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TECHNICAL NOTE

Quantifying Wet Muck Entry Risk for Long-term Planning in Block Caving

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Abstract
Wet muck entry is one of the major geotechnical risks associated with long-term production goals in cave mining. The objective of this research is to quantify the effect of the main risk variables related to wet muck entry in an effort to prioritize and confront these variables accordingly. Logistic regression modeling was carried out using mine data from Pipa Norte Mine (PNM) and Sur Andes Pipa Mine (SPM), both located at El Teniente Mine. A confusion table was employed to calibrate the model, while a scatter plot and an error relative frequency histogram were used to validate it. The results indicated that ore draw and environmental conditions are the main risk variables associated with wet muck entry. The aforementioned metrics show an acceptable agreement between mine and modeled data. Hence, we used these results to create a statistically significant predictive model, which may be useful for the risk evaluation of numerous long-term plans. Based on optimal calibrated conditions, the predictive model is a powerful instrument not only to identify high-risk zones susceptible to wet muck entry but also to make long-term preventive decisions, which could lead in mitigating the risks of wet muck entry in cave mines.

Keywords Wet muck entry · Logistic regression · Risk assessment · Long-term ore reserves recovery

1 Introduction

Block caving is a mining method in which ore blocks or panels are undermined causing the rocks to cave, and thus allowing broken ore to be removed at drawpoints (Hartman and Mutmansky 2002). Once the cave subsidence propagates to the surface, accumulated water and fine material may enter the draw column through the subsidence zone (Brown 2004). This material composed of unsorted fine particles and water that is mixed in proportions that can potentially flow by gravity (Jakubec et al. 2012) is called wet muck. The term wet muck entry describes wet muck observed at drawpoints, as shown in Fig. 1a. According to the literature, early wet muck entry has been globally recognized as a crucial geotechnical issue in several cave mines, such as IOZ Mine (Hubert et al. 2000), DOZ Mine (Syaifullah et al. 2006; Samosir et al. 2008; Widijanto et al. 2012), El Teniente Mine (Becerra 2011; Ferrada 2011), and Kimberley underground mines (Holder et al. 2013). Because this phenomenon generates delays in mine production schedules, significant economic losses, and mining safety problems, the assessment of wet muck entry is a critical step in risk analysis for cave mines.

Butcher et al. (2005) have suggested that four factors are required to trigger wet muck entry. These include the capacity for water accumulation, the presence of potential wet muck-forming minerals, a disturbance in the ore column, and the ability for wet muck to discharge at a drawpoint. On the other hand, Navia et al. (2014) have analyzed a historical extraction database at Diablo Regimiento Mine in El Teniente Mine and concluded that draw height and uniformity of draw are the main variables controlling wet muck entry. However, there is not yet a consensus on how to define the risk variables or their impact on wet muck entry. Consequently, additional studies to address the likelihood of future wet muck entry, based on key risk variables, are needed.

To assess the wet muck entry risk, two approaches have been applied: deterministic and multivariate statistical methods. The deterministic approach could be

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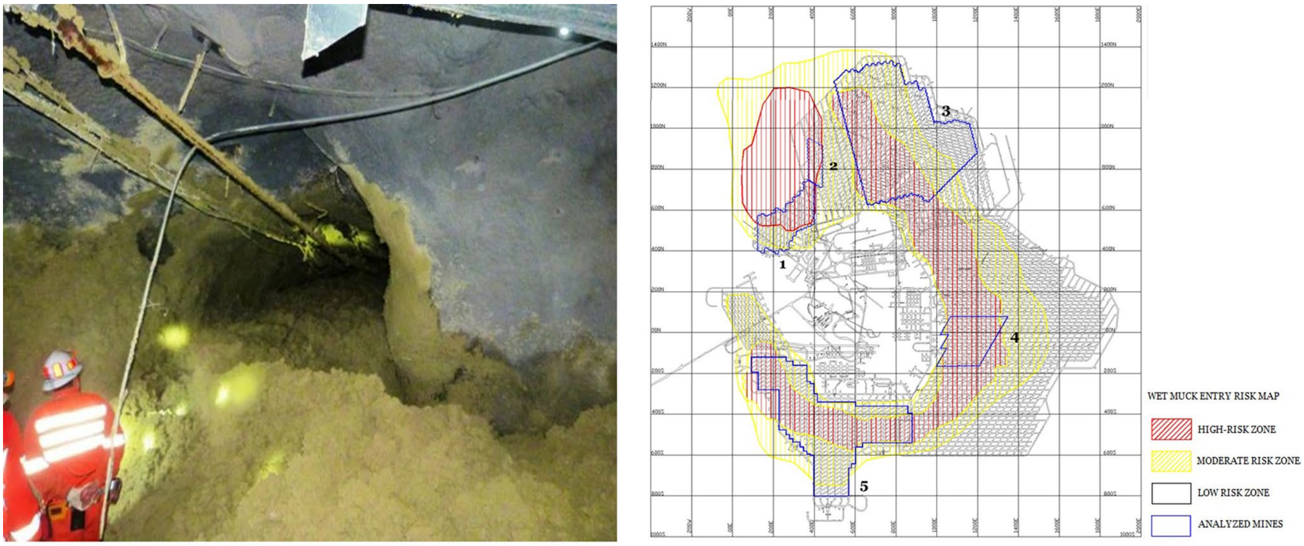

a b

Fig. 1 **a** Wet muck observed at a drawpoint during mine operation in *El Teniente* Mine (Codelco 2014); **b** Wet muck entry risk map (including different mine's layout) used in *El Teniente* Mine's methodology for long-term planning (1 *Pipa Norte* Mine, 2 *Sur Andes Pipa* Mine, 3 *Reservas Norte* Mine; 4 Block-1 *Esmeralda* Mine; 5 *Diablo Regimiento* Mine). The red zone (high-risk zone) describes the area with low elevation (topographic gutter), less than 500 m, with intermittent flows from melting snow and rainfall. This area is characterized by the presence of historical wet muck flows. The yellow zone (intermediate-risk zone) corresponds to the area within the topographic gutter with an elevation higher than 500 m, where wet muck inflows were registered. The remaining area classified as white zone (low-risk zone) indicates an area with high elevation (greater than 600 m) located outside the topographic gutter's influence, where wet muck inflows were unregistered (González and Brzovic 2017). (Color figure online)

implemented, but it requires complete data to define the weights of each variable. El Teniente Mine has adopted a deterministic method for long-term risk assessment, in which the analysis is based on controlled draw criteria from a wet muck risk map. This map is shown in Fig. 1b, indicating the principal cave operations and the three types of risk zones. Ore reserves located within the high-risk area (red zone) are restricted to extract 130% of the in-situ column to mitigate the occurrence of wet muck entry. Ore reserves located within the intermediate-risk area (yellow zone) are planned to extract 160–180% of the in-situ column, depending on the mine operation. Ore reserves placed within the low-risk (white zone) have no restrictions on extraction and can be planned according to economic criteria (Codelco 2016a, b). On the other hand, the second approach is the multivariate statistical method, which could be appropriate due to its ability to estimate the event's likelihood, evaluating the relationship between the dependent variable and a set of independent variables. The most suitable multivariate statistical method is logistic regression because it is useful for analyzing data that include a binary response variable (presence or absence of wet muck entry) and the independent explanatory variables (wet muck entry risk variables) (McCullagh and Nelder 1989; Hosmer et al. 2013). The main advantage of this method is its ability to minimize the uncertainties through the use of maximum likelihood estimates (Geng and Sakhanenko 2015). Garcés et al. (2016) attempted to integrate wet muck risk assessment in long-term planning based on the application of multivariate logistic regression to estimate ore reserve recovery before wet muck entry. Nevertheless, comprehensive discriminant analysis of risk variables was not included in their work. Hence, further investigations were required to focus on incorporating the main risk variables into long-term risk assessment of wet muck entry.

