

Article

Quantitative Seismic Interpretation of Reservoir Parameters and Elastic Anisotropy Based on Rock Physics Model and Neural Network Framework in the Shale Oil Reservoir of the Qianjiang Formation, Jiangnan Basin, China

Zhiqi Guo ^{1,*}, Tao Zhang ², Cai Liu ¹, Xiwu Liu ^{3,4,5} and Yuwei Liu ^{3,4,5}

¹ College of Geoexploration Science and Technology, Jilin University, Changchun 130021, China; liucaai@jlu.edu.cn

² SINOPEC Geophysical Research Institute, Nanjing 211100, China; zhangt_0323@126.com

³ State Key Laboratory of Shale Oil and Gas Enrichment Mechanisms and Effective Development, Beijing 100083, China; liuxw.syky@sinopec.com (X.L.); liuyw.syky@sinopec.com (Y.L.)

⁴ SinoPEC Key Laboratory of Shale Oil and Gas Exploration and Production Technology, Beijing 100083, China

⁵ SinoPEC Petroleum Exploration and Production Research Institute, Beijing 100083, China

* Correspondence: guozhiqi@jlu.edu.cn

Abstract: Quantitative estimates of reservoir parameters and elastic anisotropy using seismic methods is essential for characterizing shale oil reservoirs. Rock physics models were established to quantify elastic anisotropy associated with clay properties, laminated microstructures, and bedding fractures at different scales in shale. The inversion schemes based on the built rock physics models were proposed to estimate reservoir parameters and elastic anisotropy using well log data. Based on the back propagation neural network framework, the obtained rock physical inversion results were used to establish the nonlinear models between elastic properties and reservoir parameters and elastic anisotropy of shale. The established correlations were applied for quantitative seismic interpretation, converting seismic inversion results to the reservoir parameters and elastic anisotropy to characterize the shale oil reservoir comprehensively. The predicted elastic anisotropy of the shale matrix reflects the lamination degree and the mechanical properties of the shale, which is critical for the effective implementation of hydraulic fracturing. The calculated elastic anisotropy of the shale provides more accurate models for seismic modeling and inversion. The obtained bedding fracture parameters provide insights into reservoir permeability. Therefore, the proposed method provides valuable information for identifying favorable oil zones in the study area.

Keywords: shale oil; rock physics model; reservoir parameters; elastic anisotropy; quantitative seismic interpretation



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1. Introduction

With the growing development of shale oil reservoirs, it is critical to conduct quantitative seismic interpretation by incorporating rock physical results and artificial intelligence technologies for better characterization of sweet spots and reliable prediction of favorable areas in shale oil reservoirs. The quantitative seismic interpretation, estimating reservoir properties and elastic anisotropy of the shale from seismic elastic attributes based on rock physical inversion results, can reduce uncertainty in reservoir characterization.

Shale presents the inherent anisotropy owing to the preferred orientation of clay minerals and laminated microstructures. Shale anisotropy can be further enhanced in the presence of bedding fractures developed along the weak planes of the lamination in the solid matrix. These properties impact shale mechanics and consequently affect hydraulic fracturing for the effective development of shale oil reservoirs. Therefore, it is necessary to conduct rock physical modeling for better descriptions of the elastic anisotropy of shale.

The microstructure of organic-rich shale was considered as the layered distribution of clay minerals and kerogen by rock physical modeling methods based on the Backus averaging theory [1–4]. Experimental studies by Vernik [5] and Vernik and Liu [6] indicate that the stress-related anisotropy of shale can be attributed to the presence of bedding fractures related to overpressure.

Meanwhile, clay minerals dominate the inherent anisotropy of shale [7]. Accordingly, the relationship between elastic anisotropy and distribution patterns of clay minerals was investigated based on rock physical modeling [8,9]. The impact of the clay minerals and laminated organic matter on shale anisotropy was also investigated [10–13]. In addition, the sensitivity of the seismic reflections to kerogen or pressure in anisotropic shale was analyzed based on rock physical modeling [14–18]. Guo et al. [19] introduced the clay lamination index parameter into the rock physics model to describe the influence of the lamination degree of clay minerals on shale anisotropy. Accordingly, the authors developed an inversion method for anisotropy parameter estimates based on the proposed model. Recent studies on shales from different regions by Sayers and Doer [20,21] imply that clay mixtures present particular elastic properties owing to the widely existing interparticle region that has an effective bulk modulus close to the water and a low nonzero shear modulus, providing a method for describing the properties of bound water. Guo and Liu [22] characterized the shale gas reservoir in the Longmaxi Formation using a comprehensive seismic rock physics method. In their studies, elastic anisotropy of shale was investigated based on seismic modeling and inversion integrated with the rock physical model.

Despite the successful applications of the above methods, reservoir property estimates were primarily performed using well log data. Meanwhile, seismic inversion mainly provided the estimates of the anisotropic parameters. Reservoir characterization using seismic methods for a detailed description of reservoir properties remains a challenging task. However, the quantitative seismic interpretation, integrating rock physics methods for particular hydrocarbon reservoirs and various artificial intelligence algorithms, can provide a practical way to realize an effective reservoir characterization over a larger area by utilizing reservoir parameters estimated by the rock physics model in a borehole. Hopfield [23,24] proposed a feedback interconnection network, known as the Hopfield network, to solve associative memory and optimization calculation problems by defining energy functions. Rumelhart and McClelland [25] proposed the multi-layer feedforward and Back Propagation (BP) algorithm to solve nonlinear problems. Liu et al. [26] used a three-layer the BP neural network (BPNN) to quantify reservoir parameters and realized lithology identification using logging data for reservoir characterization. Compared with the traditional method, the BPNN has the advantages of fully utilizing logging information through adaptive learning and nonlinear mapping. Lu et al. [27] utilized the BPNN to predict well log data by reconstructing the network energy function. The real data application results showed that the optimized BPNN provided more accurate and stable prediction results with improved computational efficiency. Jia et al. [28] improved the BPNN by introducing the optimized error back transmission algorithm and learning factors. The authors used the developed method to predict fractures based on logging data and achieved good application results. Wang et al. [29] built a BPNN model based on logging data. They established the nonlinear mapping relationship between elastic properties and reservoir parameters for identifying reservoir fluid. Recently, Deng et al. [30] applied the BPNN for shale gas characterization based on rock physical inversion of reservoir parameters.

In this paper, anisotropic rock physics models were constructed using effective medium theories based on petrophysical analyses of the Qianjiang shale formation, Jiangnan Basin, China. Then, model-based inversion methods were proposed to predict the clay properties, elastic anisotropy of the shale, and bedding fractures using well log data. Next, the BPNN algorithm was applied to establish the nonlinear quantitative correlations between elastic properties and reservoir parameters using measured and inverted well logs. Based on the established correlations, the elastic anisotropy and reservoir parameters of the target shale

layer were predicted by the quantitative interpretation of seismic-inverted elastic properties. The obtained results provide essential information for improved characterization of the shale oil reservoir.

2. Analyses of Well Log Data and Microstructure Features of Shale

The well log data of the shale formation in Qianjiang sag, Jiangnan Basin are shown in Figure 1. The rhythmic structure contains the interbedding of salt rock and shale, with some shale segments proven to be oil-bearing.

