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Multi-constraint two-step intelligent prestack seismic inversion and its application: A case study in the Junggar Basin, Northwest China

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Abstract

Prestack seismic inversion serves as a bridge connecting seismic observations to subsurface rock properties, enabling quantitative estimation of elastic parameters, such as P-wave velocity (V_p), S-wave velocity (V_s), and density (ρ), which provides direct evidence for reservoir prediction and fluid identification. However, simultaneously inverting V_p , V_s , and ρ from prestack data is a highly nonlinear and ill-posed problem. Traditional inversion methods often struggle to achieve an optimal balance among accuracy, stability, and physical consistency. In recent years, deep learning has offered new insights through its powerful nonlinear mapping capabilities. However, purely data-driven models rely heavily on large labeled datasets and often overlook physical laws, leading to inversion results that lack geological consistency. To overcome these limitations, this paper proposes a multi-constraint two-step intelligent prestack inversion method. First, near-angle seismic data were used to robustly invert P-wave impedance (I_p). Then, employing TransUNet as the core network, a multi-constraint joint loss function was constructed to systematically integrate four types of prior information: (i) seismic data matching to ensure consistency with observed data. (ii) Physical relationship constraints linking I_p , V_p , and ρ . (iii) Empirical statistical relationships from well logs to regularize the ill-posed ρ inversion. (iv) Well data fitting to realize the matching of inversion results at well locations. This achieved high-precision inversion of V_p , V_s , and ρ under the dual guidance of data driving and physical mechanisms. Tests on the Marmousi 2 model and actual shale reservoir data from the Junggar Basin demonstrated that the proposed method significantly improved inversion accuracy, stability, and noise resistance for all three parameters, particularly ρ , validating its potential for practical applications.

Keywords: Prestack seismic inversion; Multiple constraints; TransUNet; Two-step method

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1. Introduction

Prestack seismic inversion serves as a critical bridge connecting seismic observations to subsurface rock properties. By analyzing and processing amplitude variations with incident angle in prestack gathers, this approach enables quantitative estimation of elastic parameters, such as P-wave velocity (V_p), S-wave velocity (V_s), and density (ρ), providing direct evidence for reservoir lithology identification, property prediction, and fluid detection. The accuracy of these parameters directly determines the reliability of subsequent reservoir modeling and hydrocarbon evaluation, making them core tasks in geophysical exploration.¹

However, simultaneously inverting V_p , V_s , and ρ from prestack seismic data presents a highly nonlinear and ill-posed problem.^{2,3} The challenges primarily arise from three aspects: firstly, the limited frequency band of seismic data and noise interference lead to significant non-uniqueness in inversion results;⁴ secondly, ρ parameters are considerably less sensitive to seismic amplitudes compared to velocity parameters, particularly at small to medium incident angles, resulting in generally low inversion accuracy—a persistent challenge in the field of prestack inversion;^{5,6} finally, the complex physical coupling relationships among these three parameters make it difficult for traditional methods to maintain this inherent consistency during the inversion process.

To address these challenges, geophysicists have developed a series of inversion theories and methods. Early deterministic inversion methods, such as linear inversions based on Zoeppritz approximations, including Aki and Richards⁷ or Shuey⁸ equations, offer high computational efficiency and good lateral continuity. However, their linearization assumptions limit their application accuracy in complex structures or under large incident angles.⁹ To improve resolution, the Bayesian inversion framework, represented by sparse-spike inversion, has been widely adopted. By incorporating prior constraints such as the Cauchy,¹⁰ Laplace,¹¹ or generalized Gaussian distribution,¹² it effectively highlights the sparse reflectivity characteristics of strata. While such approaches improve vertical resolution to some extent, they often struggle to quantify inversion uncertainty effectively and tend to become trapped in local optima. On the other hand, stochastic inversion methods, such as geostatistical inversion^{13,14} and Markov Chain Monte Carlo approaches,¹⁵ can provide high-resolution inversion results and uncertainty assessments. However, their substantial computational costs and strong dependence on well control limit their application in large-scale practical production.¹⁶⁻¹⁹

In recent years, artificial intelligence technologies,

particularly deep learning, have opened new pathways for prestack inversion through their powerful nonlinear mapping capabilities.²⁰⁻²² By constructing deep neural networks such as convolutional neural networks (CNN),^{23,24} recurrent neural networks,^{25,26} and U-Net,²⁷ researchers can directly learn complex mappings from seismic data to elastic parameters. The TransUNet architecture, which integrates the global modeling capabilities of transformers,²⁸ has shown particular promise in capturing both local waveform details and global geological structural features from seismic data.²⁹ However, purely data-driven deep learning methods still face significant challenges. First, these methods rely heavily on large quantities of high-quality labeled data, whereas the limited number of wells in actual working areas often leads to network overfitting and insufficient generalization.³⁰ Second, purely data-driven models learn only from statistical correlations, making it difficult to ensure that inversion results comply with known physical laws and intrinsic parameter relationships, raising concerns about the physical consistency of results.^{31,32}

To overcome these limitations, the concept of deeply integrating physical mechanisms with data-driven approaches has emerged.³³ Physics-informed neural networks incorporate wave equations or Zoeppritz-based approximations as physical constraints into loss functions, guiding networks to learn solutions that conform to physical laws and significantly improving the reliability and structural rationality of inversion results.^{34,35} Biswas *et al.*³¹ achieved promising results in unsupervised prestack inversion using physics-guided CNNs. These studies demonstrate that incorporating prior information is key to improving the generalization capability and robustness of deep learning methods.³⁶ Nevertheless, current methods still require further investigation in areas such as handling strong multi-parameter coupling, addressing fragmented information utilization, and systematically integrating multi-source information (physical laws, empirical statistics, well data, etc.).

It should be noted that although this study uses shale reservoirs as an application scenario and shale that exhibits significant anisotropic characteristics,³⁷ this work aims to provide a new, reliable solution to a fundamental reservoir characterization problem—improving inversion accuracy of conventional elastic parameters, particularly ρ . The shale example serves only to validate the proposed method's effectiveness. Therefore, this study is conducted under the assumption of isotropic media and has not incorporated anisotropic parameters.

In view of these considerations, we proposed a multi-constraint fusion-driven stepwise intelligent inversion method for prestack three-parameter inversion. This

method developed a dual closed-loop inversion workflow driven by well data while integrating physical laws and empirical statistical relationships. First, near-angle seismic data were used to robustly invert P-wave impedance (I_p). Then, using full-angle seismic data with TransUNet as the core network framework, a multi-constraint joint loss function was developed to systematically integrate four types of prior information: seismic data matching, physical relationship constraints, empirical statistical relationships, and well data fitting. This achieved prestack three-parameter inversion under dual guidance from data-driven constraints and physical mechanisms. Finally, through testing on the Marmousi 2 model and actual shale reservoir data from the Junggar Basin, the proposed method demonstrated superior performance in improving inversion accuracy, stability, and noise resistance for three parameters, especially ρ .

2. Materials and methods

2.1. Stepwise inversion workflow for prestack three parameters

This study developed an intelligent dual closed-loop workflow guided by well data and integrating physical and empirical constraints for accurate prestack three-parameter inversion. The overall architecture is shown in Figure 1. The workflow employed a two-step inversion strategy. In the first step, as indicated by the green arrows and boxes in the figure, near-angle seismic data were input into Inversion Model 1 to obtain I_p . In the second step, as indicated by the red arrows and boxes, full-angle seismic data were input into Inversion Models 1 and 2 to derive the final V_p , V_s , and ρ . The workflow primarily incorporated the following four constraint mechanisms:

- (i) Seismic response matching constraint ($Loss_1$): This constraint minimized the difference between synthetic and actual seismic records, enabling closed-loop correction at the seismic response level. Synthetic seismograms were generated via forward modeling based on the Aki–Richards approximation and convolution model. Physically, it guaranteed that inverted parameters could accurately reconstruct field seismic records via reflectivity-wavelet convolution in forward modeling, which complied with seismic wave propagation laws. This constraint supplied effective information within the seismic frequency band, maintained regional consistency and lateral continuity, and served as the essential bridge between seismic observations and subsurface petrophysical properties. The corresponding objective function is defined as Equation 1:

$$Loss_1 = \frac{1}{XY} \sum_{i=1}^X \sum_{j=1}^Y \|S(i, j) - \tilde{S}(i, j)\|_2^2 \quad (1)$$

where S and $\tilde{S}$ are the actual and synthetic seismic records, respectively. X and Y are the number of samples in the horizontal and vertical directions, and i and j are the current horizontal and vertical sample indices.

