Managing too little and too much water: robust mine-water management strategies under variable climate and mine conditions

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Managing too little and too much water: robust mine-water management strategies under variable climate and mine conditions

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Abstract:

Mine-water managers need tools to guide robust management strategies that can address the challenges of climate-influenced water scarcity and unregulated discharge. We aimed to identify those factors driving the risks of insufficient water supply for mine production and unpermitted discharge of mine-affected water in a way that is robust to heterogeneity between extreme climatic variability and mine sites. Using 16 coal mines in the Bowen Basin of Queensland, Australia, as a case study, we combined a model of complex mine-water management systems (C-HSM) with global sensitivity analysis (eFAST) to identify influential mine-water management factors. Comprehensive model diagnostics for the 16 mine-water systems under three climate conditions revealed that the uncertainty of key mine-water management indicators, and the contributions of model input parameters differed substantially between climate conditions and mine sites. We then applied four criteria from decision theory into the total sensitivity effects produced by the eFAST method, and developed sensitivity indicators that were robust to heterogeneity between climates and mine sites. These sensitivity indicators provide mine-water managers with options to guide the development of effective management strategies and the collection of additional information based on their own risk preference. While our results indicate some general management strategies that will be robust under multiple conditions, we caution that mine-water managers’ experience in dealing with challenges caused by too little and too much water cannot be blindly transplanted from one mine to another, or from one climate condition to another.

Keywords: mining; adaptive water management; water scarcity; unregulated discharge; systems modelling; robust sensitivity analysis
1. Introduction

Water is an essential resource that plays a central part in coal and mineral extraction, and good management of mine water is critical for the mining industry to achieve ‘social license to operate’, profitability, and sustainability (Kunz and Moran, 2014). In catchments where mining activities occur, the industry’s rapid growth in water demand and strong purchasing power for water licenses are generating conflict over the allocation of water resources between sectors (Nguyen et al., 2014), and this is likely to intensify into the future (Bryan et al., 2016). The coal mining industry in particular is currently facing multiple, complex water resource management challenges such as securing sufficient water for operations during water-limited periods and avoiding non-compliant discharge of mine-affected water (i.e., worked water) during extreme rainfall events (Gao et al., 2016b). Climatic variability exacerbates these challenges, and conventional methods of mine-water resource management such as building regional water infrastructure are not sufficient to address them (Côte et al., 2010).

Australian coal—a $40 billion (all $ in AUD) export industry—operates in one of the most variable climates in the world (Sharma and Franks, 2013). Severe droughts exacerbate conflicts between water users, especially in water stressed areas (Kirby et al., 2014). In Queensland—the world’s largest coking coal exporting region, responsible for more than half of the total worldwide coking coal exports (Queensland Government, 2016)—most coal mines have built storages for fresh and worked water in response to a decade of drought. These storages are designed to capture as much runoff, and reuse as much worked water as possible. However, high-rainfall periods have caused major problems for mine operators in managing excess water, while still meeting discharge quantity and quality regulations when pumping off-site. Excess water can lead to a series of environmental and socio-economic risks (Kemp et al., 2010). For example, during the 2010-11 high-rainfall period, overflows from mine-water storages and incoming floods reduced coal production in Queensland by more than 30 million tonnes, causing $5.7 billion in lost revenue (Queensland Government, 2011). The mine discharge caused a number of unnatural deaths of marine creatures, and brought underlying hazards to surrounding environment and residents (Queensland Floods Commission of Inquiry, 2012). This high rainfall period followed several years drought and mine-water managers were unprepared for the sudden switch between dry and wet conditions (Loechel et al., 2013).

Water management strategies are required that are effective despite variability in climate and mine conditions. The interactions of mining activities with water resources are site-specific and exhibit complex system behaviour characterised by non-linearities such as feedback effects (Northeay et al., 2016). External perturbations (e.g. climatic variability) and management strategy changes may lead to unexpected system consequences. To make better-informed management strategies, mine-water managers need to understand the dynamics of heterogeneous mine-water systems under extreme climatic variability (Barrett et al., 2014), and understand those factors within a system which are most influential on system behavior. Specifically, they need to know which factors most strongly affect insufficient water supply for mine production and the illegal discharge of worked water. Managers also need to understand how these influential factors change under different climatic conditions and between mine sites. However, existing tools are unable to meet the needs. New tools are needed that can inform the management of complex, climate-induced drought and discharge management challenges in mine water by identifying influential system parameters in a way that is robust to mine heterogeneity and climatic variability.

The tools that have been traditionally used to guide the design of mine-water system facilities and the operation of mine water are engineering models, such as OPSIM (Water Solutions, 2012) and GoldSim
(GoldSim Technology Group, 2005). Typically, these models have been developed for specific operations, representing site components, day-week-month operations, and processes based on mathematical representation and simulation. In most of these models, an underlying assumption is that only factors/parameters that are associated with discharge risk are rainfall and runoff (Cote and Moran, 2008). These models do not sufficiently capture the complexity and dynamics of a mine-water system such as water use tasks, cause-and-effect relationships, and complex feedback mechanisms among system components. Therefore, these models are not well suited to addressing the two strategic risks in mine sites, namely too little and too much water (Kunz and Moran, 2016).

