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4D data management and modelling in the assessment of deep underground mining hazard

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Abstract

A framework is presented for quantitative assessment of deep underground mining hazard. It is general in the sense that it may be applied to many types of underground geotechnical and mining challenges. We present a case study illustrating the methodology from the former Xstrata Craig Mine in Sudbury, now closed, which experienced significant fault-slip rockbursting while in operation. The general approach described is statistical, based on data from a site history that quantitatively assesses correlations between falls of ground and various objectively measurable criteria. The hazard criteria are in the categories of geology, rock quality, stress, seismicity, development geometry and production sequencing, blasting, and various geotechnical monitoring systems. The criteria are modelled throughout the mine area of interest and quantitatively combined into an overall hazard index using weights established by the statistical correlation. In the Craig Mine example, several criteria in each of the major categories were modelled and combined to yield independent estimations of hazard in the ore zone and footwall. The statistical analysis clearly showed that individual hazard criteria could be quantitatively correlated to the experience of fault-slip rockbursting, with significantly different results in the ore zone and footwall.

Modelling the hazard criteria can be challenging, not least because many of the key criteria, and thus the resulting models, are four-dimensional. In practice the 4D nature of the problem is handled by time-stepping a 3D model. The modelling requires interpretational judgement in terms of how data such as structure, rock quality, and seismicity, often located far into the rock mass away from development, manifest hazard on the mine infrastructure where it is experienced. A 4D data management system is required to make the modelling efficient, particularly if it is set up to respond to real time data. Using the Craig Mine case study, we review the key design elements of such a 4D data management foundation, a 4D modelling system, and the 4D deep underground mining hazard assessment framework resulting from their integration.

1 Introduction

The premise of this work is that zones of elevated groundfall hazard in an operating mine may be identified by quantitative combination of a number of observable or computable input variables. This study demonstrates that hazard assessment from combining multiple inputs is more effective than interpretation of any single input and provides a useful result for experienced ground control engineers to interpret within the overall operational mining context. Neither spatial nor temporal prediction of actual groundfalls is a reasonable expectation in a dynamic environment where the inputs exhibit complex inter-relationships and substantial uncertainty. However, proactive identification of groundfall hazard zones in space and time provides opportunity for operations to mitigate safety risk and production disruption. This approach is similar to that taken in global seismology where the foundation of risk estimation is maps demarcating elevated seismic hazard zones on a relative scale, as opposed to predicting the occurrence of individual earthquakes. Successful methods of computational identification of groundfall hazard may also serve as a foundation for the inclusion of a geotechnical perspective in design optimisation.

Each type of groundfall hazard, with its independent conceptual model, must be analysed independently. Hazard is assumed to be a computable spatial property that can be portrayed on a 3D model of mine development. It is a property of mine development or rock interface surfaces (e.g. drift walls, stope backs, shaft walls), not a property of the rock mass in which the mining takes place. This is because falls of ground always occur at rock interfaces, no matter the underlying cause or the proximity of that cause within the rock mass. A map of relative or absolute probability of ground failure at defined (x, y, z) locations on mine development surfaces we term a 'geohazmap', which is expected to vary in time. A generalised 'hazard equation' for a given hazard type is assumed to be a function of many layers of input data, which may be written generally as:

$$\text{hazard}\ (x, y, z, t) = f\ (\text{geology, rock quality, stress, development, mine production}) \tag{1}$$

Where geology, rock quality, stress, development, and mine production are categories that may each represent a number of observable or computable variables.

Establishment of actual variables to use in any particular case requires site-specific geotechnical reasoning and experimentation with case study data. Speculative relationships must be tested empirically, so an initial data compilation and distillation must be made. This study focuses on a single hazard example at Xstrata's (now Sudbury Integrated Nickel Operations – A Glencore Company) Craig Mine in Sudbury, Ontario. The most important groundfall hazard at Craig Mine, now closed, was fault-slip rockbursting. There was a reasonably rich data set to draw on from the mining history. The essence of this case study was to use available data sets describing the mine condition and the history of rockbursting to retrospectively determine the possibility of estimating relative hazard forecast. It thus falls broadly within the term 'back-analysis'.

2 Methodology

We have adapted our hazard estimation procedure from experience in mineral exploration targeting, which is a conceptually similar process in a different application. In both cases the general principle is to combine multiple data streams to determine spatial zones with desired statistical characteristics. The objective is to statistically identify (x, y, z) locations, otherwise difficult to discern, where certain special combinations of conditions exist. In the remainder of this paper we sometimes use the words 'targets' or 'targeting' to refer generically to the process of identifying zones within an earth model that satisfy certain criteria (in this case elevated groundfall hazard).

A GOCAD™-based, multi-disciplinary 'Common Earth Model' (McGaughey 2006) is created as the computational support for the various hazard criteria. The hazard criteria are modelled as quantitative or classified properties on a triangulated 'hazard surface' which, in this case, is specified to be the entire set of Craig Mine Zones 10 and 11 development wireframe surfaces, including drifts, ramps, and stopes. Hazard criteria are typically a combination of interpreted rock properties such as lithology, rock quality, and physical properties, and non-rock property variables such as depth, stress, and proximity to faults. Target locations of elevated hazard are identified, ranked, and classified by computing and analysing a score at each location (vertex) on the wireframe surface. A quantitative, probabilistic approach is taken to computation of the score function by correlating a set of rockburst occurrence 'training data' with the modelled hazard criteria.

The method described here is inspired by a history of its successful application in 2D Geographic Information Systems (GIS) in mineral exploration going back to the 1980s and 1990s (see for example Bonham-Carter 1994, 1997), and more recent experimentation in 3D for exploration applications (Apel & Böhme 2006; Caumon et al. 2006). The Bayesian Weights-of-Evidence algorithm deployed at the core of our statistical analysis is based on the work of Apel and Böhme (2006) with their 'Predict' GOCAD module.

