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Influence of filling characteristics on rock physical properties of deep carbonate reservoirs based on digital rock modeling

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Abstract

Deep carbonate reservoirs are rich in oil and gas resources and are important targets for exploration. This study focuses on the Maokou Formation carbonate reservoir in the Sichuan Basin, which exhibits significant heterogeneity, complex karst characteristics, and filling phenomena. Due to the limited number of carbonate samples with representative filling characteristics and the difficulty of characterizing different types of fillings with similar densities using high-precision X-ray computed tomography, the rock physical properties of carbonate rocks with different filling minerals in the Maokou Formation reservoir are unclear. This makes it difficult to establish a system for the reservoir's physical properties and fluid-sensitive parameters. This study integrates thin-section and image analyses to statistically characterize the filling minerals and proposes two approaches for constructing 3D digital rock models that incorporate karst and filling features of the Maokou Formation reservoir. Additionally, accurate P-wave velocity (V_p) and S-wave velocity (V_s) for different types of fillings were obtained using rock-physics experiments, providing precise input parameters for digital rock simulations. Several typical samples were selected to conduct acoustic experiments under varying confining pressures to measure V_p and V_s . This study analyzed the elastic properties of the rock under different mineral-filling proportions, filling orientations, and fluid-filling characteristics in the Maokou Formation carbonate reservoir, providing support for the extraction of the reservoir's physical properties and fluid-sensitive parameters, as well as for quantitative reservoir prediction.

Keywords: Deep carbonate reservoirs; Filling characteristics; Digital rock; Rock-physics experiment; Numerical simulation

1. Introduction

Carbonate strata host abundant oil and gas resources globally, representing a significant target for hydrocarbon exploration and a viable pathway for China's energy transition. In recent years, advancements in exploration technologies have progressively extended carbonate exploration into deep and ultra-deep formations. According to drilling engineering standards, formations with burial depths exceeding 4,500 m are classified as deep, while those deeper than 6,000 m are considered ultra-deep.^{1,2} Over the past two decades, several large and medium-sized carbonate oil and gas fields have been discovered in the Sichuan, Tarim, and Ordos Basins.³ Notable examples include the Upper Permian–Lower Triassic reef and shoal carbonate gas fields in Puguang, Yuanba, and Longgang in the Sichuan Basin,⁴ as well as the Sinian–Lower Cambrian reef and shoal carbonate gas field in Anyue.⁵ In addition, recent discoveries in the Permian Maokou and Qixia formations of the Sichuan Basin have revealed carbonate reservoirs modified by fracture–fluid interaction.⁶

Since the initial gas detection in the Middle Permian Maokou Formation in the Sichuan Basin in 1957, significant exploration efforts have focused on two main reservoir types: weathering crust karst reservoirs formed at the top of the Maokou Formation due to the Dongwu Movement, and structure–fracture reservoirs closely associated with the evolution of paleo–uplifts. These efforts have led to the discovery of a series of karst–fracture carbonate gas reservoirs.^{7,8} Since 2000, discoveries in the northern and southeastern Sichuan regions have revealed a new type of hydrothermal dolomite reservoir within the Maokou Formation.^{9–11} Starting in 2015, comprehensive geological investigations have been conducted on Maokou Formation reservoirs in northwestern Sichuan. These studies indicated the development of platform–margin reef–shoal reservoirs, and subsequent drilling has confirmed their presence. Several wells have since been drilled in the Qijiang and Yuanba areas targeting the Maokou Formation. The results indicate that the reef–shoal matrix at the platform margin is generally tight, and the effective reservoir type is primarily dissolution–enhanced shoal facies formed through superimposed karstification. Petrographic observations reveal that weathering crust karstification is well developed in the area, with abundant dissolution fractures and caverns. However, these features are often heavily filled with calcite, algal debris, etc., resulting in poor preservation of effective cavities and unclear rock–physics properties of carbonate rocks.¹²

Rock–physics experiments are the most direct method for obtaining rock properties.^{13–15} While traditional petrophysical experiments have long been considered the

most direct and effective research approach, acquiring typical samples from wells remains challenging. Due to limitations in both the quantity and quality of rock samples, it is difficult to study variations in individual filling factors. In recent years, the rapid development of digital rock physics has provided a new approach for rock property analysis.^{16–22} Digital rock physics involves the use of mathematical methods, computational technology, and high-resolution imaging to construct digital models under specific geological constraints.^{23–26} These models are then analyzed through numerical simulations to derive equivalent physical parameters. In practice, digital rock physics has made significant advancements in the calculation of electrical properties,^{27–28} elastic properties,^{29–30} and permeability properties,^{31–32} among others.

The construction of digital rock models is a crucial method for studying the petrophysical filling characteristics of the Maokou Formation reservoir in the Sichuan Basin. An accurate digital rock model serves as the foundation for numerical simulations and petrophysical analysis. Digital rock technology employs mathematical modeling, computer image processing, and high-resolution computed tomography (CT) imaging to digitally represent rock samples and subsequently use numerical simulations to derive rock properties. Among these, high-precision X-ray CT scanning of real drilled rock samples is the most commonly used modeling technique.^{33–34} The digital rock 3D image is reconstructed from a large number of X-ray projections taken from various angles. The reconstruction is a grayscale image where the brightness corresponds to the CT value of the material within the sample.³⁵ Another method for obtaining 3D images of rock microstructure involves stochastic modeling techniques, sometimes referred to as 2D-to-3D reconstruction.^{36–37} The core idea of this approach is to estimate the statistical properties of rock samples by analyzing two-dimensional images, such as those obtained through scanning electron microscopy. The advantage of this method is its ability to generate a large number of digitized samples with similar microstructural characteristics. However, the resulting images cannot fully represent real rock samples, limiting their application. In recent years, with the continuous advancement of computer hardware and software and the development of artificial intelligence, neural networks have emerged in the field of digital rock modeling and have shown promising applications.^{38–43} However, current generative networks based on unsupervised learning methods still face challenges in considering the actual rock structures, making it difficult to construct digital models that accurately represent the complex internal filling structures of real rocks.

The rock samples from the Maokou Formation reveal complex karst and filling structures at the surface and within the rock. Through density measurements, the densities of different fillings can be determined, and these densities are found to be very similar. However, CT scanning faces challenges in distinguishing rock structures with similar densities. This is primarily due to the imaging principle of CT, which relies on differences in X-ray absorption between materials. When mineral densities are close together, the difference in CT values (which reflect the linear attenuation coefficient) may be smaller than the device's resolution threshold, leading to insufficient grayscale contrast. Additionally, partial-volume effects (polyphase mixing within a single voxel) and noise interference (such as quantum noise and beam-hardening artifacts) further obscure boundary information. Conventional image segmentation algorithms, such as thresholding methods, struggle to accurately separate pore and mineral phases under low-contrast conditions. This issue is especially pronounced when the mineral particle size approaches or falls below the scan resolution (micron level), significantly reducing discrimination ability. Therefore, it is challenging to accurately segment filling assemblages with similar densities using gray values alone. As a result, constructing a numerical rock filling model of the Maokou Formation using CT scanning becomes difficult. The relevant CT scan experimental tests are described in detail in Section 2. In this study, by collecting and analyzing rock surface and thin-section data from actual sampling in the

Sichuan Basin, the proportion and structure of different fillings were quantified. These statistical results were then integrated with a numerical modeling approach to propose two methods for constructing 3D digital rock models that consider karst and filling characteristics for the Maokou Formation reservoir. Subsequently, the elastic properties of the rock were calculated using numerical simulations. This method allows digital rock modeling to fully incorporate the filling structure and proportion of the real rock, enabling precise control over the components of the filling model. This, in turn, facilitates a deeper study of how different filling characteristics impact the reservoir.

2. Modeling approaches

2.1. Digital rock modeling based on computed tomography

High-resolution CT scanning is one of the most widely employed and essential techniques for constructing digital rock models. It is extensively used in studies of rock porosity and pore structure due to its ability to precisely capture the internal microstructure of rock samples. In this study, CT scans were conducted on rock samples with complex filling structures from the Sichuan Basin at varying resolutions. The resulting images and analyses are shown in Figure 1.

