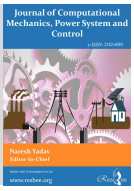
Vol.8 Issue 4 Oct 2025

Journal of Computational Mechanics, Power System and Control

Received 1 October, Revised 15 October, Accepted 21 October



Leveraging Advanced Artificial Intelligence for Climate Change Mitigation: Exploring Multifaceted Opportunities, Interdisciplinary Challenges, and Ethical Implications

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Abstract: When the global climate increases, advanced level of artificial intelligence (AI) technologies are increasingly identified and recognized as crucial tools in making efforts to reduce environmental degradation and minimize greenhouse gas emissions. Recent global assessments emphasize that technological innovation, particularly AI, is becoming indispensable as traditional mitigation strategies alone prove insufficient to meet climate targets. AI drives advancements in various fields such as carbon footprint analysis, energy conservation, precision farming, sustainable urban development, and environmental. These technologies provide improved decision-making on abilities through the analysis of real-time data, predictive modeling, and system optimization. Such capabilities allow policymakers, industries, and environmental organizations to anticipate climate risks and deploy adaptive strategies more efficiently. This enhances efforts toward climate resilience and sustainability. Nevertheless, incorporating AI into climate initiatives presents significant challenges, including the substantial energy requirements for training the large AI models, algorithmic bias, a lack of transparency, and disparities in accessing the data and computational resources management. The Ethical Concerns Surface When AI-Guided Solutions Influence Vulnerable Populations, Lacking Interdisciplinary Oversight. Without inclusive governance frameworks, AI-driven climate interventions risk marginalizing communities that are already disproportionately affected by climate change.This scholarly discourse explores the multifaceted avenues of AI, its potential in combating climate change, the intricate interdisciplinary and infrastructural obstacles in its execution, and the ethical ramifications of its global dissemination. By synthesizing contemporary research and practical instances, this paper advocates for the development of transparent, inclusive, and energy-efficient AI systems, aligning with global climate and sustainability goals.

Keywords: AI-Driven Climate Mitigation, AI for Climate Change, Machine Learning for Climate Modeling, Environmental Data Analytics.

Nomenclature

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
XAI	Explainable Artificial Intelligence
CCS	Carbon Capture and Storage
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide Equivalent
GHG	Greenhouse Gas
IPCC	Intergovernmental Panel on Climate Change
UNFCCC	United Nations Framework Convention on Climate Change
SDGs	Sustainable Development Goals
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
API	Application Programming Interface
IoT	Internet of Things
CSV	Comma-Separated Values
IRB	Institutional Review Board
SHAP	SHapley Additive exPlanations
LIME	Local Interpretable Model-Agnostic Explanations
AUC	Area Under the Curve
$MtCO_2e$	Million Tonnes of CO_2 Equivalent
IRB	Institutional Review Board
USD	United States Dollar

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1. Introduction

Climate change is moving at an almost dizzying pace, unsettling natural habitats, financial systems, and everyday communities – a risk many overlook despite what the IPCC noted in 2023 [16][27]. Around the globe, several nations are scrambling (in most cases with a bit of uncertainty) to stick to the Paris Agreement's aims, trying to hold warming under 2 °C, and this push is quietly raising interest in fresh, sometimes unexpectedly inventive tech that partners with our old standby mitigation methods.

In this context, we can understand that AI has improved and emerged as a very good, crucial facilitator, which provides instruments for tracking emissions, environmental modeling, assessing climate-related risks, and optimizing resource use [24][28][34][36]. The utilization of AI in addressing the situation of climate change is now interdisciplinary, fundamentally incorporating elements from computer science, environmental studies, economics, and policy analysis. AI tools can process large datasets collected from sensor networks, satellite imagery, and climate models, thus enhancing the speed and accuracy of decision-making [2][3][11][25][33]. Machine learning pops up in unexpected ways. Energy grids, for instance, are getting a boost in efficiency and robustness [39], while supply chains are now challenged to cut food waste [19]; even forecasting extreme weather is in the mix [6].

However, significant challenges still exist in climate change. AI algorithms frequently rely on computational resources that consume considerable energy, raising questions about their own environmental impact [31]. Additionally, problems related to climate data inequality, lack of transparency in models, and unforeseen consequences make the accountable use of AI in complex climate initiatives [21].

