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ORIGINAL CONTRIBUTION

H. Zahiri
D. R. Palamara
P. Flentje
G. M. Brassington
E. Baafi

A GIS-based Weights-of-Evidence model for mapping cliff instabilities associated with mine subsidence

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H. Zahiri · D. R. Palamara
P. Flentje · E. Baafi (✉)
School of Civil, Mining,
and Environmental Engineering,
University of Wollongong,
Wollongong, NSW 2522, Australia
E-mail: danielp@uow.edu.au
E-mail: ebaafi@uow.edu.au
Tel.: +61-2-42214089
Fax: +61-2-42213038

G. M. Brassington
BHPBilliton, Illawarra Coal Holdings Pty
Ltd, Port Kembla, NSW 2505, Australia

Abstract The Weights-of-Evidence (W-of-E) technique was applied, within a geographic information system (GIS), to derive a model of rockfall potential associated with mining-induced subsidence. The purpose of the model was to describe the potential for rockfalls from up to 60 m high steep sandstone gorges and slopes associated with proposed underground longwall operations within the immediate vicinity of a previously mined area. Ten known rock falls associated with the previous mining operation were used as training points. Six evidential themes were considered-slope, cliff height, planform curvature, profile curvature, the distance of the cliff areas from the longwall panels, and the distance of the cliff areas from the river. Two models were created, one based on a mine layout in which longwall panels extend beneath the steep areas of a nearby river, and a second in which the mine layout is modified so that mining does not occur directly beneath or within 50 m of the steep slopes. This is to allow for the comparison of rockfall potential based on different mining configurations. The results demonstrate that the W-of-E method is a suitable tool for mine subsidence impact assessment, and suggest that not mining directly under the Nepean river may decrease rockfall potential, on average, by approximately ten times. Numerous limitations with the results, relating to the availability of appropriate evidential theme data and the accuracy of training points, are discussed.

Keywords Subsidence impacts · Cliffs · Weights-of-Evidence · GIS · Longwall mining impacts · Australia · New South Wales · Southern Coalfield

Introduction

The vertical and horizontal surface movements associated with longwall coal mining are known to have considerable impacts upon natural features. Some features that are particularly susceptible to damage from mining-induced subsidence are cliff areas and steep slopes, in part because of their intrinsic instability. In the state of New South Wales, Australia, numerous rock falls have been observed in association with underground coal mining operations in both the southern and western Coalfields (Kay 1991). There is increasing legislative and social pressure for coal mine operators to understand and prevent cliff falls for reasons of public safety, environmental sustainability, and aesthetics. This warrants the investigation of methods that will assist in predicting rock falls associated with mine subsidence and consequently act as a decision support tool for mine layout configuration. This paper exams the suitability of the Weights-of-Evidence (W-of-E) method for this purpose.

The W-of-E technique can be easily and rapidly applied within a geographic information system (GIS) environment because of the existence of a freely available extension for ArcView and ArcGIS. Produced by Kemp et al. (2001) and Sawatzky et al. (2004), the extensions allow a probabilistic model to be constructed in the GIS using training points (i.e., known occurrences of the feature under consideration), and evidential themes (data sets relevant to the prediction of the feature). The W-of-E method applies a Bayesian approach to combine different datasets relating to a particular phenomenon by weighting each factor; a detailed description of the mathematical formulation of the method is available in Bonham-Carter (1994) and Bonham-Carter et al. (1989), though an understanding of this is not critical for the GIS-based application of the method. The method calculates the weight for each predictive factor based on the presence or absence of the training point theme units (D) within the area of each binary predictor theme (B), as indicated in Bonham-Carter et al. (1989):

$$W^{+} = \ln\frac{P(B|D)}{P(B|\overline{D})}$$

$$W^{-} = \ln\frac{P(\overline{B}|D)}{P(\overline{B}|\overline{D})}$$

where P is probability and ln is the natural log. A positive weight (W^{+}) indicates that the evidential theme is present at the training point locations and the magnitude of this weight is an indication of the positive correlation between the presence of the evidential theme and the training points. A negative weight (W^{-}) indicates the absence of the evidential theme and shows the level of negative correlation. The difference between the two weights is known as the contrast, C ($C = W^{+} - W^{-}$); the magnitude of the contrast reflects the overall spatial association between the evidential theme and the training points (Bonham-Carter et al. 1989).

The method can be applied where sufficient data are available to estimate the relative importance of evidence themes by statistical means (Spiegelhalter 1986). Although some knowledge of the processes involved is required in order to determine which factors are worth pursuing, the W-of-E method can be considered a 'data-driven' technique, wherein the system is characterized by the connections in the underlying data, and an in-depth knowledge of the physical mechanisms is not needed (Solomatine 2002).

