Seismic Reservoir Prediction and Deep-Water Sedimentary Analysis: A Survey

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Abstract

Seismic reservoir prediction and deep-water sedimentary analysis are pivotal in modern geophysical exploration, offering profound insights into subsurface geological formations and their hydrocarbon potential. This survey paper explores the integration of seismic data interpretation, rock physics, and basin-scale geological assessments to enhance hydrocarbon reservoir predictions, especially in challenging environments like deep-water settings. The evolution of seismic exploration techniques, particularly 2D and 3D methods, has significantly advanced exploration precision, enabling the identification of complex geological settings. Deep-water sedimentary analysis is critical for understanding sedimentary features influenced by dynamic processes, essential for offshore reservoir predictions. Despite advancements, challenges persist in accurately characterizing carbonate reservoirs and addressing computational demands in seismic inversion. Emerging techniques like machine learning and hybrid optimization methods offer promise in overcoming these challenges, enhancing the reliability of seismic characterization. The integration of multidisciplinary approaches, including joint inversion and multi-data integration, is emphasized for improving subsurface property estimations. As the field advances, the continuous development of these methodologies is crucial for optimizing hydrocarbon recovery and addressing the complexities of subsurface environments. This survey underscores the significance of these interdisciplinary techniques in advancing geophysical exploration and hydrocarbon reservoir characterization.

1 Introduction

1.1 Overview of Seismic Reservoir Prediction and Deep-Water Sedimentary Analysis

Seismic reservoir prediction and deep-water sedimentary analysis are pivotal in geophysical exploration, providing critical insights into subsurface geological formations and hydrocarbon potential. These methodologies leverage seismic data interpretation and geological assessments to enhance the understanding of sedimentary basins, thereby improving hydrocarbon reservoir predictions. The evolution of seismic techniques, particularly 2D and 3D methods, has significantly refined exploration accuracy, especially in complex geological settings such as the Mundaú subbasin, where tectono-sedimentary evolution is crucial for hydrocarbon system characterization [1, 2].

Seismic reservoir prediction serves as a foundational technology for geological exploration [3]. The integration of 3D seismic data with advanced computational techniques exemplifies technological progress, enhancing subsurface structure identification and hydrocarbon reserve estimation [4]. Estimating acoustic impedance from seismic data is vital for identifying subsurface structures, which is essential for effective hydrocarbon exploration [5].

Deep-water sedimentary analysis is essential for understanding sedimentary feature morphology and distribution, influenced by dynamic processes such as turbidity and contour currents. This knowledge is critical for offshore reservoir predictions and optimizing hydrocarbon extraction [6]. Moreover,

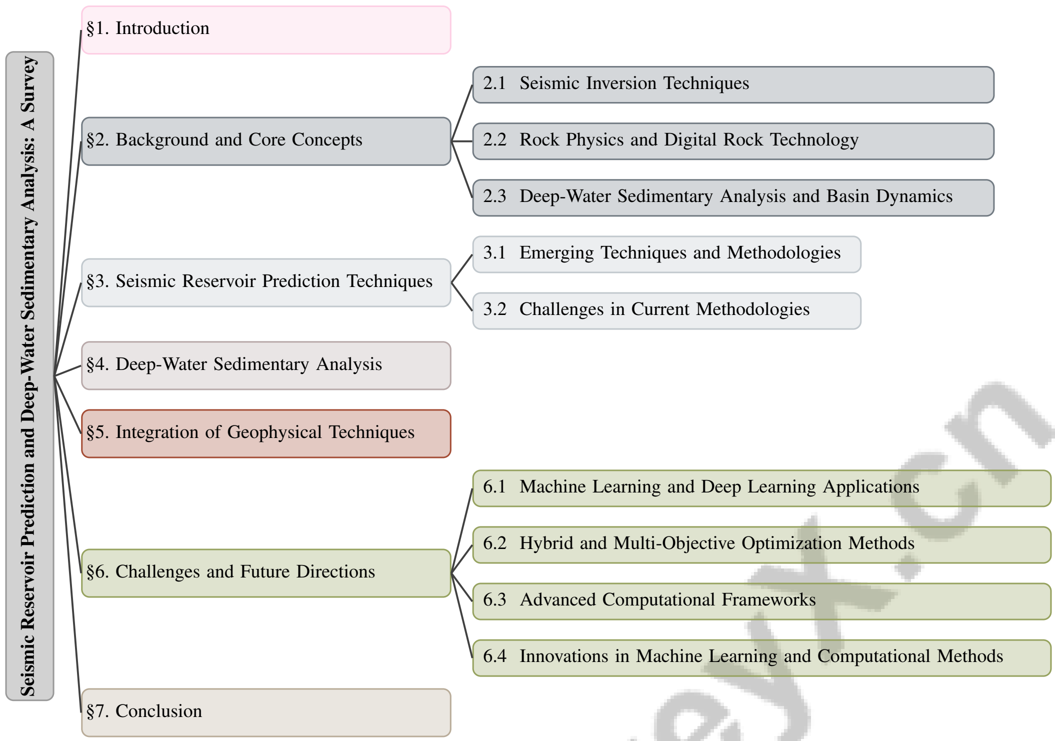

Figure 1: chapter structure

seismic simulations are integral to geophysical applications, ranging from earthquake monitoring to oil and gas prospecting [7], with acoustic wave propagation simulations being crucial for various applications, including medical imaging and structural analysis [8].

Seismic reservoir prediction and deep-water sedimentary analysis are indispensable in geophysical exploration, providing a robust framework for understanding complex subsurface environments and optimizing hydrocarbon recovery. The integration of advanced seismic technologies and sophisticated methodologies, such as machine learning and geostatistical simulations, significantly enhances hydrocarbon reservoir exploration and characterization, leading to improved predictions of reservoir behavior in complex geological settings [9, 10, 11, 12].

1.2 Importance in Geophysical Exploration

Seismic reservoir prediction and deep-water sedimentary analysis play a crucial role in enhancing the understanding and characterization of hydrocarbon reservoirs, providing essential insights into subsurface geological formations. This facilitates more accurate predictions of hydrocarbon locations and volumes, particularly in complex depositional systems found in deep-water environments like the Mundaú subbasin, which require high-resolution data and sophisticated methodologies for accurate geological interpretation [2]. The interplay between turbidity and contour currents significantly affects sediment transport and bedform characteristics, which are vital for understanding sedimentary processes and reservoir quality.

