Mine Water and the Environment (2019) 38:447–462
https://doi.org/10.1007/s10230-019-00600-w

TECHNICAL ARTICLE

Incorporating Hydrologic Uncertainty in Industrial Economic Models: Implications of Extreme Rainfall Variability on Metal Mining Investments

Jyrki Savolainen[1] · Daniele Pedretti[2,3] · Mikael Collan[1]

Received: 29 June 2018 / Accepted: 26 February 2019 / Published online: 11 March 2019

Abstract
Water balance uncertainties have long been known to lead to potential environmental hazards, but their effect on economic profitability of mines is an under-studied field of research. Historical rainfall data are analyzed using the extreme value theory (EVT) and the peak over threshold method (POT). The resulting distributions are used as inputs into a system dynamics techno-economic metal mining investment profitability model, and simulation analysis is performed. The proposed methodology incorporates rainfall extremes and uncertainty into techno-economic modeling of metal mining operations. A case study with real-life historical rainfall data was used to illustrate the relationship between hydrologic uncertainty and the economic value of a metal mining investment.

Keywords Open pit flooding · Temporary mine shutdown · Investment analysis · System dynamics modeling · Extreme rainfall events

Introduction

Large, irreversible industrial investments with heavy initial capital layouts, such as the metal mines that are the focus of this research, are designed to operate for decades in uncertain technical and market environments. Investors are faced with a trade-off between constructing lower water-related risk designs and declining economic returns. This means that ex-ante planning of these investments is very important from the point of view of being able to secure the long-term technical and economic sustainability of mining investments. It also implies that the planning models used should be able to capture the type and kind of uncertainty that surrounds the analyzed investments (Collan et al. 2016) and properly reflect their complexity (Ashby 1958).

In this vein, our research focuses on metal mining investments and specifically on the modeling and analysis of the relationships between water management risks and mining economics. The profitability of mining projects can be severely threatened by improper water management (ICMM 2012). Quantification of the cumulative effects of mine water management is, however, difficult, and it is common that water management policies and decision making include conflicting interests (Zhang et al. 2014).

Brown (2010) reviewed the current water management planning policies of mines and found that mine water evaluations are unreliable, and that the magnitude of errors in the estimation of economic losses due to improper water management are often significant. Some of the most important reasons highlighted by Brown (2010) leading to failures to successfully predict the effects of mine-water management include (a) high uncertainty of initial data, (b) computational complexity of analysis (methods), and (c) perceiving water management as a secondary issue in a mining project. According to Gao et al. (2014), current water balance

✉ Jyrki Savolainen
jyrki.savolainen@lut.fi

Daniele Pedretti
daniele.pedretti@unimi.it

Mikael Collan
mikael.collan@lut.fi

1 LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland

2 Geological Survey of Finland (GTK), Vuorimiehentie 5, 02150 Espoo, Finland

3 Dipartimento di Scienze della Terra "A. Desio", Università degli Studi di Milano (UNIMI), Via Mangiagalli 34, 20133 Milan, Italy

models are not sufficiently reliable for evaluating long-term water management strategies, particularly when dealing with climate change scenarios. Water management costs can constitute as much as 10% of the total investment in a mine (e.g. Fleming 2016), and the inability to estimate the consequences of an erroneous water balance in a mining project analysis can lead to severe economic losses.

Despite the importance of water management issues for mining project profitability, there seems to be little written on the economic effects of mine water management. This lack of research may be due to the lack of models that simultaneously embed economic and environmental variables in a suitable model. The purpose of this work was to demonstrate that a recently developed system dynamics (SD) metal mining investment model (Savolainen et al. 2017a, b) could be extended and successfully used to quantitatively explore the effects of water management on the value of a metal mining investments within a risk-based framework. We illustrate how dynamic variables that depend on probabilistic thresholds and characterize the distribution of historical rainfall events, when evaluated using the extreme value theory, EVT (e.g. Gilli and Këllezi 2006; Pedretti and Beckie 2016; Serinaldi and Kilsby 2014; Pedretti and Irannezhad 2018), can be used to assess the feasibility of mining investments. The SD-based model provides a completely new approach that circumvents some of the limitations of traditionally adopted static and/or deterministic investment analyses (e.g. Bartrop and White 1995; Bhappu and Guzman 1995; Eves 2013; Lawrence 2002; Smith 2002) used in the metal mining industry.

Typically, system dynamics are modeled using stochastic processes, which treat input parameters as random variables. The randomness of these parameters is generally linked to the poor predictability of fluctuations in stock markets, societal and economic crises, and consumer habits and demand (e.g. Banerjee and Siebert 2017; Caballero and Pindyck 1992; Gilli and Këllezi 2006; Wernerfelt and Karnani 1987; Zachary 2014). When the performance of industrial activities depends directly on the variability in environmental conditions, long-term economic investments must also embed other sources of uncertainty that are linked to the endemic variability of natural phenomena. Because of geological, atmospheric, and ocean-related processes, several potential extreme phenomena can occur, such as intense rainfall events or temperatures, leading to flooding, heat waves or droughts (e.g. Easterling et al. 2000; Kløve et al. 2014; Luoma et al. 2013; Merz et al. 2004; Schmidt-Thomé et al. 2013, 2015).

Incorporating environmental variables into economic models is not a straightforward task (e.g., Garrick et al. 2012). It requires a versatile dynamic simulation method that can predict the feasibility and profitability of an investment by simultaneously capturing (a) the technical and economic complexity of large industrial investments and (b) the random occurrence of natural events. SD models provide a promising approach in this sense, although they have not yet been widely applied to incorporate environmentally driven source of uncertainty. SD models are generally used for evaluating complex real investments by means of non-linearity and feedback loop structures (Forrester 1994; Inthavongsa et al. 2016; Johnson et al. 2006; O'Regan and Moles 2006; Tan et al. 2010). Größler et al. (2008) discussed the use of SD models in the operations management context. They pointed out that the power of SD models lies in their ability to present how system components interact. Qureshi (2007) studied the value of a company using a SD approach, although they assumed no variability in the input parameters used (i.e. they used a purely deterministic approach).

SD models are potentially well-suited to accounting for undesired economic losses due to the non-linear nature of hydrologic processes that can lead to water security issues. Côte et al. (2007) evaluated mine water treatment using a SD approach. Garrick et al. (2012) described water security as the ability to deal with (or predict the impact of) the probability of occurrence of high impact hazardous events. This could, for instance, be the probability of flooding due to the occurrence of extreme rainfall events (e.g. Merz et al. 2004). Garrick et al. (2012) maintained that decision makers should focus on a system's vulnerability and develop the ability to "anticipate, cope with, resist and recover" from water security risks. System dynamics investment models linked to the variability of hydrologic events would be ideal tools to develop such abilities and support the decision-making process. This work is among the first to illustrate how real-world environmental data can be used with a SD metal mining model to study the effects of water risks on metal mining project feasibility.

The paper presents the methodology used to describe hydrologic and the economic variability and an approach to combine them in a unique investment model. It describes how the approach can improve predictive outcomes and presents a case study of a long-term mining investment using real-world precipitation data.

Methodology

Modeling Metal Mines with System Dynamics

The SD model of metal mining investments used in this research was introduced in Savolainen et al. (2017a), where its key SD characteristics—namely modularity and feedback loops—were presented in detail. The model mimics the characteristics of real-world mining investments, where different aspects—most importantly production rates, cashflow (CF), and the balance sheet—simultaneously affect the overall economic profitability of the mining investments studied. These "aspects" are presented as stand-alone sub-models tied together by immediate, or delayed, interactions that originate from feedback/feed-forward loops and stocks.

As a simple example of the SD model, production during a long metal price recession results in a series of negative cash-flow periods (*feed-forward*). This in turn decreases the accumulated cash balance (*stock*), which in turn inhibits production (*feedback*) in the long-term. In other words, a permanent abandonment option would be exercised in the simulation if the cash runs out and the accumulation of losses to the owners is stopped. The SD model accounts not only for the variability in key parameters, but more importantly models the reactions to changes by altering the outcomes when the changes occur. For example, one can create a trigger for temporary mine closure to limit economic losses and save the remaining ore reserves for the future.

The importance of modeling operational changes in metal mines is supported by Moel and Tufano (2002) who studied North American gold mines. They showed that most existing mines have been closed for some period of time. During times of lower metal prices, it may be economically favorable to temporarily stop mining and wait for the prices to recover. However, as mine closing and opening decisions entail large capital and operational costs, metal prices should be well below or above break-even profitability before making a decision to temporarily close or open, respectively, an operation. The hysteresis effect of real investments has been discussed, e.g. Dixit and Pindyck (1994) and Dixit (2004).

The SD model used is generic in the sense that the number of sub-models attached to it is not limited. For the purposes of this study, we created a stand-alone SD water management sub-model with a (water) stock and feedback loop interaction. This sub-model is attached to the SD model. It should be noted that the water balance sub-model may be replaced by any hydrogeological model. A schematic diagram of the SD model used is presented in Fig. 1, and a detailed function block-diagram of the water management sub-model is shown in Fig. 2a. The model is created in and runs on the Matlab®/Matlab Simulink® software environment.

