Geostatistical Analysis to Inform the Design and Construction of Tunnel and Caverns to relocate Water Service Reservoirs to Caverns

J. G. Grasmick
Emprise Concepts, United States of America

A. Al-Nuaimi, F. Lee, J. Lee
AtkinsRéalis, Hong Kong

D. J. Steele, M. Thompson
Chun Wo Construction & Engineering Co., Ltd, Hong Kong

ABSTRACT: In geotechnical and geological engineering, we frequently face uncertainty in terms of differences between over-simplified models described in tender documents and the reality of full-scale construction and the apportioning of geotechnical risks. It is not easy to document intrinsic geological variability, the spatial variation in geotechnical parameters, rock mass quality variations, the existence of anomalies such as boulders or voids, and the differences between laboratory sampling/testing and in situ behavior. A valuable tool for assessing spatial variability and uncertainty is geostatistics. Geostatistics not only helps predict geotechnical parameters but also plays a crucial role in ground risk management. By quantifying uncertainty in spatial distribution of soil and rock properties, engineers can better plan for potential risks and variability in construction phases. This paper presents the successful implementation of geostatistics in enhancing the geotechnical understanding and designs for the relocation of fresh and saltwater service reservoirs to caverns at Diamond Hill.

1 INTRODUCTION

1.1 *Project Description*

The project involves the relocation of the existing Service Reservoirs to underground rock caverns within Strategic Cavern Area No. 26. The project location and general arrangement of the access tunnel and caverns is shown in Figure 1. The primary works of this project include: i) Construction of four caverns for accommodating the reservoirs and associated facilities, and ii) Construction of a vehicular access tunnel (VAT), approximately 645m long, connecting the caverns to the portal at Lion Rock Road.

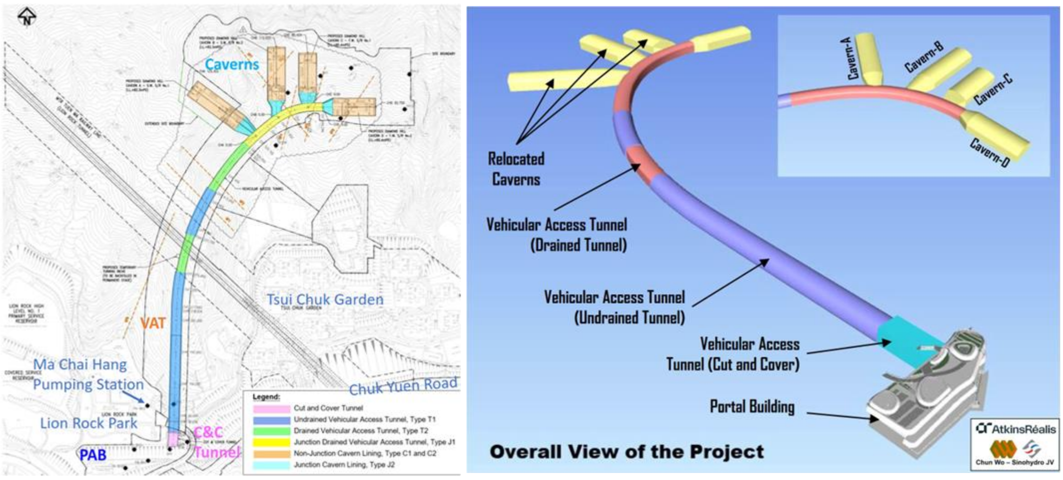

Figure 1. Project layout (a) and plan view of the proposed VAT and Caverns (b).
(after Kwong A. K. et. al (2024))

The infrastructure will be primarily constructed in granitic bedrock with varying levels of weathering. One of the geological features of concern for the design is the presence of deep weathering zones and zones of weak rock. The structural geology consists of northwest-southeast and east-west inferred faults, aligned across the eastern Site extents.

A key geological constraint to be investigated are zones of weak rock resulting in reduced rock mass quality, often associated with geological structure. Rock mass quality is a major geotechnical component when designing rock mass support systems e.g. rock bolt design and hydrological designs of the tunnel and caverns. A conceptual ground model was constructed to inform the ground conditions and associated constraints.

