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REVIEW

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AI-enabled strategies for climate change adaptation: protecting communities, infrastructure, and businesses from the impacts of climate change

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Abstract

Climate change is one of the most pressing global challenges we face today. The impacts of rising temperatures, sea levels, and extreme weather events are already being felt around the world and are only expected to worsen in the coming years. To mitigate and adapt to these impacts, we need innovative, data-driven solutions. Artificial intelligence (AI) has emerged as a promising tool for climate change adaptation, offering a range of capabilities that can help identify vulnerable areas, simulate future climate scenarios, and assess risks and opportunities for businesses and infrastructure. With the ability to analyze large volumes of data from climate models, satellite imagery, and other sources, AI can provide valuable insights that can inform decision-making and help us prepare for the impacts of climate change. However, the use of AI in climate change adaptation also raises important ethical considerations and potential biases that must be addressed. As we continue to develop and deploy these solutions, it is crucial to ensure that they are transparent, fair, and equitable. In this context, this article explores the latest innovations and future directions in AI-enabled climate change adaptation strategies, highlighting both the potential benefits and the ethical considerations that must be considered. By harnessing the power of AI for climate change adaptation, we can work towards a more resilient, sustainable, and equitable future for all.

Keywords Artificial Intelligence, AI-powered models, Climate change adaptation, Early warning systems, Climate modeling and projections

1 Introduction

Climate change is one of the most pressing global issues of our time, and its impacts are already being felt around the world. As climate change continues to worsen, it is critical that communities, businesses, and governments take proactive steps to adapt and protect themselves from its effects. One powerful tool that can be used for this purpose is artificial intelligence (AI) (Hötte & Jee, 2022; Sharifi & Khavarian-Garmsir, 2023). This review article explores the potential of AI-enabled strategies for climate change adaptation, focusing on how they can help protect communities, infrastructure, and businesses from the impacts of climate change. Climate change is a global challenge that requires urgent and effective action

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to mitigate its impacts and adapt to the changes already underway (Hoque et al., 2022). One of the most pressing issues is the need to protect communities, infrastructure, and businesses from the effects of climate change, such as extreme weather events, sea-level rise, and droughts. In recent years, artificial intelligence (AI) has emerged as a powerful tool that can help address these challenges by enabling the development of innovative strategies for climate change adaptation. Climate change poses complex and multifaceted challenges that require innovative and adaptive strategies for effective mitigation and adaptation. AI has emerged as a powerful tool that can help address these challenges by enabling the development of innovative strategies for climate change adaptation. AI can assist in the identification of areas that are at high risk of climate-related hazards, the development of adaptation strategies for businesses and communities, the prediction of floods and wildfires, and the identification of areas at risk of landslides (Rutenberg et al., 2021). Furthermore, AI-powered climate modeling and projection systems can help policymakers and stakeholders anticipate the impacts of climate change and design effective mitigation and adaptation strategies. AI can also help in the development of early warning systems that can alert communities to impending disasters, providing them with crucial time to prepare and evacuate. However, it is crucial to address ethical considerations and potential biases associated with AI-powered climate change adaptation strategies. For example, AI systems can reflect the biases of the data used to train them, leading to unintended consequences and exacerbating existing inequalities. To ensure that AI-powered climate change adaptation strategies are inclusive, transparent, and beneficial to all, it is essential to consider the ethical implications of their development and implementation. By doing so, we can harness the power of AI to develop effective and equitable strategies for climate change adaptation. (Leal Filho et al., 2022; Griffin et al., 2023).

AI-enabled strategies can provide a range of benefits for climate change adaptation, including the ability to identify vulnerable areas and develop plans for protecting infrastructure and communities from the effects of climate change (Bag et al., 2023). For example, AI-powered sensors and drones can be used to monitor and analyze the impacts of extreme weather events in real-time, allowing for more effective response and management of the impacts. Similarly, machine learning algorithms can be used to develop predictive models for climate change impacts, enabling decision-makers to plan for the future and take proactive steps to protect communities and businesses. Moreover, AI can also be used to optimize resource use and reduce emissions, thereby mitigating the impacts of climate change (Mihiretu et al., 2023; Zhang et al., 2020). For instance, AI can be used to develop energy-efficient buildings and transportation systems, reducing carbon emissions and improving the resilience of infrastructure. AI can also help optimize energy grids, enabling the integration of renewable energy sources and reducing dependence on fossil fuels.

Despite its potential, there are also challenges associated with the use of AI for climate change adaptation (Sirmacek & Vinuesa, 2022). These include ethical and social issues, such as privacy concerns and unequal access to technology, as well as technical challenges related to data quality and interpretation. It is crucial that these challenges are addressed in the development and deployment of AI-enabled strategies for climate change adaptation. In this article, we will explore the potential of AI-enabled strategies for climate change adaptation and how they can help protect communities, infrastructure, and businesses from the impacts of climate change. We will discuss the various applications of AI in climate change adaptation, the challenges associated with its implementation, and the policy implications of its use. By providing a comprehensive overview of this topic, we hope to stimulate further research and development in this critical area of climate change mitigation and adaptation.

2 AI-enabled vulnerability assessment

One of the key benefits of AI is its ability to analyze large amounts of data quickly and accurately. This makes it an invaluable tool for identifying areas that are most vulnerable to the impacts of climate change, such as areas at risk of flooding, landslides, or drought (Nost & Colven, 2022). By using AI to analyze data such as climate models, satellite imagery, and weather patterns, governments and communities can develop targeted adaptation plans that are tailored to the specific risks faced by each area (Table 1). Climate change is a complex issue that poses significant risks to society, the environment, and the economy. One of the primary challenges in addressing climate change is developing effective adaptation strategies that can mitigate the risks and impacts of climate change. To develop effective adaptation strategies, governments and communities need to have access to accurate and relevant information about the specific risks faced by each area. Artificial intelligence (AI) has the potential to help governments and communities address this challenge by analyzing large amounts of data such as climate models, satellite imagery, and weather patterns to develop targeted adaptation plans (Chen et al., 2021). In this review, we will explore the use of AI in climate change adaptation and how it can help governments and communities develop tailored adaptation plans.

