

A Petrel-Based Reproducible Workflow for Integrated Static Reservoir Characterization Using Synthetic Seismic and Well-Log Data

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Abstract

Static reservoir characterization integrates seismic interpretation, well-log analysis, structural modeling, facies simulation, petrophysical property modeling, and uncertainty analysis. In practice, however, project-specific decisions are often incompletely documented, limiting auditability, transferability, and reproducibility. This study presents the Reproducible Integrated Reservoir Modeling Workflow (RIRMW), a Petrel-based methodological framework that formalizes reservoir modeling as a modular chain of declared inputs, transformations, parameter records, quality-control gates, outputs, and provenance information. RIRMW is demonstrated with a location-independent synthetic dataset comprising seismic sections, a seismic attribute map, formation markers, and multi-curve well logs. The workflow constructs a fault-constrained structural framework, simulates sandstone, shaly-sandstone, and shale facies, distributes effective porosity, horizontal permeability, and water saturation, and evaluates geological uncertainty using multiple stochastic realizations and percentile summaries. The demonstration produces internally consistent structural, facies, and property models while preserving an explicit record of modeling assumptions and acceptance criteria. RIRMW does not replace geological judgment or claim software-independent numerical replication; it makes judgment points and Petrel implementation choices inspectable and repeatable. The framework provides a practical bridge between industrial subsurface-modeling environments and reproducible petroleum geoscience and can be transferred to field datasets after project-specific calibration and validation.

1. Introduction

Three-dimensional static reservoir models are central to subsurface evaluation because they provide the geological and petrophysical framework used for volumetric estimation, well planning, uncertainty analysis, and subsequent dynamic simulation. Their construction requires the integration of measurements and interpretations that differ in scale, support, resolution, and uncertainty. Seismic data provide laterally extensive but vertically limited information; well logs provide high-resolution one-dimensional measurements; and geological concepts guide interpolation between sparse observations. The resulting model is therefore not a direct image of the subsurface but a structured hypothesis constrained by available data and modeling choices (Ringrose and Bentley 2015; Caers 2011).

Contemporary reservoir-modeling platforms make it possible to combine seismic interpretation, well correlation, structural framework construction, facies modeling, and petrophysical property simulation within a shared environment. Petrel is widely used for this purpose because it supports multidisciplinary data integration and standardized subsurface workflows from exploration through reservoir development (SLB 2026). Nevertheless, availability of an integrated software platform does not itself guarantee a reproducible study. Project outcomes remain sensitive to interpretation choices, grid design, upscaling rules, variogram parameters, random seeds, property transforms, conditioning data, and quality-control decisions. When these elements are distributed across software dialogs, screenshots, personal notes, and undocumented iterations, a technically plausible model can be difficult to audit or reproduce.

This reproducibility problem is especially important in computational geoscience, where scientific conclusions increasingly depend on complex digital workflows. FAIR principles extend beyond datasets to algorithms, tools, and workflows, emphasizing findability, accessibility, interoperability, and reusability of research objects (Wilkinson et al. 2016; Goble et al. 2020). Reproducibility does not require the elimination of expert judgment; rather, it requires that judgment, assumptions, parameterization, and provenance be recorded sufficiently for an informed practitioner to repeat the procedure and evaluate alternative choices. Recent guidance similarly emphasizes transparent computational environments, explicit workflow descriptions, and reusable supporting artifacts (Caprarelli 2023; de Visser et al. 2023; Wilkinson et al. 2025).

Reservoir modeling presents an additional challenge because uncertainty is intrinsic. Sparse conditioning data permit many geological realizations that can honor the same observations, and two-point or multiple-point geostatistical methods can generate alternative spatial arrangements with different connectivity and volumetric consequences (Deutsch and Journel 1998; Strebelle 2002; Mariethoz and Caers 2014; Remy et al. 2009). Structural interpretation is also non-unique and can materially affect reservoir compartmentalization (Bond et al. 2007; Wellmann and Caumon 2018). Seismic-guided workflows, seismic-data integration, stochastic inversion, and high-resolution geostatistical studies demonstrate the value of explicitly integrating multiscale constraints (Dubrule 2003; Koneshloo et al. 2017; Abuzaied et al. 2023; Ren et al. 2019). Consequently, a reproducible workflow should preserve not only a preferred model but also the reasoning, parameters, and ensemble evidence used to characterize uncertainty (Pyrzcz and White 2015).

Existing reservoir-modeling literature provides strong foundations for geostatistical simulation, structural modeling, model design, and uncertainty assessment (Journel and Huijbregts 1978; Pyrcz and Deutsch 2014; Ringrose and Bentley 2015). However, these components are frequently described independently or reported as case-specific sequences. A practical need remains for a concise framework that translates reproducibility principles into checkpoints that can be executed in a commercial, multidisciplinary modeling environment without presenting the software itself as the scientific novelty.

This paper introduces the Reproducible Integrated Reservoir Modeling Workflow (RIRMW), specified for implementation in Petrel and demonstrated using reproducible synthetic seismic and well-log data. The contributions are fourfold: (1) a modular workflow architecture connecting inputs, transformations, quality-control gates, and outputs; (2) a parameter and provenance register that exposes consequential modeling decisions; (3) an uncertainty protocol based on multiple stochastic realizations and statistical summaries; and (4) a synthetic demonstration that can be shared without field-confidentiality restrictions. The objective is not to propose a new geostatistical algorithm or software package. It is to formalize how established methods are assembled, checked, documented, and transferred as a reproducible static reservoir-characterization experiment.

2. RIRMW framework

2.1 Design principles

RIRMW treats a reservoir-modeling study as a directed sequence of auditable modules rather than a collection of software operations. Each module contains five elements: declared inputs, an explicit transformation, a parameter record, a quality-control gate, and versioned outputs. A module is advanced only when its acceptance criteria are met or when a documented exception is approved. This design separates geological judgment from hidden software state and allows later changes to be traced to their downstream effects.

The framework comprises a workflow map, data dictionary, interpretation register, parameter register, quality-control checklist, realization manifest, and results summary. Together these artifacts document what entered the model, how it was transformed, which settings were used, what checks were applied, and which outputs were retained. Petrel provides the implementation environment, while RIRMW supplies the study design and provenance logic. The six-module architecture and its quality-control gates are summarized in Table 1, and the integrated workflow sequence is shown in Fig. 1.

[Insert Table 1 near here]

Table 1
Modular architecture of RIRMW and the required quality-control gates.

Module	Principal inputs	Core operation	QC gate	Recorded output
M1 Data and interpretation	Synthetic seismic, attributes, logs, markers	Import, datum/unit checks, horizon and fault interpretation	Coordinate, unit, marker and tie consistency	Validated interpretation set
M2 Structural framework	Horizons, faults, zonation	Fault framework, surfaces, pillar/corner-point grid	No unintended gaps; acceptable cell geometry; horizon order	Versioned structural grid
M3 Facies	Upscaled logs, trends, conceptual geology	Indicator or training-image-guided stochastic simulation	Proportions, conditioning and connectivity checks	Facies realizations and seed register
M4 Properties	Facies, porosity, permeability, saturation logs	Facies-conditioned SGS and transforms	Histogram, variogram, cross-plot and bound checks	Property realizations
M5 Integration	Structure, facies and properties	Assemble static model and compute summaries	Geological consistency and volumetric sanity checks	Integrated static model
M6 Uncertainty	Alternative seeds and parameter scenarios	Generate, rank and summarize realizations	Coverage of plausible range and reproducible manifest	P10/P50/P90 summaries and representative cases

[Insert Fig. 1 near here]

2.2 Reproducibility levels

Because Petrel is proprietary and its internal algorithms and file formats may vary across versions, RIRMW distinguishes procedural repeatability from exact numerical reproducibility. Level 1 requires repeatability by the original modeler using the same project and software version. Level 2 requires independent procedural reproduction by another trained user using the documented inputs and settings. Level 3 requires numerical comparison of key outputs within predefined tolerances. Exact cell-by-cell identity is not assumed for stochastic operations unless the algorithm, random seed, software build, grid ordering, and conditioning sequence are identical. This layered definition avoids overstating reproducibility while providing measurable expectations.

