United Nations Climate Change
Technology Executive Committee

TECHNICAL PAPER

Artificial Intelligence for Climate Action:

Advancing Mitigation and Adaptation in Developing Countries

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Executive Summary

Climate change is one of the most pressing challenges of the 21st century, requiring rapid and coordinated action across communities, sectors, approaches, and technologies to mitigate greenhouse gas (GHG) emissions and enhance adaptation to climate impacts. It disproportionately affects developing countries, including Least Developed Countries (LDCs) and Small Island Developing States (SIDS), which are highly vulnerable to significant consequences of climate change, including rising sea levels, extreme weather events, and shifting agricultural conditions. These threats jeopardize socio-economic stability and environmental sustainability in these regions, making climate adaptation and mitigation strategies essential.

This technical paper, prepared by the Technology Executive Committee (TEC) under the Technology Mechanism Initiative on AI for Climate Action (#AI4ClimateAction Initiative), offers a comprehensive overview for policymakers, practitioners, and researchers navigating opportunities, challenges, and risks of the use of AI for climate action in developing countries, with a focus on LDCs and SIDS as these countries face unique vulnerabilities to climate change. AI-driven solutions can become potential enablers for adapting to climate impacts and reducing GHG emissions. However, risks and challenges also exist, which need to be addressed for the effective and sustainable use of AI in climate action.

In mitigation AI can enable the reduction of energy waste and the optimization of energy consumption and distribution; scale the identification of emission hotspots and optimize industrial processes while tracking their carbon footprint. AI-driven renewable energy management systems can enhance energy grid efficiency, forecast power demand, and optimize solar and wind energy deployment. AI tools can be also used to analyse data from transportation systems to reduce fuel consumption through traffic optimization and route planning. The integration of AI into emission reduction strategies can accelerate progress towards decarbonization and help nations meet their climate commitments.

In the context of adaptation, AI can enhance early warning systems by predicting extreme weather events such as hurricanes, floods, and droughts, enabling proactive disaster risk management. AI-driven urban resilience tools can be used to support infrastructure planning by identifying vulnerabilities and optimizing land use. Additionally, AI-assisted resource and ecosystem management solutions can help improve biodiversity conservation, sustainable water use, and land restoration efforts when coupled with satellite imagery.

Despite its potential, AI adoption in developing countries presents numerous challenges. Many developing countries, and in particular LDCs and SIDS, face digital infrastructure limitations, including unreliable internet connectivity, inadequate computing power, and a lack of skilled professionals to develop and deploy AI systems. The digital divide hinders their ability to adopt AI-driven climate solutions and addressing this divide requires significant investment in digital transformation and capacity-building programmes. Furthermore, the availability and accessibility of high-quality climate data remain significant barriers as many developing countries lack comprehensive and reliable datasets for AI-driven decision-making. Without robust data-sharing frameworks and cybersecurity measures, AI applications outputs may be unreliable or prone to exploitation. Moreover, bias and inequity in AI systems can perpetuate social disparities if algorithms are not designed with inclusivity in mind. Therefore, a proper governance framework is needed to mitigate these potential risks and digital divide. Also, increased energy and water consumption and carbon footprints can have negative consequences and pose threats to global climate goals. The resource intensity of AI, including its energy and water consumption, raises concerns about sustainability, particularly in regions with limited natural resources, and these have to be taken into account when considering AI as an enabler for climate action.

To ensure AI serves as an enabler of climate resilience in developing countries, in particular LDCs and SIDS, policymakers and stakeholders must prioritize capacity-building initiatives, strengthen digital infrastructure, and establish inclusive governance frameworks. By fostering collaborations, including between governments, academia, and the private sector, developing countries can build AI expertise and ensure responsible AI deployment. Creating regional AI research centres and knowledge-sharing platforms can further enhance local capacity and facilitate AI adoption tailored to the specific needs of each country.

This technical paper concludes with a set of recommended priority actions, to be used to realize the potential of AI in climate action: (a) addressing the digital divide should focus on expanding digital infrastructure and investing in AI capacity-building programmes to empower developing countries to leverage AI effectively for climate action; (b) enhancing data availability and access requires stronger climate data collection efforts and the promotion of open-data initiatives to support AI model development and deployment; (c) strengthening AI governance under the UNFCCC involves creating regulatory frameworks to ensure AI transparency, fairness, and accountability, preventing bias and misuse while fostering ethical AI adoption; (d) addressing gender bias and social inequalities by designing AI models with inclusive approaches to prevent discrimination and ensure equitable climate benefits is important; (e) managing the energy and water consumption of AI, among others, should be taken into account, encouraging the development of energy-efficient AI systems and promoting sustainability in AI operations; (f) enhancing global collaboration for AI in climate action is necessary, strengthening cooperation between governments, UN agencies, private-sector actors and other stakeholders to facilitate responsible AI adoption and address existing regulatory gaps.

Implementing these recommendations will allow developing countries, especially LDCs and SIDS, to harness AI as a strategic tool to implement climate action at scale. Addressing lack of infrastructure, sustainability concerns, data, and governance gaps, will not only strengthen local capacities but also create opportunities for innovation and collaboration, ensuring these countries actively participate in global climate efforts while addressing their unique climate challenges.

Abbreviations and acronyms

4-AIDE: AI-based Disaster and Emergency Management Framework

ACO: Ant Colony Optimization

AI: Artificial Intelligence

AIoT: Artificial Intelligence of Things

AIS: Automatic Identification System

ANFIS: Adaptive Neuro-Fuzzy Inference System

ANFIS-ACO: Adaptive Neuro-Fuzzy Inference System with Ant Colony Optimization

ANFIS-GA: Adaptive Neuro-Fuzzy Inference System with Genetic Algorithm

ANFIS-PSO: Adaptive Neuro-Fuzzy Inference System with Particle Swarm Optimization

ANNs: Artificial Neural Networks

APSO: Advanced Particle Swarm Optimization

AR: Augmented Reality

ARIES: Artificial Intelligence for Ecosystem Services

ARIMA: Autoregressive Integrated Moving Average

ARMA: Autoregressive Moving Average

ASALs: Arid and Semi-Arid Lands

AUV: Autonomous Underwater Vehicle

AVs: Autonomous Vehicles

AWS: Amazon Web Services

BERT: Bidirectional Encoder Representations from Transformers

BBBC: Big Bang–Big Crunch

BiLSTM: Bidirectional Long Short-Term Memory

BMKG: Indonesia Meteorological Administration

BMP: Best Management Practices

BN: Bayesian Network

BO: Bonobo Optimizer

BOA: Butterfly Optimization Algorithm

BR: Bayesian Regularization

CAPTAIN: Conservation Area Prioritization through Artificial Intelligence

CARDS: Augmented Computer-Assisted Recognition of Denial and Scepticism

CAVs: Connected and Autonomous Vehicles (CAVs)

CCSTU: CO2 capture, storage, transportation, and utilization

CDNN: Convolutional Deep Neural Networks

CFD–GA: Computational Fluid Dynamics–Genetic Algorithm

CLIP: Contrastive Language–Image Pre-training

CNNs: Convolutional Neural Networks

CO2: Carbon Dioxide

COA: Coyote Optimization Algorithm

COP28: 28th meeting of the Conference of the Parties to the UNFCCC

COP29: 29th meeting of the Conference of the Parties to the UNFCCC

CR1000X: Campbell CR1000X datalogger

CS: Crow Search

CTCN: Climate Technology Centre and Network

CV: Computer Vision

DCS: Digital Climate Station

DDFS: Direct Dual Fuel Stratification

DDM: Data-Driven Modelling

DES: Distributed Energy System

DL: Deep Learning

DNNs: Deep Neural Networks

DPG: Digital Public Goods

DRM: Disaster Risk Management

DSS: Decision Support Systems

DTR: Diurnal Temperature Range

EC-DAQS: Environment and Climate Data Acquisition System

EMPIRIC_AI: Enhancing Cyclone Resilience through AI in Pacific Island Countries

EO: Earth Observation

ERF: Extreme Random Forest

ES: Expert Systems

ESA: European Space Agency

ESMs: Earth System Models

EW4All: UN Early Warnings for All Initiative

FAIR: Forward Artificial Intelligence for Rural Development

FAIS: Flood Analytics Information System

FTMA: Fine-Tuning Metaheuristic Algorithm

GA: Genetic Algorithm

GANs: Generative Adversarial Networks

GBM: Gradient Boosting Machine

GenAI: Generative Artificial Intelligence

GEO: Group on Earth Observations

GEOGLOWS: GEO Global Water Sustainability

GFDL: Geophysical Fluid Dynamics Laboratory

GFDRR: Global Facility for Disaster Reduction and Recovery

GHG: Greenhouse Gas

GIZ: Deutsche Gesellschaft für Internationale Zusammenarbeit

GMDH: Group Method of Data Handling

GoCD: Government of the Commonwealth of Dominica

GoSL: Government of Saint Lucia

GPS: Global Positioning System

GPT-3: Generative Pre-trained Transformer 3

GRU: Gated Recurrent Unit

GVC: Global Value Chain

GWP: Global Warming Potential

HASTE: High-speed Assessment and Satellite Tracking for Emergencies

HCS: High Carbon Stock

HCSA: High Carbon Stock Approach

HRAI: High-Resolution Aerial Imagery

HRES: Hybrid Renewable Energy System

HVAC: Heating, Ventilation, Air Conditioning

I2PDM: Intelligent and Integrated Pest and Disease Management

IFRC: International Federation of Red Cross and Red Crescent Societies

IHME: Institute for Health Metrics and Evaluation

IKS: Indigenous Knowledge Systems

IoT: Internet of Things

IPM: Integrated Pest Management

IRSA: Improved Reptile Search Algorithm

ITU: International Telecommunication Union

IUU: Illegal, Unreported, and Unregulated (fishing)

IVR: Immersive Virtual Reality

KNN: K-Nearest Neighbours

LDCs: Least Developed Countries

LDRI: Local Development Research Institute

LIDAR: Light Detection and Ranging

LLMs: Large Language Models

LSTM: Long Short-Term Memory

LULC: Land Use and Land Cover

LULUCF: Land Use, Land-Use Change, and Forestry

MAANN: Mode Adaptive Artificial Neural Network

MAE: Mean Absolute Error

MBE: Mean Bias Error

MERRA-2: Modern-Era Retrospective Analysis for Research and Applications, Version 2

MIROC5: Model for Interdisciplinary Research on Climate, Version 5

ML: Machine Learning

MLFFNN: Multilayer Feed-Forward Neural Network

MLP: Multilayer Perceptron

MPAs: Marine Protected Areas

MQTT: Message Queuing Telemetry Transport

MVCA: Multi-Variant Change Vector Analysis

NASA: National Aeronautics and Space Administration

NDCs: Nationally Determined Contributions

NGO: Non-Governmental Organization

NIS: National Innovation Systems

NLP: Natural Language Processing

NSE: Nash–Sutcliffe Efficiency

NSGA-II: Non-dominated Sorting Genetic Algorithm II

NWM: Neural Weather Models

ODK: Open Data Kit

ORESTE: Organization, Rangement et Synthèse de Données Relarionnelles

PICs: Pacific Island Countries

POEVs: Privately Owned Electric Vehicles

POVs: Privately Owned Vehicles

PSO: Particle Swarm Optimization

PyCCS: Pyrogenic Carbon Capture and Storage

RAG: Retrieval-Augmented Generation

RF: Random Forest

RMSE: Root Mean Square Error

RNNs: Recurrent Neural Networks

SAEVs: Shared Autonomous Electric Vehicles

SAR: Synthetic Aperture Radar

SAVs: Shared Autonomous Vehicles

SDGs: Sustainable Development Goals

SDM: Species Distribution Model

SEEDS: Sustainable Environment and Ecological Development Society

SfM: Structure from Motion

SIDS: Small Island Developing States

SoS: System of Systems

SPI: Standard Precipitation Index

SRC: Stage-Discharge Rating Curve

SVM: Support Vector Machine

SVR: Support Vector Regression

Swarm ANFIS: Swarm Adaptive Neuro-Fuzzy Inference System

SWAT: Soil and Water Assessment Tool

TEC: Technology Executive Committee

Tmax: Maximum Temperature

Tmean: Daily Mean Temperature

Tmin: Minimum Temperature

TNAs: Technology Needs Assessments

TRiSM: Trust, Risk, and Security Management

UAV–SfM: Unmanned Aerial Vehicle–Structure from Motion

UNDRR: United Nations Office for Disaster Risk Reduction

UNESCO: United Nations Educational, Scientific, and Cultural Organization

UNFCCC: United Nations Framework Convention on Climate Change

USAID: United States Agency for International Development

V2G: Vehicle-to-Grid

VBA: Village Based Advisor

VGG-19: Visual Geometry Group 19-layer Neural Network

VOCs: Volatile Organic Compounds

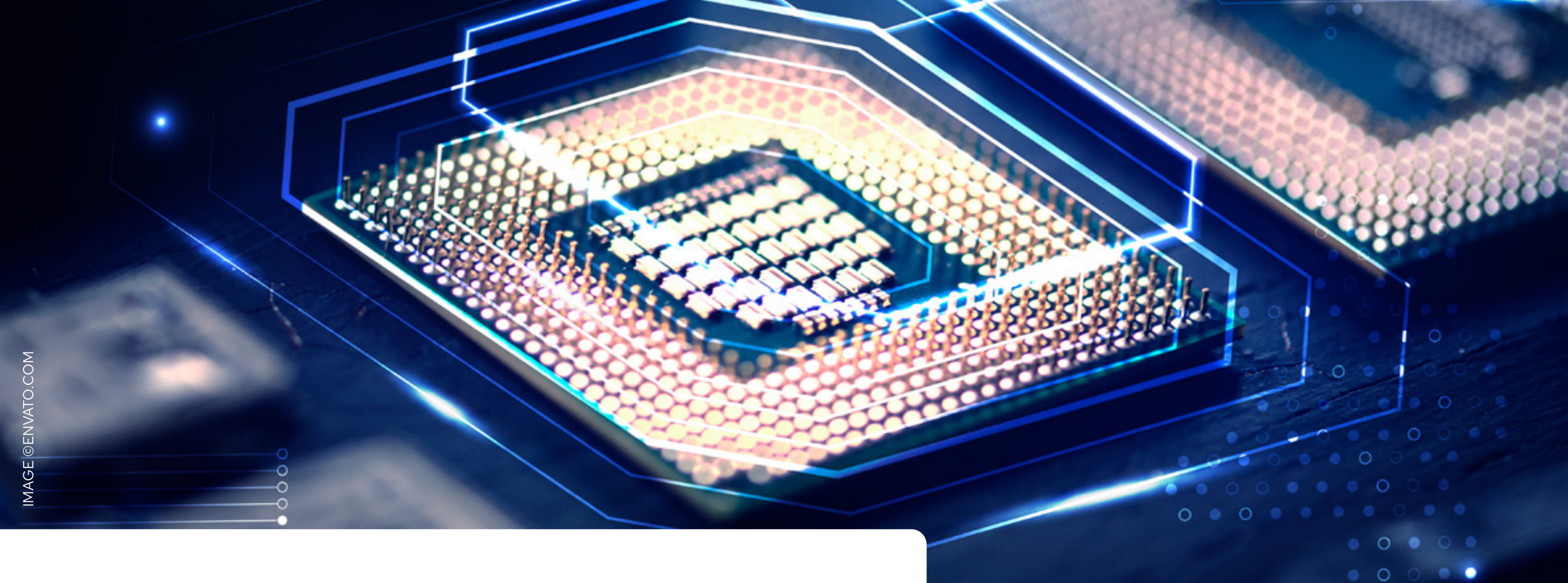
VR: Virtual Reality

WANFIS: Wavelet Adaptive Neuro-Fuzzy Inference System

WMO: World Meteorological Organization

WRF: Weather Research and Forecasting Model

YOLO: You Only Look Once



1. Introduction

Countries are increasingly recognizing the potential of AI as an enabler to aid climate action and as a tool to achieve their climate change targets. An analysis of the 169 Nationally Determined Contributions (NDCs) showed that by February 2024, 57 developing countries mentioned applying digital technologies to support their NDCs, including five of them that directly referred to AI. AI-enabled systems show the potential to support both climate change mitigation and adaptation, ranging from forecasting natural disasters to optimizing food production to enhancing energy system efficiency (UNFCCC, 2024c).

This technical paper positions itself as a document to provide comprehensive information on AI for climate action, by exploring its opportunities, challenges, and risks with a particular focus on the vulnerability of LDCs and SIDS. An extensive literature review and collection of case studies have been used to provide holistic and balanced information on this issue.

1.1. Aim and Objectives of the Technical Paper

The accurate prediction and monitoring of sea level rise are important for the protection of coastal areas and the planning of risk mitigation strategies. Various AI-based methods have been developed to address this complex issue, significantly enhancing the accuracy and efficiency of sea level predictions. Techniques like hybridization, ensemble modeling, data decomposition, and algorithm optimization are identified as key strategies for enhancing sea level predictions. DL, in particular, has shown superior performance due to its ability to automatically extract features and store memory, making it more effective than traditional ML models. This technical paper aims to outline the major roles, opportunities, and challenges of AI in climate action. The following objectives serve as a guide to addressing the complex interplay between AI technologies and climate change mitigation and adaptation, particularly in the context of developing countries, LDCs, and SIDS:

- Explore AI's role as a technological tool to advance and scale up transformative climate solutions for mitigation and adaptation in developing countries, with a focus on LDCs and SIDS.

- Address the challenges and risks posed by AI, particularly those relevant to climate action, including concerns about energy consumption and its environmental impact, data security, gender bias, the digital divide, and harmful practices.

- Showcase the opportunities and challenges associated with existing AI applications in developing countries, particularly LDCs and SIDS, in addressing climate change and improving environmental outcomes.

- Provide recommendations to policymakers on leveraging AI as a technological tool to advance and scale up transformative climate solutions while overcoming identified risks and challenges.

1.2. Defining Artificial Intelligence

Artificial Intelligence is the discipline focused on the research and development of mechanisms and applications of AI systems. AI systems are engineered systems that generate outputs such as content, forecasts, recommendations, or decisions for a given set of human-defined objectives (ISO/IEC 22989:2022(E)) by leveraging sophisticated algorithms, computational resources, and reliable and comprehensive datasets. The escalating availability of data, coupled with advancements in computational power, machine learning algorithms, and cloud computing, are some of the key drivers behind the renewed interest in AI over recent years. In order to work efficiently and in real time, AI applications rely on an optimal internet connection, without which data transmission would be impaired.

The AI stack can be described with a five-layer structure:

- **Hardware:** The complete CPU/GPU design and production chain, from raw materials and rare earth elements to advanced microelectronics manufacturing.

- **Cloud Infrastructure:** Data centres providing computing power, data storage, and platforms, encompassing energy supply, cooling, security, and redundancy.

- **Internet Infrastructures:** Physical networks (cables, towers, servers, exchange points) and end-user devices enabling internet connectivity and data transfer.

- **Software & Libraries:** AI frameworks and development tools.

- **Applications and Services:** AI-based solutions in areas such as computer vision, language processing, robotics, finance, agriculture, manufacturing, energy, media, healthcare, transportation, and education.

Machine Learning (ML) is the process of optimizing model parameters through computational techniques, such that the model's behaviour reflects the data or experience. ML algorithms can be applied in various use cases and domains thanks to their capacity for pattern recognition. However, effective application depends on the size, quality, and representativeness of the available data, as well as the appropriateness of the ML algorithm selected for the problem, which often requires testing multiple models to achieve the best predictions. A training-validation split is typically used when the dataset is sufficiently large and robust. In this approach, the training set helps the algorithm learn patterns from features and labels, whereas the test or validation set measures accuracy and generalization. After testing, model parameters are adjusted to address errors and enhance performance.

1.3. The Specificity of Least Developed Countries and Small Island Developing States in the Climate Change Context

While climate change poses challenges globally, its impacts are disproportionately severe for Least Developed Countries (LDCs) and Small Island Developing States (SIDS). SIDS and LDCs, due to their high exposure and fragility, are among the most vulnerable to climate change and the least emitting. Notably, SIDS and LDCs contribute minimally to, or bear almost no responsibility for, climate change, yet their specific geographical and socio-economic conditions make them exceptionally susceptible to its adverse effects (Mohan, 2023). Although the Paris Agreement endorses that developed countries should lead in providing assistance and establishing a framework for finance, substantial funding is still necessary for SIDS and LDCs to meet their climate objectives (Mohan, 2023).

LDCs and SIDS face heightened vulnerability to the adverse effects of climate change due to their limited capacity or resources to implement adaptive and mitigation measures. They are particularly exposed to climate risks such as rising sea levels, increased frequency and intensity of extreme weather events, and changing precipitation patterns, as well as shifts in agricultural conditions. These shifts, driven by changing temperatures, rainfall, and growing seasons, threaten food security and necessitate agricultural adaptation strategies like crop diversification and efficient water management. Moreover, these countries face significant challenges in reducing emissions or transitioning to low-carbon economies due to a reliance on inexpensive fossil fuels, limited renewable energy infrastructure, and the degradation of critical blue carbon ecosystems, such as mangroves and seagrasses, which play a key role in carbon sequestration. Addressing these challenges requires adaptation and mitigation strategies tailored to their unique contexts and needs (Havukainen et al., 2022; Filho, W. L. et al., 2020; Leal Filho et al., 2021; Tokunaga et al., 2021).

1.4. Artificial Intelligence as a Driver of Adaptation and Mitigation in Vulnerable Regions

In SIDS and LDCs, AI-driven technologies are being leveraged to improve early warning systems for natural disasters (Albahri et al., 2024; Kuglitsch et al., 2022a), providing more timely and accurate alerts to vulnerable populations. Beyond disaster preparedness, AI tools are being leveraged in LDCs to optimize agricultural practices, enabling regions to better adapt to shifting climate conditions by improving crop resilience and water resource management (Chen et al., 2023; Jain et al., 2023; Leal Filho et al., 2022) and strengthen climate communication channels in coastal regions facing extreme weather events (Chakravarty, 2023a). Furthermore, there are several examples of AI systems used to assist in the reduction of GHG emissions, advancing renewable energies, and improving environmental modelling and climate predictions (Bibri, 2024; Kaack et al., 2022; Sandalow et al., 2023; Zhao et al., 2024).

1.5. Risks and Challenges of AI in Climate Action

Integrating AI into climate action is challenging both in developed and developing countries. Concerns span its potential environmental, ethical, and societal impacts, including its high energy and water consumption (Brevini 2020; IEA, 2024a; Ligozat et al., 2021; Luccioni, 2023; Raman et al., 2024; Yokoyama et al., 2023), data quality, security and privacy risks (Ansari et al., 2022; Habbal et al., 2024; Jada and Mayayise, 2024; Paracha et al., 2024; Wazid et al., 2022), biases, including gender bias (Lima et al., 2023; Nadeem et al., 2020, 2022; Patón-Romero et al., 2022), spread of misinformation (Galaz et al., 2023b; Chu-Ke and Dong, 2024; Rojas et al., 2024; Treen et al., 2020), and the digital divide (Bentley et al., 2024; Celik, 2023; Lutz, 2019;). While AI systems have significant potential to address climate challenges, these risks highlight the need for careful governance, ethical frameworks, and sustainable practices to ensure that the benefits of AI are fully realized without exacerbating existing inequalities or causing unintended harm.

Environmental costs are growing as AI models – especially Deep Learning (DL) and Generative AI (GenAI) – are highly resource- and energy-intensive, requiring substantial computational power and large-scale data processing. This energy consumption must be carefully evaluated since it can offset the potential climate benefits these technologies offer if not effectively managed (Dolby, 2023; Kumar and Davenport, 2023; Saenko, 2023).

Security concerns are also a challenge in deploying AI, especially in critical areas like climate action and environmental monitoring. Being software, each AI system is vulnerable to cyber attacks, data breaches, and malicious manipulation of algorithms, which can compromise data integrity and decision-making (Ansari et al., 2022; Wazid et al., 2022). The integration of AI and ML introduces new security vulnerabilities, necessitating robust security measures and protocols to safeguard data integrity and privacy, including encryption, regular audits, and the use of secure infrastructure (Goldblum et al., 2022; Paracha et al., 2024; Rosenberg et al., 2021), ensuring AI applications remain trustworthy and effective in their intended use.

Without adequate data, the potential for ML applications remains constrained, particularly in addressing climate change. Data scarcity, especially in developing countries, reflects a broader issue of unequal access to key resources like AI, a challenge inadequately explored in current literature (Walsh et al., 2020). For instance, essential digital data – such as localized climate projections and weather forecasts, which are critical for optimizing farming practices – remains sparse in many regions (Balogun et al., 2020). Tackling data availability and access is essential for successfully implementing AI and ML-driven solutions to mitigate climate impacts.

AI can exacerbate inequalities without careful design, mainly through biases in algorithm development, data collection, and geographic coverage (McGovern et al., 2022a). Gender and demographic biases, inadequate infrastructure, and limited digital literacy hinder AI adoption in LDCs and SIDS (Ozor et al., 2023; UNFCCC, 2023) and may result in false assumptions and inequitable climate responses if unaddressed. Bridging these gaps requires investment in capacity-building, improved data collection, and infrastructure. Because ML models rely heavily on large, reliable datasets – often sparse in developing countries – combining rule-based, physics-informed, and domain-informed ML approaches can alleviate data constraints. Additionally, misinformation about climate change can spread faster than fact-checkers can respond (Rojas et al., 2024), undermining trust in policies and delaying action. These disparities and risks need to be addressed for equitable AI-driven climate solutions.

1.6. Artificial Intelligence and International Climate Frameworks and Resolutions

AI is increasingly being recognized in global climate governance as a tool to enhance climate action, improve decision-making, and strengthen transparency and accountability. While AI is not explicitly mentioned in the Paris Agreement or the 2030 Agenda for Sustainable Development, its applications directly support the achievement of climate and sustainability goals, including through Nationally Determined Contributions (NDCs), climate finance mechanisms, and capacity-building initiatives.

In March 2024, the United Nations General Assembly (UNGA) adopted a landmark resolution on AI, emphasizing the need for safe, secure, and trustworthy AI systems (United Nations, 2024a). Backed by over 120 Member States, the resolution underscores AI's potential to accelerate progress on the Sustainable Development Goals (SDGs) while ensuring human rights protections across the AI life cycle. It also calls for global cooperation to bridge the digital divide, enhance digital literacy, and support equitable access to AI technologies, particularly in developing countries. This resolution establishes a foundational international framework for integrating AI into climate action, particularly by reinforcing ethical and responsible AI deployment for climate monitoring, adaptation, and mitigation.

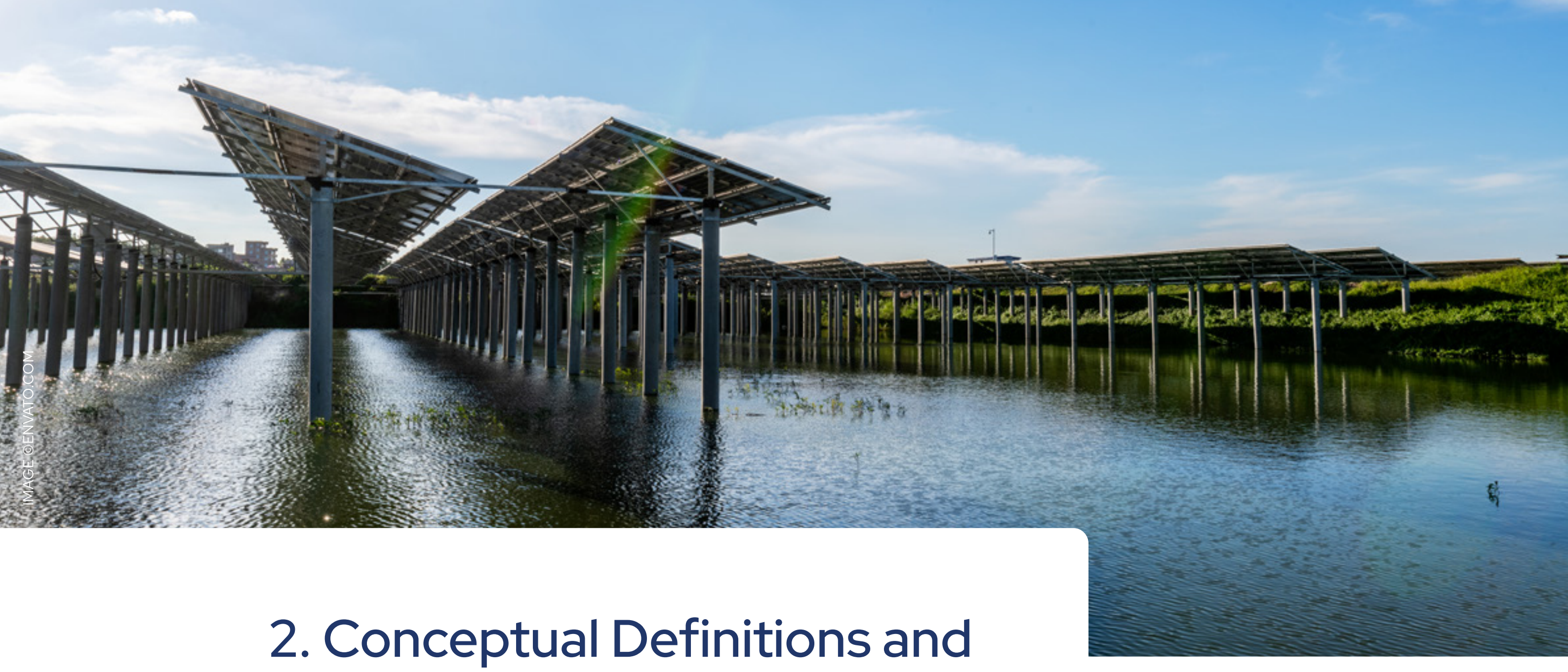
Beyond this resolution, global efforts are underway to regulate and standardize AI applications, ensuring they align with climate objectives. Discussions on AI governance and sustainability are emerging within international climate institutions. These focus on AI's role in monitoring emissions, optimizing renewable energy systems, supporting early warning systems, and improving carbon market integrity.

In November 2023 at COP28, Parties noted the Technology Mechanism Initiative on AI for Climate Action and requested the Technology Executive Committee (TEC) and the Climate Technology Centre and Network (CTCN) to implement the initiative and enhance awareness of AI and its potential role and impact.

Altogether, these initiatives signal a growing international consensus on the need for AI to complement efforts in addressing climate goals.

1.7. Structure of the Technical Paper

This paper is structured as follows: **Section 2** introduces and describes the key concepts underlying AI and its applications in climate action. **Section 3** outlines the methodology employed in this paper. **Section 4** delves into AI for climate action in developing countries, presenting case studies and best practices, and providing detailed insights into their impacts and the lessons learned, which can benefit other developing countries. **Section 5** explores the role of AI in implementing the Technology Mechanism Joint Work Programme and TNA outcomes. **Section 6** discusses the risks and challenges associated with AI deployment for climate action in developing countries. **Section 7** presents policy options for leveraging AI as a tool for advancing and scaling transformative climate solutions in developing countries while addressing the identified challenges and promoting sustainable development. **Section 8** provides conclusions and recommendations, summarizing the key findings of the paper and offering actionable steps for policymakers, as well as researchers and practitioners. **Section 9** is a call to action for these stakeholders to collaborate and harness AI technologies in driving climate action and sustainable development.



2. Conceptual Definitions and Discussions: Artificial Intelligence for Climate Action

This section provides an overview of AI, its subsets, models, methods, paradigms, and applications in the context of climate actions. Understanding these AI concepts is crucial for designing informed policy frameworks and governance mechanisms for responsible and effective AI-driven climate action.

AI is the discipline focused on the research and development of mechanisms and applications of AI systems. AI systems are engineered systems that generate outputs such as content, forecasts, recommendations, or decisions for a given set of human-defined objectives (ISO/IEC 22989:2022(E)). AI systems can be used for different purposes and be engineered in a way that makes them capable of updating the parameters in the model from the new data they are exposed to over successive updates or iterations (Sharifani and Amini, 2023; Shinde and Shah, 2018; Verma et al., 2024).

ML models can be effectively utilized across various paradigms, including supervised learning, unsupervised learning (including GenAI) and reinforcement learning (Donti and Kolter, 2021; Naeem et al., 2023). In supervised learning, models are trained on labelled data, making them ideal for tasks such as classification and regression, where specific outcomes are known in advance. Unsupervised learning, on the other hand, does not rely on labelled data and is used to identify patterns and structures within datasets, such as clustering or anomaly detection. Reinforcement learning involves training models through trial and error, where an agent learns to make decisions by receiving feedback from the environment, making it particularly useful for applications requiring sequential decision-making, such as robotics or game-playing. Each of these paradigms provides unique capabilities and approaches to solving complex problems, enabling the development of versatile and powerful ML applications. Here, it suffices to point out that supervised learning is particularly effective for climate-impact forecasting, whereas unsupervised methods excel in identifying novel climate patterns, and reinforcement learning optimizes resource allocation and decision-making under climate uncertainty.

Deep Learning (DL) is a subset of Machine Learning (ML) that utilizes Artificial Neural Networks (ANNs). While inspired by simplified models of biological neurons, ANNs function in a fundamentally different way to the human brain, as they lack the dynamic adaptability, biochemical signalling, and complex interconnectivity of biological neural systems. They are formed by nodes, arranged in units, in turns distributed in a series of layers. The number of units for each layer depends on the complexity of the task the ANNs have been conceived to solve and may vary from a few dozen to millions. The learning process of an Artificial Neural Network involves updating the connection strength (weight) of a node. By using the error between the predicted value and the correct value, the weight in the network is adjusted so that the error is minimized and an output closer to the target is obtained (Su-Hyun et al., 2018). These layers are particularly effective in recognizing patterns for handling various tasks including predictive modelling and adaptive control. For this reason, they offer promising applications in climate research such as analysing satellite imagery to detect deforestation patterns and track ice sheet melting, enhancing extreme weather forecasting through more precise modelling of atmospheric conditions, and optimizing renewable energy management by predicting solar and wind power output based on meteorological data.

The recent development of complex neural networks has unlocked various applications in the field of Computer Vision (CV) by enabling high accuracy image classification and target detection. CV significantly enhances adaptation strategies by automating the monitoring of climate-induced changes such as coastal erosion or habitat degradation, informing timely interventions. This is particularly useful for processing a vast number of satellite images with a plethora of applications from monitoring the evolution of coastal erosion or marine oil spills detection.

The application of ML to Natural Language Processing (NLP) has recently gained momentum for representing and analysing human language computationally. The field of NLP is related to different theories and techniques that focus on the interaction between computers and humans through natural language. NLP is essential for analysing climate-related policy documents, facilitating climate education, and enhancing public engagement through clear, actionable communication. NLP methods enable AI systems to understand and process human language data from scientific reports, policy documents, or social media to gauge public sentiment and disseminate information about climate change effectively. This capability aids in synthesizing information, generating insights, and enabling decision-making for climate action. While still in development, GenAI can simulate climate models to predict future scenarios and develop adaptive strategies based on individual or regional climate data.

GenAI systems are mostly trained using self-supervised learning, a paradigm where the system optimizes its model to predict part of its input from other parts of its input without the need of manual labelling of the training dataset as text, images, audio, or code as outputs in response to prompts, based on learned patterns. By enabling the creation of general purpose services in text, image, and audio creation companies developing those tools, and using a freemium business model, enabled wide access to GenAI. Large Language Models (LLMs) are specialized for tasks like text generation, summarization, translation, and question-answering, and excel at producing coherent and contextually relevant text. ML includes models like linear regression for predicting continuous variables, logistic regression for binary classification, and decision trees for both regression and classification tasks. DL features models such as Convolutional Neural Networks (CNNs) for image recognition, Recurrent Neural Networks (RNNs) for sequential data, and transformers for NLP.

In the realm of CV, models like You Only Look Once (YOLO) enable real-time object detection, while Faster R-CNN is valuable for object detection and image recognition. NLP leverages models like BERT (Bidirectional Encoder Representations from Transformers) for text classification and sentiment analysis and LSTM (Long Short-Term Memory) for language modelling and sequence prediction.

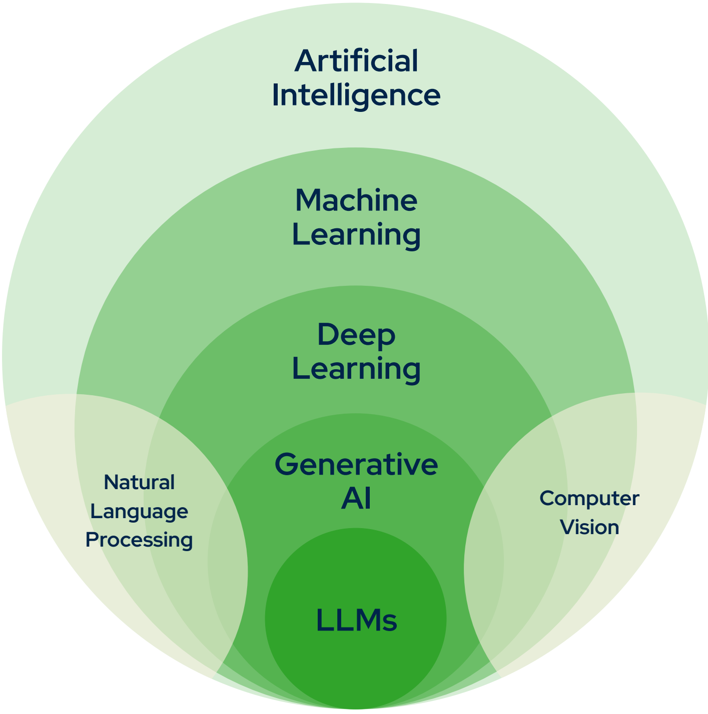


Figure 1. Artificial Intelligence and its subfields or domains

This adaptability is particularly beneficial in addressing climate change mitigation and adaptation challenges. For example, ML models are frequently used to solve optimization problems.

3. Methodology

The methodology of this paper includes a thorough literature review to assess the landscape of AI's benefits, risks, and challenges, coupled with case study inputs provided by stakeholders involved in AI for climate action in developing countries to gather diverse insights and experiences. These case studies aimed to identify practical and impactful AI applications and capture a range of perspectives relevant to ongoing efforts. In addition, the TEC facilitated a rigorous peer review process involving multidisciplinary expertise to ensure the paper reflects diverse expert opinions and is aligned with the challenges faced by developing countries, particularly SIDS and LDCs.

3.1. Justification of 2017–2024 Time frame

The timeline from 2017 to 2024 was based on several key factors. First, there have been rapid technological advancements in AI, ML, and related fields during this period. Also, the proliferation of AI research specifically targeting climate action has been particularly notable since 2017. Moreover, global awareness and urgency about climate change have increased during 2017–2024.

3.2. Literature Review

A comprehensive literature review was conducted to provide an overview of the current state of play regarding the utilization of AI for climate action in developing countries. In terms of the latter, the review included recent theoretical and empirical studies that addressed these regions in the context of AI for climate change, along with the existing best practices and lessons from developed countries that they can adopt to maximize positive outcomes and overcome difficulties or obstacles in implementing AI solutions for climate action. The methodological approach to the literature review encompassed the following steps:

Defining search criteria: This initial step involved setting precise search criteria to ensure a comprehensive and targeted review of relevant literature. Keywords and phrases were carefully chosen to capture a wide array of publications pertinent to the application of AI to climate action in developing countries. The search criteria were aligned with the thematic focus of the paper, which includes exploring current AI applications in climate mitigation and adaptation strategies, analysing case studies from LDCs and SIDS, and evaluating the benefits and challenges of AI adoption, with the aim of providing recommendations for policymakers and stakeholders to enhance AI's role in advancing climate strategies in these regions.

Selecting databases: A selection of key academic databases was made to source relevant scholarly articles, research papers, and reports. The databases chosen include Web of Science (WoS), Scopus, ScienceDirect, SpringerLink, and Google Scholar. These databases were selected for their comprehensive coverage of multidisciplinary literature on AI applications in climate action. The literature review specifically prioritized studies conducted in developing countries, including LDCs and SIDS, aligning with the thematic scope of this technical paper.

Inclusion and exclusion criteria: Publications from 2017 to 2024 were selected to ensure the review reflects the most recent developments in the field. The focus is on peer-reviewed articles, research papers, and reports that directly address the opportunities, applications, challenges, and risks of AI in climate action. Peer-reviewed sources were prioritized. Non-peer-reviewed sources and publications outside this time frame were excluded.

Search and selection: Relevant publications were identified through a comprehensive search across selected databases using specific keywords and phrases related to AI applications in climate action. The search included terms such as 'artificial intelligence for climate mitigation/adaptation' and 'machine/deep learning for climate change', among others. These publications were subsequently scrutinized based on their abstracts and alignment with the research objectives.

Detailed analysis: A comprehensive review of selected scholarly articles, research papers, and reports was conducted to extract nuanced insights into AI's benefits, risks, and challenges for climate action in developing countries, with particular emphasis on LDCs and SIDS. Relevant information – spanning AI applications, observed outcomes, challenges, geographical variations, and policy implications – was systematically extracted and categorized according to predefined themes. Each source underwent critical evaluation based on factors such as peer-reviewed status, methodological transparency, relevance to the research objectives, and consistency of findings, ensuring methodological rigour and credibility for a robust synthesis of findings.

Synthesis of findings: Insights from the analysis were then consolidated to create a cohesive overview of AI's role in climate action across developing countries. This integrated perspective identifies key patterns and relationships, serving as the foundation for subsequent sections of the technical paper and informing discussions on strategies to optimize AI-driven climate solutions.

3.3. Call for Case Study Submissions

A call for case study submissions was made to a range of stakeholders actively involved in AI for climate action activities in developing countries, specifically targeting those engaged in research or the implementation of AI-related projects relating to SIDS and LDCs. The call was extended to academic researchers, practitioners, industry professionals, and policymakers who are directly involved in the deployment and management of AI technologies in various domains. These submissions were instrumental in gathering in-depth insights and first-hand accounts of the opportunities and challenges associated with AI projects. The primary goal of these discussions was to unearth relevant case studies that could be detailed in the thematic chapters of the paper, thereby providing concrete examples of how AI is being applied in real-world settings in developing countries, particularly SIDS and LDCs. This approach ensured that the paper was grounded in actual experiences and practices, enhancing its practical value to stakeholders in similar contexts.

3.4. Peer Review

A peer-review group was established to provide specific suggestions for improvements to the draft technical paper. The composition of the peer-review group reflects a strategic effort to include diverse knowledge and perspectives on AI for climate action. This group was comprised of 13 experts from academia, industry, NGOs, governmental bodies, and international organizations who are recognized for their work in AI, climate science, policy implementation, and related issues. The peer review of the draft technical paper was conducted in July 2024. Key aspects of their involvement included:

- **Validation of content:** They scrutinize the draft to verify the scientific accuracy and relevance of the content, ensuring that it reflects the latest advancements and understandings in the field.
- **Inclusion of case studies:** Members propose additional case studies that illustrate successful applications or ongoing initiatives of AI in climate action, particularly those that are pertinent to the challenges faced by SIDS and LDCs.
- **Structural feedback:** They provide critical feedback on the structure and presentation of the paper to improve its readability, impact, and ability to communicate key messages effectively to policymakers as well as practitioners and researchers.


IMAGE ©ENVATO.COM

4. Artificial Intelligence for Climate Action in Developing Countries

This section offers a comprehensive analysis of existing literature and empirical evidence, focusing on how AI algorithms have been leveraged in addressing climate challenges across different global contexts, including both the benefits and risks associated with AI adoption in LDCs and SIDS while examining the regulatory landscapes that influence AI deployment. The case studies have been selected from inputs provided through the call for case study submissions and various literature, including the CTCN knowledge product on AI technologies used in developing countries in the Asia–Pacific region (CTCN & NIGT, 2024).

4.1. Early Warning Systems

AI and ML algorithms have been used for the following:

- **Flood warning systems:** AI systems that use rainfall data, river levels, and weather patterns collected by Internet of Things (IoT) sensors to predict flood events have been effectively implemented in several regions, providing communities with timely alerts and enabling proactive measures to minimize damage.

- **Food security early warning systems:** AI systems that use data from weather stations, satellite imagery, and soil sensors have provided harvest management insights and predictions helping farmers optimize planting and harvesting times, manage resources more efficiently, and anticipate potential issues such as pest infestations or adverse weather conditions.

- **Hurricane prediction models:** Combining satellite and remote sensing data with AI-driven analysis improves the prediction of hurricane paths and intensity, enhancing disaster preparedness and evacuation planning. AI-enhanced early warning systems have led to improvements in forecast accuracy, longer lead times for warnings, and better resource allocation for emergency response, as seen in recent hurricane seasons.

- **Wildfire detection:** Integrating data from IoT sensors on temperature, humidity, and wind speed with AI algorithms has improved the ability to detect and predict wildfires. This early detection allows for timely deployment of firefighting resources, minimizing the destruction caused by these fires.

CASE STUDY

UN EARLY WARNINGS FOR ALL INITIATIVE (EW4ALL)

Country: LDCs and SIDS - Ethiopia
Entities involved: Microsoft, Planet Labs PBC, University of Washington Institute for Health Metrics and Evaluation (IHME), United Nations Office for Disaster Risk Reduction (UNDRR)

Brief description

The Early Warnings for All Initiative, co-led by the World Meteorological Organization (WMO) and the United Nations Office for Disaster Risk Reduction (UNDRR), with collaboration from the International Telecommunication Union (ITU), and the International Federation of Red Cross and Red Crescent Societies (IFRC), is a high-level initiative to help to ensure that everyone on Earth is protected from hazardous weather, water, or climate events through life-saving early warning systems by the end of 2027. With human-induced climate change leading to more extreme weather conditions, the need for early warning systems is more crucial than ever. Systems that warn people of impending storms, floods or droughts are not a luxury but a cost-effective tool that saves lives and reduces economic losses.

Early warning systems have helped decrease the number of deaths and have reduced losses and damages resulting from hazardous weather, water or climate events. But major gaps still exist, especially in SIDS and LDCs. The United Nations Secretary-General, António Guterres, in 2022 called for a global effort to ensure that early warning systems protect everyone on Earth by 2027.

Climate Change Mitigation and/or Adaptation Impacts and Results

Microsoft, Planet Labs and the University of Washington Institute for Health Metrics and Evaluation (IHME), are employing AI, satellite imagery, and predictive modeling to accurately estimate the population sizes of communities that are at greatest risk from climate change, as well as tracking population growth over time. Gaining a clear understanding of where people live is foundational to taking preparatory measures and providing essential resources.

In collaboration with UNDRR and other partners under the Early Warnings for All Initiative, Ethiopia's Ministry of Irrigation and Lowlands and the Ethiopian AI Institute are utilizing AI-driven methods to identify communities at risk of disaster impacts. This initiative is expected to expand to additional Early Warnings for All priority countries, addressing evolving disaster preparedness needs.

Previous applications of AI and satellite imagery have demonstrated potential in identifying at-risk communities. In collaboration with our non-profit partner SEEDS in India, we apply AI and high-resolution satellite imagery to pinpoint homes that are vulnerable to destruction in cyclone-prone areas. This enables SEEDS, their partners, and local governments to focus their disaster preparedness and response outreach efforts on the most high-risk regions, thereby saving lives and reducing damage.

Recent catastrophic events in Libya and Morocco have also underscored the critical importance of swiftly comprehending the magnitude and specifics of affected populations and regions. Time is of the essence in such situations. Recent applications of high-resolution satellite data from Planet Labs PBC, combined with AI, have shown potential in assisting affected communities. The initiative aims to support response and recovery efforts by sharing this valuable information.

Challenges and Lessons Learned Regarding Development and Implementation

The journey of developing and implementing the EW4All Initiative is associated with several key challenges and also provides valuable lessons:

The Importance of Comprehensive Global Mapping: One critical lesson learned from this project is the stark realization that, in developed countries, there exists an illusion that the maps are up-to-date and fully representative of where people reside. However, the 2023 earthquake in Afghanistan revealed a significant gap: a majority of those affected in rural areas were not accounted for on any existing maps. This underscored the urgent need to ensure that every individual on the planet is mapped, a goal that is now more attainable using AI and thanks to the availability of Planet's daily satellite data. This capability represents an innovative step towards achieving comprehensive global mapping, which is crucial for effective disaster response and resource allocation.

The Challenge of Accessible AI Tools in Disaster Response: Another key lesson from this project concerns the accessibility of AI tools in disaster response scenarios. The project highlighted that the tools required to run AI models in disaster-affected areas remain too complex for end-users, particularly those in organizations that need mapping data but lack in-house software development expertise. This gap was a primary driver behind the development of Project HASTE (High-speed Assessment and Satellite Tracking for Emergencies). Project HASTE is an open-source tool designed to eliminate the need for advanced software development skills, enabling a broader range of users to leverage AI for rapid and effective disaster response. This innovation is anticipated to enhance the efficiency and inclusivity of disaster management efforts worldwide.

CASE STUDY

AI4SIDS

Country: SIDS
Entities involved: The University of the West Indies, St. Augustine Campus, as part of the AI for Climate Research Cluster within the TTLAB Data Science Group.

