

Original Paper

Geophysical prediction of organic matter abundance in source rocks based on geochemical analysis: A case study of southwestern Bozhong Sag, Bohai Sea, China

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ABSTRACT

The Bozhong Sag is the largest petroliferous sag in the Bohai Bay Basin, and the source rocks of Paleogene Dongying and Shahejie Formations were buried deeply. Most of the drillings were located at the structural high, and there were few wells that met good quality source rocks, so it is difficult to evaluate the source rocks in the study area precisely by geochemical analysis only. Based on the Rock-Eval pyrolysis, total organic carbon (TOC) testing, the organic matter (OM) abundance of Paleogene source rocks in the southwestern Bozhong Sag were evaluated, including the lower of second member of Dongying Formation (E_3d_2), the third member of Dongying Formation (E_3d_3), the first and second members of Shahejie Formation (E_2s_{1+2}), the third member of Shahejie Formation (E_2s_3). The results indicate that the E_2s_{1+2} and E_2s_3 have better hydrocarbon generative potentials with the highest OM abundance, the E_3d_3 are of the second good quality, and the E_3d_2 have poor to fair hydrocarbon generative potential. Furthermore, the well logs were applied to predict TOC and residual hydrocarbon generation potential (S_2) based on the sedimentary facies classification, using $\Delta\log R$, generalized $\Delta\log R$, logging multiple linear regression and BP neural network methods. The various methods were compared, and the BP neural network method have relatively better prediction accuracy. Based on the pre-stack simultaneous inversion (P-wave impedance, P-wave velocity and density inversion results) and the post-stack seismic attributes, the three-dimensional (3D) seismic prediction of TOC and S_2 was carried out. The results show that the seismic near well prediction results of TOC and S_2 based on seismic multi-attributes analysis correspond well with the results of well logging methods, and the plane prediction results are identical with the sedimentary facies map in the study area. The TOC and S_2 values of E_2s_{1+2} and E_2s_3 are higher than those in E_3d_3 and E_3d_2 , basically consistent with the geochemical analysis results. This method makes up the deficiency of geochemical methods, establishing the connection between geophysical information and geochemical data, and it is helpful to the 3D quantitative prediction and the evaluation of high-quality source rocks in the areas where the drillings are limited.

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1. Introduction

Organic matter (OM) abundance is a significant part of source rocks evaluation (Tissot et al., 1987; 1987). Although the traditional geochemical tests are accurate enough, it is also difficult to obtain three-dimensional (3D) distribution of source rocks and petroleum resource prediction in the areas with few drillings and samples.

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Geophysical methods are also significant for the research of source rocks, the well logs and seismic data are important supplements to the geochemical testing (Passey et al., 1990; Magoon and Dow, 1991; Zhu and Jin, 2002; Zhang and Zhu, 2007; Løseth et al., 2011).

Well logging is widely used in the petroleum exploration with high vertical resolution. Researchers have already started to identify source rocks using well logs such as natural gamma ray (GR), sonic transit time (DT), density (DEN) and resistivity (RD) logs (Beers, 1945; Swanson, 1960; Schmoker and Hester, 1981, 1983; Meyer and Nederlof, 1984; Herron, 1988). Total organic carbon (TOC) is one of the significant parameters of OM abundance. The common method for TOC prediction is $\Delta\log R$ method, which is a quantitative evaluation model based on resistivity, porosity logs (generally DT) and thermal maturity parameter (LOM). It can be applied to terrestrial and marine source rocks, in which the resistivity logs mainly identify hydrocarbons in the pores of source rocks, and the porosity logs are mainly used to identify the solid kerogen (Passey et al., 1990; Kenomere et al., 2017; Sêco et al., 2019; Aziz et al., 2020; Tenaglia et al., 2020). Scholars have proposed various improved $\Delta\log R$ methods (Liu et al., 2014, 2021; Hu et al., 2015; Wang et al., 2016; Zhao et al., 2016; Zhu et al., 2019). Logging multiple linear regression method is also a popular method to predict the TOC. The well logs have high correlation coefficients with TOC are selected and then the multiple linear regression method is used to calculate the TOC. However, this method has regional limitations and it is difficult to be popularized (Aziz et al., 2020).

Although well logs combined with geochemical data could evaluate the vertical heterogeneity of source rocks more accurately, the sparse well logs and geochemical data in areas with few drillings hinder 3D prediction of the source rocks. Therefore, additional research with seismic methods is needed. Previous studies mainly used post-stack seismic data to predict source rocks by combining the seismic facies and seismic attributes (Zhang and Zhu, 2007; Gupta et al., 2013; Infante-Paez et al., 2017). In general, the study of seismic response in source rocks should be based on the sequence stratigraphy method. After well-seismic calibration, picking up various seismic attributes (amplitude, frequency, phase, etc.), and performing single attribute correlation analysis with TOC curves, and then establishing mathematical model by selected seismic attributes with high correlation coefficients. Finally, the mathematical model obtained by training is applied to the 3D seismic data volume (Løseth et al., 2011; Li et al., 2014; Ji et al., 2018; Qin et al., 2018). Seismic inversion is also an extensive method to quantitatively evaluate OM abundance of source rocks (Chen, 2014; Badics et al., 2015; Tao et al., 2015; Wang et al., 2016; Infante-Paez et al., 2017; Niu et al., 2017; Chen et al., 2018; Chopra et al., 2018; Mahmood et al., 2018; Paris and Stewart, 2020; Sahoo et al., 2021). After petrophysical analysis, scholars found that there are good correlations between TOC and elastic parameters such as P-wave impedance and pre-stack density inversion results, so the TOC prediction can be calculated by post-stack or pre-stack seismic inversions. In recent years, the shale rock physics and pre-stack AVO analysis have become focused areas. Some published articles reported that source rocks have significant class IV AVO characteristics, that is, the intensity of negative reflection amplitude decreases with the increase of offset (Carcione et al., 2011; Løseth et al., 2011; Del Monte et al., 2018). Numerous studies on the petrophysics of organic-rich shale have been reported, which has laid foundation for the study of the relationship between kerogen and petrophysical elastic parameters of source rocks (Vernik and Nur, 1992; Vernik and Landis, 1996; Carcione, 2000; 2001, 2015; Hansen et al., 2019; Del Moro et al., 2020; Zhao et al., 2020; Matava et al., 2021).

In recent years, the application of neural network methods for

petroleum exploration are becoming very popular, so lots of models for predicting TOC by machine learning have also been proposed. Based on petrophysical analysis, several well logs have significant correlations with OM abundance were selected, and applied different machine learning algorithms to establish models for prediction (Huang and Williamson, 1996; Kamali and Mirshady, 2004; Bolandi et al., 2015; Tan et al., 2015; Verma et al., 2016; Ji et al., 2018; Wang and Peng, 2018; Shalaby et al., 2019; Wang et al., 2019; Zhao et al., 2021).

Researchers have conducted some geophysical studies for the source rocks of the Bohai Bay Basin. Based on geochemical characteristics, well logging and seismic data. Niu et al. (2017) used post-stack impedance inversion to predict the TOC of the Shahejie Formation source rocks in the Liaoxi Sag, Bohai Bay Basin. Cai et al. (2018) predicted TOC of Shahejie Formation source rocks in the Liaodong Sag of Bohai Bay Basin by using post-stack multi-attribute fusion method. Wang et al. (2019) proposed a six-layer convolutional neural network (CNN) method to predict TOC, S_1 and S_2 of Dongying Sag, Bohai Bay Basin. By modifying the model parameters, Liu et al. (2014, 2021) introduced the proportion coefficient K, which was considered to be an integrated reflection of kerogen, porosity and hydrocarbon components, proposed the variable overlay-coefficient $\Delta\log R$ method (V- $\Delta\log R$), and satisfactory prediction results have been obtained in Dongying and Zhanhua Sag, Bohai Bay Basin. In general, there were few geophysical studies for source rocks of Bozhong Sag, especially in the aspect of seismic research. In addition, the published articles were mainly based on post-stack seismic data, and there were few cases of using pre-stack seismic data to predict source rocks. Moreover, the pre-stack seismic data contain more reservoir information, and can describe the reservoirs and hydrocarbons more accurately, which contributes to more accurate evaluation of source rocks (Hampson et al., 2005; Sen and Stoffa, 2013; Zhao et al., 2021).

Based on organic geochemical analysis, this study compares multiple well logging methods, preferably BP neural network for prediction of TOC and S_2 , and then combines seismic inversion (P-wave impedance, P-wave velocity, density inversion results) and seismic attributes to predict the 3D distribution of TOC and S_2 . A geochemistry-logging-seismic workflow of terrestrial deep source rocks evaluation method is established in the southwestern Bozhong Sag of Bohai Bay Basin.

2. Geological settings

The Bohai Bay Basin is located in the eastern part of the North China Block, with an area of nearly 2×10^5 km², including a land area of 1.2×10^5 km², and it is a Cenozoic lacustrine pull-apart basin, which resulted in the disappearance of the Upper Cretaceous strata, denudation of the Mesozoic and Paleozoic sediments (Watson et al., 1987; Allen et al., 1997; Sun et al., 2008; Zhou et al., 2009; Feng et al., 2016; Yu et al., 2020; Fu et al., 2022). The Bozhong Sag is the largest hydrocarbon-rich Sag and the Cenozoic depositional center of the Bohai Bay Basin, covering an area of 8660 km², with a thick layer of Cenozoic deposition, surrounded by the Shijutuo Uplift, Shaleitian Uplift, Chengbei Lower Uplift and Bonan Lower Uplift. A series of significant exploration discovery have been made in the Bozhong Sag, and several large and medium-sized oil and gas fields such as BZ19-4, PL19-3, BZ13-1 and CFD6-4 have been discovered (Xie et al., 2018; Yin et al., 2020; Yu et al., 2020). In recent years, the Tianjin Branch of CNOOC discovered a large gas field in the deep Archean metamorphic exposed-hill of the Bozhong 19-6 (BZ19-6) structure and a large oil field in Archean granite gneiss buried-hill oilfield of the Bozhong 13-2 (BZ13-2) in the southwestern Bozhong Sag (Shi et al., 2019, 2021; Xu et al., 2019; Xue et al., 2020; Yin et al., 2020; Li et al., 2021) (Fig. 1).

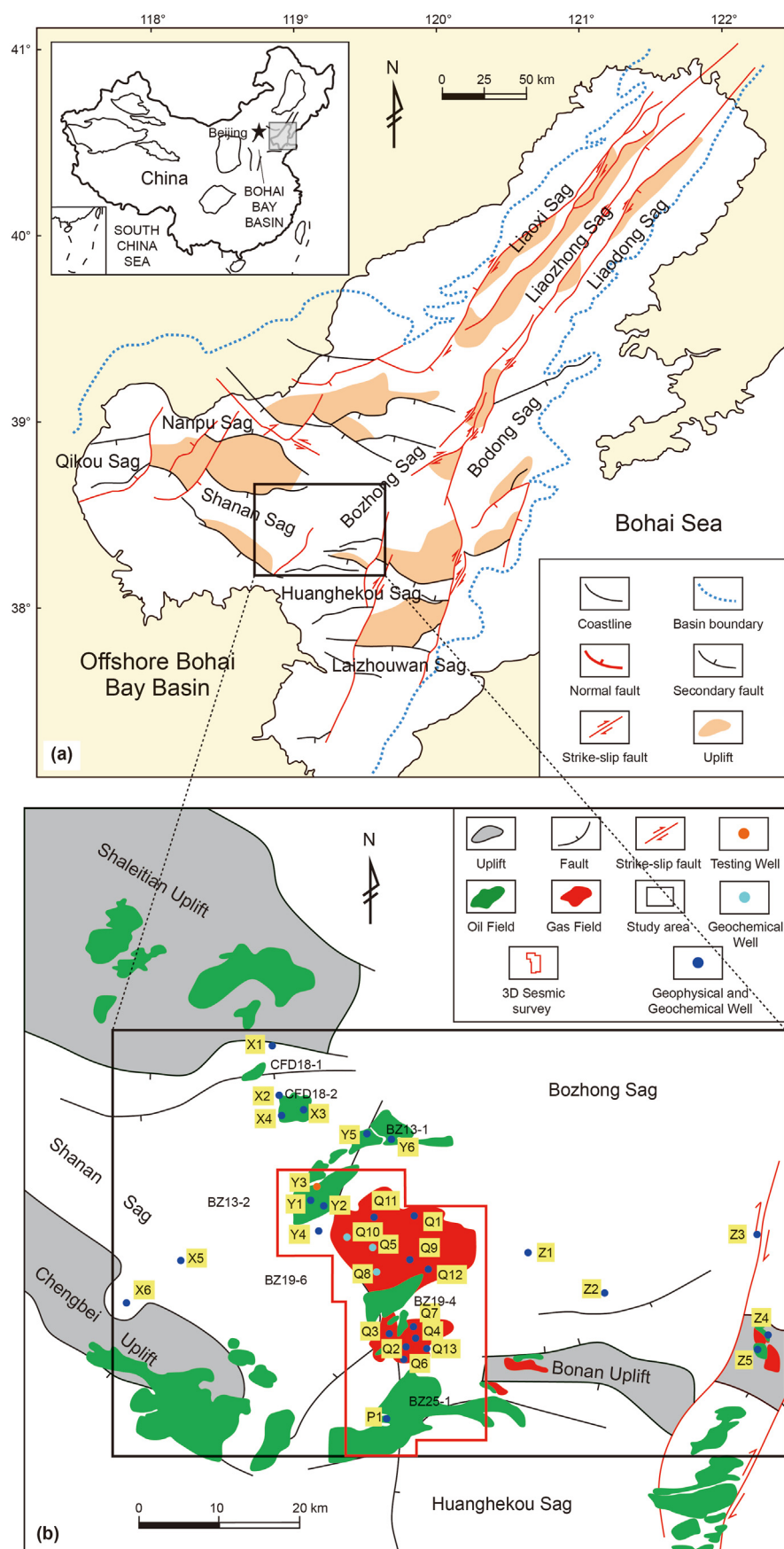


Fig. 1. (a) The location of the offshore Bohai Bay Basin (Feng et al., 2016; Fu et al., 2022). (b) Location map of southwest part of Bozhong Sag.

