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Uncertainty in AI-aided Engineering Geological Modelling

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Abstract

Assessing risk for projects where lack of understanding of geotechnical conditions could have major impact has always been a challenge. Software approaches for formulating electronic engineering geological models (EGMs) are helping improve understanding of basic geology for complex project sites. However, irrespective of whether the project is for civil transportation, a hydropower tunnel or dam foundation or for an underground or surface mining project, assessing geological/geotechnical risk nowadays requires detailed evaluation of enormous data volumes, that may obscure relevant, small but important facts. Sorting through data to eliminate errors is critical. Maximizing simplicity in modelling strategy, which is good practice in geotechnics, does not equally apply to digital EGM modelling; as representation of complex geology (or behaviour) must capture all relevant characteristics and details. AI's entry into all electronic platforms is raising other issues that are not always reducing uncertainty in the interpretation of geological data. While AI assisted synthesis of data has the potential to improve processing, wrongly used it will negatively impact uncertainty. For EGM building, establishing geological provenance needs proper understanding of domains in order to allow extrapolation of geological data from known locations into areas with less subsurface information. AI generated options of splined smooth form geological interpretation surfaces sometimes may be correct, but often can be seriously wrong. Smooth extrapolation may work in some sedimentary environments and perhaps in some zones of extreme metamorphic folding, but for heavily faulted ground such interpretations can be completely erroneous. This paper, which is based on work being undertaken by the C-28 committee of the IAEG aimed at developing methodologies for assessing risk and uncertainty in building electronic EGM's using modern geological modelling software, addresses some of these uncertainty challenges.

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[1]*International Association of Engineering Geology and the Environment (IAEG), Working group of the Technical Committee C28 focused on "Reliability quantification of the geological model in large civil engineering projects"*

Keywords

Engineering Geological Models, Uncertainty, Rock Engineering, AI, Risk.

1 Introduction

Engineering geologists and engineers need accurate and reliable subsurface engineering geological models (EGMs) for project design. To accurately represent the subsurface geological environment, the EGM must use all the geological and geotechnical data that is available, not just part data sets (Fookes, 1997, Dematteis et al., 2023, Baynes, and Parry, 2022). However, developing a comprehensive and accurate EGM takes time and diligence to ensure reliability. Computational statistics and AI approaches to examine massive investigation data can help in reducing model building uncertainty, but equally, too much data can overwhelm focus. Mechanical processing ***without*** appropriate geological understanding and regional structural matching can seriously misrepresent reality. Correct geological domaining to gain detailed structural fabric insight is the best path forward to reducing uncertainties and maximizing EGM reliability (Carter & Barnett, 2021). For project success, quantifying uncertainties that arise and change during EGM construction is a most effective way to manage and reduce risk (IAEG-C28, 2025).

EGM reliability depends on how well the predicted engineering geological conditions from the model match actual conditions. Engineering decision-making can only be optimized with correctly predicted rockmass and soil behaviour/performance. To reduce EGM uncertainty, project engineering reliability and strategies must be assessed through careful geological and geotechnical risk assessment, irrespective of whether for surface or underground civil transportation, hydropower or mining applications.

AI's entry into all electronic platforms raises other issues, many of which don't necessarily always reduce geological data interpretation uncertainty. While AI data synthesis can improve processing, misuse can increase uncertainty. Extrapolating geological data from known locations to areas with less subsurface information, requires geological provenance and domain knowledge. Splined smooth-form lithological interpretation surfaces generated by AI can thus be very accurate or very inaccurate. For instance, extrapolating characteristics for heavily faulted ground is much more complex than often the case for sedimentary and extreme metamorphic fold zones, where geometrical fold forms can be much smoother. The IAEG C-28 committee is thus focused on evaluatingthese types of issues that potentially can lead to increased EGM uncertainty when inappropriately using modern geological modelling software tools.

