

Original Paper

Diagenetic origins of low resistivity pays in low-permeability sandstone reservoirs: Insights from petrology, hydrochemistry, and machine learning



Yu-Xi Sun^{a,b}, Liang Chen^{c,*}, Yuan Qi^{a,b}, Han-Cheng Ji^{a,b,**}, Yi-Ping He^d, Yan-Qing Shi^{a,b}, Si-Cong Wang^{a,b}, Shuang-Qi Feng^{a,b}, Bo-Yuan Zhao^{a,b}, Ru-Feng Deng^e

^a State Key Laboratory of Petroleum Resources and Engineering, China University of Petroleum (Beijing), Beijing, 102249, China

^b College of Geosciences, China University of Petroleum (Beijing), Beijing, 102249, China

^c College of Science, China University of Petroleum (Beijing), Beijing, 102249, China

^d No. 5 Oil Production Plant, Changqing Oilfield Company, PetroChina, Xi'an, 710200, Shaanxi, China

^e Kunlun Digital Technology Co., Ltd., Beijing, 102206, China

ARTICLE INFO

Article history:

Received 9 June 2025

Received in revised form

6 February 2026

Accepted 24 July 2026

Available online 29 July 2026

Edited by Xiu-Fang Hu

Keywords:

Low resistivity pay

Diagenesis

Irreducible water

Formation water salinity

Fluid identification

Machine learning

ABSTRACT

Low-permeability sandstone reservoirs containing low resistivity pays (LRPs) are widely encountered within the Triassic Yanchang Formation in the Jiyuan area, Ordos Basin, China. The resistivity of these reservoirs can be as low as 2 Ω m, leading to misinterpretation by conventional logging methods. Previous studies have primarily focused on resultant factors such as conductive minerals and clay minerals. However, how different diagenetic processes couple and control low resistivity remains unclear. This study focuses on the Chang 2 interval of the Yanchang Formation, integrating petrology, hydrochemistry, and machine learning (ML) to address these challenges. Results reveal that compaction-induced concentration of formation water and feldspar dissolution are critical controls on LRP formation. Dissolution processes not only release ions such as Na⁺ and Cl[−], increasing formation water salinity, but also produce authigenic clay minerals like kaolinite, which obstruct pore throats and trap highly saline irreducible water, significantly reducing reservoir resistivity. Additionally, dissolution generates larger pores (diameter >10 μm), enabling more stable conductive networks and further lowering resistivity. In terms of fluid identification, the two newly constructed fluid-sensitive parameters exhibit strong explanatory capability, and the RF-PFN model outperforms other ML methods in distinguishing fluid properties. Prediction case studies show that LRPs preferentially develop in areas characterized by higher sandstone content, high porosity, and intensive dissolution effects. These findings provide critical insights and practical frameworks for evaluating and predicting similar low-permeability sandstone reservoirs worldwide.

© 2026 The Authors. Publishing services by Elsevier B.V. on behalf of KeAi Communications Co. Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Low resistivity pays (LRPs) are characterized by resistivity that is on par with or lower than that of adjacent water layers (Worthington, 2000; Hamada et al., 2001; Bai et al., 2021; Gao et al., 2022). These oil layers are often misinterpreted as water

layers in conventional well logging, resulting in the omission of many potential oil-bearing intervals (Hamada et al., 2001; Iqbal et al., 2019). Research on LRP has increased steadily in major petroliferous basins worldwide in recent decades, including those in California and Colorado in the United States (Sonnenberg, 2021), the Ordos and Junggar basins in China (Li et al., 2010; Guo et al., 2023; Qi et al., 2023; Wang et al., 2023a), the Gulf of Mexico (Hodgkins and Howard, 1999; Hamada et al., 2001), the Middle East (Hamada et al., 2001; Salisu et al., 2023), and East Africa (Mashaba and Altermann, 2015).

Low resistivity in sandstone reservoirs can primarily be attributed to two mechanisms: (1) The reservoir exhibits high

* Corresponding author.

** Corresponding author.

E-mail addresses: chl825@cup.edu.cn (L. Chen), jhch@cup.edu.cn (H.-C. Ji).

Peer review under the responsibility of China University of Petroleum (Beijing).

Nomenclature

Abbreviations

Ana	Anatase
Ank	Ankerite
Cal	Calcite
Car	Carbonate cement
Chl	Chlorite
Dol	Dolomite
FD	Feldspar dissolution
I/S	Illite–smectite mixed layer
ill	Illite
IRP	Intergranular residual pore
Kao	Kaolinite
K-spar	K-feldspar
Plag	Plagioclase feldspar
Qz	Quartz
Sid	Siderite

Symbols

a	Lithology factor
C_{sor}	Sorting coefficient
C_{var}	Variation coefficient
m	Cementation exponent
P_{50}	Median capillary pressure, MPa
P_d	Displacement pressure, MPa
R_t	Formation resistivity, $\Omega\cdot\text{m}$
$R_{\text{wa-Rt}}$	Formation water resistivity by R_t , $\Omega\cdot\text{m}$
$S_{\text{w-irr}}$	Irreducible water saturation, %
$S_{\text{w-mov}}$	Movable water saturation, %
ϕ	Core porosity, %
ϕ_{irr}	Irreducible water porosity, %
$\phi_{\text{irr-mac}}$	Irreducible water porosity in macropores, %
$\phi_{\text{irr-mes}}$	Irreducible water porosity in mesopores, %
$\phi_{\text{irr-mic}}$	Irreducible water porosity in micropores, %
ϕ_{nmr}	NMR porosity, %
ϕ_{mov}	Movable water porosity, %

actual water saturation but still produces hydrocarbons without water, primarily due to trapped irreducible water in its micropores (Hamada and Al-Awad, 2000; Hamada et al., 2001; Pratama et al., 2017); (2) The calculated water saturation of the reservoir exceeds its actual saturation, a phenomenon attributed to the development of conductive minerals, such as clay minerals and metal sulphides, which form a conductive network and, in turn, affect resistivity logging (Hamada et al., 2001; Salisu et al., 2023). Additionally, high-salinity formation water, poor oil–water separation caused by low-amplitude tectonics, and drilling mud intrusion due to drilling operations have also been suggested as contributing factors to low resistivity (Li et al., 2010; Tian et al., 2010; Abdollah-Pour et al., 2016; Qi et al., 2023).

Furthermore, in terms of fluid identification, conventional logging interpretation methods, such as Archie's formula, often tend to overestimate water saturation (Tudge et al., 2014; Xiao et al., 2021). To address this issue, scholars have proposed several improved models, including the clay-rich sandstone Simandoux model and the ion-conduction Waxman-Smits model (Simandoux, 1963; Waxman and Smits, 1968; Clavier et al., 1984; Tudge et al., 2014). Meanwhile, qualitative cross-plot evaluation methods are also widely applied, using conventional logging to distinguish fluid properties (Li et al., 2010; Bai et al., 2021). However, these traditional approaches generally rely on localized patterns or are designed for only one type of LRP mechanism. They are often unreliable when dealing with LRPs formed by multiple mechanisms (Guo et al., 2025). In recent years, the rapid development of machine learning (ML) in geosciences has provided new perspectives for the identification of LRPs. Gao et al. (2022) integrated logging from reservoirs and adjacent shales, used DBSCAN to construct the feature space, and applied a multilayer perceptron (MLP) model for fluid classification. Lou et al. (2024) employed the MAHAKIL algorithm to address class imbalance and subsequently built an XGBoost classifier. Guo et al. (2025) constructed formation-water-sensitive variables and combined them with ML to evaluate hydrocarbon-bearing properties. Compared with traditional methods, ML excels at handling multi-factor coupling, strong nonlinearity, and highly heterogeneous data, providing robust data-driven solutions for complex LRP interpretation (Sun et al., 2026).

Despite these advances, several key knowledge gaps remain. Most previous studies have treated conductive minerals, clay

content, and high-salinity formation water as isolated resultant factors (Bai et al., 2021; Salisu et al., 2023). However, low resistivity is fundamentally the cumulative outcome of multiple diagenetic processes acting over geological timescales (Li et al., 2025). It is still unclear how different diagenetic processes (such as compaction, meteoric leaching, organic acid dissolution, and ion exchange) jointly reshape pore structures and hydrochemistry. In particular, feldspar dissolution has a dual influence: it creates secondary pores while generating authigenic clays that can impair pore connectivity (Yuan et al., 2019; Cao et al., 2022). How these competing effects evolve and ultimately govern resistivity remains insufficiently understood. Furthermore, most ML approaches for LRP identification remain black boxes, and model decisions are rarely linked to the mechanisms that form LRPs.

Against this background, this study integrates petrology, hydrochemistry, and ML to systematically investigate the diagenetic origins of LRPs in the Chang 2 interval of the Triassic Yanchang Formation. Specifically, we (1) characterize mineralogical, petrophysical, and hydrochemical attributes to determine their direct controls on resistivity; (2) identify the key diagenetic processes that govern resistivity and elucidate their associated modifications of pore structures, clay minerals, and hydrochemistry; and (3) construct fluid-sensitive parameters and, together with conventional logging, evaluate and compare the performance of multiple ML models for fluid property identification. This study aims to improve the understanding of LRPs in the Ordos Basin and provide insights applicable to the exploration of similar LRPs worldwide.

2. Geological setting

The Ordos Basin is one of China's most significant petroliferous basins, covering an area of approximately 250,000 km² (Li et al., 2021; Wang et al., 2023b). The basin is subdivided into six secondary tectonic units: the Yimeng Uplift, the Western Thrust Zone, the Tianhuan Depression, the Yishan Slope, the Jinxi Flexure Zone, and the Weibei Uplift (Fig. 1(a); Lai et al., 2016; Wang et al., 2023b). Under the influence of the Indosinian orogeny, the basin gradually transitioned from a Paleozoic cratonic basin to a Mesozoic depression basin, with a shift in sedimentary environment from marine to continental facies (Bai et al., 2022; Li et al., 2024a). During the sedimentation of the Triassic Yanchang Formation, a

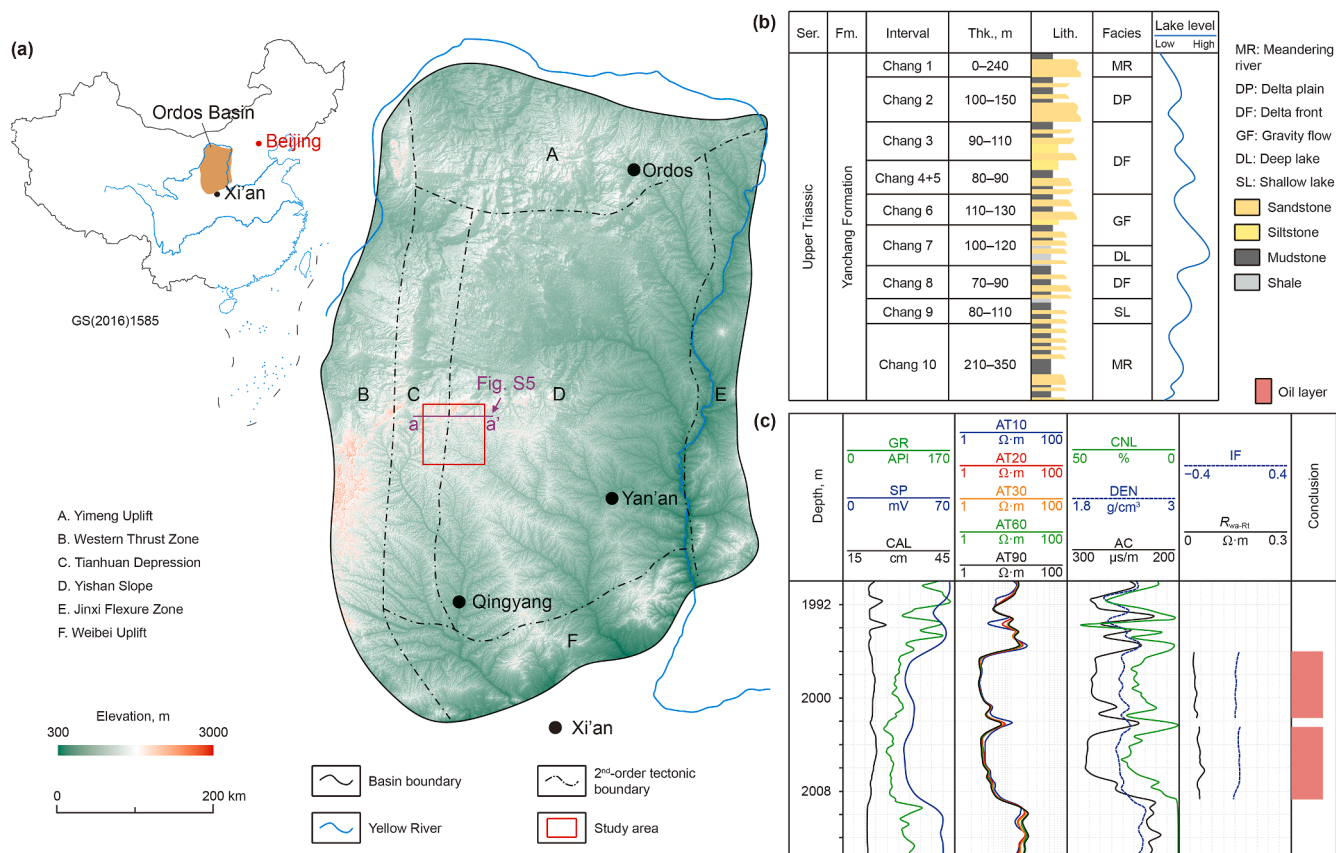


Fig. 1. (a) Tectonic units of the Ordos Basin and the location of the Jiyuan area; (b) generalized stratigraphic column of the Upper Triassic Yanchang Formation, showing facies and relative lake level change; (c) logging responses of the Chang 2 LRP in the Jiyuan area.

terigenous clastic system dominated by fluvial and lacustrine facies developed (Lin et al., 2024a). Based on sedimentary evolution, the Yanchang Formation is vertically divided into ten intervals, from bottom to top, namely: Chang 10 to Chang 1 (Fig. 1(b); Yang et al., 2020).

