British Journal of Multidisciplinary and Advanced Studies,6(4)21-45, 2025
Business and Management Sciences
Print ISSN: 2517-276X
Online ISSN: 2517-2778
https://bjmas.org/index.php/bjmas/index

Financial Modeling for Climate Resilience: The Role of AI in Measuring Long-Term Environmental Impact

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doi: https://doi.org/10.37745/bjmas.2022.04934 Published August 02, 2025

Citation: Ukatu C., Achimugu D., Anaege A.E. (2025) Financial Modeling for Climate Resilience: The Role of AI in Measuring Long-Term Environmental Impact, *British Journal of Multidisciplinary and Advanced Studies*, 6(4)21-45

Abstract: *Artificial intelligence (AI) is increasingly applied to climate finance as a tool for modeling risks, forecasting environmental changes, and supporting sustainability metrics. This study presents a scoping review of 38 peer-reviewed articles to examine how AI methods are used in financial modeling for climate resilience. Using PRISMA guidelines, articles were sourced from Scopus, Web of Science, and Google Scholar and analyzed through thematic coding. The results show that AI techniques, particularly machine learning, deep learning, and hybrid models, are widely adopted for applications including emissions forecasting, carbon pricing, ESG investment analysis, and climate adaptation planning. Four major thematic areas emerged: (1) predictive modeling of climate-related financial risk, (2) AI-driven ESG and carbon finance tools, (3) long-term environmental impact assessment, and (4) AI-supported strategies for business and infrastructure resilience. Despite progress, challenges persist around data access, model interpretability, and integration with financial decision-making frameworks. Few studies fully assess the environmental footprint of AI systems or their deployment in under-resourced regions. The review identifies gaps in empirical validation, regional diversity, and ethical standards. It calls for a collaborative research agenda focused on explainable AI, standardized indicators, and inclusive data systems. Findings provide a roadmap for integrating AI responsibly into climate finance, enabling more resilient economic planning and environmental governance.*

Keywords: artificial intelligence, climate finance, ESG Investment, carbon forecasting, climate resilience, machine learning

INTRODUCTION

Climate change poses one of the greatest challenges to sustainable development in the 21st century. According to recent studies, global temperature increases, rising frequency of extreme weather, rising seas, and loss of biodiversity threaten human infrastructure as well as natural systems (Abbass et al., 2022; Shivanna, 2022). Such occurrences have not just environmental impacts but also economic impacts, with long-term implications for the national treasury, business operations, and financial markets. With climate risk becoming even more systemic, stakeholders are getting more interested in climate resilience in financial decision-making (Song et al., 2025). Climate finance refers to investment and planning for reducing greenhouse gas emissions as well as climate impacts. Climate finance makes use of instruments such as green bonds, climate insurance, carbon trading, and public-private partnerships (Bhandary et al., 2021). One area becoming popular is in financial models considering future climate risk in valuation, risk assessment, as well as portfolio planning in a better way (Chakrabarty & Nag, 2023). However, modeling long-term climate impacts is quite challenging. It means dealing with uncertainty, non-linearity, feedback, as well as large amounts of inhomogeneous data. Standard financial models are typically incapable of such sophistication. Most are grounded in history and assume linearity as well as stationarity, which do not hold when facing changing climate dynamics. For example, current discounted cash flow (DCF) models may not adequately price long-term risk for extreme climate events or changes in regulations (Omopariola & Aboaba, 2019). There is, therefore, a gap in investment planning in both the private as well as public sectors. Artificial Intelligence (AI) is becoming a potential solution to such modeling limitations. AI, in particular, machine learning (ML) as well as deep learning (DL), can manage big data, discover hidden structures, as well as model non-linear associations. For climate resilience, AI is being used for climate scenario simulation, financial exposure to environmental risk assessment, as well as optimizing low-carbon investments. Some applications for AI also include early warning, predictive infrastructure maintenance, as well as ESG (Environmental, Social, and Governance) investment scoring models (Singh & Goyal, 2023; Awijen et al., 2024).

Current studies suggest AI can refine climate forecast accuracy and help financial parties anticipate physical and transition climate risk. For instance, Kumar et al. (2024) suggest the role of AI in improving early warning systems and weather forecasts. Yin et al. (2025) suggest DML methods can approximate AI-driven climate-related financial risk impacts mainly through enabling resource efficiency and green finance. The research suggests AI's double ability to diminish and mimic climate risk. In climate finance, AI is enabling investors in tracing emissions, estimating ESG compliance, and building sustainable portfolio strategies. Patro et al. (2025) developed a carbon finance index involving generative adversarial networks (GANs) for analyzing the decarbonization readiness of the supply chain. Pérez-Pérez et al. (2024) used deep learning models for estimating energy costs for transition risk, facilitating companies in making informed planning. The research indicates an emergent transition toward data-driven financial systems able to predict and manage long-term environmental risk. Despite the potential of AI, climate financial modeling's inclusion remains emergent. Most research is either technical, focused on the algorithmic nature of AI, or narrowly confined to the environmental sciences without translating directly to financial frameworks. There is further concern about AI systems' carbon footprint. Bashir et al. (2024) indicate that the rising energy demand for generative AI models must be balanced against their

Print ISSN: 2517-276X
Online ISSN: 2517-2778
https://bjmas.org/index.php/bjmas/index

advantages for the environment. The dilemma indicates the need for balanced, context-specific evaluation for AI's role.

The successful use of AI in financial modeling for climate resilience is also hampered by the lack of data, regulatory uncertainty, and interpretability issues. Mehryar et al. (2024) comment that the majority of AI climate risk models are not very explainable, thus making them difficult for financial institutions and policy officials to employ in practical applications. Olawade et al. (2024) mention issues such as poor data infrastructure and a lack of AI capacity, mostly in the developing regions. These challenges suggest that while AI holds promise, its application must be grounded in inclusive and transparent design principles. In the literature, few reviews systematically map how AI has been applied across both environmental and financial domains with a specific focus on climate resilience. While there are numerous studies on AI for sustainability or AI in ESG investing, integrated reviews that evaluate long-term impact modeling in a financial context are rare. Mondal et al. (2024) used PLS-SEM and fsQCA to explore AI's role in carbon neutrality and resilience but noted that more conceptual and cross-sectoral synthesis is needed. Another overlooked area is the time horizon of risk assessment. Most current models focus on short- to mid-term impacts. However, climate resilience requires planning over decades. For instance, models should account for changing weather patterns, future policy shifts, and adaptive behaviors in both human and natural systems. Long-term environmental impact modeling requires dynamic and probabilistic approaches; which AI is well suited to support — yet this potential is underexplored in financial literature. There is also a lack of comparative insight into different AI methods used for financial applications in this space. Some studies rely on supervised learning (e.g., regression trees, neural networks), while others use unsupervised methods (e.g., clustering, dimensionality reduction). The methodological diversity makes it hard to assess what works best under different contexts. A consolidated overview is needed to understand not only the "what" and "how" but also the "where" and "why" of AI applications in financial climate modeling.

