Ecological risk assessment of acid rock drainage under uncertainty: The fugacity approach

Getnet D. Betrie\textsuperscript{a,}\textsuperscript{*}, Rehan Sadiq\textsuperscript{b}, Kevin A. Morin\textsuperscript{c}, Solomon Tesfamariam\textsuperscript{b}

\textsuperscript{a} Research Center, Athabasca University, Edmonton, AB, Canada
\textsuperscript{b} School of Engineering, University of British Columbia, Kelowna, BC, Canada
\textsuperscript{c} Minesite Drainage Assessment Group, Surrey, BC, Canada

\textbf{HIGHLIGHTS}

- A methodology for ARD risk assessment during a pre-mining stage was developed.
- A model that accounts uncertainties was developed to simulate metals at mine sites.
- Uncertainty in effect characterization was estimated based on probability bounds.
- Risk characterization methods using p-boxes was presented.
- The methodology demonstrated at a mine site where data are limited.

\textbf{ARTICLE INFO}

\textbf{Article history:}
Received 5 December 2014
Received in revised form 6 July 2015
Accepted 21 July 2015
Available online 28 September 2015

\textbf{Keywords:}
Risk analysis
Fugacity model
Acid rock drainage
Uncertainty
Probability bounds analysis

\textbf{ABSTRACT}

Acid rock drainage (ARD) is a major environmental problem that poses serious ecological risks during and after mining activities. To minimize the ecological risks and to lower remediation costs in the mining industry, ecological risk assessment is highly important in various phases of mining. In this study, a methodology for ecological risk assessment using probability bounds is presented. The methodology is demonstrated with a case study at a mine site. A fugacity-based model was employed to conduct the exposure characterization. Median lethal concentrations from toxicity studies were used to derive predicted no-effect concentrations (PNEC) and to characterize the effect of copper and zinc on the receptors. Probabilistic risk-quotient and overlaps between distributions of exposure and effect were employed to characterize risk. Data and parameter uncertainties in exposure, effect, and risk characterizations were propagated and quantified using a probability bounds approach. The exposure modeling results showed that the predicted concentrations of copper and zinc slightly exceeded the observed concentrations. The results of the effect characterization showed that the derived effect concentrations for copper and zinc are acceptable compared with guideline values. The risk characterization result indicated that a high probability of ecological risk may exist due to metals that are transported into a nearby lake. Moreover, the results showed that the methodology handles uncertainties due to imprecision and randomness in an integrated manner.

\textsuperscript{*} Corresponding author.
\textit{E-mail addresses:} getnet.betrie@alumni.ubc.ca, gbetrie@athabascau.ca (G.D. Betrie).

http://dx.doi.org/10.1016/j.eti.2015.07.004
2352-1864/© 2015 Elsevier B.V. All rights reserved.
1. Introduction

Acid rock drainage (ARD) is a major environmental problem in Canada and other parts of the world (Gray, 1997; Verburg et al., 2009). ARD is generated when sulfide-bearing material reacts with oxygen and water during and after mining activities (Morin and Hutt, 2001; Price, 2009). This reaction changes relatively insoluble chemical species within sulfide minerals into more easily dissolved free ionic species (e.g., Cu, As and Zn) or secondary minerals (e.g., sulfates, carbonates and hydroxides). Moreover, the oxidation of some sulfide minerals produces acidity that may lower the drainage pH. A lower drainage pH can increase the rate of sulfide oxidation, the solubility of many products of sulfide oxidation and the rate of weathering for other minerals.

ARD poses environmental risks such as elimination of biological species, significant reduction in ecological stability, and bioaccumulation of metals in flora and fauna (Gray, 1997, 1998). In Canada, the remediation costs of these damages were estimated at 7 billion dollars in 1995 (Feasby and Tremblay, 1995). To minimize environmental risks and to lower remediation costs, ecological risk assessments are highly important in various phases of mining. Ecological risk assessments evaluate the likelihood that adverse ecological effects may occur or are occurring as a result of exposure to one or more contaminants (US EPA, 1992).

Guidelines for ARD management have been developed in Canada and internationally (e.g., Price and Errington, 1998 and Verburg et al., 2009). Risk assessment in the guidelines is conducted following characterization, prediction and mitigation steps. In the characterization step, sources, pathways, and receptors are characterized. The drainage chemistry of ARD is predicted using laboratory or modeling techniques in the prediction step. The predicted chemistry for each contaminant is compared with regulatory values to estimate risk and mitigation measures are implemented in the mitigation step. The guidelines recommend uncertainty analysis at pre-mining, operational, and post-mining phases, but a methodology has not been presented. This paper presents a new methodology to conduct risk assessment under uncertainty during a pre-mining phase, where hydrogeological information that characterizes a mine site is limited.

