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MODELING OF WET MUCK ENTRY AT EL TENIENTE MINE IN LONG-TERM PLANNING

TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN MINERÍA

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Resumen

Modelamiento Del Agua Barro En La Mina El Teniente En La Planificación A Largo Plazo

La minería de Caving representa actualmente una opción de explotación masiva y de bajo costo en minería subterránea. Sin embargo, este método se ve afectado por desafíos operacionales tales como los eventos de agua barro. Las principales consecuencias de los eventos de agua barro son accidentes que afectan a trabajadores, infraestructuras mineras y equipos, generando exceso de dilución, retrasos en la producción, pérdidas de reservas e incluso cierres parcial o permanente de las faenas mineras. Por lo anterior, se han implementado modelos de riesgo de ingreso de agua-barro que permiten evaluar planes mineros. En este trabajo son desarrollados cuatro nuevos modelos de declaración de barro para la planificación de largo plazo en la minería de Block Caving, con el objetivo de representar las diversas condiciones de los sectores productivos de la mina El Teniente (DET).

Esta tesis contempla una estructura de trabajo de 5 etapas. En primer lugar, se estableció el estado del arte del barro en minería de caving, considerando como se forma, de donde proviene, los tipos de barro, como afecta este en las operaciones subterráneas y los modelos realizados hasta la fecha. En segundo lugar, del estado del arte se determinaron las variables criticas para las declaraciones de barro y se construyeron las bases de datos. En tercer lugar, se llevó a cabo el análisis univariable, con el fin de ver la correlación de cada variable por si sola. En cuarto lugar, se realizó el análisis multivariable para determinar los modelos multivariables, calibrando en base a KPIs de rendimiento, como la precisión, sensibilidad y especificidad, y también considerando el error del tonelaje (diferencia de tonelaje entre el dato real y el estimado). Finalmente, en la última etapa, se realiza la aplicación del modelo en sectores productivos con planes a largo plazo, prediciendo las declaraciones de barro.

Entre los modelos desarrollados, las siguientes variables fueron utilizadas: razón de extracción (%), material quebrado extraído (%), precipitación anual y mensual (mm), primario extraído (%), fragmentación d_{50} (m) y vecinos barro (0 a 6). Las variables relacionadas con la litología y fragmentación fueron estimadas con el software FlowSim BC 6.3, un simulador de flujo gravitacional, calibrado para este estudio con datos mina de los sectores de DET: Sur Andes Pipa y Pipa Norte (Cuenca Norte), Reservas Norte y Dacita (Cuenca Reno), Esmeralda (Cuenca Centro) y Diablo Regimiento (Cuenca Sur).

Los mejores modelos calibrados incorporaron las variables críticas de riesgo antes mencionadas, logrando precisiones aceptables de 69%, 71%, 72% y 75%, con errores de tonelaje promedio por punto de extracción de 6%, 10%, 9% y 15%, para las cuencas Sur, Reno, Norte y Centro, respectivamente. De esta manera, se generan modelos con cualidades de predicción conservadoras, la cual entrega confianza a la hora de realizar una planificación a largo plazo. Adicionalmente, los modelos se pueden utilizar para evaluar planes a largo plazo en sus propias "cuencas" o sectores productivos y también en sectores que estén en cotas inferiores, permitiendo contribuir en la planificación y toma de decisiones que puedan minimizar los riesgos causados por el barro.

Abstract

Caving mining currently represents a massive and low-cost exploitation option in underground minig. However, this method is affected by operational challenges such as wet muck events. The main consequences of wet muck events are accidents that affect workers, mining infrastructure and equipment, generating excess dilution, production delays, loss of reserves and even partial or permanent closure of mining operations. Due to the above, wet muck entry risk models have been implemented to allow the evaluation of mining plans. In this study, four new wet muck entry risk models are developed for long-term planning in Block Caving mining, with the objective of representing the various conditions of the productive sectors of the El Teniente mine (DET).

This thesis contemplates a 5-stage work structure, In the first place, the literature review of mud in caving mining was established, considering how it is formed, where it comes from, the types of mud, how it affects underground operations and the models made up to the date. Secondly, from the literature review, the critical variables for the wet muck declarations were determined and the databases were built. Third, the univariate analysis was carried out, in order to see the correlation of each variable by itself. Fourth, multivariate analysis was performed to determine multivariate models, calibrating based on performance KPIs such as accuracy, sensitivity, and specificity, and also considering tonnage error (tonnage difference between actual and estimated data). Finally, in the last stage, the application of the model is carried out in productive sectors with long-term plans, predicting the wet muck declarations.

Among the models developed, the following variables were used: extraction ratio (%), broken material extracted (%), annual and monthly precipitation (mm), primary extracted (%), fragmentation d_{50} (m) and drawpoint neighbor wet muck (0 to 6). The variables related to lithology and fragmentation were estimated with the FlowSim BC 6.3 software, a gravitational flow simulator, calibrated for this study with mine data from the DET sectors: Sur Andes Pipa and Pipa Norte (North Basin), Reservas Norte and Dacita (Reno Basin), Esmeralda (Center Basin) and Diablo Regimento (South Basin).

The best calibrated models incorporated the aforementioned critical risk variables, achieving acceptable accuracies of 69%, 71%, 72% and 75%, with average tonnage errors per drawpoint of 6%, 10%, 9% and 15%, for the South, Reno, North and Center basins, respectively. In this way, models have conservative prediction qualities are generated, which provides confidence when carrying out long-term planning. Additionally, the models can be used to evaluate long-term plans in their own "basins" or productive sectors and also in sectors that are at lower levels, allowing them to contribute to planning and decision-making that can minimize the risks caused by wet muck entry.

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1 Introduction

Over the years, mining deposits are deeper and deeper, and the associated costs and problems are more and more relevant. These conditions involve great challenges to carry out sustainable and profitable caving mining since mine activities take place in a much more challenging environment (Araneda, 2020).

Caving mining currently represents a low-cost and massive exploitation option (Flores 2014, Skrzypkowski et al. 2022). However, its productive and economic attractiveness is affected by some challenges that operations must overcome, such as mud events (or also called wet muck events), which generate numerous problems in underground mining, causing accidents that have affected workers, mining infrastructure, equipment, in addition to excess dilution, production delays, loss of reserves, and even partial or permanent closures. of mining operations (Butcher, et al, 2005; Jakubec & Clayton, 2012; Navia et. al, 2014).

In particular, mud is the main cause of the wet muck events and is generated by fine particles that mix with aqueous substances in different types of conditions, such as mountain melting, tailings seepage, aquifers, and meteorological conditions (snow and rain). This mixture travels through the column of broken material and generates problems at the drawpoints, causing wet muck events, such as landslides, runoff, and mudrush, in addition to the constant filtering of water in the drifts and drawpoints (Jakubec, et al., 2012; Ginting & Pascoe, 2020).

Wet muck declarations have been reported in different underground mines around the world, such as El Teniente in Chile (Ferrada, 2011), IOZ and DOZ in Indonesia (Huber, et al., 2000; Widijanto, et al., 2012; Edgar, et al., 2020; Ginting & Pascoe, 2020). Some mitigation and control tools used in the operation range from drainage tunnels that allow the transfer of mud to lower levels or to the outside of the mine, remote-controlled equipment and risk and criticality classification matrices for drawpoints, considering moisture (qualitative and quantitative) and the amount of fine material, which is a preventive way of closing drawpoints to avoid the risk of accidents to people (Samosir, 2008; Edgar, et al., 2020).

There are also tools to model wet muck declarations, at the "El Teniente" mine, wet muck entry risk models have been implemented that allow mining plans to be evaluated (Garcés, et al., 2016; Castro, et al., 2018; Pérez, 2021; Navia, 2021). Most of these models are used for long-term planning, which has presented good results based on real information from wet muck declarations. However, the majority of these models do not consider variables related to the fragmentation or lithology present in the broken column, variables that are closely related to the formation of mud. Therefore, there is an opportunity for improvement the current models by including these new variables focused on the material as it is secondary fragmentation,

1.1 Objectives & Hypothesis

1.1.1 General Objective:

Generate new knowledge about risk models of wet muck entry in long-term mine planning, including new variables such as fragmentation and/or lithologies present at the drawpoint.

1.1.2 Specifics objectives

- Define the literature review of mud and the effect it has on operations.
- Analyze and determine the critical variables that influence in wet muck declarations.
- Develop an algorithm that allows prediction of wet muck declarations at a drawpoint.
- Propose wet muck entry risk models considering new variables and new data.
- Calibrate and validate wet muck entry risk models.
- Assess or apply wet muck entry risk models.

1.1.3 Hypothesis

Including new variables such as lithologies and fragmentation present during the extraction, generate robust, accurate term models with low tonnage error.

1.2 Thesis structure

Chapter 2 establishes the literature review of the thesis, carrying out a review of the bibliographical background of mud, beginning with its formation, where it comes from, types of mud, mud in underground operations, and the models that have been developed to date. At the end of the chapter are the respective conclusions of the literature review.

Chapter 3 contains the research articles with the results, discussion, and conclusions of the thesis. The first paper focuses on the model developed for the Reservas Norte basin and its application to a plan for the sector. The second paper presents the rest of the models developed for the North, Center, and South basins, and the application of the North basin model for the Invariant Panel sector. The first paper was presented at the Caving 2022 conference, the second paper was submitted to the International Journal of Mining Science and Technology. Finally, in Chapter 4, the conclusions and general recommendations of the thesis are presented.

2 Literature review

This chapter covers the review of the information available in the literature regarding wet muck declarations, how mud is formed, types of mud, their input in caving mining operations, control and mitigation tools and the models that have been presented by different authors so far.

2.1 Mud in mining and Wet muck events

Mud events or also called wet muck events are formed by a mixture of four elements: fine granulometry material, water, a disturbance and a discharge point, which can generate a sudden event within a drawpoint (Butcher, et al., 2005). In particular, mudruhes can occur when more than 30% of the material is smaller than 5 [cm] and humidity is greater than 8.5% (Samosir, 2008).

2.1.1 Types of mud

Due to variations in the percentage of moisture that the mud has, it is possible to classify it into two main categories that stand out in the consistency of this material in the mine (Jakubec & Clayton, 2012):

According to the percentage of moisture:

- Fluid mud
- Slimy Mud

Depending on where the mud comes from:

- Internal mud
- External mud
- Mix of Internal and External

2.1.2 Fluid mud

Fluid mud has a high water content (up to 50%), includes large rocks up to 3 m, capable of flowing easily on horizontal surfaces of great lengths. The mud in this case resembles a fine suspension and generally looks more like a discharge of water than a mudflow, the latter having a higher viscosity and therefore a higher percentage of mass with respect to water. An example of the fluid mud is shown in Figure 1(a).

2.1.3 Viscous mud

Viscous Mud has a low moisture content (17–23%), generally exhibits properties that show a change in its viscosity over time, and tends to be stiff. This material would not flow freely under gravity, but if stress is added to it, under certain conditions, it could be mobilized and forced out of the drawpoint and, despite its high viscosity, can be destructive. Figure 1(b) shows the extreme case of rigid viscous mud coming out of the drawpoint.

Figure 1: (a) Example of a fluid mud at Cullinan, De Beers. (b) Example of a very stiff-surfaced mud bulge from the drawpoint at the Northparkes mine, Rio Tinto (Jakubec & Clayton, 2012).

2.1.4 Internal mud

They come from the formation of mud produced by the reduction in the size of shale or other clay-forming rocks and clay-rich minerals, located in the column of broken ore within the caving zone. Also included are fines that accumulate as a result of secondary fragmentation processes. In figure 2 and 3 two mud generating scenarios can be seen.

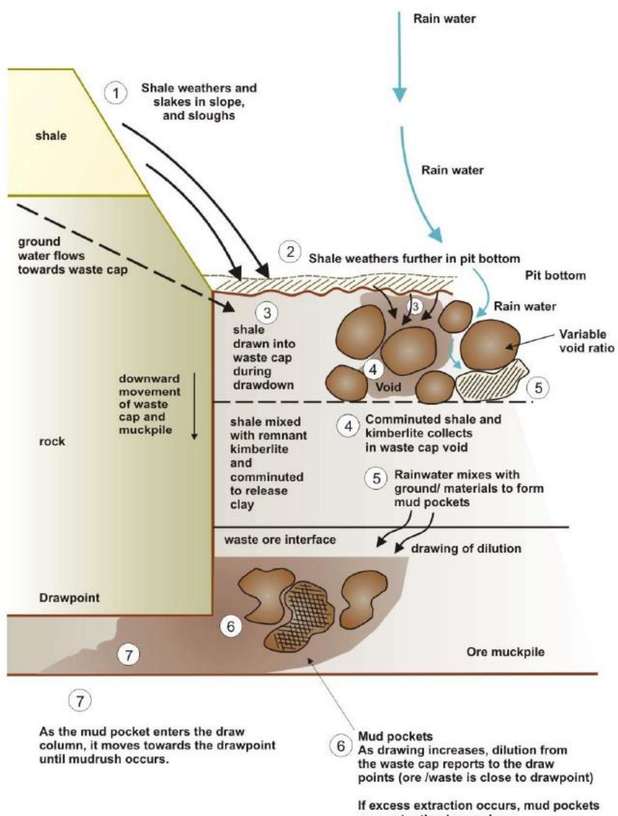

Figure 2: Primary scenario for the occurrence of internal mudrush (Butcher, et al., 2005).

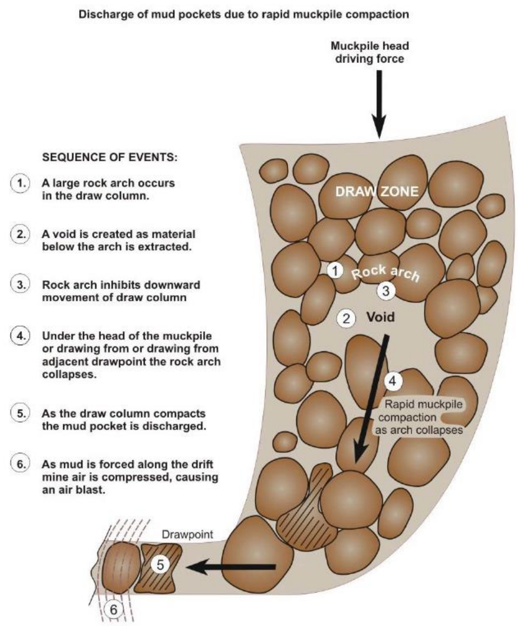

Figure 3: Mud discharge resulting from the compaction of the fragmented material column (Butcher, et al., 2005).

2.1.5 External mud

They come from the formation of mud in external conditions to those presented in the underground environment of the rock mass, they are produced by three sources tailings deposition, fills with failure material, and slope failures (Brown, 2003). Figure 4 shows an example of mud formation due to slope failure.

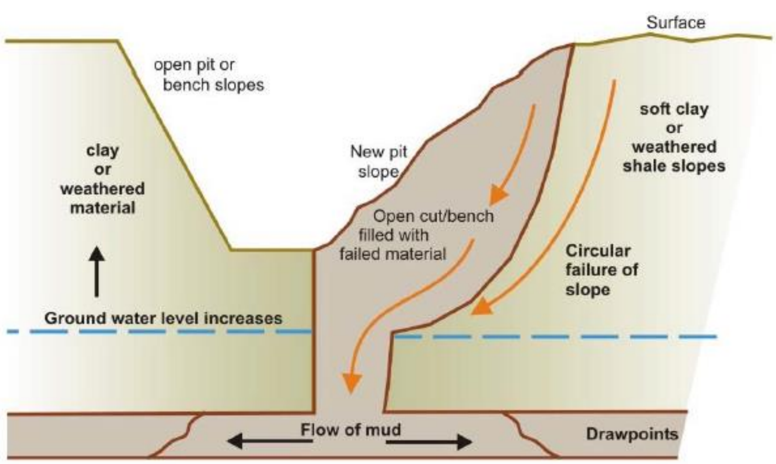

Figure 4: Mechanism of mud formation due to slope failure (Butcher, et al., 2005).

2.2 Definitions of mud events according to the distance affected

El Teniente Division has classified the mud events into mudrush, runoff and mud slides, considering key characteristics of their behavior such as: the magnitude of their force and speed, the linear distance that they travel in the drifts and infrastructure and/or work personnel. Below are the definitions according to the El Teniente Division (SGC-GRL-DET, 2017).

2.2.1 Mudrush

Violent discharge of mud that occurs in the zone of influence of an extraction area, through the existing infrastructure inside the underground mine, such as production drifts and drawpoints. The displacement of the mud covers a significant surface of the works involved (on the gradient for distances greater than 20 linear meters, interrupting the operational process, and may cause damage to infrastructure and/or people.

2.2.2 Runoff

Sliding of muddy material infiltrated from the upper levels through the existing infrastructure inside the underground mine, such as production drifts, drawpoints, haulage drifts, ventilation drifts and others. The sliding of this muddy material occurs slowly and in a limited manner, reaching distances of less than 20 linear meters, and does not affect the infrastructure of the sector.

2.2.3 Mud slide

Displacement of material from the slope at the drawpoint or inside the ore pass, product of saturation by moisture or water, which does not involve a relevant movement of the ore column. The displacement of this material may or may not be projected into the drifts, without exceeding the gradient, its influence is less than runoff and it does not cause significant interference to the production process.

2.3 Mud in cave mining operations

Caving mines are operations susceptible to mudrush because they present the four forming elements mentioned by Butcher (2005), fine mineral generated by secondary fragmentation present in the column of broken material, water accumulation (infiltration of groundwater), the disturbance generated by the constant extraction and the discharge point (drawpoint). Below are case studies of mining operations with mud event problems.

2.3.1 Kimberley Mine

The Kimberley Mine is an underground operation that is located in Kimberley, South Africa and is made up of three mines Dutoitspan, Bultfontein and Wesselton. The mud events in this mine are due to the breaking of the kimberlite and the water infiltrated by the rains in the extraction column. These mud events at Dutoitspan have caused severe damage to the mine infrastructure, and the death of a worker (Holder, et al., 2013). From operational experiences, ways to combat a mudrush have been determined (Butcher, et al., 2005):

- Maintain a controlled uniform extraction, avoiding over-extraction of drawpoints.
- Install drainage, close to where water accumulates (generally on the surface).

Also, a risk rating for mud events was adopted, where all the key factors that contribute to the risk of mud events at drawpoints are evaluated, as set out below (Holder et al, 2013):

- • Surface water infiltration
- • Groundwater infiltration
- • Moisture condition of the drawpoint
- • Percentage of dilution at the drawpoint
- • Mine drainage
- • Extraction uniformity
- • Structural condition of the drawpoint
- • Extraction from the drawpoint
- • Drawpoint hang-up

Each of the above variables is assigned a score based on the characteristics of the drawpoint to then calculate the total score for risk classification and determine mitigation measures as appropriate, as shown in the Table 1.

Table 1: Mud event risk matrix (Modified from Holder et al, 2013)

Total Score and Risk Color	Risk Rating	Risk Tolerance	Mitigation
0 - 30	Low	n/a	None, unless conditions change..
30 - 45	Moderate	Acceptable	Review strategies to extraction control and drainage of affected areas and increase monitoring..
45 -60	High	Unwanted	Restrict access to danger zones, reduce extraction in affected drawpoints, guarantee that mitigation measures are complied with.
>60 (Red Zone)	Very High	Unacceptable	Immediate evacuation from Red Zone, urgent management intervention to ensure implementation of necessary mitigation measures.

2.3.2 PT Freeport

One of them is the Freeport Indonesia mines (Widodo, 2018). The place where the Freeport mining operation is located has high rainfall events reaching 5,500 mm/year (Samosir, et al., 2008). The water inflow in to the cave comes from two sources, wsurface runoff from the abandoned pit and groundwater (Ginting & Pascoe, 2020). Freeport Indonesia considers a group of various mines in operation. The extraction at Freeport Indonesia began through open pit mining, and later it has had mineral extraction through underground mining, with mines such as GBT, IOZ (Intermediate Ore

Zone), DOZ (Deep Ore Zone) (Figure 5). Today, a couple of mines like GBC (Grasberg Block Cave) and DMLZ (Deep Mill Level Zone) are ramping up.