According to previous studies, the Bozhong Sag has experienced rifting and depressional periods since the Cenozoic, with relatively independent extensional and strike-slip fractures, and strike-slip is the main control factor for tectonic movement, trap formation and petroleum accumulation since its Cenozoic deposition (Qi et al., 1995a, 1995b; Feng et al., 2016; Wang et al., 2017; Xie et al., 2018; Yu et al., 2020). Researchers have extensively evaluated the source rocks in the Bohai Sea area, including four significant Paleogene source-rock intervals, namely: (1) the third member of the Shahejie Formation (E_{2s3}), (2) the first and second members of the Shahejie Formation (E_{2s1+2}), (3) the third member of the Dongying Formation (E_{3d3}) and (4) the lower second member of the Dongying Formation (E_{3d2}). Previous studies have reported OM characteristics, hydrocarbon generation history, depositional environment based on organic biomarkers, stable carbon isotope and trace elements, the source rocks in Bozhong Sag were further studied (Li et al., 2001; Hao et al., 2010, 2011; Wang et al., 2015; Jiang et al., 2016, 2019; Yin et al., 2020; Chen et al., 2021). However, the lacustrine source rocks in Bozhong Sag have significant heterogeneity, and source rocks in different sub-sags may have different hydrocarbon generation potentials (Hao et al., 2010, 2011; Wang et al., 2022), and the studies on quantitative evaluation of source rocks in Bozhong sub-sags were insufficient. The source rocks of E_{2s3} , which are the most important source rocks in Bozhong Sag, represent lacustrine, fan delta sedimentary facies. The thickness of E_{2s1+2} source rocks are thinner than that of E_{2s3} , representing shore-shallow lacustrine, braid-delta and fan delta sedimentary facies. The sedimentary facies of E_{3d3} and E_{3d2} are river-delta and lacustrine sedimentary facies, and their contribution to petroleum accumulation in Bozhong Sag could not be ignored (Hao et al., 2010; Jiang et al., 2016) (Fig. 2).

3. Samples and methodology

In this study, the data of 31 wells (X1, X2, X3, X4, X5, X6, Y1, Y2, Y3, Y4, Y5, Y6, Q1, Q2, Q3, Q4, Q5, Q6, Q7, Q8, Q9, Q10, Q11, Q12, Q13, P1, Z1, Z2, Z3, Z4 and Z5), the pre-stack CRP gathers, post-stack seismic data and seismic horizons in the southwestern Bozhong Sag were collected, the 3D seismic survey covers approximately 800 km². A total of 718 mudstone samples were collected for TOC testing and Rock-Eval pyrolysis. The Rock-Eval pyrolysis and TOC data of several wells (Q4, Q11, X5, X6, Z1) have been reported, but they were used for research on organic facies, sedimentary environment of source rocks, and oil-source correlation. These data have not been used for geophysical prediction of source rocks (Wang et al., 2020, 2022; Yin et al., 2020). All the above experimental results were analyzed and identified in the Bohai experimental center of CNOOC, State Key Laboratory of Continental Dynamics of Northwest University, and State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum. The logging data and seismic data were obtained from the Tianjin Branch of CNOOC.

3.1. Geochemical analysis and geophysical data

- 1) TOC analysis. TOC was tested using CS-230 carbon and sulfur analyzer. First, the mudstone samples were crushed to 80 mesh, weighed to take 0.3 g sample and put into a quartz crucible. Then 5% dilute hydrochloric acid was added and then it was heated at 80 °C to remove the inorganic carbon. The selected samples shall be washed with pure water and dried at 60 °C. Finally, the crucible in which the samples were placed in the CS230 carbon and sulfur analyzer to determine the TOC.
- 2) Rock-Eval pyrolysis. For Rock-Eval pyrolysis using ROCK EVAL 6 pyrolyzer, the mudstone samples were crushed to 100 mesh and

then 60 mg of samples were weighed and heated for pyrolysis and placed in the Rock-Eval pyrolyzer.

- 3) The well logs mainly include sonic transit time (DT and DTS), P-wave (converted from DT), S-wave (converted from DTS), density (DEN), deep resistivity (RD) and natural gamma ray (GR). The wells involved in the logging prediction methods include: X1, X2, X3, X4, X5, X6, Y1, Y2, Y3, Y4, Y5, Y6, Q1, Q2, Q3, Q4, Q6, Q7, Q9, Q11, Q12, Q13, P1, Z1, Z2, Z3, Z4 and Z5.
- 4) Seismic data inline direction is north-south, crossline direction is east-west. Seismic bin size is 25 m × 12.5 m, the post-stack seismic data with the traditional processing of amplitude recovery and residual amplitude compensation, static correction, suppress multiple waves, velocity analysis, pre-stack time migration. For pre-stack simultaneous inversion, gather conditioning is needed. The wells involved in the seismic inversion and attributes analysis within the seismic workings include: Y1, Y2, Y4, Q1, Q2, Q3, Q4, Q6, Q7, Q9, Q11, Q12, Q13 and P1.

3.2. Well logging evaluation of organic matter abundance in source rocks

Generally, source rocks are mainly marine carbonate rocks or terrestrial lacustrine mudstones, which mainly consist of rock matrix and pores, and the rock matrix of non-source rocks are mainly clay minerals (montmorillonite, kaolinite, illite, etc.), non-clay minerals (quartz, feldspar, carbonate minerals, etc.) and kerogen, and as the source rocks mature, the solid kerogen will evolve into oil and gas entering the pore and drive out the pore water (Fig. 3). The rock physical differences (P-wave velocity, density, resistivity, etc.) between kerogen and other clastic particles (such as quartz, feldspar, and carbonate minerals) in source rocks are more significant, so the variability of component content (the OM abundance) of source rocks could be identified by well logging methods (Passey et al., 1990; Zhao et al., 2016).

A total of 620 groups data of TOC and S_2 of the southwestern Bozhong Sag were selected, including 312 groups in E_{3d2} , 142 groups in E_{3d3} , 59 groups in E_{2s1+2} , and 107 groups in E_{2s3} . Based on $\Delta\log R$ method, generalized $\Delta\log R$ method, multiple linear regression and BP neural network method, the determination coefficient R^2 and average relative errors of the prediction models in different intervals and sedimentary facies are compared. In order to select the suitable and unified method, the data of different intervals are unified together for comparison and optimization.

3.2.1. Adapting Passey et al. (1990) method to estimate TOC

The $\Delta\log R$ method is one of the most classical logging prediction methods for estimating TOC proposed by Passey et al. (1990). The RD logs and the DT logs are superimposed in reverse in the non-source rocks intervals, and the part where the two logs completely overlap in a certain range is the baseline. Since the sonic transit time value of kerogen is generally larger than that of inorganic minerals such as quartz and feldspar, the resistivity value of oil and gas is higher than inorganic-rich intervals, a certain separation between the baselines will be generated, and the separation is designated as $\Delta\log R$, that is

$$\Delta\log R = \log_{10}(R/R_{\text{baseline}}) + 0.02 \times (\Delta t - \Delta t_{\text{baseline}}) \quad (1)$$

In Eq. (1), where R is the resistivity log value, R_{baseline} is deep resistivity baseline value, Δt is sonic transit time log value, $\Delta t_{\text{baseline}}$ is sonic transit time baseline value, respectively. And the $\Delta\log R$ separation is linearly related to TOC values through the maturity parameter (LOM) in Eq. (2). In general, LOM can be obtained from a variety of laboratory analysis and testing, burial and thermal

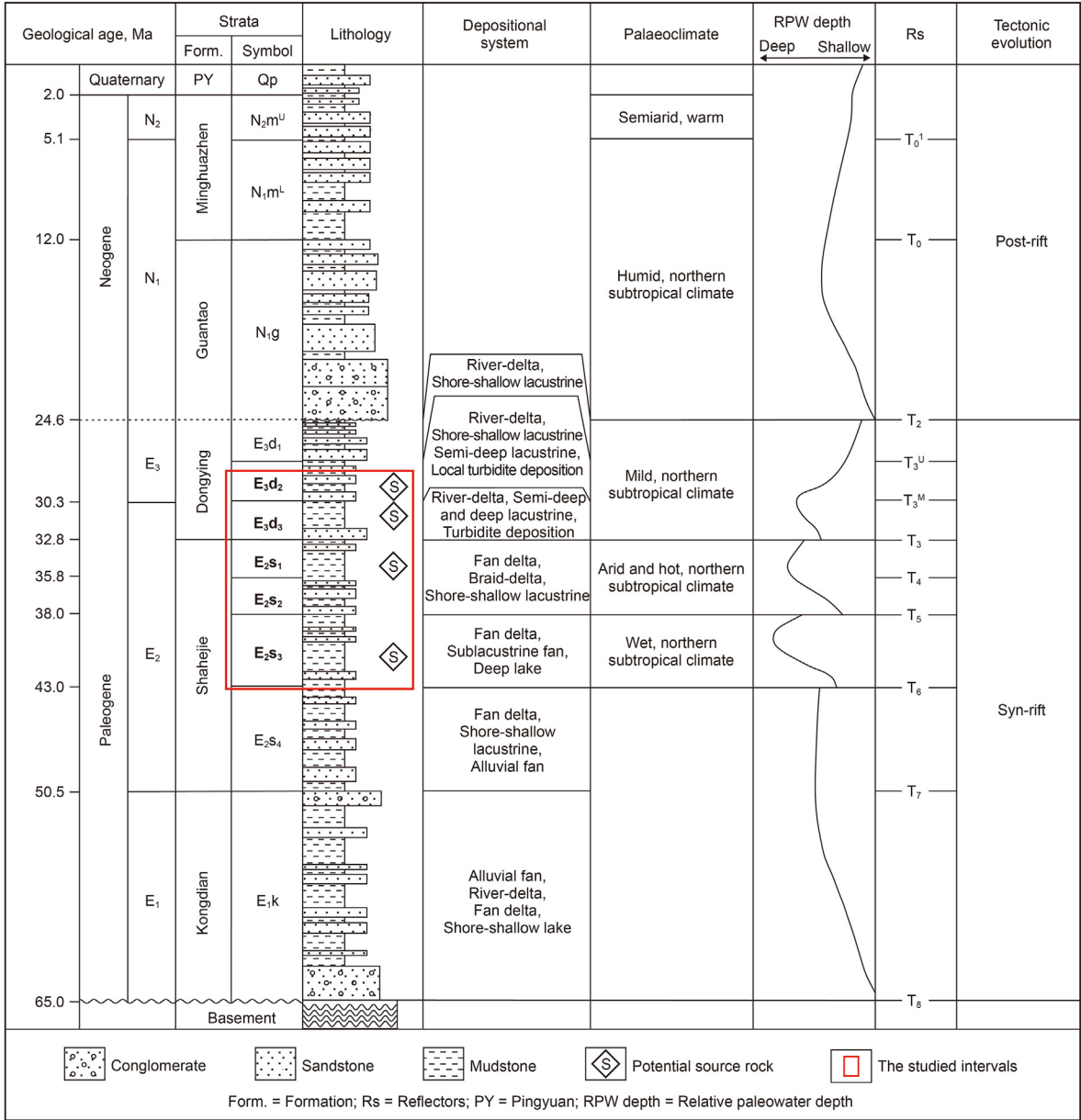


Fig. 2. Generalized stratigraphy of the Bohai Bay Basin modified from (Hao et al., 2010, 2011; Li et al., 2021). Possible source rock and reservoir intervals are marked. Form = Formation; PY = Pingyuan; RPW Depth = Relative paleo-water; Rs = Reflectors.

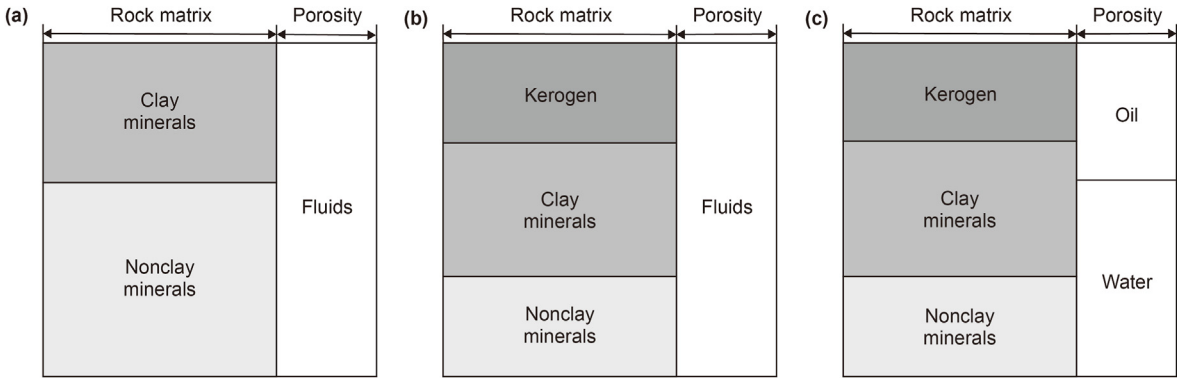


Fig. 3. Petrophysical models of non-source, immature and mature source rocks modified from (Passey et al., 1990; Zhao et al., 2016). (a) Non-source rocks model. (b) Immature source rocks. (c) Mature source rocks.

history. LOM determine the accuracy of TOC prediction.

$$\text{TOC} = (\Delta \log R) \times 10^{(2.297 - 0.1688 \times \text{LOM})} + \Delta \text{TOC} \quad (2)$$

3.2.2. Adapting generalized $\Delta \log R$ method to estimate TOC

The $\Delta \log R$ method produced a more apparent amplitude difference between the RD and DT logs superimposed on the intervals of mature source rocks (Fig. 4), and the generalized $\Delta \log R$ method is a method proposed by (Hu et al., 2015) for deep intensive compaction formations in the terrestrial facies, which takes into account that the relationship between TOC values and $\Delta \log R$ is not a simple linear relationship, and needed to introduce LOM, but the conductive component of the terrestrial source rocks makes the separation of the immature source rocks intervals implicit to be calculated, thus introducing the GR log, which is more sensitive to the terrestrial intensive compaction formations, and this article also introduce the DEN log, which is sensitive to the OM. The generalized $\Delta \log R$ method considering GR and DEN is obtained:

$$\text{TOC} = [a \times \log_{10}(\text{GR}) + b \times \text{DEN} + c] \times \Delta \log R + \Delta \text{TOC} \quad (3)$$

where a , b , and c are fitting coefficients and ΔTOC is the background value of OM abundance, and Eq. (3) is used in combination with Eq. (1).

3.2.3. Adapting multiple linear regression to estimate TOC

Multiple linear regression method is also a popular method to calculate the OM abundance of source rocks. It was found that the correlations between logging parameters and OM abundance parameters (TOC and S_2) were inapparent, so the mathematical relationship between multiple logging parameters with TOC and S_2 could be considered for the prediction.

According to previous studies, the P-wave velocity of kerogen is generally 1700–2300 m/s, the P-wave velocity of clay minerals such as kaolinite and illite are generally 3000–4000 m/s, while the P-wave velocity of minerals such as quartz, feldspar and calcite is generally above 4000 m/s. Therefore, the OM in the source rocks would result in the decrease of the P-wave velocity (the increase of DT values) (Mavko et al., 2020). The density of kerogen is generally 1.3–1.4 g/cm³, while the density of other minerals such as quartz,

feldspar, calcite are higher than 2.0 g/cm³, therefore, the OM enrichment would result in the decrease of DEN values. Moreover, kerogen contains radioactive elements such as U, Th, K, etc., which will affect the RD and GR (Mavko G et al., 2020).