Two phases of ground investigation (GI) were carried out during preliminary (Phase 1) and construction (Phase 2) design works. Phase 1 GI included horizontal directional, inclined and vertical drillholes, with targeted cross-hole seismic geophysical surveys. Phase 2 GI consisted of eight additional project-specific drillholes carried out to verify previous evidence of weak zones and potential fault alignments within the optimized CSD cavern layout.

1.2 *Motivation for Geostatistical Analysis*

Due to the complexity and variability of the geology, the aforementioned GI techniques were used to update the ground model with bedrock levels, stratigraphic units and rock and soil geotechnical properties. The Rock Mass Quality Q-system (Grimstad & Barton, 1993) was used to numerically characterise extracted rock core samples. The accuracy and predictive patterns are impacted by the isolated nature of GI sampling locations, particularly when estimating and extrapolating trends in geological lithostratigraphy and patterns in their respective rock mass quality between drillholes. Without careful verification, this often leads to ground risk associated with data confidence.

To address this, geostatistical evaluation of the sample data was conducted to: (i) isolate confidence limits for bedrock surfaces and predict deep weathering zones and intermittent extents of weak zones; (ii), Q-value and RQD data to evaluate against the stratigraphic data; (iii) serve as an aid for the design enhancement of the caverns and geological/geotechnical data interpretation.

The geostatistical analysis was also conducted in two phases. Phase 1 utilized existing to Phase 1 GI data prior to additional drillholes carried out under the Project. Phase 2 integrated the latest drillhole data along with all previously existing GI data. The Phase 1 geostatistical model integrated forty-three existing horizontal, vertical and inclined drillholes in the vicinity of the proposed cavern and VAT. The Phase 2 model included eight additional drillholes. Of these, seven are located in the cavern area, while one is situated in a deep weathering zone at the proposed VAT, as interpreted in the Phase 1 model. Q Value measurements extracted from cross-hole seismic tomography data in five drillholes south of the caverns was also integrated into the Phase 2 model.

2 GEOSTATISTICS

2.1 *Background*

Geostatistical evaluation/modeling is a statistical approach used to analyze and model spatial data, where the data points are associated with specific geographic locations. It aims to understand and quantify the spatial variability and patterns within the data, allowing for predictions and interpolation at unobserved locations.

The purpose of geostatistical evaluation/modeling is to provide valuable insights into the spatial structure and distribution of the data. It helps to identify trends, assess uncertainty, and make informed decisions based on spatial relationships. This technique is particularly useful in fields such as geology, environmental science, agriculture, hydrology, and mining, where understanding the spatial variability of properties like soil characteristics, pollutant concentrations, or mineral deposits is essential for effective management and decision-making (Chiles and Delfiner, 1999).

The main advantages of geostatistical evaluation/modeling are:

1. Spatial interpolation: Geostatistics allows for the estimation of values at unobserved locations, filling gaps in spatial data and creating continuous surfaces.

2. Quantifying uncertainty: It provides measures of uncertainty associated with the predictions, enabling decision-makers to assess risk and reliability.
3. Data-driven decisions: Geostatistical models are built directly from the spatial data, allowing for more informed and data-driven decisions.
4. Better resource management: By understanding spatial patterns, geostatistical evaluation can optimize resource allocation and utilization, such as ground investigation and engineering design, leading to more efficient management.
5. Improved predictions: The spatial relationships considered in geostatistical models often result in more accurate predictions compared to simpler interpolation methods.

Overall, geostatistical evaluation/modeling is a powerful tool for analyzing spatial data, providing valuable information for a wide range of applications, and enhancing decision-making processes in various industries.

2.2 *Approach*

This section outlines the approach the develop the geostatistical models. For categorical variables (e.g., stratigraphy), the Pluri-Gaussian Simulation approach was used. For continuous variables (e.g., Q-core, RQD, etc.), the Turning Bands Simulation approach was used. Discussion on the 3D grid geometry and data unfolding are also provided in this section.

2.2.1 *Pluri-Gaussian Simulation*

Pluri-Gaussian Simulation (PGS) is a well-established geostatistical method used to model the spatial variability of categorical variables, such as stratigraphic units or lithotypes (Armstrong, et al., 2011). It is an extension of traditional Gaussian simulation such that multiple Gaussian distributions are combined to create more flexible and realistic representations of the spatial variability.