- (ii) Physical relationship constraint ($Loss_2$): Leveraging the stable and effective inversion of I_p , this constraint enforced the deterministic rock-physics relationship $I_p = V_p \cdot \rho$. By penalizing deviations from this relationship, the constraint avoided mathematically valid but physically contradictory combinations of V_p and ρ , mitigated the ill-posedness of the inversion, and ensured physical consistency among all inverted results. We introduced the following loss function as a constraint (Equation 2):

$$Loss_2 = \frac{1}{XY} \sum_{i=1}^X \sum_{j=1}^Y \|\tilde{I}_p(i, j) - \tilde{V}_p(i, j) \cdot \tilde{\rho}(i, j)\|_2^2 \quad (2)$$

where, $\tilde{I}_p$, $\tilde{V}_p$, and $\tilde{\rho}$ are the inverted I_p , V_p , and ρ , respectively.

- (iii) Empirical formula constraint ($Loss_3$): Based on the statistical relationship between V_p and ρ from well logs, this loss function imposed a constraint on the ρ term, optimizing network parameters and enhancing the stability and reliability of ρ inversion. Although less rigorous than deterministic physical laws, it provided crucial statistical guidance on density inversion, which was notoriously insensitive to seismic amplitude variations, thereby regularizing the solution space and improving inversion stability. The updated objective function can be written as Equation 3:

$$Loss_3 = \frac{1}{XY} \sum_{i=1}^X \sum_{j=1}^Y \|\tilde{\rho}(i, j) - a \cdot (\tilde{V}_p(i, j))^b\|_2^2 \quad (3)$$

where a and b are empirical coefficients fitted from well data.

- (iv) Well data fitting constraint ($Loss_4$): Equation 4 minimizes the difference between the inverted results and the true values at the well locations, serving as a supervised learning signal. This ensured that the network's predictions at sparse but accurate control points matched true formation information, providing high-frequency constraints from well logs and preventing the inversion from drifting into

geologically implausible scenarios. The objective function is given by:

$$Loss_4 = \frac{I}{NM} \sum_{i=1}^N \sum_{j=1}^M \|m(i, j) - \tilde{m}(i, j)\|_2^2 \quad (4)$$

where, N is the number of wells, M is the total number of samples in time for a single well, m and $\tilde{m}$ are the true and inverted three-parameter values at the well location, respectively.

In summary, this study developed a joint loss-function system that integrates multiple constraints (Equation 5). This system not only ensured spatial prediction rationality through seismic response matching but also enhanced inversion stability via physical and empirical constraints, and guaranteed reliability at well locations through well data fitting. The synergistic action of these constraints achieved deep integration between data-driven learning and physical mechanisms, resulting in a final prediction model with high accuracy, strong generalization, and good spatial continuity.

$$Loss_{total} = \alpha Loss_1 + \beta Loss_2 + \gamma Loss_3 + \eta Loss_4 \quad (5)$$

where, α , β , γ , and η are weight coefficients for $Loss_1$, $Loss_2$, $Loss_3$ and $Loss_4$, respectively. Since $Loss_1$ and $Loss_4$ represent the losses between the fitted actual data and the synthetic or inverted data, they possess clear physical meanings, making the minimization of these two terms highly reliable; accordingly, α and η are generally set to 1. In contrast, $Loss_2$ and $Loss_3$ are derived from inversion results or fitting relationships with relatively lower reliability, so β and γ are typically set between 0 and 0.5 and are manually adjusted based on the inversion performance to achieve

optimal results. These coefficients are adjusted based on the quality and credibility of the seismic, inversion, and well log data. During training, the Adam optimizer iteratively updates the network parameters by minimizing the total loss function to achieve optimal prediction performance.

2.2. Network architecture

The aforementioned workflow primarily involves two inversion networks, both utilizing the TransUNet architecture. This architecture integrates the local feature-extraction capability of CNN with the global dependency modeling strength of the Transformer within a U-Net encoder-decoder framework. It aims to establish the complex nonlinear mapping between prestack seismic gathers and the three parameters. Figure 2 shows the network structure with an encoder and a decoder.

2.2.1. Encoder part

The encoder is responsible for extracting both local and global features from the input data, comprising CNN and transformer modules. The CNN module captures multi-scale waveform responses and structural features from seismic data by adjusting the dilation rates of convolutional layers to control the receptive field. The Transformer module performs global modeling of the input data using self-attention, capturing long-range dependencies in both vertical and horizontal directions. The core computation of self-attention is as follows:

For an input sequence $I \in \mathbb{R}^{L \times d_m}$ (sequence length L , feature dimension d_m), query (Q), key (K), and value (V) matrices are obtained via linear transformations ($Q = IW^Q$, $K = IW^K$, $V = IW^V$). Here, W^Q , W^K , and $W^V \in \mathbb{R}^{d_m \times d_k}$ are learnable weight matrices, and d_k is the projection dimension. The attention is then calculated as Equation 6:

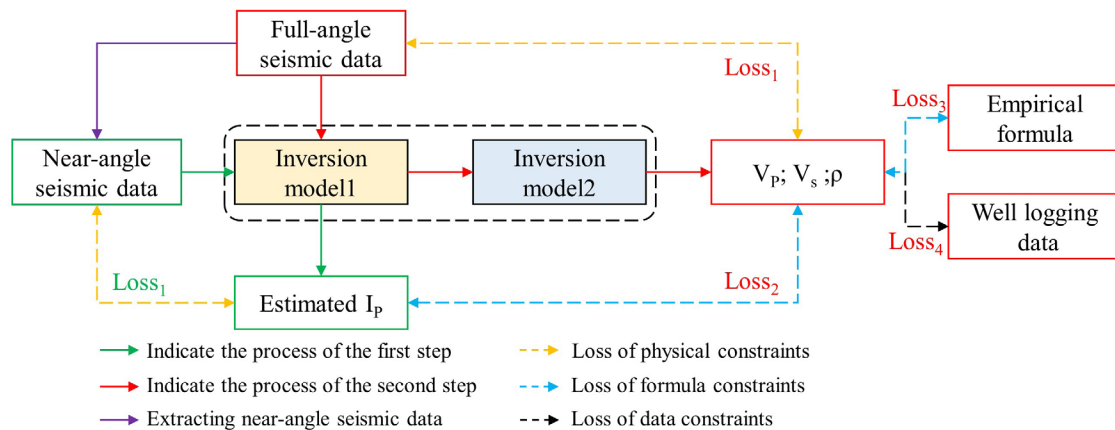


Figure 1. Stepwise inversion workflow for prestack three parameters

$$\text{Attention}(Q, K, V) = \text{soft max}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (6)$$

where, QK^T is used to compute the correlation scores between all positions, $\sqrt{d_k}$ is applied for scaling to prevent vanishing gradients, and the softmax function normalizes the scores so that each position can incorporate global information.

In implementation, the input data is first processed through six 3×3 convolutional layers to capture local patterns and details, thereby forming initial shallow features. These features are then linearly projected into a transformer encoder. Following the classical architecture, the encoder comprises multi-head self-attention layers, feed-forward network layers, layer normalization, and residual connections. To balance model expressiveness with computational efficiency, we configure the encoder with four attention heads, a hidden dimension of 512, and a depth of $n = 6$ transformer layers. Leveraging its multi-head self-attention mechanism, the network effectively captures vertical depositional patterns and lateral distributions, ultimately outputting deep features that incorporate long-range dependencies and global contextual information.

