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A Risk-Based Approach to Mine-Site Rehabilitation: Use of Bayesian Belief Network Modelling to Manage Dispersive Soil and Spoil

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Abstract: Dispersive spoil/soil management is a major environmental and economic challenge for active coal mines as well as sustainable mine closure across the globe. To explore and design a framework for managing dispersive spoil, considering the complexities as well as data availability, this paper has developed a Bayesian Belief Network (BBN)-a probabilistic predictive framework to support practical and cost-effective decisions for the management of dispersive spoil. This approach enabled incorporation of expert knowledge where data were insufficient for modelling purposes. The performance of the model was validated using field data from actively managed mine sites and found to be consistent in the prediction of soil erosion and ground cover. Agreement between predicted soil erosion probability and field observations was greater than 74%, and greater than 70% for ground cover protection. The model performance was further noticeably improved by calibration of Conditional Probability Tables (CPTs). This demonstrates the value of the BBN modelling approach, whereby the use of currently best-available data can provide a practical result, with the capacity for significant model improvement over time as more (targeted) data come to hand.

Keywords: mine rehabilitation; predictive probabilistic modelling; environmental risk; soil erosion; adaptive decision-making

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1. Introduction

Dispersive spoil/soil management is a significant environmental and economic issue in parts of Australia and internationally [1]. In Australia, the management of dispersive mine spoil is particularly significant for the coal mining industry, where spoil materials frequently derive from dispersive pedological and geological profiles. This presents challenges for the management of spoil in active mines, sustainable mine closure [2], and the rehabilitation/management of historic or abandoned mine sites. For example, in the Bowen region of the state of Queensland, Australia, the instantaneous liability for rehabilitating dispersive spoil dumps is estimated at $AU2 to 3 billion. As a result, dispersive spoil management has been the focus of numerous industry funded projects (e.g., [1,3–8]). However, while the causes of dispersion are relatively well understood, functional integration of the processes that lead to failure of dispersive mine spoil, the interaction of erosion processes, and the physical and chemical properties of dispersive materials, remains incomplete.

Dispersive soils typically contain an excess of sodium relative to calcium and magnesium [9] and display sodic properties such as weak aggregate stability and spontaneous dispersion of clay particles in contact with water [1,10]. Tendency to disperse is a function of the cation suite, osmotic pressure, physical bonding agents (such as carbon), oxides and carbonates, and the external forces an aggregate is exposed to [8,11,12]. Such soils are common across Australia and in the state of Queensland, where they cover approximately 25 per cent of the state [1,13]. Dispersive spoil materials also exist in sediments overlying deposits in coal mines and, where they occur, present significant problems for post-mining rehabilitation and site management, including poor conditions for plant establishment, increased risk of surface and tunnel erosion, and ultimately, slope failure [1,14]. Such conditions severely compromise the ability to achieve critical objectives for mine closure that relate to a safe, non-polluting, stable and productive post-mining landform [15].

A number of studies have investigated the management and rehabilitation of dispersive spoil/soil material [1,16]. However, while the mechanisms of dispersion-related erosion are well understood and the importance of spoil/soil characteristics, vegetation cover, landform design and interception structures relatively well known, there are limited risk-based decision support frameworks to enable evaluation of the cost and effectiveness of alternative rehabilitation design options to achieve improved rehabilitation outcomes.

Improved mine spoil management is expected to achieve a number of significant benefits, both to industry and the environment. These may include enhanced capacity to meet mine closure criteria; improved regulation of closure criteria; improved post-closure land capability; improved community acceptance of post-closure land condition; reduced contribution to cumulative impacts; enhanced social license to operate; and, in eastward draining catchments in Queensland, improved Great Barrier Reef water quality. Returning dispersive soil/spoil to a safe, stable, non-polluting productive use or conservation outcome requires consideration of the soil/spoil resource, as well as the environmental and production systems it interacts with. It requires a transdisciplinary and non-reductionist consideration of the system complexity [11].

To investigate and better understand the interconnected nature of dispersive spoil management, we developed a conceptual model using a graphical Bayesian Belief Network (BBN) framework to capture the range of interacting variables in dispersive spoil management systems, including spoil physical and chemical characteristics; spoil treatment regimes; site characteristics; site management practices including revegetation and hard engineering works; and the process-based interactions between these [5,6,17]. Populating this using expert-derived and empirical data, we were able to integrate numerous factors within the BBN framework to develop a predictive, probabilistic, risk-based decision support system within which the outcomes of different environmental and management scenarios might be tested. Building such a model is expected to contribute to a better understanding of dispersive mine spoil/site dynamics and priorities for empirical data collection at mine sites. Ultimately, this study aims to build capacity to support mined-land rehabilitation to safe, stable, non-polluting landforms suitable for relinquishment. In this paper, we describe the model creation and its application to improve mine spoil management, including rehabilitation decisions, through adaptive, evidence-based best practice dispersive mine spoil management.

2. Bayesian Belief Network Models

Bayesian modelling frameworks such as BBNs are used to conceptualise and analyse management systems [18,19] and are particularly useful in natural resource management (NRM) contexts, where long-term data are often lacking [7,20]. BBNs are probabilistic graphical system models that capture cause and effect relationships (referred to as conditional dependencies, i.e., 'if this, then that, dependent on these) between key variables that influence particular outcomes. They can be used to predict the probable outcome and effectiveness of particular management decisions and system changes (e.g., those predicted for climate change) [21]. Bayesian network modelling is increasingly applied in many disciplines to map, analyse and predict system behaviour in complex management decision contexts [22,23].

Unlike deterministic modelling approaches that use quantitative parameters and initial conditions to simulate outputs [24], BBNs use probabilistic expressions to characterize the strength of the relationships between variables [25,26]. This means that BBNs 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 such models can be easily updated as new knowledge or data become available [21].

BBNs have significant value in management applications, where they enable prediction of the likelihood of particular outcomes given the condition or state of each constituent factor in the model, thereby allowing the likely risk associated with a management decision to be assessed prior to implementation [23,27]. While reductionist/deterministic sub models can be coupled together in a BBN to enhance understanding of system function, BBNs have the added advantage that, where data limitations of deterministic models can result in significant uncertainties in model outputs [28], this uncertainty is captured within the probabilistic BBN framework.

BBN model outcomes are testable through structured model evaluation processes. Sensitivity analysis tools can be used to identify key causal factors within the model; this can also highlight specific knowledge gaps. Because probability information rapidly propagates through a BBN, 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 [21,29]. A significant advantage of BBNs over other modelling approaches in decision-making contexts is their relative simplicity. They have a graphical interface, are readily interpreted and allow explicit documentation of assumptions and uncertainties, making them easier to understand and use than most modelling frameworks. This also makes them particularly useful as a communication tool for engaging with stakeholders (e.g., policymakers and practitioners), where they can be used to develop a broader understanding of the modelled system [21].

BBNs provide an explicit and transparent representation of (present understanding of) the system of interest [30]. Critically, BBNs also enable the explicit treatment of uncertainty [21]. The simplicity of the BBN model 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 [31], although Pollino and Henderson [20] argue for model parsimony, where possible.

Bayesian Belief Network (BBN) Background

As indicated above, the BBN is a graphical system model that represents cumulative probability distributions over all the variables modelled. It has a static topology and consists of nodes with random variables, edges with causal relationships and their states, and probabilistic dependency of variables [32].

