



## Permeability Estimation Using HFU Method Enhanced by Bootstrap Forest AI-Approach for FZI Prediction in Mishrif Reservoir, Southern Iraq

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### ABSTRACT

The exploitation of artificial intelligence (AI) with the hydraulic flow unit technique (HFU) to enhance permeability prediction is an important step in reservoir characterization. HFU classifies the reservoir into distinct petrophysical properties, which are then used in permeability estimation. They are a function of the flow zone indicator (FZI), which is determined based on core permeability and porosity. Core measurements are often costly, time-consuming, and only cover limited intervals; therefore, it is necessary to use other techniques to predict FZI in unsampled intervals and wells. Thus, an advanced artificial intelligence method called Bootstrap Forest is employed to predict the FZI value from well logs. In this research, 889 core samples of six wells from the Buzurgan Oilfield's Mishrif Formation are used to identify the number of HFUs based on three techniques: probability plot, RQI versus  $\Phi_z$  analysis, and histogram analysis. Their utilization reveals that 10 HFUs represent this formation with a correlation coefficient ranging between 0.950 and 0.996. Core measurements and logs are used to construct the Bootstrap Forest model in cored wells, which yielded a high coefficient of determination ( $R^2$ ) of 0.999 and a low root mean squared error (RMSE) of 0.01, indicating that it is an effective model for predicting FZI based just on log data for uncored wells. Finally, the effective porosity is used with the predictive FZI to estimate the permeability, resulting in a perfect match between estimated and core permeability.

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# حساب نفاذية الصخور باستخدام طريقة HFU بمساعدة تقنيات الذكاء الصناعي "Bootstrap Forest" للتنبؤ بقيمة FZI في تكوين مشرف، جنوبي العراق

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المخلص	معلومات الارشفة
تم استثمار الذكاء الصناعي لتحسين التنبؤ بنفاذية الصخور والتي تعد خاصية مهمة في توصيف المكامن استناداً الى تقنية HFU. هذه التقنية تصنف المكامن الى اقسام ذات خواص بتروفيزيائية معينة ثم يستخدم التصنيف في تحديد قيمة النفاذية لاحقاً. تعتمد هذه التقنية على قيمة FZI والتي تُحسب اعتماداً على نفاذية لباب الصخرة ومساميتها. عادةً ما تكون قياسات النفاذية من اللباب الصخري مكلفةً ومستغرقةً الكثير من الوقت مغطياً أعماقاً محدده من البئر، لذلك وجب استخدام تقنيات أخرى للتنبؤ بقيمة FZI وذلك بتوظيف تقنية Bootstrap Forest احدى تقنيات الذكاء الصناعي المتقدمة لإيجاد قيمة FZI من خلال تسجيلات مجسات الابار التي لم يستخرج منها لباب صخري. في هذا البحث، تم استخدام 889 عينة لباب صخري استخرجت من ستة آبار مخترقةً تكوين مشرف بحقل بزركان النفطي للتعرف على عدد HFU اعتماداً على ثلاث طرق: مخطط الاحتمالية وتحليل RQI مع $\Phi$ وتحليل المدرج التكراري حيث استنتج ان عشر وحدات تمثل هذا التكوين بقيمة R2 عالية تتراوح ما بين (0.950 و 0.996). تم استخدام قيم اللباب الصخري وتسجيلات المجسات لبناء نموذج Bootstrap Forest الذي اعطى قيمة R2 عالية تصل الى 0.999 وقيمة RMSE قليلة تساوي 0.01 مما يدل على كفاءة النموذج للتنبؤ بمقدار نفاذية الصخور. وأخيراً تم استخدام مسامية الصخور الفعالة مع قيمة FZI المتنبأة لحساب نفاذية الصخور، ولتعطي تطابقاً متميزاً بين القيمة المقدرة من النموذج والمحسوبة من اللباب الصخري.	<p>تاريخ الاستلام: 21- يناير - 2025</p> <p>تاريخ المراجعة: 19- فبراير - 2025</p> <p>تاريخ القبول: 20- مارس - 2025</p> <p>تاريخ النشر الالكتروني: 01- ابريل - 2026</p> <p>الكلمات المفتاحية: حساب النفاذية، الخواص المكامن، وحدات الجريان الهيدروليكية، تقنيات الذكاء الصناعي، طريقة بوتستراب فورست،</p> <p>المراسلة: الاسم: ليث عبد علي</p> <p>Email: <a href="mailto:l.hamza1708@coeng.uobaghdad.edu.iq">l.hamza1708@coeng.uobaghdad.edu.iq</a></p>

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## Introduction

State permeability refers to the rock's ability to transmit fluid, which is a vital factor in reservoir characterization and management, and it is important for predicting hydrocarbon production. Estimation of permeability in a carbonate reservoir presents a significant challenge due to its pronounced heterogeneity. Generally, permeability is determined from core analysis, well-test analysis, and well-logs. Core permeability measurement provides a high degree of accuracy, but it is often costly, time-intensive, and restricted to specific well intervals (Hmeed and Hamd-Allah, 2023; Mohammadian *et al.*, 2022; Zhang *et al.*, 2019). Therefore, it is quite necessary to use other methods to predict permeability in unsampled wells. In the well test analysis, the flow rate and pressure changes are measured throughout the testing period to estimate the average permeability within the reservoir, which is not recognized for a specific depth (Tadayoni and Valadkhani, 2012). The indirect well log method offers continuous recording of physical parameters through the wellbore, enabling indirect permeability estimation. Well-log tools such as sonic log, bulk density log, NMR logs, and neutron porosity log enhance comprehension of the dataset. However, they may produce less satisfactory results, attributed to the uncertainties in the empirical parameters representing varying reservoir conditions. The inherent limitations of the conventional approach emphasize the necessity for more advanced techniques in permeability estimation (Al-Ameri and Hamd-Allah, 2023; Balan *et al.*, 1995; Mohammadian *et al.*, 2022; Zhang *et al.*, 2019).

