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ORIGINAL PAPER

Intelligent prediction and integral analysis of shale oil and gas sweet spots

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Abstract

Shale reservoirs are characterized by low porosity and strong anisotropy. Conventional geophysical methods are far from perfect when it comes to the prediction of shale sweet spot locations, and even less reliable when attempting to delineate unconventional features of shale oil and gas. Based on some mathematical algorithms such as fuzzy mathematics, machine learning and multiple regression analysis, an effective workflow is proposed to allow intelligent prediction of sweet spots and comprehensive quantitative characterization of shale oil and gas reservoirs. This workflow can effectively combine multi-scale and multi-disciplinary data such as geology, well drilling, logging and seismic data. Following the maximum subordination and attribute optimization principle, we establish a machine learning model by adopting the support vector machine method to arrive at multi-attribute prediction of reservoir sweet spot location. Additionally, multiple regression analysis technology is applied to quantitatively predict a number of sweet spot attributes. The practical application of these methods to areas of interest shows high accuracy of sweet spot prediction, indicating that it is a good approach for describing the distribution of high-quality regions within shale reservoirs. Based on these sweet spot attributes, quantitative characterization of unconventional reservoirs can provide a reliable evaluation of shale reservoir potential.

Keywords Shale reservoir · Machine learning · Support vector machine · Sweet spot prediction

1 Introduction

Shale oil and gas reservoirs are increasingly valued worldwide due to their unique characteristics (Sayers 2005; Vanorio et al. 2008). In recent years, various countries have increased investment in developing their shale reservoirs. A typical shale reservoir is known with the following features: high TOC (total organic content), complex pore space, strong anisotropy, complicated distribution of hydrocarbon, micro-fractures developed and extremely low matrix permeability (Dong et al. 2014; Sayers 2013). Great variations in the spatial distribution of the features listed above results in a complex distribution of hydrocarbon accumulation in shales as well as a huge variance between individual sweet spots. In addition, the complex microstructure and anisotropy make it difficult to characterize shale reservoirs in a geophysical way (Sondergeld and Rai 2011; Deng et al. 2015). Moreover, the large variation in styles of shale sweet spot attributes makes it difficult to identify the key factors required to integrate information from different data types with different scales (Chapman et al. 2003). In particular, the prediction of the intensity of multi-scale and multi-angle fractures in horizontally laminated shale reservoirs is a critical challenge (Doveton and Merriam 2004; Ding et al. 2017).

The comprehensive evaluation of shale oil and gas reservoir sweet spots requires consideration of both geological and engineering factors, in order to analyze the storage capacity and development potential. Geological elements include depth, thickness, lithology, porosity, hydrocarbon saturation, TOC content and TOC maturity and, ultimately, the oil and/or gas in place. Engineering

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sweet spots consider stress, pressure, fracture distribution, brittleness and anisotropy (Ouenes 2012; Chopra et al. 2013).

Many geophysical methods have been established in order to predict sweet spots of shale plays. Doveton and Merriam (2004) used NMR logging information to study the mineral composition and geology of shale reservoirs by analyzing their geochemical characteristics. Singh et al. (2008) generated a lithofacies classification based on core samples. They defined the depositional sequences and reservoir stratigraphy by analyzing gamma logs and seismic data. Zhang (2012) and Zhang and Sun (2012) started to study the shale oil and gas accumulation process, to allow isolation of the crucial factors controlling shale oil reservoir quality and abundance; they also studied core and log data to establish a sweet spot evaluation method based on five indexes, which are the mineral components, geochemistry, reservoir properties, hydrocarbon saturation and fracturing potential. The practical application of this method proved that log data play an important role in evaluating shale reservoirs. Lu et al. (2012) divided shale reservoirs into dispersed (invalid) resources, neutral resources and rich resources by using the threefold relationship between hydrocarbon saturation and source rock TOC, which leads to an equation to quantify the production potential of shale reservoirs. Chen (2014) determined the inversion-sensitive parameters through a joint analysis of TOC measurements and geophysical inputs, which established the most suitable equation to allow inversion for TOC distribution based on the prestack seismic inversion density cube, in the Jiaoshiba area of the Sichuan Basin. Gading et al. (2013) pointed out that the description (scope, thickness and abundance) of shale reservoirs may be obtained through the analysis of seismic data, based on the relationship between TOC and rock properties established in petrophysical analysis. Nieto et al. (2013) came up with a workflow to predict lithology, which starts from a lithofacies classification based on rock physics, and then set up an a priori distribution of each facies, and the posterior distribution of each facies was inverted based on a Bayesian scheme using seismic data. Chopra et al. (2013) used a joint approach to cross plot the well logs and seismic data to identify abnormal areas, which represent oil and gas accumulations and highly brittle zones, respectively. Bachrach and Sayers (2014) argued that the conventional inversion method is not applicable to anisotropic shale reservoirs and proposed an AVAZ (amplitude versus incident and azimuthal angle) inversion approach that works with orthogonal anisotropy reservoirs such as fractured shale. The application of this inversion to wide-azimuth seismic data helped to understand rock properties in complex shale reservoirs and their development (hydrofracturing) potential. More generally, however, the current approach to sweet spot predictions is mostly based on geochemical analysis of core data and the petrophysical analysis of well logs. The deliverables from these studies are one of the key reservoir attributes, either TOC or brittleness, which only describes either the geological or engineering aspect of the shale reservoir sweet spots.