Figure 1 shows the cyclical series of steps we undertake in projects of this type. The first five steps can be completed, usually within a couple of days, by the project team. What we have found works well is an initial brainstorming session with site personnel, facilitated by a neutral moderator, to quantitatively and realistically ascertain the hazard forecasting objective and the conceptual model that establishes the geotechnical context. There may be uncertainty in the conceptual model or possibly competing conceptual models put forth by the team. Typically agreement amongst the team on a quantitative objective and conceptual model is only arrived at after some meaningful discussion, and this was the case with the Craig Mine hazard project. Quantitative hazard criteria, required data, and overall model design (extents, depth, scale, resolution) follow directly from a careful setup of objective and conceptual model. If there are competing conceptual models the model must be designed to support and test each of them. Although these first five project steps are fast and inexpensive to complete, we have seen major projects start without them, proceeding directly to data compilation and model construction, which greatly reduces the chances of project success.

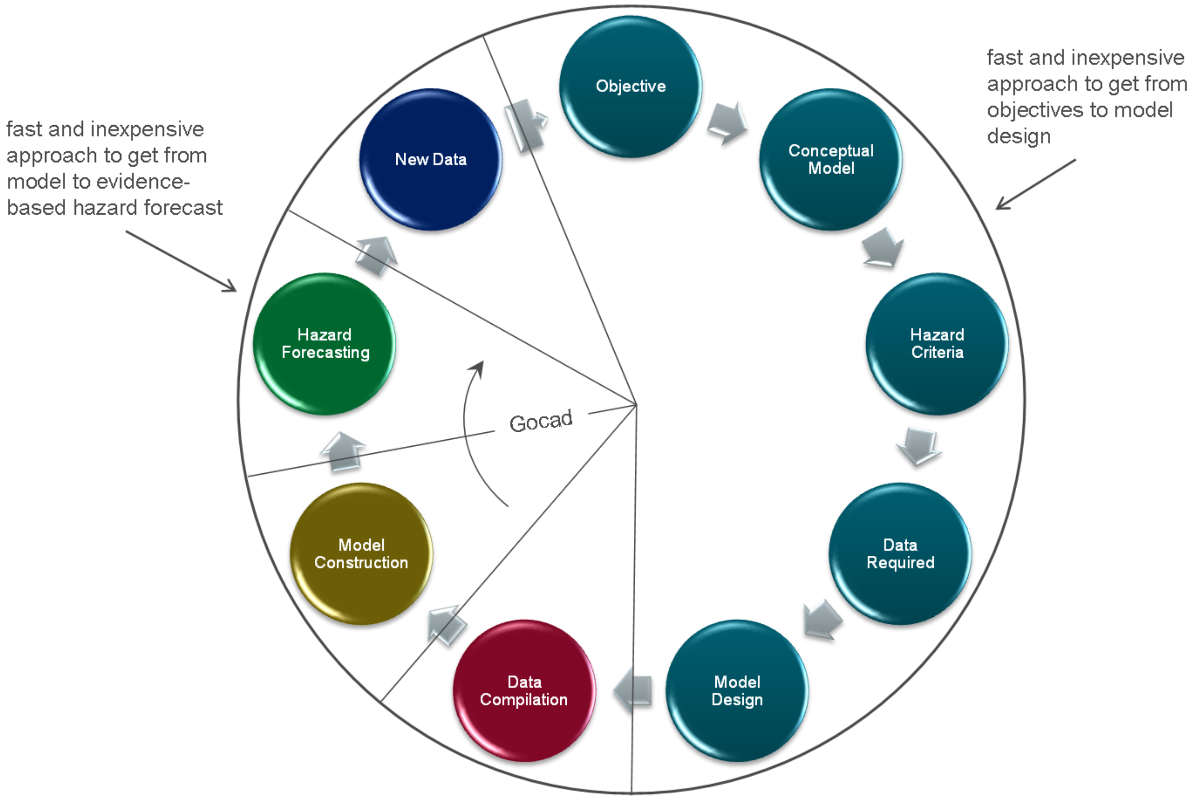

Figure 1 Project flow for assessment of geotechnical hazard

Data compilation is always the most expensive and time-consuming part of this type of project, particularly when there is a lot of multi-disciplinary data and several custodians are involved. It is our experience that if projects falter, they typically falter at this stage, although the failure can usually be attributed to inadequate project planning and model design. Model construction simply requires an adept GOCAD modeller and some time, typically a few weeks. If the project has been set up well, the resulting model will give the statistical analysis the best possible chance of success of identifying meaningful hazard zones. In this case data compilation took months of calendar time (although not many actual work hours), beginning in July 2008. Enough data was on hand to complete a first pass of the modelling in February 2009, but data (or modifications to data) were still forthcoming to the completion of the project.

The hazard forecasting analysis was accomplished using ‘Targeting Workflow’, a custom-designed, GOCAD-based software workflow we have created that takes as input a multivariate model containing the set of targeting criteria and produces a target list as indicated in Figure 2. It takes the user through a sequence of pre-processing, statistical modelling, and post-processing steps. It provides a number of statistical investigations of input data and hazard validation procedures, in addition to offering both knowledge-driven and data-driven approaches. Knowledge-driven expert-system approaches rely on expert users to convert opinions on the relevance of input data to the hazard estimation, based on experience, into numerical scores used in the combination of multiple data streams. Knowledge-driven systems do not require historical groundfall events for users to set weighting systems for the input data streams. In contrast, data-driven systems use statistical methods to set weights for individual data streams depending on their correlation with historical groundfalls. They are thus unbiased but require construction of the site history. Bias can still affect the process in a number of ways from selection and modelling of hazard criteria to interpretation of several statistical tests carried out by the workflow.

