Artificial Intelligence in Climate Resilience: Evaluating Contributions to SDG 13

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Abstract

In recent years, there has been a significant increase in artificial intelligence (AI) approaches for Sustainable Development Goals (SDGs), particularly SDG 13: Climate Action. Several AI technologies, such as machine learning, deep learning neural networks, and big data analytics present new tactics to tackle the complex problems of climate change. Via improving decision-making, predicting future outputs, and effectively managing vast data, these technologies help increase the accuracy of climate forecasts, optimization of resource allocation, while enabling faster responses to climatic change impacts. Yet, numerous challenges remain despite these advances including the need for high-quality data and robust algorithms as well as addressing ethical concerns, such as privacy of information with reference to the environmental effects of AI. With the help of systematic literature review, the present study investigates emerging patterns and analyses the findings to identify how AI can improve climate resilience and support mitigation and adaptation efforts in alignment with SDG 13. It underscores the need for ongoing innovation, interdisciplinary cooperation, and constructive legislation. Evidence indicate that AI has the potential to greatly enhance climate resilience if technical and ethical issues are properly addressed.

1. Introduction

1.1. Climate change

Climate change is one of the pressing matters of the 21st century and needs to be addressed with solutions for communities to be resilient to the impacts of climate change to avoid significant loss of life and property (Eckardt et al., 2022). The Intergovernmental Panel on Climate Change (IPCC) states that without significant mitigation efforts, global temperatures could rise between 1.5°C and 2°C by the end of this century, and it has consistently warned that this could lead to severe and potentially irreversible consequences (Intergovernmental Panel on Climate Change (IPCC, 2018; 2021). The impacts of global warming are increasingly evident, particularly in vulnerable regions where limited infrastructure and resources exacerbate the risks posed by climate-related hazards. For example, rising sea levels threaten the existence of small island developing states (Nurse et al., 2014, Robinson, 2018), while Sub-Saharan Africa is increasingly vulnerable to severe droughts, such as the 2015-2016 El Niño-induced drought in Ethiopia, which affected over 10 million people and worsened food and water insecurity (Mera, 2019). Similarly, as the pace of urbanization quickens in South Asia, areas like Delhi and Karachi are facing extreme heatwaves that disproportionately impact the urban poor. The 2015 heatwave in India, which led to over 2,000 deaths (Satyanarayana et al., 2020), highlighted the urgent need for targeted adaptation and mitigation strategies in these vulnerable urban areas. (Nguyen, 2024) studied the mortality rates among older people living in hot regions in Southern Vietnam, and found that both heatwaves and cold waves are the major reasons. According to the latest IPCC report (IPCC, 2023), human activities like burning fossil fuels, unsustainable land use, excess consumption of energy, and other factors are the major reasons behind global warming. The study by Liu et al. (2023) assessed future shared socio-economic pathways (SSPs) and concluded that the probabilistic flood risk for the city of Monte Carlo will increase by 51.3% under the SSP2-4.5 scenario and by 67.4% under the SSP5-8.5 scenario.

1.2. Sustainable Development Goal 13: Climate Action

Sustainable Development Goal 13 (SDG 13), established by the United Nations (UN) as part of the 2030 Agenda for Sustainable Development, aims to catalyse global efforts to combat climate change and its impacts (*The Sustainable Development Goals Report*, 2023). This goal targets the reduction of greenhouse gas (GHG) emissions, enhancement of resilience, and improvement of adaptive capacities to mitigate and adapt to climate-related challenges. It sets a key target to 'strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries' (United Nations, 2015). Beyond this, SDG 13 advocates for integrating climate concerns into national development policies and developing financial mechanisms to support these objectives. Furthermore, three of its four targets—13.1, 13.2, and 13.b—emphasize raising awareness and building capacity (Box 1), which are crucial for fostering a resilient and adaptive global response to climate change (Sami Neha et al., 2017).

13.1 Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries.
13.2 Integrate climate change measures into national policies, strategies, and planning.
13.3 Improve education, awareness-raising, and human and institutional capacity on climate change mitigation, adaptation, impact reduction, and early warning.
13.a Implement the commitment undertaken by developed-country parties to the United Nations Framework Convention on Climate Change to a goal of mobilizing jointly $100 billion annually by 2020 from all sources to address the needs of developing countries in the context of meaningful mitigation actions and transparency on implementation and fully operationalize the Green Climate Fund through its capitalization as soon as possible.
13.b Promote mechanisms for raising capacity for effective climate change-related planning and management in least developed countries and small island developing states, including focusing on women, youth, and local and marginalized communities.
*Acknowledging that the United Nations Framework Convention on Climate Change is the primary i*nternational, intergovernmental forum for negotiating the global response to climate change. (UN Sustainable Development)

Box 1. Objectives as per SDG 13

1.3. Artificial Intelligence

The concept of artificial intelligence (AI) indicates the ability of machines to learn from experience, adjust to new inputs, and perform human-like tasks to interpret external data correctly to achieve specific goals and tasks through flexible adaptation (Filho, 2019). This field has gained broader attention with significant advances in data collection and aggregation, analytics, and the availability of suitable computer processing power (Singh et al., 2023). In 2015, the AI market was worth $200 million. It is estimated that by 2025, it will amount to nearly $90 billion (UNEP, 2019).

Recent AI methods represent cutting-edge advancements in the climate change field, characterized by the rise of machine learning (ML), deep learning (DL), and neural network (NN) architectures (Figure 1). ML can be regarded as a sophisticated statistical analysis tool and is used for making predictions based on the information that the user has. There are two types of ML methods: 'supervised learning' and 'unsupervised learning'. In supervised learning, the aim is to get predictions for new data, whereas, in unsupervised learning, new insights and trends can be interpreted using large volumes of data (Delua, 2021). Neural networks are made up of node layers: input layer, hidden layers (one or more), and output layer. A study by Moghanlo et al. (2021) showed that an Artificial Neural Network (ANN) can be used to understand the effects of climate change on the dust phenomenon until 2050 for Zanjan city.

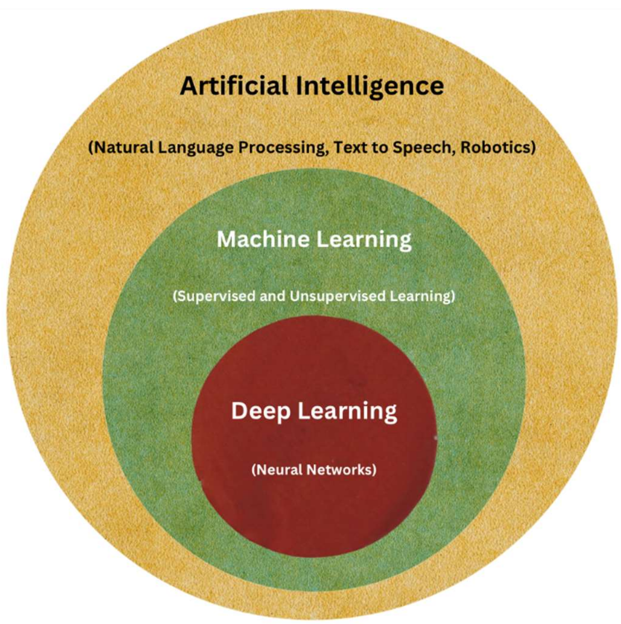

Figure 1. An overview of Artificial Intelligence

Other emerging AI technologies, such as transfer learning, which leverage pre-trained models to enhance performance with limited data (Hassan et al., 2022), and quantum computing, with potential applications in various fields (Singh, et al., 2024), are part of the broader shift toward data-driven approaches that solve complex problems across diverse domains (Liyu 2024). These methods have propelled AI into new frontiers, enabling systems to learn from data, recognize patterns, and make predictions with remarkable accuracy.

