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# Decoding Earth's Secrets: The Full-Waveform Inversion and Machine Learning Revolution in Seismic Imaging

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**ABSTRACT**

Seismic imaging has revolutionized our understanding of subsurface structures and led to significant advances in geophysical exploration and hydrocarbon recovery. This article reviews recent innovations in seismic imaging technologies, particularly applications of full waveform inversion (FWI) and machine learning (ML). These cutting-edge techniques improve the resolution and accuracy of subsurface models, enabling more efficient and precise resource extraction. We examine recent case studies from major basins, including the North Sea, the Gulf of Mexico and the Niger Delta, and show how these technologies have been successfully used to improve exploration results. By comparing traditional methods with these advanced techniques, we highlight the significant added value they offer, such as: higher detection accuracy, lower exploration costs and increased security. The paper also highlights the need for operators in the Niger Delta Basin to adopt these innovations to remain competitive and environmentally compliant. By integrating FWI and ML into their exploration workflows, operators can achieve more reliable seismic interpretations, resulting in better decision making and optimized resource management.

## 1.0 INTRODUCTION

Seismic imaging is a cornerstone of geophysical exploration. It provides important insights into subsurface structures and facilitates the discovery and extraction of hydrocarbon resources. Traditional seismic imaging techniques, while effective, often struggle with limitations in resolution and accuracy, particularly in complex geological environments. Recent advances in full waveform inversion (FWI) and machine learning (ML) have significantly improved seismic imaging capabilities, providing unprecedented detail and precision. Machine learning (ML) is also increasingly being applied to seismic imaging, improving the capabilities of FWI (Brown *et al.,* 2019). ML algorithms can help reduce cycle skipping, improve start up models, and even create autonomous velocity models (Dickinson *et al.,* 2017). Integrating ML with FWI has the potential to revolutionize seismic imaging and enable the industry to better understand complex geological structures, improve hydrocarbon recovery and reduce exploration risks (Landolsi *et al.,* 2016). This article examines these technological advances, their applications in different basins and their potential impact on exploration and production activities in the Niger Delta Basin. The growing size of data sets (Arrowsmith *et al.,* 2022), on the one hand the need to shorten the time from collection to delivery, and on the other hand the increasing power of computing systems have made the use of data-driven methods an attractive tool for industry and researchers (Farbod. *et al.,* 2023). The exploration and production of hydrocarbon reserves depends heavily on accurate imaging of the subsurface. Seismic imaging was the cornerstone of this effort. It provided insights into the subsurface structure and helped identify potential reservoirs. However, traditional seismic imaging methods have limitations, especially in complex geological environments. The need for greater accuracy and resolution has driven the development of new technologies, and two approaches have emerged as game-changers: Full Waveform Inversion (FWI) and Machine Learning (ML).

### *Full-Waveform Inversion (FWI)*

FWI is an advanced seismic imaging technique that uses complete waveform data to create high-resolution subsurface models. Full Waveform Inversion (FWI) is a velocity model creation tool that utilizes the entire seismic waveform to produce high-resolution subsurface images (Kato *et al.,* 2018). By minimizing the difference between recorded and modelled data, FWI can accurately capture subtle changes in seismic wave fields, resulting in better imaging results (Gauthier *et al.,* 1986). FWI has the potential to overcome the limitations of traditional seismic imaging methods and provide greater resolution and accuracy in complex geological environments (Williamson, 1990). The beauty of FWI Imaging lies in its ability to adapt to various geophysical survey scenarios and handle complex subsurface conditions. As a model fitting technique that minimizes differences between observed and modelled seismic waveforms, it can reproduce more features of the actual model that are not always well illuminated by traditional seismic imaging due to survey design, illumination gaps, noise, residual multipliers, etc. FWI iteratively incorporates these features into the model to better fit the different types of measured waves (Adriana *et al.,* 2023). Below is an example of seismic imaging using FWI.