The Targeting Workflow was deployed in this project using a data-driven approach since a reasonably rich data set of historical groundfall was available. The data-driven approach that we have currently implemented is Weights-of-Evidence, which has a large literature in application to 2D spatial problems, including exploration, environmental, and geotechnical. (Other well-established data-driven approaches are logistic regression and probabilistic neural networks, which presumably represent viable alternatives to the Weights-of-Evidence approach adopted here.)

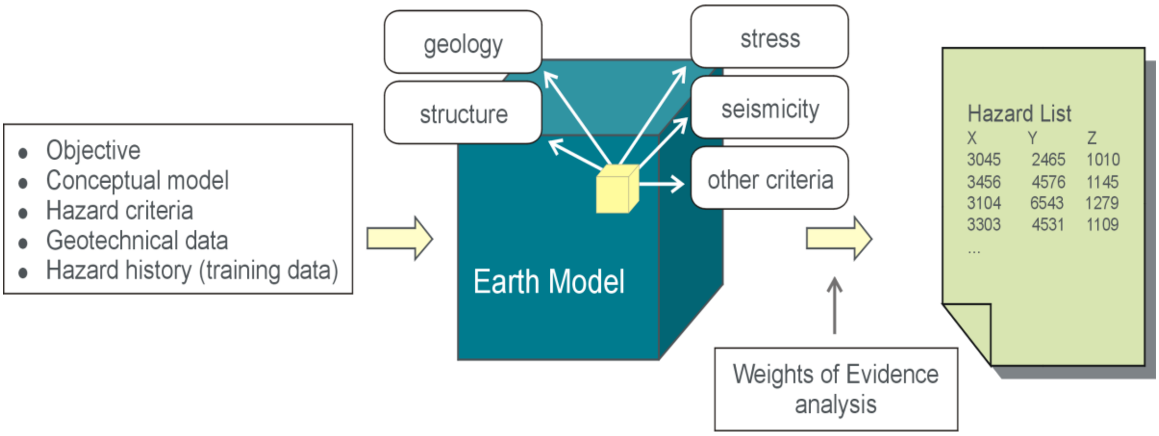

Figure 2 The Targeting Workflow (Weights-of-Evidence) algorithm is applied on an earth model data structure corresponding to the rock interface where failure may occur (the mine development wireframe), on which multiple hazard criteria are modelled

3 Conceptual hazard model

The conceptual hazard model in this case is a speculative description of how groundfall due to fault-slip rockbursting is related to the mine environment, development, production, and any other relevant factors. Development of a provisional conceptual hazard model is a necessary step in determining the nature of the 3D model to be built, its required components, and the data sets needed to construct it. The following list of potentially relevant conceptual model factors was compiled in a brainstorming session held at Craig Mine with site personnel at project inception. The list defines the criteria to be included in the modelling.

- Mine development characteristics: ground support, geometry, orientation, development rate, sequencing with respect to other development.
- Mining method: blasthole stoping versus cut-and-fill.
- Rock environment: lithology, rock quality, waste gaps between ore zones, proximity to lithological contact, contrast between soft (mineralised zones) and stiff rock, unconfined compressive strength, stiffness, jointing, alteration, backfill water, drilling and other process water.
- Acting stress: background stress, perturbation due to structure, mine-induced stress.
- Stress indicators: disking, spalling (no overcoring or borehole breakout data was available).
- Fault structure: ‘subtle’ faults that result in fault-slip, large structures that cause stress perturbations, fault proximity and orientation, hanging wall versus footwall structure, type of structure, structural intersections.
- Production: extraction ratio, blast times and sizes, fill cycles related to water, ground control logs giving reports of snapping and popping ground (‘unusual occurrence database’).

4 Model construction

Model construction is the process of creating a 3D GOCAD model of the mine development surface and establishing the individual hazard criteria properties on it. The final output of the hazard estimation process is the creation of a groundfall hazard estimation property on the surface, as a function of the individual hazard criteria. Model construction requires technical knowledge of the modelling application and, significantly, interpretational decision-making. The interpretational decisions are of two types:

1. Decisions on how individual hazard criteria are to be created on the hazard surface. For example, in this study the team believed that fault-slip tendency, the ratio of shear to normal stress on mapped fault segments in 3D, could be a significant hazard criterion. We decided to class this property into low, medium, and high categories, determine proximity of the hazard surface to fault segments of those three classes, and map that value as a property onto the hazard surface.
2. Decisions on how irregularly sampled and uncertain data are propagated throughout the model. Examples include the geostatistical simulation of geotechnical rock properties or observations such as rock quality, breaks, and disking.

Examples illustrating both data and modelled hazard criteria are shown in Figures 3 and 4.

