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Machine learning-based analysis of factors controlling the reservoir productivity of the Maokou Formation, Sichuan Basin

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ABSTRACT

By 2024, the proven natural gas reserves of the Maokou Formation in the central Sichuan Basin had exceeded $1.5 \times 10^{11} \text{ m}^3$, suggesting great potential for hydrocarbon exploration. However, this formation exhibits small reservoir thicknesses and pronounced lateral heterogeneity due to sedimentation and erosion. These characteristics lead to significantly varying single-well production, complicating the identification of major controlling factors in high production and reducing the prediction accuracy of sweet spots. To identify the key geological factors controlling the gas production in the Maokou Formation, this study investigated the geological and seismic characteristics of the dolomite reservoirs in this formation. The primary geological factors influencing single-well production were explored using a machine learning approach—an enhanced random forest (RF) prediction model based on Shapley additive explanations (SHAP) values (also referred to as the SHAP-enhanced RF model). Accordingly, an optimal combination of geological parameters for high production was determined, followed by the identification of sweet spots. The results demonstrate that the SHAP-enhanced RF model allows for the effective quantification of the relative importance of various factors. The most critical factors affecting the gas production in the Maokou Formation include burial depth, natural gamma-ray value, the spatial distance of bright spots (defined as the time thickness of bright spots relative to the base of the second member of the Maokou Formation), and paleogeomorphology. High-yielding wells typically feature a joint advantage of multiple critical factors. A strong synergistic effect is prone to occur when several optimal factors fall within their optimal ranges simultaneously. In this case, high production capacity might be achieved. Compared to an equal-weight RF model, the SHAP-enhanced RF model yielded a mean absolute error (MAE) decreasing by 18.6%, thereby enhancing prediction accuracy and reliability. The findings of this study can serve as a valuable guide for production planning and well placement optimization in the Maokou Formation.

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1. Introduction

Deep strata (burial depths: > 4500 m) in the Sichuan Basin contain abundant carbonate rock-hosted hydrocarbon resources. Several large- to medium-scale gas fields have been discovered in the basin's multi-layered platform margin zones, including the Sinian Anyue gas field along the Deyang-Anyue rift trough in the central Sichuan Basin (He X et al., 2023; Tang QS et al., 2024) and the Puguang, Yuanba,

and Longgang gas fields in the surrounding area of the Kaijiang-Liangping trough (Guo TL et al., 2024). These discoveries highlight the potential for the exploration of reef-shoal reservoirs in carbonate platform margin zones. In 2021, shoal-facies dolomite reservoirs located in the platform margin zone of the Maokou Formation were encountered during the drilling of well JT1 on the northern slope of the Central Sichuan paleo-uplift, with a high gas flow rate of $112.8 \times 10^4 \text{ m}^3/\text{d}$ tested. This result reveals the tectono-sedimentary differentiation characteristics of the Maokou Formation in the basin. The development of large Permian platform margin zones provides favorable geological conditions for the formation of large-scale gas fields (Yang Y et al., 2021). Subsequently, shoal-facies dolomite reservoirs were also encountered during the drilling of several wells

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placed in the platform margin zone of the Maokou Formation. In most of these wells, yielded high gas flow rates were tested, demonstrating significant potential for dolomite reservoir exploration in the platform margin zone of the Maokou Formation.

Current studies have revealed that under the influence of sedimentation and erosion, the shoal-facies dolomite reservoirs in the Maokou Formation exhibit thin individual layers, strong lateral heterogeneity, significantly different longitudinal physical properties, and complex seismic reflections (Liu JW et al., 2022; Zhao H et al., 2023; Kuang MZ et al., 2024; Xu SY et al., 2024; Tan XC et al., 2025). These characteristics lead to inaccurate predictions of the spatial distributions of both reservoirs and production sweet spots. For instance, wells with similar spacing or seismic reflection patterns exhibited highly varying tested gas flow rates, and even some wells with relatively thick reservoirs failed to yield high production. Evidently, the dominant factors controlling high production of gas plays in the Maokou Formation on the northern slope remain poorly understood, hindering the efficient exploration and exploitation of this formation. Many studies have been conducted to investigate sedimentary reservoirs and hydrocarbon accumulation processes (Yang YM et al., 2021; Zhu DC et al., 2021; Zhang Y et al., 2022; Huang SP et al., 2023; Kuang MZ et al., 2024; Xie WR et al., 2024; Yi HY et al., 2024). Liao Y et al. (2023) constructed a facies-controlled reservoir prediction model, confirming that gas in the Maokou Formation originates primarily from the Cambrian source rocks and is jointly controlled by faults and reservoirs. By investigating the stratigraphic sequence filling and reservoir genesis of the Maokou Formation, Tan XC et al. (2025) established a reservoir prediction model based on log-seismic correlation-derived sedimentary landforms. Zhao H et al. (2023) proposed a model for the exploration of reservoirs along faults in the Maokou Formation by comprehensively analyzing the seismic response characteristics of the reservoirs and the distribution patterns of high-yielding wells. Xie JP et al. (2025) proposed a reflection coefficient decomposition method, which improves the prediction accuracy of thin dolomite reservoirs in the Maokou Formation by eliminating the shielding effect of the strong reflector at the top of the formation. Zhang H et al. (2017, 2020) advanced seismic data reconstruction by developing a non-uniform curvelet transform method and an anti-aliasing projection onto convex sets (POCS) interpolation approach, both of which improve seismic data quality and allow for more reliable reservoir prediction. Based on a comprehensive analysis of sedimentary facies zones and paleogeomorphology in the Maokou Formation, along with reservoir prediction, Tang HQ et al. (2024) concluded that, compared to reservoir and fault factors, sedimentary factors should be prioritized in the reservoir evaluation of the Maokou Formation. The above studies demonstrate that the formation of reservoirs in the Maokou Formation is governed by multiple factors. Although these studies have somewhat improved the prediction

accuracy of thin dolomite reservoirs in the Maokou Formation, they focused primarily on single-factor analysis, without considering the combined contribution of multiple factors. Additionally, methods used to analyze influential factors in these studies are primarily qualitative and rely on subjective interpretation. Consequently, the dominant factors controlling the formation, accumulation, and high production of the Maokou Formation reservoirs are yet to be ascertained.

Machine learning approaches offer great advantages in multi-parameter identification, nonlinear relationship analysis, and high-dimensional data mining. They have been applied to the assessment and dominant factor analysis of reservoir productivity (Chen YY et al., 2021; Huang DY et al., 2023; Hui G et al., 2023), yielding certain results. For instance, by combining grey relational analysis with RF, Xue T et al. (2021) identified seven dominant factors influencing shale oil productivity, including porosity, oil saturation, and brittleness index, based on data from over 180 horizontal wells in the Qingcheng oilfield. Accordingly, they established an assessment model for sweet spots to optimize well placement and fracturing parameters, enhancing single-well productivity. Employing a deep learning-based extreme gradient boosting (XGBoost) model, Wang Z et al. (2022) predicted the initial productivity of unconsolidated sandstone reservoirs and identified pore structure, crude oil viscosity, and grain size as the most significant factors influencing productivity. Qi Y et al. (2024) constructed a multivariate regression model based on data from 55 wells in the Xi 233 well block of the Qingcheng oilfield. Using this model and the analysis of SHAP values, they identified the probability of penetration, oil zone length, and proppant intensity as the dominant factors controlling shale oil production, providing a basis for the production prediction and fracturing optimization of individual wells. Employing the RF and XGBoost algorithms, Tong SK et al. (2024) identified factors like soaking time, stable water cut, fracturing fluid volume, and formation thickness as key controls governing tight oil production. These studies highlight the potential of machine learning for revealing key production drivers. Additionally, Jiang XM et al. (2025) conducted a SHAP-based interpretability analysis of an Optuna-LightGBM model, finding that the key features identified aligned highly with geological understanding, thereby providing valuable guidance for model optimization and log feature selection. Beyond the oil and gas sector, machine learning methods have also demonstrated strong performance in other geoscience resource prediction domains. For example, Eftekhari M and Khashei-Siuki A (2025) successfully predicted groundwater level fluctuations in arid regions using random forest and decision tree methods, demonstrating the broad applicability of such approaches in complex geoscientific systems.

To address the challenges in the development of the Maokou Formation in the study area, this study thoroughly investigated the seismic and geological characteristics of thin shoal-facies dolomite reservoirs in the study area by combining previous results. A machine learning approach was employed to identify the dominant factors controlling the single-well production of the Maokou Formation. By

analyzing the optimal relationships among these factors, this study determined the optimal geological parameter combination contributing to high production of the formation. The purpose is to provide technical support for the exploration and exploitation of thin reservoirs and further improve the drilling success rate.