This study selected typical samples, MK1 and MK2, obtained from wells for CT scanning modeling research. The MK1 sample measured 125 mm in length and 100 mm in diameter, containing a large amount of ellipsoidal calcite

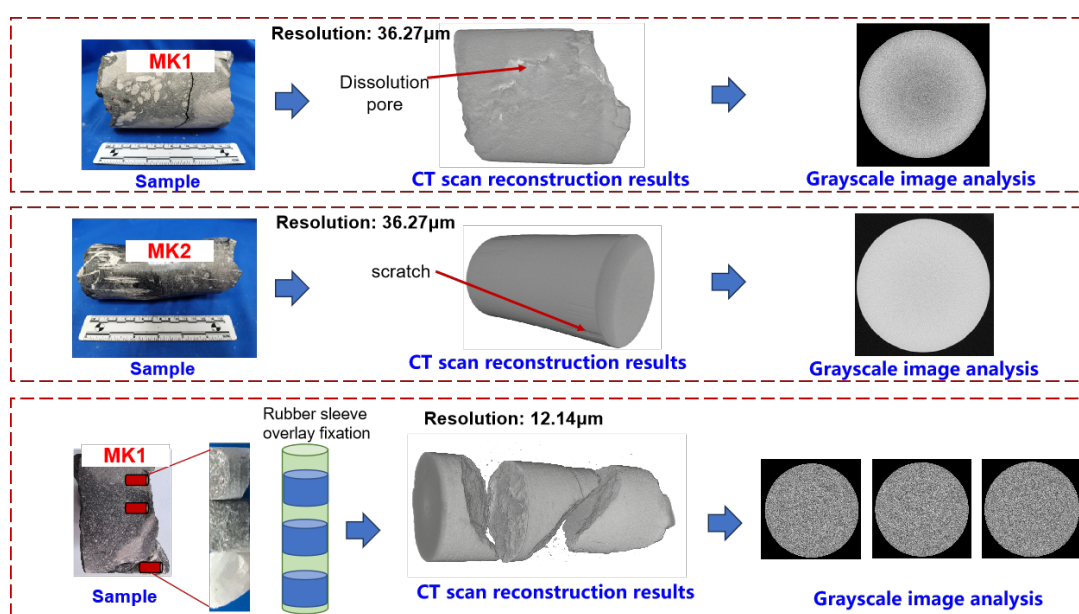


Figure 1. Computed tomography (CT) scanning modeling. Results of CT scanning modeling and grayscale analysis of rocks from the Sichuan Basin at different resolutions.

filling material and elongated algal debris filling strips. The MK2 sample measures 165 mm in length and 65.06 mm in diameter, with a large amount of banded calcite filling material. As illustrated in Figure 1, at a resolution of 36.27 μm , CT scans of full-diameter rock samples MK1 and MK2, which feature complex filling structures, indicate that distinguishing different types of fillings based on grayscale values is challenging. To address this, a smaller section of the MK1 sample was drilled, spliced, and secured using a rubber sleeve, then subjected to a high-resolution CT scan at 12.14 μm . However, the high-resolution results still failed to differentiate filling structures effectively using grayscale segmentation methods. This limitation arises from the principle of CT scanning, which relies on variations in X-ray absorption rates to differentiate materials. The similar densities of different filling materials result in minimal differences in X-ray absorption rates, leading to low grayscale contrast. These findings highlight the inadequacy of conventional CT scanning techniques for modeling rocks with complex filling structures, underscoring the need to explore alternative research methodologies.

2.2. Method 1: Digital rock modeling based on mineral filling information fusion

Constructing an equivalent three-dimensional (3D) digital rock model based on rock surface characteristic analysis is a feasible and effective modeling approach. The overall workflow is divided into four main steps. First, high-resolution images of the rock surface are acquired by focusing a high-precision camera on the center of the rock sample. Second, binary image segmentation is performed. This involves a series of preprocessing techniques (such as denoising, smoothing, and edge enhancement) to improve grayscale contrast, followed by threshold segmentation to distinguish different mineral components. In the third step, structural parameters of the segmented filling features are statistically analyzed. These include measurements of area, Feret diameter (i.e., maximum diameter), aspect ratio, and spatial proportion of each isolated filling region, thereby providing a quantitative foundation for digital rock reconstruction. Finally, based on the extracted surface filling information, an equivalent 3D digital rock model is constructed, and the elastic properties of the rock are evaluated through numerical simulations.

In this study, a typical carbonate rock sample, MK3, from the Maokou Formation in the Sichuan Basin, was selected as the example. The MK3 sample was a plunger sample obtained by drilling, and its experimentally measured porosity was 0.9%. The detailed information of the sample can be found in Table 1. The modeling process for the first three steps is illustrated in Figure 2.

By rotating the same sample by 90° and capturing images at each interval, a complete 360° coverage of the surface information of the plunger sample was achieved. After obtaining the rock images, they underwent preprocessing and segmentation. Subsequently, statistical analysis was conducted based on the aspect ratio and Feret diameter of the different segmented features.

The types and structural characteristics of the 15 most volumetrically significant filling components are summarized in Table 2. An equivalent 3D digital rock model can then be constructed based on multiple parameters, including the distribution of aspect ratios and corresponding Feret diameters of the identified features.

Table 1. Basic physical property information of typical samples

Sample	Length (mm)	Diameter (mm)	Density (g/cm ³)	Porosity (%)	Permeability (mD)
MK3	47.33	25.22	2.66	0.90	0.000322
MK4	56.01	25.19	2.62	2.33	0.009010
MK5	48.50	25.22	2.67	0.66	0.000218
MK6	28.97	25.13	2.62	2.01	0.001120
MK7	52.31	25.28	2.67	2.92	0.014800

The digital rock model construction process for the MK3 sample is illustrated in Figure 3. This study used ImageJ (VERSION, National Institutes of Health, United States) for structural information extraction and statistics, and the open-source Python library Puma for equivalent 3D digital rock model reconstruction. Equivalent models with different aspect ratios were built for the filling materials, and these models were then combined to form a statistically representative equivalent 3D digital rock model. In the samples shown in Figure 3, for calcite filling, structures with aspect ratios of 0.875, 0.625, and 0.125 account for 2.47%, 8.9%, and 11.26% of the volume, respectively. For algal debris filling, structures with aspect ratios of 0.125, 0.625, and 0.875 account for 8.55%, 9.85%, and 9.23% of the volume, respectively. The calcite filling is shown in gray and white, while the algal debris filling is shown in blue. The final digital rock model is obtained by combining the six models. The overall calcite filling ratio is 22.64%, and the algal debris filling ratio is 27.63%.