The majority of shale sweet spot parameter prediction methods (e.g., TOC content, maturity and mineral constituents) are reliant on laboratory measurement and well-logging data, which are difficult to obtain directly from seismic data. Limited by the 3D distribution of core samples and well logs, the spatial delineation of shale sweet spots from seismic is a key challenge. Furthermore, there is no standardized quantitative criterion for directly describing shale oil and gas reservoir sweet spots using seismic attributes, let alone a good consideration of the geological implications. Nevertheless, large amount of work is required to benchmark the results from traditional single-attribute evaluations and this is likely to be biased by subjective interpretation. Therefore, it is critical to develop a new integrated sweet spot prediction method to allow for the accounting of multiple shale reservoir attributes concurrently. Machine learning and artificial intelligence (AI) are new ways to analyze the integral different types of sweet spot. AI was firstly proposed by Turing in 1950. With decades of development, AI is performed in all walks of life. In terms of the oil industry, many techniques, like neural networks, genetic algorithms, are used to explore for hydrocarbon. Zhang et al. (1997) used an interactive intelligent technology to interpret fine structure. Yuan et al. (2009) performed swarm intelligence optimization to geophysical data inversion, and the results came up with higher convergence speed and accuracy compared with conventional genetic algorithm and simulated annealing. Zhang et al. (2011) introduced a support vector machine in volcanic reservoir prediction. Mou et al. (2015) also performed SVM to identify the lithofacies of volcanic rocks in the eastern depression of the Liaohe Basin. Chen et al. (2014) predicted shale TOC content and free hydrocarbon content by means of an RBF (radical basis function) neural network approach, which resulted in accurate prediction results. Xiao et al. (2014) set up an evaluation method for shale mineral constituents based on conventional logging data by introducing a genetic algorithm into the inversion. Zhang et al. (2015) predicted the spatial distribution of organic carbon using a seismic inversion approach calibrated by wells. Ji et al. (2016) introduced a frequency-domain prestack sparse Bayesian learning inversion method to retrieve P and S wave impedance reflectivity. Yuan et al. (2017) derived a time-variant deconvolution method based on sparse Bayesian learning in order to obtain a high-quality reflectivity image. And they used a machine learning technique to classify seismic waveforms and introduced conventional neural networks into first-break picking (Yuan et al. 2018). Fu et al. (2018) used deep learning method to predict reservoirs using multi-component seismic data.

This paper introduced a new approach for the intelligent prediction of shale sweet spots by utilizing AI machine learning technology in conjunction with multi-scale information such as geology, well drilling, logging and seismic data. This method is then applied to a shale reservoir field example to identify production sweet spots.

2 Method and principle

We use fuzzy logic theory constrained by petrophysical studies, to jointly assess the contribution of multiple seismic attributes, based on information such as geology, drilling data, logging and seismic data. This study leads to a training model which can be improved by AI machine learning technology. This AI model can be then used to predict shale reservoir properties, such as porosity, fracture density, TOC content, brittleness, pressure, stress and other geological and engineering sweet spot-related attributes. Furthermore, this model is controlled by production histories, which give a comprehensive index to allow characterization of shale sweet spot development.

The workflow we propose is shown (Fig. 1).

2.1 Evaluation of attributes

Geological analysis, structural interpretation, logging evaluation and attribute calculation constitute the prerequisites for the successful prediction of multiple shale oil and gas sweet spots. Seismic attributes include amplitude, frequency, phase and attenuation. During the reservoir evaluation, hundreds of attributes are generated, which make the selection of the ones sensitive to sweet spots very challenging.

We use fuzzy mathematics theory to evaluate the contribution degree of various attributes for sweet spot prediction to select the sensitive ones. Assume A is a fuzzy mode in the given domain $\mathbf{U}$, and x_1, x_2, x_3, …, x_n are n objects lining up for identification in $\mathbf{U}$. According to the maximum subordination principle, if

$$A(x_i) = \max\{A(x_1), A(x_2), \ldots, A(x_n)\}, \tag{1}$$

then x_i is preferentially regarded as the sensitive one and it has been selected by the fuzzy mode A.

In Eq. (1), x_i represents the seismic attributes used in the evaluation, while $A(x_i)$ stands for the contribution degree of the ith attribute. This can be obtained by correlation coefficient evaluation or mean square error calculation. When carefully applied within thresholds, a list of highly sensitive sweet spot attributes can be generated. A fuzzy mathematics set is different from a classical set. A fuzzy set has no specific boundary, which has the benefit that it can build the mathematic model flexibly. A fuzzy set indicates the degree of subordination for each element. Hence, the eigenfunction of a fuzzy set can only range from 0 to 1, which shows the degree of subordination. The typical workflow to select a single attribute by using fuzzy mathematical model can be summarized as follows:

1. Calculate the correlation degree between training samples and target of prediction, which can be used to judge the contribution value of each attribute.
2. Two boundaries of a fuzzy set can be decided by choosing the maximum value ($c_{\max}$) and minimum value ($c_{\min}$) of all the correlation coefficients among different attributes.
3. The contribution of each attribute can be calculated based on the maximum subordination principle of fuzzy theory. The relative equations are shown below:

