

Original Article

AI-Augmented Climate Modeling and Geoengineering Optimization

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Abstract: Climate change poses one of the most significant challenges to global ecosystems, economies, and human societies. Accurate climate modeling and effective intervention strategies are essential for mitigating its impacts. Traditional climate models, while valuable, often face limitations in computational efficiency, data assimilation, and prediction accuracy. Recent advancements in Artificial Intelligence (AI) offer transformative potential in enhancing climate modeling by integrating large-scale data, learning complex nonlinear relationships, and generating high-resolution forecasts. AI-augmented climate models can analyze vast datasets from satellites, sensors, and climate observatories, improving predictions of extreme weather events, temperature anomalies, and precipitation patterns. Beyond prediction, AI also plays a crucial role in optimizing geoengineering strategies, including Solar Radiation Management (SRM) and Carbon Dioxide Removal (CDR). By simulating diverse geoengineering scenarios and assessing potential risks, AI enables decision-makers to identify strategies that maximize climate mitigation benefits while minimizing unintended consequences. This research explores the convergence of AI, climate modeling, and geoengineering optimization, highlighting state-of-the-art machine learning techniques, hybrid AI-physical models, and real-world applications. Additionally, it discusses the ethical, environmental, and policy challenges associated with AI-driven climate interventions. Case studies demonstrate the successful application of AI in modeling atmospheric phenomena, ocean fertilization strategies, and urban climate engineering solutions. The paper underscores the importance of continued research, interdisciplinary collaboration, and the development of transparent, explainable AI models to ensure responsible and effective climate interventions. By leveraging AI, humanity can gain more accurate insights into climate dynamics and optimize intervention strategies, ultimately contributing to global sustainability and resilience in the face of climate change.

Keywords: AI-augmented climate modeling, geoengineering optimization, machine learning, deep learning, Solar Radiation Management (SRM), Carbon Dioxide Removal (CDR), extreme weather prediction, hybrid models, climate intervention, sustainability, risk assessment, environmental ethics, data-driven climate solutions