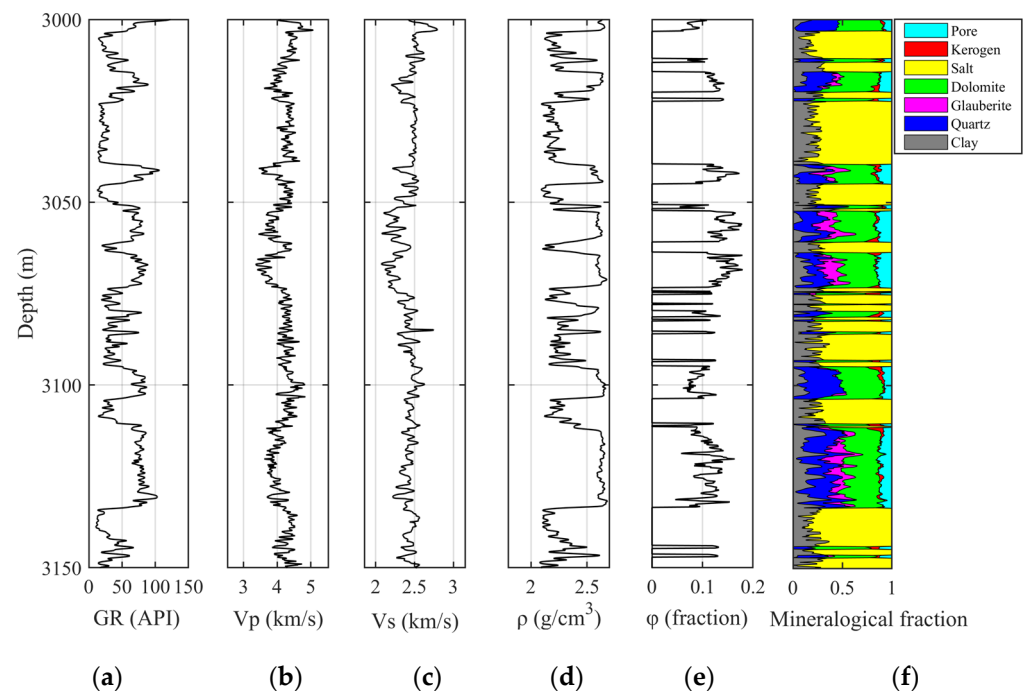


Figure 1. Well logs of the shale oil formation, including gamma-ray values (a), velocities of P-wave (b) and S-wave (c), density (d), porosity (e), and volumetric fractions of constituents (f).

The shale formation has lower wave velocities and higher porosity and density than the salt formation. In terms of mineral composition, salt is the primary component of salt formation, with a small number of clay minerals in the salt rock. Unlike clay-rich shale, the shale formation in this study contains relatively complex mineral compositions, reflecting the specific depositional environment of the terrestrial salt lake basin. The primary minerals consist of clay, quartz, dolomite, and a small amount of glauberite. The content of the primary minerals is comparable, approximately 22%, 25%, and 30% for clay, quartz, and dolomite, respectively. Meanwhile, the content of kerogen in shale is relatively low. The porosity of the shale formation can be up to 20%, and the permeability can reach approximately 1 mD, relatively higher than those of typical shale reservoirs.

As suggested by Zhong et al. [31], the impact of compaction and consolidation leads to preferred orientations of clay minerals. The clay mixture presents a laminated fabric at the microscale, which makes the shale matrix exhibit a bedding structure at the macro level. Hence, the shale presents an inherent vertical transverse isotropy (VTI) anisotropy. In addition, bedding fracture associated with the lamination increases permeability and is another source of VTI anisotropy besides the intrinsic anisotropy related to clay minerals. Figure 2 shows the scanning electron microscope (SEM) image of the sampled shale cores. As shown in Figure 2a, bedding fractures are developed along the weak planes of laminated fabrics in the host matrix of shale, providing seepage paths for fluid flow. In Figure 2b, the preferred orientations of clay minerals are apparent. At the same time, analyses indicate that the clay matrix primarily consists of illite and smectite. Additionally, petrophysical analysis indicates that kerogen mainly distributes in cavities without presenting layered structures.

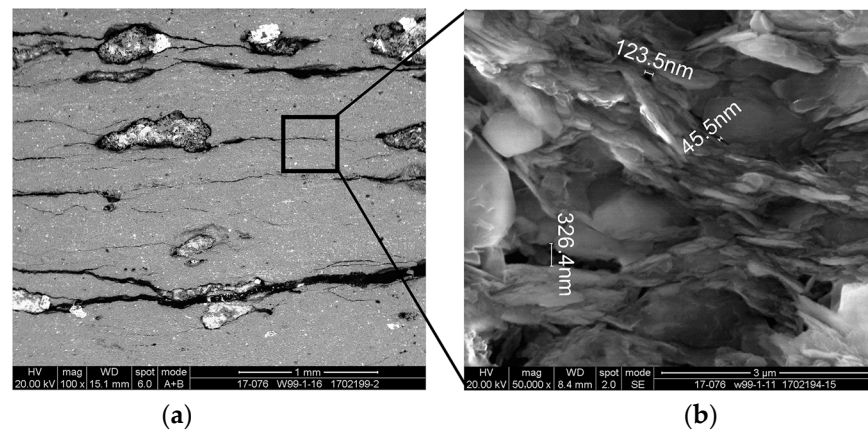


Figure 2. SEM images of the sampled cores showing microstructures of the shale (a) and the closeup illustrating preferred orientations of clay minerals (b).

Based on the above observation and analysis, we designed the schematic diagram of the shale, as shown in Figure 3. For the complex features of the shale illustrated in Figure 3, any individual model cannot adequately describe the elastic anisotropy of the shale. It is more appropriate to develop the rock physical modeling method by integrating suitable models, as is discussed in the next section.

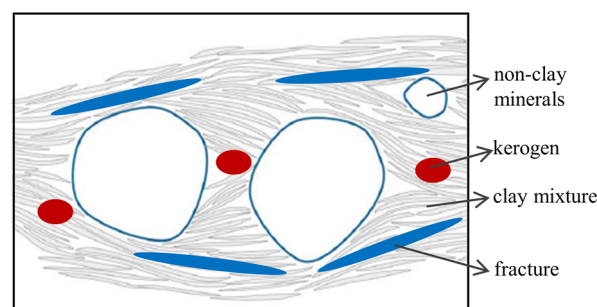


Figure 3. Schematics for rock physical modeling (modified after Sayers and Doer [21]).

3. Rock Physical Modeling and Inversion Using Well Log Data

3.1. Rock Physics Models for Shale and Clay Mixture

Figure 4 shows the rock physical workflow for the shale, corresponding to the schematic diagram in Figure 3. The elastic properties of compositions for rock physical modeling are shown in Table 1.

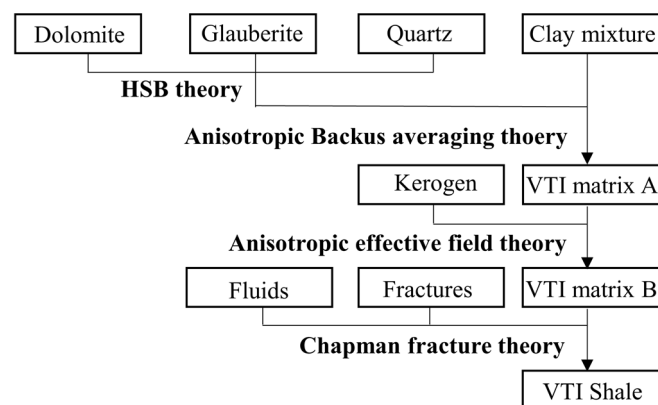


Figure 4. Flowchart of the shale model.

Table 1. Properties of compositions for rock physical modeling [32].

