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Development of a wet muck spill susceptibility tool for short-term prediction through a logistic regression approach

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Abstract

The Grasberg mining complex in Papua, Indonesia, consists of three caving operations and an open stope mine. Two of the caves, the Grasberg Block Cave (GBC) and the Deep Mill Level Zone (DMLZ), are ramping up to full production, while the Deep Ore Zone (DOZ) cave will cease operations in 2022. The DOZ has had a history of production interruptions due to wet muck spill events. The newer caves expect to be affected by similar wet muck hazards due to the presence of fines and saturated material at the muck pile, overlying open pit in the case of the GBC and overlying caves in the case of the DMLZ, high annual rainfall, and complex topography at the subsidence that directs surface and groundwater into the cave.

To proactively manage this hazard, experience from the DOZ cave mine is being applied to improve the understanding of drawpoint wet muck spill susceptibility. The combination of fines generated through secondary fragmentation from the high draw columns and saturation from the intense surface and groundwater inflow results in wet muck material at the drawpoint, providing the cause while mucking activities provide the trigger. Other contributing factors included in the analysis are the uniformity of draw and neighbouring drawpoint conditions.

Although the consequences of wet muck spill events are high, they are still relatively rare, resulting in an imbalanced dataset. To overcome this challenge, cost-sensitive learning is incorporated into the logistic regression model for significant variables selection, thus developing a wet muck susceptibility tool. This tool aims to identify individual drawpoint susceptibility to wet muck spill events based on a simple material classification and measures of draw performance. The approach has been successful in describing historical drawpoint susceptibility at the DOZ. Furthermore, this study provides a concept applicable to other wet muck susceptible cave mines.

Keywords: *caving operation, wet muck spill, machine learning, wet muck susceptibility tool*

1 Introduction

Wet inrushes are known by several different names, including wet muck spills and mud rushes, and are defined as sudden inflows of unsorted fine grain particles and water discharged from drawpoints or other underground openings (Butcher et al. 2000; Jakubec et al. 2016). This phenomenon exposes caving operations to safety, operational, and economic risks. Their occurrence increases as a cave matures, which has provoked many questions about the conditions that will lead to a spill. In addition, it is difficult to predict exactly when one of these events will occur due to randomness and difficulty ascertaining when certain conditions are met. A better understanding of these conditions can provide insights for managing future events.

The occurrence of a wet muck spill is a complex process requiring the simultaneous presence of four elements within the drawpoint vicinity (Butcher et al. 2000): (1) potential mud-forming materials (i.e. fines), (2) accumulation of water, (3) disturbance of the mud in the form of drawing or other mining activities, and (4) a discharge point. All of these elements are part of the nature of caving operations and are largely unavoidable. Findings from various caving operations have summarised that fines generation is a function of geology and the comminution process in the cave zone, while water originates from either surface precipitation or nearby aquifers.

The history of wet muck spills at the Grasberg mining complex, including the Deep Ore Zone (DOZ), has led to insights into the causative and triggering factors, including complex geological conditions, high annual rainfall, uneven draw, suspension of operation, and static and dynamic disturbance (Widijanto et al. 2012). Several cave mines around the world, such as the El Teniente mining complex, Cadia East mine, Palabora mine, and Kimberley mine, have also been impacted by various forms of inrushes, including wet muck spills, dry muck spills, and water inrushes. The inrush characteristics, susceptibility, and severity are different depending on the hydrogeological conditions, cave geometry, operational history, and orebody geology of each mine. Current knowledge and mitigation strategies are largely anecdotal and rely on experience from historical inrushes. Several of the strategies, such as drawpoint closures and tonnage restrictions, are believed to help limit the number of high-risk drawpoints. However, the success rates are unknown, and these strategies negatively impact production rates while still being unable to resolve the progressive appearance of mud at a drawpoint.

This paper summarises the author's thesis on the development of a new wet muck spill susceptibility tool based on a logistic regression analysis of historical data from the DOZ mine in Indonesia. The overall goal of this research is to improve short-term spill prediction at the Grasberg mining complex and provide a general conceptual framework that can be adapted to other wet muck susceptible cave mines.

2 History of wet muck spills at the Deep Ore Zone mine

The Grasberg mining complex, operated by PT Freeport Indonesia (PTFI), is located in the southern area of Jaya Wijaya Mountains, West Papua, Indonesia. Four mines are currently operating: three caving operations at the DOZ, Deep Mill Level Zone (DMLZ) and Grasberg Block Cave (GBC) mines, and the Big Gossan stoping mine (Casten et al. 2020). In addition, PTFI has several potential future operations, including the Kucing Liar and Gajah Tidur resources. Figure 1 illustrates the general layout of the different mines belonging to the Grasberg mining complex.