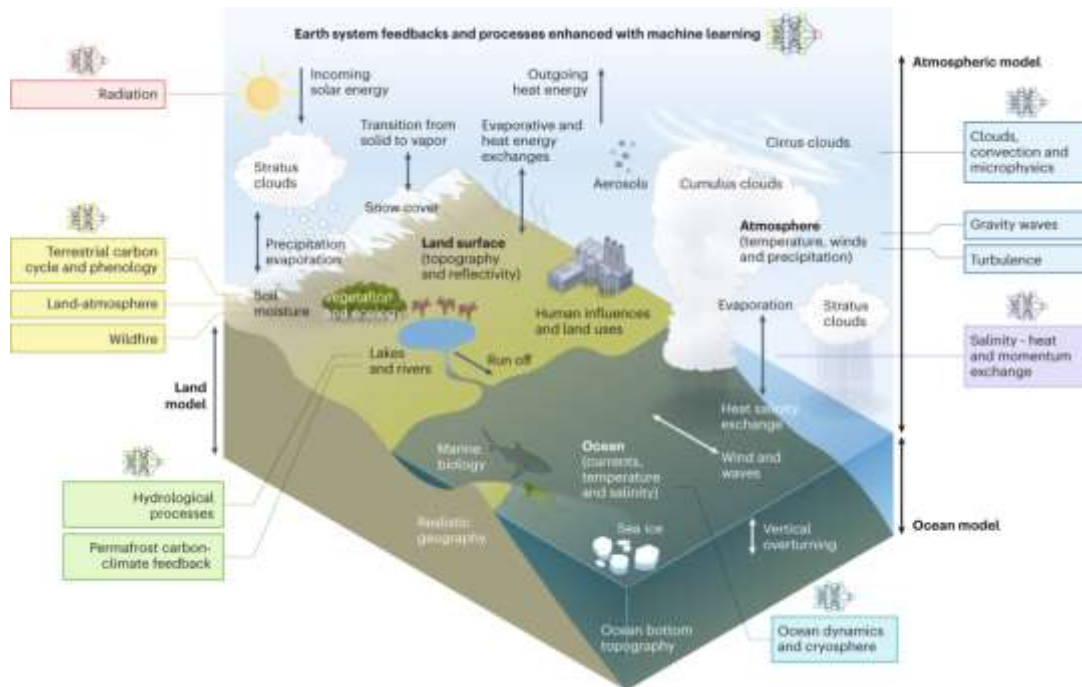
I. INTRODUCTION

Climate change is an unprecedented global challenge with wide-ranging impacts on ecosystems, human societies, and economic systems. Rising temperatures, changing precipitation patterns, and increasing frequency of extreme weather events underscore the urgent need for accurate climate predictions and effective mitigation strategies. Traditional climate modeling techniques, including General Circulation Models (GCMs) and Earth System Models (ESMs), have been instrumental in understanding the dynamics of the atmosphere, oceans, and land surfaces. However, these models often face limitations in handling the growing complexity of climate systems, computational demands, and uncertainties arising from incomplete observational data.

Recent advances in Artificial Intelligence (AI) offer transformative opportunities to enhance climate modeling and optimize geoengineering interventions. Machine learning and deep learning algorithms can analyze massive datasets, uncover nonlinear relationships, and generate high-resolution climate predictions with improved accuracy. By integrating AI with traditional physical models, hybrid approaches can leverage the strengths of both methods, enhancing predictive capabilities while reducing computational costs.

Beyond predictive modeling, AI has emerged as a powerful tool for geoengineering optimization. Geoengineering, which includes techniques such as Solar Radiation Management (SRM) and Carbon Dioxide Removal (CDR), aims to deliberately intervene in the Earth's climate system to mitigate global warming. AI can simulate diverse geoengineering scenarios, optimize deployment strategies, and assess potential risks, enabling policymakers and scientists to make informed, data-driven decisions.

This research explores the convergence of AI, climate modeling, and geoeengineering optimization, highlighting state-of-the-art methodologies, real-world applications, and the challenges associated with ethical, environmental, and governance considerations. By leveraging AI-driven insights, humanity can enhance the understanding of climate dynamics and develop more effective, sustainable strategies to combat climate change. This integration represents a promising frontier for achieving global resilience and sustainability in the face of escalating climate risks.



II. FUNDAMENTALS OF CLIMATE MODELING

Climate modeling is the cornerstone of understanding and predicting Earth's complex climate system. These models simulate the interactions between the atmosphere, oceans, land surfaces, and ice, enabling scientists to anticipate long-term changes and extreme weather events. Traditional climate models, primarily General Circulation Models (GCMs) and Earth System Models (ESMs), rely on mathematical equations derived from the laws of physics, thermodynamics, and fluid dynamics. GCMs focus on simulating atmospheric and oceanic circulation patterns, while ESMs integrate biogeochemical cycles such as carbon and nitrogen to capture the feedback mechanisms critical for understanding climate change.

Despite their significant contributions, conventional climate models face several limitations. They often require immense computational resources, particularly for high-resolution simulations, which restricts their temporal and spatial granularity. Additionally, uncertainties in model parameters, incomplete observational data, and the inherent complexity of nonlinear climate processes can lead to prediction errors. This is particularly challenging when forecasting localized or extreme events, such as hurricanes, droughts, or sudden shifts in ocean currents.

To address these challenges, Artificial Intelligence (AI) has emerged as a complementary tool for climate modeling. Machine learning techniques, including supervised learning, neural networks, and deep learning, can identify complex, nonlinear relationships within large-scale climate datasets that traditional models may overlook. AI-driven models excel at pattern recognition, anomaly detection, and probabilistic forecasting, enabling more accurate and timely predictions. For instance, neural network models can analyze satellite imagery, remote sensing data, and historical climate records to generate high-resolution, near-real-time climate forecasts.

Hybrid modeling approaches, which combine AI with traditional physics-based models, represent a particularly promising direction. These models leverage AI to correct biases, fill observational gaps, and optimize computational efficiency while retaining the physical interpretability of conventional climate simulations. By

integrating AI into climate modeling, researchers can enhance predictive accuracy, improve scenario analysis, and generate actionable insights for policymakers and stakeholders.