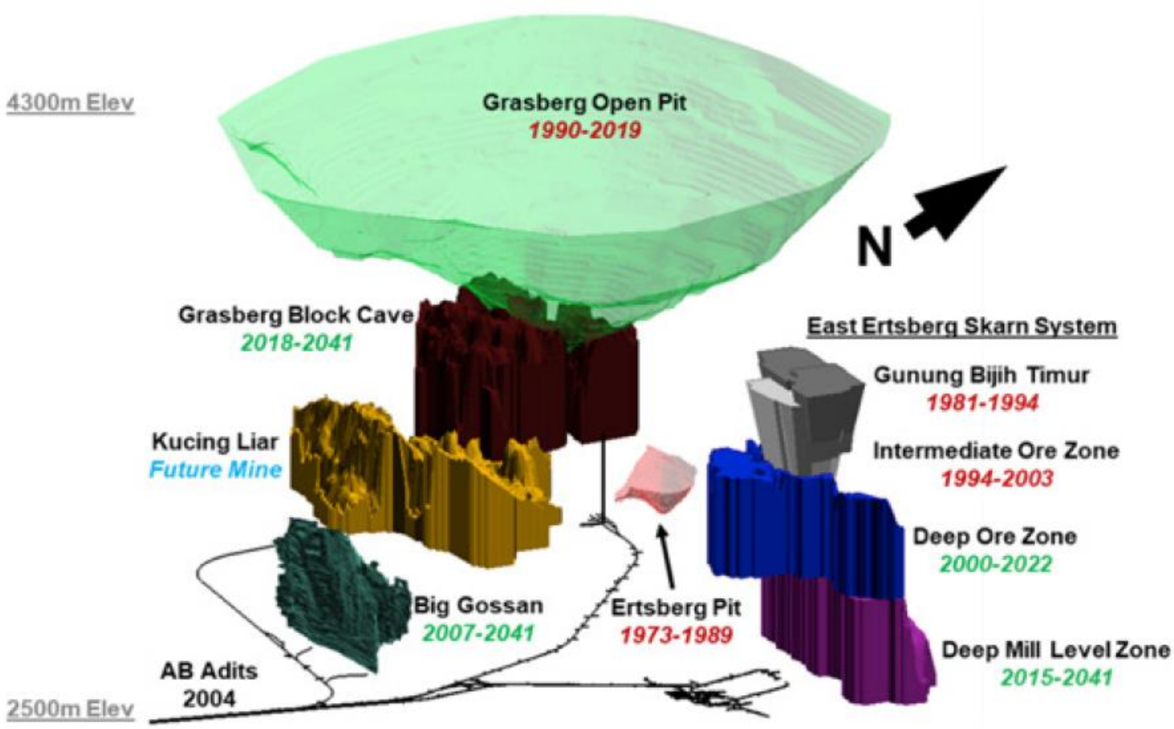

Figure 5: Freeport Indonesia Underground Mines (Casten, et al., 2020)

The IOZ mud contains a large amount of fine material, between 25-50% (< 2 mm), for this type of material it has been determined that 8% moisture is needed for the mud to flow (Huber, et al. al., 2000; Widijanto, et al., 2012). The sudden wet muck entry in this mine can be due to blasting, equipment movements, increased pore pressure, changes in stress, or falling material (Huber, et al., 2000). For the above and the safety of people in Freeport, they have chosen to use remote equipment.

As mining deepened, an increase in fines was seen at the DOZ mine, and with a high extraction rate, it created a high risk of mud. In DOZ it was determined that the main sources of water were surface water that infiltrated through subsidence due to high rainfall, but there are also sources of groundwater, which is water trapped in the old sectors, and water that infiltrates through the faults, since these act as preferential routes for water (Widijanto, et al., 2012). In DOZ, as in IOZ, the mudrush are recorded with a quantity of fines greater than 20% (<2mm) and a water content greater than 8.5% or more, with 80% saturation. Based on this, Freeport evaluates each drawpoint based on its moisture and quantity of fines, to see if the extraction is manual or remotely controlled, using the matrix shown in the Table 2:

Table 2: Matrix to classify the status of drawpoints in Freeport Indonesia (Samosir, et al., 2008; Edgar, et al., 2020; Ginting & Pascoe, 2020)

Level of wetness/ water content	**Material size ≥ 5 cm (M)**		
	M > 70% (dominated by coarse material)	**30% < M ≤ 70% (mixture of coarse and fine / medium material)**	**M ≤ 30% (dominated by fine material)**
< 8.5% (dry)	A1	B1	C1
8.5 – 11% (moist)	A2	B2	C2
≥11% (wet)	A3	B3	C3

Green – any loader; yellow – any loader close supervision; red – remote loader

At Freeport, it has been shown that non-uniform extraction causes differences in porosity, which can increase water in the extraction column. They have also determined that a continuous extraction must be carried out, if this is not the case and a drawpoint is closed due to mud, the water migrates towards neighboring drawpoints. As long as the mud is in a dynamic state and the material is constantly extracted, the risk of mudrush is low. The latter is due to the constant movement of the reservoir facilitates drainage. Other measures that have been implemented are:

- Drainage through perforations
- Automate processes so as not to put people at risk
- Supervision of drawpoints with qualified personnel
- Rain monitoring, with alerts if they exceed expectations.

The classification system was update in 2018, due to the increase in mudrush at the mine. As part of the classification system update, the mine start using the historical information of drawpoints and the probability of a mudrush (Edgar, et al., 2020). For this classification, the following Table 3 shows the factors are used to obtain a final risk score:

Table 3: Parameters included in the Freeport Risk Matrix Update (Edgar, et al., 2020)

Factor	**Low**	**Medium**	**High**	**Factor weight**
Classification	A1,A2,B1,C1	A3	B2,B3,C2,C3	30 %
Isolated draw	0-1 DP	2-5 DP	6-9 DP	20 %
Extraction height	0 m-100 m	100 m-200 m	>200 m	10 %
Mudrush frequency	<10	10-20	>20	20 %
Mudrush volume	<500 m^3	500 m^3-100 m^3	>100 m^3	10 %
Mudrush distance	<75 m	75 m-100 m	>150 m	10 %
Punctuation	1	2	3	n/a

When obtaining the final score, the risk of the drawpoint is classified based on the Table 4:

Table 4: Updated Risk Matrix (Edgar, et al., 2020)

Colour	Category	Risk score
Green	Low Risk	0 – 1.5
Yellow	Medium Risk	1.6 – 2.0
Red	High Risk	2.1 – 3.0

In this way, new security measures were included:

- Increase exclusion distance after a mudrush
- Mud drawpoints are reinforced with shotcrete.
- Exclusion time of 24 hr after mudrush
- Haulage level trucks load in reverse
- Remote equipment

2.3.3 El Teniente, CODELCO

The El Teniente mine is located in the city of Rancagua, O'Higgins region in the central part of Chile. The El Teniente mine, has had wet muck events in several of its mines, some of which are: Diablo Regimiento, Reservas Norte, Pipa Norte, Pipa Andes sur, Esmeralda, among others. The mud in El Teniente mine is mainly due to rainwater or snow accumulated on the surface that infiltrates the mine and the fine ore formed due to the caving mining process.

Initially, long-term planning at El Teniente mine was deterministic, based on controlled extraction (Castro, et al., 2018) using the risk map shown in Figure 6. The use of this risk map is based on define the extraction of the drawpoints based on the area in which they are located, with 130% of the column being in situ for high-risk areas (red on the map), which are those drawpoints with a topography height of less than 500 m. An extraction between 160%-180% is allowed for the medium risk zone (drawpoints in yellow), these points have a topography height greater than 500 m and less than 600 m. The low-risk areas do not have an extraction limitation due to the risk wet muck entry, because these points have a distance from the topography greater than 600 m (Castro, et al., 2018).

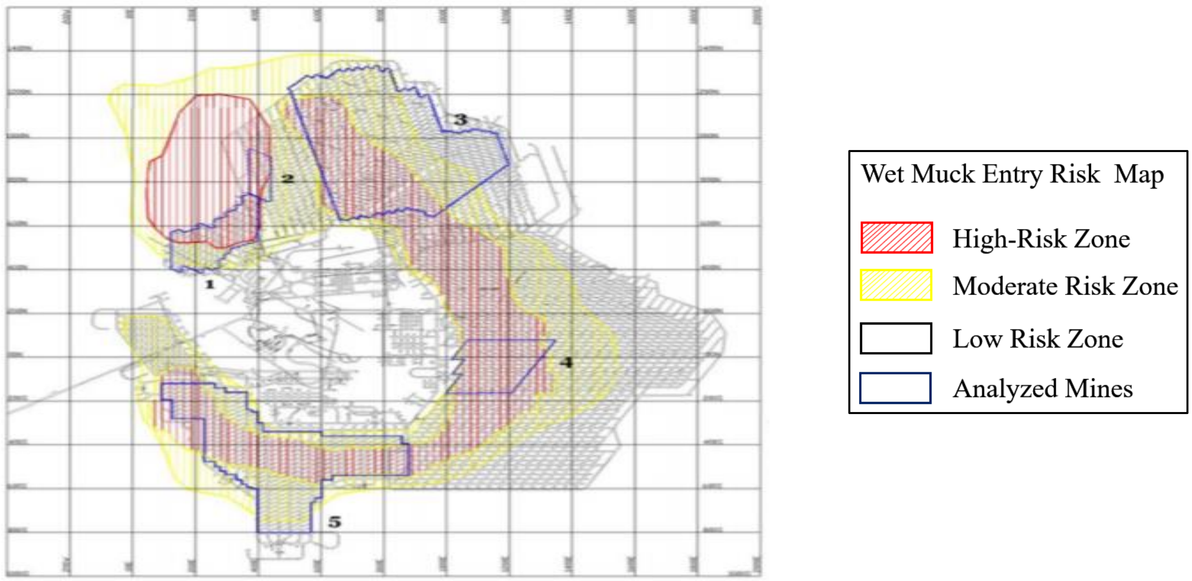

Figure 6: Risk zone in DET, image extracted from (Castro, et al., 2018)

Based on the risk of mudrush in El Teniente, it has been determined that constant monitoring, controlled extraction and favorable mining design are needed. Preventive measures have been taken for the wet muck entry, such as monitoring the extraction column, fragmentation and moisture. A criticality matrix has been implemented, as shown in Figure 7, which has visual moisture and the amount of fine mineral as input data, which is complemented by the criteria of the experts.

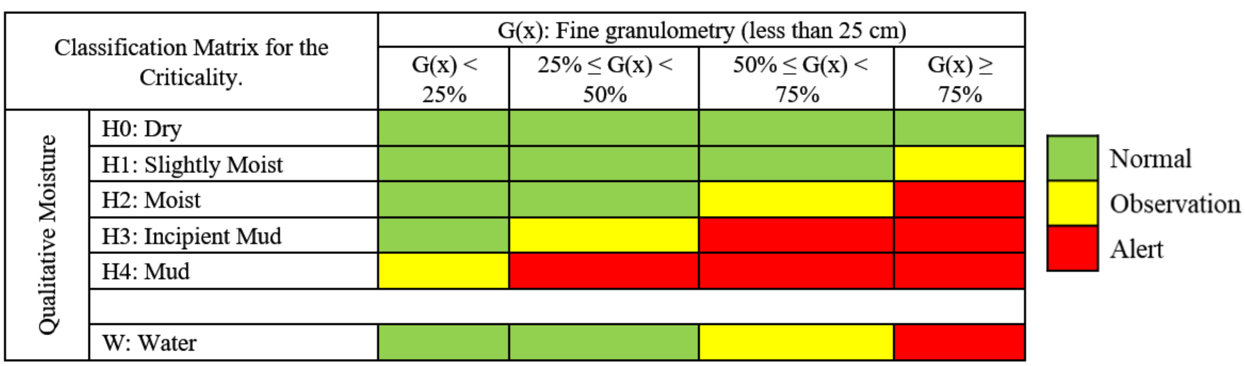

Figure 7: Classification Matrix for the Criticality, DET (Salazar, et al., 2016)

Different extraction strategies have been implemented according to the moisture and the quantity of fines at the drawpoint, restricting the extraction of the drawpoints with wet muck and limiting the extraction of its neighboring drawpoints (Figure 8). (Ferrada, 2011).

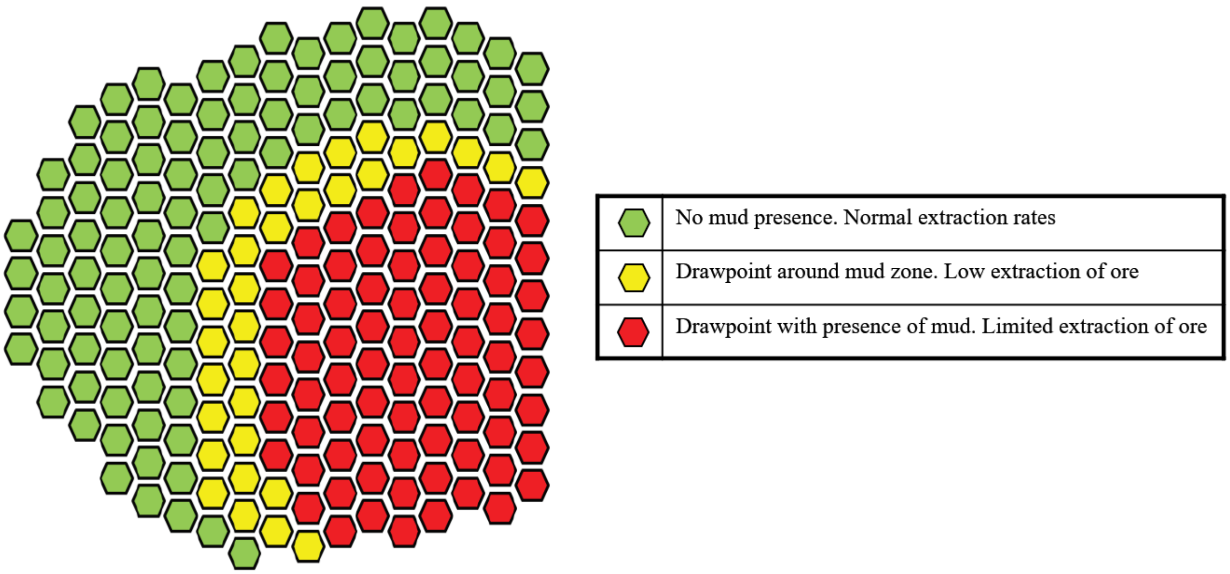

Figure 8: Extraction strategy at El Teniente mine (Ferrada, 2011)

As some sectors have been abandoned due to the wet muck entry, leaving unextracted reserves, industrial mud extraction tests have been carried out at the El Teniente mine to assess the feasibility of recovering these reserves (Soto, 2018). Within the long-term planning of mines under wet muck entry risk, different models have been developed to assess this risk in mining plans, which have begun to be used in the El Teniente mine.

2.4 Wet muck entry modeling

2.4.1 The Navia model (2014)

The declarations of mud or also called wet muck entry have been modeled by different authors, Navia et al., (2014) analyzed the drawpoints in the state of mud in the Diablo Regimiento mine. Based on the model proposed by Navia et al., (2014) it is possible to determine that the drawpoints declared with mud correspond in the first instance to those drawpoints that are connected to an old sector. Therefore, he determines that the connection of the Caving with old sectors or with the topography, creates favorable channels for the entry of fine material and water. For this reason, it is important to identify possible areas where water can accumulate or to study the old sectors. On the other hand, he attributes that an irregular extraction from a drawpoint favors the wet muck entry.

The Navia model makes a first approximation to determine the wet muck entry through a multivariate logistic regression model. According to the model, the variables that should be included are:

i) Amount of fine material contained in the drawpoint
ii) Height of the extracted column
iii) Time of year (because the occurrence of wet muck entry is higher in spring, compared to with another season of the year, due to the snow melting)
iv) Speed of extraction.

The accuracy of the model developed by Navia et al., (2014) is 74%.

Equation 1: Wet muck risk model proposed by (Navia, et al., 2014)

$$ln\frac{p}{1-p} = 14 - 15 * DR - 0.142 * FN + 0.014 * DH + 0.174 * S \quad (1)$$

Where:

DR: Draw rate (ton/m^2 día)

FN: Fine material contained in the drawpoint (%)

DH: Height of draw (HOD) (m)

S: Season of the year (Winter, Summer, Autumn and Spring)

For the implementation of variables such as the quantity of fines in risk models, it is necessary to predict this for the long term. One way of doing this is associated with the broken that exists in old sectors, being able to determine when this material enters a drawpoint can provide information on the wet muck entry. One way to do this in long-term planning may be through gravitational flow simulators, which allow inferring when the broken from the old sector enters a mine located below. On the other hand, to determine the fineness and size of this material, it would be necessary to implement a model that can predict secondary fragmentation in a long-term plan.

2.4.2 Garcés model (2016)

The Garcés model (Garcés, et al., 2016) continues with the quantifications of the wet muck risk through multivariate models. His work is based on a mine located in the Pacific sector, called Quebrada Teniente. This mine is located under old mines and is composed of a primary and secondary rock column.

When analyzing the historical data of wet muck declarations and its occurrence, two wet muck entry mechanisms are visualized, one vertical, to later continue with a lateral mechanism, as shown in the Figure 9.

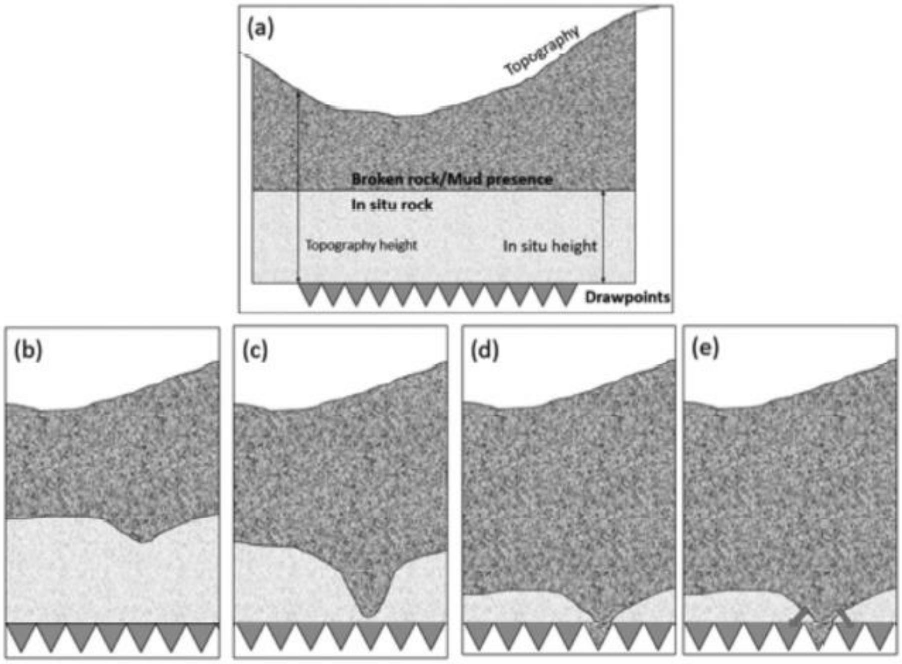

Figure 9: Mechanisms of vertical and lateral wet muck entry, observed by Garcés, et al., 2016.

The data used for the elaboration of this model is from the year 2004 to 2015. In this period, 93 drawpoints were registered in a mud state and the following variables were analyzed:

- Extraction
- In-situ column height
- Primary column height
- Distance to topography
- Number of neighbors in mud state
- Season of the year (summer-winter)

A multivariable model is made by using logistic regression, this model is formed by two wet muck entry classifiers, one is for vertical entry and the other for lateral entry.

For the elaboration of the model, the databases are balanced, both for vertical and lateral mud entry. The balance consists of forming a database composed of ¼ data with mud input and ¾ with records of drawpoints without being declared in a mud state.

In this study, it was determined that the variables that govern the vertical wet muck entry are the height of primary rock and extraction. On the other hand, for the lateral wet muck entry mechanism, the influencing variables are extraction, season of year, the number of neighbors of the drawpoint in the mud state and the height of the primary rock, the model can be observed in the next equation:

Equation 2 Wet muck entry risk model

$$P(x) = \begin{cases} P_V(x) \ = \frac{e^{-0.415-0.008*hp_r+0.384*E}}{1+e^{-0.415-0.008*hp_r+0.384*E}} & If\ MN = 0,\ \ for\ CP_V \\ \\ P_L(x) \ = \frac{e^{-2.03+1.39*E+0.79*S+0.65*MN-0.009*hp_r}}{1+e^{-2.03+1.39*E+0.79*S+0.65*MN-0.009*hp_r}} & If\ MN = 0,\ \ for\ CP_L \end{cases} \tag{2}$$

Given the variables used in this model, it is difficult to generalize or implement it in other mines to assess the wet muck entry risk. The latter, due to the use of physical variables typical of the mine such as the height of primary rock.

The model is calibrated, for which it is determined that the cutoff probability for the vertical model is 40% and for the lateral model it is 45%. The associated tonnage error is of -24Kt. In other words, declares a drawpoint in mud state 24Kt before what is declared in the mine.

In order to determine a better fit of the model, it is necessary to evaluate its error by means of the number of mud drawpoints declared by the model i.e. both real mud and false mud, and estimate the non-mud drawpoints in the same way.

2.4.3 Castro model (2018)

The study areas to carry out the model of wet muck entry by Castro et al., (2018) were North Pipa and South Andes Pipa. Both sectors are under the topographic gutter and whose shape on the surface has influenced the accumulation of water and its subsequent infiltration into the mine to form wet muck.

