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Applying risk-based principles of dispersive mine spoil behaviour to facilitate development of cost-effective best management practices

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Executive summary

Dispersive spoil material on mine sites represents a significant operational, environmental and economic challenge to mining operations. Better understanding of the chemical and physical characteristic of spoil material and its behaviour under different climatic and management regimes is needed to inform site-specific management decisions.

This industry-funded project has developed, parameterised and tested a prototype Bayesian network (BN) model which integrates a range of biophysical (climate, spoil characteristics, vegetation cover) and management (landform, spoil amendment, runoff management) variables.

Where available, quantitative data were used to parameterise the model; however, in many instances, existing data were too few and it was necessary to use qualitative information (expert judgement). The process of developing the model identified serious data deficiencies which should inform future data collection strategies.

An ongoing iterative process, with targeted data collection and feedback from industry decision makers and discipline experts, will support improvements in the model, which has significant potential to inform adaptive evidence-based best practice dispersive mine spoil management.

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Introduction

Sustainable closure of coal mines is a significant challenge to the mining industry in Australia. This is particularly the case where the nature of spoil materials makes minesite rehabilitation more difficult and costly. Dispersive spoil/soil management is a significant environmental and economic issue in parts of Australia and internationally (Vacher et al., 2004). For example, 20,000 ha of mining disturbed land in Queensland's Bowen Basin comprises dispersive spoil; at a rehabilitation cost of $100,000 to $150,000/ha, this currently represents a liability of some $2 to $3 billion (Glenn Dale, pers.com.).

Dispersive spoil/soil typically contains an excess of sodium relative to calcium and magnesium (Qadir and Schubert, 2002) and displays sodic properties such as weak aggregate stability and spontaneous dispersion of clay particles in contact with water (Minserve, 2004; Vacher et al., 2004). Such soils are common across Australia and in Queensland, where they cover approximately 25 per cent of the state (Shaw et al., 1994; Vacher et al., 2004). Dispersive spoil material is also common in sediments overlying coal deposits and, where they occur, present significant problems for post-mining rehabilitation and site management, including poor conditions for plant establishment and increased risk of surface and tunnel erosion and, ultimately, slope failure (Vacher et al., 2004; Howard et al., 2011). Such conditions can severely compromise the ability to achieve critical objectives for mine closure which relate to a safe, non-polluting, stable and productive post-mining land form (DEHP, 2014; Glenn Dale, pers. com.).

A number of studies have investigated the management and rehabilitation of dispersive spoil/soil material (e.g. Minserve, 2004; Vacher et al., 2004). However, while the mechanisms of dispersion-related erosion are well understood and the importance of spoil/soil characteristics, vegetation cover, landform design (slope length, gradient) and interception structures are well recognised, there is limited risk-based decision support to enable practitioners to cost-effectively manage dispersive spoil and thereby improve rehabilitation outcomes (Glenn Dale, pers.com.).

The key objective of this project was to develop a risk-based decision support framework to inform practical, cost-effective management of dispersive spoil on minesites in Queensland. Benefits of improved spoil management will include enhanced capacity to meet closure criteria; improved regulator consideration of required closure criteria; improved post-closure land capability; improved community acceptance of post-closure land capability; reduced contribution to cumulative impacts; enhanced social licence to operate; and, in eastward draining catchments in Queensland, improved Great Barrier Reef water quality (Glenn Dale, pers.com.).

Environmental risk assessment

Risk assessment involves the collection, integration and analysis of relevant information for the assessment and prioritisation of risks or hazards pertaining to a particular objective and the evaluation of likelihoods (i.e. probabilities of occurrence) and consequences of adverse events. Risk management then involves the development of strategies to minimise, monitor, and control the probability and/or impact of these. The outcome of a risk assessment and risk management process is improved understanding of risks for a given system, and guidance on the implementation of appropriate risk reduction strategies (Linkov et al., 2006; Williams and Johnson, 2017).

Risk implies uncertainty. Uncertainty is inherent in complex dynamic interactive (e.g. environmental) systems, particularly where our understanding of a problem is still evolving. Environmental management is an archetypal 'wicked problem' in which it can be difficult to gauge the effectiveness of management decisions. This is exacerbated when there are long time lags in response, as well as a lack of long-term monitoring of outcomes. Such situations require explicit consideration and quantification of uncertainties (Williams and Johnson, 2017).

The ability to model and predict risks in complex dynamic ecosystems was, until relatively recently, limited due to difficulties in (i) quantifying the causal relationships between multiple interacting factors and outcomes, and (ii) capturing uncertainty. Bayesian network (BN) tools—based on Bayes' theorem which describes the likelihood or probability of an event given prior knowledge of the conditions related to the event—are increasingly used to understand and manage such systems (Hart and Pollino, 2008; Pollino and Henderson, 2010).

This project takes a Bayesian network modeling approach to describe and predict the probable behaviour of dispersive spoil rehabilitation performance.

Bayesian network models

Bayesian modelling frameworks such as Bayesian Networks (BNs) are frequently used to conceptualise and analyse complex management systems (Pollino et al., 2006; Liedloff and Smith, 2010) and are particularly useful in NRM contexts, where long term data are often lacking (Pollino and Henderson, 2010). They allow the integration of a range of data types—including expert opinion—where data are limiting; facilitate identification of key knowledge gaps; and enable explicit analysis of uncertainty associated with potential management and/or environmental scenarios.

