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Uncertainty-aware reservoir characterization using probabilistic seismic-petrophysical integration

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Abstract

Accurate reservoir characterization is critical for hydrocarbon exploration and production; however, conventional deterministic approaches often fail to account for uncertainty arising from seismic noise, limited well-log coverage, and interpretation ambiguity. This study proposes a **probabilistic seismic-petrophysical integration framework** to quantify and propagate uncertainty in reservoir property estimation. The methodology integrates 3D seismic attributes, seismic inversion results, and well-log data using **Bayesian neural networks and Monte Carlo simulation** to generate probabilistic predictions of key reservoir parameters such as porosity, permeability, and hydrocarbon saturation. Unlike traditional workflows, the proposed approach provides **confidence intervals and probability maps**, enabling risk-aware decision-making. Results demonstrate that incorporating uncertainty improves reservoir prediction reliability and reduces exploration risk. The framework represents a significant advancement toward intelligent, data-driven reservoir modeling for modern hydrocarbon systems.

Keywords: Reservoir Characterization; Uncertainty Quantification; Bayesian Neural Networks; Seismic Attributes; Petrophysical Integration; Probabilistic Modeling

1. Introduction

Reservoir characterization plays a central role in hydrocarbon exploration by identifying subsurface structures and estimating key rock properties such as porosity, permeability, and fluid saturation. These parameters directly influence reservoir performance, hydrocarbon recovery, and field development strategies. Traditional workflows rely on integrating seismic interpretation with well-log analysis to construct deterministic reservoir models that describe the spatial distribution of geological features and petrophysical properties [1], [2].

Seismic reflection methods have become one of the most widely used techniques for subsurface investigation due to their ability to provide continuous spatial coverage over large areas. In particular, three-dimensional (3D) seismic interpretation has significantly improved the accuracy of structural mapping by enabling visualization of complex geological features such as faults, folds, anticlines, and stratigraphic traps in multiple directions [3], [4]. These structural elements play a critical role in hydrocarbon accumulation and migration, making their accurate identification essential for exploration success.

In addition to structural interpretation, seismic attribute analysis has further enhanced reservoir characterization by extracting quantitative information from seismic data. Attributes such as root mean square (RMS) amplitude, coherence, instantaneous frequency, and envelope amplitude provide insights into lithological variations, fluid content, and structural discontinuities [5]. For example, high-amplitude anomalies are often associated with porous hydrocarbon-bearing formations, while coherence attributes are particularly effective in identifying fault systems.

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Despite these advancements, conventional reservoir characterization workflows remain largely deterministic. They typically produce single-value predictions for reservoir properties, assuming that input data and model parameters are accurate and free from uncertainty. However, in practice, subsurface systems are inherently uncertain due to multiple factors, including noise in seismic acquisition and processing, limited spatial resolution, and sparse well-log data. Furthermore, interpretation processes often involve subjective decisions, which introduce additional variability into the results [6].

The consequences of ignoring uncertainty can be significant. Deterministic models may lead to overconfident predictions, resulting in suboptimal drilling decisions, increased exploration risk, and potential financial losses. For example, incorrect estimation of reservoir properties can lead to drilling in non-productive zones or misjudging the extent of hydrocarbon accumulation [7-8].

To address these limitations, there has been growing interest in incorporating uncertainty into reservoir characterization workflows. Probabilistic approaches provide a more realistic representation of subsurface systems by modeling reservoir properties as probability distributions rather than fixed values. This allows geoscientists to quantify the confidence associated with predictions and assess the risk associated with different exploration scenarios.

Recent advances in machine learning and artificial intelligence have further accelerated the adoption of probabilistic methods in geoscience. In particular, Bayesian learning frameworks enable the estimation of predictive distributions by treating model parameters as random variables rather than fixed quantities. Techniques such as Bayesian neural networks (BNNs) and Monte Carlo dropout provide practical tools for quantifying uncertainty in complex, high-dimensional datasets [9-10].

