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3D geological models: A reliable depiction of nature or a sketch of our biases?

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Abstract

3D models represent the modelling team's hypotheses about the most likely rock mass configuration, constructed from limited and sparse data (often as little as 1/100,000 or 0.00 1% of the rock mass). Therefore, modelling requires reliable professional judgement, which involves making decisions based on one's beliefs about the information. This judgement is crucial for assessing the trustworthiness of data and interpolating between sample locations. Sound judgement adds value to the interpretation and modelling process. However, since judgement is influenced by personal opinions and beliefs, modellers must balance objectivity with subjective intuition, biases, and uncertainties. They must proactively prevent negative factors – such as guesses, gut feelings, and overconfidence – from entering the model, which still providing experience-based input to supplement the purely mathematical interpolation. Modellers and model users must recognise that a model is merely a sketch of a human interpretation about the rock mass, normally derived from sparse data points, whereas the rock mass itself is a product of natural processes and laws. While a model can be visually appealing or numerically sophisticated, it is unlikely to accurately depict nature's complexity. This work, based on open pit case studies, highlights the importance of explaining intuition, biases, and uncertainties when constructing geological, structural, or geotechnical models. It also discusses how to ensure these models are at least reliable hypotheses about the complex nature they aim to represent.

Keywords: *3D geological modelling, 3D structural model, uncertainties*

1 Introduction

Three-dimensional (3D) geological models play a crucial role in geoscience and engineering, providing a visual and numerical representation of subsurface conditions. However, these models are constructed from limited and often sparse data, leading to inherent uncertainties, limiting the accuracy of the model itself (Liang et al. 2021).

3D geological models are constructed using data from various sources, such as boreholes, geophysical surveys, and surface mapping. The limitations of geological data, including its sparsity and scale, mean that models are not exact replicas of nature but rather interpretations based on available information. This idea can be further expanded by employing the model-dependent realism concept (Hawking & Mlodinov 2010), which defines that reality is merely a constructed best-case model of the facts we are aware of. Under geological modelling terms, this concept indicates that the reality we are representing in our model is dependent on the awareness, knowledge and judgement of the interpreter. In other words, an interpreter cannot be expected to create an accurate representation of the reality if they are not aware of what that reality might be (Boult et al. 2016).

An example in this direction is a study conducted by Bond et al. (2007) which demonstrated that multiple geologists presented with identical data often produced significantly different structural interpretations, underscoring the subjective element of geological modelling. This is because often, geologist and geological

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modellers tend to let personal beliefs and empirical knowledge drive the data interpretation process. As demonstrated in Elmo et al. (2022), empirical knowledge is not universally correct, and if experience (empirical knowledge) is considered equal to knowledge, then it means that experience is a process by which uncertainties are reduced as more experience is gained. However, experience alone won't be enough for geologists to have the complete knowledge and understanding of a rock mass. Hence, models should be viewed as interpretative hypotheses that carry an inner risk defined not only by uncertainties but also by subjective intellectual biases.

This paper aims to provide a brief introduction into what could be called the 'geological modelling paradox': 3D geological models are an essential tool for decision-making purposes, but, at the same time, they are heavily influenced by biases, uncertainties and subjective judgements.

Hence, this paper tries to provide a summary and overview of the type of biases and uncertainties that influence the geological modelling process, along with some insight on methodologies to reduce the impact of biases, uncertainties and subjective judgement in the modelling outcome.

2 Bias, uncertainty and subjective judgement

The interpretative process that is followed to develop both conceptual geological hypotheses from a variety of datasets, which are often sparse, and their representation into 3D models, is directly or indirectly controlled and influenced by a variety of factors. The key factors are:

- data-related bias
- cognitive bias, affecting the interpretation made by the interpreter/modeller
- modelling bias, controlled by the software and the visualisation tools chosen.

It is important to remember that bias and uncertainties go hand in hand. Biases often act as either sources or amplifiers of uncertainty throughout the interpretation and modelling processes (Liang et al. 2021; Elmo et al., 2022) (Figure 1).