This is not a new problem. It's actually a common myth that more sophistication in modelling and analysis alone reduces risk. This has long been pointed out by industry leaders, (eg., Peck, 1976, Hoek, 1994, 2009). The problem is however becoming moreacute with the advent of AI. Figure 1 attempts to capture the reality of the comparative limited degree of real risk minimization of sophistication without substantive extra data. Compare the blue shaded red and black line extents, and note line AB in the right diagram replicates C-D′ in the left diagram, while blackline A′B replicates the D′ baseline.

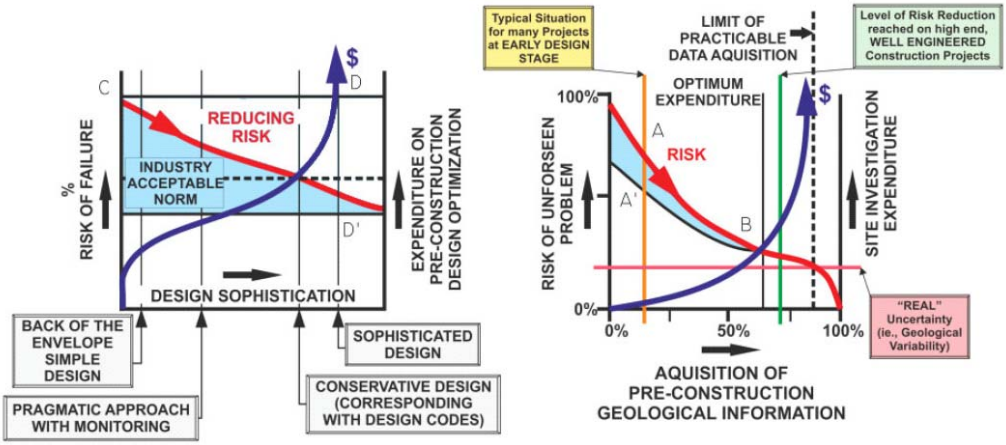


Fig. 1. Knowledge reduces uncertainty more than modelling sophistication (Carter & Marinos, 2020, after Carter, 1992).

Only with acquisition of additional hard site investigation (SI) data can conceptual and observational knowledge increase, leading to real reduction of risk, thereby increasing reliability in an EGM. How much early project risk is tolerable should prescriptively determine EGM acceptable uncertainty. This definition of acceptable uncertainty must however include evaluation of geological complexity early in project life, because inadequate understanding of geological complexity often leads to inadequate EGM reliability. EGMs without enough site-specific data to adequately reflect actual geological complexity can mislead and prevent identification of construction or operational flaws in project design concepts.

Location, setting, and geology (and their interrelationships)must be interactively considered in building an EGM, as interplay between each of these components will exhibit very different uncertainties. Insufficient knowledge and observer bias can cause *conceptual, (epistemic) uncertainty*that will result often in poor EGM builds. Natural geological system/provenance/domain variability and randomness will always create *observational (aleatory) uncertainty*. Reducing both types of uncertainty necessitates feedback loops allowing learning from predictive inaccuracies of an EGM throughout model building, so as to better reflect conceptual-observational variability dynamics associated with improved data. After structural failure of an EGM to replicate reality, the Observational Model must be refined using data, not opinions about that new data. Both quantitative and qualitative checks need applying to determine a conceptual model's uncertainty and track improvements in its reliability.

To avoid an EGM modeller's subjective judgments clouding proper interpretation and appropriate EGM building, an iterative EGM Conceptual Model building process must be followed. This should be built around objective interpretation of measurable facts, models and case histories from literature, merged with hard data from geological/geotechnical field mapping and investigation drilling, plus any available site monitoring information. Testing the accuracy of an EGM by sequentially adding new data is a good way to verify components of an EGM (and improve them if the EGM cannot predict project ground conditions and behaviour correctly). Figure 2 shows how every EGM needs to be properly matched to ground conditions. Understanding of geological provenance is key to defining pathways through this diagram to reduce conceptual and observational data uncertainties, thereby improving EGM reliability.

