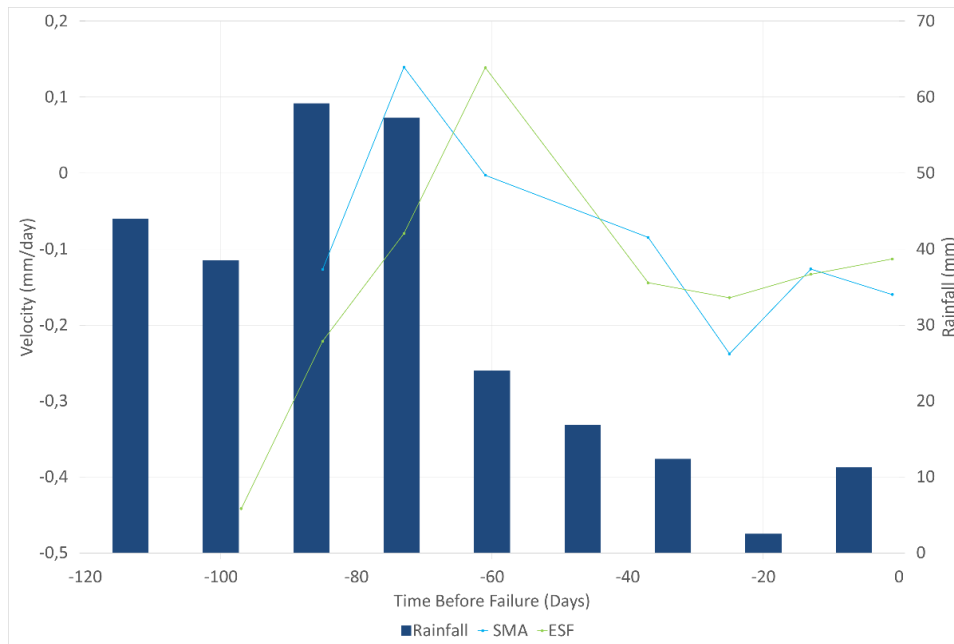


Figure 49: Average daily slope velocity and rainfall for all radar points included within the failure on 30 April 2021.

The velocity for all the most active radar points included within the failed area can be seen in Figure 50.

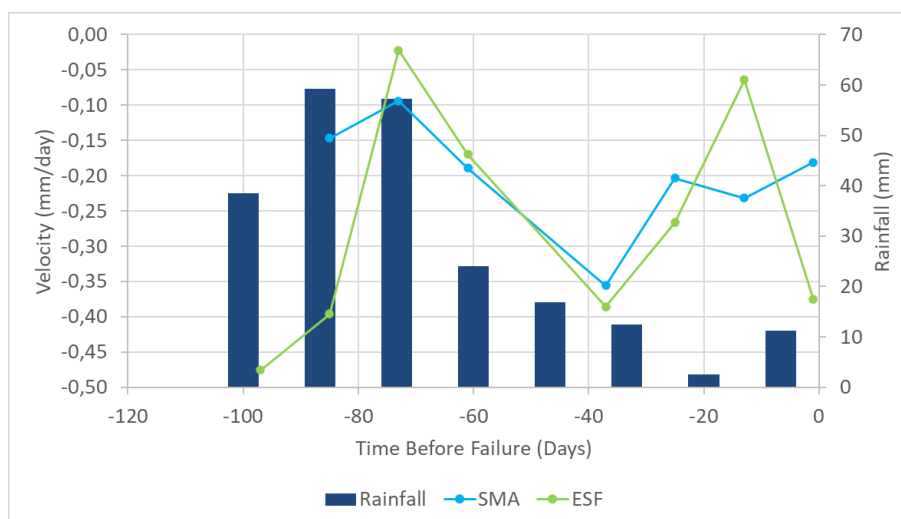


Figure 50: Average daily slope velocity and rainfall for the most active radar points included within the failure on 30 April 2021.

The inverse velocity plot for the highwall failure that occurred on 30 April 2021 can be seen in Figure 51.