1.4. Integrating artificial intelligence and climate resilience

Addressing climate change impairment with the help of AI presents a possibility of benefiting SDG 13, and this is why it is important to ensure its broad-based adoption into local plans. These days, AI technologies have been utilized in climate resilience for impact management by predicting floods, droughts, melting of icebergs, and developing strategies for adaptation and mitigation accordingly. For example, the Deep Thunder project by IBM provides weather forecasts with extremely high resolution (Jain, 2023), and a flood prediction system based on AI from Google issues warnings in time for flooding regions such as Accra, Ghana (Afra et al., 2022; Nearing, 2024). As per a study, AI has the potential to reduce energy consumption in buildings by 30-50% (Chen et al., 2023).

Deep learning, which is a subset of machine learning, has developed into a dominant technology for addressing climate-related challenges by providing powerful methods for identifying vulnerabilities, reducing risks, and enhancing resilience among communities and businesses (Akter et al., 2023; Singh, 2024). Convolutional Neural Networks (CNNs) can classify, recognize, and predict trends in climate change and environmental data (Gentine et al., 2018; Kareem et al., 2021). Additionally, Recurrent Neural Networks (RNNs) offer a more sophisticated approach to modelling complex relationships in time-series data, which is crucial for understanding long-term climate trends and variability (Han, 2021). Artificial Neural Network (ANN), Nearest Neighbours Classification (NNC), and Support Vector Machine (SVM), are some other methods to predict and classify flash floods in arid regions to make the communities resilient to climate change (Nakhaei et al., 2023). Future advancements, such as AI's integration with Internet of Things (IoT) and blockchain, could enhance real-time data processing, improving climate-resilient strategies (Rolnick et al., 2022; Vinuesa et al., 2020).

The integration of AI technologies in potential areas to achieve climate resilience is shown in Figure 2. The application of AI technologies like machine learning (ML), deep learning (DL), neural networks and natural language processing (NLP) in climate research areas including weather and climate, renewable energy and grid management, carbon capture and storage, agriculture and policy and finance can help achieve climate resilience and climate action goals such as adaptation goals (climate disaster risk reduction, improved forecasts), effective mitigation measures (reduced GHG emissions, smart grid management, precision agriculture) and improved policy and finance integration.

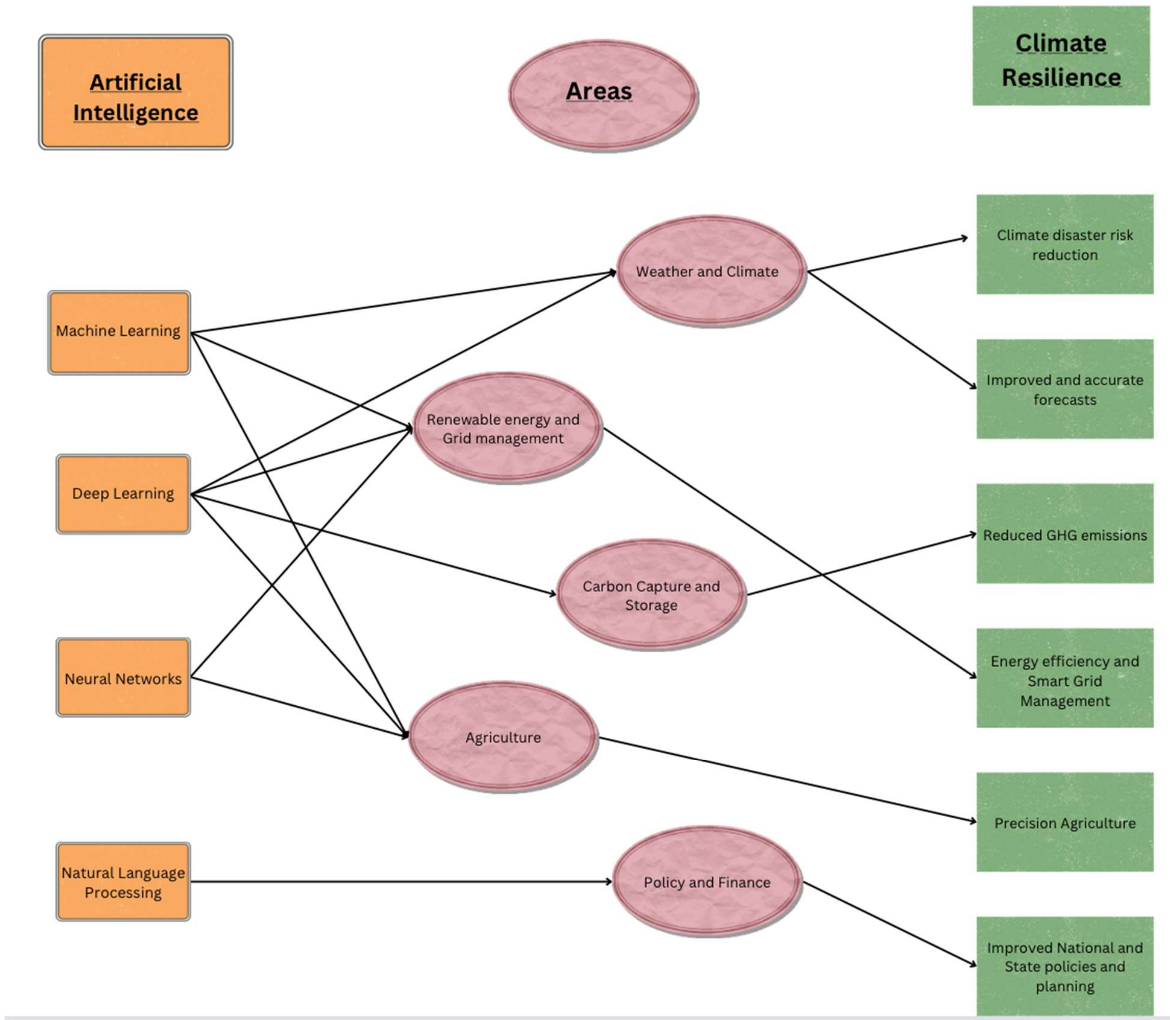

Figure 2. Integration of AI to achieve climate resilience

2. Methodology

A systematic approach was employed to gather and analyse relevant literature on AI in climate resilience, focusing on climate mitigation, adaptation, and SDG 13. The methodology involved identifying, selecting, and synthesizing key research papers to meet the study's objectives and outcomes. Scopus was the main database used for searching the research studies, however relevant studies were also extracted from Web of Science, Google Scholar databases, and other relevant sources, with search terms such as "Artificial Intelligence," "Machine Learning," "Deep Learning," "Climate Change Mitigation," "Climate Adaptation," "Climate Resilience," Climate action, Sustainable Development Goals 13 and "SDG 13." The search yielded numerous articles, which were subjected to inclusion criteria, encompassing peer-reviewed articles published in English between 2014-2024, focusing on AI in climate resilience, mitigation, adaptation, and targeting SDG13. Exclusion criteria ruled out studies, not directly addressing AI in the context of climate change, mitigation, and adaptation with a special focus on SDG13 targets. Key information was extracted after identifying and selecting relevant articles, including the authors, publication year, research methods, and primary findings. This data was synthesized to generate insights into trends, patterns, and implications within the field. The quality of each study was evaluated based on its methodology, relevancy, and contributions to understanding AI and the climate resilience domain. The study particularly focused on and attempted to answer the following research questions (RQs):

RQ1: How is AI currently being applied to enhance climate resilience?

