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Quantifying Rehabilitation Risks for Surface-strip Coal Mines Using a Soil Compaction Bayesian Network in South Africa and Australia: To Demonstrate the R^2AIN™ Framework†

R^2AIN™ framework and soil compaction Bayesian network

Vanessa D. Weyer*,† Alta de Waal,‡§ Alex M. Lechner,‖# Corinne J. Unger,††‡‡ Tim G. O'Connor,§§ Thomas Baumgartl,‡‡ Roland Schulze,‖‖ and Wayne F. Truter,##

†Centre for Environmental Studies, University of Pretoria, P.O. Box 1456, Kloof, 3640, South Africa, e-mail address: vweyer@global.co.za

‡Department of Statistics, University of Pretoria, Private Bag X20, Hatfield, Pretoria, 0028, South Africa, e-mail address: Alta.DeWaal@up.ac.za

§Centre for Artificial Intelligence Research (CAIR), Pretoria, 0028, South Africa

‖School of Environmental and Geographical Sciences, University of Nottingham Malaysia Campus, Semenyih, Selangor, Malaysia, e-mail address: alex.lechner@nottingham.edu.my

#Centre for Water in the Minerals Industry, Sustainable Minerals Institute, University of Queensland, St Lucia, Brisbane, Queensland, 4072, Australia, e-mail address: a.lechner@uq.edu.au

††University of Queensland Business School, University of Queensland, St Lucia, Brisbane, Queensland, 4072, Australia, e-mail address: c.unger@business.uq.edu.au

‡‡Centre for Mined Land Rehabilitation, Sustainable Minerals Institute, University of Queensland, St Lucia, Brisbane, Queensland, 4072, Australia, e-mail addresses: t.baumgartl@uq.edu.au

§§South African Environmental Observation Network, P.O. Box 2600, Pretoria, 0001, South Africa, e-mail address: tim@saeon.ac.za

‖‖Centre for Water Resources Research, School of Agriculture, Earth and Environmental Sciences, University of KwaZulu-Natal, Private Bag X01, Scottsville, 3209, South Africa, e-mail address: schulzer@ukzn.ac.za

##Department of Plant and Soil Sciences, University of Pretoria, Private bag X20, Hatfield, Pretoria, 0028, South Africa, e-mail address: wayne.truter@up.ac.za

*Address correspondence to vweyer@global.co.za

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Highlights

- An integrated mine rehabilitation risk assessment (R^2AIN™) framework is described
- The framework was designed for surface-strip coal mine rehabilitation planning
- A soil compaction Bayesian network is demonstrated in South Africa and Australia
- Probabilistic predictions for rehabilitation risk are achievable using this process
- Research directions to develop a fully synthesised R^2AIN™ model are discussed

ABSTRACT

Environmental information is acquired and assessed during the environmental impact assessment process for surface-strip coal mine approval. However, integrating these data and quantifying rehabilitation risk using a holistic multi-disciplinary approach is seldom undertaken. We present a rehabilitation risk assessment integrated network (R^2AIN™) framework, that can be applied using Bayesian networks (BNs), to integrate and quantify such rehabilitation risks. Our framework has seven steps, including key integration of rehabilitation risk sources and the quantification of undesired rehabilitation risk events to the final application of mitigation. We demonstrate the framework using a soil compaction Bayesian network (BN) case study in the Witbank Coalfield, South Africa and the Bowen Basin, Australia. Our approach allows for a probabilistic assessment of rehabilitation risk associated with multi-disciplines to be integrated and quantified. Using this method, a site’s rehabilitation risk profile can be determined before mining activities commence and the effects of manipulating management actions during later mine phases to reduce risk, can be gauged, to aid decision making.

Keywords

Integrated models and frameworks, multi-disciplinary mine rehabilitation planning, cumulative effects, risk assessment, mine closure

INTRODUCTION

Surface-strip coal mining is a highly destructive land use, more so than underground coal mining (Tongway and Ludwig 2011). During the process of removing coal, wastes are placed above ground, exposing them to weathering with toxicity problems likely. Extensive changes to landcover and drainage also occur. Rehabilitation aims to ameliorate these, at times, dramatic changes and helps anthropomorphic landscapes to blend back into their regional context.

The need to evaluate risks associated with mine rehabilitation, as part of closure and post-closure risk, is stipulated by leading practice guidelines and legislation (Australian Government et al. 2016a; 2016b; 2016c; Chamber of Mines of South Africa 2007; Department of Environmental Affairs 2015; International Council on Mining and Metals 2008). Despite being advocated, rehabilitation risk assessment, is however conducted with minimum requirements being met. Weyer et al. (2017) found that guidelines and consultants' approval reports for rehabilitation of surface-strip coal mines in South Africa and Australia fall between vulnerable and adequate but are not yet resilient. Information is gathered, but seldom analysed, with limited integration and rehabilitation risk determination. Others further concur that rehabilitation risk is rarely addressed early in mining operations (Corder et al. 2010; McCullough et al. 2018).

Risk is defined by the International Organization for Standardization (2018) as the effect of uncertainty on objectives, where an effect is a deviation from the expected and where objectives can have different aspects and categories and where these can be applied at different levels. Risk is expressed in terms of risk sources, potential events, their consequences and their likelihood. The Council of Standards Australia & New Zealand (2009) define an 'event', (also an 'incident' or 'accident'), as an occurrence or change in circumstances that may have several sources and causes. Risk is characterised by reference to these potential events.

In the context of mine rehabilitation, a potential unwanted risk event, could include soil compaction, soil erosion or landform failure among other. Sources of these events could emanate from inherent pre-existing site conditions, derived from the site’s geology, soils, topography, climate, vegetation and landcover or from site mining management actions. For any site, if rehabilitation risk is not addressed and rehabilitation consequently fails, that site is unlikely to support a sustainable post-mining land use identical or similar to that which existed pre-mining (e.g., agriculture or natural vegetation); rather a novel system is likely to emerge (Doley and Audet 2013). Risk profiles, describing a set of risks, are also stipulated by International Organization for Standardization (2018). Risk events determine the overall level of site rehabilitation risk, i.e. a site’s risk profile, that should be constrained by addressing individual and collective/ interacting risk events.

Soil compaction is regarded as a common and severe risk event of mine rehabilitation, that can contribute to rehabilitation failure (Anglo Coal Environmental Rehabilitation Improvement Group 2009; Chamber of Mines of South Africa 2007; Minerals Council of Australia 1998; Rethman 2006; Saperstein et al. 1991). Soil is a non-renewable resource and the prevention of soil compaction is important, inter alia for future global food security (Hamza and Anderson 2005; Lal 2009; Mueller et al. 2010; Nawaz et al. 2013), but also for protecting the soil resource and preventing negative consequences to the environment (Alaoui et al. 2018). Soil compaction adversely affects soil storage and supply of water and nutrients through: increasing soil bulk density and soil strength, and decreasing porosity, soil water infiltration and water holding capacity. As a result, plant water and nutrient use efficiency, and plant growth and production are reduced, while the risk of water-logging, runoff and soil erosion are increased (Hamza and Anderson 2005). Soil compaction may result from natural and/ or anthropogenic risk sources, with anthropogenic risk sources having more severe consequences (Batey 2009; DeJong-Hughes et al. 2001; Limpitlaw et al. 2005; Nawaz et al. 2013). Natural risk sources are mainly related to soil properties and climate variables, whilst anthropogenic risk sources are linked to management practices and machinery use (Batey 2009; DeJong-Hughes et al. 2001). Natural and anthropogenic risk sources interact and may combine to influence soil compaction (Troldborg et al. 2013).