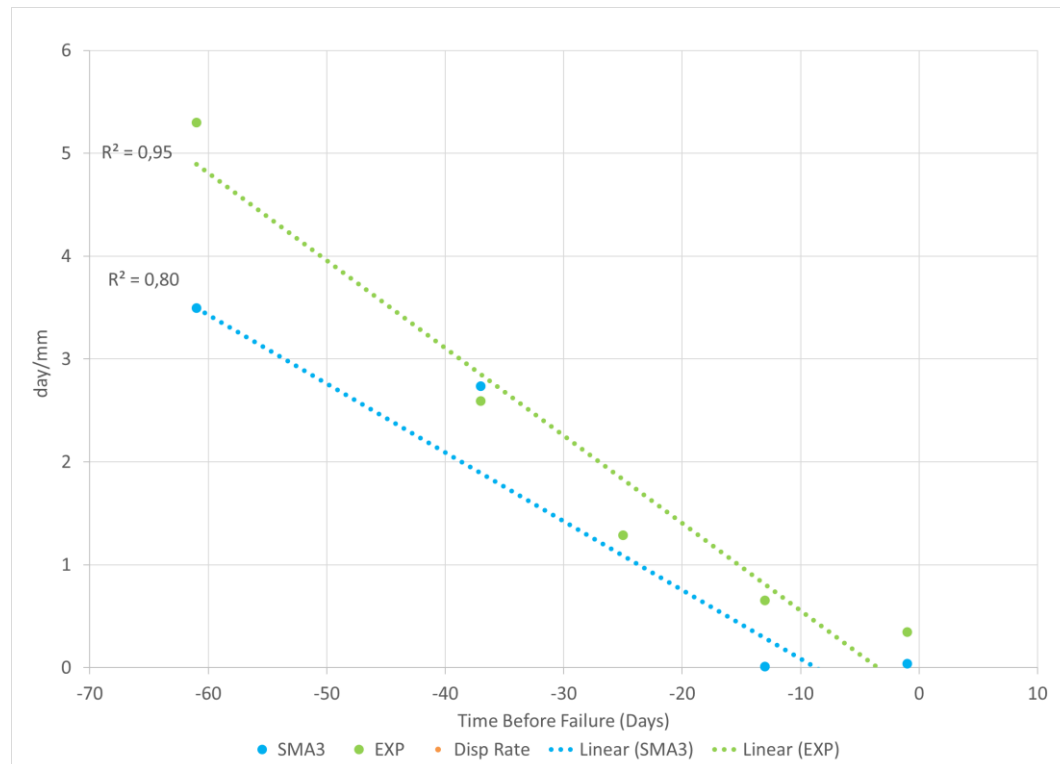


Figure 51: Inverse velocity plots for the highwall failure on 30 April 2021.

The predicted failure dates for the SMA and ESF were 8,73 days and 3,48 days before the failure respectively. The R^2 values for the SMA and ESF were 0.80 and 0.95 respectively. A total of seven displacement measurements from nine radar points were analysed for the failure prediction. The last measurement was taken on the day of the failure.

The predicted failure dates, based on the most active points for the SMA and ESF, were 4,8 days before and 0,7 days after the failure respectively, refer to Figure 52.