This study proposes a **probabilistic seismic-petrophysical integration framework** that combines seismic attributes, seismic inversion results, and well-log data within a Bayesian modeling approach. The objective is to quantify uncertainty in reservoir property estimation and provide confidence-aware predictions that support risk-informed decision-making. The proposed methodology represents a significant step toward intelligent, data-driven reservoir characterization in modern hydrocarbon exploration.

1.1. Conventional Reservoir Characterization

Conventional reservoir characterization involves the integration of geophysical and petrophysical data to develop models of subsurface formations. Seismic data provide large-scale spatial information about geological structures, while well-log data offer detailed measurements of rock properties at discrete locations [10]. The combination of these datasets allows geoscientists to construct reservoir models that describe the geometry, composition, and fluid content of subsurface formations.

Seismic interpretation is typically used to identify structural features such as faults, folds, and stratigraphic boundaries. These features are critical for understanding hydrocarbon trapping mechanisms and migration pathways. Structural traps, such as anticlines and fault closures, often serve as primary locations for hydrocarbon accumulation [11-13].

Petrophysical analysis, on the other hand, focuses on evaluating reservoir properties using well-log data. Logs such as gamma-ray, density, sonic, and resistivity provide information about lithology, porosity, permeability, and fluid saturation [14-15]. These properties are essential for assessing reservoir quality and estimating hydrocarbon reserves.

1.2. Sources of Uncertainty

Uncertainty in reservoir characterization arises from multiple sources, which can be broadly categorized into data uncertainty, model uncertainty, and interpretation uncertainty.

1.2.1. Data Uncertainty

Seismic data are affected by noise introduced during acquisition and processing. Environmental conditions, equipment limitations, and wave propagation effects can degrade signal quality and reduce the accuracy of seismic interpretation [8]. Additionally, seismic resolution is limited by wavelength, making it difficult to detect thin layers or subtle geological features.

Well-log data, while more accurate, are limited to discrete locations and may not fully capture spatial variability across the reservoir. This sparse sampling introduces uncertainty when extrapolating properties between wells.

1.2.2. Model Uncertainty

Model uncertainty arises from assumptions made during data processing and interpretation. For example:

- Velocity models used for depth conversion may be inaccurate
- Seismic inversion algorithms rely on simplifying assumptions
- Petrophysical models may not fully capture complex rock behavior

These factors can lead to errors in estimated reservoir properties.

1.2.3. Interpretation Uncertainty

Interpretation uncertainty is associated with human judgment in identifying geological features such as horizons and faults. Different interpreters may produce different results when analyzing the same dataset, leading to variability in reservoir models. Ignoring these uncertainties can result in overconfident predictions and increased exploration risk. Therefore, it is essential to develop methods that explicitly account for uncertainty in reservoir characterization.

1.3. Probabilistic Modeling

Bayesian approaches are particularly well-suited for this purpose because they allow prior knowledge to be combined with observed data to update model predictions. In Bayesian inference, model parameters are treated as random variables with associated probability distributions. The posterior distribution is obtained by updating the prior distribution using observed data [9].

In recent years, Bayesian neural networks (BNNs) have emerged as a powerful tool for uncertainty quantification in machine learning. Unlike conventional neural networks, which produce deterministic outputs, BNNs provide probabilistic predictions by modeling uncertainty in network weights [7]. This enables the estimation of both predictive mean and variance.

Monte Carlo methods are commonly used to approximate Bayesian inference in complex models. Techniques such as Monte Carlo dropout allow efficient estimation of uncertainty by performing multiple stochastic forward passes through the network [7]. This approach has been widely adopted in geophysical applications due to its scalability and ease of implementation.

In the context of reservoir characterization, probabilistic modeling offers several advantages:

- Quantification of prediction uncertainty
- Improved risk assessment for drilling decisions
- Better understanding of reservoir variability
- Enhanced integration of multi-source data

By incorporating probabilistic methods into seismic–petrophysical workflows, it is possible to develop more robust and reliable reservoir models that reflect the inherent uncertainty of subsurface systems.