In Pluri-Gaussian simulation (PGS), two independent Gaussian Random Functions (GRFs) are used. These GRFs represent different geological types or lithotypes in the 2D space. This space is divided into rectangles, each representing a lithotype according to a rule called the lithotype rule. Each lithotype has specific thresholds on both GRFs, which are related to its proportion in the area. These proportions are estimated from the conditional borehole data and a defined search radius using log-likelihood in a non-stationary case (Figure 2).

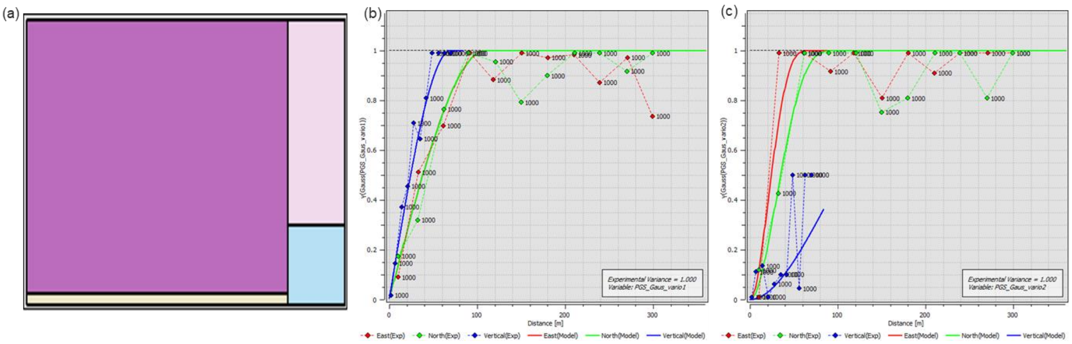

Figure 2: Lithotype rule (a) and the variograms for Gaussian variables (b, c) representing the spatial correlation structure of the stratigraphic unit data.

To analyze the spatial relationships, simple variograms of the indicators for all lithotypes are developed (Figure 2). These variograms provide valuable information about the spatial variability and correlations between the lithotypes. Additionally, cross-variograms are calculated to examine how the different lithotypes interact with each other.

In the simulation, borehole data is honored such that predicted values at the locations of the available data are always equal to the corresponding data, known as conditional simulation.
When performing conditional simulations, the lithotypes are converted into values in the gaussian scale using an iterative technique known as the Gibbs sampler. Estimates are made at unsampled locations in the gaussian scale before converting back to the categorical (i.e., lithotype) scale. The PGS aims to reproduce (1) the contact relationships between lithotypes, (2) lithotype proportions, (3) the spatial correlation structure, and (4) available conditioning data.

2.2.2 *Turning Band Simulation*
The Turning Bands Simulation (TBS) method is a technique used to generate spatially correlated random fields of continuous variables (Mantoglou and Wilson, 1982). The method involves dividing a simulation field into ‘bands’ and simulating values within each band, rotating the correlation direction in a circular manner. The process is repeated several times, each with different random seeds and rotations, to obtain multiple realizations of the random field.

The spatial correlation of a parameter is modeled by a variogram, which quantifies the dissimilarity, or variability, between pairs of data points at different distances and directions. The experimental variogram is computed from the available data, to which a model variogram is fitted. The model variogram quantifies the general underlying spatial structure of the data and is used in the interpolation or kriging to generate predictions at unsampled locations.

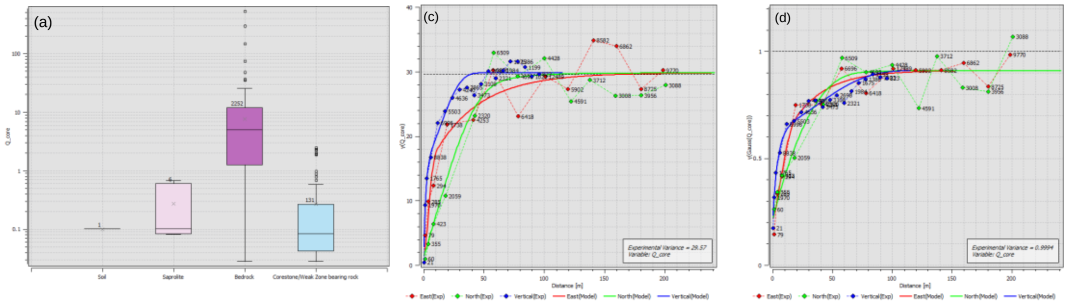

Figure 3: Box plot of Q-core distribution for each stratigraphic unit (a). Raw (b) and Gaussian (c) variograms for Q-core.