Increasingly, systems models (e.g., Côte et al., 2010) have been used to describe the dynamics of the whole mine-water system and evaluate the effectiveness of water management options. Low-level detail of the mine-water system is neglected and system elements, such as individual water storages, input and output fluxes, and different uses of water, are typically aggregated as a set of water objects (Woodley et al., 2013). In parallel, global sensitivity analysis has become the state-of-the-art technique for identifying critical model input parameters and quantify the impact of their variation on model outputs (Saltelli et al., 2008). Global sensitivity analysis extensively and simultaneously explores multi-parameter space and calculates the effect of interactions between parameters (Peeters et al., 2014). In particular, the extended Fourier Amplitude Sensitivity Test (eFAST) method can quantify both the first-order and total effects with high computational efficiency (Cosenza et al., 2013). In the context of land-use projections under global change, Gao et al. (2016a) extended these techniques by proposing robust global sensitivity analysis which employs scenario analysis with decision theory to identify influential model parameters under deep uncertainty (Gao and Bryan, 2016). Robust global sensitivity analysis applied to models of mine-water systems dynamics has potential to identify those parameters which significantly affect strategic water management risks in mine sites.

This paper addresses the need for the robust identification of influential parameters for managing complex mine-water systems under variability in climate and mine conditions by combining systems modelling and robust global sensitivity analysis. We believe this is the first work that applies a global sensitivity analysis into a mine water use model for addressing cleaner production and sustainability issues of the mining industry. We used the climate-driven hierarchical systems model (C-HSM) of mine-water circuits (Gao et al., 2014a) to develop systems models for 16 coal mines in the Bowen Basin in Queensland, Australia (Zhang et al., 2014). We applied the eFAST method to the C-HSM under extreme dry, normal, and extreme wet climatic conditions to quantify the uncertainty and sensitivity of key mine-water storage and discharge outputs resulting from the variation in 320 (20 × 16) input parameters to the regional C-HSM. We further developed sensitivity indicators that can be used as a reference set for guiding robust management strategies under both climatic and mine uncertainty when the combined methodology is unavailable for a specific mine. The results provide insights into those parameters most likely to influence mine-water storage and discharge under variable climates and with site-specific complexity. We discuss the implications and applicability of the methods and results for mine-water management more broadly.

2. Methods

2.1. Study region

The case study covers an area of more than 63,000 square kilometres in the Bowen Basin, Queensland, Australia (Figure 1). The climate of the Basin is characterised by distinct dry and wet seasons. Droughts cause competition between water users in rural areas, notably miners, farmers, and rural townships. For example, during 2010-2011, intense rainfall events experienced in the basin coal mining
region led to extensive flooding of mine pits, damage to transportation routes, on-going disruption to the production and export of coal, reduced state royalties, and community outrage over the effects on downstream water quality caused by the discharge of pit water into streams. Compounding these difficulties, this high rainfall period followed several years during which the security of water supply for production was threatened by drought, possibly leading to more conservative water management strategies in pits and dams being adopted on site, rather than shedding water from site.

16 mines from this basin were selected as representative case studies from across the landscape consisting of mountain ranges, native grasslands, Brigalow forests and distinctive wetlands. 10 of the 16 mines are open-cut, four are underground, and the other two are combined mines. The type of mines determines the typical mine-water operations and management practices. Local climates (in particular rainfall-runoff and evaporation dynamics) (Chen et al., 2015) and geographical features (such as elevation and slope) (Liu et al., 2016) are known to drive mine-water dynamics, including water storage capacity and annual unregulated discharges.

Climate data from three recent periods (01/07/2001 – 30/06/2005, 01/07/2005 – 30/06/2010, and 01/07/2010 – 30/06/2011) were selected to represent the extreme dry, normal, and extreme wet conditions. The dry period had a severe drought event (QCCCE, 2007), the wet period included a significant flooding period (October 2010–March 2011) (Queensland Floods Commission of Inquiry, 2012), and the normal period was between the dry and wet periods (Historical annual rainfall data at the 16 sites during the three periods are presented in Supplementary Material Figure A1).

2.2. Overview of C-HSM
The C-HSM was developed to align with Australia’s water accounting standard for the mining industry (Danoucaras et al., 2014). The model includes components of a simulator (for representing a mine-water system and simulating the effects of management options) and an optimiser (for calibrating the model and exploring optimal pathways for managing mine water) (Figure 2).

![Diagram of the C-HSM](image)

**Figure 2.** Systems diagram of the C-HSM for a single coal mine.

The simulator represents the whole mine-water system (including all water storages, flows, and tasks) as a number of water objects and relationships between these objects. Five types of basic model objects are included in the component: water store, water task, treatment plant, water input, and water output. Water store represents a water storage on site. All water storages in a site are aggregated into either the raw water store or the worked water store, depending on what water (raw or worked) a water storage receives and stores. Water task is a mining activity that demands water for a specific purpose. Treatment plant is a facility that is used to convert low-quality water to high-quality water. Water input and output represent water exchange between external sources and the mine-water system.

We built the regional C-HSM and calibrated the model site-by-site during the period 01/07/1977—30/06/2007 with rainfall and evaporation data as inputs (Côte et al., 2008). The daily rainfall and evaporation data for the calibration and the three simulation periods for the 16 sites were downloaded from the SILO website (http://www.longpaddock.qld.gov.au/silo/datadrill/index.php). The details of system design, sub-model design, implementation, calibration, and data sources are presented in Gao *et al.* (2014a). The simulated time series worked water storage, as well as volume and concentration of unregulated discharge of 16 sites are demonstrated in Figures B1-B16 (Supplementary Material).
2.3. Input parameters and output variables

Twenty model parameters were chosen for the robust global sensitivity analysis of each mine in the regional C-HSM (20 × 16 = 320 parameters for the regional model, Table 1). These parameters are variable and general for each mine site, representing key factors that affect insufficient water supply and illegal mine-water discharge. We applied a uniform distribution to all parameters because of the lack of information on their prior probability distributions. We also used ±30% of a reference value as borders of variation range when there is no information to determine a parameter’s range (following Van Oijen et al., 2005).