Integrated environmental assessment and modelling can assist with joint consideration of natural and anthropogenic risk sources, during all mine phases, to indicate soil compaction risk. Integrated assessment is a process that combines multiple and diverse components across their social, organisational and conceptual boundaries to provide a comprehensive analysis of the problem (Hamilton et al. 2015). Integrated modelling facilitates this, by providing a single platform to explore the linkages and feedbacks amongst different system components, including social, economic and ecological aspects of natural or anthropogenic factors (Hamilton et al. 2015). Some researchers refer to integration as cumulative effects or impacts (Franks et al. 2013).

Several integrated frameworks and models have been developed for natural resource management (Ban et al. 2013; Barton et al. 2012; Borsuk et al. 2012; Farmani et al. 2012; Henriksen et al. 2012; Johnson and Mengersen 2012; Koen et al. 2017; Uusitalo et al. 2012; van Delden et al. 2007; Varis et al. 2012). Few have, however been developed for mining applications (Kirsch et al. 2014; Lechner et al. 2017; Maczkowiack et al. 2013; Williams 2001), and even fewer that are specific to soils. Bayesian networks (BNs) were used to investigate the vulnerability of peat to erosion (Aalders et al. 2011) and for assessing the risk of soil degradation, particularly soil compaction (Troldborg et al. 2013). This research was in response to a need to identify 'risk areas' as part of the European Union Soil Framework Directive (European Commission 2006) and focused on agriculture in Scotland, but the approach is applicable to other land uses and threats, including mining and rehabilitation failure. BNs are the most popular risk assessment technique used in these integrated frameworks and models mentioned, although other potential tools are available that could have been used, such as bow-ties analysis, fault and event trees and failure mode effect analysis.

BNs are graphical models for reasoning under uncertainty, where nodes represent a set of random variables, whilst connecting arrows/ arcs represent direct causal connections between them, in directed acyclic graphs. The quantitative strength of the connections between variables is modelled, using probability calculus, allowing probabilistic beliefs about them to be updated automatically, as new information becomes available (Korb and Nicholson 2011; Xu et al. 2016). Due to their ability to deal with uncertainty in a natural way, BNs are advantageous (Barton et al. 2008). Further they can combine data with expert knowledge (Pollino et al. 2007); they provide a high level of prediction accuracy, despite small sample sizes and/ or incomplete datasets (Renken and Mumby 2009); variables can be specified as probability distributions, conditional on the configuration of parent variables (Barton et al. 2008); and they facilitate integrated modelling (Borsuk et al. 2004; Kragt et al. 2011). We present a similar framework approach to that of Troldborg et al. (2013), together with a case study using a Bayesian network (BN) model. Our approach differs in that our framework and model’s design is aligned with leading practice, mine approval, environmental impact assessment and mine rehabilitation processes. It further incorporates multi-discipline integration with familiar risk assessment concepts.

In this paper we therefore describe a framework that can be applied using BNs to integrate and quantify rehabilitation risk to support surface-strip coal mine rehabilitation planning decisions. We demonstrate its application using a BN case study, by assessing a single component of that framework, viz. a soil compaction risk event. We develop the soil compaction BN structure, quantify it using expert knowledge, and gauge its utility by field testing it on two mines, with differing site characteristics, one mine situated in South Africa and the other in Australia. We validate the BN by conducting sensitivity analysis and accuracy testing concurrently with field testing. Soil compaction pre-mining phase ‘vulnerability probabilistic’ risk predictions, as well as mining to post-mining phase ‘diagnostic or prescription probabilistic’ risk predictions, are demonstrated. Rehabilitation risk profile calculations for each mine are provided. We conclude by discussing research directions leading towards the development of a fully synthesised model emanating from the framework presented.

FRAMEWORK DEVELOPMENT

Framework development is the first step in quantitative modelling (Argent et al. 2016; Gupta et al. 2012; Liu et al. 2008; McCann et al. 2006). The Rehabilitation Risk Assessment Integrated Network (R^2AIN™) framework (Fig. 1) was developed to support the assessment of mine site rehabilitation risk, both at the pre-mining phase and for different management scenarios during the mining to post-mining phases.

The framework is applied using a seven-step process: (1) identify rehabilitation risk events of potential concern; identify natural (2) and anthropogenic (3) risk sources relevant to each identified risk event; (4) integrate risk sources using BNs; (5) quantify each rehabilitation risk event using BNs and sum their cumulative values; (6) evaluate rehabilitation risk against known risk criteria; and (7) reduce rehabilitation risk, with controls, which could include adapting management actions from identified anthropogenic sources. These steps are triggered by the detection of undesired rehabilitation risk events, allowing for the assessment of their sources, to quantifying their end-effect, until lastly, mitigation is applied to reduce possible risk.

The framework is consistent with the ISO 31000 - *Risk management standard* process (Council of Standards Australia & New Zealand 2009; International Organization for Standardization 2018; South African Bureau of Standards Standards Division 2009), where risk assessment includes: risk identification, analysis and evaluation (Fig. 1, outer two rings).

Framework steps (1), (2) and (3) are part of the risk identification process, defined by ISO 31000 as finding, recognising and describing risks, encompassing the identification of risk sources, events, their causes and their potential consequences. A risk source is defined as an element, which alone or in combination with other sources, has the potential to give rise to risk; for example, geology, soil and climate. Wet soil is a risk source for soil compaction, as an example. An unwanted event is defined as an occurrence or change of circumstances that may have several causes and consequences. Framework steps (4) and (5) perform a risk analysis, which characterises the nature and level of risk and includes risk estimation. Framework step (6) is part of risk evaluation, where the results of the risk analysis process are compared with risk criteria to determine whether the risk and/ or its magnitude is acceptable or tolerable. This step enables decisions to be made about the significance of the risk and the requirement, or otherwise, for risk treatment. Framework step (7), to reduce rehabilitation risk with controls, falls within the ISO 31000 risk treatment process, the purpose of which is to select and implement options for addressing risk. The International Organization for Standardization (2018), also describes an ongoing process of monitoring and review, which connects with all risk processes. To facilitate an improved understanding of concepts, we will describe the R^2AIN™ framework in greater detail in the following sections. Specific examples will be provided of how the framework could be applied using BN modelling.

Step 1: Identify rehabilitation risk events

Rehabilitation risk events are categorised into three risk event domains: a) substrate/ soil failure, b) water failure and c) vegetation failure (Fig. 2). This categorisation is based on the view that rehabilitation starts from the bottom-up, and that if you can get the substrate/ soil correct and reduce risks here, you will likely achieve a successful outcome with vegetation establishment. Water is the interface between the two and it is therefore important that risks are minimised in this domain too. Relationships exist between the domains, with feedback mechanisms affecting restoration success (Perring et al. 2015). The three risk event domains are categorised further into seven risk event types (Fig. 2). Risk events are then ordered within these types in levels from L1 (low risk) to L6 (high risk), based on their importance as a contributor to rehabilitation failure. As noted previously, soil compaction is regarded as a severe risk event that can contribute to rehabilitation failure. Soil compaction has therefore been classed as high risk (highlighted red in Fig. 2). All identified rehabilitation risk events require the development of separate BN component models, and each should be capable of computing an end risk percentage. Risk events falling in the L6 level, should be prioritised. To quantify a site's cumulative rehabilitation risk, and hence to create a fully synthesised model, requires the coupling of all contributing rehabilitation risk event BN component models. Listed risk events are dynamic; as the full model evolves, additional risk events may be identified, and some may become redundant. Continuous updating of these will be required.