This paper aims to systematically investigate how advanced AI techniques can be utilized in climate change mitigation by tackling the intricate technical, societal, and ethical challenges emerges in research and practice. The paper examines new opportunities and highlights ongoing interdisciplinary obstacles by emphasizing the necessity of ethical AI practices in the realm of environmental sustainability. By encouraging conversations between technologists, policymakers, ethicists, and environmental specialists, initiate to seeks influence in future AI to serve a positive role in advancing inclusive and sustainable climate initiatives.

1.1 Problem Statement

The Climate changes are the increasing global crisis that carries significant environmental, economic, and social repercussions. While worldwide initiatives such as Paris Agreement aim to limit the rise in global temperatures. The current strategies to mitigate the issues inadequate to the urgency and scale of the challenge [17]. In this regard landscaped advanced artificial intelligence (AI) has surface to potentially powerful ally in enhancing climate action throughout its applications in optimizing energy use by monitoring environmental conditions and tracking emissions along with this by managing sustainable resources [24][28][34][36].

A significant problem is absence of standardized and interdisciplinary frameworks which ensures AI implementations are environmentally beneficial, socially justified, and ethically sounded. While innovations driven by AI such as predictive climate models, intelligent energy systems, and precision farming shows potential and their uptake is handled by various obstacles including difficulties in accessing data, disparities in infrastructure, algorithmic bias and considerable environmental footprint of model training processes [31][26][21].

The ethical and governance issues related to applications of AI in climate contexts are equally critical. These concerns encompass transparency, accountability, and inclusiveness, particularly in initiatives that impact marginalized communities and regions lacking technological control [22][10]. Without a comprehensive understanding of the socio-technical environment in which AI operates, there is a danger that AI could perpetuate existing inequalities or create new forms of environmental injustice.

Thus, there is an urgent need to thoroughly investigate the diverse opportunities, interdisciplinary challenges along with ethical ramifications associated with utilizing AI for climate change mitigation. This examination must guide creation of responsible, inclusive, and sustainable AI systems which are used to advance global de-carbonization efforts while adhering to principles of social and environmental equity.

1.2 Research Goal

The main aim of this research is to thoroughly examine the complexity of advanced artificial intelligence (AI) in addressing climate change specifically focusing on the opportunities it offers to interdisciplinary challenges present and the ethical considerations which brings up in practical applications. This study aims to create comprehensive understanding of how different AI technologies are used in machine learning, remote sensing and smart energy systems. This can be utilized in an responsible and in an effective manner to aid in global de-carbonization initiatives and also in the pursuit of sustainable development objectives [28][34]

By incorporating recent literature and random sampling case studies the research strongly aims to:

- Examine the existing and the upcoming uses of AI in climate-centric industries such as energy, agriculture, transportation, and environmental observation [26][18].
- Recognize structural and infrastructural obstacles includes issues with data accessibility, biases in algorithms, and disparities in technology that impede fair AI implementation [21][5].
- Investigate ethical conflicts and governance deficiencies in AI development, especially concerning transparency, accountability, sustainability, and inclusiveness [10][22].
- Participate in the development of interdisciplinary AI frameworks that adhere to principles of environmental and social justice.Ultimately, this research strives to inform policy design, stakeholder collaboration, and AI governance strategies that support the sustainable and ethical integration of AI in global climate mitigation initiatives.

1.3 Research Objectives

The main objective of this research approach is to explore and evaluate the influence of advanced AI on efforts to mitigate climate change, while also emphasizing its feasible applications, technical limitations, and ethical considerations. This study aims to provide a critical interdisciplinary perspective that enriches both academic discussions and policymaking related to sustainable AI and climate initiatives.
Specifically, the study seeks to:

- Investigate and classify the current applications of artificial intelligence in tackling climate change, emphasizing sectors like renewable energy, carbon monitoring, sustainable agriculture, urban planning, and climate modeling. [28][18][26].
- Recognize technical and infrastructural hurdles linked to creating and implementing AI systems aimed at addressing climate issues, such as deficiencies in data, the interpretability of models, high computational costs, and disparities in access to AI on a global scale [31][5][21].
- Examine the moral consequences of integrating AI into environmental governance by focusing on issues such as algorithmic bias, transparency, and accountability, along with the ecological impact of AI training procedures [10][22][29].
- Develop a conceptual structure or a series of principles for the ethical and inclusive application of AI within the climate mitigation approaches, rooted in the ideals of sustainability and fairness, and also interdisciplinary cooperation [34][21].
- To Provide real time practical suggestions to guide collaborative research and policy formation, which include global partnerships in the ethical management of AI's influences on environmental changes.