The conditional probabilities can be estimated at each node of the network. For the variable A with a range of states (conditions):

$$A = \{a_1, a_2, \ldots, a_n\} \tag{1}$$

The joint probability distribution of A is then:

$$P(A_1, \ldots, A_n) = \prod_{i=1}^{n} P(A_i | A_{i+1}, \ldots, aA_n) \tag{2}$$

P(A) by marginalisation is then:

$$P_{(a)} = \sum_{i}^{n} P(a, b_i) \tag{3}$$

We can include more conditional probabilities into previous equations by involving more events, e.g., B [33] as:

$$B = \{B_1, B_2, \ldots, B_m\} \tag{4}$$

In general, expert knowledge (i.e., a person's belief) in a statement depends on the body of knowledge K. Degree of belief P(A | K) depends on an uncertain event, *A*, which is conditional on *K*. When we have two events, A and B, we can write belief as P(A | B,K) or, for simplicity, P(A | B). Using joint probabilities, we can explain conditional probability as:

$$P(\mathrm{A}|B) = \frac{P(A,B)}{P(B)} \tag{5}$$

All data in a BBN are represented in terms of the probability or likelihood of particular outcomes, given the condition or state of each constituent factor in the model, thereby allowing the risk associated with a management decision to be assessed (and understood) prior to implementation.

3. Materials and Methods

3.1. Bayesian Belief Network Model Setup

We developed a BBN model of dispersive mine spoil behaviour using Norsys Netica™ software (Norsys Software Corp, Vancouver, BC, Canada, 1992–2017 [34]). The model integrates key factors (variables) and the relationships between these—represented by boxes and arrows, respectively (e.g., Figure 1)—to graphically describe the rehabilitation of Queensland coal mine sites.

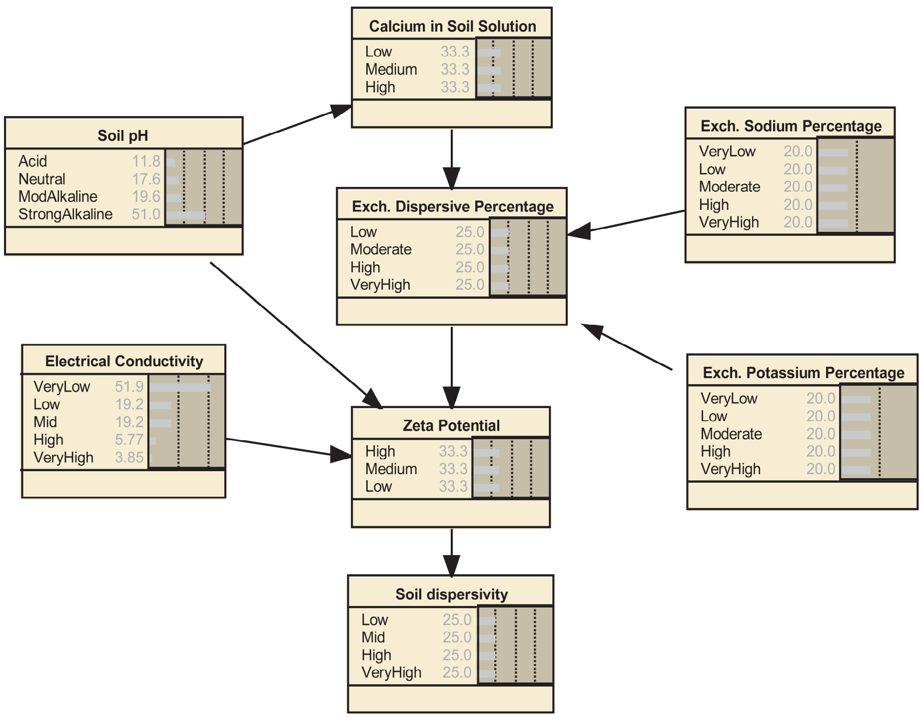

Figure 1. A Simple Bayesian Belief Network model, an example of a sub model for soil chemistry.

An iterative process was used to develop and refine the structure of a prototype dispersive mine spoil risk model, which was then parameterised using both quantitative data, where available, and qualitative information (expert judgement) and informed by published literature. This model captured the key elements (i.e., landform, soil chemistry, biophysical components and management actions, as well as their interactions) that affect dispersive spoil behaviour and slope stability.

Ongoing improvement of the model has continued, as data are acquired under multiple site conditions. This has enabled further validation and improvement of the model. Limited data to train and test a BBN model may restrict the applicability of the model as a decision support tool; however, as we show here, a well-developed model with enough expert knowledge may overcome this constraint.

3.1.1. Developing the Conceptual Framework

We initially consulted industry representatives, assessed a number of rehabilitated mine sites and reviewed the scientific literature [5]. This process was used to develop an understanding of the issues and management constraints associated with dispersive spoil on mine sites, in general, and in the state of Queensland, in particular, where climatic variability is a key challenge. From this, a preliminary conceptual BBN framework was developed, based in part on an expanded form of the Universal Soil Loss Equation [35], which was conceptualised to include tunnelling influences (Figure 2). The model incorporated inherent site characteristics and influences, as well as management techniques used to modify the effect of these characteristics or influences on erosion; this was further refined based on feedback from industry experts [5].

