Improving Early Mine Design using Reference Class Forecasting of Mine Water

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Abstract

Integrating projections of mine water chemistry early into the mine design process—prior to relevant site-specific data being available—provides the greatest opportunity for improving environmental outcomes with the lowest increases to overall schedule and cost. An approach derived from behavioral economics, "Reference Class Forecasting" (RCF), is applied here in a mine water quality context to identify a preliminary design basis for rock stockpiles. The RCF evaluation, as demonstrated in this paper, required a relatively low level of project definition, yet identified order of magnitude reductions necessary for constituents of interest and screened out other constituents from further review.

Keywords: Mine water scoping design reference class forecast

Introduction

Hydrogeochemical forecasts of future mine water chemistry can provide valuable technical bases for the design of future mining projects. However, construction of a hydrogeochemical model requires a high degree of project-specific and site-specific knowledge to establish the conceptual framework for modeling and to inform model parameter values. Developing the mine plan, site water balance, baseline water quality evaluation, and results from a geochemical characterization program requires considerable time and resources before model results are available.

Further, mine development timelines continue to lengthen (Heijlen *et al.* 2021). The current average lead time to operations for a new nickel mine is over 17 years, with increasingly complex environmental review and permitting (ER&P) occupying a substantial part of that timeline. The combined effect of extended development timelines and commitment to a specific project definition during ER&P creates an inherent conflict: either the ER&P-committed mine design is out of date by the time permit decisions are imminent; or that ER&P must begin so far in advance of mine design that probabilistic modeling is hindered by numerous unconstrained assumptions that unduly restrict the subsequent mine design. Both are undesirable situations from the perspectives of the project, the regulator and the public process.

This conflict between state of project knowledge and project timelines exists in other contexts. Budget forecasting for major multi-year capital projects requires cost estimates long in advance of detailed project design. The general rule of thumb is that the earlier in the project lifecycle that problem areas are identified, the more effectively management of those issues can be integrated into the project – resulting in better decision making, better design, and lower overall project cost. However, the conflicts between mine design and extended ER&P effectively constrain projects from applying best informed design principles for water management at the most advantageous stage of the process (Fig. 1).

An alternative approach for early mine water quality design is presented in Reference Class Forecasting (RCF). RCF is borne out of economic theories originally by Kahneman & Tversky (Tversky and Kahneman 1974) (Kahneman 1979) and further developed by Flyvbjerg (2007) in transportation project

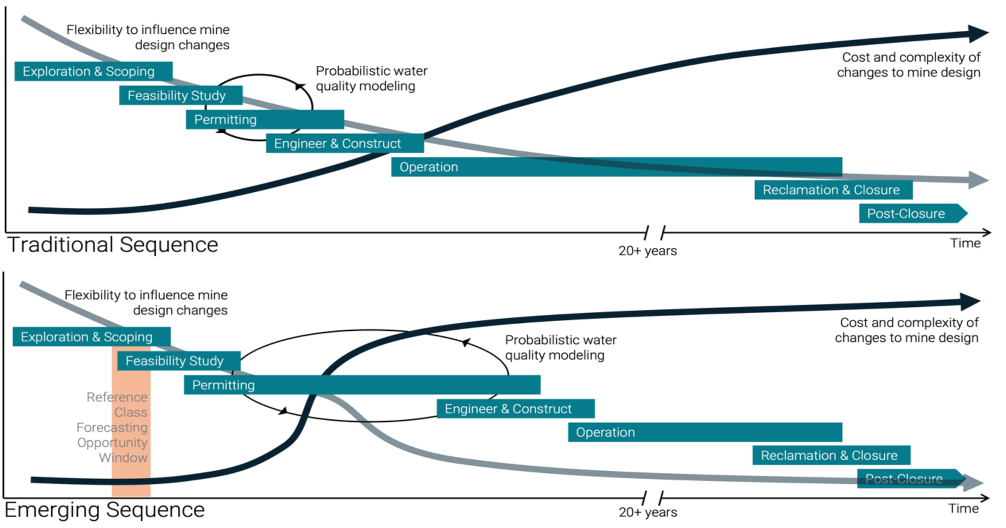

***Figure 1** Mine development sequence with respect to design flexibility and cost to integrate changes. The inflection point between flexibility to integrate design changes and cost/complexity of executing changes is shifting earlier in project timelines as the permitting processes become longer and contingent on modelling.*