2.2.2. Decoder part

The decoder is designed to perform multi-scale feature fusion and restore spatial resolution from the deep feature representations. Through three successive upsampling stages, it progressively enlarges the spatial dimensions of the deep features. At each skip connection, the CNN-extracted shallow features are concatenated with the corresponding upsampled features across scales. A repeated sequence of convolution, upsampling, and feature concatenation operations gradually reconstructs the spatial architecture of the parameter volume, enabling precise localization of geological interfaces such as thin layers. Finally, a 1×1 convolutional layer maps and integrates the channels to produce the target parameter inversion result, matching the input data dimensions.

In summary, the TransUNet architecture, through its hybrid design and multi-scale feature fusion, provides core algorithmic support for high-precision elastic parameter inversion under complex geological conditions. Embedding this structure within the dual closed-loop system, combined with the progressive multi-constraint mechanism, establishes a solid technical foundation for elastic parameter inversion.

2.2.3. Evaluation of prediction results

We use the mean absolute error (MAE), root-mean-square error (RMSE), and correlation coefficient (R) as evaluation

metrics for the three-parameter inversion results. MAE is the average of absolute differences between inverted and actual values. A smaller MAE indicates better inversion performance. Its value range is $[0, +\infty)$. This metric weights all errors equally and is relatively robust to outliers. The formula is shown in **Equation 7**:

$$MAE = \frac{1}{n} \sum_{i=1}^n |m_i - \tilde{m}_i| \quad (7)$$

An RMSE is the square root of the average of squared errors. Its value range is $[0, +\infty)$. A smaller RMSE indicates that the inverted values are closer to the true values. Since errors are squared values, RMSE is more sensitive to large errors, reflecting the impact of outliers. The formula is shown in **Equation 8**:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (m_i - \tilde{m}_i)^2} \quad (8)$$

The R measures the linear correlation between two variables, ranging from $[-1, 1]$. The sign indicates the direction of the correlation, while the absolute value indicates the strength. An absolute value closer to 1 signifies stronger linear correlation, and closer to 0 signifies weaker correlation. The formula is shown in **Equation 9**:

$$R = \frac{1}{n} \frac{\sum_{i=1}^n (m_i - \mu_m)(\tilde{m}_i - \mu_{\tilde{m}})}{\sqrt{\sum_{i=1}^n (m_i - \mu_m)^2} \sqrt{\sum_{i=1}^n (\tilde{m}_i - \mu_{\tilde{m}})^2}} \quad (9)$$

In these formulas, m_i and $\tilde{m}_i$ represent the i -th actual and inverted values, respectively. n is the total number of samples. μ_m and $\mu_{\tilde{m}}$ are the means of the actual and inverted values, respectively.

3. Results

3.1. Prestack three-parameter inversion under noise-free conditions

Based on the Marmousi 2 model, this study used selected V_p , V_s , and ρ data to synthesize prestack seismic records at three incidence angles (10° , 20° , and 30°) using a Ricker wavelet with a dominant frequency of 30 Hz. Low-pass filtering was applied to the three-parameter data to construct corresponding low-frequency models. Ten traces were uniformly selected from the known three-parameter profiles as labels for subsequent data-driven tasks. **Figure 3A–C** displays the seismic data at the three angles. **Figure 3D–F** shows the known three-parameter profiles, with black solid lines indicating the positions of

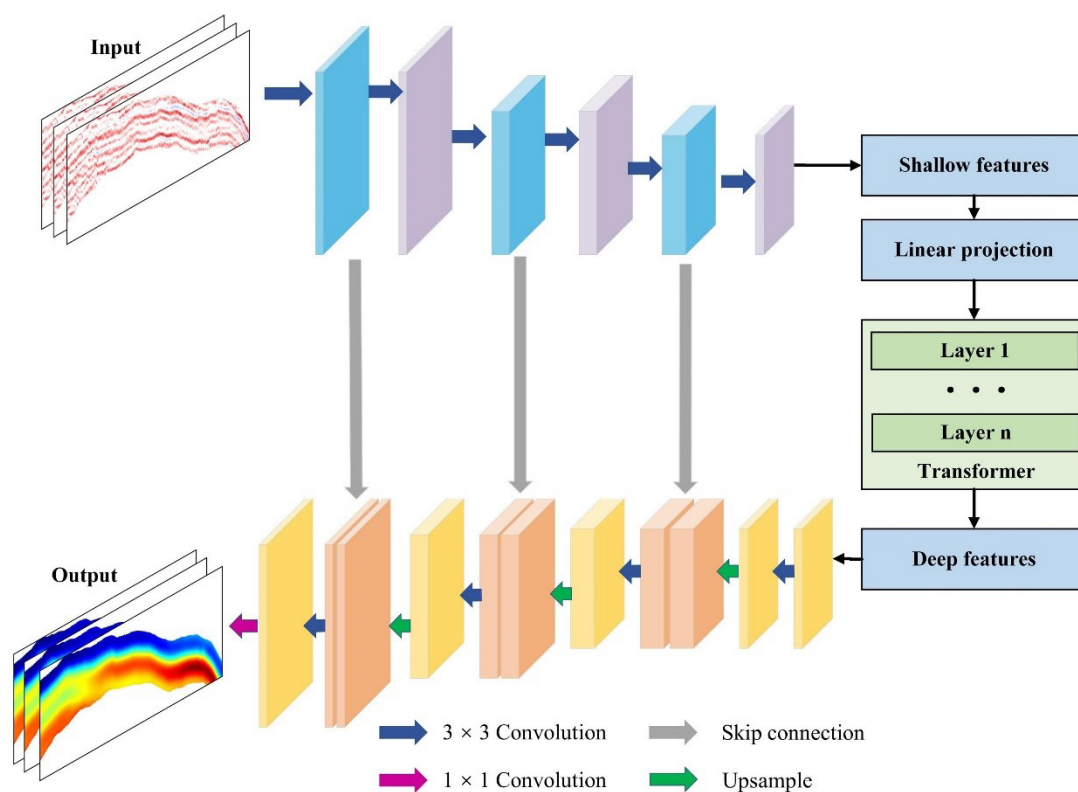


Figure 2. TransUNet network architecture. It comprises two primary components: an encoder and a decoder. The encoder is responsible for feature extraction, while the decoder performs feature fusion and restores the spatial resolution.

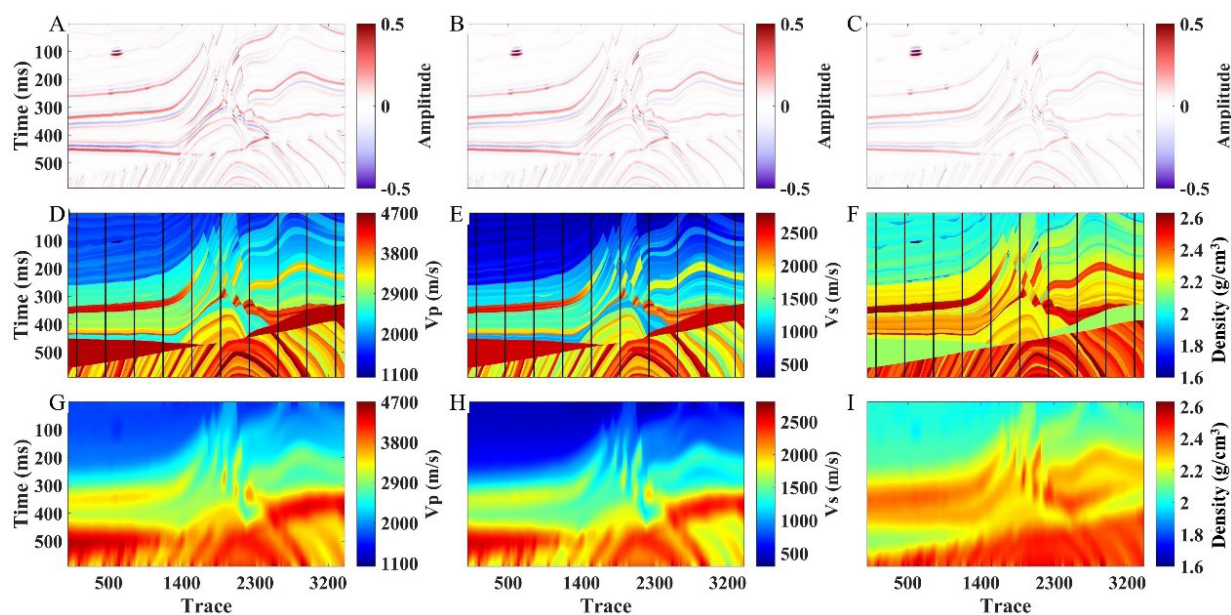


Figure 3. Seismic data, elastic parameters and the corresponding low-frequency models. The seismic data at (A) 10°, (B) 20°, and (C) 30°. The elastic parameters of (D) P-wave velocity, (E) S-wave velocity, and (F) density. The low-frequency models of (G) P-wave velocity, (H) S-wave velocity, and (I) density. The black solid lines indicating the positions of the uniformly selected ten pseudo-well traces. The low-frequency models are generated using a 10 Hz low-pass filter.

the uniformly selected 10 pseudo-well traces. Figure 3G–I presents the constructed low-frequency models for the three parameters, spanning 0–10 Hz.