The remainder of this paper is organized as follows: Sections 2 and 3 present an uncertainty analysis and ecological risk analysis, respectively. Section 4 presents and discusses the results of this study. Finally, Section 5 summarizes and concludes the findings of this study.

2. Uncertainty analysis

Data and parameter uncertainties may originate from randomness due to natural variability and from imprecision due to systematic measurement errors or expert opinions (Walker et al., 2003; Baudrit et al., 2006). Various methods exist to quantify parameters and input data uncertainties. These approaches include Monte Carlo analysis, probability bounds (p-boxes), random set theory, and possibilistic analysis (Ayyub and Klir, 2010). In cases where data and parameters are represented by random and imprecise variables, separate methods must be used to propagate these uncertainties (Hoffman and Hammonds, 1994; Ferson and Ginzburg, 1996). In this study, the probability bounds approach is used to quantify and propagate data and parameter uncertainties.

A p-box is an approach used to represent imprecise probability. Imprecise probability is a generalization of probability when one is not able to define a precise probability function \( P \) for an event \( x \) (Walley, 1991). An imprecise probability function \( P(x) \) is characterized by its lower probability \( P_l(x) \) and upper probability \( P_u(x) \). Lower probability and upper probability functions map an event \( x \in X \) into interval values between zero and one (Ferson et al., 2003). The lower and upper bounds of a p-box associated with a random variable \( X \) give the possible range of probabilities that \( X \) exceeds any particular value. These bounds are close together when the imprecision is small but may be far apart when it is large. In this study, the concept of a p-box was implemented in the risk assessment using Risk Cal 4.0 software (Ferson, 2000).

3. Ecological risk analysis

Ecological risk assessments evaluate the likelihood that adverse ecological effects may occur or are occurring as a result of exposure to one or more stressors (US EPA, 1992). An assessment comprises problem formulation, exposure characterization, effect characterization, and risk characterization (USEPA, 1998).

3.1. Problem formulation

Problem formulation defines assessment endpoints, a conceptual model, and an analysis plan. The assessment endpoints express the environmental value that is to be protected. They are defined based on the mine’s management goals in this study, which are to protect at least 90% of the fish species 90% of the time from stressor exposure in a nearby lake. The conceptual model for the risk assessment consists of the source of the stressors, media, exposure pathways, and receptors. The stressors are elevated copper and zinc released from waste rock. The media that could be contaminated are groundwater and surface water. The potential exposure pathways are ingestion, contact, and consumption of lower-trophic-level organisms. The receptors are fish species that inhabit the lake, which are Oncorhynchus kisutch, Cottus asper, Gasterosteus aculeatus, Oncorhynchus clarki and Salvelinus malma. In the analysis plan, a risk hypothesis of the study is evaluated that was copper and zinc may cause a permanent reduction in the fish species in the lake.
3.2. Exposure characterization

Exposure characterization is often conducted using measured environmental data or using fate-and-transport models (Solomon et al., 1996). Fate and transport models are used to estimate environmental concentrations of contaminants/stressors. Such models for the mining industry are well-documented in the literature (Perkin et al., 1995; Caruso et al., 2008). Although these models are expected to provide accurate predictions, they have inherent uncertainties such as model, parameter, and data uncertainties (Walker et al., 2003; Caruso et al., 2008).

Exposure characterization is conducted using a fugacity-based model in this study. The model estimates the distributions of chemical in multimedia based on the complexity of transport and transformation processes (Mackay et al., 1983; Diamond et al., 1992; Ling et al., 1993). It uses equivalence (Q, mol/m$^3$) as the controlling variable instead of using concentration (C, mol/m$^3$). A linear relationship exists between these quantities (i.e., C = QZ'), where Z’ is the equivalence capacity, which depends on the characteristics of a chemical, medium, and temperature. The value of the equivalence capacity for water ($Z_w'$) is defined as 1.0, and the values for other media are obtained by multiplying $Z_w'$ and the partition coefficient of a medium. Rates of various processes, such as advection, diffusion, and chemical transformation, are expressed as the product of equivalence and a transport or transformation parameter value (m$^3$/h). There are three types of transport or transformation parameter values:

(i) For chemical transport by advective flow, $A = G \cdot Z'$, where $G$ is a mass–phase flow rate in m$^3$/h,
(ii) For a chemical transport by diffusion, $D = USZ'$, where $U$ and $S$ are the mass transfer coefficient in m/h and area in m$^2$, respectively, and
(iii) For chemical transformation by reaction, $T = VklZ'$, where $V$ is the compartment volume (m$^3$), and $k$ is a first-order rate constant (h$^{-1}$).