It was found that AI can be a powerful tool in climate change adaptation by analyzing large amounts of data

Table 1 Comparison of AI-powered vulnerability assessment tools for climate change adaptation

AI Technology	Purpose	Input Data	Outcomes	Example Applications	Reference
Machine Learning	Predicting future climate patterns and changes	Climate models, historical climate data, satellite imagery	Projections of future temperature, precipitation, and other climate variables	Informing climate policy, guiding adaptation strategies	(Linardos et al., 2022)
Deep Learning	Analyzing satellite imagery to detect changes in land use and vegetation	Satellite imagery, climate data, land use maps	Identification of changes in land use patterns and vegetation cover	Monitoring deforestation, guiding land use planning	(Catani, 2021)
Natural Language Processing	Analyzing social media data to assess public perceptions of climate change	Social media data (e.g. tweets, posts, and messages related to climate change)	Analysis of public sentiment and opinions on climate change	Engaging the public in climate action and advocacy	(Tounsi & Temimi, 2023)
Computer Vision	Mapping and monitoring land use changes and urban development	Satellite imagery, land use maps, urban planning data	Identification of changes in land use patterns and urban development	Informing land use planning and management, guiding urban development	(Oh et al., 2020)

to identify vulnerabilities and develop targeted adaptation plans (Simeoni et al., 2023). For example, AI can be used to analyze satellite imagery to identify areas at risk of flooding or erosion due to sea-level rise. By applying machine learning algorithms to large datasets of satellite imagery, AI models can identify patterns and relationships that may be missed by human analysts and make predictions about how different areas may be affected by rising sea levels. One example of this is a project called FloodNet, which uses AI to analyze satellite images and predict flooding in real-time (Gangisetty & Rai, 2022). The system uses deep learning algorithms to analyze images of rivers and other bodies of water, and predict the likelihood and severity of flooding based on factors such as water level, water velocity, and terrain. Another example is a project called CoastalDEM (Kulp & Strauss, 2018), which uses AI to create high-resolution elevation maps of coastal areas. The system combines satellite imagery with machine learning algorithms to identify and correct errors in elevation data, and create more accurate and detailed maps of coastal regions. This information can be used to identify areas at risk of flooding or erosion due to sea-level rise, and develop targeted adaptation strategies to protect vulnerable communities and infrastructure. Overall, the use of AI for analyzing satellite imagery offers a powerful tool for identifying areas at risk of flooding or erosion due to sea-level rise, and developing effective adaptation strategies to mitigate those risks. However, there are also challenges and limitations to consider, such as the need for high-quality data, the potential for bias and error in AI models, and the need for expert oversight and interpretation of results (Samuels et al., 2022).

Similarly, AI can analyze climate models to identify areas that are likely to experience changes in temperature and precipitation patterns. By applying machine learning algorithms to large datasets of climate model output, AI models can identify patterns and trends that may be missed by human analysts, and make predictions about how different regions may be affected by climate change (Yang et al., 2022). One example of this is a project called the DeepSD (Deep Learning for Spatiotemporal Data) framework, which uses AI to analyze climate model data and predict changes in temperature and precipitation patterns at the regional scale. The system uses deep learning algorithms to identify complex relationships between different climate variables and make predictions about how those variables may change in the future. Another example is a project called the Climate Informatics Toolbox, which provides a suite of machine learning tools for analyzing climate model data. The toolbox includes algorithms for clustering, classification, and regression analysis, which can be used to identify patterns and trends in climate data and make predictions about future climate conditions. Overall, the use of AI for analyzing climate model data offers a powerful tool for identifying areas that are likely to experience changes in temperature and precipitation patterns due to climate change and developing effective adaptation strategies to mitigate those impacts. However, there are also challenges and limitations to consider, such as the need for high-quality data, the potential for bias and error in AI models, and the need for expert oversight and interpretation of results (Tian et al., 2022).

By analyzing this data, governments and communities can develop targeted adaptation plans that are tailored to the specific risks faced by each area. It was also found that there are several challenges to the use of AI in climate change adaptation. One of the primary challenges is the quality and availability of data. AI relies on large amounts of high-quality data to develop accurate models and predictions. However, in many areas, there is a lack of high-quality data, which can limit the effectiveness of AI in developing adaptation plans (Sirmacek & Vinuesa, 2022; Tessema et al., 2021). Another challenge is the interpretability of AI models. AI models can be highly complex, making it difficult for policymakers and stakeholders to understand how they work and how to interpret their results. This can make it difficult for governments and communities to make informed decisions about adaptation strategies.

3 Safeguarding infrastructure and communities from climate change impacts

AI can also be used to develop plans for protecting infrastructure and communities from the effects of climate change. For example, AI-powered models can be used to simulate the impact of rising sea levels on coastal infrastructure, helping governments and businesses to develop effective adaptation strategies. AI can also be used to develop early warning systems for natural disasters, such as hurricanes and floods, allowing communities to prepare and evacuate before disaster strikes (Table 2).

AI can be used to develop plans for protecting infrastructure and communities from the effects of climate change by analyzing data from climate models, satellite imagery, and weather patterns. By doing so, it can help identify areas that are at high risk of flooding, erosion, or other climate-related hazards, allowing stakeholders to take proactive measures to mitigate potential impacts. These data sources can include climate models, historical weather patterns, topography, and land-use data (Argyroudis et al., 2022; Qerimi & Sergi, 2022). For example, using AI-powered flood modeling, stakeholders can predict the potential impact of sea-level rise or extreme

Table 2 AI Technologies for early warning systems in climate change adaptation (Shao et al., 2021; Islam, 2022; Ferro Azcona et al., 2022; Argyroudis et al., 2022)

AI Technology	Purpose	Data Inputs	Outputs	Example Applications
Machine Learning	Predicting floods	Sensor data (rainfall, river level)	Flood risk maps and alerts	Flood prediction and warning systems (Lawal et al., 2021)
Deep Learning	Predicting wildfires	Satellite and weather data	Fire risk maps and alerts	Wildfire prediction and warning systems (Park et al., 2020)
Natural Language Processing	Social media monitoring for disaster response	Tweets, posts, and messages related to disasters	Analysis of public sentiment, identification of people in need, and coordination of rescue efforts	Disaster response and emergency management (Linardos et al., 2022)
Computer Vision	Identifying areas at risk of landslides	Satellite and weather data	Landslide risk maps and alerts	Landslide prediction and warning systems (Wang et al., 2021)

weather events on coastal infrastructure and communities. By analyzing data on topography, land use, and urban development, AI can identify areas that are more vulnerable to flooding and erosion, allowing stakeholders to take proactive measures such as building sea walls, relocating vulnerable infrastructure, or implementing zoning regulations to reduce risk. Similarly, AI-powered systems can analyze weather patterns to identify areas that are likely to experience an increased frequency or intensity of extreme weather events such as hurricanes, tornadoes, or droughts. This information can be used to inform infrastructure planning, emergency preparedness, and risk management. Overall, AI can help stakeholders to identify and mitigate the potential impacts of climate-related hazards, protecting infrastructure and communities from the effects of climate change (Rana et al., 2022).

