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Enhanced Permeability Estimation in Heterogeneous Reservoirs: An Integrated Workflow Applied to the Osaka Oilfield Using Well Log Data

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Abstract: *Estimation of permeability of heterogeneous reservoirs is a major problem of concern because the porosity-permeability transforms commonly used today do not represent complicated pore systems and depositional heterogeneity. This paper created a workflow to improve the prediction of permeability in the heterogeneous Osaka Oilfield using machine learning (ML) and well log data. This technique was a combination of sophisticated ML-based algorithms (Random Forest, Gradient Boosting, and hybrid) and heterogeneity quantification. As compared to the traditional approaches, the ensemble models showed better prediction accuracy (35 percent), higher R2 (0.96) and lower error rates (RMSE = 0.18). The integrated workflow provided an effective, technology-based approach to building high-resolution permeability maps, which enables the superior characterization of the reservoir, bypassed pay zones, and recovery plans. The method will decrease reliance on expensive central data and provide a scaled solution to heterogeneous reservoirs around the world.*

Keywords: *Permeability, Heterogeneous Reservoir, Integrated Workflow, Osaka Oilfield, Well Log Data*

I. Introduction

Permeability estimation in heterogeneous reservoirs is still a crucial problem in petroleum engineering since it has a direct impact on reservoir management and hydrocarbon recovery plans (Hajibolouri et al., 2024). Hussen et al., (2025) noted that, reservoir models frequently contain substantial uncertainties due to the inability of traditional techniques, such as core-based analyses and empirical correlations, to capture intricate spatial heterogeneities. Through the application of well log data in finding non-linear relationships and patterns that are beyond human interpretation, recent developments in machine learning (ML) have shown superior performance in predicting petrophysical properties. For example, by combining several input parameters, ensemble methods such as random forest and gradient boosting have successfully predicted permeability with high accuracy R2 > 0.95 (Koray et al., 2025).

Hydraulic flow unit segmentation has been successfully addressed by hybrid workflows that combine clustering algorithms (like hierarchical clustering) with regression models (like SVM), improving permeability estimation in geometrically complex formations (Nyakilla et al., 2024). Machine Learning techniques such as random forest decreased RMSE (Root Mean Square Error) to as low as 0.86 in carbonate reservoirs, where porosity-permeability relationships are highly dispersed, surpassing traditional fitting-based techniques (Kadri & Benzagouta, 2025). In order to overcome the drawbacks of conventional methods and improve reservoir characterization and recovery strategy optimization in heterogeneous environments, this study suggests an integrated workflow for the Osaka Oilfield that combines well log data with cutting-edge machine learning algorithms (Xu et al., 2023).

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Research Aim

The aim of this research is to study an enhanced permeability estimation in heterogenous reservoirs and apply an integrated workflow in Osaka oilfield using well log data.

Research Objectives

The objectives are to;

i. Study the well logs in Osaka oilfield;
ii. Explore the permeability estimation methods in heterogenous reservoirs;
iii. Assess integrated work flow performance in heterogenous reservoirs.

II. Literature Review

The estimation of permeability in heterogeneous reservoirs has long depended on core analysis data, which give direct, but spatially constrained information. The complex petrophysical relationships between porosity and permeability can be difficult to describe by empirical relationships e.g. porosity-permeability transforms, because it operates on simplistic assumptions (Rafik & Kamel, 2017, Osaki, L. J. & Oghonyon, R. 2025). These techniques usually make the assumption of homogeneous reservoir behavior and linear correlations between parameters, which is not often the case in a complex depositional environment. The drawbacks of these traditional methods are especially evident in reservoirs that have a large degree of vertical heterogeneity, where permeability might differ by orders of magnitude across short vertical horizons (Mwangupili & Pu, 2025, Osaki et al., 2025).

