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WET MUCK ENTRY MODELING FOR BLOCK CAVING

TESIS PARA OPTAR AL GRADO DE MAGISTER EN MINERÍA

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RESUMEN

El método *block caving* ha sido aplicado exitosamente como método subterráneo masivo para depósitos minerales extensos y profundos. Sin embargo, durante el proceso de propagación de la subsidencia hacia la superficie, el agua acumulada en el macizo o en superficie puede entrar a la columna de extracción, mezclándose con el material rocoso fragmentado. Cuando esta mezcla se produce con material rocoso fino, la entrada de barro puede convertirse en uno de los principales riesgos operacionales en minas de hundimiento. Por este motivo, la evaluación del riesgo de entrada de barro a los puntos de extracción representa un rol importante en la recuperación de reservas, tanto para el corto como para el largo plazo. Hasta la fecha, pocas investigaciones han abordado el análisis de las variables de riesgo claves asociadas con la entrada de barro; en consecuencia, aún existen importantes limitaciones relacionadas con la identificación y cuantificación del grado de asociación entre las variables de riesgo operacionales mineras y la entrada de barro.

Esta investigación tiene por objetivo estudiar y cuantificar la influencia de las principales variables de riesgo asociadas con la entrada de barro, por medio del análisis estadístico utilizando datos mina colectados desde División El Teniente y el método de regresión logística.

La metodología de la investigación está compuesta de tres etapas. En primer lugar, se llevó a cabo un análisis univariable para estudiar el grado de asociación entre las variables de riesgo y la entrada de barro. En segundo lugar, se empleó la regresión logística multivariable para analizar la interrelación de las variables de riesgo claves relacionadas con la entrada de barro. Como resultado, se obtuvo el mejor modelo predictivo ajustado para el corto y largo plazo, respectivamente, con la finalidad de estimar la probabilidad de entrada de barro. La calibración y validación de los modelos se realizó utilizando los datos minas con los cuales fueron construyeron, con el objetivo de medir la capacidad predictiva para la entrada de barro. Finalmente, se emplearon los modelos predictivos para crear mapas de susceptabilidad (zonas de riesgo en base a probabilidades) de entrada de barro, tanto para el corto como el largo plazo, los que permiten identificar zonas propensas a la entrada de barro en cada punto de extracción.

A partir de los resultados obtenidos, las conclusiones de este estudio indican que las variables de riesgo claves corresponden a la cavidad de subsidencia (canalón de subsidencia), porcentaje de extracción de la columna in situ, infiltración de agua, uniformidad de la extracción, y área vecina con barro en los puntos de extracción. Adicionalmente, la capacidad predictiva de los modelos se consideró como aceptable para la estimación del tonelaje extraído antes de la entrada de barro, debido a que la precisión de los modelos fue estimada en 84% para el modelo de planificación de corto plazo y 81% para el modelo de planificación de largo plazo. Por lo tanto, los resultados presentados demuestran que, utilizados en condiciones óptimas de calibración y validación, estos modelos predictivos pueden servir como una importante herramienta para delimitar zonas susceptibles a la entrada de barro. Del mismo modo, estos modelos predictivos pueden ser utilizados para evaluar diferentes planes de producción del corto y largo plazo en minería de hundimiento. Esto último, podría permitir tomar decisiones preventivas que eviten o minimicen la pérdida de reservas causadas por el fenómeno de la entrada de barro.

ABSTRACT

Block caving has been succesfully applied as bulk undergroud mining method for large, deep orebodies. Once the cave subsidence propagates to the surface, the accumulated water may enter the extraction column. Because of that, wet muck entry has been identified as one of the major operational risks in cave mines. Therefore, the risk assessment of wet muck entry is an important part of ore reserve recovery process for both short and long-term mine planning. Up to date, wet muck entry key variables are poorly understood. Thus, additional studies to identify and quantify the degree of association between risk variables and wet muck entry are needed.

This research aims to study and quantify the influence of the principal risk variables related to wet muck entry through the execution of several statistical analyses using mine data collected from *El Teniente* mine, and using the logistic regression approach.

The research methodology considered three stages. First, a univariate analysis were carried out to study the degree of association between main risk variables and wet muck entry. Second, the multivariate logistic regression method was used to analize the interrelationship of key risk variables related to wet muck entry. As a result, a best-fitted multiple predictive models were obtained to estimate the likelihood of wet muck entry. The calibration and validation of the models were performed to estimate its prediction capability. Finally, the predictive models were used to create a group of wet muck entry susceptible maps to identify the risk zones prone to wet muck entry based on wet muck entry likelihood in each drawpoint.

To conclude, this study indicates that the key risk variables for wet muck entry are topographic gutter, percentage of ore extraction from the in situ column, water infiltration, uniformity of draw, and neighboring wet muck area at drawpoints. In addition, since models' accuracy were estimated as 84% for short-term planning and 81% for long-term planning, the predictive ability of the models were found to be reliable in terms of ore tonnage drawn prior to wet muck entry at drawpoints. Therefore, the results presented in this research demonstrate that; if the model is applied under optimal calibration and validation, these predictive models can provide an important tool to delineate zones prone to wet muck entry. Moreover, they can be also used to evaluate different short and long-term production plans for block caving, allowing preventive decisions that will avoid or minimize the ore reserve losses caused by the wet muck entry phenomena.

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If you don't have shadows, you're not standing in the light

A mis abuelitos, Carlos y Humberto, las luces de mi vida,
este logro también es suyo

CAPÍTULO 1

INTRODUCCIÓN

1.1. PREÁMBULO

La minería de hundimiento, o *block caving*, es un método subterráneo de extracción masiva de mineral fundamentado en la acción de la gravedad, donde el cuerpo mineralizado es socavado basalmente para iniciar el hundimiento natural de la columna. La propagación del hundimiento es continua en la medida que la roca fragmentada sea extraída desde la base del sistema (i.e. punto de extracción), hasta alcanzar la superficie (Brown, 2004). Sin embargo, una vez que el hundimiento se propaga hasta la superficie, el agua superficial y el material fino pueden ingresar directamente a la columna de mineral desde la zona de subsidencia (Brown, 2004). Este material compuesto de mineral fino y húmedo, mezclado en proporciones que le permiten fluir por acción de la gravedad, es llamado barro (*wet muck* en inglés) (Jakubec et al., 2012). Así, la entrada de barro (*wet muck entry*, en inglés) es definida como la presencia de barro en los puntos de extracción. Durante los últimos años, la entrada de barro ha sido identificada —al igual que estallidos de roca, *airblasts*, colapsos, entre otros— como uno de los principales riesgos operacionales en minería de hundimiento (Heslop, 2000), el que puede causar retrasos en la extracción de mineral; innumerables pérdidas en las reservas de mineral; y problemas en la seguridad, tales como accidentes graves en los sectores productivos, daño en equipos mineros, e incluso, accidentes fatales de trabajadores.

Algunos investigadores han realizados estudios para explicar y prevenir la entrada de barro durante la explotación minera. Butcher *et al.* (2005) han postulado, basado en revisión de la literatura, que se requieren cuatro elementos simultáneamente para generar la entrada de barro. Estos factores corresponden a (i) la capacidad para acumular de agua, por ejemplo, agua superficial o subterránea; (ii) la presencia de mineral formador de barro, es decir, material de granulometría fina; (iii) perturbación dentro de la columna de roca, como por ejemplo la extracción de mineral, o tronaduras en nivel de producción y hundimiento; y (iv) un punto de descarga para el barro, es decir, un punto de extracción En tanto, Navia *et al.* (2014) han concluido, en base a un análisis histórico de extracción de la mina Diablo Regimiento en División El Teniente, que la altura extraída y la uniformidad de la extracción son variables que controlan el fenómeno de ingreso de barro. En términos de prevención de ingreso de barro, diversos autores han sugerido realizar una extracción uniforme y continua de mineral húmedo para mantener en constante movimiento al mineral fragmentado, tanto para evitar la formación de conos de extracción (o *sink-holes*), como para drenar la columna de mineral, y así reducir el contenido de agua o humedad sobre el punto de extracción (Hubert, *et al.*, 2000; Butcher *et al.*, 2005; Samosir *et al.*, 2008; Widijanto *et al.*, 2012; Jakubec *et al.*, 2012). Sin embargo, en la literatura aún no hay consenso acerca del nivel de importancia de las variables críticas relacionadas con el fenómeno. Además, no es posible cuantificar los efectos que tienen estas variables en la probabilidad de entrada de barro. Por lo tanto, se necesitan estudios que permitan cuantificar las variables críticas y estimar la probabilidad entrada de barro durante la explotación de minas de hundimiento.

En consecuencia, la presente investigación tiene por objetivo analizar y cuantificar el efecto de diferentes variables de riesgo asociadas a la entrada de barro y, además, desarrollar un modelo predictivo de entrada de barro a los puntos de extracción. De esta forma, se pretende utilizar los resultados del estudio en la planificación minera de *block caving* durante el corto y largo plazo. Para ello, se utilizó el método de regresión logística como herramienta análisis y una base de datos de diferentes sectores productivos ubicados en División El Teniente.

1.2. MOTIVACIÓN

Como ha sido mencionado, se requieren estudios que permitan predecir la entrada de barro a los puntos de extracción durante la operación minera. Esta problemática surge en respuesta a la necesidad de planificar las reservas de mineral considerando el riesgo de ingreso de barro. Actualmente, División El Teniente utiliza un método determinístico para planificar las reservas de corto y largo plazo, como se observa en la Fig. 1. Este mapa se obtiene a partir de un análisis estadístico histórico de diferentes variables (por ejemplo, presencia de canalón, precipitaciones, sectores antiguos con presencia de barro, sobre-extracción, entre otros factores). Por ejemplo, para efectos de la planificación minera de largo plazo, en aquellos puntos de extracción ubicados en la zona de alto riesgo (color rojo), se establecen reservas de mineral equivalentes al 130% de su altura in-situ; en tanto, para puntos de extracción con riesgo medio (color amarillo) y riesgo bajo (color blanco), es posible planificar reservas en torno al 160% - 180% dependiendo del sector explotado (Codelco, 2016).

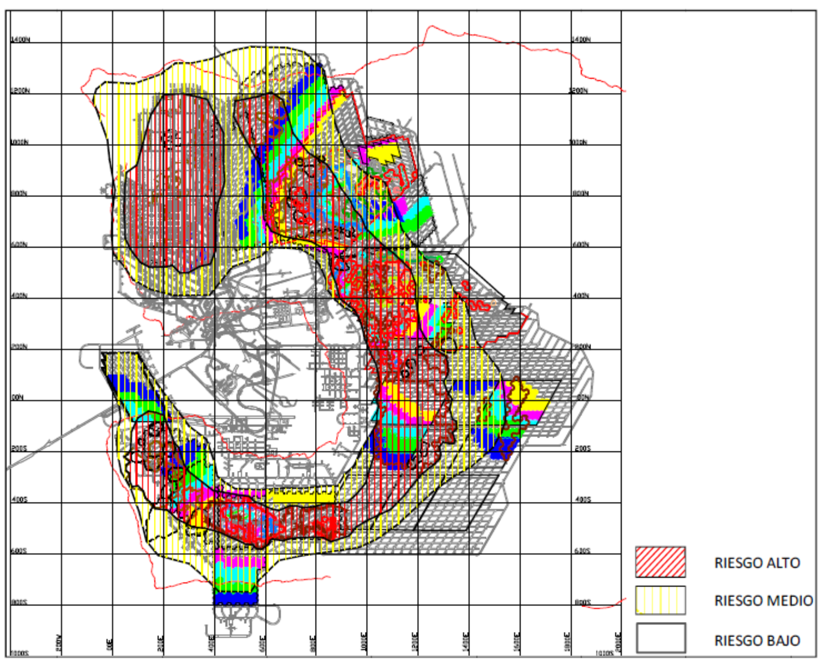

Fig. 1 Plano de riesgo de ingreso de barro para mina El Teniente (Codelco, 2014)

Sin embargo, esta metodología no permite cuantificar la relación que posee cada una de las variables críticas con la entrada de barro. Por lo tanto, resulta fundamental desarrollar un método para estimar la probabilidad de entrada de barro a los puntos de extracción. De esta forma, los planificadores de minas pueden conocer los parámetros críticos que afectan en la entrada de barro durante el proceso de extracción, e identificar los sectores productivos con mayor susceptibilidad (es decir, mayor probabilidad) a la entrada de barro. En consecuencia, este estudio tiene por finalidad mejorar el proceso de toma de decisiones para la planificación de corto y largo plazo en minas de *caving*.