Quantifying wet muck entry risk could give miners insight into critical parameters during both production and geotechnical planning. This work aims to study the relative influence of the main risk variables associated with wet muck entry for long-term risk assessment in cave mining. In this paper, we conducted an analysis of wet muck entry status at drawpoints to define the conditions for wet muck entry modes to occur and subsequently, quantified the relationship between risk variables and wet muck entry. Finally, we proposed a multivariate predictive model for the recognition of high-risk areas susceptible to wet muck entry. This research has proven to be a useful tool to assess wet muck entry risk during planning processes in block caving.

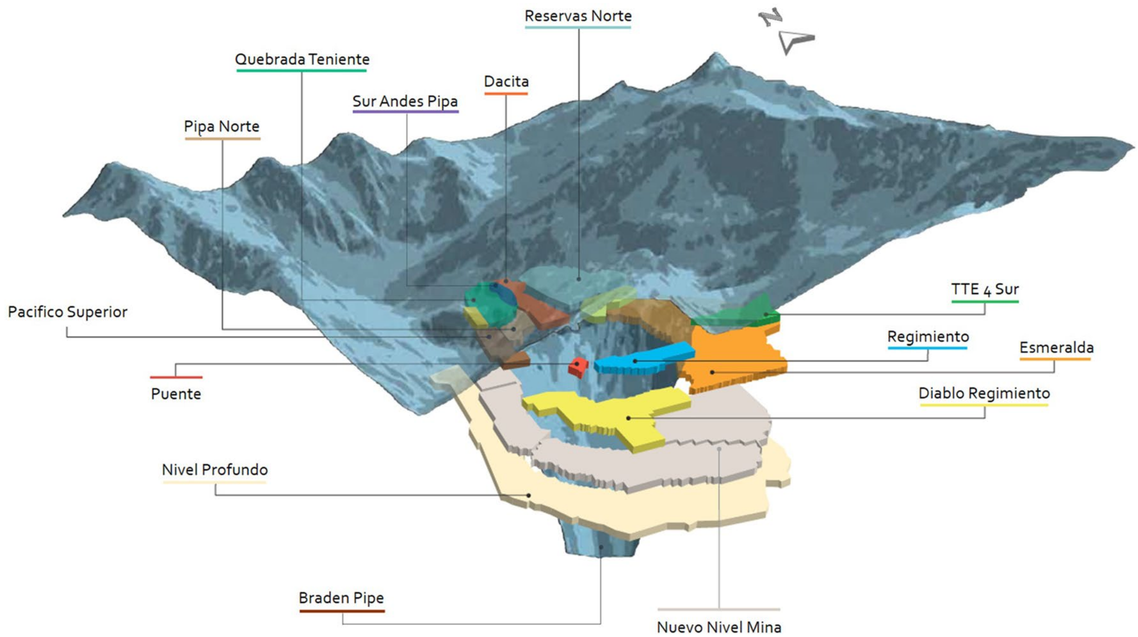

Fig. 2 Isometric view of productive sectors at El Teniente Mine, indicating the location of the studied mine database (Codelco 2016a, b)

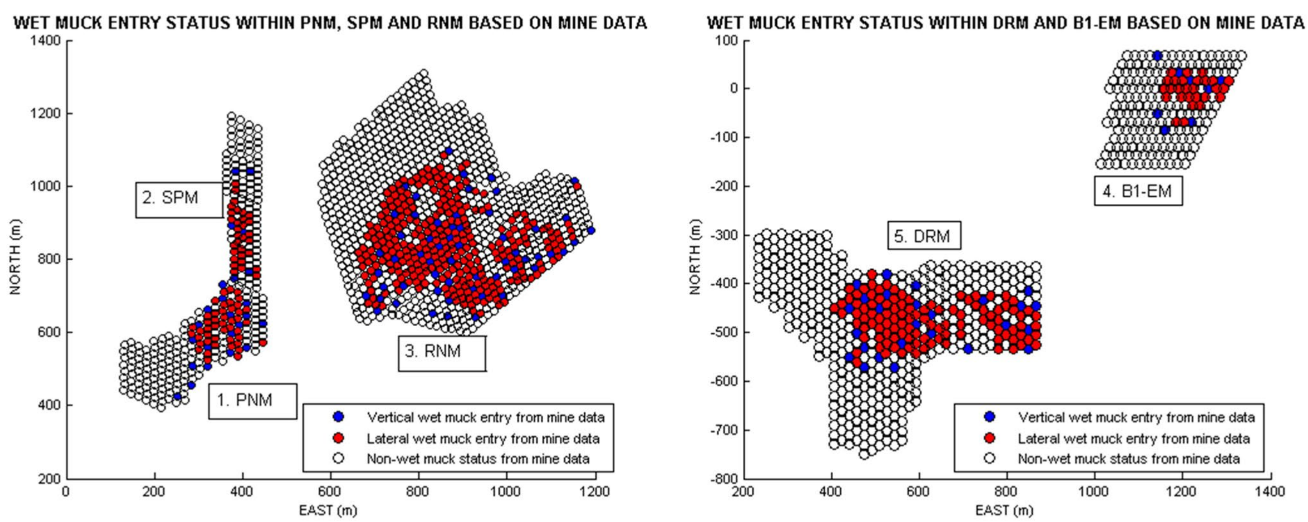

Fig. 3 Analysis of historical wet muck entry mode at *El Teniente* Mine; (1) *Pipa Norte* Mine (PNM); (2) *Sur Andes Pipa* Mine (SPM); (3) *Reservas Norte* Mine (RNM); (4) Block-1 *Esmeralda* Mine (B1-EM); (5) *Diablo Regimiento* Mine (DRM)

2 Background at *El Teniente* Mine

2.1 Wet Muck Entry Mode at *El Teniente* Mine

Mine data were provided from mine sectors at *El Teniente* Mine such as *Diablo Regimiento* Mine (DRM), *Reservas Norte* Mine (RNM), Block-1 *Esmeralda* Mine (B1-EM), *Pipa Norte* Mine (PNM) and *Sur Andes Pipa* Mine (SPM) from 2000 to 2017 to analyze the wet muck entry mode. These mines are mainly located under a topographic gutter (similar to a topographic depression) around Braden pipe, as shown in Fig. 2, and extensively operated in the high-risk zone of wet muck entry (Fig. 1b). Currently, the mines mentioned above represent nearly 78% of *El Teniente* Mine's daily production (roughly 91,000 tons per day).

