
CO₂ Prediction and Reservoir Characterization in Pre-salt Carbonates of the Santos Basin: A Survey

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Abstract

This survey presents an in-depth analysis of CO₂ prediction and reservoir characterization within the pre-salt carbonate formations of the Santos Basin, Brazil. Emphasizing the integration of geophysical methods and multi-attribute analysis, the study highlights advanced seismic inversion techniques, such as the ADDIN-I method, which enhance impedance prediction accuracy crucial for understanding subsurface properties. Electromagnetic modeling and joint inversion approaches further bolster CO₂ detection capabilities by integrating diverse datasets, thereby improving model robustness. The incorporation of deep learning, including conditional generative adversarial networks and recurrent neural networks, significantly improves geophysical data analysis accuracy and efficiency, aligning with economic and environmental objectives. Multi-attribute analysis, through seismic attributes integration, provides a comprehensive understanding of reservoir properties, facilitating the identification of geological features influencing CO₂ storage. Advanced analytical techniques, like the SFA-GTM method, enhance seismic data interpretation, contributing to more accurate reservoir models. Geological modeling approaches, supported by geostatistical and Bayesian methods, offer robust frameworks for capturing the complexities of pre-salt carbonates, optimizing resource extraction and CO₂ storage strategies. The survey underscores challenges in data quality, technological limitations, and uncertainty in CO₂ storage, advocating for future research to enhance predictive capabilities through network architecture refinement, parameter selection automation, and advanced monitoring systems integration. These advancements aim to achieve sustainable and efficient resource management practices, supporting economic growth and environmental protection.

1 Introduction

1.1 Significance of CO₂ Prediction and Reservoir Characterization

The prediction of CO₂ presence and characterization of reservoirs in the pre-salt carbonates of the Santos Basin carry significant economic and environmental implications. Accurate subsurface velocity field predictions are essential for seismic processing, which directly influences reservoir characterization and hydrocarbon volume calculations, impacting economic viability and environmental considerations [1]. Classifying water saturation from seismic attributes enhances reservoir characterization accuracy, leading to improved resource management [2]. A comprehensive quantitative approach is vital for understanding the spatial and temporal distribution of depositional and diagenetic aspects in these reservoirs, crucial for effective CO₂ prediction and characterization [3].

Precise lithology discrimination is critical for minimizing errors in permeability and hydrocarbon volume predictions, directly affecting fluid flow properties essential for efficient resource extraction and management [4]. Integrating geophysical and well-log data is emphasized to develop comprehensive and reliable reservoir models that address the complexities of pre-salt carbonate formations [5]. The urgent need to mitigate greenhouse gas emissions and combat climate change further underscores the

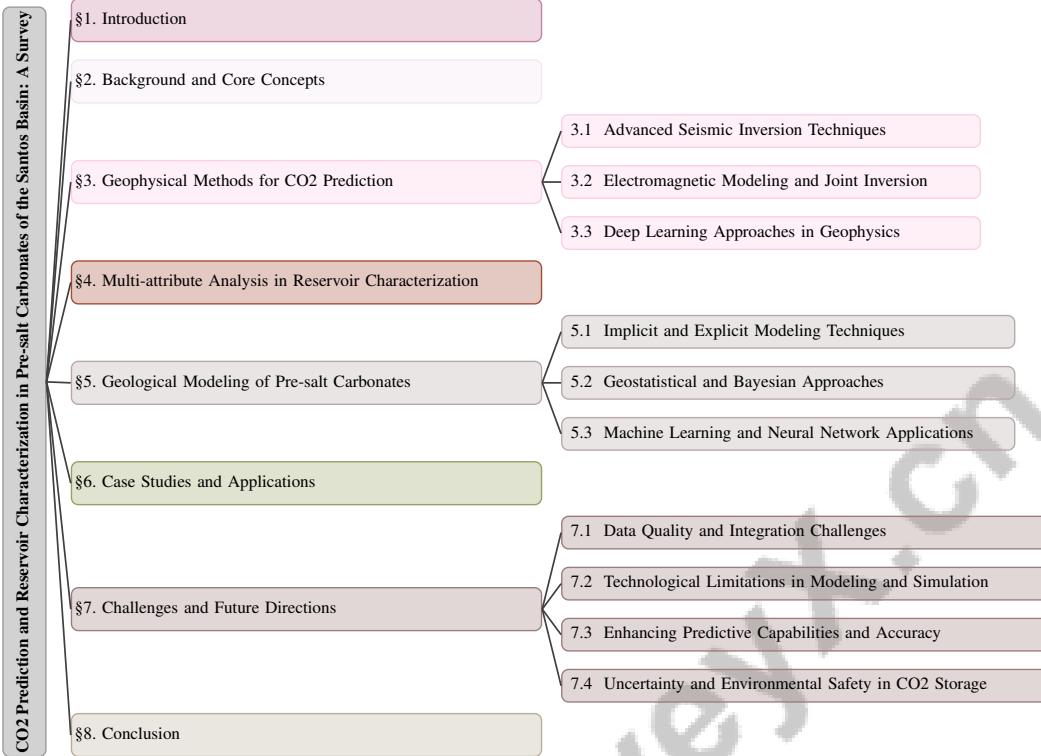


Figure 1: chapter structure

importance of effective CO₂ storage technologies, as explored in extensive surveys of CO₂ storage solutions [6]. Collectively, these efforts highlight the critical role of CO₂ prediction and reservoir characterization in achieving economic benefits and environmental sustainability.

1.2 Integration of Geophysical Methods and Multi-attribute Analysis

Integrating geophysical methods with multi-attribute analysis marks a significant advancement in CO₂ prediction and reservoir characterization, particularly in the Santos Basin's complex pre-salt carbonate formations. This synergy enhances the accuracy and efficiency of subsurface evaluations, essential for economic and environmental objectives. Deep learning algorithms, especially convolutional neural networks (CNNs), are powerful tools for lithology classification from micro-CT images, improving geological interpretation precision [4]. Such advancements are pivotal for reducing uncertainties in reservoir models and enhancing permeability and hydrocarbon volume predictions.

Combining multi-attribute analysis with geophysical data allows for a comprehensive understanding of subsurface characteristics, facilitating the identification of geological features and processes that influence CO₂ storage capabilities. Understanding the physical and geochemical processes involved in CO₂ storage is crucial, as highlighted in surveys categorizing existing research into various geological formations [6]. By merging these methods, researchers can develop robust models that account for complex reservoir interactions, optimizing resource extraction and ensuring environmental safety.

These integrated techniques not only enhance CO₂ presence predictions but also improve overall reservoir characterization. This comprehensive approach is vital for addressing the challenges of greenhouse gas emissions and climate change, facilitating the advancement of robust CO₂ storage technologies. These technologies involve injecting CO₂ into suitable geological formations, necessitating careful modeling, monitoring, and verification to ensure safe containment. By integrating these elements, we can deepen our understanding of the involved physical processes and enhance capacity estimations, ultimately supporting fossil fuel use while mitigating environmental impacts [6, 7, 5]. The synergy between geophysical methods and multi-attribute analysis is thus a cornerstone of modern reservoir management strategies, offering significant potential for advancing both economic and environmental objectives in the energy sector.