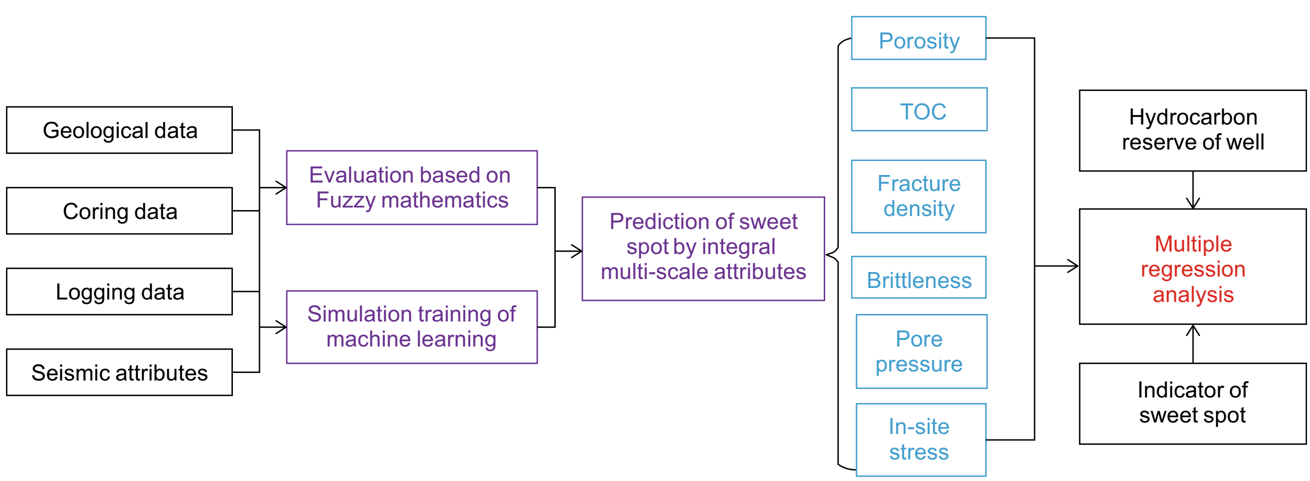


Fig. 1 Workflow for intelligent shale reservoir sweet spot prediction and quantitative characterization

$$A(x) = \begin{cases} 0, & x \le c_{\min} \\ \dfrac{x - c_{\min}}{c_{\max} - c_{\min}}, & c_{\min} < x < c_{\max} \\ 1, & x \ge c_{\min} \end{cases} \tag{2}$$

where x is the correlation coefficient.

4. Sorting the calculated contributions and selecting the optimum attribute with high contribution, which can be used to guide the following artificial intelligent learning process and comprehensive prediction of reservoir characteristics.

Multi-attribute analysis is also necessary after single-attribute selection. The selected attributes should first have relatively high contribution. Meanwhile, the selected attributes should be relatively independent in order to avoid redundancy between them.

2.2 Model training

Constrained by well logs, the seismic attributes selected from the attributes fed into the fuzzy mathematics workflow can be used as inputs for the training of an intelligent prediction model that uses machine learning methods. The training model can be described mathematically as:

$$\{(\mathbf{X}_1, y_1), (\mathbf{X}_2, y_2), \ldots, (\mathbf{X}_i, y_i)\}; \quad \mathbf{X}_i \in R^d,\ y_i \in R \tag{3}$$

where $\mathbf{X}$ is a multi-dimensional vector. d shows the number of dimensions which indicates the number of seismic attributes. y is the dependent variable which represents the well log curves. $\mathbf{X}$ and y have the same subscript i which is the number of samples involved in AI training. i is decided by the intersection between logging data and seismic data after well-seismic calibration.

The purpose of machine learning is to establish a complex mathematical model expressing the relationship between y and $\mathbf{X}$, namely the construction of a model that can describe the relationship between target sweet spots and selected attributes. The equation is listed below:

$$y = f(\mathbf{X}) = \langle \mathbf{w}, \mathbf{X} \rangle + b, \quad \text{with } \mathbf{w} \in R^d,\ b \in R \tag{4}$$

where $\mathbf{w}$ is weight vector, b is the constant deviation, and $\langle \mathbf{w}, \mathbf{X} \rangle$ indicates a generated function which shows the linear or nonlinear relationship between them. R means real number set, and R^d indicates a d-dimensional set. Machine learning is a process of multivariate nonlinear regression.

A support vector machine (SVM) is used for the model training process in our machine learning algorithm, and it has several strengths: (1) It is based on a statistical learning theory to obtain the support vector applicable to limited samples. (2) Kernel functions are used to map the high-dimensional space without increasing computational complexity to address the curse of dimensionality. (3) Optimum solutions can be obtained for this L2 convex optimization problem. (4) Regarding the target optimization, empirical risk and confidence range may be taken into account simultaneously to ensure the generalization ability of the models, on the basis of structural risk minimization. (5) Regarding application and implementation, rigorous theoretical and mathematical backgrounds are available to mitigate the impact of experiential elements and make it easy to control.

To ensure the generalization of our machine learning model, regularization constraints are added to construct target functions of the convex quadratic optimization problem of SVM in this paper, as shown below:

$$\min \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \tag{5}$$

Among them, C is a regularization operator which controls the weight of regularization. Generally, a higher C value indicates stronger generalization ability and lower accuracy, and vice versa. l is the number of support vectors, and ξ_i and ξ_i^* stand for slack variables.

To solve above the convex quadratic optimization problem, the constraint condition is given below:

$$\text{Subject to} \begin{cases} y_i - \langle \mathbf{w}, \mathbf{X}_i \rangle - b \le \varepsilon + \xi_i \\ \langle \mathbf{w}, \mathbf{X}_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{6}$$

The variables have the same meaning as those in Eq. (5).

Then, dual decomposition and KKT optimization conditions are applied, together with the gradient algorithm, to solve the SVM quadratic planning problem.

The principle analysis and target prediction can be achieved based on known sampling points by applying support vector theory to the regression problem. For the intelligent prediction of shale sweet spots, there are many characteristic dimensions involved in the calculation. Normally, the relationship between target function and input parameter is nonlinear, which requires nonlinear regression analysis. To solve this problem, the original characteristic space is mapped to the high-dimensional characteristic space through a nonlinear transform, which constructs a linear decision function in the high-dimensional space to represent the nonlinear decision function of the original space.

$$y = f(\mathbf{X}) = \langle \mathbf{w}, \phi(\mathbf{X}) \rangle + b \tag{7}$$

In Eq. (7), ϕ represents a mapping function from original space to high-dimensional space.

