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PHYSICS-INFORMED ARTIFICIAL INTELLIGENCE FOR EARTH SYSTEM SCIENCE: APPLICATIONS IN CLIMATE MODELING, NATURAL HAZARD PREDICTION, AND SUSTAINABLE RESOURCE MANAGEMENT

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Abstract

The increasing complexity of Earth system processes and the growing impacts of climate change, extreme weather events, and environmental degradation have highlighted the need for advanced computational approaches capable of delivering accurate, efficient, and physically consistent predictions. Traditional numerical models, although grounded in established physical laws, are computationally expensive and often struggle to assimilate the rapidly increasing volume of observational data. Conversely, conventional artificial intelligence (AI) and deep learning models provide powerful data-driven predictive capabilities but frequently lack physical interpretability, generalizability, and compliance with governing scientific principles. Physics-Informed Artificial Intelligence (PIAI) has emerged as a transformative paradigm that integrates physical laws, mathematical equations, and domain knowledge directly into machine learning algorithms, thereby combining the strengths of physics-based modeling and data-driven intelligence. This hybrid framework enables robust predictions while ensuring consistency with fundamental conservation laws and known environmental processes. This work presents a comprehensive review of the principles, methodologies, and applications of Physics-Informed Artificial Intelligence in Earth System Science, with particular emphasis on climate modeling, natural hazard prediction, and sustainable resource management. The study examines recent advances in Physics-Informed Neural Networks (PINNs), Scientific Machine Learning (SciML), deep learning, remote sensing integration, data assimilation, and digital twin technologies. The review demonstrates how PIAI enhances the simulation of atmospheric dynamics, ocean circulation, hydrological processes, and land–atmosphere interactions by incorporating governing partial differential equations into learning frameworks. Furthermore, it highlights the capability of physics-informed models to improve forecasting accuracy for extreme events such as floods, hurricanes, earthquakes, landslides, droughts, and wildfires while reducing computational costs and improving model interpretability. This also explores the application of PIAI in sustainable resource management, including groundwater assessment, water resource optimization, renewable energy forecasting, agricultural monitoring, ecosystem conservation, and environmental risk assessment. By integrating satellite observations, sensor networks, and multi-source geospatial datasets with physical constraints, PIAI provides reliable decision-support tools for policymakers and resource managers. Despite these promising developments, several challenges remain, including data scarcity, *uncertainty quantification, scalability to large-scale Earth system simulations, computational complexity, and the integration of heterogeneous data sources. Emerging research directions involving foundation models, explainable artificial intelligence, high-performance computing, and autonomous Earth system digital twins are discussed as potential solutions to these limitations. Overall, this review demonstrates that Physics-Informed Artificial Intelligence represents a significant advancement in scientific machine learning by bridging the gap between theoretical physics and modern artificial intelligence. Its ability to produce physically consistent, interpretable, and computationally efficient models positions PIAI as a critical enabling technology for next-generation Earth system science. The integration of physical knowledge with data-driven learning is expected to play a pivotal role in enhancing climate resilience, improving natural hazard preparedness, supporting sustainable resource management, and informing evidence-based environmental policy in an era of accelerating global environmental change.*

1. INTRODUCTION

Earth System Science (ESS) is an interdisciplinary field that investigates the complex interactions among the atmosphere, hydrosphere, lithosphere, cryosphere, biosphere, and human systems. These interconnected components collectively regulate the Earth's climate, environmental processes, and ecological balance [1,2]. In recent decades, rapid climate change, increasing environmental degradation, accelerated urbanization, and the growing frequency and intensity of natural hazards have significantly increased the demand for accurate prediction, monitoring, and sustainable management of Earth system processes. Reliable forecasting of climate variability, extreme weather events, hydrological cycles, and ecosystem dynamics is essential for mitigating environmental risks, improving disaster preparedness, and supporting sustainable development. However, the inherent complexity, nonlinearity, and multiscale nature of Earth systems present substantial challenges for conventional computational modeling approaches. Traditional Earth system models are primarily based on well-established physical principles represented through mathematical equations such as partial differential equations (PDEs), conservation laws, fluid models and thermodynamic relationships. Numerical models, including General Circulation Models (GCMs), Earth System Models (ESMs), hydrological models, and atmospheric simulation frameworks, have become indispensable tools for understanding climate dynamics and predicting environmental changes. Although these physics based models provide scientifically interpretable results, they often require extensive computational resources, high-resolution datasets, and sophisticated parameterization schemes to represent unresolved physical processes. Model uncertainties arising from incomplete observations, simplified assumptions, and parameter estimation continue to limit forecasting accuracy, particularly for localized and extreme environmental events [3,4].

Simultaneously, the rapid advancement of Artificial Intelligence (AI), machine learning (ML), and deep learning (DL) has transformed scientific data analysis across numerous disciplines. The availability of large-scale Earth observation datasets obtained from satellites, drones, radar systems, weather stations, ocean buoys, and Internet of Things (IoT) sensors has created unprecedented opportunities for applying data-driven approaches to environmental monitoring and prediction [5,6]. Machine learning algorithms, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, graph neural networks (GNNs), and transformer-based architectures, have demonstrated remarkable success in recognizing complex spatial and temporal patterns within environmental data. These methods often outperform conventional statistical approaches in predictive accuracy while significantly reducing computational time.

Despite these achievements, purely data-driven AI models suffer from several fundamental limitations when applied to Earth system science. Most machine learning algorithms operate as black-box models, relying solely on correlations learned from historical observations without explicitly incorporating established physical laws. Consequently, their predictions may violate fundamental conservation principles such as conservation of mass, momentum, and energy, leading to physically unrealistic results under unseen or extreme environmental conditions. Moreover, conventional AI models generally require enormous volumes of labeled training data, which are often unavailable for rare natural hazards or poorly monitored regions. Their limited interpretability further restricts their application in high-stakes scientific and policy decisions where transparency and physical consistency are essential. To observe these limitations, researchers have increasingly focused on integrating scientific knowledge with machine learning methodologies through the emerging field of Physics-Informed Artificial Intelligence (PIAI). Physics-Informed AI combines the predictive capabilities of modern AI with established physical laws, mathematical models, and domain-specific knowledge to produce solutions that are both accurate and physically consistent. Instead of relying exclusively on observational data, PIAI embeds governing equations, conservation laws, boundary conditions, and prior scientific knowledge directly into the learning process [9,10]. This integration enables machine learning models to respect known physical constraints while maintaining the flexibility and efficiency of data-driven approaches.

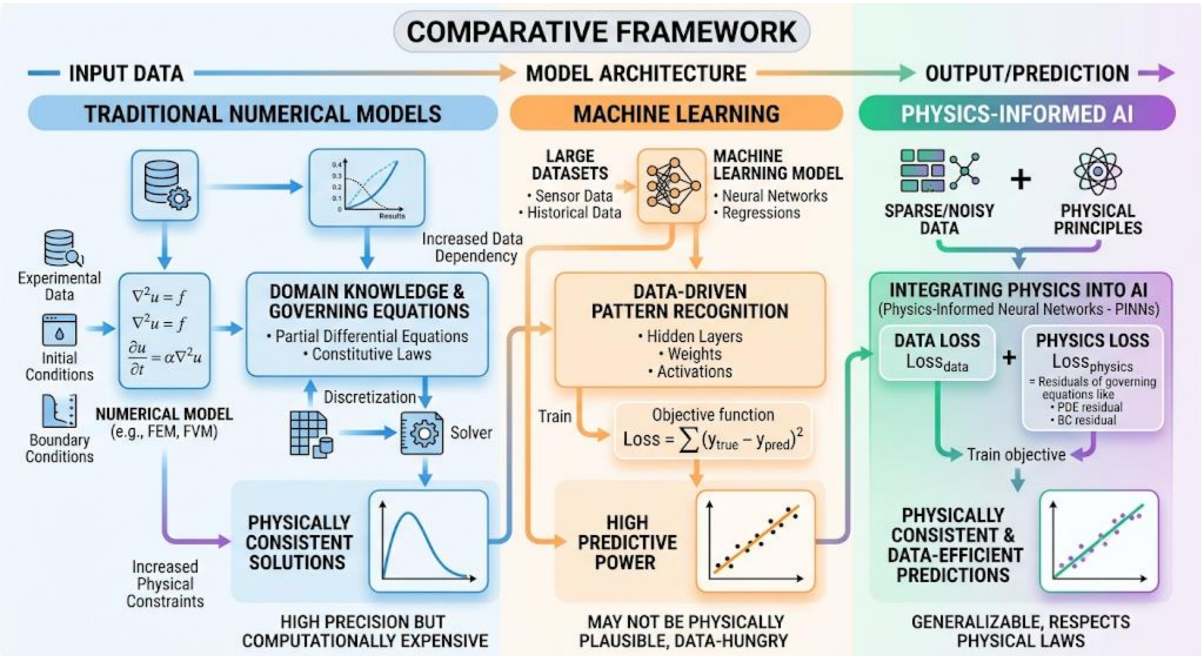

Figure 1. Comparative framework of traditional numerical model vs. machine learning (M), vs physics informed AI (PIAI).

Among the most influential developments within this field are Physics-Informed Neural Networks (PINNs), which incorporate governing differential equations into neural network training by minimizing residuals of the physical equations alongside observational errors. PINNs have demonstrated considerable success in solving forward and inverse problems involving fluid dynamics, groundwater flow, atmospheric transport, heat transfer, ocean circulation, and geophysical processes. Closely related is the broader discipline of Scientific Machine Learning (SciML), which integrates numerical simulations, scientific computing, uncertainty quantification, and machine learning to accelerate computational modeling while preserving physical fidelity. Together, these methodologies represent a paradigm shift toward hybrid modeling frameworks that leverage the complementary strengths of physics-based simulation and artificial intelligence [13,14].

