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Review

Leveraging artificial intelligence for research and action on climate change: opportunities, challenges, and future directions

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ABSTRACT

Research and action on climate change (RACC) represent a complex global challenge that requires a systematic and multi-dimensional approach. Although progress has been made, persistent limitations in data processing, modeling, and scenario evaluation continue to hinder further advances. Artificial Intelligence (AI) is emerging as a powerful tool to address these challenges by integrating diverse data sources, enhancing predictive modeling, and supporting evidence-based decision-making. Its capacity to manage large datasets and facilitate knowledge sharing has already made meaningful contributions to climate research and action. This paper introduces the RACC theoretical framework, developed through a systematic integration of the research paradigms of the three IPCC Working Groups (WGI, WGII, and WGIII). The RACC framework provides a comprehensive structure encompassing four key stages: data collection, scenario simulation, pathway planning, and action implementation. It also proposes a standardized approach for embedding AI across the climate governance cycle, including areas such as climate modeling, scenario development, policy design, and action execution. Additionally, the paper identifies major challenges in applying AI to climate issues, including ethical concerns, environmental costs, and uncertainties in complex systems. By analyzing AI-supported pathways for mitigation and adaptation, the study reveals significant gaps between current practices and long-term objectives—especially regarding content, intelligence levels, and governance structures. Finally, it proposes strategic priorities to help realize AI's full potential in advancing global climate action.

1. Introduction

Climate change is one of the most critical global challenges, posing serious threats to natural ecosystems and sustainable socio-economic development. The effects of global warming are becoming increasingly evident, with the Earth's average surface temperature having risen by approximately 1.1 °C since the pre-industrial era. This warming has been accompanied by rising sea levels, shrinking glaciers and ice caps, and more frequent and intense extreme weather events [1]. These changes have profound and far-reaching impacts on biodiversity, food security, water resources, and human health, highlighting the urgency of addressing climate change [2].

The global community recognizes the need for immediate and coordinated efforts to mitigate and adapt to climate change. However, effectively tackling this crisis requires more than high-level agreements—it demands advanced tools and methods to uncover the underlying mechanisms of climate change, project future scenarios, design effective response strategies, and turn planning into concrete actions. This comprehensive and systematic process—including scientific research, policymaking, and implementation—is hindered by key challenges such as limited data availability, forecast uncertainty, and the complexity of decision-making.

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Artificial Intelligence (AI) refers to the ability of computer systems to perform tasks that typically require human intelligence, enabled by technologies such as Machine Learning (ML), which extracts patterns from data; Deep Learning (DL), which identifies complex and hidden relationships; Natural Language Processing (NLP), which interprets and generates text; and Computer Vision (CV), which analyzes images and videos [3]. These capabilities position AI as an emerging and powerful tool in climate change research.

A notable example is Google's "Flood Hub" early warning system, which uses CV for accurate flood mapping and ML with LSTM-based dynamic models to deliver reliable flood forecasts up to five days in advance [4]. In carbon monitoring, AI is driving significant advances: DL applied to drone and satellite data enables tree-level carbon stock estimation [5], while the integration of GONGGA's atmospheric inversion with two AI-enhanced dynamic global vegetation models greatly improves the accuracy of carbon sink predictions, allowing for near real-time global carbon budget tracking [6]. These developments mark a shift from static assessments to dynamic, intelligent monitoring—offering new technical support for climate governance and advancing global climate action [7].

This paper reviews current applications of AI across the research and action process on climate change (RACC) and identifies key challenges facing the field. It examines how AI technologies are being integrated into climate science, assessing both their potential benefits and possible drawbacks, including ethical concerns and the environmental footprint of large-scale AI deployments. Looking ahead, the paper outlines emerging AI applications in areas such as scientific discovery, climate impact assessments, and the development of adaptation and mitigation strategies. By analyzing trends at the intersection of AI and climate science, this study aims to contribute to innovative approaches that support more effective and timely responses to the climate crisis.

2. Framework for responding to climate change

2.1. General process

The Intergovernmental Panel on Climate Change (IPCC) plays a central role in synthesizing and presenting the latest scientific knowledge on climate change at the global level [8]. Fig. 1 illustrates the structure and content of IPCC reports and the underlying logic that connects them. Working Group I (WGI) focuses on the physical science basis of climate change, providing the scientific foundation for Working Group II (WGII), which addresses impacts, adaptation, and vulnerability, and for Working Group III (WGIII), which focuses on mitigation. For example, estimating the remaining carbon budget depends on understanding climate sensitivity [9], while projecting future climate impacts requires advanced models that simulate the Earth system [10].