Following the proposed workflow, two inversion models were trained using the synthetic three-angle seismic data, low-frequency models, pseudo-well data, and wavelets. The training epoch was set to 600 with a batch size of 128. The weights in the total loss function (α , β , γ , and η) were set to 1.0, 0.5, 0.5, and 1.0, respectively. The trained models were then used for inversion, with the outputs designated as proposed. For systematic comparison, an alternative intelligent method was designed. This method used a single inversion network directly from seismic data to the three parameters, without physical or empirical constraints, keeping all other settings identical. The corresponding inversion results were denoted as intelligent. Additionally, the results obtained using the direct inversion method with L_2 -norm constraints were denoted as traditional for comparative analysis. During the aforementioned inversion process, the synthetic seismic data were generated through forward modeling using the Aki–Richards approximation and the convolution model. Correspondingly, the inversion was also performed using this approximation equation to ensure consistency in the forward modeling process. The objective function adopted in the traditional method is given by Equation 10:

$$J(m) = \arg \min \|S - Gm\|_2^2 + \lambda \|m - m_0\|_2^2 \quad (10)$$

where S represents the observed seismic data, G denotes the forward modeling operator, m is the parameter to be inverted, m_0 is the low-frequency model corresponding to the inversion parameters, and λ is the regularization parameter. The generalized inverse method was used as the optimization algorithm.

The inversion results from the three methods are shown in Figure 4, and the absolute errors compared to the true models are shown in Figure 5. Figure 4 shows that all three methods can effectively invert the three-parameter profiles. Compared to the known profiles, the proposed method yielded better results, particularly in the areas marked by black rectangles and arrows. The error profiles in Figure 5 clearly show that the proposed method generally exhibited smaller errors. Differences among the three methods were more pronounced near the upper unconformity of the wedge-shaped body in the lower-left corner for both velocity profiles (red rectangle) and around the lens body in the upper-left corner for the ρ profile (red rectangle).

Figure 6 shows the inversion results for the 666th trace (a blind well). In Figure 6A–C, the black solid and dashed

lines represent the true model and low-frequency model, respectively. The blue, green, and red solid lines represent results from the traditional, intelligent, and proposed methods, respectively. Purple boxes highlight key areas. For V_p and V_s (Figure 6A and 6B), the differences among the three methods were subtle, but within the purple boxes, the proposed method aligned more closely with the true values. For ρ (Figure 6C), the traditional method showed substantial oscillations and fluctuations, performing worse compared to the intelligent method.

Table 1 presents the evaluation metrics (MAE, RMSE, R) for the three inversion results against the true values. Lower MAE and RMSE, and a higher R , indicate better performance. Analysis showed that the proposed two-step constrained method maintained good accuracy for V_p and V_s inversion while significantly improving the ρ inversion results. Specifically, for V_p inversion, it reduced MAE by 38.2% compared to the traditional method and by 28.8% compared to the intelligent method. For V_s inversion, MAE was reduced by 38.1% and 28.4%, respectively. In ρ inversion, MAE decreases by 17.6% and 24.2%, respectively. Furthermore, the proposed method achieved substantially lower RMSE and higher R , particularly in ρ inversion, where R achieved 0.9771. These results demonstrate that the proposed approach not only improved inversion accuracy and stability but also enhanced the physical consistency among parameters.

Table 1. A comparison of the inverted results using the three inversion methods on the seismic data (noise-free)

Target parameter	Method	MAE	RMSE	R
V_p (m/s)	Tradition	80.5872	138.0611	0.9885
	Intelligence	69.9539	111.0208	0.9925
	Proposed	49.7904	79.6904	0.9961
V_s (m/s)	Tradition	70.0194	116.1000	0.9865
	Intelligence	60.5759	94.0233	0.9911
	Proposed	43.3690	69.9909	0.9950
ρ (g/cm ³)	Tradition	0.0289	0.0443	0.9654
	Intelligence	0.0314	0.0481	0.9595
	Proposed	0.0238	0.0366	0.9771

Abbreviations: MAE: Mean absolute error; RMSE: Root-mean-square error.

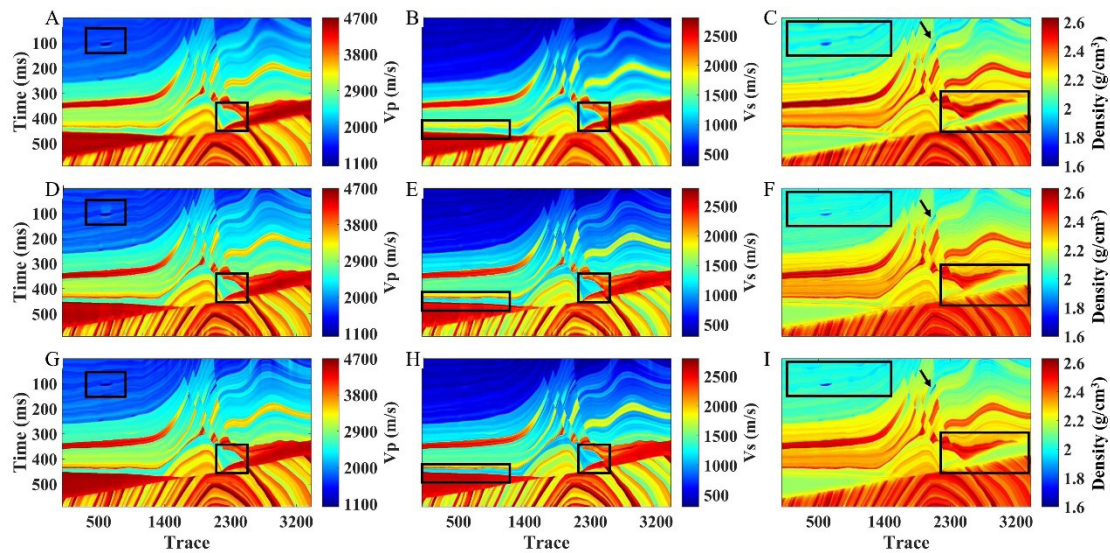


Figure 4. The inversion results of elastic parameters using three different methods. The predicted elastic parameters using the traditional method: (A) P-wave velocity, (B) S-wave velocity, and (C) density. The predicted elastic parameters using the intelligent method: (D) P-wave velocity, (E) S-wave velocity, and (F) density. The predicted elastic parameters using the proposed method: (G) P-wave velocity, (H) S-wave velocity, and (I) density.