The use of the W-of-E method in a spatial environment was pioneered by the application of the technique to mineral potential mapping (Bonham-Carter et al. 1983, 1988, 1989; Campbell et al. 1982). Since then, the GIS-based W-of-E method has been successfully applied to data-driven modeling in a number of diverse geoscience applications. Although it has not been previously applied to the assessment of mine subsidence impacts, the suitability of the technique for this purpose is evident in its successful use in other studies examining susceptibility, spatial relationships, and the distribution of particular features. Lee and Choi (2004) applied the method using a variety of environmental parameters to produce landslide susceptibility maps for a region in Korea, while numerous researchers have demonstrated its potential for predicting the location of gold and copper mineralization (Asadi and Hale 2001; Carranza and Hale 2002; Tangestani and Moore 2001), the location of flowing wells (Cheng 2004), and spatial associations between faults and seismicity (Daneshfar and Benn 2002).

Rockfall modelling

For this study the Weights-of-Evidence method was used to evaluate rock fall potential associated with proposed mine workings and demonstrate the suitability of the tool for mine layout configuration purposes. Two models were developed corresponding to two alternate proposed mine panel layouts. The study area is situated in the southern Coalfield, near the township of Douglas Park (at approximately 150.75°E, 35.20°S), which is roughly 55 km southwest of Sydney and 40 km northwest of the city of Wollongong (Fig. 1). Mining in this area occurs at a depth of 400–500 m, within the Bulli Seam, which has a working thickness of between 2.5 and 3.5 m in this area (NSW Department of Mineral Resources 2003). Two rivers are situated within the study area-the Cataract river and the Nepean river, both of these have sections that had been previously mined under. Cliff sections flank both the river channels with heights in excess of 50 m in places. Up to ten observed rock falls (two on the cliffs of the Nepean river, eight along the cliffs of the Cataract river) are associated with local mining activity that has occurred within the last two decades (Fig. 2).

The study site is located within the erosional peneplain known as the Woronora pleateau. The Woronora plateau formed during the Eocene (Young and MacDougall 1985) approximately 50–55 million years before the present (mybp). It consists of a mature peneplain generally developed on the Hawkesbury sandstone and is deeply dissected with inherited drainage patterns. The Hawkesbury sandstone is a flat lying middle triassic quartzose sandstone with a maximum thickness up to 250 m. The Woronora plateau was tilted to the north during the Pliocene, up to 5 mybp (Branagan and Packham 1967).

Materials and methods

Figure 3 shows a generalized flow chart for the implementation of the Weights-of-Evidence method. The first

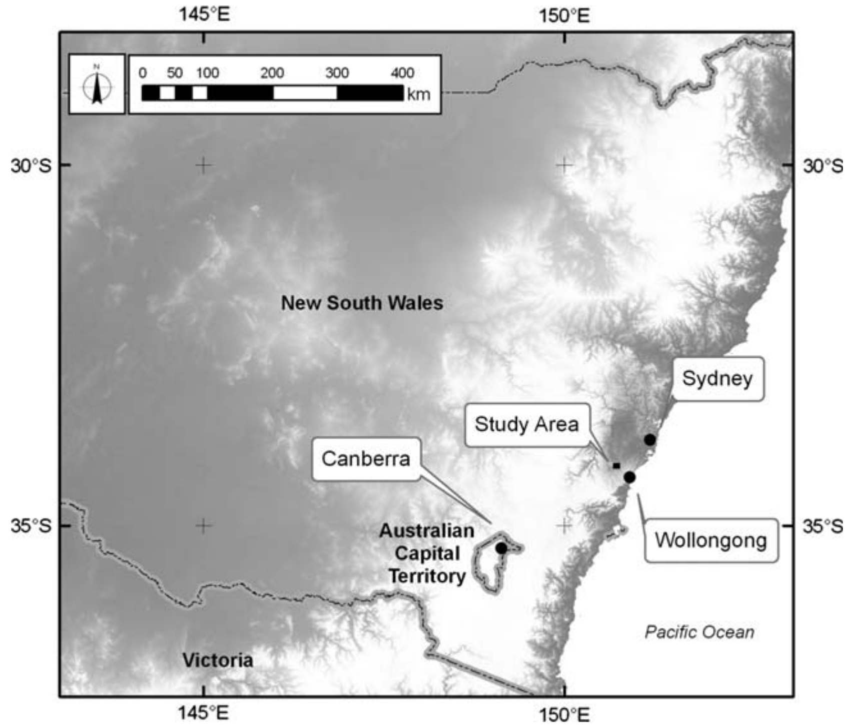

Fig. 1 The location of the study area within New South Wales, Australia

three steps can be considered as the 'pre-study' stage and are concerned mainly with determining the nature of the problem, the goals of the modeling process, the data that are available and potential limitations. The most important step in this stage is the selection of the predictor variables, termed evidential themes, to be used in the model. Clearly, data availability is a key consideration at this stage of the process. Once selected, the necessary data need to be incorporated into a GIS and manipulated in order to conform to the data structures required by the Arc-SDM extension.

During the primary weighting step, two weights (positive and negative) are calculated for each evidential theme by the Arc-SDM extension, based on the spatial association between the selected training points and the evidential themes.