The study period includes data from July 2003 to February 2017. This period covereds an amount of 94 drawpoints declared in a mud state.

The variables that were used in this study to develop a model were:

- Topographic gutter
- Extraction
- Drawpoint neighborhood with wet muck entry
- Montly water flow rate
- Distance to topography
- Column height of in-situ material
- Column height of primary rock

In this study, wet muck entry is divided vertically and horizontally, for which a wet muck entry risk model is developed for each of these mechanisms. The database for the vertical wet muck entry model is composed of 24 drawpoints in the mud state and 72 drawpoints without the mud state. On the other hand, the case of lateral wet muck entry is composed of 70 drawpoints in the mud state and 210 without the mud state. The complete database was used to calibrate and validate the wet muck entry risk model.

The univariate shows the variable that has the greatest influence or correlation with wet muck entry is the topographic gutter or also called risk zones. This variable indicates whether or not a drawpoint is below the area where water can accumulate, this can be observed by the chi square test and odds ratio, since they are the maximum values in this analysis, indicating its great influence on the wet muck entry risk (Table 5).

For example, it is indicated that "the probability that a drawpoint under the risk zone has 7.16 times more probability of having wet muck entry than a drawpoint that is located outside the risk zone." (Castro, et al., 2018)

Table 5: Univariate analysis of the wet muck entry risk (Castro, et al., 2018)

Variable	Statistical significance (p value)	Chi-squared test (χ^2)	Coefficient	Odds ratio
Topographic gutter	< 0.001	446.30	1.97	7.16
Extraction	< 0.001	407.01	1.16	3.19
Drawpoint nerighborhood 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

The indicated risk area refers to the entire gutter formed by mining extraction, which results in a conservative variable, because there are mines that are completely under this subsidence area. Although this entire area is susceptible to the accumulation of water, there is no discretization that allows to determine different places with greater or lesser probability of accumulation of water.

The results obtained by Castro model indicate that the main conditions for a drawpoint to be contaminated with mud are to be under a risk zone, in an area with neighbors in a mud state, and to have over-extraction. The wet muck entry for the vertical mechanism is controlled by the variables of extraction, infiltrated water, the height of the primary column, and topographic depression or risk zones. It should be noted that the primary rock height and topographic depression variables are input data to the model that do not vary over time. Physical variables such as the height of the primary rock limit the generalization of the model to assess the risk of wet sludge entering other mines, on the other hand, the risk zones may vary over time depending on the extraction carried out, so considering it as a static variable, presents an opportunity for improvement in the evaluation of the risk of entry of wet manure. The lateral water-mud entry mechanism is determined by the following variables: water flow, extraction, number of neighbors in the mud state, and topographic depression. The wet muck entry risk model is:

Equation 3 Mud-water ingress risk model (Castro, et al., 2018)

$$P_{wm}(x) = \begin{cases} P_v(x) & = \frac{e^{-1.62+0.57*E+0.001*FR-0.003*hp_r+0.59*TD}}{1+e^{-1.62+0.57*E+0.001*FR-0.003*hp_r+0.59*TD}} \\ \\ P_l(x) & = \frac{e^{-4.06+1.83*E+0.001*FR+1.70*TD+0.53*N_{wm}}}{1+e^{-4.06+1.83*E+0.001*FR+1.70*TD+0.53*N_{wm}}} \end{cases} \quad (3)$$

When calibrating this model, it is obtained that the cutoff probability is 0.58 for the vertical wet muck entry model and 0.6 for the lateral model. With these values, he obtains a sensitivity of 70%, a specificity of 93% and an 84% accuracy of the model when calibrated, which are very good results for a model.

2.4.4 Pérez model (2021)

In the Pérez (2021) model, data from Blocks 1 and 2 of the Esmeralda mine of the El Teniente Division (DET) were used. The objective of the model was to study the wet muck entry in long-term planning.

The Esmeralda mine is located at elevation 2,210 of the El Teniente mine, characterized by having upper sectors with depleted reserves, such as Teniente 5 located at elevation 2,284 and Teniente 4 south at elevation 2,372. The data used for this study are from 2011 to early 2018.

The variables selected in the Perez model were:

- Estimated risk zones
- Broken material entry
- Infiltrated water flow
- Height of draw (HOD)
- Number of neighbor drawpoints in mud state

Within the univariate analysis, all these variables have a statistical significance with the wet muck entry (Table 6). The most important is the number of neighbor drawpoints in mud state, the broken material entry, and the estimated risk zones 4 and 2. On the other hand, the risk zone of case 1 does not present sufficient statistical evidence to indicate a relationship with wet muck, and was verified through contingency tables. It is also important to note that the higher the beta, the greater the weight of the variable in the model.

In this last variable, the risk zone was chosen that considers the two lowest drawpoints in the topography plus its neighborhood, which is the one that provided the best model according to a comparison of the log-likehood ratio parameter (-2logL) that measures the probability change between models, therefore, the model that minimizes this parameter is chosen (Castro, et al., 2018).

Table 6: Summary of the univariate analysis, modified from (Pérez, 2021)

Variable	Beta coefficient	Significance (%)
HOD (m)	0.01	0
Water flow (l/s)	0.0022	5
Broken material entry (dichotomous)	3.55	0
Neighbour drawpoints in mud state (#)	2.07	0
Risk Zone 1 (dichotomous	22.341	99.9
Risk Zone 2 (dichotomous	2.203	0
Risk Zone 3 (dichotomous	1.447	6.4
Risk Zone 4 (dichotomous	1.79	0
Risk Zone 5(dichotomous	1.082	1.5

The wet muck entry risk model has 81% accuracy, specificity and sensitivity, it is generally considered that a good prediction capacity of a model is over 80% accuracy. Next, the Pérez model (2021) is presented in equation 4:

$$P(x) \;=\frac{e^{-4.0100+0.0022*E+0.0035*Q+2.3177*QE+1.1674*VB+0.8927*ZR}}{1+e^{-4.0100+0.0022*E+0.0035*Q+2.3177*QE+1.1674*VB+0.8927*ZR}} \tag{4}$$

Where:

E: HOD (m)

Q: Water flow (l/s)

QE: Broken material entry (dichotomous)

VB1: Neighbour drawpoints in mud state (#)

ZR4: Estimated Risk Zone 4 (dichotomous)

2.4.5 Navia model (2021)

The risk models presented by Navia (2021) are proposed for both the long and the short term, data from the Diablo Regimiento sector of the El Teniente mine were used, with historical information from November 2013, which corresponds to the initial date of extraction of the sector.

In the first place, the identification of relevant variables for the wet muck entry in the Diablo Regimiento sector was carried out, which were:

- Neighborhood with the mud state
- Draw uniformity
- Distance to topography
- Percentage of fines
- Cumulative height of draw
- Moisture observed

- Horizontal distance to drawpoints with mud in the old upper sector
- Zone under drawpoints with mud in old sectors
- Presence of mud at a drawpoint in the same drawbell
- Belonging to the starting area.

The second part of this work begins with the creation of predictive models for the wet muck entry, through logistic regression as a predictive technique for dichotomous events (Navia, 2021). Twelve models were developed considering the mentioned variables, of which only 3 presented high predictive quality. The variables that obtained a better fit in these models were:

$\boldsymbol{x_1}$: Moisture at the drawpoint, according to the El Teniente classification, from 1 (dry) to 5 (wet).

$\boldsymbol{x_2}$: Neighborhood with the mud state, with values from 1 to 6.

$\boldsymbol{x_3}$: Draw uniformity, with a binary value where is 1 if the draw or extraction is non-uniform or semi-uniform and 0 if the extraction is uniform.

$\boldsymbol{x_4}$: Cumulative height of draw, with a binary value, where 1 indicates that the drawpoint has 90% or more of the in-situ column removed, otherwise 0.

$\boldsymbol{x_5}$: Horizontal distance to drawpoints with mud in the old upper sector, with a continuous value in meters.

Model 6:

$$p(x) \;\; = \frac{\exp\left(-6.105+1.419*x_1+0.943*x_2+0.769*x_3+0.521*x_4-0.024*x_5\right)}{1+\exp\left(-6.105+1.419*x_1+0.943*x_2+0.769*x_3+0.521*x_4-0.024*x_5\right)} \tag{5}$$

With a Specificity: of 81%; Sensitivity: of 79% and Accuracy of 81%.

Model 5:

$$p(x) \;\; = \frac{\exp\left(-6.593+1.414*x_1+0.930*x_2+0.713*x_3+0.892*x_4\right)}{1+\exp\left(-6.593+1.414*x_1+0.930*x_2+0.713*x_3+0.892*x_4\right)} \tag{6}$$

With a Specificity: of 81%; Sensitivity: of 79% and Accuracy of 81%.

Model 4:

$$p(x) \;\; = \frac{\exp\left(-6.189+1.416*x_1+1.049*x_2+0*x_3+0.803*x_4\right)}{1+\exp\left(-6.593+1.414*x_1+0.930*x_2+0.713*x_3+0.892*x_4\right)} \tag{7}$$

With a Specificity: of 84%; Sensitivity: of 71% and Accuracy of 82%.

2.5 Summary of wet muck entry models

A summary of all wet muck entry models reviewed in this study is shown in Table 7. The models are evaluated by KPIs such as Sensitivity, Specificity and Accuracy:

- The Sensitivity or True Positive Rate determines the success rate of when an event actually occurs.
- The Specificity or True Negatives Rate determines the success rate of when an event does not actually occur.
- Precision is the combination of Sensitivity and Specificity, since it determines the success rate of when an event actually occurs or not.

Table 7: Summary of wet muck entry risk models for long-term and short-term planning (after Pérez, 2021)

Model (Author)	**Model variables**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**	**Comment**
Model 1 - (Navia, et al., 2014)	Extraction rate (ton/m^2 día) Fine material in drawpoint (%) HOD (m) Season of the year (binary)	NA	NA	74	A variable that provides information on the fine material extracted can be included in the wet muck entry risk model.
Model 2 - (Garcés, et al., 2016)	-Extraction (%) -Primary column height (m) -Number of neighbors in mud state (#) -Season of the year (summer or winter - binary)	NA	NA	NA	The model is calibrated based on the actual tonnage of wet muck entry versus the simulated one. The model declares the mud drawpoints at -24Kt on average. And it can include accuracy, sensitivity, and specificity.
Model 3 - (Castro, et al., 2018)	-Extraction (%) -Column height of primary rock (m) -Topographic gutter - Montly water flow rate (l/s) - Drawpoint neighborhood with wet muck entry (#)	70	93	84	The mud-water ingress risk model is conservative in its definition of risk zones and can be complemented with variables that provide information throughout the life of mine (LOM).
Model 4 (Pérez, 2021)	Height of draw (m) Infiltrated water flow (l/s) Neighbour drawpoints in mud state (#) Broken material entry (binary)	81	81	81	The mud water ingress risk model presents an opportunity for improvement by considering new variables such as secondary fragmentation and present lithologies that vary throughout the LOM.

	Estimated risk zones (binary)				
Model 5 (Navia, 2021)	Moisture (1 a 5) Neighborhood with the mud state (1 a 6) Draw uniformity (binary) Cumulative height of draw (binary) Horizontal distance to drawpoints with mud in the old upper sector (m)	89	79	81	Navia, (2021), made 12 models of which the one with the best prediction quality is the one shown in the table, this is the only short- and long-term model. This model can be complemented by adding variables related to secondary fragmentation and lithologies, the humidity variable could also be considered quantitatively.

2.6 Conclusions of the literature review

Wet muck entries have become one of the main risks of caving mining: Therefore, it is necessary to have a tool to be able to predict them and avoid any type of accident and/or catastrophe such as generating dilution or loss of reserves. Different mines in the world have developed measures to mitigate mud, such as drainage tunnels that reduce the amount of accumulated water, control the draw uniformity to allow natural drainage of the mine; implement autonomous equipment for the extraction of mud and reduce the exposure of workers. Water-mud risk classification systems have also been implemented at the drawpoints, considering variables such as the quantity of fines in the material, qualitative and quantitative moisture, dilution, hang-ups, state of the drawpoint, and variables associated with the mud events as linear distance, volume, and frequency.

Wet muck declarations condition long-term planning, generating delays in extraction, loss of reserves, affecting the safety of workers, and having to upgrade their manual equipment to autonomous to continue extraction (for example at PT Freeport); it is for the above that it is necessary to build wet muck entry risk models. In the past, long-term multivariable models have been implemented, which have presented good results based on real information from wet muck declarations. However, there is an opportunity for improvement, since most of the models do not consider variables related to the fragmentation and/or lithology present in the extraction, variables that in theory and operation are strongly related to the formation of mud and could help to improve understanding of wet muck entry. Therefore, this study focuses on analyzing the inclusion of these variables in the wet muck entry models. Six groups of variables to be analyzed are presented below:

1. **Historical Extraction:**
   - Extraction ratio
   - Height of draw
2. **Lithologies**
   - Primary rock, Secondary rock, Broken material and Talus material
3. **Fragmentation**
   - d_{50}
4. **Water**
   - Water flow rate, Precipitation and Season of the year
5. **Mud**
   - Drawpoint neighbor wet muck y Historical mud sectors
6. **Topography**
   - Vertical distance to surface

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3 Research articles

3.1 Paper 1: Modeling of Wet muck entry at El Teniente for long-term planning

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R Castro, *Universidad de Chile, Chile*

E Viera, *División El Teniente, CODELCO, Chile*

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Caving 2022: Fifth International Conference on Block and Sublevel Caving, Australian Centre for Geomechanics, Perth, pp. 545-560, https://doi.org/10.36487/ACG_repo/2205_37

Abstract

The intrusion of wet muck and fines and the potential of mud rushes pose safety risks for workers, equipment and infrastructure at El Teniente. Wet muck can also result in the loss of reserves because of the need to close drawpoints when large amounts of fine materials and moisture are observed. This article presents the analysis and the development of a mathematical model to estimate wet muck entry for long-term planning applications at El Teniente. The models have been imbedded in BCRisk®, which is a machine-learning software that estimates hazards associated with the extraction process for underground mines. Four basins of El Teniente were included in the study of wet muck control: North, Center, South, and Reno. Each basin has mines with different characteristics in each exploitation sector. Consequently, models were built for each of the basins to represent its distinct reality.

Several variables were investigated to define which determine the phenomenon. The variables include tonnage extracted or draw rate, amount of water entering the cave, season of the year, presence of mud in neighboring drawpoints or sectors that have been closed due to wet muck above, and changes in surface or depressions. In addition, flow variables such as fragmentation and lithologies have been included and estimated with FlowSim 6.3® for increased precision. Results indicate that the classification models can reproduce the phenomenon with an acceptable precision of 71% and an average tonnage error per drawpoint of 7 to 10%. These results have been useful for long-term planning at El Teniente mine to predict wet muck entry and define when and where autonomous LHD may be required for the extraction of wet muck in the future.

Keywords: *draw control, mine planning, underground mining, geotechnical hazards, large-term, short-term, wet muck, mud.*

1 Introduction

Caving mining currently represents a productive and economic option; however, it is affected by challenges such as wet muck entry, defined as when the operation declares wet muck in a drawpoint, which can cause accidents and affect workers, mining infrastructure, and equipment. Wet muck entry can also generate excess dilution, delays in production, loss of reserves and even partial or permanent closure of mining operations (Butcher et al. 2005; Jakubec & Clayton 2012; Navia et al. 2014). Mud entry in caving mining is generated by fine particles that mix with aqueous substances in different types of conditions, such as melting ice in the mountains, tailings filtration, aquifers, and weather conditions (snow and rain). This mixture travels through the column of broken material and reaches the drawpoints, causing water filtration and in some cases mud events, such as landslides, runoff, and mudrush (Ginting & Pascoe 2020).

Wet muck entry has been recorded in different underground mines around the world, such as El Teniente in Chile (Ferrada 2011), IOZ and DOZ in Indonesia, Ekati in Canada, (Edgar et al. 2020; Hubert et al. 2000; Ginting & Pascoe 2020; Jakubec & Woodward 2020; Widijanto et al. 2012). Some mitigation and control tools used range from drainage tunnels that allow the transfer of mud to lower levels or to the outside of the mine, remote-controlled equipment. Risk and criticality matrices for drawpoints have also been used considering humidity (qualitative and quantitative) and the amount of fine material; this information can help to avoid drawpoint closure and the risk of accidents (Samosir 2008; Edgar et al. 2020).

There are also models that predict wet muck entry, in particular for the El Teniente Division. Wet muck entry risk models have been implemented that allow evaluation of mining plans (Castro et al. 2018; Garcés et al. 2016; Pérez 2021; Navia 2021). Most of these models are used for long-term planning; however, so far some mud-forming variables such as secondary fragmentation and the lithology present at drawpoints have not been fully studied. Adding the d50 fragmentation, broken material extracted in drawpoint, extraction ratio, and annual precipitation should improve the accuracy and robustness of the wet muck models to create a useful tool applicable to the El Teniente division.

2 Background at El Teniente Division

2.1 Wet muck at El Teniente Division

Mining data was provided by the sectors or mines of the El Teniente division including Pipa Norte Mine (PNM), Sur Andes Pipa Mine (SPM), Reservas Norte Mine (RNM), Dacita Mine (DM), Esmeralda Mine (EM), Diablo Regimiento Mine (DRM), among others, from 1999 to 2021 to analyze mud entry in the mine. These mines are primarily located below a topographic trough (similar to a topographic depression) around the Pipa Braden, as shown in Figure 1.

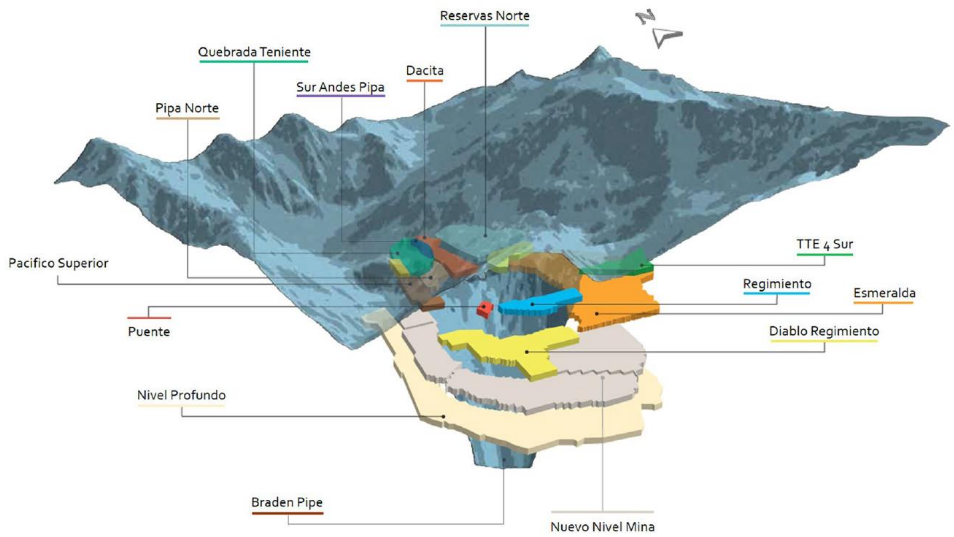

Figure 1 Isometric view of the productive sectors of the El Teniente division (Codelco 2016a, 2016b)

To understand wet muck entry in the sectors of the El Teniente Division, Butcher et al. (2005) have suggested that four factors are required to trigger wet muck entry. These include the holding capacity of water, the presence of possible mud-forming minerals, a disturbance in the ore column, and the mud discharge capacity at a drawpoint, Figure 2 shows a schematic representation of the wet muck phenomenon and some of its main variables.

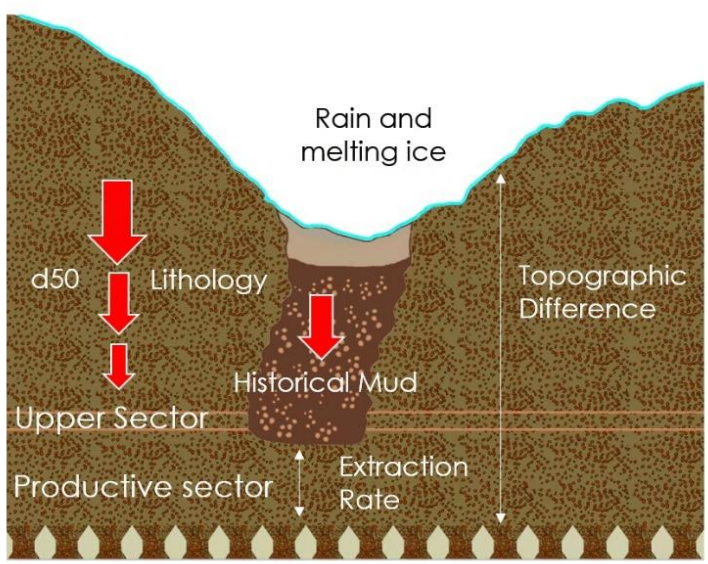

Figure 2 Conceptualization of the problem of mud entry in the El Teniente Mine

Variables such as the secondary fragmentation that is generated along the ore column, the extraction ratio based on the height in situ, lithology, and the accumulated precipitation over time are broken down from the aforementioned factors. The old sectors with historical mud and the difference in height between a drawpoint and the topography are also considered. All of these variables are considered critical to understanding mud entry and are considered in this study.