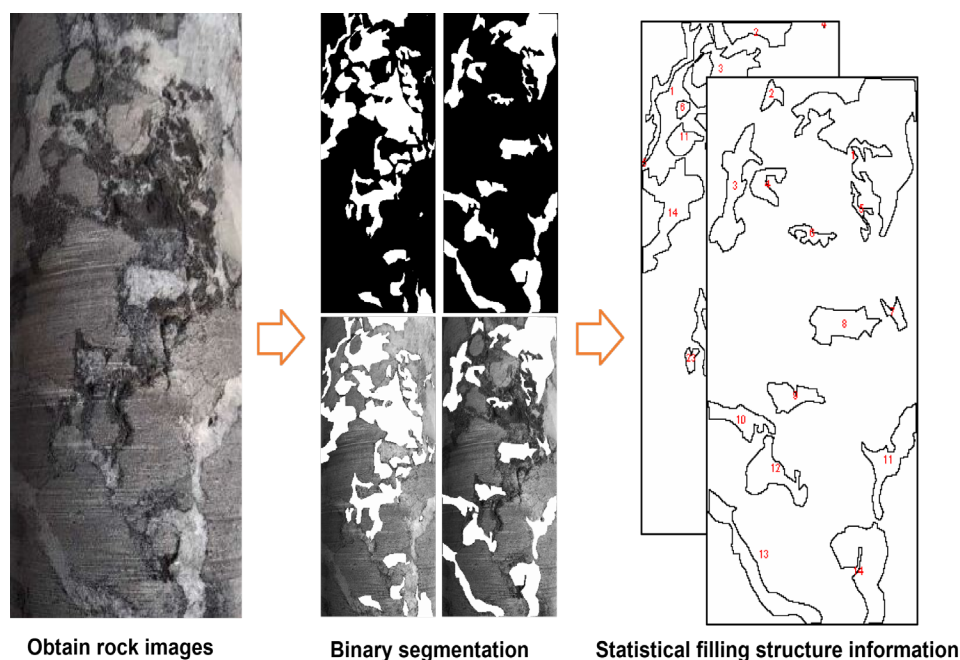


Figure 2. Workflow of rock image processing

Table 2. Main filling and structural information of typical samples

Filling material	Feret diameters (pixel)	Area (pixel)	Proportion (%)	Aspect ratio
Calcite	307.519	35,616	9.893261	0.625
Algal debris	186.724	13,958	4.048552	0.718
Algal debris	206.693	12,198	3.538060	0.395
Algal debris	203.961	12,069	3.500643	0.669
Calcite	242.074	9,082	2.522759	0.294
Algal debris	165.012	8,054	2.336083	0.698
Calcite	137.906	6,493	1.803598	0.793
Algal debris	150.841	6,267	1.817759	0.455
Algal debris	132.201	4,877	1.414586	0.860
Algal debris	153.587	3,392	0.983858	0.257
Calcite	107.815	3,177	0.882494	0.421
Algal debris	108.241	3,159	0.916276	0.881
Algal debris	101.597	2,811	0.815337	0.544
Algal debris	104.547	2,737	0.793874	0.443
Algal debris	85.615	2,707	0.785172	0.783

After conducting representative volume element analysis on multiple sample models, we set the digital rock grid to $200 \times 200 \times 200$, ensuring grid sensitivity while maximizing computational efficiency. To further verify whether the rock-filling information collection was sufficient, additional rock sectioning experiments were conducted to obtain more detailed internal structural information. This also enabled the exploration of methods for jointly constructing digital rocks using information from multiple thin sections.

2.3. Method 2: Digital rock modeling based on rock-section reconstruction

This section introduces an alternative method for studying rock-filling materials that involves sequentially slicing rock samples to obtain layer-by-layer filling information, followed by the construction of a digital rock model. This approach has both advantages and limitations. The primary advantage is that it allows for more accurate calculation of the filling structure and proportion within the rock's internal space, especially when CT scanning methods are unable to achieve this level of precision. As a result, a more accurate digital model of the filling can be constructed. However, the main limitation is that this method is irreversible, and the sequential cutting process can damage the rock, leading to the loss of potentially valuable and representative samples.

The rock sample MK6 selected for this study is shown

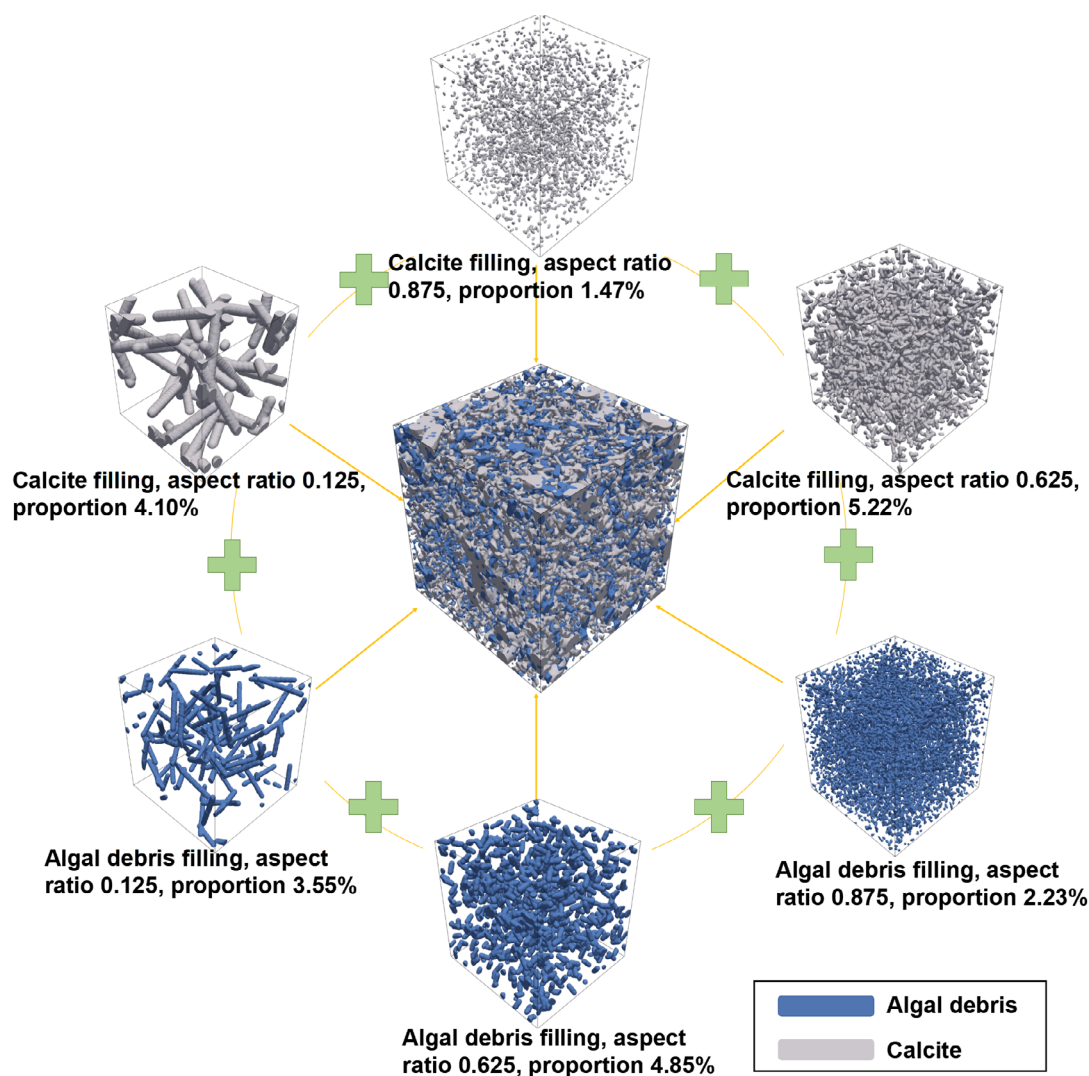


Figure 3. Construction of the digital rock model

in Figure 4, with a density of 2.62 g/cm^3 , porosity of 2.01%, and permeability of 0.001120 mD. The white regions represent calcite band fillings, the darker areas correspond to algal debris, and the remaining portions represent the rock matrix.

The MK6 sample was cut from top to bottom, with the filling structure at the upper end being more complex. In regions with abundant mineral infill structures, the slice thickness was controlled to 2–3 mm, whereas in regions with insufficient infill structures, the slices were made thicker or left unprocessed. The subsequent construction of the digital rock model was also carried out strictly in accordance with this cutting ratio. To further ensure the representativeness of the slices, efforts were made to preserve the complete mineral infill structure within a single slice whenever possible, thereby enabling the

digital rock model to more accurately reflect the actual rock fabric. This adaptive cutting approach is designed to capture as much detailed and complete filling structure information as possible, providing a solid foundation for the subsequent construction of digital rock models.

