Study and Classification of Porosity Stress Sensitivity in Shale Gas Reservoirs Based on Experiments and Optimized Support Vector Machine Algorithm for the Silurian Longmaxi Shale in the Southern Sichuan Basin, China

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ABSTRACT: To understand the characteristics of variation in porosity and permeability, the physical properties of the shale reservoir under different stress conditions play an important role in guiding shale gas production. With the shale of the Wufeng–Longmaxi Formation in the south of the Sichuan Basin as the research object, stress-dependent porosity and permeability test, high-pressure mercury injection, and scanning electron microscope test were performed in this study to thoroughly analyze the variation in physical properties of different shale lithofacies with effective stress. Besides, the stress sensitivity of different lithofacies reservoirs was evaluated by using parameters such as pore compressibility coefficient (PCC) and porosity sensitivity exponent (PSE), while the optimized support vector machine (SVM) algorithm was adopted to predict the coefficient of reservoir porosity sensitivity. According to the research results, the porosity and permeability of shale reservoirs decline as a negative exponential function. When the effective stress falls below 15 MPa, the damage rate of permeability/porosity increases rapidly with the rise of effective stress. By contrast, the permeability curvature of the shale reservoirs plunges with the rise of effective stress. It was discovered that a higher siliceous content results in a higher permeability curvature of shale, indicating the greater stress sensitivity of the reservoir. The ratio of matrix porosity to microfracture porosity determines the PSE, which is relatively low, and low aspect ratio pores contribute to high porosity compressibility and stress sensitivity. Young’s modulus shows a negative correlation with pore compressibility and a positive correlation with Poisson’s ratio. High clay minerals have a large number of low aspect ratio pores and a low elastic modulus, which leads to both high PCC and low PSE. Based on the principal component analysis, a multiclassification SVM model was established to predict the PSE, revealing that the accuracy of the sigmoid, radial basis function (RBF), and linear kernel function is consistently above 70%. According to error analysis, the accuracy can exceed 80% with the RBF kernel function and appropriate penalty factor. The research results serve to advance the research on the parameters related to overburden pressure, porosity, and permeability. Moreover, the optimized SVM algorithm is applied to make a classification prediction, which provides a reference for shale reservoir exploration and development both in theory and practice.

1. INTRODUCTION

As an essential unconventional energy source, shale gas is abundant and widely distributed in China, which can alleviate the pressure on the global natural gas supply and demand gap. It is expected to become the most crucial substitute for conventional oil and gas resources. In recent years, the exploration and development of Longmaxi shale have processed

Received: May 31, 2022
Accepted: August 19, 2022
Published: September 12, 2022
substantial breakthroughs in the Sichuan Basin, showing a good resource potential and attracting increasing interest.\textsuperscript{5–9} Compared with conventional reservoirs, the permeability of shale is the crucial influence factor that affects gas slippage, adsorption/desorption, and diffusion.\textsuperscript{6,14,16,18,19} Meanwhile, due to the changing depositional environment, petrographic composition, natural fracture development degree, water saturation, and tectonic deformation, the shale has a complex pore network consisting of organic matter (OM) and mineral matrix.\textsuperscript{12,13} As porous medium reservoirs, the shale is identified as pore–fracture type reservoirs, showing the ultranatural matrix porosity and permeability, low strength, large deformation, and strong stress sensitivity.

Shale porosity and permeability are essential reservoir characteristics that directly affect shale gas production, impacting the fluid flow of the desorbed methane, gas well production, and gas storage capacity.\textsuperscript{6,14,19} In the early stage of shale gas exploitation, the fracture pore closes with shale reservoir pressure increasing, and the shale permeability decreases with an increase in effective stress. The free gas and the desorbed gas flow from the matrix to the fracture channels. During the substantial stage of shale gas release, the pore pressure declines, and the effective stress of the matrix increases in shale matrix shrinkage, resulting in the original pore–fracture system being compressed, which will cause a continuous decrease in both the matrix permeability and fracture space of the shale reservoir.\textsuperscript{14,16,18,19} Considering the effect of stress on shale reservoirs throughout the entire shale gas well production, the permeability and porosity reduction rate is unsynchronized and nonlinear in the matrix and fracture systems related to the stress-dependent effects.\textsuperscript{18–20} Therefore, it is essential to investigate the permeability and porosity characteristics under the effective pressure and study the stress sensitivity mechanism of the shale matrix permeability, which would have a significant influence on the estimated ultimate recovery.

A considerable amount of previous works have studied the relationship between the permeability and stress of different types of rocks, including coal, sandstone, granite, and shale, which have obtained remarkable results.\textsuperscript{16,19} Previous studies on the relationship between the effective permeability and variable confining pressure have mainly focused on experimental and theoretical studies. According to Poiseuille’s equation of the deformation spheres, Jones postulated that a logarithmic empirical could analyze the fractured carbonate permeability with respect to effective stress in experimental studies.\textsuperscript{21} Walsh observed the theoretical derivation procedure of the logarithmic relationship to describe the stress sensitivity.\textsuperscript{22} Gangi derived two polynomial decay formulas of permeability with confining pressure for whole and fractured rocks with theoretical studies, respectively, whereas the function is too complicated to apply.\textsuperscript{23} Among the research mentioned above, the experimental measurements of shale permeability are typically conducted under constant effective stresses. The permeability of different types of rocks commonly decreases due to an increase in effective stress. However, there are various pressure-dependent permeability fitting models, including the exponential, power, logarithmic, and binomial types, which can describe the relationship between the permeability and the effective stress of the rock. Reyes and Ossanya reported the steady-state method to measure the effective stress coefficient of four shale cores in Oklahoma with variable confining pressure, suggesting that the permeability exhibits the highest degree of exponential relationship with the stress.\textsuperscript{24} Dong et al. studied the porosity and permeability of shale samples and obtained a power law equation to describe the permeability of sandstone, and silty shale varies with effective stress.\textsuperscript{25} Chalmers et al. used the pulse method to show that shale has strong stress sensitivity by changing the effective stress.\textsuperscript{26} Chen et al. considered a theoretical correlation between shale permeability and effective pressure, which can match the experimental data for different gas shales.\textsuperscript{27} Shi and Durucan used theoretical and empirical equations to fit experimental data. They developed Gangi’s phenomenological permeability models to describe the relationship between effective stress and permeability of intact and fractured porous rocks.\textsuperscript{28} Different models can depict various permeability performances of rocks.\textsuperscript{5} In general, the stress-dependent permeability of shale and sandstone was characterized by an exponential function in experimental data and field practice, with the simple and adaptable forms in shale.

In recent years, scholars have paid attention to calculating the effective porosity sensitivity exponent (PSE) accurately. The effective PSE is critical for evaluating the compression characteristic under effective pressure, which describes the relationship between porosity and permeability.\textsuperscript{29} The shale compressibility exponent represents the influence of rock mechanics parameters and the compression characteristic of the reservoir.\textsuperscript{19} The permeability damage rate is reflected in the percentage of the permeability damage of the shale reservoir under effective stress.\textsuperscript{17} The PSE reveals the geometric characteristics of the pores and indicates the variations in the porosity under effective stress.\textsuperscript{16} David et al. defined stress sensitivity-related parameters, including the pore compressibility coefficient (PCC) and the PSE.\textsuperscript{29} Zhang et al. developed several types of pore models (the circular, elliptical pores, and fractures) and investigated the effect of pore geometry and rock elastic properties on pore compressibility.\textsuperscript{18,19} Ming et al. adapted the porosity/permeability stress damage rate and permeability curvature to analyze and compare the difference in stress sensitivity between shale, coal, and sandstone reservoirs.\textsuperscript{30} Ma et al. use the porosity/permeability stress damage rate and permeability curvature of coal reservoirs to analyze the sensitivity of different low-rank coal reservoirs.\textsuperscript{31} Some scholars research the influencing factors of stress sensitivity by considering the local geology characteristics and formation pressure.\textsuperscript{17,19} Ghanizadeh et al. concluded that the permeability coefficients strongly depend on permeating fluid, moisture content, anisotropy, effective stress, and other factors.\textsuperscript{32} In addition, some scholars have used finite element technology and nuclear magnetic resonance to analyze the relationship between the anisotropy characteristics of rock–stress-dependent permeability, pore variation characteristics, water–rock reaction, seepage capacity, and gas well productivity. Although various studies have investigated the stress sensitivity of shale, there is also a lack of systematic studies to predict the PSE of shale with the in situ effective stress, and the influence factors have rarely been analyzed.