Table 1. Selected input parameters for each mine in the C-HSM.

<table>
<thead>
<tr>
<th>Parameter group</th>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
<th>Value range</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production</td>
<td>CoalProductionRate</td>
<td>Annual coal production</td>
<td>Mt/yr</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Raw water store</td>
<td>RawStoreCapacity</td>
<td>Capacity of the raw water store</td>
<td>ML</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RawStoreCatchArea</td>
<td>Catchment area of the raw water store</td>
<td>ha</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RawStoreSurfaceArea</td>
<td>Surface area of the raw water store</td>
<td>ha</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RawStoreInitialLevel</td>
<td>Initial water level of the raw water store</td>
<td>n/a</td>
<td>0</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Worked water store</td>
<td>WorkedStoreCapacity</td>
<td>Capacity of the worked water store</td>
<td>ML</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WorkedStoreCatchArea</td>
<td>Catchment area of the worked water store</td>
<td>ha</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WorkedStoreDistCatchProp</td>
<td>Disturbed catchment proportion to the total catchment area of the worked water store</td>
<td>n/a</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WorkedStoreSurfaceArea</td>
<td>Surface area of the worked water store</td>
<td>ha</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WorkedStoreInitialLevel</td>
<td>Initial water level of the worked water store</td>
<td>n/a</td>
<td>0</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WorkedStoreInitialConcen</td>
<td>Initial salt concentration in the worked water store</td>
<td>Mg/L</td>
<td>1000</td>
<td>30000</td>
<td></td>
</tr>
<tr>
<td>Water tasks</td>
<td>WaterTaskCHPPTotal</td>
<td>Total water demand for coal handling and preparation plant (CHPP)</td>
<td>ML/Mt</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WaterTaskCHPPRawProp</td>
<td>Raw water proportion to total CHPP water demand</td>
<td>n/a</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WaterTaskCHPPLossRate</td>
<td>Loss rate of water in the CHPP water task</td>
<td>n/a</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WaterTaskDustSupp</td>
<td>Total water demand for dust suppression</td>
<td>ML/Mt</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WaterTaskDustSuppRawProp</td>
<td>Raw water proportion to total water demand for dust suppression</td>
<td>n/a</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WaterTaskUnderground</td>
<td>Total water demand for underground use</td>
<td>ML/Mt</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>WaterTaskUndergroundLossRate</td>
<td>Loss rate of water in the task for underground use</td>
<td>n/a</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Climate</td>
<td>RainfallVariationFactor</td>
<td>A single factor that all time-series rainfall values were varied by this factor</td>
<td></td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Others</td>
<td>PipelineSupply</td>
<td>Pipeline supply (supply from surface water, groundwater, desalinated sea water, and/or third party water)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Then, the global sensitivity of three model outputs was evaluated (Table 2) based on the variation in the parameters (Table 1). WorkedStoreDryIndicator quantified the risk of being ‘too dry’ for the worked store. WorkedDischargeVolume and WorkedDischargeConcentration quantified the extent of discharge damage in terms of the volume and salt concentration of unregulated discharge of worked water.

Table 2. Selected three output variables in the analyses.

<table>
<thead>
<tr>
<th>Output variable</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>WorkedStoreDryIndicator</td>
<td>Percentage of time that the worked water storage is below 25% full of the storage capacity</td>
<td>n/a</td>
</tr>
<tr>
<td>WorkedDischargeVolume</td>
<td>Average annual volume of unregulated discharge of worked water</td>
<td>ML/year</td>
</tr>
<tr>
<td>WorkedDischargeConcentration</td>
<td>Average salt concentration of unregulated discharge of worked water</td>
<td>Mg/L</td>
</tr>
</tbody>
</table>

2.4. The eFAST method
eFAST attributes the variance of a given model output to the contribution of each parameter and provides measure of a parameter’s first-order and total sensitivity effects (Saltelli et al., 1999). The method encodes different parameters using different frequencies and the Fourier transformation is applied to quantify how strongly a parameter’s frequency to the variance (Marino et al., 2008). The total number of model simulations was 1,968,000 for 20 parameters and for the 16 mines under the three climatic conditions. The detailed calculation procedure is provided in the Supplement C (Supplementary Material). Following Cosenza et al. (2014), we identified a parameter $i$ with its total eFAST sensitivity effect $S_{Ti} > 0.1$ as influential one.

2.5. Robust sensitivity indicators

To integrate parameter sensitivity estimates across different uncertain conditions and provide decision makers with new sensitivity indicators that are robust to the uncertainty, Gao et al. employed four decision criteria from decision theory (maximax, weighted average, minimax regret, and limited degree of confidence) to the development of robust sensitivity indicators (Gao et al., 2016a). We used these decision criteria to identify influential model parameters acceptably well under climatic and mine uncertainty by incorporating different risk attitudes of the decision maker.

We applied the four criteria to the calculation of a sensitivity indicator ($S_{RT,m}^{\text{criterion}}$) for each input parameter ($x_i$) that is robust to different climatic conditions (dry, normal, and wet) in mine $m$ ($m \in \{M2, M3, \ldots, M17\}$) based on the eFAST’s total sensitivity indices $S_{Ti,m,c}$ ($c \in \{\text{dry, normal, wet}\}$). Then, a sensitivity indicator ($S_{RT,i}^{\text{criterion}}$) that is further robust to the heterogeneity of mine sites (16 different mine conditions) is computed by applying the four criteria into ($S_{RT,M2}^{\text{criterion}}, S_{RT,M3}^{\text{criterion}}, \ldots$, and $S_{RT,M17}^{\text{criterion}}$).

