

Hybrid AI Models Combining Physics-Based Simulations and Data-Driven Approaches in Geophysics

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ABSTRACT

Hybrid AI models, often referred to as Physics-Informed Machine Learning (PIML) or Scientific Machine Learning (SciML), integrate first-principle physics (governing PDEs, conservation laws, and symmetries) with data-driven deep learning to overcome the limitations of purely mechanistic or purely empirical approaches in geophysics. These models embed physical constraints directly into neural architectures (Physics-Informed Neural Networks — PINNs), loss functions, or operators (Fourier Neural Operators — FNO, Neural ODEs), enabling data-efficient, physically consistent, and generalizable solutions. Key techniques include multi-objective loss balancing (LRA, GradNorm, SA-PINN), neural operators for parametric PDE solving, and symbolic regression methods like SINDy for equation discovery. Applications span seismic imaging and full-waveform inversion (velocity model reconstruction), reservoir engineering (history matching with 61% RMSD improvement), geotechnical stability (tunneling and slope predictions), and atmospheric/climate modeling (ClimODE for value-conserving forecasts, NVIDIA Earth-2 digital twins with FourCastNetv2). These hybrids reduce computational costs, improve robustness in small-data regimes, bridge synthetic-to-real domain gaps, and support uncertainty quantification. Challenges remain in loss balancing, spectral bias, and scaling to multimodal geo-foundation models. Overall, hybrid AI represents a transformative paradigm for subsurface imaging, resource management, hazard prediction, and climate resilience in geophysics.

Keywords: Physics-Informed Neural Networks (PINNs), Scientific Machine Learning, Hybrid AI Geophysics, Full-Waveform Inversion, Neural Operators, ClimODE, Reservoir History Matching, Geotechnical Piml, Equation Discovery (SINDy), Earth-2 Digital Twins, Loss Balancing, Multi-Physics Integration

Introduction

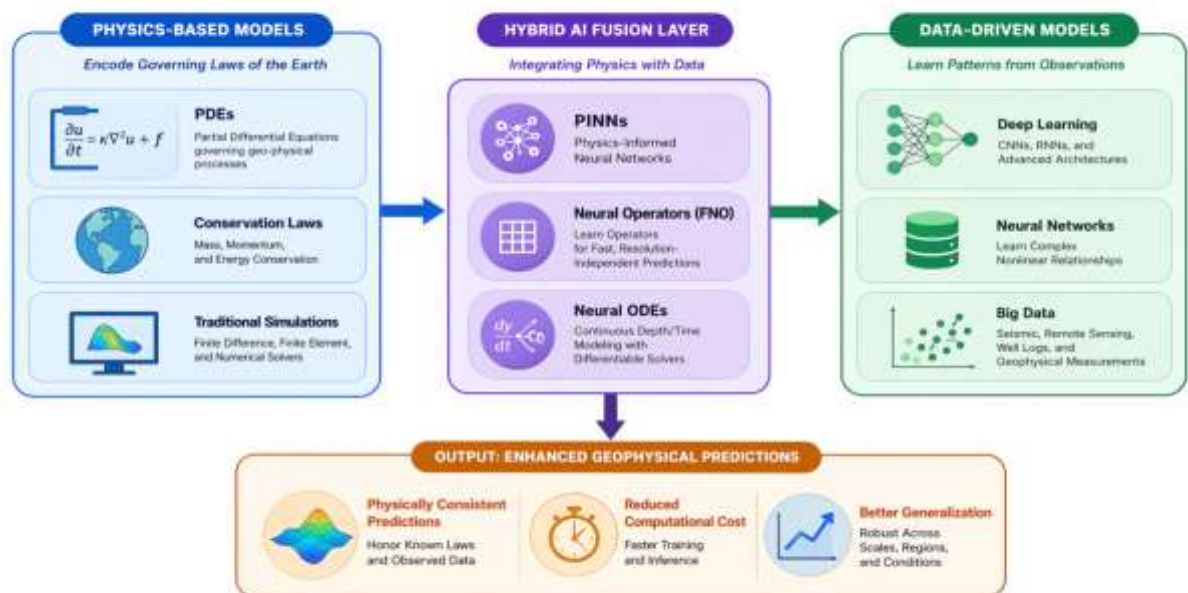
The investigation into the Earth's subsurface and atmospheric processes has historically been divided into two primary epistemological frameworks: the mechanistic, which relies on the rigorous application of first-principle physics, and the empirical, which extracts patterns from observational data (Zhang et al., 2023). In recent years, the limitations of each approach in isolation have become increasingly apparent. Physics-based simulations, while highly interpretable and grounded in fundamental laws, frequently suffer from prohibitive computational costs and an

inability to account for processes that are incompletely understood or too complex to parameterize (Karniadakis et al., 2021). Conversely, pure data-driven artificial intelligence (AI) models, particularly deep learning architectures, have demonstrated success in pattern recognition but often produce results that are physically inconsistent, lack generalizability to out-of-sample scenarios, and require enormous quantities of labeled data (Raissi et al., 2019).