In summary, the fundamentals of climate modeling lie in simulating complex Earth systems using physics-based equations. However, the growing capabilities of AI allow researchers to overcome traditional limitations, providing high-resolution forecasts, uncovering hidden patterns, and supporting decision-making in climate adaptation and mitigation strategies. The convergence of AI and climate modeling forms the foundation for the next generation of predictive and prescriptive climate science.

III. AI IN CLIMATE PREDICTION

Artificial Intelligence (AI) has emerged as a transformative tool for climate prediction, enabling more accurate forecasts of temperature, precipitation, and extreme weather events. Traditional climate models often struggle with high-dimensional, nonlinear climate data and the enormous variability inherent in the Earth's systems. AI algorithms, particularly machine learning and deep learning, can analyze large datasets, recognize hidden patterns, and generate probabilistic predictions with high precision.

A. Sub-Topic: Extreme Weather Event Forecasting

One of the most critical applications of AI in climate prediction is forecasting extreme weather events, such as hurricanes, heatwaves, floods, and droughts. These events often have devastating impacts on human societies, ecosystems, and economies. AI models leverage historical climate data, satellite imagery, and sensor networks to detect early warning signals and predict event trajectories. For instance, deep neural networks can process temporal sequences of climate variables to predict hurricane intensification or flash flood occurrence with higher accuracy than conventional models.

By integrating AI into predictive frameworks, scientists can generate real-time forecasts and scenario analyses. AI-driven models excel in handling uncertainty, providing probabilistic outputs that help policymakers assess potential risks and implement timely mitigation strategies. Additionally, AI can optimize resource allocation for disaster preparedness, such as evacuation planning, flood barrier deployment, and emergency response coordination.

Recent studies demonstrate that hybrid AI-physical models outperform traditional climate models in both speed and accuracy. For example, AI-enhanced General Circulation Models (GCMs) can reduce computational time while improving predictions of temperature extremes and precipitation anomalies. These advancements not only support immediate disaster response but also inform long-term climate adaptation policies.

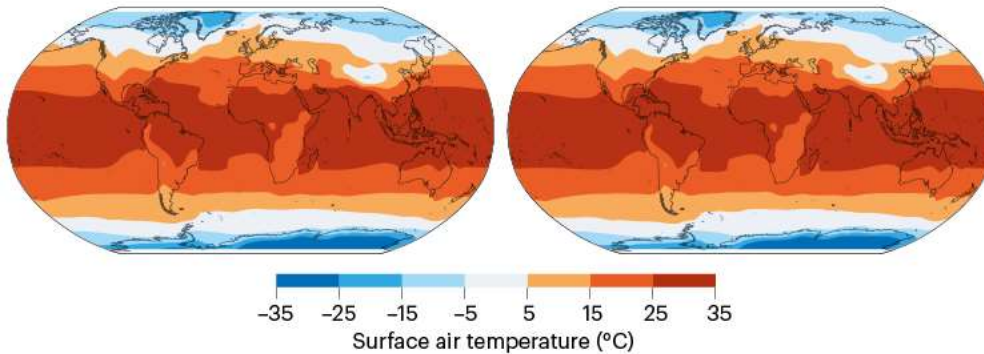
In summary, AI in climate prediction enhances the accuracy, speed, and reliability of forecasting extreme events. By combining machine learning techniques with physical climate models, researchers can better anticipate the impacts of climate change, optimize preparedness measures, and reduce human and economic losses. This integration is a key step toward resilient and informed climate management.