The Jiyuan area lies at the convergence of the Tianhuan Depression and the Yishan Slope (Fig. 1(a)). The Chang 2 interval is dominated by delta plain subfacies (Yin et al., 2019; Lu et al., 2024), and is predominantly composed of fine-grained arkoses and lithic arkoses, with poor compositional and structural maturity. It is classified as a medium-porosity, low-permeability reservoir (Gao et al., 2007; Li et al., 2010), characterized by complex oil–water distribution, influenced by high shale content and strong heterogeneity, with LRPs occurring (Fig. 1(c)). Although the logging responses vary with fluid properties, their value ranges overlap significantly, making it difficult to clearly delineate fluid boundaries. This complicates the accurate determination and differentiation of oil content within the reservoir (Fig. S1).

3. Data and methods

In order to gain a comprehensive understanding of the reservoir rock composition, pore structure, and other related properties, 55 oil-impregnated core samples from 14 wells were selected for analysis. Experiments, including thin section preparation, scanning electron microscopy (SEM), X-ray diffraction (XRD), high-pressure mercury intrusion (HPMI), and nuclear magnetic resonance (NMR), were carried out at the China University of Petroleum (Beijing). Additionally, several HPMI reports, formation water analysis reports, well logging data, and monthly production

reports were collected. All the aforementioned materials were provided by the No. 5 Oil Production Plant of the PetroChina Changqing Oilfield Company.

3.1. Experimental methods

Thin sections were prepared by impregnating the samples with blue resin to visually highlight the microscopic pore structure. The clastic components and diagenetic characteristics were examined using a Leica DM2500 P optical microscope under both cross-polarized light (XPL) and plane-polarized light (PPL). A quantitative analysis of the mineral content was performed at 200–300 points in each sample. Additionally, an FEI Quanta 200 F SEM, equipped with an energy-dispersive X-ray spectrometer, was used to observe the mineral distribution and pore structure.

XRD was used to quantify the mineral composition and content of the rocks. The analysis of whole rock and clay minerals was conducted using a Rigaku D/MAX2500 V/PC X-ray diffractometer. For the clay mineral analysis, the samples were subjected to drying, alkali digestion, and heating at 500 °C.

HPMI was used to obtain quantitative information on the pore structure of the rocks. Core samples were subjected to mercury intrusion at 20 °C using an AutoPore IV 9500 mercury intrusion apparatus. The maximum pressure for mercury injection was 200 MPa.

NMR was used to evaluate the physical properties and pore distribution of rock samples. Core samples were completely saturated with saltwater under a pressure of 20 MPa and then subjected to centrifugation. The NMR T_2 relaxation times were measured at 25 °C using a MesoMR23-060H-I NMR instrument.

3.2. ML workflow

3.2.1. Feature variables

As shown in Fig. 2, the ML process is organized into a workflow for clarity and ease of reference. Perforated interval logging data collected from 297 wells were sampled at 0.125 m intervals, resulting in a total of 6324 samples. The water–liquid ratio (WLR) over the previous three months for each well was used as the dependent variable (Y), with the following categories: oil layer ($WLR \leq 30\%$), oil–water layer ($30\% < WLR \leq 70\%$), oil-bearing water layer ($70\% < WLR \leq 95\%$), and water layer ($WLR > 95\%$). Nine types of logging data, sensitive to lithology, physical properties, and formation fluids, were used as independent variables (X): acoustic (AC), caliper (CAL), gamma ray (GR), deep lateral resistivity (RILD), medium lateral resistivity (RILM), eight lateral resistivity (RLL8), spontaneous potential (SP), formation water resistivity (R_{wa-Rt}), and invasion factor (IF). Among these, R_{wa-Rt} (Eq. (1)) combines the oil content with the physical properties of the reservoir, while IF (Eq. (2)) quantifies the effect of drilling mud invasion. Both parameters are widely regarded as comprehensive indicators for evaluating reservoir oil content (Tian et al., 2010; Bai et al., 2017). Fig. S2 shows the top five features with the most significant differences, illustrating that these two constructed parameters have strong potential for distinguishing fluid properties.

$$R_{wa-Rt} = \varphi^m \times R_t/a \quad (1)$$

$$IF = (RILM - RILD)/RILD \quad (2)$$

3.2.2. Data processing

After excluding missing values and outliers, 3680 samples from 182 wells were retained for further analysis. Due to high-frequency fluctuating noise in the logging data, Gaussian smoothing was applied to reduce noise. Additionally, feature standardization was performed to minimize scale differences between variables, allowing the model to better capture underlying patterns in the data. For dataset partitioning, 5-fold stratified group cross-validation was used to ensure that samples from the same well were not included in both the training and test sets, while maintaining consistent proportions of each category in the test sets.

3.2.3. Model construction and evaluation

For model construction, several commonly used ML algorithms in petrophysics were selected as baseline models, including logistic regression (LR), support vector machine (SVM), random forest (RF), and deep neural network (DNN) (Breiman, 2001; Noble, 2006; LaValley, 2008; LeCun et al., 2015). In addition, this study employed two new models, the Tabular Prior-data Fitted Network (TabPFN) and the Random Forest Prior-data Fitted Network (RF-PFN). TabPFN is a recently proposed Transformer-based model for tabular data prediction, leverages large-scale prior training on synthetic datasets to achieve remarkable generalization performance under small-sample conditions (Hollmann et al., 2025; PriorLabs, 2025a). RF-PFN is an extension of RF that incorporates TabPFN's Bayesian prior inference into each leaf node, allowing local prior reasoning within the ensemble (PriorLabs, 2025b).

To address the issue of severe class imbalance in the dataset, the support vector machine–synthetic minority oversampling technique (SVM–SMOTE) was applied, which focuses on minority class samples near the decision boundary, thereby improving the model's performance and enhancing overall classification accuracy (Guo et al., 2024). Additionally, majority voting was used to aggregate prediction results, ensuring consistent interpretation for the same sand layer or perforated interval. Model evaluation metrics included the macro average area under the receiver operating characteristic curve (AUC), the macro average area under the precision–recall curve (PR–AUC), F1-score, recall, and specificity (TNR) (Thakur, 2024). Finally, SHapley Additive exPlanations (SHAP) were used to interpret the model, helping to better understand the contribution of each feature to the prediction results (Lundberg and Lee, 2017).

4. Results

4.1. Petrological and mineralogical characteristics

Thin section and XRD analysis results indicate that the Chang 2 sandstones in the Jiyuan area consist primarily of fine-grained arkoses and lithic arkoses (Figs. 3 and S3(a)). Quartz constitutes the predominant clastic component (38.30%–70.50%; av. 47.46%; Fig. 4(a)). Feldspar (11.20%–39.40%; av. 15.52%) mainly consists of

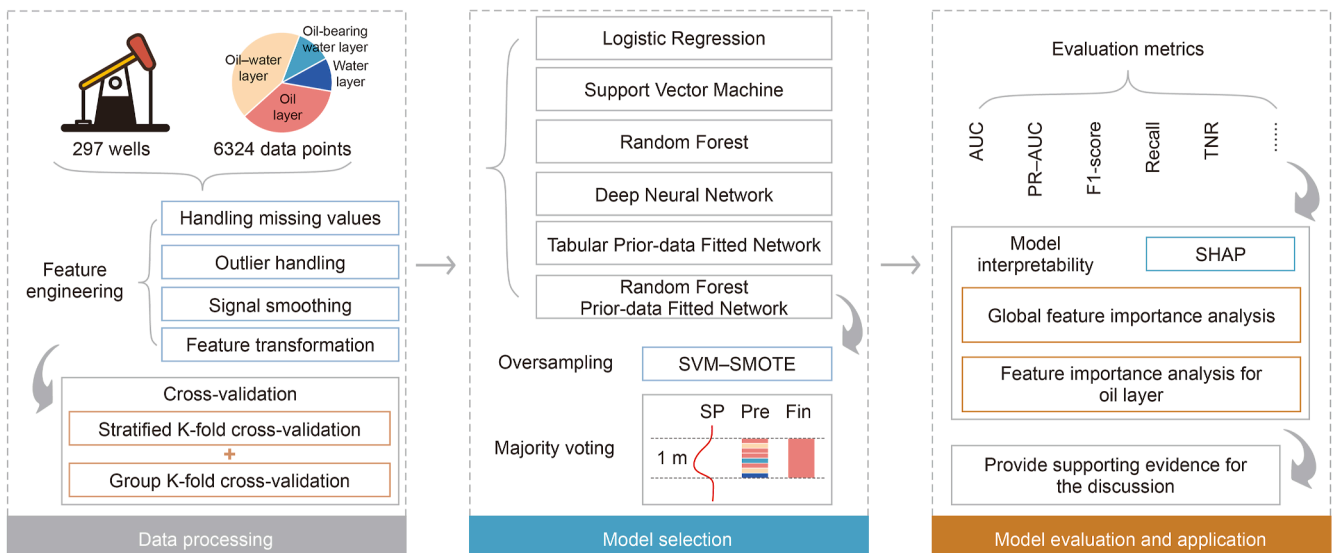


Fig. 2. Workflow for reservoir fluid identification based on ML.

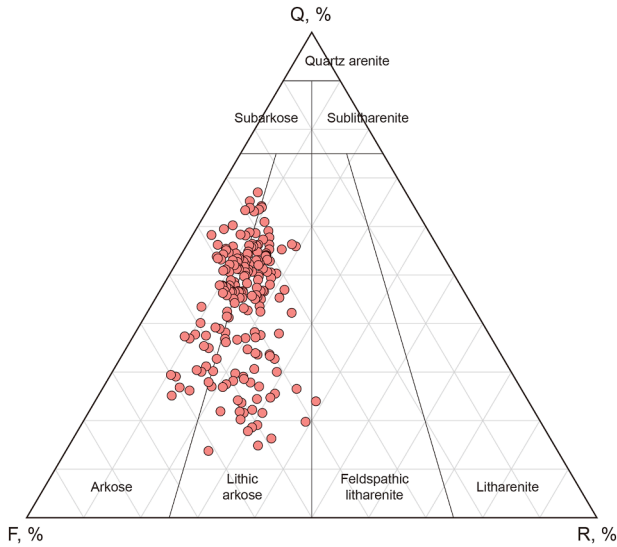
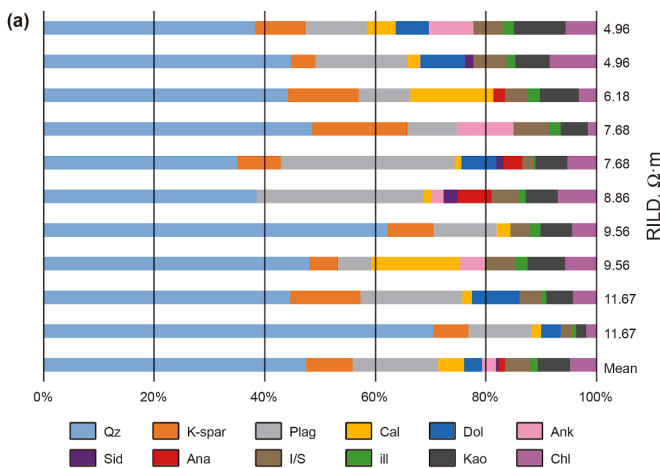


Fig. 3. Q–F–R ternary diagram of sandstone composition plotted based on Folk et al. (1970).

plagioclase. Lithic fragments primarily comprise phyllite, eruptive rock, and quartzite. Clay minerals occur in relatively high amounts (6.40%–22.40%; av. 16.48%). Kaolinite appears in a worm-like form and fills the pores (av. 5.83%; Fig. S3(b)–(e)). Chlorite primarily occurs as autochthonous chlorite films (av. 4.72%; Fig. S3(f)). Illite–smectite mixed layer (av. 4.41%) and illite (av. 1.52%) are commonly found in the pores and throats (Fig. S3(e) and (g)). Carbonate minerals are primarily developed between particles or as replacements of clastic particles (av. 10.44%; Fig. S3(h) and (i)). Conductive minerals occur in low content, primarily anatase and siderite.

Fig. 4(b) shows the correlation analysis results between XRD mineral content and resistivity. Kaolinite ($R^2 = 0.531$) and clay minerals ($R^2 = 0.486$) exhibit a significant negative correlation, indicating that an increase in the content of kaolinite and clay minerals leads to a notable decrease in electrical resistivity. In contrast, other minerals, such as the illite–smectite mixed layer, have little to no effect on resistivity.



4.2. Petrophysical properties

Petrophysical experiments on 30 core samples indicate that porosity ranges from 8.28% to 19.9% (av. 15.27%), while permeability ranges from 0.03 mD to 24.50 mD (av. 1.13 mD). A significant positive correlation exists between porosity and permeability ($R^2 = 0.582$; Fig. 5(a)). The reservoir exhibits typical medium porosity and low permeability characteristics.

Additionally, data from 2794 wells drilled in the Yanchang Formation (including Chang 2, Chang 4 + 5, Chang 6, Chang 8, and Chang 9 intervals), which were production-tested as oil layers, were collected. Resistivity was analyzed in conjunction with log-interpreted porosity and permeability (Fig. 5(b)). The results indicate a significant negative correlation between porosity and resistivity across the Yanchang Formation as a whole ($R^2 = 0.122$; $P \leq 0.001$). Compared to other intervals, the Chang 2 interval exhibits higher porosity, similar permeability, and lower resistivity.

4.3. Pore types

Thin section observations and statistical analysis indicate that the pore types mainly consist of primary and secondary pores. Primary pores are intergranular residual pores affected by compaction and cementation, typically triangular or polygonal in shape (av. 3.43%; Fig. S4(a)–(d)). Secondary pores are primarily formed by the dissolution of feldspar. These pores are often associated with clay minerals, mainly kaolinite, which accumulates in the pores to form micropores (av. 3.57%; Fig. S4(b)–(f)).

4.4. Pore structures

4.4.1. HPMI analyses

HPMI results indicate that the pore throat radius ranges from 8.88 μm to 13.04 μm (av. 11.25 μm). The displacement pressure ranges from 0.04 MPa to 2.74 MPa (av. 0.36 MPa). The median capillary pressure ranges from 0.93 MPa to 16.84 MPa (av. 3.49 MPa). The maximum mercury intrusion saturation ranges from 65.90% to 91.20% (av. 81.35%). The capillary pressure curves exhibit a relatively flat, downward concave shape (Fig. 6(a)). Overall, the reservoir is characterized by lower displacement pressure, lower median capillary pressure, and a complex pore structure.

