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BCRisk applications for rill swell hazard analysis in PC1: case study at Cadia East Operations

J Lett *Newcrest Mining Limited, Australia*

RL Castro *Universidad de Chile, Chile*

M Pereira *Universidad de Chile, Chile*

A Osorio *Newcrest Mining Limited, Australia*

P Alvarez *BCTEC Engineering and Technology, Chile*

Abstract

Several geotechnical hazards can affect productivity and safety at a drawpoint level in caving mines, including rockbursts, inrushes, collapses and air blasts. One such issue observed at Cadia East Panel Cave 1 (PC1) and Panel Cave 2 (PC2) sectors is the rill swell of fines (RS), a phenomenon in which a large volume of dry, fine material suddenly enters the extraction drives from a drawpoint. In order to gain an understanding of this phenomenon, a conceptual model was proposed. Additionally, a detailed exploratory analysis and subsequent logistic regression modelling were conducted to investigate this hazard from field observation at the PC1 sector at Cadia East Operations (CVO). The analysis indicated that the main variables influencing rill swell probability are the height of draw (HOD), the previous rill swell event, the location of the drawpoint relative to the cave back shape, the extraction rate, and draw control variables such as uniformity and Delta HOD. Based on the statistical analysis, a logistic regression model was built, thus classifying the drawpoints under high and low risk at PC1. The fitted model was able to classify the rill swell events in the short-term, obtaining an accuracy of 87%. The mathematical models have been implemented in BCRisk®, a machine-learning and draw control software currently used at the mine. The results of the BCRisk implementation in PC1 and PC2 show that hazard models are a useful tool for geotechnical analysis and mine planning at Cadia East operations. Results from this study have been useful in defining and controlling short-term planning parameters to mitigate the rill swell hazard.

Keywords: *inrush, rill swell, mine planning, underground mining, geotechnical hazards*

1 Introduction

Block caving is a mining method in which ore blocks or panels are undercut, causing the rocks to cave and thus allowing broken ore to be removed at drawpoints (Hartman & Mutmansky 2002). Historically, this method was used for relatively shallow, massive and low strength orebodies, which produced fine fragmentation. There is now a tendency for block and panel caving to be used in stronger orebodies which produce coarser fragmentation. This enables more widely-spaced drawpoints and more productive items of equipment to be used (Brown 2012). In this context, the current caving operations are subject to several operational hazards, including rockbursts, collapses, subsidences, airblasts and inrushes (wet and dry), which could be experienced during the different stages of caving (Flores-Gonzalez 2019).

During caving propagation, secondary fragmentation, fines migration, and internal rilling take place. These processes can provide fine material that can lead to an inrush event. Dry inrushes, also called rill swell events, are defined as a phenomenon in which large volumes of fines suddenly enter the extraction drives through a drawpoint (BCTEC 2019). These rill swell events can impact operations due to interruptions in operational productivity as extraction location availability is hindered. These interruptions make prognosticating rill swell events necessary for mine planning.

This study investigates the relative influence of the main variables associated with rill swell occurrence for short-term risk assessment at Cadia East Panel Cave 1 (PC1) sector. An analysis was conducted to define the conditions under which rill swells occur. The results were then used to quantify the relationship between hazard variables and the frequency of rill swell events. A multivariate predictive model using the BCRisk® software tool (BCTEC 2018) was created and calibrated using historical data from PC1 to identify areas at high risk of rill swell events.

2 Background at Cadia East

2.1 Mine site

Cadia East is a large panel caving operation located approximately 25 km from the city of Orange in central New South Wales, 250 km west of Sydney (Figure 1). The deposit consists of two macroblocks, Cadia East PC1 and Cadia East Panel Cave 2 (PC2) (Figure 2). The combined operations achieve an annual production output of 30 Mt (Orrego et al. 2020).