2. Overview of the study area

The study area, located in the central Sichuan Basin, shows landforms dominated by mountains and hills, along with relatively gentle relief (Fig. 1). The subsurface structure in this area is the northern slope of the central Sichuan paleo-uplift, occurring as a northwest-inclined monoclinic structure overall. This structure shows similar structural morphologies across the shallow, intermediate, and deep layers. Its shallow part is dominated by reverse faults formed by compression, while its intermediate and deep parts primarily exhibit normal

and strike-slip faults formed by extensional and strike-slip processes. The study area lies near the large platform margin zone of the Permian Maokou Formation. The favorable paleogeomorphic location contributes to well-developed dolomitized reservoirs. Wells in the study area yielded high gas flow rates and were tested, suggesting considerable exploration potential. However, due to erosion in the Maokou Formation, the reservoirs exhibit strong heterogeneity and uneven thicknesses. As a result, the dominant factors controlling high production of gas plays in the study area remain elusive, restricting their large-scale exploitation.

3. Geological and seismic characteristics of reservoirs in the Maokou Formation

3.1. Geological characteristics

The Permian strata in the study area were formed in a

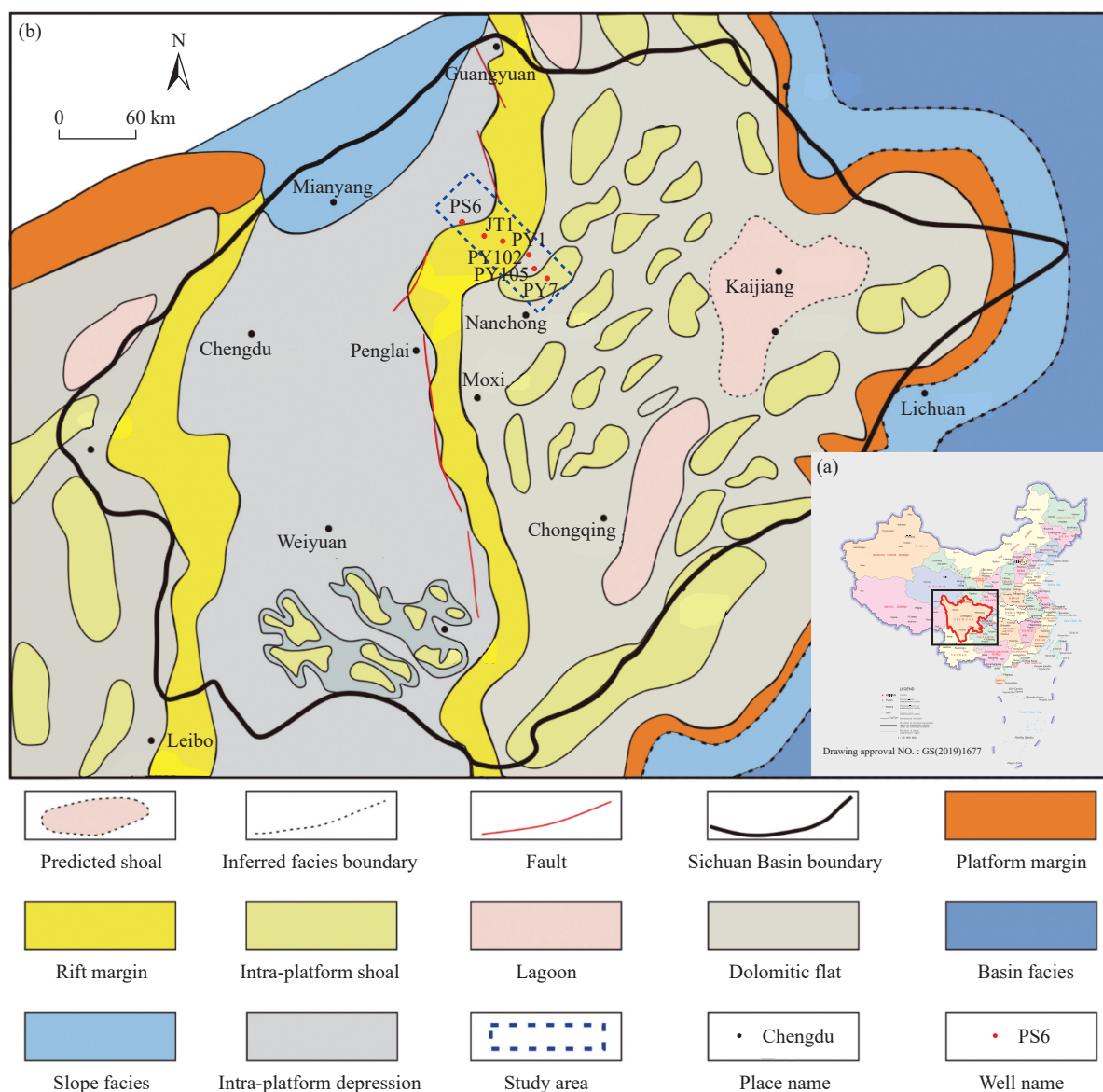


Fig. 1. a—Geographical location of the study area within China; b—tectonic framework and sedimentary facies of the Sichuan Basin with the study area and well locations.

tectonic setting characterized by early uplift and late rifting, which controlled the Permian uplift-depression pattern of this area. Therefore, the deposition of the second member of the Maokou Formation (also referred to as the Mao 2 Member) was controlled by both paleo-uplift and rifting, leading to the formation of two-stage shoal dolomites. These dolomites show a distribution pattern characterized by one uplift and one margin, creating favorable conditions for the formation of shoal reservoirs in the Maokou Formation. Concurrently, under the action of continuous extension, the platform margin of the Mao 2 Member experienced multi-stage shallow migration and evolution, leading to the formation of two-stage large-scale shoals with intense dolomitization. As a result, the Mao 2 Member contains shoal-facies dolomite reservoirs, which vary greatly both laterally and vertically. The NW-SE-oriented stratigraphic correlation section shows that the reservoirs are aligned well with the paleogeomorphic highs of the Maokou Formation (Fig. 2). Specifically, the early-stage shoal reservoirs occur in the paleogeomorphic highs of the lower sub-member of the Mao 2 Member (within the PY102-PY101-PY13-PY105 well blocks), while the late-stage shoal reservoirs are observed in the paleogeomorphic highs formed at the end of the deposition of the Mao 2 Member (within the S6-JT1-PS2-PY3 and PY7-PY106 well blocks), suggesting vertical migration. Overall, the late-stage shoal reservoirs are more developed than their early-stage counterpart.

Regarding petrological characteristics, the reservoir segment in the study area consists primarily of fine-grained dolomites, residual bioclastic dolomites, siliceous dolomites, and dolomitic limestones (Fig. 3). In contrast, the non-reservoir segments are dominated by tight bioclastic micritic limestones, which serve as the primary lithology for vertical and lateral sealing of gas plays. As a result, multiple independent gas plays are formed. The reservoir spaces include intercrystalline pores, intercrystalline dissolution pores, and karst caves, which are effectively connected by well-developed fractures. Data from some wells reveal that the cored intervals show fracture and karst cave densities of 0.9 items/m and 14 items/m, respectively. The karst caves are mostly small, accounting for 72% of the total reservoir spaces. Overall, the reservoirs are of the fractured-vuggy type. Therefore, shoals control the spatial locations of reservoirs, while fractures and vugs further modify the reservoir space, resulting in the complex and varying seismic reflection characteristics of the reservoirs.

3.2. Seismic response characteristics

Currently, paleogeomorphology is considered to govern the development of reservoirs in the Maokou Formation. The flattened seismic section reveals that two-stage shoals occur within the Maokou Formation, as manifested by intermittent medium to weak wave crest reflections. Moreover, these shoals show differences in the time from the base of the Longtan Formation. The early-stage shoals occur in the PY13-PY7 well blocks, approximately 25–30 ms away from the base of the Longtan Formation. At the end of the

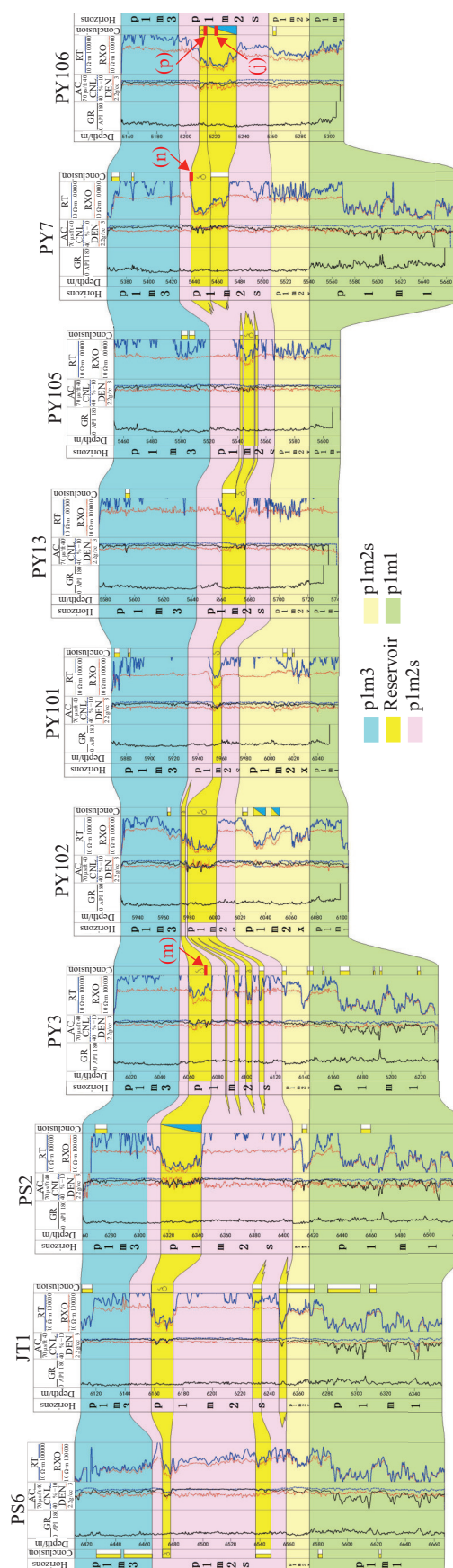


Fig. 2. Well-correlation section of the Mao 2 Member.

