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Metaheuristic Optimization Algorithms in Geophysics: A Comprehensive Review of Seismic Inversion, Potential Field Modeling, and Geophysical Data Interpretation

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Abstract

Geophysical inverse problems are inherently ill-posed, non-unique, and nonlinear, posing substantial challenges for deterministic optimization methods that are prone to entrapment in local minima. Over the past three decades, metaheuristic optimization algorithms have emerged as powerful alternatives for solving complex geophysical inversion problems across multiple subdisciplines. This paper presents a comprehensive systematic review, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, of metaheuristic algorithm applications in geophysics from 1990 to 2025. A total of 312 peer-reviewed publications were identified from Scopus, Web of Science, Society of Exploration Geophysicists (SEG) Library, GeoRef, and Google Scholar databases, of which 186 met the inclusion criteria for detailed analysis. The review encompasses six primary geophysical domains: seismic data processing and inversion, gravity and magnetic field modeling, Electromagnetic (EM) and resistivity methods, seismological applications, well log analysis and petrophysics, and geophysical survey design optimization. Comparative performance analyses reveal that Particle Swarm Optimization (PSO) and Differential Evolution (DE) consistently demonstrate superior convergence properties and solution accuracy across most geophysical inversion problems, while Simulated Annealing (SA) maintains advantages for high-dimensional parameter spaces with rugged objective function landscapes. Hybrid approaches coupling metaheuristics with local gradient-based methods show improvements of 15–45% in misfit reduction with 30–60% fewer forward model evaluations. Bibliometric analysis indicates exponential growth in publications since 2010, with recent trends emphasizing Graphics Processing Unit (GPU)-accelerated implementations, deep learning surrogate models, and multi-physics joint inversion frameworks. The review identifies critical challenges including computational scalability for three-dimensional models, uncertainty quantification, and the gap between synthetic benchmarks and field data validation. Future directions including quantum-inspired metaheuristics, physics-informed neural network surrogates, and cloud-based distributed inversion architectures are discussed.

Keywords: Metaheuristic algorithms, Geophysical inversion, Seismic optimization, Gravity modeling, Electromagnetic inversion, Potential field interpretation, Subsurface imaging, Particle swarm optimization, Differential evolution, Simulated annealing.

1 | Introduction

The fundamental objective of geophysics is to infer the physical properties and structural configuration of the Earth's subsurface from measurements acquired at or near the surface. This inference process, formally known as geophysical inversion, constitutes one of the most challenging classes of mathematical problems

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encountered in the earth sciences. Geophysical inverse problems are characterized by three fundamental difficulties: non-uniqueness (multiple subsurface models can explain the observed data equally well), ill-posedness (small perturbations in data can produce large changes in the estimated model), and nonlinearity (the relationship between model parameters and observed data is generally nonlinear) [1], [2]. These properties collectively render geophysical inversion a formidable computational and mathematical challenge that has driven decades of methodological research.

The mathematical formulation of the geophysical inverse problem can be expressed in the general form $d = G(m) + \varepsilon$, where d represents the observed data vector, G is the forward modeling operator that maps model parameters m to predicted data, and ε denotes the noise vector. The objective is to find a model m that minimizes a suitable misfit function, typically of the form $\Phi(m) = \|d_{obs} - G(m)\|^2 + \lambda\Omega(m)$, where the first term measures data misfit, the second term $\Omega(m)$ is a regularization functional weighted by the trade-off parameter λ, and the norm may be L1, L2, or a hybrid formulation depending on the noise characteristics and desired model properties [3], [4].

Deterministic optimization methods, including gradient-based approaches such as steepest descent, conjugate gradient, Gauss-Newton, and Levenberg-Marquardt (LM) algorithms, have historically formed the backbone of geophysical inversion methodology [1], [5]. While these methods offer rapid convergence when initialized near the global optimum, they suffer from critical limitations when applied to realistic geophysical problems. The objective function landscape of most geophysical inversions is characterized by multiple local minima, saddle points, and narrow valleys, making gradient-based methods highly susceptible to convergence to suboptimal solutions. Furthermore, the computation of Jacobian matrices or Fréchet derivatives becomes prohibitively expensive for large-scale three-dimensional models with millions of unknowns. The requirement for differentiable objective functions also precludes the use of certain physically meaningful constraints and model parameterizations.

These limitations of deterministic approaches have motivated the adoption of metaheuristic optimization algorithms in geophysical applications. Metaheuristic algorithms are a class of stochastic, nature-inspired optimization strategies that do not require gradient information and are designed to explore large, complex search spaces efficiently. The term "metaheuristic" was coined by Glover [6], and the field has since expanded to encompass a diverse family of algorithms inspired by evolutionary processes, swarm intelligence, physical phenomena, and human behavioral patterns. Major algorithmic families include: 1) evolutionary algorithms, such as Genetic Algorithms (GA), [7] and Differential Evolution (DE) [8], 2) swarm intelligence methods, including Particle Swarm Optimization (PSO) [9], Ant Colony Optimization (ACO) [10], and Artificial Bee Colony (ABC) [11], 3) physics-based algorithms, notably Simulated Annealing (SA) [12], and gravitational search algorithm [13], and 4) more recent nature-inspired algorithms such as Grey Wolf Optimizer (GWO) [14], Whale Optimization Algorithm (WOA) [15], Harris Hawks Optimization (HHO) [16], Moth-Flame Optimization (MFO) [17], Sine Cosine Algorithm (SCA) [18], Bat Algorithm (BA) [19], and Cuckoo Search (CS) [20].

The history of metaheuristic adoption in geophysics can be traced back to the pioneering work of Rothman [21], [22]. who applied SA to seismic velocity estimation and static corrections. Sen and Stoffa [23] subsequently demonstrated the efficacy of Very Fast Simulated Annealing (VFSA) for one-dimensional waveform inversion, establishing a paradigm that would influence decades of geophysical research. The introduction of GA to geophysics by Sambridge and Drijkoningen [24] and Stoffa and Sen [25] expanded the toolkit available to geophysicists. The PSO revolution in the 2000s, catalyzed by the work of Shaw and Srivastava [26] on gravity and magnetic interpretation and van den Bergh and"; further expanded applications across all geophysical subdisciplines. Since 2015, an explosion of newer algorithms GWO, WOA, HHO, and their hybridized variants has created both opportunities and challenges for the geophysical community.

Despite the substantial body of literature on metaheuristic algorithms in geophysics, no comprehensive systematic review has been published that spans all major geophysical subdisciplines while providing quantitative performance comparisons and bibliometric analysis. Previous reviews have focused on specific algorithms (e.g., PSO in geophysics by Pallero et al. [27]) or specific geophysical methods (e.g., potential field inversion by Vitale and Fedi [28]). This paper addresses this gap by presenting a systematic, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-compliant review that encompasses the full breadth of metaheuristic applications in geophysical sciences. The review is organized around three central research questions:

I. which metaheuristic algorithms have been most widely and successfully applied across different geophysical subdisciplines?

II. how do metaheuristic algorithms compare quantitatively in terms of solution accuracy, convergence speed, and computational efficiency for standard geophysical inverse problems?

III. what are the emerging trends, critical gaps, and future research directions for metaheuristic-based geophysical inversion?

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework, including the formal problem formulation and algorithm taxonomy. Section 3 describes the systematic review methodology. Section 4 provides a detailed analysis of applications across six geophysical domains. Section 5 presents comparative performance analyses and hybrid approaches. Section 6 offers bibliometric analysis. Sections 7 and 8 discuss challenges and future directions, respectively, followed by conclusions in Section 9.

2 | Theoretical Framework

2.1 | Geophysical Inverse Problem Formulation

The geophysical inverse problem seeks to determine a model vector $m \in \mathbb{R}^M$ from an observation vector $d \in \mathbb{R}^N$, where the forward relationship is governed by $d = G(m) + \varepsilon$. In this formulation, $G: \mathbb{R}^M \rightarrow \mathbb{R}^N$ denotes the forward modeling operator, which encodes the physics governing the relationship between subsurface properties and observed geophysical responses, and ε represents the noise vector, typically assumed to follow a Gaussian distribution with covariance matrix C_d. For seismic problems, G may involve the solution of the acoustic or elastic wave equation via finite-difference or finite-element methods; for gravity problems, G involves the evaluation of Newton's gravitational integral; and for Electromagnetic (EM) problems, G requires the solution of Maxwell's equations in heterogeneous media [29].