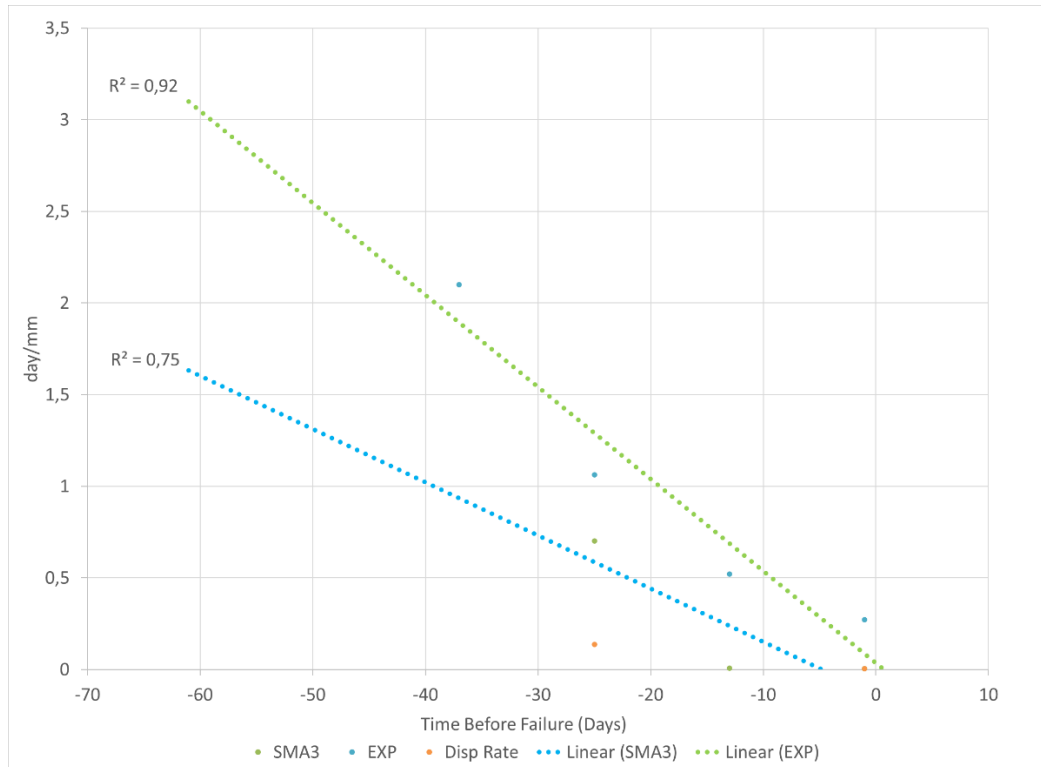


Figure 52: Inverse velocity plots for the highwall failure on 30 April 2021, based on the most active points.

The R^2 values for the SMA and ESF were 0.75 and 0.92 respectively. A total of six displacement measurements from a cluster of five radar points were analysed for the failure prediction. The last measurement was taken on the day of the failure. The measurement that was taken on the day mere hours before the failure recorded significant slope acceleration; therefore, increasing the accuracy of the failure prediction.

4.1.6 Highwall failure, 21 June 2021

The velocity for all the radar points included within the failed area can be seen in Figure 53.

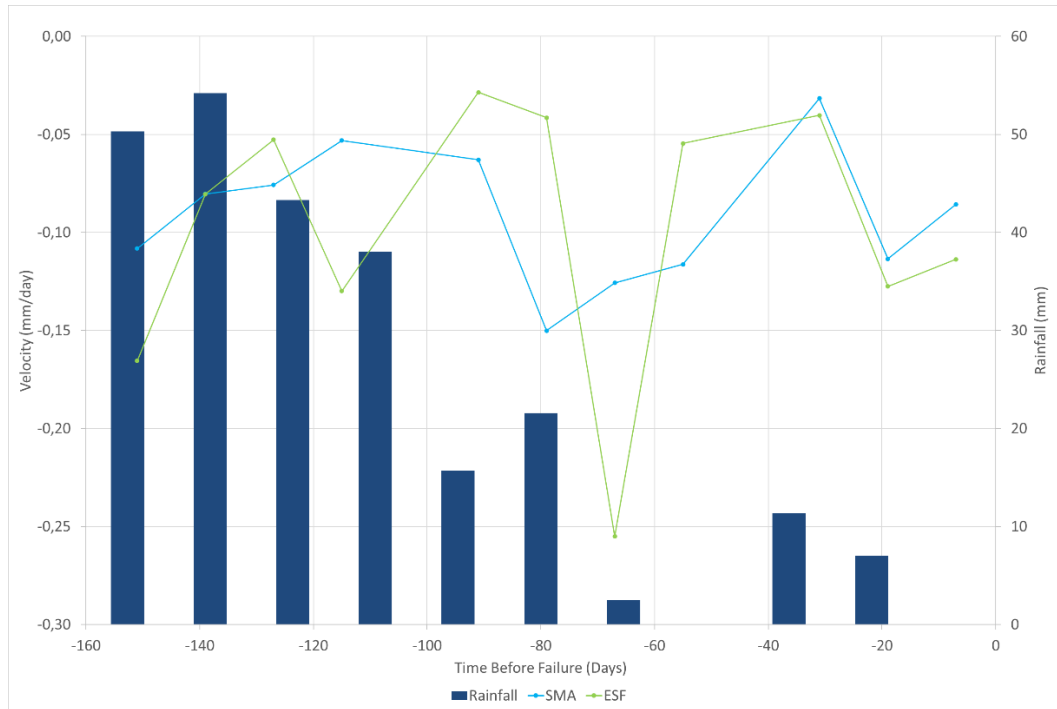


Figure 53: Slope velocity and rainfall for all the radar points included within the failure on 21 June 2021

Take note of the fluctuation of the velocity of the slope movement, since no clear trend can be observed. This was possibly due to continuous mining activities that occurred on the bench.

The velocity for all the most active radar points included within the failed area can be seen in Figure 54. Take note of the constant velocity of the slope at around 0,5 mm/day.