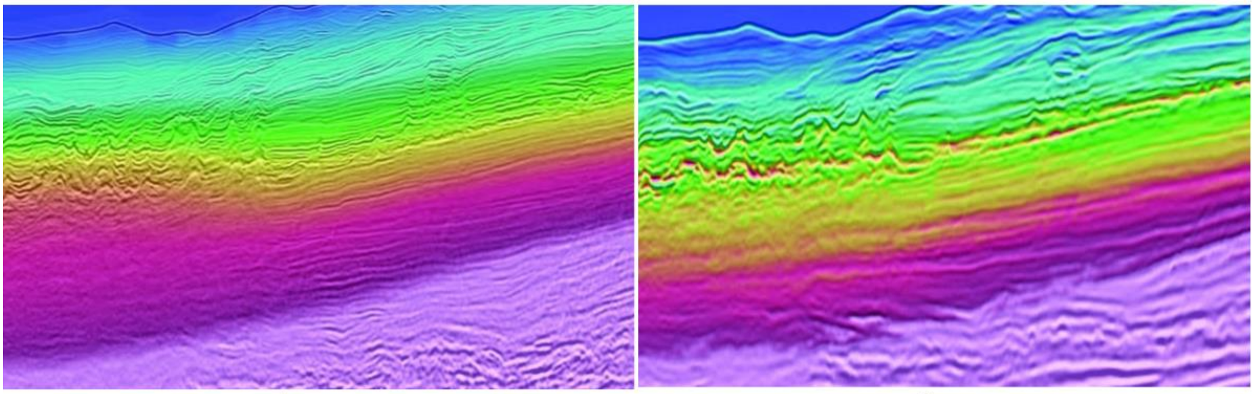


Fig.1: a) Original Kirchhoff PSDM line (no deghosting applied) from 2010 overlaid with the tomography-based velocity model from 2010 (the mass transport complexes in the shallow section generate signal absorption and scattering). b) Latest 2023 hi-res DM FWI (40Hz) derived velocity model and associated FWI Image (enhanced image resolution with increased S/N, better illumination, and improved amplitude consistency) (Adriana *et al.*, 2023).

In recent years, FWI has helped industry solve complex imaging challenges such as: e.g., seeing through gas clouds, resolving heterogeneities at shallow velocities (channels), etc. However, most applications reported to date have used models simply parameterized using P-wave velocity and density with the extension to include simple anisotropic media representations (e.g. VTI). Incorporating other effects necessary to explain realistic wave propagation (e.g. attenuation, elasticity) into modelling and inversion schemes remains a significant challenge for future FWI development and real data applications, especially since even the simplest acoustic FWI case suffers from data quality issues, lack of low frequency signal, lack of sufficiently long offsets and illumination angles. Therefore, the FWI workflow is highly data dependent and is often adapted to the geology we are trying to image. Another challenge we face is the transition from transmission regime FWI to migration-like FWI to obtain short-wave perturbations in subsurface parameters. The basic principle of FWI can be formulated as an optimization problem. Given the observed seismic data $d_{obs}$ and the synthetic data design $d_{syn}$ generated from a model m, the goal is to minimize the difference between $d_{obs}$ and design:

$\min_m ||d_{obs} - d_{syn}(m)||^{2.}$

This involves iteratively updating the model m to reduce the misfit. The inversion process is controlled by the gradient of the misfit function, which can be calculated using adjoint state methods. FWI has made significant advances in computational algorithms and hardware that enable more efficient and accurate inversions. Recent studies such as Virieux and Operto (2021) have demonstrated the effectiveness of FWI in complex geological environments, including salt diapirs and fault zones. Case studies from the North Sea and Gulf of Mexico have demonstrated significant improvements in image sharpness and depth resolution.