Step 2 & 3: Identify natural and anthropogenic risk sources

Rehabilitation risk was assessed for the pre-mining to post-mining phases through identifying first the natural and then the anthropogenic risk sources (Fig. 2). The natural risk source identification process is applicable mostly to the pre-mining environmental baseline. Natural risk sources fall within seven types: geology, soils, topography, vegetation, hydrology, climate and landcover. These conform with the 'environmental domain evaluative criteria' defined by Weyer et al. (2017), who emphasized their importance as foundation rehabilitation factors. They influence the potential for rehabilitation failures as well as opportunities, since they determine the long-term viability of land for sufficient ecosystem restoration and are important for building a landscape from the bottom-up. The seven types enable a linkage with the multi-disciplinary specialist studies that are undertaken as part of the mine approval phase.

Anthropogenic risk sources fall within five types: machinery management, soil management, slope management, site disturbance, and site contamination. These are based on mine planning and design, as well as actions that carry risk from human error, which may affect risk events.

The natural and anthropogenic risk source identification processes may be undertaken individually or collectively for each mine phase assessment outcome. Not all identified categories may be applicable to each rehabilitation risk event being evaluated.

Steps 4 & 5: Integrate risk sources and quantify risk events with BNs

Risk source integration (step 4) and quantification of risk events (step 5) are undertaken using BNs. This involves the conceptual qualitative component and the quantitative component of the BN model development process, respectively. These processes are demonstrated and described in the section dealing with the soil compaction risk event case study.

Step 6: Evaluate rehabilitation risk against risk criteria

During step 6, the results from the integration of the identified risk sources (step 4) and the quantification of the risk events (step 5) are compared against defined '*rehabilitation risk criteria*' (RRC), i.e. acceptable quantitative levels of risk outcome, to determine whether the risk or its magnitude is acceptable or tolerable. At present, RRC have not been defined as they lie outside the scope of this research. During the next phase of research, RRC need to be developed. This evaluation will aid decisions about risk treatment and the application of controls which take place in step (7). A body of research exists for: rehabilitation completion criteria and performance indicators, rehabilitation and restoration monitoring, Australian ecological restoration standards, soil condition and geomorphic stability (Blommerde et al. 2015; Hancock et al. 2003; McDonald et al. 2016; Tongway and Hindley 2004). However, these are not specific to *'rehabilitation risks'*. As individual risk event BN models are developed and tested by industry, within the R^2AIN™ framework, the outcomes could be used to develop acceptable RRC. These could then be used to specify performance-based rehabilitation completion criteria.

Step 7: Reduce rehabilitation risk with controls

To prevent or reduce rehabilitation risk, controls must be applied. Controls may include taking a 'no-go' decision not to develop a high-risk site, developing a lower risk portion of a site, or preventing or reducing rehabilitation risk with mitigation or by manipulating management actions within the identified anthropogenic risk sources. The effects of manipulating management actions are demonstrated and described in the section on case study results and discussion.

CASE STUDY: SOIL COMPACTION RISK EVENT

In the previous section, soil compaction was identified as an L6 high risk, i.e. a risk event of concern and prioritised for BN component model development. In this section, we illustrate step (4) integration and step (5) quantification of the R^{2}AIN™ framework by developing soil compaction BN models for two mine sites (Fig. 3). The first site is Anglo American's Kleinkopje (now Khwezela Bokgoni) Colliery, which is situated in the Witbank Coalfield, Mpumalanga Province, South Africa (26°0'38.33"S 29°13'25.50"E). The second site is the Caval Ridge coal mine of BHP Billiton Mitsubishi Alliance Coal Operations (BMA), which is situated in the Bowen Basin, Queensland, Australia (22°8'40.33"S 148°3'52.08"E). South Africa and Australia were chosen for comparison, to establish the extent of regional applications of the R^{2}AIN™ framework and its BN component models. The chosen sites have very different site characteristics, allowing final model outcomes to be confirmed. A rehabilitation risk of concern, associated with Kleinkpopje, is likely to be soil compaction, as it is well known that South African soils other than the Vertisols, are highly susceptible to compaction (Chamber of Mines of South Africa 2007). Caval Ridge is likely to be affected more by soil erosion, due to the common occurrence of sodic soils in Australia, which typically produce high rates of runoff and erosion (Dale et al. 2018; Loch 2010; Shaw et al. 1994).

Integrate natural and anthropogenic risk sources with BNs

Step (4) of the R²AIN™ framework is the integration of risk sources using BNs. The Knowledge Engineering for Bayesian Networks (KEBN) process by Korb and Nicholson (2011) was used to develop the BN models. This process describes the development of a BN as starting with defining the nodes and their states. For the soil compaction models, nodes represent risk sources and variables that influence them. The states of a node are defined as the possible mutually exclusive states in which that node can exist. The second step is to connect the nodes with directed arcs. Two nodes may be connected if one affects the other or causes the other, with the arc indicating the direction of the effect. In other words, the arcs in the BN structure indicate causal connections between the nodes. The result of this step is a BN structure that captures the qualitative information of the model.

We developed two soil compaction BN models using Hugin® v.8.1. educational software (HuginExpert 2018); one for the pre-mining phase and another for the mining to post-mining phase (Fig. 4). For the pre-mining phase BN model, relevant natural risk sources were included: topography (block 1), vegetation (block 2), hydrology (block 3), soils (block 4) and climate (block 5). The pre-mining phase model may also be described as representative of inherent rehabilitation risk. The natural risk sources were integrated as component models to the target node ‘pre-mining soil compaction risk’ (block a). For the mining to post-mining phases BN model, the pre-mining phase BN model was combined with an anthropogenic risk sources BN component model, which included machinery (block 6) and soil management (block 7) risk sources. The target node is ‘mining to post-mining soil compaction risk’.

Variables for all risk source component model nodes, their states and values, can be found in Table 1 & 2. The full versions of these tables, including their supporting references can be found in Appendix A, Supplemental data. States were defined as L-low, M-medium and H-high (in some cases only low and high), to align with mine approval environmental impact assessment and rehabilitation process terminology. Values were defined based on universal parameters (i.e. can be applied to any region and include well known specialist terminology) or regional South African and Australian parameters. All the end nodes of the component models were set as percentage risk, ranging from 0 – 100 in discretised states, to quantify risk individually for each component model.

Quantify rehabilitation soil compaction risk event with BNs

Step (5) of the R^2AIN™ framework is the quantification of rehabilitation risk events. This step assumes a BN structure, which is the output of step (4). Relationships between nodes in a BN are quantified among connecting nodes by specifying conditional probability distributions for each node. The probabilities are based on expert knowledge or they can be machine learned, where data are available.

Child nodes (i.e. nodes with arcs feeding into them from parent nodes) have conditional probability tables (CPTs) that represent combinations of all states of their parent nodes. These increase exponentially in size as more nodes are added to the parent set. Whilst this is not a problem with machine-learned probabilities, it becomes problematic when experts need to provide the numbers. Several knowledge engineering techniques exist to facilitate knowledge elicitation and also to check for inconsistency and bias (Johnson et al. 2010; Korb and Nicholson 2011). De Waal et al. (2016) introduced a 3D elicitation technique that relies on experts' colour pattern recognition capabilities rather than their ability to encode probabilities. To visualise the assessment, the one-dimensional CPT can be collapsed into a colour formatted matrix, using spreadsheet software. A pattern is created that can alleviate the tediousness of working through a long CPT in which not all the probabilities are visible at once.