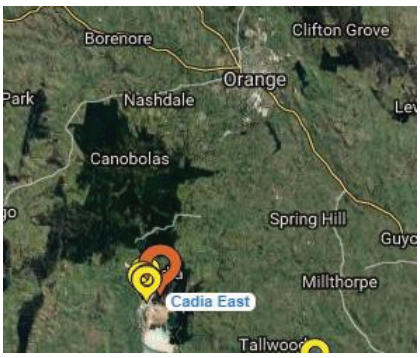


Figure 1 Cadia East location

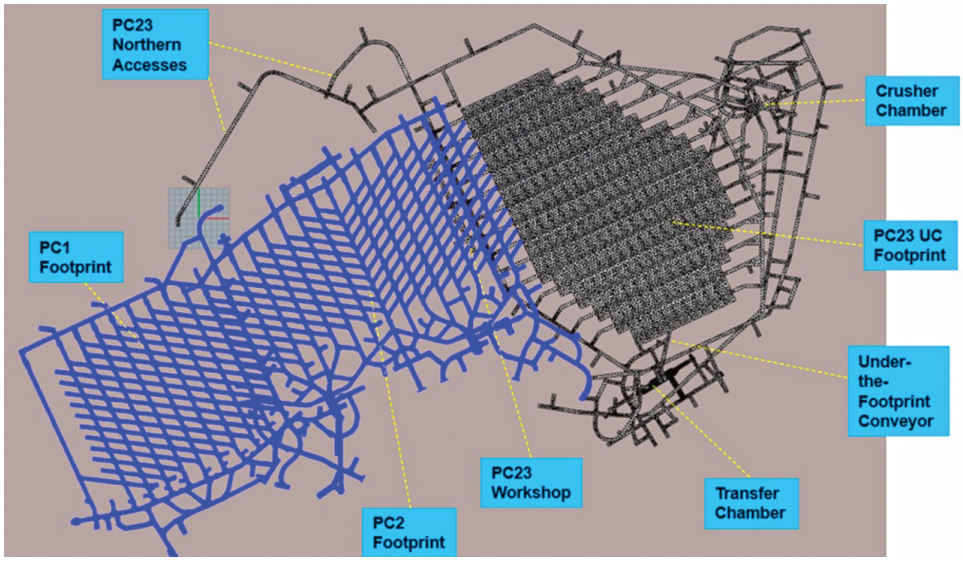


Figure 2 Plan view of Cadia East

PC1 block was subjected to intensive preconditioning (hydraulic fracturing from Gallery 5050) and DDE (blasting) for a column height of 400 m from the production level (4650 mRL), as shown in Figure 3. Hydraulic fracturing was performed to depths of 500 m from the surface (maximum-depth hole) to propagate the caving effectively.

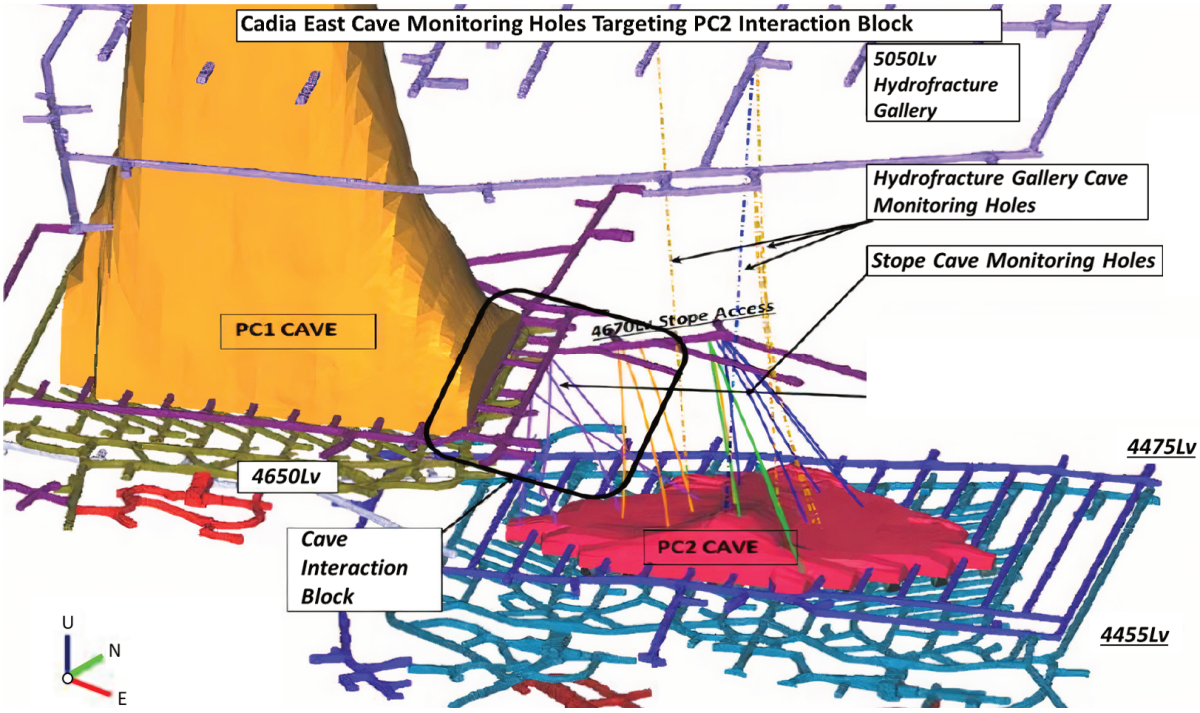


Figure 3 Cadia East PC1-S1 and PC2-S1 footprints (Lett et al. 2016)

The production level layout is shown in Figure 4. For PC1, the drawpoint spacing at the production level is 16 × 20 m. The total number of drawpoints in the block is 218 (10 extraction drives from 100 to 118). At this stage, only 146 drawpoints out of 218 are actively extracted. Extraction drives 100 to 104, and the northern half of 106 has been closed due to subsidence effects caused by the PC2 sector that is 195 m underneath PC1 on its eastern side. Historical rill swell events from the active 146 drawpoints were used in this study.

