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# Modelling of wet muck entry at El Teniente for long-term planning

**O Salas** *Universidad de Chile, Chile*

**R Castro** *Universidad de Chile, Chile*

**E Viera** *Codelco, Chile*

**K Basaure** *Codelco, Chile*

**F Hidalgo** *Codelco, Chile*

**M Pereira** *BCTEC Engineering and Technology, Chile*

## 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 paper 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 neighbouring 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 mud rush (Ginting & Pascoe 2020).

Wet muck entry has been recorded in different underground mines around the world, such as El Teniente in Chile (Ferrada 2011), Intermediate Ore Zone and Deep Ore Zone 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 analyse 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.

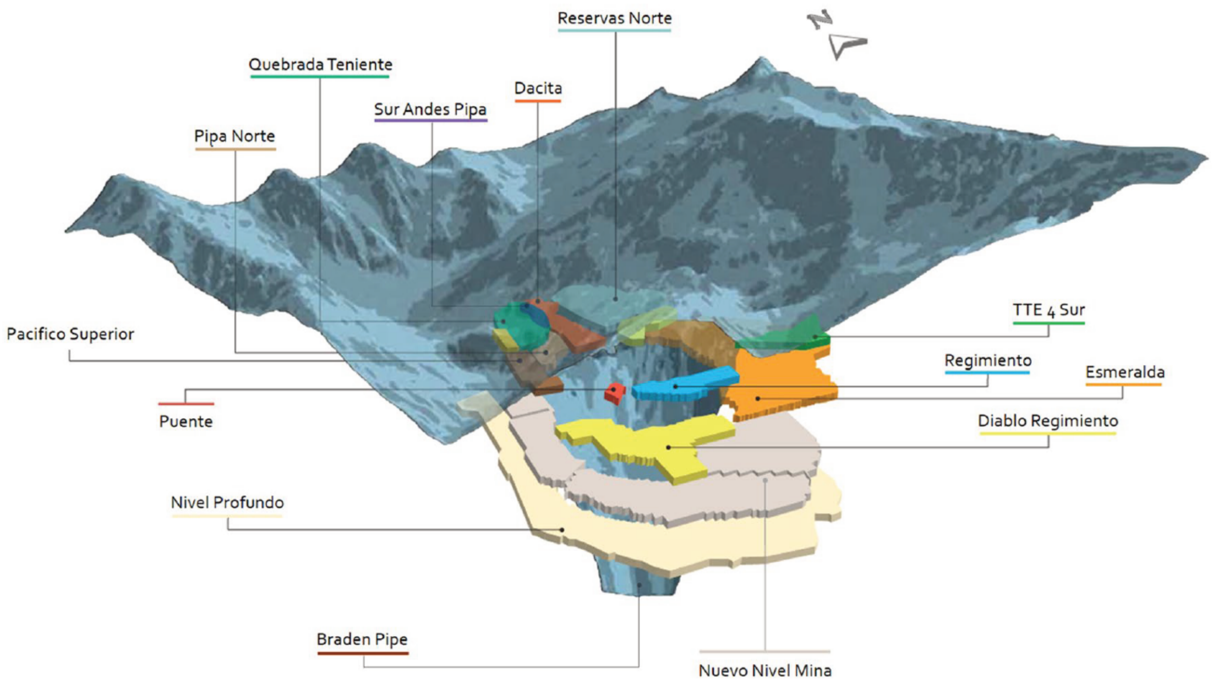


**Figure 1 Isometric view of the productive sectors of the El Teniente division (Codelco ET Mine 2016a, 2016b)**

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.

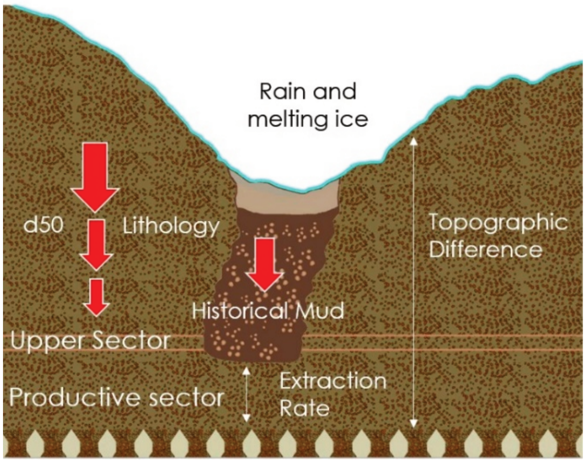


**Figure 2 Conceptualisation of the problem of mud entry in the El Teniente mine**

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.