The emergence of hybrid AI models frequently categorized under Physics-Informed Machine Learning (PIML) or Scientific Machine Learning (SciML) represents a strategic synthesis designed to reconcile these methodologies (Karniadakis et al., 2021). By embedding governing physical laws, such as partial differential equations (PDEs), symmetries, and conservation principles, directly into the architecture and optimization processes of neural networks, researchers are developing models that are simultaneously data-efficient, robust, and scientifically sound (Okazaki, 2024). This paradigm shift is fundamental to how geoscientific knowledge is generated in domains ranging from seismic imaging and reservoir engineering to climate forecasting and geotechnical stability analysis (Chen et al., 2024). The integration of physics-based and data-driven paradigms is illustrated in Figure 1, which highlights how hybrid AI frameworks combine mechanistic understanding with data adaptability. This conceptual framework underpins the development of physics-informed models across geophysical applications.

Figure 1: Conceptual Framework of Hybrid AI Models in Geophysics

Physics-Data Integration for Smarter Earth Modeling



Methodological Frameworks for Physics-Data Integration

The integration of physical priors into machine learning pipelines is executed through several distinct strategies, each tailored to specific data availability and the complexity of the underlying physical system. These methodologies can be

categorized based on where the physical knowledge is injected: the training data, the network architecture, the loss function, or the inference stage (Willard et al., 2020).

Physics-Informed Neural Networks and Loss Function Regularization

The most prevalent architecture is the Physics-Informed Neural Network (PINN). In a PINN, the governing physical equations are incorporated into the neural network's loss function as a regularization term (Cuomo et al., 2022). This ensures that the model's predictions fit the observed data while adhering to known physical laws (Ahmadi et al., 2025). The total loss function, L , is typically expressed as:

$$L = L_{\text{data}} + \lambda L_{\text{phys}}$$

where L_{data} represents the error between predicted and observed values, L_{phys} represents the residual of the governing physical equations, and λ is a weighting coefficient that controls the relative importance of physical consistency (Barreau & Shen, 2024).

The effectiveness of this approach depends on the proper optimization of these competing objectives. Multi-objective loss balancing remains a significant area of active research, as imbalances in the gradients of L_{data} and L_{phys} can lead to training instability (Maghami et al., 2025). Advanced weighting strategies, such as Learning Rate Annealing (LRA) and Gradient Normalization (GradNorm), help prevent one term from dominating the training process (Bischof, 2021).

Table 1. Comparison of Multi-Objective Loss Balancing Schemes for PINNs

Loss Balancing Method	Mechanism	Primary Advantage
Learning Rate Annealing (LRA)	Adjusts the learning rate for each loss component based on its gradient magnitude.	Prevents one term from dominating the training process (Bischof, 2021; Zhang et al., 2025).
Gradient Normalization (GradNorm)	Scales loss terms to ensure their gradients have a similar norm.	Improves convergence stability in complex multi-scale problems (Bischof, 2021; Zhang et al., 2025).
Self-Adaptive (SA-PINN)	Assigns trainable weights to individual training points or loss terms.	Automatically identifies "hard-to-train" regions of the domain (Zhang et al., 2025).
Relative Loss Balancing (ReLoBRaLo)	Uses a random lookback mechanism to balance relative loss contributions.	Demonstrated to be faster and more accurate for benchmark PDEs (Bischof, 2021).
Primal-Dual (PD) Optimization	Reformulates the problem into primal and dual sub-problems solved iteratively.	Enhances robustness against sensitivity to parameter initializations (Barreau & Shen, 2024).

Neural Operators and Continuous-Time Dynamics

While PINNs solve specific instances of PDEs, neural operators such as the Fourier Neural Operator (FNO) aim to learn the solution operator across various parameter spaces. This allows the model to map input parameters and state variables to solutions without requiring retraining for new boundary conditions (Yuan et al., 2025).

Furthermore, the integration of Neural Ordinary Differential Equations (Neural ODEs) allows for the modeling of continuous-time dynamics. This approach is exemplified by the ClimODE framework, which implements the advection principle from statistical mechanics to model weather changes as the spatial movement of quantities over time (Azizzadenesheli et al., 2024). By enforcing value-conserving dynamics, such models promote stability in long-horizon forecasts, ensuring that quantities like mass or energy are conserved during simulation (Verma et al., 2024).