The IPCC's scenario analysis framework integrates the work of all three groups by combining physical science, impact assessments, and mitigation strategies into coordinated evaluations of climate risks and response options [1,10]. In this process, emissions scenarios are developed under different socio-economic drivers using Integrated Assessment Models (IAMs) (WGIII), then input into climate models to generate projections of future climate change (WGI). These projections are subsequently applied in impact assessment models to evaluate risks, vulnerability, and adaptation needs (WGII) [1,8]. Through this interconnected process, the IPCC provides a comprehensive view of climate change and identifies actionable pathways for global mitigation and adaptation.

Over the past two decades, we have been actively involved in core research across all three IPCC Working Groups. Building on this experience, we developed the RACC framework (Fig. 2) by systematically integrating the research paradigms of WGI, WGII, and WGIII. The RACC framework makes two main contributions:

(1) Harmonization of IPCC research frameworks: By creating a unified structure that links climate observation, adaptation, and mitigation research and actions, RACC identifies critical challenges in climate change research from a process-oriented perspective.

(2) Standardized AI-climate research interface: RACC maps the application of AI technologies across four critical stages—data collection, modeling and forecasting, pathway assessment, and action implementation—supporting the standardization of this emerging interdisciplinary field.

The RACC framework comprises four main phases:

(1) Data collection and status analysis: This phase involves compiling historical climate data, emissions inventories, and socio-economic indicators to analyze the current state of the climate system and its driving forces.

(2) Scenario analysis and modeling forecasts: Here, various climate scenarios are generated and evaluated using predictive models to project climate futures under different mitigation and adaptation strategies, providing a scientific basis for policy development.

(3) Pathway assessment and planning: Based on modeled scenarios, this phase assesses potential response strategies, evaluates their feasibility, and develops action plans aligned with specific climate goals.

(4) Action implementation and monitoring: This final phase focuses on executing selected strategies and continuously monitoring progress, allowing for timely adjustments based on emissions reductions or adaptation outcomes.

2.2. Challenges and opportunities

The RACC framework offers a structured approach for guiding research and actions related to climate change. However, the complexity of climate systems and decision-making processes presents significant barriers [11]. This study identifies four key challenges within the RACC framework (Fig. 2):

(1) Scarcity of data resources: Data quality and availability are foundational to climate research. Meteorological data often suffer from sparse station networks and incomplete historical records, while socio-economic data are hindered by inconsistent statistical practices and low spatial–temporal resolution. These limitations reduce the accuracy of climate risk assessments and weaken the policy basis for emissions accounting and adaptation planning [12].

(2) Uncertainties in future projections: These arise from three main sources: [13].

(i) Model limitations: Climate models rely on simplified parameterizations that introduce systematic biases [14].

(ii) Downscaling deficiencies: Translating global model outputs to regional scales can amplify errors due to methodological imperfections [15,16].

Scenario uncertainties: Non-climatic factors such as future socio-economic developments are difficult to quantify, leading to large variability in emissions scenarios [8]. These compounded uncertainties affect the reliability of future climate projections.

(3) Complexities in assessment and decision-making: Climate pathway evaluations must consider not only costs and benefits but also broader socio-economic and environmental dimensions [17]. Yet key indicators—such as technological change and policy implementation costs—are difficult to quantify. Moreover, Integrated Assessment Models (IAMs) are computationally demanding, and their outputs are sensitive to initial assumptions. Traditional optimization methods often struggle to balance multiple objectives