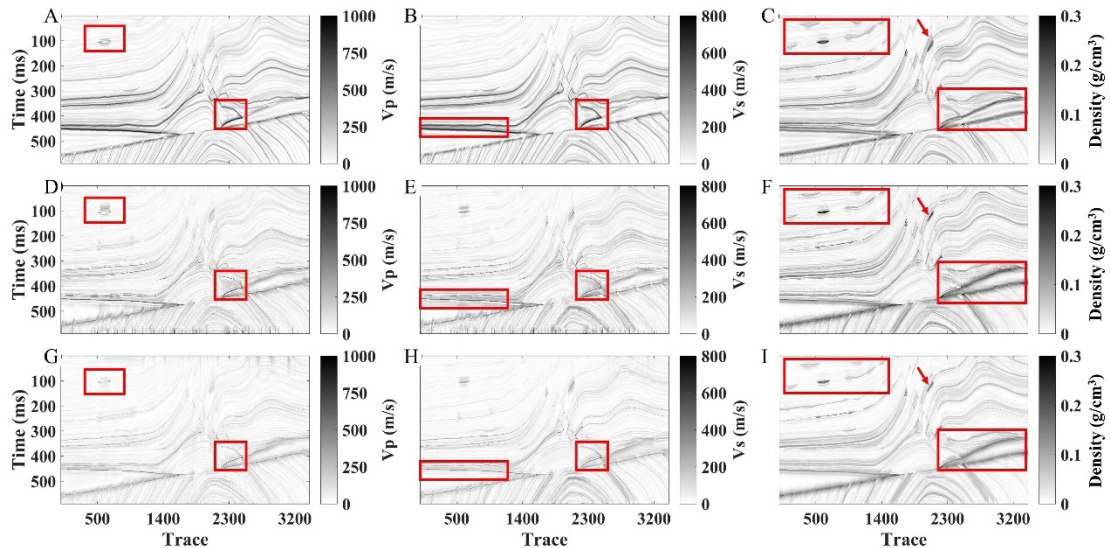


Figure 5. The absolute error between the inversion results from the three different methods and the true values. The absolute error using the traditional method: (A) P-wave velocity, (B) S-wave velocity, and (C) density. The absolute error using the intelligent method: (D) P-wave velocity, (E) S-wave velocity, and (F) density. The absolute error using the proposed method: (G) P-wave velocity, (H) S-wave velocity, and (I) density.

3.2. Prestack three-parameter inversion under noisy conditions

To test the robustness of the proposed method, 20% random Gaussian noise was added to the synthetic seismic data. The three methods were then applied to invert the noisy data. Figure 7 shows the inversion results, and Figure 8 shows the absolute errors. The layout is the same as Figures 4 and 5. All three methods exhibited some noise resistance, but the traditional method and intelligent method performed slightly worse, with visible noise in the

inverted V_s and ρ profiles. Compared with the proposed method, the baseline method showed poorer overall results, with noticeable differences in the areas marked by black or red rectangles and arrows.

Figure 9 shows the results for the 666th trace with 20% noise. In Figure 9A–C, the black solid and dashed lines represent the true model and low-frequency model, respectively. The blue, green, and red solid lines represent results from the traditional, intelligent, and proposed methods, respectively. As observed, the inversion results

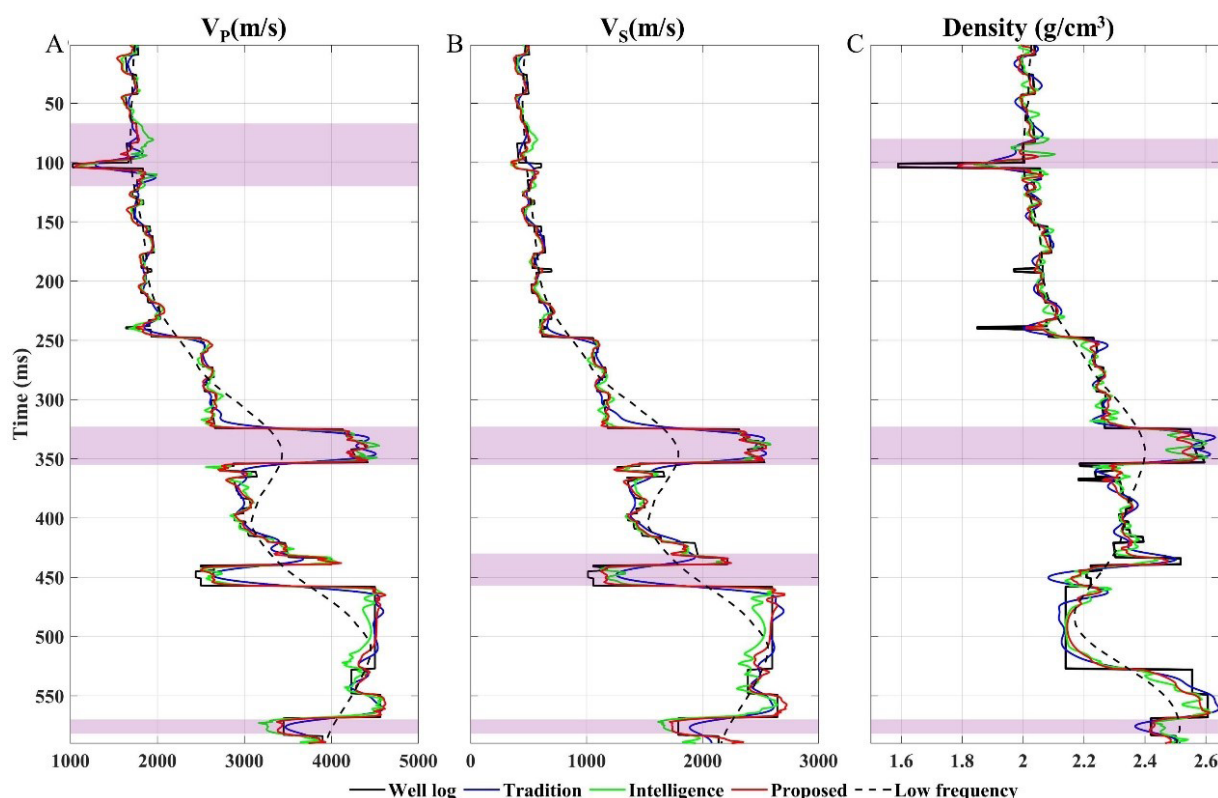


Figure 6. The inverted results of the 666th trace data (noise-free). (A) A comparison of the inverted (A) P-wave velocity, (B) S-wave velocity, and (C) density using the three inversion methods. The solid lines in black, blue, green, and red represent true data, results from the traditional, intelligent, and proposed methods, respectively, while the black dashed line represents the low-frequency model.

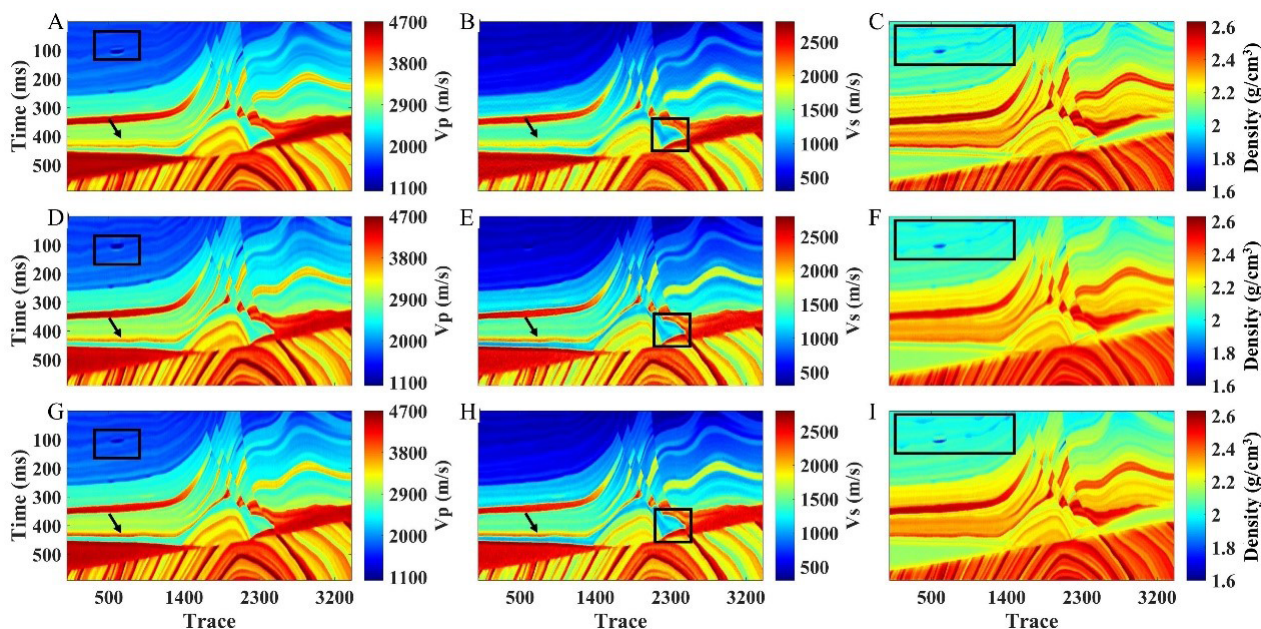


Figure 7. The inversion results of elastic parameters using three different methods (with 20% noise). The predicted elastic parameters using the traditional method: (A) P-wave velocity, (B) S-wave velocity, and (C) density. The predicted elastic parameters using the intelligent method: (D) P-wave velocity, (E) S-wave velocity, and (F) density. The predicted elastic parameters using the proposed method: (G) P-wave velocity, (H) S-wave velocity, and (I) density.