Research Aim

To explore how Artificial Intelligence (AI) is applied in financial modeling to support climate resilience and assess long-term environmental impacts, using insights from literature.

Research Objectives

1. To map the current applications of AI in climate-related financial modeling.
2. To identify the dominant AI methods, financial use-cases, and environmental modeling domains.
3. To uncover key research gaps and challenges in applying AI for climate resilience and long-term sustainability forecasting.

Research Questions

1. In what ways is AI currently being applied to financial modeling for climate resilience and environmental sustainability?
2. What AI techniques and financial domains dominate the literature on AI-driven climate finance?
3. What challenges and knowledge gaps exist in using AI to model long-term environmental impacts for financial decision-making?

METHODOLOGY

Review Type and Approach

This study adopts a scoping review approach, guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. A scoping review is well-suited for mapping broad and emerging research areas, especially where the topic spans multiple disciplines (Gottlieb et al., 2021). In this case, the intersection of Artificial Intelligence (AI), financial modeling, and climate resilience involves both technical and social domains, making the scoping method a suitable choice. Following standard review protocols, this study also draws from the methodological guidance provided by Arksey and O'Malley's five-stage scoping review framework (Westphaln et al., 2021).

PRISMA guidelines were applied in the identification, screening, and inclusion phases of literature selection. The review process began with the collection of academic articles from three major databases, followed by manual screening, coding, and thematic categorization (Page et al., 2021). Although the review process reflects systematic rigor, the inclusion of a broad set of topics and conceptual relationships justifies its classification as a scoping rather than a narrowly focused systematic review. Thematic analysis was further utilized after the selection of articles in order to extract and summarize insight. Thematic analysis is an inductive qualitative method useful in discovering patterns in large textual data (Kiger & Varpio, 2020). Themes in the current study were developed after open coding on the articles, and the patterns were refined after iterations.

Search Strategy

To determine relevant literature, three central academic databases were searched: Web of Science, Scopus, and Google Scholar. The databases were selected because they offer complete coverage of peer-reviewed articles on climate science, AI, and financial applications (Mienye et al., 2024). The search was conducted in April and March 2025. Search strings were constructed with Boolean operators to connect keywords in three central areas: (1) artificial intelligence, (2) climate change/environmental modeling, and (3) finance/resilience. For example, search terms were the following:

("artificial intelligence" OR "machine learning" OR "deep learning") AND

("climate change" OR "climate resilience" OR "environmental impact") AND

("financial modeling" OR "climate finance" OR "ESG" OR "carbon finance")

The initial search yielded about 583 papers. Duplicates were removed and the search narrowed down further according to titles and abstracts, leaving 129 papers. Following full-text relevance checks, 38 papers were selected for final inclusion.

Table 1: Search Strings and Databases Used

Database	Search Strings (Keywords and Boolean Operators)	Justification
Scopus	("artificial intelligence" OR "machine learning" OR "deep learning") AND ("climate change" OR "climate resilience") AND ("finance" OR "financial modeling" OR "ESG")	Comprehensive database for peer-reviewed journals in technology, business, and environmental science
Web of Science	("AI" OR "ML" OR "DL") AND ("environmental impact" OR "carbon finance" OR "climate forecasting") AND ("financial modeling" OR "resilience")	High-quality multidisciplinary index for scientific literature
Google Scholar	("AI for climate" OR "AI and ESG investing" OR "AI climate modeling")	Broader coverage including emerging and grey literature

Inclusion and Exclusion Criteria

Clear criteria were developed to determine which studies to include in the review. These are shown in table 2 below.

Table 2: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles published between 2019 and 2025	Articles published before 2019 or outside the specified time range
Studies written in English	Non-English language publications
Articles that discuss AI applications (ML, DL, GAN, etc.) related to climate resilience or finance	Articles focused only on AI techniques without reference to environment or finance
Papers with abstract-level reference to climate modeling, ESG, carbon finance, or environmental impact	Opinion pieces, editorials, book chapters, or conference proceedings
Articles applying AI to financial modeling of environmental or sustainability outcomes	Studies addressing environmental science only, without financial or modeling context

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Online ISSN: 2517-2778
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Screening Process

The screening and selection process for this review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The aim was to ensure transparency and methodological rigor in identifying relevant studies. The detailed process is outlined in the PRISMA flow diagram below.