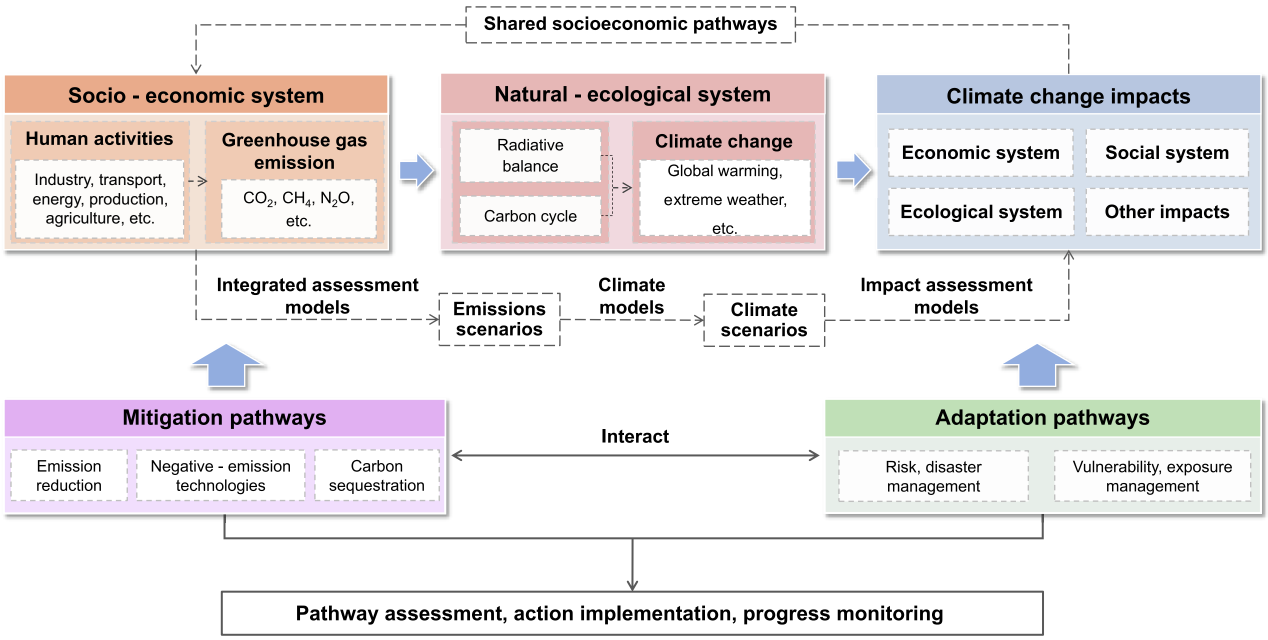

Fig. 1. Scope and framework of climate change research based on IPCC reports: key components of mitigation, adaptation, and the physical science basis.

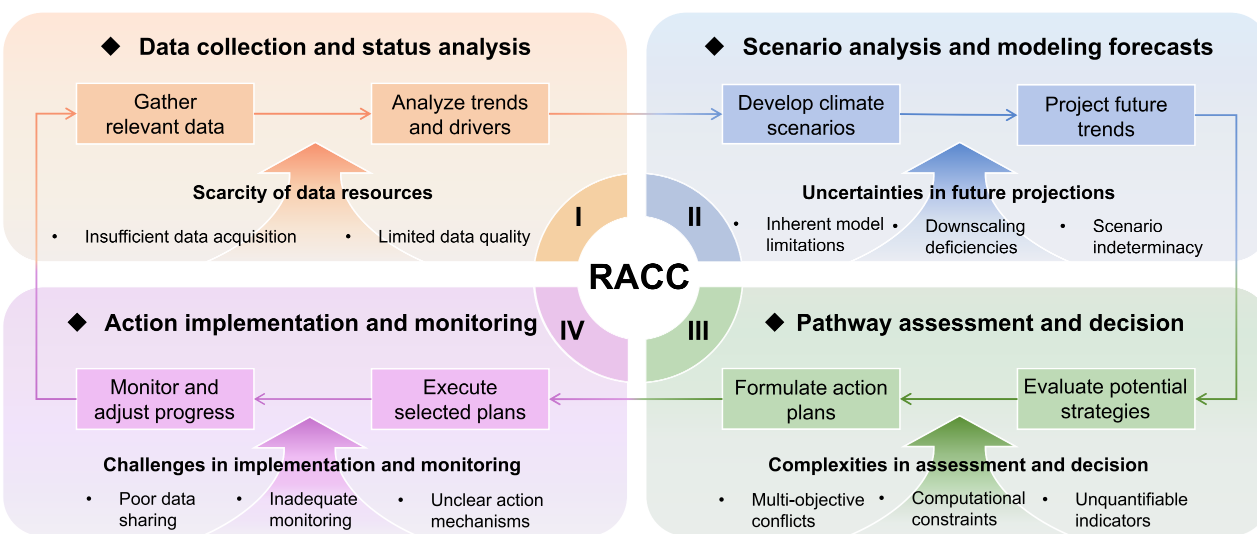

Fig. 2. Framework and challenges of research and action on climate change (RACC): key steps in mitigation, adaptation, and decision-making, highlighting current gaps and opportunities for improvement.

under complex constraints, limiting their usefulness for policy evaluation.