After the primary weighting step the evidential theme data are reclassified in order to convert from multiclass data to binary or ternary class data; this maximizes the spatial association between the evidential themes and the training points. The Arc-SDM extension then calculates final weights for each evidential theme to produce the response theme containing, in this case, probabilities of rockfall occurrence.

Although the W-of-E technique is 'data-driven', it is evident that some knowledge of which factors are likely to be relevant is needed. Through the iterative aspect of the model development stage, factors with little weight (i.e., that do not assist with prediction) can easily be excluded and new ones incorporated (Fig. 3). Similarly, the Arc-SDM extension provides feedback, which allows the user to iteratively refine the way in which factors are classified for use in the model.

The variety of potentially relevant factors for the assessment of mining-induced cliff instabilities is discussed in detail by Waddington Kay and associates (2002). The factors chosen in this project for use as evidential themes represent only a small subset of those outlined by Waddington Kay and associates, and are limited to those that are readily derived within a GIS environment using a digital elevation model (DEM). The evidential themes used in the analyses include:

- slope (in degrees),
- planform curvature,
- profile curvature,
- cliff height (i.e., the height of the surface above the river channel),
- the distance of the cliff sections to the mine workings (longwall panels),
- the distance of the cliff sections to the adjacent watercourses.

Themes that are primary DEM attributes, such as slope, planform curvature, and profile curvature, were derived within the GIS (Arc-GIS 9.1) from a 1 m DEM (from airborne laser scan data) using the standard functions. The 'cliff height' theme represents the height of each cell above the nearest point in the watercourse

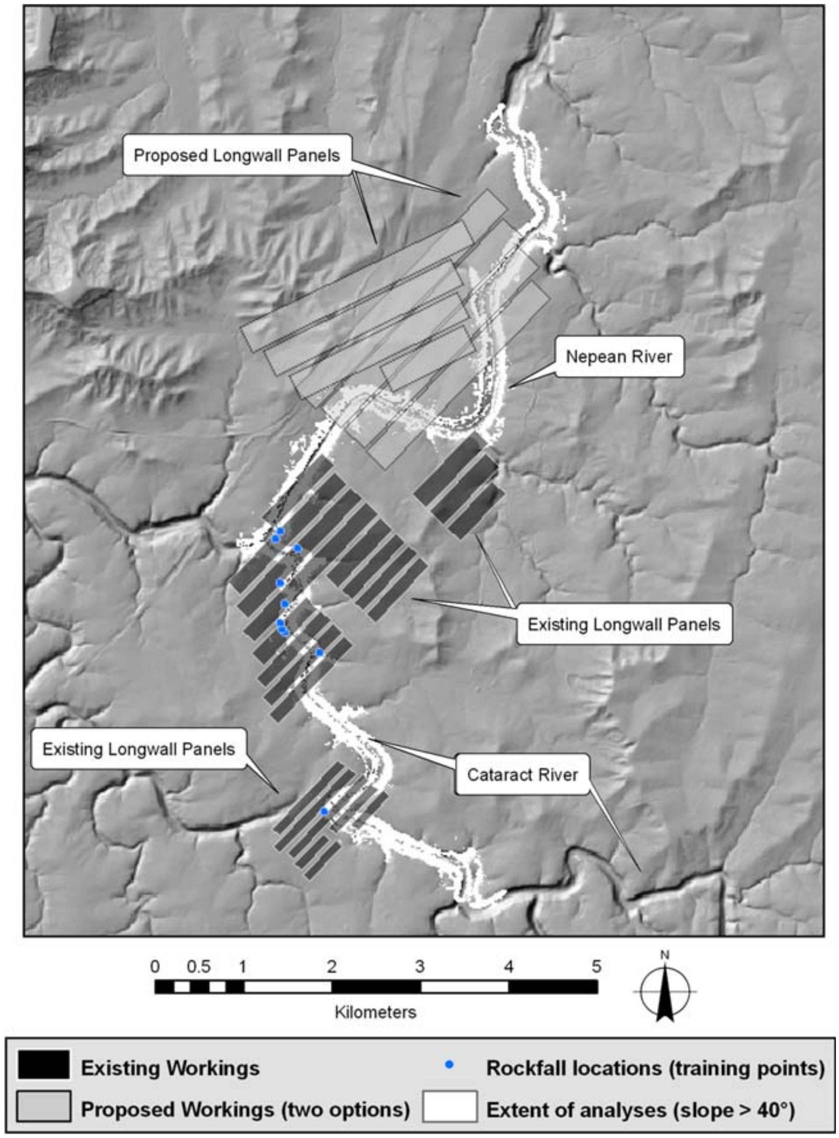

Fig. 2 The study area showing the location of the existing and sample proposed workings

dataset, and as such is a measure of the vertical distance between the surface height and the height of the adjacent river channel. The distances to both the watercourses and the longwall panels were calculated in the GIS as straight-line distances. Two different versions of the evidential theme based on distance to the longwall panels were used—one with the proposed longwalls running directly under the river and the associated cliffs (the 'old' mine layout), the other with proposed panels occurring near the river but not directly beneath it (the 'new' mine layout). This is to quantify any changes in rock fall potential based on the longwall panel location and demonstrate the use of Weights-of-Evidence for mine layout planning. Only areas with steep slopes (i.e., slopes greater than 40°) were considered in the modeling process (Fig. 2).