In this study, a steady-state model based on probability bounds was developed to simulate fate-and-transport of heavy metals and to account for data and parameter uncertainties at a mine site. The mine system consists of waste rock, soil layers, an aquifer and solid particles. A conceptual model showing different mechanisms of transport in three layers is shown in Fig. 1. Waste rock is assumed to be the source of copper and zinc metal emissions ($E_S$) into the soil. Intermediate transports through diffusion and advection were considered. The diffusion of copper and zinc from water to soil ($D_{WS}$), soil to water ($D_{SW}$), water to solid particles ($D_{WSP}$), and solid particles to water ($D_{SPW}$) is calculated based on mass transport coefficients. The values of advection through the soil ($A_{sl}$) and the aquifer ($A_{gw}$), which correspond to the transport of copper and zinc through water pores of the soil and the aquifer, are calculated based on infiltration and groundwater flow rates, respectively. An algorithm for calculating the concentrations of copper and zinc in soil, solid particles, and water is presented in Table 1.

The input parameters of the fate and transport model are provided in Table 2. A clay till thickness ($d_{sl}$) of 10 m and aquifer thickness ($d_{gw}$) of 700 m were used. The clay till overlies an aquifer that is considered homogeneous and well mixed. The aquifer has a length and width of 1000 m. It is assumed that flow rates through the clay till ($G_{sl}$) and aquifer ($G_{gw}$) are gravity
Algorithm for computing heavy metal concentrations in soil, water, and solid particles.

Table 1
Algorithm for computing heavy metal concentrations in soil, water, and solid particles.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Parameters and equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Define physico-chemical properties of contaminants</td>
<td>Partitioning with soil (K_d) and molecular weight (MW)</td>
</tr>
<tr>
<td>Define media physical properties.</td>
<td>Length (l), width (w), thickness of aquifer (d_{gw}) and soil (d_{sd}), and bulk density (BD)</td>
</tr>
<tr>
<td>Define flow rates in the soil and aquifer</td>
<td>Flow rates in the soil (G_{sd}) and aquifer (G_{gw})</td>
</tr>
<tr>
<td>Calculate the mass transport capacity (Z') of all layers</td>
<td>Soil-water mass transport coefficient (U_{11})</td>
</tr>
<tr>
<td>Calculate the A-values of advection</td>
<td>Advection in the aquifer (A_{gw} = Z'<em>w \cdot C</em>{gw}) and soil (A_{sd} = Z'_sd)</td>
</tr>
<tr>
<td>Calculate the D-values of diffusion</td>
<td>Diffusion from the soil to water (D_{sw} = SU_{11}Z'<em>w), water to soil (D</em>{ws} = SU_{11}Z'<em>s), and solid particles to water (D</em>{psw} = PU_{11}Z'_p)</td>
</tr>
</tbody>
</table>

