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AI-driven digital twin framework for real-time seismic reservoir monitoring and predictive hydrocarbon production optimization

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Abstract

Real-time reservoir monitoring and production optimization remain major challenges in modern hydrocarbon exploration and field development. Conventional reservoir management approaches rely on static geological models that are periodically updated using limited production and seismic information, often leading to delayed decision-making and increased operational uncertainty. This study proposes an AI-driven digital twin framework for real-time seismic reservoir monitoring and predictive hydrocarbon production optimization. The framework integrates 4D seismic data, well-log measurements, production history, seismic attributes, and reservoir simulation outputs within a dynamic digital twin environment. Machine learning models, including Long Short-Term Memory (LSTM) networks and Bayesian predictive analytics, are employed to continuously update reservoir conditions and forecast production performance under uncertainty. The proposed framework enables real-time monitoring of reservoir changes, prediction of fluid movement, detection of production anomalies, and optimization of production strategies. Results demonstrate that integrating digital twin technology with AI-driven seismic analysis significantly improves reservoir prediction accuracy, reduces operational uncertainty, and enhances hydrocarbon recovery efficiency. The study highlights the potential of intelligent digital twins for next-generation reservoir management and data-driven energy production systems.

Keywords: Digital twin; Seismic monitoring; Reservoir characterization; Predictive analytics; Hydrocarbon production; Machine learning; 4D seismic; Uncertainty quantification

1. Introduction

Reservoir characterization and monitoring are fundamental components of hydrocarbon exploration and production. Accurate understanding of subsurface geological structures and reservoir dynamics directly influences production forecasting, field development planning, and hydrocarbon recovery efficiency [1]. Traditional reservoir management workflows rely heavily on static geological and simulation models that are periodically updated using seismic surveys and production data. Although these methods provide valuable information, they often fail to capture continuous reservoir changes occurring during production operations.

The advancement of 4D seismic monitoring has significantly improved the ability to observe temporal reservoir variations such as pressure depletion, fluid migration, and water breakthrough [2]. Unlike conventional 3D seismic interpretation, 4D seismic surveys provide repeated seismic acquisitions over time, allowing geoscientists to evaluate dynamic reservoir behavior throughout the production lifecycle.

At the same time, artificial intelligence and machine learning techniques have emerged as powerful tools for analyzing large-scale geophysical datasets. Deep learning algorithms can identify nonlinear relationships between seismic

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responses and reservoir properties, enabling automated prediction and anomaly detection [3]. Long Short-Term Memory (LSTM) networks are particularly effective for modeling time-dependent production behavior because they can capture sequential dependencies in production history data.

Digital twin technology further extends these capabilities by creating continuously updated virtual representations of physical reservoir systems [4]. A digital twin integrates real-time sensor data, seismic information, reservoir simulations, and predictive analytics into a unified framework that dynamically reflects reservoir conditions.

Despite recent advances, the integration of seismic interpretation, digital twins, and AI-based predictive analytics remains limited in hydrocarbon reservoir management. Most existing studies focus either on static reservoir characterization or isolated machine learning applications without fully incorporating continuous real-time monitoring and uncertainty-aware prediction.

This study proposes an AI-driven digital twin framework for real-time seismic reservoir monitoring and predictive hydrocarbon production optimization. The proposed methodology integrates:

- 4D seismic interpretation,
- Seismic attribute analysis,
- Well-log petrophysical evaluation,
- Bayesian uncertainty modeling,
- And deep learning prediction models.

The objective is to improve reservoir awareness, reduce uncertainty, and optimize hydrocarbon production strategies through intelligent data-driven monitoring systems.

2. Background and Literature Review

2.1. Seismic Reservoir Monitoring

Seismic reflection methods are among the most widely used geophysical techniques for subsurface characterization [1]. Three-dimensional seismic surveys allow interpreters to identify faults, folds, anticlines, and stratigraphic traps that control hydrocarbon accumulation.