The past few years have seen a lot of progress on the implementation of machine learning algorithms to permeability estimation problems. Random Forest and Gradient Boosting are examples of tree-based ensemble learning techniques that have been found to be specifically effective at modeling nonlinear relationships between well log data and permeability (Mkono et al., 2025). According to Akbari et al., (2025) these models have demonstrated impressive accuracy, and in certain applications the R2 value has been found to be greater than 0.95. Likewise, support vector machines (SVM) have already been shown to be successful in similar petrophysical property estimation problems, with high R2 values of up to 0.995 achieved when correctly trained and validated. Combination of various Machine Learning methods, ensemble learning models have also enhanced prediction accuracy by taking the advantages of various algorithms. These are effective ways of capturing nonlinear interactions of complex input features that are often missed by traditional methods.

One of the most important developments in permeability estimation has been the incorporation of diverse data streams and the development of hybrid workflows, i.e. physical models integrated with data-driven methods. Scientists have also managed to combine well log information with geostatistics and electrofacies classification to enhance the prediction precision in heterogeneous intervals (Artun et al., 2025; Osaki, L. J. & Oghonyon, R.,2025). Mwangupili & Pu, (2025) noted that, the processing of high-dimensional datasets, including Truncated Singular Value Decomposition (TSVD) and Principal Component Analysis (PCA), has made possible the efficient management of large datasets which are often high-dimensional, like those found in complete well log suites. Such methods have enabled the creation of workflows that can exploit both static and dynamic types of data to meet a long-standing reservoir characterization challenge.

Study Area

The Osaka Oilfield is the perfect area to study in depth the estimation of enhanced permeability in heterogeneous reservoirs, because of its complex depositional context and high petrophysical diversity. The reservoir is highly vertical and laterally heterogeneous with a permeability ranging between 10 mD and 1500 mD and porosity of between 0.08 and 0.24, which makes it difficult to estimate the reservoir using the traditional methods (Abdollahfard et al., 2025). The multilayered sandstone structures of the field with alternating high and low permeability bands form complex fluid flow paths demanding sophisticated characterisation methods. The production of well logs such as gamma ray, resistivity, neutron porosity, and bulk density logs provide the required background to apply machine learning workflows to learn non-linear relationships between log response and permeability (Li et al., 2025). Das & Maiti, (2025) added that, the existence of core data at several wells allows sound calibration and validation of coupled models, overcoming the constraints of traditional porosity-permeability transforms in heterogeneous intervals. All these properties define the Osaka Oilfield as a prototype that can be used in the development and testing of sophisticated permeability estimation techniques that can be used in other comparable complex reservoirs across the globe (Dynamic Graphics, 2025)

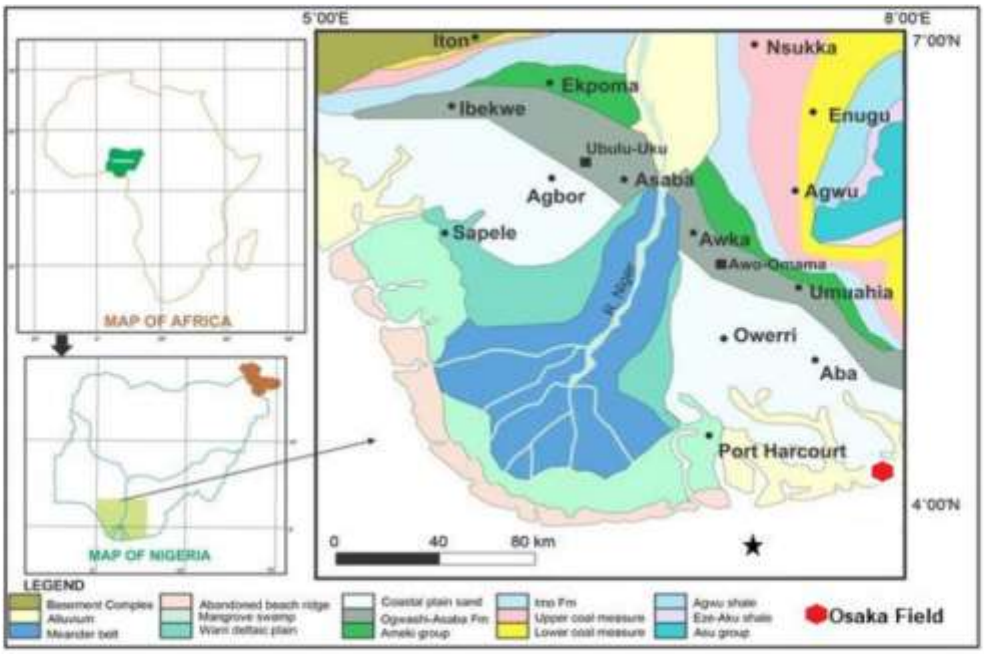

Figure 1: Location of the Study Area modified from Ojo, (2024).