3. Synthetic data and experimental design

3.1 Purpose and scope of the synthetic demonstration

The demonstration dataset was designed to exercise the complete workflow without implying a specific field location. It represents a faulted, layered clastic reservoir containing sandstone, shaly sandstone, and shale. Synthetic inputs allow the workflow logic, parameter records, and figure outputs to be shared without confidentiality constraints. The dataset is not intended to reproduce the geostatistical signature or economic performance of a particular reservoir.

All synthetic arrays and research figures were generated deterministically in Python using NumPy and Matplotlib with random seed 20260809. The model domain contains 120 × 90 lateral cells and 48 conceptual vertical layers. Structural surfaces combine smooth sinusoidal regional trends with two prescribed fault offsets. Spatially correlated Gaussian fields were produced by repeated neighborhood averaging and combined with deterministic trends to assign sandstone, shaly-sandstone, and shale classes. Facies-dependent porosity means were perturbed by correlated noise; permeability was derived using a log-linear porosity transform; and water saturation was assigned inversely to porosity with bounded correlated variation. Seismic traces were generated from horizon reflectivity convolved with a 32-Hz Ricker wavelet and additive Gaussian noise. Three uncertainty realizations use independent fixed seeds while preserving the same trend and facies thresholds. The complete generation script, random seeds, and supporting numerical arrays accompany the manuscript as supplementary material. The synthetic dataset and modeling specifications are summarized in Table 2.

[Insert Table 2 near here]

Table 2
Synthetic demonstration dataset and modeling specifications.

Element	Synthetic specification	Role in workflow
Seismic section	Layered reflectivity with interpreted top, base, seal and normal faults	Constrains horizons and structural discontinuities
Attribute map	RMS-amplitude/coherence-style map with fault lineaments and stratigraphic banding	Supports lateral interpretation and discontinuity QC
Well logs	Gamma ray, deep/shallow resistivity, density, neutron, sonic and derived porosity	Defines zones, lithology and petrophysical transforms
Facies classes	Sandstone, shaly sandstone and shale	Categorical geological model
Property ranges	Effective porosity 0–40%; horizontal permeability 0.1–1000 mD; water saturation 0–1	Continuous-property simulation bounds
Uncertainty ensemble	Multiple stochastic facies/property realizations with recorded seeds	Tests variability, connectivity and statistical range

3.2 Seismic and well-log interpretation

The interpretation stage identifies the top-reservoir, base-reservoir, and sealing horizons and maps fault discontinuities. Horizon picks are checked for stratigraphic order, lateral continuity, and consistency with the synthetic well markers. Fault sticks and surfaces are inspected for unintended intersections, abrupt

terminations, and implausible displacement changes. An interpreted synthetic cross-section provides the structural control used by the subsequent framework (Fig. 2).

A complementary synthetic attribute map is used to evaluate the lateral continuity of faults and stratigraphic patterns (Fig. 3). The attribute is treated as supporting evidence rather than an independent truth model. Interpretations are accepted only where the cross-sectional and map-view evidence are mutually consistent or where uncertainty is explicitly flagged.

The synthetic well-log composite combines lithology-sensitive and porosity-sensitive curves within a common depth reference (Fig. 4). Gamma ray supports shale-volume estimation; density, neutron and sonic responses provide complementary porosity indicators; and resistivity supports saturation interpretation. The workflow records curve mnemonics, units, environmental corrections, cutoffs, and the equations used to derive modeled properties. Archie-type saturation relationships are applicable to clean formations but require explicit calibration and caution in shaly intervals (Archie 1942).

3.3 Structural framework and grid

The structural model is built from fault surfaces and gridded horizons in a sequence that preserves fault relationships and stratigraphic order. The corner-point grid is refined around faults and reservoir intervals while avoiding unnecessary resolution outside the modeled objective. Cell quality is evaluated using volume, angle, aspect-ratio, and collapsed-cell checks. Structural uncertainty is represented by alternative interpretations or perturbations where data do not uniquely determine fault geometry (Wellmann and Caumon 2018). The resulting three-dimensional structural framework is shown in Fig. 5.

[Insert Fig. 5 near here]

3.4 Facies and petrophysical property modeling

Categorical modeling distributes sandstone, shaly sandstone, and shale within the structural grid. Facies proportions and vertical trends are derived from the synthetic well observations and conceptual depositional organization. Indicator simulation or multiple-point concepts may be selected according to the geological style; the selected method, neighborhood, trends, seed, and conditioning priority are recorded. Multiple-point approaches are particularly useful when curvilinear or connected geological patterns cannot be represented adequately by two-point statistics alone (Strebelle 2002; Mariethoz and Caers 2014). Every realization is checked against conditioning data, target proportions, vertical trends, and connectivity expectations. Representative layers from the resulting facies model are shown in Fig. 6.

[Insert Fig. 6 near here]

Continuous properties are modeled within facies to prevent unrealistic mixing of distinct rock populations. Effective porosity is simulated using sequential Gaussian simulation after normal-score transformation and variogram analysis. Horizontal permeability is linked to porosity through facies-

specific transforms with residual variability, and water saturation is modeled within physical bounds while preserving its inverse relation to reservoir quality. The workflow stores transformation equations, variogram models, search neighborhoods, random seeds, and back-transformation settings. Minimum acceptance criteria follow the principle that realizations must reproduce conditioning data and relevant univariate, bivariate, and spatial statistics (Leuangthong et al. 2004). The principal modeling parameters and acceptance criteria are listed in Table 3, and the resulting reservoir-property maps are shown in Fig. 7.

[Insert Table 3 near here]

Table 3 Core parameter register and acceptance criteria for the synthetic experiment.		
Object	Recorded parameters	Acceptance criterion
Structural grid	Grid dimensions, layering, fault framework version	Positive cell volumes; correct horizon order; no unintended gaps
Facies	Algorithm, proportions, trends, neighborhood, seed	Exact hard-data conditioning; plausible proportions and connected bodies
Porosity	Transform, variogram, neighborhood, seed, bounds	0–40%; conditioned values honored; target histogram/variogram reproduced
Permeability	Facies transform, residual model, bounds	0.1–1000 mD; positive values; expected porosity relation
Water saturation	Transform, facies dependence, bounds	0–1; expected inverse association with reservoir quality
Realization	Software version, run date, scenario ID, seed	Manifest complete and output uniquely traceable

[Insert Fig. 7 near here]

3.5 Model integration and uncertainty assessment

The integrated static model combines the structural grid, categorical facies, and continuous properties without changing their individual conditioning relationships. Integration QC verifies that property values remain within the correct facies and stratigraphic zones, faults partition the intended cells, and the active-cell volume is stable. Summary maps, histograms, cross-plots, and volumetric calculations are generated from the same versioned realization to avoid mixing outputs from different project states. The integrated three-dimensional static reservoir model is shown in Fig. 8.

