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A wet muck risk model's impact for the Diablo Regimiento sector at El Teniente mine

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ABSTRACT

The intrusion of wet muck with its potential for mud rushes poses significant risks to workers, equipment, and infrastructure at El Teniente Mine, as well as at other underground operations around the world. This article presents the development of a probabilistic model that incorporates both a logistic regression model and a risk level classification model to estimate high and medium-risk zones for wet muck events in short-term mine planning at El Teniente. The model has been integrated into BCRisk®, a machine-learning software designed to estimate hazards associated with the extraction process for underground mines. The most significant variables associated with the occurrence of wet muck events were identified through univariate and multivariate analyses. These operational, environmental, topographic, and lithological variables were then incorporated in the model to determine high and medium-risk zones for wet muck events in the Diablo Regimiento sector. Operational variables included uniformity and extraction rate, while environmental and topographic variables included the distance from the drawpoint to the surface, laboratory moisture of drawpoint, and precipitation. Additionally, a variable related to the extracted lithology, specifically the percentage of material from upper sectors or broken ore, was integrated, which was obtained from FlowSim BC v6.3 gravity flow software.

The results highlight the precision and predictive capability of the probabilistic model. In the Diablo Regimiento sector, the probabilistic model accurately predicted 86% of high-risk wet muck events and successfully identified high-risk zones within the operational footprint. This risk modeling approach emerges as a fundamental tool for short-term planning and decision-making, aiming to minimize the risks associated with wet muck events at El Teniente Mine. The robustness and predictive capacity of this model make it suitable for applications in future sectors facing similar challenges related to the occurrence of wet muck events.

Keywords: Underground mining, geotechnical hazards, short-term, wet muck events, mud events, uniformity, extraction rate.

1 INTRODUCTION

Currently, multiple open-pit mines have reached the depth limit at which they will no longer be economically profitable, which has motivated many mines to transition to an underground mining method (Fuentes & Caceres, 2004). Block and Panel Caving are among the underground methods that have gained greater relevance since their high productivity and low operational costs make them profitable extraction methods for massive and low-grade deep deposits (Hustrulid & Bullock, 2001; Khodayari & Pourrahimian, 2015). However, due to the size and depth of current and future caving operations, these methods are prone to various critical geotechnical risk events, such as rock bursts, collapses, subsidence, air blasts, and wet and dry inrushes, which have become common challenges for the mining industry (Cuello & Whiteman, 2020). Wet inrushes, specifically mudrushes, are the subject of concern in this work.

The industry and available literature use several terms to describe inrush events. Butcher et al. (2000) define mudrushes as sudden entries of mud from drawpoints or other underground openings. These wet inrushes may have very different origins but can produce the same results: injuries, loss of lives, damage to property, excessive dilution, and production delays or, in the extreme case, mine closure (Jakubec, 2012).

Mudrushes are one result of wet muck entry in caving mining. This wet muck material is generated by fine particles that mix with aqueous substances under different types of conditions, such as mountain thaw, tailings leakage, issues with aquifers, and adverse weather conditions (snow and rainfall). This muck mixture can travel through the column of broken material, reach the drawpoints (DP), and cause events, such as landslides, runoff, and mudrush, which can be triggered by material extraction, induced seismicity, and/or subsidence (Jakubec, 2012; Flores, 2019; Ginting & Pascoe, 2020; Salas et al., 2022).

Wet muck events have been recorded around the world in underground mines, such as El Teniente (DET), Chile (Ferrada, 2011), Palabora, South Africa (Paerzold et al. 2020), IOZ and DOZ in Indonesia (Huber et al., 2000; Widijanto, et al.,2012; Edgar et al., 2020; Ginting & Pascoe, 2020). Some tools used to mitigate and control wet muck are drainage tunnels that allow mud to be transferred to lower levels or outside the mine, tele-remote operated equipment in critical areas, risk matrices for the workers, and controlled extraction (Samosir, 2008; Edgar et al., 2020).

For long-term planning, El Teniente mine has implemented wet muck entry risk models to evaluate mining plans (Navia et al. 2014; Garces et al., 2016; Castro et al., 2018; Perez, 2021; Salas 2022), these models are based on the use of regression techniques (Hosmer et al., 2013) as they allow for the study of binary responses, occurrence or non-occurrence of a phenomenon. However, until now, no wet muck risk model has been considered for short-term planning.

To enable the future prediction of wet muck events occurrence in drawpoints, studies were needed that would incorporate operational variables such as uniformity, moisture, fragmentation, among others. With this information, high, medium, and low-risk areas could be identified so that extraction strategies could be defined for short-term planning.

This article presents a methodology for predicting the risk of wet muck events at Diablo Regimiento using logistic regression. Additionally, it introduces software that implements these risk models and enables DET to make short-term planning decisions.

2 BACKGROUND OF EL TENIENTE DIVISION

2.1 Wet muck at El Teniente

El Teniente is the largest underground copper mine in the world and the sixth-largest copper mine in terms of reserve size. El Teniente is located approximately 80 kilometers south of the city of Santiago, Chile and 50 km east of the city of Rancagua, between 2,200 and 3,200 meters above sea level.