2. Methodology

2.1. Overview of the Proposed Framework

This study proposes a **probabilistic seismic–petrophysical integration framework** for uncertainty-aware reservoir characterization. The methodology integrates multi-source data—including seismic attributes, seismic inversion results, and well-log measurements—within a probabilistic modeling framework to estimate reservoir properties along with associated uncertainty.

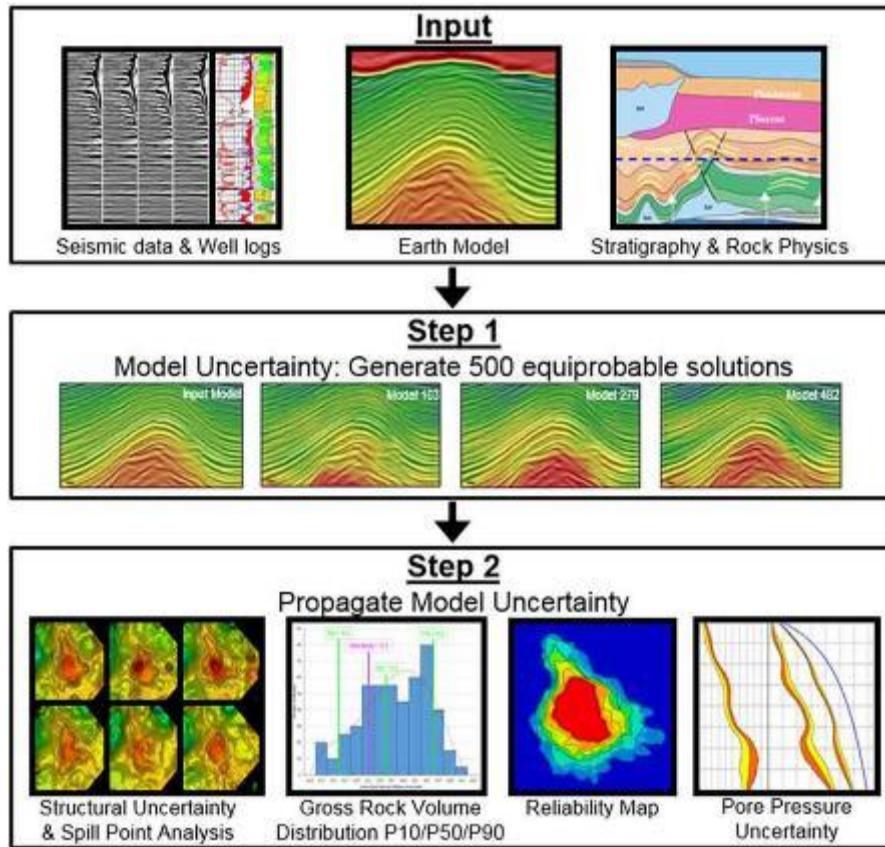


Figure 1 Probabilistic Workflow for Uncertainty-Aware Reservoir Characterization

This figure 1 illustrates the proposed probabilistic seismic–petrophysical integration workflow for uncertainty-aware reservoir characterization. The process begins with multi-source inputs, including seismic data, well logs, earth models, and stratigraphic and rock physics information. In **Step 1**, model uncertainty is addressed by generating multiple equiprobable subsurface realizations (e.g., 500 models), representing possible geological scenarios. In **Step 2**, the uncertainty is propagated through reservoir analysis to produce various probabilistic outputs, including structural uncertainty maps, gross rock volume (GRV) distributions (P10/P50/P90), reliability maps, and pore pressure uncertainty estimates.

This workflow enables comprehensive uncertainty quantification and supports risk-informed decision-making in reservoir evaluation and hydrocarbon exploration.