Modellers and interpreters should always be aware of the existence of these biases, they carry inner uncertainties, and result is a reduction of the accuracy of a 3D model. Regardless of its downstream use, each step required to develop a 3D geological model does carry bias and uncertainties, which will be propagated throughout the entire modelling processes. As a result, any geotechnical, hydrogeological or resource model that is based on a 3D geological model will inevitably carry uncertainties.

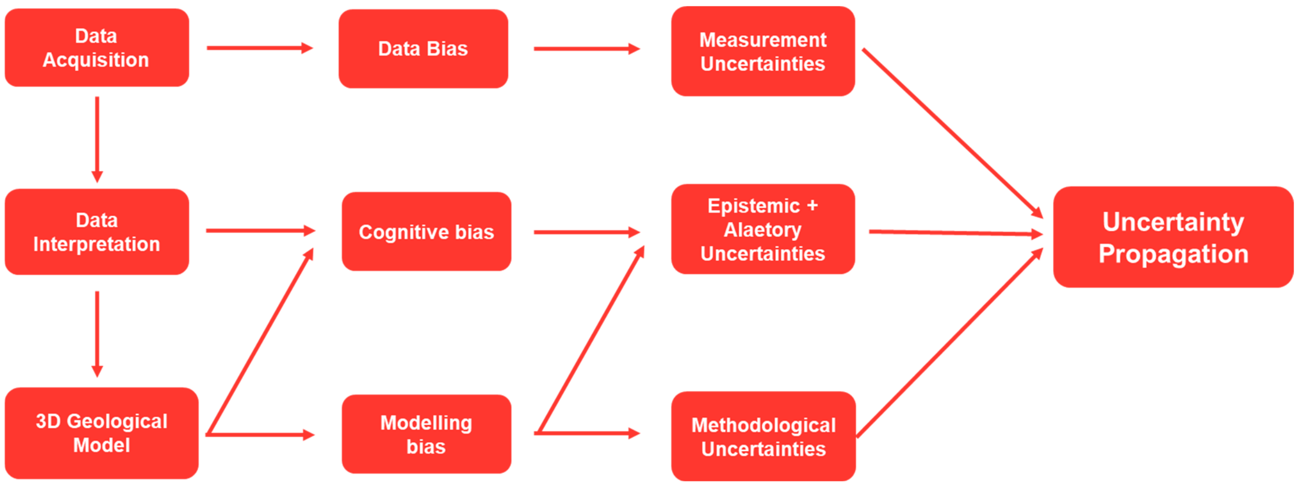

Figure 1 Diagram representing the correlation between biases and uncertainties in geological modelling. The left column presents a simplified modelling workflow: from data acquisition to the final three-dimensional geological model. The central column shows the biases associated with each modelling step. The right column represents the uncertainties related to each bias

2.1 Data-related bias

Geological data are quite often unevenly distributed within a specific project area due to several reasons, such as, but not limited to, access, costs, and priority areas dictated by project/mine schedule. This can lead not only to data gaps but can also drive over-representation of the areas with higher datapoints and the under-representation of the areas with less data points in the resulting 3D model.

In addition to the spatial distribution, geological data inevitably carry variable levels of detail and errors. Depending on the purpose of the data collection, certain features may be under-represented or over-represented. Errors may be derived from either instrumental inaccuracies, or human errors, or a combination of the two.

Instrumentation inaccuracies can be attributed to calibration errors, environmental factors, or human collection issues. Calibration tests are conducted in both a sterile laboratory setting and again in field setting to mitigate discrepancies in testing environments, however, not all external factors can be controlled or measured in a field setting. External causes such as temperature, humidity, dust and debris, and lack of GPS signal can cause equipment to malfunction or perform at a substandard level.

Data inaccuracies due to human error (not to be confused with cognitive bias elaborated below) refers to the methodological errors introduced by the data collector. These can include, but are not limited to, data entry errors, improper calibration techniques, incorrect equipment use, inadequate training for the task or data miscommunication between field staff.

Hence, when integrating datasets of different quality and scale, such as field mapping data, geophysical survey, and borehole data, geologists must be aware as this process can introduce inconsistencies and misalignments (measurement uncertainties), further limiting the accurate interpretation of geological information.