1.3 Structure of the Survey

This survey is meticulously structured to provide a comprehensive analysis of CO₂ prediction and reservoir characterization within the pre-salt carbonates of the Santos Basin, Brazil. The paper is organized into several key sections, each focusing on critical aspects of the topic.

The survey begins with an **Introduction** that establishes the significance of CO₂ prediction and reservoir characterization, alongside the integration of geophysical methods and multi-attribute analysis, setting the stage for the detailed discussions that follow.

Section 2: Background and Core Concepts delves into the geological setting of the Santos Basin and elucidates fundamental concepts such as CO₂ prediction, geophysical methods, multi-attribute analysis, geological modeling, and reservoir characterization. This foundational knowledge is crucial for understanding subsequent sections.

In , the discussion centers on innovative geophysical techniques utilized for predicting CO₂ behavior in pre-salt carbonate reservoirs. This includes advanced seismic inversion methods for improved subsurface imaging, electromagnetic modeling for assessing geological formations' electrical properties, and the integration of deep learning algorithms, particularly convolutional neural networks, for enhancing lithological classification and petrophysical property estimation from seismic data. These approaches address the challenges of characterizing complex carbonate geology and leverage recent advancements in machine learning to optimize data interpretation and enhance CO₂ storage monitoring and modeling efforts [8, 4, 6].

Section 4: Multi-attribute Analysis in Reservoir Characterization examines the integration of seismic attributes in reservoir characterization by utilizing advanced analytical techniques, including non-linear transformation methods such as Generative Topographic Maps and Radial Basis Functions, as well as wavelet multiresolution analysis for improved data processing and noise estimation [9, 6, 10].

provides an overview of methodologies employed in geological modeling, emphasizing implicit and explicit modeling techniques. It discusses integrating geostatistical and Bayesian methods to enhance geological interpretations' reliability, along with incorporating advanced technologies such as machine learning and neural networks. These innovations are particularly relevant for addressing pre-salt carbonate reservoir characterization complexities, facilitating improved lithological classification and pattern recognition in microtomographic images of carbonate rocks, ultimately contributing to more accurate reservoir modeling and management strategies [4, 6, 5].

offers an in-depth examination of real-world examples and case studies demonstrating effective CO₂ prediction and reservoir characterization within the Santos Basin. This section highlights practical applications and tangible outcomes of carbon capture and storage technologies, detailing the methodologies employed and the significance of these findings in advancing geological CO₂ storage understanding. By focusing on the unique characteristics of the Aptian pre-salt carbonate reservoirs, it underscores geological factors' influence on reservoir quality and the successful implementation of monitoring techniques to ensure environmental safety and efficiency in CO₂ sequestration efforts [6, 5, 3].

In , the survey outlines prevailing challenges in the carbon capture and storage (CCS) field, such as effective modeling, monitoring, and capacity estimation of CO₂ in geological formations. It further explores promising future research avenues and technological innovations that could address these obstacles, ultimately contributing to advancing CCS technologies and their implementation in mitigating greenhouse gas emissions [6, 7, 11, 5].

Finally, the **Conclusion** synthesizes the survey's key findings, reinforcing the importance of integrating geophysical methods and multi-attribute analysis for effective reservoir characterization and CO₂ prediction. This structured approach facilitates a thorough understanding of carbon capture and storage technologies, encompassing essential concepts, modeling procedures, monitoring techniques, and associated risks, thereby laying a solid foundation for future innovations and advancements in the field [6, 7].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Geological Setting of the Santos Basin

The Santos Basin, located offshore in southeastern Brazil, is renowned for its prolific hydrocarbon reserves, largely due to its extensive pre-salt carbonate formations. The Aptian carbonate rocks and the Barra Velha Formation (BVF) are particularly significant for reservoir characterization, given their complex geological properties and variability in porosity and permeability [3]. The heterogeneous carbonate facies of the BVF present challenges and opportunities in understanding reservoir properties.

The geological intricacies of the Santos Basin are shaped by various depositional and diagenetic processes over geological time, critically influencing the spatial distribution of reservoir quality essential for hydrocarbon extraction and CO₂ storage. The pre-salt formations beneath a thick salt layer act as an effective seal, trapping hydrocarbons and CO₂, enhancing the basin's potential for CO₂ storage in saline aquifers, depleted reservoirs, and unmineable coal beds [6].

A comprehensive understanding of the Santos Basin's geological characteristics is crucial for optimizing resource extraction and developing effective CO₂ storage solutions. Integrating geological, geophysical, and geochemical data is necessary for constructing accurate models of these complex carbonate systems. Advanced modeling techniques significantly improve our understanding of reservoir heterogeneity, essential for devising effective hydrocarbon recovery and CO₂ sequestration strategies. These models optimize resource extraction and ensure safe greenhouse gas containment, addressing economic and environmental goals in climate change mitigation [9, 12, 11, 5, 6].

2.2 Key Concepts

Exploring pre-salt carbonate reservoirs in the Santos Basin requires a nuanced understanding of inter-related concepts, including CO₂ behavior prediction, advanced geophysical methods for subsurface imaging, multi-attribute analysis for data integration, geological modeling for simulating reservoir conditions, and detailed reservoir characterization to assess heterogeneities and diagenetic processes affecting reservoir quality. This integrated approach is vital for optimizing resource extraction and implementing effective carbon capture and storage strategies [4, 6, 3].

Accurate CO₂ prediction is crucial for environmental and economic considerations, involving the integration of geophysical methods such as seismic and electromagnetic (EM) modeling to assess subsurface characteristics. Seismic impedance inversion, for instance, provides high-resolution data critical for understanding reservoir properties, while water saturation classification from seismic attributes enhances model accuracy [13].

Geophysical methods are pivotal in reservoir characterization, offering insights into subsurface structures and properties. Techniques like seismic inversion and EM modeling facilitate the interpretation of complex geological datasets, improving subsurface model precision [11]. Bayesian inference for nonlinear inverse problems is instrumental in inferring unknown high-dimensional spatial fields, crucial for accurate subsurface evaluations and resource management [14].

Multi-attribute analysis integrates various seismic attributes to develop a comprehensive understanding of reservoir properties, essential for identifying seismic facies critical for effective reservoir characterization [6]. This integration allows for detailed subsurface analysis, facilitating the identification of key geological features and processes influencing CO₂ storage capabilities.

Geological modeling, particularly through advanced implicit methods, enables the creation of intricate 3D geological models that accurately depict subsurface structures [5]. These models are crucial for understanding the spatial distribution of facies and diagenetic processes directly affecting reservoir quality and CO₂ storage potential. Accurate estimation of reservoir model variables like permeability and porosity is essential for effective resource management and is often achieved through the integration of seismic data and sophisticated modeling techniques [8].

Reservoir characterization amalgamates geological, geophysical, and petrophysical data to develop accurate subsurface models. This process is vital for optimizing hydrocarbon recovery and ensuring safe, efficient CO₂ storage. Advanced algorithms and data integration methods address challenges associated with traditional classification techniques, contributing to more reliable and efficient resource

extraction strategies [13]. Collectively, these methodologies enhance the predictive capabilities and accuracy of subsurface models, aligning with economic and environmental objectives.