BNs can provide valuable support in adaptive management contexts (Pollino et al., 2006; Pollino and Henderson, 2010). All data in a BN is represented in terms of its probability; hence, uncertainty is propagated throughout the model. This enables the likelihood of particular outcomes to be predicted, given the condition or state of each constituent factor in the model, and thereby allows the risk associated with a management decision to be assessed (and understood) prior to implementation.

BN model development

Bayesian Networks (BNs) are probabilistic graphical system models that capture cause and effect relationships (referred to as conditional dependencies; i.e. 'if this, then that') between key variables that influence particular outcomes. They provide explicit and transparent representation of (present understanding of) the system of interest (Stow and Borsuk, 2003). Critically, BNs also enable explicit treatment of uncertainty (Pollino and Henderson, 2010). The simplicity of the BN structure (comprising a set of variables and causal links between these) also allows a large number of state variables to be included, often without greatly increasing model complexity or the computational power required to run the model (Letcher et al. 2004), although Pollino and Henderson (2010) argue for model parsimony, where possible.

Application of BNs

BNs are used to explore relationships between factors and system outcomes associated with particular objectives, and can be used to predict the probable outcome/effectiveness of particular management decisions and system changes (e.g. those predicted for climate change) (Pollino and Henderson, 2010). Unlike many other modelling approaches, BNs use probabilistic, rather than deterministic, expressions to characterise the strength of relationships between variables (Borsuk et al., 2004). This means that BNs can incorporate both quantitative and qualitative information, as well as information of variable quality—such as subjective assessments (e.g. expert opinion) of the probability that a particular outcome will occur—where data may be limiting. Uncertainty is reflected in the model as the likelihood of the system being within a set of defined states for each variable. A further advantage of using probability is that models can be easily updated as new knowledge or data becomes available (Pollino and Henderson, 2010).

BN model outcomes are testable through structured review processes. Sensitivity analysis tools can be used to identify key causal factors within the model; this can also highlight specific knowledge gaps. Further, because information rapidly propagates through the network, the effect of particular management interventions or changed conditions can easily be examined, through scenario analysis, within the modelling framework, facilitating the examination of alternative decisions to optimise a particular outcome (Pollino et al. 2008; Pollino and Henderson, 2010).

A significant advantage of BNs over other modelling approaches in decision-making contexts is their relative simplicity. They are graphically based, readily interpreted and allow explicit documentation of assumptions and uncertainties, making them easier to understand and use than most modeling frameworks. This also makes them particular useful as a communication tool for engaging with stakeholders (e.g. policy makers), where they can be used to develop a broader understanding of the modelled system (Pollino and Henderson, 2010).

Limitations of BNs

Despite their significant advantages, BNs also have a number of limitations. In particular, BNs do not readily well-represent dynamic feedback processes. Further, while BNs can incorporate qualitative (and possibly subjective) information, there are risks and limitations associated with different types of information and the sources of information used in creating a model need to be transparently documented. For example, while expert judgement is often critical in environmental management in the absence of the necessary science (Drescher et al., 2013), caution should be exercised, particularly when this is used to create BNs for use in decision making, as cognitive and knowledge-based bias can be an issue (Anderson, 1998; Baddeley et al., 2004; Burgman, 2005). Hence, models based on expert judgment should not been seen as a substitute for data or research (Drescher et al., 2013).

In summary, Bayesian networks can support decisions in complex and uncertain domains by assembling disparate information in a consistent and coherent framework and incorporating the uncertainties inherent in natural systems and decisionmaking. However, they should be informed by process-based understanding and verified against comprehensive datasets.

Aims

The project aims were to develop a (predictive probabilistic) decision support framework to inform understanding of dispersive mine spoil/site dynamics, data collection priorities and, ultimately, improved management of dispersive mine spoil on minesites in Queensland, Australia.

Model development

In this project, we developed a Bayesian Network (BN) model of dispersive mine spoil behaviour using Norsys Netica™ software (Norsys Software Corp, 1992–2017). This type of model integrates key factors (variables) and the relationships between these—represented by boxes and arrows, respectively—to graphically describe the systems of concern (Figure 1).

