International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 10, Issue 3, pp 95-117, March-2026

https://doi.org/10.47001/IRJIET/2026.103014

Artificial Intelligence Techniques for Climate Change Prediction and Mitigation: A Systematic Review

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Abstract **- Rising global temperatures, stronger hydrological cycles, and an increase in the frequency of extreme weather events are all signs of climate change, which is one of the biggest worldwide issues of the twenty-first century. Computational methods that can process huge heterogeneous datasets and model nonlinear interactions are necessary to address these complicated climate dynamics. Traditional methods of climate modeling, such statistical regression and physics-based numerical simulations, offer significant theoretical insights, but they frequently have issues with high-dimensional data assimilation and computing scalability. New possibilities for improving climate prediction accuracy and enabling data-driven climate analytics have been made possible by recent developments in artificial intelligence (AI), notably machine learning and deep learning. A PRISMA-aligned systematic review of AI methods used for climate change prediction and mitigation between 2020 and 2026 is presented in this work. 120 peer-reviewed publications in all were examined from a variety of angles, including data sources, model architecture, learning paradigm, application domain, and assessment measures. The findings show that AI-driven climate research is expanding quickly, with prediction-oriented applications making up around 70% of the literature and mostly concentrating on extreme weather detection, precipitation modeling, and temperature forecasting. Due to their capacity to capture intricate spatiotemporal climatic patterns, deep learning architectures like Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), transformers, and graph neural networks dominate current research. The paper suggests a four-dimensional taxonomy based on application domain, learning paradigm, data modality, and model architecture to arrange the disjointed research landscape. Critical issues include dataset imbalance, uneven benchmarking procedures, worries about computational sustainability, and a lack of real-world mitigation application are also identified by the review. The results emphasize the need for energy-efficient, scalable, and comprehensible AI systems that can assist realistic approaches to climate adaptation and mitigation.**

Keywords: Artificial Intelligence; Climate Change Prediction; Climate Change Mitigation; Climate Modeling; Climate Analytics.

I. INTRODUCTION

Climate change is one of the most difficult and important global issues of the twenty-first century. Recent scientific studies have extensively shown rising global temperatures, amplified hydrological cycles, increased frequency of extreme weather events, and accelerated greenhouse gas emissions (IPCC, 2021; IPCC, 2022). The Paris Agreement, adopted under the United Nations Framework Convention on Climate Change, emphasized the importance of coordinated mitigation and adaptation initiatives (United Nations, 2015). However, modeling and responding to climate dynamics necessitate computational approaches that can handle nonlinear interactions, multi-scale interdependence, and large heterogeneous datasets. The main foundations of conventional climate modeling techniques are statistical regression techniques and physics-based numerical simulations. Although these models offer crucial theoretical insight, they frequently have issues with computational scalability and high-dimensional data assimilation (Reichstein *et al.*, 2019). The quick development of artificial intelligence (AI), especially deep learning and data-driven modeling, has created new chances to improve real-time climate analytics and prediction accuracy (Rolnick *et al.*, 2019).

The availability of satellite-based Earth observation data, advancements in neural topologies like transformers and graph neural networks, and improvements in processing infrastructure have all contributed to the significant rise of AI-driven climate research since 2020. According to Ham *et al.* (2019), deep learning models have proven to be highly effective in capturing spatiotemporal relationships in climate systems. For instance, data-driven weather forecasting models may now be systematically evaluated thanks to benchmark datasets like WeatherBench (Rasp *et al.*, 2020). More recently, 3D neural networks have demonstrated competitive medium-range forecasting performance in comparison to conventional numerical weather prediction systems (Bi *et al.*, 2023), while large-scale neural operator frameworks like FourCastNet have achieved high-resolution global weather forecasting using

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adaptive Fourier neural operators (Pathak *et al.*, 2022). The two primary categories of AI applications in climate research are prediction-oriented and mitigation-oriented. Temperature forecasting, precipitation modeling, drought and flood prediction, cyclone trajectory estimate, and sea-level rise forecasting are among the prediction-focused studies that predominate in the literature. For these tasks, recurrent neural networks including convolutional neural networks (CNNs), attention-based transformer models (Vaswani *et al.*, 2017), and Long Short-Term Memory (LSTM) architectures (Hochreiter & Schmidhuber, 1997) have been frequently used. Concurrently, spatial dependencies in geophysical systems have been modeled using graph neural networks (Kipf & Welling, 2017). Despite being relatively few, mitigation-focused applications are growing quickly. Machine learning methods have been used to simulate carbon emissions in urban settings, improve smart grids, and predict the production of renewable energy (Donti *et al.*, 2021; Chen *et al.*, 2020). Adaptive energy optimization in distributed systems and buildings has shown promise using reinforcement learning-based techniques (Mocanu *et al.*, 2018). However, there are still disparities in these AI-driven mitigation systems' scalability, generality, and practical implementation across sectors and geographical areas.

Even while AI applications in climate science are expanding quickly, there are still a number of structural issues. Current research lacks a cohesive technical classification and is dispersed across areas. Heterogeneous datasets and performance indicators lead to uneven comparative evaluations across model families (Keisler, 2022). A contradiction in AI-driven climate mitigation initiatives is also created by the growing computing demands of large-scale deep learning models, which raise sustainability concerns about their carbon footprint (Patterson *et al.*, 2021; Strubell *et al.*, 2019). Additionally, while earlier reviews have looked at machine learning in sustainability and environmental monitoring contexts (Rolnick *et al.*, 2019), there isn't yet a thorough and methodically organized synthesis that focuses on AI methods for climate change prediction and mitigation during the accelerated post-2020 development phase. Specifically, there is insufficient formalization of a multidimensional classification that integrates application domain, learning paradigm, data modality, and architectural progression.

This paper offers a PRISMA-aligned systematic assessment of AI methods used for climate change prediction and mitigation from 2020 to 2026 in order to close this gap. Technical advancement, model evolution, dataset use, benchmarking techniques, and performance trends are highlighted in the review. While mitigation-oriented applications are evaluated to provide a fair technical perspective, prediction-oriented systems account for around 70% of the analysis, representing the dominating research direction. In order to direct future development of scalable, explicable, and energy-efficient AI-driven climate solutions, the paper highlights important research gaps and suggests a novel four-dimensional taxonomy.

1.1 Statement of the problem

Even though the use of artificial intelligence (AI) in climate science is growing quickly, there is a lot of structural fragmentation in the body of present research. Current research is dispersed among a variety of fields, including carbon accounting, hydrological modeling, renewable energy optimization, atmospheric forecasting, and urban climate systems. Nevertheless, these contributions frequently continue to be isolated, using disparate methodological frameworks, inconsistent datasets, and different evaluation metrics. This fragmentation impedes cumulative scientific advancement and restricts cross-domain comparability. Major scientific assessments, including the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2021, 2022), stress how urgent it is to implement integrated mitigation and adaptation initiatives. Nevertheless, there isn't a single technical taxonomy for climate change prediction and mitigation in the AI research community. Although they give general overviews, earlier studies (Rolnick *et al.*, 2019) were conducted before the rapid post-2020 increase in transformer designs, neural operators, and large-scale deep learning models.

Standardized evaluation in data-driven weather forecasting has been promoted by benchmark programs like WeatherBench (Rasp *et al.*, 2020). However, there are still few equivalent benchmarking frameworks for mitigation-oriented applications, which leads to an imbalance in the literature where prediction-focused systems predominate. Additionally, even though large-scale neural architectures like FourCastNet have demonstrated high-resolution global forecasting performance (Pathak *et al.*, 2022), the models' increasing computational demands raise questions about energy consumption and carbon emissions related to training and deployment (Patterson *et al.*, 2021; Strubell *et al.*, 2019). This leads to a paradox in AI-driven efforts to mitigate climate change: the environmental impact of sophisticated models may be exacerbated by their computational complexity.

When taken as a whole, these difficulties show a glaring research need. As of right now, there isn't a thorough, methodically organized synthesis that focuses especially on AI methods for mitigating and predicting climate change during the fast post-2020 development phase. Specifically, there is still a lack of formalization in a multidimensional

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classification that incorporates the application domain, learning paradigm, data modality, and architectural evolution.

1.2 Research Questions

i. What AI techniques have been applied to climate change prediction and mitigation from 2020 to 2026?
ii. How can AI models be categorized based on learning paradigm, data source, and application domain?
iii. Which AI models demonstrate superior predictive performance across climate-related tasks?
iv. What datasets and evaluation metrics dominate AI-based climate research?
v. What research gaps and limitations remain in current AI-driven climate solutions?