Brief description

The AI-Driven Climate Resilience Platform for SIDS (AI4SIDS) aims to enhance disaster preparedness and resilience in SIDS through AI-driven solutions. By integrating real-time data, predictive analytics, AI-driven models including Large Language Models (LLMs), and IoT technologies, it provides actionable insights for governments and communities, enabling more effective disaster risk management with minimal human intervention. This transformative platform, leveraging advanced AI technologies like GPT-4 for real-time data analysis and OpenAI's Whisper for speech-to-text conversion, AI4SIDS provides localized weather alerts, educational tools, and predictive analytics that empower communities to act before disaster strikes. This female-led project was the winner of the AI Innovation Grand Challenge hosted by the Technology Executive Committee in partnership with Enterprise Neurosystem.

Climate Change Mitigation and/or Adaptation Impacts and Results

AI4SIDS is currently under development, and it aims to integrate cutting-edge technologies to offer comprehensive solutions, including:

- Real-time Data Collection: Autonomous processing of data from IoT sensors, social media, weather forecasts, and more.
- Predictive Analytics: Advanced algorithms powered by GPT-4 predict climate events, allowing governments and communities to prepare in advance.
- Localized Alerts: Multi-channel alerts delivered via mobile, SMS, TV, and radio in local languages.
- Educational Resources: Tailored materials to raise community awareness and improve disaster readiness.
- Automated Feedback Loops: Enables governments to refine and optimize disaster response strategies.

CASE STUDY

EARLY WARNINGS SYSTEM FOR CROP PHENOTYPING AND FOOD AND NUTRITION SECURITY

Country: Kenya
Entities involved: : Local Development Research Institute (LDRI), Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) – FAIR Forward.

Brief description

The cooperation between LDRI and GIZ's FAIR Forward enables smallholder farmers to use AI technology for crop yield prediction and monitoring in Kenya. The AI Early Warning System developed by LDRI, and FAIR Forward enhances harvest management for smallholder farmers by delivering timely and accurate crop yield predictions. By integrating data from weather stations, satellite imagery, and soil sensors, the system provides precise, localized information, enabling farmers to anticipate adverse conditions and implement proactive measures. This results in reduced crop losses due to climate variability and optimized resource use. The system incorporates local languages, including Kiembu, Luhya, Kikuyu, and Kiswahili, to enhance accessibility for diverse farming communities, thereby broadening its potential impact.

Climate Change Mitigation and/or Adaptation Impacts and Results

The Early Warning System enables farmers to make informed decisions, thereby minimizing crop losses and optimizing resource use in the face of climate variability. By offering precise, localized information, the system helps farmers anticipate and mitigate potential climate threats. For instance, monitoring 400 farms across 6 agro-ecological zones in Kiambu and Embu counties has demonstrated the system's capability to accurately predict crop yields and identify potential crop failures. The integration of local languages – such as KiEmbu, Luhya, Kikuyu, and Kiswahili – ensures that the system's advice is accessible and actionable for a diverse range of farmers, increasing its effectiveness across different linguistic communities. Additionally, the project has created two open, quality datasets, including a land-use/farm boundary estimation dataset and a temporal image-based dataset, which enhance the system's ability to provide actionable insights. The development of algorithms for analysing earth observation data further supports crop-specific early warning mechanisms and predictive climate-change recommendations.

There are ongoing discussions to expand the system to Uganda and Tanzania, with adaptations for new crops and regions, further supporting the agricultural community across East Africa. This initiative addresses both immediate agricultural needs and contributes to long-term food security and economic stability in the region.

Challenges and Lessons Learned Regarding Development and Implementation

Challenges encountered during the implementation of the initiative included ensuring data accuracy from diverse sources, integrating AI models with local agricultural practices, and addressing language barriers. The project highlighted the importance of community involvement, continuous adaptation to local contexts, and robust evaluation metrics. Expanding to new regions and crops required careful planning and collaboration with local stakeholders. Extreme drought tendencies caused acute food insecurity for 4.2 million people in Kenya, particularly in the Arid and Semi-Arid Lands (ASALs). Farmers mistrusted inconsistent weather predictions and relied on indigenous signs. Involving farmers in data collection has built trust and ensured data accuracy. Training and equipping Village Based Advisors (VBAs) with smartphones and the ODK software was critical for efficient data collection.

IMAGE ©ENVATO.COM

4.2. Earth Observation

Through the use of satellites, EO data provide unequivocal evidence of the changes taking place on Earth by monitoring parameters such as temperature, sea levels, atmospheric gases, ice, and forest coverage. This scientific data supports our understanding of how the complex Earth system works and aims to provide decision-makers with hard evidence of the need for putting forward adaptation and mitigation plans.

In this context AI algorithms present a wide range of applications including transforming a satellite image to a street map, cloud detection in order to reduce the volume of data to be downlinked to the ground, autonomous detection, and classification of maritime vessels, as well as forest monitoring and anomaly detection. The following areas highlight the key applications in this regard:

4.2.1. Examination of Sea Level Rise and Coastal Transformations

The accurate prediction and monitoring of sea level rise are important for the protection of coastal areas and the planning of risk mitigation strategies. Various AI-based methods have been developed to address this complex issue, significantly enhancing the accuracy and efficiency of sea level predictions. Techniques like hybridization, ensemble modelling, data decomposition, and algorithm optimization are identified as key strategies for enhancing sea level predictions. DL, in particular, has shown superior performance due to its ability to automatically extract features and store memory, making it more effective than traditional ML models.

The use of AI in monitoring sea level rise has been critical for SIDS like the Maldives, where rising waters pose a significant threat to infrastructure and communities (UNFCCC, 2023). AI models enhance the accuracy of sea level predictions by analysing satellite imagery and oceanographic data in real time, allowing policymakers to develop proactive coastal defense strategies and disaster preparedness measures.

Balogun and Adebisi (2021) integrate a broad range of ocean-atmospheric variables to predict sea level variations along the West Peninsular Malaysia coastline using LSTM models. Their findings suggest that atmospheric processes significantly influence prediction accuracy and that combining oceanic and atmospheric variables significantly improves model performance. The LSTM model, which incorporates both types of variables, demonstrates the highest accuracy in most locations or regions, underscoring the importance of considering multiple influencing factors in sea level prediction.

Ishida et al. (2020) develop an hourly-scale coastal sea level estimation model using LSTM network. The model includes the effects of gravitational attractions, seasonality, storm surges, and global warming. Results show that the LSTM model accurately reconstructs these effects and improves prediction accuracy when incorporating long-term duration temperature data, demonstrating the robustness of DL in sea level forecasting.

CASE STUDY

SAFEGUARDING COASTAL ECOSYSTEMS: SOLOMON ISLANDS' INTEGRATED COASTAL ZONE MANAGEMENT (ICZM) WITH AMAP

Country: Solomon Islands
Entities involved: Government of the Solomon Islands, CTCN

Brief description

The degradation of coastal ecosystems, such as mangroves, poses a significant threat to the country's biodiversity, food security, and resilience to climate change. Mangroves play a crucial role in coastal protection, providing a natural barrier against storms and erosion. To address these challenges, the G Government of the Solomon Islands, with support from the CTCN's technical assistance project, has implemented ecosystem-based adaptation solutions for mangrove protection. The development of AI-based Mangrove Adaptive mapping tools in Pacific Island regions (AMAP), the output of the CTCN technical assistance (TA), represents a significant step in this direction.

AMAP processes satellite images, filtering out those with excessive cloud cover and removing clouds from the remaining images. It then calculates a mangrove-specific index to facilitate mangrove detection. The U-Net deep learning algorithm is employed to classify mangroves based on the mangrove-specific index. This enables the generation of detailed maps illustrating mangrove distribution, aiding in conservation, restoration, and management efforts. AMAP leverages historical climate data and climate change scenarios to develop models using various machine learning algorithms. These models are then combined through an ensemble approach to predict changes in vegetation species, including mangroves.

Climate Change Mitigation and/or Adaptation Impacts and Results

Improved Monitoring: AMAP facilitates the assessment of mangrove health and distribution over time, supporting the identification of areas requiring protection or restoration. Enhanced Management: The system equips managers with the information needed to make informed decisions about conservation and adaptation strategies, which ensures the sustainable management of mangrove ecosystems.

Climate Change Adaptation: AMAP's ability to predict future habitat distributions under different climate change scenarios supports the development of proactive adaptation measures to protect mangroves and the communities that depend on them. Resource Optimization: By automating the analysis of satellite imagery and providing detailed mangrove maps, AMAP saves valuable time and resources, allowing for more efficient and effective conservation efforts.

4.2.2. Detection of Deforestation and Forest Degradation

Deforestation is a critical global environmental challenge with far-reaching implications for biodiversity, climate change, and livelihoods. Satellite imagery and IoT sensors, combined with AI algorithms, enable the detection and monitoring of deforestation and forest degradation. AI models analyse high-resolution optical and laser-based satellite images, often coupled with ground-truth data, to identify changes in forest cover, detect illegal logging activities, and monitor forest health over time. They can aid in mitigating climate change by implementing efficient and precise sustainable forest management practices to decrease deforestation (Liu et al., 2021). They can distinguish between different types of vegetation and land cover, making it possible to accurately track the extent and rate of deforestation. Haq et al. (2024) explored the application of AI, IoT, and remote sensing in addressing deforestation. These technologies facilitate real-time monitoring, early detection, and intervention in activities like illegal logging, plant diseases, and forest fires. By analysing the strengths and limitations of IoT, satellite imagery, drones, and AI algorithms, the study underscores their potential in forest conservation.

Nguyen-Trong and Tran-Xuan (2022) focused on improving forest cover change detection using AI-based remote sensing techniques in Viet Nam. Traditional methods, such as multi-variant change vector analysis (MVCA) and normalized difference vegetation index, rely heavily on domain knowledge to set threshold values, limiting their applicability. The study proposed a new method utilizing multi-temporal Sentinel-2 imagery and a U-Net-based AI segmentation model to detect coastal forest cover changes. This approach minimizes the need for extensive domain knowledge by harnessing available datasets and ground-truth labels. The results showed a high accuracy of 95.4% in detecting forest changes and outperformed the traditional MVCA method by 3.8%, highlighting its effectiveness in forest resource management and planning in Viet Nam.

In Project Guacamaya (Elliott, 2024) in Colombia the CinfonIA Research Centre, the Instituto Sinchi and Microsoft's AI for Good Lab are using best-in-class AI models to monitor deforestation and protect the biodiversity of the ecosystem. This project combines satellite imagery, camera traps, and bioacoustics data to monitor and analyse deforestation patterns rapidly and accurately reducing the time required to identify deforestation hotspots, enabling quicker response and intervention. The initiative supports conservation efforts and aids in the creation of precise maps and data crucial for reforestation and carbon capture projects.

Dominguez et al. (2022) utilized a dense neural network for spatial data modelling and an LSTM for temporal data on deforestation to forecast incremental deforestation and deforestation rates in the Amazon rainforest. By comparing prediction results and continuously retraining the model with new data, the authors were able to estimate future forest loss rates, enabling proactive measures. Their approach effectively produced deforestation risk maps, which were validated in study areas in Madagascar and Mexico and demonstrated the techniques' reliability.

Recent AI initiatives by World Resources Institute (WRI) have made open, high-resolution global remote sensing datasets available for the first time. These maps provide a valuable basis for monitoring and protecting forests worldwide, especially under newly introduced deforestation regulations, such as the EU Deforestation Regulation (European Commission, 2023) that require accurate forest monitoring for traceability. Lang et al. (2023) created a global canopy height map with a 10 m ground sampling distance, utilizing a probabilistic DL model that combines GEDI LIDAR data with Sentinel-2 optical imagery. This approach improves canopy-top height retrieval, quantifies uncertainty, and enhances the mapping of tall canopies with high carbon stocks, which are critical for effective carbon and biodiversity modelling. According to this map, only 5% of the global landmass is covered by trees taller than 30 m, and only 34% of these tall canopies are located within protected areas. This approach can support ongoing forest conservation efforts and foster advances in climate, carbon, and biodiversity modelling.

However, there remains a need for more precise local adaptation and validation, particularly through the integration of ground reference data collected through direct on-site observation, as this enhances the accuracy of AI models by correcting biases, refining predictions, and ensuring alignment with real-world environmental conditions. These ground reference data are crucial for improving the accuracy and relevance of remote sensing data and ensuring that local conditions and community needs are adequately considered. Such validation is important for the development and refinement of existing AI approaches and global maps in the field of forest monitoring and protection. For example, in Côte d'Ivoire and Ghana, where cocoa cultivation is a significant driver of forest loss, integrating ground reference data, such as field-based deforestation assessments and satellite-derived land cover classifications, has proven important for accurate mapping and understanding of the impact of agricultural expansion (Kalischek et al., 2023). Similarly, in Southeast Asia, where commodity-driven deforestation affects carbon stocks and biodiversity, an automated approach using DL for canopy height estimation from GEDI LIDAR and Sentinel-2 imagery has been developed. This method provides high-resolution maps of canopy top height with an accuracy of 86%, classifies High Carbon Stock (HCS) forests and degraded areas and has produced the first high carbon stock map for Indonesia, Malaysia, and the Philippines (Lang et al, 2021). The combination of ground-based validation and AI-driven modelling in such applications strengthens the precision of local adaptation strategies, demonstrating how AI can enhance forest monitoring and protection through improved accuracy and classification of at-risk areas.

CASE STUDY

AI FOR FOREST CONSERVATION: AI-GENERATED INDICATIVE HIGH CARBON STOCK MAPS IN INDONESIA AND INDIA

Country: Indonesia
Entities involved: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) – FAIR Forward, JKPP (Network for Participatory Mapping), ETH Zürich Ecovision Lab, High Carbon Stock Approach (HCSA) foundation, Indonesian government agencies, including Bappenas (Indonesia's National Development Planning Agency).

Brief description

In Indonesia, the FAIR Forward initiative has collaborated with JKPP, HCSA and Bappenas to create an AI-driven, large-scale indicative map of high carbon stock (HCS) forests. This project involves comprehensive field data collection (Figure 1) across key regions such as Sumatra, Kalimantan, and West Papua. Biomass data are collected from ground forest plots and validation points to ensure accurate mapping. The project utilizes remote sensing technology and ML to identify and classify HCS areas, which include primary forests, regenerating forests, and mixed agroforestry landscapes. The HCS approach is currently being scaled to India with the Government of Goa to build forest fire maps and accurate biomass maps. The project will create open-source, AI-based tools for early forest fire detection and monitoring through community engagement and volunteering. Given the global relevance of this subject, the open tools will utilize remote sensing and ML to potentially create a global carbon stock map.

Climate Change Mitigation and/or Adaptation Impacts and Results

The HCS maps developed through this initiative are crucial for Indonesia's climate change mitigation strategies by providing detailed carbon stock data that enhances carbon accounting and conservation planning. For example, in Kalimantan, the project has leveraged field plot data and remote sensing technologies to delineate extensive high carbon stock forest areas. This approach not only aids in effective conservation planning but also fortifies climate change mitigation strategies by prioritizing the protection of both primary and regenerating forests.

The integration of Free, Prior, and Informed Consent (FPIC) alongside indigenous knowledge enriches the conservation process, ensuring that local rights are respected and that conservation strategies benefit from local expertise. This approach fosters trust and collaboration between communities and conservationists, leading to more sustainable and culturally sensitive outcomes.

The open-access nature of these datasets also facilitates global research and promotes international cooperation. By making data available for public use, the initiative supports a broader understanding of forest dynamics and climate change impacts. Collaboration with national and regional agencies ensures that this data is effectively incorporated into land use planning frameworks, including Indonesia's new forest conservation policy. This policy uses HCS maps to guide sustainable land use and forest protection, showing the project's impact on shaping national strategies for climate resilience and forest conservation.

Challenges and Lessons Learned Regarding Development and Implementation

The project faced several key challenges: Ensuring data accuracy across diverse landscapes required tailored approaches and extensive field validation, highlighting the need for collaboration with local experts to address landscape-specific issues. Integrating traditional knowledge with advanced biomass data proved crucial yet challenging, underscoring the importance of engaging local communities to enrich the contextual understanding of forest ecosystems. Navigating the complexities of Free, Prior, and Informed Consent (FPIC) and managing data sharing with local communities involved addressing varied cultural, legal, and ethical considerations. This demonstrated the necessity of a robust FPIC process, continuous community engagement, and transparent data governance to build trust and ensure ethical data use. Logistical challenges in field data collection, including coordinating with local partners and managing activities in remote areas, emphasized the importance of careful planning and strong partnerships. Additionally, the implementation of advanced technologies like GIS and ML required significant capacity-building among local stakeholders, revealing that training and support are crucial for effective technology use. Overall, the project highlights the need for a collaborative approach that integrates technology with local knowledge while ensuring ethical and effective data practices.

CASE STUDY: AI FOR FORECASTING AND PREVENTING DEFORESTATION IN THE BRAZILIAN LEGAL AMAZON

Country: Brazil
Entities Involved: Amazon Institute of People and Environment (Imazon), Pará State Public Prosecutor's Office (MPPA), Environmental Agency of Altamira-PA, Fundo Vale, Climate and Land Use Alliance (CLUA), Microsoft Brazil

Brief description

The PrevisIA project leverages AI and satellite imagery to detect and forecast deforestation in Brazil's Legal Amazon. By integrating historical deforestation data, topographical variables, and socio-economic indicators, the system predicts deforestation risks with high precision. A key feature of PrevisIA is its AI model that annually detects the emergence of unofficial roads – strong predictors of deforestation and fires – using Sentinel-2 imagery. Approximately 95% of deforestation occurs within 5.5 km of roads, and 90% of fires within 4 km.

The initiative is structured around three pillars:

i) AI-driven road detection using high-volume satellite data;
ii) Risk forecasting and dissemination via a geospatial dashboard; and
iii) Collaborative enforcement with government partners.

A working group led by the Pará State Prosecutor's Office monitors deforestation and acts on AI-generated alerts through fines, embargoes, or legal action. Forecast accuracy has reached 73% within a 4 km radius, strengthening legal and administrative enforcement.

Figure 2: Training sessions on transferring geospatial technology

Climate Change Mitigation and/or Adaptation Impacts and Results

PrevisIA's AI forecasts have informed targeted enforcement actions in Pará, a high-deforestation zone. Reports produced at municipal and property levels enable prosecutors to identify illegal deforestation and initiate sanctions. Since 2024, risk-based notifications are issued to landowners based on AI-detected alerts. The project demonstrates a scalable model for integrating AI into legal action, forest governance, and climate mitigation.

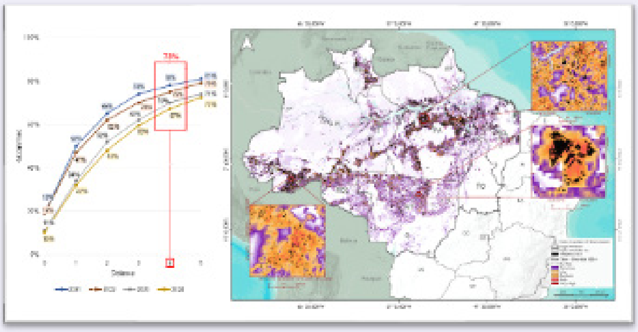


Figure 3: PrevisIA forecast assessment against PRODES' deforestation data for 2021 to 2024. The average accuracy for this period is 73% up to 4 km

Challenges and Lessons Learned Regarding Development and Implementation

Key lessons include the importance of predictive over reactive enforcement and the need for continuous geospatial capacity-building within legal institutions. Scaling the project across Brazil's Amazonian states requires financial sustainability, for which REDD+ projects are being considered. Integrating adaptation plans to address concurrent climate risks, such as extreme droughts, is essential to protecting both forests and local communities.

4.2.3. Detection of Pollution Sources

In addition to harming human health, pollution hinders sustainable ecological growth. AI and ML algorithms applied to the analysis of satellite imagery and IoT data can streamline the identification and monitoring of pollution and its sources by analysing the spectral signatures of various pollutants and chemicals.

Remote sensing, in particular historical aerial photographs, have been useful in monitoring and documenting changes at hazardous sites over time, providing reliable data for pollution detection and mitigation (Popescu et al., 2024; Mertikas et al., 2021). Jia et al. (2021) developed a new modelling method to forecast soil arsenic levels using high-resolution aerial imagery (HRAI). This method employs cameras mounted on aircraft to capture high-resolution (0.1–0.5 m) images of large areas. Four different ML algorithms were constructed to predict arsenic risk levels, with the Extreme Random Forest (ERF) algorithm achieving higher level prediction and accuracy. Remote sensing and aerial imagery provide continuous spatial data which, when combined with ML models, produce highly accurate maps of hazardous substances in the environment – something that standard geostatistical techniques could not achieve (Popescu et al., 2024).

One notable application of AI in environmental monitoring is the use of electronic nose (E-nose) technologies. These technologies employ olfactory algorithms to analyse sensor data and detect hazardous chemicals by their unique chemical signatures, allowing for immediate response to potential threats (Jeong and Choi, 2022; Popescu et al., 2024). E-nose technologies have diverse applications, including monitoring urban air quality, detecting industrial leaks, and identifying hazardous materials (Jeong and Choi, 2022) including volatile organic compounds (VOCs), methane and emissions from industrial activities.

Challenges remain, such as ensuring the accuracy and reliability of these sensors and finding optimal methods to integrate them at scale into current environmental monitoring systems.

4.2.4. Biodiversity Monitoring and Assessment

Ecosystem biodiversity plays an important role in countering climate change, and AI systems can support its monitoring and assessment by helping identify various species and habitats from satellite images, providing data on species distribution and habitat health, usually a task that would require manual data annotation and extensive time consumption without the support of AI.

Numerous examples demonstrate the growing use of AI in enhancing biodiversity monitoring and conservation efforts. Rule-based systems like Artificial Intelligence for Ecosystem Services (ARIES) are among the most common and popular tools for modelling ecosystem services (Bibri, 2024; Nishant et al., 2020). Empirical studies further validate these applications (Domisch et al., 2019; Sharps et al., 2017; Willcock et al., 2018). As noted by Death (2015), ARIES integrates multiple ML models to understand complex ecological relationships, thereby improving the accuracy and effectiveness of biodiversity conservation strategies.

In addition to ARIES, other AI algorithms play a significant role in biodiversity and ecosystem health. CNNs are used to analyse and classify high-resolution images for species identification and habitat mapping, providing critical data for conservation efforts (Christin et al., 2019). Random Forest (RF) algorithms are employed to model species distribution and predict biodiversity patterns by integrating various environmental variables (Cutler et al., 2007). Moreover, Bayesian Networks (BN) aid in understanding complex ecological interactions and predicting the impacts of environmental changes on ecosystem health (Marcot et al., 2006).

CASE STUDY

USING ML TO IDENTIFY PRIORITY SITES FOR INTEGRATING MANGROVE RESTORATION WITH SUSTAINABLE AQUACULTURE INTENSIFICATION

Country: Indonesia and the Philippines
Entities involved: This project brought together experts from academia, conservation organizations, and the tech industry, including Arizona State University, Conservation International (CI), Konservasi Indonesia, and Thinking Machines. Funding was provided by the Climate Change AI Innovation Grants programme, with support from the Quadrature Climate Foundation, Schmidt Futures, and the Future Earth Canada Hub.

Brief description

In this example of an AI-powered climate solution applied in LDCs, a diverse team of academics, conservation practitioners, and tech industry experts developed a rapid assessment tool, powered by AI and Earth observation data, to identify and validate priority sites in Indonesia and the Philippines for deploying loans to shrimp farmers. This aimed to improve shrimp production and restore mangroves in the Climate Smart Shrimp (CSS) programme.

Shrimp aquaculture has grown 100-fold over the last 40 years, from an estimated 74,000 metric tonnes in 1980 to 7.5 million metric tonnes in 2022. This rapid growth has come at the cost of critical coastal ecosystems, especially mangroves. While deforestation rates have decreased from 0.21% (1996–2010) to 0.04% (2010–2020), at least 35% of global mangroves were deforested in the late 20th century, and the ecosystem services and climate benefits they provided remain lost.

Conservation International's CSS programme supports communities' livelihoods and food security while also improving coastal resilience and adaptation to climate change. The initiative provides resources for small- and medium-sized farmers to sustainably intensify production on a portion of their farm in exchange for mangrove restoration on the remainder of the farm. This enables smaller farms to be more competitive within the global commodity shrimp market while providing sustained funding and opening available parcels for coastal mangrove restoration. But not all aquaculture farms are suitable for such an approach.

This project used ML and Earth observation data to identify and classify aquaculture farms that are abandoned or low productivity. The team then combined this information with open data on sea level rise, flood risk, infrastructure access, historical mangrove cover, and other attributes to identify viable sites for CSS. Identifying a pipeline of optimal sites accelerates CI's ability to engage farmers, industry, and communities, and scale CSS.

Climate Change Mitigation and/or Adaptation Impacts and Results

The site assessment tool enables CI and its project partners to apply CSS more efficiently and to effectively support livelihoods and food security in shrimp aquaculture geographies while providing climate mitigation, climate adaptation, and coastal resilience benefits for coastal communities.

The site assessment tool enables CI and its project partners to apply CSS more efficiently and to effectively support livelihoods and food security in shrimp aquaculture geographies while providing climate mitigation, climate adaptation, and coastal resilience benefits for coastal communities.

While the tool was designed to streamline the implementation of CSS, it can also guide conservation practitioners on where to focus other nature-based solution approaches. The tool can identify areas that are suitable candidates for restoring mangroves to increase forest cover and are also viable for intensifying shrimp aquaculture to contribute towards food security and support local livelihoods.

While the tool in its current form helps CI to rapidly evaluate the hundreds of thousands of potential hectares where CSS might be implemented and find optimal locations, slight updates or changes to the scoring criteria could make this tool applicable in a wide range of coastal restoration applications.

Challenges and Lessons Learned Regarding Development and Implementation

In development and implementation of the tool, we encountered several challenges and learned an important lesson, namely:

- Public data on aquaculture production in LDCs are not available, restricting the use of potential AI approaches. We spent substantial resources developing training datasets for ML.
- Spatially explicit data on land cost and land tenure are also not available for many LDCs. As CI has developed more CSS sites, it has become clear that these two variables are critical determinants of project viability. We attempted to use proxy data related to land value and ownership, but we had insufficient resources to develop robust datasets.

AI tool developers need to consider unintended uses prior to product development.

The study by Hirn et al. (2022) investigated the complex patterns of species coexistence in diverse ecological communities using GenAI. Understanding these patterns is crucial for biodiversity conservation, yet traditional experimental approaches struggle with the complexity caused by indirect interactions among species. To address this challenge, the authors applied cutting-edge ML techniques, specifically Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), to predict species coexistence in vegetation patches.

The GANs were highly effective in reproducing realistic species compositions and identifying species' preferences for different soil types. Similarly, the VAEs demonstrated high accuracy, achieving above 99%. The study revealed that high-order species interactions tend to suppress the positive effects typically seen in simpler interactions. By analysing artificially generated data, the researchers could identify pioneer species capable of promoting greater biodiversity in distinct patches. The findings highlight the potential of GenAI in advancing ecological research by overcoming the limitations of traditional methods and offering new insights into species coexistence and community assembly. This approach opens opportunities for deeper exploration of biodiversity maintenance in complex ecosystems.

4.2.5. Nuanced Land Use Alterations

Land and climate interact in complex ways through multiple biophysical and biochemical feedback. Changes in land use patterns significantly impact climate dynamics through alterations in carbon storage, GHG emissions, and ecosystem resilience. AI-powered analysis of satellite imagery can speed up the detection of subtle changes in land use, such as urban expansion, agricultural activities, and infrastructure development across different spatial and temporal scales. By comparing these datasets, spatial land planning becomes more efficient, enhancing the rationality and feasibility of planning schemes (Chen et al., 2023). Moreover, aerial imaging analysis to identify physical surface materials or human land use highly advance urban land use investigations, providing substantial cost and time savings (Chen et al., 2023). AI systems can be leveraged to enhance land classification by making it possible to analyse a vast quantity of data, recognizing patterns and so facilitating decision-making. Kerins et al. (2020) demonstrated the viability of automated urban land use/land cover mapping using ML models and satellite imagery. The researcher developed customized models for 11 cities in India and used these models to generate comprehensive maps of the corresponding cities at multiple points in time. By tracking these changes over time, AI systems aid in understanding the impacts of human activities on the environment and in planning sustainable land use practices.

AlDousari et al. (2022) utilized Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) to evaluate and predict changes in land use and cover in Kuwait. Nguyen et al. (2021) proposed a method for openly accessing existing data and Sentinel-2 satellite imagery through ML algorithms, subsequently using land use maps to study the impact of land use changes on sustainable development through both local and global indicators. Recent studies underscore the growing role of ML in environmental management in land-use classification. Talukdar et al. (2020) focused on the application of ML classifiers for satellite-based land-use and land-cover classification, highlighting the technology's ability to enhance accuracy and efficiency in monitoring changes in terrestrial ecosystems. Nonetheless, DL models are highly effective for categorizing land cover or land use and can achieve high accuracy in classifying different types of habitations (Alem and Kumar, 2020). CNNs, which excel in many image classification tasks, outperform SVMs, RF, and K-Nearest Neighbours (KNN) in land cover and land use classification (Carranza-García et al., 2019).

A recent empirical study by Guzder-Williams et al. (2023) proposed a ML method to automate the production of intra-urban land use maps using Sentinel-2 imagery, which is particularly beneficial for developing countries, as well as LDCs and SIDS. The novel neural network architecture created for this task produced 5-m resolution land use maps for a global sample of 200 cities, spanning 78 countries and various population sizes. The model reduces computational resources. The main results showed high accuracy, with tier-1 and tier-2 achieving 86% and 79% accuracy, respectively, and tiers 3 and 4 achieving 75% and 71%. Additionally, a roads-only model compared favourably with existing datasets, and an Informal Settlement Classifier accurately classified 87% of informal settlements. These findings demonstrate the potential for regularly updated, global intra-urban land use maps at a fine resolution to support urban planning and policymaking in resource-limited regions.

Another empirical study by Bindajam et al. (2021) investigated the dynamics of Land Use and Land Cover (LULC) changes and their impact on ecosystem services value (ESV) from 1990 to 2028 in Abha-Khamis, Saudi Arabia. Using SVM classification, they mapped LULC for 1990–2018 and analysed changes using a delta change method and a Markovian transitional probability matrix (TPM). The authors found that urban areas increased by 334.4% from 1990 to 2018. The TPM indicated that built-up areas were the most stable LULC type, while agricultural land, scrubland, exposed rocks, and bodies of water were increasingly converted into urban areas. The study also predicted future LULC for 2028 using an artificial neural network-cellular automata model, indicating significant urban expansion at the expense of natural ecosystems.

4.2.6. Monitoring of Carbon Dioxide and Methane Emissions

AI algorithms can also be leveraged to enhance the analysis of vast amounts of data on carbon dioxide (CO2) and methane emissions collected by remote sensing technologies. By providing real-time insights they could be beneficial in verifying compliance with emission reduction commitments, understanding emission sources, and guiding policy decisions to address climate change effectively. Das et al. (2020) proposed a robot designed for deployment in unknown and uneven environments, capable of recognizing hazardous gases such as CO2 and liquefied petroleum gas with an average accuracy of 98%. The robot is equipped with AI to avoid collision obstacles, detect the presence of humans, and map the locations of detected gases in real-time using a GPS module. Jualayba et al. (2018) designed a monitoring and warning system equipped with sensors for hydrogen, liquefied petroleum gas, and methane. This system uses colour-coded indicators to display safety statuses based on detected gas levels. When a medium level of gas is detected, an exhaust fan is activated. At dangerous levels, an alarm buzzer is triggered to alert people about the gas leakage and the need to reduce the concentration of the detected gas.

Li et al. (2021) focused on the optimization of internal combustion engine performance using a novel approach that couples ANN with GA. Their method, targeting the Direct Dual Fuel Stratification (DDFS) strategy, improved the accuracy and stability of performance predictions and was more efficient than traditional methods. The ANN-GA approach achieved higher fuel efficiency and lower nitrogen oxide emissions while reducing computational time significantly – by over 75% compared to the conventional Computational Fluid Dynamics–Genetic Algorithm (CFD–GA) methods. This efficiency stems from the ANN's lower computational demands and its ability to manage large datasets and variable parameters effectively, highlighting its potential to enhance engine performance optimization further. Overall, the ANN-GA method demonstrates superior accuracy, efficiency, expandability, and flexibility in optimizing the DDFS strategy.

ML is increasingly being applied to enhance various CO2 management processes. Indeed, the increasing urbanization and industrial activities in metropolitan areas have escalated air pollution levels, necessitating advanced air quality prediction and monitoring systems. Schürholz et al. (2020) developed a context-aware air quality prediction model using LSTM DNN, integrated with data from pollution sources and users' health profiles. This model, implemented through the My Air Quality Index (MyAQI) tool in Melbourne, demonstrated high precision (90–96%) in predicting air quality, displaying its adaptability to individual health conditions. Similarly, Sowmya and Ragiphani (2022) proposed an air quality monitoring system leveraging IoT devices and AI tools to manage air pollutants effectively. Their system employs sensors to measure harmful gases and utilizes SVM algorithm for future air quality predictions. This approach aims to enhance public awareness and enable proactive measures to maintain indoor air quality. Almalawi et al. (2022) employed linear regression, support vector regression (SVR), and gradient boosting decision trees to develop a model for analysing the air quality index using sensor data. Alimissis et al. (2018) utilized ANN and multiple linear regression, discovering that ANNs offer computational advantages, especially when the density of air quality monitoring networks is limited.

Furthermore, these can contribute to achieving carbon neutrality by reducing GHG emissions and mitigating climate change (Jahanger et al., 2023; Sahil et al., 2023). This entails optimizing energy use, improving efficiency in various sectors, and enhancing the deployment of renewable energy technologies. AI applications can also help in monitoring and managing carbon footprints in industries, cities, and across energy systems, making processes more sustainable and less carbon intensive. Additionally, AI systems can predict the behaviour of CO2 in storage sites and monitor these sites to ensure the permanent trapping of the gas underground (Kushwaha et al., 2023). Furthermore, AI's ability to develop innovative carbon storage methods, such as creating promising materials for sustainable CO2 management, represents another significant strength (Zhang, Z. et al., 2022).

The main challenges and risks that can be encountered while deploying AI systems for the use cases presented in Section 4.2 are:

- **Data Scarcity:** Sparse sensor networks and limited historical data can reduce the accuracy of analyses and early warning systems.
- **Technical and Financial Constraints:** High costs for satellite data or advanced computing hardware/software can be prohibitive.
- **Connectivity and Power Reliability:** Unreliable internet or electricity limits the real-time transfer and processing of EO data.
- **Capacity Gaps:** Shortage of local experts who can interpret data and maintain analytical systems.

4.3. Climate Simulation and Prediction

Machine learning (ML) can be leveraged to improve climate modelling by enhancing the accuracy of weather predictions and understanding climate change impacts. It helps identify patterns in climate data, aiding decision-making and policy development. With the vast data from Earth observation satellites, AI and ML have become essential for weather forecasting and disaster response. These advanced algorithms predict extreme weather events like hurricanes and floods by analysing historical and real-time data, highlighting the importance of improved observational techniques.

4.3.1. Climate Modelling

NASA and IBM Research have collaborated to develop the Prithvi foundational model for weather and climate, an AI-powered tool designed to improve weather and climate forecasting at both regional and global scales (Barnett, 2024). This model leverages NASA's extensive datasets, such as MERRA-2, and uses AI to detect patterns that can be applied across various weather and climate scenarios. The model is part of NASA's strategy to produce actionable, high-resolution climate projections that can inform decision-making for communities, organizations, and policymakers. The Prithvi model enhances applications like severe weather detection, localized forecasts, and improving spatial resolution in climate models. Developed in collaboration with IBM, Oak Ridge National Laboratory, and other partners, the model is designed to scale across regions while maintaining resolution and capturing complex atmospheric processes even with incomplete data. The Prithvi model is one of several in the Prithvi family that aligns with NASA's open science principles to democratize access to scientific data. It will be available later this year on Hugging Face, a platform for ML and data science. This initiative is a step forward in making NASA's vast Earth observation archives more accessible and impactful for the global community.

AI's capabilities in data processing and collection enhance the accuracy of digital model predictions, bridging the gap between these models and real-world conditions, thus leading to more accurate forecasts of future outcomes (McGovern et al., 2017). High-quality climate predictions are important for understanding the impacts of various GHG emission scenarios and for developing effective strategies to mitigate and adapt to climate change (Bonan and Doney, 2018).

AI systems can aid in mitigating climate change by improving the prediction of extreme weather events. Weather forecasting is fundamentally a data issue, and as the volume of data analysed by AI increases, its accuracy will improve, thereby reducing the impacts of extreme weather events (Chen et al., 2023). By analysing vast amounts of historical weather data, AI models can identify patterns and anomalies, enabling the development of more accurate forecasting models. These improved predictions help in better preparing for and responding to severe weather, ultimately reducing potential damage, and enhancing resilience. Indeed, advanced ML and DL techniques are being widely applied to identify complex patterns and correlations that may not be immediately apparent to human analysts. For example, ML techniques such as RF and SVM can be used to analyse climate data to predict weather patterns and extreme events. DL techniques, including CNNs and RNNs, are particularly effective in processing large volumes of data and capturing intricate temporal and spatial dependencies, which are essential for accurate climate modelling and prediction, thereby improving early warning systems. To do so, they process data from various sources, including satellite imagery, weather station records, and ocean buoys, to generate comprehensive datasets. Evidence suggests that incorporating big data mining and neural networks into the weather prediction workflow can enhance the accuracy of forecasts (Shultz et al., 2021). This revolves around whether DL approaches could entirely replace current numerical weather models and data assimilation systems. Integrating

AI with numerical climate simulation data can effectively bridge observation data gaps, thereby reducing uncertainty and bias in climate predictions (Kadow et al., 2020). Existing weather forecasting technologies based on physical and numerical models are often inaccurate and limited, as they do not account for variables like global warming, whereas AI technologies can predict long-term climate change and short- to medium-term extreme weather events more effectively (Jeon and Kim, 2024).

Lopez-Gomez et al. (2023) focused on improving extreme heat forecasts using neural weather models (NWMs) with convolutional architectures. Trained on historical data, these models predicted surface temperature anomalies globally for up to 28 days. The study found that using custom loss functions tailored to emphasize extremes significantly improved heatwave prediction accuracy. This method also maintained general temperature prediction skills and showed better performance than existing models' overall lead times.

From an empirical perspective, real-world implementations of AI and ML techniques are increasingly proving their value in enhancing climate prediction and disaster preparedness. Kagabo et al. (2024) developed a precise rainfall forecast model using ML techniques, specifically LSTM networks, to predict extreme rainfall events in Rwanda. The study analysed extensive historical rainfall data and found that LSTM outperformed other algorithms such as CNNs and GRUs, achieving up to 99.8% accuracy. The research emphasized LSTM's ability to handle data irregularities, significantly improving forecast results and enhancing disaster preparedness and risk mitigation efforts in Rwanda. Similarly, AI is being leveraged through a United Nations initiative in Africa to support communities vulnerable to climate change in countries such as Burundi, Chad, and Sudan (WEF, 2024). The IKI Project employs AI technology to forecast weather patterns, enabling communities and authorities to better prepare for and adapt to climate change impacts.

4.3.2. Climate Scenario Simulations and Adaptation Strategies

AI drives significant improvements in the simulation of climate scenarios, offering robust tools for evaluating adaptation strategies and providing decision-makers with actionable insights. By harnessing advanced ML algorithms and data analytics, AI systems enhance the accuracy and efficiency of climate models by processing vast amounts of climate data, identifying complex patterns, and predicting future climate conditions under various scenarios. These capabilities enable researchers to explore potential impacts of different environmental policies and practices, thereby aiding in the development of effective and responsive climate action plans. Moreover, AI-driven simulations facilitate a deeper understanding of regional climate changes, aiding in tailoring adaptation measures to local contexts and improve resilience against climate-related risks.

Bonan and Doney (2018) examined recent advancements in ESM that incorporate both terrestrial and marine biospheres. These models effectively capture the interactions between the physical and biological components of the Earth System (ES), providing valuable insights into climate impacts on critical societal issues such as crop yields, wildfire risks, and water availability. However, despite these advances, further research is needed to address model uncertainties and improve the translation of observations into abstract model representations.

In the study by Bowes et al. (2019), LSTM networks and RNNs were used to forecast groundwater table responses to storm events in Norfolk, Virginia. Similarly, Jeon et al. (2018) utilized deterministic and decision support models to evaluate the performance of BMPs under various climate scenarios, refining BMPs for future conditions. In urban settings, Skiba et al. (2018) used artificial neural networks to model the economic dependence between urban policy and energy efficiency, offering insights for energy-efficient urban development.

Van der Woude et al. (2024) introduced an innovative application of ANN to forecast biocapacity and ecological footprint, specifically focusing on forest land indicators in Latin America and the Caribbean until 2030, aligning with SDGs. By forecasting these indicators, the study sought to aid in strategic planning and decision-making processes that enhance environmental sustainability and support climate change adaptation efforts in the region. It serves as a key blueprint for other developing regions seeking to strengthen their environmental sustainability and climate mitigation efforts.

While many arid regions are found in less developed countries, where the challenges of water scarcity and harsh living conditions can exacerbate developmental issues, it is important to note that arid regions can exist in both developing and developed countries. Adikari et al. (2021) evaluated and compared the effectiveness of three prominent AI-based approaches – CNNs, LSTM, and Wavelet decomposition functions combined with the Wavelet Adaptive Neuro-Fuzzy Inference System (WANFIS) – in forecasting floods and droughts in arid and tropical regions. The study measures fluvial floods by the run-off change in rivers and meteorological droughts using the Standard Precipitation Index (SPI). The findings reveal that the CNN model excels in flood forecasting, while the WANFIS model shows superior performance in meteorological drought forecasting, irrespective of the climatic region. Additionally, the CNN model demonstrates enhanced accuracy in applications with multiple input features.

CASE STUDY

FORTIFYING ETHIOPIA'S NATIONAL PARKS: BUILDING RESILIENCE AGAINST WILDFIRES AND EXTREME WEATHER

Country: Ethiopia
Entities involved: This project includes a wide range of stakeholders: national meteorological and hydrological services in target countries and regions; NGOs 'on the ground,' such as the Red Cross Climate Centre, civil society bodies, civil protection authorities, and first responder organizations, local communities, academic institutions; and research organizations, national and regional governments, private sector and dedicated lighthouse stakeholders such as African Union, UNEP, UNDP, and ESA. All these stakeholders will benefit from MedEWSa's aim of translating complex climate information into actionable knowledge.

Brief description

Natural hazards, such as extreme weather events, are exacerbated by anthropogenic climate change. As a result, emergency responses are becoming more protracted, expensive, frequent, and stretching limited available resources. This is especially apparent in rapidly warming regions. The MedEWSa (Mediterranean and pan-European Forecast and Early Warning System against natural hazards) project addresses these challenges by providing AI-powered novel solutions to ensure timely, precise, and actionable impact and finance forecasting, and early warning systems that support the rapid deployment of first responders to vulnerable areas. .

Climate Change Mitigation and/or Adaptation Impacts and Results

Through eight selected pilot sites (areas in Europe, the southern Mediterranean, and Africa with a history of natural hazards and extreme events with cascading effects), four MedEWSa twin sites will be created:

1. Twin #1: Greece (Attica) – Ethiopia (National Parks): wildfires and extreme weather events (droughts, wind)
2. Twin #2: Italy (Venice) – Egypt (Alexandria / Nile Delta): coastal floods and storm surges
3. Twin #3: Slovakia (Kosice) – Georgia (Tbilisi): floods and landslides
4. Twin #4: Spain (Catalonia) – Sweden (countrywide): heatwaves, droughts, and wildfires.

The twins will bridge areas with different climatic/physiographic conditions, yet subject to similar hazards, and are well positioned to deliver long-term bidirectional knowledge transfer. They will demonstrate the transferability and versatility of the tools developed in MedEWSa.

Challenges and Lessons Learned Regarding Development and Implementation

MedEWSa will improve the current Decision Support Data System by:

- Automatizing the process-chain from identification of active fire to real-time simulations, to assessing high risk areas, to producing alerts, and consequently optimizing the response time.
- Enhancing the spatiotemporal information by improving the spatial resolution especially in the urban-rural interface and developing indicators at the sub-seasonal to seasonal timescales.
- Advancing models and systems regarding the fire spread capability for large-scale domains (mixed wind scenarios, simulation time optimization), and the forest fire danger rating system.
- Standard Operating Procedures and update of the Forest Fire Bulletin to trigger early actions (patrolling areas at risk) and rapid deployment of first responders mitigation measures (prescribed burnings), and preparedness activities.

Table 1 presents an overview of various adaptation strategies facilitated by AI. It details themes, AI applications, specific aims, findings, and contributions of various studies related to AI-driven climate adaptation strategies. It includes a wide range of applications and scenarios that highlight the potential of AI in climate action. The strategies assessed range from AI-driven agricultural practices to advanced disaster response systems. The integration of AI with IoT is known as AIoT.

Table 1 serves as a valuable tool for decision-makers to compare the most viable AI-supported adaptation strategies, ensuring informed and strategic planning in mitigating the impacts of climate change in LDC and SIDS.

Table 1: Studies on adaptation strategies using Artificial Intelligence models

Theme	AI Applications	Objectives	Key Contributions	Citations
Groundwater table forecasting	LSTM Networks, RNN	To model and forecast groundwater table response to storm events in a coastal city.	LSTM networks outperformed RNNs in predictive accuracy; effective for real-time forecasting of groundwater table levels.	Bowes et al. (2019)
Best management practices (BMP) performance in agricultural watershed	Deterministic Models (SWAT), Decision Support Models (NSGA-II)	To evaluate changes in BMPs on total phosphorus loads under different climate change scenarios.	SWAT and NSGA-II helped refine BMPs for future climate scenarios; highlighted the need for adaptive BMPs.	Jeon et al. (2018)
Climate change impact on crop yield	Statistical Downscaling, GA	To predict climate change impacts on pearl millet yield using genetic algorithms.	Demonstrated potential for energy-efficient renovations in urban settings using neural networks.	Skiba et al. (2017)
Flood analytics	AIoT, CNN	To advance flood analytics using AIoT in flood situational awareness and risk assessment.	AIoT prototype improved flood warning and situational awareness; successfully tested during hurricane-driven floods.	Samadi (2022)
Drought forecasting	ANN, ANFIS, SVM	To compare ANN, ANFIS, and SVM models in drought forecasting.	SVM model provided the highest accuracy in drought forecasting compared to ANN and ANFIS.	Mokhtarzad et al. (2017)
Crop yield prediction	DNN, Semiparametric	To model and predict crop yields under different climate change scenarios using ML methods.	ML approach showed less severe negative impacts on corn yield than traditional methods, especially in warmest scenarios.	Crane-Droesch (2018)
Urbanization and climate impact	Dynamic Simulation, Weather Research and Forecasting Model (WRF)	To investigate the impact of future urbanization on local climate under different climate change scenarios.	WRF simulations indicated significant warming and public health risks due to urbanization and climate change by 2030.	Yeung et al. (2020)

4.3.3. The Role of Artificial Intelligence in Decreasing Energy Consumption in Climate Modelling

Significant energy savings can be achieved by creating software frameworks and libraries tailored to minimize energy consumption in AI. Techniques such as optimized runtime scheduling, sparse modelling, ensemble modelling, task parallelization, and resource-aware programming can enhance software performance while reducing energy demands. These optimizations not only benefit the environment but also lead to more cost-effective and scalable AI solutions.

For example, sparse modelling techniques focus on identifying and utilizing the most relevant variables and data points, thus simplifying the models. This leads to reduced computational complexity, faster simulations, and efficient data processing. By focusing only on key variables, sparse models require less computational power, thus conserving energy. Simplified models run faster, reducing the time and energy needed for simulations. In addition, sparse models streamline data handling, minimizing the energy required for data storage and analysis. Given the complexity of climate and its varied impacts on populations, Grames and Forister (2024) employed a Bayesian sparse modelling approach to select from 80 climate metrics. They applied this method to 19 datasets covering bird, insect, and plant populations. For phenological datasets, mean spring temperature often emerged as a key climate driver. This climate variable selection approach is valuable for identifying relevant climate metrics, especially when there is limited physiological or mechanistic information, and is applicable across different studies on population responses to climate. Overall, sparse modelling makes climate simulations more efficient, leading to significant energy savings.

Žust et al. (2021) presented an ensemble DL method for forecasting sea levels in the Adriatic Sea, which surpasses traditional ocean circulation models in terms of both accuracy and computational efficiency. By using a diverse set of models, researchers can identify and prioritize the most accurate and efficient ones, reducing the need for extensive runs of less effective models. More accurate predictions reduce the need for repeated simulations, saving computational energy.

Enhancing efficiency in AI research will reduce its carbon footprint and make it more accessible, ensuring that DL studies are not limited to those with the largest financial resources (Schwartz et al., 2020). The AI community has recently started to address the environmental impacts of ML/DL programmes. Research highlights the energy consumption and carbon footprint associated with training DL, NLP, and GenAI models alike. The concept of Green AI or Computing was proposed to encourage more environmentally friendly AI practices (Raman et al., 2024; Schwartz et al., 2020). Green AI denotes "AI research that yields novel results while taking into account the computational cost, encouraging a reduction in resources spent" (Schwartz et al., 2020). Researchers are focused on optimizing algorithms, hardware, and data centre operations to lower energy consumption and minimize the carbon footprint of AI systems (Wheeldon et al., 2020).