Advances in Seismic Imaging and Full-Waveform Inversion

Seismic Full-Waveform Inversion (FWI) is a high-resolution imaging technique used to reconstruct subsurface velocity models by minimizing the difference between observed and modeled seismic data. Traditional FWI is non-linear and computationally expensive (Cheng & Alkhalifah, 2025).

Physics-Driven Deep Learning for Velocity Reconstruction

Hybrid AI models address these challenges by augmenting traditional gradient-descent algorithms with physics-informed deep convolutional neural networks (DCNs). In these frameworks, the acoustic or elastic wave equation serves as a fundamental constraint (Adepehin et al., 2025). Models like InversionNet map raw seismic data to velocity models with a significant reduction in computational cost, enabling inference on resource-constrained edge devices (Rucker et al., 2017).

Table 2. Hybrid Seismic Imaging Architectures and Their Impacts

Seismic Architecture	Component Integration	Primary Benefit
U-Net + Gravity Equations	Integrates gravity forward equations as a constraint term.	Enhances recovery of deep subsurface density structures (Huang et al., 2021).
InversionNet	Raw seismic data to velocity model mapping.	Enables inference on edge devices with minimal delay (Adepehin et al., 2025).
ResNet-101 + Attention	Learns mapping from low-frequency to high-frequency features.	Improves resolution of RTM images without traditional adjoint solvers (Cheng & Alkhalifah, 2025).
Physics-Constrained GP	Gaussian Process with wave equation priors.	Predicts solutions with high accuracy using small training datasets (Karniadakis et al., 2021).

Overcoming Domain Gaps with Synthetic-to-Real Transfer

A persistent challenge in seismic AI is the "domain gap" the discrepancy between synthetic training data and real-world field data. Hybrid models mitigate this by improving the realism of synthetic datasets through advanced physics modeling. Incorporating the elastic wave equation rather than the acoustic approximation allows for more accurate arrival amplitudes that closely mirror field data (Nurtas et al., 2025). Additionally, integrating sedimentary priors and structural geological knowledge into synthetic data generation captures essential reflection events that are often absent in purely data-driven simulations (Ghyselincks et al., 2026).

Reservoir Engineering and Petrophysical Performance

Management of underground storage and hydrocarbon recovery relies on accurate reservoir simulations and history matching. Traditional grid-based methods are time-consuming and prone to human error (Okon et al., 2025).

Hybrid History Matching and Property Prediction

Research indicates that combining traditional reservoir simulators with machine learning significantly enhances prediction accuracy. In the Sarir C-Main field study, a hybrid workflow using Long Short-Term Memory (LSTM) networks and Transfer Learning outperformed traditional history-matching predictions, achieving a 61.2% improvement in Root Mean Square Deviation (RMSD) (MDPI, 2024). Techniques such as Dynamic Time Warping (DTW) have proven robust in filling data gaps, which are a common challenge in reservoir management (Al-Nouti et al., 2024).

Optimization of Enhanced Oil Recovery (EOR)

Water-alternating-gas (WAG) injection is a critical EOR technique, yet its performance is sensitive to operational strategies. Hybrid models combining Genetic Algorithms (GA) and Artificial Neural Networks (ANN) have been developed to optimize these parameters (Ghorbanpour & Khodapanah, 2025). In the Niger Delta region, an ANN-GA hybrid model achieved R^2 values exceeding 0.97 for porosity, permeability, and water saturation (Nassabeh et al., 2024). The integration of post-hoc physics refinement where priors derived from the Archie-Simandoux model are blended as soft regularizers ensures that these predictions remain geologically consistent (Abdulsada et al., 2025).

Geotechnical Applications: Stability and Infrastructure

In geotechnical engineering, the connection between geophysical phenomena and geostructural processes is harnessed to improve predictive models for tunneling, slope stability, and foundation engineering (Yuan et al., 2025).

Small-Data Challenges and Physics-Guided Regularization

A major constraint in geotechnical site investigations is the sparsity of data; borehole records and soil tests are expensive and provide only point-wise information. PIML addresses this by embedding governing physical principles often differential equations describing soil mechanics or hydrology into the machine learning framework (Harle & Wankhade, 2025).

