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Artificial Intelligence in Climate Change Mitigation and Adaptation: A Review of Emerging Technologies and Real-World Applications

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Abstract

Artificial Intelligence (AI) is increasingly recognized as a transformative tool in addressing the dual imperatives of climate change mitigation and adaptation. This review provides a comprehensive synthesis of the current state of AI applications that contribute to reducing greenhouse gas emissions and enhancing resilience to climate-related hazards. It systematically examines advances in machine learning, optimization, and data-driven decision support across key domains including renewable energy forecasting, energy system optimization, land-use planning, disaster risk management, precision agriculture, and water resource allocation. The paper also analyzes the enabling infrastructure required for scalable and ethical deployment, such as data interoperability, model interpretability, and integration with physical system models. The findings from existing literature indicate that AI has significantly improved predictive capacity, operational efficiency, and adaptive planning in climate-related contexts. However, persistent challenges ranging from data scarcity and geographic bias to the carbon footprint of AI systems and governance limitations continue to constrain equitable implementation. The review concludes by identifying critical research gaps and proposing a strategic roadmap focused on interdisciplinary collaboration, equitable data frameworks, and policy alignment with global climate objectives. By critically appraising both the potential and limitations of AI, this review contributes to the research on how intelligent systems can be leveraged to support sustainable, inclusive, and scientifically grounded climate action.

Keywords: Artificial Intelligence; Climate Change Mitigation; Climate Adaptation; Machine Learning; Environmental Sustainability; Renewable Energy Forecasting; Disaster Risk Prediction.

1. Introduction

The accelerating threats of climate change demand innovative tools for both mitigation reducing greenhouse gas emissions and adaptation adjusting human systems to climate impacts. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative levers in this context. AI can enhance forecasting, optimize energy systems, support climate risk assessments, and inform adaptive strategies across sectors [1-3]. To contextualize the breadth of AI's role in climate mitigation and adaptation, Figure 1 outlines key application domains including energy systems,

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agriculture, urban resilience, and natural resource management providing a visual roadmap for the review that follows. This review provides a comprehensive overview of AI's current and emerging roles in climate change mitigation and adaptation, identifies enabling technologies and data considerations, and outlines barriers and future research trajectories. We collected literature through a systematic search of academic databases and open-source reviews, focusing on the last five years of development. The paper is structured to guide the reader from foundational motivations through technical tools, application domains, challenges, and future directions.

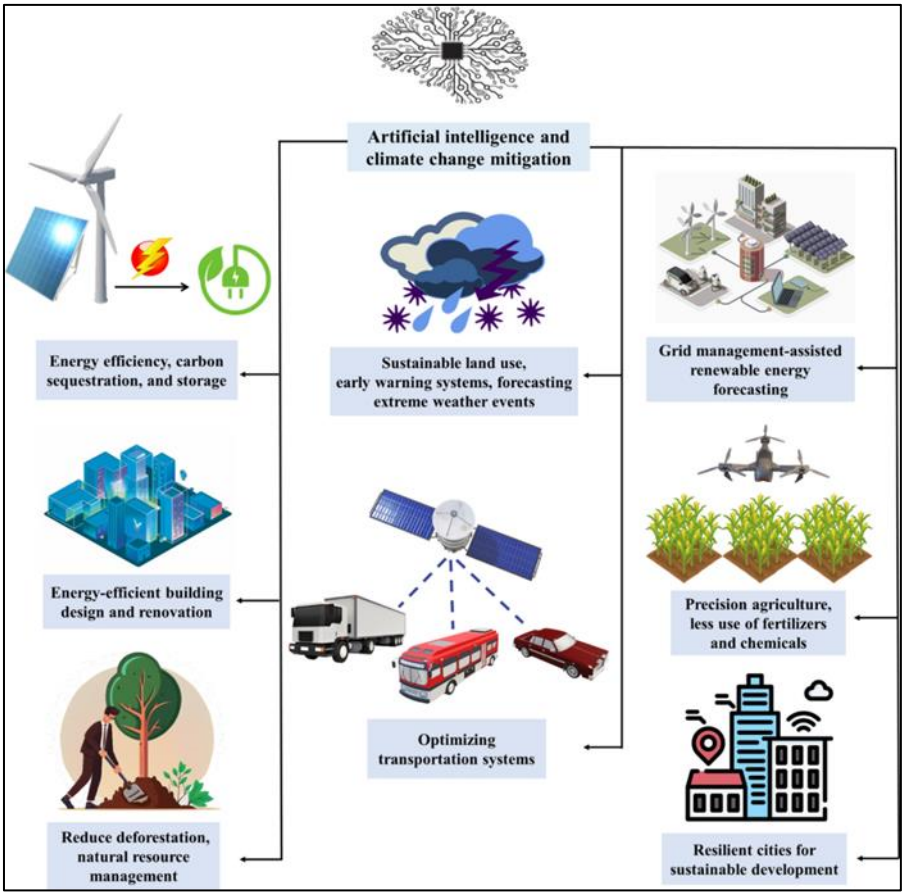


Figure 1 Overview of AI Applications Across Sectors (Reproduced with permission from Chen et al. [3])

1.1. Background and Relevance of AI in Climate Science

AI and ML capabilities have grown significantly, enabling powerful applications in climate sciences, energy systems, and environmental modelling. According to Rolnick et al. [4], ML is well-suited to address climate challenges across systems such as smart grids, demand forecasting, and disaster response, calling on the ML community to engage deeply in climate-relevant problems. In parallel, Hamdan et al. [5] highlight that AI methods now underpin predictive modelling of climate patterns and impact assessment, including biodiversity loss and carbon sequestration, by integrating meteorological, oceanic, and geospatial data. The urgency of climate action also underscores adaptation needs. The IPCC's Sixth Assessment Report [6] stresses that adaptation investments are lagging even as certain societies face escalating risks, particularly vulnerable regions where mitigation alone is insufficient. Several other authors further emphasize that the window for effective adaptation is closing rapidly, amplifying the importance of tools that can anticipate hazards and deliver resilience [5-7].