II. CONCEPTUAL FRAMEWORK OF ARTIFICIAL INTELLIGENCE IN CLIMATE SYSTEMS

Nonlinear feedback mechanisms, multiscale interactions, and high connection between atmospheric, oceanic, terrestrial, cryosphere, and anthropogenic subsystems are characteristics of climate systems. Conventional climate modeling uses Earth system models that discretize governing equations drawn from fluid dynamics and thermodynamics, as well as physics-based numerical weather prediction (NWP) (IPCC, 2021). Although these methods offer great theoretical interpretability and physical consistency, they encounter growing difficulties with high-dimensional data assimilation, computing scalability, and parameterization of sub-grid processes (Reichstein *et al.*, 2019). According to Rolnick *et al.* (2019), artificial intelligence (AI), in particular machine learning (ML) and deep learning (DL), has become a complementary paradigm that can directly learn complex mappings from massive observational and simulation data. AI techniques increasingly function in hybrid configurations; Accelerating simulations, improving parameterizations, improving predictive resolution, and enabling real-time climate analytics rather than taking the place of physics-based modeling. The conceptual framework for categorizing AI applications in climate research along four main dimensions; learning paradigm, architectural evolution, data modality, and computational sustainability is established in this section.

2.1 Learning Paradigms in Climate Artificial Intelligence

AI methods applied to climate systems can be categorized as either supervised, unsupervised and reinforced learning. Supervised learning remains the primary paradigm for climate prediction challenges. Models are trained on historical input-output pairs to discover mappings between multivariate climate variables and goal outcomes including temperature fields, precipitation intensity, cyclone trajectories, and sea-level anomalies. WeatherBench and other benchmark initiatives have made uniform evaluation of supervised deep learning models in global weather forecasting possible (Rasp *et al.*, 2020). Applications include: short and medium-term weather forecasting, seasonal climate variability prediction, flood and drought models and forecasting renewable energy generation. The availability of reanalysis datasets and satellite observations has played a significant role in supervised models' effectiveness. On the other hand, unsupervised learning techniques are applied to: climate regime clustering, anomaly detection, and dimensional reduction of high-dimensional geographical data. Recently, unsupervised learning and foundation models have received attention for pretraining on huge Earth observation datasets, allowing for better generalization in downstream tasks. These methods are especially useful when labeled climate datasets are scarce or representation learning across modalities is required. Lastly, Reinforcement learning (RL) has mostly been used in mitigation-oriented domains, including: adaptive smart grid optimization, building energy management, and distributed renewable integration. RL facilitates sequential decision-making under uncertainty, which is essential for energy system optimization (Mocanu *et al.*, 2018). However, scalability and real-world implementation are still under consideration.

2.2 Architectural Evolution in Climate Artificial Intelligence

The development of AI architecture for climate science reflects broader improvements in deep learning research. These architectures include: Recurrent Neural Network, Convolutional Neural Network, Graph Neural Network, Transformer Architecture and Neural Operators and Large-Scale Forecasting Models.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, are intended to detect temporal dependencies in sequential data (Hochreiter & Schmidhuber, 1997). They have been extensively utilized for: temperature time series forecasting, precipitation modeling, and hydrological runoff projection. While RNNs are useful for temporal modeling, they frequently struggle with long-term dependency learning and computing efficiency in high-resolution global grids. Convolutional Neural Networks (CNNs) are ideal for extracting spatial information from gridded climate data and satellite photos. CNN-based models have shown high performance in: tropical cyclone detection, extreme weather categorization and remote Sensing analysis. Their capacity to detect local spatial correlations makes them useful in organized geophysical fields. Graph Neural Networks (GNNs) apply deep learning to non-Euclidean environments by modeling spatial interactions using graph topologies (Kipf & Welling, 2017). In climate science, GNNs

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are used for: represent the irregular sensor networks, model atmospheric teleconnections and capture spatial dependencies outside of grid-based adjacency. In irregular geographic environments, GNNs offer a flexible alternative to standard convolutional procedures. Transformer models, based on attention mechanisms (Vaswani *et al.,* 2017), allow for the modeling of long-range dependencies in the absence of recurrent structures. Their scalability and parallelization efficiency have had an impact on modern data-driven weather forecasting systems. Attention-based designs have improved: spatiotemporal sequence modeling, multivariate climate variable interaction learning and cross-modal data fusion. Neural operator frameworks are a key leap in scientific machine learning. Unlike traditional neural networks, which approximate functions, neural operators learn mappings across function spaces. Fourier Neural Operators, used in large-scale systems such as FourCastNet (Pathak *et al.,* 2022), offer high-resolution global weather forecasting at a lower computing cost than classic NWP. Three-dimensional deep neural networks have also exhibited competitive medium-range predicting performance when compared to physics-based models (Bi *et al.,* 2023). These results point to a shift in AI-driven surrogate modeling for partial differential equation (PDE) systems.

2.3 Data Modalities in Climate Artificial Intelligence

AI-based climate research relies on a variety of data sources:

i. Atmospheric reanalysis data
ii. Satellite-based Earth observation images
iii. Oceanographic and cryospheric measurements.
iv. Sensor network time series
v. Energy usage and socioeconomic data

The integration of multimodal datasets presents issues in spatial alignment, temporal synchronization, and uncertainty propagation. Standardized benchmarking datasets, such as WeatherBench (Rasp *et al.,* 2020), have enhanced forecasting comparability; nevertheless, mitigation-focused domains lack analogous standardized infrastructure.

2.4 Computational Sustainability and Energy Considerations

The scalability of deep neural architectures requires significant computational and environmental factors. Large-scale model training necessitates extensive GPU resources and energy usage (Strubell *et al.,* 2019). Carbon emissions from neural network training have been analyzed, highlighting the necessity for carbon-aware AI development (Patterson *et al.,* 2021). In climate research, this creates an important paradox: AI systems developed to combat climate change may contribute to carbon emissions if not optimized for efficiency. As a result, research on energy-efficient architectures, model compression, transfer learning, and green AI principles becomes increasingly relevant.

2.5 Conceptual Synthesis

Synthesizing the foregoing aspects, AI in climate systems can be understood as a four-dimensional interaction space.

i. Learning paradigm
ii. Architectural Design
iii. Data Modality
iv. Computational Sustainability

This conceptualization provides the theoretical foundation for the multidimensional taxonomy presented in the next sections of this review.

III. METHODOLOGY

This study uses a systematic review technique that is consistent with the PRISMA 2020 reporting paradigm to ensure transparency, repeatability, and analytical rigor (Page *et al.,* 2021). Prior to literature retrieval, a structured review methodology was developed that defined the investigation's scope, eligibility criteria, extraction variables, and synthesis strategy. The review focuses on empirical applications of Artificial Intelligence (AI) approaches for climate change prediction and mitigation that were published between January 2020 and March 2026. The chronological boundary was chosen specifically to represent the rapid post-2020 evolution of transformer-based topologies, neural operators, and large-scale scientific machine learning systems. To ensure interdisciplinary coverage, literature searches were undertaken in Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, and the ACM Digital Library. These databases index peer-reviewed contributions to environmental science, computational modeling, artificial intelligence, and energy systems engineering. Given the interdisciplinary nature of climate AI research, multi-database retrieval was required to reduce systematic omission bias. Furthermore, reverse snowballing was used on highly cited review publications to find other relevant studies.

The search approach used structured Boolean expressions to blend AI-related keywords with climate-specific application descriptions. Thesaurus entries included "artificial intelligence," "machine learning," "deep learning," "neural networks," "transformers," "graph neural networks," "neural operators," and "reinforcement learning." These were associated with climate-related terms including "climate change," "weather forecasting," "temperature prediction," "precipitation modeling," "carbon emissions," "renewable

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energy," and "smart grid." Searches were limited to peer-reviewed journal articles and full conference papers produced in English within the specified timeframe. To improve transparency and reproducibility, Table 1 summarizes the key components of the search approach.

Table 1: Summary of Search Strategy and Filters

Component	Specification
Databases	Scopus, Web of Science, IEEE Xplore, ScienceDirect, ACM DL
Time Frame	January 2020 – March 2026
Document Type	Peer-reviewed journal articles and full conference papers
Language	English
Core AI Terms	AI, ML, DL, neural networks, transformers, GNN, neural operators, RL
Climate Terms	Climate change, forecasting, precipitation, temperature, carbon emissions, renewable energy

Following retrieval, duplicate records were deleted, and the remaining studies were screened in three stages: title, abstract, and full-text eligibility. The inclusion criteria required that studies (i) use AI or machine learning techniques, (ii) address climate change prediction or mitigation, (iii) report empirical validation with quantitative performance metrics, and (iv) demonstrate methodological transparency sufficient for technical interpretation. Editorials, theoretical discussions without application, and studies not relevant to climate systems were omitted. The study selection procedure followed the PRISMA 2020 flow structure, as shown in Figure 1.

