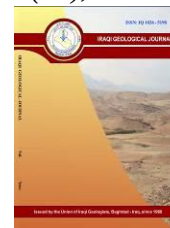




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1 Evaluation of Rock Typing Methods in a Carbonate Reservoir: A Case Study 2 of the Jeribe-Euphrates Formation in the Fauqi Oil Field, Southern Iraq

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Abstract

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Accurate rock typing is essential for reservoir characterization because heterogeneous carbonate reservoirs exhibit complex pore systems that weaken conventional porosity-permeability relationships. This study presents a comprehensive comparative evaluation of conventional and machine learning-based rock typing techniques for the Jeribe-Euphrates carbonate reservoir in the Fauqi Oil Field, southern Iraq. Unlike previous studies that focused on a single classification approach, this work systematically compares Hydraulic Flow Units, Discrete Rock Types, the Winland (R35) method, Lorenz curve analysis, Accumulated Correlation analysis, and machine learning clustering techniques using a unified dataset. The analysis was conducted on 179 core samples with porosity and permeability measurements. HFU, DRT, Winland, Lorenz, and Accumulated Correlation methods were applied to classify reservoir rocks, whereas K-means and Expectation-Maximization algorithms were used to evaluate machine learning-based rock typing. The performance of each method was quantitatively assessed using regression equations, coefficients of determination (R^2), variance, standard deviation, and coefficient of variation. The results indicate a weak overall porosity-permeability relationship ($R^2 = 0.2675$), confirming the pronounced heterogeneity of the studied reservoir. Among all evaluated approaches, the HFU method provided the most consistent and reliable rock classification, identifying four hydraulic flow units with the lowest statistical variability (variance = 0.017423) and the most reliable reservoir-quality characterization. Although the DRT and machine learning approaches achieved high R^2 values for some individual classes, their overall classifications exhibited greater variability and lower consistency. Incorporating the Winland pore throat radius (R35) improved clustering performance but did not outperform the HFU approach. Overall, the results demonstrate that the HFU method is the most suitable approach for defining hydraulic flow units in heterogeneous carbonate reservoirs, providing a reliable framework for reservoir characterization, static geological modeling, and flow unit identification.

Keywords: Complex carbonate reservoirs; Rock typing; Porosity; Permeability; Petrophysical correlations

3 1. Introduction

4 Reservoir characterization is an essential part of hydrocarbon exploration and production (Hasoon
5 and Farman, 2024). The carbonate reservoirs are especially difficult to assess because of their high
6 heterogeneity and tightness caused by depositional and diagenetic processes (Haghighi et al., 2011;
7 Faidhllah and Hamd-Allah, 2023; Balaky et al., 2023). These processes directly affect rock type, storage
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capacity and flow characteristics, which in turn affect reservoir evaluation and development strategies (Mazzullo and Chilingarian, 1992; Wardlaw, 1996; Khalid et al., 2024). The efficiency of hydrocarbon storage and production is therefore strongly affected by the intrinsic complexity and multiscale nature of carbonate pore systems (Fallah-Bagdash et al., 2020; Kakemem et al., 2021; Abouelresh et al., 2022; Ghasemi et al., 2022; Khalid et al., 2024). To improve reservoir performance prediction, reservoir rocks must be classified according to their geological characteristics and depositional attributes (Ali and Al-haleem, 2023; Amin and Al-haleem, 2024). Accurate identification of flow units based on detailed rock typing is essential for constructing reliable dynamic reservoir models (Amin and Al-haleem, 2024). Several conventional rock typing methods have been developed for reservoir characterization based on core data, such as Hydraulic Flow Units (HFU), Discrete Rock Types (DRT), Winland pore throat radius (R35) method, Lorenz curve analysis and Accumulated Correlation analysis. Recently, machine learning techniques have been proposed as an alternative method to rock typing in carbonate reservoirs.

The Jeribe and Euphrates formations are significant carbonate reservoirs in Iraq. The depositional environment, diagenetic evolution and reservoir characterization of the Jeribe and Euphrates formations have been the subject of several studies in Iraq (Taher et al., 2011; Al Dalawy, 2012; Abdul-Aziz and Abdul-Hussain, 2021; Naji et al., 2022; Aqrabi et al., 2023; Mishkil, 2023). Although these studies have enhanced the understanding of these carbonate reservoirs, a detailed comparison of conventional rock typing methods and ML-based clustering methods for the Jeribe-Euphrates reservoir is still limited. Therefore, this study aims to evaluate and compare the performance of conventional rock typing methods and machine learning (ML)-based clustering techniques to identify the most reliable approach for rock typing and flow unit characterization of the Jeribe-Euphrates reservoir in the Fauqi Oil Field.

1.1. Geological Setting

The Fauqi Oil Field is located in Missan Governorate in southern Iraq. It is located around 50 km to the northeast of Ammara city and about 175 km north of Basrah city (Fig. 1).

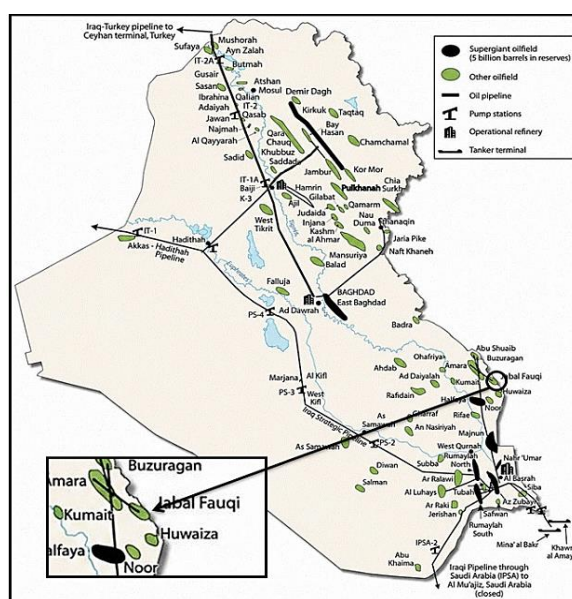


Fig. 1. Location map showing Iraqi Fauqi Oil Field

From a structural perspective, the field comprises two domes creating northwest–southeast-oriented anticlines in the northern and southern areas. Part of the northern dome stretches into Iranian territory. The field area is approximately 23 km long and around 7 km wide (Taher et al., 2011; Abdul-Aziz and Abdul-Hussain, 2021; Naji et al., 2022). The stratigraphic succession of the Fauqi Oil Field (Fig. 2) comprises two main reservoir intervals, namely the Asmari and Mishrif reservoirs. In the Fauqi Oil Field, the Asmari reservoir consists of the Jeribe–Euphrates, Upper Kirkuk, and Middle–Lower Kirkuk formations. The present study focuses on the Jeribe–Euphrates Formation, which forms the upper part of the Asmari reservoir and has an average thickness of approximately 40 m. The formation is composed predominantly of dolomite (approximately 85%) with thin interbeds of shale (Taher et al., 2011; Abdul-Aziz and Abdul-Hussain, 2021; Naji et al., 2022).

