Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 4 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

AI-Driven Predictive Modeling of Environmental and Climate Patterns Using Machine Learning and Remote Sensing Data for Sustainable Decision-Making

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ABSTRACT

The integration of Artificial Intelligence (particularly machine learning and deep learning) with Geographic Information Systems and remote sensing data has revolutionized predictive modeling of environmental and climate patterns, enabling dynamic, high-resolution analysis for sustainable natural resource management and decision-making. This GeoAI paradigm leverages multi-modal satellite observations (Sentinel-2, Landsat, MODIS), IoT sensors, and advanced architectures such as CNNs for spatial feature extraction, LSTMs for temporal dependencies, Vision Transformers for attention-based modeling, and Physics-Informed Neural Networks (PINNs) to embed physical laws into data-driven predictions. Applications span flood susceptibility mapping, wildfire forecasting, groundwater potential assessment, precision agriculture, forest monitoring, and carbon accounting, often outperforming traditional numerical models in accuracy, speed, and scalability while addressing sub-grid phenomena. Hybrid systems combining physics-based constraints with AI improve interpretability and robustness, supporting real-time early warning, policy formulation, and adaptive strategies. Despite challenges including high computational energy demands, model transferability across regions, and the need for explainable AI, this convergence offers a powerful pathway toward proactive climate resilience, biodiversity conservation, and sustainable development.

Keywords: GeoAI, Machine Learning Climate Modeling, Remote Sensing, Physics-Informed Neural Networks, Predictive Environmental Analytics, Digital Twins, Flood Risk Mapping, Precision Agriculture, Wildfire Detection, Sustainable Decision-Making, Essential Climate Variables, Explainable AI

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Volume 4, Issue 4 (2026)

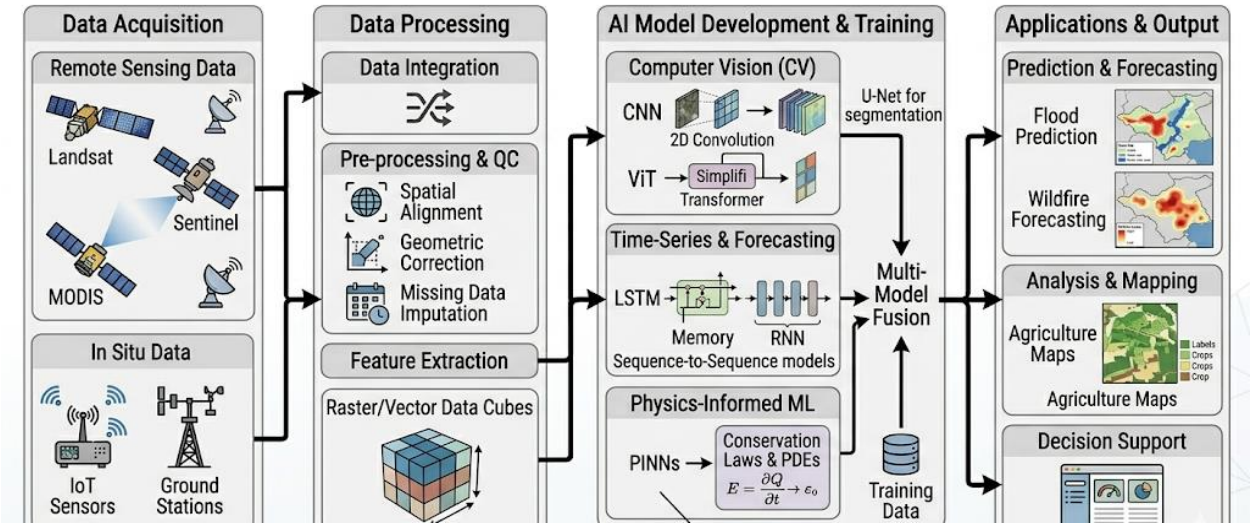
Online ISSN 3007-3197
Print ISSN 3007-3189