El Teniente mine has experienced wet muck events in several sectors, including Diablo Regimiento, Reservas Norte, Pipa Norte, Pipa Andes Sur, Esmeralda, among others. These sectors are mainly located below a topographic depression around the Pipa Braden, as shown in Figure 1.

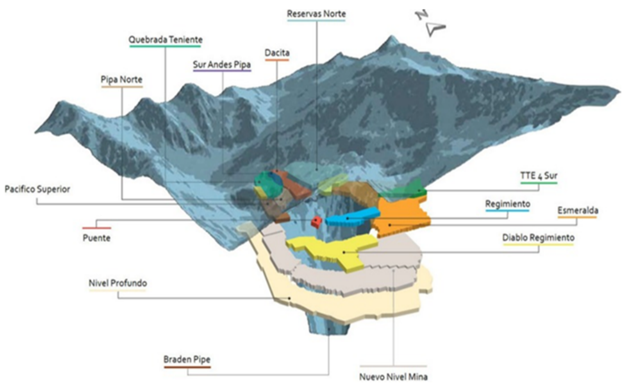

Figure 1 Isometric view of productive sectors at El Teniente Mine (Codelco 2016).

The history in the underground mine of Division El Teniente is marked by accidents related to the sudden entry of ore with the presence of wet muck in drawpoint, production level galleries, or transfer shafts. The last event with fatal consequences occurred in the Regimiento mine in October 2007. Conclusions drawn from the investigation indicated that the genesis of this material originated from upper levels, compounded by water inflows into the cavity due to topographical changes on the surface.

According to Butcher et al. (2005), four factors are required to trigger wet muck entry. These include the ability to accumulate water, the presence of potential mud-forming minerals, a disturbance in the mineral column, and the ability to discharge mud at drawpoints. The mud at El Teniente is mainly due to rainwater or snow accumulated on the surface that infiltrates into the mine and mixes with fine ore formed due to secondary fragmentation that occurred during the caving process (Salas, 2022). Figure 2 shows a schematic representation of the wet muck phenomenon and some of its main variables.

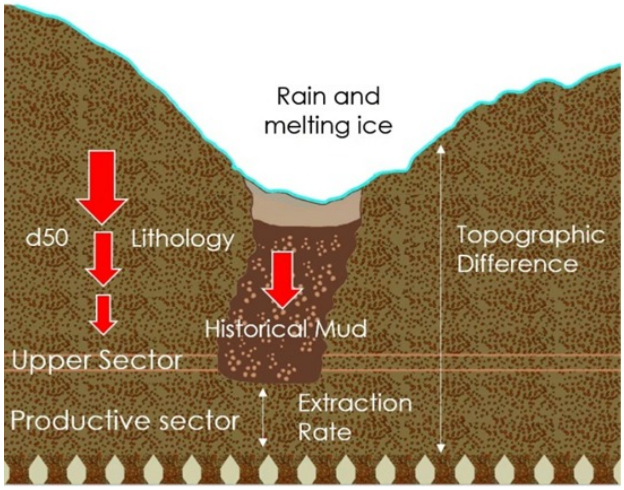

Figure 2 Conceptualization of the problem of wet muck entry in the Teniente Mine (Salas, 2022).

2.2 Study Area

El Teniente Mine produces approximately 3.9 million tons per month, with a daily extraction of 130,000 tons (Codelco, 2016). On the other hand, the Diablo Regimiento sector contributes around 700,000 tons monthly, accounting for 18% of the total tonnage extracted from the El Teniente Mine. This significant contribution underscores the importance of the Diablo Regimiento sector in the mine's overall production.

To model wet-muck-event risk at the Diablo Regimiento sector, the mining database from 1999 to 2021 was provided by El Teniente Division for analysis of wet-muck events. The information analyzed included historical extraction data for each drawpoint (DP). Table 1 and Figure 3 show the drawpoints analyzed and the wet muck events reported for Diablo Regimiento sector.

Table 1 Wet muck events in Diablo Regimiento sector

Productive sector	Drawpoints analyzed	Drawpoints with wet muck events
Diablo Regimiento	594	21

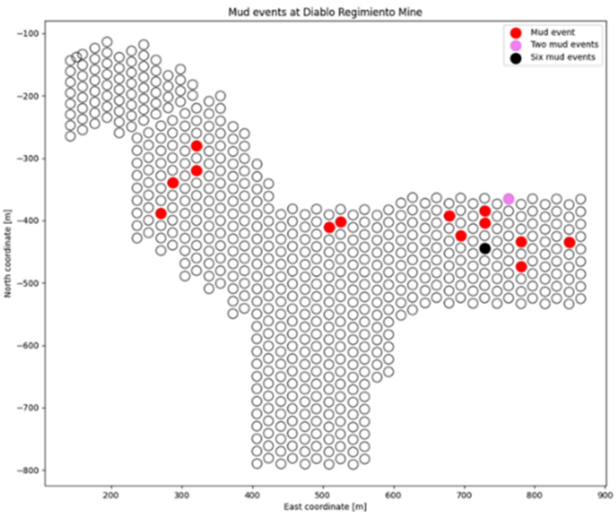

Figure 3 Wet muck events reported at the Diablo Regimiento sector.

The mining database was used to study the independent correlation of each variable with the wet muck events and to select the critical variables. A univariate analysis methodology of logistic regression was first conducted (Hosmer et al. 2013) followed by a multivariate analysis that divided the database into a training dataset to generate the equations for the logistic regression model and a validation dataset to assess the performance of the logistic model.