3 Geophysical Methods for CO₂ Prediction

Category	Feature	Method
Advanced Seismic Inversion Techniques	Data Handling Techniques Classification and Representation Precision and Accuracy	SVDD[2] E4D-HM[10] BMARS[14], DG[13]
Electromagnetic Modeling and Joint Inversion	Optimization and Transformation	MOPSO[7], SFA-GTM[9]
Deep Learning Approaches in Geophysics	Substitute Modeling Data Consistency and Reliability Network Architecture Design Sequential Data Analysis Uncertainty Representation	cGAN[1] PFRS[15] ADDIN-I[16] GRU-PPE[8] DIN-UQ[11]

Table 1: This table presents a comprehensive overview of geophysical methods employed for enhancing CO₂ prediction accuracy in pre-salt carbonate formations. It categorizes the methodologies into advanced seismic inversion techniques, electromagnetic modeling and joint inversion, and deep learning approaches, detailing specific features and methods utilized within each category. The table serves as a reference for understanding the diverse applications and technological advancements in geophysical analysis for CO₂ storage and reservoir characterization.

This section explores advanced geophysical methodologies that enhance CO₂ prediction accuracy within pre-salt carbonate formations, focusing on seismic inversion techniques integral for interpreting complex subsurface characteristics and reservoir characterization. Table 1 provides a detailed classification of geophysical methods, highlighting the advanced techniques and approaches used to improve CO₂ prediction accuracy in pre-salt carbonate formations. Table 3 offers a detailed classification and comparison of advanced geophysical methods, underscoring their significance in enhancing CO₂ prediction accuracy in complex geological settings. ?? illustrates the hierarchical classification of geophysical methods for CO₂ prediction, highlighting advanced seismic inversion techniques, electromagnetic modeling and joint inversion, and deep learning approaches. Each category is further divided into specific methodologies and applications that enhance CO₂ prediction accuracy and reservoir characterization, thereby providing a comprehensive overview of the tools available for geophysical analysis in this context.

3.1 Advanced Seismic Inversion Techniques

Advanced seismic inversion techniques significantly enhance CO₂ prediction accuracy in pre-salt carbonate formations. Seismic impedance inversion, notable for providing high-resolution data, is essential for understanding subsurface properties. The ADDIN-I method, utilizing a dual-branch architecture with attention mechanisms, improves impedance prediction accuracy by effectively managing seismic data complexities [16]. Non-linear approaches like the SFA-GTM method, employing Generative Topographic Maps for unsupervised classification, capture seismic data complexities vital for accurate reservoir characterization and CO₂ prediction [9].

Seismic inversion methods, categorized into linearized Bayesian and geostatistical inversion, enhance subsurface model reliability through adaptability to diverse data integration challenges [5]. The ensemble 4D seismic history matching approach, using wavelet-based sparse representation, refines inversion by focusing on significant coefficients, enhancing historical data matching accuracy [10]. High-order discontinuous Galerkin finite element methods improve wave propagation simulation accuracy, enhancing seismic inversion fidelity and CO₂ prediction [13]. Additionally, Support Vector Data Description (SVDD) methods address imbalanced dataset challenges, refining classification processes [2].

Collectively, these techniques form a comprehensive toolkit for enhancing CO₂ prediction and reservoir characterization. By synthesizing various data sources, they improve subsurface structure understanding, facilitating effective resource management aligned with economic growth and environmental sustainability. This understanding is critical for CO₂ storage in geological formations, where monitoring and modeling ensure safe containment and greenhouse gas emission mitigation [9, 6, 7, 5].

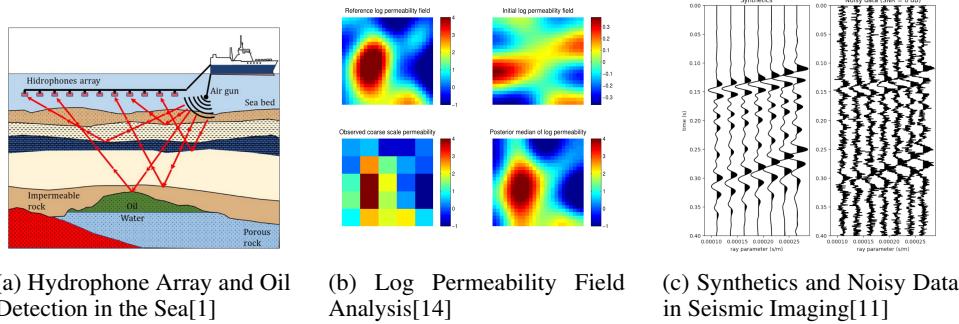


Figure 2: Examples of Advanced Seismic Inversion Techniques

As shown in Figure 2, geophysical methods for CO₂ prediction have advanced significantly through sophisticated seismic inversion techniques. The hydrophone array example emphasizes acoustic data's role in identifying underwater resources and potential CO₂ storage sites. Log permeability field analysis is crucial for understanding subsurface fluid flow and evaluating CO₂ sequestration feasibility. The comparison of synthetic and noisy data in seismic imaging highlights the challenges in reconstructing subsurface images from often noisy data. These examples demonstrate the diverse applications of advanced seismic inversion techniques in enhancing CO₂ prediction and management through effective subsurface exploration and monitoring [1, 14, 11].

3.2 Electromagnetic Modeling and Joint Inversion

Electromagnetic (EM) modeling and joint inversion techniques are crucial for improving CO₂ detection in complex geological settings of pre-salt carbonate formations. These methods enhance subsurface property characterization by integrating diverse geophysical datasets. High-order edge elements and supervised h + p refinement strategies in 3D electromagnetic modeling improve accuracy and computational efficiency, addressing challenges in simulating 3D geophysical electromagnetic responses [17].

A notable advancement in joint inversion is the Multi-Objective Particle Swarm Optimization (MOPSO), optimizing time-domain electromagnetic (TDEM) and vertical electrical sounding (VES) data simultaneously, enhancing subsurface model robustness and CO₂ detection [7]. The SFA-GTM method, used for seismic facies analysis, exemplifies non-linear transformation methods' adaptability in geophysical data interpretation, enhancing electromagnetic data analysis [9].

The integration of electromagnetic modeling and joint inversion techniques significantly enhances geophysical methods' predictive capabilities, providing a detailed understanding of subsurface conditions. Recent advancements in carbon capture and storage (CCS) technology improve resource extraction efficiency and develop robust CO₂ sequestration solutions, aiming to mitigate greenhouse gas emissions and facilitate continued fossil fuel use, aligning with economic growth and environmental sustainability goals. The integration of advanced modeling, monitoring, and verification techniques in CCS supports safe and effective CO₂ containment, ensuring long-term environmental stability [6, 7, 5].

Figure 3 illustrates the hierarchical structure of key concepts in electromagnetic modeling and joint inversion techniques, highlighting advancements in 3D modeling, joint inversion, and carbon capture and storage (CCS) technologies. This visualization further emphasizes the interconnectedness of these advancements and their collective impact on improving subsurface understanding and CO₂ detection.