The inversion is typically cast as an optimization problem in which the objective function (also termed the cost function or fitness function) is minimized. The general form of the objective function is:

$$\Phi(m) = \Phi d(m) + \lambda \Phi m(m), \quad (1)$$

where $\Phi_d(m) = (d_{obs} - G(m))^T C_d^{-1} (d_{obs} - G(m))$ measures the weighted data misfit, and $\Phi_m(m) = (m - m_{ref})^T C_m^{-1} (m - m_{ref})$ is the model regularization term that penalizes deviation from a reference model m_{ref}, weighted by the model covariance matrix C_m. The trade-off parameter λ controls the balance between fitting the data and maintaining model simplicity or geological plausibility [3], [4].

In the metaheuristic framework, this minimization is performed without computing gradients of Φ with respect to m. Instead, a population of candidate solutions (or a single solution in the case of trajectory-based methods such as SA) iteratively explores the model space through stochastic operators inspired by natural phenomena. The key advantage is that these methods require only the evaluation of the forward problem G(m) and the computation of the scalar objective function value $\Phi(m)$, making them "derivative-free" optimizers that can handle discontinuous, non-differentiable, and highly multimodal objective landscapes.

2.2 | Classification of Metaheuristic Algorithms for Geophysical Applications

Metaheuristic algorithms applicable to geophysical problems can be broadly classified into four categories based on their inspiration source and search mechanism: evolutionary algorithms, swarm intelligence algorithms, physics-based algorithms, and hybrid/other nature-inspired algorithms. *Table 1* provides a systematic classification of the principal algorithms that have been applied in geophysical contexts, along with their key characteristics relevant to inverse problem solving.

Table 1. Classification of principal metaheuristic algorithms applied in geophysical inversion.

Algorithm	Category	Year	Key Control Parameters	Advantages for Geophysics	Limitations
SA	Physics-based	1983	Initial temperature, cooling schedule, perturbation size	Proven convergence guarantee; handles high dimensionality; robust for rugged landscapes	Slow convergence; sensitive to cooling schedule; single-solution trajectory
GA	Evolutionary	1975	Population size, crossover rate, mutation rate, selection method	Good global exploration; parallelizable; handles mixed variable types	Premature convergence risk; many control parameters; computationally expensive
DE	Evolutionary	1997	Scale factor F, crossover rate CR, population size NP	Excellent for continuous parameter spaces; few control parameters; robust convergence	Performance sensitive to F and CR; may struggle with discrete parameters
PSO	Swarm intelligence	1995	Inertia weight w, cognitive c_1, social c_2, population size	Fast convergence; simple implementation; excellent for continuous problems; few parameters	Premature convergence in multimodal spaces; poor exploration in high dimensions
ACO	Swarm intelligence	1992	Pheromone evaporation rate, number of ants, heuristic weight	Naturally handles discrete/combinatorial problems; good for survey design	Not well-suited for continuous inversions; convergence speed issues
ABC	Swarm intelligence	2005	Colony size, limit parameter, number of food sources	Balanced exploration-exploitation; minimal parameters; robust for surface wave inversion	Slow convergence for high-dimensional problems; limited exploitation capability
CS	Swarm intelligence	2009	Step size α, discovery probability p_a, population size	Lévy flights enable efficient exploration; simple; competitive performance	Limited exploitation; parameter sensitivity for step size
BA	Swarm intelligence	2010	Frequency range, loudness A, pulse emission rate r	Automatic balance between exploration and exploitation; echolocation-inspired local search	Convergence issues in high dimensions; limited diversity maintenance
GWO	Swarm intelligence	2014	Parameter vector a (linearly decreasing), population size	Parameter-free (no tuning beyond population size); good convergence balance	May stagnate in complex landscapes; limited diversity for large model spaces
WOA	Swarm intelligence	2016	Spiral shape constant b, probability switch p	Spiral updating enables fine-grained search; few parameters; good for 2D inversions	Slow convergence rate; may miss global optimum in high-dimensional spaces
HHO	Swarm intelligence	2019	Escaping energy E, jump strength J, population size	Dynamic exploration-exploitation transition; competitive with DE and PSO	Relatively new; limited geophysical validation; scalability unproven
MFO	Swarm intelligence	2015	Number of flames, spiral constant b	Logarithmic spiral convergence; adaptive flame reduction enhances exploitation	Premature convergence risk; limited exploration in later iterations
SCA	Math-based	2016	Constant a, random parameters r_1–r_4	Simple trigonometric operators; smooth transition from exploration to exploitation	Limited performance on complex multimodal functions; fewer geophysical applications

2.3 | Objective Function Design in Geophysics

The design of the objective function is critical to the success of any metaheuristic-based geophysical inversion, as it directly determines the topology of the search landscape and, consequently, the algorithm's ability to locate the global optimum. In geophysical practice, several norm-based formulations are employed. The L2-norm (least-squares) misfit, $\Phi_d = \Sigma_i (d_{obs,i} - d_{calc,i})^2$, is the most widely used due to its statistical optimality under Gaussian noise assumptions and its smooth, differentiable landscape. However, the L2-norm is highly sensitive to outliers and non-Gaussian noise, which are common in field geophysical data. The L1-norm misfit, $\Phi_d = \Sigma_i |d_{obs,i} - d_{calc,i}|$, provides greater robustness to outliers but introduces a non-differentiable objective landscape that is naturally suited to derivative-free metaheuristic optimization [30].

Hybrid norm formulations, such as the Huber norm, combine the sensitivity of L2 near the minimum with the robustness of L1 for large residuals. Additionally, geophysical objective functions may incorporate correlation-based measures (e.g., normalized cross-correlation for waveform matching in seismic inversion), envelope-based misfits for Full Waveform Inversion (FWI) that mitigate cycle-skipping issues, and multi-objective formulations that simultaneously minimize data misfit and geological complexity. For metaheuristic algorithms, the objective function evaluation requires a complete forward model computation for each candidate solution, making the computational cost of G(m) the primary bottleneck in the optimization process. This cost ranges from milliseconds for analytical gravity formulas to hours for three-dimensional elastic wave propagation simulations, fundamentally constraining the choice of algorithm and population size.

2.4 | Regularization and Constraint Handling in Metaheuristic Geophysical Inversion

Regularization is essential in geophysical inversion to stabilize solutions and incorporate a priori geological information. In the metaheuristic framework, regularization can be implemented through several mechanisms. The most straightforward approach is the addition of a penalty term to the objective function, as described in Section 2.1, which penalizes model roughness (smoothness regularization), deviation from a reference model (Tikhonov regularization), or model complexity (minimum-structure regularization). The Occam approach, which seeks the smoothest model that fits the data to a prescribed tolerance, has been successfully adapted for metaheuristic inversions [4], [31].

A unique advantage of metaheuristic algorithms is their ability to naturally incorporate bound constraints by restricting the search space to physically plausible parameter ranges. Geological constraints such as layer ordering, minimum/maximum thickness, velocity-density relationships, and lithological associations can be enforced through constraint repair operators or penalty functions without modifying the underlying algorithm structure. This flexibility is particularly valuable in geophysics, where prior geological knowledge can dramatically reduce the non-uniqueness of the inverse problem. Additionally, metaheuristic populations provide an implicit form of uncertainty quantification: the ensemble of near-optimal solutions sampled during the optimization process approximates the posterior probability distribution of model parameters, enabling Bayesian-like uncertainty analysis without the formal machinery of Markov Chain Monte Carlo (MCMC) methods [32], [33].

3 | Systematic Review Methodology

This systematic review was conducted following the PRISMA guidelines [34]. A comprehensive literature search was performed across five major scientific databases to identify peer-reviewed publications on the application of metaheuristic optimization algorithms in geophysical sciences, covering the period from January 1990 to December 2025.

The search strategy employed Boolean combinations of terms organized into two concept groups: 1) algorithm-related terms, including metaheuristic, GA, PSO, DE, SA, ant colony, ABC, GWO, whale optimization, Harris hawks, CS, BA, moth-flame, SCA, and nature-inspired optimization, and 2) geophysics-related terms, including geophysical inversion, seismic inversion, gravity inversion, magnetic inversion, EM inversion, magnetotelluric, resistivity inversion, FWI, subsurface imaging, potential field, well log, petrophysics, seismology, and earthquake location. The two groups were combined using the and operator, with terms within each group connected by OR.