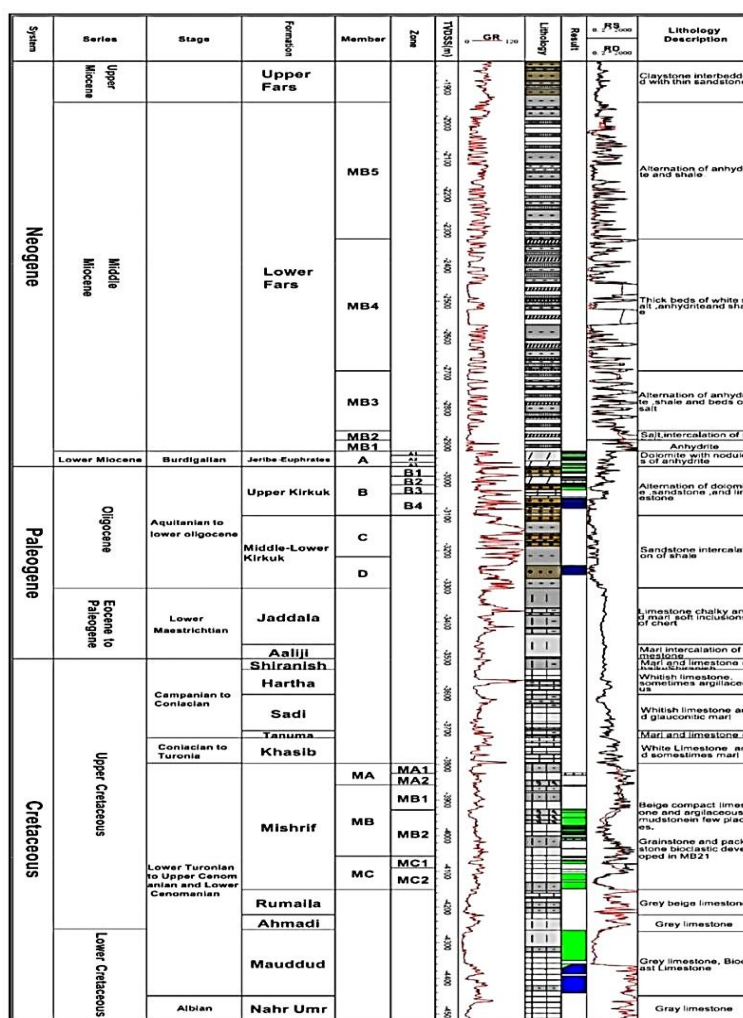


Fig. 2. Stratigraphy of Fauqi Oil Field reservoirs with average thickness (Abdul-Aziz and Abdul-Hussain, 2021)

2. Materials and Methods

This study utilized 179 core samples collected from five wells (FQ-1, FQ-9, FQ-10, FQ-11, and FQ-15) penetrating the Jeribe–Euphrates Formation in the Fauqi Oil Field. The corresponding porosity and permeability data were digitized from Al Dalawy (2012). These samples were used to evaluate and compare different rock typing methodologies applicable to heterogeneous carbonate reservoirs based on the assessment of permeability and porosity relationships.

2.1. Conventional Porosity-Permeability Relationship

Permeability and its distribution within a reservoir are key factors in reservoir characterization and production management. In many studies, permeability in uncured intervals is estimated using empirical relationships between porosity and permeability, which can be expressed as follows (Amaefule et al., 1993):

$$\log k = a\Phi + b \quad (1)$$

However, this relationship is not always accurate, as permeability is strongly controlled by grain size and pore structure, whereas porosity is less sensitive to these factors. Therefore, zones with similar porosity values may exhibit significantly different permeability values, indicating the presence of different flow units within the reservoir (Amaefule et al., 1993). Accordingly, this study applies several rock typing methods based on the analysis of permeability and porosity relationships.

2.2. Hydraulic Flow Unit (HFU) Method

Hydraulic flow units (HFUs) were determined by calculating three main variables: the reservoir quality indicator (RQI) using Eq. (2), the normalized porosity index (Φ_z) using Eq. (3), and the flow zone indicator (FZI) using Eq. (4).

$$RQI = 0.0314\sqrt{(k/\Phi_{eff})} \quad (2)$$

$$\Phi_z = \Phi_{eff}/(1 - \Phi_{eff}) \quad (3)$$

$$FZI = RQI/\Phi_z \quad (4)$$

Taking the logarithm of both sides of Eq. (4) will lead to the final correlation, which is expressed as follows:

$$\log RQI = \log \Phi_z + \log FZI \quad (5)$$

where: Φ_{eff} = Effective porosity (fraction), K = Permeability (mD), RQI = Reservoir quality indicator (μm), FZI = Flow zone indicator (μm), Φ_z = Normalized porosity index (fraction)

The correlation between $\log(RQI)$ and $\log(\Phi_z)$ was plotted graphically to determine the hydraulic flow units (HFUs) having the same value of FZI. Samples located along the same line have similar porosity and pore throat properties and, therefore, similar flow characteristics (Baker et al., 2013; Alsinbili et al., 2013; Amin and Al-haleem, 2024).

2.3. Discrete Rock Type (DRT) Method

The continuous FZI values were converted into discrete rock type (DRT) values using the following equation (Garrouch and Al-Sultan, 2019):

$$DRT = 2 \ln(FZI) + 10.6 \quad (6)$$

2.4. Winland (R35) Method

The pore throat radius (R35) was calculated using the equation published by Kolodzie (1980), which was developed based on the empirical methodology presented by Winland (1972) to link porosity and permeability to pore throat radius through mercury injection capillary pressure (MICP) experiments.

$$\log(R35) = 0.732 + 0.588 \log(K_{air}) - 0.8641 \log(\Phi) \quad (7)$$

where: Φ = Porosity (%), K = Uncorrected air permeability (mD), R35 = Pore throat radius at 35% mercury saturation (microns)

Martin et al. (1997) and Porras and Campos (2001) classified petrophysical flow units according to R35 values into five main categories (Riazi, 2018; Amin and Al-haleem, 2024):

- Mega-porous: $R35 > 10 \mu\text{m}$,
- Macro-porous: $2.5 \mu\text{m} < R35 < 10 \mu\text{m}$,
- Meso-porous: $0.5 \mu\text{m} < R35 < 2.5 \mu\text{m}$,

- Micro-porous: $0.2 \mu\text{m} < R35 < 0.5 \mu\text{m}$,
- Nano-porous: $R35 < 0.2 \mu\text{m}$

2.5. Lorenz Curve Method

The Lorenz curve was used to evaluate reservoir heterogeneity by analyzing the relationship between accumulated porosity (storativity) and accumulated permeability (transmissivity). The curve was compared with the line of perfect homogeneity to evaluate the reservoir heterogeneity. In this representation, storativity was plotted on the x-axis and transmissivity on the y-axis (Krivoshchekov et al., 2023).

2.6. Accumulated Correlation Method

The accumulated correlation method was used to analyze the accumulated values of porosity and permeability to assess the relationship between the two as pore space increases (Galkin et al., 2016; Putilov et al., 2022; Krivoshchekov et al., 2023). The samples were arranged in order of increasing porosity, and the correlation coefficient was computed step by step, beginning with $n = 3$ samples and then moving up by one sample at a time. The accumulated correlation coefficient was then plotted against porosity, with the correlation coefficient on the vertical axis and porosity on the horizontal axis, to assess the complexity of the reservoir pore system (Krivoshchekov et al., 2023).