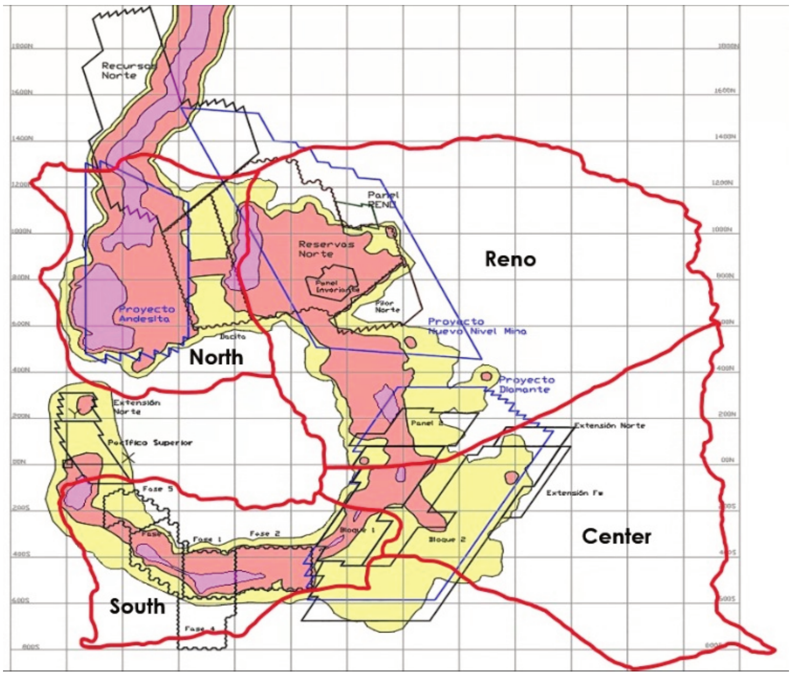


**Figure 3 Plan view of the El Teniente Division crater, showing its division into four basins (North, Reno, Center, and South)**

**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<br>Andesita |
| Reno | Reservas Norte – Dacita | Andes Norte<br>Panel Invariante |
| Center | Esmeralda Bloque 1 y 2 – Esmeralda Panel | Diamante |
| South | Diablo Regimiento | Pacifico Superior<br>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 analysed 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 analyse the predictive performance of the model.