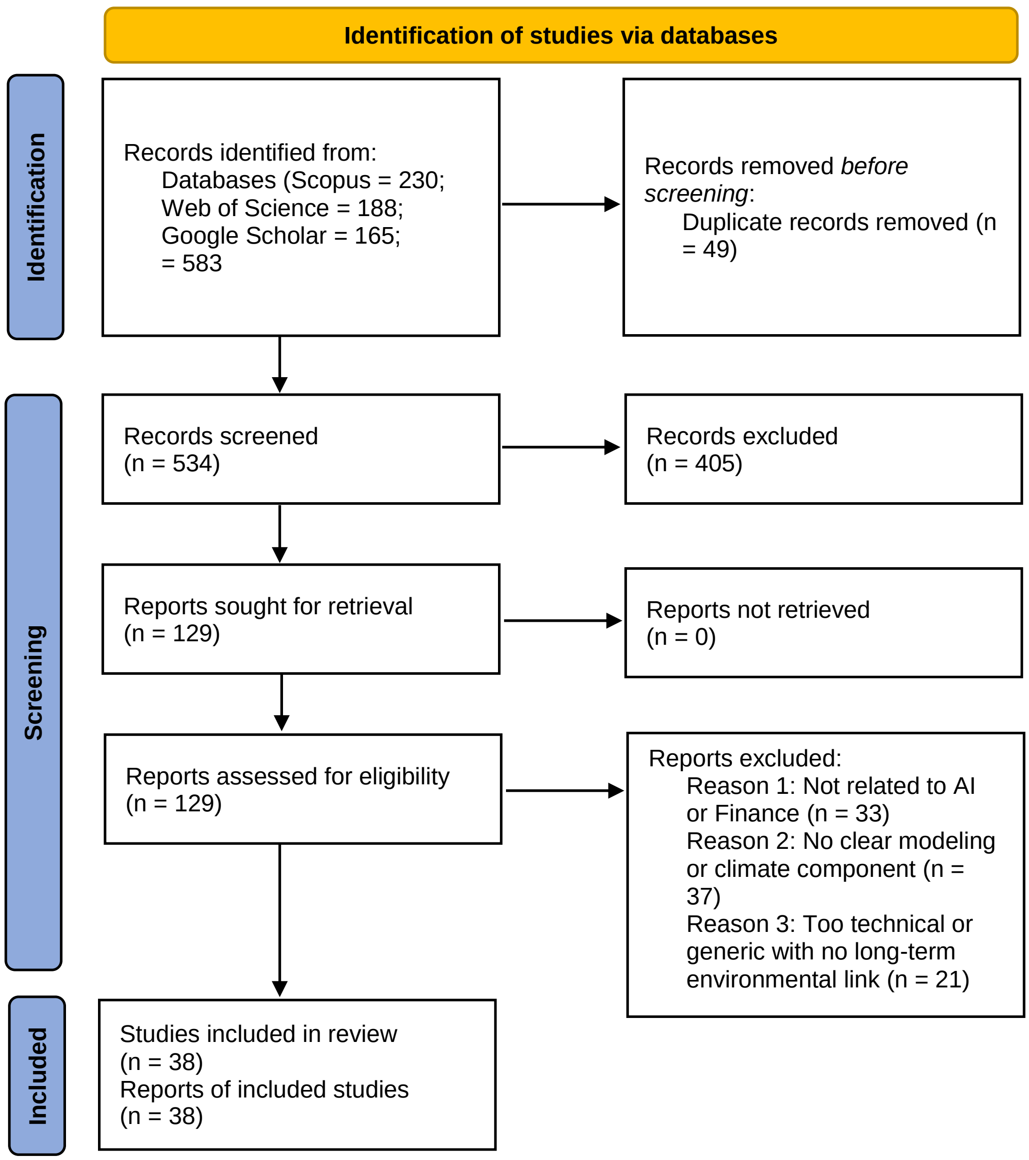

Figure 1: *PRISMA Flow Diagram of Screening Process (Page et al., 2021)*

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Online ISSN: 2517-2778
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Data Extraction Method

Following the selection of 38 studies, structured data extraction was carried out using a predefined template. Key details were collected to support descriptive and thematic analysis. Each record was reviewed to extract citation details, study focus, AI method applied, financial relevance, climate application, and region of study. The AI methods included machine learning, deep learning, generative AI, and hybrid techniques. Financial relevance was noted where AI supported climate finance, carbon forecasting, ESG assessment, or corporate climate strategy. Climate application areas such as mitigation, adaptation, transition, or resilience were also identified. Data were reviewed for consistency and completeness. The extracted information supports the summary presented in Table 4. This process helped structure the evidence base and identify patterns across sectors, geographies, and applications.

RESULTS

Descriptive Characteristics of Included Studies

SN	Citation (Author, Year)	Focus Area	AI Method Used	Financial Domain	Climate Application	Region
1	Akter et al. (2024)	Climate service innovation in industry	AI model, Deep Learning	Environmental & market performance	Climate adaptation & mitigation	Fast fashion industry, Global
2	Al-Raeei (2024)	AI & SDGs (11, 13)	Remote sensing, monitoring AI	Urban sustainability, Resource use	Energy optimization, Waste management	Global
3	Alhassan & Maiga (2025)	Socio-technical evaluation of AI in climate action	Framework analysis, Mixed methods	Energy, Carbon sequestration	Climate risk prediction, Mitigation	Global
4	Ali et al. (2024)	AI for climate prediction and mitigation	ML, Neural Networks	General resource and environmental finance	Extreme weather forecasting, Policy	Not specified
5	Alonso-Robisco et al. (2024)	AI in climate finance	ML, LDA topic modeling	Carbon markets, ESG, Climate data	Transition risk prediction	Not specified
6	Alotaibi & Nassif (2024)	AI in environmental monitoring	AI/ML, IoT, Remote sensing	Not specified	Air & water monitoring, disaster prediction	China, India, US
7	Amnuaylojaroen (2025)	AI in urban climate modeling	ML, DL	Urban resilience planning	Risk assessment, Infrastructure resilience	Asia

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Online ISSN: 2517-2778
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8	Awijen et al. (2024)	ESG stock prices under climate risk	ML, SHAP, XAI	ESG investment	Transition & physical climate risk	US (S&P 500)
9	Azizi (2024)	AI in climate change management	General AI applications	Cross-sectoral	Emissions reduction, hazard monitoring	Global
10	Bashir et al. (2024)	Sustainability impact of GenAI	GenAI efficiency models	Energy consumption, Tech sustainability	Carbon footprint modeling	Not specified
11	Bhaskar & Seth (2024)	Environmental impact of ChatGPT	Model compression, Distillation	Tech sustainability	Energy & emissions assessment	Global
12	Chen et al. (2023)	AI for climate mitigation	AI, Smart systems, Forecasting	Transport, energy, agriculture	Emissions, urban resilience	Global
13	Dwivedi et al. (2022)	Digital tech at COP26	IS tools, Digital platforms	Monitoring, ESG, E-waste	Sustainable digitization	Global
14	Greif et al. (2024)	SWOT analysis of AI for sustainability	SWOT framework	General sustainability finance	Regulation, Explainability	Global
15	Haq et al. (2022)	Forecasting environmental variables	LSTM, ANN	Forestry, Hydrology	Snow/NDVI forecasting	India (Himachal Pradesh)
16	Huntingford et al. (2019)	ML for climate preparedness	ML, Climate modeling	Disaster risk finance	Extreme event forecasting	Global
17	Islam et al. (2024)	AI and sustainability in India	AI case studies	Environmental development	Climate monitoring	India
18	Jain et al. (2023)	AI for adaptation strategies	Climate scenario AI models	Urban resilience	Infrastructure adaptation	Global
19	Kumar et al. (2024)	AI in climate forecasting	ML, DL, Bibliometric	Forecasting systems	Extreme weather, early warning	Global
20	Luqman et al. (2024)	AI and carbon neutrality	Qualitative interviews	Corporate climate goals	Business carbon strategy	Global
21	Majeed et al. (2025)	AI, finance & green energy	CS-ARDL, FGLS	Green tech & finance	Ecological footprint modeling	Emerging economies
22	Mehryar et al. (2024)	AI in climate resilience governance	Literature review, Expert interviews	Governance, Risk analysis	Resilience policy gaps	Global
23	Mondal et al. (2024)	AI in net-zero policy	PLS-SEM, fsQCA	Digital inclusion	Resilience building	Vietnam, Italy, Malaysia, Greece