Consider a child node ‘soil stockpiles’ which has three parent nodes feeding into it (with states in brackets): age (low, medium, high), double handling (low, high) and height and footprint (low, medium, high). ‘Soil stockpiles’ has two states – low and high risk. In this case we chose to assess low risk. The CPT has 18 parent node configurations to be parameterised. Table 3 illustrates the CPT: The states of age and double handling are indicated as rows and the states of height and footprint are indicated as columns. The application of conditional colour formatting on the probabilities can create a probability heat-map of the CPT. An example of an assessment is the following: Given a low risk (< 9 months old) for age, a low risk (no) for double handling and a medium risk (1.5 - 3 m, medium surface area) for height and footprint, the probability of low risk for ‘Soil Stockpiles’ is 0.7. Conversely, the probability of high risk for ‘Soil Stockpiles’ would be 0.3 (not indicated in Table 3).

CASE STUDY: RESULTS AND DISCUSSION

Once a BN is constructed, it allows for inference based on observations (Troldborg et al. 2013). In practice, this means that observations are entered as evidence into the BN and all other probabilities in the BN are updated according to this new information. The process of updating is called ‘probabilistic inference’ (also called ‘reasoning’ or ‘probability propagation’). The updated probabilities are called ‘posterior probabilities’. Evidence can be entered on any node, regardless of its position in the directed acyclic graphs. This allows the modeller to answer interventional and counterfactual questions such as, ‘Was it ‘X’ that caused ‘Y’?’ or ‘What if I do ‘X’?’.

We consider data for the two sites described earlier to perform field testing of the BN models. Field testing puts the BN into actual use, allowing utility to be evaluated (Korb and Nicholson 2011). Field testing is a sound validation method in modelling scenarios where expert knowledge is used for BN construction and parameterisation.

Pre-mining phase site predictions

Soil compaction risk was assessed for each mine site’s pre-mining phase by using the quantified pre-mining phase BN model and deciding, for all nodes, which node state and its value best described each site and selecting these. For example, Kleinkopje has a mean annual precipitation of 648 mm, therefore the ‘mean annual precipitation’ node’s state was selected as M-medium (600 – 800 mm, SA) (Appendix A, Supplemental data).

Site specific data were obtained from environmental mine approval reports in the public domain and from regional databases. The Quinary Catchment database by Schulze et al. (2011), was used to obtain South African data. Expert opinion was further sought from the paper’s authors. In cases where data were unobtainable, ‘hypothetical’ value scenarios were entered. This is not considered a weakness of this study as this paper’s main purpose is to demonstrates a process, not a fully evaluated dataset. The nodes, states and values are dynamic, and these were designed for continuous improvement with repeated model application. Data were entered into the BN models as observations (indicated with red bars) and the new information was then propagated through the rest of the BN to update the probability distributions of other nodes (indicated with green bars) (Appendix B, Supplemental data).

The climate natural source component model is illustrated as a comparative example for Kleinkopje and Caval Ridge (Fig. 5). All component models, including those also for soils, topography, hydrology and vegetation may be found in Appendix B, Supplemental data. The percentage results for the component models and their averages are listed in Table 4. Manual combining and averaging of the component models, as opposed to using BN software (in our case Hugin®) for coupling was preferred, as this prevented information from becoming diluted and allowed for the better interpretation of the multi-disciplinary information. Iwanaga et al. (2018), similarly note difficulties with component model coupling and note that this process may be error-prone.

Overall Kleinkopje was found to have a higher risk (70%), under pre-mining conditions, and therefore was considered more *vulnerable* to soil compaction than Caval Ridge (48%). The model component with the highest influence on risk for both Kleinkopje and Caval Ridge was hydrology, followed by soils. Kleinkopje had a higher hydrological risk (82%), than Caval Ridge (56%), owing to Kleinkopje having several wetlands present, with standing water and with groundwater set as being closer to the surface in contrast to the ephemeral creek systems of Caval Ridge. The soils risk for Kleinkopje was higher (76%), when compared to that of Caval Ridge (55%). A higher soil water content risk was assigned to Kleinkopje, owing to the site's mean annual temperature higher risk rating, i.e. temperature ranges are lower for Kleinkopje, suggesting that soils will be slower to dry out and therefore likely more prone to soil compaction. Hypothetical value scenarios were entered for several Kleinkopje soil nodes, as data from baseline soil studies were inaccessible. Kleinkopje had a higher topography risk (60%), compared with Caval Ridge (47%), because the state for the node 'elevation', also referred to as 'altitude', differed between the two sites, with Kleinkopje having the higher risk 'elevation' node. The input data for all other nodes were the same. The vegetation risk for Kleinkopje was higher (70%), compared with Caval Ridge (40%), as Kleinkopje was previously cultivated whereas Caval Ridge originally supported wilderness/ grazing. Kleinkopje's climate risk was higher (62%), compared with Caval Ridge (40%), as Kleinkopje had higher mean annual temperature and mean annual potential evaporation risk ratings.

Arnold et al. (2013) describe the Brigalow Belt, in which Caval Ridge falls as having average rainfall ranges of between 500 and 800 mm, yet notes that the area, owing to its location, is not dominated by seasonal rain bearing systems. The region experiences erratic rainfall patterns, with short intensive storm events during summer. The observation of online aerial photographs for Caval Ridge (Fig. 3), show erosion gullies present in unmined areas and as noted by others the common occurrence of sodic soils in Australia, is likely to predispose soils at Caval Ridge to soil erosion (Dale et al. 2018; Loch 2010; Shaw et al. 1994). The site appears to be a dry site and soil compaction would likely not be an issue. Our rehabilitation risk modelling results for Caval Ridge support this hypothesis.

Management scenarios

Poor and improved management scenarios were run for the machinery and soil management anthropogenic source component models. The Soil management component model is illustrated as a comparative example for poor and improved management (Fig. 6). The Machinery management component model may be found in Appendix B, Supplemental data. For machinery management the query was to see what the change in risk would be with a poor decision choice, viz. to use high rehabilitation risk scrapers/ bowlscapers versus an improved management choice; viz.: the use of draglines, where the focus is on the machine’s contact with the ground surface. For soil management, for both the poor and improved management scenarios, the soil was set as handled when wet. However, for the poor management scenario, the stockpiles and soil characterisation were additionally set as being poorly managed, therefore increasing the rehabilitation risk. Percentage results and averages are listed in Table 5. Overall, the poor management scenario (82%) may have risk reduced by 35 percent-points with improved management decision choices.

Mining to post-mining phase site predictions

We assessed soil compaction risk for each mine site’s mining to post-mining phase. This was achieved by combining the results from the quantified soil compaction pre-mining phase BN model with the results from the soil and machinery management anthropogenic risk source component models with their poor and improved management scenarios (Table 6).

The pre-mining phase soil compaction risk for Kleinkopje increased from 70% to 76%, with poor management, applied during the mining to post-mining phases, whilst with improved management, reduced from 70% to 59%. This is a rehabilitation risk value lower than that of the pre-mining rehabilitation risk. For Caval Ridge, the pre-mining phase soil compaction risk of 48% increased to 65% with poor management, whilst with improved management returned to 48%.