This paper systematically studies the variation characteristics of porosity and permeability in different lithofacies shale from the southern Sichuan Basin under various stress conditions. The physical property evolution curves under different stresses calculated the porosity compressibility, stress sensitivity coefficient, and PSE of different shale lithofacies. The relationship between the pore structure, mineral composition, TOC content, rock mechanical properties, and parameters related to porosity and permeability of overburden was systematically analyzed. Finally, principal component analysis (PCA) and
support vector machine (SVM) are used to establish a classification prediction model of the PSE to realize the prediction of the PSE on the longitudinal section.

2. SAMPLE AND GEOLOGICAL SETTINGS

2.1. Geology of the Sichuan Basin. The Sichuan Basin is located at the northwest edge of the Yangzi Platform. The Changning–Luzhou area in the southern part of the Sichuan Basin is bounded by the Caledonian Chuanzhong paleo uplift and the Central Guizhou uplift. The late Ordovician Wufeng–early Silurian Longmaxi Formation is located in the center of deepwater shelf sedimentation in southern Sichuan (Figure 1). The bottom of the Upper Ordovician Wufeng Formation is in integrated contact with the lower Linxiang Formation tuffs. The top of the Longmaxi Formation is in integrated contact with the carbonate rocks of the Lower Silurian Shiniulan Formation. The lithology of the Wufeng Formation–Longmaxi Formation from bottom to top is dark grey siliceous, carbonaceous shale in the lower deepwater shelf phase, grey-dark grey clay shale in the middle shallow water-deep water shelf phase, and light grey–gray siltstone in the upper shallow water shelf phase. At the bottom of the—Longmaxi formation, the organic-rich shale system is stable, widely distributed, and the main exploration target area (Figure 1).

2.2. Samples Collection. In this study, 57 shale samples were collected from the Wufeng–Longmaxi Formation in the southern Sichuan Basin. All of which originated from 4 wells (N18, N13, N16, and L7) at 2500 to 3500 m in the Luzhou–Changning area. The depth, porosity, and TOC content of samples are listed in Table 1.

3. EXPERIMENTS AND METHODOLOGY

3.1. Organic Geochemistry and Petrology. TOC can not only generate gas but also provide the main space for gas storage. The structure of the organic matters within the connected and isolated pore network is essential for gas storage capacity and shale porosity. The organic geochemistry was performed on powered shale using a CS230 carbon and sulfur analyzer in a copper utensil. Following the nation strand of GB/T 19145-2003, the 100 mg powered were placed in the crucible with 5% concentrated HCl at the temperature of 80 °C to remove the inorganic carbonates minerals and washed with distilled water to remove the retained hydrochloric acid to eliminate the bias in the result. The XRD experiment can provide mineralogy results, which quantitatively analyze the prominent peaks of X-ray diffraction pattern curves. The measurements were performed on a Bruker D8 DISCOVER following SY/T 5163-2010. The XRD analysis and TOC measurement were performed at the Analytical Experiment Center of Southwest Oil and Gas Field Company, CNPC.

3.2. Porosity and Bulk Density Test. The samples were cut with cylinders ranging in diameter from 3 to 4 cm for the porosity and bulk density measurement. In this study, the plunger liquid saturation porosity method was used to calculate porosity. According to GB/T 29172-2012, the plunger liquid saturation porosity method includes three main steps, measuring the dry core quality, the density of core with confine density fluid-saturated, and the quality submerged in saturated liquid. The shale matrix porosity values can be determined using eq 1.
### Table 1. Basic Information of Samples

| sample | depth (m) | TOC (wt %) | density (g/cm$^3$) | porosity (%) | permeability (mD) | mineral composition (%) | lithofacies |
|--------|-----------|------------|---------------------|--------------|-------------------|-------------------------|-------------|
|        |           |            |                     |              |                   |                          |             |
| L7-1   | 1650.4    | 0.10       | 2.65                | 1.85         | 0.0004            | 52.2                    | 47.8        | S-3         |
| L7-2   | 1653.7    | 0.39       | 2.66                | 1.88         | 0.0013            | 51.3                    | 46.2        | S-3         |
| L7-3   | 1656.1    | 0.44       | 2.66                | 1.82         | 0.0012            | 48.4                    | 49.4        | M-2         |
| L7-4   | 1660.3    | 1.21       | 2.63                | 2.52         | 0.0018            | 51.8                    | 41.3        | S-3         |
| L7-5   | 1663.0    | 0.99       | 2.68                | 1.53         | 0.0013            | 58.6                    | 37.3        | S-3         |
| L7-6   | 1664.9    | 1.04       | 2.68                | 2.45         | 0.0007            | 49.0                    | 47.6        | M-2         |
| L7-7   | 1667.0    | 1.08       | 2.61                | 1.90         | 0.0006            | 47.1                    | 43.8        | S-3         |
| L7-8   | 1674.0    | 1.21       | 2.63                | 2.19         | 0.0002            | 50.2                    | 45.6        | S-3         |
| L7-9   | 1683.0    | 0.77       | 2.63                | 2.49         | 0.0007            | 49.0                    | 49.5        | M-2         |
| L7-10  | 1689.2    | 1.26       | 2.72                | 2.96         | 0.0005            | 59.5                    | 40.1        | S-3         |
|        |           |            |                     |              |                   |                          |             |
| N16-1  | 2268.3    | 0.86       | 2.57                | 2.53         | 0.0025            | 47.2                    | 41.0        | M-2         |
| N16-2  | 2273.2    | 0.99       | 2.56                | 2.85         | 0.0075            | 48.1                    | 42.6        | M-2         |
| N16-3  | 2278.2    | 1.07       | 2.58                | 2.03         | 0.0026            | 58.9                    | 28.3        | S-3         |
| N16-4  | 2283.9    | 1.02       | 2.55                | 2.58         | 0.0054            | 63.0                    | 23.2        | S-2         |
| N16-5  | 2290.0    | 0.91       | 2.58                | 1.90         | 0.0035            | 63.6                    | 24.4        | S-2         |
| N16-6  | 2293.7    | 1.17       | 2.60                | 2.71         | 0.0029            | 47.1                    | 34.0        | S-3         |
| N16-7  | 2298.5    | 1.19       | 2.56                | 2.35         | 0.0020            | 57.2                    | 27.0        | S-3         |
| N16-8  | 2304.0    | 0.31       | 2.59                | 1.45         | 0.0024            | 49.1                    | 37.0        | S-2         |
| N16-9  | 2308.6    | 4.83       | 2.43                | 6.10         | 0.0043            | 56.1                    | 22.8        | S-2         |
| N16-10 | 2316.8    | 3.07       | 2.50                | 3.89         | 0.0018            | 59.1                    | 10.7        | S-1         |
| N16-11 | 2320.2    | 4.93       | 2.40                | 5.61         | 0.0014            | 72.6                    | 12.9        | S-2         |
| N16-12 | 2326.0    | 1.17       | 2.59                | 1.85         | 0.0017            | 38.2                    | 26.3        | S-3         |
| average| 1.43      | 2.62       | 2.85                |              | 0.0163            | 51.4                    | 39.9        | 8.7         |

