

REVIEW ARTICLE

Wave-equation migration: Advances, artificial intelligence enhancement, comparisons, and outlook

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Abstract

Wave-equation-based seismic migration is a core technology for high-resolution subsurface imaging in applications such as hydrocarbon exploration and geothermal resource assessment. It provides a more complete physical description of seismic wave propagation than ray-based migration methods, and is therefore essential for imaging complex geological structures characterized by strong velocity contrasts and steeply dipping reflectors. This paper presents a systematic review and comparative analysis of wave-equation prestack depth-migration methods, including reference-velocity-based one-way wave-equation depth migration (OWDM), accurate-velocity-based OWDM, reverse-time migration, and full-wave-equation depth migration. The theoretical foundations, wavefield extrapolation characteristics, imaging mechanisms, and numerical implementations of these methods are examined within a unified framework. Particular emphasis is placed on clarifying the intrinsic limitations of one-way wave-equation migration in handling turning waves and large propagation angles, and on contrasting the strengths and weaknesses of time-domain versus depth-domain full-wave-equation migration. Based on representative numerical experiments and field data examples, the imaging performance, computational efficiency, and practical applicability of the four migration schemes are comprehensively compared. In addition, recent advances in artificial intelligence-assisted seismic imaging are reviewed, focusing on wavefield propagator design and migration artifact suppression. This review provides practical guidance for selecting appropriate migration strategies in complex geological settings and offers insights into future developments of wave-equation-based seismic imaging.

Keywords: Wave-equation migration; Seismic imaging; Research progress; Imaging comparison

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1. Introduction

Seismic imaging technology is of great significance in promoting oil and gas exploration and development, geothermal resource assessment, carbon dioxide sequestration monitoring, and related fields. As energy resources are extensively exploited, exploration has become increasingly challenging. The search for mid-to-deep reservoirs, ultra-shallow formations, buried hills, lithologic traps, and complex structural or fractured reservoirs has emerged as a key research focus, posing new challenges for exploration seismology—particularly in seismic-wave migration imaging. Advancements in high-resolution seismic imaging techniques are critical for improving the exploration of both conventional and unconventional hydrocarbon resources. Beyond hydrocarbon exploration, high-resolution seismic imaging is also critical for emerging energy technologies, such as carbon capture and storage (CCS) and geothermal energy development. Accurate migration methods are essential for monitoring fluid movement in CCS reservoirs and characterizing fracture networks in geothermal systems, highlighting the broader societal relevance of advancing wave-equation-based techniques.

Since its inception in the 1960s, seismic imaging has evolved significantly, progressing from early manual and human-computer migration methods to digital wave-equation-based techniques enabled by advances in scientific computing.¹ Early migration approaches were rooted in Huygens' principle, which treats every point on a wavefront as a secondary source. The exploding reflector model (ERM), which assumes simultaneous explosions of all points at the subsurface, laid the foundation for modern imaging.² Subsequent developments introduced frequency-wavenumber one-way wave migration derived from ERM and other wave-equation formulations.

One-way wave migration can be regarded as a practical implementation of ERM under the paraxial assumption. Integral migration methods based on ray-tracing theory also contributed to the theoretical foundation of modern imaging.³ In addition to seismic reflection imaging, the diffraction imaging theory provides a special solution for small-scale structure.⁴ These early techniques laid the groundwork for rapid advances in migration, with progress closely tied to improvements in computational hardware. Enhanced computing power has facilitated a transition from post-stack to prestack migration, from time migration to depth migration (which better accounts for velocity variations), from 2D to 3D migration, from ray-based algorithms to wave-equation migration

employing exact solutions, from one-way wave migration to full-wave-equation migration, and, more recently, from traditional methods to artificial intelligence (AI)-assisted migration imaging.

This review systematically analyzes the evolution of one-way and full-wave-equation migration methods, focusing on comparisons of wavefield propagation and imaging performance among the current mainstream wave-equation-based migration methods. Specifically, it highlights advancements in wave-equation migration and their constraint, with discussions of their prospects for seismic exploration.

2. Research progress on wave-equation-based migration

Limited to a 2D case in this review, the acoustic constant-density second-order wave equation is given as:

$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial z^2} = \frac{1}{v^2} \frac{\partial^2 u}{\partial t^2} \quad (1)$$

where u is the pressure wavefield, v denotes the medium velocity, x and z are spatial coordinates, and t is time.

The full wave equation can be formulated in either the time or frequency domain as:

$$\frac{\partial^2 u}{\partial t^2} - Qu = 0 \quad (2)$$

$$\frac{\partial^2 \tilde{u}}{\partial z^2} + H\tilde{u} = 0 \quad (3)$$

where $\tilde{u} = \text{FFT}[u]$ denotes the frequency-domain wavefield, $Q = v^2 \left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial z^2} \right)$, and $H = \frac{\omega^2}{v^2} + \frac{\partial^2}{\partial x^2}$, where ω is frequency.

The wave-equation prestack depth migration can be categorized into one-way wave-equation migration and full-wave-equation migration based on the propagation characteristics of the wavefields.

2.1. Advances in one-way wave-equation depth migration

Over the past few decades, one-way wave-equation depth migration (OWDM) has played a crucial role in seismic imaging. From the perspective of wave-equation solutions, conventional seismic acquisition records only the wavefield

at the surface, providing a single boundary condition. To facilitate the solution process, the acoustic wave equation is decomposed into two independent one-way wave equations: the downgoing and upgoing wave equations.

Assuming a homogeneous medium, the one-way wave equation can be derived from the full second-order wave equation as:

$$\frac{\partial \tilde{u}}{\partial z} = \pm i k_z \tilde{u} \quad (4)$$

where $k_z = \sqrt{\frac{\omega^2}{v^2} - k_x^2}$ is the square-root operator, also called the vertical wavenumber, at the core of depth-domain extrapolation.

Then, the adjacent-layer iteration equation can be written as:

$$\tilde{u}(z + \Delta z) = e^{\pm i k_z \Delta z} \tilde{u}(z) \quad (5)$$

where Δz is the depth-step length.

The fundamental strategy of OWDM involves extrapolating the source wavefield using the downgoing wave equation and backpropagating the receiver wavefield using the upgoing wave equation. These wavefields are then propagated downward in depth, and imaging is performed using an imaging condition. Since the one-way wave equations are derived from the full wave equation, OWDM retains its capability to handle complex media.

2.1.1. Reference-velocity-based one-way wave migration

The earliest OWDM method employs the Fourier transform to convert the original wave equation from the time-space domain to the frequency-wavenumber domain. It utilizes only the upgoing wave equation to compute the propagation operator and recursively extrapolate the wavefield for imaging. OWDM methods are computationally efficient and stable, making them suitable for large-scale imaging. As a classical migration scheme, the phase-shift (PS) method⁵ assumes that velocity varies only in the depth direction. Therefore, this method is effective only when the velocity is uniform or varies strictly in the vertical direction, and it performs poorly in media with lateral velocity variations. Around the same period, frequency-domain finite-difference (FD) techniques were

introduced into seismic migration imaging.⁶ However, these methods suffered from severe limitations in imaging at large angles.