Ten rock falls documented in an internal report by the mine operator, BHP Billiton, were used as the training points in the model. Because of positional inaccuracies in the recorded location of the ten rockfalls, some minor adjustment of the rock fall positions was undertaken to ensure that they are situated on cliff areas (based on slope values from the 1 m topographic data).

Results

The output of the W-of-E modeling process consists of two raster files, one for each mine layout, with associated lookup tables listing probability for rockfall potential. The magnitude of the probability values is of limited use because the model has not been verified in the field and it

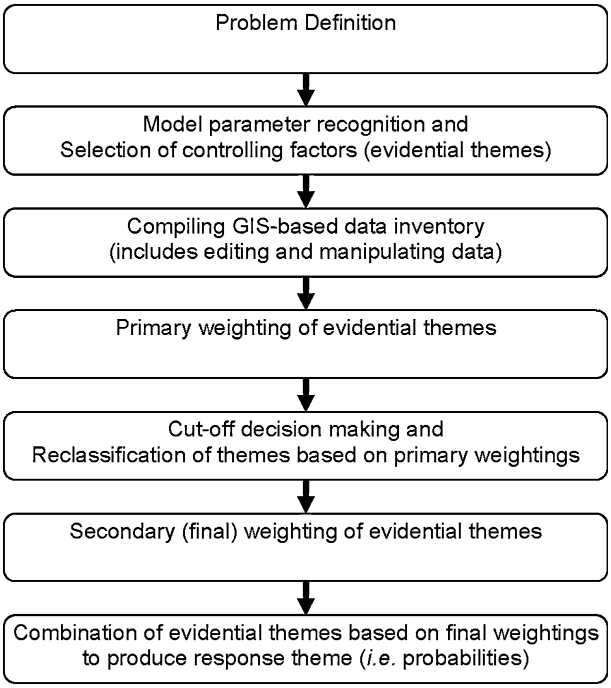

Fig. 3 A generalized flowchart for the implementation of the Weights-of-Evidence methodology

is acknowledged that not all of the critical factors relating to rockfall susceptibility have been included. Furthermore, the magnitude of the probability values varies with the size of both the study area and the unit cell for modeling purposes, both of which are arbitrary. Of greater interest, however, is the relative value between:

1. the probabilities associated with the known rockfalls over the existing workings,
2. the probabilities associated with the mine layout that extends beneath the cliffs of the Nepean river,
3. the probabilities associated with the alternate, 'new', mine layout in which longwalls do not extent to the cliffed areas of the Nepean river, and
4. the probabilities for rockfall potential in areas not proximal to mining.

Five zones of interest were isolated in order to gauge the relative probability values for each of these classes (Fig. 4). The statistics for the probabilities in each zone are summarized in Table 1, and Fig. 5 compares the mean probability values for each zone for both results ('new' and 'old' mine layout configurations).

Note that the probability values for the entire study, including areas proximal to the training points, vary between the two models, which differ only in the position of the proposed mine layout because of the difference weighting that the distance to workings evidential theme receives in each case. Consequently, the probabilities in the zone of the existing workings are generally higher with the 'new' mine layout (longwalls not extending under cliffs) than with the 'old' mine layout (longwalls mining under cliffs). This is because the W-of-E method calculates the probability of occurrence based on the extent of the evidential theme in the study area (relative to the number of training points which occur in that area). As Fig. 2 demonstrates, parts of the 'old' mine layout are situated directly within the study area, whereas with the 'new' layout the longwall panels are distant from the indicated study area. The spatial extent of the distance to workings evidential theme classes, which occur in the study area, is therefore greater with the 'old' layout, and consequently the rockfall probability as a function of distance to workings is likely to be lower (because no rockfalls have been recorded in this area).

A comparison between the mean probability values for zones 3 and 4 for the 'old' mine proposal and zone 5 (the existing workings), indicates that rockfall susceptibility associated with mining under the cliffs of the Nepean river is on average approximately five times lower than that which was modeled for the area in zone 5 which has been mined under. The probability for rockfalls independent of mining, as summarized in zone 1, is in turn roughly eight-to-ten time lower, on average, than that of zones 3 and 4 associated with the 'old' mining proposal.

The cliffs of the Cataract river are considerably steeper and higher than those of the Nepean, which explains why the previous mining operations under the cliffs of the Cataract river (zone 5) exhibit much higher mean potential for rockfalls than mining under the Nepean river would (zones 3 and 4 in the model with the 'old' configuration). A comparison of the background values for both rivers (zone 1, Nepean, and zone 2, Cataract), confirms this, with the latter displaying mean probabilities that are also roughly five times greater in both models.