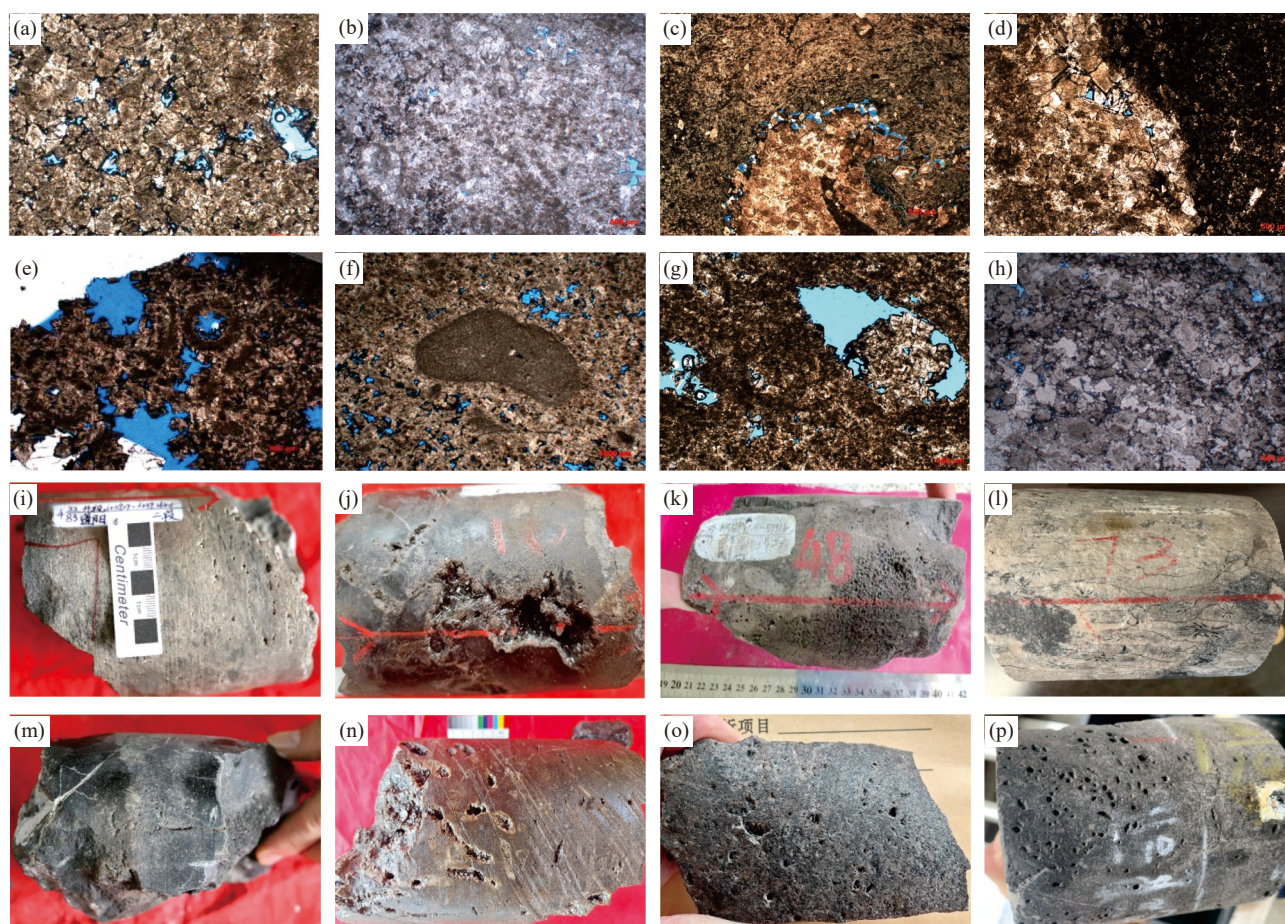


Fig. 3. Sedimentary and reservoir characteristics of the Mao 2 Member. a–Well PY1, fine-grained dolomite, 6006.74–6006.86 m; b–well PY3, fine-grained dolomite with dissolution pores and microfractures, 6071.14 m; c–well PY3, dolomitic limestone, 6059.75 m; d–well PY1, siliceous dolomite, 6013.19 m; e–well PY1, residual bioclastic dolomite; f–well PY3, fine-grained dolomite, 6072.05 m; g–well PY1, dolomitic limestone, 5991.1 m; h–well PY3, siliceous dolomite, 6066.2 m; i–well PY3, fine-grained dolomite; j–well PY106, gray dolomite, with dissolution holes and caves, 5721.77 m; k–well PY1, gray dolomite with dissolution holes, 5995.49 m; l–well PY1, grayish coral limestone, 5999.93 m in; m–well PY3, fine-grained dolomite, 6072.05 m; n–well PY7, fine-grained dolomite with organism cavities, 5438.65 m; o–well PS20, fine-grained dolomite with dense dissolution holes and caves, 6142.95 m; p–well PY106, fine-grained dolomite with residual particles, 5213.75 m.

deposition of the Mao 2 Member, the westward migration of the paleogeomorphic highs led to the formation of late-stage shoals in the PS6-JT1-PS2 and PY3-PY12 well blocks. These shoals are approximately 20 ms away from the base of the Longtan Formation. Meanwhile, the paleogeomorphic lows (e.g., intershoal channels and intershoal depressions) exhibit weak hydrodynamic forces, leading to the deposition of tight micritic limestones, which serve as the primary rock masses for lateral sealing of gas plays (Fig. 4).

Exploration practices show that reservoir heterogeneity significantly impacts single-well productivity in the Maokou Formation. For example, in wells PY8, PY7, PY12, and PY105, daily gas flow rates of 10.68×10^4 m³/d, 2.1×10^4 m³/d, 5.4×10^4 m³/d, and 20.63×10^4 m³/d were tested, respectively, all representing low production. In contrast, in well PY10, featuring the same well spacing and a slightly unfavorable paleogeomorphic location, a high gas flow rate of 101.12×10^4 m³/d was tested. These findings indicate that the single-well production of the Maokou Formation is jointly affected by multiple geological parameters.

The reservoirs of the Maokou Formation in the study area

show two developmental patterns. In the first pattern, the middle-upper part of the Maokou Formation shows weak wave crest reflections with poor continuity. The reservoirs in this part exhibit thicknesses ranging from 15 m to 30 m, favorable physical properties, and a high development degree. They are predominantly of the vuggy and fractured-vuggy types, typified by those in wells PS6 (Fig. 5a) and PY7 (Fig. 5b). In this second pattern, the middle-upper part of the Maokou Formation displays wide and weak wave trough reflections with moderate continuity. The shoal reservoirs exhibit thicknesses ranging from 2 m to 10 m and a low development degree. They are predominantly of the fractured-vuggy and porous types, typified by wells PY1 (Fig. 5c) and PY12 (Fig. 5d).

Previous studies generally consider that reservoirs with the first pattern hold higher productivity than those with the second pattern. However, significantly different daily gas flow rates of 146.09×10^4 m³/d and 2.1×10^4 m³/d were tested in newly drilled wells PS6 and PY7, both of which show the first developmental pattern of reservoirs. In contrast, in well PY1, which displays the second developmental pattern, a daily gas flow rate of 156.55×10^4 m³/d was tested. These