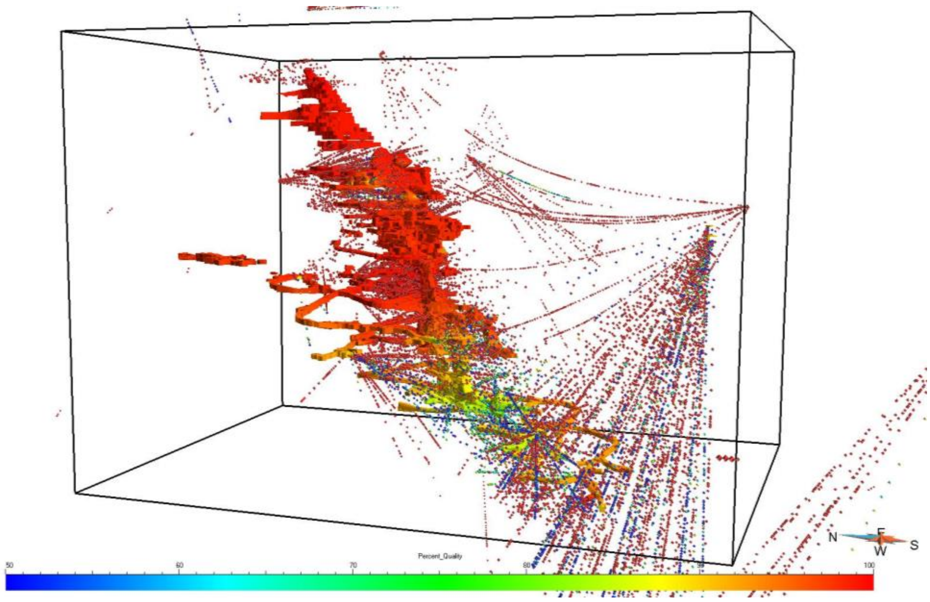

Figure 3 Model of the underground development surfaces on which the hazard is to be estimated, with rock quality (RQD) shown as the hazard criteria modelled on the mine development wireframe and as point data from drillholes. The rock quality data were geostatistically interpolated from the geotechnical drillhole database into a 3D block model which was then sampled onto the development surface

Model construction is complicated by the fact that the mine environment is dynamic. The mine development evolves, as do many individual hazard criteria, such as stress, microseismic activity, and age of development. This is handled by selecting a series of snapshots which capture the state of the mine at instants in time. The snapshots are chosen to coincide with historical groundfalls so that we can statistically analyse the state of the mine environment variables at the time of groundfall occurrence. For this project we created 19 separate mine models to correlate to 19 historical falls of ground believed to be caused by fault-slip rockbursting.

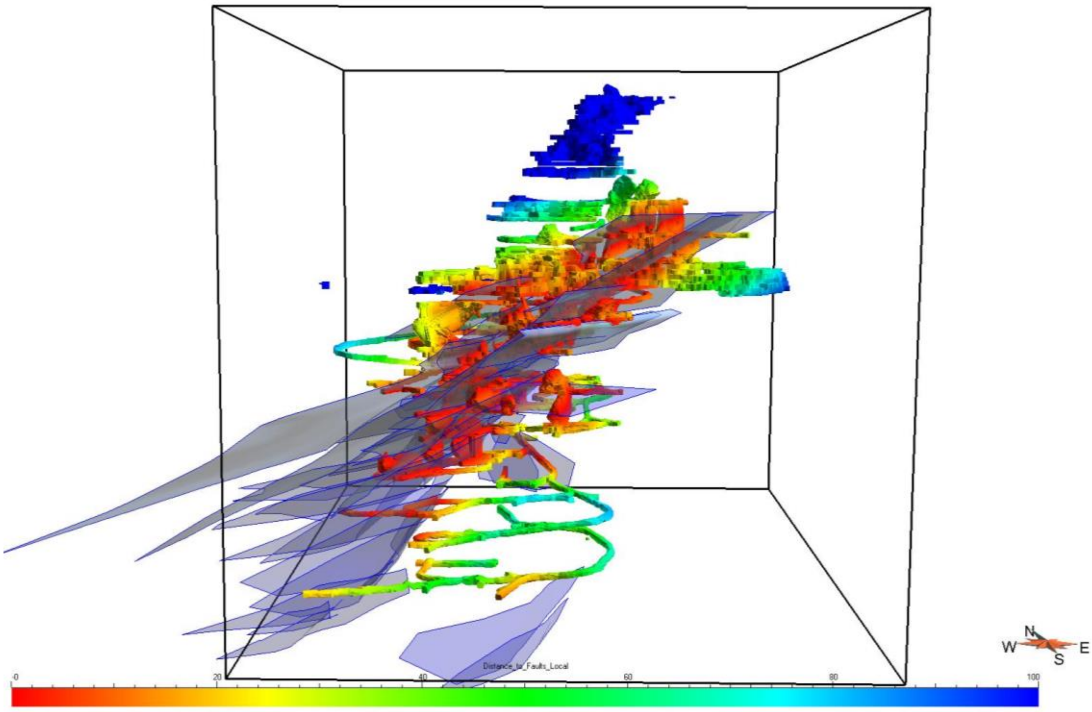

Figure 4 Model of underground development wireframe surfaces on which hazard is to be estimated, with distance to faults shown as hazard criteria in colour. Proximity to the nearest fault surface is calculated in 3D using the spatial modelling tools within GOCAD

5 Hazard assessment

In the model construction phase described in the previous section, all potentially relevant features of the conceptual hazard model were converted to quantitative hazard criteria mapped onto the hazard wireframe surface (the set of drifts and stopes under analysis). For this study we have 19 separate such models, each representing a different time snapshot coinciding with a historical fault-slip rockburst.

The objective of the hazard assessment process is creation of a new property on the hazard surface that represents a relative groundfall hazard everywhere on that surface. This will be done as a function of time, thus the output groundfall hazard assessment will exist on all 19 hazard surface snapshots.

We are using a data-driven expert system approach in this project because the extensive groundfall history is available to use as training data for the purpose of establishing statistical correlations of modelled hazard criteria and groundfall. The data-driven method we have implemented is Weights-of-Evidence. In the remainder of this section we present an overview of the Weights-of-Evidence approach, and describe its extension to 4D hazard forecasting.

5.1 Weights-of-Evidence concept

Weights-of-Evidence is a quantitative probabilistic method for combining data in support of a certain hypothesis. It was originally developed as a non-spatial technique in medical diagnosis to predict disease but was applied to mineral exploration targeting in the early 1990s by Bonham-Carter and others to predict the potential locations of new mineral deposits (Figure 5). This 2D map-based technique allowed for a statistical evaluation of spatial relationships between known occurrences of mineral deposits and multiple evidential datasets which represent criteria indicative of the mineral deposit occurring. For a complete summary of the Weights-of-Evidence process in mineral potential modelling, refer to Thiart et al. (2006), Agterberg et al. (1990), Agterberg and Cheng (2002), and Bonham-Carter (1994). The theory we use in this study is based on the Weights-of-Evidence techniques developed and described in the text by Bonham-Carter (1994).