2.3 Critical Variables for the wet muck events

In the analysis, variables were identified and classified into four groups, considering their characteristics and their relationship with the occurrence of wet muck events:

- **Operational Variables:** This set of variables aims to detect any irregularities in the extraction process that may contribute to the occurrence of wet muck events.
- **Extracted ore characteristics**: This set of variables is intended to identify formations of fine material or those with characteristics conducive to wet muck generation such as lithology and fragmentation.
- **Environmental Variables:** These variables are focused on identifying sources of water or mud that may increase the risk of wet muck event occurrence.
- **Geometric Variables:** This set of variables aims to evaluate proximity to potential sources of water or mud, the shape of the surface (depression), and distance to the surface.

Variables that can explain the problem of wet muck events were developed from this information as shown in Table 2.

Table 2 Types of variables considered in the analysis

Groups of variables	Variables
Operational	Extraction ratio [%] Uniformity [%] Height of draw [m] Maximum difference in average extraction rate [t/m2-day]
Extracted ore characteristics:	Estimated fragmentation (d50) [m] Primary rock extracted in the drawpoint [%] Secondary rock extracted in the drawpoint [%] Broken material extracted in the drawpoint [%] Talus* material extracted in the drawpoint [%]
Environmental	Maximum water flow rate [l/s] Precipitation [mm] Observed moisture [qualitative] Laboratory moisture [%] Inactive neighbor mud [boolean] Upper sector with wet muck events [boolean]
Geometric Variables	Distance to the surface [m] Risk zones (topographic depression)

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

3 METHODOLOGY

In this study, a probabilistic model of wet muck events was developed for short-term mine planning, incorporating operational, environmental, geometric, and ore characteristics. To develop the probabilistic model, a univariate analysis was initially performed to determine the statistical significance of each variable individually with wet muck events using the Chi-square Test (Walpole et al. 2012) and logistic regression (more detailed information about logistic regression can be found in Hosmer et al. (2013). From this information, a multivariable logistic model and a risk-level classification model were constructed. Integrating the information from the multivariable logistic model and the risk-level classification, a probabilistic model was then developed, which considers performance indicators such as the true positive rate, the true negative rate, overall accuracy, and the areas identified as high and medium risk for wet muck events. A summary of the methodology used to construct our probabilistic model is presented below.

3.1 Univariate Logistic Regression Analysis

An independent analysis was conducted to assess the risk of wet muck event occurrences using univariate analysis. The relationship between various risk factors and the incidence of mud events was investigated using the Chi-square Test ($\chi2$) and the Odds Ratio (OR).

The Odds Ratio can estimate the likelihood of a wet muck event with x=1 (presence) in comparison to drawpoints with x=0 (absence) (Hosmer et al. 2013). For instance, if a drawpoint reported mud and is situated in a high-risk zone with a history of wet muck events, an odds ratio of OR=3 suggests that the probability of wet muck event in the risk zone is three times higher than in areas with no history of wet muck events.

To identify variables that significantly affect the occurrence of wet muck events, the p-value in the univariate analysis was set to a critical value of 0.1. The results are presented in Table 3, which offers an overview of the variables and their influence on wet muck events.

Table 3 Summary of selected risk variables based on physical properties of wet muck event and mine practice

Variable	Description	Relationship with wet muck events
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.	Directly proportional
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 events.	Directly proportional
Primary ore 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 events.	Inversely proportional
Secondary ore 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 rock, represents the permeable layer; therefore, the higher the percentage of secondary ore extracted, the greater the probability of wet muck events.	Directly proportional

Variable	Description	Relationship with wet muck events
Broken ore extracted in DP	Represents remaining material from upper sectors (primary + secondary).	Directly proportional
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 events.	Directly proportional
Fragmentation d50 [m]	Represents the fragmentation present in the extraction. When the size d50 decreases, the probability of wet muck events increases due to the increase in the amount of fines in the DP.	Directly proportional
Maximum 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 events also increases.	Directly proportional
Precipitation at 15, 30, 60 days	Precipitation measurements at various time intervals. An increase in precipitation indicates that the probability of wet muck events increases.	Directly proportional
Inactive neighbor mud	Represents the quantity of drawpoints in the vicinity that have recorded wet muck events. A higher number of drawpoints with wet muck events increases the probability of wet muck events.	Directly proportional
Upper sector with wet muck events	Composed of the mud polygons of productive sectors at higher levels. If a drawpoint is in that area, the probability of wet muck events increases.	Directly proportional
Uniformity	Represents whether the extraction at the drawpoint is uniform compared to the planned extraction, i.e., if there is a deviation in the extraction control. A low percentage of uniformity increases the probability of wet muck events.	Inversely proportional
Maximum difference in average extraction rate at 15 and 30 days	Represents the maximum difference average extraction velocity in the cluster of neighboring drawpoints. A higher difference in extraction velocity between a drawpoint and its neighbors increases the probability of wet muck events.	Directly proportional
Laboratory moisture	Represents the percentage of moisture of the drawpoints, measured in the laboratory. Higher moisture increases the probability of wet muck events.	Directly proportional
Distance to the surface	Considers the distance to surface water sources (snow melt and rainwater). A shorter distance to water/mud sources increases the probability of wet muck events.	Inversely proportional
Risk Zone	Represents the zone limited by a predetermined distance. If a drawpoint is in this area, the probability of wet muck events increases.	Directly proportional