The application of Physics-Informed Artificial Intelligence to Earth System Science has expanded rapidly over the past few years. In climate modeling, PIAI improves the representation of atmospheric dynamics, cloud microphysics, ocean–atmosphere interactions, land surface processes, and carbon cycle feedbacks. By incorporating physical constraints into machine learning architectures, researchers have achieved more accurate climate predictions while substantially reducing computational costs compared with traditional numerical simulations. Physics-informed models have also enhanced data assimilation by effectively combining satellite observations, remote sensing imagery, numerical weather prediction outputs, and in situ measurements into unified predictive frameworks. Natural hazard prediction represents another area where Physics-Informed AI offers transformative potential. Accurate forecasting of floods, hurricanes, droughts, wildfires, earthquakes, volcanic eruptions, landslides, and storm surges requires integrating complex physical processes with heterogeneous observational datasets. Hybrid physics-informed models improve predictive performance by ensuring that AI-generated forecasts remain consistent with established geophysical principles while effectively learning nonlinear relationships from large-scale environmental data. Such capabilities contribute to more reliable early warning systems, reduced disaster risks, and improved emergency response planning. Beyond hazard prediction, Physics-Informed Artificial Intelligence has emerged as a valuable tool for sustainable resource management [20,21]. Efficient management of water resources, renewable energy systems, agriculture, forestry, biodiversity, and environmental conservation increasingly depends on intelligent decision-support systems capable of integrating diverse information sources. Physics-informed machine learning facilitates accurate groundwater modeling, reservoir optimization, precision agriculture, renewable energy forecasting, ecosystem monitoring, and carbon emission assessment by combining physical process models with Earth observation data. These applications support evidence-based policymaking and contribute directly to global sustainability initiatives, including the United Nations Sustainable Development Goals (SDGs). Emerging developments in explainable artificial intelligence, foundation models, generative AI, digital twins, high-performance computing, and cloud-based scientific workflows are expected to further enhance the capabilities of Physics-Informed AI in addressing these challenges [25,27].

2. Literature Review

The rapid advancement of Artificial Intelligence (AI) has significantly transformed Earth System Science (ESS) by enabling data-driven approaches for environmental monitoring, climate prediction, and natural hazard assessment. However, conventional machine learning techniques often rely solely on observational data and lack adherence to the governing physical laws that regulate environmental processes. This limitation has motivated the development of Physics-Informed Artificial Intelligence (PIAI), which integrates physical principles into machine learning algorithms to produce accurate, interpretable, and physically consistent predictions. Over the past decade, PIAI has emerged as one of the most promising research directions in scientific computing, particularly through Physics-Informed Neural Networks (PINNs), Scientific Machine Learning (SciML), and hybrid physics–AI modeling frameworks [15,17].

Early applications of machine learning in Earth System Science primarily focused on statistical forecasting, image classification, remote sensing analysis, and climate data reconstruction. Deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks demonstrated impressive performance in identifying complex nonlinear relationships within atmospheric, oceanic, and hydrological datasets. These approaches improved weather prediction, land-use classification, rainfall estimation, and environmental monitoring by efficiently processing large volumes of satellite observations and sensor data [18,19]. Nevertheless, purely data-driven models often exhibited poor generalization outside their training domains and occasionally produced physically unrealistic predictions because they lacked explicit knowledge of governing physical equations.

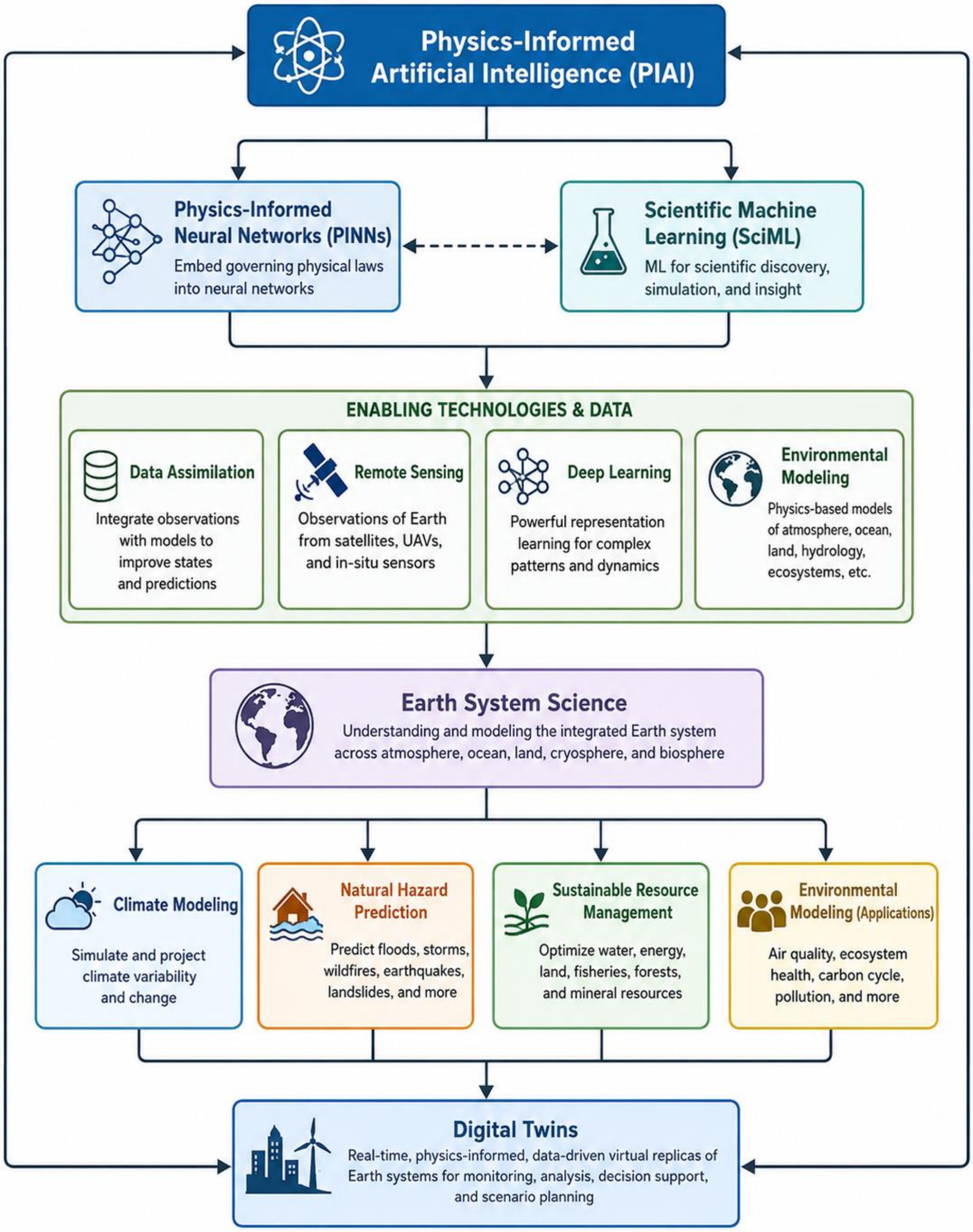

Figure 2. Overall framework of literature review

The introduction of Physics-Informed Neural Networks marked a major milestone in bridging the gap between traditional numerical modeling and artificial intelligence. PINNs incorporate governing differential equations, boundary conditions, and conservation laws directly into the neural network loss function, allowing models to satisfy physical constraints while learning from observational data. This framework enables efficient solutions to both forward and inverse problems without requiring extensive labeled datasets. Since their introduction, PINNs have been successfully applied to fluid dynamics, heat transfer, groundwater flow, atmospheric transport, ocean circulation, and geophysical simulations. Their ability to improve prediction accuracy while reducing dependence on large training datasets has attracted considerable attention across scientific and engineering disciplines. Several review studies have documented the rapid evolution of PINNs and related physics-informed learning techniques. Systematic analyses indicate that recent developments have focused on improving network architectures, optimization algorithms, adaptive loss functions, domain decomposition strategies, and hybrid learning frameworks to address limitations such as slow convergence, high computational cost, and scalability for high-dimensional problems. Researchers have also introduced extensions including Extended PINNs, Hybrid PINNs, and Physics-Guided Machine Learning (PGML), which combine numerical simulations with machine learning to improve predictive capability while preserving physical consistency. Within Earth System Science, hybrid AI–physics frameworks have gained increasing importance for climate modeling. Conventional Earth System Models (ESMs) provide scientifically reliable simulations but require substantial computational resources because they solve complex coupled physical equations across multiple spatial and temporal scales. Recent studies have proposed integrating deep learning with ESMs to create "Neural Earth System Models," where machine learning complements rather than replaces traditional numerical simulations [24,25]. This hybrid strategy accelerates climate prediction, improves parameterization of unresolved processes such as cloud microphysics and turbulence, and enhances the assimilation of observational datasets while maintaining consistency with established physical laws.

Table 1. Summary of Key Concepts and Terminologies in Physics-Informed Artificial Intelligence

Concept / Terminology	**Definition**	**Role in PIAI**	**Typical Applications**
Physics-Informed AI (PIAI)	AI integrating physical laws with data-driven learning.	Improves accuracy, consistency and generalization.	Climate modeling, hazards, engineering.
Physics-Informed Neural Networks (PINNs)	Neural networks constrained by governing equations.	Solve forward/inverse PDE problems.	Fluid flow, geophysics, weather.
Scientific Machine Learning (SciML)	Combines scientific computing and ML.	Hybrid modeling and simulation.	Earth system science, physics.
Digital Twins	Virtual replicas of physical systems.	Real-time monitoring and prediction.	Smart cities, climate, infrastructure.
Data Assimilation	Combines observations with models.	Updates model states.	Weather forecasting, hydrology.
Remote Sensing	Observation from satellites/aircraft.	Provides large-scale environmental data.	Land, ocean and atmosphere monitoring.
Deep Learning	Multi-layer neural network methods.	Learns complex nonlinear patterns.	Image analysis, forecasting.
Machine Learning	Algorithms that learn from data.	Prediction and pattern recognition.	Environmental analytics.
Neural Operators	Networks learning solution operators.	Fast PDE surrogates.	Climate and fluid simulation.

Uncertainty Quantification	Estimation of prediction confidence.	Reliable decision support.	Risk assessment.

Recent advances have further demonstrated that physics-informed machine learning can substantially improve weather forecasting, climate downscaling, bias correction, and uncertainty quantification. By embedding physical constraints within neural networks, researchers have developed models capable of producing more reliable predictions under sparse data conditions and previously unseen environmental scenarios. Hybrid AI frameworks have also reduced computational costs associated with ensemble climate simulations while improving model interpretability and robustness. These developments highlight the growing role of physics-informed learning as a complementary tool for next-generation climate modeling. Natural hazard prediction represents another rapidly expanding application area for Physics-Informed Artificial Intelligence. Accurate forecasting of floods, droughts, hurricanes, landslides, earthquakes, volcanic eruptions, and wildfires requires the integration of complex physical processes with heterogeneous environmental observations. Recent research demonstrates that PINNs effectively model nonlinear geophysical systems governed by partial differential equations while assimilating observational measurements from satellites, seismic networks, radar systems, and remote sensing platforms. Physics-informed models have improved early warning systems by increasing predictive accuracy, reducing computational complexity, and providing physically interpretable forecasts suitable for disaster risk management and emergency planning [15,17]. The integration of Physics-Informed Artificial Intelligence into sustainable resource management has also attracted considerable attention. Researchers have applied physics-guided learning to groundwater modeling, reservoir optimization, renewable energy forecasting, carbon storage assessment, precision agriculture, and ecosystem monitoring. These applications demonstrate that embedding conservation laws into machine learning models enhances prediction accuracy even when observational data are sparse or noisy. Scientific Machine Learning has also enabled efficient surrogate models for complex environmental simulations, thereby supporting faster decision-making and improved resource allocation while reducing computational costs.