This suggests that rockfalls are, on average, five times more likely along the Cataract river than along the Nepean river if only the aforementioned evidential themes are considered and mining is not present. A comparison of the probability statistics for zones 3 and 4 for both models shows that rockfall susceptibility associated with the 'new' mine layout in these zones is the same as the background value for the Nepean river.

The general reduction of rockfall probability associated with the 'new' mine layout is further demonstrated in Fig. 6, which compares the distribution of probability values between the two models for zones 3 and 4 combined. It can be seen that for the 'new' mine layout there are no areas in which the percent probability exceeds 0.1%, and that the area for which a probability of zero percent is evident is ~59% compared to 39% for the 'old' mine layout. The results suggest that by not mining directly under the cliffs of the Nepean river there should be no significant increase in rockfall potential, and that the 'new' mine layout involves a significant reduction in

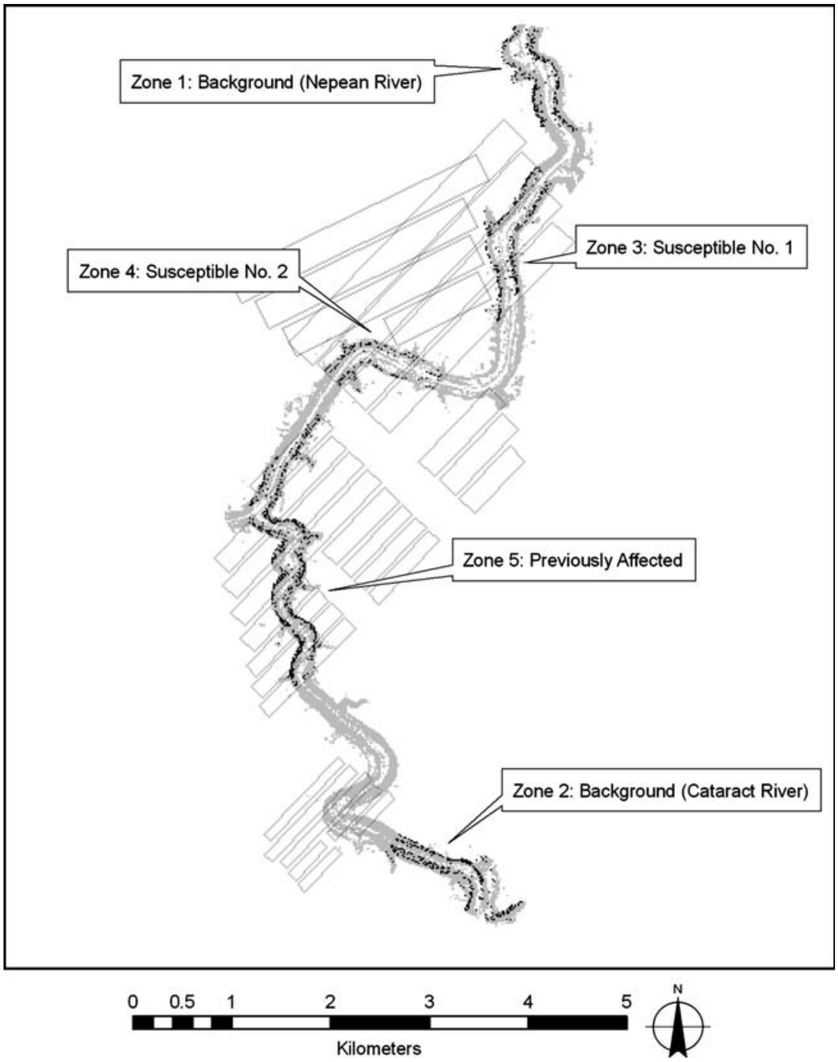

Fig. 4 Five areas of interest through which the model results are interpreted. The areas are labeled as zones 1 to 5 and correspond to background areas (distant from any proposed or existing mining; zones 1 and 2), susceptible areas (these overly the proposed longwalls associated with the original proposal; zones 3 and 4) and the previously affected area (within which nine of the ten training points occur; zone 5). The properties of the probability results for each of these zones are described in Table 1 and Fig. 5

Table 1 Probability (%) summary statistics for each zone for the 'new' and 'old' mine layouts

Zone	Description	Area (m^2)	'Old' mine layout probability			'New' mine layout probability		
			Max	Mean	SD	Max	Mean	SD
1	Background (Nepean river)	56,642	2.1165	0.0006	0.0128	2.1163	0.0005	0.0121
2	Background (Cataract river)	75,554	1.0477	0.0031	0.0350	1.0476	0.0026	0.0295
3	Susceptible area no.1	55,176	4.5576	0.0061	0.0808	2.1163	0.0007	0.0132
4	Susceptible area no. 2	29,774	4.5576	0.0046	0.0885	0.5161	0.0004	0.0076
5	Affected area (existing workings)	138,383	11.7832	0.0245	0.2967	15.6300	0.0333	0.3974

For all zones, the minimum value is zero. The relatively high standard deviation indicates that the results are highly variable spatially. The unit area for both models is 1 m^2, and consequently the area of each zone also corresponds to the number of observations in the mean values

the mean potential for rockfall as well as a reduction in the extent of the study area which exhibits increased rockfall potential. More robust modeling and field evaluations would be required in order to increase the confidence level of this statement.

