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Technology Executive Committee

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Draft technical paper on AI for climate action

Cover note

I. Background

1. As per Activity A.4.1 of its rolling workplan (2023–2027), the TEC is exploring the role of artificial intelligence (AI) and applied machine learning as enablers of climate solutions.

2. At TEC 28, the TEC considered a draft concept note for the development of a technical paper on AI for climate action and requested the activity group on digital technologies to revise the concept note to reflect the discussion at the meeting and to prepare the technical paper for consideration at TEC 29.

3. The TEC activity group that supports the implementation of this activity continued working intersessionally and, based on the revised concept note, developed the technical paper with the assistance of a consultant supported by UNIDO. The development of the technical paper also included a peer-review process to solicit expert views and examples of AI powered climate action in developing countries, in particular from LDCs and SIDS.

4. At TEC 29, the co-leads of the activity group, supported by a consultant, will present the draft technical paper contained in the annex.

II. Scope of the note

5. The annex to this note contains the draft technical paper on AI for climate action.

III. Expected action by the Technology Executive Committee

6. The TEC will be invited to consider the draft technical paper contained in the annex and provide guidance to the activity group with a view to finalizing the draft after TEC 29.

Annex

Draft technical paper on AI for climate action

Artificial Intelligence and Applied Machine Learning for Climate Action: Advancing Mitigation and Adaptation in Developing Countries

Draft Technical Paper

Executive Summary

Climate change presents one of the most pressing challenges of the 21st century, requiring rapid action spanning many communities, sectors, approaches, and tools to mitigate and adapt to its impacts more effectively. It disproportionately affects developing countries, including Least Developed Countries (LDCs) and Small Island Developing States (SIDS). These regions are highly vulnerable to climate impacts such as rising sea levels, extreme weather events, and changing agricultural conditions, which threaten their socio-economic stability and environmental resilience. Artificial Intelligence (AI) has been identified as offering significant opportunities to accelerate climate action through its applications in various domains. Leveraging AI can play a significant role in supporting mitigation efforts and enhancing resilience. AI can be used to design powerful tools for monitoring, predicting, and managing climate-related issues, thereby providing data-driven insights and innovative solutions for effective climate action.

This report explores the potential of AI in addressing climate challenges in developing countries, particularly LDCs and SIDS, examining its applications and benefits as well as associated challenges and risks, while providing policy recommendations to foster its sustainable and inclusive integration in these regions. It aligns with the mandate outlined in the Technology Mechanism and its Initiative on AI for Climate Action and relevant decisions from COP 28 and CMA 5 (decisions 9/CP.28, 1/CMA.5, 14/CMA.5), as well as responds to the UNGA resolution on AI. The report's specific objectives are fourfold:

1. 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.
2. Address the challenges and risks posed by AI, particularly those relevant to Climate Action, including concerns about energy consumption and its climate and environmental impact, data security, gender bias, the digital divide, and harmful practices.
3. 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.
4. Showcase the opportunities and challenges of existing AI applications in developing countries, in particular for LDCs and SIDS in addressing climate change and improving environmental outcomes.

This technical report adopts a comprehensive approach by integrating a detailed literature review to assess the current benefits, risks, and challenges of AI for climate action. It includes semi-structured interviews with stakeholders engaged in AI initiatives for climate action to identify pertinent case studies for inclusion. This is supported by peer-reviewed sources for added rigor and quality assurance and enhanced clarity and impact.

Key findings underscore the key role of AI in advancing and scaling up transformative climate solutions for mitigation and adaptation in developing countries:

- AI-enabled satellite imagery and sensor network analysis significantly enhance monitoring of sea level rise, deforestation, greenhouse gas (GHG) emissions, and climate-related events, providing valuable information for informed decision-making.

- AI algorithms advance the prediction of extreme weather events and the assessment of climate impacts on ecosystems by analyzing large datasets, identifying patterns, and generating precise forecasts. This facilitates the development of adaptive strategies to mitigate risks and enhance resilience by providing more accurate and actionable insights.
- AI interventions optimize fisheries, agriculture, and water management practices, promoting sustainability through improved resource efficiency and conservation efforts.
- AI and Artificial Intelligence of Things (AIoT) enhance energy systems' efficiency by enabling real-time energy optimization, predictive maintenance, and the balancing of supply and demand. AIoT also supports the deployment of renewable energy technologies through advanced monitoring, control, and automation of energy systems, as well as the integration of renewable sources into the grid. This facilitates a smooth transition towards low-carbon economies and contributes to the reduction of greenhouse gas (GHG) emissions.
- Predictive analytics powered by AI substantially aid in disaster preparedness and post-disaster recovery efforts by providing more accurate forecasts and real-time risk assessments. This enhances community resilience and minimizes socio-economic impacts by enabling communities to implement earlier and more effective preparedness measures, such as targeted evacuations and strategic resource allocation, which significantly reduce potential damage. In the aftermath of disasters, AI-driven analytics optimize the coordination of relief efforts and resource distribution, accelerating recovery and rebuilding processes.
- AI tools play a key role in raising awareness and educating on climate change impacts by delivering personalized and accessible information through various platforms. These engage local communities and organizations by tailoring content to specific audiences, making complex climate data understandable and actionable. AI encourages active participation in adopting sustainable practices, thereby fostering widespread involvement in climate action initiatives, by providing real-time insights and fostering interactive dialogue.