Recent advancements in seismic data acquisition, processing, and interpretation have markedly improved the ability to tackle challenges in hydrocarbon exploration, particularly regarding data integration, noise reduction, and subsurface reservoir characterization. Techniques such as Full-Waveform Inversion (FWI) and 4D seismic inversion have enhanced subsurface model resolution by effectively reconstructing complex geological features and fluid dynamics. The incorporation of machine learning and advanced geostatistical algorithms has further improved seismic data interpretation, enabling geoscientists to derive more accurate insights into reservoir properties and optimize exploration strategies. These advancements contribute to a more robust understanding of hydrocarbon reservoirs, ultimately aiding in efficient resource extraction and management [9, 13, 14, 11, 10]. However, challenges remain, particularly in accurately characterizing carbonate reservoirs

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due to their heterogeneity and complex fluid distribution. The integration of geophysical information into reservoir modeling through geostatistical methods has shown effectiveness in addressing some of these challenges. Additionally, joint inversion of Direct Current (DC) and Magnetotelluric (MT) data offers a sophisticated approach to understanding subsurface electrical and electromagnetic properties, providing vital information for comprehensive reservoir characterization.

Caution is essential in interpreting seismic data, particularly regarding the potential underestimation of intrusive volumes, which underscores the importance of understanding magmatic systems in hydrocarbon migration. These advancements contribute to more environmentally friendly and efficient seismic surveys, addressing economic and ecological challenges in hydrocarbon exploration. The inadequacy of subsurface model resolution and fault detection, as illustrated in the Soda Lake geothermal field, highlights the need for improved seismic characterization techniques [4]. Furthermore, traditional methods like Finite Difference (FD) and spectral element methods are computationally intensive, complicating real-time simulations [7].

Integrating advanced geophysical techniques into exploration frameworks is crucial for enhancing the precision and effectiveness of hydrocarbon reservoir characterization. This integration facilitates improved seismic imaging and inversion processes, essential for understanding complex carbonate reservoirs, while fostering collaborative efforts among geoscientists, petrophysicists, and engineers throughout exploration and production phases. By utilizing comprehensive datasets, including 3D seismic data and well-log information, these techniques ultimately lead to more informed exploration and production strategies, maximizing hydrocarbon recovery from challenging reservoirs [10, 11, 14].

1.3 Structure of the Survey

This survey is structured to provide a thorough examination of seismic reservoir prediction and deep-water sedimentary analysis, focusing on their roles in geophysical exploration and hydrocarbon reservoir characterization. The paper is organized into several key sections, each addressing specific aspects of the topic to ensure a coherent exploration of the subject matter.

The survey begins with an **Introduction** that highlights the significance of seismic reservoir prediction and deep-water sedimentary analysis in modern geophysical exploration, establishing the foundational context for subsequent discussions.

The **Background and Core Concepts** section delves into the fundamental principles underlying seismic reservoir prediction, deep-water sedimentary analysis, and related geoscientific techniques, examining seismic inversion techniques, rock physics, digital rock technology, and deep-water sedimentary dynamics.

In the **Seismic Reservoir Prediction Techniques** section, various methodologies employed in seismic reservoir prediction are explored, emphasizing both established and emerging techniques, alongside the challenges of current methodologies and potential solutions.

The **Deep-Water Sedimentary Analysis** section focuses on analyzing deep-water sedimentary environments, discussing their significance in reservoir prediction and the techniques used for sedimentary basin analysis.

The integration of different geophysical techniques is examined in the **Integration of Geophysical Techniques** section, highlighting the interdisciplinary nature of the field and the importance of combining seismic data interpretation with geological assessments, including discussions on joint inversion, multi-data integration, and the incorporation of geological knowledge into modeling.

In the section titled **Challenges and Future Directions**, the survey thoroughly examines the key obstacles currently faced in seismic reservoir prediction and deep-water sedimentary analysis, highlighting potential avenues for future advancements and innovations. Emphasis is placed on integrating machine learning techniques, hybrid optimization strategies, and sophisticated computational frameworks, including the application of deep learning approaches for seismic inversion and joint learning methods to enhance model accuracy with limited well log data [15, 9, 16, 11].

The **Conclusion** section provides a comprehensive overview of the primary findings related to seismic reservoir prediction and deep-water sedimentary analysis, emphasizing their critical role in enhancing geophysical exploration techniques and improving hydrocarbon reservoir characterization. This analysis is grounded in various methodologies, including complex seismic trace analysis and geostatistical simulations, contributing to a deeper understanding of subsurface geological formations and their hydrocarbon resource potential [10, 11].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Seismic Inversion Techniques

Seismic inversion techniques transform seismic reflection data into detailed subsurface models, elucidating lithological and fluid properties essential for geophysical exploration. These techniques include deterministic, stochastic, and hybrid approaches, each with unique advantages for subsurface characterization. Deterministic methods like Full-Waveform Inversion (FWI) minimize discrepancies between observed and synthetic data through gradient-based optimization, though they can encounter cycle-skipping due to local minima [17]. Advanced methods such as Coupled Time-lapse FWI integrate subsurface flow and rock physics to improve property estimation [18].

Stochastic approaches, like geostatistical inversion, offer probabilistic frameworks to address uncertainties in subsurface models but are computationally demanding [19]. Innovations such as TFP-CSIN, which combines deep learning with time-frequency information, aim to enhance impedance prediction resolution [20]. Hybrid techniques that merge machine learning with traditional methods are increasingly popular for improving prediction accuracy and efficiency, enabling accurate reservoir models without extensive labeled data [15]. Quantum annealing has been explored for seismic traveltime inversion, reformulating it as Quadratic Unconstrained Binary Optimization (QUBO) problems for efficient processing [21].

Acoustic impedance estimation is crucial in predicting subsurface properties from seismic data, aiding in detailed stratigraphic interpretation [15]. Advances in computational power and machine learning integration are enhancing the accuracy and efficiency of seismic inversion, allowing for large-scale data analysis and improved modeling [9, 22, 11, 23, 15]. These methodologies are indispensable for developing accurate subsurface models and advancing geophysical exploration.

2.2 Rock Physics and Digital Rock Technology

Rock physics is integral to seismic reservoir prediction, linking seismic data with subsurface geological properties. It enhances interpretation and prediction of attributes like lithology, porosity, and fluid saturation [24]. Advanced rock physics models improve these predictions, though challenges like cycle skipping persist [25]. Digital rock technology complements rock physics by enabling pore-scale modeling through high-resolution imaging, facilitating virtual experiments on rock samples to understand fluid flow and mechanical behavior [26]. Accurate modeling of transport properties is crucial for understanding fluid dynamics and permeability, influencing hydrocarbon recovery [4]. Data-driven approaches like Rational Function Neural Networks (RafNN) derive rock physics models from field data, focusing on seismic wave velocities and rock properties [27].