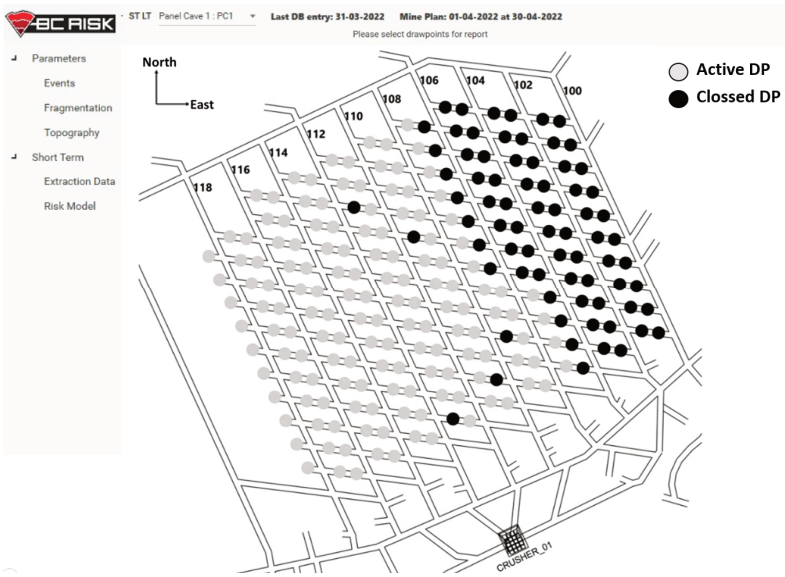
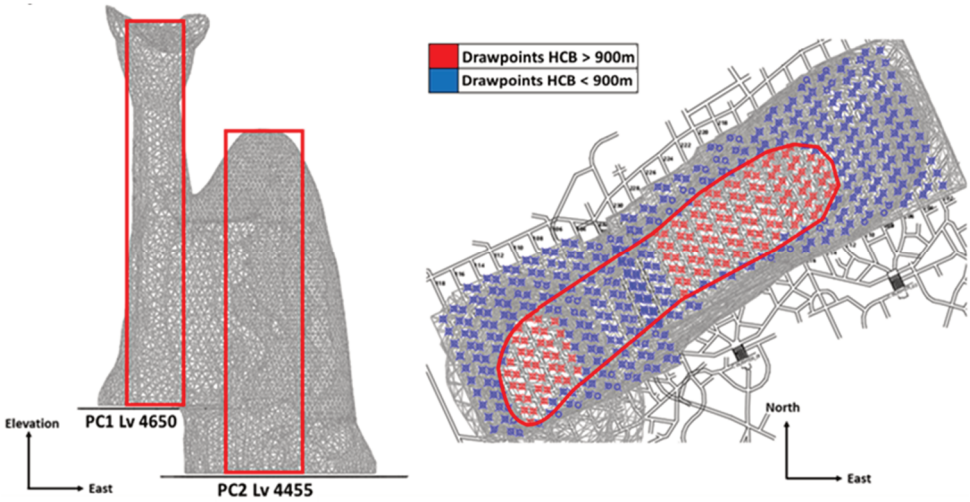


Figure 4 Production level at Cadia East PC1 in BCRisk Software (BCTEC 2022)

3 Rill swell entry mode

The analysis was executed using the historical extraction data from May 2011 to October 2021. Since February 2016, 551 rill swell events were registered in specific zones of the footprint at PC1. The Height of Cave Back (HCB) over 900 m is projected on PC1 and PC2, as shown in Figure 5a. These areas are

encompassed within the cave back polygon (CBP) shown in Figure 5b). Rill swell events tended to happen at the boundaries of the CBP.



(a) (b)

Figure 5 (a) Overview of cave back, (b) Plan view of the cave back polygon (CBP) in red

The closer the drawpoint was to the CBP, the higher the chances were of a rill swell event. For PC1, a Critical Zone (CZ) was defined as a ring of three drawpoints around the CBP (see Figure 6), and 91% of rill swell events in PC1 happened at drawpoints inside the CZ.