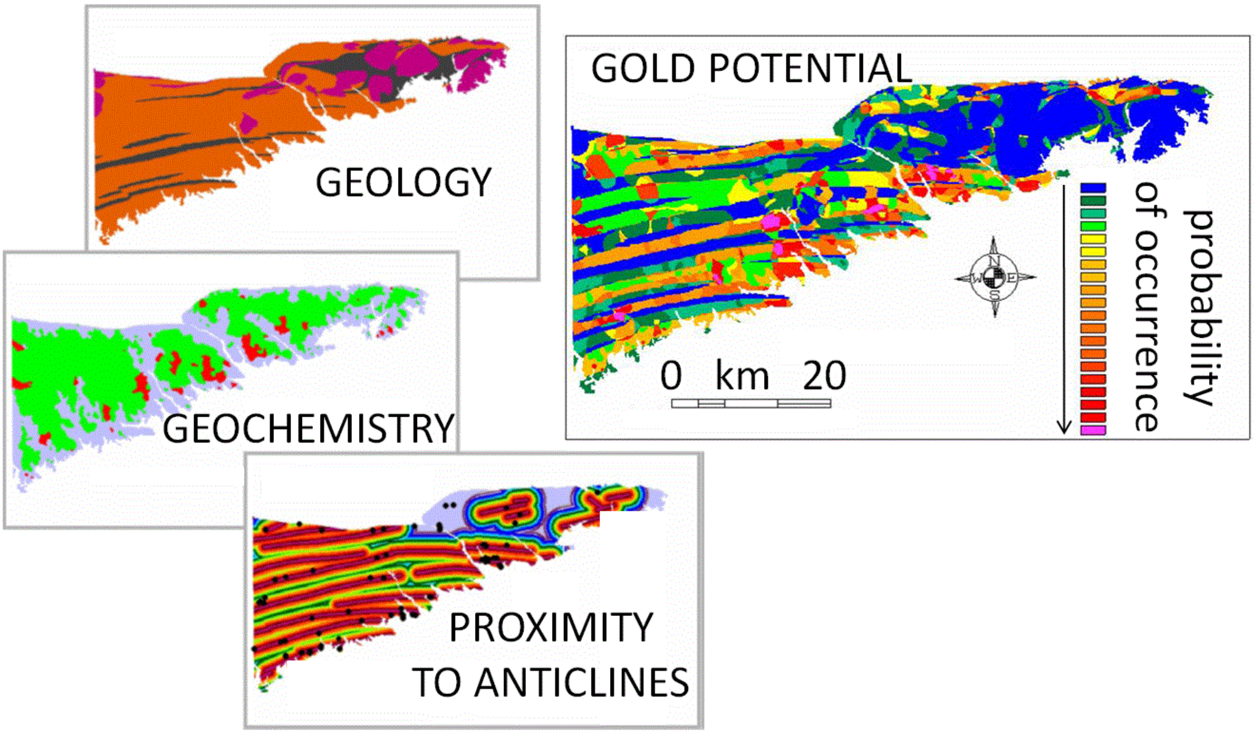

Figure 5 2D Weights-of-Evidence mineral potential mapping example showing input data layers (geology, geochemistry, and proximity to anticlines) and output ranked gold potential map (from Bonham-Carter et al. 1989)

In this study we extend the techniques of geospatial 2D Bayesian Weights-of-Evidence modelling to a 4D mine environment. Groundfalls replace mineral occurrences and geotechnical data replace mineral exploration data but conceptually the process is identical. We introduce time as a variable as it is critical to geotechnical hazard analysis.

Some of the benefits of using Weights-of-Evidence, as opposed to other predictive modelling techniques, are that the approach is systematic, quantitative, and unbiased in that spatial associations and relative value of the input data are computed statistically. In contrast to techniques such as artificial neural networks, Weights-of-Evidence provides clear rules relating each input criterion to the output target or risk, in addition to manual inspection and control of the hazard equation. It is not a black box.

5.2 Extension to 4D geotechnical hazard analysis

Extension of existing 3D modelling capabilities to accommodate 4D hazard forecasting requires a significant amount of data manipulation. Figure 6 indicates the general process of data preparation from discretised variables in a 3D grid model to a hazard forecast on the mine surface at various 'time stamps', which correspond to the state of the mine at the times of rockburst occurrence.

A 3D grid containing all static properties (e.g. rock code, faults) plus multiple versions of dynamic properties (e.g. seismicity, age of development) for each time stamp is created (Figure 6(a)). Static and dynamic variables as well as the groundfall that occurred at each time stamp are separated into a series of multiple individual 3D models, one for each time stamp (Figure 6(b)). The models are then reduced to the region representing the mine development surfaces at the point in time when the groundfall occurred (Figure 6(c)). Each of these cells contains its 3D location coordinates, a time stamp classification (with a date), property values for each of the static and dynamic variables, and a flag as to whether it corresponds to a rockburst location or not. The group of mine development locations over time, with all relevant criteria, is assembled for the statistical correlation analysis (Figure 6(d)). This is an acceptable procedure as the Weights-of-Evidence algorithm works on a data point by data point basis and does not take into account values from neighbouring cells. The Weights-of-Evidence algorithm is performed in one step on the data structure shown in Figure 6(d). The output is a statistically optimal combination of weighted input criteria in the form of an estimated rockburst probability, which is finally mapped to the appropriate 3D mine development surfaces for evaluation and interpretation (Figure 6(e)).