RQ2: What impact does AI have on achieving the targets of SDG 13?

RQ3: What are the key challenges and limitations in deploying AI for climate resilience?

To find out the answer to the above questions, documents such as research papers, reports, websites content on AI intervention related to climate action have been explored and analyzed using bibliometric and content analysis technique. In addition, we conducted interviews with some of the experts working in AI and climate change domain. The views of these experts were instrumental in complementing the findings of this study.

2.1 Publication trend and analysis

Temporal patterns in AI research for climate resilience

As per the studies (n=625) extracted mainly from the Scopus database, AI inclusion in SDG 13 has gained momentum only in the last decade. Figure 3 reflects a growing trend from 2015 (post adoption of the SDGs by UN in 2015), with a particularly sharp increase starting in 2021 and peaking in 2024. This suggests a substantial rise in interest, and research activity in the field over the past few years distribution of the studies' publication years, spanning from 2014 to 2024.

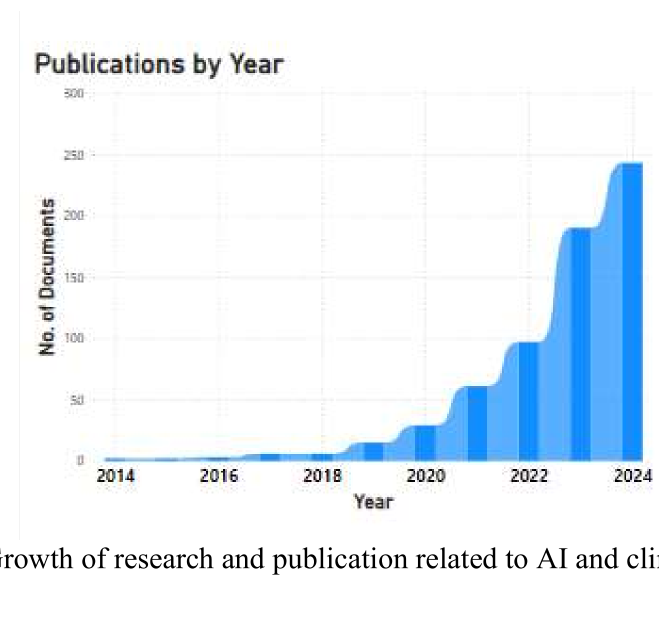

Figure 3. Growth of research and publication related to AI and climate resilience

Top contributors to AI research for climate resilience

Among the top countries which are actively publishing on AI for climate resilience include the United States, China, India, Germany, and the United Kingdom (Figure 4) which have shown significant global engagement in producing documents on related areas. The United States is leading the way with (n=132) documents. China and India follow closely, with n=106 and n=86 documents, respectively, thereby underscoring their significant role in global research and policymaking, particularly in AI technology and climate action. European nations, such as Germany and the United Kingdom also show strong contributions, with 73 and 63 documents, reflecting their established research capacities and active participation in international discussions. Other countries like Italy, Australia, Canada, the Netherlands, and Sweden, also contribute substantial documents and demonstrate meaningful involvement, thereby suggesting a broad global interest. The diversity in document production across these countries indicates not only leadership from the major players but also the potential for international collaboration, especially in advancing global priorities such as sustainability and technological innovation. This distribution of document production emphasizes the varied yet interconnected roles various nations can play in shaping the global discourse and policies in these critical areas.

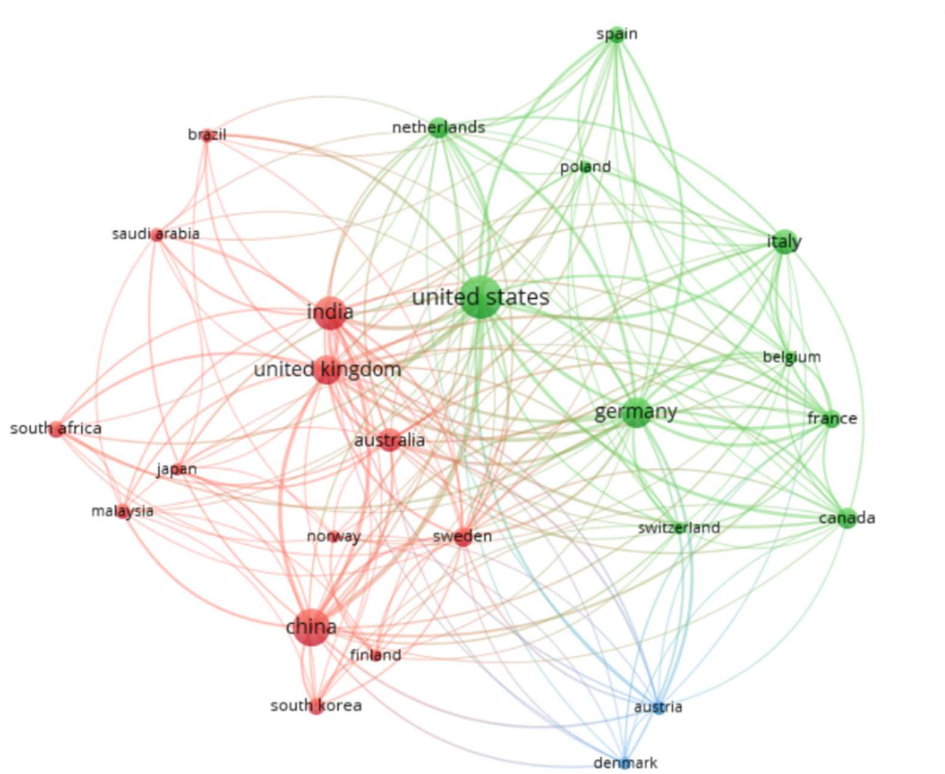

Figure 4. Region-wise publications and collaborations between different countries on AI for climate resilience

Prominent concepts from the publications

The publication statistics also reveal that the topics of climate change, machine learning, artificial intelligence, deep learning, forecasting, mitigation, climate modelling, and sustainable development are much-researched areas as far as the last decade is concerned. The bibliometric and content analysis was done using VOSviewer version 1.6.20. The co-occurrence keyword threshold was taken as 15 as shown in Figure 5.

