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Application of seismic multi-attribute inversion based on wireless network sensor in Dongying delta foreset

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Research

Keywords: wireless network sensor, seismic multi-attribute inversion, deep neural network (DNN), delta foreset

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Application of Seismic Multi-Attribute Inversion Based on Sensor Network and Deep Neural Networks

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Abstract: Seismic attributes, which are extracted from seismic information, are physical indexes used specificallyfor the measurement of geometric, dynamic, or statistical characteristics of seismic data. Current methods for seismic multi-attribute inversion include linear and nonlinear methods. By adopting the wireless module of NFC24l01, combined with the seismic data acquisition sensor, constitutes an intelligent network sensor, and then it sends the collected data to the topmost machine for analysis.Methods for the nonlinear inversion of seismic multi-attributes usually employ tools such as neural networks and support vector machines (SVMs)for mapping. Hence, inversion results obtained via nonlinear methodsare more accurate than those obtained via linear methods. In this work, with spontaneous-potential (SP) curves as the objective of nonlinear inversion, an optimized seismic attribute combination for the inversion of SP curves was identified, and the nonlinear inversion of seismic multi-attributes was achieved via the use of a deep neural network (DNN) to obtain 3D SP data. Finally, the foresetting process of a sand body of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta was illustrated via the horizon slice of the SP data.

Keywords: Sensor network; seismic multi-attribute inversion; deep neural network; delta foreset

1. Introduction

Seismic attributes are closely related to reservoir parameters. However, the seismic data acquisition way is less concerned. Wireless sensor network (WSN) is a set of advanced technology in the integration of information technology, it is not only a universal computer, and also the effective

extension of human senses, the data transmission and exchange as the center, as a kind of self-organized and distributed network, a large number of sensor nodes in sensor network to provide the data, even in very poor conditions, also can do real-time monitoring, cooperative awareness and information collection, and send the monitoring data.This makes wireless sensor networks widely used in many fields.

Seismic attribute analysis involves the prediction of reservoir parametersbased on seismic attributes[1-3] and has played an increasingly important role in the exploration and exploitation of oil and gas. Seismic attributes are closely related to reservoir parameters[4], but they have no direct analytic relation. The basic concept of the nonlinear inversion of seismic multi-attributes[5,6]is to establish a nonlinear relation of seismic multi-attributes and reservoir parameters via mathematical methods(e.g., multi-variable stepwise regression, neural networks, support vector machines (SVMs), and the co-Kriging method[7-9] and obtain information required by reservoir prediction.

In this work, spontaneous-potential (SP) curves were employed as the objective of the nonlinear inversion of seismic multi-attributes.First, an optimized seismic attribute combination for the inversion of SP curves was identified via nonlinear regression. Then, 3D SP data was obtained by the nonlinear inversion of seismic multi-attributes based on a deep neural network (DNN). Finally, the foresetting process of a sand body of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta was illustrated by the horizon slice of the SP data body. The practical application results indicate the good application performance and great potential of the proposed nonlinear inversion of seismic multi-attributes.

2. Principles and methods

2.1 Optimization of seismic attributes

The optimization of seismic attributes aims to retrieve the optimized attribute combination from various seismic attributes via stepwise regression methods[10]. First, the correlations between each single attribute and the conversion curve were calculated, and the attribute with the highest correlation was retained. Then, the second, third, …, x^{th} (where x refers to the designated maximum attribute number) optimized attributes were retrieved from the remaining attributes according to the root mean square criterion.

2.2 Convolution operator

The value of the parameter to be inverted at the sampling point of the curve is dependent on both its attribute and several points above and below the corresponding seismic attribute point. Therefore, the value of the parameter to be inverted at the sampling point of the curve is correlated to points above and below the corresponding seismic attribute point to further improve the stability of the multi-attribute inversion solution. This can be achieved by the convolution operator:

$$L = \omega_0 + w_1^m * A_1 + w_2^m * A_2 + ... + w_n^m * A_n \,, \tag{1}$$

where L refers to the parameter to be inverted, $\omega_0$is a constant, $w_1^m, w_2^m, \cdots, w_n^m$ are convolution operators, m refers to the length of the convolution operator, and $A_1, A_2, \cdots, A_n$ are N attributes retrieved via the optimization of attribute combination.

Eq. (1) can be simplified as:

$$L = Aw. \tag{2}$$

For accurate data model parameters, the convolution operator can be expressed as:

$$w = A^{-1}L \ . \tag{3}$$

However, practical data cannot accurately fit the model due to experimental error:

$$L = Aw + e_i \ \ , \tag{4}$$

where e_i refers to the error.

The most effective way to obtain the unique solution of a model parameter is the minimization of the sum of square of errors:

$$q = e^T e = \sum_{i=1}^{5} (L_i - \sum_{j=1}^{12} A_{ij} w_j)^2 \tag{5}$$

or

$$q = (L - Aw)^T (L - Aw) \ \ , \tag{6}$$

where q refers to the sum of square of errors, T refers to the matrix transposition, L_i refers to the parameter to be inverted, A_{ij} refers to the seismic attribute, and w_j refers to the convolution operator.

The derivation of Eq. (6) leads to:

$$\frac{\partial q}{\partial w_j} = \frac{\partial\left[L^T L - L^T A w - w^T A^T L + w^T A^T A w \right]}{\partial w_j} . \tag{7}$$

The canonical equation is:

$$2A^T A w = 2A^T L . \tag{8}$$

The estimated least squares solution of the parameter can be obtained:

$$\hat{w} = \left[A^T A \right]^{-1} A^T L . \tag{9}$$

In this way, the convolution operator is obtained.

2.3 Deep neural network

A DNN is essentially a modified version of conventional neural networks,and its structure is illustrated in Fig. 1. A typical DNN consists of an input layer, output layer, and several hidden layers. Each layer has several nodes that are connected by weights, and the results of the output layer are determined by the weights[11,12]. In this study, a DNN consisting of one input layer, one output layer, and three hidden layers was used. Herein, a convolution operator is involved, and the seismic attribute is convoluted with the convolution operator before being used as the input of the DNN.