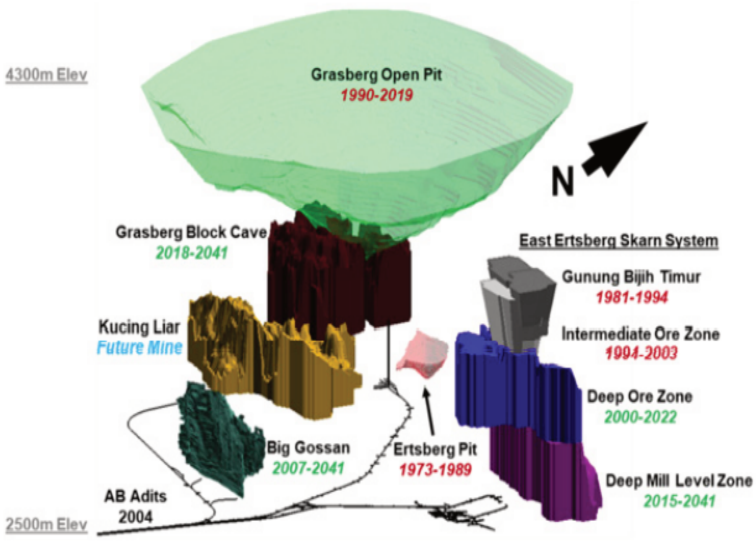

Figure 1 The general layout of the PTFI Grasberg mining complex (Casten et al. 2020)

The DOZ mine is the third lift of the block cave mine in the East Ertsberg Skarn System (EESS), after the Gunung Bijih Timur (GBT) and Intermediate Ore Zone (IOZ) mines. By 2019, the DOZ mine had produced 300 million tonnes of ore since it opened in 2000 (Casten et al. 2020). The extraction level is at a depth of approximately 1,200 m below the surface and includes 1,347 drawpoints across 39 panels with column heights up to 750 m. The extraction level was constructed with an offset herringbone layout to minimise wet muck flow distances. The Grasberg mining complex is operating with complex geological and hydrogeological features, steep mountainous topography, and high average annual rainfall of 5,500 mm, which creates wet muck spill challenges at the DOZ mine (Widijanto et al. 2012).

The Grasberg mining complex underground operation has a long history of wet muck spills since the GBT and IOZ operations (Hubert et al. 2000). The wet muck was generally understood to originate from comminution within the draw column combined with high rainfall (Edgar et al. 2020). The DOZ mine experienced its first spill in 2003 (Ginting & Pascoe 2020) and had recorded more than 1,900 spills as of 5 July 2019 (Figure 2).

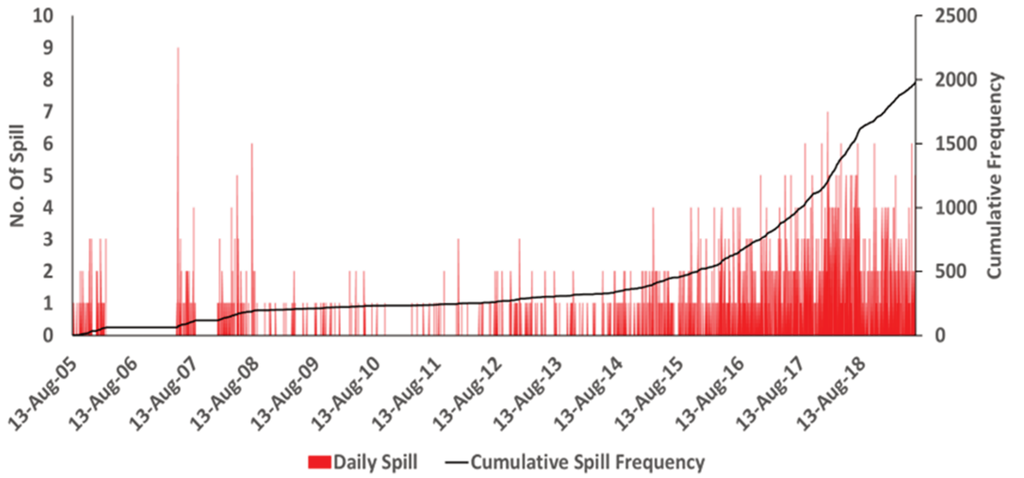

Figure 2 Historical wet muck spills at the DOZ mine, up to 5 July 2019

Spill frequency significantly increased from 2015 onwards due to the cave experiencing more saturation, which in turn led to an increasing drawpoint closure rate to maintain safety. Very large spills have also occurred with up to 6,000 m^3 total volume; these spills flowed beyond the exclusion gate with a total distance of up to 150 m (Edgar et al. 2020). For reference, these large spill volumes are comparable to the volume of the drawbells, which are approximately 6,350 m^3.

PTFI classified a drawpoint as having the potential to generate a wet muck spill where the following criteria are met:

1. Unsorted material with greater than 20% sand-sized particles (grain size <2 mm).
2. Material must be at least 80% saturated or greater than 8.5% water content.
3. Drawpoint toe must be loosely packed (less than 90% relative density).

Drawpoint wet muck classification (Table 1) is mapped through weekly visual observations of material grain size (A, B, C) and water content (1, 2, 3). The drawpoint wet muck classification was originally derived from the IOZ operation and aimed to determine the loading procedure based on the drawpoint condition (Call & Nicholas Inc. 1998).

Table 1 PTFI drawpoint wet muck classification system (modified from Widijanto et al. 2012)

Wetness/water content	Grain size (M) > 5 cm		
	M ≥ 70% (coarser grained)	70% ≥ M ≥ 30% (medium grained)	M ≤ 30% (finer grained)
Dry (<8.5%)	A1	B1	C1
Moist (8.5–11.0%)	A2	B2	C2
Wet (>11%)	A3	B3	C3
Green	Any loader		
Yellow	Any loader with close supervision		
Red	Remote loader		

3 Development of the wet muck spill susceptibility tool

3.1 Overview of the machine learning approach

The wet muck database was developed based on daily data recorded by PTFI for all 1,347 drawpoints at the DOZ mine between January 2008 and June 2019, including spill locations and operational activities that are associated with potential wet muck causative and triggering factors. The database consisted of 2.4 million daily drawpoint records, including 1,853 total spills that occurred from 374 drawpoints. In total, 177 variables were identified with potential links to spatial and temporal patterns of wet muck accumulation, migration, and spills. The variables considered in the analysis are categorised as follows:

1. Wet muck conditions: drawpoint and neighbouring drawpoint wet muck classification.
2. Sources of fines generation: height of draw (HoD), overlying cave condition, and surface subsidence.
3. Sources of water: rainfall.
4. Operational activities: draw rates, mucking activities, and Uniformity Index (UI).