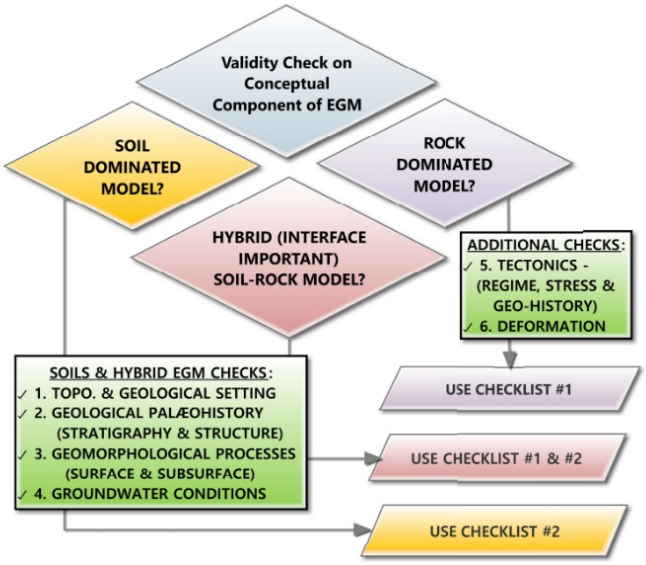


Fig. 2. Suggested approach for verification of an EGMconceptual framework
(see Dematteis et al, 2023 for Checklists for (#1) Rock sites, (#2) Soil Sites)

2 Sources of Uncertainty

Given that there will always be uncertainty in an EGM due to natural geological variability across a project site, irrespective of how much data is gathered (right diagram in Figure 1), the most important task of EGM building is quantifying and minimizing those aspects of uncertainty that are tractable. Tackling the two principal uncertainty issues that complicate building EGM models (ie., *conceptual, (epistemic) uncertainty*– related to lack of understanding of the geological setting, and actual ground conditions and *observational (aleatory) uncertainty* – related to inadequate data representativeness, for the zone being modelled), however, requires significant diligence on the part of the EGM builder.

2.1 Conceptual Model Uncertainty

Site conditions, participant knowledge, and inexperience affect EGM conceptual model uncertainty. Other factors of importance are: project works size and position; quality and quantity of observational data; representativeness of observational data; geotechnical complexity; stress and deformation history; modeller prejudice. The model builder must consider all these aspects and also consider conceptual bias problems that may affect his/her model build. It is important to recognize and minimize any bias. Bond et al. (2008) identified four biases that need consideration: (i) availability bias – splitting easily acquired versus difficult to acquire data, (ii) anchoring bias: accepting “expert”

or "dominant" published opinion, (iii) confirmation bias: only considering or interpreting data that supports one's own hypothesis, and (iv) positive-thinking bias – due to ignoring conflicting data, or misinterpreting controlling structures.

2.2 Observational Model Uncertainty

If a robust conceptual EGM has enough observational data, its uncertainties become solely data-related. More measurements and better distribution can potentially reduce data uncertainty, but while reduction of systematic uncertainty may be feasible with better data quality and coverage, inherent geological variability (Figure 1, right diagram) can never be eliminated. So, some degree of uncertainty must be expected and conveyed to engineers and others who might be using the EGM. Solid conceptual understanding, based on "in-depth" assessment of field and laboratory measurement data provides the benchmarking necessary to accurately assess this degree of remnant uncertainty, so that all potential users can be made aware of model limitations.

3 Uncertainty in AI generated EGMs – Benefits and Complications

AI approaches are attractive for synthesizing and making sense of large amounts of data. In consequence, AI is becoming more widely used in all fields, including engineering geology, but it brings new uncertainties hitherto not an issue of concern to applied engineering geology or rock mechanics.