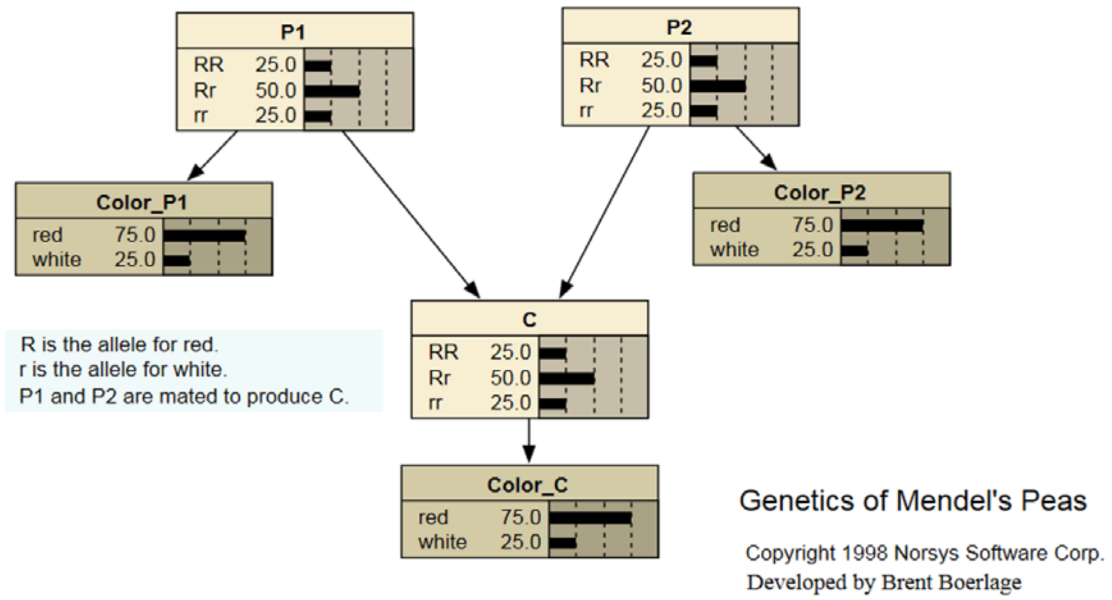

Figure 1. Simple BN model example (Source: Norsys Software Corp, 1992–2017)

In this study, we used an interative process (described below) to develop the model structure and populate the dispersive mine spoil risk model. The objective, in developing this BN, was initially to capture the key elements (both biophysical and management) and interactions between these that impact on slope stability. Lack of data with which to train and test the model currently constrain its applicability as a decision support tool; however, development of the conceptual model captures the current process based understanding of the issues associated with in situ management of dispersive materials and may inform future data collection with which the model may be further improved and validated. To enable data input by industry, a user interface has also been developed and ongoing improvement in the model is planned as data accumulate (Glenn Dale, pers. com.).

Developing the conceptual framework / BN structure

We initially reviewed the scientific literature and met with industry representatives to develop an understanding of the issues, drivers and management constraints associated with dispersive spoil management on minesites in general and in Queensland, in particular, where climatic variability is a key challenge. From this, a preliminary integrated conceptual BN framework was developed which incorporated both scientific and management criteria. Through an iterative process, this was further refined based on feedback from industry experts.

The BN influence diagram (i.e. the model) was constructed using ‘nature’ (or ‘chance’) nodes, which describe the potential empirical states exhibited by each component within the system. We incorporated the physical and chemical characteristics of mine spoil, rainfall regimes, vegetation cover and landform, as well as spoil amendment, runoff management and other management interventions. The model was initially designed, using a soil science lens, to capture the physical and chemical elements of the spoil material; this was then expanded to incorporate the influence of site characteristics and management actions on these. Variables were integrated (i.e. links between these were defined) according to current mechanistic/process-based understanding to create a graphical representation of the system. The model was then spatially arranged as a number of pseudo ‘sub-models’, although these are not discrete as interactions between individual variables in different sections of the model occur. The model includes a small set of endpoints: ‘surface erosion risk’, ‘slope performance’ and ‘tunnelling risk’.

Environmental management issues are inherently both multivariate and multidimensional. Pollino and Henderson (2010) discuss the tension between model complexity or ‘truthfulness’ and the need for model parsimony to ensure that models do not exceed the ‘power’ of the data or incorporate so much detail that model accuracy is compromised. The number of parameters and interactions included in the ‘dispersive spoil’ BN model framework was reduced over several iterations; however, it remains relatively complex. User feedback and targeted data collection and its incorporation into the model are required to inform further refinement of the model.

Model parameterisation

Variables (‘nodes’) in the model were categorised into variable states (‘conditions’) which encompass the expected range of values for each variable. These were defined as either Boolean (e.g. true or false), categorical (e.g. high, medium, low) or continuous (value range divided into sub-ranges with discrete values). To the extent possible, node state sub-ranges were identified based on documentary evidence of relevance (e.g. response thresholds for chemical parameters). Where such evidence was lacking, states for continuous variables were defined based on terciles of the value range of the parameter and categorical states were based on stakeholder advice.

Behind each variable in the model sits a Conditional Probability Table (CPT), which specifies the likelihood of the system being within each of the states defined for each variable. CPTs were parameterised using a combination of evidence from the literature, quantitative data (with probabilities defined by the frequency distribution of the data) and input by the model developers (i.e. expert opinion), who collectively have prior experience in soil science, mine site rehabilitation, and dispersive spoil and environmental management[1]. Elicitation of expert opinion from a wider range of informed stakeholders was not feasible, given their geographic spread. Hence, at present, the probability values applied represent an educated first guess and the BN model is a base working model which can be further developed and refined over time with data collection and feedback from industry.

Model analysis

Model validation

Model validation has not been conducted as there is no comprehensive dataset currently available with which to validate the model.

Model sensitivity testing

The sensitivity of the model response to variation in each of the model terms across the observed range within the model dataset (with CPTs predominantly derived from expert judgement) was tested in Netica™. This analysis checks the relative strength of relationships between variables (Pollino and Henderson, 2010) and quantifies the level of influence of each variable on model outcomes, expressed as a percentage reduction in variance (Norsys Software Corp, 1992–2017). Given the inability to validate the model, sensitivity analysis was conducted to test the logic of the expert derived model relationships in the model. Steps for conducting this analysis are outlined in Appendix C.

