Use of Groundwater Numerical Model to Support Decision Making At Large Open Pit

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Abstract

Predictive simulations of a Large Open Pit groundwater numerical model were used to support investment decisions on dewatering and depressurization infrastructure. As the obtained results are deterministic, an uncertainty analysis was developed applying the linear Monte Carlo methodology.

A series of numerical models were run using 100 random combinations of hydraulic conductivities ranging within conceptual values. Results were validated in the calibration period to assess their compliance with the conceptual understanding and calibration standards used as reference. Model outputs were interpreted as a probability of occurrence and enabled providing confidence limits to the predictive flow rates to be managed.

Keywords: Dewatering, depressurization, oredictive simulations, uncertainty analysis.

Introduction

Presence of water in mining operations has an adverse effect (Read & Stacey 2009; Beale & Read 2013). Pore pressure in the rock mass reduces pit slope stability (Hoek & Bray 1981; Sullivan 2007), while seepage in pit slopes generates surface water flow, that lead to losses in efficiency, unsafe working conditions, and higher costs of operation.

Groundwater numerical models are commonly used as a tool in the decision-making process related with slope designs and, dewatering and depressurization infrastructure planning. They are based on conceptual models that are developed from geological and hydrogeological interpretation and hydraulic tests field data, which are subject to different levels of uncertainty. These models are typically calibrated against measured water levels, pore pressures and seepage zones. Even when they comply with state-of-the-art calibration standards and may accurately reflect field data, the models will always have a level of uncertainty that needs to be assessed. Uncertainty analysis of predictive simulations is recommended before using them as support tools.

Life of Mine (LoM) of the open pit under study extends for at least 40 years, and will become one of the deepest worldwide, facing big depressurization challenges to maintain slope stability and dewatering requirements to support mining operations.

As some decisions rely on the accuracy of hydrogeological characterization and numerical models built with it, it is crucial to lower the risk related to the uncertainties of available information and predictive simulations. Besides increasing the number of boreholes and hydraulic tests to improve conceptual understanding and numerical representation, which involves time and considerable costs, a way to face this uncertainty is by identifying the main parameters that affect predictive simulation results and developing an uncertainty analysis. This methodology allows going from a deterministic to a probabilistic approach where results are interpreted as the probability of occurrence that helps to account for the risk of the decisions made.

Background Information and Conceptual Model

Situated in the highlands of the Atacama Desert, the main recharge to the open pit comes from precipitation occurring from

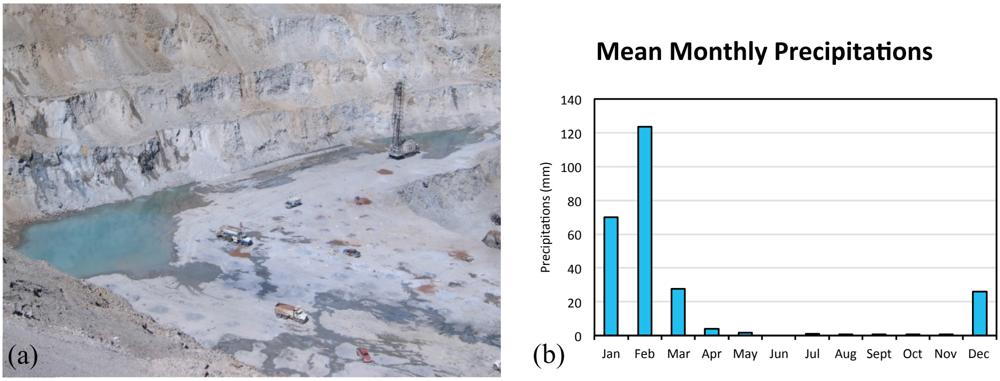

Figure 1 *(a) Pit floor flooding due to seepage. (b) Mean monthly precipitations in the vicinity of the pit.*

December to March (fig 1b). Groundwater flows through low to very low permeability rocks and is mainly controlled by faults that generate anisotropy and high heterogeneity. Outflows take place through creeks, evapotranspiration, seepage in the pit (fig 1a) and active dewatering and depressurization infrastructure.

