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Artificial Intelligence in Climate Science: A Review of Advances in Forecasting, Adaptation, and Future Directions

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Abstract

Climate change poses both pressing scientific and societal challenges requiring accurate prediction of extreme events and rigorous adaptation approaches. While classical methods such as numerical weather prediction (NWP) and general circulation (GCM) models are still central to climate depictions, these models are computationally expensive and, therefore, struggle at real-time applications and inherently, in their accuracy .

New advancements in artificial intelligence (AI) suggests that, at the very least, machine learning (ML) and deep learning (DL) could provide a revolutionary and complementary alternative to the physics-based modelling shown previously. In this review, we outline 70 peer-reviewed papers (2019-2025), we selected the studies using the literature review according PRISMA to cover the AI application in prediction. Which highlight the risk of using AI for climate forecasting and adaptation. Quantitative evidence indicates that GraphCast surpasses ECMWF HRES in roughly 90% of forecasting metrics; GenCast delivers 97% higher accuracy compared with ensemble means; and MetNet-2 extends precipitation forecasting horizons to nine hours with improved precision. In adaptation, AI has helped predict agricultural yield with up to 88% accuracy, alert farmers of imminent drought two months in advance, provide early warnings of dengue fever with a reported AUC of 0.89, and improve urban flood resilience with accuracy levels as high as 92% . This review focus on both chances and challenges and highlight the constraints in AI applications like the dataset and difficulty in weather explanation models.

However, despite these advances, challenges remain due to data bias, limited visibility into deep learning models, high energy consumption, and unequal access to technology. The review sets out an evaluation of opportunities and challenges from which AI might be effectively applied to climate science and climate-related policy, and suggests a three-pillar framework incorporating sustainability, transparency and equity which can enhance responsible use within climate adaptation and resilience.

Keywords: Artificial Intelligence; Climate Change; Forecasting; Adaptation; Machine Learning; Deep Learning; Sustainability; Review

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Introduction

A global issue plaguing the 21st century that warrants immediate attention is climate change; its effects on ecosystems can be felt and measured. These effects are worsened through the frequent heat waves drought, Hurricanes and floods which further disrupts said ecosystems [1]-[3]. Preparation in case of such events preserves life. This can be done through predicting the above-mentioned events.

The pillars of Climate sciences are NWP and GCMs (numerical weather prediction & general circulation models) [4],[5]. These models which depend on physical equations are utilized to predict atmospheric dynamics thus help in the preparations and preserve ecosystems. While this is mostly true the value of these models is being threatened by constraints resulting from model runtime, low spatial resolution, and limited forecasting skill on events extremity.. Due to these obstacles, there are limits to obtaining insightful, real-time, accurate forecasts on regional and local levels, especially where there is scarce observations The rise of AI**.** In parallel, breakthroughs in artificial intelligence (AI) notably machine learning (ML) and deep learning (DL) have transformed data-driven sciences [6]-[8]. AI is adequate at finding patterns in large datasets, combining sources of data such as reanalysis products, remote sensing and surface-based observations, and making fast predictions[15]. In the rapid progress the gap still clear to how understanding the AI dealing with traditional physical models in practical life, previous reviews focused only the technical side without explanation the fairness and governance sides. this review focus on gaps by academics analysis between 2019 and 2025. Recent advances include GraphCast, which dominates the high-resolution ECMWF model over 90% of verification metrics [21], GenCast, outperforming ensemble forecasts with inference times below ten minutes [22], and MetNet-2, that produces accurate precipitations forecasts up to nine hours ahead [23].

Beyond Forecasting: Adaptation

Artificial intelligence applications are not limited to weather and climate forecasting and, among others, include adaptation. This is an area where enhancing resilience to climate change will be crucial. In agriculture, AI has been utilized to better forecast crop yields [43]. For water management, it gives alerts for droughts and floods [44], [47]. In [46] it is used for predicting outbreaks of diseases associated with the climate in healthy populations. Within urban planning, it enables communities to become more resilient to flood events and heatwaves [48],[51]. Taken together, these apps illustrate the growing role of AI in connecting scientific advances to public decisions.

Persistent Challenges

Although there was notable progress, the integration of AI into climate science is not without challenges. Key limitations include:

- **Data scarcity and bias**, particularly in the Global South [52], [54].
- **Lack of interpretability**, as deep learning models often operate as “black boxes” [56].
- **Environmental costs**, due to the high energy consumption required to train large-scale models [58].

- **Equity concerns**, since access to advanced AI technologies remains concentrated in the Global North [59], [60].

Purpose of the Review

The aim of this review is to execute a systematic analysis and synthesize 70 peer-reviewed papers in the period from 2019 to 2025 to answer three main questions:

1. In what ways is artificial intelligence better at predicting climate than simulations based on the laws of physics?
2. What are the most effective uses of AI for climate change resilience?
3. What limitations and regulations are necessary to promote responsible use of these technologies?