### *Machine Learning in Seismic Imaging*

Machine learning has become a powerful tool in geophysical exploration, offering new possibilities for processing and interpreting seismic data. ML algorithms can automatically detect patterns and anomalies in seismic datasets, significantly reducing the time and effort required for manual interpretation. These technologies help interpret large data sets by identifying patterns and anomalies that may be difficult for human analysts to detect. Machine learning algorithms can help with denoising seismic data, automatic fault detection, and even predicting reservoir properties based on historical data. ML algorithms are constantly being implemented for almost all steps in the seismic processing and interpretation workflow, primarily for automation, reducing processing time, efficiency, and in some cases improving results. Several ML techniques have been applied to seismic imaging, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and unsupervised learning methods. These techniques have been used for fault detection, horizon selection and reservoir characterization. For example, Araya-Polo *et al.*, (2018) used CNNs to automate fault detection in 3D seismic volumes, achieving remarkable accuracy and consistency compared to traditional manual methods. Similarly, Zhang *et al.*, (2020) used RNNs for seismic facies classification and demonstrated significant improvements in computational efficiency and interpretation accuracy. The main reason for moving to fully data-driven methods is to mitigate some of the disadvantages of current technologies and methods, which can be divided into three categories. The first aspect is efficiency.

Currently we use complex workflows that require many parameters and solutions that require an experienced operator based on analysis, testing and evaluation carried out with a Galilean approach (trial and error). This process requires time and expertise. It's nice to have technologies that can deliver results directly in a computer-based process without making decisions. The second aspect is bias. Different technologies and different operators produce different results, which are distorted in an uncontrolled manner by the decisions made during the process. The goal of an ML application would be to obtain results that are more repeatable and, in a sense, more “objective” because they come from a process that only addresses the precise information in the data. The third aspect is effectiveness. Every processing and interpretation technique have intrinsic limitations, and depending on the method and choice, the results allow us to “see” different things. The aim is to have methods that automatically deliver high-quality results and reflect comprehensive information about the subsurface. All these limitations are the reasons for investing in ML techniques. This idea undoubtedly represents a revolution in the way we perform seismic processing and interpretation, but many issues related to ML implementation need to be addressed (Farbod *et al.*, 2023). For example, wave propagation inside the Earth is much more complex than wave propagation in human organs used for medical imaging. Therefore, fine-tuning already trained ML models from other disciplines (also called transfer learning) is useless for seismic processing and interpretation tasks in most cases. Additionally, training ML models from scratch relies heavily on abundant labelled data, which is challenging in seismic exploration as there is no solid foundation for accurate data.

## 2. Case Studies

**The North Sea basin:** This has been a testing ground for many advanced seismic imaging techniques. Recent applications of FWI have resulted in improved imaging of complex salt structures, which are critical for accurate hydrocarbon exploration. According to a study by (Warner *et al.,* 2017), the implementation of FWI in the North Sea resulted in a 30% increase in drilling success rates, highlighting the practical benefits of this technology.

**Gulf of Mexico:** FWI and ML techniques have been widely used to improve subsurface imaging in Deepwater environments in the Gulf of Mexico. A notable case is the Mad Dog field, where FWI was used to resolve complex subsurface structures, resulting in the identification of new drill targets and a subsequent increase in reserve estimates by 20%.

**Niger Delta:** The Niger Delta basin, with its complex deltaic and turbiditic systems, poses significant challenges to traditional seismic imaging methods. However, recent studies have shown that FWI and ML can significantly improve image accuracy in this region. A study by Olowookere *et al.,* (2022) demonstrated the successful application of FWI in resolving deep hydrocarbon traps in the Niger Delta, resulting in more accurate reservoir delineation and improved hydrocarbon recovery. For operators in the Niger Delta Basin, the use of FWI and ML technologies is not only beneficial but also essential. The complex geology of the region, characterized by intricate fault systems and heterogeneous sedimentary layers, requires advanced imaging techniques to ensure successful exploration and production activities. By using these technologies, operators can achieve improved hydrocarbon recovery and reduced environmental impact.