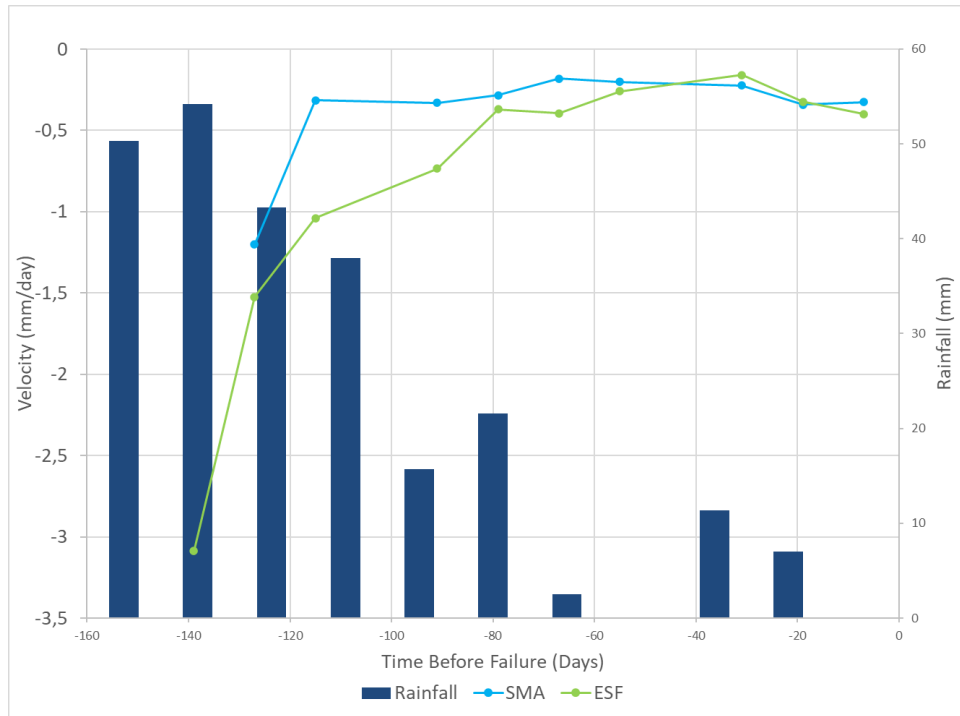


Figure 54: Average daily slope velocity and rainfall for the most active radar points included within the failure that occurred on 21 June 2021.

The inverse velocity plot for the highwall failure that occurred on 21 June 2021 can be seen in Figure 55.

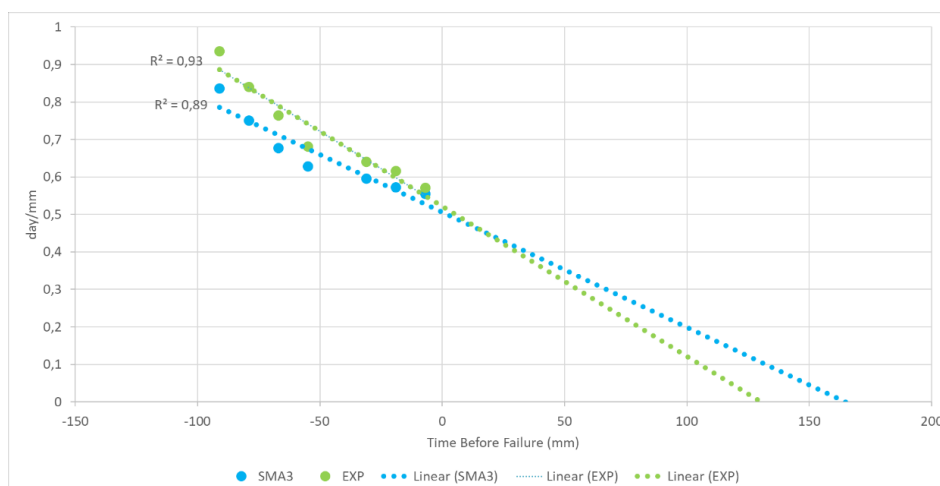


Figure 55: Inverse velocity plots for the high wall failure on 21 June 2021.

The predicted failure dates for the SMA and ESF were 163,25 days and 130,35 days after the failure respectively. The R^2 values for the SMA and ESF smoothing were 0.89 and 0.92 respectively. A total of 14 displacement measurements from 113 radar points were analysed for the failure prediction. The last measurement was taken seven days before the failure.

The predicted failure dates, based on the most active points for the SMA and ESF were 19,9 days and 4,3 days after the failure respectively, refer to Figure 56.