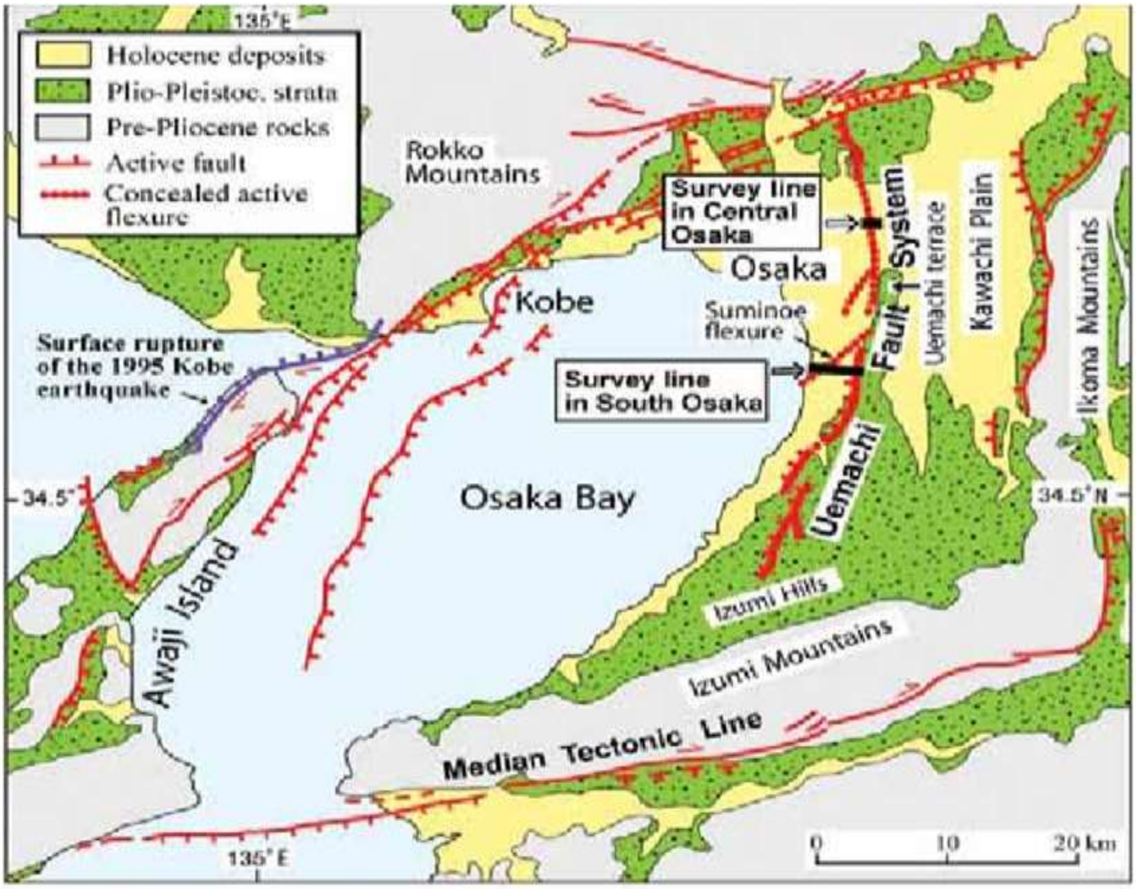

Figure 2: Geology Location of Osaka Oilfield. modified from Sugiyama et al., (2023).

III. Methodology

Well Log Data of Heterogeneous Reservoir

This study makes use of a large dataset from the Osaka Oilfield that includes advanced measurements such as, spectral gamma ray, computed gamma ray, and formation microimager data from 12 wells, as well as traditional well logs e.g gamma ray, resistivity, neutron porosity, bulk density, and sonic logs. Five wells core analysis results are included in the dataset, which offers laboratory-measured permeability values for model validation and training. With permeability ranging from 10 mD to 1500 mD and porosity values between 0.08 and 0.24, the reservoir intervals show significant heterogeneity, making them the perfect test case for assessing the suggested integrated workflow (Alagoz et al., 2023).