The integration of rock physics and digital rock technology is enhanced by computational techniques such as intrusive automatic differentiation, which improves gradient computation in coupled time-lapse waveform inversion [18]. New methods like velocity-porosity supermodels and deep neural networks address geological conditions without parameter tuning, overcoming limitations in existing models [28].

2.3 Deep-Water Sedimentary Analysis and Basin Dynamics

Deep-water sedimentary analysis and basin dynamics are vital for understanding complex sedimentary environments crucial for reservoir prediction [1]. Classifying sediment waves into net-erosional cyclic steps, net-depositional cyclic steps, and antidunes helps elucidate sediment transport mechanisms and seabed morphology [29]. These structures, shaped by dynamic processes like turbidity currents, form deep-water architectural elements, each with unique seismic characteristics [30].

Distinguishing between turbidites, contourites, and hemipelagites is challenging due to overlapping processes, yet essential for understanding sedimentary processes and reservoir quality [31]. Basin dynamics involve geological and sedimentary process interactions influencing basin evolution. Challenges include the presence of interior voids and non-smooth velocity models, which traditional FWI methods may overlook, necessitating advanced wave field reconstruction techniques [32, 33].

Multidimensional approaches enhance sedimentary system analysis, integrating various datasets to address challenges in seismic data inversion and environment characterization [34]. This holistic approach is crucial for overcoming limitations posed by noise and non-repeatable data, complicating seismic data inversion for reservoir property retrieval [13]. Understanding deep-water sedimentary environments and basin dynamics is crucial for predicting and characterizing hydrocarbon reservoirs, offering insights into overpressuring mechanisms and geological processes influencing reservoir formation [35]. Continuous advancements in analytical and computational methods will further enhance the interpretation of complex sedimentary environments and improve reservoir prediction reliability.

3 Seismic Reservoir Prediction Techniques

Category	Feature	Method
Emerging Techniques and Methodologies	Direct Data Utilization	RafNN[27]
Challenges in Current Methodologies	Machine Learning Enhancements	VPS[28], EnTK[36], WNS[7]
	Advanced Computational Methods	N/A[37], QASTI[21]
	Data Integration Techniques	WRI[38], CTFWI[18], TFP-CSIN[20], JLSI[15]
	Efficiency Optimization	MLMC[39]

Table 1: Table summarizing the emerging techniques and challenges in seismic reservoir prediction methodologies. The table categorizes various features and methods under two main sections: emerging techniques, with a focus on data utilization, and challenges in current methodologies, highlighting advancements in machine learning, computational methods, data integration, and efficiency optimization.

The integration of advanced methodologies is essential for improving subsurface exploration accuracy and efficiency in seismic reservoir prediction. This section delves into emerging innovations that are reshaping seismic analysis, focusing on novel computational methods and machine learning frameworks. As illustrated in Figure 2, the hierarchical structure of seismic reservoir prediction techniques categorizes these emerging methodologies alongside the challenges they present. Table 1 provides a comprehensive summary of the emerging techniques and challenges in seismic reservoir prediction methodologies, detailing the key features and methods that are shaping the field. Additionally, Table 4 presents a detailed comparison of emerging computational techniques in seismic reservoir prediction, emphasizing the unique features and applications of each methodology. The advanced computational techniques and machine learning frameworks depicted in the figure are key innovations that underscore the transformative potential in reservoir characterization and predictive capabilities within complex geological settings. Furthermore, the current challenges highlighted in the figure emphasize the pressing need for improved inversion accuracy and computational efficiency, which will be explored in the following subsection.

3.1 Emerging Techniques and Methodologies

Method Name	Computational Techniques	Integration Strategies	Application Scenarios
RafNN[27]	Rational Function Networks	Joint Learning Frameworks	Noise Reduction
TFP-CSIN[20]	Bi-GRU And Cnn	Closed-loop Network	Weak Reflection Areas
CTFWI[18]	Automatic Differentiation	Coupled Inversion Framework	Co2 Sequestration Setup
WNS[7]	Wavenet Architecture	Deep Neural Network	Real-time Applications
VPS[28]	Deep Learning Model	Unified Model	Data Scarcity
WRI[38]	Randomized Linear Algebra	Stochastic Variable Projection	Large-scale Applications

Table 2: Overview of emerging computational techniques and methodologies in seismic reservoir prediction, highlighting various methods, their computational approaches, integration strategies, and application scenarios. The table categorizes methods such as RafNN, TFP-CSIN, and WRI, providing insights into their contributions to noise reduction, reservoir characterization, and large-scale applications.

The seismic reservoir prediction field is evolving through advanced computational techniques and machine learning. Temporal Convolutional Networks (TCNs) have emerged as a significant innovation, modeling seismic traces as sequential data to enhance understanding of long-term dependencies

