Minimum Acceptance Criteria for Conditioning Subsurface Modeling using Generative AI

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ABSTRACT

Generative AI (genAI) has resulted in new reservoir modeling capabilities with the promise of geological realism of rule-based geostatistical and physics-based models and the unlimited data conditioning of pixel-based geostatistical models. genAI allows the combination of dense conditioning and complicated, realistic reservoir heterogeneity due to its ability to learn image patterns and replicate them while honoring conditioning. However, the common practices are based on ocular inspection of the generated realization. Quantitative statistical measures are essential for robust model checking given the importance of these reservoir models to support high-value subsurface development decisions but are not common, established practices.

We propose genAI-generated reservoir realization minimum acceptance checks, and statistical measures to check the goodness of these conditioned models. The proposed checks are applied to both categorical data (e.g., facies) and continuous data (e.g., porosity) distributions. We check the following criteria: (a) data distribution reproduction, (b) spatial continuity reproduction, (c) geobody Connectivity, (d) local data conditioning, (e) patterns and artifacts, and (f) uncertainty, by comparing these criteria between training images and GenAI-generated images.

The data distribution reproduction is checked through histograms and QQ plots of property of interest. Figure 1 depicts the use of QQ plots to compare porosity distributions. The spatial continuity reproduction is checked through experimental semi-variograms and dispersion variance comparisons. The geobody connectivity is checked by counting the number of disconnected geobodies in the images. The local data conditioning and uncertainty are checked by calculating entropy and standard deviation by-pixel calculations. Figure 2 represents the by-pixel entropy calculation for different number of locations conditioning. The resulting error from data conditioning is reported using the F1 score for categorical data and relative error for continuous data. The patterns and artifacts are checked using n-point pattern statistics checks. Finally, dimensionality reduction techniques check image similarity.

Our minimum acceptance criteria allow for an enhanced evaluation of genAI realizations for subsurface reservoir model quality assurance and confidence for the application of these genAI realizations to support resource development decision-making.

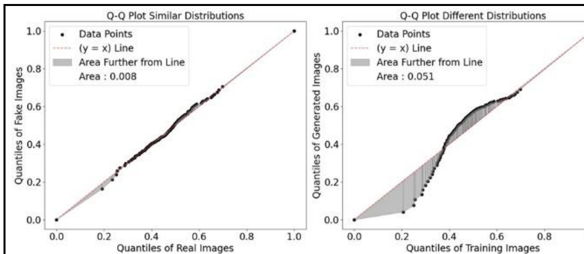

Figure 1 QQ plots for distribution comparisons.

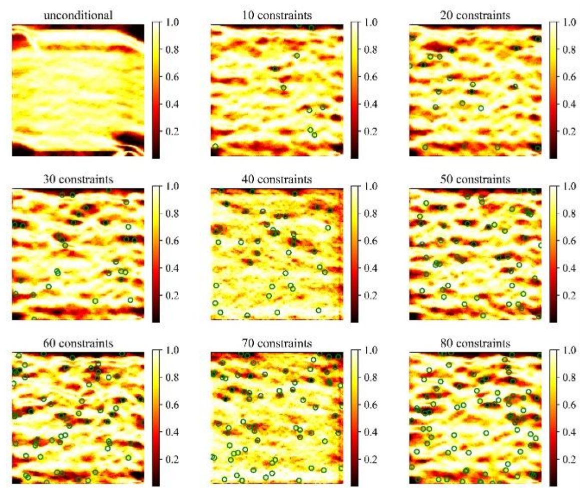

Figure 2 The entropy maps of the unconditional realizations and conditional realizations for different numbers of constraints which are depicted in green circles.

Figure 1 shows the difference in the QQ plot divergence area for similar (left) and different (right) distributions. The smaller area indicated better distribution reproduction. Figure 2 shows lower entropy values consistently at the conditioned locations, indicating that the conditioning process reduces the uncertainty of facies reproduction.

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