Modeling Rainfall Extremes

The probability of rainfall events is modeled in this work using the extreme value theory (EVT). The foundation of EVT stems from the need to estimate the probability of events that are less frequent but more intense than common low-intensity events (e.g. Coles 2001). EVT is used to describe the stochastic frequency (or probability of occurrence) of rainfall events using parametric analysis and distributions with heavy tails. Traditionally, daily rainfall events have been statistically described using heavy-tailed models, such as the Generalized Extreme Values (GEV) model (Papalexiou and Koutsoyiannis 2013), the Gamma model (Aksoy 2000), and the Generalized Pareto (GP) model (Solari et al. 2017; Van Montfort and Witter 1986). The modeling described in the paper is for precipitation falling as rain and is not relevant for precipitation falling as snow.

The question of which EVT model best describes the data is currently debated in the literature, in light of the potential implications of non-stationarity of the time series

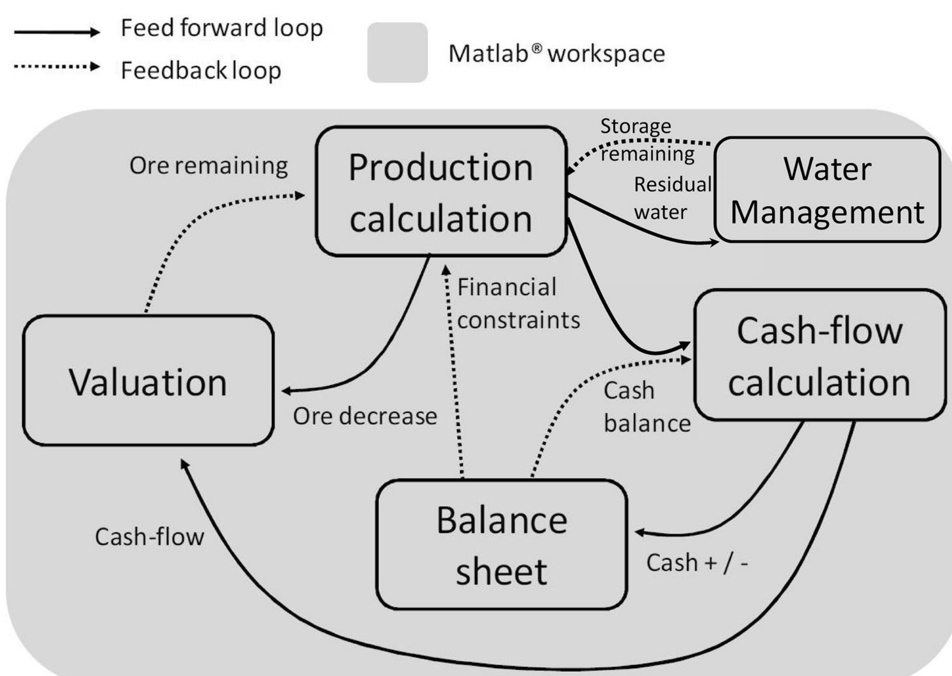


Fig. 1 Schematic diagram of the applied system dynamics model of a metal mining investment

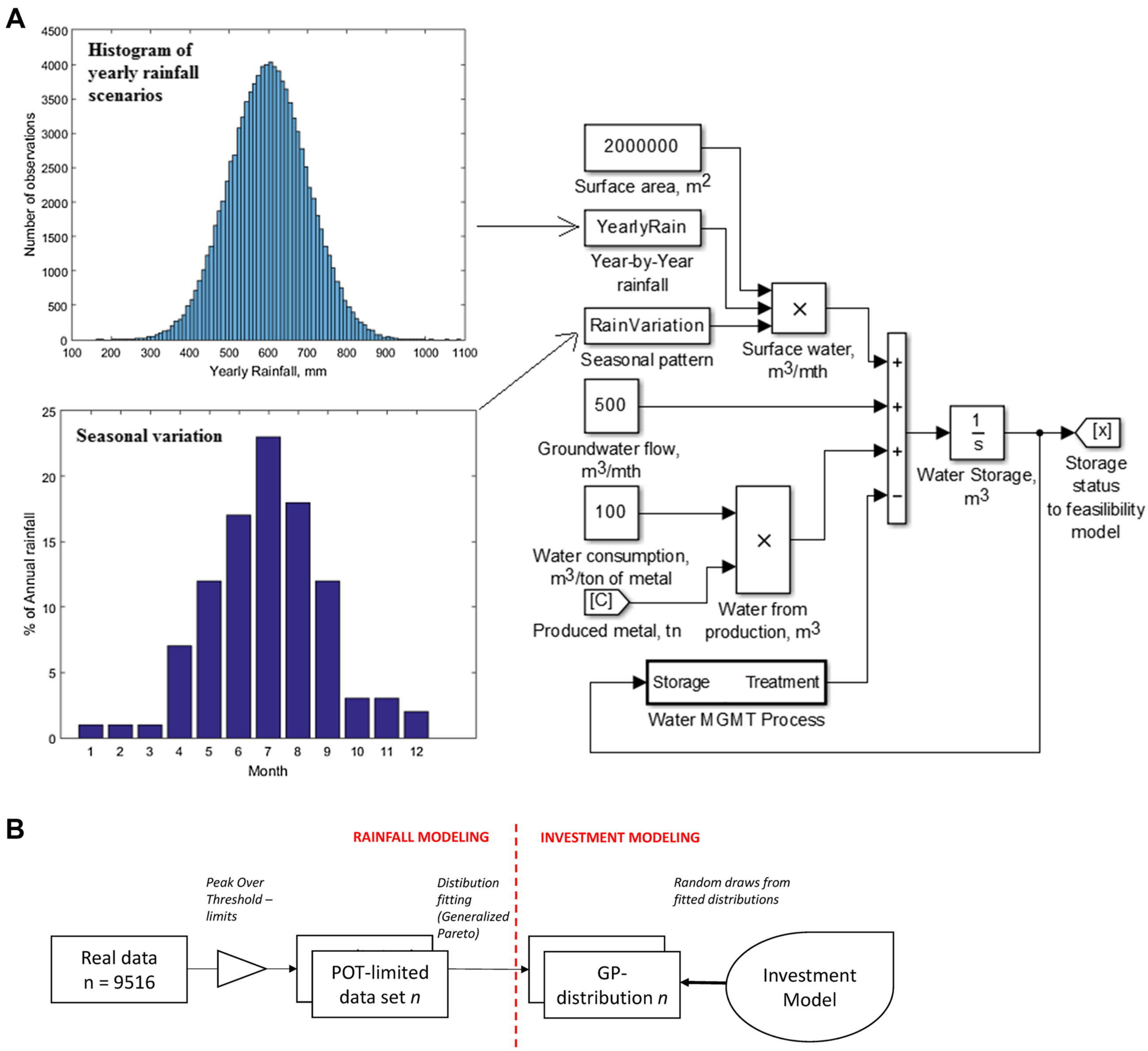


Fig. 2 Rainfall data input to metal mining investment model. **a** The general model structure from the input file to the output binary decision, with a Gaussian distribution illustrative of a probabilistic distribution of entry data. **b** The sequence of steps for application to the specific dataset tried in this work using the Generalized Pareto model fitting the peak-over-threshold statistics

used, driven by changes in the climate and other time-dependent factors (e.g. Milly et al. 2008; Serinaldi and Kilsby 2015; Pedretti and Irannezhad 2018). This debate falls outside the scope of this research, given that the main purpose of this work was to illustrate how to incorporate general hydrologic uncertainty in industrial economic models. We used an established approach based on the well-known stationary peak-over-threshold (POT) analysis method (e.g. Smith 1990; Coles 2001; Pedretti and Beckie 2016; Pedretti and Irannezhad 2018), which evaluates the parametric distribution of the extremes of empirical rainfall distributions that exceed a given threshold, θ. The implication of the selection of a different modeling approach is left open for a future extension of the analyses in this paper.

Using a stationary POT model, it can be shown that the GP model represents a robust solution to describe the tails of the empirical rainfall distributions (e.g., Serinaldi and Kilsby 2014). This is particularly true for increasing thresholds, as the distributions tend to follow a power-law function for $\theta \to \infty$. The probability density function (pdf) of the GP model can be defined as (e.g. Pedretti and Beckie 2016):

$$g(r|k,\sigma,\theta) = \left(\frac{1}{\sigma}\right)\left(1 + k\,\frac{r-\theta}{\sigma}\right)^{-1-1/k}, \tag{1}$$

where r is the daily rainfall intensity [mm/day], k is the shape, and σ is the scale. The parameter k controls the power-law tailing of the distribution; for a specified θ and σ, a larger k determines a larger amount of extreme rainfall events. Conversely, the parameter σ controls the total variability of the data (similar to the standard deviation in a Gaussian model); for specified θ and k, a larger σ determines a broader distribution of values having the same power-law geometry (controlled exclusively by k). The best fitting parameters of the GP model can be found in several ways. As for other power-law models, the best-suited parametric estimation approach is usually found by means of maximum likelihood estimation, MLE (Clauset et al. 2009).

Despite the expected better fit of the GP model for increasing thresholds, θ cannot increase indefinitely, as a larger θ also corresponds to a lower amount of POT samples, n_p. A trade-off between fitting capability and n_p must be found. Finding an optimal threshold $\left(\theta_e\right)$ has been the subject of multiple studies and is currently being debated (e.g. Solari et al. 2017). The visual assessment of probability plots provides a first-cut approach to evaluating θ_e. Less subjective, more quantitative methods can also be used. A consolidated approach is the goodness-of-fit test, based on the Kolmogorov–Smirnov (KS) test, in which a distance is quantified between the empirical distribution function of the samples, F, and the cumulative distribution function of the modeled distribution, G. We define D as the sum of this distance, such that:

$$D(\theta) = F(r|\theta) - G(r|\theta), \tag{2}$$

using Eq. 2, θ_e is the optimal threshold, above which D tends to a constant, quasi-asymptotic value close to zero, as illustrated with an example that follows.