Reservoir characterization presents a formidable challenge simply because of the inherent uncertainty connected with reservoir heterogeneity, which pertains to the reservoir properties variation. To mitigate this complexity, the hydraulic flow unit (HFU) is employed to aggregate core samples with analogous lithological and petrophysical attributes into a unique unit. This approach enables the estimation of detected petrophysical reservoir properties and mitigates the expense of coring operations. The HFU is associated with the Flow Zone Indicator (FZI), which is driven from the reservoir quality index (RQI) and normalized porosity ( $\Phi_z$ ). The FZI offers a quantitative method to interpret the relationship between macroscopic properties, such as porosity and permeability, and microscopic features, such as distribution and pore throat size (Al-Rikaby and Al-Jawad, 2024; Amaefule *et al.*, 1993; Astsauri *et al.*, 2024; Borhani and Emadi, 2011; Man *et al.*, 2021). In the literature, various methods like RQI versus  $\Phi_z$  cross plot, histogram analysis, and probability plot have been employed to classify and analyze the reservoir into HFUs. When the reservoir is divided into distinct flow units, the permeability within a specific unit can be estimated with high precision (Borhani and Emadi, 2011; Kharrat *et al.*, 2009). Although the HFU method yields results that match laboratory-cored permeability, it isn't easy to classify HFU in uncored wells and determine the permeability value. Therefore, it is necessary to find a supplementary method or technique to determine the value of FZI used to predict permeability.

Rapid and economical assessments of reservoir parameters are achieved through the effective integration of conventional evaluation methods with machine learning techniques such as Bootstrap Forest. This makes a transition towards more precise and efficient reservoir characterization, which then enhances the decision-making speed in reservoir management (Astsauri *et al.*, 2024; Ayal and Sadeq, 2024; Khaled *et al.*, 2022). Previous studies have employed some of the AI algorithms: Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGB), and an adaptive network fuzzy inference system (ANFIS), to accurately predict the permeability (Abnavi *et al.*, 2021; Al Hussein and Hamd-Allah, 2024; Man *et al.*, 2021; Salman *et al.*, 2022; Sebtosheikh *et al.*, 2015).

In this study, an AI technique called Bootstrap Forest combines the expected response values from several decision trees cultivated using a bootstrapped sample from the training set (Hastie *et al.*, 2005). It is employed together with the HFU method to estimate permeability using 889 core and log data from six wells of the Mishrif Formation within Buzurgan Oilfield. The Mishrif Formation contains about 30% of Iraq's total oil reserves (Abdula, 2020). Checking the model accuracy is through  $R^2$  and RMSE. Furthermore, validating the model in one well within the case study to confirm the model's efficacy and reliability.

## Study Area

Buzurgan Oilfield is located within the Missan oilfields in southeastern Iraq near the Iraqi-Iranian border. Structurally, Buzurgan Oilfield is an NW-SE axis anticline covering approximately 353.40 km<sup>2</sup>. It consists of two domes (Fig. 1) showing the location of the target field, the structure, and orientation of the north and south domes (CNOOC, 2017). Buzurgan Oilfield was discovered in 1970 and operated in November 1976 from the Mishrif reservoir with a regular well pattern and large well spacing ( $> 800$  m). The principal target interval within Buzurgan Oilfield is the Cretaceous Mishrif carbonate reservoir, which is stratigraphically subdivided into seven zones: MA, MB11, MB12, MB21, MB22, MC1, and MC2. MB21 is the main pay zone characterized by one pressure system, a structural reservoir with edge water, and a wide oil-water transition zone. It contributes approximately 95% oil production of the Buzurgan Oilfield (CNOOC, 2017). Figure 2 shows the stratigraphy description of the Mishrif Formation-Buzurgan oil field.