(4) Challenges in implementation and monitoring: Practical climate action often faces vague mandates, unclear responsibilities, and weak incentives, undermining coordination and effectiveness [18]. After implementation, limited real-time monitoring and inadequate data prevent timely evaluations and adaptive management. Poor data sharing and transparency across regions and sectors further exacerbate these problems. Information asymmetries and accumulated errors in monitoring also impair strategy refinement.

At its core, the challenge for RACC lies in the data constraints of climate governance. Inadequate or low-quality data hinder model accuracy and predictive power, leading to biased assessments of mitigation and adaptation options, and ultimately delaying effective action. Addressing these challenges will require next-generation technological systems that can enhance the scientific foundation of climate research and governance.

3. Application of AI in RACC

AI, first introduced in 1956, is a field of science and technology focused on enabling computers to simulate and perform tasks typically associated with human intelligence [19]. By the mid-1980s, AI technologies were already being applied in basic climate research, helping to analyze complex systems and predict environmental patterns. In the current era—characterized by rapid advances in parallel computing, big data, and ML—the potential for AI in climate research and governance has expanded significantly.

Pioneering studies have explored the diverse connections between AI and climate change. AI is now seen as a key tool for reducing emissions in major sectors such as construction, transportation, energy, and manufacturing [3], as well as for improving climate adaptation strategies [20]. Reviews of AI applications in climate-related research highlight its capacity to support better understanding and more effective responses to climate challenges [21]. However, most of these studies focus on specific domains, and a comprehensive review of AI's role across the full climate change research process remains lacking.

Drawing on the RACC framework and AI's diverse capabilities, this study aims to categorize and synthesize current research on AI applications in climate action (Fig. 3). We examine how AI is integrated into various stages of the RACC framework—data collection and analysis, scenario modeling, pathway assessment, and progress monitoring—highlighting its role in improving the accuracy, efficiency, and scalability of climate research and response.

3.1. Accelerating data collection and basic science research

Traditional climate research has long been constrained by limited data availability and uneven data quality. AI, with its advanced data processing capabilities, can automatically extract valuable insights from large, heterogeneous datasets. This ability has driven transformative developments in many areas of climate science.

AI's strength in geosciences spans three major areas:

(1) Structured data processing: AI enables efficient classification and feature extraction from observational records, satellite imagery, and reanalysis datasets. This improves the accuracy of climate monitoring and early warning systems [22,23], and supports ongoing tracking and management of greenhouse gas emissions [24]. For example, computer vision techniques can analyze satellite images in real-time to monitor glacial retreat [25] or detect urban emission hotspots, thereby integrating pollution and carbon management [26].

(2) Unstructured data mining: Natural language processing (NLP) enables AI to extract climate-relevant information from reports, policy documents, and even social media [27]. This integration of diverse information sources supports the development of more comprehensive climate impact assessments [28,29].

(3) Improving data quality: ML and DL methods offer innovative solutions for filling spatial and temporal gaps in datasets. They can interpolate variables such as temperature and precipitation [30], and DL-based image restoration has been shown to outperform traditional kriging or PCA-based methods in reconstructing missing climate data [31].

In addition to efficient data handling, AI contributes to scientific understanding by uncovering complex interactions within climate systems [22]. For instance, a new AI-powered multiscale model for drought prediction not only achieves high accuracy but also reveals nonlinear links between sea surface temperature anomalies and regional droughts [32]. Another study developed a Koopman neural operator (KNO), which recasts nonlinear partial differential equations (PDEs) as linear problems, improving both accuracy and computational efficiency [33].

Despite these strengths, AI's effectiveness in data collection and analysis still depends on the quality of traditional observational infrastructure. In regions with sparse observations—such as remote or low-income areas—AI models may face significant limitations.

3.2. Improving model performance and scenario prediction

Uncertainty in future climate projections stems from model limitations, coarse spatial resolutions, and uncertain scenario assumptions. AI offers promising ways to reduce these uncertainties through better parameterization, improved downscaling, and enhanced scenario simulations.