2.7. Machine Learning Clustering

Machine learning clustering was applied to evaluate its capability for rock type classification using the available core dataset. Two unsupervised clustering algorithms, K-means and Expectation–Maximization (EM), were implemented using the calculated Flow Zone Indicator (FZI) values. Subsequently, the pore throat radius (R35) was incorporated into the FZI parameter set to assess its effect on clustering performance and rock type discrimination.

1. The K-means algorithm is one of the most widely used clustering algorithms, where data is divided into a number of groups based on the proximity of the data to the group center. The most widely used distance is the Euclidean distance:

$$d(i, j) = \sqrt{\sum_{k=1}^p |X_{ik} - X_{jk}|^2}, \quad (8)$$

In equation (8): $\mathbf{i} = (X_{i1}, X_{i2}, \dots, X_{ip})$, $\mathbf{j} = (X_{j1}, X_{j2}, \dots, X_{jp})$.

It involves initial cluster center selection, followed by iterative updating of cluster assignments until some stopping criteria, usually associated with optimal clustering (Zhao et al., 2017).

2. The Expectation-Maximization (EM) algorithm is an iterative maximum likelihood estimation technique for estimating model parameters. It does this by maximizing a lower bound on the likelihood known as the Q-function. In each iteration, we do the following two steps: the Expectation (E-step) and the Maximization (M-step). In the E-step, we compute what is called the expected value of complete data. In the M-step, the Q-function is maximized with respect to the unknown parameters. The process is repeated until the convergence criterion is satisfied, which results in stable parameter estimates (Xu and Jordan, 1996; Borman, 2004; Sammaknejad et al., 2019).

3. Results and Discussion

The relationship between Φ and k based on core data was analysed to assess the reservoir quality and flow properties of the Jeribe-Euphrates Formation (Fig. 3). The data points in the scatter plot show

a wide range of porosity values from 0.014 to 0.245, and permeability values from 0.07 to 77 mD. There is a general increasing trend, but the relationship is weak with $R^2 = 0.2675$.

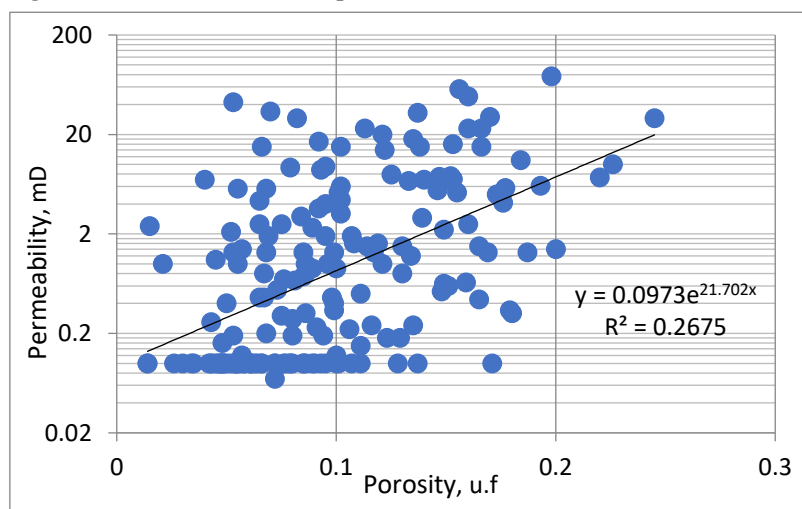


Fig. 3. Porosity-permeability relationship for core samples of the Jeribe-Euphrates Formation, Fauqi Oil Field

This result demonstrates that porosity alone cannot sufficiently explain the observed variations in permeability, which are attributed to the heterogeneous pore system of the Jeribe-Euphrates Formation. Similar observations were reported by Salman et al. (2022) and Faidhlah and Hamd-Allah (2023), who studied heterogeneous carbonate reservoirs and concluded that porosity–permeability relationships are generally weak in such reservoirs.

3.1 Hydraulic Flow Unit (HFU) Method

Based on the analyzed core data, reservoir rocks were classified into four Hydraulic Flow Units (HFUs) using the derived FZI equations. Figure 4a shows the HFU classification based on the RQI- Φz cross-plot, whereas Fig. 4 b presents the porosity-permeability relationships for the identified units. The corresponding empirical regression equations, coefficients of determination (R^2), and sample numbers (n) for each HFU are summarized in Table 1.

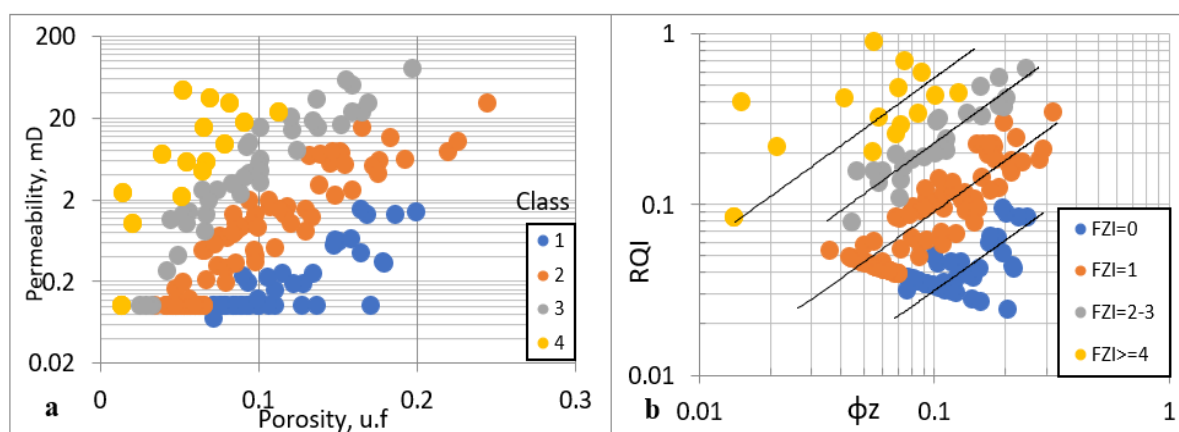


Fig. 4. (a) Hydraulic flow units (HFUs) classification using the RQI– Φz cross-plot; (b) Porosity–permeability cross plot for the identified hydraulic flow units (HFUs)

The HFU classification greatly improves the coefficients of determination (R^2) compared with the overall dataset and demonstrates more homogeneous hydraulic flow behavior within each HFU. Each

HFU contains samples that have similar pore-throat characteristics and hydraulic flow behavior. HFU-4 has the highest reservoir quality, with the highest permeability and better flow capacity, while HFU-1 has the poorest reservoir quality, with permeability lower than 2 mD. Such results agree with those reported by Salman et al. (2022), Faidhlah and Hamd-Allah (2023), and Ha et al. (2023), who stated that the HFU approach helps to improve the porosity-permeability correlation.

