
HARNESSING ARTIFICIAL INTELLIGENCE FOR ENVIRONMENTAL HAZARD PREDICTION: MODELS, METHODOLOGIES, AND REAL-WORLD APPLICATIONS

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ABSTRACT

Floods, wildfires, hurricanes, earthquakes, and droughts are becoming more frequent and severe as a result of climate change, urbanization, and environmental degradation. These catastrophes pose serious threats to human lives, ecosystems, and economic systems. Traditional forecasting approaches, while valuable, frequently struggle with the nonlinear and dynamic nature of environmental systems. In recent years, Artificial Intelligence (AI) has emerged as a transformative tool in environmental hazard prediction, providing more accurate, adaptable, and real-time forecasting. This article examines how environmental forecasting systems can incorporate AI methods including machine learning, deep learning, and hybrid models. It investigates how artificial intelligence uses huge, complex datasets from satellite photography, remote sensing, meteorological sources, and real-time sensor networks to model and predict environmental dangers. The article demonstrates the versatility and usefulness of AI models by discussing numerous dangers in detail, such as flood forecasting using neural networks, wildfire detection using image recognition algorithms, and earthquake early warning systems based on pattern recognition.

Furthermore, the article examines real-world case studies and pilot initiatives from throughout the world, providing insight into both successful implementations and current issues. It also addresses crucial challenges such as data quality, model interpretability, infrastructure inequities, and ethical concerns in the use of AI for public safety.

This article emphasizes AI-based forecasting's expanding significance in catastrophe planning, policymaking, and long-term risk management by exploring both its potential and limitations. It promotes a collaborative, data-driven approach to creating more resilient communities in the face of rising environmental risks.

1. INTRODUCTION

In an era of rising environmental instability, the ability to accurately forecast natural hazards has become an essential component of worldwide disaster risk reduction efforts. Floods, hurricanes, wildfires, earthquakes, and droughts pose increasing threats to human life, infrastructure, agriculture, and ecosystems. As climate change increases, these dangers become more frequent, intense, and unpredictable, necessitating the need for more reliable and timely forecasting techniques.

The importance of environmental hazard forecasting is not only in saving lives, but also in reducing economic losses and increasing resilience. Early warning systems based on exact forecasting enable governments, emergency responders, and communities to plan for disasters, allocate resources more efficiently, and mitigate the overall impact of extreme events. Forecasting models are thus critical instruments for proactive climate adaption and sustainable development planning.

Statistical regression, numerical weather prediction (NWP), and deterministic simulations are examples of traditional forecasting techniques that frequently fail to capture the intricate, nonlinear interactions present in environmental systems. These models rely largely on historical data, make rigid assumptions, and require massive processing power to mimic changing climate trends. As a result, their forecasts may be erroneous, delayed, or insufficient in constantly changing scenarios particularly in areas with low data infrastructure.

The rise of artificial intelligence (AI) has resulted in a paradigm shift in environmental research and risk management. AI models, particularly those based on machine learning and deep learning, can process large, multidimensional datasets, uncover hidden patterns, and learn from real-time data. This allows for more adaptive, accurate, and speedier forecasts than traditional methodologies. As AI advances, its application in hazard forecasting has enormous potential for altering disaster preparedness and establishing climate-resilient civilizations.

2. AI TECHNIQUES FOR ENVIRONMENTAL FORECASTING

AI tools are transforming environmental forecasting by increasing the accuracy, speed, and application of predictions in climate research, meteorology, and ecological monitoring. These innovations make it possible to better prepare for catastrophic weather occurrences, combat

climate change, and manage resources sustainably. The following is a detailed examination of key AI methodologies and their applications.

Core AI Techniques:

- **Machine Learning (ML) and Deep Learning**

LSTM Networks: Long Short-Term Memory networks excel at forecasting time-series data, particularly for environmental variables such as snow cover, vegetation patterns, and weather. These models employ historical data to forecast trends over multiple years, with hyperparameter adjustment for stability¹².

Convolutional Neural Networks (CNNs) are used for image-based applications like detecting deforestation, mapping air pollution, and identifying marine heatwaves. CNNs analyse satellite photos to track ecological changes in real time³⁴.

Predictive modelling uses historical climate data and machine learning to simulate scenarios such as sea-level rise, drought patterns, and species extinction risks. These models enable policymakers to assess mitigation solutions⁵.