Climate models are limited by incomplete knowledge of multiscale interactions in the climate system. As a result, models rely on simplified parameterizations, which reduce simulation reliability [14]. AI provides an alternative: instead of relying on predefined physical assumptions, it learns multivariate nonlinear relationships from observational and high-resolution simulated data [34–36]. This approach has significantly improved the parameterization of key processes such as microphysics, convection, and radiative transfer [37–39].

For downscaling, ML and DL methods use nonlinear mapping to transform coarse model outputs into finer-scale projections [40,41], improving predictions of temperature and precipitation [42,43]. Inspired by image super-resolution (SR) in computer vision, AI-based SR methods have also enhanced downscaled climate projections [44–46].

AI-based climate prediction models are a growing field. For short- and medium-term forecasting, AI improves accuracy for extreme weather events [47], while also supporting sub-seasonal to inter-decadal predictions [23,48]. For emission scenarios, AI can both analyze drivers (e.g., economic, environmental, urban trends) [49–51] and directly model emissions within specific sectors, offering more targeted and reliable scenario planning [52,53].

While AI improves model performance, it must be guided by strong physical and socioeconomic foundations. AI-driven climate models should be constrained by conservation laws and climate process knowledge. Similarly, scenario forecasting must account for economic and policy dynamics to avoid misleading extrapolations.

3.3. Upgrading assessment methods and decision planning

Effective climate strategies depend on sound assessments of mitigation and adaptation pathways. AI supports this process by improving data acquisition, optimizing integrated assessment models (IAMs), and enhancing multi-objective decision-making [54].

AI facilitates accurate emissions estimates [26], real-time energy tracking [55], and identification of climate-vulnerable infrastructure [56], helping governments assess costs and benefits

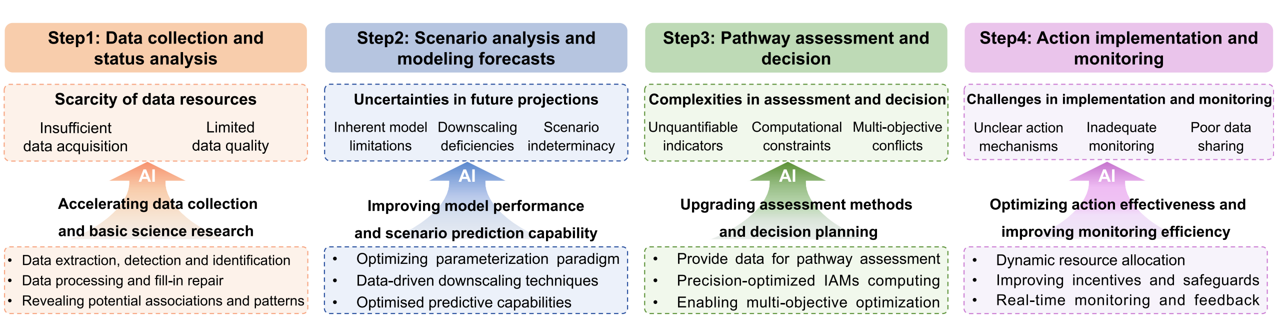

Fig. 3. Applications of AI in climate change research: AI's role in enhancing climate data collection, modeling, decision-making, and action monitoring.

of potential climate strategies. NLP also helps extract climate action data from policy texts and news [57,58], supporting evaluation of instruments such as carbon pricing.

IAMs, which involve complex systems and large parameter spaces, benefit from AI in several ways. AI can improve spatial resolution compatibility across IAM modules using downscaling methods already tested in agriculture, wind speed, and land temperature studies [59–61]. For computational efficiency, a deep-learning emulator of GCAM (a leading IAM) can simulate scenarios 100 times faster while maintaining over 95% accuracy, dramatically reducing simulation costs [62]. AI also improves sensitivity analysis and uncertainty quantification, making IAMs more transparent and robust [63].

For selecting optimal pathways, AI enhances existing algorithms (e.g., particle swarm optimization, genetic algorithms) used by policymakers to balance objectives such as emission reduction, cost, and infrastructure protection [64,65]. These techniques have been successfully applied in energy management [66], infrastructure planning [67], and industrial processes [68]. Recent studies even combine AI with agent-based search to solve complex optimization problems more efficiently [69].