Scenario testing

Again with caveats due to our inability to validate the model, we ran some preliminary scenarios to test the potential impact of management decisions on output parameters of the model (specifically, ‘surface erosion risk’ and ‘tunnelling risk’). To do this, the neutral BN model was modified to identify scenarios (i.e.

[1]CPTs for spoil characterstics were predominantly developed, based on USQ background IP, by USQ team members; CPTs for management interventions were predominantly derived by Verterra, based on expert understanding.

the variable conditions) which would support two possible outcomes in terms of surface erosion/tunnelling risk: (i) ‘good’ condition at 100% of sites (i.e. best case scenario); and (ii) ‘poor’ condition at 100% of sites (i.e. worst case scenario). Steps for conducting this analysis are outlined in Appendix D.

Results and Discussion

Dispersive spoil risk management BN

The BN framework

The final working model (Figure 2) consists of a total of 104 variables, comprising six submodels: Climate; Spoil – chemical characteristics; Spoil – physical characteristics; Vegetation; Management; and Risk. The ‘Spoil – chemical characteristics’ submodel was replicated over three spoil layers (Layers 1–3) representing a topsoil layer, a capping layer and buried spoil. Similarly, the ‘Spoil – physical characteristics’ submodel was replicated for Layers 1 and 2.

Details of the parameter states for each of the variables in the model and how these were defined are presented in Appendix A. Conditional Probability Tables (CPTs) for each variable are presented in Appendix B.

Figure 2 Dispersive spoil risk management BN model (Please see accompanying PDF/A3 foldout page)

Model sensitivity

Model sensitivity analysis was conducted for several key output variables within the model (Figures 3–10). Results indicate reasonable sensitivity to variables that would logically be expected to strongly influence the variable in question (although, given that the model was constructed based on expert opinion, this is a somewhat circular argument). Greatest sensitivity is apparent to variables which are closely positioned within the current model structure, reinforcing the need to simplify the model by reducing the number of links wherever possible (as recommended by Pollino and Henderson, 2010). Training and validation of the model based on a comprehensive dataset will eventually facilitate this, subject to investment in strategic data collection. Currently, given the inability to validate the model, results of the sensitivity analysis should not be used either to reduce the complexity of the model or to support decision making without further industry review.

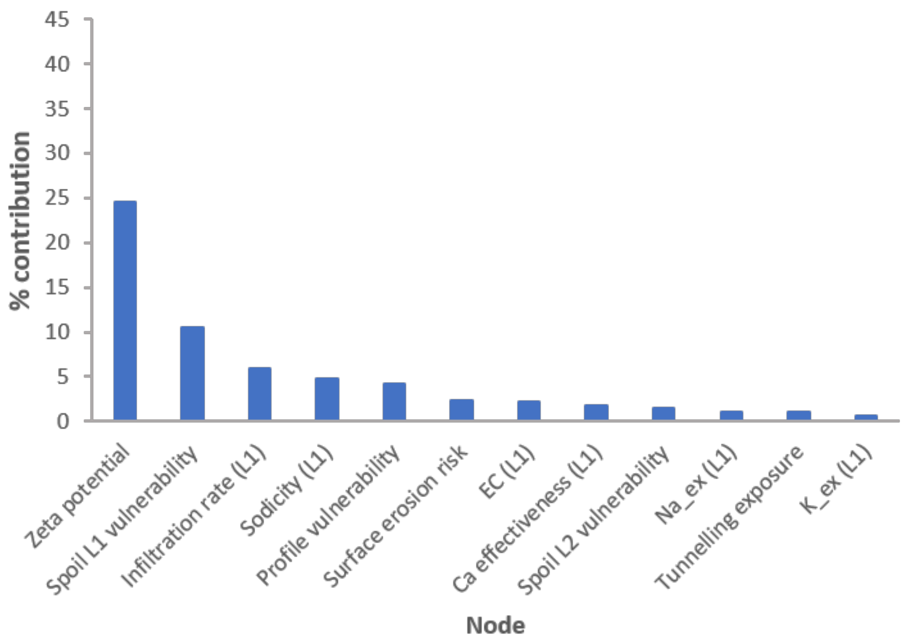

Figure 3 Sensitivity analysis result – Level 1 (L1) spoil dispersivity (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