Table 2
Representation of parameter and data uncertainties in the fugacity model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Units</th>
<th>Variable type</th>
<th>Value/distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Molecular weight of Cu and Zn, respectively</td>
<td>MW</td>
<td>g/mol</td>
<td>Constant</td>
<td>63.6 and 65.39</td>
</tr>
<tr>
<td>Aquivalence capacity</td>
<td>Z'_w</td>
<td></td>
<td>Constant</td>
<td>1</td>
</tr>
<tr>
<td>Width</td>
<td>w</td>
<td>m</td>
<td>Constant</td>
<td>1000</td>
</tr>
<tr>
<td>Length</td>
<td>l</td>
<td>m</td>
<td>Constant</td>
<td>1000</td>
</tr>
<tr>
<td>Thickness of aquifer</td>
<td>d_{gw}</td>
<td>m</td>
<td>Constant</td>
<td>712</td>
</tr>
<tr>
<td>Thickness of soil</td>
<td>d_{sd}</td>
<td>m</td>
<td>Constant</td>
<td>10</td>
</tr>
<tr>
<td>Soil–water mass transport</td>
<td>U_{11}</td>
<td>m/h</td>
<td>Imprecise</td>
<td>t\minmax∼(10^{-9},10^{-6})</td>
</tr>
<tr>
<td>Density of solids</td>
<td>BD</td>
<td>kg/m^3</td>
<td>Imprecise</td>
<td>t\minmaxmode∼(1840, 1981, 1965)</td>
</tr>
<tr>
<td>Flow rates in soil</td>
<td>G_{sd}</td>
<td>l/s</td>
<td>Imprecise</td>
<td>t\minmax∼(1, 6)</td>
</tr>
<tr>
<td>Flow rates in aquifer</td>
<td>G_{gw}</td>
<td>l/s</td>
<td>Imprecise</td>
<td>t\minmax∼(0.5, 4)</td>
</tr>
<tr>
<td>Partition coefficient of Cu</td>
<td>log K_{dCu}</td>
<td>l/kg</td>
<td>Random</td>
<td>t\lognormal∼(3.5, 1.7)</td>
</tr>
<tr>
<td>Partition coefficient of Zn</td>
<td>log K_{dZn}</td>
<td>l/kg</td>
<td>Random</td>
<td>t\lognormal∼(4.1, 1.6)</td>
</tr>
<tr>
<td>Copper concentration</td>
<td>C_{Cu}</td>
<td>mg/l</td>
<td>Imprecise</td>
<td>t\mmms∼(0.0015, 3.2, 0.31, 0.82)</td>
</tr>
<tr>
<td>Zinc concentration</td>
<td>C_{Zn}</td>
<td>mg/l</td>
<td>Imprecise</td>
<td>t\mmms∼(0.023, 18, 4.97, 0.78)</td>
</tr>
</tbody>
</table>

Table 2 shows the parameter types (constant, random or imprecise) and values. The imprecise variables are defined by their statistics such as mmms (minimum, maximum, mean, and standard deviation), minmaxmode (minimum, maximum, and mode) or minmax (minimum and maximum). The random variable of the partitioning coefficient is defined using a lognormal distribution, and the distribution’s parameter and shape are obtained from Allison and Allison (2005). The concentrations of copper and zinc are multiplied by a dilution factor (dl) to obtain the concentrations of copper and zinc in the lake. The dilution value is obtained by measuring the effective surface area of the lake using the Google Earth Pro program (Google, 2013), and its depth was assumed. To validate the developed model, the observed data at the lake were used to construct p-boxes with Kolmogorov–Smirnov 95% confidence bounds and compared against the predicted outputs visually.

3.3. Effect characterization

The characterization of ecological effects presents the relationship between stressor levels and ecological effects. Ecological effects are characterized using the response of receptors to stressors. The response is obtained from laboratory tests (Solomon et al., 1996). The tests include the “median lethal concentration” (LC_{50}) and the “no observed effect concentration” (NOEC). LC_{50} is the concentration that is required to kill 50% of the test population, whereas NOEC is the concentration at which no long-term or chronic effects occur in the test population. Extrapolating these toxicity data from

Driven and that the copper and zinc are transported by advection. The soil–water mass transport coefficient (U_{11}) is obtained from the literature (Diamond et al., 1992; Ling et al., 1993). Table 2 also shows the parameter types (constant, random or imprecise) and values. The imprecise variables are defined by their statistics such as mmms (minimum, maximum, mean, and standard deviation), minmaxmode (minimum, maximum, and mode) or minmax (minimum and maximum). The random variable of the partitioning coefficient is defined using a lognormal distribution, and the distribution’s parameter and shape are obtained from Allison and Allison (2005). The concentrations of copper and zinc are multiplied by a dilution factor (dl) to obtain the concentrations of copper and zinc in the lake. The dilution value is obtained by measuring the effective surface area of the lake using the Google Earth Pro program (Google, 2013), and its depth was assumed. To validate the developed model, the observed data at the lake were used to construct p-boxes with Kolmogorov–Smirnov 95% confidence bounds and compared against the predicted outputs visually.
test samples to the population (e.g., species) introduces data uncertainty (Hall et al., 1998). Thus probability bounds approach is used to quantify the uncertainty associated with the effect data.