AI's relevance thus stems not only from its ability to enhance modelling and forecasting, but also from its potential to optimize systems such as energy networks and agricultural supplies and to support decision-makers in high-stakes, time-sensitive scenarios. The EuropeanDestinE digital twin initiative, for example, pairs AI with high-performance computing to simulate climate extremes and aid policy responses starting in 2024.

1.2. Objectives and Scope of the Review

This review synthesizes the current state of AI-driven mitigation and adaptation applications by examining their technological, policy, and contextual dimensions. It surveys AI uses across renewable energy optimization, industrial and transport systems, carbon modelling, early warning systems, adaptive agriculture, water resource management,

and ecosystem monitoring, drawing from recent systematic studies. The analysis addresses technical and data considerations such as quality, interpretability, hybrid modelling approaches, domain adaptation, and uncertainty quantification, while also engaging with ethical, policy, and governance issues including bias, access inequities in the Global South, transparency, and regulation. Emphasis is placed on both global and region-specific contexts, particularly Africa, where data scarcity and local applicability are crucial. Covering literature from 2019 to mid-2025, the work applies a semi-structured systematic approach involving database searches, relevance screening, and thematic extraction across mitigation and adaptation domains.

1.3. Organization of the Paper

The review is organized in a coherent sequence, moving from conceptual framing to practical applications and future outlook. It begins with an examination of AI in climate change mitigation, encompassing topics such as energy forecasting and renewable integration, industrial and transport system optimization, carbon modelling, emissions reduction, and land use applications. This is followed by a focus on AI in climate change adaptation, which includes early warning systems, risk prediction, smart urban planning, urban heat resilience, precision agriculture, adaptive farming, and AI-enabled water resource management. Technical and data considerations are then explored, addressing interpretability, hybrid physical–statistical systems, data interoperability, transfer learning, and remote sensing integration. The discussion next turns to challenges, limitations, and ethical concerns, such as data bias, the energy footprint of AI models, geographic fairness, and governance frameworks. The policy and governance section links AI initiatives to climate goals, highlights collaborative platforms and open data ecosystems, and offers recommendations for global scaling. The review concludes by synthesizing insights across sections, identifying knowledge gaps, and proposing a strategic roadmap for future interdisciplinary research and action.

2. The Role of AI in Climate Change Mitigation

2.1. AI for Renewable Energy Forecasting and Grid Integration

The integration of AI into renewable energy forecasting has become a key driver of more efficient and reliable grid operations. According to Ukoba et al. [8], global renewable energy share rose to nearly 29% of power generation in 2020, with AI helping to manage variability and intermittency in solar and wind systems. Machine learning models such as decision trees, random forests, LSTM, and ensemble methods have been widely deployed to improve accuracy of generation forecasts by combining weather and historical power data.

Findings from Rajaperumal & Christopher [9] indicate that advanced models like CNN-LSTM and ensemble methods (XGBoost, LightGBM, Extra Trees) offer superior accuracy in wind power forecasting, often outperforming traditional statistical approaches. CNN-LSTM was shown to have lower error metrics in test cases, while ensembles provided robust performance for real-time applications. Hybrid architectures combining GRU and ResNext, tuned via metaheuristics and using PCA for dimensionality reduction, achieved low normalized RMSE and MAPE for solar and PV forecasting, demonstrating the effectiveness of deep learning–based hybrid designs. Beyond forecasting, AI supports real-time grid integration. The UK's national grid uses solar forecasting improved by about 33%, based on systems using roughly 80 input variables, while similar models improved wind forecasts through data-driven ensemble techniques. These improvements enable grid operators to reduce reliance on backup fossil generation and enhance stability. Integration of IoT with AI further strengthens performance. A study in Journal of Big Data explains how the synergy of IoT, satellite, and weather data enables real-time forecasting, predictive maintenance, and anomaly detection, thereby enhancing renewable energy system reliability and grid resilience [10-12].

2.2. Machine Learning in Optimizing Industrial Energy Efficiency

AI also plays a crucial role in reducing industrial sector emissions through energy optimization and predictive maintenance. In operations such as power plants, ML models can optimize turbine performance. A systematic review reports that applying ANN and SVM to high-load turbine parameters improved efficiency by 1–5% across load modes compared to baseline operations. Similarly, ML techniques have been used in buildings and manufacturing. According to a systematic review by Ardabili et al. [13], deep learning, hybrid, and ensemble models outperform linear regression and standalone methods in forecasting building energy consumption and demand, indicating high robustness and accuracy in applications to urban energy systems. The integration of AI-driven monitoring and control systems in industrial operations enables real-time process optimization, leading to substantial reductions in energy consumption and associated emissions. As illustrated in Figure 2, machine learning algorithms can process high-frequency sensor data, identify inefficiencies, and dynamically adjust operational parameters to maintain optimal performance. This end-to-end approach spanning data acquisition, predictive modeling, and automated control embodies the core principles discussed in this section on AI-enabled industrial energy efficiency. [13-15].