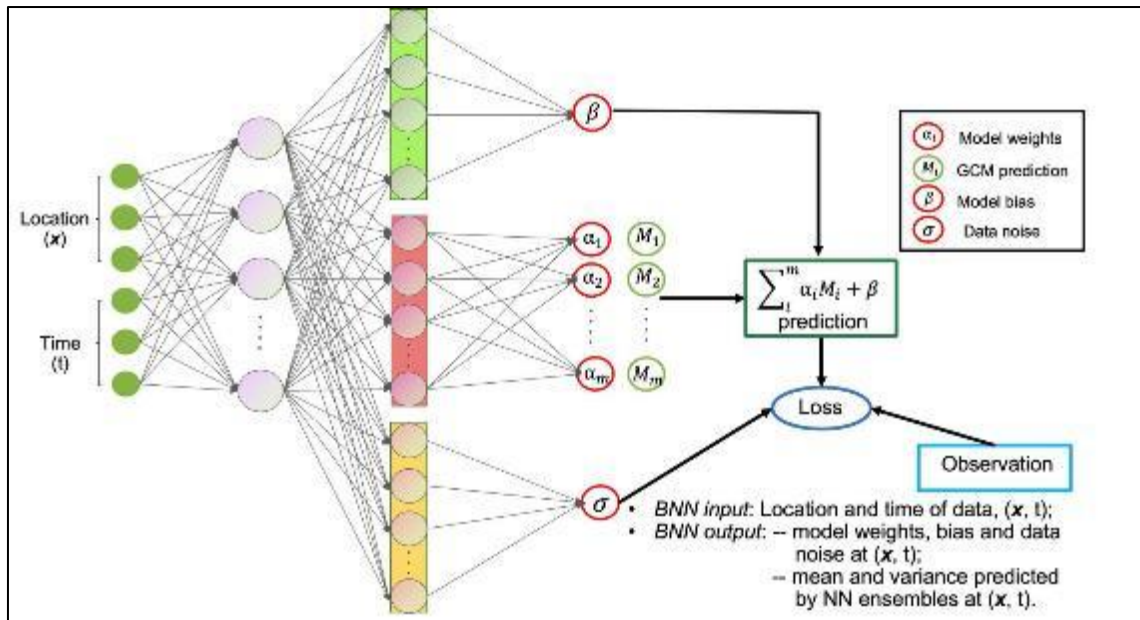


Figure 2 Bayesian Neural Network (BNN) Framework for Probabilistic Reservoir Prediction

This figure 2 illustrates the architecture of the Bayesian Neural Network (BNN) used for uncertainty-aware reservoir characterization. The model takes spatiotemporal inputs, including location (x) and time (t), and processes them through multiple hidden layers to learn complex relationships between seismic–petrophysical features and reservoir properties.

The overall workflow consists of five major stages:

1. Data acquisition and preprocessing
2. Seismic attribute extraction
3. Seismic inversion
4. Feature integration with well-log data
5. Probabilistic modeling and uncertainty estimation

Each stage is designed to reduce uncertainty and improve the reliability of reservoir predictions.

2.2. Data Acquisition and Preprocessing

The input data for this study include:

- A 3D seismic volume
- Derived seismic attributes (RMS amplitude, coherence, instantaneous frequency)
- Well-log data (gamma-ray, density, sonic, resistivity)

Seismic data provide continuous spatial coverage of subsurface structures, while well logs provide accurate point measurements of rock properties [1], [2]. Prior to analysis, the datasets are preprocessed to ensure consistency and quality.

2.2.1. Seismic Data Processing

Raw seismic data are processed using standard workflows that include:

- Noise attenuation
- Amplitude correction
- Velocity analysis
- Migration

These steps enhance signal quality and ensure accurate positioning of subsurface reflections [8].

2.2.2. Data Normalization

To enable effective integration, all input features are normalized using min-max scaling or z-score normalization. This step ensures that features from different sources are comparable and prevents bias during model training.