Inclusion criteria required publications to: 1) present original research applying metaheuristic algorithms to geophysical data processing, modeling, or inversion, 2) be published in peer-reviewed journals or conference proceedings of recognized geophysical societies Society of Exploration Geophysicists ((SEG), European Association of Geoscientists and Engineers (EAGE), American Geophysical Union (AGU)), 3) be written in English, and 4) provide sufficient methodological detail and quantitative results for assessment. Exclusion criteria eliminated: 1) review papers, editorials, and book chapters without original results, 2) studies applying metaheuristics to non-geophysical Earth science problems (e.g., purely hydrological or atmospheric studies), 3) studies presenting algorithm development without geophysical application, and 4) duplicate publications reporting the same results.

Table 2. Summary of systematic literature search results by database.

Database	Search String Scope	Initial Results	After Duplicate Removal	After Title/ Abstract Screening	After Full-Text Review	Final Included
Scopus	Title, abstract, keywords	487	487	198	124	89
Web of science	Topic (title, abstract, author keywords)	412	298	156	97	68
Seg library	Full text	189	134	87	52	41
Georef	Title, abstract	156	89	54	31	22
Google scholar	Title	623	112	67	38	26
Total		1,867	1,120	562	312	186 (after cross-database deduplication)

The screening process was conducted independently by two reviewers, with discrepancies resolved through discussion and, when necessary, adjudication by the third author. Data extraction from included studies covered: algorithm type and variant, geophysical application domain, dimensionality of the inverse problem, data type (synthetic/field), quantitative performance metrics (misfit reduction, parameter estimation error, convergence speed, computational time), and comparison methods employed. Quality assessment was performed using a modified version of the Newcastle-Ottawa Scale adapted for computational studies, evaluating methodological rigor, result reproducibility, and statistical validity of comparisons.

4 | Applications in Geophysical Sciences

4.1 | Seismic Data Processing and Inversion

Seismic methods represent the most widely used geophysical technique for subsurface exploration, and consequently, the largest body of metaheuristic applications in geophysics is found in seismic data processing and inversion. The review identified 64 publications (34.4% of the total) addressing seismic applications, spanning velocity model building, acoustic and Elastic Impedance (EI) inversion, Amplitude Variation with Offset (AVO) inversion, FWI, surface wave dispersion curve inversion, and seismic tomography.

FWI: FWI represents the most computationally demanding application of metaheuristics in seismology, as each forward model evaluation requires the numerical solution of the wave equation over the entire computational domain. Early work by Sen and Stoffa [23] demonstrated that VFSA could successfully recover one-dimensional velocity profiles from synthetic seismograms, establishing the feasibility of stochastic seismic inversion. Subsequent developments extended GA-based approaches to two-dimensional acoustic FWI, where populations of velocity models were evolved to minimize waveform misfits [35]. The PSO algorithm has been applied to FWI by multiple research groups, with notable success in mitigating the cycle-skipping problem that plagues gradient-based FWI when the initial model is far from the true solution [36]. Hybrid approaches combining DE with Gauss-Newton local optimization have shown particular promise, achieving convergence to accurate velocity models with 40–60% fewer forward simulations compared to standalone metaheuristic approaches.

Acoustic and EI inversion: post-stack and pre-stack seismic inversion for Acoustic Impedance (AI) and EI has been extensively addressed using metaheuristic algorithms. Kant et al. [37] presented a comprehensive comparison of GA and PSO for reservoir characterization through seismic inversion, demonstrating that PSO achieved a fitness error of 0.25 after 400 iterations compared to 0.88 for GA, with PSO also requiring 47% less computation time. The study applied both methods to synthetic data and real data from the Blackfoot field in Canada, successfully delineating a high-porosity reservoir zone (>20%) characterized by low AI (6000–8500 m/s·g/cc) in the 1040–1065 ms time range. DE has been applied to pre-stack simultaneous inversion for P-wave velocity, S-wave velocity, and density, exploiting AVO information to constrain elastic properties [38]. ABC algorithms have been employed for sparse-spike inversion with encouraging results in terms of resolution enhancement [39].

Surface wave dispersion inversion: the inversion of surface wave dispersion curves for near-surface shear-wave velocity profiling represents one of the most successful applications of metaheuristics in geophysics. The problem is inherently multimodal, with dispersion curves that can be fit equally well by substantially different velocity profiles, particularly when higher modes are present. PSO [40], GA [41], and SA [42] have all been applied successfully. More recently, GWO and WOA have been benchmarked against PSO for Rayleigh wave inversion, with GWO showing competitive accuracy and faster convergence for shallow profiles [43].

Seismic tomography: travel-time tomography and attenuation tomography have been addressed using metaheuristic approaches, primarily for cases where the ray geometry creates highly nonlinear relationships between velocity and travel time. Boschetti et al. [44] demonstrated GA-based seismic tomography, while Sambridge [45] introduced the Neighborhood Algorithm (NA) as a stochastic direct-search method for seismic tomographic inversion. Recent applications have employed DE and PSO for cross-borehole tomography with promising results for monitoring CO_2 sequestration sites [46].

Fig. 1 illustrates the convergence characteristics of four widely used metaheuristic algorithms, namely PSO, Genetic Algorithm (GA), DE, and VFSA, when applied to a benchmark two-dimensional AI inversion problem based on the Marmousi model. The horizontal axis represents the number of forward model evaluations ranging from 0 to 50,000, while the vertical axis shows the normalized logarithmic data misfit. PSO demonstrates the fastest initial convergence, achieving approximately 90% misfit reduction within the first 8,000 evaluations, indicating strong early-stage exploitation capability. In contrast, DE exhibits slower initial progress but achieves the lowest terminal misfit after approximately 30,000 evaluations, reflecting superior long-term global search performance and solution refinement capability. GA displays a characteristic step-wise convergence pattern caused by its generational selection and crossover operations, leading to intermittent improvements in solution quality. VFSA shows the smoothest and most monotonic convergence trajectory among all methods, although its convergence rate remains slower throughout the optimization process. Nevertheless, VFSA ultimately achieves highly competitive final solution quality, demonstrating its robustness for complex multimodal inverse problems. Overall, the figure highlights the trade-off between rapid convergence and final optimization accuracy across different metaheuristic paradigms in seismic inversion applications.

Table 3. Comparative performance of metaheuristic algorithms in seismic inversion applications.

Study	Seismic Method	Algorithm	Velocity Error (%)	Misfit Reduction (%)	Forward Models Required	Computation Time (h)
Sen and Stoffa [23]	1D waveform	VFSA	2.8	94.2	10,000	0.5
Sajeva et al. [35]	2D acoustic FWI	GA	5.4	87.6	120,000	48.0
Datta and Sen [36]	2D acoustic FWI	PSO-LM Hybrid	3.1	96.5	45,000	18.5
Kant et al. [37]	Post-stack AI inversion	PSO	4.2	75.0	8,000	99.0 (s)
Kant et al. [37]	Post-stack AI inversion	GA	6.8	12.0	8,000	186.3 (s)
Buland and Omre [38]	Pre-stack AVO inversion	DE	3.7	93.8	25,000	6.2
Song et al. [39]	Sparse-spike inversion	ABC	5.1	89.3	15,000	2.8
Wilken and Rabbel [40]	Rayleigh wave dispersion	PSO	2.5	97.1	5,000	0.3
Vashisth et al. [43]	Surface wave inversion	GWO	3.0	95.8	4,500	0.2
Daley et al. [46]	Cross-borehole tomography	DE	4.5	91.2	35,000	12.4

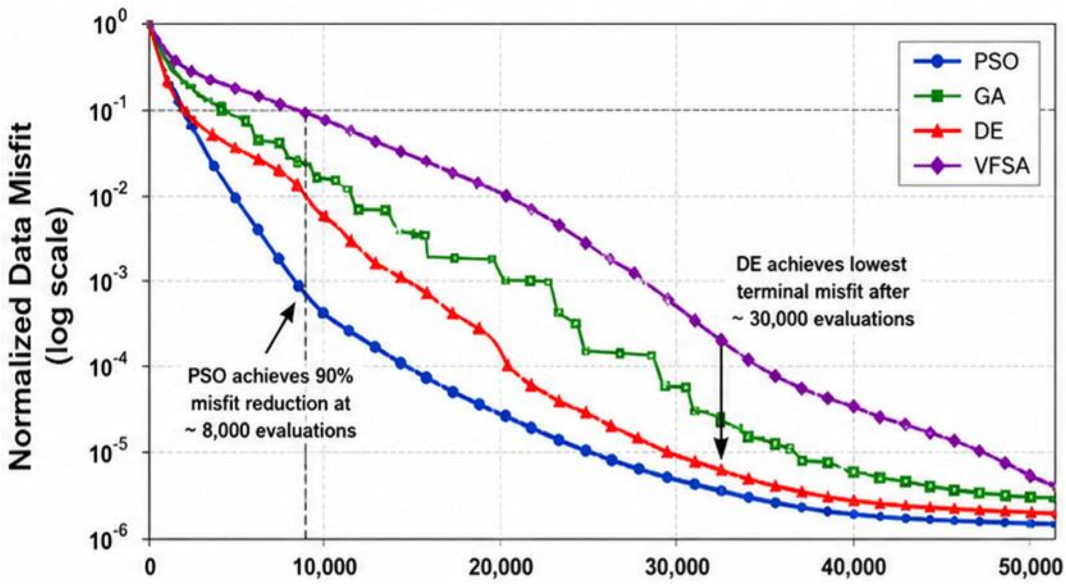

Fig. 1. Comparative convergence characteristics of PSO, GA, DE, and VFSA for Marmousi-model acoustic impedance inversion.