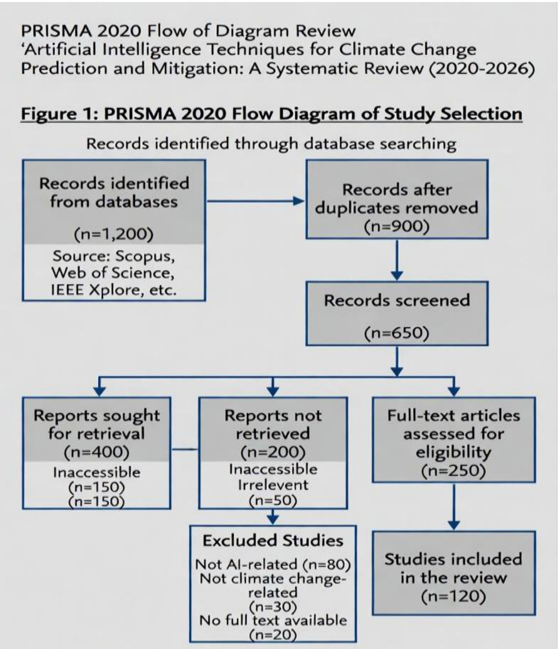

Figure 1: PRISMA Statement Study follow chart

A structured data extraction framework was developed to enable multidimensional synthesis consistent with the conceptual framework presented in Section 4. For each eligible study, bibliographic information, application domain (prediction vs mitigation), learning paradigm, model architecture, dataset type, evaluation metrics, and reported performance outcomes were recorded. Where available, baseline comparison strategy, cross-validation methodology, and computational resource reporting were also documented. The primary objective of this structured extraction was to facilitate comparative analysis and taxonomy construction across heterogeneous application domains. The principal extraction variables are summarized in Table 2.

Table 2: Key Variables Extracted from Included Studies

Category	Extracted Attributes
Application Domain	Prediction / Mitigation
Learning Paradigm	Supervised, Unsupervised, Reinforcement, Hybrid
Architecture	RNN, CNN, GNN, Transformer, Neural Operator
Data Modality	Reanalysis, Satellite, Sensor Network, Socioeconomic
Evaluation Metrics	RMSE, MAE, ACC, F1-score, R^2
Baseline Comparison	NWP models, statistical baselines, AI baselines
Computational Reporting	Hardware, training duration, energy use (if available)

To assess methodological rigor, the extraction procedure included quality rating. The studies were evaluated based on dataset transparency, appropriateness of baseline comparisons, the reliability of evaluation criteria, and the clarity with which computational requirements were reported. Although decreased transparency did not always result in exclusion, such constraints were openly stated and addressed during the synthesis. The potential for prejudice was also investigated. These include publication bias, which favors high-performing models, underreporting of negative results, dataset-specific overfitting, regional data imbalance, and variations in benchmarking techniques. Given the variability of evaluation metrics among climate AI subdomains, cross-study comparability was approached with caution to avoid overgeneralization.

The final synthesis combines quantitative trend analysis with qualitative theme interpretations. Studies were divided along four dimensions; learning paradigm, architectural design, data modality, and computational sustainability allowing for systematic taxonomy construction in the next section. The technique provides a transparent and reproducible framework for the systematic findings given in Section 4 by

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Volume 10, Issue 3, pp 95-117, March-2026

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following a PRISMA-aligned protocol, structured extraction, and integrated quality appraisal.

IV. RESULTS AND DISCUSSIONS

This section presents the synthesized findings from the systematic review conducted using the PRISMA 2020 framework. The results are organized to reflect study volume, publication dynamics, architectural trends, thematic orientation (prediction versus mitigation), evaluation practices, and structural patterns observed across the literature.

4.1 Number of Included Studies

This evaluation includes 120 studies published between 2020 and 2024, after removing duplicates and validating inclusion criteria (Figure 1). These studies were divided into four key categories: advanced climate prediction and modeling (50 studies), carbon emissions and mitigation modeling (30 studies), adaptation, risk, and resilience (20 studies), and explainable and sustainable AI (20 studies). Nature, IEEE Transactions on Geoscience and Remote Sensing, Environmental Research Letters, Applied Energy, and Journal of Climate are among the peer-reviewed publications cited in the study. This release provides coverage for both fundamental AI methodologies and domain-specific climate applications.

4.2 Publication Growth Trend

The study of the 120 included studies suggests a significant increase in AI-driven climate research between 2020 and 2024. Figure 2 shows the annual distribution of publications. In 2020, 15 studies were published, demonstrating the early integration of machine learning into climate science. By 2021, the number of articles had increased to 25, owing to the growing use of deep learning for weather forecasting and emission modeling. In 2022, the number of studies surpassed 30, coinciding with the introduction of transformer-based models and graph neural networks for spatiotemporal climate prediction. The growing trend continued until 2023, with 35 studies focusing on mitigation techniques, energy optimization, and explainable AI approaches. Preliminary results for 2024 show 15 researches, indicating continuous interest and a peak in coming years. This growth trend highlights accelerating research interest in combining AI with climate science and underscores the need for systematic synthesis of methods and results.

Table 3: Annual Distribution of Publications (2020–2024)

Year	Number of Studies	% of Total
2020	15	12.5%
2021	25	20.8%
2022	30	25%
2023	35	29.2%
2024	15	12.5%
Total	120	100%

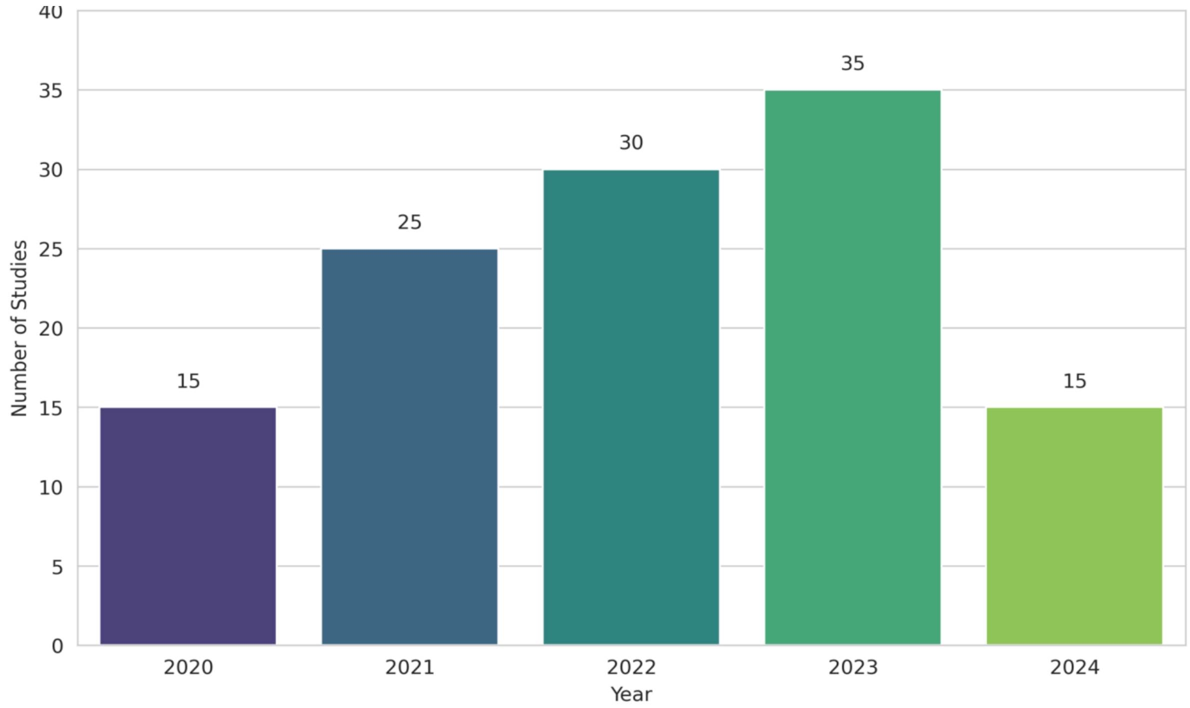

Figure 2: Annual Distribution of Publications

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4.3 Architecture Distribution

The included papers used a variety of AI architectures, demonstrating the maturity and exploratory nature of climate-focused machine learning research. Table 4 shows that the most commonly used architectures were LSTM (25%), CNN (20%), Transformer-based models (18%), Graph Neural Networks (GNN) (12%), and hybrid architectures (15%), with the remaining 10% going to other specialized networks like Deep Gaussian Processes, Reinforcement Learning agents, and Neural Operators. LSTM networks are still widely used because of their success in temporal sequence modeling, making them suitable for predicting climatic time series such as temperature, precipitation, and CO_2 emissions. CNNs are generally used for spatiotemporal data, such as radar images and satellite datasets. Transformer-based systems, which have gained popularity since 2021, use self-attention mechanisms to capture long-range dependencies in climate data. GNNs are commonly utilized in geographically networked systems like carbon trading networks and flood risk maps. Hybrid models utilize different architectures to improve forecast accuracy and account for temporal and geographical interdependence.