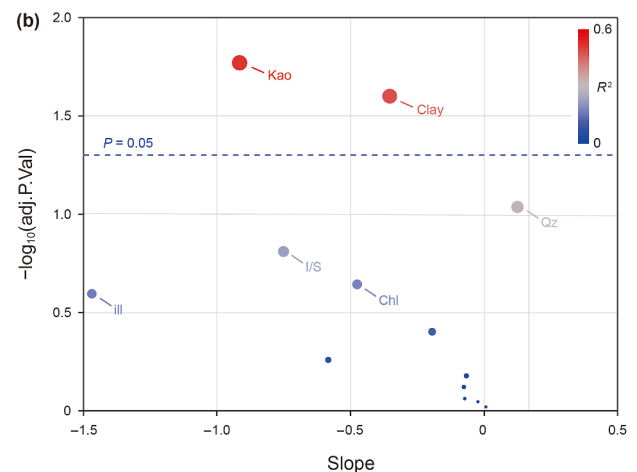


Fig. 4. (a) Mineral composition revealed by XRD; (b) volcano-style plot showing the results of the correlation analysis between mineral content and resistivity. The X-axis represents the slope, the Y-axis represents the negative base-10 logarithm of the adjusted P value, and the color variable corresponds to the coefficient of determination (R^2). The dashed line denotes the significance threshold corresponding to an adjusted P value of 0.05.

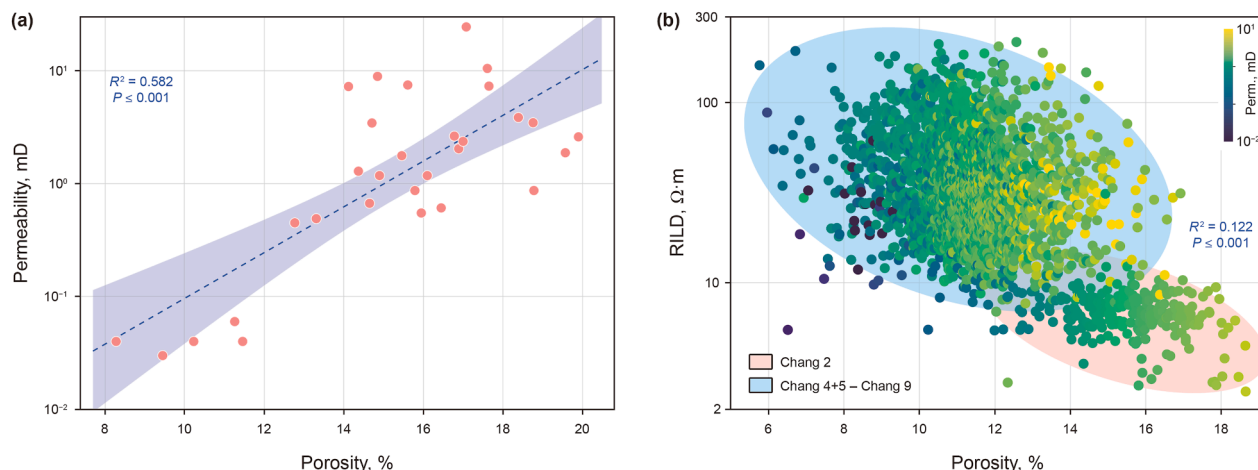


Fig. 5. (a) Correlation between core porosity and permeability; (b) correlations among log-interpreted porosity, permeability, and resistivity.

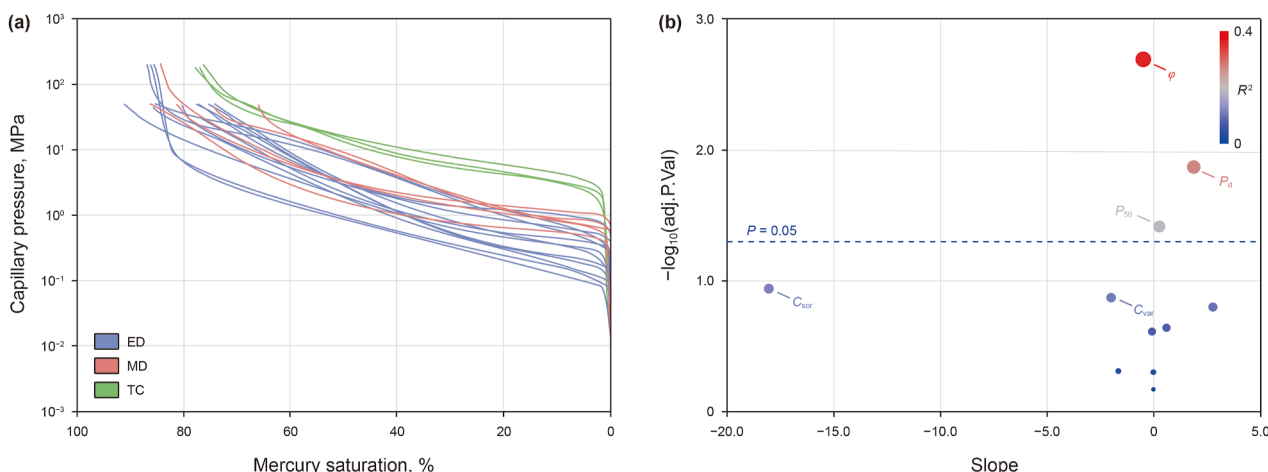


Fig. 6. (a) Capillary pressure curve characteristics of low resistivity pays. The three diagenetic facies of ED, MD, and TC are explained in section 4.6; (b) correlation analysis between pore structure parameters obtained from HPMT and resistivity.

Correlation analysis of the HPMT parameters with resistivity reveals (Fig. 6(b)) that core porosity shows a significant negative correlation with resistivity ($R^2 = 0.419$), while the displacement pressure ($R^2 = 0.294$) and median capillary pressure ($R^2 = 0.217$) show a significant positive correlation with resistivity. This indicates that pore size has an important control on resistivity. The variation coefficient ($R^2 = 0.133$) and sorting coefficient ($R^2 = 0.120$) show a weakly significant negative correlation. This suggests that the poorer the sorting of pore distribution, or the more complex the pore throat structure, the lower the resistivity.

4.4.2. NMR analyses

The T_2 relaxation times effectively reflect the pore size distribution of the porous medium (Pires et al., 2019; Elsayed et al., 2022; Wei et al., 2023). Smaller pores exhibit shorter T_2 values, whereas larger pores exhibit longer T_2 values (Luo et al., 2024). According to Cai's NMR pore size classification standard (Cai et al., 2013), approximately 37.83% of the pores are classified as macropores, 43.11% as mesopores, and 19.07% as micropores. Fig. 7(a) presents the NMR T_2 spectrum of the sample in a fully saturated water state. The curve exhibits a multi-peak distribution, with the main peak varying across different samples, though most peaks fall between 1 and 100 ms.

The saturation of movable water (S_{w-mov}) and irreducible water (S_{w-irr}) is determined by centrifuging fully saturated core samples (Pires et al., 2019). The results indicate that S_{w-irr} is generally high (av. 67.33%). The irreducible water content was approximately 22.68% in macropores, 52.71% in mesopores, and 24.61% in micropores. The NMR T_2 spectrum of the samples after centrifugation is presented in Fig. 7(b), with the main peak of the curve centered between 1 and 10 ms. This indicates that the irreducible water in the samples is primarily developed in the mesopores.

The NMR magnetic parameters, such as NMR porosity (φ_{nmr}), irreducible water porosity (φ_{irr}), and irreducible water porosity for different pore sizes ($\varphi_{irr-mac}$, $\varphi_{irr-mes}$, and $\varphi_{irr-mic}$), were analyzed by correlating them with resistivity (Fig. 7(c)). The results indicate that both core porosity ($R^2 = 0.520$) and φ_{nmr} ($R^2 = 0.511$) exhibit a significant negative correlation with resistivity, consistent with the results presented in the previous section. φ_{irr} ($R^2 = 0.580$) also exhibited a significant negative correlation, whereas S_{w-irr} ($R^2 = 0.388$) exhibited a weakly significant positive correlation. This suggests that resistivity is primarily influenced by the absolute volume of irreducible water in the pores, rather than its relative volume. Additionally, for different pore sizes, $\varphi_{irr-mic}$ ($R^2 = 0.385$) exhibited a weakly significant positive correlation, whereas $\varphi_{irr-mac}$ ($R^2 = 0.350$) exhibited a weakly significant

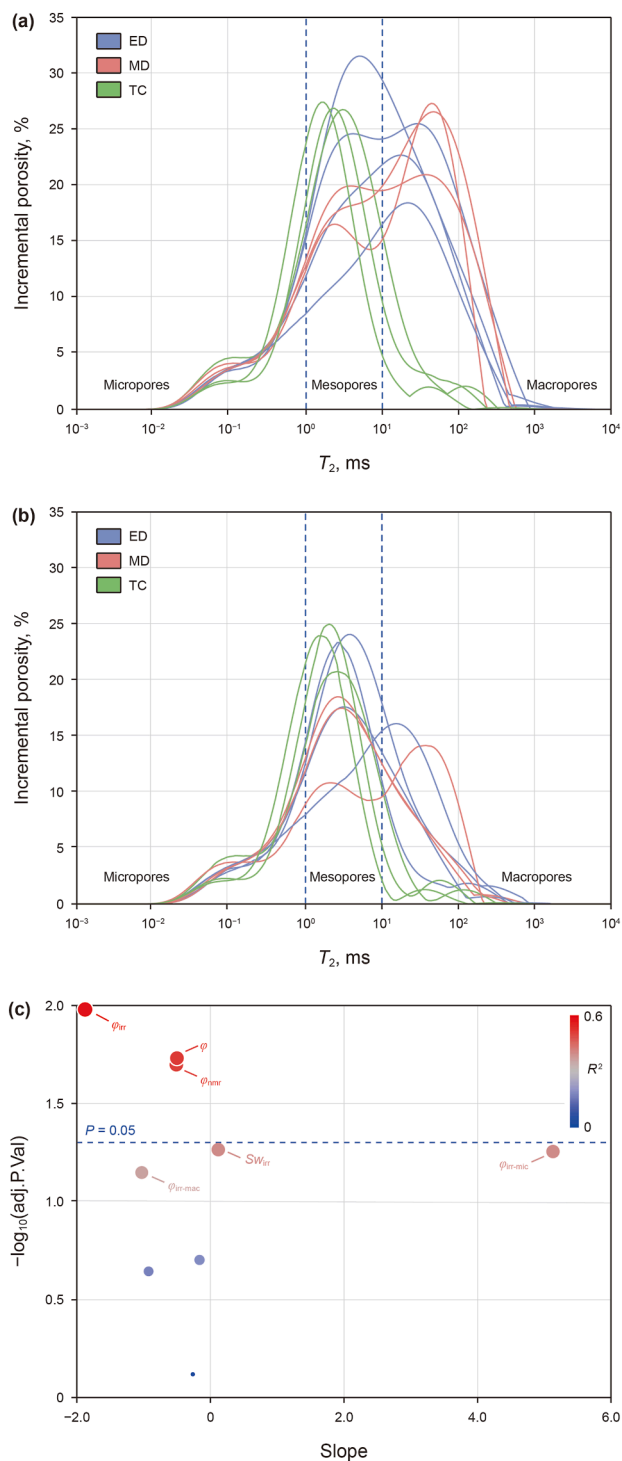


Fig. 7. Pore size and distribution revealed by NMR. (a) Fully saturated water state; (b) post-centrifugation state; (c) correlation analysis between rock parameters obtained from NMR and resistivity. The three diagenetic facies of ED, MD, and TC are explained in Section 4.6.

negative correlation. This may suggest that different pore size distributions exert varying influences on resistivity.

4.5. Hydrochemistry characteristics

The total dissolved solids (TDS) of the formation water range from 25.00 ppk to 137.99 ppk (av. 88.79 ppk; Fig. 8(a)). This is

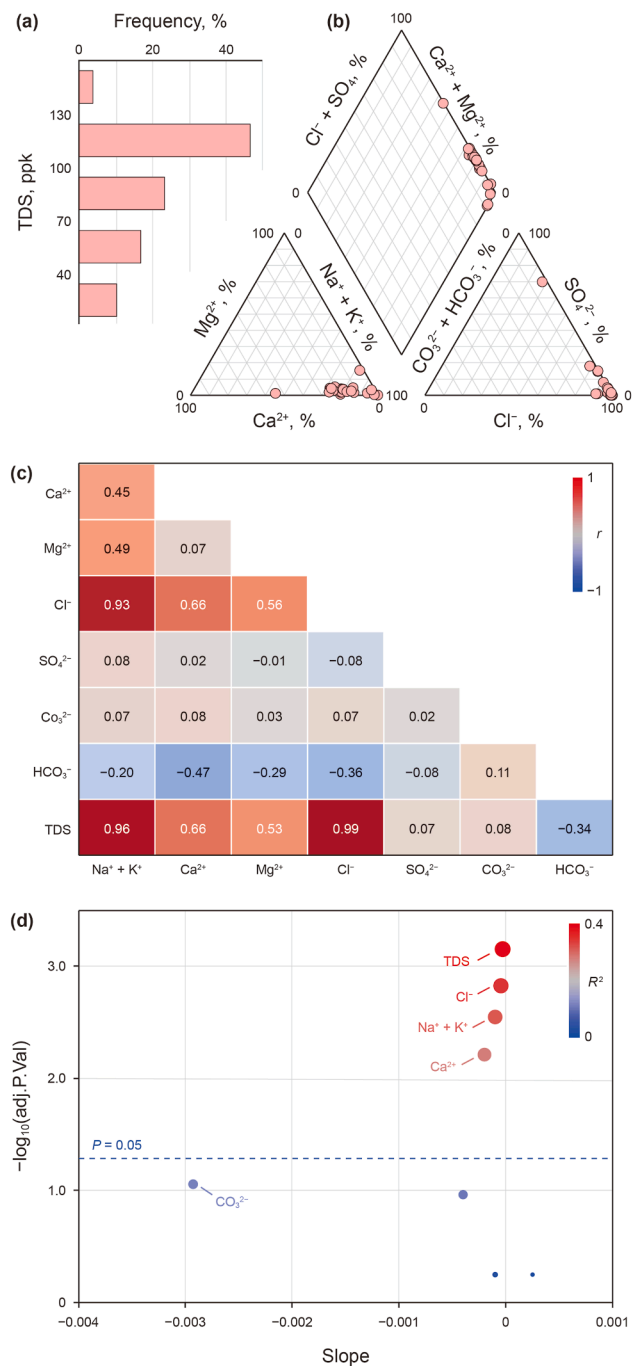


Fig. 8. (a) Histogram of formation water salinity distribution; (b) trilinear diagram of hydrochemical types based on Piper (1944); (c) Pearson correlation matrix of hydrochemical indicators of formation water; (d) correlation analysis between hydrochemical indicators of formation water and resistivity.

approximately 2.54 times the TDS of normal seawater (av. 35.00 ppk). According to the Bethke's classification criteria for stratum water (Bethke et al., 1991), the formation water is primarily brine. Cations are primarily dominated by Na⁺ + K⁺ (av. 26.61 ppk), while anions are predominantly dominated by Cl⁻ (av. 52.91 ppk).