An assumption of the TBS method is that the data is normally distributed. Therefore, the raw data is transformed to a Gaussian distribution (Rivoirard, 1994). The raw variograms are analyzed to interpret the spatial correlation structure of the data, whereas the variograms of the Gaussian transformed data are used for the simulation, which is back-transformed to the raw data space after.

In the simulation, the borehole data is honored such that predicted values at the locations of the available data are always equal to the corresponding data, known as conditional simulation. Interpolation is performed using ordinary kriging, which assumes that the spatial correlation is stationary across the study area but allows for the local estimation of the mean.

2.2.3 *3D Grid Geometry*
The 3D model (grid) consists of blocks, or voxels, with dimensions of 1 m x 1 m x 1 m. The model extends vertically from elevation 60 m to the ground surface (which varies between elevations of 82.42 m and 268.52 m), and laterally over approximately the site formation boundary extent. This equates to a total of 9,602,901 blocks at which geological and geotechnical parameters are estimated.

2.2.4 *Data and Model Unfolding*
Unfolding, based on the Landmark Multi-Dimensional Scaling method (Silva and Tenenbaum, 2004), is performed to flatten complex geological structures. The grid and borehole data are flattened to evaluate and model the data in the original stratigraphic system to better estimate the spatial correlation. The topographic surface is used as the input for the unfolding algorithm. The variogram analysis and simulation are performed in the unfolded space, after which the grid is back-transformed to the original space.

3 GEOSTATISTICAL MODELS

3.1 *Uncertainty Quantification*

The geostatistical models are summarized herein. The summary consists of the parameter distribution, the spatial correlation model, 3D renderings of the block model, including most probable or median estimate and associated uncertainty, and discussion/interpretation of the model for the corresponding parameter. Additional sections and data files are provided in appendices.

When evaluating data that does not follow a normal distribution, it is considered best practice to use robust statistical measures to summarize the data. Typical statistical measures such as mean and standard deviation can be skewed by 'extreme' values. Therefore, the median (i.e., 50% percentile) is used to summarize the simulation as it is the middle of the set of realizations at each block for continuous variables (Q-core, RQD, Permeability, UCS). Uncertainty is quantified here using Quartile coefficient of dispersion (QCD) which is a measure of relative variability in realizations at a particular grid block (Equation 1).

$$QCD = \frac{Q_3 - Q_1}{Q_3 + Q_1} \tag{1}$$

where Q_1 and Q_3 are the first (25%) and third (75%) quartiles, respectively.

For categorical variables (i.e., Stratigraphic units), the unit with the highest probability at each block represents the 'most probable'. Uncertainty is quantified by entropy (*H*), which refers to the degree of uncertainty or randomness, indicating the variability and lack of information about the distribution of possible unit classifications (Equation 2).

$$H = -\sum_i p_i * \log(p_i) \tag{2}$$

where p_i is the probability of category i.

3.2 *Phase 1 - Stratigraphic Units*

The stratigraphic unit classification in the digitized GI data from Phase 1 contains a total of 14205.28m of core log, consisting of 37.7% Bedrock, 12.7% Corestone/Weak Rock, 37.7% Saprolite and 11.8% Soil. Three dimensional renderings of the most probable (i.e., most frequently predicted stratigraphic unit) and entropy (i.e., uncertainty) are shown in Figure 4.

The geostatistical model can also be used to derive confidence limits for the bedrock surface. Figure 5 presents the probability of bedrock along the centerline of the VAT tunnel and Caverns. The transparency scale increases with decreasing bedrock probability to better illustrate the most likely bedrock depth. It can be observed that the confidence limit for the bedrock surface is higher along the VAT section than the Cavern sections. Taking the height of the interquartile range (75% quantile minus 25% quantile) as the confidence limit, the VAT section has a confidence limit of approximately 15-20 m, whereas the Cavern sections have a confidence limit of approximately 5-10 m.