- **Hybrid Physical-AI Systems**

Replace computationally demanding components (e.g., convection parameterizations) with neural networks to reduce processing time while preserving accuracy. Improving spatial resolution for small-scale weather phenomena (e.g., thunderstorms, urban heat islands) while minimizing computing costs. Improving statistical post-processing to correct systematic mistakes in weather forecasts is a practice perfected since the 1990s⁶.

¹ Scientific Reports, <https://www.nature.com/articles/s41598-022-16665-7> (last visited on June 1, 2025)

² : Ferebee S. Predicting, “Tomorrow: A Review of Machine Learning’s Role in Shaping Environmental Forecasts” *Premier Journal of Science*, 1 (2024)

³ Science direct, <https://www.sciencedirect.com/science/article/pii/S2773049224000278> (last visited on June 1, 2025)

⁴ Research gate, <https://www.linkedin.com/pulse/ai-climate-change-modeling-predicting-mitigating-impact-prakhar-jain-spniif> (last visited on June 1, 2025)

⁵ *Ibid.*

⁶ Encyclopedie, <https://www.encyclopedie-environnement.org/en/air-en/artificial-intelligence-and-weather-forecasting/> (last visited on June 1, 2025)

- **Fully AI-Driven Models**

Cutting-edge systems like Pangu-Weather and Graph Cast demonstrate AI's potential to replace traditional models entirely. Trained on 40+ years of data, these models rival physical systems like the ECMWF in medium-range weather forecasting, particularly for storms and tropical cyclones⁷.

3. DATA SOURCES AND PROCESSING

Accurate environmental hazard forecasting is dependent on the quality, variety, and relevance of input data. Large, diversified datasets are required by artificial intelligence (AI) models in order to find trends and anticipate the occurrence, magnitude, and impact of environmental occurrences. This section describes the primary data sources utilized in AI-based hazard forecasting, as well as the key data pretreatment and feature engineering techniques that improve model performance.

- **Remote Sensing Data, Satellite Imagery, and GIS**

Remote sensing technologies provide continuous and large-scale observations of the Earth's surface, making them critical for environmental monitoring. Satellites collect high-resolution imaging and spectral data, which is critical for detecting changes in land use, vegetation, temperature, water bodies, and atmospheric conditions.

Satellite imagery from platforms such as NASA's MODIS, ESA's Sentinel, and NOAA's GOES is used to track thermal anomalies, precipitation, sea surface temperature, and vegetation indices.

Geographic information systems (GIS) provide geographic data integration, analysis, and visualization. GIS is used to create danger maps, identify sensitive areas, and combine environmental and socioeconomic data. Applications include monitoring wildfire spread, mapping flood-prone areas, and determining drought severity.

- **Meteorological and Hydrological Datasets**

Meteorological and hydrological data are essential for predicting atmospheric and water-

⁷ *Ibid.*

related dangers. These data are gathered from ground-based weather stations, radar systems, buoys, and automated sensors. Meteorological data contains factors like rainfall, temperature, humidity, wind speed, and air pressure. These are critical for predicting weather extremes such as cyclones and heatwaves.

Hydrological data includes river discharge levels, groundwater depth, soil moisture, and reservoir inflow/outflow records. This data is critical for flood prediction, water resource management, and landslide risk assessment. National meteorological offices, global repositories (such as the ECMWF and NOAA), and research organizations all supply data.

- **Data Preprocessing and Feature Engineering**

Raw environmental data is frequently noisy, fragmentary, and in various formats. To ensure the effectiveness of AI models, data must be pre-processed a critical step in preparing it for analysis and training.

Data preparation tasks include the following:

- I. Cleaning missing or inconsistent entries.
- II. Normalizing or scaling data values.
- III. Handling outliers and abnormalities.
- IV. Alignment of datasets in terms of both time and space

Feature engineering is the process of developing meaningful input variables (features) from raw data to improve model accuracy. Examples include calculating vegetation indices (e.g., NDVI), deriving slope from digital elevation models (DEM), and calculating rainfall-runoff coefficients. Domain-specific information is frequently used to discover the most predictive variables for a particular danger.

Artificial intelligence models can provide accurate, rapid, and context-sensitive hazard forecasts by combining remote sensing, geospatial analysis, and real-time meteorological and hydrological inputs, as well as rigorous preprocessing. Integrating and transforming raw data into high-quality features are critical procedures that have a direct impact on prediction system success.