Geology consists of pyroclastic and volcanics deposits with plutonic intrusives, covered by alluvial, colluvial and glacial sediments. Hydrogeological units (HU) (fig 2a) are separated by the main structures that have been identified either as hydraulic barriers (LP3, LP4 and LP5) to groundwater flow or as conduit faults (LP1 & LP2) that favour it. This criterion also matches with different lithologies, grouping HUs with similar characteristics, like the predominance of sedimentary rocks over volcanic ones. Subsequently, these groups have been subdivided considering their hydraulic response to the pit drainage, accounting for areas of similar hydraulic conductivity.

A large amount of data has been collected since the operation started in the mid-1990s with the pre stripping of the open pit. More than 100 Vibrating Wire Piezometers (VWP) with 2 to 5 sensors at different depths have been installed and more than 80 dewatering wells are active in the vicinity of the pit. Most of these infrastructures are connected to wireless networks, enabling real time data to be gathered by the operation from areas with difficult access which lowers the risk of errors from manual data collection. Collected data are regularly analysed and compared with the existing conceptual model to verify and adjust conceptual understanding.

New hydraulic test data were used to assess the definition of hydrogeological units and the hydraulic conductivity ranges that were assigned to them, suggesting no changes or reinterpretation was needed from what had been determined in previous conceptual models. A general trend of lower permeability with depth is observed from hydraulic tests (fig 2b), following what has been noted in crystalline rocks due to greater total stress acting on the rock at larger depths (Beale & Read 2013).

Geological mapping of fault zones focussed on estimating their potential permeability by describing the clay content observed in core logs from drilled boreholes. This information was used to confirm the hydraulic characterization of the main faults zones that control flow direction in the study area.

Numerical Model

A 3D groundwater model was developed using MINEDW™ (Azrag *et al*. 1998: Itasca Denver, 2019), which uses a finite-element approach to simulate groundwater flow in both saturated and unsaturated domains. MINEDW simulates the excavation of a pit by allowing the elevation of nodes to vary through time, adjusting the zone of relaxation (ZOR) based on the mining schedule and predicting pore pressures that can be used in geomechanical modelling.

The model grid consists of triangular prism elements with variable horizontal and vertical sizes depending on their location in

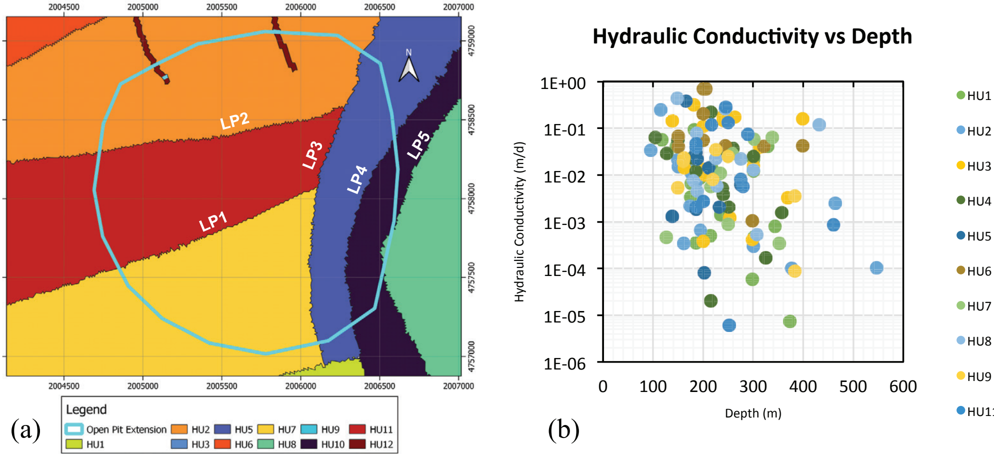

Figure 2 (a) Plan view of Hydrogeological Units and Principal Faults in the open pit. (b) Relation between Hydraulic Conductivity and depth of hydraulic tests.

the model domain. Elements within the open pit and fault zones areas are 15 to 16 m, and gradually increase their size to the boundaries of the model, reaching 500 m horizontally and 750 m vertically. This model has a total of 7,268,487 nodes and 14,197,601 elements. The vertical extension is from the topography of the area 4,600 m.a.s.l. to 2,000 m.a.s.l.