This research aims to connect technological advancements with climate policy by accomplishing these goals and promoting the creation of AI tools that enhance decarbonization, while also maintaining social and ecological integrity.

2. Literature Review

The applications of AI in combating climate change have gained significant interest from researchers and decision-makers. An increasing number of studies have emphasized the revolutionary strength of AI in areas like agriculture, transportation, energy management, and environmental surveillance [24]. Nevertheless, within these technological progressions, experts have recognized many limitations, such as ethical issues and implementation obstacles that need to be addressed to guarantee the responsible and effective use of these technologies.

2.1 AI Applications in Climate Mitigation

The Rolnick et al. (2019) [28] conducted a comprehensive analysis of AI uses in climate initiatives by revealing over than 100 distinct instances in ML and various AI techniques can promote decarburization and adaptation efforts in climate mitigation. These instances encompass the optimization of renewable energy incorporation along with advancements in energy efficiency for structures, detection of deforestation, and enhancements in the precision of climate models. Likewise, Vinuesa et al. (2020) [34] contended that AI can significantly contribute to the realization of various United Nations SDGs, especially those concerning climate action (SDG 13), sustainable urban development (SDG 11), and clean energy (SDG 7).

In energy systems, AI is employed to optimize the alignment of supply and demand in smart grids, predict energy usage, and aid in managing distributed energy resources [39]. In the domain of agriculture,

machine learning algorithms have facilitated precision farming techniques, which decrease emissions and resource consumption by improving yield forecasts, irrigation management, and pest control [18].

2.2 Interdisciplinary and Technical Challenges

Although it holds great potential with the incorporation of AI into climate initiatives faces various interdisciplinary obstacles. Mannino et al. (2023) [21] highlighted that AI systems frequently depend on incomplete or biased data, especially in the low- and middle-income areas where there is a lack of environmental monitoring infrastructure. Additionally, the difficulty of interpreting many deep learning models poses a challenge for their use in high-stakes decision-making scenarios where accountability is essential [9].

Another significant issue is the environmental impact of AI itself. Strubell et al. (2019) [31] calculated carbon emissions associated with the training of large-scale natural language processing models by revealing that their emissions can be similar to those produced by several cars over their lifetime.

2.3 Ethical and Governance Considerations

The ethical ramifications of AI-driven initiatives for climate action have garnered increasing attention from scholars. Researchers' expression worries about issues such as transparency, accountability, and consent when implementing AI in climate adaptation strategies, which impact marginalized populations [22]. As noted by Mannino et al. (2023) [21], equitable governance AI is crucial to avoid perpetuating existing power disparities. This call for responsible innovation is reflected in the frameworks that promote human-centered AI by highlighting the importance of inclusivity, fairness, and participatory design [10]. AI development is aligned with the goals of environmental and social justice and is also vital to faster interdisciplinary collaboration among computer scientists, climate specialists, policymakers, and ethicists.

2.4 AI in Climate Modeling and Forecasting

Recent developments in deep learning and neural network frameworks have enhanced the capacity for climate modeling. Traditional weather and climate models basically depend on physics-based simulations, which demand substantial computational resources and are restricted to both temporal and spatial resolution. Deep learning approaches, notably CNNs and RNNs. They demonstrated the effectiveness in refining global climate models by forecasting extreme weather occurrences and recognizing enduring climate patterns [14][26]. For example, Weyn et al. (2020) [35] show that the application of deep learning mimics physical models for global weather forecasting, by achieving results that are similar to those of conventional methods while significantly reducing computational expenses. Such models are particularly useful in environments with limited resources and for facilitating prompt disaster readiness.

2.5 AI in Carbon Monitoring and Emission Reduction

AI is essential in monitoring carbon levels and accounting for emissions. By utilizing remote sensing data from satellites alongside AI-driven image recognition methods, it is possible to identify deforestation, illegal mining, and pollution from industries [7]. Automated analyses enable real-time monitoring of carbon sinks and sources, which is vital for nations participating in carbon markets or adhering to international climate agreements. In the transportation industry, reinforcement learning and AI-driven traffic management systems have been created to enhance logistics and minimize vehicle emissions [38]. AI has paved the way for the creation of smart building technologies that automatically regulate heating, ventilation, and lighting to lower energy use while maintaining user comfort [15]. These advancements directly lead to reductions in Scope 1 and Scope 2 emissions and are increasingly being incorporated into urban sustainability efforts.