	Density (kg/m ³)	Bulk Modulus (GPa)	Shear Modulus (GPa)
Quartz	2650	38	44
Glauberite	2350	37	10
Dolomite	2870	95	45
Kerogen	1300	2.9	2.7
Oil	700	0.57	0
Water	1040	2.25	0

Firstly, after using the Hashin–Shtrikman boundary (HSB) [32] to obtain the elastic moduli of solid non-clay minerals, we employed the anisotropic Backus averaging [10] to calculate the VTI anisotropy of shale matrix composed of clay mixtures and the non-clay minerals.

Next, the anisotropic effective field model [21] was applied to compute the elastic anisotropy of shale with kerogen as pore-infilling material saturated in the VTI matrix. The anisotropic effective field model is suitable for putting soft materials into solid rock [33]. The model computes effective elastic stiffness C_{ijkl}^{eff} as follows:

$$C_{ijkl}^{\text{eff}} = C_{ijkl}^{(0)} + c \left[(C_{ijkl}^{(1)} - C_{ijkl}^{(0)})^{-1} + (1 - c)P_{ijkl} \right]^{-1} \quad (1)$$

where $C_{ijkl}^{(0)}$ is the stiffnesses of the matrix; $C_{ijkl}^{(1)}$ represents the stiffnesses of the inclusion; and c indicates the proportion of the inclusion. Meanwhile:

$$P_{ijkl} = \int_V G_{ik,lj}(x - x') dx' |_{(ij)(kl)} \quad (2)$$

where $G(x)$ represents the Green's function of the host rock.

Based on the tensorial basis [33], C_{ijkl}^{eff} can be linearized as follows:

$$C^{\text{eff}} = C_1^{\text{eff}} T^{(1)} + C_2^{\text{eff}} T^{(2)} + C_3^{\text{eff}} T^{(3)} + C_4^{\text{eff}} T^{(4)} + C_5^{\text{eff}} T^{(5)} + C_6^{\text{eff}} T^{(6)} \quad (3)$$

where the subscripts $ijkl$ were neglected for simplified expressions, the matrices T in Equation (3) were related to $C^{(0)}$, $C^{(1)}$, c , and P .

Finally, the Chapman fracture model [34,35] was used to describe the additional VTI anisotropy caused by bedding fractures embedded in the shale matrix. The anisotropic stiffnesses C_{ijkl} of a fractured medium are represented as:

$$C_{ijkl} = C_{ijkl}^{\text{iso}} - \varphi C_{ijkl}^1 - \varepsilon C_{ijkl}^2 \quad (4)$$

where C_{ijkl}^{iso} is the stiffnesses of the unfractured isotropic host rock, C_{ijkl}^1 and C_{ijkl}^2 are the terms of fractures and pores introduced into the background; φ denotes porosity; and ε represents the fracture density.

The method depicts fluid flow in the pore spaces consisting of equant pores and fractures. The computed frequency-dependent complex stiffnesses are:

$$C_{ijkl} = C_{ijkl}(\lambda, \mu, \omega, \tau, \varphi, \varepsilon, \kappa_f) \quad (5)$$

where λ and μ are the Lamé's constants of the host rock; ω denotes frequency; τ is the relaxation time; and κ_f represents the bulk module of fluids.

Previous studies have introduced the clay lamination index to describe the degree of the preferred orientation of clay minerals and the aspect ratio to describe the geometry of bedding fractures [19,22,36,37]. However, based on experimental measurements and

theoretical modeling, Sayers and Doer [21] found that clay minerals tend to exist in the form of a mixture [21]. The clay mixture is composed of the solid illite/smectite mixture and interparticle medium with a bulk modulus close to the water and a shear modulus much smaller than the bulk modulus. The clay mixture is the primary factor that causes laminated shale fabrics at the microscale, consequently affecting the inherent VTI anisotropy of shale.

Accordingly, Figure 5 shows the rock physical model proposed for the clay mixture. The elastic anisotropy of the illite/smectite particles was described with the anisotropic Backus averaging model [10]. Then, based on the anisotropy effective field model [21], the soft interparticle medium was introduced to obtain the corresponding VTI anisotropy stiffnesses of the clay mixture.

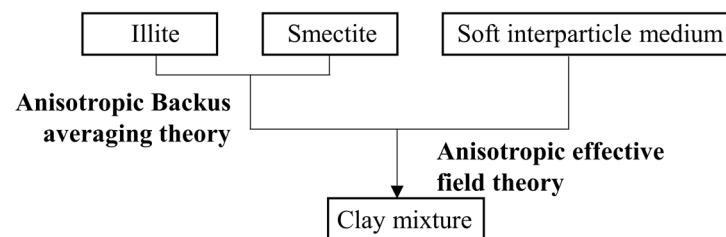


Figure 5. Flowchart of the clay mixture model.

3.2. Rock Physical Inversion for Clay Mixture Properties

Two factors primarily affect the shale VTI anisotropy, including the inherent anisotropy related to the clay mixture and the additional anisotropy associated with bedding fractures in the shale matrix. Accordingly, model-based inversion methods were proposed to estimate corresponding reservoir parameters. Figure 6 shows the rock physical inversion procedure that computes the parameters associated with the clay mixture and bedding fractures. Wave velocities of the clay mixture ($V_{p\text{-clay}}$ and $V_{s\text{-clay}}$) and the bedding fracture aspect ratio (α_H) were regarded as the fitting parameters to be retrieved. These parameters were predicted by finding the best match between wave velocities calculated by the rock physics model and those measured in the borehole. In solving the objective function, the particle swarm particle filter algorithm was applied to realize multi-parameter optimization.

The inversion results are illustrated in Figure 7, including wave velocities of shale (V_p and V_s), α_H , $V_{p\text{-clay}}$, $V_{s\text{-clay}}$, and the corresponding velocity ratio $V_{p\text{-clay}}/V_{s\text{-clay}}$. Rock physical inversion was only conducted for the shale layers. In Figure 7a,b, the actual wave velocity logs (black) are in good agreement with the fitting curves obtained in the inversion (red), indicating that the built model and inversion method are applicable to the shale oil reservoir. The obtained α_H in Figure 7c can be used to evaluate the geometry of bedding fractures. The α_H values approaching zero correspond to the thin and penny-shaped fractures, and the values approaching 1 indicate the equant pores. In Figure 7d, we note that the predicted $V_{s\text{-clay}}$ is abnormally low, so the $V_{p\text{-clay}}/V_{s\text{-clay}}$ ratio in Figure 7e has a high value, generally >2 . The estimated $V_{p\text{-clay}}/V_{s\text{-clay}}$ is far greater than the corresponding velocity ratio for common solid minerals. This result can be explained by the specific properties of the interparticle region with much lower but nonzero shear moduli [21].

Figure 8 shows the workflow to compute the clay mixture properties based on the proposed rock physical model in Figure 5. Predicted velocities in Figure 7 were used as fitting parameters in the objective function to predict the fraction of illite (f_{illite}) and that of soft interparticle region (f_{soft}). The obtained results are shown in Figure 9. As shown in Figure 9a,b, the calculated clay mixture velocities (red curve) fit well with the input values (black curve), justifying the applicability of the developed model for the clay mixture. The predicted results of f_{illite} and f_{soft} in Figure 9c,d can provide insights into the microstructural characteristics of the shale oil reservoir in the study area.