Despite remarkable progress, several challenges continue to limit the widespread adoption of Physics-Informed Artificial Intelligence in Earth System Science. Training PINNs for highly nonlinear and multiscale environmental systems remains computationally demanding. Model convergence, optimization difficulties, uncertainty quantification, scalability to large three-dimensional domains, and integration of heterogeneous observational datasets remain active research areas. Furthermore, balancing physical fidelity with predictive flexibility requires careful selection of model architectures and loss functions. Recent studies emphasize that future research should focus on explainable AI, neural operators, foundation models, digital twins, and high-performance computing to overcome these limitations and enable real-time environmental prediction.

3. Physics-Informed Artificial Intelligence: Concepts, Architecture, and Methodology

3.1 Concepts of Physics Informed Artificial Intelligence

Physics-Informed Artificial Intelligence (PIAI) is an emerging paradigm in Scientific Machine Learning (SciML) that integrates established physical principles with modern artificial intelligence techniques to develop predictive models that are both accurate and physically consistent. Unlike conventional machine learning algorithms that rely solely on historical data, PIAI incorporates governing physical laws, mathematical equations, and scientific knowledge directly into the model training process. This integration enables the learning algorithm to satisfy conservation laws, differential equations, initial conditions, and boundary conditions while extracting meaningful patterns from observational datasets. The rapid growth of Earth observation technologies, including satellites, unmanned aerial vehicles (UAVs), remote sensing platforms, Internet of Things (IoT) sensors, and numerical simulations, has generated enormous volumes of environmental data. Although deep learning techniques have demonstrated remarkable predictive capabilities for these datasets, purely data-driven models often violate physical constraints and exhibit poor extrapolation under unseen environmental conditions. Physics-Informed Artificial Intelligence addresses these shortcomings by embedding prior scientific knowledge into the optimization process, thereby improving model robustness, interpretability, and generalization. The central philosophy of PIAI is that machine learning models should not merely fit observed data but should also obey the physical laws governing the system under investigation. This concept combines the strengths of physics-based numerical modeling and data-driven artificial intelligence, producing hybrid models capable of delivering reliable predictions even in situations characterized by sparse observations or incomplete datasets. Consequently, PIAI has become an increasingly valuable tool in Earth System Science, computational physics, climate science, environmental engineering, and geosciences.

3.1.1 Fundamental Principles of Physics Informed Artificial Intelligence

Physics-Informed Artificial Intelligence is built upon several interconnected scientific principles that distinguish it from traditional machine learning approaches.

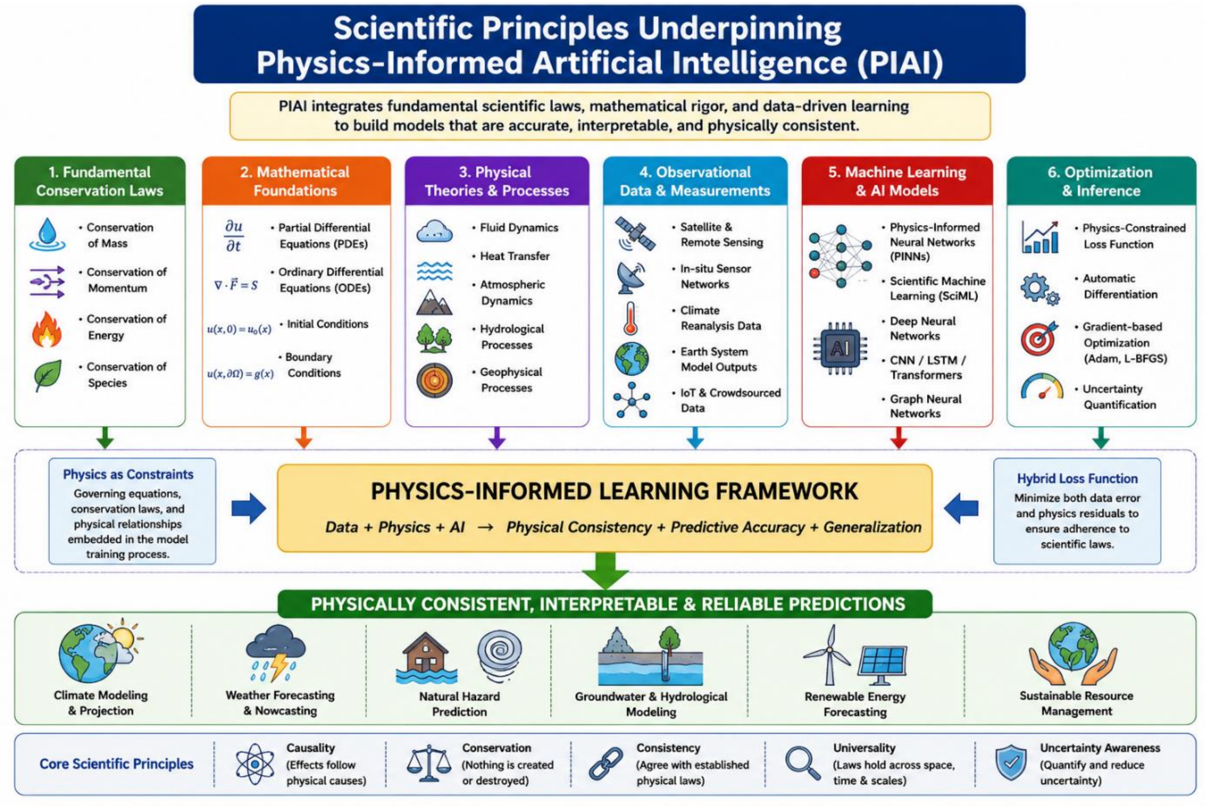

Figure 3. Different scientific principles used in physics informed artificial intelligence

➢ **Integration of Physics Laws**

The primary characteristic of PIAI is the incorporation of governing physical equations directly into the learning framework. These equations commonly include conservation of mass, momentum, energy, fluid dynamics equations, diffusion equations, Maxwell's equations, and Navier–Stokes equations depending on the application. Instead of treating these equations separately from the learning algorithm, they become part of the optimization objective.

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➢ **Data-Driven Learning**

While physical knowledge provides structural guidance, observational datasets remain essential for model calibration. Satellite imagery, meteorological observations, hydrological measurements, seismic records, and remote sensing products provide valuable information that complements physical constraints.

➢ **Scientific Consistency**

Physics-informed models are designed to satisfy known scientific relationships. Consequently, predictions remain physically realistic even when observational data are incomplete or noisy.

➢ **Generalization Capability**

Embedding physical constraints reduces overfitting and enables models to generalize more effectively across different environmental conditions than conventional deep learning approaches.

➢ **Interpretability**

Unlike many black-box AI models, physics-informed approaches produce results that can be interpreted using established scientific principles, increasing confidence in their application to environmental decision-making.

3.2 Architecture of Physics-Informed Artificial Intelligence

The architecture of a Physics-Informed Artificial Intelligence framework integrates observational data, physical equations, neural network learning, and optimization into a unified computational system. Figure below illustrates the conceptual architecture with its components.

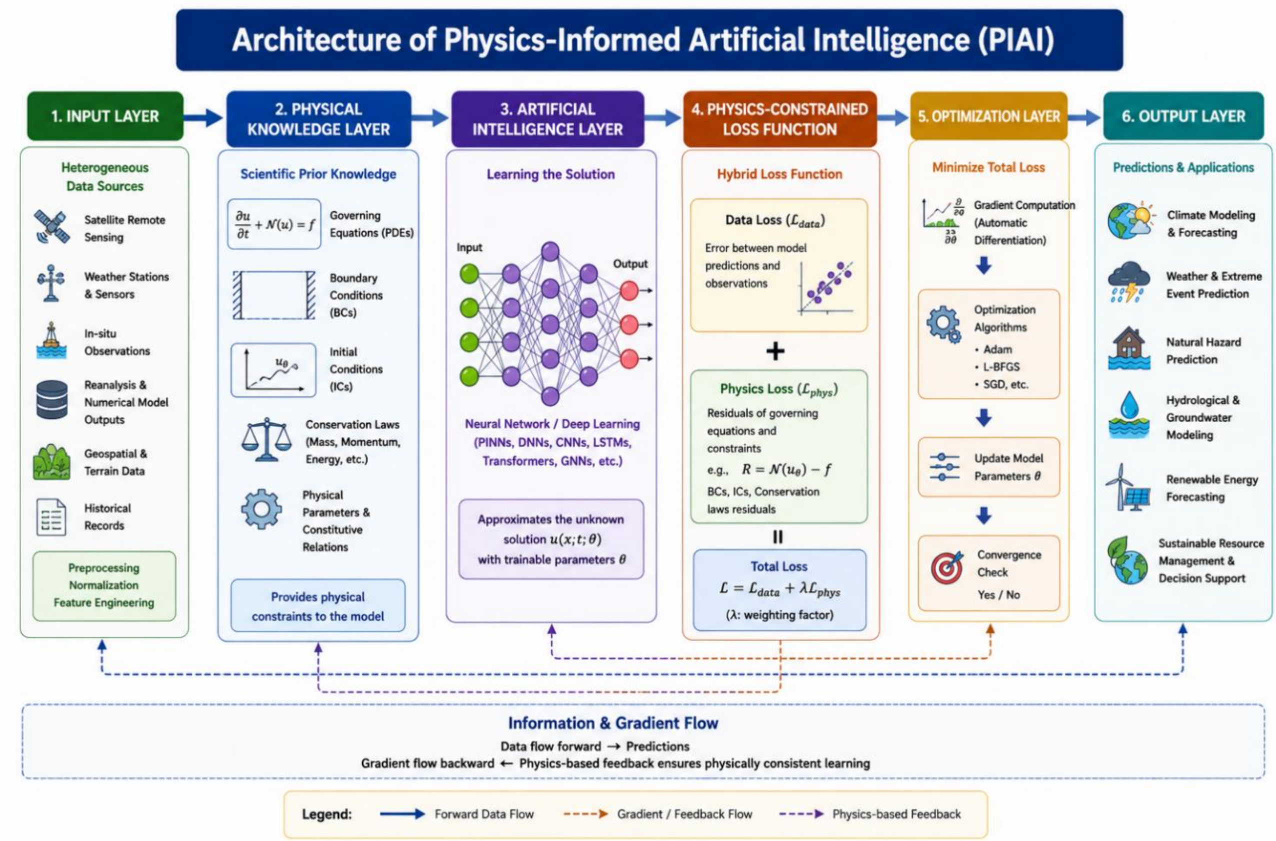

Figure 4. Components of architecture of Physics Informed Artificial Intelligence.