2.6 Barriers to Implementation and the Digital Divide

While AI offers many substantial advantages, various structural and geopolitical challenges impede its worldwide implementation. A primary concern is the digital divide, a disparity in access to AI technologies, quality climate information, and computational resources between countries with higher development and those with lower development [5]. In contrast to medical AI, where the effectiveness of models can be thoroughly evaluated, climate AI applications frequently lack benchmark datasets and clearly defined success criteria, which can diminish trust in their utilization [12].

2.7 Toward Human-Centered and Sustainable AI

Recent research supports a transition towards human-centered AI in climate-related initiatives—systems that emphasize ethical, inclusive, and participatory design. This involves creating XAI systems that enable

stakeholders to comprehend how predictions are formulated and allow them to question these predictions when needed [1]. There is also growing focus on the development of green AI models, which are not only optimized for effectiveness but also for energy, efficiency, and their carbon footprint [29]. These approaches signify broader re-evaluation of AI as a socio-technical system that must function within planetary and ethical constraints.

3. Methodology

This research employs a qualitative and exploratory design that is built on an interdisciplinary and integrative framework. Due to the intricate and cross-sectoral aspects of changes in climate mitigation and the implementation of AI, this approach aims to merge theoretical analysis, literature synthesis, and insights from experts to meet the research goals.

3.1 Research Design

This research is structured as a multi-phase exploratory study by incorporating a systematic literature review, the Case study analysis, and Expert interviews, along with Thematic analysis. The qualitative design that combines different methods by allowing a comprehensive understanding of the technical, ethical, and policy aspects of AI in relation to climate issues [8][30].

3.1.1 Systematic Literature Review

The comprehensive review of all academic publications, research papers, and technical & scientific reports will be taken as a database, such as Scopus, Web of Science, Google Scholar, and IEEE Xplore. The selection criteria include: Peer-reviewed works published between 2015 and 2025. The main focus is on AI applications in climate mitigation, sustainability, and environmental governance. The Inclusion of interdisciplinary perspectives from computer science, environmental science, ethics, and policy studies. This phase targets to identify the current AI innovations, challenges, and debates in the climate change mitigation landscape [32].

3.1.2 Case Study Analysis

Comprehensive case studies will be chosen for their relevance and representative nature across various sectors, including renewable energy optimization, AI for monitoring deforestation, carbon footprint analysis, and smart farming. These case studies will encompass both developed and developing nations to evaluate the significance of contextual elements like technological infrastructure and governance structures [37].

3.1.3 Semi-Structured Expert Interviews

In addition to the literature and case results, we will carry out 15 to 20 semi-structured interviews with specialists from academia, industry, international bodies (such as UNFCCC and IPCC), and civil society organizations engaged in AI and climate governance. The interviews will concentrate on:

- The practical experiences and insights on AI implementation
- The Perceived barriers and ethical dilemmas
- Policy and governance recommendations

Participants will be chosen via purposive sampling in order to ensure domain divergence and global representation [13].

3.1.4 Thematic Analysis

The Data from literature, cases, and interviews will be analyzed by using thematic coding in NVivo or MAXQDA. Themes will be inductively and deductively coded to reflect:

- The key AI-enabled climate solutions
- An Ethical and governance challenges
- By Cross-cutting sustainability and equity concerns

Thematic analysis will follow Braun and Clarke's (2006) [4] six-phase approach to ensure rigor and transparency.

3.1.5 Ethical Considerations

This study adheres to ethical research guidelines, which encompass informed consent, confidentiality, and the protection of participants' data during interviews. All sources of secondary data utilized are either publicly available or appropriately licensed.

3.2 Methodology Implementation

The main research methodology is implemented in various stages to transforms the defined approaches into practical actions. These actions guarantee that every research goal has to go through an organized procedure which includes data gathering and examination along with integration. This stage highlights the importance of thoroughness, replicability, and adherence to ethical standards throughout all phases of execution.