2.2 Basins of the El Teniente Division

El Teniente mine is contained within a subsidence crater, which in turn can be divided into four basins: North, Reno, Center, and South, as shown in Figure 3. For the purpose of this study, mud entry models were constructed for each of basins, using the mine database from each of them (Table 1). Once the model is built, it can be applied to future evaluations of the same mine or sector as well as to mines or sectors that are at a lower level.

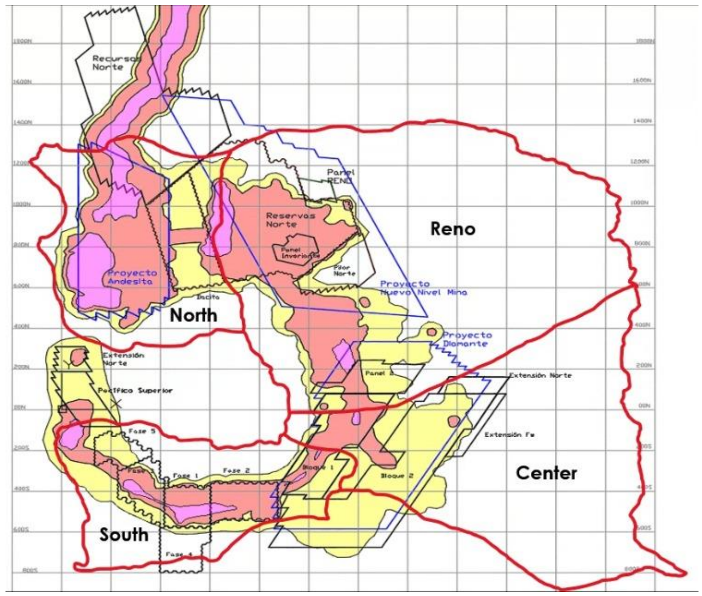

Figure 3 Plan view of the El Teniente Division crater, showing its division into four basins (North, Reno, Center, and South)

Table 1 Classification of mud entry models according to the basin, the base mine, and the possible mine of application

Models / Basins	**Base Mine**	**Possible Application Mines.**
North	Pipa Norte - Sur Andes Pipa	Recursos Norte Andesita
Reno	Reservas Norte - Dacita	Andes Norte Panel Invariante
Center	Esmeralda Bloque 1 y 2 - Esmeralda Panel	Diamante
South	Diablo Regimiento	Pacifico Superior Pacifico Central

2.3 Study Area

The study area includes the Reno Basin, which is made up of the productive sectors of Reservas Norte (NN) and Dacita (DT). The information analyzed contains the historical extraction for 1,395 drawpoints (DP) from January 1999 to August 2021. Figure 4 shows the wet muck entry. To date there are 462 DP (33% of the database), 432 belong to Reservas Norte, and 30 to Dacite. This database was used to study the independent correlation that each of the variables has with mud entry and to choose the critical variables of the problem using a univariate analysis methodology of logistic regression. Subsequently, a multivariate analysis was performed, which included dividing the database into a training database used to generate the equations of the logistic regression model and another for prediction to analyze the predictive performance of the model.

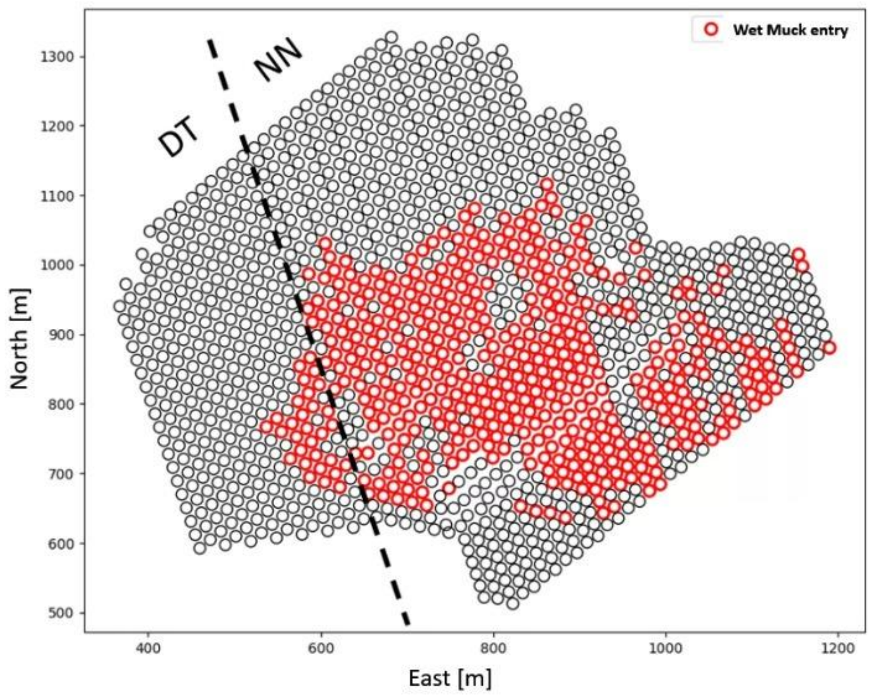

Figure 4 Wet muck entry from the Reservas Norte (NN) and Dacita (DT) sector

2.4 Critical Variables for the Wet muck entry

In the analysis, four types of information were considered: historical extraction, lithologies and fragmentation, water and mud, and topography. Variables that can explain the problem of mud entry were developed from these types of information, such as those briefly mentioned in Table 2 and described in Table 3.

Table 2 Information considered in the analysis and example of the variables

Information group	Variables
1. Historical extraction	Height of draw [m] Extraction Ratio [%]
2. Lithologies and fragmentation	Primary rock extracted in the DP [%] Secondary rock extracted in the DP [%] Broken material extracted in the DP [%] Talus* material extracted in the DP [%] D50 [m]
3. Water and mud	Average water flow rate [L/s] Precipitation [mm] Historical Mud Sectors [dichotomic] DP Neighbor Wet muck [1 to 6]
4. Topography	Distance to the surface [m]

***Talus: Represents fill material that occurs due to the effect of subsidence in the crater (rilling effect), this is a permeable material.**

Table 3 Summary of the variables analyzed in the study

Variable	Symbol	Unit	Type	Description
Height of draw	HOD	(m)	Continuous	Represents the cumulative extracted column height of a DP in a period
Extraction Ratio	ER	(%)	Continuous	Percentage of in-situ column extracted.
Primary rock extracted in DP	PRIM	(%)	Continuous	Percentage of primary rock extracted in the month, [variable estimated by FlowSim]
Secondary rock extracted in DP	SEC	(%)	Continuous	Percentage of secondary rock extracted in the month [variable estimated by FlowSim]
Broken material extracted in DP	BM	(%)	Continuous	Percentage of broken material extracted in the month [variable estimated by FlowSim]
Talus material extracted in DP	TAL	(%)	Continuous	Percentage of Talus material extracted in the month, [variable estimated by FlowSim]
D50	D50	(m)	Continuous	Fragmentation size estimated by FlowSim

Average water flow rate	Q	(l/s)	Continuous	Long-term representation of water infiltration in DP
Precipitation at 30, 60, 90 days, semi-annual and annual	P30, P60, P90,Ps,Pa	(mm)	Continuous	Long-term representation of the infiltration of water by precipitation in the DP, in various time intervals
Historical Mud Sectors	HMS	-	Categorical	Composed of the mud polygons of productive sectors at higher levels; if a point is in that area (1), otherwise (0)
DP Neighbor wet muck	Nwm	-	Continuous	Number of DP in the neighborhood of a point that have declared mud entry.
Distance to the surface	D_S	(m)	Continuous	Distance between the DP and the surface.

3 Methodology

In this work, an analysis of the critical variables was carried out to determine the wet muck entry at a drawpoint using logistic regression as a tool to help long-term planning. First, a univariate analysis was performed to find the first relationship between variables and mud entry occurrence. Then, performing multivariate analysis, a predictive model was created to calculate the probability of wet muck entry. One of the advantages of the current methodology is that variables associated with mineral extraction, such as the lithology present in the extraction, the size of fragmentation, states of the drawpoint, and meteorological and topographic conditions, were incorporated in the modeling of wet muck for each drawpoint. A brief summary of the methodology to construct the predictive models is described below. For more detailed information on logistic regression, see Hosmer et al. (2013).

3.1 Univariate Logistic Regression Analysis

Wet muck entry risk variables were independently assessed using univariate analysis. The Chi-square Test (χ^2) and the Odds Ratio (OR) were applied to analyze the relative relationship between the independent variables and the mud entry reports (dependent variable or interest).

The Odds Ratio determines how likely it is that mud enters a drawpoint or not, with x = 1 (presence of mud) and with x = 0 (absence of mud) (Hosmer et al. 2013). For example, if a drawpoint declared to have mud is located below the risk zone associated with historical mud sectors, then the odds ratio OR = 3 means that the probability of mud entry between the drawpoints located in the risk zone is three times greater than the probability in the drawpoints not located in the risk zone (Castro et al. 2018).

In the univariate analysis, a statistical significance (p-value) of 0.1 is used as the critical value to determine whether each independent variable is statistically significant with mud inlet. All the variables that resulted in a significantly less than or equal to 0.1 were included in the multivariate logistic regression analysis. Table 4 shows the influence of variables in wet muck entry.

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

Variables	Description
Height of draw	Indicates the permeability properties of the unexcavated materials that make up the ore column (composed of primary and secondary rock), which controls water movement and infiltration to drawpoints.
Extraction Ratio	Represents both the increase in rock permeability promoted by subsidence propagation and the formation of fine material due to secondary breakage through the ore column. A higher Extraction Ratio increases the probability of wet muck entry.
Primary extracted in DP	Represents the percentage extracted from the primary rock. This competent rock represents the impermeable layer; therefore, the higher the percentage of primary rock extracted, the lower the probability of wet muck entry.
Secondary extracted in DP	Represents the percentage extracted from the secondary rock. This rock is less competent than the primary rock and together with the broken, represents the permeable layer; therefore, the higher the percentage of secondary extracted, the greater the probability of wet muck entry.
Broken material extracted in DP	Represents the same as the percentage of secondary rock because the material is fragmented. Similarly, then, the higher the percentage of broken material extracted, the greater the probability of wet muck entry.
Talus material extracted in DP	Represents fill material that occurs due to the effect of subsidence in the crater (rilling effect). This is a permeable material; therefore, the higher the percentage of talus extracted, the greater the probability of wet muck entry.
D50	Represents the fragmentation present in the extraction. When the size d50 decreases, the probability of wet muck entry increases due to the increase in the amount of fines in the DP.
Average water flow rate	Long-term representation of the water infiltration expected to be observed in the DP during extraction; therefore, if the water flow increases, the probability of wet muck entry also increases.
Precipitation at 30, 60, 90 days, semi-annual and annual	Precipitation measurements at various time intervals. An increase in precipitation indicates that the probability of wet muck entry increases.
Historical Mud Sectors	DP with mud declared in old or superior sectors. This is a categorical variable for which if the DP is under a sector with mud, it obtains a value of 1 and 0 otherwise.
DP Neighbor wet muck	Corresponds to the risk that the mud could spread to the surrounding areas (neighboring drawpoints)
Distance to the surface	Considers the distance to surface water sources (snow melt and rainwater)

3.2 Multivariate logistic regression analysis

The correlation between different variables with the occurrence of wet muck entry was tested using multivariable logistic regression, which delineates the association between the dichotomous response variable, Y (the occurrence or not of wet muck entry), and x the collection of variables of risk. 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 probability 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 probability of mud entry (i.e., $Y = 1$) would be given by the equation 1 according to Hosmer et al. (2013):

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

The coefficients of the logistic regression model are $\beta = \beta_0, \beta_1, \beta_2, \beta_3, \dots, \beta_n$, which can be determined through methods based on the maximum likelihood methodology (Geng and Sakhanenko 2015). In this analysis, the criterion of statistical significance (p-value) was adopted. For a risk variable to remain in the multivariate logistic regression model, statistical significance was set at 0.05 (Hosmer et al. 2013).

3.3 Calibration and validation of the predictive model

The calibration of the fitted model was evaluated by comparing the actual mud data from the mine with the data obtained from the model based on the value of a cutoff probability. The cutoff probability allows the drawpoints to be ranked on one of the response values (i.e., 1 or 0) using different probability levels. The cutoff probability is defined as the minimum probability value for a drawpoint to be classified as mud; therefore, drawpoints with a probability value greater than the cut-off value were classified as having mud entry. An algorithm was created to obtain a probability value that delivers the most adjusted predictive models, using the variables that were ranked as significant to determine wet muck entry.

With the results of the cutoff probability, a contingency table (Table 5) was built that allowed the calculation of four possible outcomes. For example, if the actual value is positive and is classified as positive, then it is counted as a true positive (TP); otherwise, it is counted as a false negative (FN). The symbology used in the confusion matrix is as follows (Witten et al. 2017):

Table 5 Confusion matrix or contingency table

Confusion matrix		**Prediction**	
		Positives	Negatives
Real	Positives	True Positives (TP)	False Negatives (FN)
	Negatives	False Positives (FP)	True Negatives (TN)

To evaluate the contingency table, the cutoff probability allows three main performance KPIs to be calculated, with the aim of maximizing these leading indicators described by Witten et al. (2017):

$$\text{Sensibility} = TPR = \frac{TP}{TP+FN} * 100 \tag{2}$$

$$\text{Specificity} = TFR = \frac{TN}{TN+FP} * 100 \tag{3}$$

$$\text{Accuracy} \ = \frac{TP+TN}{TP+TN+FP+FN} * 100 \tag{4}$$

Where:

- Sensitivity is the ability to predict mud entry (or the true positive rate).
- Specificity is the ability to predict non-mud entry (or false positive rate).
- Accuracy is the ability to predict mud and non-mud entry.

After calibrating the predictive model, validation of the cutoff probability was performed by comparing actual mine data and data predicted by the model with respect to ore tonnage mined prior to wet muck entry. This stage aims to minimize the mined ore tonnage error, which is defined as the difference between the actual and modeled mined ore tonnage. The validity of the predictive model is graphically represented in a scatter plot, where the correlation between the modeled ore tonnage extracted (Y-Axis, Vertical) and the ore tonnage extracted from the mine data (X-Axis, Horizontal) is observed. In addition, a heat map was presented for the tonnage error on which the points with the greatest error can be observed. The calibrated model is validated if the defined cutoff probability results in a scatterplot with a high degree of correlation between the model and mine data and if the error distribution is close to zero. The evaluation of the model follows the logic shown in Figure 5.

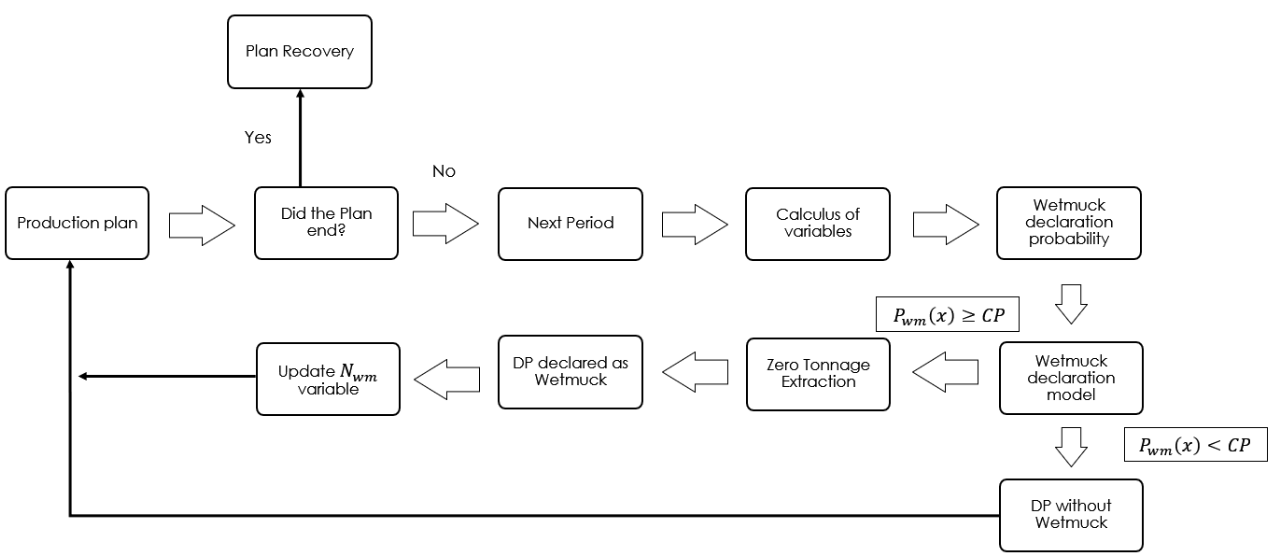

Figure 5 **Schematic diagram of the algorithm used to calibrate the wet muck entry risk model, based on a monthly estimate of wet muck entry, modified from (Castro et al. 2018). Nwm represents the number of drawpoints in the neighborhood with mud**

4 Result and Discussion

4.1 Univariate Analysis

Univariate analysis was performed for 16 critical variables, of which only 11 were statistically significant (p-value $\leqslant$ 0.1). Table 6 shows a summary associated with the metrics obtained in this analysis. In particular, the variables Extraction Ratio, Historical Mud Sectors, and DP Neighbor wet muck are those with the highest Odds Ratio values. Firstly, if the Extraction Ratio increases by 50%, the probability of wet muck entry into a DP would increase by 57%. Secondly, if the Historical Mud Sectors variable is 1 or if a drawpoint is within the Historical Mud Sectors, the probability that mud enters the DP increases by 112%. Finally, if the DP has 1 DP Neighbor with wet muck, the probability that a mud entry will occur rises to 33%. The rest of the variables have a lower degree of statistical association with wet muck entry due to the low values of the Chi-squared test and the Odds Ratio.

Table 6 **Risk variables and their correlation with wet muck entry, ordered by statistical significance (p-value)**

Variable	Coefficient	Chi-squared test (χ^2)	Odds Ratio	Statistical significance (p value)
Height of draw	0.004	361.34	1.004	<0.001
Extraction Ratio	0.898	405.56	2.456	<0.001
Primary rock extracted in DP	-0.029	621.56	0.972	<0.001
Secondary rock extracted in DP	0.032	827.29	1.033	<0.001
DP Neighbor with wet muck	0.286	167.69	1.331	<0.001
Historical Mud Sectors	0.753	64.59	2.124	<0.001
Broken material extracted in DP	0.010	22.08	1.010	<0.001
Annual precipitation	0.001	23.11	1.001	<0.001
Semi-annual precipitation	0.000	9.80	1.000	0.001
D50	0.020	21.09	1.020	0.002
Distance to the surface	0.001	4.12	1.001	0.042
Precipitation at 90 days	0.000	3.68	1.000	0.051
Average water flow rate	-0.001	1.73	0.999	0.203

Precipitation at 60 days	<0.001	0.37	1.000	0.542
Precipitation at 30 days	<0.001	0.08	1.000	0.781
Talus material extracted in DP	-150.150	46.42	0.000	0.953

The above analysis indicates that mud inflow generally occurs under conditions of over-extraction (with high extraction ratio) for those drawpoints located below a Historical Mud Sector and with DP Neighboring wet muck. Therefore, as a preliminary conclusion based on the univariate analysis, the daily tonnage extracted should be taken into account during the long-term planning process considering the areas where there is wet muck. This analysis was useful to identify the main variables related to wet muck entry. However, it does not consider the correlation between the variables, which is evaluated in the multivariate analysis.

4.2 Multivariate Analysis

In the Multivariate Analysis, more than 30 mud entry models were analyzed. As an example in Table 7, fifteen models are shown, of which model Nº 15 was the one that gave the best results. Although the univariate analysis showed that the variables of Average water flow rate, Talus material extracted in DP, and Precipitation at 30, 60 and 90 days were not statistically significant, they were also included in the analysis. In this way it was verified that these variables were not contributing to the models.