Predicting the presence or absence of a wet muck spill constitutes a classification problem where the outcome is binary encoded, with spill indicated by a value of 1 and no spill indicated by a value of 0. The susceptibility model for wet muck spills at the DOZ mine was developed using the Python programming language through the 'LogisticRegression' package from Scikit-Learn. Logistic regression (logistic or logit model) is a regression technique that analyzes the relationship between one or more independent variables as well as a binary or dichotomous outcome and estimates the probability of occurrence by fitting the data with a logistic curve, as shown in Equation 1 (Hosmer et al. 2013), where β is the coefficient of each variable and x is the variable. This approach provides ease of interpretation, is straightforward to develop and improve, and is able to identify patterns in a large dataset.

Multivariate logistic regression:

$$P(Y=1)=\frac{e^{\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n}}{1+e^{\beta_0+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n}} \quad (1)$$

Prior to the machine learning analysis, the model was compiled with the hypothetical wet muck spill causative and triggering factors. Each of the hypothetical variables were explored to identify any patterns in the database. The analysis started from a Univariate Logistic Regression (ULR) model considering one variable at a time, and then gradually built into a Multivariate Logistic Regression (MLR) model. Variables that did not show any relationship and/or poor performance metrics were excluded from the analysis. The research workflow is illustrated in Figure 3. Further detail on the workflow is outlined in Varian (2022).

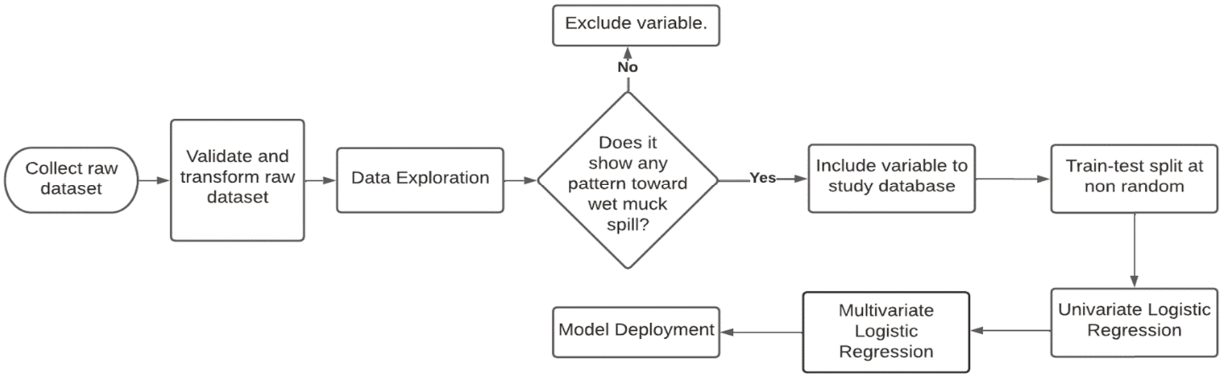

Figure 3 The cost-sensitive logistic regression development concept for wet muck spill susceptibility analysis (Varian 2022)

Logistic regression is a supervised machine learning technique that requires two sets of data: a training set and a test set. The training set is used for the learning process and estimates the relationship between input and output data, while the testing set evaluates the relationships derived by measuring the success of the predictions using unseen data. Since the wet muck spill database has a temporal nature, the train-test datasets must be divided. In this study, data between 2008 and 2016 were used for training and data after 2017 were used for testing. The train-validation dataset was processed using the 'TimeSeriesSplit' function from the Python Scikit-learn library, which divides the dataset into defined iterations, referred to as folds, for validation and the parameter hyper-tuning stage. During the train-test split process, numerical variables were standardised to prevent biases that would otherwise be introduced when using variables with different units and/or scales. Categorical data with multiple classes were converted into several binary columns that represent each class.

The dataset was observed to be severely imbalanced, as spills did not occur on a daily basis over the total observation period. In total, there were 1,809 spills and 2.4 million no-spills over the 11.5 years of operational history covered by the database. If not treated, the model result tends to bias to the majority class observation (King & Zeng 2001). To address this issue, a cost-sensitive algorithm was used to assign equal weighting for both spill and no spill observations. Since the minority class is observed at spill, higher cost (weight or penalty) is assigned to the misclassification of minority class. The minority class weight can be calculated using Equation 2 where w_i is the minority class weight, n is the number of observations, k is the total number of classes, and n_i is the number of observations in the minority class.

Minority class weight:

$$w_i = \frac{n}{k \cdot n_i} \tag{2}$$

A confusion matrix, also known as a contingency table, was used to measure the classifier performance, and represents the counts of actual and predicted values from the test dataset (Kuhn & Johnson 2013), including:

- True positives (TP): model correctly predicts a spill outcome.
- False positives (FP): model incorrectly predicts a spill outcome.
- True negatives (TN): model correctly predicts a no-spill outcome.
- False negatives (FN): model incorrectly predicts a no-spill outcome.