AI CLIMATE MODEL WORKS AT SPEED

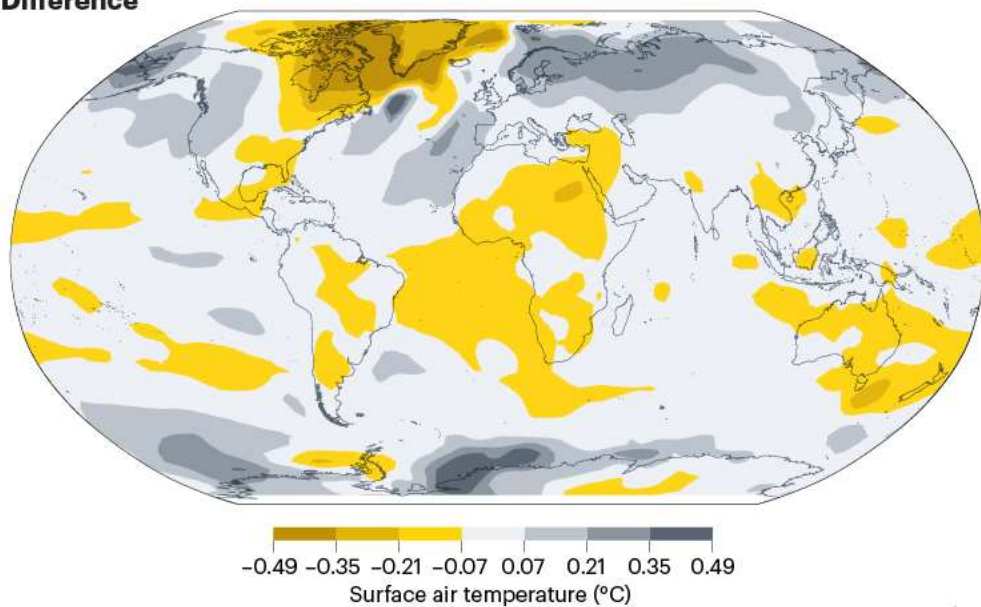
In projections of global surface air temperature up to the year 2100, output from the QuickClim climate emulator (right), a machine-learning system, closely matches that of the physics-based climate model it is trained on (left). However, QuickClim generates the output about one million times faster.

Physics-based model

AI-based emulator



Difference



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B. Geoengineering: Concepts and Controversies

Geoengineering refers to deliberate, large-scale interventions in the Earth's climate system aimed at mitigating the effects of global warming. As greenhouse gas emissions continue to rise and traditional mitigation strategies struggle to keep pace, geoengineering has gained attention as a potential complementary approach to climate change management. The two primary categories of geoengineering are Solar Radiation Management (SRM) and Carbon Dioxide Removal (CDR). SRM techniques aim to reflect a portion of incoming solar radiation back into space, thereby reducing global temperatures. Examples include stratospheric aerosol injection, cloud brightening, and reflective surface enhancement. CDR strategies focus on removing carbon dioxide from the atmosphere and storing it in terrestrial, oceanic, or geological reservoirs, such as afforestation, bioenergy with carbon capture and storage (BECCS), and ocean fertilization.

Despite their theoretical promise, geoengineering techniques are highly controversial. One major concern is the uncertainty surrounding their environmental impacts. For instance, SRM could alter precipitation patterns, disrupt monsoons, or affect regional climates in unforeseen ways. Similarly, large-scale ocean fertilization may impact marine ecosystems and biodiversity. Ethical considerations also arise, as geoengineering

could shift the burden of risk disproportionately among countries or communities, raising questions of climate justice.

Moreover, governance and regulation present significant challenges. Global coordination is essential to prevent unilateral geoengineering actions that could have transboundary consequences. Currently, there is limited international legal framework to guide the deployment of geoengineering technologies, and public perception often leans toward skepticism due to perceived risks.

AI integration offers a pathway to address some of these uncertainties. By simulating geoengineering scenarios, analyzing complex interactions, and predicting potential side effects, AI can support more informed decision-making. However, the effectiveness of AI-driven geoengineering optimization depends on high-quality data, accurate climate models, and consideration of ethical and societal implications.

In conclusion, geoengineering represents both an opportunity and a challenge in the fight against climate change. While it holds the potential to mitigate global warming, uncertainties, ethical dilemmas, and governance issues necessitate careful evaluation. Combining AI with geoengineering research provides a promising avenue to optimize strategies, minimize risks, and ensure that interventions are both scientifically grounded and socially responsible.