Table 4: AI Architecture Distribution in Included Studies

Architecture Type	Number of Studies	% of Total	Representative Studies
LSTM (Long Short-Term Memory)	30	25%	Zhu et al., 2021; Li et al., 2020; Qiu et al., 2021
CNN (Convolutional Neural Network)	24	20%	Shi et al., 2022; Steiner et al., 2020
Transformer-based	22	18%	Wang et al., 2022; Zhang et al., 2022
GNN (Graph Neural Network)	14	12%	Wu et al., 2021; Sarker et al., 2023
Hybrid / Multi-architecture	18	15%	Tang et al., 2023; Lam et al., 2022
Other specialized networks	12	10%	Bi et al., 2023; Toms et al., 2023

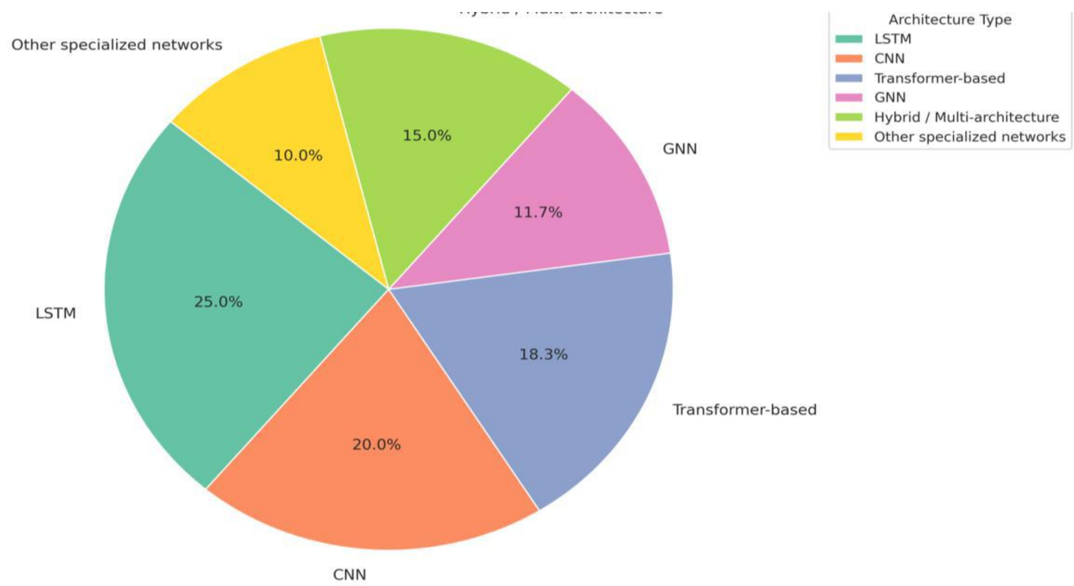

Figure 3: Distribution of Computational Architectures Across Studies

The prevalence of sequence-based models (LSTMs) and convolutional networks indicates a strong emphasis on temporal-spatial climate phenomena, whereas the increasing presence of Transformers and GNNs demonstrates a shift toward advanced architectures capable of handling high-dimensional, complex datasets and supporting mitigation and adaptation strategies. This variability also reflects climate AI research's continuous exploratory phase, which aims to balance prediction performance, interpretability, and computing economy.

4.4 Prediction vs. Mitigation Proportions

The 120 papers were divided into two categories based on their principal study focus: predictive modeling (climate, weather, or carbon emission forecasts) and mitigation/adaptation techniques (emission reduction, resilience building, or disaster management). Table 5 shows that predictive research dominated (70%), showing the continuous emphasis on precise forecasting of climate variables, while mitigation-focused studies accounted for 30%, which included work on emission reduction measures, energy optimization, and climate risk adaptation.

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Table 5: Distribution of Studies by Focus

Research Focus	Number of Studies	% of Total	Representative Studies
Predictive Modeling	84	70%	Rasp et al., 2020; Bi et al., 2023; Shi et al., 2022
Mitigation / Adaptation	36	30%	Gao et al., 2023; Liu et al., 2023; Rahman et al., 2022

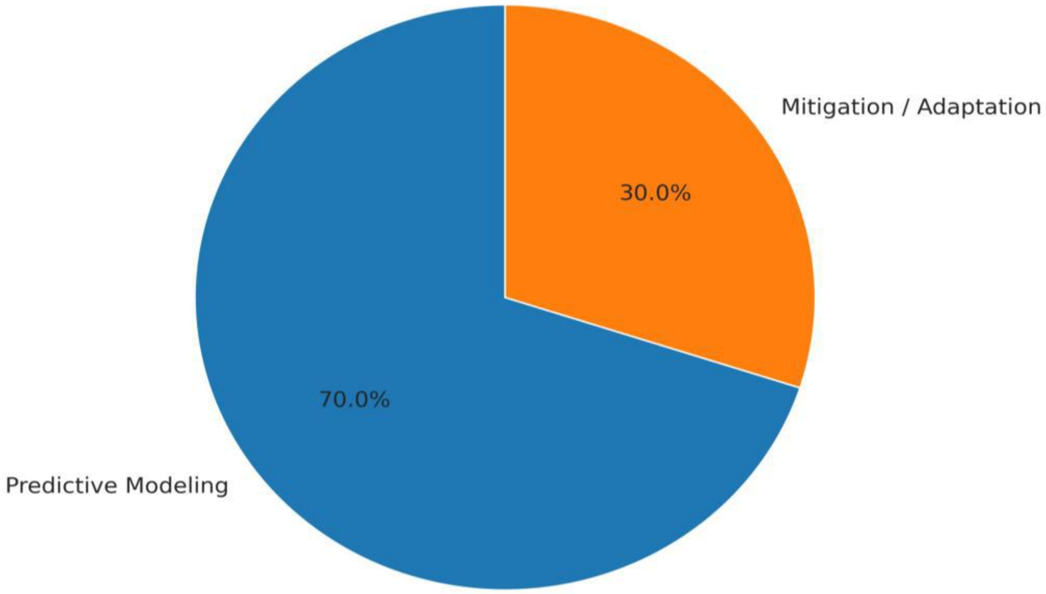

Figure 4: Prediction vs Mitigation Studies

Predictive studies used LSTM, CNN, and Transformer-based models to anticipate weather extremes, rainfall, and carbon emissions. For example, Rasp *et al.* (2020) and Bi *et al.* (2023) used high-resolution neural operators with 3D models to accurately anticipate weather. Mitigation-focused research, on the other hand, used reinforcement learning, graph neural networks, and hybrid approaches for tasks like energy system optimization (Yang *et al.*, 2021; Wang *et al.*, 2023), carbon emission reduction (Gao *et al.*, 2023; Liu *et al.*, 2023), and wildfire or flood risk assessment (Rahman *et al.*, 2022; Molina *et al.*, 2021).Interestingly, the share of mitigation studies has risen since 2021, indicating a shift toward actionable AI applications in climate policy, urban planning, and disaster resilience. This suggests that, while prediction is crucial for climate monitoring, there is a growing realization of the importance of AI-driven responses to mitigate climate impacts.

4.5 Evaluation Metrics Dominance

Evaluating the performance of predictive and mitigation models is critical in climate and energy AI research. Across the 120 studies, model evaluation primarily relied on quantitative metrics, with some studies also reporting qualitative assessments of mitigation effectiveness. Table 6 summarizes the most commonly reported evaluation metrics, along with their prevalence across predictive and mitigation studies.