According to 3D cross-plot analysis (Fig. 5), it is found that the correlations of DT, DEN, RD and GR with TOC and S_2 decrease in southwestern Bozhong Sag. Therefore, the calculation formula of TOC and DT, DEN, RD and GR logs is established in Eq. (4), where d , e , f , g and h are fitting coefficients:

$$\text{TOC} = d \times \text{DT} + e \times \text{DEN} + f \times \text{RD} + g \times \text{GR} + h \quad (4)$$

3.2.4. Adapting BP neural network method to estimate TOC

BP (back propagation) neural network is a multi-layer feed-forward neural network trained according to the error back propagation algorithm. Its topology includes input layer, hidden layer and output layer (Fig. 6), and the core theory is that the training samples are input from the input layer, processed by multiple hidden layers and output to the output layer, if the desired output is not obtained, the hidden layers back propagate and pass the error signal to the neurons in the previous layer, and then adjust the weights and thresholds so that the error between the actual output and the desired output is minimized. This process is called back propagation (Huang and Williamson, 1996; Kamali and Mirshady, 2004; Bolandi et al., 2015; Tan et al., 2015; Verma et al., 2016; Ji et al., 2018; Wang et al., 2017; Shalaby et al., 2019; Wang et al., 2019; Zhao et al., 2021). To obtain the desired output results, the prediction of the network can be optimized by adjusting the number of layers of the hidden layer or increasing the number of neuron nodes in a single hidden layer. Only nonlinear separation problems require multiple hidden layers, and the neural network model with a single hidden layer can effectively approximate arbitrary continuous functions. In this study, the BP neural network model with a single hidden layer is constructed, and its mathematical formulas are as follows in Eqs. (5)–(8):

Input layer:

$$x^{(i)} \quad (5)$$

Hidden layer:

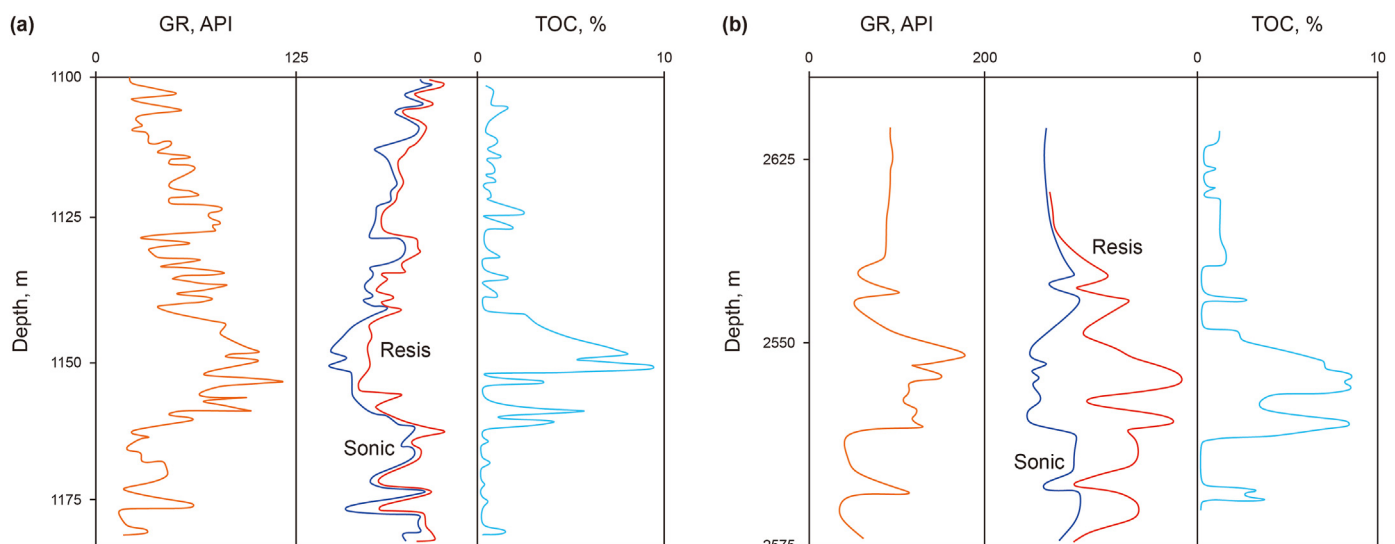


Fig. 4. (a) Sonic/resistivity overlay difference and calculated TOC profile of immature source rocks. (b) Sonic/resistivity overlay difference and calculated TOC profile of mature source rocks modified from (Passey et al., 1990; Hu et al., 2015).

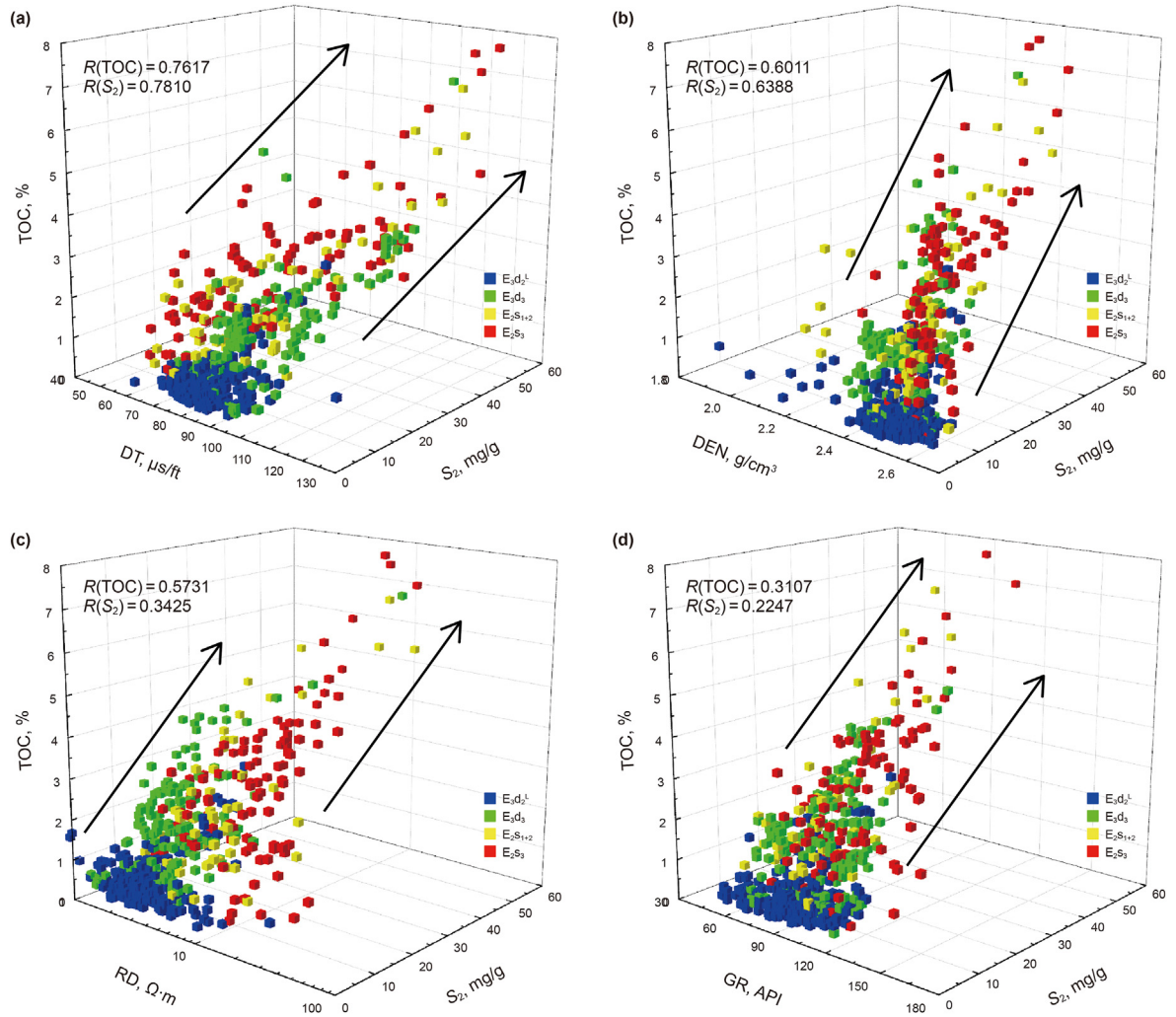


Fig. 5. Correlation analysis diagram between logging parameters and OM abundance (TOC and S₂). (a) DT, (b) DEN, (c) RD, (d) GR.

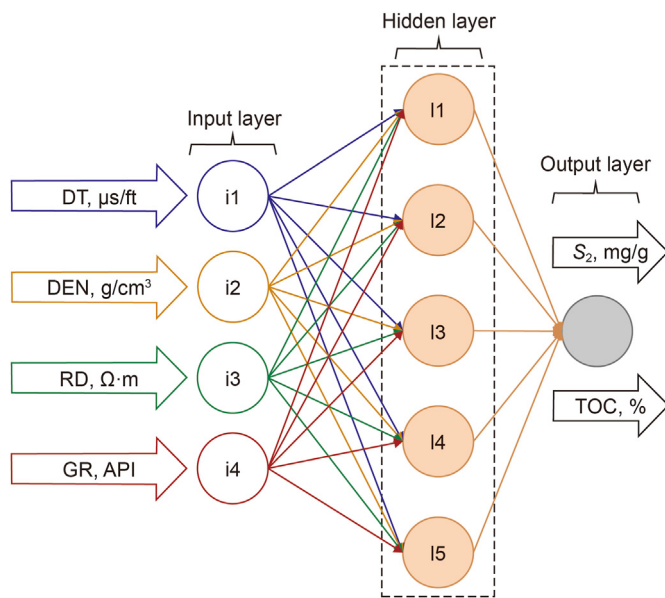


Fig. 6. Diagram indicates formulation of input petrophysical data to TOC and S₂ by a three layered artificial neural network modified from (Bolandi et al., 2015).

$$a_1^{(i)} = f(w_1 x^{(i)} + b_1) \quad (6)$$

Output layer:

$$\hat{y}^{(i)} = f(w_2 a_1^{(i)} + b_2) \quad (7)$$

The output expression after several training sessions is

$$Y = \sum_{j=1}^m \left[w_{2jk} \times f \left(\sum_{i=1}^n w_{1ij} \times x^{(i)} + b_{1j} \right) \right] + b_{2k} \quad (8)$$

where $x^{(i)}$ is the feature vector of the output layer; $f(\cdot)$ is the activation function; w_{1ij} is the weight from the input layer to the hidden layer; b_{1j} is the threshold from the input layer to the hidden layer; w_{2jk} is the weight from the hidden layer to the output layer; b_{2k} is the threshold from the hidden layer to the output layer.

Similarly, chloroform bitumen "A", hydrocarbons formed before pyrolysis S₁, S₂ and other OM abundance parameters can also be calculated by this method.

3.3. Seismic prediction of organic matter abundance in source rocks

3.3.1. Pre-stack simultaneous inversion

Based on the pre-stack CRP gathers, well logs data, geological data, etc., the pre-stack simultaneous inversion is performed (Hampson et al., 2005; Sen and Stoffa, 2013; Chen et al., 2018) (14 inversion wells, namely, Y1, Y2, Y4, Q1, Q2, Q3, Q4, Q6, Q7, Q9, Q11, Q12, Q13, P1), and after the gather conditioning processes, wavelet extraction, well seismic calibration, low frequency model establishment. The pre-stack inversion data results such as P-wave, density, S-wave, P-wave impedance, and P-wave and S-wave velocity ratios were obtained to provide the basis for multi-attributes prediction of TOC and S_2 .

A. Pre-stack gather conditioning. The original seismic data is pre-stack CRP gathers, which has low signal-to-noise ratio, no flattening of the events, and large differences in wavelet morphology, etc. Therefore, to obtain more accurate inversion results, the original CRP gathers are needed gather conditioning before the pre-stack inversion. It can be seen that after pre-stack gather conditioning, the reflection horizons of the gathers are flattened and the signal-to-noise ratio and resolution are improved, which can be used for pre-stack simultaneous inversion and OM abundance prediction in the southwestern Bozhong Sag (Fig. 7).

B. Wavelet selection and generation of synthetic seismogram. After obtaining the CRP gathers by the pre-stack gather conditioning, it is necessary to perform well-seismic calibration by correlating well logs with the seismic data. In this work, we extract the zero-phase statistical wavelet to make synthetic seismogram. The synthetic seismogram is further calibrated and compared with the actual seismic traces near wells, and the corresponding horizons were traced and adjusted repeatedly with the aim of obtaining accurate and reliable time-depth relationships at the well locations. Fig. 8 shows the synthetic seismogram results of well Q2 and well Q3, with the geological strata on the far left, the P-wave velocity logs on the red curve, the density logs on the blue curve, and the blue seismic traces are the synthetic seismogram, red seismic traces are the seismic traces near wells, and the actual seismic traces near wells are shown on the far right. The yellow boxes at the top and bottom are the target intervals. It can be seen that the synthetic seismogram results in the target formations are satisfactory, with correlation coefficients of 0.8410 for well Q2 and 0.8020 for well Q3.

C. Establishment of low frequency model. After establishing the reliable seismic time-depth relationship, a low-frequency model needs to be built with the help of logging information (Mahmood et al., 2018). The pre-stack simultaneous inversion requires the establishment of the pre-stack P-wave impedance, the P-wave velocity and the density models to constrain the inversion results, filling the low-frequency portion of the seismic frequency spectrum.

D. Pre-stack simultaneous inversion results. The final inversion results were obtained through several inversion analyses and improvements. Fig. 9 shows the P-wave impedance, P-wave velocity and density inversion results (Inline 4938) over well Q7, the well position was inserted into the well logs, and its color bar and the inversion results color bar were adjusted to be consistent, the inversion results near wells correspond well with the well logs, so the inversion results have high credibility.

3.3.2. Multi-attributes fusion analysis based on neural network

Then multiple attributes of the seismic traces near wells are extracted and combined with the P-wave impedance, P-wave velocity and density inversion results to perform multi-attributes analysis with TOC and S_2 . The multi-attributes fusion prediction of several attributes has the highest correlation coefficients with TOC and S_2 are performed using the neural network method to obtain the TOC and S_2 prediction curves for the wells within the seismic data, and then the neural network-trained model is applied to the entire seismic data to obtain the TOC and S_2 3D prediction results.

According to the analysis of the previous well logging parameters cross-plots (Fig. 5), it is found that the OM abundance parameters (TOC, S_2) of source rocks had the highest correlation coefficients with DT and DEN logs, so this study uses the P-wave velocity, density and P-wave impedance inversion results combined with post-stack seismic data for multi-attributes optimization and analysis.