[Insert Fig. 8 near here]

Geological uncertainty is evaluated using an ensemble of stochastic realizations rather than a single deterministic model. Alternative random seeds vary the local facies and property arrangement while maintaining common conditioning data and global constraints. Scenario-level changes may additionally

vary structural interpretation, facies proportions, or variogram ranges. The realization manifest prevents accidental comparison of outputs generated from different assumptions. Percentile summaries are reported using a stated ordering convention because P10 and P90 can be used differently across disciplines. The stochastic realizations and associated uncertainty summaries are shown in Fig. 9.

[Insert Fig. 9 near here]

4. Results

4.1 Workflow execution and traceability

The synthetic experiment demonstrates that all six RIRMW modules can be executed as a connected, auditable sequence. The workflow map preserves the dependency between interpretation, structure, facies, properties, integration, and uncertainty. Each retained output is linked to its input version and parameter record. This is the principal result of the framework: the preferred static model is accompanied by the information needed to understand how it was produced and to repeat the procedure within the stated reproducibility level.

The seismic and well-log interpretation produced a coherent top/base reservoir interval and a fault pattern that could be represented in the three-dimensional framework. Grid QC retained positive cell volumes and consistent stratigraphic ordering in the displayed model. Because the inputs are synthetic, these observations demonstrate internal consistency rather than validation against an independently observed subsurface truth.

4.2 Facies and property outcomes

The facies model reproduces three categorical rock classes with laterally connected sandstone bodies separated or surrounded by shaly sandstone and shale. The property models preserve the intended facies dependence: high effective porosity and permeability are concentrated in the better-quality sandstone pathways, whereas higher water saturation is more common in poorer-quality regions. The displayed ranges—0–40% effective porosity, 0.1–1000 mD horizontal permeability, and 0–1 water saturation—are synthetic design bounds, not estimates for a field reservoir.

The integrated model shows that faults, stratigraphic layering, facies connectivity, and petrophysical variability can be inspected simultaneously. This integrated view exposes errors that may not be apparent in isolated property displays, such as property leakage across facies boundaries, discontinuities at fault blocks, or inconsistent layering. In RIRMW, these visual checks supplement rather than replace quantitative acceptance criteria.

4.3 Uncertainty outcomes

The three displayed stochastic realizations honor a common structural framework and facies vocabulary but differ in local arrangement and connectivity. The aggregate synthetic porosity distribution has a

mean of 17.6%, a median of 17.3%, and percentile values of 8.2% and 27.8% for P10 and P90, respectively. These values demonstrate the reporting mechanism and should not be interpreted as reserves or field forecasts. A real application would extend the ensemble to include structural, petrophysical, and scenario uncertainty and would test whether the number of realizations adequately stabilizes decision-relevant statistics. The principal demonstration outputs and their interpretation are summarized in Table 4.

[Insert Table 4 near here]

Table 4
Demonstration outputs and their interpretation.

Output	Synthetic result	Interpretive significance
Structural framework	Faulted, layered corner-point model	Provides compartment and stratigraphic architecture
Facies model	Sandstone, shaly sandstone and shale realizations	Represents categorical heterogeneity and connectivity
Effective porosity	0–40%; mean 17.6% in uncertainty summary	Represents storage-quality variability
Horizontal permeability	0.1–1000 mD synthetic range	Represents transmissibility contrast
Water saturation	0–1 synthetic range	Represents fluid-saturation variability
Uncertainty summary	P10 8.2%, P50 17.3%, P90 27.8% for porosity	Demonstrates ensemble reporting, not field reserves

5. Discussion

5.1 Scientific and practical contribution

RIRMW contributes a reproducibility layer to established reservoir-modeling practice. Its novelty lies in the formal organization of the workflow, not in replacing accepted structural or geostatistical algorithms. The framework makes consequential decisions explicit, assigns quality-control gates to each module, and preserves a manifest linking scenarios, seeds, and outputs. This addresses a recurrent weakness of project-based modeling in which the final model is retained but the decision trail is fragmented.

The framework is compatible with Petrel's multidisciplinary integration capabilities while remaining conceptually separable from the software. Petrel is treated as the implementation environment, not as the scientific contribution. This distinction matters for transferability: the module definitions, parameter register, and acceptance criteria can be implemented in another platform, although file formats, algorithms, and numerical outcomes may differ. The framework therefore supports procedural reproducibility more strongly than exact software-independent replication.

5.2 Geological uncertainty and model non-uniqueness

The ensemble results reinforce the principle that a single static model should not be equated with the subsurface. Alternative realizations can satisfy the same hard data while producing different connectivity and spatial statistics. Geostatistical simulation is valuable because it samples this non-uniqueness, but an ensemble is meaningful only when its parameter ranges and geological scenarios are defensible (Caers 2011). RIRMW addresses this by requiring a scenario statement, seed register, acceptance checks, and a transparent ranking or summarization rule.

Uncertainty is not limited to stochastic seeds. Structural interpretation, facies concepts, variogram ranges, property transforms, contacts, and cutoffs can all affect model outcomes. In a field application, these sources should be organized hierarchically and propagated according to their decision relevance. Representative realizations may then be selected using volumetric, connectivity, or flow-response proxies, recognizing that static ranking does not guarantee equivalent dynamic behavior (Oliveira et al. 2017).

5.3 Reproducibility under proprietary software

A proprietary environment imposes limits on transparency because source code and some numerical implementation details are unavailable. RIRMW cannot remove that limitation. It mitigates it by recording the software release, project state, input checksums or identifiers, object dependencies, algorithm selections, parameter values, seeds, and exported summaries. Where licensing permits, non-proprietary supporting artifacts—tables, parameter manifests, synthetic inputs, and result summaries—should be deposited in an accessible repository. This is consistent with applying FAIR principles pragmatically to workflows and metadata even when every digital object cannot be openly distributed (Wilkinson et al. 2016).

For submission to a computing-focused journal, a conceptual Petrel workflow alone may be insufficient. A stronger computational contribution would require an openly available framework implementation, machine-readable manifests, validation scripts, or a platform-independent reference workflow. The present manuscript establishes the scientific specification for such an implementation and provides a complete synthetic demonstration, but it should not claim an open-source software contribution unless those artifacts are released.

5.4 Limitations

Four limitations define the scope of this study. First, the dataset is synthetic and cannot demonstrate predictive performance in a field reservoir. Second, the displayed ensemble is illustrative and does not establish convergence of uncertainty statistics. Third, the workflow focuses on static characterization and does not include history matching or dynamic simulation. Fourth, exact numerical reproducibility may depend on Petrel version, algorithm implementation, grid ordering, and license-controlled functionality. These limitations are deliberate: the purpose is to test and communicate the workflow architecture before applying it to confidential or operational datasets.

