A Survey of Ocean Bottom Nodes and Geophysical Methods for Carbonate Reservoir Characterization and Prediction

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Abstract

Ocean bottom nodes (OBNs) and advanced geophysical methods have revolutionized subsurface exploration by enhancing the precision and reliability of hydrocarbon reservoir identification and evaluation. OBN technology captures high-fidelity seismic data, crucial for detailed subsurface characterization, while innovations in seismic imaging, such as high-order exponential integrators and GAN-based inverse modeling, improve accuracy and efficiency. Bayesian inversion techniques further advance lithology and fluid prediction, offering promising directions for complex geological settings. Recent developments in machine learning and data integration have automated seismic interpretation, achieving an average F1 measure of 0.798 in hydrocarbon reservoir prediction. Challenges remain in handling complex geological features and quantifying uncertainties, necessitating the development of generalized models adaptable to varying conditions. Future research should focus on enhancing data quality, integrating AI with IoT, and refining models to better represent spatial heterogeneity and variable reaction rates. The continued evolution of these technologies promises to further enhance subsurface exploration, supporting informed decision-making in hydrocarbon resource development.

1 Introduction

1.1 Significance of Subsurface Exploration

Subsurface geological exploration is essential for identifying hydrocarbon reservoirs, crucial for meeting rising global energy demands. The heterogeneous nature of these formations requires advanced technologies for accurate interpretation and prediction of reservoir characteristics. Seismic imaging serves as a fundamental tool, providing detailed subsurface maps necessary for hydrocarbon exploration [1]. Accurate segmentation of salt bodies within seismic images is vital for distinguishing hydrocarbon-rich zones from barren areas, thus optimizing exploration efforts.

The integration of data science and machine learning has significantly improved predictions regarding the spatial distribution of rock formations, particularly in hydrocarbon-rich coastal regions. These technologies not only bridge existing knowledge gaps but also enhance exploration efficiency by offering new insights into reservoir characteristics. Additionally, modeling the geometrical evolution of pore spaces due to fluid-solid interactions is critical for reservoir engineering and oil recovery, highlighting the importance of sophisticated modeling techniques [2].

Uncertainty quantification remains a major challenge in subsurface exploration, particularly regarding seismic horizon tracking and reservoir property prediction. Addressing these uncertainties is crucial for improving exploration accuracy. Advanced geophysical methods, such as Bayesian inversion techniques, have been developed to mitigate these challenges, thereby enhancing the reliability of subsurface characterizations [3].

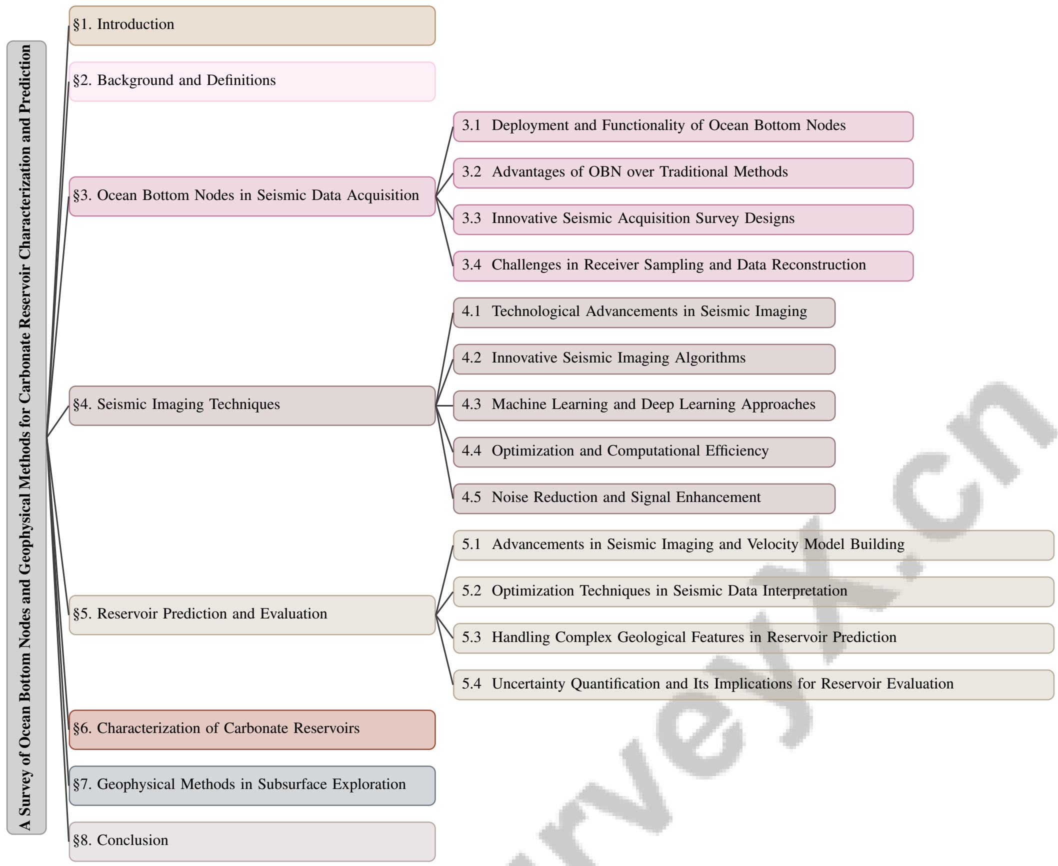

Figure 1: chapter structure

Exploration of carbonate rocks, which serve as archives of past oceanic conditions and hosts for economic resources, underscores the multifaceted nature of subsurface exploration [4]. The geological storage of carbon dioxide and the estimation of uncertainties associated with CO2 generation from carbonate-clay reactions further stress the need for comprehensive exploration strategies [5].

1.2 Role of Advanced Geophysical Methods

Advanced geophysical methods have significantly improved the accuracy and reliability of subsurface exploration by addressing the complexities of geological formations. The integration of Full Waveform Inversion (FWI) in the frequency domain has refined subsurface imaging processes, utilizing complete seismic waveforms to enhance geological predictions [6]. Quantum annealing in seismic travel time inversion exemplifies innovative approaches that redefine traditional methodologies [7].

Deep learning, particularly through convolutional neural networks (CNNs), has automated the segmentation process in seismic imaging, crucial for detecting subsurface features such as salt bodies accurately [8]. These networks have been utilized for lithology classification and mineral content prediction directly from drill core images, demonstrating their versatility across diverse geophysical tasks [9]. Additionally, deep learning techniques have been employed to represent the entire inverse map, offering novel solutions to the inverse wave scattering problem and enhancing resolution for complex subsurface issues [10].

Innovative approaches like physics-informed neural networks (PINNs) incorporate physical laws into the learning process, thereby enhancing exploration accuracy [11]. New data augmentation methods leveraging CNNs further improve data quality and interpretation, bolstering the reliability of subsurface exploration [12].

The increasing complexity of models necessitates standardized evaluation frameworks, highlighting the need for benchmarks that accurately reflect model capabilities in practical applications [13].

Machine learning techniques have proven pivotal in solving complex oil and gas industry challenges, enhancing prediction, classification, and clustering tasks [14]. Advanced techniques such as the Convolved Hidden Markov Model (CHMM) improve the efficiency of Bayesian inversion for reservoir characterization, addressing computational demands [3]. The Bayesian approach to seismic imaging systematically translates image uncertainty into horizon tracking uncertainty, further enhancing exploration reliability [15].

Digital Rock Typing (DRT) addresses the limitations of traditional rock typing methods, particularly in accurately assessing carbonate rock properties [16]. Machine learning-based image analysis, including Deep Convolutional Neural Networks (DCNN), automates the description, classification, and interpretation of thin sections, subsurface core images, and seismic facies, thereby improving the efficiency and accuracy of subsurface exploration [4]. These advancements underscore the critical role of innovative geophysical methods in overcoming traditional limitations and enhancing the efficacy of hydrocarbon reservoir identification and evaluation.

1.3 Importance of Ocean Bottom Nodes (OBN)

Ocean Bottom Nodes (OBN) technology is crucial for seismic data acquisition, offering significant advantages in challenging environments where traditional methods may falter. Deploying OBNs on the seafloor enables the capture of high-fidelity seismic data essential for accurate subsurface imaging and reservoir characterization. This capability is particularly vital in complex geological settings, such as pre-salt reservoirs, where circular shot OBN acquisition geometry maximizes seismic illumination using refracted wave energy [17].

The increasing size and complexity of seismic data necessitate automated interpretation methods for efficient information management [18]. When integrated with advanced imaging frameworks like the Joint Recovery Model, OBN technology enhances image quality while minimizing costly survey replication, thus optimizing data acquisition processes [19]. Furthermore, combining physics-informed approaches with data-driven methods enhances the robustness and accuracy of seismic solutions, surpassing purely data-driven techniques [20].