1.3. OBJETIVOS DEL ESTUDIO

El objetivo general de esta investigación es identificar y cuantificar el efecto de las principales variables de riesgo que participan en la entrada de barro a los puntos de extracción. De esta manera, se pretende mejorar la toma de decisiones durante la planificación de largo y de corto plazo.

Para cumplir con lo anterior, se proponen los siguientes objetivos específicos claves de la investigación:

1. Analizar e identificar las variables críticas que participan en la entrada de barro, utilizando la regresión logística univariable como herramienta analítica.

2. Cuantificar la interrelación de múltiples variables críticas con la entrada de barro a los puntos de extracción, por medio de un análisis de regresión logística multivariable.

3. Desarrollar un algoritmo que permita calcular la probabilidad diaria de entrada de barro, predecir la entrada de barro a los puntos de extracción, y estimar las reservas recuperadas (en toneladas) antes de la entrada de barro, utilizando un plan de producción como dato de entrada.

4. Construir un mapa de susceptibilidad para la entrada de barro a los puntos de extracción para los sectores productivos estudiados.

1.4. ALCANCES DE LA INVESTIGACIÓN

En el desarrollo de este estudio, se han adoptado los siguientes enfoques y limitaciones.

i. La base de datos utilizada contiene información proveniente de distintas minas en División El Teniente entre enero de 2001 y febrero de 2017. Los sectores productivos analizados corresponden a Pipa Norte, Sur Andes Pipa, y Diablo Regimiento.

ii. El error durante el proceso de calibración y validación de los modelos predictivos se realiza a nivel de punto de extracción.

iii. Los modelos predictivos se utilizan para calcular la probabilidad (evaluación del riesgo) de ingreso de barro en cada punto de extracción, utilizando un plan de producción como dato de entrada (input). El resultado de la evaluación (output) corresponde a la estimación de reservas recuperadas desde el plan de producción de entrada. Por lo tanto, el output no representa un nuevo plan de producción, pues no incluye criterios de planificación, por ejemplo, los empleados en División El Teniente.

1.5. METODOLOGÍA GENERAL DEL ESTUDIO

La metodología para el desarrollo de esta investigación se enfoca en analizar los datos colectados, con el fin de lograr los objetivos anteriormente mencionados. La Fig. 2 resume las etapas de la presente metodología de trabajo.

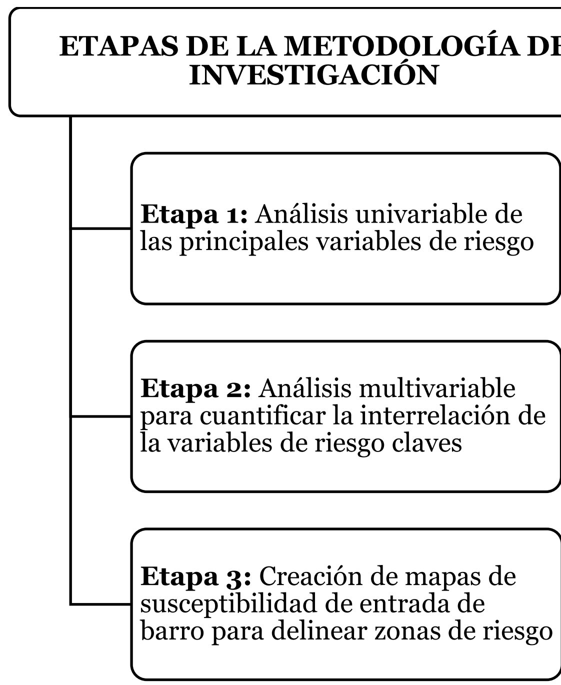

Fig.2 Descripción esquemática de la metodología de trabajo

1.6. RESUMEN DE LA INVESTIGACIÓN

Los resultados de este estudio son presentados en los siguientes artículos.

Art.1: Castro, R., Garcés, D., Brzovic, A., and Armijo, F. 2017. Quantifying wet muck entry risk for long-term planning in block caving. Article to be submitted to Rock Mechanics and Rock Engineering.

Art. 2: Garcés, D., and Castro, R. 2017. Analyzing the role of draw strategy on wet muck entry risk for short-term cave planning. Article to be submitted to the Canadian Geotechnical Journal.

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CAPÍTULO 2

ARTÍCULO 1

QUANTIFYING WET MUCK ENTRY RISK FOR LONG-TERM PLANNING IN BLOCK CAVING

Paper to be submitted to Rock Mechanics and Rock Engineering

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Abstract

Wet muck entry is one of the major operational 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 associated with 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 above-mentioned metrics show an acceptable agreement between mine and modeled data, therefore, we used our results to create a statistically significant predictive model, which may be useful for the evaluation of different long-term cave production plans. Based on optimal calibrated conditions, the predictive model is a powerful instrument to identify high-risk zones susceptible to wet muck entry and to make preventive long-term decisions that could mitigate losses of planned ore reserves.

Keywords

Wet muck entry, logistic regression, risk assessment, long-term ore reserves recovery

1 Introduction

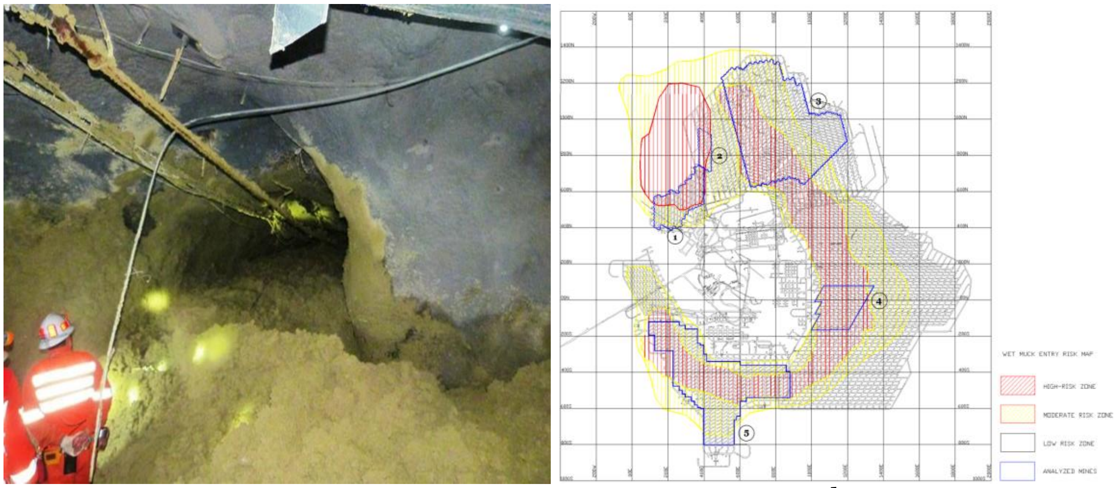
Block caving is a mining method in which ore blocks or panels are undermined causing the rocks to cave, and thus, allowing broken ore to be removed at drawpoints (Hartman and Mutmansky, 2002). Once the cave subsidence propagates to the surface, accumulated water and fine material may enter the draw column 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 an important issue in several cave mines, including: 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 mine safety problems, the assessment of wet muck entry is a critical step in risk analysis for long-term planning.

In the one hand, Butcher *et al*. (2005) have suggested that four factors occurring simultaneously trigger wet muck entry. These include capacity for water accumulation, presence of potential wet muck-forming minerals, disturbance in the ore column, and the capacity 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; therefore, 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 for long-term planning, two approaches have been used: deterministic and multivariate statistical methods. The deterministic approach could be easily implemented, but it requires a complete dataset to define the statistical weights of each variable. For instance, *El Teniente* Mine has adopted a deterministic method for long-term planning, in which the definition of ore reserves is based on the weights of each drawpoint's *in-situ* column obtained from a wet muck risk map, as shown in Fig. 1b. The high-risk area is determined by using this risk map (red zone), and subsequently, ore reserve columns within it are restricted to 130 percent of the in-situ column; whereas drawpoints located in medium- and low-risk areas are restricted between 160 to 180 percent of the in-situ column (Codelco, 2016).

Correspondingly, the second alternative is the multivariate statistical method, which could be an appropriate approach due to its ability to estimate the event's likelihood, as it considers the relationship between the dependent variable (wet muck entry) and a set of independent variables (wet muck entry risk variables). Among the multivariate statistical methods, the logistic regression is the most useful for analyzing data that include a binary response variable (McCullagh and Nelder, 1989; Hosmer et al., 2013), in this very case, the presence or absence of wet muck entry. The main advantage of this method is its capacity to minimize the uncertainties through the use of maximum likelihood estimates (Geng and Sakhanenko, 2015). Garcés et al. (2016) attempted to integrate a wet muck risk assessment model in long-term planning based on the application of multivariate logistic regression by estimating ore reserve recovery prior to wet muck entry. Nevertheless, a comprehensive discriminant analysis (i.e. analysis of data using univariate logistic regression) of risk variables was not included in their work. Consequently, further investigations were required to focus on incorporating the main risk variables into wet muck entry risk assessment for long-term planning.

Quantifying wet muck entry risk gives mine planners insight into critical mine parameters during the long-term planning process. Thus, this work aims to study the effect of the main risk variables controlling the wet muck entry on long-term planning in cave mining. In this paper, we firstly conducted an analysis of wet muck status at drawpoints in the *El Teniente* Mine to define the conditions for wet muck entry modes; then, we 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. The proposed research has proven to be a useful tool to assess wet muck entry risk for mine planners in block caving.



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 permanent flows from melting snow and rain fall. This area is characterized by the presence of historical wet muck flow. The yellow zone (intermediate-risk zone) corresponds to the area within the topographic gutter with an elevation greater than 500 m, and registered wet muck inflows. The white zone (low-risk zone) indicates an area with high elevation (greater than 600 m) located outside the topographic gutter's influence, and unregistered wet muck inflows (González and Brzovic, 2017)**

2 Database and study area

2.1 Wet muck entry database at El Teniente Mine

Mine data was collected from different sectors at *El Teniente* Mine, including the *Diablo Regimiento* Mine (DRM), the *Reservas Norte* Mine (RNM), the Block-1 *Esmeralda* Mine (B1-EM), the *Pipa Norte* Mine (PNM) and the *Sur Andes Pipa* Mine (SPM). The dataset includes information from 2000 to 2017. These mines are mainly located under a topographic gutter (similar to a topographic depression) around the Braden pipe (Fig. 2), and extensively operated in the high-risk zone of wet muck entry. Currently, the above-mentioned mines represent nearly 78% of the *El Teniente* Mine's daily production (about 91,000 tonnes per day).

