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A Study on the Role of Artificial Intelligence and Machine Learning in Addressing Climate Change

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Abstract: Climate change is one of the major significant global challenges, affecting ecosystems, economies, and human well-being. Traditional methods used for climate analysis and environmental monitoring always face significant challenges in handling the large and complex datasets produced by climate systems. In this study Artificial Intelligence (AI) and Machine Learning (ML) are used as powerful data driven tools for understanding, predicting, and mitigating the effects of climate change. This study highlights the role of AI and ML techniques in addressing climate-related issues including weather forecasting, climate modelling, disaster prediction and energy optimization. AI based models enable the analysis of large volumes of environmental data from satellites, sensors and historical records and help for more accurate predictions and informed decision-making. Nowadays various machine learning algorithms such as neural networks, deep learning and regression models are increasingly used to identify climate patterns, find environmental risks and develop sustainable solutions. The paper also focuses on the application of AI in renewable energy management and smart agriculture emphasizing its potential to enhance climate resilience. Also, the challenges associated with AI implementation such as data quality and computational requirements are discussed. This study focuses that AI and ML can play a transformative role in commuting climate change by improving predictive capabilities and supporting sustainable development strategies. The findings suggest that integrating AI-based technologies with environmental policies can significantly contribute to global efforts in climate change mitigation and adaptation, covering the way for a more sustainable and climate-resilient future.

Keywords: Artificial Intelligence, Machine Learning, Climate Change, Predictive Modelling, Data Analytics, Smart Systems.

I. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) have come out as transformative tools to address the complex and many different ways of accepting climate change [1]. Climate change poses unparalleled challenges to ecosystems and human societies globally, requiring advanced technological capabilities to analyse large and complex environmental data for better understanding and prediction [1, 2]. ML algorithms have significantly advanced recently, enabling advancements in climate research by identifying complex feedbacks and long-distance climate connections within the Earth system that are difficult to capture through conventional equations or models [3].

AI helps to predict accuracy and computational efficiency, integrating multi-source data to improve climate risk assessments, resource optimization, and infrastructure resilience, which are vital for sustainable urban planning and climate change adaptation [2, 3].

AI-driven models help to provide robust frameworks for the forecasting future climate revealing the magnitude and dynamics of climate impacts over the diverse systems and geographies [4]. Furthermore, AI applications extend beyond prediction; they assist in mitigating climate change by optimizing energy management and improving sustainable agricultural practices [5]. However, challenges remain, including the opacity ("black-box" problem) of AI models and data quality limitations [6]. AI and ML offer powerful means to both understand and address climate change impacts.

They are enabling rapid data collection, pattern analysis, and scenario testing which supports decision-making. Some are as predictive models facilitate equitable governance and sustainable outcomes by offering actionable insights to policymakers and communities, therefore empowering climate-resilient strategies and adaptation measures. Furthermore, AI applications extend beyond prediction; they assist in mitigating climate change by optimizing energy management, analysing industrial emissions, and improving sustainable agricultural practices to reduce environmental footprints [6, 7].

AI helps real-time environmental monitoring through advanced techniques like remote sensing and integration with the help of Internet of Things (IoT), which strengthens capabilities of air and water quality assessment, biodiversity monitoring, and disaster management. However, challenges remain, including the opacity ("black-box" problem) of AI

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models, data quality limitations, and the need for transparent and ethical AI deployment in climate contexts. AI and ML offer powerful means to both understand and address climate change impacts, driving innovations in mitigation, adaptation, and sustainable development worldwide [7].

II. RELATED WORK

The most effective for AI and machine learning ML techniques employed in climate modelling and prediction include an amount of range of advanced algorithms customized to predict the accuracy, computational efficiency, and multi-source data integration. Machine learning and deep learning methods play essential roles for improving climate risk evaluation and modifying strategies [2].

Artificial Neural Networks (ANNs), including variations like Feed-Forward Neural Networks (FFNN) and Recurrent Neural Networks (RNN), have shown strong performance in climate-related work for event prediction such as flood forecasting. In one study on Nile flooding in South Sudan, FFNN achieved up to 95% accuracy, while groups of methods like Gradient Boosting and AdaBoost also proved high classification accuracy (93.7% and 91.6%, respectively). These models excel by non-straight-line relationships in data and time-related in climate data [7].