2.2 Cognitive bias

As with all other sciences, geology is a science susceptible to cognitive biases (Wilson et al. 2019). Geologists, drawing upon their knowledge, beliefs and past experiences, may inadvertently introduce subjective judgements into their interpretations of geological data, leading to the introduction of epistemic uncertainties in the interpretation process (Figure 1) (Caers 2011; Liang et al. 2021; Elmo et al. 2022). This leads to decisions during the interpretative and modelling process that are not fully data-driven, but controlled by personal believes, intuitions and lack of knowledge (Wilson et al. 2019; Elmo et al. 2022). This can result in what is known as confirmation bias, where preconceived expectations and prior knowledge influence the understanding of the data. Preconceived expectations or hypothesis, such as conceptual models that geologist have established over time for a specific area, can lead to selectively incorporating data or interpreting ambiguous features in ways that align with a pre-existing hypothesis, while willingly or unwillingly discounting contradictory evidence. This would inevitably result in the reinforcement of incorrect assumptions and increase in the inaccuracy of the model even as new data are collected.

In addition, data types and initial interpretations and hypotheses could significantly impact the interpretation and subsequent modelling process. Early interpretations or observations made on a limited amount of oriented borehole data could ‘anchor’ the modeller’s assumptions (anchoring bias), even when other data sources or later data would suggest alternative geometries or geological complexities. Anchoring bias goes hand in hand with what could be defined as expertise-induced bias, which tends to increase as geoscientists increase their experience or knowledge. Experienced geoscientists might unconsciously apply or interpret familiar frameworks, patterns, and/or geometries even in geological context where those frameworks are not applicable. Limited experience and knowledge also impact the data interpretation process by limiting the identification and understanding of the geological complexity of a site, resulting in an inaccurate and/or oversimplified model.

Experience and limited awareness of cognitive biases and data-related biases would ultimately lead to overconfidence. Experts may overestimate the accuracy and ‘reality’ of their interpretations or underplay the inherent uncertainty in subsurface data. Overconfidence can lead to models that appear robust but fail to account for plausible alternative scenarios.

An example in this direction is provided in Figure 2 (a, b and c). The example represents a geological interpretation related to a limestone quarry, where the development of a 3D geological model was crucial for understanding the thickness of quarry materials and predicting the location and geometries of weak layers that could potentially affect the stability of the quarry. The area consists of middle Miocene limestone formation, which is divided into three members: upper limestone, middle limestone, and lower limestone. These members represent 5 different facies: shelf, front reef, inter-reef, back reef, and core reef facies. The formations are identified based on the fossil assemblage and significant marker layers such as the presence of sandstone and muddy limestone. Two interpretations were made for the area: Model A (Figure 2a) developed by a senior geologist who did not take part in the mapping campaign and based the interpretation on their experience and data collected by another geoscientist and Model B (Figure 2b) developed by a junior structural geologist and 3D modeller who had taken part in the field mapping campaign and took the time to reconcile the structural features identified in the field and in the boreholes with the overall structural setting of the area (Figure 2c). Given the seniority of the geologist responsible for the first model, Model A was initially used for geotechnical designs.

Model A’s geologist’s overconfidence in their geological and structural geology knowledge, coupled with the limited review and analysis of the available dataset, led to the misidentification of a key structural feature within a stratigraphic unit (middle limestone) mapping campaign. The apparent increase in thickness observed in borehole data was interpreted to be the result of thickness variability within the unit, and not an indication of possible structural complexities. This resulted in an oversimplification of the 3D geological model (Figure 2a). Additionally, the geologist failed to recognise the folding structure in the mapping area, considering the bedding patterns as representations of joints and not as folded bedding. In contrast, Model B did incorporate the structural complexities identified in the field, allowing for the definition and prediction of possible areas of concerns for stability purposes. As indicated above, Model A was initially chosen for design purposes, resulting in stability challenges as soon as construction started as the geological complexities, absent in Model A, were not considered in the design.