Despite these advancements, challenges remain. Climate planning depends on large volumes of socioeconomic data, often fragmented across sectors and institutions. This fragmentation, along with concerns over privacy, limits AI's full potential in unified decision-making.

3.4. Optimizing implementation and monitoring

Successful climate action depends on adaptive implementation and real-time monitoring. AI can analyze regional development stages, resources, and climate policies to support more equitable and efficient resource allocation [70]. Dynamic models informed by real-time data allow for coordinated planning between governments and sectors [71,72].

This allows governments and sectors to collaborate more effectively, ensuring that resources are distributed based on actual needs and climate goals. By optimizing resource allocation, AI can improve resource utilization efficiency, reduce coordination barriers between sectors, leading to more unified and cohesive climate strategies.

AI also helps promote climate action. It can guide technology deployment (e.g., renewables) [74], support innovation in low-carbon solutions [73], and enhance public engagement through tools like personal carbon footprint calculators [75] and personalized learning systems [76].

However, fragmented data across countries and sectors remains a serious barrier. In areas with poor infrastructure, AI systems underperform, resulting in biased assessments and weak governance strategies. To address this, AI can support the development of cross-border and cross-sector data-sharing platforms. When combined with blockchain, such platforms ensure transparent, secure, and tamper-proof climate monitoring [77,78].

After actions are taken, AI tools can validate policy effectiveness using ML [79], analyze public sentiment with NLP [80], and monitor environmental outcomes using satellite imagery [81–84]. These tools allow for evidence-based adjustments and continual refinement of strategies.

4. Challenges and risks associated with AI

While AI has proven to be a powerful tool for improving data collection, scenario analysis, modeling, and pathway assessment in climate change research, it also introduces several significant challenges and risks (Fig. 4) that could limit or offset its benefits for climate action. These challenges include technical and ethical concerns, the high energy use and carbon footprint of AI systems, and uncertainties surrounding their real-world application.

(1) Technical and ethical risks.

AI applications in climate change bring both ethical dilemmas and technical limitations:

Data gaps and climate justice. Many developing countries and remote regions lack adequate monitoring infrastructure and statistical systems, leading to large data gaps. This scarcity limits the effectiveness of AI-driven climate models and contributes to unfair outcomes in climate governance due to algorithmic bias. In the spatial dimension, for example, small island developing states (SIDS) often suffer from underestimated sea-level rise risks and economic losses, which can skew the allocation of international climate funds [85]. In the social dimension, AI models trained on mobile phone data to estimate urban carbon emissions may overlook the mobility and energy consumption patterns of low-income populations, resulting in biased and unjust policy decisions [86].

Data sovereignty and privacy. Climate-focused AI relies on diverse and often sensitive datasets. Cross-border data sovereignty disputes, combined with fragmented domestic data governance, can hinder transparency and collaboration [87]. Many of these datasets—especially those related to meteorology, disaster early warning, energy, and public health—are tied to national security and societal stability [88]. At the individual level, smart energy monitoring tools in homes, while useful for climate action, can expose personal behavioral patterns and raise privacy concerns [89].

Model interpretability. Trust in AI depends on model transparency. Many AI models, especially deep learning systems, are often described as "black boxes" due to their opaque decision-making processes. This lack of interpretability can limit scientific acceptance and slow policy uptake. Strategies to address this include integrating physical constraints into AI frameworks and providing clearer explanations of model outputs, thereby ensuring scientifically valid and comprehensible results [47].

(2) Energy consumption and carbon footprint.

The development and deployment of AI demand substantial computational resources, leading to high energy use and associated emissions. In 2023, AI processors consumed an estimated 7–11 TWh of electricity—around 0.04% of global electricity use—and this figure is expected to rise tenfold by 2027 [90]. In early 2024, the World Economic Forum warned that AI development could trigger an energy crisis.

To address this, both supply-side and demand-side solutions are needed to reduce AI's carbon footprint. On the supply side, energy-efficient chips, green data centers, and optimized algorithms can significantly cut emissions during training and development phases [91,92]. On the demand side, strategies like edge computing, dynamic inference optimization, and model sharing can help reduce operational energy consumption [93]. However, the practical adoption of these measures still faces technical, financial, and institutional barriers.