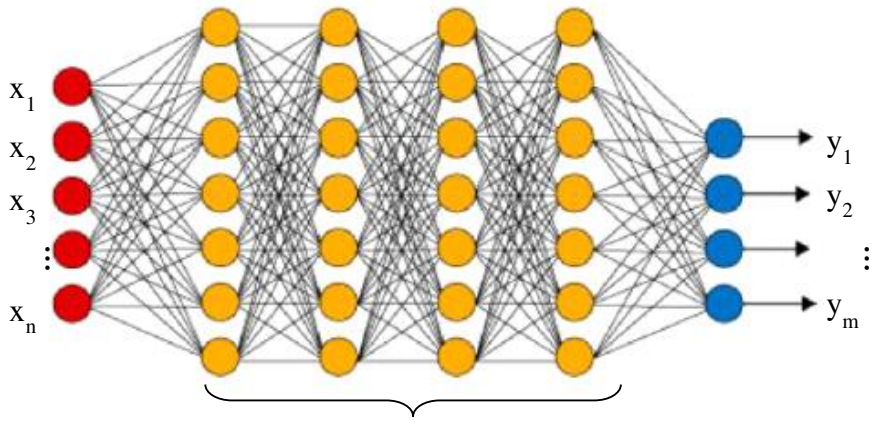

Fig. 1. Schematic of the DNN structure.

The optimized weights of nodes in hidden layers can be calculated via the learning process of the DNN, and network training can be realized by employing a training set as the input of the DNN. Weight determination can be regarded as a nonlinear optimization process, the objective of which is the minimization of the mean square error of the practical target log value and predicted target log value. Solutions can be obtained by methods such as back propagation[11,12].

In summary, seismic multi-attribute inversion involves the establishment of a nonlinear relation of seismic multi-attributes and SP via mathematical methods. The SPs of strata are calculated based on the log data of known wells, and the lithology of strata can be identified by the inversion of SP parameters based on seismic data[13,14].

3. Practical applications

Delta is a product of the combination of water basin, the river input, tides, waves, and the impact of factors such as tectonic and climate, with complex composition and sedimentary characteristics, sedimentary environment. Delta is a kind of very important sedimentary environment. Many oilfields in China, such as daqing oil field, shengli oilfield, changqing gas field, xinjiang oilfield, delta sand body are main reservoir and is an important part in oil and gas gathering. For Member 3 of the Shahejie Formation in the Dongying Delta, the sedimentary period was the peak of fault subsidence[15,16], during which large-scale delta systems were developed. In previous studies[17,18], the intermediate section in Member 3 of the Shahejie Formation in Dongying Delta was divided into nine stages (labeled as z1 through z9). However, the distribution range and location of the convolutional sand body of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta remain unclear. In this study, the foresetting range and process of the sand body of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta were illustrated by the horizon slice of the SP data obtained via seismic multi-attribute inversion.

According to the velocity curves of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta forest, the velocity of sandstone is slightly higher than that of mudstone, while characteristic impedances of sandstone and mudstone are not significantly different. Indeed, the longitudinal wave velocities of sandstone and mudstone are concentrated in the range of

3000-4500 m/s, as shown in Fig. 2. Therefore, it is highly difficult to directly distinguish sandstone and mudstone via wave velocity or characteristic impedance. Further analysis of the SP curves reveals that the SPs of mudstone are concentrated in a high-value zone, while those of sandstone are concentrated in a low-value zone. Therefore, it can be concluded that sandstone and mudstone can be effectively distinguished, and the forest sand body in the delta can be identified by SPs.

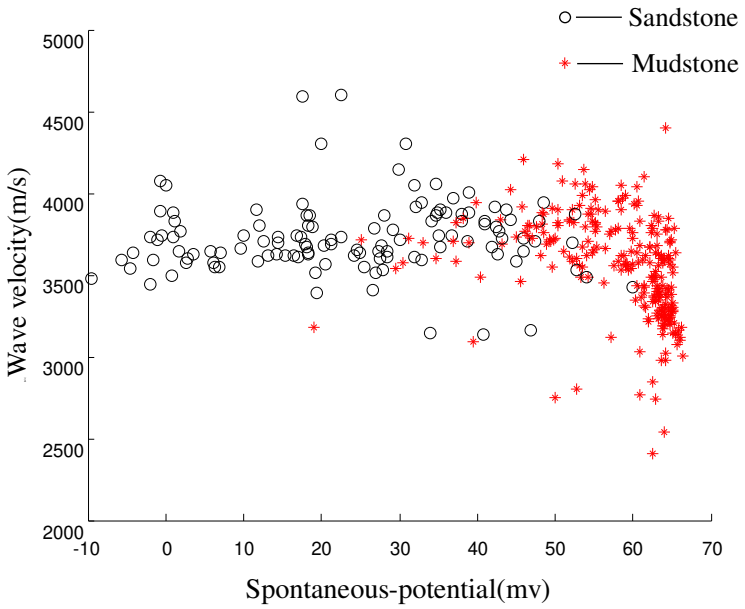

Fig. 2. Wave velocity vs.SP of sandstone and mudstone in the target area.

In the target area, inversion wells were selected to be uniformly distributed. To enhance the inversion performance, the SP curves of some logs involved in multi-attribute inversion were normalized, as presented in Fig. 3.