3.3 Deep Learning Approaches in Geophysics

Deep learning techniques have significantly advanced CO₂ prediction accuracy and efficiency in geophysical data analysis within pre-salt carbonate formations. Conditional generative adversarial networks (cGANs) serve as surrogates for full-waveform inversion (FWI), generating detailed velocity models that capture complex subsurface features and enhance prediction accuracy [1]. The ADDIN-I

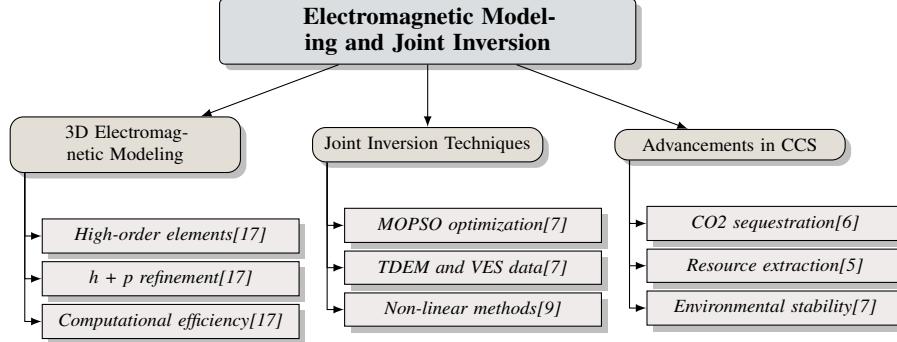


Figure 3: This figure illustrates the hierarchical structure of key concepts in electromagnetic modeling and joint inversion techniques, highlighting advancements in 3D modeling, joint inversion, and carbon capture and storage (CCS) technologies.

Method Name	Methodological Techniques	Application Domains	Performance Enhancements
cGAN[1]	Cgan Architecture	Reservoir Characterization	Prediction Accuracy
ADDIN-I[16]	Bi-GRU, Tcn	Seismic Impedance Inversion	Improved Prediction Accuracy
GRU-PPE[8]	Rnns	Petrophysical Property Estimation	Improved Estimation Accuracy
PFRS[15]	Cnns	Reservoir Characterization	Prediction Accuracy
DIN-UQ[11]	Invertible Networks	Reservoir Characterization	Computational Efficiency

Table 2: Overview of deep learning methods applied in geophysical data analysis, highlighting their methodological techniques, application domains, and performance enhancements. The table includes methods such as cGAN, ADDIN-I, GRU-PPE, PFRS, and DIN-UQ, which are utilized for reservoir characterization, seismic impedance inversion, and petrophysical property estimation, among others.

method integrates deep learning in seismic impedance inversion, employing a dual-branch structure and attention mechanisms to enhance high-frequency weak signal extraction, crucial for accurate seismic interpretation and reservoir characterization [16]. Recurrent neural networks (RNNs) model well-log data as sequences, leveraging temporal dependencies to improve CO2 prediction, essential for understanding dynamic reservoir processes [8].

The Prior Falsification and Regularization Strategies (PFRS) method ensures synthetic training data consistency with real seismic data, enhancing predictive models' reliability for CO2 prediction and reservoir characterization [15]. Deep invertible networks transform Gaussian random inputs into model space, mimicking actual posterior distribution sampling, enhancing uncertainty parameterization and accommodating geological data uncertainties [11].

The integration of advanced deep learning techniques marks a significant advancement in CO2 prediction and reservoir characterization methodologies. Recent applications of convolutional neural networks (CNNs) have improved lithological classification of Brazilian pre-salt carbonate rock microtomographic images, achieving accuracy rates of up to 81.33

Feature	Advanced Seismic Inversion Techniques	Electromagnetic Modeling and Joint Inversion	Deep Learning Approaches in Geophysics
Enhancement Technique	Dual-branch Architecture	Multi-objective Optimization	Conditional Gans
Data Integration	Seismic Data Complexities	Geophysical Datasets	Seismic And Well-log
Application Domain	Subsurface Properties	Co2 Detection	Reservoir Characterization

Table 3: This table provides a comparative analysis of three advanced geophysical methodologies: seismic inversion techniques, electromagnetic modeling and joint inversion, and deep learning approaches in geophysics. It highlights the enhancement techniques, data integration strategies, and application domains associated with each method, emphasizing their roles in improving CO2 prediction accuracy and reservoir characterization in pre-salt carbonate formations.

4 Multi-attribute Analysis in Reservoir Characterization

4.1 Integration of Seismic Attributes

Integrating seismic attributes is essential for refining reservoir characterization in pre-salt carbonate formations. This approach leverages seismic impedance, amplitude envelope, and seismic sweetness as key predictor variables to enhance subsurface interpretations and model accuracy [2]. Such integration enables detailed analysis, identifying crucial geological features for effective reservoir management.

The ADDIN-I method exemplifies advancements in feature extraction, improving seismic data prediction accuracy through a dual-branch architecture and attention mechanisms to capture high-frequency weak signals [16]. This enhancement is critical for developing accurate subsurface models, supporting optimal resource extraction strategies.

Similarly, the SFA-GTM method demonstrates the potential of seismic attribute integration by efficiently handling large datasets and performing non-linear transformations, leading to improved facies classification [9]. These transformations enable a nuanced understanding of seismic data, enhancing subsurface model accuracy.

Geostatistical methods are pivotal for integrating geophysical information and well-log data, forming a comprehensive framework for understanding subsurface properties. This integration is crucial for accurately estimating reservoir variables such as porosity and permeability, vital for effective resource management and CO₂ storage [5]. By synthesizing diverse data sources and employing advanced methodologies, seismic attribute integration significantly enhances the predictability and precision of subsurface models, supporting both economic and environmental goals in resource management, particularly in CO₂ capture and storage scenarios [7, 12, 11, 5, 6].

4.2 Advanced Analytical Techniques and Frameworks

Advanced analytical techniques and frameworks are crucial for refining multi-attribute analysis in reservoir characterization, especially within complex geological settings like pre-salt carbonate formations. Integrating multiple geophysical methods provides a more nuanced understanding of reservoir properties, facilitating robust models that accurately represent subsurface structures and processes [7].

Geostatistical principles are key in generating synthetic data consistent with real seismic data, enhancing predictive models' reliability [15]. This consistency is vital for improving subsurface evaluations' accuracy and optimizing resource extraction strategies.

Non-linear transformation methods, employed by the SFA-GTM approach, enhance analytical capabilities by handling large datasets and accurately interpolating missing values, essential for precise facies classification [9]. These capabilities allow for detailed seismic attribute analyses, improving reservoir model predictability.

Innovative methodologies like the ADDIN-I method, which utilizes a dual-branch architecture and attention mechanisms, showcase advanced techniques' potential in refining feature extraction. This approach enhances the capture of high-frequency weak signals, crucial for accurate seismic interpretation and reservoir characterization [16]. Leveraging these advanced analytical techniques enables geophysicists to develop more accurate and efficient models of subsurface structures, supporting both economic and environmental objectives in resource management.