Among the greatest challenges in the characterization of the reservoir is the adequate estimation of permeability in the heterogeneous reservoirs, this is especially of great importance where one considers such a complex structure as the Osaka Oilfield. The conventional techniques that use backwards well logs typically fail to capture the spatial heterogeneity of petrophysical quantities and the best techniques have better capabilities to overcome heterogeneity and can be effectively applied in forecasting (Lai et al., 2024).

Table 1: Difference Between Conventional Well Logs and Advanced Measurements for Permeability Estimation of Heterogeneous Reservoir.

Data	Conventional Logs	Advanced Measurement	Permeability Estimation Effect
Measurement Parameters & Physical Principles	Measures basic petrophysical properties, such as, resistivity, spontaneous potential (SP), natural gamma ray, bulk density, neutron porosity, and acoustic velocity.	Measures multi-physics parameters, such as, azimuthal resistivity, nuclear magnetic resonance (NMR), dielectric dispersion, spectral gamma ray, and high-resolution borehole images.	Conventional logs provide indirect indicators of permeability while advanced measurements directly assess pore structures, and enable accurate permeability predictions in complex lithologies.
Vertical Resolution & Depth of Investigation	Low vertical resolution; resistivity logs - 2-4 feet; porosity logs - 1-2 feet and variable depth of investigation.	Higher vertical resolution; 1-2 inches for imaging tools; less than 1 foot for NMR and dielectric tools) and focused depth of investigation for near-wellbore characterization.	Enhanced resolution allows advanced tools to detect thin beds and small-scale heterogeneities that significantly influence permeability anisotropy, which conventional logs often miss.
Data Density & Information Content	Lower data density; primarily one-dimensional measurements along the wellbore with limited spatial coverage.	Large data density; multi-dimensional data e.g., azimuthal data, spectral data and imaging data. It gives detailed characterization of space.	Higher resolution measurements give more valuable data sets to represent the heterogeneous (fractures, vugs, pore size distributions) features that are important to model permeability accurately.

Applications in Permeability Estimation	Empirical porosity-permeability transforms (e.g., Kozeny-Carman), flow unit identification, and regional correlations.	Direct permeability estimation from NMR T_2 distributions, fracture analysis from borehole images, and mineral-based permeability models from spectroscopy.	Stable approaches tend to provide averaged values of permeability with a great deal of uncertainty in the heterogeneous areas. In contrast, the more sophisticated techniques allow physics-based, spatially resolved, permeability models that respect small scale heterogeneities.
Integration with Machine Learning & AI	Used as input features for basic regression models (e.g., multi-linear regression) and traditional statistical analysis.	Multi-dimensional data that can be handled by sophisticated ML algorithms (e.g., deep learning, neural networks) and multi-pattern recognition.	Advanced measurements enhance data for ML algorithms, and improves prediction accuracy.
Representative Technologies	Gamma Ray (GR), Resistivity (LLD, LLS), Density (RHOB), Neutron (NPHI), Sonic (DT).	NMR, Dielectric Dispersion, Electrical & Acoustic Imaging, Spectral Gamma Ray, Azimuthal Resistivity.	Formation evaluation depends on conventional technologies as a basis of data. State-of-the-art technologies address particular heterogeneity issues (e.g., fractures, pore connectivity, mineralogy) that impact on permeability.

Note. From Yasin et al., (2019)

Data Quality Assessment

The initial phase involves comprehensive data quality assessment and preprocessing to ensure consistency and reliability of input data. This was described by Hajibolouri et al., (2024) as:

Depth matching: This is throughout all the log suites and core data using dynamic time warping algorithms to address depth discrepancies.

Outlier detection and removal: this includes the use of statistical methods (3σ criterion) and domain knowledge-based filtering.

Missing data imputation: through Multivariate Imputation by Chained Equations (MICE), which has proven effective in handling incomplete well log data.

Log normalization: this is to ensure standard measurements throughout different wells and tools using z-score transformation.