from all three methods degraded under noisy conditions relative to the noise-free case, exhibiting increased noise-induced fluctuations. This was particularly evident in the V_s and ρ inversion outcomes. However, within the region marked by the purple box in the figure, the results of our proposed method clearly align more closely with the true values. Moreover, the advantages of the proposed approach were more pronounced in the inversion of V_s and ρ .

Table 2 presents the evaluation metrics for the noisy case. The analysis indicated that noise degraded performance across all inversion methods. Nevertheless, the proposed method consistently demonstrated superior accuracy and robustness. Specifically, for V_p inversion, the proposed method achieved MAE reductions of 30.31% and 20.83% compared to traditional and intelligent methods, respectively, with RMSE decreasing by 30.53% and 20.47%, respectively. In V_s inversion, MAE was lowered by 41.40% and 19.90%, and RMSE by 40.66% and 20.12%, respectively. The ρ inversion showed the most substantial improvements, with MAE reduced by 33.95% and 22.19%, RMSE decreased by 29.00% and 22.20%, and R increased by 7.70% and 1.79% relative to the two baseline methods, respectively. These results affirm that the proposed method maintained higher overall accuracy and greater robustness compared to existing approaches.

Table 2. A comparison of the inverted results using the three inversion methods on the seismic data (with 20% noise)

Target parameter	Method	MAE	RMSE	R
V_p (m/s)	Tradition	102.7359	164.3678	0.9837
	Intelligence	90.4232	143.5943	0.9875
	Proposed	71.5926	114.2027	0.9922
V_s (m/s)	Tradition	101.0245	155.3812	0.9755
	Intelligence	73.9123	115.4408	0.9865
	Proposed	59.1995	92.2067	0.9915
ρ (g/cm ³)	Tradition	0.0377	0.0538	0.9050
	Intelligence	0.0320	0.0491	0.9576
	Proposed	0.0249	0.0382	0.9747

Abbreviations: MAE: Mean absolute error; RMSE: Root-mean-square error.

3.3. Application to real data

We applied the proposed method to real two-dimensional prestack three-angle seismic data from a shale reservoir in the Junggar Basin, China (5°, 12.5°, and 20°, shown in Figure 10A–C). The study area contains three wells (W1, W2, W3), covers 1,100 common depth points, and has a record length of 390 ms. The sampling interval was 2 ms. Only the target zone data were displayed. The reflection structure in this area showed relatively minor overall variations, but the lower middle part between wells W2 and W3 exhibited weaker reflection amplitudes. W1 and W3 were used as training wells, while W2 served as the blind well to validate the model's inversion performance.

Wavelet estimation and low-frequency model construction (Figure 10D–F) were performed based on the seismic data and well logs. The input data were normalized for network training. Model parameters and constraint weights were adjusted iteratively based on inversion results until satisfactory outcomes were achieved.

The inversion results of the three methods are presented in Figure 11. Figure 11A–C shows the three-parameter inversion results obtained using the traditional method, Figure 11D–F corresponds to those of the intelligent method, and Figure 11G–I displays the results of the proposed method. In each row, the V_p , V_s , and ρ are arranged from left to right. It can be observed that all three methods yielded reasonably good reconstructions of the V_p . However, noticeable differences were observed in the V_s and ρ profiles. For the V_s , the result of the traditional method closely resembled the low-frequency model, making it difficult to effectively distinguish the two sets of strata within the black rectangle in the figure. The intelligent method result exhibited noticeable noise, which also hindered clear identification of the strata. In contrast, the proposed method delivered a more accurate V_s inversion, showing good agreement with well log data. Regarding ρ inversion, the traditional method produced profiles with considerable fluctuations, corresponding to the darker-colored areas in the image. The intelligent method failed to adequately represent the reservoir within the black rectangle. On the other hand, the ρ inversion result from the proposed method was overall more stable compared to other methods, clearly revealing ρ variations and providing a better characterization of the reservoir features.

A comparison of the three inversion results at trace 526 is presented in Figure 12. In Figure 12A–C, the black solid and dashed lines represent the true model and low-frequency model, respectively. The blue, green, and red solid lines represent results from the traditional, intelligent, and proposed methods, respectively. In the region marked

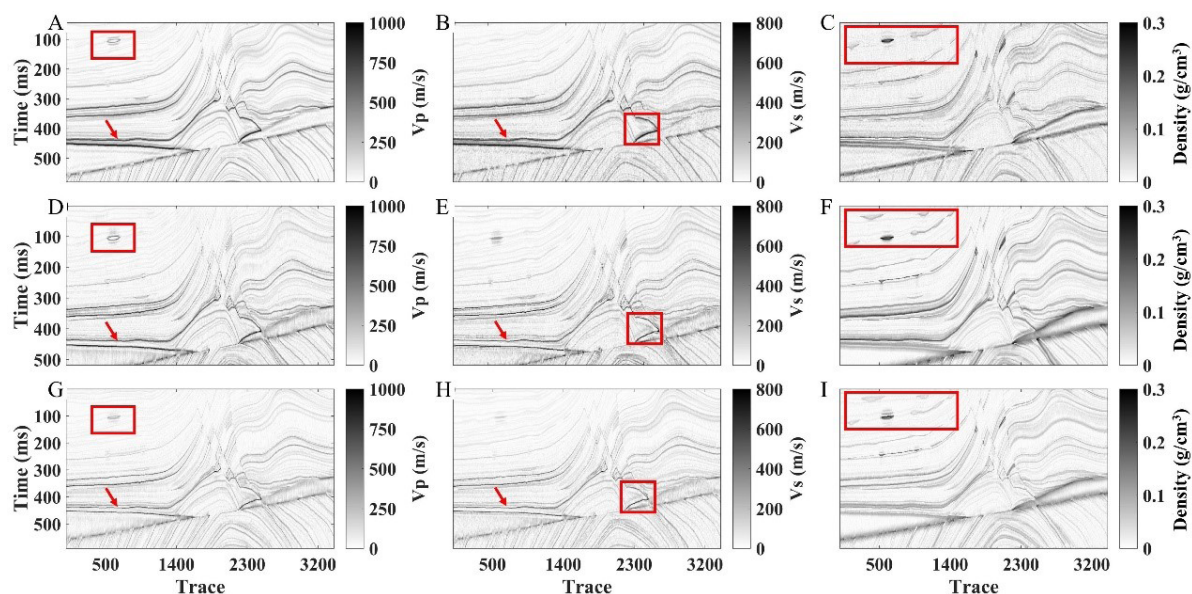


Figure 8. The absolute error between the inversion results from the three different methods and the true values (with 20% noise). The absolute error using the traditional method: (A) P-wave velocity, (B) S-wave velocity, and (C) density. The absolute error using the intelligent method: (D) P-wave velocity, (E) S-wave velocity, and (F) density. The absolute error using the proposed method: (G) P-wave velocity, (H) S-wave velocity, and (I) density.