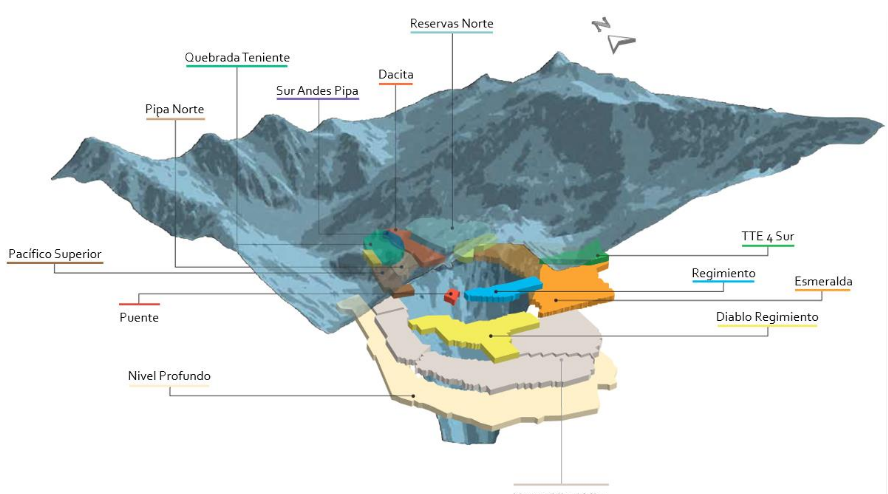
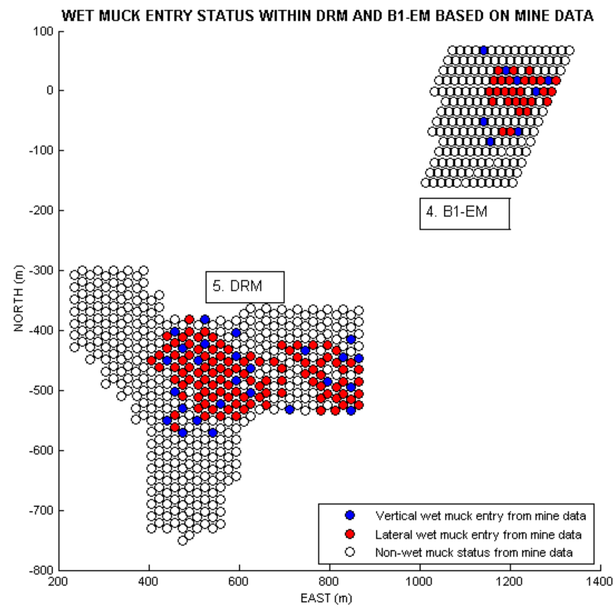


Fig. 2 **Isometric view of productive sectors at El Teniente Mine, indicating the location of the studied mine database (Codelco, 2016)**

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 in Fig. 3); therefore, we 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, we 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.



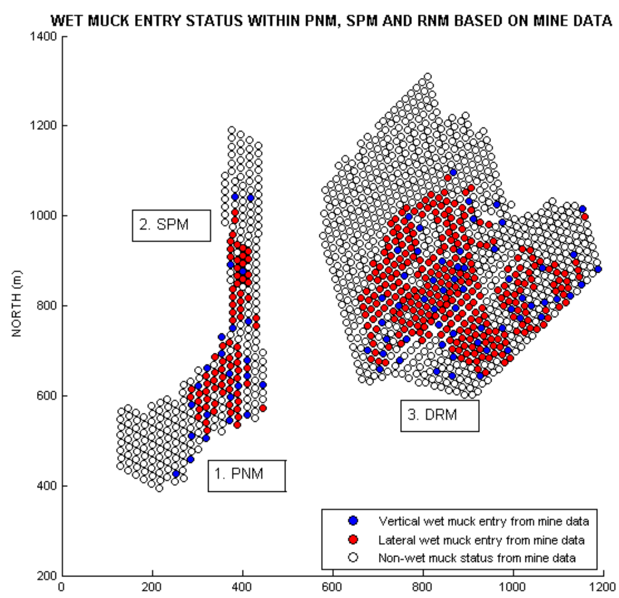


Fig.3 **Analysis of historical wet muck entry mode at El Teniente Mine; 1. Pipa Norte Mine (PNM); 2. Sur Andes Pipa Mine (SPM); 3. Reservas Norte Mine (RNM); 4. Block-1 Esmeralda Mine (B1-EM); 5. Diablo Regimiento Mine (DRM)**

Summarizing this analysis, the wet muck entry mode was 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. Fig. 4a shows the initial condition of a cave mine, in which the in-situ and broken wet ore columns are defined. The cave-back 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.

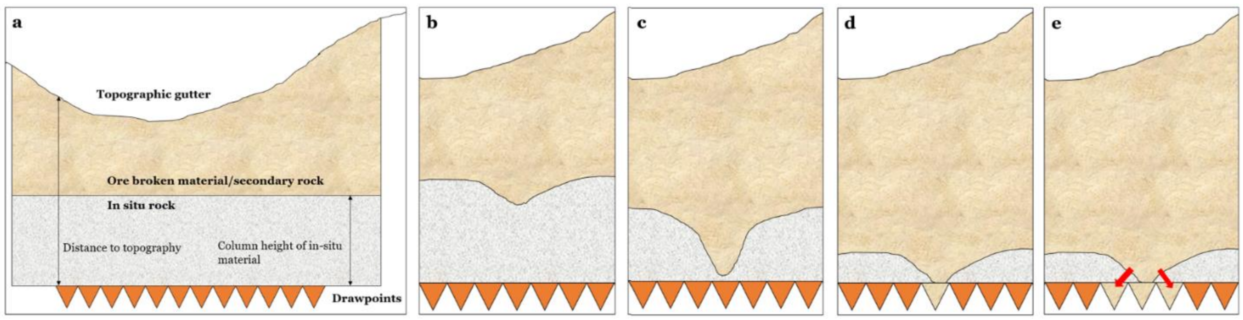


Fig. 4 Schematic cross-section view through a cave mine, showing the wet muck entry mode proposed in this research

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 and datasets

The *Pipa Norte* Mine (PNM) and the *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 the Braden pipe that has been formed due to caving subsidence from previous mine exploitations (Fig. 5). Historically, the topography of this area was recognized as a key factor to accumulate water, which directly impacts on water infiltration to cave mines (Codelco, 2016).

The PNM and SPM data was gathered from 317 drawpoints in production between July 2003 and February 2017. Among them, 94 data records (30% of the database) were declared with wet muck status. This database was employed to independently study the relationship between the risk variables and the presence of wet muck entry. This analysis was carried out using the univariate analysis of the logistic regression approach.

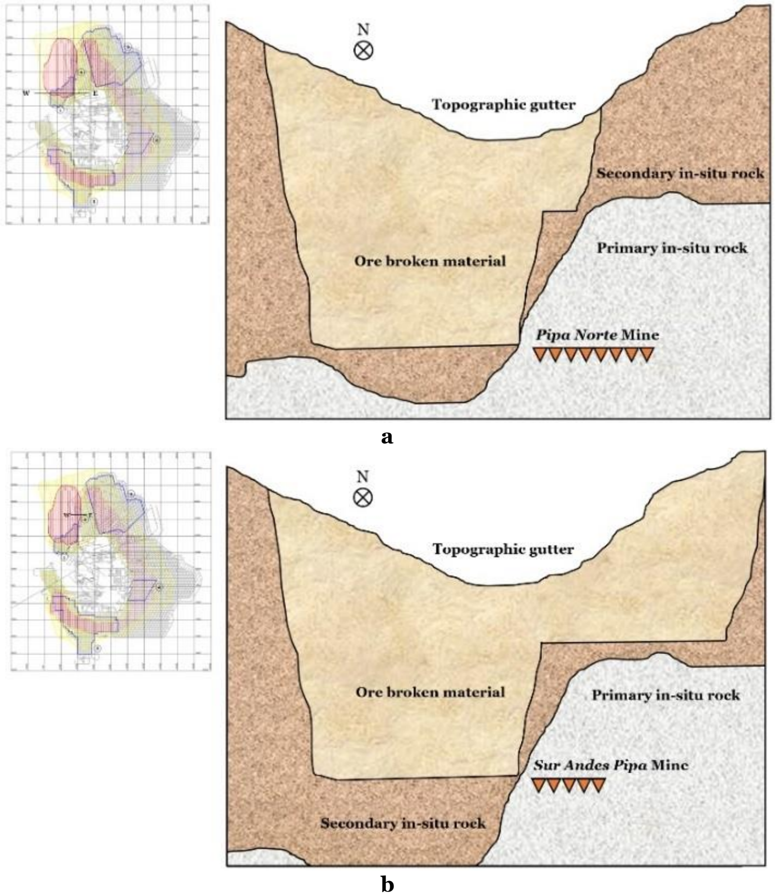


Fig. 5 **Schematic east-west cross-section showing the location and initial conditions of the study area; a. Pipa Norte Mine, and; b. Sur Andes Pipa Mine**

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 statuses 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 selected 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.

2.3 Wet muck entry risk variables

Considering that the aim of this study was to evaluate 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, presence of topographic gutter, and drawpoint neighborhood with wet muck entry. A more detailed description of the variables and terms involved in this research are summarized in Table 1a and Table 1b.

Table 1
a. 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 (day). 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 0 value if the drawpoint is not situated under the topographic gutter around Braden pipe, otherwise 1 value 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 0 to 6 neighboring drawpoints with wet muck entry status

b. Description of the terms used in this research

Terms	Description
In-situ tonnage	Indicates the tonnage of ore (or material) naturally presents 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

Finally, Table 2 summarizes the criteria adopted for the purposeful selection of risk factors based on both the physical conditions for wet muck entry and the cave experiences gained throughout cave operation at *El Teniente* Mine.

Table 2
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 fine material formation due to 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 rates follow the 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 by primary and secondary rock)
Column height of primary rock	Represents the material with the lowest permeability within the ore column, thus, drawpoints with high column height of primary rock have less likelihood of wet muck entry
Distance to topography	Considers the distance to the superficial water source (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 directly the state of water source
Drawpoint neighborhood with wet muck entry	Indicates the risk that wet muck could be laterally spread to the surrounding areas (neighboring drawpoints)

3 Method

3.1 Risk-factor strength association analysis

In this work, several risk factors 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. The stages proposed to develop the predictive model are described below.

3.1.1 Univariate logistic regression analysis

Risk variables for wet muck entry were independently assessed using a univariate logistic regression analysis to study the strength association with wet muck entry. Chi-squared test (χ^2) and odds ratio (OR) were applied to analyze the relative relationship between the variables. First, we considered the null hypothesis that the coefficient of each analyzed variable is equal to zero (Hosmer *et al.*, 2013). Then, we used the Chi-squared test (χ^2) to reject the null hypothesis in the case of p-value≤0.2, and therefore, the analyzed variable was statistically significant.

Correspondingly, 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), as it can be seen in (1) (Hosmer *et al.*, 2013). For instance, if a drawpoint with 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 non-situated below the topographic gutter. A detailed discussion of the odds ratio is given in Hosmer *et al.* (2013).

$$Odds\ ratio\ (x) = \frac{P(Y=1|x)}{P(Y=0|x)} = \frac{\left(\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}\right)}{\left(\frac{e^{\beta_0}}{1+e^{\beta_0}}\right)} = e^{\beta_1} \tag{1}$$

In the univariate analysis, the variables found 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 $x = (x_1, x_2, x_3, \dots, x_n)$. Therefore, the conditional likelihood that wet muck entry is present (i.e. $Y = 1$) would be given by the following equation (Hosmer *at al.*, 2013)

$$P(Y = 1|x) = p(x) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\dots+\beta_n x_n}}{1 + e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\dots+\beta_n x_n}} \tag{2}$$

Where $\beta = \beta_0, \beta_1, \dots, \beta_n$ are the logistic regression model coefficients, which can be determined through special 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 ($-2\log\mathcal{L}$). In the case of the statistical significance, we used the Chi-squared test (χ^2) as mentioned in the previous section. Therefore, for a risk variable to remain in the multivariate logistic regression model, the p-value was set at 0.05. Secondly, the log-likelihood ratio measures the likelihood change 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).

3.3 Calibration and validation of the predictive model

The calibration of the predictive 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. Drawpoints with a likelihood above the cut-off value were classified as wet muck entry (i.e. $Y = 1$), whereas those with lower cut-off probabilities were classified as non-wet muck entry (i.e. $Y = 0$). To obtain the cut-off value, an algorithm that includes the key risk variables and the best-fitted predictive models (i.e. vertical and lateral inflow of wet muck models) was created. This algorithm enables the estimation of the daily likelihood of wet muck entry for each drawpoint.