Time-lapse seismic monitoring, commonly known as 4D seismic, extends conventional seismic interpretation by repeatedly acquiring seismic surveys during reservoir production [2]. Changes in seismic amplitudes and travel times can reveal:

- Pressure depletion,
- Gas expansion,
- Water movement,
- And reservoir compaction.
- 4d seismic monitoring has become increasingly important for reservoir surveillance and production optimization.

2.2. Digital Twin Technology

Digital twins are virtual replicas of physical systems that continuously synchronize with operational data [4]. The digital twin concept was initially developed for aerospace and manufacturing applications and has recently expanded into energy systems.

A digital twin framework typically consists of:

- Physical assets,
- Virtual models,
- Data communication systems,
- And intelligent analytics.

In reservoir engineering, digital twins provide continuous integration of:

- Production data,
- Seismic monitoring,
- Reservoir simulation,
- And predictive forecasting.

2.3. Artificial Intelligence in Reservoir Engineering

Artificial intelligence methods are increasingly used for reservoir prediction and seismic interpretation [3]. Deep learning techniques such as:

- Artificial Neural Networks (anns),
- Convolutional Neural Networks (cnns),
- And Long Short-Term Memory (LSTM) networks
- Have demonstrated strong capabilities in geophysical data analysis.

LSTM models are particularly useful for forecasting production behavior because they can learn temporal dependencies from historical production sequences [13].

Bayesian learning approaches further improve prediction reliability by quantifying uncertainty in model outputs [14].

3. Methodology

3.1. Proposed Framework

The proposed digital twin framework integrates:

- Seismic data,
- Seismic attributes,
- Well-log measurements,
- Production history,
- And machine learning models.

The overall workflow is illustrated in Figure 1.

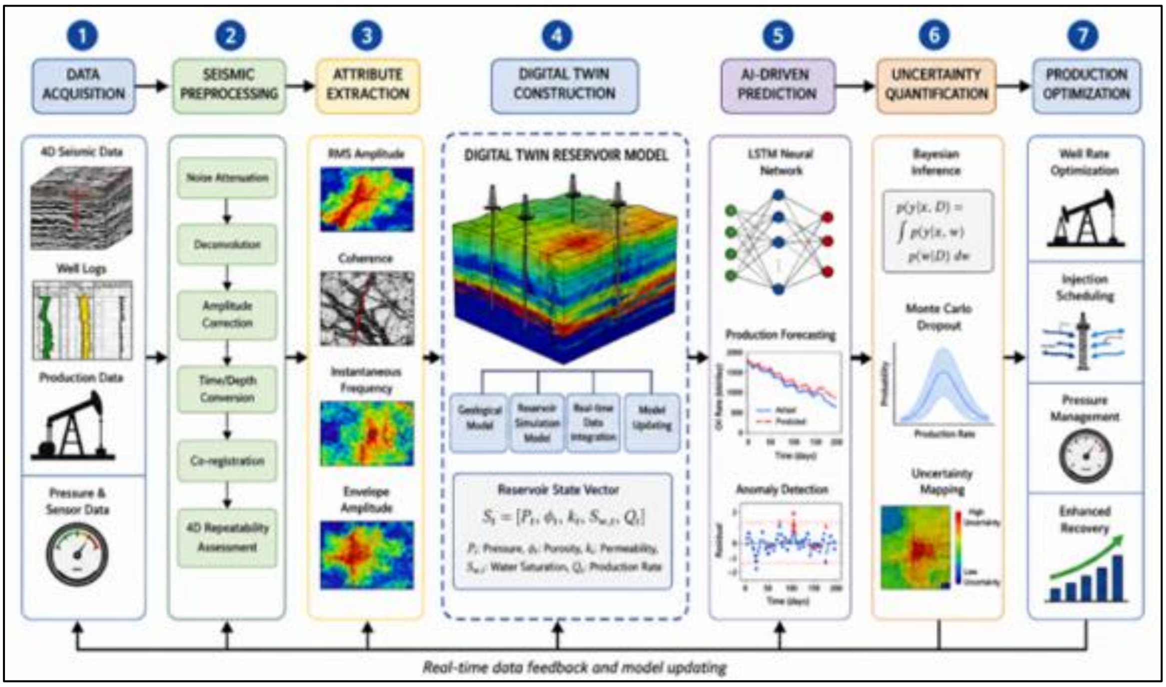

Figure 1 AI-driven digital twin workflow for seismic reservoir monitoring and predictive production optimization