3.2 Multivariate Logistic Regression Analysis

To test the correlation between risk variables and the occurrence of wet muck events, a multivariable logistic regression was used. This method evaluated the association between the binary response variable (i.e., the occurrence or non-occurrence of wet muck events) and a collection of risk variables represented by the vector $x = (x1, x2, x3, \ldots, xn)$. In this way, the coefficient of each risk variable was determined, and its statistical significance could be assessed. The conditional probability of wet muck events given a set of n independent risk variables is represented by equation (1), where the logistic regression coefficients are $\beta = \beta0, \beta1, \beta2, \beta3, \ldots, \beta n$, and can be estimated using maximum likelihood methods.

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

To remain in the multivariable logistic regression model, a risk variable had to be statistically significant with a p-value of 0.05. This method relied on the probability of the response variable, considering the set of risk variables (Hosmer et al., 2013; Geng and Sakhanenko, 2015).

Logistic regression models require two types of data: a training set and a test set. The training set was used to learn and estimate the relationship between the input and output data, while the test set was used to evaluate the model's accuracy on previously unseen data. However, it was discovered that the database was unbalanced because wet muck events were not recorded daily during the evaluation period. Diablo Regimiento sector had only 21 wet muck events in a total of approximately 16.9 years of extraction history.

To overcome this imbalance, a balanced database of both wet muck events and non-event cases was created for the training set. The first set included all wet muck event cases, while the second set included the drawpoints that were not affected by wet muck events. Following King & Zeng's (2001) recommendation, the "non-event" database was sampled to be two to five times larger than the "event" database. This ensured that the new database included all the wet muck events from the "event" database.

The "non-event" database was then reduced to represent 75% of the new database, which resulted in a size three times larger than the "event" database. Each case from the ‘non-event’ database was selected randomly stratified by the HOD distribution of the complete mine. The new database should represent all the stages of the life of the mine such that the model could be used for new sectors.

3.3 Calibration and validation of the logistic model

The calibration of the model was determined by comparing actual wet muck data from the mine with data generated by the model using a cutoff probability (CP) value. The cutoff probability enabled the sorting of drawpoints into one of two response categories, namely 1 or 0, using varying probability levels. The cutoff probability was defined as the minimum probability value for which a drawpoint is classified as wet muck, with drawpoints having a probability value greater than the cutoff value considered as having a wet muck event. An algorithm was developed to identify the probability value that provides the most accurate logistic model, using significant variables to identify wet muck events.

The results of the cutoff probability were used to construct a contingency table that facilitated the calculation of four possible outcomes (see Table 4). For instance, if the actual value was positive and classified as such, it would be considered a true positive (TP); otherwise, it would be considered a false negative (FN). The symbols used in the confusion matrix are described by 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 confusion matrix, the cutoff probability allows three main performance KPIs to be calculated to maximize the leading indicators described by Witten, et al., 2017 (equations 2, 3 and 4):

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

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

$$\textbf{\textit{Accuracy}} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} * 100. \qquad (4)$$

Sensitivity is the ability to predict wet muck event (or true positive rate). Specificity is the ability to predict non-wet muck event (or false positive rate), and Accuracy is the ability to predict both wet muck and non-wet muck events.

After calibrating the logistic model for wet muck events, a second stage was performed. In this stage, a conditional model was developed to categorize the level of risk in the drawpoints based on variables such as visual moisture, estimated fragmentation from FlowSim BC 6.3 (d50), height of draw (HOD), and previous wet muck events (PWME). The model evaluation aimed to determine whether a drawpoint is at high risk, as illustrated in Figure 4.

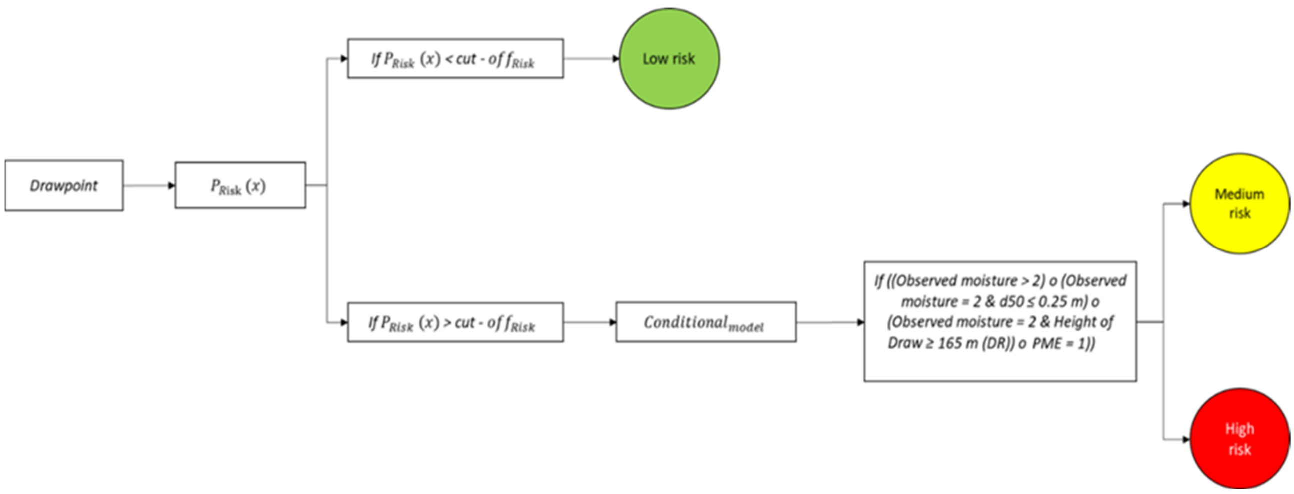

Figure 4 Schematic diagram of the risk level classification algorithm.