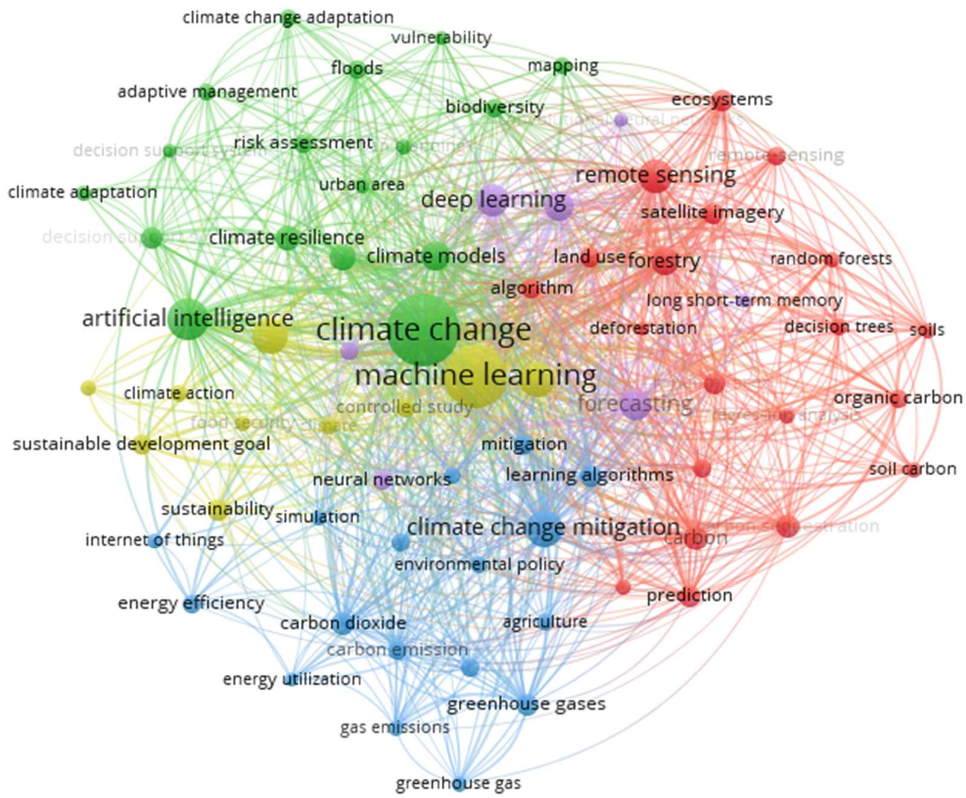

Figure 5. Keyword analysis displaying network visualization using VOSviewer

3. Application of AI for Climate Action

The UN-led AI Advisory Body represents a pivotal moment in the global effort to harness AI for addressing environmental challenges, underscoring the growing recognition of AI's potential in this field (UN, 2023). AI is transforming climate action by providing advanced tools that boost mitigation and adaptation efforts by analysing complex datasets, simulating future scenarios, and offering actionable insights to policymakers and practitioners (Bengio et al., 2021). A report by Boston Consulting Group (BCG) mentions the importance of AI in the reduction of emissions and the effects of greenhouse gases (GHGs) (Maher et al., 2022) , and analyses that GHG emissions can be reduced by 2.6–5.3 gigatons of carbon dioxide equivalent

(CO2e) using AI (Degot et al., 2021). AI is already making a considerable impact across the key areas of climate action, including natural disaster response, climate modelling, climate-smart agriculture, energy efficiency, etc., while demonstrating its critical role in tackling the multifaceted challenges of climate change.

3.1. AI in weather and climate modelling

Traditional climate models rely on complex equations and significant computational power to simulate future climate scenarios (Porwal et al., 2024). This takes a lot of time and energy and seems relatively inefficient in the present-day scenario, where AL/ML methodologies are efficient at analysing future scenarios and have been employed to enhance the accuracy and efficiency of traditional climate models. For instance, Reichstein et al. (2019) highlight the potential of AI to improve Earth system models by learning from vast amounts of data, enabling better predictions of climate variability and change, while ensuring consumption of significantly less energy. In managing extreme weather events, AI systems analyse meteorological data to predict the path and impact of hurricanes, floods, and wildfires, thereby enabling better emergency preparedness and response (Scher et al., 2019; Varshney, 2019). For instance, deep learning models have been employed to improve the fine-scale prediction of climate change by leveraging techniques like super-resolution mapping and recurrent neural networks (RNNs) to refine spatial dependencies and temporal dynamics (Deep & Verma, 2024). Additionally, the emergence of AI foundation models, which draw from advances in transformer models and physics-informed machine learning, are poised to generalize across multiple climate modelling tasks, improving accuracy in predictions for phenomena, such as hurricanes and atmospheric rivers (Mukkavilli et al., 2023). However, the rapid adoption of AI also introduces new vulnerabilities, including the risk of adversarial attacks that could distort climate projections, necessitating robust defences and ethical considerations (Calengor et al., 2024). AI also plays a crucial role in climate intervention analysis, such as optimizing techniques like Marine Cloud Brightening to meet regional climate targets while preventing tipping points, underscoring AI's potential in large-scale environmental management (Kramea et al., 2023). As AI continues to evolve, its applications in climate science will likely expand, offering new pathways for climate prediction and intervention.

A US-based non-profit AI research company called Ai2 believes that ML and modern programming languages can improve climate models and could provide projections of local trends of average and extreme weather events like heatwaves and extreme precipitation (Climate Modeling., 2024. In another study (Agrawal et al., 2019) used a machine learning method called U-Nets, which is a type of convolutional neural network (CNN), for precipitation nowcasting (short-term high-resolution predictions) from radar images and concluded that the ML approach can outperform the traditional numerical methods. The CNN model is a better alternative to dynamical forecast systems for predicting the detailed zonal distribution of sea surface temperatures (Ham et al., 2019). Thus, El Niño Southern Oscillation (ENSO) events can be better predicted which can further help prepare for extreme events across various regions. According to a report by the Met Office (Artificial Intelligence for Numerical Weather Prediction, 2022), AI is the way forward for efficient weather prediction. ML weather models like Pangu-Weather (Bi et al., 2022), GraphCast (Lam et al., 2022), and FourCastNet (Pathak et al., 2022) have advanced in forecasting weather conditions. It was also mentioned in their reports that ML models are more efficient and less expensive as compared to physics-based simulators.

GraphCast is an emerging machine-learning weather prediction model developed by Google DeepMind, which is more efficient than traditional weather prediction methods. It can be re-trained with recent data which will enable to capture of weather patterns (Lam et al., 2023), thereby improving the overall performance of GraphCast. Pangu-Weather is a deep learning-based model developed by Huawei that exhibits better short- to medium-range forecasts and extreme weather forecasts, such as tracking of tropical cyclones. The study by Bi et al. (2022) predicted typhoons (occurred previously) using the Pangu-Weatherm model. They compared the results with ECMWF-HRES and concluded that Pangu-Weather exhibited a much higher deterministic forecast with better accuracy (Figure 6). Fourier Forecasting Neural Network, also known as FourCastNet, is a deep-learning weather forecasting model that helps in short- to medium-range weather forecasting. It can generate a week-long prediction in seconds. Pathak et al., (2022) concluded that FourCastNet model was able to forecast hurricanes in the Atlantic Ocean and make landfall on the eastern coast of North America. They also stated that FourCastNet is about 45000 times more efficient than a traditional numerical weather prediction (NWP) model, making it a better choice for ensemble forecasting. The report concluded that the FourCastNet model was able to forecast the hurricanes in the Atlantic Ocean and make landfall in the eastern coast of North America. They also stated that FourCastNet is about 45,000 times more efficient than a traditional numerical weather prediction (NWP) model, making it a better choice for ensemble forecasting (Pathak et al., 2022).

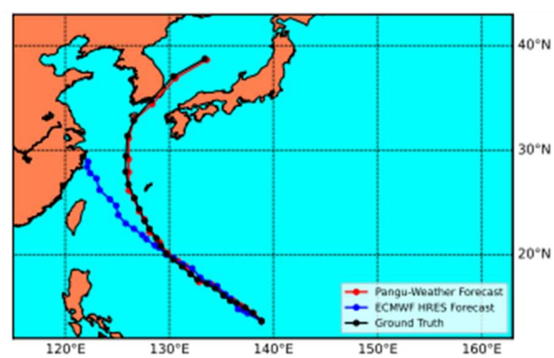

Figure 6. Forecast for Typhoon Kong-rey (30-09-2018) at 00UTC by Pangu-Weather model (red), ECMWF HRES model (blue) and the actual track (black) (Bi et al., 2022)

NASA and IBM have collaborated and come up with a new AI foundation model for weather and climate called 'Prithvi-weather-climate' which will be available later in 2024. The model is pre-trained using 40 years of weather and climate data from NASA's Modern-Era Retrospective analysis for Research and Applications (MERRA-2) (Blumenfeld, 2024). This can improve the resolution and analyse regional and local weather and climate conditions.