To address this limitation, OWDM algorithms have undergone extensive optimization, particularly in approximating the vertical wavenumber to better accommodate laterally varying velocity media. The PS plus interpolation method⁷ and the split-step Fourier (SSF) migration algorithm⁸ were subsequently developed. The SSF method introduces a time-shift correction term in the frequency-space domain to mitigate phase distortions caused by lateral velocity variations. Further refinements to the SSF algorithm partially improved phase accuracy, yet its fundamental limitation in imaging complex inhomogeneous media remains unresolved.⁹

Due to limited compensation for low-order perturbations, these algorithms only provide accurate imaging positions when lateral velocity variations are weak. By incorporating a quadratic correction term into the SSF method, the Fourier finite-difference (FFD) migration algorithm was proposed.¹⁰ This approach significantly improved imaging for large-angle wave propagation and enhanced imaging accuracy in laterally varying velocity media. Based on the FFD method, researchers attempted to improve imaging precision in complex media by introducing more accurate polynomial coefficients derived from global optimization strategies, leading to the development of optimized FFD migration techniques.¹¹⁻¹³ Similar to the FFD approach, the generalized screen propagator (GSP) extends the phase-screen operator based on scattering theory.¹⁴ GSP decomposes velocity perturbations into a background velocity field and an in-layer perturbation term. Various hybrid migration methods based on GSP operators have been developed to improve propagation angles, amplitude preservation, stability, adaptability, and amplitude compensation.¹⁵⁻¹⁷

Both the FFD and GSP methods employ higher-order corrections to address lateral velocity variations and operate in dual domains based on the SSF algorithm. However, their implementations differ: FFD expands the operator using a second-order Taylor series around the reference velocity, followed by continued fraction expansion and FD corrections in both the frequency and spatial domains. In contrast, GSP transforms the square-root operator from the reference velocity field to the correct velocity field and then applies a Taylor expansion to separate spatial and wavenumber variables, enabling alternating corrections in the frequency-space and frequency-wavenumber domains, as expressed as:

$$\left\{ \begin{aligned} k_z^{SSF} &= \frac{\omega}{v(x, z)} - \frac{\omega}{v_r} + \sqrt{\frac{\omega^2}{v_r^2} - k_x^2} \\ k_z^{FFD} &= k_z^{SSF} + \frac{v(x, z) - v_r}{a + b} \frac{\partial^2}{\partial x^2} \\ k_z^{GSP} &= k_z^{SSF} + \omega \sum_{j=1}^n a_j \left(\frac{\omega}{v^2(x, z)} - \frac{\omega}{v_r^2} \right)^j \\ &\quad \times \left[\left(\frac{\omega}{\sqrt{\frac{\omega^2}{v_r^2} - k_x^2}} \right)^{2j-1} - v_r^{2j-1} \right] \end{aligned} \right. \quad (6)$$

where v_r is the reference velocity, which is often used as the mean velocity in the SSF and FFD method, and the minimum velocity in the GSP method.

Since OWDM methods separate the full acoustic wave equation into up- and downgoing components, imaging amplitude in one-way wave operators is typically achieved by introducing compensation factors or auxiliary functions in the equations. These methods have made progress in improving large-angle imaging and amplitude preservation.

2.1.2. Accurate-velocity-based one-way wave migration

Directly discretizing the lateral velocity and calculating the accurate value of the square-root operator at each discrete point are necessary to solve the wave equation in laterally varying velocity media. The idea of using accurate horizontal velocities to calculate one-way propagators with the generalized phase-shift (GPS) operator¹⁸ was proposed to overcome the limitations of the traditional OWDM methods, which rely on reference-velocity approximations. Another way to solve the accurate one-way wave propagator is with an eigen decomposition (ED) of the Helmholtz operator,¹⁹ enabling OWDM to image strongly laterally varying media. Specifically, in terms of matrix transformation theory, the self-adjoint matrix $H = k_z^2$ can be decomposed into a multiplication of eigenvalues and eigenvectors, so that:

$$H = VMV^T \quad (7)$$

where the superscripted T represents the matrix transpose and matrices and denote the eigenvalues and eigenvectors of, respectively.

$$H = \begin{bmatrix} \frac{\omega^2}{v^2(x_1)} & 0 & \cdots & 0 \\ 0 & \frac{\omega^2}{v^2(x_2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\omega^2}{v^2(x_n)} \end{bmatrix} + \begin{bmatrix} \frac{-2}{(\Delta x)^2} & \frac{1}{(\Delta x)^2} & 0 & 0 \\ \frac{1}{(\Delta x)^2} & \frac{-2}{(\Delta x)^2} & \ddots & 0 \\ 0 & \ddots & \ddots & \frac{1}{(\Delta x)^2} \\ 0 & 0 & \frac{1}{(\Delta x)^2} & \frac{-2}{(\Delta x)^2} \end{bmatrix} \quad (8)$$

Furthermore, the eigenvalues and eigenvectors of the sub-functions can be expressed as:

$$k_z = \sqrt{H} = V\sqrt{M}V^T \quad (9)$$

Following the above two solutions, improvements were made for an accurate one-way migration method. The migration/inversion methods driven by one-way wave operators for imaging multiples are constructed with a closed-loop least-squares framework. The GPS operator is fast and, therefore, frequently used in reflection waveform imaging and inversion.²⁰ The accurate one-way wave-migration operator can be enhanced by adding amplitude-correction terms to optimize true-amplitude calculation performance, with precise discrete velocities to compute the square root of the Helmholtz operator. By using a best-fit matrix decomposition operator based on the infinity norm, high-precision imaging was achieved with low-order expansions.²¹ Also, with a Jacobi–Anger expansion to approximate the one-way operator²² or using the Padé to approximate the propagator calculated in the pseudo-wavenumber domain via the Helmholtz operator,²³ the imaging results were more accurate than those using the Taylor series.

The generalized one-way wave PS operators were used to drive surface and internal multiple reflections and to estimate reflectivity, thereby proposing the full-wavefield migration (FWM) framework.²⁴ Subsequently, FWM was improved by combining surface multiples and internal multiples to image a 3D salt dome model.²⁵ The accurate one-way wave operator can also be integrated into the FWM framework,²⁶ thereby improving the accuracy of reflectivity estimation.

The comparison of propagating-phase accuracy is shown in Figure 1, which demonstrates that the ED operator fits the slowness in very strongly laterally varying media better than the GPS operator, owing to its avoidance of accuracy leakage from the Fourier transform, though both calculate full lateral velocity grids.

2.2. Progress on full-wave-equation migration

In homogeneous media, the phase and amplitude information calculated by the one-way wave migration is consistent with that of the full-wave-equation migration. For heterogeneous media, although the accurate-velocity-

based one-way wave migration can achieve an imaging range of 90 degrees, it is essentially an approximation of the full wave equation and thus cannot fully support calculations for arbitrary propagation angles or achieve amplitude fidelity owing to a loss of traveling wavefield. Simplified propagation assumptions can lead to loss of resolution and inaccurate imaging in complex media.²⁷ In contrast, full-wave-equation migration, based on solving the complete wave equation, can handle turning waves and arbitrary angles. Therefore, since their introduction, full-wave-equation migration algorithms have gained widespread attention.