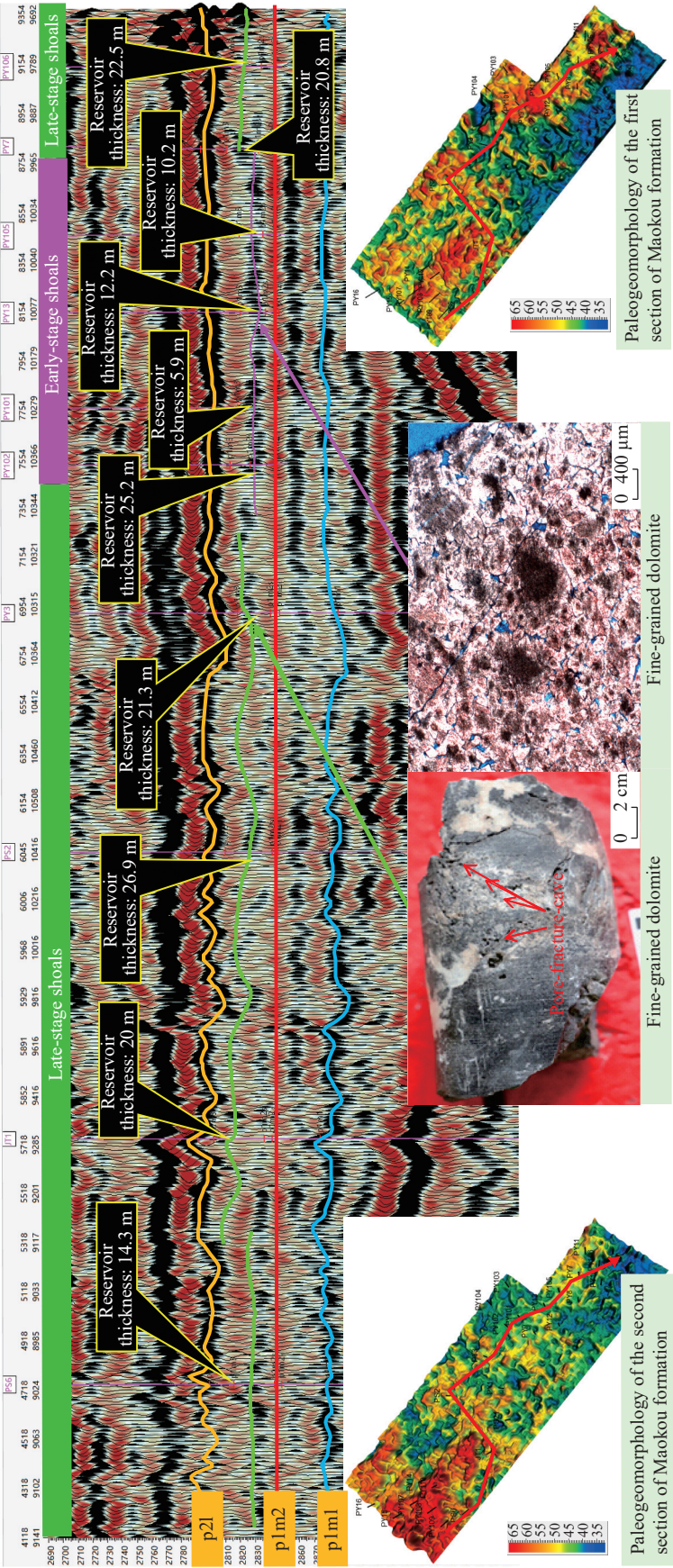


Fig. 4. Well-correlation seismic section of the Maokou Formation.

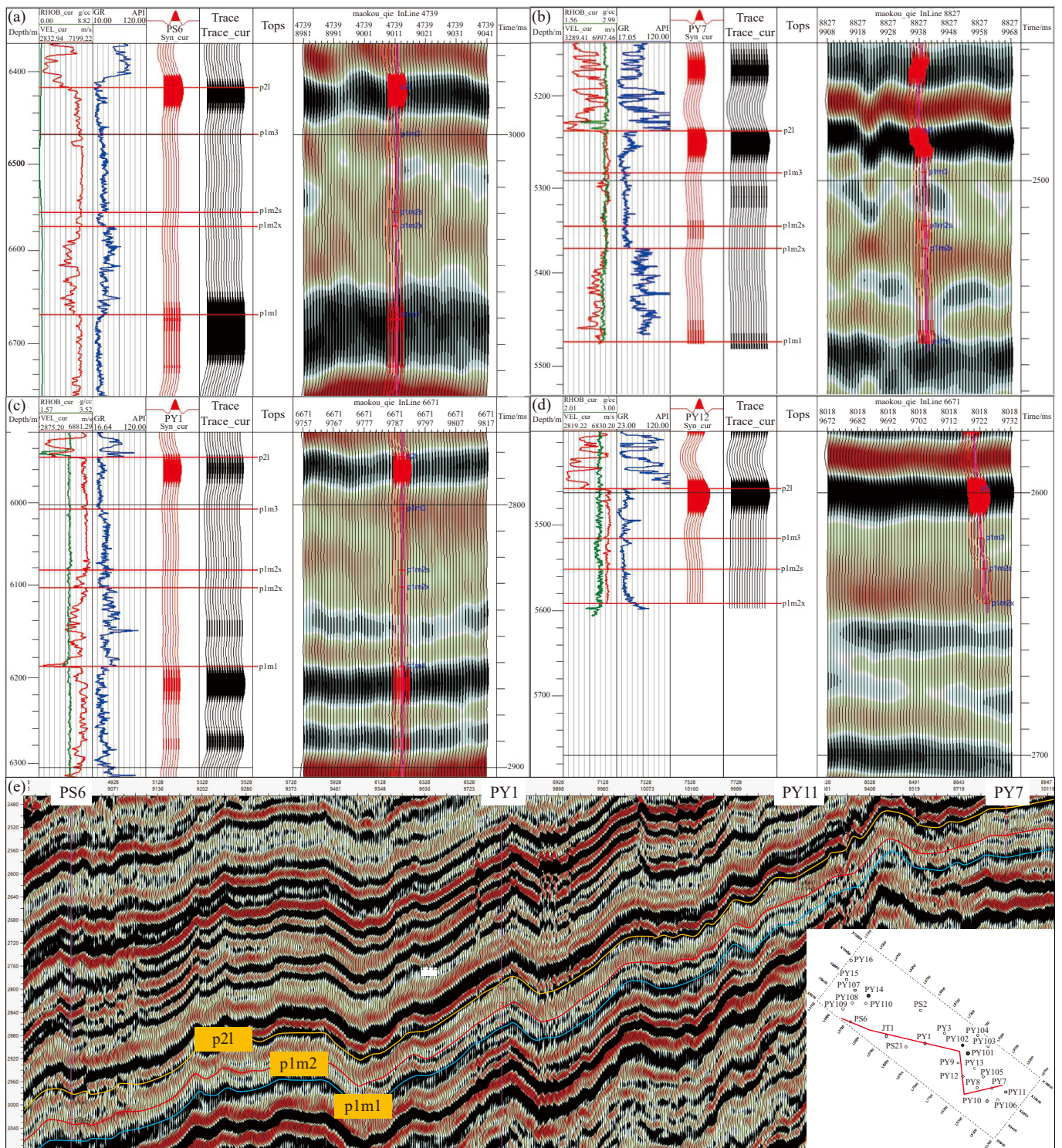


Fig. 5. Seismic characteristics of the Maokou Formation reservoirs in typical wells. a–Synthetic seismogram of well PS6; b–synthetic seismogram of well PY7; c–synthetic seismogram of well PY1; d–synthetic seismogram of well PY12; e–seismic section crossing wells PS6, PY1, PY12, and PY7.

results challenge the earlier geological understanding. Among eight wells with the first development pattern, five yielded industrial productions, suggesting a high production rate of 62.5%. In contrast, seven wells with the second development pattern showed a high production rate of 42.9%. Therefore, the above developmental patterns based on seismic identification fail to completely reflect the high-production characteristics of the Maokou Formation (Fig. 5e).

Studies reveal coupling relationships of high-yielding wells in the Maokou Formation with paleogeomorphology (Fig. 6a) and trough number (Fig. 6b). Specifically, a higher paleogeomorphic part and a larger trough number generally correspond to higher tested gas flow rates. However, the prediction accuracy is merely about 50%. Stratigraphic characteristics have also been identified as a significant factor influencing high production in the Maokou Formation, with

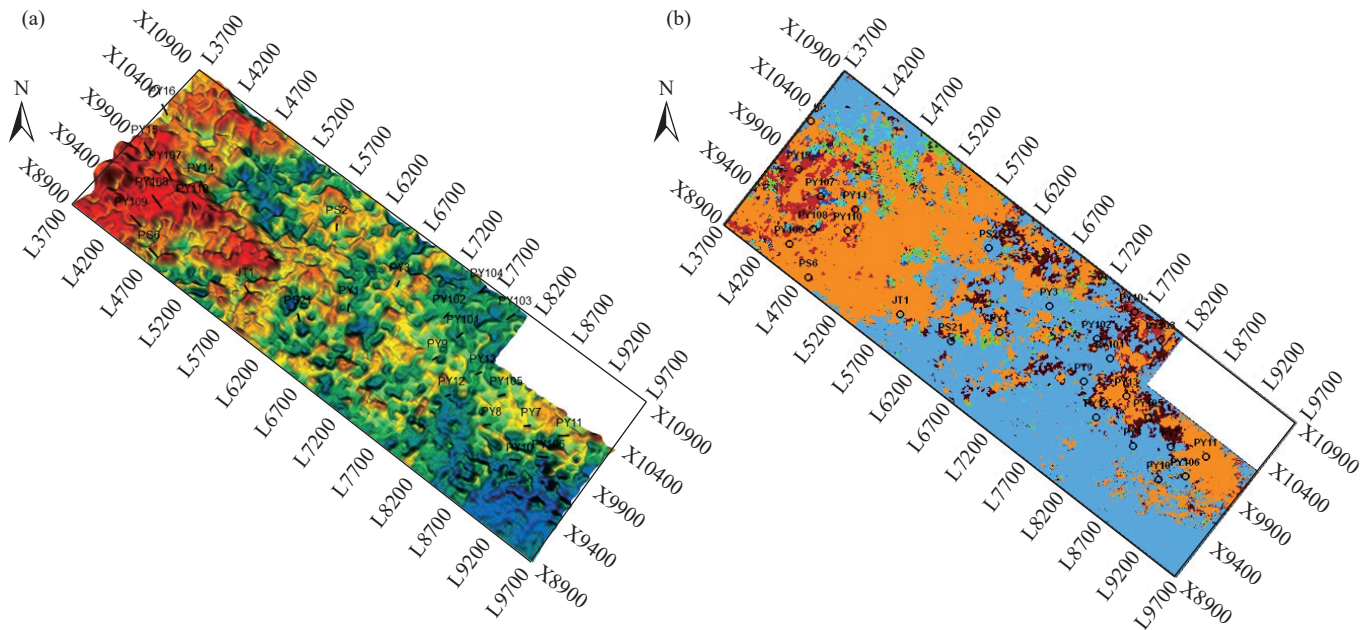


Fig. 6. Maps showing sedimentary landforms (a) and the trough number distribution (b) in the Mao 2 Member.