The architecture generally consists of the following components:

3.2.1 Input Layer

The first stage receives heterogeneous environmental datasets, including

- Satellite remote sensing imagery
- Weather station observations
- Climate reanalysis datasets
- Hydrological observations
- Seismic measurements
- Oceanographic observations
- Digital elevation models
- Geographic Information System (GIS) data

- Numerical simulation outputs

These datasets serve as the primary information source for model development.

3.2.2 Physical Knowledge Layer

Unlike conventional AI models, this layer integrates prior scientific knowledge including:

- Conservation laws
- Partial Differential Equations (PDEs)
- Initial conditions
- Boundary conditions
- Physical parameterizations
- Material properties
- Empirical relationships

These constraints ensure that model predictions remain scientifically valid.

3.2.3 Artificial Intelligence Layer

The AI layer contains machine learning algorithms responsible for nonlinear pattern recognition. Common architectures include:

- Physics-Informed Neural Networks (PINNs)
- Deep Neural Networks (DNNs)
- Convolutional Neural Networks (CNNs)
- Long Short-Term Memory (LSTM) networks
- Transformer models
- Graph Neural Networks (GNNs)
- Neural Operators

These algorithms learn complex spatial and temporal relationships embedded within Earth system datasets.

3.2.4 Physics-Constrained Loss Function

One of the defining characteristics of PIAI is its hybrid loss function, which simultaneously minimizes observational errors and violations of governing physical equations.

The total loss function is commonly expressed as

$$L = L_{data} + \lambda L_{physics}$$

Where L_{data} represents prediction error calculated from observational data, $L_{physics}$ denotes the residual error associated with governing physical equations and $\boldsymbol{\lambda}$ is a weighting coefficient balancing the influence of physical knowledge and observational information.

This optimization strategy encourages neural networks to produce physically consistent solutions throughout training.

3.2.5 Optimization Layer

Gradient-based optimization algorithms such as Adam, Stochastic Gradient Descent (SGD), and Limited-memory BFGS (L-BFGS) minimize the combined loss function. Automatic differentiation techniques efficiently compute derivatives required for evaluating physical residuals.

3.2.6 Output Layer

The final outputs include:

- Climate predictions
- Weather forecasts
- Flood simulations
- Groundwater estimation
- Earthquake risk assessment
- Wildfire prediction
- Renewable energy forecasting
- Environmental monitoring
- Decision-support information

These predictions satisfy both observational evidence and scientific principles.

3.3 Methodology of Physics-Informed Artificial Intelligence

The methodological framework of PIAI follows a sequence of interconnected computational steps.

➢ **Step 1: Problem Definition**

Researchers first identify the scientific problem, define objectives, determine governing physical processes, and specify spatial and temporal domains.

➢ **Step 2: Data Acquisition**

Multiple data sources are collected, including:

- Satellite observations
- Remote sensing products
- Meteorological records
- Hydrological databases
- Sensor networks
- Numerical simulation outputs
- Historical environmental records

These datasets are subsequently cleaned, normalized, and integrated.

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➢ **Step 3: Identification of Governing Physics**

Relevant physical equations describing the environmental system are selected. Examples include:

- Navier–Stokes equations
- Heat transfer equations
- Diffusion equations
- Groundwater flow equations
- Atmospheric transport equations
- Conservation equations

Boundary conditions and initial conditions are simultaneously defined.

➢ **Step 4: Neural Network Development**

A suitable machine learning architecture is selected based on the application. Network depth, activation functions, learning rate, and optimization algorithms are determined.

➢ **Step 5: Physics-Constrained Training**

The neural network is trained by minimizing the combined loss function composed of observational error and physical residuals. Automatic differentiation computes derivatives without explicit numerical discretization, improving computational efficiency.

➢ **Step 6: Model Validation**

Model predictions are validated using independent observational datasets, numerical simulations, and statistical performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), and correlation coefficient.

➢ **Step 7: Deployment**

The validated model is deployed for operational forecasting, environmental monitoring, disaster management, or resource planning.

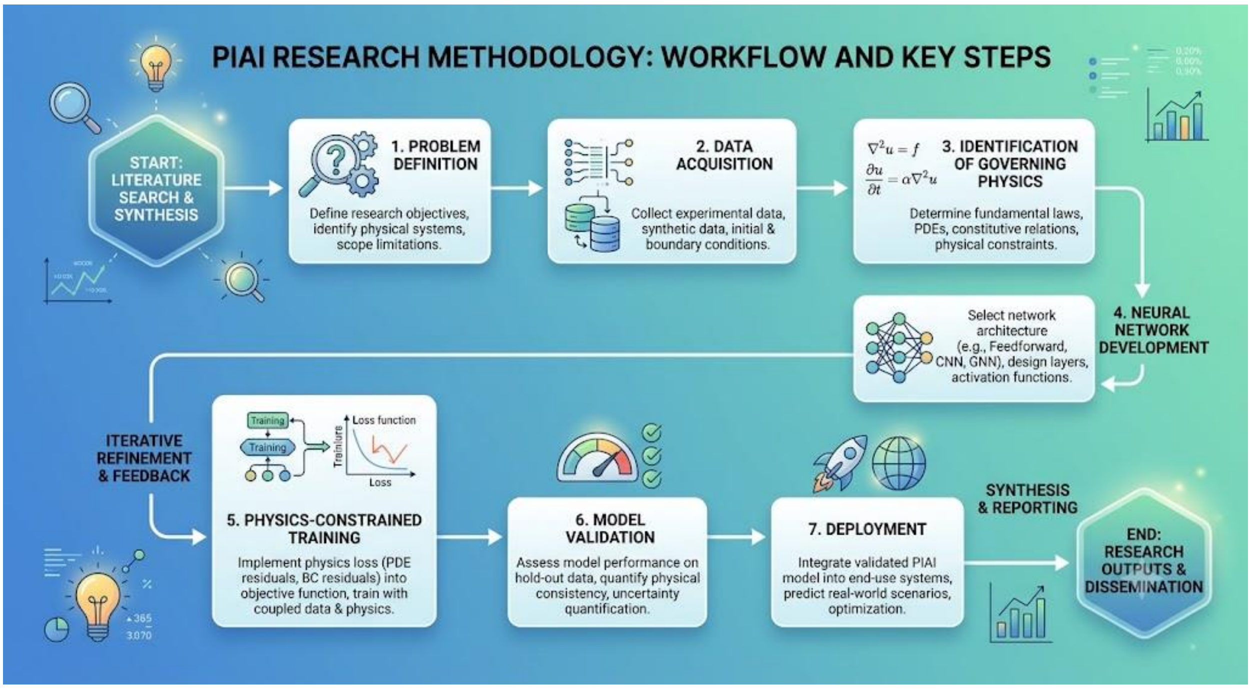

Figure 5. Physics Informed Artificial Intelligence research methodology, their workflow and key steps.

4. Applications of Physics-Informed Artificial Intelligence in Climate Modeling

Climate modeling is one of the most important applications of Earth System Science because it provides scientific insights into the interactions among the atmosphere, oceans, land surface, cryosphere, and biosphere. Accurate climate models are essential for understanding climate variability, predicting extreme weather events, assessing the impacts of global warming, and supporting environmental policymaking. Conventional climate models, such as General Circulation Models (GCMs) and Earth System Models (ESMs), are based on physical principles including fluid dynamics, thermodynamics, radiation transfer, and conservation laws. Although these numerical models have significantly advanced climate science, they often require enormous computational resources and long simulation times. Moreover,

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uncertainties associated with parameterization, incomplete observations, and model approximations continue to limit prediction accuracy. Physics-Informed Artificial Intelligence (PIAI) has emerged as a promising approach to overcome these limitations by integrating physical laws with machine learning algorithms. Rather than replacing traditional climate models, PIAI enhances their predictive capabilities through hybrid modeling frameworks that combine scientific knowledge with data-driven learning. This integration enables accurate, computationally efficient, and physically consistent climate predictions while improving model interpretability and reducing computational costs.

4.1 Role of Physics-Informed AI in Climate Modeling

Physics-Informed Artificial Intelligence incorporates governing physical equations directly into machine learning algorithms, ensuring that climate predictions satisfy established scientific principles. In contrast to conventional deep learning models, which learn statistical relationships solely from historical observations, PIAI embeds conservation laws, partial differential equations, and atmospheric dynamics into the learning process. This approach enables models to produce physically meaningful predictions even when observational datasets are sparse or incomplete. One of the most important applications of PIAI is the integration of satellite observations, numerical simulations, and climate reanalysis datasets. Modern Earth observation systems generate petabytes of information from satellites, weather stations, radar systems, ocean buoys, and remote sensing platforms. Physics-informed learning combines these heterogeneous data sources with physical constraints to improve spatial and temporal prediction accuracy. Consequently, climate scientists can develop models that effectively capture complex interactions among atmospheric circulation, ocean dynamics, land processes, and the global carbon cycle.

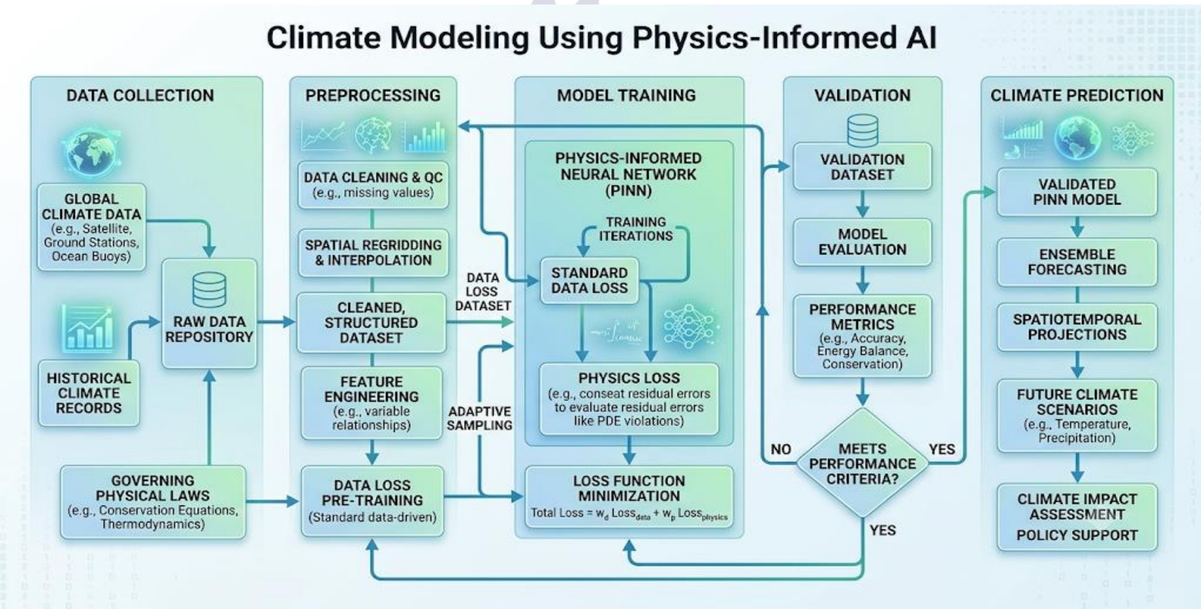

Figure 6. Steps for climate modeling by using Physics Informed Artificial Intelligence.