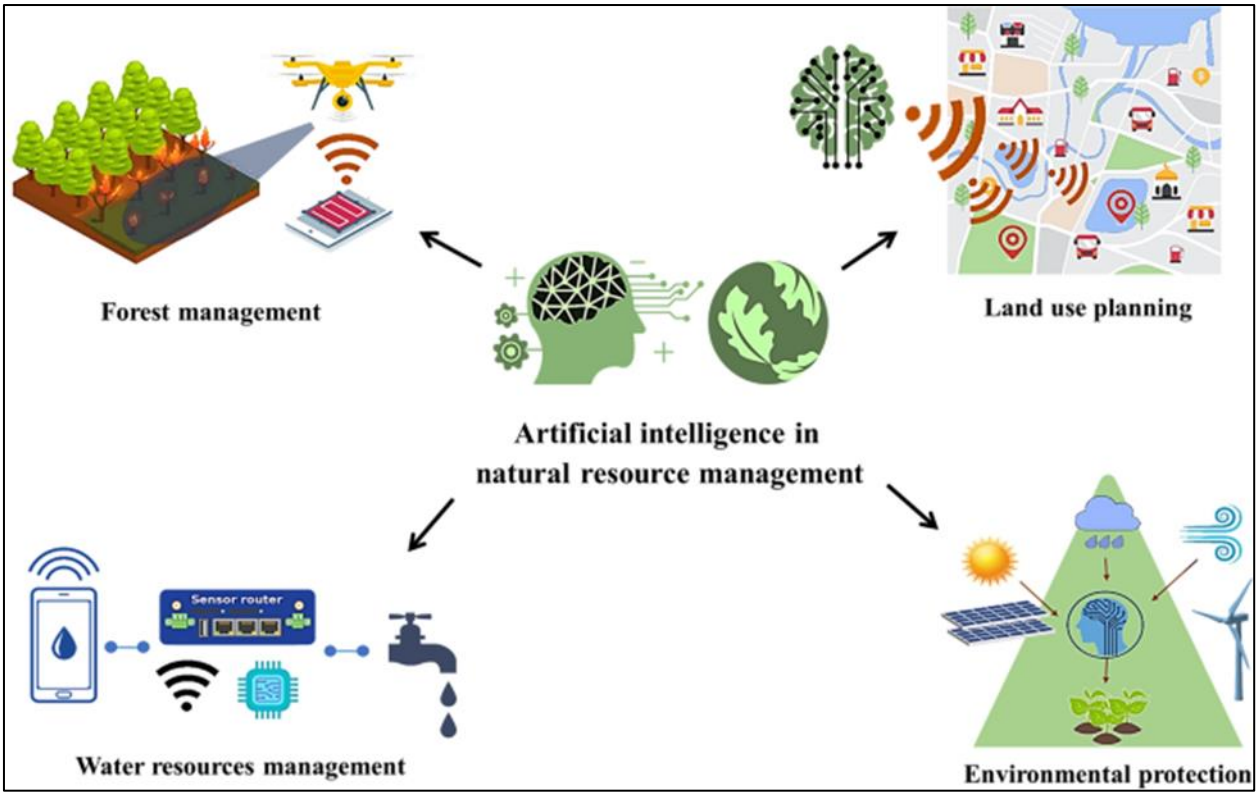


Figure 2 AI applications in natural resource and industrial process management

Empirical case studies cited by Time (2025) illustrate commercial benefits: AI-driven HVAC optimization at 45 Broadway in Manhattan resulted in 15.8% reduction in energy use, cutting 37 metric tons of CO_2 and saving USD 42 000 annually. These real-world deployments validate AI's capacity to reduce operational emissions in commercial and institutional settings. Further, utilities are deploying AI-powered predictive maintenance platforms. Business Insider reports that companies like Duke Energy and startups such as Rhizome apply ML to monitor transformer networks and predict equipment failures, reducing outages by up to 72% in some cases thereby lowering unplanned emissions and improving grid reliability [16-20].

2.3. Carbon Footprint Prediction and Reduction using AI Models

AI can assist organizations in mapping and reducing their carbon emissions footprint. AI-driven models are increasingly being used in power enterprises to model carbon emissions linked to operational parameters. For example, decision tree and support vector machine approaches have been contrasted with transformer and RNN models in modeling power plant outputs and emissions—though each method has trade-offs between interpretability and complexity.

The emerging field of "Green AI" emphasizes sustainability in AI itself. Verdecchia et al. [21] highlights that Green AI research focuses on monitoring model footprints, hyperparameter tuning for energy efficiency, and benchmarking often yielding energy savings of 50–115% in laboratory settings. Such work promotes the dual goal of reducing carbon emissions both from the systems AI helps manage and from AI's own energy usage. Economic analysis bolsters AI's mitigation credentials: it is estimated that AI could reduce emissions by 3.2 to 5.4 billion tonnes annually by 2035 up to 25% of emissions in sectors like power, transport, and food even exceeding emissions generated by data centres and AI infrastructure. AI applications that enhance renewable integration, optimize operations, and predict demand are central to this potential [21-23].

2.4. AI in Carbon Markets and Emissions Trading Platforms

While less developed than forecasting and optimization domains, AI is being explored in carbon markets, trading platforms, and emissions offset analysis. Advanced AI models can support pricing algorithms, risk assessments, and verification of carbon offsets by analyzing large volumes of transaction data and satellite/remote sensing imagery to detect land-use change or deforestation. Several pilot initiatives use AI to strengthen emissions trading transparency by automatically identifying fraudulent offset claims or tracking deforestation through combined image classification

and geospatial analytics. Although peer-reviewed evaluations are scarce, emerging projects like AI-supported satellite monitoring for REDD+ programmes show promise [5,22,23].

Regulatory bodies have begun assessing how ML can validate carbon removal claims. These efforts include integrating AI with blockchain and IoT to provide end-to-end traceability in emissions reduction projects. While rigorous reviews are still forthcoming, the trajectory points to a growing role for AI in governance of carbon markets [20,21].

2.5. Applications in Land Use Management and Deforestation Prevention

AI supports climate mitigation via land use interventions, including deforestation monitoring, reforestation planning, and ecosystem carbon sequestration tracking. Machine learning combined with satellite data enables near-real-time detection of land cover changes. For instance, projects using convolutional neural networks on satellite imagery have effectively identified illegal forest loss, triggering quicker enforcement responses. Similarly, AI assists in prioritizing reforestation areas by analyzing soil, climate, and historical land use variables thereby supporting climate-smart planning. Models trained on biodiversity and carbon stock datasets can help optimize restoration siting and species choices.