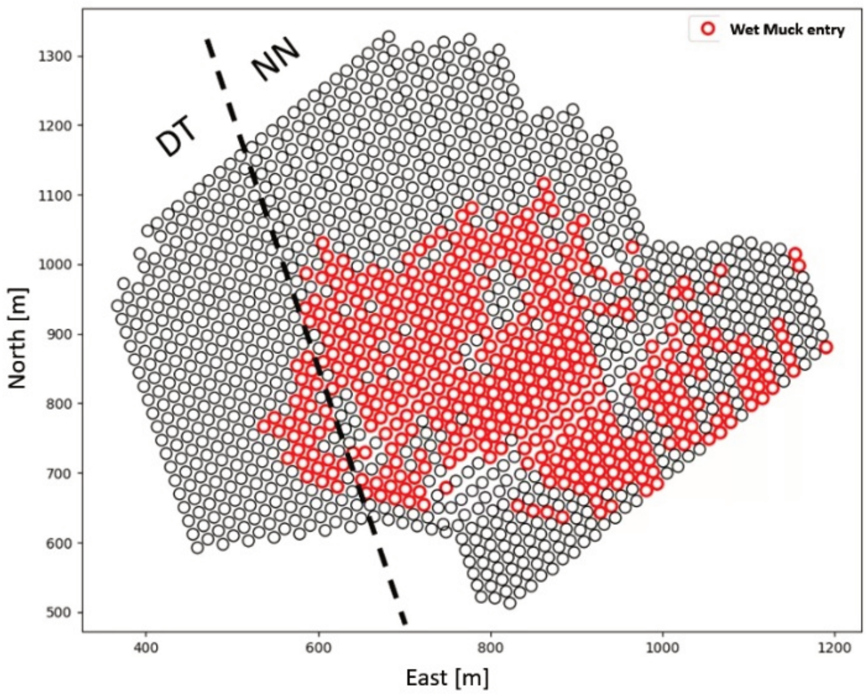


**Figure 4 Wet muck entry from the Reservas Norte (NN) and Dacita (DT) sector**

## 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 |
|---|---|
| Historical extraction | Height of draw (m)<br>Extraction ratio (%) |
| Lithologies and fragmentation | Primary rock extracted in the DP (%)<br>Secondary rock extracted in the DP (%)<br>Broken material extracted in the DP (%)<br>Talus* material extracted in the DP (%)<br>D50 (m) |
| Water and mud | Average water flow rate (L/s)<br>Precipitation (mm)<br>Historical mud sectors (dichotomic)<br>DP neighbour wet muck (1 to 6) |
| 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 analysed 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 neighbour wet muck | Nwm | – | Continuous | Number of DP in the neighbourhood 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 modelling 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 ($\chi 2$) and the Odds Ratio (OR) were applied to analyse 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. |

| Variables | Description |
|---|---|
| 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 neighbour wet muck | Corresponds to the risk that the mud could spread to the surrounding areas (neighbouring 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):

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

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 & 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 cutoff 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 maximising these leading indicators described by Witten et al. (2017):

$$\text{Sensibility} = TPR = \frac{TP}{TP+FN} * 100 \quad (2)$$

$$\text{Specificity} = TFR = \frac{TN}{TN+FP} * 100 \quad (3)$$

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

where:

Sensitivity = ability to predict mud entry (or the true positive rate).

Specificity = ability to predict non-mud entry (or false positive rate).

Accuracy = 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 minimise the mined ore tonnage error, which is defined as the difference between the actual and modelled mined ore tonnage. The validity of the predictive model is graphically represented in a scatter plot, where the correlation between the modelled 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.

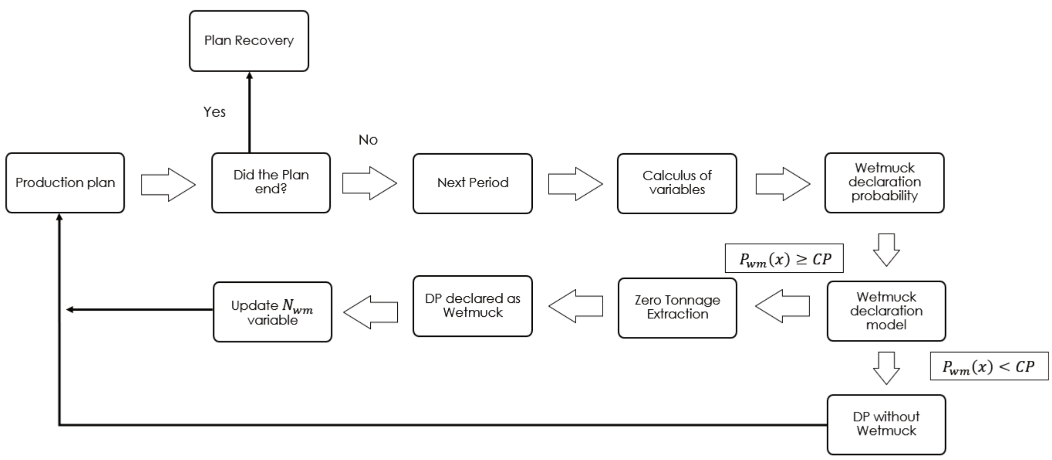


**Figure 5 Schematic diagram of the algorithm used to calibrate the wet muck entry risk model, based on a monthly estimate of wet muck entry, modified from (Castro et al. 2018). Nwm represents the number of drawpoints in the neighbourhood with mud**

# 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 neighbour 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 neighbour 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.

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

| Variable | Coefficient | Chi-squared test ($\chi 2$) | 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 neighbour 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 |

## 4.2 Multivariate analysis

In the multivariate analysis, more than 30 mud entry models were analysed. As an example in Table 7, 15 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 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:

$P_{wm}(x)$ = 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 maximise the performance KPIs of the model. After evaluating several cutoff probabilities, the optimal cutoff value to correctly identify mud entry was 0.7725. The modelled wet muck entry is presented in Figure 6. In this, the black polygon is the area where drawpoints were declared as wet muck at August 2021, date on which the main performance KPIs are calculated.