In coastal environments, accurate forecasting is vital for effective seismic data acquisition, and OBN technology plays a critical role in achieving this accuracy [21]. The ability of OBNs to provide detailed and reliable data in such settings underscores their importance in modern geophysical exploration. As the complexity of seismic data continues to grow, the adoption of OBN technology is expected to expand, further enhancing the precision and efficiency of subsurface exploration efforts.

1.4 Overview of Paper Structure

This paper provides a comprehensive survey of the utilization of ocean bottom nodes (OBN) and advanced geophysical methods in characterizing and predicting carbonate reservoirs. The initial section introduces the significance of subsurface exploration and the pivotal role of advanced geophysical techniques in hydrocarbon reservoir identification. It elaborates on the importance of OBN technology in seismic data acquisition, particularly in complex geological settings. The background section defines key terms and concepts, offering foundational understanding of ocean bottom nodes, seismic imaging, reservoir prediction, and carbonate reservoir characterization.

Subsequent sections delve into the deployment and functionality of OBNs, highlighting their advantages over traditional seismic acquisition methods and exploring innovative survey designs that enhance data acquisition. The discussion extends to seismic imaging techniques, examining technological advancements, novel algorithms, and the integration of machine learning approaches to improve imaging resolution and accuracy.

The paper explores reservoir prediction and evaluation methods, focusing on advancements in seismic imaging, optimization techniques, and strategies for addressing complex geological features. It highlights the complexities and innovative techniques involved in characterizing carbonate reservoirs, particularly through advanced imaging technologies such as Micro-Computed Tomography (uCT) and Magnetic Resonance Imaging (MRI), along with machine learning algorithms like the Image Resolution Optimized Gaussian Algorithm (IROGA) and the Machine Learning Difference of Gaussian Random Forest (MLDGRF). These methods enhance the accuracy and efficiency of determining petrophysical properties, such as porosity and lithology, from 3D images of heterogeneous carbonate

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rocks, addressing challenges posed by traditional petrographic analysis, which is often labor-intensive and requires specialized expertise. Recent advancements in automated image processing and deep learning techniques further streamline the classification and interpretation of carbonate structures, ultimately improving data acquisition and reproducibility in geological studies [4, 22].

Finally, the survey reviews the integration of various geophysical methods in subsurface exploration, discussing innovations in seismic data processing and the benefits of hybrid and multidisciplinary approaches. The concluding section synthesizes key findings and implications of using OBN and advanced geophysical methods, highlighting future directions and potential advancements in the field.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Key Concepts in Subsurface Exploration

Subsurface exploration leverages diverse methodologies to characterize geological formations, with a primary focus on hydrocarbon reservoir identification and evaluation. A major challenge in this domain is the noise contamination in seismic signals, complicating seismic event analysis [23]. Addressing this issue is crucial for enhancing seismic data clarity and reliability.

Geological carbon storage is a critical area within subsurface exploration, necessitating precise imaging techniques to monitor CO2 leakage and maintain storage site integrity [19]. This involves identifying potential leakage pathways and accurately characterizing subsurface anomalies. Understanding buried geophysical sources, such as poles and dipoles that induce anomalies in datasets, is essential for elucidating subsurface structures and their implications [24].

Magnetic inversion and susceptibility provide insights into the magnetic properties of geological formations, crucial for interpreting magnetic survey data and characterizing subsurface structures [25]. The SAMERA geophysical sensor network exemplifies innovation in capturing and processing geophysical wave signals to generate real-time subsurface images [26].

Advancements in digital rock imaging, particularly through super-resolution deep learning models, significantly enhance the resolution and quality of digital rock images [27]. This improvement is pivotal for visualizing and analyzing subsurface formations. Covariance functions are vital for modeling the dependence structure of spatial processes, aiding in understanding spatial relationships and variations within geophysical datasets [28].

Seismic traveltime inversion is key in subsurface exploration, especially in carbon storage scenarios where seismic data is used to infer subsurface velocity structures critical for accurate imaging [7]. Manual interpretation of seismic data remains complex and labor-intensive, highlighting the need for automated and efficient data processing techniques [18].

Challenges in obtaining comprehensive data on offshore rifted margins due to high costs and time constraints necessitate indirect geophysical methods [29]. These methods provide valuable insights without extensive direct sampling, enhancing exploration efficiency. Physics-informed neural networks (PINNs) integrate data with physical laws, represented as partial differential equations (PDEs), to improve the accuracy of subsurface models [11].

Uncertainty quantification in seismic imaging is critical, as uncertainties can significantly impact data interpretation accuracy [30]. Effective inversion of DC resistivity and magnetotelluric (MT) data is another challenge in achieving accurate subsurface models [31]. Modeling pore space geometry changes due to reactive flow processes is essential for understanding subsurface dynamics [2]. Additionally, quantifying CO2 production through carbonate-clay reactions under high temperature and pressure underscores the complexities of subsurface exploration [5].

The ability to quantify and utilize uncertainty in modeling is pivotal for informed decision-making in subsurface exploration [32]. Evolving technologies and methodologies promise to enhance the precision and reliability of hydrocarbon reservoir identification and evaluation.

2.2 Geophysical Methods and Their Integration

Integrating various geophysical methods is essential for comprehensive insights into subsurface formations, particularly in hydrocarbon reservoir exploration and characterization. Techniques such as seismic, magnetic, and gravitational surveys are often combined to enhance the resolution and reliability of subsurface models. The Joint Recovery Model exemplifies this integration by relating observed time-lapse data to perturbations in acoustic impedance, enabling high-resolution image generation from non-replicated data [19], especially when traditional data replication is unfeasible due to logistical or financial constraints.

Probabilistic interpretations of geophysical datasets, such as those imaging polar and dipolar sources, accommodate inherent uncertainties in subsurface exploration [24]. This framework is crucial for understanding complex geological settings where deterministic models may be inadequate.

In digital rock imaging, super-resolution techniques have been benchmarked for their effectiveness in reconstructing high-resolution images from low-resolution counterparts, emphasizing physical accuracy in petrophysical analyses [27]. Integrating advanced imaging techniques with traditional geophysical methods enhances the overall quality and reliability of subsurface models.

Developing novel evaluation frameworks that incorporate user feedback and contextual understanding offers a nuanced approach to assessing geophysical methods. Unlike previous benchmarks focused primarily on surface-level metrics, these frameworks provide deeper insights into the practical applicability and effectiveness of various geophysical techniques [13]. This holistic approach ensures that geophysical methods are continually refined and adapted to meet the evolving challenges of subsurface exploration.

In recent years, the advancement of seismic data acquisition has been significantly influenced by the development of Ocean Bottom Nodes (OBNs). These nodes represent a paradigm shift in the way seismic data is collected, offering numerous advantages over traditional methods. To illustrate this transformation, Figure 2 provides a comprehensive overview of the hierarchical structure of OBNs. This figure highlights not only their deployment and functionality but also the innovative survey designs that have emerged alongside them. Furthermore, it categorizes advanced data processing techniques, applications, and the benefits of OBNs, while addressing the challenges related to receiver sampling and data reconstruction. By integrating innovative methodologies with OBN technology, the quality and reliability of seismic data acquisition can be significantly enhanced, underscoring the importance of this evolution in the field.

3 Ocean Bottom Nodes in Seismic Data Acquisition

3.1 Deployment and Functionality of Ocean Bottom Nodes

Ocean Bottom Nodes (OBNs) are strategically positioned on the seafloor to capture high-quality seismic data, proving advantageous in complex geological settings by minimizing water column interference and enhancing data resolution, crucial for accurate subsurface characterization and hydrocarbon evaluation [3]. The functionality of OBNs is enhanced by advanced data processing techniques. Machine learning tailored for coastal regions refines seismic interpretation, improving hydrocarbon reservoir predictions [21]. Bayesian inversion frameworks, utilizing categorical Markov chains and Gaussian spatial variables, significantly boost seismic data quality [3].

Innovative models, such as the Capillary Network Model (CNM), simulate fluid flow and reactive processes affecting pore geometry, providing insights into subsurface conditions that influence seismic wave propagation [2]. Deep learning techniques, including Deep Convolutional Neural Networks, automate geological feature identification, enhancing subsurface model accuracy [4]. Wave-equation-based inversion techniques, supported by extensive training datasets, generate high-fidelity seismic images, refining subsurface imaging processes [33]. Combined with probabilistic modeling, these methods estimate geological processes like CO_2 generation from carbonate-clay reactions, impacting seismic data interpretation [5].

OBNs, through advanced processing techniques and analytical models, significantly enhance seismic data acquisition reliability. They are essential in contemporary geophysical exploration for capturing high-fidelity seismic data in complex environments, facilitating precise subsurface characterization and hydrocarbon reservoir evaluation. Techniques like full-waveform inversion (FWI) and machine learning algorithms, along with circular shot acquisition geometry, optimize deep reservoir illumination, crucial for oil and gas exploration, carbon sequestration, and environmental monitoring [17, 18, 34].