As shown in Figure 4, multi-attribute analysis plays a crucial role in enhancing reservoir characterization and subsurface resource management. The advanced analytical techniques and frameworks illustrated here demonstrate the integration of numerical methods and electromagnetic data interpretation. For example, the performance assessment of a numerical method for solving partial differential equations is depicted through graphs showing the relationship between run-time and error metrics across varying parameters. Additionally, the comparison of synthetic and predicted data for electromagnetic measurements highlights the alignment between modeled and observed data over time. A colorful grid with labeled squares exemplifies a categorical classification system, representing different attributes within the reservoir. Collectively, these examples underscore the importance of sophisticated analytical tools in improving the precision and reliability of reservoir characterization processes [17, 7, 10].

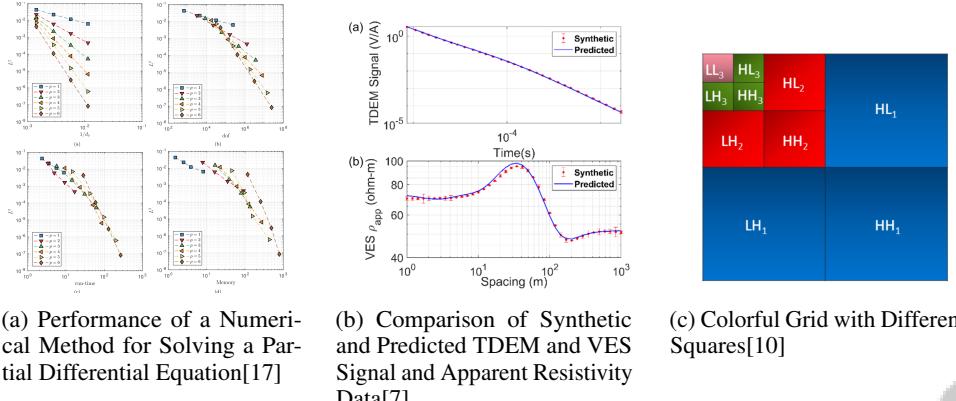


Figure 4: Examples of Advanced Analytical Techniques and Frameworks

5 Geological Modeling of Pre-salt Carbonates

5.1 Implicit and Explicit Modeling Techniques

The geological modeling of pre-salt carbonates in the Santos Basin is significantly enhanced by implicit and explicit modeling techniques, each providing unique advantages in capturing the complex structures of these formations. Implicit modeling, illustrated by GemPy, employs scalar field interpolation to generate models that integrate intricate geological structures and the interactions among various layers [12]. This technique is particularly beneficial in complex geological settings requiring nuanced subsurface representations.

Conversely, explicit modeling techniques facilitate direct representation of geological boundaries and interfaces, yielding clear depictions of subsurface structures. The integration of explicit modeling with advanced geostatistical inversion methods improves the reliability and detail of reservoir models, effectively accommodating uncertainties compared to traditional deterministic methods [5]. This is vital for accurately characterizing reservoir properties and predicting CO₂ storage potential in pre-salt carbonates.

The synergy between implicit and explicit modeling is further enhanced by high-order numerical methods, such as the discontinuous Galerkin formulation, which provides a symmetric treatment of the anisotropic viscoelastic wave equation. This method improves wave propagation simulations, yielding high-fidelity data essential for refining geological models [13]. Additionally, wavelet transforms in seismic data processing, as demonstrated in ensemble 4D seismic history matching, aid in reducing data size and noise estimation, thereby improving input data quality for geological modeling [10].

To address uncertainties in geological modeling, deep invertible networks present a novel approach by parameterizing uncertainty through posterior distribution approximation of model parameters. This method minimizes Kullback-Leibler divergence, offering a robust framework for uncertainty quantification in geological models [11]. By integrating these advanced techniques, geophysicists can develop comprehensive and accurate models of pre-salt carbonates, supporting resource management and CO₂ storage optimization.

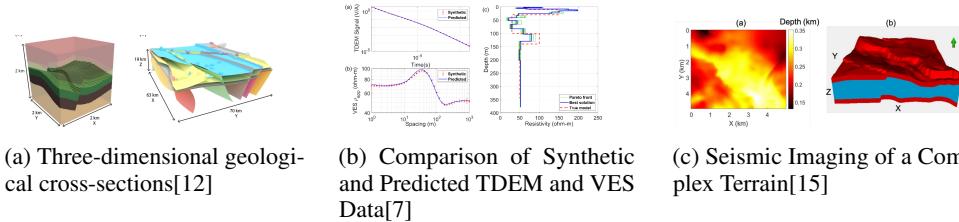


Figure 5: Examples of Implicit and Explicit Modeling Techniques

As shown in Figure 5, implicit and explicit modeling techniques are crucial for understanding and visualizing subsurface structures in geological modeling of pre-salt carbonates. The figures illustrate a comprehensive approach, with three-dimensional geological cross-sections highlighting diverse layers and compositions, a comparative analysis of synthetic and predicted TDEM and VES data validating predictive models, and seismic imaging of complex terrains depicting depth variations. Together, these visualizations emphasize the effectiveness of both modeling techniques in capturing intricate geological details, enhancing our understanding of pre-salt carbonate reservoirs [12, 7, 15].

5.2 Geostatistical and Bayesian Approaches

Geostatistical and Bayesian approaches are pivotal in geological modeling of pre-salt carbonates, providing methodologies to capture uncertainties and spatial variability in these complex formations. Geostatistical methods, particularly within the GemPy framework, create stochastic geological models that reflect the spatial distribution of features. GemPy's open-source platform utilizes modern computational libraries to develop detailed subsurface models, incorporating multiple data sources and geological constraints, essential for accurately representing pre-salt carbonate heterogeneity [12].

Bayesian inference further enhances model reliability by allowing geoscientists to update parameters using prior knowledge and observational data, resulting in more robust subsurface predictions. Deep invertible networks exemplify advancements in uncertainty quantification, enabling analytical computation of output density functions, thus providing a clearer understanding of probability distributions of model parameters [11].

The combination of geostatistical and Bayesian methods facilitates the development of probabilistic geological models crucial for effective resource management and CO₂ storage planning. By integrating advanced geostatistical methodologies with deep learning techniques, geophysicists can tackle subsurface heterogeneity and uncertainty more effectively, enhancing predictions regarding reservoir properties. This comprehensive approach supports informed decision-making in reservoir characterization and management, aligning with both economic and environmental objectives in the Santos Basin's pre-salt carbonate formations [11, 5].

5.3 Machine Learning and Neural Network Applications

Machine learning and neural network applications have revolutionized geological modeling, particularly in the intricate pre-salt carbonate formations of the Santos Basin. Advanced computational techniques, such as recurrent neural networks (RNN) and wavelet multiresolution analysis, provide innovative methodologies for interpreting seismic data, enhancing reservoir characterization by accurately estimating petrophysical properties and managing data uncertainties [8, 9, 15, 10].

Conditional Generative Adversarial Networks (cGANs) showcase the potential of machine learning in geological modeling by generating high-resolution velocity models from seismic images and auxiliary data, significantly improving accuracy while reducing computational costs [1]. This method captures intricate subsurface details, facilitating precise reservoir property predictions.

The Fourier Neural Operator (FNO) further enhances modeling by predicting pressures and saturations across various scenarios without extensive numerical simulations [18]. This approach leverages neural networks for efficient data processing, improving computational efficiency and model accuracy.