The essence of the misclassification cost in this study considers that even when a wet muck spill might not occur at a high spill-susceptible drawpoint, the operation can minimise operational, economic, and safety risks by classifying a drawpoint as spill-susceptible when all factors are present. Wet muck spills have a severe impact that can lead to fatalities, operational delays, and economic losses, which require an early detection tool. In this context, it is more important to alert the operator of a potential wet muck spill rather than predict exactly when and where it will happen. The false positive can be tolerable because it classifies the drawpoint as spill-susceptible when all wet muck factors are present. Although it is important for the model to precisely predict future wet muck spills, from a hazard and safety perspective, it is more important for the model to alert the operation to all potential wet muck spills, with the trade-off of a high number of false alarms. Since a high number of false negatives are less tolerable, the model prioritises a high recall score (Varian 2022). Furthermore, the imbalanced database has a very low spill observation rate. Any hypothesised causative and triggering factors of wet muck spills can be present, but with the result of no-spill, which provides a high false positive rate even if the model is set to achieve high precision.

3.2 Exploratory data analysis to identify patterns

The frequency of wet muck spills was observed to increase as the DOZ mine and cave matured, with a significant increase in the period 2015–2016 in parallel with the increased reporting of wet muck drawpoints (Figure 4). The majority of spills during this period occurred at wet muck class drawpoints (mainly B3 and C3). There were numerous events where the spill drawpoint was classified as coarse material and moist/wet conditions, while the adjacent drawpoint was classified as a wet muck drawpoint, with finer grained, lower permeability, and wetter material. Water from these low permeability drawpoint cannot drain properly from the drawpoint, which able to form wet muck and flow to the adjacent drawpoint (Figure 5). Once triggered, a spill can occur from a coarser drawpoint, with material originating from its adjacent water-saturated drawpoint.

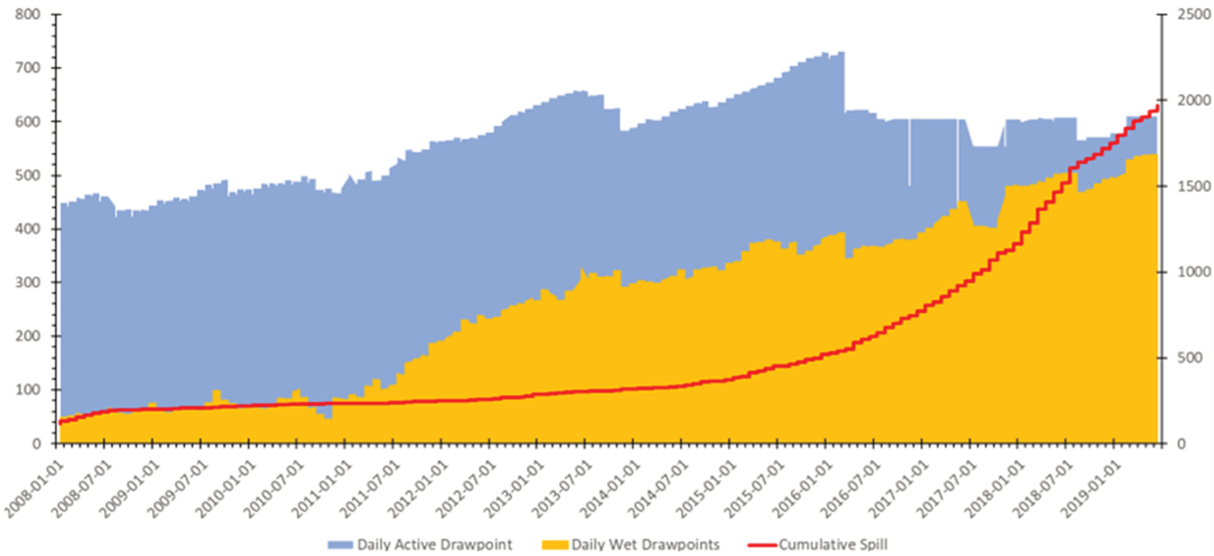

Figure 4 Monthly wet muck spills at DOZ versus total number of active drawpoints

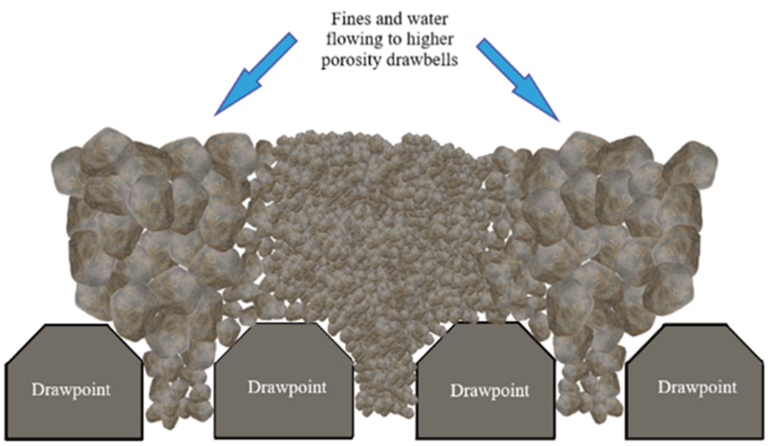

Figure 5 Example of material migration from finer drawbell to coarser drawbell due to difference in porosity (Varian 2022)

Wet muck spills tend to occur when there is a high concentration of wet muck neighbouring drawpoints in the vicinity. This also indicates that the area is highly saturated. It is hypothesised that wet muck conditions at a drawpoint indicate similar conditions above the drawbell, with material able to flow following the preferential path created by mucking activities following the direction of cave advancement.