Table 1. Regression analysis of rock types identified by the HFU method

Class	n	Regression Dependence	Determine Coefficient
1	42	$y = 0.0196e^{19.3x}$	0.6587
2	83	$y = 1699.7x^{3.2502}$	0.8875
3	38	$y = 13495x^{3.3295}$	0.9316
4	16	$y = 4773.5x^{2.2459}$	0.7143

*Y—permeability, mD, X—porosity, u.f

3.2. Discrete Rock Type (DRT) Method

The DRT classification resulted in 12 rock types with DRT values ranging from 6 to 17 (Fig. 5). The regression analysis results for each DRT class are summarized in Table 2.

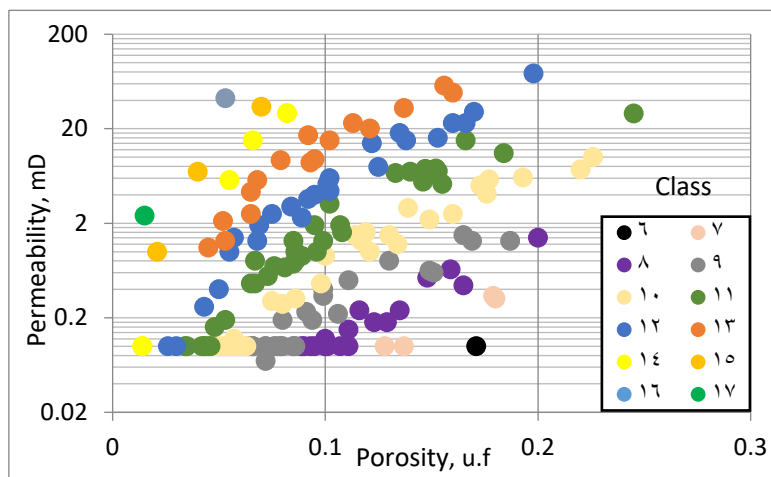


Fig. 5. Porosity–permeability relationships of DRT rock types in the Jeribe–Euphrates Formation, Fauqi Oil Field

Table 2. Regression analysis of rock types identified by the DRT method

Class	n	Regression Dependence	Determine Coefficient
1	1	N/A	N/A
2	4	$y = 0.0037e^{24.917x}$	0.9795
3	18	$y = 0.0087e^{25.345x}$	0.9263
4	28	$y = 208.94x^{2.9236}$	0.8966
5	38	$y = 973.15x^{3.1413}$	0.9738
6	38	$y = 2958.4x^{3.2283}$	0.9691
7	25	$y = 8420.7x^{3.2037}$	0.9772
8	16	$y = 15675x^{3.0623}$	0.9565
9	5	$y = 72807x^{3.1675}$	0.9968
10	3	$y = 84298x^{2.9312}$	0.9996

11	1	N/A	N/A
12	1	N/A	N/A

* N/A = Not applicable because the class contains only one sample.

The DRT method generally improved the porosity–permeability relationship within individual rock types, with most classes exhibiting high coefficients of determination ($R^2 > 0.95$), except for classes 3 and 4. However, reliable porosity–permeability relationships could not be established for classes 1 and 11–12 because each class contains only a single sample. In addition, some classes were represented by only a few samples, which may have contributed to the relatively high R^2 values. This result is consistent with the findings of Belhouchet and Benzagouta (2019) and Krivoshekchekov et al. (2023), who showed that the DRT approach produces good porosity–permeability relationships within individual rock types but also results in a higher number of rock types, which may complicate their distribution and application during reservoir geomodelling.

3.3. Winland (R35) Method

Depending on this method, the reservoir was divided into five classes, as shown in Fig. 6, while the results of the regression analysis for each class are illustrated in Table 3.

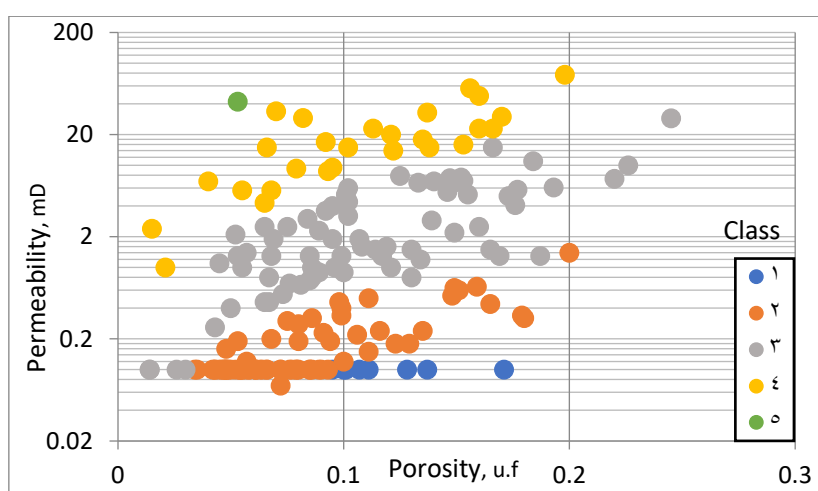


Fig. 6. Porosity–permeability relationship of Winland (R35) rock types in the Jeribe–Euphrates Formation, Fauqi Oil Field.

Table 3. Regression analysis of Winland (R35) rock types

Class	n	Description	Regression Dependence	Determine Coefficient
1	8	Nano pores	$y = 8E-16\ln(x) + 0.1$	6E-15
2	72	Micro pores	$y = 0.0499e^{13.617x}$	0.6438
3	71	Meso pores	$y = 93.579x^{1.6812}$	0.6476
4	27	Macro pores	$y = 17.282\ln(x) + 61.976$	0.376
5	1	Mega pores	N/A	N/A

In the studied reservoir, nanopore-dominated rocks are associated with permeability values below 0.2 mD and represent poor-quality reservoir units. Rocks with micropores, mesopores, macropores and megapores, on the other hand, tend to have higher permeability and reservoir quality. Although the Winland method proved to be a good means of subdividing the reservoir into various rock types, the porosity–permeability relationships for several of the classes are relatively weak. This is especially true of classes 1 and 4, where the coefficient of determination (R^2) is low, meaning there is not a strong

correlation between porosity and permeability. This is consistent with the findings of Amin and Al-haleem (2024) and Krivoshechekov et al. (2023), who performed rock typing studies on carbonate reservoirs and reported poor porosity-permeability relationships for some Winland classes. Thus, the Winland method seems to be restricted to some carbonate reservoirs that are heterogeneous and should be combined with other rock typing methods instead of being used as a single rock typing method.

3.4. Lorenz Curve Method

The reservoir was classified into six rock types based on the changes in the slope of the Lorenz curve (Fig. 7), and the porosity–permeability relationships of the identified rock types are shown in Fig. 8.