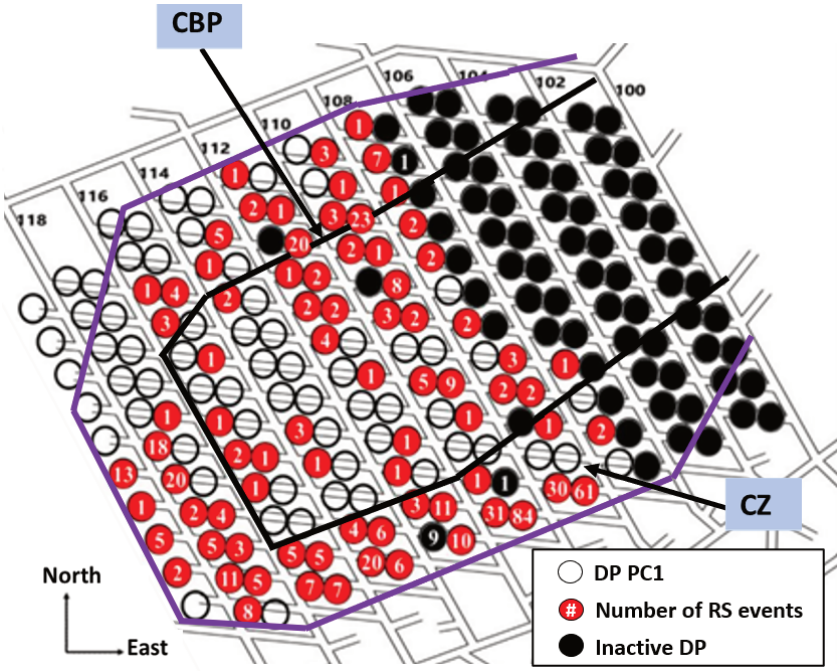


Figure 6 Definition of CZ and number of rill swell events observed between May 2011 to October 2021 at PC1

It could be inferred that rill swell events are related to a preferential flow of fine fragmented rock all along the fixed boundary imposed by the unbroken (in situ) rock. This is shown as a conceptual scheme in Figure 7. As shown, fines would also be produced from the shearing between the stagnant in situ rock and the broken mineral that is under the flow.

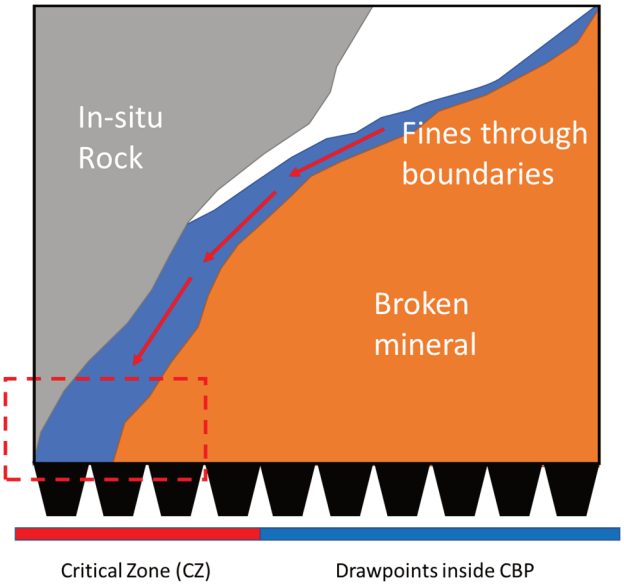


Figure 7 Conceptual scheme that represents the internal rilling along the hard boundary

3.1 Rill swell entry datasets

The dataset was statistically analysed to find the correlation with mining variables. Figure 8 shows the number and location of rill swell events per drawpoint at PC1. It was observed that 469 (85%) of the registered events happened at drawpoints where a rill swell event had previously been observed. This means that drawpoints affected by a rill swell event have a higher probability of being affected again, which was termed a 'memory effect.'

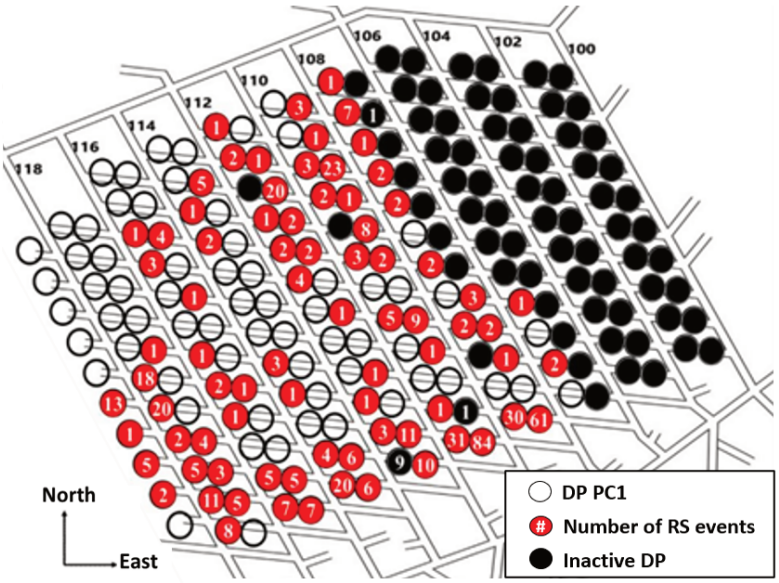


Figure 8 Number of RS events registered per drawpoint at PC1

The study aimed to evaluate rill swell risk; essential risk variables were selected based on exploratory analysis. Three kinds of variables that could trigger a rill swell event were identified: the cave shape defining the Critical Zone (CZ), previous events (PE), and draw control variables such as the height of draw (HOD), the maximum extraction rate, the HOD difference in the neighbourhood (Delta HOD) and the uniformity index. Table 1 shows the main variables that influence rill swell events and the conclusions of exploratory analysis.