Advanced deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are widely used in environmental and climate data analyses, including surface water management and air quality forecasting. CNNs effectively extract dimensional features from remote sensing images, while LSTMs are particularly suited for sequential time-series data, enabling improved streamflow forecasting and climate variability predictions [8].

Random Forest (RF) and Support Vector Machines (SVM) are also outstanding ML techniques due to their robustness and effectiveness in handling multi-dimensional input features, especially in agricultural climate impact predictions like crop yield under abnormal climate conditions. Also learning methods, including stacking-based approaches, enhance model performance by combining multiple weak learners [9].

In addition to supervised learning techniques, emerging approaches like Explainable AI (XAI) are gaining importance for understanding complex climate models and transparency in predictions, which is critical for policymaker trust and decision support.

Hybrid AI-physics models that are made domain knowledge and physical environmental models with data-driven AI further improve the reliability and interpretability of climate forecasts. These frameworks, such as the Physics-Constrained Neural Network (PCNN), allow for decade-long simulation stability while retaining physical consistency, effectively replacing traditional parameterization schemes with high-speed AI surrogate models [10].

III. METHODOLOGY

These methods improve the accuracy of climate predictions compared to single-model approaches together multiple models to reduce incorrect assumptions, variance, and uncertainty inherent in individual models. These methods collect diverse predictions, which often balance out errors and biases that single models may show due to limitations in structure, data, or training. For instance, a multi-model ensemble approach, using genetic algorithms and Bayesian model averaging on runoff predictions under climate plot, produced more reliable and accurate results than any individual rainfall–runoff model by evening out individual model biases and undefined [11].

In practice, ensembles composed of models with different structures or trained on varied data partitions tend to perform better than a single best model. This is because ensemble members complement one after another by capturing different f patterns in the data, leading to increased robustness and generalization of predictions. Reducing correlation among ensemble members by methods such as data partitioning or using different model architectures enhances the benefits of combining predictions [12].

Furthermore, ensemble techniques not only improve central prediction accuracy but also help to improve uncertainty quantification, which is critical in climate modelling for risk assessment and decision-making. They provide a collection of predictions that include measures of variability and reliability, unlike many single-model outputs that may lack such complete error characterization. By combining multiple independent forecasts, ensemble methods also reduce the risk of overfitting that can affect single models and help produce more stable, trusted predictions across varied climatic conditions [13].

In summary, ensemble methods improve climate prediction accuracy by collective diverse models to reduce errors, balance biases, enhance robustness, and provide unpredictability quantification, thereby delivering more reliable and actionable climate forecasts than single-model approaches.

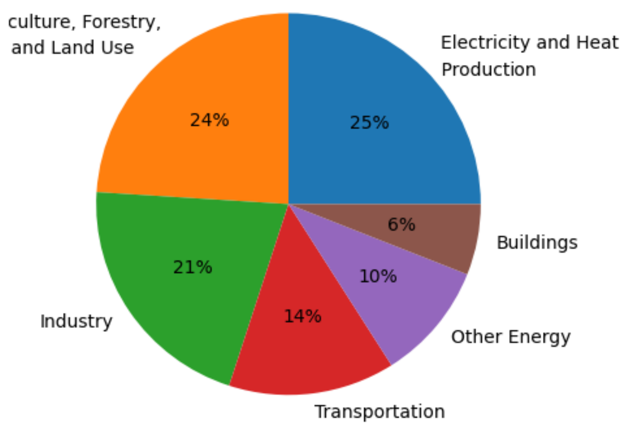

Fig 1: Global Gas Emission by Economic Sector

- **Electricity and Heat Production (25%):** The burning of coal, natural gas, and oil for electricity and heat is the largest source of global emissions.
- **Agriculture, Forestry, and Other Land Use (24%):** Emissions in this sector come primarily from agriculture (livestock and crop cultivation), land clearing, and deforestation.
- **Industry (21%):** This involves emissions from fossil fuels burned on-site for energy in manufacturing and raw material processing, as well as chemical, metallurgical, and mineral transformation processes.
- **Transportation (14%):** Fossil fuels burned for road, rail, air, and marine transportation contribute significantly to CO_2 levels.
- **Other Energy (10%):** This includes emissions from the energy sector that are not directly associated with electricity or heat production, such as fuel extraction, refining, processing, and transportation.
- **Buildings (6%):** This sector refers to emissions arising from on-site energy generation and the burning of fuels for heating or cooking in residential and commercial buildings.