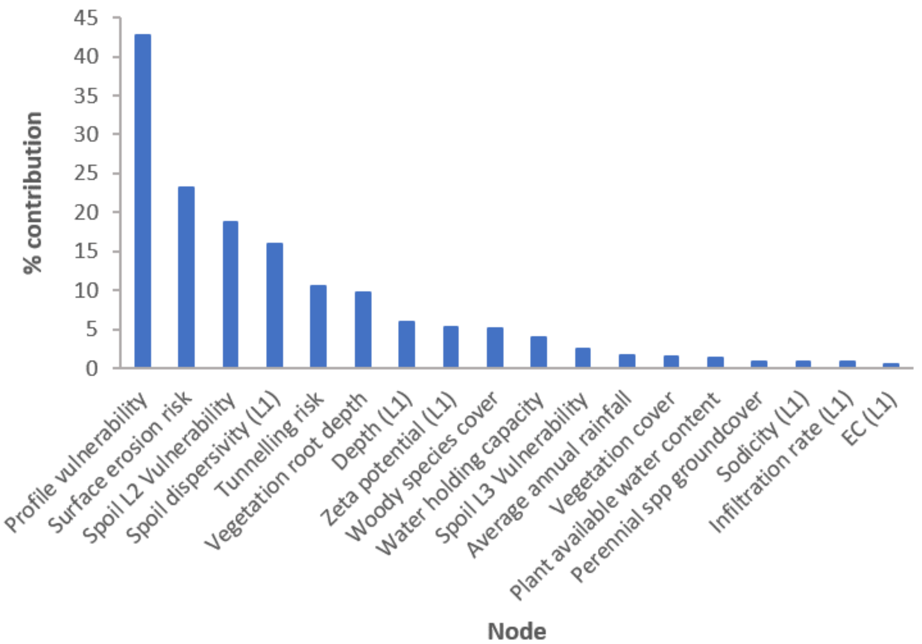

Figure 4 Sensitivity analysis result – Level 1 (L1) spoil vulnerability (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

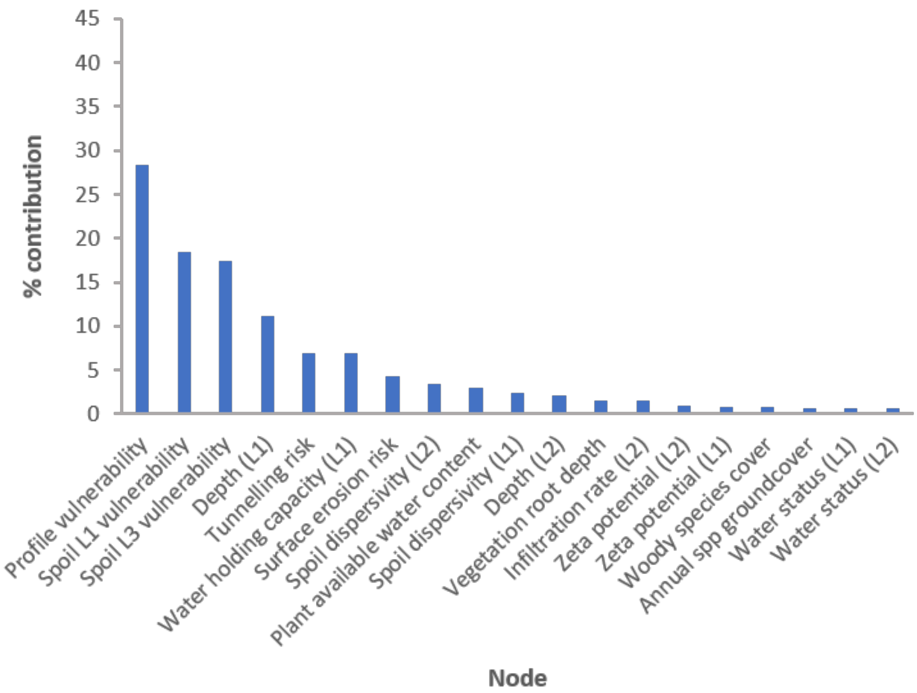

Figure 5 Sensitivity analysis result – Level 2 (L2) spoil vulnerability (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

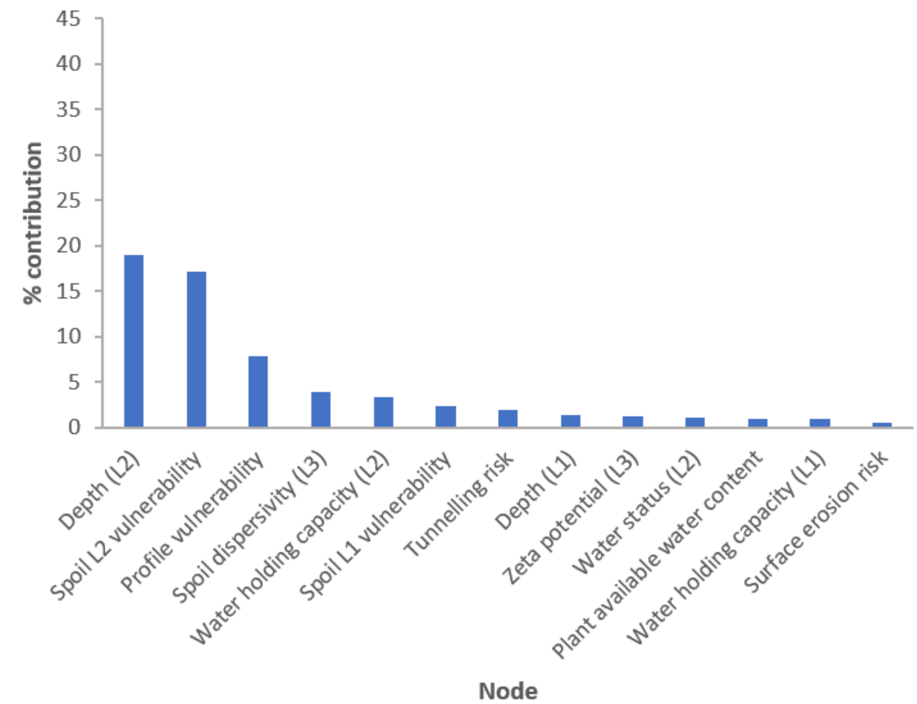

Figure 6 Sensitivity analysis result – Level 3 (L3) spoil vulnerability (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