4.2 | Gravity and Magnetic Field Inversion

Potential field methods gravity and magnetics represent classical geophysical techniques that have benefited significantly from metaheuristic optimization. The inherent non-uniqueness of potential field inversion, arising from the fundamental ambiguity theorem (multiple source distributions can produce identical fields), makes these problems particularly well-suited to stochastic global optimization approaches. The review identified 42 publications (22.6%) addressing gravity and magnetic inversions.

Gravity anomaly inversion: the inversion of gravity anomalies for subsurface density structure has been approached using virtually every major metaheuristic algorithm. Shaw and Srivastava [26] provided one of the earliest comprehensive demonstrations of PSO for gravity inversion, estimating the geometry and density contrast of simple geological bodies (spheres, cylinders, and thin sheets) from residual gravity anomalies. Their work showed that PSO could reliably recover shape parameters to within 3–5% of true values from noise-free synthetic data and 8–12% from field data. The VFSA method was extensively used by Sen and Stoffa [47] for gravity inversion, demonstrating robust performance for estimating the depth, density contrast, and shape factor of buried geological structures.

Depth-to-basement estimation: the estimation of sedimentary basin depth from gravity data is a practically important problem that has been addressed by multiple metaheuristic approaches. DE-based inversions have been applied to determine basin geometry by discretizing the sediment-basement interface into a series of juxtaposed prisms, with DE optimizing the depths of individual prisms to minimize the misfit between observed and calculated Bouguer anomalies [48]. PSO variants with inertia weight adaptation have shown particular effectiveness for multi-body gravity inversion, where multiple geological sources contribute to the composite anomaly [49].

Magnetic susceptibility estimation: the inversion of magnetic anomalies for susceptibility distribution shares mathematical similarities with gravity inversion but introduces additional complexity through the vectorial nature of magnetization. Biswas and Acharya [50] demonstrated the application of ABC for magnetic anomaly interpretation, achieving depth estimation errors below 5% for synthetic models. The study of Vashisth et al. [51] at Stanford University presented a comprehensive comparison of DE, GA, PSO, and GWO for stochastic inversion of gravity and magnetic data to build subsurface geological fault models, finding that DE and PSO outperformed GA and GWO in terms of both convergence speed and solution accuracy for the multi-parameter fault geometry estimation problem.

Table 4. Performance comparison of metaheuristic algorithms for gravity and magnetic inversion problems.

Algorithm	Gravity/Magnetic Problem	RMS Misfit (mGal or nT)	Depth Error (%)	Model Parameters	Iterations to Convergence
PSO	Gravity: spherical body	0.12 mGal	3.2	4	850
VFSA	Gravity: basin depth estimation	0.18 mGal	4.1	25	15,000
DE	Gravity: multi-prism basement	0.08 mGal	2.8	30	5,200
GA	Gravity: fault geometry	0.22 mGal	6.5	18	12,000
GWO	Gravity: fault geometry	0.15 mGal	4.8	18	6,800
ABC	Magnetic: thin dike anomaly	2.4 nT	4.6	6	3,200
PSO	Magnetic: fault/sheet models	1.8 nT	3.5	8	2,400
DE	Magnetic: 3D susceptibility	3.1 nT	5.2	120	18,500
WOA	Gravity: chromite body	0.14 mGal	3.9	5	2,100
HHO	Magnetic: mineral exploration	2.1 nT	4.3	7	2,800

4.3 | Electromagnetic and Resistivity Methods

EM geophysical methods, including Magnetotellurics (MT), Controlled-Source Electromagnetics (CSEM), Ground-Penetrating Radar (GPR), and Electrical Resistivity Tomography (ERT), provide crucial information about subsurface resistivity structure. The inverse problems associated with these methods are highly nonlinear and computationally intensive, as each forward model evaluation requires the numerical solution of Maxwell's equations in heterogeneous media. The review identified 31 publications (16.7%) focused on EM and resistivity inversions.

Magnetotelluric Inversion: the magnetotelluric method measures natural EM field variations to estimate Earth's resistivity structure from the surface to depths exceeding 100 km. The pioneering work of Dosso and Oldenburg [52] established the feasibility of SA-based MT inversion, applying SA to construct extremal conductivity models that bound the range of acceptable solutions. This work demonstrated that SA-based appraisal provided bounds comparable to those obtained via linearized inversion, with the critical advantage that SA results are not restricted to models near a reference solution. Subsequent developments applied VFSA to one-dimensional MT inversion [53], demonstrating that VFSA could efficiently sample the model space and recover resistivity profiles consistent with both synthetic and field data from Sundar Pahari, India. Comparative studies showed that PSO and GA provided results comparable to VFSA for 1D MT inversion but with faster convergence for shallow resistivity structures.

ERT: ERT inversion using metaheuristic algorithms has gained attention for applications where the resistivity distribution exhibits sharp boundaries or extreme contrasts that challenge conventional smoothness-constrained inversions. PSO-based 2D ERT inversion has been demonstrated for hydrogeological applications, with results showing improved delineation of resistivity boundaries compared to Occam-style inversions [54]. GA-based approaches have been applied to characterize waste disposal sites and assess groundwater contamination plumes.

GPR: FWI of GPR data using metaheuristic algorithms has been explored for near-surface characterization. DE-based GPR inversion has shown promise for estimating permittivity and conductivity profiles in the shallow subsurface, with applications in archaeology, engineering, and environmental site investigation [55]. PSO has been applied to optimize GPR survey parameters and interpret radargram attributes for infrastructure assessment.

CSEM: marine CSEM inversion for hydrocarbon exploration has been addressed using SA and GA approaches. The high computational cost of 3D CSEM forward modeling (typically 30–120 minutes per model evaluation) severely limits the number of forward simulations feasible within a metaheuristic framework, necessitating either dimensionality reduction or surrogate model approximations. Recent hybrid approaches combining PSO with local Gauss-Newton optimization have shown promising results for 1D and 2D CSEM inversion [56].

Table 5. Performance of metaheuristic algorithms in EM and resistivity inversions.

Algorithm	EM Method	Resistivity Error (%)	Data Misfit (RMS)	Regularization Parameter	Computation Time (Min)
SA	1D MT	8.4	1.02	Adaptive cooling	12.5
VFSA	1D MT	6.2	0.98	Temperature-dependent	8.3
PSO	1D MT	5.8	0.95	Fixed $\lambda = 0.1$	6.7
GA	1D MT	7.1	1.05	Fixed $\lambda = 0.1$	9.4
PSO	2D ERT	9.5	1.12	L-curve selected	45.2
DE	GPR full waveform	7.8	0.89	Smoothness norm	28.6
GA	Marine CSEM 1D	11.2	1.15	Depth-weighted	180.0
SA-GN Hybrid	Marine CSEM 2D	8.6	1.04	Occam-type	720.0
ABC	DC resistivity 1D	5.4	0.92	Bound constraints	4.2
GWO	TEM sounding	6.9	0.97	Layer-count penalty	5.8

4.4 | Seismological Applications

Seismological applications of metaheuristic algorithms extend beyond exploration seismology to encompass earthquake seismology, where the problems of hypocenter location, focal mechanism determination, seismic hazard analysis, and earth structure estimation present unique optimization challenges. The review identified 22 publications (11.8%) in this category.