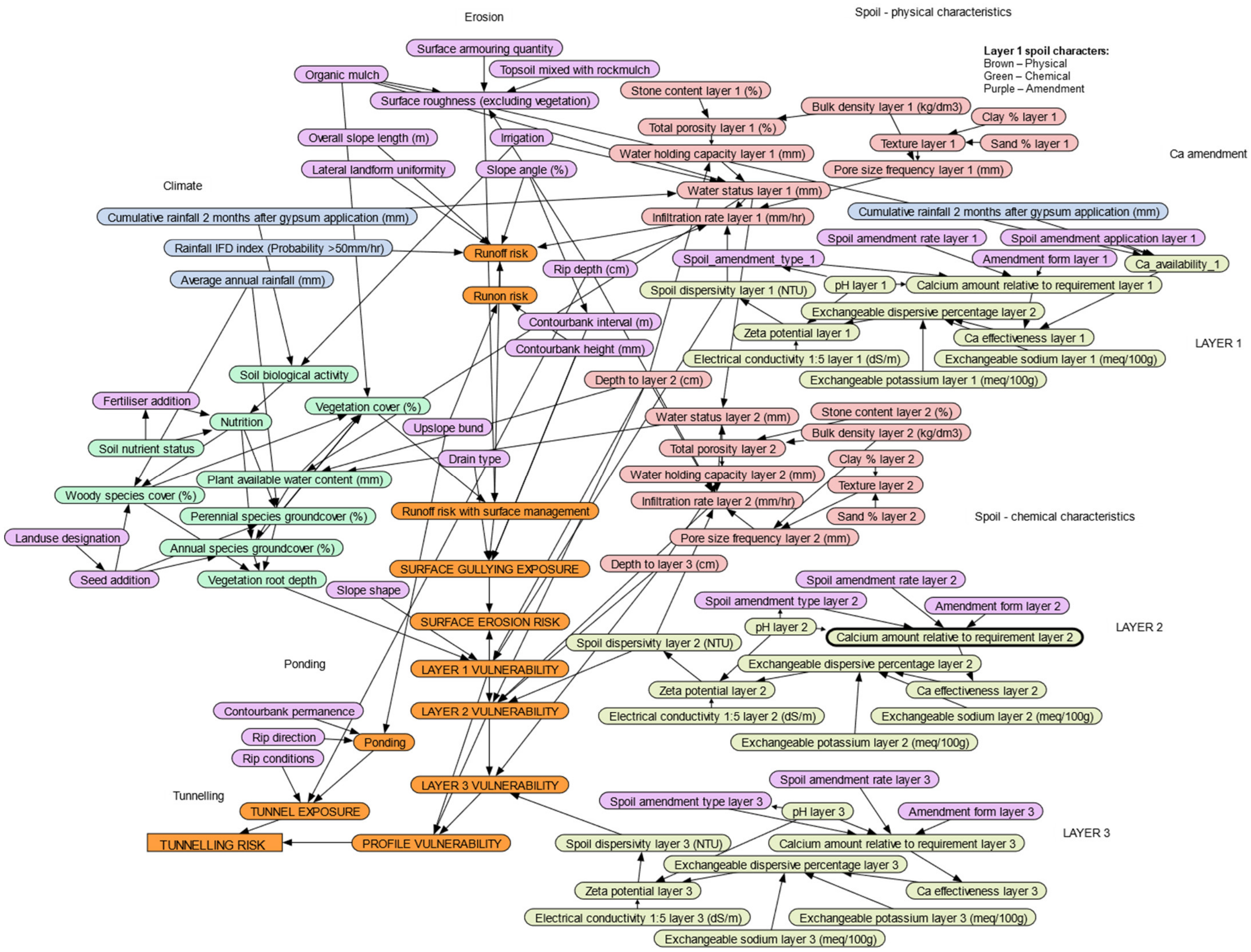

Figure 2. Bayesian Belief Network model for risk management of dispersive spoils. The model was constructed using 'nature' or 'chance' nodes, which describe the potential empirical states exhibited by each component within the system.

The resulting BBN influence diagram (Figure 2) incorporates the following groups of characteristics:

- Climatic conditions;
- Inherent soil characteristics (physical, chemical, biological);
- Landform characteristics;
- Management practices to modify inherent soil characteristics and mitigate erosion;
- Vegetation characteristics and management practices; and
- Tunnelling initiation factors.

Within the BBN model, the six groups of factors listed above were classified within a risk management framework [27,33] into two categories:

1. Vulnerability to erosion: based on the inherent soil (e.g., dispersibility, erodibility) and site characteristics (e.g., landform design), related climatic factors and management practices that modify erodibility; and
2. Exposure: based on an evaluation of the stresses inflicted by land management and climate (e.g., exposure to erosive energy forces such as cumulative rainfall, rainfall intensity, frequency, duration).

In this way, the model presents erosion risk as a matrix of exposure by vulnerability in a manner similar to the intersection between likelihood and consequence in a conventional risk assessment matrix. These are expressed in the endpoints: 'erosion risk' and 'tunnelling risk' (Figure 2).

3.1.2. Theoretical Framework for Soil Vulnerability to Erosion

Soil erosion is a function of the interaction between energy inputs driving eroding processes on soil and soil landscape and management. These include the erosivity of rainfall (e.g., kinetic energy of raindrops); the depth and velocity of any overland flow; ground cover; and chemical energy causing repulsion between soil particles.

Soil landscape and management include slope; slope length; erodibility of the soil (i.e., physical, chemical and biological properties responsible for structural integrity); surface cover; and land management techniques implemented in both management and site amelioration (e.g., contour banks, surface armouring).

The interaction of energy inputs and soil and site characteristics describing surface erosion is well described by the Revised Universal Soil Loss Equations (RUSLE) [35]:

$$A = R \times K \times LS \times P \times C \tag{6}$$

where A is soil loss (tonnes/ha); R is rainfall erosivity factor calculated from the kinetic energy of each rainstorm x intensity; K is soil erodibility factor; LS is slope length and steepness based on slope length in meters and angle in %; P is erosion control practices such as contouring to correct for variation in slope shape; and C is a management factor, ranging from near 0 for high quality management to 1.0 for continuous fallow.

Tunnelling presents a different form of erosion common on sodic soils, but not accommodated by the RUSLE. Crouch (1976) [36] described a five-step process that can lead to tunnelling:

1. Surface cracking due to desiccation;
2. Rapid infiltration into the cracks, and saturation of a subsurface layer;
3. Dispersion of the saturated layer;
4. Movement of the dispersed particles in soil water due to a hydrostatic gradient that produces lateral flow. Generation of a "subsurface rill" or tunnel results from this movement. Over time and with increased flow volumes, the tunnel will increase in size and may merge with other tunnels; and
5. Expansion of the tunnel inlet and outlet. Tunnel inlets typically start as small holes generated from subsurface cracks. Progressive collapse may cause this inlet point to become a large depression although the tunnel inlet size may remain small depending on the volume of water concentrated at this point.

Dispersive soils are more pre-disposed to tunnelling than non-dispersive soils. Factors that may give rise to tunnel initiation include soil cracking due to drying, ripping (especially under dry conditions), rotted out tree stumps, poorly aligned contour bunds and occurrence of ponding. Each of these factors requires consideration in a mechanistic model attempting to describe the behaviour of dispersive spoil. Hence, the Universal Soil Loss Equation for surface erosion is expanded to include factors that describe tunnel formation/erosion.

$$\text{Soil loss} = \text{Hillslope erosion} + \text{Tunnel erosion} \tag{7}$$

$$\text{Soil loss} = f(\mathrm{E_s\ E_r\ S\ ScL_m}) + f(\mathrm{R\ S_w\ P_o}) \tag{8}$$

where E_s is erosivity; E_r is erodibility; S is slope condition; ScL_m is soil surface cover; L_m is land management; S_w is soil water concentration; and P_o is ponding.

Average annual soil loss in Equation (8) can also be explained in more detail as

$$\text{Soil loss} = f(\mathrm{RKLSCP}) + f\left(\mathrm{R_{dep}\ R_{dir}\ Ca\ S_w\ P_o}\right) \tag{9}$$

where *R* is rainfall erosivity index; K is soil erodibility factor; LS is a topographic factor (L is for slope length and S is for slope); C is a cropping factor; P is conservation practice; R_{dep} is ripping depth; R_{dir} is rip direction; and Ca is cracking area.

The Revised Universal Soil Loss Equation [37], in combination with the above description of tunnelling, was used to build the conceptual framework of the BBN model (Figure 2) to guide understanding and improvements in management. Variables presented in Figure 3 were integrated by building links between them according to current mechanistic understanding to create a graphical representation of surface and tunnel erosion on mine sites. The model was then spatially arranged as a number of pseudo 'sub-models' (Figure 2), although these are not discrete as interactions between individual variables in different sections of the model occur.

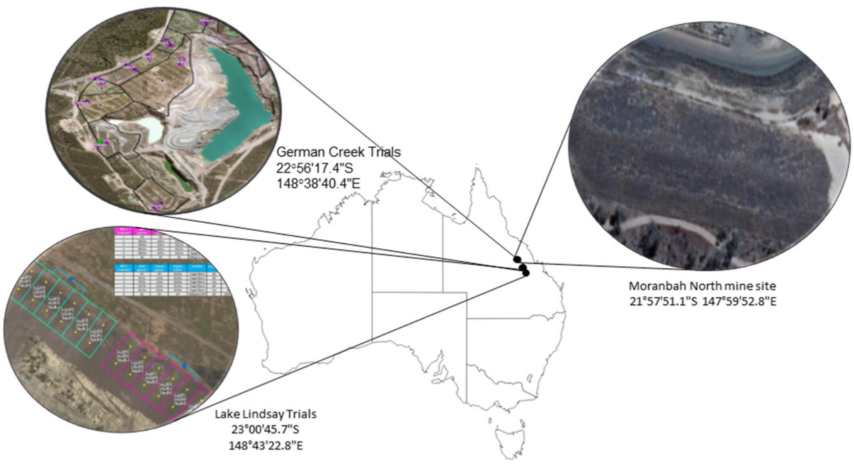

Figure 3. Location and aerial map of experimental sites.