Table 1 Risk factor and exploratory analysis

Risk factor	Exploratory analysis conclusions
HOD [m]*	Height of draw (HOD) is linked to the secondary fragmentation process; when fragments come from higher up in the column, they stay in the column for a longer time. For that reason, the larger the HOD, the larger the amount of fines. Rill swell events were registered after 60 m of HOD; however, 90% of the events occurred over 180 [m] of HOD.
Critical Zone (CZ)	The closer the drawpoint is to the Cave Back Polygon (CBP), the higher the chances are of a rill swell event. It was observed that 88% of rill swell events happened inside a CZ, defined as within three drawpoints of the CBP. It was observed that HOD is higher at the centre of PC1 (inside CBP). Events located in the CZ had a lower HOD.
Previous rill swell event (PE)	Once a drawpoint has been affected by a rill swell event, there is an increase in the probability of being affected again. Of the rill swell events registered, 85% happened at drawpoints where a rill swell event had previously been observed.
Maximum extraction rate at drawpoint (DP) scale in the last 30 days [tonnes/day]	High extraction rates could be a trigger for rill swell events. According to the events database, 83% of rill swell events occur with extraction rates over 300 [tonnes/day].
Uniformity Index 3D basis (%) **	It was observed that the general extraction could be related to an isolated draw, which will accelerate the entry of fines material due to the formation of a preferential path to the drawpoint. 50% of rill swell events happened with a uniformity index below 20%.
Delta HOD	Rill swell are linked to HOD difference in the neighbourhood: 98% of rill swell events occur with extraction differences of 20 [m].

*HOD: This represents the amount of mineral extracted from a drawpoint (tonnes), considering the area of influence from the drawpoint (A [m^2]) and a typical density (ρ [tonnes/m^3]), the extracted height could be calculated according to the following equation $\boldsymbol{HOD} = \frac{\boldsymbol{tonnes}}{\boldsymbol{A*\rho}}$.

**Uniformity index: The uniformity index, defined by Susaeta (2004), represents the regularity of drawpoint extraction compared to neighbouring drawpoints.

4 Modelling

A multivariate statistical method was used to assess the rill swell risk because of the method's ability to estimate an event's likelihood by evaluating the relationship between a dependent variable and a set of independent variables. The most suitable multivariate statistical method is logistic regression because it can analyse data that include a binary response variable (presence or absence of rill swell) and the independent explanatory variables (rill swell risk variables) (McCullagh & Nelder 1989; Hosmer et al. 2013). The main advantage of this method is its ability to minimise the uncertainties using maximum likelihood estimates (Geng & Sakhanenko 2015).

4.1 Risk factor strength association analysis

In this work, several risk variables were critically evaluated to quantify rill swell risk for short-term planning using logistic regression. Through this approach, a predictive model was developed to calculate the likelihood of rill swell events based on the main risk variables. The main advantage of the method is that variables associated with ore draw are incorporated into the estimation of the daily likelihood of having a rill swell event for each drawpoint. A brief introduction to developing the predictive model is described in Sections

4.2 and 4.3. A more detailed presentation of the logistic regression method may be found in Hosmer et al. (2013).

4.2 Univariate logistic regression analysis

Risk variables for rill swell were independently assessed using univariate logistic regression analysis to study the strength of association. An odds ratio (OR) was applied to analyse the relative relationship between the variables. The OR is capable of estimating how likely it is for a rill swell event to be present or absent among those drawpoints with x = 1 (presence) as compared to those drawpoints with x = 0 (absence) (Hosmer et al. 2013). For instance, if a drawpoint with the presence of rill swell is located inside the critical zone, then an OR = 3 suggests that the likelihood of rill swell among drawpoints situated inside the critical zone is three times greater than the likelihood of rill swell among the drawpoints outside the critical zone. A detailed discussion of the odds ratio is given in Hosmer et al. (2013). The variables found to be significant were included in the multivariate logistic regression.

4.3 Multivariate logistic regression analysis

The interrelationship of different risk variables with the occurrence of rill swell was tested using multivariate logistic regression. In this stage, rill swell datasets were used to derive the quantification of the main risk variables.