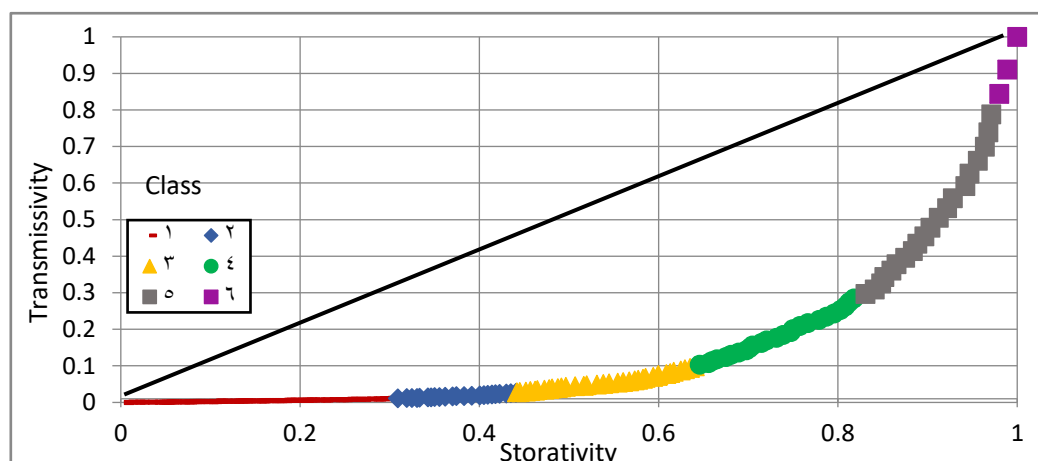


Fig. 7. Rock type classification using the Lorenz curve in the Jeribe–Euphrates Formation, Fauqi Oil Field

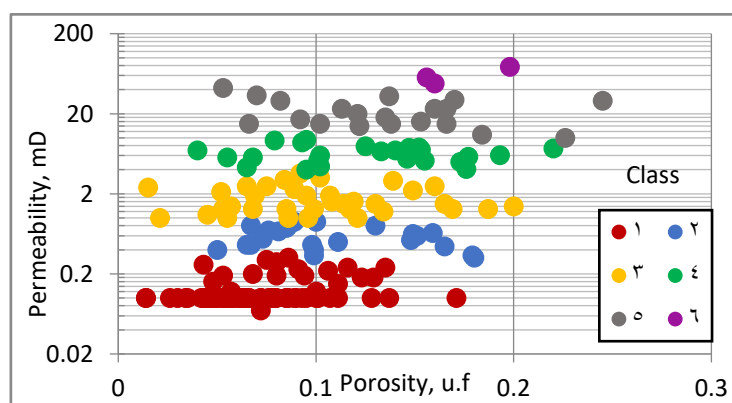


Fig. 8. Porosity–permeability relationships of Lorenz rock types in the Jeribe–Euphrates Formation, Fauqi Oil Field

The slope changes of the Lorenz curve suggest that the studied reservoir is heterogeneous, with variations in rock type. Permeability seems to be the most important parameter determining this classification, and rock types with similar permeability can have different porosity values due to differences in pore systems and pore connectivity. The porosity–permeability relationships are generally low (R^2) for the identified rock types, though. This interpretation is in line with the results of Al Dalawy (2012), who found that the Jeribe-Euphrates and Upper Kirkuk reservoir units in the Fauqi Oil Field are laterally and vertically petrophysically heterogeneous, a result of depositional and diagenetic processes. Al-Saad (2010) reported that the Jeribe-Euphrates Formation has a low-porosity, low-permeability

matrix, whereas natural fractures play a major role in increasing permeability and reservoir performance. In addition, mineralogical changes have been shown to strongly influence the petrophysical characteristics of these reservoir units (Mishkil, 2023). The results of these studies support the geologically heterogeneous reservoir characteristics identified by the Lorenz curve analysis.

3.5. Accumulated Correlation Method

This approach is based on analyzing the cumulative variation of the correlation coefficient between porosity and permeability as porosity increases. The results of this classification are presented in Fig. 9, where eight rock types can be distinguished according to changes in trend behavior. The porosity–permeability relationships for the identified rock types are presented in Fig. 10, while the regression analysis results for each identified class are summarized in Table 4.

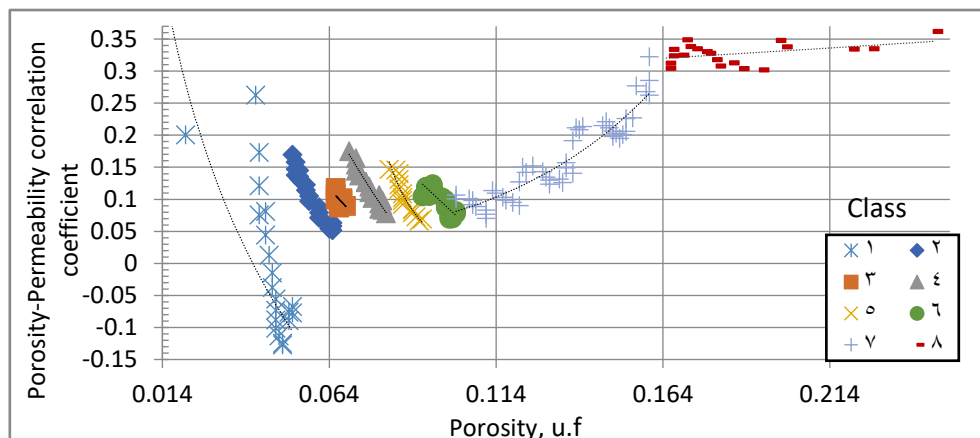


Fig. 9. Porosity–permeability correlation coefficient versus porosity in the Jeribe–Euphrates Formation, Fauqi Oil Field.

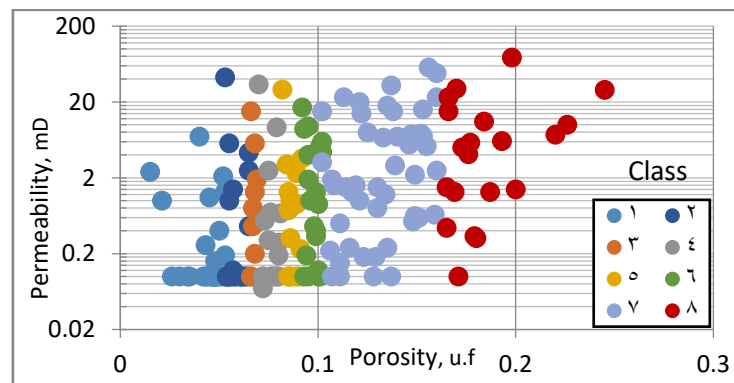


Fig. 10. Porosity–permeability relationships of Accumulated Correlation rock types in the Jeribe–Euphrates Formation, Fauqi Oil Field.

Table 4. Regression analysis of rock types identified by the Accumulated Correlation method

Class	n	Regression Dependence	Determine Coefficient
1	27	$y = -0.417\ln(x) - 1.3311$	0.2143
2	20	$y = 2E-08x - 5.388$	0.9696
3	9	$y = -0.373\ln(x) - 0.9082$	0.3865
4	17	$y = -0.621\ln(x) - 1.4818$	0.9423
5	16	$y = 4E-10x - 7.955$	0.8992
6	20	$y = -4.8847x + 0.5728$	0.7485

7	48	$y = 0.01e20.489x$	0.8664
8	20	$y = 0.273e0.9716x$	0.1877

Y— Porosity-Permeability correlation coefficient, X—porosity, u.f

The coefficients of determination (R^2) range from 0.1877 to 0.9692, indicating considerable variation in the strength of the porosity-permeability relationships among the identified rock types.