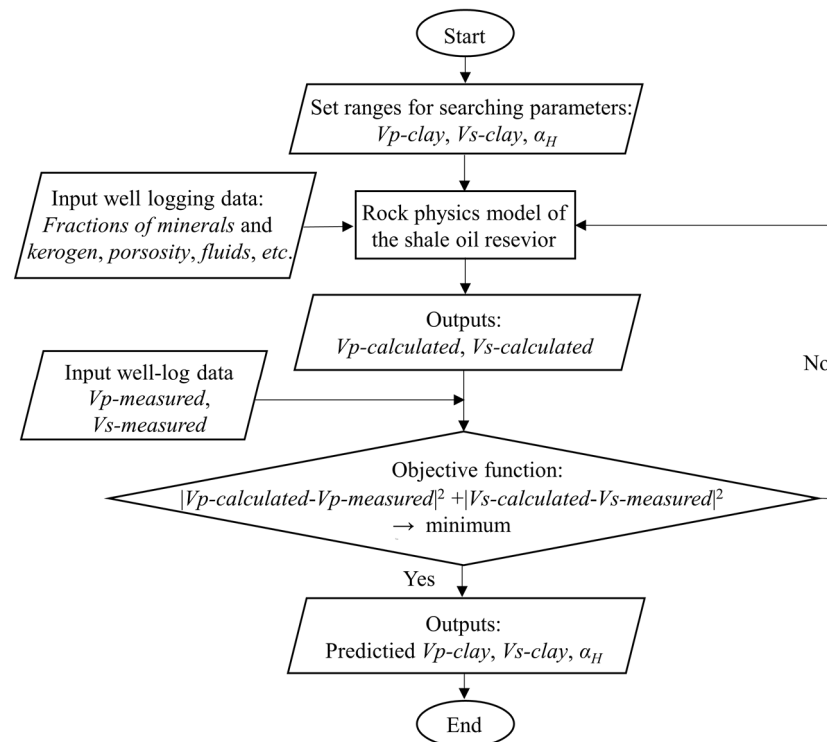


Figure 6. Flowchart of the model-based inversion to estimate the parameters associated with the clay mixture and bedding fractures.

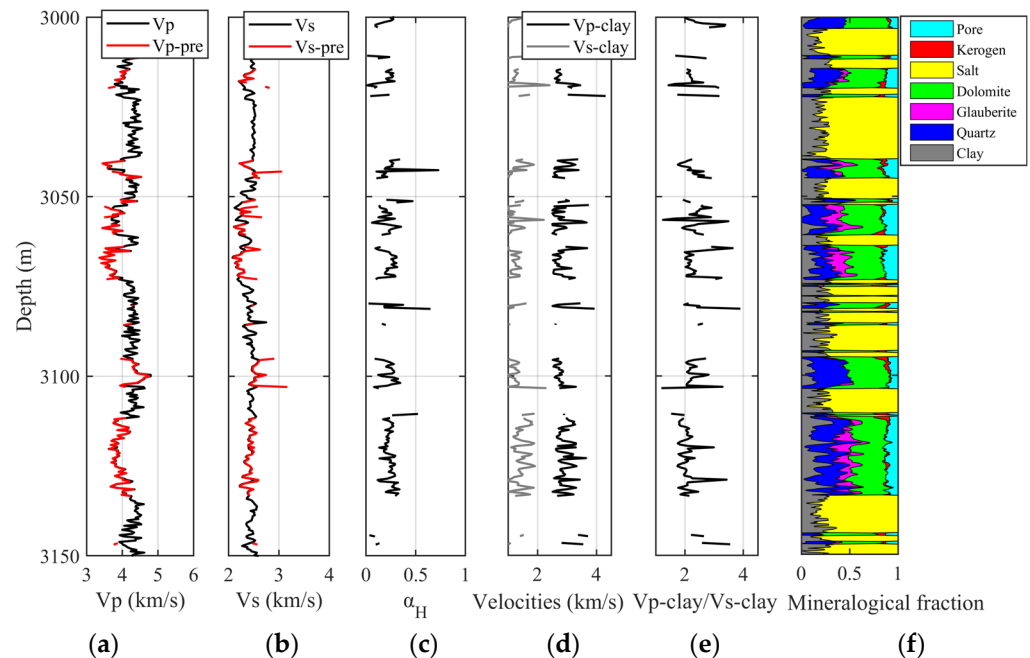


Figure 7. Inversion results of the parameters related to bedding fractures and the clay mixture. Velocities of P-wave (a) and S-wave (b) of shale, the aspect ratio of bedding fractures (c), wave velocities of the clay mixture (d) and corresponding velocity ratio (e), and volumetric fractions of constituents (f).

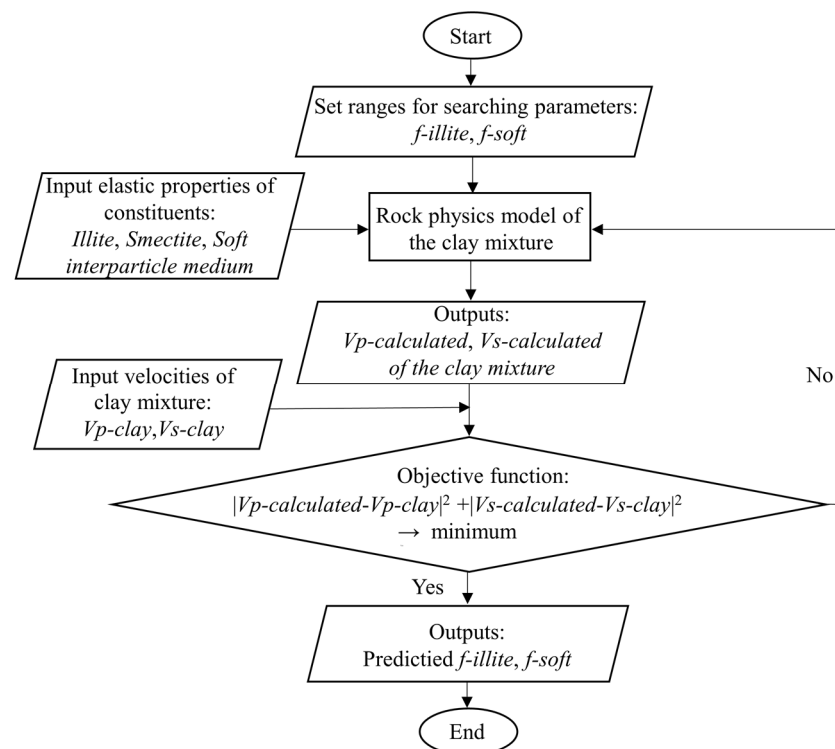


Figure 8. Flowchart for the inversion of the clay mixture properties.