Multivariate logistic regression delineates the association between the dichotomous response variable Y (i.e. the occurrence or non-occurrence of swell rill of fines) and the collection of risk variables. The purpose of this analysis was to estimate the coefficient of each risk variable and test the associated statistical significance.

Multivariate logistic regression depends on the likelihood of the response variable occurring, considering a set of independent risk variables designated by the vector x = (x_1, x_2, x_3, …, x_n). Therefore, the conditional likelihood that a rill swell event is present (i.e. Y = 1) would be given by the following Equation 2 according to Hosmer et al. (2013):

$$P(Y = 1|x) = p(x) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\cdots+\beta_n x_n}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\cdots+\beta_n x_n}} \quad (1)$$

where β_i, i = 1….n coefficients are the logistic regression model coefficients, which can be determined through particular methods based on the maximum likelihood methodology (Geng & Sakhanenko 2015).

Logistic regression models require two sets of data: events and non-events. The first set includes all the rill swell cases in the database. The second set corresponds to drawpoints not affected by rill swell events. All the proposed variables were calculated at a daily scale for all drawpoints in both datasets.

The database from May 9, 2011, to October 28, 2021, represents the complete historical extraction of PC1. The total database contains 827 310 cases of extraction, and the frequency of rill swell events in the total database shows these events occur in less than 2% of the extraction cases. A logistic regression model constructed with the database presented could underestimate the probability of rill swell events. To avoid this issue, a strategy of logistic regression was applied to rare cases (King & Zeng 2001). First, all the rill swell events were included. The 'No Event' database was then sampled and reduced to represent 75% of a new database. Each case from the 'No Event' database was selected randomly stratified by the HOD distribution of the complete mine, presented in Figure 9. The new database should represent all the stages of the life of the mine such that the model could be used for new sectors.

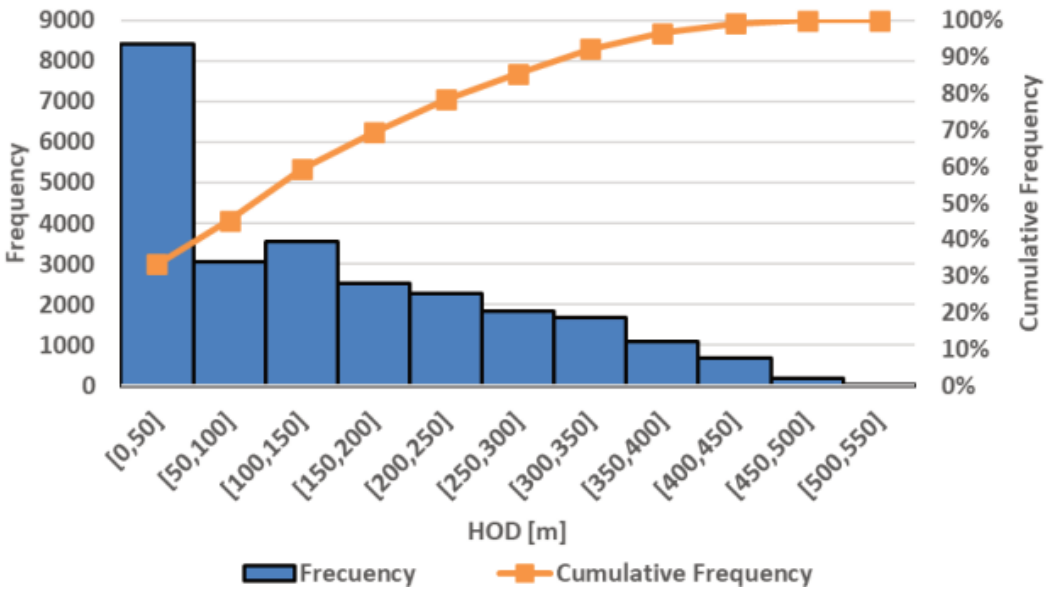


Figure 9 HOD distribution of PC1 (May 2011 to October 2021)

The model was constructed using the event database from February 2016 to October 2021. The new database for the rill swell risk classification model contains 2204 cases and follows a proportion of 1:3, consisting of 551 rill swell events (25%) and 1653 non-rill swell events (75%).

4.4 Calibration and validation of the predictive model

An approach for calibrating and validating the multivariate predictive model was carried out in this section. The calibration of the fitted model was assessed by comparing the mine data, and the modelled rill swell depending on the value of a cutoff probability. The cutoff probability allows the drawpoints to be classified into one of the response values (i.e. 1 or 0) using different levels of likelihood. The cutoff probability is defined as the minimum likelihood value for a drawpoint to be labelled as rill swell; therefore, drawpoints with a likelihood value above the cutoff value were classified as high-risk, whereas those with lower cutoff probabilities were classified as low-risk, as are shown in the Section 5.2. An algorithm was created to obtain the cutoff value, which includes the key risk variables and the best-fitted predictive models. This algorithm enables the daily likelihood of rill swell to be estimated for each drawpoint.