The recent comprehensive study by Raman et al. (2024) focused on Green AI, utilizing thematic analysis and BERTopic modelling to explore this field. The study identified significant advancements in Green AI, particularly in the areas of energy optimization and sustainable computational practices. It highlighted three main thematic clusters: responsible AI for sustainable development, advancements in Green AI for energy optimization, and big data-driven computational advances. Among these, the study emphasized the importance of sustainable neural computing and cognitive AI innovation, showcasing how AI technologies can be optimized for energy efficiency and reduced environmental impact. These findings underscore the critical role of Green AI in promoting environmental sustainability within the AI research community, providing valuable insights for future research and policymaking aimed at integrating sustainability into AI research and development, including climate modelling.

Furthermore, the AI community has developed various tools to evaluate the energy consumption of ML models. For example, Anthony et al. (2020) highlighted the energy consumption and carbon footprint associated with training NLP models. Henderson et al. (2020) underscored the need for systematic reporting of the energy and carbon footprints of ML practices. The authors introduced a framework that facilitates this reporting by providing a simple interface for tracking real-time energy consumption and carbon emissions, along with generating standardized online appendices. This framework is utilized to create a leaderboard for energy-efficient reinforcement learning algorithms, aiming to incentivize responsible research in this field and serve as a model for other areas of ML. Based on case studies using this framework, the authors propose strategies for mitigating carbon emissions and reducing energy consumption. Lacoste et al. (2019) proposed methods to quantify the carbon emissions of ML, while Lannelongue et al. (2021) introduced the concept of Green Algorithms to measure the carbon emissions of computational tasks. These impacts are primarily expressed in terms of energy consumption and associated greenhouse gas (GHG) emissions.

The main challenges and risks that can be encountered while deploying AI systems for the use cases presented in Section 4.3 are:

- Model Bias: Models trained on global datasets may not capture local climate nuances, leading to inaccurate regional forecasts.
- Computational Demands: Running complex climate models often requires high-performance computing infrastructure, which can be lacking.
- Lack of Local Data: Insufficient regional data inputs, such as rainfall patterns or sea-level measurements, reduce model accuracy.
- Dependence on External Providers: Reliance on foreign institutions for modelling expertise can result in limited local capacity-building.

4.4. Resource Management

Effective resource management is important for sustainable development and directly impacts climate change mitigation and adaptation efforts. AI-enabled interventions have shown significant promise in optimizing the management and preservation of natural resources. AI systems can be leveraged to improve resource management practices across various domains and contribute to broader climate resilience strategies by integrating advanced data analytics, ML, and real-time monitoring.

4.4.1. Artificial Intelligence Interventions in Fisheries Management and Marine Life Preservation

Human activities pose considerable threats to marine ecosystems, making effective management and conservation crucial. AI technologies have advanced the ability to monitor and manage fish stocks and Marine Protected Areas (MPAs). The application of AI and automation can improve marine conservation efforts, particularly in safeguarding marine ecosystems and defining MPAs (Şeyma, 2023). ML algorithms analyse data from satellite imagery, sonar, and other remote sensing technologies to track fish populations and their movements. This allows for more accurate assessments of fish stock levels, which is key to sustainable fisheries management. Marine life preservation would also benefit blue carbon strategy in LDCs and SIDS that utilizes coastal ecosystems for carbon sequestration.

AI research has improved marine resource management, encompassing water pollution monitoring, pollutant tracing, pollution reduction and prevention strategies, acidification mitigation, and habitat and species protection through various AI models and techniques (Bibri et al., 2023). These include ML, DL with CNNs and RNNs, GA, ML-based Species Distribution Models (SDMs), and time series forecasting, in addition to Autonomous Underwater Vehicles (AUVs), and Remotely Operated Vehicles (ROVs), nano satellites, drones, and robots (Bakker, 2022; Şeyma, 2023). For example, ML techniques can be employed to analyse underwater photographs, enabling the identification and categorization of marine species (Moniruzzaman et al., 2017). Also, Watanabe et al. (2019) determined that an autonomous monitoring system utilizing optimally controlled robots is necessary. They employed a DL algorithm known as YOLOv3 to detect underwater sea life and floating debris on the ocean surface, achieving sensitivities of 69.5% and 77.2%, respectively.

AI techniques can be integrated into decision support systems (DSS) to enhance decision-making. These rely on various data sources, analytical models, and user interfaces to help users make informed decisions in the context of environmental sustainability and climate change. This includes assessing ecosystem services, species conservation, water chemistry and quality, and hydro-meteorological forecasting (Nishant et al., 2020). When DSS include ML, FL, and NLP, they can provide more advanced and intelligent support. Automating and leveraging AI enhances the management of maritime resources by developing AI-based decision support systems that effectively manage fisheries and improve the establishment of MPAs (Şeyma, 2023). Automation and AI have the potential to transform marine research by introducing new perspectives and enhancing data collection and processing.

Villon et al. (2018) developed and evaluated a CNN for identifying fish species in underwater images, comparing its performance to human abilities in terms of speed and accuracy. Using a diverse dataset of 900,000 images, the CNN was trained to recognize 20 different fish species, including whole fish bodies, partial fish bodies, and environmental elements such as reef bottoms or water. The CNN's accuracy was tested against human performance on a test set of 1197 images representing nine species. The results showed that the CNN achieved a correct identification rate of 94.9%, higher than the human accuracy rate of 89.3%. The CNN was particularly effective at identifying fish partially obscured by corals or other fish, and in processing smaller or blurrier images, while humans were better at identifying fish in unusual positions, such as twisted bodies. It is notable that efficient monitoring of marine biodiversity is instrumental to understanding and mitigating the impacts of climate change on marine ecosystems, as it helps track species distribution shifts, detect changes in population dynamics, and assess the health of marine habitats affected by warming oceans, acidification, and other climate-related changes.

Illegal fishing is closely related to climate change in several significant ways. Climate change can lead to shifts in ocean temperatures, currents, and ecosystems, causing fish populations to move to new areas, which can result in overfishing in some regions and underfishing in others, driving some fishers to engage in illegal fishing practices to maintain their catch levels. Moreover, climate change impacts, such as ocean acidification and changes in sea temperature, can stress fish populations and reduce their numbers, leading fishers to resort to illegal methods to compensate for declining stocks. Since the onset of the Industrial Revolution, the acidity of surface ocean waters has risen by approximately 30% (NASA, 2024). This increase is attributed to higher CO_2 emissions from human activities, which lead to its greater absorption by the ocean. Moreover, economic pressures play a role, as communities reliant on fishing for their livelihoods may face increased economic strain due to the effects of climate change on fish availability and distribution, prompting some to turn to illegal fishing as a means of survival. Furthermore, climate change can damage critical marine habitats like coral reefs and mangroves, which are essential for the life cycles of many fish species. The destruction of these habitats forces fish to migrate, creating new challenges for legal and sustainable fishing practices and potentially increasing illegal fishing activities.

CASE STUDY

AI FOR REAL-TIME CORAL REEF MONITORING AND CONSERVATION

Country: Fiji, the Maldives, Palau, Solomon Islands, and Vanuatu
Entities involved: Australian Institute of Marine Science

Brief description

ReefCloud's AI utilizes advanced algorithms trained on the Australian Institute of Marine Science (AIMS)'s Long-term Monitoring Programme data to identify and classify coral reefs from images automatically. This allows for rapid and accurate assessment of reef health, standardizing collected data with 80–90% accuracy and analysing coral reef composition at a speed 700 times faster than traditional manual methods. ReefCloud employs a cloud-based platform that enables users to upload, access, and share data from anywhere in the world. This facilitates collaboration among researchers and managers and supports the processing of large image datasets. ReefCloud Analytics processes millions of quality-controlled point annotations to identify trends and patterns in coral reef health data and offer the possibility to visualize reefs in 3D. This informs conservation and management decisions by providing detailed insights into reef composition and condition over time.

Climate Change Mitigation and/or Adaptation Impacts and Results

Improved Monitoring: ReefCloud provides a rapid and accurate way to assess coral reef health, helping to track changes over time and identify areas that need protection.

Enhanced Management: The system provides managers with the information needed to make informed decisions about conservation and restoration efforts.

Resource Optimization: By analysing coral reef composition with 80–90% accuracy and 700 times faster than traditional manual assessment, ReefCloud saves weeks to months of labour, freeing up precious reef management resources.

Challenges and Lessons Learned Regarding Development and Implementation

For the successful deployment of AI monitoring systems in a global community, it is important to ensure a user-friendly platform and standardized data collection.

Appana et al. (2022) focused on combating IUU fishing by developing an edge technology-based AI system for MPAs. The system utilizes low-cost, solar-powered edge computing devices on buoys equipped with video cameras and processors to detect illegal fishing through AI-based image recognition. The results showed that the system effectively detects and monitors vessels engaged in illegal activities, reducing overfishing. The edge devices process data locally and a stealth drone collects and reports the data, providing continuous 24/7 surveillance. This technology offers real-time alerts of illegal fishing activities to governments and NGOs, supporting the protection of MPAs.

Cheng et al. (2023) investigated the use of AI in analysing fishing vessel behaviour to enhance management practices, prevent illegal fishing, identify fishing grounds, and assess the impact of harvesting on fishery resources. With the development of advanced vessel-tracking systems, a wealth of real-time data on fishing vessels is now available, allowing for detailed analysis of their behaviour. To effectively handle this large volume of data, AI algorithms are increasingly applied. Various sources for studying fishing vessel behaviour are covered, along with AI methods used to monitor and extract behavioural patterns, and research on the physical, ecological, and social factors affecting these behaviours is synthesized.

Bakker (2022) examined an innovative approach to digitally driven earth system governance in marine biodiversity conservation: Artificial Intelligence-enabled, mobile marine protected areas (MMPAs). This form of ocean governance operates in real-time and can potentially cover vast oceanic areas, utilizing digital hardware that gathers data from various sources such as nano-satellites, drones, environmental sensor networks, digital bioacoustics, marine tags, and deep-sea UAVs. The collected data are then analysed using ML algorithms, CV, and ecological informatics techniques. Scientists and regulators are increasingly advocating for the use of these AI-powered systems in global ocean management due to their ability to provide adaptive, real-time responses to environmental changes and disturbances. By enhancing the monitoring and protection of marine environments, MMPAs can detect and respond to illegal activities and overfishing in real-time, ensuring more effective enforcement of conservation regulations.

Samaei and Hassanabad (2024) focused on the intersection of marine industries, seas, and AI within the framework of sustainable development. Key findings include the successful implementation of AI for autonomous navigation, predictive maintenance, marine traffic management, environmental monitoring, intelligent port operations, and smart aquaculture. AI technologies, such as reinforcement learning, ML, neural networks, GA, and IoT sensors, have significantly improved efficiency, accuracy, and 24/7 operational capabilities.

4.4.2. Artificial Intelligence Interventions in Farming Management

AI is revolutionizing farming management by providing data-driven insights and adaptive strategies that enhance agricultural productivity and sustainability, while enabling farmers to navigate changing climate conditions more effectively.

AI and applied ML techniques are being leveraged to enhance agricultural practices. By integrating advanced algorithms and real-time data analysis, AI tools empower farmers with critical information to make informed decisions. This technological advancement is significant for addressing the challenges posed by climate change and the increasing demand for food production.

Nath et al. (2024) focused on the innovative potential of AI in the agricultural and food processing industries, emphasizing its implications for sustainability and global food security. They highlighted the increasing integration of AI technologies, such as ML, DL, and neural networks, in these sectors to enhance various farming processes, including crop yield optimization, herbicide use, weed identification, and fruit harvesting. The study concluded that AI boosts the efficiency, sustainability, and productivity of agri-food systems and underscored the need to expand its application across the agri-food supply chain, thereby contributing to global food security and addressing key agricultural challenges.

Precision farming technologies use AI to analyse data from various sources, such as satellite imagery, drones, and sensors to monitor crop health, soil conditions, pest infestations, optimal planting times, air quality, and weather patterns. These data-driven approaches and actionable insights enable precise resource management, leading to increased yields and reduced environmental impact. AI-driven precision agriculture, combined with genome analysis and editing techniques, can produce crops that are well-suited to the land and optimize plant production (Joseph et al., 2021).

Rustia et al. (2022) addressed the main bottleneck in Integrated Pest Management (IPM), which is the lack of reliable and immediate crop damage data. To tackle this issue, they developed an Intelligent and Integrated Pest and Disease Management (I2PDM) system. This AIoT-based system uses edge computing devices to automatically detect and recognize major greenhouse insect pests, such as thrips and whiteflies, and to measure environmental conditions like temperature, humidity, and light intensity. The results showed that the system significantly supported farm managers in IPM-related tasks, leading to a substantial yearly reduction in insect pest counts, with decreases as high as 50.7%. The study concluded that the I2PDM system represents a significant advancement in IPM through automated, long-term data collection and analysis. This innovative approach opens up new possibilities for sustainable and data-driven IPM, encouraging collaboration among farm managers, researchers, experts, and industries to implement more effective pest management practices.

Dheeraj et al. (2020) explored the role of AI and IoT technologies in mitigating climate change by creating environmentally friendly and high-performing systems. By integrating IoT and AI, data collected from field sensors are analysed to monitor various environmental factors such as soil moisture, weather conditions, fertilization levels, soil composition, temperature, and irrigation systems. The results indicate that this integration helps increase crop production, leading to higher incomes for farmers.

Among the climate change challenges related to agriculture are altered growing seasons, increased pest and disease pressures, and extreme weather events. AI systems can help farmers develop adaptive strategies to navigate these challenges. Precision agriculture utilizes these systems to identify pests, accurately and rapidly detect crop diseases, predict yields, and optimize fertilizer and pesticide use using ML, DL, and CV (Chen et al., 2023). Herbicides or other chemical residues can be left on plant products due to chemical spray transfer, often caused by wind blowing tiny droplets of spray solution onto nearby crops or fields (Creech, 2015). Precision spraying technology addresses this issue by drastically reducing the quantity of herbicide required and applying it only where weeds are present. This targeted application can significantly lessen the environmental impact, lower costs, reduce crop damage, and minimize excessive chemical residues (Balafoutis et al., 2017), thereby adapting agricultural practices to changing environmental conditions.

Additionally, Swaminathan et al. (2023) reported that robots equipped with AI and CV for monitoring and spraying weeds could reduce chemical usage on crops by 80% and cut herbicide costs by 90%. In precision fertilization, a fertilizer application model calculates the required fertilizer input, which is then applied using a variable rate applicator after assessing the soil's nutrient levels and dividing the field into a grid (Elbeltagi et al., 2022).

ML models can predict the impacts of climate change on crop yields and recommend adaptive measures, such as changing planting dates, selecting resilient crop varieties, and implementing water-saving technologies. Du et al. (2021) developed a high-efficiency water and fertilizer control system for cotton cultivation that uses soil conductivity thresholds to optimize the use of water and fertilizer. This system, which monitors soil conductivity and moisture content, resulted in a 10.89% reduction in resource usage. Moreover, accurately calculating reference evapotranspiration is important for meeting crop water needs, providing essential data for effective water management and sustainable agriculture.

Elahi et al. (2019) estimated the target values of agrochemicals for rice farms while maintaining current yield levels in the Hafizabad and Sheikhupura districts of Pakistan. The authors found that pesticide inputs could be reduced by 52.6% and pure nitrogen fertilizer inputs by 43.6%, leading to a favourable and significant impact. Putra et al. (2020) modelled the storage and release of nutrients through fertilizer application to simulate the availability and loss of nutrients in oil palm cultivation. This approach helps determine and maintain the nutrient balance at specific sites by adjusting fertilizer application accordingly.

4.4.3. Artificial Intelligence for Water Resource Management

AI applications in water resource optimization have garnered significant research attention in recent years. These applications aim to enhance the conservation and efficient use of water resources. AI systems play a role in optimizing water resource management. AI and ML algorithms analyse data from sensors, satellite imagery, and weather forecasts to predict water demand and supply, optimize irrigation schedules, and detect leaks in water distribution systems. These technologies help in conserving water, improving water use efficiency, and ensuring the sustainable management of water resources.

Among the major AI models used in water resource management are ANNs, SVM, decision trees (especially random forests), multiple regression, autoregressive moving average models (ARMA), and spline regression, with genetic algorithms (GA) also being widely utilized (Bibri, 2024; Bibri et al., 2023; Nishant et al., 2020). Widely used ML models often combine ANN, including adaptive neuro-fuzzy inference systems (ANFIS). For instance, ANNs and ANFIS can be used to predict streamflow and analyse water quality parameters. In the study by Rashid and Kumari (2023), these two techniques were utilized to predict velocity and pressure in the Gadhra (DMA-5) water distribution network in Jharkhand, India. For predicting velocity, flow rate and diameter were used as independent variables, while for predicting pressure, elevation and demand were the independent variables. The dataset was split with 80% used for training, testing, and validation, and 20% for evaluation. Sensitivity analysis was conducted with ANN-LM to explore the relationships between variables.

Sharma et al. (2024) focused on modelling the stage–discharge relationship, which is important for accurate discharge estimation needed in reservoir operations, hydraulic structure design, and flood and drought control. It compared a conventional stage–discharge rating curve (SRC) method with three data-driven techniques: ANN, ANFIS, and SVM. The results showed that the ANFIS model using the Gaussian membership function outperformed the SRC, ANN, and SVM models. Given the importance of precise groundwater level estimation for crop cultivation, daily life, and sustainable growth, Jithendra and Basha (2023) developed prediction models using hybrid techniques that integrate ANN, ANFIS, and an Improved Reptile Search Algorithm (IRSA) to help prevent resource depletion. IRSA was used to optimize the parameters of ANN and ANFIS, enhancing the forecasting models' effectiveness. Comparisons between ANN-IRSA, ANFIS-IRSA, traditional ANN, and ANFIS on the same datasets showed that the ANFIS-IRSA model performed best.

Adaptive intelligent dynamic water resource planning, a streamlined approach that utilizes AI technology, enhances water efficiency, and sustains the water environment in urban areas (Xiang et al., 2021). Liu et al. (2019) improved the stability and reliability of the projection tracking water quality evaluation model by adding dynamic inertia weights to the moth flame algorithm, thereby enhancing regional water environment evaluation accuracy. Afzaal et al. (2020) employed RNNs and LSTM to address the dynamic inputs of climate change in Prince Edward Island, Canada.

CASE STUDY

AI ARTIFICIAL INTELLIGENCE FOR WATER MANAGEMENT IN THE RED RIVER DELTA

Country: Viet Nam
Entities Involved: Brescia University (Italy) and Thuyloi University (Viet Nam), supported by Climate Change AI

Brief description

This project focuses on the use of AI techniques for the water management of the Red River Delta area in Viet Nam (Figure 4). In this area, the complex river network is characterized by the presence of a system of dams designed to address sometimes conflicting objectives: (i) generating hydropower to foster the local economy and social activities, (ii) regulating the flood events occurring downstream during the rainy season, (iii) supplying water for agriculture in the low flow season and (iv) contrasting Sea Water Intrusion (SWI) in the estuaries of the rivers. Constraints include the need to ensure the dam's safety by not exceeding a maximum or minimum water level.

Figure 4: The Red River Delta area in Viet Nam

With the aim of developing adaptive water management systems, this work studies the feasibility of using AI techniques to identify policies for the current and projected climatic conditions. In particular, our project focuses on optimizing water supply for agriculture and energy production in the low-flow season while contrasting SWI in the Red River Delta. We aim to use optimization methods like Genetic Algorithms (GAs) and AI planning algorithms to automatically generate control policies for water resource management of the Hoa Binh reservoir, the first hydroelectric reservoir on the Da River while considering different constraints.

Climate Change Mitigation and/or Adaptation Impacts

The project aims to enhance water management systems to address climate change, urbanization, and population growth, focusing on both mitigation and adaptation. Efficient water management will reduce water stress and ensure a reliable supply for agriculture, industry, and domestic use, which is crucial as climate change exacerbates scarcity. It will also mitigate sea-level rise effects and saline intrusion into freshwater sources by controlling water releases and storage, maintaining balance in river deltas and estuaries. Additionally, the project enhances renewable energy production by optimizing water usage for hydropower, reducing reliance on fossil fuels, and lowering carbon emissions. It supports local economies by ensuring a steady water supply for various uses, fostering social development, and reducing vulnerability to climate-induced economic disruptions.

Challenges and Lessons Learned Regarding Development and Implementation

The process of data analysis is challenging due to an absence of homogeneity in the collected data, such as variations in recording time intervals and the presence of missing data on certain days. Consequently, prior to utilization, a data screening and correction procedure must be executed to rectify any inconsistencies or irregularities. Moreover, the complexity of the irrigation system in the Red River Delta, consisting of approximately 30 irrigation areas, requires precise determination of water requirements. This necessitates a dedicated research effort to ensure accuracy and reliability, which is beyond the scope of this research. In this context, the demand indicated in Decision 50, issued by the Vietnamese government in 2023 was selected as the reference framework. This strategic choice facilitates alignment with authoritative mandates and provides a robust foundation for subsequent analyses. The available models of the Red River Delta are data-driven approximations of its dynamics rather than precise descriptions of the system's physical evolution, increasing the reliance on good-quality data.

The main challenges and risks that can be encountered while deploying the AI use cases presented in Section 4.4 are:

- **Data Integration Challenges:** Resource data (e.g., for agriculture or fisheries) may be fragmented or outdated, impairing AI's effectiveness.
- **Inadequate Monitoring Infrastructure:** Limited deployment of sensors or monitoring equipment can hamper real-time resource tracking.
- **Socio-economic Inequities:** If AI tools are only accessible to a privileged few (e.g., large-scale commercial entities), smallholder farmers or local fishers may be sidelined.
- **Regulatory and Policy Gaps:** Weak governance structures can lead to mismanagement or uneven distribution of benefits (e.g., water allocation).

4.5. Energy Management

Energy management is a critical component in the fight against climate change, where optimizing the generation, operation, distribution, transmission, and consumption of energy can lead to substantial reductions in greenhouse gas (GHG) emissions. Enhancing energy efficiency, developing renewable energy, and increasing its contribution to decarbonizing each of its end-users are crucial strategies for tackling or mitigating climate change.

4.5.1. Real-time Energy Management

AI algorithms, such as neural networks and ML, are used to analyse vast amounts of data from smart grids, allowing for real-time adjustments that enhance energy efficiency (Farghali et al., 2023). Predictive analytics help in forecasting energy demand, reducing wastage, and balancing supply and demand dynamically. As climate change challenges intensify, AI is increasingly recognized as one of the key solutions to mitigate these challenges. AI can be seamlessly integrated with IoT and renewable energy systems, enhancing energy supply, optimizing decision-making, and enabling autonomous control, thereby acting as a significant driving force in the energy sector (Bibri, 2024; Rane et al., 2024a). Indeed, AI has the potential to innovate the energy sector, presenting new opportunities for improving energy efficiency and achieving sustainable development objectives (Baysan et al., 2019; Farghali et al., 2023).

AI systems can be leveraged to enhance the distribution and transmission of energy by optimizing the grid planning for reducing losses. AI techniques can be applied to develop smart grid systems that adapt to changes in energy demand and supply in real-time, ensuring efficient energy distribution and minimizing transmission losses. In the energy sector, the integration of AI can enhance energy utilization efficiency by predicting energy demand, optimizing production and consumption, and enabling intelligent control systems (Chen et al., 2023; Shoaei et al., 2024). These advancements lead to reduced energy costs, decreased environmental pollution, and promote sustainable development (Ahmad et al., 2021; Khalilpourazari et al., 2021; Lee and Yoo, 2021). For example, AI applications in smart meters and home automation systems provide consumers with insights into their energy usage patterns, helping them reduce consumption and lower energy bills. AI-driven demand response systems can shift or reduce power usage during peak times, thus flattening the demand curve and avoiding strain on the grid. Moreover, AI systems can provide early identification of maintenance needs for grid elements and generating facilities, and propose optimized preventive maintenance road maps, resulting in reduced equipment downtime and favouring reliability.

Furthermore, Ding et al. (2024) explored the potential of AI to enhance energy efficiency and reduce carbon emissions in medium-sized office buildings in the United States. They developed a methodology to assess emissions reductions by focusing on equipment, occupancy influence, control and operation, and design and construction. By evaluating six scenarios across different climate zones, the researchers found that AI systems could reduce energy consumption and carbon emissions by 8% to 19% by 2050. Moreover, they can lower cost premiums, increasing the adoption of high energy efficiency and net zero buildings. When combined with supportive energy policies and low-carbon power generation, they could potentially achieve a 40% reduction in energy consumption and a 90% reduction in carbon emissions compared to business-as-usual scenarios by 2050. This study highlights AI's significant potential to transform energy efficiency and carbon emission reductions in commercial buildings.

AI integrated with IoT have been increasingly utilized to improve energy efficiency, optimize energy management systems, and support Sustainable Development Goals (SDGs), especially SDG 7 and hence SDG 13. The examined studies in Table 2 – empirical studies, experimental studies, case studies, and reviews – focus on these applications, detailing their themes, objectives, AIoT techniques applied, application areas, and key findings. Table 2 provides a comprehensive overview and comparative analysis, offering insights into the diverse ways AIoT are being leveraged to tackle energy challenges and transform energy management practices.

Table 2: Artificial Intelligence applications in energy management

Research Description	Objectives	AI or AIoT Techniques	Application Areas	Key Findings	References
AI in smart power system transient stability	To review AI applications in addressing transient stability issues in smart power grids.	ML, DL, Big Data	Smart power grids	AI improves transient stability assessment and control in smart grids, enhancing reliability and efficiency.	Guo et al. (2023)
AI and digital technologies in the energy sector	To analyse the adoption and impact of AI and digital technologies in the energy sector.	AI, Big Data, IoT, Robotics, Blockchain	Energy sector	AI systems enhance job skills, firm performance, and energy sector innovation.	Lyu and Liu (2021)
IoT and AI for energy efficiency	To develop a system architecture for centralized energy efficiency using AI and IoT.	IoT, ML	Energy management systems	AI and IoT technologies improve scalability, automation, and efficiency in energy management, beneficial for smart industry and homes.	Tomazzoli et al. (2020)
AI in smart buildings for energy management	To review AI applications in smart buildings for enhancing energy efficiency.	ANN, ML, Big Data	Smart buildings	AI systems reduce energy consumption, improve control, reliability and automation in smart buildings, enhancing efficiency.	Farzaneh et al. (2021)

Table 2 (continued): Artificial Intelligence applications in energy management

Research Description	Objectives	AI or AIoT Techniques	Application Areas	Key Findings	References
AI for thermal comfort prediction and control in buildings	To evaluate AI methods for optimizing thermal comfort and energy use in buildings.	ML	Building energy management	AI systems optimize energy use while maintaining occupant thermal comfort, improving energy efficiency in buildings.	Ngarambe et al. (2020)
AI in prediction, optimization, and control of thermal energy storage systems	To assess AI techniques in optimizing thermal energy storage systems.	Particle Swarm Optimization PSO, ANN, SVM, ANFIS	Thermal energy storage	AI systems improve design and performance of thermal energy storage systems, demonstrating significant accuracy.	Olabi et al. (2023)
Applicability of ML techniques in agriculture and energy sectors	To explore ML techniques' applicability in smart agriculture and energy production.	ML algorithms	Agriculture, energy	ML enhances predictive accuracy and efficiency in smart farming and energy production, addressing key challenges.	Arumugam et al. (2022)
AI and ML for energy consumption and production in emerging markets	To review AI and ML applications in optimizing energy consumption and production in emerging markets.	AI, ML	Emerging energy markets	AI and ML techniques optimize energy consumption, production, and grid management, addressing issues in developing countries.	Mhlanga (2023)

CASE STUDY

OPTIMIZING HOUSEHOLD ENERGY CONSUMPTION: INDIA'S TATA POWER EZ HOME

Country: India
Entities involved: Tata Power (Indian company)

Brief description

Electricity distributors face the complex challenge of balancing supply and demand across millions of households, each with unique consumption patterns. As India integrates more renewable energy sources into its grid, this balancing act becomes even more intricate. The variability of solar and wind power generation, combined with the diverse and often unpredictable nature of household energy consumption, creates a significant challenge for energy management. This challenge is further complicated by the fact that household energy consumption is largely driven by individual behaviours and routines. Factors such as weather conditions, work schedules, holidays, and even major events can significantly influence electricity usage. Traditional methods of forecasting and managing household energy consumption often fail to capture these nuances, leading to inefficiencies and potential grid instability. Recognizing these challenges, Tata Power, one of India's largest integrated power companies, has developed the EZ Home platform. This AI-powered solution leverages machine learning and Internet of Things (IoT) technologies to optimize household energy consumption, control appliances, and enhance overall energy efficiency. By integrating smart home automation features, EZ Home aims to provide a seamless and energy-efficient living experience. EZ Home uses IoT technology to allow users to operate, schedule, and monitor household appliances, including lighting, fans, air conditioners, and more, via smartphone applications or voice commands. AI-powered Motion Sensors: The system includes AI-powered Passive Infrared (PIR) Motion Sensors that can control attached appliances based on human presence. .

Climate Change Mitigation and/or Adaptation Impacts and Results

Reduced Energy Waste: By optimizing energy consumption and distribution, EZ Home reduces the need for overproduction and minimizes energy loss during transmission and distribution.

Enhanced Energy Efficiency: The platform promotes energy-saving practices and technologies, contributing to overall energy efficiency at the household level.

Lowered Carbon Footprint: By reducing energy waste and promoting efficient energy use, EZ Home directly contributes to lowering greenhouse gas emissions at the household level. Energy Management Analytics: EZ Home provides end-users with data on their actual and predicted consumption at various levels (product, room, and home), helping them manage their energy use more effectively.

Seamless Integration: The EZ Home devices are designed for easy installation and offer backwards compatibility, allowing for integration into existing home setups without extensive rewiring.

4.5.2. Artificial Intelligence for the Efficient Use and Deployment of Renewable Energy Technologies

AI models can be used to accurately predict the output of renewable energy sources (El-Abbadi and Elyoubi, 2023; Rane et al., 2024), such as solar and wind, thereby enhancing energy production and handling transmission and distribution congestions. Accurate prediction helps in integrating renewable energy into the grid more effectively, by reducing the needs of spinning reserves in the power system and optimizing the connection to back-up generators just in time, ensuring a stable supply and reducing reliance on fossil fuels. The integration of AI can optimize the performance of renewable energy systems by adjusting parameters in real time. For example, reactive power contribution from renewable generators can anticipate consumption patterns towards guarantee appropriate voltage levels without further equipment or contribution of non-renewable generators.

In addition, the integration of AIoT in the renewable energy sector is driving significant advancements in how sustainable energy is generated, managed, and optimized, thus becoming increasingly crucial for advancing sustainable energy solutions. Rane et al. (2024) explored the synergy between AI, IoT, and edge computing in renewable energy applications. IoT devices facilitate real-time data collection, which, when combined with AI and ML, enhances system responsiveness and efficiency. Data connections and IoT sensors are integral to distributed energy resources (DERs), generating extensive data that can enhance system efficiency and add value beyond simple monitoring thanks to AI techniques (El Himer et al., 2022). By integrating AI with IoT, new opportunities arise in the energy sector for optimizing performance and creating additional benefits.

The examined studies in Table 3 – empirical studies, experimental studies, case studies, and reviews – focus on AI applications in renewable energy, examining their themes, objectives, AI or AIoT techniques applied, application areas, and key findings. These studies cover various aspects, from energy generation prediction and storage optimization to the integration of renewable sources into power grids. Table 3 presents a detailed overview and comparative analysis to understand the impact and potential of AI and AIoT in enhancing the efficiency, optimization, and reliability of renewable energy systems.

Table 3: Artificial Intelligence and Artificial Intelligence of Things applications in renewable energy

Research Description (Theme)	Objectives	AI/AIoT Techniques	Application Areas	Key Findings	Citations
AI and numerical models in hybrid renewable energy systems (HRESs)	To review AI applications in optimizing HRESs integrated with fuel cells.	GA, PSO, simulated annealing, RF, KNN, SVM, ANN	Solar photo-voltaic, wind energy, fuel cells	AI-based modelling identifies conditions for maximum power production, predicting drawbacks during unexpected load peaks.	Al-Othman et al. (2022)
Bio-inspired algorithms in maximum power point tracking for PV systems	To review bio-inspired algorithms for maximum power point tracking in PV systems under partial shading.	ANN, FL Control, bio-inspired algorithms	Photovoltaic systems	Bio-inspired algorithms effectively track the global maximum power point, outperforming traditional methods under partial shading.	Guiqiang et al. (2018)
AI-based solar radiation prediction model for green energy utilization	To develop AI-based models for accurate solar radiation prediction.	ANN, SVM, RF	Solar energy systems	AI models, especially ANN, show superior performance in predicting solar radiation, improving energy management and planning.	Alassery et al. (2022)
AI support for integrating variable renewable energy sources	To evaluate AI's potential in managing integration costs of variable renewable energy sources.	AI, data-intensive technologies	Variable renewable energy sources	AI systems reduce integration costs of VREs, enhancing system value and efficiency.	Boza and Evgeniou (2021)

Table 3 (continued): Artificial Intelligence and Artificial Intelligence of Things applications in renewable energy

Research Description (Theme)	Objectives	AI/AIoT Techniques	Application Areas	Key Findings	Citations
Large-scale renewable integrations for carbon neutrality	To analyse AI techniques for large-scale renewable energy integrations and carbon neutrality transition.	AI techniques	Multi-energy systems, renewable energy	AI techniques optimize operational control and effectiveness of large-scale renewable integrations, aiding in carbon neutrality.	Liu et al. (2022)
ML for high-temperature reservoir thermal energy storage	To optimize high-temperature reservoir thermal energy storage using ML.	ANN, GA	Thermal energy storage	ML techniques optimize HT-RTES site selection and performance, aiding in renewable energy storage.	Jin et al. (2022)
AIoT for renewable energy systems	To explore AIoT applications in enhancing renewable energy systems.	AIoT	Solar, wind energy systems	AIoT improves efficiency and performance of renewable energy systems through enhanced data utilization.	El Himer et al. (2022)
AI for predictive maintenance of renewable energy systems	To assess AI-assisted predictive maintenance in renewable energy systems.	AI techniques	Wind farms	AI assistance improves maintenance efficiency and fault detection in wind farms.	Shin et al. (2021)
Hybrid AI and IoT model for renewable energy generation	To develop an IoT-based system for renewable energy generation using AI models.	ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS)	Household, industrial energy systems	AI models enhance renewable energy generation efficiency, with ANN outperforming ANFIS.	Puri et al. (2019)

Table 3 (continued): Artificial Intelligence and Artificial Intelligence of Things applications in renewable energy

Research Description (Theme)	Objectives	AI/AIoT Techniques	Application Areas	Key Findings	Citations
Comparison of AI methods for solar radiation estimation	To compare various AI methods for estimating daily global solar radiation.	Group Method of Data Handling (GMDH), Multilayer Feed-Forward Neural Network (MLFFNN), ANFIS, ANFIS-PSO, ANFIS-GA, ANFIS-ACO	Solar energy systems	GMDH model outperforms others in predicting global horizontal irradiance.	Khosravi et al. (2018)
AI for optimizing thermal energy storage systems	To explore AI applications in optimizing thermal energy storage systems.	PSO, ANN, SVM, ANFIS	Thermal energy storage systems	AI techniques optimize, predict, and control the performance of thermal energy storage, enhancing efficiency and reliability.	Olabi et al. (2023)
AI in renewable energy systems	To review AI applications in renewable energy systems.	ANN, LSTM, RNNs, CNNs, GA, PSO	Renewable energy systems	AI and ML techniques significantly improve modelling and optimization of renewable energy systems.	Shoaei et al. (2024)
AI for energy storage in hybrid renewable energy sources	To optimize energy storage systems in hybrid renewable energy sources.	Group Method of Data Handling (GMDH), Multilayer Feed-Forward Neural Network (MLFFNN), ANFIS, ANFIS-PSO, ANFIS-GA, ANFIS-ACO	Hybrid renewable energy sources	The proposed AI technique optimizes ESS for hybrid renewable energy, outperforming recent methods.	Banu et al. (2022)

Table 3 (continued): Artificial Intelligence and Artificial Intelligence of Things applications in renewable energy

Research Description (Theme)	Objectives	AI/AIoT Techniques	Application Areas	Key Findings	Citations
Adaptive artificial neural network for renewable energy generation prediction	To propose a novel adaptive neural network for renewable energy prediction.	Mode Adaptive Artificial Neural Network (MAANN), Advanced Particle Swarm Optimization (APSO), Jaya Algorithm, Fine-Tuning Metaheuristic Algorithm (FTMA)	Solar and wind energy systems	The proposed algorithm significantly reduces prediction errors compared to conventional methods.	Zamee and Won (2020)
AI in off-grid hybrid renewable energy system optimization	To find optimal design for off-grid hybrid renewable energy systems.	Bonobo Optimizer (BO), Big Bang–Big Crunch (BBBC), Crow Search (CS), Genetic Algorithm (GA), Butterfly Optimization Algorithm (BOA)	Off-grid hybrid renewable energy systems	BO technique achieved optimal solutions with the lowest annualized system cost and quick convergence.	Farh et al. (2022)
AI for managing renewable power curtailments	To minimize renewable power curtailments using AI.	DL, Gated Recurrent Unit (GRU)	Wind and solar energy systems	AI methods significantly reduce curtailments, with AWEs outperforming BESSs in cost and operational efficiency.	Shams et al. (2021)

Table 3 (continued): Artificial Intelligence and Artificial Intelligence of Things applications in renewable energy

Research Description (Theme)	Objectives	AI/AIoT Techniques	Application Areas	Key Findings	Citations
Optimal sizing of hybrid renewable energy systems	To propose optimal sizing of hybrid renewable energy systems using AI.	GA, ABC	PV/battery and PV/wind turbine/ battery systems	Heuristic algorithms outperform deterministic algorithms in finding optimal solutions for HRESs.	Demolli et al. (2021)
AI for improving performance of renewable energy conversion and storage	To enhance performance of solar water heaters using AI.	ANN	Solar water heaters	ANN optimizes performance of PV-powered solar water heaters, improving efficiency and reliability.	Asiri et al. (2022)
Comprehensive analysis and synthesis of AI and ML applications in renewable energy	Examine AI and ML applications across renewable energy for efficiency, reliability, and sustainability.	AI, ML, IoT, Blockchain and Edge Computing	Renewable energy forecasting, smart grids, energy management, energy storage systems	AI and ML techniques enhance efficiency, reliability, and sustainability in renewable energy systems through precise forecasting, optimized energy production and distribution, and predictive maintenance.	Rane et al. (2024)

While the application of AI in domains, such as thermal comfort prediction and control, fault detection and diagnosis, energy storage optimization, and demand response, has shown promising results in enhancing energy efficiency, reducing waste, and promoting sustainable development (Fang et al., 2023; Rane et al. 2024), its effectiveness is an ongoing process that heavily relies on the accuracy of input data and the appropriate selection of AI algorithms (Arumugam et al., 2022; Ouadah et al., 2022). Moreover, the lack of accessible data and skilled AI experts poses a significant barrier to its widespread application in energy efficiency . Nevertheless, the integration of AI and AIoT in energy systems has demonstrated substantial potential in enhancing energy conservation, optimizing renewable power deployment and generation, and supporting sustainable development goals, making renewable energy technologies more broadly suitable and reliable, towards a complete energy transition.

The main challenges and risks that can be encountered while deploying AI systems for the use cases presented in Section 4.5 are:

- **High Initial Costs:** Procuring and maintaining AI-driven energy optimization systems can be too expensive for smaller utilities and governments.
- **Grid Instability:** Frequent power outages or inconsistent energy supply disrupt AI systems that rely on continuous data streams.
- **Limited Technical Skills:** Shortage of trained engineers and data scientists undermines the long-term sustainability of AI solutions.
- **Risk of Lock-In:** Dependence on proprietary software or external vendors can constrain local autonomy and innovation.

4.6. Transport Management

As the global population continues to urbanize and industrial activities expand, the efficiency of transportation systems becomes increasingly critical. AI has emerged as an innovative or a beneficial technology in transport management, offering solutions to optimize operations, enhance safety, and reduce environmental impacts.

4.6.1. Artificial Intelligence Interventions in Transport Management

AI-driven technologies can enhance the development of smarter and more sustainable transportation networks, which is crucial for mitigating greenhouse gas emissions. The transportation sector accounts for nearly one-third of global emissions (Solaymani, 2022), making it essential to reduce these emissions as part of climate change initiatives. AI optimizes routes considering traffic patterns and weather, improving fuel efficiency, and decreasing travel times . By enhancing transportation systems, AI offers promising solutions for reducing the carbon footprint (Fatemidokht et al., 2021).

AI-powered traffic management systems use real-time data from sensors and GPS to monitor traffic flow and dynamically adjust signals, reducing idling and unnecessary detours. These systems can greatly enhance efficiency and result in significant cost savings and reduced emissions (Chen et al., 2023). Moreover, the integration of AI with sustainable transportation methods, like bicycle-sharing schemes, has been shown to improve urban mobility through better data management using technologies like IoT (Puri et al., 2020). AI also enhances public transit by optimizing scheduling and encouraging lower-emission transportation modes (Nikitas et al., 2020; Olayode et al., 2020). This involves analysing data to predict demand and adjust routes, accordingly, promoting more sustainable options (Chen et al., 2023).

The rise of autonomous vehicles (AVs) represents a significant transformation in transportation. AVs can reduce accidents and emissions by improving fuel efficiency and traffic patterns (Tyagi and Aswathy 2021). Furthermore, the concept of Shared Autonomous Electric Vehicles (SAEVs) offers benefits by alleviating congestion and reducing greenhouse gas emissions (Ahmed et al., 2023). Studies show that adopting SAEVs could lower emissions and costs, providing substantial environmental and economic advantages compared to privately owned vehicles (Jones and Leibowicz, 2019).

4.6.2. Artificial Intelligence for Industry Production

AI can enhance the efficiency of logistics and supply chain operations, reducing costs and emissions. They can also improve load management, predict maintenance needs, and optimize routes by utilizing data-driven insights, leading to more efficient and reliable freight transportation systems. The integration of AI in these sectors enhances operational efficiency and contributes to environmental sustainability and climate change mitigation by minimizing the adverse effects of industrial activities and freight transport.

AI has the potential to transform supply chain management by enhancing decision-making processes and automating various tasks to reduce supply bottlenecks. AI systems can monitor and identify issues with specific food products, and aiding supply chain management during large-scale food supply can forecast demand more accurately, helping to adjust storage needs and prevent overstocking or shortages. This ensures that perishable goods are sold while still fresh, reducing waste (Lutoslawski et al., 2021). AI systems also enhance livestock supply chains by aiding in production planning, quality control, and predicting maintenance needs before they arise (Helo and Hao, 2022). Within storage facilities, AI combined with IoT sensors can continuously monitor and adjust conditions, such as temperature and humidity, optimizing the life cycle of perishable goods while minimizing waste and energy consumption (Wang et al., 2022). Furthermore, AI is used to optimize food distribution routes and vehicle loads, which helps reduce carbon emissions from the food supply chain (Yaiprasert and Hidayanto, 2023).

Moreover, Cohen et al. (2023) noted that pre-component production necessitates significant data analysis. They emphasized that if component data problems arise during modelling, it can lead to waste and reduce the enterprise's productivity, ultimately causing resource waste. Cioffi et al. (2020) focused on intelligent manufacturing, emphasizing a fully integrated and collaborative production system. This system is designed to respond in real time to evolving conditions within the factory, supply network, and according to customer needs. Dwivedi et al. (2021) indicated that AI systems enhance efficiency by integrating management methods, such as combining AI with lean production. This approach allows each production link to calculate its efficiency, thereby reducing waste of raw materials due to idleness and helping enterprises optimize their production lines. The primary role of AI in this context is as a tool for data analysis, enabling the interpretation and evaluation of results to improve energy and resource management. The extensive use of fossil fuels in manufacturing processes is a major contributor to significant CO2 emissions (Yue and Gao, 2018).

Various studies have explored different facets of AI applications, highlighting their practical implications and the significant challenges they present. Liu et al. (2024) provided a comprehensive analysis and synthesis of AI applications in the modular construction industry. Their systematic exploration underscores the advancements in AI technologies, such as ANNs and ML, which enhance production efficiency, optimize logistics, and improve operational management. Yang et al. (2021) proposed a new model for intelligent manufacturing in the process industry. This model emphasizes the deep integration of industrial AI and the Industrial Internet, leveraging AI for optimal decision-making, autonomous control systems, and improved operational management. The study highlights

AI's effective role in traditional process industries through enhanced decision-making and control systems. Plathottam et al. (2023) offered a detailed analysis of AI/ML technologies, identifying key areas where AI can improve efficiency, such as predictive maintenance, quality assurance, and process optimization. However, the authors highlight significant challenges, including data acquisition, security risks, and trust issues, which must be addressed to fully leverage AI's potential in manufacturing.

Furthermore, recent studies highlight the significant potential of AI in enhancing global economic dynamics and firm performance. Liu et al. (2024) focused on the broader impact of AI on the Global Value Chain (GVC) position of the manufacturing industry. Using extensive panel data from 61 countries, their findings reveal that AI improves the GVC position by enhancing production efficiency, boosting technological innovation, and reducing trade costs. The study is particularly insightful for policymakers, emphasizing AI's more pronounced impact in developing countries and various manufacturing sectors, thereby promoting global competitiveness.

The main challenges and risks that can be encountered while deploying the AI use cases presented in Section 4.6 are:

- **Inadequate Infrastructure:** Poor road networks and limited public transport options reduce the potential impact of AI optimization.
- **Connectivity Constraints:** Unstable communications infrastructure can disrupt real-time tracking and data-sharing.
- **Uneven Benefits:** Improvements in transport logistics may serve only well-connected urban areas, leaving out rural regions.
- **Privacy and Security Concerns:** Collecting mobility data without strong data protection regulations can expose citizens to misuse.

4.7. Disaster Risk Reduction

Disaster risk reduction involves strategies to minimize the damage caused by natural and human-made disasters. AI systems play an important role in enhancing both preparedness and recovery efforts.

The International Organization of Migration (IOM) reports that climate has now become the leading driver of internal displacements (more than conflict). Migration induced by environmental factors such as climate change or natural disasters is on the rise, and only expected to increase. IOM is a leading organization on climate mobility, working at community and national levels to support prevention, preparedness, response, and recovery. Early action and disaster risk reduction are key pillars in IOM interventions to support millions of women, men, and children, especially in a world of growing climate-related humanitarian emergencies. In 2020, 30.7 million people were internally displaced by disasters; a number three times greater than those displaced by conflict and violence (9.8 million people). Of those displaced by disasters, 98% faced weather and climate hazards. Climate and weather-related disasters have affected a further 1.7 billion people globally during the past decade. These numbers are expected to rise as the frequency, duration, and intensity of natural hazards worsen. However, Microsoft is partnering with the IOM so they can use AI and analytics capabilities to better understand the impact of climate-induced migration and improve their humanitarian efforts.

4.7.1. Predictive Analytics Shaping Evacuation Planning

AI models aid in shaping evacuation planning through predictive analytics. AI systems can predict the potential impact of disasters, related to floods, hurricanes, earthquakes, and heatwaves, by analysing historical data and real-time inputs. Indeed, advancements in AI for processing climate big data enable the identification of more comprehensive future climate change scenarios and the development of intelligent early warning systems (Leal Filho et al., 2022). Climate change predictions enable authorities to identify high-risk areas and develop effective evacuation routes and strategies. For instance, AI models can simulate various disaster scenarios and assess their potential outcomes, providing valuable insights into the best evacuation practices. AI can also be used to determine the ideal placement of traffic sensors to avoid bottlenecks during such evacuations (Gazzea, 2023). This predictive capability ensures that evacuation plans are timely and tailored to the specific dynamics of an impending disaster, thereby enhancing the safety and efficiency of evacuations.

In the context of extreme weather disasters, AI applications enhance public engagement in climate issues and stimulate collective action by accurately predicting and visualizing climate change risks (Alemany et al., 2019; Walsh et al., 2020). These AI-driven insights aid decision-support efforts through real-time monitoring, thereby improving situational awareness and enabling timely interventions (Anbarasan et al., 2020; Booth, 2018; Samadi, 2022; Walsh et al., 2020). AI can contribute to climate change mitigation by enhancing the prediction of extreme weather events (McGovern et al., 2017; Shultz et al., 2021). Huntingford et al. (2019) highlighted the potential of ML in climate change preparedness in terms of its ability to provide enhanced warnings of extreme weather events. AI models are adept at identifying complex patterns and correlations, allowing them to forecast the likelihood and potential severity of extreme weather events with greater accuracy. This predictive capability improves intelligent early warning systems, providing timely alerts and enabling proactive measures to reduce the impact of these events (Leal Filho et al, 2022; Rolnick et al., 2022).

Anbarasan et al. (2020) proposed a flood detection system integrating IoT, big data, and Convolutional Deep Neural Networks (CDNN) to enhance flood prediction accuracy. Their system pre-processes data to eliminate redundancies and applies CDNN for classification, outperforming ANN and DNN. Samadi (2022) introduced the Flood Analytics Information System (FAIS), which combines AI, big data, and IoT to provide real-time flood monitoring and situational awareness. FAIS successfully integrates crowd intelligence, ML, and NLP to improve flood risk assessments and response strategies. Khalilpourazari and Pasandideh (2021) presented a robust optimization model for flood evacuation planning, leveraging AI to optimize shelter locations and helicopter routes, significantly improving rescue rates and cost efficiency.