Linearization of the problem by mapping to higher dimensions will result in a significant increase in computation cost, namely the so-called curse of dimensionality. In this case, we introduce a support vector mechanism into the idea of a kernel function, to minimize computation costs. The generalized kernel function is expressed as:

$$K(\mathbf{X}_i, \mathbf{X}_j) = \phi(\mathbf{X}_i)^T \phi(\mathbf{X}_j) \tag{8}$$

The kernel function that we choose is the radial basis function (RBF) which is shown below. This function can effectively fit the nonlinear relationship between different sweet spot attributes.

$$K(\mathbf{X}_i, \mathbf{X}_j) = \exp(-\gamma |X - X'|^2) \tag{9}$$

2.3 Comprehensive characterization

To provide a comprehensive quantification of the reservoir sweet spot without biased assessment, multivariate regression analysis techniques can be used. In addition, the regression can be constrained by production indexes estimated from well logs or production data.

Given that there are limited samples in practice, the multivariate model is constructed as below:

$$y = \sum_{i=1}^{n} a_i m_i + B \tag{10}$$

where a_i is the weight factor of the ith attribute, m_i is a specific attribute, and B is a constant.

The least squares solution of the target function in such a multivariate regression is listed below:

$$\min\left(\sum_{j=1}^{m}\left(y_j - \sum_{i=1}^{n} a_i m_{i,j} - B\right)^2\right) \tag{11}$$

Among them, i is the number of the multivariate function and j represents the number of samples.

By solving the least square problem, a multivariate function is established to describe the relationship between oil and gas production and the sweet spot parameters, making a comprehensive quantitative characterization of reservoir sweet spots possible.

3 Application example

Porosity and fracture density are linked to the storage capacity, transmissibility and production of oil and gas in shale reservoirs. In addition, brittleness is linked to the mineral contents of reservoirs and affects the stimulation potential of reservoirs. Moreover, TOC, HI (hydrogen index) and kerogen type are related to the mass and type of hydrocarbons generated and retained within the pore network; pore pressure could be used to describe the accumulation of hydrocarbons; fracture pressure is related to the production potential of reservoirs. To describe overall development potential of shale oil and gas reservoirs, porosity, fracture density, brittleness, TOC, pore pressure and fracture pressure are all considered for sweet spot prediction.

The above-proposed method is applied to a typical shale reservoir in China, to prove the potential of the method in a real case. Our target area is located in Southwest China. The exposed formations are mainly Jurassic and Triassic. The Jurassic Formation is located in the North and West. Among these exposed formations, the earliest formation is the middle Jurassic Shajiemiao group, and the oldest formation is Silurian. A typical anticline and syncline structure was developed in target area, the anticline shows high-steep characteristics, while the syncline is relatively gentle. A typical phenomenon of this area is faulting. These faults are developed in a northeast direction which may result from a compressive tectonic stress in the NW–SE direction. Based on the interpretation results from 3D seismic data, these faults are typically reverse faults in a compressive structure system.

3.1 Example I, brittleness prediction

We demonstrate the proposed method by firstly predicting the brittleness of a shale reservoir, where the relationship between brittleness, well logs and seismic attributes is constructed by machine learning. Brittleness is a critical reservoir parameter, which is controlled by depositional environment, mineral composition and the natural fracturing of the shale. It is often regarded as a key production factor of shale reservoirs.

The fuzzy mathematics technique has been applied to assess the contribution degree of various seismic attributes. There are two steps to define the sensitive attributes. The first step is called single-attribute definition, and many types of attributes are detailed in this step. The cross-correlation between each attribute and brittleness (goal prediction) is calculated, and we will call it contribution. High contribution means high relationship between that attribute and brittleness. The second step is called multi-attribute analysis. In this step, we intend to decrease the redundancy of the selected attributes defined in step 1. The cross-correlation is calculated between them, and the attribute with highest value of cross-correlation is deleted. The remaining attributes are listed in Table 1, which have high relationships with brittleness and strong orthogonality with each other.

Based on attribute optimization results, the support vector machine algorithm was applied to the machine learning process to train our model. The trained model represents the relationship between target reservoir brittleness and the above five seismic attributes. A comparison between the predicted brittleness and well log measured

Table 1 List of sensitive seismic attributes of brittleness prediction

Attribute name	Frequency decomposition energy	Formation density	TOC	V_p/V_s ratio	Shear wave impedance
Contribution	82%	76%	75%	68%	50%