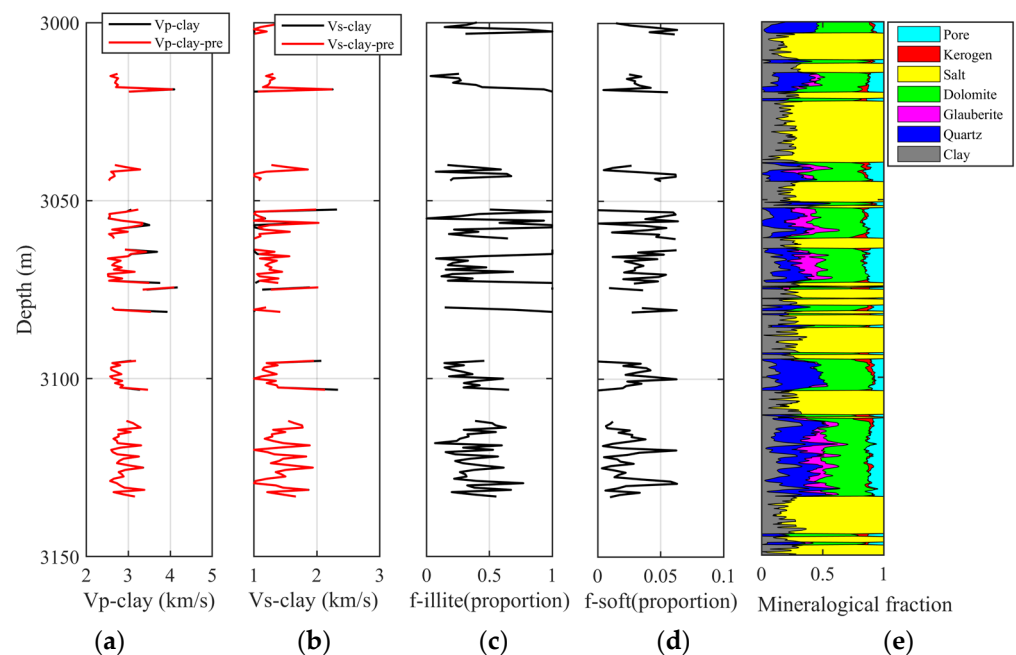


Figure 9. Inverted results of the properties clay mixture, including Vp-clay (a) and Vs-clay (b) of the clay mixture, f-illite (c), and f-soft (d) in the clay mixture. Volumetric fractions of constituents (e).

3.3. Estimate of Elastic Anisotropy for Clay Mixture and Shale

Based on the results shown in Figures 7 and 8, the related properties are known for rock physical modeling for the clay mixture and shale with the proposed models. That is, elastic anisotropy of the shale from microscale to macroscale can be calculated with the models in Figures 4 and 5. Accordingly, the calculated results are shown in Figure 10. The P-wave anisotropic parameters of the clay mixture and that of the solid particles are different, as shown in Figure 10a. This result can be interpreted by the low bulk modulus of

the interparticle region, which enhances elastic anisotropy due to strong contrast in elastic properties between relevant components. In addition, because the interparticle medium has a nonzero but very small shear modulus [21], it has little impact on shear waves, making the corresponding S-wave anisotropic parameters exhibits negligible differences, as shown in Figure 10b. Meanwhile, because bedding fractures developed in the solid matrix can significantly enhance the VTI anisotropy of shale, the anisotropic parameters of the overall shale in Figure 10c,d are both higher than those of the shale matrix. In addition, the calculated anisotropic parameters of the shale can provide more accurate models for seismic modeling and inversion.

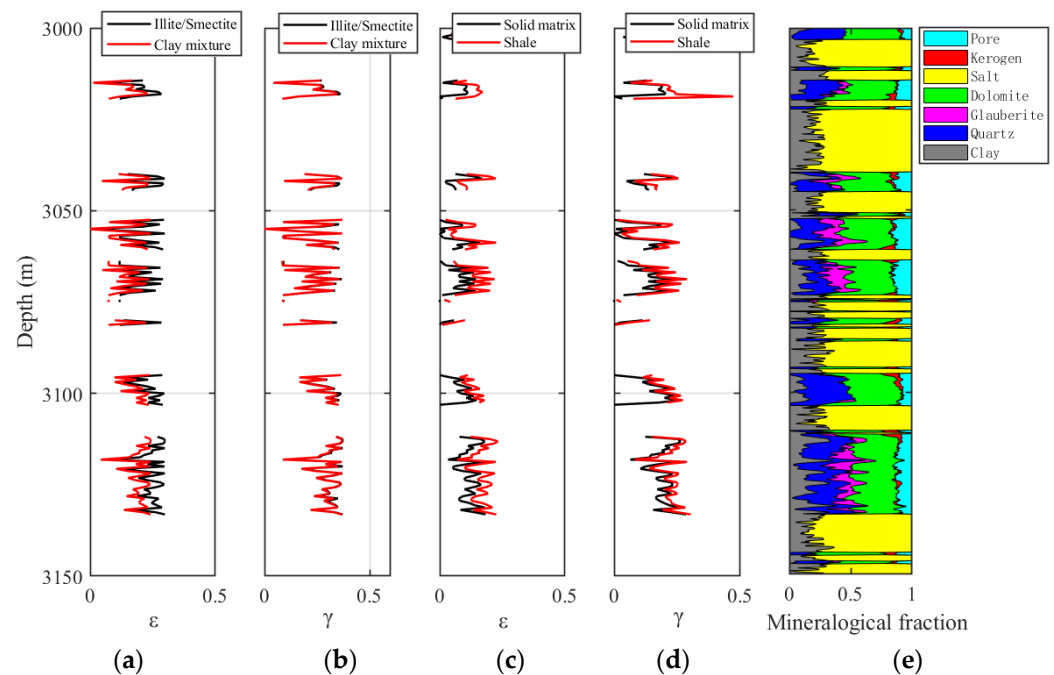


Figure 10. Inverted anisotropic parameters of the solid illite/smectite particles (a), clay mixture (b), shale matrix (c), and the overall shale (d). Volumetric fractions of constituents (e).

4. Quantitative Seismic Interpretation Based on the BPNN Framework

4.1. Framework of the BPNN for Quantitative Seismic Interpretation

In this study, the reservoir parameters of the shale oil reservoir were inverted using the well log data based on the constructed rock physics models. Then, nonlinear correlations between the estimated reservoir parameters and elastic properties of the shale oil reservoir were constructed based on the BPNN algorithm. After that, the established correlations were utilized to characterize the target shale oil reservoir by converting seismic-inverted elastic properties to the parameters with reservoir implications.

A typical three-layer BPNN structure is shown in Figure 11, consisting of the input layer, hidden layer, and output layer. The BPNN belongs to the tutor learning algorithm, where the algorithm adjusts the weight of the network connection by inputting training data into the network and calculating the error between the output value and the expected value of the network. The BPNN is robust and has excellent flexibility and self-adaptability in solving nonlinear problems and therefore was used in this study to establish quantitative correlations between reservoir parameters and elastic properties.

As shown in Figure 12, the BPNN framework was established for quantitative seismic interpretation of the reservoir parameters based on the rock physical inversion results. The training samples used in the BPNN framework are from the results obtained in Figures 1, 7, 9 and 10, containing the data of 500 depth intervals for the shale formation. Specifically, 70% (350 depth sampling) of the well log data of V_p , V_s , and corresponding

predicted reservoir parameters of the shale formation were used as input training samples, and the remaining 30% (150 depth sampling) were adopted as the test samples.

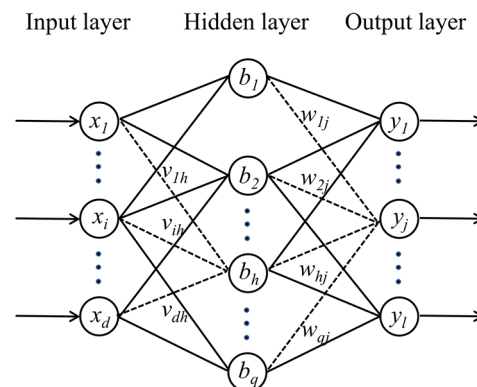


Figure 11. Schematics of the BPNN structure.