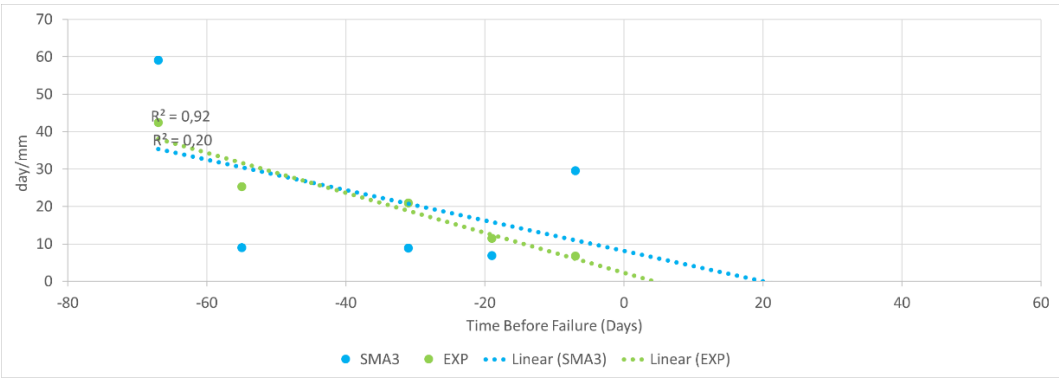


Figure 56: Inverse velocity plot based on the most active points for the highwall failure on 21 June 2021.

The R^2 values for the SMA and exponential smoothing were 0.20 and 0.92 respectively. A total of five displacement measurements from a cluster of five radar points were analysed for the failure prediction. The last measurement was taken seven days before the failure.

4.1.7 Data smoothing techniques and prediction accuracy

The predicted failure times and regression line values are summarised in Table 4 and Table 5. By excluding the failures that had been affected by external influences such

as excessive rain or mechanical unconfinement and the regression line values that were below 0,7, an average failure accuracy was calculated for the different smoothing techniques.

The ESF resulted in more accurate time to failure predictions than the SMA (refer to Table 5). The poor regression line values were due to the high degree of noise included in the satellite data. Contrary to what had been found in the literature, the ESF resulted in a better fit to the regression line than the SMA (Carlà et al., 2017a). This might be because the datasets that were analysed for this project, in general, included an excessive amount of noise. Positive values indicate a predicted failure date after the actual failure and negative values indicate a predicted failure date before the actual failure date in Table 4.

Table 4: Difference between actual and predicted failure dates. Positive values indicate a predicted failure date after the actual failure and negative values indicate a predicted failure date before the actual failure date.

Failure Date	SMA	ESF	Radar Points	Comments	Acquisition*
21-Jun-21	+163,25	+130,35	Whole area	External influence	7 days
21-Jun-21	+19,99 [†]	+4,26	Active points	External influence	7 days
30-Apr-21	-8,73	-3,48	Whole area	Usable data	0 days
30-Apr-21	-4,82	+0,92	Active points	Usable data	0 days
01-Jan-21	+13,57 [†]	+141,1 [†]	Whole area	External influence	3 days
01-Jan-21	+5,77	+60,91 [†]	Active points	External influence	3 days
22-Oct-20	-38,41	-40,71 [†]	Whole area	Usable data	9 days
22-Oct-20	-5,37	-13,86	Active points	Usable data	9 days
30-Mar-19	-14,94 [†]	-33,71 [†]	Whole area	Noise	5 days
30-Mar-19	-15,36 [†]	-17,49	Active points	Usable data	5 days

*† Regression line value below 0.7. Data is not valid. * Time difference between the last acquisition date and failure date.*

Table 5: Summary of regression line values.

	30-Mar-19	22-Oct-20	01-Jan-21	30-Apr-21	21-Jun-21	Average	Standard Deviation	Poor Fit	Accuracy (days)
SMA (WA)*	0,23	0,79	0,68	0,80	0,80	0,66	0,22	2	23,57
SMA (AP)**	0,52	0,94	0,73	0,75	0,21	0,63	0,25	2	5,10
ESF (WA)*	0,54	0,53	0,53	0,95	0,94	0,70	0,20	3	3,48
ESF (AP)**	0,74	0,99	0,64	0,92	0,92	0,84	0,13	1	10,76

*WA – All radar points included in the failure zone

**AP – Only the most active radar points within the failure zone

The inaccurate failure dates might be explained by the fact the failure predictions were not applied from a true OOA point as proposed in the literature. (Rose & Hungr, 2007). Furthermore, the low deformation values recorded result in the predictions being severely affected by noise that cannot necessarily be filtered out. Except for the failure date prediction for the highwall failure that occurred on 30 April 2021, based on the most active radar points and smoothed with the ESF, all the valid inverse plots indicated a failure date before the actual failure date.