For the selected cut-off probability, a contingency table was constructed, which allowed 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 as follows:

$$TPR = \frac{TP}{TP + FN}; \qquad TNR = \frac{TN}{TN + FP}; \qquad ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

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 prior to wet muck entry. 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 distribution of the error is near zero.

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≤0.2). Table 3 summarizes the association metrics obtained in this analysis.

Table 3
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 (β_i)**	**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

Based on Table 3, the results show that extraction, presence of topographic gutter, and drawpoint neighborhood with wet muck entry have the highest statistically predictive power for the occurrence of wet muck entry. Firstly, 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 located outside the topographic gutter area. Secondly, the extraction has an odds ratio of 3.19, meaning that if a drawpoint has drawn 150 percent in its in-situ column, wet muck entry likelihood will increase 3.19 times compared to a drawpoint that has drawn 50 percent its in-situ column. Thirdly, the number of drawpoints in the neighborhood with wet muck entry is the third major risk variable associated with wet muck entry, which has an odds ratio estimated of 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 to 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.

Considering 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. Univariable analysis is 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 a 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 4).

Table 4

a. Multivariate logistic regression modeling for vertical mode of wet muck entry

Model	**Coefficient (β_i)**	**Std. error**	***p*-value**	**Odds ratio**	**log-likelihood ratio**
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 roc*k*	-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. Multivariate logistic regression modeling for vertical mode of wet muck entry

Model	**Coefficient (β_i)**	**Std. error**	***p*-value**	**Odds ratio**	**log-likelihood ratio**
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	

For the vertical inflow mode of wet muck, variables such as ore draw and environmental conditions (topographic conditions, columns height variables and water infiltration) have physical impact on the occurrence of vertical wet muck entry; hence, three predictive models were developed (Table 4a). Based on the p-value given in Table 4a, 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 physical significance with wet muck entry, and p-value at approximately 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 4a. Consequently, vertical inflow of wet muck mode during cave operations is mainly controlled by extraction, water infiltration, and the presence of a topographic gutter.

Regarding the lateral mode of wet muck entry, the multivariate analysis considers ore draw, wet muck entry areas and environmental conditions (topographic conditions, columns height of material and water infiltration) as risk variables; therefore, three models were built (Table 4.b). Most of the risk variables presented in Table 4b 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 included 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 4b, 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 presence of a topographic gutter and 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 drawing more than the over-draw in 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 greater likelihood of wet muck entry, compared to drawing from others with more favorable conditions. Finally, based on equation (2), the best-fitted multivariate predictive model is defined as

$$p_{wm}(x) = \begin{cases} p_v(x) = \dfrac{exp(-1.62+0.57E+0.001FR-0.003h_{pr}+0.59TD)}{1+exp(-1.62+0.57E+0.001FR-0.003h_{pr}+0.59TD)} & If\ N_{wm} = 0, for\ CP_v \\ \\ p_l(x) = \dfrac{exp(-4.06+1.83E+0.001FR+1.70TD+0.53N_{wm})}{1+exp(-4.06+1.83E+0.001FR+1.70TD+0.53N_{wm})} & If\ N_{wm} > 0, for\ CP_l \end{cases} \quad (4)$$

Where $p_{wm}(x)$ indicates the wet muck entry likelihood; $p_v(x)$ and $p_l(x)$ denote the vertical and lateral wet muck entry likelihood, respectively; CP_v and CP_l specify the cut-off probability for vertical and lateral wet muck entry models, respectively; and $\mathrm{N_{wm}}$ indicates the number of neighbor drawpoints with wet muck entry status. 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

Particularly in this research, the calibration stage involves the development of an algorithm to assess the 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 the monthly water infiltration), 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 CP_v and CP_l to define the occurrence or non-occurrence of wet muck entry at drawpoints.

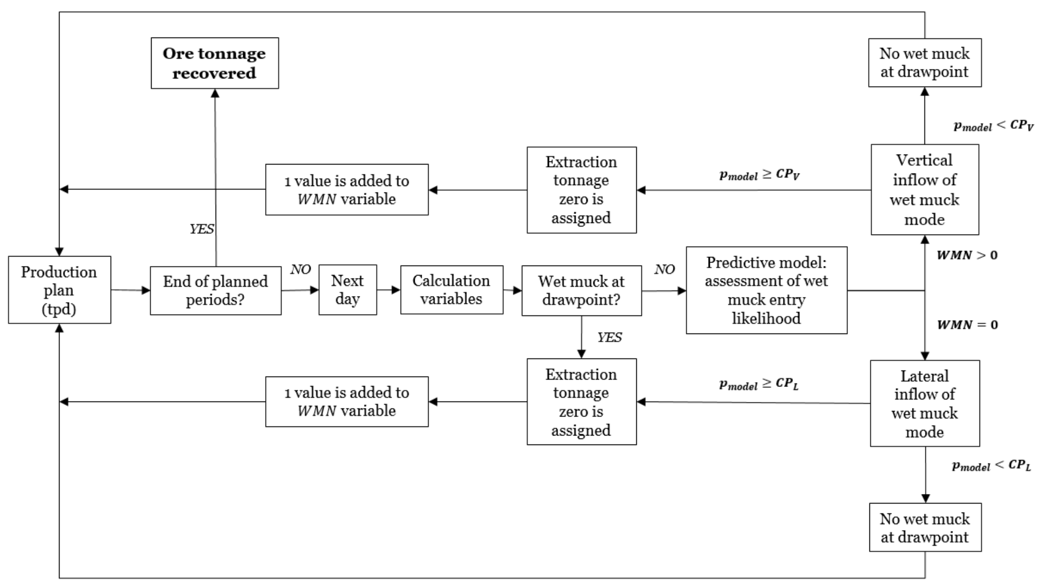


Fig. 6 Schematic diagram of the algorithm and its elements used to calibrate and validate the modeled data based on the estimation of the daily likelihood of wet muck entry. The above diagram represents the procedure for one evaluated drawpoint.

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 CP_v and 0.60 for CP_l. In total, 85% of wet muck entry data and 84% of non-wet muck entry data were correctly classified (Table 5). 80 observations of wet muck entry were accurately classified because of the unfavorable operational conditions of the analyzed drawpoints (i.e. drawpoints with 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. On the contrary, 15 of the wet muck entry observations were misclassified by the predictive model because they had favorable operational conditions, namely, drawpoints with non-over-draw conditions and situated outside both the topographic gutter and non-wet muck entry neighboring areas. The model's 84% accuracy demonstrates substantial discrimination for predicting the presence or absence of wet muck entry at drawpoints.

Table 5
Summary of results for the contingency table and performance metrics for the model calibration process

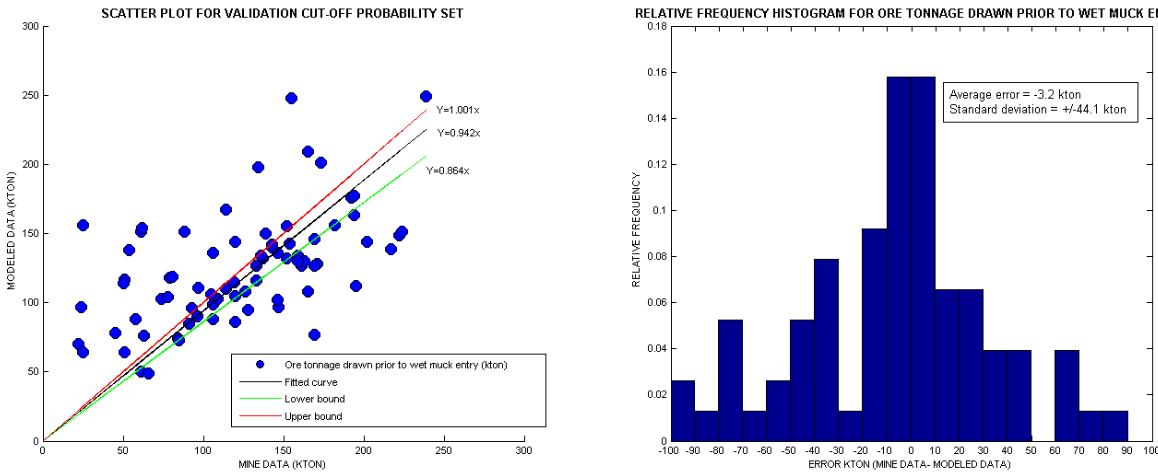
(a)		**Logistic model**	
		1	0
Reality	1	TP	FN
	0	FP	TN
(b)		**Predictive model (modeled observations)**	
		1 (115)	0 (202)
Mine data	1 (94)	80	15
	0 (223)	35	187
(c)			
Sensitivity	70%		
Specificity	93%		
Model accuracy	84%		

(a) 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 (0 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.

In order to validate the calibrated predictive model, the algorithm was applied to estimate drawn ore tonnage prior to wet muck entry. Using the defined cut-off probability, the occurrence or non-occurrence of wet muck entry was established by the calibrated model. The validation stage was carried out considering mine data between 2003 and 2017 and the 317 drawpoints from the PNM and the SPM. The 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 prior to wet muck entry. In addition, Fig. 7a displays the 95 percent 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 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 approximately -3.2 $\pm$ 44.1kton, therefore, this metric performance is distributed around zero.

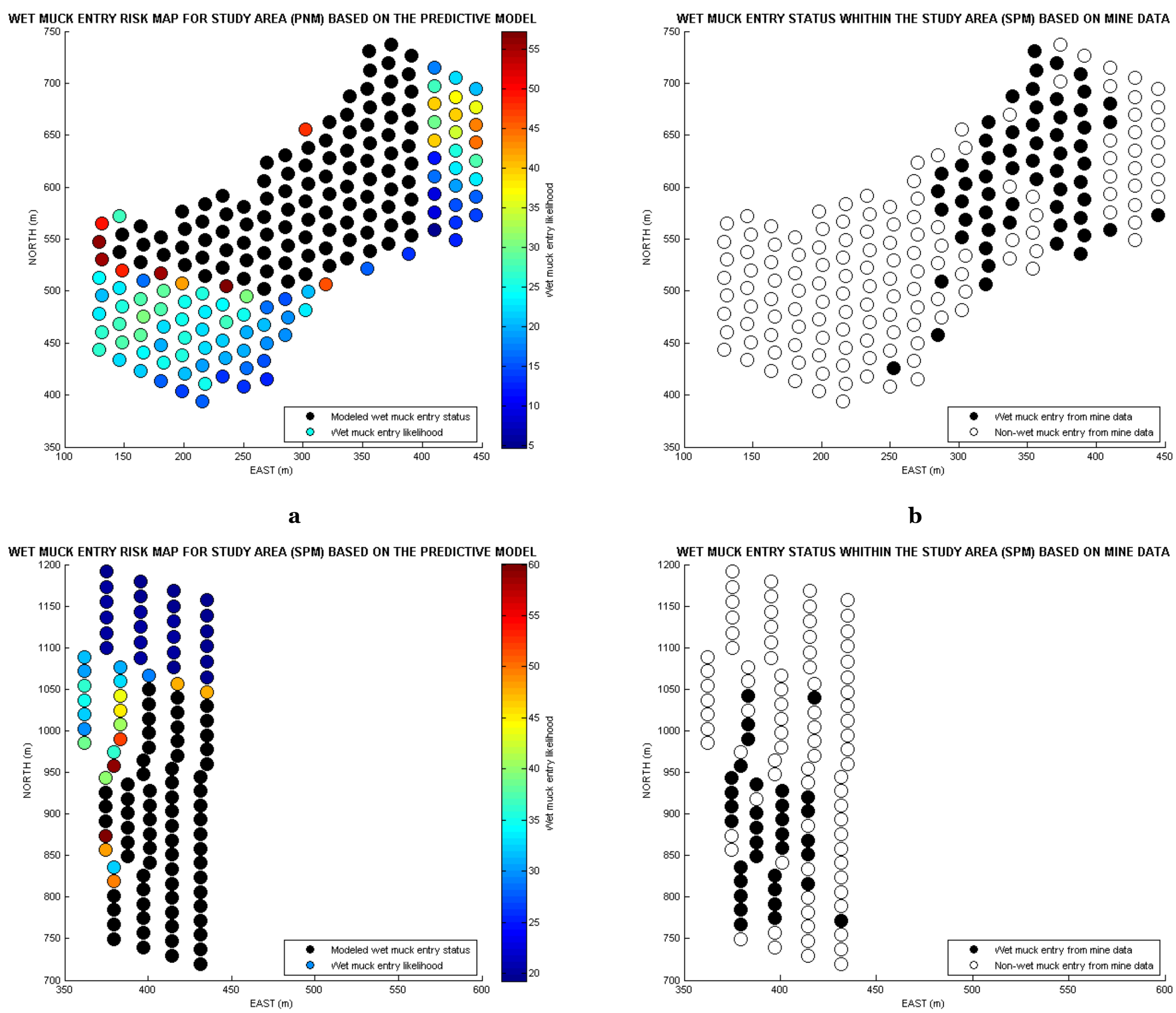
Based on the calibration and validation results, we concluded that the predictive model has a considerable discrimination capability for predicting drawpoints susceptible to wet muck entry within the study area; therefore, it could be employed to assess wet muck entry risk for long-term planning applications.