cost forecasting. It provides an alternative to 'inside' (or bottom up) cost buildups, which rely on a detailed breakdown of steps and assignment of cost to each, by instead looking for 'outside' similar projects that create a reference class from which costs for the project of interest may be more accurately estimated.

Once a target project is identified, RCF is approached as a 3-step process per Flyvbjerg:

(1) Identifying a relevant reference class of past, similar projects. The class must be broad enough to be statistically meaningful but narrow enough to be truly comparable with the specific project.

(2) Establishing a probability distribution for the selected reference class. This requires access to credible, empirical data for a sufficient number of projects within the reference class to make statistically meaningful conclusions.

(3) Comparing the specific project with the reference class distribution, in order to establish the most likely outcome for the specific project.

The principle of RCF was adopted here for scoping-level assessments of mine project water quality to more effectively integrate water quality design into mine planning. Early RCF-based planning (See Fig. 1, lower panel) brings the benefit of limiting the scope of water modeling requirements to streamline ER&P scopes without increasing water quality risk. The outcomes of a scoping-level mining project water quality RCF are threefold: (1) screen out constituents that are unlikely to influence project design, (2) identify constituents that are likely to drive project design, including an order of magnitude of the reductions required, and (3) identify constituents for which a forecast is unclear and further review is necessary.

Methods

Development of Mine Water Quality Database

Globally, mining companies regularly sample and measure water as part of permitting requirements and in many jurisdictions those data become publicly available through local regulatory agencies. However, those water quality data tend to lack the contextual framing necessary to enable comparative use of the information.

A database of mine water quality was constructed targeting ore from magmatic nickel-copper-platinum group elements (Ni-Cu-PGE) deposits. Available water quality measurements were associated with site metadata that include the local climate, primary ore mineralogy, dominant sulfide mineralization, host lithology, characteristic waste lithologies, mining and processing types and rates, and USGS mineral deposit type. In addition, water samples were associated with proximal mine features (mine pits, rock stockpiles, tailings basins, catchment ponds) that may influence water chemistry. This information was sourced from mine permit applications, financial reporting, environmental review documents and published research findings and efficiently extracted from those sources via automated machine algorithms. The digital data were scrutinized through a quality assurance / quality control process that involved multiple review criteria, including order of magnitude error, analyte mismatch, and digit rounding issues. The database presently contains information from 39 unique mines, 1,556 unique sample locations, covers 108 unique analytes and includes a total of 1,374,045 unique water quality measurements – all with the associated contextual metadata.

Application of RCF Approach

The mine feature targeted for this demonstrative RCF evaluation is a waste rock stockpile generated from an open pit Ni-Cu-PGE magmatic sulfide ore mine. This theoretical mine ("Project mine") will obtain ore from a deposit located in the upper latitudes of the United States.

Identify a reference class

The RCF approach echoes prior work on geoenvironmental models (for example, Plumlee and Nash (1995)), which posit that geological characteristics and their associated geochemical processes exert a fundamental control on the "environmental behavior" of mineral deposits, with factors such as climate, and mining and milling methods representing potentially subordinate controls on the same. This evaluation leverages operational data from a reference class of four Ni-Cu-PGE deposits. Due to the orogenesis of this deposit type, these mines are expected to broadly share lithological characteristics of both the host intrusive body and, less so, the surrounding country rock (Naldrett 2004). Table 1 summarizes a comparison between the mines selected to comprise the reference class for this evaluation and the Project mine. Criteria in Table 1 are:

- **Description:** Indicates mining method.
- **Climate:** Indication of net precipitation and temperature at site.
- **Deposit Type:** All mines in this evaluation are mining Ni-Cu-PGE deposits. Criterion indicates the "Secondary Deposit Type", per Appendix 3 of Mudd and Jowitt (2022).
- **Waste Rock Lithologies:** General lithologic context for rocks that report to the waste rock stockpile and/or waste rock management area. All mines are expected to manage mafic to ultramafic (M-UM) igneous compositions, with or without additional rock types.
- **Stockpile Contact Water Characteristics:** Select general water chemistry parameters associated with waste rock storage. While all mines have waste rock contact water with neutral pH, there is notable variability in specific conductance and, consistent with this, sulfate concentration.

Establish a distribution of expectations

The mine water quality database was queried to obtain a dataset consisting of water quality observations from the reference class at sampling locations associated with waste rock stockpile seepage or runoff. Sampling locations selected were upstream of water treatment or other mitigative approaches. Analytes reported as below method detection limits were assessed as half of the respective limit. Observations were averaged on a monthly time basis, although this resulted in aggregation of a negligible portion of the dataset as most data were recorded on a monthly or longer frequency. For each analyte, concentrations were ordered numerically and plotted as a probability distribution. Due to the overall similarity between the Project mine and those in the reference class, no site-specific adjustments to probability distributions were applied.

Compare project to reference class

This evaluation was intended to identify the chemical constituents which will comprise the design basis for water treatment or other mitigative measures to be applied to a future waste rock stockpile ("constituents of interest") by comparing likely untreated future water quality relative to one or more benchmarks. Therefore, in addition to the probability distribution of water quality expectations, evaluation thresholds are needed to serve as evaluation benchmarks, and decision criteria are selected to formally define the acceptable level of uncertainty under which the comparison is made.

Set evaluation thresholds. Evaluation thresholds were derived in this evaluation from twenty-two potentially relevant water quality standards and incorporated project risk tolerance (see example under "Set decision criteria"). Two sets of evaluation thresholds were used. One set of evaluation thresholds ("Primary" threshold) was set to be equal to the most restrictive of the potentially applicable water quality standards. A second set of evaluation thresholds ("Secondary" threshold) was defined at 25% of these same standards. These thresholds were selected as aligned with acceptable project risk at a scoping level of evaluation.

Set decision criteria. Decision criteria are an expression of risk tolerance that balance the value of the consequence of a wrong decision against the cost/time to obtain additional certainty.

For this evaluation, the goal was to inform mine design based on water quality expectations. Under-projections (i.e., falsely rejecting an expectation that stockpile contact water will be above a water quality standard) were deemed to be of greater potential consequence than over-projections (falsely accepting the same), as they carry risks of a mine design that will result in exceedances to water quality criteria. However, both under and over projections have negative consequences, and thus, both risks of false acceptance and rejection are managed through establishment of decision criteria.

Table 1 Project site and associated reference class mine stockpile features.

	Project Mine	Mine A	Mine B	Mine C	Mine D
Description	Open pit	Open pit to underground	Underground	Open pit	Open pit to underground
Climate (Country, Köppen-Geiger code)	United States, Dfb	Spain, Csa	United States, Dfb	Finland, Dfc	Canada, ET
Deposit Type	Small M-UM Intrusion-related	Small M-UM Intrusion-related	Small M-UM Intrusion-related	Layered Intrusive	Small M-UM Intrusion-related
Waste Rock Lithologies	M-UM intrusives, metasediments	Breccia with M-UM fragments, calc-alkaline volcanics, and carbonates	Peridotite, metasediments	M-UM intrusives, mica schists, shales	M-UM intrusives, gneiss
Stockpile Contact Water Characteristics					
pH	---	7.9	7.5	6.6	7.3 – 7.7
Specific Conductance	---	3,300	2,500	5,000	200
Sulfate	---	1,700	1,100	1,600	Not available

Constituents are excluded from the design basis if the 99th percentile (P99) is *less than* the Primary threshold (i.e., the water quality standard). This is intended to limit the probability of falsely rejecting an expectation of water quality exceedances to less than 1%.