Combined with Piper's trilinear diagram (Piper, 1944), the ionic composition of the Chang 2 formation water is similar to that of seawater, with a water type of Cl⁻-Na⁺ (Fig. 8(b)). The correlation heatmap between hydrochemical indicators can explain the ionic sources and the reasons for TDS variations (Fig. 8(c); Qu et al., 2023; Lin et al., 2024b). Among them, Cl⁻ ($r = 0.99$) and Na⁺ + K⁺ ($r = 0.96$)

showed the strongest correlations with TDS. This suggests that hydrochemical processes associated with Cl^- and $\text{Na}^+ + \text{K}^+$ are the primary cause of the increase in TDS.

The correlation between hydrochemical indicators and resistivity is shown in Fig. 8(d). The results indicate that TDS, Cl^- , $\text{Na}^+ + \text{K}^+$, and Ca^{2+} all exhibit significant negative correlations with resistivity, with the most notable correlation being for TDS ($R^2 = 0.341$). Based on the previous analysis, it can be inferred that Cl^- , $\text{Na}^+ + \text{K}^+$, and other enriched ions affect TDS and significantly reduce resistivity.

4.6. Diagenetic facies types and characteristics

The Chang 2 sandstones in the Jiyuan area are mainly characterized by mechanical compaction, feldspar dissolution, and widespread precipitation of kaolinite. Based on the dominant diagenesis, mineral assemblages, and pore structure, three major diagenetic facies were identified. Fig. 9 and Table 1 show the representative diagenetic characteristics and petrophysical properties of each facies. Their characteristics are summarized as follows.

Relatively extensive dissolution with kaolinite-rich facies (ED): This facies is characterized by extensive feldspar dissolution and abundant in situ precipitation of kaolinite. It shows relatively high porosity (av. 16.60%), and a high φ_{irr} (av. 10.06%). HPMI results indicate generally low displacement pressures. The equivalent NaCl concentration derived from SP indicates relatively high formation water salinity (av. 78.71 ppk). Correspondingly, it shows the lowest formation resistivity (av. 5.62 $\Omega\cdot\text{m}$).

Relatively moderate dissolution facies (MD): This facies shows moderate feldspar dissolution and good pore connectivity, and clay minerals are poorly developed. The NMR T_2 spectrum is generally bimodal, indicating a high proportion of movable water compared with the other facies. The equivalent NaCl concentration is the lowest among the three facies, with an average of 53.14 ppk. The corresponding average resistivity is 7.94 $\Omega\cdot\text{m}$.

Table 1
Statistical summary of petrophysical properties for different diagenetic facies.

Parameters	Statistics	Diagenetic facies		
		ED	MD	TC
Porosity, %	Mean	16.60	15.44	9.81
	Min	11.46	12.77	8.28
	Max	19.90	17.00	11.26
Irreducible water saturation, %	Mean	63.60	58.29	81.34
	Min	49.66	54.02	75.73
	Max	82.13	61.86	84.85
Irreducible water porosity, %	Mean	10.06	9.66	8.44
	Min	9.33	9.30	8.09
	Max	11.65	10.23	8.65
T_2 cutoff, ms	Mean	14.11	19.90	6.44
	Min	6.43	17.12	4.84
	Max	18.15	24.45	7.90
Equivalent NaCl concentration, ppk	Mean	78.71	53.14	93.00
	Min	45.25	32.74	71.31
	Max	138.14	111.98	132.84
RILD, $\Omega\cdot\text{m}$	Mean	5.62	7.94	11.22
	Min	3.02	4.57	9.55
	Max	7.76	9.55	11.75

Tightly compacted facies (TC): This facies has generally fine grain sizes, and ductile minerals show compaction deformation. Pore types are mainly composed of intergranular residual pores. It shows the highest displacement pressures, and irreducible water dominates the pore space. Although the $S_{\text{w-irr}}$ (av. 81.34%) is high, the φ_{irr} (average 8.44%) is lower than other facies. This facies exhibits the highest formation water salinity (av. 93.00 ppk), and the highest resistivity (av. 11.22 $\Omega\cdot\text{m}$).

4.7. Fluid identification using ML

4.7.1. Performance comparison of multiple ML methods

Fig. 10 presents the performance of six ML algorithms. Among them, RF-PFN and RF demonstrate a significant

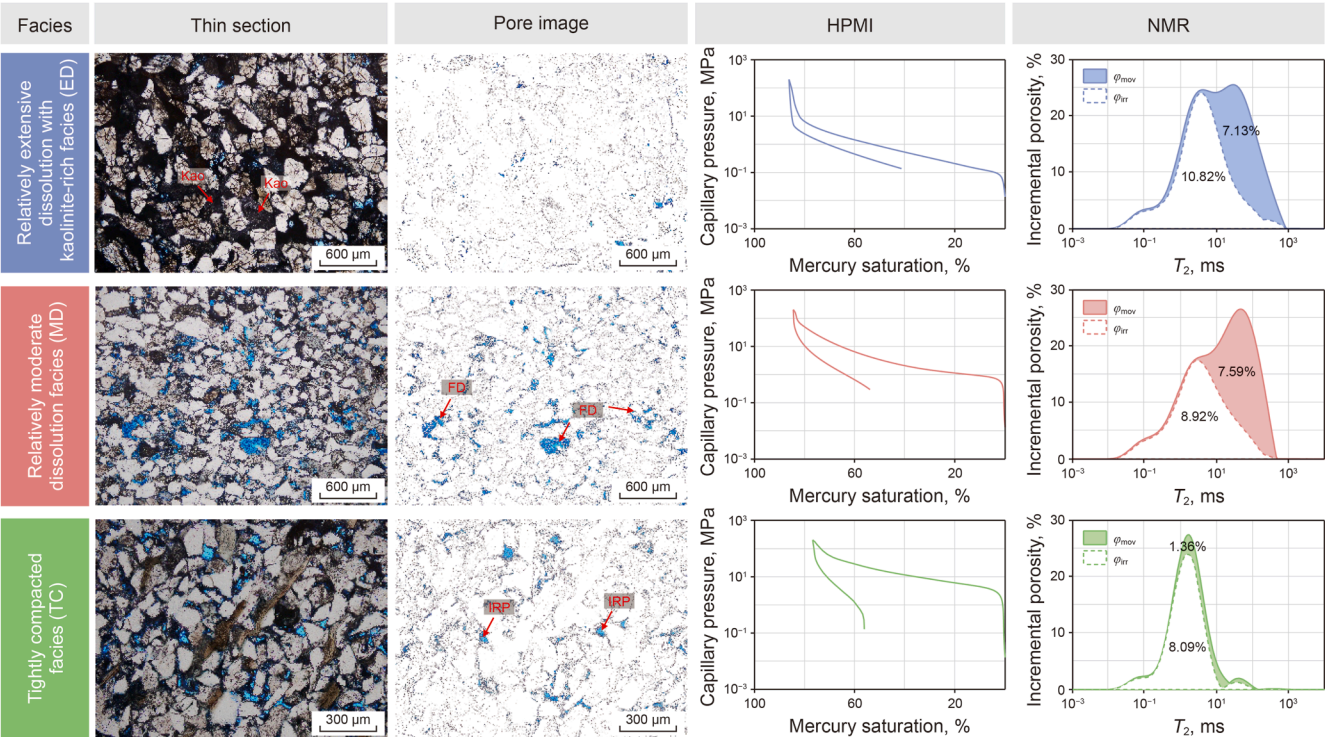


Fig. 9. Typical characteristics of three diagenetic facies, including thin sections, pore images, HPMI, and NMR results.

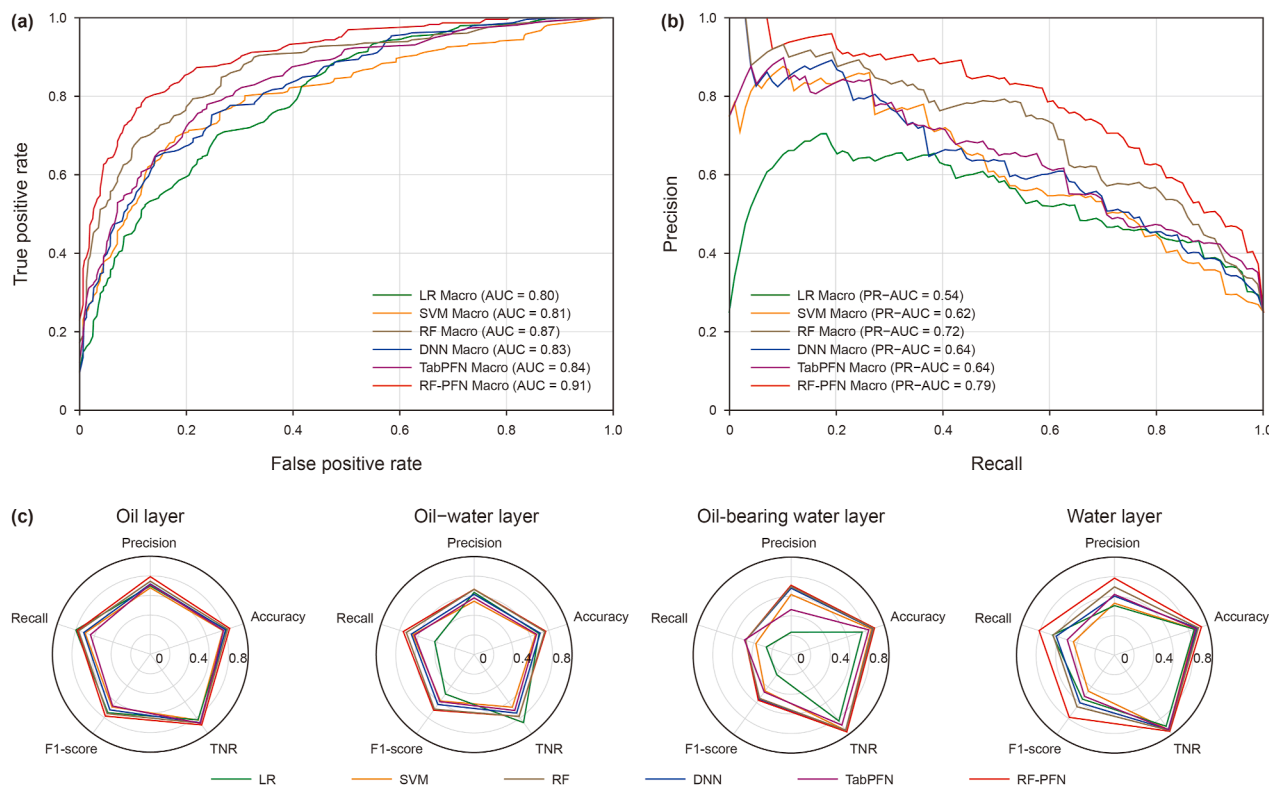


Fig. 10. Performance of the six ML models on the validation set. (a) AUC; (b) PR-AUC; (c) performance across different fluid properties.

performance advantage, with AUCs of 0.91 and 0.87, and PR-AUCs of 0.79 and 0.72. In contrast, TabPFN and DNN perform more weakly, with AUCs of 0.84 and 0.83, and a PR-AUC of 0.64 for both. It is noteworthy that all models exhibit relatively low PR-AUC (Fig. 10(b)), which can be primarily attributed to the imbalanced dataset. Although the models performed relatively well in the oil layer and the oil-water layer, their performance dropped significantly in the oil-bearing water layer and the water layer with fewer samples (Fig. 10(c)). This indicates that the models may not have fully captured the features and patterns of the minority classes during the learning process. Overall, RF-PFN demonstrated superior robustness and adaptability to minority classes, achieving higher accuracy and lower misclassification rates in identifying various fluid properties.

4.7.2. Interpretability of ML

Fig. 11(a) shows the SHAP values of each feature across different fluid properties, emphasizing their relative importance in model prediction. R_{wa-Rt} and RILD exhibit consistently high SHAP values across all categories, indicating that these two features exert a dominant influence on the model's predictions. In contrast, GR, CAL, and RLL8 generally show low SHAP values, suggesting a relatively minor contribution to model predictions.

For the oil layer, the top five contributing features are R_{wa-Rt} , RILD, AC, IF, and SP (Fig. 11(b)). Among these, R_{wa-Rt} and RILD remain the primary drivers. Although AC, IF, and SP contribute less significantly, they still provide supplementary information that enhances the model's discriminative capability. Other features exhibit SHAP values mostly distributed around zero, implying a relatively limited impact on oil layer identification.