3.2. AI in early warning systems

Early warning systems (EWS) are crucial for building climate resilience, particularly in vulnerable regions. AI-powered systems can analyse meteorological data in real-time to predict extreme weather events, such as hurricanes, floods, and droughts. For example, Lavers et al. (2020) demonstrated the use of AI in improving flood forecasting accuracy by integrating machine learning models with hydrological data. These AI-driven early warning systems can warn local communities about imminent disasters, thereby reducing the adverse effects of climate-related disasters. For instance, in Mozambique, the biosphere reserves use AI to predict and analyse flooding trends (UNFCCC, 2023). AI methods like Gradient Boost (GB) classifier selects the best features for predicting floods, and the random forest (RF) method is efficient in validating the onset of floods (Torky et al., 2023). Le Jian et al. (2023) in their study predicted emergency department attendances (EDAs) using risk factors, such as air pollutants, heatwaves, landscape fires, and socioeconomic status (SES) with the help of machine learning methods like random forest (RF), decision tree (DT), and geographical random forest (GRF). The study by Youssef et al. (2023) found that the RF model was most accurate in predicting floods in the Hasher-Fayfa Basin, Saudi Arabia. The Support Vector Machine (SVM) algorithm captures spatiotemporal characteristics to predict droughts in Pakistan (Khan et al., 2020) better than the k-Nearest Neighbour (KNN). Zhang et al. (2022) analysed flash droughts in China using ML techniques, namely, multiple linear regression (MLR), long short-term memory, (LSTM) and random forest (RF), and concluded that these ML methods showed valuable insights about flash droughts and monitoring.

3.3. Renewable energy forecasting and smart grid management

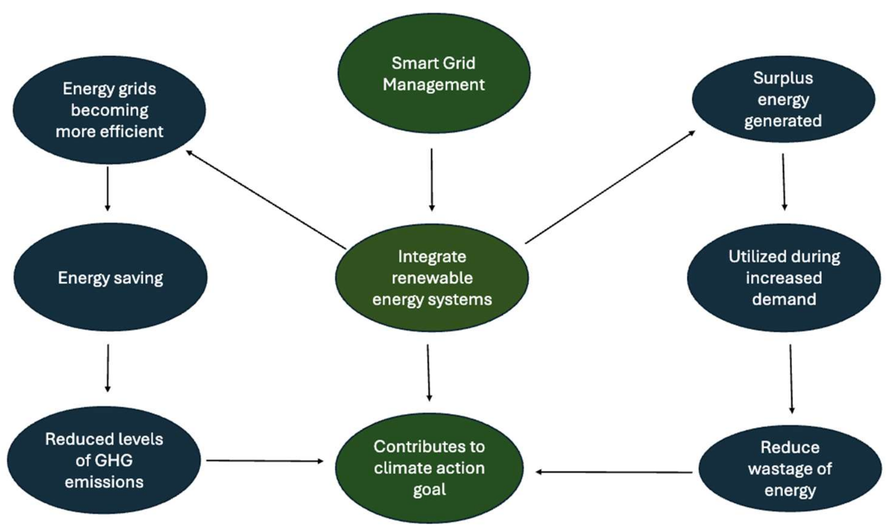

Figure 7. Representation of how renewable energy forecasting and smart grid management can help achieve climate action goals

AI applications in renewable energy forecasting and smart grid management are crucial to achieve energy efficiency and improving system reliability (Figure 7). Renewable energy is considered as a cleaner alternative to fossil fuels and can increase the capacity of the electric energy systems (Wang et al., 2019). Prediction of renewable energy like solar and wind is very important for grid-effective energy management. ML and DL algorithms like regression models, neural networks, and SVM are efficient in understanding long-term patterns and relationships among variables. Spatial forecasting for renewable energy can be done for multiple locations and temporal forecasting can forecast renewable energy over various periods. Choosing a potential site for installing RE plants is crucial for efficient production of electricity and other forms of energy on the grids. Some AI methods can help with the tilt angles of solar panels to trace the movement of the sun for efficient use of solar energy (Ukoba et al, 2024). A report by REN21 (2020) stated that global GHG emissions in 2019 were stabilized where energy efficiency along with renewables was the main contributor. The Infosys report by Dash (2024) also stated that in Germany, an ML-based early warning system is used to take real-time data from wind turbines and solar panels to predict the energy that will be generated in the following 2 days. Rockwell Automation developed an AI-based system for a battery manufacturer to identify the solar panels causing massive losses and further notify users of maintenance requirements. This also helps in real-time energy data monitoring. They have achieved about 35% increased uptime for solar operations and reduced manpower service by 50% (Rockwell Automation, 2023).

Integrating renewable energy into power grids can promote the use of clean energy. Moreover, the application of AI in grids can help achieve smart grid management (Integrating Renewable Energy Sources into Grids | McKinsey). Figure 7 shows how integrating renewable energy and grid management can help achieve climate action. The major benefit of smart grids is that one can save a great deal on electricity as it can help manage electricity use and allow choosing the best times to buy electricity. Consider a scenario where the solar farm can generate excess energy. The surplus energy can be distributed into a smart grid, which can be used during increased demand. This can be a solution for energy shortage in the future. This contributes to energy grids becoming more energy efficient and reducing the emissions of GHGs. Further, installing smart meters at homes can collect and analyze the energy consumption data (Yussuf et al., 2024). Rockwell Automation has implemented a real-time energy monitoring and alerting system for tracking energy losses occurring within the global textile and carpet manufacturing plants. They have saved about 4.5% on the annual energy bill and reduced 12% on energy due to inefficiencies in the equipment. They have successfully implemented energy forecasting and managing workflow by creating alerts and notifications when abnormalities are detected (Rockwell Automation, 2023).

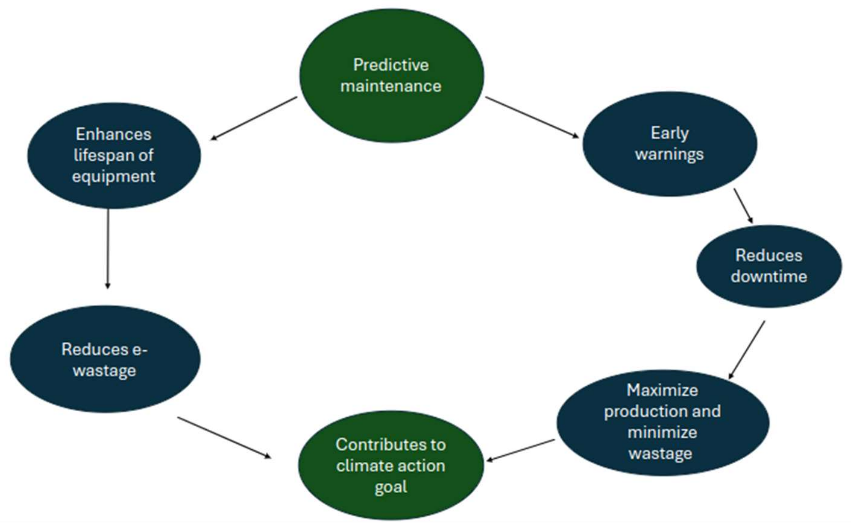

Figure 8. Representation of how smart predictive maintenance can help achieve climate action goals

AI has significant application in predictive maintenance which helps detect failures and faults even before they occur. Figure 8 shows how predictive maintenance can help achieve climate action. For instance, the faults and failures can be predicted by using 'fault detection'. AI can reduce downtime and maximize energy output, ensuring optimal performance and longevity of the renewable infrastructure. Moreover, AI can aid in limitations related to manual inspection which involves risk of life for the inspectors (Chen et al., 2023).