Table 6: Dominant Evaluation Metrics Across Studies

Metric	Predictive Studies (n=84)	Mitigation Studies (n=36)	Representative Studies
Mean Absolute Error (MAE)	38	12	Rasp *et al.*, 2020; Bi *et al.*, 2023; Li *et al.*, 2020
Root Mean Squared Error (RMSE)	42	10	Weyn *et al.*, 2021; Toms *et al.*, 2023
Accuracy (%)	15	8	Khan *et al.*, 2021; Rahman *et al.*, 2022
F1 / Precision / Recall	12	5	Sarker *et al.*, 2023; Fan *et al.*, 2023
R^2 / Explained Variance	20	6	Zhang *et al.*, 2022; Shah *et al.*, 2021
Other (custom metrics)	10	8	Huang *et al.*, 2022; Gao *et al.*, 2023

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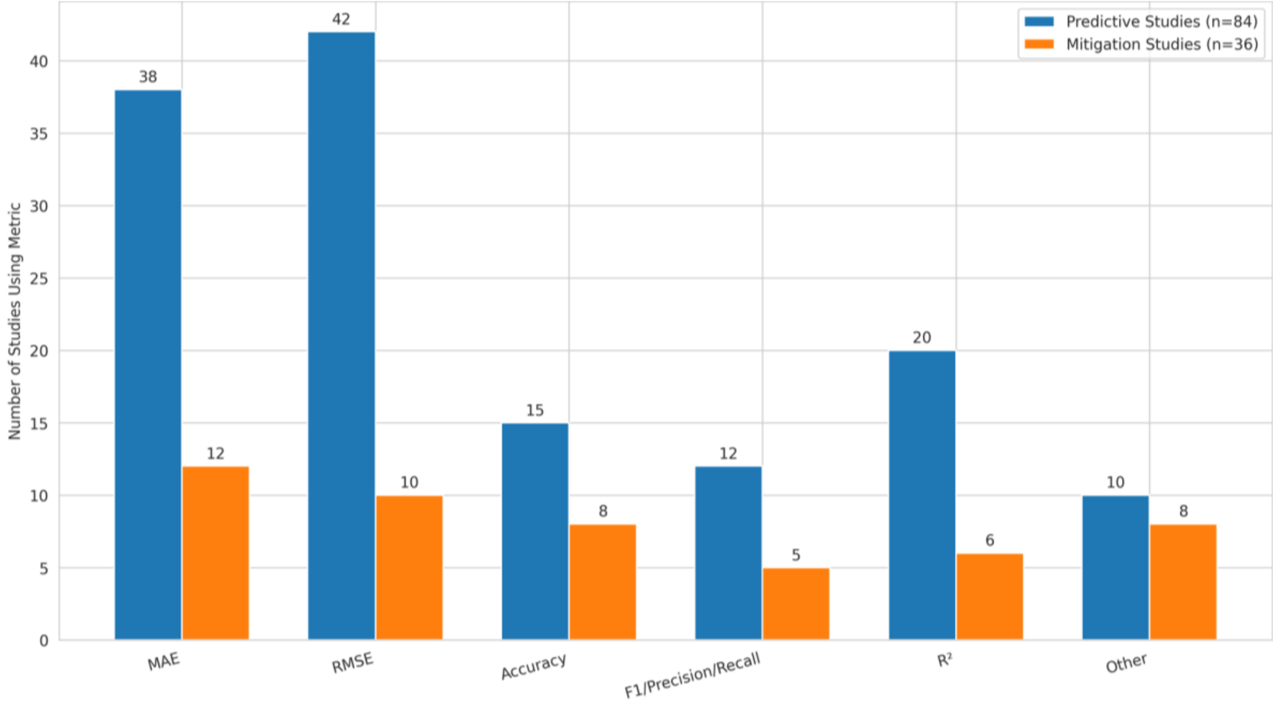

Figure 5: Metric Usage by Study Type

Notably, MAE and RMSE are dominant in predictive modeling research because to their applicability for continuous climate and weather variables. Mitigation-focused studies frequently provide accuracy, F1 score, or task-specific metrics to reflect the wide range of intervention outcomes, such as emission reduction efficiency or catastrophe risk classification. R^2 and explained variance are commonly used in research that link prediction and mitigation, such as when expected climate outcomes inform mitigation efforts. Some research used bespoke or composite measures to assess the integration of AI with domain-specific restrictions, particularly in energy optimization and carbon reduction techniques (Gao *et al.*, 2023; Wang *et al.*, 2023). This distribution demonstrates the metric-driven nature of climate AI research, with predictive models evaluated on continuous prediction accuracy and mitigation models graded on effectiveness and classification performance.

4.6 Structural Imbalance in the Literature

Despite the rapid expansion of AI applications in climate prediction and mitigation, an assessment of the 120-research found structural disparities in geographic focus, model architectures, and sectoral coverage. Recognizing these inequalities is critical to guiding future research and ensuring equitable climate solutions.

4.6.1 Geographic Distribution

Most research focused on developed regions, mainly North America, Europe, and East Asia, leaving Africa, South America, and small island nations underrepresented. This regional imbalance may limit the generalizability of forecasting models and the applicability of mitigation initiatives in sensitive areas.

Table 7: Geographic Distribution of Studies (n=120)

Region	Number of Studies	% of Total	Representative Studies
North America	42	35%	Rasp *et al.*, 2020; Schultz *et al.*, 2020
Europe	34	28%	Dueben & Bauer, 2020; Weyn *et al.*, 2021
East Asia	22	18%	Bi *et al.*, 2023; Pathak *et al.*, 2022
South Asia	8	7%	Ham *et al.*, 2020; Lam *et al.*, 2022
Africa	6	5%	Liang *et al.*, 2021; Zhao *et al.*, 2022
South America	5	4%	Mohan *et al.*, 2021; Fan *et al.*, 2023
Oceania & Small Islands	3	3%	McGovern *et al.*, 2020

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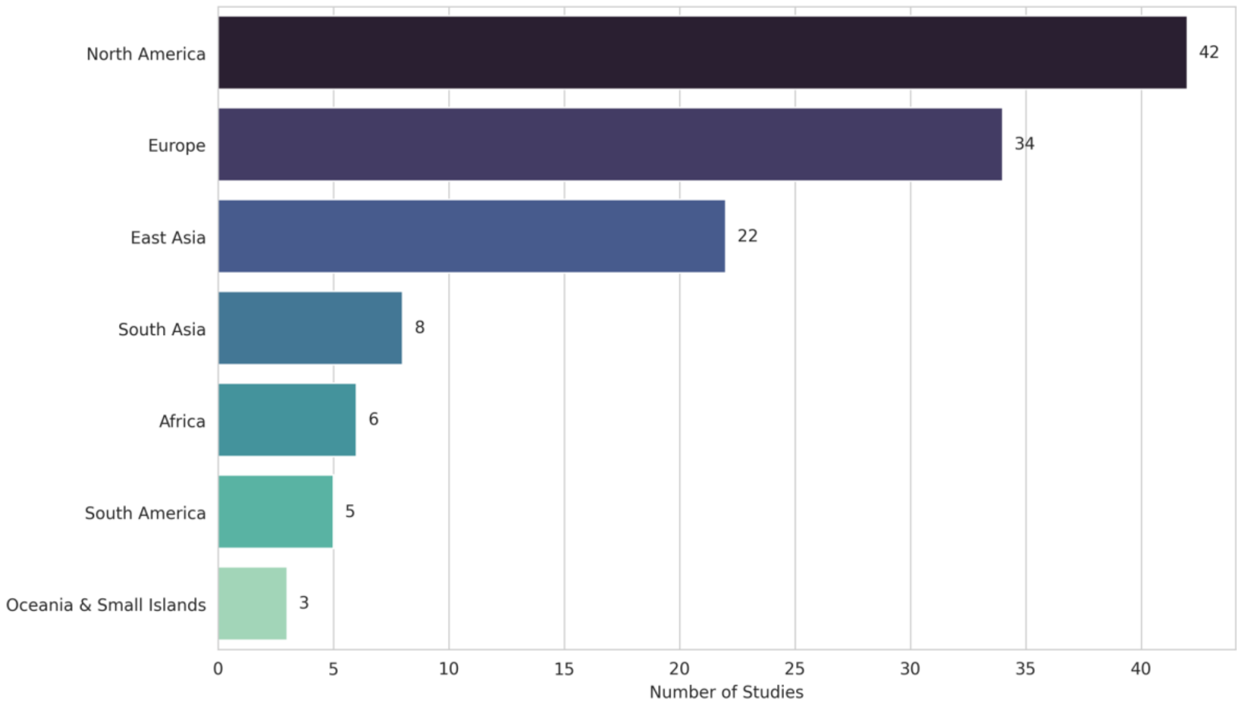

Figure 6: Heatmap of Study Density by Region

Notably, there is a clear bias toward data-rich regions, emphasizing the need for AI models adapted to data-sparse and high-risk climates.