Table 1: Global Gas Emission by Economic Sector

Sector	% of Global Emission
Electricity and Heat Production	25%
Agriculture, Forestry, & Land Use	24%
Industry	21%
Transportation	14%
Other Energy	10%
Buildings	6%

IV. RESULT

A. Breakthroughs in Climate Modelling and Prediction

- Precision and Speed: AI has increased the speed of mapping Antarctic icebergs by 10,000 times compared to human researchers [14]
- Extreme Weather: Machine Learning models now provide minute-level forecasts for precipitation ("nowcasting") and more accurately predict cyclone intensity and heatwave localization than traditional physics-based models [14, 15].
- Digital Twins: High-resolution "Digital Twins" of the Earth use AI to simulate various climate policy scenarios, helping governments visualize the impact of urban planning on heat islands and flood risks before implementation [16].

B. Optimization for Mitigation

- Energy Efficiency: AI-driven smart grids have improved the load factor of renewable energy (wind and solar) by up to 20%, ensuring a more stable supply to the electrical grid [17].
- Methane Detection: AI-enabled satellite monitoring identifies industrial methane leaks with 30% higher precision, facilitating rapid repairs in the oil and gas sectors [14, 17].
- Industrial Decarbonization: AI platforms combining satellite imagery with sensor data help heavy industries (mining, steel, and cement) reduce their operational emissions by 20–30% [14].

C. Environmental Trade-offs (The "Paradox")

- Energy Demand: While AI helps reduce emissions, the infrastructure required to run it is energy-intensive. As of 2026, data centers in tech hubs like Ireland are projected to account for nearly 35% of national energy use [18].
- Carbon Footprint: Training a single large-scale AI model can emit as much CO_2 as 300 round-trip flights between New York and San Francisco [19].
- Water Consumption: AI is a significant consumer of fresh water for cooling data centers; a typical 20-50 question interaction with a chatbot can consume roughly half a litre of water [19].

V. CONCLUSION

Artificial intelligence (AI) and machine learning (ML) have become indispensable tools in addressing the multifaceted

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challenges posed by climate change. These technologies enhance our ability to analyse complex climate systems, improve predictive accuracy, and enable proactive climate risk management. AI and ML facilitate deeper understanding of teleconnections within the Earth system, sharpen early warning systems for extreme events, and provide actionable insights to policymakers, urban planners, and communities for resilient adaptation and sustainable development strategies.

In conclusion, the synergy of AI and ML with climate science offers transformative potential to understand, predict, and counteract climate change impacts more effectively.

VI. FUTURE WORK

A. Addressing the "Green AI" Paradox

While AI provides solutions for decarbonization, the infrastructure required to run it poses a significant environmental risk. In 2024–2025, it was found that training a single large-scale model can consume as much water as a small town uses in a day due to cooling needs.

- Energy-Efficient Algorithms: Future work is shifting from "Red AI" (prioritizing accuracy at any computational cost) to "Green AI", which integrates energy efficiency as a primary evaluation metric.
- Hardware Innovation: Spiking Neural Networks (SNNs) are a major research focus for 2026. Inspired by the human brain, these networks process data in discrete "spikes" rather than continuous streams. This "event-driven" processing can reduce energy consumption by up to 100x compared to traditional artificial neural networks.
- Data Center Cooling: Research is moving toward immersion cooling and closed-loop systems, which can reduce freshwater use in data centers by up to 70%.

B. Bridging the Global South Data Gap

A significant "digital divide" exists where the Global North leads in AI investment, but the Global South faces the most acute climate vulnerabilities.