Although systematic literature reviews on these applications remain limited, several NGO and technology collaborations report success in forest conservation using AI-driven image analysis and anomaly detection. These practical tools contribute to greenhouse gas reduction by preserving carbon stocks and enabling data-driven land stewardship [24-26].

3. The Role of AI in Climate Change Adaptation

3.1. AI for Climate Risk Prediction and Early Warning Systems

AI is playing an increasingly critical role in developing climate risk prediction models and early warning systems. Machine learning tools are now capable of detecting early warning signs of disasters such as heavy rainfall, floods, droughts, landslides, and harmful algal blooms events often exacerbated by climate change. Such systems can analyze high-volume climate data and surface anomalies indicative of upcoming extreme events. Google's Flood Hub uses ML to process satellite imagery, water gauge readings, and weather forecasts to deliver riverine flood predictions up to seven days ahead and has scaled to over 60 countries across Africa, Asia-Pacific, Latin America, and Europe [25,26]]. Findings from Time News indicate that AI-based hurricane and flood forecasts, satellite image analysis, and real-time alert systems are enhancing disaster preparedness and evacuation planning around the world. Efforts like the UN's global initiative and platforms such as SOFF reflect growing institutional uptake of AI in early warning systems.

In regions like Australia, AI models such as those from the Early Warning Network (EWN) and FloodMapp integrate radar, remote sensing, and hydrological data to generate alerts for hailstorms and flood events. These tools are strengthening collaboration between national meteorological services and private sector partners. However, challenges remain in data bias, calibration, and transparency—especially in regions where baseline sensor infrastructure is weak or inconsistent [21,27].

Recent literature highlights that AI-enhanced prediction and early warnings contribute significantly to climate preparedness. Yet authors uniformly caution that expert oversight, robust validation, and scalable data pipelines are essential to avoid false positives and to maintain trust [20,23,26].

3.2. Urban Heat Island Mitigation and Smart City Planning

AI-assisted interventions offer promising strategies for mitigating urban heat islands (UHIs) and supporting climate-resilient urban planning. Cities can leverage machine learning and GIS datasets to locate optimal sites for green infrastructure such as green roofs, rain gardens, bioswales, and urban forests that reduce stormwater runoff and urban heat simultaneously. Examples from Calgary, New York, and Bangkok show that AI-driven site selection for vegetation projects can significantly enhance environmental outcomes. A study introduced a digital-twin framework that incorporates a Spatiotemporal Vision Transformer (ST-ViT) to forecast heat stress at fine spatial resolution on a university campus in Texas. Findings demonstrate that the ST-ViT model enables planners to view likely heat stress hotspots informing shade placement, building orientation, or cooling installations. Similar approaches are being adapted to urban environments to drive localized design and retrofitting choices.

Beyond siting, AI is applied to building energy systems to manage HVAC operations dynamically. One scenario report details how AI-driven building control can modulate HVAC based on occupancy, grid demand, and ambient conditions to minimize heat contributions and reduce energy consumption while keeping indoor comfort high. Together, these coordinated tools help cities target heat mitigation tactics geographically and operationally. Thus, emerging AI-enabled

UHI mitigation blends high-resolution environmental sensing with optimization and digital-twin simulations to drive smarter urban planning. However, authors note the need for explainable models, inclusive design processes, and careful integration with socio-economic factors like accessibility, equity, and cost-benefit trade-offs [28-30].

3.3. AI-Assisted Agricultural Adaptation and Precision Farming

AI supports agricultural adaptation by enabling precision farming that responds to climate variability and resource constrains. A research overview on climate adaptation states that AI-powered agricultural models incorporating weather, soil, crop, and historical yield data can recommend planting times, crop varieties, and targeted interventions to reduce climate-driven risks. These models facilitate resource-efficient decisions in farming environments challenged by erratic weather and water scarcity. According to information in the FT Tech for Growth Forum 2025, organizations such as Digital Green and Tomorrow.io deliver AI-enabled advisory services via multilingual chatbots and SMS to thousands of farmers in India, Kenya, and Ethiopia, helping optimize irrigation, pest control, and crop management in semi-arid and rainfed areas [31]. This enhances yield, resource use efficiency, and resilience.

Precision agriculture further benefits from IoT integration. Some authors have presented a five-layer framework combining AI and IoT for local weather forecasting to deliver high-resolution, real-time meteorological insights to farms enabling actionable irrigation and planning decisions. Although empirical validation remains nascent, the conceptual model highlights potential gains in forecast utility and sustainability. Applications include AI-based irrigation scheduling (soil moisture + weather prediction), early stress detection via drone and multispectral imaging, and resources targeting (e.g., fertilizer) only where needed. These interventions reduce water, fertilizer, or pesticide use contributing to both adaptation and mitigation goals. Real-world deployment in India's "cluster AI farming" initiative further underscores the potential for scalable, farmer-driven systems [32,33].

3.4. Disaster Management and Climate Resilience Systems

AI is integral to disaster management and resilience planning, improving situational awareness before, during, and after climate-induced emergencies. Time reports on AI-assisted systems that process satellite imagery, sensor data, and forecasts to support disaster preparedness through real-time assessments and optimal response coordination. The UN-led Global Initiative on Resilience aims to institutionalize such AI-based tools across hazard-prone regions. Machine learning models are enhancing post-disaster response via automated damage assessment classifying structural damage, flooding extent, or burned areas using pre- and post-event satellite imagery. This accelerates relief allocation and recovery planning. AI also supports decision-making dashboards for coordinating evacuation, medical assistance, and resource allocation across agencies [5,24].

Furthermore, digital-twin platforms like the EU's DestinE initiative integrate high-resolution climate and hazard models with AI to simulate extreme events and stress-test urban infrastructure [13]. These simulations enable planning for floods, heatwaves, and sea-level rise, helping cities adopt resilience-informed investments, zoning, or emergency protocols. Authors emphasize that, while AI provides rapid analytic capabilities, robust validation, cross-agency integration, and inclusion of vulnerable communities are essential to ensure equity and utility [34,35].