It is also important to remember that the inherent randomness of geological processes would ultimately limit the possibility of having a complete knowledge and understanding of the geological conditions of a site (Quigley et al. 2019). This falls under the category of the aleatory uncertainties that every interpretation will inherently carry and cannot be reduced by additional data or improved understanding of a site. This is especially enhanced in complex structural and geological settings, where multiple deformational phases create geometries between faults, folds and lithological contacts that cannot be fully predicted in a 3D model, even at an operational level.

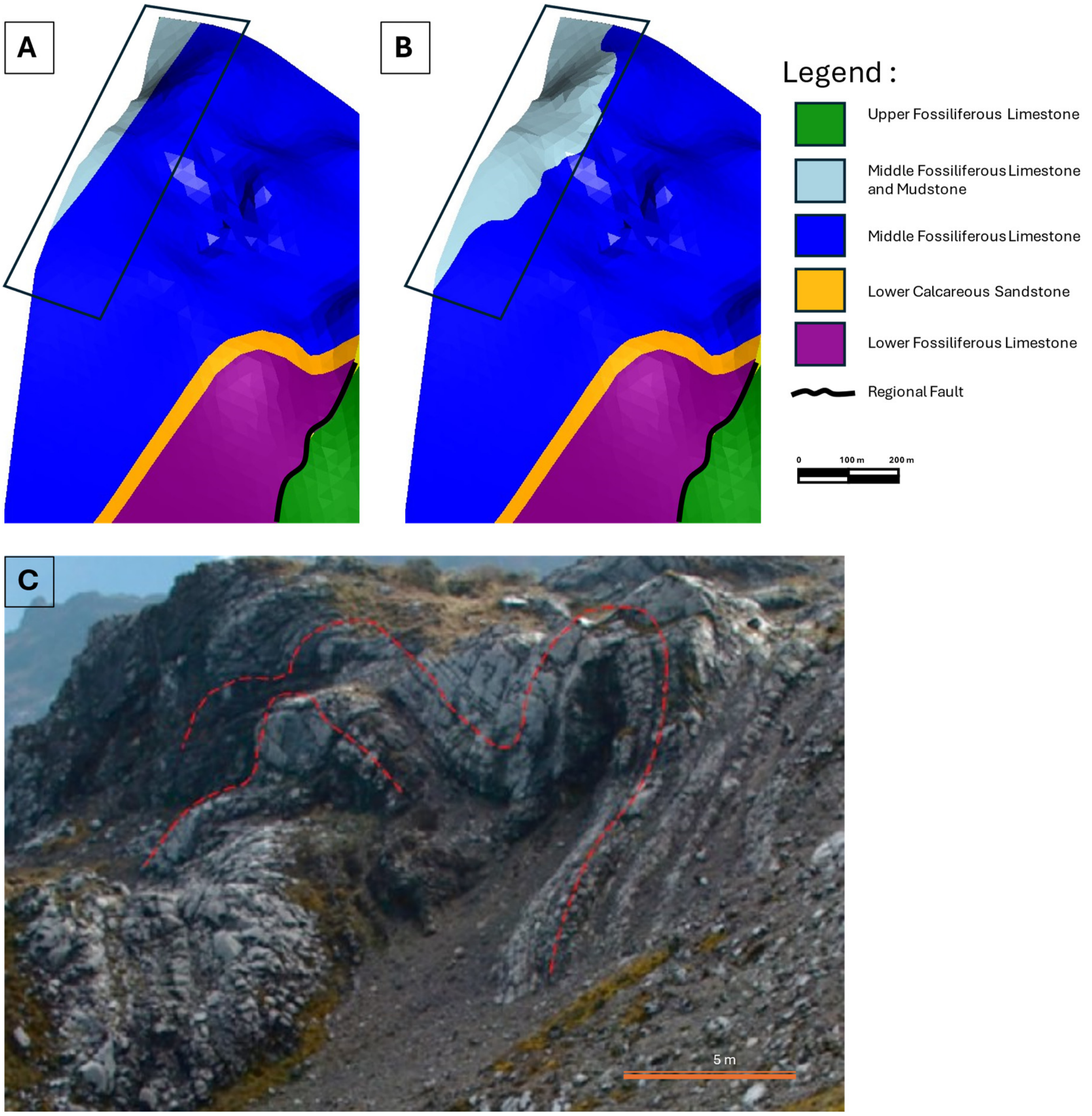

Figure 2 (a) The first 3D model oversimplifies the middle limestone unit and does not represent the fold; (b) The 3D model encompasses the folds within the middle limestone; (c) Evidence of folding within middle limestone