The Phase 1 geostatistical model identified areas of high entropy (i.e., uncertainty), which guided the planning and placement of additional GI to build a robust data set for Phase 2. The Phase 2 model produced the most probable geological strata based on all available GI data (additional and existing GI). These strata informed the interpretation of the final geological profiles, with a particular emphasis on the rockhead profile, which is critical for design input.

Concurrently, the Unfolding approach (Landmark Multi-Dimensional Scaling) was applied using topographic and ground investigation (GI) data. This method enabled simulation of granitic weathering profiles, i.e., rock mass had increased weathering near the surface and reduced in severity with depth. This is typical of Hong Kong lithology.

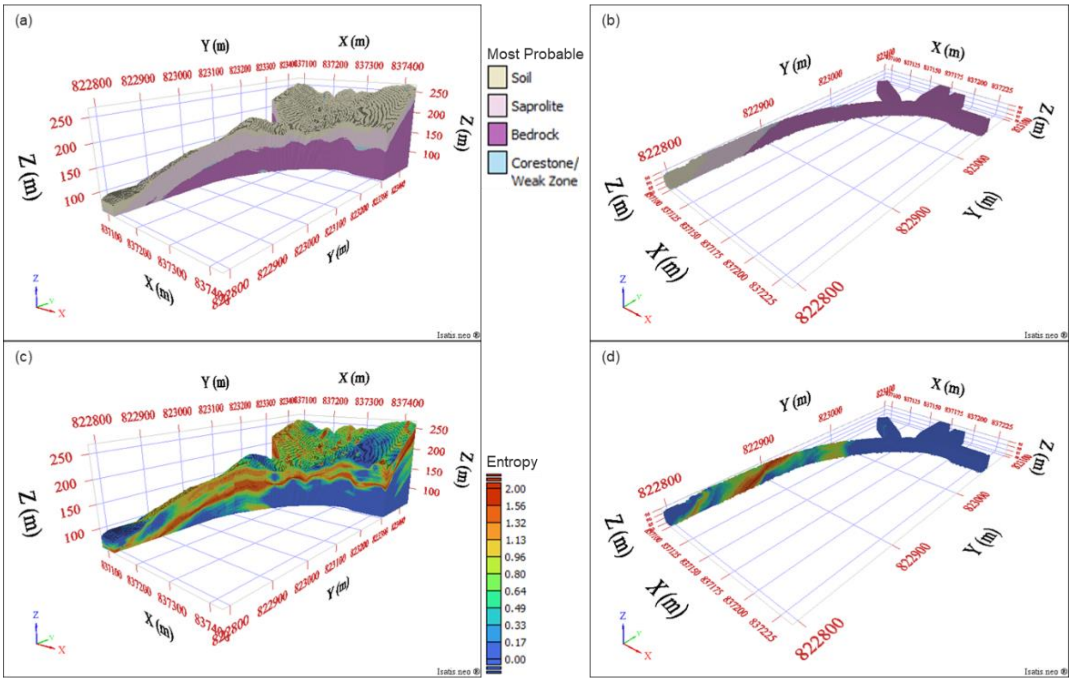

Figure 4. 3D renderings of the geostatistical model for stratigraphic units. Most probable stratigraphic unit for the full model (a) and isolated VAT and Caverns geometry (b). Uncertainty, represented by Entropy, for the full model (c) and isolated VAT and Cavern (d).