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Introduction

The global climate system is currently navigating a period of unprecedented variability, characterized by the intensification of extreme weather events, the shifting of ecological boundaries, and the acceleration of planetary warming. Traditional climate models, which have historically relied upon General Circulation Models (GCMs) and physics-based numerical simulations (Qiu et al., 2024). Are increasingly confronted by significant bottlenecks related to computational intensity, the inability to resolve sub-grid scale phenomena, and a relative lack of real-time adaptability to the modern deluge of heterogeneous environmental data. In response to these long-standing challenges, a paradigm shift is occurring toward the integration of Artificial Intelligence (AI), specifically machine learning (ML) and deep learning (DL), with the expansive observational capabilities of remote sensing (RS) technologies (Li & Xiao, 2025). This convergence provides a transformative framework for multi-risk modeling and hazard forecasting, enabling the synthesis of vast datasets from satellite imagery, Internet of Things (IoT) sensors, and historical meteorological records into actionable insights for sustainable decision-making (Masud et al., 2025). This convergence of Artificial Intelligence and remote sensing is best understood through a unified GeoAI framework. Figure 1 illustrates the complete pipeline from multi-source data acquisition to AI-driven environmental decision outputs.

Figure 1: GeoAI Framework for Environmental and Climate Prediction



The Evolution of Environmental Intelligence and Predictive Frameworks

The transition from traditional numerical modeling to AI-driven environmental intelligence represents more than just a change in computational tools; it is a fundamental shift in how human societies interpret and interact with planetary systems. Conventional monitoring approaches often lack the spatial coverage and temporal frequency necessary to resolve complex agricultural-climate interactions or provide timely alerts for rapid-onset disasters (Ali Abdel Moley, 2023). Historical models

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Print ISSN 3007-3189
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struggle to adapt in real-time as needed, often failing to characterize the multi-scale, highly variable nature of modern climate change (Kamran et al., 2025). The current era of environmental intelligence is defined by the "Compute the Planet" initiative, which leverages ML, remote sensing, and sensor data fusion to convert varied observations into decision-ready products, such as situational awareness maps, ecosystem condition metrics, and hazard indicators (Malakar, 2022).

Recent research emphasizes the necessity of unified big data and AI-driven frameworks that can simulate a wide range of environmental hazards, including floods, heatwaves, and droughts (Gomes et al., 2025). These frameworks are designed to handle the complexity and unpredictable nature of climate phenomena by identifying intricate patterns and non-linear relationships that traditional models may overlook (Sathvara et al., 2024). By integrating AI with physics-based models, researchers are developing hybrid systems that enhance predictive accuracy and scientific groundedness while significantly reducing the computational barriers typically associated with high-resolution global projections (Slater et al., 2023).

Comparative Paradigms in Climate Modeling

Table 1. Comparative Paradigms in Climate Modeling

Feature	Conventional Numerical Methods (GCMs)	AI-Driven Predictive Models	Hybrid Physics-Informed Systems (PINNs)
Primary Logic	Differential equations & physical laws	Data-driven pattern recognition	Integrated physics-data learning
Computational Demand	Extreme (supercomputers required)	High for training; low for inference	Optimized; requires fewer labeled data
Resolution	Coarse (struggles with sub-grid scales)	High (capable of km-scale downscaling)	High (resolves sub-grid dynamics)
Real-Time Capability	Low (long simulation run times)	High (rapid-response alerts)	High (dynamic and adaptive)
Interpretability	High (based on causality)	Low ("black box" challenges)	Moderate to High (theory-guided)
Data Requirements	Low (relies on physical priors)	Extreme (requires massive labeled sets)	Balanced (physical laws act as regularizer)

The outcomes of modern AI-driven studies hold profound implications for resource allocation, policy formulation, and sustainable development planning (Onoja & Ajala, 2023). As the urgency to address climate change intensifies, the synergy between AI and climate science offers a resilient path forward, empowering scientists and policymakers with the insights necessary to navigate a rapidly changing planet (Ayadi et al., 2025).

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Volume 4, Issue 4 (2026)

Online ISSN 3007-3197
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Remote Sensing: The Observational Foundation of Environmental AI

Remote sensing technologies provide the essential multi-modal data streams required for training and validating AI models. Through the use of satellites, aerial platforms, and ground-based sensors, researchers can gather continuous, dynamic states of the atmosphere, land, and oceans (Kazanskiy et al., 2025). These systems allow for the extraction of various ecological metrics, which are critical for understanding land-use dynamics, quantifying water and carbon fluxes, and monitoring crop health at scales ranging from individual fields to entire continents (Montanaro et al., 2021).