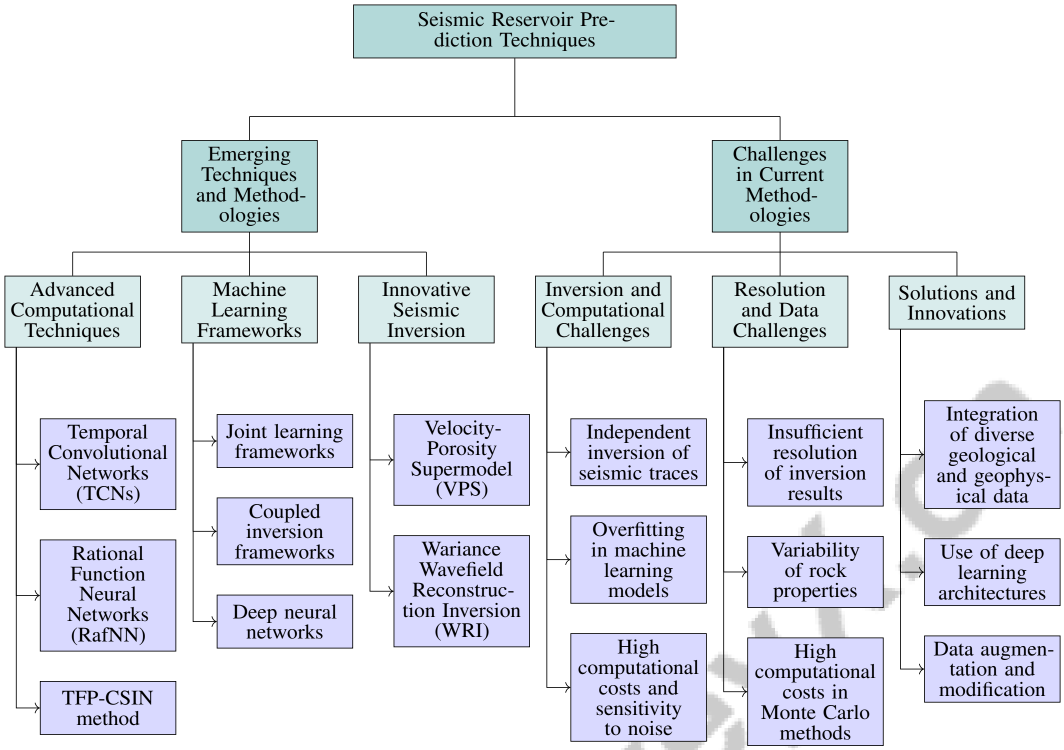


Figure 2: This figure illustrates the hierarchical structure of seismic reservoir prediction techniques, categorizing emerging methodologies and challenges. The advanced computational techniques and machine learning frameworks are key innovations, while current challenges highlight the need for improved inversion accuracy and computational efficiency.

within seismic signals and improve subsurface property predictions like acoustic impedance. TCNs effectively address challenges such as gradient vanishing in Recurrent Neural Networks and overfitting in Convolutional Neural Networks, achieving a high average r^2 coefficient of 91

Data-driven techniques like Rational Function Neural Networks (RafNN) streamline modeling by deriving accurate rock physics models directly from data, circumventing complex theoretical frameworks [27]. The TFP-CSIN method further enhances seismic inversion resolution, especially in weak reflection areas, facilitating precise reservoir characterization [20].

Joint learning frameworks, which train identical network architectures on different datasets with soft weight constraints, exemplify machine learning's potential to enhance seismic inversion processes. Coupled inversion frameworks integrating full-waveform inversion with subsurface flow and rock physics models enable direct estimation of intrinsic properties from seismic data [18].

Advanced seismic inversion techniques, combined with automatic fault detection, have significantly improved fault imaging resolution and reliability, surpassing conventional methods [4]. Deep neural networks predicting seismic responses represent a promising research direction, inspired by deep learning's success in approximating complex physical phenomena [7].

The introduction of a velocity-porosity supermodel (VPS) using artificial neural networks allows effective prediction of elastic properties from rock properties without parameter tuning [28]. Additionally, the Wariance Wavefield Reconstruction Inversion (WRI) addresses optimal slack variable approximation through low-rank stochastic approximation of wave-equation error covariance, improving convergence and scalability [38].

Emerging techniques in seismic reservoir prediction, especially those leveraging advanced machine learning and deep learning approaches, are significantly transforming subsurface exploration. These innovations enhance hydrocarbon reservoir characterization by improving impedance and velocity model estimations, integrating diverse datasets, and enabling robust interpretations in challenging geological conditions. Techniques such as TCNs and joint learning frameworks effectively address noise and data scarcity, leading to more efficient and reliable predictions of hydrocarbon-bearing formations [9, 11, 23, 12].

As illustrated in Figure 3, this figure categorizes the emerging techniques and methodologies in seismic reservoir prediction into computational techniques, joint learning frameworks, and advanced models. Each category highlights key innovations that enhance subsurface exploration and characterization. The figure showcases how seismic inversion transforms seismic reflection data into quantitative rock-property descriptions, crucial for interpreting subsurface layers. Additionally, the depiction of parallel processing in pipeline systems exemplifies advancements in computational methodologies, enhancing data processing efficiency in seismic studies. Flowcharts illustrating factors affecting water saturation in rocks provide insights into the complex interrelationships among rock type, porosity, permeability, and capillary pressure. Collectively, these innovations contribute to a comprehensive understanding of reservoir characteristics, optimizing resource extraction and management [36, 40, 11]. Table 2 presents a comprehensive categorization of emerging computational techniques and methodologies in seismic reservoir prediction, illustrating the diverse methods, their computational techniques, integration strategies, and specific application scenarios.

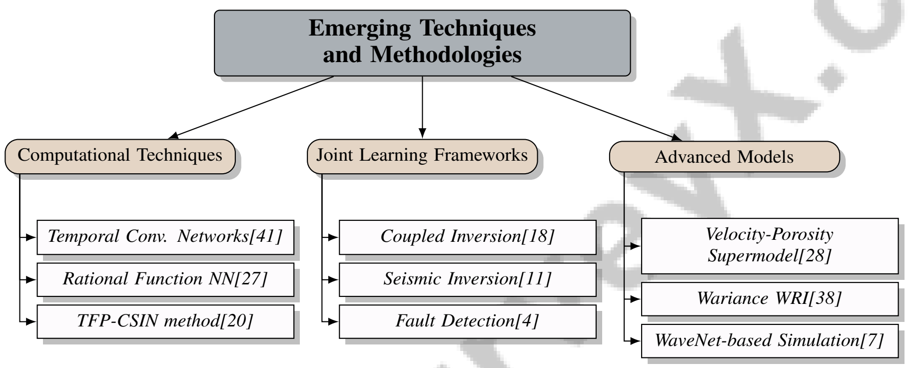


Figure 3: This figure illustrates the emerging techniques and methodologies in seismic reservoir prediction, categorized into computational techniques, joint learning frameworks, and advanced models. Each category highlights key innovations and methodologies that enhance subsurface exploration and characterization.