Next, we need to extract the seismic attributes near wells and make correlation analysis with the TOC and S_2 curves predicted by BP neural network method. Figs. 10 and 11 are the TOC and S_2 curves of Well Q2, Q3, Q4 and Q12, and the seismic traces near wells, P-wave impedance, P-wave velocity and density. In order to make a satisfying match between TOC/ S_2 curves and seismic attributes, it is necessary to time shift, smooth and filter logs (the

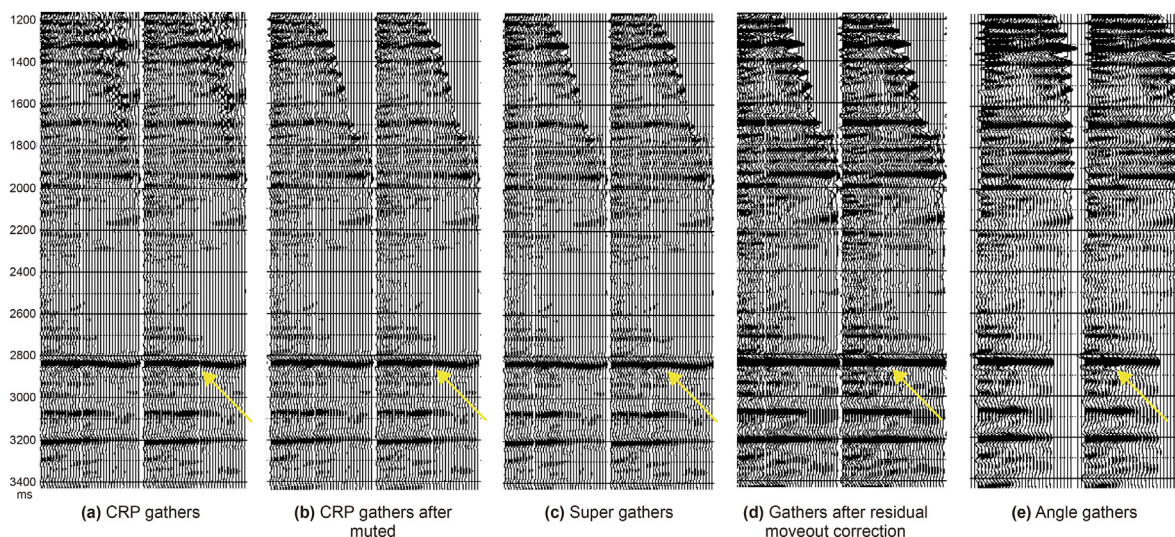


Fig. 7. Pre-stack gather conditioning processes. (a) CRP gathers, (b) CRP gathers after muted, (c) super gathers, (d) gathers after residual moveout correction, (e) angle gathers.

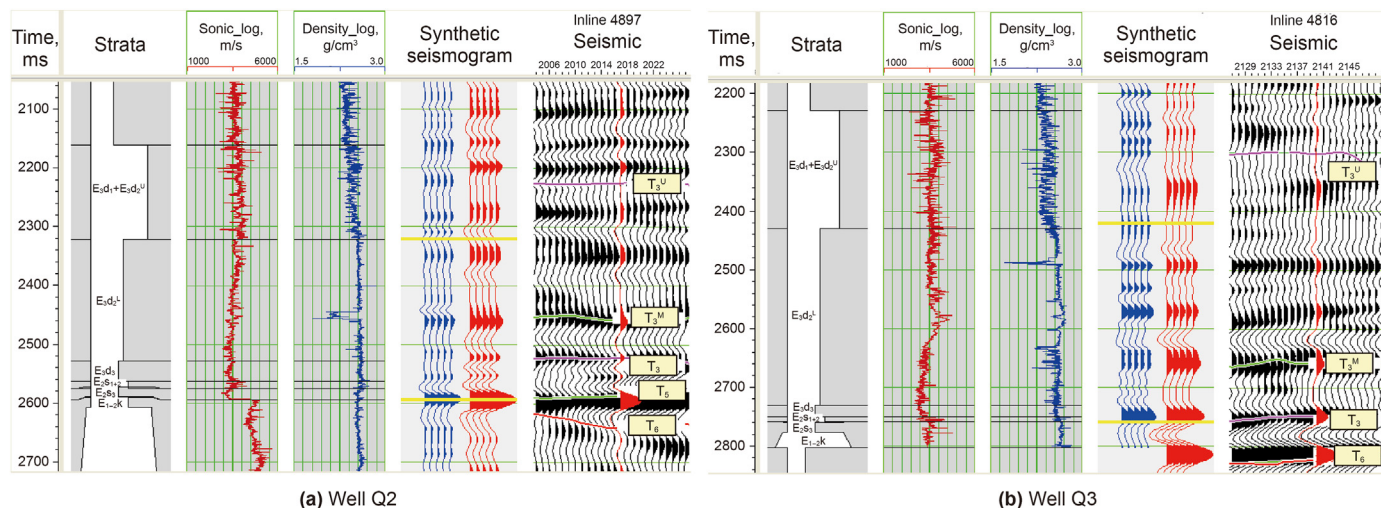


Fig. 8. Synthetic seismogram results of Well Q2 and Q3. (a) Well Q2, (b) Well Q3.

black curves on the left are the TOC and S_2 curves predicted by BP neural network method, and the red curves are the TOC and S_2 curves after time shift, smoothing and filtering) (Figs. 10 and 11).

The multiple attributes of the seismic traces near wells are extracted to combine the values of P-wave impedance, P-wave velocity, and density inversion results for multi-attributes analysis. [Tables 1 and 2](#) are the TOC and S_2 multi-attributes correlations analysis results, respectively. It can be seen that when performing TOC multi-attributes analysis prediction. It is found that when the number of attributes is 5 (reciprocal of P-wave velocity, reciprocal of density, integrated absolute amplitude, dominant frequency, and reciprocal of P-wave impedance) ([Table 1](#)), the correlation coefficient is the highest and the error is the lowest. The correlation coefficient between the logging prediction TOC curves and seismic near wells prediction TOC for 13 wells is 0.6378, and the overall correlation coefficient is 0.7797 when using neural network training. When performing S_2 multi-attributes analysis prediction, the highest correlation coefficient and the lowest error were found when the number of attributes was 3 (reciprocal of P-wave velocity, reciprocal of P-wave impedance, and integrated absolute amplitude) ([Table 2](#)), the overall correlation coefficient between the logging predicted S_2 curves and the seismic near wells prediction S_2 for 13 wells is 0.6187, and the overall correlation coefficient is 0.7175 when using neural network training.

4. Results

4.1. OM abundance of source rocks

OM abundance evaluation is an important part of source rocks research (Peters, 1986; Hakimi and Ahmed, 2016). TOC, S₁, S₂, and genetic potential (S₁+S₂) are used to evaluate the OM abundance of source rocks in the southwestern Bozhong Sag. Table 3 shows the OM abundance characteristic parameters of source rocks in southwestern Bozhong Sag. There are many sedimentary facies types in this area, including semi-deep and deep lake facies, braided river delta, sublacustrine fan, shore and shallow lake facies. The debris samples may be silty mudstone or siltstone, resulting in low TOC and T_{max} values.

The TOC of E3d_2 source rocks ranges from 0.35% to 3.56% (avg. 0.85%), S_2 values are 0.18 to 15.57 mg/g (avg. 2.30 mg/g). The TOC of E3d_3 source rocks ranges from 0.45% to 5.33% (avg. 2.19%); S_2 values are 0.13 to 31.03 mg/g (avg. 8.03 mg/g). The TOC of E2s_{1+2} source rocks ranges from 0.25% to 6.90% (avg. 2.84%); S_2 ranges from 0.24

to 54.29 mg/g (avg. 12.93 mg/g). The TOC of E₂S₃ source rocks ranges from 0.80% to 7.76% (avg. 3.10%); S₂ mainly ranges from 1.27 to 58.32 mg/g (avg. 14.75 mg/g) (Table 3).

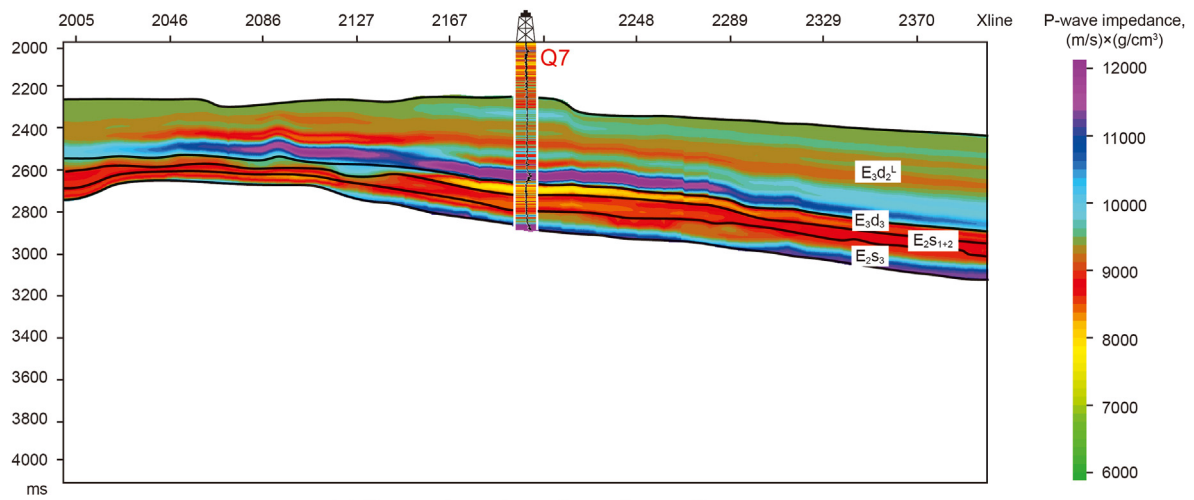
Based on the cross-plots between the S_2 and TOC (Fig. 12a), the cross-plots between the S_1+S_2 and TOC (Fig. 12b), the frequency distribution of TOC and S_1+S_2 (Fig. 12c and d), it can be seen that the OM abundance of Shahejie Formation is higher than that of Dongying Formation. E_2S_{1+2} and E_2S_3 source rocks have higher OM abundance values, which indicating better hydrocarbon generative potential. The hydrocarbon generation potential of E_3d_3 is relatively weak, which are evaluated as fair-good source rocks. The E_3d_2 source rocks are poor to fair quality source rocks, the hydrocarbon generation potential of E_3d_1 is relatively poor (Fig. 12).

4.2. Logging prediction results and comparison

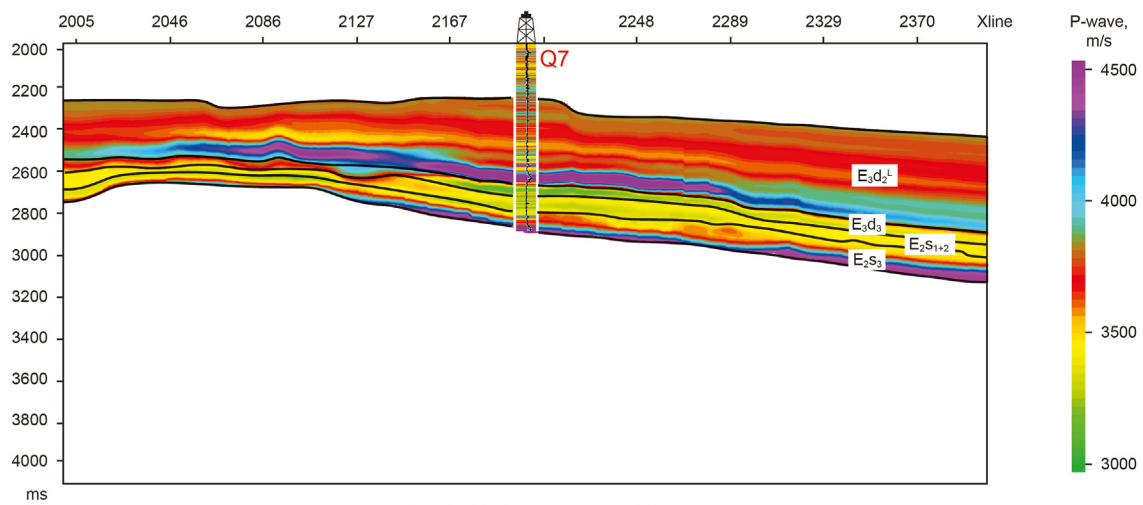
Comparing the determination coefficient R^2 and the average relative error of four methods (Fig. 13 and Table 4). The generalized $\Delta\log R$ method has a higher prediction accuracy compared with Passy's method because it takes into account intensive compaction of source rocks in terrestrial facies; the correlation coefficient R^2 and average relative error of the generalized $\Delta\log R$ method are slightly better than multiple linear regression method. Compared with the other three methods, the prediction accuracy of BP neural network method is higher (Fig. 13).

According to the comparison results of correlation coefficients of each TOC prediction method (Table 4), it can also be seen that the generalized $\Delta\log R$ method has better results for different sedimentary facies prediction models than the Passy's $\Delta\log R$ method. For example, the determination coefficients are significantly improved in the semi-deep and deep lacustrine facies of E₃d₂ and E₃d₃ source rocks, while the correlation coefficients of the generalized $\Delta\log R$ and the multiple linear regression methods have their own advantages, respectively. It is difficult to compare and prioritize the four models of different sedimentary facies, so it is necessary to conduct a unified analysis; the determination coefficient R^2 of BP neural network method is roughly above 0.80 in different sedimentary facies models, which is higher than the other three methods. The prediction accuracy of BP neural network is better than multiple linear regression and $\Delta\log R$ series methods in southwestern Bozhong Sag.