2.3 Modelling bias

The modelling approach and software used to develop the 3D model carry error and uncertainties that derive from both software constraints and limitations and also modelling methodologies and workflows that are not adequate for either the geological and or geotechnical complexities to be represented and or the usability of the model for downstream analysis and designs.

As demonstrated by Stoch at al. (2022) and Reid & Cowan (2023), the choice of algorithm and interpolations methods plays a crucial role in determining how data gaps are filled, with the risk of potentially smoothing out certain features, leading to a simplification of the geological complexities, or exaggerating others, leading to for example over-continuous fault systems. This means that the selection of the interpolation method should be carefully considered to ensure that it aligns with the specific goals of the modelling process. Furthermore, software constraints can also significantly influence modelling outcomes. Modelling tools may come with inherent limitations or default settings that can unknowingly impact the results. It’s essential for modellers to be fully aware of these constraints and settings to ensure that they are not inadvertently influencing the outcomes of the model. This is valid for geotechnical and hydrogeological models too. The choice of interpolation algorithm, boundary conditions, and software constraints are all critical factors that can greatly influence the accuracy and reliability of 3D models (geological, geotechnical and hydrogeological models). Careful consideration and awareness of these factors are essential for producing meaningful and reliable modelling outcomes.

3 Mitigation strategies and model communication

Geological models are, by nature, uncertain constructs, shaped by sparse data, subjective interpretation, and the limitations of modelling tools. As previously discussed, these models are not only vulnerable to bias during interpretation but also throughout the modelling workflow. When left unexamined or poorly communicated, these compounded uncertainties can mislead critical decisions in geotechnical design, resource estimation, and risk assessment.

To address and mitigate these uncertainties and biases, two complementary approaches are proposed:

- bias and uncertainty mitigation strategies (Section 3.1)
- transparent model communication (Section 3.2).

The first approach aims to provide tools and strategies to identify, manage, quantify (if and when possible) and manage source of bias and uncertainty, while the second ensures that the limitations, assumptions, uncertainty and confidence levels of the model are honestly and clearly conveyed to the stakeholders to allow for informed decision-making and planning.

3.1 Mitigation strategies

Recognising the presence of data-related, cognitive and modelling biases and how they propagate uncertainties throughout the modelling process is the key first step in mitigating their impacts on the final 3D geological model. A combination of dedicated steps within the interpretation and modelling workflow, and bias and uncertainties awareness between the model users and decision-maker could provide effective mitigation strategies. Table 1 provides a list of some of the potential strategies, tailored to each source of bias and uncertainties, that should be employed to limit the impacts of bias and uncertainties in geological modelling.

Table 1 Suggested mitigation strategies

Source of bias	Type of uncertainty	Type	Mitigation strategy
Data-related bias	Measurement uncertainties	Data acquisition	Establish data collection procedures that provide tools to: 1. employ the people with the right training and skills for each data collection type 2. maintain consistency in how the data is collected 3. limit subjectivity even at the data acquisition stage 4. empower data collector to report on the reliability and uncertainties related to the data collected. Develop artificial intelligence (AI) and automated data collection tools to limit the subjectivity in data collection. Report and record expected errors that even AI-based tools will induce.
		Historic dataset	Conduct strength and reliability analysis of existing datasets prior to commence the data analysis and interpretation task to assess usability, strength and reliability of the historic dataset (Table 2).