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24	Olawade et al. (2024a)	AI for net-zero	AI optimization	Energy, emissions	Climate tech applications	Global
25	Olawade et al. (2024b)	AI in environmental monitoring	AI/ML	Air & water quality	Pollution management	Developing countries
26	Patro et al. (2025)	AI for carbon finance indexing	GANs, PCA, Clustering	Carbon finance, supply chains	Readiness scoring	Global
27	Pérez-Pérez et al. (2024)	AI for transition risk in firms	ML, DL	Energy cost projection	Transition scenario modeling	Developing countries
28	Pimenow et al. (2024)	AI and energy sustainability	ML Review	Energy systems	Carbon optimization	China, India, UK, US
29	Pimenow et al. (2025)	AI & regional ecosystem sustainability	Scoping review	Ecosystem management	Agriculture, water, forest	Africa, Asia, EU, LatAm
30	Singh & Goyal (2023)	AI for business resilience	Deep Learning	Corporate climate risk	Infrastructure risk mitigation	Global
31	Srivastava & Maity (2023)	AI in urban adaptation	AI–ML case framework	City planning	Urban sustainability	Global (regional cases)
32	Tripathi et al. (2024)	Landscape of AI in sustainability	Scientometric + Semantic	Cross-sectoral	AI trends and gaps	Global
33	Uddin et al. (2024)	AI carbon forecasting in SCM	Emissions model	Supply chains, green finance	Carbon tracking	Global
34	Ukoba et al. (2025)	Predictive AI for climate impact	ML, Predictive analytics	Climate governance	Scenario planning	Global
35	Uriarte-Gallastegi et al. (2024)	AI for energy efficiency	Multi-case AI study	Energy & emission management	Efficiency + occupational risk	Multiple sectors
36	Vinuesa et al. (2020)	AI and SDGs	Expert elicitation	Sustainability governance	Goal alignment, digital inequality	Global
37	Yin et al. (2025)	AI mitigating climate risk	Double ML	Green finance	Risk differentiation by country	170 countries
38	Yu et al. (2024)	AI carbon emissions audit	Emissions quantification	AI model auditing	Carbon cap models	Global

Table 4 presents a summary of the 38 studies included in this review. Each record gives the main area of concentration, AI methods employed, financial application, climate use, and geographical coverage. The papers reflect wide geographical and thematic coverage, which testifies to the growing use of artificial intelligence in financial modeling related to climate change and long-term environmental changes. Many papers (e.g., Akter et al., 2024; Singh & Goyal, 2023) took account of AI applications in the business and industry setting, mostly related to climate adaptation and climate resilience. Other papers, for example, Alonso-Robisco et al. (2024) and Patro et al. (2025), took direct account of financial instruments like ESG investment, carbon indexing, and climate finance policy.

There are various AI approaches documented, from machine learning (ML), deep learning (DL), generative adversarial networks (GANs), to explainable AI (XAI). The methods were applied in various financial sectors such as carbon finance, transition planning for firms, green investment, and supply chain planning. Such studies as Bashir et al. (2024) and Yu et al. (2024) catalogued the AI system's environmental footprint, putting forward a meta-perspective on sustainability in AI applications. Applications in climate in the sampled studies span from mitigation, adaptation, emission prediction, policy planning, to tracking the environment. For instance, Haq et al. (2022) dealt with predicting environmental factors based on the LSTM and ANN frameworks, while Olawade et al. (2024a, 2024b) made further additions to the knowledge on AI-based net-zero planning and pollution management, respectively.

At the regional level, while some papers addressed global or multi-national cases, others narrowed down on regions such as India (Haq et al., 2022; Islam et al., 2024), Asia (Amnuaylojaroen, 2025), or new emerging markets such as Vietnam and Malaysia (Mondal et al., 2024). Developed nations also featured prominently, especially in research on ESG stock risks and AI regulation (Awijen et al., 2024; Dwivedi et al., 2022).

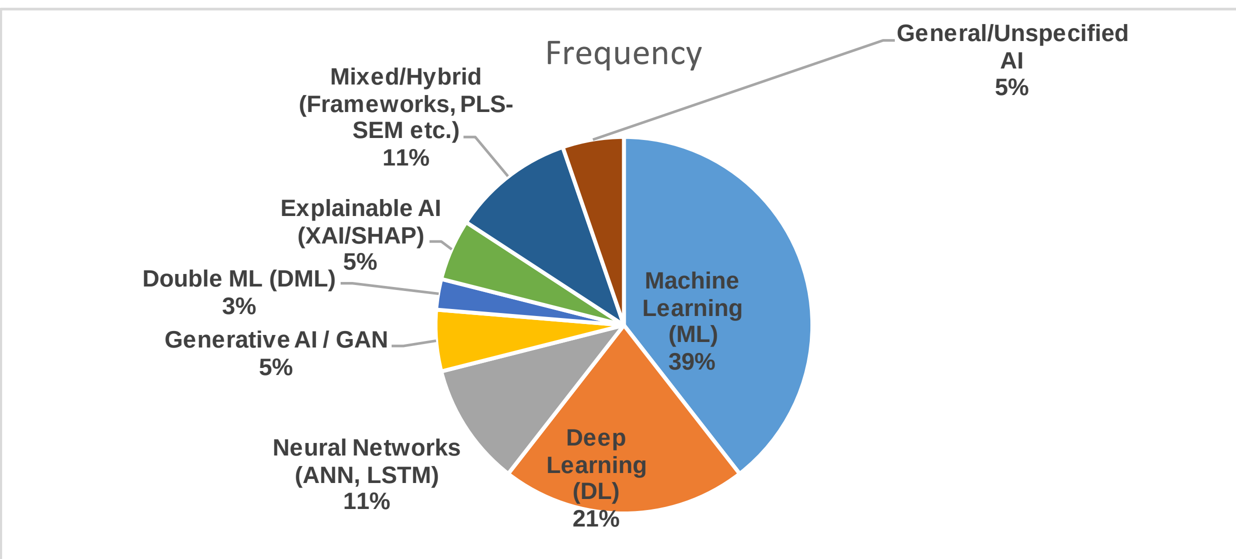

Figure 2: Bar Chart: Frequency of AI Techniques Used (e.g., ML, DL, GAN, DML)