3.2 Challenges in Current Methodologies

Method Name	Computational Challenges	Data Limitations	Integration of Techniques
JLSI[15]	-	Limited Well Log	Transfer Learning
CTFWI[18]	Intrusive Automatic Differentiation	Sparse Datasets	Coupled Inversion Framework
TFP-CSIN[20]	High Computational Costs	Limited Well Log	Machine Learning
QASTI[21]	Computational Expense	Sensitivity TO Noise	Quantum Annealing Integration
WNS[7]	Computationally Expensive	Limited Well Log	Deep Learning
VPS[28]	-	Limited Well Log	Deep Neural Networks
MLMC[39]	High Computational Cost	-	-
WRI[38]	Computational Demands	-	Stochastic Optimization Techniques
EnTK[36]	High Computational Costs	Limited Well Log	Machine Learning Integration
N/A[37]	High Computational Costs	Insufficient Resolution Sensitivity	Machine Learning Augmentation

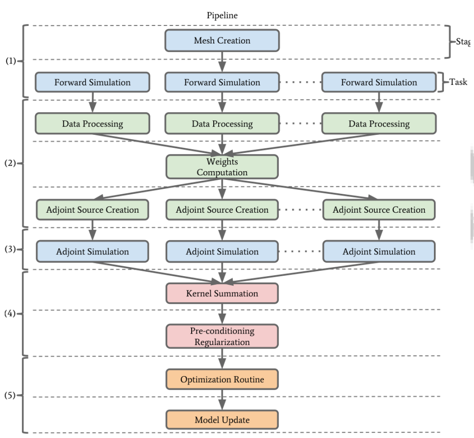
Table 3: Summary of computational challenges, data limitations, and integration techniques in current seismic reservoir prediction methodologies. The table highlights the specific difficulties faced by various methods, such as high computational costs and limited data availability, and the advanced techniques employed to address these issues.

Seismic reservoir prediction methodologies face significant challenges that impede effective subsurface formation characterization. A primary issue is the independent inversion of seismic traces, which neglects spatial correlations between neighboring traces, leading to inconsistent estimations [23]. This limitation is compounded by the overfitting of machine learning models trained on limited well log data, impairing their generalization capabilities [15]. Additionally, the decoupled nature of traditional inversion methods results in inaccuracies, as seismic data do not directly detect intrinsic properties [18].

Insufficient resolution of inversion results arises from methods that predominantly utilize time-domain seismic data [20]. Classical seismic inversion approaches are also burdened by high computational costs and sensitivity to noise, restricting effectiveness in processing noisy seismic data [21]. The iterative updates required for wavefield simulation are computationally intensive, posing challenges for real-time applications [7].

Variability of rock properties under different geological conditions complicates the selection of appropriate rock physics models (RPMs) that perform well across diverse scenarios [28]. Moreover, high computational costs associated with standard Monte Carlo methods limit the feasibility of obtaining reliable estimates for quantities of interest [39]. The augmented wave equation, integral to Wariance Wavefield Reconstruction Inversion (WRI), poses substantial computational demands, hindering large-scale application [38].

To address the complexities of seismic reservoir prediction, innovative methodologies leveraging advanced computational techniques and machine learning algorithms are essential. These approaches can enhance reliability and accuracy by integrating diverse geological and geophysical data, employing data augmentation and modification, and utilizing deep learning architectures. Recent studies demonstrate that machine learning can significantly improve predictions of hydrocarbon-bearing formations in challenging coastal environments, achieving substantial quality improvements. Additionally, integrating deep learning solutions into seismic inversion processes shows promise in accelerating workflows and enhancing subsurface model resolution. By harnessing these cutting-edge techniques, researchers can extract valuable insights from complex datasets, ultimately leading to more effective reservoir characterization and management strategies [9, 22, 42, 12].



(a) A Pipeline for Solving Partial Differential Equations (PDEs) Using a Mixed Finite Element Method (MFEM)[36]

```python
def forward(model, nt, dt, h, order=2):
    shape = model.shape
    m = DenseData(name="m", shape=shape,
                  space_order=order)
    m.data[:] = model  # Set model data
    u = TimeData(name='u', shape=model.shape,
                 time_dim=nt, time_order=2,
                 space_order=order)
    η = DenseData(name="η", shape=shape,
                  space_order=order)

    # Derive stencil from symbolic equation
    eqn = m * u.dt2 - u.laplace + η * u.dt
    stencil = solve(eqn, u.forward)[0]

    op = Operator(stencils=Eq(u.forward, stencil),
                  nt=nt, subs={s: dt, h: h},
                  shape=shape, forward=True)
    # Source injection code omitted for brevity

    op.apply()
```

(b) A Python code snippet for solving a differential equation using a symbolic equation solver[37]

Figure 4: Examples of Challenges in Current Methodologies

As illustrated in Figure 4, current methodologies in seismic reservoir prediction face significant challenges, particularly in accurately and efficiently solving partial differential equations (PDEs) that model subsurface phenomena. Two examples highlight these challenges: the Mixed Finite Element Method (MFEM) pipeline, outlining a structured approach to solving PDEs, and a Python code snippet demonstrating a granular approach using symbolic equation solving for differential equations. These examples underscore the technical intricacies and computational demands of current methodologies, emphasizing the necessity for innovative solutions to overcome these challenges [36, 37]. Table 3 provides a comprehensive overview of the challenges and techniques associated with current seismic reservoir prediction methodologies, illustrating the complexity and diversity of approaches in addressing subsurface characterization challenges.

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Feature	Temporal Convolutional Networks (TCNs)	Rational Function Neural Networks (RafNN)	TFP-CSIN
Data Handling	Sequential Data Modeling	Data-driven Modeling	High-resolution Inversion
Computational Technique	Two-dimensional Integration	Rational Function Approximation	Enhanced Seismic Resolution
Application Focus	Acoustic Impedance Prediction	Rock Physics Models	Weak Reflection Areas

Table 4: This table provides a comparative analysis of three advanced methodologies used in seismic reservoir prediction: Temporal Convolutional Networks (TCNs), Rational Function Neural Networks (RafNN), and TFP-CSIN. It highlights the distinct features, computational techniques, and application focuses of each method, illustrating their roles in enhancing data handling, computational efficiency, and application in seismic analysis.

4 Deep-Water Sedimentary Analysis

4.1 Significance of Deep-Water Sedimentary Environments

Deep-water sedimentary environments are crucial for reservoir prediction due to their complex sedimentary processes and structural features. Understanding sediment supply systems is vital for hydrocarbon exploration. In the Rakhine Basin, for instance, the interplay of turbidity and contour currents shapes seabed morphology and sediment transport, influencing reservoir quality and distribution [29]. The architectural complexity of these environments, such as sill-complexes, affects petroleum systems by acting as barriers or conduits for hydrocarbon migration. Enhanced seismic imaging, like the Joint Inversion Strategy (JIS), improves the depiction of these features, resulting in clearer acoustic impedance models and better reservoir modeling [38].

In carbonate reservoirs, Digital Rock Typing (DRT) refines geological modeling by accurately determining rock types based on lithology, permeability, and capillary pressure. Advanced imaging techniques, such as micro-Computed Tomography (μCT) and Magnetic Resonance Imaging (MRI), facilitate non-destructive analysis of these properties. Integrating digital rock physics bridges geology, petrophysics, and reservoir simulations, enhancing predictions in oil and gas exploration [40, 43, 26, 1]. Additionally, sub-resolution porosity (SRP) affects rock properties like permeability and fluid breakthrough times, emphasizing the significance of deep-water sedimentary environments in reservoir characterization.