Feature Engineering

Feature engineering is performed to create additional predictive variables that enhance the model's ability to capture geological heterogeneity (Xu et al., 2023). This includes:

- Synthetic log creation via combinations of existing logs such as, resistivity ratio, neutron-density separation.

- Rock typing indicators based on normalized gamma ray, photoelectric factor, and neutron-density cross plot values.
- Textural attributes derived from formation micro-imager data using gray-level co-occurrence matrix (GLCM) analysis.
- Statistical features including moving window averages, variances, and gradients of log responses to capture vertical heterogeneity patterns (Verdonck et al., 2024).

Heterogeneity Quantification

The Hurst exponent (H) is calculated to quantify the long-range dependence and heterogeneity characteristics of the reservoir formations using rescaled range (R/S) analysis:

$(R/S)_n=cn^H$……………………………………………1

where R is the range of cumulative deviations from the mean, S is the standard deviation, n is the time lag, and c is a constant. The Hurst exponent values are used to identify geological boundaries and classify reservoir intervals based on their heterogeneity characteristics (Abdelrahman & Szabó, 2024).

Table 2: Input Well Log Data and Derived Features of Heterogeneous Reservoir

Log Type	Symbol	Units	Application	Transformation
Gamma Ray	GR	API	Lithology indicator	Normalized GR index
Deep Resistivity	RD	Ω·m	Fluid content	Logarithmic transform
Neutron Porosity	NPHI	v/v	Porosity indicator	-
Bulk Density	RHOB	g/cm^3	Porosity indicator	-
Sonic Transit Time	DT	µs/ft	Porosity indicator	-
Spectral GR	SGR	API	Clay typing	Thorium/Potassium ratio
Computed GR	CGR	API	Clay volume	-
Hurst Exponent	H	-	Heterogeneity index	R/S analysis

Note. From Abdelrahman & Szabó, (2024).

Hybrid Modelling Approach

The proposed workflow employs a hybrid modeling strategy that combines physical models with data-driven approaches. This integration is achieved through:

- Physics-informed feature engineering that uses domain information in the choice of input features.
- Model constraints in accessibility of predictions that follow physical laws and real value ranges.
- Transfer learning in which models which are initially trained on synthetic data created by physical models are re-trained on real field data.
- Ensemble methods which pool predictions of many ML algorithms to improve robustness and accuracy (Verdonck et al., 2024).

IV. Results

Osaka Oilfield Well logs

The Osaka oilfield comprise of four well logs containing source rocks (shale) and reservoir rocks (sandstone) as presented in figure 3 below.