Connecting the Rainfall Model to the Metal Mining Investment Model

The SD mining model can embed multiple parametric models to describe $g(r|k, \sigma, \theta)$. The selected distribution is used to generate a set of Monte Carlo simulations of the investment model, as illustrated in Fig. 2b. The SD model uses a discrete monthly time-step, and monthly aggregated rainfall data were created and used as input to the model. Using a shorter step time would be unlikely to produce any additional insights to the cash-flow (CF) modeling due to the joint uncertainty caused by several parameters. We believe that the monthly time-step is robust enough to allow for good control of the model and give accurate enough analysis for the purposes of this research. The total timeframe of SD simulations performed was set to 300 months.

A random monthly rainfall input to the investment model was created as follows:

- 31 random daily precipitation events were drawn from the modeled GP distribution and summed to generate the monthly precipitation for each of the 300 simulated months. We assumed that varying the length of individual months (from 27 to 31 days) would not play a significant role, considering the overall simulation accuracy.
- The obtained sum of random draws was multiplied by 365/12/31 ($\approx$0.98) to represent the average length ($\approx$30.4 days) of a month in a year, so in fact every month was assumed to be $\approx$30.4 days long.

The other key parameters used in the SD metal mine model are listed in Table 1. We note that in Savolainen et al. (2017b), the water balance model assumed a Gaussian distribution with a mean cumulative annual precipitation R of 600 mm, a standard deviation of 150 mm, and an arbitrary water output limit of 200,000 m^3/month. In the present study, we increased the output to 300,000 m^3/month to cope with the overall larger water amounts derived from the empirical distribution fitting. The critical limit of water balance, l_{crit}, to avoid pit flooding was set to 1 Mm^3. No seasonal patterns of water flows (e.g. Fernández-Álvarez et al. 2016; Sahu et al. 2009) or possible discrete changes in water flows (Rapantová et al. 2012) were considered. In the case of an operating mine, these characteristics could be derived from measured

Table 1 Numerical values of key uncertainties (adopted from Savolainen et al. 2017b)

Variable	Unit	Pessimistic	Most likely	Optimistic	Volatility, %
Reserve size	Tons	72,000	140,000	210,000	–
Metal yield	Tons/month	1000	1200	1400	10
Production ramp	Tons/month	50	100	200	–
Unit cost	EUR/ton	4000	3500	3000	–
Fixed cost (operating)	EUR/month	3,500,000	3,000,000	2,500,000	–
Fixed cost (closed)	EUR/month		500,000		
Construction time	Months	36	24	12	–
Construction cost	EUR	80,000,000	60,000,000	40,000,000	–
Unit price	EUR/ton	14,000	16,000	18,000	5
Exchange rate	USD/EUR		1.1		–

precipitation data and a detailed hydro-geological model and added to the water balance sub-model for additional insight.

Traditionally, metal mining investments have been valued using static net present value (NPV) calculations, or other discounted cash-flow (DCF) based approaches. According to Brennan and Schwartz (1985a, b), a metal mine can be valued analogically to a financial option. That is, the owner of the metal mine holds an *option* to operate the mine when the metal sales price exceeds the cost of production, and the option to temporarily close the mine during metal market price recessions. In addition to the temporary closure option, other flexibilities to steer metal mine profitability exist, such as mine planning, contracting, and expanding production—these are typically referred to as *real options* (e.g. Savolainen 2016; Newman et al. 2010).

In this paper, we view the effective and active water management of a metal mine as a real option (RO) that has an effect on the overall economic return from the mine. To determine the real option value (ROV), Trigeorgis (1993) proposed the following method, based on comparing an investment's NPV with and without the real option:

$$[\text{Value of Real Options}] = [\text{Expanded NPV}] - [\text{Passive NPV}]. \tag{3}$$

In Eq. 3 [Expanded NPV], refers to a case in which the value of real options has been taken into account (e.g. by considering the effect of temporary mine closure), and [Passive NPV] is the static NPV under a fixed operation mode.

Model Application: A Case Study

As an illustrative example of how SD models can be used to generate relevant and high-quality decision support for mining operations in a way that combines economic and environmental analyses, we analyzed the effects of extreme rainfall events on a hypothetical metal mine operating in a location potentially exposed to flooding.

Modeling the Flooding of an Open-pit Mine

The problem is conceptualized as presented in Fig. 3. An open-pit metal mine is designed to optimally operate under normal (non-flooded) conditions (Fig. 3, top). The mined ore is fed into the concentration plant, where water is used for ore processing. Residual water from the concentrator is pumped to a water-storage facility before final treatment and discharge. Under anomalous, or undesired conditions, such as a pit flooding event (Fig. 3, bottom), water accumulates in the pit after collapsing the drains. The pit flooding causes the mine to temporarily interrupt ore processing, resulting in a negative cash flow and economic losses. Given that the SD model combines the use of hydrologic and economic variables, the two major ingredients for estimation of economic losses associated with flooding events are:

a. the probability of occurrence of volumes of water that cause flooding of the open pit; and

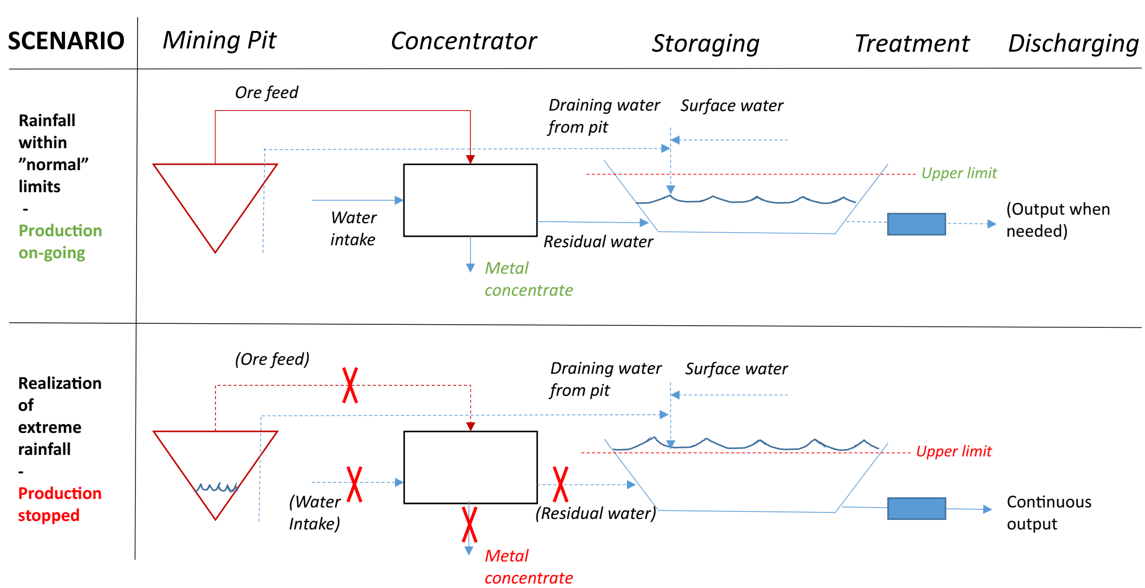


Fig. 3 Conceptual model of the problem analyzed in this research. Above: Designed operation mode: residual water from concentrate production and open pit is pumped into storage and treated. Below: Extreme rainfall event: only water from the open pit is pumped into storage and treated—there's no room to store residual water from concentrate production and the production is stopped to avoid flooding of the mining pit

b. the estimation of the economic damage caused by the ensuing interruption to ore production.

The probability of flood waters entering the open pit (a) can be calculated in several ways. It is reasonable to associate these volumes with excessive run-off resulting from extreme precipitation, expressed, for example, as daily precipitation rates r [mm/day]. During extreme events, rainfall rates tend to exceed evaporation and infiltration rates and the storage capacity of the subsurface, generating run-off (e.g. Boughton 2007). Because the occurrence of extreme rainfall events is random at a given site, the occurrence of run-off and pit flooding is also random and can be estimated in two general ways. The most correct yet unrealistic option (in many practical mining conditions) is through the direct measurement of flooding volumes. Very often, rainfall is sparsely distributed upgradient of open pits and results in diffuse sources of run-off entering the open pit that are not necessarily funneled in a single stream or water body (where a gauge station could be located). Due to this difficulty, an indirect approach is used to estimate the probability of flood events, based on a water balance model and measured rainfall from a weather station located at a mining site (e.g. Beven 2012; Chiew et al. 1993). Here, we used the water balance model approach. Since we are interested in evaluating the effects of hydrologic randomness on economic investments, we used a simplified stochastic modeling approach, in which we assigned the same probability of occurrence of rainfall extremes to the occurrence of pit flooding events characterized by a specific water volume. In reality, the two probabilities may be different, given that the amount of run-off generated from precipitation inputs can be highly nonlinear (e.g. Bo et al. 2018; Romanowicz et al. 2006). Nevertheless, the conclusions of this study from the method demonstration point of view are not limited by this assumption, as such non-linearities, derived from the mine specific hydrologic model, can be included when dealing with a real world case.