The Dimensionality of Sensor Resolution

The effectiveness of remote sensing data is governed by four primary dimensions of resolution: spatial, spectral, temporal, and radiometric (Zhu et al., 2018). Achieving the optimal balance between these dimensions is a central challenge in instrument design, as technical trade-offs are often necessary (Sigurdarson et al., 2025).

Spatial Resolution: This refers to the size of the smallest object that can be resolved on the ground, defined by pixel size (Edgar et al., 2019). High-resolution imagery (Landsat at 30m or Sentinel-2 at 10m) is critical for monitoring urban heat islands, land cover changes, and forest degradation (Van Thong et al., 2024).

Spectral Resolution: This describes the ability of a sensor to measure specific, narrow wavelength intervals across the electromagnetic spectrum (Vollmer, 2021). High spectral resolution is essential for differentiating between subtle variations in vegetation health or identifying specific pollutants in aquatic environments (Gholizadeh & Kopačková, 2019).

Temporal Resolution: This is the frequency with which a sensor revisits a specific location (Wang et al., 2024). High temporal resolution is vital for tracking dynamic phenomena such as storm progression, wildfire spread, and seasonal vegetation changes (Zhang et al., 2024).

Radiometric Resolution: This indicates the sensitivity of an instrument to small differences in electromagnetic energy, typically measured in bits (Capriglione et al., 2019). Higher radiometric resolution provides better discrimination between subtle energy differences, which is crucial for water quality assessments and atmospheric monitoring (Adjovu et al., 2023).

Principal Satellite Missions and Application Focus

Table 2 Principal Satellite Missions and Core Climate Applications

Satellite Mission	Agency	Primary Sensor Resolution	Core Climate Applications
Sentinel-2	ESA	10m - 60m (Spatial)	Land cover, biodiversity, agriculture
Landsat-8/9	NASA/USGS	30m - 100m	Urban planning, geology,

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Print ISSN 3007-3189

		(Spatial)	coastal change
MODIS (Terra/Aqua)	NASA	250m - 1km (Spatial)	Global weather, sea surface temperature
GOES-R Series	NOAA	0.5km - 2km (Spatial)	Real-time storm tracking, nowcasting
Sentinel-5P	ESA	7km x 3.5km (Spatial)	Methane monitoring, air quality, ozone

Despite the wealth of information provided by these platforms, gaps in spatial and temporal coverage remain, particularly in regions with persistent cloud cover or in inaccessible remote areas (Amani et al., 2020). The integration of satellite data with Internet of Things (IoT) networks and edge computing offers a solution, allowing for the real-time analysis of climate conditions in underserved regions (Kua et al., 2021).

Machine Learning Architectures in Environmental Modeling

The extraction of complex patterns from multi-source environmental data requires sophisticated machine learning and deep learning architectures. These models are capable of identifying non-linear relationships and discerning subtle trends that traditional statistical methods often overlook (Chen et al., 2024).

Deep Learning and Computer Vision for Spatial Analysis

Deep learning (DL) has emerged as the exclusive focus for many recent developments due to its ability to automatically learn hierarchical representations from large volumes of data (Sarker, 2021). Convolutional Neural Networks (CNNs), such as ResNet50, VGG16, and GoogleNet, are particularly effective for tasks involving image recognition and spatial feature extraction (Dhillon & Verma, 2020). These architectures have demonstrated remarkable success in classifying land cover, detecting anomalies in vegetation health, and identifying environmental hazards like wildfires and ocean plastic pollution (Binetti et al., 2024).

Recurrent Neural Networks and Sequence Modeling

For climate patterns that are inherently temporal, such as precipitation cycles, temperature fluctuations, and sea-level rise, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are the preferred architectures (Hasan et al., 2024). LSTMs are specifically designed to address the "vanishing gradient" problem in standard RNNs, allowing them to capture long-term dependencies in sequential climate data (Wani et al., 2024).