Correspondingly, in order to employ 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 and Fig. 8c). In addition, Fig. 8b and Fig. 8d 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.



a b

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**



a b

c d

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**

The use of the multivariate logistic regression approach was found 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. Certainly, 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) as required. Lastly, the results obtained herein provide meaningful long-term planning 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 assessed for each month 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, thus, re-planning the ore reserves to mitigate ore loss.
- This method will enable the development of calibrated and validated predictive models for cave mines using their own mine and wet muck status data.

It is important to mention that in order 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.

6 Conclusions

In this article, the quantification of wet muck entry risk for long-term cave 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 ore reserve recovery. The best-calibrated model incorporates the most important risk variables causing wet muck entry at the study area: ore draw, water infiltration, 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 as 84%. In addition, the predictive ability of the model was found to be reliable for the estimation of ore tonnage drawn prior to wet muck entry at drawpoints. Therefore, performed under optimal calibration and validation (i.e. utilizing a cut-off probability set of CP_v: 0.58 and CP_l: 0.60), this predictive model can provide an important instrument to delineate zones prone to wet muck entry and can be used to evaluate different long-term plans for block caving, allowing preventive decisions to be made that will avoid or minimize ore reserve losses 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 plans 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, relative time since last extraction, types of lithology and material fragmentation, and presence or absence of moisture at drawpoints. Additionally, further study of draw strategies to minimize wet muck entry risk would be useful. To analyze how draw strategy influences the likelihood of wet muck entry for short-term planning, in a subsequent study we will consider the risk variables draw rate and uniformity of draw.

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CAPÍTULO 3

ARTÍCULO 2

ANALYZING THE ROLE OF DRAW STRATEGY ON WET MUCK ENTRY RISK FOR SHORT-TERM CAVE PLANNING

Paper to be submitted to the Canadian Geotechnical Journal

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Abstract

Caving methods rely on gravity to propagate the cave upwards through the ore column. Hence, once cave subsidence has reached the surface, water accumulated, and fine material may enter the drawn column through the subsidence zone, being wet muck entry a main operational risk in cave mining. This article presents a risk assessment of wet muck entry for caving mines employing the logistic regression approach based on the binary response of the phenomenon. In this research, we have postulated that the analysis of draw strategy as a risk variable associated with wet muck entry will enhance the risk assessment in short-term cave planning. The study was carried out using mine information from *Diablo Regimiento* Mine at *El Teniente* Mine, in which a multivariate predictive model was obtained, with draw control and environmental conditions being the key risk variables related to wet muck entry. A confusion table was built to calibrate the best-fitted multivariate predictive model, whereas scatter plot and relative frequency histogram were employed to validate the best-calibrated model. The results of the metrics expressed that the predictive model had an adequate capability to reproduce both the wet muck entry status at drawpoints and the ore tonnage drawn prior wet muck entry. Operated under its optimal cut-off probability, this research serves as an important tool for the identification of key risk variables related to the inflow of wet muck, and the delineation of high-risk zones vulnerable to wet muck entry, where short-term planning preventions could be made to reduce ore reserves losses.

Keywords

Wet muck entry, logistic regression, risk assessment, long-term ore reserves recovery

1 Introduction

Block caving refers to a bulk underground mining method that offers high productivity and low operative costs. Since block caving relies on gravity to break up the ore and permit to be drawn, surface water and groundwater may enter the broken ore column once cave propagation reaches the surface. Therefore, early wet muck entry has become one of the major operational risks to be considered in caving mines, especially for those mines with lack of draw control and a high capability to accumulate fine material and water into the caved columns (Heslop, 2000; Jakubec *et al.*, 2012).

Wet muck entry is defined as an event where there is saturated fine material observed at drawpoints (Castro *et al.*, 2017). Early wet muck entry has been identified as a significant issue during cave operations (Hubert et al., 2000; Syaifullah et al., 2006; Samosir et al., 2008; Becerra, 2011; Ferrada, 2011; Widijanto et al., 2012; Holder et al., 2013). Thus, the evaluation of wet muck entry is a key element within risk assessment in short-term planning because this phenomenon could lead to considerable economic losses and negative consequences in mine safety.

Several variables involved in wet muck entry have been studied over the years. Based on the literature review of mine experiences, Butcher *et al.* (2005) postulated that there are four main elements in the occurrence of wet muck entry: (i) the presence of water (as surface water or groundwater reservoirs); (ii) the presence of fine material within the drawn column; (iii) a disturbance in the caved ore column (the ore extraction process, for instance); and (iv) the capacity for the wet muck to discharge. In addition, some authors have suggested using draw control to reduce the propagation of wet muck into surrounding area. In this sense, it has been expressed that even and continuous ore extraction generates a decreased risk of the formation of draw cones, which provides a progressive spread of wet muck into the ore columns (Heslop, 2000; Hubert et al., 2000; Butcher et al., 2005; Samosir et al., 2008; Jakubec et al. 2012; Ferrada, 2011; Widijanto et al., 2012). Nevertheless, these works have not analyzed the effect of draw strategies on the occurrence of wet muck entry. Hence, additional research regarding the quantification of draw strategy variables, such as uniformity of draw or draw rate, on the wet muck entry likelihood are needed.

In terms of wet muck entry modes, Castro *et al.* (2017, submitted) indicates that there are two main general modes of wet muck entry: vertical descent of wet muck through the caved ore column to the first drawpoints with wet muck status; and lateral diffusion from initial wet muck areas to its neighboring drawpoints.

To date, the assessment of wet muck entry risk in cave planning has been carried out using two approaches: deterministic and multivariate statistical analysis. In the case of the deterministic method, it consists on a simpler and more direct approach to analyze the variables related to wet muck entry, but it requires the complete mine information for the definition of weights regarding each risk variable. This approach has been adopted at *El Teniente* Mine for the determination of ore reserves during long-term planning based on a wet muck entry risk map. A more detailed explanation of the methodology followed by *El Teniente* Mine could be found in Castro *et al.* (2017, submitted). On the contrary, the multivariate statistical analysis could be a proper classifying technique due to its ability to permit both the discrimination of the key risk variables and the quantification of their relationship. According to Castro *et al.* (2017, submitted), the most suitable multivariate statistical method for the assessment of wet muck entry risk is logistic regression since it can analyze data that includes a binary dependent variable, i.e., the presence or absence of the phenomenon within mine database. In their work, they used a multivariate logistic regression to address the key risk variables associated with wet muck entry; however, this study is limited to a basic inclusion of draw strategies since the variable ore drawn column does not consider neither the role of uniformity of draw nor draw rate on the estimation of wet muck entry risk.

Under wet muck entry conditions, ore reserves recovery is a key issue for any caving operations. During extraction, the reliable identification of wet muck entry at drawpoints will strongly affect the scheduling of short-term planning. Thus, the inclusion of draw control variables, such as extraction rate or uniformity of draw, into a predictive model is of fundamental importance for risk assessment process. Certainly, if during mine production a model is able to predict the wet muck entry, mitigation actions can be taken in order to increase the productivity of the whole system.

This article aims to analyze the importance of draw control on wet muck entry by quantifying the effects of uniformity of draw and draw rate, as key draw strategy variables, on wet muck entry likelihood for short-term planning. In this work, we developed a methodology through a statistical approach of the principal risk variables related to wet muck. The results obtained herein could serve as a useful instrument to both identifying key risk variables and assessing wet entry risk for short-term planning in cave mines.

2 Data and method

2.1 Study area

The study area selected for this research is the *Diablo Regimiento* Mine at *El Teniente* mine. *Diablo Regimiento* Mine is situated below an old mine (Regimiento Mine, as shown in Fig. 1), which represents the main source of water accumulation. Moreover, *Diablo Regimiento* Mine is located under a topographic depression around Braden pipe, called topographic gutter, that has been generated due to caving subsidence from previous mine exploitations. Since this topographic condition allowed the accumulation of superficial and ground water, wet muck entry has been identified as one of the main operational risk that affects the compliance of Diablo Regimiento Mine's production plan at El Teniente Mine (Codelco, 2016).

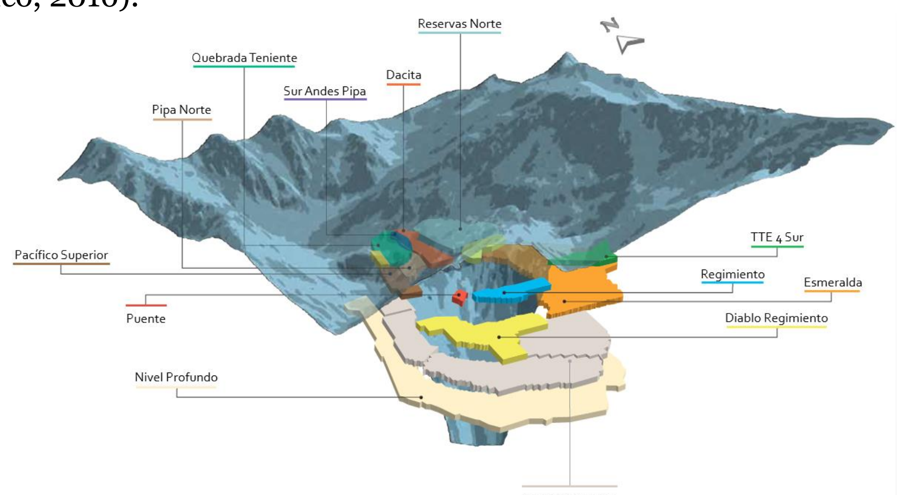


Fig. 1 Isometric view of productive sectors at El Teniente Mine, indicating the location of the *Diablo Regimiento* Mine (Codelco, 2016)

2.2 Database

The data collected from *Diablo Regimiento* Mine contained mine information of 458 drawpoints. The dataset considered a period between January 2005 to December 2016, from which 148 data records (32 percent of the database) are declared as wet muck entry status. This database was used to analyze the relative association between risk variables related to wet muck entry using the univariate analysis of the logistic regression technique.

After the univariate analysis, the database was divided according to the wet muck entry modes postulated by Castro *et al.* (2017): vertical and lateral inflow of wet muck datasets. This subdivision attempted to integrate wet muck entry modes into multivariate predictive modeling. Firstly, the vertical inflow of wet muck dataset included 43 wet muck and 129 non-wet muck statuses data selected from the initial database (i.e., the database containing mine data of 458 drawpoints) employing stratified sampling. Secondly, the lateral inflow of wet muck dataset contained 105 wet muck and 315 non-wet muck statuses data selected by stratified sampling of the initial database.

2.3 Wet muck entry risk variables

To assess wet muck entry risk and avoid overtraining the models, we have chosen the potential risk variables related to wet muck entry based on operational performance experience gathered from cave operations, listed as follows: extraction, draw rate, uniformity of draw, column height of in-situ material, column height of primary rock, distance to topography, topographic gutter, season, and drawpoint neighborhood with wet muck status (see their definitions in Table 1a). In addition, Table 1b details the terms involved in the definition of the above-mentioned risk variables.