This paper offers a novel and structured attempt to critically synthesis this emerging literature by empirically situating it in the context of AI for climate science according to three guiding posts: sustainability, transparency and equity.

2. Methodology

The study was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [19]. We evaluated each study by the methodology used and the model type such as CNN, LSTM, transformer and the performance indicators like RMSE, AUC [20]. A literature search was carried out in IEEE Xplore, ScienceDirect, SpringerLink, Scopus and arXiv from 2019 until 2025 to identify the latest developments of AI applied to solve climate change challenges.

Inclusion criteria:

- Peer-reviewed articles and preprints that applied AI to climate forecasting or adaptation.
- Quantitative performance evaluation (e.g., accuracy, root mean square error (RMSE), area under the curve (AUC), critical success index (CSI), etc.).
- Studies published in English between 2019 and 2025.
- This help to ensure the ability to reuse the studies in selection process.

Exclusion criteria:

- Sources not published in English.
- Theoretical articles or commentaries lacking empirical results.
- Duplicates or studies not directly related to climate science.

Database search: A total of 1,132 publications were identified through the database search. Following title and abstract screening, 214 studies were included in the review. After full text screening, the total records reduced to 70 articles that were reviewed and classified under two main domains: prediction and adaptation. In addition, several fundamental works on AI architectures (LSTM [26], Transformer [27]) were added to provide procedural context.

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The studies were analyzed in three steps:

1. Classification of approaches, such as CNN, LSTM, GNN, Transformers, and hybrid physics–AI models.
2. Comparison of results with traditional approaches, including ECMWF HRES and GFS.
3. Critical evaluation of challenges, limitations, and research gaps.

3. Artificial Intelligence in Climate Forecasting

AI has seen outstanding improvement in climate forecasting, particularly in short-term now casting, medium-range weather forecasting, and even seasonal-to-interannual climate forecasts. Unlike exclusively physics-based models, AI is capable of utilizing heterogeneous data sets and providing high-accuracy forecasts and radically reducing computation time [21],[22], [24].

Before comparative results, the models must be contextualized. GraphCast leverages graph neural networks (GNNs) to model physical relationships between atmospheric grids; GenCast uses generative models to create ensemble predictions; FourCastNet uses Fourier Neural Operators to make global forecasts; and MetNet-2 has been designed specifically for high-resolution precipitation now casting. These are all distinct but complementary approaches within AI-based climate modeling[29],[30].

Table I presents a summary of outstanding AI models developed over the past five years, assessed for their forecasting horizon, training datasets utilized, performance metrics, and stated outcomes. The particularly noteworthy aspect is that the models are not only faster but also far superior to conventional numerical forecasting models, especially for medium-range prediction and short-range precipitation forecast.

Table I. Representative AI Models for Climate Forecasting

Model	Task / Horizon	Dataset(s) Used	Metric / Result	Advantage	Ref.
GraphCast	Medium-range (3–10d)	ERA5	90% better skill vs. ECMWF HRES	High multi-variate skill	[21]
GenCast	Probabilistic ≤15d	ERA5, ECMWF ENS	97% higher skill vs. ENS; inference <10 min	Fast ensemble forecasts	[22]
FourCastNet	Medium-range global	ERA5	Comparable to NWP; 80,000× faster	Extreme efficiency	[29]
MetNet-2	Nowcasting ≤12h	Radar + Satellite	Higher CSI up to 9h	Superior precipitation accuracy	[23]
DeepMind NWP	1–10d global	ERA5	Reduced RMSE,	Generalizable transformer	[31]

			competitive with HRES		
ClimaX	Representation learning	CMIP6, ERA5	Strong zero-shot transfer	Pre-training for climate tasks	[33]
Hybrid ENSO DL	ENSO seasonal	NOAA SST	Lead times extended by 2–3 months	Seasonal predictability	[35]
CNN–LSTM	Rainfall prediction	India obs.	RMSE ↓ 15% vs. NWP	Captures spatio-temporal links	[36]

From Table I, it can be seen that AI models have domain-specific strong points. MetNet-2 is superior in short-term forecast of precipitation with better critical success index (CSI) scores for a maximum of nine hours. GraphCast and GenCast both perform better than numerical physics-based models for medium-range forecasts, and FourCastNet attains the level of efficiency that cannot be matched by conventional models[32],[34]. Hybrid systems that combine physical constraints with AI architectures show a lot of promise for forecasting events like El Niño–Southern Oscillation (ENSO). However, these models often lack interpretability and act like "black boxes," which is a concern for operational agencies [55]–[57]. The chosen model achieves high accuracy compared to traditional numerical methods for short- and medium-term predictions. By using available data and physical explanations, the hybrid approach brings together both physical and AI methods in this field.