HUs and structural model were explicitly incorporated independently into the model from the 3D geometries, which enables making individual changes to assigned hydraulic parameters to perform sensitivity or uncertainty analysis. Twenty-five years of excavation sequence of the open pit was incorporated implicitly from real monthly topographies, to match the monthly time-step temporal discretization. Annual topographies were included for predictive simulations considering mining development for the next 40 years.

Zone of Relaxation (ZOR) is explained by the decompression of the different materials that compose the rock mass due to continuous

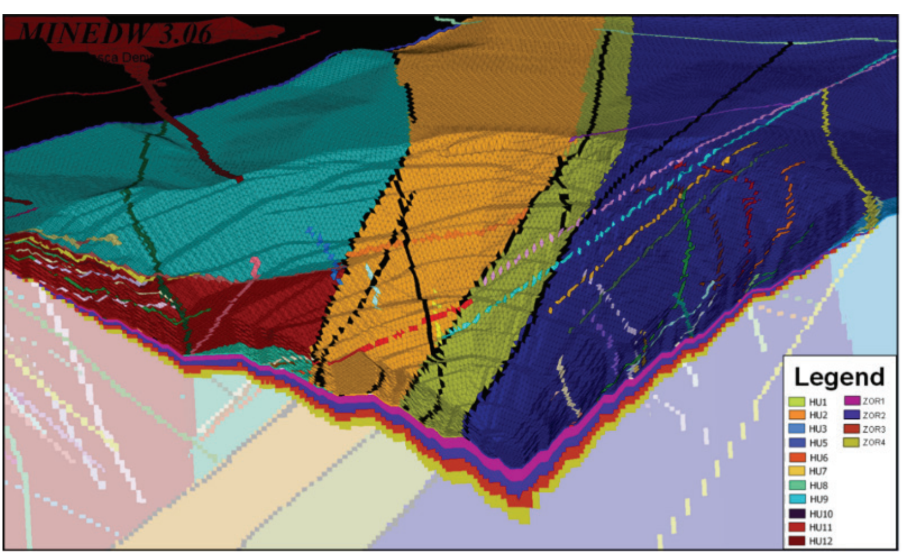

Figure 3 Hydrogeological Units and Zone of Relaxation of the open pit. Visualization in MINEDW software.

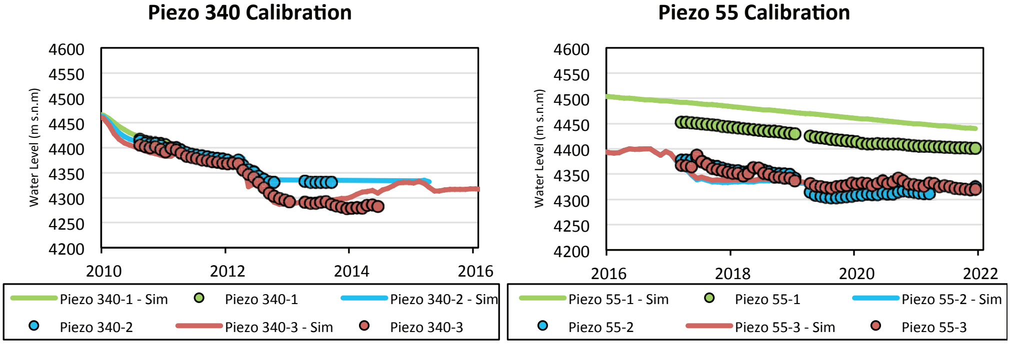

Figure 4 *Calibration examples for different piezometers. Dots represent field data and lines simulations.*

lithostatic unloading and blast operations, which result in increased permeability in the pit slopes, and is directly related to the "damage factor D" defined in slope stability models (Itasca 2014). Following geomechanical modelling previously done, ZOR has been considered in the groundwater model with a total thickness of ¼ of the depth of the pit for each time step, divided into 4 uniform layers that account for its total thickness (fig 3). Different ZOR configurations were sensitized, showing that this criterion fits the best for the calibration period.