Advanced methods, including the Bayesian sequential approach, provide more accurate time-lapse estimates for reservoir identification compared to traditional techniques. Understanding model parameter uncertainties through Multi-Objective Grey Wolf Optimization (MOGWO) enhances comprehension of deep-water sedimentary environments. Randomized preconditioners further improve inversion accuracy in seismic imaging, demonstrating potential for enhanced reservoir prediction [21].

A thorough understanding of deep-water sedimentary environments is essential for optimizing hydrocarbon exploration strategies. Differentiating sediment facies, such as turbidites, contourites, and hemipelagites, enables geoscientists to develop effective models for predicting reservoir behavior and identifying potential hydrocarbon deposits in complex deep-water systems [35, 31]. Integrating various observational scales and advanced analytical techniques is critical for overcoming complexities in these environments, leading to improved reservoir characterization.

4.2 Techniques for Sedimentary Basin Analysis

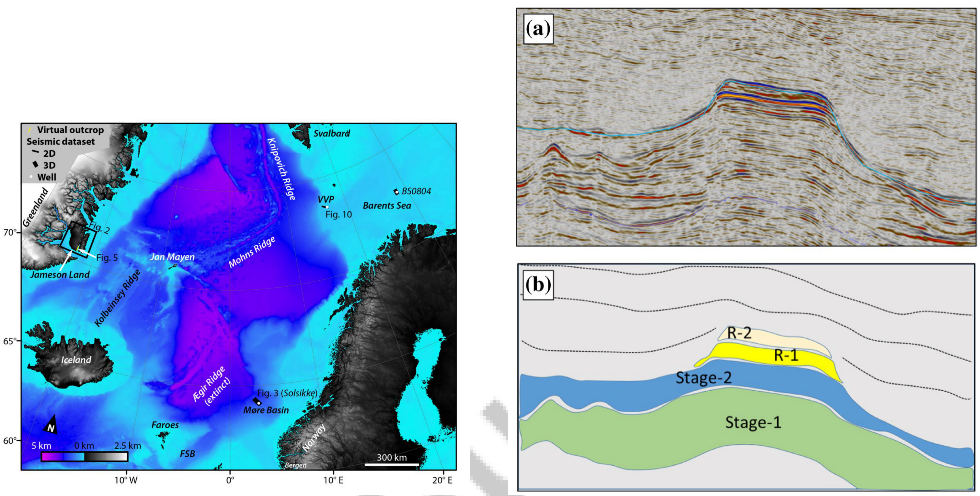
Sedimentary basin analysis plays a pivotal role in geophysical exploration, offering insights into geological processes that influence subsurface formations and hydrocarbon reservoir characteristics. Advanced techniques have been developed to enhance understanding of sedimentary basin dynamics, particularly in identifying causes of overpressure, such as disequilibrium compaction, fluid expansion, diagenesis, tectonic compression, and pressure transfer. These techniques provide distinct insights into reservoir characterization and improve modeling accuracy. Recent studies emphasize the influence of organic matter content on geophysical log parameters in hydrocarbon source rocks, necessitating adjustments in analyses to accurately assess overpressure origins [35, 11].

Quantum computational intelligence has emerged as an advanced technique for seismic traveltime inversion, utilizing quantum computing to address complex geophysical challenges. Simulations using Qiskit on various synthetic models demonstrate its potential in enhancing seismic data processing efficiency [44].

The integration of deep learning in seismic data interpretation, particularly through Deep Learning Seismic Inversion (DLSI), allows for direct litho-type classification from seismic data, bypassing traditional inversion processes. This method enhances lithological classification efficiency, providing a more direct and potentially accurate means of interpreting seismic data [45]. Emphasizing physical accuracy in segmentation is crucial for reliable downstream analysis, as shown in studies focused on geological feature identification precision [43].

Digital rock technology significantly contributes to sedimentary basin analysis by providing detailed imaging and simulation methods that focus on pore-scale dynamics. This technology facilitates in-depth examinations of rock properties and fluid behavior within sedimentary basins, yielding valuable data for reservoir characterization [26].

High-performance computing techniques, such as those employed in simwave, enable full-waveform inversion and reverse-time migration, serving as benchmarks for high-performance computing research and improving seismic imaging resolution [8].



(a) Virtual Outcrop Seismic Dataset[46]

(b) Seismic and Stratigraphic Analysis[14]

Figure 5: Examples of Techniques for Sedimentary Basin Analysis

As illustrated in Figure 5, integrating advanced seismic and stratigraphic techniques is crucial for enhancing understanding of sedimentary basin dynamics. The Virtual Outcrop Seismic Dataset provides a three-dimensional view of the subsurface, highlighting varying depths, particularly in the deepest crustal sections. This visualization is complemented by a two-dimensional overlay of the Arctic region, marking seismic lines, wells, and key geological features. The Seismic and Stratigraphic Analysis image features a dual-panel composition that presents a seismic section with colored seismic lines and a stratigraphic section that delineates subsurface layers, facilitating geological formation identification. Together, these techniques offer comprehensive insights into the structural and compositional intricacies of sedimentary basins, proving invaluable for geological exploration and analysis [46, 14].

5 Integration of Geophysical Techniques

5.1 Integration of Multidisciplinary Approaches

Incorporating multidisciplinary approaches in geophysical exploration enhances seismic reservoir predictions and deep-water sedimentary analyses. By integrating advanced seismic interpretation methods, like machine learning-based inversion and joint learning schemes, with comprehensive geological assessments, researchers can refine subsurface models, improving rock property estimations and hydrocarbon potential evaluations. This holistic approach addresses challenges such as lateral discontinuities and noise in seismic data, facilitating detailed subsurface reconstructions essential for resource exploration [9, 10, 23]. The fusion of geophysical techniques with geological insights allows for cohesive integration of diverse data types, including seismic, electromagnetic, and well log data, enhancing subsurface property predictions. Advanced computational methods, as discussed by Moon et al., improve numerical stability and computation speed, efficiently tackling diverse geophysical challenges [47].