The LC50 response of these species to copper and zinc were obtained from the AQUIRE database (US EPA, 2014). To consider the effect of pH on toxicity, toxicity tests that are conducted with pH ranges 4–6 were used in this study. The predicted-no-effect concentration (PNEC), which is the concentration below which the fish species are protected, was derived by dividing the LC50 value by 10, as suggested in the literature (Roman et al., 1999). The PNEC values are assumed to represent any possible exposure pathways.

3.4. Risk characterization

The risk characterization phase involves estimating of the probability of adverse effects on selected endpoints. In this phase, risk is estimated and described, and uncertainties and assumptions are summarized. Risks are estimated by comparing exposure and effects data using either the risk-quotient method or distributions (Solomon et al., 1996; Hall et al., 1998; USEPA, 1998, 2001). In this study, two methods compose the risk characterization: the degree of overlap between p-boxes of exposure and effect and the probabilistic risk-quotient.

The first method compares the degree of overlap between the p-boxes of exposure and effect. First, the effect concentration at the lower or upper bound that is defined to protect the assessment endpoints is calculated. Second, this concentration is recorded on the lower or upper bound of the exposure, and its corresponding non-exceedance level is computed. Third, the risk value is calculated by subtracting the non-exceedance values from one. The second method computes the probability that a randomly selected exposure concentration is greater than the effect concentration. In this case, the computed risk-quotient will have a p-box rather than a deterministic value.

4. Results and discussion

The validation of the exposure model is presented in Fig. 2. This figure depicts the lower and upper bounds of the cumulative distribution functions of the observed and predicted concentrations of copper and zinc in the lake. The observed p-boxes are computed with Kolmogorov–Smirnov 95% confidence bounds based on eleven values. The lower and upper bounds provide concentration values that are not exceeded at a given percentile level. For example, the upper bounds of copper and zinc show that their predicted concentrations do not exceed 0.027 and 0.186 mg/L, respectively, at the 80% probability level.

The predicted copper concentration underestimated the lower bound of the observed concentration as shown in this figure. The upper bound of the observed concentration of copper is underestimated between the 0 and 0.8 probability levels and overestimated at probability levels higher than 0.8, as shown in the figure. The predicted concentration of zinc underestimated the lower bound of the observed concentration of zinc. For the upper bound, the observed zinc concentration is well estimated, underestimated, and overestimated at the probability levels of 0–0.4, 0.4–0.5, above 0.5, respectively.

The distance between the lower and upper bounds indicates the degree of uncertainty due to imprecision. The uncertainty band of the predicted copper ranges from 0 to 0.035 mg/L, whereas the uncertainty band of the observed copper ranges
Fig. 3. Derived and regulatory PNEC concentrations of copper and zinc.

from 0.003 to 0.033 mg/L. Similarly, the uncertainty band of the predicted zinc ranges from 0 to 0.198 mg/L, whereas the uncertainty band of the observed concentration of zinc ranges from 0.028 to 0.16 mg/L.

The reason this model slightly overestimated the observed concentrations is most likely attributed to metals removal by chemical processes that were not represented in the model. The literature shows that chemical processes, such as precipitation, ion exchange and reduction–oxidation, remove heavy metals in aquatic systems (Luo and Yang, 2007; Sommerfreund et al., 2010). However, this model excludes those important processes; consequently, the maximum values of the predicted concentrations of copper and zinc are higher than their observed counterparts.

The reason for the difference between the shape of the observed and predicted p-boxes is discussed as follows. The smooth edges of the predicted p-boxes are attributed to the types of distributions (e.g., minmax, mmms, minmaxmode, and lognormal) used to represent the input parameters of the exposure and effect assessments. However, the rough edges of the observed p-boxes are attributed to the small sample sizes used to compute the p-boxes.

The results of the effect characterization (i.e., the PNEC-derived probability box) for copper and zinc are shown in Fig. 3. Note that the PNECs of zinc copper and zinc represent concentrations below which the fish species in the lake are protected. The probability boxes of copper and zinc have ranges of values at different percentile levels. For instance, the PNEC concentration of copper varies within 0.002–0.01, 0.002–0.014, 0.003–0.029, and 0.027–0.055 at the 10th, 30th, 60th, and 99th percentiles, respectively. Similarly, the PNEC concentration of zinc varies within 0.001–0.002, 0.001–0.003, 0.001–0.007, and 0.003–0.01 at the 10th, 30th, 60th, and 99th percentiles, respectively. These probability boxes of copper and zinc are validated by comparing them with the Canadian regulatory value (PNEC-Regulatory) for freshwater, which is obtained from Canadian Environmental Quality guidelines (CCME). The guideline value of copper overlaps with the lower bound of copper PNEC values up to the 58th percentile. The guideline value of zinc falls between the lower and upper bound distributions of zinc, from the 30th to 99th percentiles. It is worth noting that the guideline values are constant at various percentiles because they are deterministic estimates. The results of these comparisons indicate that the derived PNEC probability boxes of copper and zinc are acceptable.