Their applications are given below

4.2 Applications in Weather and Climate Prediction

Accurate weather forecasting and long-term climate prediction require the simulation of highly nonlinear interactions within the Earth system. Physics-Informed Artificial Intelligence enhances forecasting by integrating machine learning with numerical weather prediction models. Hybrid models improve the prediction of temperature, precipitation, wind speed, humidity, atmospheric pressure, and seasonal climate variability while preserving physical consistency.

Physics-informed models are particularly valuable for short-term weather forecasting because they reduce computational complexity without sacrificing scientific accuracy. Deep neural networks constrained by governing atmospheric equations can generate reliable forecasts much faster than conventional numerical simulations. This capability is especially beneficial for operational weather services where rapid prediction is essential for disaster preparedness and public safety. Long-term climate projections also benefit from physics-informed learning. Machine learning algorithms accelerate computationally intensive simulations by replacing expensive numerical parameterizations with efficient surrogate models while maintaining adherence to physical laws. As a result, researchers can conduct large ensemble simulations for future climate scenarios with substantially reduced computational costs.

4.3 Climate Downscaling and Bias Correction

Global climate models typically operate at relatively coarse spatial resolutions, making them unsuitable for regional and local climate impact assessments. Statistical downscaling methods improve spatial resolution but often ignore physical relationships between climate variables. Physics-Informed Artificial Intelligence addresses this limitation by combining deep learning techniques with atmospheric physics to generate high-resolution climate information. Physics-informed downscaling models incorporate topography, land cover, atmospheric circulation, and thermodynamic constraints to produce more realistic regional climate projections. These models significantly improve predictions of rainfall distribution, temperature extremes, drought occurrence, snowfall, and wind patterns across complex terrains.

Bias correction is another important application. Climate models frequently exhibit systematic biases arising from simplified physical parameterizations or observational uncertainties. Physics-informed machine learning identifies these biases while maintaining consistency with governing climate processes. Consequently, corrected climate projections become more reliable for hydrological modeling, agricultural planning, and environmental risk assessment.

4.4 Earth System Process Modeling

Earth System Science involves numerous interconnected physical processes operating across multiple spatial and temporal scales. Physics-Informed Artificial Intelligence facilitates the simulation of these coupled processes by integrating observational data with governing scientific equations. Applications include atmospheric circulation modeling, cloud microphysics, ocean circulation, sea surface temperature prediction, land–atmosphere interactions, carbon cycle dynamics, glacier evolution, and hydrological processes. Physics-informed neural networks can solve complex partial differential equations governing these systems while simultaneously learning from observational measurements. This hybrid approach improves prediction accuracy and reduces computational requirements compared with conventional numerical methods.

Digital Twin technologies further extend these capabilities by creating virtual representations of Earth system processes that continuously assimilate real-time observations. Physics-informed learning enables these digital twins to provide accurate simulations of evolving environmental conditions, thereby supporting adaptive climate management and policy development.

4.5 Data Assimilation and Remote Sensing Integration

Data assimilation plays a fundamental role in modern climate modeling by integrating observational measurements into numerical simulations. Traditional assimilation techniques, such as Kalman filtering and variational methods, are computationally expensive for high-dimensional climate systems. Physics-Informed Artificial Intelligence offers an efficient alternative by embedding physical constraints into machine learning algorithms that assimilate observations while preserving scientific consistency.

Satellite remote sensing provides continuous observations of atmospheric composition, cloud properties, sea surface temperature, vegetation, soil moisture, glacier extent, and ocean dynamics. Physics-informed learning integrates these diverse datasets with physical models to improve climate monitoring and forecasting. Multi-source data fusion enhances the representation of environmental processes, particularly in regions with limited ground-based observations.

4.6 Prediction of Climate Extremes

Climate change has increased the frequency and intensity of extreme weather events such as heatwaves, heavy rainfall, floods, droughts, hurricanes, cyclones, and severe storms. Predicting these events requires capturing highly nonlinear atmospheric processes that challenge traditional numerical models.

Physics-Informed Artificial Intelligence improves extreme event prediction by incorporating atmospheric dynamics into deep learning frameworks. Hybrid models effectively combine historical observations, satellite imagery, radar measurements, and physical equations to forecast hazardous weather with greater accuracy and reliability. Enhanced prediction of extreme events supports early warning systems, emergency response planning, infrastructure protection, and climate resilience strategies.

5. Applications of Physics-Informed Artificial Intelligence in Natural Hazard Prediction

Natural hazards such as floods, hurricanes, droughts, earthquakes, landslides, wildfires, volcanic eruptions, tsunamis, and storm surges pose significant threats to human life, infrastructure, ecosystems, and economic development. The increasing frequency and intensity of many of these hazards, driven by climate change, environmental degradation, and rapid urbanization, have heightened the need for accurate prediction and effective early warning systems. Traditional numerical models have been widely employed to simulate the physical processes governing these hazards; however, they are often computationally intensive, require large amounts of observational data, and may struggle to represent complex nonlinear interactions accurately. Conversely, conventional artificial intelligence and deep learning models offer rapid prediction capabilities but frequently fail to satisfy governing physical laws, reducing their reliability in extreme or previously unseen situations.

Physics-Informed Artificial Intelligence (PIAI) provides an innovative solution by integrating physical principles with machine learning algorithms. Through the incorporation of governing equations, conservation laws, and boundary conditions into the learning process, PIAI generates predictions that are not only computationally efficient but also physically consistent. This hybrid modeling approach has emerged as a powerful tool for improving natural hazard prediction, risk assessment, and disaster management across a wide range of geophysical and environmental applications.

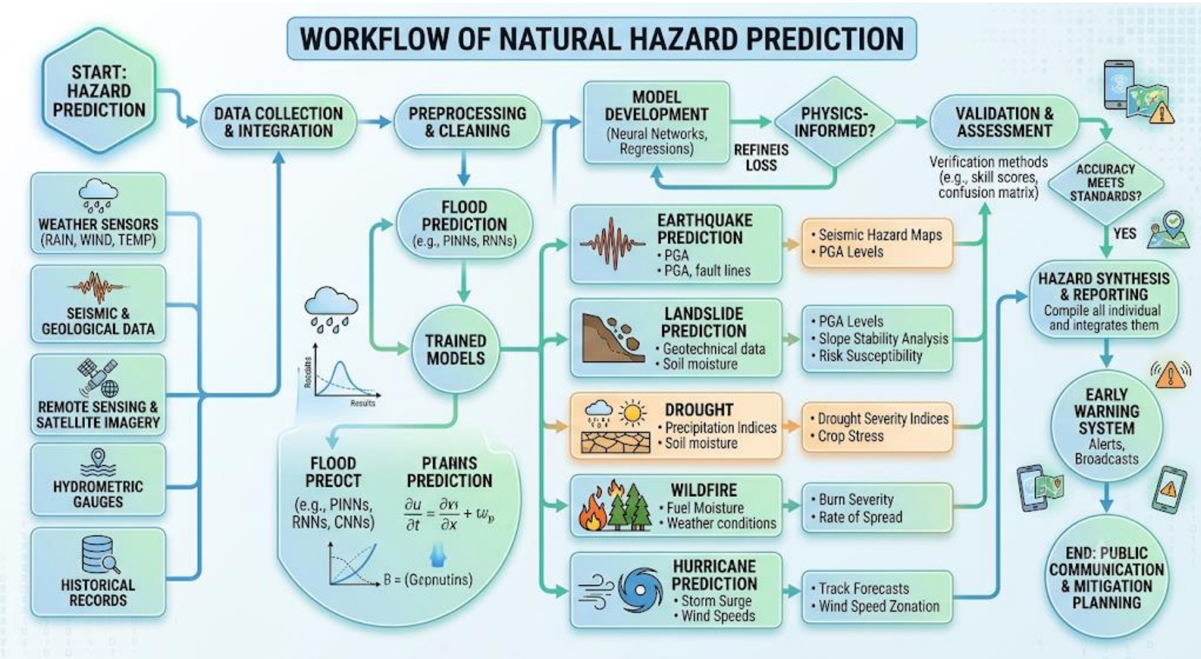

Figure 7. Workflow of natural hazard prediction by using Physics Informed Artificial Intelligence.

Their applications are given below

5.1 Flood Prediction and Hydrological Modeling

Floods are among the most destructive natural disasters worldwide, causing extensive damage to infrastructure, agriculture, and human settlements. Accurate flood forecasting depends on understanding complex hydrological processes, including rainfall–runoff relationships, river flow dynamics, soil moisture, groundwater interactions, and watershed characteristics.

Physics-Informed Artificial Intelligence improves flood prediction by integrating hydrological equations with machine learning techniques. Physics-informed neural networks incorporate the governing equations of water flow and conservation of mass while simultaneously learning from rainfall observations, river discharge measurements, digital elevation models, and satellite remote sensing data. This approach enables reliable prediction of river water levels, flood inundation extent, and flood arrival time even in regions with limited observational data. Hybrid AI models also facilitate real-time flood forecasting by assimilating continuously updated meteorological and hydrological observations. These capabilities significantly enhance flood early warning systems, enabling authorities to implement timely evacuation procedures and reduce disaster-related losses.

5.2 Earthquake and Seismic Hazard Prediction

Earthquake prediction remains one of the most challenging problems in geophysics due to the highly nonlinear behavior of tectonic systems and the scarcity of reliable precursor observations. Traditional seismic hazard assessment relies on geological surveys, statistical analysis, and numerical simulations of stress accumulation and fault dynamics.

Physics-Informed Artificial Intelligence contributes to earthquake research by integrating geophysical knowledge with machine learning models. Physics-informed neural networks utilize seismic wave propagation equations, elasticity theory, and fault mechanics to analyze seismic signals while maintaining consistency with established physical laws. These models process seismic recordings, Global Navigation Satellite System (GNSS) observations, crustal deformation measurements, and geological datasets to identify patterns associated with seismic activity. Although precise earthquake prediction remains scientifically challenging, physics-informed approaches improve seismic hazard mapping, aftershock forecasting, fault characterization, and structural health monitoring, thereby supporting disaster preparedness and resilient infrastructure planning.