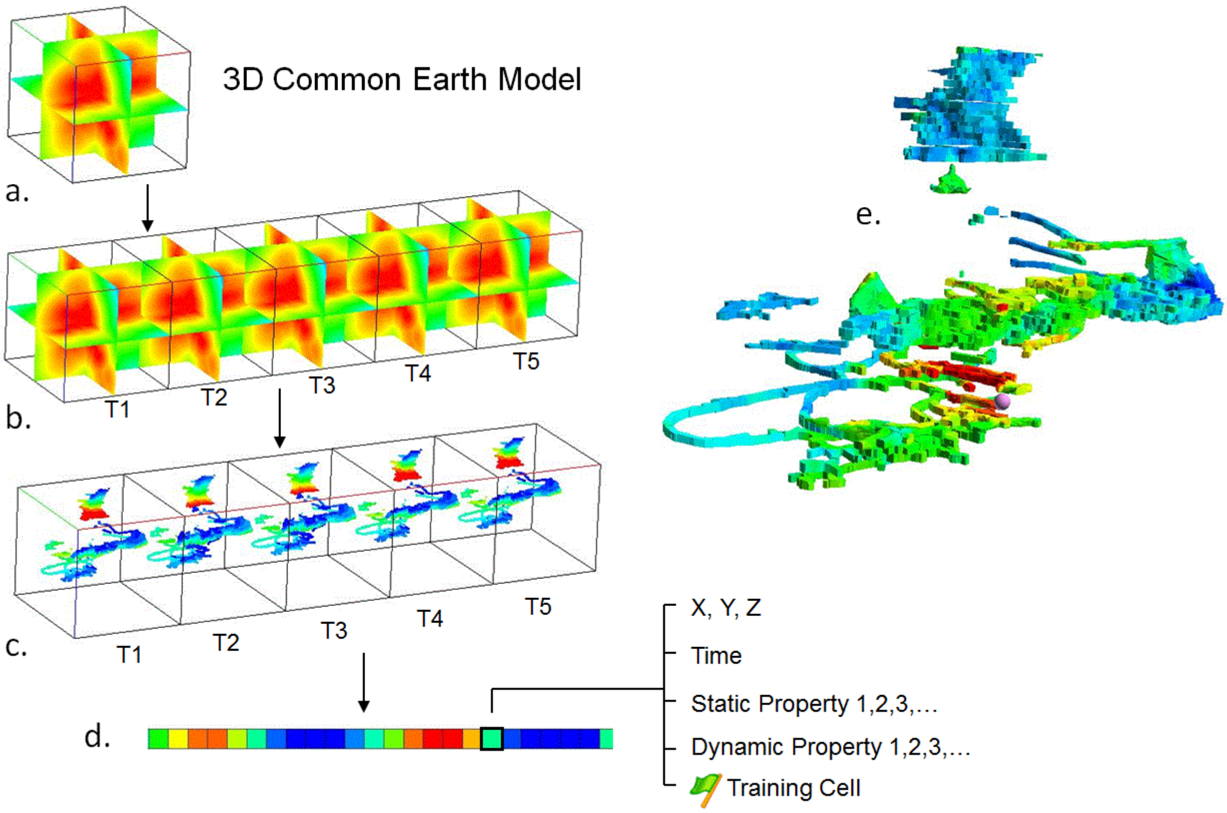

Figure 6 Groundfall forecasting process in 4D; (a) 3D grid containing all variables to be modelled for one time stamp; (b) data from five different time stamps separated spatially; (c) model volume restricted to extents of the hazard surface; (d) data structure used for computing hazard; and (e) result of hazard computation mapped back onto the 3D hazard surface for one time stamp

6 Craig Mine case study

In this section we apply the 4D Weights-of-Evidence back-analysis procedure described in the preceding sections to rockburst-induced groundfall hazard estimation at Craig Mine Zones 10 and 11. All Weights-of-Evidence modelling is a statistical assessment of the correlation between known occurrences of some condition (rockburst-induced groundfall in this case) and multiple sets of measurable data. The process described here is a true quantitative tool for hazard back-analysis because the problem explicitly includes time as a variable. This phenomenological approach to back-analysis may be seen as complementary to other approaches more typically practiced in geotechnical engineering.

6.1 Model area and training data

Geotechnical hazard analysis using 4D Weights-of-Evidence was performed on two separate model areas at Craig Mine: the ore zone model and the footwall model. They were treated separately because of a belief that the conceptual models for ore zone falls of ground (FOGs) and footwall FOGs may differ. The locations of known groundfalls, used as training data, were divided into two subsets based on whether they were located above or below the footwall contact. The footwall model contained eight known FOGs and the ore model contained 11 known FOGs, as listed in Table 1. The location of each FOG was represented as a cell in the discretised 3D model used for computing the hazard forecast. Cells within a 10 m buffer of the FOG cells were also included as training data because of uncertainty in precise spatial location of both the rockbursts and the modelled hazard criteria.

Table 1 List of rockburst FOGs used as training data in the Craig Mine hazard forecast, subdivided into footwall groundfalls and ore zone groundfalls

Time stamp	Date of FOG	Footwall model	Ore zone model
T1	November 6 2003		✓
T2	March 4 2004	✓	
T3	June 3 2004	✓	
T4	August 19 2004		✓
T5	August 29 2004		✓
T6	November 30 2004		✓
T7	July 7 2005		✓
T8	July 24 2005	✓	
T9	August 16 2005	✓	
T10	October 27 2005	✓	
T11	October 31 2005	✓	
T12	April 3 2006		✓
T13	May 21 2006		✓
T14	September 11 2006		✓
T15	June 22 2007		✓
T16	December 1 2007		✓
T17	March 4 2008	✓	
T18	April 19 2008		✓
T19	December 24 2008	✓	

The hazard forecast computed within the discretised 3D models for each of the two conceptual models was confined to cells that intersected the extents of the hazard surface at each time stamp). In this case study, 19 time stamps were determined based on the dates of each of the 19 groundfalls. The eight time stamps in the footwall model comprise 438,310 data points (grid cells) on which all hazard criteria were evaluated and the 11 time stamps in the ore model contain 613,758 data points (grid cells).