- **Ground-Based Sensors and IoT Networks**

IoT (Internet of Things) devices, outfitted with sensors for temperature, humidity, air quality, water quality, and other parameters, form enormous networks that collect real-time environmental information⁸⁹.

These sensors are deployed in urban, rural, and remote environments. They provide granular and continuous data streams for monitoring and predictive modelling¹⁰.

- **Weather Stations and Ocean Buoys**

Traditional weather stations and ocean buoys are still necessary for gathering meteorological and oceanographic data (e.g., temperature, wind speed, precipitation, sea surface temperature). These sources are frequently used with satellite and IoT data to improve model accuracy¹¹¹².

- **Drones and Aerial Sensors**

Drones with AI-powered sensors can collect climate and environmental data from difficult-to-reach or hazardous regions, augmenting satellite and ground-based networks¹³.

- **AI Model Training and Analysis**

Algorithms like decision trees, support vector machines, and neural networks (including CNNs and LSTMs) are trained on historical and real-time data to find patterns, forecast trends, and detect abnormalities¹⁴.

Air quality, temperature, and vegetation indices are just a few examples of the environmental variables that can be accurately predicted over time using LSTMs and other recurrent models. CNNs scan satellite and drone imagery to classify land cover, detect deforestation, and monitor

⁸ Markersite, <https://makersite.io/how-ai-is-transforming-environmental-monitoring-and-conservation/> (last visited on June 1, 2025)

⁹ Iot for all, <https://www.iotforall.com/iot-and-environmental-monitoring-with-sensor-networks> (last visited on June 1, 2025)

¹⁰ Inrate, <https://inrate.com/blogs/ai-climate-data-collection-and-analysis/> (last visited on June 1, 2025)

¹¹ EMB Global, <https://blog.emb.global/ai-in-predicting-climate-change-patterns/> (last visited on June 1, 2025)

¹² Lunartech, <https://www.lunartech.ai/blog/ai-in-climate-modeling-and-environmental-monitoring> (last visited on June 1, 2025)

¹³ *Ibid.*

¹⁴ *Ibid.*

disasters.

- **Real-Time and Predictive Analytics**

AI provides real-time analysis of sensor and satellite data, resulting in timely alarms for pollution surges, harsh weather, and other environmental threats¹⁵.

Predictive models employ historical data to estimate future situations, which supports early warning systems and proactive resource management¹⁶.

4. APPLICATIONS OF AI IN SPECIFIC ENVIRONMENTAL HAZARDS

Artificial intelligence (AI) has proven to be an effective tool for tackling a wide range of environmental dangers, with features that improve prediction accuracy, speed, and spatial resolution. AI facilitates early warning systems and strategic reaction planning by utilizing different datasets and advanced algorithms. This section investigates how artificial intelligence (AI) is applied to various environmental dangers and demonstrates its impact across fields.

- **Flood Prediction**

Floods are one of the most common and devastating natural disasters. AI models, particularly neural networks, random forests, and support vector machines, are utilized to forecast flood frequency, severity, and extent. AI combines real-time hydrological data (such as river flow and precipitation) with topography and land-use information. Recurrent Neural Networks (RNNs) and LSTM models are useful for forecasting river discharge and rainfall-runoff trends. For example, Google AI's flood forecasting system has been deployed in India and Bangladesh, offering real-time alerts using deep learning models.

- **Earthquake Forecasting**

While earthquakes are still difficult to predict with high certainty, AI is being used to detect seismic precursors, analyse foreshock-aftershock sequences, and improve early warning systems. Support Vector Machines (SVMs) and deep learning models can classify seismic

¹⁵ *Ibid.*

¹⁶ *Ibid.*

events and predict epicentres using historical and real-time seismic data. AI can also aid with post-quake damage prediction by analysing satellite pictures and infrastructure databases.

- **Wildfire Detection and Spread Modelling**

Climate change and poor land management practices are causing wildfires to become more severe. AI helps with both early detection and spread modelling. Convolutional Neural Networks (CNNs) use satellite and drone data to detect fire outbreaks. Hybrid models that include meteorological, topography, and vegetation data forecast how flames would spread based on wind direction, humidity, and fuel availability. Countries such as the United States, Australia, and Canada use real-time AI systems to monitor wildfires.

