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TECHNICAL ARTICLE

Reliable Trade-offs Between Environment and Economy: Implications for Mine Dewatering and Managed Aquifer Recharge

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Abstract

The relationship between environmental and economic drivers in mine dewatering is complex, with many competing interests. Traditionally, numerical groundwater models have been used to assess the efficacy of dewatering designs, both with respect to the expected dewatering rates and to estimate the potential effects on sensitive groundwater receptors. However, the outputs of interest from the groundwater models depend on uncertain model inputs, which means these outputs are also subject to uncertainty. Herein, we quantitatively explore the tradeoff between dewatering costs and environmental effects within the framework of reliability-based multi-objective optimization using a synthetic case study designed to mimic many facets of real-world mine dewatering. The framework explicitly considers model input uncertainty and seeks to map the trade-offs between cost, environmental impact, and reliability. We also explore the cost implications of uncertainty and hydrogeologic data collection. The results demonstrate that formal management optimization outperforms a standard dewatering strategy in both environmental and economic outcomes, allowing for simultaneous improvement in both objectives. When widely recognized hydrogeologic uncertainties are explicitly included in the optimization, the economic and/or environmental ``cost'' of reliability is quantifiable, and, through calibration to pre-mining hydrogeologic data, the tradeoffs between reliability, economic costs and environmental outcomes are improved compared to the uncalibrated analysis. However, high levels of reliability come with substantial economic and/or environmental costs, and a highly reliable zero-impact environmental outcome is not feasible. Ultimately, we show that formal reliability-based management optimization enables decision makers to choose their level of acceptable risk and to understand the economic and environmental costs associated with this choice.

Keywords Uncertainty analysis · Multi-objective optimization · Reliability · Modeling · Groundwater

Introduction

As demand for metals and minerals increases and internal and external pressure on mining companies to operate with a focus on water stewardship intensifies, mine water replenishment may become ever more central to mine operations, particularly in arid and semi-arid regions (Miller et al. 2021; Sloan et al. 2023). The reuse of water from dewatering operations is already a fairly common practice across a range of mine types and locations, ranging from beneficiation and process water, leaching, cooling, and dust suppression (Miller et al. 2021). Less common, though growing in interest and application, is managed aquifer recharge (MAR) of surplus mine water (Sloan et al. 2023). Given sufficient quality or pre-treatment, mine MAR can support other beneficial uses in water-stressed areas such as agriculture as well as meet regulatory targets of zero discharge or minimal impacts to groundwater-dependent ecosystems (GDE; Sloan et al.

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2023). There are many competing challenges to implementing MAR and effectively controlling groundwater near open pits at mine sites. Overdesigning the dewatering scheme to favor slope stability can greatly affect nearby GDEs, stall water level rebound post-closure, and produce mounding from the larger surplus volumes, whereas under-designing the dewatering scheme can be catastrophic for both human safety and the economic interests of the operating mine. These competing challenges are confounded by the high degree of hydrogeologic complexity and uncertainty that are often associated with mineralized areas (Sperling 1990; Sperling et al. 1992).

Model-based optimization is a useful tool to support the goals of an operating mine as it can simulate disparate objectives (e.g. minimize operational [OPEX] and capital [CAPEX] costs, maximize profit), constraints (e.g. discharge permits, water treatment plant capacity), and numerous decision variables (e.g. locations, depths, and rates of dewatering wells) present. Firmani (2024) developed a linear optimization software program that integrated results from a pit dewatering groundwater model, an ore processing model, and a tailings storage facility (TSF) model to evaluate the net present cost of constructing evaporation ponds or an additional water treatment plant to optimize the life of the existing TSF. Their analysis, which relied entirely on pre-existing models, demonstrates how model-based optimization can save cost and enhance sustainability of mine water management. A limitation of this approach (acknowledged by Firmani (2024) and to be addressed in future work) is the use of deterministic models in the optimization. Other examples in the literature of single-objective and multi-objective dewatering optimization using deterministic forward modeling include: Dong et al. (2025), Jiang et al. (2013), Ma et al. (2023), and Sun et al. (2024). Neglecting the uncertainty inherent in all models (Doherty and Moore 2020) exposes the decision-maker to the risk of adopting a solution that, while feasible in terms of constraints, may, in reality, have a low probability of being feasible, and/or may produce unexpected and undesired trade-offs in economic or environmental outcomes.

Accounting for uncertainty in decision-making introduces the notion of"reliability" (Bear et al. 2010); highly-reliable management solutions are solutions that have a high probability of success, despite the recognized sources of uncertainty. Sperling et al. (1992) demonstrated the effects of hydrogeologic uncertainty on the trade-off between pit wall slope angle and profit by coupling numerical flow and slope stability model and expressing uncertainty through conditional Monte Carlo simulations of hydraulic conductivity. They found that the effect of hydrogeologic uncertainty was large enough that both groundwater control strategies considered to increase reliability of desired pore pressures (e.g. horizontal drains and slope flattening) led to an overall increase in expected profit for the mine. This is due to the high cost of slope failure, particularly as the mine deepens. Aside from the study described above, the authors could find no examples of explicitly incorporating uncertainty or reliability into mine water management optimization in the public domain, speaking to a lack of tools, computational resources, or perhaps ignorance among practitioners. That is, to the author's knowledge, the use of reliability-based constrained multi-objective optimization to explore the tradeoff of environmental and economic outcomes under uncertainty for a mine dewatering design is novel.

Recent advances in low-cost, high-dimensional inverse methods and genetic algorithms that handily deal with nonlinear optimization problems have enabled the explicit representation of reliability as an objective in model-based optimizations (Coulon et al. 2024; White et al. 2022), heretofore referred to as a "reliability" objective.

This work presents a proof of concept for applying multi-objective optimization under uncertainty to a synthetic mine dewatering and injection modeling case study and discusses the implications for sustainable groundwater management. Within multi-objective optimization analyses, the goal is to find pareto-optimal solutions to the dewatering design problem, where pareto-optimal solutions are dewatering designs that represent the best-possible trade-off between the competing objectives, which, in this study, are cost, environmental impact, and reliability. For example a pareto-optimal solution is sought for a dewatering design that cannot improve any of the three primary decision making objectives without degrading the other two objectives. We focus on these three objectives because of the natural tension and tradeoffs between economic and environmental outcomes and because of the direct effect that reliability has on the economic-environmental tradeoff. In our experience, these three objectives are at the core of most groundwater modeling decision making.

To explore management ramifications of formal optimization, and incorporating uncertainty and/or calibration outcomes into the optimization to seek reliability estimates, four dewatering and borehole injection design analyses are presented using the synthetic model:

1. A "standard solution", where dewatering and injection wells are simply "switched on" and run at a constant rate of the duration of active mining; the model is given the best-fit calibrated values for hydrogeologic properties and boundary conditions. We believe this solution is more-or-less representative of the current state of practice;
2. A "calibrated model" case, where formal Pareto-optimal solutions are sought using a deterministic model that has the best-fit calibrated parameter values;

3. An "uncalibrated reliability" case, where reliable Pareto-optimal solutions are sought using parameter uncertainties defined only by expert knowledge and/or literature values;
4. A "calibration-constrained reliability" case, where reliable Pareto-optimal solutions are sought using parameter uncertainties that remain after calibration to hydrogeologic data collected before mining activities begin.