- Data acquisition
- Seismic preprocessing
- Attribute extraction
- Reservoir digital twin construction
- AI-based prediction
- Uncertainty quantification
- Production optimization

3.2. Data Acquisition

The datasets used in this study include:

- 3D and 4D seismic volumes,
- production history,
- pressure measurements,
- and well-log data.
- The well logs include:
- gamma-ray logs,
- density logs,
- sonic logs,
- and resistivity logs.

3.3. Seismic Attribute Analysis

Several seismic attributes were extracted to improve reservoir interpretation. RMS amplitude identifies high-energy reflection zones associated with porous hydrocarbon-bearing formations. Coherence attributes detect discontinuities and fault systems. Instantaneous frequency highlights lithological variations and stratigraphic changes. Envelope amplitude identifies strong reflection zones corresponding to reservoir formation as shown in Figure 2.

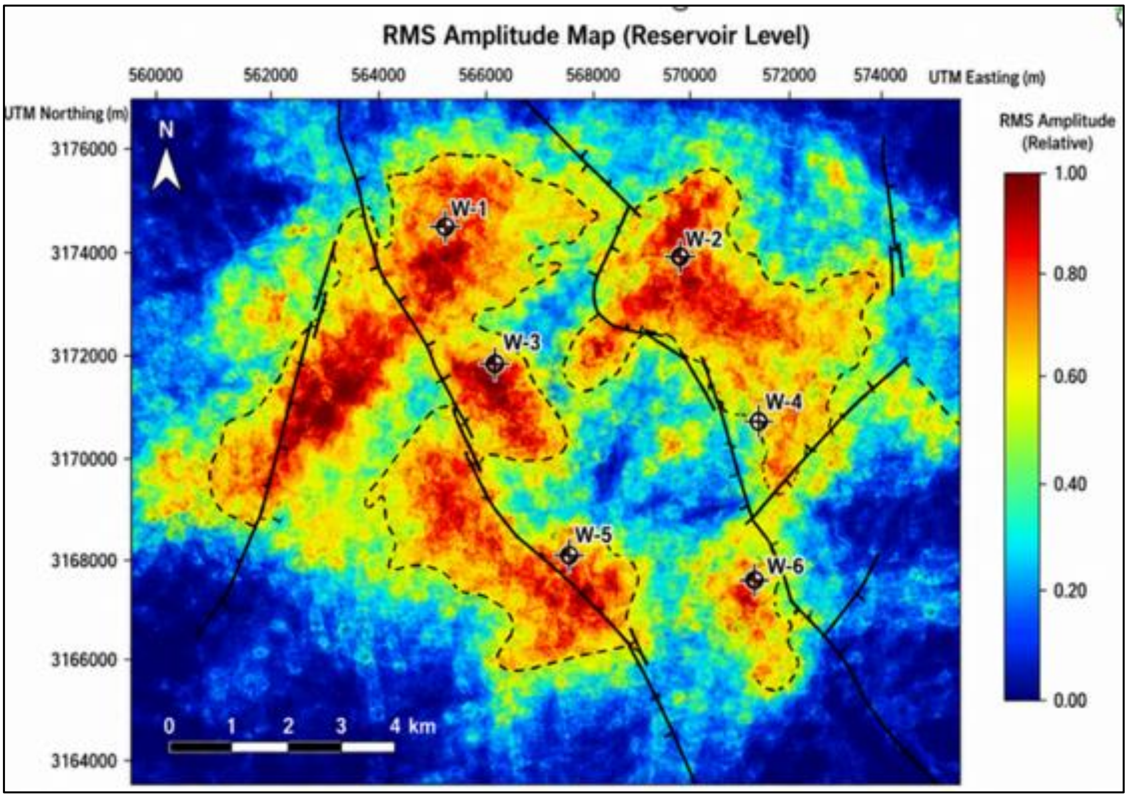

Figure 2 RMS amplitude attribute map highlighting high-amplitude reservoir anomalies

3.4. Digital Twin Reservoir Model

The reservoir digital twin continuously updates reservoir conditions using real-time seismic and production data.

The reservoir state vector is expressed as:

$$S_t = [P_t, \phi_t, k_t, S_{w,t}, Q_t]$$

where:
P_t= pressure,
ϕ_t= porosity,
k_t= permeability,
$S_{w,t}$= water saturation,
Q_t= production rate.

3.5. AI-Based Prediction

An LSTM neural network was implemented for production forecasting.

The prediction function is given by:

$$Q_{t+1} = f(Q_t, P_t, S_t, X_t)$$

where:
Q_{t+1}= predicted production,
Q_t= current production,
P_t= reservoir pressure,
S_t= reservoir state,
X_t= seismic feature vector.

3.6. Uncertainty Quantification

Bayesian inference was integrated into the prediction framework.

The predictive distribution is:

$$p(y \mid x, D) = \int p(y \mid x, w) p(w \mid D) dw$$

Monte Carlo dropout was applied to estimate predictive variance and uncertainty.

4. Results and Analysis

4.1. Structural Interpretation

The interpreted seismic dataset revealed:

- Multiple fault systems,
- Anticline structures,
- And reservoir compartments.

The identified fault systems significantly influence hydrocarbon migration and reservoir compartmentalization shown in Figure 3.