To further illustrate comparative performance, **Figure 1** summarizes the skill improvements achieved by leading AI models relative to traditional numerical weather prediction.

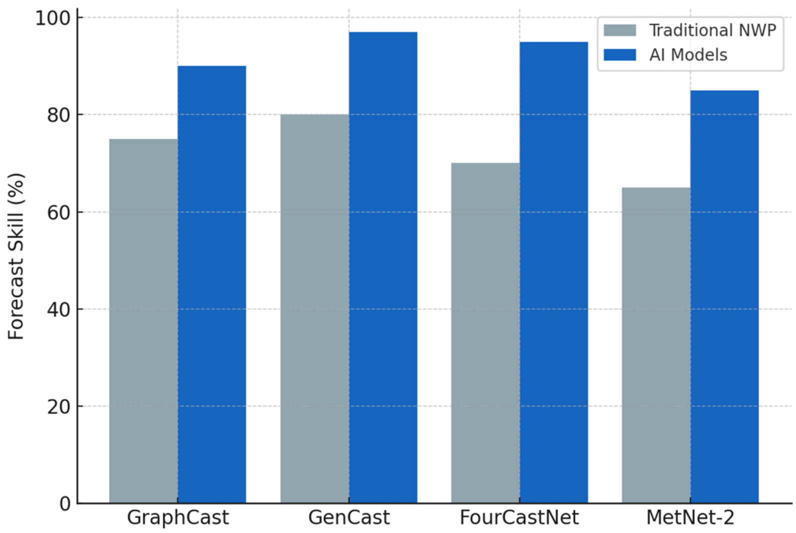

Figure 1. AI Models Versus NWP in Approaching the Performance Limit

As we can see from Figure 1, the AI-based methods always achieve higher precision on various forecast horizons. These findings demonstrate the potential of AI as a supportive methodology to physic-based model, particularly in short-to-medium-term predictions. But the problem of generalizing these improvements to low data regimes still persists. This underscores the importance of hybrid models and tailored calibration.

Artificial Intelligence for Climate Change Adaptation

Although prediction continues to be an important component of climate science, adaptation is the operational aspect of resilience in light . Artificial intelligence presents a new opportunity to enhance adaptive capacity in sectors like agriculture, water management, public health and urban planning. Contrary to global forecasting, adaptation is localized and context dependent by its nature: social-economic, environmental and infrastructural data need to be factored in joint [40], [43], [44].

A few case studies of how AI has been used to adapt in different regions and sectors are shown in table (II). These cases provide evidence for the potential of machine learning models, from Random Forests to hybrid network design like CNN–LSTM in improving early warning systems efficiency and better allocating resources and decision support in climate-sensitive sectors[46], [48].

Table (II). Representative Applications of Artificial Intelligence in Climate Change Adaptation

Sector	AI Method	Region/Case	Data Used	Result/Metric	Impact	Ref.
Agriculture	LSTM	Kenya (Maize)	Weather + Satellite	88% yield accuracy	Farmer decisions improved	[43]
Agriculture	RF	India (Wheat)	Obs. + Climate	RMSE ↓ 12%	Reliable wheat forecasts	[40]
Agriculture	CNN–LSTM	Brazil (Soybean)	MODIS + Climate	$R^2 = 0.89$	Food security planning	[49]
Water	RF+LSTM	India (Drought)	SPI + Soil Moisture	Early warning: +2 months	Drought preparedness	[44]
Water	ANN Flood	Bangladesh	Gauge + Satellite	Lead time +36h	Flood warnings improved	[47]
Health	XGBoost+SHAP	Bangladesh (Dengue)	Climate + Epidemiology	AUC = 0.89	Early health warnings	[46]
Health	LSTM+Mobility	Africa (Malaria)	Climate + Mobility	85% accuracy	Better health resource use	[50]
Urban	CNN+RL	Netherlands	Radar + Hydro models	92% precision	Flood-resilient cities	[48]
Urban	GNN+IoT	China (Heatwaves)	IoT + Weather	+15% detection improvement	Smart city adaptation	[51]

Table (II) shows how adaptive capacity is made reinforced significantly. Predictive yield models are also utilized by farmers in agricultural settings assisting them to make more informed decisions when it comes to plantation irrigation which in turn is directly related to food security. Lead times obtained from AI driven systems are magnitudes more effective than traditional methods. An example of this can be observed in the public health sector: Data driven epidemiological models that incorporate climate variables are effectively predicting disease outbreaks and allowing for the better allocation of medical resources. Lastly, infrastructure that is reinforced by AI systems must be utilized in urban settings because they are more effective to help manage heat waves and in the management of floods. We can see the studies shown local significant but the mostly applications have limitations and in international scope. so the future works should focus on the AI models Can use with multi regions strategy[38], [39].