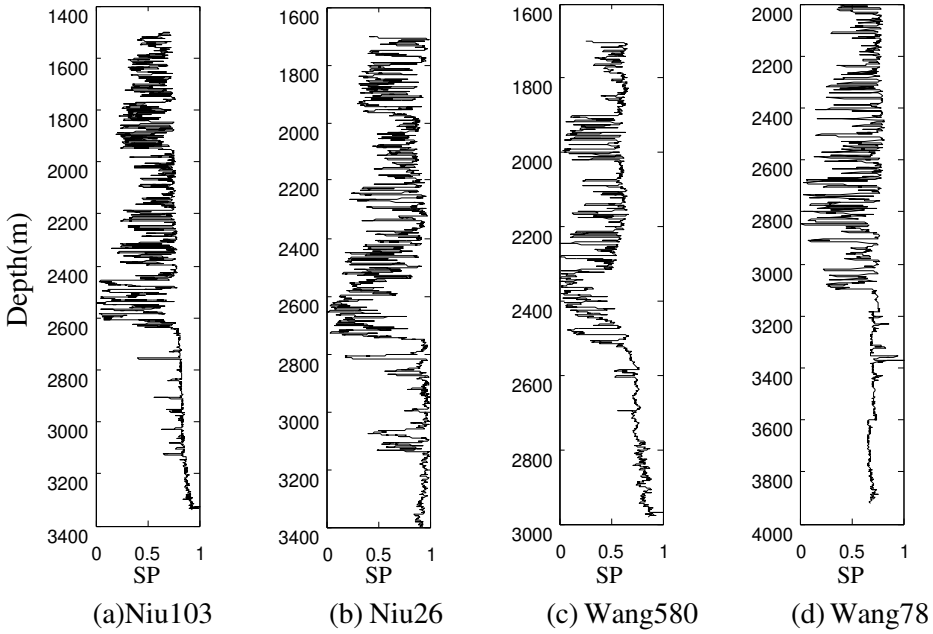

Fig. 3. SP curves of some logs involved in multi-attribute inversion (after normalization).

The optimization of the seismic attribute combination was first conducted. In Fig. 4, the *x*- and *y*-axes denote the quantity of seismic attributes and the error, respectively. As the quantity of seismic attributes increases, the training error decreases, while the testing error decreases and then increases,indicating that abundant seismic attributes lead to degraded system stability and reduced prediction accuracy. Therefore, the first five seismic attributes were employed as the input of the DNN, as exhibited in Table 1.

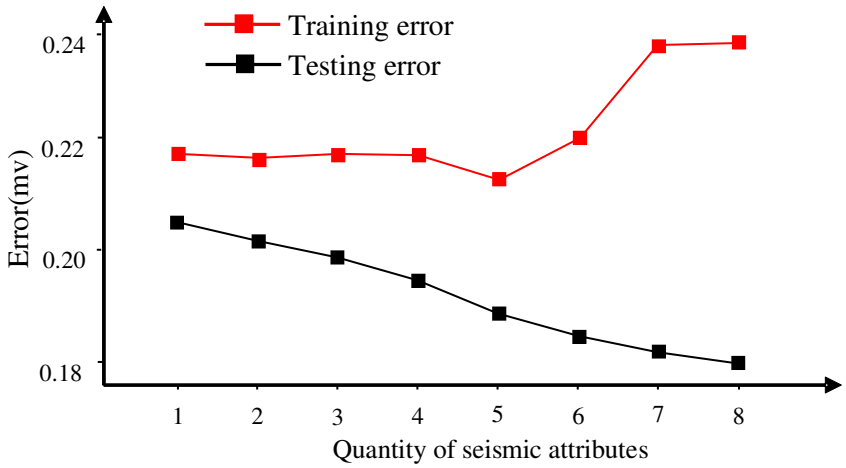

Fig. 4. Quantity of seismic attributes vs. error.

Table 1. The first five seismic attributes used for multi-attribute inversion.

	Seismic attribute	Training error	Cross-test error
1	Average frequency	0.209	0.221
2	Absolute amplitude	0.204	0.226
3	Transient phase	0.201	0.227
4	Band-pass filtering	0.200	0.223
5	Apparent polarity	0.198	0.220

Fig. 5 shows an east-west well section of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta as obtained by multi-attribute SP inversion. As is evident, the inversion results are highly consistent with the SP curves of all wells. Additionally, section-by-section inversion reveals that this delta is a prograded delta with provenance in the southeast area. The development of the subfacies are delta plain, delta front, and front delta, successively.

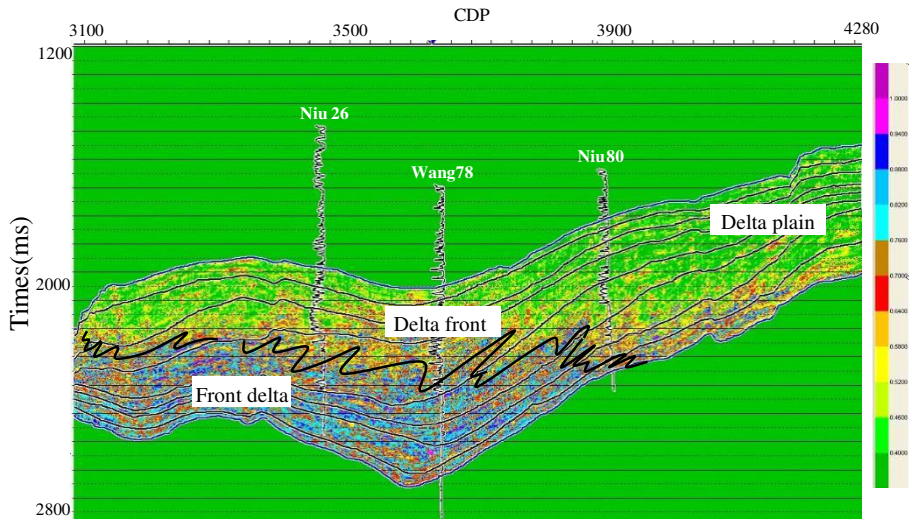

Fig. 5. Well section of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta as obtained by multi-attribute SP inversion.