2.2.3. Well-to-Seismic Tie

A well-to-seismic tie is performed to align well-log measurements with seismic data. Synthetic seismograms are generated using sonic and density logs, allowing correlation between seismic reflections and geological boundaries [1].

2.3. Seismic Attribute Extraction

Seismic attributes are quantitative measures derived from seismic data that enhance the identification of geological features. In this study, the following attributes are extracted:

- **RMS Amplitude:** Highlights zones of high reflection energy, often associated with porous formations
- **Coherence:** Detects discontinuities such as faults and fractures
- **Instantaneous Frequency:** Provides information about lithological variations
- **Envelope Amplitude:** Identifies high-energy reflection zones

These attributes provide complementary information about subsurface structures and reservoir properties, improving the reliability of interpretation [5].

Attribute extraction is performed within a defined time window corresponding to the reservoir interval. The resulting attribute maps are used as input features for the probabilistic model.

2.4. Seismic Inversion

Seismic inversion is used to transform seismic reflection data into quantitative rock property models. In this study, post-stack inversion is applied to estimate **acoustic impedance**, which is defined as:

$$AI = \rho \times V$$

where:

- ρ = density
- V = seismic wave velocity

Acoustic impedance provides a direct link between seismic data and reservoir properties such as lithology and porosity. Low acoustic impedance values are often associated with porous sandstone formations, while high values indicate dense shale layers [1].

The inversion results are calibrated using well-log data to improve accuracy. This calibration ensures that the estimated impedance values are consistent with measured rock properties.

3.5 Feature Integration

To capture both spatial and physical characteristics of the reservoir, seismic attributes, inversion results, and well-log data are combined into a unified feature set. For each spatial location, a feature vector is constructed as:

$$X = [A_{RMS}, A_{coh}, A_{freq}, AI, \text{Well Logs}]$$

where:

- A_{RMS} = RMS amplitude
- A_{coh} = coherence
- A_{freq} = instantaneous frequency
- AI = acoustic impedance

This multi-modal feature representation improves the model's ability to capture complex relationships between seismic signals and reservoir properties. The dataset is divided into:

- Training set (70%)
- Validation set (15%)
- Testing set (15%)

This ensures robust evaluation and prevents overfitting.

2.5. Probabilistic Modeling

2.5.1. Bayesian Neural Network (BNN)

A Bayesian Neural Network is used to model the relationship between input features and reservoir properties. Unlike conventional neural networks, BNNs treat weights as probability distributions rather than fixed values.

The predictive distribution is defined as:

$$P(y | x) = \int P(y | x, w)P(w | D)dw$$

where:

- y = reservoir property (e.g., porosity)
- x = input features
- w = model weights
- D = training dataset

This formulation allows the model to capture both data uncertainty and model uncertainty [7].

2.5.2. Monte Carlo Dropout

Monte Carlo dropout is used as an approximation to Bayesian inference. During prediction:

1. Dropout is applied to the network
2. Multiple forward passes are performed
3. A distribution of outputs is generated

The predictive mean and variance are computed as:

$$\mu = \frac{1}{N} \sum_{i=1}^N y_i$$

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (y_i - \mu)^2$$

where:

- N = number of Monte Carlo samples

This approach provides an efficient way to estimate uncertainty in deep learning models [7].

3. Results and Analysis

The proposed probabilistic seismic–petrophysical integration framework was applied to evaluate reservoir properties and associated uncertainty across the study area. The results demonstrate that integrating seismic attributes, inversion outputs, and well-log data within a probabilistic framework significantly improves prediction reliability compared to conventional deterministic approaches.