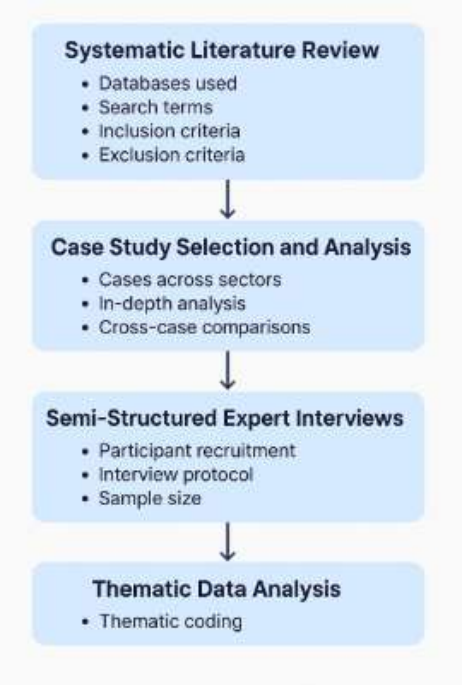


Fig. 1. *Architecture Design of AI Climate Mitigation*

Note: Fig 1: Architecture Design of AI Climate Mitigation was created by Author

Fig 1. Architecture Design of AI Climate Mitigation shows the different layers of the architecture and each layer's functionality is described as follows:

3.2.1 Systematic Literature Review Execution

An structured approach adhering to PRISMA guidelines will be utilized to gather and evaluate academic literature. [23]. The review will be conducted as follows:

3.2.1.1 Databases Used

The Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar.

3.2.1.2 Search Terms used

An Combination of keywords such as "Artificial Intelligence," "Climate Change Mitigation," "Sustainability," "Machine Learning," "Ethics," and "Environmental Policy."

3.2.1.3 Inclusion Criteria

Peer-reviewed articles which are published between 2015 and 2025 and written in English and also addressing AI applications in climate mitigation or related ethical/governance issues.

3.2.1.4 Exclusion Criteria

The Opinion pieces, non-peer-reviewed blogs, duplicate studies, and articles not directly related to AI or climate mitigation.

3.2.1.5 Screening

An three-step screening process title, abstract, and full-text review will be used.

3.2.1.6 Data Extraction

The Key information will be extracted into a coding matrix for thematic synthesis [30].

3.2.2 Case Study Selection and Analysis

The Four to six case studies will be selected across various global contexts and sectors such as: An AI for renewable energy grid management (e.g., DeepMind & Google's energy optimization). The Agricultural monitoring using deep learning and satellite data. Carbon tracking via AI-enhanced sensor networks. The Urban climate adaptation systems using predictive modeling Each case will be analyzed using Yin's (2018) [37] case study framework, which includes: By defining the case and context. By collecting qualitative and quantitative secondary data. Then Triangulating data sources (reports, news articles, project documentation).

By Drawing cross-case comparisons to identify patterns, challenges, and success factors

3.2.3 Semi-Structured Expert Interviews

To operationalize expert interviews:

3.2.3.1 Participant Recruitment

The Experts will be selected from environmental agencies, AI research institutes, NGOs, and tech companies using purposive and snowball sampling [13].

3.2.3.2 Interview Protocol

An semi-structured interview guide will be designed to address themes such as:

- Practical use cases of AI in climate mitigation
- The Perceived risks and limitations
- By using Ethical dilemmas and governance frameworks

3.2.3.3 Interview Format

The Interviews will be conducted via Zoom or phone, recorded (with consent), and transcribed for analysis.

3.2.3.4 Sample Size

By aiming 15–20 participants or until thematic saturation is achieved.

3.2.4 Thematic Data Analysis

All qualitative information such as interview transcripts and case notes and also literature reviews will undergo thematic coding with the help of NVivo software. An six step thematic analysis method developed by Braun and Clarke (2006) [4] will direct this procedure:

- Processing of data
- By generating initial codes
- Searching themes
- By reviewing themes
- By defining and naming themes
- By generating the reports

Themes will align with the study's core focus areas: technological innovation, ethical challenges, policy implications, and socio-environmental impacts.