|        |           |            |                     |              |                   |                          |             |
| N18-1  | 2324.7    | 1.21       | 2.61                | 4.80         | 0.0028            | 34.2                    | 51.2        | 14.6        | CM-1       |
| N18-2  | 2332.9    | 0.90       | 2.64                | 3.85         | 0.0007            | 44.9                    | 44.1        | 11.0        | M-2        |
| N18-3  | 2336.8    | 1.16       | 2.62                | 4.26         | 0.0019            | 42.0                    | 41.6        | 16.4        | M-2        |
| N18-4  | 2357.2    | 0.94       | 2.62                | 3.86         | 0.0003            | 34.3                    | 28.7        | 37.0        | M          |
| N18-5  | 2362.1    | 0.79       | 2.72                | 1.29         | 0.0014            | 34.2                    | 31.8        | 34.0        | M          |
| N18-6  | 2376.2    | 1.21       | 2.61                | 3.37         | 0.0054            | 57.3                    | 31.7        | 11.0        | S-3        |
| N18-7  | 2402.4    | 3.48       | 2.51                | 4.86         | 0.0348            | 50.2                    | 14.2        | 35.6        | S-1        |
| N18-8  | 2408.4    | 7.99       | 2.54                | 7.02         | 0.4730            | 65.2                    | 20.6        | 14.2        | S-2        |
| average| 2.21      | 2.608      | 4.16                |              | 0.0650            | 45.3                    | 33.0        | 21.7        |           |

|        |           |            |                     |              |                   |                          |             |
| N13-1  | 2489.2    | 0.91       | 2.60                | 5.28         | 0.0009            | 43.4                    | 39.2        | 17.4        | M-2        |
| N13-2  | 2495.2    | 0.95       | 2.59                | 5.30         | 0.0012            | 45.8                    | 40.7        | 13.5        | M-2        |
| N13-3  | 2500.8    | 0.81       | 2.58                | 4.19         | 0.0008            | 55.0                    | 32.5        | 12.5        | S-3        |
| N13-4  | 2506.1    | 1.01       | 2.60                | 5.05         | 0.0009            | 57.7                    | 30.3        | 12.0        | S-3        |
| N13-5  | 2516.8    | 0.95       | 2.61                | 3.43         | 0.0008            | 59.0                    | 27.8        | 13.2        | S-3        |
| N13-6  | 2522.1    | 1.06       | 2.59                | 3.96         | 0.0005            | 57.4                    | 27.8        | 14.8        | S-3        |
| N13-7  | 2526.6    | 1.14       | 2.58                | 3.82         | 0.0007            | 54.9                    | 32.5        | 12.6        | S-3        |
| N13-8  | 2531.9    | 1.13       | 2.58                | 4.49         | 0.0112            | 48.8                    | 39.5        | 11.7        | M-2        |
Table 1. continued

| sample   | depth (m) | TOC (wt %) | density (g/cm³) | porosity (%) | permeability (mD) | mineral composition (%) |
|----------|-----------|------------|-----------------|--------------|-------------------|-------------------------|
| N13-9    | 2536.4    | 1.77       | 2.54            | 5.43         | 0.0319            | 51.0 36.9 12.1 S-3      |
| N13-10   | 2542.2    | 2.20       | 2.55            | 5.86         | 0.0067            | 49.7 36.2 14.1 M-2      |
| N13-11   | 2547.8    | 2.29       | 2.55            | 5.98         | 0.0402            | 43.2 42.6 14.2 M-2      |
| N13-12   | 2552.8    | 3.00       | 2.51            | 6.30         | 0.0165            | 60.1 28.0 11.9 S-3      |
| N13-13   | 2558.9    | 3.17       | 2.50            | 5.70         | 0.6340            | 62.5 24.2 13.3 S-2      |
| N13-14   | 2564.6    | 4.51       | 2.46            | 7.39         | 0.0083            | 50.5 25.1 24.4 S-3      |
| N13-15   | 2569.3    | 3.36       | 2.47            | 5.39         | 0.0034            | 72.6 10.7 16.7 S-2      |
| N13-16   | 2574.8    | 3.69       | 2.51            | 5.63         | 0.0324            | 61.5 9.4 29.1 S-1       |
| average  | 2.00      | 2.553      | 5.20            | 0.0494       | 54.6 30.2 15.2     |

\[ \Phi = \frac{m_3 - m_1}{m_3 - m_2} \]  

(1)

where \( \Phi \) is the porosity, m₁ under the air is the quality of core, m₂ is after saturated liquid, under the liquid quality of core, m₃ is removing the liquid on the surface of the rock core under the air. The bulk density was calculated from the measured difference between the rock and liquid volume.

3.3. Stress-Dependent Permeability and Porosity Experiments. To quantitatively analyze and predict the different depths of porosity and permeability of shale, stress-dependent permeability and porosity experiments were used to study the physical property of shale reservoirs under different confining pressures. A PoroPerm PDP-200 Pulse permeameter was used to determine shale matrix permeability and porosity values by increasing the effective confining pressures of shale at a restrained pore pressure. The pulse decay measurement technique was used to measure permeability ranging from 0.00001 to 10 mD. In this study, the permeability and porosity of shale cores under confining pressure increase from 5 to 35 MPa with a constant pressure interval 5 MPa. Each constant pressure point was sustained for a sufficiently long time (at least 30 min) to determine the gas permeability and porosity at each stress point. The effective stress for the rock samples can be defined using the equation

\[ \sigma_{eff} = P_{conf} - n_k P_{pore} \]  

(2)

where \( P_{pore} \) is the pore pressure, MPa; \( P_{conf} \) is the confining pressure, MPa; \( n_k \) represents the permeability effective stress coefficient. For sandstones and carbonates minerals, \( n_k \) is slightly more than unity. However, \( n_k \) is approximately equal to unity in the illite-rich shale. As can be seen from eq 4, a higher value of \( \gamma \) corresponds to a stable loss in permeability changing in permeability in the stress sensitivity. A high-stress sensitivity coefficient corresponds to a greater degree of variation in effective stress, resulting in a significant decrease in permeability. The larger the stress sensitivity coefficient, the smaller the permeability of shale with the same change of effective pressure. Conversely, the smaller the value of the stress sensitivity coefficient, the less sensitive the shale permeability.

Previous studies have noted that the pore compressibility is expressed as follows

\[ C_\phi = -\frac{1}{\Phi} \frac{d\phi}{dp} \]  

(5)

The relationship model between porosity and pore volume strain can also be expressed as

\[ k = k_0 e^{-\gamma P_{eff}} \]  

(3)

where \( k \) is the permeability, and \( k_0 \) is the permeability under specific stress conditions; \( P_{eff} \) is the effective stress, and \( \gamma \) is a constant related to the characteristic of the rock corresponding to permeability modulus coefficient. In particular, the stress sensitivity coefficient can be written as

\[ \gamma = -\frac{1}{k} \frac{dk}{dp} \]  

(4)

3.4. Models for Describing Shale Reservoir Stress Sensitivity. The permeability modulus is generally used to determine stress sensitivity. The predecessors used the power, exponential, binomial, or logarithmic models to describe the permeability of coal and other tight rocks under different stress conditions. Different rock types correspond to models with different relationships. Jones pointed out that the relationship between permeability and effective stress in fractured rocks is consistent with a logarithmic model. Walsh et al. reported that the permeability and effective stress expressions are consistent with a logarithmic model based on the fractured plate model. The previous study showed that the power and logarithmic models are equivalents. The tubular pore model describes stress sensitivity in porous rocks such as sandstones, and its mathematical model possesses a good correlation. For the southern Sichuan Basin shale, most scholars have used an exponential function to describe the effective stress-dependent permeability relationship, which is given as

\[ k = k_0 e^{-\gamma P_{eff}} \]  

(3)

where \( k \) is the permeability, and \( k_0 \) is the permeability under specific stress conditions; \( P_{eff} \) is the effective stress, and \( \gamma \) is a constant related to the characteristic of the rock corresponding to permeability modulus coefficient. In particular, the stress sensitivity coefficient can be written as

\[ \gamma = -\frac{1}{k} \frac{dk}{dp} \]  

(4)

As can be seen from eq 4, a higher value of \( \gamma \) corresponds to a stable loss in permeability changing in permeability in the stress sensitivity. A high-stress sensitivity coefficient corresponds to a greater degree of variation in effective stress, resulting in a significant decrease in permeability. The larger the stress sensitivity coefficient, the smaller the permeability of shale with the same change of effective pressure. Conversely, the smaller the value of the stress sensitivity coefficient, the less sensitive the shale permeability.