The Rise of Transformers and Attention Mechanisms

A significant recent development in environmental AI is the application of Vision Transformers (ViTs) and other attention-based models (Yun, 2025). By utilizing self-attention mechanisms, these models can weigh the importance of different spatial and temporal features across an entire dataset, often outperforming traditional CNNs in tasks such as tree species identification and forest carbon accounting (Ardohain, 2025). Meta-analyses of deep learning performance in forestry reveal that ViT-based

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Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

models can achieve a pooled species-classification accuracy of 96.3%, representing a substantial improvement over standard convolutional approach (Singh et al., 2025).

Physics-Informed Neural Networks (PINNs): Bridging Data and Theory

While purely data-driven machine learning has shown great promise, it often faces limitations in scientific domains where data may be sparse, noisy, or where the "black-box" nature of models hampers scientific trust (Atmakuru, 2025). Physics-Informed Neural Networks (PINNs) represent a transformative paradigm that addresses these challenges by embedding the knowledge of physical laws typically expressed as partial differential equations (PDEs) directly into the training process of a neural network (Klapa Antonion et al., 2024).

Mathematical Foundations of PINNs

The core innovation of PINNs is the incorporation of governing physical equations as soft constraints within the neural network's loss function (Cuomo et al., 2022). This ensures that the model's predictions not only match the observed data but also remain consistent with fundamental principles such as the conservation of mass, energy, and momentum (Welty et al., 2020).

In a typical physics-informed neural network (PINN) application, the total loss function LL is defined as:

$L=Ldata+\lambda physLphys+\lambda bcLbcL=Ldata+\lambda physLphys+\lambda bcLbc$

where LphysLphys represents the residual of the physical equation, ensuring the model respects the underlying science (Bai et al., 2023).

Strategic Applications in Climate Science

PINNs are being deployed across a diverse range of Earth system domains to solve problems that were previously computationally intractable or data-limited (Costa, 2024).

Atmospheric Boundary Layers: PINNs are used to simulate stratified forced convection, a process critical for understanding heat and mass exchange in a warming world (Hughes et al., 2021).

Hydrological Downscaling: Researchers have demonstrated that PINNs can solve the Saint-Venant equations (SVE) to simulate flow at the sub-grid scale, outperforming simple linear interpolation by accurately resolving topography (Feng et al., 2023).

Periodic Phenomena: Novel architectures, such as PINT (Physics-Informed Neural Time Series), integrate the Simple Harmonic Oscillator (SHO) equation as a physical prior to improve long-term weather inference (Park et al., 2025).

AI-Driven Climate Analytics for Sustainable Decisions

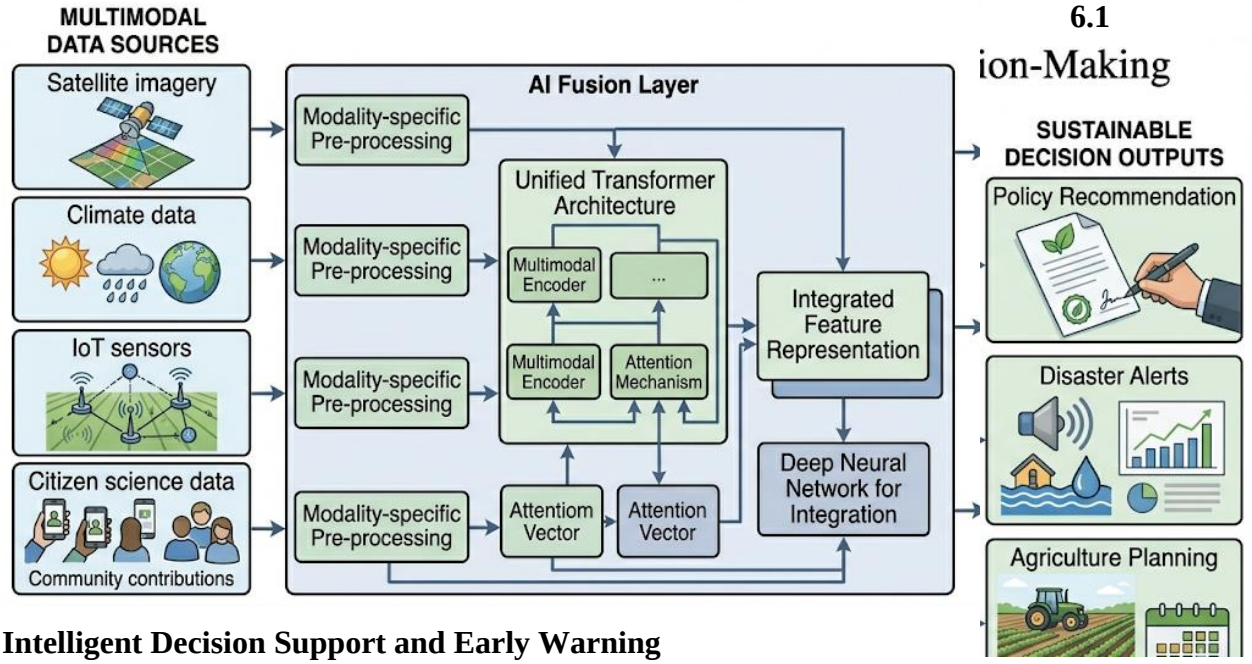
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Volume 4, Issue 4 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