By implementing improved management choices, soil compaction risk calculations can be reduced, sometimes to values lower than a pre-mining baseline. This is not impossible, particularly if a site was originally severely degraded, the rehabilitation risk factors were mostly in the high-risk range and an emphasis was placed on applying multiple improved management actions. Not all mines start from a pristine and healthy well managed condition. Examples include historical land degradation from overgrazing, droughts and intense rainfall, prior to metalliferous mining in the Hunter Valley, New South Wales, Australia (Green 1989) and the clearing of the Brigalow Belt Bioregion, Australia (Arnold et al. 2013).

To justify the mining of high-risk sites, during mine approval, a mining company could commit to improved rehabilitation management actions as mitigation, the magnitude of which would depend on the amount of risk to be reduced. A risk value lower than the pre-mining baseline, is an indicator that the site in ‘principle’ could be improved to a more optimum state, provided most of the improved management mitigation actions are applied. In reality it is difficult to match pre-mining landuse standards, for productive agriculture or biodiversity, let alone achieving higher standards (Butler and Anderson 2018; Doley et al. 2012; Erskine and Fletcher 2013).

CONCLUSIONS

By applying a framework approach, we were able to summarize our abstract state of knowledge about the structure and working of our rehabilitation risk assessment system. The R^{2}AIN™ framework enabled us to integrate multi-disciplines that inform soil compaction risk from pre-mining onwards. Using this baseline, we were able to gauge responses to soil and machinery management scenarios that would occur during the mining to post-mining phases, to reduce rehabilitation risk. The use of BNs allowed us to quantify soil compaction risk and to segregate risk into contributing multi-disciplines for analysis. Cross-links between multi-disciplines were not made, although these relationships occur. The multi-disciplinary approach was adopted to allow alignment with environmental impact and risk assessment processes. Due to their graphic nature and their ability to integrate and quantify multi-disciplinary risk, BNs demonstrate benefits over other popular alternative risk assessment techniques, such as fault and event tree analysis, as well as bow-tie analysis.

The R^2AIN™ framework should have the potential to be globally applied to any mining type and to any development activity. The case study soil compaction BN model, however, is region specific but highly applicable for environments with extended periods of time with high soil moisture leading to higher susceptibility to compaction. It was developed for use in the Witbank Coalfield, South Africa and the Bowen Basin, Australia. The states (i.e. low/ medium or high) are fixed, however their values (i.e. ranges of 600 - 800 mm rainfall etc.), were set for each of these regions and where possible universal values were used. The soil compaction BN model could be adapted for use in other southern or northern hemisphere mining countries by re-setting the regional values, specific to each query country. Use should be made of region relevant systems, such as Schulze (1997) and Tongway and Hindley (2004). When applying the model to a mine site, the state of either low, medium or high would be selected, based on the state range values set for that region and whether the site falls within the low, medium or high categories. The CPT weightings will be different, based on experts' contributions relevant to each region and the risk event being investigated. The framework and the soil compaction BN model are designed for strategic use, to guide site specific specialist investigations. The need for detailed site investigation is supported by others (Rethman 2006; Troldborg et al. 2013).

Soil compaction risk was assessed for each mine site's pre-mining phase by using the quantified soil compaction pre-mining phase BN model. For the mining to post mining phases, the pre-mining phase BN model was combined with the soil and machinery management BN models, running poor and improved management scenarios. Should a user wish to attain greater sensitivity in results, the pre-mining phase BN model could be adapted and applied as an intermediate additional step, particularly for progressive rehabilitation risk queries. Some nodes would then remain static. For example, some climate variables do not change over the short-term (if climate change is not factored in), whilst others will alter, particularly the soils and topography nodes, which may be influenced by mining activities.

Future research

This paper has shown that the R^{2}AIN™ framework defines a process for the development of a future synthesis R^{2}AIN™ model, inclusive of prioritised rehabilitation risk event BNs. The soil compaction case study demonstrates the methodology and its workability. Probabilistic rehabilitation risk is quantifiable with calculations permissible for separate multi-disciplines for each site. Site rehabilitation risk profiling before mining activities commence is possible and the effects of manipulating management actions during the latter mine phases to reduce risk, can be gauged, to aid decision making. Resilient rehabilitation planning; qualitative and quantitative multi-discipline integration and upfront rehabilitation risk determination is facilitated.

This research could be used to inform mine rehabilitation policy, firstly by stipulating the need for the use of the R^{2}AIN™ framework for rehabilitation risk assessment for upfront mine approval and closure planning. Secondly, by proposing the use of BNs for quantification calculations, during upfront planning and in addition with progressive rehabilitation and financial relinquishment. It could be incorporated into financial provision requirements, with possible financial incentives given for meeting targets set. The framework is intended to assist professionals to better evaluate rehabilitation risk and to aid authority decision making. This methodology is generalised enough to allow its application to other research fields, where there is a need to quantify and integrate multi-discipline risks from several contributing and interacting systems.

Alpha and beta testing should be conducted (Korb and Nicholson 2011) by developing each rehabilitation risk event BN, with the full R^2AIN™ model, for each site application. Alpha testing refers to the intermediate test of the system by in-house staff, not directly involved in developing it, but who have expert BN experience, such as other BN modellers. Beta testing involves the application of the system by an end-user, to identify flaws and opportunities for improvement, such as testing by mining industry rehabilitation professionals. Lastly acceptance testing is required, whereby end-users will need to be sufficiently familiar with the framework, BN process and software to use these with confidence for their specific needs. After this it will be possible to make the risk event BNs and the R^2AIN™ model available to industry for implementation. Rehabilitation Risk Criteria emanating from a future synthesis R^2AIN™ model should then be investigated for inclusion in the development of performance-based rehabilitation completion criteria.

A rigorous evaluation process should be implemented. Evaluation of a BN includes more informal methods such as case-based evaluation where cases are generated to test a wide variety of scenarios to which the BN model could be exposed to (Korb and Nicholson 2011). More formal methods include explanation methods, such as 'most probable explanation' (MPE) (Kwisthout 2011) which can be thought of as the most plausible explanation for the observed findings. Explanation methods are useful in evaluating a BN as the independence-dependence relations in a BN structure are not always obvious to users of the model. The explanation of conclusions drawn about the domain using the BN contribute to the acceptance of the BN model by domain experts and users (Korb and Nicholson 2011).

For industry to accept and use the R^2AIN™ framework, the risk event BNs and a R^2AIN™ model benefits must be evident. Potential benefits include simplicity of use, data improvement and improved products leading to early detection of rehabilitation risks. Long-term cost savings are possible, when rehabilitation risks are detected early, allowing mitigation measures to be implemented in a timely manner, or alternative decisions to be made thereby reducing rehabilitation liability later in the mine's life. The tools presented provide an improved scientific system for mine rehabilitation planning than that currently available.

The R^2AIN™ framework and a future synthesis R^2AIN™ model inclusive of rehabilitation risk event BNs are intended to be evidence based, yet practical. These tools facilitate the placing of data into a validated system for practical use and analysis, in contrast to collecting data and leaving it in mine approval documentation with limited application. This research bridges industry practicalities with scientific foundations.

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Contributions from David Doley, Andrew Butler, Rudolph Botha and Martin Platt are acknowledged. Anglo American are thanked for providing data for Kleinkopje. Nigel Berjak is thanked for preparing the mine site locality figures. The University of Pretoria and the Coaltech Research Association are thanked for funding the research. We would like to thank the anonymous reviewers who provided constructive feedback on the manuscript which resulted in significant improvements.

Disclaimer

The authors declare no conflicts of interest. The peer-review process of this article was managed by the Editorial Board without the involvement of V Weyer.