Previous studies have noted that the pore compressibility is expressed as follows

\[ C_\phi = -\frac{1}{\Phi} \frac{d\phi}{dp} \]  

(5)

The relationship model between porosity and pore volume strain can also be expressed as

\[ \frac{k}{k_0} = \left( \frac{\phi}{\phi_0} \right) ^\alpha \]  

(6)

where \( \alpha \) is the PSE, describing the porosity–permeability relationship caused by the loading process, \( \phi \) is the porosity, and \( \phi_0 \) is the porosity at effective stress. It has been noted that the power-law exponent \( \alpha \) is sensitive to both the material and its change process and that there is no universal \( \alpha \) for porous media. Based on 1, David deduced the following expressions

\[ \gamma = \alpha C_\phi \]  

(7)

This equation shows that the stress sensitivity factor \( \gamma \) is the product of the \( \alpha \) and the pore compressibility coefficient \( C_\phi \). Thus, the PSE can be expressed as

\[ \alpha = \frac{\gamma}{C_\phi} \]  

(8)
The PSE is 2 for ideal circular capillary pores and 3 for ideal fractures. Hence, a tight and fractured pore model has a PSE ≥ 3. The power index α is sensitive to both the material and its evolutionary processes, and there is no universal α for all porous media. Therefore, analysis of overburden porosity/permeability-related parameters needs to be carried out for different lithofacies shales.

3.5. PCA Optimized by SVM. PCA is a convenient way of reducing the dimensionality of the data and expressing the data in such a way as to highlight their similarities and differences. PCA is a powerful tool for analyzing data using fewer synthetic variables to reflect as much information as possible from the original variables. The method of the PCA can retain the ultimate information by reducing the number of dimensions.

SVM was developed as a data-driven supervised machine learning theory designed for performing statistical inference for solving classification and regression problems. As a popular statistical learning theory, the merits of the SVMs have been applied to a wide variety of the issues, such as medical imaging, bioinformatics, remote sensing recognition, and geologic lithofacies identification.25,45 Their methods for discrimination involve finding the optimum hyperplane boundary in the N-dimensional space, called the feature space, with linear inequality constraints, which distinguish separate data of opposing classes.46,47 especially, the SVMs can reduce the dimensionality by projecting the input data into a high-dimensional space with the kernel-based methods and conduct the nonlinear function-fitting in an elegant manner (Figure 2).

The SVM algorithm for the dichotomy classification problem can be defined as the training data \( X = \{x_1, \ldots, x_n \subseteq R^n \} \), and their corresponding labels classified by \( Y = \{y_1, \ldots, y_N \subseteq \{-1,1\} \} \), where \( i = 1, 2, 3, \ldots, n \). The problem is to find a decision function \( f: R^n \rightarrow \{-1,1\} \) and predict the new label from previously unseen data points to reduce the possibility of misclassification.47

A linear SVM is the decision function

\[
f(x) = \text{sign}(w \cdot x - b)
\]

where \( w \) and \( b \) define the hyperplane \( w \cdot x = b \) and

\[
\text{sign}(z) = \begin{cases} 
-1, & \text{otherwise} \\
1, & \text{if } z \geq 0 
\end{cases}
\]

where \( w \) is called the weight vector and lies in a direction perpendicular to the hyperplane. By convention and for ease of calculation, \( w \) is a unit vector. The offset, \( b \), is defined as the distance along \( w \) from the axis origin to the hyperplane.

The details of the equations used for separating the hyperplane and SVM algorithm can be found in Vapnik et al.47 There are many kernel functions used in computing SVM classification.47 This study uses the scikit learn python machine learning library to construct an SVM algorithm with multiple kernel functions and penalty coefficients optimized by PCA to classify the PSE.

4. RESULTS AND DISCUSSION

4.1. TOC Content, Porosity, and Lithofacies Classification. TOC content of the 57 Longmaxi shale samples in wells L7, N16, N13, and N18 averaged 1.43 ± 1.80, 1.99, and 2.20 wt %, respectively, ranging from 0.50 to 9.20 wt % (L7), 0.35 to 4.65 wt % (N16), 0.48 to 10.73 wt % (N13), and 0.35 to 4.65 wt % (N18) in absolute terms (Table 1). With the increase of depth, the TOC content gradually increased. The TOC content of some samples is greater than 2 wt %, which indicates that the Wufeng–Longmaxi shale has moderate to excellent source rock potential.

The porosity, measured by the liquid saturation method, of shale samples from wells L7, N16, N13, and N18 averaged 2.85%, 2.99%, 4.16%, and 5.20%, respectively (Table 1). The porosity of samples from wells N13 and N18 was much larger than those of samples from well L7 and N16 due to the different burial depths of the Longmaxi Shale. The value of permeability is higher than those of samples from well L7 and N16 due to the different burial depths of the Longmaxi Shale. The value of permeability has similar trends with the porosity. The average permeability is observed from different wells, with wells N15 and N18 having much higher average permeability than wells N16 and L7, indicating the role of depth in controlling shale porosity and permeability.
Clay and quartz minerals are the most abundant components in shales with the clay content from wells L7, N16, N13, and N18 averaging 39.63%, 27.52%, 30.21%, and 32.98%, respectively, with corresponding siliceous contents of 48.58%, 48.58%, 45.39%, and 46.84%. Figure 4. Stress-dependent permeability and porosity of the Longmaxi shale. (a) M-2 lithofacies, (b) M lithofacies, (c) S-3 lithofacies, (d) S-2 lithofacies.

Figure 5. Change in the shale coefficient with various lithofacies of compressibility under different buried depth conditions. (a) L7 well; (b) N13 well; (c) N16 well; (d) N18 well.
33.62%, 48.58%, and 42.76%, respectively. Among them, the predominant siliceous mineral is quartz, and the rest of the siliceous minerals are almost entirely plagioclase. Furthermore, the dominant of clay is illite/smectite mixed-layer minerals. A certain amount of illite and chlorite is also found in the shale samples.

According to the classification of mudstone, the ternary diagram minerals analysis to wells N13, N16, L7, and N18 Longmaxi shale samples in the southern Sichuan basin, four primary lithofacies groups can be described, namely argillaceous/siliceous mixed shale lithofacies (M-2), clay-rich siliceous shale lithofacies (S-3), mixed siliceous shale lithofacies (S-2), and mixed shale lithofacies (M) (Figure 3 and Table 1). Most shale samples are found in M-2, S-3, M, and S-2 areas.