In lithological classification, deep learning techniques have made significant strides. Automated methods for lithological classification enhance reservoir characterization efficiency and accuracy, addressing the complexities of pre-salt carbonate lithologies [4]. This automation reduces uncertainties in reservoir models and improves predictability.

The Gated Recurrent Unit (GRU) method processes seismic data sequentially, capturing temporal dependencies to enhance geological modeling accuracy [8]. By modeling these dependencies, GRUs provide insights into dynamic reservoir processes, leading to more accurate subsurface models.

Moreover, the Bayesian Multivariate Adaptive Regression Splines (BMARS) emulator-based approach significantly boosts computational efficiency in Bayesian inference for spatial inverse problems, demonstrating substantial time savings while maintaining predictive accuracy [14].

The integration of advanced machine learning techniques, particularly RNNs and convolutional neural networks (CNNs), into geological modeling marks a transformative leap in the field. These

technologies enhance the estimation of complex petrophysical properties from seismic data and improve lithological classification of carbonate rock micro-CT images, addressing challenges posed by subsurface non-linearity and heterogeneity. Additionally, open-source tools like GemPy facilitate the construction of intricate 3D geological models, allowing researchers to leverage machine learning and Bayesian inference for stochastic modeling and inversion. Collectively, these innovations streamline geological investigations and promote reproducibility in geoscientific research [8, 4, 12]. By integrating these sophisticated techniques, geophysicists can develop more accurate and efficient models, supporting both economic and environmental objectives in resource management.

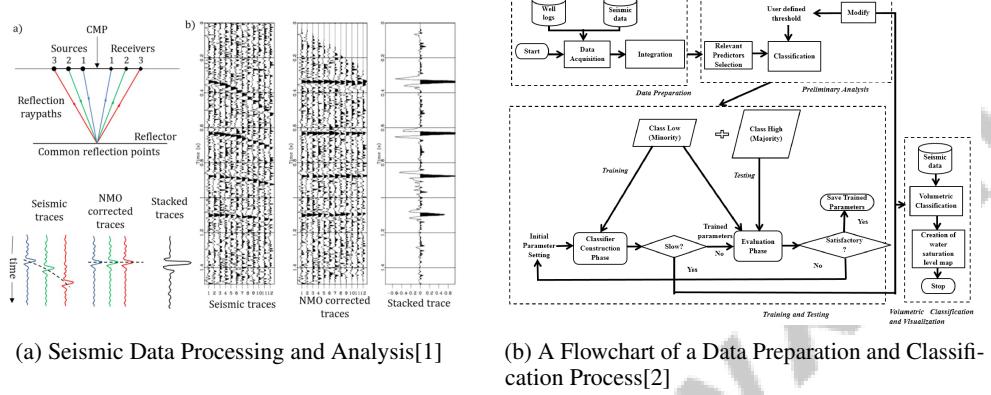


Figure 6: Examples of Machine Learning and Neural Network Applications

As shown in Figure 6, the field of geological modeling, particularly concerning pre-salt carbonates, has witnessed significant advancements through machine learning and neural networks. Examples include seismic data processing and analysis, which enhance signal quality for accurate subsurface interpretation, and a systematic flowchart for data preparation and classification that outlines the acquisition of well logs and seismic data, leading to effective classification. These instances underscore the transformative potential of these technologies in refining geological models and enabling more accurate predictions of complex subsurface structures like pre-salt carbonates [1, 2].

6 Case Studies and Applications

6.1 Validation through Real-world Applications

Benchmark	Size	Domain	Task Format	Metric
HEFEM[17]	1,368,969	Geophysics	3D Controlled-source Electro-magnetic Method (csem)	L2-norm error, Convergence rate

Table 4: This table presents a representative benchmark used for validating electromagnetic modeling techniques within the domain of geophysics. It details the benchmark name, size, domain, task format, and evaluation metrics, highlighting the use of the HEFEM benchmark in 3D controlled-source electromagnetic method simulations for assessing L2-norm error and convergence rate.

Advanced techniques for CO₂ prediction and reservoir characterization have proven effective in practical scenarios, enhancing subsurface evaluations and resource management. The Support Vector Data Description (SVDD) framework, for example, facilitates the classification of water saturation levels from seismic attributes, crucial for precise reservoir characterization and optimizing hydrocarbon extraction alongside CO₂ storage strategies [2].

In electromagnetic (EM) modeling, the integration of high-order edge elements with $h + p$ refinement strategies has significantly improved the accuracy and efficiency of 3D EM simulations. Table 4 provides a detailed overview of the benchmark utilized in electromagnetic modeling, illustrating its significance in enhancing the accuracy and efficiency of geophysical simulations. These advancements, validated through benchmark studies, provide valuable insights for geophysical modeling in both academic and industrial contexts, thereby enhancing subsurface property understanding essential for CO₂ prediction and reservoir management [17].

The Prior Falsification and Regularization Strategies (PFRS) method, validated through case studies, showcases its effectiveness in CO₂ prediction and reservoir characterization by aligning synthetic training data with real seismic data, thus bolstering the reliability of predictive models [15].

Additionally, the Bayesian Multivariate Adaptive Regression Splines (BMARS) emulator has demonstrated its practical application in hydrocarbon reservoir characterization using both simulated and real data, improving prediction accuracy and computational efficiency [14].

These examples underscore the efficacy of sophisticated techniques in enhancing CO₂ prediction and reservoir characterization, thereby supporting resource management. Such advancements not only drive economic efficiency but also align with environmental sustainability goals by facilitating safe CO₂ storage in geological formations and improving petrophysical property estimation accuracy through innovative machine learning approaches [9, 11, 8, 5, 6].

6.2 FNO in Reservoir Management

The Fourier Neural Operator (FNO) method has revolutionized reservoir management by enhancing the prediction and optimization of subsurface conditions. It excels in predicting pressure and saturation distributions under unseen conditions, crucial for effective reservoir management and optimization [18]. By addressing complex reservoir dynamics, FNO provides a robust framework for managing uncertainties and variability in subsurface formations.

Utilizing neural operators, the FNO method enables rapid simulations of reservoir behavior without the extensive computational demands of traditional numerical methods. This efficiency is particularly beneficial for real-time decision-making during CO₂ injection and storage operations. The ability to forecast reservoir responses across diverse scenarios optimizes resource extraction and storage strategies, promoting economic returns while mitigating environmental risks associated with carbon capture and storage technologies. Advanced modeling techniques, such as FNO, allow stakeholders to optimize well placements, control strategies, and permeability variations, ensuring effective management of geological formations for CO₂ storage amidst climate change challenges [6, 18].

Furthermore, integrating FNO into reservoir management workflows fosters adaptive strategies that dynamically respond to changing reservoir conditions. This adaptability is vital for maintaining optimal performance throughout the reservoir lifecycle, from exploration and development to production and closure, particularly in managing uncertainties in geological models and optimizing fluid flow behavior in both hydrocarbon and carbon storage reservoirs [6, 18]. The FNO method thus supports sustainable and efficient resource management practices by providing a comprehensive understanding of reservoir dynamics.