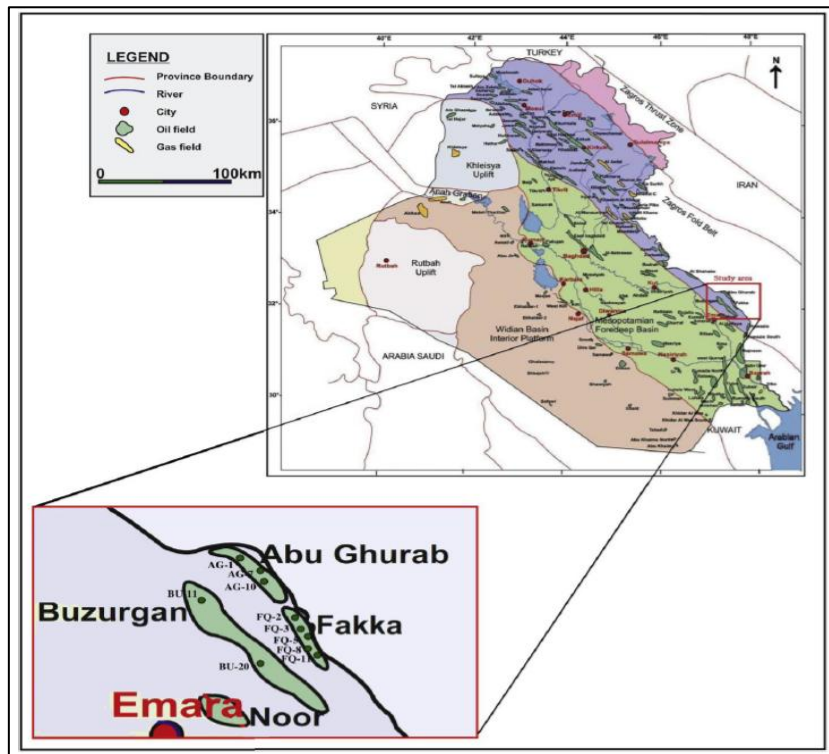


Fig. 1. A map showing the location of Buzurgan Oilfield (CNOOC, 2017).

Age	Formation	Lithology	Description	Symbol
Neocene	Bachitary, upper, Medium, and Lower Fars		Represent by Clay, Shale, anhydrite, some sandstone, Clay shale and White Dolomite	Shale
				Clay
Lower Miocene to Oligocene	Asmari		Limestone, Dolomite and Anhydrite, and Dolomitic shale	Anhydrite
				Sandstone
Cretaceous			Clay, limestone, Clay shale, Sandstone, and Dolomite	
Turonian to upper Cenomanian	Mishrif		Mainly Limestone and characterized by thin layer on the top, limestone vary from soft to medium and hard (Mudstone, Packstone, Wackstone, Grainstone)	Limestone

Fig.2. Stratigraphy description of Mishrif Reservoir- Buzurgan Oilfield (Hussein, 2012).

## HFU Identification and FZI determination for cored wells

For reservoir characterization, accurately predicting of permeability is important to understand hydrocarbon production (Faidhllah and Hamd-Allah, 2023). The HFU method initially introduced by Amaefule et al. 1993 is driven from the modified equation of Kozeny Carman 1927:

$$k = \left( \frac{1}{K_T S_{vgr}^2} \right) \times \left( \frac{\phi_e^3}{(1-\phi_e)^2} \right) \quad (1)$$

Where:  $\phi_e$ : effective porosity;  $k$ : permeability in  $m^2$ ;  $S_{vgr}$ : specific surface area per unit grain volume;  $K_T$ : pore-level effective zoning factor.

The HFU method incorporates the normalized porosity ( $\phi_z$ ) and reservoir quality index (RQI) for FZI prediction. The calculation of these parameters can be achieved through the following two equations:

$$RQI = 0.0314 \sqrt{\frac{k}{\phi_e}} \quad (2)$$

$$\phi_z = \frac{\phi_e}{1-\phi_e} \quad (3)$$

In this method, plotting RQI against  $\phi_z$  on a log scale enables the identification of HFUs for samples that exhibit similar slopes. The samples of each slope correspond to similar petrophysical and pore throat characteristics. The Flow Zone Indicator (FZI) for each HFU is calculated from the intercept of the trend line with  $\phi_z$  equals one unit. FZI for each sample can be calculated using the following equation:

$$FZI = \frac{1}{\sqrt{F_s \tau S_{gv}}} = \frac{RQI}{\phi_z} \quad (4)$$

Where:  $F_s$  = shape factor;  $\tau$  = tortuosity.

After identifying the HFUs and determining their FZI values, permeability can be estimated based on FZI values as in the following equation.

$$K = 1014 * FZI^2 * \frac{\phi_e^3}{(1-\phi_e)^2} \quad (5)$$

The researchers identify the number of HFUs of formations using porosity and permeability core data through some methods including: RQI vs.  $\phi_z$  analysis, probability plot and histogram analysis. The histogram provides quick preliminary overview of HFUs. RQI and  $\phi_z$  are computed using Equations (2 and 3). Samples that align on a straight line have similar petrophysical preparties and classified as a single HFU. Probability plot of FZI demonstrates greater suitability for determining the number of HFUs, as it facilitates a more straightforward and dependable identification process (Abbaszadeh *et al.*, 1996; Abnavi *et al.*, 2021; Alobaidi, 2016; Amaefule *et al.*, 1993).

## Permeability estimation in un-cored intervals and wells

To leverage from the HFU method in predicting rock permeability in un-cored wells, it is essential to accurately determine FZI (Man *et al.*, 2021; Mohammadian *et al.*, 2022; Salman, *et al.*, 2022; Sebtosheikh *et al.*, 2015). Various (AI) models are used to predict FZI from well logs. In this paper, the Bootstrap Forest method is employed to construct a model for determining the FZI value in the uncored intervals and wells using both well logs data and FZI from the cored well. This model is then validated using performance criteria, the coefficient of

determination ( $R^2$ ), and the root mean squared error (RMSE) for generalization of the model in order to predict the FZI values in other wells. The input logs data included NPHI, RHOB, DTC, RXO, RT, SP, and GR logs, while log FZI served as the output for the Bootstrap Forest model. Finally, by using the model prediction (FZI) and  $\phi_e$ , Eq. (5) can be used to calculate permeability.