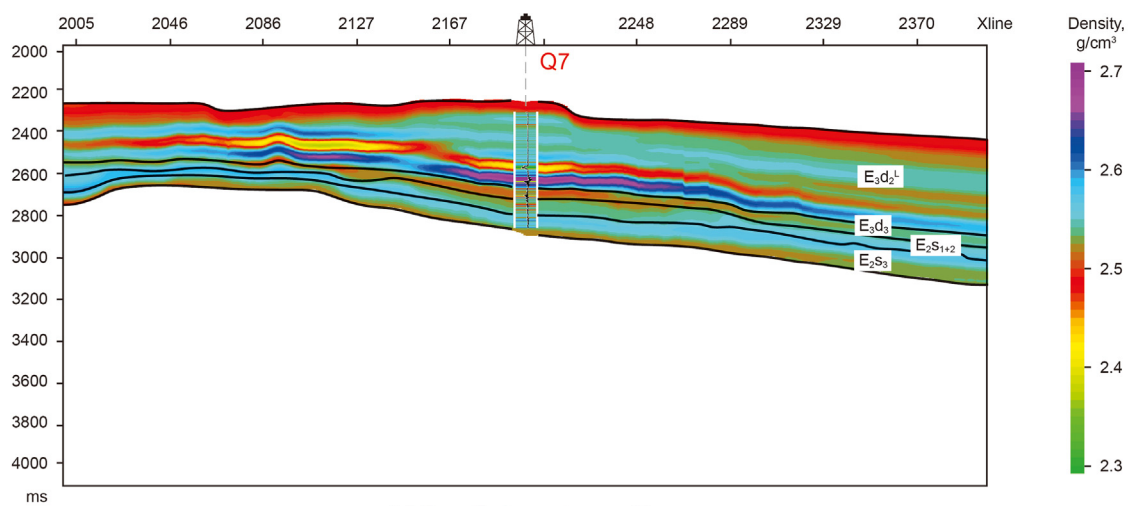
According to the above analysis, the S_2 of source rocks in southwestern Bozhong Sag was also predicted using BP neural network method. Fig. 14 shows the TOC and S_2 prediction profiles of



(a) P-wave impedance inversion profile



(b) P-wave inversion profile



(c) Density inversion profile

Fig. 9. Pre-stack simultaneous inversion results. (a) P-wave impedance, (b) P-wave, (c) Density.

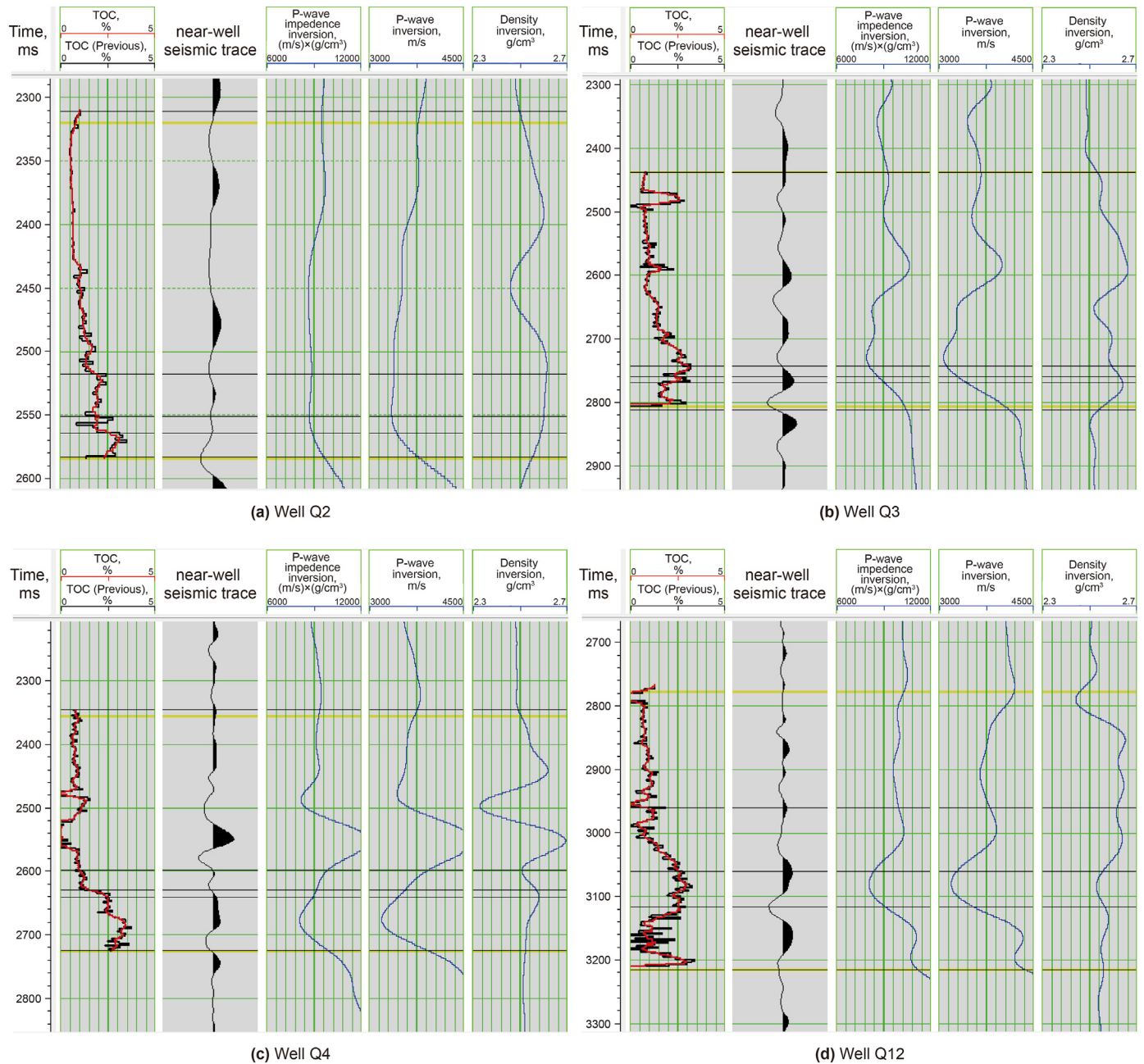


Fig. 10. Calibration diagram of TOC curves of typical wells and inversion trace of seismic data, P-wave impedance, P-wave velocity and density inversion results near wells. (a) Well Q2, (b) Well Q3, (c) Well Q4, (d) Well Q12.

well Q3 in the study area, and it can be obviously seen that the prediction results of BP neural network method in TOC and S_2 are in good agreement with the organic geochemical data. The OM abundance (TOC, S_2) values of $E_3d_1^2$ source rocks are low, the OM abundance values of the source rocks of E_2s_{1+2} and E_2s_3 are higher, and that in E_3d_3 source rocks are medium (Fig. 14).

4.3. Seismic prediction results of organic matter abundance

Figs. 15 and 16 show the TOC and S_2 seismic prediction profiles across the inversion wells, and the logging prediction TOC and S_2 curves are inserted at the well locations. The logging and seismic near well prediction results correlation coefficient for TOC is 0.7797, and the logging and seismic near well prediction results correlation

coefficient for S_2 is 0.7175, indicating that the neural network combined with seismic multi-attributes (post-stack seismic attributes, P-wave velocity, P-wave impedance and density inversion results) to predict TOC and S_2 of source rocks is feasible (Figs. 15 and 16).

In order to prove the prediction accuracy of the model, we used well Y3 that was not involved in pre-stack simultaneous inversion, to test the model (Fig. 17), and obtained the TOC and S_2 profiles across the well Y3. The logging and seismic near well prediction results correlation coefficient for TOC is 80.32%, and the average relative error is 10.58%. However, the S_2 value of the seismic near well Y3 (especially the source rocks of E_3d_3 interval) is high (the value ranges from 5.2 to 8.5), which is consistent with the trend of prediction results of logging method, indicating that the prediction

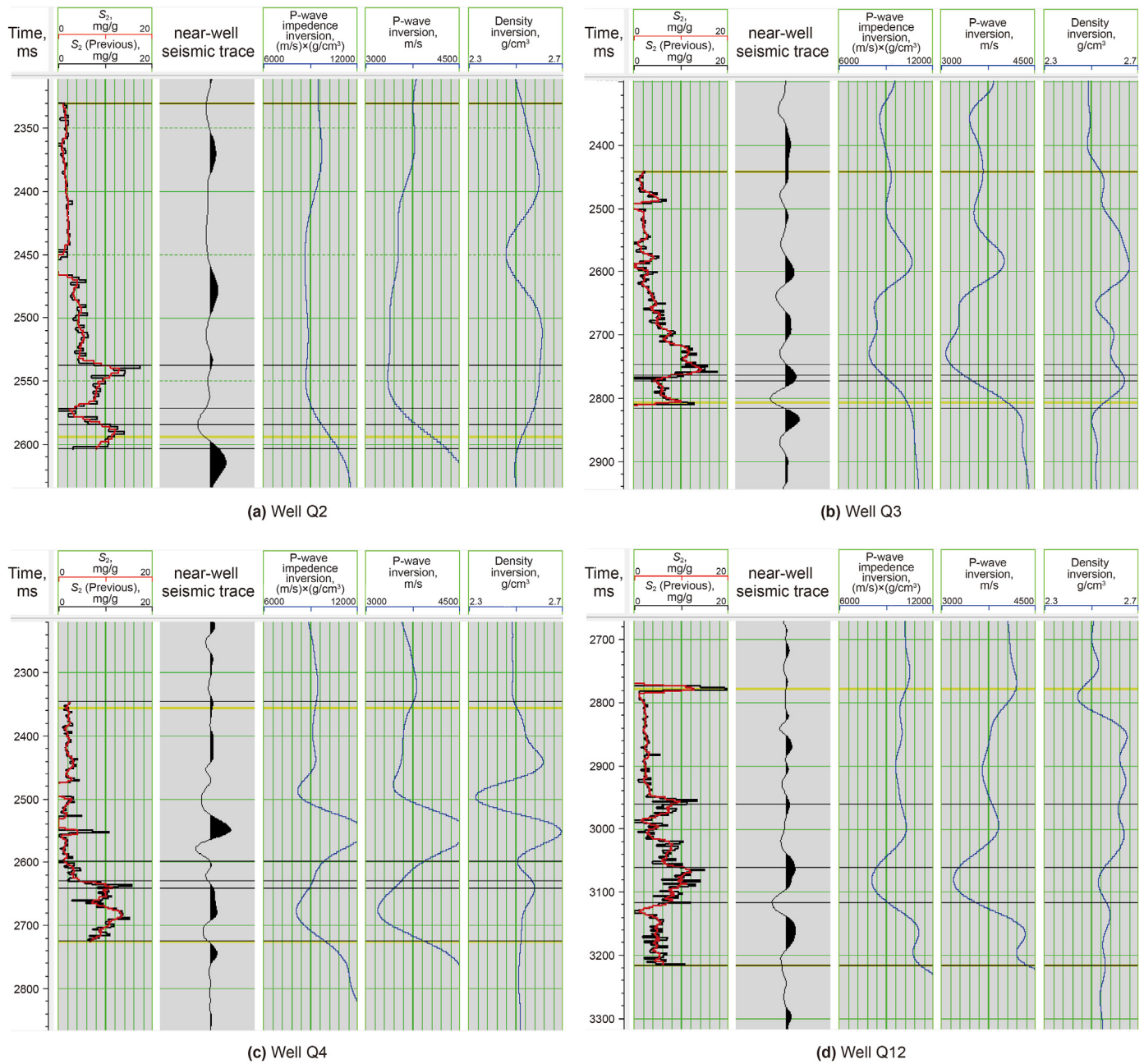


Fig. 11. Calibration diagram of S_2 curves of typical wells and inversion trace of seismic data, P-wave impedance, P-wave velocity and density inversion results near well. (a) Well Q2, (b) Well Q3, (c) Well Q4, (d) Well Q12.

Table 1
Table of TOC and seismic multi-attributes correlation analysis.

Target curve	Final attribute	Training error	Validation error
TOC	Reciprocal of P-wave velocity	0.775878	0.806666
TOC	Reciprocal of density	0.752918	0.787887
TOC	Integrated absolute amplitude	0.736557	0.790879
TOC	Dominant frequency	0.721891	0.794449
TOC	Reciprocal of P-wave impedance	0.708371	0.767903
TOC	Average frequency	0.692053	0.779249
TOC	Amplitude weighted phase	0.688232	0.778316
TOC	Instantaneous phase	0.685239	0.777785
TOC	Apparent polarity	0.683159	0.783618
TOC	Derivative of instantaneous phase	0.682065	0.786299
TOC	Amplitude weighted cosine phase	0.679798	0.785816

Table 2
Table of S_2 and seismic multi-attributes correlation analysis.

Target curve	Final attribute	Training error	Validation error
S_2	Reciprocal of P-wave velocity	3.104438	3.286747
S_2	Reciprocal of P-wave impedance	2.828075	2.991783
S_2	Integrated absolute amplitude	2.748946	2.949182
S_2	Density squared	2.719773	3.392887
S_2	Amplitude weighted frequency	2.692451	3.379546
S_2	Dominant frequency	2.661405	3.444809
S_2	Amplitude weighted phase	2.640017	3.439983
S_2	Average frequency	2.627350	3.570451
S_2	Apparent polarity	2.618618	3.626040
S_2	Amplitude envelope	2.612385	3.633032
S_2	Instantaneous phase	2.606557	3.631869

Table 3
Geochemical characteristics of the source rocks.

Formation	TOC, %	S_1 , mg/g	S_2 , mg/g	S_1+S_2 , mg/g	T_{max} , °C	HI, mg/g
$E_3d_2^1$	0.35–3.56 (0.85)	0.01–5.26 (0.47)	0.18–15.57 (2.30)	0.28–16.25 (2.78)	402–451 (437)	49.12–630.44 (242.21)
E_3d_3	0.45–5.33 (2.19)	0.03–6.38 (1.91)	0.13–31.03 (8.03)	0.33–32.16 (9.93)	393–493 (441)	8.96–774.48 (334.45)
E_2S_{1+2}	0.25–6.90 (2.84)	0.02–6.21 (2.20)	0.24–54.29 (12.93)	0.26–59.80 (15.11)	397–457 (434)	14.59–1019.53 (393.45)
E_2S_3	0.80–7.76 (3.10)	0.16–7.59 (2.16)	1.27–58.32 (14.75)	1.62–63.99 (16.93)	418–468 (439)	52.27–1269.75 (426.85)

Note: The values in the brackets represent the arithmetic mean.