(1) Maximax

The maximax criterion aims to captures all influential factors under different uncertain conditions (Anderson et al., 2012). For an input parameter $x_i$, this criterion selects the alternative index $S_{T_i,m,c'}$ from climatic condition $c'$ that maximises the maximum payoff. A payoff $p_{O_{T_i,m,(a,b)}}$ is defined as the difference in the total sensitivity index between an alternative $S_{T_i,m,a}$ and the state of nature $S_{T_i,m,b}$.

$$p_{O_{T_i,m,(a,b)}} = S_{T_i,m,a} - S_{T_i,m,b}$$

(6)

All combinations of three alternatives and three states of nature form a $(3 \times 3)$ payoff table. The criterion first chooses the maximum payoff for each alternative, and then identifies alternative $c'$ with the largest maximum payoff. Thus, for the input parameter $x_i$, the robust sensitivity indicator $S_{RT,i}^{\text{max}}$ is identified as $S_{T_i,m,c'}$:

$$S_{RT,i}^{\text{max}} = \underset{c'}{\text{max}} S_{T_i,m,c} = S_{T_i,m,c'}$$

(7)

where $\underset{c'}{\text{max}}$ is a selection operation that finds the final alternative $c'$ from the $(3 \times 3)$ payoff table in terms of the condition of $\underset{a}{\text{max}}(\underset{b}{\text{max}}(p_{O_{T_i,m,(a,b)} }))$.

The criterion is then applied to $S_{T_i,m,c'}$ ($c'$ might be different for different mines) to obtain a sensitivity indicator ($S_{RT,i}^{\text{max}}$) that is robust to both extreme climatic conditions and mine heterogeneity, as shown in (8) and (9):
\[ p_{T_i,d,e,c'} = S_{T_i,d,c'} - S_{T_i,e,c'} \]  

(8)

Here, payoff \( p_{T_i,d,e,c'} \) is defined as the difference between an alternative \( S_{T_i,d,c'} \) (total sensitivity index for benchmark mine \( d \)) and the state of nature \( S_{T_i,e,c'} \) (total sensitivity index for candidate mine \( e \)). All combinations of 16 alternatives and 16 states of nature from a \((16 \times 16)\) payoff table. The criterion first chooses the maximum payoff for each alternative, and then identifies alternative \( m' \) with the greatest maximum payoff.

\[ S^{\text{max}}_{RT_i} = \max_m \left( \max_e \left( p_{T_i,d,e,c'} \right) \right) \]

(9)

where \( \max_m \) is a selection operation that determines the final alternative \( m' \) from the \((16 \times 16)\) payoff table in terms of the condition of \( \max_e \left( p_{T_i,d,e,c'} \right) \).

(2) Weighted average

The weighted average criterion is suitable when the probabilities of uncertain situations are known. To find influential parameters under three climatic conditions, this criterion calculates the robust sensitivity indicator \( S^{\text{avg}}_{RT_i,m} \) by averaging three total sensitivity indices \( S_{T_i,m,c} \) with different weights. \( S^{\text{avg}}_{RT_i,m} \) is defined as the sum of the product of the weight \( \beta_c \) of each climatic condition \( c \) and the total sensitivity index \( S_{T_i,m,c} \) for mine \( m \).

\[ S^{\text{avg}}_{RT_i,m} = \sum_c (\beta_c \cdot S_{T_i,m,c}) \]

(10)

In this way, \( S^{\text{avg}}_{RT_i,M2}, S^{\text{avg}}_{RT_i,M3}, \ldots \), and \( S^{\text{avg}}_{RT_i,M17} \) are calculated and can be further averaged over climatic conditions to \( S^{\text{avg}}_{RT_i} \):

\[ S^{\text{avg}}_{RT_i} = \sum_m (\beta_m \cdot S^{\text{avg}}_{RT_i,m}) \]

(11)

Since information is available neither on each benchmark mine’s contribution to constitute the best robust sensitivity indicator for a candidate mine to be assessed (such as similarity of a benchmark mine and a candidate mine), nor on each climatic condition’s contribution (such as the importance of a climatic condition for a model output variable or the occurrence probability of each climate) to the best robust sensitivity indicator, equal weights were chosen for all mines and for all climatic conditions.

(3) Minimax regret

The minimax regret criterion (Anderson et al., 2012) minimises the regret (opportunity loss) of choosing the wrong case — regret of accepting sensitivity indices that the future will not follow. The regret \( r_{T_i,m,(a,b)} \) is defined the absolute difference in total sensitivity index between the alternative \( a \) and a state of nature \( b \):

\[ r_{T_i,m,(a,b)} = |S_{T_i,m,a} - S_{T_i,m,b}| \]

(12)

where \( S_{T_i,m,a} \) and \( S_{T_i,m,b} \) are total sensitivity indices for \( a \) and \( b \), respectively.
The regret values from all combinations of three climatic alternatives and three climatic states of nature can constitute a regret table. For each input parameter \(x_i\), the robust sensitivity indicator \(S_{\text{reg}}^{\text{avg}}\) is identified as \(S_{T_i,m,c''}^{\text{reg}}\) for unknown climatic conditions:

\[
S_{T_i,m}^{\text{reg}} = \frac{\text{reg,}_c}{\text{reg,}_c} S_{T_i,m,c} = S_{T_i,m,c''}
\]

(13)

where \(\frac{\text{reg,}_c}{\text{reg,}_c}\) is a selection operation that determines the final alternative \(c''\) from the regret table in terms of the condition of \(\min_a (\max_b (r_{T_i,m,a,b}) )\).