Fig. 6 illustrates the slice of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta as obtained by multi-attribute SP inversion. As can be observed, the foresting process of the delta sand body consists of several stages. At the z7 stage, the target area was dominated by a deep/semi-deep lake, delta lobes coming from the southeast and northeast areas pronograde towards the

northwest and borders, and foreset sand body was concentrated in the east area. At the z5 stage, the target area was still dominated by a deep/semi-deep lake, while the delta sand body significantly pronograde towards the northwest. Additionally, provenance from the Weibei Hump delta in the southeast provided sufficient supply; progradation was significant, and the prograded sand body crossed the middle part of the target area. At the z3stage, the lake basin area shrank drastically, and deep/semi-deep lake sediments were only distributed in the northwest part of the target area. Additionally, delta lobes from the northeast and south are asmerged and prograded westwards, provenance from the Weibei Hump provided continuous supply via two main river channels,and the sand body thickness was maximized in this area. At the z1 stage, the foreset sand body prograded to the west part of the target area, deep/semi-deep lake sediment in the target area nearly disappeared, delta lobes from northeast and south areas merged,and the pattern was not very sharp. Additionally, river channels for provenance supply intertwined with each other.

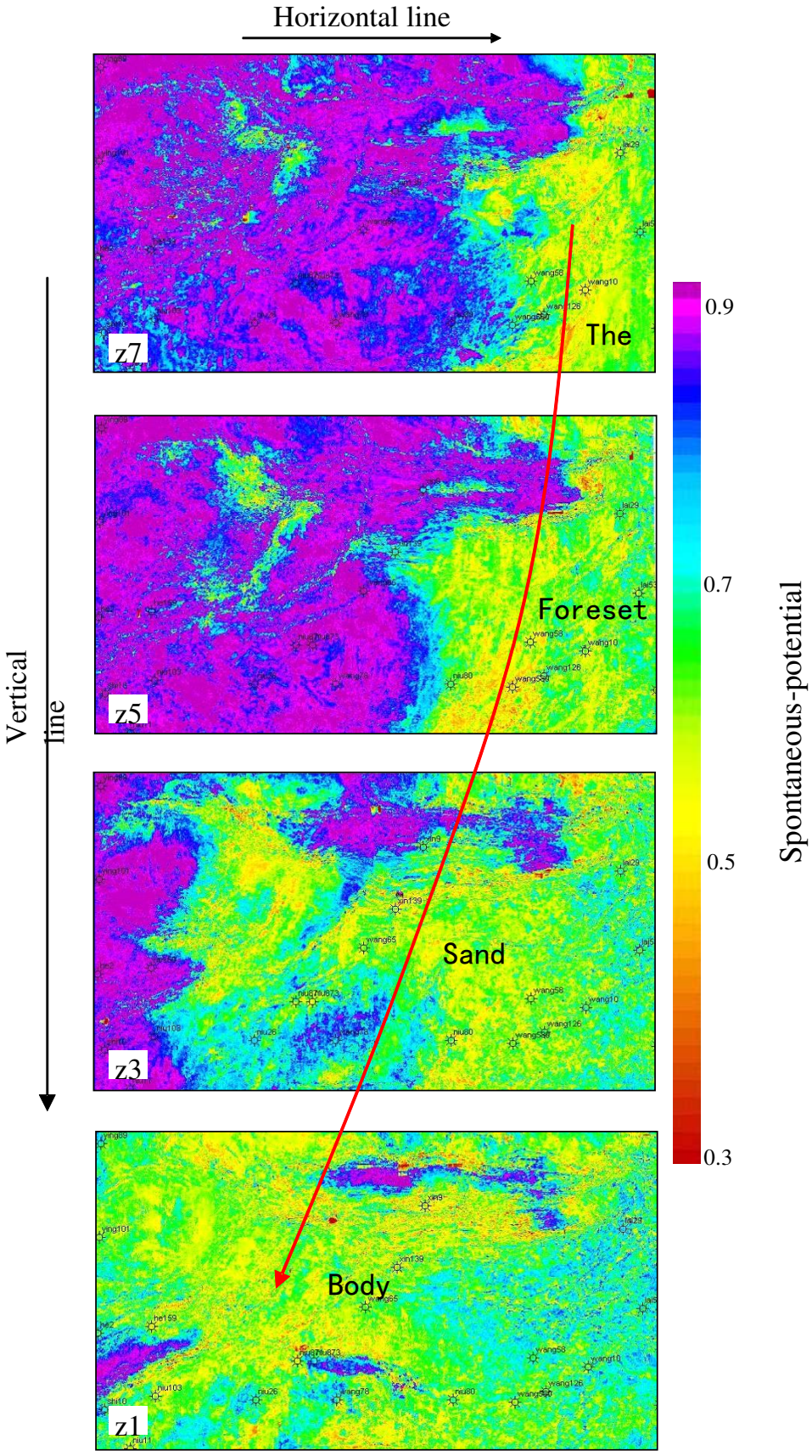

Fig. 6. Horizon slice of the intermediate section in Member 3 of the Shahejie Formation in the

Dongying Delta as obtained by multi-attribute SP inversion. The yellow is sand; green is silt; purple is mud and blue is silty-mud.

4. Conclusions

Seismic multi-attribute inversion has been an effective method for lithological inversion, especially for areas where it is difficult to distinguish sandstone and mudstone bycharacteristic impedances. In this study, the foresetting process of the sand body of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta was described by the nonlinear inversion of seismic multi-attributes with SP curves as the objective of nonlinear inversion. Seismic multi-attribute nonlinear inversion is essentially a modified version of conventional seismic inversion methods. This method does not rely on any specific forward model or seismic wavelets, and is suitable for many applications.

List of abbreviations

(SVMs) Support Vector Machine Svm

Declarations

Availability of data and material

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

declares that he has no conflict of interest.

* Research involving human participants and/or animals

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

* Informed consent

All authors agree to submit this version and claim that no part of this manuscript has been published or submitted elsewhere.