## 3. IMPORTANCE OF FWI AND ML IN SEISMIC IMAGING.

**Noise removal in raw data prior to wavelet processing**: ML proves crucial for denoising raw seismic data before applying wavelet processing. The Real Image Denoising Network (RIDNet), a convolutional neural network (CNN), is used because of its efficiency in noise attenuation. Case studies from the Eastern Mediterranean, the Faroese Shetland Basin and off the coast of Malaysia show significant noise reduction and improved wave field generation. These examples can all be seen in the First Break article (Julien-Oukili *et al.,* 2024). An example from Malaysia is shown below.

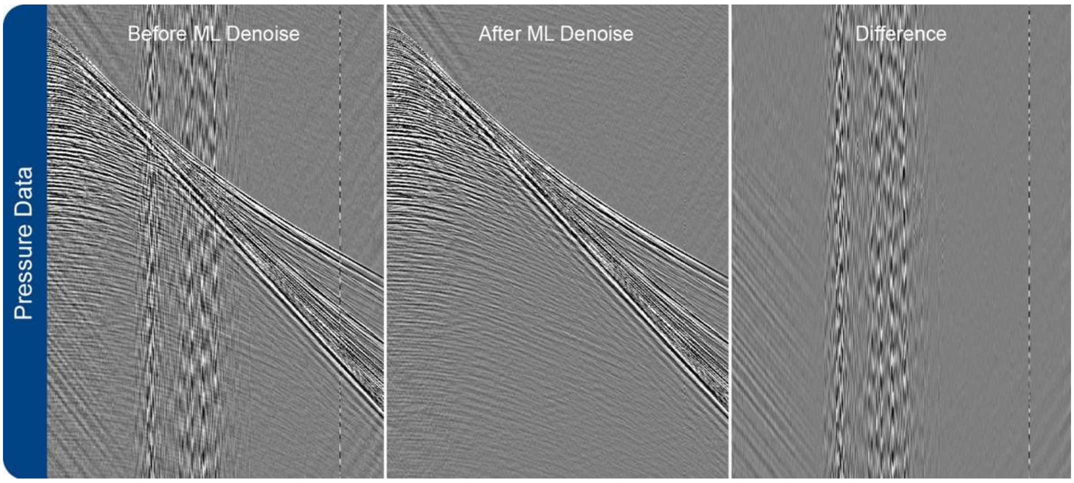


Fig 2: Shots were gathered from shallow water Sarawak, offshore Malaysia. RIDNet was applied to hydrophone data. The raw hydrophone data shows towing noise at far offsets and spurious noisy traces (Julien-Oukili *et al.,* 2024).

**Enhanced Detection Accuracy**: The main advantage of FWI and ML is their ability to provide high-resolution subsurface images, allowing for more accurate detection of hydrocarbon deposits. This increased accuracy leads to better drilling decisions and reduces the risk of dry wells. Additionally, FWI and ML help with noise attenuation in the image area after migration. Migration noise, often problematic in seismic images, is effectively mitigated using ML techniques. A CNN-based denoising approach, particularly the U-Net architecture, is showing success in offshore Newfoundland and Norway. This technique significantly improves the signal-to-noise ratio, improves structural interpretation, and supports quantitative interpretation workflows (Julien-Oukili *et al.,* 2024).

**Cost Reduction**: These advanced techniques reduce the need for extensive exploratory drilling by improving the precision of subsurface models, thereby reducing operating costs. ML algorithms can also automate many aspects of seismic data interpretation, reducing time and labour costs.

**Environmental and Safety Benefits:** Accurate subsurface imaging also contributes to safer drilling operations by identifying potential hazards such as overpressure zones and unstable formations. This protects the environment and ensures the safety of personnel and equipment.

## 3. CONCLUSION

The integration of full waveform inversion and machine learning into seismic imaging represents a significant advance in geophysical exploration. These technologies offer significant accuracy, efficiency and safety improvements, making them invaluable tools for operators worldwide. For the Niger Delta Basin in particular, the adoption of these advanced techniques is critical to optimizing resource management and ensuring sustainable development. As the geophysical community continues to innovate, the future of seismic imaging is promising for unlocking new opportunities in hydrocarbon exploration and beyond.

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