Data Accessibility

Data are contained in the Supplemental Data and any further required data are available upon request from the corresponding author, Vanessa D. Weyer, at vweyer@global.co.za.

SUPPLEMENTAL DATA

Supplemental Information, Appendix A. Risk source component BN model tables. Two tables are included: a table with natural risk source component model nodes, states and their values with input site specific data for Kleinkopje and Caval Ridge shown; and a table with anthropogenic risk source component model nodes, states and their values with input data for poor and improved management scenarios shown.

Supplemental Information, Appendix B. Risk source component BN model figures. Five figures are included showing comparative BN modelling results for Kleinkopje and Caval Ridge for: soils, climate, topography, hydrology, vegetation. A further two figures are included showing comparative BN modelling results for poor and improved management scenarios for machinery management and soil management.

ORCID

Vanessa D Weyer ID https://orcid.org/0000-0003-3960-578X

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List of Figures

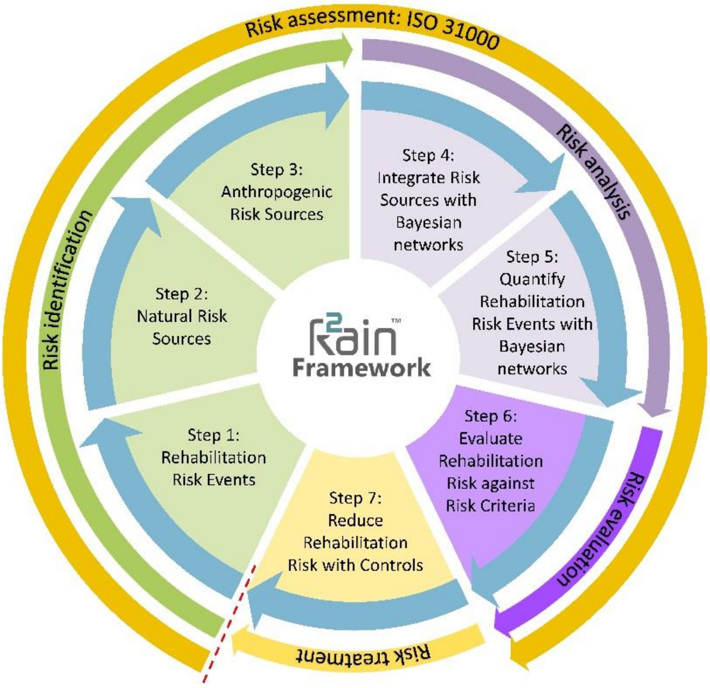
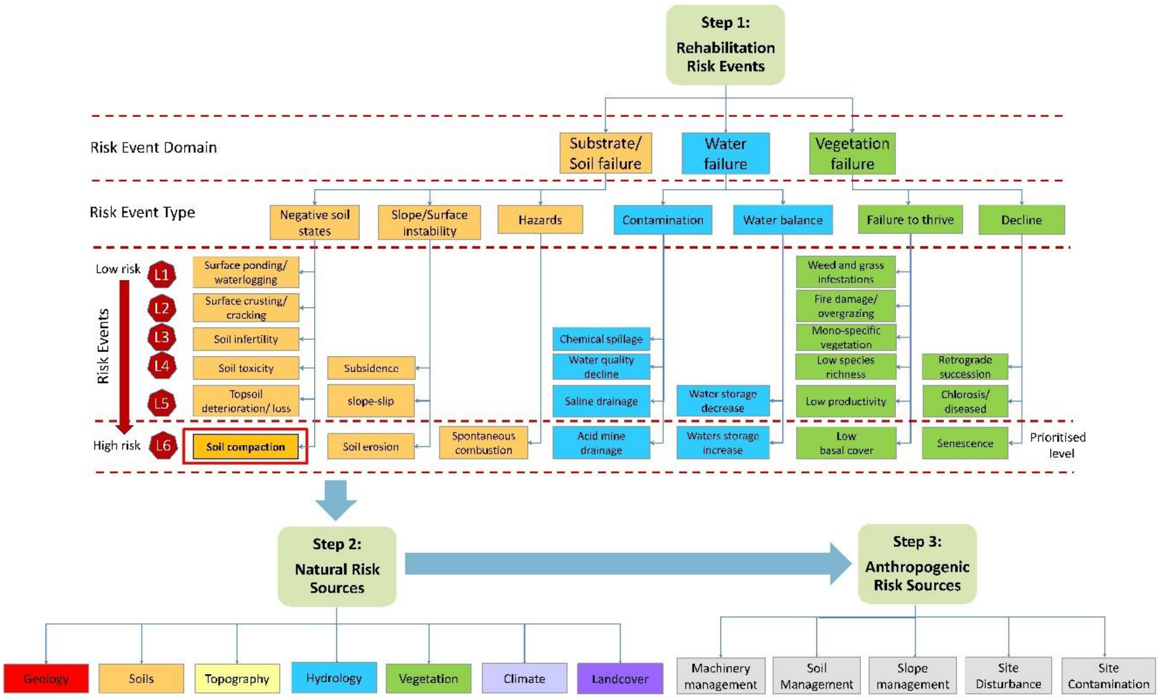
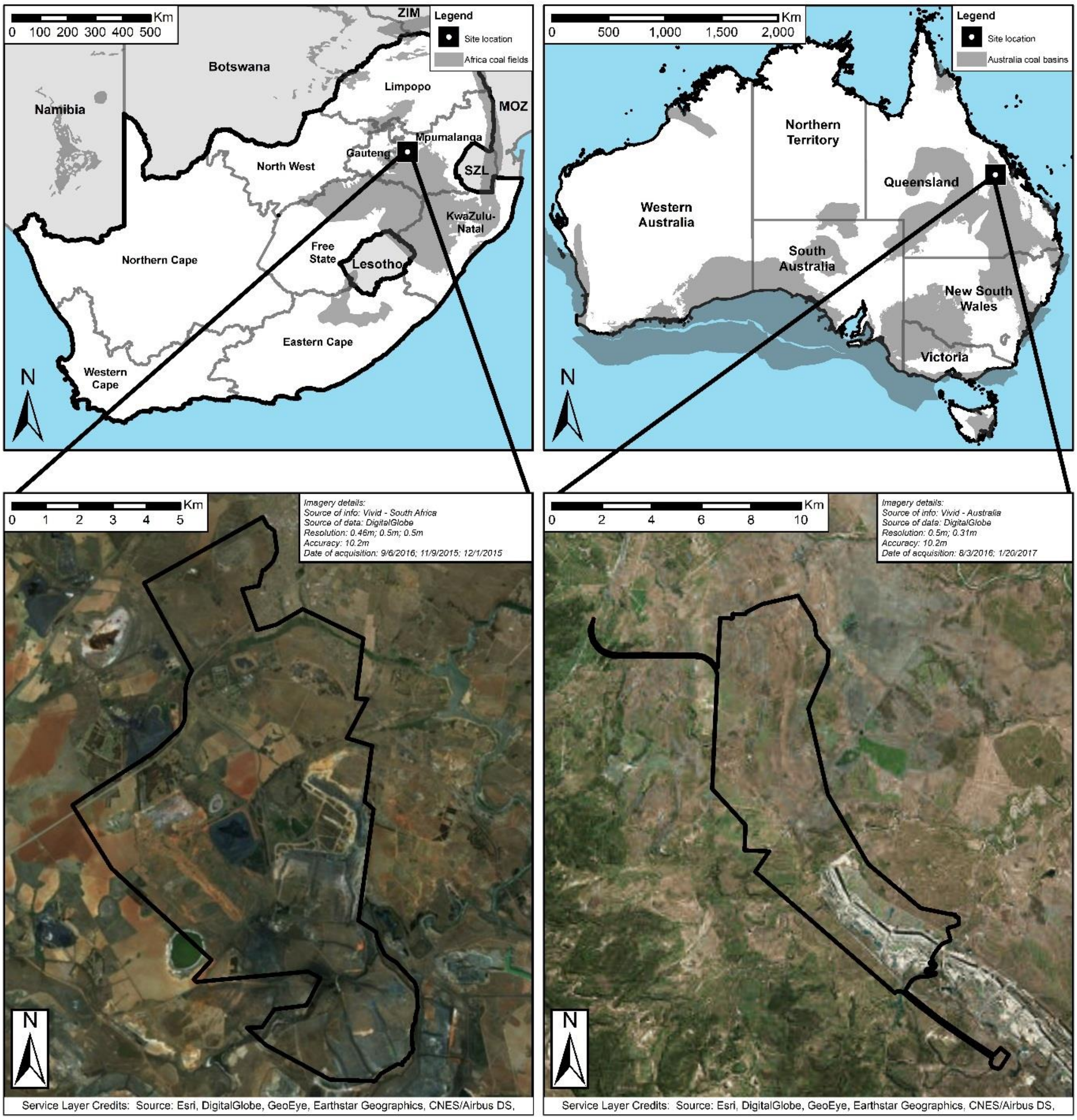