Based on the literature, it was expected that the accuracy of the failure prediction should improve the closer the last measurement was taken before the actual failure date (Carlà et al., 2019). This was observed from the time to failure predictions that had no external influences. The most accurate prediction had a measurement hours before the actual failure. By utilising satellites with shorter revisit times, the accuracy of time to failure predictions should be improved.

4.2 Numerical Modelling Results

By utilising the displacement monitoring data from the ground-based radar the accuracy of the predicted displacement and failure location of the model was improved. The initial model strength parameters were based on literature studies. Strength parameters from laboratory data will remain a logical starting point for numerical models, but the utilisation of radar data does have the ability to improve the accuracy of the numerical models.

The displacement predicted by the FEM model in Figure 57 correlates well with the displacement measured by the ground-based radar at the time of failure.

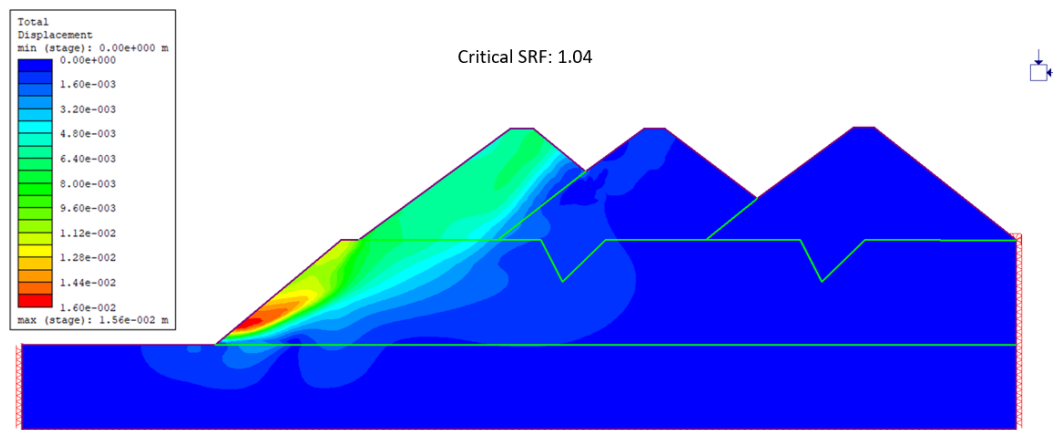


Figure 57: FEM indicating the total displacement of 15.6 mm at an SRF of 1.04.

The radar measured a relative range of approximately 16 mm and the FEM predicted a displacement of 15.6 mm at an SRF of 1.04. The position of the predicted displacement correlated with the position of the actual failure that had occurred on the low wall. The strength parameters for the finite element numerical models were reduced by approximately 6% to ensure that the predicted displacement was within 5% of the actual measured displacement.

5 CONCLUSION

5.1 Inverse Velocity

The average error of the failure time to failure predictions ranged from 3,48 to 23,57 days, a significantly larger margin of error than a couple of hours reported in the literature. The accuracy of time to failure predictions based on InSAR data must improve to add real value to mining operations. This may be achieved by improving data processing to remove the noise and by utilising satellites with shorter revisit times. Time to failure predictions that are several days out will negatively impact production and safety in the mine. It was observed that the accuracy of the failure predictions did improve the closer the last measurement was taken to the actual failure date. It should be noted that displacement measurements from satellites will take several days to be processed and will therefore only become available several days to weeks after the measurements have been taken.

The external influences such as mechanical unconfinement, excessive rain and pre-existing planes of weaknesses must all be considered when attempting to predict the time to failure. The most accurate time to failure prediction was for a circular failure that occurred in sand material which had no external influences and limited measurement noise.

The time to failure predictions based on ground-based radar proved to be significantly more reliable and accurate. This reaffirms the importance of having real-time monitoring on site. Time to failure predictions should still only be used as a guideline

and a reasonable factor of safety should be used when utilising the inverse velocity technique to prolong production underneath a potentially unstable slope.

5.2 Numerical Model Calibration

The displacement measured by the ground-based radar correlated well with the magnitude and position of the displacement predicted by the FEM. The original strength parameters of the site had to be decreased by 6% to achieve this. It increased the confidence in the numerical model, as it was a close representation of what was observed in the pit. This assisted in minimising the geotechnical uncertainty.