Typically the key objectives of EGM modelling are aiding project design engineers understand ground conditions and helping in providing operational decision support for:(i) inferring design-relevant soil, rock and/or rockmass properties from practical proxies (geophysical and other index tests, drilling and downhole and other imaging data), (ii) defining constitutive behaviour to help accelerate numerical solvers without producing physically implausible outputs, and (iii) assisting in improving classification and hazard prediction (relating to palpable problems of deformation, slope instability, or rockburst potential for example). To make an AI method choice for best applicability to engineering geological problems, it is recommended by Zhao and Wu (2025) to follow a "matching" philosophy. Their review paper suggests that *Convolutional Neural Networks*(**CNN**s)are commonly applicable for images/raster/3-D data, utilizing small filters (kernels) that slide over the data to automatically extract features (edges, textures, shapes), progressively building more "abstract" representations in the subsequent layers;*Long Short-Term Memory* (**LSTM**) and *Temporal Convolutional Network* (**TCN**) approaches they suggest are most appropriate for evaluation of time-series monitoring and pattern recognition in signals (e.g., microseismic trends). *Ensemble Methods* they report to have found to work best for assessing high-stakes non-linear hazards (eg., rockbursts, for both interaction and classification), while they suggest *Physics-Informed Neural Networks* (PINNs) or hybrid *Machine Learning* (ML) –numerical schemes as seeming most appropriate to apply when governing *Partial Differential Equations* (PDEs) and boundary/initial conditions constrain solutions. Based on these indications, in engineering geological practice, **PINNs** seem to have most applicability and also some distinct advantages over conventional, solely knowledge-based, intuition, because:

a) They can work even with limited data, because the physics of the deemed appropriate mechanism acts as a "regularizer" of widely diverse data;
b) They can produce continuous solutions (smooth interpolation in space/time); and
c) They prove useful for inversion and parameter estimation under physical constraints.

Conversely, **PINNs** are affected by the following limitations:

d) Training is often delicate: balancing the weights of data and physics terms is not trivial.
e) They may struggle with very complex/highly nonlinear problems or sharp discontinuities.
f) They do not always outperform classical numerical methods in speed/robustness; however, they are often quite effectiveas hybrid approaches (physics + ML).

3.1 Case Examples

To examine the application of AI approaches to engineering geological problems, three case records are explored, with two cases targetting methodologies using AI for synthesizing near-real-time data streams and one case examining the complexities of applying AI in the context of EGM construction.

The first two examples illustrate some of the advantages of AI application for rapid data synthesis in engineering geological applications. They illustrate how good control and near real time management

of data streams can help improve understanding while minimizing epistemic uncertainties. The third example, which is more directly focused to the problems of electronic EGM building, highlights the opposite, where direct AI application without significant experienced modeller manual intervention has the potential to disrupt workflows and increase uncertainty by introducing errors and unnecessary complications into the modelled environment.

3.1.1 Case Record #1

In the first case, targeted to aid synthesis of vast volumes of data, Hansen et al, 2024 applied AI to try to generate near-real-time Q-system support estimate predictions from Measure-While-Drilling (MWD) data streams. They applied *tuned tabular ensemble* approaches plus a CNN "very poor quality" backstop and an additional rule layer to analyze the collected MWD data (penetration rate, torque, thrust, rotation, flush return, etc.), along with drillhole geometry, benchmarked to existing Q-system recommendations derived from the Grimstad & Barton, 1993 chart. Based on their AI-assisted data analysis, their methodology successfully gave predictions of Q and appropriate support recommendations (e.g., bolt spacing and shotcrete thickness). Along with reporting some degree of uncertainty and transition flags, they reported thathuman override was found necessary to be incorporated to force appropriateness.