The MK6 model construction process is illustrated in Figure 5. After cutting the entire rock into 8 sections, 17 slices containing internal filling structures were obtained. First, filtering and denoising were applied to the slices at different positions to suppress image noise. Next, accurate three-phase image segmentation was performed, dividing the images into calcite filling (white), matrix (gray), and algal debris filling (black) based on grayscale values. Finally, a 3D digital rock model with spatially correlated filling structures was constructed by progressively interpolating the contours of the 17 slices. Based on component

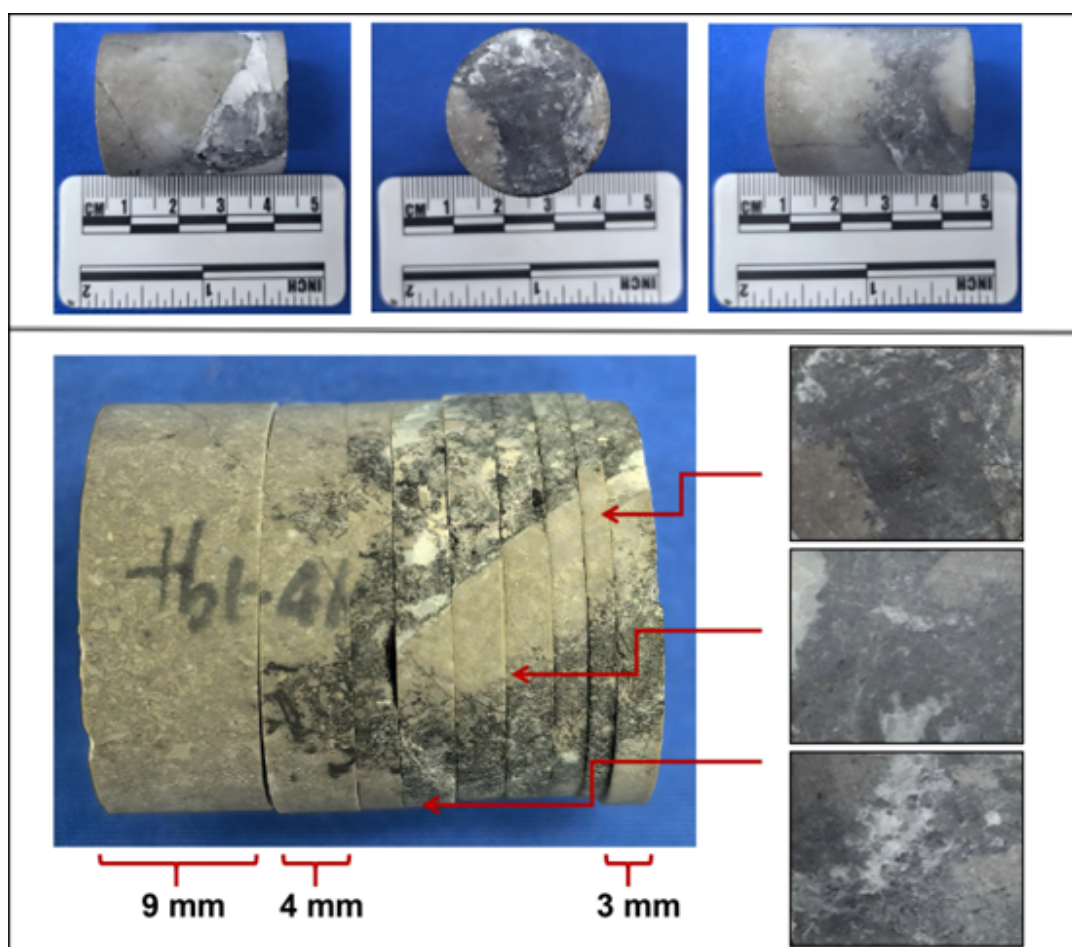


Figure 4. Investigation of typical fill structure in the rock (MK6) section

statistics, the resulting model consisted of 66.82% matrix, 5.81% calcite filling, and 27.37% algal debris filling. The numerical simulation results of the two digital rock modeling methods and the comparative verification with rock-physics experiments are detailed in the next section.

3. Numerical simulation

3.1. Method for obtaining numerical simulation parameters

The first step in the workflow of digital rock physics is to construct a digital rock model, and the second step is to perform numerical simulation on it to obtain the corresponding rock properties. This study employed a multi-component static elastic parameter simulation method based on the finite element method for numerical simulation work. After calculating the stress and strain values of rocks through finite element analysis, the longitudinal and transverse wave velocities or other elastic moduli were calculated based on the generalized Hooke's

law for isotropic media. Static finite element numerical simulation requires the elastic moduli (bulk modulus K , shear modulus μ , etc.) of different mineral components in the rock as simulation parameters; therefore, accurate parameter selection is crucial for ensuring the reliability of numerical simulation results.

The full-diameter rock obtained from the well in the Sichuan Basin was cut to obtain internal sections, and thin sections were prepared for analysis. The results are shown in Figure 6. The black region in the upper part of the rock generally exhibits a calcareous structure with algal cementation, primarily composed of mud-microcrystalline calcite and rich in algae. Small algal pellets and algal aggregates are formed between detrital fragments, which is described in this paper as algal detritus filling. The middle section of the rock is almost entirely composed of calcite based on mineral composition and has undergone weak recrystallization, which is referred to in this paper as the matrix. The white strip at the lower end of the rock