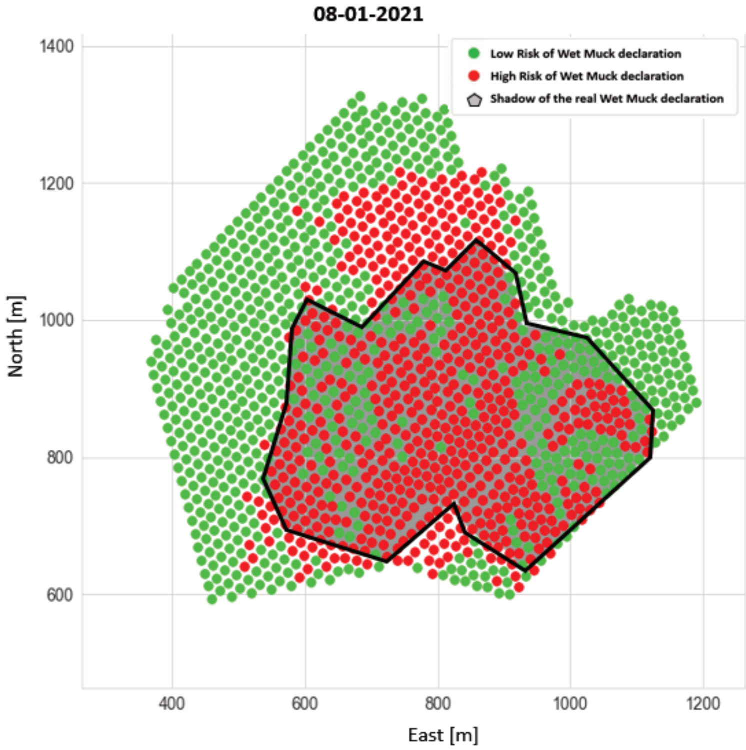


**Figure 6 Wet muck entry modelled in the Reno Basin for August 2021. In red are the DPs with high wet muck entry risk and in green the DPs with low wet muck entry risk**