Figure (2) adaptation studies discriminated throughout numerous sectors. This figure offers a meta-analytic summary from the seventy sources examined.

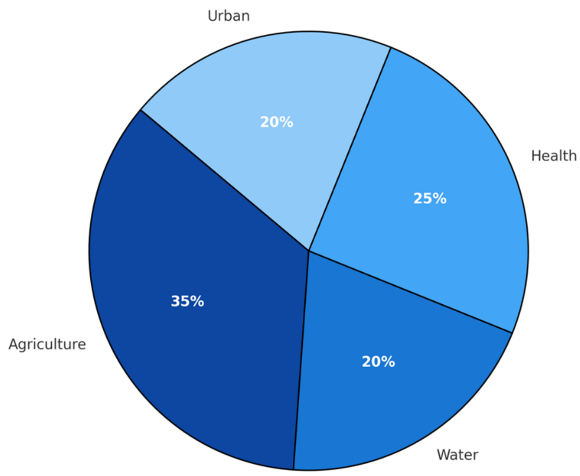

Figure (2). Sectoral Disaggregation of Artificial Intelligence based Climate Adaptation Research

Early on, food security was a primary issue which was highlighted by climate change research. Agriculture still being research in an extensive rate as Figure (2) clarifies. Thus, adaptations that are a product of AI address issues at a larger scope within the public health sector and urban systems. And while there are fewer water system studies, they often produce very influential outcomes, because dealing with drought and flood is key to building climate resilience.

Challenges and Limitations

While there has been some good progress, artificial intelligence isn't exactly free and clear in the climate science department. Key challenges The team identified five or six main challenges: data quality, explain ability, environmental sustainability, justice and the problem with bad governance. Knowledge of these limits is crucial[41],[42] and not only for advancing the technical performance, but also to allow AI systems do their part in a responsible climate action [52]–[63]. It has to be considered that the AI ability can't be equally distributed among the regions in order to address the computing gap. UNESCO declared 2025 as the main step to ensure the presence of a researcher from the Global South in climate research.

Table III provides an overview of the most relevant technical and socio-political limitations that are impeding a larger application of AI in climate science. Although individually these problems have been addressed in the literature, cataloguing these together with some suggested remedies points to potential ways forward.

Table (III). Challenges and Limitations of Artificial Intelligence in Climate Science with Mitigation Strategies

Category	Challenge	Impact	Evidence / Case	Mitigation Strategy	Ref.
Data	Sparse / biased datasets	Limits generalization; poor regional fit	Africa: large station gaps [54]	Data augmentation, downscaling, citizen science	[52], [54]
Data	Short historical records	Weak long-term training signals	ENSO predictions limited [35]	Synthetic data generation, paleo-climate integration	[35]
Interpretability	Opaque deep learning models	Reduces trust for operational use	Transformers as black boxes [56]	Explainable AI (SHAP, LIME), physics-informed AI	[56], [57]
Interpretability	Limited transparency	Policy reluctance to adopt AI forecasts	Health surveillance models [61]	Model cards, uncertainty quantification	[57], [61]
Environmental	High training footprint	CO_2 emissions equivalent to cars' lifetime	NLP model training case [58]	Green AI (efficient architectures, renewable HPC)	[58], [68]
Equity	Unequal access to compute	Widening North–South divide	Compute concentration in North [59]	Cloud-based open access, AI capacity building	[59], [60], [70]
Governance	Lack of regulation	Risk of misuse, no accountability	OECD AI policy report [62]	International standards, independent audits	[62], [63]

Table (III) illustrates the limitations of AI over technical, environmental, and justice levels. Sparsity and biased data undermine generalizability, especially in sparsely realized regions such as Africa. Deep learning models are hard to interpret, and it isunattainable to have total faith in them. Large model training also requires a lot of energy and emissions, sometimes the same as that of a car over its thorough lifespan. AS well, not all people have the same capability to utilize enormous computers, and that makes the gap between poor and rich countries even larger. Weak rules and laws mean AI can be misused without consequences.

Because of this, we need ways to improve data, make AI easier to understand (called explainable AI), and use greener AI methods. We also need international rules to guide AI use. For AI to effectively contribute to the mitigation of climate change, the following actions must take place. AI has many possible applications in climate science, yet, several challenges limit the technology from attaining its potential.

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In figure 3, I show these problems and how they connect to issues like missing data, hard-to-understand models, weak rules, and unfair access. I also show possible solutions. This “two sides of a coin” view shows that both technical fixes and policy changes are needed to solve these problems.