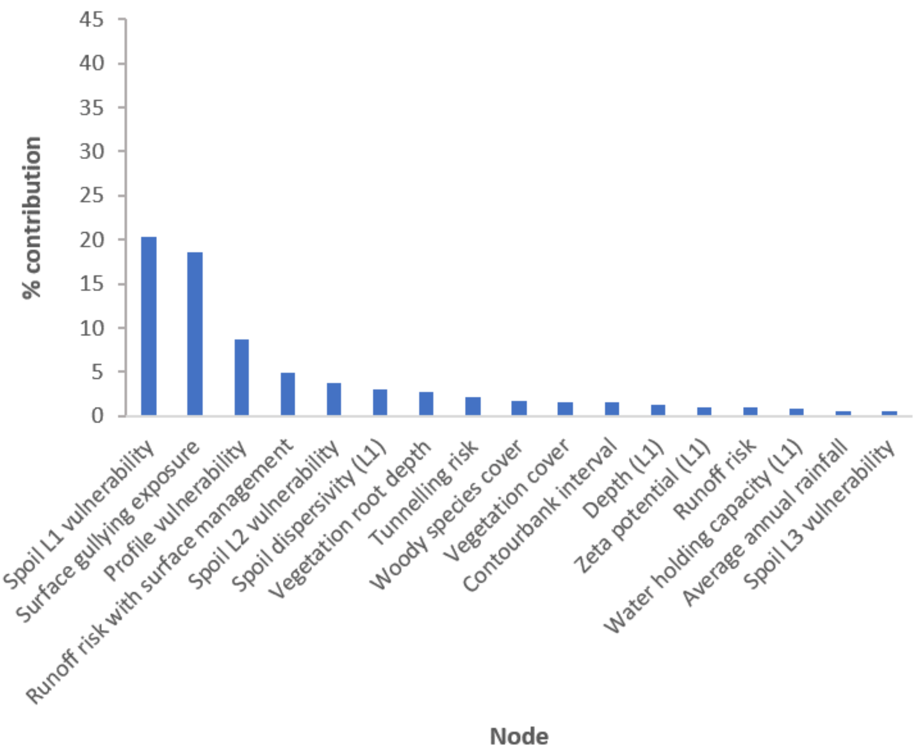

Figure 7 Sensitivity analysis result – Surface erosion risk (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

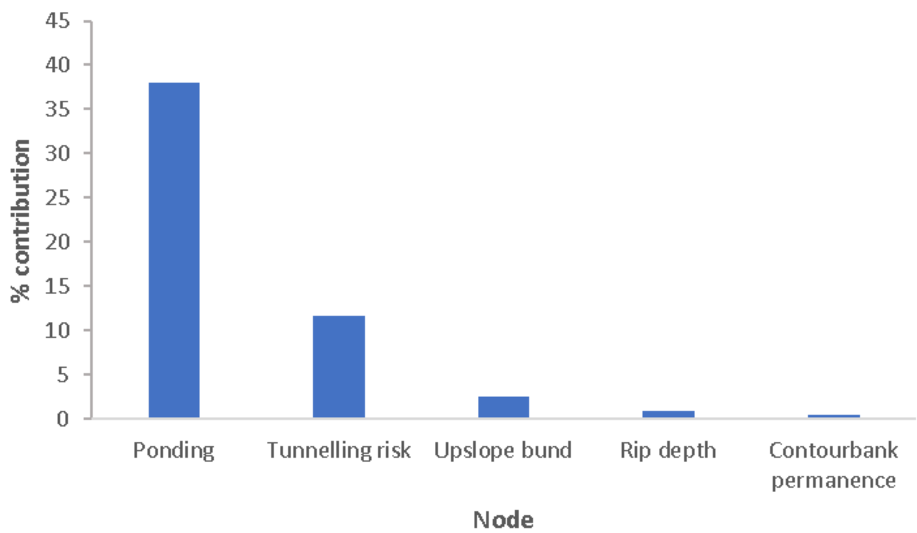

Figure 8 Sensitivity analysis result – Tunnel exposure (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