Figure 2 presents the frequency of AI techniques used across the 38 included studies. Machine learning was the most frequently applied method, appearing in 15 studies. Deep learning techniques were reported in 8 papers, often in combination with other models. Neural networks such as ANN and LSTM were used in time-series and environmental forecasting. Generative approaches such as GAN and DML were less common but present in specific financial and risk modeling applications. Explainable AI techniques (e.g., SHAP) were used for ESG assessments. Several studies adopted hybrid frameworks combining statistical models with AI components.

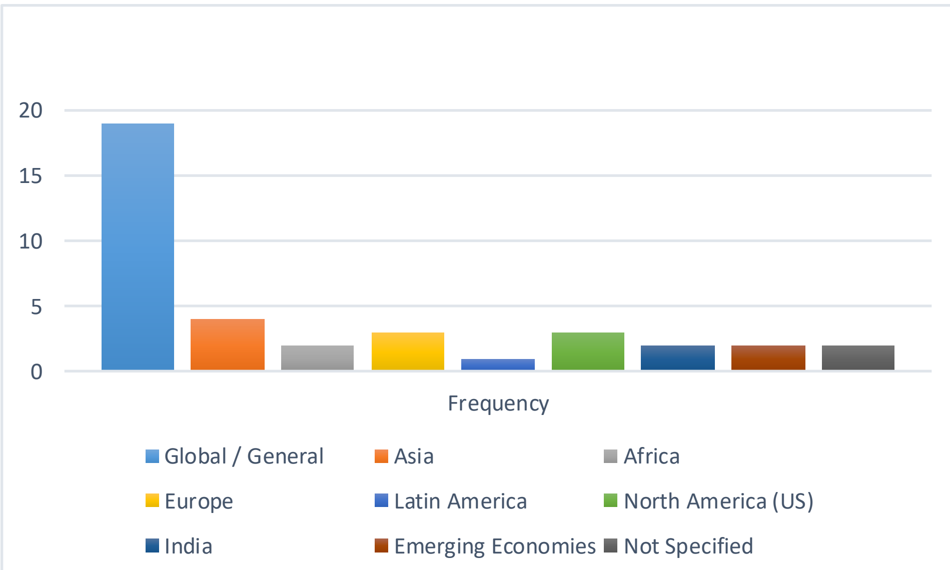

Figure 3: *Geographical Distribution of Studies (Map or Bar Plot by Region)*

Figure 3 illustrates the geographical distribution of the studies. Most papers reported findings with global or multi-regional scope, while others focused on specific regions such as Asia, North America, and Europe. A few studies addressed climate-related AI applications in Africa and Latin America. India appeared as a distinct location in multiple studies. This distribution reflects both the global relevance and the regional focus of AI applications in climate resilience research.

Domains and Applications of AI

The selected studies reveal that artificial intelligence is applied across a range of domains relevant to climate resilience and financial modeling. These domains include climate forecasting, emissions tracking, ESG risk analysis, adaptation planning, and environmental monitoring. Each domain addresses different challenges, but all contribute to improving long-term sustainability outcomes and supporting financial decision-making under climate risk. Many studies use AI for environmental forecasting, which helps in simulating extreme events and climate scenarios. Others focus on financial analysis, particularly ESG scoring and carbon finance mechanisms. AI is also widely applied in planning tools that support business adaptation to climate impacts. Monitoring systems that use machine learning and remote sensing to track environmental changes are another frequent application. These areas are associated with certain environmental and fiscal targets.

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Online ISSN: 2517-2778
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Table 5 indicates the connection between such AI applications and climate and economic targets, along with related examples taken from the literature review.

Table 5: AI Application Domains Mapped to Environmental and Financial Goals

AI Application Domain	Environmental Goal	Financial / Strategic Goal	Example Studies
Climate forecasting & simulation	Improve accuracy of climate models and risk projections	Inform insurance models, disaster risk finance	Kumar et al. (2024); Haq et al. (2022); Huntingford et al. (2019)
ESG analysis & investment risk	Support sustainability disclosures and emissions tracking	Inform green investment, manage ESG portfolio exposure	Awijen et al. (2024); Alonso-Robisco et al. (2024); Dwivedi et al. (2022)
Carbon indexing & emissions trading	Quantify emissions, assess pollution impacts	Enable carbon trading, evaluate finance readiness	Patro et al. (2025); Yu et al. (2024); Pérez-Pérez et al. (2024)
Climate adaptation in business	Support resilience strategies, reduce carbon footprint	Strengthen operations, reduce risk from climate disruption	Singh & Goyal (2023); Luqman et al. (2024); Alhassan & Maiga (2025)
Environmental monitoring & early warning	Detect pollution, assess biodiversity, monitor hazards	Reduce loss, guide planning, support sustainable operations	Alotaibi & Nassif (2024); Jain et al. (2023); Olawade et al. (2024b)

Thematic Analysis

AI for Predictive Financial Modeling of Climate Risks

One of the higher-level threads throughout the studies is the use of AI for climate risk prediction in financial applications. ML and DL models are frequently utilized to project future climate scenarios and their implications for markets and financial instruments. They can be utilized to forecast the effect of climate variability on investment products, insurance products, and firm valuations. Other research uses such models to approximate transition risk exposure, such as the financial impact of policy changes or shifts in consumption behavior. For example, Awijen et al. (2024) forecasted ESG stock price movements under both transition and physical climate risk using explainable AI models. Yin et al. (2025) also adopted a double machine learning method to illustrate the prospective applications of AI in climate risk reduction in the use of green finance and effective resource allocation.