After selecting the cutoff probability, a contingency table was constructed, which permitted the calculation of four possible outcomes. On the one hand, if the real value is positive and classified as positive, it is counted as a true positive (TP); otherwise, it is counted as a false negative (FN). On the other hand, if the real value is negative and is classified as negative, then it is counted as a true negative (TN); otherwise, it is counted as a false positive (FP) (Fawcett 2006). To evaluate the contingency table, the cutoff probability enables the calculation of three main performance metrics, described by Fawcett (2006) as follows.

$$TPR = \frac{TP}{TP+FN}; TNR = \frac{TN}{TN+FP}; ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Where TPR is the true positive rate (also called sensitivity), TNR is the false positive rate (also known as specificity), and ACC is the accuracy of the best-calibrated model.

5 Results and discussion

Once the proposed variables were assessed as significant in the occurrence of rill swell events, the next step was to incorporate the variables into BCRisk®, a mine planning software tool that supports extraction planning by assessing the primary hazards confronting cave mines at the drawpoint level. BCRisk® uses a multivariable model that delivers a numerical value between 0–1, which is the probability of having an event in each drawpoint. In this case, the focus were rill swell events: P(rill swell).

5.1 Tested models

To find the best set, several combinations of variables resulting in different rill swell risk models were tested (see Table 2). The objective was to find a combination of variables that has the best performance regarding the following requirements:

- Maximise the number of predicted events correctly (sensibility).
- Maximise the total accuracy that represents the ability to predict an event or no event.
- Minimise the overestimation of the model, i.e. the risk classification model should not define the complete footprint as a high-risk area.

Table 2 Models analysed

Variable	A	B	C	D	E
HOD (m)	X	X	X	X	X
PE (Boolean 0–1)	X	X	X	X	X
CZ (Boolean 0–1)	X	X	X	X	X
Max draw rate – 30 days (tonnes/day)	X	X	X	X	X
Uniformity Index – 1 day (%)	X			X	
Uniformity Index – 3 days (%)		X			X
Delta HOD (m)				X	X

The mode D obtained the best fit and was implemented in the BCRisk 4.0 software. Equation 3 shows the model selected and the variables included in it.

$$P_{RS}(x) = \frac{e^{-4.006+0.004HOD+2.631PE+1.082CZ+0.0002MD-0.695U+0.0007DH}}{1+e^{-4.006+0.004HOD+2.631PE+1.082CZ+0.0002MD-0.695U+0.0007DH}} \quad (3)$$

Where:

$P_{RS}(x)$ = probability of having a rill swell event.

HOD = height of draw (m).

PE = previous event (Boolean 0–1).

CZ = critical zone (Boolean 0–1).

MD = max draw rate – 30 days (tonnes/day).

U = uniformity Index-1day (%).

DH = delta HOD (m).

5.2 Calibration of the risk classification model

As was discussed in Section 4.4, drawpoints with a probability above the cutoff probability will be classified as high-risk of experiencing a rill swell event. The aim of calibration process is to define the cutoff which minimise the classification error, this means maximise the sensitivity, specificity and accuracy of the model. The calibrated model obtained the following results:

- The model achieve a sensitivity of 87%, this means that of 551 RS events, 479 events were classified correctly as high-risk.
- The model achieve a specificity of 87%, this means that of 826 759 non-rill swell events, 719 280 no events were classified correctly as low-risk.

- The model has an 87% global accuracy, this means that of 827,310 cases, 719,759 cases were classified correctly.

Figure 10 shows an example of the application of calibrated model to define high-risk zones in a plan view of 1 January 2017. As of this date, two drawpoints evidenced the rill swell, and the model accurately classified them as high-risk, as shown in Figure 10.