During disasters, the coordination of response efforts is critical to minimizing harm and ensuring a swift recovery. AI systems facilitate this coordination by integrating data from multiple sources, including satellite imagery, sensor networks, and social media feeds. AI models can significantly aid disaster relief efforts by mapping floods, locating refugee camps using satellite data (Logar et al., 2020), as well as identifying the populations most in need of assistance. This integration provides real-time situational awareness (Abid et al., 2021; Samadi, 2022), allowing responders to understand the scope and scale of the disaster as it unfolds. Furthermore, AI systems optimize resource allocation by analysing the availability and location of emergency resources such as medical supplies, personnel, and equipment. This real-time optimization ensures that resources are deployed where they are most needed, enhancing the overall effectiveness of the disaster response.

Lee and Chien (2020) explored AI and IoT in robotic disaster response, highlighting the potential of AIoT in coordinating robotic swarms for search and rescue operations, thus improving the efficiency and effectiveness of disaster response. Swarna and Bhaumik (2022) explored the integration of AI and IoT devices to enhance the prevention, response, and recovery phases of disaster management. The study focuses on developing a platform that combines multiple AI components, IoT devices, and data sources into a unified system to improve disaster management practices. The study resulted in the creation of an integrative AI platform designed to oversee real-time data collection and analysis through IoT devices. Two use cases in disaster prevention were highlighted, demonstrating the platform's capability to implement predictive monitoring and efficient response strategies.

Raza et al. (2020) focus on enhancing communication infrastructure in disaster-affected areas using AI and social media platforms to form resilient communication networks. The researchers propose a user-centric approach to create communication networks in areas where the infrastructure has been compromised due to natural disasters related to floods, earthquakes, and storm surges. The proposed solution involves forming ad hoc clusters to enable emergency communications, utilizing a novel cluster formation framework that supports both single and multi-hop communication. Their innovative approach maximizes communication throughout and accurately classifies disaster impact areas, thereby facilitating better coordination and response. The ML techniques used to classify disaster-prone areas showed promising results, suggesting that this approach could effectively restore communications and provide situational awareness during disasters.

Saleem and Mehrotra (2022) examined the emergent use of AI and social media for disaster management. The primary aim is to highlight how AI systems can process disaster-related content from social media to aid disaster response organizations in making effective decisions. The research underscores the importance of timely and relevant information, which social media provides during disasters, offering real-time insights from affected communities. It also presents case studies demonstrating new approaches for disseminating and acquiring time-sensitive information during disasters. The findings underscore the potential of AI-based systems to exploit social media data for improving the efficiency and effectiveness of disaster management strategies.

4.7.2. Post-Disaster Risk Assessment: A Multi-faced Approach

AI-driven risk assessment tools help identify vulnerable areas and populations, enabling targeted interventions before disasters strike (Kuglitsch et al., 2022b). Authorities can enhance their preparedness strategies by harnessing the power of AI, ensuring more effective and timely interventions during disasters. Ghaffarian et al. (2023) examined the role of Explainable AI (XAI) in enhancing Disaster Risk Management (DRM) by improving decision-making processes. The authors identified various types of hazards and disasters, risk components, and AI and XAI methods. The findings indicate a significant increase in the use of XAI techniques for DRM, underscoring the growing importance of transparency and interpretability in AI applications. The study highlights the need for multi-hazard risk analysis, the integration of XAI in early warning systems, and the incorporation of causal inference methods to enhance DRM strategy planning and effectiveness.

Sun et al. (2020) emphasize the increasing damage and socio-economic losses caused by natural hazards. The study reviews AI applications across the four phases of disaster management. In the mitigation and preparedness phases, AI techniques assist in risk assessment, early warning systems, and community education to enhance disaster readiness. The response phase sees the highest concentration of AI applications, leveraging real-time data processing, optimizing resource allocation, and improving situational awareness. In the recovery phase, AI systems aid in damage assessment and efficient resource allocation for rebuilding efforts. Additionally, the study identifies challenges such as data quality, system integration, and ethical considerations, aiming to inspire further research and advancements in AI to address these issues effectively.

Exploring the potential of AI in disaster risk management, Velev and Zlateva (2023) emphasize the numerous challenges in applying AI to this field. These challenges include the necessity for high-quality and diverse data, ensuring compatibility with existing systems and technologies, addressing ethical and social implications, and the need for continuous research and development. Additionally, they underscore the critical importance of data privacy and security, given that AI applications in disaster management often involve handling sensitive information. The study aims to analyse these challenges to ensure that AI systems are developed and utilized in ways that are fair, equitable, and effective in mitigating the impacts of disasters. Similar topics are addressed in the technical reports of the ITU/WMO/UNEP Focus Group on AI for Natural Disaster Management (ITU, 2024a).

Salluri et al. (2020) utilized CNN for object detection in disaster scenarios, focusing on floods and earthquakes. Their study demonstrated high accuracy with pre-trained models like VGG-19, aiding in efficient disaster recovery operations. Equipped with AI algorithms, these technologies can analyse vast amounts of visual data to identify and quantify damage to infrastructure, homes, and natural landscapes. Zhang et al. (2023) proposed a hybrid learning approach combining AI and crowdsourced data to improve the generality of disaster damage assessment models, demonstrating substantial improvements over traditional methods. Sun et al. (2020) highlighted the importance of AI in disaster response and recovery, showcasing its ability to enhance the assessment of damage and socio-economic losses resulting from natural hazards and prioritization of recovery efforts. The authors concluded that, in the recovery phase, AI is key to swiftly assessing damage and efficiently allocating resources for rebuilding efforts. Abid et al. (2021) highlighted AI's important role in enhancing recovery operations by facilitating rapid data analysis and visualization, enabling governments to make quicker and more informed decisions in the aftermath of a disaster. By analysing large volumes of data from various sources, ML models can quickly identify the most affected areas and prioritize them for immediate action. This enhances the overall efficiency and effectiveness of recovery operations and streamlines the reconstruction process. Khajwal et al. (2022) focused on the reliability of automated post-disaster building damage classification using AI and multi-view imagery. Current AI applications in post-disaster damage assessment often lack detailed classification of damage levels and are based on limited aerial or satellite imagery. To address these limitations, the authors propose using comprehensive visual data from multiple ground and aerial views of buildings. A Multi-view Convolutional Neural Network (MV-CNN) architecture is employed to combine information from different views, providing a spatially aware damage prediction model. The model is trained and validated on a dataset of geotagged, expert-labelled images of buildings affected by Hurricane Harvey. The findings demonstrate that the proposed model achieves reasonably good accuracy in predicting damage levels, offering a more reliable tool for AI-assisted disaster management.

Arachie et al. (2020) focused on identifying critical sub-events after large-scale disasters using unsupervised learning on social media data. Their method effectively filtered and ranked relevant information, enhancing emergency responders' ability to manage crises. The findings demonstrate that their unsupervised learning framework effectively identifies and ranks important sub-events, thereby aiding emergency responders in making informed decisions for resource allocation and response planning. This post-disaster analysis is validated through quantitative experiments on data from Hurricane Harvey and the 2015 Nepal Earthquake, showing its effectiveness over baseline methods.

The initiative led through national and international cooperation and partnership highlights the use of DL techniques and aerial imagery to improve climate resilience in the Caribbean housing sector (Tingzon et al., 2023; World Bank, 2023). This approach leverages advanced AI methods to generate critical housing stock data rapidly, aiding disaster risk management and supporting climate adaptation efforts in SIDS.

CASE STUDY

MAPPING HOUSING STOCK CHARACTERISTICS FROM AERIAL AND STREET VIEW IMAGES USING DL FOR CLIMATE RESILIENCE IN THE CARIBBEAN

Country: Dominica, Saint Lucia, Grenada
Entities Involved: The World Bank, Global Facility for Disaster Reduction and Recovery (GFDRR), Government of the Commonwealth of Dominica (GoCD), and Government of Saint Lucia (GoSL)

Brief description

The Caribbean region is among the most vulnerable globally to climate risks due to the increasing frequency and severity of natural hazards like tropical cyclones, landslides, and floods. Small Island Developing States (SIDS) often sustain the highest levels of damage, particularly in the housing sector. Accurate and up-to-date information on the spatial distribution and characteristics of buildings is crucial for effective vulnerability assessment and disaster risk management. However, traditional house-to-house surveys are expensive and time-consuming, creating significant obstacles.

To address this, a project was initiated to develop a workflow that rapidly generates critical baseline housing stock data using high-resolution drone images and DL techniques. Leveraging CV, particularly the Segment Anything Model and CNNs, this project automates the generation of exposure data maps. The goal is to enable government agencies to identify damaged buildings following a disaster swiftly and cost-effectively and proactively detect at-risk structures before a disaster occurs. This initiative, under the Digital Earth for Resilient Housing and Infrastructure in the Caribbean, seeks to improve the climate resilience of the housing sector in SIDS in the Caribbean. Future expansions of this methodology are planned for countries in Asia and the Pacific.

Climate Change Mitigation and/or Adaptation Impacts and Results

The project has produced building footprint and roof type classification maps for Dominica (see example in Figure 5), Saint Lucia, and Grenada, which are essential for climate risk and vulnerability assessments. Additionally, building characteristics such as material type, completeness, and condition have been extracted from street-view photos to further support these assessments.

Figure 5: An AI-generated map of building footprints in Salisbury, Dominica. Drone image is taken from OpenAerialMap

Figure 6 illustrates the sequence of roof material classification and changes in a Caribbean housing sector pre- and post-disaster in Colihaut, Dominica. The four images provide a comparative visual analysis that highlights the impact of disasters on roof materials and the effectiveness of the classification approach in both pre- and post-disaster contexts.

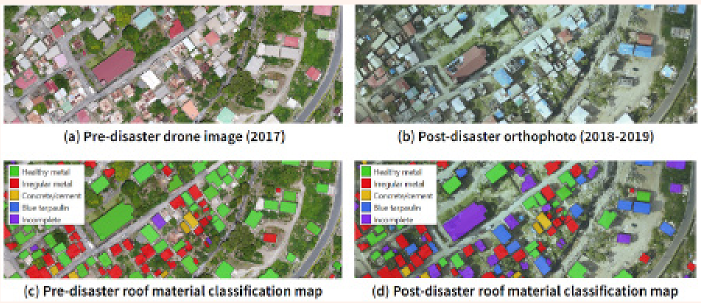


Figure 6: Pre- and post-disaster roof material classification maps in Colihaut, Dominica

Challenges and Lessons Learned Regarding Development and Implementation

One of the initial challenges was identifying the exposure data gaps in the target regions and defining the relevant building characteristics that could feasibly be extracted from drone and street-view images. This project underscored the critical importance of extensive stakeholder engagement for the successful adoption of AI technologies.

This work also highlighted the necessity of building local capacity within government agencies and the importance of democratizing capacity through open-source tools and datasets. Bridging the gap between data, action, and impact requires robust collaboration among technical experts, social scientists, government stakeholders, and local communities..

The main challenges and risks that can be encountered while deploying AI systems for the use cases presented in Section 4.7 are:

- **Incomplete Hazard Data:** Limited historical records of disasters (e.g., cyclones, storm surges) weaken AI-based risk assessments.
- **Failure of Critical Systems:** When disasters strike, power and connectivity may go down, rendering AI-driven warning systems inoperable.
- **Unequal Access to Warnings:** Without widespread mobile or internet coverage, communities in remote areas may miss alerts.
- **Over-reliance on Tech:** AI systems might overshadow local knowledge or traditional coping mechanisms, potentially eroding community resilience.

4.8. Emerging Large Language Model Applications

LLMs represent a promising new frontier in climate action, offering game-changing potential, especially in developing countries where resources and expertise are often limited. Despite the considerable excitement surrounding these technologies, it is important to acknowledge that many LLM applications are still in the early stages of development, and research in this area remains in its infancy. However, the accessibility and affordability of LLMs will provide a unique opportunity for these regions to leverage cutting-edge technology and innovative solutions that can enhance climate resilience and sustainability.

The introduction of ClimateGPT, a model family of domain-specific LLMs, marks a significant leap in applying AI to climate science (Thulke et al., 2024). ClimateGPT synthesizes interdisciplinary research on climate change, designed to provide in-depth, accurate, and accessible insights across various aspects of climate science. The family includes multiple model sizes, such as ClimateGPT-7B, 13B, and 70B, each tailored to address different facets of climate-related information needs. In the spirit of transparency and collaboration, all versions of ClimateGPT are made publicly available. This openness facilitates widespread access and use, encouraging further research, development, and innovation in AI-driven climate solutions.

For developing countries, particularly SIDS and LDCs, LLMs can serve as powerful tools to overcome barriers related to resource constraints and technical expertise. By tapping into the capabilities of LLMs, these regions can gain access to advanced predictive modelling, data analysis, and decision-making tools that were previously out of reach. The potential impact of LLM applications in these areas is significant, as they can drive meaningful improvements in various sectors critical to climate action.

CASE STUDY

AI ENABLER FOR CLIMATE SOLUTIONS

Country: China
Entities involved: Climind

Brief description

Climind is an AI platform designed to tackle the complexities of climate change by leveraging the power of LLMs and Retrieval-augmented Generation (RAG). It offers an array of features that enhance decision-making and efficiency in climate action through advanced NLP capabilities. Key functionalities include Climind Ask, which provides expert search capabilities, Climind Read with indexed search, and AI-driven analysis of regulatory documents. By integrating comprehensive corporate climate data with mitigation measures, Climind enables precise report generation, carbon pricing insights, climate risk assessments, and carbon trading information.

Climate Change Mitigation and/or Adaptation Impacts and Results

Climind, an AI-powered climate co-pilot, has significantly impacted climate change mitigation and adaptation efforts. By providing access to a comprehensive actionable climate data infrastructure, Climind enables precise climate policy/news search, comprehensive climate risk assessments, and more. Climind's AI-driven insights support sustainable finance initiatives, guiding companies in reducing their carbon footprints and improving energy efficiency. Additionally, Climind aids policymakers in developing effective climate strategies, contributing to the global transition towards a low-carbon economy.

Challenges and Lessons Learned Regarding Development and Implementation

The development and implementation of Climind faced several challenges. One major issue was the lack of authentic and real-time climate data, as the general AI models are primarily trained on internet data. Structuring this data to be useful for climate applications proved to be time-consuming and costly. Additionally, the slow adoption of AI within the climate sector posed a significant hurdle. Despite these challenges, it became evident that accelerating the industry's adoption of AI is crucial. Climind's potential application in time-consuming tasks, such as ESG reporting and the development of IPCC literature review, highlighted the need for efficiency and speed in climate science. This experience underscored the importance of continuous innovation and the integration of advanced technologies to enhance climate action.

LLMs are indeed becoming increasingly accessible due to the availability of pre-trained models (e.g., GPT, BERT) through APIs and platforms, which smaller organizations and start-ups in developing countries can leverage without needing to train them from scratch. This increased accessibility and affordability offer new opportunities for these organizations to implement and scale AI-driven solutions that address climate challenges more effectively.

The emerging applications of LLMs (Table 4) hold promise for LDCs and SIDS, focusing on use cases that are highly relevant to these regions and could significantly enhance their climate resilience and sustainability efforts.

Table 4: Emerging applications of Large Language Models in enhancing climate resilience and sustainability for LDCs and SIDS

Application Area	Use Case
Knowledge Access and Capacity-building	• Multilingual climate information chatbots providing localized climate data and adaptation strategies • AI-powered educational platforms offering personalized climate change curricula • Interactive policy guides helping local officials understand and implement climate regulations • Virtual assistants supporting climate scientists and researchers in data analysis and literature review • Language translation services facilitating access to global climate research for non-English speakers
Climate-resilient Agriculture	• Conversational AI systems providing farmers with crop management advice and market information • LLM-powered apps interpreting weather forecasts and satellite imagery for local agricultural planning • Virtual agronomists assisting with pest identification and management strategies • AI-driven systems for documenting and sharing traditional ecological knowledge • Chatbots helping smallholder farmers access climate-smart agriculture techniques
Disaster Preparedness and Response	• Multilingual early warning systems delivering personalized emergency instructions • AI assistants supporting disaster response coordinators in resource allocation and logistics • Chatbots providing mental health support and coping strategies during climate-related disasters • LLM-enhanced systems for rapid damage assessment and needs analysis post-disaster • Virtual agents assisting in the development and updating of local disaster preparedness plans

Table 4 (continued): Emerging applications of Large Language Models in enhancing climate resilience and sustainability for LDCs and SIDS

Application Area	Use Case
Climate Migration	• Climate and natural hazard early warning systems • Early warning on migration for early action and disaster risk reduction to human and economic loss • Climate change and natural disaster monitoring • Monitoring and predictive analysis of human mobility and migration to address prevention, preparedness, response, and recovery
Climate Finance and Project Development	• AI-powered proposal writing assistants for climate project funding applications • LLM systems supporting the development of nationally determined contributions (NDCs) • Virtual consultants assisting in climate risk assessments for infrastructure projects • Chatbots guiding small businesses through green certification processes • AI assistants supporting the monitoring, reporting, and verification (MRV) of climate projects
Policy Analysis and Decision Support	• LLM-based systems analysing and summarizing climate policy documents for decision-makers • AI-driven scenario analysis tools for climate adaptation planning • Virtual policy advisors assisting in the development of climate-resilient regulations • Sentiment analysis tools gauging public opinion on climate policies from social media data • LLM-enhanced stakeholder engagement platforms for participatory climate planning
Clean Technology Adoption	• AI assistants guiding users through the installation and maintenance of renewable energy systems • Chatbots providing energy-saving tips and personalized recommendations for households • Virtual technicians supporting the troubleshooting of clean energy technologies • LLM-powered platforms facilitating knowledge sharing on locally-appropriate clean technologies • AI systems assisting in the adaptation of clean technologies to local contexts and needs

Table 4 (continued): Emerging applications of Large Language Models in enhancing climate resilience and sustainability for LDCs and SIDS

Application Area	Use Case
Biodiversity Conservation	• LLM-enhanced citizen science platforms for species identification and ecosystem monitoring • AI assistants supporting indigenous communities in documenting and preserving biodiversity knowledge • Virtual rangers providing information on protected areas and conservation guidelines • Chatbots educating tourists about responsible eco-tourism practices • LLM systems assisting in the analysis of biodiversity data for conservation planning
Climate Communication and Awareness	• AI-driven personalized climate communication tailoring messages to individual concerns and values • LLM-powered fact-checking tools combatting climate misinformation • Virtual climate educators providing interactive lessons on climate science and action • Sentiment analysis tools helping climate communicators refine their messaging strategies • Chatbots engaging citizens in local climate initiatives and volunteer opportunities

While Large Language Models (LLMs) are becoming more accessible, significant barriers remain for developing countries, particularly SIDS and LDCs. High computational demands, costs of fine-tuning, and deployment challenges limit access in resource-constrained regions. The extensive infrastructure and expertise required for effective training are typically available only to large tech companies in developed nations, rendering LLMs out of reach for many organizations in developing areas. In contrast, smaller AI/ML models with lower computational needs are often more practical in these contexts. Most major LLMs are trained primarily on English-language data, reducing their effectiveness in non-English-speaking regions and exacerbating the digital divide. The centralization of LLM development by companies like OpenAI, Google, and Meta further limits the influence of smaller players from developing countries. This disparity has implications for knowledge representation and inclusivity in AI systems, as these models often overlook diverse global perspectives. Overall, while LLMs are accessible on certain platforms, their practical use is largely restricted to well-resourced entities, making smaller, specialized AI/ML models more feasible for developing countries. Addressing these challenges requires initiatives for democratizing AI resources, including multilingual training data and adaptable AI models.

The main challenges and risks that can be encountered while deploying the AI use cases presented in Section 4.8 are:

- **Language and Cultural Bias:** Many LLMs are trained on data primarily from dominant languages and cultures, overlooking local dialects and contexts.
- **High Computational Requirements:** LLMs demand significant processing power, often placing them out of reach for institutions lacking infrastructure.
- **Risk of Misinformation:** LLMs can generate plausible sounding but factually incorrect information if not carefully curated and verified.
- **Data Privacy and Sovereignty:** Using external LLM services might involve sending local data to remote servers, raising sovereignty and confidentiality issues.

4.9. Education and Community Engagement

Education and community engagement are critical components in the global effort to combat climate change. AI systems offer innovative tools and approaches that can enhance these efforts by making climate information more accessible, engaging, and actionable. There are various ways in which AI systems can support education and community engagement and contribute to empowering communities to take informed actions towards a sustainable future.

4.9.1. Raising Awareness of Climate Change through the Use of Artificial Intelligence

AI systems can play a critical role in raising awareness about climate action by providing powerful tools for data visualization, predictive modelling, and scenario analysis. These tools can help illustrate the impacts of climate change, highlight the benefits of mitigation and adaptation strategies, and demonstrate the urgency of taking action.

At COP28, Parties emphasized the need to raise awareness about the potential roles and impacts of AI in advancing the outcomes of technology needs assessments and the joint work programme of the Technology Mechanism for 2023–2027 (Decision 9/CP.28, Decision 1/CMA.5, Decision 14/CMA.5). The Technology Mechanism Initiative on AI for Climate Action provides a platform for policy discussions, raises awareness about the potential of AI for climate action, facilitates knowledge exchange among stakeholders, and supports capacity-building efforts to harness AI and develop locally-led climate solutions.

Public awareness campaigns can utilize AI to personalize messages and reach a broader audience through social media and other digital platforms, and AI systems can help identify and target key demographics in this process, ensuring that climate action messages resonate with diverse audiences.

In reference to "Visualizing the Future: Artificial Intelligence in Climate Action" (UNDP, 2024), an educational session demonstrated the power of images in raising awareness by using GenAI in scenario planning and citizen participation, where participants interacted with AI through their mobile phones, gaining new insights and contributing unique perspectives. This approach made climate change more tangible and urgent, fostering greater engagement from the audience and showing how this methodology can enhance citizen involvement, anticipate climate risks, and support inclusive, effective policy-making (UNDP, 2024). The next subsection will document how other AI-powered educational tools can contribute to raising awareness of AI for climate action.

4.9.2. Artificial Intelligence-powered Tools for Climate Change Education

AI-powered educational tools can improve climate change education by providing interactive and engaging learning experiences. For instance, AI-driven simulations and virtual reality environments can allow students to explore the effects of climate change in immersive ways. Intelligent tutoring systems can offer personalized learning pathways, adapting to each student's knowledge level and learning style. These tools can also provide real-time feedback and assessments, helping educators tailor their instruction to meet the needs of their students. Moreover, AI systems can curate and recommend up-to-date educational content, ensuring that learners have access to the latest scientific findings and resources.

Recent studies have explored the potential of Virtual Reality (VR) technology to enhance awareness of climate change. Thoma et al. (2023) aimed to determine whether VR visualization impacts climate change awareness and environmental attitudes more effectively than traditional media. Using a model of the Aletsch glacier melting over 220 years, the study found that environmental awareness increased significantly only in VR conditions, suggesting VR's potential to foster attitude change, regardless of the sophistication of the VR environment. Dhunnoo et al. (2023) conducted a case study with urban planning professionals to assess the effectiveness of Immersive Virtual Reality (IVR) in raising climate change awareness. Utilizing mobile LIDAR technology to create navigable urban models, participants could interact with a simulated inundated environment. Feedback indicated that IVR is a valuable educational tool, enhancing understanding of climate change impacts and the necessity of building resilient environments. Xu et al. (2022) focused on developing a VR application to simulate sea level rise and its effects on local scenery by 2100. This study highlighted VR's potential as a high-quality educational tool, offering a more immersive experience than traditional media. The ongoing work includes porting the system to Augmented Reality (AR) and further evaluation of the tool's effectiveness.

AI systems can analyse vast amounts of climate data, creating more accurate and dynamic VR simulations that reflect real-time changes in the environment. AIoT integrates AI systems with connected devices, allowing for real-time data collection and updates to VR environments, making simulations more interactive and responsive (Bibri, 2023). These technologies can provide personalized and context-specific information, improving the educational impact of VR and AR applications. AI tools enable VR experiences to become more engaging and informative, ultimately fostering greater awareness and proactive behaviour towards climate change mitigation and adaptation. AI has demonstrated significant importance in processing vast troves of data to enhance immersive experiences and enable human-like intelligence in virtual agents using ML, DL, NLP, among others (Huynh-The et al., 2023). This capability can enhance AI-powered tools for climate change education by providing more engaging and interactive learning environments. With these advanced AI techniques, educational tools can simulate complex climate scenarios, provide personalized learning experiences, and offer real-time feedback, thereby improving understanding and fostering proactive responses to climate change challenges.

Furthermore, understanding the factors influencing AI acceptance is important for effectively integrating AI-powered tools into educational settings, particularly for enhancing climate change education. Osman and Yatam (2024) highlighted the importance of perceived usefulness, ease of use, and technological innovativeness in shaping the acceptance of AI and its enabled transformations. Among these factors, perceived ease of use is identified as the most influential, highlighting the necessity for user-friendly interfaces and streamlined processes. Practical implications for higher education institutions include the need for targeted interventions to boost technological innovativeness and foster a positive organizational climate conducive to innovation.

4.9.3. Artificial Intelligence-powered Tools for Promoting Sustainable Practices

AI systems can support the promotion of sustainable practices by providing insights into individual and collective behaviours and suggesting actionable steps to reduce environmental impact. For example, AI-powered apps can track energy consumption, waste production, and carbon footprint, offering tailored recommendations for improvement to citizens, communities, businesses, and organizations. These tools can also facilitate community initiatives by identifying local sustainability challenges and opportunities.

Kasinidou (2023) focused on the growing necessity for public AI literacy due to the burgeoning role of AI in daily life. This project sought to understand public perceptions of AI across different demographics, including children and adults, and to promote AI literacy through an open course tailored to various groups, such as educators, adults, the elderly, and children. Key findings revealed that after a short course on AI, participants gained a better understanding of AI, recognized its positive and negative aspects, and acknowledged the importance of educating both children and adults about AI. These findings can be extended to raise awareness of AI's role in climate change by incorporating climate-focused AI education in public literacy programmes. Enhancing public understanding of AI's applications in environmental contexts can drive more informed support for AI-driven climate initiatives.

Table 5 provides a comparative analysis of various studies, offering insights into how AI systems contribute to sustainability and showcasing the diverse applications of AI across different sectors in fostering sustainable practices.

Table 5: Artificial Intelligence-powered tools for promoting sustainable practices

Research Theme	Applied Methods	Type of Sustainable Practices	AI Application Areas	Key Findings	Citations
AI in promoting green HRM practices	AI, data analytics	Energy optimization, waste reduction	Human resource management	AI systems enhance efficiency in recruitment, reduce bias, and promote eco-engagement among employees.	John and Pramila (2024)
AI in adopting green HRM practices	AI	Organizational sustainability, green environment	Human resource management	AI systems aid in adopting green HRM practices, shifting focus from profit maximization to sustainability.	Gupta (2021)
AI in sustainable finance	AI, ESG	Environmental problem-solving, financial stability	Financial management	AI systems help recognize environmental issues, support sustainable finance, and enhance decision-making.	Rani and Singh (2024)
The convergence of business intelligence (BI), AI, and sustainability	BI, AI, IoT, ML, Big Data, Blockchain, Edge Computing	Resource efficiency, environmental footprint reduction	BI, sustainable development	Integration of BI, AI, IoT, ML, and Big Data improves operational efficiency and minimizes waste.	Rane et al. (2024)

Table 5 (continued): Artificial Intelligence-powered tools for promoting sustainable practices

Research Theme	Applied Methods	Type of Sustainable Practices	AI Application Areas	Key Findings	Citations
AI and ML for green shipping	AI, ML	Emission reduction, environmental stewardship	Maritime industry	AI-driven technology improves vessel operations, decreases emissions, and promotes sustainability.	Nguyen et al. (2024)
AI and AR in fashion industry	AI, AR, ORESTE	Waste mitigation, return reduction	Fashion industry	Consumers prefer AI-powered mobile applications for camera-assisted measurements and synchronized suggestions.	Karadayi-Usta (2024)
AI in real estate for ESG	AI, ML, RF	Energy efficiency, sustainable real estate	Real Estate industry	AI algorithms assess energy efficiency and other attributes, impacting property prices and promoting informed decision-making.	Walacik and Chmielews-ka (2024)
AI in sustainable education	AI	Environmental responsibility, resource efficiency	Education	AI systems enhance sustainability education through personalized learning, curriculum development.	Harish et al. (2023)

4.9.4. Artificial Intelligence-powered Tools for the Engagement of Local Communities in Climate Action

Engaging local communities in climate action is important for driving grassroots change. AI systems can enhance community engagement by providing platforms for collaboration and communication. For instance, AI-driven social media analysis can identify influential community members and organizations based on carefully selected criteria, helping to amplify their voices and mobilize support. AI systems can also facilitate participatory decision-making by analysing community feedback and integrating it into policy development. Furthermore, they can support local climate initiatives by providing tools for monitoring and reporting progress, ensuring transparency and accountability.

Investigating the societal impact of AI from a human-centred perspective has become an important area of study (Shneiderman, 2020). Previous works in citizen science have identified various methods of utilizing AI to engage the public in research. These methods include maintaining participant engagement, ensuring data quality, classifying and labelling objects, predicting user interests, and interpreting data pattern (Ceccaroni et al., 2019; Franzen et al., 2021; Lotfian et al., 2021; McClure et al., 2020). While these works investigated the challenges of designing AI systems that enable citizens to participate in research projects on a large geographic scale in a generalized way, an area that has received little attention is how scientists can co-create AI systems with local communities to address context-specific concerns and influence a particular geographic region. Therefore, Hsu et al. (2022) investigated how AI can be leveraged to engage and empower local communities in addressing societal and environmental issues. They emphasized the importance of integrating hyperlocal, context-specific community data and knowledge into AI systems. Participatory design and ethnographic methods ensure that AI systems are tailored to the specific needs of local communities. The authors argue for a community citizen science (CCS) approach, where local people are treated as collaborators rather than mere participants. This approach helps create AI systems that are more aligned with community needs and expectations. However, it also requires continuous adaptation of these systems to account for the dynamic nature of community issues and long-term social changes. The CCS framework, a subset of citizen science, is advantageous for co-creating solutions and generating social impact with communities dedicated to pursuing the Sustainable Development Goals (Fritz et al., 2019).

CASE STUDY

COMMUNITY INNOVATION LABS FOR CLIMATE RESILIENCE (CO_LABS PROJECT)

Country: Indonesia
Entities involved: Deutsche Gesellschaft für Internationale Zusammenarbeit (GZ) – FAIR Forward, Common Room Networks Foundation

Brief description

The Community-based Innovation Lab for Climate Resilience (Co_LABS) Project addresses climate change challenges in Indonesia, particularly in rural and remote areas like Pulo Aceh and Maros, Indonesia. This initiative establishes community-based innovation labs that serve as collaborative platforms for local engagement in climate resilience. These labs integrate local knowledge with advanced technologies such as AI and IoT to develop and implement sustainable practices. Key activities include conducting baseline studies, enhancing local capacity, and creating AI-driven solutions and remote sensing applications tailored to the needs of the blue economy. The project also emphasizes the integration of local traditional knowledge with modern technological tools to address climate adaptation and mitigation effectively.

Climate Change Mitigation and/or Adaptation Impacts and Results

The Co_LABS Project was launched by the planting of 500 mangrove seedlings in Maros, which directly contributes to coastal protection and carbon sequestration. This action not only addresses climate change directly but also enhances biodiversity and resilience of coastal ecosystems. The integration of AI and IoT technologies has led to improved environmental monitoring and management. In Maros, the use of IoT sensors has optimized fish farming operations, increasing efficiency and sustainability. Capacity-building workshops, conducted in Bandung and planned for Pulo Aceh and Maros, have empowered local communities with the skills needed to manage and operate these technologies effectively. These workshops are crucial for ensuring that technology adoption leads to long-term climate resilience and sustainable development.

Challenges and Lessons Learned Regarding Development and Implementation

One significant challenge was integrating advanced technologies, like AI and IoT, with traditional community practices. For example, ensuring that the IoT sensors developed were user-friendly and met the local needs required to adapt technology for the context of small-scale fish farms in Maros and subsistence agriculture in Pulo Aceh. Extensive capacity-building efforts were necessary to make these technologies accessible and understandable for community members. The project also encountered difficulties in fostering active community engagement. This challenge highlighted the importance of ongoing support and training to build trust and involvement. Clear communication strategies and the involvement of local leaders were essential to address this issue. Lessons learned include the need for adaptable technology solutions that align with local conditions and practices, as well as the importance of continuous training and development of local leadership to sustain project outcomes and ensure the technologies' long-term success.

Incorporating indigenous knowledge (IK) into local AI models can enhance climate action strategies by integrating traditional ecological wisdom. AI can document and analyse IK, preserving it for broader climate solutions, such as mapping traditional land-use practices and predicting outcomes. Collaboration with indigenous communities is vital to ensure respectful representation.

In the specific context of climate change, Chakravarty (2023b) proposed the integration of AI and ML with Indigenous Knowledge Systems (IKS) to enhance climate communication channels, particularly for extreme weather events in coastal regions. They found that blending AI/ML with IKS can improve the accuracy and timeliness of climate predictions and mitigation strategies. AI models can, by harnessing local knowledge, be finely tuned to the specific contexts of indigenous communities, demonstrating a practical application of how AI can be enriched with traditional ecological wisdom to foster climate resilience. Akanbi and Masinde (2018) developed a rule-based drought early warning system using IK. Their research demonstrated that local IK could be effectively integrated into AI models to forecast drought conditions. The system enhances the accuracy and relevance of drought predictions and emphasizes the importance of incorporating IK into AI to address environmental challenges more effectively. Balehegn et al. (2019) documented the indigenous weather and climate forecasting knowledge of Afar pastoralists in Ethiopia. They found that traditional methods, when combined with modern AI systems, offer dynamic and accurate weather predictions.

Molino (2023) explored inter-religious perspectives on AI and IK for environmental preservation, emphasizing the ethical dimensions required for sustainable practices. Overall, leveraging traditional wisdom alongside advanced technology can lead to more robust and culturally sensitive climate action strategies, improving predictive capabilities and resilience. Continued collaboration between indigenous communities and tech experts is essential for accurately representing IK and benefitting both local and global ecosystems.

The main challenges and risks that can be encountered while deploying the AI use cases presented in Section 4.9 are:

- **Digital Literacy Gaps:** Low levels of computer and internet literacy hinder the effective use of AI-based educational tools.

- **Unequal Access:** Communities without stable internet or sufficient devices cannot benefit from AI-driven educational platforms or apps.

- **Cultural Relevance:** Educational AI tools often lack localized content or language support, limiting their impact in diverse settings.

- **Sustainability and Maintenance:** Once external funding ends, ongoing updates and technical support for AI-based education programmes may lapse.

4.10. An Overview of Artificial Intelligence Applications in Key Areas for Climate Action in Developing Countries

Drawing on insights from the comprehensive set of reviewed studies addressing the critical areas of climate change mitigation and adaptation, Table 6 outlines AI applications organized by core topics such as climate resilience and adaptation, sustainable energy access and transition, sustainable land use and biodiversity, climate finance and economic resilience, and governance and capacity-building. Highlighted areas of particular importance for LDCs and SIDS underscore the unique challenges and opportunities these regions face in their efforts to combat climate change and achieve SDGs.

Table 6: Artificial Intelligence applications in key areas for climate action in developing countries

Category	Sub-category	Details
	Public Health Systems	**Vector-borne disease prediction and control using AI and local data** AI-driven heatwave impact mitigation and alert systems **Air quality monitoring and improvement for urban areas** Healthcare resource allocation optimization **AI-powered telemedicine for remote areas**
	Climate-resilient Infrastructure	**AI-assisted vulnerability assessment for high-risk infrastructure** Designing climate-resilient buildings and roads using AI simulations Predictive maintenance for critical infrastructure **Urban planning tools for climate adaptation** **AI-optimized disaster-resistant energy systems**
	Climate Migration	**Climate and natural hazard early warning systems** **Early warning on migration for early action and disaster risk reduction to human and economic loss** **Climate change and natural disaster monitoring** Monitoring and predictive analysis of human mobility and migration to address prevention, preparedness, response and recovery
Sustainable Energy Access and Transition	**Renewable Energy Integration**	**AI-optimized microgrid systems for rural electrification** Solar and wind resource assessment using satellite data and ML **Energy demand prediction for grid stability** Smart energy storage management **AI-driven demand-side management in energy-scarce contexts**

Table 6 (continued): Artificial Intelligence applications in key areas for climate action in developing countries

Category	Sub-category	Details
	Energy Efficiency	' Building energy management systems for tropical climates ' Industrial process optimization for key industries ' **Smart city energy solutions for urban areas** ' AI-powered improved cookstove technologies ' Energy-efficient transportation for urban centres
	Clean Technology Localization	' **AI-assisted adaptation of clean technologies to local needs** ' Supply chain optimization for local manufacturing ' **AI-driven technology needs assessment** ' Skill development using AI-enhanced learning platforms ' **AI tools for local innovation ecosystems**
Sustainable Land Use and Biodiversity	**Deforestation Prevention and Reforestation**	' **Real-time satellite-based forest monitoring and alert systems** ' AI-driven reforestation planning ' Illegal logging detection with drone imagery and ML ' **Community-based forest management tools** ' Agroforestry optimization for small-scale farmers
	Biodiversity Conservation	' **Species distribution modelling under climate change** ' AI-powered acoustic monitoring systems ' **Ecosystem health monitoring with remote sensing and ML** ' Wildlife corridor planning with climate projections ' **AI-assisted marine ecosystem management**
	Sustainable Agriculture and Land Management	' AI-powered precision agriculture tools ' **Soil health monitoring with low-cost sensors** ' Crop rotation and intercropping optimization ' **Sustainable livestock management in arid regions** ' AI-assisted erosion control and land restoration planning
Climate Finance and Economic Resilience	**Access to Climate Finance**	' **AI-driven project proposal development and funding matching** ' Climate risk assessment tools for vulnerable sectors ' **AI-enhanced monitoring of climate project outcomes** ' **Blockchain-based systems for climate finance tracking** ' AI-powered microinsurance solutions

Table 6 (continued): Artificial Intelligence applications in key areas for climate action in developing countries

Category	Sub-category	Details
	Economic Diversification	AI-assisted market analysis for climate-resilient industries Skills matching platforms for green job transitions **Supply chain resilience planning tools** Circular economy optimization **AI-powered eco-tourism development planning**
	Disaster Risk Financing	**AI-enhanced parametric insurance models** **Automated damage assessment tools using satellite imagery** Risk pooling mechanisms optimization **Early warning systems linked to automatic payouts** AI-enhanced catastrophe modelling for data-scarce environments
Governance and Capacity-building	**Climate Data Management and Analytics**	**Low-cost, AI-enabled sensor networks for environmental monitoring** Data quality improvement techniques **AI-powered climate services for local decision-makers** Participatory sensing platforms for community-level data collection **Knowledge management systems for South–South learning**
	Policy Support and Decision-making	Climate policy impact simulation tools Multi-criteria decision analysis systems **AI-assisted stakeholder engagement tools** Compliance monitoring systems **AI-supported development and tracking of NDCs**
	Technology Transfer and Localization	**AI-driven technology needs assessment and matching** South–South cooperation platforms **Localized capacity-building programmes** AI solutions for rapid prototyping Intellectual property management tools for climate technologies
	Ethical AI and Digital Inclusion	**AI solutions optimized for low-resource environments** Tools for identifying and mitigating AI bias **Data privacy and security frameworks** Gender-responsive AI systems **AI governance frameworks for LDCs and SIDS**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5. Artificial Intelligence for the Implementation of the Technology Mechanism Joint Work Programme and Technology Needs Assessment Outcomes

The potential of AI to bolster climate action strategies is outlined in the Technology Mechanism Joint Work Programme (2023–2027) and TNAs outcomes for SIDS and LDCs. This section reviews the thematic areas covered by the aforementioned framework and identifies opportunities where AI-powered solutions can enhance their implementation.

The #AI4ClimateAction Initiative is strategically aligned with the Technology Mechanism Joint Work Programme, highlighting the collaborative efforts of the TEC and the CTCN. The initiative emphasizes six priority areas: national systems of innovation, water-energy-food systems, energy systems, buildings and resilient infrastructure, business and industry, and technology needs assessments. Each of these areas is central to addressing the intersection of AI and climate action, focusing on both mitigation and adaptation strategies.

The initiative also directly supports the rolling work plan of the TEC (2023–2027) and the CTCN Programme of Work (2023–2027), which outline comprehensive strategies for advancing climate technologies in developing countries, with particular attention to LDCs and SIDS. Through these work plans, the #AI4ClimateAction Initiative will guide the development and deployment of AI technologies that align with global climate goals, ensuring that they are scalable, context-specific, and inclusive of local needs and conditions.

More specifically, activities under the #AI4ClimateAction Initiative are designed to align with the TEC objectives of enhancing innovation, scaling up technology transfer, and providing policy recommendations to foster the effective deployment of climate technologies. The Initiative will support capacity-building, facilitate knowledge sharing, and contribute to policy development, helping countries integrate AI into their national climate strategies.

The joint work with the CTCN further strengthens this effort by focusing on technology deployment and technical assistance, offering a pathway to practical implementation in countries that need it most. This integration ensures that AI applications are not only technologically advanced but are also socially and environmentally sustainable, helping to bridge the gap between technology innovation and on-the-ground impact in climate-vulnerable regions.

By effectively utilizing AI within these focus areas, the #AI4ClimateAction Initiative aims to accelerate progress towards the Sustainable Development Goals (SDGs), with special emphasis on SDG 13 (Climate Action), while also aligning with the broader objectives set forth by the Paris Agreement.

By drawing on insights from Section 4, which explores AI applications across various domains of climate action, the following subsections highlight the relevant thematic areas.

5.1. Artificial Intelligence for the Implementation of the Technology Mechanism Joint Work Programme (2023–2027)

The Technology Mechanism Joint Work Programme outlines strategic priorities and key thematic areas where AI can play an important role in enhancing climate resilience and sustainability in developing regions. Based on the findings of Section 4, the following sub-chapters detail how AI-powered solutions can support these initiatives and bolster their implementation.

5.1.1. National Systems of Innovation

AI systems can advance National Innovation Systems (NIS) by facilitating more efficient and effective research, development, and deployment of new technologies tailored to local climate challenges.

AI itself reflects as a co-evolution of corporate and NIS. Lundvall and Rikap (2022) evaluated China's progress in AI and underscored the co-evolution of corporate innovation systems and China's national innovation system. Furthermore, Kouakou and Szego (2024) found that higher NIS performance enhances AI integration, suggesting that policies aimed at improving NIS performance can positively impact the integration of AI technologies in innovation activities. Key dimensions of NIS performance, such as technological diversification, knowledge localization, and originality, significantly boost AI integration, showing similar marginal effects. Moreover, the study highlighted an inverted-U shaped relationship between the cycle time of technologies and the level of AI integration in innovation activities.

Developing countries can improve their innovation ecosystems, foster collaboration among research institutions and industries, and streamline the commercialization of new technologies. Strengthening national innovation systems is of high relevance for developing countries, particularly LDCs and SIDS, to create their own AI solutions. Relying solely on importing AI applications from the developed countries can lead to increased debt and dependency, which can be detrimental to their economic stability and sovereignty. Developing indigenous AI capabilities allows LDCs and SIDS to reduce their reliance on foreign technologies, which often come with high costs and can exacerbate national debt. These countries can develop cost-effective and contextually relevant AI solutions tailored to their specific needs and challenges by investing in local innovation and research. This approach promotes economic independence and sustainability, fostering a more resilient and self-sufficient economy.

AI applications designed in the developed countries may not always be suitable for the unique socio-economic and environmental conditions of LDCs and SIDS. Local innovation systems can create AI solutions that are better suited to addressing specific issues such as agricultural productivity, climate resilience, healthcare, and disaster management. These countries can ensure that the solutions are more effective and impactful by focusing on locally relevant AI technologies.

Investing in national innovation systems also involves building local capacity and expertise in AI and related fields. This investment can lead to a more skilled workforce capable of developing, implementing, and maintaining AI systems. Moreover, it encourages knowledge transfer and fosters a culture of innovation and technological advancement. Educational institutions and research centres play a role in this process, offering training and development programmes to nurture local talent.

Developing home-grown AI solutions can create significant economic opportunities and jobs within LDCs and SIDS. This development can stimulate the local economy, providing employment in research, development, implementation, and maintenance of AI technologies. It can also lead to the growth of tech start-ups and industries, further enhancing economic diversification and resilience.

By developing their own AI solutions, LDCs and SIDS can help bridge the digital divide that often exists between developed and developing countries. Local innovation can lead to more affordable and accessible technologies, ensuring that a larger portion of the population can benefit from AI advancements. This inclusivity is crucial for achieving broader social and economic development goals.

However, there are challenges in building robust national innovation systems, including limited financial resources, lack of infrastructure, and insufficient technical expertise. International cooperation and support from developed countries, international organizations, and private sector stakeholders can support in addressing these challenges. Initiatives such as technology transfer, funding for research and development, and collaborative projects can help build the necessary infrastructure and capabilities.

5.1.2. Water-Energy-Food Systems

AI-powered solutions can address the interconnected challenges of water-energy-food systems by optimizing resource use and improving efficiency.

Indeed, the interconnected nature of water-energy-food systems demands integrated approaches facilitated by AI. Advanced algorithms and sensor networks enable real-time monitoring and predictive analytics, optimizing resource management and enhancing resilience against climate-induced stresses. Case studies from developing countries underscore successful implementations of AI in enhancing agricultural productivity, sustainability practices, and water management strategies.

5.1.3. Energy Systems

AI has the potential to transform energy systems by improving efficiency and reliability in production, distribution, and consumption, while promoting renewable technologies. Efficient energy systems are crucial for sustainable development. AI enables predictive maintenance, optimizes energy distribution, and integrates renewable sources. By forecasting weather patterns, AI can enhance the operation of wind, solar, and thermal energy, maximizing output and grid stability. It also monitors energy grids to detect anomalies, prevent outages, and balance supply and demand in real time. AI-driven smart grids facilitate the integration of distributed resources, fostering a decentralized and resilient energy system. Additionally, case studies highlight AI's effectiveness in boosting energy efficiency and lowering GHG emissions in developing countries.

5.1.4. Buildings and Resilient Infrastructure

By leveraging AI applications in building management systems, significant improvements can be made in energy efficiency, structural resilience, and maintenance processes, all of which support climate-resilient infrastructure development.

Energy efficiency and building management: AI systems optimize various aspects of building management, including heating, ventilation, air conditioning (HVAC), lighting, and other operational systems. By analysing real-time data, they can adjust these systems to reduce energy consumption and enhance occupant comfort. For instance, they can predict the optimal times to heat or cool a building based on weather forecasts and usage patterns, leading to substantial energy savings.

Predictive maintenance: AI-driven predictive maintenance is another key application. AI systems can predict potential failures before they occur, allowing for pre-emptive repairs by continuously monitoring the health of infrastructure assets. This extends the lifespan of assets and reduces maintenance costs and prevents unexpected downtime. Predictive maintenance uses data from various sensors and historical performance records to identify signs of wear and tear, ensuring timely interventions.

Resilient infrastructure design and construction: AI systems support the design and construction of resilient infrastructure by analysing environmental data and simulating the impacts of various hazards, such as floods, earthquakes, and extreme weather events. These simulations help engineers and architects design buildings and infrastructure that can withstand such events, thereby enhancing resilience. AI systems can model different scenarios and their potential impacts, providing valuable insights that inform better disaster preparedness strategies and building practices.

Sustainability: AI systems contribute to sustainability in the construction and operation of buildings by promoting the use of eco-friendly materials and energy-efficient technologies. They can assess the environmental impact of different building materials and construction methods, recommending the most sustainable options. During the operational phase, they continuously optimize energy and resource use, contributing to lower carbon footprints and more sustainable living environments.

5.1.5. Business and Industry

AI-powered analytics help minimize environmental footprints, optimize supply chains, and meet regulatory standards, leading to lower costs and improved innovation. In business operations, AI automates routine tasks, analyses large datasets for insights, and optimizes logistics, resulting in reduced errors and better decision-making. It aids in demand forecasting, inventory management, and waste reduction, enhancing service delivery. In manufacturing, AI can enhance production through predictive maintenance, which anticipates equipment failures, and real-time quality control that identifies defects, ensuring consistent product quality. Data analytics and machine learning further optimize production schedules and resource allocation, improving efficiency and reducing energy consumption.

5.1.6. Emerging and Transformational Adaptation Technologies

Emerging adaptation technologies require innovative approaches driven by AI to effectively mitigate the evolving risks and impacts of climate change and other global challenges. AI technologies offer innovative solutions for climate adaptation, significantly enhancing adaptive capacity and resilience across various domains.

AI systems play a critical role in improving early warning systems by analysing extensive environmental data to predict extreme weather events and issue timely alerts to vulnerable communities. This predictive capability is instrumental in minimizing the human and economic toll of climate-related disasters, enabling proactive measures and swift responses.

In ecosystem monitoring and nature-based solutions, AI systems optimize site selection and monitor project progress in initiatives such as reforestation and wetland restoration. By enhancing ecosystem resilience and promoting carbon sequestration and biodiversity conservation, these AI-driven interventions contribute significantly to sustainable environmental management.