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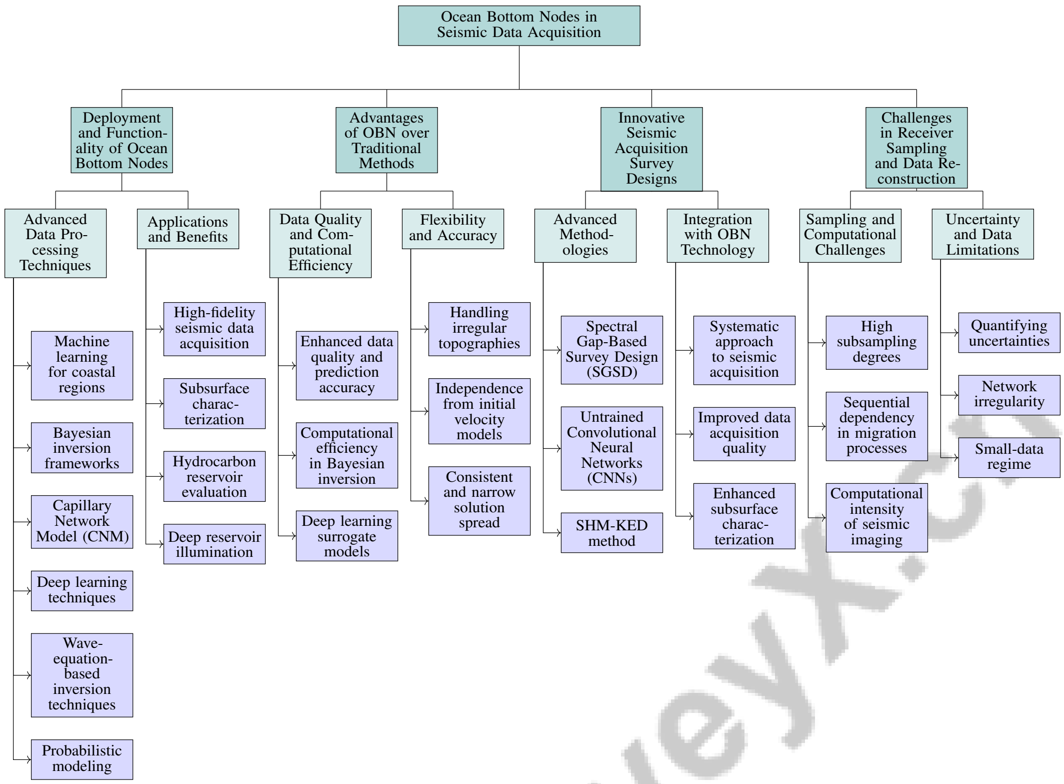


Figure 2: This figure illustrates the hierarchical structure of Ocean Bottom Nodes (OBNs) in seismic data acquisition, highlighting their deployment and functionality, advantages over traditional methods, innovative survey designs, and challenges in receiver sampling and data reconstruction. The diagram categorizes advanced data processing techniques, applications, and benefits of OBNs, as well as the integration of innovative methodologies with OBN technology to improve seismic data acquisition quality and reliability.

3.2 Advantages of OBN over Traditional Methods

OBNs surpass traditional seismic techniques, particularly in complex geological environments, by utilizing full seismic waveforms, which enhance data quality and prediction accuracy [6]. This capability improves subsurface imaging resolution and reservoir characterization. OBNs generate seismic data that aligns with subsurface processes like CO2 migration, enhancing monitoring and interpretation quality, vital for geological carbon storage [35].

As illustrated in Figure 3, the advantages of Ocean Bottom Nodes (OBN) over traditional seismic methods include enhanced data quality, computational efficiency, and flexibility in handling complex geological environments. Key technologies highlighted in the figure encompass the use of full seismic waveforms and Bayesian inversion frameworks, which contribute to improved data processing capabilities.

OBNs offer computational efficiency and higher acceptance rates in Bayesian inversion frameworks, improving computational demands and data processing capabilities compared to traditional methods [3]. They facilitate deep learning surrogate models, reducing computational costs and managing high-dimensional data effectively [36]. Improved segmentation accuracy through the use of unlabeled data minimizes human bias [1], complemented by self-supervised learning approaches that enhance noise suppression [37].

OBNs handle irregular topographies and are independent of initial velocity models, common limitations in traditional methods [38]. This flexibility allows for more accurate subsurface exploration in challenging environments. OBN technology results in a consistent and narrow spread of solutions in multi-objective optimization, indicating high confidence in parameter estimates and a clearer understanding of uncertainty, crucial for informed decision-making in subsurface exploration and reservoir evaluation [31].

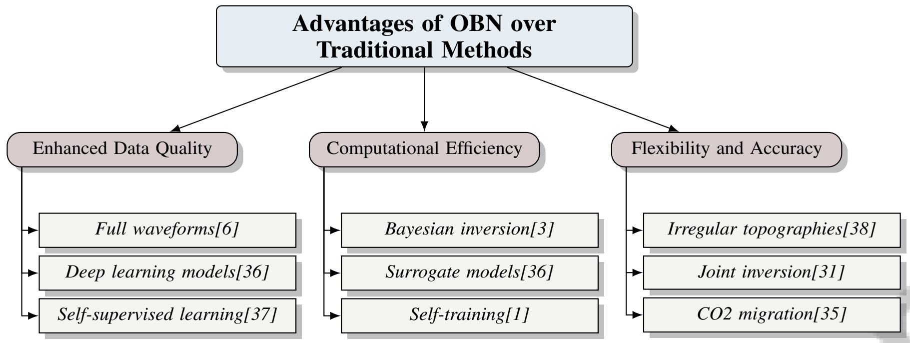


Figure 3: This figure illustrates the advantages of Ocean Bottom Nodes (OBN) over traditional seismic methods, highlighting enhanced data quality, computational efficiency, and flexibility in handling complex geological environments. Key technologies include the use of full seismic waveforms, Bayesian inversion frameworks, and the ability to manage irregular topographies and CO_2 migration effectively.

3.3 Innovative Seismic Acquisition Survey Designs

Innovative seismic acquisition survey designs improve data acquisition by incorporating advanced methodologies, particularly with OBN technology. The Spectral Gap-Based Survey Design (SGSD) optimizes seismic data acquisition by leveraging the spectral gap in sampling schemes [39]. Untrained Convolutional Neural Networks (CNNs) enhance adaptability to various imaging scenarios, providing robustness in complex geological settings [40]. The SHM-KED method, employing a hybrid Ensemble Smoother with Multiple Data Assimilation (ES-MDA) algorithm, improves reservoir modeling by integrating sparse data effectively [41].

Organizing methods into stages—exploration, drilling, production optimization, and reservoir management—highlights a systematic approach to seismic acquisition design [14]. Categorizing methods by application area and machine learning techniques provides a structured framework for implementing innovative survey designs leveraging OBN technology.

These advancements underscore the importance of integrating novel methodologies with OBN technology to enhance data acquisition processes. By optimizing sampling schemes and incorporating adaptive and hybrid techniques, these innovative seismic survey designs improve seismic data acquisition quality and reliability, leading to more accurate subsurface characterization and better hydrocarbon reservoir evaluation through methods like compressive sensing and low-rank matrix recovery. Deep learning approaches enhance seismic data resolution and artifact reduction, while machine learning algorithms facilitate effective subsurface structure analysis, enabling efficient reconstruction of under-sampled seismic data and robust uncertainty quantification [39, 42, 18, 43, 44].

3.4 Challenges in Receiver Sampling and Data Reconstruction

Receiver sampling and data reconstruction in seismic acquisition face challenges impacting subsurface exploration fidelity and reliability. Achieving adequate receiver sampling in ocean bottom acquisition is constrained by costs, leading to high subsampling degrees complicating wavefield reconstruction [45]. Sequential dependency of depth levels in migration processes hinders effective parallelization and data processing efficiency [46].

Seismic imaging's computational intensity complicates data reconstruction efforts. High-performance computing is essential to manage vast data volumes and algorithm complexity, often prohibitively expensive on traditional systems [47]. The exponential growth in convolutional kernel numbers with increasing pooling stages in deep networks leads to infeasible memory requirements, complicating receiver sampling and data reconstruction [48].

Quantifying uncertainties in seismic imaging presents another critical challenge due to high data dimensionality, necessitating extensive computational resources and sophisticated data management strategies [30]. The computational demands of evaluating forward models and extensive sampling for high-dimensional Gaussian random fields slow the convergence of Markov Chain Monte Carlo (MCMC) methods, complicating uncertainty incorporation into subsurface models [49].