more developed fractures associated with higher gas production. However, wells PY12 and PY13, with the same developmental degree of fractures, yielded daily gas production of $5.4 \times 10^4 \text{ m}^3/\text{d}$ and $50.46 \times 10^4 \text{ m}^3/\text{d}$, respectively, with a coincidence rate of merely about 32%. Therefore, although exhibiting a strong positive nonlinear relationship with gas production, fracture development is not a primary factor. The exploration practices of other strata indicate that a larger reservoir thickness corresponds to a higher tested gas flow rate. However, reservoirs with a thickness of 20.8 m in well PY7 yielded daily gas production of $2.1 \times 10^4 \text{ m}^3/\text{d}$, while those with a thickness of 20.4 m in well PY10 yielded daily gas production of $101.12 \times 10^4 \text{ m}^3/\text{d}$, suggesting an overall coincidence rate of only 22%. Therefore, a larger reservoir thickness might not necessarily contribute to high gas production in the Maokou Formation. Overall, high production in the Maokou Formation cannot be determined based on a single mode or a single factor since it exhibits strong nonlinear relationships with multiple factors. Using a RF-based machine-learning approach, this study explored these nonlinear relationships, assessed parameter sensitivity, and identified their optimal combinations, aiming to enhance high single-well productivity.

4. Principle of parameter sensitivity analysis based on machine learning

To explore the dominant factors controlling the high production of reservoirs in the Maokou Formation, this study developed a machine learning-based model to analyze these factors. Furthermore, the SHAP method was introduced to quantitatively assess the sensitivity of various parameters. As a game theory-based interpretability technique, the SHAP method measures the marginal contributions of various parameters to the model's prediction outcomes. This enables

the effective identification of key factors that significantly influence production prediction, thereby providing a quantitative foundation for analyzing the factors driving high production in the Maokou Formation.

4.1. Principles and equations of SHAP values

The SHAP values can be calculated based on the Shapley Value theory (Shapley LS, 1951). Specifically, given a model prediction $f(x)$, where $x = (x_1, x_2, \dots, x_n)$ is the input feature vector, the SHAP value of feature i can be calculated using the following equation:

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (1)$$

where $\phi_i(f)$ is the SHAP value of feature i ; $S \subseteq N \setminus \{i\}$ are all possible subsets of features excluding i ; $f(S)$ is the model prediction when feature subset S is used as input, and $f(S \cup \{i\})$ is the prediction when feature i is added to subset S as input.

Eq. 1 accounts for all possible feature combinations, enabling precise quantification of the contributions of various parameters to the model output. On this basis, SHAP values deliver excellent performance in model interpretability and feature sensitivity analysis. These values satisfy the principle of local accuracy. In other words, for any given input x , the model prediction can be exactly reconstructed using the sum of the SHAP values of all features and a baseline value (Eq. 2):

$$f(x) = \phi_0 + \sum_{i=1}^n \phi_i \quad (2)$$

where $f(x)$ is the model output; ϕ_0 is the baseline value (i.e., expected model output), and ϕ_i is the SHAP value of feature i .

This property ensures that the contributions of all features are transparent and interpretable, and that the sum of the contributions fully reconstructs the prediction of the model. This helps researchers understand the combined impacts of various features on the outcomes of the model.

Additionally, SHAP values satisfy the interaction decomposition principle. In the case of the presence of interactions among features, SHAP values can effectively capture and decompose the contributions of these interactions to the output of the model. For instance, the interaction between features i and j can be quantified using the following equation:

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i, j\}} \frac{|S|!(|N| - |S| - 2)!}{|N|!} [f(S \cup \{i, j\}) - f(S \cup \{i\}) - f(S \cup \{j\}) + f(S)] \quad (3)$$

Eq. 3 indicates that SHAP values can quantify the independent contribution of individual features while also revealing interactions among features. The interaction decomposition allows for a detailed analysis of synergistic effects between variables, enabling a thorough exploration of the factors and their interdependencies that affect high production in the Maokou Formation.

4.2. Enhancement of the RF model

In this study, the RF model was primarily employed to analyze the dominant factors controlling high production in the Maokou Formation. As an ensemble learning method that integrates multiple decision trees with their predictions, the RF model demonstrates a high capability to achieve nonlinear fitting. The standard prediction equation of this model is as follows (Eq. 4):

$$\hat{y}_{RF}(x) = \frac{1}{M} \sum_{m=1}^M \hat{y}_m(x) \quad (4)$$

where $\hat{y}_{RF}(x)$ is the prediction of the RF model for input sample x ; $\hat{y}_m(x)$ is the output of the m th decision tree for input sample x , and M is the total number of trees.

Based on the assumption that all trees contribute equally, the traditional RF model takes the simple average of the predictions of all decision trees. However, this equal-weight averaging neglects the differences in generalization ability and interpretability among various trees. If certain trees perform significantly better or worse than the ensemble average, simple averaging may dilute signals from trees that perform well and amplify noise from those that give poor performance, thereby reducing prediction accuracy and the reliability of sensitivity assessments.

To address the limitation mentioned above, this study proposed a weighted ensemble approach based on the consistency of SHAP values (also referred to as the SHAP consistency-based weighted ensemble approach). The core idea of this approach is to assess the reliability of each tree based on the consistency between the SHAP values of this tree and those of the ensemble forest and then to reassign

weights accordingly. Specifically, the SHAP values of various trees and the ensemble forest are calculated, and then the Pearson correlation coefficient between them is used as the weighting factor, which is defined as follows (Eq. 5):

$$w_m = \frac{\text{cov}(SHAP_m, SHAP_{RF})}{\sigma_{SHAP_m} \sigma_{SHAP_{RF}}} \dots \quad (5)$$

where w_m is the weight of the m th tree; $SHAP_m$ and $SHAP_{RF}$ are the SHAP value vectors of the m th tree and the ensemble forest, respectively; cov is the covariance, and σ is the standard deviation.

The final weighted prediction is then obtained by aggregating the outputs various trees with the assigned weights (Eq. 6):

$$\hat{y}_{\text{weighted}}(x) = \sum_{m=1}^M w_m \hat{y}_m(x) / \sum_{m=1}^M w_m \quad (6)$$

where $\hat{y}_{\text{weighted}}(x)$ is the weighted prediction of the improved random forest model for input sample x .

By incorporating SHAP-based weighting, the weighted ensemble approach effectively accounts for differences in the performance of various trees and improves overall model robustness. To validate the effectiveness of this approach, a cross-validation was conducted for a comparative analysis of the original and enhanced RF models. The results show that the SHAP consistency-based weighted ensemble approach reduced the average prediction error of the model by approximately 18.6% compared to the traditional method (Fig. 7), thus enhancing the model stability and generalization ability.

5. Reservoir productivity analysis of the Maokou Formation

5.1. Cross plots between tested gas flow rate and geological parameters

To determine the dominant factors controlling high production in the Maokou Formation, the relationships between the tested gas flow rate and geological parameters

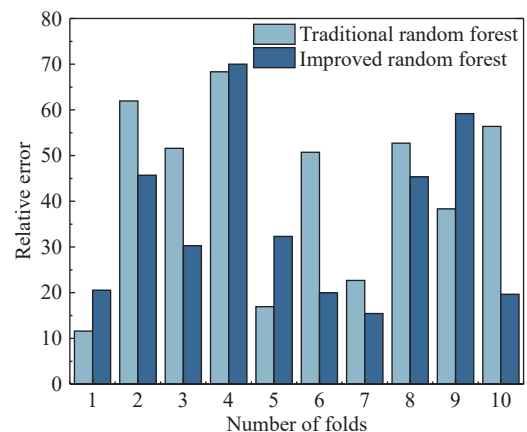


Fig. 7. Prediction errors of the traditional and enhanced RF models.

were analyzed using traditional cross plots. Consequently, a set of geological parameters were selected, including burial depth, spatial distance of bright spot reflections, natural gamma-ray value, paleogeomorphology, reservoir thickness, developmental degree of fractures, wellhead-to-fault distance, and various seismic attributes.