Given that groundwater models are typically already developed for a range of purposes at most mine sites, this study seeks to show that model-based optimization under uncertainty may present substantial value for decision support at a modest additional effort, especially when considering the potential economic and/or environmental costs of unrecognized risks when planning for mining activities.

Methods

The dewatering and injection optimization workflow was conducted within the PEST++ (pestpp) decision-support modeling software universe (Welter et al. 2015; White et al. 2020). The general steps in the workflow, illustrated in Fig. 1, consisted of:

1. Constructing the initial model input files;

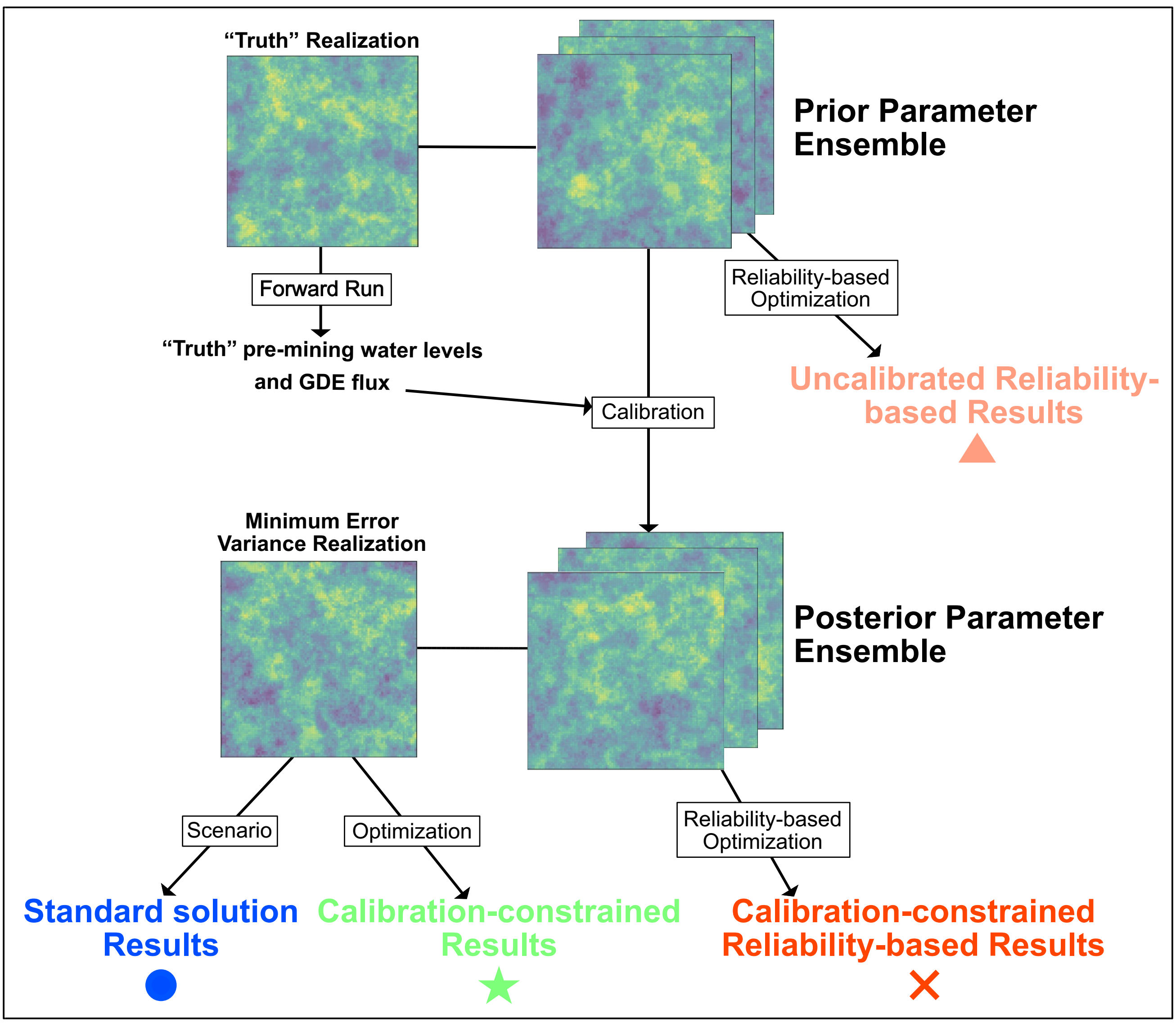

Fig. 1 Schematic workflow of the four dewatering and borehole injection design analyses. Note that colors and symbols correspond with the color flood of reliability in Fig. 5

2. Constructing the PEST-model interface, representing model input uncertainty as parameters and dewatering and injection system controls as decision variables;
3. Defining parameter uncertainties, representing expected variability and spatial patterns of hydrogeologic property and boundary condition uncertainties;
4. Drawing the initial parameter ensemble using standard stochastic sampling techniques and evaluating this ensemble with the model, essentially preforming a simple Monte Carlo analysis;
5. Selecting a "truth" parameter set from the Monte Carlo results, ensuring the selected truth is feasible with respect to the required pit groundwater levels during active mining, and using pre-mining groundwater level values at selected locations and the pre-mining GDE flux from the truth model as "observations" from an unseen groundwater system;
6. Completing calibration with an iterative ensemble smoother (White 2018), yielding a calibration-constrained parameter ensemble, i.e. an ensemble that respects expected parameter variability but also matches the pre-mining “truth” groundwater level and GDE flux observations;
7. Completing several constrained multi-objective optimization analyses (White et al. 2022) using both the uncalibrated and calibration-constrained parameter ensembles to explore the implications of uncertainty and reliability in dewatering design optimization.

This modeling analysis workflow is implemented using python, Flopy, and pyEMU (White et al. 2016) such that it is entirely scripted and fully reproducible. We note that all of the software tools used in our analyses are open-source and freely available.

Model Setup

The synthetic model was designed to be complex enough to represent the sources of uncertainty commonly encountered in mine dewatering and simple enough to be stable and efficient for the many forward runs required by multi-objective optimization under uncertainty. The model, shown in Fig. 2, was constructed in MODFLOW-6 (Hughes et al. 2017; Langevin et al. 2017) using the Python programming interface FloPy (Bakker et al. 2016; Hughes et al. 2024).