A number of previous studies have identified precipitation extremes as one key variable limiting the global distribution of economic growth, because private investors prefer developed countries without water security related risks (e.g. Dadson et al. 2017; Khan et al. 2017). Therefore, embedding a real-world probability-based model with either real-world rainfall or run-off events is valuable in terms of obtaining more information on the profitability effects of these events and generally in making the model more holistic and realistic.

The estimation of the economic damages caused by interruptions in ore production (b) depends on the market situation at the time of the interruptions. Regardless of the water balance, it may sometimes be favorable to temporarily stop mining during the recession of prices. In our illustrative example, the cost to temporary stop the mine was set at 1.2 million Euros (M€) and the re-opening cost was set at 0.5M€ (see Table 1). These costs effectively restrict the shutdown-restart flexibility of the investment only to situations caused by critical water imbalances.

The first step in calculating the rainfall-related financial risk to mining is to compute the probability of a pit flooding event that can generate an economic loss. Using the pdf of rainfall events, *g(r)* (Eq. 1), the current level of water storage, *l(T)*, is written as:

$$l(T) = \int_0^T r(t)g(r)dt + \int_0^T \left[\textit{residual water from production}\right](t)dt - \int_0^T \left[\textit{discharge}\right](t) + l(T_0), \tag{4}$$

where *l(T)* is constrained to be ≥ 0, which is met by automatic adjustments of the *residual water* and *discharge* terms in the SD model (the residual water term is set to zero by a temporary stoppage of production), and the initial level is between $0 \leq l(T_0) \leq l_{max}$.

As explained in the previous section, we assume that the uncertainty in rainfall is the key factor affecting the probability of pit flooding. The probability of pit flooding (and the volume of water entering the pit) is assumed to be fully characterized by rainfall probability *g(r)*, which is associated with the probability of pit flooding $g(f)$ through the expression:

$$g(r) + l_{crit} = g(f), \tag{5}$$

where l_{crit} is the critical level of water storage needed to avoid pit flooding. During periods of critical water storage levels, we assign the same probability used for an extreme rainfall event to a flooding event that can potentially prevent open pit mining and generate an economic loss of an uncertain magnitude. While this is a simplification of the hydrologic process, we note that the essential randomness of events in the investment model is preserved. Because a probabilistic function is used in modeling rainfall and thus the risk of "mining failure," we conclude that this linear transformation does not have an effect on the conclusions drawn.

Equations 4 and 5 dictate the behavior of the water-balance sub-model (see Fig. 2a). The water storage level depends directly on stochastic pit flooding volumes during rainfall events, as well as on the fixed water inflows from metal concentrate production and mine dewatering. Thus, the amount of water is directly linked to the probability of the extreme rainfall events, $g(r)$. The monthly metal output in the production sub-model is fixed by default, and the production on/off decision serves as a binary control variable that is based on the actual level of water storage.

That is, a temporary stoppage decision will set the *residual water from production*–term (Eq. 4) to zero and steers the overall water-balance.

As a summary of the problem setting: the investment model dynamically tracks the development of the water-balance at the mining site, and, if pit flooding occurs, stops the production of metal concentrate to ease the water situation. It is noted here that the water management continues "as-is" and keeps on accruing operational costs to the owners. Using this logic, running *n* rounds of pseudo-random simulations (Monte Carlo) on the investment model with random rainfall realizations derived from historical data, the probability and magnitude of the economic effects of rainfall (events) can be estimated using Eq. 3. If the project runs out of cash, the metal mining operation is abandoned, and the accumulation of production and water management related costs stops. The costs related to permanent shutdown are assumed to be included in the pre-paid environmental provision, which is (modeled here as) a part of the initial investment cost. For the purposes of this research, we have left out a detailed consideration of the full economic consequences of a permanent mine shutdown from our model and "only" focused on the normal state of the operations, including temporary shut-down periods.

Peak-over-threshold Evaluation of Rainfall Variability

We applied the SD model and the proposed method to a metal mining case with real rainfall observation data from the Äänekoski-Kalaniemi weather station in Finland. The precipitation data were used to estimate the rainfall-model parameters for the water balance model (Figs. 1, 2). The collected data consist of daily rainfall measured between Jan 4, 1965 and Feb 22, 2016 by the Finnish Meteorological Institute, and can be considered an adequate set of data for the purposes of runoff modeling. However, as in many other rainfall series, the available dataset is incomplete. Here, approximately 50% of the data are missing, as 9,516 measurements for a total of 18,987 days exist. However, the selected POT-method is robust enough to handle the presence of missing records. Indeed, the approach works even with strongly incomplete time series, where a minimal number of records exists, and is able to build an empirical distribution that reflects the overall variability of rainfall events.

The resulting empirical cumulative distributions (Eq. 1) of the estimated rainfall using the GP model are shown in Fig. 4a. Figure 4 also displays the other tested best-fitting heavily tailed models in the form of probability plots, namely *Gamma, Gaussian, GEV*, and *LOG* (logarithmic) models. Each panel shows a different result for increasing the rainfall threshold, θ, applied to the source data as a filter. We note that the observed rainfall data span from 0 to 70 mm/day, and most observations lie between 0 and 20 mm/day, with a probability of $\approx 99\%$. Put another way, rainfall events with intensities of up to 20 mm/day are expected at least once every 100 days. Naturally, more extreme events, grossly exceeding 20 mm/day, have an even lower probability of occurrence. For instance, a rainfall event of 40 mm/day is expected once every 1000 days, given that its probability lies somewhere around 0.1%. Although the frequency of high-intensity events becomes many times lower than that of low-intensity events (e.g. the estimated 10-fold difference), it is of fundamental importance to properly calculate the occurrence of the highly improbable, rare events, from the water-security point of view. That is, high-volume, low-probability events are essentially the events that are associated with the potential extreme run-off volumes and consequently pit flooding risk and temporary mine closure.

The probability plots in Fig. 4a emphasize the extremes of the distributions. While all the tested models result in the same behavior for low probabilities ($P < 10\%$), at the extremes, no model provides a good fit with the empirical data (marked with circles). The best-fitted Gaussian model (black line) seems to largely underestimate the extremes, as the calculated probability of occurrence of events with intensity $r > 30$ mm/day is virtually non-existent. In contrast, the GEV model (dashed yellow line) tends to overestimate the extreme values, given that an event with an intensity of 70 mm/day has a probability of 5%, which corresponds to a theoretical frequency of one event every 20 days. The GP (solid red line) also overestimates the extremes of the data for $\theta = 0$ mm/day. However, consistent with the theoretical behavior of this model, the GP tends to increase "matching of the extremes" with an increasing θ. While the other models still incorrectly estimate the probability of rare events, the GP provides a satisfactory fit with all the used empirical data for $\theta > 1$ mm/day, including the very intense, least frequent events (e.g., $r = 70$ mm/day).

An optimal threshold for the empirical dataset, θ_e, can be found by using the Kolmogorov-Smirnoff test (Eq. 2). This is illustrated in Fig. 4b, where the cumulative distance D is plotted against θ. In this case, the distance goes to an asymptotic minimum value $D \approx 10$ for $\theta = 3$ mm/day or larger values. As such, the threshold $\theta_e = 3$ mm/day can be identified as an optimal value, when taking into account the trade-off between realistic extreme events fitting (= increasing θ) and the preservation of the original data (= decreasing θ). We still considered and used a range of values for θ to study the sensitivity of the results with regard to θ to highlight the importance of the selection of the threshold, θ, and the corresponding GP parameters (k, σ). The best-fitting parameters for θ range between 0 and 9 mm/day (Table 2).

Using an increasing threshold, θ, in GP modeling (0–9 mm in this study) leads to a decreasing number of simulated rainy days, with higher daily sums. In other words, the