Table 7 Summary of Models made for the Reno Basin

Variable \ Models	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Height of draw											X			X	
Extraction Ratio	X	X	X	X	X	X	X	X	X	X		X	X		X
Primary rock extracted in DP												X			
Secondary rock extracted in DP											X			X	
DP Neighbour wet muck	X	X	X	X	X						X		X	X	
Historical Mud Sectors	X	X	X	X	X	X						X			
Broken material extracted in DP						X	X	X	X	X	X			X	X
Annual precipitation					X										X
Semi-annual precipitation				X						X				X	
D50	X	X	X	X	X	X	X	X	X	X		X			X
Distance to the surface									X						
Precipitation at 90 days			X								X				

Average water flow rate			X
Precipitation at 60 days	X	X	X
Precipitation at 30 days	X	X	
Talus material extracted in DP			X

Table 8 below shows the results of the best wet mud input model for the Reno Basin, which is represented by the following formula:

$$P_{wm}(x) = \frac{e^{-1.768+0.214ER+0.031BM-2.104d50+0.0005AP}}{1+e^{-1.768+0.214ER+0.031BM-2.104d50+0.0005AP}} \quad (5)$$

Where:

$P_{wm}(x)$: Indicates the probability of wet muck entry, given a CP (Cutoff Probability)

ER: Extraction Ratio [%], defined as the ratio between the height of draw (HOD) and the in-situ primary rock height

BM: Broken material extracted in DP [%]

D50: d50 fragmentation [m]

AP: Annual Precipitation [mm]

Table 8: Wet muck entry model for the Reno Basin

Variable	Coefficient	Odds Ratio	Description
Extraction Ratio [%]	0.214	1.239	A 50% increase in Extraction ratio increases wet muck entry probability by 11%.
Broken material extracted in DP [%]	0.031	1.031	An 11% increase in the Percentage of Broken material extracted in the DP increases wet muck entry probability by 59%.
d50 fragmentation [m]	-2.104	0.122	A decrease in fragmentation size d50 of -0.05[m] in DP increases wet muck entry probability by 11%.
Annual Precipitation [mm]	0.0005	1.000	An increase of 600 [mm] in Annual Precipitation [mm] increases wet muck entry probability by 35%.
Constant	-1.768	-	-

4.3 Calibration and Validation of the Reno Basin Model

In the calibration stage, several cutoff probabilities were tested to build contingency tables, with the aim of finding a multivariable predictive model that would maximize the performance KPIs of the model. After evaluating several cutoff probabilities, the optimal cutoff value to correctly identify mud entry was 0.7725. The modeled wet muck entry is presented in Figure 6. In this, the black polygon area is the real wet muck observed at August 2021, date on which the main performance KPIs are calculated.

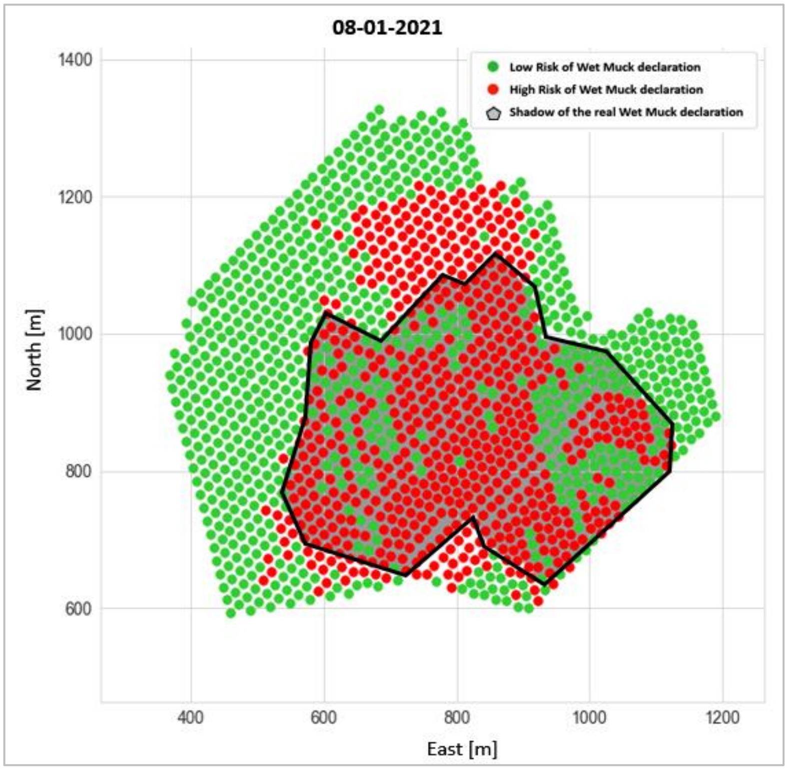

Figure 6 Wet muck entry modeled in the Reno Basin for August 2021. In red are the DPs with high wet muck entry risk and in green the DPs with low wet muck entry risk

The model obtained the following results for the main performance KPIs:

- True Positive Rate of 73%

$$TPR = \frac{TP}{TP+FN} = \frac{337}{337+125} = 73\% \tag{6}$$

- True Negative Rate of 70%

$$TNR = \frac{TN}{TN+FP} = \frac{655}{655+278} = 70\% \tag{7}$$

- Model accuracy of 71%

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{337+655}{337+655+278+125} = 71\% \tag{8}$$

Continuing with the model results for the Reno Basin, the average tonnage per drawpoint for the Reno Basin is approximately 162kt, and the average tonnage error was -16.4kt (10% error) with a deviation of ±6.5kt. The comparison between the real and modeled wet muck entry is represented in the dispersion diagram of Figure 7, an acceptable adjustable R^2 of 0.72 was obtained.

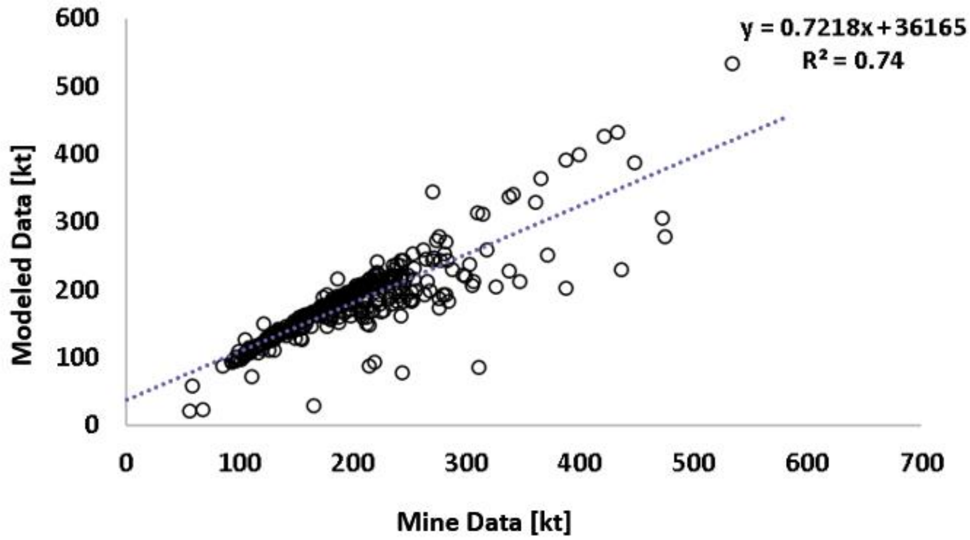

Figure 7 Dispersion plot between the mine tonnage data and the modeled

4.4 Application of the Reno Basin Model

Once the model was calibrated, it was used to evaluate the future plan of the Reno Basin from September 2021 to June 2037 (Figure 8). The Plan contemplates a total of 53.1 planned tons, considering the Dacita and Reservas Norte sector. FlowSim software was used to estimate the flow variables such as: the percentage of broken material and the D50 fragmentation. On the other hand, to construct the annual precipitation variable, an annual precipitation variation of -5.1% was obtained, estimated by the Center for Climate and Resilience Research (CR2.cl) from an extensive database. In addition, actual data from the last 5 years (2017 -2021) were used to predict through June 2037 the estimated rainfall that would occur applying the annual variation of 5.1%. The annual precipitation variable obtained based on this information is represented in Figure 9:

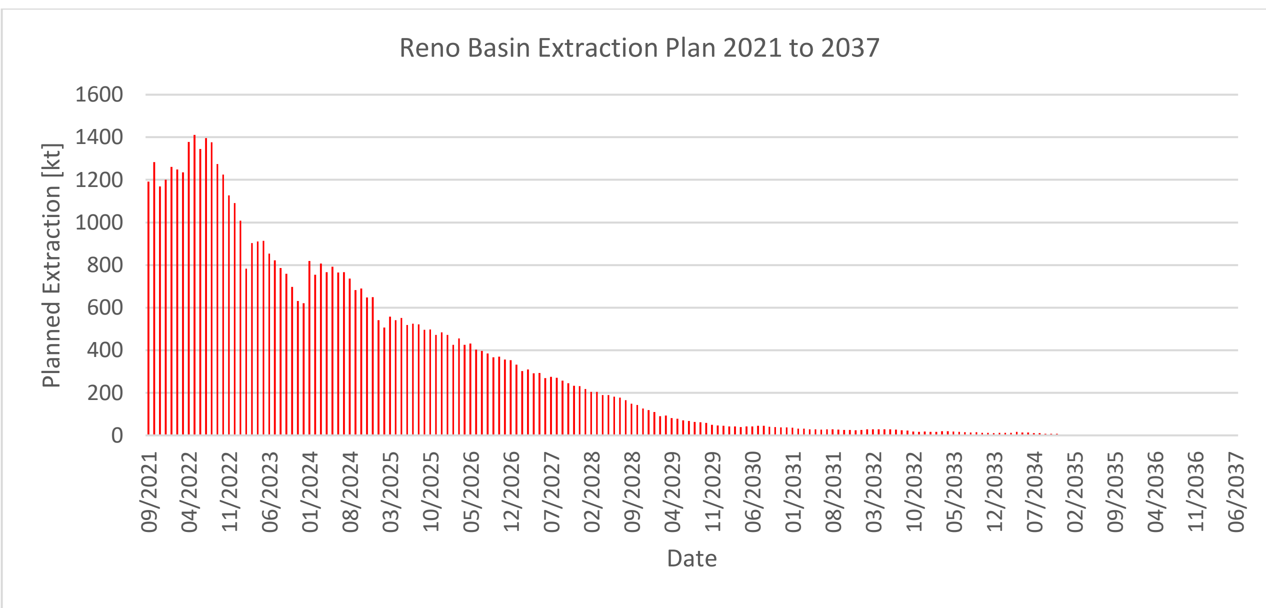

Figure 8 Long-term mining planning for the Reno Basin from September 2021 to June 2037

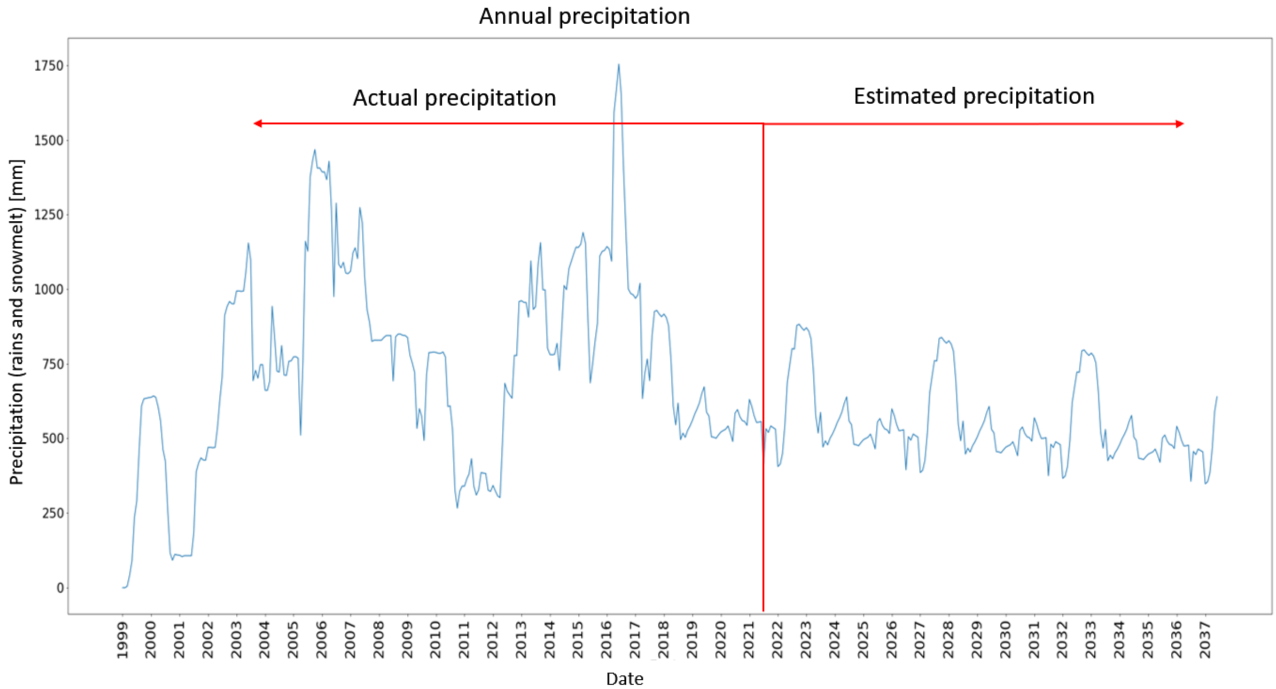

Figure 9 Actual Annual precipitation until 2021. Estimated Precipitation from 2021 onwards constructed from data based on CR2.cl information

Finally, Figure 10 and Table 8 show the results obtained for the application of the Reno-Dacite Sector until the year 2037. From 2021 to 2037, 267 drawpoints were modeled to have wet muck entry (approximately 20% of the total planned extraction). This indicates a total of 42.3 M dry tons can be expected, representing approximately 80% of the planned extraction.

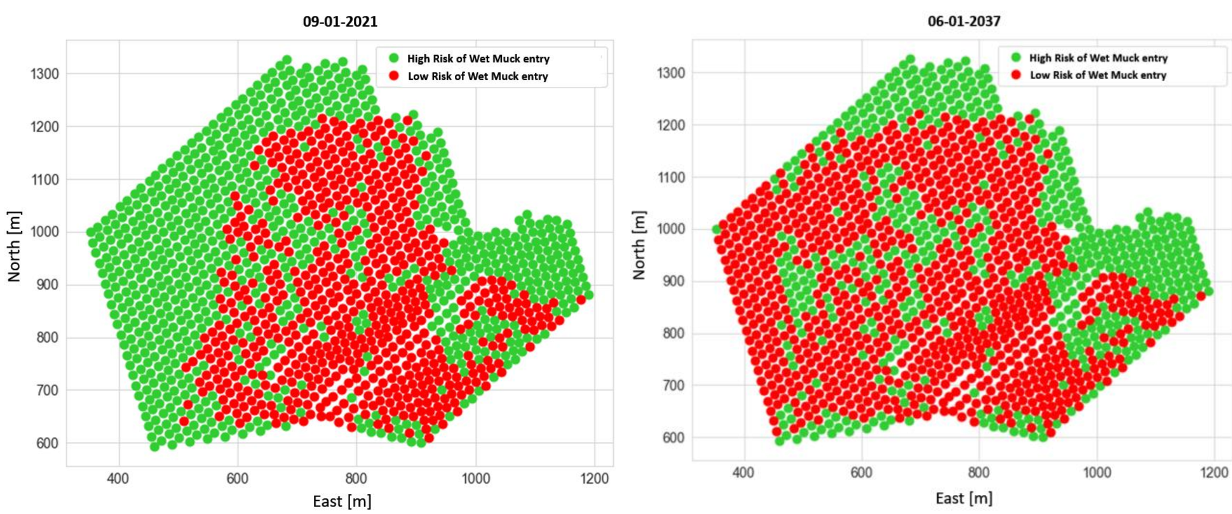

Figure 10 Application of the Reno Basin Model, for the initial period: September 2021 and final period: June 2037

Table 8Reno Basin 2037 plan dry and wet tons result

Parameters	Values	Percentage
Number of DP with wet muck entry	267	63%
Plan tons [Mt]	53.1	100%
Dry tons [Mt]	42.3	80%
Wet tons [Mt]	10.8	20%
Average height of draw[m]	183	-
Average extraction ratio [%]	131	-

In Figure 11, the extraction plan is shown considering the results of the application of the Reno basin model. According to our models, wet muck enters the plan from the first month and continues gradually decreasing until 2030, with approximately 50% entering in 2025.

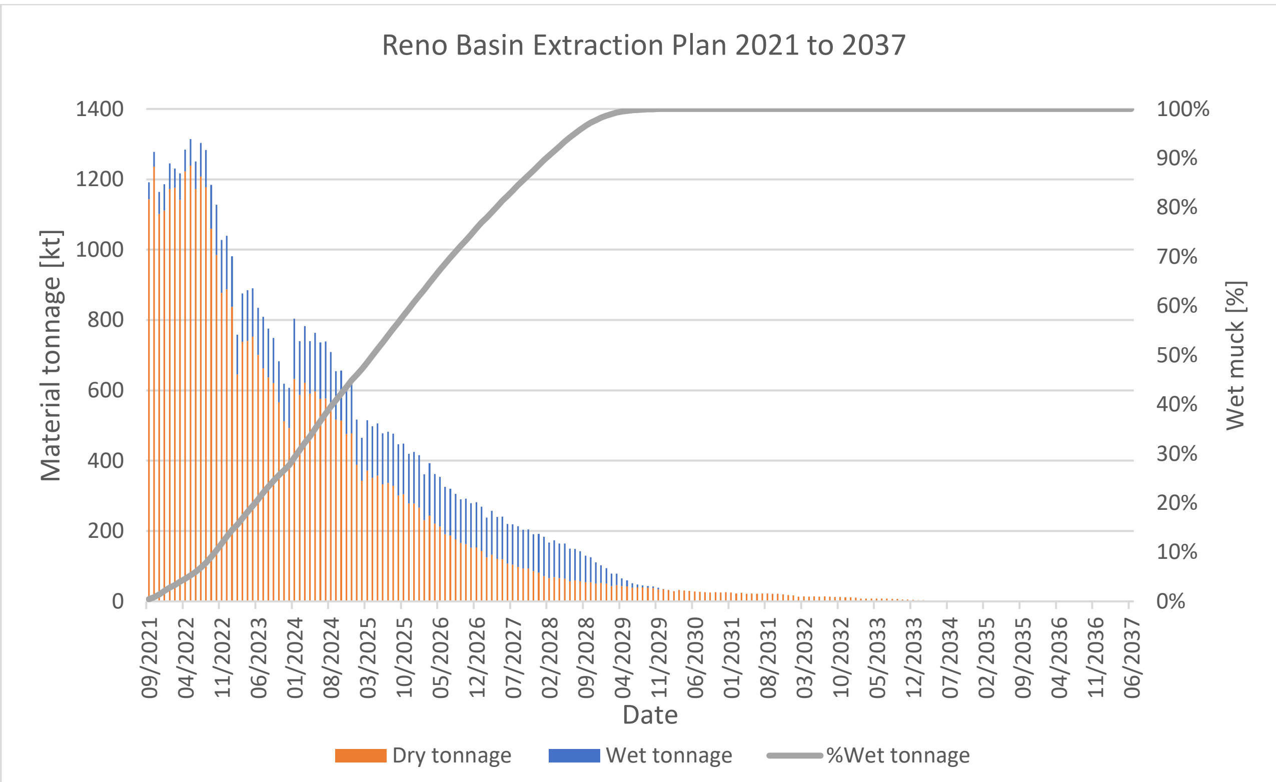

Figure 11 Results of the application of the Reno Basin model, considering dry and wet tons

5 Conclusions

In this study, the quantification of wet muck entry risk for the long-term evaluation and planning for the El Teniente Reno Basin was analyzed and evaluated. Multivariate logistic regression was used, which incorporated variables associated with extraction, such as the extraction ratio. One of its advantages is the applicability of this variable to other sectors. Variables were also added associated with fragmentation such as D50 and the lithology present in the extraction as the percentage of Broken material at the drawpoint, which were simulated with the FlowSim software and calibrated with mine data. In addition, a variable directly related to water — the annual precipitation variable — was considered, which is one of the main factors that generates wet muck entry. The best calibrated model incorporated the aforementioned critical risk variables, achieving an acceptable accuracy of 71% for the final date in August 2021. This precision is accompanied by the low average tonnage error for PE -16.4 kt (10% of the average total per PE), generating a wet muck entry risk model with conservative prediction qualities, which generates confidence when carrying out long-term planning. The extensive data that was included in the models (from 1999 to 2021) has to be considered in the same way. By applying the Reno Basin model, it was determined that the dry tons correspond to 80% of the Plan with a value of 42.3 Mt and a HOD of 183 m. As shown, wet muck enters from the first month in a limited way and is expected to reaching 20% of the Plan by the year 2030. This information can be used to plan safer extraction using autonomous vehicles in those places most likely to have wet muck entry or use other strategies to mitigate the risks involved in the expected hazards of wet muck.

This predictive model successfully determines zones prone to wet muck entry and, as demonstrated, can be used to evaluate long-term plans in the same Reno Basin of the El Teniente Division contributing to planning and decision-making that can minimize the risks caused by wet muck entry. Furthermore, the models developed here could be applied to sectors below the currently modeled sectors in the future.