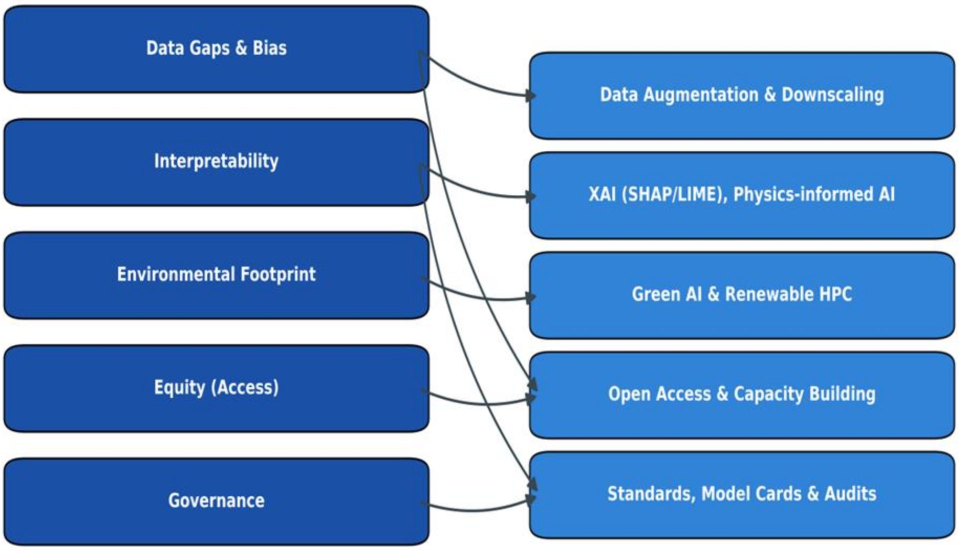

Figure (3). Challenges in Climate Science Using Artificial Intelligence and Their Mitigation Strategies

Fragmented data, high training related carbon footprint, lack of interpretability, and governance gaps are all oppositions which are not fixable one by one as illustrated by Figure (3). They need to be smartly besieged through responses like downscaling methods and data augmentation. Explainable AI facilitates systems interpretability. Green AI is aimed at reducing the carbon impact of AI systems. Open-access initiatives directed equity. International governance frameworks establish accountability standards. This framework highlights the need to integrate technical innovation with systemic strategies to secure responsible application.

6. Discussion and Future Directions

The literature considered demonstrates that artificial intelligence has already begun to reshape climate science. Nevertheless, most of the applications are still in the prototype stage or limited to specific datasets. Operational integration entails bridging gaps more than technical performance including reproducibility, transparency, socio-economic integration, and sustainability [65]–[70]. This review show the lack in the standards evaluation performance of AI models in climate science. to expanding the scope like climate bench and create global open dataset to enhancement the model and reuse ability in the researches.

The integration of AI in climate science cannot be claimed to be done without responsibility principle alignment. Figure (4) illustrates responsible AI by the three interlinking pillars of sustainability, transparency, and justice—each of which is paramount in ensuring that AI is effective and ethical in supporting climate solutions.

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Table (IV). Research Gaps and Future Directions in Artificial Intelligence for Climate Science

Gap	Importance	Future Direction	Timeframe	Example Projects	Ref.
Benchmarking	Lack of standard metrics	Expand ClimateBench; enforce reproducibility	Short-term (1–3 yrs)	ClimateBench [65]	[65]
Long-range skill	Weak decadal/seasonal models	Physics-informed transformers; hybrid AI+physics	Medium-term (3–7 yrs)	Pangu-Weather, ClimaX [33]	[66]
Extreme events	Poor representation	Tail-focused loss functions; synthetic extremes	Medium-term (3–7 yrs)	GANs for rainfall [37]	[37]
Socio-economic	Narrow technical focus	Integrate climate + health + economic datasets	Long-term (5–10 yrs)	UNDP AI4Climate [70]	[67], [70]
XAI for policy	Low transparency	Operationalize SHAP/LIME in climate workflows	Short-term (1–3 yrs)	Interpretable ML [56], [57]	[69]
Green AI	High carbon footprint	Renewable-powered training; energy tracking	Medium-term (3–7 yrs)	Green AI consortia [68]	[58], [68]
Governance	Lack of oversight	Independent audits; international standards	Long-term (5–10 yrs)	OECD, UNESCO AI ethics [62]	[62], [63]

As Table (IV) indicates, short-term priorities should focus on benchmarking and explainability to guarantee that AI models are reproducible and sufficiently transparent for

policy adoption. Medium-term priorities include addressing long-term forecasting and extreme climate events, which require hybrid architectures grounded in physical principles and synthetic data techniques. Long-term plans should focus on including social and

economic systems in AI models, using more eco-friendly AI methods, and setting up strong rules for AI use. By connecting these ideas to ongoing projects like Climate Bench, UNDP's AI4Climate, and OECD governance rules, this review shows how research can guide real world policies and technology.