5. Discussion

5.1. Origins of high-salinity formation water

The ionic ratio coefficients of formation water may indicate the hydrogeological environment and the water-rock interactions (Schoeller, 1977; Owen et al., 2015; Zhou et al., 2020). Among these, the $\gamma(\text{Na}^+/\text{Cl}^-)$ coefficient and the Schoeller indices (Eqs. (3) and (4)) are generally sensitive to the extent of ion exchange (Schoeller, 1977; Li et al., 2024b; Lin et al., 2024b). The $\gamma(\text{Na}^+/\text{Cl}^-)$ coefficient for standard seawater averages 0.85, while formation water resulting from the dissolution of salt rocks averages approximately 1. Formation water leached by meteoric water typically has a value greater than 1. The $\gamma(\text{Na}^+/\text{Cl}^-)$ coefficient for Chang 2 sandstones averages 0.56, which shows a significant negative correlation with TDS ($R^2 = 0.276$; Fig. 12(a)). Negative Schoeller indices suggest that Ca^{2+} and Mg^{2+} in solution have exchanged with Na^+ in minerals, while positive indices indicate the occurrence of reverse ion exchange (Qu et al., 2023; Lin et al., 2024b). The Schoeller indices for 97% of the samples in the study area exhibit positive values (Fig. 12(b)). Collectively, these indices suggest that formation water is primarily influenced by ion exchange, with higher TDS formation water undergoing a more pronounced degree of ion exchange.

$$\text{CAI-I} = [\text{Cl}^- - (\text{Na}^+ + \text{K}^+)] / \text{Cl}^- \quad (3)$$

$$\text{CAI-II} = [\text{Cl}^- - (\text{Na}^+ + \text{K}^+)] / (\text{HCO}_3^- + \text{SO}_4^{2-} + \text{CO}_3^{2-}) \quad (4)$$

According to Gaillardet et al. (1999), the relationship between different sodium-normalized mole ratios can indicate the contributions of carbonate, silicate, and evaporite end-members. In Fig. 12(c), the sample points are located between the evaporite and silicate end-members. This suggests that the formation water is

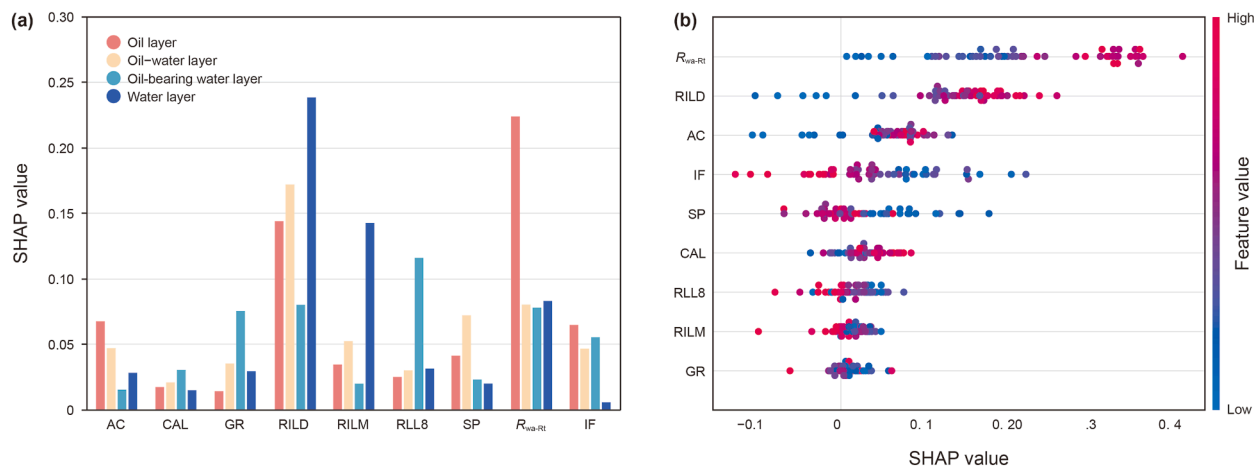


Fig. 11. (a) Feature importance analysis across different fluid properties; (b) contribution of each feature variable to the model's "oil layer" decision-making.

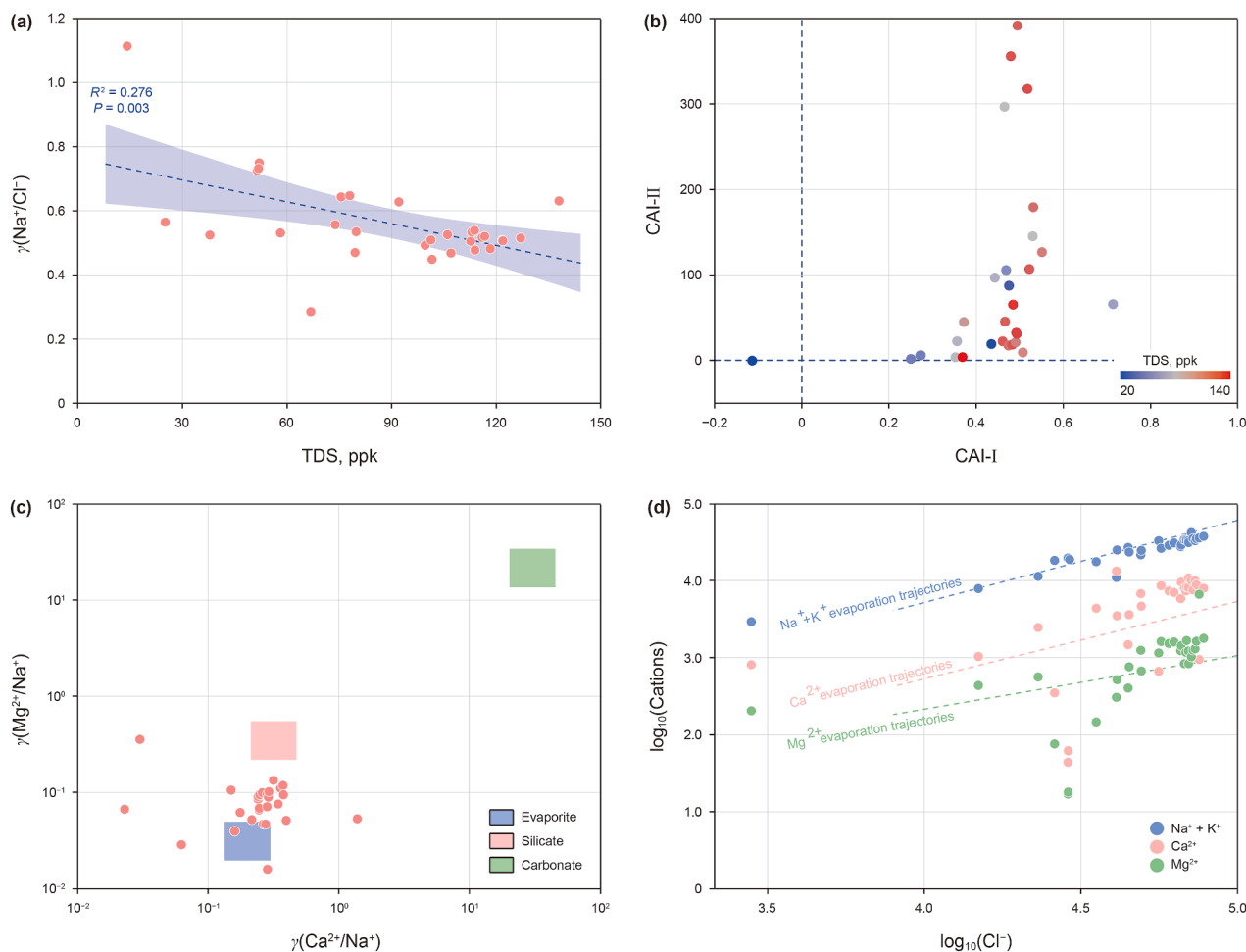


Fig. 12. (a) Correlation between TDS and $\gamma(\text{Na}^+/\text{Cl}^-)$ coefficient; (b) correlation of Schoeller indices; (c) correlation between $\gamma(\text{Ca}^{2+}/\text{Na}^+)$ and $\gamma(\text{Mg}^{2+}/\text{Na}^+)$ coefficients, modified from Gaillardet et al. (1999); (d) logarithmic relationship between Cl^- and major cations in formation water, modified from Hanor (1994).

primarily influenced by the dissolution of evaporites and silicates. However, the Triassic in the Jiyuan area, along with the overlying and underlying strata, is devoid of salt rocks. The precipitation of Ca^{2+} and Mg^{2+} during the evaporation concentration process may be the primary reason that the samples tend toward the evaporite end-member. Additionally, the enrichment of Cl^- in the sedimentary

basin is primarily attributed to the dissolution of salt rocks or evaporation concentration. Therefore, the degree of cation enrichment or depletion can be quantified by comparing the trend of cation variations relative to Cl^- with the seawater evaporation curve (Hanor, 1994; Davisson and Criss, 1996). In Fig. 12(d), the cation concentration exhibits a linear positive correlation with Cl^-

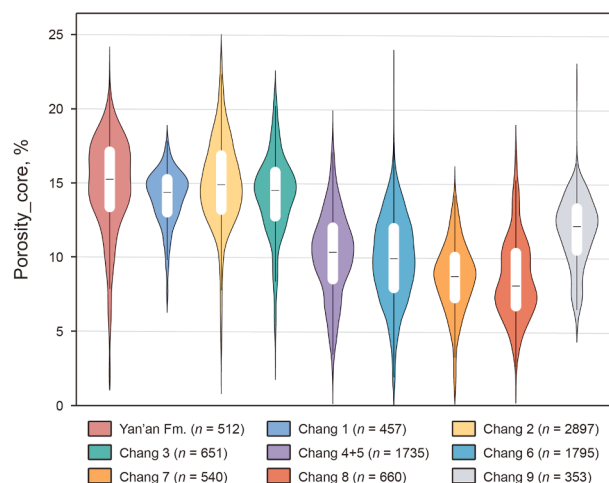


Fig. 13. Vertical trends in porosity for the Yanchang and Yan'an formations, modified from Sun et al. (2026).

concentration. $\text{Na}^+ + \text{K}^+$ aligns well with the seawater evaporation curve, showing slight depletion overall, indicating that $\text{Na}^+ + \text{K}^+$ is controlled by the concentration of the original formation water. Ca^{2+} and Mg^{2+} are primarily located above the evaporation curve, exhibiting enrichment characteristics.

Generally, during the shallow burial stages, formation water mainly consisted of meteoric water with relatively low TDS. As burial depth increased, compaction-induced concentration effects raised the concentrations of Na^+ , K^+ , and Cl^- , resulting in increased salinity. In relatively closed systems, water–rock

interactions such as silicate mineral dissolution and reverse ion exchange further enhanced solute enrichment.

5.2. How does diagenesis affect resistivity

During diagenesis, silicate minerals such as feldspar were typically dissolved by acidic fluids (Glasmann, 1992; Lai et al., 2018; Yuan et al., 2019). These acidic fluids mainly originate from meteoric leaching or kerogen maturation in source rocks (Giles and Marshall, 1986; Surdam and Crossey, 1987; França et al., 2003; Bjørlykke and Jahren, 2012; Cao et al., 2022; Zhang et al., 2023). Meteoric leaching of clastic reservoirs generally occurs in shallow sandstones (<200 m) during sedimentation, or within approximately 200 m below unconformities formed during uplift (Bjørlykke and Jahren, 2012). In the Jiuyuan area, the Indosinian orogeny during the Early Jurassic caused differential uplift, leading to varying degrees of weathering and erosion at the top of the Yanchang Formation. This process resulted in the development of a regional unconformity with the overlying Jurassic strata (Figs. S5 and S6; Deng et al., 2020). Vertically, the succession adjacent to the unconformity exhibits noticeably higher porosity (Fig. 13). Microscopically, the dissolution pores exhibit multi-phase dissolution, accompanied by early carbonate cementation (Figs. S3(h) and (i) and S4(d)). We also observe collapsed deformation of feldspar secondary pores (Fig. S4(e)). During early diagenesis, the acidic fluids required for the dissolution of feldspar are provided by freshwater infiltration through regional unconformities and undercut channels (Fig. 14(a); Yuan et al., 2019). Dissolved products are transported out of the dissolution zone, which contributes to the improvement of the reservoir's physical properties (Giles, 1987; Giles and de Boer, 1990; Yuan et al., 2017).

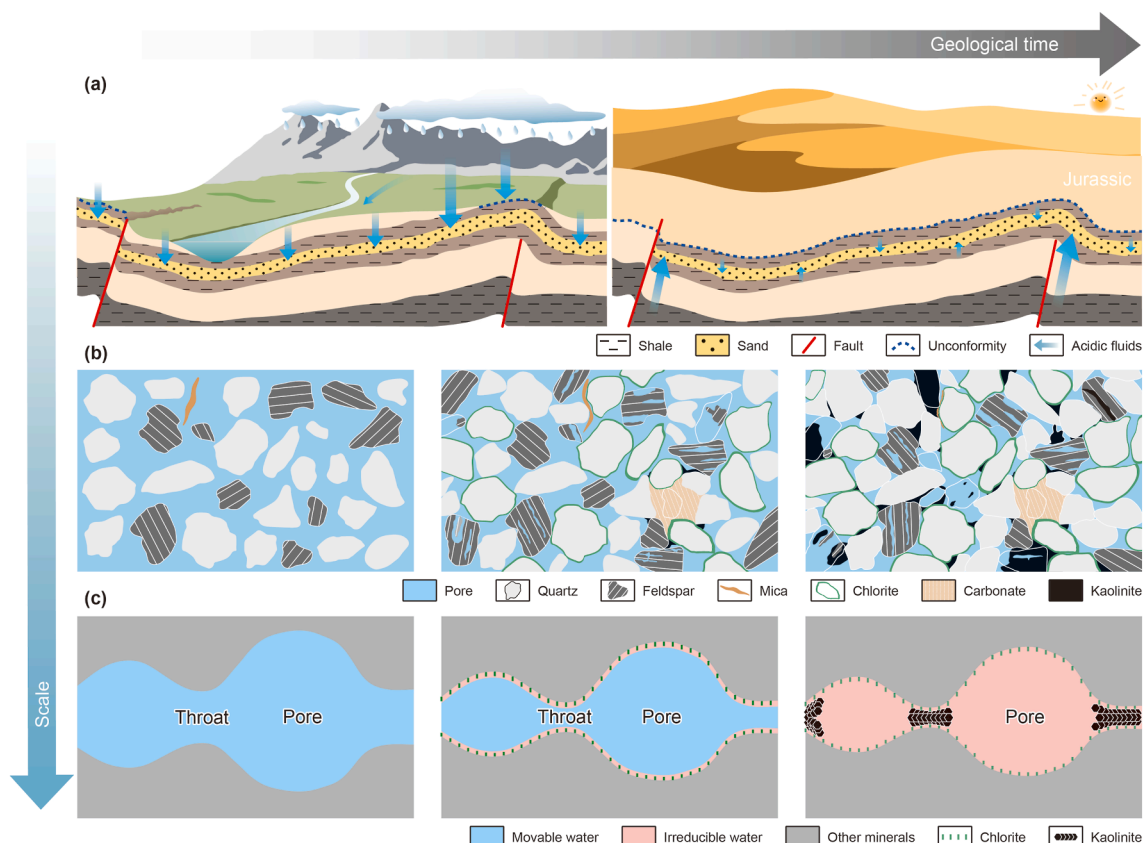


Fig. 14. Reservoir evolution model over geological time and scale. (a) Regional sandbody scale; (b) thin section scale; (c) pore–throat scale.