3.2 Paper 2: Wet muck entry model at El Teniente for long-term planning – Study case: North, Center and South basin.

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Abstract

Wet muck is a problem in underground mines due to the consequences it brings to the safety of workers, equipment, mining infrastructure, drawpoints, production drifts, and productive sectors generating a loss in reserves. The wet muck phenomena are associated with a large quantity of fine materials and moisture present in drawpoints. This study presents an analysis and development of a mathematical model to estimate wet muck entry for long-term planning applications at El Teniente. Four basins of El Teniente were included in the study of wet muck control: North, Center, South, and Reno. Each basin has mines with different characteristics in each exploitation sector. Consequently, models were built for each of the basins to represent its distinct reality. In particular, the results include models of the North, Center, and South basins. The models have been imbedded in a machine-learning software that estimates hazards associated with the extraction process for underground mines. To understand the phenomenon were investigated several variables were associated with historical extraction as extraction ratio and HOD, amount of water entering the cave, season of the year, presence of mud in neighboring drawpoints or sectors that have been closed due to wet muck above, and changes in surface or depressions. Also, this study includes granular flow variables and lithologies. Also, the fragmentation has been included and estimated with a granular flow simulator, the information was validated and calibrated with data of El Teniente mine. Results indicate that the classification models can reproduce the phenomenon with an acceptable precision between 69% and 75% and an average tonnage error per drawpoint of 6 to 15%. These results have been useful for long-term planning at El Teniente mine to predict wet muck entry and define when and where autonomous LHD may be required for the extraction of wet muck in the future.

Keywords: *draw control, geotechnical hazards, mine planning, mudrush, underground mining, wet muck.*

1 Introduction

Block caving is a high productive and low operational cost, underground method (Hartman & Mutmansky, 2002; Brown, 2007; Araneda, 2020). However, there are different risk such as wet muck entry, which can cause serious accidents and affecting workers, mining infrastructure and equipment. Additionally, wet muck entry can occasion excessive dilution, slow production rates, loss of reserves and even partial or permanent closure of mining operations (Butcher, et al, 2000; Heslop, 2000; Syaifullah, 2006; Butcher, et al, 2005; Jakubec & Clayton, 2012; Navia et al., 2014; Ginting & Pascoe, 2020).

Wet muck entry in caving mines is produced by fine materials less than 2 mm in size (Call & Nicholas Inc. 1998), that accumulate under a variety of conditions, for example: filtration of tailings, aquifers, weather conditions such as snow and rain, mixing with aqueous substances. Therefore, as a cave matures, more fine materials are generated within the cave (Laubscher, 2000). Fine materials have been shown to rapidly percolate down through the draw columns, accumulating in drawbells and filling the voids between larger blocks (Pierce, 2010). When a significant amount of fine material is accumulated, cushioning may occur, where larger blocks are found to be floating in a matrix of fines (Dorador, 2016). This mixture reaches the drawpoints, resulting in water filtration and possibly mud events such as landslides, spills, and mud rushes (Ginting & Pascoe, 2020). In fact, the wet muck intrusion has been recorded in various underground mines around the world, such as El Teniente in Chile (Ferrada, 2011), IOZ and DOZ in Indonesia, Ekati in Canada, (Edgar et al., 2020; Hubert, et al., 2000; Ginting and Pascoe, 2020; Jakubec & Woodward, 2020; Widijanto, et al., 2012).

In some Block caving mines some of the control and mitigation tools used to manage wet muck entry risk are (Butcher et al., 2005; Ginting & Pascoe, 2020, Salazar et al., 2016; Castro et al., 2018; Saepulloh et al., 2022): Drawpoint classification and inspection (Monitoring the extraction column, fragmentation, moisture, rain and critically matrix for the drawpoints). Automate processes (full tele-remotes in high-risk areas). Exclusion zones (tele-remote loading exclusion zones, exclusion zone on back-to-back drawpoint: sister drawpoint on the same drawbell and exclusion zone under sudden inflow of TARP: Trigger Action Response Plans, uses trigger levels for rainfall amounts over set time periods, 25 mm in one hour, 40 mm in two hours or 50 mm in three hours, when the trigger points are exceeded, all underground personnel are evacuated to surface). Drawpoint bunding and stabilization (bund height of 1.5 or 2 m, wall to wall). Draw control (bogging wet muck drawpoints, tele-remote plan, hang-up remediation and uniformity draw). Dewatering (Drainage tunnels and in-pit pump system to ensure no water presented into the underground workings). Training and communication (supervision of drawpoints with qualified personnel)

Different tools are commonly used to quantify the risk, such as the one mentioned above, the critical matrix for drawpoints, which is used taking into account the moisture content (qualitative and quantitative) and the amount of fine material. All this information can help to avoid the closure of drawpoints and the risk of accidents (Samosir, 2008; Edgar, et al., 2020). There are also models that predict wet muck entry, such as the models developed of “El Teniente mine” (DET). These wet muck entry risk models were performed to allow mining plans to be evaluated (Navia et al., 2014; Garcés, et al., 2016; Castro et al., 2018; Navia, 2021; Castro et al., 2022).

The wet muck risk models included variables related to the ore extraction, the season of the year, the distance to surface, the distance to historical sectors with mud, the risk zone associated with surface, the flow of water, the observed moisture, and, the neighbor drawpoint with mud. The accuracy of the models ranges between 74% and 84%, and they consider different time scales and productive sectors (e.g. Diablo Regimiento, Quebrada Blanca, Suapi y Pipa, Esmeralda (Navia, 2021; Garces et al., 2016; Castro et al., 2018; Castro et al., 2022).

Most of these models have been applied for long-term planning; however, some wet muck formation variables such as the secondary fragmentation and the lithology have not been fully investigated. Thus, this study improves the accuracy and robustness of wet mud risk models including these variables. Also, most models use the risk zone variable provided by the DET. However, risk area is related as a variable for comparison of the results of the models (risk areas for the entry of wet manure) and not as a variable that is part of them.

2 Background at El Teniente Mine

2.1 El Teniente Mine

El Teniente Mine (DET), is one of the bigger underground mining operations in the world and currently produces 145ktpd, with a copper grade of 0.88% in 7 Panel Caving mines: Esmeralda, Dacita, Reservas Norte, Diablo Regimiento, Pilar Norte and Pacífico Superior (Cornejo et al. 2020). DET is located 50 km from the city of Rancagua, began to be exploited in 1905 and currently has more than 4,500 km of underground gallery built.

DET has provided mining data by the productive sectors including Pipa Norte (PN), Sur Andes Pipa (SP), Reservas Norte (RN), Dacita (DT), Esmeralda (ES), Diablo Regimiento (DR), among others, from 1999 to 2021 with the aim of analyze wet muck entry in mine. These mines are primarily located below a topographic trough (similar to a topographic depression) around the Pipa Braden, as shown in Figure 1.

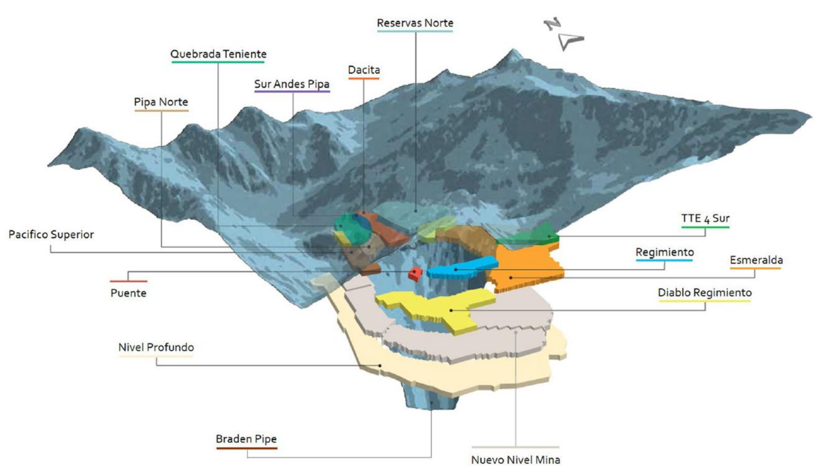

Figure 1: Isometric view of El Teniente Mine (Codelco 2016a, 2016b)

2.2 Wet muck conceptualization at El Teniente Mine

To understand wet muck entry in drawpoints, Butcher et al. (2005) studied the factors required to trigger wet muck entry, these include the holding capacity of water, the presence of possible mud-forming minerals, a disturbance in the ore column, and the mud discharge capacity at a drawpoint. Figure 2 shows schematic representation of the wet muck phenomenon and some of its main variables. Here, the wet muck entry is represented in three stages: Initial Stage, First Drawpoint with wet muck and Drawpoint neighbor with wet muck. In every stage, exist four steps for the wet muck entry at El Teniente Mine, these starts with the water accumulation, later this water infiltrates the mine through preferential flows causing the formation of wet muck and reaching the productive sectors. Below is a brief explanation of each of these steps.

Steps for the wet muck entry at El Teniente Mine:

1. **Water accumulation:**
   Mainly generated by precipitation and melting ice.
2. **Preferential flows:**
   Preferential flow paths for fine material and water.
3. **Wet muck formation:**
   Due to the combination of fine material, water and a disturbance (mining or subsidence).
4. **Production sector:**
   As a consequence of the extraction, the wet muck enters the drawpoints, arriving first at the drawpoint with the highest extraction rate or extraction ratio.

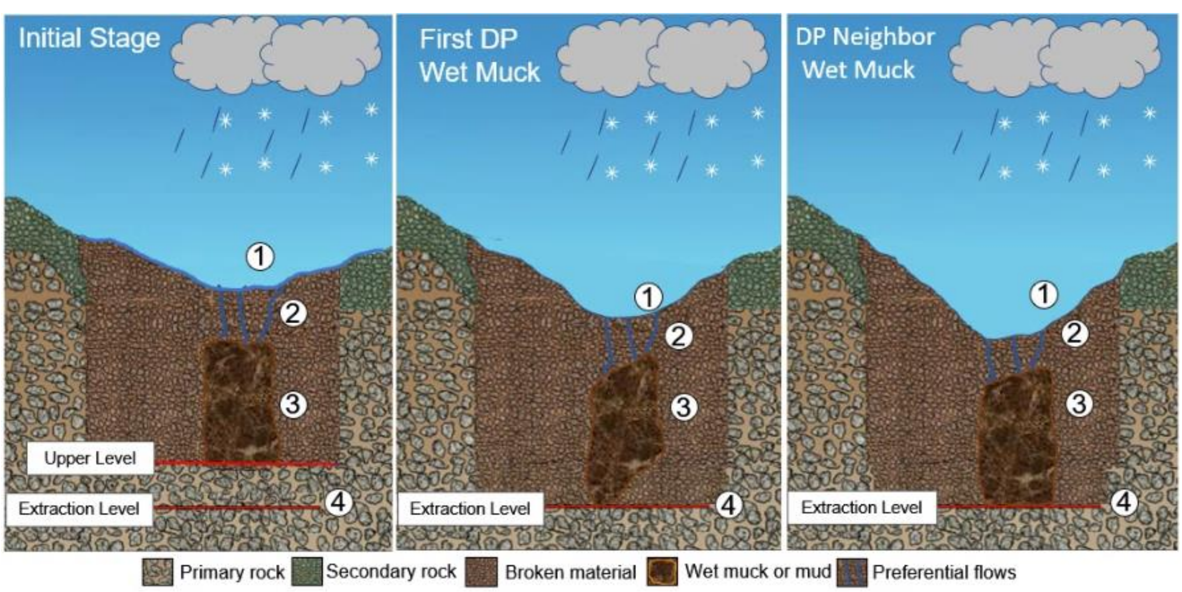

Figure 2: Conceptual map of wet muck phenomenon in the “El Teniente” mine

2.3 Basins of the El Teniente Mine

El Teniente mine has a subsidence crater, which can be divided into four basins: North, Reno, Center, and South, as shown in Figure 3. In this study, mud entry models were constructed for each of basins, using the mine database summary in Table 1.

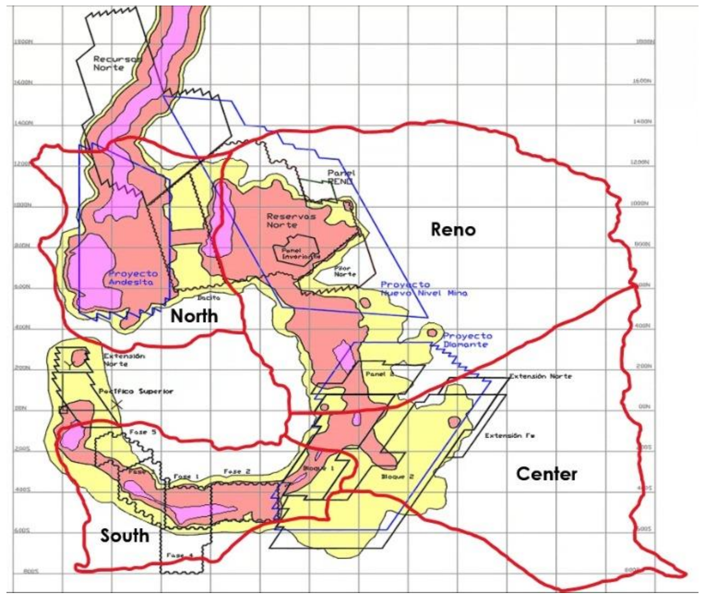

Figure 3: Plan view of the El Teniente crater of subsidence divided into four basins (North, Reno, Center, and South).

Table 1: Classification of mud entry models according to the basin, the base mine, and the possible mine of application.

Models / Basins	Base Mine	Possible Application Mines.
North	Pipa Norte - Sur Andes Pipa	Recursos Norte Andesita
Reno	Reservas Norte - Dacita	Andes Norte Panel Invariante
Center	Esmeralda Bloque 1 y 2 - Esmeralda Convencional	Diamante
South	Diablo Regimiento	Pacífico Superior Pacífico Central

2.4 Study Area

This article presents the study of wet muck entry in the North, Center, and South Basin. North Basin includes the productive sectors of Pipa Norte (PN) and Sur Andes Pipa (SP), Center Basin corresponds to the sectors of Esmeralda Bloque 1 y 2 (B1 & B2), and Esmeralda Convencional (ES) and the South Basin the productive sector is Diablo Regimiento (DR). The information analyzed contains the historical extraction for each drawpoints (DP) from January 1999 to August 2021, for the three basins. Table 2 shows the wet muck reported for each basin.

Table 2: Wet muck declarations in North, Reno, Center and South Basins

Basin	DP analyzed	DP declared wet muck	Wet muck in productive sectors
North	361	114	- 63 DP declared in Pipa Norte - 51 DP declared in Sur Andes Pipa
Center	1330	229	- 153 DP declared in Esmeralda Convencional - 74 DP declared in B1 - 2 DP declared in B2
South	590	194	- 194 DP declared in Diablo Regimiento

Figure 4 shows the wet muck reported. This database was used to study the independent correlation that each variable has with the mud entry and to select the critical variables. Here, a univariate analysis methodology of logistic regression was used. Subsequently, a multivariate analysis was performed, dividing the database into a training database used to generate the equations of the logistic regression model and another to analyze the predictive performance of the model.

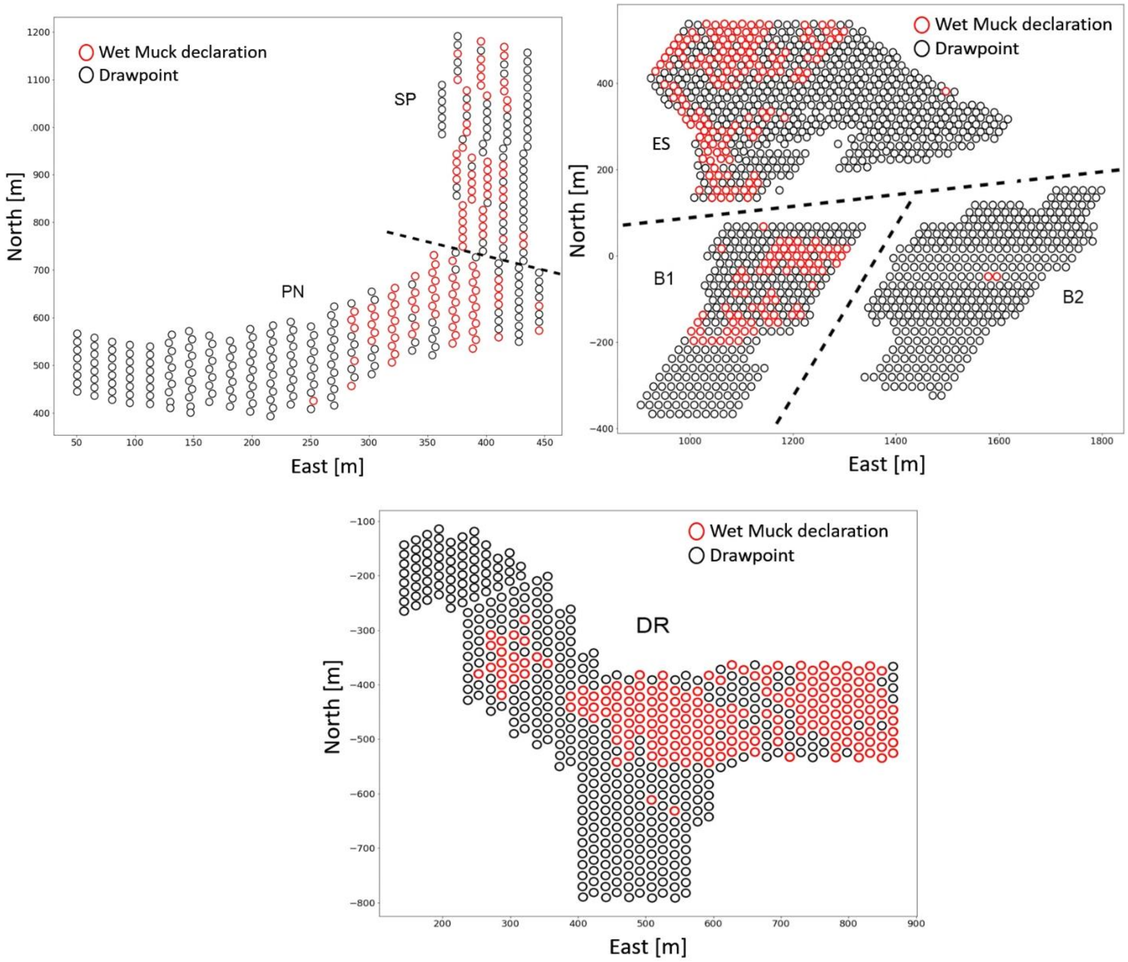

Figure 4: Wet muck declarations from the Sur Andes Pipa (SP), Pipa Norte (PN), Esmeralda Convencional (ES), Esmeralda Bloque 1 (B1) & Bloque 2 (B2) and Diablo Regimiento (DR) sector.

3 Methodology

In this work, an analysis of the critical variables was carried out to determine the wet muck entry at a drawpoint using logistic regression (Hosmer et al. 2013) as a tool to help long-term planning. This tool has shown good result to study mud entry problem (Navia et al., 2014; Garcés et al., 2016; Castro et al., 2018; Navia, 2021; Castro et al., 2022). First, a univariate analysis was performed to find the relationship between variables and mud entry occurrence. Then, a predictive model was created to calculate the probability of wet muck entry (P_{wm}) by performing a multivariate analysis. One of the advantages of the current methodology is that the variables associated with ore extraction were incorporated, such as the lithology present in the extraction, the size of fragmentation, states of the drawpoint, and meteorological and topographic conditions, these variables were incorporated in the modeling of wet muck for each drawpoint. From this type of information, risk variables were developed that can explain the wet muck entry, such as those mentioned and described in Table 3.