6.2 Hazard criteria

Hazard criteria are the geotechnical factors that may be related to groundfall. They are represented in the GOCAD model as continuous or discrete variables (Table 2). Some of these variables are static, for example rock code, disking and proximity to the orebody. Others are dynamic and vary with time, for example age of mine development, stress and microseismic density. The overall model contained 19 different versions of the dynamic variables representing the data at each of the 19 different time stamps.

Conversion of raw geotechnical data to modelled hazard criteria is an interpretational step. The process is performed in such a way as to maximise the spatial correlation between hazard criteria and FOG locations. This requires knowledge of the specific mine site as well as an understanding of how the data are captured and processed. For example, disking measurements from drillhole points were run through a 3D geostatistical simulation to produce a continuous property on the hazard surface, microseismic point data were grouped into six month time windows upon which cluster density was computed, and fault slip tendency on fault segments were classified and represented as distance properties.

Table 2 List of static and dynamic variables representing the hazard criteria

Static properties	Rock code
	Core breaks
	Disking
	Proximity to drift intersections
	Proximity to fault terminations
	Proximity to fault surfaces
	Proximity to footwall contact
	Proximity to hanging wall contact
	Proximity to ore boundary
	RQD
	Orientation of development
	Proximity to high fault slip tendency
	Proximity to fault intersections
	Ground support classification
	Mining method
Dynamic properties	Microseismic event density
	Locally averaged Es/Ep
	Locally averaged seismic moment
	Locally averaged static stress drop
	Locally averaged local magnitude
	Age of development
	Locally averaged apparent stress

6.3 Modelling results

Continuous and discrete hazard criteria are converted to binary properties for our current implementation of the Weights-of-Evidence technique (there are alternative formulations that use multi-class or 'fuzzy' class-membership properties). Each geotechnical criterion is divided into two classes based upon a threshold or cut-off value that best separates regions of the hazard surface containing a large proportion of training data (i.e. have a history of groundfall) from those regions containing few to no training data (no groundfall). The effectiveness of this binary classification in separating regions of hazard from non-hazard, per variable, is the essence of the statistical correlation test between the groundfall training data and the input hazard criteria. Positive weights 'W+' (a measure of the tendency for FOGs to occur in the favourable binary classification of the variable) and negative weights 'W-' (a measure of the tendency for FOGs to not occur in the unfavourable binary classification of the variable) are computed for each criterion as a measure of the degree of correlation with the training. The 'studentised contrast', the difference between the positive and negative weight, normalised by standard deviation, is the index used to as the summary statistic indicating the overall degree of correlation between each criterion and the history of rockbursting. See Bonham-Carter (1994) for detailed explanation of the Weights-of-Evidence terms and their meaning.

For the ore model hazard forecast, the following variables were removed due to poor spatial correlation with the groundfalls: microseismic event magnitude, distance to fault terminations, ground support type, distance to ore, and disking. Other variables removed from the ore model hazard forecast due to the fact that they are too highly correlated with each other and would thus bias the hazard forecast were: distance to faults and fault slip tendency. The remaining variables used in the ore zone model are listed in Table 3 including the weights and contrast for each. A similar analysis was carried out for the footwall, with the results shown in Table 4.

Table 3 Weights and contrast values for each of the hazard criteria used to compute the hazard forecast for the ore zone model. The table is ordered by degree of correlation between the measured criterion and rockbursting in the ore zone

Criteria	Class	W+	W-	Studentised contrast
Microseismic event density	Upper	2.786	-0.726	38.4
Age of development	Lower	2.262	-0.585	31.2
Mining method	Drift	1.578	-0.822	25.7
Locally averaged static stress drop	Upper	1.181	-0.353	16.4
RQD	Lower	1.186	-0.311	15.6
Proximity to fault surfaces	Lower	0.451	-1.55	12.6
Rock code	LGBX	0.480	-0.509	10.5
Proximity to drift intersections	Upper	0.419	-0.209	6.8
Proximity to ore boundary	Upper	0.664	-0.110	6.7
Disking	Lower	0.797	-0.060	5.7

Table 4 Weights and contrast values for each of the hazard criteria used to compute the hazard forecast for the footwall model. The table is ordered by degree of correlation between the measured criterion and rockbursting the ore zone

Criteria	Class	W+	W-	Studentised contrast
Disking	Lower	1.322	-1.189	20.6
Core breaks	Upper	1.334	-1.041	20.5
RQD	Lower	1.349	-0.305	14.8
Proximity to ore boundary	Upper	0.766	-0.944	14.2
Proximity to high fault slip tendency	Lower	0.635	-1.396	13.2
Microseismic event density	Upper	1.527	-0.119	10.8
Orientation of development	Lower	0.365	-0.445	7.4
Proximity to drift intersections	Lower	0.263	-0.737	7.3

6.4 Hazard assessment

The hazard forecast was computed for each of the time stamps in the ore and footwall models (shown here only for the footwall model in Figure 11). All but one of the known rockbursts was located within regions of high hazard potential indicating that there is a statistical association between the groundfalls and the input variables. In general, the key hazard variables in the ore model are primarily correlated to mining activity while footwall key variables are more highly correlated to rock quality. The groundfalls in the ore zone have a different hazard criteria signature then those in the footwall and thus the initial assumption that separate conceptual models apply to the ore zone and footwall is justified. It is noteworthy that typical rockburst hazard assessment systems, including that used at the case study site, rely primarily on microseismic data. This study has shown conclusively that there are a series of easily measured or modelled variables in the footwall that have a stronger correlation to rockbursting. In the ore zone microseismic event density was the strongest correlative variable with rockbursting, however we have demonstrated in that case that supplementing microseismic analysis with other variables greatly improves the ability to forecast zones of elevated rockburst hazard.