Moreover, AI-driven innovation facilitates the development of new technologies resilient to climate impacts. These advancements bolster infrastructure durability but also promote sustainable practices essential for long-term adaptation and mitigation strategies. AI systems contribute to building climate-resilient communities and enhancing overall societal resilience by fostering the adoption of resilient technologies.

Furthermore, AI systems empower community engagement by facilitating participation and awareness through educational tools. These initiatives empower local populations to actively engage in climate adaptation efforts, fostering a sense of ownership and collective action towards building resilient communities.

In terms of policy and governance, AI systems support evidence-based policymaking by analysing comprehensive datasets on climate impacts, adaptation strategies, and societal vulnerabilities. This analytical capability aids governments in developing effective climate policies and regulations that address local challenges and promote SDGs.

Overall, AI's integration into emerging adaptation technologies underscores its instrumental role in advancing climate resilience strategies. Developing countries can leverage AI's capabilities to enhance their resilience to climate change impacts while fostering sustainable development and environmental stewardship.

In summary, AI-powered solutions offer significant potential to support the implementation of the Technology Mechanism Joint Work Programme across various thematic areas. From enhancing NSI and optimizing water-energy-food systems to revolutionizing energy systems, buildings, and infrastructure, AI technology can drive efficiency, sustainability, and resilience. It can play a central role in achieving the objectives of the joint work programme and advancing the global goals of sustainable development by addressing the unique challenges and opportunities in business and industry, as well as fostering the development of emerging adaptation technologies.

5.2. The Role of the CTCN in Technical Assistance and Capacity-building-Projects

The CTCN has already initiated several technical assistance and capacity-building projects that align with AI's potential. It has been actively supporting countries in deploying digital technologies and innovative solutions to address climate change challenges. By facilitating the exploration and integration of emerging digital tools, including AI and IoT, CTCN assists countries in building resilience and enhancing climate adaptation efforts. Table 7 showcases examples of CTCN's technical assistance initiatives across various countries, highlighting the outcomes and impacts of these digital interventions in diverse climate contexts (CTCN, 2023).

Table 7: Examples of CTCN technical assistance initiatives on emerging digital technologies for climate action

Examples of the CTCN Technical Assistance	Country Outcome and Impacts
Exploring emerging digital technologies and piloting digital tools: CTCN supports countries in exploring the climate potential of emerging technologies such as AI, IoT, cloud computing, blockchain, and open data, while developing and piloting locally-adapted digital solutions to drive climate adaptation and increase resilience in communities.	**Cambodia:** Climate risk assessment for subnational adaptation and establishment of a local climate information system (LISA) for climate change adaptation. **Eswatini:** Strengthening the National Disaster Management Agency's (NDMA) application of UAV and remote sensing technology for vulnerability assessments and response planning. **Georgia:** Building up integrated monitoring and early warning forest fires detection systems in the Borjomi-Kharagauli National Park by innovative remote sensing tools. **Nepal:** Customized weather and climate information system for climate-resilient agriculture. **Samoa:** Development of a framework and methodology to measure carbon sinks from the forestry sector using Earth observation. **South Africa:** Tree monitoring for climate adaptation in the City of Mbombela. **Sudan:** Soil erosion valuation to support climate-resilient agriculture and food security.

CTCN's technical assistance efforts have laid a foundation for digitalization in climate action, incorporating various innovative tools and platforms. While AI has not yet been a primary focus within most of these projects, elements related to AI, such as ML for predictive analytics and the use of IoT for real-time data collection, have been integrated. These aspects represent a starting point that could be expanded to include more AI-driven applications explicitly. Future initiatives could harness AI's potential more strategically to support comprehensive climate action, leveraging its ability to process vast amounts of data, improve decision-making, and optimize climate-related interventions.

The existing groundwork laid by the CTCN through its digitalization efforts creates promising opportunities for the integration of AI into climate action in developing countries. CTCN can significantly advance climate resilience and adaptation strategies in LDCs and SIDS by enhancing current projects with more AI-driven tools and technologies. Expanding these initiatives will be crucial for scaling AI's role in tackling the diverse and evolving challenges posed by climate change globally.

Initiatives like CTCN's capacity-building programmes aim to support the adoption of AI in climate technology by providing training and resources to local stakeholders. These programmes also offer technical assistance, such as developing digital platforms for climate data management and early warning systems powered by AI. Additionally, CTCN has facilitated technical assistance projects focused on integrating digital tools into climate adaptation and mitigation efforts. For instance, AI-driven tools have been developed in collaboration with local governments and institutions to enhance agricultural resilience, improve water resource management, and optimize energy systems. These efforts align with the objectives of the Technology Mechanism, demonstrating AI's relevance in supporting capacity-building and technical assistance in LDCs and SIDS.

Expanding on these examples highlights how AI applications are already being explored and applied within the context of the Technology Mechanism Joint Work Programme. This integration ensures that AI is positioned as a key enabler for achieving the technology and capacity-building goals set out by the TEC and CTCN, ultimately enhancing the effectiveness and scalability of climate actions in developing countries.

5.3. Artificial Intelligence for the Implementation of TNA Outcomes

TNAs provide a road map for technology deployment aligned with national climate priorities. The implementation of TNAs is essential for developing countries to identify and prioritize their technology needs for effective climate action. These assessments encompass a range of thematic areas, including energy, agriculture, water management, infrastructure, and industry, among others. Each TNA identifies specific technology needs and proposes action plans to integrate these technologies into national climate strategies. The main focus is on how AI-powered solutions can support and enhance the implementation of TNA outcomes across the following thematic areas, including technology action plans and capacity-building initiatives, drawing on insights and findings from Section 4 of the technical paper, which explores AI applications in climate action across diverse domains. Among the key opportunities identified, AI-powered solutions can support the implementation of TNA outcomes in energy sector, agriculture and food security, water management, infrastructure and resilient construction, industry and manufacturing and disaster risk reduction. Effective AI implementation aligned with TNA outcomes depends, however, on international cooperation, targeted policy frameworks, and strategic investments in digital infrastructure and local expertise.

5.4. Artificial Intelligence-powered Solutions Supporting Sustainable Development Goals

AI has the potential to accelerate the achievement of SDGs by providing innovative solutions to some of the most pressing global challenges. In the context of climate action and sustainable development, AI systems can support the implementation of TNA outcomes by enhancing efficiency, improving decision-making, and fostering resilience. An outline of specific SDGs and targets is presented in Table 8 where AI-powered solutions can make a substantial impact, demonstrating how AI can be strategically leveraged to promote sustainable development and climate resilience. These targets were selected based on their direct relevance to climate action, technology needs, and areas where AI applications have demonstrated or hold strong potential for impact.

Table 8: AI-powered solutions aligned with SDG goals and targets for promoting sustainable development and climate resilience

SDG	Target	AI-powered Solution
SDG 2: Zero Hunger	**Target 2.3:** Double the agricultural productivity and incomes of small-scale food producers	• AI-powered precision agriculture: Using AI to provide real-time advice on crop management, pest control, and efficient irrigation techniques to smallholder farmers, thus increasing productivity and sustainability.
SDG 6: Clean Water and Sanitation	**Target 6.4:** Increase water-use efficiency and ensure sustainable withdrawals and supply of fresh water	• AI for water management: Utilizing AI to optimize water distribution, monitor water quality, and predict water scarcity issues, enhancing sustainable water use and management.
SDG 7: Affordable and Clean Energy	**Target 7.2:** Increase the share of renewable energy in the global energy mix	• AI in renewable energy optimization: Implementing AI-driven systems to optimize the integration and operation of renewable energy sources like solar and wind, improving efficiency and reliability.
SDG 9: Industry, Innovation, and Infrastructure	**Target 9.4:** Upgrade infrastructure and retrofit industries to make them sustainable, with increased resource-use efficiency	• AI in smart infrastructure: Designing AI-based solutions for developing climate-resilient infrastructure, predictive maintenance, and optimizing resource use in industries.
SDG 11: Sustainable Cities and Communities	**Target 11.5:** Reduce the adverse effects of natural disasters	• AI for disaster risk management: Deploying AI-powered early warning systems and decision support tools to enhance disaster preparedness and response, minimizing the impacts of extreme weather events.

Table 8 (continued): AI-powered solutions aligned with SDG goals and targets for promoting sustainable development and climate resilience

SDG	Target	AI-powered Solution
SDG 13: Climate Action	**Target 13.1:** Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters	• AI in climate resilience: Using AI to develop adaptive strategies, improve disaster response, and enhance the resilience of communities to climate impacts.
SDG 14: Life Below Water	**Target 14.2:** Sustainably manage and protect marine and coastal ecosystems	• AI for marine ecosystem management: Implementing AI technologies to monitor marine biodiversity, predict climate impacts on marine life, and support sustainable fisheries management.
SDG 15: Life on Land	**Target 15.1:** Ensure the conservation of terrestrial and freshwater ecosystems	• AI in biodiversity conservation: Utilizing AI to monitor and protect biodiversity, manage conservation areas, and detect illegal logging and poaching activities.
SDG 17: Partnerships for the Goals	**Target 17.6:** Enhance international cooperation on and access to science, technology, and innovation	• AI for global collaboration: Facilitating international cooperation and knowledge sharing through AI platforms, supporting global climate initiatives, and ensuring equitable access to AI technologies.

6. Risks and Challenges of Using AI for Climate Action in Developing Countries

Even though the main risks and challenges have been highlighted in each subsection of Section 4, this section takes a more structured approach by delving deeper into the primary challenges and risks associated with the deployment of AI in SIDS and LDCs. The selection of these topics ¬ Energy and Water Consumption, Data Security, Digital Divide, Biases, and Youth Misrepresentation – is based on their criticality to AI adoption in these contexts. Energy and water consumption are particularly pressing due to infrastructure constraints in SIDS and LDCs, where high resource demands could limit AI deployment. Data security was prioritized over data availability due to the heightened vulnerability of digital infrastructures in these regions. Many LDCs and SIDS lack strong data protection policies, cybersecurity frameworks, and institutional capacity to manage digital risks, making AI systems particularly susceptible to data breaches, cyber attacks, and manipulation. These vulnerabilities not only threaten sensitive information but can also undermine trust in AI-driven climate initiatives, hindering adoption and scalability. The digital divide remains a major obstacle to AI accessibility, affecting equitable participation in AI-driven climate solutions. Biases in AI models disproportionately affect marginalized communities, reinforcing structural inequalities. Lastly, youth misrepresentation is crucial given the demographic trends in many LDCs, where young populations play a pivotal role in future innovation but face systemic exclusion from decision-making, financing, and capacity-building opportunities. These five dimensions, therefore, represent key barriers that require targeted interventions to ensure inclusive and responsible AI deployment in climate action.

6.1. Energy and Water Consumption

AI systems, particularly high-computation models, require significant amounts of energy for training and operation, and in many LDCs and SIDS, energy resources are already constrained or heavily reliant on fossil fuels. Additionally, water consumption is a key sustainability concern, as cooling AI data centres and infrastructure can strain limited freshwater supplies, particularly in water-scarce island nations.

The life cycle of AI technologies – including their development, deployment, use, application, maintenance, and disposal – systematically stresses energy supplies and contributes to GHG emissions. These impacts are categorized into direct, indirect, rebound, and systemic effects, which pose varied risks to environmental sustainability (Bibri et al., 2023). Direct effects include not only the energy-intensive processes involved in training and running AI models, which contribute to GHG emissions, but also the energy demands of data storage, cooling systems, and data transmission associated with these technologies. They are especially significant when AI relies on data centres powered by non-renewable energy sources.

Indirect effects involve the secondary impacts of widespread AI adoption, such as driving up overall electricity demand, increasing water usage for cooling systems, and accelerating the depletion of natural resources. The indirect effects also include the increased demand for the production of hardware components and infrastructures that support AI, which require significant energy and resources.

Rebound effects occur when efficiency improvements or innovations inadvertently lead to higher overall consumption, counteracting intended energy savings. In the case of AI, enhanced model performance and efficiency can increase demand, thereby expanding AI applications in ways that raise total resource consumption.

Systemic effects go beyond these direct, indirect, and rebound consequences by capturing the broader, interconnected, and long-term impacts of AI technologies on the environment and society as a whole. Systemic effects can involve the following:

- The way AI-driven processes influence societal behaviours, such as increased reliance on energy-intensive technologies.
- The cumulative and compounding impacts of widespread AI adoption on infrastructure, resource extraction, and waste production.
- The creation of feedback loops where AI ecosystems might reinforce unsustainable practices, thereby exacerbating environmental degradation.

In the context of AI and climate change, systemic effects highlight the interconnected and cascading consequences of AI adoption across multiple layers of society and the environment. These effects are often difficult to predict and can lead to unintended ripple effects that extend beyond immediate energy consumption. Addressing these challenges requires comprehensive strategies that integrate sustainable development, optimize resource use, and ensure responsible AI governance to mitigate these cascading impacts. Recognizing these challenges and proactively addressing them enables society to leverage AI in paving the way for a sustainable future. In this context, proactive measures include accelerating the decarbonization of electric grids, fostering markets for low-carbon materials, and promoting the development of energy-efficient hardware. Optimizing AI algorithms and encouraging sustainable practices in AI development are also critical steps towards reducing the environmental footprint of AI.

The International Telecommunication Union (ITU, 2024b; 2024c) underscores the impact of the information and communications technology (ICT) sector on environmental sustainability, with a special emphasis on the role of AI, as part of its Green Digital Action Initiative. While the ICT sector provides unparalleled opportunities for advancing sustainability, such as optimizing energy systems, implementing smart grids, enhancing industrial efficiency, and offering valuable insights into climate change patterns, it also poses substantial environmental challenges, including increased energy and water consumption, GHG emissions, and the demand for critical raw materials. The Green Digital

Action initiative focuses particularly on AI's impact in this broader context emphasizing the need to address the environmental implications of AI to ensure sustainable AI development by enhancing the energy efficiency of AI systems and promoting the use of renewable energy sources for powering data centres.

6.1.1. Quantify the Artificial Intelligence Carbon Footprint

AI depends on data centres that require significant energy to compute, analyse, and categorize data (Brevini et al, 2021). Training DL models requires substantial computation time and resources, as they learn a comprehensive representation for better data analysis, with costs increasing further if they engage in continuous learning. Anthony et al. (2020) introduced Carbontracker, a tool designed to monitor and forecast the carbon footprint associated with training DL models. The tool aims to provide insights into the environmental impact of AI training processes by accurately tracking energy consumption and resulting carbon emissions (Anthony et al., 2020). A study published in 2019 attempted for the first time to quantify the energy consumption of running AI programmes and found that a typical AI training model in NLP can emit over 284 tonnes of CO2 equivalent (Strubell et al., 2019).

With the growing adoption of AI, the energy consumption of data centres is increasingly under scrutiny, highlighting the need for more accurate data collection and improved assessment practices. The report published by IEA (2024a) points out significant uncertainties regarding the electricity demand of data centres, influenced by factors like the pace of AI deployment, the variety of AI applications, and the potential for advances in energy efficiency. As stated in the executive summary of the report (IEA, 2024a), electricity consumption from data centres and AI systems is projected to double by 2026. Today, data centres account for around 1% of global electricity consumption, and annual electricity consumption from data centres globally is about half of the electricity consumption from household IT appliances, like computers, phones and TVs. By 2026, their total electricity consumption could surpass 1000 terawatt-hours (TWh). However, when considered in a broader context of total electricity consumption growth globally, the contribution of data centres is modest. Global aggregate electricity demand grows by 6750 TWh by 2030. While growing digitalization, including the rise of AI, is one factor, continued economic growth, electric vehicles, air conditioners, and the rising importance of electricity-intensive manufacturing are all bigger drivers.

At the same time, the IEA emphasizes that the increasing integration of AI into data centre operations could contribute both to higher energy demand and potential efficiency gains. Advancements in energy-efficient cooling technologies, AI-driven energy optimization, and workload distribution strategies have been identified as crucial factors in mitigating consumption increases. Furthermore, regional disparities in data centre electricity demand remain an area of concern, with certain locations experiencing greater grid strain due to high concentrations of AI-driven workloads. To mitigate this substantial rise in energy consumption, updated regulations and technological advancements, especially focused on efficiency improvements, will be essential. Additionally, the IEA underscores the importance of enhancing monitoring mechanisms to refine projections and enable proactive energy planning. To accurately track historical developments and better predict future trends, enhanced monitoring and detailed electricity usage data for the data centre industry will be critical (EAI, 2024a).

Numerous studies have assessed the energy consumption required for producing and training GenAI models. Researchers estimated that the development of GPT-3 consumed approximately 1287 megawatt hours of electricity and generated 552 tonnes of CO2 equivalent (Saenko, 2023). In addition to the direct energy consumption, there are significant environmental costs linked to the production and operation of AI models. These include the extraction of rare minerals for graphics processing units (GPUs) and the vast amounts of water required to cool large data centres (Luccioni, 2023). Data centres, which are integral to AI operations, consume massive amounts of both energy and water, primarily for air conditioning systems. Notably, training the LaMDA language model is estimated to have used around one million litres of water (Dolby, 2023). Moreover, there are location-specific variables that influence the energy and water usage of LLMs. For example, Microsoft reported that its data centres in Asia are significantly less water-efficient than those in the Americas (Dolby, 2023). Seasonal factors also play a role, as hotter summers lead to greater water consumption due to the increased need for cooling and higher evaporation rates (Dolby, 2023). These studies collectively highlight the multifaceted environmental impact of GenAI models, extending beyond energy consumption to include broader resource use and location-dependent inefficiencies.

Researchers estimate that training a model like GPT-4 generates approximately 300 tonnes of carbon for its entire training process (Kumar and Davenport, 2023; Deeb and Garel-Frantzen, 2023). As AI technology advances, this carbon footprint is expected to grow because the increasing complexity of models and the larger datasets they require will demand even more energy (An et al., 2023). On the user side, a GenAI query has been found to produce four to five times more carbon emissions than a typical Google search or other search engine query (Saenko, 2023). Although the energy consumption per query is less than that of training the model, the sheer volume of queries contributes to significant energy use, accounting for up to 90% of the total energy consumed by GenAI (Kumar and Davenport, 2023). In addition to energy demands, GenAI models also have notable water consumption impacts. For instance, it is estimated that interacting with ChatGPT for 20 to 50 queries could require the equivalent of a 500-millilitre bottle of water, depending on where the electricity powering the interaction is generated (Dolby, 2023). Overall, the electricity demand for training LLMs like GPT-4 and operating AI systems can lead to substantial carbon emissions, depending on the energy mix of the data centres involved. Notably cutting-edge, rapidly evolving developments in ultra-low-power consumptions integrated circuits hold a potential to scale down both the data centres and computational energy of AI algorithms.

According to Luers et al. (2024), AI currently contributes a small fraction of global GHG emissions – approximately 0.01% – and even with rapid growth rates, its operational footprint is not expected to be a significant contributor to GHG emissions in the foreseeable future. The sector's rapid evolution makes it nearly impossible to reliably predict the energy and resource implications of AI technologies beyond a few years. Some studies simply extrapolate past trends in AI electricity use, but these projections often overlook critical social, economic, and technological factors, leading to significant forecasting errors (Masanet et al., 2020). Moreover, taking an overly simplistic view of the indirect emissions linked to AI risks underestimating its potential to drive climate solution breakthroughs, such as rapidly advancing battery technology or optimizing renewable energy systems (Luers et al., 2024).

To accurately assess AI's environmental impact, there is a need for holistic scenarios that explore alternative futures, considering factors like resource use, technological advancements, and economic shifts (Luers et al.,2024).

6.1.2. Green Computing and Alternatives

The ongoing research in green AI, or green computing generally, is dedicated to creating AI technologies that are environmentally sustainable. This burgeoning field aims to reduce the carbon footprint and energy consumption associated with AI development and deployment (Lannelongue et al., 2021; Verdecchia et al., 2022; Wheeldon et al., 2020; Yokoyama et al., 2023). Researchers strive to minimize the environmental impact of AI systems by optimizing algorithms, enhancing hardware efficiency, and improving data centre operations as AI systems can achieve similar performance with lower energy use. Green AI initiatives often include developing metrics and standards to evaluate and promote the sustainability of AI technologies (Schwartz et al., 2020; Raman et al., 2024).

From a different perspective, in the rapidly evolving landscape of GenAI, Small Language Models (SLMs) are gaining attention as a resource-efficient alternative to the traditionally large and energy-intensive models like LLMs. SLMs offer a more sustainable approach by leveraging fewer parameters, which results in reduced computational and energy demands.

Instead of the trillion-parameter LLMs that consume considerable resources, SLMs are emerging as smaller-scale, lightweight models that can leverage energy and compute resources more efficiently for specific, purpose-built functions. This shift is particularly important as AI models become increasingly integrated into various sectors where energy efficiency and accessibility are critical.

Additionally, in the energy-intensive pre-training phase, even the power savings differential between SLMs is significant. The Llama 2 7B SLM generated 30.22 tCO2EQ of carbon emissions, while the larger Llama 2 70B SLM generated a significantly larger 291.42 tCO2EQ in emissions. This stark difference highlights the potential of SLMs to contribute to more sustainable AI practices, especially as energy consumption becomes a growing concern in the tech industry. In theory, SLMs may eventually be less prone to bias, as they train on smaller, more tightly managed datasets.

Furthermore, software defined storage, an emerging technology, enables dynamic scaling of memory resources in a virtual (cloud-based) AI infrastructure architecture. This flexibility enables more efficient use of resources, particularly during intensive AI tasks. Once the task is complete, these memory resources can be efficiently scaled down, and physical memory can be spun down when larger AI workloads are no longer in operation. This approach, already employed by the SWIFT global financial system for real-time AI anomaly detection, significantly reduces data centre power consumption in AI applications and offers similar benefits for Edge AI use cases.

While AI has the potential to drive significant advancements in climate action, its deployment in developing countries must be carefully managed to avoid exacerbating energy and water resource challenges. In many developing countries, including LDCs and SIDS, the growth of data centres remains limited, often due to infrastructure constraints and high operational costs. Consequently, a significant portion of AI-related data processing for these regions occurs in data centres located in more developed regions, where electricity consumption and water usage are not substantial concerns.

6.2. Data Security

Many LDCs and SIDS lack strong data protection policies, cybersecurity frameworks, and institutional capacity to manage digital risks. This makes AI systems particularly susceptible to data breaches, cyber attacks, and manipulation, which can undermine trust in AI-driven climate initiatives.

Data security is paramount worldwide. Handling large datasets raises significant privacy and cybersecurity concerns – particularly in regions with weak regulatory frameworks – where sensitive information can be misused or exposed to cyber threats. AI systems, as all the software, also remain vulnerable to data poisoning and other adversarial attacks, underscoring the need for secure data-handling practices.

Recent studies (Paracha et al., 2024; Rosenberg et al., 2021; Goldblum et al., 2022) discuss critical risks like adversarial ML, data poisoning, and backdoor attacks, offering strategies to enhance resilience. Implementing comprehensive data protection laws, clear data governance guidelines, and effective enforcement mechanisms is vital to ensure public trust and participation in AI initiatives. Moreover, as AI applications in climate action integrate diverse datasets, maintaining consistent security and privacy standards is essential for safeguarding both the technology and the data it relies on.

AI security management involves adopting measures and practices designed to protect AI systems and the data they process from unauthorized access, breaches, and malicious activities. This includes threat identification (Kumar and Kumar, 2023), access control (Song et al., 2023), and security awareness and training (Solomon et al., 2022), as well as continuous monitoring and updates to security protocols to adapt to emerging threats. Cybersecurity involves protecting digital systems, including computers, servers, networks, and related data, from malicious attacks. It safeguards internet-connected information and communication systems from malicious attacks and threats (Li and Liu, 2021).

Incorporating comprehensive threat identification methods can help detect potential risks, such as data breaches, unauthorized access, adversarial attacks, and insider threats (Rosenberg et al., 2021; Goldblum et al., 2022), which are critical for maintaining the integrity of AI systems. Moreover, implementing robust access control mechanisms ensures that only authorized individuals can interact with AI systems and their data, further enhancing security. To achieve this, continuous security awareness and training programmes are crucial to equip stakeholders with the knowledge to recognize and mitigate security threats. By integrating these security measures, organizations can create a resilient AI infrastructure capable of withstanding various threats and ensuring the ethical use of AI technologies. Managing and mitigating the potential harms caused by the malicious use of AI is a serious concern in the development and deployment of AI technologies.

The impact of AI on cybersecurity is dual-sided, presenting both negative and positive aspects. On the positive side, AI-driven automation using ML algorithms has successfully prevented attackers from using traditional attack methods on systems. This has enhanced the efficiency and effectiveness of cybersecurity measures, allowing for real-time responses to emerging threats. Integrating cybersecurity with ML encompasses two main aspects: ensuring the cybersecurity of environments where ML is deployed and leveraging ML to enhance cybersecurity measures (Wazid et al., 2022). This integration offers multiple benefits, such as providing increased security for ML models, improving the performance of cybersecurity methods, and enabling the effective detection of zero-day attacks through the use of techniques such as anomaly detection. Jada and Mayayise (2024) found that while AI can influence cybersecurity across its entire life cycle, providing advantages such as automation, threat intelligence, and enhanced cyber defense, it can introduce challenges like adversarial attacks and the necessity for high-quality data, which could result in inefficiencies. Liu and Zhang (2023) found that employing DL technology for computer network security detection enhances security performance. This approach is characterized by high safety performance, a high detection rate, and a low false alarm rate. It enables timely monitoring of network vulnerabilities and effectively detects security attacks on the computer network.

Within the context of AI Trust, Risk, and Security Management (AI TRiSM), data security holds particular significance. The increasing reliance on AI systems brings emerging concerns related to risk, trust, and security. The AI TRiSM framework is a theoretical approach to implementing AI in organizations and (Habbal et al., 2024) included five illustrative scenarios that highlight its effectiveness.

6.3. Digital Divide and Equitable Access to Artificial Intelligence for Climate Action

In SIDS and LDCs access to electricity and ICT infrastructure is often limited, restricting the ability of end-users to benefit from AI solutions and hindering the local AI ecosystem to develop relevant localized applications. In many rural and remote areas, unreliable electricity and poor internet connectivity can make it difficult to deploy and maintain AI technologies. For example, farmers in remote areas may not be able to access AI-driven agricultural advice due to lack of internet access, limiting their ability to benefit from advanced farming techniques. Nevertheless, in developing countries, satellite internet emerges as a promising solution to bridging the digital divide, especially in rural and remote areas where traditional broadband infrastructure is either lacking or entirely non-existent.

Since the emergence of ICT, the digital divide has highlighted significant disparities in access to and use of digital resources and technologies among different user groups or populations. This divide, originally framed around access to and use of computers and the internet, has evolved with technological advancements. The advent of AI exacerbates these inequalities due to the high demand for computational resources, context-specific AI training and testing data, access to pre-trained models, specialized knowledge, and advanced infrastructure, which are often concentrated in more developed regions and among more privileged groups. In this context, infrastructure entails the foundational systems and services required to deploy and support AI technologies effectively. This includes physical hardware such as data centres, network connectivity, and cloud computing resources needed for processing large datasets and running complex AI models. It also encompasses software infrastructure like platforms for AI development, databases, and APIs, as well as organizational structures that support AI operations, such as technical support and maintenance teams.

The prevailing economic landscape of machine learning (ML) as a technological domain suggests a trend towards a natural monopoly, presenting complex challenges and implications across various sectors. Research has addressed how this concentration within the AI market impacts broader dimensions, highlighting the need for a critical reassessment of AI development and deployment strategies in the context of global digital equity and local solution generation. Based on the literature, some ML-based applications may exhibit the traits of a natural monopoly (Narechania, 2021). This market concentration leads to numerous economic, social, and political issues, such as reduced innovation and quality, the potential for bias and misinformation, safety risks due to single points of failure, and a lack of democratic oversight and digital sovereignty. Moreover, market concentration and the current structure of the AI (research) ecosystem drive an AI monoculture, which incentivizes the development of marketable and profitable AI systems, without considering the public interest and maximizing society's wellbeing (Ahmed et al., 2023). This pertains specifically to fields where market gaps and market failures prevail, such as last-mile services in global majority countries. As a core feature of policy-making, education, and training programmes for AI and climate change, governments should prioritize addressing the global digital divide, which currently leaves billions worldwide without internet access (Sandalow et al., 2023) and skilled professionals without the opportunity to develop meaningful localized solutions due to prevailing data poverty and the compute divide (Besiroglu et al., 2024).

It is particularly important to note that data scarcity greatly affects the efficacy of AI-driven climate change initiatives, especially in SIDS and LDCs. These regions often face challenges that exacerbate the digital divide, affecting their ability to implement advanced AI solutions for climate action. This includes fewer weather stations, limited access to advanced satellite imagery, and sparse sensor networks, which are key to gathering the comprehensive environmental data needed to train AI models, restricted access to global data sets due to high costs or licensing restrictions.

Unequal access to both physical and digital resources is an aspect that remains inadequately explored in current literature (Walsh et al., 2020).

6.3.1. Closing the Data Divide

Addressing this gap involves improving data collection infrastructures, including the generation and use of disaggregated environmental and demographic data (by gender, age, geographic location (rural/urban, coastal/inland), income level or socio-economic status, indigenous identity, etc.), and advocating for open data initiatives, as well as fostering international collaborations to democratize knowledge transfer and ensure equitable access to AI technologies and climate data.

These efforts are complemented by training programmes for local personnel, including youth stakeholders, in data management and analysis. Furthermore, open data initiatives that promote the sharing of climate data enhance accessibility and utility, especially in regions with limited resources. Synthetic data generation also plays a role where real data are lacking, enabling the training of more adaptable AI models. Moreover, collaborative AI development that integrates input from local stakeholders and international experts ensures the creation of tailored solutions that address specific regional challenges and enhance climate resilience effectively. Additionally, data-poor contexts can especially benefit from the development of novel approaches to making AI training more efficient (Gunasekar et al., 2023) and research focusing on smaller, task-specific models (Varon et al., 2024). These advancements are often driven by open-source AI, which has played a role in democratizing access to AI tools and enabling innovation, particularly in resource-constrained environments.

CASE STUDY

CLOSING THE CLIMATE DATA DIVIDE IN DEVELOPING COUNTRIES

Country: LDCs and SIDS
Entities Involved: Microsoft AI for Good Lab, Planet Labs PBC, African Development Bank, African Risk Capacity, African Climate Foundation

Brief Description

Access to reliable climate data is essential for governments and decision-makers in developing countries to mitigate the worst effects of climate change. Efforts to democratize access to climate data align with broader global initiatives to accelerate progress towards the 17 Sustainable Development Goals (SDGs), adopted by UN member states in 2015 as part of the 2030 Agenda for Sustainable Development. High-quality climate data can unlock adaptation and resilience projects, ensuring that available resources are directed to areas where they can have the greatest impact, both before and in the aftermath of climate-related disasters. However, the developing countries face a significant gap in both reliable climate data and the availability of data scientists to analyse and apply it. Research indicates that for every data scientist in the developing countries, there are approximately five in the developed countries, creating disparities in the ability to translate climate data into actionable insights. In Africa, this gap widens further, with one data scientist for every 14 in the developed countries. This imbalance contributes to what has been termed the 'climate data divide' – a challenge that ongoing initiatives seek to address.

Microsoft is working to help close that climate data divide through the AI for Good Lab and new partnerships underway across developing countries to accelerate action. The AI for Good Lab applies AI, ML, and statistical modelling to tackle climate-related challenges in partnership with leading nonprofits, research institutions, NGOs, and governments as part of its portfolio to help solve humanity's biggest challenges. By offering our technology and expertise, we are helping advance the local development of scalable solutions. In 2022, the Lab announced its expansion to Nairobi, Kenya, where a team of world-class data scientists is working to improve climate resilience across Africa.

Climate Change Mitigation and/or Adaptation Impacts and Results

It is a challenging time for planet Earth and no nation is immune from the risks and perils faced by the ongoing impacts of climate change. There is additional complexity in that the consequences of this existential threat to our planet's survival are unevenly distributed among the world's countries, with a greater burden falling on the developing countries. The developing countries have contributed far less than the developed countries to the actual causes of climate change, yet they have been disproportionately impacted by extreme climate events including droughts, floods, storms and, heatwaves, which contribute to other problems like food insecurity and exacerbate existing challenges like poverty. Between 2008–2018, there were 2.2 billion people in the developing countries that were under high climate risk.

In September 2022, a collaboration with Planet Labs PBC and The Nature Conservancy led to the development of the Global Renewables Watch – a first-of-its-kind living atlas designed to map and measure all utility-scale solar and wind installations on Earth using AI and satellite imagery. The Global Renewables Watch provides data that helps both researchers and policymakers understand current renewable energy capacities and assists decision-makers in search of effective options for renewable energy development. Access to high-quality data is critical to enabling measurement and realization of the SDGs.

Challenges and Lessons Learned Regarding Development and Implementation

Addressing and mitigating the effects of climate change requires collaboration across industry, government, academia, and civil society. During initial discussions with Kenyan stakeholders on the expansion of climate AI initiatives, it was emphasized that an ideal outcome would involve African researchers leading projects that benefit Africa within Africa. To support this approach, collaborations have been established with organizations such as the African Development Bank, African Risk Capacity, and the African Climate Foundation, focusing on improving climate resilience through data and AI. These partnerships aim to facilitate the generation of additional climate data and drive continued research. In addition to these partnerships, cooperation has been initiated with the Kenya Red Cross Society, PATH, the Institute for Health Metrics and Evaluation (IHME), and the Integrated Food Security Phase Classification (IPC) to enhance the translation of climate data into actionable insights.

CASE STUDY

EMPIRIC_AI: AI-ENABLED ENSEMBLE PROJECTIONS OF CYCLONE RISK FOR HEALTH INFRASTRUCTURE IN PACIFIC ISLAND COUNTRIES AND TERRITORIES

Country: Pacific Island Countries including Fiji, Tonga, Vanuatu, and Solomon Islands
Entities Involved: Dr. Chris Horvat, Dr. Berlin Kafoa, Dr. Craig McClain, Dr. Michelle McCrystall, Dr. Liz McLeod, Dr. Eileen Natuzzi, Dr. Subhashni Taylor, Dr. Callum Webster

Brief Description

Pacific Island Countries (PICs), such as Fiji, Tonga, and the Solomon Islands are among the most susceptible to devastating tropical cyclones and climate change impacts yet lack robust climate-specific data. The region comprises 10,000 islands and atolls, but many of these are too small to be accurately represented in large-scale global climate models. As these climate models are used to project future climate change demonstrated in IPCC climate assessment reports, the inability to effectively represent these islands means that future climate change projections are limited across the region.

Around 10 tropical cyclones form in the South Pacific every year. Limited data and infrequent storms require the construction of resilient healthcare facilities in PICs. The EMPIRIC_AI (EMulation of Pacific Island Risk to Infrastructure from Climate) project addresses these issues using new statistical modelling and AI techniques. Thousands of observationally-constrained synthetic tropical cyclones are tracked using a statistical model, and a modified U-net is employed to emulate the pan-Pacific impacts of these storms. This network allows for a rapid sampling of possible future states and developing a statistical range of impacts of tropical cyclones at different hospital sites across PICs such as potential number of landfalls, wind, and rainfall. By leveraging these data, health governing bodies can make informed decisions regarding future healthcare infrastructure planning.

Climate Change Mitigation and Adaptation Impacts

The primary aim of this project is to give site-specific projections of climate change impacts on different health facilities across the Pacific Island Countries. These insights can identify hospital sites at the highest risk from future tropical cyclones and extreme weather events and can inform mitigation or adaptation measures that might be needed for those specific sites, including preparation for flooding events or potential relocation of hospital sites to limit continuing climate change impacts on the health capacity of each region.

Challenges and Lessons Learned Regarding Development and Implementation

A key challenge in the EMPIRIC_AI project involves navigating the intersecting domains of policy, healthcare, climate science, and data science. This multifaceted challenge arises because each discipline poses distinct questions and often operates with asymmetric knowledge bases. Specifically, the climate metrics that impact individual Pacific hospitals are uniquely detailed, and comprehensive qualitative data at the sectoral, national, or Pacific-wide level is hard to come by. Addressing this issue requires a nuanced approach to contextualizing climate data and adapting AI tools for stakeholders, which is being tackled through in-depth qualitative surveying and collaborative efforts.

Much of the progress made in AI research in recent years was realized thanks to open-source and open science practices. Open-source AI, in particular, has played a role in democratizing access to cutting-edge tools and frameworks, enabling broader participation in AI development and innovation. However, the rapid growth of open-source AI has also led to a complex and sometimes chaotic landscape, with numerous projects, standards, and approaches emerging independently.

In response, new open-source standards and alliances are emerging to bring order to this complexity. Organizations such as the Linux Foundation's LF AI & Data, the Open Neural Network Exchange (ONNX), and the AI Open Network are working to establish common frameworks and guidelines that promote interoperability, transparency, and collaboration. These efforts are crucial in ensuring that open-source AI remains a cohesive and accessible resource, particularly for data-poor contexts where proprietary solutions may be out of reach. These initiatives are helping to unlock the full potential of AI across diverse applications and settings by fostering a more structured and unified open-source ecosystem. Moreover, to strengthen local AI ecosystems and enable skilled professionals to develop localized AI solutions, access to open AI training data and open-source models is paramount, in addition to reliable infrastructure (Gimpel, 2024).

6.3.2. Right to Development

The digital divide is also intertwined with the gender divide and thus it impairs the right to development of vulnerable populations and, at a broader scale, the ability of SIDS and LDCs to fully engage in climate action and sustainable development. As AI technologies become increasingly relevant for climate mitigation and adaptation, disparities in digital infrastructure and literacy risk excluding developing nations from the benefits of AI-driven climate solutions.

Bentley et al. (2024) explored the implications of the digital divide on how people interact with AI technologies. The authors highlight that unequal access to digital technologies and disparities in digital literacy can deepen societal inequities and limit the ability of communities to engage with AI-powered climate adaptation measures. They introduced the concept of 'digital confidence,' which encompasses awareness, familiarity, and competence in using digital technologies, and surveyed 303 individuals to assess how these factors influence attitudes towards AI. The study found that digital confidence is significantly affected by demographic factors such as gender, age, income, and access to technology. Women, older individuals, people with lower incomes, and those with less access to digital tools reported lower levels of digital confidence. This lack of digital confidence could hinder participation in AI-based climate resilience initiatives, such as AI-powered early warning systems, precision agriculture, and smart water management solutions.

Lutz (2019) addressed inequalities in access to digital technologies, extending this discussion to emerging technologies like IoT and AI-powered systems. The author highlights disparities in digital skills and technology usage, linking these to new work forms such as the gig economy and the sharing economy. In the context of climate action, unequal digital access can also limit participation in global carbon markets, AI-driven disaster risk reduction, and climate-smart supply chain management. Ensuring digital inclusivity is essential to empower developing nations to harness AI for climate adaptation, resilience-building, and sustainable economic transitions.

This is not just about improving technical skills or increasing access to technology, but also about gaining control over data and AI governance. This can help prevent scenarios where data from these countries are used to feed algorithms that primarily benefit companies and economies elsewhere. Moreover, developing local AI solutions can stimulate local economies, spur innovation, and provide more relevant technological solutions that address local needs effectively. It is important that these efforts go beyond just setting up infrastructure. Comprehensive strategies should include developing competencies to allow individuals to engage with and benefit from AI technologies fully.

Moreover, public investment in AI infrastructure aimed at public interest projects can increase accessibility for communities with lower incomes. Subsidies, public-private partnerships, and other innovative financial mechanisms can reduce the cost of AI technologies, making them more accessible and promoting equitable technological advancements. These multifaceted approaches are important for closing the digital divide and enhancing the capacity of communities worldwide to leverage AI for sustainable development. Capacity-building programmes are key to ensuring that local populations have the knowledge to develop and maintain AI solutions. Training programmes for local engineers, data scientists, and policymakers can help build a sustainable ecosystem for AI development in developing countries.

Critical perspectives on this issue suggest examining the intricate layers of how technology is not just a tool for progress but also a potential instrument of power that can reinforce or challenge existing global inequalities. The dialogue around digital sovereignty and local AI ecosystem development is therefore deeply tied to broader discussions about economic independence, cultural integrity, and equitable growth within the global technological landscape and thus with the Right to Development. In that context, AI governance must ensure that SIDS and LDCs have the agency to implement AI-driven climate strategies that align with their specific needs and development pathways.

6.4. Biases

In the context of AI applications for climate action, it is important to acknowledge the impacts of spatial and temporal biases in the training data on algorithmic bias. Spatial biases arise when the geographic distribution of the training data is uneven, potentially leading to AI models that perform well in certain regions but poorly in others. Temporal biases occur when the training data does not adequately capture the variability over time, which can result in models that are less robust to future changes or anomalies. These biases can significantly affect the reliability and fairness of AI predictions and interventions, necessitating careful consideration during the model development and training phases. For instance, training an AI model to predict urban heat requires careful selection of spatial resolution, as a low resolution might average out extreme values in smaller neighbourhoods and overlook critical hotspots, while a higher resolution can reveal these peaks but potentially introduce noise (McGovern et al., 2022a).

McGovern et al. (2022b) emphasize the critical need for ethical and responsible implementation. It dispels the misconception that the environmental sciences are immune to AI's unintended societal impacts, such as those seen in criminal justice and finance systems. The study presents examples showing how AI can introduce similar biases and negative consequences in environmental contexts, despite the perceived objectivity of data and algorithms. By stimulating discussion and research, the authors aim to prevent the environmental science community from repeating mistakes made in other fields. They advocate for precautionary measures to ensure AI is used responsibly, harnessing its potential to address climate and environmental injustices. While focusing on weather and climate, the study's conclusions apply broadly across all areas of environmental science.

Furthermore, bias can exacerbate inequalities if AI systems are not meticulously designed and managed, leading to unfair outcomes that disproportionately affect marginalized groups. For example, AI-powered climate prediction models may under-represent regions with sparse data, leading to inadequate disaster preparedness measures in vulnerable communities. Similarly, biases in AI-driven carbon credit markets could disproportionately benefit wealthier nations, reinforcing existing disparities in global climate finance. Therefore, ensuring accessible AI technologies involves creating tools and systems that are user-friendly and widely available and ideally developed in a co-creative manner with diverse communities (The Collective Intelligence Project, 2024).

Promoting climate-specific digital and algorithmic literacy is essential to empower users to engage with AI-driven climate applications critically and effectively. For instance, if AI-based early warning systems rely on biased training data, they may fail to provide timely alerts to remote or marginalized populations, leaving them disproportionately exposed to climate hazards. Unbiased AI outcomes are necessary to ensure fairness and equity in climate adaptation and mitigation efforts, which requires rigorous testing and validation processes to detect and mitigate biases. Moreover, AI system providers must ensure that development is conducted with a human rights-based approach, emphasizing the protection of human rights. In the climate domain, this means ensuring that AI-driven resource allocation, emissions tracking, and sustainability assessments are equitably applied across regions and populations.

Effective regulation is needed to establish standards and guidelines that promote equitable access and use of AI technologies in climate action and address market concentration. The UN and EU have launched significant initiatives to regulate AI development, with growing attention to ensuring its responsible use in climate governance. Addressing these factors allows for progress towards a more equitable AI landscape where AI-driven climate action benefits all sectors and contributes to sustainable and inclusive development.

In addition, biases in AI-powered climate modelling, emissions tracking, and environmental monitoring can lead to skewed results, undermining the effectiveness of AI solutions. Incomplete or biased data can/will perpetuate existing inequalities and result in climate policies that do not address the needs of under-represented populations. For example, if AI-based deforestation monitoring is trained primarily on satellite imagery from temperate regions, it may fail to accurately detect land degradation in tropical forests, leaving critical ecosystems unprotected. Similarly, if AI-driven energy transition models prioritize developed nations' infrastructure, they may overlook viable renewable energy solutions for LDCs and SIDS.

Governments and organizations need to implement stringent data protection laws, establish clear guidelines for data handling, and ensure that there are enforcement mechanisms in place to prevent bias in AI-driven climate assessments. Moreover, transparency in data collection processes and the involvement of local communities in AI-based environmental monitoring can help build trust and ensure that the data collected is representative and useful for climate action and available to benefit local communities.

Risks related to the deployment of AI systems encompass equity and inclusion issues related to environmental injustice and social inequality. These challenges stem from systemic discrimination and deep-rooted prejudices against specific groups, communities, or regions. Misuse of AI systems can perpetuate and even exacerbate existing inequalities if they reinforce these entrenched biases. Previous AI models have demonstrated biased predictions when applied to racial minorities, leading to harmful and potentially serious consequences (Columbia University, 2024). Therefore, it is crucial to design and implement AI with a conscious effort to address and rectify these long-standing issues to ensure fair and equitable outcomes for all. As concluded by UNESCO (2020), "Algorithmic failures are ultimately human failures that reflect the priorities, values, and limitations of those who hold the power to shape technology. We must work to redistribute power in the design, development, deployment, and governance of AI if we hope to realize the potential of this powerful advancement and address its perils." Ensuring AI fairness in climate decision-making requires a conscious effort to address systemic biases and empower historically disadvantaged communities to participate in AI-driven climate governance.

The broader issue of representation bias in AI extends beyond gender bias and is a significant concern, particularly in developing countries. This bias arises from the data scarcity and digital divide prevalent in these regions, which can lead to AI systems trained on existing datasets that fail to accurately represent local realities. The lack of comprehensive and diverse data results in AI models that may not be fit for purpose, as they often lack the necessary contextual understanding to address specific challenges faced by communities in developing countries.

To overcome this limitation, it is essential that efforts to build AI solutions for these regions occur in tandem with targeted data collection initiatives. These initiatives should aim to equip AI tools with the appropriate context, ensuring that they can effectively solve local problems and contribute to meaningful development. AI systems can be better tailored to address the nuanced challenges these areas face by incorporating diverse, and disaggregated datasets that reflect the unique socio-economic, cultural, and environmental conditions of developing countries, ultimately leading to more equitable and impactful outcomes.

Especially, gender bias in AI poses a significant challenge to its effective use for climate action in both developed and developing countries. Unless carefully designed and implemented, AI systems can perpetuate and even exacerbate existing gender inequalities, especially as economic systems often obscure the crucial contributions of women in ensuring food security, healthcare, and climate resilience, due to the informal nature of their work in these sectors. This bias can manifest in various ways, such as under-representation of women in data used for training AI models or gender-insensitive design of AI applications. Addressing gender bias requires a conscious and deliberate effort and investments to include diverse contributions and perspectives in the development and deployment of AI technologies. Ensuring that AI solutions for climate action are gender-responsive can help promote more inclusive and equitable outcomes.

The UNFCCC report "Progress, Good Practices, and Lessons Learned in Prioritizing and Incorporating Gender-responsive Adaptation Action" (2023) offers an in-depth analysis of how gender-responsive strategies are being integrated into climate change adaptation efforts worldwide. It underscores the necessity of involving both women and men in the formulation and execution of these strategies to address gender-specific climate impacts, i.e., the importance of equitable gender representation in decision-making processes, demonstrating effective practices and lessons from various countries. It identifies existing gaps and challenges, such as the need for more gender-disaggregated data and increased funding for gender-responsive projects and provides recommendations to enhance resilience and promote gender equality in adaptation initiatives.

As AI-driven climate solutions become more widespread, integrating gender considerations into AI-based adaptation planning is critical to ensuring inclusive and effective climate action. AI models used for early warning systems, resource allocation, and climate-smart agriculture must account for gender-specific vulnerabilities and contributions to avoid reinforcing existing inequalities. For example, AI-powered disaster response systems should ensure that data collection processes incorporate gender-disaggregated information to prioritize the needs of women, who are often disproportionately affected by climate-induced displacement and resource scarcity.

Table 9 summarizes the approaches and outcomes of gender-responsive climate adaptation strategies from several LDCs and SIDS from the UNFCCC report.

Table 9: Gender-responsive climate adaptation strategies in LDCs and SIDS

Country	Gender-responsive Actions	Challenges Addressed	Outcomes/Benefits
Burkina Faso	Outlined women's vulnerabilities, promoted precipitation harvesting techniques, and addressed water scarcity.	Women are more dependent on affected resources, less access to agricultural inputs and land, longer distances for water.	Enhanced resilience of women farmers, improved water management, and reduced vulnerability to extreme weather events.
Fiji	Ensured women's participation in decision-making and access to economic resources and financial services, recognized women's social roles.	Limited recognition of women's contributions in adaptation activities.	Increased women's involvement in adaptation activities, empowered women through economic opportunities, and promoted sustainable resource use.
Saint Lucia	Committed to gender equality, collected gender-disaggregated data, conducted gender assessments, and developed gender-responsive strategies.	Lack of gender-disaggregated data on adaptation needs.	Better understanding of gender-differentiated impacts, informed decision-making, and inclusive adaptation strategies.
Guatemala	Developed a gender strategy for NDC, implemented ecosystem- and community-based adaptation actions with women's participation.	Ensuring women's participation and reducing vulnerabilities.	Empowered women through participation in restoration and conservation projects, enhanced resilience of ecosystems and communities.
Guinea-Bissau	Developed gender action plans, used gender-sensitive budgeting, and trained women in food safety and entrepreneurship.	Allocating resources for gender equality and women's empowerment.	Strengthened resilience of vulnerable coastal areas, improved climate information systems, and enhanced women's economic opportunities and food safety knowledge.