Table 1

a. Summary and definition of the risk variables employed in this study

Variable	Symbol	Unit	Type	Definition
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
Draw rate	DR	(t/m^2/day)	Continuous	Calculated by the average ratio between draw and drawpoint area, considering the drawpoint cluster over 30 days
Uniformity of draw	UD	-	Continuous	Calculated by the average ratio between the tonnage extracted with uniformity of draw and the total extracted tonnage of the drawpoint cluster over 30 days. It can be calculated using the uniformity of draw index given by Susaeta (2004). This variable is expressed as decimal from 0 to 1
Column height of in-situ material	h_i	(m)	Continuous	Measure of the column height of uncaved ore rock before 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. 0 default value if the drawpoint is not situated under the topographic depression around Braden pipe, otherwise 1 value if it is
Season	S	-	Categorical	Variable that expresses the effect of precipitation (snow and rain) on wet muck entry. It is equal to 0 value if the evaluated period is spring or summer, otherwise 1 value if it is autumn or winter
Drawpoint neighborhood with wet muck status	N_{wm}	-	Continuous	Measure of the number of drawpoint with *wet muck* entry status on the surrounding area (neighboring drawpoints). It considers 0 to 6 neighboring drawpoints with wet muck entry status

b. Description of the terms used to define the risk variables analyzed un this research

Terms	**Description**
In-situ tonnage	Indicates the tonnage of ore (or material) naturally present within the rock mass before any mining activity
Drawpoint area	Measure of the area under draw (m²). It can be calculated using the *El Teniente*'s production level layout as $(d_{pd} \cdot d_{ed}/2)$, in which d_{pd} indicates the distance between production drifts and d_{ed} represents the distance between extraction drifts
Uniformity of draw	Measure of draw control practice (uniform draw or isolated draw). It can be calculated using the uniformity index proposed by Susaeta (2004) as follow: $IU = \Delta + \Gamma \cdot \frac{(t_p - t_{min})}{t^2{}_{max} \cdot n} \cdot \sum(t_{max} - t_i)$ Where Δ is the number of inactive drawpoints in the drawpoint neighborhood; Γ is a parameter equal to 99/89; t_p is the extracted tonnage from the drawpoint p under analysis in a specific period; t_{min} and t_{max} are the minimum and maximum extracted tonnage, respectively, in the neighborhood drawpoint at the same period; t_i is the extracted tonnage of the analyzed drawpoint at the same period and n is the number of drawpoints that belong to the neighborhood of drawpoint p, including the studied drawpoint
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. For instance, in a production level layout at *El Teniente* Mine, a drawpoint has at maximum six neighboring drawpoints

Finally, Table 2 provides the criteria used to select the main risk variables based on physical characteristics of wet muck entry and operational cave experiences achieved throughout mine operation.

Table 2
Summary of risk factor selected 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 fine material formation due to secondary breakage through the ore column. Based on mine data, the propensity of wet muck entry tends to raise with the increase of ore extraction.
Draw rate	Indicates the formation of subsidence cones (also called rat-holes draw patterns) if daily ore drawn is not controlled. Based on mine data and experience, high draw rates contribute to rapidly spreading the wet muck into the drawn columns
Uniformity of draw	Denotes the capacity for water and fine material redistribution through the broken ore column, providing a dynamic state within the column. It is expected that if the material being constantly drawn (i.e., a high uniformity of draw), the wet muck entry risk decreases
Column height of in-situ material	Indicates the permeability properties of the uncaved materials constituting the ore column (composed by primary and secondary rock)
Column height of primary rock	Represents the material with the lowest permeability within the ore column, thus, drawpoints with high column height of primary rock have less wet muck entry likelihood
Distance to topography	Considers the distance to the superficial water source (melting snow and rain water)
Topographic gutter	Signifies the high-risk zone associated to the preferential water accumulation in the lowest surface level, hence, controlling directly the state of water source
Season	Signifies a representation of the water infiltration to cave operation as a result of snow and rain precipitation during autumn and winter
Drawpoint neighborhood with wet muck status	Indicates the risk in which wet muck could be laterally spread to the surrounding areas

2.3 The modeling strategy

In this research, we aimed to critically analyze risk variables associated with wet muck entry, and secondly, to develop a predictive model for the risk assessment of wet muck entry likelihood into short-term cave planning based on the key risk variables. The chosen method includes the employment of logistic regression as a statistical analytic tool. Through its usage, the main advantage of this methodology is the inclusion of variables related to draw strategy, environmental conditions and drawpoints status into the estimation of daily likelihood for the occurrence of wet muck entry at each drawpoint. The adopted modeling strategy is composed of four stages, and is based on the work carried out by Castro *et al.* (2017).

In stage one, we studied the strength association between each risk variable and the occurrence of wet muck entry using univariate logistic regression. Chi-squared test (χ^2) and odds ratio (OR) were performed as measures of association to quantify independently the degree of relationship between risk variables and the phenomenon. In this step, the statistical significance was based on rejecting the null hypothesis that the coefficients of the studied variables are zero by using the Chi-squared test (Hosmer *et al.*, 2013). We considered a p-value≤0.2 to reject the null hypothesis and consequently, the variables founded significant can be included in the multivariate logistic regression modeling.

During the second stage, we analyzed the interrelationship of different risk variables with the occurrence of wet muck entry using multivariate logistic regression. In this stage, vertical and lateral inflow of wet muck datasets, alongside multivariate logistic regression, were employed to examine the strength association between the variables, test their statistical significance, and derive the correspondent predictive models. Multivariate logistic regression was used to determine the likelihood of future occurrence of wet muck entry based on a dependent binary variable, Y (presence or absence of wet muck entry) and multiples explanatory key variables, x (independent variables). The conditional probability of having wet muck entry (i.e., $Y = 1$) is given by the following equation (Hosmer *at al.*, 2013)

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

Where the vector $\beta = \beta_0, \beta_1, \ldots, \beta_n$ is the logistic regression model coefficient which can be determined through special methods based on the maximum likelihood methodology (Geng and Sakhanenko, 2015). The statistical significance for a risk variable to remain within the multivariate model (i.e. to reject the null hypothesis that the coefficient of each analyzed variable is equal to zero using the Chi-squared test) was set at 0.05 (i.e., p-value≤0.05). In addition, the log-likelihood ratio ($-2\log\mathcal{L}$) was adopted as a measure of the likelihood change between the fitted and the saturated model (Hosmer et al., 2013). In accord with Allison (2012), the most acceptable model corresponds to the one which minimizes the log-likelihood ratio.

In stage three, we calibrated the best-fitted models by comparing the real wet muck entry data to the prediction of the wet muck entry model, depending on a cut-off probability. The cut-off probability can classify the drawpoints' wet muck entry likelihood as either 1 value for the presence of wet muck entry, or 0 value for its absence. Drawpoints with wet muck entry likelihood above the cut-off value were classified as wet muck entry, whereas those with lower cut-off value were classified as non-wet muck entry. An algorithm proposed by Castro *et al.* (2017) that permits the incorporation of vertical and lateral inflow of wet muck predictive models to estimate daily wet muck entry likelihood for each drawpoint was utilized to define the cut-off probability set; furthermore, a contingency table was built for each cut-off probability to measure the association between the modeled and mine data. The construction of the contingency table allows the calculation of four possible outcomes: if the real value is positive and it is classified as positive, then it is counted as a true positive (TP); if it is classified as negative, then it is counted as false negative (FN). Accordingly, if the real value is negative and it is classified as negative, then it is counted as a true negative (TN); otherwise if it is classified as positive, it is counted as a false positive (FP) (Fawcett, 2006). To build the contingency table, we made use of several cut-off probabilities to enable the calculation of three main performance metrics, described as follows

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

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 calibrated model.

Finally, in stage four, we validated the cut-off probability previously defined using the real data concerning drawn ore tonnage prior to wet muck entry, and the drawn ore tonnage estimated by the above-mentioned algorithm. The objective of this stage was to minimize the difference between real and modeled drawn ore tonnage. The evaluation of the short-term prediction capability of the calibrated model was represented on a scatter plot that graphics the degree of correlation between modeled data (vertical axis, y) and mine data (horizontal axis, x). Moreover, the defined cut-off probability validation was carried out employing a relative frequency histogram for the drawn ore tonnage error, which analyzes the proportion of error values for each class intervals. It is expected that the calibrated model could be valid if the cut-off probability contributes both to a scatter plot with strong positive correlation between modeled and mine data, and to set the error's distribution roughly around zero.

4 Results and discussion

4.1 Univariate logistic regression association analysis

An univariate logistic regression analysis was carried out to study the main operational and environmental characteristics associated with wet muck entry. The univariate analysis identified that the nine risk variables were statistically significant (i.e., p-vale≤0.2), as can be observed in Table 3

The variables topographic gutter, uniformity of draw, and drawpoint neighborhood with wet muck status have demonstrated a considerably strong relationship with wet muck entry based on the odds ratio value, whereas the variables extraction and draw rate have resulted in a less strong measure association with the occurrence of wet muck entry. Finally, the remaining risk variables have slightly statistical degree of relation with wet muck entry because of the lowest values regarding the Chi-squared test and the odds ratio.

In terms of odds ratio, *topographic gutter* is the main risk variable related to wet muck entry since its odds ratio is estimated as 8.96, which means that the drawpoints situated below the lower surface depression zone has an 8.96 times higher likelihood for wet muck entry occurrence, in contrast to drawpoints located outside the topographic gutter. Secondly, the variable *uniformity of draw* has an odds ratio value of 0.128, indicating that the wet muck entry probability among the drawpoints which have drawn ore with complete uniformity of draw is 0.13 times the wet muck entry likelihood for those drawpoints with isolated draw (i.e., 0 percent of uniformity of draw value). Finally, *drawpoint neighborhood with wet muck status* is the third main risk variable associated with wet muck entry since its odds ratio is 7.7, meaning that each one-unit increment in the variable drawpoint neighborhood with wet muck entry (for instance, three neighboring drawpoints with wet muck status instead of two neighboring drawpoints) provides 7.7 times higher wet muck entry likelihood at drawpoints.

Table 3
Risk variables and their relative relationship with wet muck entry, sorted by strength association from the odds ratio

Variable	Statistical significance (*p*-value)	Chi-squared test (χ^2)	Coefficient	Odds ratio
Topographic gutter	<0.001	508.00	2.19	8.96
Uniformity of draw	<0.001	423.64	-2.05	0.128
Drawpoint neighborhood with wet muck status	<0.001	392.71	2.07	7.70
Extraction	<0.001	312.11	1.28	3.59
Draw rate	<0.001	295.45	1.13	3.10
Season	0.18	47.95	0.20	1.22
Distance to topography	<0.001	94.46	-0.04	0.96
Column height of primary rock	<0.001	157.46	-0.014	0.986
Column height of in-situ material	0.11	134.14	-0.004	0.996

Based on these results, the strong relationship between the main risk variables and wet muck entry risk suggests that the inflow of wet muck generally arises from drawpoints placed below the topographic gutter, surrounded by wet muck areas, and operated under poor uniformity of draw practices. Thus, this analysis provides mine planners a guideline for the ore reserves quantification during short-term planning process, in which planned ore reserves must consider both environmental condition of each drawpoints and draw control practices.

4.2 Multivariate logistic regression analysis

In the case of multivariate logistic regression, the main objective of the modeling is to analyze both the interrelationship of key risk variables and wet muck entry likelihood throughout cave operations. Multivariate logistic regression was carried out employing vertical and lateral inflow, resulting in two predictive models as presented in Table 4.