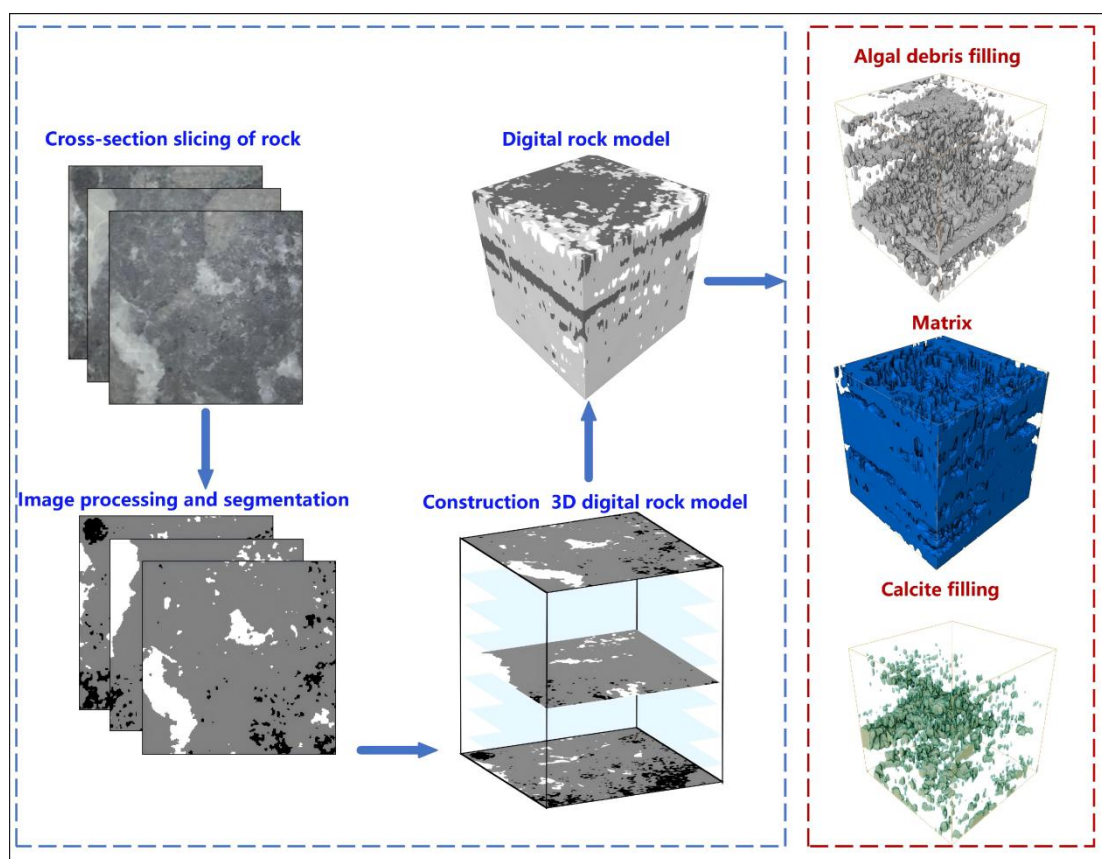


Figure 5. Model construction process for the MK6 sample

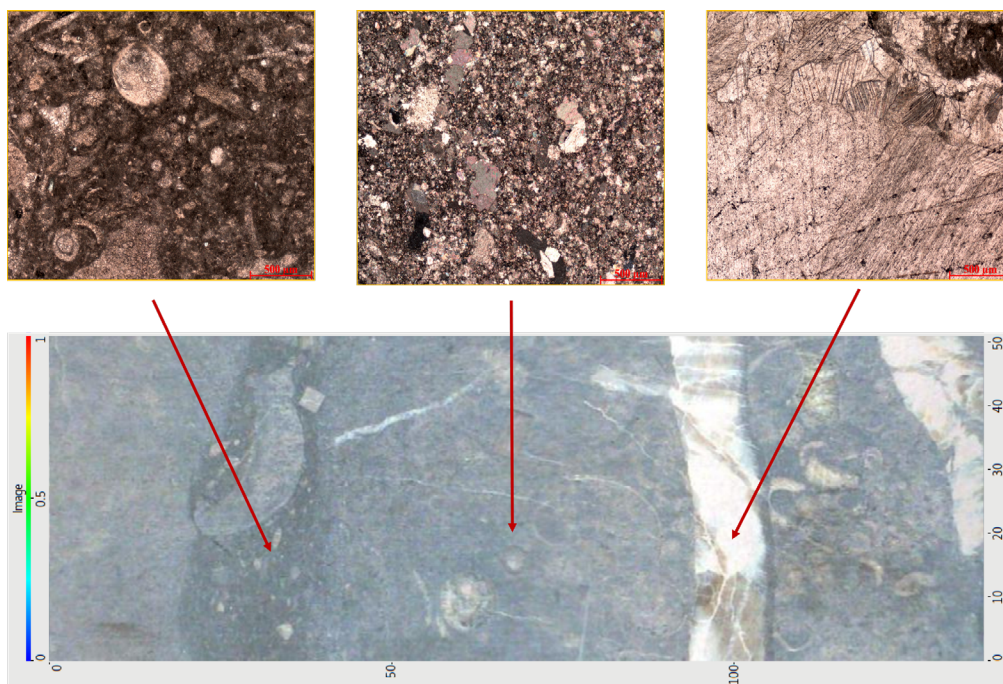


Figure 6. Rock thin sections. Analysis of thin sections of different components in the rock plane.

primarily consists of mud-microcrystalline calcite, with some algal sandstone detritus, and bright calcite fills the fractures in the rock, which is described as calcite filling in this paper.

The filling minerals and characteristics of the Maokou Formation are complex, and accurate elastic moduli of minerals can ensure the accuracy of numerical simulation calculations. In this study, a high-resolution rock-physics multi-parameter field rapid-scanning experimental system was applied to directly measure the elastic moduli of various components under normal pressure by scanning the rock plane. This provides accurate simulation parameters for digital rock numerical simulation. The test results are shown in Figure 7.

Figure 7A shows a full-diameter rock sample from the Sichuan Basin, comprising continuous calcite filling bands and a large number of algal debris filling areas. The calcite filling is off-white, the algal debris filling is off-black, and the matrix is gray. The test was conducted from top to bottom according to the red vertical line, and the results are displayed in Figure 7B and 7C. Accurate acoustic velocities of calcite filling, algal debris filling, and matrix were then

obtained and subsequently converted into elastic moduli to derive simulation parameters based on experimental test results (Table 3).

The elastic moduli measured in this experiment were used as digital rock simulation parameters. It should be noted that these elastic parameters corresponded to the dry frames of matrix, calcite mineral, and algal debris fillings.

Table 3. Bulk modulus and shear modulus of the main filling materials in typical samples

Filling material type	Matrix	Calcite	Algal debris
Bulk modulus (GPa)	53.4	39.4	48
Shear modulus (GPa)	28.7	19	22.5

3.2. Method 1 reliability verification

In this paper, the MK3 sample was selected for analysis,

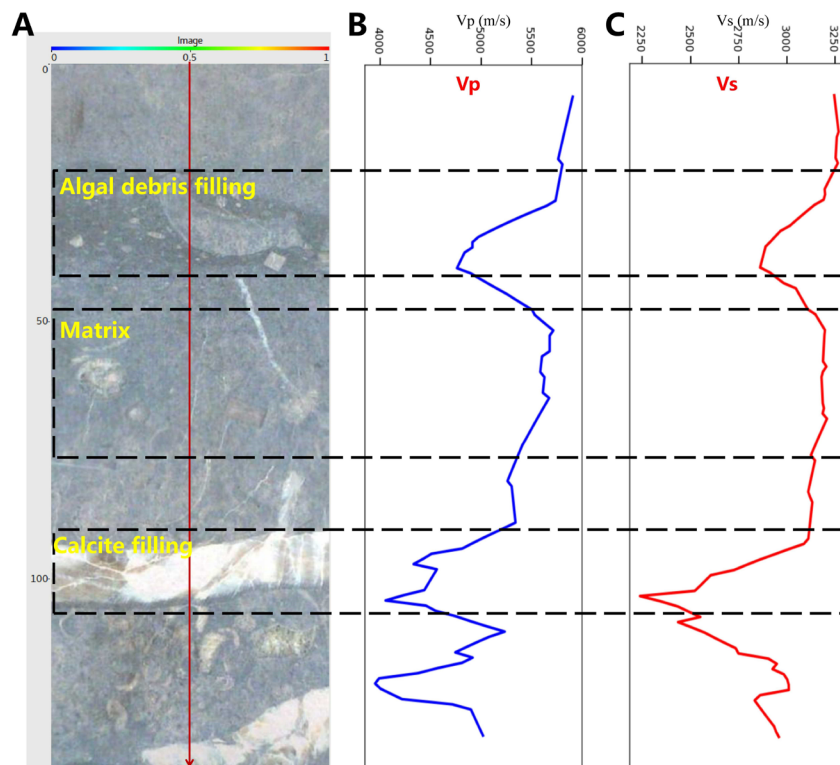


Figure 7. Fill material velocity analysis. Velocity scanning of the entire rock and velocity analysis of the fill material and matrix. (A) Full-diameter rock sample from the Sichuan Basin. (B) P-wave velocity (V_p). (C) S-wave velocity (V_s).

modeling, and numerical simulation, and the simulation results were compared with the experimental results under different pressures. The pressure-dependent ultrasonic velocities were calculated using:

$$V = \frac{L}{t} \quad (1)$$

where L is the effective propagation distance through the rock specimen, and t is the corresponding wave travel time. Since the specimen geometry remained unchanged during each measurement stage and the dimensional variation induced by confining pressure was much smaller than the travel-time variation, the uncertainty in wave velocity was considered to be dominated primarily by the travel-time determination. Among the various potential error sources, first-arrival identification was found to be the dominant contributor, especially at low confining pressures where microcrack closure was incomplete, and the received waveform was relatively less stable.

As shown in Figure 8, the uncertainty ranges were significantly smaller than the overall increase in wave velocity induced by confining pressure. This indicates that the observed growth of both V_p and V_s with increasing confining pressure is well above the measurement uncertainty and therefore reflects a real physical response of the rock. In particular, the increase in wave velocity at lower confining pressures was more pronounced, which is consistent with the progressive closure of pre-existing pores and microcracks. At higher confining pressures, the rate of increase became smaller, while the uncertainty remained relatively limited, suggesting that the measured trends are stable and statistically meaningful over the full pressure range. Overall, the uncertainty analysis confirms that the experimental ultrasonic velocity data are sufficiently reliable for interpreting the pressure-dependent acoustic response of the tested rock specimens.

The simulation results are shown in Figure 9A and 9B. The blue dots represent the P- and S-wave velocities under 15–105 MPa pressure, and the red dots represent the P- and S-wave velocities obtained by digital rock simulation. The numerical simulation represents the rock elastic parameters at normal temperature and pressure; therefore, the experimental velocities were lower than those measured at 15 MPa (it is expected that the experimental velocities measured under confining pressure are higher than those under atmospheric conditions). To validate the numerical results, the experimental data were extrapolated to 0 MPa using linear regression analysis. At 0 MPa, the relative errors for V_p and V_s were 0.34% and 0.47%, respectively.

$$\text{Relative error (\%)} = \frac{|\text{Experimental value} - \text{Simulated value}|}{\text{Experimental value}} \quad (2)$$

These results demonstrate excellent agreement between the numerical simulation and experimental measurements, thereby validating the accuracy of the digital rock-physics approach.