Source of bias	Type of uncertainty	Type	Mitigation strategy
			Identify data gaps and assess how the spatial distribution of the available usable data will affect the data interpretation and hypothesis generation process.
Cognitive bias	Epistemic uncertainties	Knowledge-based uncertainties	Continuative training for geoscientists about both technical and geological skills and common cognitive biases to empower their decision-making skills during the data interpretation processes.
			Allow for the development of multiple working hypothesis, as they force the user to consider and compare alternative interpretations given the available dataset, limiting the effect of confirmation biases.
			Conduct 'blind' data interpretations to analyse the data without pre-existing background information to minimise any anchoring bias.
			Establish a peer review system led by skilled, experienced and competent geologists to identify potential subjective assumptions and or inconsistency.
	Aleatory uncertainties	Randomness in geological processes	Use high-resolution and multi-scale data acquisition strategies to favour denser sampling (i.e. closely spaced boreholes; continuative detailed mapping pit walls) to better capture natural variability of the rock mass.
			As per the epistemic uncertainties, test multiple working hypotheses to assess ranges of possible outcomes based on the same datasets.
Modelling bias	Methodological uncertainties	Modelling approaches and workflows	Establish modelling guidelines based on accepted geological modelling best practices (SRK Consulting 2021), integrated with modelling checklists to limit subjective decisions while modelling.
			If the modeller uses third-party data or third-party interpretations, establish guidelines for proper data transfer to avoid miscommunications or errors.
			Establish peer review system lead by skilled, experienced and competent geologists and geological modellers.
			Follow and iterative modelling approach in which models are continuously updated and hypotheses tests as new data becomes available.
			Communicate effectively assumptions and limitations of the generated 3D geological model, as well as the uncertainties and confidence ratings associated with the developed model.
Uncertainty propagation			Perform integrated uncertainties quantification studies (Cears 2011; Liang et al. 2021) to quantify the uncertainties associated to the developed 3D geological model.
			In cases of high aleatory and epistemic uncertainties, employ probabilistic, stochastic or Bayesian modelling techniques to evaluate multiple scenarios and assess ranges of possible outcomes. This would assist in better representing spatial variability and uncertainty distributions.

It is important to mention that subjective judgement not only influences the generation of working hypothesis and 3D geological model, but also the way that data is collected as indicated in Section 2.1. Hence, given the fact that geological hypothesis and models are based on the available data, it is worth expanding further on ways to evaluate and review the available data.

Before commencing the data interpretation and modelling processes, it is important to first assess quality, usability and reliability of the input data. A quality of information analysis developed by WSP, based on the work conducted by Banks et al. (2020), is an essential tool ahead of geological modelling exercise as it allows users to:

- identify valuable information and gaps that need to be filled to create a valid lithological–stratigraphic–rheological–structural model
- identify low-value information that should be set aside to prioritise high-value data that will significantly enhance the model's value and accuracy
- prioritising future data collection to maximise the model's value and reduce uncertainties.

An example of a quality of information carried out by WSP for an open pit operation is presented in Table 2. The results are obtained by analysing each data source to:

- identify errors that would prevent the immediate use or visualisation in a 3D modelling software
- assess the reliability of each data source.

The analysis result helps understand the complexity of the information and its formats, determines which data adds or erodes value, and identifies reliable primary and secondary data sources for the modelling process. This, in turn, aids in communicating the data bias and identifying any uncertainties within the data that could be propagated through the geological interpretation and 3D geological model if not mitigated.

To date, the major reporting codes such as JORC, NI43-101 and S-K 1300 do not provide standardised procedures to assess and disclose the reliability and adequacy of the data used for both the geological interpretation and all the models generated based on it (resource estimation, geotechnical and hydrogeological models). The codes rely on the professional judgement and transparency of the qualified persons in defining how data quality was assessed and whether it is sufficient to support the geological analysis and modelling. The lack of a standardised procedure across the major reporting codes leaves room for subjective interpretations, which can propagate bias and uncertainties especially in complex geological settings.