Discussion

One of the most significant benefits associated with the GIS-based W-of-E method is the role it can play in mine

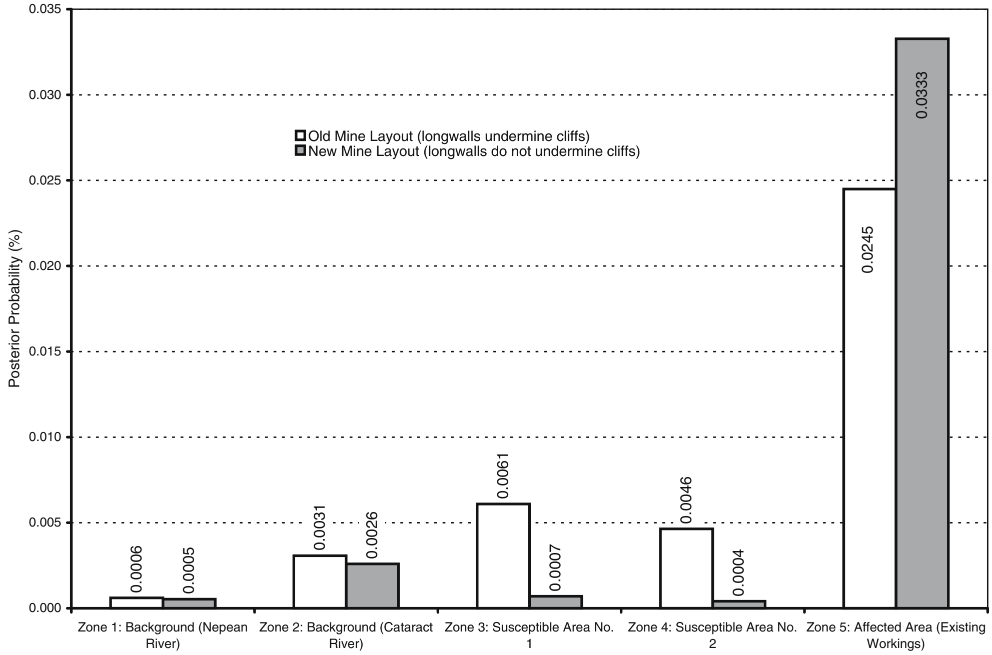

Fig. 5 Mean probability for rockfall occurrence within each zone

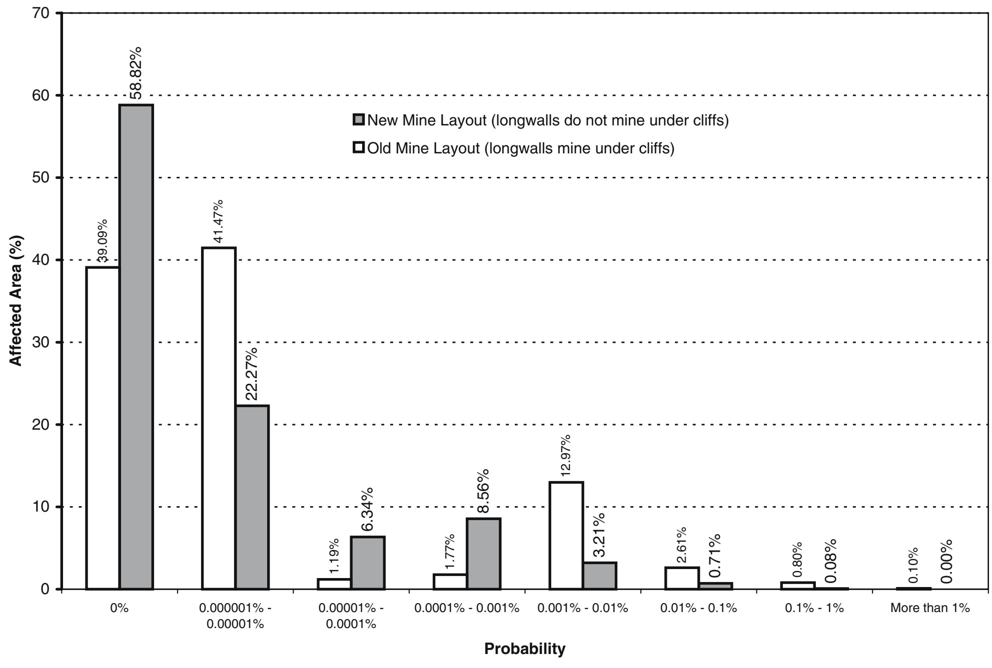

Fig. 6 The distribution of rockfall probability for zones 3 and 4, based on affected area. The graph demonstrates that the overall magnitude of rockfall probability, as well as the spatial extent of areas exhibiting higher rockfall potential, is much reduced when the 'new' mine layout is used in place of the 'old' mine layout

configuration and the development of subsidence management plans. The ease with which alternate models can be produced, for example in which the location of the longwall panels have been modified but other factors are constant, demonstrates the capabilities of both GIS and probabilistic modeling for mine layout evaluation. The results shown here indicate that rockfall potential along the cliffs of the Nepean river is greatly reduced if mining does not extend directly beneath the cliff areas. The probabilities for rockfalls in the cliff sections nearest to the alternate mine layout are similar to those of cliff sections that are quite distant from any workings. This suggests that rockfall susceptibility associated with the 'new' mine layout will be similar to background levels.