Various cave draw strategies have been implemented at the DOZ mine since the beginning of the operation. The increase of wet muck spills has forced the operation to adapt to the wet muck condition. The exploratory data analysis shows that spills occurred at various draw rates, which suggests that mucking activity acts as a triggering factor for wet muck spills (Figure 6). The majority of spills occurred when there were drawpoint mucking activities. Active mucking loosens the drawpoint toe material causing the rapid loss of confinement result in undrained failure of saturated fine material in the drawpoint or drawbell. However, there were no significant patterns identified between spill events and adjacent drawpoint mucking or consecutive mucking. Furthermore, HoD was also identified as a potential significant variable, where spills tended to occur at DOZ once the HoD was greater than 170 m.

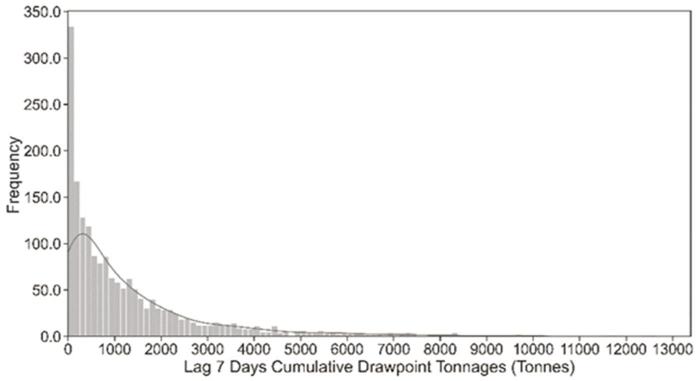

Figure 6 Previous seven days cumulative tonnages at spill drawpoints

Wet muck spill also correlates when the updated UI values greater than two and up to three day period. An updated UI matrix was developed building on the original work by Susaeta (2004). The original UI was developed for the layout at the El Teniente mine in Chile, which was operating in mostly dry conditions. In contrast, the DOZ drawpoint layout is constructed with an offset herringbone pattern, for which most drawpoints have seven nearest neighbours (five along the minor apex and two along the major apex). Site experience have indicated that Susaeta's UI might not be applicable under wet conditions and needs to be modified for semi-uniform to isolated draw. The updated UI matrix that was developed for this study is shown in Table 2, with the drawpoint vicinity illustrated in Figure 7.

Table 2 Proposed UI matrix for the DOZ mine

Number of inactive drawpoints	Specific index of uniformity				
	0–0.2	0.2–0.4	0.4–0.6	0.6–0.8	0.8–1.0
0	Uniform	Uniform	Uniform	Non-uniform	Non-uniform
1	Uniform	Uniform	Non-uniform	Non-uniform	Non-uniform
2	Uniform	Non-uniform	Non-uniform	Non-uniform	Non-uniform
3	Non-uniform	Non-uniform	Non-uniform	Non-uniform	Non-uniform
4	Non-uniform	Non-uniform	Non-uniform	Non-uniform	Non-uniform
5	Non-uniform	Non-uniform	Non-uniform	Non-uniform	Non-uniform
6	Non-uniform	Non-uniform	Non-uniform	Non-uniform	Non-uniform
7	Non-uniform	Non-uniform	Non-uniform	Non-uniform	Non-uniform

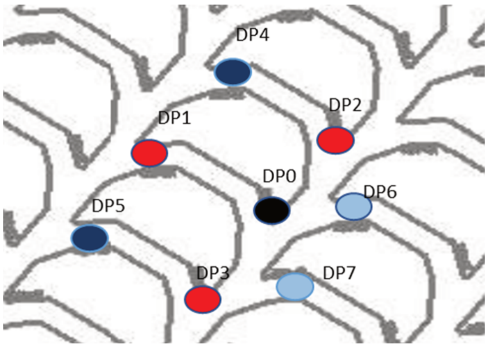

Figure 7 Proposed radius of influence for DP0, considering one major pillar, one minor pillar to the north and south (along the extraction drive), and one adjacent drawpoint

3.3 Univariate and Multivariate Logistic Regression results

A total of 177 variables were initially assessed individually against the DOZ historical wet muck spill occurrences using the ULR analysis. Statistically significant variables were selected based on the confusion matrix and their capability to predict spill and no-spill conditions. The majority of the variables tested had a very low precision score between 0 and 0.03, while recall scores varied between 0.34 and 1.

Since the DOZ mine has been using drawpoint classification to indicate a drawpoint wet muck susceptibility condition, the MLR reveals the susceptibility model improvement from a one-dimensional matrix into multi-dimensional matrices by gradually adding significant variables identified from the ULR stage. A decision framework for variable addition or exclusion at this stage is illustrated in Figure 8.

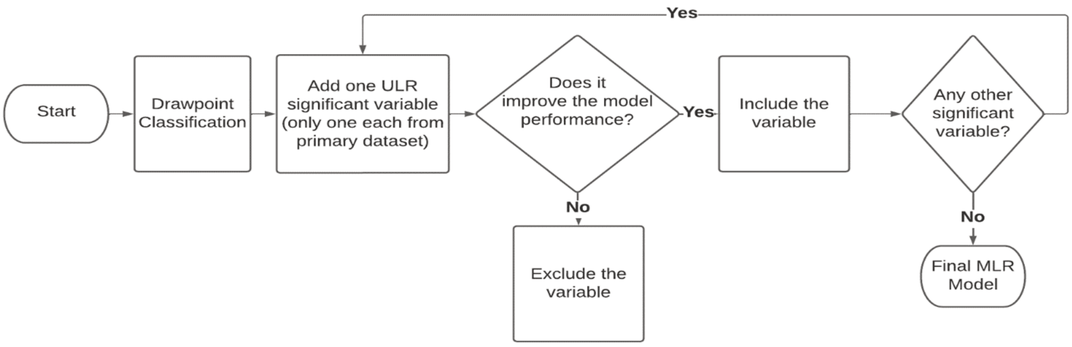

Figure 8 Variable inclusion/exclusion flow chart in the Multivariate Logistic Regression process (Varian 2022)