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Authors' contributions

YuanyuanWang was responsible for the collection of experimental data, and CuiWang was responsible for the simulation and simulation of the experiment

Acknowledgements

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Availability of data and material

The datasets used and analysed during the current study are available from the corresponding author.

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Figure 1:

Title: Schematic of the DNN structure

Legend: Figure 1 show Schematic of the DNN structure

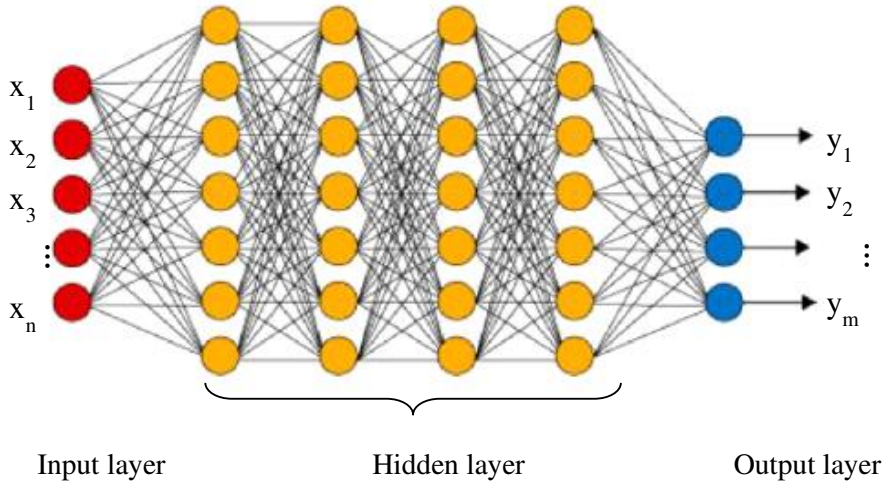

Figure 2:

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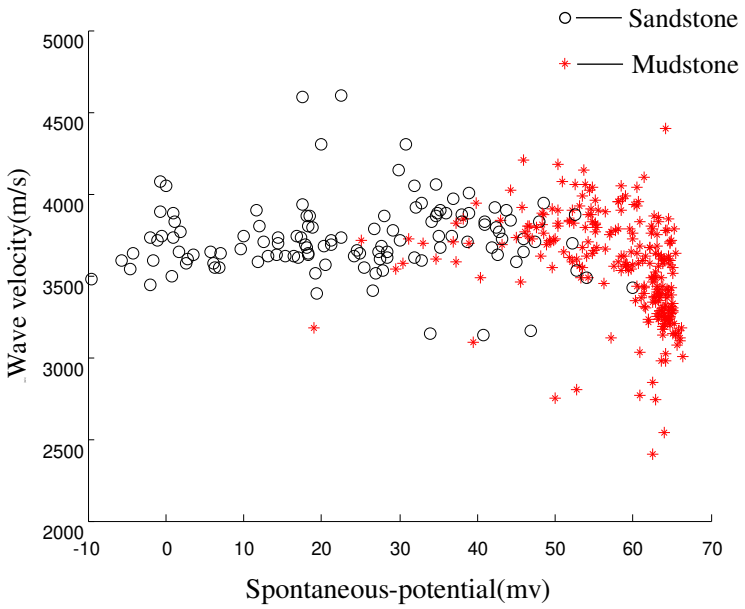
Legend: Figure 2 show Wave velocity vs.SPof sandstone and mudstone in the target area



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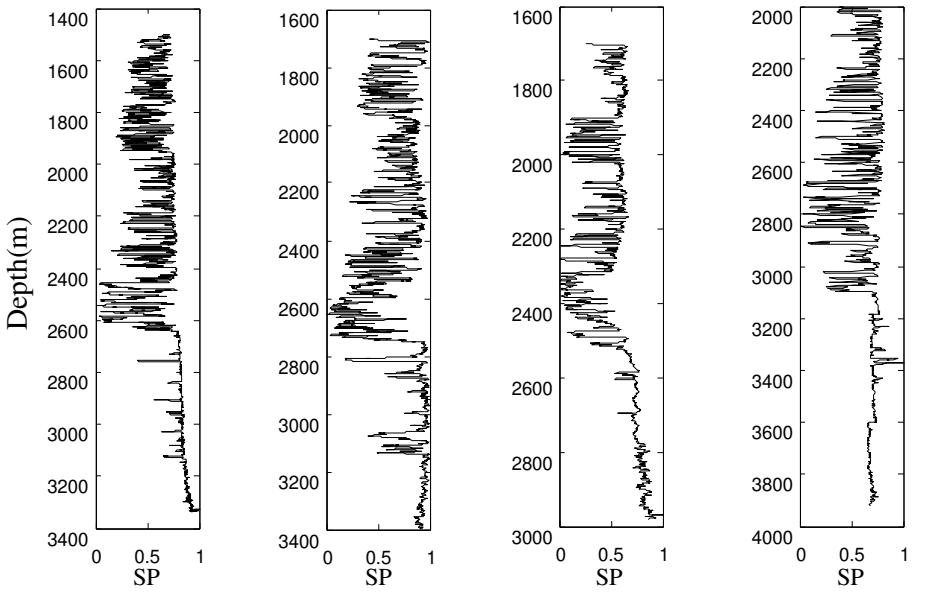

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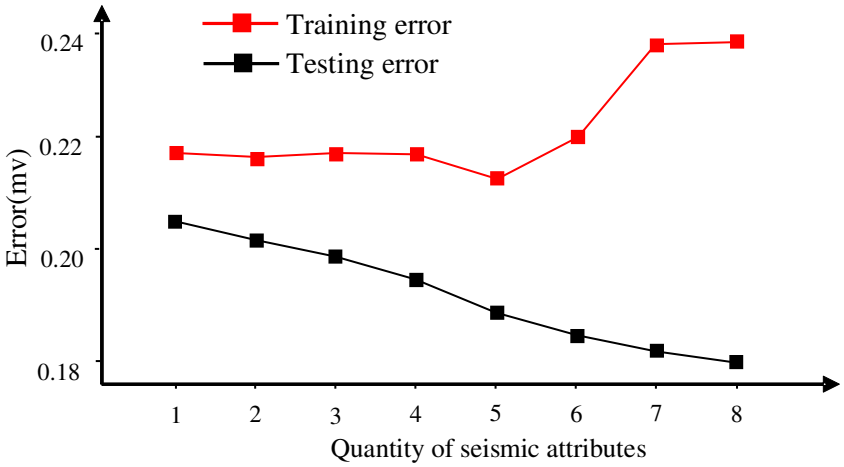