Network irregularity, leading to spatial sampling aliasing and incomplete data, limits the utilization of acquired seismic data [50]. Existing methods struggle to capture complex, nonlinear relationships in well log data, necessitating extensive hyperparameter tuning and large training datasets [51].

The limited number of seismic sensors and high data acquisition costs result in a 'small-data regime' that restricts data-driven methods' generalizability and accuracy [12]. Existing wavefield reconstruction techniques may face challenges when data do not conform well to low-rank assumptions, limiting their effectiveness [52].

Addressing these challenges requires innovative computational methods and advanced modeling techniques. Developing distributed computing frameworks and efficient algorithms can alleviate the computational burdens of seismic data processing [47]. Leveraging data augmentation and transfer learning strategies can enhance the robustness and adaptability of data-driven models, improving performance in subsampled and irregularly sampled environments [45]. By tackling these challenges, seismic data acquisition and reconstruction can be significantly improved, enhancing the overall accuracy and reliability of subsurface exploration efforts.

4 Seismic Imaging Techniques

Category	Feature	Method
Technological Advancements in Seismic Imaging	Neural Network Architectures	DT[53], DLS-RTM[36]
Innovative Seismic Imaging Algorithms	Efficiency-Focused	AA[54]
Machine Learning and Deep Learning Approaches	Enhanced Neural Architectures	PINNtomo[38], U-Net+ResNet[55], DL-DCA[9], PNN-SI[56]
	Data Generation and Adaptation	cGAN-SBE[44], TLWR[45]
	Imaging and Analysis Techniques	WDP[57], DRT[16]
Optimization and Computational Efficiency	Optimization Techniques	TT[58], BL-FWI[59]
	Dynamic Resource Management	CTWS[60], S-RTM[61]
	Efficient Data Handling	RBC-RTM[62]
	Integration and Enhancement	NNLSM[63], RSS-FWI[64]
Noise Reduction and Signal Enhancement	Unsupervised Techniques	DD[23], UL1OT[65], SRA[66], SSDCN[37]
	Signal Quality Enhancement	DLOPy[67], LRRM[50]

Table 1: This table presents a comprehensive overview of the latest methods and techniques employed in seismic imaging, categorized into five key areas: technological advancements, innovative algorithms, machine learning and deep learning approaches, optimization and computational efficiency, and noise reduction and signal enhancement. Each category highlights specific features and methods, along with relevant references, illustrating the diverse strategies used to enhance the accuracy and efficiency of seismic data interpretation. The table serves as a valuable resource for understanding the integration of cutting-edge technologies in modern geophysical research.

The integration of emerging technologies with established methodologies has transformed seismic imaging, enhancing both accuracy and efficiency in subsurface exploration. Table 1 provides a detailed summary of the various methodologies and innovations in seismic imaging, emphasizing the role of machine learning and computational techniques in advancing subsurface exploration. Additionally, Table 5 offers a comparative overview of the various methodologies and innovations in seismic imaging, focusing on technological advancements, innovative algorithms, and machine learning approaches, and their impact on optimization and computational efficiency in subsurface exploration. This section explores the technological innovations that have driven these advancements, with a focus on machine learning and deep learning techniques that have significantly improved the resolution and reliability of seismic data. The following subsections highlight key technological innovations that have reshaped seismic imaging practices and their implications for contemporary geophysical research.

4.1 Technological Advancements in Seismic Imaging

Recent advancements have substantially improved seismic imaging resolution and accuracy through innovative methodologies and computational techniques. As illustrated in Figure 4, the key technological advancements in seismic imaging can be categorized into three main areas: deep learning methods, innovative inversion techniques, and frequency enhancement strategies. Each category encompasses specific methodologies that contribute to enhancing seismic imaging resolution and accuracy.

Deep learning algorithms enable direct extraction of velocity models from seismic data, addressing limitations of traditional methods like tomography and Full-Waveform Inversion (FWI) [53]. Encoder-decoder architectures efficiently map uncertain velocity fields to seismic images, reducing the computational burden associated with reverse time migration (RTM) [36].

Self-supervised learning, exemplified by SSDCN, enhances seismic imaging by leveraging self-similarity features to suppress noise in common reflection point (CRP) gathers [37]. This approach reduces data noise sensitivity, improving the clarity of seismic images essential for accurate subsurface characterization.

The Conditional Normalizing Flow Inversion method integrates data-driven priors with conventional physics-based inversion, enhancing robustness and reliability [33]. Predictive deep learning methods improve imaging quality in complex environments, such as salt formations, by overcoming traditional velocity model generation challenges [56]. Deep learning networks enhance seismic frequency across low and high ends, eliminating sidelobes and improving resolution, providing insights into complex geological formations [44].

The PINNtomo method addresses conventional seismic tomography limitations by accurately recovering long-wavelength features without relying on initial models [38]. These advancements in seismic imaging technologies, particularly through deep learning and machine learning integration, significantly enhance subsurface exploration accuracy and dependability. By expanding the frequency bandwidth of seismic data, these innovations yield high-resolution images that offer critical insights into complex geological formations. Automated image-focusing analysis and predictive neural networks facilitate velocity error identification and accurate model construction, advancing subsurface exploration technologies applicable in oil and gas exploration, environmental monitoring, and carbon sequestration [56, 68, 18, 34, 44].

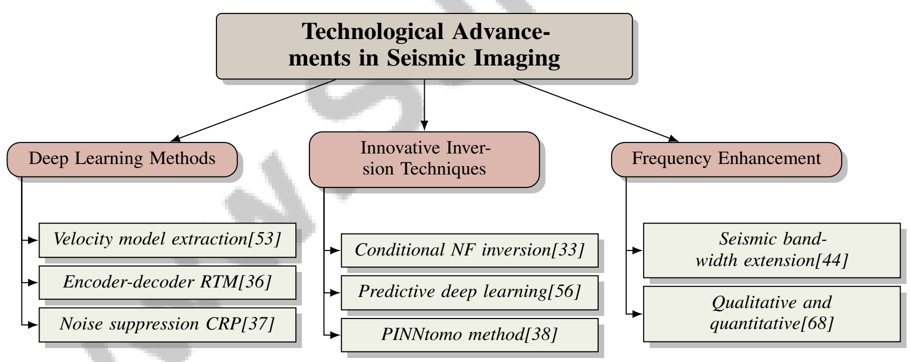


Figure 4: This figure illustrates the key technological advancements in seismic imaging, highlighting three main categories: deep learning methods, innovative inversion techniques, and frequency enhancement strategies. Each category encompasses specific methodologies that contribute to enhancing seismic imaging resolution and accuracy.

4.2 Innovative Seismic Imaging Algorithms

Advancements in seismic imaging algorithms have significantly enhanced the quality and efficiency of subsurface exploration. Neural network least squares migration (NNLSM) optimizes quasi-reflectivity images and quasi-migration Green's functions, offering a more efficient alternative to traditional least squares migration methods [63]. This approach improves seismic image resolution while reducing computational demands.

Integrating optimal transport distances into seismic data processing enhances the convexity of the Full-Waveform Inversion (FWI) problem, improving robustness [69]. Anderson acceleration enhances the steepest descent algorithm, significantly reducing computational costs and improving convergence rates in seismic inversion processes [54].

Generative Adversarial Networks (GANs) in seismic inverse modeling generate extensive datasets swiftly, providing a robust framework for model accuracy and uncertainty assessment [70]. A bilevel learning approach optimizes design parameters from training images, refining the FWI process and improving imaging quality [59].

A novel framework categorizing seismic imaging algorithms within the MapReduce paradigm emphasizes computational task parallelization, enhancing scalability and efficiency [47]. These innovative algorithms enhance capabilities by improving resolution, efficiency, and adaptability in subsurface exploration. Utilizing advanced deep learning techniques, these algorithms broaden the frequency bandwidth of seismic data, yielding higher resolution images that accurately reflect subsurface structures. This enhancement eliminates artifacts from seismic wavelets and integrates geo-spatial information from multiple wells, ensuring precise geological constraints during inversion. Additionally, applying image processing and computer vision methodologies aids in effectively analyzing seismic volumes, addressing interpretation challenges and facilitating reliable geological feature identification critical for oil and gas exploration, environmental monitoring, and carbon sequestration [44, 18].