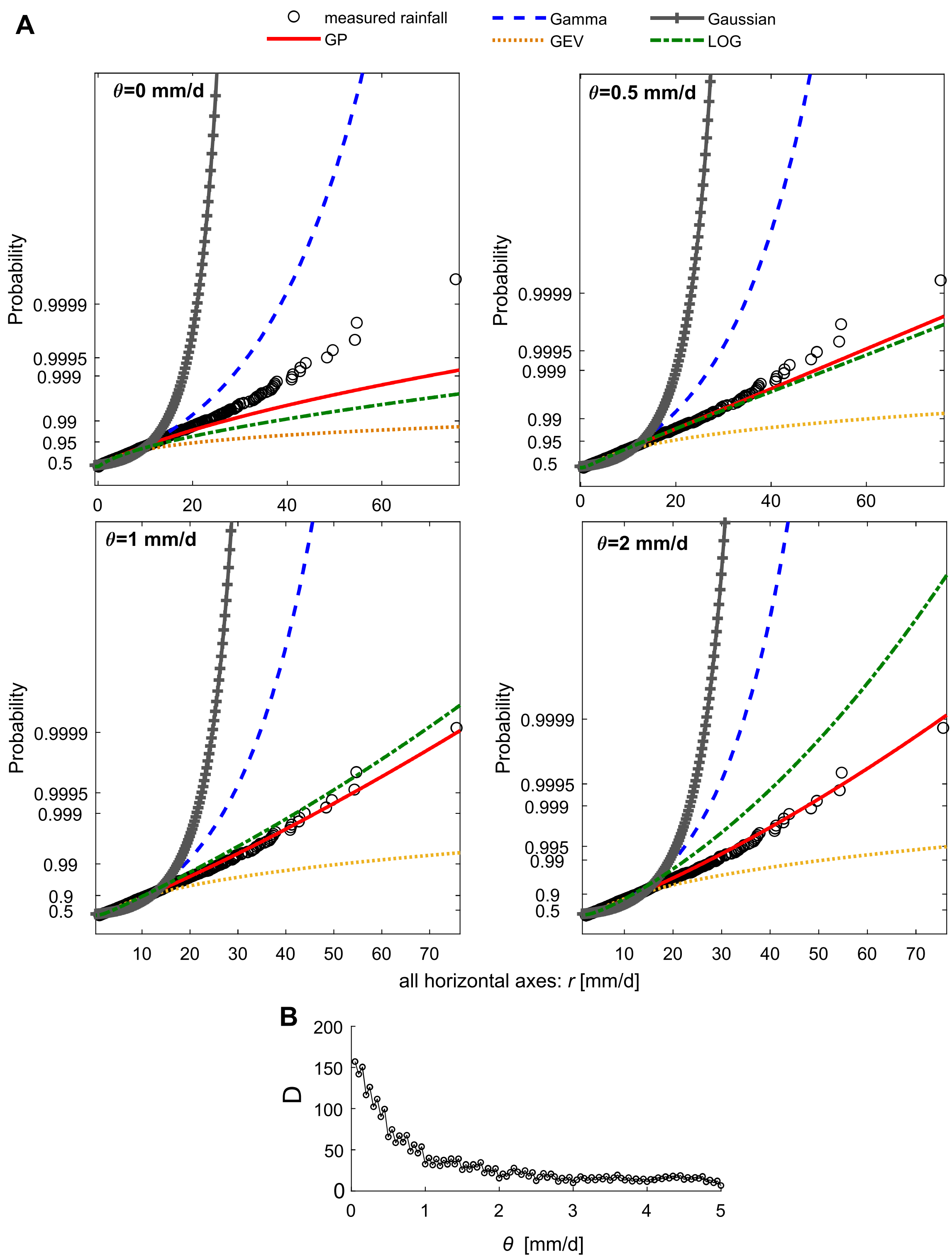


Fig. 4 **a** Empirical cumulative distributions of measured daily rainfall intensity, r, with different distribution fittings (*GP* generalized pareto, *GEV* generalized extreme value, *LOG* logarithmic). **b** The Kolmogorov–Smirnov test for estimating the optimal threshold, θ_c, for GP-model fitting

Table 2 Rainfall distribution parameters from distribution fitting and comparison with the actual data

POT-limit	Distribution parameters		Sample size		Avg. yearly rainfall		0.999 perc of daily rainfall	
mm/day	k	sigma	n	vs. Act	mm/year	vs. Act	mm/day	vs. Act
Actual			9082	–	1150	–	41.00	–
Naïve[a]		*149*			*1188*[b]	*38*	*4.52*	*− 36.48*
0.0	0.347	2.289	9082	0	1249	99	68.76	27.76
0.1	0.265	2.655	8614	− 468	1248	98	55.65	14.65
0.3	0.126	3.518	7563	− 1519	1251	101	38.63	− 2.37
0.5	0.044	4.268	6737	− 2345	1236	86	35.66	− 5.34
1.0	− 0.049	5.507	5547	− 3535	1249	99	31.73	− 9.27
2.0	− 0.139	7.355	4140	− 4942	1224	74	33.41	− 7.59
3.0	− 0.197	9.010	3204	− 5878	1188	38	34.60	− 6.39
4.0	− 0.243	10.569	2535	− 6547	1210	60	35.96	− 5.04
5.0	− 0.291	12.387	1955	− 7127	1182	32	36.65	− 4.35
6.0	− 0.332	13.978	1582	− 7500	1188	38	38.16	− 2.84
7.0	− 0.379	15.843	1255	− 7827	1197	47	38.88	− 2.12
8.0	− 0.429	17.851	998	− 8084	1191	41	39.40	− 1.60
9.0	− 0.483	20.021	798	− 8284	1197	47	39.99	− 1.01

The most realistic fitting in relation to the original data is achieved using POT threshold of 3 mm/day

[a]Normal distribution

[b]Based on naive analysis of actual data: [avg rainfall, mm/day] * [365 days/year]

random drawing for these distributions suggests illogically that there is a minimum amount of rain, greater than zero, that can fall daily (e.g. >1 mm/day). We use uniformly distributed data to compensate for the reduction in the number of samples, n_p, as θ increases, and we formulate the estimation of cumulative rainfall over a period of T days as follows:

$$R_c = T\left[\frac{n_p}{N}\overline{r_{GP}} + \left(1 - \frac{n_p}{N}\right)U_\theta\right], \tag{6}$$

where N is the total number of samples, $\overline{r_{GP}}$ is the mean value of the GP-estimated rainfall values exceeding θ that enclose the fitting parameters k and σ, and U_θ is a uniformly distributed random number between 0 and θ.

Results and Discussion

The SD model is used to evaluate the implications of the hydrologic modeling parameters discussed above on the overall profitability of the mine. Figure 5 shows the mean net present value (NPV, circles) resulting from over 1000 Monte Carlo simulation runs that in the context of this case correspond to over one thousand simulated rainfall accumulations and their effect on mine profitability. The red line is the reference NPV (23.1 M€) that represents the attainable "benchmark" value of the project excluding water-balance issues. The results show that not taking water balance issues into account will result in an unrealistic over-estimation of project value if a rainfall event causes the temporary shutdown of the open pit. It can be noted that all results generated with the SD model using empirical data-based rainfall distributions are below the benchmark NPV. Table 3 shows the results, which indicate a clear non-linear loss of NPV as total rainfall increases.

To evaluate the effects of different proportions (probabilities) of extreme rainfall events, we extended the interpretation of the simulation results to include simulations with generic GP parameters. In this case, the total rainfall is not constrained by the empirical data set, as the daily rainfall is calculated exclusively based on the contribution of POT values. In this vein, we calculate the cumulative yearly rainfall as:

$$R_{un} = 365\,\overline{r_{GP}}, \tag{7}$$

where R_{un} is the unconstrained cumulative annual rainfall, in contrast with the constrained cumulative yearly rainfall, R_c, calculated using Eq. 1, and depends exclusively on the GP parameters k and σ used to run the simulations.

The mean NPV results attained (Fig. 5, cross-marks) imply that there is a certain limit of annual rainfall (R < 1086 mm/year) that has no effect on the economic value of the mining operation. We refer to this condition as an "economically safe zone." An "uncertainty zone" is found when R is between 1086 and 1609 mm/year, during which the NPV moves from positive values to strongly negative values. This suggests that the value of the project declines dramatically as capacity constraints in water management