Out of the 177 variables tested, eight variables were considered to be significant. The MLR model confirmed that PTFI's existing drawpoint classification system is a good predictor of wet muck spills. Mucking activity indicated by a binary condition of a drawpoint mucking activity identified as a triggering factor where over 14-days period showed highest precision-recall score. This study improves the susceptibility analysis by adding dimensionality from a two-parameter drawpoint classification matrix to an eight-parameter matrix, which is able to improve current spill and no-spill outcomes. Following is the order of significant variables, from highest to lowest: (1) drawpoint classification, (2) 14-day drawpoint mucking activity, (3) total number of wet muck neighbours within 36 m, (4) two-day consecutive mucking activity, (5) adjacent drawpoint classification, (6) three-day UI within the seven nearest drawpoints, (7) HoD, and (8) 14-day adjacent drawpoint mucking activity.

Although the UI is not one of the strongest explanatory variables, it is still an important factor that can be controlled, with the goal of achieving uniform draw, when all of the uncontrollable contributing factors are present. Variables such as the 14-day drawpoint mucking activity, 14-day adjacent drawpoint mucking, two-day consecutive mucking, and three-day UI within the seven nearest drawpoints are recommended to be controlled in order to reduce drawpoint wet muck susceptibility. The intercept was set at -6.83 and the coefficient distribution for each variable is illustrated in Figure 9.

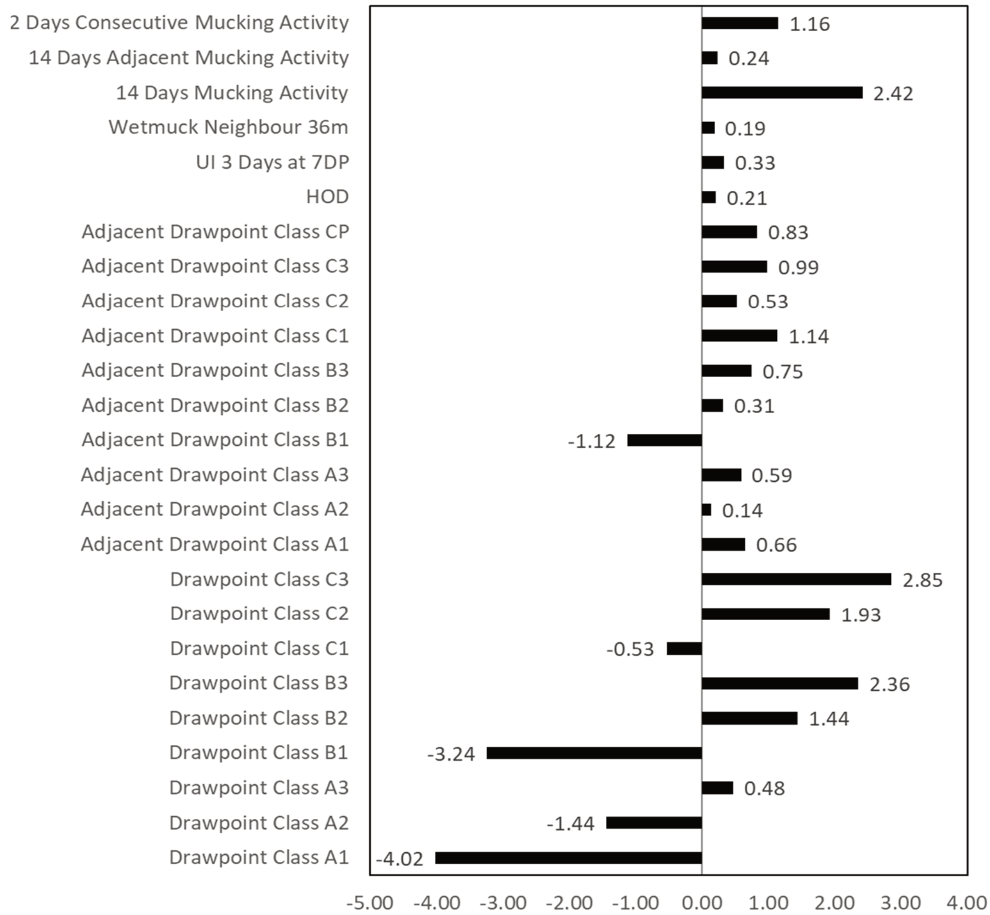

Figure 9 Proposed wet muck susceptibility model coefficient using 100% of the data as the training set

While the susceptibility model performance generally shows a good result, there are a few key limitations identified as follows:

- Analysis of the observational datasets, such as drawpoint classification and wet muck neighbouring drawpoints within 36 m, is challenging because observations can be subjective and vary between different mine workers mapping and recording the data at different times.
- A logistic regression model is a generalised model that assumes a linear relationship between the logit link function and explanatory variables. However, wet muck spills are a complex problem that may involve non-linear relationships.
- The susceptibility model predicts a short-term drawpoint susceptibility to wet muck spills. Calculations with higher temporal inputs might not result in higher accuracy. In addition, the model cannot predict the exact time and location of wet muck spill occurrence.