Other research, like Pérez-Pérez et al. (2024), uses AI to offer transition cost scenarios for businesses, e.g., energy consumption behavior and carbon pricing. Such modeling for prediction enables firms to account for losses or gains potentially made under different environmental policy scenarios. This aligns with the broader goal of climate finance—to ensure capital is allocated in ways that reduce vulnerability and build resilience. Forecasting tools are also used for early warning systems and risk rating. Kumar et al. (2024) explored how AI can enhance the accuracy of climate forecasts and early warnings for extreme weather events. These insights are crucial for insurers, governments, and investors seeking to price risk more accurately and avoid exposure to unpredictable losses.

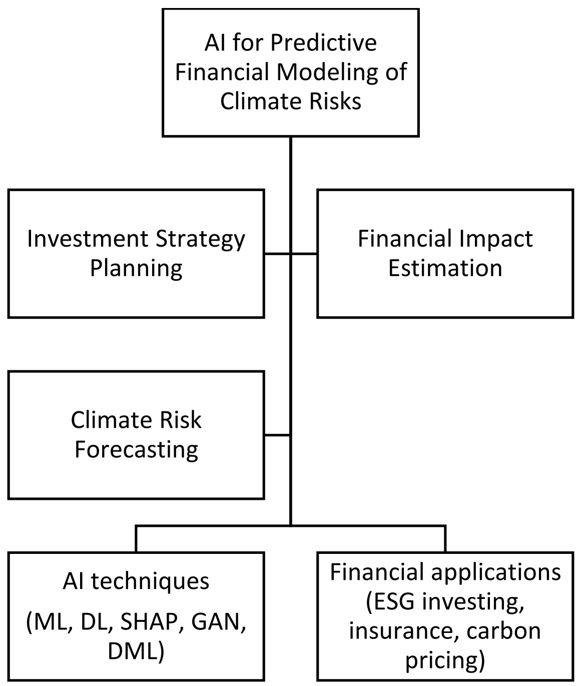

Figure 4: Thematic Map of AI Use Cases in Climate Finance

Fig. 4 shows principal applications for AI in climate finance based on the studies synthesized. The broad-based theme (predictive financial modeling with AI) is then decomposed into three subthemes: Climate Risk Forecasting, Estimation of Financial Impact, and Planning for Investment Strategy. Each branch converges to basic tools like ML/DL, generative models, or scenario-based simulation. The map also shows the areas of financial impact, like ESG investment, carbon finance, and insurance modeling. Illustrative cases like Yin et al. (2025), Awijen et al. (2024), and Pérez-Pérez et al. (2024) are evidence for deployment in risk prediction as well as pricing mechanisms.

AI in ESG & Carbon Finance Metrics

Studies considered in this paper are aimed at advocating for the use of artificial intelligence in enabling ESG investment screening and carbon finance systems. Such publications highlight the potential for AI in boosting transparency, speed, and accuracy in determining the ESG track record and in valuing carbon-linked financial metrics. AI techniques, such as ML and XAI, are used for climate financial risk and ESG stock volatility estimation. Awijen et al. (2024) made use of ML models and SHAP modeling for analyzing climate risk factors on the price of ESG stocks. The inflation, pollution, and climate indices data were incorporated into their model, which provides an interpretable means for estimating risk exposure.

Studies on carbon finance use AI to construct indices for measuring carbon finance readiness or predicting emissions trading performance. Patro et al. (2025) developed a carbon finance index driven by Generative Adversarial Networks (GANs) and Principal Component Analysis (PCA). The authors categorized nations based on carbon finance potential and provided a decision-support system for global climate finance allocation. Yu et al. (2024) assessed the emissions of 79 AI systems and projected their carbon impact. Their work supports carbon accounting for technology systems and introduces a dashboard-style emissions tracking model that could inform carbon pricing or cap-setting frameworks. These studies highlight how AI not only enhances financial analytics but also contributes to policy and market design in sustainable finance. Some studies address ESG evaluation in the broader sense, such as Alonso-Robisco et al. (2024), who used Latent Dirichlet Allocation (LDA) to identify ML's applications across ESG, carbon markets, and biodiversity. Figure 6 (see below) presents the most representative studies within this theme and summarizes their key focus, AI technique, and contributions to ESG or carbon finance.

Table 6: Key Studies Focused on ESG/Carbon Finance

Citation	Focus Area	AI Methods Used	Contribution to ESG/Carbon Finance
Awijen et al. (2024)	ESG stock price analysis	ML, SHAP, XAI	Predicts ESG stock movements using climate and financial data
Patro et al. (2025)	Carbon finance readiness index	GANs, PCA, Clustering	Ranks countries by carbon market potential
Yu et al. (2024)	AI carbon emissions assessment	Emissions modeling, audit tools	Measures environmental cost of AI systems
Pérez-Pérez et al. (2024)	Financial modeling of climate transition risks	ML, DL	Predicts firm energy use and cost under climate scenarios
Alonso-Robisco et al. (2024)	ESG and carbon finance trend mapping	LDA topic modeling	Identifies ML applications in climate finance subfields
Vinuesa et al. (2020)	AI and Sustainable Development Goals	Expert elicitation	Maps AI's enabling/inhibiting roles across ESG-related SDGs
Luqman et al. (2024)	AI in carbon neutrality strategy (corporate)	Qualitative case analysis	Highlights AI's strategic role in emissions reductions
Singh & Goyal (2023)	AI in business climate resilience	DL	Ties climate risk forecasting to corporate ESG adaptation
Bashir et al. (2024)	Sustainability of GenAI	GenAI energy audit	Measures carbon cost of AI growth, relevant for ESG policies
Olawade et al. (2024a)	AI for Net-Zero	Optimization AI	Supports energy reduction strategies in corporate settings

AI for Long-Term Environmental Impact Assessment

Another prominent theme is the application of artificial intelligence to evaluate long-term environmental impacts. These studies focus on forecasting pollution trends, analyzing land use changes, and supporting lifecycle assessments (LCA) with data-driven methods. AI aids in the assessment of long-term effects on the environment for industrial, technological, and financial decisions.