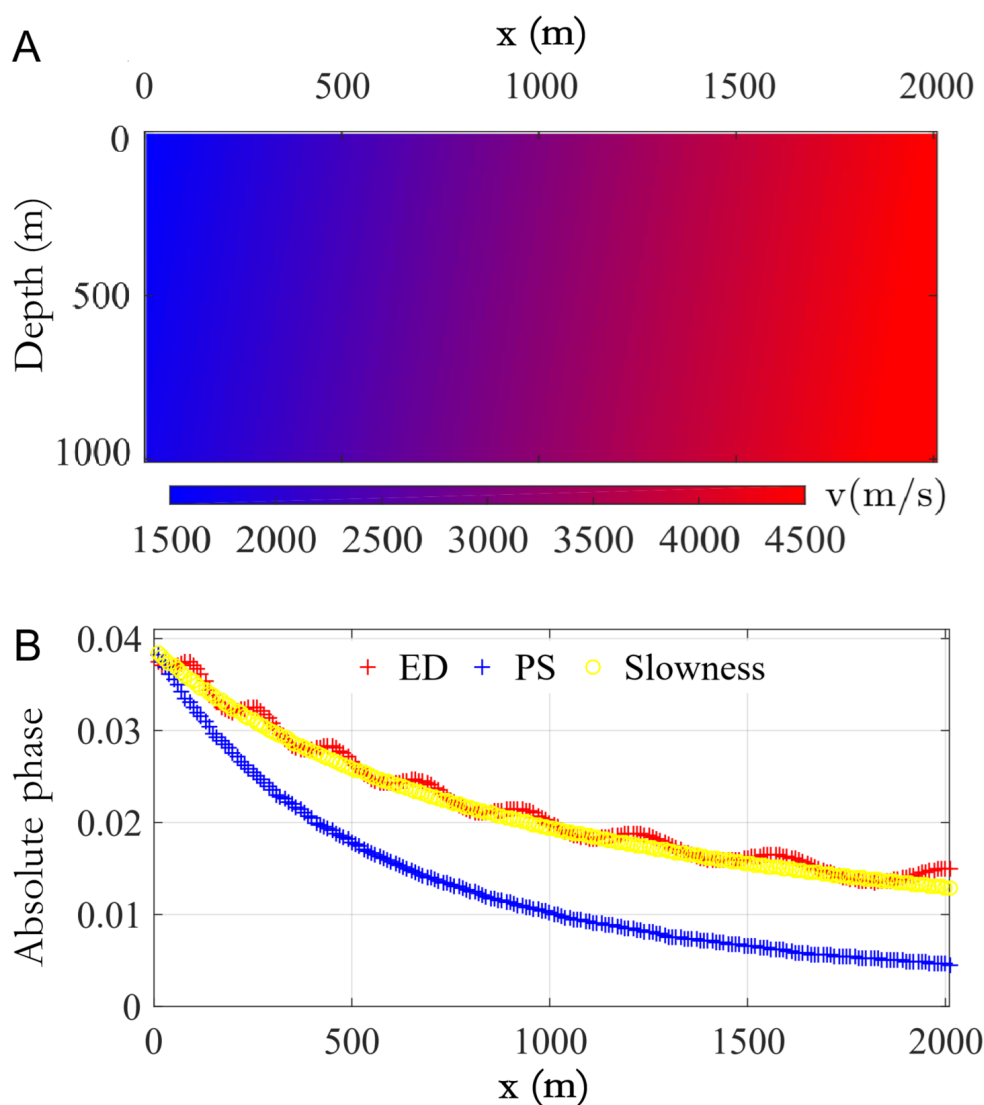


Figure 1. A comparison of propagating phase in inhomogeneous medium. (A) The inhomogeneous medium with strong lateral velocity gradients. (B) Comparison of the phase imaging accuracy between eigen decomposition (ED) and generalized phase-shift (GPS) operators. Reprinted with permission from Li *et al.*²⁶ Copyright © 2024 IEEE.

The wave equation is a function of time and space. To perform wave propagation, the wavefield is generally reconstructed in the time and space domains. With a space-independent and time-independent rewriting, by defining

$U = \begin{bmatrix} u \\ u_t \end{bmatrix}$ and $\tilde{U} = \begin{bmatrix} \tilde{u} \\ \tilde{u}_z \end{bmatrix}$, the propagating wavefield can be further expressed regarding the full wave equation as:

$$\frac{\partial U}{\partial t} = \begin{bmatrix} 0 & 1 \\ Q & 0 \end{bmatrix} U \quad (10)$$

$$\frac{\partial \tilde{U}}{\partial z} = \begin{bmatrix} 0 & 1 \\ -H & 0 \end{bmatrix} \tilde{U} \quad (11)$$

Furthermore, the recursive equation can be formulated as:

$$\begin{cases} U(t + \Delta t) = e^{\begin{bmatrix} 0 & 1 \\ Q & 0 \end{bmatrix} \Delta t} U(t) & \text{RTM} \\ \tilde{U}(z + \Delta z) = e^{\begin{bmatrix} 0 & 1 \\ -H & 0 \end{bmatrix} \Delta z} \tilde{U}(z) & \text{FWDM} \end{cases} \quad (12)$$

where Δt is the time step.

According to execution principles, mainstream full-wave-equation migration is divided into reverse-time migration (RTM)^{28,29} and full-wave-equation depth migration (FWDM),³⁰ based on **Equation 12**. Furthermore, wave-equation migration strategies can be further classified into one-step and two-step approaches based on how the wavefield is processed. One-step migration involves the concurrent extrapolation and imaging of the wavefield. In contrast, two-step strategies involve an initial wavefield decomposition—separating the recorded data into up- and downgoing components—followed by independent imaging. These two-step methods are particularly effective for improving numerical stability and preserving diffraction energy, thereby enhancing the resolution of small-scale geological features, such as faults and fractures, within wave-equation migration workflows.³¹

2.2.1. Progress on reverse-time migration

As a representative full-wave-equation migration method, RTM utilizes the FD technique to solve the wave equation by forward propagating the source wavefield and backward propagating the receiver wavefield. Theoretically, RTM offers superior accuracy in imaging complex structures because it is based on the two-way wave equation and does not rely on dip-angle limitations inherent in other

migration methods. Research on RTM has primarily focused on three key areas: improving imaging accuracy, preserving amplitude, and improving computational efficiency.

Mainly caused by imaging upgoing and downgoing wavefields at large angles, and by a part of the interactions between forward-forward and backward-backward wavefields, strong low-frequency noise is introduced into RTM imaging results, severely degrading imaging accuracy and quality. Thus, prestack RTM filtering techniques were developed to suppress these noises.^{32,33} Since RTM solves the full acoustic wave equation, it inherently possesses an amplitude-preserving imaging potential. True-amplitude recovery methods primarily account for spherical spreading and subsurface absorption effects. In high-frequency approximations, the angle-domain Hessian matrix was used as a weighting function for correction during wave propagation, or amplitude-compensated imaging conditions were applied to improve imaging amplitude.^{34,35}

However, RTM requires storing either the forward-propagated or backward-propagated wavefield during computation, leading to huge memory consumption and low computational efficiency, which limits its industrial applications. Two primary strategies have been proposed to address this challenge: algorithmic optimization to reduce computational complexity and wavefield storage requirements, such as checkpointing, partial snapshot storage, and graphic processing unit acceleration, to enhance efficiency.³⁶⁻³⁹

Least-squares RTM (LS-RTM) reformulates imaging as a least-squares inversion, addressing issues such as migration artifacts, amplitude imbalances, and noise contamination caused by acquisition geometry and wave-propagation effects.⁴⁰⁻⁴⁴ By accounting for the anisotropies of wave propagation, the method has also been extended to tilted transverse isotropic and vertical transverse isotropic media.⁴⁵⁻⁴⁷ LS-RTM, when implemented with wavefield extrapolation in the time domain, can map primary and surface-related multiple reflections into the imaging results, showing significant progress in multiple-wave imaging.⁴⁸⁻⁵¹ With rapid development in recent decades, RTM has made significant progress and is widely used in the geophysical industry. However, it still suffers from high storage and computational costs, sensitivity to velocity model errors and data quality, and internal multiple cross-talk.

2.2.2. Progress on full-wave-equation depth migration

Depth migration propagates the wavefield along the depth axis. The FWDM was pioneered by solving the full acoustic

wave equation using the classical Runge–Kutta method, with a maximum-velocity truncation filter to suppress evanescent waves during wavefield extrapolation.³¹ Building upon this framework, subsequent research has further advanced full-wave-equation-based algorithms.