### 4.2. Relationship between Shale Matrix Porosity and Permeability with Effective Stress

| Lithofacies | $C_p$ | $R^2$ | Initial Porosity (%) | Initial Permeability (mD) | TOC (%) | Rock Density (g/cm$^3$) | Water Saturation (%) |
|-------------|-------|-------|-----------------------|--------------------------|---------|-------------------------|---------------------|
| M-2 max     | 0.032 | 0.999 | 5.10                  | 0.136                    | 0.984   | 2.32                    | 2.96                |
| min         | 0.002 | 0.880 | 0.78                  | 0.058                    | 0.354   | 0.001                   | 0.31                |
| ave         | 0.017 | 0.944 | 1.98                  | 0.095                    | 0.895   | 0.016                   | 1.26                |
| S-3 max     | 0.035 | 0.993 | 5.32                  | 0.131                    | 0.982   | 0.048                   | 4.51                |
| min         | 0.001 | 0.889 | 0.75                  | 0.059                    | 0.654   | 0.000                   | 0.10                |
| ave         | 0.018 | 0.945 | 2.05                  | 0.094                    | 0.904   | 0.007                   | 1.51                |
| S-2 max     | 0.015 | 0.959 | 4.70                  | 0.260                    | 0.990   | 0.634                   | 7.99                |
| min         | 0.002 | 0.760 | 1.46                  | 0.075                    | 0.861   | 0.001                   | 0.91                |
| ave         | 0.007 | 0.886 | 3.41                  | 0.116                    | 0.929   | 0.161                   | 3.74                |
| M max       | 0.030 | 0.996 | 1.60                  | 0.103                    | 0.946   | 0.013                   | 2.25                |
| min         | 0.004 | 0.890 | 0.86                  | 0.088                    | 0.862   | 0.000                   | 0.79                |
| ave         | 0.016 | 0.943 | 1.31                  | 0.095                    | 0.902   | 0.004                   | 1.29                |

**Figure 6.** Relationship between the porosity stress loss rate and effective stress in different lithofacies of the Longmaxi shale. (a) M-2 lithofacies; (b) M lithofacies; (c) S-3 lithofacies; (d) S-2 lithofacies.

The detailed information is presented in Table 2. The critical relationship between the porosity stress loss rate and effective stress in different lithofacies can be seen in Figure 6. The relationship is further discussed in Section 4.2. The details of shale lithofacies classification methods can be referred to in a previous study. Applying the ternary diagram minerals analysis to wells N13, N16, L7, and N18 Longmaxi shale samples in the southern Sichuan basin, four primary lithofacies groups can be described, namely argillaceous/siliceous mixed shale lithofacies (M-2), clay-rich siliceous shale lithofacies (S-3), mixed siliceous shale lithofacies (S-2), and mixed shale lithofacies (M) (Figure 3 and Table 1). Most shale samples are found in M-2, S-3, M, and S-2 areas.
between shale bulk porosity and effective stress can be gleaned from Giles’s compaction data following a negative exponential function.\textsuperscript{33} In general, the porosity of the shale samples decreases with increasing effective stress in the negative exponential function. The pore compressibility coefficient can reflect the change in shale volume when the stress increases.\textsuperscript{17,31,53} The exponential function is expressed to describe the stress-dependent porosity of shale

\begin{equation}
\phi_i = \phi_0 e^{-C_p p}
\end{equation}

where \(\phi_i\) is the porosity under specific effective stress, \(\phi_0\) is the porosity under the initial effective pressure, \(C_p\) is the coefficient of compressibility (MPa\(^{-1}\)), and \(p\) is the effective stress (MPa).

This result is consistent with the value of the previous analysis. Furthermore, the coefficient of compressibility values from different Longmaxi lithofacies has also been statistically analyzed. The compressibility coefficient of the lithofacies \(M\) varies between 0.03 and 0.004 MPa\(^{-1}\), with an average of 0.01557 MPa\(^{-1}\), whereas the lithofacies of S-2 average at 0.007 MPa\(^{-1}\) and range between 0.002 and 0.015 MPa\(^{-1}\). The coefficient of compressibility of the S-2 lithofacies is lower in the Longmaxi samples than those in M, S-3, and M-2 lithofacies, indicating that the porosity of S-2 lithofacies is less susceptible to vertical stress (Figure 4).

The gas permeability of shale reservoirs can reflect the seepage ability and shale gas recovery in shale samples. Geofluid flow

\begin{table}
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline
 lithofacies & parameter & 4 & 8 & 10 & 15 & 20 & 30 & 4 & 8 & 10 & 15 & 20 & 30 \\
\hline
 M-2 & AVE & 4.45 & 10.90 & 14.06 & 24.84 & 30.00 & 36.26 & 24.66 & 62.14 & 71.72 & 82.50 & 88.01 & 93.45 \\
 & SD & 4.62 & 10.27 & 11.81 & 14.45 & 16.71 & 20.20 & 12.31 & 9.72 & 8.66 & 7.05 & 5.27 & 3.09 \\
 S-3 & AVE & 5.84 & 13.20 & 17.04 & 26.62 & 32.19 & 38.52 & 25.24 & 63.56 & 72.76 & 81.35 & 87.22 & 93.03 \\
 & SD & 5.86 & 12.00 & 13.80 & 15.98 & 18.04 & 21.22 & 14.30 & 11.05 & 9.91 & 7.19 & 5.96 & 4.05 \\
 S-2 & AVE & 1.09 & 3.55 & 5.07 & 12.84 & 15.41 & 17.64 & 21.61 & 62.27 & 70.26 & 84.57 & 89.55 & 94.30 \\
 & SD & 1.30 & 4.16 & 4.13 & 7.02 & 9.10 & 11.20 & 5.10 & 9.75 & 9.24 & 9.02 & 6.31 & 3.49 \\
 M & AVE & 2.13 & 6.37 & 12.89 & 22.68 & 26.90 & 32.30 & 33.29 & 68.56 & 76.11 & 84.40 & 89.44 & 94.42 \\
 & SD & 1.74 & 3.89 & 9.53 & 18.79 & 19.83 & 21.92 & 7.40 & 5.07 & 4.31 & 1.02 & 0.52 & 0.85 \\
\hline
\end{tabular}
\caption{Porosity and Permeability Stress Loss Rate of the Different Lithofacies from the Longmaxi Shale\textsuperscript{4}}
\end{table}

\textsuperscript{4}AVE means average; SD means standard deviation.
simulation is the key that requires models that shows the relationship between permeability and depth in shale gas development. In the previous study, the laboratory experiment results show that the sandstone and granitic rocks near a fault zone exhibited an exponential relationship. With a similar relationship between shale porosity and effective stress, the exponential function is expressed to describe the stress-dependent permeability of shale. Due to nonlinear fitting of experimental data, it is found that the negative exponential function of permeability with the increase of effective stress. The adjusted exponential function for the stress-dependent permeability is defined as follows

\[ K_i = K_0 \, e^{-\gamma P} \]

where \( K \) is the permeability under specific effective stress (10\(^{-3}\) \( \mu \)m\(^2\)), \( K_0 \) is the permeability under the initial effective pressure (10\(^{-3}\) \( \mu \)m\(^2\)), and \( \gamma \) is the stress sensitivity coefficient (MPa\(^{-1}\)). Via the negative exponential fit formula analyses, the stress sensitivity coefficient of different lithofacies has been obtained, ranging from 0.058 nm to 0.260 MPa\(^{-1}\), with an average of 0.109 MPa\(^{-1}\). The larger the value of \( \gamma \), the more sensitive the samples permeability is to variation in the effective stress (Figure 4). The table shows that the different lithofacies have a similar average stress sensitivity coefficient, which indicates that the impact of mineral composition on the stress sensitivity coefficient is not obvious.