Table 3: Summary of selected risk variables based on physical properties of mud inlet and mine practice

Information Group	Variables	Description
Historical extraction	Height of draw (HOD) [m]	Indicates the permeability properties of the unexcavated materials that make up the ore column (composed of primary and secondary rock), which controls water movement and infiltration to drawpoints.
	Extraction Ratio (ER) [%]	Represents both the increase in rock permeability promoted by subsidence propagation and the formation of fine material due to secondary breakage through the ore column. A higher Extraction Ratio increases the probability of wet muck entry.
Lithology	Primary extracted in DP (PRIM) [%]	Represents the percentage extracted from the primary rock. This competent rock represents the impermeable layer; therefore, the higher the percentage of primary rock extracted, the lower the probability of wet muck entry.
	Secondary extracted in DP (SEC) [%]	Represents the percentage extracted from the secondary rock. This rock is less competent than the primary rock and together with the broken, represents the permeable layer; therefore, the higher the percentage of secondary extracted, the greater the probability of wet muck entry.
	Broken material extracted in DP (BM) [%]	Represents the same as the percentage of secondary rock because the material is fragmented. Similarly, the higher the percentage of broken material extracted, the greater the probability of wet muck entry.
	Talus material extracted in DP (TAL) [%]	Represents fill material that occurs due to the effect of subsidence in the crater (rilling effect). This is a permeable material; therefore, the higher the percentage of talus extracted, the greater the probability of wet muck entry.
Fragmentation	d_{50} [m]	Represents the rock fragmentation present in the extraction. When the size d_{50} decreases, the probability of wet muck entry increases due to the increase in the amount of fine material in the DP.
Water	Average water flow rate (Q) [L/s]	Long-term representation of the water infiltration expected to be observed in the DP during extraction; therefore, if the water flow increases, the probability of wet muck entry also increases.
	Precipitation at 30, 60, 90 days, semi-annual and annual (P30, P60, P90,Ps,Pa) [mm]	Precipitation measurements at various time intervals. An increase in precipitation indicates that the probability of wet muck entry increases.
	Seasons: Summer, Autumn, Winter and Spring	Correspond to the season of the year in which a DP is found. This is a categorical variable for which if the DP is found in the season of the year, it obtains a value of 1 and 0 otherwise.
Mud	Historical Mud Sectors (HMS)	DP with mud declared in old or superior sectors. This is a categorical variable for which if the DP is under a sector with mud, it obtains a value of 1 and 0 otherwise.
	DP Neighbor wet muck (Nwm)	Corresponds to the risk that the mud could spread to the surrounding areas (neighbor drawpoints)

Topography	Distance to surface (DS) [m]	Considers the distance to surface water sources (snow melt and rainwater)

3.1 Univariate Logistic Regression Analysis

Wet muck entry risk variables were independently assessed using univariate analysis. The Chi-square Test (χ^2) and the Odds Ratio (OR) were applied to determine the relative relationship between the independent variables and the mud entry reports (dependent or interest variable).

The Odds Ratio determines how likely it is that mud enters a drawpoint or not, with x = 1 (presence of mud) and with x = 0 (absence of mud) (Hosmer et al. 2013). For example, if a drawpoint declared to have mud is located below the risk zone associated with historical mud sectors, then the odds ratio OR = 3 means that the probability of mud entry between the drawpoints located in the risk zone is three times greater than the probability in the drawpoints not located in the risk zone (Castro et al. 2018).

In the univariate analysis, a statistical significance (*p-value*) of 0.1 is used as the critical value to determine whether each independent variable is statistically significant with mud inlet. All the variables that resulted in a significantly less than or equal to 0.1 were included in the multivariate logistic regression analysis.

3.2 Multivariate logistic regression analysis

The correlation between different variables with the occurrence of wet muck entry was tested using multivariable logistic regression, which delineates the association between the dichotomous response variable, Y (the occurrence or not of wet muck entry), and x the collection of variables of risk. 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 probability of the response variable, considering a set of n independent risk variables designated by the vector $x = (x_1, x_2, x_3, \ldots, x_n)$. Therefore, the conditional probability of wet muck entry (i.e., $Y = 1$) would be given by equation (1) according to Hosmer et al. (2013).

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

In equation (1), the coefficients of the logistic regression model are $\beta = \beta_0, \beta_1, \beta_2, \beta_3, \ldots, \beta_n$, which can be determined through methods based on the maximum likelihood methodology (Geng and Sakhanenko 2015). In this analysis, the criterion of statistical significance (*p-value*) was adopted. For a risk variable to remain in the multivariate logistic regression model, statistical significance was set at 0.05 (Hosmer et al. 2013).

3.3 Calibration and validation of the predictive model

The calibration of the fitted model was evaluated by comparing the actual mud data from the mine with the data obtained from the model based on the value of a cutoff probability (CP). The cutoff probability allows the drawpoints to be ranked on one of the response values (i.e., 1 or 0) using different probability levels. The cutoff probability is defined as the minimum probability value for a drawpoint to be classified as mud; therefore, drawpoints with a probability value greater than the cut-off value were classified as having mud entry. An algorithm was created to obtain a probability value that delivers the most adjusted predictive models, using the variables that were ranked as significant to determine wet muck entry.

With the results of the cutoff probability, a contingency table was built that allowed the calculation of four possible outcomes. For example, if the actual value is positive and is classified as positive, then it is counted as a true positive (TP); otherwise, it is counted as a false negative (FN). The symbology used in the confusion matrix is as follows (Witten, et al., 2017):

Table 4: Confusion matrix or contingency table.

Confusion matrix		Prediction	
		Positives	**Negatives**
Real	**Positives**	True Positives (TP)	False Negatives (FN)
	Negatives	False Positives (FP)	True Negatives (TN)

To evaluate the contingency table, the cutoff probability allows three main performance KPIs to be calculated, with the aim of maximizing these leading indicators described by Witten, et al., 2017 (equations 2, 3 and 4),

$$\text{Sensibility} = TPR = \frac{TP}{TP + FN} * 100 \tag{2}$$

$$\text{Specificity} = TFR = \frac{TN}{TN + FP} * 100 \tag{3}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} * 100 \tag{4}$$

where the sensitivity is the ability to predict mud entry (or the true positive rate), the specificity is the ability to predict non-mud entry (or false positive rate), the accuracy is the ability to predict mud and non-mud entry.

After calibrating the predictive model, validation of the cutoff probability was performed by comparing actual mine data and data predicted by the model with respect to ore tonnage mined prior to wet muck entry. This stage aims to minimize the mined ore tonnage error, which is defined as the difference between the actual and modeled mined ore tonnage. The validity of the predictive model is graphically represented in a scatter plot, where the correlation between the modeled ore tonnage extracted (Y-Axis, Vertical) and the ore tonnage extracted from the mine data (X-Axis, Horizontal) is observed. In addition, a heat map was presented for the tonnage error on which the points with the greatest error can be observed. The calibrated model is validated if the defined cutoff probability results in a scatterplot with a high degree of correlation between the model and mine data and if the error distribution is close to zero. The evaluation of the model follows the logic shown in Figure 5.

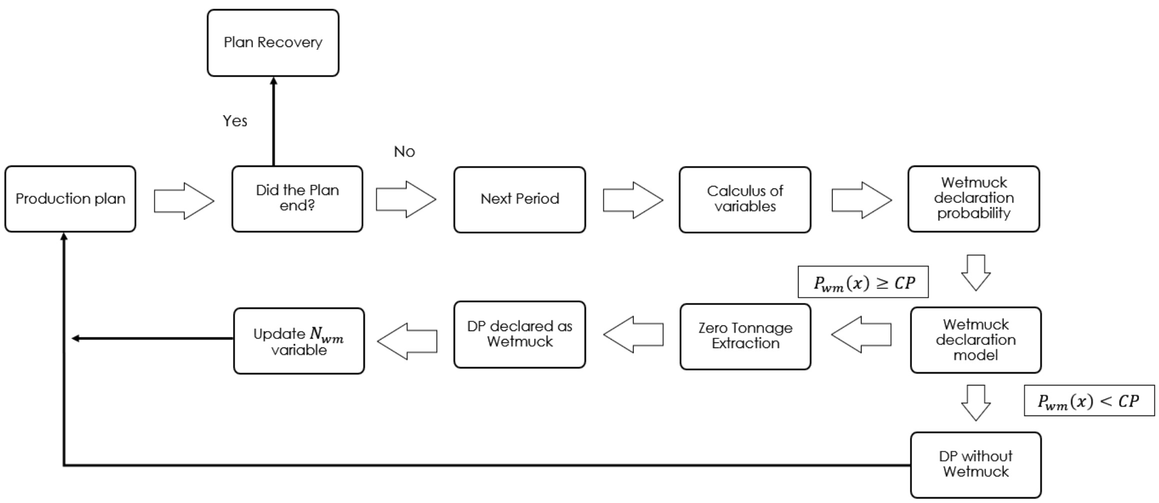

Figure 5: Schematic diagram of the algorithm used to calibrate the wet muck entry risk model, based on a monthly estimate of wet muck entry, (after Castro, et al., 2018). $\boldsymbol{N_{wm}}$ **represents the number of drawpoints in the neighborhood with mud,** $\mathbf{P_{wm}}$ **represents the probability of wet muck entry and CP is the cutoff probability.**

4 Result and Analysis.

4.1 Univariate Analysis

Univariate analysis was performed for the three models, in North basin was analyzed for 24 critical variables, of which only 20 were statistically significant (*p-value* $\leqslant 0.1$), in Center basin 34 critical variables and 21 were statistically significant, and in South basin 33 critical variables and 18 were statistically significant. Table 5, 6 and 7 show a summary associated with the metrics obtained in this analysis. In general, the variables Primary Rock extracted in drawpoint, d_{50}, semi-annual precipitation, broken material extracted in drawpoint, Extraction Ratio, Drawpoint Neighbor with wet muck, Distance to surface, among others. The rest of the variables have a lower degree of statistical association with wet muck entry due to the low values of the Chi-squared test and the Odds Ratio.

The above analysis indicates that mud inflow generally occurs under conditions of over-extraction (with high extraction ratio), with the presence of broken material (with a low d_{50} sizes and no primary rock) at drawpoint for those drawpoints with neighbors with wet muck. Therefore, as a preliminary conclusion based on the univariate analysis, the daily tonnage extracted should be taken into account during the long-term planning process considering the areas where there is wet muck. This analysis was useful to identify the main variables related to wet muck entry. However, it does not consider the correlation between the variables, which is evaluated in the multivariate analysis.

Table 5: Risk variables and their correlation with wet muck entry, ordered by statistical significance (p-value) for North Basin.

Variable	Coefficient	Chi-squared test (χ^2)	Odds Ratio	Statistical significance (p value)
Primary rock extracted in DP [%]	-0.023	83.87	0.977	<0.001
d_{50} [m]	-4.050	68.90	0.017	<0.001
Semi-annual precipitation [mm]	0.002	55.94	1.002	<0.001
DP Neighbor with wet muck	0.315	46.62	1.370	<0.001
Broken material extracted in DP [%]	0.018	44.18	1.018	<0.001
Talus material extracted in DP	0.144	23.06	1.155	<0.001
Extraction Ratio [%]	0.704	32.66	2.022	<0.001
Precipitation at 90 days [mm]	0.002	27.22	1.002	<0.001
Precipitation at 60 days [mm]	1.436	19.70	4.204	<0.001
Secondary rock extracted in DP [%]	0.002	19.90	1.002	<0.001
Winter-Spring	0.012	23.08	1.012	<0.001
Height of draw [m]	0.956	16.47	2.601	<0.001
Summer	0.003	30.88	1.003	<0.001
Winter-Spring-Autumn	1.773	30.88	5.888	<0.001
Spring	-1.773	9.61	0.170	0.001
Annual precipitation [mm]	0.619	7.68	1.857	0.005
Height in-situ [m]	0.001	8.28	1.001	0.006
Winter	-0.007	4.43	0.993	0.031
Precipitation at 30 days [mm]	0.424	3.55	1.528	0.047
Average water flow rate [L/s]	0.002	2.47	1.002	0.090
Winter- Autumn	0.001	1.79	1.001	0.183
Autumn	0.252	0.46	1.287	0.506
Distance to surface [m]	-0.151	0.15	0.860	0.699
Historical Mud Sectors	-0.001	88.46	0.999	0.959

Table 6: Risk variables and their correlation with wet muck entry, ordered by statistical significance (p-value) for Center Basin.

Variable	Coefficient	Chi-squared test (χ^2)	Odds Ratio	Statistical significance (p value)

d_{50} [m]	-3.024	243.01	0.049	<0.001
Broken material extracted in DP [%]	0.023	241.4	1.023	<0.001
Primary rock extracted in DP [%]	-0.023	238.8	0.977	<0.001
Distance to surface [m]	-0.013	188.02	0.987	<0.001
Topographic depression [m]	0.102	162.98	1.107	<0.001
Delta distance to surface [m]	-0.096	158.52	0.908	<0.001
Height of draw [m]	0.003	106.99	1.003	<0.001
Historical Mud Sectors	1.851	105.43	6.366	<0.001
Extraction Ratio [%]	0.376	100.87	1.456	<0.001
DP Neighbor with wet muck	0.317	67.64	1.373	<0.001
Maximum delta of HOD with its neighbors [m]	0.053	49.73	1.054	<0.001
Delta of HOD [m]	0.053	45.75	1.054	<0.001
Annual precipitation [mm]	0.001	39.25	1.001	<0.001
In-situ Height [m]	-0.001	20.82	0.999	<0.001
Average water flow rate [L/s]	0.002	17.24	1.002	<0.001
Semi-annual precipitation [mm]	0.001	11.95	1.001	<0.001
Winter- Autumn	-0.45	11.31	0.638	0.001
Winter	-0.395	5.8	0.674	0.021
Spring	0.318	4.7	1.374	0.027
Summer	0.238	2.64	1.269	0.098
Winter-Spring-Autumn	-0.238	2.64	0.788	0.098
Autumn	-0.248	2.45	0.78	0.126
Depression Zone 5 (100 m)	0.324	1	1.383	0.295
Precipitation at 30 days [mm]	-0.001	0.58	0.999	0.455
Precipitation at 60 days [mm]	0	0.56	1	0.461
Cumulative distance delta to surface [m]	-0.001	0.22	0.999	0.638
Secondary rock extracted in DP [%]	0.004	0.11	1.004	0.732
Cumulative topographic depression [m]	0	0.03	1	0.859
Winter-Spring	-0.014	0.01	0.986	0.914
Precipitation at 90 days [mm]	0	0	1	0.952
Depression Zone 4 (80 m)	-11.203	0.68	0	0.968

Table 7: Risk variables and their correlation with wet muck entry, ordered by statistical significance (p-value) for South Basin.

Variable	**Coefficient**	**Chi-squared test (χ^2)**	**Odds Ratio**	**Statistical significance (p value)**
Broken material extracted in DP [%]	0.026	226.99	1.026	<0.001
Primary rock extracted in DP [%]	-0.026	225.58	0.974	<0.001
Height of draw [m]	0.009	223.97	1.009	<0.001
Extraction Ratio [%]	1.238	203.66	3.449	<0.001
DP Neighbor with wet muck	0.325	106.28	1.384	<0.001
Depression Zone 5 (100 m)	1.681	101.1	5.371	<0.001

Maximum delta of HOD with its neighbors [m]	0.008	76.84	1.008	<0.001
Cumulative distance delta to surface [m]	-0.011	73.04	0.989	<0.001
Cumulative topographic depression [m]	0.011	72.61	1.011	<0.001
Delta HOD [m]	0.009	69.43	1.009	<0.001
Distance to surface [m]	-0.01	65.21	0.99	<0.001
d_{50} [m]	-1.792	54.59	0.167	<0.001
In-situ Height [m]	-0.003	51.66	0.997	<0.001
Historical Mud Sectors	0.98	38.82	2.664	<0.001
Depression Zone 4 (80 m)	0.896	38.38	2.45	<0.001
Depression Zone 3 (60 m)	0.397	4.69	1.487	0.024
Topographic depression [m]	0.014	3.82	1.014	0.041
Average water flow rate [L/s]	-0.001	4.75	0.999	0.049
Spring	-0.228	1.68	0.796	0.204
Winter	0.172	1.13	1.188	0.281
Precipitation at 90 days [mm]	0	0.91	1	0.332
Winter-Autumn	0.125	0.75	1.133	0.386
Delta distance to surface [m]	-0.004	0.36	0.996	0.543
Annual precipitation [mm]	0	0.19	1	0.659
Secondary rock extracted in DP [%]	-0.013	0.23	0.987	0.662
Precipitation at 60 days [mm]	0	0.15	1	0.702
Precipitation at 30 days [mm]	0	0.08	1	0.773
Summer	0.041	0.06	1.042	0.801
Winter-Spring-Autumn	-0.041	0.06	0.96	0.801
Winter-Spring	-0.022	0.02	0.978	0.879
Depression Zone 2	0.028	0.01	1.028	0.919
Autumn	-0.013	0.01	0.987	0.938
Semi-annual precipitation [mm]	0	0.002	1	0.965

4.2 Multivariate Analysis

In the Multivariate Analysis, more than 30 mud entry models were analyzed for each basin. As example, tables 8, 9 and 10 show the variables considered for each model, fifteen models for each basin, of which model Nº 15 given the best results.

Table 8: Summary of Models made for the North Basin.

	Models														
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Primary rock extracted in DP [%]		**X**					**X**								
Semi-annual precipitation [mm]			**X**	**X**								**X**			
DP Neighbor wet muck	**X**	**X**	**X**	**X**			**X**	**X**	**X**	**X**		**X**	**X**	**X**	**X**
Broken material extracted in DP [%]	**X**				**X**						**X**		**X**	**X**	**X**
Talus material extracted in DP [%]	**X**			**X**											
d_{50} [m]					**X**	**X**				**X**	**X**		**X**	**X**	
Extraction Ratio [%]						**X**	**X**	**X**	**X**	**X**		**X**			**X**
Secondary rock extracted in DP [%]			**X**		**X**	**X**		**X**		**X**	**X**	**X**	**X**	**X**	**X**

Winter-Autumn	**X**							**X**				**X**			**X**
Height of draw [m]	**X**	**X**	**X**	**X**	**X**								**X**	**X**	
Winter-Spring-Autumn									**X**	**X**					
Annual precipitation [mm]		**X**							**X**						
Distance to surface [m]			**X**												
Precipitation at 30 days [mm]						**X**	**X**				**X**			**X**	**X**
Historical Mud Sectors				**X**											

Table 9: Summary of Models made for the Center Basin.

	Models														
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Topographic depression [m]								**X**		**X**			**X**		
Delta Distance to Surface [m]												**X**			
Broken material extracted in DP [%]	**X**	**X**	**X**	**X**		**X**		**X**				**X**	**X**	**X**	**X**
Primary rock extracted in DP [%]		**X**					**X**								
Height of draw [m]		**X**	**X**							**X**		**X**			
Extraction Ratio [%]	**X**			**X**	**X**	**X**	**X**	**X**	**X**		**X**		**X**	**X**	**X**
d_{50} [m]				**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**			**X**	**X**
Distance to surface [m]	**X**				**X**	**X**			**X**		**X**			**X**	**X**
Delta HOD [m]											**X**				
DP Neighbor wet muck	**X**	**X**				**X**	**X**	**X**				**X**	**X**		
Historical Mud Sectors						**X**			**X**		**X**			**X**	
Annual precipitation [mm]				**X**	**X**	**X**	**X**	**X**	**X**			**X**		**X**	**X**
Average water flow rate [L/s]													**X**		
In-situ Height [m]										**X**					
Semi-annual precipitation [mm]		**X**								**X**					
Winter-Autumn		**X**													
Precipitation at 30 days [mm]			**X**												
Secondary rock extracted in DP [%]			**X**												

Table 10: Summary of Models made for the South Basin.

	Models														
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Extraction Ratio [%]	**X**	**X**					**X**	**X**	**X**	**X**	**X**		**X**	**X**	**X**
Height of draw [m]			**X**	**X**	**X**	**X**						**X**			**X**
Broken material extracted in DP [%]	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**		**X**	**X**		**X**		**X**
Primary rock extracted in DP [%]		**X**		**X**	**X**	**X**	**X**		**X**						
DP Neighbor wet muck									**X**	**X**	**X**	**X**			
Delta Distance to Surface [m]						**X**							**X**	**X**	
Cumulative topographic depression [m]							**X**								
Depression Zone 5 (100 m)				**X**	**X**					**X**	**X**				
Distance to Surface [m]		**X**	**X**					**X**							
d_{50} [m]								**X**				**X**		**X**	
In-situ height [m]			**X**									**X**			
Depression Zone 4 (80 m)												**X**			
Historical Mud Sectors		**X**											**X**		
Topographic depression [m]	**X**														

Average water flow rate [L/s]					**X**						**X**				
Annual precipitation [mm]	**X**	**X**	**X**	**X**		**X**	**X**	**X**				**X**	**X**	**X**	**X**
Precipitation at 90 days [mm]									**X**	**X**					

Table 11, 12 and 13 below show the results of the best wet mud input model for the North, Center and South basin, which is represented by the equations 5, 6 and 7.

$$North\ Basin: P_{wm}(x) = \frac{e^{-3.282+0.178ER+0.014BM+0.01SR+0.262Nwm+1.333WS+0.001P30}}{1+e^{-3.282+0.178ER+0.014BM+0.01SR+0.262Nwm+1.333WS+0.001P30}} \quad (5)$$

$$Center\ Basin: P_{wm}(x) = \frac{e^{8.07+0.144ER+0.014BM-1.03d50-0.017DS+0.001AP}}{1+\ e^{8.07+0.144ER+0.014BM-1.03d50-0.017DS+0.001AP}} \quad (6)$$

$$South\ Basin: P_{wm}(x) = \frac{e^{-1.768+0.141ER+0.004BM-0.031PR+0.0005AP}}{1+e^{-1.768+0.141ER+0.004BM-0.031PR+0.0005AP}} \quad (7)$$

Here, $P_{wm}(x)$ indicates the probability of wet muck entry, given a CP (Cutoff Probability), ER is the extraction ratio [%], BM is the broken material extracted in DP [%], SR is the secondary rock extracted in DP [%], N_{WM} is the Neighbor DP with wet muck [1 to 6], AP is the Annual Precipitation [mm], P30 is the precipitation at 30 days [mm], and d_{50} is the mean fragment size[m].