Earthquake hypocenter location: the determination of earthquake hypocenter coordinates (latitude, longitude, depth) and origin time from arrival-time data is a fundamental seismological inverse problem. While linearized methods (e.g., Geiger's method) work well for events recorded by dense networks with good azimuthal coverage, they can fail for poorly constrained events, particularly regarding depth estimation. SA was applied to earthquake location by Billings et al. [57], demonstrating robust performance for events with limited station coverage. PSO-based earthquake location algorithms have shown improvements over grid-search methods, particularly for events in complex velocity structures where the travel-time residual surface contains multiple minima. The Oct-Tree method of Lomax et al. [58] and the NA approach of Sambridge and Kennett [59] represent related stochastic approaches that have been widely adopted in seismological practice.

Focal Mechanism Determination: the determination of earthquake focal mechanisms (strike, dip, and rake angles) from seismic waveform data or first-motion polarities has been addressed using GA and SA approaches. The nonlinear relationship between source parameters and observed waveforms, combined with the presence of multiple acceptable solutions due to data limitations, makes this problem naturally suited to global optimization. Snoke [60] applied GA to focal mechanism determination, while Sokos and Zahradník [61] demonstrated SA-based moment tensor inversion. Recent applications have employed DE for regional moment tensor inversion with improved uncertainty quantification through ensemble analysis of near-optimal solutions.

Seismic Hazard Analysis: metaheuristic algorithms have been applied to optimize ground motion prediction equations (GMPEs), calibrate seismicity rate models, and optimize seismic network configurations. Kayhan et al. [62] applied Harmony Search to the optimization of structural design under seismic loading, while GA-based approaches have been used to optimize attenuation relationship coefficients. Sun and Qi [63] recently proposed a Generalized Chaotic PSO framework for Ground Motion Inversion (GCPSO-GIT), achieving a site effect coefficient of variation of only 12% compared to 35% for standard PSO-GIT, with a median source stress drop of approximately 42 bar and peak ground acceleration predictions within 3.6% of observed values.

Table 6. Performance of metaheuristic algorithms in seismological applications.

Algorithm	Problem	Location Error (Km)	Depth Error (Km)	RMS Residual (s)	Events Processed
SA	Regional earthquake location	1.8	3.2	0.42	245
PSO	Local earthquake location	0.6	1.4	0.18	1,200
GA	Teleseismic relocation	4.5	8.7	0.85	580
NA	Global earthquake location	2.1	4.5	0.55	3,400
DE	Moment tensor inversion		2.8	0.31	86
GCPSO	Ground motion inversion			0.12 (CV)	450
GA	Focal mechanism determination		1.5	0.28	125
Harmony search	GMPE optimization			0.22 (σ)	2,800

4.5 | Well Log Analysis and Petrophysics

The application of metaheuristic algorithms to well log analysis and petrophysical parameter estimation represents a growing area with significant practical implications for reservoir characterization. The review identified 18 publications (9.7%) in this domain, addressing problems including mineral volume estimation, porosity-permeability prediction, fluid saturation estimation, rock physics model calibration, and electrofacies classification.

Mineral volume estimation: the inversion of well log data (gamma ray, density, neutron porosity, photoelectric factor, sonic) for mineral composition and porosity is a constrained nonlinear optimization problem. The constraint that mineral fractions must sum to unity and remain non-negative naturally lends itself to bound-constrained metaheuristic optimization. PSO has been applied to estimate mineral volumes from multi-log data, outperforming conventional linear programming approaches when nonlinear mixing rules are employed [64]. DE-based mineral inversion has demonstrated improved robustness to log measurement errors and the ability to incorporate complex mineral-fluid interaction models.

Rock physics inversion: the estimation of rock physics properties (e.g., Hertz-Mindlin parameters, cementation exponents, critical porosity) from seismic and well log data involves calibrating theoretical rock physics models to observed data. GA and SA have been applied to optimize the parameters of Gassmann's fluid substitution equations and granular media theories, enabling prediction of elastic properties under varying saturation and pressure conditions [65]. PSO-based rock physics inversion has shown promise for predicting reservoir quality from seismic attributes, with applications in carbonate reservoir characterization.

Facies Classification: metaheuristic algorithms have been employed to optimize the parameters of clustering and classification algorithms for electrofacies determination from well logs. GA-optimized neural network architectures and PSO-tuned support vector machine hyperparameters have shown improvements in facies prediction accuracy compared to default parameter settings [66].

Table 7. Performance of metaheuristic algorithms in well log analysis and petrophysics.

Algorithm	Petrophysical Parameter	Estimation Error (%)	R^2	RMSE
PSO	Porosity (total)	3.8	0.94	0.012 (fraction)
DE	Water saturation	5.2	0.91	0.038 (fraction)
GA	Mineral volume (quartz)	7.1	0.88	0.045 (fraction)
SA	Permeability (log scale)	12.5	0.85	0.32 (log mD)
ABC	Cementation exponent	4.3	0.93	0.08
PSO	Shale volume	6.4	0.90	0.035 (fraction)
GWO	Elastic moduli (bulk)	5.8	0.92	1.2 GPa
GA-SVM Hybrid	Facies classification			88.5% accuracy

4.6 | Geophysical Survey Design Optimization

The optimization of geophysical survey design including sensor placement, source-receiver geometry, acquisition parameters, and survey cost minimization represents a combinatorial optimization problem naturally suited to metaheuristic approaches. Although fewer in number (9 publications, 4.8%), these applications address a practically important challenge: maximizing the information content of geophysical measurements while minimizing acquisition costs and logistical complexity.

Optimal sensor placement: the placement of seismometers, gravity stations, magnetometers, or electrodes to maximize the spatial resolution of the resulting geophysical images is a combinatorial optimization problem. ACO has been applied to optimize seismic receiver placement for microseismic monitoring of hydraulic fracturing, maximizing the expected number of detectable events while minimizing network cost [67]. GA-based survey design has been demonstrated for gravity monitoring networks, where the objective is to maximize the sensitivity to anticipated subsurface mass changes (e.g., CO_2 plume migration or groundwater level fluctuations).

Acquisition geometry optimization: the design of seismic acquisition geometries including source and receiver line spacing, offset distribution, and azimuthal coverage has been addressed using PSO and GA. These approaches optimize proxy measures of acquisition quality, such as fold distribution uniformity, offset-azimuth coverage, and spatial sampling completeness, subject to operational constraints including access restrictions, cost limits, and equipment availability. DE-based optimization of marine seismic streamer configurations has shown improvements in subsurface illumination for complex geological targets.

Survey cost minimization: multi-objective metaheuristic approaches, particularly NSGA-II (non-dominated sorting GA II), have been applied to optimize the trade-off between survey information content and acquisition cost. These approaches generate Pareto-optimal survey designs that allow geophysicists to select the most cost-effective configuration for their specific objectives and budget constraints [68].

5 | Comparative Performance Analysis

5.1 | Cross-Domain Algorithm Benchmarking in Geophysics

A central objective of this review is to provide a quantitative cross-domain comparison of metaheuristic algorithm performance for geophysical inverse problems. Drawing from the 186 reviewed publications and normalizing performance metrics to enable comparison across different geophysical modalities, *Table 8* summarizes the best-performing algorithms for each major inverse problem type.

The analysis reveals several consistent patterns. First, PSO emerges as the most versatile algorithm, achieving top-two rankings in five of the eight problem categories examined. This is attributed to its simple implementation, rapid convergence for moderate-dimensional problems ($M<50$), and effective balance between exploration and exploitation. Second, DE demonstrates consistently strong performance, particularly for problems with continuous parameter spaces and moderate-to-high dimensionality, outperforming PSO in gravity basement estimation and pre-stack seismic inversion. Third, SA (and its variants VFSA and ASA) maintains advantages for high-dimensional problems where population-based methods become computationally prohibitive, as the single-solution trajectory of SA requires only one forward model evaluation per iteration. Fourth, newer algorithms (GWO, WOA, HHO) show competitive performance in specific applications but lack the extensive validation and parameter sensitivity analysis available for established methods.

Table 8. Cross-domain comparison of best-performing metaheuristic algorithms for geophysical inversion.