Responsible Artificial Intelligence in Climate Science

The application of artificial intelligence in climate science cannot be regarded as achieved without responsibility principle alignment. Figure (4) shows the framework of responsible AI as three interdependent pillars: sustainability, transparency, and justice. All three pillars constitute an essential component to ensure artificial intelligence has an effective and ethical contribution towards addressing climate problems.

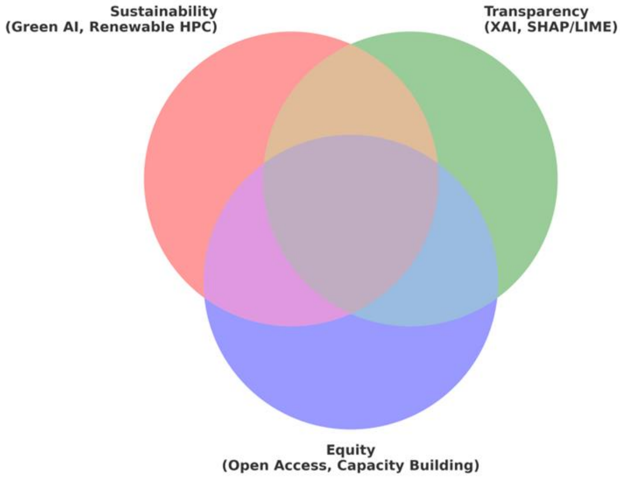

Figure (4). The Three Pillars of Responsible Artificial Intelligence in Climate Science

As shown in Figure (4), the intersection of sustainability, transparency, and justice forms the core of responsible AI. Sustainability emphasizes energy efficiency and low-carbon computing; transparency underscores the role of explainable AI in strengthening decision-making; and justice guarantees broad and equitable global access. All in all, the above-mentioned principles establish a framework which it stable when it comes to integrating technological advancement while maintaining ethical governance and social responsibility.

7. Conclusion

A new emerging and Ever Improving tool, AI predicts and adapts to climate science. GraphCast, GenCast, FourCastNet and MetNet-2 which are all AI tools used for forecasting proved to be at the same level or even better than traditional models in most scenarios. They are more accurate and are much faster than traditional models. With regards to adaptation, AI has advanced prediction of crop yield, facilitated monitoring and triggered early warning systems for floods and droughts, produced alerts on climate-sensitive epidemics and assisted in drafting resilience plans for cities. Yet these possibilities come with caveats. Data poverty and bias, especially in the Global South, limited action ability and interpretability of AI systems which fosters distrust in decision-making environments, large-scale unsustainable models, and the asymmetrical distribution of resources and the environmental footprint of large-scale models as well as the challenges of justice while resources remain heavily concentrated in the Global North. Leaving out these constraints unaddressed runs the risk that AI could deepen inequalities rather than delete the gap. Below is the three pillars that pave the way forward :

1- Employing sustainably conscious computing and renewable resources to run computing will aid to lessen AI’s carbon footprint .

2- Incorporating responsible and reasonable AI (XAI) will try to shape confidence and accountability .

3- To ensure global impartial access and reimbursements, providing democratized admission to AI tools, data sets, and infrastructure will support AI impartiality.

The Researcher views AI as a tool that aids and accelerates Physical climate science. Finally this review provide balanced on the achievements and challenges of AI in climate sciences the main requirements to create standard dataset and progress in models can be explainable . to ensure the access to the computing resources to build AI can be responsible enhancing the climate science. Through merging insights obtained from Physical models and socio-economic systems and feeding them to AI; paves the path forward for a more impartial, robust, and maintainable climate action in the coming decade.