One way AI can assist in protecting infrastructure is by developing early warning systems. These systems can be designed to detect early signs of climate change-related hazards such as flooding, landslides, or wildfires. AI-powered models can analyze historical data, weather patterns, and other relevant information to identify potential risks and send alerts to authorities and communities at risk (Scoville et al., 2021). AI can also be used to simulate the potential impact of climate change on critical infrastructure, such as transportation systems, energy grids, and water supply networks. By running simulations, stakeholders can identify potential vulnerabilities and develop strategies to reduce risks. For example, AI can be used to simulate the potential impacts of rising sea levels on coastal infrastructure, helping stakeholders to identify areas that are at high risk of flooding, erosion, or other climate-related hazards. These simulations can help stakeholders to visualize the potential impacts of climate change on their communities and infrastructure, allowing them to take proactive measures to mitigate potential impacts (Ilango, et al., 2023). AI-powered simulations can also help stakeholders to identify potential risks and opportunities associated with climate change impacts. By analysing data such as climate models, satellite imagery, and weather patterns, AI systems can help businesses to identify potential risks and opportunities associated with climate change impacts. This information can help businesses to make more informed decisions about where to invest, where to build, and how to adapt their operations to better withstand the impacts of climate change. In addition to identifying potential vulnerabilities, AI can also be used to develop plans for protecting infrastructure and communities from the effects of climate change. For example, AI-powered systems can help stakeholders to develop strategies for adapting infrastructure to be more resilient to climate change impacts, such as retrofitting buildings to withstand extreme weather events or developing green infrastructure to mitigate flooding (Stringer et al., 2021).

Moreover, AI can aid in developing adaptation strategies for businesses and communities. For example, AI can help identify opportunities for businesses to transition to more sustainable practices or develop new products and services to address climate change challenges. Communities can also use AI to develop climate adaptation plans, such as relocating buildings or infrastructure, increasing the use of green spaces, or implementing flood-resistant measures. First, AI-powered risk assessments can help identify areas that are at high risk of climate-related hazards, allowing stakeholders to take proactive measures to mitigate potential impacts. For example, AI can analyze data such as climate models, satellite imagery, and weather patterns to detect patterns and identify the early signs of an impending disaster. Second, AI-powered simulations can help stakeholders to assess the potential risks of climate change impacts on infrastructure and businesses (Bag et al., 2023). By running simulations, stakeholders can identify potential vulnerabilities and develop strategies to reduce risks. For instance, AI can simulate the impact of rising sea levels on coastal infrastructure and identify areas that require additional protection or relocation. Third, AI can aid in the development of early warning systems by analyzing real-time data and detecting patterns that could indicate an impending disaster. This can allow stakeholders to take proactive measures to protect their communities, infrastructure, and businesses. Finally, AI can help businesses and communities to adapt to climate change impacts by providing real-time data and insights. For example, AI-powered systems can provide information on changing weather patterns, crop yields, and water availability, allowing businesses to make informed decisions about their operations (Dorward & Giller, 2022).

The widespread use of IoT devices has made it possible to collect enormous amounts of geolocated data, which has helped with climate change adaptation by revealing important details about the climate system. Real-time monitoring capabilities are provided by these gadgets, which can record a variety of environmental parameters like temperature, humidity, air quality, and precipitation patterns. We can comprehend the intricate relationships and dynamics within the climate system better by integrating this data with AI models.

IoT device data can potentially address biases and inaccuracies in AI models, which is one of its key benefits. Climate models are frequently created using historical and current data, which are inherently subject to errors and limitations. These models rely on parameterization strategies that might introduce biases as a result of a lack of knowledge about or imperfect understanding of particular processes.

The accuracy and dependability of AI models can be improved by utilising the geolocated data collected from IoT devices. A stronger set of projections and predictions can be made by validating and calibrating climate models with the help of this additional data. Additionally, the widespread adoption of IoT devices enables a more thorough and localised data collection, which can assist in identifying and mitigating potential biases in AI models and guarantee that adaptation strategies are more accurate and successful across various geographical areas.

As a result, addressing biases and inaccuracies in AI models used for climate change adaptation is significantly possible with the integration of data from IoT devices. We can enhance the performance and reliability of AI models by combining real-time, geolocated data with historical and modern datasets, resulting in better decision-making and better protection of communities, infrastructure, and businesses from the effects of climate change.

3.1 AI-powered models

The rising sea levels caused by climate change pose a significant threat to coastal infrastructure around the world. As the oceans continue to warm and expand and as land-based ice melts, sea levels are projected to rise by up to a meter or more by the end of this century. This presents a major challenge for governments, communities, and businesses, which must find ways to protect their coastal infrastructure and populations from the risks posed by rising sea levels (Gill et al., 2023). Artificial intelligence (AI) can play a crucial role in this effort, by providing tools to simulate the impact of rising sea levels on coastal infrastructure and to develop adaptation strategies that are tailored to specific areas. One of the key-ways in which AI can be used in this context is through the development of AI-powered models that simulate the effects of rising sea levels on coastal infrastructure (Aruta and Guinto 2022). These models can consider a range of factors, including the topography of the land, the location of infrastructure such as buildings and roads, and the expected impact of storm surges and other extreme weather events. By analyzing this data, AI-powered models can generate detailed simulations of the impact of rising sea levels on coastal infrastructure, providing insights that can help communities, businesses, and governments plan and prepare for the challenges ahead.

AI-powered models can be used to simulate the impact of rising sea levels on coastal infrastructure. By integrating large datasets of climate and infrastructure data with machine learning algorithms, these models can predict the effects of sea level rise on coastal communities and infrastructure, and evaluate the effectiveness of different adaptation strategies (Hoppit et al., 2022). For example, a project called CoastalAI uses AI to simulate the effects of sea level rise on coastal infrastructure in the United States. The system uses machine learning algorithms to analyze large datasets of climate and infrastructure data and make predictions about how different types of infrastructure (such as roads, bridges, and buildings) will be affected by rising sea levels (Fig. 1). This information can be used to develop targeted adaptation strategies to protect vulnerable infrastructure and communities. The CoastalAI model begins by gathering data on a variety of factors that contribute to the vulnerability of coastal infrastructure to sea level rise, such as the height of buildings and roads, the elevation of coastal land, and the proximity to areas at risk of flooding (Bhagat et al., 2022; Chau, 2006). This data is then combined with climate data, such as projections of sea level rise and storm surge risk, to create a comprehensive picture of the coastal region and its vulnerability to climate change. Once the data has been collected and analyzed, machine learning algorithms are used to make predictions about how sea