4.3 Machine Learning and Deep Learning Approaches

Method Name	Modeling Techniques	Application Areas	Enhancement Strategies
U-Net+ResNet[55]	Cnn Architecture	Salt Body Delineation	Resnet Enhancements
DL-DCA[9]	Convolutional Neural Networks	Mineral Content Prediction	Transfer Learning
PINNtomo[38]	Physics-informed Neural Networks	Velocity Model Inversion	Physics-informed Regularization
PNN-SI[56]	Neural Network	Wavefield Reconstruction	Probabilistic Interpretations
WDP[57]	Cnns	Seismic Imaging	Weak Deep Prior
DRT[16]	Deep Learning	Rock Type Classification	Machine Learning Algorithms
TLWR[45]	Convolutional Neural Networks	Wavefield Reconstruction	Transfer Learning
cGAN-SBE[44]	Conditional Gan	Bandwidth Extension	Transfer Learning

Table 2: Overview of various machine learning and deep learning methods applied in seismic imaging, detailing their modeling techniques, application areas, and enhancement strategies. The table highlights the diverse approaches used to improve data quality and interpretability in geophysical studies.

Machine learning and deep learning techniques have significantly advanced seismic imaging, providing innovative solutions that enhance subsurface data quality and interpretability. Table 2 provides a comprehensive summary of machine learning and deep learning methodologies utilized in seismic imaging, illustrating their respective modeling techniques, application areas, and enhancement strategies. Generative Adversarial Networks (GANs) align models with geological knowledge and seismic data, facilitating more accurate inversion [70]. Convolutional Neural Networks (CNNs), combined with architectures like U-Net and ResNet, automate geological feature delineation, such as salt bodies, enhancing characterization accuracy and efficiency [55]. CNNs also predict mineral content and lithology from visual data, showcasing versatility in geophysical applications [9].

The PINNtomo method integrates physics-informed neural networks in seismic imaging, approximating traveltime factors and velocity fields while enforcing regularization based on the eikonal equation [38]. Predictive neural networks generating salt body probability cubes provide valuable initialization and regularization tools for FWI, improving convergence and model accuracy [56].

Innovative strategies like the weak deep prior method enable flexibility by allowing deviations from CNN outputs according to a Gaussian distribution, facilitating rapid updates without the forward operator [57]. The DRT method employs advanced digital imaging and machine learning techniques to accurately characterize complex rock textures and properties [16].

Transfer learning enhances CNN training efficiency for reconstructing wavefields from subsampled seismic data, leveraging information from neighboring frequency slices to improve accuracy [45]. Deep learning architectures improve seismic data by learning correlations between well log data and seismic traces, enhancing resolution and clarity [44]. Conditional normalizing flows applied in inversion processes capture the conditional distribution of unknowns given observed data, providing a robust approach to inversion [33].

Method Name	Computational Techniques	Optimization Strategies	Technological Integration
BL-FWI[59]	Bilevel Learning Approach	Bilevel Optimization Framework	Supervised Learning Strategy
NNLSM[63]	Gradient Descent Methods	Sparsity Regularization	Convolutional Neural Networks
RSS-FWI[64]	Randomized Sketching Techniques	Projected Source Optimization	Random Sketching Matrix
TT[58]	Time-tiling	Auto-tuner Determining	-
CTWS[60]	Mpi One-sided Communication	Cyclic Token-based	-
S-RTM[61]	Serverless Architecture	Resource Usage Optimization	Serverless Computing
RBC-RTM[62]	Random Boundary Conditions	Parameter Optimization	Advanced Technologies

Table 3: This table presents a comprehensive overview of various methods employed in seismic imaging, detailing the computational techniques, optimization strategies, and technological integrations utilized in each approach. The methods include bilevel learning, convolutional neural networks, randomized sketching, and serverless computing, each contributing to enhanced efficiency and accuracy in geophysical exploration.

4.4 Optimization and Computational Efficiency

Optimization and computational efficiency are crucial in seismic imaging due to vast data volumes and complex computations inherent in modern geophysical exploration. High-order methods enable larger time steps, reducing computational costs and enhancing efficiency [71]. Bilevel learning methods optimize design parameters by learning from training data, directly influencing the quality of reconstructions [59].

Integrating deep convolutional neural networks (CNNs) with sparse least squares migration, as seen in NNLSM, reduces computational costs while enhancing denoising capabilities [63]. Randomized source sketching methods maintain essential data features while reducing computational burdens, facilitating faster convergence [64].

Time-tiling, a loop nest optimization technique, partitions computations across time iterations to exploit data locality, improving runtime efficiency [58]. The CTWS method exemplifies dynamic task distribution, adjusting based on real-time workload to minimize idle times and enhance execution speed [60].

Serverless computing frameworks, such as the serverless Reverse Time Migration (RTM) workflow, reduce operating costs by leveraging cloud computing resources to dynamically scale processing power [61]. The Random Boundary Conditions Reverse Time Migration (RBC-RTM) method enhances efficiency by reconstructing the forward-propagated wavefield while minimizing storage needs [62].

Table 3 provides a detailed comparison of different methods used in seismic imaging, highlighting their computational techniques, optimization strategies, and technological integrations to enhance efficiency and effectiveness in subsurface exploration. These optimization strategies and computational techniques enhance the efficiency and effectiveness of seismic imaging, enabling more accurate and timely subsurface exploration. By integrating state-of-the-art computational methods, such as deep learning models and convolutional neural networks, with innovative modeling techniques, recent advancements in seismic imaging are expected to significantly enhance both the quality and reliability of subsurface structure analysis. These methods improve the frequency bandwidth of seismic data, increasing resolution and reducing artifacts, and automate seismic image focusing analysis for accurate velocity error estimation. This comprehensive approach allows for more precise geological feature interpretation, ultimately benefiting applications in environmental monitoring, carbon sequestration, and oil and gas exploration [44, 18, 34].

4.5 Noise Reduction and Signal Enhancement

Noise reduction and signal enhancement are fundamental in seismic data processing, directly influencing the accuracy and reliability of subsurface exploration. Noise contamination adversely affects the signal-to-noise ratio (SNR), critical for subsequent analyses [23]. Effective noise suppression techniques are essential for improving data quality, particularly near-surface sensors where strong noise disturbances are prevalent [66]. Table 4 provides a comprehensive overview of the methods employed for noise reduction and signal enhancement in seismic data processing, illustrating their application contexts and the resultant benefits in improving data quality and signal clarity.

Method Name	Techniques Used	Application Context	Outcome Benefits
DD[23]	Deep Neural Network	Seismic Imaging	Snr Improvements
SRA[66]	Autoencoder Neural Network	Near-surface Sensors	Improved Data Quality
UL1OT[65]	Proximal Splitting Algorithms	Seismic Imaging Applications	Improved Data Quality
DLOPy[67]	Bootstrap Method	Obs Deployments	High Accuracy
LRRM[50]	Rank-reduction Method	Seismic Imaging	Improved Data Quality
SSDCN[37]	Bernoulli Sampling	Crp Gathers	Enhanced Signal-to-noise

Table 4: Summary of various noise reduction and signal enhancement methods utilized in seismic data processing, detailing the techniques employed, application contexts, and outcome benefits. The table highlights the diverse approaches and their effectiveness in improving signal-to-noise ratio and data quality across different seismic imaging applications.

Unsupervised machine learning frameworks have emerged as promising solutions for denoising seismic datasets, enhancing SNR and improving data quality [66]. These frameworks learn from data without labeled examples, providing robust noise removal solutions in complex geological settings. Advanced algorithms like the unbalanced L^1 optimal transport method address cycle-skipping issues, refining imaging processes [65].

In marine seismic imaging, understanding and mitigating fold caustics are critical for enhancing signal quality. Novel approaches incorporating FIO calculus address these challenges, yielding clearer and more accurate images [72]. Effective orientation measurement techniques, such as DLOPy, account for lateral refraction and uneven geographical data coverage, enhancing signal quality [67].

The Local Rank Reduction Method (LRRM) improves reconstruction of missing traces while preserving small-scale features, resulting in superior data quality compared to traditional global methods [50]. This is crucial for maintaining data integrity and ensuring accurate subsurface characterizations.

Noise suppression in seismic data processing remains a critical research focus, as it directly influences subsequent imaging and reservoir prediction effectiveness [37]. By implementing advanced noise reduction and signal enhancement techniques, clarity and reliability of seismic data can be significantly improved, facilitating more accurate and efficient subsurface exploration.

Feature	Technological Advancements in Seismic Imaging	Innovative Seismic Imaging Algorithms	Machine Learning and Deep Learning Approaches
Optimization Approach	Deep Learning Integration	Neural Network Optimization	Generative Models
Computational Efficiency	Improved Accuracy	Enhanced Scalability	Automated Feature Delineation
Application Area	Subsurface Exploration	Model Accuracy	Geophysical Applications

Table 5: This table provides a comparative analysis of the key features across three primary areas of seismic imaging: technological advancements, innovative algorithms, and machine learning approaches. It highlights the optimization approaches, computational efficiency, and application areas pertinent to each category, demonstrating the integration of deep learning and innovative computational techniques in enhancing seismic imaging capabilities. The table serves as a comprehensive overview, underscoring the significant contributions of these methodologies to subsurface exploration and geophysical research.