Recent advancements in FWDM have revolutionized imaging capabilities through systematic improvements for the evanescent-wave filtering techniques, significantly enhancing energy preservation for steeply dipping geological structures.^{52,53} Critical progress stems from three interconnected developments: the integration of physical boundary conditions to refine imaging fidelity, the inclusion of a wavefield separation strategy that enables precise depth-domain modeling of wavefield reception,^{54–58} and the strategic expansion of FWDM frameworks through anisotropic media adaptations.⁵⁹ These synergistic innovations collectively broaden the operational scope of depth-migration algorithms while simultaneously elevating computational efficiency and imaging precision through the diversification of propagation-operator formulations to address complex wavefield dynamics.

3. Comparisons of the wave-equation migration method

The differences in wavefield propagation between RTM and FWDM are illustrated in Figure 2, which indicates reflected

waves propagate from the reflection interface to the surface on the time profile in RTM; in contrast, in FWDM, they are mapped at the mirror position of the reflection interface (the bottom of the model), which is caused by a folding effect due to the incomplete propagating wavefield in the time domain.

In seismic imaging, the four wave-equation-based migration schemes—reference-velocity-based OWDM, accurate-velocity-based OWDM, RTM, and FWDM—differ significantly in imaging quality, computational efficiency, and geological applicability. RTM computes the wavefield in the time domain, while OWDM and FWDM are calculated in the frequency domain. RTM and FWDM both use the full wave equation; theoretically, they have similar imaging capabilities. Figure 3 shows a variable background velocity model. Figure 4 compares the impulse responses of RTM, reference-velocity-based OWDM, accurate-velocity-based OWDM, and FWDM. Using the FD-based RTM forward-modeling impulse response as the reference standard, the wavefront positions of the standard response pulse are outlined in white dashed lines in this figure. The comparison reveals that the phase information obtained by the accurate-velocity-based OWDM and FWDM methods aligns well with the RTM response curve; the reference-velocity-based OWDM method significantly deviates beyond about 75°, as indicated by the black arrow.

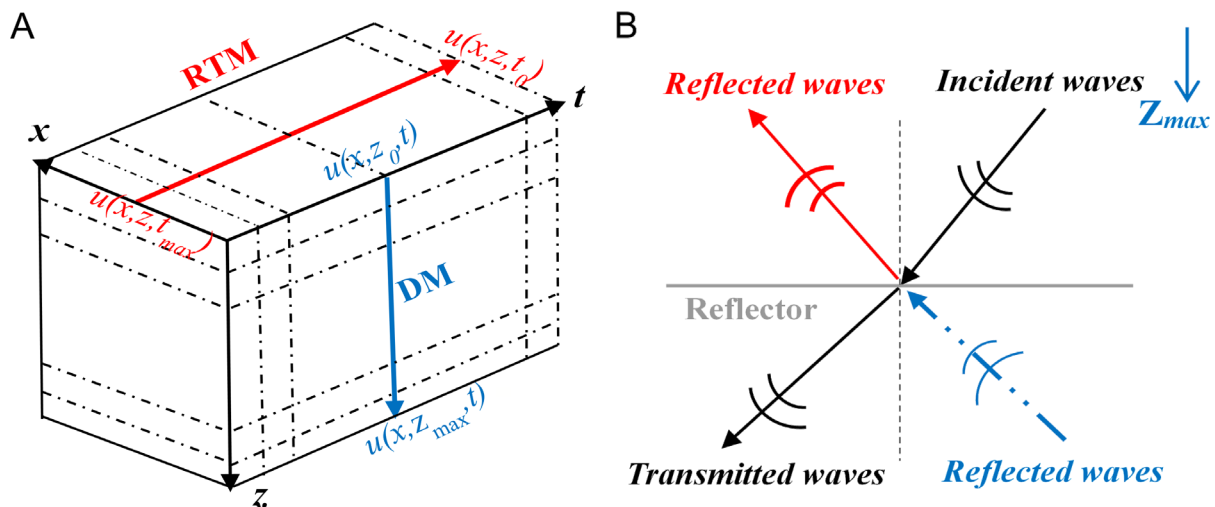


Figure 2. Comparison of wavefield extrapolation in reverse-time migration (RTM) and full-wave-equation depth migration (FWDM). (A) The difference in data extrapolation methods between RTM and depth migration (DM). (B) The difference in wave propagation between RTM and FWDM at the reflection interface: Reflected waves in RTM propagate from the reflection interface to the surface on the time profile, whereas in FWDM, they are mapped at the mirror position of the reflection interface, caused by the folding effect. Reprinted with permission from Li *et al.*⁵⁸ Copyright © 2024 Society of Exploration Geophysicists.

Figure 5 shows numerical results demonstrating that the reference-velocity-based OWDM method struggles to accurately image subsurface structures beneath the salt dome. This difficulty arises from phase errors induced by strong lateral velocity variations and steeply dipping reflectors with large scattering angles. Additionally, reference-velocity-based OWDM uses the minimum velocity as the reference velocity rather than the accurate lateral velocity, which tends to produce imaging artifacts due to phase errors (Figure 5B). The high-velocity salt body further complicates RTM, where internal multiples generate false reflectors below the salt. A comparison of the migrated sections in Figure 5C and 5D shows that the FWDM delivers a clearer and more coherent structural image with reduced noise compared to conventional RTM. However, the reflector polarity in the FWDM result is not fully consistent, because the bottom and top of the salt should be opposite. A slight phase difference between the two results stems from differences in their numerical implementations. The polarity discrepancy typically originates from the evanescent-wave filtering techniques or the specific PSs used to stabilize the Helmholtz operator in heterogeneous media. Furthermore, the folding effect at reflection interfaces, caused by the periodicity of the frequency domain and incomplete time-domain wavefield reconstruction, can lead to mirror-image artifacts that interfere with the primary reflector's phase.

This methodology capitalizes on turning wave energy to resolve vertical structural geometries, with quantitative validations presented in Figure 6. These comparisons

substantiate that OWDM has the inherent constraint of imaging vertical structure, even when using accurate velocity. However, full-wave-equation migration schemes (RTM and FWDM) can image vertical formations—a capability fundamentally rooted in their rigorous incorporation of the full wave equation and propagating wavefield.

Figure 7 displays the Marmousi velocity model, while Figure 8 presents the imaging results obtained from four distinct wave-equation migration methodologies. The conventional OWDM method, employing the mean velocity in each lateral grid as the reference velocity, demonstrated limited efficacy in resolving dipping structures. The accurate-velocity-based OWDM, FWDM, and RTM approaches yielded comparable imaging accuracy. Notably, FWDM exhibited extended lateral imaging coverage in deeper model sections (below 2.5 km), as indicated by the red rectangles. A comparative analysis revealed RTM's superior performance in shallow structural imaging (0–1,000 m depth), contrasting with FWDM's enhanced imaging fidelity in deeper geological formations. This discrepancy stems from fundamental differences in wavefield extrapolation: RTM implementation delivers superior resolution in shallow layers through comprehensive wavefield reconstruction, whereas the FWDM preserves intricate structural features in deeper strata through rigorous acoustic wavefield modeling.