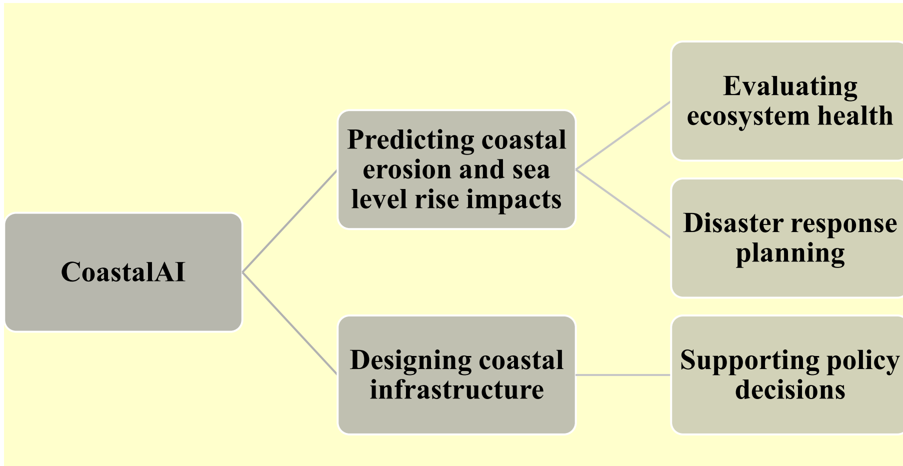

Fig. 1 CoastalAI: AI-powered simulation of the impact of sea level rise on coastal infrastructure (Kulp & Strauss, 2018)

level rise will affect different types of infrastructure. For example, the system may predict that certain roads or buildings will be at risk of flooding, or that certain areas may be more susceptible to erosion due to rising sea levels. Based on these predictions, the CoastalAI model can then be used to develop targeted adaptation strategies to protect vulnerable infrastructure and communities. For example, the system may recommend the construction of sea walls or other protective barriers, or the relocation of vulnerable infrastructure to safer areas. Overall, the CoastalAI model offers a powerful tool for simulating the impact of sea level rise on coastal infrastructure and developing targeted solutions to protect vulnerable communities. However, as with all AI models, there are limitations and potential sources of bias to consider, and expert oversight and interpretation of results are necessary to ensure that the model is used effectively and ethically.

Another example is a project called Deltares, which uses AI to simulate the impact of sea level rise on coastal infrastructure in the Netherlands. The system combines large datasets of climate and infrastructure data with machine learning algorithms to create detailed models of the coastal region and predict the effects of sea level rise on different types of infrastructure (MacLeod et al., 2021; Yost et al., 2021). This information can be used to develop effective adaptation strategies to protect vulnerable communities and infrastructure. The Deltares model begins by collecting data on a range of factors that contribute to the vulnerability of coastal infrastructure to sea level rise, such as the height of buildings and roads, the elevation of coastal land, and the proximity to areas at risk of flooding (Fig. 2). This data is then combined with climate data, such as projections of sea level rise and storm surge risk, to create a comprehensive picture of the coastal region and its vulnerability to climate change. Once the data has been collected and analyzed, machine learning algorithms are used to create a detailed model of the coastal region and predict the effects of sea level rise on different types of infrastructure. For example, the system may predict how sea level rise will affect the stability of the soil and the risk of erosion, or the impact on different types of infrastructure such as buildings, roads, and drainage systems. Based on these predictions, the Deltares model can then be used to develop targeted adaptation strategies to protect vulnerable infrastructure and communities (Shao et al., 2021). For example, the system may recommend the construction of new protective structures such as sea walls or dikes, or the relocation of infrastructure to safer areas. Overall, the Deltares model offers a powerful tool for simulating the impact of sea level rise on coastal infrastructure and developing targeted solutions to protect vulnerable communities. However, as with all AI models, there are limitations and potential sources of bias to consider and expert oversight and interpretation of results are necessary to ensure that the model is used effectively and ethically. Hence, the use of AI-powered models for simulating the impact of sea level rise offers a powerful tool for evaluating the effectiveness of different adaptation strategies and developing targeted solutions to protect coastal infrastructure and communities (Islam, 2022). However, there are also challenges and limitations to consider, such as the need for high-quality data, the potential for bias and error in AI models, and the need for expert oversight and interpretation of results.

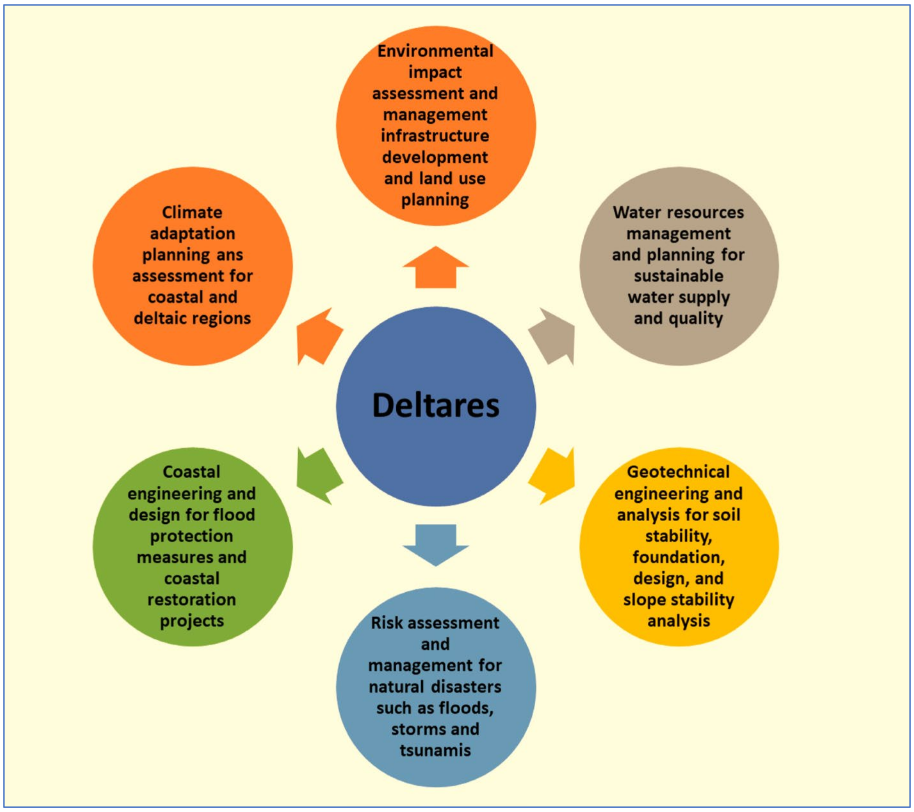

Fig. 2 Deltares AI simulation modules to assess the impact of sea level rise on coastal infrastructure (adapted from MacLeod et al., 2021; Yost et al., 2021)