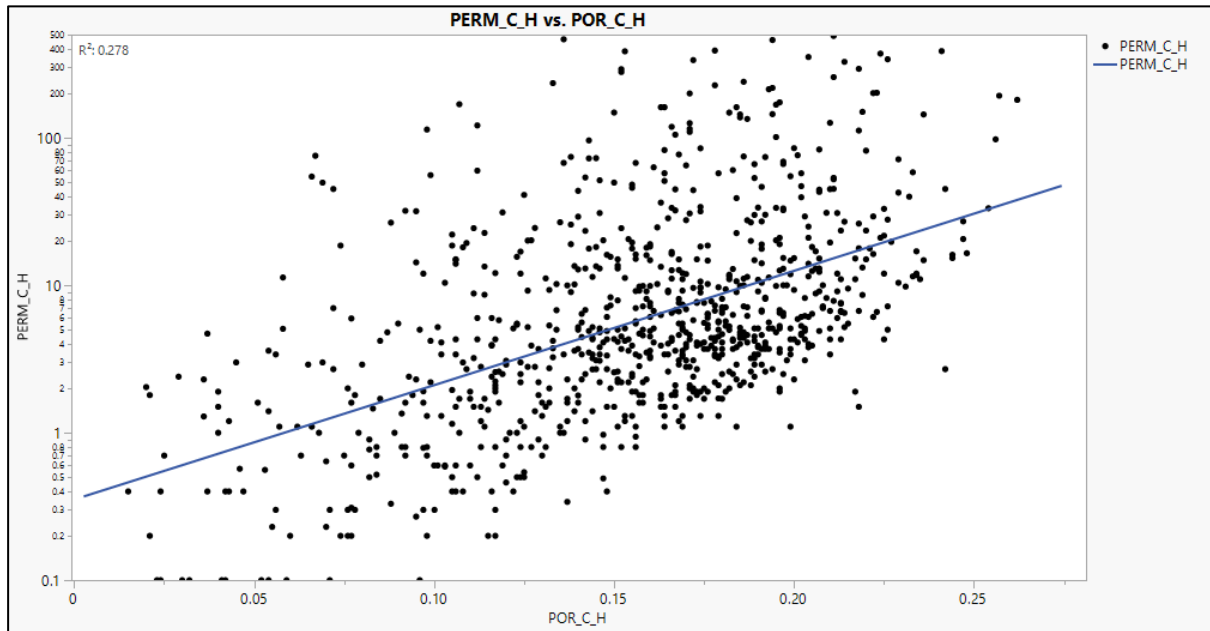
## Results and Discussion

### Data collection and analysis

Predicting permeability in the carbonate reservoir relies on 889 data points of core and well logs data. Table (1) presents a detailed summary for core data, while Figure (3) depicts the relationship between permeability and porosity in the core. The significant dispersion in the relationship between porosity and permeability core data appears in the low  $R^2$  of 0.278, highlighting the formation heterogeneity. Therefore, porosity alone is insufficient to analyze and explain the observed permeability variation.

**Table 1: Statistical summary of the core dataset for six wells.**

Property	Data points	Mean	Standard deviation	max	min
Permeability	889	22.178	56.308	491.200	0.100
porosity		0.1555	0.0466	0.2620	0.0150



**Fig. 3. Core porosity versus core permeability for sampled wells.**

The distribution of FZI is observed to be non-normal, as illustrated in Figure 4A. Consequently, direct prediction of FZI from well logs has led to inaccurate results. To approximate FZI data to a normal distribution, a logarithmic transformation is employed as presented in Figure 4A. For a preliminary summary of the data from well logs, Table 2 shows their statistics, and Figure 4A displays the histogram of each parameter. Additionally, cross plots between the input and the output parameters are shown in Figure 4B.

As demonstrated in Figure 4B, there is no discernible relationship between the log data and the resulting FZI value, so it is not possible to create a linear or multiple equation to find the resulting FZI. Consequently, it is necessary to find alternative techniques to deal with this issue.

### Identifying the Hydraulic flow unit

A non-normal distribution is evident in the qualitative examination of the FZI data, as shown in Figure 4A. Despite efforts to normalize FZI data into a logarithmic transformation,

the resultant distribution remains non-normal as presented in Figure 4A. This persistence can be ascribed to the direction of fluid flow (permeability) on FZI. As a result, accurately determining the number of the HFUs by using a probability plot is essential.

The probability plot is a statistical method for evaluating the normality of a dataset. The identification of multiple straight lines in the plot is significant evidence of distinct hydraulic flow units, each characterized by a normal distribution. As illustrated in Figure 5, ten lines suggest the presence of ten HFUs in the Mishrif Formation. Nevertheless, it is essential to note that this method relies on both visual interpretation and statistical analysis, which may introduce subjectivity to the results. Therefore, caution is required when analyzing these findings. Despite its constraints, the probability plot remains a valuable technique in data analysis, offering information about the behavior and characteristics of subsurface reservoirs.