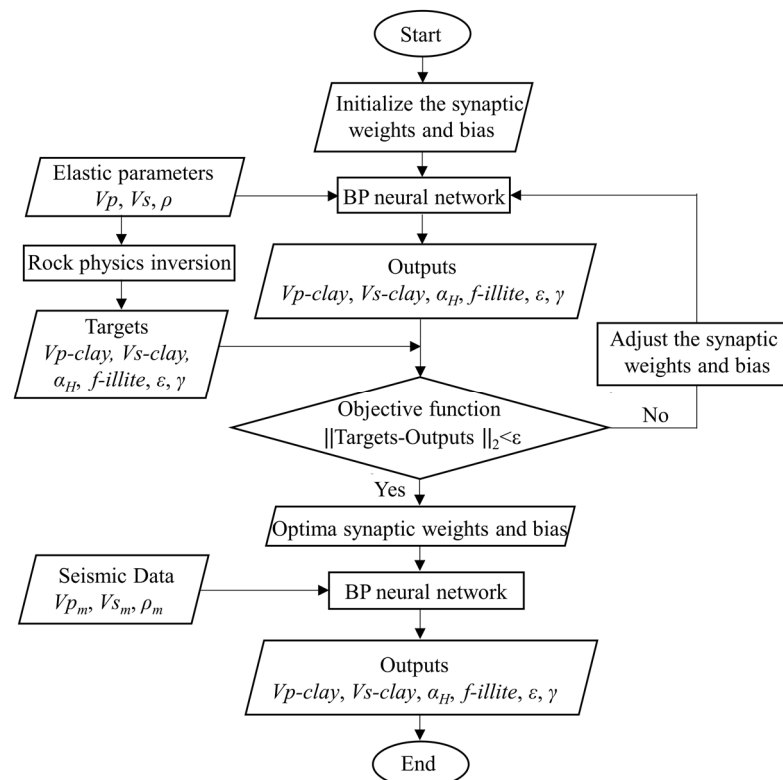


Figure 12. Flowchart of the BPNN to obtain nonlinear correlations between reservoir parameters and elastic properties for quantitative seismic interpretation.

Six different BPNNs were established to obtain the correlations between (V_p, V_s, ρ) and $V_{p\text{-clay}}, V_{s\text{-clay}}, \alpha_H, f\text{-soft}, \epsilon, \gamma$, respectively. In the established BPNN frameworks, the elastic properties (V_p, V_s, ρ) were set as input layer data, while the reservoir parameters were regarded as the output layer data. Accordingly, the input layer contains three neurons for each neural network, the hidden layer contains five neurons, and the output layer has one neuron, respectively. The log-sigmoid transfer function was used in the neural network as the activation function. Meanwhile, the training process adopted the Levenberg–Marquardt algorithm as the optimization method.

4.2. Test of the Established BPNNs

Figure 13 shows the mean square error (MSE) convergence curves of the corresponding BPNNs for establishing quantitative correlations between reservoir parameters and elastic properties. The solid blue line is the training curve, representing the convergence degree of the MSE of the training sample in the training network. The solid green line is the validation curve corresponding to the convergence degree of the MSE for the validation sample in the training network. The solid red line is the test curve, indicating the degree of MSE convergence for the test sample in the testing process. With the increase in the number of iterations, the MSE represented by the training and test curves reduces to the preset value. Two dotted green lines indicate the best validation performance and its epoch, respectively, with the green circles indicating the corresponding intersection points.

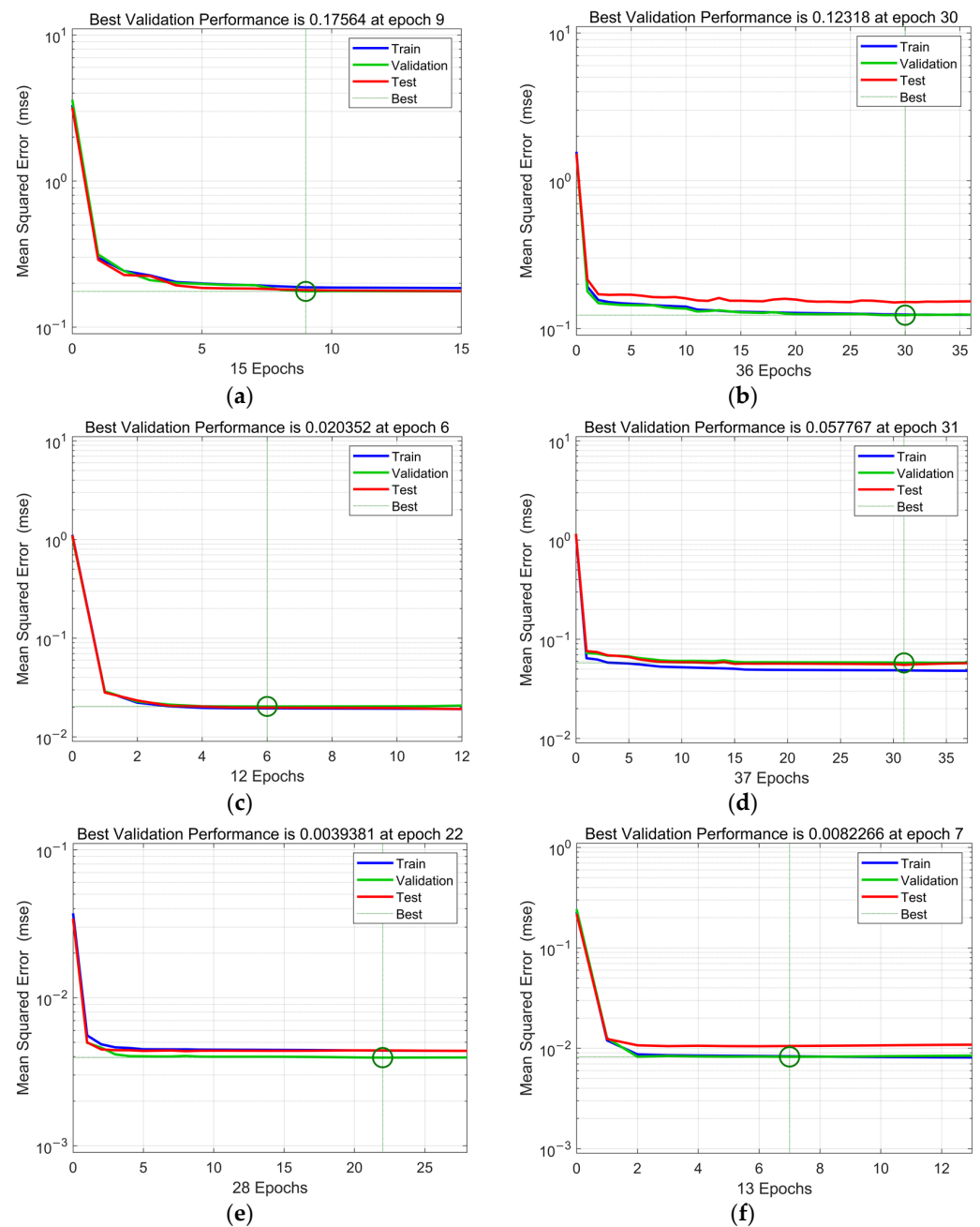


Figure 13. Convergence curves of the BPNNs for establishing nonlinear correlations between elastic properties and Vp-clay (a), Vs-clay (b), α_H (c), f-illite (d), ϵ (e), and γ (f).

The prediction results for the test samples are shown in Figure 14. The black curves represent the data obtained using the proposed model-based inversion method, and the red curves are the estimated results using the established BPNNs. The predicted results are in good agreement with the actual data. The results validate that the established BPNNs can be used for quantitative seismic interpretation of the reservoir parameters in the study area. It should be noted that the curves in Figure 14 represent test data extracted from well log data instead of actual logging curves in the borehole.