Environmental management issues are inherently both multivariate and multidimensional [19,38]. Pollino and Henderson (2010) [20] 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' BBN model framework was reduced over several iterations; however, it remains relatively complex. Ongoing targeted data collection and its incorporation into the model are required, along with user feedback, to inform further refinement.

3.1.3. Key Factors Influencing Erosion of Dispersive Mine Spoil

Rainfall Erosivity

When rainfall exceeds infiltration capacity, surface runoff results [39] and slope gradient of the land surface increases its ability to detach and transport soil particles in proportion with the depth, velocity and volume of the flow [40]. Where water concentrates, rills and gullies can form and significantly increase sediment transport capacity and soil erosion rate. The higher rate of soil particle detachment in dispersive soils on steep slopes can accelerate sediment transport and erosion [41,42]. In addition to the direct impact of rain, water that accumulates or ponds and finds preferential flow paths through dispersive soil may lead to tunnelling due to the dispersion of fine clay particles into the water stream moving through the soil under gravity [43].

Soil Characteristics Affecting Erodibility

The erodibility of soil is related to its physical, chemical and biological properties and to the nature of the erosion process (e.g., runoff depth) and mechanism (e.g., runoff or splash detachment). In the development of the BBN model, we have considered seven factors that influence the erodibility of dispersive soil:

1. the composition and ratio of exchangeable cations (variously measured as ESP and CROSS) [44,45];
2. the overall cation suite and magnitude of exchange capacity (CEC) [46];
3. the concentration of salts in the soil solution (EC) [11,46,47];
4. the nature of the clay minerals present (e.g., smectites which have a significant swelling potential) [47,48];
5. the percentage of clay present [49];
6. pH, as it influences the solubility of salts, electrolyte balance and net charge of ions in the soil solution [1,49,50];
7. Zeta (electrokinetic) potential, as it affects the net charge available for clay–water interactions [11,12].

This portion of the model was built to consider not only the inherent stability, but also the effect of changes in the soil solution (e.g., rainfall or irrigation) on the attractive and repulsive forces governing soil/spoil aggregate stability. Simplification of this pseudo-sub-model could be provided by a direct measure of aggregate stability [51], but this would disallow the use of historical soil data, as aggregate stability in water is not part of the traditional suite of measures; instead, a reliance on chemical proxies such as ESP would ensue.

3.2. Model Parameterisation

Variables ('nodes') in the BBN 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 limiting, 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, empirical data, quantitative data (with probabilities defined by the frequency distribution of the data) (e.g., [33,52,53]) 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. Expert opinion was established based on the observations and outcomes of laboratory and field studies of both soils and spoil management. The probability values applied represent the best initial estimate and the BBN model is a base working model that can be iteratively improved and refined over time with additional data collection and feedback from industry.

3.3. Model Analysis

3.3.1. Model Sensitivity Testing

The sensitivity of the model response to variation in each of the model terms across the observed range of data from which the CPTs were derived was tested in Netica™. This analysis checks the relative strength of relationships between variables [21] and quantifies the level of influence of each variable on the model outcomes, expressed as a percentage reduction in variance [34]. Sensitivity analysis was conducted to test the logic of the expert derived relationships in the model.

3.3.2. Scenario Testing

Noting the need for further validation and iterative improvement, preliminary scenario testing was carried out to investigate the impact of modelled management decisions on predicted output parameters of the model (specifically, 'erosion risk' and 'tunnelling risk'). To do this, the neutral BBN model was modified to identify scenarios (i.e., the variable conditions) that would support two possible outcomes in terms of 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).

3.3.3. Model Validation

The validation of the BBN model is an important step, providing confidence in its use as a decision support tool. BBN validation can include evaluating model performance for prediction, sensitivity analysis, and comparison with other modelling results and historical data [54,55].

The initial parameterized consensus BBN model described in this paper was built on a combination of established literature, expert opinion and feedback from industry stakeholders with experience in dispersive mine site rehabilitation. It has provided the basis for subsequent targeted data collection from a range of post-treatment observations and preliminary results from dedicated field trials (described below). This has enabled model validation, which, along with ongoing feedback from industry decision makers and discipline experts, has supported updating and improvements in the model.

3.4. Field Trials–Data Collection for Model Validation

Field trial sites were established at three open cut coal mines in the Bowen Basin in the state of Queensland, Australia. These sites included two on rehabilitated spoil pits and one on a spoil stockpile from an underground mine (Figure 3). Spoil at all sites displayed high exchangeable sodium percentage (ESP) and susceptibility to erosion. The rainfall across all sites ranged from 544 to 616 mm/year. For all sites, erosive rainfall events exceeding 50 mm/h can be expected with an average return period of five years [6]. Notwithstanding, in the absence of any amelioration of dispersive spoil conditions, all sites also exhibit considerable erosion on less intense rainfall events. Data obtained from the field trials were used to validate the developed BBN model.

3.4.1. Lake Lindsay

A comprehensive trial was established at Lake Lindsay (Figure 3) in March 2018. This trial provides a valuable, long-term resource as a benchmark for current best practice and as a leading indicator of expected post-closure performance; it also provides an opportunity to integrate all learnings from the project. The trial implements a full framework of considerations comprising the mechanistic model outlined in Section 3.1.1. and includes an untreated control and standard practice (full rock mulch to 0.5 m) treatment. The replicated trial is designed to test varying combinations of gypsum application rates and irrigation on highly dispersive spoil (mean ESP of 24% for replicate 1 and 38% for replicate 2) with slopes of 10%. Standard treatments across trial plots include: depth of gypsum treatment in the underlying sub-soil and overlying topsoil; spoil ripping depth and sequencing (pre-topsoil application); fertiliser (custom designed to address all plant nutritional deficiencies); soil organic matter amendment; and seed sowing with topsoil cultivation and a successional seed mix composition.

The site experiences a distinct summer rainfall, receiving an average of 604 mm/yr in the period from December to March when the average monthly rainfall exceeds 50 mm. The frequency of rain days per week with rainfall of greater than 50 mm is greater than 0.5 days in weeks 1 to 10 and 49 to 52. Mean summer maximum temperatures range from 32.7 to 33.6 °C and a mean winter minimum temperature range from 8.1 to 9.7 °C, and evaporation significantly exceeds rainfall in all months of the year.

For treatments other than the standard rock mulch treatment, the base rehabilitation activities were:

(a) Ripping of spoil (pre-topsoiling) to a depth of 20 cm;
(b) Application of topsoil to a depth of 15 cm;
(c) Incorporation of organic matter into the topsoil at a rate of 52 t/ha (to achieve a target organic matter content of 2%);
(d) Application of a custom fertiliser blend to address all identified nutrient deficiencies;
(e) Cultivation of topsoil (post fertiliser, organic matter and, where relevant, gypsum, to a depth of 15 cm; and
(f) Application of a successional seed mix at the rate of 42 kg/ha.

Soil chemistry details and details of the treatment combinations of the Lake Lindsay site trials are presented in Table S2 in Supplementary Materials.

Revegetation at the Lake Lindsay site was designed as a successional seed mix, with a choice of pasture species adapted to the region. Seed was lightly harrowed into the topsoil to a maximum depth of 50 mm in a major variation to the common practice of deep ripping. This was to avoid bringing dispersive material to the surface, avoid loss of seed in deep rip lines, avoid compaction with heavy machinery, and deposit seed below the surface at a depth conducive to emergence following adequate rainfall to sustain early growth following germination.