The results indicate that parameters such as paleogeomorphology, burial depth, reservoir thickness, acoustic impedance, and average trough amplitude show slightly strong correlations with the tested gas flow rate (Fig. 8). In contrast, the overall correlations between the tested gas flow rate and geological parameters remain weak, indicating their strong nonlinear relationships. These findings suggest that machine learning approaches are required to further assess the sensitivity and influence of various parameters on gas production.

5.2. Machine learning-based analysis of factors controlling high production

Traditional methods struggle to accurately quantify the relative importance of various geological parameters due to the strong nonlinear relationships among these parameters. In this study, the SHAP-enhanced RF model was employed to analyze the sensitivity of multiple critical geological parameters. This model can capture potential interactions among parameters while revealing the influence of various parameters on gas production. The following sections focus on identifying dominant factors controlling high production, analyzing single-factor production response patterns, exploring synergistic mechanisms between parameters, and explaining the causes of single-well production differences.

5.2.1. Sensitivity of geological parameters

Fig. 9 displays the SHAP-based ranking and quantitative analysis results of the sensitivity of geological parameters.

Sensitivity percentage represents the relative contribution of a parameter, calculated as the average SHAP value of the parameter divided by the total contribution of all parameters. Burial depth exhibited the highest sensitivity percentage (34.15%), indicating that this parameter significantly influences gas production in the Maokou Formation. Natural gamma-ray value and paleogeomorphology showed sensitivity percentages of 14.80% and 11.91%, respectively, suggesting that the physical properties and location of reservoirs also exert considerable influence on the gas productivity. The developmental degree of fractures and acoustic impedance demonstrated sensitivity percentages of 10.68% and 8.32%, respectively, suggesting moderate to low impacts. In contrast, the spatial distance of bright spot reflections, reservoir thickness, average trough amplitude, and wellhead-to-fault distance all showed sensitivity percentages below 8%, with the wellhead-to-fault distance displaying the lowest sensitivity percentage (3.75%). These results differ from the findings from other formations, where the reservoir thickness acts as a dominant factor. This difference highlights the complexity of factors controlling the productivity of the Maokou Formation. Nevertheless, the mechanisms by which various parameters influence single-well production need to be further investigated.

5.2.2. Relationships between various parameters and production

Although sensitivity analysis provides insights into the importance of various parameters in predicting single-well production, it does not characterize parameter responses nor identify the optimal parameter ranges. To address this issue, this study conducted a response analysis using a trained production prediction model. Specifically, by changing the value of a parameter while keeping other parameters unchanged, the impact of this parameter on the predicted production was examined.

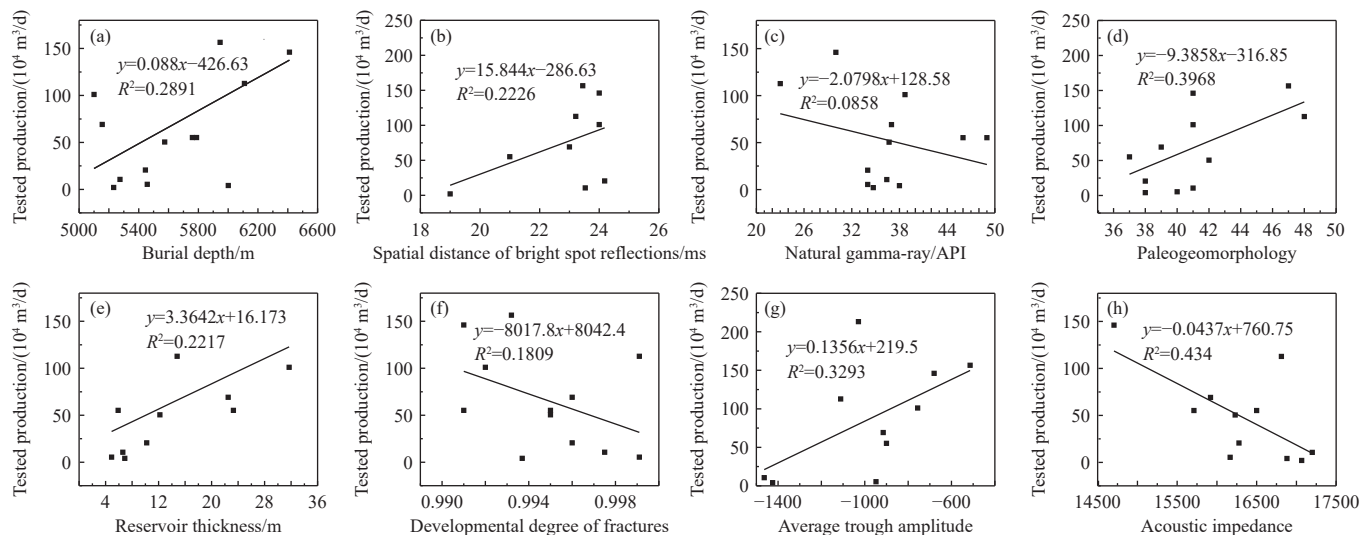


Fig. 8. Cross plots showing the relationships of the tested gas flow rate of the Maokou Formation with critical geological parameters. a–Tested daily gas flow rate vs. burial depth; b–tested daily gas flow rate vs. spatial distance; c–tested daily gas flow rate vs. natural gamma-ray value; d–tested daily gas flow rate vs. paleogeomorphology; e–tested daily gas flow rate vs. reservoir thickness; f–tested daily gas flow rate vs. developmental degree of fractures; g–tested daily gas flow rate vs. average trough amplitude; h–tested daily gas flow rate vs. acoustic impedance.

The results indicate that all parameters exhibited distinct nonlinear relationships with predicted production (Fig. 10). These parameters displayed distinct changes and well-defined optimal ranges, where specific values drive significant variations in predicted production. Such threshold-like behavior suggests that the impacts of various parameters are highly sensitive within critical value ranges rather than increasing progressively. Therefore, these optimal ranges should be fully leveraged during well placement and parameter optimization in field gas recovery. High production in the Maokou Formation might be achieved in cases where multiple geological parameters fall within their optimal ranges simultaneously.

5.2.3. Differences in single-well production

In the study area, some wells with similar reservoir thicknesses and geological settings yielded significantly different production. This suggests that high production in these wells might be driven by specific geological factors. To accurately identify the primary causes of the differences in

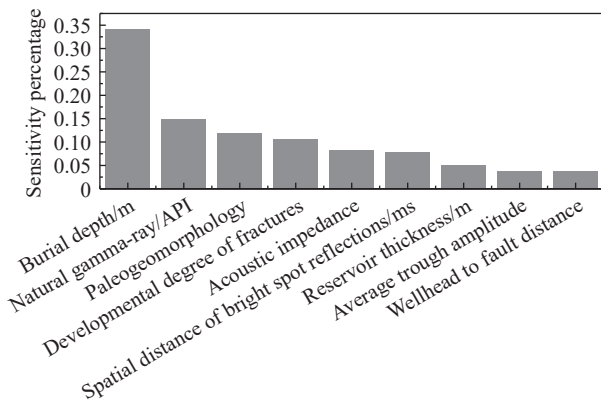


Fig. 9. Sensitivity ranking of geological parameters based on SHAP values.

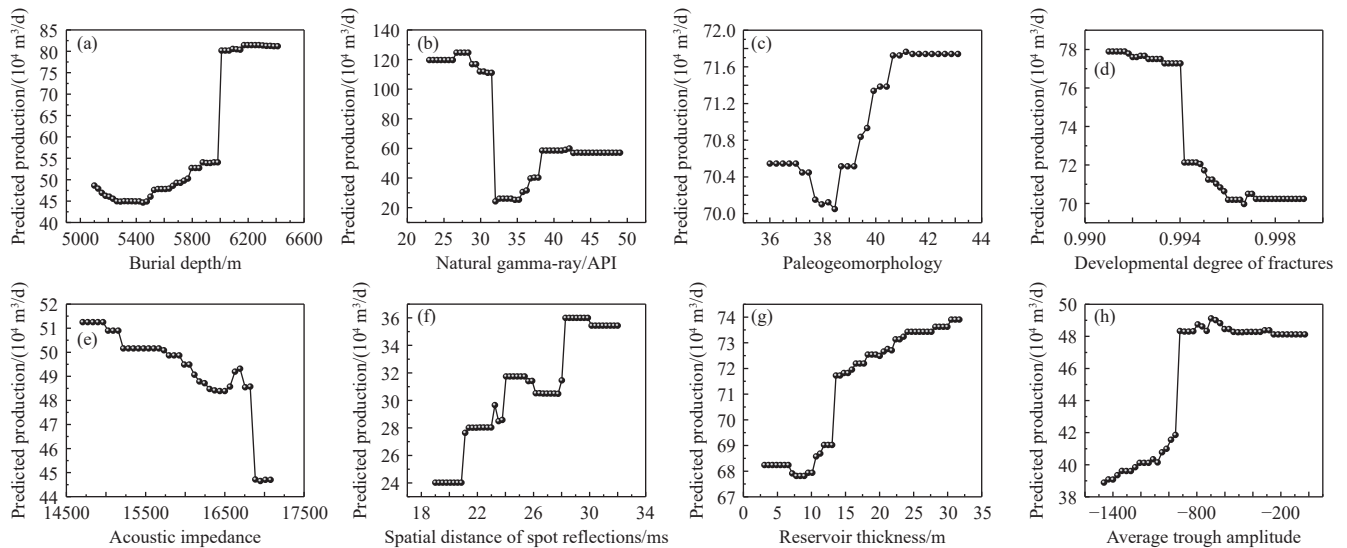


Fig. 10. Relationships between various parameters and predicted production. a–Predicted production vs. burial depth; b–predicted production vs. natural gamma-ray value; c–predicted production vs. paleogeomorphology; d–predicted production vs. developmental degree of fractures; e–predicted production vs. acoustic impedance; f–predicted production vs. spatial distance of bright spot reflections; g–predicted production vs. reservoir thickness; h–predicted production vs. average trough amplitude.

single-well production, this study quantified the contributions of various parameters and revealed the geological differences across wells and their control mechanisms by conducting SHAP-based single-well analysis based on representative high-yielding and stripper wells.