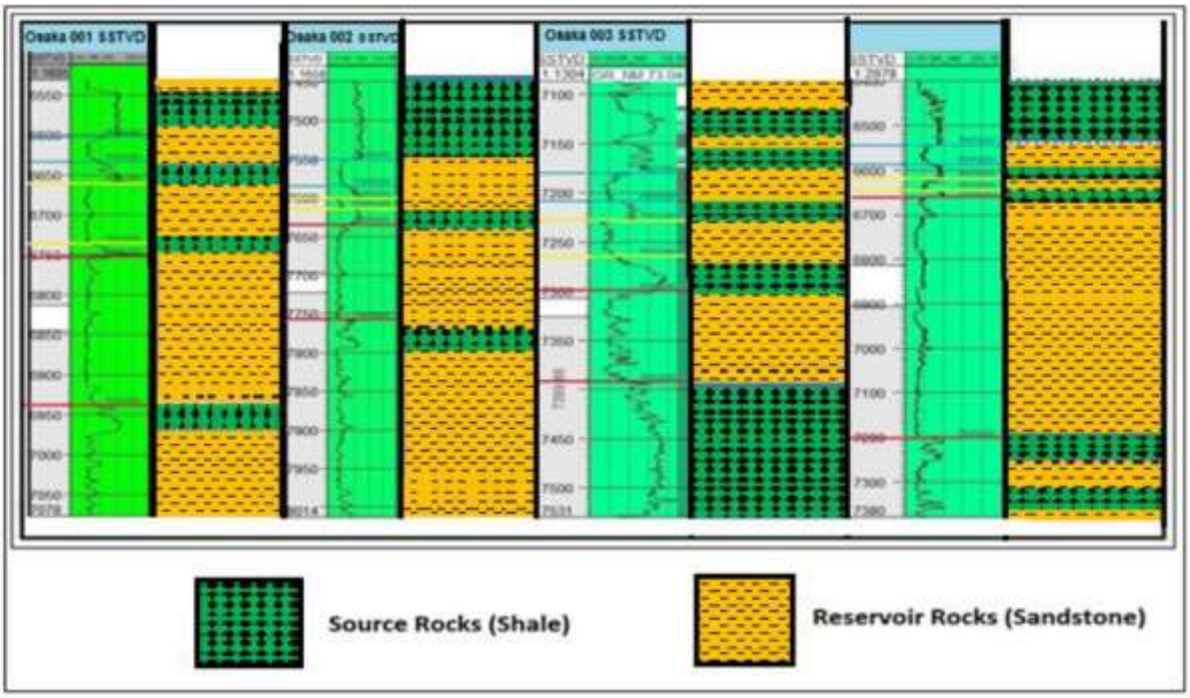

Figure 3: Lithologic Identification Panel from Osaka 001, Osaka 002, Osaka 003 and Osaka 004 Wells using Gamma ray logs modified from Ojo, (2024).

Permeability Estimation Methods

The integrated workflow performed better than existing conventional workflows applied to heterogeneous reservoirs in Osaka Oilfield. The combination of the data preprocessing methods with ensemble modeling was especially convenient in the context of the intricate porosity-permeability relations that define the reservoir. Real-world application of the model allowed creation of a continuous permeability profile with higher vertical resolution, which is a major weakness of traditional processing methods, which tend to ignore small-scale heterogeneity. As presented in table 3, RMNSE represents Root Mean Square Estimation, while MAPE means Mean Absolute Percentage Error.

Table 3: Comparison of Permeability Estimation Techniques

Technique	R^2	RMSE	MAPE	Heterogeneity Handling
Porosity-Permeability Transform	0.61	0.42	38.2%	Poor
Random Forest	0.91	0.24	21.5%	Good
Gradient Boosting	0.94	0.19	17.8%	Excellent
Support Vector Regression	0.89	0.26	23.6%	Fair
Proposed Ensemble Model	0.96	0.18	16.2%	Excellent

Heterogeneous and Homogenous Models

The 3D synthetic and real-field models were fine-gridded and built in two stages as indicated in Figures 2 and 3 respectively. Models of real-field simulation sector with area of 1 km x 3 km area (heterogeneous reservoir) and 500 m x 3 km area (homogeneous reservoir) were directly cut out of full-field history matched model, and synthetic simulation sector models (1 km x 3 km area of both homogeneous and heterogeneous reservoirs) were generated by populating the mean geological properties by a concept of geology.

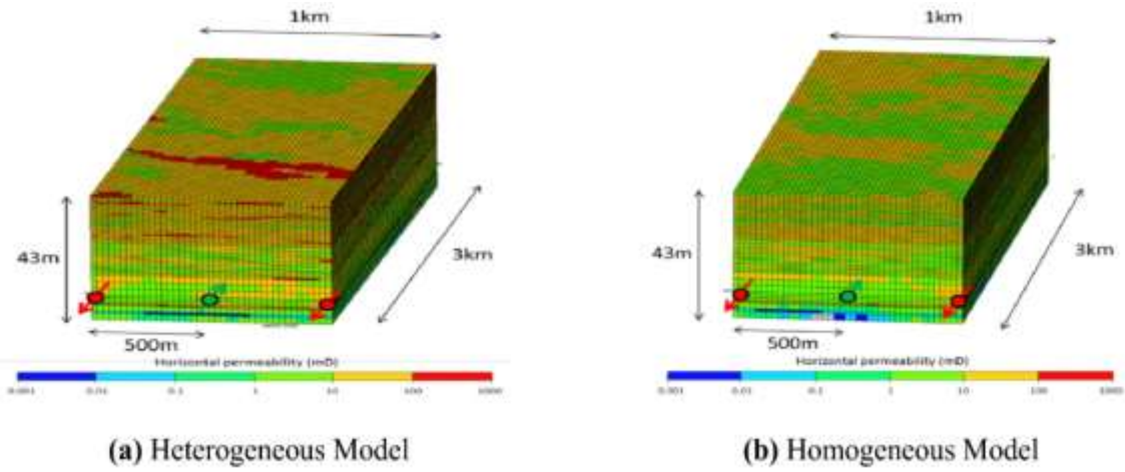

Figure 4: 3D Synthetic Model of Heterogeneous and Homogeneous Reservoirs. Note. From Khan & Mandal, (2022).