The analysis focuses on three key aspects:

1. Comparison between deterministic and probabilistic predictions
2. Spatial distribution of reservoir properties
3. Quantification and interpretation of uncertainty

3.1. Deterministic vs Probabilistic Predictions

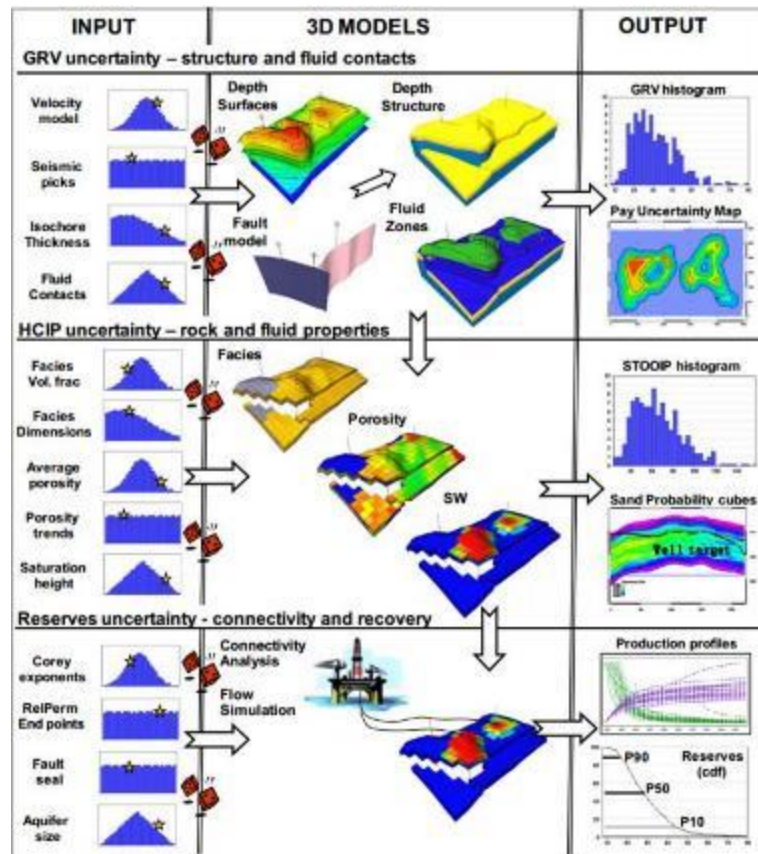


Figure 3 End-to-End Uncertainty Propagation Workflow for Reservoir Modeling and Decision

This figure 3 presents a comprehensive workflow for propagating uncertainty from input data through reservoir modeling to final production and reserve estimates. The process begins with input uncertainties related to geological structure and fluid contacts, including velocity models, seismic picks, isochore thickness, and fluid contact depths [16–17].