The results indicate that burial depth emerged as the most significant negative factor for the stripper well, with a SHAP value of -15.72 . This finding suggests that burial depth might produce a negative impact on reservoir pressure and eventually influence the gas production (Fig. 11a). Additionally, natural gamma-ray value (SHAP value: -2.41) and wellhead-to-fault distance (SHAP value: -1.50) also contributed negatively to the gas production of the stripper well. Although the spatial distance of bright spot reflections (SHAP value: $+3.60$), developmental degree of fractures (SHAP value: $+2.64$), and paleogeomorphology (SHAP value: $+2.30$) delivered advantages, these advantages were insufficient to overcome the adverse impacts of burial depth and lithological conditions, leading to low gas productivity.

In contrast, multiple critical parameters exhibited significant positive effects in the high-yielding well. Burial depth (SHAP value: $+19.93$) contributed most significantly to the gas production, followed by the spatial distance of bright spot reflections (SHAP value: $+3.60$), paleogeomorphology (SHAP value: $+2.30$), acoustic impedance (SHAP value: $+2.15$), and reservoir thickness (SHAP value: $+1.61$) sequentially. These positive factors form a synergistic pattern for enhancing the productivity of the high-yielding well. Although the natural gamma-ray value and developmental degree of fractures showed slightly negative contributions, they produced limited impacts on the overall gas productivity (Fig. 11b).

5.2.4. Effects of multi-parameter interactions and prediction of play fairways

Although single-factor analysis can reveal the nonlinear

effects of individual parameters on gas production, actual productivity frequently results from multi-factor coupling, with some high-production conditions emerging only under specific parameter combinations. To explore the synergistic relationships of critical parameters, this study assessed the combined contributions of parameters in a multi-dimensional

space by analyzing the effects of parameter interactions based on SHAP values.

The interaction intensity map suggests that the combination of burial depth, acoustic impedance, and spatial distance of bright spot reflections showed the strongest interactions (Fig. 12a). Burial depth and acoustic impedance

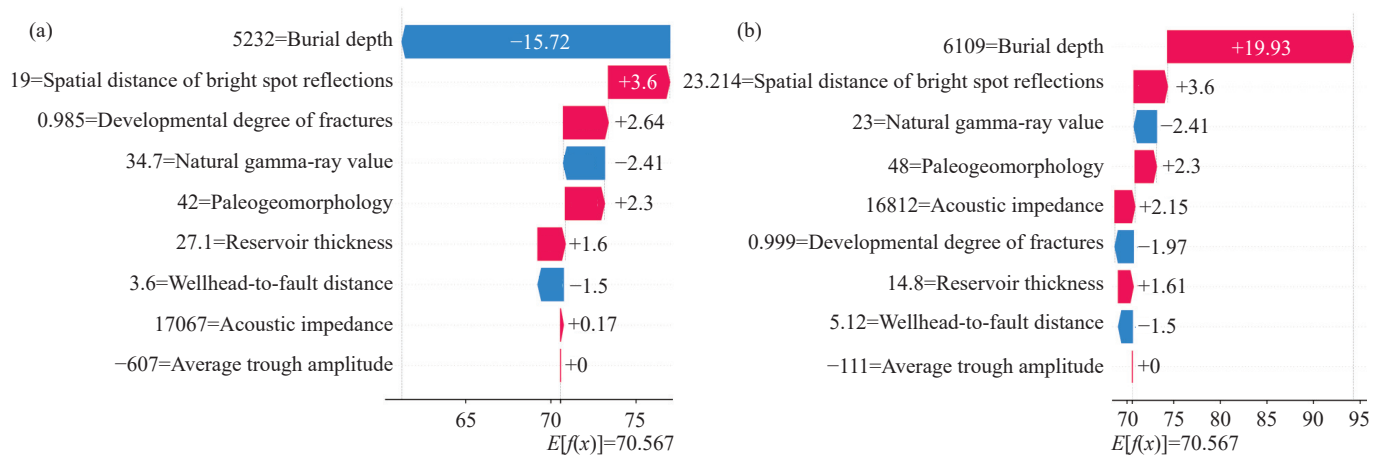


Fig. 11. a–SHAP values of geological parameters for a stripper well; b–SHAP values of geological parameters for a high-yielding well.

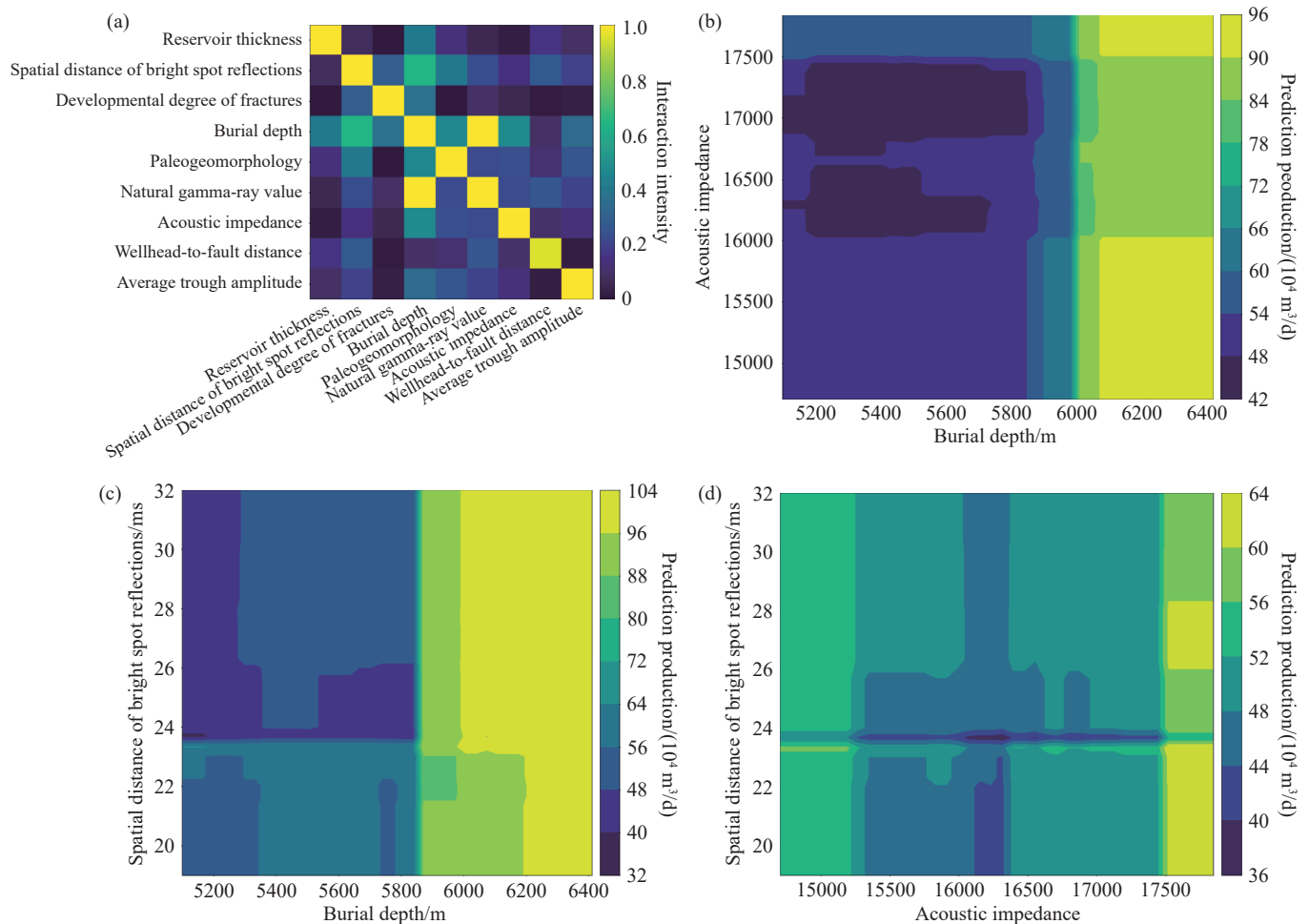


Fig. 12. Interactions among geological parameters. a–Heatmap of interaction intensity; b–2D partial dependence plot (PDP) for burial depth and acoustic impedance; c–2D PDP for spatial distance of bright spot reflections and burial depth; d–2D PDP for acoustic impedance and spatial distance of bright spot reflections.

exhibited a significant nonlinear interaction (Fig. 12b). Specifically, burial depths of 6000–6400 m and acoustic impedance below 16000 yielded an optimal synergistic effect on predicted production, indicating optimal conditions for high production. Furthermore, the effect of multi-parameter interactions on the gas production peaked (Fig. 12c) as the spatial distance of bright spot reflections exceeded 24 ms (Fig. 12d). These findings suggest that the combination of a high burial depth, low acoustic impedance, and a moderately high spatial distance of bright spot reflections represents a favorable geological configuration for high production. In practical applications, this parameter combination can serve as critical criteria for well placement and production planning, and areas that satisfy these criteria should be prioritized for drilling.