The analysis was executed using both the historical extraction and drawpoint status data. It was observed that some drawpoints presented wet muck status despite the non-presence of wet muck in surrounding areas (blue dots

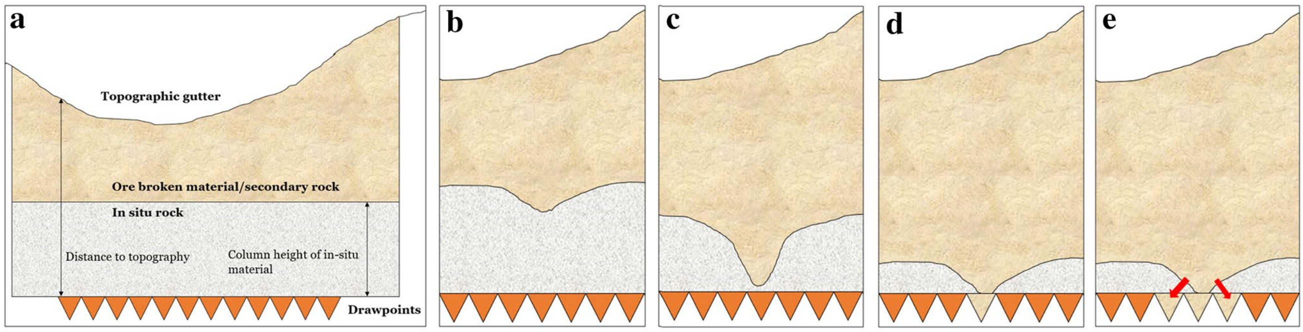

Fig. 4 Schematic cross-section view through a cave mine, showing the wet muck entry mode proposed in this research

in Fig. 3); therefore, it was postulated that in these cases wet muck initially descends vertically through the ore column to drawpoints, corresponding to a vertical mode of wet muck entry. The analysis of the remaining drawpoints (red dots in Fig. 3) indicated that wet muck status was always observed in the presence of wet muck in the neighboring areas (i.e., area affected by drawpoint initiators of wet muck entry). Considering this result, it was supposed that wet muck has another entry mode, in which wet muck laterally diffuses from the initial wet muck area to its neighboring drawpoints; thus, corresponding to a lateral mode of wet muck entry.

A preliminary conclusion of this initial data review of wet muck entry mode is presented as shown in Fig. 4. The schematic representation is illustrated based on the typical configuration at *El Teniente* Mine. Nevertheless, it could be extended to other ore column configurations. Figure 4a shows the initial condition of a cave mine, in which the in-situ and broken wet ore columns are defined. The caveback grows until caving connects with the broken wet ore interface (Fig. 4b), and, then, the broken material begins to move down to drawpoints due to gravity (Fig. 4c). The first drawpoint declared with wet muck status (Fig. 4d) reveals a vertical inflow mode of wet muck. Ore extraction continues around this drawpoint; thus, wet muck is laterally expanded to its neighboring area, as can be seen in Fig. 4e. This second mode corresponds to a lateral inflow of wet muck.

These results indicated that it was necessary to separate the database into two; one dataset regarding vertical inflow of wet muck, and the other concerning lateral inflow of wet muck.

2.2 Study Area

The *Pipa Norte* Mine (PNM) and *Sur Andes Pipa* Mine (SPM) at *El Teniente* Mine were chosen for our study area based on the quality of available mine data, especially regarding the measures of water infiltration to cave operations. The study area is located under both a river basin known as *El Teniente* Basin, and the topographic gutter around Braden pipe that has been formed due to caving subsidence from previous mine exploitations, as shown schematically in Fig. 5. Historically, the topography of this area was recognized as a critical factor to accumulate water,

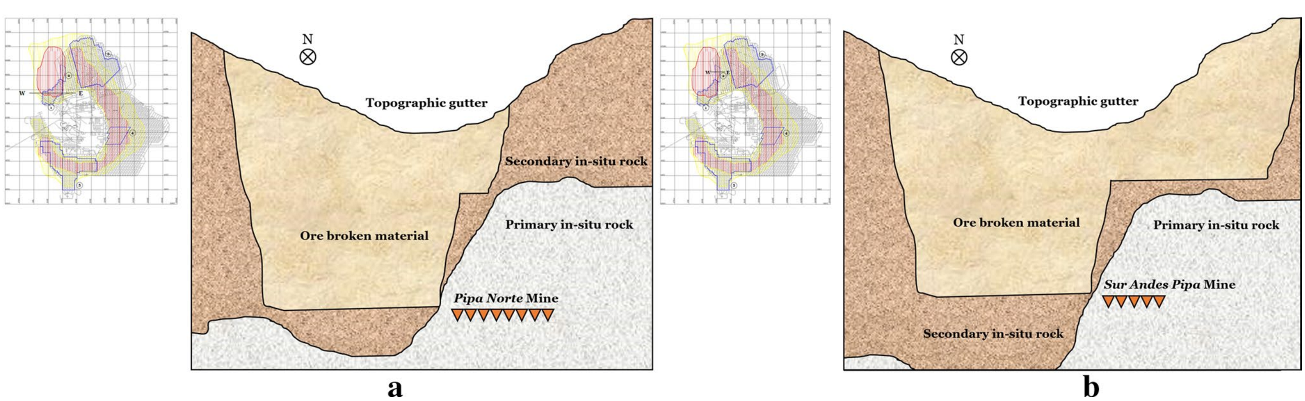

Fig. 5 Schematic east–west cross-section showing the location and initial conditions of the study area; **a** *Pipa Norte* Mine, and **b** *Sur Andes Pipa* Mine

which directly impacts on water infiltration to cave mines (Codelco, 2016).

Regarding the geotechnical characterization, Fig. 5 also depicts the three main rock types within the study area. First, the ore broken unit is composed of unconfined caved material resulting from secondary fragmentation due to caving process. This unit is located within the subsidence zone of previous mine operations. Second, the secondary rock unit corresponds to an in-situ ore rock type, which is a moderately competent, permeable rock due to the presence of several faults and open fractures within the intact rock. This characteristic has led to an increasing accumulation of groundwater, and thus this unit is considered as a considerable aquifer when cave mines are operating. Moreover, the primary in-situ rock unit is described as a very competent, massive, and impermeable rock type because open joints are rarely found within the intact rock and faults have a very low frequency of occurrence in line sampling (0.1 m^{-1}) (Brzovic and Villaescusa 2006). Consequently, a high primary in-situ rock column tends to decrease the likelihood of wet muck entry at drawpoints with this geotechnical property compared to those drawpoints that do not present this characteristic. The principal geotechnical parameters of the lithological units within the study area are summarized in Table 1 (Codelco 2014).

2.3 Wet Muck Entry Datasets

The PNM and SPM data were gathered from 317 drawpoints between July 2003 and February 2017, from which 94 data records (30% of the database) were declared with wet muck status. This database was employed to independently study the relationship of the risk variables to the presence of wet

Table 1 Geotechnical parameters for each lithological unit within the study area

Lithological unit	Rock type	UCS (MPa)	E (GPa)	c (MPa)	ϕ (°)
Mafic complex *El Teniente* (CMET) Fw	Primary rock	108 ± 10	50 ± 8	23	40
Andesite	Primary rock	151 ± 3	40 ± 2	20	44
Mafic complex *El Teniente* (CMET) Fw	Secondary rock	45 ± 15	40 ± 15	12	35

Table 2 Description of the terms used in this research

Terms	Description
In-situ tonnage	Indicates the tonnage of ore (or material) naturally present within the rock mass before any mining activity
Primary rock	Refers to a strong, less-fractured and low permeability ore rock mass, which is termed as primary rock at *El Teniente* Mine
Secondary rock	Refers to a weak, fractured and high permeability ore rock mass at *El Teniente* Mine
Drawpoint neighborhood/Cluster	Defines the number of drawpoints that are a part of the vicinity of the studied drawpoint vicinity. For instance, in a production level layout at *El Teniente* Mine, a drawpoint has at maximum six neighboring drawpoints

Table 3 Summary of variables used in this research

Variable	Symbol	Unit	Type	Description
Extraction	E	(%)	Continuous	Calculated by the ratio between accumulated drawn tonnage and in-situ tonnage for each period. This calculation is a measurement of over-draw of the in-situ column
Column height of in-situ material	h_i	(m)	Continuous	Measure of the column height of uncaved ore rock previous to mine operation
Column height of primary rock	h_{pr}	(m)	Continuous	Measure of the column height of in-situ primary rock
Distance to topography	h_{t}	(m)	Continuous	Estimate of the column height measured from the undercut level to the surface. This variable considers the column height of in-situ ore and the column height of broken material
Topographic gutter	TG	–	Categorical	Variable based on the location of the drawpoint. It is equal to zero if the drawpoint is not situated under the topographic gutter around Braden pipe, otherwise one if it is not
Monthly water flow rate	FR	(l/s)	Continuous	Variable that expresses average daily water flow rate infiltrated per month within the production level
Drawpoint neighborhood with wet muck entry	N_{wm}	–	Continuous	Measure of the drawpoint number with wet muck entry status on surrounding areas (neighboring drawpoints). It considers zero to six neighboring drawpoints with wet muck entry status

muck entry. This analysis was carried out using the univariate analysis of the logistic regression approach.