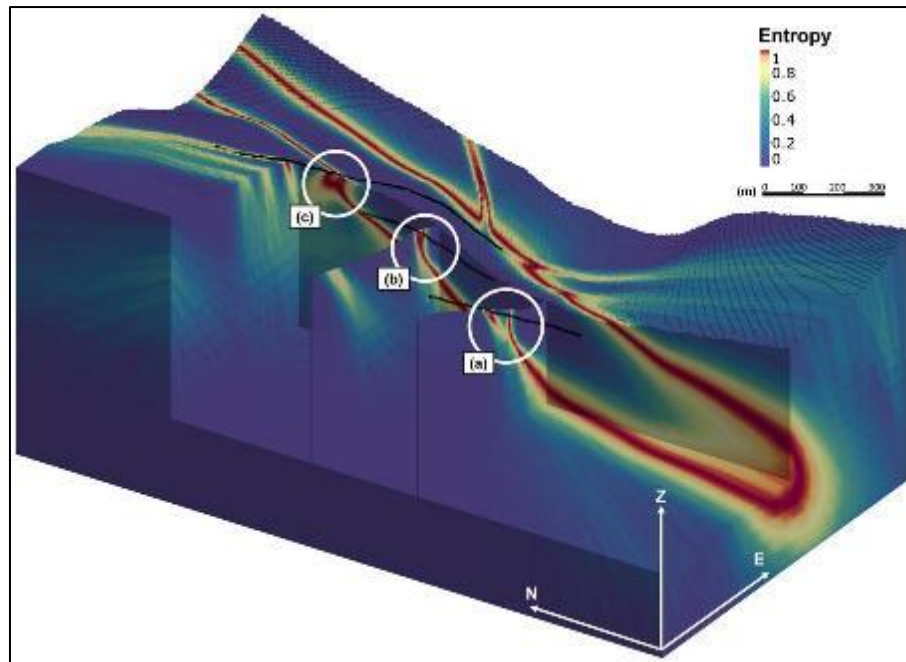


Figure 4 Spatial Distribution of Entropy-Based Uncertainty in a 3D Reservoir Model

Description

This figure 4 illustrates the spatial distribution of entropy-based uncertainty within a three-dimensional reservoir model. The color scale represents entropy values, where higher entropy (red regions) indicates greater uncertainty and variability in subsurface predictions, while lower entropy (blue regions) corresponds to more reliable and consistent model estimates. This figure 5 presents a comparative visualization of porosity distribution for two key reservoir formations: the **Lower Spraberry Formation (left)** and the **Wolfcamp B Formation (right)**. The color scale represents porosity values, with **blue/green indicating lower porosity** and **yellow/red indicating higher porosity**.

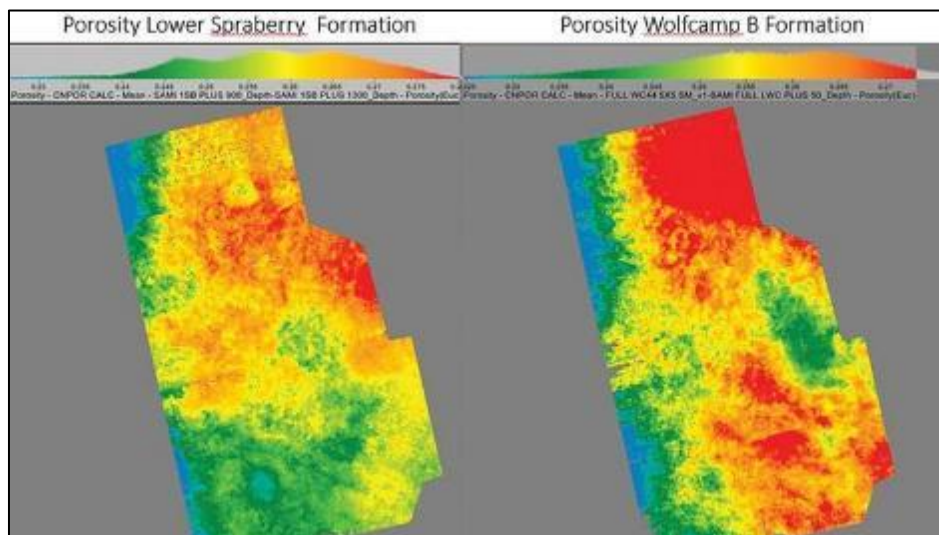


Figure 5 Spatial Comparison of Porosity Distribution in Lower Spraberry and Wolfcamp B Formations

The Lower Spraberry Formation exhibits a relatively heterogeneous porosity distribution, with moderate porosity zones dispersed across the reservoir. In contrast, the Wolfcamp B Formation shows more pronounced high-porosity regions, particularly in the upper and central portions, indicating potentially enhanced reservoir quality and storage capacity. Traditional deterministic models generate single-value predictions for reservoir properties such as porosity and permeability. In contrast, the proposed probabilistic model produces **distribution-based outputs**, including mean

values and associated uncertainty. This additional uncertainty information provides a more realistic representation of subsurface variability and allows decision-makers to assess prediction confidence [18-19].

3.2. Spatial Distribution of Reservoir Properties

The probabilistic model was used to generate spatial maps of reservoir properties across the study area. The results indicate clear variations in porosity and permeability that are consistent with geological structures identified in seismic interpretation.