Constituents are included in the design basis if the P99 observation of the Reference Class probability distribution is *greater than* the Primary threshold, *and* the 50th percentile (P50) observation *is greater* than the Secondary threshold (i.e., 25% of the water quality standard). This set of decision criteria isolates constituents for which there is greater than a 1% chance of being observed above the water quality standard, and no more than 50% chance of being present at or above 25% of the water quality standard. The use of the Secondary threshold in this case manages the risk of overengineering the system by limiting "acceptance" to constituents that are likely to be present at concentrations near the standard.

Constituents are classified "undetermined" (i.e., more study is needed) if the P99 observation of the Reference Class probability distribution is *greater than* the Primary threshold, *and* the 50th percentile (P50) observation *is less* than the Secondary threshold. In this case, observations are too variable; while at least 1% are above the water quality standard, half or more are well below it. Either additional information is required, or a decision may be made to adopt an adaptive management approach for the risk of overengineering for this constituent.

Results and Discussion

Example cumulative distribution function (CDF) plots of water quality constituents from the identified reference class of mine stockpiles are shown in Fig. 2 (Step 2 of the RCF process). The primary and secondary water quality thresholds defined for each constituent are displayed within the CDF plots as a solid and dashed vertical line, respectively. The full results of the RCF constituent screening according to the defined acceptance criteria for the project are summarized in Table 2 (Step 3 of the RCF process).

In this evaluation, the RCF narrowed the scope of constituents from a starting list of twenty-two by ruling out eight constituents that were unlikely to have any bearing on mine design, six with likely design influence and eight for which further site-specific evaluation would be recommended including an indication of degree of necessary reduction for each of the latter two groups. The

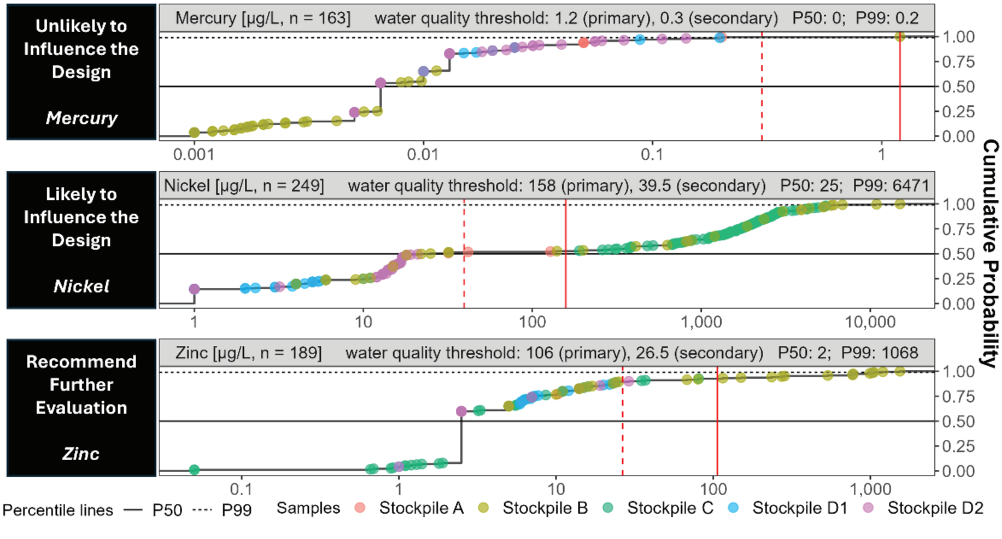

Figure 2 Example CDF plots for water quality constituents from mine stockpile reference class. Primary and secondary evaluation thresholds are identified by solid and dashed vertical lines, respectively.

resultant list of focus areas can be integrated into early mine planning to evaluate a range of management techniques and associated cost/benefits to best inform the mine plan and upcoming ER&P processes which may include: formal regulatory applicability assessments of target water quality standards, reassessing mine design to limit exposure of constituents of concern, evaluation of source control techniques that limit mobilization to water, passive/semi-passive/active control technology evaluations, regulatory relief options and adaptive risk management approaches that evolve over time.