Risk assessment: ISO 31000
Risk identification
Risk analysis
Risk evaluation
Risk treatment
Step 1: Rehabilitation Risk Events
Step 2: Natural Risk Sources
Step 3: Anthropogenic Risk Sources
Step 4: Integrate Risk Sources with Bayesian networks
Step 5: Quantify Rehabilitation Risk Events with Bayesian networks
Step 6: Evaluate Rehabilitation Risk against Risk Criteria
Step 7: Reduce Rehabilitation Risk with Controls
R2ain Framework

Figure 1



Step 1: Rehabilitation Risk Events
Risk Event Domain
Substrate/ Soil failure
Water failure
Vegetation failure
Risk Event Type
Negative soil states
Slope/Surface instability
Hazards
Contamination
Water balance
Failure to thrive
Decline
Low risk
High risk
Risk Events
L1
L2
L3
L4
L5
L6
Surface ponding/ waterlogging
Surface crusting/ cracking
Soil infertility
Soil toxicity
Topsoil deterioration/ loss
Soil compaction
Subsidence
slope-slip
Soil erosion
Spontaneous combustion
Chemical spillage
Water quality decline
Saline drainage
Acid mine drainage
Water storage decrease
Waters storage increase
Weed and grass infestations
Fire damage/ overgrazing
Mono-specific vegetation
Low species richness
Low productivity
Low basal cover
Retrograde succession
Chlorosis/ diseased
Senescence
Prioritised level
Step 2: Natural Risk Sources
Step 3: Anthropogenic Risk Sources
Geology
Soils
Topography
Hydrology
Vegetation
Climate
Landcover
Machinery management
Soil Management
Slope management
Site Disturbance
Site Contamination

Figure 2


Km
0 100 200 300 400 500
ZIM
Legend
Site location
Africa coal fields
Botswana
Namibia
Limpopo
MOZ
Mpumalanga
Gauteng
North West
SZL
KwaZulu-Natal
Northern Cape
Free State
Lesotho
Eastern Cape
Western Cape
N
Km
0 500 1,000 1,500 2,000
Legend
Site location
Australia coal basins
Northern Territory
Queensland
Western Australia
South Australia
New South Wales
Victoria
N
Km
0 1 2 3 4 5
Imagery details:
Source of info: Vivid - South Africa
Source of data: DigitalGlobe
Resolution: 0.46m; 0.5m; 0.5m
Accuracy: 10.2m
Date of acquisition: 9/6/2016; 11/9/2015; 12/1/2015
N
Service Layer Credits: Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS,
Km
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Source of data: DigitalGlobe
Resolution: 0.5m; 0.31m
Accuracy: 10.2m
Date of acquisition: 8/3/2016; 1/20/2017
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Service Layer Credits: Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS,

Figure 3

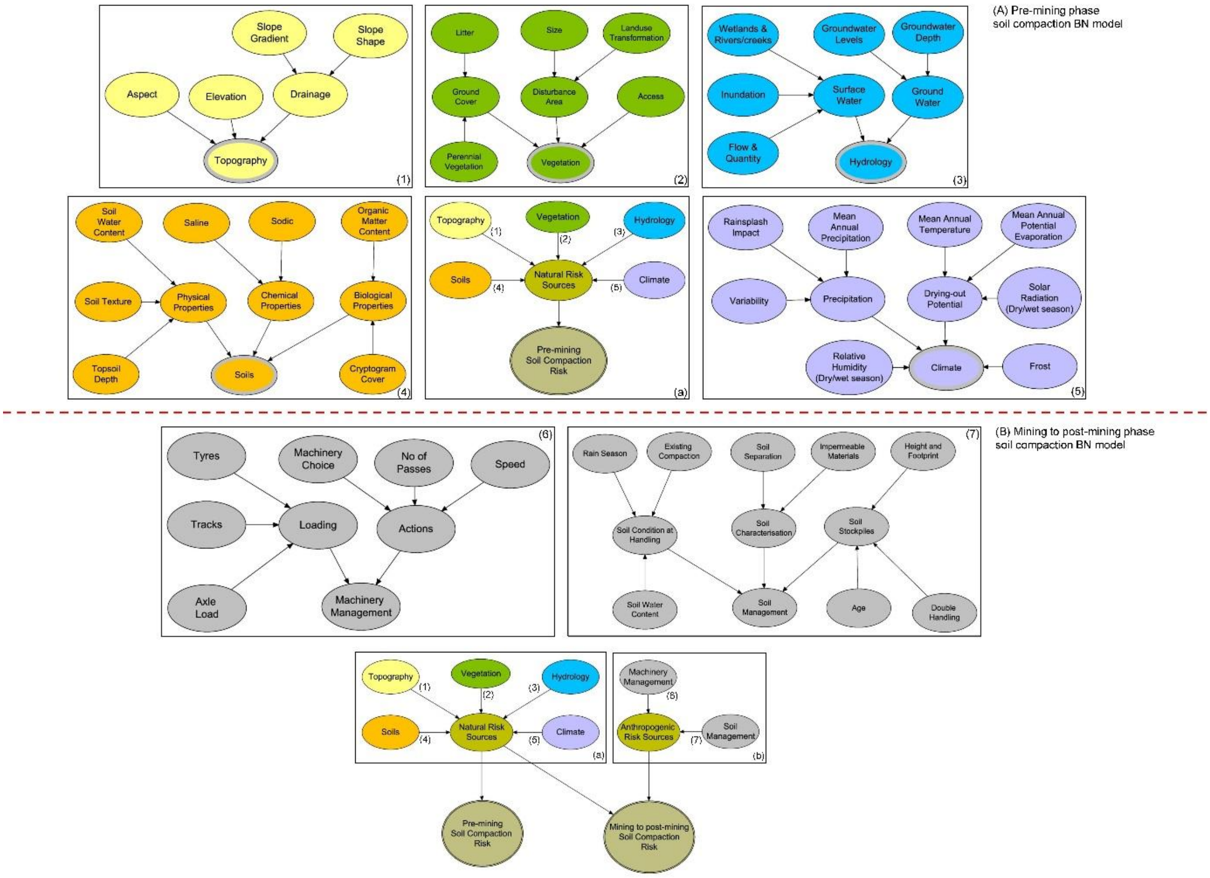
(A) Pre-mining phase soil compaction BN model
Slope Gradient
Slope Shape
Aspect
Elevation
Drainage
Topography
(1)
Litter
Size
Landuse Transformation
Ground Cover
Disturbance Area
Access
Perennial Vegetation
Vegetation
(2)
Wetlands & Rivers/creeks
Groundwater Levels
Groundwater Depth
Inundation
Surface Water
Ground Water
Flow & Quantity
Hydrology
(3)
Soil Water Content
Saline
Sodic
Organic Matter Content
Soil Texture
Physical Properties
Chemical Properties
Biological Properties
Topsoil Depth
Soils
Cryptogram Cover
(4)
Topography
Vegetation
Hydrology
Soils
Natural Risk Sources
Climate
Pre-mining Soil Compaction Risk
(a)
Rainsplash Impact
Mean Annual Precipitation
Mean Annual Temperature
Mean Annual Potential Evaporation
Variability
Precipitation
Drying-out Potential
Solar Radiation (Dry/wet season)
Relative Humidity (Dry/wet season)
Climate
Frost
(5)
(B) Mining to post-mining phase soil compaction BN model
Tyres
Machinery Choice
No of Passes
Speed
Tracks
Loading
Actions
Axle Load
Machinery Management
(6)
Rain Season
Existing Compaction
Soil Separation
Impermeable Materials
Height and Footprint
Soil Condition at Handling
Soil Characterisation
Soil Stockpiles
Soil Water Content
Soil Management
Age
Double Handling
(7)
Machinery Management
Anthropogenic Risk Sources
Soil Management
(b)
Mining to post-mining Soil Compaction Risk