3.4.2. German Creek East

Field trials at German Creek East were established in November 2014 (Figures 3 and 4) on batter slopes of approximately 20% to test the effect of a range of treatments:

(a) rock mulch to 500 mm;
(b) rock mulch to 250 mm;
(c) rock mulch to 100 mm with gypsum; and
(d) contour benching with rock-lined drains.

These trials demonstrate the geotechnical influence of rock armouring on erosion rather than the influence of vegetation. Erosion assessment found a distinct trend of increasing sheet and rill erosion with decreasing rock armouring. Sheet erosion increased from minor for the 250 and 500 mm rock mulching treatments, to moderate for the 100 mm rock mulch and contour bank treatments. Rill erosion increased from minor/moderate for the 250 and 500 mm rock mulching treatments, to moderate/severe for the 100 mm rock mulch and contour bank treatments. While no sites exhibited gully erosion, minor tunnel erosion was recorded on the 100 mm rock mulch and contour bank treatments.

3.4.3. Moranbah North

Moranbah North mine site is located approximately 16 km north of Moranbah and 145 km southwest of Mackay within the Bowen Basin, eastern Queensland. The trial site is one of a number of spoil dumps excavated from underground access workings. The spoil is covered with topsoil and stabilised for the life of the mine without amendment. The site experiences a distinct summer rainfall, receiving an average of 544 mm/year in the months from December to March when average monthly rainfall exceeds 50 mm. Soil and vegetation data were collected in December 2019.

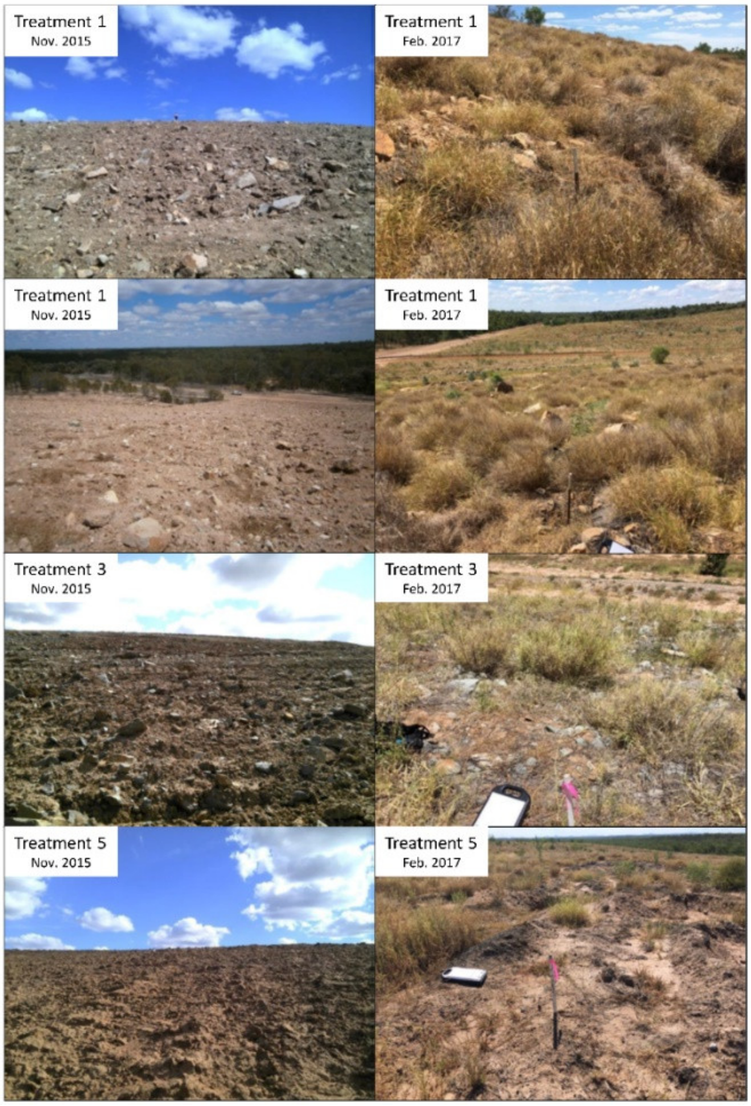

Figure 4. The experimental trials at German Creek East in November 2015 and February 2017. The selected spoil treatments are full rock mulch at 500 mm (Treatment 1), Gypsum + 100 mm rock mulch (Treatment 3) and Topsoil, rip, seed, and gypsum (Treatment 3).

3.5. Updating of CPTs

A BBN model that is established from expert opinion and the published literature can be improved by incorporating additional available datasets to calibrate the CPTs [56,57] as new data become available over time. The Dirichlet distribution for CPT columns intuitively interprets the combined data (expert beliefs and observed data) [58]; however, considering the small number of available datasets, we applied a manual calibration [24]. To do this, the CPTs of the initial expert-elicited BBN model were updated, where possible, from the available spoil characteristics and environmental covariates using the Lake Lindsay site data collected 18 months post treatment (Figure 5).

The numerical observed data for relevant environmental covariates and spoil physical and chemical characteristics, listed below, were initially converted to categorical data based on the categories and classifications described for the expert elicited CPT dataset and the conditional probabilities modified to match the observed conditions. Other conditional probabilities were not adjusted and remain as expert opinion.

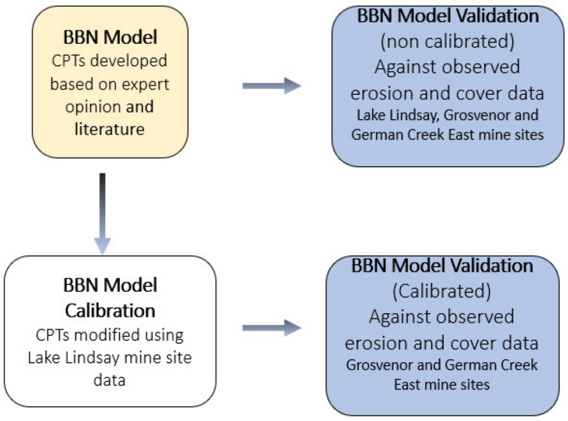

Figure 5. The process used for the BBN model development, calibration and validation.

Major variables (nodes) updated were:

- Layer 1 Calcium amount
- Layer 1 Exchangeable dispersion percentage
- Layer 1 Calcium availability
- Topsoil organic matter
- Nutrition
- Surface Gullying Exposure
- Erosion Risk
- Vegetation Cover
- Layer 2 Calcium amount
- Layer 2 Exchangeable dispersion percentage

The BBN model was then validated using observed data from German Creek East and Moranbah North sites (Figure 5).

4. Results and Discussion

4.1. Dispersive Spoil Risk Management–The BBN Framework

The prototype BBN framework for dispersive spoil risk management (Figure 2) consisted of a total of 104 variables, comprising six sub-models: Climate; Spoil–chemical characteristics; Spoil–physical characteristics; Vegetation; Management; and Risk. The 'Spoil–chemical characteristics' sub-model was replicated over three spoil layers (Layers 1–3) representing a topsoil layer, a capping layer and buried spoil. Similarly, the 'Spoil–physical characteristics' sub-model 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 Section 3.2.

4.2. BBN Model Validation

The BBN model was confirmed to provide a reliable representation of relative erosion risk based on the Lake Lindsay results 18 months post-treatment. While the model might not yet be accepted as a definitive decision tool predicting spoil rehabilitation performance due to the uncertainty inherent in longer-term conditions such as variation in rainfall intensity, Table 1 shows that the likelihood of occurrence of gully erosion in the field (regardless of severity) has already been predicted by the BBN model. Agreement between predicted soil erosion probability and field observation was 74%, 100% and 75% for Lake Lindsay, Moranbah North, and German Creek East, respectively (Table 1). Instances were also observed where erosion was predicted by the BBN model (despite applying treatments) but no gully occurred 18 months post treatment, although this may be a matter of time and may occur later.