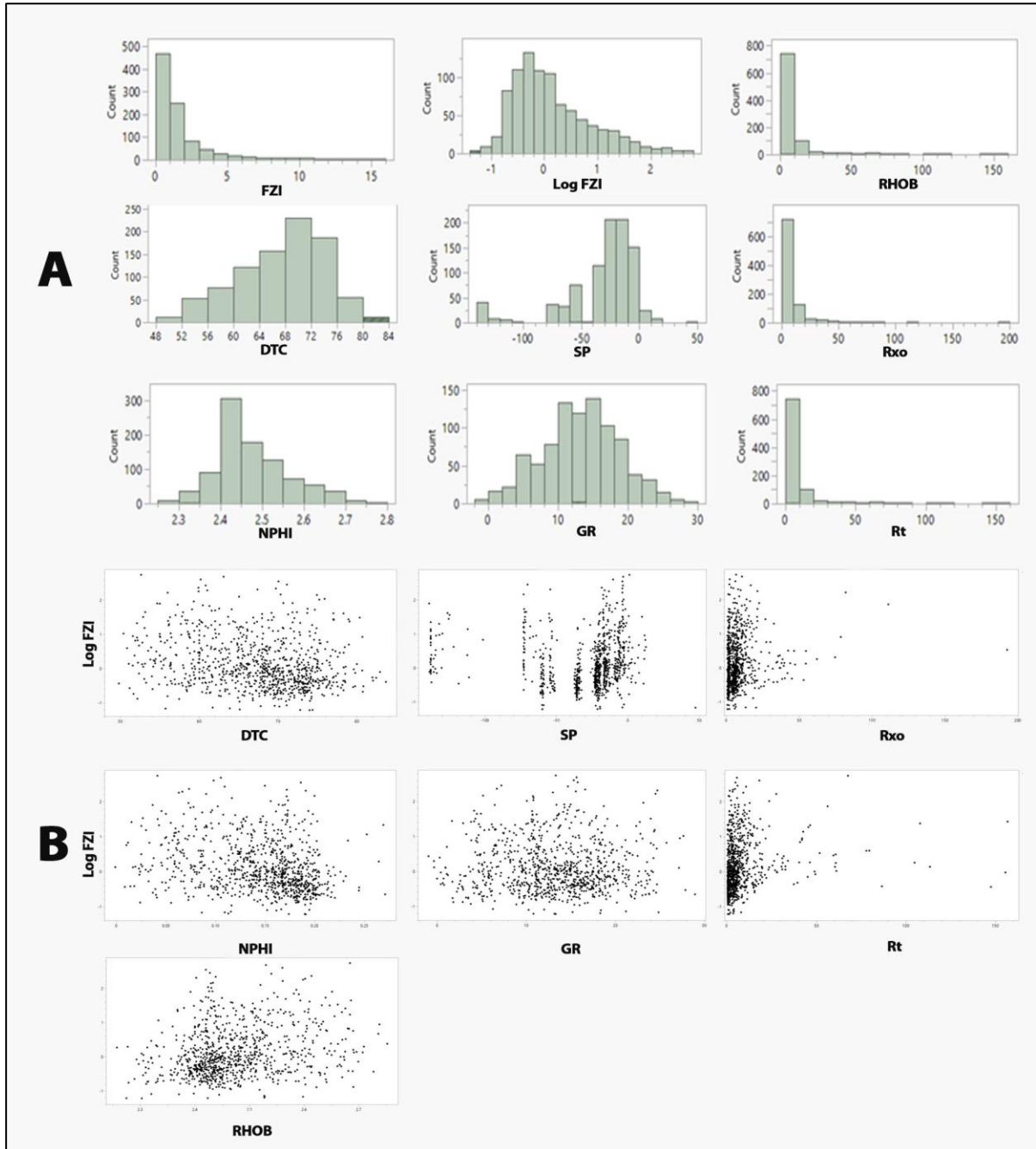
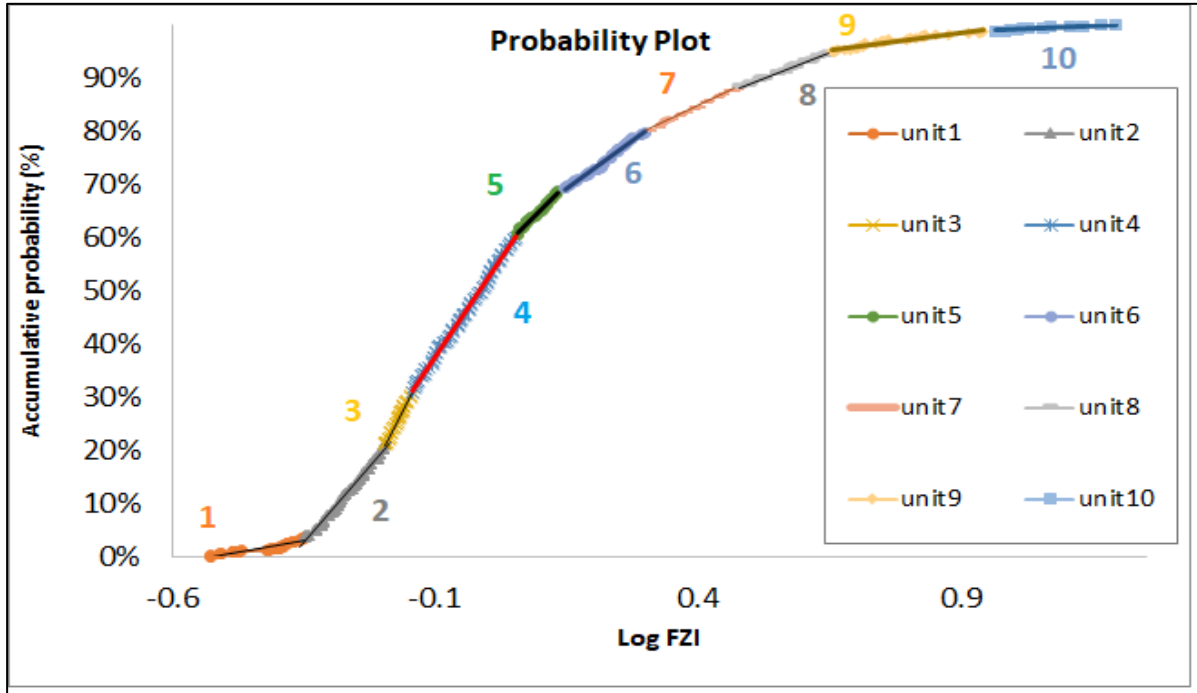


Fig. 4. Core porosity versus core permeability for sampled wells: A) Histograms; B) Cross plots.