Figure 4

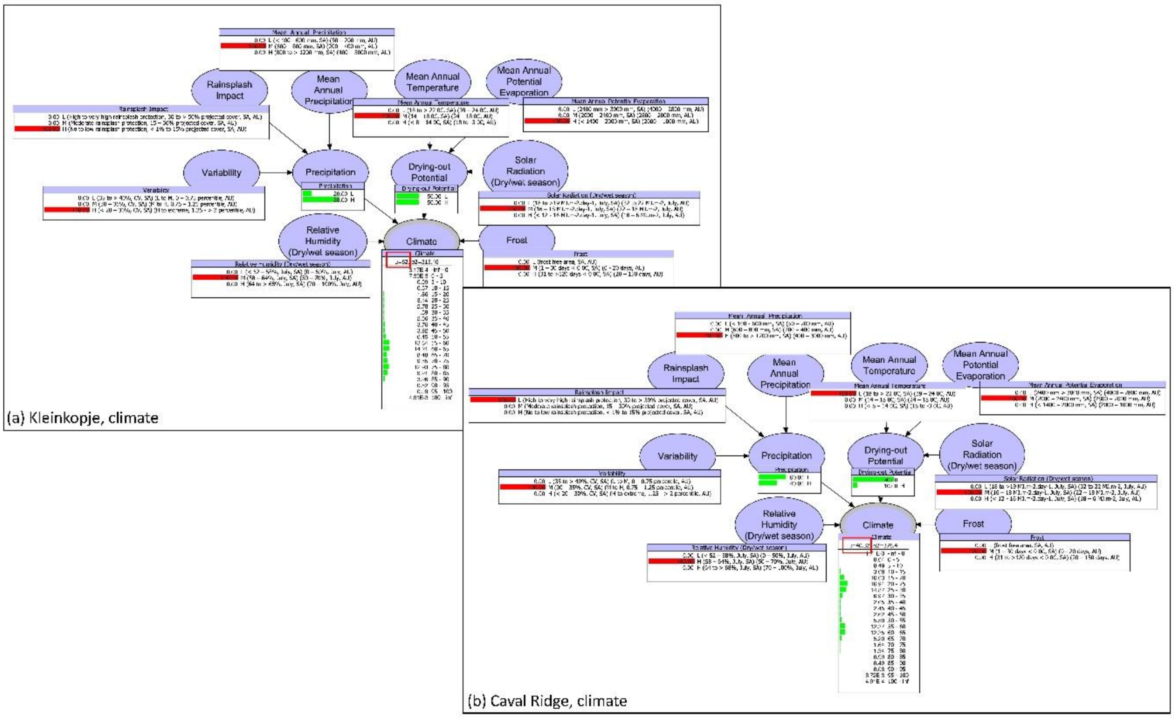
Rainsplash Impact
Mean Annual Precipitation
Mean Annual Temperature
Mean Annual Potential Evaporation
Variability
Precipitation
Drying-out Potential
Solar Radiation (Dry/wet season)
Relative Humidity (Dry/wet season)
Climate
Frost
(a) Kleinkopje, climate
(b) Caval Ridge, climate

Figure 5

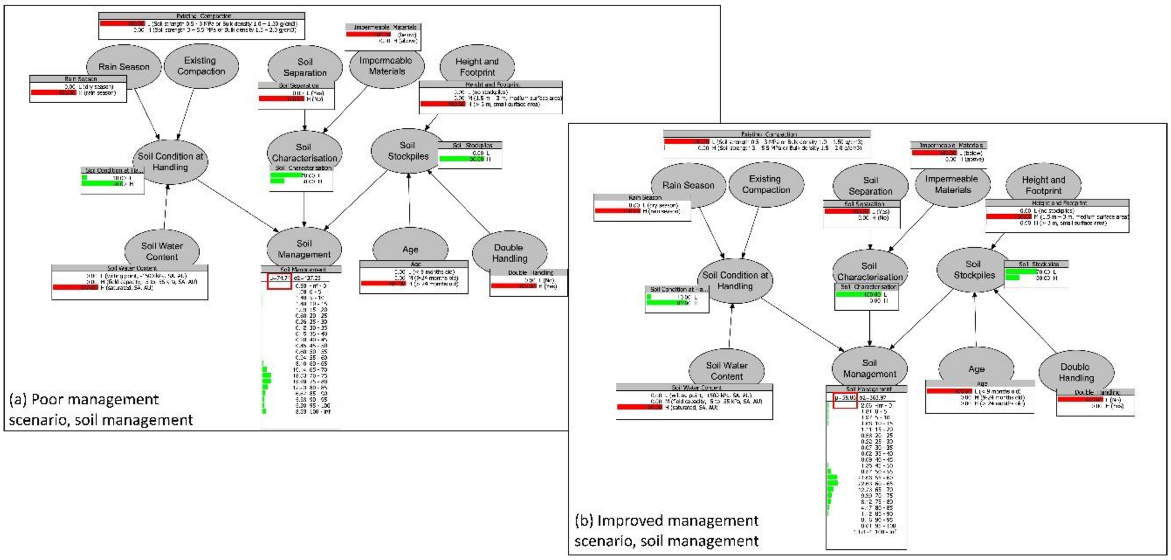
Rain Season
Existing Compaction
Soil Separation
Impermeable Materials
Height and Footprint
Soil Condition at Handling
Soil Characterisation
Soil Stockpiles
Soil Water Content
Soil Management
Age
Double Handling
(a) Poor management scenario, soil management
(b) Improved management scenario, soil management

Figure 6