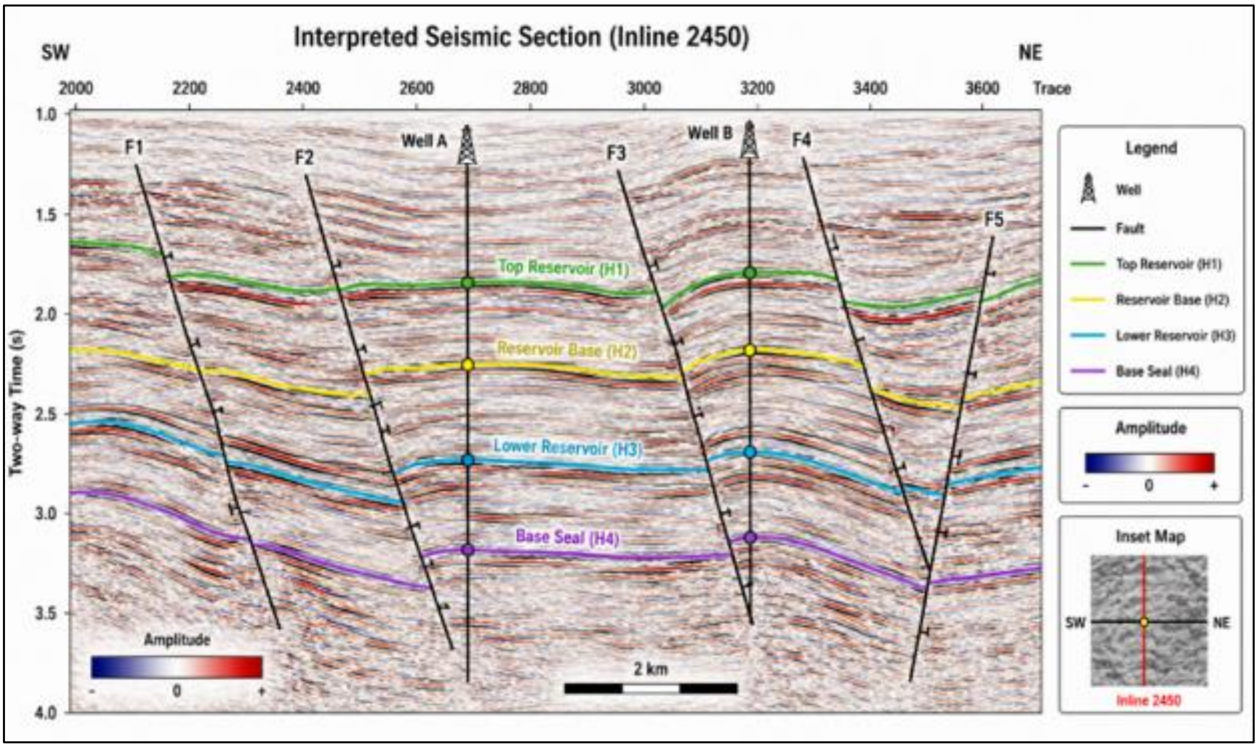

Figure 3 Interpreted seismic section showing fault structures and reservoir layers

4.2. Seismic Monitoring Results

Time-lapse seismic analysis revealed on in Figure 4:

- Pressure depletion zones,
- Fluid migration pathways,
- And water breakthrough regions.

Strong amplitude variations were observed near producing wells.