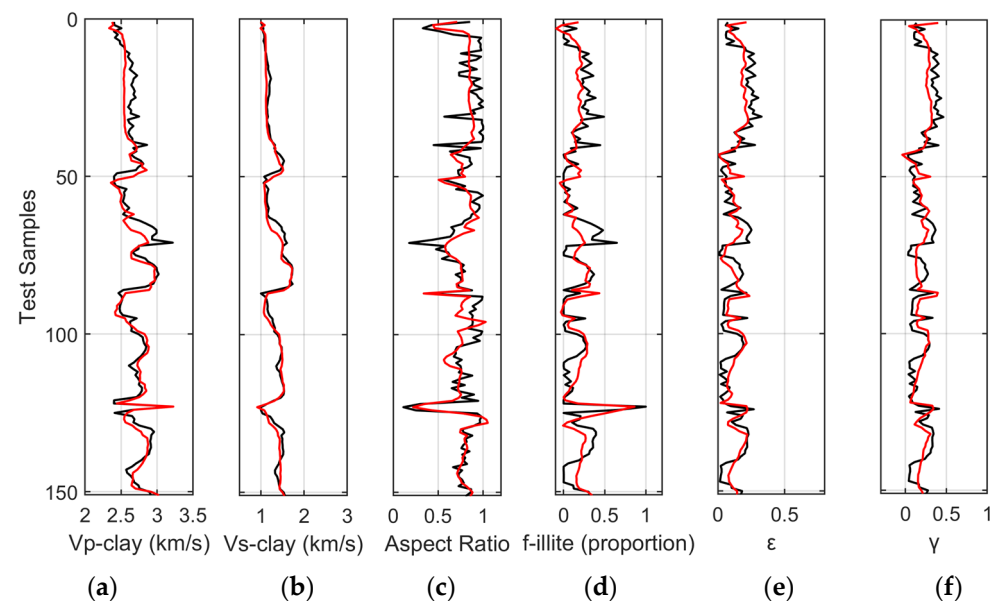


Figure 14. Test of the established BPNNs. The black curves represent real data, and the red curves correspond to predicted results of Vp-clay (a), Vs-clay (b), aspect ratio (c), f-illite (d), ϵ (e), and γ (f).

4.3. Real Data Applications

Then, the established BPNNs were used to convert seismic-inverted elastic properties to reservoir parameters and elastic anisotropy of the shale oil reservoir in Qianjiang Basin, China. Figure 15 shows the input wave velocities of the target shale obtained using pre-stack seismic inversion (density not displayed for simplicity). The predicted results of the reservoir parameters using the BPNNs are illustrated in Figure 16, including Vp-clay, Vs-clay, f-illite, α_H , and anisotropic parameters ϵ and γ of the shale matrix. Wave velocities of the shale (Figure 15a,b) and those of the clay mixture (Figure 16a,b) are relatively higher in the southwest region while they do not necessarily coincide with each other in local areas. Higher velocities of the clay mixture (Vp-clay and Vs-clay) generally indicate a larger amount of the high-velocity illite minerals (f-illite), as shown in Figure 16c. The aspect ratio α_H of bedding fractures in Figure 16d describes the geometry of bedding fractures. A smaller α_H corresponds to thin and penny-shaped fractures, indicating potentially higher connectivity of pore spaces for fluid flow and, therefore, higher permeability of the shale. Anisotropic parameters ϵ and γ of the shale matrix reflect the degree of intrinsic anisotropy associated with fabrics, which provides insights into the mechanical properties of shale rock. Higher intrinsic anisotropy of the shale may affect the effectiveness of hydraulic fracturing.

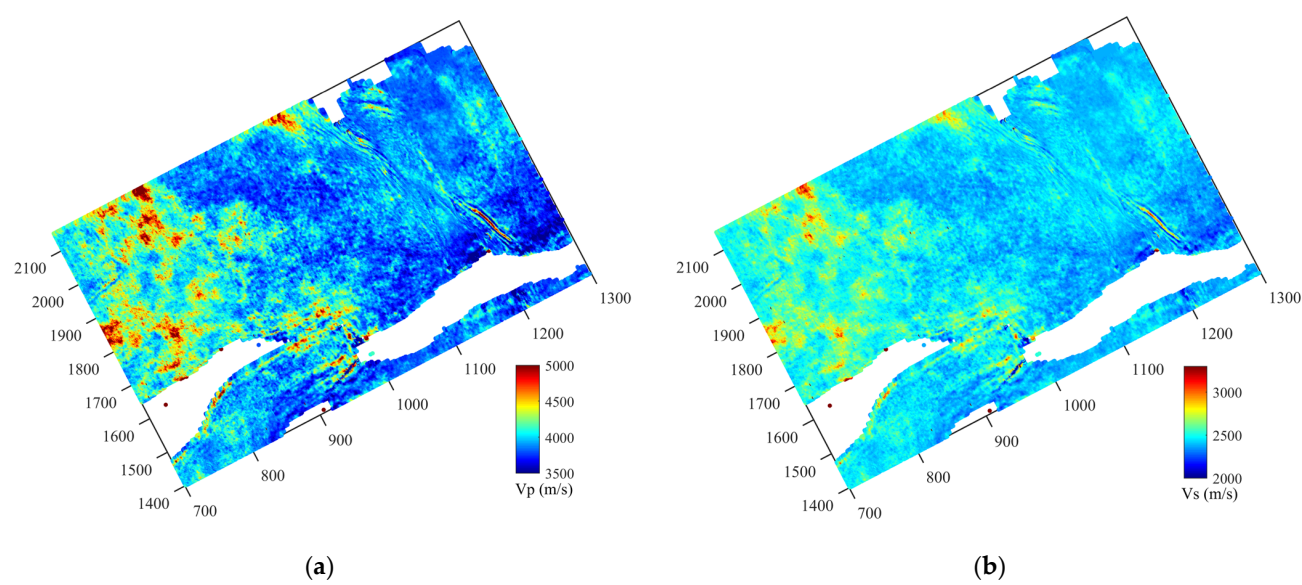


Figure 15. P-wave (a) and S-wave (b) velocity of the target shale from pre-stack seismic inversion.