Table 11: Wet muck entry model for the North Basin.

Variable	Coefficient	Odds Ratio	Observation
Extraction Ratio [%]	0.178	1.195	A 10% increase in Extraction Ratio increases wet muck entry probability by 2%.
Broken material extracted in DP [%]	0.014	1.014	A 10% increase in the Percentage of Broken material extracted in the DP increases wet muck entry probability by 15%.
Secondary rock extracted in DP [%]	0.010	1.010	A 10% increase in the Percentage of Secondary rock extracted in the DP increases wet muck entry probability by 11%.
DP Neighboring wet muck [1 to 6]	0.262	1.300	If a DP increase by 1 DP Neighboring wet muck increases wet muck entry probability by 30%
Winter-Spring [Boolean]	1.333	3.792	If a DP is found in Winter or Spring increases wet muck entry probability by 2.79 times.

Precipitation at 30 days [mm]	0.001	1.001	A 100 [mm] increase in the Precipitation at 30 days increases wet muck entry probability by 11%
Constant	-3.282	-	-

Table 12: Wet muck entry model for the Center Basin.

Variable	Coefficient	Odds Ratio	Observation
Extraction Ratio [%]	0.144	1.154	A 10% increase in Extraction Ratio increases wet muck entry probability by 2%.
Broken material extracted in DP [%]	0.014	1.014	A 10% increase in the Percentage of Broken material extracted in the DP increases wet muck entry probability by 15%.
d_{50} fragmentation [m]	-1.030	0.357	A 0.1 [m] decrease in d_{50} fragmentation size in the DP increases wet muck probability by 11%
Distance to surface	-0.017	0.984	A 10 [m] decrease in the Distance to surface in the DP increases wet muck probability by 19%
Annual Precipitation [mm]	0.001	1.001	A 100 [mm] increase in the Annual Precipitation increases wet muck probability by 11%
Constant	8.070	-	-

Table 13: Wet muck entry model for the South Basin.

Variable	Coefficient	Odds Ratio	Observation
Extraction Ratio [%]	0.141	1.239	A 10% increase in Extraction Ratio increases wet muck entry probability by 1.4%.
Broken material extracted in DP [%]	0.004	1.031	An 10% increase in the Percentage of Broken material extracted in the DP increases wet muck entry probability by 4%.
Primary rock extracted in DP [%]	-0.031	1.031	A 10% decrease in the Percentage of Primary rock extracted in the DP increases wet muck entry probability by 36%.
Annual Precipitation [mm]	0.0005	1.000	A 100 [mm] increase in Annual Precipitation increases wet muck entry probability by 5%.
Constant	-1.768	-	-

4.3 Calibration and Validation models

In the calibration stage, several cutoff probabilities were tested to build contingency tables. These tables are developed to find a multivariable predictive model that maximize the model performance of the KPIs. Table 14 shows the main performance of KPIs for the builted models:

Table 14: Results of the main performance KPIs for North, Center and South Basin.

Model or Basin	True Positive Rate	True Negative Rate	Accuracy
North	74%	71%	72%
Center	70%	76%	75%

South	68%	70%	69%

In Figure 6, actual wet muck entries are shown in gray for each basin. The mud entry that are incorrectly estimated are indicated in red circles. Dark-red circles show the correctly estimated wet mud entry points.

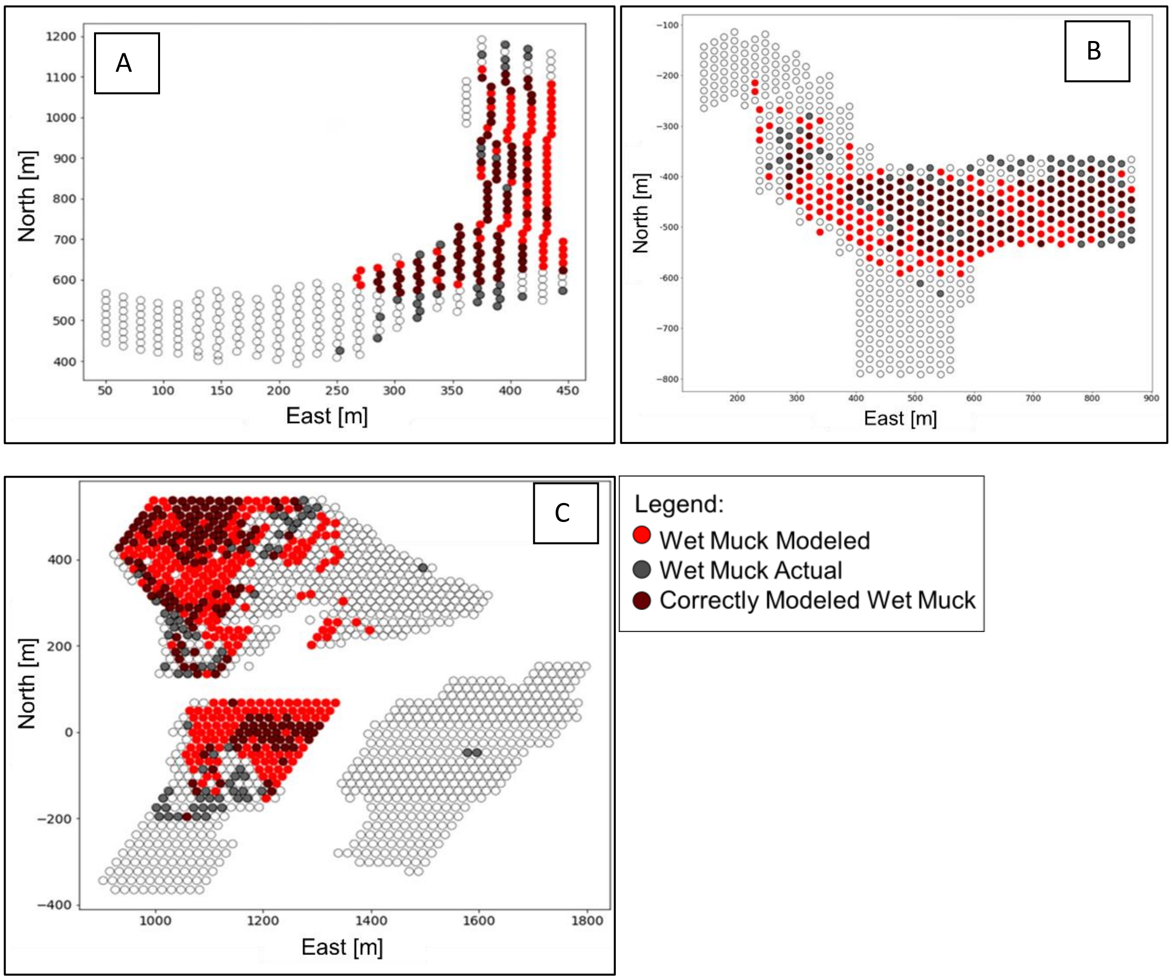

Figure 6: Wet muck entry modeled and actual for August 2021 in A: North, B: South and C: Center Basin.

In terms of extracted tonnage, Table 15 shows tonnage results of North, Center and South basins. The comparison between the real and estimated wet muck entry is illustrated in the dispersion diagram of Figure 7, where acceptable adjustable R^2 of 0.71, 0.73 and 0.77 were obtained, respectively.

Table 15: Model tonnage results for North, Center and South basin.

Model or Basin	Average tonnage per DP	Average tonnage error	Adjustable R^2
North	146kt	-13.4kt (9%) ±6.9kt	0.71
Center	160kt	-24.0kt (15%) ±12.4kt	0.73

South	196kt	-12.3kt (6%) ±8.3kt	0.77

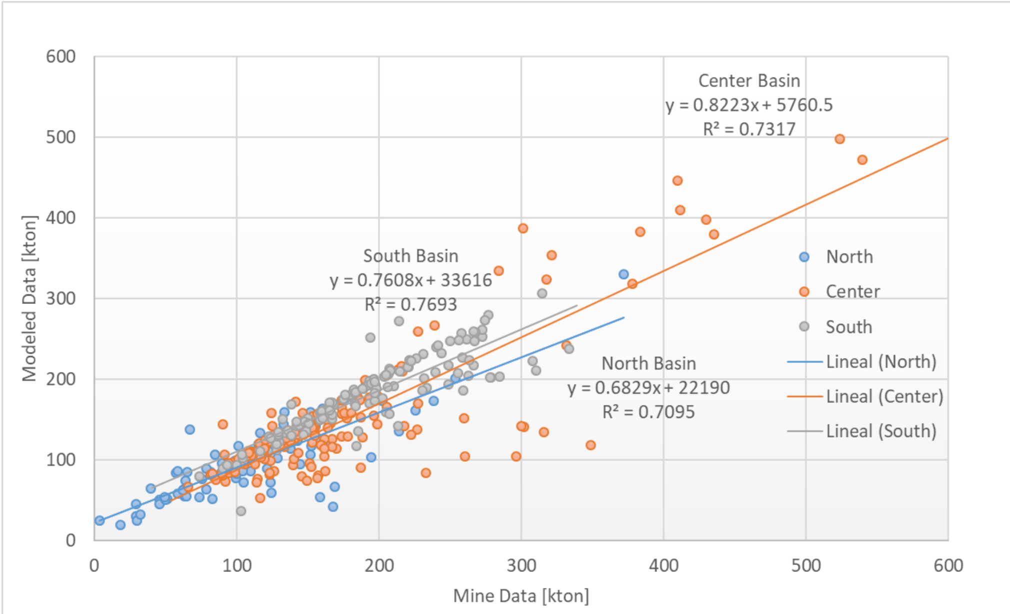

Figure 7: Dispersion plot between the mine tonnage data and the modeled for North, South and Center Basin

A comparison was made with the results of the Castro et al. (2022) and Navia (2021) models, in the same period of time. First, the Castro et al. model (2022), used a database (DB) from July 2011 to February 2018, with 458 DP and 52 with wet muck entry, achieving an accuracy of 81%. On the other hand, in the model of this study, 1330 DP and 200 DP with wet muck entry were used, reaching an accuracy of 77%. Regarding the comparison with the Navia model (2021), it uses a DB from August 2009 to November 2015, with 576 DP and 96 with wet muck entry, reporting an accuracy of 81%. In contrast, the model in this study achieved an accuracy of 84% and considered 590 PE and 123 PE mud.

In the first comparison, the precision of the proposed model was close but lower than the reported by Castro et al. (2022). However, the data used in this study is more extensive than that used by other authors (more DP and time scale), accomplishing built models that represent the whole extraction history of DET. In addition, the risk zone variable provided by the DET is omitted, since it is related as a variable for comparing the results of the wet muck entry risk zones and not as a variable that is part of the model. Despite of that greater precisions are achieved compared to Navia (2021). The comparison of the models reveals that the models must update their databases year after year, to build more realistic models, because the critical variables for mud formation can behave differently over the years, for example, rainfall in a drought year.

5 Conclusions

This article presents the risk quantification of wet muck entry for long term evaluation and planning for El Teniente Mine (DET). The models of North, Reno, Center and South basin were built through a multivariate logistic regression, these have several variables in common associated to the tonnage planned such as extraction ratio, granting an advantage of applicability of these variables in other productive sectors. Also, variables associated with rock fragmentation and lithology drawpoints, were included through gravity simulation in FlowSim BC 6.3 and calibrated with Database from DET. Additionally, precipitation variables were included, which provides a direct relation to water, which is one of the main factors that generates wet muck entry.

The best calibrated models for North, Center and South incorporated the aforementioned critical risk variables, achieving an acceptable accuracy of 72%, 75% and 69% respectively. This precision is accompanied by the low average tonnage error for DP -13.4 kt, -24.0kt and -12.3kt (9%, 15% and 6% of the average total per DP) for North, Center and South basin, resulting in wet muck entry risk models with conservative prediction qualities, giving confidence when carrying out the planning long-term. Also, these predictive models successfully determine zones prone to wet muck entry and, as demonstrated, can be used to evaluate long-term plans in the basins of the El Teniente mine contributing to planning and decision-making that can minimize the risks caused by wet muck entry. Furthermore, the models developed here could be applied to sectors below the currently modeled sectors in the future.

4 General Conclusions

In this study, the quantification of the risk of wet muck entries in long-term planning was analyzed and evaluated. The study area included the El Teniente mine, which is divided into four basins: North, Reno, Center, and South. For the construction of the models, univariate and multivariate logistic regression was used.

The long-term models built in this study have in common variables associated with the planned tonnage such as the extraction ratio, giving an advantage of applicability of this variable in other sectors. In addition, variables associated with the fragmentation and lithology present in the extraction were simulated with the FlowSim BC 6.3 software and calibrated with mine data. Precipitation variables were also added, which are directly related to water, which is one of the main factors that generate mud. All these variables are not included in previous models and were relevant in the statistical evaluation, demonstrating a correlation with the wet muck declarations.

Long-term models achieve acceptable accuracies of 69%, 71%, 72%, and 75% with average tonnage errors per drawpoint of 6%, 10%, 9%, and 15%, for the South, Reno, North, and Center, respectively. Continuing with the application in Reno-Dacita's future (2021 to 2037) delivers as a result 42.5 Mt of dry material, representing 80% of what was planned. The average HOD was 183 m, with 267 (63%) drawpoints with wet muck entry.

The results of the wet muck entry risk models indicate conservative prediction qualities (due to their negative tonnage error), generating confidence when carrying out long-term planning. The existing information on the wet muck declarations and the low existing error of the study makes it possible to consider predictive models as a tool to determine zones prone to wet muck entry, and, as demonstrated, can be used to evaluate long-term plans in their respective basins of the El Teniente Division contributing to planning decisions-making can minimize the risks caused by wet muck entry. Furthermore, the models developed here could be applied to sectors below the currently modeled sectors in the future.

The comparison of the models reveals that the models must update their databases year after year, to build more realistic models, because the critical variables for wet muck formation can behave differently over the years, for example, rainfall in a drought year.

5 Recommendations & future work

Based on the critical variables analyzed, it is recommended to take special care at the drawpoints that have extraction over 100% of the in-situ column, with the presence of broken material and fine fragmentation (d50 < 25 cm), and abundant accumulated precipitation. This is because all these variables turned out to be the most critical to determining the wet muck entry in the long term.

Search and group all the necessary information to evaluate the models in their respective basins or lower levels of the El Teniente Division, determining dry tonnage and the dry height of draw, as shown in the following table:

Table 8: Applications of the long-term models of the El Teniente mine.

Model – Basin	Application
North	Andesita Recursos Norte
Reno	Andes Norte
Center	Esmeralda Bloque 1 y Bloque 2 Diamante
South	Pacifico Superior Pacifico Central

An opportunity for improvement is obtained by unifying the models, this leads to the challenge of grouping the extensive information of all the basins, determining the critical variables to group them in a single model and be able to carry out applications in any mine or productive sector of DET.

6 Bibliography

Araneda, O, 2020. 'Codelco: present, future and excellence in projects'. Proceedings of the Eighth International Conference & Exhibition on Mass Mining (MassMin 2020), pp. 1-9.

Brown ET, 2007. 'Block Caving Geomechanics: International Caving Study 1997-2004'. Julius Kruttschnitt Mineral Research Centre, The University of Queensland, Australia

Butcher, R, Joughin, W & Stacey, T, 2000. 'Methods of combating mudrushes in diamond and base metal mines'. SRK Consulting and The Safety in Mines Research Advisory Committee.

Butcher, R, Stacey, T & Joughin, W, 2005. 'Mud rushes and methods of combating them'. J S Afr Inst Min Metall vol.105, no. 11, pp. 817–824Ferrada, 2011.

Call & Nicholas Inc., 1998. 'IOZ Wetmuck Study', PT Freeport Indonesia, internal report.

Castro, R, Garcés, D, Brzovic, A & Armijo, F, 2018. 'Quantifying Wet Muck Entry Risk for Long-term Planning in Block Caving', Rock Mechanics and Rock Engineering, https://doi.org/10.1007/s00603-018-1512-3.

Castro R, Pérez, A & Gómez, R, 2022. 'Evaluating Wet Muck Risk in Block Caving Mines: A New Model (under review)', Int. J. Rock Mech. Min. Sci.

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

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

Cornejo, J, Lasagna, G, País, G & Alarcón, H, 2020. 'Simulation approach for development muck planning'. Proceedings of the Eighth International Conference & Exhibition on Mass Mining, MassMin 2020, pp.

Dorador L, 2016. 'Experimental Investigation of the Effect of Broken Ore Properties on Secondary Fragmentation During Block Caving', PhD thesis, The University of British Columbia, Vancouver 646-657.

Edgar, I, Prasetyo, R & Wilkinson, M, 2020. 'Deep Ore Zone mine wet ore mining empirical learnings, mining process evolution and development pathway'. Proceedings of the Eighth International Conference & Exhibition on Mass Mining, MassMin 2020, pp. 385-393.

Ferrada, M, 2011. 'Gravity Flow Under Moisture Conditions – Control and Management of Drawpoint Mudflow'. 35th APCOM Symposium Application of computer and operations research in the minerals industry, pp. 761-764.

Flores, G, 2014. 'Future challenges and why cave mining must change', in 3rd International symposium on block and sublevel caving, pp. 23–52.

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

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

Ginting, A & Pascoe, N 2020. 'Grasberg open pit to Grasberg block cave transition wetmuck and mine design'. Proceedings of the Eighth International Conference & Exhibition on Mass Mining, MassMin 2020, pp. 357-369.

Hartman, H & Mutmansky, J, 2002. 'Introductory Mining Engineering'. John Wiley & Sons, Second Edition.

Heslop, T, 2000. 'Block caving – Controllable risk and fatal flaws'. MassMin 2000.

Holder, A, Rogers, A, Bartlett, P & Keyter, G, 2013. 'Review of mud rush mitigation on Kimberley's old scraper drift block caves'. The Journal of The Southern African Institute of Mining and Metallurgy, Volumen 113, pp. 529-537.

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

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

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

Jakubec, J & Woodward, R, 2020. 'Incline caving at Ekati Diamond Mine'. Proceedings of the Eighth International Conference & Exhibition on Mass Mining, MassMin 2020, pp. 195-206.

King, G & Zeng, L, 2001. 'Logistic Regression in Rare Events Data. Political Analysis'.

Laubscher, D, 2000. 'A practical Manual on Block Caving', Julius Kruttschnitt Mineral Research Centre, Brisbane.

Navia, I, Castro, R & Valencia, M, 2014. 'Statistical analyses of mud entry at Diablo Regimiento sector - El Teniente's Mine'. Caving 2014, pp. 372-378.

Navia, I, 2021. 'Multivariable modeling to predict mud entrance in Block Caving operation', s.l.: Tesis para optar al grado de Magister en Minería, Universidad de Chile.

Pérez, A, 2021. 'Modelamiento del riesgo de ingreso de agua-barro en minas de Block Caving con aplicación en la planificación minera de largo plazo', s.l.: Tesis para optar al grado de Magister en Minería, Universidad de Chile.

Pierce, M, 2010. 'A Model for Gravity Flow of Fragmented Rock in Block Caving Mines', The University of Queensland, St Lucia.

Saepulloh, D, Hassell, R & Albrecht, J, 2022. 'Managing the risk of uncontrolled flow of material (mudrush) at Argyle Diamond Mine', in Y Potvin (ed.), Caving 2022: Fifth International Conference on Block and Sublevel Caving, Australian Centre for Geomechanics, Perth, pp. 583-596, https://doi.org/10.36487/ACG_repo/2205_40

Salazar, M, Mejias, O, Diez, E & Urbina, S, 2016. 'Actualización de metodología para clasificación de humedad cualitativa en puntos de extracción y actualización de matriz de criticidad para la mejor toma de decisiones'.

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

Skrzypkowski, K, Gómez, R, Zagórski, K, Zagórska, A, Gómez-Espina, R, 2022. 'Review of underground mining methods in world-class base metal deposits: Poland and Chile experience'. Energies; Mining Innovation: Volume III.

Syaifullah, T, Widijanto, E & Shrikant, A, 2006. 'Water Issues in DOZ Block Cave Mine, PT Freeport Indonesia'. MassMin2006, pp. 361-368.

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

Widodo, L, Widijanto, E & Sunyoto, W, 2018. 'Fuzzy-based prediction of spatio-temporal distribution of wet muck in block cave mine of PT freeport Indonesia'. Journal of Engineering and Technological Sciences ·, 50(2), pp. 291-313.

Witten, I, Frank, E, Hall, M & Pal, C, 2017. 'Data mining, Practical machine learning tools and techniques'. Four ed. s.l.: Elsevier.