C. AI-Driven Optimization of Geoengineering

Artificial Intelligence (AI) plays a critical role in optimizing geoengineering strategies, providing tools for simulation, prediction, and decision-making that were previously unattainable. Geoengineering interventions, such as Solar Radiation Management (SRM) or Carbon Dioxide Removal (CDR), involve complex interactions within the climate system. Small changes in deployment strategies can lead to disproportionately large or unintended consequences. AI helps address this complexity by processing vast datasets, running simulations at scale, and identifying optimal intervention pathways.

D. Sub-Topic: Simulation and Risk Assessment

Simulation and risk assessment are central to AI-driven geoengineering optimization. Machine learning models can integrate historical climate data, satellite observations, and outputs from traditional climate models to simulate multiple geoengineering scenarios rapidly. These simulations allow researchers to evaluate potential outcomes, including temperature changes, precipitation shifts, and regional climate impacts. For example, AI-based models can predict the effects of stratospheric aerosol injection on global and regional temperatures, highlighting areas at higher risk of drought or ecosystem disruption.

Moreover, AI enhances risk assessment by quantifying uncertainties and providing probabilistic forecasts. Unlike traditional deterministic models, AI models can account for nonlinear relationships and feedback loops within the climate system. This capability allows decision-makers to identify strategies that maximize mitigation benefits while minimizing adverse effects. For instance, reinforcement learning algorithms can optimize the timing, location, and intensity of geoengineering interventions to achieve desired climate outcomes without triggering harmful side effects.

Beyond environmental modeling, AI also facilitates scenario optimization for policy and governance. By integrating economic, social, and ethical considerations, AI can rank geoengineering strategies based on effectiveness, risk, and feasibility. This multidimensional optimization is critical for responsible deployment, as it ensures interventions are not only scientifically sound but also socially acceptable.

In summary, AI-driven optimization transforms geoengineering from a theoretical concept into a more practical and data-informed strategy. Through advanced simulation, probabilistic risk assessment, and multi-criteria optimization, AI enables researchers and policymakers to evaluate potential interventions with unprecedented precision. This approach ensures that geoengineering strategies can be deployed responsibly, efficiently, and safely, supporting global efforts to mitigate climate change while minimizing unintended consequences.

E. Case Studies and Applications

The practical applications of AI in climate modeling and geoengineering demonstrate its transformative potential in addressing global climate challenges. Several case studies highlight how AI-driven models are being used to simulate, predict, and optimize interventions, improving both the accuracy and efficiency of climate mitigation strategies.

One notable example is stratospheric aerosol injection (SAI). Researchers have used machine learning algorithms to simulate the dispersal of aerosols in the stratosphere, analyzing their effects on global temperatures, regional precipitation patterns, and atmospheric circulation. By processing large datasets from satellites, climate sensors, and historical records, AI models can predict optimal injection locations and quantities to maximize cooling effects while minimizing unintended environmental consequences. These simulations provide critical insights into both the feasibility and risks associated with SRM techniques.

Another application is ocean fertilization, a Carbon Dioxide Removal (CDR) strategy that involves adding nutrients to ocean regions to stimulate phytoplankton growth, which absorbs CO₂ from the atmosphere. AI models have been employed to optimize nutrient dosing, identify suitable ocean regions, and assess potential impacts on marine ecosystems. Predictive algorithms evaluate both carbon sequestration potential and ecological risks, enabling more targeted and sustainable interventions.

Urban climate management represents a third area of application. AI-driven models are increasingly used to optimize strategies for urban cooling, such as green infrastructure deployment, reflective surfaces, and building orientation adjustments. By integrating real-time climate data with predictive models, cities can implement interventions that reduce urban heat islands, manage stormwater, and enhance overall resilience against climate-related hazards.

In addition to these examples, AI is also applied in hybrid climate modeling, combining physics-based models with machine learning to improve predictive accuracy. These hybrid approaches allow researchers to simulate extreme weather events, temperature anomalies, and carbon cycle dynamics with higher precision than traditional models alone.