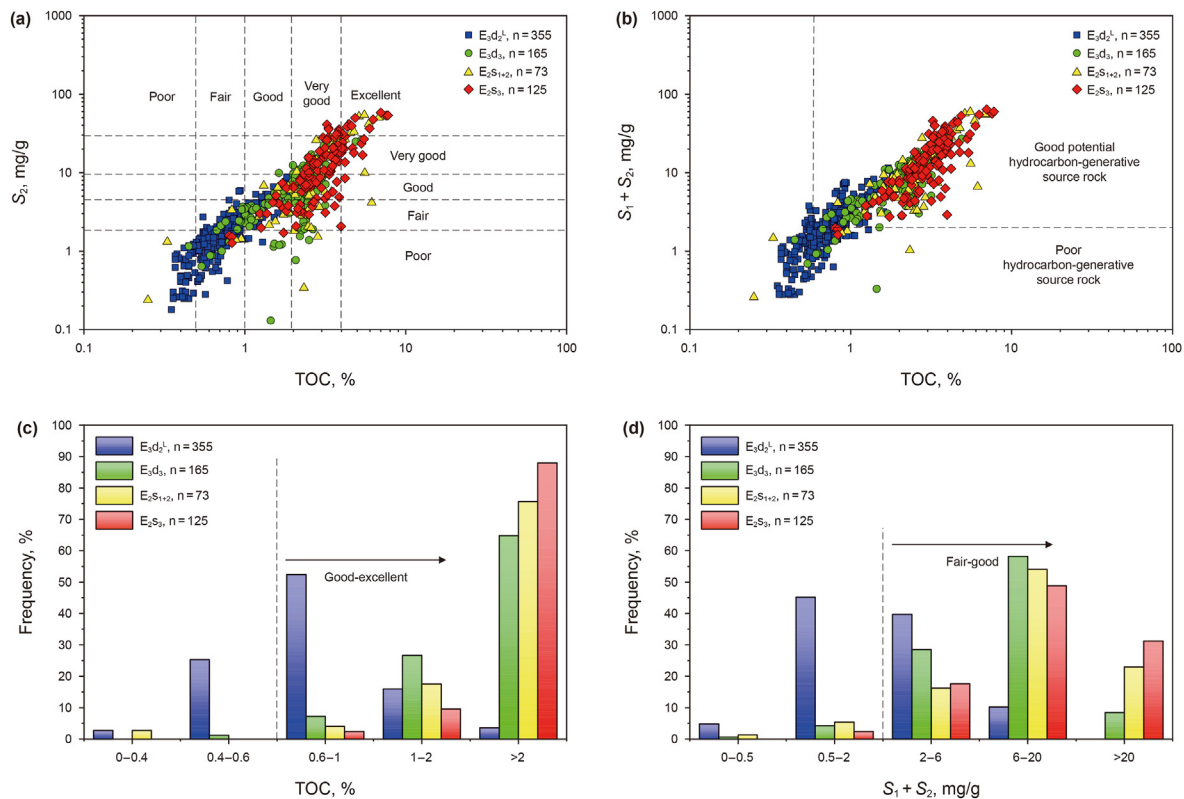


Fig. 12. Geochemical characteristics of source rocks in the study area. (a) Plot of TOC vs. S_2 (after Hakimi and Ahmed, 2016), (b) TOC vs. S_1+S_2 (after Hakimi and Ahmed, 2016), (c) Frequency diagrams of TOC, (d) Frequency diagrams of S_1+S_2 .

model has better prediction ability, and that the area near well Y3 is the high-quality source rocks deposition area with good hydrocarbon generation potential (Fig. 17).

The advantage of seismic method is that it has a high horizontal resolution, and can effectively identify the source rocks that have no samples. Therefore, the evaluation of TOC and S_2 requires not only comparing the seismic near well prediction results with the

logging prediction results, but also making plane distribution of the TOC and S_2 seismic prediction results, and further using the sedimentary facies maps to verify the credibility of this method (Figs. 18, 19 and 20).

As in Fig. 18a, the black dotted bordered rectangle is the seismic workings. During the $E_3d_2^1$ depositional stage, there are mainly braided river delta facies within the seismic workings (the areas of

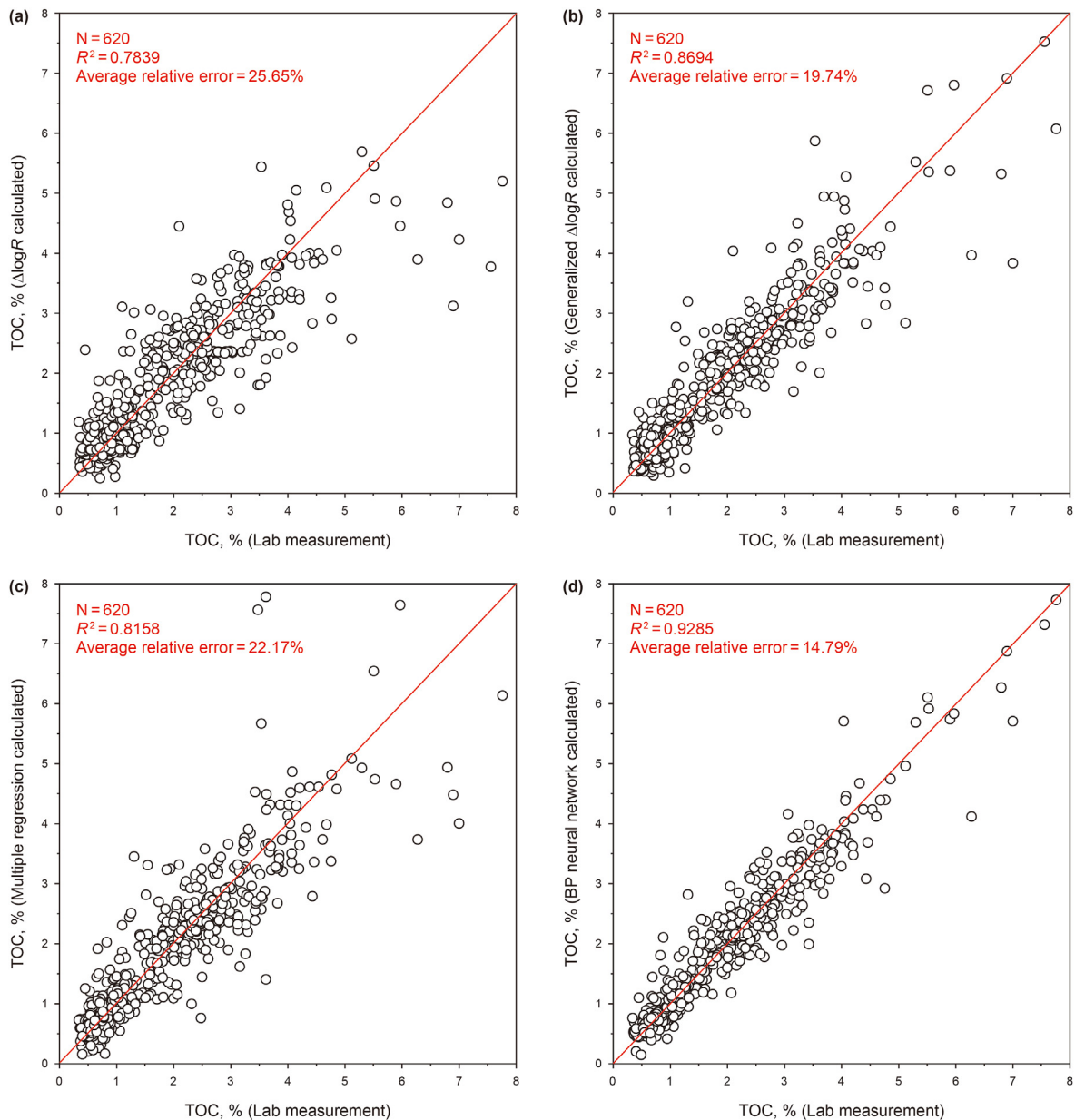


Fig. 13. Four methods to predict TOC determination coefficients, average relative errors analysis charts. (a) Passey's $\Delta\log R$ method, (b) generalized $\Delta\log R$ method, (c) multiple linear regression method, (d) BP neural network method.

Table 4
Comparison of determination coefficient R^2 of different TOC prediction methods.

Strata	Sedimentary facies	$\Delta\log R$ method	Generalized $\Delta\log R$ method	Multiple linear regression	BP neural network
E_3d_2	Braided river delta	0.7632	0.7822	0.7505	0.9086
	Fan delta	0.0482	0.6187	0.7056	0.8492
	Shore-shallow lacustrine	0.6889	0.8125	0.3590	0.8305
	Semi-deep and deep lacustrine	0.1371	0.6131	0.6317	0.8026
	Sublacustrine fan	0.1707	0.2096	0.3409	0.8131
E_3d_3	Braided river delta and fan delta	0.6911	0.8735	0.8656	0.9520
	Shore-shallow lacustrine	0.4012	0.8512	0.7653	0.8755
	Semi-deep and deep lacustrine	0.0195	0.5633	0.6216	0.7162
	Sublacustrine fan	0.5473	0.5518	0.5256	0.9088
E_2S_{1+2}	Shore-shallow lacustrine and braided river delta	0.5124	0.6912	0.4290	0.8156
E_2S_3	Braided river delta	0.5583	0.6932	0.7009	0.9254
	Fan delta	0.1972	0.5281	0.4990	0.6429
	Semi-deep and deep lacustrine	0.2960	0.4676	0.3640	0.6851

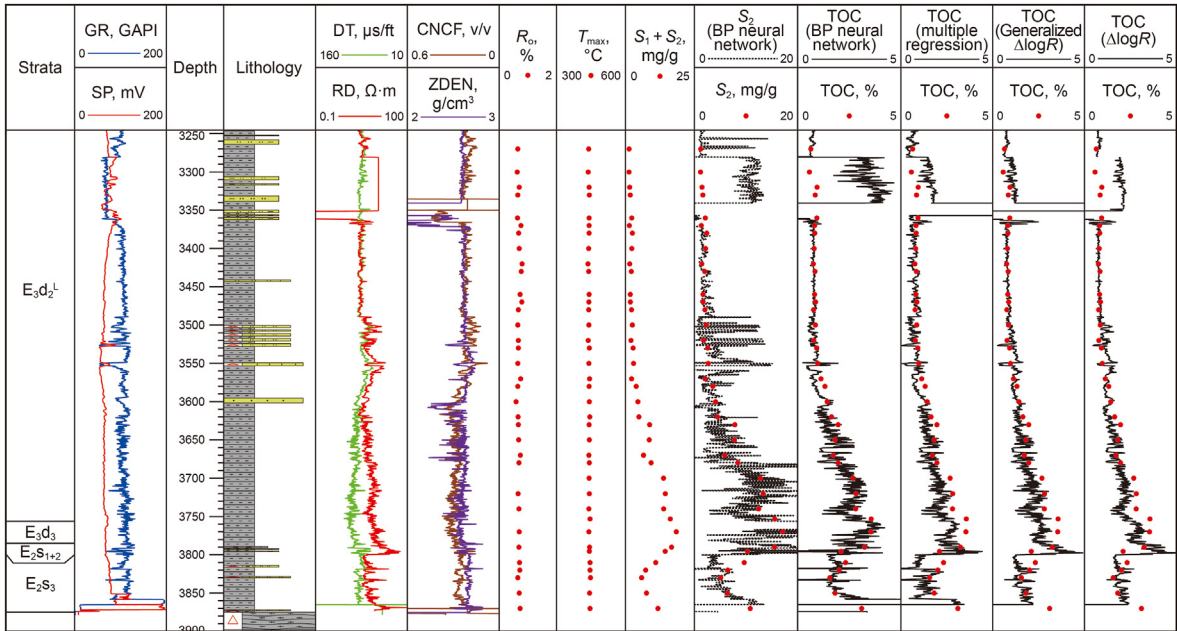


Fig. 14. TOC and S_2 prediction results of well Q3.

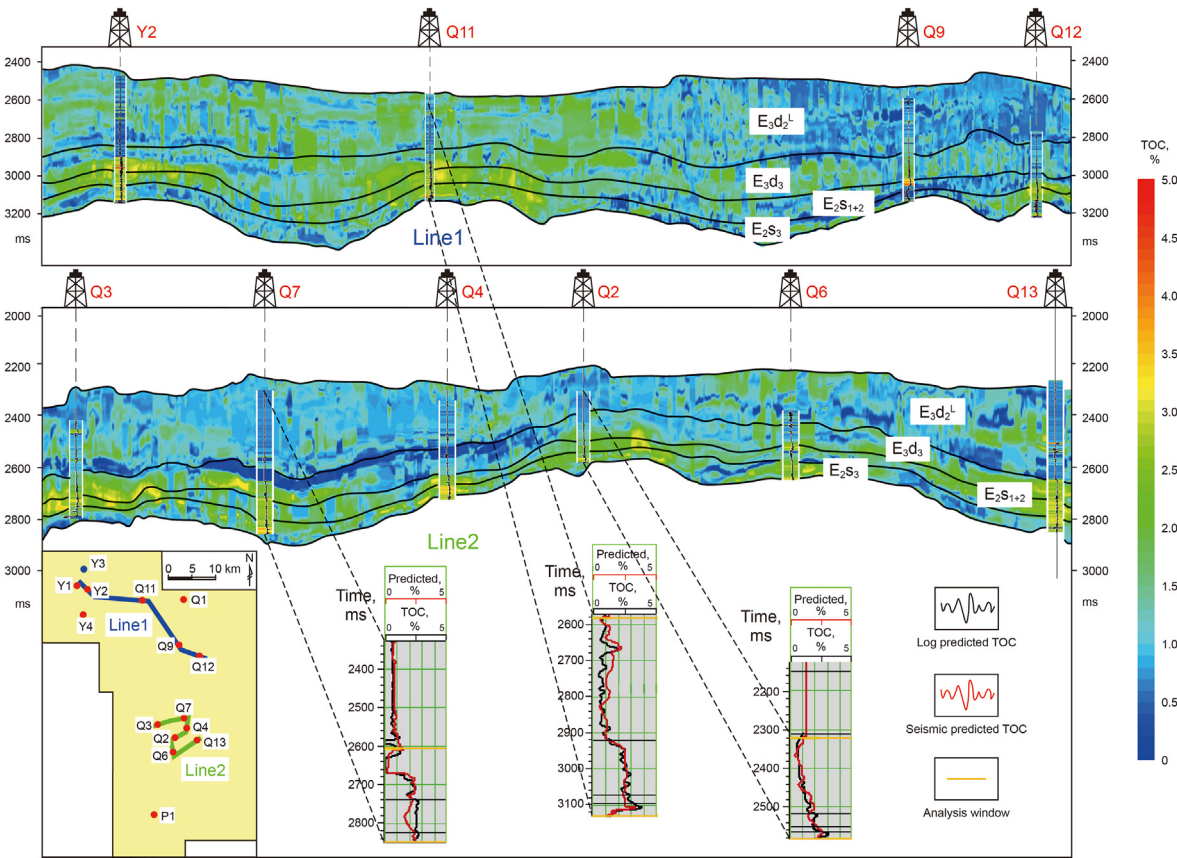


Fig. 15. The TOC prediction results of wells connection section.

well Q2, Q3, Q4, Q6, Q7 and Q13), which are not conducive to the formation of good-quality source rocks, while the areas of well Y1, Y2, Q1 and Q11 are sublacustrine fan, semi-deep and deep lacustrine facies, which are conducive to the deposition of good-quality

source rocks. As in Figs. 19a and 20a, the TOC in the areas of well Y1, Y2, Q1 and Q11 ranges from 1.0% to 2.0% and S_2 ranges from 2 to 6 mg/g, which are fair to good source rocks. The TOC in areas of well Q2, Q3, Q4, Q6, Q7 and Q13 ranges from 0% to 0.4% and S_2 ranges