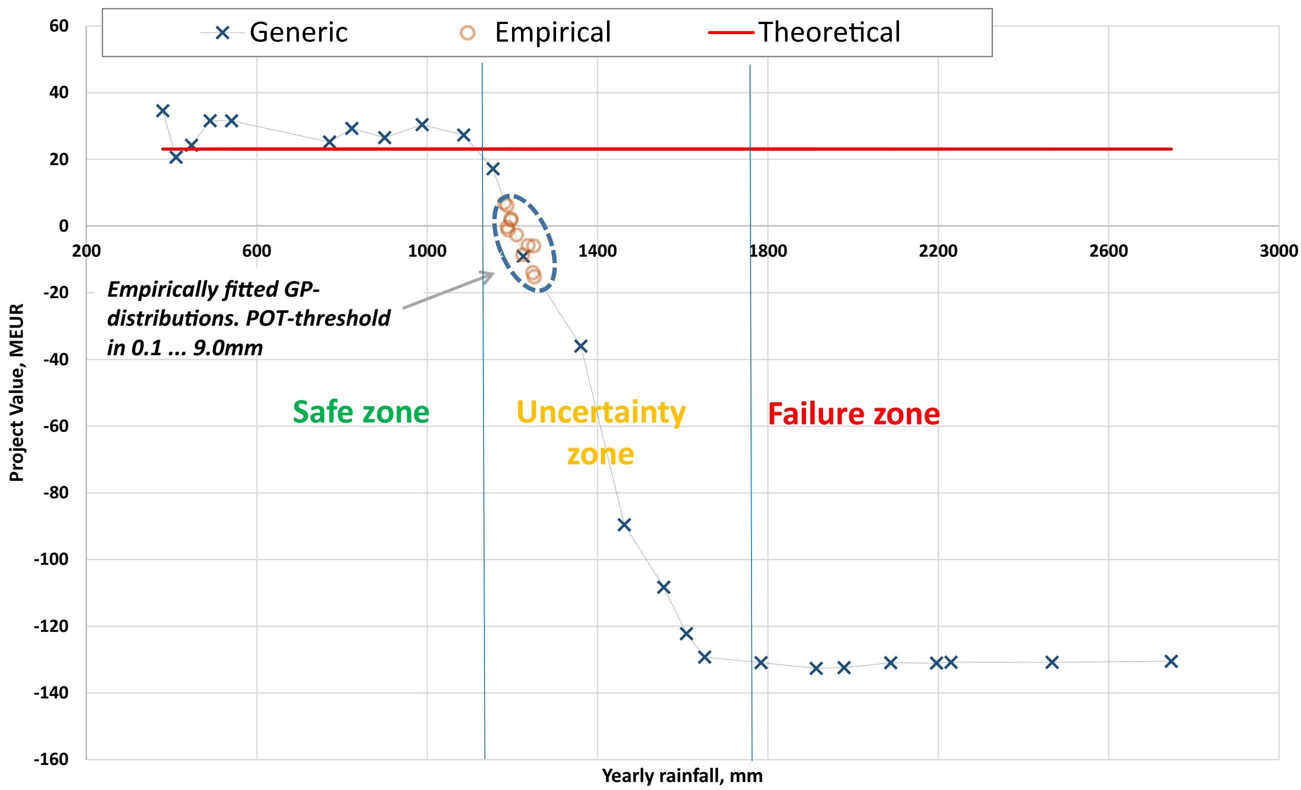
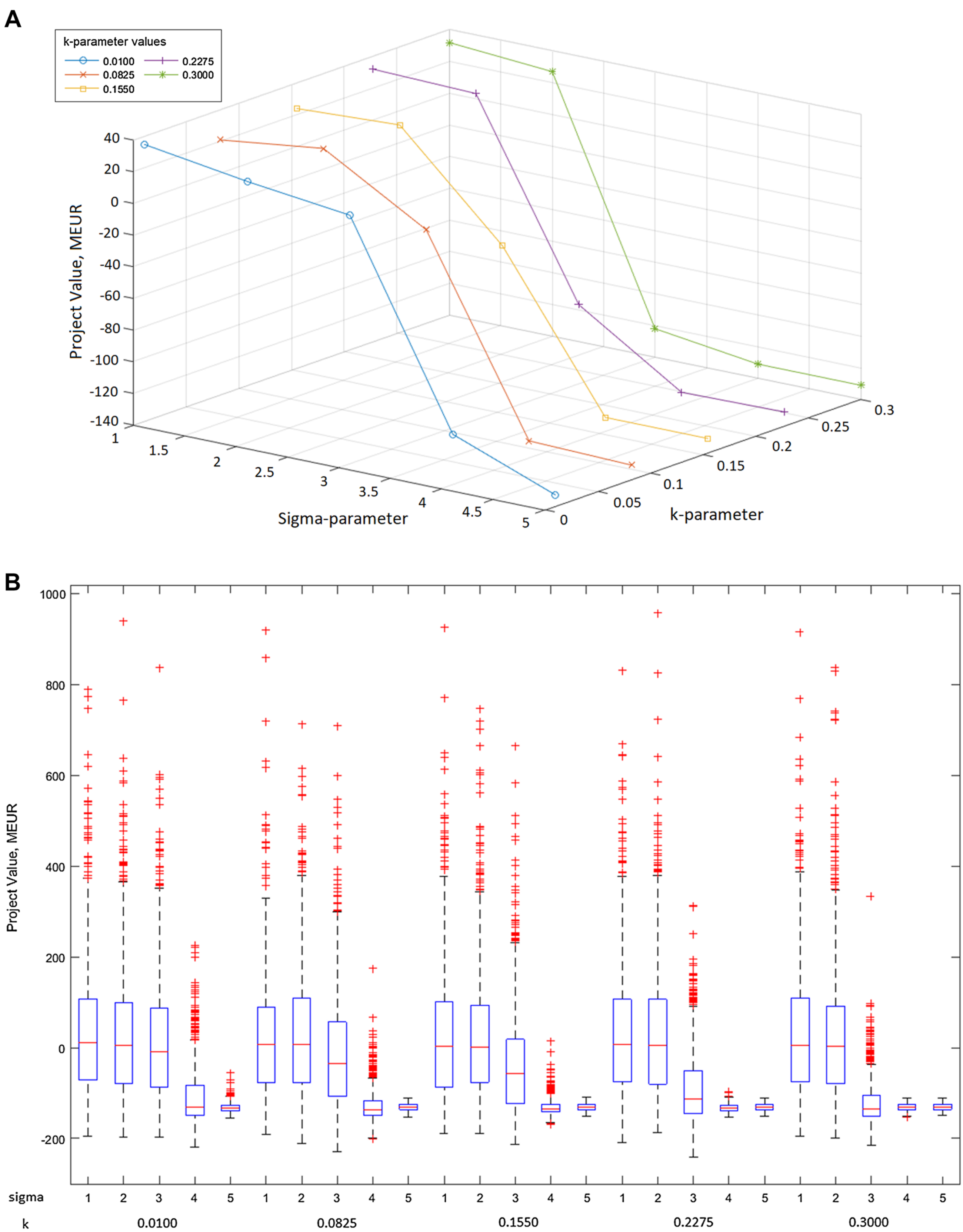


Fig. 5 Sensitivity analysis of the project value (NPV) in millions of € (MEUR), as a function of the total cumulative yearly rainfall occurring at the mining site and directly related to flooding volumes. The red line represents results from a model that does not consider the water balance restrictions, and shows that the negative effects of high rainfall to the profitability are not captured properly. Accounting for the water balance creates a much more realistic and credible picture of the profitability of the mining investment under different rainfall conditions, and creates an incentive for investing in water treatment, because uncontrolled problems with water are likely to cause greater costs than the additional investments into proper water management would entail

Table 3 Monte Carlo simulation results ($n = 1000$ rounds/row) of a feasibility analysis of metal mining investment using different POT-threshold assumptions in creating GP-distribution for the investment model's input

GP-model's	Net present value			ROV(*)	Abandons	Value lost	Diff
POT-thresh, mm	Mean M€	< 0, n	> 0, M€	M€	n	M€	vs. Naïve
Unconstr.	23.1	494	129.0	65.2	146	–	19.2
Naïve	3.9	568	124.4	53.7	187	− 19.2	–
0.0	− 26.5	656	100.5	34.6	254	− 49.6	− 30.3
0.1	− 14.0	599	101.2	40.6	217	− 37.0	− 17.8
0.3	− 15.1	637	112.0	40.7	192	− 38.2	− 19.0
0.5	− 5.7	590	114.4	46.9	214	− 28.8	− 9.5
1.0	− 5.8	592	110.6	45.1	199	− 28.9	− 9.6
2.0	− 8.4	600	113.8	45.5	204	− 31.5	− 12.2
3.0	− 0.2	575	119.7	50.9	186	− 23.3	− 4.1
4.0	− 2.5	569	107.4	46.3	168	− 25.6	− 6.4
5.0	6.9	539	115.2	53.1	178	− 16.2	3.0
6.0	6.1	546	114.1	51.8	174	− 17.0	2.3
7.0	2.2	555	111.4	49.6	177	− 20.9	− 1.6
8.0	− 1.1	577	118.0	49.9	196	− 24.2	− 5.0
9.0	1.8	571	119.7	51.4	170	− 21.3	− 2.1

The NPVs are compared to the case without having water balance modeling in place ('unconstrained') to calculate 'Value Lost, M€'—indicator


A
k-parameter values
0.0100
0.0825
0.1550
0.2275
0.3000
Project Value, MEUR
Sigma-parameter
k-parameter
B
Project Value, MEUR
sigma
k
0.0100
0.0825
0.1550
0.2275
0.3000

◂**Fig. 6** **a** Ensemble-mean net project values as a function of GP parameters. The yearly water balance is unconstrained and increases for larger k and/or σ. **b** Box-plot summary of project value distributions (i.e., box sizes in the figure) from the sensitivity analysis. The line inside each box represents the sample median and shows the possible skewness of the results. The box-sizes and whisker-lengths emphasize the uncertainty of the results by representing the 25th and 75th statistical centiles. The red plus-signs in the diagram indicate statistical outliers (> 1.5 times the box height (interquartile range) of the top or bottom of the box)

seriously inhibit the operational efficiency. That is, the mine suffers from temporary shutdowns due to exceedance of critical water storage levels. A "failure zone" can be defined as $R > 1609$ mm/year, where the NPV becomes and remains negative, independent of any additional increase in pit flooding volumes.

From the point of view of the annual rainfall events, the NPV of the case study is in the zone of uncertainty. This result suggests that the long-term profitability of the mining operation will likely suffer from water-balance issues, given the uncertainty in rainfall variability derived from the historical data and the simulated water management measures on-site. From the project management perspective, it makes sense to study the feasibility of either adding water treatment capacity to allow greater discharge (which may be constrained by the environmental permit), or to increase water storage.

Figure 6a presents a three-dimensional plot of the sensitivity of the mean NPV to a set of extreme rainfall parameters. The selected range of parameters reflects typical values reported in the literature (e.g. Serinaldi and Kilsby 2014) and is in line with the best-fitting parameters, empirically obtained from the MLE analysis from weather data for the Äänekoski-Kalaniemi case study. The sensitivity analysis indicates that there is a clear relationship between project value and the GP parameters. Rainfall distributions are predominantly controlled by the k (shape) and σ (scale), although the parameter σ has a larger effect on the NPV than does k. For example, when $k = 0.01$ or $k = 0.3$, all scenarios with $\sigma = 1$ are in the safe zone economically and the NPV remains positive, while all scenarios with $\sigma = 5$ fall in the failure zone, regardless of the k value (see also Fig. 6b). The extension of the uncertainty zone, on the other hand, depends on the bivariate combination of the parameters k and σ. For $\sigma = 3$, a heavy distribution tail ($k = 0.3$) implies a shutdown of the mining operation, while a light tail ($k = 0.01$) implies a safe condition. The sensitivity analysis shows that the SD model is able to handle extreme parameters and capture the non-linear complex relationship between water-balance issues and profitability, via mine production and cash flows.