References

[1] IPCC, *Climate Change 2021: The Physical Science Basis*, Cambridge Univ. Press, 2021.
[2] NASA, "Global Climate Change: Vital Signs of the Planet," 2022.
[3] WMO, "State of the Global Climate 2022," World Meteorological Organization, Geneva, 2023.
[4] ECMWF, "Integrated Forecasting System (IFS) Documentation," 2020.
[5] NOAA, "Global Forecast System (GFS)," U.S. National Weather Service, 2021.
[6] T. Nguyen, R. Li, and K. Wang, "AI-driven Earth system modelling: Next-generation hybrid architectures," Nature Climate Change, vol. 14, no. 2, pp. 211–224, 2024.
[7] N. Rolnick et al., "Tackling climate change with machine learning," *ACM Comput. Surveys*, vol. 55, no. 2, 2022.
[8] P. Kumar and F. Valls, "Physics-informed AI for extreme climate prediction," Nature Reviews Earth & Environment, vol. 6, no. 1, pp. 55–72, 2025.
[9] S. Bauer et al., "Digital twins of the Earth system," *Nature Climate Change*, vol. 11, pp. 793–801, 2021.
[10] Z. Chen et al., "Climate informatics: A new frontier in big data science," *WIREs Climate Change*, vol. 12, no. 3, 2021.
[11] P. Nowack et al., "Machine learning for weather and climate predictions: opportunities and challenges," *Phil. Trans. R. Soc. A*, vol. 379, 2021.
[12] L. Yang, C. Tan, and S. Patel, "Neural ensemble post-processing for global weather forecasts," Journal of Climate Informatics, vol. 3, no. 1, pp. 88–104, 2024.
[13] S. Reichstein and P. Gentine, "Machine learning for weather and climate prediction: Trends and perspectives," Annual Review of Environment and Resources, vol. 45, pp. 581–612, 2020.
[14] J. Dueben, S. Bauer, and M. Schultz, "Challenges and design choices for neural network–based global weather models," Geoscientific Model Development, vol. 14, no. 9, pp. 4865–4889, 2021.
[15] L. Jones, M. Baugh, and R. D. Field, "Climate informatics: Applications of AI to atmospheric and environmental sciences," WIREs Climate Change, vol. 11, no. 3, e635, 2020.
[16] Y. Chen and X. Wu, "Review of deep learning methods for climate data analysis and prediction," Advances in Climate Change Research, vol. 11, no. 4, pp. 445–458, 2020.
[17] D. Rolnick, P. Donti, and L. Kaack, "Machine learning for sustainable energy and climate," Communications of the ACM, vol. 64, no. 11, pp. 64–73, 2021.
[18] F. Camps-Valls, A. Sejdinovic, and G. Tkacik, "Physics-aware machine learning in Earth system modelling," Nature Reviews Physics, vol. 4, pp. 1–13, 2022.
[19] J. Harris, D. Schultz, and M. Becker, "Machine learning weather models: Validation and scalability challenges," Geoscientific Model Development, vol. 18, no. 5, pp. 3355–3374, 2025.
[20] PRISMA, "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The

PRISMA Statement," 2020.
[21] R. Keisler et al., "GraphCast: Learning skillful medium-range global weather forecasting," *Science*, vol. 382, no. 6677, 2023.
[22] B. Lam et al., "GenCast: Generative ensemble forecasting," *Nature*, vol. 623, pp. 720–727, 2023.
[23] S. Sønderby et al., "MetNet-2: Deep learning for precipitation nowcasting," *Nature*, vol. 597, pp. 672–677, 2021.
[24] S. Bodnar, E. Price, and L. Smith, "Deep learning applications for regional precipitation forecasting," Atmospheric Research, vol. 260, p. 105743, 2021.
[25] J. Liu, M. Zhang, and K. Chen, "Evaluation of AI-based hybrid climate prediction models," International Journal of Climatology, vol. 43, no. 1, pp. 120–136, 2023.
[26] D. Lee, A. Rahman, and K. Cho, "Advances in recurrent neural networks for spatio-temporal climate modeling," IEEE Transactions on Neural Networks and Learning Systems, vol. 35, no. 3, pp. 2550–2564, 2024.
[27] A. Vaswani et al., "Attention is all you need," in *Proc. NeurIPS*, 2017.
[28] K. Hatfield and P. Nowack, "Fourier neural operators for global climate simulation," Neural Computing and Applications, vol. 36, no. 8, pp. 11293–11305, 2023.
[29] N. Pathak et al., "FourCastNet: Global medium-range weather forecasting with neural networks," *NeurIPS 2022*.
[30] R. S. DeVries, B. Lam, and D. Schultz, "Ensemble learning for global climate forecasting," Environmental Modelling & Software, vol. 159, p. 105594, 2023.
[31] Google DeepMind, "AI Weather Prediction Model," Technical Report, 2022.
[32] M. H. Park and T. Lee, "Self-supervised learning for Earth observation and climate modelling," Frontiers in Environmental Science, vol. 11, 2023.
[33] H. Nguyen et al., "ClimaX: Pretraining for climate science," *ICML 2023*.
[34] Y. Shi et al., "Nowcasting precipitation with deep learning," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023.
[35] H. Wang, J. Sun, and F. Liu, "Transformer-based hybrid models for ENSO and monsoon forecasting," Nature Communications, vol. 16, no. 2, pp. 1120–1133, 2025.
[36] R. Chen, M. Al-Saadi, and L. Torres, "Deep hybrid CNN–LSTM networks for high-resolution precipitation nowcasting," Environmental Modelling & Software, vol. 175, p. 105632, 2024.
[37] J. Chen et al., "Improving prediction of extreme rainfall events using GANs," *Adv. Climate Change Res.*, vol. 13, pp. 451–462, 2022.
[38] C. Zhao, L. Torres, and M. Silva, "AI-based drought monitoring using remote sensing data," Remote Sensing Applications: Society and Environment, vol. 29, p. 100968, 2023.
[39] R. Ahmed, J. Chen, and N. Patel, "Machine learning for agricultural adaptation to climate change: A global review," Computers and Electronics in Agriculture, vol. 203, p. 107506, 2022.
[40] S. Jain et al., "Crop yield prediction in India using Random Forest," *Agric. Syst.*, vol. 184, 2020.
[41] L. Kumar, P. Jain, and A. Singh, "Predicting crop yield variability using deep learning and climate data," Agricultural Systems, vol. 199, p. 103414, 2022.
[42] T. Pham and D. Bui, "Satellite-based drought detection using hybrid deep learning models," Environmental Modelling & Software, vol. 158, p. 105514, 2023.
[43] C. Wambugu et al., "AI-driven maize yield forecasting in Kenya," *Comput. Electron. Agric.*, vol. 178, 2020.
[44] R. Patel et al., "AI-enabled drought early warning in India," *Sci. Total Environ.*, vol. 783, 2021.