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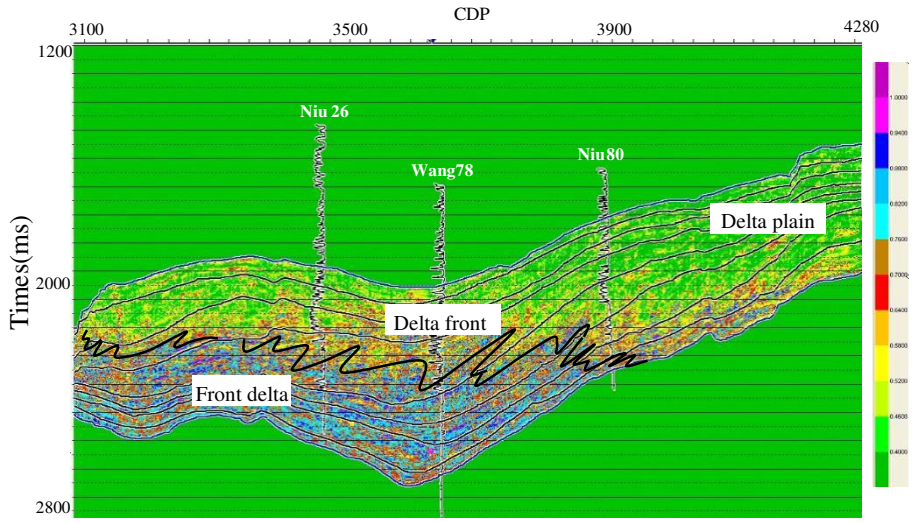

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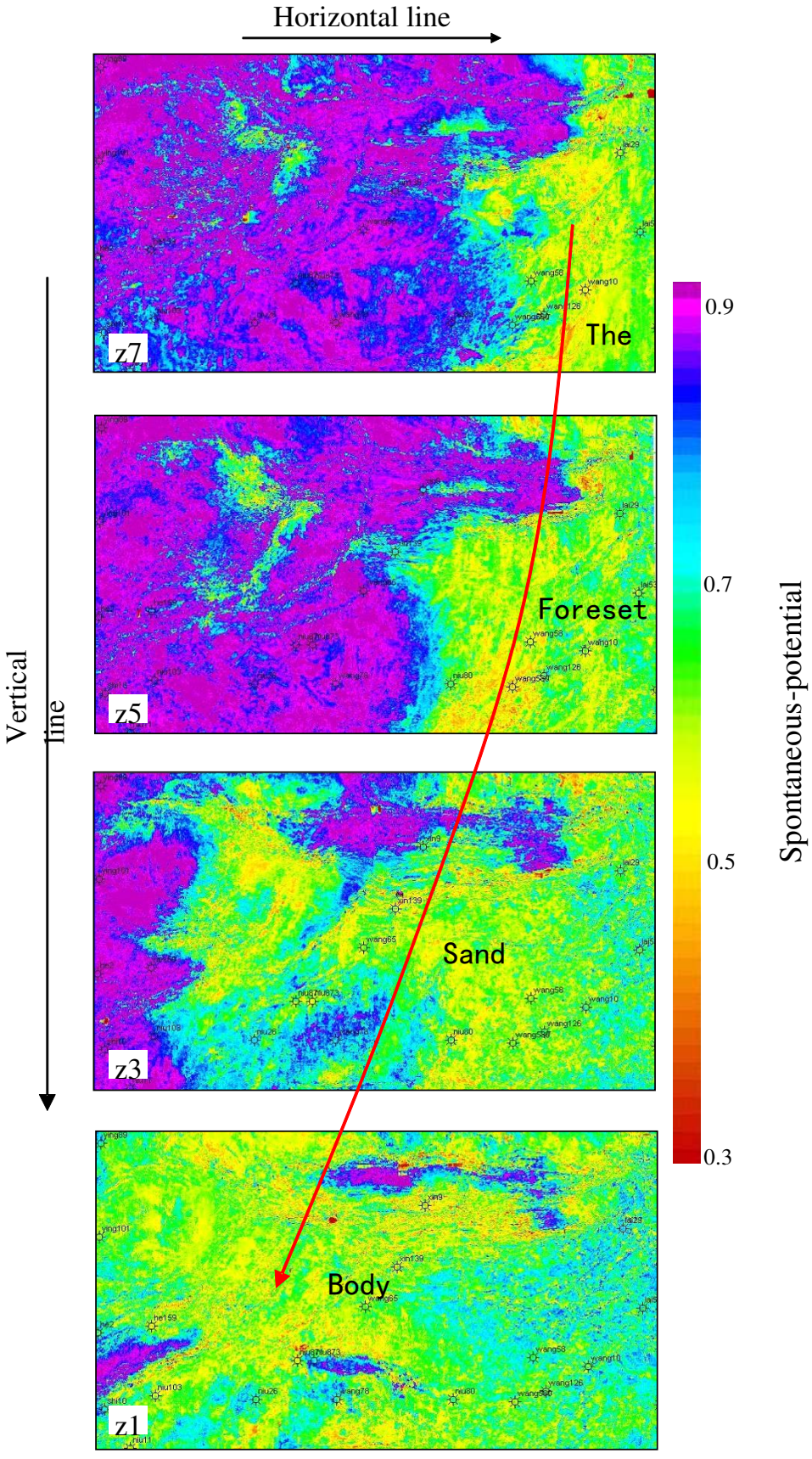
Horizontal line
Vertical line
z7
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Spontaneous-potential