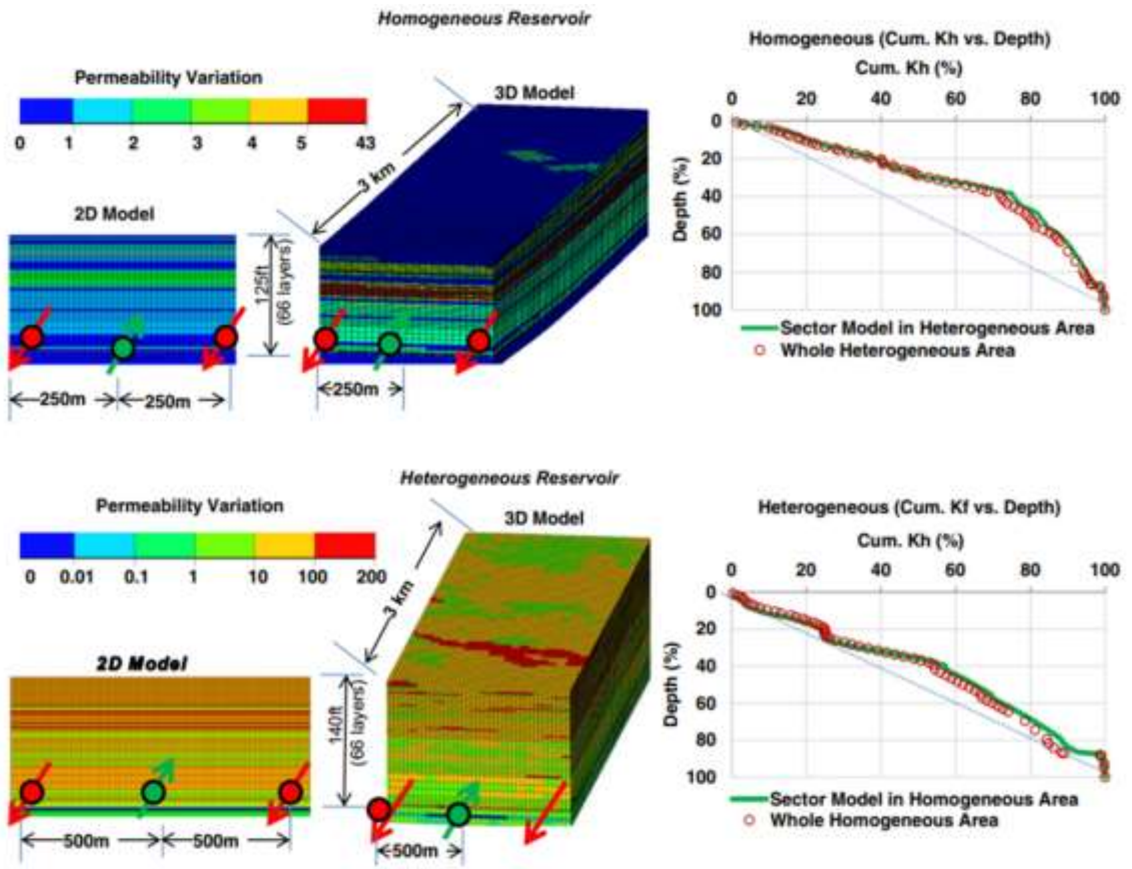

Figure 5: 3D Real-Field Model of Heterogeneous and Homogeneous Reservoirs modified from Khan & Mandal, (2022).