3.2 Use of AI to develop early warning systems

AI has the potential to revolutionize the way we develop early warning systems for natural disasters such as hurricanes and floods. By analyzing large datasets from satellites, weather stations, and other sources, AI-powered systems can detect patterns and identify the early signs of an impending disaster, allowing for a timely and effective response (Wever et al., 2022). One of the key advantages of AI-powered early warning systems is their ability to analyze vast amounts of data in real-time. This allows for the detection of subtle changes in weather patterns or ocean currents that could indicate the formation of a hurricane or the likelihood of a flood. Additionally, AI-powered systems can learn from historical data and improve their accuracy over time, making them more effective at predicting disasters. In addition to detecting the early signs of a disaster, AI-powered systems can also help to identify the areas that are most at risk (Raffaghelli et al., 2022). By analyzing topographic and demographic data, these systems can identify communities and infrastructure that are located in areas with a higher risk of flooding or hurricane damage. This allows for targeted preparation and response efforts, such as evacuations or reinforcement of critical infrastructure. Another advantage of AI-powered early warning systems is their ability to provide real-time updates and alerts to stakeholders and the public. By leveraging mobile apps and other communication technologies, these systems can provide timely and actionable information to individuals and organizations in the path of a disaster. This can help to reduce the number of casualties and minimize the damage caused by natural disasters. However, there are also limitations to the use of AI-powered early warning systems. One of the key challenges is the need for high-quality data (Zhang et al., 2023). To be effective, these systems require access to accurate and up-to-date data from a range of sources. Additionally, there are concerns around the potential for biases in the data or algorithms used by these systems, which could lead to inaccurate or unfair predictions. Another challenge is the potential for false alarms. AI-powered systems are not infallible and may generate false alarms, leading to unnecessary evacuations or disruptions. Additionally, the effectiveness of these systems depends on the response capacity and preparedness of the communities and organizations that receive the alerts. Despite these challenges, the potential of AI-powered early warning systems for natural disasters is significant. By leveraging the power of AI to analyze vast amounts of data and identify the early signs of a disaster, these systems can help to save lives and protect critical infrastructure. With further development and refinement, AI-powered early warning systems have the potential to become an essential tool for disaster preparedness and response (Table 3) (Yang et al., 2021).

AI-powered systems can detect patterns and identify early signs of an impending disaster by analyzing large volumes of data from various sources. For example, in the case of natural disasters such as hurricanes, AI systems can analyze weather data, satellite imagery, social media activity, and other relevant sources to detect patterns and predict the trajectory of the storm. AI algorithms can also analyze historical data to identify patterns and correlations that may indicate an increased risk of a disaster. For example, in the case of wildfires, AI systems can analyze past data on weather patterns, vegetation cover, and human activity to identify areas at risk of a potential wildfire outbreak (Masupha et al., 2021). Once the AI system has identified a potential risk or early warning sign, it can then issue alerts and notifications to relevant stakeholders, such as emergency responders, local authorities, and the general public. These alerts can provide critical information on the potential impact of the disaster and recommended actions to minimize its effects. In addition to detecting patterns and issuing alerts, AI-powered systems can also assist in disaster response efforts by providing real-time updates on the location and intensity of the disaster, analyzing data on affected populations and infrastructure, and assisting in resource allocation and logistics planning. Overall, AI-powered systems offer a powerful tool for detecting early warning signs of disasters and facilitating effective disaster response efforts (van der Stam et al., 2023). However, as with all AI applications, there are limitations and potential sources of bias to consider, and expert oversight and interpretation of results are necessary to ensure that the system is used effectively and ethically.

Machine learning can be used to predict floods by analyzing historical data and identifying patterns that could indicate the potential for flooding (Table 4). By inputting data such as weather patterns, water levels, and other relevant information, machine learning algorithms can identify the likelihood of flooding and provide early

Table 3 Comparison of AI-powered early warning systems for natural disasters

AI Technology	Purpose	Data Inputs	Outputs	Example Applications
Machine Learning	Predicting floods	Sensor data (rainfall, river level)	Flood risk maps and alerts	Flood prediction and warning systems (Mosavi et al., 2018)
Deep Learning	Predicting wildfires	Satellite and weather data	Fire risk maps and alerts	Wildfire prediction and warning systems (Park et al., 2020)
Natural Language Processing	Social media monitoring for disaster response	Tweets, posts, and messages related to disasters	Analysis of public sentiment, identification of people in need, and coordination of rescue efforts	Disaster response and emergency management (Tounsi & Temimi, 2023)
Computer Vision	Identifying areas at risk of landslides	Satellite and weather data	Landslide risk maps and alerts	Landslide prediction and warning systems (Tengtrairat et al., 2021)

Table 4 Comparison of machine learning algorithms for flood prediction using various input variables

Machine Learning Technique	Data Source	Performance Metric	Reference
Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)	Streamflow data from river gauges	Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)	(Mosavi et al., 2018)
Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF)	Streamflow data from river gauges	Correlation Coefficient (CC) and Mean Absolute Percentage Error (MAPE)	(Seydi et al., 2023)
Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM)	Rainfall, streamflow, and topographic data	Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)	(Guo et al., 2022)
Artificial Neural Networks (ANN), Support Vector Regression (SVR), Decision Trees (DT), and Random Forest (RF)	Rainfall and river discharge data	Correlation Coefficient (CC) and Root Mean Square Error (RMSE)	(Lawal et al., 2021)

warning to those at risk. For example, a machine learning algorithm could analyze rainfall patterns in a particular area and identify the likelihood of flooding based on the volume of rainfall and other factors such as topography and soil moisture. The algorithm could then provide early warning to those in the affected area, giving them time to prepare and take necessary precautions. Machine learning can also be used to identify areas that are at higher risk of flooding, allowing stakeholders to prioritize resources and take proactive measures to mitigate potential impacts. This could involve developing flood barriers, building infrastructure that can withstand flooding, or relocating vulnerable populations to safer areas.

Deep learning is a subset of machine learning that involves training artificial neural networks to make predictions or decisions based on input data. In the context of wildfire prediction, deep learning algorithms can be trained using historical data on weather conditions, vegetation, terrain, and other relevant factors to predict the likelihood and severity of wildfires in a given area. Deep learning models for wildfire prediction typically use convolutional neural networks (CNNs), which are well-suited for analyzing spatial data such as satellite imagery or aerial photographs (Table 5). These models can be trained on large datasets of historical wildfire events and associated environmental conditions, allowing them to learn complex patterns and relationships between different factors. Once trained, deep learning models can be used to generate predictive maps of areas that are at high risk of wildfires, or to forecast the potential spread and intensity of ongoing fires. This information can help emergency responders to allocate resources and plan evacuation routes and can also aid in long-term planning for wildfire prevention and mitigation efforts.