Figures

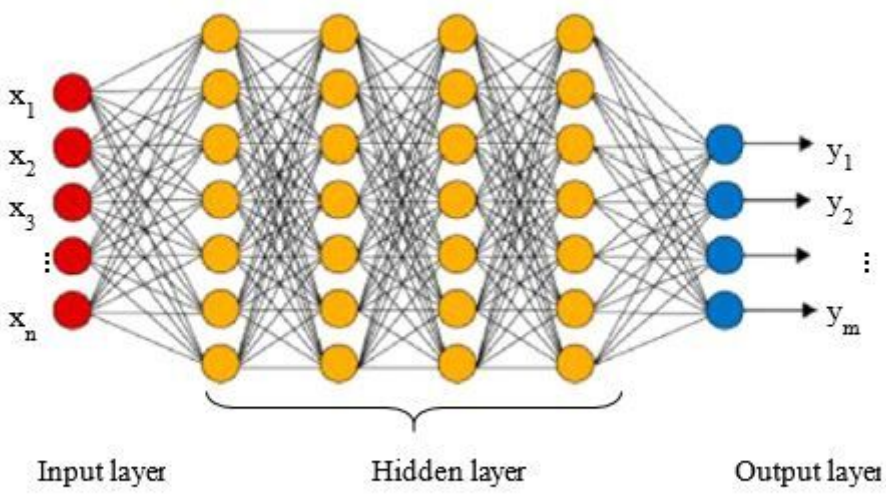
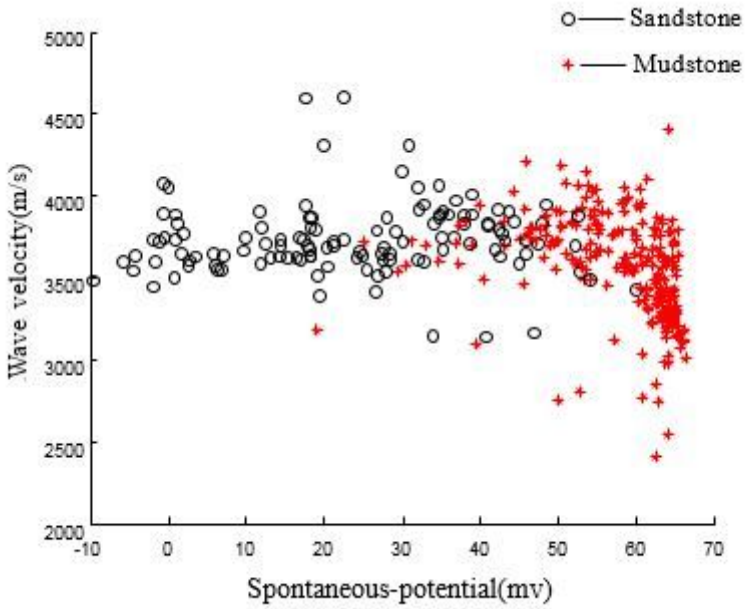


Figure 1

Schematic of the DNN structure



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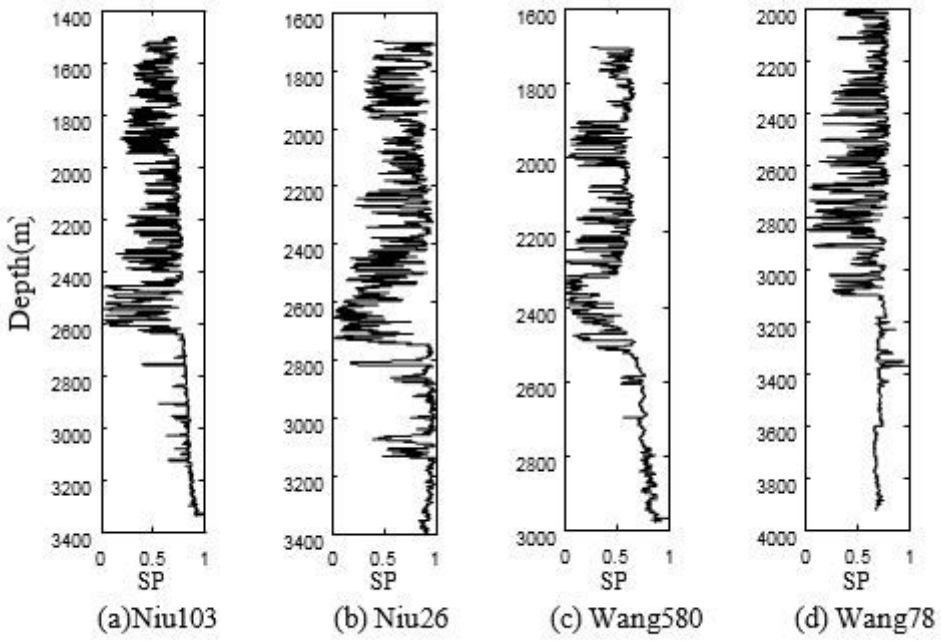

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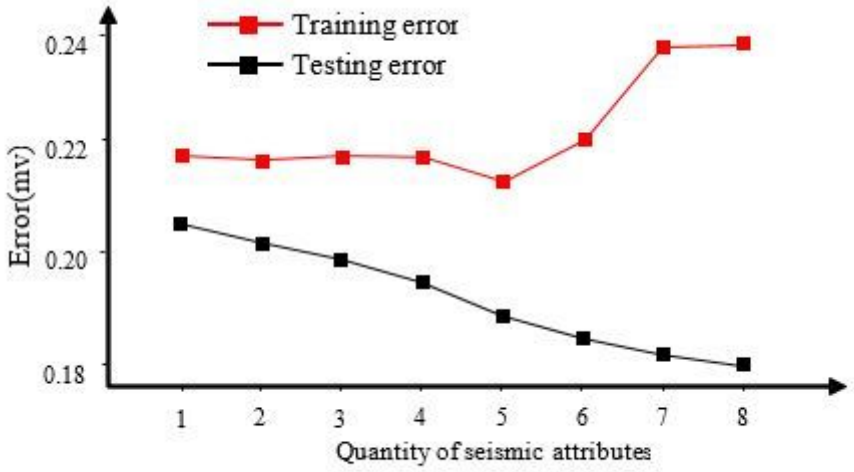