Furthermore, MK4 and MK5 samples were selected for the same experiments and simulation tests. The results are shown in Figure 9C–F. The simulation results demonstrate that the digital rock model construction results matched well with the experimental results. When the experimental data were extrapolated to 0 MPa, the relative errors between simulated and experimental values were 0.31% and 0.85% for V_p and V_s of MK4, respectively, and 0.38% and 0.47% for those of MK5, respectively. These quantitative comparisons demonstrate that the digital rock model construction methodology exhibits consistent accuracy and reliability across different rock samples. The detailed information of the three samples used for verification is shown in Table 1.

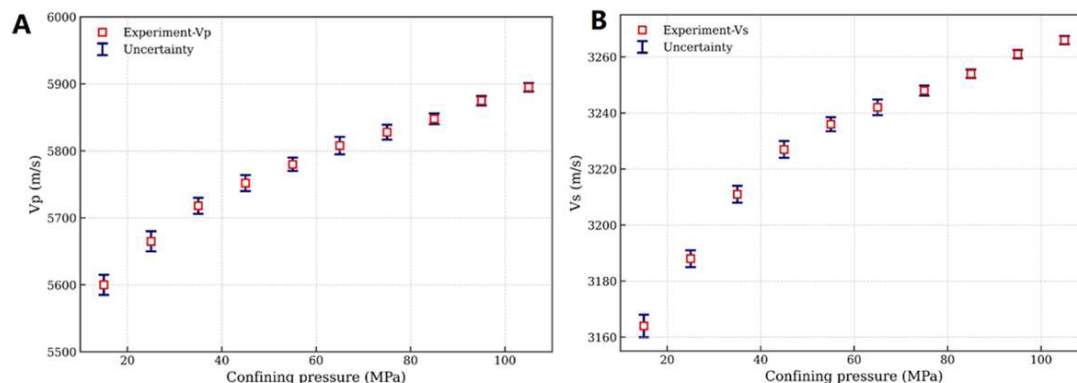


Figure 8. Uncertainty analysis of acoustic testing under variable confining pressure for the MK3 sample. (A) P-wave velocity (V_p). (B) S-wave velocity (V_s).

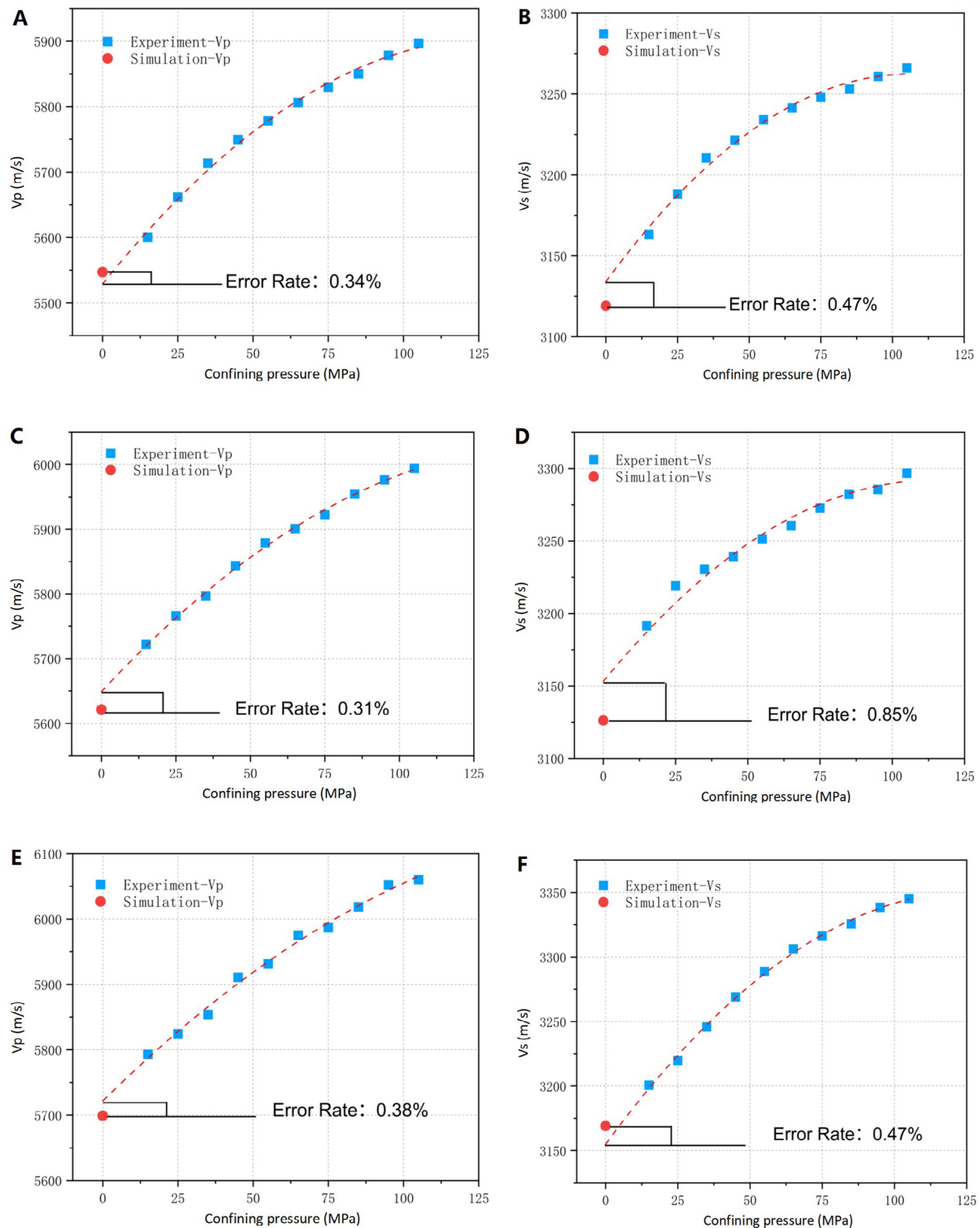


Figure 9. Experimental and simulation results of typical samples. (A) P-wave velocity (V_p) of MK3. (B) S-wave velocity (V_s) of MK3. (C) V_p of MK4. (D) V_s of MK4. (E) V_p of MK5. (F) V_s of MK5.

3.3. Method 2 reliability verification

In this study, sample MK6 was selected for experimental measurements and numerical simulations to validate the reliability of Method 2. The experimental and numerical simulation results are shown in Figure 10. The blue circles represent the experimental test results under a confining pressure of 15–105 MPa, the green squares represent the simulation results of the 3D model obtained using the model construction method described in Method 1, the red stars represent the results from the sequential slicing method introduced in this section, and the red dashed line represents the fitting line for the experimental data. Digital rock models constructed using Method 1 exhibited relative errors of 1.5% (Vp) and 0.81% (Vs) when validated against experimental measurements at 0 MPa confining pressure. Models developed using Method 2 demonstrated significantly higher accuracy, with corresponding errors reduced to 1.1% and 0.45%. Therefore, the model constructed using the method presented in this section better aligns with the actual rock filling structure and filling ratio, making the resulting 3D digital rock model more representative of the real situation. Consequently, the reliability of the numerical simulation results is slightly enhanced. The experimental and simulation results of different methods are shown in Table 4.

In summary, the method of cutting rock samples to examine their internal filling materials and structures is feasible. Compared to the surface-based modeling approach described in Method 1, Method 2 offers higher accuracy and provides a more precise depiction of the filling ratio and structural details within the rock. Additionally, the numerical simulation results of this model are closer to the experimental predictions. However, this method has irreversible destructive effects on the rocks and requires

significant labor costs, making it challenging for large-scale studies and for quickly obtaining relevant insights through rock physics to guide oil and gas exploration.

In summary, while both methods achieved similar accuracy, Method 1 offers the significant advantage of being non-destructive, thus representing a more valuable approach for rock-filling material characterization.

4. Application

4.1. Analysis of rock physical characteristics with different mineral filling ratios

Based on the above modeling and simulation methods, a digital rock model with variable calcite content was constructed to explore the influence of different filling ratios. The calcite mineral filling content varied from 2% to 42% (Figure 11), while the algal debris filling content was kept constant at 4%. An increase in calcite content was accommodated by a corresponding decrease in matrix content. The elastic characteristics at different calcite mineral filling contents were explored using static finite element simulation, and the results are shown in Figure 12.