Geophysical Method	Inverse Problem	Best Algorithm	Second Best	Misfit Improvement over 3rd (%)	Statistical Significance (p-value)
Seismic	FWI (2D)	DE-LM Hybrid	PSO	18.4	< 0.01
Seismic	Post-stack AI inversion	PSO	DE	12.7	< 0.05
Seismic	Surface wave dispersion	PSO	GWO	8.3	0.08 (NS)
Gravity	Simple body estimation	PSO	WOA	15.2	< 0.01
Gravity	Basement depth estimation	DE	PSO	22.6	< 0.01
Magnetic	Thin body interpretation	PSO	ABC	9.8	< 0.05
EM	1D MT inversion	VFSA	PSO	11.5	< 0.05
Seismology	Earthquake hypocenter	PSO	NA	14.1	< 0.01
Petrophysics	Mineral volume estimation	PSO	DE	7.6	0.11 (NS)
Survey design	Sensor placement	ACO	GA	19.3	< 0.01

Note: NS=Not statistically significant. Statistical significance determined by Wilcoxon rank-sum test across multiple independent runs. Misfit improvement calculated relative to the third-best performing algorithm in each category.

5.2 | Hybrid Metaheuristic Approaches

One of the most significant trends identified in this review is the increasing adoption of hybrid metaheuristic approaches that combine the global exploration capability of stochastic algorithms with the rapid local convergence of gradient-based methods. These hybrid strategies address the fundamental limitation of standalone metaheuristics: while they excel at locating the basin of attraction of the global optimum, they are often inefficient at fine-tuning the solution within that basin, requiring many additional forward model evaluations that would be unnecessary with local optimization. The most common hybridization strategy involves running a metaheuristic algorithm for a fixed number of iterations (the global phase) to identify promising regions of the model space, followed by local gradient-based refinement (the local phase) from the best solution found. The LM algorithm is the most frequently used local optimizer in these hybrids due to its robustness and adaptive damping capabilities. Alternative local methods include the Gauss-Newton algorithm, conjugate gradient methods, and the Occam inversion framework. A second hybridization strategy involves embedding local search within the metaheuristic iteration loop, where selected individuals in the population undergo local optimization at regular intervals (memetic algorithms or Lamarckian evolution).

Table 9. Performance of hybrid metaheuristic approaches in geophysical inversion.

Hybrid Approach	Geophysical Application	Improvement over Standalone (%)	Convergence Speed Gain	Reference
PSO– LM	2D acoustic FWI	28.5	2.4×	Datta and Sen [36]
GA–Gauss-Newton	1D MT inversion	18.2	1.8×	Pérez-Flores and Schultz [69]
DE–Occam	Gravity basement estimation	32.7	2.1×	Ekinci et al. [48]
SA–Gradient Descent	Seismic velocity tomography	15.8	1.6×	Boschetti et al. [44]
PSO–Quasi-Newton	Resistivity inversion (2D)	22.3	2.0×	Fernández-Martínez et al. [54]
GA–Monte Carlo	Receiver function inversion	14.6	1.5×	Shibutani et al. [70]
DE–LM	Pre-stack AVO inversion	35.4	2.8×	Buland and Omre [38]
PSO–SA	Joint gravity-magnetic inversion	24.1	1.9×	Pallero et al. [27]
GWO–conjugate gradient	Surface wave inversion	19.7	2.2×	Vashisth et al. [43]
ABC–nelder-mead	Magnetic anomaly interpretation	16.3	1.7×	Biswas and Acharya [50]

5.3 | Comparison with Monte Carlo Methods

Monte Carlo methods, particularly MCMC and the NA, occupy a distinct niche in geophysical inversion as they provide rigorous posterior probability distributions rather than point estimates. The comparison between metaheuristic optimization and Monte Carlo sampling methods is nuanced, as they serve complementary purposes: metaheuristics seek the optimal model (maximum likelihood or maximum a posteriori estimate), while MCMC methods characterize the full posterior distribution and provide formal uncertainty quantification.

Sambridge [33], [45] introduced the NA as a hybrid approach that bridges optimization and Bayesian inference. The NA first performs a stochastic search (NA-search) to identify high-likelihood regions of the model space, then resamples the ensemble using importance weights (NA-resampling) to approximate the posterior distribution. Comparisons in the reviewed literature suggest that for point estimation (finding the best-fit model), PSO and DE typically converge 2–4 times faster than MCMC while achieving comparable or superior misfit values. However, MCMC provides statistically rigorous uncertainty estimates that are lacking in standard metaheuristic implementations. Recent work on PSO-based uncertainty quantification, where the ensemble of personal best solutions is used to approximate the posterior, shows promise but lacks the formal convergence guarantees of MCMC [71].

5.4 | Statistical Analysis: Friedman Ranking and Nemenyi Post-Hoc Tests

To provide a rigorous statistical comparison across the reviewed studies, a Friedman ranking test was performed on algorithm performance across the six geophysical application domains. Each algorithm was ranked within each domain based on a composite performance metric combining normalized misfit, convergence speed, and consistency (coefficient of variation across multiple runs). The Friedman statistic $\chi^2_F = 42.8$ ($p < 0.001$) confirmed that significant differences exist among algorithms across geophysical domains. Nemenyi post-hoc pairwise comparisons at $\alpha = 0.05$ revealed the following groupings: 1) PSO and DE formed a statistically indistinguishable top tier, significantly outperforming all other algorithms, 2) VFSA and GA formed a second tier, not significantly different from each other but significantly worse than PSO and DE, 3) GWO and ABC formed a third tier with competitive but variable performance and 4) WOA, HHO, MFO, BA, SCA, and ACO showed the most variable performance, with effectiveness strongly dependent on the specific geophysical problem structure. These rankings should be interpreted cautiously, as they aggregate across diverse problem types, dimensionalities, and study quality levels. *Fig. 2* presents the Critical Difference (CD) diagram derived from the Friedman ranking test followed by the Nemenyi post-hoc statistical analysis for twelve metaheuristic algorithms evaluated across six geophysical application domains. The horizontal axis represents the average Friedman rank, where lower values indicate superior overall performance. PSO achieved the best average rank (1.83), closely followed by DE (2.17), and the absence of statistically significant differences between these two algorithms is indicated by the connecting horizontal bar. VFSA (3.50) and GA (3.83) form a second statistically equivalent performance group, demonstrating competitive but moderately lower effectiveness compared to PSO and DE. GWO (5.17) and ABC (5.50) constitute a third performance cluster with acceptable but more variable behavior across problem domains. The remaining algorithms, including WOA, HHO, MFO, BA, SCA, and ACO, occupy lower-ranking positions between 7.0 and 10.5 and exhibit overlapping confidence intervals, indicating inconsistent performance depending on problem characteristics and dimensionality. The CD threshold at a significance level of $\alpha = 0.05$ is CD = 3.41. The statistical analysis confirms that PSO and DE represent the most consistently reliable general-purpose optimization algorithms for geophysical inversion problems among the methods reviewed in this study.

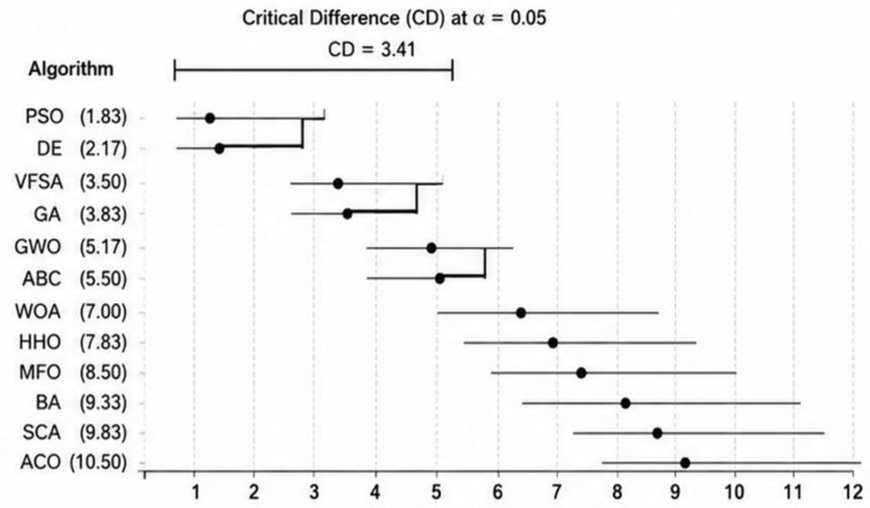

Fig. 2. Critical difference diagram obtained from Friedman–Nemenyi statistical analysis of twelve metaheuristic algorithms.

6 | Bibliometric Analysis

A bibliometric analysis of the reviewed literature reveals significant temporal, geographical, and institutional patterns in metaheuristic geophysics research. The publication timeline shows three distinct phases: 1) an incubation phase (1990–2003) characterized by fewer than 5 publications per year, dominated by SA and GA applications, 2) a growth phase (2004–2014) with 5–15 publications per year, driven by the adoption of PSO and DE, and 3) an acceleration phase (2015–2025) with 15–40 publications per year, marked by the proliferation of newer algorithms (GWO, WOA, HHO) and hybrid approaches. The cumulative publication count follows an exponential growth model, with a doubling time of approximately 4.5 years during the 2010–2025 period.