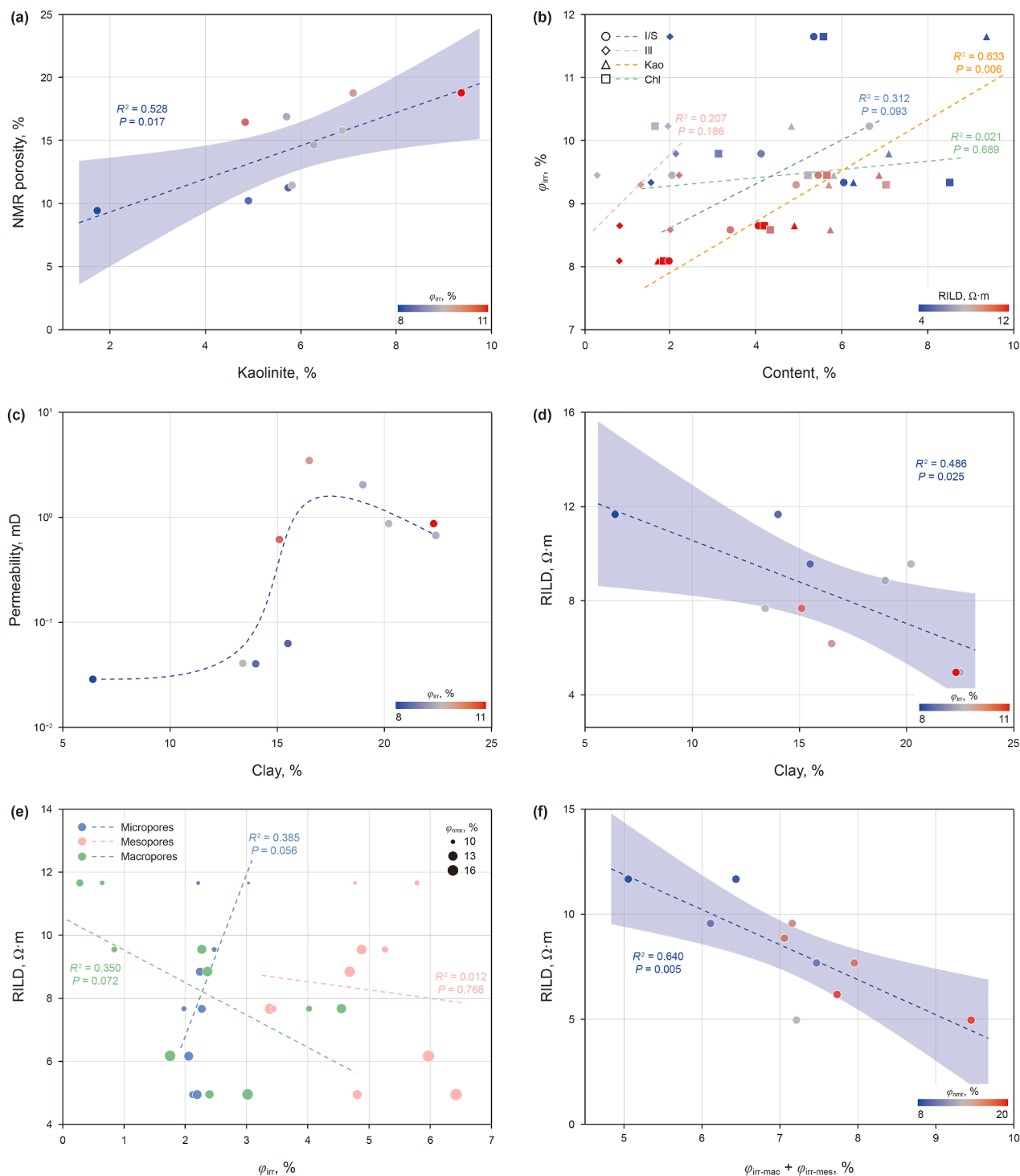


Fig. 15. A series of correlations among minerals, porosity, and resistivity, illustrating the control of diagenesis on pore structure and resistivity. (a) Correlation among kaolinite, ϕ_{nrmr} , and ϕ_{irr} ; (b) correlation among the contents of different clay minerals, ϕ_{irr} and resistivity; (c) correlation among total clay mineral content, permeability, and ϕ_{irr} ; (d) correlation among total clay mineral content, RILD, and ϕ_{irr} ; (e) correlation among irreducible water porosity retained in different pore sizes, resistivity, and ϕ_{nrmr} ; (f) correlation among irreducible water trapped in larger pores ($>10 \mu m$), resistivity, and ϕ_{nrmr} .

As diagenesis progresses, organic acids generated by the thermal evolution of kerogen take over this role, continuing to dissolve feldspar and forming authigenic minerals such as kaolinite, which accumulate in the pores (Figs. S3(b)–(e) and 14(b); Chuhan et al., 2000; Yuan et al., 2015; Lai et al., 2016). Both ϕ_{nrmr} ($R^2 = 0.528$) and ϕ_{irr} ($R^2 = 0.633$) exhibit significant positive correlations with

kaolinite content (Fig. 15(a) and (b)). This suggests that feldspar dissolution increases porosity, while the associated kaolinite accumulation increases irreducible water and ultimately influences resistivity. In addition to kaolinite, the enrichment of other clay minerals further increases pore structure complexity. Fig. 15(c) shows that permeability decreases once the clay

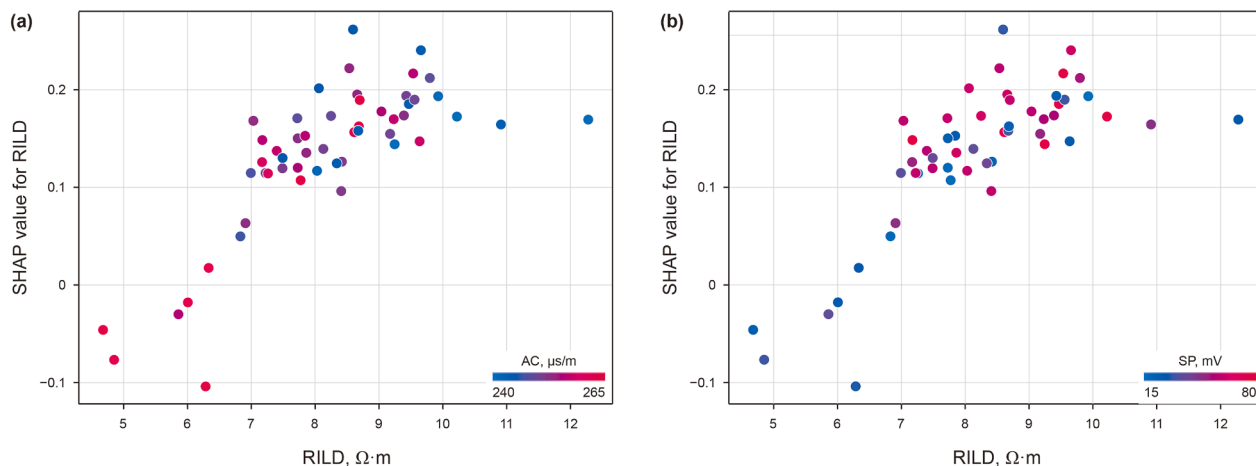


Fig. 16. Interaction of RILD with two feature variables during the model's "oil layer" decision-making. (a) AC; (b) SP.

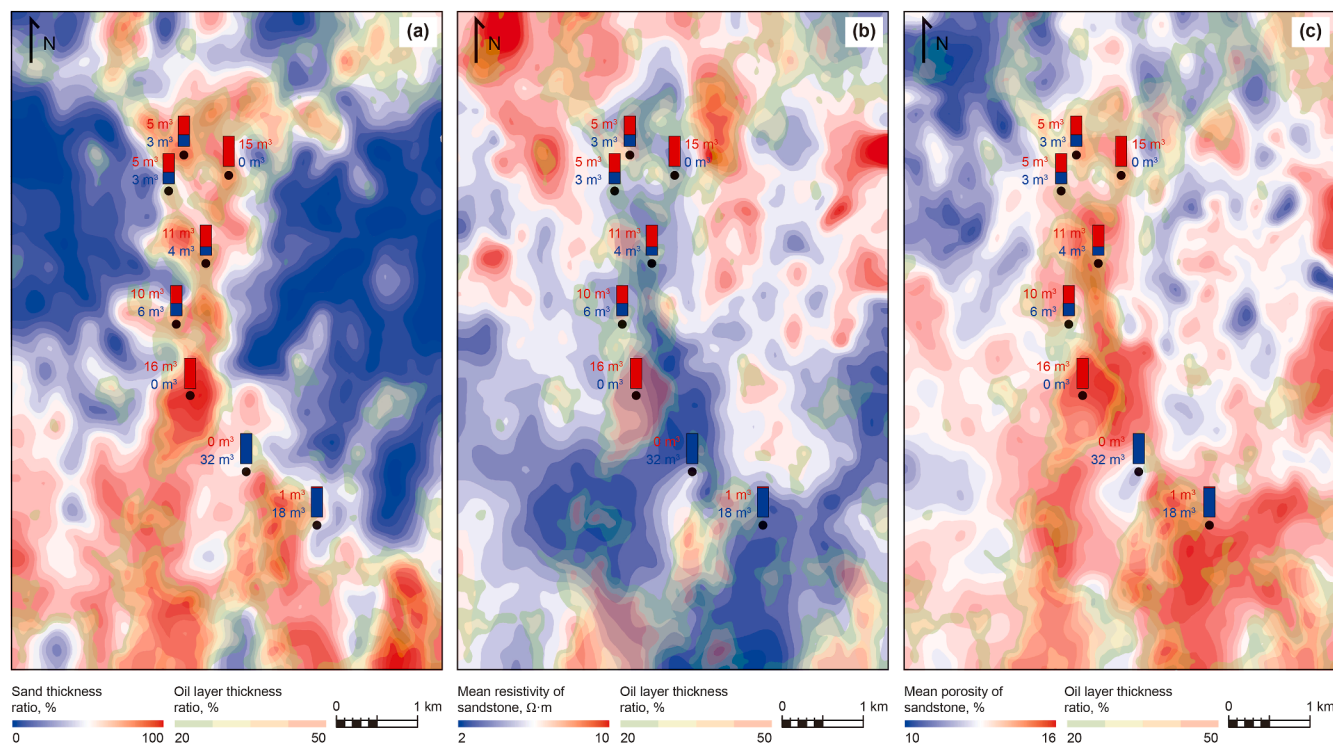


Fig. 17. ML identification results and planar distribution of other attributes in the P reservoir. (a) Sand thickness ratio; (b) mean resistivity of sandstone; (c) mean porosity of sandstone.

mineral content exceeds a critical threshold (16.50%). Given that permeability is primarily controlled by the average throat radius (Gao and Li, 2015; Jiang et al., 2023), such clay accumulation can also block pore throats, leading to higher irreducible water and lower resistivity (Figs. 14(c) and 15(d)).

NMR analysis reveals that irreducible water trapped in different pore sizes exerts varying influences on resistivity (Fig. 7(c)). The correlation between φ_{irr} and resistivity varies with pore size: it is positively correlated in micropores ($<10\ \mu\text{m}$) but negatively correlated in macropores ($>100\ \mu\text{m}$), while no correlation is observed in mesopores ($10\text{--}100\ \mu\text{m}$) (Fig. 15(e)). Moreover, the correlation between φ_{irr} and resistivity in relatively large pores

($>10\ \mu\text{m}$), including mesopores and macropores ($R^2 = 0.640$) (Fig. 15(f)), exceeds the correlation between overall φ_{irr} and resistivity ($R^2 = 0.580$) (Fig. 7(c)). This may be because micropores have limited pore volume and poor connectivity, making it difficult for ions to conduct electricity. In contrast, larger pores ($>10\ \mu\text{m}$) provide more volume for fluids and increase the number of conductive pathways.

SHAP dependency plots are used to characterize interactions between indicator features and other variables (Chan et al., 2022; Lai et al., 2024). Particular attention is given to the more discrete samples located in the lower left corner of Fig. 16, which exert a negative influence on the model's oil-layer predictions.

Geophysically, these samples exhibit relatively high porosity and elevated ionic concentrations. This combination of high porosity and high salinity is consistent with the characteristics of the ED facies. Diagenetic facies analysis shows that the ED facies has higher total porosity, but much of the pore space is filled by clay minerals, which reduces the effective porosity. In addition, the high equivalent NaCl concentration indicates relatively high formation water salinity. These observations suggest that, within a relatively confined diagenetic environment, feldspar dissolution contributes both to pore-throat blockage and to increased TDS through ion release and fluid consumption. The resulting high-salinity water tends to be trapped as irreducible water within blocked pores, further enhancing electrical conductivity. Overall, the LRP in the Chang 2 interval of the Jiyuan area represent the cumulative effect of multiple diagenetic processes acting over a prolonged geological timescale (Fig. 14).

5.3. Fluid identification in LRP

In this study, we combined two fluid-sensitive parameters (R_{wa-Rt} and IF) with well logs to identify LRPs. Furthermore, we compared the impact of these parameters on model performance. The results show that removing them led to a decline in overall model performance (Fig. S7), with AUC decreasing by approximately 3.30% and PR-AUC decreasing by about 7.59%. This indicates that these two parameters make a significant contribution to the model's ability to identify minority classes (the water layer). The model tends to classify intervals with higher R_{wa-Rt} values as oil layers, similar to the SP, reflecting the ionic concentration of formation water (Radhakrishna and Gangadhara Rao, 1990; Díaz-Curiel et al., 2022). The IF displays a broad SHAP distribution, reflecting its strong explanatory ability in quantifying invasion-induced resistivity alterations. Overall, these findings highlight the potential of these parameters in assisting the identification of oil-bearing zones in LRPs.

Regarding model performance, RF excels due to its ensemble-based decision tree learning, which effectively captures the strong nonlinear relationships in low-permeability sandstone reservoirs (Sun et al., 2026). In contrast, TabPFN leverages global priors learned from large-scale synthetic tabular data. However, its generalization decreases when applied to geological data, which exhibits significant heterogeneity and localized patterns. RF-PFN outperforms both models by combining the structural diversity of random forests with the local Bayesian inference capabilities of TabPFN at the leaf nodes. This hybrid approach allows RF-PFN to capture both geological heterogeneity and facies-driven patterns while incorporating prior knowledge, resulting in enhanced robustness in identifying LRPs.