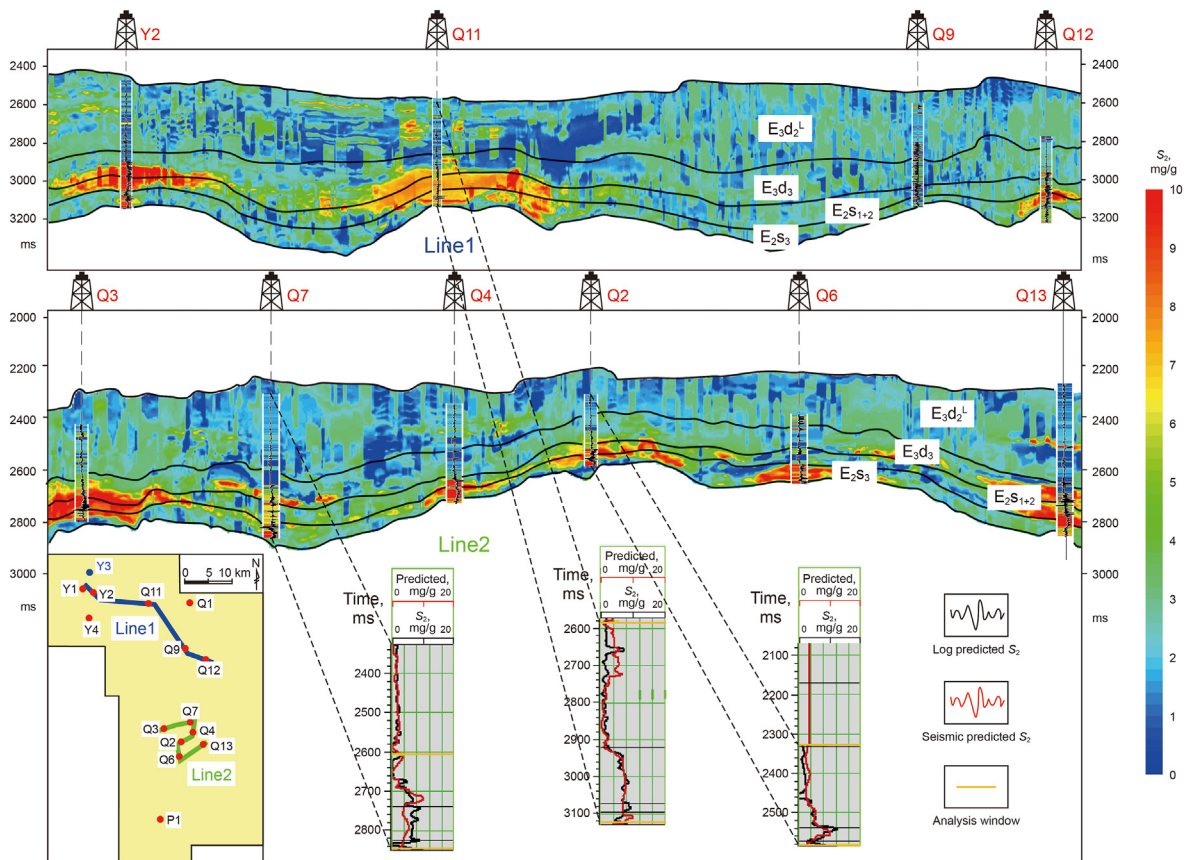


Fig. 16. The S_2 prediction results of wells connection section.

from 0 to 2 mg/g, and the quality of source rocks is poor. The OM abundance of source rocks in the north is better than that in the south, and shows a trend of gradually decreasing from north to south.

As in Fig. 18b, during the E_3d_3 depositional stage, the areas of well Y1, Y2, Y4, Q1 and Q11 in the seismic workings are mainly semi-deep and deep lacustrine facies, the areas of well Q2, Q3, Q4, Q6, Q7, Q13 and P1 are shore-shallow lacustrine facies, and the northern part is favorable for the deposition of good-quality source rocks. As Figs. 19b and 20b, the TOC in the areas of well Y4 and Q11 and the western part of the workings ranges from 1.0% to 2.5% and S_2 ranges from 2 to 6 mg/g, which are fair to good quality source rocks, and TOC in the areas of well Q2, Q3, Q4, Q6, Q7 and Q13 ranges from 0.2% to 0.6% and S_2 ranges from 1 to 3 mg/g, the source rocks are poor to fair quality.

As in Fig. 18c, during E_2S_{1+2} depositional stage, the seismic workings are mainly shore-shallow lacustrine facies, and the western part of the workings are semi-deep and deep lacustrine facies. As in Figs. 19c and 20c, the TOC in areas of well Y2, Q3, Q7 and Q11 ranges from 1.0% to 3.0%, and S_2 ranges from 2 to 8 mg/g, which are good to very good quality source rocks, TOC in the areas of well Q1, Q9 and Q12 is low, ranging from 0.2% to 0.6%, and S_2 ranges from 1 to 4 mg/g, represent fair quality source rocks.

As in Fig. 18d, during the E_2S_3 depositional stage, semi-deep and deep lacustrine facies are developed in the areas of well Y1, Y2, Y4, Q4, Q7, Q9, Q11, Q12 and Q13, sublacustrine fan facies are developed in the areas of well Q2, Q3 and Q6, and shore-shallow lacustrine facies are developed in area of well Q1. As in Figs. 19d and 20d, the TOC in the areas of well Q2, Q3, Q4, Q6, Q7 and Q13 ranges from 1.0% to 3.0%, and S_2 ranges from 2 to 10 mg/g, which are very good

to excellent quality source rocks, and TOC in the areas of well Y1, Y4, Q1, and Q9 is lower, ranging from 0.6% to 1.0%, and S_2 ranges from 2 to 4 mg/g, source rocks are fair quality.

5. Discussions

5.1. Passey et al. (1990) method

Among the methods for estimating TOC from well logs, Passey's $\Delta\log R$ method is based on rigorous petrophysical model derivation and includes fewer well logs (redundant information), using the Wyllie formula and the Archie formula to overlap the porosity logs (usually DT) with the resistivity logs (usually RD). The combination of sonic transit time logs and resistivity logs could eliminate the influence of porosity on the logging response from OM (Passey et al., 1990). However, this method requires the determination of the baseline value, and different baselines are used for different wells and even different intervals, which makes the operation of this method more complicated (Liu et al., 2014, 2021; Zhao et al., 2016). Furthermore, the determination of ΔTOC is mainly based on the empirical, geological settings and geochemical data, which also has significant uncertainty. The overlay-coefficient not only eliminates the effect of on the porosity logging response for OM, but also affects the relative ability to identify kerogen and hydrocarbon fluids. To determine the overlay-coefficient, the proportion of kerogen and hydrocarbon fluids in the source rock should be considered, and the overlay-coefficient value of 2 is not objective enough. Finally, LOM is introduced into the equation, which is generally obtained from a large number of sample analyses (such as vitrinite reflectance, thermal alteration index, Rock-Eval T_{max}

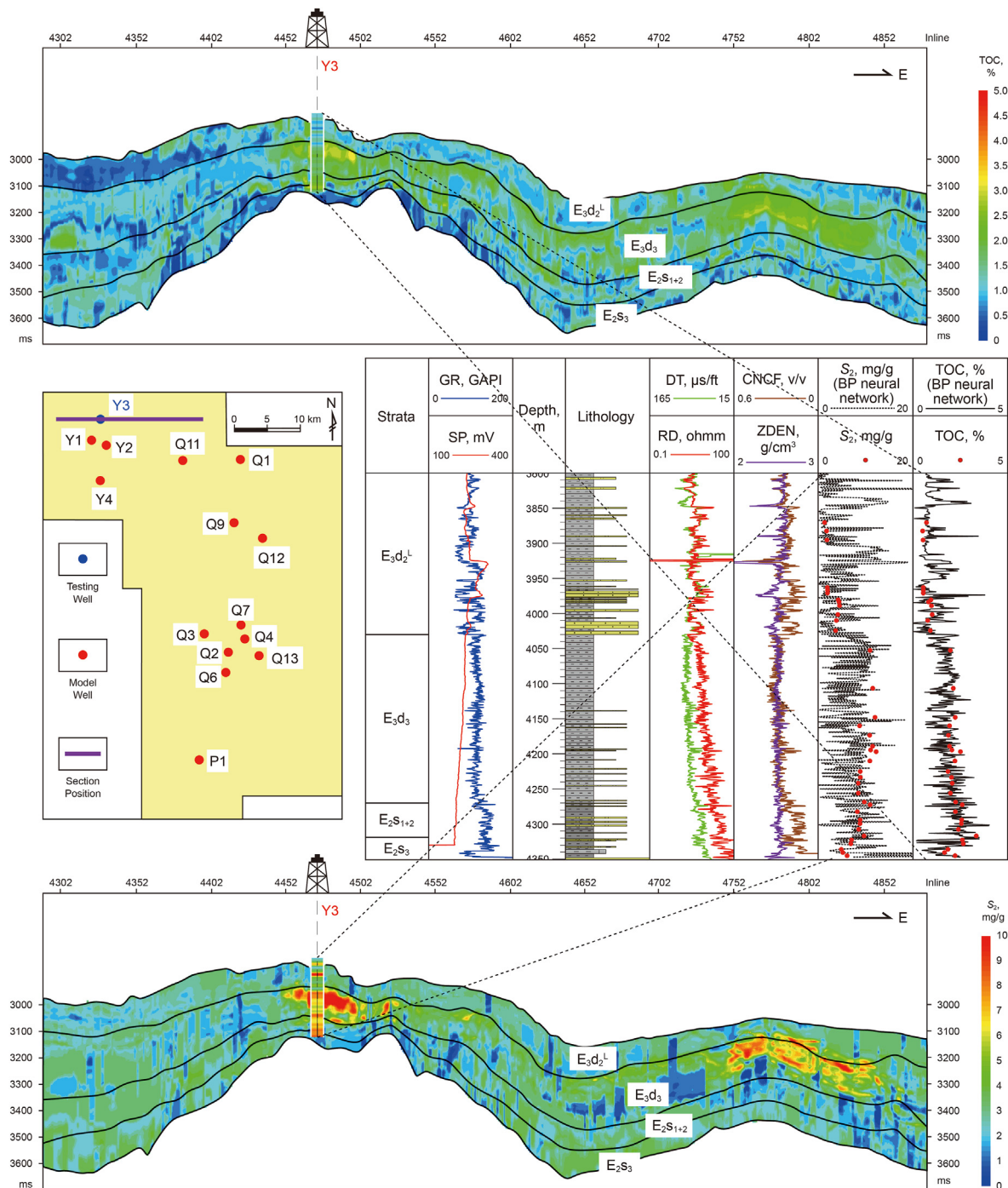


Fig. 17. The TOC and S_2 prediction results of the section cross the well Y3.

analysis), or from burial history and thermal history evaluation (Liu et al., 2014, 2021; Wang et al., 2016; Zhao et al., 2016; Zhu et al., 2019).

5.2. The generalized $\Delta\log R$ method

The generalized $\Delta\log R$ method includes GR and DEN logs, which take into account: A single log curve is easy to be interfered, and multiple logging curves have significant anti-interference ability. The radioactive elements such as U, Th and K usually contained in continental mudstone will lead to high natural gamma value. In

addition, terrestrial facies intervals have intensive compaction effect, while GR log is less affected by compaction effect by compaction and more sensitive to the changes of deep continental source rocks (Hu et al., 2015; Liu et al., 2021). The $\Delta\log R$ method and its improvement methods are widely used in major petroliferous basins, including Songliao Basin, Bohai Bay Basin, Sichuan Basin (Liu et al., 2014, 2021; Hu et al., 2015; Zhao et al., 2016; Zhu et al., 2019) and the Western Basin of Canada (Wang et al., 2016). The $\Delta\log R$ method and its improved methods have been applied effectively in both marine and terrestrial sequences. In particular, some large shale gas fields had been found in the Sichuan Basin in

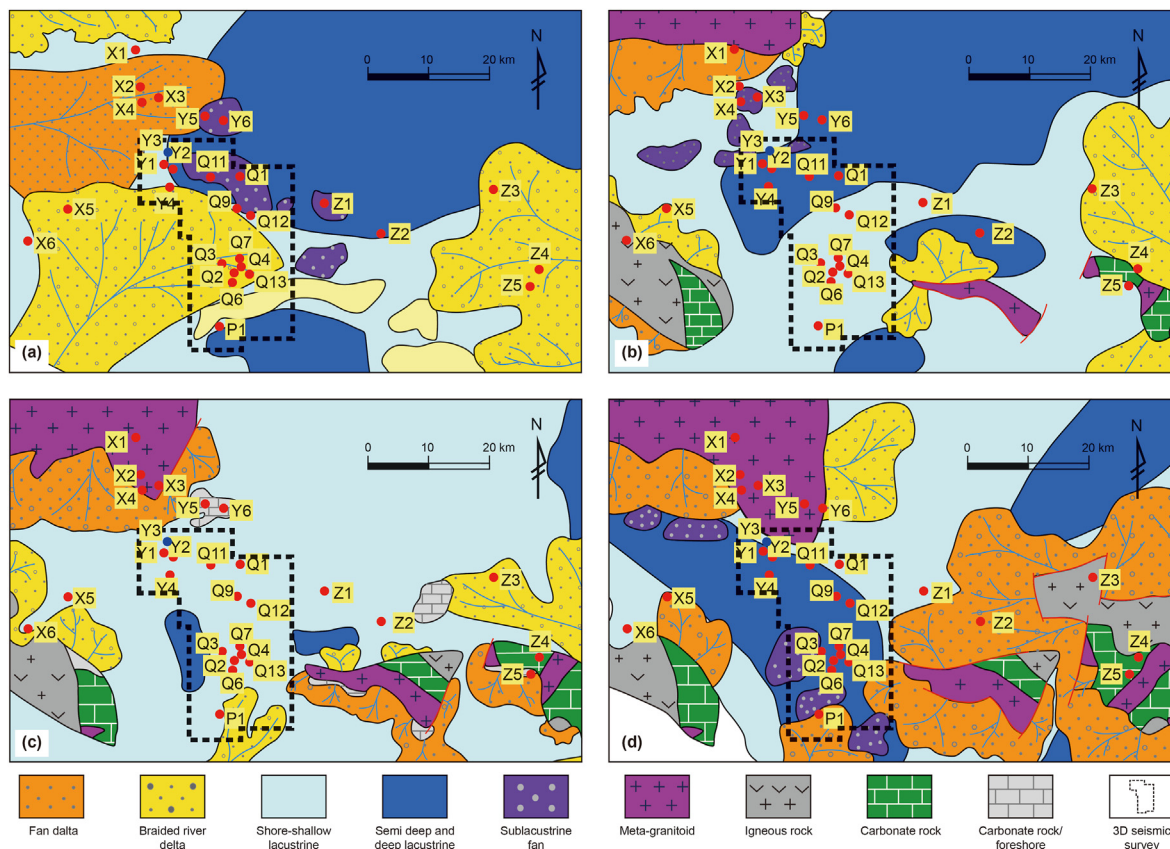


Fig. 18. Sedimentary facies diagrams of southwestern Bozhong Sag (modified from the Exploration and Development Research Institute of CNOOC Tianjin Branch). (a) E_3d_2 , (b) E_3d_3 , (c) E_2S_{1+2} , (d) E_2S_3 .

recent years. The research on geophysical prediction of organic-rich mudstones has become focused issues (Zhao et al., 2016, 2020; Chen et al., 2018; Zhu et al., 2019). In this study, it is found that the prediction accuracy of the $\Delta\log R$ method is relatively low, which may be related to the complexity of geological settings of the Bozhong Sag. The geological settings of rapid subsidence results in significant differences in the burial depth, sedimentary facies, lithology and organic geochemical characteristics of source rocks from each well.