The minimax regret criterion is then applied to \(S_{T_i,m}^{\text{reg}}\), \(S_{R_{T_i},m_2}^{\text{reg}}\), \(S_{R_{T_i},m_3}^{\text{reg}}\), \(\ldots\), and \(S_{R_{T_i},m_{17}}^{\text{reg}}\) to obtain a sensitivity indicator \(S_{R_{T_i}}^{\text{reg}}\) that is robust to both mine heterogeneity and climatic conditions, as shown in (14) and (15):

\[
r_{T_i,(d,e),c''} = |S_{T_i,d,c''} - S_{T_i,e,c''}|
\]

(14)

Here, the regret \(r_{T_i,m,e,c''}\) is defined as the absolute difference between the total sensitivity index of alternative \(S_{T_i,d,c'}\) and the state of nature \(S_{T_i,e,c''}\). All combinations of 16 alternatives and 16 states of nature form a \((16 \times 16)\) regret table. \(S_{R_{T_i}}^{\text{reg}}\) is calculated as:

\[
S_{R_{T_i}}^{\text{reg}} = \frac{\text{reg,}_m}{\text{reg,}_m} (\frac{\text{reg,}_c}{\text{reg,}_c} S_{T_i,m,c}) = S_{T_i,m'',c''}
\]

(15)

where \(\frac{\text{reg,}_m}{\text{reg,}_m}\) is a selection operation that determines the final alternative \(m''\) from the \((16 \times 16)\) regret table in terms of the condition of \(\min_{d} (\max_{e} (r_{T_i,(d,e),c''}))\).

(4) Limited degree of confidence (LDC)

The LDC criterion (McInerney et al., 2012) balances weighted average and minimax regret, and the weighting in LDC can be regarded as the limited degree of the decision maker’s confidence in probabilities of uncertain situations (here, limited degree of confidence in each benchmark mine’s contribution or each climatic condition’s contribution to constitute the best robust sensitivity indicator for a candidate mine). The robust sensitivity indicator \(S_{T_i,m}^{\text{LDC}}\) is shown below:

\[
S_{T_i,m}^{\text{LDC}} = \gamma_m \cdot S_{T_i,m}^{\text{avg}} + (1 - \gamma_m) \cdot S_{T_i,m}^{\text{reg}}
\]

(16)

Where \(S_{T_i,m}^{\text{avg}}\) and \(S_{T_i,m}^{\text{reg}}\) are the robust sensitivity indicators produced from the weighted average and the minimax regret criteria, respectively; and \(\gamma_m (0 \leq \gamma_m \leq 1)\) represents the decision-maker’s degree-of-confidence in the climatic conditions’ contributions/probabilities in mine \(m\). Here, we set \(\gamma_m = 0.5\) due to no further information on the confidence level.

Similarly, the LDC criterion is applied to \(S_{T_i}^{\text{avg}}\) and \(S_{T_i}^{\text{reg}}\) to obtain \(S_{T_i}^{\text{LDC}}\):

\[
S_{T_i}^{\text{LDC}} = \gamma \cdot S_{T_i}^{\text{avg}} + (1 - \gamma) \cdot S_{T_i}^{\text{reg}}
\]

(17)

where \(\gamma = 0.5\).
2.6. Non-parametric Kruskal–Wallis test

To identify significant differences between mine sites and under different climatic conditions, we used non-parametric Kruskal–Wallis test (Corder and Foreman, 2009) which does not require normality in the data. $\alpha = 0.05$ was used as the level of significance in the test. We further used Dunn’s test (Dunn, 1964) as a *post hoc* procedure after the Kruskal–Wallis test to report the dissimilarity results among all possible pairwise comparisons.

3. Results

We firstly applied eFAST in uncertainty and sensitivity analyses of the C-HSM under the three climatic conditions and for the 16 mine sites. Then, based on the total sensitivity indices, we developed robust indicators using the four decision-making criteria. We illustrated how the uncertainty and sensitivity behaved differently under different climatic conditions and between different sites, and how robust indicators were developed for three outputs WorkedStoreDryIndicator, WorkedDischargeVolume, and WorkedDischargeConcentration.

3.1. Between-mine and between-period differences in model outputs

Between-mine uncertainty and between-climate uncertainty in the three outputs were both significant under the specified variation in input parameters (Figure 3, and Supplementary Material Tables D1-D4). For a single mine, during the dry period, the distributions of WorkedStoreDryIndicator were generally higher than those during the normal and wet periods (Figure 3). During the wet period, the average annual discharge volume of worked water (represented by WorkedDischargeVolume) distributed more frequently in a higher level than those during the other two periods for each mine. The distributions of average salt concentration of unregulated worked water discharge were also higher during the wet period, however, with some exceptions (in mines M9, M11-13, and M15).

For an output such as WorkedDischargeVolume (Figure 3), some mines had a more normal distribution (e.g., M10), while some were more skewed (e.g., M6). For an output, although some mines had similar distributions, they differed in magnitude (e.g. M9 and M10 for WorkedStoreDryIndicator).

Significant between-climate and between-mine differences in the three model outputs were identified by the Kruskal–Wallis test and the Dunn’s test (Supplementary Material Tables D1-D4). Therefore, ignoring impacts of climatic conditions and mine heterogeneity on output uncertainty in a typical global sensitivity analysis could result in a biased and unrepresentative view of model structure, performance, and output uncertainty.
Figure 3. Quantified uncertainty distributions for the three outputs in the 16 mines under dry, normal, and wet climatic conditions. The violin plot represents empirical distributions of model outputs. The red band inside the box plot represents the second quartile (median); the bottom and top edges of the box are the lower hinge (the 25th percentile, Q1) and the upper hinge (the 75th percentile, Q3), and the whiskers extend to $1.5 \times (Q3 - Q1)$.