Table 4 summarizes the analysis performed for three models of each wet muck entry mode, in which it has provided the estimated model coefficients (β_i) and its standard error, the statistical significance of the risk variables (p-value), the association strength given by the odds ratio (e^{β_i}), and the log-likelihood ratio of the three models. Variables that did not contribute significantly to the models fit were removed from the multivariate analysis. With this procedure, the variables *distance to topography* and *season* have to be eliminated from vertical inflow of wet muck modeling, whereas the topographic and columns height variables were excluded into lateral inflow of wet muck modeling since they were not significant at 0.05 level.

Table 4
a. Multivariate logistic regression modeling for vertical inflow of wet muck mode

Model	**Coefficient (β_i)**	**Std. error**	***p*-value**	**Odds ratio (e^{β_i})**	**log-likelihood ratio**
Model 1					
Extraction	0.56	0.69	0.012	1.74	
Draw rate	0.38	0.64	0.023	1.47	
Column height of primary rock	-0.006	0.003	0.053	0.994	103.2
Topographic gutter	0.20	0.50	0.054	1.23	
Constant	-0.67	1.20	0.031	0.51	
Model 2					
Extraction	1.06	0.65	0.004	2.89	
Draw rate	0.16	0.58	0.073	1.18	
Column height of in-situ material	-0.009	0.005	0.061	0.99	110.7
Topographic gutter	0.65	0.54	0.026	1.92	
Constant	-4.23	1.42	0.003	0.02	
Model 3					
Extraction	0.93	0.64	0.049	2.55	
Draw rate	0.24	0.56	0.067	1.27	119.3
Topographic gutter	0.34	0.49	0.054	1.41	
Constant	-2.33	0.82	0.004	0.10	

b. Multivariate logistic regression modeling for lateral inflow of wet muck entry mode

Model	**Coefficient (β_i)**	**Std. error**	***p*-value**	**Odds ratio (e^{β_i})**	**log-likelihood ratio**
Model 1					
Extraction	1.13	0.32	<0.001	3.09	
Uniformity of draw	-1.24	0.56	0.026	0.29	
Drawpoint neighborhood with wet muck status	1.06	0.12	<0.001	2.88	394.2
Season	0.59	0.26	0.028	1.80	
Constant	-4.63	0.58	<0.001	0.01	
Model 2					
Extraction	1.18	0.31	<0.001	3.26	
Uniformity of draw	-1.17	0.55	0.033	0.31	
Drawpoint neighborhood with wet muck status	1.05	0.11	<0.001	2.85	409.0
Constant	-4.31	0.55	<0.001	0.01	
Model 3					
Extraction	1.59	0.27	<0.001	4.89	
Uniformity of draw	-1.58	0.19	0.001	0.21	536.8
Constant	-4.03	0.47	<0.001	0.02	

Additional examination of Table 4a and Table 4b provides the following analysis:

- The degree of association of the risk variables related to wet muck entry given by their odds ratio values are in line with the results already presented in the univariate analysis. However, it can be observed that the difference between univariate and multivariate odds ratio values arises since the quantification of models coefficients consider the relative interrelationship of each risk variable included in the model.
- When comparing the results of the log-likelihood ratio among the vertical inflow of wet muck models, it can be concluded that model 1 was improved by using the variable *column height of primary rock* as a risk variable since it has the lower log-likelihood ratio. However, the difference between the criterion value is moderate and thus, the predictive potential associated to the variable *column height of primary rock* is less critical than *extraction*, *draw rate*, and *topographic gutter*.

- Considering the above-mentioned result, vertical wet muck entry mode is mainly controlled by *extraction*, *draw rate* and topography conditions during cave operations.
- Based on the log-likelihood ratio among the lateral inflow of wet muck models, the lower metric value resulted in model 1 explains that the predictive performance was enhanced by including the variables *drawpoint neighborhood with wet muck status* and *season*. Moreover, the high difference observed among model 2 and model 3 indicates that the predictive power of model 2 increased drastically by including *the drawpoint neighborhood with wet muck status* as a variable, compared to the slight difference between model 1 and model 2 resulting from the inclusion of the variable *season* in model 1. Therefore, this result proves that the variable *drawpoint neighborhood with wet muck status* is the most important controlling variable for the lateral inflow of wet muck entry mode.

Unlike the work carried out by Castro *et al.* (2017), this research has provided a multivariate predictive model which includes draw strategy variables into the assessment of wet muck entry for short-term planning process. Accordingly, this predictive model allows mine planners to quantify the understanding of poor draw control (i.e., over-draw of in-situ tonnage and high-rate isolated draw) for those drawpoints situated in risk environmental conditions (i.e., zones placed near wet muck surrounding areas and under the topographic gutter, with low height columns of primary rock, and during autumn or winter season) could induce the increase of wet muck entry likelihood, in contrast to drawpoints with most favorable non-wet muck entry conditions. Conclusively, the best-fitted multivariate predictive model is delineated as follows

$$p_{wm}(x) = \begin{cases} p_v(x) = \dfrac{e^{-0.67+0.56\cdot E+0.38\cdot DR-0.006\cdot h_{pr}+0.20\cdot TD}}{1+e^{-0.67+0.56\cdot E+0.38\cdot DR-0.006\cdot h_{pr}+0.20\cdot TD}} & \text{If } N_{wm}=0, \text{for } CP_v \\ \\ p_l(x) = \dfrac{e^{-4.34+1.15\cdot E+0.93\cdot UD+0.30\cdot N_l+0.48\cdot N_{wm}+0.22\cdot S}}{1+e^{-4.34+1.15\cdot E+0.93\cdot UD+0.30\cdot N_l+0.48\cdot N_{wm}+0.22\cdot S}} & \text{If } N_{wm}>0, \text{for } CP_l \end{cases} \tag{3}$$

Where $p_{wm}(x)$ denotes the wet muck entry likelihood; $p_v(x)$ and $p_l(x)$ denote the vertical and lateral wet muck entry likelihood, respectively; CP_v and CP_l specify the cut-off probability for vertical and lateral wet muck entry models, respectively; and N_{wm} indicates the number of neighbor drawpoints with wet muck entry status. In the next section, the model calibration and the cut-off probabilities validation are presented and discussed.

4.3 Calibration and validation of the predictive model

As mentioned in the Modeling Strategy Section, this work is based on a predictive algorithm developed by Castro et al. (2017). This algorithm enables the calculation of daily wet muck entry likelihood considering both the extraction cave plan and the best-fitted multivariate predictive model, as schematized in Fig. 2. Employing this procedure, cut-off probability could be established to define the occurrence or non-occurrence of wet muck entry at drawpoints. Mine data from 2005 to 2016 were used to analyze the predictive performance of the best-fitted predictive model.

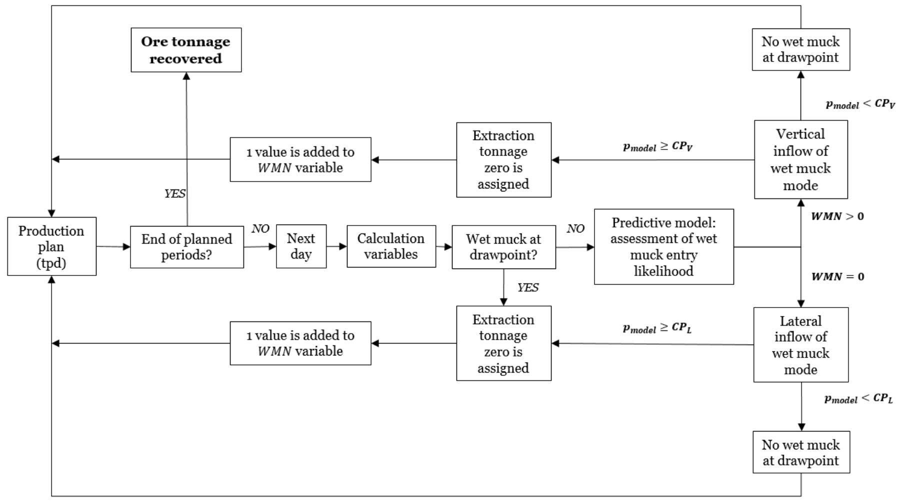


Fig. 2 **Representation of the procedure and elements composing the algorithm employed to calculate daily wet muck entry likelihood. This scheme depicts the procedure for one analyzed drawpoint (Castro *et al.*, *2017*)**

After analyzing 81 cut-off probabilities combinations through the use of the predictive algorithm, the cut-off probabilities that provide the best-performing predictive identification of wet muck entry observations from mine data were established as 0.7 for CP_v and 0.6 for CP_l. In terms of the total occurrences percentages, 92% of wet muck entry data and 76% of non-wet muck entry data were correctly classified by the predictive model, as summarized in Table 5.

Table 5
Summary of results for the contingency table and performance metrics for the calibration on the model

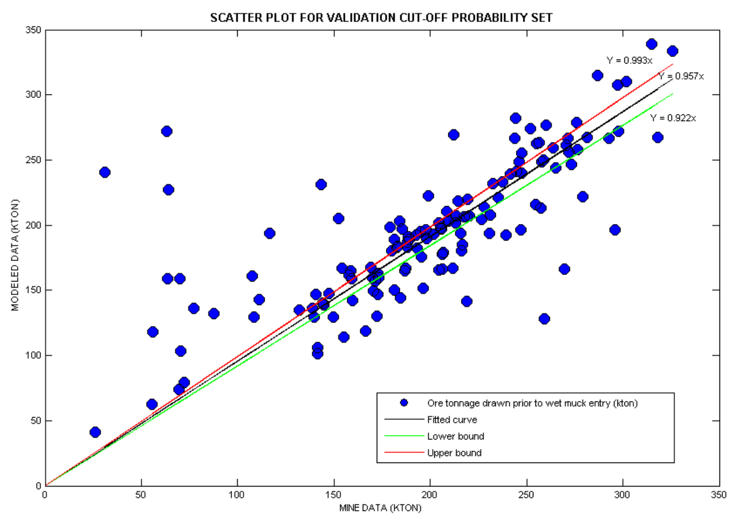
(a)		**Logistic model**	
		1	0
Reality	1	TP	FN
	0	FP	TN
(b)		**Predictive model (modeled observations)**	
		1 (211)	0 (247)
Mine data	1 (148)	136	75
	0 (310)	12	235
(c)			
Sensitivity	92%		
Specificity	76%		
Model accuracy	81%		

(a) 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: 0.7 and CP_l: 0.6. The drawpoints with an estimated probability above 0.7 for vertical or lateral inflow of wet muck mechanism 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 (0 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.

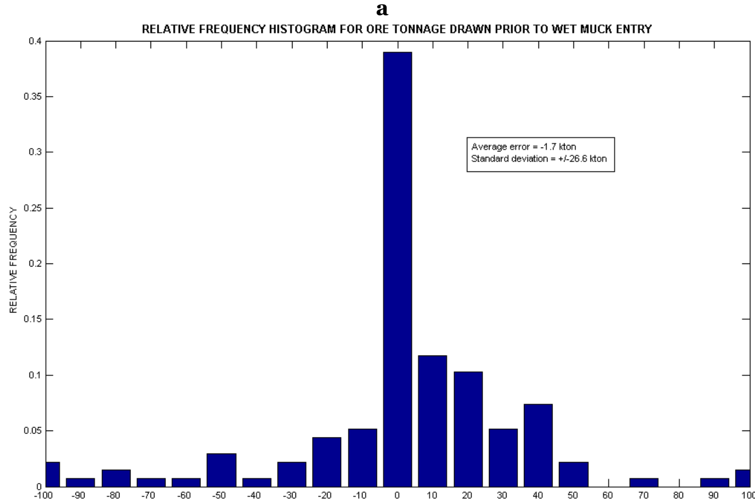
Examining separately the obtained results from Table 5, 136 of the wet muck entry data were accurately classified due to the unfavorable mine conditions of the examined drawpoints (i.e., over-draw conditions, poor uniformity of draw, high number of neighboring drawpoints with wet muck status, and drawpoints located under the topographic gutter). A different situation appears for 75 of the non-wet muck entry observations, which were misclassified because they exhibited the same aforementioned unfavorable conditions that induce wet muck entry at drawpoints. As a result of the calibration process, an accuracy of 81% was obtained for the predictive model, which indicates an adequate discrimination to predict the presence or absence of wet muck entry at drawpoints.