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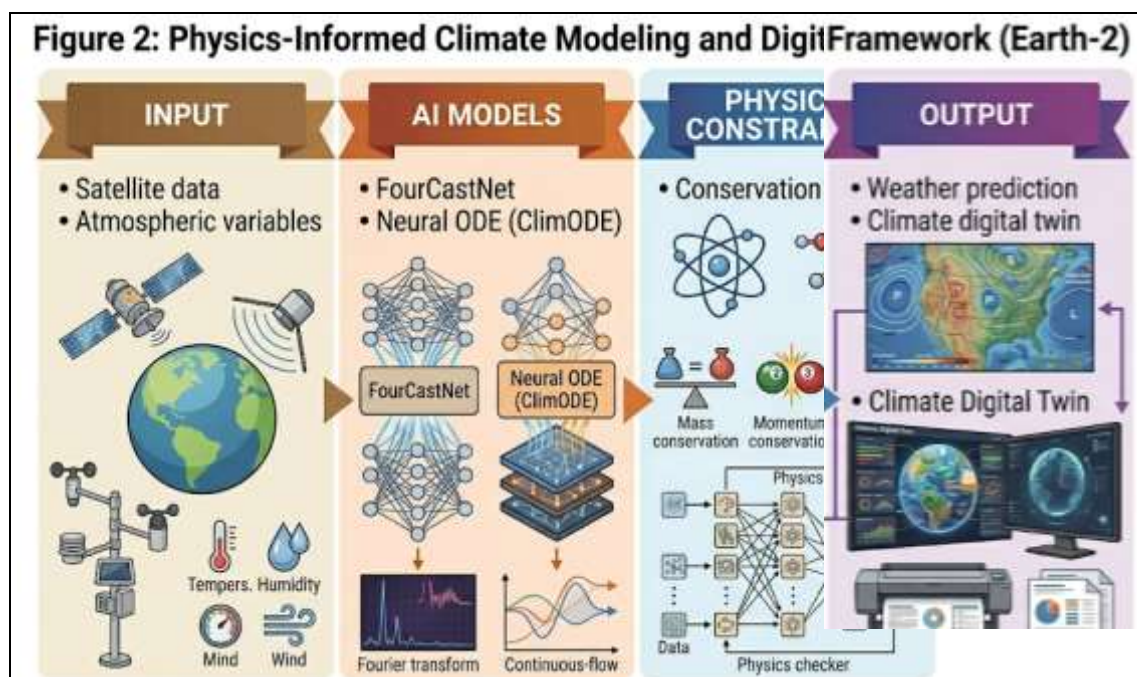
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<http://amresearchreview.com/index.php/Journal/about>**Table 3. Applications of PIML in Geotechnical Infrastructure**

Geotechnical Task	Physics-AI Mechanism	Key Benefit
Tunneling Deformations	Incorporates soil Poisson's ratios and tunnel depth into neural networks.	Faster and more accurate ground movement predictions than FEA (Liu et al., 2023).
Slope Stability	Integrates hydromechanical coupling principles into PIML.	Improved landslide risk assessment under non-stationary conditions (Yuan et al., 2025).
Soil Constitutive Modeling	Embeds elastoplastic principles into recurrent neural architectures.	Captures path-dependent behavior of granular materials (Yuan et al., 2025).
Site Investigation	Uses PIML to interpret sparse borehole and site data.	More reliable characterization of soil properties across large sites (Yuan et al., 2025).

Atmospheric Science and Climate Modeling

The application of hybrid AI to weather and climate forecasting has accelerated over the last five years, driven by the need for models that are faster than traditional numerical weather prediction systems but more physically consistent than pure deep learning (Ahmadi et al., 2025). Figure 2 illustrates the architecture of hybrid AI-based climate modeling systems, including digital twin frameworks such as Earth-2. These systems integrate observational data with physical laws to generate accurate and stable forecasts.



Value-Conserving Dynamics and ClimODE

Traditional data-driven models often neglect underlying physics and lack uncertainty quantification. The ClimODE model addresses these flaws by implementing a continuous-time process based on the advection principle (Havaei et al., 2025). By focusing on the advection equation, ClimODE ensures that the total "mass" of weather quantities remains constant, which promotes stability over long-term forecasts (Han et al., 2025). Furthermore, the model integrates a Gaussian emission model to capture diurnal variations and provide uncertainty estimates (Verma et al., 2024).

The NVIDIA Earth-2 Platform and Digital Twins

NVIDIA's Earth-2 platform represents a major industrial effort to create a digital twin of the Earth's climate. At the heart of this ecosystem is FourCastNetv2, which utilizes a Spherical Fourier Neural Operator to improve model stability and accuracy on global grids (Pathak et al., 2022). The ability to generate large ensemble forecasts thousands of slightly varied initial states allows for the quantification of extreme event likelihoods (Edwards, 2025).