Natural Language Processing (NLP) is a subfield of AI that deals with the interaction between computers and human language (Table 6). It can be used in social media monitoring for disaster response by analyzing large amounts of unstructured data from social media platforms to identify relevant information such as tweets, posts, and comments related to an ongoing disaster (Sufi, 2022; Sufi & Khalil, 2022). NLP can help emergency response teams quickly identify affected areas, monitor the sentiment of people affected by the disaster, and understand their needs in real-time. This can help teams efficiently allocate resources and respond to the disaster more effectively. For example, during the Hurricane Harvey disaster in 2017, the United States Coast Guard used NLP to monitor social media platforms and identify people who needed help. They used NLP to identify tweets

Table 5 Examples of deep learning techniques used for wildfire prediction

Deep Learning Model	Examples	Performance
Convolutional Neural Networks (CNN)	- Detecting wildfire through satellite imagery- Identifying smoke plumes and flames through real-time video analysis	Achieved an accuracy of 97% in detecting wildfires from satellite images (Oh et al., 2020)
Recurrent Neural Networks (RNN)	- Predicting wildfire intensity and spread based on weather patterns and historical data—Analyzing sensor data to predict the likelihood of a wildfire event	Outperformed traditional regression models by up to 12% in predicting wildfire spread (Mohan et al., 2021)
Generative Adversarial Networks (GAN)	- Generating synthetic wildfire images to aid in training CNN models- Creating simulated wildfire scenarios to test emergency response strategies	Generated high-quality synthetic images with a 50% reduction in data requirements (Park et al., 2020)

Table 6 Examples of AI-powered natural language processing applications for disaster response through social media monitoring

NLP Application	Description	Example
Sentiment analysis	Evaluates the sentiment of social media posts related to disasters, such as positive or negative, to inform response efforts	Analyzing tweets during Hurricane Harvey to identify areas with the most negative sentiment and target response efforts accordingly (Tounsi & Temimi, 2023)
Named entity recognition	Identifies specific people, locations, and organizations mentioned in social media posts related to disasters	Identifying the names of shelters and evacuation centers mentioned in social media posts during a wildfire (Sufi, 2022)
Topic modeling	Identifies common themes or topics discussed in social media posts related to disasters	Identifying frequently mentioned topics such as "road closures" or "evacuation orders" during a hurricane (Anthopoulos & Kazantzi, 2022)
Information extraction	Extracts specific pieces of information from social media posts related to disasters, such as requests for assistance or reports of damage	Identifying requests for assistance or reports of missing persons in social media posts during a flood (Sufi & Khalil, 2022)

with specific hashtags related to the disaster and then analyzed the tweets to identify the location and severity of the crisis. This allowed them to quickly respond to people in need of help and allocate resources more efficiently. Overall, NLP can play a crucial role in disaster response by providing real-time information and insights to emergency response teams, enabling them to make more informed decisions and respond more effectively to disasters (Kuglitsch et al., 2022; Linardos et al., 2022; Tounsi & Temimi, 2023).

Computer vision is a field of AI that involves teaching computers to interpret and understand visual data from the world around us. This technology can be used to identify areas that are at risk of landslides by analyzing satellite imagery, aerial photographs, and other forms of visual data (Ma et al., 2021; Wang et al., 2021). This involves using algorithms to detect features such as changes in terrain, soil erosion, and vegetation patterns that may indicate areas at risk of landslides. For example, machine learning algorithms can be trained to analyze satellite imagery and identify areas that have experienced landslides in the past, as well as factors such as soil composition and vegetation cover that may contribute to landslides. For example, certain soil types and rock formations are more susceptible to landslides than others. Vegetation cover can also play a role, as excessive growth or deforestation can impact soil stability. By analyzing visual data, such as satellite imagery and aerial photographs, computer vision technology can identify areas with these risk factors and provide insights into where landslides are more likely to occur (Tengtrairat et al., 2021; Catani, 2021). This can help stakeholders take proactive measures to mitigate potential impacts, such as through improved land management practices or targeted infrastructure investments. By analyzing this data, stakeholders can identify areas at risk of landslides and develop strategies to reduce the risk of damage to infrastructure and communities. Computer vision algorithms can be trained to recognize patterns and features that are associated with landslide-prone areas, such as steep slopes, changes in vegetation cover, and soil types. By analyzing large amounts of data over time, these algorithms can also detect changes in these patterns that may indicate an increased risk of landslides. One example of computer vision being used for landslide risk assessment is the Landslide Reporter project, which uses crowdsourcing and machine learning to identify areas at risk of landslides from satellite imagery (Table 7). This project has been successful in identifying new landslide events and could help communities to take proactive measures to mitigate potential impacts (A, Sudha, and Francis 2022; Prakash et al., 2021).

4 AI-powered simulations for infrastructure and business risk assessment

AI-powered simulations can be used to assess infrastructure and business risk in the face of climate change impacts (Table 8) (Anthopoulos & Kazantzi, 2022; Guo et al., 2023). These simulations can provide insights into the potential impacts of climate change on physical infrastructure, such as buildings, roads, and bridges, as well as on business operations and supply chains (Fioravanti et al., 2022).

By combining climate modeling data with infrastructure and business data, AI-powered simulations can help stakeholders to assess the potential risks of climate change impacts, such as flooding, sea level rise, and extreme weather events. For example, AI-powered simulations can help to predict how flooding and storm surge impacts will affect critical infrastructure, such as power plants, hospitals, and transportation networks (In et al., 2022). AI-powered simulations can also be used to assess the potential economic impacts of climate change on businesses and industries. By analyzing supply chain data, market trends, and financial data, AI systems can help businesses to identify potential risks and opportunities associated with climate change impacts, such as shifts in consumer demand for certain products or changes in

Table 7 Examples of computer vision applications for landslide risk assessment

Image Processing Technique	Examples
Object Detection	Identifying potential landslide areas based on changes in soil and vegetation cover in satellite imagery (Prakash et al., 2021)
Image Segmentation	Identifying areas prone to landslides by segmenting high-resolution aerial images based on texture and color patterns. (A, Sudha, and Francis 2022)
Remote Sensing	Using LiDAR and other remote sensing techniques to generate 3D maps of terrain and identify areas with high slope angles, soil erosion, and other factors that increase the risk of landslides (Wang et al., 2021)
Feature Extraction	Extracting features such as slope, aspect, curvature, and vegetation density from satellite and aerial imagery to identify areas with higher landslide susceptibility (Tengtrairat et al., 2021)
Machine Learning	Developing machine learning models using historical landslide data, terrain characteristics, and other relevant features to predict landslide risk in new areas (Catani, 2021)