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%

$$TNR = \frac{TN}{TN+FP} = \frac{655}{655+278} = 70\% \quad (7)$$

- Model accuracy of 71%

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

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

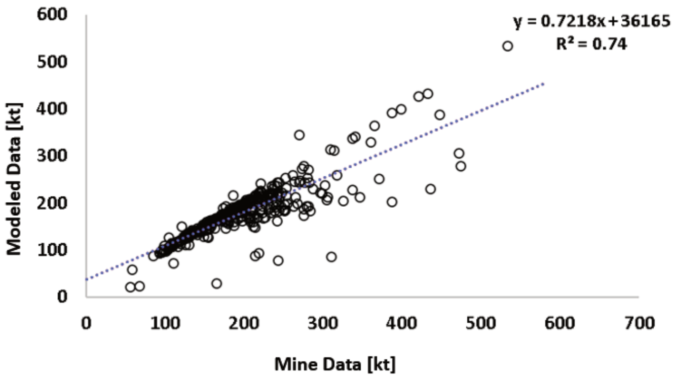


**Figure 7 Dispersion plot between the mine tonnage data and the modelled**

## 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 five 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.

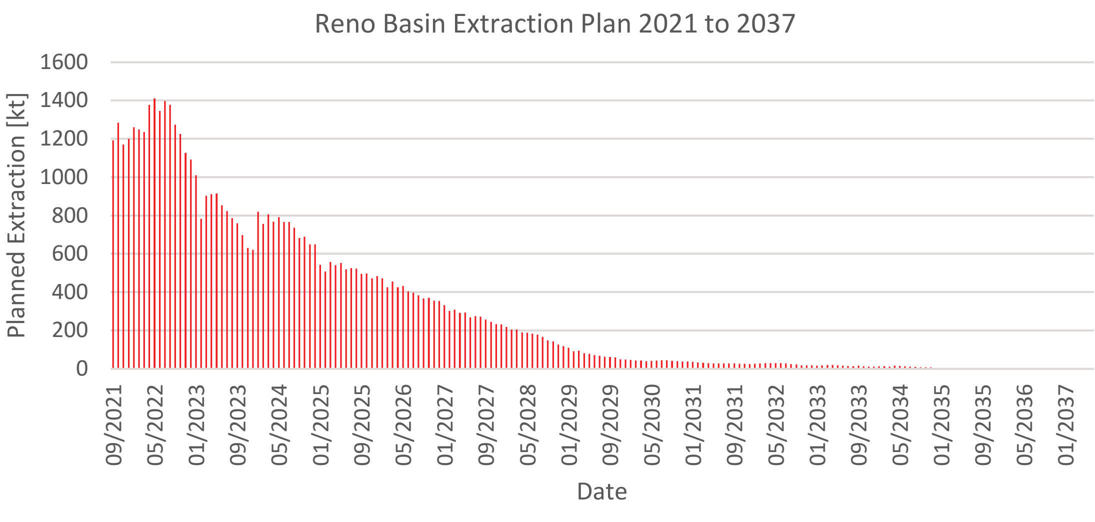


**Figure 8 Long-term mining planning for the Reno Basin from September 2021 to June 2037**

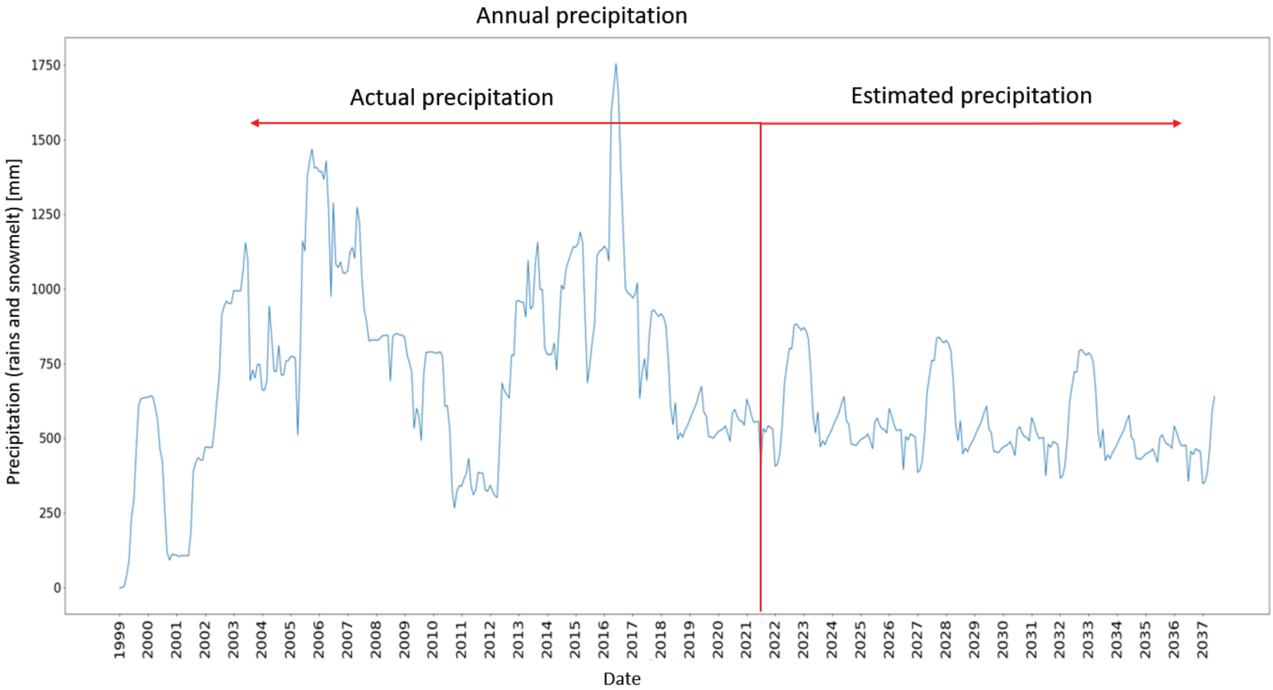


**Figure 9** Actual annual precipitation until 2021. Estimated precipitation from 2021 onwards constructed from data based on CR2.cl information

Finally, Figure 10 and Table 9 show the results obtained for the application of the Reno-Dacite Sector until the year 2037. From 2021–2037, 267 drawpoints were modelled 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.