6. Conclusions

RIRMW formalizes integrated static reservoir characterization as a reproducible sequence of data validation, interpretation, structural framework construction, facies modeling, property modeling, integration, and uncertainty assessment. Specified for Petrel implementation and demonstrated with reproducible synthetic seismic and well-log data, the framework couples every modeling module to an explicit parameter record, quality-control gate, and versioned output.

The synthetic application produced internally consistent structural, facies, porosity, permeability, and saturation models and demonstrated ensemble-based uncertainty reporting. The scientific value of the framework is not a new simulation algorithm but a transparent architecture for assembling established methods, exposing expert decisions, and tracing outputs to their assumptions. The approach can improve auditability and transferability in multidisciplinary reservoir studies, provided its parameterization is calibrated to real data and its reproducibility claims acknowledge the constraints of proprietary software.

Future work should implement the RIRMW manifests and QC tests in open, machine-readable form; evaluate the workflow on a public benchmark or field dataset; quantify sensitivity to structural and geostatistical parameter choices; and connect representative static realizations to dynamic simulation. These developments would strengthen both the computational contribution and the evidence for decision-relevant reproducibility.

Declarations

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Competing interests: The author declares no competing interests relevant to the content of this article.

Author contributions: The sole author was responsible for the study conception, workflow design, synthetic demonstration, interpretation, manuscript preparation, and approval of the submitted version.

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

Data availability: All data generated or analysed during this study are included in this published article and its supplementary information files.

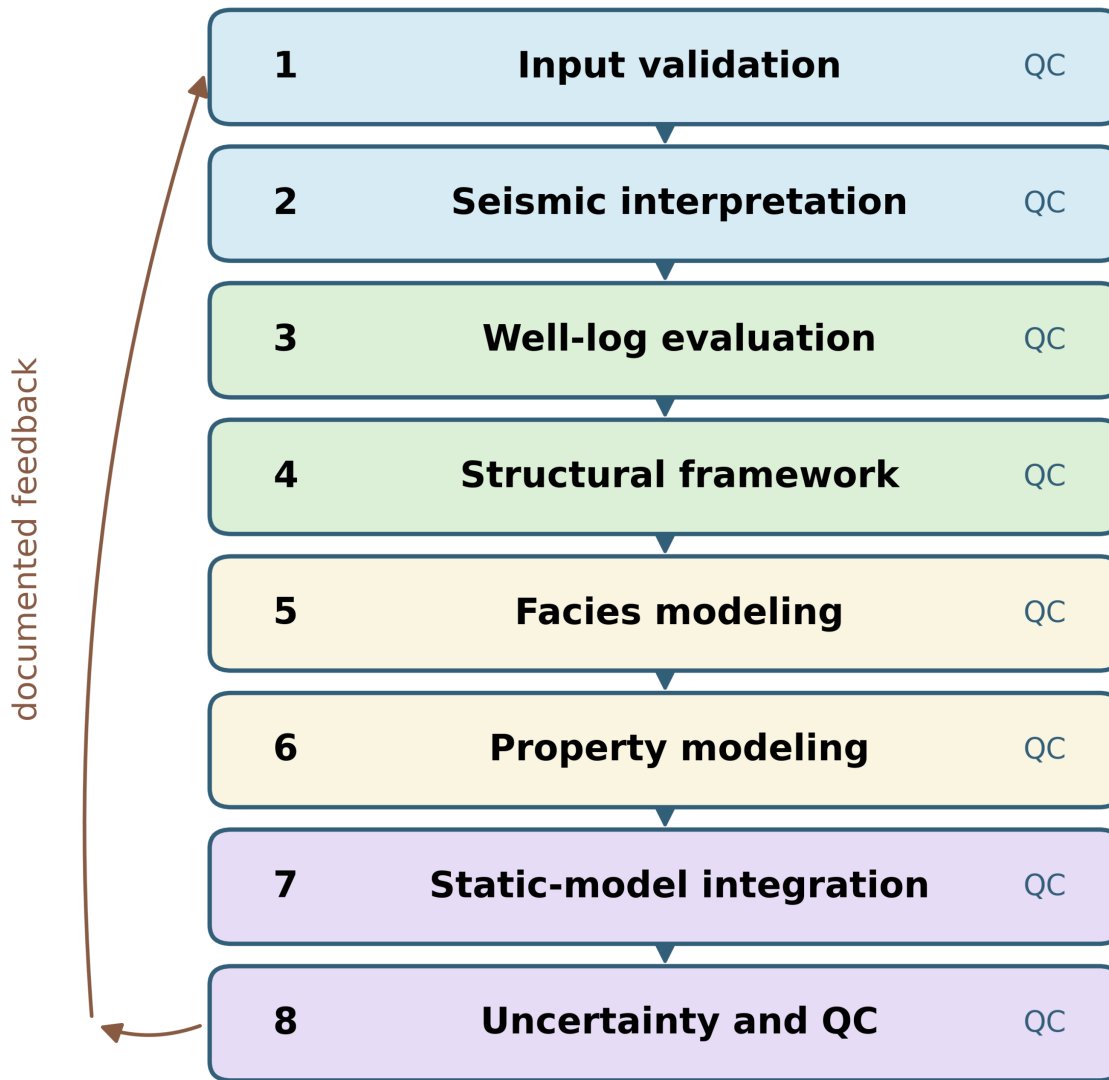
Use of artificial intelligence tools: OpenAI ChatGPT was used to assist with manuscript drafting and editing, development of the deterministic Python figure-generation code, and document formatting. No generative-image model was used for the research figures. The author reviewed and approved the manuscript, code, numerical outputs, interpretations, and references and accepts full responsibility for the integrity and accuracy of the submitted work.

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Figures



Outputs: parameter register • model versions • QC evidence • uncertainty summaries

Figure 1

Integrated Petrel workflow for static reservoir characterization. The RIRMW sequence links synthetic-data validation, seismic and well-log interpretation, structural framework construction, facies and property modeling, model integration, and geological uncertainty assessment through explicit quality-control gates