To accomplish the multivariate analysis, the database was subdivided into two new datasets to incorporate the wet muck entry modes in the development of the predictive model. The vertical inflow of wet muck dataset is composed of 24 wet muck, and 72 non-wet muck entry stratified samples selected from the initial database. The lateral inflow of wet muck entry data contains 70 wet muck and 210 non-wet muck entry stratified samples chosen from the initial database. The dataset for multivariate analysis was used to train (i.e., data used to derive the logistic regression equations) and test (i.e., data used to analyze the predictive performance of the logistic regression model) the predictive model.

2.4 The Wet Muck Entry Risk Variables

As the aim of this study was to evaluate the wet muck entry risk, essential risk variables were selected based on cave experience learned through mine operations. Seven risk variables were considered: extraction, water flow rate, column height of in-situ material, column height of primary rock, column height of topography, the presence of topographic gutter, and drawpoint neighborhood with wet muck entry. A more detailed description of the variables involved in this research is summarized in Table 2, 3.

Finally, Table 4 summarizes the criteria adopted for the selection of risk factors based on both the physical conditions for wet muck entry and the cave experience gained throughout cave operation.

3 Method

3.1 Risk-Factor Strength Association Analysis

In this work, several risk variables were critically evaluated to quantify wet muck entry risk for long-term planning using logistic regression as a statistical approach. Through this approach, a predictive model was developed to calculate the likelihood of wet muck entry based on the main risk variables. The main advantage of the current method is that variables associated with ore draw, environmental conditions and drawpoint status are incorporated into the estimation of the daily likelihood of having wet muck entry at each drawpoint. A brief introduction to developing the predictive model is described below. A more detailed presentation of logistic regression may be found in Hosmer et al. (2013).

3.1.1 Univariate Logistic Regression Analysis

Risk variables for wet muck entry were independently assessed using univariate logistic regression analysis to study the strength of association. Chi-squared test (χ^2) and odds ratio (OR) were applied to analyze the relative relationship between the variables.

The odds ratio is capable of estimating how likely it is for wet muck 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 wet muck entry is located under the topographic gutter, then an odds ratio OR $= 3$ means that the likelihood of wet muck entry among drawpoints situated below the topographic gutter is three times greater than the likelihood of wet muck entry among the drawpoints not situated below

Table 4 Summary of selected risk variables based on physical properties of wet muck entry and mine practice

Risk factor	Selection criterion
Extraction	Represents both the increment of rock permeability promoted by caving propagation and the fine material formation due to the secondary breakage through the ore column. Based on mine data, the propensity of wet muck entry tends to rise with the increase of ore extraction
Monthly water flow rate	Signifies a long-term representation of the water infiltration expected to be observed at drawpoints during cave operation. Therefore, high water flow increase of the likelihood of wet muck entry
Column height of in-situ material	Indicates the permeability properties of the uncaved materials constituting the ore column (composed of primary and secondary rock), which controls water movement and infiltration to drawpoints
Column height of primary rock	Represents the material with the lowest permeability within the ore column, which allows water to delay its infiltration to mine areas. Thus, drawpoints with a high column height of primary rock present less likelihood of wet muck entry
Distance to topography	Considers the distance to superficial water sources (melting snow and rain water)
Topographic gutter	Signifies the high-risk zone associated with the preferential water accumulation in the lowest surface level, hence, controlling the state of water sources directly
Drawpoint neighborhood with wet muck entry	Indicates the risk that wet muck could be laterally spread to the surrounding areas (neighboring drawpoints)

the topographic gutter. A detailed discussion of the odds ratio is given in Hosmer et al. (2013).

In univariate analysis, the statistical significance (p value) of 0.2 is used to determine if each independent variable is statistically significant with wet muck entry. The variables found to be significant were included in the multivariate logistic regression.

3.1.2 Multivariate Logistic Regression Analysis

The interrelationship of different risk variables with the occurrence of wet muck entry was tested using the multivariate logistic regression. In this stage, vertical and lateral inflow of wet muck datasets were used to derive the quantification of the main risk variables.

Multivariate logistic regression delineates the association between the dichotomous response variable, Y (the occurrence or non-occurrence of wet muck entry), and the collection of risk variables, x. The purpose of this analysis was to estimate the coefficient of each risk variable and test its statistical significance.

Multivariate logistic regression depends on the likelihood of the response variable, considering a set of n independent risk variables designated by the vector $x = (x_1, x_2, x_3, \ldots, x_n)$. Therefore, the conditional likelihood that wet muck entry is present (i.e., $Y = 1$) would be given by the following equation according to Hosmer et al. (2013).

$$P(Y = 1|x) = p(x) = \frac{e^{\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n}}{1 + e^{\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n}} \tag{1}$$

where $\beta = \beta_0, \beta_1, \ldots, \beta_n$ are the logistic regression model coefficients, which can be determined through particular methods based on the maximum likelihood methodology (Geng and Sakhanenko 2015).

In this analysis, two criteria were adopted: the statistical significance (p-value), and the log-likelihood ratio ($-2\log\mathcal{L}$). First, the statistical significance for a risk variable to remain in the multivariate logistic regression model was set at 0.05. s, the log-likelihood ratio measures the change of likelihood between the fitted and saturated model (Hosmer et al. 2013). In general, the most desirable fitted-model corresponds to the one which minimizes the log-likelihood ratio (Allison 2012).

3.2 Calibration and Validation of the Predictive Model

A novel 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 modeled muck entry depending on the value of a cut-off probability. The cut-off probability allows the drawpoints to be classified into one of the response values (i.e., 1 or 0) using different levels of likelihood. The cut-off probability is defined as the minimum likelihood value for a drawpoint to be labeled as wet muck entry status; therefore, drawpoints with a likelihood value above the cut-off value were classified as wet muck entry, whereas those with lower cut-off probabilities were classified as non-wet muck entry. An algorithm was created to obtain the cut-off value which includes the key risk variables and the best-fitted predictive models (i.e., vertical and lateral inflow of wet muck models). This algorithm enables the estimation of the daily likelihood of wet muck entry for each drawpoint.

After selecting the cut-off 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, then it is counted as a true positive (TP); otherwise, it is counted as 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 cut-off probability enables the calculation of three main performance metrics, described by Fawcett (2006) as follows.

$$\begin{aligned} &\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}; \quad \mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}}; \\ &\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \end{aligned} \tag{2}$$

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.

After calibrating the predictive model, the validation of the cut-off probability was executed comparing the real and modeled data regarding drawn ore tonnage before wet muck entry. The validation stage aims to minimize the drawn ore tonnage error, which is defined as the subtraction between real and modeled drawn ore tonnage. The validity of the predictive model is graphically represented on a scatter plot, which displays the degree of correlation between modeled drawn ore tonnage (plotted along the vertical axis) and drawn ore tonnage from mine data (plotted along the horizontal axis). Additionally, a relative frequency histogram for the error was presented to examine the proportion of error values for each corresponding class interval. The calibrated model is validated if the defined cut-off probability results in a scatter plot with a high degree of correlation between modeled and mine data, and if the error's distribution is near zero.