Further, incorporating AI in predictive maintenance for solar and wind turbines helps in the effective utilization of renewable energy, thereby increasing demand for installation, which can significantly help achieve a reduction in carbon footprint. Amazon Web Services (AWS) has designed a tool called 'Amazon Monitron' which specializes in predictive maintenance with the help of machine learning. This tool has the advantage of easy monitoring of any industrial equipment in minutes and can detect faults in rotating systems like exhaust fans, pumps, motors, and others. The trends can be detected through an application on the phone by technicians (Amazon Web Services [AWS], 2024). The operational efficiency in Baxter improved significantly as they saved about 500 machine hours of downtime using Amazon Monitron (AWS case study, 2024). Further, in the oil and gas industry, the model can assess the drilling equipment to reduce environmental hazards and ensure safety of the workers (Canda, 2024). Therefore, with the application of machine learning in predictive maintenance, the lifespan of the equipment will increase, which will further reduce wastage, prevent degradation of the environment, and contribute to climate action goal.

3.4. Carbon sequestration and storage

Carbon is one of the dangerous GHGs that gets released into the environment especially due to unchecked human activities. Capturing carbon from the atmosphere is an initiative to combat climate change (Priya et al., 2023) and to achieve net-zero target. The study also emphasized the fact that the ML methods can effectively help capture carbon dioxide (CO2). A study by the School of Chemistry and Chemical Engineering at the University of Surrey concluded that the carbon capture systems were able to capture 16.7% more CO_2 by using 36.3% less energy from UK's national grid with the use of AI and ML algorithms (Fisher et al., 2024). AI-enabled carbon capture in mitigating climate change helps achieve climate action targets (SDG 13) by optimizing real-time capturing of CO_2 (Priya et al., 2023).

Rockwell Automation provides a product called 'carbon footprint monitoring' and reporting to achieve the net-zero target. This helps track emissions and gives an idea of areas that need reduction. Further, it improves sustainability performance and provides financial benefits. They have managed to achieve a 50% reduction in comparison to manual monitoring. (Rockwell Automation, 2024). A London-based company called Mortar IO focuses on decarbonizing buildings using AI to digitize and plan carbon reduction for buildings with immediate effect (Google blogs, 2023). Moreover, adopting AI can reduce carbon emissions by 8% to 19% by 2050 (Ding et al., 2024).

Energy efficiency translates to reducing energy costs and emission footprint. The goal of energy efficiency is to provide similar or enhanced services using less energy. This energy resource can help us achieve decarbonization and net-zero targets (Energy Efficiency | Understand Energy Learning Hub, n.d.). A study by Merabet et al. (2021) stated that the application of AI techniques in Heating, Ventilation, and Air-Conditioning (HVAC) installations has saved energy on an average between 21.81% and 44.36% and improved comfort between 21.67% and 85.77%. In this study, the application of AI has been discussed in achieving energy efficiency through renewable energy forecasting, smart grid management, predictive maintenance, and carbon capture and storage.

3.5. Precision agriculture

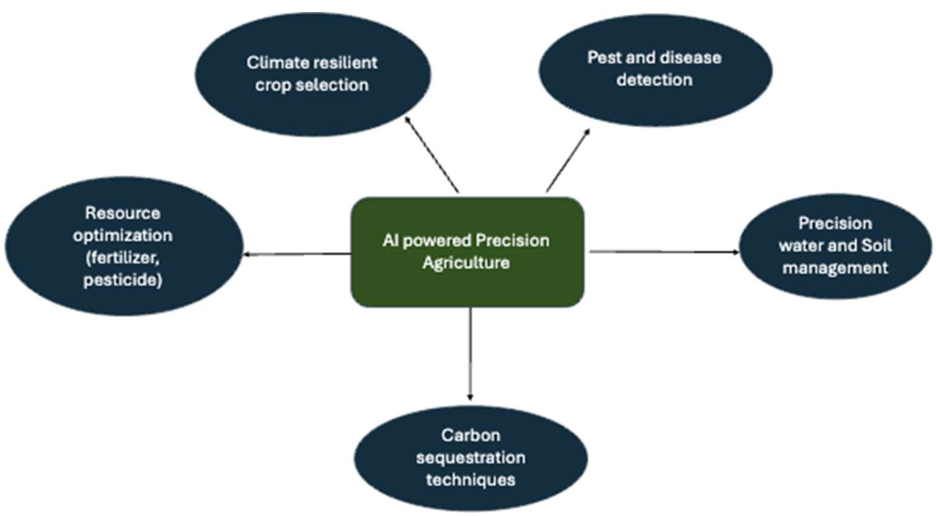

Figure 9. AI powered Precision Agriculture

AI adoption in farming is on the rise, with Statista predicting that the global AI agriculture market will expand to $2.6 billion by 2025. AI in agriculture enhances resource efficiency, thereby reducing the environmental footprint of farming activities through areas like pest and disease detection, precision water, and soil management, crop classification and carbon sequestration as given in Figure 9. Raji E (2024) in his study highlights the role of data-driven decision-making in enhancing agriculture practices with the help of remote sensing, IoT sensors, historical records, climate data, and crop performance metrics.

According to the Food and Agriculture Organization (FAO), precision agriculture technologies, including AI, have the potential to increase global crop yields by up to 20%. AI-driven precision agriculture has been shown to reduce water usage by up to 30% while increasing crop yields by 10-15% (Penubelli, 2024). Similarly, AI-guided precision sowing improves crop emergence rates by 15% (Avalekar & Patil, 2024) and boosts agricultural productivity by 12% (Javaid, 2024), optimizing land use and reducing the pressure to convert natural habitats into farmland.

Moreover, AI's role in herbicide application has led to more targeted and efficient use of chemicals, significantly reducing their environmental impact. Technologies like See & Spray™, which use computer vision and machine learning to target weeds, can reduce herbicide usage by up to 77% (Mississippi State University Extension, 2022). This not only minimizes soil and water contamination but also lowers GHG emissions from chemical production and application.

Studies highlighted that disease classification from images can be done using Convolutional Neural Network (CNN) architectures for different plants with different diseases (Mohanty et al., 2016); with image recognition technique (Automated AI integrated vehicles and robots) weed and pest from crops can be located and destroyed (Garske, Bau, & Ekardt, 2021) ; relationships between weather data and pest occurrence can be retrieved using long short-term memory (LSTM) networks for forecasting future pest attacks (Xiao et al., 2019; Domingues et al., 2022). In the realm of disease management, hyperspectral imaging and 3D laser scanning—AI-powered technologies—collect precise data on crop health, enabling better monitoring and decision-making. These tools, along with biosensors that monitor soil moisture and fertility, enhance the efficiency of resource usage and reduce the environmental impact of farming operations (Javed et al., 2023).