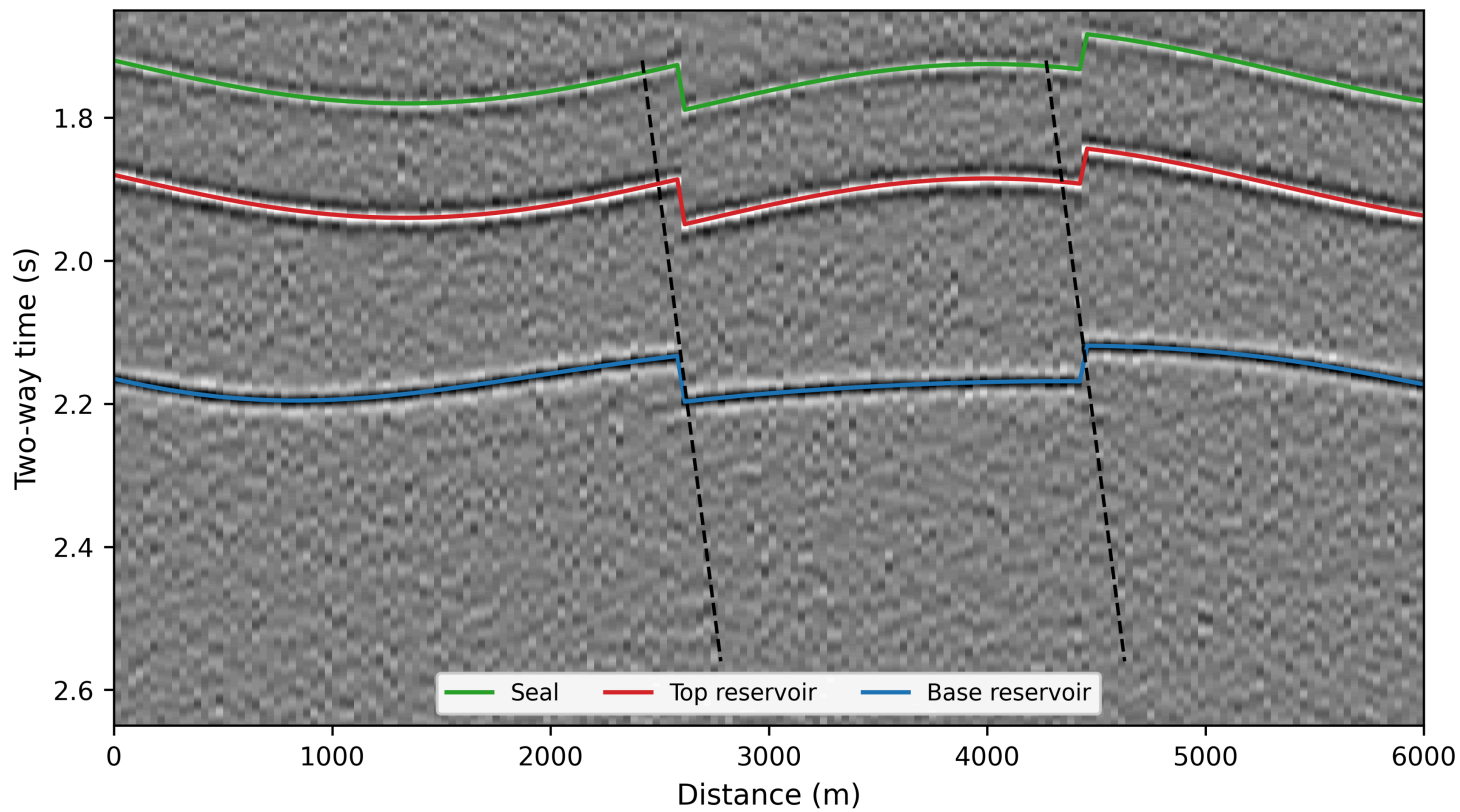


Figure 2

Synthetic seismic cross-section with interpreted horizons and faults. The top-reservoir, base-reservoir, and sealing horizons, together with structural discontinuities, provide the constraints for construction of the three-dimensional framework

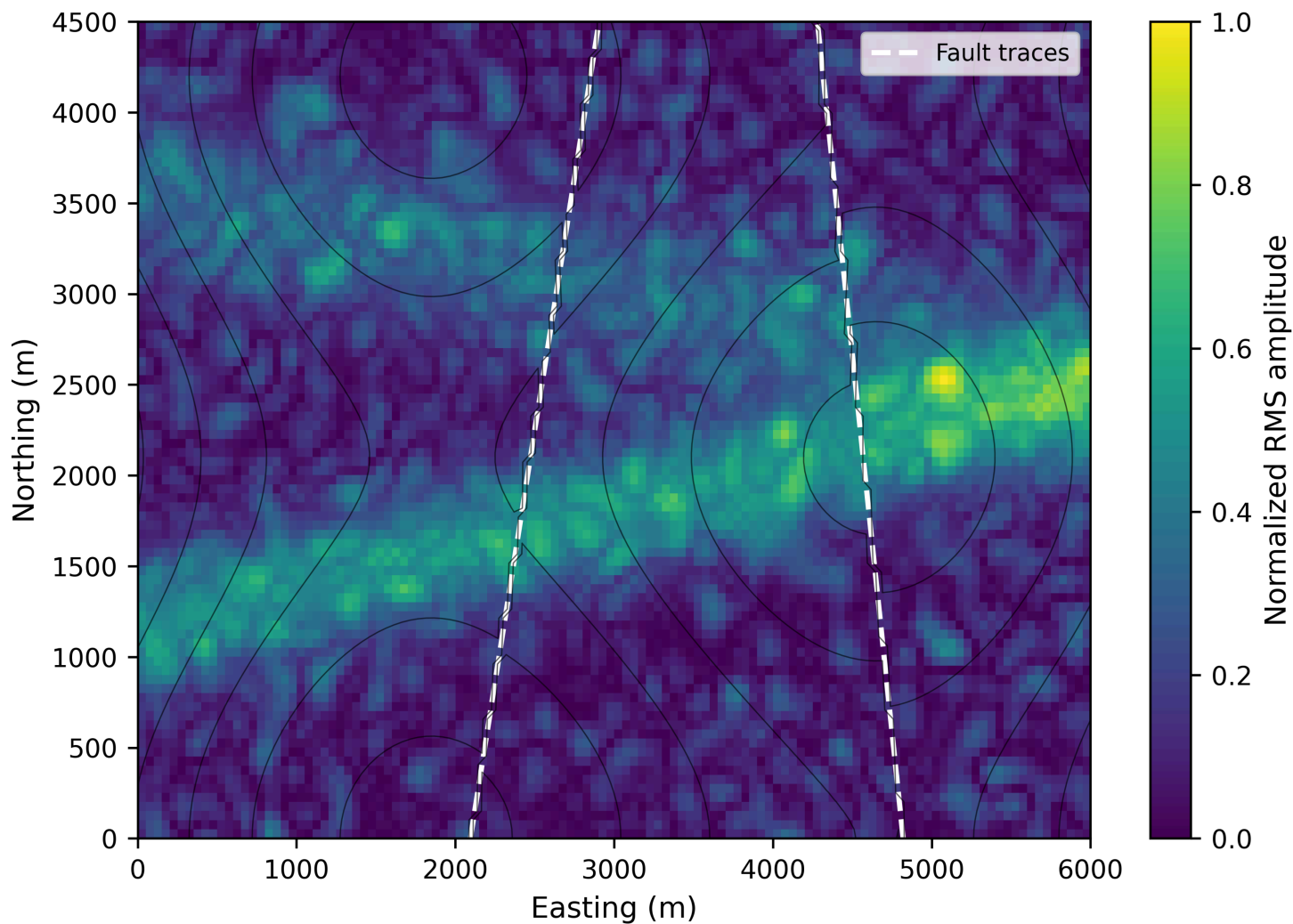


Figure 3

Synthetic seismic attribute map showing fault lineaments and stratigraphic banding. The map-view response supports structural interpretation and the assessment of lateral reservoir geometry