7 Data management

One important lesson from this case study and others of a similar nature that we have carried out is that operations do not typically have the data management infrastructure to readily provide data to a comprehensive, multi-disciplinary 4D analysis. This situation is manageable where hazard assessment updates are only required ‘offline’ on an intermittent basis. Ongoing or near real time operational assessment of hazard requires up-to-date access to all of the data types required for calculation, including microseismic and other monitoring data. The type of data management system required for maximally effective, ongoing hazard assessment consists of a purpose-built relational database system connected to live data feeds, as summarised in Mol et al. (2012) and Lopez-Pacheco (2013).

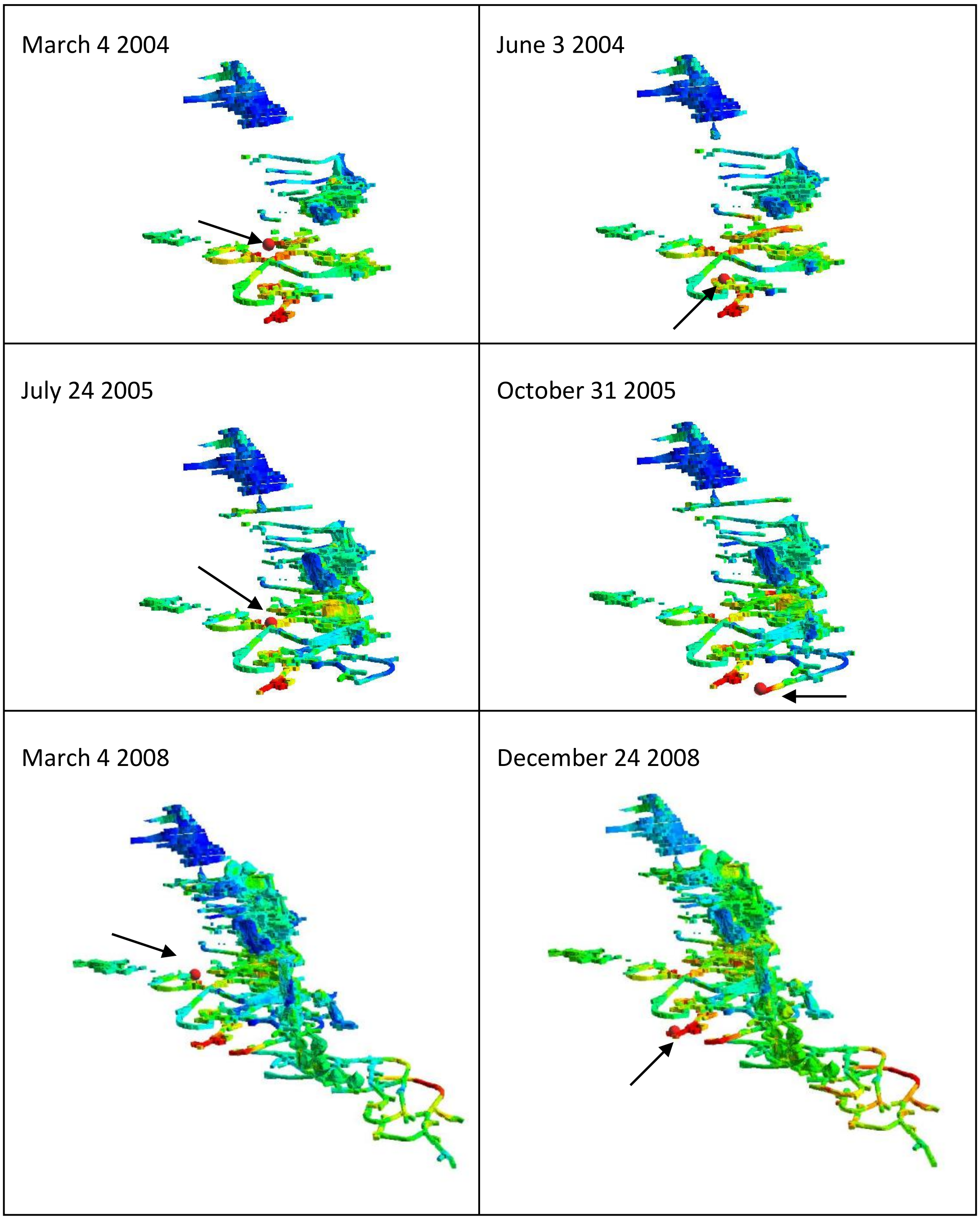

Figure 7 Hazard forecast result mapped onto the hazard surface at various time stamps for the footwall model. Footwall FOGs are displayed as spheres and indicated by arrows

8 Conclusions

The key conclusion is that the quantitative, statistical approach employed in this project for forecasting groundfall hazard related to fault-slip rockbursting at Craig Mine Zones 10 and 11 was effective. The results are very promising for the prospect of deploying an operationally important method of assessing zones of elevated groundfall hazard. The same hazard formulation can also be used as a design tool for mine planning, so that geotechnical risk could be quantitatively included alongside other mine design criteria.

We followed a project process that was successful and has been similarly successful in other broadly similar projects in both geotechnical hazard forecasting and mineral exploration targeting. We recommend this process, or processes with similar steps, continue to be used on similar projects in the future.

This project is the first we are aware of that formally combined a time history of mining and groundfall into a single computational 4D statistical analysis. Much of the project effort was dedicated to formulating a practical methodology to achieve this, and to the computer modelling required to implement it.

Finally, the principal conclusion of this work is that it is demonstrated that technologies and methods exist that make it practically possible and reasonably inexpensive to construct a coherent, quantitative, multi-disciplinary 4D mine model to serve as a framework for effective estimation and forecast of geotechnical hazard.

Acknowledgement

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