The comparative analysis of land seismic data imaging in Figure 9 compared the performances of the four migration

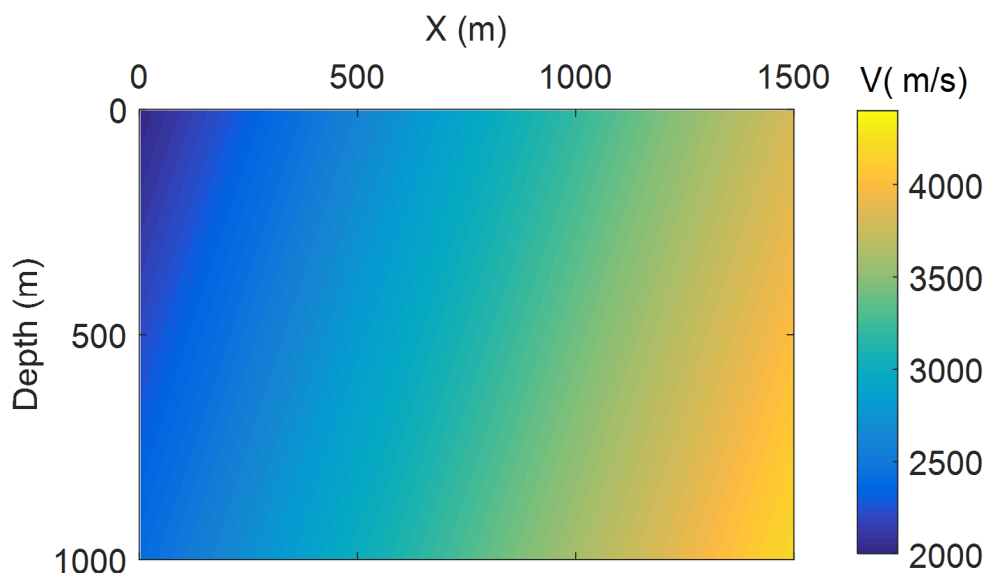


Figure 3. Background velocity model. Reprinted from Li and Liu.²¹

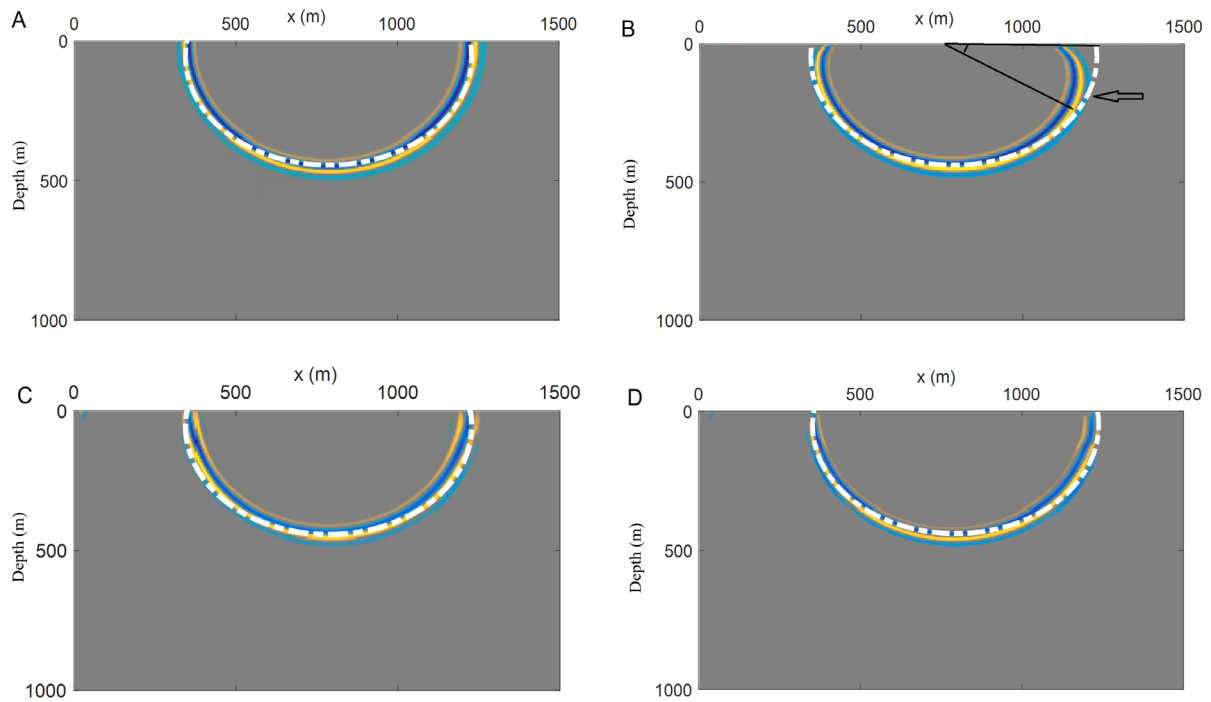


Figure 4. The impulse responses in media with lateral and vertical variations of velocity. (A) the finite-difference method. (B) Reference-velocity-based one-way wave-equation depth migration (OWDM). (C) Accurate-velocity-based OWDM. (D) Full-wave-equation depth migration. Reprinted from Li and Liu.²¹

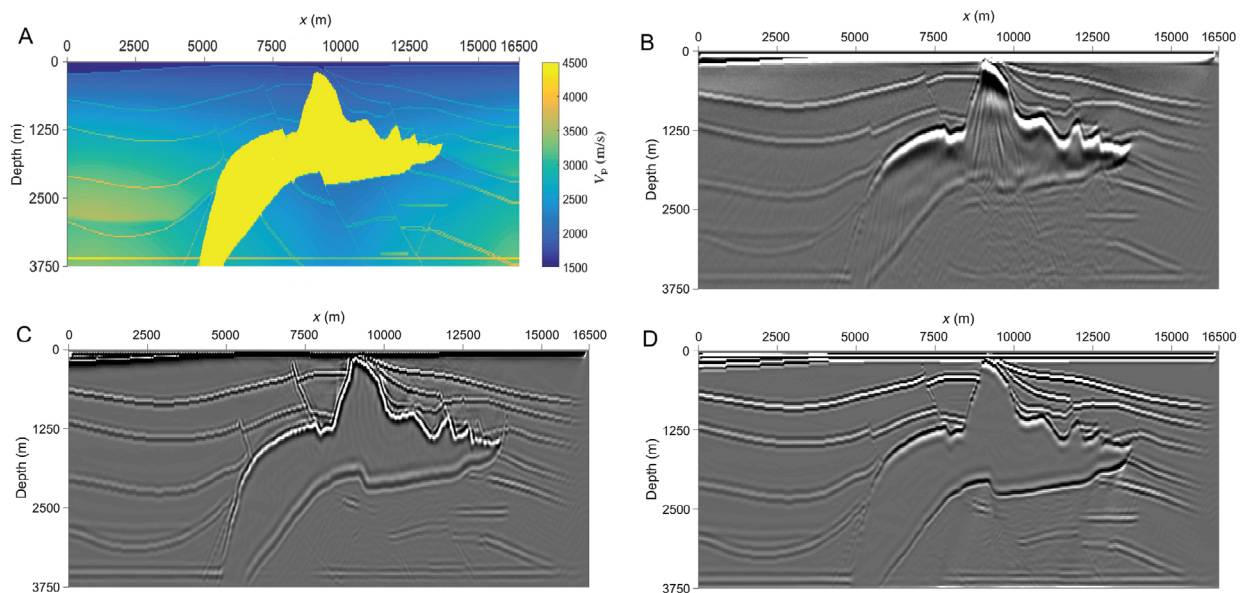


Figure 5. Velocity model and imaging results. (A) Velocity model. (B) Reference-velocity-based one-way wave-equation depth migration. (C) Reverse-time migration. (D) Full-wave-equation depth migration. Reprinted with permission from You and Cao.⁵⁵ Copyright © 2020 Society of Exploration Geophysicists.