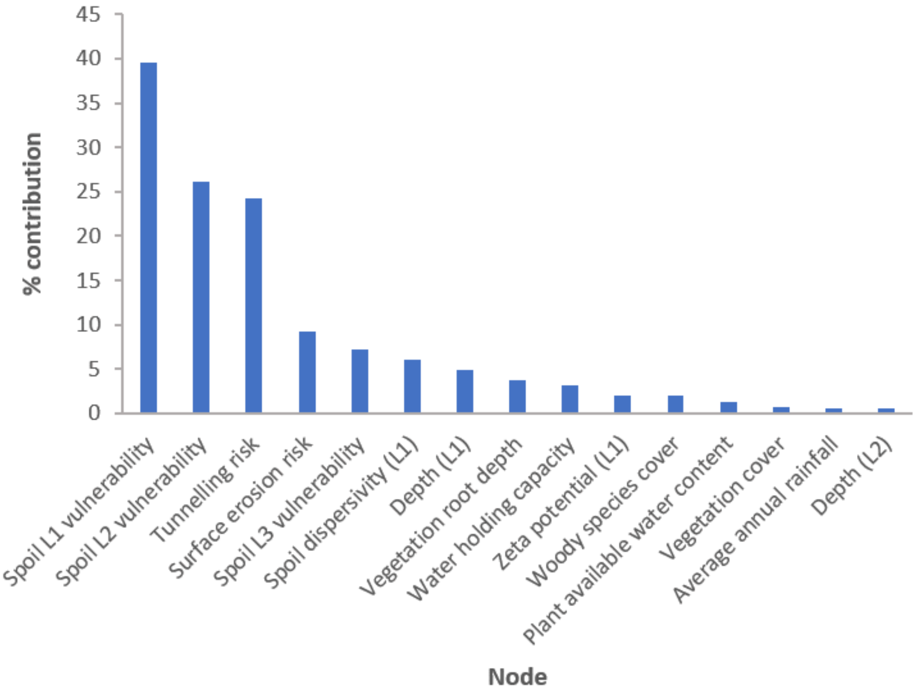

Figure 9 Sensitivity analysis result – Profile vulnerability (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

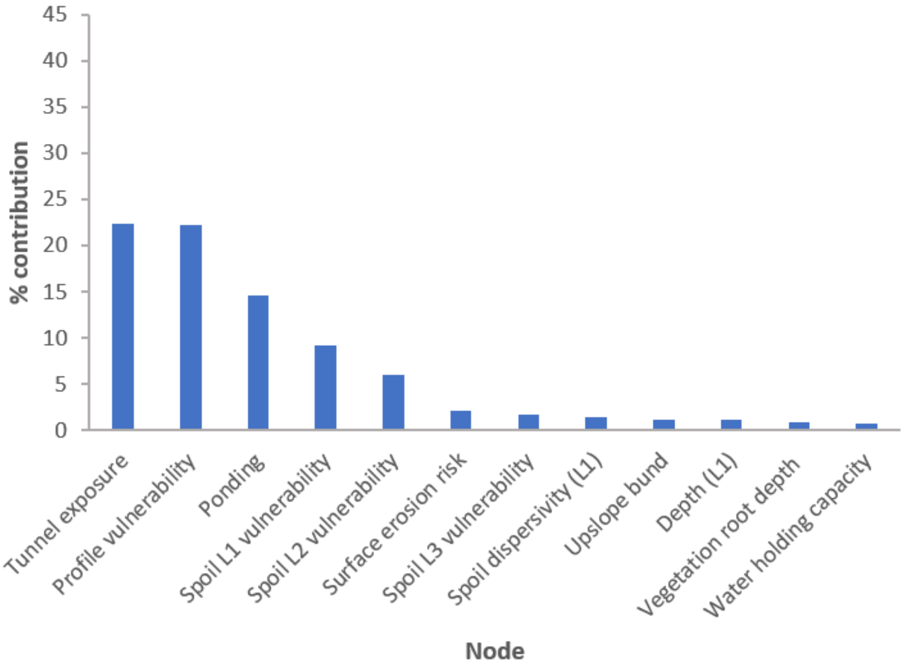

Figure 10 Sensitivity analysis result – Tunnelling risk (nodes with >0.5% variance reduction values are presented; both preceding and subsequent nodes in the model are included).

Model scenarios

Tables 1 and 2 present the analysis results for best and worst case surface erosion risk and tunnelling risk scenarios. These results indicate that, for the most part, the model is operating logically. However, it is stressed that these examples are provided for illustrative purposes only and should not be used to support decision making without further industry review and/or model validation based on comprehensive data collection.

Table 1 Best and worst case scenarios for surface erosion risk. Values are reported for nodes identified in the sensitivity analysis (Figure 7) only. (See Appendix C for clarification of states.) Values representing the greatest probability of occurrence are in bold type.

Node	State	Best case probability %	Worst case probability %
Surface erosion risk	low	100	0
	medium	0	0
	high	0	100
Spoil L1 vulnerability	low	**50.9**	8.76
	moderate	27.7	15.3
	high	14.8	27.4
	very high	6.66	**48.6**
Surface gullying exposure	nil	**67.7**	18.5
	low	19.7	16.9
	moderate	9.19	27.3
	high	3.41	**37.3**
Profile vulnerability	low	**49.9**	18.0
	medium	18.6	16.8
	high	16.1	18.9
	very high	15.4	**46.4**
Runoff risk with surface management	very low	**41.8**	21.7
	low	25.6	17.5
	medium	18.1	23.4
	high	14.5	**37.3**
Spoil L2 vulnerability	low	**34.4**	16.2
	moderate	24.9	21.8
	high	22.7	24.6
	very high	18.0	**37.4**
Spoil dispersivity (L1)	low	**46.4**	25.6
	moderate	20.1	19.9
	high	11.4	16.1
	very high	22.2	**38.4**
Vegetation root depth	shallow	23.7	**42.8**
	medium	24.4	24.4
	deep	**51.9**	32.8
Tunnelling risk	low	**29.7**	18.2
	medium	22.6	18.6