3.5. Enhancing Water Resource Management Using AI

AI is transforming water resource planning and management, a crucial adaptation need as climate shifts alter hydrology globally. Research on hydrology highlights that AI models can predict water quality and contamination events more accurately than traditional statistical methods, by analyzing nonlinear relationships among sensor-derived data, pollutant sources, and spatiotemporal trends. Systems integrating IoT sensors and MCN-LSTM architectures can detect anomalies in real-time, enabling proactive mitigation [24,36].

AI-based water governance tools model supply and demand interactions, drought risk, and resource allocation. More broadly, AI tools can forecast consumption demand across sectors and reduce waste via leak detection and distribution optimization. Platforms like Waterplan exemplify how AI now mines unstructured datasets and applies semantic understanding to integrate expert-reviewed data, reports, and monitoring streams enabling dynamic water risk assessments even in data-scarce regions [36]. Such systems can provide up-to-date risk scores, early drought alerts, and policy insights adjusted to local context.

Research affirms that AI-driven water management systems enhance resilience by combining predictive analytics, dynamic resource optimization, contamination monitoring, and drought/flood forecasting, ultimately supporting adaptation strategies that preserve water security under climate uncertainty [5,6,36].

4. Technical and Data Considerations

To frame the discussion in this section, Table 1 provides a comprehensive overview of key technical and data considerations in AI for climate modeling, summarizing methods, advantages, limitations, and examples.

Table 1 Technical Considerations in AI for Climate Modeling

Consideration	Methods/Techniques	Pros	Cons	Applications	Examples	References
Data Quality & Interoperability	ESMF standards, grid remapping	Consistent inputs, scalable models	Resolution/format disparities	Earth-system integration	NeuralGCM hybrid	[37, 38]
Transfer Learning	Meta-transfer, domain adaptation	Reduces data needs, improves generalization	Distribution shifts	Lake temperature prediction	U.S. Midwest lakes	[39, 40]
Domain Adaptation	Feature space alignment	Handles geographical/temporal shifts	Feature constancy required	Regional climate projections	CMIP6 ensembles	[40, 42]
Uncertainty Quantification	Bayesian Neural Networks (BNNs)	Probabilistic outputs, trust enhancement	Computational intensity	Ocean dynamics modeling	LRP/SHAP explainability	[43]
Explainability	XAI (SHAP, LRP)	Feature importance revelation	Tradeoffs in confidentiality	High-stakes decisions	Hybrid surrogates	[43, 44]
Remote Sensing Integration	Deep learning fusion	Spatial coverage + accuracy	Harmonization complexity	Land-use change detection	African forest biomass	[45, 46]
Hybrid Modeling	Physics + ML (e.g., NeuralGCM)	Speed and accuracy gains	Validation needs	Forecasting ensembles	Climate extremes simulation	[38, 44]
Multi-Modal Fusion	IoT + satellite data	Enriched insights	Equity in access	Agriculture monitoring	Soil carbon mapping	[47]

4.1. Data Quality, Interoperability, and Climate Model Integration

High-quality, interoperable datasets are foundational to credible AI-based climate modeling. According to the Earth System Modeling Framework (ESMF), a core objective is to facilitate interoperability between diverse Earth-system modeling components such as atmosphere, ocean, and land modules through standardized metadata, grid remapping, and data provenance protocols. This infrastructure exemplifies how models and data formats can be harmonized, enabling AI systems to ingest and process heterogeneous inputs consistently. Challenges in practice arise because observational datasets and model outputs vary significantly in resolution, format, and metadata standards [37,38]. The integration of satellite, aerial, and ground-based data requires careful preprocessing e.g., alignment between SAR and optical imagery without which errors and delays occur during downstream modeling. Additionally, disparities in data availability across regions, especially in developing areas, exacerbate inequities and limit AI applicability in those contexts.

To bridge Earth system models with AI, hybrid architectures such as NeuralGCM (a neural-network-augmented general circulation model) combine physics-based simulation with machine learning to enhance both speed and accuracy. NeuralGCM uses decades of reanalysis and observation-based input and has demonstrated increased forecasting skill while reducing computational cost relative to traditional GCMs. Such hybrid models benefit from interoperable data protocols and emphasize the importance of adhering to shared community infrastructure standards like ESMF or ARIES. Ensuring data quality and interoperability supported by frameworks like ESMF enables robust integration of AI and

physical climate models. Without standardized metadata, harmonized grids, and consistent provenance, AI applications may produce inconsistent or unreliable results. This highlights both the opportunity and necessity of robust data governance in environmental AI systems [38].

4.2. Transfer Learning and Domain Adaptation in Environmental Modeling

Transfer learning (TL) has become a critical approach in climate modeling, particularly to address labeled data scarcity in under-monitored regions. According to Willard et al. [39], meta-transfer learning applied to lake temperature prediction significantly improved performance when transferring from monitored to unmonitored lakes in the U.S. Midwest. This strategy leverages models trained on rich source data and adapts them to novel target domains with minimal local data. PNAS recently published work showing that TL can reduce uncertainty in multimodel temperature projections by more than 50%, by constraining ensembles of CMIP6 Earth system model outputs using observational data. These findings underscore TL's capacity to enhance regional climate projection fidelity even where historical observations are sparse [39-41].

Domain adaptation, a variant of TL where the feature space remains constant but data distributions differ, addresses challenges from geographical or temporal shifts. According to formal surveys, domain adaptation enables models trained on one climate region or time period to generalize to others despite shifts in data distributions. For environmental applications, including predictions under future climate regimes, domain adaptation frameworks support robust model generalization across regimes [40,42].

"Climate-invariant" ML frameworks explicitly encode physical constraints into learning algorithms to improve model stability under shifting climate regimes. This approach yields models with higher offline accuracy, data efficiency, and generalizability across diverse atmospheric scenarios. Together, transfer learning, domain adaptation, and climate-invariant machine learning offer powerful tools to overcome data scarcity and generalization challenges, enabling AI models to operate reliably across regions and future climate regimes [40-42].