We performed fluid property interpretation for more than 300 wells in the P reservoir of the Jiyuan area using the established ML model. The P reservoir is a typical LRP, with oil layer resistivity as low as 2 $\Omega \cdot m$. The results indicate that this reservoir mainly forms a structure-lithologic trap jointly controlled by impermeable barriers and small-scale structural noses (Fig. S8). The oil-bearing layers are primarily distributed within high-sand-content distributary channels, which are characterized by extremely low resistivity and relatively high porosity (Figs. 17 and S9). In high-sand-content regions, sandstones exhibit better connectivity and commonly develop sand-sand contacts between adjacent channels. Such connectivity likely enhances the migration of acidic fluids, promoting the formation of secondary dissolution pores and high porosity zones (Lu et al., 2024). During the 2024 exploration program, eight wells were deployed in this reservoir (Fig. 17), and the production tests showed that wells drilled in high-sand-content areas yielded better results.

6. Conclusions

This study focused on the Chang 2 LRPs in the Jiyuan area of the Ordos Basin, utilizing an integrated approach that combined petrology, hydrochemistry, and ML. The research elucidates the mechanisms by which diagenesis influences resistivity. The primary findings are summarized as follows.

- (1) The ion concentration of formation water is predominantly controlled by diagenetic processes, including the dissolution of silicate minerals, the compaction-induced concentration, and others. These processes enrich ions such as Cl^- , $Na^+ + K^+$, and Ca^{2+} , ultimately leading to high-salinity formation water. Additionally, reverse ion exchange in a confined diagenetic environment significantly affects the evolution of formation water.
- (2) The dissolution of silicate minerals, such as feldspar, enhances reservoir porosity while generating significant amounts of authigenic clay minerals, such as kaolinite. The accumulation of these clay minerals within pore throats increases reservoir complexity and leads to a marked reduction in permeability. Consequently, high-salinity formation water becomes trapped as irreducible water, increasing conductivity and lowering resistivity. Additionally, the increased connectivity and volumetric fraction of highly saline water in larger pores ($>10 \mu m$) increase the number of conductive pathways and further reduce resistivity.
- (3) RF-PFN integrates the structural diversity of RF with the local Bayesian inference of TabPFN, thus showing superior robustness for LRP identification. The two sensitive parameters (R_{wa-Rt} and IF) show strong potential in characterizing ionic concentration variations and invasion effects. Their removal results in a decline in model performance (AUC and PR-AUC decreased by 3.30% and 7.59%, respectively). These methods provide a practical and effective solution for fluid identification in low-permeability sandstone reservoirs.

CRedit authorship contribution statement

Yu-Xi Sun: Writing – original draft, Visualization, Software, Conceptualization. **Liang Chen:** Writing – review & editing, Methodology, Conceptualization. **Yuan Qi:** Visualization, Investigation, Formal analysis. **Han-Cheng Ji:** Supervision, Project administration, Funding acquisition. **Yi-Ping He:** Resources. **Yan-Qing Shi:** Validation, Formal analysis. **Si-Cong Wang:** Investigation, Formal analysis. **Shuang-Qi Feng:** Investigation. **Bo-Yuan Zhao:** Investigation. **Ru-Feng Deng:** Formal analysis.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT (OpenAI) in order to improve the readability and language clarity of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

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

Acknowledgements

This study was financially supported by the National Science and Technology Major Project of China (2025ZD1403906), the National Natural Science Foundation of China (U2341292), the Science Foundation of China University of Petroleum, Beijing (2462023BJR011), and the CNPC Innovation Fund (2021D002-0102). The authors sincerely thank PetroChina Changqing Oilfield Company for providing samples and data access. Special appreciation is extended to the anonymous reviewers for their constructive comments and the journal editors for their diligent work.

Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.petsci.2026.07.048>.

References

- Abdollah-Pour, R., Torres-Verdin, C., Sepehrnoori, K., et al., 2016. Depth variation of wettability alteration during oil-base mud-filtrate invasion and corresponding effects on resistivity logs. *J. Petrol. Sci. Eng.* 147, 593–604. <https://doi.org/10.1016/j.petrol.2016.08.029>.
- Bai, Z., Tan, M.J., Shi, Y.J., et al., 2021. Reservoir characteristics and control mechanism of resistivity low-contrast oil pays in Chang 8 tight sandstone of Longdong West area, Ordos Basin. *J. Petrol. Explor. Prod. Technol.* 11 (6), 2609–2620. <https://doi.org/10.1007/s13202-021-01195-1>.
- Bai, S.T., Wan, J.B., Yang, R.X., et al., 2017. Summary on formation water resistivity evaluation methods. *Prog. Geophys.* 32 (2), 566–578. <https://doi.org/10.6038/pg20170216> (in Chinese).
- Bai, J.L., Zhao, J.F., Ren, Z.L., et al., 2022. Paleogeographic and sedimentary evolution of Meso-Neoproterozoic strata in the Ordos Basin, western North China Craton. *J. Petrol. Sci. Eng.* 215, 110600. <https://doi.org/10.1016/j.petrol.2022.110600>.
- Bethke, C.M., Reed, J.D., Oltz, D.F., 1991. Long-range petroleum migration in the Illinois Basin. *AAPG Bull.* 75 (5), 925–945. <https://doi.org/10.1306/0c9b2899-1710-11d7-8645000102c1865d>.
- Bjørlykke, K., Jahren, J., 2012. Open or closed geochemical systems during diagenesis in sedimentary basins: Constraints on mass transfer during diagenesis and the prediction of porosity in sandstone and carbonate reservoirs. *AAPG Bull.* 96 (12), 2193–2214. <https://doi.org/10.1306/04301211139>.
- Breiman, L., 2001. Random forests. *Mach. Learn.* 45 (1), 5–32. <https://doi.org/10.1023/A:1010933404324>.
- Cai, Y.D., Liu, D.M., Pan, Z.J., et al., 2013. Petrophysical characterization of Chinese coal cores with heat treatment by nuclear magnetic resonance. *Fuel* 108, 292–302. <https://doi.org/10.1016/j.fuel.2013.02.031>.
- Cao, Y.C., Yuan, G.H., Wang, Y.Z., et al., 2022. Successive formation of secondary pores via feldspar dissolution in deeply buried feldspar-rich clastic reservoirs in typical petroliferous basins and its petroleum geological significance. *Sci. China Earth Sci.* 65 (9), 1673–1703. <https://doi.org/10.1007/s11430-020-9931-9>.
- Chan, M.C., Pai, K.C., Su, S.A., et al., 2022. Explainable machine learning to predict long-term mortality in critically ill ventilated patients: A retrospective study in central Taiwan. *BMC Med. Inf. Decis. Making* 22 (1), 75. <https://doi.org/10.1186/s12911-022-01817-6>.
- Chuhan, F.A., Bjørlykke, K., Lowrey, C., 2000. The role of provenance in illitization of deeply buried reservoir sandstones from Haltenbanken and North Viking Graben, offshore Norway. *Mar. Petrol. Geol.* 17 (6), 673–689. [https://doi.org/10.1016/S0264-8172\(00\)00014-3](https://doi.org/10.1016/S0264-8172(00)00014-3).
- Clavier, C., Coates, G., Dumanoir, J., 1984. Theoretical and experimental bases for the dual-water model for interpretation of shaly sands. *Soc. Petrol. Eng. J.* 24 (2), 153–168. <https://doi.org/10.2118/6859-PA>.
- Davison, M.L., Criss, R.E., 1996. Na–Ca–Cl relations in basinal fluids. *Geochim. Cosmochim. Acta* 60 (15), 2743–2752. [https://doi.org/10.1016/0016-7037\(96\)00143-3](https://doi.org/10.1016/0016-7037(96)00143-3).
- Deng, X.Q., Cheng, D.X., Zhou, X.P., et al., 2020. Formation hydrochemical characteristics and genesis of the Lower Jurassic, Ordos Basin. *Acta Sedimentologica Sin* 38 (5), 1099–1110 (in Chinese). <https://doi.org/10.14027/j.issn.1000-0550.2019.080>.
- Díaz-Curiel, J., Miguel, M.J., Biosca, B., et al., 2022. Using SP logs to estimate the water quality of borehole layers in the Duero Basin (Iberian Peninsula). *Hydrol. Sci. J.* 67 (6), 925–938. <https://doi.org/10.1080/02626667.2022.2050731>.
- Elsayed, M., Isah, A., Hiba, M., et al., 2022. A review on the applications of nuclear magnetic resonance (NMR) in the oil and gas industry: Laboratory and field-scale measurements. *J. Pet. Explor. Prod. Technol.* 12 (10), 2747–2784. <https://doi.org/10.1007/s13202-022-01476-3>.
- Folk, R.L., Andrews, P.B., Lewis, D.W., 1970. Detrital sedimentary rock classification and nomenclature for use in New Zealand. *N. Z. J. Geol. Geophys.* 13 (4), 937–968. <https://doi.org/10.1080/00288306.1970.10418211>.
- França, A.B., Araújo, L.M., Maynard, J.B., et al., 2003. Secondary porosity formed by deep meteoric leaching: Botucatu eolianite, southern South America. *AAPG Bull.* 87 (7), 1073–1082. <https://doi.org/10.1306/02260301071>.
- Gaillardet, J., Dupré, B., Louvat, P., et al., 1999. Global silicate weathering and CO₂ consumption rates deduced from the chemistry of large rivers. *Chem. Geol.* 159 (1–4), 3–30. [https://doi.org/10.1016/S0009-2541\(99\)00031-5](https://doi.org/10.1016/S0009-2541(99)00031-5).
- Gao, H., Li, H.Z., 2015. Determination of movable fluid percentage and movable fluid porosity in ultra-low permeability sandstone using nuclear magnetic resonance (NMR) technique. *J. Petrol. Sci. Eng.* 133, 258–267. <https://doi.org/10.1016/j.petrol.2015.06.017>.
- Gao, J.B., Pang, X.Q., Wang, Z.X., et al., 2007. Characteristics and master control factors of petroliferous properties of low permeability clastic reservoirs of Yan-chang Formation in the Upper Triassic of Jiyuan area in Ordos Basin. *J. China Univ. Petrol. Ed. Nat. Sci.* 31 (1), 5–12. <https://doi.org/10.3321/j.issn:1000-5870.2007.01.002> (in Chinese).
- Gao, L., Xie, R.H., Xiao, L.Z., et al., 2022. Identification of low-resistivity-low-contrast pay zones in the feature space with a multi-layer perceptron based on conventional well log data. *Petrol. Sci.* 19 (2), 570–580. <https://doi.org/10.1016/j.petsci.2021.12.012>.
- Giles, M.R., 1987. Mass transfer and problems of secondary porosity creation in deeply buried hydrocarbon reservoirs. *Mar. Petrol. Geol.* 4 (3), 188–204. [https://doi.org/10.1016/0264-8172\(87\)90044-4](https://doi.org/10.1016/0264-8172(87)90044-4).
- Giles, M.R., de Boer, R.B., 1990. Origin and significance of redistributional secondary porosity. *Mar. Petrol. Geol.* 7 (4), 378–397. [https://doi.org/10.1016/0264-8172\(90\)90016-A](https://doi.org/10.1016/0264-8172(90)90016-A).
- Giles, M.R., Marshall, J.D., 1986. Constraints on the development of secondary porosity in the subsurface: Re-evaluation of processes. *Mar. Petrol. Geol.* 3 (3), 243–255. [https://doi.org/10.1016/0264-8172\(86\)90048-6](https://doi.org/10.1016/0264-8172(86)90048-6).
- Glasmann, J.R., 1992. The fate of feldspar in brent group reservoirs, north sea: A regional synthesis of diagenesis in shallow, intermediate, and deep burial environments. *Geol. Soc. Lond. Spec. Publ.* 61, 329–350. <https://doi.org/10.1144/GSL.SP.1992.061.01.17>.
- Guo, J.Q., Wu, H.Y., Chen, X.L., et al., 2024. Adaptive SV-Borderline SMOTE-SVM algorithm for imbalanced data classification. *Appl. Soft Comput.* 150, 110986. <https://doi.org/10.1016/j.asoc.2023.110986>.
- Guo, J.Z., Li, Y., Wang, Y.X., et al., 2023. Identification of an oil-bearing layer by formation water resistivity: A case study of the Jurassic reservoir, Southwest Ordos Basin. *Geophysics* 88 (4), B151–B162. <https://doi.org/10.1190/geo2022-05871>.
- Guo, J.Z., Wang, Y.X., Li, Y., et al., 2025. Visual representation of machine learning for low-contrast pay logging identification using 2D formation water resistivity variables. *Mar. Petrol. Geol.* 181, 107518. <https://doi.org/10.1016/j.marpetgeo.2025.107518>.
- Hamada, G.M., Al-Awad, M.N.J., 2000. Petrophysical evaluation of low resistivity sandstone reservoirs. *J. Can. Petrol. Technol.* 39 (7). <https://doi.org/10.2118/00-07-TN>.
- Hamada, G.M., Al-Blehed, M.S., Al-Awad, M.N., et al., 2001. Petrophysical evaluation of low-resistivity sandstone reservoirs with nuclear magnetic resonance log. *J. Petrol. Sci. Eng.* 29 (2), 129–138. [https://doi.org/10.1016/S0920-4105\(01\)00095-X](https://doi.org/10.1016/S0920-4105(01)00095-X).
- Hanor, J.S., 1994. Physical and chemical controls on the composition of waters in sedimentary basins. *Mar. Petrol. Geol.* 11 (1), 31–45. [https://doi.org/10.1016/0264-8172\(94\)90007-8](https://doi.org/10.1016/0264-8172(94)90007-8).
- Hodgkins, M.A., Howard, J.J., 1999. Application of NMR logging to reservoir characterization of low-resistivity sands in the Gulf of Mexico. *AAPG Bull.* 83 (1), 114–127. <https://doi.org/10.1306/00AA9A16-1730-11D7-8645000102C1865D>.
- Hollmann, N., Müller, S., Purucker, L., et al., 2025. Accurate predictions on small data with a tabular foundation model. *Nature* 637 (8045), 319–326. <https://doi.org/10.1038/s41586-024-08328-6>.
- Iqbal, M.A., Salim, A.M.A., Baioumy, H., et al., 2019. Identification and characterization of low resistivity low contrast zones in a clastic outcrop from Sarawak, Malaysia. *J. Appl. Geophys.* 160, 207–217. <https://doi.org/10.1016/j.jappgeo.2018.11.013>.
- Jiang, M.L., Fang, H.X., Liu, Y., et al., 2023. On movable fluid saturation of tight sandstone and main controlling factors: Case study on the Fuyu oil layer in the Da'an oilfield in the Songliao Basin. *Energy* 267, 126476. <https://doi.org/10.1016/j.energy.2022.126476>.
- Lai, J., Wang, G.W., Ran, Y., et al., 2016. Impact of diagenesis on the reservoir quality of tight oil sandstones: The case of Upper Triassic Yanchang Formation Chang 7 oil layers in Ordos Basin, China. *J. Petrol. Sci. Eng.* 145, 54–65. <https://doi.org/10.1016/j.petrol.2016.03.009>.
- Lai, J., Wang, G.W., Wang, Z.Y., et al., 2018. A review on pore structure characterization in tight sandstones. *Earth Sci. Rev.* 177, 436–457. <https://doi.org/10.1016/j.earscirev.2017.12.003>.
- Lai, Y.W., Wan, G.C., Qin, X.X., 2024. Decoding China's new-type industrialization: Insights from an XGBoost-SHAP analysis. *J. Clean. Prod.* 478, 143927. <https://doi.org/10.1016/j.jclepro.2024.143927>.
- LaValley, M.P., 2008. Logistic regression. *Circulation* 117 (18), 2395–2399. <https://doi.org/10.1161/CIRCULATIONAHA.106.682658>.
- LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. *Nature* 521 (7553), 436–444. <https://doi.org/10.1038/nature14539>.
- Li, Y.R., Liu, B., Hu, Z.M., et al., 2025. Conductive characterization of shale reservoir induced by pore fluids: A case study of Longmaxi Formation in Southern Sichuan region. *Fuel* 387, 134412. <https://doi.org/10.1016/j.fuel.2025.134412>.