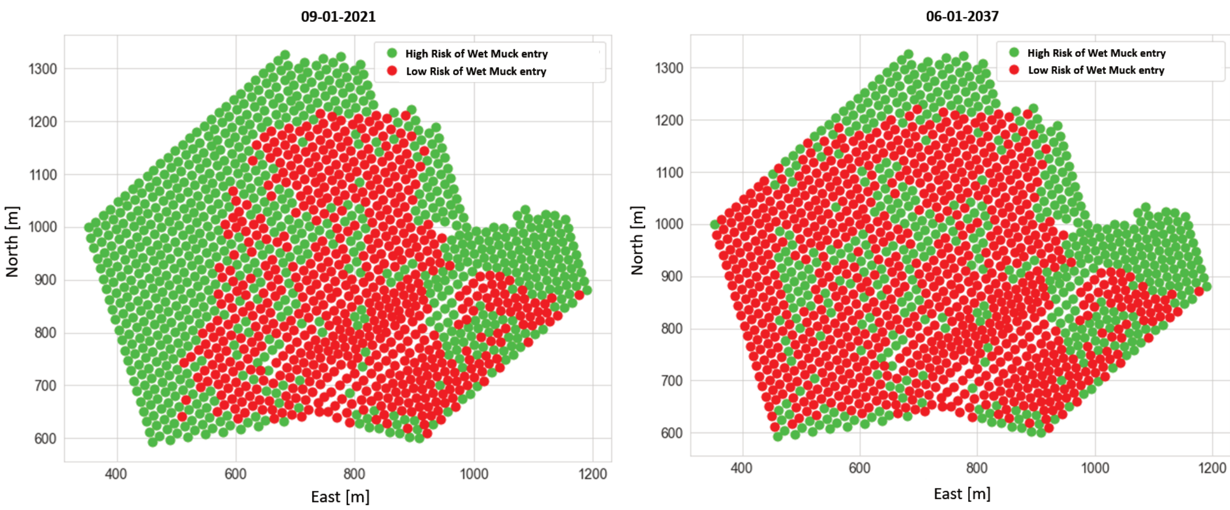


**Figure 10** Application of the Reno Basin Model, for the initial period: September 2021 and final period: June 2037

**Table 9 Reno 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.

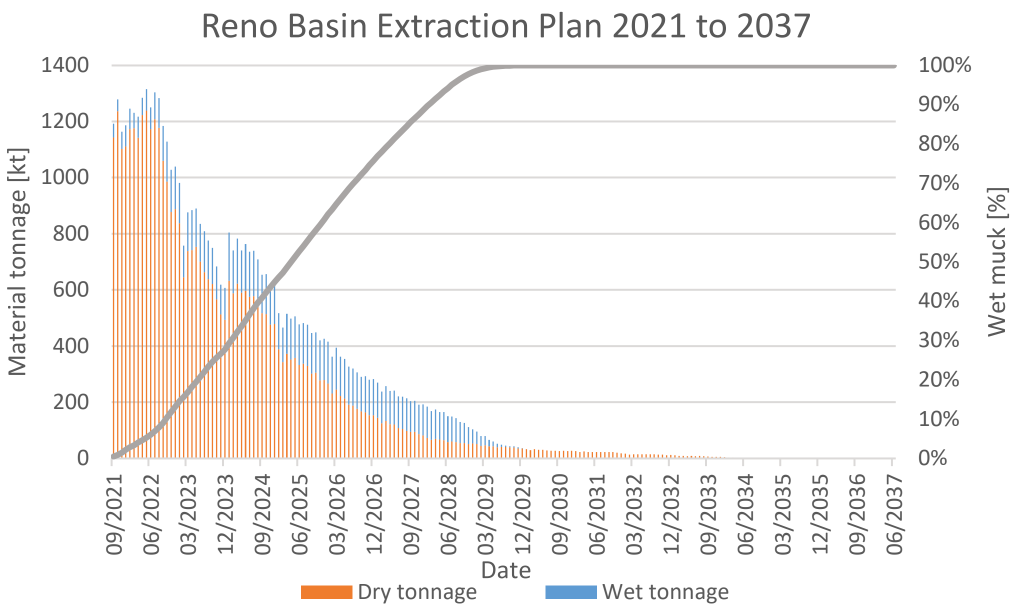


**Figure 11 Results of the application of the Reno Basin model, considering dry and wet tons**

# 5 Conclusion

In this study, the quantification of wet muck entry risk for the long-term evaluation and planning for the El Teniente Reno Basin was analysed 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 minimise the risks caused by wet muck entry. Furthermore, the models developed here could be applied to sectors below the currently modelled sectors in the future.

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