These case studies highlight how LDCs and SIDS are tackling the gender-specific impacts of climate change to promote gender equality and women's empowerment through tailored adaptation strategies. To maximize the effectiveness of these approaches, AI can play a role in improving gender-responsive adaptation strategies by ensuring that climate risk assessments, financial assistance programmes, and resilience-building initiatives are informed by equitable and unbiased data. AI-driven climate models must be trained to recognize gender-specific vulnerabilities to prevent reinforcing biases in climate planning and policy implementation.

The report calls for ongoing support to ensure that gender-responsive measures are integrated into national adaptation plans. The analysis of gender bias in the use of AI for climate action in developing countries relates to the thematic areas addressed in Section 4, as follows:

Early Warnings and Disaster Risk Reduction: AI can reinforce male-dominated perspectives, overlooking women's specific vulnerabilities in disaster response and risk reduction (Varona et al., 2021). Social and economic inequalities, such as restricted mobility and limited access to information, further heighten these risks.

Resource Management: AI-driven systems for resources management in water, agriculture, fisheries, and forests often neglect women's critical roles, leading to inefficient and unjust resource allocation and conservation efforts.

Energy Management: AI in energy systems can deepen gender inequalities by ignoring women's reliance on traditional biomass, and their role in driving the energy transition in life-sustaining sectors (food transformation), while men have greater access to modern energy sources, equipment, and training.

Transport Management: AI-driven transport systems that prioritize efficiency over safety may fail to consider women's specific schedules and security needs, limiting their safe mobility.

Education and Community Engagement: AI tools that disregard gender disparities in technology access can widen the digital divide, restricting opportunities for women.

Various international organizations have made recommendations for integrating gender perspectives into public policies and educational programmes to address gender biases in AI. Studies have begun to explore the intersection of AI and gender equality under the UN SDGs; research has identified societal roots and technical factors contributing to gender bias in AI.

The Paris Agreement acknowledges that when taking action to address climate change, Parties should respect, promote and consider gender equality and empowerment of women. Gender considerations are increasingly being prioritized in climate funds and funding mechanisms (Schalatek, 2022). In addition to gaining access to climate finance and capacity-building, developing countries – primarily LDCs and SIDS – have advocated for enhanced technology transfer to aid their climate change adaptation efforts and ensure gender inclusivity.

6.5. The Role of AI in Accelerating Fossil Fuel Extraction and Exploitation, Spreading Climate Misinformation, and Promoting Consumerism

While AI holds significant promise for driving positive change, it also carries risks when applied in ways that conflict with environmental sustainability objectives. For instance, AI has been widely deployed to enhance fossil fuel exploration and extraction, increasing efficiency and profitability in an industry responsible for nearly 90% of global CO_2 emissions (IEA, 2023). This widespread use of AI in fossil fuel operations risks extending the economic viability of carbon-intensive industries, directly contradicting global efforts to transition to renewable energy. Moreover, AI-driven targeted advertising fosters consumerism and unsustainable behaviours, driving demand for products and services that contribute to environmental degradation. These AI-enabled systems influence consumption patterns on a massive scale, shaping global markets and intensifying resource depletion.

Additionally, AI systems are increasingly being exploited to generate and disseminate climate misinformation at unprecedented scales, undermining evidence-based policy discussions. For example, AI-powered disinformation campaigns have been found to manipulate public perception by downplaying climate risks, delaying regulatory action, and fostering distrust in climate science (Galaz et al., 2023a). The rapid evolution of AI-generated content, combined with opaque social media algorithms, creates a landscape where false climate narratives spread faster than fact-based discourse.

Eremin and Selenginsky (2023) focused on the application of AI methods in oil and gas production, illustrating how AI technologies have become critical in optimizing processes from planning and complication prevention to drilling and production capacity enhancements. Their study emphasizes the use of AI models in predicting reservoir properties, such as permeability and porosity, using log and seismic data. These accurate predictions allow engineers to better manage hydrocarbon recovery. Additionally, AI systems, trained on extensive datasets from real experiments, simulations, and field logs, can predict potential complications and emergencies. Overall, AI contributes to improving efficiency and boosting hydrocarbon recovery in the oil and gas industry. In some cases, AI systems have increased production levels by up to 5%, with projections indicating that AI could generate up to $425 billion in value for the sector by 2025 (ICLR, 2024).

Galaz et al. (2023) and Treen et al. (2020) describe the role of AI-driven misinformation in shaping public opinion, emphasizing the need for regulatory measures and interdisciplinary strategies to counteract its impact. Chu-Ke and Dong (2024) highlight the dangers of AI-generated disinformation, calling for strengthened ethical AI development, regulatory oversight, and public AI literacy initiatives.

Treen et al. (2020) further demonstrate how AI-driven misinformation exacerbates scepticism and polarization, particularly on social media platforms, which amplify confirmation bias and echo chambers. All three studies stress the urgency of addressing misinformation through a multi-pronged approach, integrating policy, education, and technology-based solutions. While the perspectives differ, they all stress that the evolution of AI and digital platforms poses significant challenges that must be addressed through collaboration, governance, and cross-disciplinary research. The integration of ethical AI practices, improved literacy, and interdisciplinary efforts will be crucial in mitigating the adverse impacts of misinformation and promoting more accurate and reliable climate communication.

However, AI can be also leveraged to address the growing threat of climate change misinformation on social media, which is outpacing the capacity of human fact-checkers. For example, Rojas et al. (2024) developed a two-step hierarchical machine learning model to detect and classify climate misinformation, improving the accuracy and efficiency of content moderation. The study introduces the Augmented Computer Assisted Recognition of Denial and Scepticism (CARDS) model, specifically designed to categorize climate-related claims on Twitter (officially known as X). By analysing five million climate-themed tweets over a six-month period in 2022, the study found that more than half of contrarian climate claims involved attacks on climate actors. These spikes in misinformation were driven by four main stimuli: political events, natural events, contrarian influencers, and convinced influencers. The findings emphasize the potential of automated tools to help detect and mitigate the spread of climate misinformation in real time, providing valuable insights for combating online disinformation. This model offers a new direction for leveraging ML to tackle climate change denial and scepticism, which has significant implications for both policy and public discourse.

Moreover, micro-targeting ML techniques can be leveraged for digital nudging in order to foster more sustainable habits and behavioural changes shift, (Bartmann, 2022) as presented in Section 4.8.

7. Policy Options for the Use of AI as a Technological Tool for Advancing and Scaling Up Transformative Climate Solutions for Mitigation and Adaptation Action in Developing Countries

7.1. Deploy AI tools for Climate Change Mitigation and Adaptation Strategies

Policymakers could consider the promotion and use of AI tools and systems on proven cases of AI for climate action included in this paper such as on early warning systems for disaster risk reduction (UN Early Warnings for All Initiative), AI-driven crop monitoring to enhance food security (Early Warnings System for Crop Phenotyping and Food and Nutrition Security in Kenya), and AI-based environmental monitoring for ecosystem protection (AMAP Mangrove Mapping in the Solomon Islands).

7.2. Develop Inclusive and Sustainable Artificial Intelligence Policies

Energy efficiency: Formulate policies that promote the development and deployment of energy-efficient AI technologies. Encourage innovations in green computing to reduce the environmental footprint of AI systems. This includes incentivizing research into energy-saving algorithms and hardware, supporting the transition to renewable energy sources for data centres and communication networks, and setting standards for energy efficiency in AI applications. Implement policies that require a life cycle assessment of AI systems to evaluate their environmental impact from development to deployment. Encourage the development of cooling technologies that minimize water usage.

Data security and Sovereignty: Implement robust data protection laws that ensure the security of data used in AI applications. Enhance cybersecurity measures to protect sensitive data and implement strict protocols for data access and management. This includes establishing guidelines for data collection, storage, and sharing, ensuring that data governance frameworks are in place to address concerns about unauthorized access, data breaches, and misuse of information. Policies should also mandate regular security audits and compliance checks, promote the use of encryption technologies, and foster a culture of transparency and accountability in data handling practices. Moreover, enhancing public awareness about data security issues is key to building trust in AI systems. In addition, data governance frameworks should respect and uphold data sovereignty principles, particularly the rights of indigenous peoples and local communities to retain ownership, control, and access to the data that relates to them. This includes ensuring that data used in AI modelling is collected, processed, and shared in a legitimate way.

Digital divide: Invest in digital infrastructure to improve access to AI technologies in developing countries, with a focus on LDCs and SIDS. This includes expanding internet connectivity, enhancing computing capabilities, ensuring a reliable power supply, and making essential AI development resources available as digital public goods. Develop strategies to bridge the digital divide by ensuring equitable access to electricity, ICT infrastructure, datasets and models, and AI skills. This involves investing in AI research relevant to developing countries with a focus on LDCs and SIDS, public infrastructure for AI development, digital literacy programmes, particularly in remote and underserved areas, and providing training on AI technologies, and incorporate bias detection and mitigation techniques in AI model development. Policies should also focus on making AI tools and resources openly accessible and affordable to all communities, thereby fostering inclusive growth, innovation, and quality. Develop ethical frameworks that govern the use of AI, ensuring that AI applications are free from biases, thus promoting fairness and equity in AI deployment and enabling benefit-sharing with local communities.

7.3. Integrate Indigenous Knowledge, Gender-responsive Approaches, and Youth Stakeholder Innovation

Incorporate Indigenous Knowledge: Indigenous knowledge systems provide localized environmental insights that have been refined over centuries and can enhance the effectiveness of AI applications in specific climate contexts. However, their integration should be targeted and relevant, ensuring that AI solutions respect, validate, and complement traditional knowledge rather than replace or misrepresent it. To ensure meaningful integration of indigenous knowledge in AI systems, policies should:

- Engage Indigenous Communities in AI Co-design – Ensure participatory approaches in AI model development where local knowledge is applicable, avoiding nominal inclusion.

- Develop Ethical Practices – Establish clear data-sharing agreements that respect indigenous values over environmental data and avoid misappropriation of traditional knowledge.

- Incorporate Cultural Context in AI-Driven Climate Communication – Ensure AI-powered climate advisory platforms use culturally appropriate language, narratives, and risk perception frameworks for effective decision-making in local communities.

Gender-responsive AI policies: Ensure that AI policies and programmes are inclusive and address gender and demographic disparities. Invest in the generation of gender disaggregated data to document and recognize the crucial contributions of women in climate action, such as the care economy, climate resilient agriculture and food security, water management, and energy transition. Promote the active participation of women in AI-related fields through targeted education, training programmes, and career opportunities.

Include Youth in AI Policy Development and Climate Solution Innovation: Engage youth stakeholders to democratize the development and implementation of AI policies and programmes that are age-responsive and integrate the needs of children and youth. Promote stronger interlinks among youth leaders in digital technologies and the innovation ecosystem to support youth-led initiatives in AI policy and climate action. Such efforts should recognize and harness the unique experiences, perspectives, and skills of children and youth.

7.4. Promote Socially Inclusive Artificial Intelligence Development

Inclusive AI development: Ensure that AI development and deployment processes and governance are inclusive, considering the needs and perspectives of marginalized communities, including women and indigenous groups, and low-income populations, as well as the youth. Develop policies that promote equitable access to AI technologies and their governance, focusing on affordability, infrastructure development in underserved areas, and the reduction of digital illiteracy barriers. This includes fostering capacity-building initiatives to enable meaningful participation in AI-driven climate solutions.

Community Engagement in AI-Driven Climate Solutions: Community engagement is most relevant in AI applications where local knowledge, risk perception, and contextual adaptation are critical to implementation. This includes:

- Early Warning and Disaster Preparedness – AI-based early warning systems for floods, cyclones, and droughts must incorporate community-level participation to ensure that alerts reach vulnerable populations through accessible communication channels, such as radio, mobile alerts in local languages, or community leaders as trusted messengers.

- Climate-resilient Agriculture – AI applications that provide precision agriculture recommendations should integrate local farming knowledge to ensure AI-driven advisories align with traditional farming techniques rather than imposing one-size-fits-all solutions. Engaging smallholder farmers in training and feedback loops ensures the usability of AI tools.

- Sustainable Land and Resource Management – AI applications in deforestation monitoring and biodiversity conservation should involve local stakeholders in validating AI-generated insights and ensuring that AI-driven policy decisions do not conflict with customary land rights or sustainable resource use practices.

- Energy Access and Electrification – When AI models are used to optimize renewable energy distribution in remote or off-grid areas, engagement with local communities ensures that deployment strategies prioritize energy needs and do not exacerbate existing inequalities in energy access.

- Recognizing Care Work in Climate Resilience – AI applications should be designed to recognize and integrate the vital role of unpaid care work – predominantly carried out by women in all their diversity – in sustaining the climate resilience of local communities.

7.5. Foster International Cooperation, Capacity-building, and Knowledge Sharing

Establish collaborative frameworks: Strengthen international partnerships and cooperative frameworks to facilitate knowledge exchange, technology transfer, and capacity-building, in line with the provisions of the UNFCCC and the Paris Agreement. Partnerships should involve international organizations, multilateral climate finance mechanisms, and private sector stakeholders, fostering a global, inclusive effort to tackle climate change.

Capacity-building programmes: Implement training programmes and workshops to build local expertise in AI and climate science. This can be achieved through partnerships with educational institutions, international organizations, and the private sector to provide training and education. Targeting government officials, technical experts, and community leaders will enhance their understanding and application of AI in climate action, empowering local communities to leverage AI technologies effectively.

Open data platforms and digital public goods: Promote the use of open data platforms and registering datasets and models to enable countries to share climate-related data and models. This facilitates collective learning and innovation, allowing for transparent exchange and access to valuable climate information, which can enhance the accuracy and applicability of climate predictions. Open data platforms standardize data collection methods, ensure consistency, and foster regional and global cooperation, ultimately accelerating the development and deployment of effective climate action strategies tailored to specific needs. The Digital Public Goods (DPG) registry provides open-source software, open data, open AI models, open standards, and content that adhere to privacy and other applicable laws and best practices, do no harm, and help attain SDGs. A DPG registry would typically catalogue such resources to promote access, facilitate sharing, and encourage the development and use of these tools in various sectors, including education and climate action. This kind of registry aims to support global development by making high-quality digital solutions widely accessible and promoting international cooperation in the digital space, particularly in supporting under-resourced areas or communities. By leveraging DPG in the form of open data and open-source AI models, countries can improve the accuracy and applicability of climate predictions and enhance their overall resilience to climate impacts.

7.6. Establish Robust Monitoring and Evaluation Frameworks

Impact assessment: Develop monitoring and evaluation frameworks to assess the impact and effectiveness of AI applications in climate action. This includes setting performance metrics and regularly reviewing progress to ensure AI solutions are effective and aligned with climate goals. Use these assessments to refine policies and strategies continuously.

Transparency and accountability: Ensure transparency in AI initiatives by making data, methodologies, and findings publicly accessible to stakeholders. This openness fosters trust and enables independent verification of results, ensuring that AI applications in climate action are transparent and reliable. Establish mechanisms to track the progress of AI projects, identify areas for improvement, and address any issues that arise. Regular reporting and feedback loops are important to maintain accountability and ensure that AI-driven climate solutions meet their intended goals effectively.

7.7. Invest in and Foster Artificial Intelligence Research, Development, and Innovation

Localized AI solutions: Prioritize funding for AI research and development projects that are tailored to local contexts and address specific climate challenges faced by developing countries, with a focus on LDCs and SIDS. Encourage innovation in AI research and applications that can directly benefit these regions.

Interdisciplinary and applied research: Promote interdisciplinary and applied research at the convergence of computer science and climate science. Establish pathways for enhancing the technical maturity of AI applications in climate change mitigation and adaptation through targeted research, development, and demonstration initiatives.

Support for start-ups and innovation hubs: Create supportive environments for start-ups and innovation hubs focusing on AI for climate action. Provide grants, tax incentives, and incubation support to foster innovation in the private sector.

8. Conclusions and Recommendations

8.1. Conclusions

The use of AI to combat climate change presents opportunities, challenges, and risks for developing countries. Based on the findings in the preceding chapters, this paper draws conclusions and offers recommendations. It recognizes that the presented findings are likely to change in the near future due to the rapid evolution of AI usage.

The Role of AI in Advancing Climate Solutions: AI and ML can support efforts to adapt to and mitigate the effects of climate change, including by improving disaster risk preparedness, energy efficiency, sustainable mobility, resource management and industrial transformation. Unlike traditional modelling techniques, AI systems can rapidly analyse vast, multi-source datasets in real time, enhancing forecasting accuracy and enabling more adaptive decision-making in uncertain situations.

For example, applying AI to agriculture and fisheries can optimize crop yields, manage fish stocks, combat illegal fishing, and safeguard marine ecosystems through predictive analytics, image recognition, and automated monitoring tools. Similarly, integrating AI into transport networks, and industrial operations can accelerate the transition to low-carbon economies by optimizing logistics, reducing emissions through smart control systems, and enabling predictive maintenance.

Predictive and Adaptive Capabilities for Climate Resilience: AI-powered forecasting, integrated with real-time data from Internet of Things (IoT) sensors, can be leveraged to enhance early warning systems and strengthen resource management. These predictive capabilities are particularly relevant in regions that are vulnerable to climate change, such as SIDS and LDCs, where extreme weather events pose significant risks. Leveraging AI-driven models enables governments and local communities to enhance their capacity to adapt to disasters and safeguard infrastructure, livelihoods, and ecosystems.

Optimizing Resource Use Through AI: AI-driven solutions in agriculture, fisheries, energy grids, transportation, and industrial processes can reduce emissions and bolster sustainability. However, maintaining and scaling AI-driven systems in developing contexts requires enhanced capacity-building efforts and investment in digital infrastructure to ensure long-term effectiveness.

Embedding Cultural and Local Context in AI Solutions: Incorporating local contexts into AI solutions is essential for addressing the unique challenges and opportunities present in different regions. Socio-economic factors, such as local languages, traditions, access to resources, influence how communities interact with technology and the effectiveness of different solutions. Geographic factors, such as climate, infrastructure, and natural resources, also shape the specific needs and priorities of local populations.

Understanding and integrating these local contexts enables the development of AI systems that better serve the diverse needs of communities, ensuring that technological advancements contribute to inclusive low-emission and climate-resilient development.

Enabling AI Deployment: The successful deployment of AI for climate action in developing countries, in particular SIDS and LDCs, requires an enabling environment that includes:

- **Infrastructure Development:** Reliable electricity, broadband connectivity, and access to cloud computing to support AI deployment.
- **Skill Development:** Strengthening technical expertise through capacity-building programmes to ensure the effective customization and maintenance of AI systems.
- **Financial Support:** Securing investments from bilateral and multilateral sources, including from the Green Climate Fund (GCF), the Adaptation Fund, the Global Environment Facility (GEF), the Least Developed Countries Fund (LDCF) and the Special Climate Change Fund (SCCF) to scale up AI-driven climate technologies.
- **Governance and Policy Frameworks:** Establishing legal mechanisms that promote the responsible use of AI, protect data privacy, and encourage open-source AI solutions.

Challenges and Risks in AI-driven Climate Action: Despite its potential, the adoption of AI for climate action faces significant barriers, including:

- **High Costs and Limited Resources:** Many developing countries, particularly SIDS and LDCs, lack the capital to invest in AI infrastructure and maintain advanced digital technologies.
- **Data Scarcity and Quality Issues:** AI models require large, high-quality, gender disaggregated datasets to function effectively, yet many regions lack sufficient localized data.
- **Digital Divide and Exclusion Risks:** Connectivity gaps and low digital literacy levels may marginalize vulnerable populations, limiting equitable access to AI solutions.
- **Security and Privacy Concerns:** Inadequate data protection frameworks could lead to data misuse, unauthorized access, or cyber vulnerabilities.
- **Bias and Equity Challenges:** AI models trained on data from high-income countries, and male-dominated economic sectors may overlook local contexts and existing inequalities, potentially reinforcing inequalities in climate response strategies.
- **Disinformation and Manipulation Risks:** The use of AI, particularly generative models and algorithmic targeting, can amplify climate-related disinformation, mislead public opinion, and undermine trust in climate science, particularly within information ecosystems that are either poorly regulated or highly vulnerable.

Opportunities for Inclusive and Equitable AI Adoption

- **Open-source and Shared Platforms:** Encouraging global collaboration while respecting local data sovereignty to ensure AI applications are accessible and tailored to regional needs.

- **Hybrid Approaches:** Combining rule-based systems with machine learning techniques to enable effective AI deployment in environments with limited data.

- **Targeted Funding and Partnerships:** Leveraging climate finance instruments and forging partnerships with universities, NGOs, and technology firms to develop AI solutions adapted to specific regional challenges.

- **Inclusive AI Design:** Engaging under-represented groups, including women, youth, and indigenous communities in AI development to ensure that diverse, local perspectives shape context-specific climate solutions.

8.2. Recommendations

- Promote the use of open-source AI applications in climate change mitigation and adaptation strategies in developing countries, ensuring they are deployed and are the most suitable tool for the task.

- Encourage the use of AI for climate action by promoting supportive policies, local training, and resources to empower stakeholders to use AI to reduce GHG emissions and build climate-resilience.

- Integrate AI technologies into national and regional climate strategies where they can enhance areas such as early warning systems, optimization of resource allocation, and data-driven decision-making in climate adaptation and mitigation efforts.

- Strengthen global partnerships and knowledge sharing by fostering international cooperation and developing capacity-building programmes to enhance the skills and capabilities of local stakeholders, promoting knowledge-sharing and collaboration to maximize AI's potential in climate strategies.

- Develop inclusive and sustainable policies and establish governance approaches, enabling data-driven decision-making and access to climate regulatory frameworks and state-of-the-art research.

- Reduce the energy consumption and carbon footprint of AI by implementing energy-efficient algorithms, promoting the use of Small Language Models (SLMs), and adopting renewable energy sources for AI infrastructure.

- Strengthen data security and ethical governance by developing robust data governance frameworks to ensure privacy, security, and ethical use of data, protecting against unauthorized access and breaches.

- Address gender bias by applying inclusive design practices, generating and using diverse datasets, and establishing gender-responsive policies, particularly in climate-related applications.

- Bridge the digital divide through equitable access by investing in infrastructure development and capacity-building initiatives in developing countries to promote equitable access to AI technology and resources.
- Invest in AI research, development, and innovation tailored to local contexts and priorities by:
  - Collaborating with local communities, governments, and organizations to identify specific climate challenges and priorities;
  - Supporting research initiatives that create AI solutions aligned with the unique environmental, social, and economic conditions of different regions;
  - Allocating funding for local AI innovation hubs to foster relevant and sustainable home-grown solutions;
  - Expanding access to AI resources for climate solutions by facilitating the availability of AI tools, data, and technical expertise to support effective, locally relevant AI-driven climate responses at local and national levels in regions facing significant climate challenges.
- Enable AI deployment for climate action in developing countries with a focus on SIDS and LDCs by facilitating relevant infrastructure and skills development, financial support and the establishment of governance and policy frameworks.
- Integrate local knowledge into AI-powered solutions:
  - Engaging local and indigenous communities to incorporate traditional knowledge into datasets and the development of AI models for local context-specific climate action. This is particularly relevant in sectors such as land management, disaster preparedness, and biodiversity conservation, where local insights complement AI-generated predictions.
- Ensure gender-responsive approaches in AI development by:
  - Investing in gender disaggregated data generation, collection and use to feed AI-powered climate solutions;
  - Involving women and gender experts throughout all phases of the design, development, and implementation of such solutions;
  - Promoting inclusivity by addressing the specific needs, contributions, and lived experiences of women and girls, particularly in contexts where socio-economic disparities limit access to climate technologies;
  - This is especially pertinent in climate adaptation policies, disaster resilience planning, and AI applications in sectors such as sustainable agriculture and water resource management, where gender-differentiated vulnerabilities and contributions must be considered.

- Establish robust monitoring and evaluation frameworks to assess the impact, effectiveness, and ethical implications of AI applications in achieving climate goals by:
  - Developing clear metrics and indicators to evaluate the impact of AI on environmental, social, and economic outcomes relating to climate goals;
  - Implementing regular monitoring processes to adjust AI interventions based on their effectiveness;
  - Establishing ethical review boards to oversee AI projects, ensuring adherence to ethical guidelines and preventing the exacerbation of inequalities or environmental challenges.

References

1. Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: an overview. Sustainability, 11, 189. https://doi.org/10.3390/su11010189

2. Abid, S. K., Sulaiman, N., Chan, S. W., Nazir, U., Abid, M., Han, H., Ariza-Montes, A., & Vega-Muñoz, A. (2021). Toward an integrated disaster management approach: How artificial intelligence can boost disaster management. *Sustainability, 13*(22), 12560. https://doi.org/10.3390/su132212560

3. Accarino, G., Chiarelli, M., Fiore, S., Federico, I., Causio, S., Coppini, G., & Aloisio, G. (2021). A multi-model architecture based on Long Short-Term Memory neural networks for multi-step sea level forecasting. Future Generation Computer Systems, 124, 1-9. https://doi.org/10.1016/j.future.2021.05.008

4. Adebisi, N., Balogun, A.-L., Min, T. H., & Tella, A. (2021). Advances in estimating Sea Level Rise: A review of tide gauge, satellite altimetry, and spatial data science approaches. Ocean & Coastal Management, 208, https://doi.org/10.1016/j.ocecoaman.2021.105632

5. Adikari, K. E., Shrestha, S., Ratnayake, D. T., Budhathoki, A., Mohanasundaram, S., & Dailey, M. N. (2021). Evaluation of artificial intelligence models for flood and drought forecasting in arid and tropical regions. Environmental Modelling & Software, 144, 105136. https://doi.org/10.1016/j.envsoft.2021.105136

6. Aditama, G. K. L., Wijaya, S. K., Siagian, S. B., & Nugroho, W. (2023). Developing an IoT-Based Digital Climate Station at Dramaga Climate Observational Station. IOP Conference Series: Earth and Environmental Science, 1167(1), 012033. https://doi.org/10.1088/1755-1315/1167/1/012033

7. Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: status quo, challenges and opportunities. Journal of Cleaner Production, 289, 125834. https://doi.org/10.1016/j.jclepro.2021.125834

8. Ahmed, A. A., Nazzal, M. A., Darras, B. M., & Deiab, I. M. (2023). Global warming potential, water footprint, and energy demand of shared autonomous electric vehicles incorporating circular economy practices. *Sustainable Production and Consumption, 36*, 449–462. https://www.sciencedirect.com/science/article/abs/pii/S2352550923000246

9. Ahmed, A. N., Othman, F. B., Afan, H. A., Ibrahim, R. K., Fai, C. M., Hossain, M. S., Ehteram, M., & Elshafie, A. (2019). Machine Learning Methods for Better Water Quality Prediction. Journal of Hydrology, 578, Article ID: 124084 https://www.sciencedirect.com/science/article/abs/pii/S0022169419308194

10. Ahmed, N., Wahed, M., & Thompson, N. C. (2023). The Growing Influence of Industry in AI Research. https://www.science.org/doi/10.1126/science.ade2420

11. Akanbi, A. K., & Masinde, M. (2018). Towards the development of a rule-based drought early warning expert systems using indigenous knowledge. In 2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD). https://doi.org/10.1109/ICABCD.2018.8465465

12. Al-Othman, A., Tawalbeh, M., Martis, R., Dhou, S., Orhan, M., Qasim, M., & Ghani Olabi, A. (2022). Artificial intelligence and numerical models in hybrid renewable energy systems with fuel cells: advances and prospects. Energy Conversion and Management, 253, 115154. https://doi.org/10.1016/j.enconman.2021.115154

13. Alam, E., Sufian, A., Das, A. K., Bhattacharya, A., Ali, M. F., & Rahman, M. M. H. (2021). Leveraging Deep Learning for Computer Vision: A Review. 2021 22nd International Arab Conference on Information Technology (ACIT), Muscat, Oman, 1-8. https://doi.org/10.1109/ACIT53391.2021.9677361

14. Alassery, F., Alzahrani, A., Khan, A. I., Irshad, K., & Islam, S. (2022). An artificial intelligence-based solar radiation prophesy model for green energy utilization in energy management system. Sustainable Energy Technologies and Assessments, 52, 102060. https://doi.org/10.1016/j.seta.2022.102060

15. Albahri, A. S., Khaleel, Y. L., Habeeb, M. A., Ismael, R. D., Hameed, Q. A., Deveci, M., Homod, R. Z., Albahri, O. S., Alamoodi, A. H., & Alzubaidi, L. (2024). A systematic review of trustworthy artificial intelligence applications in natural disasters. *Computers and Electrical Engineering, 118*(Part B), 109409. https://doi.org/10.1016/j.compeleceng.2024.109409

16. AlDousari, A. E., Kafy, A. A., Saha, M., Fattah, M. A., Almulhim, A. I., Faisal, A.-A., Al Rakib, A., Jahir, D. M. A., Rahaman, Z. A., Bakshi, A., Shahrier, M., & Rahman, M. M. (2022). Modelling the impacts of land use/land cover changing pattern on urban thermal characteristics in Kuwait. Sustainable Cities and Society, 86, 104107. https://doi.org/10.1016/j.scs.2022.104107

17. Alemany, S., Beltran, J., Perez, A., & Ganzfried, S. (2019). Predicting hurricane trajectories using a recurrent neural network. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 33, pp. 468–475). https://ojs.aaai.org/index.php/AAAI/article/view/3819

18. Alexandru, M., Dragoș, C., & Bălă-Constantin, Z. (2022). Digital Twin for automated guided vehicles fleet management. Procedia Computer Science, 199, 1363–1369. https://doi.org/10.1016/j.procs.2022.01.172

19. Amiri, Z., Heidari, A., & Navimipour, N. J. (2024). Comprehensive survey of artificial intelligence techniques and strategies for climate change mitigation. *Energy, 308*, 132827. https://doi.org/10.1016/j.energy.2024.132827

20. Ampatzidis, Y., Partel, V., & Costa, L. (2020). Agroview: cloud-based application to process, analyze and visualize UAV-collected data for precision agriculture applications utilizing artificial intelligence. Computers and Electronics in Agriculture, 174, 105457. https://doi.org/10.1016/j.compag.2020.105457

21. Amprius (2024), How Drones are Used in the Aftermath of Disasters, https://amprius.com/drones-disasters/#:~:text=Drones make it easier to, and plan their actions accordingly

22. An, J., Ding, W., & Lin, C. (2023). ChatGPT: Tackle the growing carbon footprint of generative AI. *Nature*, 615, 586. https://doi.org/10.1038/d41586-023-00843-2

23. Anbarasan, M., et al. (2020). Detection of flood disaster system based on IoT, big data, and convolutional deep neural network. Computer Communications, 150, 150-157. https://doi.org/10.1016/j.comcom.2019.11.022

24. Ansari, M. F., Dash, B., Sharma, P., & Yathiraju, N. (2022). The impact and limitations of artificial intelligence in cybersecurity: A literature review. International Journal of Advanced Research in Computer and Communication Engineering. Available at SSRN: https://ssrn.com/abstract=4323317

25. Anshuman, J., & Mallick, B. (Eds.). (2023). *Innovative Agriculture: Strategies and Concepts in Extension* (1st ed.). AkiNik Publications. https://www.akinik.com/products/2547/innovative-agriculture-strategies-and-concepts-in-extension

26. Anthony, L. F. W., Kanding, B., & Selvan, R. (2020). Carbontracker: Tracking and Predicting the Carbon Footprint of Training Deep Learning Models. https://arxiv.org/pdf/2007.03051 Appana, S., Gogia, A., Potineni, A., Ravipati, Y., & Shyamsunder, N. (2022). Edge technology based artificial intelligence system for ocean patrol and surveillance. International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), 8(4), 182–192. https://doi.org/10.32628/CSEIT22845

27. Arachie, C., et al. (2020). Unsupervised detection of sub-events in large scale disasters. Proceedings of the AAAI Conference on Artificial Intelligence, 34(01), 354-361. https://doi.org/10.1609/aaai.v34i01.5370

28. Arumugam, K., Swathi, Y., Sanchez, D. T., Mustafa, M., Phoemchalard, C., Phasinam, K., & Okoronkwo, E. (2022). Towards applicability of machine learning techniques in agriculture and energy sector. Materials Today: Proceedings, 51, 2260–2263. https://doi.org/10.1016/j.matpr.2021.11.394

29. Aschwanden, G., Wijnands, J. S., Thompson, J., Nice, K. A., Zhao, H. F., & Stevenson, M. (2021). Learning to walk: Modeling transportation mode choice distribution through neural networks. Environment and Planning B: Urban Analytics and City Science, 48(2), 186–199. https//doi.org/10.1177/2399808319862571

30. Asiri, S. A., Salilih, E. M., Alfawaz, K. M., Alogla, A. F., Abu-Hamdeh, N. H., & Nusier, O. K. (2022). Improve the performance of renewable energy conversion and storage via ANN in a system of solar water heater with variable speed photovoltaic circulating pump. International Journal of Energy Research. Advance online publication. https://doi.org/10.1002/er.8268

31. Avalon-Cullen, C., Caudill, C., Newlands, N.K., & Enenkel, M. (2023). Big Data, Small Island: Earth Observations for Improving Flood and Landslide Risk Assessment in Jamaica. Geosciences, 13(64). https://doi.org/10.3390/geosciences13030064

32. Azevedo, B. F., Rocha, A. M. A. C., & Pereira, A. I. (2024). Hybrid approaches to optimization and

33. machine learning methods: A systematic literature review. Machine Learning. https://doi.org/10.1007/s10994-023-06467-x

34. Bagstad, K. J., Reed, J. M., Semmens, D. J., Sherrouse, B. C., & Troy, A. (2016). Linking biophysical models and public preferences for ecosystem service assessments: a case study for the Southern Rocky Mountains. Regional Environmental Change, 16, 2005–2018. https://doi.org/10.1007/s10113-015-0756-7

35. Bahari, N. A. A. B. S., Ahmed, A. N., Chong, K. L. et al. Predicting Sea Level Rise Using Artificial Intelligence: A Review. Archives of Computational Methods in Engineering 30, 4045–4062 (2023). https://doi.org/10.1007/s11831-023-09934-9

36. Bakhmat, N. (2024). Artificial intelligence in higher education: Possibilities of using. Pedagogical Education: Theory and Practice, 35(2-2023), 161-173. https://doi.org/10.32626/2309-9763.2023-161-173

37. Bakker, K. (2022). Smart oceans: Artificial intelligence and marine protected area governance. Earth System Governance, 13, 100141. https://doi.org/10.1016/j.esg.2022.100141

38. Balehegn, M., Balehey, S., Fu, C., & Makoto, N. (2019). Indigenous weather and climate forecasting knowledge among Afar pastoralists of northeastern Ethiopia: Role in adaptation to weather and climate variability. Pastoralism, 9(8). https://doi.org/10.1186/s13570-019-0143-y

39. Balogun, A. L., & Adebisi, N. (2021). Sea level prediction using ARIMA, SVR and LSTM neural network: assessing the impact of ensemble Ocean-Atmospheric processes on models' accuracy. Geomatics, Natural Hazards and Risk, 12(1), 653–674. https://doi.org/10.1080/19475705.2021.1887372

40. Balogun, A. L., Marks, D., Sharma, R., Shekhar, H., Balmes, C., Maheng, D., Arshad, A., & Salehi, P. (2020). Assessing the potentials of digitalization as a tool for climate change adaptation and sustainable development in urban centres. Sustainable Cities and Society, 53, 101888. https://doi.org/10.1016/j.scs.2019.101888

41. Banerjee, C., Nguyen, K., Fookes, C., & Karniadakis, G. (2024). Physics-Informed Computer Vision: A Review and Perspectives. arXiv preprint arXiv:2305.18035. https://doi.org/10.48550/arXiv.2305.18035

42. Banu, J. F., Mahajan, R. A., Sakthi, U., Nassa, V. K., Lakshmi, D., & Nadanakumar, V. (2022). Artificial intelligence with attention-based BiLSTM for energy storage system in hybrid renewable energy sources. Sustainable Energy Technologies and Assessments, 52, 102334. https://doi.org/10.1016/j.seta.2022.102334

43. Barnett, J. (2024). NASA, IBM Research to Release New AI Model for Weather, Climate, https://science.nasa.gov/open-science/ai-model-weather-climate/

44. Bartmann, M. (2022). The Ethics of AI-Powered Climate Nudging – How Much AI Should We Use to Save the Planet? *Sustainability, 14*(9), 5153. https://doi.org/10.3390/su14095153

45. Baysan, S., Kabadurmus, O., Cevikcan, E., Satoglu, S. I., & Durmusoglu, M. B. (2019). A simulation-based methodology for the analysis of the effect of lean tools on energy efficiency: an application in the power distribution industry. Journal of Cleaner Production, 211, 895–908. https://doi.org/10.1016/j.jclepro.2018.11.217

46. Benefo, E., Tingler, A., White, M., Cover, J., Torres, L., Broussard, C., Shirmohammadi, A., Pradhan, A., & Patra, D. (2022). Ethical, legal, social, and economic (ELSE) implications of artificial intelligence at a global level: A scientometrics approach. AI and Ethics, 2(4), 667–682. https://doi.org/10.1007/s43681-021-00124-6

47. Bentley, S. V., Naughtin, C. K., McGrath, M. J., Irons, J. L., & Cooper, P. S. (2024). The digital divide in action: How experiences of digital technology shape future relationships with artificial intelligence. AI and Ethics. https://doi.org/10.1007/s43681-024-00452-3

48. Besiroglu, T., Bergerson, S. A., Michael, A., Heim, L., Luo, X., & Thompson, N. (2024). The Compute Divide in Machine Learning: A Threat to Academic Contribution and Scrutiny? https://doi.org/10.48550/arXiv.2401.02452

49. Bibri, S. E. (2023). The Metaverse as a Virtual Model of Platform Urbanism: Its Converging AIoT, XReality, Neurotech, and Nanobiotech and Their Applications, Challenges, and Risks. Smart Cities, 6(3), 1345–1384. https://www.mdpi.com/2624-6511/6/3/65

50. Bibri, S. E. (2024). Artificial Intelligence and Artificial Intelligence of Things Solutions for Smarter Eco-Cities: Advancing Environmental Sustainability and Climate Change Strategies. In *Artificial Intelligence of Things for Smarter Eco-Cities: Pioneering the Environmental Synergies of Urban Brain, Digital Twin, Metabolic Circularity, and Platform*. Routledge Taylor & Francis Group. https://doi.org/10.1201/9781003536420

51. Bibri, S., Krogstie, J., Kaboli, A., & Alahi, A. (2023). Smarter Eco-Cities and their Leading-edge Artificial Intelligence of Things Solutions for Environmental Sustainability: A Comprehensive Systemic Review. Environmental Science and Ecotechnology, Vol.19, http://dx.doi.org/10.1016/j.ese.2023.100330

52. Bibri S.E., Huang J., Krogstie J. (2024a) Artificial Intelligence of Things for Synergizing Smarter Eco-City Brain, Metabolism, and Platform: Pioneering Data-driven Environmental Governance, Sustainable Cities and Society, 105516. https://doi.org/10.1016/j.scs.2024.105516

53. Bibri, S. E., Huang, J., Jagatheesaperumal, S. K., & Krogstie, J. (2024b). The synergistic interplay of artificial intelligence and digital twin in environmentally planning sustainable smart cities: A comprehensive systematic review. Environmental Science and Ecotechnology, 20, 100433. https://doi.org/10.1016/j.ese.2024.100433

54. Bindajam, A. A., Mallick, J., Talukdar, S., Islam, A. R. M. T., & Alqadhi, S. (2021). Integration of artificial intelligence-based LULC mapping and prediction for estimating ecosystem services for urban sustainability: past to future perspective. Arabian Journal of Geosciences, 14, 1-23. https://link.springer.com/article/10.1007/s12517-021-08251-4

55. Birhane, A. (2020). Algorithmic Colonization of Africa. *SCRIPT-Ed, 17*(2), 389–409. https://doi.org/10.2966/scrip.170220.389

56. Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M. S., Bohg, J., Bosselut, A., Brunskill, E., & et al. (2022). On the opportunities and risks of foundation models. https://doi.org/10.48550/arXiv.2108.07258

57. Bonan, G. B., & Doney, S. C. (2018). Climate, ecosystems, and planetary futures: The challenge to predict life in Earth system models. Science, 359, eaam8328. https://doi.org/10.1126/science.aam8328

58. Booth, M. (2018). Climate change and the neglected tropical diseases. In Rollinson, D., & Stothard, J. R. (Eds.), Advances in Parasitology, 100, 39–126. https://pubmed.ncbi.nlm.nih.gov/29753342/

59. Bowes, B. D., Sadler, J. M., Morsy, M. M., Behl, M., & Goodall, J. L. (2019). Forecasting Groundwater Table in a Flood Prone Coastal City with Long Short-term Memory and Recurrent Neural Networks. 11(5), 1098. https://doi.org/10.3390/w11051098

60. Boza, P., & Evgeniou, T. (2021). Artificial intelligence to support the integration of variable renewable energy sources to the power system. Applied Energy, 290, 116754. https://doi.org/10.1016/j.apenergy.2021.116754

61. Brevini, B. (2020). Black boxes, not green: mythologizing artificial intelligence and omitting the environment. Big Data & Society, 7(2), 2053951720935141. https://journals.sagepub.com/doi/full/10.1177/2053951720935141

62. Brock, A., Donahue, J., & Simonyan, K. (2018). Large scale GAN training for high fidelity natural image synthesis. In International conference on learning representations. https://arxiv.org/abs/1809.11096

63. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., ... Amodei, D. (2020). Language models are few-shot learners. Proceedings of NeurIPS, 1877–1901. https://arxiv.org/abs/2005.14165

64. Butler, E. & Lupton, D. (2024) Generative AI Technologies Applied to Ecosystems and the Natural Environment: A Scoping Review, ADM+S Working Paper Series 2024 (10), ARC Centre of Excellence for Automated Decision- Making and Society, DOI: 10.60836/k7fv-7991

65. Castelli, M., & Manzoni, L. (2022). Generative models in artificial intelligence and their applications. Applied Sciences, 12(9), 4127. https://www.researchgate.net/publication/360154609_Special_Issue_Generative_Models_in_Artificial_Intelligence_and_Their_Applications

66. Ceccaroni, L., Bibby, J., Roger, E., Flemons, P., Michael, K., Fagan, L., & Oliver, J. L. (2019). Opportunities and risks for citizen science in the age of artificial intelligence. Citizen Science: Theory and Practice, 4(1), 29. https://doi.org/10.5334/cstp.241

67. Celik, I. (2023). Exploring the determinants of artificial intelligence (AI) literacy: Digital divide, computational thinking, cognitive absorption. Telematics and Informatics, 83, 102026. https://doi.org/10.1016/j.tele.2023.102026

68. Chakravarty, P. (2023a). Climate communication channels, AI, and indigenous wisdom: A triad approach for adaptation in the era of global boiling. September 2023. https://doi.org/10.25810/wq39-sp67

69. Chakravarty, P. (2023b). Climate communication channels: An innovative approach integrating AI/ML and indigenous knowledge systems for extreme weather events prediction and mitigation in coastal regions. National Symposium on Tropical Meteorology (TROPMET 2023). https://scholar.colorado.edu/concern/presentations/m039k6299

70. Chen, L., Chen, Z., Zhang, Y., et al. (2023). Artificial intelligence-based solutions for climate change: a review. Environ Chem Lett. https://doi.org/10.1007/s10311-023-01617-y

71. Chen, L., Msigwa, G., Yang, M., Osman, A. I., Fawzy, S., Rooney, D. W., & Yap, P.-S. (2022b). Strategies to achieve a carbon neutral society: a review. Environmental Chemistry Letters, 20, 2277–2310. https://doi.org/10.1007/s10311-022-01435-8

72. Chen, C., Nguyen, D. T., Lee, S. J., Baker, N. A., Karakoti, A. S., Lauw, L., Owen, C., Mueller, K. T., Bilodeau, B. A., Murugesan, V., & Troyer, M. (2024). Accelerating computational materials discovery with artificial intelligence and cloud high-performance computing: From large-scale screening to experimental validation. *arXiv*. https://doi.org/10.48550/arXiv.2401.04070-

73. Chen, Z., Zhu, Z., Jiang, H., & Sun, S. (2020b). Estimating daily reference evapotranspiration based on limited meteorological data using deep learning and classical machine learning methods. Journal of Hydrology, 591, 125286. https://doi.org/10.1016/j.jhydrol.2020.125286

74. Cheng, X., Zhang, F., Chen, X., & Wang, J. (2023). Application of Artificial Intelligence in the study of fishing vessel behavior. Fishes, 8(10), 516. https://doi.org/10.3390/fishes8100516

75. Cheong, E. (2022). Community Awareness Education in the Era of Artificial Intelligence: The Third Neighbor. Korean-German Society for Educational Science, 27(3), 97-116. https://doi.org/10.26894/kdge.2022.27.3.97

76. Christin, S., Hervet, É., & Lecomte, N. (2019). Applications for deep learning in ecology. Methods in Ecology and Evolution, 10(10), 1632–1644.