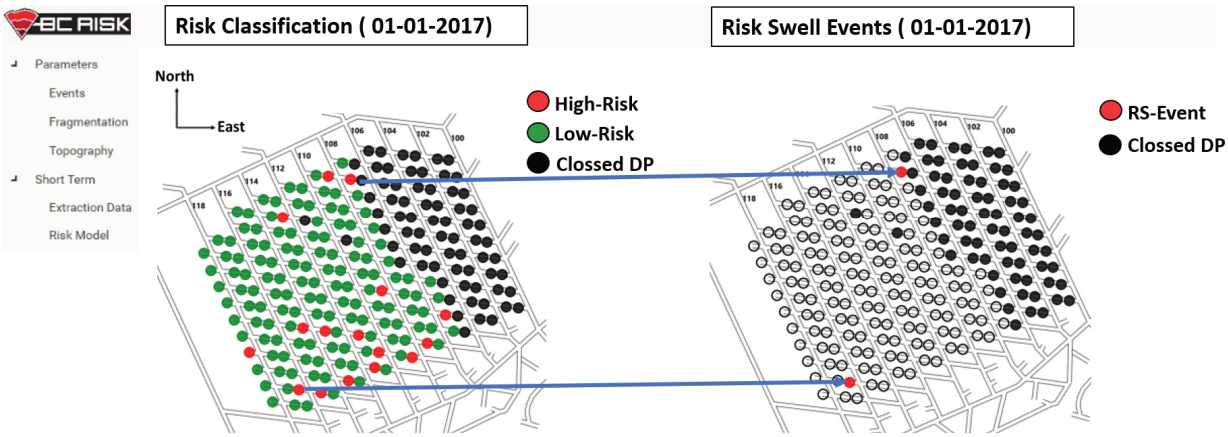


Figure 10 Risk map classification on 1 January 2017

Figure 11 summarises the risk classification for the drawpoints affected by rill swell on a monthly scale between February 2016 and October 2021. The red bars represent RS events classified correctly as high-risk, while the green bars represent rill swell events that the model could not predict, and were classified as low-risk.

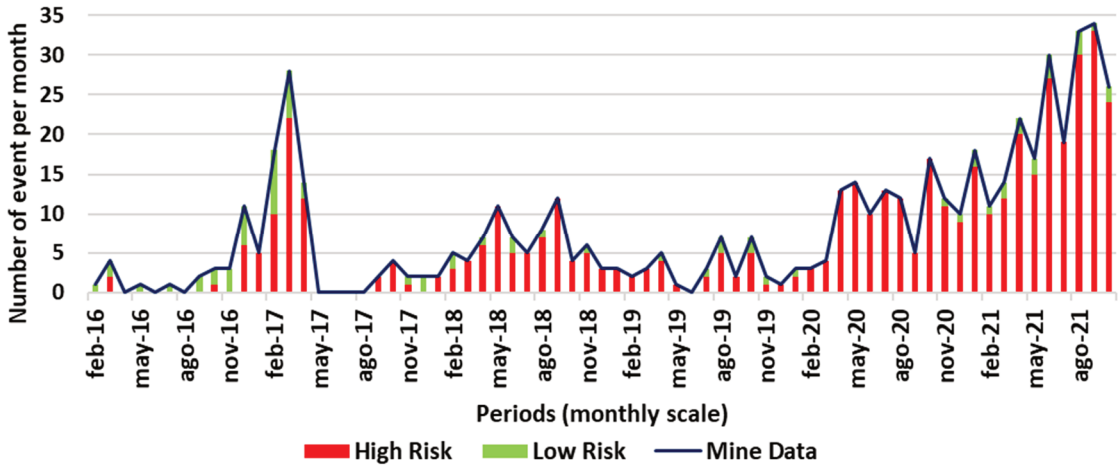


Figure 11 Ability of the model to classify previous rill swell events using historical data

6 Conclusion

In this article, the quantification of rill swell events for short-term risk assessment and planning was presented and discussed. This methodology employs a multivariate logistic regression, incorporating key risk variables associated with rill swell events. The results presented in this research demonstrate that logistic regression is a suitable approach for the evaluation of a short-term rill swell hazard. The best calibrated model incorporates the most important risk variables causing rill swell in this study: height of draw, critical zone, previous event, uniformity index, draw rate and delta HOD.

Using the cutoff probability set revealed in this study, the model's accuracy was estimated at 87%. In addition, the predictive ability of the model was found to be reliable for the estimation of rill swell events. Therefore, performed under optimal calibration and validation, this predictive model can provide a relevant instrument

to delineate zones prone to rill swell events and can be used to evaluate numerous short-term plans for caving mines, allowing preventive decisions to be made that would minimise the risks caused by rill swell or other phenomena such as wet muck and hang-ups. This research shows that BCRisk® is a useful tool to assess rill swell events during short-term planning processes in block caving.

7 Recommendations

Results of this study and BCRisk® software analysis have been introduced to mining operations and geotechnical teams at the Cadia Valley Operation to be utilised for short-term production planning. The variables that influence the probability of a rill swell event in a mature cave can be influenced through appropriate mine planning. It is understood that the frequent occurrence of significant rill swell events can adversely impact operational productivity and safety. Cadia Valley Operational teams will be focusing on optimising the variables to manage the rill swell hazard:

- Maximum extraction rate.
- Height of draw differential within a drawpoint cluster.
- Drawpoint Uniformity index.

BCRisk® software can monitor these variables regularly and analyse the impacts of short-term planning on managing the rill swell hazard. As this is a regressive model, it is recommended that the model is updated using the most recent data on a minimum quarterly frequency to optimise calibration with in situ data. The Cadia Valley Operations operational teams will be working closely with BCTEC to update the model and analyse future changes in rill swell risk for PC1 and PC2.

Acknowledgement

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