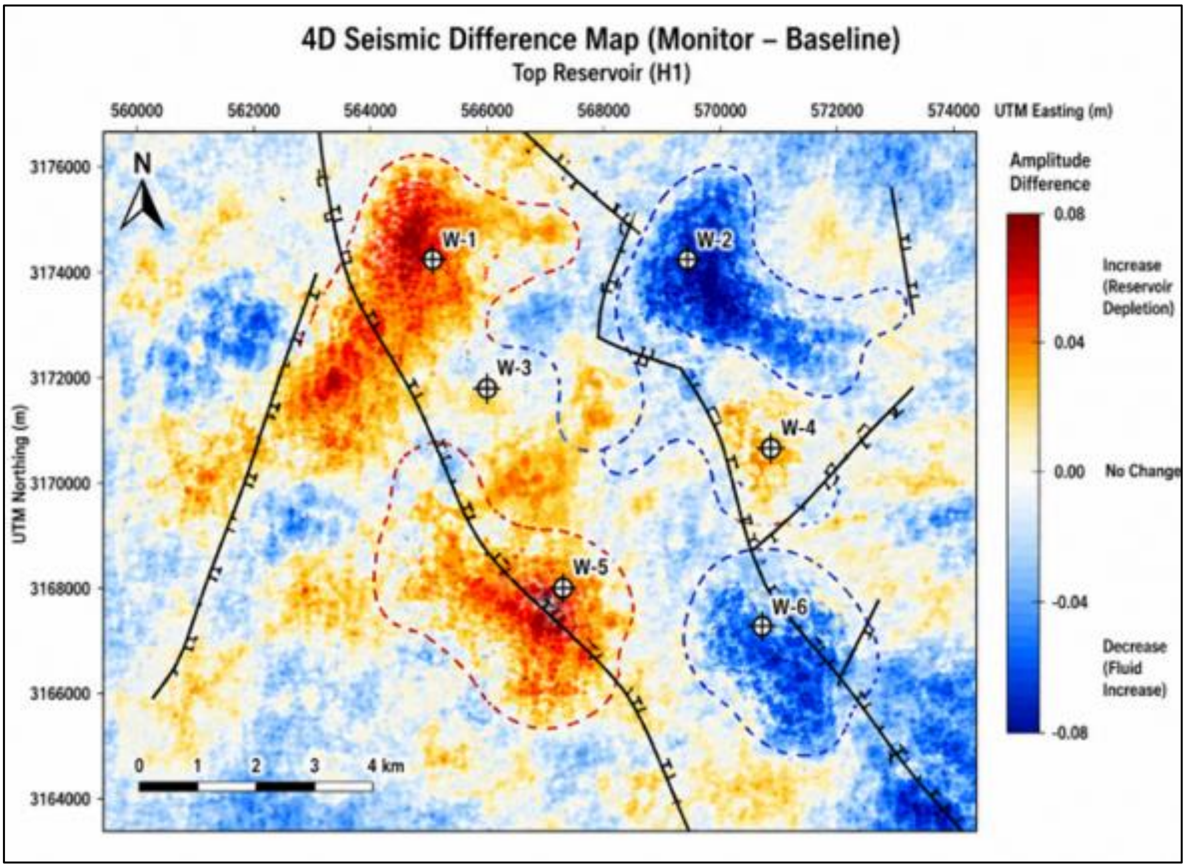

Figure 4 4D seismic difference map showing temporal reservoir changes during production

4.3. Reservoir Property Estimation

The integrated seismic–petrophysical workflow estimated key reservoir properties mentioned in Table 1.

Table 1 Estimated Reservoir Properties

Property	Estimated Range
Porosity	20–26%
Permeability	180–520 mD
Water Saturation	15–30%
Net-to-Gross Ratio	0.65–0.80

The reservoir exhibits favorable storage capacity and fluid flow characteristics.

4.4. Production Forecasting