- **Cyclone and Hurricane Tracking**

Tropical cyclones and hurricanes pose significant risks to coastal communities. AI improves forecasts for their formation, trajectory, strength, and landfall time. AI models use satellite photos, sea surface temperatures, and atmospheric pressure data to track storm systems. Ensemble learning approaches increase predicted accuracy by merging results from many models. AI can also help with impact assessments, which involves calculating affected populations and infrastructure for improved disaster preparedness.

- **Drought Forecasting**

Droughts occur gradually but have long-term socioeconomic and environmental consequences. AI can aid in anticipating drought onset, length, and severity. Variables used in machine learning models include soil moisture, temperature, rainfall patterns, and vegetation indices. Time-series forecasting with LSTMs identifies early signals of protracted dry weather. AI is combined with agricultural decision-support systems to help drought-prone areas plan their water use and crops.

By customizing AI methodologies for specific risks, researchers and organizations can create more responsive, data-driven systems that reduce risk and safeguard communities. As models evolve, their integration with local knowledge and policy frameworks will become critical for long-term resilience.

5. CASE STUDIES AND REAL-WORLD IMPLEMENTATIONS

The use of AI in environmental hazard forecasting is no longer limited to research laboratories. Governments, technology businesses, and research organizations all across the world are using AI-powered systems to manage disasters. This section includes major case studies and country-specific implementations that demonstrate the actual benefits, limitations, and innovations of AI-based hazard prediction.

1. AI in Disaster Management Systems

- Google AI – Flood Forecasting (India & Bangladesh)

Google has developed an AI-based flood forecasting system that combines hydrological modelling and machine learning in partnership with local governments and organizations such as the Central Water Commission (India). The system generates real-time flood alerts based on satellite data, rainfall records, and river level statistics. AI models assess present water levels and predict how they will change in the following 48 hours. Since 2020, millions of people have received notifications via Google Search and Maps, with better accuracy and lead times.

- IBM's Watson – Emergency Response and Risk Analytics

IBM's artificial intelligence platform Watson has been developed for use in emergency response systems, particularly in disaster-prone areas of the United States. Watson's capabilities include real-time data ingestion, natural language processing, predictive analytics, and visualization tools, which help authorities prepare for and respond to natural catastrophes more effectively.

During hurricane seasons, agencies such as the Federal Emergency Management Agency (FEMA) used Watson to assess incoming weather data, social media activity, and infrastructure vulnerability maps. The AI engine assisted in creating risk heatmaps, prioritizing regions for evacuation or supply distribution, and forecasting post-disaster impacts such as power shortages and flooding.

Watson's ability to combine multiple data sources and give actionable insights, rather than just raw forecasts, sets it apart. This makes it a dependable decision-support tool in time-sensitive catastrophe situations.

2. Country-Specific Implementations

- India – Floods, Landslides, and Agricultural Droughts

India, one of the world's most climate sensitive countries, has made pre-emptive steps to integrate artificial intelligence into its disaster management system. AI is now being employed in a variety of sectors. The Indian Space Research Organisation (ISRO) and the National Remote Sensing Centre (NRSC) use machine learning to map landslides based on topography elevation, land cover type, and rainfall patterns. The Ministry of Earth Sciences is looking at AI applications in monsoon forecasting, which is crucial for agriculture. Private companies such as Sat Sure use artificial intelligence and satellite data to monitor drought conditions, crop stress, and groundwater supply, assisting both the government and insurance companies in developing drought response plans.

Artificial intelligence (AI)-based hydrological models that mimic rainfall-runoff dynamics using real-time sensor inputs are being piloted in urban flood forecasting programs in cities like Chennai and Hyderabad.

- Japan – Earthquake and Tsunami Early Warning Systems

Japan's placement on the Pacific Ring of Fire exposes it to frequent seismic activity and tsunamis. It has made significant investments in earthquake early warning systems (EEWS), which rely significantly on artificial intelligence. Japanese authorities and colleges apply deep learning algorithms to detect earthquake precursors and classify real-time seismic data for early event detection. AI algorithms improve tsunami forecast accuracy by combining pressure sensor data from the ocean floor, tectonic movement patterns, and historical occurrence records. The Japan Meteorological Agency has integrated AI to eliminate false warnings and speed up alerts issued to the public and transportation systems.

These initiatives have resulted in speedier reaction times, allowing trains to stop, buildings to turn off critical systems, and people to evacuate within seconds of notice, eventually saving lives.