The model comprises a single layer with a uniform land-surface elevation of 110 m and a bottom elevation of 0 m. The domain area is 4 km ^{2} with 100 rows and 100 columns 20 m in length. The simulation is discretized into three stress periods. The first stress period represents a steady-state pre-development condition with upgradient inflow represented by general head boundary (GHB) conditions and downgradient flow to a GDE represented by drain boundary

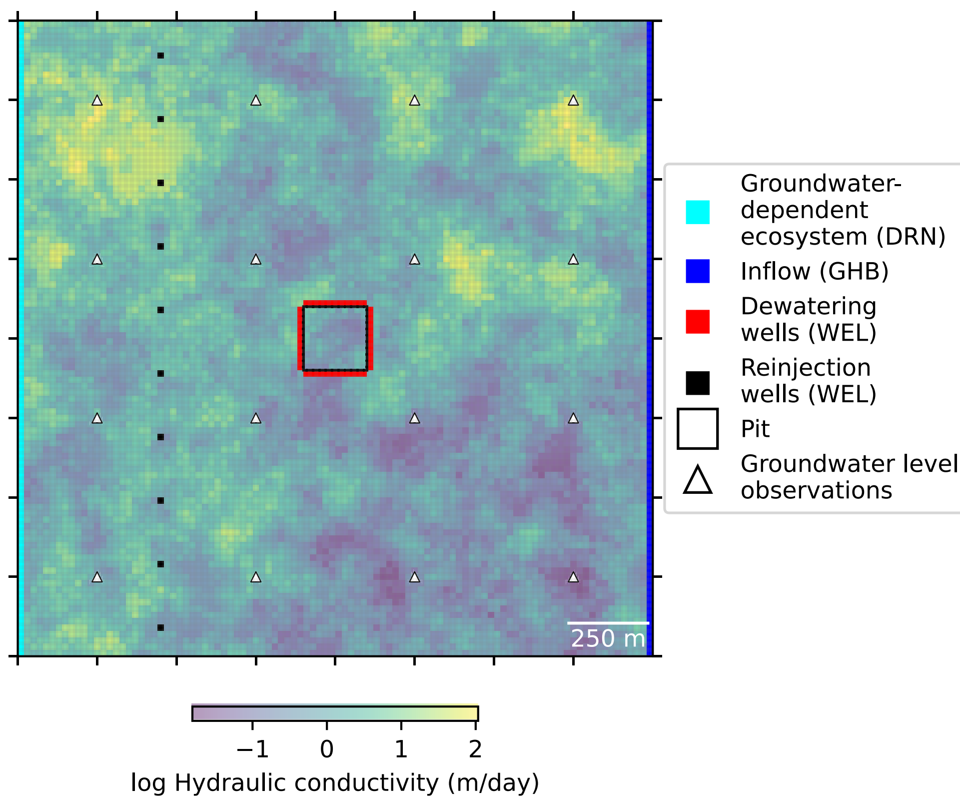

Fig. 2 MODFLOW-6 model domain and locations of boundary conditions. The “truth” hydraulic conductivity field is shown

conditions. The second stress period represents a 10-year transient mining development and operations period. This transient period includes dewatering wells surrounding the open 200 m × 200 m pit and downgradient injection wells implementing managed aquifer recharge (MAR), to mitigate the effects of dewatering on the GDE. The 40 dewatering wells are initially assigned a uniform pumping rate of 250 m ^{3}/d and the 10 injection wells are initially assigned a uniform injection rate of 500 m ^{3}/d. The final stress period represents a transient 100-year post-closure recovery period, where the extraction and injection wells are turned off and the mine is assumed to be backfilled. A small diffuse recharge rate of 3.65 mm/yr was applied at the surface throughout the simulation, assuming the synthetic model is located in an arid climate.

Uncertainty Framework

Following the reasoning laid out in White et al. (2021), a highly parameterized approach to representing uncertainty was employed. In short, using a very large number of parameters in the inverse problem is now very computationally efficient with ensemble methods. It is an effective approach to allow information from observations to flow to the appropriate parameters at the appropriate times and locations, and hedges against parameter compensation and the corresponding predictive bias that comes from lumping or fixing otherwise uncertain model inputs during the history-matching/calibration process (Knowling et al. 2019; Markovich et al. 2022). Adjustable multiplier parameters were assigned to represent spatial uncertainty in hydraulic conductivity (K), specific yield, and recharge via grid, pilot point, and layer constant parameters. Cell-by-cell drain boundary conditions representing the GDE were given adjustable conductances to reflect uncertainty in GDE flux, and cell-by-cell GHB boundary conditions representing the upgradient inflow were given adjustable conductances and heads to reflect uncertainty in the upgradient inflow. This resulted in a total of 31,406 adjustable parameters.

Collectively, the upper and lower bounds of the parameters shown on Table 1 were used to define "prior" (or precalibration) expected parameter uncertainties. Combined with geostatistical correlations for spatially distributed properties (i.e. horizontal K and specific yield) and recharge, we generated a prior parameter ensemble, which is a collection of 500 uncalibrated, but plausible, parameter sets called realizations. This prior parameter ensemble is subsequently used to demonstrate the effect of uncalibrated but plausible uncertainties on the reliability-based optimization. The prior parameter ensemble is also used in the calibration and calibration-constrained uncertainty analysis described in the next section.

Table 1 XXX

Parameter group	Lower multiplier bound	Upper multiplier bound
Horizontal K	0.001	1000
Specific Yield	0.512	1.728
Recharge	0.512	1.728
GDE Drain Conductance	0.25	4
GHB Head	− 4	4
GHB Conductance	0.5	2

Calibration and Calibration-Constrained Uncertainty Analysis

To evaluate the role of parameter uncertainty and calibration within a reliability-based dewatering and MAR optimization, we used our synthetic groundwater model to generate a "truth" or reference reality (the true horizontal K field is shown on Fig. 2). This truth was selected by running the 500 parameter sets in the previously-described prior parameter ensemble through the MODFLOW-6 model with a uniform dewatering well rate of 250 m ^{3}/d (10,000 m ^{3}/d cumulative rate) and an injection well rate of 500 m ^{3}/d (5,000 m ^{3}/d cumulative rate). Once this simple Monte Carlo analysis was complete, we selected the parameter set that yielded simulation results of feasible pit groundwater levels during active mining and was nearest the mean of the expected cost of the dewatering system.

With the truth parameter set, we ran MODFLOW-6 forward to yield "true" pre-mining groundwater levels and pre-mining groundwater flux to the GDE boundary. These simulated pre-mining groundwater levels and flux measurement were subsequently used as calibration observation data. With this approach, we can mimic the real-world situation where the true hydrogeologic properties and system boundary conditions are unknown/uncertain, and all that is available are some state measurements from the aquifer system.

Armed with the "true" pre-mining groundwater level and GDE flux observations and the prior parameter ensemble, we used an iterative ensemble smoother to modify the realizations in the parameter ensemble such that they become "calibrated." That is, the iterative ensemble smoother adjusted the values of each parameter realization until the resulting model outputs better match the available pre-mining groundwater levels and GDE-flux estimate. Ultimately, the iterative ensemble smoother process yielded a calibration-constrained parameter ensemble that can be used in reliability-based optimization.

Within the calibration-constrained parameter ensemble, there is also a single "best-fit" realization that we refer to as the "calibrated model" (i.e. the minimum error variance solution as described in Moore and Doherty (2005)). This single parameter set was used to demonstrate some aspects of dewatering and injection optimization design below.

Optimization Framework

Completing formal constrained multi-objective optimization requires the definition of several important algorithmic components, including decision variables, constraints, objectives, and how uncertainty (and therefore reliability) will be represented. The decision variables in the optimization analyses, i.e. the model inputs that were adjusted in the optimization process, comprised:

- Pumping rates for each of the 40 dewatering wells;
- The start of the dewatering period;
- Dewatering duration;
- Injection rates for each of the 10 injection wells;
- The start of the injection period;
- Injection duration.