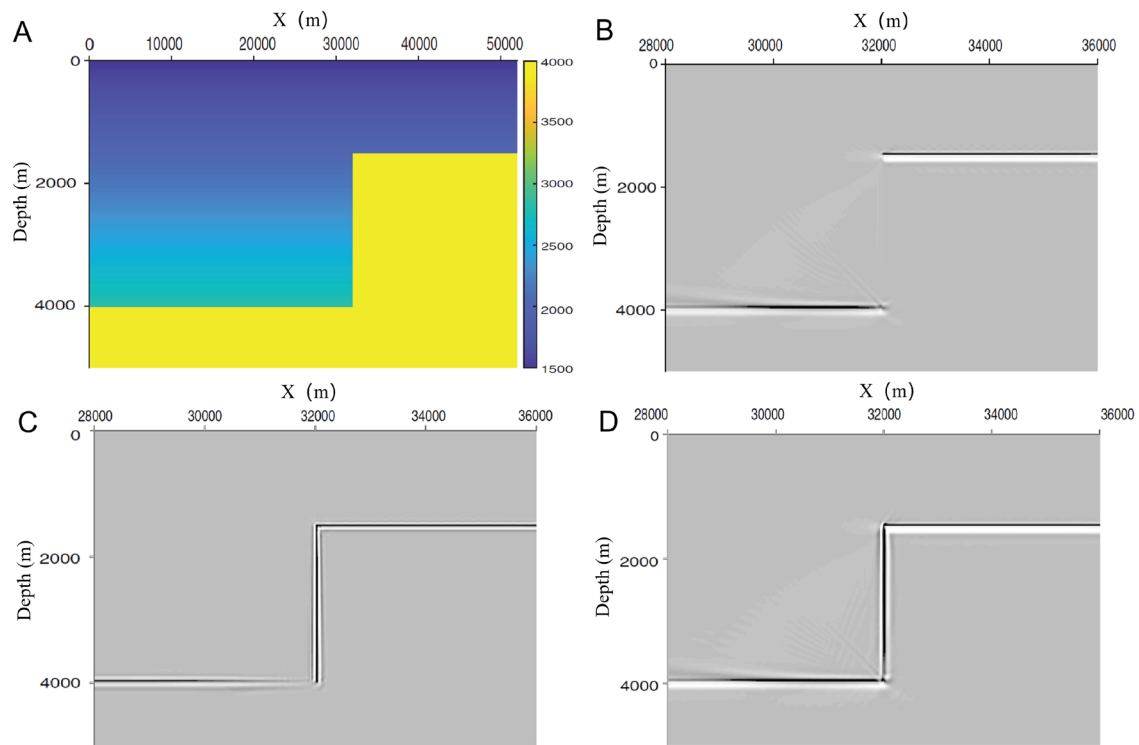


Figure 6. Comparison of depth-domain full-wavefield extrapolation based on wavefield separation imaging with one-way wavefield extrapolation and reverse-time migration (RTM). (A) Vertical velocity model. (B) One-way wave-equation depth migration. (C) Conventional RTM. (D) Full-wave-equation depth migration. Reprinted with permission from You *et al.*⁵⁷ Copyright © 2022 Society of Exploration Geophysicists.

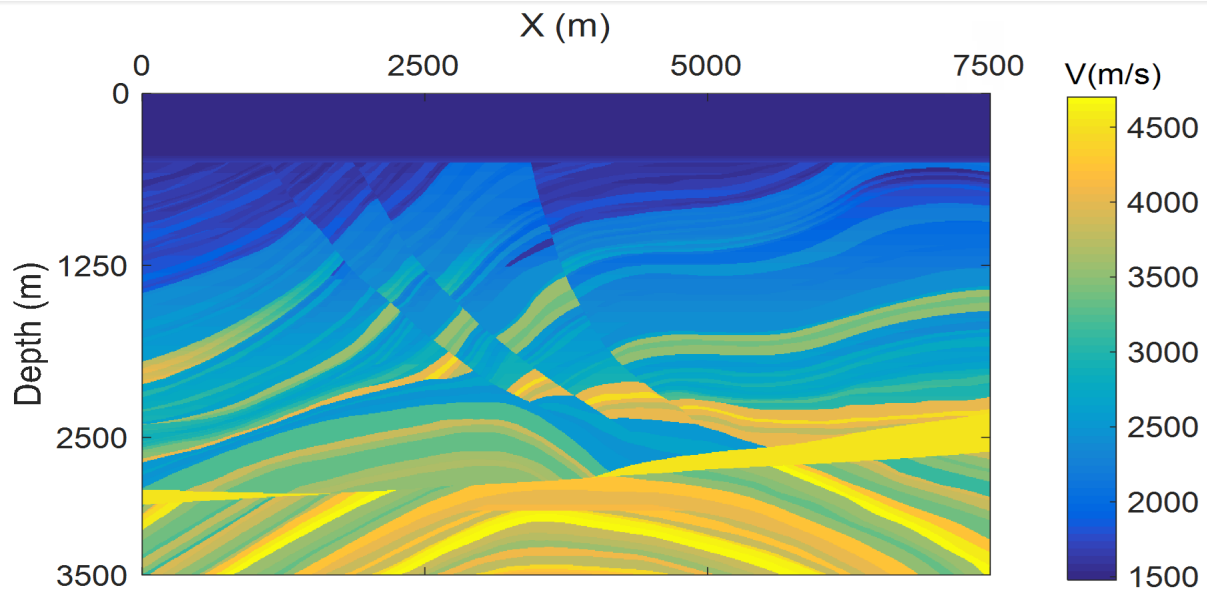


Figure 7. The Marmousi velocity model

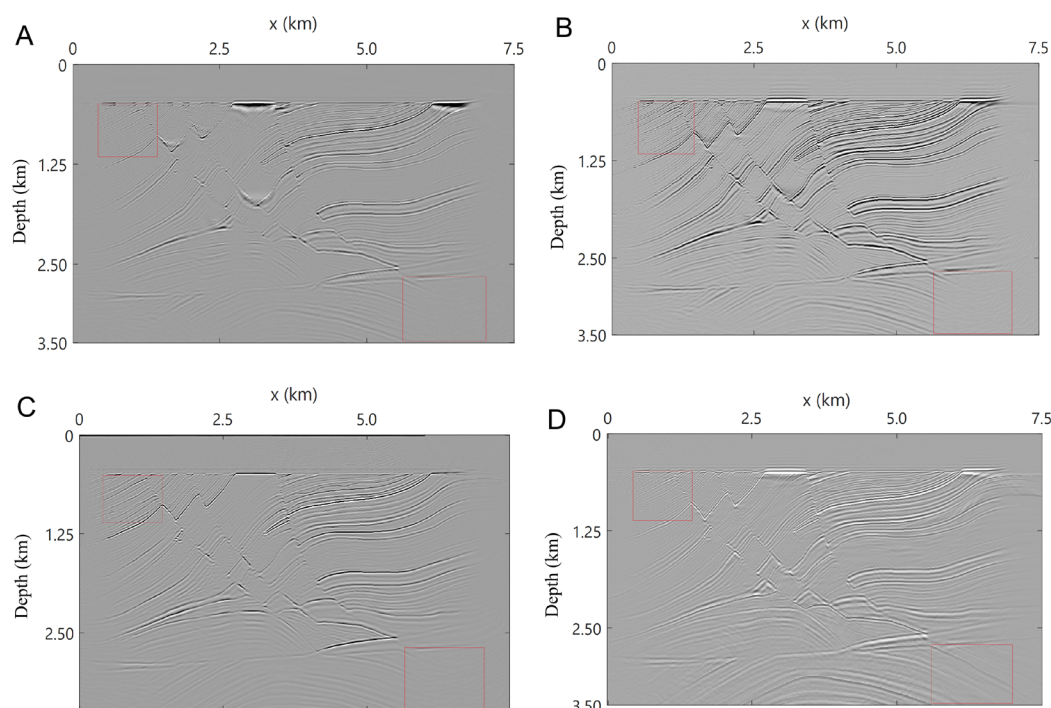


Figure 8. Migrated results. (A) Reference-velocity-based one-way wave-equation depth migration (OWDM). (B) Accurate-velocity-based OWDM. (C) Conventional reverse-time migration. (D) Full-wave-equation depth migration.

methods. The accurate-velocity-based OWDM method produced a clearer image than the reference-velocity-based OWDM technique. This enhancement is particularly evident in improving the phase continuity of seismic events and in delineating subtle stratigraphic features, as exemplified by micro-curved structural elements. The FWDM approach demonstrated superior geophysical fidelity, with more stable kinematic positioning, enhanced structural coherence, and higher-resolution imaging of complex geological interfaces. Although FWDM and RTM preserved two-way going-wave information and accounted for multi-directional wavefield propagation, the conventional RTM produced a slightly different profile, especially in deep layers, which may be due to sensitivity to an inaccurate migration velocity model and to noise in real data. This technological advancement primarily originates from extrapolating wavefield in depth direction, and it mitigates kinematic artifacts prevalent in conventional migration outputs.