3.4 UBC-ICaRN Wet Muck Susceptibility Model

A spreadsheet-based wet muck spill susceptibility prediction tool, named the UBC-ICaRN Wet Muck Spill Susceptibility Tool, was developed based on the eight most significant variables identified in the MLR model analyses. The aim of this tool is to provide the daily probability of a wet muck occurrence for every drawpoint, calculated using the MLR equation (Equation 1). Since there is uncertainty in the model, specifying only one spill susceptibility cut-off threshold (e.g. 0.5) may not be effective in assisting operational planning. Different strategies and mitigation procedures can be applied to different susceptibility thresholds.

The following interim thresholds for wet muck susceptibility are suggested following a traffic light protocol (green, yellow, red):

1. Low susceptibility: spill probabilities between 0 and 0.4, colour-coded green.
2. Medium susceptibility: spill probabilities between 0.4 and 0.75, colour-coded yellow.
3. High susceptibility: spill probabilities between 0.75 and 1, colour-coded red.

These susceptibility threshold cut-offs are defined based on the model test set results (Figure 10). Out of 776 wet muck spills between 2018 and June 2019, the model was able to predict the majority of these events, with 723 (93%) being classified as high susceptibility and 49 (6.3%) being classified as medium susceptibility. Only 4 (0.5%) were misclassified as having a low susceptibility to a wet muck spill. Due to the imbalanced nature of the dataset, a high false positive (false alarm) rate cannot be avoided. There were 86,183 false alarms, where drawpoints experienced no-spill but were classified as high susceptibility. As shown in Figure 11, if the threshold is lowered by 0.1 at each susceptibility level, the model only misclassifies two spills within the low susceptibility class, but with the trade-off of a higher false alarm rate. In contrast, if the spill susceptibility threshold is increased by 0.1 at each susceptibility level (Figure 12), the model misclassifies eight spills within the low susceptibility class. However, it reduces the false alarms to 64,629 cases.

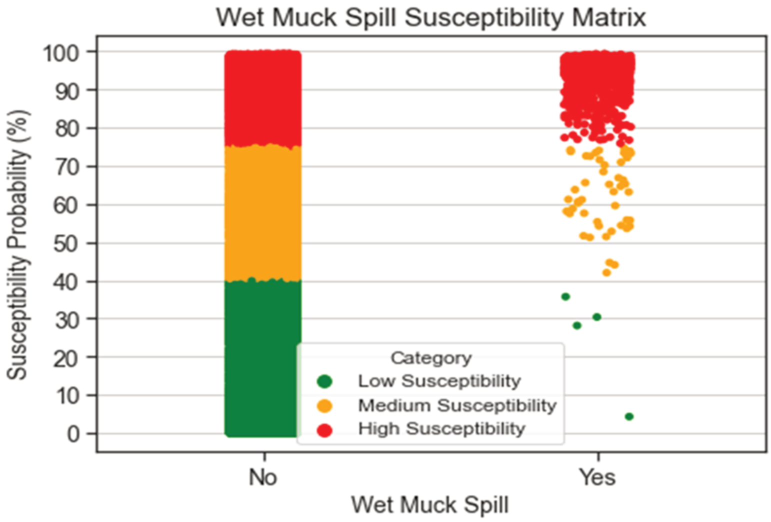

Figure 10 Proposed model performance on the test set with interim susceptibility thresholds

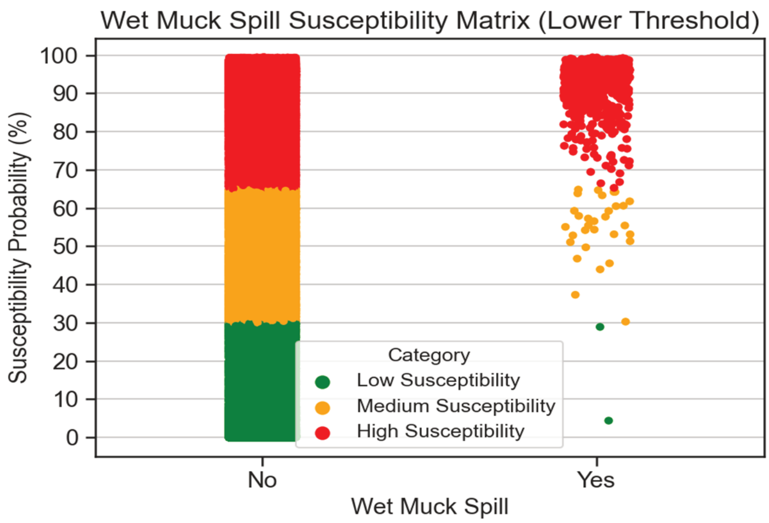

Figure 11 Proposed model performance on the test set with lower susceptibility thresholds

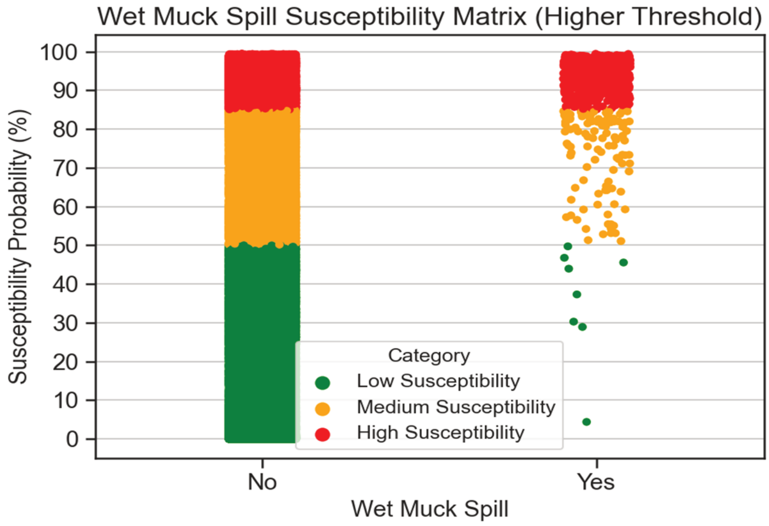

Figure 12 Proposed model performance on the test set with higher susceptibility thresholds