Through these 54 decision variables, the temporal and spatial aspects of both the dewatering and injection systems were the subject of optimization analyses. We note that all dewatering wells are active during the same”dewatering period” and all injection wells are active during the same “injection period”, respectively, which represents a relatively simple operating schedule.

The following constraints were specified in the optimization, i.e. conditions that must be satisfied by the optimal solutions:

- Maximum head in the pit does not exceed a 80 m during each stress period and time step that represents active mining operations (5–10 years). We note this constraint is derived directly from simulation results, and is therefore subject to uncertainty in as much as it is influenced by uncertain parameters (described above);
- Water levels at the injection wells do not exceed the land surface (110 m) at any point, during mining development, operations, and post-closure;
- Extraction rates for each dewatering well are allowed to range from 0 (off) to 500 m ^{3}/d;
- Injection rates for each injection well are allowed to range from 0 to 1000 m ^{3}/d;
- The start of the dewatering and injection periods are allowed to range from the beginning of the development period to the beginning of the operations period (0–5 years);
- The dewatering and injection durations must last a minimum of one year and are bounded by the end of the operations period (mine closure).

With the defined decision variables and within the feasible space defined by the constraints, the multi-objective optimization analysis seeks to optimize three competing management objectives:

- Minimize the total present value cost of the dewatering (and optional injection) system (f_1, Eq. 1), which consists of capital and operational costs during mine development and operations. It is assumed that there are no costs in the post-closure recovery period;
- Minimize the total volume deficit of groundwater that would otherwise be discharged to the GDE during the all stages of the mining life cycle: mine development and operations and post-closure recovery period (f_2, Eq. 4);
- Maximize reliability(R, Eq. 5), i.e., minimize the probability that the pit and injection site groundwater level elevation constraints will be violated given the uncertainty of the simulated groundwater system, as represented by the parameters.

The three optimization objectives can be formulated as:

$$Minimize\ f_1 = \sum_{t=1}^{T} \frac{1}{(1+r)^t}\left(CPX_t + OPX_t\right) \tag{1}$$

$$CPX_t = c_{a,ext}N_{t,ext} + c_{a,inj}N_{t,inj} + c_{pipeline} \tag{2}$$

$$OPX_t = c_{p,ext}V_{t,ext} + c_{p,inj}V_{t,inj} + c_{import}V_{t,penalty} \tag{3}$$

where f_1 is the present value of all costs (USD), t is the number of years from present, T is the total number of years from present, r is the discount rate (%), CPX_t are the capital costs in year t (USD), OPX_t are the operating costs in year t (USD), N_t is the total number of wells installed in year t, c_a is the unit cost of activation (installation and development) for a well (USD), $c_{pipeline}$ is the cost of installation of the MAR pipeline, which occurs the year in which the injection wells are installed (USD), V_t is the total volume extracted by wells in year t (m^3), c_p is the unit cost of pumping per unit volume for a well (USD/m^3), c_{import} is the unit cost of extra water for MAR (USD), $V_{t,penalty}$ is the volume of extra water to bring into the MAR system when $V_{t,inj}$ is greater than $V_{t,ext}$ (m^3), and the subscripts *ext* and *inj* refer to extraction and injection wells, respectively. Table 2 shows the assumed OPEX and CAPEX costs.

$$Minimize\ f_2 = \sum_{t=1}^{T_d} V_{deficit,t} \tag{4}$$

where f_2 is the total volume deficit of groundwater that would otherwise have been discharged to the GDE over the entire mining life cycle (m^3), T_d is the total number of days

Table 2 YYY

Name	Symbol	Value	Unit	Type
Cost of Activating Injection Well	$c_{a,inj}$	200,000	USD	CAPEX
Cost of MAR System Pipeline	c_{import}	500,000	USD	CAPEX
Cost of Activating Extraction Well	$c_{a,ext}$	100,000	USD	CAPEX
Unit Cost of Injection Per Unit Volume	$c_{p,inj}$	0.5	USD/m ^{3}	OPEX
Unit Cost of Extraction Per Unit Volume	$c_{p,ext}$	0.15	USD/m ^{3}	OPEX
MAR Water Importation Cost Per Unit Volume	$c_{pipeline}$	1.5	USD/m ^{3}	OPEX
Discount Rate	r	0.07	fraction	OPEX

where there was a volume deficit and $V_{deficit,t}$ is the volume deficit to the GDE on day t. There is a volume deficit to the GDE on days for which the volume to the GDE is less than the simulated pre-mininig volume of groundwater discharged to the GDE.

$$Maximize\ R = 1 - P_F \tag{5}$$

where R is the reliability (%) and is equal to the probability that all the constraints will be satisfied simultaneously for a given set of decision variable values. R can also be defined as $1 - P_F$ where P_F is the overall failure probability, i.e., the probability that all the constraints will be violated. Adding an additional objective of maximizing reliability is a category of reliability-based design optimization (RBDO) (Deb et al. 2009). Conceptually, reliability is evaluated within the optimization solution process by evaluating the prior or calibration-constrained parameter ensemble for a given set of decision variables, counting how many realizations satisfy all of the constraints and dividing by the total number of realizations. It should be clear that the more uncertainty in the parameters and the more that the constraint(s) are influenced by these parameters, the larger the range of simulated conditions at the constraints and the more realizations may violate the constraints. So there is a potentially complex and nonlinear relation between parameter uncertainty and reliability, one that our optimization analyses explicitly recognize and account for.

The optimization analyses presented herein were completed using meta-heuristic evolutionary approaches with a population of 100 individuals, where each individual in the population has a unique set of decision variable values that are generated using a particle-swarm optimization (PSO) (Kennedy and Eberhart 1995; Siade et al. 2020) technique. The non-dominated sorting genetic algorithm NSGA-II (Deb et al. 2002) was used as the environmental selector to determine which individuals have the highest fitness values in a multi-objective non-dominated sense to continue to the next generation. Each optimization analysis was run for 250 generations.

It is important to note that a wide range of generators and selectors have been put forward in the literature. We chose PSO based on previous success in applying this generator in groundwater settings; NSGA-II has proven to be an exceptionally successful algorithm for seeking Pareto frontiers in a wide range of problem settings. However, other generators and/or selectors may perform more efficiently in different settings (e.g. Wolpert and Macready (1997)). A comparative study of the optimal efficiency of meta-heuristic evolutionary algorithms for mine dewatering design is beyond the scope of this work.

We also included a “standard solution” to the dewatering optimization design that represents what we believe is a typical approach used in applied groundwater modeling to support dewatering design; this solution operates all dewatering wells at a constant 250 m^3/d (10,000 m^3/d cumulative rate) extraction rate for the full development and active mining periods and all injection wells at 500 m^3/d (5000 m^3/d cumulative rate) during the active mining period. Note this standard solution, like the calibrated model solution (discussed previously), uses the minimum error variance parameter set found through calibration. We compare the results of the formal optimization analyses to the simulation results of the standard solution throughout the remainder of the paper to emphasize the value of more advanced dewatering design analyses.