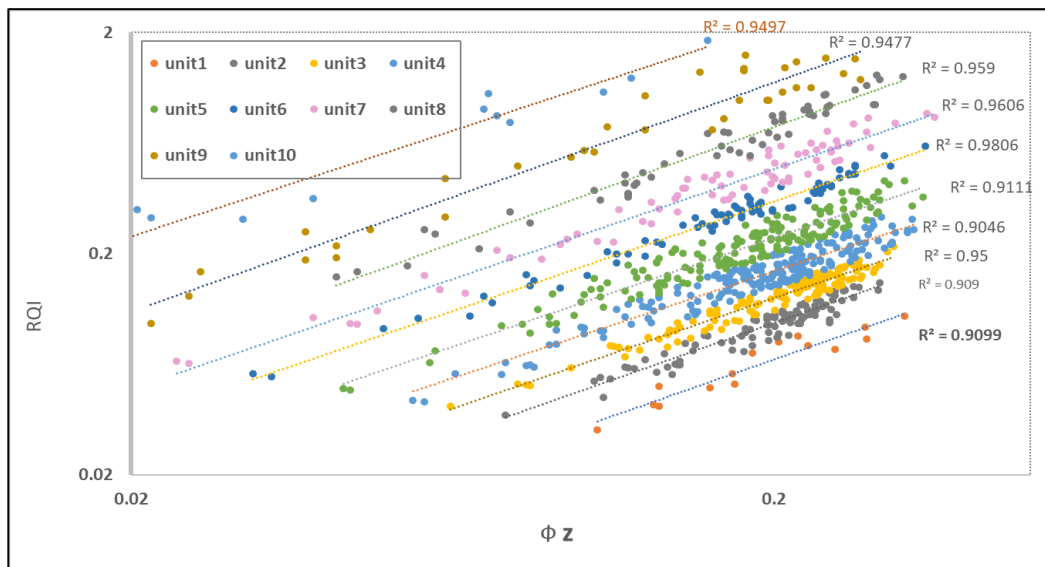
**Table 1: Statistical summary of well-log parameters.**

Property	Data points	Mean	Standard deviation	max	min
DTC		67.389	6.659	83.660	49.810
SP		-31.05	31.23	47.18	-139.20
Rxo	889	7.64	11.427	192.69	0.50
GR		13.199	5.429	28.960	-1.000
RHOB		2.4700	0.0847	2.7500	2.2500
Rt		7.444	14.290	156.800	0.329
NPHI		0.144	0.047	0.270	0.000



**Fig. 5. HFUs identification through Probability plot of log FZI.**

The final method employed to identify HFUs is plotting RQI vs.  $\Phi z$  as illustrated in Figure 6. In this method, points that exhibit similar FZI values tend to align on a straight line, indicating similar pore throats. Each straight line corresponding to similar FZI values is classified as a single HFU. Furthermore, the FZI values for HFUs are determined from the straight lines that intersect with  $\Phi z$  equal to one. Data analysis is performed using JMP and Techlog 2015.3 for all the above methods.



**Fig.6. Plot of RQI vs. normalized porosity.**

Figure (7) indicates that the permeability and porosity relationship is improved significantly compared to whether it is a single relationship linking all data, as in Figure (3), where the value of the correction coefficient for HFUs is raised to a range between 0.950~0.996. Table 3 displays HFUs' colors, correlation coefficients, and equations for determining permeability; the high values of correlation coefficient reflect both the accuracy and high compliance of the results.