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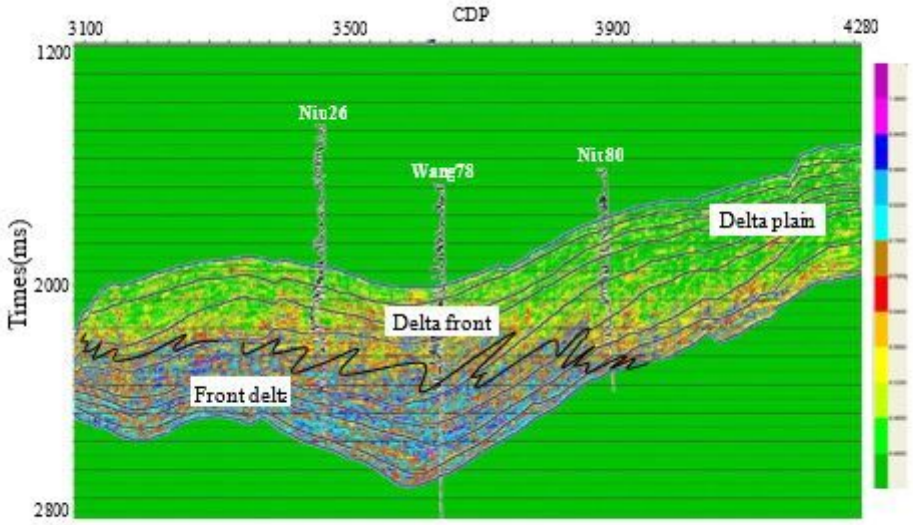
Quantity of seismic attributesvs. error



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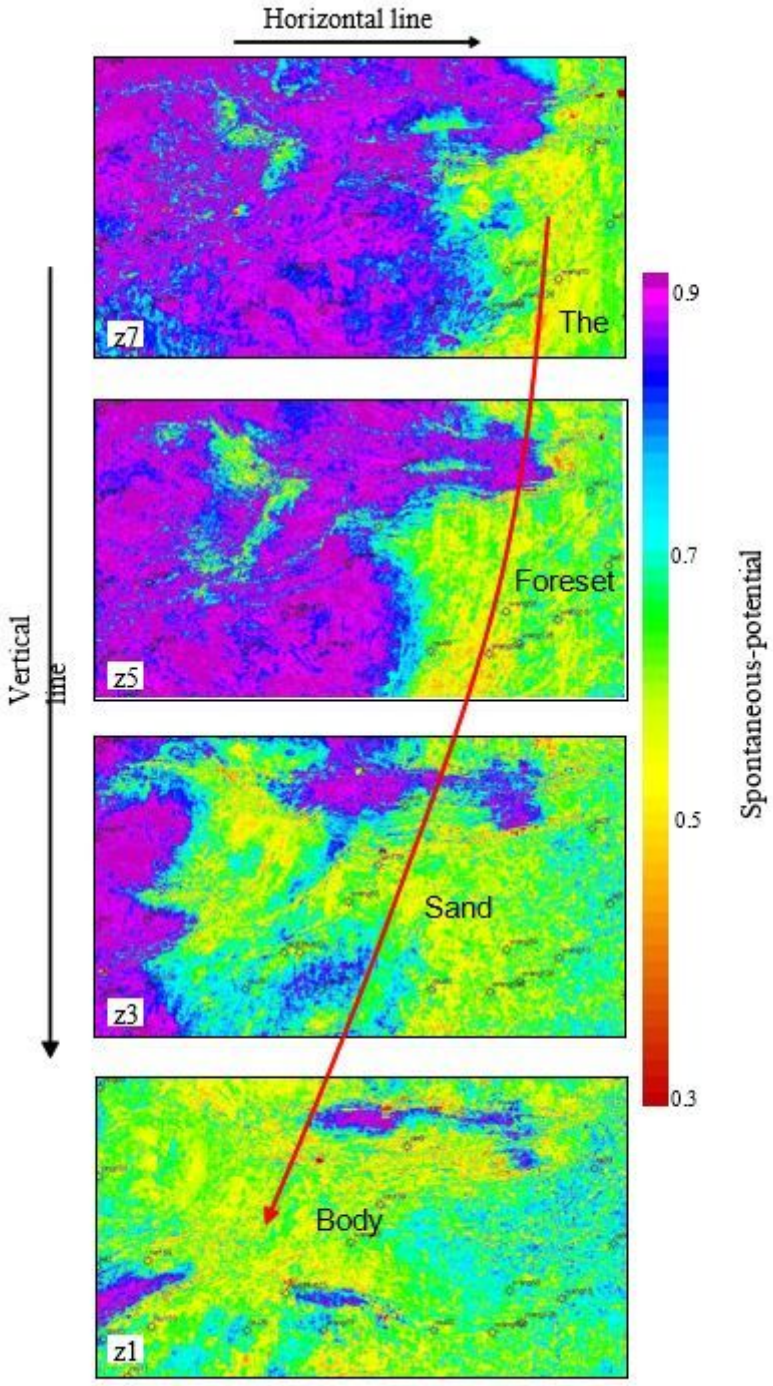

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Horizon slice of the intermediate section in Member 3 of the Shahejie Formation in the Dongying Delta as obtained by multi-attribute SP inversion