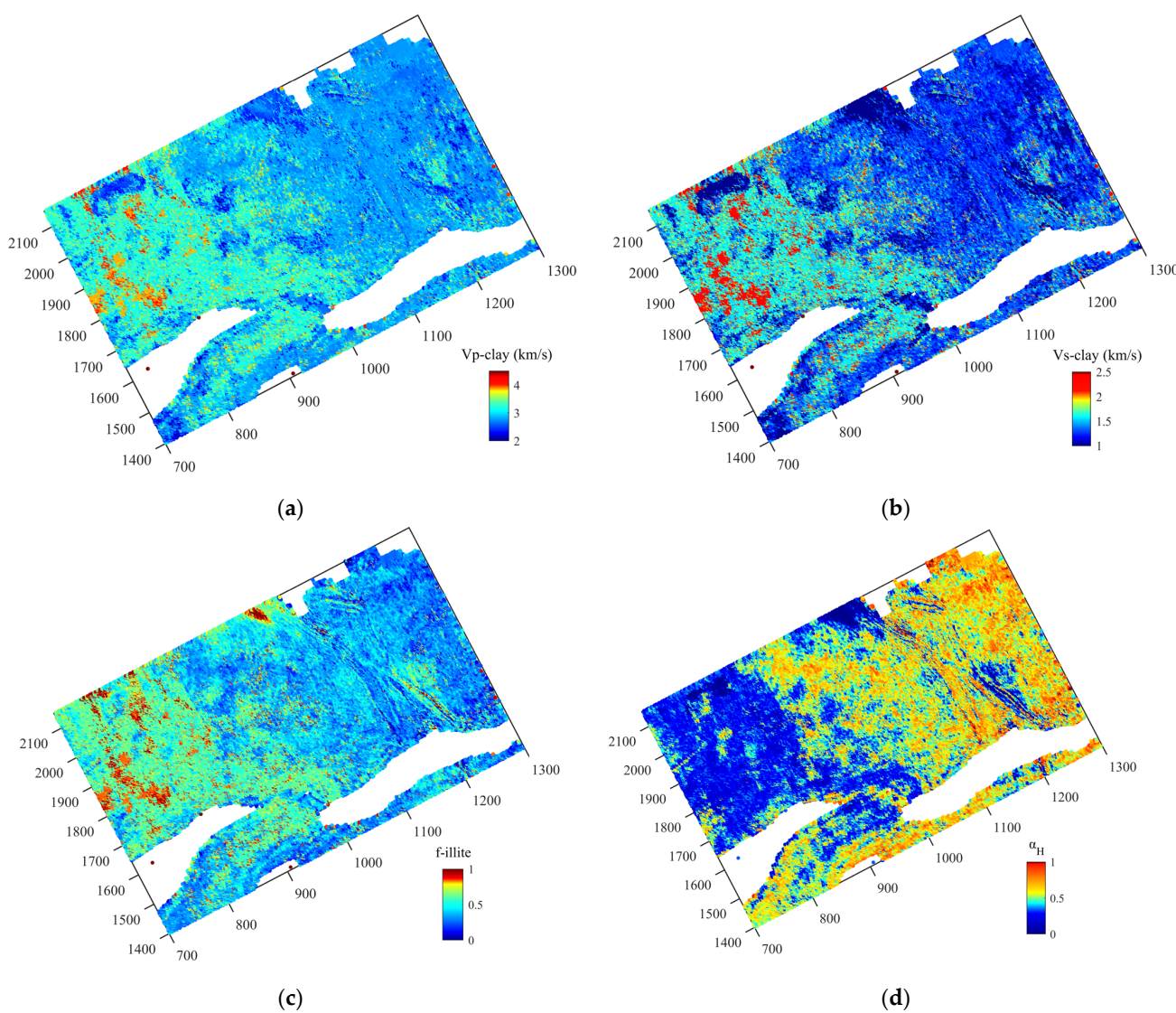


Figure 16. Cont.

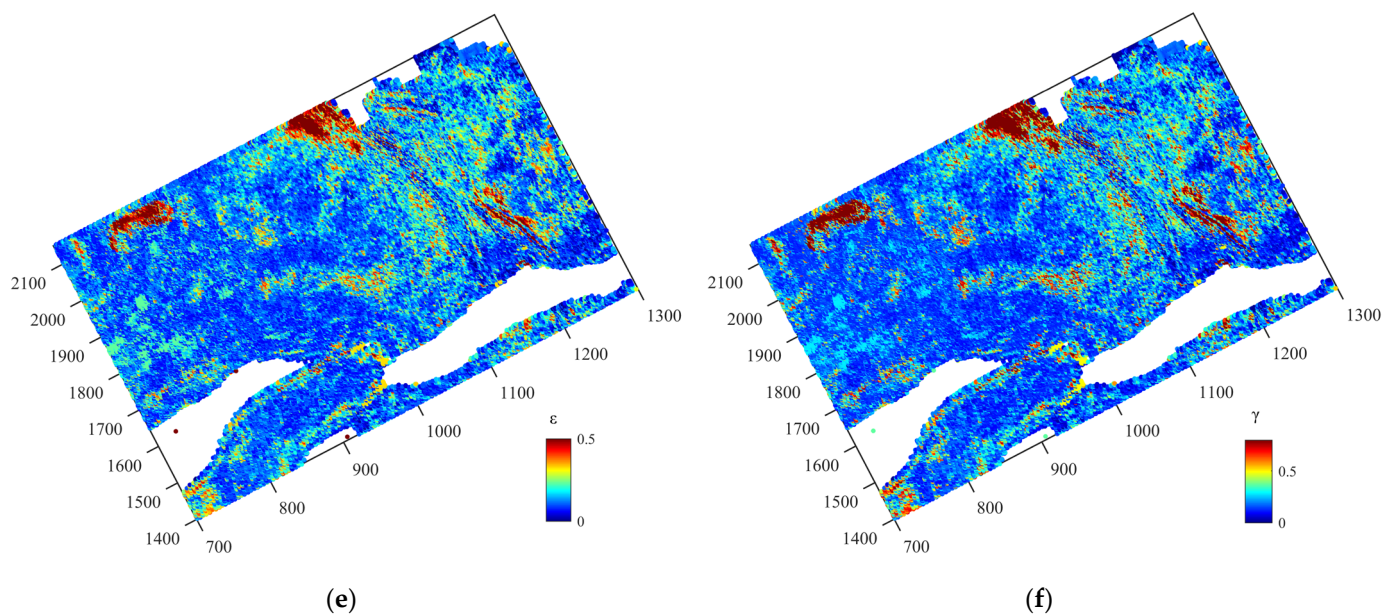


Figure 16. Quantitative interpretation for the target shale, including Vp-clay (a), Vs-clay (b), f-illite (c), α_H (d), anisotropy parameters ε (e), and γ (f) of the shale matrix.

5. Conclusions

This paper presented a framework of quantitative seismic interpretation that incorporates rock physical inversion using well log data and the BPNN algorithm to obtain nonlinear correlations between reservoir parameters and elastic properties. Then, seismic-inverted elastic properties were interpreted to the parameters with reservoir implications based on the established correlations.

The proposed rock physics models are the core of the quantitative interpretation to describe clay mixture properties and shale elastic anisotropy associated with microstructural features at different scales. Based on the proposed models, the rock physical inversion methods were proposed to predict the reservoir parameters and elastic anisotropy using well log data from the Qianjiang shale formation in the Jiangnan Basin, China. Nonlinear relationships between relevant parameters obtained using the BPNN algorithm were applied to convert seismic-inverted elastic properties to the parameters with reservoir implications and elastic anisotropy of the shale. The predicted elastic anisotropy of the solid matrix reflects the lamination degree and helps to evaluate the mechanical properties of the shale, which is critical for effective hydraulic fracturing. The calculated anisotropic parameters of the overall shale provide accurate velocity models for seismic modeling and inversion. The computed aspect ratio of the bedding fractures can be used to estimate reservoir permeability. Therefore, the obtained results facilitate shale oil reservoir characterization, providing valuable information to locate promising oil zones in the study area.

The proposed quantitative interpretation framework can inspire further studies by incorporating suitable rock physics models, inversion methods, and other sophisticated artificial intelligence algorithms for particular hydrocarbon resources. Meanwhile, appropriate reservoir parameters and elastic properties can be carefully selected for improved reservoir characterization of hydrocarbon resources after sensitivity analysis based on the advancement of rock physical modeling methods.

Author Contributions: Conceptualization, Z.G.; methodology, Z.G. and T.Z.; software, T.Z.; validation, Z.G. and T.Z.; formal analysis, Z.G. and T.Z.; investigation, Z.G. and T.Z.; resources, C.L.; data curation, X.L. and Y.L.; writing—original draft preparation, T.Z.; writing—review and editing, Z.G.; visualization, T.Z.; project administration, Z.G.; funding acquisition, Z.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

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