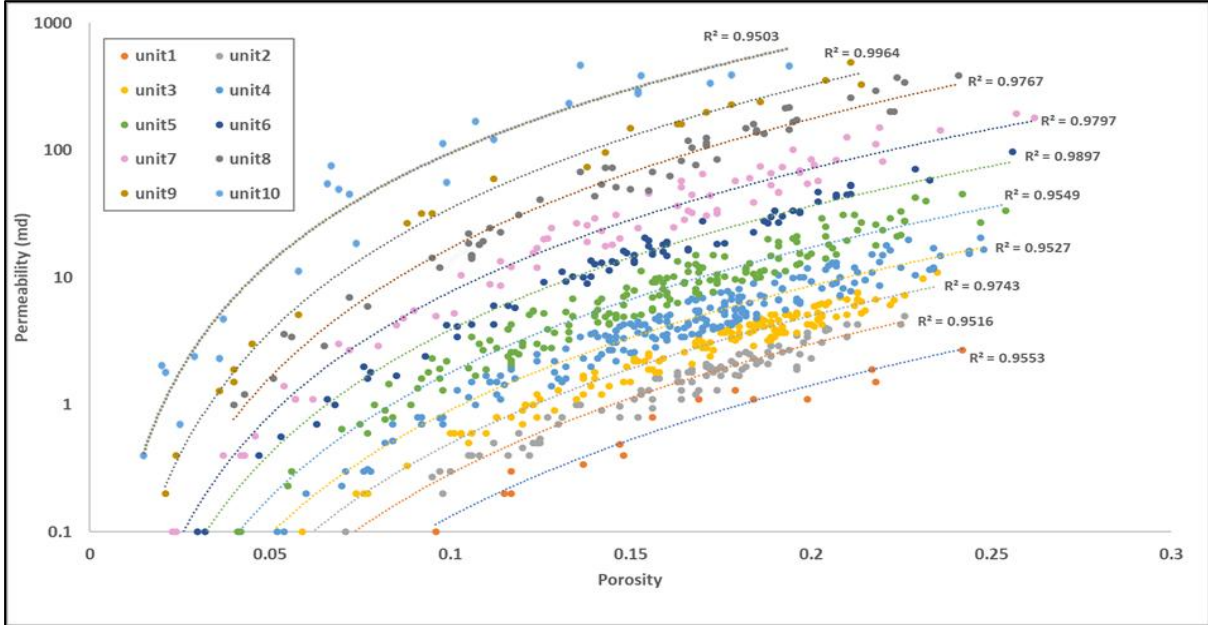


Fig. 7. Plot of permeability core against porosity core for each HFU.

Table 3: Hydraulic Flow Units' colors, correlation coefficients, and equations of permeability determination.

HFU No.	Permeability Prediction Eq.	R <sup>2</sup>	HFU Color
1	$k=354.7\Phi^{3.4288}$	0.9553	Orange
2	$k=702.63\Phi^{3.3905}$	0.9516	Grey
3	$k=1063.8\Phi^{3.3301}$	0.9743	Yellow
4	$k=1598.9\Phi^{3.247}$	0.9527	Light Blue
5	$k=3298.9\Phi^{3.2644}$	0.9549	Green
6	$k=6644.3\Phi^{3.233}$	0.9897	Dark Blue
7	$k=12790\Phi^{3.2212}$	0.9797	Pink
8	$k=40450\Phi^{3.376}$	0.9767	Dark Grey
9	$k=58293\Phi^{3.2234}$	0.9964	Orange
10	$k=68618\Phi^{2.8592}$	0.9503	Light Blue

**Permeability prediction by using Bootstrap Forest based on the HFU method**

The corporation of HFU analysis with machine learning enables rapid and precise permeability estimation, reducing reliance on expensive core sampling. Figure (8) shows the cross plots between the FZI predicted from the Bootstrap Forest method, which depends on the well log presented in Table (2), and the FZI of core data. The results of this model demonstrate a high R<sup>2</sup> of 0.999 and a low root mean square error (RMSE) of 0.01, indicating that it is an effective model for predicting FZI based just on log data. Relying on the outstanding results of the model in determining the value of FZI, it can be employed in conjunction with effective porosity in Eq. (5) to determine the rocks' permeability.

Figure 9 shows an excellent match between the core and estimated permeability on one well within the case of the study. Through the results in Figures (8 and 9), it is clear that a distinct ability to predict rock permeability values is demonstrated by the model, with a clear correspondence observed between the estimated results and the laboratory values. Therefore, it is clear that this method can be used to predict the permeability values in the heterogeneous carbonate reservoirs.

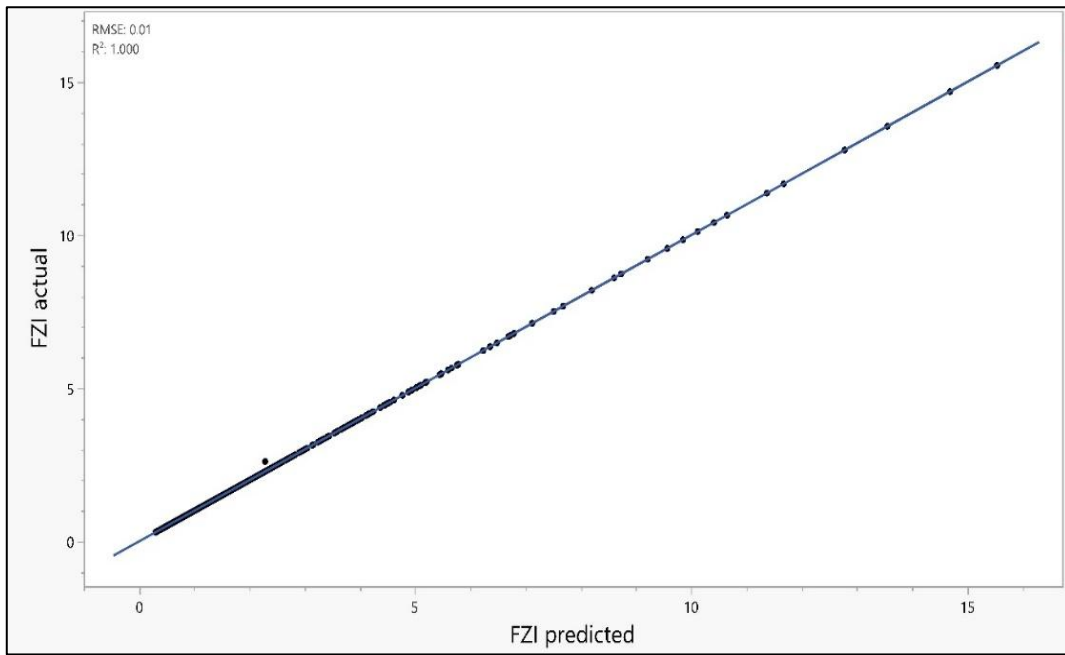


Fig. 8. Cross plot of the FZI-predicted vs. FZI-actual.