- United States – Handling Wildfires and Predicting Hurricanes

American authorities make extensive use of AI to manage disasters, especially wildfires and

hurricanes. Because of rising catastrophic wildfires in California, CAL FIRE and NASA JPL use AI-powered systems to spot smoke from the air in satellite images. Some systems can figure out the strength and direction of a fire with the aid of wind speed and humidity data. Various weather factors, dryness in vegetation and past fire events are assessed with AI to anticipate the risk of a fire breaking out. NOAA makes use of deep learning to guess how dangerous a hurricane might be and monitor its progress. Using air pressure, sea surface temperatures and satellites helps these models give better forecasts for both the near future and further ahead. Such technology is used to plan and supervise how resources will be used and activities carried out during emergencies, making sure firefighters, medical workers and evacuations are well organized.

6. CHALLENGES AND ETHICAL CONSIDERATIONS

While artificial intelligence (AI) provides unparalleled capabilities for forecasting environmental threats, its deployment is not without problems. The efficacy, fairness, and sustainability of AI systems are dependent on addressing both technical constraints and ethical quandaries. This section describes the major challenges and ethical considerations that must be overcome to ensure the proper deployment of AI in environmental forecasting.

- **Data Scarcity and Quality**

AI models are essentially data-driven, and they require enormous amounts of high-quality, organized data to work well. However, in many places, particularly in the Global South, environmental datasets are scarce, out of date, or unavailable. **Data Gaps:** Many developing countries lack dense networks of meteorological stations, hydrological sensors, and real-time satellite data, resulting in incomplete or imprecise forecasts. **Noise and Inconsistencies:** Environmental data are frequently inconsistent due to equipment failure, sensor drift, or human error in reporting. **Temporal and Spatial Resolution Issues:** Differences in data frequency (daily vs. hourly) and resolution (regional vs. local) limit AI's usefulness in hyper-local forecasting.

These data limits not only diminish model accuracy but also contribute to increased uncertainty in forecasts, thereby undermining public faith in AI-powered services.

- **Bias and Interpretability**

AI models, particularly deep learning systems, are frequently referred to as "black boxes" due

to their intricate inner workings. This opacity makes it difficult to understand and trust the outcomes, particularly in high-stakes scenarios like disaster response.

Algorithmic Bias: By reflecting the biases of their training data, models may perform differently in other ecosystems, communities, or geographical areas. For example, an AI model trained mostly on North American climate data may underperform in sub-Saharan Africa.

Decision-makers, emergency workers, and community leaders require transparent explanations of AI outcomes in order to take informed action. Lack of interpretability can impede accountability and prevent inclusion into formal decision-making processes.

- **Infrastructure Gaps in Developing Nations**

The effectiveness of AI models depends not only on data availability but also on technological infrastructure, including computing power, connectivity, and institutional capacity.

Hardware and Connectivity: Many regions at the highest risk of environmental hazards also face infrastructure limitations such as unreliable electricity, low internet penetration, and limited access to cloud computing resources.

Human Capacity: A shortage of trained personnel in AI, data science, and environmental modelling further exacerbates the challenge, leading to reliance on external or imported expertise.

Integration Challenges: Even when AI tools are available, integrating them into national disaster management systems requires compatibility with existing protocols, administrative willingness, and public acceptance.

Bridging these infrastructure gaps is critical for ensuring the equitable deployment of AI across all regions.

- **Ethical Use and Accountability**

AI systems for hazard prediction must follow ethical norms that preserve public safety, privacy, and rights. Several ethical considerations are especially important in the context of environmental forecasting:

Informed Consent and Data Privacy: The use of citizen-contributed data (for example, via mobile apps or social media) raises concerns about privacy and consent, particularly in catastrophe situations.

Transparency and accountability: In the event of a prediction failure or false alarm, it is critical to understand who is responsible—whether it is the data provider, the algorithm designer, or the deploying agency.

Equity and fairness: Artificial intelligence models should not aggravate current inequities. For example, if forecasting methods favor urban areas with more data coverage, rural or underprivileged communities may be excluded from early warning systems.

Weaponization of AI: There is also concern about dual-use applications, in which environmental AI could be co-opted for surveillance or political control in the name of disaster management.

Creating strong ethical frameworks, international standards, and governance systems is critical for mitigating these hazards and guiding responsible AI development and deployment.