Table 4. Components and Operational Capabilities of NVIDIA Earth-2

Model Component	Variables / Features	Operational Capability
FourCastNetv2	73 variables (8 single-layer, 65 multi-layer variables).	Medium-range global forecasts with predictive stability (Edwards, 2025).
NIM Microservices	Containers for simplified cloud deployment.	Rapid building of generative AI weather applications (Pathak et al., 2022).
DLESyM	Separate AI modules for atmosphere and ocean.	Stable sub-seasonal forecasts up to several months ahead (Edwards, 2025).
Earth2Studio	Multi-GPU inference and scoring tools.	Evaluation of ensemble forecasts in mere hours (Edwards, 2025).

Equation Discovery and Symbolic Regression

A paradigm-shifting application of hybrid AI is the "discovery" of governing equations directly from data. This is particularly useful in geosciences for modeling complex, non-linear phenomena that are not yet fully understood (Amiri et al., 2026).

Sparse Identification of Nonlinear Dynamics (SINDy)

The Sparse Identification of Nonlinear Dynamics (SINDy) algorithm identifies the sparsest set of terms in a predefined library of mathematical functions that can accurately describe a dynamical system (Mangan et al., 2017). This provides a tool to move from empirical observations to interpretable, quantifiable equations, accelerating discovery in disciplines where classical approaches are reaching their limits (Kaheman et al., 2020). Variants such as SINDyG account for network

structures in subsystems, while Modified SINDy (mSINDy) improves robustness in heavy noise scenarios (Brunton et al., 2016).

The Rise of Geo-Foundation Models

The success of Large Language Models has inspired the development of geo-foundation models (GeoFM) large-scale deep learning models pre-trained on vast, diverse datasets to learn transferable representations of the Earth's surface (Zadrozny et al., 2025).

Architectural Innovations for Geospatial Data

GeoFMs are typically based on vision transformer (ViT) architectures adapted to handle multispectral channels and varying spatial resolutions. A central challenge is "geo-alignment" ensuring that data from different modalities (e.g., optical satellite images vs. street view imagery) are correctly aligned (Janowicz et al., 2025).

Table 5. Overview of Specialized Geo-Foundation Model Architectures

Geo-Foundation Model	Key Feature / Innovation	Downstream Task Examples
SatMAE / Prithvi-EO	Masked autoencoders (MAE) for self-supervised learning.	Land cover classification, semantic segmentation (Zadrozny et al., 2025).
GAIR	Geographically aligned implicit representations.	Integrating overhead remote sensing with ground-level imagery (Janowicz et al., 2025).
Clay v1	Model requiring normalized spectral bands from NetCDF.	Ecosystem change detection and similarity search (Janowicz et al., 2025).
TerraTorch	Open-source framework for fine-tuning and benchmarking.	High-performance inferencing for Earth observation (Zadrozny et al., 2025).

Challenges and Future Outlook

While hybrid AI models offer transformative potential, several technical hurdles remain. Training PINNs involves minimizing multiple competing loss terms, which can lead to gradient imbalances. Furthermore, standard multi-layer perceptrons tend to learn low-frequency components more effectively than high-frequency features, a phenomenon known as spectral bias (Barreau & Shen, 2024). The future of geophysics lies in the development of "truly multimodal" GeoFMs that can handle reanalysis data, sensor time-series, and natural language descriptions alongside physical constraints (Bischof, 2021). Additionally, the integration of explainable AI (XAI) will be critical to improving the climate resilience of urban infrastructure (Mahadeva & Sindhushree, 2025; Sindhushree et al., 2025).

Conclusions

Hybrid AI models that fuse physics-based simulations with data-driven approaches mark a significant advancement in geophysics, delivering models that are more accurate, interpretable, data-efficient, and computationally tractable than traditional numerical methods or standalone deep learning. By embedding governing physical laws into neural architectures, loss functions, and operators, these frameworks ensure physical consistency while leveraging observational data to capture complex, poorly understood processes. Successful applications in seismic imaging, reservoir characterization, geotechnical engineering, and climate forecasting demonstrate tangible benefits, including faster inference, improved generalization, uncertainty quantification, and the ability to handle sparse or noisy data. Emerging geo-foundation models and symbolic regression tools further accelerate scientific discovery by learning governing equations directly from data. Nevertheless, challenges such as multi-objective loss balancing, spectral bias, domain gaps between synthetic and real data, and the need for truly multimodal integration must be addressed. Future progress will likely focus on scalable, explainable hybrid systems, real-time digital twins of Earth processes, and tighter coupling with observational networks. This physics-data synergy holds immense promise for enhancing subsurface resource exploration, natural hazard mitigation, sustainable energy management, and climate adaptation strategies in an era of increasing environmental complexity.

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