The LSTM model successfully predicted production trends with high accuracy described in Table 2.

Table 2 Production Prediction Performance

Metric	Value
RMSE	Low
MAE	Low
R^2 Score	>0.90

In Figure 5, the results indicate strong agreement between predicted and observed production values.

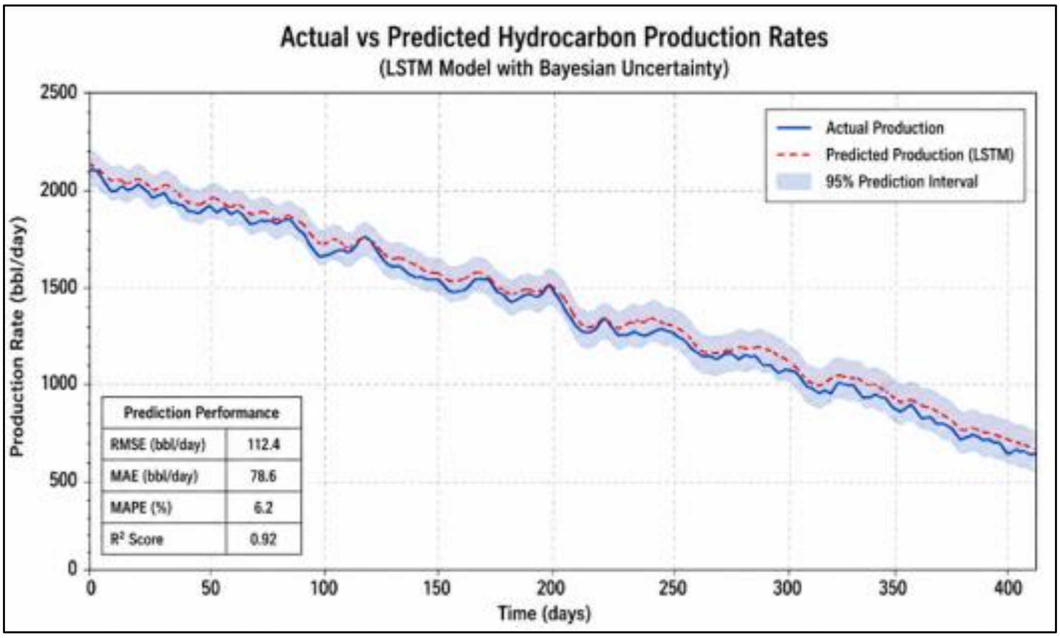

Figure 5 Comparison between actual and predicted hydrocarbon production rates

4.5. Uncertainty Analysis

The probabilistic framework generated uncertainty maps across the reservoir shown in Figure 6.