4 RESULTS AND DISCUSSION

4.1 Univariate Analysis

The univariate analysis performed for Diablo Regimiento was carried out for 31 critical variables, of which only 15 were statistically significant (p value ⩽ 0.1). Table 5 shows a summary of the metrics obtained in this analysis. Overall, variables such as laboratory moisture, visual moisture, inactive neighbor mud, extraction ratio and height of draw variables showed statistically significant correlation with the highest values of the chi-square test.

Table 5 Risk variables and their correlation with wet muck events, ordered by statistical significance (p value) for Diablo Regimiento

Variable	Coefficient	Chi-squared test statistic ($\chi 2$)	Odds Ratio	Statistical significance (p-value)
Laboratory moisture [%]	0.388	76.83	1.24	<0.001
Height of draw [m]	0.013	48.68	1.01	<0.001
Observed moisture	0.807	27.83	5.07	<0.001
Extraction ratio [%]	1.472	31.67	5.91	<0.001
Inactive neighbor mud	2.395	27.11	12.39	<0.001
Secondary extracted in the PE [%]	0.050	6.46	1.11	<0.001
Risk zone 50 m	1.610	12.06	11.06	<0.001
Primary extracted in the PE [%]	-0.018	12.56	0.97	<0.001
Uniformity 30 days [%]	1.797	9.22	0.99	0.001
Broken material extracted in the PE [%]	0.017	10.27	1.02	0.001
Distance to surface [m]	-0.013	10.35	0.97	0.003
Maximum difference in average extraction rate 30 days [t/m2-day]	1.152	6.75	0.99	0.003
Risk zone 100 m	1.810	12.16	1.00	0.004
Risk zone 80 m	1.336	9.01	1.00	0.004
Maximum difference in average extraction rate 15 days [t/m2-day]	1.023	6.16	0.99	0.004
Maximum flow rate [L/s]	0.001	0.62	1.00	0.393
Average precipitation 30 days [mm]	0.022	0.50	1.00	0.455
Fragmentation d50 [m]	0.238	0.31	1.00	0.557
Accumulated precipitation 30 days [mm]	-0.002	0.36	0.99	0.575
Accumulated precipitation 45 days [mm]	-0.002	0.33	0.99	0.596
Average precipitation 15 days [mm]	0.013	0.21	0.99	0.625
Risk zone 30 m	-0.431	0.20	1.00	0.674
Maximum average precipitation 60 days [mm]	-0.003	0.14	0.99	0.721
Historical mud sector	0.112	0.06	1.00	0.799
Maximum average precipitation 15 days [mm]	0.003	0.06	1.00	0.808
Accumulated precipitation 15 days [mm]	-0.001	0.05	0.99	0.826
Maximum average precipitation 30 days [mm]	-0.002	0.03	0.99	0.855
Accumulated precipitation 60 days [mm]	< 0.001	0.03	1.00	0.856
Average precipitation 60 days [mm]	0.004	0.01	1.00	0.919

The previous analysis indicated that wet muck events generally occur under conditions of excessive extraction (with a high height of draw), with a high percentage of moisture determined by laboratory tests and field moisture measurements, and in drawpoints where a prior wet muck event had occurred. This analysis was useful in identifying the main variables related to wet muck events.

4.2 Multivariate Analysis

In the multivariable analysis, over 40 models were assessed to predict wet muck events in Diablo Regimiento sector. Table 6 shows the analysis of 16 of the models with the final model providing the best results in terms of sensitivity, specificity, and accuracy. Although the univariate analysis showed that variables such as the percentage of primary material extracted, extraction ratio, and d50 fragmentation were not statistically significant, these were nevertheless included in the analysis. However, it was confirmed that these variables did not significantly contribute to the models' predictions.

Table 6 Summary of Models made for the Diablo Regimiento

	Models															
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Height of draw [m]	X					X	X	X						X		
Extraction ratio [%]					X				X						X	
Uniformity 30 days [%]		X	X	X			X				X	X	X			**X**
Maximum difference in								X		X			X			
Maximum difference in			X			X					X			X		**X**
Inactive neighbor mud							X								X	
Distance to surface [m]	X			X								X	X			**X**
Risk zone (Boolean)		X			X	X	X	X			X				X	
Maximum flow rate [L/s]						X			X							
Observed moisture							X					X	X		X	
Laboratory moisture [%]										X				X		**X**
Average precipitation at 15,											X				X	**X**
Maximum average	X		X	X	X		X	X								
Accumulated precipitation										X		X	X			
Primary extracted in PE [%]								X	X	X				X	X	
Broken extracted in PE [%]						X							X			**X**
Fragmentation d50 [m]				X								X	X			
Historical mud sector		X			X							X				