5.3 Recommendations

Due to the poor quality of the data that has been extracted from the historic sentinel-1 satellite, it is recommended that the utilisation of InSAR data to predict time to failure on strip mines needs to be investigated further. A target site must be identified and actively monitored with a combination of satellites such as TerraSAR-x and Paz. This will result in a shorter revisit time and higher resolution. Having a targeted monitoring site with updated digital elevation models will also improve data quality and reduce noise. The inverse velocity should be applied proactively to all slopes that show an increase in the rate of movement.

The use of an automatic slope failure prediction model, which automatically identifies the most active points on a slope, is also recommended. This would assist with identifying potential failure windows.

REFERENCE LIST

Banda, V.D., Dzwauro, R.B., Singh, S.K. & Kanyerere, T. 2021. Trend analysis of selected hydro-meteorological variables for the Rietspruit sub-basin, South Africa. *Journal of Water and Climate Change*, 12(7):3099–3123.

DOI:10.2166/wcc.2021.260

Bar, N. & McQuillan, A. 2018. 3D limit equilibrium slope stability analysis for anisotropic and faulted rock masses in Australian coal and iron ore mines, *ARMS 10, 10th Asian Rock Mechanics Symposium. The ISRM International Symposium for 2018*. Singapore, 29 October to 03 November 2018.

Berardino, P., Costantini, M., Franceschetti, G., Iodice, A., Pietranera, L. & Rizzo, V. 2003. Use of differential SAR interferometry in monitoring and modelling large slope instability at Maratea (Basilicata, Italy). *Engineering Geology*, 68(1–2):31–51.

DOI:10.1016/S0013-7952(02)00197-7

Carlà, T., Farina, P., Intrieri, E., Ketizmen, H. & Casagli, N. 2018. Integration of ground-based radar and satellite InSAR data for the analysis of an unexpected slope failure in an open-pit mine. *Engineering Geology*, 235:39–52. September 2017. DOI:10.1016/j.enggeo.2018.01.021

- Carlà, T., Intrieri, E., Di Traglia, F., Nolesini, T., Gigli, G. & Casagli, N. 2017a. Guidelines on the use of inverse velocity method as a tool for setting alarm thresholds and forecasting landslides and structure collapses. *Landslides*, 14(2):517–534. DOI:10.1007/s10346-016-0731-5
- Carlà, T., Intrieri, E., Farina, P. & Casagli, N. 2017b. A new method to identify impending failure in rock slopes. *International Journal of Rock Mechanics and Mining Sciences*, 93:76–81. January. DOI:10.1016/j.ijrmms.2017.01.015.
- Carlà, T., Intrieri, E., Raspini, F., Bardi, F., Farina, P., Ferretti, A., Colombo, D., Novali, F., et al. 2019. Perspectives on the prediction of catastrophic slope failures from satellite InSAR. *Scientific Reports*, 9(1):1–9. DOI:10.1038/s41598-019-50792-y
- Cornelius, R.R. & Scott, P.A. 1993. A materials failure relation of accelerating creep as empirical description of damage accumulation. *Rock Mechanics and Rock Engineering*, 26(3):233–252. DOI:10.1007/BF01040117
- Crosta, G.B. & Agliardi, F. 2003. Failure forecast for large rock slides by surface displacement measurements. *Canadian Geotechnical Journal*, 40(1):176–191. DOI:10.0.4.115/t02-085

Dick, G.J., Eberhardt, E., Cabrejo-Liévano, A.G., Stead, D. & Rose, N.D. 2015. Development of an early-warning time-of-failure analysis methodology for open-pit mine slopes utilizing ground-based slope stability radar monitoring data. *Canadian Geotechnical Journal*, 52(4):515–529. DOI:10.1139/cgj-2014-0028

Escobar, A., Farina, P., Leoni, L., Iasio, C. & Coli, N. 2013. Innovative use of slope monitoring radar as a support to geotechnical modelling of slopes in open pit mines. In PM Dight (ed.), *Slope Stability 2013: Proceedings of the 2013 International Symposium on Slope Stability in Open Pit Mining and Civil Engineering*, Australian Centre for Geomechanics, Perth. 793–801.
https://doi.org/10.36487/ACG_rep/1308_54_Farina

Fukuzono, T. 1985. A method to predict the time of slope failure caused by rainfall using the inverse number of surface displacement. *Landslides*, 22(2):8–13_1.
https://doi.org/10.3313/jls1964.22.2_8

Harries, N., Noon, D. & Rowley, K. 2006. Case studies of slope stability radar used in open cut mines. *Proceedings of the First International Symposium on Stability of Rock Slopes in Open Pit Mining and Civil Engineering Situations*. 335–342. The South African Institute of Mining and Metallurgy, Johannesburg.
http://www.saimm.co.za/Conferences/RockSlopes/335-342_Harries.pdf

Hooper, A., Zebker, H., Segall, P. & Kampes, B. 2004. A new method for measuring deformation on volcanoes and other natural terrains using InSAR persistent scatterers. *Geophysical Research Letters*, 31(23):1–5.