In Figure 5 and Table 2, The upper Longmaxi Formation (Well #L7, #N13 #N16, and #N18) possesses a higher compressibility coefficient than the bottom, particularly in the well of L7. The reason for this phenomenon may be the difference in the sedimentary environment. The bottom of the Longmaxi Formation is a deepwater shelf containing enrichment siliceous minerals, which are not easy to compact in accumulation. Hence, the degree of porosity reduction under pressure is limited, leading to the relatively lower value of the coefficient of compressibility. Compared with the coefficient of compressibility tendency of the Lower Silurian Longmaxi shale series, the stress sensitivity coefficient does not show a monotonous decrease with the rising depth. This may be due to the similarity of the stress sensitivity coefficients in different shale lithofacies, while it is not sensitive to differences in mineral composition. The analysis indicates that the PSE is influenced by the geometric feature of the pores in this study. In addition, the PSE depends on the scale, quantity, and distribution of the fractures and the matrix pores.

4.3. Stress Sensitivity Analysis of Shale Reservoirs. 4.3.1. Analysis of Permeability and Porosity Damage Rate. In the process of hydraulic fracturing exploiting shale gas, with the reduction of formation pressure, the effective stress operates the increase in the shale reservoir, causing the deformation of the reservoir rock, which results in a decrease in porosity and permeability, affecting the migration of fluids into the reservoir. Based on the petroleum and natural gas industry standards of China (SY/T 5336), the permeability damage rate, the porosity damage rate, and the PSE are used to evaluate the reservoir sensitivity. The porosity stress damage rate is the percentage of reservoir porosity damage under effective stress, which can be expressed as follows

\[ \text{Porosity Damage Rate} = \frac{P_{i} - P_{0}}{P_{0}} \times 100\% \]

where \( P_i \) is the effective stress at which the porosity damage rate is calculated, and \( P_0 \) is the initial effective stress.
Figure 9. Log–log plot of permeability and porosity relationship under various effective stresses. (a) M-2 lithofacies; (b) M lithofacies; (c) S-3 lithofacies; (d) S-2 lithofacies.

Figure 10. Statistics of PSE of different shale lithofacies.
where \( D_{\phi} \) is the porosity damage rate corresponding to an effective stress point \( i \) by the process of increasing stress to the highest point; \( \phi_i \) is the porosity at a given effective stress point \( i \), and \( \phi_i \) is the porosity at effective stress obtained at special effective confining pressure (Figure 6).

The permeability damage rate reflects the percentage of permeability damage of a reservoir under effective stress. Similar to the porosity damage rate, the permeability damage rate can be expressed as

\[
D_{K_i} = \frac{K_1 - K_i}{K_1} \times 100 \%
\]

(14)

\( D_{K_i} \) is the permeability stress damage rate, \%; \( K_1 \) is the permeability under the first effective stress measured by the test, mD; \( K_i \) is the permeability under a certain effective stress point, mD.

Figure 11. PSD curves obtained from MICP analyses with different shale lithofacies.

Figures 6 and 7 show the evolution of permeability and the porosity damage rate under varying effective pressure for the different lithofacies samples. With the increase in effective stress, the porosity and permeability stress loss rate under the overburden pressure of shale reservoirs show a two stage increase (Figure 6). When the effective stress is less than 15 MPa (first stage), it increases linearly, whereas the effective stress is greater than 15 MPa (second stage), the increase rate gradually slows down. Meanwhile, some example stress loss rate of porosity varies between 17.5% and 38.4%, with an average of 30% under the confining stress of 35 MPa. The porosity stress loss rate of various lithofacies at the same pressure point is more sensitive, which indicates that the porosity stress loss rate is controlled by the effective stress and is affected by its own physical properties. With the effective stress increasing, the mechanical properties exhibit different pores and fractures: a series of microcracks, macropores, mesopores, and micropores having plastic deformation with an increase in effective stress. The plastic deformation of the various lithofacies samples leads to a different porosity stress damage rate (Table 3).

When the effective stress increases to 30 MPa, the permeability stress loss rate is over 90%, indicating that permeability is linked to stress variation. This can be explained by the fact that the partial pore throat, after being compressed and deformed, forms a large number of ineffective pores under high effective stress. The loss rate of porosity and permeability with lithofacies have a different fluctuation range. As a result of the development of pores and fractures, the increasing effective pressure leads to the deformation of the pore morphology and the closure of the fracture-connecting channel, thereby leading to a significant reduction in the permeability. With the effective stress increasing, the amount of microfractures tends to close, and macropores tend to transition pores and micropores, and the shrink rate of permeability gradually slows down until it becomes stable.

Based on the porosity and permeability stress damage degree curves, the stress damage degree standard deviation is more obviously different. The volatility of the porosity loss rate generally increased with the effective rising stress of the samples studied. Those might be the reasons for the variations in the degree of rock contact type and pore morphology with an increase in effective stress. Nevertheless, there is an opposite
phenomenon that describes that the volatility of permeability loss rates decreases with a rise in effective stress. The high degree of permeability damage rate (over 90%) is the main reason. This is because almost all examples have a similar type of porosity and mechanical properties of rock under highly effective stress, which leads to the volatility degree reduction.

4.3.2. Characteristics of the Permeability Curvature. To better accurately describe these permeability changes, the permeability curvature of the lithofacies samples was calculated from the permeability under effective stress. The permeability curvature index, which represents the degree of deformation geometry and the size of bending deformation at a certain point, can be used to evaluate the decreasing permeability rate with increasing effective stress. The higher curvature of sample permeability, the more significant effective stress, indicating that the shale reservoir has better bending deformation under effective stress. A large curvature value indicates a higher degree of bending deformation of the pore–fracture system. When the curvature tends to be constant, it means that the effective stress does not affect permeability. Hence, it is more clear to characterize the rate of permeability decreasing by establishing permeability curvature. Considering the previous definition, the pore compressibility coefficient can be expressed as follows:

\[
K_L = \frac{K''}{(1 + K')^3/2}
\]  

Figure 13. Mineralogical ternary plot for the porosity (a), permeability (b), pore compressibility (c) and PSE (d).

where \(K_L\) is the permeability curvature, \(m^{-1}\); \(K'\) is the first derivative of the permeability effective stress curve; \(K''\) is the second derivative of the permeability effective stress curve. According to the stress-dependent permeability, the permeability curvature is obtained by eq 15 to describe the rate of permeability change. Figure 8 shows a similar trend with different shale lithofacies under different effective pressures. The permeability curvature has a negative exponential relationship with the increasing effective pressure, which displays that shale reservoirs are less sensitive to increasing effective pressure. Obviously, different initial permeabilities have various permeability curvature curves under different confining pressures.

As shown in Figure 8, when the effective stress is less than 15 MPa, the permeability curvature decreases continuously at high speed as the effective stress increases. When the occurrence stress is more than 15 MPa, the loss of the permeability curvature exhibits a low stable rate, which indicates that most of the pores and fractures in the shale have been compressed and deformed to a minimum. The demarcation point is consistent with the conclusions of the porosity and permeability stress.
damage rate. It is worth noting that the initial permeability of shale lithofacies strongly influences the evolution trend of the permeability curvature. To facilitate the study, the samples were divided into high $K$ (>0.01 mD), moderate $K$ (0.01 > $k$ > 0.001), and low $K$ groups (<0.001 mD) according to their initial permeability value. Figure 8a shows that with the increase in the effective stress, the decrease in the rate of permeability curvature in the high initial $K$ is higher, and the curvature value of the low and moderate $K$ group from the M-2 and S-3 lithofacies are significantly smaller than other samples under low effective stress. Figure 8b shows that in the M lithofacies, the initial permeability of the high $K$ groups has a higher value of permeability curvature than that of the low $K$ groups, which shows that the high initial permeability is easier to allow compression deformation. With the effective stress increasing, the fractures and macropores in the shale are easily deformed by compression stress, which reduces the effects on the stress of shale reservoir permeability to a certain degree.