3.2. Sensitivity of outputs to input factors under different mines and climatic conditions

We obtained the full results of total sensitivity effects for all 20 input parameters on the three output variables, for the 16 mines and during the three climatic conditions (Figure 4).

Even for single mines, different climatic conditions led to variation in parameter importance ranking and the magnitude of total effects. For instance, for WorkedDischargeVolume, the most influential parameters were identified as WaterTaskCHPPRawProp, RainfallVariationFactor, and WorkedStoreDistCatchProp under dry, normal, and wet conditions, respectively. For almost all mines, the top three most influential parameters for the output WorkedDischargeVolume differed between the three climatic conditions (Figure 4). The output WorkedDischargeConcentration had more variation in the most influential parameters (including WorkedStoreInitialLevel, WorkedStoreInitialConcen, WorkedStoreCatchArea, RainfallVariationFactor, WorkedStoreCapacity, and WorkedStoreDistCatchProp) between mines under the dry condition compared to wet. The Kruskal–Wallis test confirmed that significant between-climatic condition differences occurred in parameter
total sensitivity indices for the three outputs in mines 3, 4, 6, 8, 15, and 17; and that the between-climatic condition differences were not significant for all three outputs only in mines 11-13 (Supplementary Material Tables E1 and E2).

Figure 4. Total sensitivity indices of 20 input parameters on the three output variables for the 16 mines under the three climatic conditions. Total sensitivity indices are represented by colours in the grid cells and the influence rankings of the influential parameters ($S_{Ti} > 0.1$) are represented by numbers in the grid cells.

For the outputs WorkedDischargeVolume and WorkedDischargeConcentration, substantial differences in the total sensitivity effects of parameters were found between mines under each climatic condition.
For example, under the dry climate, the top three influential parameters ($S_{ri} > 0.1$) for the output *WorkedDischargeVolume* are different or differ in their importance ranking between mines (Figure 4). For *WorkedDischargeConcentration*, still under the dry condition, the numbers of influential parameters were 16, 15, 9, 7, 19, 3, 20, 18, 3, 7, 9, 12, 5, 13, 6, and 6, respectively (Figure 4). During the wet, the factors that can influence unregulated discharge of worked water were more limited than those under the other two climatic conditions. For the output *WorkedStoreDryIndicator*, for most mines, influential parameters were mainly from *WorkedStoreInitialLevel*, *WaterTaskCHPPRawProp*, and *WaterTaskCHPPLossRate*. Under the dry condition, the influential parameters for most mines were different (or same influential parameters but differed in their importance ranking), except M9, M11, M13, and M17 (they had same influential parameters which also differed in their magnitude). Under the wet condition, *WorkedStoreInitialLevel* became the only influential factor that could affect *WorkedStoreDryIndicator* for most mines, but exceptions still existed (M3-M5, M8, and M15) (Figure 4). Significant between-mine differences in parameter total sensitivity indices were found by the Kruskal–Wallis test for the three outputs under each climatic condition (Supplementary Material Tables E3 and E4).

3.3. Robust Sensitivity analyses

We have found significant differences in parameter sensitivity between three climates and 16 mines. In this section, by applying decision criteria we present four sets of robust sensitivity indicators that are robust to climatic conditions for each mine, and four sets of robust sensitivity indicators that are both robust to climatic variability and heterogeneity between mines (Figure 5).

For the output *WorkedStoreDryIndicator*, the four decision criteria identified *WorkedStoreInitialLevel*, *WaterTaskCHPPRawProp*, and *WaterTaskCHPPLossRate* as influential parameters that are robust to climatic conditions for most mines (except mines M5-8, M12, and M14). *WorkedStoreInitialLevel* was identified as the most influential parameter by the four criteria for most mines (except M1, M4, M5, and M15). For mines M3, M4, M7, M8, M11, and M14, the four criteria elected same influential parameters. For the output *WorkedDischargeVolume*, for most mines, six influential parameters (*WorkedStoreCatchArea, WorkedStoreDistCatchProp, WorkedStoreInitialLevel, WaterTaskCHPPRawProp, WaterTaskCHPPLossRate, and RainfallVariationFactor*) were identified by the four decision criteria. Only for mines 10 and 11, the four criteria identified same influential parameters with the same influence rankings. For the output *WorkedDischargeConcentration*, more parameters were identified as influential including *WorkedStoreCatchArea, WorkedStoreDistCatchProp, WorkedStoreInitialLevel, WorkedStoreInitialConcen, WaterTaskCHPPRawProp, WaterTaskCHPPLossRate, and RainfallVariationFactor*. Among all mines, same influential parameters were found by the four criteria only for Mine 7.

For the three output variables, the four criteria resulted in different influential parameters and their importance rankings in the robust sensitivity indicators that are robust to both climatic conditions and 16 mines. Parameters that were identified as influential only under one climatic condition, or in a few mines, could be identified as influential by the maximax criterion, but were likely to be identified as non-influential by other criteria. For instance, for the output *WorkedDischargeVolume*, some influential parameters identified by the maximax criterion, such as *RawStoreInitialLevel, WaterTaskUnderground, WorkedStoreInitialConcen*, and *WorkedStoreCapacity*, were identified as non-influential by the other three criteria. These were influential parameters when the decision maker wants to identify all parameters influential for a particular mine or for all mines. The weighted average and the minimax regret criterion differ in the aggregation method of total sensitivity indices. Therefore, they led to different influential parameters for the outputs *WorkedStoreDryIndicator* and
WorkedDischargeConcentration; and different ranking of the identified parameters for WorkedDischargeVolume. The LDC criterion in our case provided a balanced measure of the effects from the weighted average and the minimax regret criteria.