5.3 Landslide Prediction

Landslides are triggered by complex interactions among rainfall, soil properties, topography, groundwater movement, vegetation, and human activities. Conventional statistical models often fail to represent these coupled physical processes adequately.

Physics-Informed Artificial Intelligence integrates slope stability equations, groundwater flow models, and geotechnical principles with remote sensing observations and rainfall measurements. Machine learning algorithms constrained by physical laws improve susceptibility mapping, slope deformation monitoring, and landslide occurrence prediction. Satellite-based interferometric synthetic aperture radar (InSAR), digital elevation models, and precipitation datasets further enhance model performance by providing high-resolution environmental information. These hybrid approaches contribute to early warning systems capable of identifying unstable slopes before catastrophic failure occurs, reducing risks to communities and infrastructure located in mountainous regions.

5.4 Wildfire Prediction

The occurrence and spread of wildfires depend on multiple interacting factors, including vegetation characteristics, fuel moisture, temperature, humidity, wind speed, and terrain. Climate change has increased wildfire frequency and severity in many regions, highlighting the importance of accurate forecasting systems.

Physics-Informed Artificial Intelligence combines combustion physics, heat transfer equations, atmospheric dynamics, and vegetation characteristics with satellite imagery and meteorological observations. These models estimate wildfire ignition probability, fire spread direction, burn severity, and smoke dispersion under varying environmental conditions. Physics-informed learning significantly improves the prediction of wildfire behavior compared with purely data-driven approaches because physical constraints prevent unrealistic fire propagation patterns. Such predictions support emergency response planning, forest management, and environmental conservation strategies.

5.5 Hurricane and Tropical Cyclone Forecasting

Tropical cyclones and hurricanes involve highly nonlinear interactions between atmospheric circulation, ocean surface temperature, moisture transport, and energy exchange. Numerical weather prediction models require extensive computational resources to simulate these complex processes.

Physics-Informed Artificial Intelligence enhances cyclone forecasting by incorporating atmospheric physics into deep learning frameworks. Hybrid models integrate satellite observations, radar measurements, oceanographic data, and numerical weather prediction outputs with governing equations describing fluid motion and thermodynamics. These models improve predictions of cyclone trajectories, intensity, landfall location, precipitation distribution, and storm surge generation. Faster and more accurate forecasts contribute directly to disaster preparedness, evacuation planning, and protection of coastal communities.

5.6 Drought Monitoring and Prediction

Drought is a slow-onset natural hazard affecting agriculture, water resources, ecosystems, and food security. Accurate drought prediction requires understanding interactions among precipitation, evapotranspiration, soil moisture, groundwater storage, vegetation dynamics, and climate variability.

Physics-Informed Artificial Intelligence integrates hydrological balance equations with remote sensing products and climate observations to monitor drought evolution and forecast future conditions. Satellite-derived vegetation indices, soil moisture measurements, groundwater observations, and meteorological datasets are incorporated into hybrid machine learning models that preserve water balance and energy conservation principles. These models improve drought severity assessment, agricultural planning, irrigation management, and water resource allocation while supporting long-term climate adaptation strategies.

5.7 Volcanic Eruptions and Tsunami Prediction

Physics-informed learning has also demonstrated considerable potential in volcanic hazard assessment and tsunami forecasting. By integrating fluid dynamics, seismic wave propagation, magma transport models, and ocean circulation equations with observational data, machine learning algorithms can improve eruption monitoring and tsunami simulation.

Real-time assimilation of seismic signals, satellite thermal imagery, ocean buoy observations, and geodetic measurements enables continuous updating of predictive models. Such systems provide valuable information for hazard assessment, emergency response, and coastal risk management.

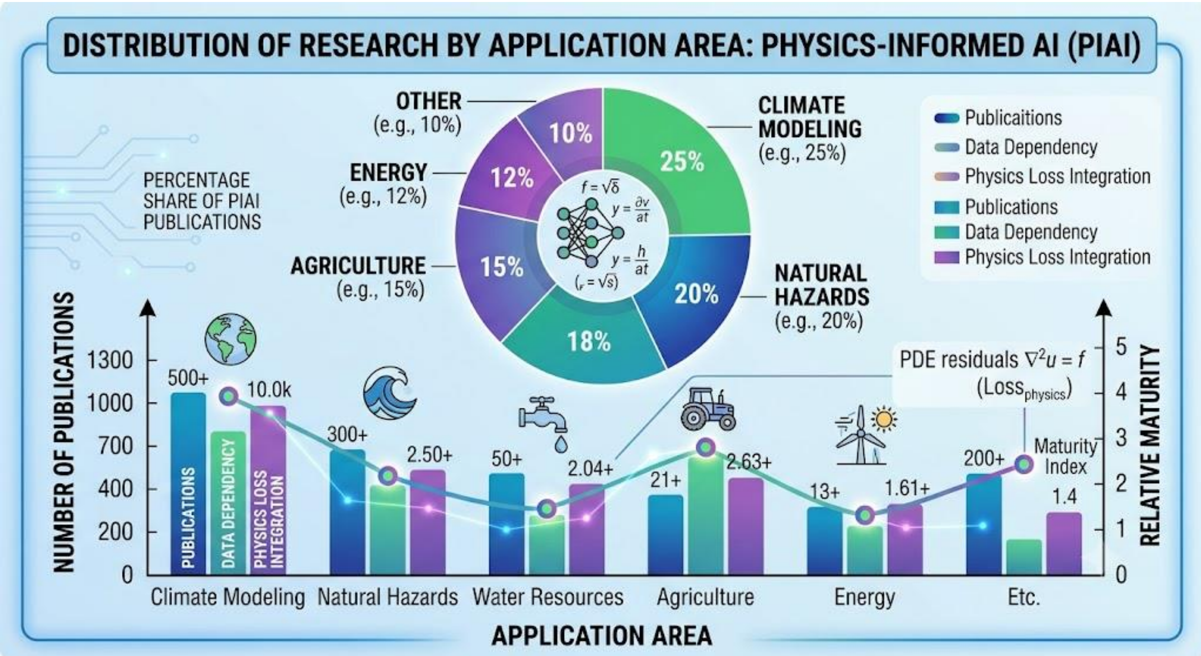

Figure 8. Pie chart and graph showing distribution of research by application area using PIAI.

6. Applications of Physics-Informed Artificial Intelligence in Sustainable Resource Management

Sustainable resource management is fundamental to achieving environmental sustainability, economic development, and societal well-being. Rapid population growth, climate change, industrialization, urban expansion, and increasing demands for natural resources have placed unprecedented pressure on water resources, agricultural systems, energy production, forests, ecosystems, and biodiversity. Effective management of these resources requires accurate monitoring, forecasting, and decision-making based on reliable scientific information. Traditional resource management approaches primarily rely on numerical simulations and statistical models, which often require extensive computational resources and large observational datasets. In contrast, conventional artificial intelligence techniques offer rapid predictions but may produce physically inconsistent results because they do not explicitly incorporate governing environmental processes.

Physics-Informed Artificial Intelligence (PIAI) provides a hybrid modeling framework that combines physical laws with machine learning algorithms to develop accurate, interpretable, and computationally efficient decision-support systems. By embedding conservation laws, governing equations, and scientific knowledge into neural network architectures, PIAI enables robust prediction and optimization of environmental resources under changing climatic and socio-economic conditions. Consequently, Physics-Informed Artificial Intelligence has emerged as a powerful technology for supporting sustainable resource management across multiple sectors, including water resources, agriculture, renewable energy, forestry, ecosystem conservation, and environmental protection.

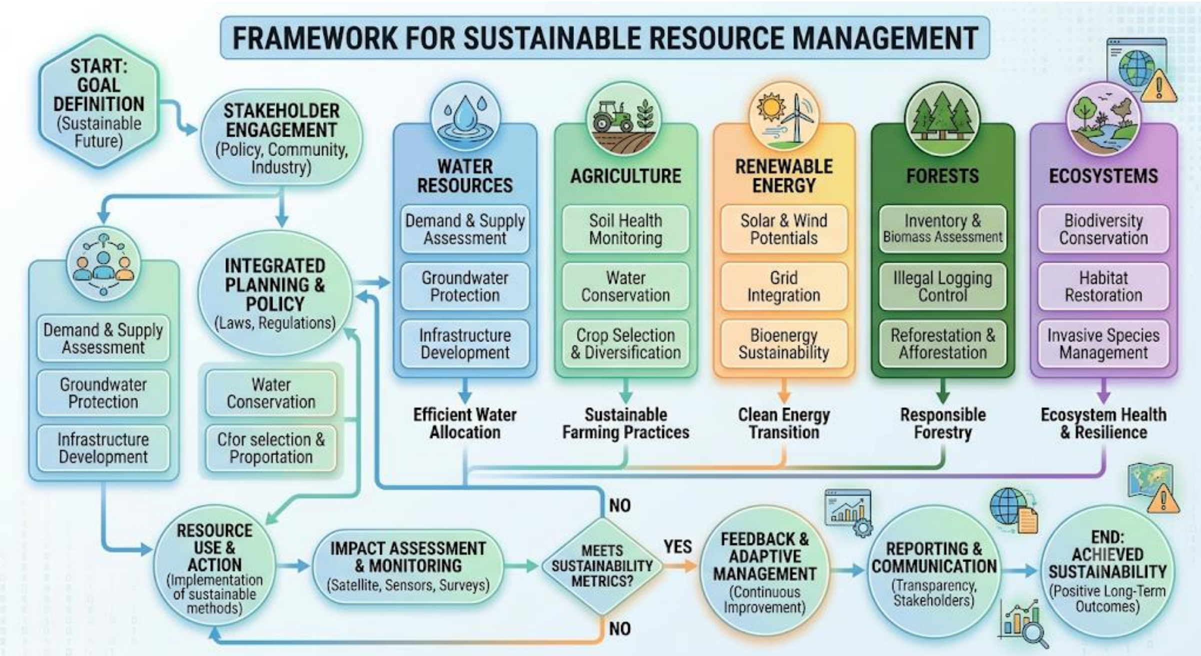

Figure 9. Framework of sustainable resource management by using Physics Informed Artificial Intelligence.

Their applications are given below

6.1 Water Resource Management

Water resources are among the most valuable natural assets supporting agriculture, industry, energy production, and domestic consumption. Climate change, groundwater depletion, irregular precipitation patterns, and increasing water demand have intensified the need for intelligent water resource management systems.