Table 1. Validation of erosion risk, i.e., occurrence of gully erosion (pre-calibration) at examined mining sites.

Site	No Trials	Treatments	Observed Gully Erosion%	Predicted Erosion Risk from BBN Model			
				Low	Medium	High	Very High
Lake Lindsay	1	Gypsum 2 & Dry	0.0	32.1	23.7	21.6	22.6
	2	Gypsum 1& Irrig.	0.0	32.0	23.8	21.3	22.9
	3	Rock mulch	0.0	26.6	23.2	22.3	27.9
	4	Gypsum 1 & Dry	1.7	32.1	23.7	21.6	22.6
	5	Gypsum 2 & Dry	20.3	29	23.8	22.4	24.8
	6	Control	0.0	28.8	23.8	22.4	25
	7	Gypsum 1 & Irrig.	0.0	29.4	23.8	22.2	24.6
	8	Rock mulch	0.0	46.5	21.8	17.9	13.8
	9	Gypsum 2 & Irrig.	18.2	50.8	21.3	16.6	11.3
	10	Gypsum 1 & Dy	12.7	49.9	21.6	17	11.5
	11	Control-	0.0	50.3	21.5	16.8	11.4
	12	Gypsum 2 & Irrig.	0.0	50.4	21.4	16.8	11.4
	13	Gypsum 2 & Dry	0.0	56.6	19.1	14.5	9.8
	14	Gypsum 1 & Irrig.	0.0	54.7	19.9	15.2	10.3
	15	Rock mulch	0.0	46.5	21.7	17.9	13.8
	16	Gypsum 1 & Dry	0.0	44.1	22.6	18.7	14.6
	17	Gypsum 2 & Dry	10.5	51.2	21.1	16.5	11.2
	18	Control	1.4	54.7	19.8	15.2	10.3
	19	Rock mulch	0.0	38	23.3	20.5	18.2
	20	Gypsum 2 &s Irrig.	0	54.7	19.8	15.2	10.3
Moranbah North	1	No treatment	NIL	32.1	23.6	21.7	22.6
	2	No treatment	NIL	39.7	22.8	19.7	17.8
	3	No treatment	NIL	46.7	21.7	17.7	14
	4	No treatment	NIL	45.4	22s	18.1	14.4
	5	No treatment	NIL	49.5	20.7	16.7	13.1
	6	No treatment	NIL	48	21.2	17.2	13.6
	7	No treatment	NIL	46.3	21.7	17.8	14.2
	8	No treatment	NIL	45	22.1	18.2	14.6
German Creek East	1	Full rock (500 mm)	0	24.9	23.2	22.7	29.2
	2	Full rock (500 mm)	0	29.4	24	22.4	24.2
	3	Gypsum & 100 mm rock	0	27.1	23.3	22.3	27.4
	4	Gypsum & 100 mm rock	0	22.1	22.4	22.5	33
	5	Contour benching & rock drains	5.4	27.1	23.5	22.5	26.9
	6	Contour benching & rock drains	36.8	20.5	21.8	22.4	35.3
	7	Half rock (250 mm)	0	24.8	23.2	22.7	29.3
	8	Half rock (250 mm)	0	55.6	19.7	14.9	9.9

The BBN model performance for prediction of ground cover level in comparison with observations was 94%, 71%, and 25% at Lake Lindsay, Moranbah North, and German Creek East, respectively (Table 2). The greater uncertainty in predicting cover at the German Creek East site relative to soil erosion may be related to the fact that soil erosion is also highly sensitive to slope gradient and soil dispersivity may have had a greater effect than cover in governing soil erosion processes in this case.

The BBN model was calibrated by modification of the CPTs using the Lake Lindsay data and the predicted erosion risk probabilities of the BBN model prior to and after calibration of CPTs were compared with observed gully erosion for Lake Lindsay, German Creek East and Moranbah North mining sites (Tables 3 and 4). In general, the updated model displayed enhanced performance with a noticeable improvement in its ability to predict erosion risk for all mining sites following calibration compared to the original BBN model.

Table 2. Validation of ground cover modelling by developed BBN model (pre-calibration) at examined mining sites. Cover below 70% was considered low because soil erosion rates typically increase sharply when ground cover is below this proportion [59].

Site	No Trials	Observed Cover %	Predicted Vegetation Cover% from BBN Mode		
			Low	Medium	High
Lake Lindsay	1	0.9 (high)	16.7	39.6	43.7
	2	1.0 (high)	12.2	40.7	47.1
	3	0.6 (Low)	16.1	43.1	42.6
	4	0.7 (medium)	14.3	40.8	44.9
	5	1.0 (high)	14.5	40.9	44.6
	6	0.9 (high)	16.2	41.3	42.4
	7	1.0 (high)	14.4	40.9	44.7
	8	0.3 (low)	23.1	40.0	36.9
	9	0.9 (high)	14.3	40.3	45.6
	10	0.9 (high)	14.5	41.0	44.4
	11	0.7 (medium)	16.0	41.1	42.8
	12	0.9 (high)	12.5	36.1	51.4
	13	0.9 (high)	13.9	37.6	48.5
	14	0.8 (medium)	14.1	37.4	48.5
	15	0.6 (Low)	15.9	38.6	45.5
	16	0.6 (Low)	16.0	38.6	45.4
	17	0.9 (high)	13.6	37.6	48.8
	18	0.7 (medium)	16.0	38.6	45.4
	19	0.20 (low)	20.0	37.9	42.1
	20	0.9 (high)	15.7	35.1	49.2
	21	0.7 (medium)	15.3	35.7	49.0
Moranbah North	1	0.2 (low)	38.5	40.4	21.1
	2	0.6 (low)	31.4	41.9	26.7
	3	0.9 (high)	32.4	41.6	25.9
	4	1.0 (high)	23.2	40.8	36.0
	5	1.0 (high)	23.5	40.9	35.6
	6	1.0 (high)	20.6	41.3	38.2
	7	1.0 (high)	21.9	41.0	37.0
	8	1.0 (high)	21.3	40.9	37.8
	9	1.0 (high)	18.6	40.3	41.1
	10	0.9 (high)	24.0	37.7	38.3
	11	1.0 (high)	29.6	40.3	30.2
	12	0.6 (Low)	26.5	40.6	33.2
German Creek East	1	0.42 (low)	36.6	40.8	22.7
	2	0.72 (medium)	28.7	40.4	30.9
	3	0.29 (low)	21.8	40.0	38.2
	4	0.12 (low)	21.5	40.7	37.8
	5	0.29 (low)	28.0	40.2	31.8
	6	0.13 (low)	36.6	41.2	22.1
	7	0.28 (low)	34.8	41.6	23.5
	8	0.99 (high)	29.9	42.0	28.2

Table 3. Validation of calibrated BBN model for prediction of erosion risk (i.e., occurrence of gully erosion) at two mining sites.