DOI:10.1029/2004GL021737

Kanda, M.J. & Stacey, T.R. 2016. The influence of various factors on the results of stability analysis of rock slopes and on the evaluation of risk. *Journal of the Southern African Institute of Mining and Metallurgy*, 116(11):1075–1081.

DOI:10.17159/2411-9717/2016/v116n11a10

Leighton, J. & Sullivan, M. 2020. InSAR in the clouds: Satellite-based monitoring at Grasberg Mine. In PM Dight (ed.), *Slope Stability 2020: Proceedings of the 2020 International Symposium on Slope Stability in Open Pit Mining and Civil Engineering*, Australian Centre for Geomechanics, Perth. 281–292.

DOI:10.36487/acg_repo/2025_14

Mandal, J., Narwal, S. & Gupte, S.S. 2017. Back analysis of failed slopes - A case study. *International Journal of Engineering Research & Technology (IJERT)*, 6(5):1070–1078. DOI:10.17577/ijertv6is050366

McQuillan, A., Yacoub, T., Bar, N., Coli, N., Leoni, L., Rea, S. & Bu, J. 2020. Three-dimensional slope stability modelling and its interoperability with interferometric radar data to improve geotechnical design. In PM Dight (ed.), *Slope Stability 2020: Proceedings of the 2020 International Symposium on Slope Stability in Open Pit Mining and Civil Engineering*. Australian Centre for Geomechanics, Perth. 1349–1358. DOI:10.36487/ACG_repo/2025_92

Osasan, K.S. & Stacey, T.R. 2014. Automatic prediction of time to failure of open pit mine slopes based on radar monitoring and inverse velocity method. *International Journal of Mining Science and Technology*, 24(2):275–280.
DOI:10.1016/j.ijmst.2014.01.021

Paradella, W.R., Ferretti, A., Mura, J.C., Colombo, D., Gama, F.F., Tamburini, A., Santos, A.R., Novali, F., et al. 2015. Mapping surface deformation in open pit iron mines of Carajás Province (Amazon Region) using an integrated SAR analysis. *Engineering Geology*, 193:61–78. DOI:10.1016/j.enggeo.2015.04.015

Raspini, F., Bardi, F., Bianchini, S., Ciampalini, A., Del Ventisette, C., Farina, P., Ferrigno, F., Solari, L., et al. 2017. The contribution of satellite SAR-derived displacement measurements in landslide risk management practices. *Natural Hazards*, 86(1):327–351. DOI:10.1007/s11069-016-2691-4

Reeves, B., Noon, D.A., Stickley, G.F. & Longstaff, D. 2001. Slope stability radar for monitoring mine walls. *Subsurface and Surface Sensing Technologies and Applications III*, 4491:57–67. November 2001. DOI:10.1117/12.450188

Rose, N.D. & Hungr, O. 2007. Forecasting potential rock slope failure in open pit mines using the inverse-velocity method. *International Journal of Rock Mechanics and Mining Sciences*, 44(2):308–320. DOI:10.1016/j.ijrmms.2006.07.014

Silva, A.F., Sotomayor, J.M.G. & Torres, V.F.N. 2021. Correlations of geotechnical monitoring data in open pit slope back-analysis - A mine case study. *Journal of the Southern African Institute of Mining and Metallurgy*, 121(121):557–564.
DOI:10.17159/2411-9717/1618/2021

Voight, B. 1989. A relation to describe rate-dependent material failure. *Science*, 243(4888):200–203. DOI:10.1126/science.243.4888.200

Woo, K.S., Eberhardt, E., Rabus, B., Stead, D. & Vyazmensky, A. 2012. Integration of field characterisation, mine production and InSAR monitoring data to constrain and calibrate 3-D numerical modelling of block caving-induced subsidence. *International Journal of Rock Mechanics and Mining Sciences*, 53:166–178.
DOI:10.1016/j.ijrmms.2012.05.008