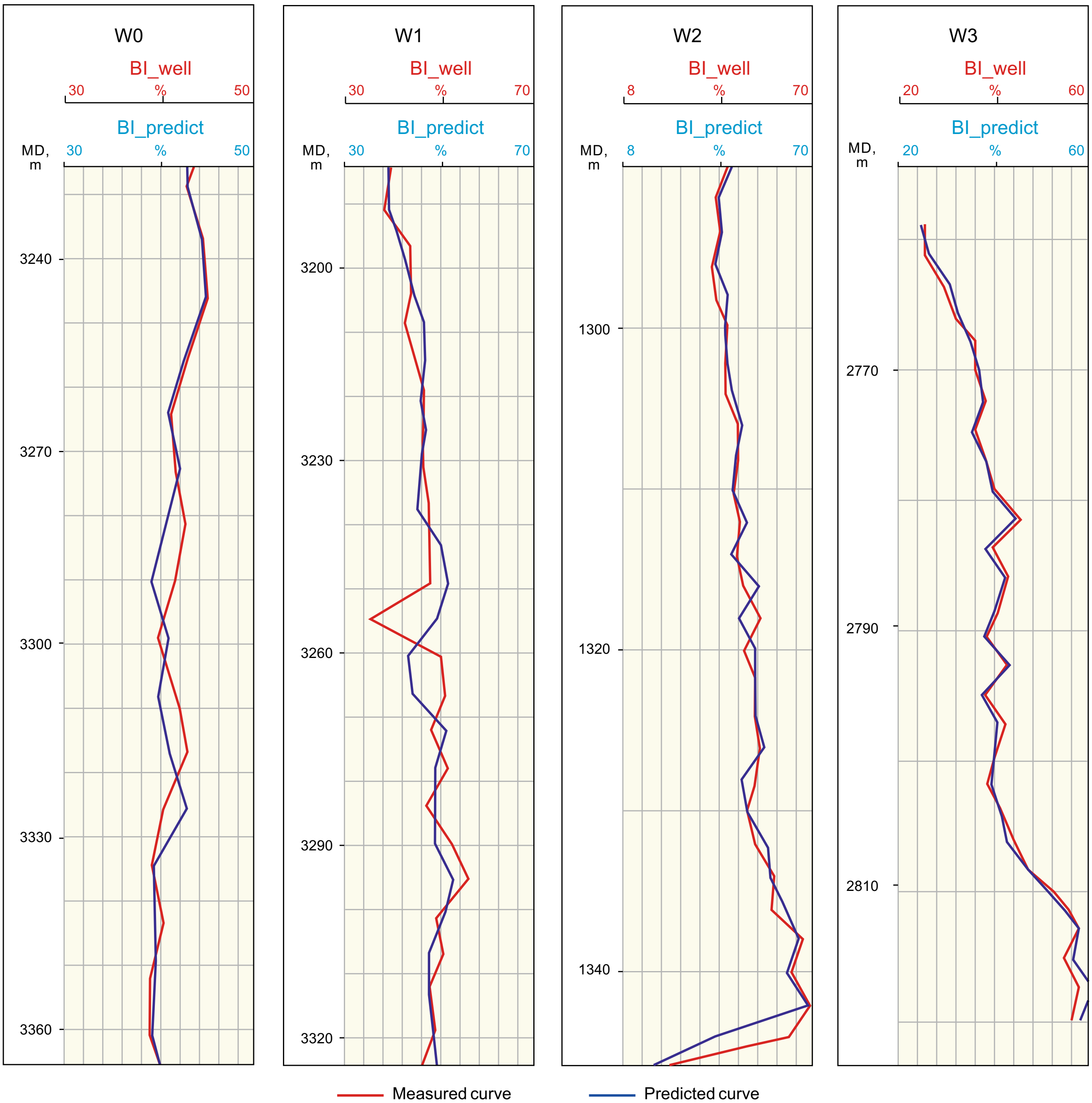


Fig. 2 Observed brittleness curves and predicted brittleness curves at well location

brittleness is shown in Fig. 2. The close match between the prediction and the observation suggests a successful training model has been generated by our proposed approach.

In addition to predictive accuracy, the other important feature of the intelligent models is their generalization ability. It means their predictive accuracy for unknown data. During the training of the model, we reserved part of the data as blind testing samples to assess the generalization ability of established AI models. The convergence displayed below shows the relationship between actual values and testing values of blind test samples, with horizontal coordinates expressed as actual values and vertical coordinates expressed as predicted values computed by the trained intelligent model. It can be seen from Fig. 3 that the data have converged reasonably well, with an L2 correlation coefficient greater than 80%.

To sum up, we obtained a brittleness predicted intelligence model with high accuracy and generalization ability by applying fuzzy mathematics and a machine learning technique. Subsequently, the model was used for brittleness prediction within a seismic subvolume. Prediction results are shown below.

The contrast in the diagram above showed the brittleness prediction results from our proposed approach (Fig. 4b) and those from the conventional single-parameter regression approach. It can be easily seen that the intelligent prediction method can comprehensively apply many selected seismic attributes, establish the internal relationships between target sweet spots and input attributes through a machine learning method and obtain prediction results with much higher accuracy with a better match to the well logs.

Besides, in order to testify the accuracy of our attribute cube, we compare borehole logging curves, traditional method prediction and our prediction which are subtracted from previous results (Fig. 5). The red curve, blue curve and pink curves represent brittleness logging data, traditional prediction and our prediction. Our results show higher accuracy with more details.

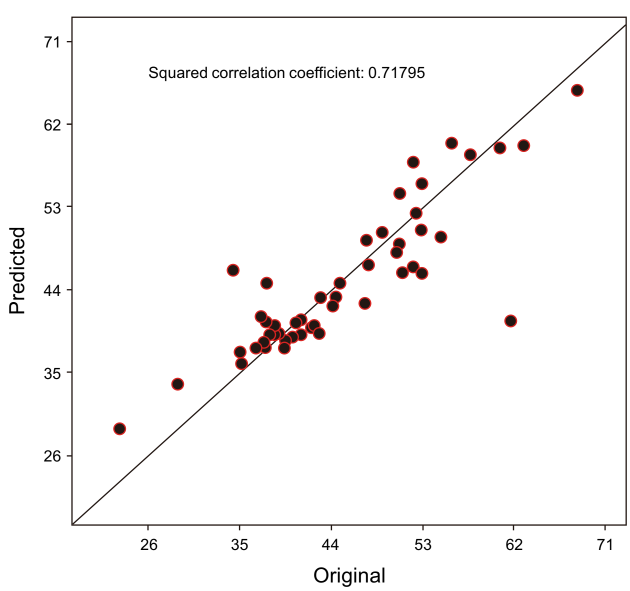


Fig. 3 Convergence test based on the blind test data. *X*-axis represents the true value, and on the *Y*-axis are the predictions of brittleness. Most of the predictions converge along the diagonal line