However, AI for climate action faces significant challenges and risks that must be addressed for more effective and inclusive implementation:

- The energy and water consumption of AI technologies pose risks to countering climate efforts, necessitating innovations in green AI and responsible resource management.
- Concerns about data security, including unauthorized access, breaches, misuse, privacy risks, and biases in data collection, are critical issues that require robust governance frameworks and ethical guidelines. These concerns are particularly relevant to climate-related data, where accurate and secure data collection is essential for informed decision-making. Any breach or misuse of climate data could undermine efforts to address climate change, leading to mistrust and potentially harmful consequences for policy development and implementation.
- The digital divide, characterized by unequal access to electricity, ICT infrastructure, datasets, and models, significantly impacts climate action by limiting the ability of developing countries to effectively utilize AI-driven solutions. This disparity hampers their capacity to gather and analyze climate data, develop adaptive strategies, and participate in global climate initiatives. Addressing the digital divide is crucial for ensuring that all regions can contribute to and benefit from climate action. Without equitable access, these regions may become more vulnerable to climate impacts, weakening global efforts to mitigate and adapt to climate change. Therefore, focusing on fair and just access to AI

technology and resources and capacity-building initiatives is essential to bridge this gap and support inclusive and effective climate action worldwide.

- Bias, in particular gender bias in AI applications can perpetuate inequalities if not addressed through inclusive design and gender-responsive policies. This finding is relevant to climate action because gender bias in AI can lead to unequal access to resources and benefits from climate initiatives. If AI applications are not designed inclusively, they may overlook the specific needs and challenges faced by women, who are often disproportionately affected by climate change. The effect of not addressing this bias could result in climate strategies that fail to fully support all affected populations, potentially worsening gender disparities. Addressing gender bias ensures that climate action is more equitable and effective for everyone.
- AI can contribute to worsening environmental challenges by fueling consumerism through targeted advertising, intensifying fossil fuel exploration and extraction, and amplifying the spread of climate misinformation, all of which pose serious issues to environmental sustainability efforts globally.

Overcoming these challenges is key to fostering an inclusive and ethically sound implementation of AI solutions in climate action, thereby ensuring equitable distribution of benefits and minimizing risks across communities in developing countries.

AI holds potential to accelerate climate action in developing countries, including LDCs and SIDS, and to harness this potential effectively, policymakers are recommended to:

- Promote open-source AI applications in climate change mitigation and adaptation strategies in developing countries, ensuring their deployment when they are the most suitable tool for the task.
- Foster international cooperation, capacity-building, and knowledge sharing in AI for climate action.
- Develop inclusive and sustainable policies and governance approaches, enabling data-driven decision-making and access to climate policies and research.
- **Address AI energy consumption and carbon footprint, data security, gender bias, and the digital divide** by:
    - Implementing energy-efficient algorithms, promoting the use of Small Language Models (SLMs), and adopting renewable energy sources for AI infrastructure to reduce the carbon footprint
    - Developing robust data governance frameworks to ensure privacy, security, and ethical use of data, protecting against unauthorized access and breaches
    - Applying inclusive design practices to mitigate gender bias by using diverse datasets and establishing gender-responsive policies, particularly in climate-related areas
    - 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
    - Providing funding and resources for local AI innovation hubs to foster relevant and sustainable homegrown solutions.

- **Integrate indigenous knowledge and gender-responsive approaches in AI-driven climate strategies** by:
    - Engaging indigenous communities to incorporate their traditional knowledge into AI models used for climate action.
    - Ensuring that AI climate strategies are gender-responsive by involving women and gender experts in all phases of design, development, and implementation.
    - Developing AI tools that bridge traditional knowledge with modern technology, enhancing the effectiveness of climate adaptation and mitigation strategies.
- **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 pertaining 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 challenge

The report serves as a comprehensive guide for policymakers, practitioners, and researchers navigating the complex intersection of AI and related technologies and climate resilience efforts in developing countries, in particular LDCs and SIDS, offering actionable insights and recommendations to foster more effective and inclusive implementation strategies for concrete climatic action and improved environmental outcomes.