As per a study by Márquez (2024), the use of artificial intelligence (AI) to guide herbicide application led to a 40 % decrease in the amount of weed biomass can be achieved by AI use AI in comparison to traditional method of human spraying (Padhiary 2024)

AI-driven innovations in agriculture not only optimize resource use but also enhance resilience to climate change. By enabling early detection of pests and diseases, optimizing irrigation, and improving overall farm management, AI supports more sustainable agricultural practices that align with SDG 13 targets. While AI in agriculture is still in its early stages and faces challenges like the need for extensive training data, its potential to transform agriculture into a more adaptive and sustainable industry is undeniable.

3.6. Climate finance and policies integration

As per a study, despite the Paris Agreement's goal of $100 billion annually in climate finance, public contributions in 2019 reached only $65.5 billion (Toetzke, 2022), highlighting a funding gap. AI can play a pivotal role in addressing this gap by enhancing predictive analytics, optimizing investments, and improving climate risk assessments, thereby making climate finance more efficient (Zhao, 2024).

AI and machine learning applications streamline investment decisions by improving carbon price forecasts, optimizing energy costs, and enhancing data-driven strategies for mitigation and adaptation (Akter, 2024). These technologies have redirected billions toward sustainable projects. For example, a Bidirectional Encoder Representations from Transformers (BERT)-based model fine-tuned with climate data achieved 90% accuracy, showcasing AI's potential for societal impact (Toetzke et al., 2022). Platforms like BlackRock's Aladdin Climate leverage AI to assess climate risks and opportunities in investment portfolios, guiding capital toward resilient, low-carbon initiatives (Elias, 2024).

AI not only enhances climate risk assessments but also prioritizes green investments over carbon-intensive assets, driving sustainable financial returns and uncovering high-potential, underfunded areas for investment. By leveraging AI for risk assessment and optimizing investments, governments and organizations can create more effective green financial instruments and adaptive policies and can ensure transparent, efficient allocation of funds, support the enforcement of climate regulations, and accelerate the transition to a sustainable, low-carbon economy.

Table-1: Framework for AI-Enhanced Climate Resilience: Aligning Technological Innovation with SDG 13 Goals

Area	**Technologies listed**	**AI/ML methods**	**Existing Studies**	**Overall impact**	**SDG 13 Target**
Weather, Climate and Early Warning Systems	Pangu-Weather, FourCastNet, GraphCast, Google's AI-driven flood prediction system,	Deep neural networks, Long Short-Term Memory networks (LSTMs), Convolutional Neural Network (CNN)	1. LSTM showed higher skills at predicting floods as compared to the linear model (Nevo et al., 2022). 2. Deep learning methods used in weather forecasting methods are relatively more efficient than numerical models (Pathak et al., 2022, Bi et al, 2022, Lam et al, 2023)	Over 100000000 flood alerts were sent to flood affected areas in India and Bangladesh's disaster reliefs. Accurate weather forecasts can be made in relatively less time. Helps in early warning and timely dissemination of disaster relief to reduce loss of life.	Target 13.1
Agriculture	See & Spray™, (Blue River technology, Climate-Smart Agriculture (CSA)	Internet of Things (IoT) and blockchain	1. Blue river technology is the new approach to precision agriculture. It detects unwanted weed through computer vision and artificial intelligence and spraying the herbicide through robotic nozzles. 2. IoT can help monitor agricultural fields and can be tracked on smart devices (Ahmed et al., 2022).	Reduce herbicide usage by up to 77% Provide better control and management in supply-chain networks which can reduce wastage and channel supply to scarce regions	Target 13.2

Energy	Amazon Monitron, AI-enabled carbon capture and storage (CSS), Smart grids	Deep Belief Network, Stack Auto-Encoder, Recurrent Neural Network (RNN)	1. With the integration of AI and ML methods, carbon capture systems can capture relatively more CO2 by using less energy form UK's national grid (Fisher et al., 2024). 2. Integration of ML techniques in HVAC systems can save energy between 21.81 and 44.36% (Halhoul Merabet et al., 2021) 3. Electricity demand can be predicted by analyzing temperature trends (De Felice et al., 2015).	Alerts faults and failures in machinery and reduces unplanned equipment downtime with predictive maintenance. This helps in reducing GHG emissions. Carbon capture has become more efficient with the integration of AI and ML. There is a significant saving of energy in HVAC systems which helps in reducing GHG emissions. Efficient use of renewable energy can help in reducing GHG emissions. AI has the potential to reduce energy consumption in buildings by 30-50%. AI can help reduce carbon emissions by 8-19% by the year 2050.	Target 13.2
Climate Finance		Large Language Model (LLM), Natural Language	1. Monitoring climate technologies is very crucial and can be regarded as the central idea to achieving net-zero emissions as well as in policy making (Toetzke et al., 2023).	Stakeholders can engage with data and explore various policy scenarios effectively. Enhancing decision-making in the public sector including environmental policy and climate	Target 13.2, Target 13.a and Target 13.3

		Processing (NLP)	2. Exploration of scientific texts can be efficiently done with the help of NLP. This would provide deeper insights for policymakers, environmentalists and engineers (Mallick et al., 2024).	change. Enhanced predictive analytics and optimized investments make climate finance more efficient.	
Capacity Building	Chatbots, Virtual assistants.		1. AI can provide opportunities to perform efficient data analysis (Altinay et al., 2024). 2. For effective use of climate intervention technologies, capacity building is required (Dove et al., 2024) .	Enhanced capacity of AI-based research in environmental institutions. Community level capacity building in developing countries.	Target 13.3 and Target 13.b

The above framework (Table 1) illustrates the significant role AI technologies play in enhancing climate resilience, particularly in alignment with SDG 13 (Climate Action). The table categorizes AI's impact across various sectors, providing metrics and examples to demonstrate how AI improves climate predictions, reduces greenhouse gas emissions, enhances disaster response times, supports policy integration and more.

4. Challenges and Ethical Considerations

The inclusion of artificial intelligence and machine learning has brought transformative change (Mishra, 2023) but it also faces significant challenges across technical, social, ethical, and governance areas. Given below are some of the key challenges for consideration:

Interoperability of AI models is one of the main challenges and function as "black boxes," making it difficult for stakeholders to trust and fully understand the decision-making processes behind AI-driven climate solutions (Linardatos et al., 2020). Additionally, integrating AI into climate policy remains problematic, as policymakers could struggle to interpret complex models, leading to a gap between technological advancements and regulatory frameworks (Dwivedi et al., 2021).

One significant ethical worry is that AI could reinforce and widen biases that already exist. For instance, AI models trained on historical data may reinforce discrimination, neglecting certain communities or types of infrastructure (Brendel et al., 2021). To prevent this, it is important to carefully select and pre-process data, as well as monitor AI outputs for biases or errors.

Moreover, AI-powered climate adaptation strategies may unintentionally harm vulnerable communities, such as through gentrification or displacement. Engaging these communities in the development and implementation of such strategies is vital to ensure that their concerns and needs are addressed (Bartmann, 2022).).

Further, the computational demands of AI-based systems require large amounts of energy for data processing and cooling data centres, contributing significantly to global energy consumption. Studies show that training complex algorithms can produce substantial carbon emissions, and by 2030, computing could account for up to 8% of the world's energy demand (Hao, 2020; IEA, 2022; Bacchi, 2020). This raises concerns about the environmental impact and reliance on fossil fuels. (Chaudhary, 2023)

On the downside, AI's application in industries such as oil and gas has facilitated the optimization of fossil fuel extraction, which is in direct conflict with efforts to reduce GHG emissions and achieve climate targets (Kaack et al., 2022). Moreover, major technology companies, including Google and Microsoft, have faced criticism for their partnerships with fossil fuel industries, raising questions on corporate accountability in AI’s role in climate action (Greenpeace Reports, 2020).