3.1.2 Case Record #2

In the second case, Zhao and Wu, 2025 applied AI to help assess rockburst risk, by analyzing datasets of (a) microseismic event streams (counts/energy/apparent volume), (b) in situ stress proxies, (c) lithology/structure descriptors, (d) excavation cycle metadata, plus (e) limited high-quality deformation measurements. Their approach, (combining early rockburst warning microseismic signatures with geomechanical inputs, fused through *ensemble classifiers* and coupled to a physics-constrained deformation "digital twin" PINN/ML–numerical model), ultimately successfully created short-term rockburst probability estimates, with expected severity, physically constrained by deformation forecasts.

3.1.3 Case Record #3

In this case record, a partially developed and verified electronic EGM already existed, along with a very comprehensive drilling data base, with hundreds of fault and shear-zone intersections in the drilling data. Application of AI thus seemed a reasonable path forward to attempt to determine appropriate structural geology inter-relationships. The procedure utilized the Claude© AI software to initially match verified pattern/orientation geometries of a chosen fault and then duplicate that orientation, starting at the drilling data point, and growing the fault until it came close to another pre-existing fault.

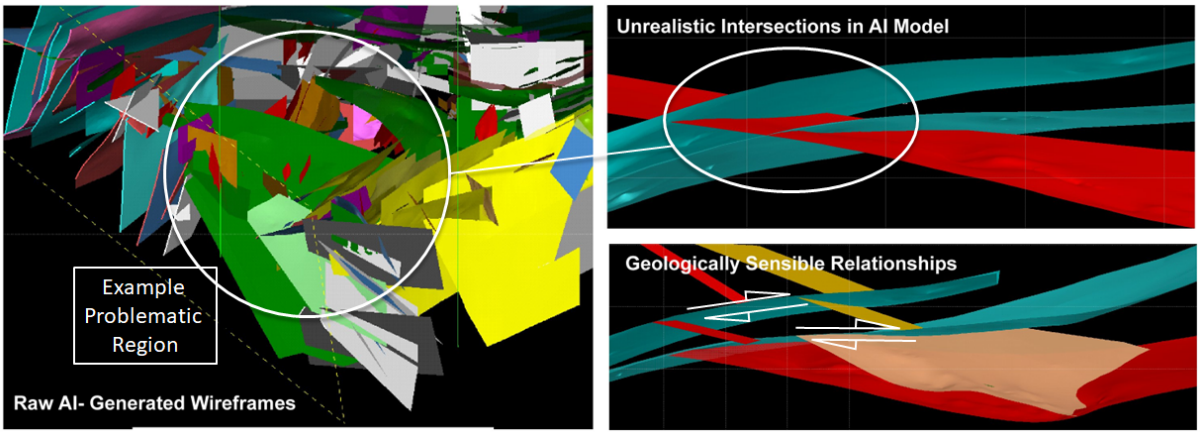


Fig. 3. Illustration of increased uncertainty introduced by "default" AI application in EGM generation, (Note left image of AI generated wireframe geometries – illustrating many problematic incorrect cross-cutting relationships and unrealistic geological frameworks; as encapsulated in top right image). Compare circled zone with more sensible geological interpretation in lower right-hand diagram. Such interrelationships should be visibly apparent in left-hand image, but aren't – necessitating many hours of manual correction of wireframes to achieve appropriate geological conditioning.

Although the application of the AI procedure in this case, as in the previous cases, maintained rigour in adhering to the factual input data points, (ref.,"screenshot" in left diagram in Figure 3), unfiltered, the AI approach generated a completely erroneous and geologically impossible wireframe structure for what should have been sympathetic faulting, (lower right diagram in Figure 3). Multiple geologically unlikely intersections and contact juxtapositions have been developed by the AI software (left diagram, as schematically illustrated in the top right hand diagram illustration), resulting in

geologically impossible fault geometries. The lower right diagram shows how the revised model needed to look, but was only achieved after a significant number of hours spent manually correcting the AI generated wireframe build to something more geologically likely.