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1. Introduction

Artificial Intelligence (AI) is the discipline dedicated to the research and development of mechanisms and applications of AI systems. An AI system is an engineered system that generates outputs such as content, forecasts, recommendations, or decisions for a given set of human-defined objectives. Machine Learning is the process of optimizing model parameters through computational techniques, such that the model's behavior reflects the data or experience. AI systems that use Machine Learning (ML) techniques are rapidly emerging as transformative technologies with profound potential across various domains. Among these, environmental sustainability and climate change stand out as areas where these innovations can drive impactful change. Research has shown that AI can act as an enabler of development targets, including environmental sustainability outcomes and addressing climate change challenges, but also as an inhibitor on some of them (Bibri 2024; Bibri et al. 2023; Chen et al. 2033; Jain et al. 2023; Leal Filho et al. 2022; Sandalow et al. 2023; Vinuesa et al. 2020).

Recent advancements in AI have demonstrated promising uses for enhancing climate modeling and prediction, improving environmental monitoring, streamlining disaster response mechanisms, optimizing resource management, advancing renewable energy systems, implementing adaptive strategies, and enabling evidence-based policies (e.g., Bibri 2024; Bibri et al. 2024a; Chen et al. 2023; Kaack et al. 2022; Rolnick et al. 2023; Popescu et al. 2024; Rane et al. 2024).

Moreover, international agreements and frameworks, such as the Paris Agreement, the United Nations' Sustainable Development Goals (SDGs), the United Nations' resolution on AI, and the European Union's AI Act, set the global agenda for climate action. The Paris Agreement, for instance, brings nations together to limit global temperature rise and reduce GHG emissions and emphasizes national commitments through Nationally Determined Contributions (NDCs). It commits countries to slow the impact of climate change and to strengthen these commitments over time, and its implementation is critical to achieve the UN SDGs. Specifically, SDG 13—Climate Action—focuses on taking urgent action to combat climate change and its impacts, underscoring the global priority of addressing climate-related challenges. This goal states that climate change poses a looming cataclysm that will impact every person across the globe in some shape or form, highlighting our current lack of preparedness for what this could mean, as underscored by the urgent need to address SDG 13. At COP28, the global stocktake acknowledges scientific evidence indicating that global greenhouse gas emissions need to be reduced by 43% by 2030, compared to 2019 levels, to limit global warming to 1.5°C, while noting that Parties are currently off track in achieving their Paris Agreement goals (United Nations Climate Change 2023a).

Furthermore, in March 2024, the United Nations General Assembly adopted a landmark resolution on AI aimed at promoting safe, secure, and trustworthy AI systems (United Nations News 2024). This resolution, supported by over 120 member states, underscores the importance of AI in advancing SDGs while ensuring the protection of human rights throughout the AI lifecycle. It calls for global cooperation to bridge the digital divide, enhance digital literacy, and ensure that AI technologies benefit developing countries equitably. This international commitment sets an important framework for integrating AI into climate action initiatives, emphasizing ethical and responsible AI deployment to address global challenges. In addition to the UN resolution on AI, the European Union has introduced comprehensive regulations through the EU's AI Act. These regulations highlight the global effort to balance innovation with ethical considerations in AI deployment.

Worth noting is that, while climate change poses significant challenges globally, its impacts are particularly severe for Least Developed Countries (LDCs) and Small Island Developing States (SIDS). Since the Kyoto

Protocol in 1997, rapid population growth and development in LDCs have underscored the need for increased climate change mitigation efforts in these regions (Havukainen et al. 2022). SIDS are among the most vulnerable to climate change, characterized by a high degree of exposure and fragility. Their unique circumstances necessitate more focused studies on the limitations of climate change adaptation, particularly concerning the specific difficulties and constraints they face (Leal Filho et al. 2021; Tokunaga et al. 2021). Notably, SIDS contribute minimally to, or bear almost no responsibility for, climate change, yet their unique geographical and socioeconomic conditions make them exceptionally susceptible to its effects (Mohan 2023). The Paris Agreement endorses that developed nations should lead in providing assistance and provides a framework for finance, and substantial funding is required for SIDS to meet their climate objectives (Mohan 2023). SIDS are particularly invested in the deployment of AI technologies, recognizing their potential benefits and navigating their unique challenges. These nations are sensitive to the risks associated with AI, due to their unique environmental and economic contexts, and they also hold significant sway on the global stage, advocating for governance that maximizes the positive impacts of AI technology (Estier 2024). However, the current AI governance landscape is indeed fragmented, which poses challenges for SIDS and LDCs in fully leveraging the potential of AI technologies. Despite many of these countries not yet having comprehensive AI strategies, there are still substantial opportunities for them to benefit from AI through a focus on well-governed deployment.