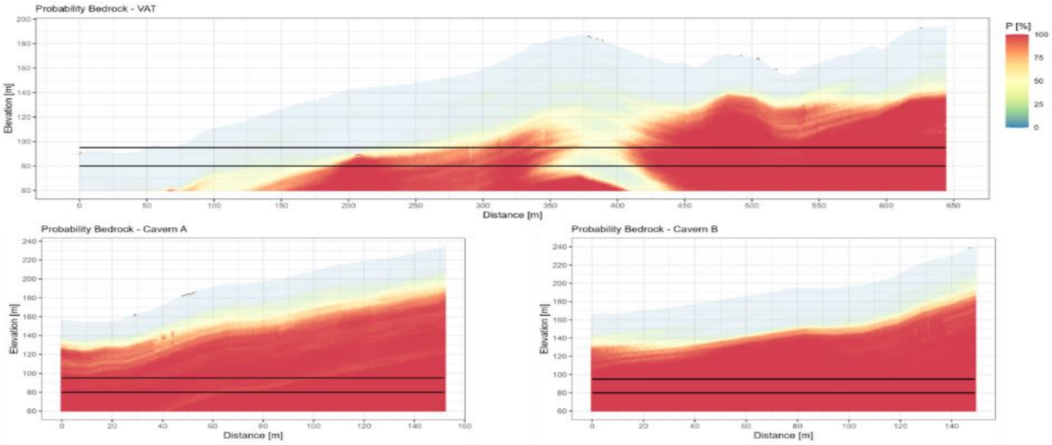

Figure 5. Profile sections showing the probability of bedrock for the VAT tunnel and two caverns.

3.3 *Phase 1 - Q-Core*

Q-core values follow the Q-system approach for jointed rock mass classification. The Q-system provides a description of rock mass stability for underground openings where low values generally indicate poor stability (or increased support needs), and high values generally indicate good stability. The Q-system is determined from three factors: (i) degree of jointing (or block size); (ii) joint friction (or inter-block shear strength); and (iii) active stress. A total of 2,390 Q-core samples are provided in the Phase 1 GI data. All Q-core data was used for the geostatistical evaluation to estimate the mean and uncertainty at each $1m^3$ block. Results demonstrated that Q-core differs across the VAT and Caverns and identified areas with high potential for poor stability (Q-core <0.8).

3.4 *Phase 2 Geostatistical Models*

The Phase 2 GI consisted of an additional eight drillholes, which provides an opportunity to update the geostatistical model and evaluate the change in prediction and corresponding uncertainty.

Phase 2 included the integration of geophysical data, namely cross-hole seismic tomography. Cross-hole seismic survey is a technique that measures the travel time of seismic waves between a source drillhole (with sparker sound source) and a receiver drillhole (with hydrophone receivers). The shear wave (S-wave) velocities were measured between five drillholes across the cavern site as shown in Figure 6 left. The velocity profiles along the survey alignment are interpreted to derive rock mass quality Q-value following ‘velocity-depth correlation’ developed by Barton (2000) (Figure 6 right). This provides additional subsurface information of the rock mass Q-value which is integrated into the geostatistical models.

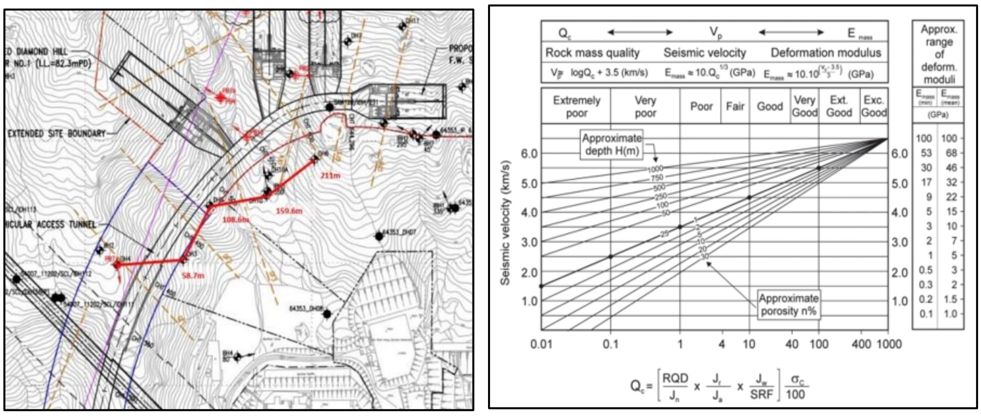

Figure 6. (left) Alignment of cross-hole seismic tomography survey between five drillholes (highlighted in red); (right) Velocity-depth correlation for rock mass quality development by Barton (2000).

Figure 7 shows a comparison between Phase 1 and Phase 2 lithostratigraphy including the comparison between the probability of bedrock surfaces. Overall, the original Phase 1 is consistent with the Phase 2 surfaces. Locally, bedrock surfaces are nearer to the surface in the Phase 2 model, particularly in areas where uncertainty in the Phase 1 model was higher. The geostatistical model shows visually how the additional GI both appraised and closed gaps in the original models and geotechnical and geological assumptions.