5.3. Multiple regression method

Compared with $\Delta\log R$ method, the multiple regression method is relatively simple to operate. In this study, the correlation coefficients of resistivity and TOC, S_2 are 0.5731 and 0.3425, respectively, which are lower than the sonic transit time and density, which may be related to the low maturity of source rocks in the southwestern Bozhong Sag. There are no hydrocarbon liquids displace formation water in the pores (Hao et al., 2010, 2011; Jiang et al., 2016; Wang et al., 2020). The comparison of prediction results shows that the prediction accuracy of multiple regression method is better than that of Passey's method. The generalized $\Delta\log R$ method uses DT, DEN, RD and GR logs, which are the same as those used by multiple linear regression, so the prediction accuracy of the multiple regression method and the generalized $\Delta\log R$ method is similar. However, the limitations of multiple regression method should not be ignored. The formulas obtained by fitting are not universal enough, different formulas need to be fitted in different geological settings, different basins and even different intervals (Mendelzon and Toksoz, 1985; Aziz et al., 2020; Liu et al., 2021). The

high correlation coefficients of DT and DEN logs with TOC and S_2 indicate that it is feasible to predict OM abundance in this region by using seismic pre-stack inversion (pre-stack P-wave velocity and density inversion results) combined with post-stack seismic attributes.

5.4. BP neural network method

The relationships between TOC and S_2 and well logging are difficult to be expressed by dominant function, which belongs to nonlinear problem, because source rocks are a kind of sedimentary rocks with significant heterogeneity (Huang and Williamson, 1996), mineral composition, pore structure, fluid properties and kerogen affect the petrophysical properties of source rocks, which lead to the great differences in well logging values (Vernik and Nur, 1992; 1996; Carcione, 2000, 2001, 2011, 2015; Hansen et al., 2019), while the neural network methods have incomparable superiority in nonlinear calculation (Kamali and Mirshady, 2004; Bolandi et al., 2015). Neural network methods have been widely used in OM abundance prediction of source rocks (Huang and Williamson, 1996; Kamali and Mirshady, 2004; Bolandi et al., 2015; Tan et al., 2015; Verma et al., 2016; Ji et al., 2018; Wang et al., 2017; Shalaby et al., 2019; Wang et al., 2019; Zhao et al., 2021). Although BP neural network method is better than $\Delta\log R$ methods in prediction accuracy, it does not establish the internal relationships between OM and rock physical parameters, and only builds the neural network model from the perspective of mathematics, without considering the influence of geological settings, and there may be overfitting situation (Liu et al., 2021). In this study, for BP neural network method, the correlation coefficient between the prediction values and the

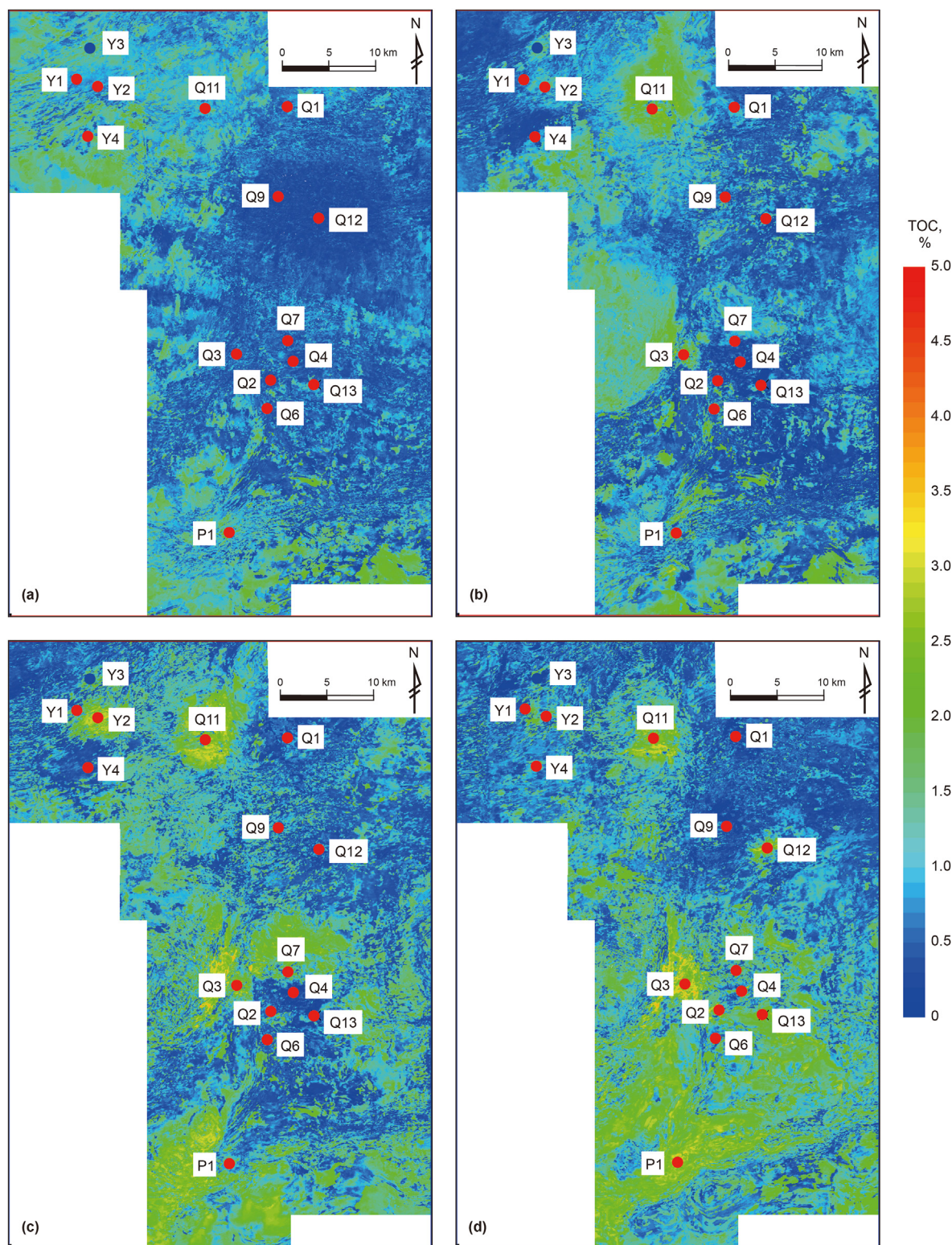


Fig. 19. The TOC planar distribution. (a) E_3d_2 , (b) E_3d_3 , (c) E_2s_{1+2} , (d) E_2s_3 .

measured values of TOC is 0.9285, and the average relative error is 14.79%, indicating that its accuracy is better than the other three methods. The source rocks (E_3d_2 , E_3d_3 , E_2s_{1+2} , E_2s_3) of the southwestern Bozhong Sag are typical continental mudstones. The tectonic movement and sedimentary environment changes in Bozhong Sag resulted in the heterogeneity of source rocks and

differences in the OM enrichment models (Hao et al., 2011; Wang et al., 2020). Therefore, the various TOC prediction methods should be compared to select one that is more consistent with the geological settings of the study area.

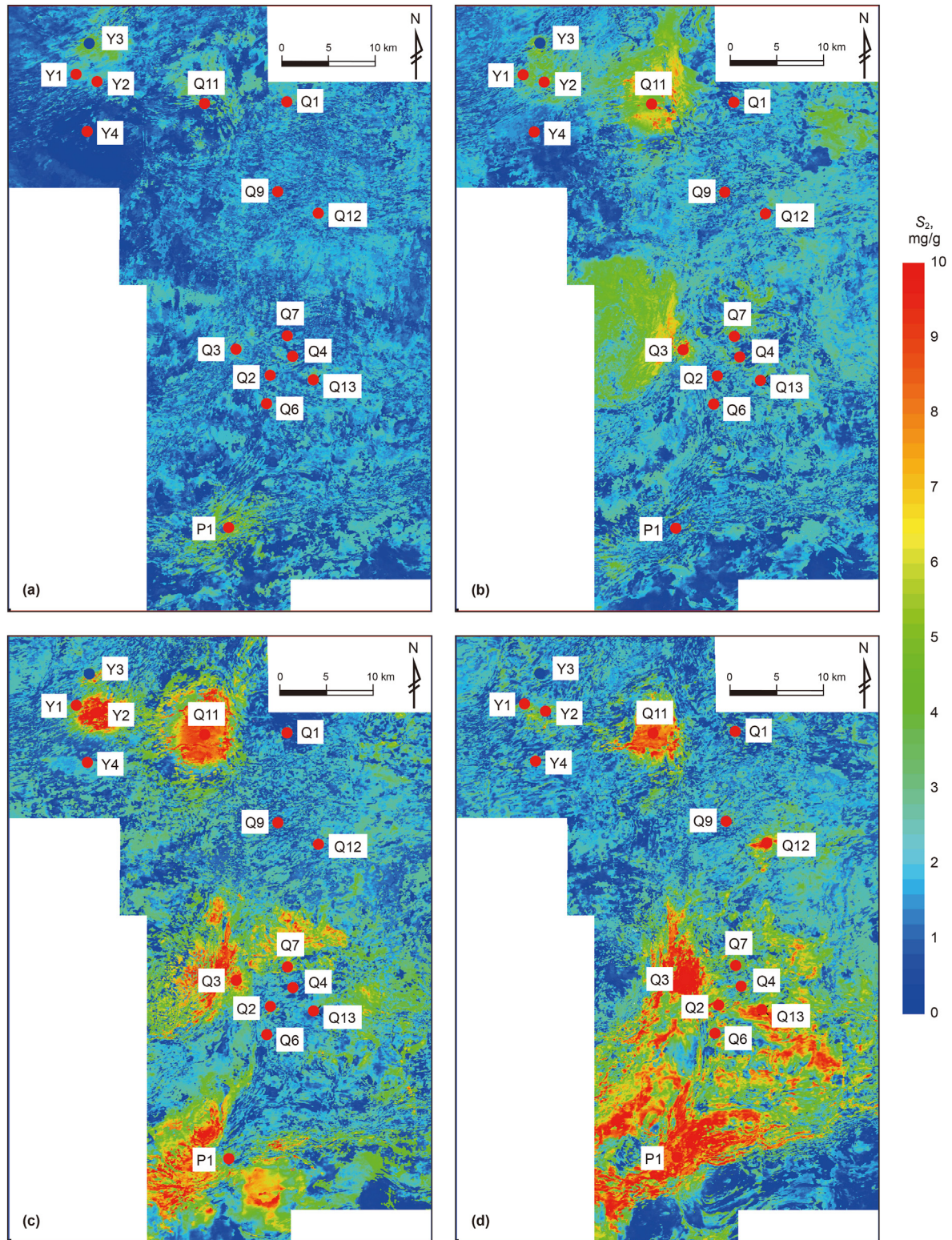


Fig. 20. The S_2 planar distribution. (a) $E_3d_2^1$, (b) E_3d_3 , (c) E_2S_{1+2} , (d) E_2S_3 .

5.5. Seismic multi-attributes fusion method

Among the methods for estimating TOC and S_2 from seismic, post-stack seismic data generally contain less information, and the logical relationships between the post-stack seismic attributes

(amplitude, frequency, phase, etc.) and the OM abundance are not clear enough. Only P-wave impedance inversion results could be obtained by post-stack seismic inversion. In the southwestern Bozhong Sag, it is found that the TOC and S_2 are positively correlated with DT (negatively correlated with P-wave velocity) and

negatively correlated with density through petrophysical correlation diagram (Fig. 5). Therefore, the P-wave impedance, P-wave velocity and density inversion results obtained by pre-stack simultaneous inversion could predict the OM abundance (TOC and S_2) more effectively, and contain more information from pre-stack seismic data, thus achieving higher inversion accuracy. However, compared with post-stack inversion, pre-stack inversion has a larger amount of computation and a longer operation time, so it is not widely used in the industry (Hampson et al., 2005; Sen and Stoffa, 2013; Chen et al., 2018). In this study, when predicting TOC of source rocks, we found that the five attributes reciprocal of P-wave velocity, reciprocal of density, integrated absolute amplitude, dominant frequency and reciprocal of P-wave impedance are the best and have the lowest prediction error. These five attributes include pre-stack inversion, post-stack inversion and post-stack seismic attributes. Moreover, TOC has the best correlation with the reciprocal of P-wave velocity and reciprocal of density, indicating that the method of combining pre-stack simultaneous inversion, post-stack inversion and post-stack seismic attributes is more effective in this study. The correlation coefficients of the seismic prediction results near well and logging prediction results are relatively high (TOC: 0.7797, S_2 : 0.7175). Geochemical analysis of well Y3 also shows a high correlation between well logging and seismic predictions, and the plane prediction results are relatively consistent with the sedimentary facies map of the southwestern Bozhong Sag, it is an effective method for the research of source rocks in the areas with low-degree exploration.

6. Conclusions

Organic geochemical testing, petrophysical analysis, pre-stack and post-stack seismic inversion, and multi-attributes analysis are integrated to evaluate OM abundance of source rocks in southwestern Bozhong Sag, Bohai Bay Basin. A summary of key observations from this study follows:

- (1) The OM abundance of Shahejie Formation is higher than that of Dongying Formation in southwestern Bozhong Sag. E_2S_{1+2} and E_2S_3 source rocks have the highest OM abundance, which indicating good to excellent hydrocarbon generative potential; E_3d_3 source rocks are fair to good quality source rocks; E_3d_2 source rocks have poor to fair hydrocarbon generative potential.
- (2) The accuracy of BP neural network method in predicting TOC and S_2 is higher than that of $\Delta\log R$ series methods and multiple linear regression method.
- (3) The seismic near wells prediction results of TOC and S_2 correspond well with the logging prediction results, and the plane prediction results are highly consistent with the sedimentary facies. The multi-attributes method, which combines pre-stack seismic inversion, post-stack seismic inversion and seismic attributes, shows high horizontal resolution and compensates the limitations of geochemistry and well logging methods.

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.

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