Numerous studies assess environmental quality on the basis of predictive modeling. Haq et al. (2022) offered snow cover, vegetation trends, and temperature predictions based on long short-term memory (LSTM) models. Such variables are important for understanding climate pattern drivers and their effects on ecosystems. Uddin et al. (2024) also established a carbon emissions supply chain prediction system. The AI-driven model was utilized in making recommendations on carbon footprint minimization as well as logistics and procurement sustainability. Other studies expressed worry about the environmental cost of AI. Yu et al. (2024) conducted a carbon audit on 79 AI systems, which indicated that energy consumption through the use of large-scale models can be a reason for high emissions. Bashir et al. (2024) also indicated the environmental cost of generative AI, which requires frameworks for balancing not only efficiency but also sustainability trade-offs. The study shows that the environmental footprint of digital infrastructure is important for consideration in long-term impact assessments.

There is a broader perspective by Chen et al. (2023), which emphasized the role of AI in climate mitigation for the energy, transport, and agriculture industries. The study suggested intelligent systems for emissions minimization, optimization in energy utilization, and smart configuration in industries. There are similar inclinations in Uriarte-Gallastegi et al. (2024), which embraced cases ranging across industries in order to illustrate AI's potential in enhancing energy effectiveness and mitigating occupant risk in the pursuit of better emissions control.

Pimenow et al. (2025) emphasized spatial and sectoral perspectives. The paper indicated the application of AI tools for regional-level management of water, forestry, and agricultural catchments. The multi-level processing capacity of AI is enabling the detection of shifts in land use as well as prospective determination regarding the threat of deforestation. This contributes to enhanced planning for long-term safeguarding of the environment.

AI for Resilience Strategy and Climate Adaptation

Researchers continue to explore the use of artificial intelligence in facilitating adaptation and constructing climate change resilience. Some studies employ AI in predicting threats and informing adaptation planning. Huntingford et al. (2019) recommended climate feedback identification and early extreme event warnings using machine learning. The study indicates AI application in the identification of complex weather systems usually not captured in mainstream models. Similarly, Kumar et al. (2024) provided an overview on AI for early warning systems putting an emphasis on improving weather forecasts using neural networks and data-centric learning. Jain et al. (2023) noted AI climate scenario modeling applications for infrastructure protection in cities. The study shows how cities can apply their expansive climate model and satellite imagery datasets to assess their risk exposure. This informs investment prioritization in areas where vulnerability can be reduced and cities can be made more resilient.

Singh and Goyal in 2023 tested strategies for firms to use AI in climate threat identification and continuity planning. The study included an extreme-event prediction deep learning algorithm and financial impact evaluation. Such tools can be utilized for risk management for operations, assets, and supply chains. Other studies also highlight integrating AI in policy and governance settings. Mehryar et al. (2024) emphasized that hazard assessment is helped through AI, but vulnerability, planning for resilience, and decision-making processes need improvement. The study recommended the inclusion of qualitative observations as well as AI-driven forecasts in a bid to strengthen local policies for adaptation. Amnuaylojaroen (2025) was concerned about sustainable urban planning. The paper outlined the deep learning frameworks that can aid in planning climate-resilient infrastructure. The paper also raised the aspect of scaling AI-driven solutions in diverse urban settings, especially where the quality of data is not the same.

DISCUSSION

These studies suggest that long-term planning and climate resilience are facilitated in different ways through the utilization of artificial intelligence. The different AI methods are employed in different environmental, financial, as well as governance sectors. The approaches differ in their complexity, their data requirements, as well as transparency.

Advanced techniques like Generative Adversarial Networks (GANs) have been adopted in building robust indices as well as in modeling subtle policy scenarios. Patro et al. (2025) applied GANs alongside Principal Component Analysis for carbon finance readiness estimation in nations. The method allowed for flexibility in modeling uncertainty as well as latent variables. However, Double Machine Learning (DML) techniques, as adopted by Yin et al. (2025), are worried about causal estimation. This is preferred when estimating the net effect of AI on climate risk subject to variation in the economy as well as institutions. Even though both models are computationally advanced, DML is concerned about interpretability as well as policy usefulness, while GANs offer superior simulation-based task performance.

Numerous studies took hybrid approaches involving neural networks, cluster-based, or optimization-based paradigms. Uddin et al. (2024) developed a conceptual framework relating carbon emission forecasting and green finance indicators in value chains. They incorporated external data flow in AI forecasting models for actionable outputs for corporate sustainability. Pérez-Pérez et al. (2024) used a hybrid ML–DL model for predicting transition risk financial impacts in firms. These examples show that integrated models are emerging as important tools for long-term planning, though their development is often resource-intensive.

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There are also implications for sustainable investment. AI models are increasingly being used to assess ESG performance, carbon risk, and green finance potential. Awijen et al. (2024) showed that interpretable ML models can forecast ESG stock prices based on climate exposure. Alonso-Robisco et al. (2024) mapped AI's role in ESG-related research areas like carbon markets and biodiversity protection. These tools could help investors identify assets vulnerable to climate risk or aligned with green policies.

Despite these strengths, policy integration remains weak in many AI applications. Mehryar et al. (2024) pointed out that most models focus on hazard and exposure assessment but lack tools to support resilience implementation. Bashir et al. (2024) and Yu et al. (2024) raised concerns about the environmental cost of developing AI, which is rarely addressed in regulation. Without clear frameworks, there is a risk of increasing emissions while using AI for mitigation planning. Also, models often ignore local knowledge and social dimensions of vulnerability, limiting their policy relevance.

Explainability is another recurring gap. Although techniques like SHAP values were applied by Awijen et al. (2024) to enhance model transparency, most deep learning models remain unclear. This makes it difficult for policymakers and non-technical users to interpret AI outputs or challenge model assumptions. Explainability is especially critical in high-stakes domains such as carbon pricing or disaster forecasting.

Several studies identify data quality and access as key barriers. Many AI models rely on structured, high-frequency datasets, which are not available in many regions. Pimenow et al. (2025) and Srivastava and Maity (2023) both highlighted disparities in data infrastructure between high-income and low-income settings. These inequalities affect both model accuracy and relevance. Institutions in developing countries also face challenges in adopting AI tools due to limited technical capacity and financial constraints.