Table 8 AI-Powered simulations for infrastructure and business risk assessment

AI System	Function	Reference
Acclimatise	Provides climate risk assessments and adaptation strategies for businesses and governments	Acclimatise (Surminski et al., 2018)
Cervest	Uses AI to provide climate intelligence to help businesses anticipate climate risks and opportunities	Cervest (Cioffi et al., 2020)
ClimateAi	Uses AI to provide climate risk analytics and forecasting for businesses	ClimateAi (Dewitte et al., 2021)
Jupiter	Uses satellite data and AI to help businesses identify and manage climate risks, such as floods and droughts	Jupiter (Ullah et al., 2023)
The Climate Service	Uses AI to provide climate risk assessments and insights for businesses	The Climate Service (Kim & Lee, 2016)

market conditions. Overall, AI-powered simulations offer a powerful tool for assessing infrastructure and business risks associated with climate change impacts. However, there are limitations to consider, such as the accuracy and reliability of data sources, and the need for expert interpretation of results (Lekidis et al., 2022). Therefore, careful consideration of the assumptions and limitations of the simulation is necessary to ensure that it is used effectively in informing climate change adaptation strategies.

5 AI-enabled climate modeling and projections

AI-enabled climate modeling and projections refer to the use of artificial intelligence (AI) techniques to improve the accuracy and reliability of climate modeling and projections. Climate modeling involves the use of computer simulations to understand how various factors, such as greenhouse gas emissions, affect the Earth's climate over time (Nost & Colven, 2022; Sirmacek & Vinuesa, 2022). Projections are then made based on these models to predict how the climate will change in the future. AI can be used to improve climate modeling and projections by analyzing large amounts of data from various sources, including satellite imagery, weather patterns, and climate models and identifying patterns and trends that may not be apparent through traditional methods. AI can also help reduce uncertainties in climate simulations and predictions, making them more accurate and reliable. There are several AI techniques that can be used in climate modeling and projections, such as machine learning algorithms, neural networks, and deep learning (Bartók et al., 2019; Leal Filho et al., 2022). These techniques can analyze complex climate data sets, identify patterns and correlations, and make predictions based on those patterns. AI-enabled climate modeling and projections have several potential benefits, such as improved accuracy and reliability, faster and more efficient analysis of climate data, and better understanding of the potential impacts of climate change on different regions and ecosystems. This information can be used to inform policy decisions and guide climate change adaptation and mitigation efforts (Alassery et al., 2022). Some examples of AI-enabled climate modeling and projection systems include Google Earth Engine, Climate.ai, IBM Watson, and Microsoft Azure (Table 9).

6 Ethical considerations and potential biases in AI-powered climate change adaptation strategies

As with any technology, there are ethical considerations and potential biases that need to be addressed when implementing AI-powered climate change adaptation strategies (Dwivedi et al., 2021). Here are some examples (Issa et al., 2022; Dwivedi et al., 2022; Barredo Arrieta et al., 2020; Scoville et al., 2021):

Table 9 Summary of AI-enabled climate modeling and projection systems

AI System	Function	Reference
Climate.ai	Uses AI to analyze climate data and generate probabilistic climate change scenarios for future climate modeling and projection	Climate.ai (Dewitte et al., 2021)
DeepMind	Uses AI to improve climate modeling accuracy by reducing uncertainties in climate simulations and predictions	DeepMind (Subramaniam et al., 2022)
Google Earth Engine	Uses AI to analyze satellite data to generate high-resolution climate models and projections	Google Earth Engine (Yang et al., 2022)
IBM Watson	Uses AI to generate climate projections and assess risks of climate impacts on infrastructure and supply chains	IBM Watson (Yigitcanlar et al., 2020)
Microsoft Azure	Uses AI to create high-resolution climate models and projections using satellite data and machine learning algorithms	Microsoft Azure (Khan et al., 2023)

1. Bias in data: AI systems rely on large amounts of data to make predictions and recommendations. However, if the data used to train the AI models is biased, this can lead to biased outcomes. For example, if the data used to train an AI system only includes historical data from certain regions or populations, it may not accurately reflect the experiences of other groups. This could result in inaccurate predictions and recommendations that could disproportionately affect vulnerable populations.
2. Lack of transparency: AI systems can be complex and difficult to understand, which can make it challenging to identify potential biases or errors. Lack of transparency in the algorithms used to develop and train AI models can also make it difficult to identify potential sources of bias.
3. Inadequate representation: AI systems may not adequately represent the diversity of perspectives and experiences needed to develop effective climate change adaptation strategies. For example, if the development team lacks diversity, it may not be able to adequately consider the needs of different groups or communities.
4. Potential unintended consequences: AI-powered climate change adaptation strategies may have unintended consequences that could negatively impact communities or ecosystems. For example, if an AI system recommends the construction of a seawall to protect against rising sea levels, this could have unintended consequences for marine ecosystems.
5. Ethical use of data: AI systems rely on large amounts of data, including personal and sensitive information. The ethical use of data is essential to protect privacy and prevent misuse of personal information.

To address these ethical considerations and potential biases, it is important to ensure that AI systems are developed and implemented with transparency, accountability, and inclusivity. This includes, ensuring that the data used to train AI models is diverse, representative, and free from bias. Promoting transparency and understanding of AI algorithms, including the decision-making processes involved. Involving a diverse range of stakeholders in the development and implementation of AI-powered climate change adaptation strategies (Stahl, 2021). Conducting regular ethical audits to identify potential sources of bias or unintended consequences. Ensuring that the use of personal and sensitive data is in compliance with ethical and legal standards. By addressing these ethical considerations and potential biases, AI-powered climate change adaptation strategies can be developed and implemented in a way that is inclusive, transparent, and beneficial to all (Lacey et al., 2015). However, as with any technology, there are ethical considerations and potential biases that must be addressed to ensure that the strategies are developed and implemented in a way that is inclusive, transparent, and beneficial to all. One ethical consideration is the potential for AI to perpetuate and amplify existing biases. For example, if historical data is used to train an AI model to predict future climate-related hazards, it may perpetuate biases that exist in the data, such as discrimination against certain communities or neglect of certain types of infrastructure (Brendel et al., 2021). To address this, it is important to carefully select and preprocess data, as well as monitor the output of AI models for any biases or errors. Another consideration is the potential impact of AI-powered climate change adaptation strategies on vulnerable communities. For example, there may be concerns that these strategies could lead to gentrification or displacement of low-income or marginalized communities. It is important to engage these communities in the development and implementation of these strategies to ensure that their concerns and needs are taken into account (Bartmann, 2022). By addressing these and other ethical considerations, AI-powered climate change adaptation strategies can be developed and implemented in a way that is inclusive, transparent, and beneficial to all. It is important to recognize that AI is not a panacea for climate change, but rather one tool among many that can be used to help protect our planet and its inhabitants.