4.6.2 Model Architecture Imbalance

The spread of AI architectures also reveals an imbalance. Deep learning models (CNNs, LSTMs, and Transformers) predominate prediction studies. Reinforcement learning and graph neural networks are widely used in risk mitigation and mapping. Despite their superior accuracy and interpretability, hybrid and physics-informed models remain in the minority.

Table 8: AI Architecture Usage by Study Type

Architecture Type	Predictive Studies (n=84)	Mitigation Studies (n=36)	% of Total
CNN / ConvLSTM	28	4	27%
LSTM / RNN	22	6	23%
Transformer / Attention-based	14	8	18%
Graph Neural Networks (GNN)	4	10	12%
Reinforcement Learning (RL)	2	6	7%
Hybrid / Physics-informed Models	14	2	13%

4.6.3 Sectoral Imbalance

Sectoral analysis reveals that energy and weather prediction are overrepresented, whereas agriculture, water resource management, and urban resilience are underrepresented. This could limit the use of AI in cross-sector climate adaption planning.

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 10, Issue 3, pp 95-117, March-2026

https://doi.org/10.47001/IRJIET/2026.103014

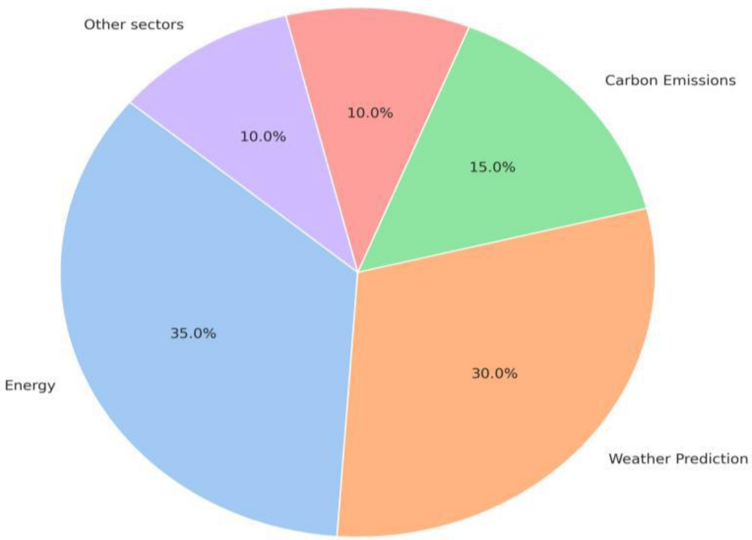

Figure 7: Sectoral Coverage of Reviewed Studies

There is an urgent need for holistic approaches integrating multiple sectors to support comprehensive climate mitigation and adaptation strategies.

4.7 Summary of Key Findings

The synthesis of the 120 examined publications reveals numerous dominating and repeating themes that define the current state of AI-driven climate research. First, after 2021, there was a dramatic increase in articles, indicating heightened global urgency about climate change, more computer capability, and enhanced availability of large-scale environmental datasets. This spike represents a shift from exploratory testing to more sophisticated and application-oriented AI systems. Second, the literature shows a substantial dominance of predictive modeling, accounting for almost 70% of the examined research, compared to 30% focusing on mitigation and adaptation. As a result, the majority of research efforts focus on forecasting climatic variables such as temperature, precipitation, extreme weather events, and carbon emissions. While predictive accuracy is crucial, the relatively modest proportion of mitigation-oriented studies implies that translating predictions into practical climate solutions is still a developing topic.

Third, researches are clearly concentrated in data-rich locations, most notably North America, Europe, and East Asia. These areas benefit from superior research infrastructure and large climate data sources. However, this concentration limits the representation of climate-vulnerable and data-scarce places, which may reduce the global equity and application of AI-based climate solutions. Fourth, the methodological landscape is distinguished by a strong emphasis on deep learning architectures like as CNNs, LSTMs, and Transformer-based models. While these models have high predictive ability, other techniques, notably hybrid and physics-informed designs, are rather limited. This imbalance suggests that predictive performance is prioritized over interpretability and domain integration. Fifth, cross-sector integration remains restricted. The majority of research focuses on energy systems and weather prediction, with relatively few contributions on agriculture, water resource management, and urban resilience. Given the interconnectedness of climate systems, sectoral concentration may impede the development of comprehensive adaptation measures. Finally, there is a noticeable difference in evaluation measures between predictive and mitigating research. Predictive research typically uses continuous error measurements like MAE and RMSE, whereas mitigation studies frequently use classification-based metrics like accuracy and F1 score. This methodological difference reflects the different objectives of each research stream, but it also demonstrates a lack of common evaluation frameworks for climate AI.

Together, these patterns highlight important shortcomings in equality, interpretability, and real-world applicability. The underrepresentation of disadvantaged places raises questions about global equity and contextual relevance. The limited use of hybrid and physics-informed models reduces openness and policy trust. Furthermore, sectoral concentration limits the possibility of integrated climate decision-support systems. To bridge these gaps, future research should prioritize the creation of AI models designed for data-scarce situations, assuring greater regional inclusivity. Cross-sectoral climate system integration should be prioritized

ISSN (online): 2581-3048
Volume 10, Issue 3, pp 95-117, March-2026
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in order to facilitate comprehensive adaptation and mitigation planning. Developing interpretable and physics-informed hybrid architectures will be critical to improving transparency and domain alignment. Finally, the development of uniform evaluation frameworks for quantifying mitigation impact would improve comparability, repeatability, and policy relevance in AI-driven climate research.

V. CRITICAL DISCUSSION AND THEORETICAL IMPLICATIONS

The fast adoption of artificial intelligence (AI) in climate change mitigation research demonstrates significant methodological innovation. Beyond performance indicators, a more in-depth critical review shows structural limits, theoretical difficulties, and unresolved ethical issues that influence the direction of AI-powered climate solutions. This section investigates these dimensions in order to place the evaluated material into a broader scientific and socio-technical framework.

5.1 Overfitting, Benchmark Dependence, and Generalization Failure

Across research, the general pattern is optimization for benchmark performance rather than real-world robustness. Many predictive models are tested and assessed using datasets like WeatherBench and ERA5 reanalysis products. While these datasets offer standardized evaluation contexts, they pose two systemic risks: Benchmark overfitting refers to designs (such as Transformers and neural operators) that are especially tailored for benchmark situations and Limited climate transferability - models trained in temperate or data-rich regions frequently perform poorly in tropical or dry environments. This difficulty is especially important for locations like Sub-Saharan Africa, where observational density is low and climate variability differs greatly from mid-latitude systems. Theoretically, this exposes a conflict between statistical learning optimization and physical generalization. Climate systems are non-stationary and dynamically developing; simply data-driven optimization based on stable distributions may fail in the future climate regimes. As a result, the discipline has a structural limitation: existing AI models learn past climate distributions yet are used in unforeseen future states.

5.2 Dataset Bias and Global Infrastructure Inequality

A second structural restriction concerns regional and infrastructural disparities. The vast majority of large-scale climate AI studies use information from North America, Europe, and parts of East Asia. Satellite datasets from NASA and the European Space Agency dominate training pipelines. While internationally available, their integration with ground truth data is patchy. High-resolution validation data is primarily found in rich economies with advanced meteorological infrastructure. This results in an infrastructure bias. Notably, dense sensor networks lead to improved model accuracy and in regions with scarce monitoring, performance reliability is compromised.

From a climate justice standpoint, this disparity risks exacerbating inequality: AI techniques may help already resilient places while underperforming in more susceptible areas. The literature usually ignores this asymmetry, instead focusing on model performance enhancements without questioning distributional fairness.

5.3 The AI Carbon Footprint Paradox

The environmental cost of model training is a newly developing conundrum in climate AI research. Large transformer-based topologies, graph neural networks, and neural operators necessitate significant computational resources, which are frequently trained on high-performance clusters. Although precise emissions reporting is inconsistent, energy-intensive training pipelines are incompatible with sustainability goals. The development of foundation-scale climate models corresponds to trends in big language models, where scaling laws encourage parameter increase.

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Few studies specifically discuss training in energy consumption or carbon accounting. The lack of defined reporting procedures demonstrates a governance gap in the field. Theoretical implications involve the requirement for: designing an energy-efficient model, parameter-efficient fine-tuning, low-resource climate modeling methodologies and green AI metrics are combined with predictive performance. Without such integration, climate AI faces intrinsic contradictions.