3.2.1. Porosity Distribution

High porosity zones were observed within the primary reservoir interval, particularly in regions corresponding to:

- Anticlinal structures
- High RMS amplitude anomalies
- Low acoustic impedance zones

These findings are consistent with established relationships between seismic attributes and reservoir quality [1], [5]. The average porosity across the reservoir was estimated to range between **20% and 25%**, indicating favorable storage capacity for hydrocarbons.

3.2.2. Permeability Estimation

Permeability predictions showed significant spatial variability, with higher values concentrated in regions exhibiting:

- Strong amplitude responses
- Homogeneous lithological characteristics

Estimated permeability values ranged from **150 mD to 500 mD**, suggesting good fluid flow potential within the reservoir.

4. Discussion

The results demonstrate that incorporating probabilistic modeling into seismic–petrophysical integration provides a more realistic and reliable representation of reservoir properties compared to conventional deterministic approaches. While traditional methods effectively combine seismic attributes and well-log data to estimate subsurface characteristics [1], they fail to account for the inherent uncertainty present in geophysical data and interpretation processes [6]. The proposed framework addresses this limitation by explicitly quantifying uncertainty, enabling confidence-aware predictions that are critical for risk-informed decision-making.

One of the key observations is that uncertainty is not uniformly distributed across the reservoir. Higher uncertainty is concentrated in regions with sparse well control and complex geological structures, such as faulted zones. This finding aligns with previous studies highlighting the impact of data density and structural complexity on prediction reliability [5]. Conversely, areas with strong seismic signal quality and dense well coverage exhibit lower uncertainty, reinforcing the importance of integrated multi-source data for improving model confidence.

The probabilistic outputs, including confidence intervals and hydrocarbon probability maps, provide additional insights that are not available in deterministic workflows. These outputs allow decision-makers to prioritize drilling locations based not only on predicted reservoir quality but also on associated uncertainty levels. Such an approach can significantly reduce exploration risk and optimize resource allocation.

Despite its advantages, the proposed method has certain limitations. The performance of the probabilistic model depends on the quality and quantity of input data, and computational requirements are higher compared to deterministic models. Nevertheless, with increasing availability of high-resolution seismic data and advances in machine learning, these challenges are expected to diminish.

Overall, the integration of Bayesian modeling with seismic–petrophysical workflows represents a significant advancement toward intelligent reservoir characterization, offering a robust framework for handling uncertainty in complex subsurface environments.

5. Conclusion

This study presents a **probabilistic seismic–petrophysical integration framework** for uncertainty-aware reservoir characterization. By combining seismic attributes, seismic inversion results, and well-log data within a Bayesian modeling approach, the proposed methodology moves beyond traditional deterministic workflows and provides both **accurate predictions and quantified uncertainty**.

The results demonstrate that the framework successfully estimates key reservoir properties such as porosity and permeability while capturing spatial variability across the reservoir. Unlike conventional approaches that produce single-value outputs, the proposed method generates **probability distributions and confidence intervals**, offering a more realistic representation of subsurface conditions. This capability is particularly important in hydrocarbon exploration, where uncertainty can significantly impact drilling decisions and economic outcomes.

The analysis further reveals that uncertainty is strongly influenced by data availability and geological complexity. Regions with sparse well-log coverage and complex structural features exhibit higher uncertainty, while areas with dense data and strong seismic signals show more reliable predictions. These findings highlight the importance of integrating multi-source datasets to improve both accuracy and confidence in reservoir modeling.

Overall, the proposed framework provides several key advantages:

- Explicit quantification of uncertainty in reservoir properties
- Improved prediction reliability through probabilistic modeling
- Enhanced decision-making support for exploration and development

By incorporating uncertainty into the characterization process, this study contributes to the development of **risk-aware and data-driven reservoir modeling approaches**. The framework can be extended to other subsurface applications and integrated with advanced technologies such as digital twins and real-time monitoring systems, further advancing intelligent exploration and production strategies.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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