High cost of the technology also hampers the process of AI integration in Climate research areas. For example, renewable energy sources can be excellent alternatives to fossil fuels, but they can be expensive to install as compared to regular energy sources and generators (Thoubboron, 2022).

Another significant impediment towards using AI-enabled CHG emissions data might be the Sovereignty concerns. There might be objections to foreign monitoring by some countries for analysis of emissions within their respective sovereign territories. Independent verification of international consensus and global GHG emissions data regarding accuracy of AI-enabled analyses would be required in realizing the potential of AI tools' benefits in monitoring GHG emissions. (Sandalow, 2023)

Lack of community focused intervention is another concern which needs to be addressed urgently. A study by WRI revealed that out of 374 community focused interventions, only around 6% incorporated local-led components, which is a very small proportion (Wright, 2023).

Lack of technical infrastructure and expertise in certain regions is another challenge which might further intensify inequalities in the global implementation of AI for climate resilience.

To address these challenges and disadvantages, ongoing adaptation of AI models is crucial to ensure they remain relevant in the face of evolving climate dynamics. Ethical considerations, including data privacy, transparency, and fairness, must be integrated into the development and deployment of AI technologies to build public trust and avoid unintended consequences (McGovern et al., 2022). Additionally, improving data quality and standardization is essential for generating reliable AI-driven insights from diverse climate data sources (Cheval et al., 2020). By addressing these technical and ethical challenges, AI can be effectively leveraged to support global climate resilience efforts while minimizing risks (Hamdan et al., 2024).

5. Future Directions and Recommendations

AI certainly offers promising opportunities across mitigation and adaptation strategies, and it is a powerful tool for addressing climate change, but with caution. Given below are some key future directions, integrating recommendations, and opportunities for leveraging AI technologies to enrich climate resilience and contribute to SDG 13.

5.1. Enhanced modelling and prediction

The enhancement of climate models and prediction capabilities is one of the most significant advancements in climate research. These days, AI-driven models offer exceptional accuracy by integrating vast datasets from satellites, IoT sensors, and historical climate records (Olawade et al.,2024).

Quantum AI (QAI) further revolutionizes these models by enabling faster and more efficient simulations of extreme weather events and long-term climate patterns, leading to timely interventions. QAI is instrumental in developing climate strategies that leverage high-resolution scientific data (Schneider, 2023).

5.2. Ethical considerations

The ethical application of AI for climate action is about ensuring fairness, transparency, and accountability. Bias mitigation is essential to prevent AI models from producing outcomes that can disproportionately affect the marginalized communities. For example, in hurricane damage assessments, AI frameworks can provide accurate, unbiased predictions to ensure fair resource allocation (Singh, et al 2024).

Another crucial direction is the development of Explainable AI (XAI), which aims to improve transparency by making complex AI models more interpretable and understandable to stakeholders (Bolón-Canedo, 2024). XAI ensures that AI systems can explain their predictions in ways that are comprehensible to humans, thereby helping to retain and strengthen public trust (Gunning et al., 2019; Arrieta et al., 2020). As AI increasingly influences critical decisions, explainability, interpretability, and accountability are vital components that must be embedded within these systems (Atzmueller, 2024).

5.3. Global data sharing, standardization, and cross-disciplinary collaboration

It is crucial to enhance standards and global data sharing, where AI facilitates the seamless exchange of climate data across borders, enabling coordinated global efforts. This is especially vital for regions like Africa and Asia, which are more vulnerable to climate impacts and could benefit from enhanced technology transfer and collaboration (Srivastava & Maity, 2023). Collaboration between countries, academia, industry, governments, and civil society can foster knowledge sharing, data exchange, and joint research effort.

5.4. Equity-focused solutions

Vulnerability assessment using AI models helps identify at-risk populations and predicts how extreme events like hurricanes will affect specific areas and supports faster recovery and better resource allocation (Singh & Hoskere, 2024). Equity-focused solutions driven by AI should prioritize regions disproportionately affected by climate change, ensuring that climate finance reaches vulnerable populations along with adequate support. AI can identify areas which are more vulnerable to flooding and erosion, thereby allowing stakeholders to take proactive measures, such as building sea walls, relocating vulnerable infrastructure, or implementing zoning regulations to reduce risk (Jain et al., 2023; Yousef, 2023). This ensures that investments are directed toward the most vulnerable regions and sectors, maximizing their effectiveness (Pinner et al., 2020).

5.5. Policy and regulatory support

A comprehensive policy framework and supportive regulation must be devised to promote the ethical and responsible use of AI in climate solutions. To best align the use of AI with climate change mitigation and adaptation pathways, Governments and international organizations can play an important role and should focus on data governance, privacy protection, algorithmic transparency, and standards for AI in climate applications (Mehrabi et al., 2021, Olawade et al., 2024). Policymakers can revitalize investment, encourage research and development by providing a conducive regulatory environment.

5.6. Skill development and education

Skill development and promoting education on AI for climate applications are essential to unlock its full potential. Various kinds of training programs should be developed to not only equip individuals, organizations, and communities with the necessary skills but also encourage capacity-building efforts, thereby focusing on diverse stakeholders, including policymakers, scientists, engineers, and practitioners to foster a multidisciplinary approach. By enhancing AI literacy and technical skills, stakeholders can effectively leverage AI tools and technologies for climate change mitigation and adaptation (Filho et al., 2022, Olawade et al., 2024).

6. Conclusion

The present study has explored various trends and the diverse applications of AI in climate resilience and how these technologies are playing a significant role in achieving SDG 13 targets. The study focused on three major areas: (1) weather and climate modelling (for better forecasts and taking better adaptation measures to minimize loss of life), (2) energy efficiency (for taking climate mitigation measures), and (3) agriculture (to avoid wastage of natural resources and being resilient to climate change). The findings determine that AI technologies have tremendous potential to address the multifaceted challenges posed by climate change, contributing significantly to both mitigation and adaptation efforts. From improving the accuracy of climate modelling and predictions to enhancing disaster risk management systems and optimizing renewable energy usage, AI is proving to be a critical enabler of climate action. The integration of AI in climate resilience efforts presents opportunities for both innovation and collaboration in climate research AI-driven solutions, such as early warning systems and smart grids are already transforming industries, making them more adaptive to climate risks. Moreover, AI's role in remote sensing, carbon capture, and resource management is helping to create sustainable ecosystems, reduce GHG emissions, and foster long-term environmental monitoring. With the help of AI tools, developed countries can ensure an equal distribution of climate-related funds to vulnerable areas, and further create a strong decision-making support system. Further, there is a need to give major attention to skill development and capacity building in organizations to realize the goal of a sustainable future. Technology advancement is another area where AI technology players can play a big role in achieving climate resilience.

Study highlights that AI acts as a facilitator in achieving SDG 13 targets, however, the application of AI must be approached with ethical considerations in mind, particularly in ensuring transparency, accountability, and fairness. Addressing issues, such as AI bias and equitable access to technology will be critical in ensuring that the benefits of AI are shared across regions, especially in developing countries, which are often the most vulnerable to climate change impacts.

In conclusion, AI's role in achieving SDG 13 is indispensable. While current advancements are promising, future research and collaborative efforts are essential to fully harness AI's potential.

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