4.3.3. Analysis of PSE. The PSE illustrates the geometrical morphology characteristics of the shale pore. A high value of the PSE indicates a sharp decrease in permeability along with the pore volume under the effective stress. The dimensionless porosity and permeability transformation rate have a linear function relationship and display a straight line under the logarithmic coordinates. Specifically, the slope of the line is the PSE. By combining eqs 1 and 4, a linear function can describe the PSE of the Longmaxi Formation in the southern Sichuan Basin. Figure 9 reveals the PSE fitting on different lithofacies. A large PSE value corresponds to a greater permeability sensitivity with porosity under the various effective stresses. The PSEs among the lithofacies shale varied, and from this study, the effect of minerals needs to be investigated. The porosity stress sensitivity exponent fitting ranges from 3.25 to 26.62, with an average of 13.07 for the M shales; from 2.54 to 48.64, with an average of 11.22 for the M-2 shale; from 2.22 to 66.54, with an average of 13.16 for the S-3 shales; and from 7.19 to 48.74, with an average of 19.37 for the S-2 group shales. Compared with the average value of PSE, the S-2 lithofacies have a higher average value, which indicates that a high content of silicate mineral will have high microfractures and numerous micro-mesopore volumes in its matrix, impacting the pores that are compressed. This study is different from the previous research results of PSE, such as carbonates samples (10−25) and sandstone (3.25−29.6). These results indicate that the impact of a decrease in porosity on the permeability of shale is less than that for sandstone and carbonates.

In a study conducted by Zhang et al., it was shown that the magnitude of the PSE depends on the matrix pores (circular and elliptical pores) and the geometry, size, and number of fractures. A high PSE causes a high-stress sensitivity factor. When the fracture size is similar to the matrix pore size, the fracture can be considered an elliptical pore, and the PSE is 2−3. When the size of the fractures is much larger than the matrix pore, the PSE is much larger than 3. Figure 10 shows the PSE of shale samples obtained from the different shale lithofacies and shows that the S-2 group shales have relatively higher values. The dual-porosity model indicated that the size of the fractures in the S-2 group is considerably more significant than the matrix pores. The presence of microfractures at various scales resulted in a PSE greater than 3. Under certain stress conditions, the pores associated with microfractures within the S-2 shale matrix are most likely to be compressed, causing a dramatic decrease in permeability. The M, M-2, and S-3 group shales have a relatively lower PSE, ranging from 0.186 to 0.221 (Table 2). The percentage of different group samples with a lower $\alpha$ are 50%, 55%, and 59.1%, respectively. With the analysis described in the dual-porosity model, the examples with less than three values

| principal component number | Eigenvalue | percentage of variance (%) | cumulative (%) |
|---------------------------|------------|----------------------------|----------------|
| 1                         | 3.05025    | 61.00509                   | 61.00509       |
| 2                         | 1.05471    | 20.69415                   | 81.69924       |
| 3                         | 0.45754    | 9.15088                    | 90.85012       |
| 4                         | 0.36515    | 7.30291                    | 98.15303       |
| 5                         | 0.09235    | 1.84897                    | 100            |
illustrate that the size of fractures and matrix pores is approximately equal, indicating the elliptical pores and slot pores in the shale matrix.

4.4. Effect of Stress Sensitivity Analysis Parameters. Shale reservoir is a type of dual-pore system medium that includes a matrix pore system and a fracture pore system. Previous results show that the stress sensitivity parameter among the shale examples varied, and the influence of the pore structure, minerals, and mechanical properties need considerable attention. Hence, the discussion is separated into three sections; the first section of the discussion evaluates the effect of the pore morphology and pore size distribution on the porosity-sensitive exponent; the second section discusses the relationship between mechanical properties and the pore compressibility. In the last section, the effect of the mineral composition and TOC content on the effect of stress-dependent porosity and permeability parameters was analyzed.

4.4.1. Pore Structure Parameters. The incremental Hg injection curves of selected four lithofacies samples are illustrated in Figure 11. The PSD plot corresponding to a minimum pore diameter of 7.2 nm is demonstrated. In PSD curves of the S-2 lithofacies shale, a significant peak is observed at about 30 μm, suggesting that it contains many microfractures. Besides, the sample presents a prominent peak at 6–20 nm, demonstrating that the lithofacies sample has a high mesopore volume. The M-2 shale lithofacies has a significant peak near 3 and 10 nm, implying abundant micropores and mesopores. The M-2 shale lithofacies exhibits a small peak at about 100 nm, which indicates a considerable number of micropores. Moreover, two significant peaks appear at 15 and 30 μm, revealing excessive microfractures in the shale lithofacies. The M shale lithofacies has a prominent peak at 7–20 nm and a small peak near 100 nm. In other words, there are abundant mesopores and macropores in the sample. The M shale lithofacies has two weak peaks at 8 and 30 μm, which confirm the existence of
microfractures. The S-3 shale lithofacies possesses relatively concentrated pore distribution, and most of them are smaller pores below 10 nm. The S-3 shale lithofacies shows a weak peak at 1 µm, and thus there may be small microfractures.

Analysis was conducted for different shale lithofacies in combination with coverage pressure pore permeability parameters and lithofacies pore size distribution characteristics. According to the results, there are a significant number of mesopores, macro pores, and highly developed micro fractures in S-2 shale lithofacies. The developmental degree of microfractures in the lithofacies is much higher than that of other samples. A considerable number of micro fractures highly contribute to permeability, and the mesopore pore size of the S-2 shale lithofacies matrix is higher than that of other shale lithofacies. When there is a similarity between the fracture width and the matrix pore size, the micro fractures in S-2 shale lithofacies can be regarded as matrix pores, with a larger ratio of matrix porosity to micro fracture porosity compared to other samples, higher PSE, and lower pore compression. The measured PSE is 22.11, which is larger than that of other shale lithofacies. Regarding M-2 shale lithofacies, both micropores and mesopores are relatively developed in the shale matrix, and there are many micro fractures. As a result, the ratio of matrix porosity to micro fracture porosity is relatively low, the porosity-sensitive exponent is relatively low, and the PCC is relatively high. The measured PSE and PCC are 3.8115 and 3.89, respectively. Many pores exist in the matrix of M shale lithofacies, similar to that of M-2 lithofacies; most are concentrated at 10 nm. However, micro fractures are less developed. The ratio of matrix porosity to micro fracture porosity of M shale lithofacies is larger than that of the M-2 sample. Hence, the PSE is larger than that of M-2 lithofacies, and the PCC is smaller than that of M-2 lithofacies. The measured PSE and PCC are 4.9052 and 2.11, respectively. The S-3 lithofacies sample matrix has more micropores and fewer micro fractures. Owing to the great difference in the radius of micropores and micro fractures, the ratio of matrix porosity to micro fracture porosity of the S-3 sample is lower than that of M lithofacies and M-2 lithofacies. Consequently, the PSE of the lithofacies is less than S-2, and the corresponding pore compressibility is higher than that of M and M-2.

To sum up, the pore structure of the shale samples has a significant influence on the PSE value and pore compressibility value. The ratio of matrix porosity to fracture porosity determines the PSE. A higher matrix/micro fracture porosity ratio indicates higher PSE, and a lower ratio implies a lower PSE. Meanwhile, the lower the pore aspect ratio, the higher the pore compressibility coefficient and the higher the matrix/micro fracture porosity ratio and pore aspect ratio, the lower the pore compressibility.