Results & Discussion

Deterministic Optimization

Figure 3 shows the deterministic multi-objective optimization analysis using the minimum-error-variance parameter set derived from calibration as well as the standard solution (red dot), where “deterministic” indicates that optimization analysis did not explicitly consider uncertainty and therefore does not provide reliability estimates. The “knee” solution is indicated on the pareto front; the knee solution is the pareto-optimal solution that is a minimum normalized distance to the ideal solution given the objectives. Some important points should be made regarding the interpretation of this Pareto front. First, every point along the Pareto front represents a feasible and pareto-optimal dewatering design,

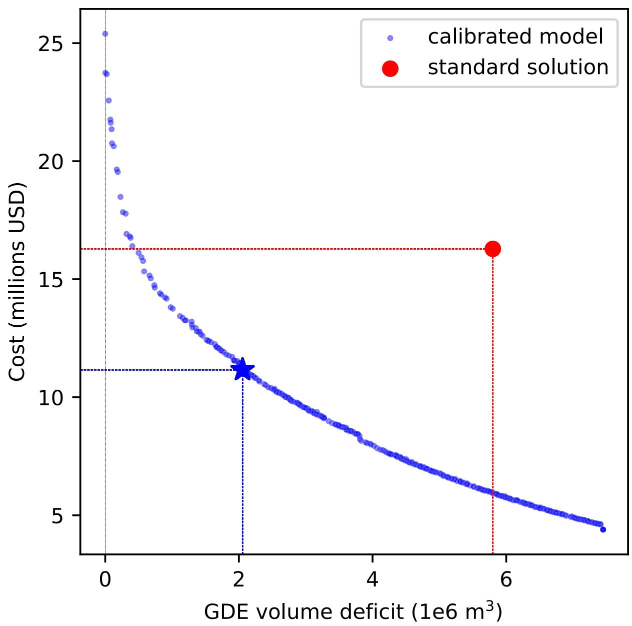

Fig. 3 Summary of deterministic optimization analyses. Stars mark the solutions that are a minimum-normalized-distance from the ideal solution (i.e. the "knee" solution). A standard reference solution (red dot) is feasible but sub-optimal with respect to both objectives

one that satisfies the required groundwater levels in the proximity of the pit and the injection sites while minimizing both costs and GDE impacts. Second, the cheapest feasible dewatering design is ≈ 5 million USD (near the lower right corner of Fig. 3) and this dewatering design disregards any change in the simulated groundwater flux to the GDE. Starting at the cheapest design, any effort to reduce the impact to the GDE results in an increase in cost, in a monotonic and increasing rate. Finally, in seeking (near) zero GDE impact, the Pareto front becomes nearly vertical (in the upper left of Fig. 3), which is a depiction of so-called "diminishing returns", where achieving even a trivial additional reduction in GDE impact results in substantial cost increase.

It is important to recognize the value of formal management optimization, which in this analysis can be estimated directly by comparing the standard solution with the deterministic Pareto front. Comparing the knee solution, we see the standard solution unnecessarily costs approximately 4 million dollars more (i.e. 25% more), and is associated with considerably more GDE volume deficit (50% more). In fact the standard solution GDE volume deficit ($\approx 6\times10^6$ m^3) is nearly equivalent to the maximum GDE volume deficit found through the optimization process ($\approx 7\times10^6$ m^3). However, for a 6×10^6 m^3 GDE volume deficit, the optimization found solutions that cost 5 million dollars, which is nearly 11 million dollars less than the standard solution cost of almost 16 million dollars. Looking at the standard solution through the alternative lens of a fixed cost, if 16 million dollars was the allocated budget for dewatering, the optimal solution yields a GDE volume deficit of $\approx 1.5\times10^6$ m^3, compared to the excessive 6×10^6 m^3 from the standard solution.

In summary, any Pareto front solution below and to the left of the red dot on Fig. 3 is a feasible dewatering design that is either cheaper, more effective at protecting the GDE, or both. This range of solutions provided by multi-objective optimization provides decision makers a full range of optimal and feasible dewatering designs, so the ultimate choice of dewatering design with respect to cost and GDE impact(s) is theirs to make.

Uncertainty and Reliability-Based Optimization

Reliability-based optimization analyses were completed using both a prior parameter ensemble and a calibration-constrained parameter ensemble to represent model input uncertainties within the optimization process. These analyses do not yield only a single Pareto front, but a range of Pareto fronts corresponding to different reliabilities. Therefore, they offer insights into the reliability of a given dewatering design in the context of the trade-off between cost and GDE volume deficit.

While there is a link between model output uncertainty (such as those estimated through calibration-constrained uncertainty analysis) and reliability-based design optimization, it is somewhat counter-intuitive. We demonstrate this relationship using the standard solution, where we want to evaluate the uncertainty in the simulation results, mimicking the practice of estimating uncertainty in important model outputs. This is accomplished using the calibration-constrained parameter ensemble from the iterative ensemble smoother to evaluate the uncertainty in the simulated response to the standard dewatering and injection design–essentially, a simple Monte Carlo analysis (Fig. 4). While this is a straight-forward analysis that yields the desired uncertainty estimates that can be presented in standard ways (i.e. Figure 4), within the context of reliability-based design optimization, the results reveal a more interesting aspect. If we filter the results of these Monte Carlo analysis to only show calibration-constrained realizations that are feasible, that is, the realizations that satisfy both the pit and the injection groundwater level constraints, only 10 of the 50 realizations used are feasible. In the other realizations, at least one of the constraints is violated. This indicates that the standard design has a low reliability of ≈ 20%, or put pessimistically, the standard solution has an 80% chance of not satisfying the dewatering design requirements. This result highlights the importance of explicitly considering uncertainty and reliability within the optimization solution process.

Reliability-based optimization analyses were completed using both a prior parameter ensemble and a

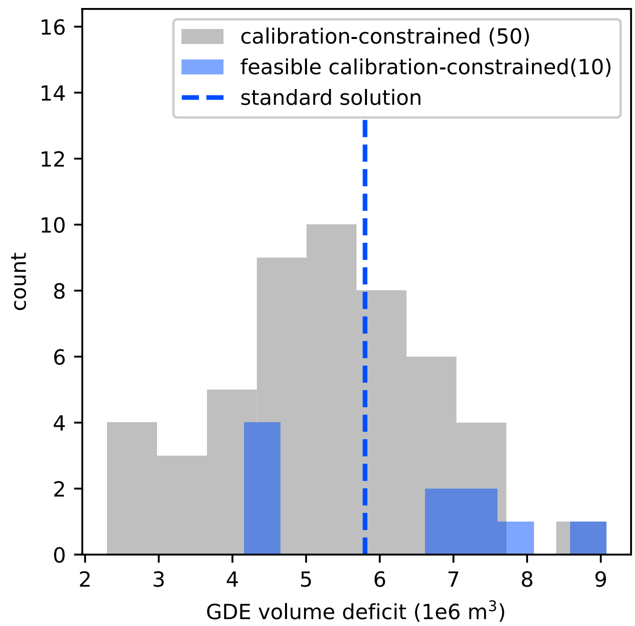

Fig. 4 Summary of the standard solution to the dewatering and injection design evaluated using the calibration-constrained parameter ensemble. The subset of realizations that are feasible (i.e. that satisfy both the pit and the injection groundwater level constraints) are shown and indicate that this design is only 20% reliable

calibration-constrained parameter ensemble to represent model input uncertainties within the optimization process. These analyses do not yield only a single Pareto front, but a range of Pareto fronts corresponding to different reliabilities. Therefore, they offer insights into the reliability of a given dewatering design in the context of the trade-off between cost and GDE volume deficit.