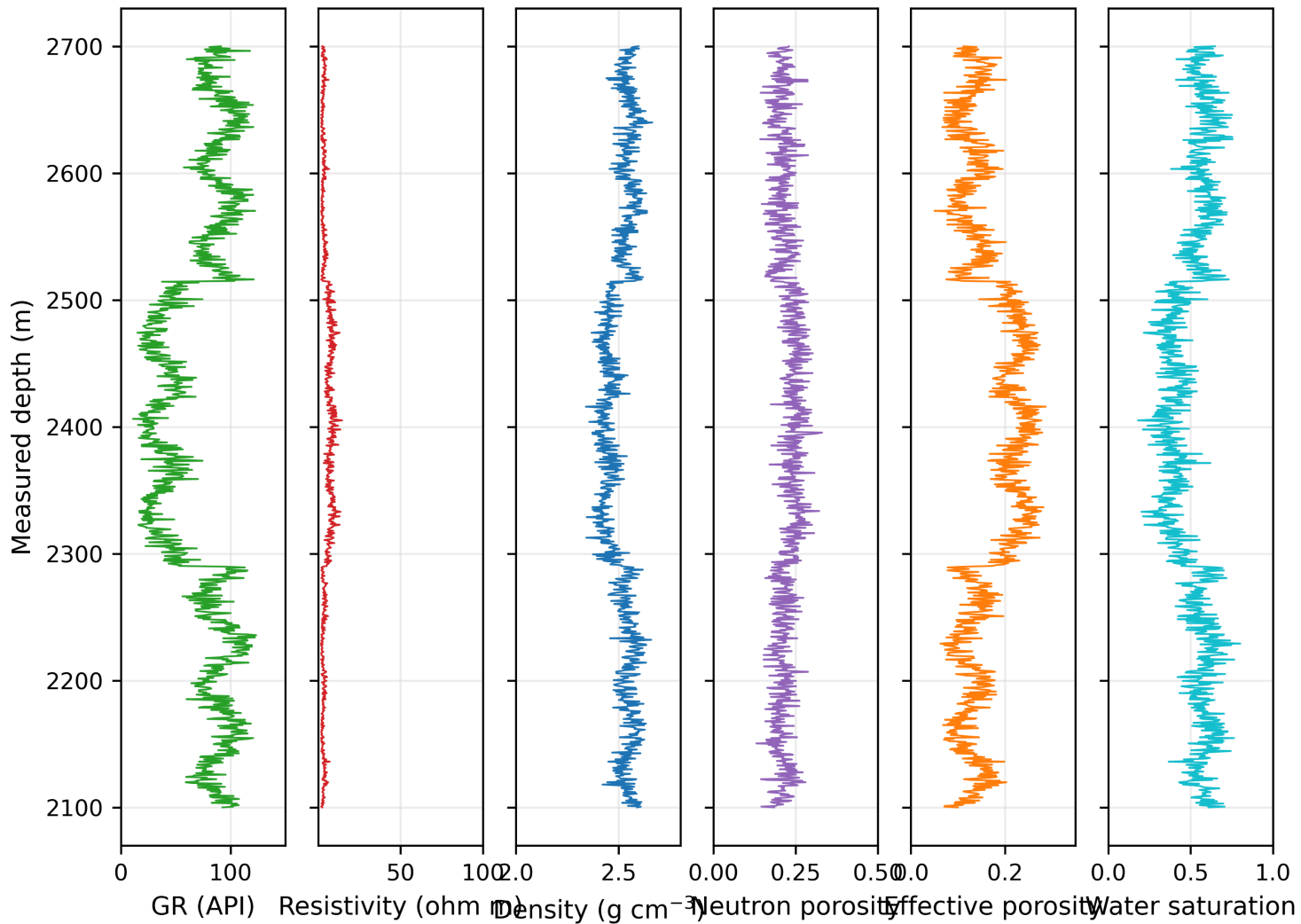


Figure 4

Synthetic well-log composite used for petrophysical evaluation. Gamma ray, resistivity, density, neutron, sonic, and derived porosity responses support lithology identification, reservoir-zone correlation, and estimation of shale volume, effective porosity, permeability, and water saturation

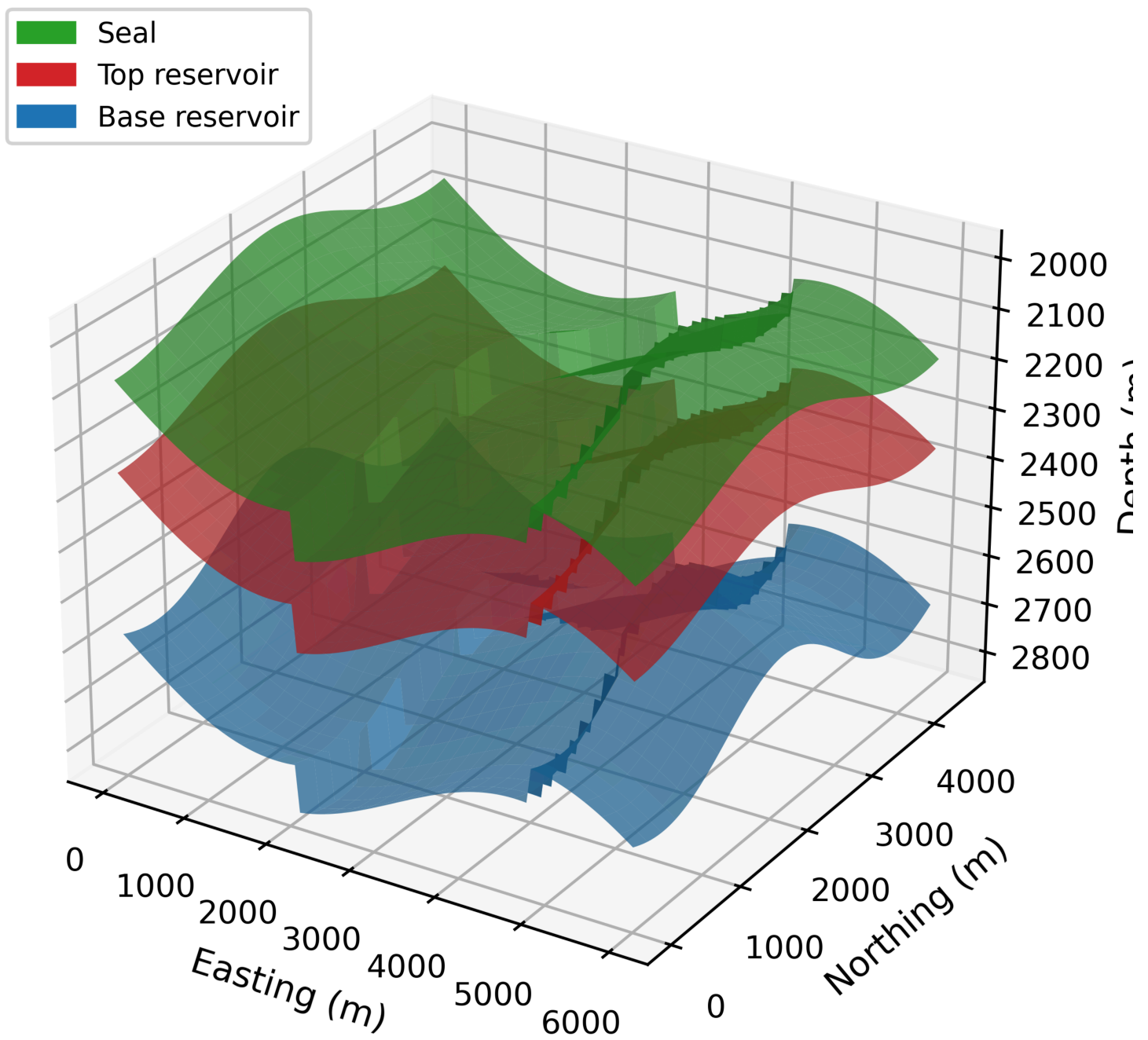


Figure 5

Three-dimensional structural framework model. Interpreted horizons and faults define the reservoir architecture, fault-block configuration, and gridded framework used for facies and petrophysical property modeling