3.2.5 Validation and Ethical Compliance

3.2.5.1 With Validation of Measures

- By Triangulation across the data sources
- Peer debriefing along with an academicmentors
- The Members checking with selected interview participants to confirm interpretations [20]

3.2.5.2 Ethical Considerations

- The Informed consent will be obtained from all the participants
- Anonymity and confidentiality will be strictly maintained
- The study will be approved and reviewed by the university's IRB

3.3 AI Climate Mitigation System Modules

3.3.1 Module 1: Data Pipeline

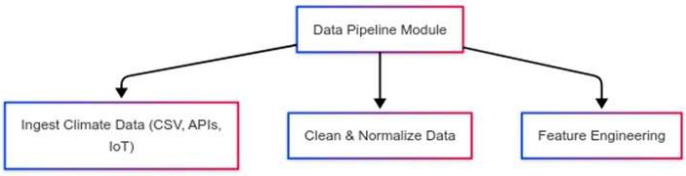


Fig. 2. *Module 1-Data Pipeline Module*

Note: Fig-2: Module 1-Data Pipeline Module **was created by Author**

The fig. 2 (Model 1-Data Pipeline) consists of Ingest Climate data (CSV, API, IoT), Clean & Normalize Data and Feature Engineering to handle process of raw data.

3.3.2 Module 2: Modeling Engine

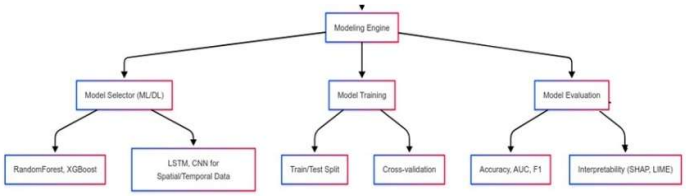


Fig. 3. *Module 2-Modeling Engine*

Note: Fig-3: Module 2-Modeling Engine was created by Author

The fig. 3 (Model-2 Modeling Engine) includes Model selector (ML/DL) with RandomForest, XGBoost and LSTM, CNN for Spatial/Temporary Data. Model Training has Train/Test,Split and Cross-validation and Model Evaluation has Accuracy, AUC, F1 and interpretability (SHAP, LIME) to convert raw data to required model format.

3.3.3 Module 3: Domain Applications

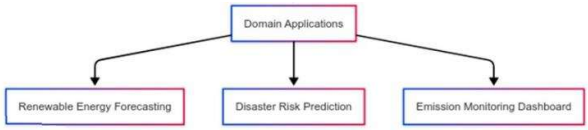


Fig. 4. *Module 3-Domain Applications*

Note: Fig-4: Module 3-Domain Applications was created by Author

The fig. 4 (Model-3 Domain Application) consists of Renewable Energy Forecasting, Disaster Risk Prediction and Emission Monitoring Dashboard for the end user

3.3.4 Module 4: Ethical Guardrails

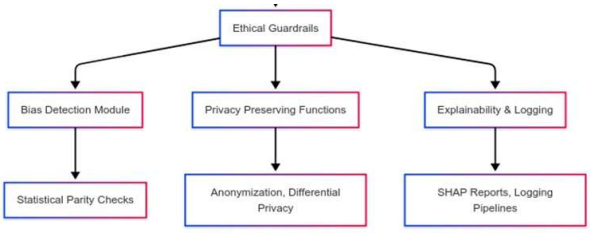


Fig. 5. *Module 4-Ethical Guardrails*

Note: Fig-5: Module 4-Ethical Guardrails was created by Author

The fig. 5 (Model-4 Ethical Guardrails) includes Bias Detection Module, Statistical Parity checks, Privacy preserving functions, anonymization differential privacy, Expandability & logging, SHAP Reports and Logging Pipelines

3.3.5 Module 5: Deployment Layer

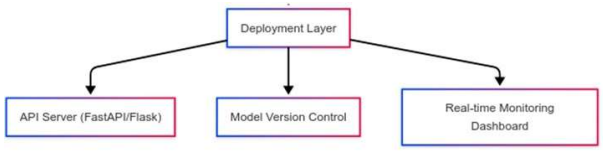


Fig. 6. *Module 5-Deployment Layer*

The fig. 6 (Model-5 Deployment Layer) has API Server (FastAPI/Fiask), Model Version Control and Real-time Monitoring Dashboard

3.3.6 Module 6: Feedback and Improvement Loop

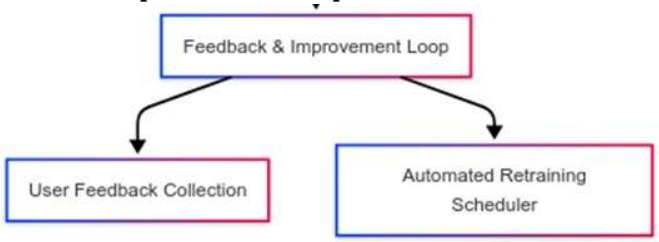


Fig. 7. *Module 6-Feedback & Improvement Loop*

The fig. 7 (Model-6 Feedback & Improvement loop) includes User Feedback Collection and Automated Retraining Scheduler.