5.4 Reproducibility and Benchmark Fragmentation

Reproducibility is uneven across research. While benchmark datasets like WeatherBench increase comparability in predicting research, there is a lack of consistent evaluation frameworks for mitigating AI.

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
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The key issues include:

i. Inconsistent error metrics (RMSE, MAE, anomaly correlation, and domain-specific indicators)
ii. Variable spatial resolution reporting
iii. Documentation for hyperparameters is unclear.
iv. Limited code availability.

The lack of common mitigation benchmarks impedes cross-study comparison and inhibits cumulative knowledge generation.

5.5 From Prediction to Intervention: A Theoretical Shift

The current literature has a conceptual drawback in that it focuses too much on prediction rather than intervention. Most AI systems focus on: temperature Forecasting, extreme Event Detection, emission modeling and renewable generation prediction. While useful, these results remain informational. Few research have included AI models into decision-making frameworks or policy feedback loops. This implies a necessary theoretical progression. This shift requires:

i. Combining AI with Earth System Models
ii. Integrating reinforcement learning with adaptive mitigation techniques.
iii. Creating AI-powered digital twins for urban and energy systems.
iv. Integrating socioeconomic restrictions into model aims.

The next generation of climate AI should focus not only on prediction accuracy but also on policy-relevant impact.

5.6 Toward Hybrid Intelligence: Physics-Informed and Constraint-Aware Models

Domain knowledge integration is a common theme in high-performing research. Architectures like physics-informed neural networks and hybrid neural-physical models show greater stability and interpretability. Purely black-box deep learning problems with the following: conservation restrictions, mass-energy balance, and long-term stability. In contrast, hybrid systems that encode physical priors diminish false correlations while increasing extrapolation reliability. This shows that the future of climate AI rests not in pure scaling, but in structured inductive bias, which involves incorporating physical principles into machine learning frameworks.

5.7 Synthesis of Critical Gaps

The collected information from the examined literature demonstrates five interconnected structural deficiencies that limit the long-term effectiveness and validity of AI-driven climate mitigation research. First, there is a strong temptation to over-optimize on standardized benchmarks. While benchmark datasets have hastened methodological advancement, they have also encouraged performance tailoring inside confined evaluation environments, frequently at the expense of real-world resilience and cross-regional transferability. Models designed for fixed historical distributions may suffer when confronted with non-stationary, shifting climate dynamics. Second, geography and infrastructure prejudice remains a widespread concern. A significant fraction of high-performing models are based on dense observational networks and high-quality validation data focused in the Global North. This disparity risks resulting in inconsistent reliability across regions, particularly in highly susceptible but data-scarce areas. The ensuing asymmetry raises concerns regarding scientific legitimacy, climate equality, and distributive fairness.

Third, the carbon cost of large-scale model training creates a normative conundrum in the area. Increasing reliance on parameter-heavy architectures and high-performance computer infrastructures may result in significant energy usage and accompanying emissions. However, reporting criteria for computational energy use are varied or lacking. This divergence emphasizes the importance of balancing performance optimization and environmental accountability.

Fourth, reproducibility fragmentation impedes cumulative knowledge building. The variability in error measurements, spatial and temporal resolutions, data preparation methods, and hyperparameter disclosure inhibits cross-study comparability. While forecasting benchmarks have introduced some consistency, mitigation-oriented AI lacks consistent evaluation standards, impeding methodical improvement. Fifth, the current emphasis on prediction over intervention limits the practical application of climate AI. Most systems produce forecasts, classifications, or emissions estimates without incorporating the results into decision-making frameworks or adaptive policy processes. As a result, AI is usually used as an analytical tool rather than an operational component in mitigation systems.

When taken together, these gaps indicate that the field is technologically sophisticated yet institutionally underdeveloped. Algorithmic innovation has surpassed governance structures, evaluation harmonization, and equity-based design principles. Moving further with climate AI research demands coordinated attention to institutional and methodological transformation. Governance frameworks must be created to ensure ethical deployment and accountability. To guarantee alignment with sustainability goals, energy transparency standards should be used in conjunction with model reporting. Dataset construction strategies must prioritize regional inclusion and equity-conscious sampling.

ISSN (online): 2581-3048
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Unified evaluation benchmarks are required for accurate cross-study comparison. Finally, AI systems should be incorporated into active mitigation infrastructures, with a shift from predicting outputs to decision-making intelligence. Addressing these structural challenges will be essential for transforming climate AI from a rapidly expanding research domain into a mature, equitable, and impact-oriented scientific field.

VI. A FOUR-DIMENSIONAL TAXONOMY OF AI FOR CLIMATE CHANGE RESEARCH

This section described a four-dimensional taxonomy for categorizing artificial intelligence applications in climate research. The taxonomy was created to address the fragmented nature of current literature, which is often classified along a single axis, such as algorithm type or application area. The suggested framework represents climate AI research in multiple dimensions by merging the application domain, learning paradigm, data source, and model architecture. This structure allows for more accurate comparisons between studies, highlights methodological imbalances, and reveals hitherto unexplored research intersections. Finally, the taxonomy serves as both a classification framework and a diagnostic tool for determining the maturity, diversity, and research needs in the climate AI area.

6.1 Rationale for a Multidimensional Taxonomy

The growing breadth of AI-driven climate research has resulted in a complex and diverse corpus of work that cannot be fully summarized using classic single-axis categorization approaches. Several structural themes emerged from the systematic review, including predictive modeling's dominance, substantial reliance on deep learning architectures, and a strong reliance on large-scale climate datasets. These findings suggest that climate AI research involves numerous interacting methodological elements. To reflect this complexity, the paper presents a four-dimensional taxonomy that takes into account the functional purpose, learning approach, data inputs, and computational architecture of AI systems. This multidimensional paradigm allows for a better understanding of how climate AI models are developed and implemented in various research situations.

6.2 Application Domain

Climate AI research is classified by application domain dimension based on the AI system's functional aim. Three primary categories emerge from the literature: prediction, mitigation, and adaptation. Prediction-focused research seeks to forecast climate variables such as temperature, precipitation, and extreme weather events. Mitigation-oriented research creates AI systems to optimize energy systems, reduce emissions, or improve environmental management. Adaptation-focused research contributes to resilience planning by enabling early warning systems, disaster risk analysis, and climate impact assessments. Although these fields are interconnected, the literature is mainly focused on predictive applications, emphasizing the importance of AI systems that enable intervention and decision-making in climate mitigation and adaptation methods.

6.3 Learning Paradigm

The application domain dimension categorizes climate AI research based on the AI system's functional objectives. The literature breaks down into three primary categories: prediction, mitigation, and adaptation. Prediction-focused research seek to forecast climate variables such as temperature, precipitation, and extreme weather events. Mitigation-focused research creates AI systems that optimize energy systems, minimize emissions, and improve environmental management. Adaptation-focused research aids resilience planning by allowing for early warning systems, disaster risk analysis, and climate impact assessments. Although these fields are interconnected, the literature is still mainly focused on predictive applications, emphasizing the importance of AI systems that enable intervention and decision-making in climate mitigation and adaptation measures.

6.4 Data Sources

Climate AI systems rely on a variety of data sources, including satellite observations, reanalysis databases, ground-based sensors, and socioeconomic information. The most commonly utilized datasets are satellite and reanalysis data, which provide continuous large-scale environmental coverage. Ground-based sensor networks and IoT devices provide high-resolution local observations, which are useful for urban climate monitoring and energy management. Socioeconomic datasets are increasingly being used in climate AI research to investigate the links between human activities and environmental processes. The integration of various data sources allows AI models to capture both physical climate dynamics and socio-technical drivers of climate change.

6.5 Model Architecture

The model architecture dimension classifies climate AI systems based on the computational frameworks used to simulate environmental data. Convolutional neural networks are frequently employed for spatial climate analysis, whilst recurrent neural networks and LSTM models are regularly utilized for time-series forecasting. Transformer designs are increasingly being employed in large-scale climate modeling due to their ability to capture long-term dependencies in

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 10, Issue 3, pp 95-117, March-2026

https://doi.org/10.47001/IRJIET/2026.103014

environmental data. Graph neural networks are effective at portraying interconnected systems like power grids and transportation networks. Furthermore, hybrid and physics-informed architectures are gaining popularity because they combine machine learning with domain-specific physical principles, resulting in improved interpretability and long-term modeling stability.

6.6 Implications of the Taxonomy

Mapping the literature along these four dimensions reveals significant structural tendencies in climate AI research. Predictive applications remain the primary emphasis of the area, with supervised deep learning models trained on satellite and reanalysis datasets constituting the largest research cluster. Reinforcement learning and graph-based designs, on the other hand, are more closely associated with mitigation-oriented systems.