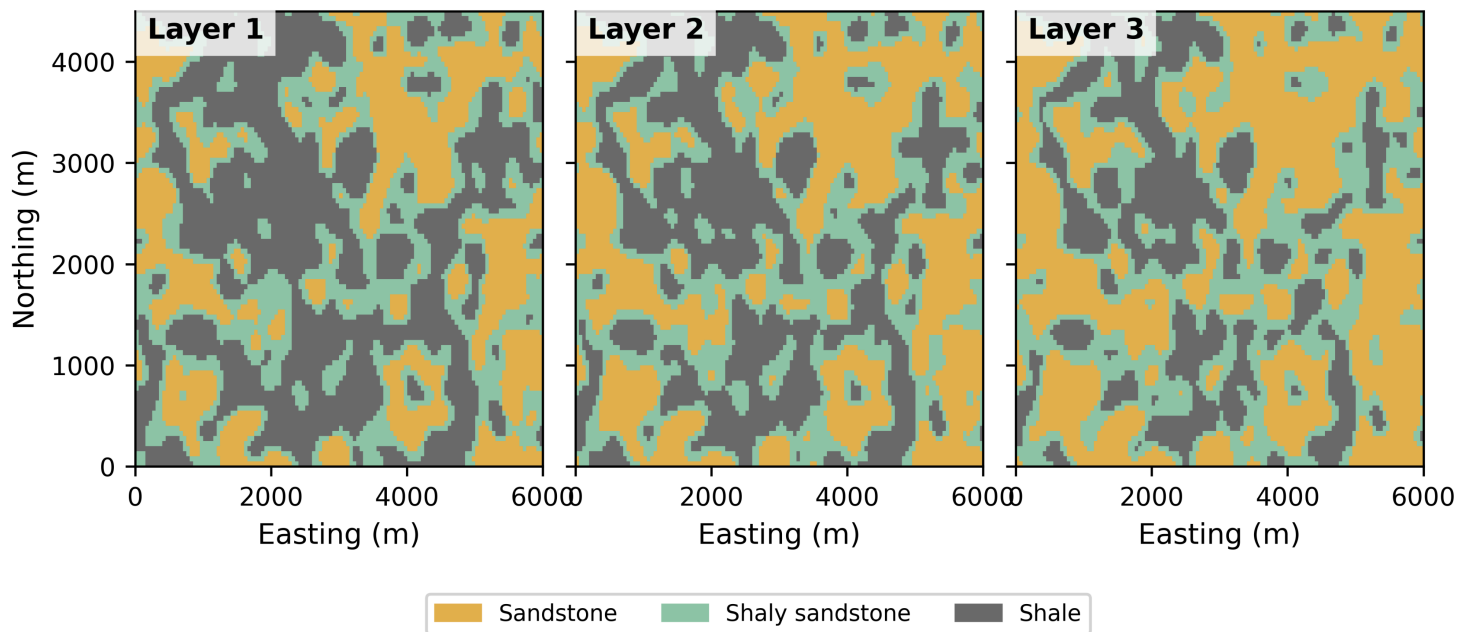


Figure 6

Representative layers from the synthetic facies model. The stochastic distributions of sandstone, shaly sandstone, and shale represent spatial variability and geological continuity within the fault-constrained reservoir framework

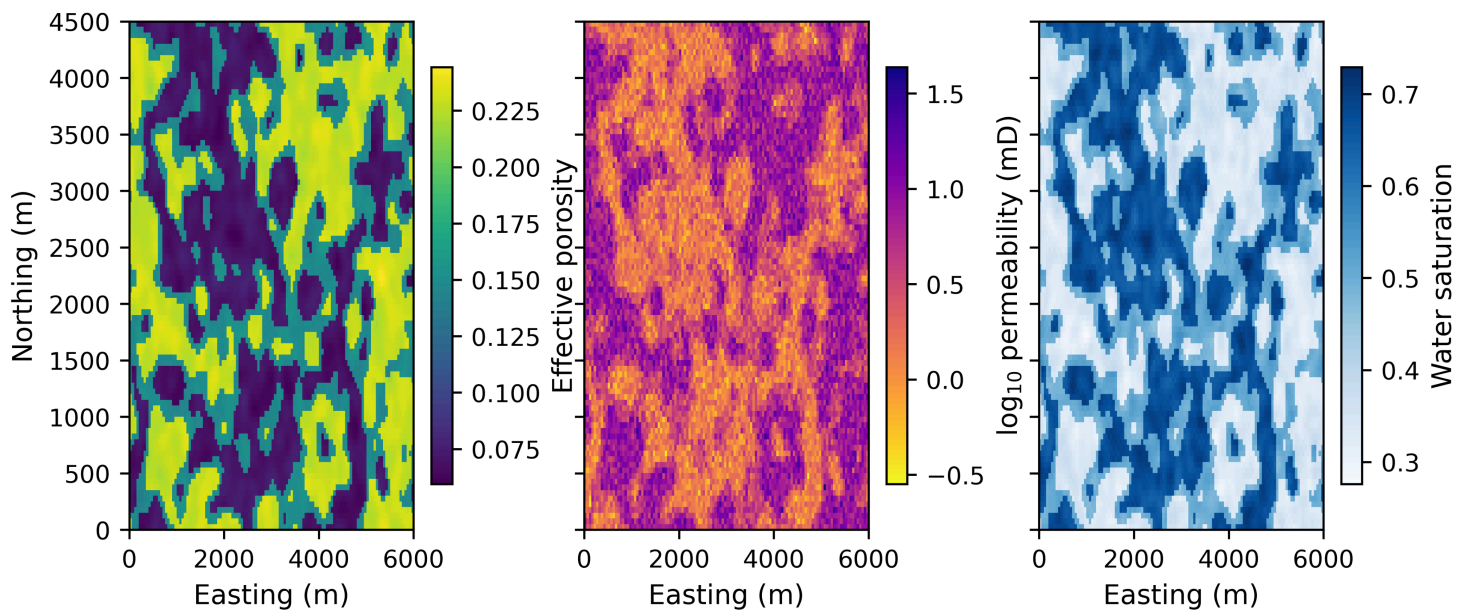


Figure 7

Reservoir-property maps showing (a) effective porosity, (b) horizontal permeability, and (c) water saturation. The panels illustrate spatial heterogeneity and the expected relationships between reservoir quality and fluid saturation