Calibration and Simulations

Calibration of the numerical model considers water levels and its trends due to depressurization or pressurization, and vertical hydraulic gradients that have been measured in VWP sensors at different depths (fig 4). Results indicate that while the calibration meets the recommended standards (Barnett et at 2012; SEA 2012), with a standard root mean square error (SRMS) of 6.2% (recommended <10%), mean absolute error (MAE) of 35.7 m and normalized MAE (nMAE) of 4.6% (recommended <5.0%), it also reproduces mapped seepage faces and flow rates defined in the conceptual model.

After calibration, the numerical model is used to make predictive simulations for different time horizons. Short-term predictions are used to understand location of seepage faces and groundwater presence within a bench depth, to plan for depressurizations and dewatering needs as the mine progresses.

Medium-term predictions are used to assess pore pressure distribution for slope stability analysis, and to plan for future dewatering and depressurization infrastructure. This simulation is also used to estimate potential dewatering flow rates to plan for water management infrastructure.

As the Life of Mine extends for 40 years, the pit is expected to reach dimensions that require careful stability analysis of slope designs. Hence, the main output from Long-term predictions is pore pressure distribution for specific long-term topographies that are key for the operation. As the pit expands to areas with less amount of field data, it is expected that uncertainty of long-term predictive simulations increases.

Uncertainty Analysis

Uncertainty is caused by different factors and depends on the complexity of the hydrogeological system (fig 5), with four main sources affecting numerical models at different levels (Middlemis *et al.* 2019); structural and conceptual, parameterization, measurement error, and scenario uncertainties, including climate change variations. Considering these sources, it is important to define an objective for the uncertainty analysis outcome, making sure it answers the management questions.

In this study, medium-term predictive simulations were used to plan for dewatering and depressurization wells and, other related water management infrastructure, based on the expected location of groundwater within the pit, seepage faces and the flow rates that need to be managed.

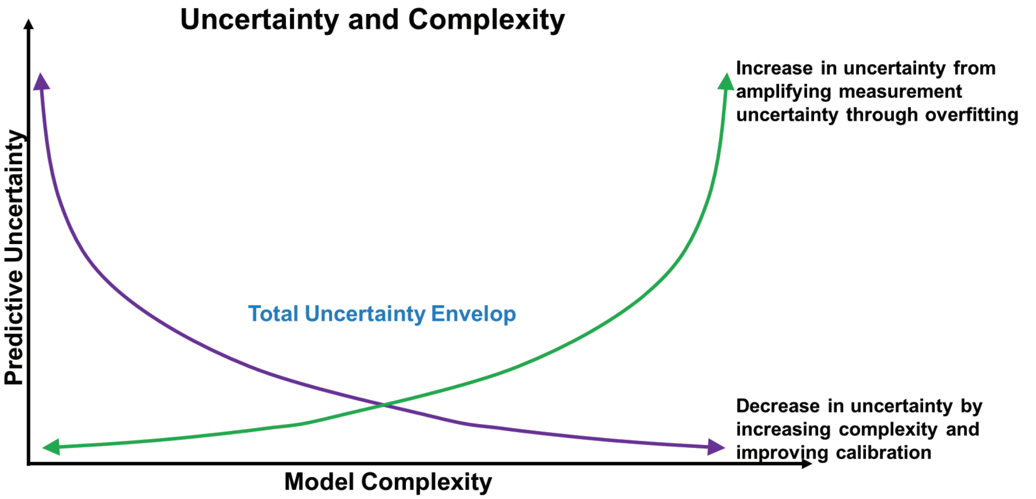

Figure 5 *Relation of the Total Uncertainty and Model Complexity (Adapted from Barnett* et al. *2012).*

As the calibrated model provides deterministic results based on the calibration of hydraulic parameters, which don't necessarily account for their specific distribution within the different hydrogeological units, nor if these are linked, a "Deterministic modelling with linear probability quantification" uncertainty analysis was developed (Middlemis H & Peeters LJM 2018). This methodology is less complex than a Bayesian analysis, but it provides an understanding regarding uncertainty, and is not subjective as an analysis of subjective probability (Barnett *et al* 2012).