4.3. Uncertainty Quantification and Explainability of AI Predictions

Quantifying uncertainty and ensuring explainability are essential when AI informs high-stakes climate decisions. Bayesian neural networks (BNNs) provide a natural mechanism for uncertainty quantification by treating weights as distributions rather than fixed values. Clare et al. [43] applied BNNs to ocean dynamics modeling and used explainable AI (XAI) methods such as Layer-wise Relevance Propagation (LRP) and SHAP values to reveal which features drive predictions—enhancing trust and identifying where the model aligns (or misaligns) with physical understanding.

Hybrid models such as NeuralGCM also address uncertainty by combining physical model outputs with machine learning surrogates, enabling faster ensemble simulations that systematically explore parameter and structural uncertainties more efficiently than full climate models. Integrating ML surrogate models facilitates broader uncertainty quantification through ensemble generation or scenario sampling.

Explainability methods are critical because complex models can act as opaque "black boxes" a concern flagged by regulators and climate stakeholders alike. XAI tools help highlight model decisions, but also bring trade-offs: exposing feature importance could be misused or reveal proprietary insights, so balancing transparency with confidentiality remains a challenge. Integrating methods for uncertainty quantification (e.g., BNNs, ensemble surrogates) and explainable AI significantly improves the credibility and interpretability of AI-driven climate tools critical for policy relevance and stakeholder engagement [39,43,44].

4.4. Integration of Remote Sensing and Ground-Based Data

Fusing remote sensing with ground-based data enriches AI models with spatial coverage and in situ accuracy. Persello et al. [45] reviewed deep learning in remote sensing, concluding that combining satellite imagery with domain-specific expertise enables scalable detection of land-use change, deforestation, and urbanization key for climate modeling and mitigation planning.

Applications in forest biomass estimation illustrate this well: recent deep learning and transformer-based models integrate satellite data with limited field measurements to map above-ground biomass (AGB), especially in African tropical forests. While high-resolution data offer promise, the lack of ground truth data in regions like the Congo Basin constrains model accuracy highlighting the need for expanded in situ observation networks alongside AI-based predictions.

Complementary applications in agriculture and land-use monitoring also benefit from this multimodal fusion. Reuters reports on AI-powered soil carbon mapping tools that combine spectral remote sensing, digital probes, and terrain data reducing reliance on manual core sampling and enabling scalable soil carbon forecasting in regenerative agriculture

[45,46]. Despite potential, integrating these diverse modalities requires robust processing pipelines. Ur Rehman et al., [47] noted that multi-modal fusion including satellite imagery, IoT sensor data, and climate archives presents technical complexity around data harmonization, temporal alignment, and anomaly detection. Inequities in data access and computational resources further complicate adoption in resource-poor regions.

Integration of remote sensing with ground-based measurements enriches environmental AI models with scale and fidelity but also introduces substantial technical and equity challenges that must be addressed for global applicability.

5. Challenges, Limitations, and Ethical Considerations

5.1. Data Scarcity in the Global South and Model Bias

Data scarcity in Global South regions poses a fundamental challenge to effective AI deployment. Research funding and climate science outputs remain heavily concentrated in institutions from the Global North one analysis found that 78% of climate-related research on Africa is funded by European or North American institutions, limiting local agency and relevance of models for local contexts. As a result, datasets and predictive models often inadequately reflect regional environmental conditions, leading to biased or less accurate climate projections and risk assessments. The study by Roldan-Hernandez et al. [48] emphasizes how this skew in data availability leads to what is frequently termed "parachute science" research conducted by outsiders without sustainable partnerships, undermining capacity building in vulnerable communities. Machine learning models trained on inadequate or inconsistent datasets may systematically misrepresent risks or omit locally important variables, such as indigenous land-use practices or vernacular adaptation strategies. This bias can exacerbate inequities in resource allocation and decision-making support.

Model bias becomes especially problematic when AI tools are used for policy or operational decision-making in adaptation and mitigation contexts. The findings by Ukoba et al. [49] highlight that AI risk predictors trained primarily on northern-latitude climate data perform poorly when applied in equatorial or tropical regions due to unmodeled microclimates and localized weather patterns. These limitations point to a pressing need for context-sensitive modelling frameworks. Addressing these gaps requires expanding data infrastructure, promoting open-access platforms that host localized observational data, and fostering collaborative partnerships where local researchers lead data collection and model creation. Only then can AI tools be calibrated to more accurately reflect diverse climatic realities and ensure equitable benefits across regions.

5.2. Energy Intensity and Carbon Footprint of AI Models

The environmental footprint of AI models themselves has emerged as a major challenge for sustainability-focused applications. Data centers powering AI systems account for approximately 2.5–3.7% of global greenhouse gas emissions, comparable in scale to the aviation industry. The electricity consumption of AI-specific compute particularly generative models and large-scale training is a growing driver behind this impact. Training GPT-3 consumed roughly 1,287 MWh and emitted approximately 552 metric tons of CO_2 equivalent to the lifetime emissions of five cars. Similarly, the 176-billion-parameter BLOOM model emitted around 25–50 tons of CO_2 depending on whether hardware manufacturing and lifecycles are included. In many cases, inference operations cumulatively produce more emissions over time than initial training, especially when deployed at scale for billions of queries.

Water usage is another significant environmental externality. Large data centers require substantial freshwater for cooling: training GPT-3 reportedly consumed around 700,000 liters of water, and global AI water withdrawal is projected to reach 4.2–6.6 billion m^3 by 2027—comparable to half of the UK's total water withdrawal. The strain this creates is notably severe in water-stressed regions both within and beyond the Global South. These environmental costs present an ethical tension: deploying AI tools to mitigate climate impacts while simultaneously generating substantial emissions and resource usage. Practitioners and policymakers must weigh net benefits carefully, embrace carbon-aware scheduling, optimize for energy-efficient architectures, and consider sustainable hardware sourcing and lifecycle management [47, 50-52].