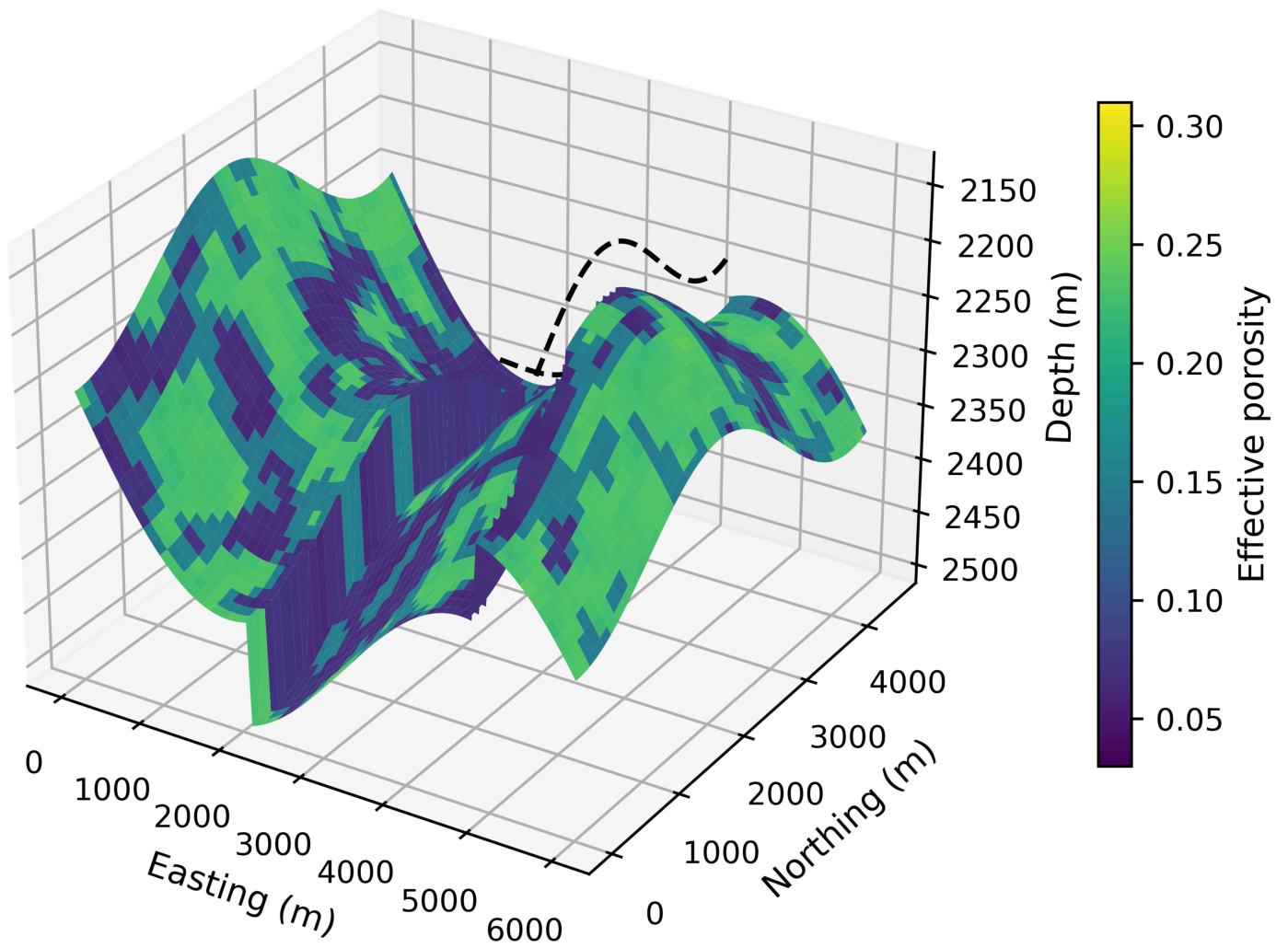


Figure 8

Integrated three-dimensional static reservoir model. Structural architecture, faults, facies distributions, and porosity are combined to provide a unified representation of reservoir geometry, quality, and internal heterogeneity

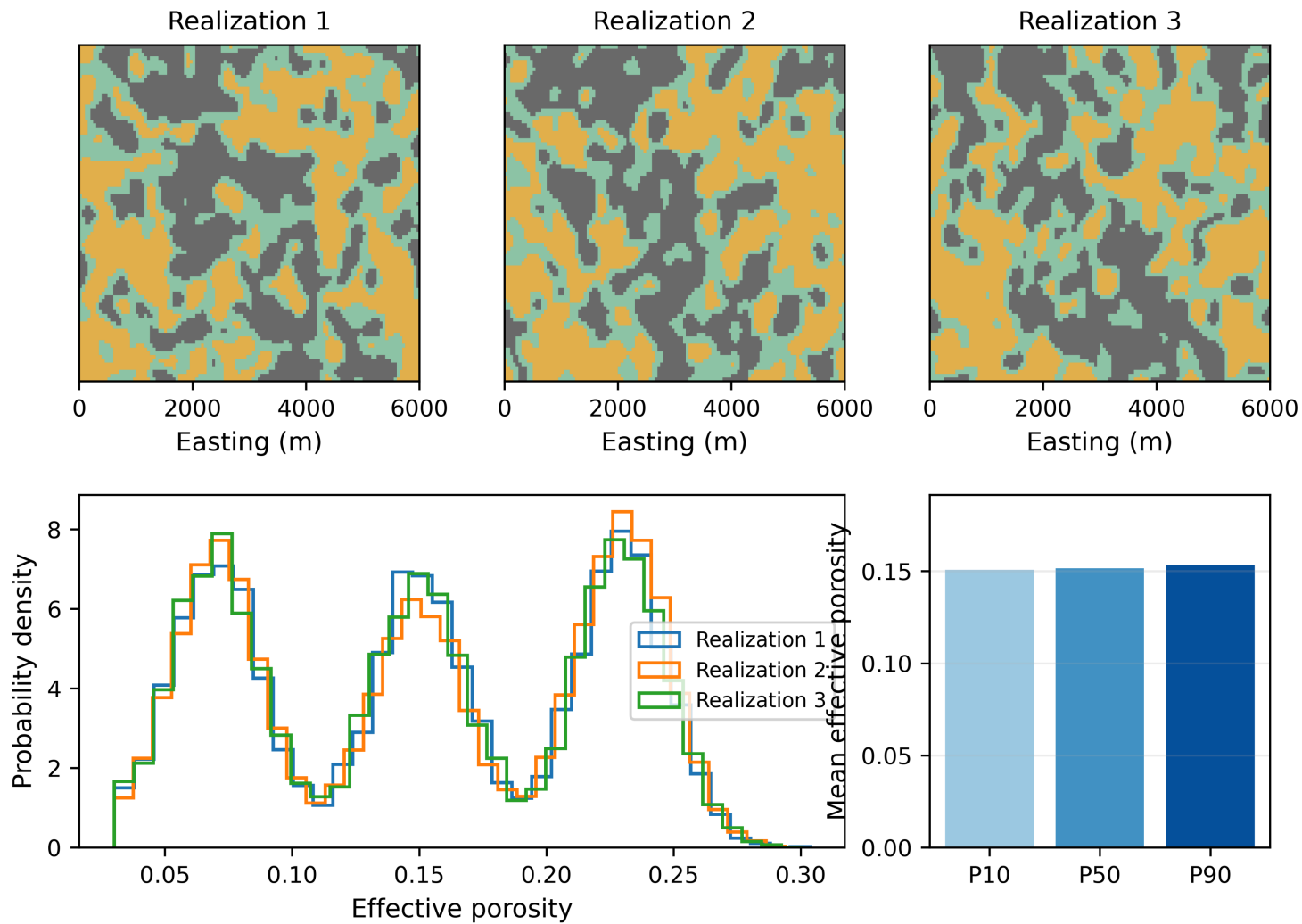


Figure 9

Geological uncertainty assessment. Three stochastic facies realizations demonstrate variability in spatial connectivity, while the combined porosity distribution and P10–P90 statistics summarize the resulting range of property outcomes