Therefore, the uncertainty analysis was carried out by running the numerical model with 100 random combinations of hydraulic conductivities, varying their values within those defined by the conceptual model. Results of each model were validated in the calibration period to determine if they reproduced the assumptions indicated in the conceptual model and the calibration standards used as reference, and these validated results were used to understand the probability of seepage flow rates and pumping rates from dewatering and depressurization wells.

Results and Discussion

Outputs from the uncertainty analysis were interpreted as a probability due to its normal distribution, enabling the definition of confidence limits. Total expected seepage flow rate for 2015 is expected to be between 3,400 to 7,900 m^3/d with 90% of

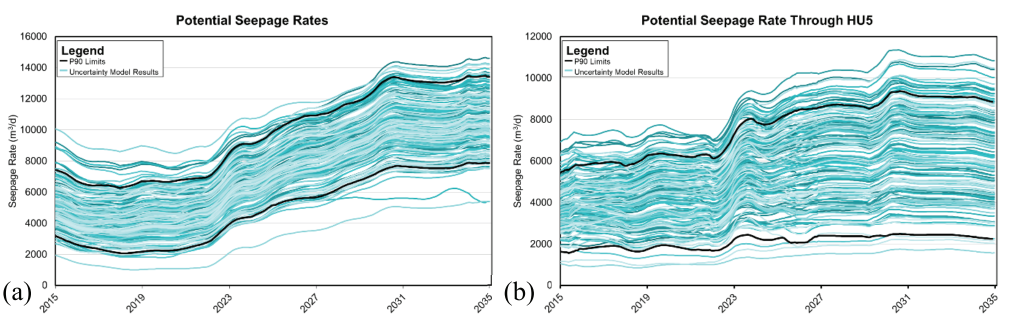

Figure 6 *(a) Total Seepage flow to the pit; (b) Seepage flow through HU5 unit.*

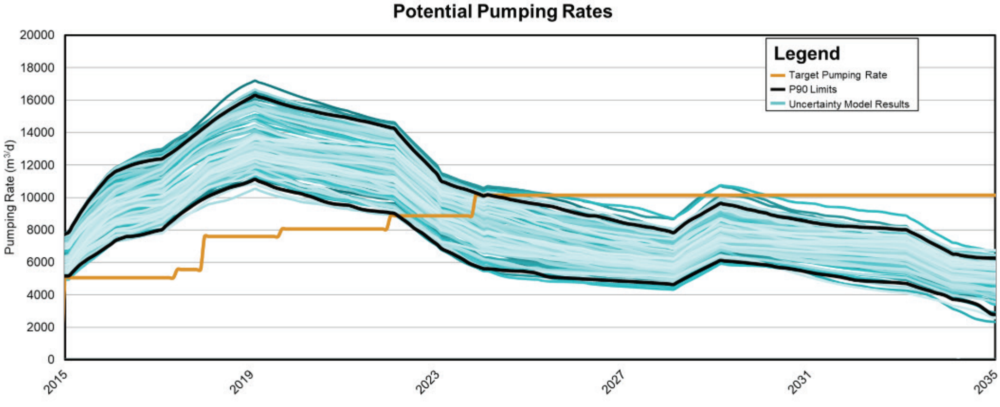

***Figure 7** Pumping wells flow rates.*

confidence (fig 6a), with most of it seeping through HU5 (1,800 to 5,200 m3/d) (fig 6b). The higher groundwater contribution and variability of predictions throughout the simulation period, suggests that HU5 represent the most uncertain unit and that further hydrogeological characterization is of high priority.