Table 5 Risk variables and their relative relationship with wet muck entry, sorted by strength association from the odds ratio (univariate analysis of association)

Variable	Statistical significance (p value)	Chi-squared test (χ^2)	Coefficient	Odds ratio
Topographic gutter	< 0.001	446.30	1.97	7.16
Extraction	< 0.001	407.01	1.16	3.19
Drawpoint neighborhood with wet muck entry	< 0.001	387.81	0.82	2.27
Monthly water flow rate	0.006	229.69	0.003	1.003
Distance to topography	< 0.001	148.82	-0.019	0.981
Column height of in-situ material	< 0.001	93.63	-0.007	0.993
Column height of primary rock	< 0.001	74.71	-0.006	0.994

4 Results and Discussion

4.1 Risk Factors Strength of Association Analysis

4.1.1 Univariate Logistic Regression Analysis

Univariate analysis was carried out for each of the seven risk variables, in which all the risk variables were statistically significant (p value $\leqslant 0.2$). Table 5 summarizes the association metrics obtained in this analysis.

Based on Table 5, the results show that variables such as extraction, the presence of topographic gutter, and drawpoint neighborhood with wet muck entry have the highest statistically predictive power for the occurrence of wet muck entry. First, the presence of a topographic gutter is the major risk variable related to wet muck entry, with an odds ratio measured as 7.16, indicating that a drawpoint located under the lower surface zone has 7.16 times higher likelihood of suffering wet muck entry, compared to a drawpoint situated outside the topographic gutter area. Second, the extraction has an odds ratio of 3.19, meaning that if a drawpoint has drawn 150% of its in-situ column, wet muck entry likelihood will increase 3.19 times compared to a drawpoint that has drawn 50% of its in-situ column. Finally, the number of drawpoints within the area surrounded by wet muck is the third major risk variable associated with wet muck entry. This variable has an odds ratio estimated as 2.27, revealing that a drawpoint with two neighboring drawpoints with wet muck status has 2.27 times higher likelihood of presenting wet muck entry compared with a drawpoint with only one neighboring drawpoint with wet muck status. The remaining risk variables have a slight statistical degree of association with wet muck entry because of the low values of the Chi-squared test and odds ratio.

Based on the above-mentioned results, the analysis indicates that wet muck entry generally occurs under over-draw conditions for those drawpoints placed below a topographic gutter and located near wet muck areas. Hence, during the long-term planning process, mine planers must bear in mind the selection of daily tonnage drawn depending on the environmental conditions of each drawpoint. The univariable analysis was useful to identify the main variables related to wet muck entry. However, it does not consider the relative relationship between risk variables, which is assessed through multivariate analysis, as indicated in the following section.

4.1.2 Multivariate Logistic Regression

Multivariate logistic regressions were performed using vertical and lateral inflow of independent wet muck entry datasets. Thus, two best-fitted predictive models were selected for each entry mode (Table 6).

For the vertical inflow mode of wet muck, variables such as ore draw and environmental conditions (topographic conditions, column height variables, and water infiltration) have a physical impact on the occurrence of vertical wet muck entry; hence, three predictive models were developed (Table 6a). Based on the p value given in Table 6a, most of the risk variables were significant at 0.05 level, whereas those with p value > 0.05 were found to be needed in the model because they have a physical significance with wet muck entry and the p value is approximately at 0.05 confidence level. Additionally, the multivariate analysis showed that the distance to topography must be eliminated from modeling since it was not statistically significant at the 0.05 level. Finally, considering the log-likelihood ratio used to analyze the degree of suitability among the models, *model 2* has the lowest value compared to the others, which means that *model 2* has a more appropriate predictive capacity, and thus it was selected as the best-fitted model for the vertical wet muck entry mode. The key risk variables included in *model 2* are in line with both the results presented in the univariable analysis and the high association of the odds ratio observed in Table 6a. Consequently, the vertical inflow of wet muck mode during cave operations is mainly controlled by extraction, water infiltration, column height of primary rock and the presence of a topographic gutter.

Table 6 Multivariate logistic regression modeling for (a) vertical mode and (b) lateral mode of wet muck entry

Model	Coefficient (β_i)	Std. error	p value	Odds ratio	log-likelihood ratio
(a)					
Model 1					
Extraction	0.76	0.75	0.031	2.13	73.59
Monthly water flow rate	0.001	0.002	0.057	1.001	
Topographic gutter	0.74	0.65	0.025	2.09	
Constant	−2.20	0.78	0.040	0.11	
Model 2					
Extraction	0.57	0.83	0.058	1.77	68.30
Monthly water flow rate	0.001	0.002	0.031	1.001	
Topographic gutter	0.59	0.70	0.063	1.81	
Column height of primary rock	−0.003	0.006	0.066	0.996	
Constant	−1.62	1.31	0.021	0.19	
Model 3					
Extraction	0.56	0.77	0.470	1.74	71.98
Monthly water flow rate	0.001	0.002	0.057	1.001	
Topographic gutter	0.78	0.66	0.024	2.17	
Column height of in-situ material	−0.004	0.003	0.022	0.996	
Constant	−1.21	1.07	0.026	0.30	
(b)					
Model 1					
Extraction	2.51	0.33	< 0.001	12.29	363.13
Monthly water flow rate	0.001	0.001	0.064	1.001	
Constant	−2.63	0.28	< 0.001	0.072	
Model 2					
Extraction	2.18	0.34	< 0.001	8.82	306.11
Monthly water flow rate	0.001	0.001	0.068	1.001	
Topographic gutter	1.91	0.43	< 0.001	6.76	
Constant	−4.10	0.50	< 0.001	0.017	
Model 3					
Extraction	1.83	0.36	< 0.001	6.23	214.65
Monthly water flow rate	0.001	0.001	0.02	1.001	
Topographic gutter	1.70	0.43	< 0.001	5.47	
Drawpoint neighborhood with wet muck entry	0.53	0.13	< 0.001	1.70	
Constant	−4.06	0.50	< 0.001	0.017	

On the other hand, regarding the lateral mode of wet muck entry, the multivariate analysis considers ore draw, wet muck entry areas and environmental conditions (topographic conditions, column height of material and water infiltration) as risk variables; therefore, three models were built (Table 6b). Most of the risk variables presented in Table 6b were statistically significant at 0.05 p value level. Although the variable monthly water flow rate is an exception, it has physical significance in the occurrence of the phenomenon, and it was nearly at 0.05 confidence level. Thus, the variable monthly water flow rate needs to be incorporated in multivariate modeling. In addition, the analysis revealed that topography and column height variables needed to be excluded from this multivariate logistic regression analysis since they were not significant at 0.05 level during the model-building step. Based on the log-likelihood ratio given in Table 6b, the considerably lower value obtained in *model 3* explains both that the predictive performance is more suitable compared to other models, and that the included variables are the most influential factors associated with lateral wet muck entry. Accordingly, *model 3*, which is principally dominated by the extraction variable, the presence of a topographic gutter, and the neighboring drawpoints with wet muck status, is selected as the best-fitted model for lateral inflow of wet muck.