- Li, C., Shi, Y., Zhou, C., et al., 2010. Evaluation of low amplitude and low resistivity pay zones under the fresh drilling mud invasion condition. *Petrol. Explor. Dev.* 37 (6), 696–702. [https://doi.org/10.1016/S1876-3804\(11\)60004-9](https://doi.org/10.1016/S1876-3804(11)60004-9).
- Li, J., Zhao, H.G., Wang, J., et al., 2024a. Sedimentary environment and provenance tracing of clastic rocks from the Triassic Yanchang Formation in the western margin of the Ordos Basin. *Acta Sedimentol. Sin.* 42 (5), 1621–1638. <https://doi.org/10.14027/j.issn.1000-0550.2022.120> (in Chinese).
- Li, Y.G., Fu, H.J., Su, X.B., et al., 2024b. Microbial coalbed gas and its geological formation process in the Jimsar region of the southern Junggar Basin, NW China. *Geoenery Sci. Eng.* 233, 212596. <https://doi.org/10.1016/j.geoen.2023.212596>.
- Lin, M.R., Xi, K.L., Cao, Y.C., et al., 2024a. Palaeoenvironmental changes in the Late Triassic lacustrine facies of the Ordos Basin of Northwest China were driven by multistage volcanic activity: Implications for the understanding the Carnian Pluvial Event. *Palaeogeogr. Palaeoclimatol. Palaeoecol.* 637, 112012. <https://doi.org/10.1016/j.palaeo.2024.112012>.
- Li, H., Zhao, H.Y., Xu, Y.X., et al., 2021. Characteristics of debrites, turbidites, and contourites in the Upper Ordovician Pingliang Formation along southwestern margin of the Ordos Basin, western China. *Arab. J. Geosci.* 14 (17), 1730. <https://doi.org/10.1007/s12517-021-08215-8>.
- Lin, Y.B., Wang, S.M., Qiao, J.W., et al., 2024b. Chemical characteristics, formation mechanisms, and geological evolution processes of high-salinity coal reservoir water in the Binchang area of the southern Ordos Basin, China. *Int. J. Coal Geol.* 291, 104574. <https://doi.org/10.1016/j.coal.2024.104574>.
- Lou, J.Y., Xu, X.H., Zhao, Z.X., et al., 2024. Fluid identification using XGBoost combined with MAHAKIL in low-permeability reservoirs. *SPE J.* 29 (1), 203–214. <https://doi.org/10.2118/217452-PA>.
- Lu, H., Yue, D., Jones, S.J., et al., 2024. Lithofacies assemblage and effects on diagenesis in lacustrine tight sandstone reservoirs: Samples from Upper Triassic Yanchang Formation, Ordos Basin, China. *Mar. Petrol. Geol.* 167, 107001. <https://doi.org/10.1016/j.marpetgeo.2024.107001>.
- Lundberg, S.M., Lee, S.I., 2017. A unified approach to interpreting model predictions. In: 31st International Conference on Neural Information Processing Systems. Curran Associates Inc., Long Beach, California, USA, pp. 4768–4777.
- Luo, J.C., Yan, J.P., Liao, M.J., et al., 2024. Evaluation of pore structure characteristics of deep clastic rocks in the Huangliu formation of LD-X area, Yinggehai Basin. *Mar. Petrol. Geol.* 167, 106969. <https://doi.org/10.1016/j.marpetgeo.2024.106969>.
- Mashaba, V., Altermann, W., 2015. Calculation of water saturation in low resistivity gas reservoirs and pay-zones of the Cretaceous Grudja Formation, onshore Mozambique Basin. *Mar. Petrol. Geol.* 67, 249–261. <https://doi.org/10.1016/j.marpetgeo.2015.05.016>.
- Noble, W.S., 2006. What is a support vector machine? *Nat. Biotechnol.* 24 (12), 1565–1567. <https://doi.org/10.1038/nbt1206-1565>.
- Owen, D.D.R., Raiber, M., Cox, M.E., 2015. Relationships between major ions in coal seam gas groundwaters: Examples from the Surat and Clarence-Morton basins. *Int. J. Coal Geol.* 137, 77–91. <https://doi.org/10.1016/j.coal.2014.11.004>.
- Piper, A.M., 1944. A graphic procedure in the geochemical interpretation of water-analyses. *EOS Trans. Am. Geophys. Union* 25, 914–928. <https://doi.org/10.1029/TR025i006p00914>.
- Pires, L.O., Winter, A., Trevisan, O.V., 2019. Dolomite cores evaluated by NMR. *J. Petrol. Sci. Eng.* 176, 1187–1197. <https://doi.org/10.1016/j.petrol.2018.06.026>.
- Pratama, E., Suhaili Ismail, M., Ridha, S., 2017. An integrated workflow to characterize and evaluate low resistivity pay and its phenomenon in a sandstone reservoir. *J. Geophys. Eng.* 14 (3), 513–519. <https://doi.org/10.1088/1742-2140/aa5efb>.
- PriorLabs, 2025a. TabPFN: Foundation model for tabular data. GitHub repository. <https://github.com/PriorLabs/TabPFN>. (Accessed 27 October 2025).
- PriorLabs, 2025b. Community extensions for TabPFN - the foundation model for tabular data. Built with TabPFN!. <https://github.com/PriorLabs/tabpf-extensions>. (Accessed 27 October 2025).
- Qi, Y., Han, D.W., Du, Y.Y., et al., 2023. Genesis of low-resistivity reservoirs in Sangonghe Formation, Mahu sag, Xinjiang Petrol. Geol. 44 (2), 151–160. <https://doi.org/10.7657/XJPG20230204> (in Chinese).
- Qu, S., Duan, L.M., Mao, H.R., et al., 2023. Hydrochemical and isotopic fingerprints of groundwater origin and evolution in the Urugulan River basin, China's Loess Plateau. *Sci. Total Environ.* 866, 161377. <https://doi.org/10.1016/j.scitotenv.2022.161377>.
- Radhakrishna, I., Gangadhara Rao, T., 1990. Evaluation of hydrogeochemical parameters with spontaneous potential logs. *J. Hydrol.* 114 (3–4), 245–257. [https://doi.org/10.1016/0022-1694\(90\)90059-7](https://doi.org/10.1016/0022-1694(90)90059-7).
- Salisu, A.M., Alqubalee, A., Bello, A.M., et al., 2023. Impact of kaolinite and iron oxide cements on resistivity and quality of low resistivity pay sandstones. *Mar. Petrol. Geol.* 158, 106568. <https://doi.org/10.1016/j.marpetgeo.2023.106568>.
- Schoeller, H., 1977. Geochemistry of groundwater. In: *Groundwater Studies—An International Guide for Research and Practice*. UNESCO, Paris, Ch. 15, pp. 1–18.
- Simandoux, P., 1963. Dielectric measurements on porous media, application to the measurements of water saturation: Study of behavior of argillaceous formations. *Rev. L'institut Francais Petrol.* 18, 193–215.
- Sonnenberg, S.A., 2021. Carrier-bed plays in the Denver and Powder River Basins. *AAPG Bull.* 105 (9), 1779–1796. <https://doi.org/10.1306/04122120060>.
- Sun, Y.X., Chen, L., Qi, Y., et al., 2026. Impact of sample size and pore structure on machine learning prediction of petrophysical properties in low-permeability sandstone reservoirs. *Geoenery Sci. Eng.* 257, 214266. <https://doi.org/10.1016/j.geoen.2025.214266>.
- Surdam, R.C., Crossey, L.J., 1987. Integrated diagenetic modeling: A process-oriented approach for clastic systems. *Annu. Rev. Earth Planet Sci.* 15, 141–170. <https://doi.org/10.1146/annurev.ea.15.050187.001041>.
- Thakur, A., 2024. Approaching (almost) any machine learning problem. <https://github.com/abhishekkthakur/approachingalmost>. (Accessed 30 May 2024).
- Tian, Z.Y., Jiang, A., Yan, W.L., et al., 2010. Resistivity correction for drilling fluid invasion using LWD and wire-line logging data: A case from high-porosity and low-permeability carbonate reservoirs, DLL oilfield, Oman. *Petrol. Explor. Dev.* 37 (4), 430–437. [https://doi.org/10.1016/S1876-3804\(10\)60044-4](https://doi.org/10.1016/S1876-3804(10)60044-4).
- Tudge, J., Lovell, M., Davies, S., et al., 2014. A novel integrated approach to estimating hydrocarbon saturation in the presence of pore-lining chlorites. *Pet. Geosci.* 20 (2), 201–209. <https://doi.org/10.1144/petgeo.2013-044>.
- Wang, X.X., Zhou, L., Wu, Y., et al., 2023b. Restoration of palaeogeomorphology and its petroleum-geological significance: Transitional-facies deposition during the Early Permian in the southeastern Ordos Basin, North China. *Geoenery Sci. Eng.* 221, 111310. <https://doi.org/10.1016/j.petrol.2022.111310>.
- Wang, Z.Y., Liu, Y.C., Lu, S.F., et al., 2023a. Differential development characteristics of secondary pores and effects on pore structure and movable fluid distribution in tight gas sandstones in the Lower Permian, northeastern Ordos Basin, China. *Geoenery Sci. Eng.* 224, 211580. <https://doi.org/10.1016/j.geoen.2023.211580>.
- Waxman, M.H., Smits, L.J.M., 1968. Electrical conductivities in oil-bearing shaly sands. *Soc. Petrol. Eng. J.* 8 (2), 107–122. <https://doi.org/10.2118/1863-A>.
- Wei, J.G., Yang, E.L., Li, J.T., et al., 2023. Nuclear magnetic resonance study on the evolution of oil water distribution in multistage pore networks of shale oil reservoirs. *Energy* 282, 128714. <https://doi.org/10.1016/j.energy.2023.128714>.
- Worthington, P.F., 2000. Recognition and evaluation of low-resistivity pay. *Pet. Geosci.* 6 (1), 77–92. <https://doi.org/10.1144/petgeo.6.1.77>.
- Xiao, L., Shi, Y.J., Li, G.R., et al., 2021. A method to predict the resistivity index for tight sandstone reservoirs from nuclear magnetic resonance data. *AAPG Bull.* 105 (5), 1009–1032. <https://doi.org/10.1306/05222018269>.
- Yang, S.F., Bao, Z.D., Wang, N., et al., 2020. Diagenetic evolution and its impact on reservoir quality of tight sandstones: A case study of the Triassic Chang 6 Member, Ordos Basin, Northwest China. *Mar. Petrol. Geol.* 117, 104360. <https://doi.org/10.1016/j.marpetgeo.2020.104360>.
- Yin, Z., Liu, Z.L., Peng, N., et al., 2019. Study on sedimentary facies features of the Upper Triassic Yanchang Formation, in the western margin, Ordos Basin. *Acta Sedimentol. Sin.* 37, 163–176 (in Chinese). <https://doi.org/10.14027/j.issn.1000-0550.2018.156>.
- Yuan, G.H., Cao, Y.C., Gluyas, J., et al., 2015. Feldspar dissolution, authigenic clays, and quartz cements in open and closed sandstone geochemical systems during diagenesis: Typical examples from two sags in Bohai Bay Basin, East China. *AAPG Bull.* 99 (11), 2121–2154. <https://doi.org/10.1306/07101514004>.
- Yuan, G.H., Cao, Y.C., Gluyas, J., et al., 2017. Reactive transport modeling of coupled feldspar dissolution and secondary mineral precipitation and its implication for diagenetic interaction in sandstones. *Geochim. Cosmochim. Acta* 207, 232–255. <https://doi.org/10.1016/j.gca.2017.03.022>.
- Yuan, G.H., Cao, Y.C., Schulz, H.M., et al., 2019. A review of feldspar alteration and its geological significance in sedimentary basins: From shallow aquifers to deep hydrocarbon reservoirs. *Earth Sci. Rev.* 191, 114–140. <https://doi.org/10.1016/j.earscirev.2019.02.004>.
- Zhang, J.F., Yan, D.T., Zhou, S.D., et al., 2023. Sedimentological and diagenetic effects on petrophysical characteristics and hydraulic flow units of Zhujiang sandstones in the Pearl River Mouth Basin, South China Sea. *Energy* 282, 128942. <https://doi.org/10.1016/j.energy.2023.128942>.
- Zhou, B.Y., Qin, Y., Yang, Z.B., 2020. Ion composition of produced water from coalbed methane wells in western Guizhou, China, and associated productivity response. *Fuel* 265, 116939. <https://doi.org/10.1016/j.fuel.2019.116939>.