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The transition from predictive modeling to sustainable decision-making requires the translation of technical AI outputs into actionable insights for policymakers, urban planners, and communities (Cina et al., 2025). Sustainable environmental governance requires integration of diverse data sources into unified decision systems. Figure 2 presents a multimodal AI framework for real-time climate decision support.

Figure 2: Multimodal AI System for Sustainable Decisi



Intelligent Decision Support and Early Warning

The integration of AI into weather-to-climate prediction is reshaping how global enterprises respond to Earth system events (Jean et al., 2025). Operational pilots illustrate the real-world impact of these technologies. In India, Google's neural GCM a model combining traditional physics with machine learning provided farmers with hyperlocal monsoon forecasts (Rana & Lone, 2025). By disseminating these AI-driven insights to 38 million farmers across 13 states, the government helped them avoid premature planting during an unusual monsoon year, protecting both income and food security (Tariqul Islam et al., 2026).

Responsible Foresight and Ethical Governance

As AI becomes more deeply integrated into climate policy, the concept of "responsible foresight" has emerged as a guiding principle (De Gasperis, 2020). This approach emphasizes that AI should be used as a supportive tool that complements rather than substitutes for human judgment, integrating values such as equity, environmental stewardship, and social justice into long-term thinking (Ogbanga et al., 2025).

Table 3 AI Applications for Climate Policy and Disaster Resilience

Policy Goal	AI Mechanism	Real-World Application Example
Disaster	GeoAI & flood	Hyperlocal monsoon alerts for 38M

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Online ISSN 3007-3197
Print ISSN 3007-3189

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Resilience	susceptibility mapping	farmers in India (Google, 2026)
Carbon Management	Multi-modal spectral carbon accounting	High-precision forest restoration tracking (Forkuo, 2026a)
Energy Transition	Hybrid LSTM/CNN forecasting models	20% improvement in wind energy output predictions (Buturache & Stancu, 2021)
Urban Sustainability	U-Net based pollution trend analysis	PM2.5 forecasting for air quality interventions in India (Amnuaylojaroen, 2024)
Wildlife Conservation	Autonomous drone & image recognition	Poaching detection in Zambia's Kafue National Park (The Sustainable Agency, 2025)

Sustainability Paradox: The Environmental Footprint of AI

While AI offers powerful solutions for climate action, its own significant ecological footprint presents a critical risk that must be proactively managed (Soundariya et al., 2025). The computational demands of training large-scale AI models are responsible for substantial greenhouse gas emissions, water consumption, and electronic waste (Oyewole & Joseph, 2025).

Energy Consumption and Carbon Intensity

Research has quantified that training a single large AI model can emit over 626,000 pounds of carbon dioxide, equivalent to the lifetime emissions of five average American cars (Martiny, 2023). Data centers currently consume between 1% and 2% of global electricity, and of that, AI is responsible for approximately 15% (Mavisclara et al., 2025). The "Green AI" movement focuses on minimizing this cost through techniques such as model compression and quantization, which can cut computational needs by 5 to 10 times (Peykani et al., 2026).

Democratizing Climate Action: Citizen Science and AI Integration

The integration of AI with citizen science provides a unique opportunity to scale and democratize climate monitoring (Duerinckx et al., 2024). Citizen science projects mobilize large numbers of volunteers to collect data across broad geographic areas, providing "on-the-ground" information that can be used to train and validate AI algorithms (Balestrini et al., 2021).