In this research, a predictive model including key risk variables involved in wet muck entry was created. This model supports the notion that over-drawing at drawpoints with risky environmental conditions (located under the topographic gutter and in wet muck neighboring areas, with low height columns of primary rock and high-water infiltration periods) could lead to a higher likelihood of wet muck entry, compared to drawing at others with more favorable conditions. Finally, the best-fitted multivariate predictive model is defined as

$$p_{\mathrm{wm}}(x) = \begin{cases} p_v(x) = \dfrac{\exp\left(-1.62+0.57E+0.001FR-0.003h_{\mathrm{pr}}+0.59TD\right)}{1+\exp\left(-1.62+0.57E+0.001FR-0.003h_{\mathrm{pr}}+0.59TD\right)} & \text{If } N_{wm}=0, \quad \text{for } \mathrm{CP_v} \\ p_l(x) = \dfrac{\exp\left(-4.06+1.83E+0.001FR+1.70TD+0.53N_{\mathrm{wm}}\right)}{1+\exp\left(-4.06+1.83E+0.001FR+1.70TD+0.53N_{\mathrm{wm}}\right)} & \text{If } N_{wm}>0, \quad \text{for } \mathrm{CP_l} \end{cases} \tag{3}$$

where $p_{\mathrm{wm}}(x)$ indicates the wet muck entry likelihood; $p_v(x)$ and $p_l(x)$ denote the vertical and lateral wet muck entry likelihood, respectively; $\mathrm{CP_v}$ and $\mathrm{CP_l}$ specify the cut-off probability for vertical and lateral wet muck entry models, respectively. In the next section, the calibration and validation of the cut-off probabilities of the predictive model are presented and discussed.

4.2 Calibration and Validation of the Predictive Model

Mainly in this research, the calibration stage involves the development of an algorithm to assess daily wet muck entry likelihood based on daily ore draw, drawpoint status, environmental conditions of drawpoints (column height of primary rock, presence of a topographic gutter and monthly water infiltration), a multivariate predictive model, and the cut-off probability. Mine data from 2003 to 2017 were included in the algorithm, and thus several cut-off probabilities were tested to build contingency tables. The algorithm is schematically explained in Fig. 6, which indicates the role of cut-off probability $\mathrm{CP_v}$ and $\mathrm{CP_l}$ to define the occurrence or non-occurrence of wet muck entry at drawpoints.

After processing several cut-off probabilities, the optimal cut-off value for correctly identifying wet muck entry observations (i.e., mine data containing wet muck entry status) was 0.58 for $\mathrm{CP_v}$ and 0.60 for $\mathrm{CP_l}$. According to Table 7b, 80 observations of wet muck entry were accurately classified because of the unfavorable operational

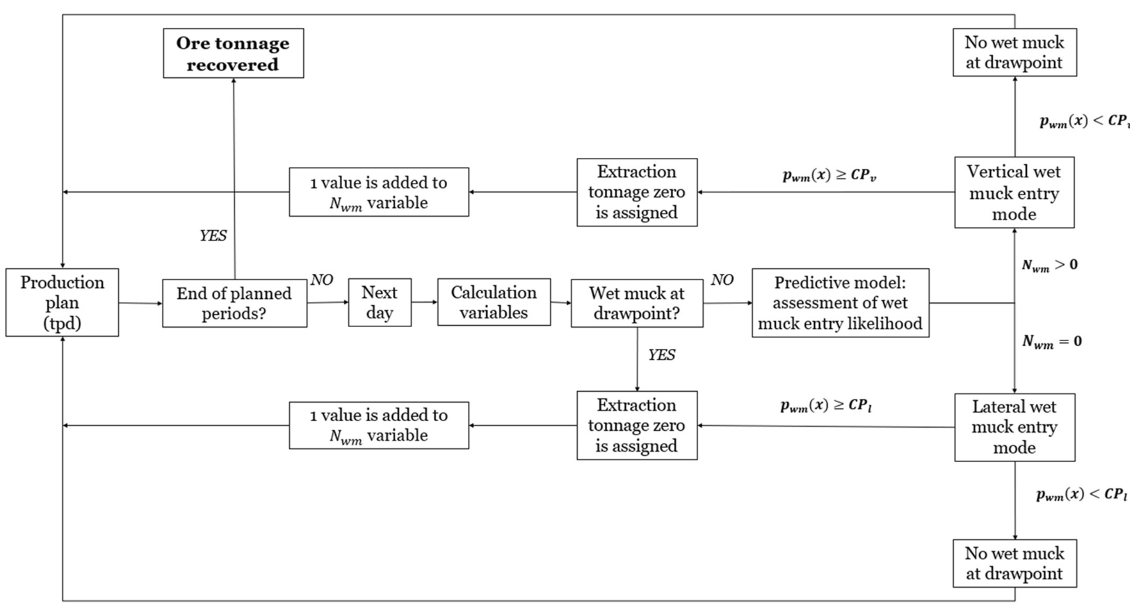

Fig. 6 Schematic diagram of the algorithm and its elements used to calibrate and validate the modeled data based on the estimation of the daily likelihood of wet muck entry. The above diagram represents the procedure for one evaluated drawpoint, where $p_{\mathrm{wm}}(x)$ is the wet muck entry likelihood; $\mathrm{CP_v}$ and $\mathrm{CP_l}$ indicate the cut-off probability for vertical and lateral wet muck entry models, respectively; and N_{wm} represents the number of drawpoints in the neighborhood with wet muck entry

Table 7 Contingency tables and performance metrics for the calibration process: (a) two-class contingency table, (b) contingency table of calibration dataset and (c) main performance parameters for the calibrated model

		Logistic model	
		1	0
(a)			
Reality	1	TP	FP
	0	FN	TN
		Predictive model	
		1 (115)	0 (202)
(b)			
Mine data	1 (94)	80	14
	0 (223)	35	188
(c)			
Sensitivity	70%		
Specificity	93%		
Model accuracy	84%		

(a) Two-class prediction definition (TP: true positive; FN: false negative; FP: false positive; TN: true negative)

(b) Contingency table of calibration step for the predictive model utilizing a cut-off probability set of CP_v: 0.58 and CP_l: 0.60. The drawpoints with an estimated probability above 0.58 and 0.60 for vertical or lateral inflow of wet muck mechanism, respectively, were categorized as wet muck entry (1 to indicate the presence of wet muck entry), whereas the remaining drawpoints were categorized as non-wet muck entry (zero to indicate the absence of wet muck entry)

(c) Main performance parameters employed to measure the degree of agreement between mine data and modeled observations for the cut-off probability set previously mentioned

conditions of the analyzed drawpoints (i.e. drawpoints with an over-draw condition and located both under the topographic gutter and near an extensive wet muck entry area). Due to the above-mentioned unfavorable conditions, 35 observations of non-wet muck entry were inaccurately classified. In addition, 14 of the wet muck entry observations were misclassified by the predictive model because they had favorable operational conditions, such as drawpoints with non-over-draw conditions and situated outside both the topographic gutter and non-wet muck entry neighboring areas. Finally, 188 drawpoints were accurately classified as non-wet muck entry since the operational and environmental conditions were favorable. In total, 70% of wet muck entry data and 93% of non-wet muck entry data were correctly classified, and hence, the model's 84% accuracy demonstrates substantial discrimination for predicting the presence or absence of wet muck entry at drawpoints (Table 7c).