5 Reservoir Prediction and Evaluation

The exploration of reservoir prediction and evaluation involves integrating diverse methodologies and technologies to enhance subsurface assessment accuracy. Central to this is the advancement of seismic imaging techniques, foundational for effective reservoir characterization. This section examines significant progress in seismic imaging and velocity model building, highlighting their contributions to improved reservoir prediction capabilities.

5.1 Advancements in Seismic Imaging and Velocity Model Building

Recent advancements in seismic imaging have improved velocity model accuracy, crucial for predicting hydrocarbon reservoirs. Integrating data-driven and physics-based approaches, such as the PINNtomo method, enhances velocity model resolution using physics-informed regularization with the eikonal equation [38]. This method constrains the inversion problem, improving subsurface characterizations. Full Waveform Inversion (FWI) faces challenges with initial velocity model sensitivity, potentially leading to local optima [56]. Bayesian inversion techniques have advanced lithology and fluid prediction, enhancing velocity model accuracy [3].

Machine learning approaches leveraging structural relationships between seismic and well log data facilitate accurate bandwidth extension without compromising geological fidelity [44]. These methods enhance geological feature delineation and velocity model precision. Traditional petrographic analysis inefficiencies for carbonate rocks have been addressed through advanced imaging techniques and machine learning models, automating analysis and improving exploration efficiency [4]. Optimization algorithms like TunaOil reduce history matching workflow runtime by 31

To illustrate these advancements, Figure 5 categorizes recent innovations in seismic imaging into three main approaches: data-driven methods, physics-based methods, and optimization techniques. This figure highlights the key methodologies and innovations in each category, providing a visual representation of how these advancements collectively enhance reservoir prediction methodologies. By incorporating advanced computational techniques and machine learning algorithms, the accuracy and efficiency of subsurface structure analysis are significantly improved. Enhanced seismic data through deep learning models broadens frequency bandwidth, leading to higher resolution imaging and reliable geological feature identification, while allowing comprehensive uncertainty assessments [44, 18].

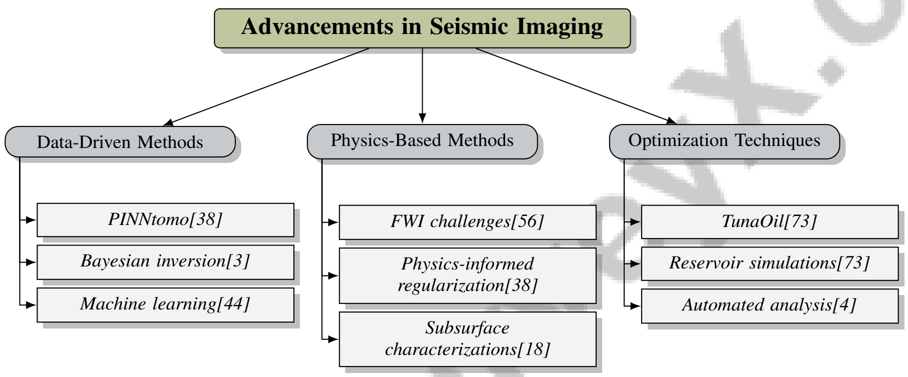


Figure 5: This figure illustrates the recent advancements in seismic imaging by categorizing them into data-driven methods, physics-based methods, and optimization techniques, highlighting key methodologies and innovations in each category.

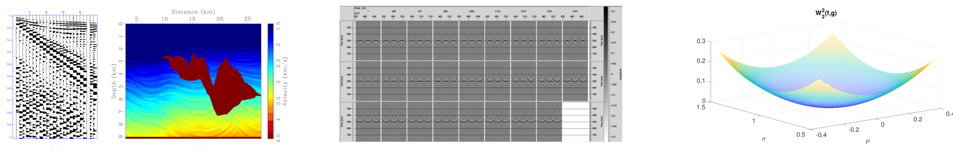
5.2 Optimization Techniques in Seismic Data Interpretation

Optimization techniques in seismic data interpretation enhance reservoir prediction accuracy and efficiency. Deep learning methods like Deep-Tomography iteratively refine velocity estimates, improving model resolution and accuracy [53]. Anderson acceleration reduces gradient evaluations for convergence, outperforming traditional methods in seismic inversion [54]. This enhances computational efficiency, making seismic data interpretation feasible for large-scale applications.

Generative Adversarial Networks (GANs) reconstruct missing data and evaluate authenticity, improving data reconstruction robustness and seismic imaging quality [42]. Autoencoder neural networks with sparsity constraints suppress noise while preserving signal characteristics, vital for accurate seismic interpretation [66]. The Constant Variable-Density Inverse method optimizes data interpretation by minimizing errors and enhancing model accuracy [74].

The Random Boundary Conditions Reverse Time Migration (RBC-RTM) method reduces execution time and storage requirements, optimizing seismic imaging processes [62]. Tile sizes and skewing factors in finite difference methods, determined by an auto-tuner, optimize runtime performance, ensuring efficient computational resource use [58].

These optimization techniques advance seismic data interpretation for reservoir prediction, employing innovative machine learning and deep learning algorithms. They enhance accuracy, efficiency, and reliability by improving seismic imaging resolution, broadening frequency bandwidth, and effectively analyzing subsurface structures. Integrating advanced image processing techniques and geo-spatial information facilitates reliable geological feature identification, contributing to better decision-making in applications like oil and gas exploration and carbon sequestration [44, 18].



(a) Seismic Wavefield and Velocity Profile[75]

(b) Time-Resolved Spectrograms of a Single-Mode Fiber[76]

(c) W2(f,g)[77]

Figure 6: Examples of Optimization Techniques in Seismic Data Interpretation

As shown in Figure 6, optimization techniques enhance reservoir prediction and evaluation in seismic data interpretation. The figure illustrates three examples: "Seismic Wavefield and Velocity Profile" offers a dual perspective on wave propagation and velocity mapping, aiding comprehensive understanding of wave dynamics and subsurface interactions. "Time-Resolved Spectrograms of a Single-Mode Fiber" highlights temporal signal response resolution, applicable to seismic data temporal analysis. "W2(f,g)" uses a color gradient to visualize optimization results, emphasizing optimization efficacy areas. These examples underscore diverse optimization technique applications, offering enhanced precision and reliability in reservoir evaluation [75, 76, 77].

5.3 Handling Complex Geological Features in Reservoir Prediction

Addressing complex geological features in reservoir prediction requires advanced methodologies for accurate seismic data interpretation amidst internal multiples and evanescent waves. Traditional techniques struggle with velocity variations and complexity from evanescent energy, leading to inaccuracies [78]. Innovative methods like propagator transfer matrices and Marchenko imaging incorporate internal multiples and evanescent waves, enhancing seismic imaging accuracy in complex settings [79].

These advanced techniques provide comprehensive subsurface understanding, particularly in geologically complex regions. By accounting for the full wavefield, including primary and multiple reflections, they offer a detailed subsurface representation. Automating image-focusing analysis with convolutional neural networks enhances reservoir prediction reliability by accurately identifying and characterizing geological features obscured by traditional methods. This approach corrects velocity errors in seismic images and improves subsurface structure interpretation, leading to better potential reservoir location delineation and geological deformation event monitoring [80, 44, 18, 34].

Machine learning models enhance complex subsurface structure interpretation by processing large datasets to uncover patterns imperceptible to human analysts. This capability is valuable in environmental monitoring, carbon sequestration, and oil and gas exploration, where accurate geological feature identification is crucial for decision-making and resource management. By leveraging algorithms from image processing and computer vision, researchers improve subsurface evaluation accuracy and efficiency, addressing seismic interpretation challenges and facilitating better predictions in complex geological environments [9, 21, 18, 22, 14]. These models enhance reservoir characteristic prediction by incorporating diverse geological and geophysical data, improving reservoir evaluation accuracy and reliability.

Overall, these advanced strategies are essential for managing challenges posed by complex geological features in reservoir prediction. Utilizing advanced imaging and machine learning algorithms, geophysicists can enhance subsurface characterizations' accuracy and reliability. This improvement facilitates precise geological structure identification, such as faults and potential hydrocarbon reservoirs, and addresses critical seismic interpretation challenges. Integrating these technologies allows better velocity error modeling, improved seismic data frequency bandwidth, and effective hydrocarbon-collecting rock formation predictions, leading to informed hydrocarbon reservoir evaluations [56, 21, 18, 34, 44].

Benchmark	Size	Domain	Task Format	Metric
HORK[71]	1,000,000	Seismic Imaging	Wave Propagation	Convergence, Dispersion Error
SRDB[27]	1,520,000	Digital Rock Physics	Image Reconstruction	PSNR, SSIM
MD-Bench[13]	50,000	Dialogue Systems	Multi-turn Dialogue Evaluation	Coherence Score, User Satisfaction Rate
RF-ML[81]	19,000	Petroleum Engineering	Regression	RMSE, CD

Table 6: This table presents a selection of representative benchmarks utilized in various domains such as seismic imaging, digital rock physics, dialogue systems, and petroleum engineering. Each benchmark is characterized by its size, domain, task format, and the specific metrics used for evaluation, offering a comprehensive overview of the diverse applications and evaluation criteria within these fields.