Integrating multidisciplinary approaches supports the development of sophisticated models accounting for complex geological processes and interactions. Incorporating geological knowledge into seismic data interpretation refines models to better depict subsurface environments. Recent studies show how mafic sill complex geometries influence seismic imaging, particularly in sedimentary basins where overlying igneous rocks obscure structures, enhancing interpretations and subsurface assessment reliability [10, 46]. Such integration is crucial for characterizing carbonate reservoirs, which are challenging due to their heterogeneity and fluid distributions.

5.2 Joint Inversion and Multi-Data Integration

Joint inversion and multi-data integration are pivotal in geophysical exploration, enhancing subsurface property estimation accuracy by utilizing multiple geophysical data sources. These techniques reduce model prediction uncertainty by coupling different data types, such as seismic and electromagnetic, addressing noise and data sparsity challenges. Joint learning approaches facilitate information sharing across datasets, leading to consistent and reliable subsurface geological structure interpretations [48, 49, 23]. The integration of multiple datasets provides a comprehensive understanding of subsurface characteristics, with each dataset contributing unique insights for a clearer geological picture.

A notable methodology is the two-dimensional Temporal Convolutional Network (2D TCN), which processes seismic data as 2D images, capturing temporal and spatial relationships to improve rock property estimations [41]. The Multi-Dimensional Newtonian Latent-space (MNML) method links multi-dimensional latent space feature perturbations to velocity perturbations, enabling effective multi-dimensional data integration in inversion processes [50]. This integration captures complex subsurface interactions and enhances inversion resolution.

Minimod, a finite difference solver, offers a portable application structure with optimized kernels for various high-performance computing platforms, crucial for managing joint inversion computational demands [51]. Combining geophysical techniques with advanced computational methods, such as modeling irrotational flow around complex structures, further enhances subsurface physical interaction capture [6]. This comprehensive data integration approach improves property estimation accuracy and supports sophisticated subsurface exploration models.

5.3 Integration of Geological Knowledge into Modeling

Integrating geological knowledge into geophysical modeling enhances subsurface property prediction accuracy and hydrocarbon exploration outcomes. Geological insights provide critical context for geophysical data interpretation, enabling more accurate subsurface formation models. This integration is vital in complex geological environments where traditional techniques may struggle with subsurface variability. Advanced methods like joint and constrained inversion, combining electromagnetic data with seismic observations, enhance model accuracy and mitigate issues like lateral discontinuities and overfitting, bolstering subsurface interpretation robustness [49, 52, 53, 23, 48].

Geological knowledge informs rock physics model selection and seismic attribute interpretation, facilitating realistic model development. Incorporating geological constraints into seismic inversion enhances subsurface property estimation accuracy. By integrating geological information, such as stratigraphic frameworks and lithological distributions, inversion algorithms better constrain solution spaces, reducing model prediction uncertainties [24].

Geological knowledge aids in geophysical model calibration and validation. Comparing model outputs with geological observations, including well log data and outcrop studies, enhances model accuracy, ensuring consistency with geological features. This iterative process integrates multiple subsurface realizations aligned with geological frameworks and rock physics, crucial for addressing subsurface investigation complexities and refining geological interpretations based on geophysical data [11, 54]. This calibration enhances geophysical prediction reliability and provides feedback for geological interpretation improvement.

Advanced computational techniques, like machine learning and data assimilation, further facilitate geological knowledge integration into geophysical modeling. These methods incorporate large, diverse datasets, allowing simultaneous consideration of multiple geological and geophysical parameters. By leveraging geological and geophysical data strengths, researchers develop comprehensive models accurately representing subsurface environment complexity [27].

Integrating geological knowledge into geophysical modeling is crucial for modern exploration strategies, enhancing subsurface interpretation accuracy by combining geophysical methods—such as seismic and electromagnetic data—through joint and constrained inversion. This multidisciplinary approach improves geological feature identification and addresses complex subsurface questions, leading to informed resource exploration decision-making [48, 10, 11]. Merging geological insights with advanced computational methods, geoscientists achieve accurate subsurface property predictions, enhancing hydrocarbon exploration and production efforts.

6 Challenges and Future Directions

6.1 Machine Learning and Deep Learning Applications

Machine learning (ML) and deep learning (DL) are integral to seismic reservoir prediction and sedimentary analysis, offering solutions that enhance both accuracy and computational efficiency. Utilizing extensive datasets from seismic surveys and well logs, these technologies address noise and data limitations, providing robust solutions for complex geological environments. The integration of ML and DL into seismic inversion has led to advancements such as physics-informed neural networks, which combine physical laws with data-driven models to improve subsurface characterizations [5]. Recent studies demonstrate DL's role in geophysical applications, particularly in seismic inversion. Techniques like Temporal Convolutional Networks (TCNs) capture long-term trends and local variations in seismic data, enhancing subsurface property estimation [20]. Joint learning frameworks, inspired by transfer learning, leverage knowledge from related datasets to enhance performance on target datasets, improving generalization and spatial context for accurate estimations.

The effectiveness of DL architectures is further exemplified by approaches like the velocity-porosity supermodel (VPS), which learns complex data relationships across lithologies that traditional rock physics models struggle to capture [28]. Quantum annealing for seismic traveltime inversion illustrates a novel approach to accurately invert velocity models from noisy data, highlighting quantum computing's potential in geophysical exploration [21]. Future research should refine encoding methods and explore second-order optimization techniques to enhance ML applications' efficiency and accuracy in geophysical exploration [17]. Integrated studies combining geophysical and geochemical data could yield deeper insights into hydrocarbon migration and maturation processes, especially in complex basins like the Mundaú subbasin [2].

The incorporation of ML and DL into seismic reservoir prediction and sedimentary analysis holds substantial potential for advancing geophysical exploration. By enhancing existing technologies and investigating innovative applications, researchers can significantly improve strategies for hydrocarbon exploration and production, facilitating precise, data-driven decision-making processes. Techniques such as geophysical and geochemical exploration, alongside advanced modeling methods like geostatistical simulations and ML algorithms, are crucial for achieving these advancements, as highlighted in studies on natural gas hydrates and seismic analysis [10, 11, 55].

6.2 Hybrid and Multi-Objective Optimization Methods

Hybrid and multi-objective optimization methods are crucial for advancing seismic reservoir prediction and sedimentary analysis, addressing the complexities of seismic data inversion. These approaches enhance geophysical models' robustness and accuracy by integrating multiple objectives, improving inversion outcomes' reliability [52]. Their strength lies in incorporating ensemble predictions and weighted contributions, refining uncertainty estimates and enhancing seismic inversion results' reliability. However, challenges persist, particularly in computational intensity during high-resolution simulations involving complex fracture networks, as demonstrated by the LSM-DFN method [56]. The significant computational demands limit their applicability in resource-constrained environments. Strong seismic coupling between model parameters further complicates multi-parameter inversion processes, challenging accurate medium property reconstruction [57].