The results of the two reliability-based optimizations are shown in Fig. 5. Each point shown represents a feasible and optimal dewatering design for a given different reliability. The results of the two reliability-based optimizations (Fig. 5) reveal the true cost of model input uncertainty, where cost is measured in both economic and environmental outcomes. First, it is important to recognize that both types of constraints—pit and injection site groundwater levels—used in the optimization are derived from model outputs, which makes them subject to substantial uncertainties, and these two constraint types are in competition with each other as it relates to minimizing costs and GDE impacts, effectively limiting the search space of the optimization to the smaller so-called "feasible region." Seeking highly reliable solutions in this situation effectively shrinks the feasible region. In fact, the prior uncertainties in the constraints precludes the existence of dewatering designs with greater than 80% reliability (Fig. 5a). Using the calibration-constrained uncertainty estimates, where uncertainties are reduced by learning from observation data, dewatering designs with greater than

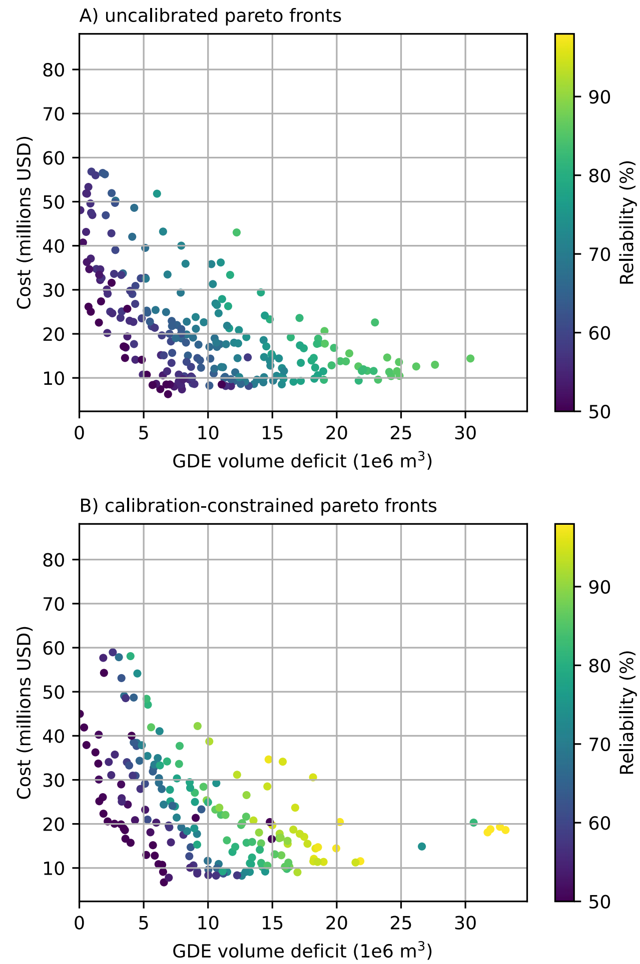

Fig. 5 Summary of reliability-base optimization analyses using: a) prior uncertainties and b) calibration-constrained uncertainties. All pareto-optimal solutions with greater than 50% reliability are shown. The effect of calibration is to compress the distance in objective space between 50% reliability and higher reliability values as well as to provide a feasible region at higher reliability levels

95% reliability do exist, albeit with substantially higher environmental and/or economic costs as shown by the yellow dots in Fig. 5b). We note that solutions of greater than 95% reliability in Fig. 5b occupy the same region of objective space as the approximately 75% prior-based reliable solutions in Fig. 5a, indicating a substantial increase in reliability from calibration for the same economic and environmental outcomes.

Based on these results, it is clear that the value of hydrogeologic data collection and calibration within a modeling analysis is to reduce model input uncertainties—those that directly influence the simulated constraint and objective responses to dewatering and injection through calibration against pre-mining groundwater system observations. That is, by learning about model inputs through calibration to site-specific information, the uncertainties in the model inputs are reduced, which results in reduced uncertainty in the quantities used in the optimization process. This learning-through-calibration translates into a narrower reliability band, and, ultimately, a larger feasible region at high levels of reliability and lower costs. We hypothesize that collection and calibration of additional pre-mining and/or early operational-phase hydrogeologic data would result in the calibration-constrained reliability-based results yielding additional highly-reliable solutions with decreased cost and improved GDE outcomes. Explicitly quantifying the value of hydrogeologic data collection in the context of reliability-based design optimization is a topic of current study.

Figure 6 compares the results of all of the optimization analyses; the standard solution is also shown. The standard solution and calibrated-model pareto front yield a reliability of 20% and 50%, respectively. Reliability-based optimization solutions with a reliability greater than 80% from Fig. 5 are shown; all solutions are color-coded according to their reliability. The cost of reliability can be directly estimated from this figure by comparing the knee solutions from the deterministic and reliability-based optimization analyses—an increase from approximately 12 million dollars to ≈ 17 million dollars for a highly reliable design in the face of well-known sources of groundwater model uncertainty. We stress however that each point shown on Fig. 6 is a feasible and pareto-optimal dewatering design that achieves the required groundwater level within the pit footprint during active mining and also avoids land-surface flooding at injection well locations.

It is important to recognize that, compared to the calibrated model deterministic pareto front (green dots in Fig. 6), a highly reliable dewatering design with zero or negligible impact on the simulated groundwater flux to the GDE does not exist. That is, no management solution exists that simultaneously satisfies the requirements that the groundwater level within the active mine footprint be at or below the desired pit bottom elevation and that the groundwater levels at injection well are kept below land surface, while also yielding a near-zero GDE volume deficit. This is because as more water is injected to prevent water deficit to the GDE, the simulated water level at the injection well locations is predicted to rise to land surface, an unacceptable situation. This important, but realistic, limitation prevents a near-zero-GDE-impact dewatering design that has a high level of reliability. We hypothesize that adding more degrees of freedom to the optimization problem, such as optimizing the location of injection wells, as well as adding more flexibility related to when dewatering and injection wells are active, may overcome this limitation.

To achieve the same 6×10^6 m^3 GDE volume deficit as the standard solution (blue dot in Fig. 6) but with high reliability, one simply traces along the y-axis from the standard solution to the nearest red 'x'. At this point, the cost has more than doubled from 17 million USD to more than 35 million USD. This hidden cost risk is not visible using the standard or deterministic calibration approaches alone—one must consider reliability explicitly to reveal this additional cost. Exposing these potential cost increases earlier in the mine planning process is expected to be highly beneficial to both mine operators and to other stakeholders.