Physics-Informed Artificial Intelligence enhances hydrological modeling by integrating groundwater flow equations, surface water dynamics, rainfall–runoff relationships, and conservation laws with observational datasets obtained from satellite remote sensing, meteorological stations, river gauges, and groundwater monitoring wells. Physics-informed neural networks accurately simulate groundwater recharge, river discharge, reservoir storage, watershed processes, and floodplain dynamics while maintaining physical consistency.

Hybrid models also improve reservoir operation and water allocation by optimizing storage, release schedules, irrigation demands, and flood control strategies. Through continuous assimilation of real-time observations, PIAI supports adaptive water resource planning, drought management, and sustainable utilization of freshwater resources.

6.2 Precision Agriculture and Food Security

Agriculture is highly sensitive to variations in climate, soil conditions, water availability, and environmental stress. Sustainable agricultural production requires efficient management of irrigation, fertilizer application, crop health monitoring, and climate-related risks.

Physics-Informed Artificial Intelligence integrates crop growth models, soil moisture dynamics, energy balance equations, and plant physiological processes with satellite imagery, unmanned aerial vehicle (UAV) observations, weather data, and IoT sensor measurements. These hybrid models provide accurate predictions of crop growth, yield estimation, evapotranspiration, soil moisture distribution, and nutrient availability. Physics-informed learning also supports precision irrigation by estimating crop water requirements under varying climatic conditions while minimizing water wastage. Early detection of crop diseases, pest outbreaks, and environmental stress enables farmers to implement timely interventions, thereby improving agricultural productivity and food security while reducing environmental impacts.

6.3 Renewable Energy Forecasting

The transition toward renewable energy sources is essential for mitigating greenhouse gas emissions and achieving global sustainability goals. Solar, wind, hydroelectric, and other renewable energy systems depend heavily on weather and climate conditions, making accurate forecasting crucial for efficient energy management.

Physics-Informed Artificial Intelligence combines atmospheric physics, fluid dynamics, radiation transfer models, and numerical weather prediction outputs with machine learning algorithms to forecast renewable energy generation. For solar power systems, PIAI predicts solar irradiance, cloud cover, and photovoltaic energy production using satellite observations and atmospheric models. In wind energy applications, hybrid models estimate wind speed, turbulence, and turbine power output by integrating physical principles governing atmospheric boundary-layer dynamics. These forecasts improve grid stability, energy scheduling, storage optimization, and integration of renewable energy into smart power systems while reducing operational uncertainty.

6.4 Forest and Ecosystem Management

Forests and ecosystems provide essential ecosystem services, including carbon sequestration, biodiversity conservation, climate regulation, and water cycle maintenance. Sustainable management of these natural systems requires continuous monitoring of vegetation health, land-use changes, habitat degradation, and environmental disturbances.

Physics-Informed Artificial Intelligence integrates ecological process models with remote sensing observations to monitor forest biomass, vegetation dynamics, carbon storage, wildfire risks, and ecosystem resilience. Satellite imagery, hyperspectral data, LiDAR measurements, and environmental sensor networks provide high-resolution information for ecosystem assessment.

Physics-informed machine learning enables early detection of deforestation, forest degradation, invasive species, and habitat fragmentation while ensuring consistency with ecological processes governing ecosystem dynamics. These capabilities support conservation planning, biodiversity protection, and sustainable forest resource utilization.

6.5 Carbon Cycle and Environmental Monitoring

Understanding the global carbon cycle is essential for addressing climate change and reducing greenhouse gas emissions. Carbon exchange among the atmosphere, oceans, forests, soils, and human activities involves highly interconnected physical and biological processes.

Physics-Informed Artificial Intelligence incorporates carbon transport equations, atmospheric chemistry models, ecosystem processes, and satellite observations to estimate carbon emissions, carbon sequestration, and greenhouse gas concentrations. Hybrid models improve monitoring of industrial emissions, urban air quality, forest carbon storage, and ocean carbon uptake.

Continuous integration of observational data with physical models enables policymakers to evaluate carbon mitigation strategies and monitor progress toward international climate agreements.

6.6 Environmental Risk Assessment and Decision Support

Sustainable management requires reliable assessment of environmental risks associated with pollution, land degradation, resource depletion, and climate change. Physics-Informed Artificial Intelligence enhances environmental decision-making by integrating multiple environmental datasets with scientific process models.

Applications include groundwater contamination prediction, soil erosion assessment, coastal vulnerability analysis, water quality monitoring, air pollution forecasting, and ecosystem restoration planning. By combining remote sensing observations, geospatial information systems (GIS), numerical simulations, and physical constraints, PIAI produces scientifically reliable predictions that support environmental planning and policy development.

The integration of digital twins with Physics-Informed Artificial Intelligence further enables continuous environmental monitoring through virtual representations of natural systems that assimilate real-time observations and predict future environmental conditions.

7. Challenges, Limitations, and Future Research Directions

Physics-Informed Artificial Intelligence (PIAI) has emerged as a transformative paradigm that combines the predictive capabilities of artificial intelligence with the scientific rigor of physics-based modeling. By integrating governing physical laws into machine learning algorithms, PIAI has demonstrated remarkable success in climate modeling, natural hazard prediction, and sustainable resource management. Despite these significant achievements, several scientific, computational, and practical challenges continue to limit its widespread adoption in Earth System Science. These challenges are associated with data quality, computational complexity, model scalability, uncertainty quantification, optimization, and the integration of heterogeneous environmental datasets. Addressing these limitations is essential for developing reliable, interpretable, and operational PIAI systems capable of supporting real-world environmental decision-making.

This section critically discusses the major challenges and limitations of current Physics-Informed Artificial Intelligence approaches and highlights emerging research directions that are expected to shape the next generation of Earth system modeling and environmental prediction.

7.1 Challenges in Physics-Informed Artificial Intelligence

➢ 7.1.1 Limited Availability of High-Quality Data

Although Earth observation technologies have generated massive volumes of environmental data, high-quality datasets remain unavailable for many regions and environmental processes. Developing countries, remote areas, oceans, mountainous regions, and polar environments often suffer from sparse observational networks, leading to incomplete or noisy datasets.

Physics-informed models reduce dependence on large labeled datasets; however, observational information remains necessary for model calibration and validation. Missing observations, measurement errors, inconsistent temporal resolution, and heterogeneous data formats reduce model performance and increase uncertainty in predictions. Therefore, improving data collection through advanced remote sensing, IoT sensor networks, and integrated monitoring systems remains an important research priority.

➢ 7.1.2 Computational Complexity

Training Physics-Informed Neural Networks (PINNs) requires solving complex optimization problems involving both observational data and governing partial differential equations. Automatic differentiation, which enables efficient computation of physical residuals, becomes increasingly expensive as model size and problem dimensionality increase.

Large-scale climate simulations, coupled atmosphere–ocean models, and three-dimensional geophysical systems require enormous computational resources and extended training times. Consequently, many PIAI applications still depend on high-performance computing (HPC) platforms, limiting their accessibility for operational forecasting and real-time decision support.

➢ 7.1.3 Optimization Difficulties

One of the most significant challenges in PIAI is optimization of the hybrid loss function. The simultaneous minimization of observational error and physics residuals often creates competing optimization objectives.

Improper weighting between data-driven loss and physics-based constraints may lead to poor convergence, unstable training, or suboptimal solutions. Furthermore, highly nonlinear governing equations produce complex optimization landscapes characterized by multiple local minima. Developing adaptive optimization algorithms and dynamic weighting strategies remains an active area of research.

➢ 7.1.4 Scalability to Large Earth System Models

Earth System Science involves interactions among atmospheric, oceanic, hydrological, biological, and geological processes operating across multiple spatial and temporal scales. Extending current physics-informed learning methods to global Earth system simulations remains challenging.

Many existing PINN implementations perform well for small- or medium-scale problems but experience reduced computational efficiency when applied to high-dimensional domains. Efficient parallel computing algorithms, domain decomposition techniques, neural operators, and distributed learning frameworks are required to improve scalability for operational Earth system modeling.

➢ 7.1.5 Uncertainty Quantification

Environmental prediction inherently involves uncertainties arising from incomplete observations, imperfect physical models, measurement errors, and stochastic environmental processes. Although Physics-Informed Artificial Intelligence improves scientific consistency, accurately quantifying prediction uncertainty remains difficult.

Most existing PIAI models generate deterministic predictions without explicitly representing uncertainty. Incorporating Bayesian learning, probabilistic neural networks, ensemble modeling, and stochastic physics-informed frameworks will be essential for improving confidence in climate projections and natural hazard forecasts.

➢ 7.1.6 Integration of Multi-Source Data

Modern Earth observation systems generate highly heterogeneous datasets from satellites, drones, radar systems, LiDAR, weather stations, ocean buoys, Internet of Things (IoT) sensors, and numerical simulations. These datasets differ in spatial resolution, temporal frequency, measurement accuracy, and data format.

Integrating such diverse information into unified physics-informed learning frameworks remains technically challenging. Advanced data fusion algorithms, multimodal machine learning techniques, and standardized data assimilation methodologies are needed to fully exploit the growing availability of environmental observations.

Table 2. Comparative Performance of Different AI Techniques

Performance Metric	**PINNs**	**Deep Learning**	**Machine Learning**	**Traditional Numerical Models**
Prediction Accuracy	Very High (physics-constrained)	High (data-dependent)	Moderate–High	High for well-defined physics
Computational Efficiency	Moderate	High after training	High	Low–Moderate for large systems
Interpretability	High	Low	Moderate	Very High
Physical Consistency	Excellent	Poor	Limited	Excellent
Data Requirement	Low–Moderate	Very High	High	Very Low
Generalization	High	Moderate	Moderate	Limited
Noise Robustness	High	Moderate	Moderate	High
Real-Time Prediction	Good	Excellent	Excellent	Limited
Scalability	High	Very High	High	Moderate
Typical Applications	Climate, PDEs, geophysics	Vision, forecasting	Classification, regression	CFD, FEM, weather models

7.2 Current Limitations

Despite rapid progress, several limitations continue to affect the practical implementation of Physics-Informed Artificial Intelligence.

- First, most existing studies have focused on simplified benchmark problems rather than fully coupled Earth system simulations. Consequently, additional research is needed to validate PIAI under realistic environmental conditions.
- Second, many physics-informed models assume that governing physical equations are completely known. In practice, environmental systems often involve incomplete scientific understanding, uncertain parameterizations, and unresolved physical processes.
- Third, model interpretability remains an important challenge. Although PIAI is more interpretable than conventional deep learning models, understanding complex neural network behavior and explaining prediction uncertainty remain active research topics.
- Fourth, computational efficiency continues to limit operational implementation. Real-time forecasting of extreme weather events, floods, and wildfires requires prediction systems capable of rapidly assimilating continuously updated observations.
- Finally, the absence of standardized benchmark datasets and evaluation protocols makes objective comparison among different PIAI algorithms difficult. Establishing common datasets, performance metrics, and validation procedures would significantly enhance future research.