Table 7 shows the results of the best wet-muck event risk model for the Diablo Regimiento, which is represented by equation 5. In addition, the variables used, and their coefficients are presented, along with a description of how each of these variables would affect the probability of a wet muck event occurring.

$$\textit{Diablo Regimiento:}P_{Em}(x) = \frac{e^{-0.08-0.588\mathbf{UNIF}+0.849\mathbf{DIF\_VEL30}-0.009\mathbf{DTOPO}+0.007\mathbf{BM}+0.571\mathbf{HLAB}+0.049\mathbf{PP30}}}{1+e^{-0.08-0.588\mathbf{UNIF}+0.849\mathbf{DIF\_VEL30}-0.009\mathbf{DTOPO}+0.007\mathbf{BM}+0.571\mathbf{HLAB}+0.049\mathbf{PP30}}} \quad (5)$$

Here, P_{Em} (x) indicates the probability of a wet muck event, given a CP (cutoff probability). UNIF represents the uniformity at 30 days [%]. BM is the broken material extracted in DP [%]. DIF_VEL30 represents the maximum difference in average extraction rate [t/m2-day], HLAB is the laboratory moisture [%], and PP30 is the average precipitation at 30-day [mm].

Table 7 A wet muck event risk model for the Diablo Regimiento

Variable	Coefficient	Odds Ratio	Description
Uniformity 30 days [%]	-0.588	0.555	A 10% decrease in uniformity increases the probability of wet muck event risk by 6%.
Maximum difference in average extraction rate 30 days [t/m2-day]	0.849	2.337	A 0.1 [t/m2-day] increase in maximum difference average extraction rate increases the probability of wet muck event risk by 9%.
Distance to surface [m]	-0.009	0.991	A 10 [m] decrease in distance to surface increases the probability of wet muck event risk by 9%.
Broken material extracted in the PE [%]	0.007	1.007	A 10% increase in broken material extracted in the PE increases the probability of wet muck event risk by 7%.
Laboratory moisture [%]	0.571	1.770	A 1% increase in laboratory moisture increases the probability of wet muck event risk by 77%.
Average Precipitation 30-day [mm]	0.049	1.050	A 5 [mm] increase in average precipitation in the last 30 days increases the probability of wet muck event risk by 28%.

4.3 Calibration and Validation models

During the calibration stage, tests were carried out with different cutoff probabilities to build contingency tables and find a multivariable predictive model that would maximize the performance KPIs of the model. After several cutoff probabilities were evaluated, it was determined that the optimal value to correctly identify wet muck events was 0.29 in Diablo Regimiento. The results of the KPIs for the model are shown in Table 8:

Table 8 Results of the main performance for Diablo Regimiento sector

Model	True Positive Rate	True Negative Rate	Accuracy
Diablo Regimiento	85%	81%	81%

The assessment for the Diablo Regimiento sector in terms of the operational footprint are shown in Table 9. The results of applying the wet muck event model August 29 - September 2, 2018, are presented in Figure 5, in which the drawpoints are categorized by the level of wet muck event risk: red being high risk, yellow being medium risk, and green being low risk. Specifically, these results indicated that 10% of the operational footprint was classified as high risk.

Table 9 Operational footprint assessment for Diablo Regimiento sector

Diablo Regimiento	18-10-2011	21-08-2013	03-05-2018	29-08-2018	02-09-2018	10-08-2019
Drawpoints in operation	172	213	296	300	303	278
Low Risk Event Drawpoints	159	204	262	260	263	258
Medium Risk Event Drawpoints	2	2	9	9	9	10
High Risk Event Drawpoints	11	7	25	31	31	10
Operational Footprint at High Risk [%]	6%	3%	8%	10%	10%	4%