(3) Unintended environmental consequences.

In addition to direct emissions from AI systems, indirect environmental risks may arise:

Energy efficiency paradox: While AI can increase efficiency in high-emission industries, it may also trigger a "rebound effect."

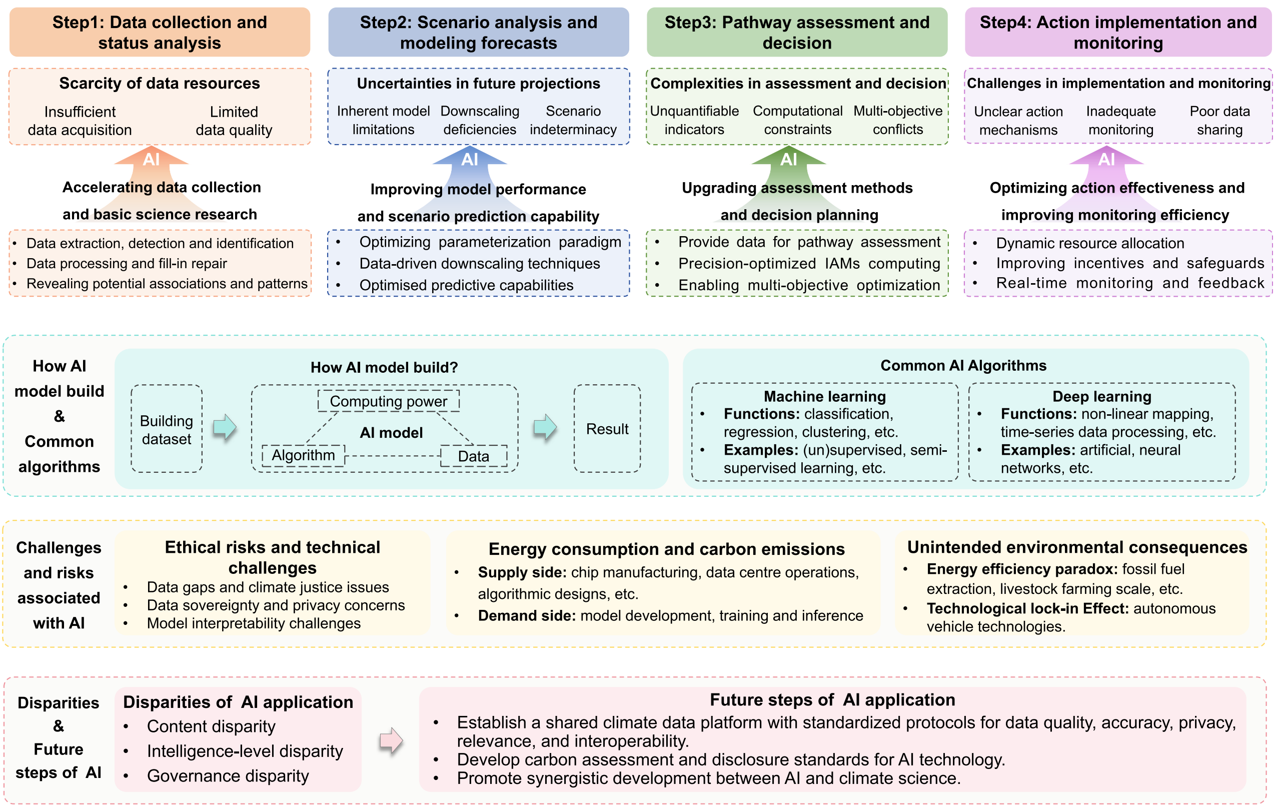

Fig. 4. Challenges, disparities, and future steps in the application of AI to climate change research.

For instance, AI-assisted oil and gas exploration can lower production costs, encouraging more fossil fuel use. Similarly, AI-driven livestock management may boost herd sizes due to improved efficiency, inadvertently increasing methane emissions [93,94];

Technological lock-in: AI may reinforce existing high-carbon development pathways. A prominent example is the deployment of autonomous vehicle technologies, which can undermine public transportation systems and deepen dependence on private car use, rather than supporting low-carbon mobility transitions [95].