A detailed feature comparison of these wave-equation migration algorithms is presented in Table 1. As exploration targets increasingly focus on deeper and more complex geological formations, selecting an optimal migration method has become critically important. Therefore, this table systematically evaluates the three types of schemes

through comprehensive numerical examples, analyzing their imaging performance and practical suitability across diverse geological scenarios. The comparative results provide valuable guidance for field applications. Note that artifacts generated by FWDM are mostly at the bottom of the model due to the frequency-domain formulation and depth-marching strategy (only downward extension). While in RTM, the wavefield is propagated in the time domain, covering the entire propagation space, which mostly causes artifacts at the top of the model due to backscatter. Thus, the artifacts appear slightly less pronounced in FWDM than in RTM for the unfiltered migration profile. Furthermore, in terms of memory usage, while RTM can be formulated in the frequency domain, it is commonly implemented in the time domain in practice, whereas FWDM is naturally formulated in the frequency domain.

4. Progress on an artificial intelligence-assisted wave-equation migration

The integration of AI and deep learning extracts medium anisotropy parameters, velocity distributions, and attenuation characteristics from seismic data. It enhances velocity modeling accuracy, enables automatic noise identification/suppression, and reduces dependence on

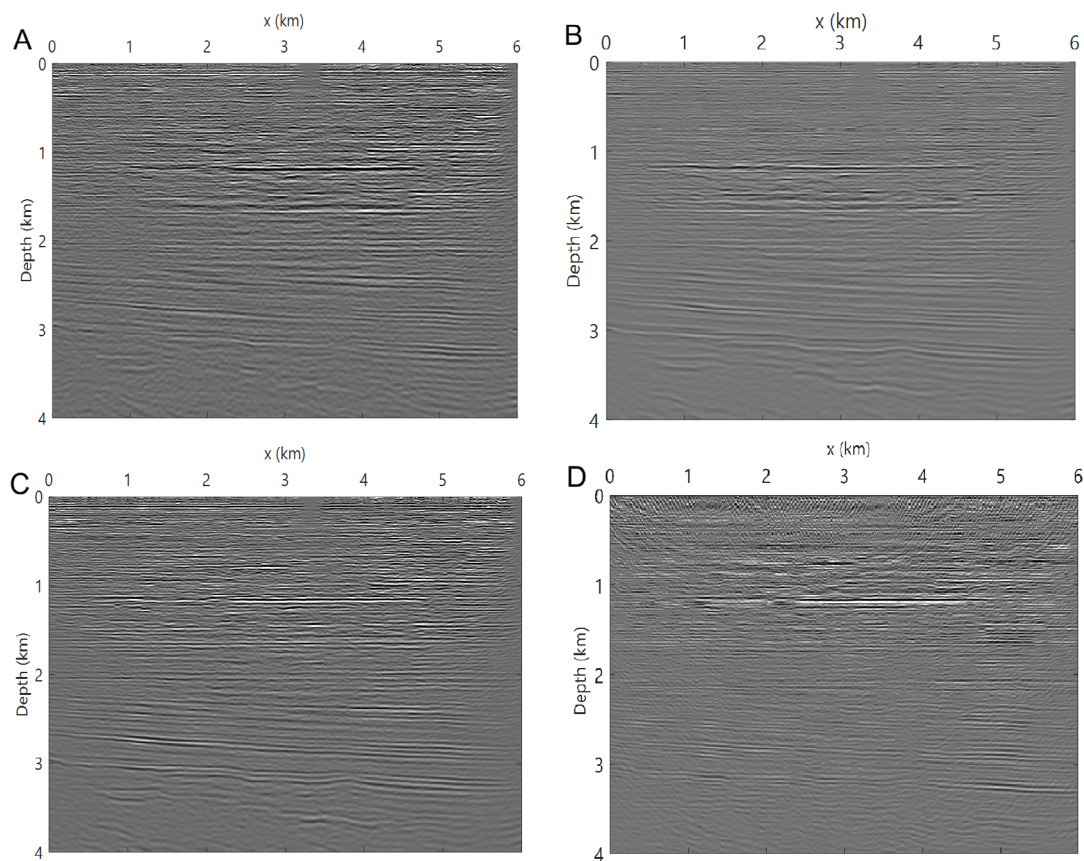


Figure 9. Migrated results from (A) reference-velocity-based one-way wave-equation depth migration (OWDM), (B) accurate-velocity-based OWDM, (C) full-wave-equation depth migration, and (D) conventional reverse-time migration.

Table 1. Comparisons of wave-equation-based migration schemes

Feature	OWDM	RTM	FWDM
Wavefield propagation	Solves the one-way wave equation in depth dimension	Solves the full wave equation in the time dimension	Solves the full wave equation in depth dimension
Dip handling	Limited to $<90^\circ$ dips (cannot handle turning waves)	Handles all dips ($0-180^\circ$)	Handles all dips ($0-180^\circ$)
Computational time cost	Low (efficient for large datasets, especially reference-velocity-based OWDM)	High (comparable to small-grid finite-difference schemes)	High (calculates Helmholtz operator and removes evanescent wave)
Memory usage	Minimal ($2 \times N_x \times N_f$)	High ($2 \times N_x \times N_z \times N_t$)	Moderate ($4 \times N_x \times N_f$)
Artifacts	Low	High (same-directional wave)	High (same-directional wave)
Algorithm flexibility	Diverse operators (e.g., GSP, FFD, GPS, ED)	Typical finite difference-based	Diverse operators (Runge–Kutta, Padé approximation, deformed one-way wave operators, etc.)
Typical use case	Initial velocity model	Subsalt imaging	Complex structures with steep dips

Abbreviations: ED: Eigen decomposition; FFD: Fourier finite-difference; FWDM: Full-wave-equation depth migration; GPS: Generalized phase-shift; GSP: Generalized screen propagator; OWDM: One-way wave-equation depth migration; RTM: Reverse-time migration.

raw data quality. By developing neural network models trained on field and synthetic datasets, AI approaches effectively correct for the amplitude distortions and multipath effects inherent in conventional migration imaging. These technological breakthroughs can not only improve the precision and efficiency of migration imaging but also pioneer novel approaches for complex geological conditions, driving geophysical imaging toward intelligent development.^{60–62}

4.1. Wavefield propagator design

Wavefield propagator design is a fundamental component of wave-equation-based high-resolution migration and modeling, as it directly governs the accuracy, stability, and computational efficiency of seismic imaging, emphasizing the importance of accurately describing wave-propagation physics for resolving complex subsurface structures.⁶³ These foundations underpin modern wave-equation migration methods and motivate ongoing developments in both numerical algorithms and data-driven approaches.