3.2 Example II prediction of multiple shale reservoir properties

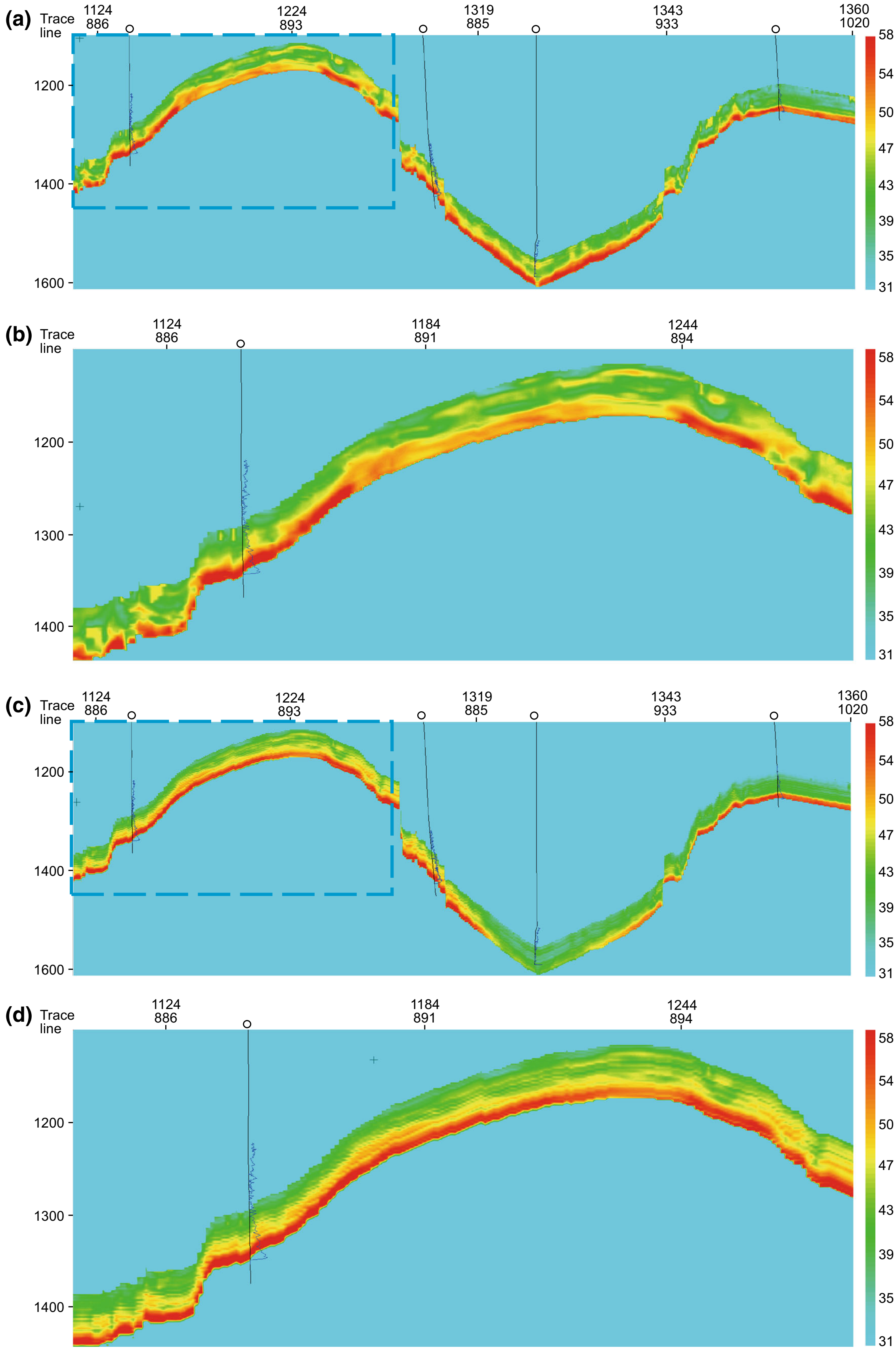
We used the same approach to predict six shale reservoir properties to characterize sweet spots. The properties were: reservoir porosity, fracture density, brittleness, TOC content, pore pressure gradient and fracture pressure gradient. These were predicated based on the intelligent method of integrating multiple attributes and the results. The procedure of prediction is similar to that of brittleness. Firstly, calculate the logging prediction of sweet spots in the boreholes. Then, combine well-logging prediction and seismic attributes based on SVM. Finally, output sweet spot cube by using AI model. The predictions are shown below (Fig. 6).

Analyzing the above six attributes, the southwest–northeast trending anticline is associated with higher porosity and pore pressures, with lower fracturing pressures, and is regarded as a better shale reservoir. Where affected by the structural setting system, the greatest fracture density develops around the faults. Rock brittleness and TOC were largely impacted by extension on the crest of the anticline, while compression was created in the synclines, and for this reason, they are distributed evenly across the whole target reservoir, with relatively smaller values proximal to the fault area.

The above six sweet spot attributes comply with the evaluation criterion of shale reservoir geological sweet spots or engineering sweet spots. A comprehensive evaluation based on these six would be beneficial to the analysis of the oil and gas reservoir and the development potential of target reservoirs. However, while conventional approaches used for the comprehensive evaluation of multiple attributes require human interpretation and are highly subjective, the multivariable regression method discussed in this paper could comprehensively analyze all the sweet spot attributes concurrently, to deliver an objective and systematic evaluation result for shale reservoir production potential.