The LDC criterion in our case provided a balanced measure of the effects from the weighted average and the minimax regret criteria.

Figure 5. Robust sensitivity indicators of 20 input parameters on the three outputs for each mine site (robust to climatic conditions) and for 16 mines (robust to both climatic conditions and mine heterogeneity) using the four decision criteria. Colours in the grid cells represent the robust sensitivity indicator values and numbers represent the rankings influences of influential parameters whose robust sensitivity indicators > 0.1. The “M2-17” rows represent robust sensitivity indicators that are robust to both three climatic conditions and 16 mines.

4. Discussion

4.1. Influence of climate and mine site heterogeneity on output uncertainty and parameter sensitivity

The uncertainty in key model outputs resulting from variation in model inputs differed between climatic conditions and between mines in distribution shape and magnitude for the output variables that
represent climate-influenced water scarcity and discharge risks (Figure 3). Generalising the specific detail of individual site configuration, the C-HSM systematically captured the essence of mine-water dynamics under 16 heterogeneous mine-water systems distributed across different landscapes and local climates (Liu et al., 2017), and are subject to different mine-water operations. Variation in reference parameters was propagated via complex model structure (interactions) to the output in a non-linear way, resulting in differing output variable distributions (Wang et al., 2013). Different climatic conditions also influenced system behavior and led to variations in output uncertainty.

We identified the total contribution of each input parameter to the variation in each output for each mine, and found that there were significant between-mine differences in parameters identified as influential contributors, in parameter contribution rankings, and in the magnitude of sensitivity indices. Climatic factors, coupling with other model parameters to drive different behaviours of the complex mine-water systems, also altered the contributions of parameters to variation in model outputs.

These findings have not been reported previously and this is the first example of the application of global sensitivity analysis to mine-water use models that we know of. These findings are important because they overturn common views of mine-water managers on “dry” and “wet” risk-associated factors. Solid evidence has been provided to support the necessity of applying global sensitivity analysis to a mine-water model for identifying critical factors underlying the aforementioned mine-water associated risks. Since the existence of significant between-climate and between-mine differences in these risks and in drivers to these risks, while there are some general consistencies, the experience of mine-water managers during one typical climatic period or from one mine cannot simply transplanted to another typical climatic period or another mine. This can also explain why it is often difficult to deal with scarcity of water and excesses in flooding, and explain the conundrum of the “hydro-illogical cycle” (DRET, 2008) in the mining industry. The significant between-climate and between-mine differences also highlight the necessity of developing sensitivity indicators that are robust to climatic regimes and sites.

There are two main limitations for further investigation with respect to assumptions in the sampling process of the global sensitivity analysis. First, we chose a uniform distribution for all parameters and a ±30% of a reference value as variation ranges. Different probability distributions (Hamby, 1994) and variation ranges (Wang et al., 2013) for a parameter could influence significantly the parameter sensitivity. The second major limitation is that we applied a single multiplier to a time-series parameter such that all time-series values are varied by this multiplier. This ignored the variation characteristics that are inherently hidden in the time-series parameter. Therefore, efforts on refining parameter probability distributions (including those of time-series parameters) and boundary conditions would improve the sensitivity analysis results.

4.2. Implications for mine-water management under extreme climates

To develop effective strategies to address the mine-water management challenges, mine-water managers must correctly identify and control the critical factors influencing the risks of insufficient water supply for mine production and unregulated discharge due to excess water. Given the fact that the interactions between mining activities and water resources are highly complex, climate-sensitive, and site-specific (Northey et al., 2016), the capability for identifying critical factors is urgently needed. We demonstrate that a combined approach of systems modelling and global sensitivity analysis can work as an effective means to inform mine-water managers of control variables for mitigating the risks of unintended consequences.
As illustrated by WorkedStoreDryIndicator, the output representing the risk of insufficient worked water storage, during the dry period, a lack of understanding about the relationship between water demand and supply, and poor preparation in design and operations for climatic and hydrological variability can cause the insecurity of worked water supply for mineral production, especially during long-term dry times (see Figure 4). There are eight influential parameters across the 16 mines under the dry conditions and these parameters implicate control measures in increasing worked water storage, reducing water loss in water tasks, increasing proportion of raw water use, and increasing captured rain water to the worked water store. To secure water supply for mining activities, Gunson et al. (2012) identified a number of mine-water reduction, reuse and recycle options; and Gao et al. (2016b) explored the potential for mine-water sharing between sites. Other options still include trading worked water between mines and other industrial users (Gao et al., 2013), and injecting excess water into groundwater aquifers during wet periods and extracting it during dry periods (Gao et al., 2014b).

At the other climatic extreme, high-rainfall events can result in excess water in the mine site, and poor management of the water can lead to a breach of the social license for operation (Wessman et al., 2014) in the event of unregulated discharge. However, relatively little unregulated discharge occurred in dry times (i.e. there were much smaller distributions in discharge volume of worked water for each site during the dry periods, see Figure 3). The factors influencing unregulated discharge in dry periods were more inclusive and diverse (i.e. more influential parameters were found for WorkedDischargeVolume and WorkedDischargeConcentration during the dry period than the other periods, see Figure 4). During wet seasons when severe unregulated discharge was more likely to occur (Figure 3), influential parameters for each of the 16 mines include WorkedStoreInitialLevel, WorkedStoreCatchArea, WorkedStoreDistCatchProp, RainfallVariationFactor, WaterTaskCHPPLossRate, and WaterTaskCHPPRawProp. These parameters are associated with the level of the worked water store, the volume of rain water captured to the worked water store, the returned water to the store from coal handling and preparation plant (CHPP), and climatic factors. These results suggest that potential management options for mitigating the risk of unregulated discharge include (1) performing regulated discharge to decrease the level of the worked water store; (2) enhancing evaporation of worked water through large-scale evaporation dams; (3) utilizing a levee system to reduce runoff into the store (DNRM, 2014); and (4) transferring returned water between mines and other industrial users (Gao et al., 2016b).