5.4 Uncertainty Quantification and Its Implications for Reservoir Evaluation

Uncertainty quantification is crucial in reservoir evaluations, influencing decision-making in hydrocarbon exploration and carbon storage. Advanced computational techniques, such as variational Bayesian inference using deep generative models, effectively capture subsurface structure complexities while accounting for uncertainties [3]. These methods provide a rigorous uncertainty assessment framework, enhancing reservoir characterization reliability.

Accounting for uncertainties in thermodynamic parameters is essential in modeling CO2 generation in deep sedimentary formations, requiring precise parameter estimation for accurate predictions [5]. Methods like SSDCN demonstrate high-fidelity noise reduction in seismic data, crucial for accurate uncertainty quantification [50]. Deep learning surrogate models provide quantified uncertainty in seismic images, addressing reservoir evaluation uncertainty quantification challenges [36].

The proposed seismic imaging workflow enhances the process by providing a reliable initial velocity model and regularization through the salt probability cube, improving convergence and subsurface imaging accuracy [56]. However, limitations include sensitivity to poor seismic-well ties and the need for diverse lithology in training data to avoid output bias [44].

The DRT algorithm effectively classifies rock types in logging and core domains, using the CAMO chart to link permeability, porosity, and pore throat networks [16]. This capability improves reservoir evaluation accuracy by providing detailed rock property insights.

Quantifying imaging process uncertainties and propagating them to horizon tracking provides systematic risk assessment [15]. Future research should focus on quantifying uncertainty through proposed regularization techniques and exploring further enhancements [33].

Integrating advanced computational techniques and incorporating uncertainty quantification into modeling processes significantly improve reservoir evaluations' accuracy and dependability. This integration addresses uncertainty sources in seismic imaging, such as data measurements and subsurface geophysical properties, critical for informed hydrocarbon exploration and development decision-making. The proposed workflow leverages Bayesian tomography and reverse time migration, employing a hybrid parallel computational strategy to enhance efficiency and reduce execution time. High data compression levels facilitate effective data management, ensuring uncertainty quantification doesn't compromise seismic imaging result integrity. These innovations enable robust subsurface condition assessments, supporting better strategic resource management choices [30, 32].

As illustrated in Figure 7, the hierarchical structure of uncertainty quantification approaches in reservoir evaluation encompasses advanced computational techniques, seismic imaging enhancements, and rock typing methods. This visual representation underscores the interconnectedness of these elements, reinforcing the importance of a comprehensive approach to uncertainty quantification in the field. Additionally, Table 6 provides a detailed overview of representative benchmarks in different domains, highlighting their size, task format, and evaluation metrics, which are integral to the discussion on uncertainty quantification in reservoir evaluation.

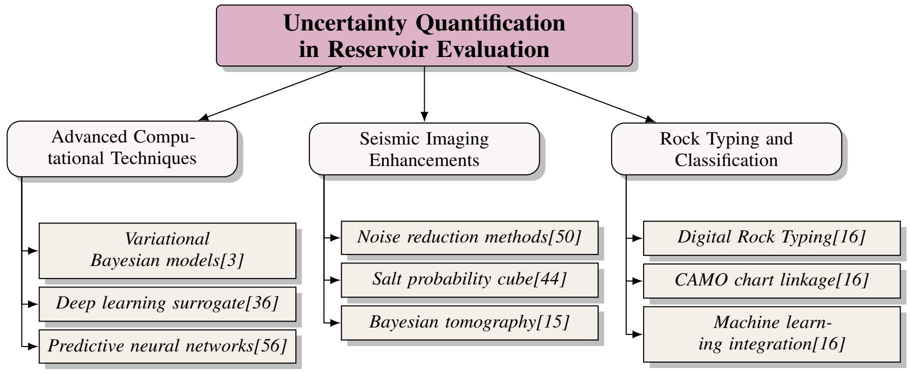


Figure 7: This figure illustrates the hierarchical structure of uncertainty quantification approaches in reservoir evaluation, focusing on advanced computational techniques, seismic imaging enhancements, and rock typing methods.

6 Characterization of Carbonate Reservoirs

6.1 Challenges in Carbonate Reservoir Characterization

The characterization of carbonate reservoirs presents significant challenges due to their inherent heterogeneity and complex pore structures. Traditional methods often fail to capture the diverse textures and compositions within these reservoirs, which can vary significantly even within a single formation. The limited integration of digital advancements further exacerbates these issues, as existing techniques inadequately characterize the intricate textures of heterogeneous carbonate formations [16]. A critical limitation is the reliance on relatively small training datasets, which hampers the generalizability and performance of models when applied to unseen carbonate types [4]. This challenge is intensified by the high costs and computational demands of traditional optimization methods, necessitating numerous simulations to identify optimal parameter configurations, thereby increasing resource requirements for characterization [73].

Spatial variability in carbonate reservoirs complicates the extrapolation of findings across different geological formations. Data quality variability, particularly in seismological datasets with low signal-to-noise ratios, can lead to model overfitting and data scarcity issues, restricting the accuracy and effectiveness of predictive models. This is especially pertinent in fields like petroleum engineering, where machine learning techniques are increasingly employed for reservoir characterization and hydrocarbon recovery estimation [14, 73, 66, 81]. Furthermore, the high degree of heterogeneity within carbonate formations complicates the accurate prediction of fluid flow dynamics, crucial for effective reservoir management.

Addressing these challenges requires developing advanced imaging techniques and sophisticated modeling approaches capable of capturing the complex dynamics of carbonate reservoirs. Incorporating real-time data processing and leveraging cutting-edge digital innovations can significantly improve the accuracy and reliability of carbonate reservoir characterizations. Deep-learning models that interpret seismic data facilitate precise identification of geological features, such as sand thickness and lithology distribution. Additionally, spatio-temporal neural networks enable high-fidelity seismic imaging, allowing effective monitoring of fluid dynamics in subsurface reservoirs, essential for optimizing exploration and development strategies. The integration of machine learning and image processing minimizes estimation errors and supports real-time monitoring and forecasting, ultimately leading to more informed decision-making in resource management [18, 22, 35, 80, 44].

6.2 Advanced Imaging and Inversion Techniques

Advanced imaging and inversion techniques have significantly enhanced the characterization of carbonate reservoirs by providing accurate and detailed insights into their complex geological properties. The integration of physics-informed neural networks (PINNs) exemplifies a cutting-edge approach that efficiently solves partial differential equations (PDEs), ensuring that the physical laws governing subsurface processes are respected, thus leading to more reliable characterizations

[11]. Quantum annealing in seismic inversion represents a novel technique that optimizes the inversion process, enhancing the resolution and accuracy of subsurface models for effective reservoir evaluations [7].

The Image Resolution Optimized Gaussian Algorithm (IROGA) and Machine Learning Difference of Gaussian Random Forest (MLDGRF) have introduced significant advancements in determining porosity and lithology within carbonate formations, achieving accuracy rates of 96.2

Digital Rock Typing (DRT) employs machine learning algorithms to classify carbonate rock types by analyzing digital images, focusing on pore throat networks, thereby enabling more precise characterization of carbonate formations [16]. The development of generalizable surrogate models across various survey areas remains a critical area for future research, incorporating realistic physical modeling to improve imaging and inversion techniques in diverse geological settings [82]. The integration of advanced imaging and inversion techniques, including deep learning models and automated image analysis, significantly enhances the characterization of carbonate reservoirs. These methods improve the resolution and accuracy of seismic data by broadening frequency bandwidths and eliminating artifacts, while enabling comprehensive petrographic analysis through automated classification of rock types. Consequently, geoscientists can obtain detailed insights into the geological properties of carbonate formations, including depositional environments and reservoir quality, facilitating more reliable assessments of hydrocarbon potential and other economic resources [4, 44, 22, 34]. By integrating innovative computational methods and machine learning approaches, these techniques promise to further enhance the precision and reliability of subsurface exploration efforts.