Table 2 Example of quality of information analysis developed by WSP based on Banks et al. (2020) to evaluate data importance, priority, and weaknesses before starting interpretation and modelling tasks

	Data source up to 18 July 2025	Priority	Importance of information	Favourability class	Unfavourable	Questionable	Neutral	Encouraging	Favourable
				Risk word	High	Relatively high	Moderate	Relatively low	Low
				Probability range	0.1–0.3	0.3–0.5	0.5	0.5–0.7	0.7–0.9
Mapping data	Regional and Anaconda exploration mapping sheet from East of Wukaya area to Bayan (pre-2007)	Primary	Priority					Encouraging, need to confirm the difference between pre-2007 and post-2007 year	
	Regional and Anaconda exploration mapping sheet from East of Wukaya area to Bayan (post-2007)	Primary	Priority						Favourable
Drilling data	Core photos	Primary	Priority						Web-portal link makes it very favourable
	Rig photos	Secondary	Supporting					Big data size at web portal link, need good network to open large size photo	
	Collar.CSV	Primary	Priority						Favourable
	Survey.CSV	Primary	Priority						Needs consistency in the way that downhole data are provided
	Geotech_interval.XLS	Primary	Priority				Good data but		

				currently not usable given the high number of duplicated interval		
	Alteration_interval_raw.XLS	Primary	Priority		Encouraging but need to confirm the simplified version that feeds the modelling workflow	
	Geotech_sampling.XLS	Tertiary	Nice to have			Favourable for geotech perspective
Additional data	Lithology modeL.DXF	Primary	Priority			Favourable but missing the detail from Anaconda mapping due to model simplification
	Alteration model.DXF	Primary	Priority			Favourable but missing the detail from Anaconda Mapping due to model simplification

3.2 Model communication

Communicating uncertainty and biases that are inherent to any geological model is a key component of the delivering of a complete model. It empowers the geologist to openly define what are the assumptions, limitations and uncertainties associated with the generated model, allowing stakeholders and decision-makers to make more informed decisions.

One of the main aspects that geologists should report on as part of a model handover is on confidence and reliability level associated with each component of the model. Confidence and reliability provide an assessment on the uncertainties related to each modelled geological unit or structure. In simple terms, geological features with assigned high confidence indicate that the feature was interpreted and modelled with sufficient data support that further data collection is not expected to significantly change the modelled featured. Medium level confidence could indicate that portions of the modelled feature are well constrained and understood, but complex geometry or data limitations make the predictions regarding the location and geometry of other portions of the modelled feature more challenging. Low confidence features have either very few supporting data points, or the dataset is such that other possible geometries or shapes are possible given the geological setting. Additionally, inferred features with no direct observation points to support them, but are purely the product of interpretation of other datasets (e.g. geophysics, topography), would also fall in the low confidence category. It is crucial to convey both confidence and uncertainties related to each modelled structural feature. Presenting the model with a seemingly consistent confidence level suggests an unjustifiable certainty in the model, which could lead to disappointment when the actual geometry and position of a target deviate from the anticipated location, resulting in changes in project schedule and budgets.

Confidence levels can be communicated as tables, maps with confidence categories, or interpolation of distance from data points. An example of a confidence rating scheme is presented in Savage et al. (2013), while tools to quantify model reliability are provided in SRK Consulting (2021). An example of model communication tool is presented in Table 3. The table presents a summary of key information associated with modelled faults to assist an open pit design study for a site in southeast Asia: type and quantity of data used to generate each fault, modelled orientation, primary geotechnical characteristics interpreted for each fault, confidence levels, uncertainties and recommendations. This helps clients plan and prioritise their operational needs more effectively.

Table 3 Example of model communication that provides a summary of the type and quantity of the data sources used for the model generation, quantitative and qualitative analysis of key geotechnical parameters for each modelled geological feature, confidence, uncertainty, and recommendations (adapted and expanded from Campbell et al. 2015 and SRK Consulting 2021)

Fault name	Year	#Oriented core data	#ATV data	#Mapping data	#Drillhole	#Photo-grammetry Data	Dip direction	Dip	RQD (min, max, mean) (%)	Thickness (min, max, mean) [cm]	Estimated persistence (m)	Infill	Timing	Confidence	Uncertainty	Recommend ations
Yakas Fault	2023	1	#N/A	2	#N/A	#N/A	335	60	30,50,60	0.1, 0.5, 0.25	100	Graphitic	Older than Massey Alunite Domain and Sakar Fault	Low	Uncertainties in the continuity of the wireframe along dip and strike and the interaction with the other faut systems.	Map and acquire detailed photogrammetry for every bench within each Pit. Downhole surveys acquired for all new boreholes to confirm this fault
Sakar Fault	2023	1	2	2	4	3	250	35	0,35,15	0.5, 1.5, 1.0	300	Rubble	Younger than Massey alunite domain, reactivate mineralise d fault	High	Uncertainty in the modelled continuity within the East Area and its interaction with the youngest Kanis fault system	Map and acquire detailed photogrammetry for every bench at each pit. Downhole surveys acquired for all new boreholes especially at 2450L of West Pit