The risk characterization was conducted by comparing the degree of overlap between the exposure and effect (PNEC) concentrations, as shown in Fig. 4. This comparison is specifically performed by comparing the lower and upper bounds of the effect concentrations at a given percentile with their respective exposure concentrations. For risk characterization with respect to the lower bound of copper, the value of the effect concentration that will be exceeded at the 10th percentile is equal to 0.002 mg/L. This concentration of copper is not exceeded 100% of the time by the lower bound of the exposure distribution. This indicates that the risk is equal to 0%, and there is no risk from copper with respect to the lower bound. For risk characterization with respect to the upper bound of copper, the value of the effect concentration that will be exceeded at the 10th percentile is equal to 0.01 mg/L. This value is not exceeded 73% of the time in the exposure distribution. This indicates that the associated risk of copper is equal to 27% with respect to the upper bound of the distribution. The estimated value of risk (27%) is not acceptable because it exceeds the acceptable risk value of 10%.

For the lower bound of zinc, the value of the effect concentration that will be exceeded at the 10th percentile is equal to 0.006 mg/L. This value is not exceeded 100% of the time at the lower bound of the exposure distribution. This indicates that the associated risk of zinc is equal to 0% and there is no risk with respect to the lower bound of zinc. For risk characterization with respect to the upper bound of zinc, the value of the effect concentration that will be exceeded at the 10th percentile is equal to 0.015 mg/L. All concentrations of the upper bound of the exposure distribution exceed 0.015 mg/L at all times. This indicates that the associated risk of zinc with respect to the upper bound is equal to 100%, and this value is beyond the acceptable level of risk of 10%.
The result of the risk characterization in terms of the risk-quotient method is presented in Fig. 5. For risk characterization with respect to the lower bounds, the results show that there is no risk for copper and zinc. Specifically, the lower bounds of copper and zinc have RQ values less than one. For the risk characterization with respect to the upper bounds, the risks for copper and zinc are equal to 69% and 100%, respectively.

The results of the risk characterization for both methods indicate that the fish are at risk from copper and zinc because the assessment endpoints that are defined to protect at least 90% of the fish species 90% of the time from stressors are not met. However, the estimated risk might be overestimated because the exposure model used in this research does not represent important processes (e.g., complexation) in aquatic systems that determine the availability and fate of metals.

5. Summary and conclusion

This paper presents a new methodology that enables ecological risk assessment under uncertainty in mine sites. The methodology has problem formulation, exposure characterization, effect characterization, and risk characterization. In the problem formulation, assessment endpoints, a conceptual model, and the hypothesis of the risk assessment were defined. In the exposure characterization, a fugacity-based model was developed to determine the fate and transport of metals from waste rock in the environment. In the effect characterization, the response of organisms to heavy metals was estimated. Data and parameter uncertainties in exposure and effect characterizations are addressed using the probability bounds approach.
In risk characterization, the likelihood of risk was estimated by comparing the degree overlaps between probability boxes of exposure and effect concentrations at a given percentile level, and the probabilistic risk-quotient methods.

The exposure modeling results show that the predicted concentrations of copper and zinc slightly overestimated the observed concentrations. The results of the effect characterization show that the derived effect concentrations for copper and zinc are acceptable because the probability bounds of the effect were within the deterministic guideline values. The risk characterization results indicate that there is a high probability of ecological risk due to metals transport into the nearby lake. This result should be interpreted carefully because the exposure model used in this study does not represent important processes, such as the complexation process, in the aquatic system. The presented methodology is better than the existing methodology because it accounts data and parameter uncertainties in exposure and effect characterizations. It could be used to assess ARD risk at a preliminary level in the mining industry, where site-characterizations data are limited. The exposure model should be replaced with better models that consider natural-attenuation factors when site-characterizations data are available.

References


Ferson, S., Ginzburg, L.R., 1996. Different methods are needed to propagate ignorance and variability. Reliab Eng Syst Saf 54 (2–3), 133–144.