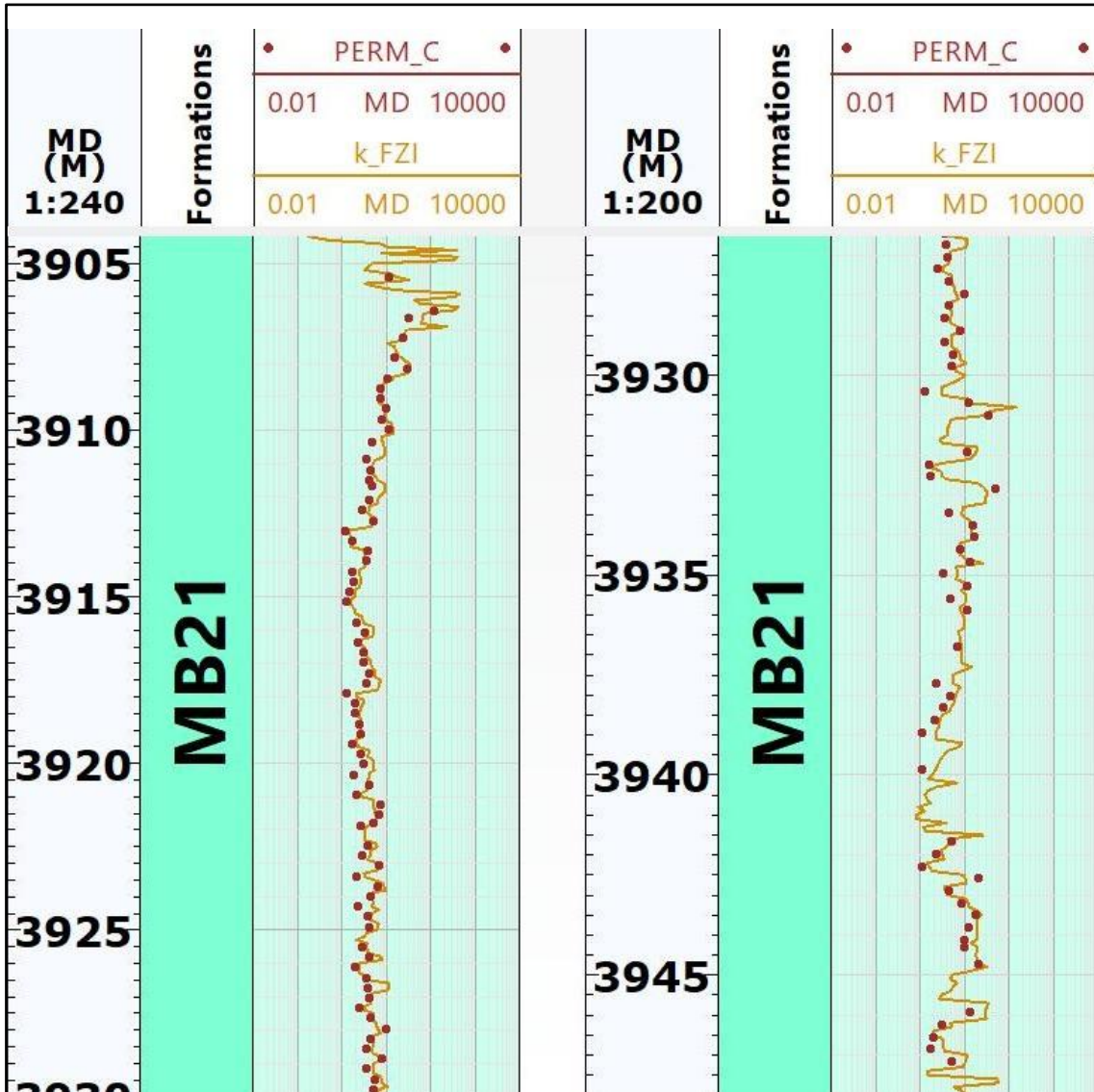


Fig. 9. K-core and K-Bootstrap.

## Conclusions

Good estimation of reservoir permeability is an important issue for developing an effective reservoir model that affects production, injection, and stimulation operations. Core data represent the most reliable source of rock permeability; however, obtaining cores from all wells and formations is not feasible due to financial and time constraints, necessitating an alternative approach.

- Porosity alone is inadequate for explaining and analyzing the variation of permeability in heterogeneous formations, as evidenced by the correlation coefficient of only 0.278 between core porosity and permeability.
- FZI values do not exhibit normal distribution, which may lead to misleading results when directly predicted from well logs. A logarithmic transformation of the FZI values is essential to approximate them to a normal distribution.
- It is not possible to create a linear or multiple equation to determine FZI, due to an indiscernible relationship between the log data and the FZI value.
- Probability plot effectively analyzes the data because it relies on both statistical analysis and visual interpretation.
- The Bootstrap Forest model effectively treats the complex data with non-uniform trends, which demonstrated a high  $R^2$  of 0.999 and a low RMSE of 0.01, indicating that it is an effective model for predicting FZI based just on log data.

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