In conclusion, AI offers major opportunities to support climate action—through better data, modeling, and decision-making—but it also brings new risks that must be addressed. These include its growing energy and carbon footprint, the challenges of ensuring fair and transparent decision-making, and broader concerns about privacy, bias, and environmental rebound effects. Addressing these challenges will require advances in energy-efficient AI design, stronger attention to equity and data governance, and a focus on interpretability and transparency. Only by actively managing these risks can AI contribute positively and sustainably to global climate goals.

5. Summary and outlook

Climate change remains a critical global challenge, threatening economic development and social progress. The rapid growth and adoption of AI technologies provide powerful tools to improve climate research and enhance responses to these threats. This paper highlights how AI is being used in key areas of climate research, examining its applications, challenges, and inequalities, and offering insights for guiding its future role (Fig. 4).

5.1. Summary

We first proposed an integrated framework for addressing climate change, based on the IPCC's three pillars—mitigation, adaptation, and impact assessment—while drawing on insights from previous studies. This framework helps identify priority areas for research and action, while also pointing to key knowledge and policy gaps.

Second, we reviewed the specific applications and emerging potential of AI in climate science and governance, mapping its contributions across the proposed framework. We also addressed the possible negative impacts of AI, acknowledging that while it offers many advantages, it also brings important risks. Our analysis suggests that AI can close many of the existing gaps in climate research and decision-making, and has the potential to transform how we study and manage climate issues. With its strengths in data processing, intelligent analysis, and operational efficiency, AI is becoming a key enabler of climate governance.

However, three major gaps currently limit the effectiveness and impact of AI in climate change research:

(1) Content disparity: Most AI applications are focused on core natural sciences and impact assessments, with relatively few efforts dedicated to supporting mitigation or adaptation pathways and decision-making. Within the RACC framework, while AI performs well in data mining and pattern detection, its role in evaluating concrete pathways or supporting behavioral decision-making remains underdeveloped. This area needs urgent attention.

(2) Intelligence-level disparity: Current applications rely mostly on Artificial Narrow Intelligence (ANI), which is effective for specific tasks like data classification or feature extraction. However, Artificial General Intelligence (AGI)—which would be needed for complex reasoning and strategic decision-making—remains largely theoretical. This is due to the lack of major breakthroughs in algorithms, theory, and computational infrastructure.

(3) Governance disparity: Regulatory systems are still catching up with the pace of AI development. Two key issues are: (i) Data governance, where the lack of international data-sharing mechanisms and weak privacy protections limit global collabora-

tion; and (ii) Technical standards, where the absence of energy use and carbon emission guidelines for AI development allows unchecked computational growth, and where limited algorithm transparency undermines trust in AI outputs.

5.2. Outlook

To address these challenges and close the existing gaps, we propose the following directions for future AI development in climate research and governance:

(1) Build shared climate data platforms: Establish an open, standardized platform to support high-quality, accurate, and privacy-respecting data sharing across borders. International organizations should work with national governments to create data-sharing protocols that respect sovereignty. At the same time, universities, research institutions, and companies can support decentralized systems—such as those based on blockchain—to enhance transparency, data protection, and efficiency.

(2) Develop carbon assessment and disclosure standards for AI: A lifecycle-based regulatory framework is needed to assess the carbon footprint of AI systems from development through deployment. National systems can take inspiration from the EU AI Act's energy efficiency rules, with the long-term goal of creating a global framework for monitoring and reducing the emissions associated with AI.

(3) Encourage deeper integration of AI and climate science: First, promote explainable AI (XAI) to improve model transparency, build trust, and support informed climate decision-making. Second, strengthen fundamental theoretical research in climate science and develop dual-driven models that combine data-driven AI approaches with physics-based, theory-driven ones. This would enhance ANI's capacity for data processing and model training while laying the foundation for future AGI applications, including scenario evaluation, mitigation/adaptation planning, and policy implementation.

By following these strategies, we can maximize the positive contributions of AI to climate science and action, while minimizing the risks. AI has the potential to become a cornerstone of sustainable climate governance—if developed and applied responsibly.

Conflict of interest

The authors declare that they have no conflict of interest.

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Author contributions

Xianchun Tan, Hongshuo Yan, and Deliang Chen designed the study. Zhe Peng and Yonglong Cheng performed the collection and analysis of the literature. All the authors conducted the results discussion. Xianchun Tan, Zhe Peng, and Hongshuo Yan wrote the first draft. Deliang Chen edited the final paper. All authors contributed to the revision.

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