Despite these challenges, hybrid optimization methods offer considerable advantages. Integrating genetic algorithms into inverse modeling can enhance computational efficiency by reducing training and inversion times [58]. Bayesian approaches, such as Bayesian Physics-Informed Neural Networks (BPINNs), have shown effectiveness in seismic inversion, though they require careful hyperparameter tuning to optimally manage complex geological structures [59]. Optimization methods also enhance facies classification and uncertainty assessment by reproducing joint distributions between variables, as evidenced by geostatistical rock physics approaches [60]. Methods incorporating Fourier integral operators, despite challenges in obtaining Sobolev estimates, show promise in improving seismic data interpretation [61].

Future research in hybrid and multi-objective optimization should focus on improving convergence rates and managing complex optimal transport scenarios, potentially through combining methods like FS-1 with the Inexact Proximal Point method [62]. Expanding benchmarks to include more complex geophysical scenarios and integrating them with emerging computational technologies could further enhance these methodologies [63]. Addressing limitations related to data diversity, lack of labeled datasets, and high computational costs associated with training large models remains critical for development.

6.3 Advanced Computational Frameworks

Advanced computational frameworks are vital in geophysical exploration, significantly enhancing seismic data processing and interpretation's precision and efficiency. These frameworks are crucial for managing large datasets essential for accurately predicting and characterizing subsurface properties. The integration of specialized optimizers within domain-specific languages, such as those developed in the Devito framework, facilitates efficient generation of optimized finite-difference C code for seismic modeling, broadening these tools' applicability in geophysical research [64]. Multi-resolution frameworks like M-ORKA have demonstrated substantial improvements in runtime and accuracy when applied to seismic data of varying resolutions, enabling efficient handling of large datasets [65].

The OPS backend integration into Devito has shown significant speedups for GPU execution compared to CPU performance, highlighting its potential for enhancing computational efficiency [64]. The Ensemble Toolkit (EnTK) exemplifies high-performance computing by abstracting complexities associated with dynamic resource allocation and fault tolerance during ensemble execution, ensuring robust and scalable computational performance essential for managing the demanding requirements of geophysical simulations [36]. Digital rock technology significantly reduces uncertainty in formation evaluation and enhances understanding of macroscopic parameters through detailed pore-scale simulations [26]. This technology enables virtual experimentation on rock samples, providing insights into fluid flow and mechanical behavior under various conditions, critical for understanding fluid dynamics and permeability in reservoir rocks.

Future research aims to develop a general parallel library based on TensorFlow for various geophysical inverse problems, enhancing method applicability [66]. Extending current approaches to 3D seismic volumes and incorporating additional datasets could further enhance model robustness [23]. The focus on reducing computational time and memory requirements underscores these frameworks' potential to revolutionize geophysical research, with future developments targeting support for high-frequency inversions and distributed computing [67].

6.4 Innovations in Machine Learning and Computational Methods

Recent advancements in machine learning (ML) and computational methods are transforming geophysical exploration, particularly in seismic reservoir prediction and sedimentary analysis. These innovations enhance the precision, efficiency, and reliability of subsurface characterizations. A significant breakthrough is the integration of deep learning (DL) models in seismic inversion workflows, exemplified by the velocity-porosity supermodel, which employs artificial neural networks to accurately learn and predict elastic properties across various lithologies, providing a versatile tool for rock physics applications [28]. Such approaches highlight the potential for improved seismic data interpretation, especially in complex geological settings.

The application of physics-informed neural networks (PINNs) in seismic inversion represents another frontier in ML innovations. This approach effectively combines physical laws with data-driven models to enhance subsurface characterizations, offering a promising avenue for addressing higher-

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dimensional seismic inversion problems and exploring alternative neural network architectures beyond fully connected networks [3]. In computational frameworks, exploring quantum computing for seismic traveltime inversion underscores the potential for high-precision seismic imaging, paving the way for future advancements in geophysical applications [21]. Integrating lossy compression algorithms with checkpointing has proven effective in enhancing seismic inversion computations' efficiency, enabling larger datasets to be processed without exceeding memory limits [68]. Future research will focus on exploring the interaction between compression errors and various parameters in Full-Waveform Inversion (FWI) and comparing multiple lossy compression algorithms to optimize performance.

The TFP-CSIN method exemplifies a key innovation in seismic inversion, utilizing a closed-loop network structure that combines Bi-GRU and CNN architectures. This approach facilitates bidirectional mapping between seismic data and impedance data while incorporating frequency and phase domain constraints, thereby enhancing seismic inversion results' resolution [20]. Moreover, the use of hyperbolic wavelets and mixed smoothness classes in anisotropic denoising and functional deconvolution has advanced computational methods, providing convergence rates free from the curse of dimensionality [69]. This innovation underscores the critical role of advanced computational techniques in managing modern geophysical exploration's complex data requirements.

Future research directions include integrating Multilevel Monte Carlo (MLMC) methods into real seismic inversion problems using actual measurement data and exploring alternative misfit functions that may yield better results in source localization [39]. By continuing to refine these technologies and exploring new applications, researchers can enhance hydrocarbon exploration and production strategies, leading to more informed decision-making in the field.

7 Conclusion

Seismic reservoir prediction and deep-water sedimentary analysis are pivotal in advancing geophysical exploration and refining hydrocarbon reservoir characterization. The integration of sophisticated seismic inversion techniques has markedly enhanced the comprehension of intricate subsurface formations, particularly within carbonate reservoirs. This integrative approach not only facilitates the identification of prime hydrocarbon exploration sites but also optimizes well placement, thereby bolstering economic feasibility.

The transition from 2D to 3D seismic methods has become indispensable in modern exploration strategies. While 3D techniques offer detailed subsurface imaging crucial for contemporary exploration, the cost-effectiveness of 2D methods ensures their continued application in specific scenarios. Furthermore, ongoing advancements in deep-water seismic prediction underscore the necessity for improved data acquisition and processing methodologies to increase prediction precision.

Nonetheless, challenges persist, particularly in the exploration of natural gas hydrates, where overcoming technical and environmental barriers is critical to fully exploit this energy resource. Additionally, while certain theoretical frameworks provide a robust basis for applications, they often fall short in addressing the complexities inherent in acoustic wave propagation, particularly in non-linear scenarios.

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