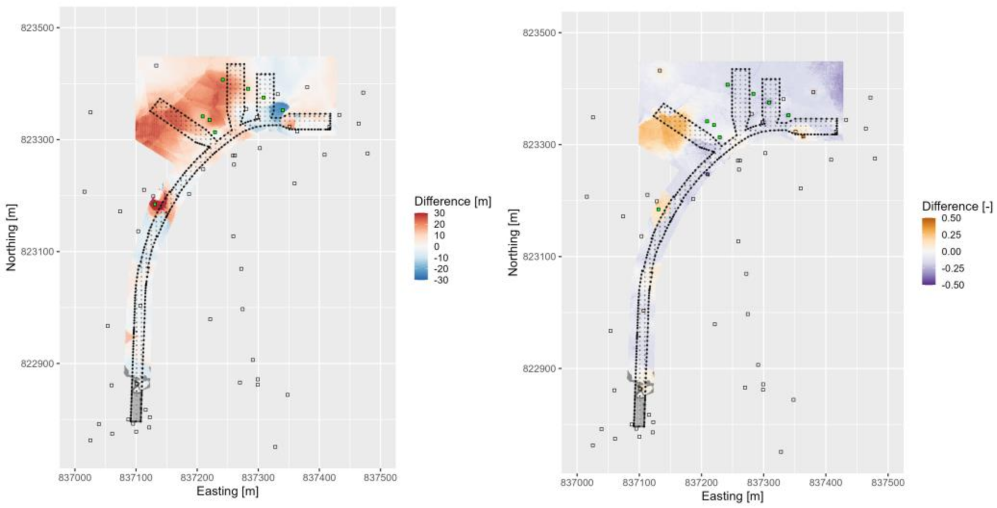

Figure 7. (left) Difference between Phase 1 and Phase 2 median rockhead elevation estimates. (right) the difference between Phase 1 and Phase 2 quantified uncertainty.

4 DISCUSSION AND CONCLUSIONS

4.1 *Summary of Results*

Uncertainty quantification is a primary benefit of geostatistical modeling. Zones of high uncertainty can inform where careful evaluation of design assumptions is critical. Interpretation of the geostatistical models suggests that there are several zones along the VAT tunnel alignment and within the caverns that have a higher statistical probability of poor stratigraphy type, poor rock quality (weak zones) or a combination of these. The geostatistical models also highlight the strong potential for mixed face conditions and transitions between contrasting ground types. Areas of low Bedrock surface cover and zones of Corestone/Weak rock will likely exhibit highly mixed face conditions. Evaluation of the geostatistical models for Q-core and RQD also highlight the potential for high-degree mixed face conditions and large differences in rock quality over short (10-20 m) distances.

As discussed in Section 3, the Phase 1 geostatistical model provided a solid benchmark for evaluating confidence in the existing GI data for charcterising the Site-specific ground conditions. Utilising the geostatistical approach to compare lithostratigraphic probability of bedrock surfaces and Q Values, shows that the Phase 1 data provided well-informed trends for initial evaluation. With the introduction of Phase 2 data, the patterns in probability were consistent, with localised areas of significant improvement, which should be expected when data gaps are present.

Finally, the integration of seismic velocity profile data provided a detailed measurement of interpreted rock mass quality Q-value 'velocity-depth correlation' developed by Barton (2000) (Figure 6 right) along geophysical survey alignments. Again, although these measurements provided an enhanced, higher resolution analysis of the predicted lithostratigraphy and Q Value distribution, the initial Phase 1 geostatistical models performed well and provided a benchmark that was only enhanced as new data became available.

4.2 *Future work*

The data-driven nature of geostatistics enables the seamless integration of new data to update the models. As data and information about the ground is collected during the excavation of the VAT and Caverns (e.g., face mapping, probing, etc.), this additional knowledge can be integrated into the geostatistical model to provide periodic updates and to reduce uncertainty in the model.

Going forward, the geostatistical model is to be integrated into the project Tunnel Data Management System (TDMS) to form a probabilistic baseline for the works. This added information will assist the engineering geologist in apportioning geotechnical risk along the tunnel alignment by ascribing a probability of encountering rock, and conversely, soil/mixed ground. In addition, the model will be verified by the addition of probing and mapping records taken as the face advances. As experience is gained, the geologist can develop greater confidence when interpreting the model and planning upcoming tunnel works.

DISCLAIMER

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