As shown in Fig. 6b, there is strong variability in project value depending on the selected rainfall modeling parameters. For low k scenarios (more symmetric distributions), the variability is much higher than for high k scenarios (more heavily tailed distributions). At the same time, the variability increases with higher σ values. However, while for low σ values all project outcomes are positive (including the statistical outliers, marked with red crosses), for large σ the median of all project outcomes tends to become negative, although a number of realizations behave differently. The reason for this observed model behavior stems from the fact that the investment model uses an aggregate of ≈ 31 daily observations with no seasonal patterns as a model input: it is statistically unlikely that a tailless distribution with high sigma-parameter would yield tens of extreme events in successive months. Therefore, the lowest project values are found in simulations with tailed distributions (large k). For example, for $k = 0.01$ and $\sigma = 3$, more than 42% of project value realizations are equal or greater than the reference NPV (23.1 M€), whereas for $k = 0.2275$ and σ = 3 the corresponding figure is only 9.3%. As such, while statistically the stochastic model suggests that on average the mining operations would fail economically (i.e. NPV < 0), if the rainfall distribution shows $k = 0.3$ and σ = 0.2275, it is possible that in approximately 1 out of 10 mining cases, the NPV is still unaffected by the adverse flooding conditions that limit production. A sensitivity analysis is provided in Table 4.

The above discussion shows that initial estimates of rainfall uncertainty can have a crucial effect on investment profitability. In real life, when estimating parameters from empirical rainfall distribution, an uncertainty in σ of one unit may not be an unusual result of analysis when the effects of subsampling complicate the estimation of GP parameters (e.g. Pedretti and Beckie 2016; Pedretti and Irannezhad 2018). While these effects reduce as the length of the analyzed time series increases, sometimes the only useful data available for a remote greenfield mining site are based on measurements from a recently-installed weather station on the site. As such, extra care is recommended when estimating long-term predictions for water balance requirements using EVT-based stochastic modeling approaches.

Conclusions

Adequately linking the randomness of environmental events to economic profitability is usually complicated by the large number of variables and processes involved, and a versatile modeling approach is required. In this work, we presented an approach that can integrate hydrologic uncertainty into a SD model of a metal mining operation. We focused in particular on a synthetic case study using real rainfall data, where we demonstrated the effect of extreme rainfall events on the resulting economic profitability of a mine. The model allows an examination of the effects of water balance issues

Table 4 Sensitivity analysis of rainfall modeling parameters

1 k	2 σ	3 NPV, M€	4 < 0, n	5 > 0, M€	6 ROV, M€	7 Ab., n	8 mm/year	9 mm/day	10 mm/month
0.0100	1.0	35	467	137	73	139	379	7.1	46.6
0.0100	2.0	25	479	129	67	145	771	14.0	97.6
0.0100	3.0	17	514	125	61	157	1155	21.9	144.8
0.0100	4.0	– 108	930	64	4	566	1555	28.4	190.8
0.0100	5.0	– 133	1000	NaN	NaN	1000	1913	36.3	225.9
0.0825	1.0	21	485	120	62	156	410	9.3	50.9
0.0825	2.0	29	464	128	69	148	823	18.5	104.1
0.0825	3.0	– 9	597	113	46	202	1226	28.4	157.8
0.0825	4.0	– 129	989	36	0	737	1651	38.9	208.5
0.0825	5.0	– 131	1000	NaN	NaN	1000	2088	44.1	268.5
0.1550	1.0	24	491	132	67	159	447	11.8	58.6
0.1550	2.0	27	498	132	66	139	900	24.2	121.4
0.1550	3.0	– 36	712	104	30	280	1361	36.9	184.5
0.1550	4.0	– 131	999	14	0	990	1784	48.6	244.0
0.1550	5.0	– 131	1000	NaN	NaN	1000	2230	60.9	290.3
0.2275	1.0	32	481	139	72	132	490	18.3	69.8
0.2275	2.0	30	487	140	72	147	988	37.3	136.0
0.2275	3.0	– 90	873	67	8	453	1463	51.6	221.5
0.2275	4.0	– 132	1000	NaN	NaN	1000	1979	70.4	278.8
0.2275	5.0	– 131	1000	NaN	NaN	1000	2467	91.3	370.0
0.3000	1.0	32	481	137	71	143	541	21.8	88.9
0.3000	2.0	27	484	132	68	159	1086	46.5	173.8
0.3000	3.0	– 122	973	47	1	643	1609	68.8	244.2
0.3000	4.0	– 131	1000	NaN	NaN	1000	2196	94.8	379.6
0.3000	5.0	– 131	1000	NaN	NaN	1000	2747	118.6	429.1

Key: [1, 2]: shape and scale parameters in GP model, respectively; [3]: Mean NPV (out of 1000 simulations); [4, 5]: number of positive simulation outcomes and their respective mean value; [6, 7]: Mean ROV and number of abandons, [8–10]: simulated distribution values (100 years)

on the long-term profitability of mining investments in a quantitative manner. A numerical example showed how the proposed method can make use of historical hydrologic data (in this case, daily precipitation) to create insights on the feasibility of an investment.

The modeled case study was found to be very sensitive to rainfall extreme variability. By using a GP model to describe the peak-over-threshold distribution of values exceeding predetermined thresholds, we found that the investment value strongly depends on both the shape (k) and scale (σ) rainfall parameters used in the GP model. For example, a change in scale parameter from $\sigma = 3$ to $\sigma = 4$ in the case study turned the expected project value from nearly positive to grossly negative. Given the difficulties in estimating statistical parameters describing variability in extreme rainfall events, sufficient safety margins must be considered when making long-term investments involving rainfall distribution uncertainty.

Water management investments that could prevent pit flooding and a temporary mine shutdown include adding water treatment and water storage. Based on the results from the illustrative case study, some general implications for decision making regarding water management investments may be suggested:

1. The results suggest that the relationship between hydrologic uncertainty and investment value distribution is non-linear and, in this case, negatively skewed; that is, higher hydrologic uncertainty leads to lower project value. Inadequate water management investments are as likely to destroy investment value as over-investing. Therefore, from a rational decision-making perspective, and assuming uncertainty of rainfall modeling variables such as incomplete historical data, the strategy for determining the size of an initial water management investment would be in the borderline area between safe and uncertain zones.
2. A gradual increase in water management capacity (storage and/or treatment) would likely result in the highest

overall returns on investment (ROI) in cases where more capacity is needed.

3. The view that water management investments are real options has been implicitly and intuitively applied in the mining industry (see point 2 above), even if the decision-making tools used may have been unable to handle the value of real options in the past.

The optimal level of water management investments will be left for future research efforts. Furthermore, the attained results could be refined by including trends into the simulation of future rainfall, e.g. to account for the effects of climate change on extreme rainfall distributions. Indeed, stochastic parameters associated with rainfall variability could be conditioned by nonstationary distributions, although uncertainty affects the actual observation of trends for limited empirical datasets (e.g. Serinaldi and Kilsby 2015; Pedretti and Irannezhad 2018).

The limitations of the study are related to the nature and availability of data. In this study, we assumed that all the relevant technical data for model building and uncertainties are parametric, whereas in real life industrial investments on the planning table often entail "non-numeric" uncertainties (such as environmental permits, technical development or changes in legal environment). In such cases, less detailed models should be considered.

With the approach proposed in this paper, a simulation-based real option study for *staged investment* of additional water management capacity could be performed by providing the SD model with an optional water management investment, which is only triggered (automatically) if the water balance is trending towards a critical level. This would radically decrease the water security risks without increasing the initial capital investment. However, the substantially longer time need to install water management capacity vs. the potentially rapid trend toward a critical water balance level must also be considered.

Acknowledgements Open access funding provided by LUT University. This research has been funded by the Finnish Cultural Foundation/Etelä-Karjalan rahasto (grant number 05172166) and the Academy of Finland project "Manufacturing 4.0".

References

Aksoy H (2000) Use of gamma distribution in hydrological analysis. Turk J Eng Env Sci 24:419–428

Ashby W (1958) Requisite variety and its implications for the control of complex systems. Cybernetica 1(2):83–99

Banerjee T, Siebert R (2017) Dynamic impact of uncertainty on R&D cooperation formation and research performance: evidence from the bio-pharmaceutical industry. Res Policy 46:1255–1271

Bartrop S, White AH (1995) Spade work: how miners value resources. JASSA (1):7–13. ISSN: 0313-5934

Beven K (2012) Down to basics: runoff processes and the modelling process. In: Rainfall-runoff modelling: the primer, 2nd edn. Wiley, New York, pp 1–23

Bhappu RR, Guzman J (1995) Mineral investment decision making: a study of mining company practices. Eng Min J. ISSN: 0095-8948

Bo L, Qiang W, Xian-Qian D, Meng-yu C (2018) Risk analysis model of water inrush through the seam floor based on set pair analysis. Mine Water Environ 37(2):281–287

Boughton WC (2007) Effect of data length on rainfall–runoff modelling. Environ Model Softw 22:406–413

Brennan M, Schwartz E (1985a) A new approach to evaluating natural resource investments. Midl Corp Fin J 3:42–47

Brennan M, Schwartz E (1985b) Evaluating natural resource investments. J Bus 58:135–157

Brown A (2010) Reliable mine water technology. Mine Water Environ 29:85–91

Caballero RJ, Pindyck RS (1992) Uncertainty, investment, and industry evolution. National Bureau of Economic Research: working paper # 4160