Recent advances in AI have enabled the development of surrogate modeling approaches that approximate wavefield propagation without traditional numerical integration. Neural operators, such as the Fourier neural operator (FNO), physics-informed neural networks (PINNs), physically constrained neural networks, and the Helmholtz neural operator, have shown strong potential in learning the mapping from model parameters to wavefields by training on high-fidelity numerical simulations and wavefield decomposition.^{64–67} Use of PINNs enables grid-free, mesh-independent prediction of wavefield solutions, significantly reducing computational costs in large-scale or multi-shot imaging scenarios. Parallelized FNO variants and U-shaped neural operators could provide orders-of-magnitude acceleration while preserving wavefield accuracy in complex media. These models can generalize across varying velocity models and acquisition settings, providing efficient and scalable alternatives to conventional FD solvers.

In addition to pure surrogate modeling, hybrid strategies have been explored, in which AI models support conventional solvers by providing local error estimation, adaptive mesh refinement, or surrogate-based solution of Green's functions, or learning low-rank structure to approximate operator mappings.^{68–70} These approaches not only enhance computational efficiency but also improve solver stability and resolution adaptivity in challenging geological settings. Furthermore, the integration of learned propagators into end-to-end differentiable modeling workflows allows for direct backpropagation through the wavefield modeling process, facilitating real-time seismic

inversion and data assimilation. Such frameworks enable the computation of gradients concerning model parameters using automatic differentiation, thereby accelerating least-squares migration, full-waveform inversion, and tomographic updates.^{71–74} Collectively, these AI-driven innovations represent a transformative direction for wave-equation-based imaging, blending physical principles with data-driven learning to achieve fast, flexible, and scalable seismic modeling.

4.2. Noise and artifact suppression

Noise and artifact suppression is a critical component of wave-equation-based migration, as these methods are inherently sensitive to both data quality and numerical implementation. Artifacts may originate from multiple sources, including limited acquisition aperture, inaccurate or poorly constrained velocity models, imperfect boundary conditions, and limitations in wavefield reconstruction or imaging conditions. The full-wave-equation migration method, in particular, is prone to generating low-frequency noise and spurious reflectors due to the cross-correlation of same-direction propagated wavefields under conditions of insufficient illumination or acquisition redundancy.

Deep learning has emerged as a transformative tool for noise and artifact suppression in seismic imaging. Supervised models, such as denoising autoencoders, support vector machines, convolutional residual networks, and generative adversarial networks (GANs), have been developed to attenuate artifacts—including backscattering, migration smiles, and acquisition footprints—without requiring explicit modeling of the underlying noise mechanisms.^{75–77} These models can be applied either in the data domain, as a preprocessing step to enhance raw seismic traces before migration, or in the image domain, to refine migrated outputs by suppressing spatially incoherent or geologically implausible features.

Trained on curated synthetic or real datasets, AI-based denoisers learn to differentiate between primary reflections and multiples, enabling selective preservation of data features while reducing noise.^{78–80} Some frameworks incorporate attention mechanisms to focus the network on geologically relevant areas and suppress irrelevant features, while others employ uncertainty-aware models to quantify confidence in the imaging output and highlight regions where noise may dominate.⁸¹ Additionally, AI-enhanced imaging conditions—such as learned cross-correlation functions, adaptive stacking weights, and dynamic similarity metrics—can be integrated directly into the migration workflow to improve real-time artifact suppression during wave-equation-based migration.^{82,83} Machine learning-based postprocessing techniques have

also shown promise in improving structural continuity and interpretability, particularly in challenging geological settings.⁸⁴ However, these approaches must be applied judiciously to avoid over-smoothing or introducing bias, especially in exploration contexts with high geological uncertainty.

Overall, a combination of improved physical imaging conditions, inversion-based regularization, and AI-driven filtering is redefining artifact-suppression strategies in wave-equation-based migration. The synergy between physics-based modeling and data-driven learning offers a path toward more accurate, efficient, and interpretable seismic imaging, while continuing challenges in generalization, training data quality, and physical interpretability remain active areas of research.

5. Discussion

Current wave-equation imaging techniques enable wavefield iteration driven by OWDM or RTM through least-squares iteration; however, one-way wave operators exhibit notable imaging-angle limitations, and LS-RTM still faces constraints from massive storage and computational demands due to time-domain wavefield backpropagation. Future improvements to least-squares-based migration could focus on computational efficiency. Considering the accuracy of wave-equation migration propagators, developing least-squares FWDM may hold significant promise for advancing reflectivity estimation accuracy through the closed-loop FWM framework for a multi-dimensional, large-scale database.

Multi-wave and multi-component seismic exploration technology acquires conventional P-wave data and captures converted PP and PS waves, substantially enriching wavefield information diversity. Compared to traditional P-wave exploration, converted waves demonstrate enhanced resolution for shallow, fine-scale structures, effectively improving imaging precision for specific geological features. Current research on FWDM remains predominantly focused on acoustic wave applications, while elastic wave and multi-wave/multi-component FWDM imaging technologies remain underdeveloped, offering substantial research value and developmental potential. A combination of separation and imaging diffractions can enhance the resolution of faults and discontinuities, particularly in complex velocity models.

Wave-equation migration with AI assistants has made great progress in enhancing imaging quality, computational efficiency, and parameter optimization, greatly advancing the practicality and intelligence of the wave-equation-based migration method. However, most AI models heavily rely on the quality and representativeness of training data;

insufficient or geographically mismatched data can lead to poor generalization and reduced imaging accuracy. Moreover, almost all existing AI approaches operate as “black-box” models, lacking physical interpretability, thereby hindering their integration with traditional geophysical theories and reducing their reliability in complex subsurface scenarios. Additionally, handling high-dimensional, nonlinear input–output relationships demands substantial computational resources, making training and deployment costly. Finally, current AI methods still struggle with challenges such as anisotropy, multiphase wavefields, and multiscale geological features, underscoring the need to further develop AI architectures that integrate with physical constraints to better meet the demands of real-world seismic exploration.

Synergistically integrated with emerging innovations and multi-source information fusion strategies, wave-equation migration will play an increasingly vital role in imaging complex geological structures and hydrocarbon exploration. This technological convergence enhances characterization capabilities for intricate subsurface targets while providing sustained developmental momentum and directional guidance for seismic imaging innovation.

6. Conclusion

Wave-equation prestack migration is a core technique in seismic imaging for resolving complex geological structures and supporting reservoir prediction. This paper systematically reviewed and compared four representative wave-equation-based migration methods: reference-velocity-based OWDM, accurate-velocity-based OWDM, RTM, and FWDM, focusing on their theoretical characteristics and imaging performance.

The OWDM methods are computationally efficient and stable, making them suitable for large-scale imaging applications. However, their reliance on approximate wavefield propagation limits their ability to image dipping structures and complex wave phenomena in heterogeneous media. Accurate-velocity-based OWDM formulations improve phase accuracy and extend the imaging range by incorporating detailed velocity information, thereby enhancing the applicability of one-way wave migration.

Full-wave-equation methods provide a more complete physical description of seismic wave propagation. RTM and FWDM effectively image steep dips and complex structures by preserving two-way wavefield interactions. Comparative results indicate that RTM generally performs well in shallow regions, whereas FWDM offers improved stability and structural continuity in deeper or more complex settings. The integration of AI into wave-equation migration workflows has enhanced wavefield propagation

and noise suppression in the migration process.

Overall, this review clarifies the strengths and limitations of current wave-equation-based migration approaches through numerical examples and provides a practical reference for method selection in seismic imaging applications.

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Conflict of interest

The authors declare they have no competing interests.

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Availability of data

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