The application of the FNO method represents a significant advancement in reservoir management, offering a powerful tool for optimizing subsurface resources. This technological progress not only aligns with economic growth but also fosters environmental sustainability by enhancing resource extraction and storage processes designed to maximize benefits while effectively mitigating adverse environmental impacts. Specifically, it improves carbon capture and storage operations, which are crucial for addressing greenhouse gas emissions and ensuring the safe containment of CO₂ in geological formations through advanced modeling, monitoring, and verification techniques [9, 6, 7, 5].

7 Challenges and Future Directions

7.1 Data Quality and Integration Challenges

Data quality and integration remain critical challenges in CO₂ prediction and reservoir characterization, particularly within complex geological environments like pre-salt carbonate formations. The computational demands of seismic modeling, essential for constructing accurate subsurface velocity models, often result in prohibitive costs for large-scale studies [11]. Furthermore, dataset imbalances, where majority classes overshadow minority ones, can skew model performance and decision-making [7, 11, 5]. This imbalance necessitates advanced methods to rectify disparities. The integration of seismic and well-log data is further complicated by differences in resolution, sensitivity, and depth, leading to inconsistencies in joint inversion models.

Variability in data quality across wells complicates reservoir characterization, affecting model robustness and reliability. Establishing correlations between seismic amplitudes and well-log properties is

challenging due to resolution discrepancies, underscoring the need for innovative methodologies like wavelet multiresolution analysis and machine learning techniques, such as recurrent neural networks, to bridge these differences [16, 10, 8, 5, 15].

The 'big data' problem in dense seismic datasets complicates history matching, leading to numerical instability with gradient-based deterministic methods. This complexity is compounded by uncertainties in traditional seismic data inversion and the need for efficient data representation techniques like wavelet multiresolution analysis to mitigate data size and noise issues. Emerging approaches, including deep learning and recurrent neural networks, are being explored to enhance petrophysical property estimation and improve prediction robustness by addressing overfitting and uncertainty quantification [8, 15, 11, 10]. However, these methods often struggle with uncertainty quantification, highlighting the need for efficient large dataset management strategies. Additionally, the computational expense of forward simulators limits extensive posterior distribution exploration, constraining Bayesian inference methods.

In petrophysical property estimation, data scarcity from drilled wells limits the generalizability of regression algorithms across survey areas. Addressing these challenges requires innovative methodologies and advanced computational techniques to enhance data integration and improve the accuracy and reliability of subsurface models. This includes leveraging multi-objective swarm intelligence for joint optimization of geophysical data and utilizing open-source stochastic geological modeling frameworks that enable the representation of complex geological structures while integrating machine learning and Bayesian inference for robust modeling and inversion processes [6, 12, 7]. Overcoming these obstacles can optimize resource extraction and CO₂ storage strategies, aligning with both economic and environmental objectives in the energy sector.

7.2 Technological Limitations in Modeling and Simulation

Technological limitations in modeling and simulation impede effective characterization of pre-salt carbonate formations. A significant limitation is the absence of comprehensive graphical user interfaces in geological modeling frameworks like GemPy, which can hinder usability for non-programmers [12]. This deficiency restricts the adoption of advanced modeling techniques in industry settings, where user-friendliness is crucial.

Moreover, inherent noise in seismic data and imperfections in modeling techniques challenge the accurate representation of complex geological features. Methods such as Prior Falsification and Regularization Strategies (PFRS) may struggle with these issues, leading to inaccuracies in subsurface models [15]. The presence of noise necessitates robust algorithms capable of filtering irrelevant data and enhancing geological interpretation precision.

The computational demands associated with high-order numerical methods, such as the discontinuous Galerkin finite element approach, exacerbate these challenges due to their complexity and the need to manage large matrices during time integration [13]. This substantial computational load limits the scalability of these techniques, making them less feasible for large-scale simulations essential for comprehensive reservoir characterization.

Addressing these technological limitations requires ongoing innovation in algorithm development and computational techniques. Enhancing the usability of modeling tools, improving noise reduction algorithms, and optimizing computational efficiency are critical for overcoming these challenges and advancing geological modeling and simulation. These advancements are vital for creating precise and reliable subsurface models, which play a crucial role in enhancing resource extraction efficiency and developing effective CO₂ storage strategies. Improved modeling and monitoring techniques, as highlighted in recent research, contribute to a better understanding of geological formations, ensuring safe CO₂ containment and optimizing natural resource extraction [6, 12].

7.3 Enhancing Predictive Capabilities and Accuracy

Future advancements in CO₂ prediction and reservoir characterization are set to significantly enhance predictive capabilities and accuracy through the integration of cutting-edge technologies and methodologies. Refining network architectures and exploring additional input parameters are promising avenues for improving model accuracy in data-driven full-waveform inversion. This can be further supported by enhancing user interfaces and expanding functionality for probabilistic modeling within

frameworks like GemPy, facilitating more sophisticated analyses and the integration of advanced machine learning techniques [12].

Automating parameter selection processes using evolutionary algorithms represents another opportunity to bolster predictive capabilities, particularly in CO₂ prediction frameworks like SVDD. Developing a label-free closed-loop framework that integrates physical models could address uncertainties in inversion results, leading to more reliable predictions of subsurface characteristics [16]. Furthermore, refining algorithms such as Multi-Objective Particle Swarm Optimization (MOPSO) to accommodate more complex datasets and exploring hybrid approaches that integrate MOPSO with other optimization techniques could enhance the robustness of joint inversion models [7].

Refining the Fourier Neural Operator (FNO) model to minimize errors at critical saturation points, alongside its integration with traditional simulation techniques, holds promise for improving reservoir management accuracy [18]. Incorporating additional datasets and advanced modeling techniques into the Comprehensive Quantitative Approach can further enhance predictive capabilities, as suggested in recent research on pre-salt carbonates [3]. Expanding existing frameworks to 3D applications and exploring various types of seismic data, such as acoustic impedance, will also contribute to more accurate subsurface evaluations [10].

Future research should prioritize developing robust integration methodologies to manage the increasing complexity of data and the challenges posed by new exploration technologies [5]. Further refinements to the BMARS emulator, including adaptive selection of basis functions and integration with other modeling frameworks, can enhance predictive capabilities [14]. Additionally, expanding datasets and exploring deeper learning models will improve estimation accuracy and generalization in CO₂ prediction and reservoir characterization [8].

Enhancing modeling techniques, developing advanced monitoring systems, and exploring new geological formations for CO₂ storage are critical areas for future research [6]. Extending methods to elastic models, incorporating hard constraints, and applying them to field data will further validate their effectiveness [11]. Collectively, these future research directions aim to advance CO₂ prediction and reservoir characterization significantly, supporting both economic and environmental objectives.

7.4 Uncertainty and Environmental Safety in CO₂ Storage

Challenges related to uncertainty and environmental safety in CO₂ storage are complex, especially within intricate geological settings like pre-salt carbonate formations. A primary concern is the inherent uncertainty in subsurface models due to limitations in data resolution and geological property variability. Such uncertainties can substantially affect predictions regarding CO₂ storage capacity and the behavior of injected CO₂ over time [11]. Developing robust uncertainty quantification methods, such as those utilizing deep invertible networks, is crucial for enhancing the reliability of subsurface models and ensuring efficient and safe CO₂ storage.