Limitations. Data availability to construct mine feature reference classes is the current limiting factor on broader application of RCF. In this example, four sites were identified for which stockpile data across the range of constituents of interest were available where a pool size approaching 20-30 sites would be ideal. Data availability is increasing as social and governance interests in data transparency drive industry and regulatory bodies to make large datasets publicly available. For example, an industry-led group has recently been assembling a database of pit lake water quality. Reference classes that are comprised of larger pools of mine feature sources will improve confidence in the outcomes of the methodology.

Conclusion

Reference class forecasting provides a rapid, empirical-based method for early-in-design projections of mine water quality. Such forecasts inform mine design for water quality at the most advantageous stage of the planning process and focus ER&P exercises on the constituents of highest interest.

In the example application in this paper, the RCF established a focus on specific constituents and a scale to which those constituents are likely to affect stockpile performance. This provides numeric goals for the design team to integrate water quality solutions at a time when full project lifecycle cost-benefits are most actively assessed. RCF can also focus the permitting team on constituents that merit a deeper evaluation during ER&P. On a more nuanced basis, RCF also prompts a project team to make conscious decisions about acceptable risk tolerance in mine water quality design.

The RCF process is most limited at this point by the availability of mine data from which to build statistically robust reference classes, but its potential for application is expected to grow as data transparency and industry interests drive more mine water quality data into the public realm.

__Table 2__ Water quality acceptance criteria and RCF-identified constituents in each outcome category.

Constituent Outcome	Acceptance Criteria			Constituents (scale of reduction expressed as P99/primary threshold)
	P99		P50	
Constituent is unlikely to influence design	< primary water quality threshold	---	---	antimony, barium, beryllium, chromium, fluoride, lead, mercury, pH
Constituent is likely to influence design	> primary water quality threshold	AND	> secondary water quality threshold	arsenic (2x), copper (8x) manganese (130x), nickel (38x) silver (4x), sulfate (14x)
Further evaluation is recommended	> primary water quality threshold	AND	< secondary water quality threshold	aluminum (8x), cadmium (5x) chloride (3x), cobalt (90x) selenium (10x), thallium (4x) TDS (7x), zinc (10x)

References

Flyvbjerg B (2007) Curbing Optimism Bias and Strategic Misrepresentation in Planning: Reference Class Forecasting in Practice. European Planning Studies 16(1):3-21. https://doi.org/10.1080/09654310701747936

Heijlen W, Franceschi G, Duhayon C, Van Nijen K (2021) Assessing the Adequacy of the Global Land-Based Mine Development Pipeline in the Light of Future High-Demand Scenarios: The Case of the Battery-Metals Nickel (Ni) and Cobalt (Co). Resources Policy 73. https://doi.org/10.1016/j.resourpol.2021.102202

Kahneman D, A Tversky (1979) Prospect Theory: An Analysis of Decision under Risk.". Econometrica 47:263-291

Mudd GM, Jowitt SM (2022) The New Century for Nickel Resources, Reserves, and Mining: Reassessing the Sustainability of the Devil's Metal. Economic Geology 117(8):1961-1983. https://doi.org/10.5382/econgeo.4950

Naldrett A (2004) Magmatic Sulfide Deposits: Geology, Geochemistry and Exploration. Springer-Verlag Berlin Heidelberg. https://doi.org/10.1007/978-3-662-08444-1

Plumlee GS, Nash JT (1995) Geoenvironmental Models of Mineral Deposits: Fundamentals and Applications. In: U.S. Geological Survey (ed).

Tversky A, Kahneman D (1974) Judgment Under Uncertainty: Heuristics and Biases. Science 185(4157):1124-1131