To correct the initial AI generated wireframe solids a collision avoidance check had first to be added to prevent all geologically improbable cross-cutting relationships. Then multiple extra rules had to be generated and applied, along with nuances, like overall boundary limits, and differentiating high confidence faults and interactions from those of lesser reliability, and keeping faults of different categories separate but still following the general rules. Although the procedures largely worked, and the AI process remained generally faithful to the objective, the controlling rules had to be manually re-applied many times in order to generate a final realistic-looking and geologically coherent model (following the structural framework shown in the lower right hand schematic diagram in Figure 3).

Reaching this finalized EGM from the original AI generated model was found more time consuming and frustrating than originally expected. Arguably it might have been more quickly generated manually. Part of the problems in the AI process workflow was that as each iteration was systematically saved, the software appeared not to have fully taken in everything that had previously been decided on the last iteration step, often missing critical minor details that were previously established. Partially this could be attributed to memory handling requirements. However, the need for significant geological expertise cannot be understated, as without repeatedly reviewing the results, "correcting" the AI generated wireframes, then moving forward, then reviewing again the output, a completely erroneous representation of likely geology would have been generated. This need for repetitive checking is a concern widely reported across the industry. It is an issue that is not only frustrating for the model builder, but leads of itself to additional errors and uncertainties due to inability to keep double checking everything as each iteration may stochastically generate new equally probable, but different wireframes to the last iteration. While software will undoubtedly improve to help eliminate many of these sorts of problems, it is clear that multiple extra algorithm rules willbe needed to be developed in the various available software codes for a variety of likely geological structural regimes to ensure that only sensible fault structure and contact intersection wireframes are feasible for the AI engine to utilize.

This latter example gives some insight into where probable uncertainty increases, due to inadequate AI conditioning to complex geological fabrics. In this case the application of unconditioned AI, clearly compromised EGM building, in contrast to the other two situations where AI has provided positive assistance in helping synthesize real-time data streams to aid understanding and decision-making.

3.2 Discussion

These examples support a common perception that AI, correctly conditioned and applied, has the potential to help reshape many aspects of rock engineering, particularly when data-driven, helping reduce epistemic uncertainty due to intrinsic data complexity resulting from uncoordinated sampling, complicated by: natural anisotropy, structural complexity, lithological heterogeneity, multiple different discontinuity types (joints/faults/fracture networks), scale effects, and multi-physics /multi-phase coupling. As demonstrated in the EGM case example, AI may not be applicable in all circumstances, though, as many natural processes are ill-understood, and therefore not immediately tractable to AI algorithm generation. For EGM building, for example, establishing geological provenance needs proper in-depth understanding of geotechnical domains, in order to allow extrapolation of geological data from known locations into areas with less subsurface information. The AI-generated "default" options for geological interpretation surfaces in Example #3 were not satisfactory and required extensive adjustments by the modeller. AI extrapolation in EGMs may work well in some sedimentary environments and perhaps in some zones of extreme metamorphic folding, where structural fabrics may be simpler, but for heavily faulted ground, such as shown in the images in Figure 3, AI initial interpretations can be completely erroneous. However, in the right circumstances, with adequate manual interaction, AI may have application for speeding up many routine EGM modelling tasks,

Widespread AI application is seen likely for assisting with routine rock and soil classification tasks, but should focus on enhancing existing methodologies, rather than replacing them. AI clearly has application to help automate procedures utilizing techniques like tuned tabular ensembles and CNNs, (eg. Case 1 - Hansen et al, 2024). It also offers significant potential for analyzing diverse data sources and enhancing methodologies, (eg., Salami et al, 2019), particularly for data-limited areas. Uncontrolled, however, there is a risk of AI inadvertently perpetuating existing classification system limitations, (such as outlined by Palmström & Broch, 2006, and by Carter, 2010). So, rather than