4.3. Decision making in mine-water management under uncertainty

The site-specific and climate-sensitive nature of mine-water systems that already include complex internal interactions make management of this resource challenging. Previous experience of the mine-water manager obtained from one site (or under one climatic condition) cannot be simply used in another mines (or under other climatic conditions). To help the manager develop efficient management strategies to address dual competing problems of too much and too little water, we provide sets of sensitivity indicators that are robust to highly variable climates and mine site heterogeneity. These robust sensitivity indicators successfully captured critical factors in addressing climate-influenced mine-water management challenges by considering the objective and level of risk aversion of the mine-water manager. No decision criterion is superior to the others. Our aim is to support the decision-making of the mine-water manager in addressing climate-associated challenges by providing a number of options. For example, if the mine-water manager does not want to miss any possible influential factors, the ‘aggressive’ maximax criterion can be chosen. To illustrate, for WorkedDischargeVolume, all influential parameters (more than 10) were selected using the maximax criterion, while only six influential parameters needed to be considered with different decision objectives and levels of risk aversion. The weighted average criterion regards uncertainty as probabilistic and suitable for the
manager who has confidence in contribution level of the 16 benchmark mine sites and climatic conditions to determine robust sensitivity indicators for a candidate site. If the manager wants to minimise the regret of choosing the worst case, the minimax regret criterion fits for this purpose. The LDC criterion is recommended for the manager who has limited confidence in using the weighted average criterion and provides a balanced measure of criteria between weighted average and minimax regret.

Sensitivity indicators that are robust to climatic variability for each mine can provide reliable information for these mine-water managers to make decisions, for example, about taking specific measures to address the mine-water management challenges, or about collecting data to refine model parameter estimates. Although it is necessary to combine system modelling with a robust sensitivity analysis to develop efficient mine-water management strategies, we provide the robust sensitivity indicators that are also robust mine heterogeneity as a reference set for management decision-making under both climatic and mine uncertainty when the combined methodology is unavailable.

5. Conclusions

Based on the comprehensive diagnostics of a regional systems model, this work has identified the key factors with the great influence on two fundamental mine-water challenges: water supply security and discharge management, across different climatic regimes and mines. We found significant differences between climatic conditions and between mines in output uncertainty, influential parameters, parameter importance ranking, and the magnitude of total sensitivity effects. The findings are new and important as they suggest the mine-water manager’s experience on dealing with the climate-coupled mine-water challenges cannot be simply copied from one mine to another, or from one climatic condition to another. The findings can explain the conundrum of the “hydro-illogical cycle” (DRET, 2008) that has constantly plagued the mining industry, and add to the understanding of the complexity and dynamics of a mine-water system such as water store-task-store cycles, demand-supply relationships, and complex feedback mechanisms among system components.

We further provided sets of robust sensitivity indicators by applying four criteria from decision theory into the total sensitivity effects. These robust indicators can provide mine-water managers with options on which to guide additional information collection and develop efficient management strategies based on the managers’ own risk preference, regardless of uncertain future climatic conditions and heterogeneity of mine sites. These indicators can help to extend the traditional measures on addressing mine-water challenges that are usually associated with rainfall and runoff (Cote and Moran, 2008). To mitigate the risk of insufficient water supply for mining operations, especially during dry periods, our results suggest increasing the storage of worked water (e.g., increasing captured rain water to the worked water store by applying the levee bank or expanding the catchment area), reducing water loss in specific water tasks (e.g., water use in the CHPP in the case study), and increasing raw water proportion in the demands of specific water tasks. During wet periods when severe unregulated discharge was most probably to happen, the factors that are associated with the level of the worked water store, the volume of rainwater captured to the worked water store, and the returned water to the store from specific water tasks, as well as climatic factors, require attention to deal with the threat posed by unregulated discharge.

Lack of understanding of the outcome uncertainty, system behaviours, and key drivers of severe outcomes can cause low effective, ineffective, or even harmful consequences of addressing the aforementioned mine-water challenges. This work has demonstrated that the necessity and usefulness of a combined methodology of system modelling and a robust sensitivity analysis in the area of
developing effective strategies for mine-water management.

Recent United Nations’ Sustainable Development Goals (SDGs), an ambitious blueprint for guiding the sustainable development of the world to 2030 (Gao and Bryan, 2017), are demanding that the mining industry incorporates relevant SDGs into its business and operations (The Atlas Team, 2016). The focuses are prioritised for the mining sector to realise a sustainable future, including addressing the stress of securing enough water for mining operations (SDG 6 Clean Water and Sanitation), enhancing mines’ resilience to climate-related hazards (SDG 13 Climate Action), and mitigating or avoiding significant adverse impacts of mining activities on land and water resources as well as the surrounding environment (SDG 3 Good Health and Well-Being, and SDG 15 Life on Land). Water use and management has been rated as number one sustainability issue to be addressed across all mining regions (ICMM, 2015). This work can serve as a piece of fundamental work to support the development of targeted and well-planned strategies aligning with the SDGs, and contribute to the cleaner production and sustainability of the mining industry.

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