5.3. Transparency, Fairness, and Decision-Making Accountability

Transparency and fairness are critical for AI deployed in climate-relevant applications yet they face significant obstacles, particularly when complex deep learning models are used in high-stakes decision-making. Models used for forecasting disaster risk or allocating resources in mitigation efforts often lack interpretability, impeding trust and accountability. Many AI developers do not disclose their models' energy impact or dataset composition, making it hard to evaluate fairness or unintended bias. Bias may arise when training datasets are not representative of all affected populations, leading to systemic misallocation or omission in decisions. Moreover, reinforcement learning and black-

box models may produce outputs that cannot be easily traced or explained. Without transparency about model assumptions, risk of misuse or misinterpretation increases especially when governments or NGOs rely on AI for resource distribution, early warnings, or carbon market management [53,54].

Regulatory frameworks are still evolving to address these issues. Observers advocate for standards requiring disclosure of energy usage, dataset provenance, and performance metrics by region or demographic group to promote fairness. Some AI ethics guidelines also emphasize the importance of human-in-the-loop systems and interpretability for climate decision support tools, ensuring that model users understand strengths and limitations. Ensuring accountability also means that developers and deploying agencies bear responsibility for potential harms—including misclassification, exclusion, or overconfidence in AI outputs. Ethical deployment practices necessitate inclusive stakeholder engagement, local validation of models, clear documentation, and feedback loops that enable affected communities to understand and contest outputs where necessary [54,55].

5.4. The Dual-Use Dilemma of AI in Climate Applications

AI tools developed for climate mitigation and adaptation can also be repurposed for harmful applications, highlighting a dual-use dilemma. Models capable of satellite image interpretation, land-use classification, or dynamic behavioral prediction, for instance, may be misused for surveillance, forced relocations, or resource extraction activities. AI infrastructure built for environmental monitoring can also bolster surveillance capitalism or empower extractive industries, undermining sustainability goals. The underlying algorithms and datasets intended for positive environmental outcomes may be applied in authoritarian contexts or for displacement without consent. Surveillance-enabled AI in some regions has been applied to monitor rural communities, nominally for environmental protection but effectively enabling enforced land-use changes raising concerns about data governance and consent. Though peer-reviewed literature is limited on these misuses, civil society observers caution against uncritical deployment [56,57].

To mitigate dual-use risks, frameworks for ethical governance must accompany technical tools. This includes policy oversight, transparency mandates on data use, consent mechanisms, and purpose-bound licensing of AI applications to ensure environmental AI is used only for its stated purposes and under accountable governance. Embedding safeguards such as access controls, encryption, and audit trails is necessary when datasets include sensitive geospatial or demographic information. Developers should engage with local communities and rights groups to co-design AI systems and specify use-cases transparently before deployment. Without such measures, climate AI tools may inadvertently undermine the very communities and ecosystems they aim to support [14,32,57].

Summarizing the multifaceted challenges discussed, Table 2 categorizes key issues in AI for climate action, their impacts, and proposed solutions to guide ethical and effective deployment.

Table 2 Challenges in AI for Climate Action and Proposed Solutions

Challenge Category	Specific Issues	Impacts	Proposed Solutions	Examples/Regions	References
Data Scarcity	Unequal distribution, Global South bias	Inaccurate models, inequities	Local data infrastructure, partnerships	Africa (78% external funding)	[48, 49]
Model Bias	Training on northern data	Poor performance in tropics	Context-sensitive frameworks	Equatorial microclimates	[49]
Energy Intensity	High CO_2 from training/inference	2.5-3.7% global emissions	Energy-efficient architectures, carbon-aware scheduling	GPT-3 (552 tons CO_2)	[50, 51]
Water Usage	Cooling demands	4.2-6.6 billion m^3 by 2027	Sustainable sourcing, efficiency metrics	BLOOM model (25-50 tons)	[52]

Transparency	Black-box models, non-disclosure	Reduced trust, bias risks	XAI standards, disclosures	Dataset provenance reporting	[53, 54]
Fairness/Accountability	Demographic omissions	Misallocation in decisions	Human-in-the-loop, ethics guidelines	Inclusive validation	[54, 55]
Dual-Use Dilemma	Repurposing for surveillance	Harm to communities	Purpose-bound licensing, audits	Geospatial data misuse	[56, 57]
Governance	Lack of oversight	Ethical harms	Consent mechanisms, encryption	Environmental monitoring risks	[57]

6. Policy, Governance, and Future Pathways

6.1. Alignment of AI Innovation with International Climate Goals

Efforts to align AI-driven climate action with international frameworks such as the Paris Agreement are underway across multilateral development banks and UN mechanisms. The Asian Infrastructure Investment Bank, for example, has developed a methodology to assess whether its financed operations support the mitigation, adaptation, and resilience objectives of the Paris Agreement a case of institutional alignment in practice. Similarly, the United Nations Framework Convention on Climate Change (UNFCCC) has adopted the **#AI4ClimateAction** initiative under its Technology Mechanism, explicitly recognizing AI's potential in climate mitigation and adaptation, particularly in least developed countries and small island developing states [58,59].

Parallel alignment is emerging through ethical frameworks specifically tailored for AI in climate contexts. The *Principles on AI for Climate Action*, proposed by the Chinese Academy of Sciences' AI Ethics Center, call for deep collaboration between AI technologists and climate stakeholders, emphasizing open-source technology, equitable access for low- and middle-income countries, and contributions toward global climate goals such as those outlined by the UNFCCC and UNESCO. These principles reflect a convergence of climate ethics and digital governance, embedding environmental sustainability into AI design norms. Finally, global governance initiatives are beginning to intersect. The United Nations Secretary-General's AI Advisory Body and the negotiating Global Digital Compact provide fora in which AI and climate policy can converge. Discussions on establishing an International Scientific Panel on AI and annual dialogues on AI governance may pave the way for integrating climate criteria into AI policy agendas. COP29 in 2025 offers another pivotal platform where UNFCCC members may further articulate AI's role in achieving Sustainable Development Goal 13 (Climate Action) within the global AI governance architecture [60-63].