Based on the five available production wells, and the predicted sweet spot attributes, we can correlate them in the same multivariable regression process. After training, the prediction and historic production data are plotted in Fig. 7, which shows very good correlation and convergence. The squared correlation coefficient is up to 0.96, which means the trained model is reliable for production prediction in unknown areas.

The prediction of shale reservoir production potential is plotted by applying this AI model to the seismic attribute cubes. After selection among these attribute cubes (shown


(a)
Trace
line
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893
1319
885
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933
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31
(b)
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1124
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1184
891
1244
894
1200
1300
1400
(c)
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◀**Fig. 4** Shale target reservoir brittleness quantitative prediction: **a** conventional method; **b** enlarged picture of conventional method; **c** method adopted in this paper; **d** enlarged picture of our method

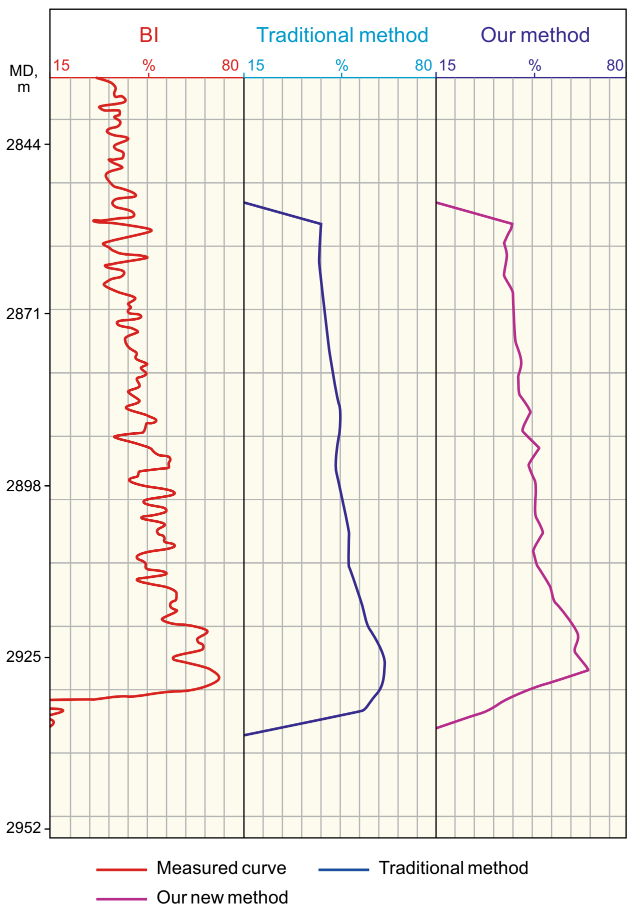

Fig. 5 Comparison of brittleness prediction between well-logging data and attribute cube

in Fig. 6), TOC and fracture pressure are deleted since these two attributes have relatively high correlation. And the final fitting equation is obtained as below:

$$y = -2.75 * \mathrm{BI} + 8.11 * \mathrm{FDEN} + 7.73 * \mathrm{POR} - 0.53 * \mathrm{PPG} + 11.6 \tag{12}$$

where y represents production. BI, FDEN, POR and PPG indicate brittleness, fracture density, porosity and pore pressure gradient, respectively.

We have extracted the attribute along the surface of the target reservoir and show it in Fig. 8.

From Fig. 8, southwest–northeast anticlinal uplifting was predicted to result in stronger production, consistent with the analytical result of a single sweet spot attribute. By contrast, comprehensive quantitative characterization evaluation was more visual, more accessible and more credible.

4 Conclusions

In this paper, an intelligent shale reservoir sweet spot prediction and comprehensive quantitative characterization techniques are developed. The method uses multi-scale and multi-resource data. Characteristics of unconventional shale reservoirs such as complex structure and lithology distribution, hydrocarbon (HC) in place, strong anisotropy and intensive shale heterogeneity are all considered to inhibit high prediction accuracy and even inapplicability of conventional geophysical techniques. Theoretically, fuzzy mathematics and machine learning techniques were used for geophysics shale sweet point prediction, with support from a vector machine algorithm which established the internal mathematical relationship between prediction objects and multiple attributes in an effective and fast way.

In terms of application, the method introduced in this paper predicts sweet spot attributes with high accuracy and high resolution while comprehensively quantifying the target production potential. This overcomes the shortcomings of conventional evaluation methods. To sum up, the method described in this paper is creative and effective in achieving shale reservoir sweet spot prediction and comprehensive quantitative characterization, providing an