Environmental safety concerns are heightened by the potential for CO₂ leakage, posing risks to ecosystems and human health. The effectiveness of geological seals, like the thick salt layers in the Santos Basin, is vital for preventing CO₂ escape from storage sites. However, the heterogeneity and complexity of these formations can introduce uncertainties regarding seal integrity, necessitating comprehensive monitoring and risk assessment strategies [6]. Integrating advanced geophysical monitoring techniques with robust geological models is essential for detecting and mitigating potential leakage pathways, ensuring the long-term security of CO₂ storage.

Additionally, the dynamic nature of CO₂ injection and associated pressure changes within the reservoir can induce geomechanical responses, potentially leading to fault reactivation or induced seismicity. These geomechanical challenges require careful assessment and management to minimize environmental risks and maintain the structural stability of the storage site. Employing high-resolution seismic monitoring and geomechanical modeling techniques can provide critical insights into reservoir behavior during CO₂ injection, facilitating the development of effective mitigation strategies [13].

To effectively address the complexities associated with uncertainty and environmental safety in CO₂ storage, a multidisciplinary approach is essential, integrating sophisticated modeling techniques, extensive monitoring systems, and thorough risk assessment frameworks. This strategy not only enhances the understanding of geological formations suitable for CO₂ injection but also ensures the long-term containment of injected CO₂, thereby mitigating potential environmental impacts. Recent

advancements in geostatistical methods and machine learning applications, such as deep invertible networks for reservoir characterization, further support this comprehensive strategy by improving the accuracy of risk assessments and monitoring processes [6, 7, 11, 5]. By enhancing the predictive capabilities and accuracy of subsurface models, researchers can optimize CO₂ storage strategies, aligning with environmental protection and climate change mitigation goals.

8 Conclusion

The survey underscores the critical role of integrating geophysical methods with multi-attribute analysis in enhancing reservoir characterization and CO₂ prediction within the complex pre-salt carbonate formations of the Santos Basin. By employing advanced seismic inversion techniques, such as the ADDIN-I method, the accuracy of impedance predictions is notably improved, facilitating a deeper understanding of subsurface properties. Additionally, the use of electromagnetic modeling and joint inversion strategies bolsters CO₂ detection capabilities, enhancing the robustness of subsurface models. The application of deep learning methodologies, including conditional generative adversarial networks and recurrent neural networks, significantly augments the precision and efficiency of geophysical data analysis, aligning with both economic and environmental goals.

The integration of multi-attribute analysis through seismic attributes provides a comprehensive perspective on reservoir properties, crucial for identifying geological features pivotal to CO₂ storage. Techniques like the SFA-GTM method refine the classification and interpretation of seismic data, yielding more accurate reservoir models. Geological modeling approaches that incorporate both implicit and explicit techniques, along with geostatistical and Bayesian methods, offer robust frameworks to capture the complexities inherent in pre-salt carbonate formations, thereby optimizing resource extraction and CO₂ storage strategies.

The survey also highlights the importance of overcoming challenges related to data quality, technological constraints, and uncertainties in CO₂ storage. Future research initiatives should aim to enhance predictive capabilities and accuracy through the development of refined network architectures, automated parameter selection, and the integration of advanced monitoring systems. Progress in these areas will enable the energy sector to implement more sustainable and efficient resource management practices, promoting economic growth while ensuring environmental protection.

References

- [1] Saraiva Marcus, Forechi Avelino, de Oliveira Neto Jorcý, DelRey Antonio, and Rauber Thomas. Data-driven full-waveform inversion surrogate using conditional generative adversarial networks, 2021.
- [2] Soumi Chaki, Akhilesh Kumar Verma, Aurobinda Routray, William K. Mohanty, and Mamata Jenamani. A novel framework based on svdd to classify water saturation from seismic attributes, 2016.
- [3] Ancilla Maria Almeida Carvalho, Youri Hamon, Olinto Gomes De Souza Jr, Nivea Goulart Carramal, and Nathalie Collard. Facies and diagenesis distribution in an aptian pre-salt carbonate reservoir of the santos basin, offshore brazil: a comprehensive quantitative approach. *Marine and Petroleum Geology*, 141:105708, 2022.
- [4] Carlos E. M. dos Anjos, Manuel R. V. Avila, Adna G. P. Vasconcelos, Aurea M. P. Neta, Lizzianne C. Medeiros, Alexandre G. Evsukoff, and Rodrigo Surmas. Deep learning for lithological classification of carbonate rock micro-ct images, 2020.
- [5] Leonardo Azevedo and Amílcar Soares. *Geostatistical methods for reservoir geophysics*, volume 143. Springer, 2017.
- [6] Temitope Ajayi, Jorge Salgado Gomes, and Achinta Bera. A review of co 2 storage in geological formations emphasizing modeling, monitoring and capacity estimation approaches. *Petroleum Science*, 16:1028–1063, 2019.
- [7] Francesca Pace, Alberto Godio, Alessandro Santilano, and Cesare Comina. Joint optimization of geophysical data using multi-objective swarm intelligence. *Geophysical Journal International*, 218(3):1502–1521, 2019.
- [8] Motaz Alfarraj and Ghassan AlRegib. Petrophysical property estimation from seismic data using recurrent neural networks, 2019.
- [9] Jatin Bedi and Durga Toshniwal. Sfa-gtm: Seismic facies analysis based on generative topographic map and rbf, 2018.
- [10] Xiaodong Luo, Tuhin Bhakta, Morten Jakobsen, and Geir Nævdal. An ensemble 4d seismic history matching framework with sparse representation based on wavelet multiresolution analysis, 2016.
- [11] Gabrio Rizzuti, Ali Siahkoohi, Philipp A. Witte, and Felix J. Herrmann. Parameterizing uncertainty by deep invertible networks, an application to reservoir characterization, 2020.
- [12] Miguel De la Varga, Alexander Schaaf, and Florian Wellmann. Gempy 1.0: open-source stochastic geological modeling and inversion. *Geoscientific Model Development*, 12(1):1–32, 2019.
- [13] Khemraj Shukla, Jesse Chan, and Maarten V. de Hoop. A high order discontinuous galerkin method for the symmetric form of the anisotropic viscoelastic wave equation, 2020.
- [14] Anirban Mondal and Bani Mallick. Spline-based bayesian emulators for large scale spatial inverse problems, 2021.
- [15] Anshuman Pradhan and Tapan Mukerji. Consistency and prior falsification of training data in seismic deep learning: Application to offshore deltaic reservoir characterization, 2021.
- [16] Wen Feng, Yong Li, Yingtian Liu, and Huating Li. Acoustic impedance prediction using an attention-based dual-branch double-inversion network, 2024.
- [17] Octavio Castillo-Reyes, Adrian Amor-Martin, Arnaud Botella, Pierre Anquez, and Luis Emilio García-Castillo. Tailored meshing for parallel 3d electromagnetic modeling using high-order edge elements, 2022.
- [18] Daniel Badawi and Eduardo Gildin. Neural operator-based proxy for reservoir simulations considering varying well settings, locations, and permeability fields, 2024.

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