6.2. Role of Open-Source Platforms and Collaborative AI Ecosystems

Open-source platforms play a transformative role in democratizing AI capacity for climate applications. The Earth System Modeling Framework (ESMF) offers shared software infrastructure for climate modeling and simulation, promoting interoperability, code reuse, and broader participation across academic and government institutions. Such open-source foundations enable more equitable access to tools and foster collective innovation, particularly in data-scarce regions. The Platform for Real-time Impact and Situation Monitoring (PRISM) serves as an example of a collaborative, open-source approach to climate risk management. Developed by the World Food Programme, PRISM integrates geospatial and socio-economic data in multiple countries, with deployments in Indonesia, Sri Lanka, Mozambique, and others, enabling real-time vulnerability mapping and climate resilience planning. Its status as a recognized Digital Public Good demonstrates how open-source design facilitates replicable, regionally tailored climate adaptation tools [64-66].

In policymaking spaces, initiatives like Pol.is and the broader open-source ethos (e.g. Citizens Code / People's Code projects) illustrate how AI platforms can support inclusive deliberation and decision-making in public administrations. While not yet widely adopted for climate policy per se, these tools show how open governance AI ecosystems can enable transparency and participatory co-design attributes essential for equitable climate AI deployment. Emerging proposals,

such as open source–based policymaking platforms integrating economic and climate data, suggest a future where public policy is itself data-driven and transparently formulated via AI collaboration.

6.3. Policy Frameworks to Regulate Responsible AI Deployment

Robust policy frameworks are essential to ensure the ethical and sustainable deployment of AI systems in climate contexts. The European Union's AI Act of 2024 is among the most advanced regulatory regimes to date, classifying AI systems into risk categories with explicit obligations around transparency, robustness, and fairness including environmental impact considerations for high-risk deployments. However, analysts note that existing legislation still lacks comprehensive treatment of energy and lifecycle emissions of AI systems [67,68].

Academic and policy experts have proposed augmenting regulation with mandatory environmental reporting for AI systems. Suggested measures include requiring disclosure of energy consumption during both training and inference phases, water usage metrics, and cumulative emissions, along with enforceable renewable energy usage targets for data centers. These proposals also call for energy-based risk assessment protocols and mechanisms such as tradable energy budgets to manage operational footprints of AI infrastructures.

On the international level, joint statements like the Principles on AI for Climate Action embed equity, ethics, and open collaboration into AI policy recommendations. They encourage multi-stakeholder participation and advocate for global platforms that facilitate transparent cooperation across climate and AI domains. National administrations play a governance both in setting norms and enabling equitable access, particularly by addressing capacity shortages, infrastructure gaps, algorithmic bias, and privacy risks especially in public sector AI climate deployments [69,70].

6.4. Scaling and Replicating Successful AI Projects Globally

Scaling proven AI interventions especially across the Global South requires attention to resource constraints, local capacity, and funding mechanisms. The UNFCCC's #AI4ClimateAction initiative explicitly facilitates knowledge sharing, capacity building, and locally led AI innovations in developing countries, with programs, Grand Challenges, and regional consultation events under the 2024–2027 workplan. At COP28 and COP29, this initiative also helped spotlight scalable AI solutions and transfer models among communities facing climate vulnerability.

On the financing front, philanthropic and multilateral efforts are beginning to fill gaps. The Bezos Earth Fund's AI for Climate and Nature Grand Challenge (2025) awarded initial funding to projects focused on biodiversity monitoring, weather forecasting, and agricultural resilience, highlighting partnerships between technologists and environmental experts as pathways to scalable impact. Similarly, proposals for taxing energy-intensive AI and crypto operations to fund climate efforts underscore a potential financing model aligned with climate justice and equitable scaling.

Finally, digital twin platforms like Destination Earth (DestinE) offer a blueprint for scaling advanced AI-powered simulations to public policy planning. Launched by the European Commission in 2022 and operating by 2024, DestinE provides detailed Earth-system modeling for policymakers, enabling cross-border learning and potential replication in other regions through shared infrastructure and open technical collaboration.

7. Conclusion

Artificial Intelligence has made substantive contributions to both climate change mitigation and adaptation by enhancing the precision, scalability, and responsiveness of environmental systems. In mitigation efforts, AI has enabled more accurate renewable energy forecasting, improved grid integration, and supported energy-efficient operations across industrial and urban infrastructures. Applications such as predictive analytics for emission reductions, optimization of resource use, and intelligent land-use planning have been particularly impactful. In adaptation domains, AI has advanced early warning systems, climate risk modeling, precision agriculture, and smart water management, supporting more timely and context-specific responses to climate variability. These technologies have also allowed for greater integration of remote sensing and real-time data into decision-making frameworks, thereby improving situational awareness and resilience planning across vulnerable sectors.

Despite these advances, the deployment of AI in environmental contexts is limited by systemic challenges including unequal data availability, insufficient cross-sectoral integration, limited model transparency, and the carbon footprint of large-scale AI computation. There is a pressing need for interdisciplinary collaboration that brings together climate scientists, data engineers, policy experts, and local communities. A forward-looking roadmap must prioritize equitable data sharing infrastructures, support for low-resource regions, and regulatory mechanisms that ensure ethical and sustainable AI design. Investment in hybrid physical-AI models, federated learning architectures, and open-source frameworks can also enhance trust, reproducibility, and broader societal participation in climate AI applications. Ultimately, the success of AI as a climate tool will depend on aligning technological innovation with social equity,

environmental ethics, and international policy frameworks such as the Paris Agreement and the UN Sustainable Development Goals.

Compliance with ethical standards

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