For field-scale production prediction, a machine learning model was trained using selected sensitive parameters, including burial depth, acoustic impedance, reservoir thickness, and paleogeomorphology. The predicted results show that several zones (in red) exhibited predicted production exceeding $70 \times 10^4 \text{ m}^3/\text{d}$, including the west to well PS6, the JT1–PY3 well cluster in the central part, and the PY106–PY7 and PY12–PY13–PY103 well clusters in the east

(Fig. 13). These zones featured favorable paleogeomorphology, seismic attributes, acoustic impedance, and reservoir thickness, with multiple favorable conditions jointly contributing to consistently high production. In contrast, zones in yellow showed predicted production around $60 \times 10^4 \text{ m}^3/\text{d}$, while blue and light-blue zones corresponded to low production, typically below $30 \times 10^4 \text{ m}^3/\text{d}$.

To validate the prediction accuracy, this study compared the tested gas flow rates with the predicted production of 14 wells in the study area (Table 1). The results indicate that most wells showed prediction errors within $\pm 15 \times 10^4 \text{ m}^3/\text{d}$, with large discrepancies observed only in two high-yielding wells (PY1 and PY3) and one stripper well (PY7). The spatial distribution of predicted production aligned well with the geological trends in burial depth, paleogeomorphology, seismic attributes, acoustic impedance, and reservoir thickness, confirming the reliability of the parameter sensitivity analysis.

Overall, the enhanced machine learning model proposed in this study demonstrates a strong generalization capability and high prediction accuracy. It enables a reliable prediction of favorable production zones in the Maokou Formation while effectively identifying the dominant geological factors

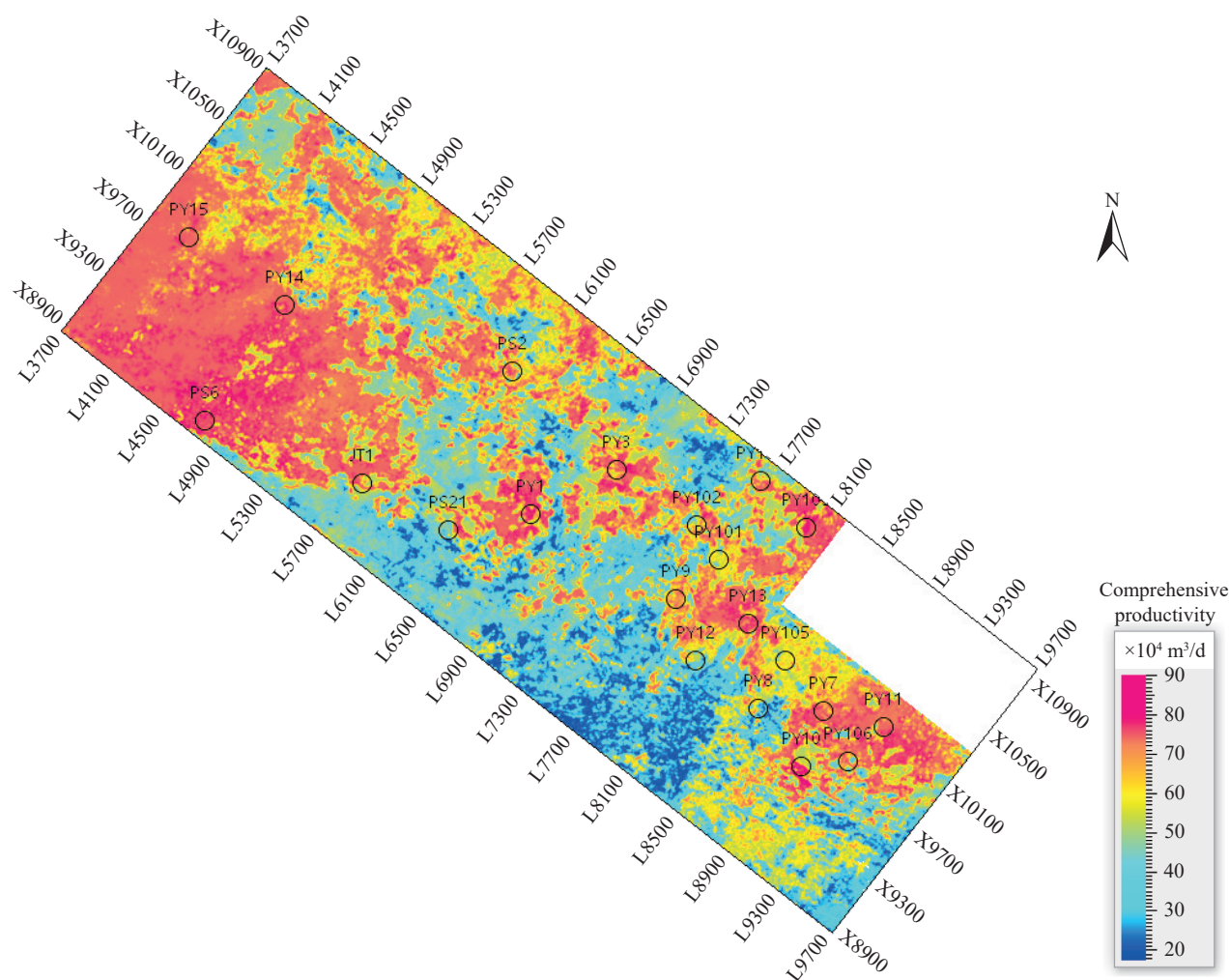


Fig. 13. Contour map showing the comprehensive productivity prediction of the Maokou Formation in the study area.

Table 1. Prediction errors of single-well production in the Maokou Formation.

Well	Tested daily gas flow rate/ ($\times 10^4$ m ³ /d)	Predicted production/ ($\times 10^4$ m ³ /d)	Error/ ($\times 10^4$ m ³ /d)	Well	Tested daily gas flow rate/ ($\times 10^4$ m ³ /d)	Predicted production/ ($\times 10^4$ m ³ /d)	Error/ ($\times 10^4$ m ³ /d)
JT1	112.8	98.1	14.7	PY10	101.12	98.3	2.82
PY3	213.15	99.5	113.65	PY12	5.4	20.4	−15.0
PY1	156.55	105.2	51.35	PY13	50.46	47.2	3.26
PS21	4.12	10.8	−6.68	PY101	55.2	56.3	1.1
PS6	146.09	135.8	10.29	PY103	55.26	52.6	2.66
PY7	2.1	53.7	−51.6	PY105	20.63	30.8	10.17
PY8	10.68	14.1	−3.42	PY106	69.19	68.4	0.79

controlling gas production, thereby supporting effective identification of sweet spots in complex carbonate reservoirs.

6. Conclusions

(i) The reservoirs of the Maokou Formation, consisting primarily of dissolution pores and vugs, show strong lateral heterogeneity due to sedimentation and erosion. The SHAP-enhanced RF model proposed in this study can identify key factors controlling the productivity in this formation by capturing the nonlinear relationships between gas production and geological parameters effectively.

(ii) Among all geological parameters, burial depth, natural gamma-ray value, spatial distance of bright spot reflections, and paleogeomorphology serve as the primary factors controlling the gas productivity, followed by the developmental degree of fractures and acoustic impedance, with wellhead-to-fault distance exerting a minor influence. High production can be achieved in cases where multiple critical parameters fall within their optimal ranges simultaneously and create synergistic effects.

(iii) High-yielding wells tend to enjoy joint advantages of multiple critical parameters. The SHAP-based interpretability approach accounts for single-well production differences, thereby supporting well placement and production planning in complex carbonate reservoirs.

(iv) Compared to well PY8 selected using a conventional method, where a daily gas flow rate of 10.68×10^4 m³/d was tested, well PS6 determined under the guidance of the proposed approach yielded a tested daily gas flow rate of 146.09×10^4 m³/d, suggesting an increase of 135.41×10^4 m³/d. However, similar improvements might be affected by a small number of wells and geological heterogeneity. Future research should validate the proposed approach using more wells in diverse settings.

CRedit authorship contribution statement

Fu-hong Zhang, Hu Zhao, and Xu-ri Huang designed the study, conducted data analysis and model development, and completed geological interpretation and result validation. Rong-rong Zhao, Huan Yu, and Xiang-qian Huang assisted in data compilation, figure preparation, and manuscript revision. All authors discussed the results and approved the final version of the manuscript.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability statement

The data used to support the findings of this study are available from the corresponding author upon request.

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