To validate the calibrated predictive model, the algorithm was applied to estimate drawn ore tonnage before wet muck entry. Using the defined cut-off probability, the occurrence or non-occurrence of wet muck entry was established within the calibrated model. The validation stage was carried out considering mine data between 2003 and 2017 and the 317 drawpoints from PNM and SPM. The resultant scatter plot (Fig. 7a) shows that for the cut-off probability, there is a high positive degree of correlation between mine and modeled data concerning ore tonnage drawn before wet muck entry. In addition, Fig. 7a displays the 95% confidence level for the cut-off probability, from which two new cut-off probabilities are obtained. In the case of the lowest confidence interval, $Y = 0.86x$ in green, the cut-off probability corresponds

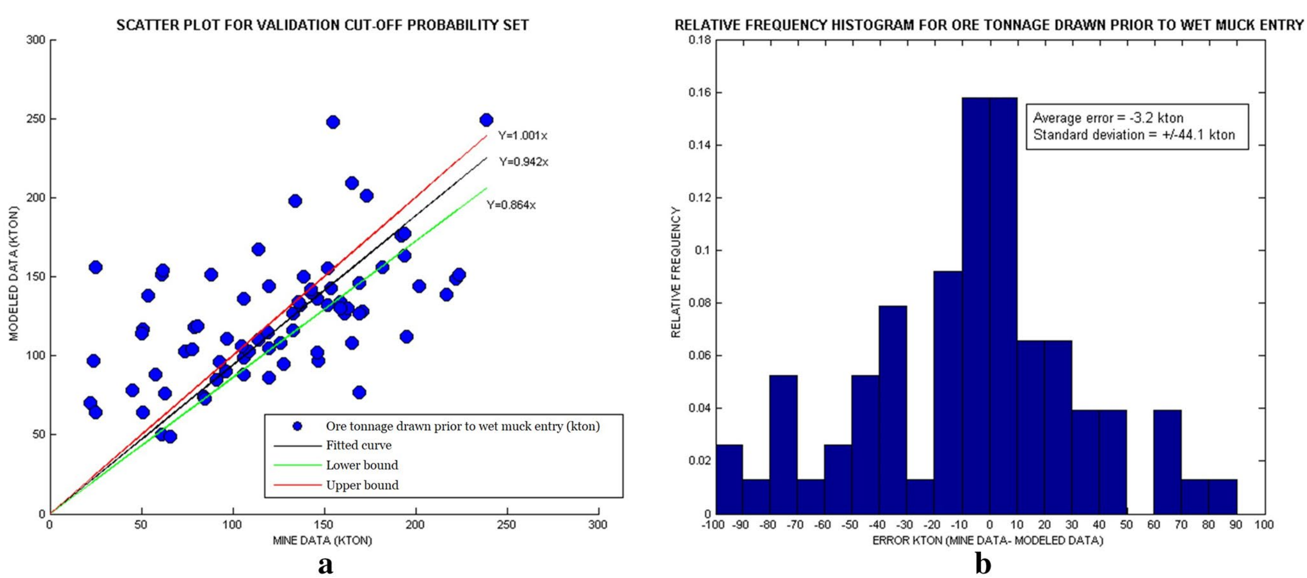

Fig. 7 **a** Scatter plot displaying ore tonnage drawn prior to wet muck entry, considering mine information from PNM and SPM, and; **b** relative frequency histogram for error between mine and modeled data based on the information gathered from PNM and SPM

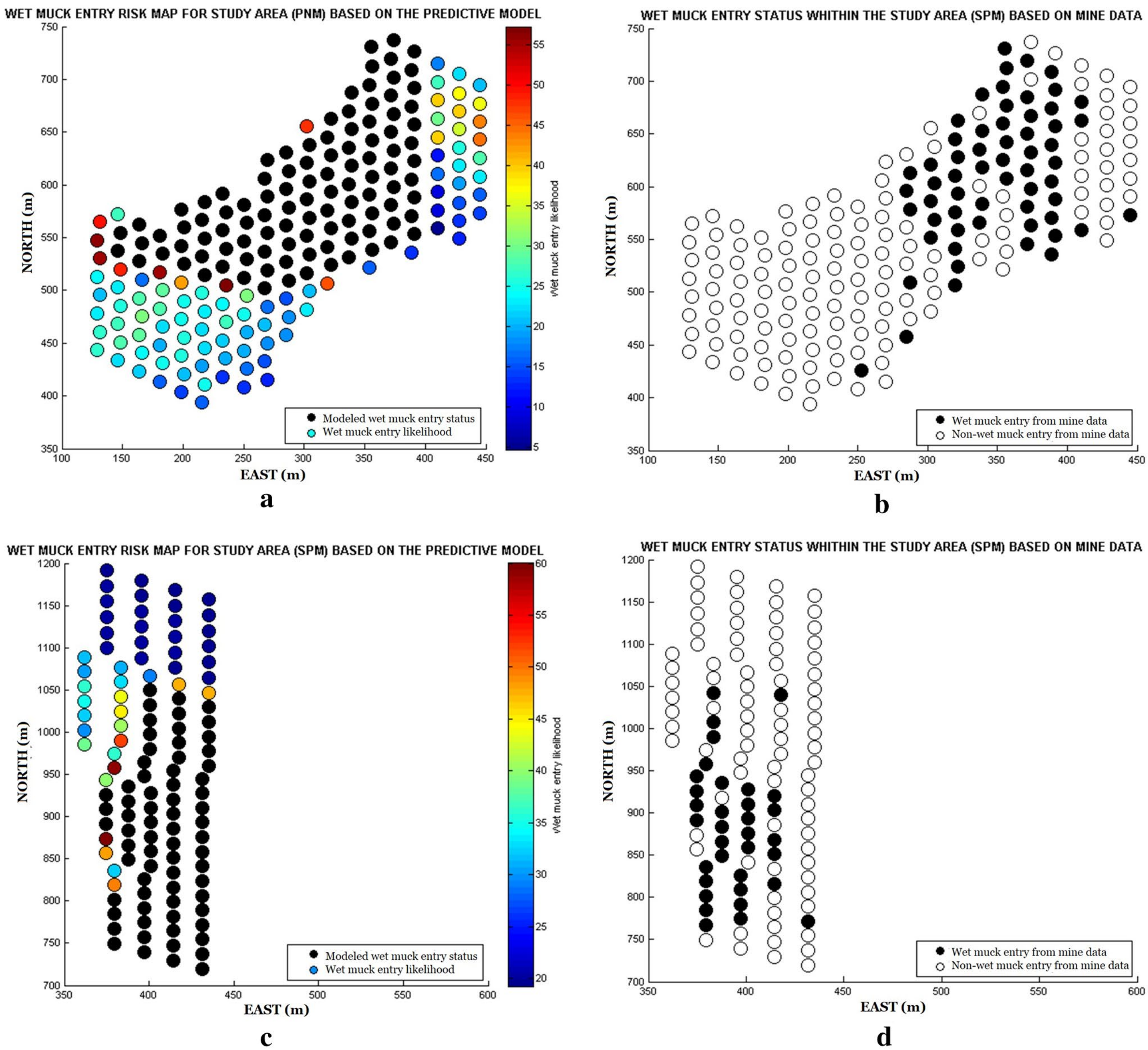

Fig. 8 Comparison between wet muck entry risk maps and mine data at the end of the evaluated periods; **a** wet muck entry risk map for PNM based on the predictive model; **b** wet muck entry status for PNM from mine data; **c** wet muck entry risk map for SPM based on the predictive model, and; **d** wet muck entry status for SP from mine data

to 0.54 for CP_v and 0.60 for CP_l, whereas for the highest confidence interval (i.e. $Y = 1.002x$ in red) the cut-off probability is 0.60 for CP_v and 0.50 for CP_l. Accordingly, the calibration error for the drawn tonnage before the occurrence of wet muck entry is near 94% with a confidence level of $\pm 8\%$. Moreover, based on the obtained relative frequency histogram shown in Fig. 7b, the average error between mine and modeled drawn tonnage data is approximate -3.2 ± 44.1kton, therefore, this metric performance is distributed around zero.

Based on the calibration and validation results, we concluded that the predictive model has a substantial discrimination capability for predicting drawpoints susceptible to wet muck entry within the study area; therefore, it could be employed to assess wet muck entry risk for long-term planning applications.