This operation must ensure a certain flow rate from dewatering and depressurization wells, so the uncertainty analysis was also focused in understanding pumping flow rates from the current wells plan with 90% confidence (fig 7). Results show that since year 2024 there is a risk that the target flow rates won't be met, suggesting the need of revisiting the current plan, via replacing lower flow rate pumping wells or adding new ones. It also indicates that further field studies should be developed to lower the conceptual uncertainty of future years, especially in areas with less amount of information.

Conclusions

Based on the current conceptual understanding, the hydrogeological numerical model developed in MINEDW reasonably simulates past and current hydrogeological conditions of the open pit and, was used to conduct predictive simulations to help with the decision making of the mine operation in different scopes. To provide additional input, an uncertainty analysis was developed over the conceptual hydraulic parameters used in the calibration, with the aim of identifying confidence limits of predictive seepage and pumping rate flow rates.

Predictive flow rates from HU5 present high variability and are found to be the highest contributor to overall seepage flows in the open pit, being above the conceptual understanding. This suggests that further characterization is needed to better understand ongoing and future hydrogeological processes as the mining progresses to improve its numerical representation. Based on the current dewatering and depressurization plan that was studied using the numerical model, predictive pumping flow rates since 2024 would not be enough to meet environmental commitments, suggesting the need of revisiting the current plan.

Investment strategical decisions regarding the definition of dewatering and depressurization infrastructure were made considering the results from the uncertainty analysis developed. It also provided input on zones within the current open pit and projected mine designs, with higher conceptual uncertainty that need to be addressed via additional hydrogeological characterization (field works) and data reinterpretation. With the new data gathered the conceptual model needs to be updated to improve the numerical tool used in the dewatering and depressurization decision-making process.

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References

Azrag, E, Ugorets, VI & Atkinson, LC. (1998). Use of a finite element code to model complex mine water problems, Proceedings of Symposium on Mine Water and Environmental Impacts, IMWA, Johannesburg.

Barnett *et al*. (2012). Australian groundwater modelling guidelines, Waterlines report, National Water Commission, Canberra.

Beale, G., Read, J. (2013) Guidelines for evaluating water in pit slope stability. CSIRO Publishing, Collingwood.

Hoek E., Bray J.W. (1981). Rock Slope Engineering, London: Institution of Mining and Metallurgy, 527.

Itasca Denver (2019). MINEDW Ver. 3.06. Denver: Itasca.

Middlemis H and Peeters LJM (2018) Uncertainty analysis – Guidance for groundwater modelling within a risk management framework. A report prepared for the Independent Expert Scientific Committee on Coal Seam Gas and Large Coal Mining Development through the Department of the Environment and Energy, Commonwealth of Australia 2018.

Middlemis H, Walker G, Peeters L, Richardson S, Hayes P, Moore C. (2019). Groundwater modelling uncertainty – implications for decision making. Summary report of the national groundwater modelling uncertainty workshop, 10 July 2017, Sydney, Australia. Flinders University, National Centre for Groundwater Research and Training, Australia.

Read, J., Stacey, P. (2009). Guidelines for Open Pit Slope Design. CSIRO Publishing, Collingwood.

Servicio de Evaluación Ambiental, SEA. (2012) Guide for the Use of Groundwater Models in the SEIA [in Spanish]. Santiago.

Sullivan, T. (2007). Hydromechanical Coupling and Pit Slope Movements, in Y Potvin (ed.), Slope Stability 2007: Proceedings of the 2007 International Symposium on Rock Slope Stability in Open Pit Mining and Civil Engineering, Australian Centre for Geomechanics, Perth, pp. 3-43.

Walker G. (2017). Predictive uncertainty in groundwater modelling: how is it best used? Discussion paper no.1 in Middlemis *et al*. 2019. Groundwater modelling uncertainty – implications for decision making. National Centre for Groundwater Research and Training, Australia.