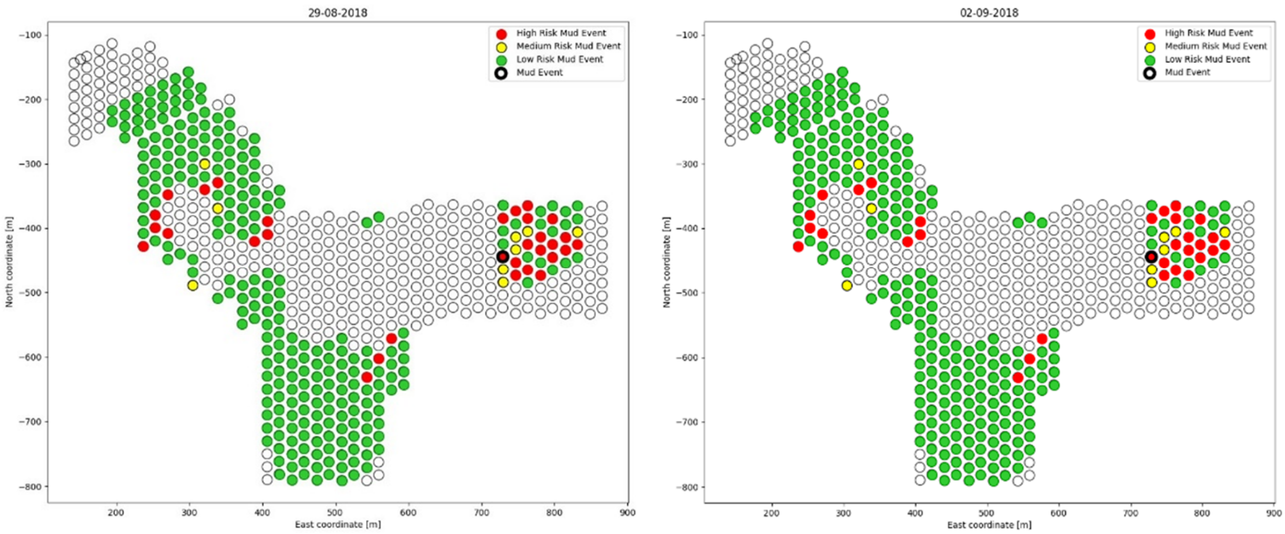

Figure 5 Wet muck event risk model for Diablo Regimiento on September 2, 2018, and August 10, 2019.

5 APPLICATION OF THE SHORT-TERM MODEL IN DIABLO REGIMIENTO

Once the model for Diablo Regimiento sector was calibrated, it was used to evaluate the extraction plans for this sector. The extraction plan covered the period from September 2021 to March 2022. To estimate the variable of percentage flow of broken material, FlowSim BC 6.3 software was used. The other variables were constructed based on the information provided by El Teniente.

5.1 Diablo Regimiento extraction

The extraction from Diablo Regimiento involved a total of 4.8 Mt planned. A bar chart depicting the extraction is shown in Figure 6.

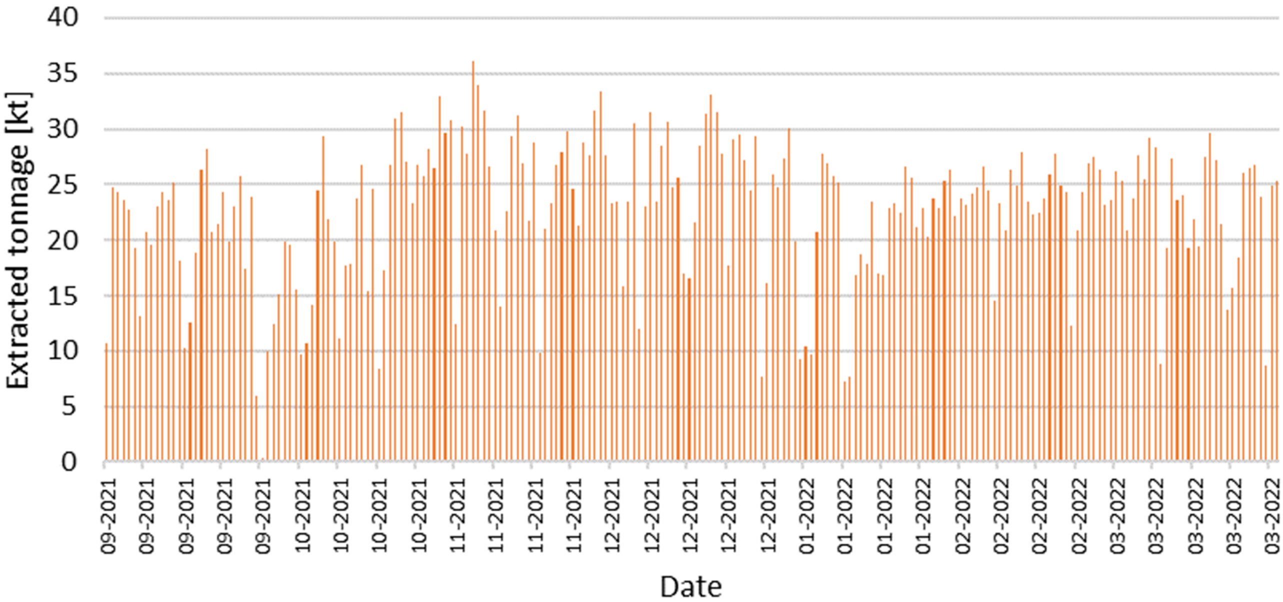

Figure 6 Extraction plan for Diablo Regimiento between September 2021 and March 2022.

Table 10 Operational footprint assessment for Diablo Regimiento sector

Diablo Regimiento	**01-09-2021**	**31-10-2021**	**01-12-2021**	**31-03-2022**
Drawpoints in operation	21	203	201	191
Low Risk Event Drawpoints	9	183	183	185
Medium Risk Event Drawpoints	6	12	14	2
High Risk Event Drawpoints	6	8	4	4
Operational Footprint at High Risk [%]	3%	4%	2%	2%