The first class is characterized by a very low coefficient of determination, indicating an unstable or negligible relationship between porosity and permeability. This class is associated with matrix-dominated rocks, including samples affected by fractures as well as intervals with poor reservoir properties.

Classes 2 to 6 show a decreasing trend in the correlation between porosity and permeability with increasing porosity. This behavior reflects fractured reservoir characteristics, where some samples exhibit relatively high permeability despite low porosity values.

Class 7 exhibits a positive relationship between porosity and permeability, indicating improved pore connectivity and fluid flow capacity. This class can be interpreted as a pore-type reservoir.

In contrast, the last class exhibits a weak positive trend in the porosity-permeability relationship. This behavior is attributed to the presence of vuggy porosity, where large pores (vugs) increase porosity without significantly enhancing permeability due to poor connectivity. Accordingly, this class can be classified as a vuggy reservoir type or a pore-cavernous (vuggy) system.

In general, the Accumulated Correlation method suggests that porosity is the most important factor in differentiating the identified rock types, while the corresponding permeability response suggests variations in pore connectivity, fractures, and vug development. However, the Lorenz curve analysis showed that permeability was the most important parameter in determining rock type. Therefore, the Lorenz curve can help to define permeability-controlled boundaries between reservoir intervals, while the Accumulated Correlation method can help define porosity-controlled boundaries based on data rather than on arbitrary porosity intervals. These complementary methods give extra information about reservoir heterogeneity and can be used for reservoir characterization and geological modeling.

3.6. Machine Learning Clustering

3.6.1. Clustering Based on the FZI Parameter

The calculated FZI parameter was used as input for the K-means and Expectation-Maximization (EM) clustering algorithms. The resulting clustering classifications are presented in Figs. 11 and 12, while the corresponding regression analysis results are summarized in Table 5.

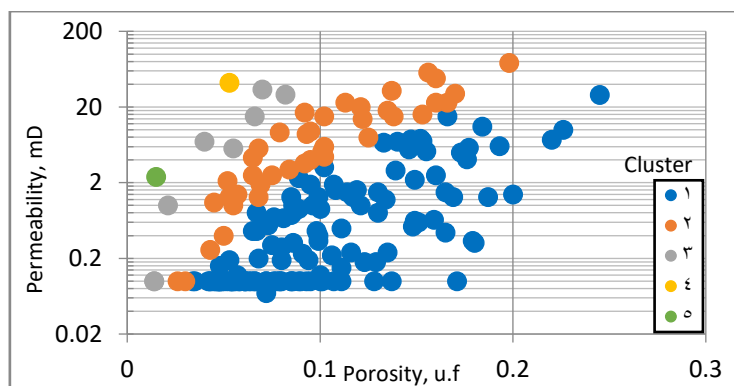


Fig. 11. Rock typing using the K-means clustering algorithm based on the FZI parameter in the Jeribe–Euphrates Formation, Fauqi Oil Field

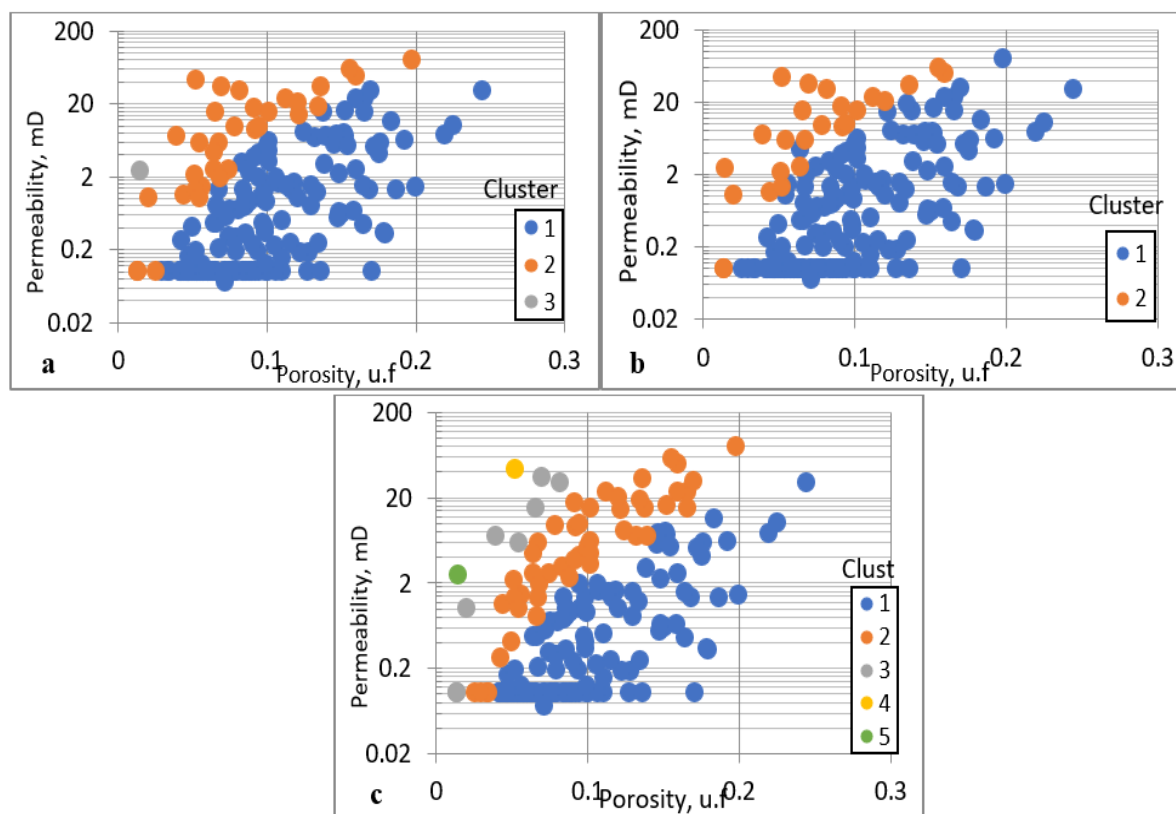


Fig. 12 (a-c). Rock typing using the Expectation–Maximization (EM) clustering algorithm based on the FZI parameter in the Jeribe–Euphrates Formation, Fauqi Oil Field

Table 5. Comparison of coefficients of determination for different numbers of clusters using the K-means and EM algorithms

Cluster	K-means						EM					
	5 Clusters			2 Clusters			3 Clusters			5 Clusters		
	n	Equation	R ²	n	Equation	R ²	n	Equation	R ²	n	Equation	R ²
1	129	$y = 141.63x^{2.4}$	0.515	154	$y = 233.36x^{2.5}$	0.437	144	$y = 0.0356e^{26.1x}$	0.489	121	$y = 0.0305e^{24.3x}$	0.565
2	40	$y = 11017x^{3.15}$	0.892	25	$y = 2116.2x^2$	0.713	32	$y = 4005.8x^{2.44}$	0.745	48	$y = 10046x^{3.1}$	0.871
3	8	$y = 100137x^{3.1}$	0.956	-	-	-	1	N/A	N/A	8	$y = 100137x^{3.16}$	0.956
4	1	N/A	N/A	-	-	-	-	-	-	1	N/A	N/A
5	1	N/A	N/A	-	-	-	-	-	-	1	N/A	N/A

*Y—permeability, mD, X—porosity, u.f

The results indicate that clustering based on the FZI parameter alone does not clearly distinguish the rock types, with the majority of samples being grouped in the first cluster. The overall clustering performance is limited, although some clusters have moderate to high coefficients of determination (R^2). This is in line with Krivoshchekov et al. (2023), who concluded that clustering based on FZI alone is not a reliable method to classify various rock types. Therefore, another parameter (e.g. Winland pore throat radius (R35)) is required to improve the clustering performance and to obtain a more accurate rock type classification.