The simulation results show that an increase in calcite content decreased bulk modulus, shear modulus, Vp, Vs, and P-wave impedance, while increasing the Vp/Vs ratio. This trend may be attributed to the input calcite filling material, which includes partially filled pores, resulting in experimentally measured elastic moduli being lower than the corresponding matrix moduli.

4.2. Analysis of rock physical characteristics in different mineral filling directions

The karst characteristics of the Maokou Formation reservoir in the Qijiang area are complex, mainly including surface karst zones (mineral randomly fillings), vertical

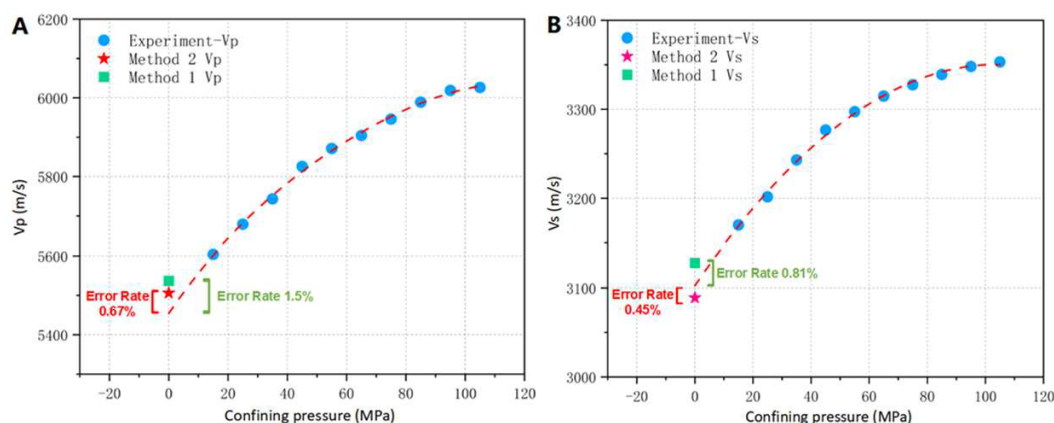


Figure 10. Comparison of experimental and simulation results for the MK6 sample. (A) P-wave velocity (Vp). (B) S-wave velocity (Vs).

Table 4. Comparison of different modeling methods and experiments

Digital rock modeling conditions	Method 1	Method 2	Rock-physics Experiment
Whether to damage the rock sample	No	Yes	No
Proportion of calcite filling material (%)	9.27	10.19	-
Proportion of algal debris filling material (%)	24.73	29.68	-
Vp obtained from numerical simulation (m/s)	5,537	5,501	-
Vs obtained from numerical simulation (m/s)	3,128	3,089	-
Vp under normal pressure (fitted through experiments) (m/s)	-	-	5,454
Vs under normal pressure (fitted through experiments) (m/s)	-	-	3,102

Abbreviations: Vp: P-wave velocity; Vs: S-wave velocity.

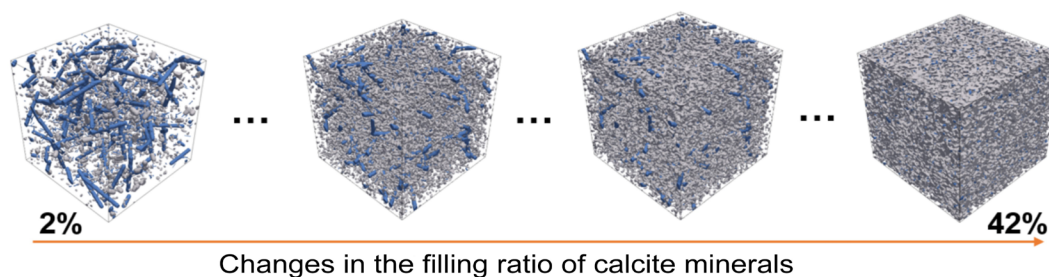


Figure 11. Schematic diagram illustrating variations in calcite filling proportion

seepage zones (mineral vertically oriented fillings), and horizontal subsurface flow zones (mineral horizontally oriented fillings). By maintaining constant filling mineral types, contents, and geometric shapes while exclusively varying the orientation of mineral fillings as a monotonic variable, we investigated the influence of filling orientation on the elastic properties of carbonate rocks. This approach establishes quantitative relationships between karst features and elastic behavior in the reservoir. All calcite filling models were updated to represent vertical and horizontal filling configurations, and numerical simulations were carried out. The results were compared with the corresponding Voigt model (theoretical upper bound) and Reuss model (theoretical lower bound).

To predict the equivalent elastic modulus of mineral particle mixtures using theoretical methods, it is necessary to know: (i) the volume content, (ii) the elastic modulus, and (iii) the geometric distribution of each component. The Voigt model, which represents the theoretical upper bound, assumes uniform strain across all components. The equivalent elastic modulus for N components can be

expressed as:

$$M_v = \sum_{i=1}^N f_i M_i \quad (3)$$

where f_i is the volume fraction of the i -th component, and M_i is the elastic modulus of the i -th component.

The Reuss model provides the theoretical lower bound for the equivalent elastic modulus:

$$\frac{1}{M_R} = \sum_{i=1}^N \frac{f_i}{M_i} \quad (4)$$

For any rock, given the volume content of each component, the equivalent modulus falls between the Voigt upper bound and the Reuss lower bound. Based on the above modeling methods, horizontal and vertical filling models with the same volume content as the samples were constructed, and numerical simulation methods were applied for calculation. The calculation results are shown in Figure 13.

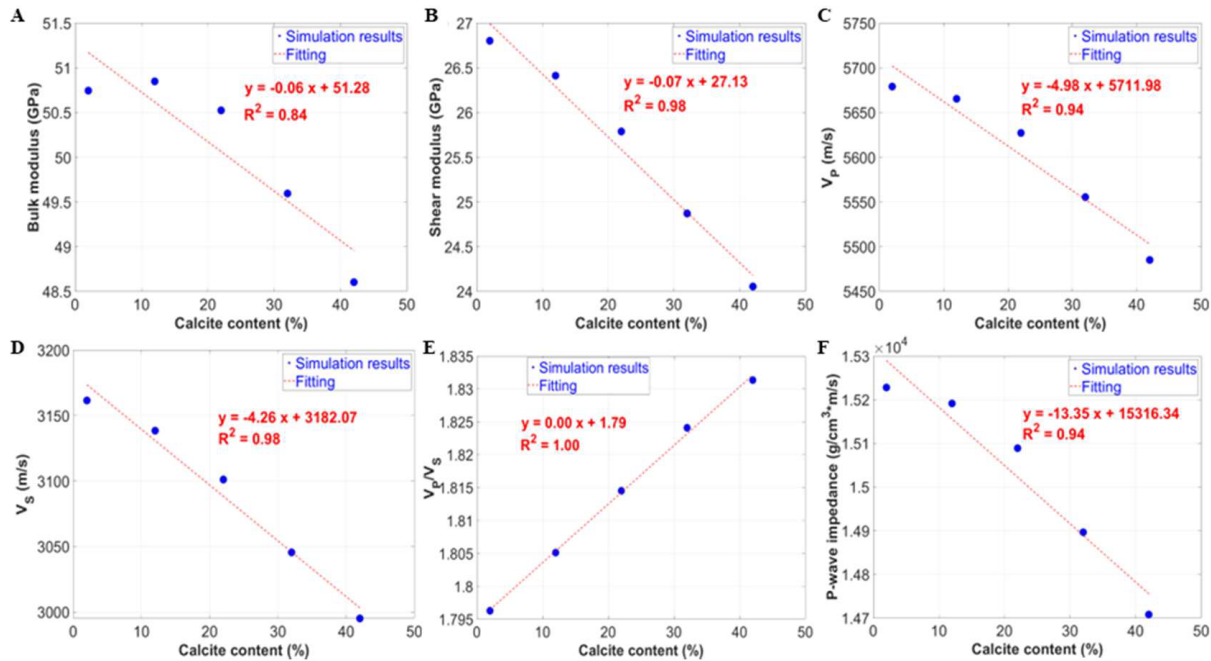


Figure 12. Studies on the content of dolomite and its elastic properties. (A) Bulk modulus. (B) Shear modulus. (C) P-wave velocity (V_p). (D) S-wave velocity (V_s). (E) V_p/V_s . (F) P-wave impedance.