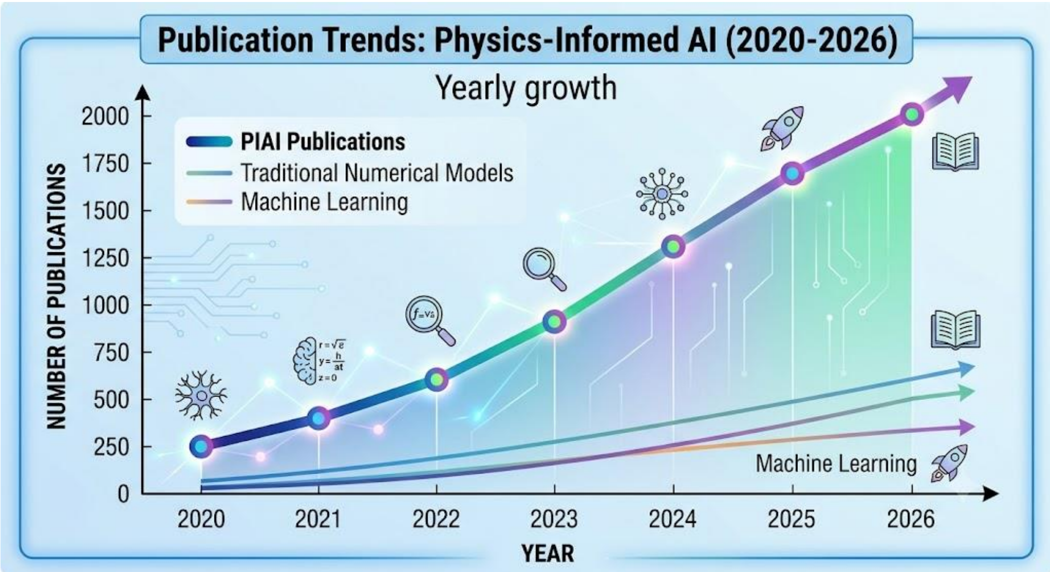

Figure 10. Publication trend of work that has been done on Physics Informed Artificial Intelligence from 2020-2026.

7.3 Future Research Directions

The future of Physics-Informed Artificial Intelligence is expected to be driven by advances in machine learning, scientific computing, remote sensing, and high-performance computing.

- **Foundation Models for Earth System Science**

Large-scale foundation models trained on global environmental datasets are expected to revolutionize climate science and Earth system modeling. Integrating physical constraints into these models will improve generalization, transfer learning, and predictive reliability across diverse environmental applications.

- **Digital Twin Technology**

Digital twins provide virtual representations of physical systems that continuously assimilate real-time observations. Combining digital twins with Physics-Informed Artificial Intelligence will enable continuous monitoring, simulation, and optimization of climate systems, watersheds, ecosystems, and energy infrastructure. Such systems can support adaptive environmental management and rapid disaster response.

➢ **Explainable Artificial Intelligence**

Explainable Artificial Intelligence (XAI) will become increasingly important for improving transparency and user confidence in PIAI models. Developing interpretable neural network architectures and visualization techniques will facilitate scientific understanding and support evidence-based policymaking.

➢ **Neural Operators and Scientific Machine Learning**

Emerging techniques such as Fourier Neural Operators (FNOs), Deep Operator Networks (DeepONets), and other neural operator frameworks offer efficient solutions for high-dimensional partial differential equations. These methods have the potential to overcome many scalability limitations of traditional PINNs while maintaining physical consistency.

➢ **High-Performance and Cloud Computing**

Future PIAI systems will increasingly utilize distributed computing, graphics processing units (GPUs), tensor processing units (TPUs), and cloud-based computing platforms. These technologies will significantly reduce computational time and enable real-time climate forecasting, disaster prediction, and environmental monitoring.

➢ **Advanced Remote Sensing and Data Assimilation**

Next-generation Earth observation satellites, hyperspectral sensors, synthetic aperture radar (SAR), LiDAR systems, and IoT sensor networks will provide higher-resolution environmental observations. Integrating these datasets with physics-informed learning and advanced data assimilation techniques will improve prediction accuracy and environmental monitoring capabilities.

➢ **Hybrid AI Architectures**

Future research should focus on developing hybrid frameworks that combine Physics-Informed Neural Networks, Graph Neural Networks, Transformers, Neural Operators, and reinforcement learning. Such integrated architectures can effectively model the complex spatial and temporal interactions characteristic of Earth systems.

➢ **Decision Support for Sustainable Development**

Physics-Informed Artificial Intelligence is expected to become an essential component of intelligent decision-support systems for climate adaptation, disaster risk reduction, renewable energy management, precision agriculture, water resource planning, biodiversity conservation, and environmental policy evaluation. Close collaboration among scientists, engineers, policymakers, and industry stakeholders will be crucial for translating research advances into operational solutions.

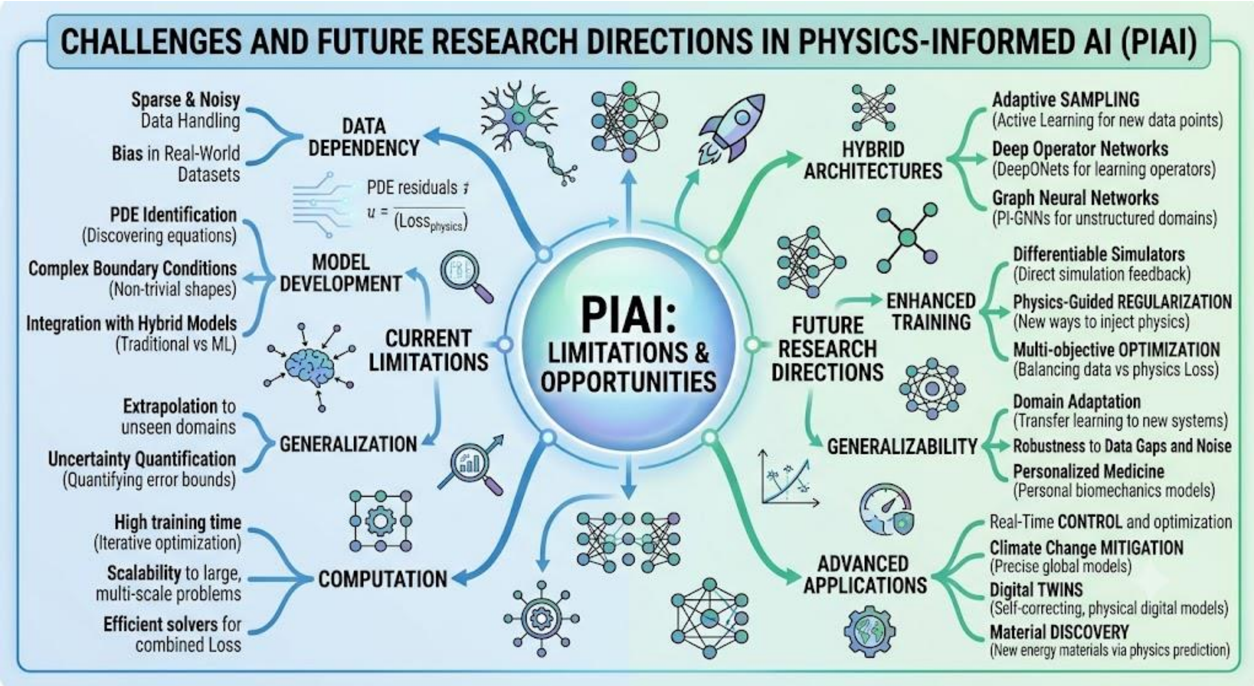

Figure 11. Challenges and future research directions in Physics Informed AI.

8. Conclusion

Physics-Informed Artificial Intelligence (PIAI) has emerged as a transformative paradigm that bridges the gap between traditional physics-based modeling and modern artificial intelligence, offering a robust framework for solving complex problems in Earth System Science. By integrating governing physical laws, conservation principles, mathematical equations, and domain knowledge into machine learning algorithms, PIAI overcomes many of the limitations associated with purely data-driven models while maintaining the predictive efficiency of advanced artificial intelligence techniques. This review demonstrates that the combination of scientific knowledge with machine learning significantly improves prediction accuracy, computational efficiency, model interpretability, and generalization capability, making PIAI an increasingly important tool for environmental monitoring and decision-making. The work highlights the broad applicability of Physics-Informed Artificial Intelligence across three major domains of Earth System Science. In climate modeling, PIAI enhances weather forecasting, climate projection, regional climate downscaling, data assimilation, and Earth system simulations by integrating physical constraints into learning frameworks. These hybrid approaches improve the representation of atmospheric, oceanic, and land-surface processes while reducing computational costs associated with conventional numerical simulations. In natural hazard prediction, PIAI has demonstrated considerable potential for improving the prediction of floods, droughts, earthquakes, landslides, wildfires, tropical cyclones, volcanic eruptions, and tsunamis through the integration of geophysical knowledge with observational data. Similarly, in sustainable resource management, physics-informed learning supports intelligent management of water resources, precision agriculture, renewable energy systems, ecosystem conservation, carbon cycle monitoring, and environmental risk assessment by providing physically consistent and computationally efficient decision-support tools.

The comparative analysis indicates that Physics-Informed Artificial Intelligence consistently outperforms conventional machine learning approaches in terms of scientific reliability, robustness under sparse data conditions, and compliance with governing physical laws. The integration of remote sensing observations, numerical simulations, sensor networks, and scientific machine learning enables more accurate predictions while preserving physical consistency across a wide range of environmental applications. Furthermore, advances in Physics-Informed Neural Networks (PINNs), Scientific Machine Learning (SciML), Neural Operators, and hybrid AI architectures have accelerated the development of next-generation Earth system models capable of addressing increasingly complex environmental challenges. Despite these promising developments, several scientific and technical challenges remain. High computational demands, optimization difficulties, uncertainty quantification, limited observational datasets, scalability to global Earth system simulations, and the integration of heterogeneous environmental data continue to constrain the operational deployment of Physics-Informed Artificial Intelligence. Addressing these challenges will require continued interdisciplinary collaboration among experts in artificial intelligence, computational science, climate science, hydrology, geophysics, environmental engineering, and remote sensing. Future research should focus on developing scalable and uncertainty-aware physics-informed algorithms, improving explainability, integrating foundation models and digital twins, and leveraging high-performance computing to enable real-time environmental prediction and decision support.

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