3.6.2. Clustering Based on the FZI and R35 Parameters

To assess the effect of incorporating the pore throat radius (R35) into the clustering process, the K-means algorithm was applied using both the FZI and R35 parameters. The resulting rock type classifications for four, five, and six clusters are presented in Fig. 13, while the regression analysis results for each clustering scenario are summarized in Table 6.

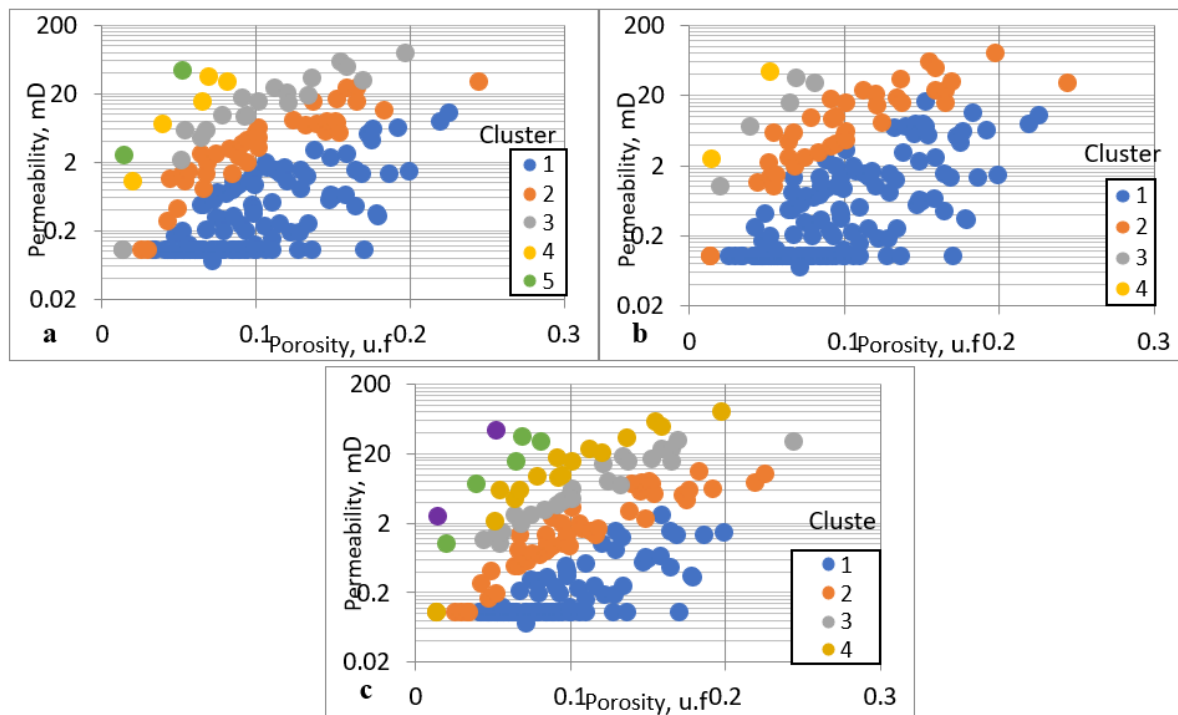


Fig. 13 (a-c). Rock typing using the K-means clustering algorithm based on the FZI and R35 parameters in the Jeribe–Euphrates Formation, Fauqi Oil Field.

Table 6. Comparison of regression analysis results for different K-means clustering scenarios based on the FZI and R35 parameters

Cluster	4 Clusters			5 Clusters			6 Clusters		
	n	Equation	R ²	n	Equation	R ²	n	Equation	R ²
1	133	$y = 0.0381e^{23.475x}$	0.499	113	$y = 0.0381e^{20.691x}$	0.527	84	$y = 0.0398e^{16.133x}$	0.550
2	39	$y = 0.4507e^{25.805x}$	0.730	39	$y = 1103.9x^{2.4799}$	0.898	47	$y = 407.76x^{2.4189}$	0.912
3	5	$y = 19601x^{2.5308}$	0.961	20	$y = 3671.3x^{2.4396}$	0.972	24	$y = 1379.2x^{2.4002}$	0.934
4	2	$y = 31.373\ln(x) + 134.16$	1	5	$y = 19601x^{2.5308}$	0.961	17	$y = 5008.8x^{2.5302}$	0.984
5	-	-	-	2	$y = 31.373\ln(x) + 134.16$	1	5	$y = 19601x^{2.5308}$	0.961
-	-	-	-	-	-	-	2	$y = 31.373\ln(x) + 134.16$	1

To further evaluate the effect of incorporating the pore throat radius (R35), the Expectation–Maximization (EM) algorithm was applied using both the FZI and R35 parameters. The resulting rock type classifications for four, five, and six clusters are presented in Fig.14, while the regression analysis results for each clustering scenario are summarized in Table 7.