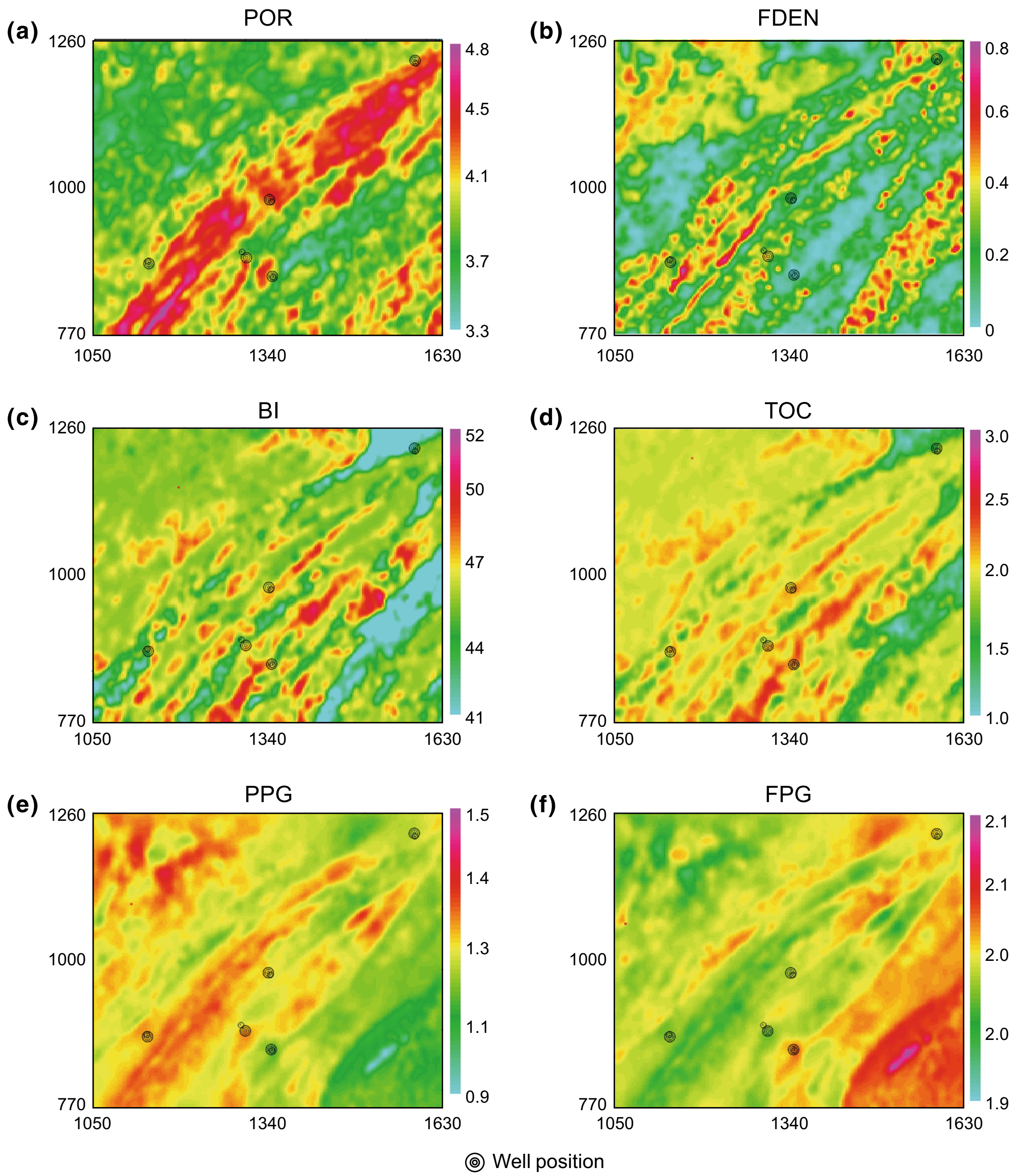

Fig. 6 Intelligently predicted results of shale sweet spot locations. **a** porosity; **b** fracture density; **c** brittleness; **d** TOC content; **e** pore pressure gradient; **f** fracture pressure gradient

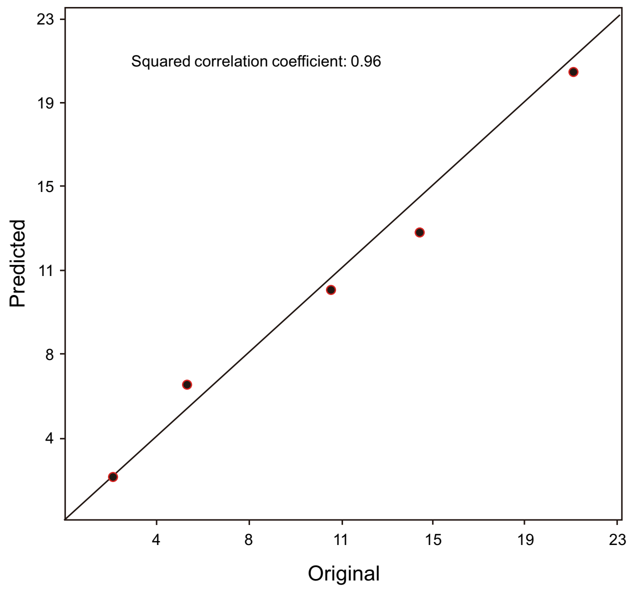

Fig. 7 Production prediction and observation based on a multiple variable AI training model. Horizontal axis is the observed production data; the vertical axis shows the predictions

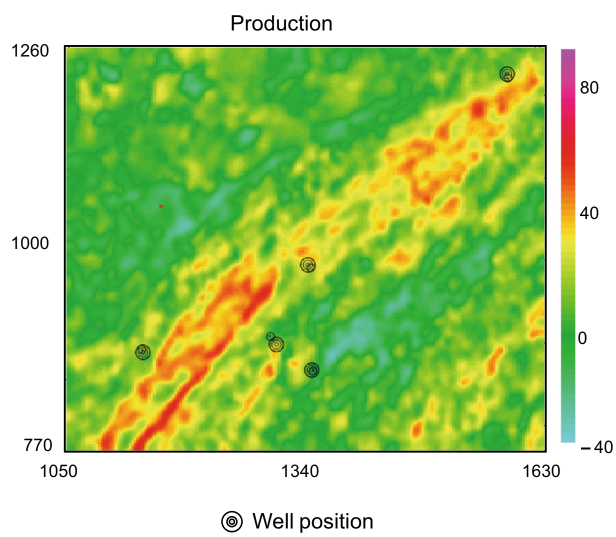

Fig. 8 Shale target reservoir quantitative comprehensive evaluation production index distribution map

effective and accurate quantitative evaluation approach to shale reservoir evaluation.

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