Overall, these case studies illustrate that AI is not merely a computational tool but a strategic enabler for climate action. By enhancing predictive capabilities, optimizing geoengineering interventions, and providing actionable insights for decision-makers, AI helps bridge the gap between theoretical climate solutions and practical implementation. This convergence of AI and climate science paves the way for more effective, sustainable, and adaptive strategies to address the urgent challenges posed by climate change.

F. Challenges and Limitations

While AI-augmented climate modeling and geoengineering optimization offer significant potential, several challenges and limitations must be addressed to ensure their effectiveness, reliability, and ethical application. These challenges span data availability, model accuracy, computational requirements, and societal considerations.

Data Quality and Availability

AI models depend on high-quality, large-scale datasets, including satellite observations, sensor measurements, historical climate records, and socio-economic information. Incomplete, noisy, or biased datasets can lead to inaccurate predictions or misinformed geoengineering strategies. Certain regions, particularly in developing countries, suffer from limited climate monitoring infrastructure, creating gaps that reduce model reliability. Additionally, integrating heterogeneous datasets from multiple sources presents challenges related to standardization, harmonization, and real-time processing.

Model Uncertainty and Interpretability

Despite their predictive power, AI models often operate as “black boxes,” making it difficult to interpret how they arrive at specific predictions. This lack of transparency can hinder scientific trust and limit policy adoption. Furthermore, AI models may overfit training data, fail to generalize to unseen climate scenarios, or

underestimate rare extreme events, potentially leading to ineffective or harmful interventions. Hybrid models combining physics-based and AI-driven approaches mitigate some of these risks, but uncertainty remains a key concern.

Computational Demands

High-resolution climate simulations and geoengineering optimization require substantial computational resources. Training deep learning models on global climate datasets or running multi-scenario geoengineering simulations can strain even advanced supercomputing facilities. Computational constraints may limit the temporal and spatial resolution of predictions, affecting their utility for precise decision-making.

Ethical, Governance, and Social Challenges

Geoengineering raises profound ethical questions. AI-driven interventions could disproportionately affect certain regions or populations, raising concerns about climate justice. Governance frameworks for geoengineering remain underdeveloped, making global coordination and regulation difficult. Public perception and societal acceptance are also crucial, as mismanagement or lack of transparency could undermine trust in AI-assisted climate interventions.

Risk of Unintended Consequences

Even with AI optimization, geoengineering interventions carry inherent risks. For example, stratospheric aerosol injection may alter precipitation patterns, affect ecosystems, or create geopolitical tensions if deployed unilaterally. AI can reduce these risks through scenario analysis and optimization, but it cannot eliminate uncertainty entirely.

In conclusion, the challenges of data quality, model uncertainty, computational constraints, and ethical considerations highlight the need for careful implementation, interdisciplinary collaboration, and transparent governance. Addressing these limitations is essential to ensure that AI-augmented climate modeling and geoengineering contribute safely and effectively to global climate mitigation efforts.

IV. FUTURE DIRECTIONS

The integration of Artificial Intelligence (AI) into climate modeling and geoengineering optimization represents a rapidly evolving frontier with significant potential to enhance our understanding of climate dynamics and inform effective mitigation strategies. Looking forward, several key directions are likely to shape the future development of AI-driven climate interventions.

A. Advancements in AI Techniques

Emerging AI methodologies, including deep reinforcement learning, generative AI, and hybrid AI-physical models, offer promising avenues for improving predictive accuracy and intervention optimization. Reinforcement learning can simulate a wide range of geoengineering strategies, dynamically adapting deployment plans to changing climate conditions and minimizing adverse outcomes. Generative AI models can synthesize high-resolution climate scenarios, enabling more granular and localized predictions. Hybrid models, which combine AI with traditional physics-based approaches, are expected to enhance both reliability and interpretability, bridging the gap between computational efficiency and scientific rigor.

B. Integration with Real-Time Monitoring

The increasing availability of high-resolution satellite data, IoT climate sensors, and remote sensing technologies provides unprecedented opportunities for AI-driven real-time climate monitoring. Future AI systems can integrate continuous data streams to update climate predictions dynamically, detect anomalies early, and optimize geoengineering interventions in near real-time. This adaptive approach will be critical for managing uncertainties and responding effectively to emerging climate threats, such as sudden extreme weather events or rapid ice sheet melting.