Extension to Real-World Settings and Limitations of Current Work

Applying these techniques in real-world settings, the issue of model error/discrepancy is ever present in real-world applied groundwater modeling. Within the framework of reliability-based constrained multi-objective design optimization, model error may manifest as bias in the simulated groundwater system response to a given dewatering strategy. While model error is unavoidable, the effects of model error can be minimized by designing an appropriate

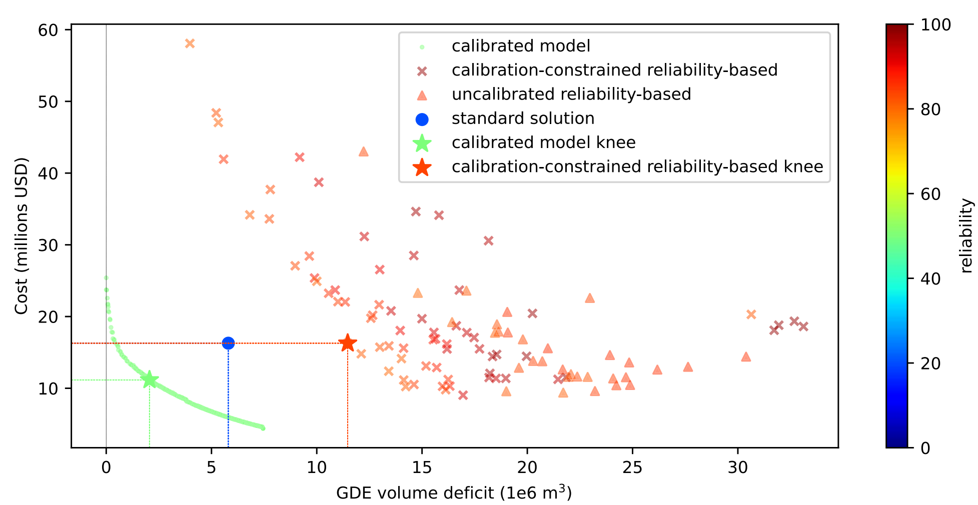

Fig. 6 Summary of all multi-objective optimization analyses. Stars mark the solutions that are a minimum-normalized-distance from the ideal solution (aka the "knee" solution). Marker colors denote reliability; reliability-based optimization solutions with reliabilities greater than 80% are shown. The standard solution and calibrated-model pareto front yield a reliability of 20% and 50%, respectively. The calibration-constrained knee solution has the same cost as the standard solution but has a higher reliability and a larger expected GDE impact

forward model and undertaking history matching using robust approaches—these two topics are beyond the scope of this work (interested readers are referred to the Groundwater Modeling Decision Support Initiative for more information on these concepts).

Any time strict constraints are being used in a real-world optimization analyses; there is a chance that the implied optimization problem is not feasible, and the chance of infeasibility only grows when reliable solutions are sought. Therefore, it is advisable to relax constraints in a constraint-penalty formulation during initial testing analyses until the strict feasibility of the problem can studied.

A key aspect of reliability-based constrained multi-objective design optimization is designing an optimization problem that yields interpretable and coherent solutions. It might be tempting to simply make every adjustable aspect of the dewatering system a unique decision variable and "let the optimizer tell you the answer". However, in our experience, this approach is rarely successful. Instead, it is advisable to start with a more simple optimization problem formulation with just a few key dewatering system aspects as decision variables, perform the optimization and understand the results, before proceeding to add complexity to the problem. This mimics the common strategy used in groundwater history matching (e.g. Haitjema 1995).

On a practical note, while this reliability-based optimization approach can theoretically be applied to any existing groundwater flow model, the number of forward runs needed for the convergence of highly reliable, Pareto-optimal solutions may be prohibitive for high-resolution, highly complex, and/or numerically unstable models. The two reliability-based optimization runs involved evaluating a decision variable population size of 100 across 250 generations with periodic re-evaluations of uncertainty using the parameter ensemble, leading to over 25,000 model runs each. The synthetic model was designed to be stable and efficient (e.g. a simulation time of <1 min) and the analysis leveraged high performance computing resources to further lower the computational hurdle. In the authors' experience, most groundwater flow models designed today have burdensome run times that preclude "out-of-the-box" application of this methodology without substantial pre-processing to cull unnecessary complexity and/or refinement. Effective decision support modeling obliges practitioners to develop numerical models with uncertainty and optimization analysis in mind. That said, current research is focused on using statistical model emulators to reduce this computational cost (e.g. Siade et al. 2020)).

One final issue that could be encountered in real-world settings is not related to the model or the technical analysis, but instead to how decision makers and stakeholder consume modeling analysis results. In our experience, many decision makers prefer a "single answer", in that they prefer to ignore uncertainty and want to be strongly guided by the modeling results, which implicitly means they are being strongly guided by the modeler who designed and implemented the modeling analysis. The key aspect of the reliability-based multi-objective optimization approach is that decision makers are given a wide range of optimal solutions along the pareto front between economy, environment, and reliability. While this theoretically empowers decision makers, some may feel decision paralysis in this setting. We have found that this issue can be overcome by early and frequent communication.

Implications for Sustainable Groundwater Management

The analyses shown in this short paper demonstrate several important aspects related to the use of numerical groundwater models to support mine dewatering design, and ultimately, to how the modeling results are used to plan for and anticipate both economic and environmental risks during active mining and post-closure periods. We show that constrained reliability-based multi-objective optimization can identify substantial cost and environmental risks early in the mine life cycle, and, more importantly, can identify the full range of optimal management strategies to minimize both of these critical decision-making elements. By exposing the trade-off between the two primary objectives (cost and environmental protection) within the context of reliability, the analyses herein enable design makers to "choose their own adventure" by selecting the cost, reliability, and expected environmental impact that meets their goals, and expectations, rather than groundwater modeling practitioners prescribing the course of action through ad hoc scenario analyses. This is in contrast to the standard solution, which resulted in sub-optimal environmental and economic outcomes (Fig. 3) and a low reliability, i.e. a high probability of failure when accounting for uncertainty (Fig. 4). We therefore question the validity of using ad-hoc manual dewatering optimization to provide adequate decision support for planning, and ultimately, sustainable groundwater resource management.

One of the more interesting outcomes from our analyses is that, for highly-reliable dewatering and injection designs, a nearly zero environmental impact solution does not exist. As stated, this is because of the constraining upper limit to simulated groundwater level rise at injection well locations. We anticipate more flexible (i.e. complex) design optimization may overcome this issue by allowing more degrees of freedom for the location of injection wells and the timing of when individual dewatering and injection wells activate. Ultimately, however, augmenting the set of decision variables and collecting more data to constrain the calibration may not overcome this issue, which itself would be a powerful result for both mine decision makers and stakeholders to understand early in the planning process.

Finally, we chose pit dewatering and MAR as a case study, given the push for more creative and innovative solutions to mining and water scarce regions, detailed in Sloan et al. (2023) and Miller et al. (2021). This reliability-based optimization approach is equally well-suited to many other aspects of the mine life cycle, including exploration, operation, and closure. Explicitly incorporating uncertainty into the optimization can provide a critical reality-check to challenging mining problems at an early stage in the planning process, at a time when the expected environmental and economic costs can be properly understood and used in decision making.

Conclusions

This modeling study explored the value of a constrained reliability-based optimization for a mine dewatering case study involving economic and environmental trade-offs. In a deterministic setting, we demonstrate that a standard dewatering solution approach is sub-optimal and that formal optimization can lead to simultaneous improvements in both economic and environmental outcomes compared to the standard solution.