77. Chu-Ke, C., & Dong, Y. (2024). Misinformation and literacies in the era of generative artificial intelligence: A brief overview and a call for future research. *Emerging Media, 2*(1), 70–85. https://doi.org/10.1177/27523543241240285

78. Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: progress, trends, and directions. Sustainability, 12(2), 492. https://doi.org/10.3390/su12020492

79. Cipollini, P., Calafat, F. M., Jevrejeva, S., Melet, A., & Prandi, P. (2017). Monitoring sea level in the coastal zone with satellite altimetry and tide gauges. Surveys in Geophysics, 38(1), 33–57. https://doi.org/10.1007/s10712-016-9392-0

80. Climate Change AI. (2023). EMPIRIC_AI: AI-enabled ensemble projections of cyclone risk for health infrastructure in Pacific Island Countries and Territories. Retrieved from https://www.climatechange.ai/innovation_grants/2023/2

81. Climind (2024), AI Enabler for Climate Solutions, https://www.climind.co/home/

82. Crane-Droesch, A. (2018). Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. Environmental Research Letters, 13(11), Article 114003. https://doi.org/10.1088/1748-9326/aae159

83. Crumpler, K., Gagliardi, G., Meybeck, A., Federici, S., Lieuw, T., Bloise, M., et al. (2020). Regional analysis of the nationally determined contributions in the Caribbean – gaps and opportunities in the agriculture and land use sectors. Environment and Natural Resources Management Working Papers No. 80. FAO, Rome. https://www.researchgate.net/publication/346732494_REGIONAL_ANALYSIS_OF_THE_NATIONALLY_DETERMINED_CONTRIBUTIONS_IN_THE_CARIBBEAN_Gaps_and_opportunities_in_the_agriculture_and_land_use_sectors

84. CTCN. (2023). Enabling systems transformations through digitalization in climate technology and policy. https://www.ctcn.org/sites/default/files/documents/231012%20CTCN%20MB%20digitalization.pdf

85. CTCN & NIGT. (2024). Integrating AI into Climate Action: Enhancing Climate Technology Capacity in Asia-Pacific Countries. https://nigt.re.kr/eng/others.do?mode=view&articleNo=4117&title=Integrating+AI+into+Climate+Action%3A+Enhancing+Climate+Technology+Capacity+in+Asia-Pacific+Countries

86. Cutler, D. R., Edwards, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). Random forests for classification in ecology. Ecology, 88(11), 2783-2792. https://esajournals.onlinelibrary.wiley.com/doi/abs/10.1890/07-0539.1

87. Daam, M. A., Chelinho, S., Niemeyer, J. C., Owojori, O. J., De Silva, P. M. C., Sousa, J. P., et al. (2019). Environmental risk assessment of pesticides in tropical terrestrial ecosystems: test procedures, current status and future perspectives. Ecotoxicology and Environmental Safety, 181, 534–547. https://doi.org/10.1016/j.ecoenv.2019.06.038

88. Death, R. G. (2015). An environmental crisis: Science has failed; let us send in the machines. Wiley Interdisciplinary Reviews: Water, 2(6), 595-600. https://wires.onlinelibrary.wiley.com/doi/10.1002/wat2.1102

89. Debus, A., Beauchamp, E., Acworth, J., Ewolo, A., Kamga, J., Verhegghen, A., Zébazé, C., & Lines, E. R. (2024). A labelled dataset to classify direct deforestation drivers from Earth Observation imagery in Cameroon. Scientific Data, 11, 564. https://doi.org/10.1038/s41597-024-03384-z

90. Deeb, D. J., & Garel-Frantzen, A. (2023). The generative AI revolution: Key impacts to the environmental and energy sectors. *The National Law Review*. https://www.natlawreview.com/article/generative-ai-revolution-key-impacts-to-environmental-energy-sectors

91. Demolli, H., Dokuz, A. S., Ecemis, A., & Gokcek, M. (2021). Location-based optimal sizing of hybrid renewable energy systems using deterministic and heuristic algorithms. International Journal of Energy Research, 45(11), 16155-16175. https://doi.org/10.1002/er.6849

92. Denning, D. E. (2019). Is quantum computing a cybersecurity threat? American Scientist, 107(2), 83–85. https://www.jstor.org/stable/26586148

93. Dheeraj, A., Nigam, S., Begam, S., Naha, S., Jayachitra Devi, S., Chaurasia, H. S., Kumar, D., Ritika, Soam, S. K., Srinivasa Rao, N., Alka, A., Sreekanth Kumar, V. V., & Mukhopadhyay, S. C. (2020). Role of artificial intelligence (AI) and internet of things (IoT) in mitigating climate change. In C. Srinivasarao et al. (Eds.), Climate change and Indian agriculture: Challenges and adaptation strategies (pp. 325–358). ICAR-National Academy of Agricultural Research Management, Hyderabad. https://www.researchgate.net/publication/366953219_Role_of_Artificial_Intelligence_AI_and_Internet_of_Things_IoT_in_Mitigating_Climate_Change-1

94. Dhunnoo, Y., Carter, A., O'Hare, D., Birt, J., & Skitmore, M. (2023). Improving climate change awareness through immersive virtual reality communication: A case study. Sustainability, 15(17), 12969. https://doi.org/10.3390/su151712969

95. Ding, C., Ke, J., Levine, M., et al. (2024). Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. *Nature Communications, 15*, 5916. https://doi.org/10.1038/s41467-024-50088-4

96. Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. Journal of Business Research, 121, 283-314. https://doi.org/10.1016/j.jbusres.2020.08.019

97. Dolby, N. (2023, September 11). Artificial intelligence can make companies greener, but it also guzzles energy. *Wall Street Journal*. https://www.wsj.com/articles/artificial-intelligence-can-make-companies-greener-but-it-also-guzzles-energy-7c7b678

98. Dominguez, D., del Villar, L. D., Pantoja, O., & González-Rodríguez, M. (2022). Forecasting Amazon rainforest deforestation using a hybrid machine learning model. Sustainability, 14(691). https://doi.org/10.3390/su14020691

99. Domisch, S., Kakouei, K., Martínez-López, J., Bagstad, K.J., Magrach, A., Balbi, S., Villa, F., Funk, A., Hein, T., Borgwardt, F., Hermoso, V., Jähnig, S.C., Langhans, S.D. (2019). Social equity shapes zone-selection: Balancing aquatic biodiversity conservation and ecosystem services delivery in the transboundary Danube River Basin. Science of The Total Environment, 656, 797–807. https://doi.org/10.1016/j.scitotenv.2018.11.348

100. Donlon, C. J., Cullen, R., Giulicchi, L., Vuilleumier, P., Francis, C. R., Kuschnerus, M., Simpson, W., Bouridah, A., Caleno, M., Bertoni, R., Rancaño, J., Pourier, E., Hyslop, A., Mulcahy, J., Knockaert, R., Hunter, C., Webb, A., Fornari, M., Vaze, P., ... Tavernier, G. (2021). The Copernicus Sentinel-6 mission: Enhanced continuity of satellite sea level measurements from space. Remote Sensing of Environment, 258, 112395. https://doi.org/10.1016/j.rse.2021.112395

101. Doorn, N. (2021). Artificial intelligence in the water domain: Opportunities for responsible use. Science of The Total Environment, 755, 142561. https://doi.org/10.1016/j.scitotenv.2020.142561

102. Donti, P. L., & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources, 46*, 719-747. https://doi.org/10.1146/annurev-environ-020220-061831

103. Du, C., Zhang, L., Ma, X., Lou, X., Shan, Y., Li, H., & Zhou, R. (2021). A cotton high-efficiency water-fertilizer control system using wireless sensor network for precision agriculture. Processes, 9(1693). https://doi.org/10.3390/pr9101693

104. Duan, M., Xia, J., Yan, Z., Han, L., Zhang, L., Xia, H., & Yu, S. (2021). Reconstruction of the radar reflectivity of convective storms based on deep learning and Himawari-8 observations. Remote Sensing, 13(3330). https://doi.org/10.3390/rs13163330

105. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71. https://www.sciencedirect.com/science/article/abs/pii/S0268401219300581

106. Durodola, O. M., Makama, E. K., Odewumi, B. J., & Nathan, A. L. (2022). Development of an Environment and Climate Data Acquisition System (EC-DAQS) for Radio Propagation Studies. Journal of Engineering Research and Reports, 22(3), 11-18. https://doi.org/10.9734/jerr/2022/v22i317526

107. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Medaglia, R., Le Meunier-FitzHugh, K., Le Meunier-FitzHugh, L. C., Misra, S., Mogaji, E., Sharma, S. K., Singh, J. B., Raghavan, V., Raman, R., Rana, N. P., Samothrakis, S., Spencer, J., Tamilmani, K., Tubadji, A., Walton, P., & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

108. El Abbadi, N., & El Youbi, M. S. (2023). Towards the use of artificial intelligence for prediction of renewable energy production. International Journal on Technical and Physical Problems of Engineering, 15(3), 143–148. https://www.iotpe.tabaelm.com/IJTPE/IJTPE-2023/IJTPE-Issue56-Vol15-No3-Sep2023/18-IJTPE-Issue56-Vol15-No3-Sep2023-pp143-148.pdf

109. Elahi, E., Weijun, C., Zhang, H., & Abid, M. (2019). Use of artificial neural networks to rescue agrochemical-based health hazards: a resource optimisation method for cleaner crop production. Journal of Cleaner Production, 238, 117900. https://doi.org/10.1016/j.jclepro.2019.117900

110. El Himer, S., Ouaissa, M., Ouaissa, M., Boulouard, Z. (2022). Artificial Intelligence of Things (AIoT) for Renewable Energies Systems. In: El Himer, S., Ouaissa, M., Emhemed, A. A. A., Ouaissa, M., Boulouard, Z. (Eds.), Artificial Intelligence of Things for Smart Green Energy Management. Studies in Systems, Decision and Control, vol 446. Springer, Cham. https://doi.org/10.1007/978-3-031-04851-7_1

111. Elliott, S. (2024), AI may hold a key to the preservation of the Amazon rainforest, https://news.microsoft.com/source/latam/features/ai/amazon-ai-rainforest-deforestation/?lang=en

112. Emaminejad, N., & Akhavian, R. (2022). Trustworthy AI and robotics: implications for the AEC industry. Automation in Construction, 139, 104298. https://doi.org/10.1016/j.autcon.2022.104298

113. Eremin, N. A., & Selenginsky, D. A. (2023). On the possibilities of applying artificial intelligence methods in solving oil and gas problems. *Izvestiya Tula State University. Earth Sciences*, (1), 201–210. https://www.researchgate.net/publication/369707693_On_the_possibilities_of_applying_artificial_intelligence_methods_in_solving_oil_and_gas_problems

114. Estier, M., Cleeland, B., & Stauffer, M. (2024) Safe and beneficial artificial intelligence for Small-Island Developing States, https://drive.google.com/file/d/1tdsZcdrgQ-oQV7ydcRqXpTIGa-5TuL4m/view?usp=sharing

115. Etmina, A., Pour-Aboughadareh, A., Mohammadi, R., Shooshtari, L., Yousefiazarkhanian, M., & Moradkhani, H. (2019). Determining the best drought tolerance indices using artificial neural network (ANN): Insight into the application of intelligent agriculture in agronomy and plant breeding. Cereal Research Communications, 47(1), 170–181. https://link.springer.com/article/10.1556/0806.46.2018.057

116. European Commission. (2021). Proposal for a Regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts. EUR-Lex. Retrieved July 9, 2024, from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206

117. European Commission. (2023). Regulation on deforestation-free products. EU rules to guarantee that the products EU citizens consume do not contribute to deforestation or forest degradation worldwide. Retrieved August 13, 2024, from https://environment.ec.europa.eu/topics/forests/deforestation/regulation-deforestation-free-products_en

118. European Union Artificial Intelligence Act. (2024). High-Level Summary of the AI Act. Retrieved May 6, 2024, from https://artificialintelligenceact.eu/high-level-summary/

119. FAIR Forward. (2023). High Carbon Stock Approach: Mapping Forests to Combat Climate Change and Protect Livelihoods in Indonesia. Retrieved from https://www.bmz-digital.global/en/high-carbon-stock-approach-mapping-forests-to-combat-climate-change-and-protect-livelihoods-in-indonesia/

120. Farghali, M., Osman, A. I., Mohamed, I. M. A., Chen, Z., Chen, L., Ihara, I., Yap, P.-S., & Rooney, D. W. (2023). Strategies to save energy in the context of the energy crisis: a review. Environmental Chemistry Letters. https://doi.org/10.1007/s10311-023-01591-5

121. Farh, H. M. H., Al-Shamma'a, A. A., Al-Shaalan, A. M., Alkuhayli, A., Noman, A. M., & Kandil, T. (2022). Technical and economic evaluation for off-grid hybrid renewable energy system using novel Bonobo optimizer. Sustainability, 14(3), 1533. https://doi.org/10.3390/su14031533

122. Farzaneh, H., Malehmirchegini, L., Bejan, A., Afolabi, T., Mulumba, A., & Daka, P. P. (2021). Artificial Intelligence evolution in smart buildings for energy efficiency. Applied Sciences, 11, 763. https://doi.org/10.3390/app11020763

123. Fatemidokht, H., Rafsanjani, M. K., Gupta, B. B., & Hsu, C. H. (2021). Efficient and secure routing protocol based on artificial intelligence algorithms with UAV-assisted for vehicular ad hoc networks in intelligent transportation systems. IEEE Transactions on Intelligent Transportation Systems, 22, 4757–4769. https://doi.org/10.1109/TITS.2020.3041746

124. Filho, W. L., Ha'apio, M. O., Lütz, J. M., & Li, C. (2020). "Climate change adaptation as a development challenge to small Island states: A case study from the Solomon Islands." Environmental Science & Policy, 107, 179–187. https://scispace.com/pdf/climate-change-adaptation-as-a-development-challenge-to-1baflebdd8.pdf

125. Franzen, M., Kloetzer, L., Ponti, M., Trojan, J., & Vicens, J. (2021). Machine learning in citizen science: Promises and implications. In Vohland, K., et al. (Eds.), The Science of Citizen Science. Springer, Cham. https://doi.org/10.1007/978-3-030-58278-4_10

126. Fritz, S., See, L., Carlson, T., Haklay, M. (M.), Oliver, J. L., Fraisl, D., Mondardini, R., Brocklehurst, M., Shanley, L. A., Schade, S., Wehn, U., Abrate, T., Anstee, J., Arnold, S., Billot, M., Campbell, J., Espey, J., Gold, M., Hager, G., He, S., Hepburn, L., Hsu, A., Long, D., Masó, J., ... West, S. (2019). Citizen science and the United Nations Sustainable Development Goals. Nature Sustainability, 2, 922–930. https://doi.org/10.1038/s41893-019-0390-3

127. Fuhr, H., Hickmann, T., & Kern, K. (2018). The role of cities in multi-level climate governance: Local climate policies and the 1.5°C target. Current Opinion in Environmental Sustainability, 30(1), 1–6. https://www.sciencedirect.com/science/article/abs/pii/S1877343517300738

128. Galán Hernández, J. J., Carrasco González, R. A., & Marín Díaz, G. (2024). The growing scientific interest in artificial intelligence for addressing climate change: A bibliometric analysis. In D. B. Ibáñez, L. M. Castro, A. Espinosa, I. Puentes-Rivera, & P. C. López-López (Eds.), Communication and Applied Technologies. ICOMTA 2023. Smart Innovation, Systems and Technologies (Vol. 375). Springer, Singapore. https://doi.org/10.1007/978-981-99-7210-4_13

129. Galaz, V., Metzler, H., Daume, S., Olsson, A., Lindström, B., & Marklund, A. (2023b). AI could create a perfect storm of climate misinformation. *arXiv*. https://doi.org/10.48550/arXiv.2306.12807

130. Gaur, L., Afaq, A., Arora, G. K., & Khan, N. (2023). Artificial intelligence for carbon emissions using system of systems theory. *Ecological Informatics, 76*, 102165. https://doi.org/10.1016/j.ecoinf.2023.102165

131. Gazzea, M., Miraki, A., Alisan, O., & et al. (2023). Traffic monitoring system design considering multi-hazard disaster risks. *Scientific Reports, 13*, 4883. https://doi.org/10.1038/s41598-023-32086-6

132. Ghaffarian, S., Taghikhah, F. R., & Maier, H. R. (2023). Explainable artificial intelligence in disaster risk management: Achievements and prospective futures. International Journal of Disaster Risk Reduction, 98, 104123. https://doi.org/10.1016/j.ijdrr.2023.104123

133. Gimpel, L. (2024). Toward Open-Source AI Systems as Digital Public Goods: Definitions, Hopes, and Challenges. In: *New Frontiers in Science in the Era of AI*. https://doi.org/10.1007/978-3-031-61187-2

134. Goldblum, M., Tsipras, D., Xie, C., Chen, X., Schwarzschild, A., Song, D., Madry, A., Li, B., & Goldstein, T. (2022). Dataset security for machine learning: Data poisoning, backdoor attacks, and defenses. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(2), 1563–1580. https://arxiv.org/abs/2012.10544

135. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, 63(11), 139-144. https://doi.org/10.1145/3422622

136. Gooding, M. (2024). Microsoft and G42 to build geothermal-powered data center in Kenya. Data Center Dynamics. Retrieved from https://www.datacenterdynamics.com/en/news/microsoft-and-g42-to-build-geothermal-powered-data-center-in-kenya/

137. Gopalan, S. S., Raza, A., & Almobaideen, W. (2020). IoT security in healthcare using AI: A survey. 2020 International Conference on Communications, Signal Processing, and their Applications (ICCSPA), Sharjah, United Arab Emirates, 1-6. https://doi.org/10.1109/ICCSPA49915.2021.9385711

138. Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. International Journal of Management Education, 18, Article 100330. https://doi.org/10.1016/j.ijme.2019.100330

139. Grames, E., & Forister, M. L. (2024). Sparse modeling for climate variable selection across trophic levels. Ecology, 105(3), e4231. https://doi.org/10.1002/ecy.4231

140. Guiqiang, L., Jin, Y., Akram, M. W., Chen, X., & Ji, J. (2018). Application of bio-inspired algorithms in maximum power point tracking for PV systems under partial shading conditions – A review. Renewable and Sustainable Energy Reviews, 81, 840–873. https://doi.org/10.1016/j.rser.2017.08.034

141. Gunasekar, S., Zhang, Y., Aneja, J., et al. (2023). Textbooks Are All You Need. https://doi.org/10.48550/arXiv.2306.11644

142. Guo, W., Qureshi, N. M. F., Jarwar, M. A., Kim, J., & Shin, D. R. (2023). AI-oriented smart power system transient stability: the rationality, applications, challenges and future opportunities. Sustainable Energy Technologies and Assessments, 56, 102990. https://doi.org/10.1016/j.seta.2022.102990

143. Gupta, J., & van der Heijden, J. (2019). Introduction: The co-production of knowledge and governance in collaborative approaches to environmental management. Current Opinion in Environmental Sustainability, 39, 45–51

144. Gupta, M. (2021). The role of artificial intelligence in adopting green HRM practices. In Reinventing manufacturing and business processes through artificial intelligence (1st ed., p. 18). CRC Press. https://www.taylorfrancis.com/chapters/edit/10.1201/9781003145011-1/role-artificial-intelligence-adopting-green-hrm-practices-minisha-gupta

145. Gupta, S., & Li, L. (2022). The potential of machine learning for enhancing CO2 sequestration, storage, transportation, and utilization-based processes: A brief perspective. JOM, 74, 414–428. https://doi.org/10.1007/s11837-021-05079-x

146. Gupta, S., Modgil, S., Kumar, A., Sivarajah, U., & Irani, Z. (2022). Artificial intelligence and cloud-based collaborative platforms for managing disaster, extreme weather and emergency operations. International Journal of Production Economics, 254, 108642. https://doi.org/10.1016/j.ijpe.2022.108642

147. Guzder-Williams, B., Mackres, E., Angel, S., Blei, A., & Lamson-Hall, P. (2023). Intra-urban land use maps for a global sample of cities from Sentinel-2 satellite imagery and computer vision. Computers, Environment and Urban Systems, 100, Article 101917. https://doi.org/10.1016/j.compenvurbsys.2022.101917

148. Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial Intelligence Trust, Risk, and Security Management (AI TRiSM): Frameworks, applications, challenges, and future research directions. Expert Systems with Applications, 240, 122442. https://doi.org/10.1016/j.eswa.2023.122442

149. Hannan, M. A., Al-Shetwi, A. Q., Ker, P. J., Begum, R. A., Mansor, M., Rahman, S. A., Dong, Z. Y., Tiong, S. K., Mahlia, T. M. I., & Muttaqi, K. M. (2021). Impact of renewable energy utilization and artificial intelligence in achieving sustainable development goals. Energy Reports, 7, 5359–5373. https://doi.org/10.1016/j.egyr.2021.08.172

150. Haq, B., Jamshed, M. A., Ali, K., Kasi, B., Arshad, S., Kasi, M. K., Ali, I., Shabbir, A., Abbasi, Q. H., & Ur-Rehman, M. (2024). Tech-Driven Forest Conservation: Combating Deforestation With Internet of Things, Artificial Intelligence, and Remote Sensing. IEEE Internet of Things Journal. https://doi.org/10.1109/JIOT.2024.3378671

151. Harish, V., Sharma, R., Rana, G., & Nayyar, A. (2023). Artificial Intelligence in Sustainable Education: Benefits, Applications, Framework, and Potential Barriers. In The Role of Sustainability and Artificial Intelligence in Education Improvement (1st ed.). Chapman and Hall/CRC. https://doi.org/10.3390/su1404197

152. Havukainen, M., Mikkilä, M., & Kahiluoto, H. (2022). Global climate as a commons – Decision making on climate change in least developed countries. Environmental Science & Policy, 136, 761-771. https://doi.org/10.1016/j.envsci.2022.08.003

153. Helo, P., & Hao, Y. (2022). Artificial Intelligence in Operations Management and Supply Chain Management: An Exploratory Case Study. *Production Planning & Control, 33*(16), 1573–1590. https://www.researchgate.net/publication/350572588_Artificial_intelligence_in_operations_management_and_supply_chain_management_an_exploratory_case_study

154. Henderson, P., Hu, J., Romoff, J., Brunskill, E., Jurafsky, D., & Pineau, J. (2020). Towards the systematic reporting of the energy and carbon footprints of machine learning. Journal of Machine Learning Research, 21(1), 10039–10081. https://www.peterhenderson.co/publication/henderson-2020-climate/

155. Hirn, J., García, J. E., Montesinos-Navarro, A., Sánchez-Martin, R., Sanz, V., & Verdú, M. (2022). A deep generative artificial intelligence system to predict species coexistence patterns. Methods in Ecology and Evolution, 13, 1052–1061. https://doi.org/10.1111/2041-210X.13827

156. Hsu, Y.-C., Huang, T.-H. K., Verma, H., Mauri, A., Nourbakhsh, I., & Bozzon, A. (2022). Empowering local communities using artificial intelligence. Patterns, 3(3), 100449. https://doi.org/10.1016/j.patter.2022.100449

157. Huang, J. Bibri, S. E., & Keel, P: (2025), Generative Spatial Artificial Intelligence for Sustainable Smart Cities: A Pioneering Large Flow Foundation Model for Urban Digital Twin, International Journal of Urban Science https://pubmed.ncbi.nlm.nih.gov/39995465/.

158. Huynh-The, T., Pham, Q. V., Pham, X. Q., Nguyen, T. T., Han, Z., & Kim, D.-S. (2023). Artificial intelligence for the metaverse: A survey. Engineering Applications of Artificial Intelligence, 117, 105581. https://doi.org/10.48550/arXiv.2202.10336

159. Ibarreche, J., Aquino, R., Edwards, R. M., Rangel, V., Pérez, I., Martínez, M., Castellanos, E., Álvarez, E., Jimenez, S., Rentería, R., et al. (2020). Flash flood early warning system in Colima, Mexico. *Sensors, 20*(18), 5231. https://doi.org/10.3390/s20185231

160. IEA. (2024a). Executive summary, https://www.iea.org/reports/electricity-2024/executive-summary

161. IEA. (2024b). Global electricity demand set to rise strongly this year and next, reflecting its expanding role in energy systems around the world. https://www.iea.org/news/global-electricity-demand-set-to-rise-strongly-this-year-and-next-reflecting-its-expanding-role-in-energy-systems-around-the-world

162. Intergovernmental Panel on Climate Change (IPCC). (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (R. K. Pachauri & L. A. Meyer, Eds.). IPCC. https://www.ipcc.ch/report/ar5/syr/

163. Intergovernmental Panel on Climate Change (IPCC). (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, ... & B. Zhou, Eds.). Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/

164. International Conference on Learning Representations (ICLR). (2024). Why your work matters for climate in more ways than you think. https://iclr.cc/virtual/2024/invited-talk/21797

165. International Telecommunication Union (ITU). (2024a). Focus Group on AI for Natural Disaster Management. Retrieved July 18, 2024, from https://www.itu.int/en/ITU-T/focusgroups/ai4ndm/Pages/default.aspx

166. International Telecommunication Union (ITU). (2024b). Green Digital Action at COP28. Retrieved from https://www.itu.int/en/mediacentre/Pages/MA-2023-11-30-ITUs-green-digital-action-at-COP28.aspx

167. International Telecommunication Union (ITU). (2024c). *Session 368: Green Digital Action. Navigating the double-edged sword: ICT's and AI's Impact on Climate Change and Environmental Sustainability*. WSIS Forum 2024. Retrieved from https://www.itu.int/net4/wsis/forum/2024/Agenda/Session/368

168. Isabelle, D. A., & Westerlund, M. (2022). A Review and Categorization of Artificial Intelligence-Based Opportunities in Wildlife, Ocean and Land Conservation. Sustainability, 14, Article 1979. https://doi.org/10.3390/su14041979

169. Ishida, K., Tsujimoto, G., Ercan, A., Tu, T., Kiyama, M., & Amagasaki, M. (2020). Hourly-scale coastal sea level modelling in a changing climate using long short-term memory neural network. Science of The Total Environment, 720, 137613. https://doi.org/10.1016/j.scitotenv.2020.137613

170. ISO/IEC 22989:2022(E), Information technology – Artificial intelligence – Artificial intelligence concepts and terminology. https://www.iso.org/standard/74296.html

171. Jada, I., & Mayayise, T. O. (2024). The impact of artificial intelligence on organisational cyber security: An outcome of a systematic literature review. Data and Information Management, 8(2), 100063. https://doi.org/10.1016/j.dim.2023.100063

172. Jahanger, A., Ozturk, I., Chukwuma Onwe, J., Joseph, T. E., & Razib Hossain, M. (2023). Do technology and renewable energy contribute to energy efficiency and carbon neutrality? Evidence from top ten manufacturing countries. Sustainable Energy Technologies and Assessments, 56, 103084. https://doi.org/10.1016/j.seta.2023.103084

173. Jain, H., Dhupper, R., Shrivastava, A., & et al. (2023). AI-enabled strategies for climate change adaptation: Protecting communities, infrastructure, and businesses from the impacts of climate change. Computational Urban Science, 3(25). https://doi.org/10.1007/s43762-023-00100-2

174. Jain, H., Vikram, A., Mohana, A., Kashyap, A., & Jain, A. (2020). Weapon detection using artificial intelligence and deep learning for security applications. 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 193¬198. https://doi.org/10.1109/ICESC48915.2020.9155832

175. Jakubik, J., Roy, S., Phillips, C. E., Fraccaro, P., Godwin, D., Zadrozny, B., ... Ramachandran, R. (2023). Foundation Models for Generalist Geospatial Artificial Intelligence. arXiv:2310.18660 [cs.CV]. https://doi.org/10.48550/arXiv.2310.18660

176. Janowicz, K. (2023). Philosophical foundations of GeoAI: Exploring sustainability, diversity, and bias in GeoAI and spatial data science. In Handbook of Geospatial Artificial Intelligence (pp. 26–42). CRC Press. https://www.taylorfrancis.com/chapters/edit/10.1201/9781003308423-3/philosophical-foundations-geoai-exploring-sustainability-diversity-bias-geoai-spatial-data-science-krzysztof-janowicz

177. Jeon, D. J., Ki, S. J., Cha, Y., Park, Y., & Kim, J. H. (2018). New methodology of evaluation of best management practices performances for an agricultural watershed according to the climate change scenarios: A hybrid use of deterministic and decision support models. Ecological Engineering, 119, 73–83. https://doi.org/10.1016/j.ecoleng.2018.05.006

178. Jeon, S., & Kim, J. (2024). Artificial intelligence to predict climate and weather change. JMST Advances, 6, 67–73. https://doi.org/10.1007/s42791-024-00068-y

179. Jeong, J., & Choi, J. (2022). Artificial intelligence-based toxicity prediction of environmental chemicals: Future directions for chemical management applications. Environmental Science & Technology, 56(12), 7532–7543. https://doi.org/10.1021/acs.est.1c07413

180. Jha, S. K., Bilalovic, J., Jha, A., Patel, N., & Zhang, H. (2017). Renewable energy: Present research and future scope of Artificial Intelligence. Renewable and Sustainable Energy Reviews, 77, 297–317. https://doi.org/10.1016/j.rser.2017.04.018

181. Jia, X., Cao, Y., O'Connor, D., Zhu, J., Tsang, D. C. W., Zou, B., & Hou, D. (2021). Mapping soil pollution by using drone image recognition and machine learning at an arsenic-contaminated agricultural field. Environmental Pollution, 270, 116281. https://doi.org/10.1016/j.envpol.2020.116281

182. Jin, W., Atkinson, T. A., Doughty, C., Neupane, G., Spycher, N., McLing, T. L., Dobson, P. F., Smith, R., & Podgorney, R. (2022). Machine-learning-assisted high-temperature reservoir thermal energy storage optimization. Renewable Energy, 197, 384–397. https://doi.org/10.1016/j.renene.2022.07.118

183. Jithendra, T., & Basha, S. S. (2023). Analyzing groundwater level with hybrid ANN and ANFIS using metaheuristic optimization. Earth Science Informatics, 16, 3323–3353. https://doi.org/10.1007/s12145-023-01097-2

184. John, J. E., & Pramila, S. (2024). Integrating AI tools into HRM to promote green HRM practices. In M. S. Kaiser, J. Xie, & V. S. Rathore (Eds.), ICT: Smart systems and technologies. ICTCS 2023. Lecture notes in networks and systems (Vol. 878). Springer, Singapore. https://doi.org/10.1007/978-981-99-9489-2_22

185. Jones, E. C., & Leibowicz, B. D. (2019). Contributions of shared autonomous vehicles to climate change mitigation. Transportation Research Part D: Transport and Environment, 72, 279-298. https://www.sciencedirect.com/science/article/abs/pii/S1361920918310861Jordan, A., Wurzel, R. K., & Zito, A. R. (2012). Still the century of government? Global governance in the face of climate change. International Environmental Agreements: Politics, Law and Economics, 12(3), 277–297

186. Joseph, A., Chandra, J., & Siddharthan, S. (2021). Genome analysis for precision agriculture using artificial intelligence: a survey. Data Science and Security, 132, 221–226. https://doi.org/10.1007/978-981-15-5309-7_23

187. Joshi, K., Kumar, V., Anandaram, H., Kumar, R., Gupta, A., & Krishna, K. H. (2023). A review approach on deep learning algorithms in computer vision. In Intelligent Systems and Applications in Computer Vision (1st ed., pp. 15). CRC Press

188. Jualayba, M., Regio, K., Quiozon, H., & Destreza, A. (2018). Hazardous Gas Detection and Notification System. In 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM) (pp. 1–4). Baguio City, Philippines. https://doi.org/10.1109/HNICEM.2018.8666358

189. Jung, J., Maeda, M., Chang, A., Bhandari, M., Ashapure, A., & Landivar-Bowles, J. (2021). The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Current Opinion in Biotechnology, 70, 15–22. https://doi.org/10.1016/j.copbio.2020.09.003

190. Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. Nature Climate Change, 12(6), 518–527. https://www.nature.com/articles/s41558-022-01377-7

191. Kaack, L., Donti, P., Strubell, E., & Rolnick, D. (2020). Artificial intelligence and climate change: Opportunities, considerations, and policy levers to align AI with climate change goals. https://eu.boell.org/sites/default/files/2021-04/Artificial%20Intelligence%20and%20Climate%20Change_FINAL_14042021.pdf

192. Kadow, C., Hall, D. M., & Ulbrich, U. (2020). Artificial intelligence reconstructs missing climate information. Nature Geoscience, 13(408–413). https://doi.org/10.1038/s41561-020-0582-5

193. Kagabo J, Kattel GR, Kazora J, Shangwe CN, Habiyakare F. Application of Machine Learning Algorithms in Predicting Extreme Rainfall Events in Rwanda. Atmosphere. 2024; 15(6):691. https://www.mdpi.com/2073-4433/15/6/691Kakani, V., Nguyen, V. H., Kumar, B. P., Kim, H., & Pasupuleti, V. R. (2020). A critical review on computer vision and artificial intelligence in the food industry. *Journal of Agriculture and Food Research*, 2, 100033. https://doi.org/10.1016/j.jafr.2020.100033

194. Kalischek, N., Lang, N., Renier, C., Daudt, R. C., Addoah, T., Thompson, W., Blaser-Hart, W. J., Garrett, R., Schindler, K., & Wegner, J. D. (2023). Cocoa plantations are associated with deforestation in Côte d'Ivoire and Ghana. *Nature Food, 4*(5), 384-393. https://doi.org/10.1038/s43016-023-00751-8

195. Kandlhofer, M., Weixelbraun, P., Menzinger, M., Steinbauer-Wagner, G., & Kemenesi, Á. (2023). Education and Awareness for Artificial Intelligence. In J. P. Pellet & G. Parriaux (Eds.), Informatics in Schools. Beyond Bits and Bytes: Nurturing Informatics Intelligence in Education. ISSEP 2023. Lecture Notes in Computer Science (Vol. 14296). Springer, Cham. https://doi.org/10.1007/978-3-031-44900-0_1

196. Karadayi-Usta, S. (2024). Role of artificial intelligence and augmented reality in the fashion industry from consumer perspective: Sustainability through waste and return mitigation. Engineering Applications of Artificial Intelligence, 133(Part A), 108114. https://doi.org/10.1016/j.engappai.2024.108114

197. Kasinidou, M. (2023). Promoting AI Literacy for the Public. In Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 2 (SIGCSE 2023). Association for Computing Machinery, New York, NY, USA, 1237. https://doi.org/10.1145/3545947.3573292

198. Kerins, P., Nilson, E., Mackres, E., Rashid, T., Guzder-Williams, B., & Brumby, S. (2020). Spatial characterization of urban land use through machine learning. Technical Note. World Resources Institute, Washington, DC. https://www.wri.org/research/spatial-characterization-urban-land-use-through-machine-learning

199. Khajwal, A. B., Cheng, C.-S., & Noshadravan, A. (2022). Multi-view deep learning for reliable post-disaster damage classification. 13th International Workshop on Structural Health Monitoring (IWSHM 2021). https://doi.org/10.48550/arXiv.2208.03419

200. Khalilpourazari, S., & Pasandideh, S. H. R. (2021). Designing emergency flood evacuation plans using robust optimization and artificial intelligence. Journal of Combinatorial Optimization, 41(3), 640-677. https://doi.org/10.1007/s10878-021-00699-0

201. Khalilpourazari, S., Khalilpourazary, S., Özyüksel Çiftçioğlu, A., & Weber, G.-W. (2021). Designing energy-efficient high-precision multi-pass turning processes via robust optimization and artificial intelligence. Journal of Intelligent Manufacturing, 32, 1621–1647. https://doi.org/10.1007/s10845-020-01648-0

202. Khosravi, A., Nunes, R. O., Assad, M. E. H., & Machado, L. (2018). Comparison of artificial intelligence methods in estimation of daily global solar radiation. Journal of Cleaner Production, 194, 342–358. https://doi.org/10.1016/j.jclepro.2018.05.147

203. Kiba, M., Mrówczyńska, M., & Bazan-Krzywoszańska, A. (2017). Modeling the economic dependence between town development policy and increasing energy effectiveness with neural networks. Case study: The town of Zielona Góra. Applied Energy, 188, 356–366. https://www.sciencedirect.com/science/article/abs/pii/S030626191631769X

204. Kim, S. S., Shin, D. Y., Lim, E. T., Jung, Y. H., & Cho, S. B. (2022). Disaster damage investigation using artificial intelligence and drone mapping. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B3-2022, 1109–1114. https://doi.org/10.5194/isprs-archives-XLIII-B3-2022-1109-2022

205. Kingma, D. P., & Dhariwal, P. (2018). Glow: Generative flow with invertible 1x1 convolutions. https://arxiv.org/abs/1807.03039

206. Klinger, D., &Yoshioka, J. (2024), Climate-Smart Shrimp Fund. https://www.climatefinancelab.org/ideas/climate-smart-shrimp-fund/

207. Koffka, K. (2023). Intelligent Things: Exploring AIoT Technologies and Applications

208. Kopelias, P., Demiridi, E., Vogiatzis, K., Skabardonis, A., & Zafiropoulou, V. (2020). Connected & autonomous vehicles – Environmental impacts – A review. *Science of The Total Environment, 712*, 135237. https://doi.org/10.1016/j.scitotenv.2019.135237

209. Kouakou, D. C. M., & Szego, E. (2024). Evaluating the Integration of Artificial Intelligence Technologies in Defense Activities and the Effect of National Innovation System Performance on its Enhancement. https://mpra.ub.uni-muenchen.de/120617/

210. Kuglitsch, M. M., Pelivan, I., Ceola, S., Menon, M., & Xoplaki, E. (2022a). Facilitating adoption of AI in natural disaster management through collaboration. *Nature Communications, 13*, 1579. https://doi.org/10.1038/s41467-022-29285-6

211. Kuglitsch, M., Albayrak, A., Aquino, R., Craddock, A., Edward-Gill, J., Kanwar, R., Koul, A., Ma, J., Marti, A., Menon, M., Pelivan, I., Toreti, A., Venguswamy, R., Ward, T., Xoplaki, E., Rea, A., & Luterbacher, J. (2022b). Artificial Intelligence for Disaster Risk Reduction: Opportunities, challenges, and prospects. *WMO Bulletin*, 71(1). https://wmo.int/media/magazine-article/artificial-intelligence-disaster-risk-reduction-opportunities-challenges-and-prospects

212. Kumar, A., & Davenport, T. (2023, July 20). How to make generative AI greener. *Harvard Business Review*. https://hbr.org/2023/07/how-to-make-generative-ai-greener

213. Kumar, D., & Kumar, K. P. (2023). Artificial intelligence-based cyber security threats identification in financial institutions using machine learning approach. 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 1–6. https://doi.org/10.1109/INOCON57975.2023.10100967

214. Kurekin, A. A., Loveday, B. R., Clements, O., Quartly, G. D., Miller, P. I., Wiafe, G., & Adu Agyekum, K. (2019). Operational monitoring of illegal fishing in Ghana through exploitation of satellite earth observation and AIS data. Remote Sensing, 11(293). https://www.researchgate.net/publication/330819763_Operational_Monitoring_of_Illegal_Fishing_in_Ghana_through_Exploitation_of_Satellite_Earth_Observation_and_AIS_Data

215. Kushwaha, O. S., Uthayakumar, H., & Kumaresan, K. (2023). Modeling of carbon dioxide fixation by microalgae using hybrid artificial intelligence (AI) and fuzzy logic (FL) methods and optimization by genetic algorithm (GA). Environmental Science and Pollution Research, 30, 24927–24948. https://doi.org/10.1007/s11356-022-19683-0

216. Lacoste, A., Luccioni, A., Schmidt, V., & Dandres, T. (2019). Quantifying the Carbon Emissions of Machine Learning. https://arxiv.org/abs/1910.09700

217. Lang, N., Schindler, K., & Wegner, J. D. (2021). High carbon stock mapping at large scale with optical satellite imagery and spaceborne LIDAR. arXiv:2107.07431. https://doi.org/10.48550/arXiv.2107.07431

218. Lang, N., Jetz, W., Schindler, K., & Wegner, J. D. (2023). A high-resolution canopy height model of the Earth. Nature Ecology & Evolution, 7(1778–1789). https://doi.org/10.1038/s41559-023-02206-6

219. Lannelongue, L., Grealey, J., & Inouye, M. (2021). Green Algorithms: Quantifying the carbon footprint of computation. Advanced Science, 8(2100707). https://doi.org/10.1002/advs.202100707

220. Leal Filho, W., Krishnapillai, M., Sidsaph, H., Nagy, G. J., Luetz, J. M., Dyer, J., Otoara Ha'apio, M., Havea, P. H., Raj, K., Singh, P., et al. (2021). Climate Change Adaptation on Small Island States: An Assessment of Limits and Constraints. Journal of Marine Science and Engineering, 9(6), 602. https://doi.org/10.3390/jmse9060602

221. Leal Filho, W., Wall, T., Mucova, S. A. R., Nagy, G. J., Balogun, A.-L., Luetz, J. M., Ng, A. W., Kovaleva, M., Azam, F. M. S., & Alves, F. (2022). Deploying artificial intelligence for climate change adaptation. Technological Forecasting and Social Change, 180, 121662. https://www.sciencedirect.com/science/article/abs/pii/S0040162522001949

222. Lee, J., & Yoo, H. J. (2021). An overview of energy-efficient hardware accelerators for on-device deep-neural-network training. IEEE Open Journal of Solid-State Circuits Society, 1, 115–128. https://doi.org/10.1109/OJSSCS.2021.3119554

223. Lee, M. F. R., & Chien, T. W. (2020). Artificial intelligence and internet of things for robotic disaster response. In 2020 International Conference on Advanced Robotics and Intelligent Systems (ARIS). https://doi.org/10.1109/ARIS50834.2020.9205794

224. Li, Y., & Liu, Q. (2021). A comprehensive review study of cyber-attacks and cyber security: Emerging trends and recent developments. Energy Reports, 7, 8176–8186. https://doi.org/10.1016/j.egyr.2021.08.126

225. Li, J. X., Zhang, T., Zhu, Y., & Chen, Z. (2024). Artificial General Intelligence (AGI) for the oil and gas industry: A review. arXiv preprint arXiv:2406.00594. https://doi.org/10.48550/arXiv.2406.00594

226. Li, Y., Skulovich, O., & Gentine, P. (2022). Soil database development with the application of machine learning methods in soil properties prediction. *Engineering Geology, 306*, 106769. https://www.sciencedirect.com/science/article/abs/pii/S001379522200254X

227. Liao, Z., Taiebat, M., & Xu, M. (2021). Shared autonomous electric vehicle fleets with vehicle-to-grid capability: Economic viability and environmental co-benefits. *Applied Energy, 302*, 117500. https://doi.org/10.1016/j.apenergy.2021.117500

228. Ligozat, A.-L., Lefèvre, J., Bugeau, A., & Combaz, J. (2021). Unraveling the Hidden Environmental Impacts of AI Solutions for Environment. arXiv:2110.11822 [cs.AI]. https://doi.org/10.48550/arXiv.2110.11822

229. Lima, R. M. de, Pisker, B., & Corrêa, V. S. (2023). Gender Bias in Artificial Intelligence: A Systematic Review of the Literature. Journal of Telecommunications and the Digital Economy, 11(2), 8–30. https://doi.org/10.18080/jtde.v11n2.690

230. Liu, Z., Janowicz, K., Currier, K., & Shi, M. (2024). Measuring Geographic Diversity of Foundation Models with a Natural Language–based Geo-guessing Experiment on GPT-4. *AGILE: GIScience Series*, 5(38). https://doi.org/10.5194/agile-giss-5-38-2024

231. Liu, J., Jiang, X., Shi, M., & Yang, Y. (2024). Impact of Artificial Intelligence on Manufacturing Industry Global Value Chain Position. Sustainability, 16(3), 1341. https://doi.org/10.3390/su16031341

232. Liu, Q., & Zhang, T. (2023). Deep learning technology of computer network security detection based on artificial intelligence. Computers and Electrical Engineering, 110, 108813. https://doi.org/10.1016/j.compeleceng.2023.108813

233. Liu, Q., Ma, Y., Chen, L., Pedrycz, W., Skibniewski, M. J., & Chen, Z. S. (2024). Artificial intelligence for production, operations and logistics management in modular construction industry: A systematic literature review. Information Fusion, 109, 102423. https://doi.org/10.1016/j.inffus.2024.102423

234. Liu, T., Sun, Y., Wang, C., Zhang, Y., Qiu, Z., Gong, W., Lei, S., Tong, X., & Duan, X. (2021). Unmanned aerial vehicle and artificial intelligence revolutionizing efficient and precision sustainable forest management. Journal of Cleaner Production, 311, 127546. https://doi.org/10.1016/j.jclepro.2021.127546

235. Liu, Y., Huang, X., & Liu, Y. (2024). Detection of long-term land use and ecosystem services dynamics in the Loess Hilly-Gully region based on artificial intelligence and multiple models. Journal of Cleaner Production, 447, 141560. https://doi.org/10.1016/j.jclepro.2024.141560

236. Liu, Z., Sun, Y., Xing, C., Liu, J., He, Y., Zhou, Y., & Zhang, G. (2022). Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: challenges and future perspectives. Energy AI, 10, 100195. https://doi.org/10.1016/j.egyai.2022.100195

237. Lopez-Gomez, I., McGovern, A., Agrawal, S., & Hickey, J. (2023). Global extreme heat forecasting using neural weather models. Artificial Intelligence for the Earth Systems, 2, e220035. https://doi.org/10.1175/AIES-D-22-0035.1

238. Lotfian, M., Ingensand, J., & Brovelli, M. A. (2021). The partnership of citizen science and machine learning: Benefits, risks, and future challenges for engagement, data collection, and data quality. Sustainability, 13(14), 8087. https://doi.org/10.3390/su13148087

239. Lu, Y., Shen, M., Wang, H., Wang, X., van Rechem, C., Fu, T., & Wei, W. (2024). Machine Learning for Synthetic Data Generation: A Review. arXiv preprint arXiv:2302.04062. https://doi.org/10.48550/arXiv.2302.04062.

240. Luccioni, S. (2023). The mounting human and environmental costs of generative AI. *Ars Technica*. https://arstechnica.com/gadgets/2023/04/generative-ai-is-cool-but-lets-not-forget-its-human-and-environmental-costs/

241. Luers, A., Koomey, J., Masanet, E., Gaffney, O., Creutzig, F., Lavista Ferres, J., & Horvitz, E. (2024). Will AI accelerate or delay the race to net-zero emissions? *Nature*. https://www.nature.com/articles/d41586-024-01137-x

242. Lundvall, B.-Å., & Rikap, C. (2022). China's catching-up in artificial intelligence seen as a co-evolution of corporate and national innovation systems. *Research Policy, 51*(1), 104395. https://doi.org/10.1016/j.respol.2021.104395

243. Lutoslawski, K., et al. (2021). Food Demand Prediction Using the Nonlinear Autoregressive Exogenous Neural Network. *IEEE Access, 9*, 146123-146136

244. Lutz, C. (2019). Digital inequalities in the age of artificial intelligence and big data. Human Behavior and Emerging Technologies, 1(2), 141–148. https://doi.org/10.1002/hbe2.140

245. Lyu, W., & Liu, J. (2021). Artificial intelligence and emerging digital technologies in the energy sector. Applied Energy, 303, 117615. https://doi.org/10.1016/j.apenergy.2021.117615

246. Mahadevkar, S., Khemani, B., Patil, S., Kotecha, K., Vora, D., Abraham, A., & Gabralla, L. (2022). A review on machine learning styles in computer vision: Techniques and future directions. IEEE Access, 10, 107293-107329. https://doi.org/10.1109/ACCESS.2022.3209825

247. Mahmood, A., Bennamoun, M., An, S., Sohel, F., Boussaid, F., Hovey, R., Kendrick, G., & Fisher, R. B. (2017). Deep Learning for Coral Classification. In P. Samui, S. Sekhar, & V. E. Balas (Eds.), Handbook of Neural Computation (pp. 383–401). Academic Press

248. Maitra, S. (2020). Artificial intelligence and indigenous perspectives: Protecting and empowering intelligent human beings. In Proceedings of the 2020 Artificial Intelligence and Ethics Society Conference (AIES'20) (pp. 320–326). https://doi.org/10.1145/3375627.3375845

249. Mannuru, N. R., Shahriar, S., Teel, Z. A., Wang, T., Lund, B. D., Tijani, S., Pohboon, C. O., Agbaji, D., Alhassan, J., Galley, J., Kousari, R., Ogbadu-Oladapo, L., Saurav, S. K., Srivastava, A., Tummuru, S. P., Uppala, S., & Vaidya, P. (2023). Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development. Information Development, 0(0). https://doi.org/10.1177/02666669231200628

250. Marasinghe, R., Yigitcanlar, T., Mayere, S., Washington, T., & Limb, M. (2024). Computer vision applications for urban planning: A systematic review of opportunities and constraints. Sustainable Cities and Society, 100, 105047. https://doi.org/10.1016/j.scs.2023.105047

251. Marcot, B. G., Steventon, J. D., Sutherland, G. D., & McCann, R. K. (2006). Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Canadian Journal of Forest Research, 36(12), 3063–3074. https://www.fs.usda.gov/pnw/pubs/journals/pnw_2006_marcot001.pdf

252. Masanet, E., Shehabi, A., Lei, N., Smith, S., & Koomey, J. (2020). Recalibrating global data center energy-use estimates: Growth in energy use has slowed owing to efficiency gains that smart policies can help maintain in the near term. *Science, 367*(6481), 984–986. https://doi.org/10.1126/science.aba3758

253. McClure, E. C., Sievers, M., Brown, C. J., Buelow, C. A., Ditria, E. M., Hayes, M. A., Pearson, R. M., Tulloch, V. J. D., Unsworth, R. K. F., & Connolly, R. M. (2020). Artificial intelligence meets citizen science to supercharge ecological monitoring. Patterns, 1(8), 100109. https://doi.org/10.1016/j.patter.2020.100109

254. McCormack, J., & Grierson, M. (2024). Building simulations with generative artificial intelligence. In D. Del Favero, S. Thurow, M. J. Ostwald, & U. Frohne (Eds.), *Climate disaster preparedness. Arts, research, innovation and society* (pp. 137–150). Springer, Cham. https://doi.org/10.1007/978-3-031-56114-6_11

255. McGovern, A., Lagerquist, R., Gagne II, D. J., Jergensen, G. E., Elmore, K. L., Homeyer, C. R., ... & Smith, T. (2022a). Spatiotemporal biases in AI models for weather and climate: Challenges and opportunities. *Nature Reviews Earth & Environment, 3*(3), 185–201. https://doi.org/10.1038/s43017-021-00232-5

256. McGovern, A., Ebert-Uphoff, I., Gagne II, D. J., & Bostrom, A. (2022b). Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science. *Environmental Data Science, 1*, e6. https://doi.org/10.1017/eds.2022.5

257. Mediterranean and pan-European Forecast and Early Warning System Against natural hazards (MedEWSa). (2024). Fortifying Ethiopia's National Parks: Building resilience against wildfires and extreme weather. Retrieved July 20, 2024, from https://www.medewsa.eu

258. Mertikas, S. P., Partsinevelos, P., Mavrocordatos, C., & Maximenko, N. A. (2021). Environmental applications of remote sensing. In Pollution assessment for sustainable practices in applied sciences and engineering (pp. 107–163). https://doi.org/10.1016/B978-0-12-809582-9.00003-7

259. Mhlanga, D. (2023) Artificial intelligence and machine learning for energy consumption and production in emerging markets: a review. Energies 16:745. https://doi.org/10.3390/en16020745

260. Microsoft (2022). Closing the climate data divide in the global south. https://blogs.microsoft.com/on-the-issues/2022/11/07/climate-data-divide-global-south/

261. Microsoft News Center (2023). UNFCCC partners with Microsoft to use AI and advanced data technology to track global carbon emissions and assess progress under the Paris Agreement, https://unfccc.int/sites/default/files/resource/UNFCCC_Microsoft_Partnership_2023.pdf

262. Mohamadi, A., Heidarizadi, Z., & Nourollahi, H. (2016). Assessing the desertification trend using neural classification and object-oriented techniques. Journal of Faculty Forestry Istanbul University. http://dx.doi.org/10.17099/jffiu.75819

263. Mohammadi, V., & Minaei, S. (2019). Artificial Intelligence in the Production Process. In A. M. Grumezescu & A. M. Holban (Eds.), Engineering Tools in the Beverage Industry (pp. 27–63). Woodhead Publishing. https://doi.org/10.1016/B978-0-12-815258-4.00002-0

264. Mohan, P. (2022). National REDD+ initiatives in Caribbean SIDS to enhance NDC implementation. Forest Policy and Economics, 144, 102844. https://www.sciencedirect.com/science/article/abs/pii/S1389934122001575

265. Mohan, P. S. (2023). Financing climate change mitigation and adaptation in Caribbean SIDS. PLOS Climate. https://doi.org/10.1371/journal.pclm.0000167

266. Mohan, P., Strobl, E., & Watson, P. (2017). Barriers to innovation and firm productivity in the Caribbean. In G. Crespi, S. Dohnert, & A. Maffioli (Eds.), Exploring firm level innovation and productivity in developing countries: The perspective of Caribbean small states (pp. 9–28). Washington, DC: Inter-American Development Bank

267. Mokhtarzad, M., Eskandari, F., Vanjani, N. J., & Arabasadi, A. (2017). Drought forecasting by ANN, ANFIS, and SVM and comparison of the models. Environmental Earth Sciences, 76(21), 729. https://link.springer.com/article/10.1007/s12665-017-7064-0

268. Molino, J. N. (2023). Interreligious views on the integration of artificial intelligence and indigenous knowledge for environmental preservation. Religion and Social Communication, 21(1). https://doi.org/10.62461/JNM110723

269. Muldoon, J., & Wu, B. A. (2023). Artificial Intelligence in the Colonial Matrix of Power. *Philosophy & Technology, 36*(4), 80. https://doi.org/10.1007/s13347-023-00687-8