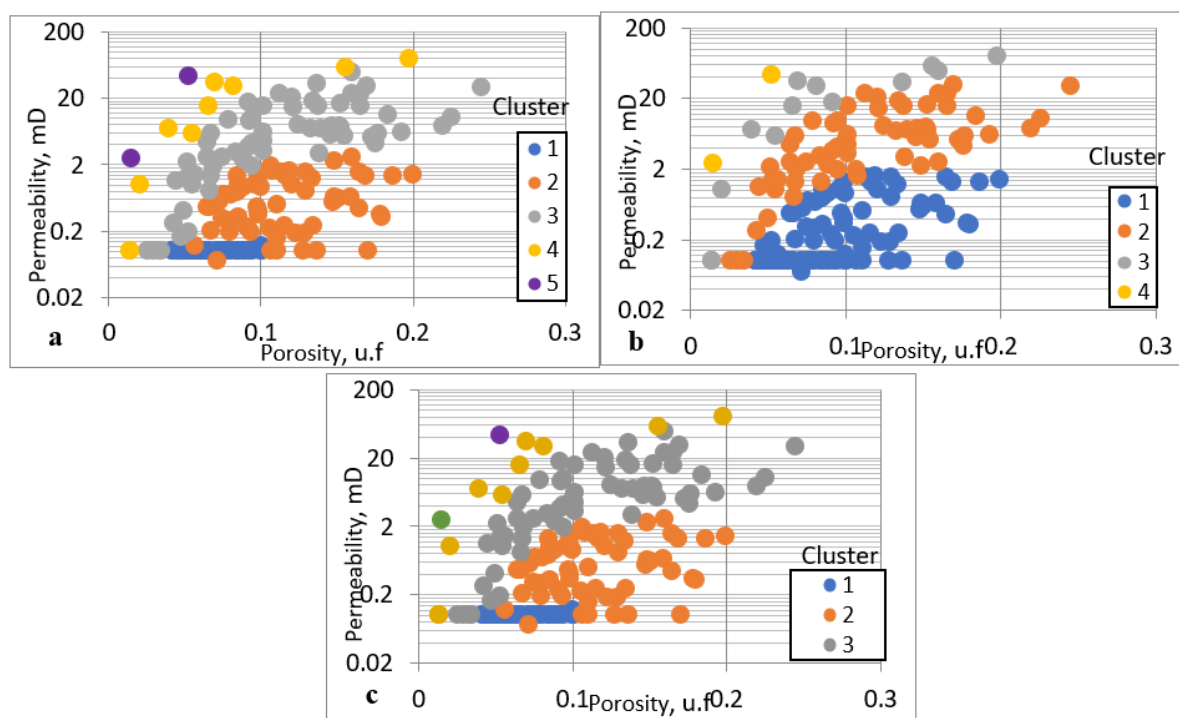


Fig. 14 (a-c). Rock typing using the Expectation–Maximization (EM) clustering algorithm based on the FZI and R35 parameters

Table 7. Regression analysis of EM clustering based on the FZI and R35 parameters

Cluster	4 Clusters			5 Clusters			6 Clusters		
	n	Equation	R ²	n	Equation	R ²	n	Equation	R ²
1	100	$y = 7.6877x^{1.4344}$	0.351	44	$y = 0.5742\ln(x) + 1.981$	0.089	44	$y = 0.5742\ln(x) + 1.981$	0.089
2	64	$y = 551.39x^{2.181}$	0.673	59	$y = 0.0975e^{0.4465x}$	0.085	59	$y = 0.0975e^{0.4465x}$	0.085
3	13	$y = 6445.6x^{2.4042}$	0.915	64	$y = 1098.2x^{2.4315}$	0.706	64	$y = 98.261x - 2.5288$	0.299
4	2	$y = 1042.1x - 13.232$	1	10	$y = 425.09x - 7.8267$	0.954	10	$y = 425.09x - 7.8267$	0.954
5	-	-	-	2	$y = 31.373\ln(x) + 134.16$	1	1	N/A	N/A
6	-	-	-	-	-	-	1	N/A	N/A

In general, the clustering performance of the FZI and R35 parameters is better than the clustering performance of the FZI parameter alone for both the K-means and EM clustering algorithms. The addition of R35 reduces the dominance of the first cluster and yields a more even distribution of samples between the resulting clusters, suggesting that pore throat data provide discrimination between the various rock types. The number of clusters is increased from 4 to 6 for the K-means algorithm, which yields better differentiation of rock types and higher R² values for most clusters, but some clusters have only a few samples and thus cannot yield a stable porosity-permeability relationship, even with high R² values. The four-cluster model, however, yields the best results for the EM algorithm, giving a more even distribution of samples and a higher regression quality than the five- and six-cluster models. The

results show that the effect of the number of clusters depends on the clustering algorithm, and more clusters do not necessarily lead to better rock type classification, especially if some clusters have just a few samples.

3.7. Choosing the Best Rock Typing Method

The results of the statistical comparison of the evaluated rock typing methods are summarized in Table 8. The statistical performance of the HFU method was the most balanced with a mean R^2 of 0.798, the lowest variance of 0.0174, the lowest standard deviation of 0.132 and the lowest coefficient of variation of 16.54%, indicating the most consistent and stable rock type classification. The DRT method, however, was able to identify more rock types and had high R^2 values for some classes with high class variability. The Winland (R35) method yielded a relatively low mean R^2 (0.333) and a high coefficient of variation (97.08%), indicating that the method is not a reliable rock typing method but can be useful for characterizing the pore-throat properties. The machine learning techniques (K-means and EM) gave different results for different number of clusters.

The six-cluster K-means model had the highest mean R^2 (0.891), but this was affected by the imbalanced classes and the small number of samples in some clusters, including one cluster with only two samples and another with five samples, resulting in an SD of 0.17 and a CV of 19.06%, which reduced the reliability of some classifications. The EM algorithm, on the other hand, gave the best results for the four-cluster model (mean R^2 = 0.735), while the five- and six-cluster models resulted in mean R^2 values of 0.567 and 0.238, respectively, and coefficients of variation of 79.67% and 154.31%. The results show that the number of clusters does not necessarily increase the clustering performance and the optimal number of clusters varies with the clustering algorithm and the sample distribution. The HFU method therefore yielded the most reliable and physically meaningful rock typing results as it is both statistically consistent and directly related to the flow behavior of fluids in the pores.

Table 8. Statistical comparison of different rock typing methods

Method	Rock types numbers	Mean R^2	Min R^2	Max R^2	Variance	St. Deviation	Variation Coefficient
HFU	4	0.79802	0.6587	0.9316	0.017423	0.131997	16.54053
DRT	12	0.72295	0.8966*	0.9968	0.190866	0.436882	60.43049
R35	5	0.33348	6E-15*	0.6476	0.104799	0.323727	97.07527
K-means	4	0.7978	0.499	1	0.053852	0.232062	29.08779
K-means	5	0.87208	0.527	1	0.038402	0.195964	22.47089
K-means	6	0.890767	0.550	1	0.02882	0.169764	19.0582
EM	4	0.735075	0.351	1	0.084653	0.290952	39.5812
EM	5	0.56726	0.085	1	0.204241	0.45193	79.66897
EM	6	0.238267	0.085*	0.9546	0.135183	0.367672	154.3111

*Zero R^2 values were excluded from the statistical analysis because some rock classes contained only a single core sample.

4. Conclusions

The results obtained confirm that the poor porosity–permeability correlation observed in the Jeribe–Euphrates Formation is due to the significant heterogeneity of the considered reservoir and its complex pore system.

A comparison of the rock-typing techniques used shows that each can provide specific information for reservoir characterization.

Among the techniques that were evaluated, the Hydraulic Flow Unit (HFU) approach was found to be the most suitable, as it had good statistical performance and a physically based classification related to pore throat characteristics and fluid flow properties.

While the Discrete Rock Type (DRT) approach helped improve porosity–permeability correlations in some classes, it also resulted in a relatively high number of rock types (12).

The Winland (R35) method was useful for pore-throat characterization, but was not satisfactory as a rock typing method alone.

The Lorenz and Accumulated Correlation methods were appropriate to highlight the reservoir heterogeneity and the presence of multiple pore systems (matrix-dominated, fractured and vuggy systems), while the machine learning methods showed that the inclusion of the R35 parameter generally improved the results but was not able to overcome the class imbalance and limited sample size of the classes.

In conclusion, HFU, which identified four hydraulic flow units (HFUs), is the best-suited method for defining hydraulic flow units and characterizing carbonate reservoir quality in the studied area.

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Declaration of Competing Interests

The authors declare that they have no competing financial interests or personal relationships that could influence the work reported in this study.

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