- Transfer Learning & Domain Adaptation: Future initiatives are utilizing Transfer Learning to assist regions with sparse historical records. By pre-training a model on a data-rich "source domain" (e.g., European weather data) and then "fine-tuning" it on a "target domain" (e.g., local precipitation in East Africa), researchers can generate high-accuracy risk assessments even with limited local data.
- Capacity Building: International efforts like the #AI4ClimateAction Initiative (2025) focuses on strengthening digital infrastructure in Least Developed Countries (LDCs) and Small Island Developing States (SIDS). This includes creating regional AI research centers to ensure that adaptation strategies are designed locally rather than imposed from the outside.

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VIII. REFERENCES

[1] C. Huntingford, E. S. Jeffers, M. B. Bonsall, H. M. Reebe and A. D. Sagar, “Machine learning and artificial intelligence to aid climate change research and preparedness. Environmental Research Letters,” 2019.

[2] T. Amnuaylojaroen, AI and Machine Learning for Climate Change Adaptation., Springer Nature, (2025)..

[3] A. K. Srivastava and S. Maity, “Machine learning applications in Earth system sciences: A review of mitigation and adaptation strategies. Global and Planetary Change,” p. 221, 2023.

[4] K. Ukoba, K. Inthavong and T. C. Jen, “Predictive modeling and equitable governance: Harnessing AI for climate-resilient urban planning. Sustainable Cities and Society,,” vol. 104, p. 105280, 2025.

[5] R. Kuma, S. Singh and A. Gupta, “AI-driven optimization for industrial emission reduction and energy management. Green Technology Reviews,,” vol. 8, no. 1, pp. 112-128, 2024.

[6] S. S. Alotaibi and A. B. Nassif, “Ethics and transparency in AI: Addressing the "black-box" problem in environmental modeling,” Journal of Artificial Intelligence and Sustainability, vol. 12, no. 2, pp. 45-60, 2024.

[7] A. M. El-Mahdy and e. al., “Flood forecasting using artificial neural networks and ensemble learning: A case study of the Nile River,” Journal of Hydrology and Climate Change, vol. 15, no. 3, pp. 201-218, 2024.

[8] J. G. Gacu and e. al., “Deep learning applications in surface water management and climate variability: A focus on CNN and LSTM architectures,” Environmental Data Science Review, vol. 9, no. 1, pp. 45-62, 2025.

[9] H. Choi, S. Park and J. Lee, “Advancements and challenges of artificial intelligence in climate modeling for sustainable urban planning. Sustainable Cities and Society,” vol. 112, p. 105542, 2025.

[10] X. Zhang and F. Yang, “Multi-model ensemble for runoff predictions under climate change scenarios using Bayesian model averaging and genetic algorithms,” Journal of Hydrology, vol. 562, pp. 536-548, 2018.

[11] G. P. Zhang and V. L. Berardi, “Improving the accuracy of autoregressive integrated moving average models with evolutionary neural networks. Expert Systems with Applications,” vol. 20, no. 2, pp. 141-147, 2001.

[12] T. S. Murray, “Uncertainty and risk assessment in climate forecasting: The role of ensemble modeling. Climate Risk Management,,” vol. 21, pp. 34-42, 2018.

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[13] G. Camps-Valls and et. al., “Artificial intelligence for modeling and understanding extreme weather and climate events,” Nature Communications, vol. 16, p. 1919, 2025.

[14] MDPI, “Artificial Intelligence-Driven Analytics for Monitoring and Mitigating Climate Change Impacts,” Engineering Proceedings, vol. 108, no. 1, 2025.

[15] H. Kioumarsi and others. al., “AI for climate system modeling and policy,” Springer Nature Research Communities, 2025.

[16] Institute and G. Research, “Green and Intelligent: The Role of AI in the Climate Transition.,” LSE Press Release, 2025.

[17] UNEP, “Navigating New Horizons: A Global Report on the Environmental Impact of AI.,” United Nations Environment Programme., 2025.

[18] Agency, “The Sustainable Environmental Impact of Generative AI: Stats & Facts for 2026.,” 2026.

[19] EESI, “ Data Centers and Water Consumption.,” Environmental and Energy Study, 2025.