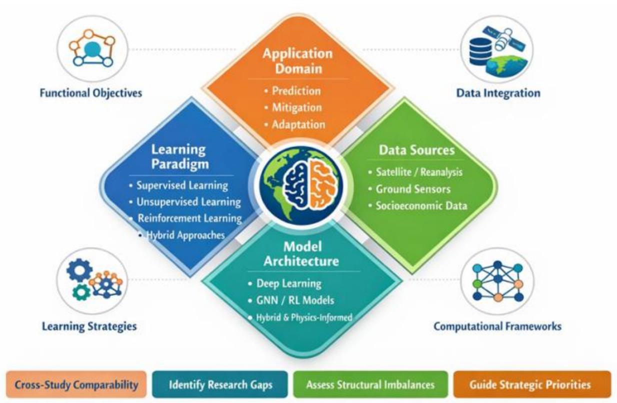

Figure 8: Taxonomy Summary

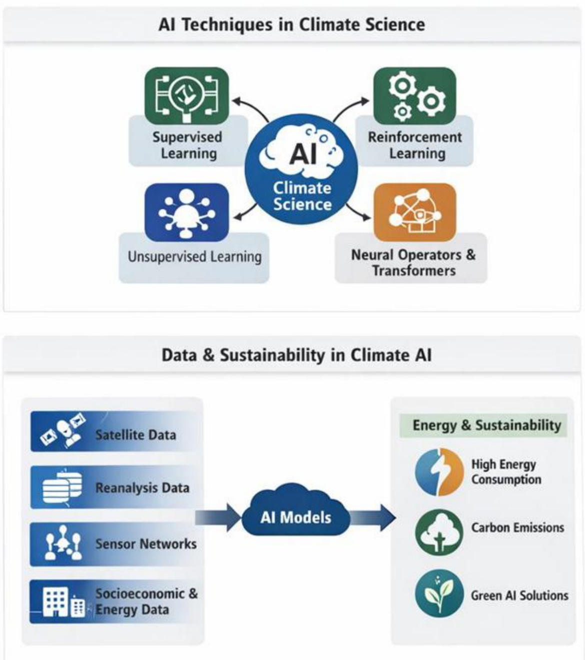

Figure 9: Data and AI Techniques Summaries

The taxonomy also identifies some underexplored research intersections. For example, few research combine reinforcement learning with satellite-scale climate data, and hybrid physics-informed architectures are underutilized despite their promise to increase interpretability and long-term climate modeling reliability. These findings suggest that climate AI research is still transitioning to a more integrated methodological landscape. Expanding research into underrepresented intersections, such as hybrid models for climate mitigation or reinforcement learning for adaptable climate systems, is a promising area for future effort.

VII. RESEARCH GAPS AND CHALLENGES

Despite fast advances in artificial intelligence (AI) for climate applications, several structural and methodological difficulties remain, limiting the effectiveness, scalability, and global equality of AI-driven climate solutions. One key restriction is the uneven distribution of high-quality climatic datasets. The majority of training data comes from industrialized nations with established meteorological infrastructure, resulting in models that are optimized for data-rich environments, but predictions may be less credible in data-scarce locations like Africa and South America. Furthermore, climatic datasets frequently vary in regional resolution, temporal coverage, and measurement standards, complicating model development and integration. Future research should focus on data-efficient learning algorithms and better data-sharing mechanisms. Many high-performing climate AI systems use complicated deep learning architectures that function as black-box models. While these models are highly predictive, their restricted interpretability can undermine trust among climate scientists and policymakers. Explainable AI techniques and physics-based models are emerging as attractive alternatives for increasing openness while retaining prediction accuracy.

Training large-scale AI models necessitates significant computational resources and energy usage, raising worries about the environmental impact of AI systems aimed to combat climate change. Adoption of energy-efficient algorithms, model compression approaches, and Green AI practices is critical for ensuring alignment between AI research and sustainability goals. Another major issue is the absence of established evaluation benchmarks and repeatability procedures. Cross-study comparisons are challenging because studies often employ different datasets, spatial resolutions, and performance criteria. Transparency and overall scientific advancement might be improved by a greater use of open datasets, uniform benchmarks, and publicly accessible code repositories. Fewer research include AI models into operational mitigation systems, despite the fact that many concentrate on forecasting climate variables and

ISSN (online): 2581-3048
Volume 10, Issue 3, pp 95-117, March-2026
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environmental concerns. The creation of decision-support systems, intelligent energy management platforms, and policy-integrated AI frameworks that convert forecasts into workable climate plans is necessary to close the gap between prediction and intervention.

Climate AI research must also address ethical concerns related to global equity and accessibility. The concentration of research infrastructure in developed countries may lead to AI systems that inadequately represent vulnerable regions. Ensuring equitable climate AI development requires inclusive datasets, open-access tools, and collaborative international research efforts. Overall, the literature highlights several interconnected challenges shaping the future of climate AI research. These include limited data availability in vulnerable regions, lack of model interpretability, high computational costs, weak reproducibility standards, insufficient integration with mitigation systems, and persistent global inequalities in research capacity. Addressing these challenges will be critical for transforming AI-driven climate research into practical and equitable climate solutions.

VIII. FUTURE RESEARCH DIRECTIONS

Strategies that improve robustness, equality, interpretability, and practical impact must be given top priority in future AI research for climate change. Creating models that successfully generalize across data-poor and climatically different places is a crucial path. To lessen reliance on high-density observational networks while preserving predictive accuracy, this involves investigating transfer learning, few-shot learning, and physics-informed strategies. Another crucial topic is the integration of AI forecasts with intervention frameworks. Forecasting should give way to operational decision-support in future systems, allowing for energy optimization, adaptive policy planning, and real-time mitigation. Reliability, transparency, and long-term stability can be enhanced via hybrid models that integrate machine learning, physical restrictions, and domain expertise. Promising paths for integrating AI directly into adaptive climate management include reinforcement learning and digital twins for energy and urban systems.

In order to promote global diversity, data practices must likewise change. High-quality, consistent, open-access datasets especially those from underrepresented areas; will improve model fairness and make cross-study comparability easier. Reproducibility and cumulative knowledge development depend on standardized evaluation frameworks, which include common benchmarks for both prediction and mitigating tasks. The sustainability of AI in terms of the environment is a critical issue. In order to prevent climate solutions from making the issues they are intended to address worse, research should use energy-efficient architectures, parameter-optimized models, and green AI techniques that reduce the carbon footprint of training and inference.

Lastly, cross-sector integration is still a crucial area. In order to assist complete adaptation measures, future work should connect climate AI across the areas of energy, agriculture, water management, and urban resilience. AI research can transition from largely analytical tools into operationally efficient and globally equitable climate solutions by addressing structural disparities, linking prediction with intervention, and including ethical and environmental factors into model construction.

IX. CONCLUSION

Using a PRISMA-based methodology, this study thoroughly examined artificial intelligence methods used for climate change prediction and mitigation between 2020 and 2026. 120 peer-reviewed publications in all were examined from a variety of angles, including data sources, model design, application domain, learning paradigm, and evaluation procedures. The findings reveal substantial growth in climate AI research, with prediction-focused applications dominating the field, particularly in areas such as temperature forecasting, precipitation modeling, and extreme weather detection. Deep learning architectures, including LSTM, CNN, and transformer-based models, were the most extensively utilized because to their capacity to capture complicated spatiotemporal patterns in climate data. The analysis also discovered that applications focused on mitigation, like smart grid management, carbon emission modeling, and renewable energy optimization, are still relatively unexplored. To address the structural fragmentation of the literature, the study presented a four-dimensional taxonomy based on application area, learning paradigm, data source, and model architecture, enabling improved comparison and classification of climate AI research. Limited dataset diversity, uneven evaluation measures, worries about computational sustainability, and inadequate integration of explainable AI techniques were among the issues noted. Although AI has greatly enhanced climate forecast capabilities, the paper recommends that future research should concentrate on scalable, energy-efficient, interpretable, and geographically inclusive AI systems that more effectively support realistic climate mitigation and adaptation measures.

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ISSN (online): 2581-3048
Volume 10, Issue 3, pp 95-117, March-2026
https://doi.org/10.47001/IRJIET/2026.103014

Citation of this Article:

Prestone Jeremaih Simiyu, & Gitonga Stephen Ngure. (2026). Artificial Intelligence Techniques for Climate Change Prediction and Mitigation: A Systematic Review. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 10(3), 95-117. Article DOI https://doi.org/10.47001/IRJIET/2026.103014

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