Enhancing Data Quality with Machine Learning

AI algorithms excel at bridging data gaps by automating data cleaning and validating inputs (Noor, 2020). In India, the UNDP Accelerator Lab developed the GeoAI platform to detect air pollution hotspots using satellite imagery and AI object detection algorithms trained by citizen scientists (Usmani, 2024). This collaborative effort detected more than 47,000 brick kilns across India, enabling regulatory action and pollution mitigation (Mondal et al., 2024).

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Volume 4, Issue 4 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

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Global Standards and Essential Climate Variables

To coordinate international climate observations, the Global Climate Observing System (GCOS) has identified a set of 55 Essential Climate Variables (ECVs) (Zeng et al., 2022). These variables, spanning atmospheric, terrestrial, and oceanic domains, are critical for characterizing the Earth's climate system (Bonan & Doney, 2018).

Categories of Essential Climate Variables

Table 4. Satellite Observation Requirements for Essential Climate Variables

Domain	ECV Sub-groups	Key Variables Requiring Satellite Observation
Atmospheric	Surface & Upper-air	Precipitation, Surface Pressure, Air Temperature, Cloud properties (GCOS, 2026)
Atmospheric	Composition	Greenhouse Gases (CO2, CH4), Ozone, Aerosols (GCOS, 2026)
Terrestrial	Hydrosphere & Cryosphere	Lakes, River Discharge, Soil Moisture, Glaciers, Ice Sheets (GCOS, 2026)
Terrestrial	Biosphere	Above-ground Biomass, Albedo, Land Cover, Fire, Leaf Area Index (GCOS, 2026)
Oceanic	Physical & Biogeochemical	Ocean Colour, Sea Surface Temperature, Sea Level, Oxygen (GCOS, 2026)

Maintaining the continuity and homogeneity of these long-term datasets is essential for underpinning assessments such as those by the Intergovernmental Panel on Climate Change (IPCC) (Wagner & Hornidge, 2025).

Critical Hurdles and the Path Forward

Despite the rapid progress in AI-driven environmental modeling, several critical barriers to operational deployment remain. Models trained in one geographic or climatic region often experience substantial performance degradation (23% to 45%) when applied elsewhere (Naik et al., 2025). This "transferability paradox" is particularly acute in agricultural and forestry monitoring, where local variations in soil, species, and climate can lead to systemic errors (Raffiee & Byun, 2020).

Success in the next era of environmental intelligence will be determined not just by average accuracy, but by robustness, transparency, and operational responsibility (Alotaibi & Nassif, 2024). Emerging roadmaps include neuro-symbolic integration and quantum-accelerated optimization, which promise to reduce computational barriers while maintaining machine-precision consistency with physical laws (Lokeshwaran & Devan, 2025).

Conclusion

AI-driven predictive modeling, empowered by GIS, remote sensing, and advanced machine learning architectures, is fundamentally transforming our capacity to understand, forecast, and manage complex environmental and climate systems. By

Online ISSN 3007-3197
Print ISSN 3007-3189

fusing vast multi-source datasets with physics-informed constraints through frameworks like PINNs, GeoAI delivers high-resolution, real-time insights that surpass the limitations of traditional GCMs in speed, granularity, and adaptability. These tools enable proactive interventions across critical domains from early flood and wildfire warnings to optimized water and agricultural resource allocation, forest health monitoring, and carbon sequestration tracking directly supporting the United Nations Sustainable Development Goals and enhancing societal resilience. While significant hurdles remain, including the substantial energy footprint of large models, challenges in model generalization, data sovereignty, and ensuring interpretability for policy trust, ongoing advancements in model compression, edge computing, hybrid neuro-symbolic systems, and responsible AI governance are addressing these gaps. The future lies in autonomous, self-improving geospatial intelligence systems and digital twins that integrate citizen science, IoT, and global satellite constellations for continuous planetary monitoring. Ultimately, the responsible and inclusive deployment of GeoAI will be pivotal in navigating the climate crisis, fostering sustainable resource stewardship, and building equitable, adaptive societies capable of thriving amid environmental uncertainty.

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