The digital rock simulations for vertically oriented mineral fillings exhibited V_p and V_s that closely matched the Voigt model predictions, whereas the horizontally filled counterparts aligned with the Reuss model results. Notably, simulations revealed moderately higher wave velocities for mineral vertically oriented fillings compared to horizontal configurations. At 40% calcite filling content, the normalized differences were 1.54% for V_p and 0.91% for V_s .

$$\text{Normalized difference(\%)} = \frac{|V_{\text{vertical}} - V_{\text{horizontal}}|}{V_{\text{vertical}}} \quad (5)$$

Consequently, mineral-filling orientation exerted a measurable though limited influence (<2%) on both V_p and V_s in carbonate rocks. In addition, both orientations displayed systematically decreasing V_p and V_s with increasing calcite content, revealing a strong linear correlation. The study of different mineral filling orientations can provide robust support for characterizing and understanding karst reservoir features.

4.3. Analysis of rock physical characteristics filled with different fluids

We have shown that while the orientation of calcite fillings influenced V_p and V_s in carbonate rocks, the magnitude of the influences remained below 2%. Therefore, we used the

Hill average to represent the overall elastic modulus of the model framework. The Hill average is expressed as follows:

$$M_{VRH} = \frac{M_V + M_R}{2} \quad (6)$$

where M_V is the Voigt upper bound, M_R is the Reuss lower bound, and M_{VRH} is the Hill average modulus. Where M can represent any elastic modulus, in this paper, M refers to both the bulk modulus and shear modulus.

To investigate the variation of rock elastic modulus with fluid saturation in the Maokou Formation of the Sichuan Basin, a representative sample (MK7) from this area (calcite filling 13.4%, algal debris filling 12.2%) was selected for digital rock modeling. Following the derivation of the dry-frame elastic moduli via the Hill model, we simulated V_p and V_s under brine saturation at variable water saturations (0, 0.25, 0.5, 0.75, 1) for both vertically and horizontally oriented pore systems.

Simulation results in Figure 14 demonstrate that V_p for vertically oriented mineral fillings exceeded those of horizontal configurations. This directional dependence aligns with the Voigt (upper bound) and Reuss (lower bound) theoretical models. V_p exhibited progressive enhancement with increasing water saturation, displaying a near-linear relationship. The variation in the simulation results for the vertical distribution of pores was slightly

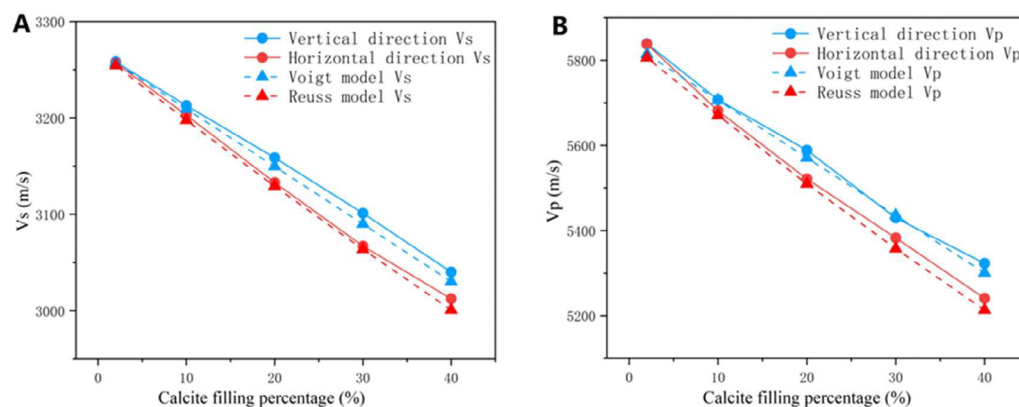


Figure 13. Comparison of the theoretical model and simulation results. (A) P-wave velocity (V_p). (B) S-wave velocity (V_s).

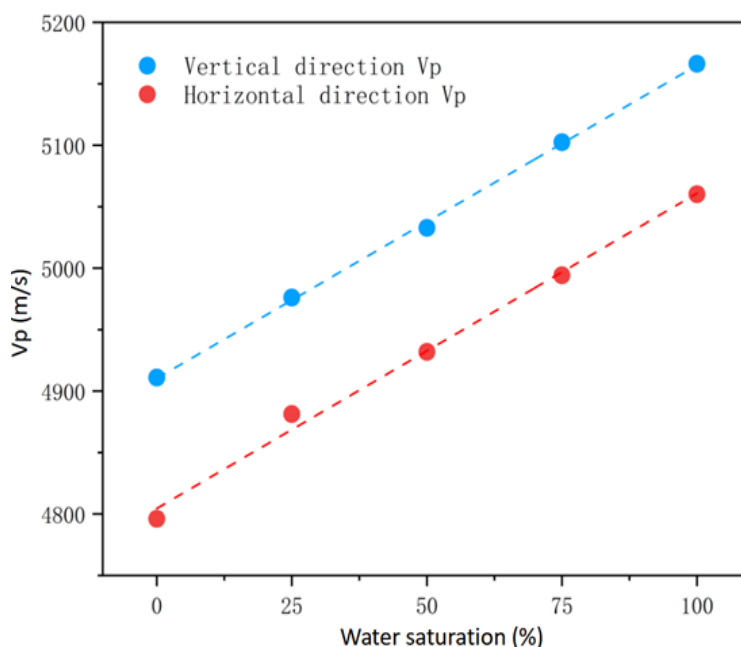


Figure 14. Simulation of P-wave velocities at different fluid saturations

lower than that for the horizontal distribution. It is important to note that water saturation has a negligible effect on V_s ; hence, those results are not displayed. This study demonstrates that fluid types within pores exert a substantially greater influence on elastic properties than pore orientation in the Maokou Formation carbonate rocks.

5. Conclusion

This study focuses on the Maokou Formation carbonate reservoir in the Sichuan Basin, characterized by significant heterogeneity, complex karst features, and pronounced

filling. The physical properties of carbonate rocks with different filling minerals, mineral proportions, and filling types in the Maokou Formation reservoir are unclear. By integrating thin-section petrography with advanced imaging analysis, we quantitatively determined the mineral compositions, volumetric proportions, and geometric configurations of pore-filling materials in rock samples. Two distinct methodologies for constructing 3D digital rock models that incorporate karst and filling characteristics were developed: Method 1 (mineral filling information fusion) and Method 2 (rock section reconstruction). The reliability of the two methods was verified using experimental data, and Method 2 offers

higher accuracy and a more precise depiction of the filling ratio and structural details within the rock. However, this method has irreversible, destructive effects on the rocks. Based on the proposed digital rock technology, this study analyzed the elastic properties of the rock under different mineral filling proportions, filling orientations, and different fluid filling characteristics. The simulation results show that an increase in calcite content decreased the bulk modulus, shear modulus, V_p , V_s , and P-wave impedance, while increasing the V_p/V_s ratio. Moreover, the digital rock simulations for vertically oriented mineral fillings exhibited V_p and V_s that closely match Voigt model predictions, whereas those for horizontally filled counterparts align with Reuss model results. In addition, this study demonstrates that fluid types within pores exert a substantially greater influence on elastic properties than pore orientation in the Maokou Formation carbonate rocks.

Nevertheless, several limitations remain, including the limited number of representative sections and the overly simplified representation of pore-fracture-filling geometries in the digital models. Future work should incorporate a broader sample base and more realistic pore-system characterization, and establish links between digitally derived elastic properties and well-log and seismic responses to support the fine-scale characterization of deep carbonate reservoirs.

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Conflict of interest

All authors are employees of SINOPEC Corp.; however, they were not involved in any activities that could constitute a conflict of interest in relation to this study.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Data are available from the corresponding author upon reasonable request.

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