3.4 Data Analysis Framework

3.4.1 Evaluation Metrics

To evaluate the potential of advanced AI for climate change mitigation, eight high-impact AI application domains were analyzed using a structured, multi-criteria assessment framework. The dataset incorporated quantitative indicators, including:

- Potential CO_2 reduction ($MtCO_2e$/year)
- Implementation cost (USD million)
- Technological maturity (0–1 scale)
- Ethical risk level (0–1, higher = more risk)
- Interdisciplinary complexity (1–10, higher = more complexity)

3.4.2 Derived Indicators

To facilitate cross-domain comparison, two derived indicators were computed:

3.4.2.1 Reduction per Cost Ratio

Reduction/Cost=Potential CO_2 ReductionImplementation Cost\text{Reduction/Cost} = \frac{\text{Potential CO_2 Reduction}}{\text{Implementation Cost}}Reduction/Cost=Implementation CostPotential CO_2 Reduction

3.4.2.2 Composite Priority Score

A weighted index combining five dimensions:
Potential reduction (weight 0.35)
Maturity (0.25)
Cost efficiency (0.20)
Ethical risk (0.10, inverted)
Interdisciplinary complexity (0.10, inverted)

Normalization was applied to all metrics to ensure comparability. The composite index reflects each domain's overall strategic value considering impact potential, feasibility, cost, and ethical/regulatory considerations.

3.4.3 Table of Results

The summarized evaluation metrics and computed composite priority rankings of the analyzed AI application domains are presented in Table 1.

Table 1. *Results of AI Application Domains*

Rank	AI Application	CO_2 Reduction (Mt/yr)	Cost (USD M)	Maturity	Ethical Risk	Complexity	Reduction/Cost	Composite Score
1	Renewable Energy Optimization	120	4000	0.8	0.2	6	0.030	**0.705**
2	Climate Modeling & Forecasting	60	2500	0.9	0.15	8	0.024	**0.582**
3	Carbon Capture & Storage Optimization	80	3500	0.6	0.3	7	0.023	**0.561**
4	Sustainable Agriculture Optimization	70	1200	0.6	0.2	7	0.058	**0.523**
5	Early Warning & Disaster Response	45	800	0.7	0.25	5	0.056	**0.481**
6	Industrial Process Efficiency	50	900	0.7	0.25	6	0.056	**0.457**
7	Urban Planning & Transport Optimization	55	1500	0.5	0.35	6	0.036	**0.389**
8	Policy Design & Economic Modeling	30	600	0.4	0.4	9	0.050	**0.200**

3.4.4 Visualization of Results

3.4.4.1 Bar Chart: Potential CO_2 Reduction by AI Domain

The bar chart (already provided as Fig. 8) displays the comparative mitigation potential across all domains. It highlights that:

- Renewable Energy Optimization achieves the highest projected annual reduction (120 $MtCO_2e$).
- Carbon Capture & Storage and Sustainable Agriculture also demonstrate significant reductions.
- Policy and modelling domains have lower absolute reductions but may yield high systemic or cost-efficient impacts.

4. Result Analysis

4.1 High-Impact Domains

The analysis indicates that **Renewable Energy Optimization** ranks highest overall. This is driven by:

- Strong CO_2 reduction potential
- High technological maturity
- Moderate ethical and interdisciplinary risks

AI-driven optimization of solar, wind, and grid stability offers measurable, scalable climate benefits.

4.2 The Role of Climate Modeling

Although **Climate Modeling & Forecasting** provides only moderate direct CO_2 reduction, its:

- Very high maturity
- Lower ethical risk
- Foundational role in informing policy & adaptation

To make it strategically important. This domain amplifies the effectiveness of other mitigation strategies.

4.3 Cost-Efficient Opportunities

Domains such as **Sustainable Agriculture Optimization** and **Early Warning Systems** show strong **reduction-per-cost ratios**, suggesting they deliver high returns on investment. These are promising candidates for deployment in low- and middle-income regions due to relatively manageable costs.