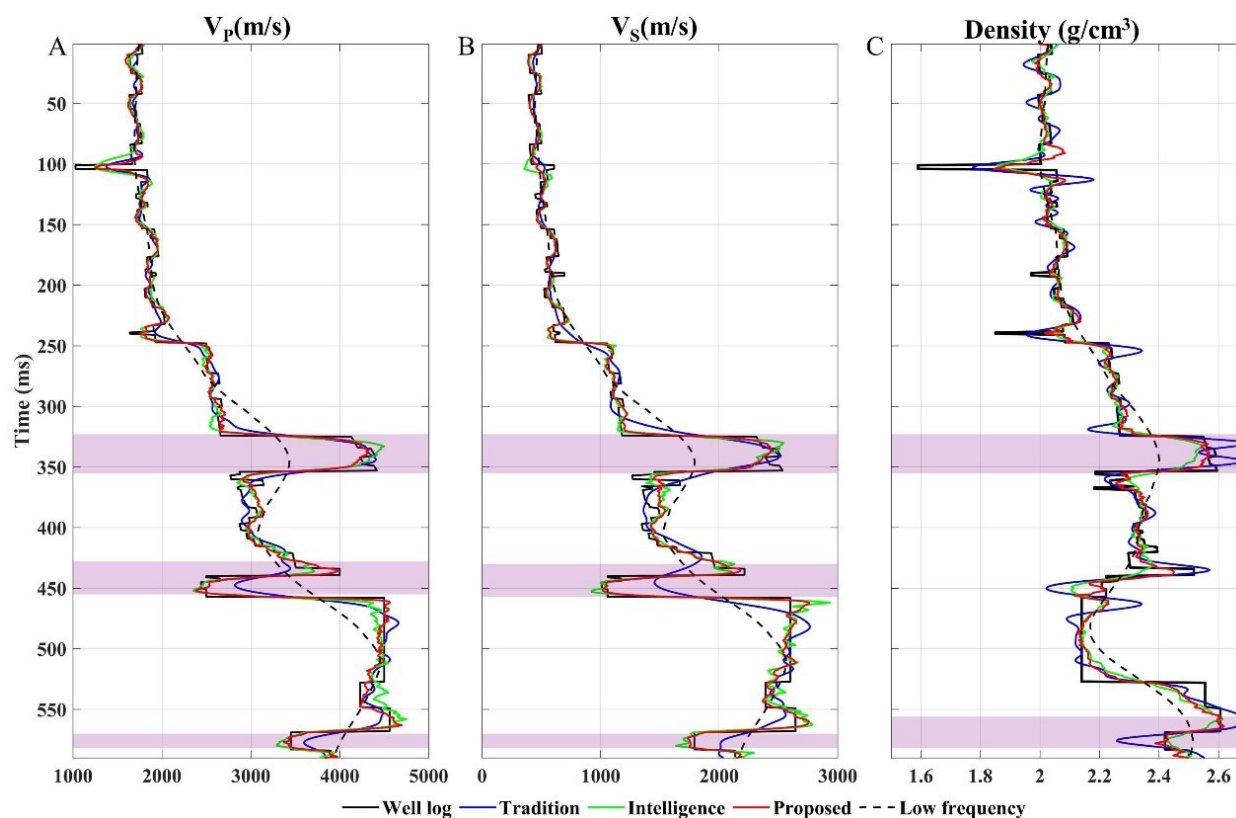


Figure 9. The inverted results of the 666th trace data (with 20% noise). A comparison of the inverted (A) P-wave velocity, (B) S-wave velocity, and (C) density using the three inversion methods. The solid lines in black, blue, green, and red represent the well log, the results from traditional, intelligent, and proposed methods, respectively, while the black dashed line represents the low-frequency model.

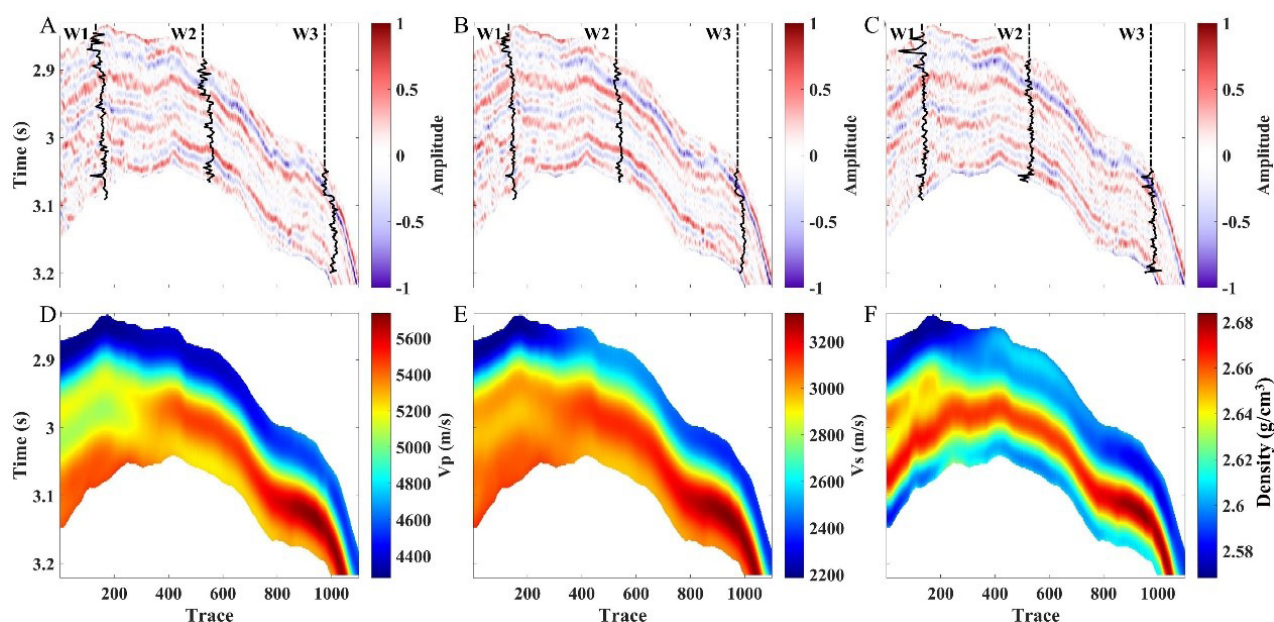


Figure 10. Seismic data and the corresponding low-frequency models. The seismic data at (A) 5°, (B) 12.5°, and (C) 20°. The low-frequency models of (D) P-wave velocity, (E) S-wave velocity, and (F) density. The black curve represents the well-log. The low-frequency models were generated using a 10 Hz low-pass filter.

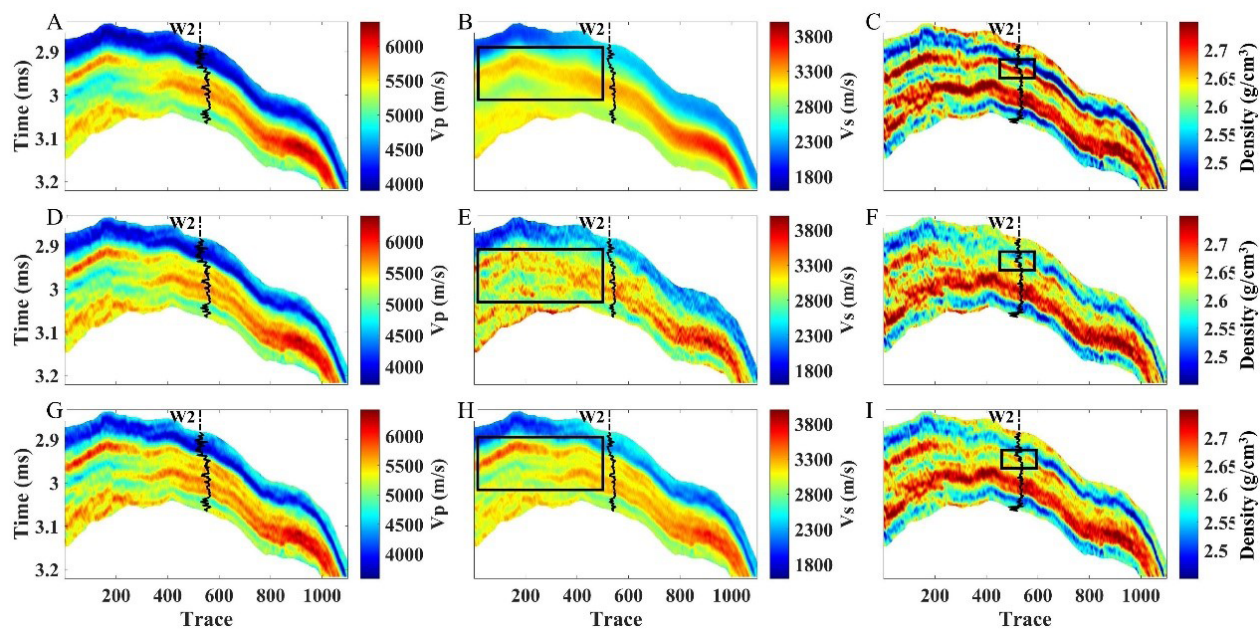


Figure 11. The inversion results of elastic parameters using three different methods on the actual seismic data. The predicted elastic parameters using the traditional method: (A) P-wave velocity, (B) S-wave velocity, and (C) density. The predicted elastic parameters using the intelligent method: (D) P-wave velocity, (E) S-wave velocity, and (F) density. The predicted elastic parameters using the proposed method: (G) P-wave velocity, (H) S-wave velocity, and (I) density. The black curve represents the well-log.