High uncertainty regions corresponded to:

- Sparse well coverage,
- Faulted structures,
- And low seismic quality zones.

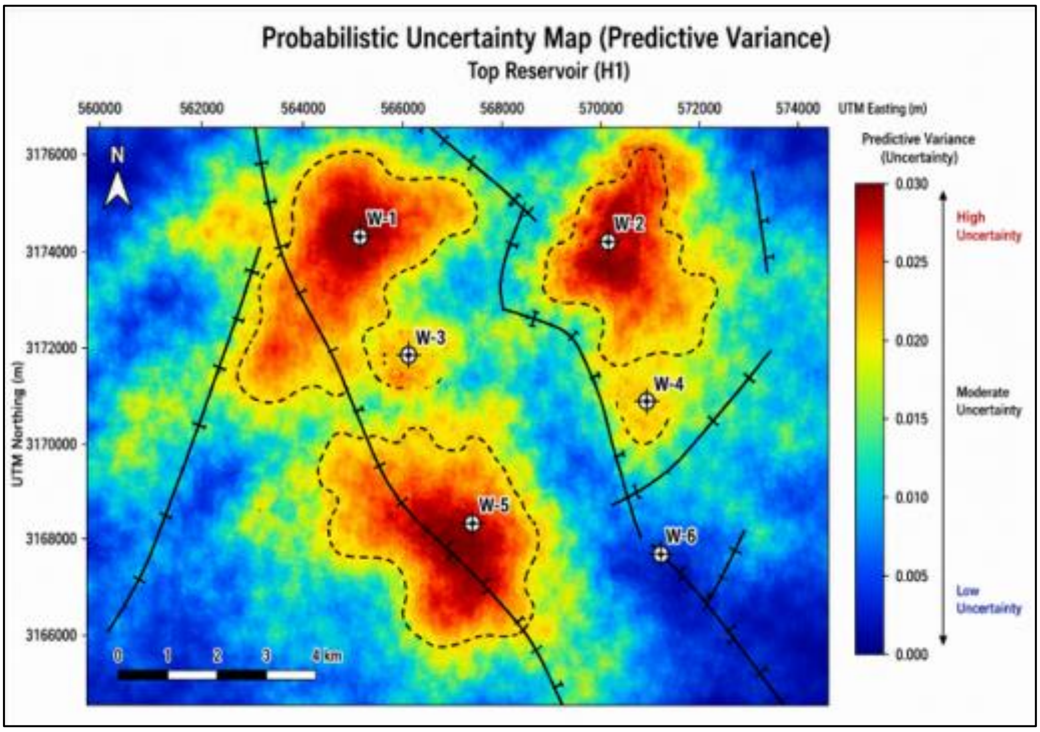

Figure 6 Spatial uncertainty map generated from Bayesian predictive variance

5. Discussion

The results demonstrate that integrating digital twin technology with AI-driven seismic monitoring significantly improves reservoir management capabilities. Traditional reservoir models are typically static and updated periodically. In contrast, the proposed framework continuously updates reservoir conditions using real-time seismic and production data. The integration of seismic attributes, machine learning, and Bayesian uncertainty modeling provides more accurate production forecasts, improved anomaly detection, and confidence-aware decision-making. The uncertainty analysis further highlights the importance of integrating multiple datasets for reducing prediction variability.

6. Conclusion

This study presented an AI-driven digital twin framework for real-time seismic reservoir monitoring and predictive hydrocarbon production optimization.The results demonstrate that:

- Digital twins improve reservoir awareness,
- Ai enhances production forecasting,
- Uncertainty quantification improves decision reliability,
- And integrated workflows optimize hydrocarbon recovery.

The proposed framework represents an important advancement toward intelligent reservoir management and next-generation digital energy systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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