Table 7: *Challenges and Gaps Identified in Literature (Grouped by Theme)*

Theme	Identified Challenge	Details / Explanation	Example Study
AI for Predictive Financial Modeling	Lack of model explainability	Many machine learning and deep learning models used for financial predictions are not transparent, making them difficult to validate in high-stakes or regulated settings.	Awijen et al. (2024), Pérez-Pérez et al. (2024)
	Overfitting and limited generalizability	Financial prediction models may perform well on training data but poorly in	Yin et al. (2025), Patro et al. (2025)

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		real-world scenarios due to unstable climate-financial interactions.	
	Limited use of causal inference	Most models focus on correlations rather than causation, limiting their usefulness for long-term investment decisions.	Alonso-Robisco et al. (2024)
AI in ESG & Carbon Finance Metrics	Inconsistent or unstandardized ESG datasets	Lack of uniform ESG reporting frameworks across countries and firms leads to poor data quality and model inconsistency.	Alonso-Robisco et al. (2024), Awijen et al. (2024)
	Difficulty in quantifying carbon offsets	Challenges exist in pricing, verifying, and modeling offsets due to poor integration with AI systems.	Patro et al. (2025), Singh & Goyal (2023)
	Bias in ESG classification algorithms	AI models used to classify ESG risk often reflect the bias in training datasets or external benchmarks.	Greif et al. (2024)
AI for Long-Term Environmental Impact Assessment	High energy consumption of AI systems	Training large models, such as GenAI and LLMs, results in significant carbon emissions, undermining sustainability goals.	Bashir et al. (2024), Yu et al. (2024)
	Poor model integration with LCA tools	Few AI systems are designed to support or integrate with life-cycle assessment frameworks.	Uddin et al. (2024), Chen et al. (2023)
	Limited long-term datasets	Lack of historical environmental data constrains AI's ability to assess long-term impacts accurately.	Haq et al. (2022), Amnuaylojaroen (2025)
AI for Resilience Strategy & Climate Adaptation	Lack of context-specific tools	Many AI models are built on global datasets and do not reflect local climate conditions or socio-political structures.	Mehryar et al. (2024), Srivastava & Maity (2023)

	Unclear links between AI outputs and decision-making	Forecasts and risk assessments are not always integrated into actionable resilience policies or plans.	Singh & Goyal (2023), Jain et al. (2023)
	Scalability issues in urban adaptation	Models may not scale well across different urban areas due to data disparities or infrastructure limits.	Amnuaylojaroen (2025), Jain et al. (2023)
Cross-cutting (All Themes)	Regional data inequality	Developing regions lack the infrastructure to generate, manage, or use high-quality environmental data for AI modeling.	Pimenow et al. (2025), Alhassan & Maiga (2025)
	Institutional barriers to adoption	Organizations lack technical capacity, regulatory clarity, or funding to deploy AI tools in climate finance.	Luqman et al. (2024), Islam et al. (2024)
	Ethical concerns around AI governance	Data privacy, fairness, and algorithmic accountability remain under-addressed in climate applications.	Vinuesa et al. (2020), Bashir et al. (2024)

Implications for Research, Policy, and Practice

The findings from this review point to a range of implications across academic research, practical application, and policy development. There are clear roles for each of the different groups of stakeholders in bridging the gaps and advancing artificial intelligence use for climate resilience and long-term environmental benefits.

Researchers must develop explainable AI models. Most current models are founded on deep learning or advanced neural networks that are black boxes. Such models are difficult to interpret or substantiate, especially in financial decision-making applications (Awijen et al., 2024; Yin et al., 2025). Future research must aim to focus on the development of explainable AI (XAI), such as SHAP and LIME, to introduce transparency to model outputs (Awijen et al., 2024). Standardization between methods and datasets is also an area that needs attention. Most research on ESG and carbon finance is founded on inconsistent indicators, which makes comparison or performance benchmarking difficult (Alonso-Robisco et al., 2024). More research on building shared taxonomies, regional benchmarking models, and hybrid models combining structured financial information and environmental indicators is required for increased generalizability (Uddin et al., 2024).

Practical applications in AI for emission projections, sustainable supply chain tracking, and climate investment tools are suggested for professionals. Carbon finance and emissions projections can be modeled, as suggested in Patro et al. (2025) and Uddin et al. (2024. Such systems can be effective for companies' preparations for future carbon pricing regulations or transition financing initiatives. Scenario planning and climate service innovations can also be facilitated in an industrial and corporate setting, as in Akter et al. (2024). Uptake is, however, poor due to capacity inadequacies and ambiguity on return on investment. Firms can be assisted in their decision-making through decision support systems that integrate financial risk modeling and climate vulnerability projections, especially in the energy, manufacturing, and logistics sectors.

For policymakers, the review highlights the necessity for regulation, funding, and ethical AI-use standards. Research suggests AI's potential climate footprint, such as carbon emissions and energy use for training large models (Bashir et al., 2024; Yu et al., 2024), which can be in direct opposition to the climate targets the models are purported to help facilitate. That is why net-zero AI development requires rules. Policymakers can also make their contribution through inclusive data infrastructure access. Most disadvantaged regions do not possess the digital infrastructure to use AI-based climate adaptation planning (Pimenow et al., 2025). Public funding programs, open-data policies, and digital literacy education can bridge such gaps. Finally, ethical control must be strengthened in order to address algorithmic bias, data security, and clarity in AI decision-making.

CONCLUSION

The paper reviewed 38 relevant studies. Most articles focused on applications relating to machine learning and deep learning in carbon predictions, transition risk, emissions indexing, as well as ESG. The study identifies the application of AI making use of predictive modeling as well as tracking environmental performance both across regions and industries. The review contributes to the knowledge base by mapping AI applications against areas of finance concentration, data access gaps, method transparency, and policy. The study indicates the need for future research in model interpretability and diversity in regional applications. There is also a need for further empirical testing in real-world financial decision-making for AI-based models. A standard assessment framework could facilitate cross-study comparisons to promote climate finance's responsible use of AI.

Recommendations

Policymakers need to establish clear regulatory procedures for overseeing the ethical use of AI in climate finance. Such procedures need to address issues regarding transparency in the model, the environmental price of computations, as well as data sharing protocols.

Public and private sectors are recommended to commit to capacity-building programs in order to ensure AI utilization in infrastructure-limited regions. They are to include funding instruments, IT tool training, and cross-sectoral networks.

Researchers need to concentrate on developing explainable AI models which comply with sustainability targets. Such methods as SHAP, LIME, or hybrid interpretable models need to be incorporated in AI-driven financial risk instruments.

Cross-industry partnerships can co-develop strong data ecosystems. Standardized ESG indicators, emission benchmarks, and climate risk inputs should be included in these to ensure consistency and comparability in models across settings.

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