Node	State	Best case probability %	Worst case probability %
	high	21.9	19.6
	very high	25.8	**43.6**
Woody species cover	low	19.0	32.2
	moderate	31.6	**33.9**
	high	**49.4**	**33.9**
Vegetation cover	low	27.4	**41.7**
	moderate	36.2	35.3
	high	**36.4**	23.0
Contourbank interval	low	**44.7**	30.4
	medium	39.4	**42.1**
	high	15.9	27.5
Depth of L1	shallow	27.7	**40.0**
	moderate	33.0	33.3
	deep	**39.2**	26.8
Zeta potential (L1)	high	22.6	31.6
	medium	34.6	**37.9**
	low	**42.9**	30.5
Runoff risk	very low	22.3	17.3
	low	**31.6**	26.2
	medium	28.8	**28.4**
	high	17.4	28.1
Water holding capacity (L1)	low	**51.6**	**63.5**
	mid	22.7	18.5
	high	25.7	18.0
Average annual rainfall	very low	17.2	**23.5**
	low	18.7	21.6
	mid	20.2	19.6
	high	21.3	18.3
	very high	**22.6**	16.9
Spoil L3 vulnerability	low	**30.4**	22.9
	moderate	22.4	22.3
	high	22.2	23.3
	very high	25.0	**31.5**

Table 2 Best and worst case scenarios for tunnelling risk. Values are reported for nodes identified in the sensitivity analysis (Figure 10) only. (See Appendix C for clarification of states.) Values representing the greatest probability of occurrence are in bold type.

Node	State	Best case probability %	Worst case probability %
Tunnelling risk	low	100	0
	medium	0	0
	high	0	0
	very high	0	100
Tunnel exposure	none	**50.2**	4.91

Node	State	Best case probability %	Worst case probability %
	low	20.6	6.09
	medium	8.27	8.29
	high	20.9	**80.7**
Profile vulnerability	low	**58.8**	10.5
	medium	21.7	11.4
	high	12.1	21.8
	very high	7.35	**56.3**
Ponding	yes	22.7	**75.7**
	no	**77.3**	24.3
Spoil L1 vulnerability	low	**43.5**	14.2
	moderate	26.6	19.8
	high	18.9	26.9
	very high	11.1	**39.1**
Spoil L2 vulnerability	low	**36.5**	14.0
	moderate	26.5	20.3
	high	21.5	26.1
	very high	15.6	**39.6**
Surface erosion risk	low	**47.8**	**29.6**
	medium	20.8	23.7
	high	17.1	22.2
	very high	14.3	24.5
Spoil L3 vulnerability	low	**32.8**	20.4
	moderate	23.6	21.0
	high	21.6	23.8
	very high	22.0	**34.8**
Spoil dispersivity (L1)	low	**43.1**	29.0
	mid	20.3	20.2
	high	12.1	15.4
	very high	24.5	**35.4**
Upslope bund	yes	**72.9**	**85.0**
	no	27.1	15.0
Depth of L1	shallow	27.7	**39.6**
	moderate	33.4	33.0
	deep	**38.9**	27.3
Vegetation root depth	shallow	27.1	**38.0**
	medium	24.7	24.6
	deep	**48.2**	37.4
Water holding capacity (L1)	low	**51.8**	**63.0**
	medium	22.7	18.7
	high	25.4	18.4

Project outcomes

Given the lack of data by which to train and validate the model, the prototype BN model developed in this project is not presented as a robust evidence-based decision support tool. It does however have significant value as a learning and discussion tool. This project has highlighted the severe lack of comprehensive robust site level data by which to characterise spoil materials, as well as the outcomes of current and historic on-site spoil management. Such data is critical to further development of the model as an effective decision-support tool.

As it stands, the model is valuable as an industry engagement and communication tool to enhance understanding of the complexity of dispersive spoil management and as evidence of the need for investment in a targeted data collection campaign.

Next steps

This project has developed an initial risk-based framework which captures current understandings of the behaviour and management of dispersive spoil on mine-sites. It has potential to increase industry understanding of the behaviour of dispersive spoil materials and to contribute to improved decision making and their on-site management. Effective dispersive spoil management will enhance the environmental performance of the mining industry and reinforce the industry's social licence to operate. However, further investment is required to develop a usable decision support tool for practical, cost-effective on-site management of dispersive spoil.

Lack of a comprehensive dataset by which to train and validate the model has constrained model development beyond the issue conceptualisation phase. An extensive field data collection program, in combination with user defined improvement and widespread industry engagement will enable this to be further developed into a consistent, reliable and informed approach to managing dispersive spoil.

An experimental adaptive management approach is also needed, in the interim, to design and test a range of management scenarios (Schreiber et al., 2004; Gregory et al., 2006). This requires a robust experimental design to operationalise an adaptive management 'learning by doing' approach (Schreiber et al., 2004), the results of which will readily inform further improvements in the model.

Conclusions

This project has developed a probabilistic predictive framework aimed at providing decision support for the practical, cost-effective management of dispersive spoil on Queensland minesites. Given the inherent complexity of the problem as well as limited data availability, it adopted a Bayesian modelling approach to represent the many interacting factors that potentially influence dispersive spoil behaviour and erosion risk and enable the incorporation of expert judgement where data were insufficient for modelling purposes.

Ongoing work with industry to build a comprehensive data set, based on the model framework, will increasingly inform development of the tool for improved decision making on minesites. Similarly, using an adaptive management approach of ongoing monitoring, evaluation and review of management decisions, it will be possible to continuously refine the model to ensure its applicability to decision making for effective on-site management of dispersive mine spoil.

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