Once the cut-off probability has been set, the validation stage considers the application of the predictive algorithm to estimate the error associated with the ore tonnage drawn prior to wet muck entry between real and modeled data. This was accomplished by using the best-calibrated predictive model (defined by the optimal cut-off probability from the calibration step), mine data from 2005 to 2016, and the 458 drawpoints from this study.

The resulting scatter plot between mine and modeled data is presented in Fig. 3a. Based on Fig. 3a, it can be observed a strong positive correlation between mine data and the predictive values from the model regarding the ore tonnage drawn before wet muck entry, where the best-fitted linear regression is estimated as $Y = 0.957$. Moreover, the scatter plot shown in Fig. 3a, exhibits the 95 percent confidence interval for the cut-off probability set, namely $Y = 0.922x$ for the lowest confidence interval (in green line), the cut-off probability corresponds to 0.54 for CP_v and 0.60 for CP_l, whereas for the highest confidence interval, $Y = 0.993x$ (in red line), the cut-off probability is 0.60 for CP_v and 0.50 for CP_l. On the other hand, Fig. 3b displays the relative frequency for the ore tonnage drawn prior to wet muck entry's error from mine and modeled data, which is distributed around zero, and the average error is estimated nearly -1.7 kt±26.6 kton.



a



b

Fig. 3 a. Scatter plot of ore tonnage drawn prior to wet muck entry from mine data and modelled data, and; b. Relative frequency histogram displaying the error between mine and modelled data.

Considering the calibration and validation results, we deduced that the multivariate predictive model develop herein is able to both acceptably predict wet muck entry status at drawpoints and reproduce satisfactory the ore tonnage drawn during cave operation; hence, the predictive model can be reliably utilized to assess wet muck entry risk for short-term planning purposes.

Based on optimal conditions, the multivariate predictive model could be used for the construction of a wet muck entry susceptibility map at the end of the operational periods, as presented in Fig. 4. This wet muck entry susceptibility map utilizes the predictive model's best-calibrated, cut-off probability to not only classify as wet muck status those drawpoints with modeled likelihood above either 0.7 for the vertical inflow of wet muck model or 0.6 for the lateral inflow of wet muck model (black dots in Fig. 4a), but to also display the current wet muck entry likelihood at drawpoints, which it is appropriate for both the evaluation of future short-term ore drawn planning, and the delineation of high-risk areas susceptible to wet muck entry. In addition, Fig. 4b depicts the wet muck entry status at the study case collected from mine data. According to this comparison, we deduced that the presented wet muck entry susceptibility map is a helpful short-term planning tool that mine planners could consult to reduce wet muck entry risk, where preventive decisions or strategies (e.g., maintain uniformity of draw and reduce draw rate for those susceptible drawpoints) could lead to a mitigation of ore reserves losses.

Regarding the development of this research, analyzing the effect of draw strategy as a short-term variable by applying the logistic regression approach was successfully accomplished. A remarkable aspect of this study is that it makes possible the incorporation of draw control and environmental variables into the multivariate predictive model to address wet muck entry risk, providing a useful tool for short-term guidelines during ore tonnage planning. The main advantages of this research were identified as follows:

- The applicability of logistic regression allows the quantification of the univariate and multivariate degree of association between the main risk variables related to wet muck entry.
- Risk assessment of wet muck entry can be carry out for each period contemplated in monthly short-term plans.
- The predictive algorithm used herein can be appropriate for the recognition of high-risk zones prone to wet muck entry to re-evaluate further draw strategies in order to reduce wet muck entry likelihood from those susceptible drawpoints.
- The development of this research and its methodology can be extended to other cave mines where wet muck entry has been registered throughout mine operations.

Nevertheless, this research has relevant limitations, described below:

- To calibrate and validate the multivariate predictive model, it is fundamental to develop an algorithm able to both include the predictive model and estimate daily wet muck entry likelihood, similar to the one presented herein.

- It is compulsory to carry out a reliable feedback by using additional mine data when available in order to maintain the adequate ability to predict ore tonnage drawn prior wet muck entry into short-term planning.

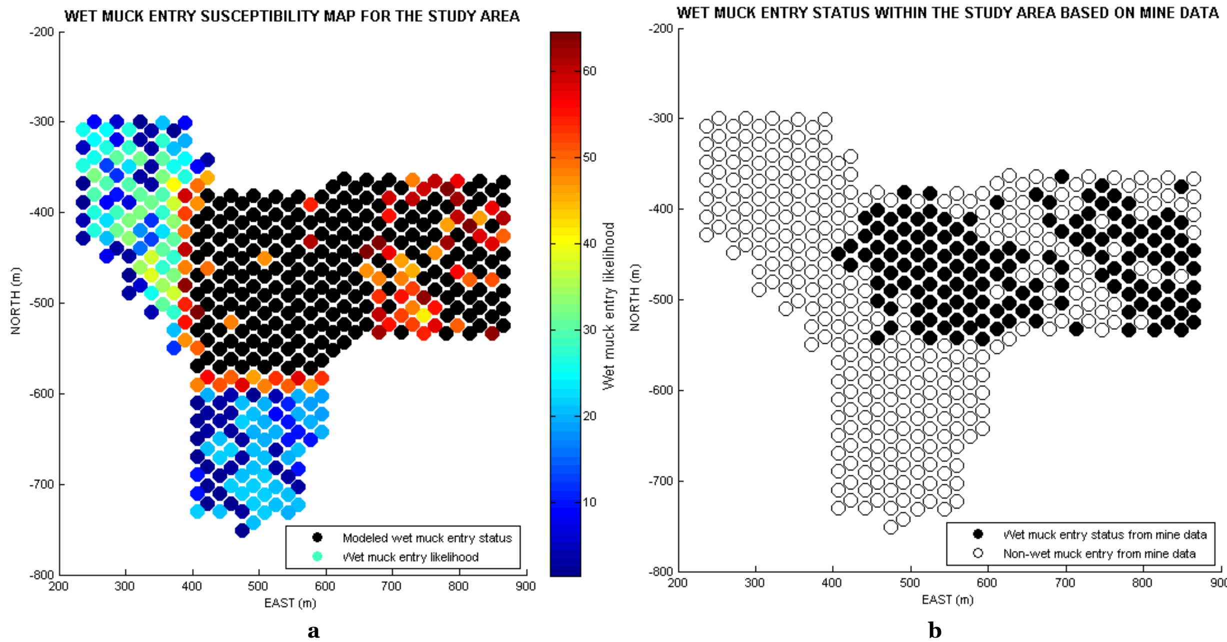


Fig. 4 a. Delineation of the wet muck entry susceptibility map for the study case, and; b. Wet muck entry status derived from mine database at *Diablo Regimiento* Mine

5 Conclusions

In this research, the analysis of draw strategy as a key risk variable related to wet muck entry was carried out. Draw strategy was found to have a considerable effect on the assessment of wet muck entry risk. Since this work involved the use of a logistic regression approach, it was possible to incorporate several main risk variables into a multivariate predictive model. The degree of relationship of the key variables associated with wet muck entry was quantified, and the results herein have proved that the topographic gutter, extraction, uniformity of draw, and wet muck surrounding areas are the main risk variables.

The best fitted and calibrated predictive model considers draw control and environmental variables to estimate daily wet muck entry likelihood for short-term planning applications. Performed under its optimal, cut-off probability, the accuracy classification of the predictive model was calculated as 81%. Furthermore, the model has demonstrated to be an efficient and reliable tool for the estimation of ore tonnage drawn prior to wet muck entry at drawpoints throughout cave operations. We conclude that the application of the methodology developed in this work could contribute as a helpful, short-term instrument to outline areas susceptible to wet muck entry, where prevention measures could be taken to minimize ore reserves losses.

Further refinement in the identification of other risk variables related to wet muck entry is needed to improve the model's prediction capability. Topics to be investigated may include the influence of fine material and water at drawpoints as risk variables, the incorporation of water flow rate into this predictive model, and the evaluation of different short-term cave plans to determine the optimal short-term draw strategy. There is also research to be conducted in terms of numerical modeling for wet muck entry phenomenon to improve and complement the results obtained through this work.

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CAPÍTULO 3

CONCLUSIONES Y TRABAJO FUTURO

4.1. CONCLUSIONES GENERALES

La actual investigación ha abordado el análisis del grado de asociación entre diferentes variables de riesgo y la entrada de barro. Además, el estudio permitió cuantificar el efecto de las variables críticas en la probabilidad de ocurrencia de la entrada de barro en los puntos de extracción. En base a los resultados obtenidos, es posible concluir lo siguiente:

- ✓ Las variables de riesgo críticas para la planificación de largo plazo corresponden a la cavidad de extracción (canalón), porcentaje de extracción de la columna *in-situ*, puntos de extracción vecinos con condición de barro, y el flujo promedio mensual de agua hacia el nivel de producción.

- ✓ Para la planificación de corto plazo (planificación mensual), los principales factores de riesgo de entrada de barro son el porcentaje de extracción de la columna in-situ, la velocidad de extracción y uniformidad del entorno de cada punto de extracción, la cavidad de extracción (canalón), y puntos de extracción vecinos con estado barro.

- ✓ Los resultados del proceso de calibración y validación del error de estimación para la planificación de corto y largo plazo, indican que los modelos predictivos tienen una capacidad aceptable de predicción, tanto para la entrada de barro como para la estimación de reservas recuperadas.

- ✓ La creación y uso de un mapa de susceptibilidad de entrada de barro basado en el uso del modelo predictivo, puede ayudar a los planificadores mineros a reducir el riesgo de entrada de barro, y mitigar la pérdida de reservas, por medio de la aplicación de estrategias operacionales preventivas (baja velocidad de extracción, uniformidad en la extracción, entre otros) en aquellos puntos de extracción con alta probabilidad de entrada de barro.

- ✓ La aplicación de esta metodología de estudio puede ser extendida a otras minas de *block caving*, utilizando sus propios datos históricos. De esta forma, es posible realizar un análisis de las variables críticas que afectan la entrada de barro a los puntos de extracción. Del mismo modo, la construcción de los modelos predictivos permite estimar la recuperación de reservas durante la planificación de corto y largo plazo, y, además, generar mapas de susceptibilidad que delimiten diferentes zonas de riesgo de entrada de barro.

4.2. RECOMENDACIONES Y TRABAJO FUTURO

Los resultados y conclusiones de esta investigación entregan una nueva perspectiva acerca del fenómeno de entrada de barro y su impacto en la planificación de corto y largo plazo en minería de *caving*.

Sin embargo, debido a las limitaciones propias de este estudio, aún existen aspectos que se recomiendan abordar para complementar este tópico en trabajos futuros.

- ✓ Incorporar otras variables, tales como tipos de litología, presencia de fracturamiento hidráulico, fragmentación del material, tiempo relativo desde la última extracción, entre otros, con el fin de estudiar sus potenciales relaciones y cuantificar sus efectos en la entrada de barro.

- ✓ Realizar un feedback con información actualizada disponible de los sectores productivos de División El Teniente, para mejorar la capacidad predictiva de los modelos obtenidos.

- ✓ Utilizar los modelos predictivos de entrada de barro durante el proceso de planificación de futuros proyectos u operaciones actuales de *block caving*, con el objetivo de seleccionar los planes de producción que minimicen el riesgo de ingreso de barro a los puntos de extracción.

- ✓ Emplear un nuevo método para analizar y cuantificar el efecto de las variables de riesgo en la entrada de barro, por ejemplo, el uso de redes neuronales (*neural networks*). De esta forma, es posible comparar y complementar los resultados obtenidos en esta investigación.

- ✓ Realizar mayor investigación a través del modelamiento numérico, integrando conjuntamente los flujos de roca y agua simulados durante el proceso de extracción de una mina de hundimiento. De esta forma, es posible mejorar los resultados y conclusiones logradas en este estudio.