by the purple rectangle, the differences between the three methods were more clearly illustrated, with the red curve overall being closer to the black well log curve.

Table 3 presents the performance evaluation of three methods on the blind well. Overall, the proposed method achieved better accuracy and stability across all

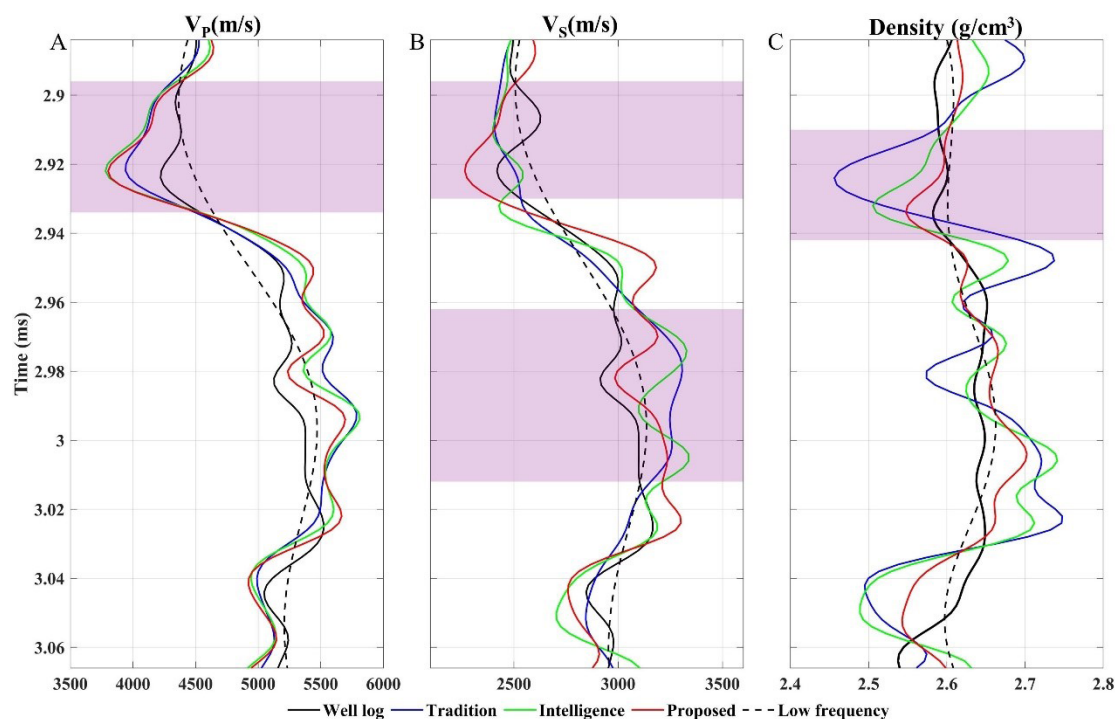


Figure 12. The inverted results of the 526th trace data. A comparison of the inverted (A) P-wave velocity, (B) S-wave velocity, and (C) density using the three inversion methods. The solid lines in black, blue, green, and red represent the well log, the results from the traditional, intelligent, and proposed methods, respectively, while the black dashed line represents the low-frequency model.

parameters. Specifically, for V_p inversion, compared to the traditional and intelligent methods, the proposed method reduced MAE by 5% and 17.03%, respectively, and lowered RMSE by 3.39% and 11.24%, while maintaining a higher R value. For V_s inversion, MAE decreased by 2.13% and 7.39%, and RMSE decreased by 16.31% and 19.89%, with further improvements in R value. In ρ inversion, the proposed method lowered MAE by 38.31% and 29.69%, reduced RMSE by 36.89% and 27.50%, and increased R by 11.24% and 36.47% compared to the two baseline methods, respectively. These results indicate that the proposed method achieved lower error and higher correlation across different inversion tasks, demonstrating overall superior performance compared to the other methods.

4. Discussion

The two-step intelligent inversion method driven by multi-constraint fusion proposed in this paper, through the construction of a multi-constraint joint loss function, effectively improved the inversion accuracy of V_p , V_s , and ρ . This study aims to provide a new solution to the fundamental problem of prestack three-parameter inversion, with its core innovation at the methodological level—namely, how to systematically integrate multi-source prior information to guide the learning process of

intelligent networks. The shale reservoir was selected as the application scenario for method validation because shale oil and gas exploration demands high accuracy in reservoir parameter prediction, thereby fully testing the effectiveness of the proposed method.

Although the proposed method achieved satisfactory results in both synthetic-model and field-data tests, certain limitations remained. First, the weights of various terms in the multi-constraint joint loss function are currently determined mainly through empirical manual tuning, lacking an adaptive adjustment mechanism, which may affect the model's generalization capability under different data conditions. Second, although the multi-constraint fusion strategy alleviated inherent challenges such as parameter coupling to some extent, in practical applications, the accuracy of prestack three-parameter inversion still faces challenges due to factors such as the limited frequency band of seismic data, noise interference, and the low physical sensitivity of ρ parameters. Looking ahead, future studies should focus on the following works: first, introducing adaptive weighting strategies that leverage uncertainty estimation or attention mechanisms to dynamically balance the contributions of various loss function terms; second, extending the proposed method from isotropic media to more complex vertical transverse

isotropy or horizontal transverse isotropy media, conducting anisotropic parameter inversion research to address the practical demands of complex reservoirs such as shale.

Table 3. A comparison of the inverted results using the three inversion methods on the real data (blind well)

Target parameter	Method	MAE	RMSE	R
V_p (m/s)	Tradition	155.3665	199.7186	0.9368
	Intelligence	181.2970	217.3702	0.9376
	Proposed	150.3665	192.9521	0.9514
V_s (m/s)	Tradition	104.6960	135.6808	0.8798
	Intelligence	110.6391	141.7022	0.8854
	Proposed	102.4695	113.5337	0.9347
ρ (g/cm ³)	Tradition	0.0522	0.0656	0.5443
	Intelligence	0.0458	0.0571	0.4437
	Proposed	0.0322	0.0414	0.6055

Abbreviations: MAE: Mean absolute error; RMSE: Root-mean-square error.

5. Conclusion

To tackle the issues of non-uniqueness and parameter coupling in prestack three-parameter inversion, this study introduces a two-step intelligent inversion method based on multi-constraint fusion. The approach builds a dual closed-loop framework that integrates well log data with constraints from physical laws and empirical relationships. It uses a step-by-step strategy, first inverting I_p before estimating all three parameters. The TransUNet architecture is used to model both local features and global dependencies. Tests on synthetic and real data, with and without noise, showed that the proposed method improved the accuracy and stability of three-parameter inversion, especially for ρ , compared to traditional and intelligent methods without physical constraints, demonstrating strong robustness. In real data applications, the method also enhances the inversion of V_s and ρ while maintaining the accuracy of V_p results.

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Conflict of interest

The authors declare that they have no competing interests.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The raw data of this study are available from the corresponding author upon reasonable request.

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