Site	No Trials	Treatments	Observed Gully Erosion%	Predicted Erosion Risk from Updated BBN Model			
				Low	Medium	High	Very High
Moranbah North	1	No treatment	0	44.3	19.9	21.7	14.1
	2	No treatment	0	44.5	19.9	21.6	14.0
	3	No treatment	0	45.1	19.9	21.3	13.8
	4	No treatment	0	50.4	19.5	18.4	11.8
	5	No treatment	0	49.3	19.7	18.9	12.1
	6	No treatment	0	51.2	19.3	17.9	11.6
	7	No treatment	0	47.8	19.6	19.8	12.8
	8	No treatment	0	49.8	19.4	18.7	12.1
	9	No treatment	0	50.6	19.3	18.3	11.9
	10	No treatment	0	50.4	19.3	18.0	12.3
	11	No treatment	0	48.9	19.4	19.2	12.5
	12	No treatment	0	46.0	20.5	20.1	13.4
German Creek East	1	Full rock (500mm)	0	37.9	31.5	21.1	9.4
	2	Full rock (500 mm)	0	32.7	31.7	24.6	11.0
	3	Gypsum + 100 mm rock	0	30.1	32.2	26.3	11.5
	4	Gypsum + 100 mm rock	0	32.9	31.6	24.6	10.9
	5	Contour benching w rock drains	5.4	29.8	29.9	27.7	12.6
	6	Contour benching w rock drains	36.8	27.0	30.3	29.6	13.2
	7	Half rock (250 mm)	0	36.6	23.4	27.1	12.9
	8	Half rock (250 mm)	0	49.1	19.9	21.3	9.68

The updated model did not underestimate or fail to predict erosion risk for any of the mining sites (Table 3). This indicates that the updated model can be considered an enhanced model for spoil erosion assessment. However, uncertainties remain due to the insufficient range of data available to adequately update all conditional probabilities in the model. In general, the updated BBN model also predicted improved vegetation cover (Table 4), especially when the observed vegetation was high, and better matched observations than the original model. Uncertainty in the prediction of vegetation cover was evident in the original BBN model when vegetation cover was low (e.g., the model predicted high; Table 2). This uncertainty was reduced to some extent in the updated BBN model. However, overall, it is likely that the ability to capture sufficient empirical data for updating CPTs will be limited by the complexity of management scenarios for which data need to be collected. To address this, a wider range of sites should be assessed from the mining and related industries, measuring erosion as a function of vegetation cover.

Bayesian Belief Network models have been extensively utilised to evaluate and predict environmental and ecosystem management but are often based only on expert opinion and without model validation [1]. Successful validation of a BBN model to represent targeted variables is paramount to providing accurate scenario output, particularly in sensitive applications, such as mine spoil management. While the systems model, presented here, has enabled us to quantify the occurrence of complex erosion associated with the diversity of consolidated mine spoils and covariates in mining sites, it is apparent that this complexity also becomes a weakness in validating such a model. The high spatial variability of spoil characteristics within and between sites also means that erosion risks should be evaluated in the long-term post-rehabilitation to reduce uncertainties in erosion risk evaluation [60,61]. This suggests that model validation should be treated as an ongoing process, which allows the use and application of the best available data but accommodates the capacity to progressively upgrade the model as resources and capacity become available, without waiting for perfect information.

Table 4. Validation of calibrated BBN model for prediction of ground cover level at two mining sites.

Site	Soil Sample No.	Observed Cover %	Predicted Vegetation Cover% from Updated BBN Model		
			Low	Medium	High
Moranbah North	1	0.2 (low)	39.6	34.9	25.5
	2	0.6 (low)	34.3	39.5	26.2
	3	0.9 (high)	29.6	37.5	32.9
	4	1.0 (high)	13.8	33.4	52.6
	5	1.0 (high)	17.5	36.2	45.9
	6	1.0 (high)	15.1	35.5	49.4
	7	1.0 (high)	25.6	35.5	38.9
	8	1.0 (high)	18.4	34.1	47.5
	9	1.0 (high)	18.0	34.1	47.8
	10	0.9 (high)	18.6	34.1	47.3
	11	1.0 (high)	24.3	3.9	40.8
German Creek East	1	0.42 (low)	35.5	36.5	28.1
	2	0.72 (medium)	35.4	36.3	28.4
	3	0.29 (low)	53.3	30.6	16.1
	4	0.12 (low)	47.6	31.1	21.3
	5	0.29 (low)	45.2	32.9	21.9
	6	0.13 (low)	46.5	32.2	21.3
	7	0.28 (low)	47.6	32.7	19.8
	8	0.99 (high)	27.6	36.0	36.3

Given the limited data by which to train and validate the model, the original prototype BBN model developed in this project may only be considered as a rudimentary decision support tool. It has, however, provided a valuable framework for further data collection to inform revision of CPTs. The resulting revised model has demonstrated the capacity for updating to better reflect observed site conditions. This demonstrates the value of the BBN modelling approach, whereby use of the currently best-available data can provide a practical result, with the capacity for significant model improvement over time as more (targeted) data come to hand.

4.3. Scenario Analysis

Qualitative analysis of the original and updated BBN models indicate acceptable performance of the model and its potential as a useful tool for scenario analysis and discussion. This might include:

- Investigation of the impact of site-specific weather and crop scenarios and their effects on soil water storage and erosion risk to inform business discussions, planning and decisions;
- Guidance on the collection of site condition monitoring data;
- Objective guidance for investment in site soil/spoil management;
- Use as a learning and discussion tool when there are limited local data.

Tables 5 and 6 present the analysis results for best- and worst-case erosion risk and tunnelling risk scenarios, respectively. These results indicate that, for the most part, the model is operating logically. These scenarios also show the value in developing a BBN and its application as a potential decision support tool for predicting the risk of surface and tunnel erosion in rehabilitated mine sites.

It should be noted 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 site-level data collection. The results of scenario analysis might differ depending on the specific spoils and contribution of the climatic conditions; hence, model outcomes may vary from one site to another. A site-specific validated model is required in order to assess the risks of surface and tunnelling erosion at each location.

Table 5. Best- and worst-case scenarios for erosion risk. Values are reported for nodes with probability of occurrence.

Node	State	Best Case Probability %	Worst Case Probability %	Node	State	Best Case Probability %	Worst Case Probability %
Surface erosion risk	low	100	0	Woody species cover	low	19.0	32.2
	medium	0	0		moderate	31.6	33.9
	high	0	100		high	49.4	33.9
Spoil L1 vulnerability	low	50.9	8.76	Tunnelling risk	low	29.7	18.2
	moderate	27.7	15.3		medium	22.6	18.6
	high	14.8	27.4		high	21.9	19.6
	very high	6.66	48.6		v high	25.8	43.6
Surface gullying exposure	nil	67.7	18.5	Runoff risk	very low	22.3	17.3
	low	19.7	16.9		low	31.6	26.2
	moderate	9.19	27.3		medium	28.8	28.4
	high	3.41	37.3		high	17.4	28.1
Profile vulnerability	low	49.9	18.0	Spoil L3 vulnerability	low	30.4	22.9
	medium	18.6	16.8		moderate	22.4	22.3
	high	16.1	18.9		high	22.2	23.3
	very high	15.4	46.4		very high	25.0	31.5
Runoff risk with surface management	very low	41.8	21.7	Spoil L2 vulnerability	low	34.4	16.2
	low	25.6	17.5		moderate	24.9	21.8
	medium	18.1	23.4		high	22.7	24.6
	high	14.5	37.3		very high	18.0	37.4
Vegetation root depth	shallow	23.7	42.8	Vegetation cover	low	27.4	41.7
	medium	24.4	24.4		moderate	36.2	35.3
	deep	51.9	32.8		high	36.4	23.0
Depth of L1	shallow	27.7	40.0	Contour bank interval	low	44.7	30.4
	moderate	33.0	33.3		medium	39.4	42.1
	deep	39.2	26.8		high	15.9	27.5
Zeta potential (L1)	high	22.6	31.6	Water holding capacity (L1)	low	51.6	63.5
	medium	34.6	37.9		mid	22.7	18.5
	low	42.9	30.5		high	25.7	18.0
Average annual rainfall	very low	17.2	23.5	Spoil dispersivity (L1)	low	46.4	25.6
	low	18.7	21.6		moderate	20.1	19.9
	mid	20.2	19.6		high	11.4	16.1
	high	21.3	18.3		very high	22.2	38.4
	very high	22.6	16.9				

Table 6. Best and worst case scenarios for tunneling risk. Values are reported for nodes identified in the sensitivity analysis only.