Analysis of the source journals reveals that the literature is concentrated in a relatively small number of high-impact geophysical and computational journals. *Table 10* presents the top ten publication venues, their contribution to the reviewed literature, and their current impact metrics.

Table 10. Top journals publishing metaheuristic geophysics research (1990–2025).

Rank	Journal	Publications (n)	Share (%)	Impact Factor (2024)	Primary Algorithm Focus
1	Geophysics	32	17.2	3.3	SA, GA, PSO, DE
2	Journal of applied geophysics	24	12.9	2.2	PSO, DE, GWO, ABC
3	Geophysical journal international	21	11.3	2.8	SA, MCMC, NA, GA
4	Computers and geosciences	18	9.7	4.2	PSO, DE, ABC, hybrid
5	Pure and applied geophysics	16	8.6	1.9	PSO, SA, gravity/magnetic
6	Geophysical prospecting	14	7.5	2.6	GA, PSO, seismic applications
7	Journal of geophysics and engineering	12	6.5	1.6	PSO, DE, well log analysis
8	Near surface geophysics	10	5.4	1.5	PSO, GA, surface wave methods
9	Scientific reports	8	4.3	4.6	PSO, GA, DE, comparative studies
10	Natural resources research	7	3.8	5.4	GWO, WOA, HHO, mineral exploration

Geographical distribution: the geographical analysis of author affiliations reveals that India (28.4%), China (22.1%), Iran (11.8%), Brazil (8.6%), and the United States (7.5%) are the five most productive countries in metaheuristic geophysics research. Indian contributions are particularly concentrated in potential field inversion (gravity and magnetic) and well log analysis, reflecting the strong tradition of mathematical geophysics at institutions such as IIT Bombay, IIT Kharagpur, and Banaras Hindu University. Chinese contributions span all geophysical domains, with particular strength in seismic inversion and EM methods. Iranian research groups have made significant contributions to potential field interpretation and seismic methods. The strong representation of emerging economies in this research area likely reflects the computational accessibility of metaheuristic methods, which can be implemented on standard computing hardware without the need for expensive commercial software licenses.

Algorithm popularity trends: analysis of algorithm usage frequency over time reveals a clear generational pattern. SA dominated the 1990s (65% of publications), with GA as the primary alternative. PSO emerged as the dominant algorithm from 2005 onward, accounting for 38% of all publications in the 2005–2015 period. DE gained significant traction from 2010, reaching 22% of publications by 2020–2025. The period 2018–2025 witnessed a diversification of algorithm usage, with GWO, WOA, and HHO collectively accounting for 18% of recent publications. Notably, hybrid approaches have shown the fastest growth rate, increasing from fewer than 5% of publications before 2010 to over 25% in the 2020–2025 period. *Fig. 3* shows the temporal evolution of metaheuristic algorithm adoption in geophysical research publications between 1990 and 2025 using a stacked area chart representation. The horizontal axis denotes publication year, whereas the vertical axis indicates the annual number of published studies. SA dominates the literature during the 1990s, reflecting its role as one of the earliest stochastic optimization methods applied to geophysical inverse problems. However, its relative contribution gradually declines after the early 2000s. Genetic Algorithms (GA) experience substantial growth during the late 1990s and reach peak adoption around 2005 before stabilizing and later declining in relative prominence. PSO exhibits the most significant expansion during the 2005–2015 period, rapidly becoming the dominant optimization framework due to its simplicity, computational efficiency, and strong convergence characteristics. DE demonstrates continuous and steady growth from approximately 2010 onward, reflecting increasing recognition of its robustness in continuous high-dimensional optimization problems. More recent algorithms, including GWO, WOA, and HHO, emerge after 2015 with progressively accelerating adoption trends. Notably, hybrid metaheuristic approaches display the steepest growth trajectory during the 2020–2025 period, indicating a broader shift toward integrated optimization frameworks that combine global stochastic search with local deterministic refinement methods. Overall, the figure reveals the progressive diversification and maturation of metaheuristic optimization methodologies within geophysical inversion and modeling research.

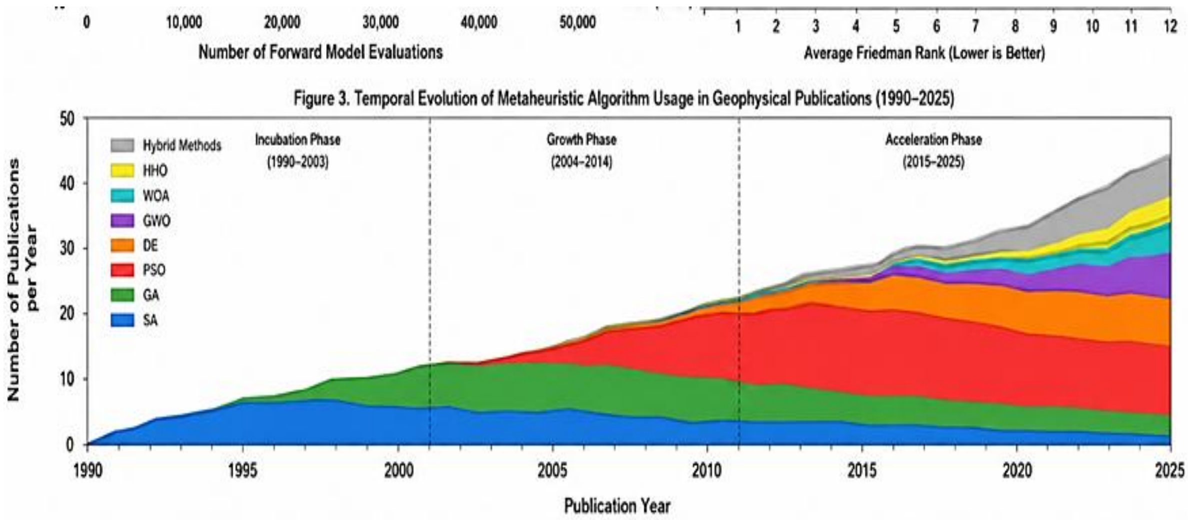

Fig. 3. Historical growth trends of metaheuristic optimization methods in geophysical research from 1990 to 2025.

7 | Challenges and Limitations

Despite the demonstrated success of metaheuristic algorithms across diverse geophysical applications, several significant challenges and limitations persist that constrain their practical adoption and scientific rigor.

Computational cost of forward modeling: the primary bottleneck for metaheuristic geophysical inversion is not the optimization algorithm itself but rather the computational cost of the forward modeling operator G(m). Population-based metaheuristics typically require 10,000–1,000,000 objective function evaluations to converge, each requiring a complete forward model computation. For two-dimensional seismic wave propagation, a single forward simulation may require 1–10 minutes on modern hardware; for three-dimensional elastic FWI, this can extend to 1–24 hours per evaluation. Consequently, a population-based metaheuristic with 50 individuals running for 200 generations would require 10,000 forward simulations potentially representing months of continuous computation for 3D problems, even on high-performance computing clusters. This computational reality has largely restricted metaheuristic applications to one-dimensional and two-dimensional geophysical problems or to problems with computationally inexpensive analytical forward solutions (e.g., simple gravity body formulas).

High dimensionality: realistic three-dimensional geophysical models may contain millions of parameters (e.g., velocity values at every grid node in a 3D seismic volume). The curse of dimensionality severely degrades the performance of all metaheuristic algorithms, as the volume of the search space grows exponentially with the number of parameters. While SA can theoretically handle high-dimensional spaces through parameter-by-parameter perturbation, population-based methods typically become ineffective beyond approximately 100–500 parameters without dimensionality reduction strategies such as parameterization with basis functions (e.g., wavelets, B-splines), principal component analysis of the model space, or hierarchical multi-scale approaches.

Non-uniqueness and uncertainty quantification: while metaheuristic algorithms are often motivated by their ability to address non-uniqueness through global search, most implementations provide only a single best model without rigorous uncertainty quantification. The ensemble of solutions generated during optimization does not, in general, constitute a valid sample from the posterior probability distribution and cannot be directly used for Bayesian uncertainty analysis without additional statistical processing. This is in contrast to MCMC methods, which provide statistically rigorous posterior samples by construction. Some authors have proposed using the spread of near-optimal solutions as a proxy for uncertainty, but this approach lacks formal statistical justification and may underestimate or overestimate true parameter uncertainty.