When uncertainty and reliability are explicitly included in the analysis, deterministic calibration followed by a standard dewatering solution was shown to be very unreliable (i.e. it resulted in a low percentage of model realizations satisfying the optimization constraints).

Constrained multi-objective optimization under uncertainty using both prior and posterior uncertainty estimates is shown to explicitly quantify the “cost” of uncertainty. We also demonstrate the role of hydrogeologic data as a means to reduce uncertainty and therefore increase in the size of the reliable feasible region, leading to an improved tradeoff between economic and environmental interests.

This work has implications for sustainable water management during all stages of the mine life cycle with applicability to mine water challenges beyond the case study presented herein. Future extensions of this work may focus on explicitly quantifying the value of pre-mining and/or early operational-phase hydrogeologic data collection to improve optimization outcomes. This data-worth analysis is related to the concept of a closed-loop, optimal-control modeling strategy, where the model is frequently updated/re-calibrated as new hydrogeologic data becomes available and optimization analyses are undertaken repeatedly to guide near-term dewatering activities. This modeling strategy is common in the petroleum reservoir engineering literature (e.g. Benndorf and Jansen 2017; Mirzaei-Paiaman et al. 2021; Van den Hof 1998).

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Data availability All of the workflow elements used to complete these analyses are available for download at https://github.com/rhugman/synth_dewater_demo, including the python environment, workflow script, and pre-compiled binaries for MODFLOW-6 and PEST++).

References

Bakker M, Post V, Langevin CD, Hughes JD, White JT, Starn JJ, Fienen MN (2016) Scripting MODFLOW model development using python and FloPy. Groundwater 54(5):733–739. https://doi.org/10.1111/gwat.12413

Bear J, Cheng HA, Bear JJ, Cheng HA (2010) Optimization, inverse, and management tools. Modeling groundwater flow and contaminant transport. Springer, pp 693–756

Benndorf J, Jansen JD (2017) Recent developments in closed-loop approaches for real-time mining and petroleum extraction. Math Geosci 49(3):277–306

Coulon C, White JT, Pryet A, Gatel L, Lemieux J (2024) An ensemble-based approach for pumping optimization in an island aquifer considering parameter, observation and climate uncertainty. HESS

Deb K, Pratap A, Agarwal S, Meyarivanm T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197

Deb K, Gupta S, Daum D, Branke J, Mall AK, Padmanabhan D (2009) Reliability-based optimization using evolutionary algorithms. IEEE Trans Evol Comput 13(5):1054–1074

Doherty J, Moore C (2020) Decision support modeling: data assimilation, uncertainty quantification, and strategic abstraction. Groundwater 58(3):327–337

Dong Z, Xie M, Chai C, Huo X, Huang Y (2025) Design of dewatering scheme for deep foundation pit with a multi-objective optimization approach based on cost controlment. Water 17(6):857

Firmani G (2024) Software development of an integrated water management optimisation model: the Roy Hill Mine case study application. Mine Water Environ 43:41–52

Haitjema HM (1995) Analytic element modeling of groundwater flow. Elsevier

Hughes HJD, Langevin CD, Paulinski SR, Larsen JD, Brakenhoff D (2024) FloPy workflows for creating structured and unstructured MODFLOW models. Groundwater 62(1):124–139

Hughes JD, Langevin CD, Banta ER (2017) Documentation for the MODFLOW-6 framework. U.S. geological survey

Jiang S, KongX YH, Zhou N (2013) Groundwater dewatering optimization in the Shengli no. 1 open-pit coalmine, inner Mongolia. China Environ Earth Sci 69:187–196

Kennedy, James, Russell Eberhart (1995) Particle swarm optimization. Proc, ICNN’95 International conf on neural networks, 4:1942–1948. IEEE

Knowling MJ, White JT, Moore CR (2019) Role of model parameterization in risk-based decision support: an empirical exploration. Adv Water Resour 128:59–73

Langevin CD, Hughes JD, Banta ER, Niswonger NG, Panday S, Provost AM (2017) Documentation for the MODFLOW-6 groundwater flow model. U.S. geological survey

Ma Z, Wang J, Zhao Y, Li B, Wei Y (2023) Research on multi-objective optimization model of foundation pit dewatering based on NSGA-II algorithm. Appl Sci 13(19):10865

Markovich KH, White JT, Knowling MJ (2022) Sequential and batch data assimilation approaches to cope with groundwater model error: an empirical evaluation. Env Soft 156:105498

Miller KD, Bentley MJ, Ryan JN, Linden KJ, Larison C, Kienzle BA, Katz LE (2021) Mine water use, treatment, and reuse in the United States: a look at current industry practices and select case studies. ACS ES&T Engineering 2(3):391–408

Mirzaei-Paiaman A, Santos SMG, Schiozer DJ (2021) A review on closed-loop field development and management. J Pet Sci Eng 201:108457

Moore CR, Doherty JE (2005) Role of the calibration process in reducing model predictive error. Water Resour Res 41(5)

Siade AJ, Cui T, Karelse RN, Hampton C (2020) Reduced-dimensional gaussian process machine learning for groundwater allocation planning using swarm theory. Water Resour Res 56(3):e2019WR026061

Sloan S, Cook PG, Wallis I (2023) Managed aquifer recharge in mining: a review. Groundwater 61(3):305–317

Sperling T, Freeze RA, Massmann J, Smith L, James B (1992) Hydrogeological decision analysis: 3. application to design of a ground-water control system at an open pit mine. Groundwater 30(3):376–389

Sperling T (1990) Risk-cost-benefit framework for the design of dewatering systems in open pit mines. PhD thesis, University of British Columbia

Sun Y, Jiang Z, TongL SJ, Cui J, Zhou X, Liu S (2024) Optimization of confined aquifer dewatering for long-deep excavation using simulation–optimization method. Undergr Space 17:246–266

Van den Hof P (1998) Closed-loop issues in system identification. Annu Rev Control 22:173–186

Welter DE, White JT, Doherty JE, Hunt RJ (2015) PEST++ version 3, a parameter estimation and uncertainty analysis software suite optimized for large environmental models. U.S. geological survey

White JT (2018) A model-independent iterative ensemble smoother for efficient history-matching and uncertainty quantification in very high dimensions. Env Soft 109:191–201

White JT, Fienen MN, Doherty JE (2016) A python framework for environmental model uncertainty analysis. Env Soft 85:217–228

White JT, Hemmings B, Fienen MN, Knowling MJ (2021) Towards improved environmental modeling outcomes: enabling low-cost access to high-dimensional, geostatistical-based decision-support analyses. Env Soft 139:105022

White JT, Knowling MJ, Fienen MN, Siade A, Rea O, Martinez G (2022) A model-independent tool for evolutionary constrained multi-objective optimization under uncertainty. Env Soft 149:105316

White JT, Hunt RJ, Fienen MN, Doherty JE (2020) Approaches to highly parameterized inversion: PEST++ version 5, a software suite for parameter estimation, uncertainty analysis, management optimization and sensitivity analysis. U.S. Geological Survey

Wolpert DH, Macready WG (1997) No free lunch theorems for optimization". IEEE Trans Evol Comput 1(1):67–82

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