Chiew FHS, Stewardson MJ, McMahon TA (1993) Comparison of six rainfall-runoff modelling approaches. J Hydrol 147:1–36

Clauset A, Shalizi CR, Newman MEJ (2009) Power-law distribution in empirical data. SIAM Rev 51:661–703

Coles S (2001) An introduction to statistical modeling of extreme values. Springer, London

Collan M, Haahtela T, Kyläheiko K (2016) On the usability of real option valuation model types under different types of uncertainty. Int J Bus Innov Res 11:18–37

Côte CM, Moran CJ, Hedemann CJ (2007) Evaluating the costs and benefits of salt management strategies at mine sites using a systems model. Mine Water Environ 26(4):229–236

Dadson S, Hall JW, Garrick D, Sadoff C, Grey D, Whittington D (2017) Water security, risk, and economic growth: insights from a dynamical systems model. Water Resour Res (In Press) 53(8):6425–6438

Dixit AK (2004) Investment and hysteresis. In: Schwartz ES, Trigeorgis L (eds) Real options and investment under uncertainty. The MIT Press, Cambridge, pp 153–178

Dixit AK, Pindyck RS (1994) Investment under uncertainty. Princeton University Press, Princeton

Easterling DR, Meehl GA, Parmesan C, Changnon SA, Karl TR, Mearns LO (2000) Climate extremes: observations, modeling, and impacts. Science 289:2068–2074

Eves C (2013) The valuation of long life mines: current issues and methodologies. In: Proc. 19th Annual Pacific-Rim Real Estate Society Conf, Melbourne Australia, pp 1–17

Fernández-Álvarez JP, Álvarez-Álvarez L, Díaz-Noriega R (2016) Groundwater numerical simulation in an open pit mine in a limestone formation using MODFLOW. Mine Water Environ 35(2):145–155

Fleming H (2016) Water management in the mining industry. Web. https://ceowatermandate.org/files/Hubert_Fleming_Stockholm_2016.pdf. Accessed 19 Nov 2018

Forrester JW (1994) System dynamics, systems thinking, and soft OR. Syst Dyn Rev 10:245–256

Gao L, Barrett D, Chen Y, Zhou M, Cuddy S, Paydar Z, Renzullo L (2014) A systems model combining process-based simulation and multi-objective optimisation for strategic management of mine water. Environ Model Softw 60:250–264

Garrick D, Hope R, McDonnell R, Penning-Rowsell E, Hansen K, Mutembwa M, Schlessinger S (2012) Water security, risk and society—strategic report on research. Findings, gaps and opportunities report. https://www.water.ox.ac.uk/wp-content/uploads/2012/06/ESRC-water-security.pdf. Accessed 19 Nov 2018

Gilli M, Këllezi E (2006) An application of extreme value theory for measuring financial risk. Comput Econ 27:207–228

Größler A, Thun J-H, Milling PM (2008) System dynamics as a structural theory in operations management. Prod Oper Manag 17:373–384

ICMM (2012) Water management in mining: a selection of case studies. ICMM, London. https://www.icmm.com/website/publications/pdfs/water/water-management-in-mining_case-studies. Accessed 19 Nov 2018

Inthavongsa I, Drebenstedt C, Bongaerts J, Sontamino P (2016) Real options decision framework: strategic operating policies for open pit mine planning. Resour Policy 47:142–153

Johnson ST, Taylor T, Ford DN (2006) Using system dynamics to extend real options use: insights from the oil & gas industry. In: Grössler A, Rouwette EAJA, Langer RS, Rowi JI, Yanni JM (eds) Proc. 24th International conf of the system dynamics society, Nijmegen, The Netherlands, p 1–31

Khan HF, Morzuch BJ, Brown CM (2017) Water and growth: an econometric analysis of climate and policy impacts. Water Resour Res 53:5124–5136

Kløve B, Ala-Aho P, Bertrand G, Gurdak JJ, Kupfersberger H, Kværner J, Muotka T, Mykrä H, Preda E, Rossi P, Uvo CB, Velasco E, Pulido-Velazquez M (2014) Climate change impacts on groundwater and dependent ecosystems. J Hydrol 518(B):250–266

Lawrence RD (2002) Valuation of mineral properties without mineral resources: a review of market-based approaches. CIM Bull 95:7

Luoma S, Klein J, Backman B (2013) Climate change and groundwater: impacts and adaptation in shallow coastal aquifer in Hanko, south Finland. In: Schmidt-Thome P, Klein J (eds) Climate change adaptation in practice: from strategy development to implementation. Wiley, New York, pp 137–155

Merz B, Kreibich H, Thieken A, Schmidtke R (2004) Estimation uncertainty of direct monetary flood damage to buildings. Nat Hazards Earth Syst Sci 4:153–163

Milly PCD, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz ZW, Lettenmaier DP, Stouffer RJ (2008) Stationarity is dead: whither water management? Science 319:573–574

Moel A, Tufano P (2002) When are real options exercised? An empirical study of mine closings. Rev Finan Stud 15:35–64

Newman AM, Rubio E, Caro R, Weintraub A, Eurek K (2010) A review of operations research in mine planning. Interfaces 40:222–245

O'Regan B, Moles R (2006) Using system dynamics to model the interaction between environmental and economic factors in the mining industry. J Clean Prod 14:689–707

Papalexiou SM, Koutsoyiannis D (2013) Battle of extreme value distributions: a global survey on extreme daily rainfall. Water Resour Res 49:187–201

Pedretti D, Beckie RD (2016) Stochastic evaluation of simple pairing approaches to reconstruct incomplete rainfall time series. Stoch Environ Res Risk Assess 30(7):1933–1946. https://doi.org/10.1007/s00477-015-1195-1

Pedretti D, Irannezhad M (2018) Non-stationary peaks-over-threshold analysis of extreme precipitation events in Finland, 1961–2016. Int J Climatol (September). https://doi.org/10.1002/joc.5867

Qureshi AM (2007) System dynamics modelling of firm value. J Model Manag 2:24–39

Rapantová N, Krzeszowski Ś, Grmela A, Wolkersdorfer C (2012) Quantitative assessment of mine water sources based on the general mixing equation and multivariate statistics. Mine Water Environ 31(4):252–265

Romanowicz RJ, Young PC, Beven KJ (2006) Data assimilation and adaptive forecasting of water levels in the River Severn catchment, United Kingdom. Water Resour Res 42:W06407

Sahu P, López DL, Stoertz MW (2009) Using time series analysis of coal mine hydrographs to estimate mine storage, retention time, and mine-pool interconnection. Mine Water Environ 28(3):194–205

Savolainen J (2016) Real options in metal mining project valuation: review of literature. Resour Policy 50:49–65

Savolainen J, Collan M, Luukka P (2017a) Analyzing operational real options in metal mining investments with a system dynamic model. Eng Econ 62:54–72

Savolainen J, Collan M, Luukka P (2017b) Integrating the effect of water balance on the economic feasibility analysis of metal mining investments. In: Wolkersdorfer C, Sartz L, Sillanpää M, Häkkinen A (eds) Mine water & circular economy, vol I. Lappeenranta University of Technology, Lappeenranta, Finland, pp 478–484

Schmidt-Thomé P, Klein J, Nockert A, Donges L, Haller I (2013) Communicating climate change adaptation: from strategy development to implementation. In: Schmidt-Thome P, Klein J (eds) Climate change adaptation in practice: from strategy development to implementation. Wiley, New York, pp 1–9

Schmidt-Thomé P, Nguyen H, Pham L, Jarva J, Nuottimäki K (2015) Climate change in Vietnam. In: Schmidt-Thomé P, Nguyen H, Pham L, Jarva J, Nuottimäki K (eds) Climate change adaptation measures in Vietnam. Springer, Cham, pp 7–15

Serinaldi F, Kilsby CG (2014) Rainfall extremes: toward reconciliation after the battle of distributions. Water Resour Res 50:336–352

Serinaldi F, Kilsby CG (2015) Stationarity is undead: uncertainty dominates the distribution of extremes. Adv Water Resour 77:17–36

Smith RL (1990) Extreme value theory. In: Ledermann W (ed) Handbook of applicable mathematics. Wiley, New York, pp 437–471

Smith LD (2002) Discounted cash flow analysis methodology and discount rates. CIM Bull 95:101–108

Solari S, Egüen M, Polo MJ, Losada MA (2017) Peaks over threshold (POT): a methodology for automatic threshold estimation using goodness-of-fit p-value. Water Resour Res 53(4):2833–2849

Tan B, Anderson JS Jr, Parker GG (2010) Evaluating system dynamics models of risky projects using decision trees: alternative energy projects as an illustrative example. Syst Dyn 26:1–17

Trigeorgis L (1993) The nature of option interactions and the valuation of investments with multiple real options. J Financ Quant An 28:1–20

Van Montfort MAJ, Witter JV (1986) The generalized Pareto distribution applied to rainfall depths. Hydrol Sci J 31:151–162

Wernerfelt B, Karnani A (1987) Competitive strategy under uncertainty. Strateg Manag J 8:187–194

Zachary DS (2014) On the sustainability of an activity. Sci Rep 4:5215. https://doi.org/10.1038/srep05215

Zhang X, Gao L, Barrett D, Chen Y (2014) Evaluating water management practice for sustainable mining. Water 6:414–433