It is important that the interim thresholds suggested above be reviewed and modified to suit the operation's risk tolerance and associated wet muck spill mitigation strategies (e.g. limiting the number of buckets per shift that can be drawn at drawpoints in each susceptibility range). For example, raising the threshold between low and medium susceptibility ranges could ease operational strategies on mucking, but result in higher false negatives that may lead to higher safety and operational risks.

For communication purposes, the calculated spill susceptibility for every open drawpoint can be plotted using the traffic light protocol. An example for the DOZ mine operation is shown as a susceptibility map for the extraction level footprint (Figure 13). This map can be used as supplementary information or as a forecasting tool by highlighting any relatively high-susceptible areas.

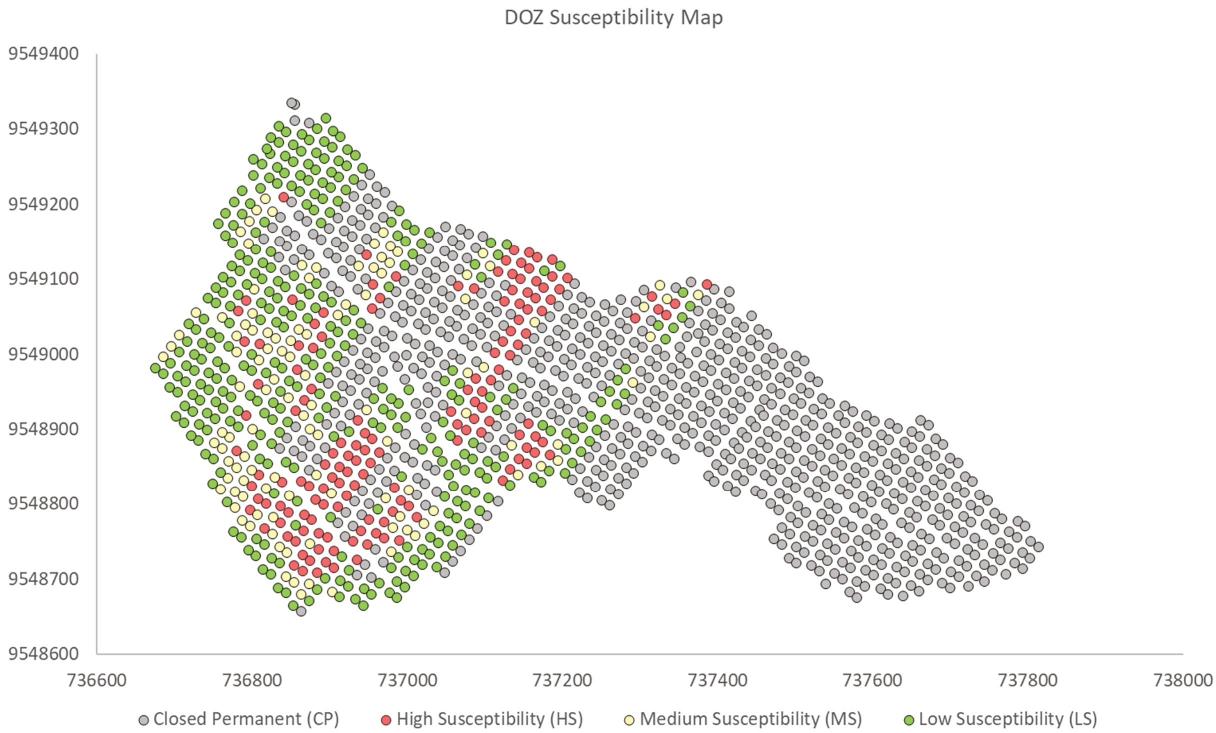

Figure 13 Example of DOZ cave footprint susceptibility traffic light protocol map

4 Conclusion

A cost-sensitive logistic regression model was used to evaluate each explanatory variable and its statistical relationship with wet muck spills. This approach allowed the model to reduce the effects of the severely imbalanced nature of the dataset, applying equal weight to spill and no-spill data. In addition, this model updates the current susceptibility tool by adding dimensionality, which results in higher predictive power. Out of 177 variables with approximately 2.5 million data observations, eight significant variables were identified that are correlated with wet muck spill occurrences at the DOZ mine.

A spreadsheet-based tool was also developed based on the eight most significant variables identified in the MLR analyses. The aim of this tool is to provide the daily susceptibility of a wet muck occurrence for every individual drawpoint in the cave footprint. Although the model results in a high false positive rate, it can be utilised as a forecasting tool to alert the operation to drawpoints that have a relatively high susceptibility to wet muck spills.

It is important to note that this model was developed only using the DOZ mine database. Direct application to other operations might not achieve similar model performance. However, this research delivers a conceptual framework – a wet muck susceptibility tool based on a cost-sensitive Multivariate Logistic Regression analysis that can be applied to other caving operations around the world that experience wet muck spill hazards. A similar workflow can be adapted with site-specific input variables to provide a site-specific susceptibility model.

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