C. Policy and Governance Frameworks

As AI-assisted geoengineering becomes more feasible, establishing robust governance and regulatory frameworks will be essential. International collaboration will be needed to set standards for data sharing, model

transparency, ethical deployment, and risk assessment. Future policies may integrate AI-generated insights to guide decision-making, ensuring that interventions are scientifically grounded, socially acceptable, and globally coordinated. Multidisciplinary collaboration between climate scientists, AI researchers, policymakers, and ethicists will be crucial to balance technological possibilities with societal considerations.

D. Public Engagement and Transparency

Public acceptance and trust are central to the responsible deployment of AI-driven geoengineering solutions. Future efforts should prioritize transparency in AI models, explainable outputs, and inclusive stakeholder engagement. Participatory approaches can help communities understand potential risks and benefits, foster equitable decision-making, and align interventions with societal values.

E. Ethical and Environmental Considerations

Continued research will be necessary to evaluate the ecological and ethical implications of AI-optimized geoengineering strategies. AI can assist in scenario planning, risk assessment, and unintended consequence modeling, but responsible deployment requires comprehensive evaluation frameworks. Emphasizing sustainability, justice, and environmental protection will remain a core priority in the design and implementation of AI-assisted climate interventions.

In conclusion, the future of AI-augmented climate modeling and geoengineering optimization lies at the intersection of technological innovation, scientific understanding, and ethical governance. By advancing AI methodologies, integrating real-time monitoring, establishing robust policies, and engaging stakeholders, humanity can harness AI to develop adaptive, effective, and responsible climate solutions. These advancements promise to transform climate science from reactive prediction to proactive intervention, contributing significantly to global resilience and sustainability in the face of accelerating climate change.

V. CONCLUSION

Artificial Intelligence (AI) has emerged as a transformative tool in addressing the growing challenges posed by climate change. By augmenting traditional climate models, AI enables more accurate predictions, high-resolution simulations, and timely identification of extreme weather events. The integration of machine learning, deep learning, and hybrid AI-physical approaches allows researchers to process massive datasets from satellites, sensors, and climate observatories, uncovering complex nonlinear relationships that conventional models often overlook. This enhanced predictive capability is critical for both understanding the trajectory of climate change and developing effective mitigation strategies.

In addition to improving climate modeling, AI plays a pivotal role in optimizing geoengineering interventions. Techniques such as Solar Radiation Management (SRM) and Carbon Dioxide Removal (CDR) involve complex and high-stakes decision-making, where small changes in deployment can have far-reaching consequences. AI-driven simulations and scenario analyses enable the assessment of potential outcomes, quantification of risks, and identification of optimal strategies, balancing efficacy with environmental safety. By providing probabilistic forecasts, AI supports informed policymaking and risk management, helping ensure that geoengineering strategies are both effective and responsible.

Despite its promise, AI-augmented climate science faces significant challenges. Data quality, model uncertainty, computational limitations, and ethical considerations pose barriers to widespread adoption. Uncertainties in predictions, potential unintended consequences of geoengineering, and governance gaps underscore the need for careful evaluation, interdisciplinary collaboration, and transparent decision-making. Ethical and social considerations, including climate justice and public engagement, are essential to ensure that interventions are equitable, socially acceptable, and environmentally sustainable.

Looking forward, advancements in AI techniques, real-time monitoring, and international policy frameworks hold the potential to transform climate modeling and geoengineering from theoretical concepts into practical, adaptive solutions. By fostering innovation while addressing ethical, environmental, and governance challenges, AI can play a central role in enhancing global resilience, mitigating climate risks, and supporting sustainable development.

In summary, AI-augmented climate modeling and geoengineering optimization represent a promising convergence of technology and environmental science. Through accurate predictions, optimized interventions, and responsible governance, AI has the potential to significantly advance global efforts to understand, mitigate, and adapt to the impacts of climate change. The integration of AI in climate science not only enhances our capacity to respond proactively but also lays the foundation for a more sustainable and resilient future.

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