7 Future directions and potential innovations in AI-powered climate change adaptation strategies

AI-powered climate change adaptation strategies are continuously evolving, and new innovations are being developed to address the complex and rapidly changing nature of climate change (Fig. 3) (Akter et al., 2021; Gill et al., 2022; Hötte & Jee, 2022). While AI can analyze a wide range of data sources, there is potential to integrate additional sources such as social media, community-generated data, and citizen science data to provide a more comprehensive picture of climate change impacts. As climate change impacts become more severe and unpredictable, there is a need for real-time monitoring and adaptation. AI-powered systems can help to provide real-time information on weather patterns, flooding, and other events, allowing for more effective responses.

AI models are continually improving in terms of their accuracy and precision. As more data becomes available, it is likely that these models will become even more accurate, enabling better predictions and more effective adaptation strategies (Dewitte et al. 2021). AI-powered climate change adaptation strategies must be developed with a focus on equity and justice. There is a risk that

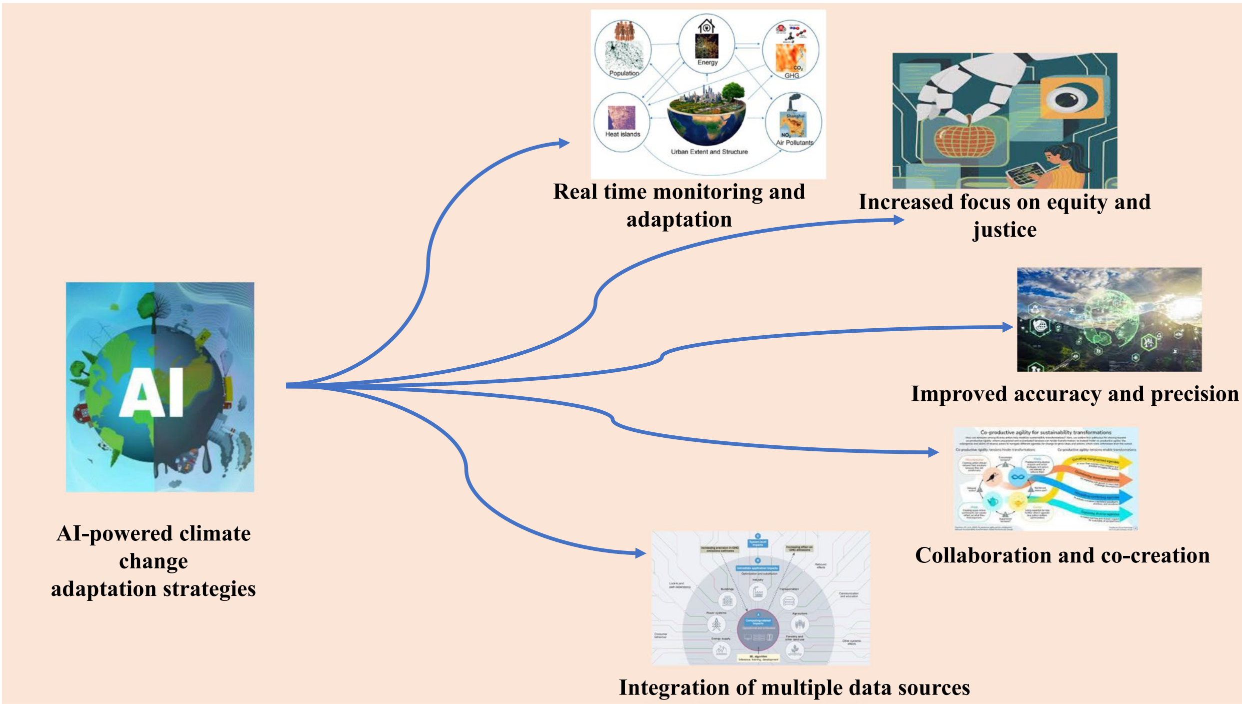

Fig. 3 Future innovations in AI-powered climate change adaptation strategies (adapted from Akter et al., 2021; Gill et al., 2022; Hötte & Jee, 2022)

these strategies could disproportionately benefit certain groups or exacerbate existing inequalities, and so it is important to ensure that they are developed with a focus on fairness and inclusivity (Pan et al., 2022). To ensure that AI-powered climate change adaptation strategies are effective, it is essential to involve a range of stakeholders in their development. This includes local communities, businesses, governments, and non-governmental organizations. Collaborative and co-creation approaches can help to ensure that these strategies are tailored to local needs and priorities. Overall, AI-powered climate change adaptation strategies have enormous potential to support communities, infrastructure, and businesses in adapting to the impacts of climate change. Continued innovation and collaboration will be essential in ensuring that these strategies are effective, equitable, and sustainable (Bag et al., 2023).

8 Conclusion

AI-enabled strategies for climate change adaptation have the potential to revolutionize the way we approach and tackle climate change. The use of AI can help identify and assess vulnerabilities in communities and infrastructure, providing more precise and accurate information to policymakers, and supporting decision-making processes. AI can also assist in developing early warning systems to help communities prepare for and respond to extreme weather events such as floods, droughts, and hurricanes. One of the most promising applications of AI in climate change adaptation is the use of AI-powered models to simulate the impact of climate change on infrastructure. Such models can be used to forecast the potential impact of rising sea levels on coastal infrastructure, identifying areas that are most at risk of flooding and erosion. AI-powered simulations can also help businesses to assess their climate-related risks and opportunities, allowing them to better prepare for the future and develop more sustainable business practices. However, there are ethical considerations and potential biases that must be considered while designing and implementing these strategies. For example, there may be concerns regarding data privacy and security, as well as the potential for AI algorithms to perpetuate existing biases and inequalities. It is crucial to ensure that AI-powered climate change adaptation strategies are developed and implemented in an inclusive and equitable manner. In terms of future directions and potential innovations, AI-powered climate change adaptation strategies are likely to become even more sophisticated and accurate in the coming years. The integration of advanced machine learning algorithms, real-time data analysis, and other cutting-edge technologies could lead to even more effective climate change adaptation strategies. Overall, AI-powered climate change adaptation strategies have the potential to significantly improve the resilience of communities, infrastructure, and businesses to the changing climate.

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