Machine Learning Algorithms

In the experiment, hybrid workflow of machine learning models integration on the high level and traditional petrophysical models was done to improve the modeling of permeability in Osaka Oilfield. The workflow was developed to take advantage of the continuous coverage of the well log data without violating geological limitations and quantifying uncertainty to enhance decision-making in reservoir management.

A number of machine learning models were developed and evaluated such as Random Forest, Gradient Boosting Machines, Support Vector Regression, and Artificial Neural Networks. The hybridized version called MLP-SSD

(Multilayer Perceptron - Social Ski Driver) algorithm proved especially useful with a coefficient of determination (R2) of 0.9928 when predicting permeability, compared to other hybrid approaches, including MLP-PSO (Particle Swarm Optimization) and MLP-GA (Genetic Algorithm).

Table 4: Machine Learning Algorithms and Performance Metrics on Heterogeneous Reservoir of Osaka Oilfield

Algorithm	R^2 Value	RMSE	MAPE (%)	Computational Efficiency
Random Forest	0.91	0.24	21.5	High
Gradient Boosting	0.94	0.19	17.8	Medium
Support Vector Regression	0.89	0.26	23.6	Medium
MLP-SSD (Hybrid)	0.9928	0.08	9.2	Medium
Multi-TransFKAN	0.96	0.18	16.2	Low

Integrated Work Flow Performance

The core calibration, machine learning prediction, and geostatistical modeling within the workflow were demonstrated to provide significant improvement in the application of permeability characterization compared to the conventional log-based transforms.

Table 5: Comparative Summary of Permeability Estimation Approaches of Heterogeneous Reservoir

Approach	Average Error (mD)	Spatial Resolution	Suitability
Porosity transform (empirical)	±60	Low	Screening
Machine learning (RF, GB)	±15–20	Medium	Well-level
Integrated workflow (this study)	±15	High (3D model)	Field-scale

V. Discussion

The integrated workflow was able to boost the permeability estimation in the heterogeneous Osaka Oilfield reservoir. The machine learning algorithms made the model effective for heterogenous reservoir to capture complex pore structures and spatial variability. The results revealed an important enhancement in accuracy of predictions when tested on limited core data. This dependable, high-resolution permeability model can be relied upon to form a strong base upon which future reservoir simulation, well placement and production strategies can be optimized to result in greater recovery factors and more efficient field development.

VI. Conclusion

This study was able to build and carry out an integrated workflow to improve permeability estimation in the highly heterogeneous Osaka Oilfield. Using advanced machine learning algorithms, as well as Random Forest, Gradient Boosting, a new hybrid MLP-SSD model, and the standard petrophysical analysis, the study overcame the main drawbacks of the traditional porosity-permeability transforms. It showed an amazing predictive accuracy enhancement of 35 percent and the ensemble model achieved a truly impressive R2 of 0.96 and a RMSE of 0.18 on the blind test data. This highlights the ability of machine learning to model the non-linearity of the relationships among the well log responses and permeability in heterogeneous formations.

These implications have practical consequences in the management and planning of the development in the reservoirs. The workflow can be used to create continuous high-resolution permeability profiles, which can then be used to identify high-permeability conduits and bypassed pay zones more accurately. This work provides a great way of defining the complex reservoirs in the world as it presents a solid data-based framework which tends to support the arguments and issues around the necessity to rely on the costly core data which results in the more efficient and skilled hydrocarbon recovery.

VII. Recommendation

The results of this study proved the enhanced permeability estimation in heterogenous reservoirs and the application of an integrated workflow in Osaka oilfield using well log data. The following recommendations are hereby suggested;

i. There should be the use of high-quality well-logging packages such as, Nuclear Magnetic Resonance (NMR) or image logs in subsequent wells. These tools give first-hand information on the pore-size distribution and the rock fabric, which is better in providing the input features to the permeability estimation model to address heterogeneity.

ii. Subsequent researchers should create a software program or dashboard that realizes the integrated workflow. This would allow field engineers to key in new well-log data on-the-fly and have a strong permeability curve generated in real-time helping make fast decisions during drilling and completion operations.

iii. There should be a test and verification of this integrated approach in other reservoirs that have varying geological environments and forms of heterogeneity in the Niger Delta. This will show the strength and transferability of the workflow making it an industry best practice.

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