entrenching systemic issues, AI should be focused on resolving the inherent limitations of the main quantitative classification systems that led to development of the original observational GSI chart concept (Marinos & Hoek, 2000, Hoek et al, 2013, Carter & Marinos, 2020). AI methodologies need to be applied to interrogate and increase training data for the systems well beyond their original, rather rock type-specific datasets (mainly hard rock Scandinavian data for Q, and mainly sedimentary coal for RMR). Other basic data sources where multiple classification systems have been utilized, need synthesis, so as to credibly extend and extrapolate the existing methodologies into more data-limited segments of the original datasets. For rock, there will also be merit for AI to be applied for credibly extending the classifications upwards into less jointed rockmasses, (per suggestions by Schlotfeldt & Carter, 2018), maybe even tackling brittle spalling (high *GSI*, high m_i, *RQD*>100%) rockmasses, or at the other extreme, weaker Mohr-Coulomb materials (almost soil) range (GSI<30, UCS<15MPa);where, as pointed out by Carter et al, 2008, the existing classifications and the Hoek-Brown failure criterion struggle. By contrast, AI methodologies for soil classification, may be more immediately effective than for rockmasses, due to the more clearly defined parameters of widely benchmarked, structured systems like the Unified Soil Classification System (USCS) and AASHTO. However, AI applied for either rock or soil classification tasks must remain geologically contextual. AI should enhance rather than replace existing methods, emphasizing development of better databases and correlations in varied geologies as basis for increasing reliability.

Currently, however, AI seems more able to help in data evaluation and manipulation tasks, particularly where characteristics of natural processes make common engineering needs (parameter estimation, hazard prediction, deformation assessment) ill-conditioned under *purely analytical* or *purely empirical approaches*. For these types of synthesizing tasks, AI can play a useful role as a complementary toolkit focused on data resolution—while acknowledging data scarcity and standardization as key barriers. Currently though, routine AI deployment in Engineering Geology is still limited by scarce nonstandard datasets, black-box opacity, lack of reproducibility, and dominance of real-time field noise; although hybrid approaches – that combine physics and AI, are promising to foster better assessment of Reliable Engineering Geological Models. (Zhao and Wu, 2025).

4 Conclusions

Solid geological understanding is essential for reducing uncertainty in EGM construction. There is still no substitute for always needing to properly establish geological provenance and domain characteristics in order to allow extrapolation of geological data from known locations into areas with less subsurface information. Current industry experience in EGM building suggests that uncorrected AI generated options of geological interpretation surfaces sometimes may be correct, but often can be seriously wrong. Manual input is thus critical in order to avoid completely erroneous AI interpretations.

Case Examples #1 and #2 demonstrate the successful application of *ensemble* AI methods in a few sectors of Engineering Geology practice. However, these "AI success stories" still do not equal routine practice due to: (i) limited and nonstandard datasets (especially for rare hazards), (ii) black-box opacity in deep models, (iii) reproducibility problems (datasets, tuning, architectures), (iv) a gap between prototypes and field-deployable tools for noisy, heterogeneous, real-time conditions, and (v) insufficient interdisciplinary coupling between AI specialists and rock-mechanics experts. Progress towards constructing reliable Engineering Geological Models will likely come from hybrid physics together with AI modelling. There is a need however to develop new workflows with structured open datasets, new standards, and more openly (non-blackbox) interpretable methodologies in order to improve AI applicability and systematically introduce uncertainty quantification into EGM construction.

AI is a powerful resource, but verifying the correctness of its methods and results still requires hours of careful work and multiple objective validation approaches. Resolution of some of such difficulties in model building may come in time with improved AI with better algorithms, but in the geological arena there is no substitute for solid understanding. While gaining extensive experience with any chosen geological modelling software (including AI applications) is fundamental, geological understanding and deep expertise based on years of core logging, mapping and site investigation and geological training is even more critical. Figure 2 and the guidelines in the C28 IAEG report (Dematteis et al, 2025), particularly the tables, presented as annexes to the report (following Dematteis et al, 2023) provide a methodology and workflow for helping reduce uncertainty by stepping through a series of controls for self-checking an EGM build.

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