Ideally, a detailed survey of historic natural rock falls in the area could be undertaken to quantify the actual background 'natural' rockfall potential in the region.

The GIS-based W-of-E approach is particularly flexible when compared to other modeling approaches (for example, knowledge-driven approaches) because it is possible to construct a model with limited predictors. For instance, the results presented here only consider a small portion of the factors relevant to mining-induced rockfalls. Nevertheless, despite the incomplete understanding of the physical mechanisms involved, and the inability to quantify spatially all of the pertinent factors, the method offers an empirical prediction of relative susceptibility to mining-induced subsidence along the cliffs of the Nepean river.

There are significant limitations, however, with the results and the application of the W-of-E method to rockfall potential modeling in general. These limitations are associated with (1) the availability of data for evidential themes, (2) the quality and nature of the training point data concerning recent and historic rock fall events (both natural and mining induced), and (3) the lack of field verification and model validation.

The reliability of the model results could be greatly improved with the inclusion of additional evidential themes such as the degree of weathering, jointing, or undercutting, or the presence of loose blocks or geological features such as faults and dykes. These themes, and more, are known to be highly relevant to cliff susceptibility in relation to subsidence in this area (Waddington Kay and associates 2002). However, many of these parameters are, at best, difficult to quantify and record spatially. For instance, the extensive fieldwork that would be required in order to map the presence and magnitude of jointing or weathering, in both the source area (within which the training points are located) and the region for which the predictions are to be made, would make the application of a rapid GIS-based model redundant. The results, therefore, should be interpreted as a relative guide for rockfall potential, and field observations of local cliff properties and the occurrence of mining-induced fractures are required for a more accurate measure of overall susceptibility. In particular, it is assumed that the model will generally underestimate rockfall potential if measures of intrinsic cliff instability, which include the aforementioned factors, are not included.

Another limitation associated with the evidential themes, in particular the DEM, relates to the timing of the events. The 1 m DEM used in these analyses was derived after the rockfall events. The values of the evidential themes (slope, cliff height, distances to workings and watercourses) at each training point site will therefore reflect the post-rockfall surface and may therefore not accurately reflect the surface conditions associated with susceptible areas prior to rockfalls.

Considerable inaccuracies in the original training point data, (i.e., the recorded rockfall locations) limit the usefulness and precision of the model results. The greatest inaccuracy relates to the representation of the rockfall locations; in this instance, each rockfall is mapped as a single point, and therefore only occupies one cell (1 m^2) in the model. This may under-represent the true distribution and extent of rockfall activity, and consequently led to the underestimation of probabilities. Extensive fieldwork and/or careful air photo interpretation would be required to accurately map the extent of the original cliff line involved in each rockfall. Although not feasible in this instance, this enhancement could be readily incorporated into similar studies at other locations.

The accuracy associated with the spatial location of each training point is also prone to error, due mainly to the limitations of non-differential GPS-based mapping. These spatial inaccuracies, along with spatial errors that are intrinsic to the DEM, introduce an unquantified element of uncertainty to the results, which is heightened by the limited sample size for training points. This element of uncertainty is increased by the use of evidential themes that are highly spatially variable, such as slope and cliff height. Even a small positional error in the training point location can lead to a large misrepresentation of source values for slope and cliff height, whereas other evidential themes like distance to river or distance to workings, which do not exhibit strong spatial variability, are less sensitive to positional errors.

Without field verification the model results cannot be validated. The relatively small number of training points used in these analyses does not allow for the partitioning of the original dataset into training and validation points. An examination of the probabilities for the actual training points (Table 2) shows values ranging from 0.004 to 1.843. The significance of this is that the highest probabilities in each raster derived from the two models do not coincide with the training point locations. That is, although the probability for rockfalls at the training point location is somewhat elevated, the actual location of rockfalls does not coincide with the most susceptible locations according to the results. This clearly indicates that the factors used in the model are not sufficient to fully quantify rockfall potential, and it is very likely that highly site specific, local parameters that can only be measured from field observations, such as weathering and undercutting, are crucial factors.