Employing the calibrated and validated predictive model, a wet muck entry risk map was created for PNM and SPM at the end of the evaluated periods, as shown in Fig. 8. All drawpoints with modeled likelihood above 0.58 for the vertical inflow of wet muck model or 0.60 for the lateral inflow of wet muck model were classified as wet muck status (black dots in Fig. 8a, c). In addition, Fig. 8b, d display a wet muck status map for PNM and SPM, respectively, considering the mine data gathered from the study area. Based on a visual comparison between these maps, we established that the wet muck entry risk map resulting from this research is appropriate for the recognition of high-risk zones prone to wet muck entry.

The use of multivariate logistic regression was founded to be applicable to the assessment of wet muck entry risk and the creation of a wet muck entry risk map for long-term planning. Using such a map, long-term mine planners can reduce wet muck entry risk and mitigate losses of ore reserves by attending to those drawpoints susceptible to wet muck entry and adopting preventive strategies, such as low draw rates, uniformity of draw, reduction of long-term ore reserves, among others. Finally, the results obtained herein provide meaningful long-term guidelines to re-define ore draw for wet muck entry high-risk zones. Several advantages of our approach include:

- The assessment of wet muck entry risk can be performed for each monthly period in long-term production plans.
- The multivariate predictive model and the application of the algorithm can be used to identify high-risk zones prone to wet muck entry, and thus re-plan the ore reserves to both reduce ore loss and mitigate the risks of wet muck entry.
- This methodology will enable the development of calibrated and validated predictive models for cave mines using their mine and wet muck status data.

It is important to mention that to improve the predictive capability of the model for future long-term planning, reliable feedback is needed as additional mine data becomes available. Furthermore, the methodology adopted in this study is applicable to future cave mine projects. However, in the case of cave mines currently in production, back-analysis of mine data is required to derive the logistic regression equations and perform both the calibration and validation steps.

5 Conclusions

In this article, the quantification of wet muck entry risk for long-term risk assessment and planning was presented and discussed. This methodology employs a multivariate logistic regression, incorporating key risk variables associated with wet muck entry. The results presented in this research demonstrate that logistic regression is a suitable approach for the evaluation of long-term wet muck entry risk. The best-calibrated model incorporates the most important risk variables causing wet muck entry at the study area: ore draw, water infiltration, the presence of topographic gutters, column height of primary rock, and neighboring wet muck area at drawpoints. Using the cut-off probability set revealed in this study, the model's accuracy was estimated at 84%. In addition, the predictive ability of the model was found to be reliable for the estimation of ore tonnage drawn before wet muck entry at drawpoints. Therefore, performed under optimal calibration and validation, this predictive model can provide a relevant instrument to delineate zones prone to wet muck entry and can be used to evaluate numerous long-term plans for caving mines, allowing preventive decisions to be made that would minimize the risks caused by wet muck phenomena.

The model's success promotes the use of logistic regression as a valuable wet muck status classifier that can be updated and enhanced as new data becomes accessible. Additional research applying the methodology to long-term risk assessment should further refine the predictive capability of the modeling methodology. Furthermore, the favorable predictions obtained from this study may be improved by adding other factors to the predictive model, such as uniformity of draw, types of lithology and material fragmentation, and presence or absence of moisture at drawpoints. Even though some broad geomechanical characteristics were included herein, further research on the analysis of rock mass quality and joint set characteristics would be useful to study and quantify the influence of these geotechnical parameters on the probability of having wet muck entry at drawpoints.

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References

Allison P (2012) Logistic regression using SAS®: theory and application, 2nd edn. SAS Institute

Becerra C (2011) Controlling drawpoints prone to pumping—El Teniente mine. In: Geomin 2011: Proceedings of the Second International Seminar on Geology for the Mining Industry, Antofagasta, Chile

Brown E (2004) Block Caving Geomechanics, 2nd edn. Julius Kruttschnitt Minerals Research Center, University of Queensland, Brisbane

Brzovic A, Villaescusa E (2006) Rock mass characterization and assessment of block-forming geological discontinuities during caving of primary copper ore at the El Teniente mine, Chile. Int J Rock Mech Min Sci, 44(4), 565–583

Butcher R, Stacey T, Joughin W (2005) Mud rushes and methods of combating them. J S Afr Inst Min Metall 105(11):817–824

Codelco ET, Mine (2014) Revision of geomechanics properties for intact rock and faults at *El Teniente* Mine (in Spanish). Mineral resources and development management. Internal report

Codelco ET, Mine (2016a) *El Teniente*'s production plan final report—PND 2016 (in Spanish). Mineral resources and development management. Internal report

Codelco ET, Mine (2016b) Update for moisture classification at drawpoints and drawpoint classification matrix to assess wet muck (in Spanish). Superintendence for production management. Internal report

Fawcett T (2006) An introduction to ROC analysis. Pattern Recogn Lett 27(8):861–874

Ferrada M, (2011) Gravity flow under moisture conditions—Control and management of drawpoint mudflow. In: APCOM 2001: Proceedings of the 35th International Symposium of Application of Computers and Operations Research in the Minerals Industry, University of Wollongong, New South Wales, Australia, pp. 761–764

Garcés D, Castro R, Valencia M, Armijo F (2016) Assessment of early mud entry risk for long term cave mining applications. In: U-Mining 2016: Proceedings of the First International Conference of Underground Mining, Santiago, Chile, pp. 439–451

Geng P, Sakhanenko L (2015) Parameter estimation for the logistic regression model under case-control study. Stat Probab Lett 109:168–177

González R, Brzovic A (2017) Potential mudrushes risk at *El Teniente* Mine. In: Mineplanning 2017: Proceedings of 5th International Seminar on Mine Planning, Santiago, Chile

Hartman H, Mutmansky J (2002) Introductory mining engineering, 2nd edn. Wiley, Hoboken

Holder A, Rogers A, Bartlett P, Keyter G (2013) Review of mud rush mitigation on Kimberley's old scraper drift block caves. J S Afr Instit Min Metall 113:529–537

Hosmer D, Lemeshow S, Sturdivant R (2013) Applied logistic regression, vol 398. Wiley, New York

Hubert G, Dirdjosuwondo S, Plaisance R, Thomas L (2000) Tele-Operation at freeport to reduce wet muck hazards. In: Massmin 2000: Proceedings of the third international conference & exhibition on mass mining, The Australasian Institute of Mining and Metallurgy, Brisbane, Australia, pp. 173–179

Jakubec J, Clayton R, Guest A (2012) Mudrush risk evaluation. In: Massmin 2012: Proceedings of the sixth international conference & exhibition on mass mining, Canadian Institute of Mining, Metallurgy and Petroleum, Ontario, Canada

McCullagh P, Nelder J (1989) Generalized linear models, 2nd edn. Chapman & Hall, London

Navia I, Castro R, Valencia M (2014) Statistical analyses of mud entry at Diablo Regimiento sector—El Teniente's Mine. In: Castro R (ed) Caving 2014: Proceedings of the third international symposium on block and sublevel caving, University of Chile, Santiago, Chile, pp. 372–378

Samosir E, Basuni J, Widijanto E, Syaifullah T (2008) The management of wet muck at PT Freeport Indonesia's Deep Ore Zone Mine. In: Massmin 2008: Proceedings of The Sixth International Conference & Exhibition on Mass Mining, Canadian Institute of Mining, Metallurgy and Petroleum, Ontario, Canada, pp. 323–332

Syaifullah T, Widijanto E, Srikant A (2006) Water issues in DOZ Block Cave Mine, PT Freeport Indonesia. In: Proceedings of the water in mining, Brisbane, Australia, pp. 361–368

Widijanto E, Sunyoto W, Wilson A, Yudanto W, Soebari L (2012) Lessons learned in wet muck management in Ertsberg East Skarn System of PT Freeport Indonesia. In: Massmin 2012: Proceedings of the sixth international conference & exhibition on mass mining, Canadian Institute of Mining, Metallurgy and Petroleum, Ontario, Canada