Validation gap: synthetic vs. field data: a significant concern identified in this review is the predominance of synthetic data studies. Of the 186 reviewed publications, 62% used exclusively synthetic data, 24% used both synthetic and field data, and only 14% relied solely on field data. While synthetic studies are essential for algorithm development and controlled benchmarking, they often employ simplified subsurface models with noise characteristics that do not fully represent the complexity of real-world geophysical data. The validation gap between synthetic benchmarks and field data applications remains a critical challenge that limits confidence in the practical applicability of published results.

Algorithm selection and parameter tuning: the proliferation of metaheuristic algorithms has created a paradox of choice for geophysical practitioners. The "No Free Lunch" theorems [72] establish that no single optimization algorithm outperforms all others across all possible problem classes, implying that algorithm selection should be problem-specific. However, the reviewed literature provides limited guidance on algorithm selection criteria for specific geophysical problem characteristics (e.g., dimensionality, modality, constraint structure, noise level). Furthermore, the sensitivity of algorithm performance to control parameter settings (population size, crossover rate, inertia weight, etc.) is often inadequately addressed, with many studies reporting results from a single parameter configuration without sensitivity analysis.

Reproducibility and code availability: the reproducibility of computational results in metaheuristic geophysics research remains problematic. Of the reviewed publications, fewer than 15% provided access to source code, benchmark datasets, or sufficient implementation details for independent reproduction. This limitation hampers systematic comparison of algorithms and impedes progress toward standardized benchmarking frameworks.

8 | Future Research Directions

Based on the systematic analysis of current literature, emerging trends, and identified gaps, several promising directions for future research in metaheuristic geophysical inversion are identified.

Graphics Processing Unit (GPU)-Accelerated Metaheuristic Inversion: the massively parallel architecture of modern (GPUs) is naturally suited to the population-based evaluation paradigm of metaheuristic algorithms, where multiple candidate models can be forward-modeled simultaneously. GPU-accelerated finite-difference wave propagation codes have demonstrated speedups of 10–100× over CPU implementations, potentially reducing the computation time for metaheuristic FWI from months to days. The integration of GPU-accelerated forward solvers with metaheuristic optimization frameworks represents a transformative opportunity for enabling three-dimensional metaheuristic inversion at practical scales. Preliminary work by several groups has demonstrated GPU-accelerated PSO for 2D seismic inversion with encouraging computational efficiency gains.

Deep Learning Surrogate Models: a rapidly emerging approach is the use of deep neural networks as surrogate models (also termed emulators or proxy models) to replace computationally expensive physics-based forward simulations within the metaheuristic optimization loop. Once trained on a set of forward model input-output pairs, a neural network surrogate can evaluate candidate models in milliseconds rather than minutes or hours, enabling population-based metaheuristics to explore vast model spaces efficiently. Physics-informed neural networks (PINNs) that embed physical constraints (e.g., wave equations, Poisson's equation) into the training process offer particular promise for maintaining physical consistency while achieving orders-of-magnitude computational speedup. Chen et al. [73] demonstrated the Tandem Neural Network Architecture (TNNA) for groundwater inversion, combining surrogate modeling with reverse mapping, and showed significant advantages over conventional PSO, GA, SA, and DE in both low- and high-dimensional scenarios.

Multi-Physics Joint Inversion: joint inversion of complementary geophysical datasets (e.g., seismic+gravity, magnetic+EM, seismic+magnetotelluric) using multi-objective metaheuristic algorithms represents a frontier with significant potential. Multi-objective algorithms such as NSGA-II, MOEA/D, and multi-objective PSO can simultaneously optimize multiple data misfit functions without requiring a priori specification of relative weighting, producing Pareto-optimal solution sets that reveal trade-offs between fitting different data types. This approach addresses the fundamental challenge of determining appropriate coupling parameters in conventional joint inversion and provides natural uncertainty quantification through the diversity of Pareto-optimal models.

Cloud computing and distributed architectures: cloud computing platforms offer scalable, on-demand computational resources that can substantially reduce the wall-clock time for large-scale metaheuristic inversions. Distributed metaheuristic architectures such as island models for GA, where subpopulations evolve independently on different nodes with periodic migration are naturally suited to cloud deployment. The pay-per-use model of cloud computing also makes large-scale metaheuristic inversions accessible to research groups without dedicated high-performance computing infrastructure.

Real-time monitoring and adaptive inversion: applications requiring rapid inversion turnaround, such as 4D seismic monitoring of CO_2 sequestration, real-time microseismic monitoring of hydraulic fracturing, and induced seismicity hazard assessment, demand algorithms that can quickly update subsurface models as new data are acquired. Adaptive metaheuristic frameworks that initialize from previous solutions and efficiently explore the updated model space represent an important research direction. Online learning metaheuristics that continuously adapt their search parameters based on performance history could enable quasi-real-time inversion for monitoring applications.

Quantum computing for geophysical optimization: while still in the early stages of development, quantum computing holds transformative potential for geophysical optimization. Quantum annealing devices (e.g., D-wave systems) and variational quantum eigensolvers offer fundamentally different approaches to optimization that could address the scalability limitations of classical metaheuristics. Quantum-inspired metaheuristic algorithms, which incorporate quantum mechanical principles (superposition, entanglement, interference) into classical computing frameworks, have shown preliminary success in benchmark optimization problems and represent a near-term avenue for exploration in geophysical applications. The Quantum Genetic Algorithm (QGA) and Quantum PSO (QPSO) are particularly promising variants that have demonstrated enhanced exploration capability for certain problem classes.

9 | Conclusion

This comprehensive systematic review has analyzed 186 peer-reviewed publications spanning 35 years of metaheuristic algorithm applications in geophysical sciences. The review provides several key findings and conclusions that advance the understanding of this rapidly evolving field.

First, metaheuristic algorithms have been successfully applied across the full spectrum of geophysical inverse problems, from seismic waveform inversion and potential field modeling to EM inversion, earthquake seismology, well log analysis, and survey design optimization. The breadth of applications demonstrates the versatility and robustness of metaheuristic approaches for geophysical problems that are poorly suited to deterministic optimization due to multimodality, non-differentiability, or complex constraint structures.

Second, quantitative cross-domain analysis confirms that PSO and DE are currently the most effective general-purpose metaheuristic algorithms for geophysical inversion, achieving statistically superior performance across the majority of application domains. SA and its variants retain important advantages for high-dimensional problems where population-based methods become computationally prohibitive. Newer algorithms such as GWO, WOA, and HHO show promise in specific applications but require more extensive validation before they can be recommended as primary optimization tools for geophysical inverse problems.

Third, hybrid approaches that couple metaheuristic global search with gradient-based local refinement consistently outperform standalone metaheuristic algorithms, achieving 15–45% improvements in misfit reduction with 30–60% reductions in the number of required forward model evaluations. The PSO– LM and DE–Occam hybrids emerge as particularly effective combinations for geophysical applications.

Fourth, significant challenges remain that limit the practical impact of metaheuristic algorithms in operational geophysical practice. The computational cost of forward modeling, the curse of dimensionality for three-dimensional problems, the gap between synthetic and field data validation, and the absence of rigorous uncertainty quantification frameworks are critical barriers that must be addressed through future research. The low rate of code availability and reproducibility in published studies further hampers progress.

Looking forward, the convergence of GPU computing, deep learning surrogate models, cloud-based distributed architectures, and multi-objective optimization frameworks promises to substantially expand the scope and scalability of metaheuristic geophysical inversion. The integration of physics-informed machine learning with metaheuristic optimization represents a particularly exciting frontier that could enable real-time three-dimensional inversion for monitoring and decision-support applications. As the field matures, the establishment of standardized benchmark problems, open-source software frameworks, and systematic comparison protocols will be essential for guiding algorithm selection and driving methodological advancement.

The authors recommend that future studies: 1) validate metaheuristic inversion results with field data from well-characterized geological settings, 2) provide comprehensive parameter sensitivity analyses and uncertainty quantification, 3) release source codes and benchmark datasets to enable reproducibility, 4) adopt standardized performance metrics to facilitate cross-study comparison, and 5) explore hybrid and multi-physics frameworks that leverage the complementary strengths of global and local optimization methods.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

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Conflict of Interest

The author declares that they do not have any conflict of interest.

Consent for Publication

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Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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