4 Implications for pit slope design practice

Geological models serve as the foundation for pit slope design, yet their inherent uncertainties and biases directly translate to engineering risk. The example shown in Figure 2 demonstrates this critical relationship where Model A's oversimplification of structural complexities can lead to stability challenges during construction, highlighting how geological model quality fundamentally impacts slope performance. For slope design practitioners, this underscores the need to transform uncertain geological interpretations into robust engineering decisions through systematic risk management approaches.

4.1 Risk-based design framework

Rather than treating geological models as deterministic inputs, geotechnical engineers should implement confidence-weighted design strategies. Using the confidence rating scheme outlined in Section 3.2, design domains can be established with varying levels of conservatism. High confidence geological zones allow for standard design factors and optimisation techniques, while medium confidence areas could warrant increased design factors and enhanced monitoring protocols. Low confidence zones would require more conservative design approaches with adaptive management strategies, recognising that these areas represent the highest potential for unexpected geological conditions.

Engineers should develop alternative stability scenarios based on different geological interpretations of the same dataset, design for the most critical credible scenario, and establish trigger criteria for design modifications as new data becomes available. This approach transforms the traditional linear design process (e.g. Read & Stacey 2009) into an iterative framework that can adapt to evolving geological understanding.

4.2 Practical implementation strategies

The quality of information analysis presented in Table 2 provides a powerful tool for targeting engineering investigations. By identifying areas where geological confidence is low but slope performance is critical, engineers can prioritise structural data collection, focus hydrogeological investigations where groundwater uncertainty significantly impacts design, and plan geotechnical drilling programs to better understand the variability of rock mass conditions. This targeted approach maximises the value of additional data collection while minimising investigation costs.

Slope design should embrace adaptive management principles that mirror the iterative geological modelling process described in Table 1. Initial designs should incorporate conservative assumptions in areas of high geological uncertainty, followed by systematic data collection during construction to validate or refute geological interpretations. As observed conditions provide new insights, geological models can be updated and future slope designs optimised accordingly.

4.3 Engineering risk communication

Building on the model communication framework presented in Table 3, slope design projects require enhanced documentation linking geological assumptions to engineering decisions. Each design sector should include a geological risk register documenting key assumptions, their confidence levels, potential failure mechanisms if assumptions prove incorrect, and contingency plans for different geological scenarios. This transparency enables informed decision-making by mine planning teams and provides a clear rationale for monitoring and mitigation requirements. The integration of uncertainty quantification into stability analysis represents a fundamental shift away from deterministic design approaches. Sensitivity analysis can identify which geological uncertainties most significantly impact stability, guiding targeted data collection efforts.

5 Conclusion

3D geological modelling is an interpretative process that transforms sparse, sometimes uncertain and unreliable data into hypothesis about the subsurface conditions of a site.

While professional judgement is essential in this process, it is inherently driven by data-related, cognitive and modelling biases. If left unmitigated, these biases propagate through the modelling process, compounding uncertainties and resulting in a 3D model that does not provide an accurate or reliable representation of the geological conditions of a site.

Despite not presenting specific tools or strategies to fully manage and mitigate bias and uncertainties, this paper aimed to remind geologists, geotechnical professionals, stakeholders and decision-makers the importance of recognising, recording and communicating bias and uncertainties. In fact, by embedding bias awareness, clear definition and transparent communication of model uncertainties and reliability, along with data gaps and outcomes of quality of information analysis, allows stakeholders and decision-makers to plan future work and prioritise areas for further data collection enabling the geologist to deliver models that are not only technically robust but also usable and reliable.

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