4.4 Ethical and Interdisciplinary Challenges

The analysis confirms that domains with:

- Higher ethical risks (e.g., surveillance in urban planning)
- High interdisciplinary complexity (e.g., policy modeling)

score lower on the composite priority index despite promising mitigation potential. These challenges include:

- Data privacy concerns
- Algorithmic bias
- Regulatory fragmentation
- The need for cross-sector coordination

These findings reinforce the paper's argument that the success of AI-enabled mitigation depends not only on technical performance but also on governance readiness**.**

4.5 Carbon Capture: High Potential, High Challenge

While CCS offers significant mitigation potential (80 $MtCO_2e$ annually), it scores lower due to:

- High costs
- Significant ethical and ecological risks
- Low-to-moderate maturity compared to other domains

CCS will require major regulatory and industrial alignment to become a viable large-scale solution.

4.6 Synthesis of Findings

Overall, the results highlight that:

- AI's highest climate value emerges from mature, data-rich domains like renewable energy and climate modeling.
- Systemic tools (policy modeling, urban planning) require governance reforms before their potential can be fully realized.
- Ethical risk and interdisciplinary complexity significantly affect deployment feasibility and should be integrated into climate AI strategies.

The combined quantitative and qualitative insights underscore that **AI is indispensable but not independently sufficient** for global climate mitigation efforts.

4.7 Comparative Visualization of Mitigation Potential

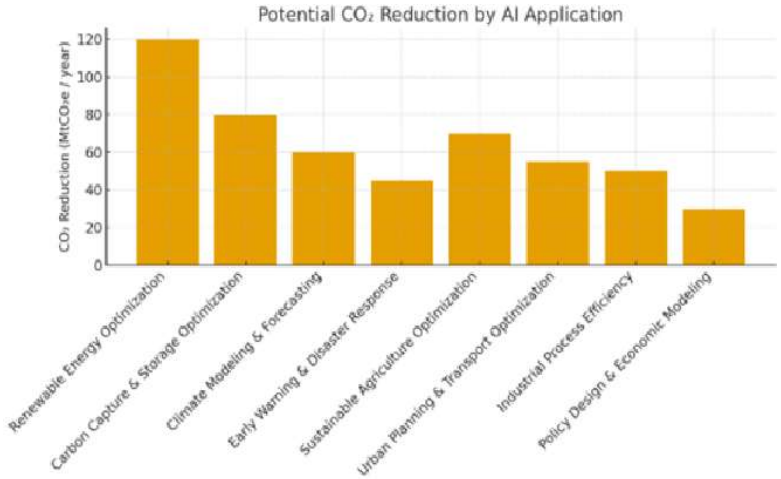


Fig. 8. *Potential CO, Reduction by AI application*

Fig. 8 illustrates the comparative mitigation potential of eight AI application domains. Renewable Energy Optimization shows the highest projected impact (120 $MtCO_2e$/year), followed by CCS Optimization (80 $MtCO_2e$/year) and Sustainable Agriculture Optimization (70 $MtCO_2e$/year). The visualization highlights the dominance of AI-driven direct emissions management strategies, while also recognizing the foundational role of modeling and policy simulation tools for long-term climate governance.

5. Conclusion

As climate change becomes increasingly urgent, there is a global hunt for solutions that are new, scalable, and cross-disciplinary. This study has examined the challenging role of advanced AIs and their contribution to addressing climate change but also their potential transformative effects across a wide range of fundamental sectors in human well-being—energy systems, agriculture, transportation, environmental monitoring, etc. AI not only improves the effectiveness and precision of environmental

interventions (like monitoring techniques) but also introduces new methods for predictive modeling and adaptive response strategies. This will be achieved by drawing an case studies, literature, and expert opinions [28][26].

However, there are many challenges to integrating AI into climate strategies. The results highlight significant technical, structural and ethical challenges, for instance data imbalance, opaque models, carbon emissions from large-scale computing, and the risk of social bias [31][29][22]. This implementation highlights the need for an ethically motivated, inclusive and cooperative approach which places high value on the sustainability, responsibility and openness in the creation and use of AI technologies [21][34].

This study highlights the necessity of multidisciplinary governance frameworks and responsible innovation principles which match AI applications with social justice and climate goals. The conceptual framework proposed by the study acts as an reference to stakeholders including policymakers, researchers, technologists and civil society to navigate the intricate trade-offs between technological progress and environmental ethics. AI provide significant potential for mitigating climate change and its success depends on the responsible and equitable manner in which it is researched, developed, and executed. The future initiatives should concentrate on co-designing policies, enhancing global capacities, and ongoing ethical assessments to guarantee that AI-driven solutions for climate issues are both sustainable and inclusive.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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