7. FUTURE PROSPECTS AND POLICY IMPLICATIONS

As the climate problem worsens, the use of artificial intelligence (AI) in environmental hazard prediction systems will become increasingly important. The future of AI in this domain depends not just on scientific breakthroughs, but also on systemic integration with policy, infrastructure, and worldwide collaboration. This section discusses the future of AI applications and provides policy options to assure ethical, inclusive, and effective deployment.

- **Integration with IoT and Edge Computing**

AI-based environmental forecasting's next frontier is its integration with the Internet of Things (IoT) and edge computing. Real-time data collection from dispersed sensor networks, such as weather stations, river gauges, seismometers, and air quality monitors, provides unparalleled granularity to prediction models.

IoT-Enabled Sensing: Smart sensors placed in the environment can constantly monitor variables such as soil moisture, water levels, temperature, and air quality. When linked to AI

systems, they provide hyper-local forecasting with fast response times.

Edge Computing: By processing data closer to the source (i.e., on the sensor or local device), edge computing reduces latency and allows for faster decision-making in time-sensitive situations such as flash floods, wildfires, or chemical releases.

Scalability and Autonomy: Combining AI with IoT and edge systems improves scalability and enables autonomous operation in remote or underserved areas, decreasing reliance on centralized data centres.

These advancements can enable local populations, particularly those in disaster-prone rural or coastal areas, to monitor threats in real time and take timely, educated action.

- **Cross-Border Data Sharing for Global Risk Prediction**

Environmental threats are not limited by national boundaries. The effects of floods, droughts, wildfires, and cyclones frequently cross international borders. As a result, international cooperation in AI-powered forecasting is critical.

Harmonizing Data Standards: Nations must work together to develop open-access databases for environmental variables, uniform metadata standards, and compatible data formats.

Regional AI Hubs: The establishment of international AI hubs, such as those inside the UN or regional blocs such as ASEAN or the EU, can help to enable the sharing of expertise and best practices, particularly in managing shared resources and ecosystems.

Disaster Diplomacy: AI can also help with diplomacy by facilitating common risk assessments, dispute settlement over environmental resources, and coordinated humanitarian aid initiatives using predictive models.

Cross-border AI collaboration will be critical to meeting the objectives of frameworks such as the Sendai Framework for Disaster Risk Reduction and the Paris Agreement.

- **Policy Recommendations for AI Adoption**

To enable appropriate and successful use of AI in environmental hazard prediction, many critical policy measures are required:

Governments should place a high priority on funding sensor networks, satellite capabilities, and national data repositories. Public-private partnerships have the potential to speed this process.

AI Governance and Ethical Oversight: Particularly in high-risk applications like hazard forecasting, precise regulatory frameworks should be put in place to supervise the development, implementation, and accountability of AI systems.

National and municipal governments require training programs and institutional assistance to interpret AI forecasts and incorporate them into policy and emergency response protocols.

Inclusive Access: Policies must ensure that AI forecasting tools reach underserved people, indigenous populations, and locations with restricted technical access.

Climate and AI Policy Integration: AI-based environmental forecasting should be integrated into broader climate resilience and adaptation policies at both national and international levels.

By implementing these ideas, governments can use AI not only as a technological tool, but also as a strategic asset in resilience development.

8. CONCLUSION

This article examined the expanding significance of Artificial Intelligence in anticipating environmental dangers from a multidisciplinary perspective. From machine learning models for flood and drought prediction to deep learning algorithms for earthquake and wildfire analysis, artificial intelligence is changing the way we comprehend, plan for, and respond to natural disasters. Real-world case studies from countries like as India, Japan, and the United States highlight the promise and utility of AI-powered systems.

However, the journey ahead is not without obstacles. Data scarcity, model bias, infrastructure inequities, and ethical quandaries all offer substantial challenges to AI's mainstream deployment. Furthermore, without proper administration, these technologies risk exacerbating existing inequities or failing to help the most vulnerable.

Although there are obstacles, AI has the power to help make societies more resilient to climate change. It promotes early precautions, boost's ability to identify problems and supports

informed decisions by everyone from local authorities to big international organizations. Combining AI with practical knowledge, public policies and inclusive infrastructure can protect people, the environment and the economy from more frequent and intense environmental issues. To make this vision come true, people involved must work together, act ethically and focus on equity. Thus, AI will assist in predicting the future and also help create a more secure and robust one.