6.3 Role of Microstructural Analysis and Digital Imaging

Microstructural analysis and digital imaging play a crucial role in enhancing the understanding of carbonate reservoirs by providing detailed insights into their complex geological properties. The application of convolutional neural networks (CNNs) to micro-CT images has significantly improved the speed and accuracy of lithological classification within carbonate rocks, enabling efficient differentiation of rock types essential for accurate reservoir characterization [83]. The integration of advanced imaging techniques, such as IROGA and MLDGRF, has demonstrated high accuracy in determining porosity and lithology within carbonate formations, achieving accuracy rates of 96.2

Standardized approaches like DLOPy are crucial for determining instrument orientations in ocean-bottom seismometers, ensuring accurate seismic data acquisition necessary for understanding carbonate reservoirs [67]. Microstructural analysis benefits from integrating genetic expression programming (GEP), which utilizes porosity and P-wave velocity as predictive indices for estimating unconfined compressive strength (UCS), explaining 95

Leveraging these advanced techniques, microstructural analysis and digital imaging significantly contribute to the precise characterization of carbonate reservoirs, facilitating more effective exploration and development strategies.

7 Geophysical Methods in Subsurface Exploration

7.1 Integration of Geophysical Methods in Subsurface Exploration

The integration of diverse geophysical methods is crucial for enhancing subsurface exploration, particularly in hydrocarbon reservoir identification. By combining seismic reflection, refraction, magnetic and gravitational measurements, and well log data, geophysicists gain a comprehensive understanding of subsurface formations. This approach aids in identifying geological structures such as faults and potential reservoirs, with advanced image processing, machine learning, and deep learning techniques improving data resolution and accuracy [29, 18, 44]. Techniques like Differential Imaging and Direct Numerical Simulation capture distinct flow characteristics across various pore sizes, providing insights into complex geological settings [84]. Fully invertible networks enhance large dataset processing without losing critical information, improving subsurface model reliability [48]. Methods such as weighted least-squares variable density pseudo-inverse Born modeling yield more accurate predictions, while versatile parametric classes of covariance enhance modeling flexibility [74, 28]. Localized 3D-FFT and multi-dimensional spectral projections facilitate saliency map computations, integrating domain knowledge through directional comparisons [85].

Time-tiling optimizations within Devito further enhance performance, streamlining data processing [58]. Utilizing historical data for parameter tuning, as demonstrated by TunaOil, enables faster simulations without sacrificing quality [73]. The integration of geophysical methods and innovative computational techniques significantly enhances subsurface exploration precision and reliability, facilitating effective seismic interpretation and improving operational decision-making through anomaly detection [29, 18, 34, 51, 44].

7.2 Innovations in Seismic Data Processing

Innovations in seismic data processing have significantly improved exploration outcomes by enhancing the accuracy and adaptability of subsurface imaging techniques. The RBC-RTM method enables faster processing with reduced computational demands, critical for efficient seismic data analysis [62]. Physics-Informed Neural Networks (PINNs) enhance geophysical data processing by integrating physical laws, leading to improved exploration outcomes [11]. The OPESCI-FD framework automates code generation, minimizing manual errors and improving efficiency [86]. Transfer learning applied to seismic data processing, especially in large-scale ocean bottom node deployments, enhances training speed and reconstruction performance [45]. Randomized source sketching methods optimize PDE solves, reducing mean squared error between estimated and true models, streamlining computational efforts [64]. Conditional Generative Adversarial Networks (GANs) generate synthetic seismic traces from well log data, extending seismic frequency bandwidth [44]. Eigenvector model descriptors, used in solving diffusion equations within synthetic models, illustrate advancements in seismic data processing [87]. These advancements, particularly through machine learning and deep learning integration, transform seismic data processing, enhancing accuracy and resolution in seismic imaging, facilitating detailed characterization of hydrocarbon reservoirs, and supporting exploration and environmental applications [44, 18].

7.3 Advanced Computational Methods

Advanced computational methods are pivotal in geophysical data analysis, improving efficiency, accuracy, and adaptability in seismic imaging processes. The integration of idempotent operators stabilizes imaging techniques, enhancing seismic data interpretation reliability [78]. The ESPG algorithm exemplifies efficient sparse seismic imaging, recovering images while estimating the source wavelet, reducing computational demands [88]. Advanced activation functions, such as the swish function, improve convergence and accuracy in solving the Helmholtz equation, crucial for seismic imaging [89]. Stochastic waveform inversion methods combining deep generative models with variational Bayesian inference provide a robust framework for approximating subsurface parameters, enhancing seismic data interpretation [90]. The randomized source sketching method significantly reduces seismic data processing costs, enhancing feasibility for large-scale geophysical analyses [64]. By automating processes like image-focusing analysis and employing sophisticated denoising frameworks, researchers achieve higher resolution seismic data that accurately reflects geological conditions, leading to more informed decision-making in subsurface exploration and resource management [47, 66, 18, 34, 44].

7.4 Hybrid and Multidisciplinary Approaches

Hybrid and multidisciplinary approaches in subsurface exploration yield significant benefits by integrating diverse methodologies and leveraging various scientific disciplines. Combining advanced image processing techniques and machine learning algorithms enhances subsurface characterizations' accuracy and reliability, particularly in complex geological environments, by improving seismic interpretation and automating velocity error analysis [32, 18, 84, 34]. Hybrid methods create a comprehensive framework for analyzing subsurface formations, leading to informed decision-making in hydrocarbon exploration and reservoir management. Concurrent use of various geophysical techniques, including seismic, magnetic, and gravitational surveys, enhances subsurface structure interpretation by providing complementary data, improving accuracy in identifying critical geological features [29, 18, 34]. Future research should focus on developing intuitive uncertainty modeling methods that prioritize decision-making relevance and explore emerging trends in computational techniques and interdisciplinary applications [32]. Embracing hybrid and multidisciplinary approaches enables geophysicists to achieve more accurate and reliable subsurface characterizations, enhancing exploration efficiency and effectiveness.

7.5 Geophysical Methodologies for Anomaly Detection

Anomaly detection in geophysical data is crucial for subsurface exploration, enhancing the understanding of geological structures and identifying potential hydrocarbon reservoirs. Techniques such as machine learning, image processing, and probability tomography improve seismic interpretation accuracy, enabling the detection of anomalies like drilling hazards and unexpected geological formations. These innovations facilitate reliable delineation of subsurface features, supporting environmental monitoring and carbon sequestration by identifying suitable geological traps with minimal leakage risk [51, 24, 18, 34]. Machine learning algorithms are increasingly employed in anomaly detection within geophysical exploration, identifying patterns and irregularities in large datasets, effectively handling complex, nonlinear relationships in geophysical data [51]. Integrating seismic, magnetic, and gravitational survey data provides a comprehensive framework for anomaly detection, as each method contributes unique insights into subsurface structures [25]. Advanced computational techniques, such as deep learning models and physics-informed neural networks (PINNs), enhance anomaly detection by incorporating physical laws into data analysis, ensuring detected anomalies align with geological principles [11]. Digital rock imaging and machine learning-based image analysis facilitate the identification of microstructural anomalies, providing insights into subsurface rock formation properties [16]. Anomaly detection enhances exploration effectiveness and informs resource extraction strategies, with recent advancements, including transformer-based models for borehole well log data analysis, demonstrating high predictive accuracy in detecting subtle anomalies, improving decision-making and risk reduction in subsurface exploration [51, 18, 21, 34].

8 Conclusion

The integration of Ocean Bottom Nodes (OBN) with advanced geophysical methodologies has markedly improved the precision and reliability of subsurface exploration, offering significant advantages over traditional techniques. OBN technology enables the acquisition of high-fidelity seismic data, providing detailed insights into subsurface formations that are crucial for the accurate identification and evaluation of hydrocarbon reservoirs. The methodologies discussed have demonstrated enhanced predictive capabilities for hydrocarbon collector reservoirs, with notable improvements in seismic interpretation achieved through advanced image processing and machine learning techniques. The successful application of Bayesian inversion techniques for lithology and fluid prediction underscores the potential for further research, particularly in complex geological settings.

Recent developments in seismic imaging, such as high-order exponential integrators and GAN-based seismic inverse modeling, have significantly advanced the accuracy and efficiency of seismic applications. These innovations contribute to improved model quality and uncertainty reduction, effectively bridging the gap between geophysical data and geological understanding. The proposed methods for uncertainty quantification in seismic imaging and horizon tracking offer systematic derivations of confidence intervals that accurately reflect data-driven uncertainties, thereby enhancing the reliability of subsurface characterizations.

Future research should focus on developing versatile models that can adapt to various geological conditions, improving data quality and exploring the integration of artificial intelligence with emerging technologies like the Internet of Things (IoT). Additionally, refining models to incorporate variable reaction rates and enhancing the representation of spatial heterogeneity could further improve predictive capabilities for practical applications. A paradigm shift in modeling approaches is necessary to better understand and quantify uncertainty, thereby informing geo-engineering decisions.

The continuous advancement of OBN technology and geophysical methods promises to further enhance the precision and reliability of subsurface exploration. By harnessing these innovations, geophysicists can gain more accurate and comprehensive insights into subsurface formations, ultimately supporting informed decision-making in hydrocarbon resource exploration and development. Future research directions may include refining the MARS model and FFT techniques and exploring their applications across diverse geological environments.

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