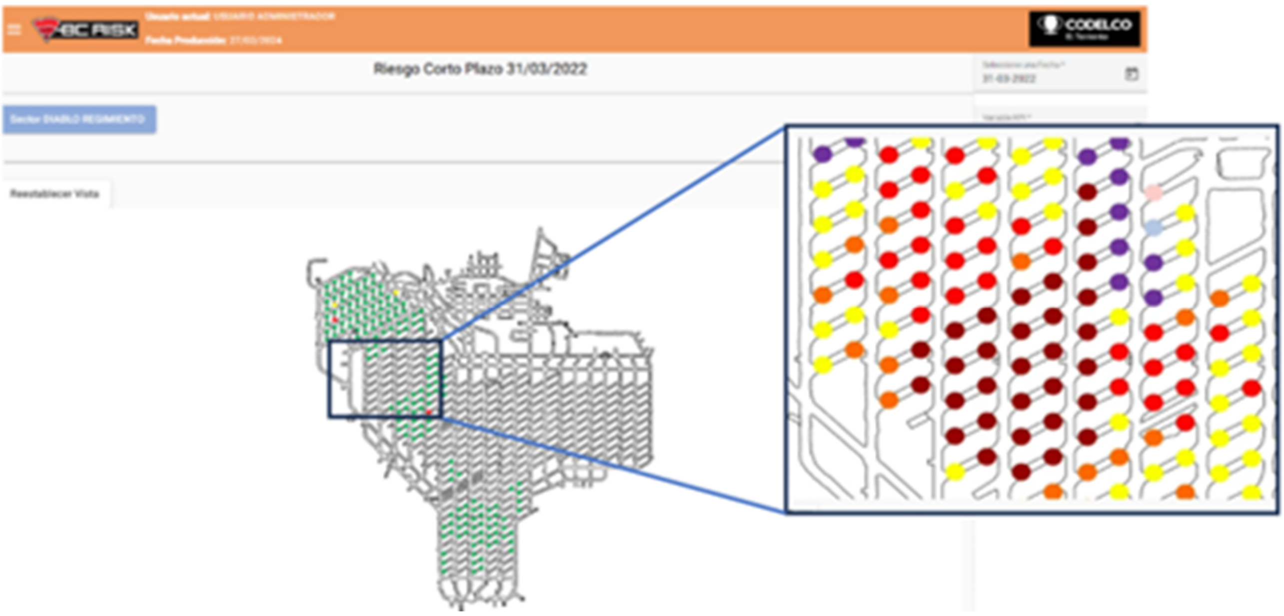

Figure 7 BCRisk application inside wet muck module at Diablo Regimiento sector on March 31, 2022 (BCTEC, 2022) in brown DP's with wet muck extraction.

5.2 Diablo Regimiento new boundaries

Table 10 and Figure 7 show the obtained results. It is worth noting that on March 31, 2022, only 2% of the operational footprint was classified as high risk.

The extraction efficiency inside the wet muck module at Diablo Regimiento has significantly improved thanks to the integration of advanced technologies such as the use of autonomous LHD for ore extraction, Near Infrared (NIR) for moisture measurements, drones for surface cavity measurement and the robust wet muck risk assessment model described here.

In terms of safety, the implementation of autonomous LHDs has significantly reduced personnel exposure to the risk zones declared by the wet muck model. Additionally, isolation polygons have been established to ensure a safe distance from wet muck extraction zones, delimited by a 60-meter radius around the area, along with a minimum stabilization period of 4 hours after extraction.

The previous strategy has enabled the inclusion of ore materials that were previously delayed due to challenging wet muck conditions. In 2022, the extraction rate exceeded 1.3 ktpd, and the target is to reach 9 ktpd by 2024. Currently, mineral extraction in wet muck zones has surpassed the objective, reaching 20 ktpd reflecting the successful adaptation to wet muck challenges through innovative approaches and strategic planning.

6 GENERAL CONCLUSIONS

In this article, the development of a probabilistic model of wet muck events in the Diablo Regimiento sector was described. The main objective of the model was to identify high and medium-risk zones so that extraction strategies could be defined that mitigate the risks associated with these events.

The short-term model incorporated operational variables such as uniformity and extraction rate, as well as environmental and geometric variables, such as the distance from the drawpoint (DP) to the surface, laboratory moisture at the DP, and precipitation. Additionally, a variable related to the extracted lithology, specifically the percentage of broken material, was included, obtained from the gravity flow software FlowSim BC v6.3 calibrated with mine data (Celhay et al., 2024).

The short-term model demonstrated a remarkable accuracy of 86% for the Diablo Regimiento sector. After applying the short-term wet muck risk model, Diablo Regimiento has reported improved use of mitigation strategies to manage the risk of wet muck and extract the benefits of the ore from this material. Currently, they are extracting 9,000 tpd of wet muck, which can be compared to previous wet muck extractions of 1,300 tpd before the short-term model was implemented. The application of the short-term model has also allowed for a decrease in the areas defined as within the high-risk zones. This reduction occurred from 4% of the operational footprint at risk on October 31, 2022 to 2% by the conclusion of the extraction plan evaluated on March 31, 2022.

The results at Diablo Regimiento reflect the successful adaptation to wet muck challenges through innovative approaches and strategic planning that could be included for different sectors and mines with wet muck conditions. These results emphasize the importance of short-term predictive models as fundamental tools for determining which zones are at high risk of wet muck events. In summary, the successfully calibrated model in this article — incorporating critical risk variables — demonstrated acceptable precision and outstanding predictive capability. This approach applied to evaluate short-term plans at Diablo Regimiento sector contributed to planning and decision-making to minimize the risks associated with mud events while optimizing the extraction benefits of managing wet muck. The robustness and predictive capacity of this model make it a desirable option for application in future sectors facing similar challenges from the occurrence of wet muck events.

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