4.4.2. Mechanical Properties. Predecessors considered that rock mechanical properties have an essential influence on pore compressibility through a huge number of experimental studies. The larger Young’s modulus, the smaller the volumetric strain, and the less likely the rock is to deform. In this study, rock mechanics experiments were performed based on XRD experiments to obtain the mechanical properties of the samples. The specific steps of the experiment can be taken as a reference. The figure demonstrates a significantly negative correlation between pore compressibility and Young’s modulus (Figure 12a). Besides, the PCC decreases with the increase in Young’s modulus. The PCC is relatively high (reaching 3.0) when Young’s modulus is less than 20 MPa; the compressibility coefficient is relatively low (mostly less than 1.0) when Young’s modulus is higher than 20 MPa. This phenomenon suggests that the PCC is more sensitive under the condition of lower Young’s modulus. There is a positive linear correlation in PCC and Poisson’s ratio (Figure 12b). The PCC increases with the increase in Poisson’s ratio. Notably, the Poisson’s ratio of the sample is generally concentrated in 0.15—0.25, and the PCC has much difference. Therefore, considering the characteristics of two different rock mechanical parameters, Poisson’s ratio is negligible, to a certain extent, for the compressibility of pores.

4.4.3. Shale Mineral and TOC. Abundant studies have been conducted by predecessors on the influencing factors of porosity and permeability, such as TOC, mineralogy, maturity, tectonic deformation compression, pore structure parameters, and pore size distribution. Note that pore structure parameters have direct influences on porosity and permeability, while mineral content and TOC content have indirect influences on the correlation coefficient of coverage pressure pore permeability by affecting the degree of pore development. In this study, the samples are divided into the high porosity group, medium porosity group, and low porosity group according to the measured porosity values, and the PCC and pore sensitivity coefficient are discussed with the double porosity model.

Previous studies have demonstrated that the sensitivity of permeability increases as the pore aspect ratio increases, while the decrease in the matrix elastic modulus leads to an increase in the sensitivity of permeability. In other words, the mechanical properties of different minerals cause differences in the pore structure and porosity sensitivity parameters. The modulus of elasticity of a mineral is related to the crystal structure of the rock and can be considered a constant. The modulus of elasticity of a shale matrix can be thought of as the modulus of elasticity of an equivalent medium formed by a mixture of various mineral components. As the content of the high modulus of elasticity minerals increases, it increases the overall modulus of elasticity of the rock. Previous rock mechanics experiments on the mineral composition of shales have shown that the highest modulus of elasticity is found in quartz, pyrite, and carbonate, followed by feldspar. In contrast, clay minerals have the lowest modulus of elasticity. Particularly, the mixed layered shale containing montmorillonite—illite has a lower Young’s modulus. Therefore, in the mineralogical ternary diagram, quartz, pyrite, and carbonate belong to the same type, and feldspar and clay minerals are another two types.

On this basis, statistical analysis was performed on porosity, permeability, porosity-sensitive exponent, and PCC. According to the results, the samples with higher porosity tend to have high brittle minerals, such as quartz and feldspar, and the content of clay is high, resulting in porosity of mostly less than 1.5% (Figure 13a). The relationship between the differential distribution of permeability and mineral composition is not significant, and some samples with low permeability usually have a higher clay content (Figure 13b). The observation under SEM reveals that most clay minerals have rich layered intergranular pores internal, and higher clay minerals indicate the decreased elastic modulus of rocks, which reflects a higher PCC. High quartz and carbonate minerals present a higher Young’s modulus. The clay minerals are difficult to be compressed between brittle particles after compaction, and the PCC is relatively low (Figure 13c). Compared with the PCC, the relationship between PSE and mineral composition is similar (Figure 13d). As suggested in previous studies, the PSE pertains to the ratio of matrix porosity to micro fracture porosity and micro fracture aspect ratio. The
The fully siliceous samples are rich in medium macro pores and microfractures, some matrix pores similar to the length of micro fractures, and possess a high ratio of matrix porosity to micro fracture porosity. Additionally, the micro fractures produced by brittle minerals are large, and the aperture ratio of micro fractures is high, leading to a low rock compressibility coefficient (Figure 14).

As far as TOC is concerned, there is a close relationship between TOC content and rock mechanical parameters. Previous studies report that OM has a significant influence on rock mechanics, and Young’s modulus decreases with the increase in TOC content. Most OM pores are squeezed by marginal brittle minerals, resulting in varying degrees of deformation (Figure 14). The higher TOC content indicates that more OM pores can be compressed, Young’s modulus of rocks decreases, and the porosity compressibility coefficient increases. Second, the interface between TOC and brittle minerals usually forms a considerable number of micro fractures with slender, narrow, and high pore size ratios in the process of diagenesis, contributing to the increased PCC and a low PSE.

4.5. Applicability of PSE Estimation Models. Previous study results have demonstrated a close relationship between the PSE and mineral composition, initial porosity, TOC, and water saturation. Considering that the PSE is usually affected by many factors, there is a partial correlation between different factors, leading to the information overlap among indicators. Therefore, the PCA of the original data can remove the correlation between the original variables and form new comprehensive indexes independent of each other to achieve dimension reduction. As observed in Table 4, the original six input vectors are converted into two input vectors through PCA, and the cumulative contribution rate of the first two principal components reaches 80% and can be employed as the detection parameter. Meanwhile, the proportion of other principal components is less than 20%, and this can be ignored. The original six input variables are replaced by two principal component vectors (PCA1 and PCA2) to effectively reduce the dimension of the input matrix. Moreover, these two principal component variables contain almost all the information of the original six variables.

After the PCA of the original data set was conducted, the PCA-SVM model was established to diagnose the fault in the rolling bearing. Similarly, the SVM classification library in the sklearn database was called for analysis. Specifically, 70% of the input attribute data was randomly selected as the training set, and the remaining 30% was used as the test set. Four kinds of kernel functions [linear, poly, RBF, and sigmoid] and different penalty factor values were selected to establish the model. According to previous studies, the larger the value of the penalty factor, the less the error allowed in the training data. A higher penalty factor value increases the accuracy while also increasing the risk of overfitting. In the establishment of models, penalty factors ranging from 0.1 to 15 were selected to establish different kernel functions (Figure 15). The relationship between the penalty factor and the accuracy rate of different SVM classification models shows that with the penalty factor increasing, the accuracy rate gradually increases. When the penalty factor reaches a certain value, the accuracy of the model changes at a slower rate. This shows that choosing a suitable penalty factor can achieve better optimization characteristics. The results reveal that the sensitivity of different kernel functions to the penalty factor value is different. Linear and sigmoid kernel functions are not sensitive to penalty factor value. Poly and RBF kernel functions are more sensitive to the penalty factor values. With the increase in the penalty factor value, the prediction accuracy increases gradually. As suggested in Figure 16, the polynomial kernel functions have poor overall accuracy. Compared with sigmoid, the accuracy of RBF and linear kernel functions is stable at more than 70%. In the SVM samples, the PCA-SVM model well predicts the PSE of the shale of the Wufeng—Longmaxi Formation in southern Sichuan. With 57 groups of PSE as the prediction data, for example, the accuracy of the model reaches 80% when using the RBF kernel function, and the penalty factor value is increased to 5.

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Complete contact information is available at:
https://pubs.acs.org/10.1021/acsomega.2c03393

https://doi.org/10.1021/acsomega.2c03393
ACS Omega 2022, 7, 33167–33185

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Z.L.: Methodology, data analyses, and writing. Z.J. and Z.L.: Conceptualization, resources, supervision, and project administration. W.W. and Z.N.: Resources and supervision. J.G. and M.W.: Method and writing. D.X. and Z.X.: Method, resources. R.C. and Y.H.: Data analyses.

Notes
The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This work is supported by the National Science and Technology Major Project of China (2017ZX05035-002), the National Natural Science Foundation of China (Grants nos. 42072151 and 41872135), and the scientific research projects of PetroChina Southwest Oil and Gas Field Company (nos. 2020-57912 and 20210604-02).

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