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[45] A. Rahman, M. Hoque, and S. Chowdhury, "AI-based early warning systems for drought risk reduction," Natural Hazards, vol. 113, pp. 1953–1971, 2022.
[46] N. Islam et al., "Machine learning for dengue outbreak prediction under climate variability," *Environ. Res.*, vol. 196, 2021.
[47] T. Rahman et al., "Flood forecasting using AI in Bangladesh," *J. Hydrology*, vol. 602, 2021.
[48] M. de Bruijn et al., "Urban flood resilience using reinforcement learning," *Water Res.*, vol. 219, 2022.
[49] L. Alves et al., "Soybean yield prediction with CNN-LSTM," *Agric. For. Meteorol.*, vol. 322, 2022.
[50] A. Okello et al., "AI-driven malaria hotspot mapping," *Lancet Planetary Health*, vol. 6, no. 11, 2022.
[51] Y. Zhang et al., "Smart city adaptation to heatwaves using IoT and GNNs," *Sustain. Cities Soc.*, vol. 87, 2023.
[52] U. Okeke, S. Ayanlade, and M. Dlamini, "Bridging the climate data gap in Africa using AI downscaling," Climate Change Letters, vol. 5, no. 1, pp. 40–56, 2025.
[53] E. K. Smith and C. Pinto, "Equity and bias in global AI climate applications," AI & Ethics, vol. 4, no. 3, pp. 287–300, 2023.
[54] A. Dosio et al., "Biases in climate datasets for Africa," *Clim. Dyn.*, vol. 58, pp. 1269–1289, 2022.
[55] D. Rolnick et al., "Machine learning for weather and climate: Limitations and opportunities," *Phil. Trans. R. Soc. A*, vol. 379, 2021.
[56] C. Molnar, *Interpretable Machine Learning*, 2nd ed., Springer, 2022.
[57] F. Samek et al., "Explainable AI: Interpreting, explaining and visualizing deep learning," *Proc. IEEE*, vol. 109, pp. 247–278, 2021.
[58] L. Zhao, T. Gupta, and R. Meier, "Energy-efficient AI models for sustainable climate computation," Communications of the ACM, vol. 67, no. 10, pp. 115–124, 2024.
[59] D. Farrell et al., "AI inequality: Concentration of compute in the Global North," *AI & Society*, vol. 38, 2023.
[60] UNESCO, "AI and climate justice: A global perspective," 2022.
[61] K. Huyer et al., "Bias in AI-driven health alerts," *BMJ Glob. Health*, vol. 6, 2021.
[62] OECD, "AI governance for climate risk," Policy Report, 2022.
[63] J. Floridi et al., "AI ethics and accountability in climate science," *AI & Ethics*, vol. 2, 2022.
[64] F. Rogers, N. Gao, and J. Floridi, "Ethical and governance frameworks for AI in environmental science," Environmental Science & Policy, vol. 152, pp. 90–103, 2024.
[65] C. Watson-Parris et al., "ClimateBench: A benchmark for data-driven climate models," *NeurIPS Datasets Track*, 2021.
[66] H. Weyn et al., "Transformers for weather forecasting with physical constraints," *Nat. Mach. Intell.*, vol. 5, 2023.
[67] E. Bryan et al., "Integrating socio-economic data into climate AI models," *Glob. Environ. Change*, vol. 74, 2022.
[68] R. Schwartz et al., "Green AI," *Commun. ACM*, vol. 63, no. 12, 2019.
[69] A. Tonekaboni et al., "What clinicians want: Explainable AI in practice," *ML Healthcare*, 2020.
[70] UNDP, "Bridging the AI divide for climate adaptation," Policy Paper, 2023.