Overall, the GIS-based Weight-of-Evidence model should therefore be seen as a preliminary step in evaluating alternative mine layouts but an important early step in the mine planning process. Because of its ease of application, the method is suitable for trialing different configurations where suitable training point data are available. Numerous intrinsic uncertainties, however, limit the reliability of the W-of-E method when used to

Table 2 Probability values (%) derived for she training point locations

Training point no.	Model results with 'old' mine layout (probability %)	Model results with 'new' mine layout (probability %)
1	0.005	0.004
2	0.069	0.095
3	0.006	0.008
4	1.336	1.844
5	0.069	0.095
6	1.133	1.564
7	0.029	0.040
8	0.116	0.161
9	0.482	0.667
10	0.006	0.008

One of the greatest limitations of the modeled results is that the training points, which correspond to the location of actual rockfalls, do not always display relatively high probabilities. This is attributable to a number of factors that are outlined in the text

predict rockfalls; comprehensive field studies and modeling are recommended for more robust impact prediction and assessment.

Conclusion

For this particular study site, the alternate mine layout in which longwalls do not directly mine under the cliffed areas is associated with a significant reduction in rockfall susceptibility when compared to a longwall configuration which extends beneath the cliffs. Field observations and model validation is required, however, before the probability values from the modeling can be used in mine layout configuration with confidence.

The Weights-of-Evidence method shows potential for use in mine orientation and susceptibility analyses, particularly where sufficient subsidence impacts have been recorded in an area proximal to that of the proposed development. The method may also be potentially used during mining to predict potential imminent impacts, by noting subsidence impacts as they occur, and using them in the model.

There are important limitations to the application of this technique for rockfall prediction arising from a lack of appropriate evidential themes, uncertainty and error in source data, and a lack of model validation. In particular, supplementary field observations are required before the results are useful for decision-making purposes.

The W-of-E technique, as applied here, can be viewed as a useful tool for mining layout configuration and impact prediction. The technique is best used as a guide for further investigations that incorporate field observations with detailed mapping and documentation of subsidence impacts, such as rockfalls.

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References

Asadi HH, Hale M (2001) A predictive GIS model for mapping potential gold and base metal mineralization in Takab area, Iran. Comput Geosci 27:901–912

Bonham-Carter GF, Chung CF (1983) Integration of mineral resources data for Kasmere lake area, Northwest Manitoba, with emphasis on uranium. Comput Geosci 15:25–45

Bonham-Carter GF, Agterberg FP, Wright DF (1988) Integration of geological datasets for gold exploration in Nova Scotia. Photogram Eng Remo Sens 54:1585–1592

Bonham-Carter GF, Agterberg FP, Wright DF (1989) Weights of evidence modelling: a new approach to mapping mineral potential. Stat Appl Earth Sci Geol Survey Can Paper 89–9:171–183

Branagan DF, Packham GH (1967) Field geology of New South Wales. Science Press, Sydney

Campbell AN, Holloster VF, Duda RO (1982) Recognition of a hidden mineral deposit by an artificial intelligence program. Science 217:972–929

Carranza EJM, Hale M (2002) Spatial association of mineral occurrences and curvilinear geological features. Math Geol 34:203–221

Cheng Q (2004) Application of weights of evidence method for assessment of flowing wells in the Greater Toronto area, Canada. Nat Resour Res 13:77–86

Daneshfar B, Benn K (2002) Spatial relationships between natural seismicity and faults, southeastern Ontario and north-central New York state. Tectonophysics 353:31–44

Kay D (1991) Effects of subsidence on steep topography and cliff lines. NERDDP Project No. 1446 End of Grant Report, pp 126, Appendices

Kemp LD, Bonham-Carter GF, Raines GL, Looney CG (2001) Arc-SDM: Arcview extension for spatial data modelling using weights of evidence, logistic regression, fuzzy logic and neural network analysis. http://www.ntserv.gis.nrcan.gc.ca/sdm/

Lee S, Choi J (2004) Landslide susceptibility mapping using GIS and the weight-of-evidence model. Int J Geogr Inf Sci 18:789–814

NSW Department of mineral resources (2003) New South Wales coal industry profile.p 257

Sawatzky DL, Raines GL, Bonham-Carter GF, Looney CG (2004) ArcSDM2: ArcMAP extension for spatial data modelling using weights of evidence, logistic regression, fuzzy logic and neural network analysis. http://ntserv.gis.nrcan.gc.ca/sdm/ArcSDM2/

Solomatine DP (2002) Data-driven modelling: paradigm, methods, experiences.In: Proceedings of the 5th international conference on hydroinformatics, Cardiff, UK, 1–5 July 2002 pp 757–763

Spiegelhalter DJ (1986) Uncertainty in expert systems. In: Gale WA (ed) Artificial Intelligence and Statistics. Addison-Wesley, Reading. pp 17–55

Tangestani MH, Moore F (2001) Porphyry copper potential mapping using the weights-of evidence model in a GIS, northern Shahr-e-Babak, Iran. Aust J Earth Sci 48:695–701

Waddington Kay and Associates (2002) Research into the impacts of mine subsidence on the strata and hydrology of river valleys and development of management guidelines for undermining cliffs, gorges and river systems. Report on Australian Coal Association Research Program (ACARP) Project No. C9067, p 186

Young RW, McDougall I (1985) The age extent and geomorphological significance of the Sassafras Basalt, southeastern New South Wales. Aust J Earth Sci 32:323–331