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
	low	20.6	6.09
	medium	8.27	8.29
	high	20.9	80.7

Table 6. *Cont.*

Node	State	Best Case Probability %	Worst Case Probability %
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
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

4.4. Further Refinement of the BBN Model

Annual and seasonal variability of rainfall and runoff risk might potentially influence the prediction of erosion risk, especially when these conditions fall outside the range of observations on which the BBN model has been validated. The main factors influencing soil erosion risks are cover (i.e., vegetation, mulch), rainfall and runoff rates along with slope gradient [41,62]. We have used the best available data and relied on the various scenarios and treatment trials from the Lake Lindsay mine site to improve expert elicited CPTs. This has been further validated by comparison of the model outputs to observed data for the German Creek and Moranbah North mines. As future data on soil erosion and spoil behaviour become available, it will be possible to incorporate this into the BBN to allow ongoing improvement of the capacity of the model to predict erosion risk at these sites.

The experimental adaptive management approach adopted has been shown to be useful in improving the model and for testing a range of management scenarios [13,63]. The initial process of developing the model identified data deficiencies, which required targeted data collection to allow updating of the model CPTs. As discussed, this new empirical data assisted in updating and improving the performance of the original BBN, increasing its value to spoil erosion risk prediction and decision-making.

The revised BBN model has potential to improve industry understanding of the behaviour and management of dispersive spoil materials and to contribute to improved decision making and site management. Effective dispersive spoil management will enhance the environmental performance of the mining industry and reinforce the industry's social license to operate. Further investment will help with continuous improvement of the model as a decision support tool for practical, cost-effective rehabilitation of dispersive spoil. Although the current available data has improved the capacity of the BBN model to predict erosion risks, an extensive field data collection program on various mine sites, in combination with ongoing user-defined improvement and widespread industry engagement, will enable the utility of the model to be further enhanced. Availability of additional data may also help the integration of process based/biophysical models with BBN modelling to develop a more comprehensive framework for scenario analysis.

The established BBN model informs adaptive, evidence-based best practice dispersive mine spoil management. An ongoing iterative process, with targeted long-term data collection from different mine sites and feedback from industry decision makers and discipline experts, will support continuing improvements in the current model. The modelling framework will help inform policy for development and implementation of dispersive spoil rehabilitation in the mining sector, both in Australia and globally.

4.5. Limitations and Opportunities of Bayesian Belief Networks

Development of the BBN for dispersive spoil management was based on current best understanding of the processes that contribute to erosion risk on these difficult to manage materials. Field trials conducted to fill some of the knowledge gaps apparent in the model have provided important but still incomplete additional understanding, but more work is required.

While the incorporation of ameliorants such as gypsum into dispersive materials has not been shown to be completely successful in previous trials, concerns over the method of incorporation used in earlier trials justifies further investigation of this approach. A small-scale trial at Lake Lindsay displayed a sharp difference in ground cover between gypsum treated spoil and no treatment. Rilling was similar between the treatments, but this had stabilised on the gypsum addition treatment, while the no gypsum treatment displayed significant sheet erosion evident from pedestalling. This highlights an important point, which is that gypsum does not instantaneously act, requiring dissolution to occur to instigate exchange process that leads to stabilisation. The BBN cannot build this dynamic into the model and assumes instantaneous action. Therefore, a level of erosion must be expected during the amelioration phase.

Analysis of field characteristics and spoil chemical data also found a negative correlation between erosion severity and cations with higher levels of iconicity (Ca^{2+}, Fe^{3+}), plus silt. This result indicates that amendment of chemical factors leading to dispersive spoil conditions, particularly low exchangeable calcium, is an important requirement to control erosion on dispersive sites. This is a significant finding that underpins the importance of characterising spoil and applying targeted amendments based on the evidence of data. However, it is not an unexpected finding, given the plethora of literature pertaining to dispersive soil management [48,64,65]. Perhaps the most important acknowledgement is that while it might be seemingly expensive to apply gypsum at the required amount per hectare and depth of dispersive soil/spoil, it is more likely that the failure to do so will result in significantly greater expense in management and maintenance in the long-term.

Despite these knowledge gaps, here we have demonstrated the strength of BBNs for decision making in a data limited environment. However, whilst such models offer great potential for providing inference in such situations, they are not suited to all environmental management applications. In particular, as information flow within BBNs is unidirectional, they are unable to represent dynamic feedback processes, which can be a limitation in some instances [66]. Furthermore, BBNs assume instantaneous system change (e.g., application of gypsum instantaneously results in reduced soil ESP, when in reality this is time dependent). Whilst this limitation is not specific to BBNs and empirical models often suffer from the same assumption, it is worth noting, and particularly so in soil systems where change is regularly dependent on time and environmental/climate factors (e.g., rainfall), due to the buffered nature of the systems. Although the use of expert opinion allows for inference where empirical data are lacking, the effect of cognitive bias must be considered [67–69] and these data alone should not be seen as a substitute when empirical data is available [66]. However, this can be overcome by undertaking model validation when empirical data become available, similar to the approach presented here.

Developing a BBN is often difficult in complex systems without empirical data, as the CPTs can become large and cumbersome to populate. This can be managed by limiting the states of each node, such that meaningful inference can still be maintained. Whilst the use of qualitative states at the nodes can be seen as a limitation, it presents an opportunity for modelling in soil systems where qualitative information is regularly used (e.g., a soil having poor structure, a clay being defined as a cracking clay, etc.) and has a meaningful influence on the outcome variable [42].

BBNs for environmental decision making are not expected to provide the ultimate modelling solution; however, they provide opportunity for empirical modelling where data are limiting. In turn, this allows informed decisions to be made and applied in the field in situations where data are insufficient, time is important and the risk of lost opportunity exceeds the risk of poor decision making [19]. BBNs therefore provide opportunity to assist land managers in decision making by leveraging limited data (qualitative and quantitative) with expert opinion and knowledge to allow for risk-based assessment of management decisions. As empirical data become available through time, we see merit in adopting other modelling methods, such as artificial neural networks or decision trees, either on their own or using a hybrid empirical-probabilistic approach (19).

5. Conclusions

This work has developed a probabilistic predictive framework to support practical and cost-effective decisions for management of dispersive spoil in Queensland mine sites. Given the inherent complexity of the problem as well as limited data availability, adoption of a probabilistic BBN modelling approach to capture processes that govern dispersive spoil processes in erosion risk was considered appropriate. This enabled incorporation of expert judgement where data were insufficient for conventional modelling purposes. Model performance was validated using field data from actively managed mine sites and the initial model was updated to better capture the relationships revealed by these data. This significantly improved the predictive capability of the model. Ongoing observation and collaboration with industry will enable a comprehensive dataset to be built, which will progressively inform further improvements in the model and increase confidence in decision making and more effective rehabilitation of dispersive spoil materials.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su132011267/s1, Supplementary material S1 Soil chemistry details at Lake Lindsay. Topsoil properties of Lake Lindsay trial site, Table S1. Rehabilitation treatments in trial site at Lake Lindsay, Table S2. Calculated gypsum requirement, Table S3.

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