270. Mura, M. T. D. (2024), Early warning systems: harnessing AI to mitigate risks, https://tech4future.info/en/early-warning-systems-ai/

271. Nadeem, A., Abedin, B., & Marjanovic, O. (2020). Gender bias in AI: A review of contributing factors and mitigating strategies. In Proceedings of the Australasian Conference on Information Systems, Wellington, New Zealand. https://aisel.aisnet.org/acis2020/27

272. Nadeem, A., Marjanovic, O., & Abedin, B. (2022). Gender bias in AI-based decision-making systems: a systematic literature review. Australasian Journal of Information Systems, 26. https://doi.org/10.3127/ajis.v26i0.3835

273. Naeem, S., Ali, A., Anam, S., & Ahmed, M. M. (2023). An Unsupervised Machine Learning Algorithms: Comprehensive Review. International Journal of Computer and Digital Systems, 13, 911–921. https://www.researchgate.net/publication/368983958_An_Unsupervised_Machine_Learning_Algorithms_Comprehensive_Review

274. Narechania, T. N. (2021). *Machine Learning as Natural Monopoly*. https://doi.org/10.2139/ssrn.3810366

275. Nath, P. C., Mishra, A. K., Sharma, R., Bhunia, B., Mishra, B., Tiwari, A., Nayak, P. K., Sharma, M., Bhuyan, T., Kaushal, S., Mohanta, Y. K., & Sridhar, K. (2024). Recent advances in artificial intelligence towards the sustainable future of agri-food industry. *Food Chemistry, 447*, 138945. https://doi.org/10.1016/j.foodchem.2024.138945

276. National Aeronautics and Space Administration (NASA). (2024). *Climate Change: How Do We Know?* Retrieved from NASA website: https://climate.nasa.gov/evidence

277. Ngarambe, J., Yun, G. Y., & Santamouris, M. (2020). The use of artificial intelligence (AI) methods in the prediction of thermal comfort in buildings: Energy implications of AI-based thermal comfort controls. Energy and Buildings, 211, 109807. https://doi.org/10.1016/j.enbiuild.2020.109807

278. Nguyen, H. A. T., Sophea, T., Gheewala, S. H., Rattanakom, R., Areerob, T., & Prueksakorn, K. (2021). Integrating remote sensing and machine learning into environmental monitoring and assessment of land use change. Sustainable Production and Consumption, 27, 1239–1254. https://doi.org/10.1016/j.spc.2021.02.025

279. Nguyen, H. P., Nguyen, C. T. U., Tran, T. M., Dang, Q. H., & Pham, N. D. K. (2024). Artificial intelligence and machine learning for green shipping: Navigating towards sustainable maritime practices. International Journal of Informatics and Visualization, 8(March), 1–17. https://dx.doi.org/10.62527/joiv.8.1.2581

280. Nguyen-Trong, K., & Tran-Xuan, H. (2022). Coastal Forest Cover Change Detection Using Satellite Images and Convolutional Neural Networks in Vietnam. IAES International Journal of Artificial Intelligence, 11, 930–938. https://doi.org/10.11591/ijai.v11.i3.pp930-938

281. Nikitas, A., Michalakopoulou, K., Njoya, E. T., & Karampatzakis, D. (2020). Artificial Intelligence, transport and the smart city: definitions and dimensions of a new mobility era. Sustainability, 12(7), 2789. https://doi.org/10.3390/su12072789

282. Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53, 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

283. NOAA Fisheries. (2022). Understanding illegal, unreported, and unregulated fishing. Retrieved from https://www.fisheries.noaa.gov/insight/understanding-illegal-unreported-and-unregulated-fishing

284. Norazman, S. H., Aspar, M. A. S. M., Abd. Ghafar, A. N., Karumdin, N., & Abidin, A. N. S. Z. (2024). Artificial Neural Network Analysis in Road Crash Data: A Review on Its Potential Application in Autonomous Vehicles. In W. H. Mohd. Isa, I. M. Khairuddin, M. A. Mohd. Razman, S. Saruchi, S. H. Teh, & P. Liu (Eds.), Intelligent Manufacturing and Mechatronics. iM3F 2023. Lecture Notes in Networks and Systems (Vol. 850). Springer, Singapore. https://doi.org/10.1007/978-981-99-8819-8_8

285. Nti, E. K., Cobbina, S. J., Attafuah, E. E., Opoku, E., & Gyan, M. A. (2022). Environmental sustainability technologies in biodiversity, energy, transportation and water management using artificial intelligence: A systematic review. Sustainable Futures, 4, 100068. https://doi.org/10.1016/j.sftr.2022.100068

286. Nunes, J. A. C., Cruz, I., Nunes, A., & Pinheiro, H. T. (2020). Speeding up coral reef conservation with AI-aided automated image analysis. Nature Machine Intelligence, 2(6), 292–292. https://www.nature.com/articles/s42256-020-0192-3

287. Olabi, A. G., Abdelghafar, A. A., Maghrabie, H. M., Sayed, E. T., Rezk, H., Radi, M. A., Obaideen, K., & Abdelkareem, M. A. (2023). Application of artificial intelligence for prediction, optimization, and control of thermal energy storage systems. Thermal Science and Engineering Progress, 39, 101730. https://doi.org/10.1016/j.tsep.2023.101730

288. Olawade, D. B., Wada, O. Z., Ige, A. O., Egbewole, B. I., Olojo, A., & Oladapo, B. I. (2024). Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. *Hygiene and Environmental Health Advances, 100114*. https://doi.org/10.1016/j.heha.2024.100114

289. Olayode, O. I., Tartibu, L. K., & Okwu, M. O. (2020). Application of artificial intelligence in traffic control system of non-autonomous vehicles at signalized road intersection. Procedia CIRP, 91, 194–200. https://doi.org/10.1016/j.procir.2020.02.167

290. Oruganti, R. K., Biji, A. P., Lanuyanger, T., Show, P. L., Sriariyanun, M., Upadhyayula, V. K. K., Gadhamshetty, V., & Bhattacharyya, D. (2023). Artificial intelligence and machine learning tools for high-performance microalgal wastewater treatment and algal biorefinery: A critical review. Science of the Total Environment, 876, 162797. https://doi.org/10.1016/j.scitotenv.2023.162797

291. Osman, A. I., Chen, L., Yang, M., Msigwa, G., Farghali, M., Fawzy, S., Rooney, D. W., & Yap, P.-S. (2022). Cost, environmental impact, and resilience of renewable energy under a changing climate: a review. *Environmental Chemistry Letters*, 21, 741–764. https://doi.org/10.1007/s10311-022-01532-8

292. Osman, Z., & Yatam, M. (2024). Enhancing Artificial Intelligence-Enabled Transformation Acceptance among Employees of Higher Education Institutions. *International Journal of Academic Research in Accounting Finance and Management Sciences*, 14(2), 289–304. https://www.researchgate.net/publication/380733434_Enhancing_Artificial_Intelligence-Enabled_Transformation_Acceptance_among_Employees_of_Higher_Education_Institutions

293. Othman, K. (2022). Exploring the implications of autonomous vehicles: A comprehensive review. *Innovative Infrastructure Solutions, 7*, 76. https://doi.org/10.1007/s41062-022-00763-6

294. Ouadah, A., Zemmouchi-Ghomari, L., & Salhi, N. (2022). Selecting an appropriate supervised machine learning algorithm for predictive maintenance. International Journal of Advanced Manufacturing Technology, 119, 4277–4301. https://doi.org/10.1007/s00170-021-08551-9

295. Ozor, N., Nwakaire, J., Nyambane, A., MuhaΘah, W., & Tonnang, H., Salifu, D. (2023). Responsible Artificial Intelligence for Africa's Agriculture and Food Systems: Challenges and Opportunities. African Technology Policy Studies Network (ATPS). http://hdl.handle.net/10625/62055

296. Paracha, A., Arshad, J., Ben Farah, M., & Ismail, K. (2024). Machine learning security and privacy: A review of threats and countermeasures. EURASIP Journal on Information Security, 2024(10). https://doi.org/10.1186/s13635-024-00158-3

297. Paramesha, Mallikarjuna, & Rane, Nitin, & Rane, Jayesh. (2024). Enhancing Resilience through Generative Artificial Intelligence such as ChatGPT. Available at SSRN: https://ssrn.com/abstract=4832533

298. Parihar, V., Malik, A., Bhawna, Bhushan, B., & Chaganti, R. (2023). From smart devices to smarter systems: The evolution of artificial intelligence of things (AIoT) with characteristics, architecture, use cases, and challenges. In AI models for blockchain-based intelligent networks in IoT systems: Concepts, methodologies, tools, and applications (pp. 1–28). Springer. https://doi.org/10.1007/978-3-031-31952-5_1

299. Patel, K., Bhatt, C., & Mazzeo, P. L. (2022). Deep Learning-Based Automatic Detection of Ships: An Experimental Study Using Satellite Images. Journal of imaging, 8, Article 182. https://doi.org/10.3390/jimaging8070182

300. Patón-Romero, J. D., Vinuesa, R., Jaccheri, L., & Baldassarre, M. T. (2022). State of Gender Equality in and by Artificial Intelligence. IADIS International Journal on Computer Science and Information Systems, 17(2), 31–48. https://iadisportal.org/ijcsis/papers/2022170203.pdf

301. Ping, B., Meng, Y., Xue, C., & Su, F. (2023). Oceanic Primary Production Estimation Based On Machine Learning. Journal of Geophysical Research: Oceans, 128, e2022JC018980. https://doi.org/10.1029/2022JC018980

302. Plathottam, S. J., Rzonca, A., Lakhnori, R., & Iloeje, C. O. (2023). A Review of Artificial Intelligence Applications in Manufacturing Operations. Journal of Advanced Manufacturing Processes, 5, e10159. https://www.researchgate.net/publication/370833924_A_review_of_artificial_intelligence_applications_in_manufacturing_operations

303. Popescu, S. M., Mansoor, S., Wani, O. A., Kumar, S. S., Sharma, V., Sharma, A., Arya, V. M., Kirkham, M. B., Hou, D., Bolan, N., & Chung, Y. S. (2024). Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. Frontiers in Environmental Science, 12, Article 1336088. https://doi.org/10.3389/fenvs.2024.1336088

304. Pournader, M. (2021). Artificial Intelligence Applications in Supply Chain Management. *International Journal of Production Economics, 241*, 108250. https://doi.org/10.1016/j.ijpe.2021.108250

305. Pullman, M., Gurung, I., Maskey, M., Ramachandran, R., & Christopher, S. A. (2019). Applying deep learning to hail detection: a case study. IEEE Transactions on Geoscience and Remote Sensing, 57, 10218–10225. https://doi.org/10.1109/TGRS.2019.2931944

306. Puri, V., Srivastava, G., Rishiwal, V., & Singh, R. K. (2019). A hybrid artificial intelligence and Internet of Things model for generation of renewable resource of energy. IEEE Access, 7, 111181-111191. https://doi.org/10.1109/ACCESS.2019.2934228

307. Puri, V., Van Le, C., Kumar, R., & Jagdev, S. S. (2020). Fruitful Synergy Model of Artificial Intelligence and Internet of Things for Smart Transportation System. International Journal of Hyperconnectivity and the Internet of Things (IJHIoT), 4(1), 43–57. https://doi.org/10.4018/IJHIoT.2020010104

308. Putra, D. P., Bimantio, M. P., Sahfitra, A. A., Suparyanto, T., & Pardamean, B. (2020). Simulation of availability and loss of nutrient elements in land with android-based fertilizing applications. In 2020 International Conference on Information Management and Technology (ICIMTech) (pp. 312–317). IEEE. https://doi.org/10.1109/ICIMTech50083.2020.9211268

309. Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., ... & Sutskever, I. (2021). Learning transferable visual models from natural language supervision. arXiv preprint arXiv:2103.00020.

310. Raj, E. F. I., Appadurai, M., & Athiappan, K. (2021). Precision farming in modern agriculture. In Smart Agriculture Automation Using Advanced Technologies (pp. 294–329). Springer. https://doi.org/10.1007/978-981-16-6124-2_4

311. Raman, R., Pattnaik, D., Lathabai, H. H. et al. Green and sustainable AI research: an integrated thematic and topic modeling analysis. J Big Data 11, 55 (2024). https://doi.org/10.1186/s40537-024-00920-x

312. Rane, N., Choudhary, S., & Rane, J. (2024a). Artificial Intelligence and machine learning in renewable and sustainable energy strategies: A critical review and future perspectives. SSRN. Available at SSRN: https://ssrn.com/abstract=4838761or http://dx.doi.org/10.2139/ssrn.4838761

313. Rane, N., Paramesha, M., Choudhary, S., & Rane, J. (2024b). Business intelligence and artificial intelligence for sustainable development: Integrating Internet of Things, machine learning, and big data analytics for enhanced sustainability. Available at SSRN: https://ssrn.com/abstract=4833996 or http://dx.doi.org/10.2139/ssrn.4833996

314. Rani, M., & Singh, R. (2024). Role of artificial intelligence in sustainable finance. In A. Chakir, J. F. Andry, A. Ullah, R. Bansal, & M. Ghazouani (Eds.), Engineering applications of artificial intelligence. Synthesis lectures on engineering, science, and technology (p. 22). Springer, Cham. https://doi.org/10.1007/978-3-031-50300-9_22

315. Ranjana, R., Subha, T., Varsha, J., & Kumar, P. (2022). Applications and implications of artificial intelligence and deep learning in computer vision. In Applications and Implications of Artificial Intelligence and Deep Learning in Computer Vision (pp. 35–52). De Gruyter. https://doi.org/10.1515/9783110750584-003

316. Rashid, A., & Kumari, S. (2023). Performance evaluation of ANN and ANFIS models for estimating velocity and pressure in water distribution networks. Water Supply, 23(9), 3925–3949. https://doi.org/10.2166/ws.2023.224

317. Raza, M., et al. (2020). Establishing effective communications in disaster-affected areas and artificial intelligence-based detection using social media platforms. Future Generation Computer Systems, 112, 1057–1069. https://doi.org/10.1016/j.future.2020.06.040

318. Reddy, K. S. P., Roopa, Y. M., L. N., K. R., & Nandan, N. S. (2020). IoT based smart agriculture using machine learning. In 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 130–134). IEEE. https://doi.org/10.1109/ICIRCA48905.2020.9183373

319. Richards, D., Worden, D., Song, X. P., & Lavorel, S. (2024). Harnessing generative artificial intelligence to support nature-based solutions. *People and Nature, 6*(2), 882–893. https://doi.org/10.1002/pan3.10622

320. Rojas, C., Algra-Maschio, F., Andrejevic, M., Coan, T., Cook, J., & Li, Y.-F. (2024). Hierarchical machine learning models can identify stimuli of climate change misinformation on social media. *Communications Earth & Environment, 5*, 436. https://doi.org/10.1038/s43247-024-01573-7

321. Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... & Bengio, Y. (2022). Tackling climate change with machine learning. ACM Computing Surveys (CSUR), 55(2), 1–96. https://doi.org/10.1145/3485128

322. Rosenberg, I., Shabtai, A., Elovici, Y., & Rokach, L. (2021). Adversarial machine learning attacks and defense methods in the cyber security domain. ACM Computing Surveys, 54(5), 1–36. https://doi.org/10.1145/3453158

323. Rustia, D. J. A., Chiu, L.-Y., Lu, C.-Y., Wu, Y.-F., Chen, S.-K., Chung, J.-Y., Hsu, J.-C., & Lin, T.-T. (2022). Towards intelligent and integrated pest management through an AIoT-based monitoring system. Pest Management Science, 78(12), 4288–4302. https://doi.org/10.1002/ps.7048

324. Saenko, K. (2023, May 23). Is generative AI bad for the environment? A computer scientist explains the carbon footprint of ChatGPT and its cousins. *The Conversation*. https://theconversation.com/is-generative-ai-bad-for-the-environment-a-computer-scientist-explains-the-carbon-footprint-of-chatgpt-and-its-cousins-204096

325. Sætra, H. S. (2023). Generative AI: Here to stay, but for good? *Technology in Society*, 75. https://www.sciencedirect.com/science/article/pii/S0160791X2300177X

326. Sahil, K., Mehta, P., Kumar Bhardwaj, S., & Dhaliwal, L. K. (2023). Chapter 20: Development of mitigation strategies for climate change using artificial intelligence to attain sustainability. In Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence (pp. 421–448). https://doi.org/10.1016/B978-0-323-99714-0.00021-2

327. Saleem, S., & Mehrotra, M. (2022). Emergent use of artificial intelligence and social media for disaster management. In Proceedings of International Conference on Data Science and Applications: ICDSA 2021, Volume 2 (pp. 195-210). Springer Singapore. https://doi.org/10.1007/978-981-16-5348-3_15

328. Saleh, M., Milovanoff, A., Posen, I. D., MacLean, H. L., & Hatzopoulou, M. (2022). Energy and greenhouse gas implications of shared automated electric vehicles. *Transportation Research Part D: Transport and Environment, 105*, 103233. https://doi.org/10.1016/j.trd.2022.103233

329. Salim, H. K., Padfield, R., Hansen, S. B., Mohamad, S. E., Yuzir, A., Syayuti, K., et al. (2018). Global trends in environmental management system and ISO14001 research. Journal of Cleaner Production, 170, 645–653. https://www.sciencedirect.com/science/article/abs/pii/S095965261732005X

330. Salluri, D. K., et al. (2020). Object detection using convolutional neural networks for natural disaster recovery. International Journal of Safety and Security Engineering, 10(2), 285–291. https://doi.org/10.18280/ijsse.100217

331. Samadi, S. (2022). The convergence of AI, IoT, and big data for advancing flood analytics research. Frontiers in Water, 4, 786040. doi:10.3389/frwa.2022.786040

332. Samaei, S. R., & Hassanabad, M. G. (2024). The crucial interplay of seas, marine industries, and artificial intelligence in sustainable development. In Eighth International Conference on Technology Development in Oil, Gas, Refining and Petrochemicals (Vol. 8). Retrieved from https://www.researchgate.net/publication/377364245_The_Crucial_Interplay_of_Seas_Marine_Industries_and_Artificial_Intelligence_in_Sustainable_Development

333. Sandalow, D., McCormick, C., Kucukelbir, A., Friedmann, J., Nagrani, T., Fan, Z., Halff, A., d'Aspremont, A., Glatt, R., Méndez Leal, E., Karl, K., & Ruane, A. (2023). Artificial Intelligence for Climate Change Mitigation Roadmap (ICEF Innovation Roadmap Project, December 2023). Available at https://www.icef.go.jp/roadmap/.

334. Saputra, M. H., & Lee, H. S. (2019). Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton. Sustainability, 11(11), 3024. https://doi.org/10.3390/su11113024

335. Sayad, Y. O., et al. (2019). Predictive modeling of wildfires: A new dataset and machine learning approach. Fire Safety Journal, 104, 130–146. https://doi.org/10.1016/j.firesaf.2019.01.006

336. Schalatek, L. (2022). Climate Funds Update: Gender and Climate Finance. Overseas Development Institute. Retrieved from www.climatefundsupdate

337. https://climatefundsupdate.org/wp-content/uploads/2022/03/CFF10-Gender-and-CF_ENG-2021.pdf

338. Schultz, M. G., Betancourt, C., Gong, B., Kleinert, F., Langguth, M., Leufen, L. H., Mozaffari, A., & Stadtler, S. (2021). Can deep learning beat numerical weather prediction? Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 379(2194). https://doi.org/10.1098/rsta.2020.0097

339. Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2020). Green AI. Communications of the ACM, 63(12), 54-63. https://doi.org/10.1145/3381831

340. Schürholz, D., Kubler, S., & Zaslavsky, A. (2020). Artificial intelligence-enabled context-aware air quality prediction for smart cities. Journal of Cleaner Production, 271, 121941. https://doi.org/10.1016/j.jclepro.2020.121941

341. Sellak, H., Ouhbi, B., Frikh, B., & Palomares, I. (2017). Towards next-generation energy planning decision-making: An expert-based framework for intelligent decision support. Renewable and Sustainable Energy Reviews, 80, 1544–1577. https://www.sciencedirect.com/science/article/abs/pii/S1364032117310833

342. Senshaw, D. A., & Kim, J. W. (2018). Meeting conditional targets in nationally determined contributions of developing countries: Renewable energy targets and required investment of GGGI member and partner countries. Energy Policy, 116(1), 433–443. https://doi.org/10.1016/j.enpol.2018.02.017

343. Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M., & Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: From physical changes to their social repercussions. Regional Environmental Change, 17(6), 1585–1600. https://doi.org/10.1007/s10113-015-0910-2

344. Serina, I., & Ranzi, R. (2023). Improving the water usage in the Delta area. A joint research project led by University of Brescia in collaboration with Thuyloi University. Retrieved from https://ai4redriver.unibs.it/

345. Şeyma, M. K. M. (2023). Utilizing artificial intelligence (AI) for the identification and management of marine protected areas (MPAs): a review. J. Geosci. Environ. Protect., 11, 118–132. https://doi.org/10.4236/gep.2023.119008

346. Sha, Y., Sobash, R. A., & Gagne, D. J. II. (2024). Improving ensemble extreme precipitation forecasts using generative artificial intelligence. *arXiv:2407.04882 [physics.ao-ph]*. https://doi.org/10.48550/arXiv.2407.04882

347. Shaamala, A., Yigitcanlar, T., Nili, A., & Nyandega, D. (2024). Algorithmic green infrastructure optimisation: review of artificial intelligence driven approaches for tackling climate change. Sustainable Cities and Society, 101, 105182. https://doi.org/10.1016/j.scs.2024.105182

348. Shaikh, A. A., Kumar, A., Jani, K., Mitra, S., García-Tadeo, D. A., & Devarajan, A. (2021). The role of machine learning and artificial intelligence for making a digital classroom and its sustainable impact on education during Covid-19. Materials Today: Proceedings. https://doi.org/10.1016/j.matpr.2021.09.368

349. Shams, M. H., Niaz, H., Na, J., Anvari-Moghaddam, A., & Liu, J. J. (2021). Machine learning-based utilization of renewable power curtailments under uncertainty by planning of hydrogen systems and battery storages. Journal of Energy Storage, 41, 103010. https://doi.org/10.1016/j.est.2021.103010

350. Sharifani, K., & Amini, M. (2023). Machine Learning and Deep Learning: A Review of Methods and Applications. World Information Technology and Engineering Journal, 10(7), 3897-3904. Retrieved from https://ssrn.com/abstract=4458723.

351. Sharma, A., Bansal, P., Chandel, A., & Kumar, R. (2024). Modelling stage–discharge relationship of Himalayan river using ANN, SVM and ANFIS. Sustainable Water Resources Management, 10(88). https://doi.org/10.1007/s40899-024-01069-4

352. Sharma, N., Sharma, R., & Jindal, N. (2021). Machine learning and deep learning applications: A vision. Global Transitions Proceedings, 2(1), 24-28. https://doi.org/10.1016/j.gltp.2021.01.004

353. Sharps, K., Masante, D., Thomas, A., Jackson, B., Redhead, J., May, L., Prosser, H., Cosby, B., Emmett, B., & Jones, L. (2017). Comparing strengths and weaknesses of three ecosystem services modelling tools in a diverse UK river catchment. Science of The Total Environment, 584–585, 118–130. https://doi.org/10.1016/j.scitotenv.2016.12.160Shin, W., Han, J., & Rhee, W. (2021). AI-assistance for predictive maintenance of renewable energy systems. Energy, 221, 119775. https://doi.org/10.1016/j.energy.2021.119775

354. Shinde, P. P., & Shah, S. (2018). A Review of Machine Learning and Deep Learning Applications. 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 1-6. https://doi.org/10.1109/ICCUBEA.2018.8697857

355. Shneiderman, B. (2020). Bridging the gap between ethics and practice: Guidelines for reliable, safe, and trustworthy human-centered AI systems. ACM Transactions on Interactive Intelligent Systems, 10(4), Article 26, 31 pages. https://doi.org/10.1145/3419764

356. Shoaei, M., Noorollahi, Y., Hajinezhad, A., & Moosavian, S. F. (2024). A review of the applications of artificial intelligence in renewable energy systems: An approach-based study. Energy Conversion and Management, 306, 118207. https://doi.org/10.1016/j.enconman.2024.118207

357. Silva, Ó., Cordera, R., González-González, E., & Nogués, S. (2022). Environmental impacts of autonomous vehicles: A review of the scientific literature. *Science of The Total Environment, 830*, 154615. https://doi.org/10.1016/j.scitotenv.2022.154615

358. Silvestro, D., Goria, S., Sterner, T., et al. (2022). Improving biodiversity protection through artificial intelligence. Nature Sustainability, 5, 415–424. https://doi.org/10.1038/s41893-022-00851-6

359. Simşek, D., Kutlu, İ., & Şık, B. (2023). The role and applications of artificial intelligence (AI) in disaster management. https://doi.org/10.31462/icearc.2023.arc992

360. Skulovich, O., & Gentine, P. (2023). A long-term consistent artificial intelligence and remote sensing-based soil moisture dataset. *Scientific Data, 10*(1), 154. https://www.nature.com/articles/s41597-023-02053-x

361. Solaymani, S. (2019). CO2 emissions patterns in 7 top carbon emitter economies: the case of transport sector. Energy, 168, 989–1001. https://doi.org/10.1016/j.energy.2018.11.145

362. Solomon, A., Michaelshvili, M., Bitton, R., Shapira, B., Rokach, L., & Puzis, R., & Shabtai, A. (2022). Contextual security awareness: A context-based approach for assessing the security awareness of users. Knowledge-Based Systems, 246, 108709. https://doi.org/10.1016/j.knosys.2022.108709

363. Son, T. H., Weedon, Z., Yigitcanlar, T., Sanchez, T., Corchado, J. M., Mehmood, R. (2023). Algorithmic urban planning for smart and sustainable development: Systematic review of the literature. Sustainable Cities and Society, 94, 104562. https://doi.org/10.1016/j.scs.2023.104562

364. Song, T., Pang, C., Hou, B., Xu, G., Xue, J., Sun, H., & Meng, F. (2023). A Review of Artificial Intelligence in Marine Science. Frontiers in Earth Science, 11, Article 1090185. https://doi.org/10.3389/feart.2023.1090185

365. Sowmya, V., Ragiphani, S. (2022). Air Quality Monitoring System Based on Artificial Intelligence. In P. Kumar Jain, Y. Nath Singh, R. P. Gollapalli, S. P. Singh (Eds.), Advances in Signal Processing and Communication Engineering (pp. 26). Springer, Singapore. https://doi.org/10.1007/978-981-19-5550-1_26

366. Spratt, A. (2023). How AI helps Kenyan small-holder farmers to adapt to climate change. BMZ Digital. https://www.bmz-digital.global/en/how-ai-helps-kenyan-small-holder-farmers-to-adapt-to-climate-change/

367. Stein, A. L. (2020). Artificial intelligence and climate change. Yale Journal on Regulation, 37, 890. https://heinonline.org/HOL/LandingPage?handle=hein.journals/yjor37&div=24&id=&page=

368. Stowell, D. (2022). Computational bioacoustics with deep learning: A review and roadmap. PeerJ, 10, e10260. https://peerj.com/articles/13152/

369. Strubell, E., Ganesh, A., and McCallum, A. (2019). Energy and Policy Considerations for Deep Learning in NLP. arXiv:1906.02243.

370. Sun, T., Gaut, A., Tang, S., Huang, Y., Elsherief, M., Zhao, J., Mirza, D., Belding, E., Chang, K. W., & Wang, W. Y. (2019). Mitigating gender bias in Natural Language Processing: A literature review. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, Florence, Italy. https://doi.org/10.18653/v1/P19-1159

371. Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. Natural Hazards, 103(3), 2631–2689. https://doi.org/10.1007/s11069-020-04124-3

372. Swarna, K. P., & Bhaumik, P. (2022). Disaster management through integrative AI. In Proceedings of the 23rd International Conference on Distributed Computing and Networking. https://doi.org/10.1145/3491003.3493235

373. Talukdar, S., Singha, P., Mahato, S., Pal, S., Liou, Y. A., & Rahman, A. (2020). Land-Use Land-Cover Classification by Machine Learning Classifiers for Satellite Observations—A Review. Remote Sensing, 12, Article 1135. https://doi.org/10.3390/rs12071135

374. Thamik, H., Cabrera, J. D. F., & Wu, J. (2024). The Digital Paradigm: Unraveling the Impact of Artificial Intelligence and Internet of Things on Achieving Sustainable Development Goals. In S. Misra, K. Siakas, & G. Lampropoulos (Eds.), Artificial Intelligence of Things for Achieving Sustainable Development Goals (Lecture Notes on Data Engineering and Communications Technologies, Vol. 192). Springer, Cham. https://doi.org/10.1007/978-3-031-53433-1_2

375. The Collective Intelligence Project. (2024). A Roadmap to Democratic AI. https://static1.squarespace.com/static/631d02b2dfa9482a32db47ec/t/65f9a1296f1a357e918f7a58/1710858559931/CIP_+A+Roadmap+to+Democratic+AI.pdf

376. The Verge. (2023). Google's new geothermal energy project is up and running. Retrieved from https://www.theverge.com/2023/11/28/23972940/google-data-center-geothermal-energy

377. Thoma, S. P., Hartmann, M., Christen, J., Mayer, B., Mast, F. W., & Weibel, D. (2023). Increasing awareness of climate change with immersive virtual reality. Frontiers in Virtual Reality, 4, 897034. https://doi.org/10.3389/frvir.2023.897034

378. Thulke, D., Gao, Y., Pelser, P., Brune, R., Jalota, R., Fok, F., Ramos, M., van Wyk, I., Nasir, A., Goldstein, H., Tragemann, T., Nguyen, K., Fowler, A., Stanco, A., Gabriel, J., Taylor, J., Moro, D., Tsymbalov, E., de Waal, J., ... Erasmus, D. (2024). *ClimateGPT:* Towards AI synthesizing interdisciplinary research on climate change. arXiv. https://doi.org/10.48550/arXiv.2401.09646

379. Tien Bui, D., Bui, Q.-T., Nguyen, Q.-P., Pradhan, B., Nampak, H., & Trinh, P. T. (2017). A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area. Agricultural and Forest Meteorology, 233, 32–44. https://doi.org/10.1016/j.agrformet.2016.11.002

380. Tingzon, I., Cowan, N. M., & Chrzanowski, P. (2023). Can AI help build climate resilience in the Caribbean? Let's look at housing. The World Bank. https://blogs.worldbank.org/en/sustainablecities/can-ai-help-build-climate-resilience-caribbean-lets-look-housing

381. Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H., & Di Minin, E. (2019). Social media data for conservation science: A methodological overview. Biological Conservation, 233, 298-315. https://www.sciencedirect.com/science/article/pii/S0006320718317609?via%3Dihub

382. Tokunaga, K., Blandon, A., Blasiak, R., Jouffray, J. B., Wabnitz, C. C., & Norström, A. V. (2021). Ocean Risks in SIDS and LDCs. *Ocean Risks 2021*. Retrieved from https://oceanrisk.earth/wp-content/uploads/2022/12/ORRAA-Ocean-Risks.pdf

383. Tomazzoli, C., Scannapieco, S., & Cristani, M. (2020). Internet of Things and artificial intelligence enable energy efficiency. Journal of Ambient Intelligence and Humanized Computing, 14, 4933–4954. https://doi.org/10.1007/s12652-020-02151-3

384. Torfi, A., Shirvani, R. A., Keneshloo, Y., Tavaf, N., & Fox, E. A. (2020). Natural language processing advancements by deep learning: A survey. https://arxiv.org/abs/2003.01200

385. Tran, N. L. D., Rañola, R. F., Ole Sander, B., Reiner, W., Nguyen, D. T., & Nong, N. K. N. (2020). Determinants of adoption of climate-smart agriculture technologies in rice production in Vietnam. International Journal of Climate Change Strategies and Management, 12(2), 238–256. https://doi.org/10.1108/IJCCSM-05-2019-0032

386. Treen, K. M. D., Williams, H. T. P., & O'Neill, S. J. (2020). Online misinformation about climate change. *WIREs Climate Change, 11*(5), e665. https://doi.org/10.1002/wcc.665

387. Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., ... & Mathis, A. (2022). Perspectives in machine learning for wildlife conservation. Nature Communications, 13(1), 792.

388. Tyagi, A. K., & Aswathy, S. U. (2021). Autonomous intelligent vehicles (AIV): Research statements, open issues, challenges, and road for future. International Journal of Intelligent Networks, 2, 83–102. https://doi.org/10.1016/j.ijin.2021.07.002

389. Ullah, A., Salehnia, N., Kolsoumi, S., Ahmad, A., & Khaliq, T. (2018). Prediction of effective climate change indicators using statistical downscaling approach and impact assessment on pearl millet (*Pennisetum glaucum* L.) yield through Genetic Algorithm in Punjab, Pakistan. Ecological Indicators, 90, 569–576. https://doi.org/10.1016/j.ecolind.2018.03.053

390. UNDP. (2024). Visualizing the Future: Artificial Intelligence in Climate Action. https://www.undp.org/acceleratorlabs/blog/visualizing-future-artificial-intelligence-climate-action

391. UNESCO. (2020). Artificial intelligence and gender equality: Key findings of UNESCO's global dialogue. Retrieved from https://unesdoc.unesco.org/ark:/48223/pf0000374174

392. UNFCCC. (2023). Progress, good practices and lessons learned in prioritizing and incorporating gender-responsive adaptation action. United Nations Framework Convention on Climate Change. https://unfccc.int/documents/632960UNFCCC. (2024a). Conference of the Parties: Report of the Conference of the Parties on its twenty-eighth session, held in the United Arab Emirates from 30 November to 13 December 2023. https://unfccc.int/sites/default/files/resource/cp2023_11a01_adv.pdf

393. UNFCCC. (2024b). Artificial Intelligence. https://unfccc.int/ttclear/artificial_intelligence

394. UNFCCC. (2024c). Artificial Intelligence for Climate Action in Developing Countries: Opportunities, Challenges and Risks. https://unfccc.int/ttclear/misc_/StaticFiles/gnwoerk_static/AI4climateaction/ea0f2596d93640349b9b65f4a7c7dd24/b47ef0e99cb24e57aa9ea69f0f5d6a71.pdf

395. United Nations Climate Change (2023a). COP28 Agreement Signals "Beginning of the End" of the Fossil Fuel Era https://unfccc.int/news/cop28-agreement-signals-beginning-of-the-end-of-the-fossil-fuel-era

396. United Nations Climate Change. (2023b). Powering climate action through Earth observations technology, https://unfccc.int/news/powering-climate-action-through-earth-observations-technology

397. United Nations Educational, Scientific and cultural organization (UNESCO) (2020). Artificial intelligence, and gender equality: key finding of UNESCO's global dialogue. Available at https://unesdoc.unesco.org/ark:/48223/pf0000374174

398. United Nations Sustainable Development Goals. (2022). Goal 14: Conserve and sustainably use the oceans, seas and marine resources. Retrieved from https://www.un.org/sustainabledevelopment/oceans/

399. United Nations. (2024a). General Assembly adopts landmark resolution on artificial intelligence. UN News. Retrieved July 21, 2024, from https://news.un.org/en/story/2024/03/1147831

400. United Nations. (2024b), Climate Action Early Warnings for All, https://www.un.org/en/climatechange/early-warnings-for-all

401. Van Assche, K Beunen, R Gruezmacher M & Duineveld M (2020) Rethinking strategy in environmental governance, Journal of Environmental Policy & Planning, 22:5, 695–708, https://www.researchgate.net/publication/342130728_Rethinking_strategy_in_environmental_governance

402. van der Woude, D., Castro Nieto, G. Y., Moros Ochoa, M. A., et al. (2024). Artificial intelligence in biocapacity and ecological footprint prediction in Latin America and the Caribbean. *Environment, Development and Sustainability*. Advance online publication. https://doi.org/10.1007/s10668-024-05101-7

403. Van der Zeeuw, A., Van Deursen, A. J., & Jansen, G. (2019). Inequalities in the social use of the Internet of things: A capital and skills perspective. New Media & Society, 21(6), 1344–1361. https://doi.org/10.1177/146144481882106

404. Varon, J., Costanza-Chock, S., & Gebru, T. (2024). Fostering a Federated AI Commons Ecosystem. *POLICY BRIEFING*. https://codingrights.org/docs/Federated_AI_Commons_ecosystem_T20Policybriefing.pdf

405. Varona, D., Lizama-Mue, Y., & Suárez, J.L. (2021). Machine learning's limitations in avoiding automation of bias. AI & Society, 36, 197–203. https://doi.org/10.1007/s00146-020-00996-y

406. Velev, D., & Zlateva, P. (2023). Challenges of artificial intelligence application for disaster risk management. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 48, 387–394. https://doi.org/10.5194/isprs-archives-XLVIII-M-1-2023-387-2023

407. Verdecchia, R., Cruz, L., Sallou, J., Lin, M., Wickenden, J., & Hotellier, E. (2022). Data-centric green AI: An exploratory empirical study. In 2022 International Conference on ICT for Sustainability (ICT4S) (pp. 35–45). https://arxiv.org/abs/2204.02766

408. Verma, T., Kishore Kumar, B., Rajendar, J., & Kumara Swamy, B. (2024). A Review on Quantum Machine Learning. In A. Kumar & S. Mozar (Eds.), Proceedings of the 6th International Conference on Communications and Cyber Physical Engineering (ICCCE, 2024), Lecture Notes in Electrical Engineering, vol. 1096. Springer, Singapore. https://doi.org/10.1007/978-981-99-7137-4_39

409. Vignudelli, S., Birol, F., Benveniste, J., Fu, L.-L., Picot, N., Raynal, M., & Roinard, H. (2019). Satellite altimetry measurements of sea level in the coastal zone. Surveys in Geophysics, 40(5), 1319–1349. https://doi.org/10.1007/s10712-019-09569-1

410. Villon, S., Mouillot, D., Chaumont, M., Darling, E. S., Subsol, G., Claverie, T., & Villéger, S. (2018). A Deep Learning Method for Accurate and Fast Identification of Coral Reef Fishes in Underwater Images. Ecological Informatics, 48, 238-244. https://doi.org/10.1016/j.ecoinf.2018.09.007

411. Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., ... & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications, 11(1), 233. https://doi.org/10.1038/s41467-019-14108-y

412. Vogl, T. M. (2021). Artificial Intelligence in Local Government: Enabling Artificial Intelligence for Good Governance in UK Local Authorities. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3840222

413. Wabnitz, C.C., Blasiak, R., Harper, S., Jouffray, J.B., Tokunaga, K., & Norström, A.V. (2021). Gender dimensions of ocean risk and resilience in SIDS and coastal LDCS. Ocean Risk Resilience Action Alliance. Retrieved from https://oceanrisk.earth/wp-content/uploads/2022/12/ORRAA-Gender-and-ocean-risk.pdf

414. Walacik, M., Chmielewska, A., Real Estate Industry Sustainable Solution (Environmental, Social, and Governance) Significance Assessment – AI-Powered Algorithm Implementation. Sustainability. 2024; 16(3):1079. https://doi.org/10.3390/su16031079

415. Walsh, T., Evatt, A., & de Witt, C. S. (2020). Artificial Intelligence & Climate Change: Supplementary Impact Report for a 1.5°C Future Oxford, 1, 1–15

416. Wamba-Taguimdje, S. L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. Business Process Management Journal. https://doi.org/10.1108/BPMJ-10-2019-0411

417. Wang, P., Yao, J., Wang, G., Hao, F., Shrestha, S., Xue, B., ... & Peng, Y. (2019). Exploring the application of artificial intelligence technology for identification of water pollution characteristics and tracing the source of water quality pollutants. Science of The Total Environment, 693, 133440. https://doi.org/10.1016/j.scitotenv.2019.07.246

418. Wang, X., et al. (2022). Application of Machine Learning to the Monitoring and Prediction of Food Safety: A Review. *Comprehensive Reviews in Food Science and Food Safety, 21*(1), 416–434

419. Wani, O. A., Akhter, F., Kumar, S. S., Babu, S., Kanth, R. H., Mir, S. A., Mahdi, S. S., Malik, A. R., Bangroo, S., Gaafar, A.-R. Z., et al. (2023). Mitigating soil erosion through biomass-derived biochar: Exploring the influence of feedstock types and pyrolysis temperature. Land, 12(12), 2111. https://doi.org/10.3390/land12122111

420. Ward, D., Melbourne-Thomas, J., Pecl, G. T., Evans, K., Green, M., Mccormack, P. C. et al. (2022). Safeguarding Marine Life: Conservation of Biodiversity and Ecosystems. Reviews in Fish Biology and Fisheries, 32, 65-100. https://doi.org/10.1007/s11160-022-09700-3

421. Wazid, M., Das, A. K., Chamola, V., & Park, Y. (2022). Uniting cyber security and machine learning: Advantages, challenges and future research. ICT Express, 8(3), 313-321. https://doi.org/10.1016/j.icte.2022.04.007

422. Wei, M. C. F., Maldaner, L. F., Ottoni, P. M. N., & Molin, J. P. (2020). Carrot yield mapping: a precision agriculture approach based on machine learning. AI, 1(2), 229–241. https://doi.org/10.3390/ai1020015

423. Wheeldon, A., Shafik, R., Rahman, T., Lei, J., Yakovlev, A., & Granmo, O.-C. (2020). Learning automata based energy-efficient AI hardware design for IoT applications. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 378(2182), 20190593. https://doi.org/10.1098/rsta.2019.0593

424. Wilhelm, R. C., Van Es, H. M., & Buckley, D. H. (2022). Predicting measures of soil health using the microbiome and supervised machine learning. *Soil Biology and Biochemistry, 164*, 108472. https://doi.org/10.1016/j.soilbio.2021.108472

425. Willcock, S., Martínez-López, J., Hooftman, D. A. P., Bagstad, K. J., Balbi, S., Marzo, A., Prato, C., Sciandrello, S., Signorello, G., Voigt, B., Villa, F., Bullock, J. M., Athanasiadis, I.N. (2018). Machine learning for ecosystem services. Ecosystem Services, 33, Part B, 165–174. https://doi.org/10.1016/j.ecoser.2018.04.004

426. Williams, D., & Shipley, G. (2021). Enhancing artificial intelligence with indigenous wisdom. Open Journal of Philosophy, 11(1), 43-58. https://doi.org/10.4236/ojpp.2021.111005

427. Willi, M., Pitman, R. T., Cardoso, A. W., Locke, C., Swanson, A., Boyer, A., ... & Fortson, L. (2019). Identifying animal species in camera trap images using deep learning and citizen science. Methods in Ecology and Evolution, 10(1), 80–91

428. Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Le Scao, T., Gugger, S., Drame, M., Lhoest, Q., & Rush, A. M. (2020). Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations (pp. 38–45). Association for Computational Linguistics (ACL). doi:10.18653/V1/2020.EMNLP-DEMOS.6

429. World Bank. (2021). Bridging the Digital Divide in Developing Countries. Retrieved from World Bank

430. World Bank. (2023). Rooftop classification for OECS countries. Data Catalog. 2024, from https://datacatalog.worldbank.org/search/dataset/0065199/Rooftop-classification-for-OECS-countries

431. World Economic Forum. (2024). 9 ways AI is helping tackle climate change, https://www.weforum.org/agenda/2024/02/ai-combat-climate-change/

432. Xu, Z., Campbell, A. G., Dev, S., & Liang, Y. (2022). An exploration of virtual reality for awareness of the climate change crisis: A simulation of sea level rise. In 8th International Conference of the Immersive Learning Research Network (iLRN 2022). arXiv. https://doi.org/10.48550/arXiv.2205.01583

433. Yaiprasert, C., & Hidayanto, A. N. (2023). AI-Driven Ensemble Three Machine Learning to Enhance Digital Marketing Strategies in the Food Delivery Business. *Intelligent Systems with Applications, 18*, 200235

434. Yang, C.-T., Chen, H.-W., Chang, E.-J., Kristiani, E., Nguyen, K. L. P., & Chang, J.-S. (2021). Current advances and future challenges of AIoT applications in particulate matters (PM) monitoring and control. Journal of Hazardous Materials, 419, 126442. https://doi.org/10.1016/j.jhazmat.2021.126442

435. Yang, M., Chen, L., Wang, J., Msigwa, G., Osman, A. I., Fawzy, S., Rooney, D. W., & Yap, P.-S. (2023). Circular economy strategies for combating climate change and other environmental issues. Environmental Chemistry Letters, 21, 55–80. https://doi.org/10.1007/s10311-022-01499-6

436. Yang, T., Yi, X., Lu, S., Johansson, K. H., & Chai, T. (2021). Intelligent Manufacturing for the Process Industry Driven by Industrial Artificial Intelligence. Engineering, 7(9), 1224–1230. https://doi.org/10.1016/j.eng.2021.04.023

437. Yeung, P. S., Fung, J. C.-H., Ren, C., Xu, Y., Huang, K., Leng, J., & Wong, M. M.-F. (2020). Investigating future urbanization's impact on local climate under different climate change scenarios in MEGA-urban regions: A case study of the Pearl River Delta, China. Atmosphere, 11(7), 771. https://doi.org/10.3390/atmos11070771

438. Yin, X., Li, J., Kadry, S. N., & Sanz-Prieto, I. (2021). Artificial intelligence assisted intelligent planning framework for environmental restoration of terrestrial ecosystems. Environmental Impact Assessment Review, 86, 106493

439. Yokoyama, A. M., Ferro, M., de Paula, F. B., Vieira, V. G., & Schulze, B. (2023). Investigating hardware and software aspects in the energy consumption of machine learning: A green AI-centric analysis. Concurrency and Computation: Practice and Experience, 35(24), e7825

440. Youssef, A., El-Telbany, M., & Zekry, A. (2017). The role of artificial intelligence in photo-voltaic systems design and control: A review. Renewable and Sustainable Energy Reviews, 78, 72–79. https://doi.org/10.1016/j.rser.2017.04.046

441. Yue, X.-L., & Gao, Q.-X. (2018). Contributions of natural systems and human activity to greenhouse gas emissions. Advances in Climate Change Research, 9(4), 243–252. https://doi.org/10.1016/j.accre.2018.12.003

442. Zamee, M. A., & Won, D. (2020). Novel mode adaptive artificial neural network for dynamic learning: Application in renewable energy sources power generation prediction. Energies, 13(23), 6405. https://doi.org/10.3390/en13236405

443. Zhang, Y., et al. (2023). On optimizing model generality in AI-based disaster damage assessment: A subjective logic-driven crowd-AI hybrid learning approach. In International Joint Conferences on Artificial Intelligence Organization. https://doi.org/10.24963/ijcai.2023/701

444. Zhang, Z., Zheng, Y., Qian, L., Luo, D., Dou, H., Wen, G., Yu, A., & Chen, Z. (2022). Emerging trends in sustainable CO2-management materials. Advanced Materials, 34, 2201547. https://doi.org/10.1002/adma.202201547

445. Zhao, X., Wang, L., Zhang, Y., et al. (2024). A review of convolutional neural networks in computer vision. Artificial Intelligence Review, 57, 99. https://doi.org/10.1007/s10462-024-10721-6

446. Zhou, C., Li, Q., Li, C., Yu, J., Liu, Y., Wang, G., Zhang, K., Ji, C., Yan, Q., He, L., et al. (2023). A comprehensive survey on pretrained foundation models: A history from BERT to ChatGPT. *arXiv preprint arXiv:2302.09419*. Retrieved from https://arxiv.org/abs/2302.09419

447. Zhu, M., Wang, J., Yang, X., Zhang, Y., Zhang, L., Ren, H., Wu, B., & Ye, L. (2022). A Review of the Application of Machine Learning in Water Quality Evaluation. Eco-Environment & Health, 1, 107–116. https://doi.org/10.1016/j.eehl.2022.06.001

448. Žust L, Fettich A, Kristan M, Ličer M (2021) HIDRA 1.0: deep-learning-based ensemble sea level forecasting in the northern Adriatic. Geosci Model Dev 14(4):2057–2074. https://doi.org/10.5194/gmd-14-2057-2021

United Nations Climate Change

TEC

UNITED NATIONS INDUSTRIAL DEVELOPMENT ORGANIZATION

About the Technology Executive Committee

The Technology Executive Committee is the policy component of the Technology Mechanism, which was established by the Conference of the Parties in 2010 to facilitate the implementation of enhanced action on climate technology development and transfer. The Paris Agreement established a technology framework to provide overarching guidance to the Technology Mechanism and mandated the TEC and CTCN to serve the Paris Agreement. The TEC analyses climate technology issues and develops policies that can accelerate the development and transfer of low-emission and climate resilient technologies.

About the United Nations Industrial Development Organization

UNIDO is a specialized agency of the United Nations with a unique mandate to promote, dynamize and accelerate industrial development. Our mandate is reflected in Sustainable Development Goal (SDG) 9: "Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation", but UNIDO's activities contribute to all the SDGs. UNIDO's vision is a world without poverty and hunger, where industry drives low-emission economies, improves living standards, and preserves the livable environment for present and future generations, leaving no one behind. UNIDO provides support to its 173 Member States through four mandated functions: technical cooperation; action-oriented research and policy-advisory services; normative standards-related activities; and fostering partnerships for knowledge and technology transfer. Our work is concentrated on three focus areas: ending hunger by helping businesses from farm to fork; stopping climate breakdown by using renewable energy and energy efficiency to reduce industrial greenhouse gas emissions; and supporting sustainable supply chains so that developing country producers get a fair deal and scarce resources are preserved.

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