LDCs and SIDS are particularly vulnerable to the adverse effects of climate change due to their limited capacity or resources to implement adaptive measures, as well as high exposure to climate risks, such as rising sea levels, increased frequency and intensity of extreme weather events, and changing precipitation patterns. Addressing these challenges requires both adaptation and mitigation strategies tailored to their specific needs and circumstances (Havukainen et al. 2022; Leal Filho et al. 2020, 2021; Tokunaga et al. 2021).

AI can be particularly transformative by offering innovative solutions to enhance climate resilience (Jain et al. 2023; Leal Filho et al. 2022) in these regions by improving early warning systems for natural disasters (Kuglitsch et al. 2022), optimizing agricultural practices to cope with changing climate conditions, and managing water resources more efficiently. AI-driven tools can provide precise and timely data to support local adaptation strategies, optimize resource allocation, and improve resilience against climate hazards.

However, the integration of AI into climate action is not without challenges. As the disruptive capacity of AI continues to drive innovation, concerns are mounting about its negative environmental, ethical, and societal impact, including energy consumption, data security, gender bias, and the digital divide. AI models, especially DL and GenAI, and the computational resources they require are highly energy-intensive, which can potentially offset their environmental or climate benefits if not managed properly (Brevini et al. 2021; Dolby 2023; Ligozat et al. 2021; Luccioni 2023; Strubell et al. 2019; Saenko 2023).

Moreover, effective AI applications require robust and reliable data, yet LDCs and SIDS often face challenges related to data scarcity, limited access to high-quality data, and concerns over data security. AI and its supporting data infrastructures introduce a new paradigm that necessitates continuous data collection to effectively feed ML algorithms. One key issue for developing countries is data scarcity. While the usability of AI model outputs heavily depends on the availability of high-quality data, hybrid approaches, such as rule-based + ML methods, physics-informed ML, and domain-informed ML, can significantly enhance data efficiency. These methods are particularly useful in scenarios with limited data and domain knowledge, enabling more effective integration and utilization of existing information.

Without adequate data, the potential use cases for AI are significantly limited. Data scarcity in climate change reflects a broader issue of unequal access to resources like AI, which remains inadequately explored in current literature (Walsh et al. 2020). For example, digital data essential for optimizing farming practices in developing countries, including local climate projections and weather forecasts, is sparse (Balogun et al. 2020). Addressing data availability and access issues is essential for the successful implementation of AI- and ML-driven solutions for climate change. Regardless, the integration of AI and ML technologies introduces new security threats and vulnerabilities, making it necessary to implement robust security measures to protect data integrity and privacy (Goldblum et al. 2022; Paracha et al. 2024; Rosenberg et al. 2021; Wazid et al. 2022).

Furthermore, the digital divide, characterized by disparities in access to AI technologies and internet connectivity, can impede the equitable adoption of AI technologies (Celik 2023; Lutz 2019; van der Zeeuw et al. 2019), particularly in remote or underserved areas. Developing countries, especially LDCs, which are already disproportionately impacted by climate change, often lack the necessary infrastructure, resources, and expertise to fully leverage AI-driven solutions. Similarly, gender bias in AI development presents a considerable obstacle to the effective utilization of AI for climate action, especially in developing countries, LDCs, and SIDS (Ozor et al. 2023; UNFCCC 2023). If not carefully designed and implemented, AI systems can perpetuate and even intensify existing gender inequalities due to biases in algorithm development, data collection, and the perspectives of those creating the technology. Addressing these disparities is imperative for inclusive climate action and the equitable adoption of AI and ML technologies. Efforts must be made to improve digital infrastructure and literacy and mitigate gender bias. Proactive measures and ethical practices can effectively address these concerns and work towards a sustainable future.

AI features prominently in many countries' latest NDCs under the Paris Agreement. Countries are increasingly recognizing the potential of AI to help achieve their climate targets by enhancing energy efficiency and improving climate resilience. The Climate Technology Centre and Network (CTCN), operating as the implementation arm of the Technology Mechanism established under the UNFCCC, has been actively supporting AI for climate action, providing technical assistance, fostering knowledge sharing, and facilitating access to climate technologies. Through its initiatives, the CTCN has helped numerous countries leverage AI to enhance their climate resilience and mitigation efforts and achieve their climate goals. For example, the CTCN has supported numerous technology requests from developing countries, including the integration of AI in climate data collection and analysis, disaster risk management, renewable energy optimization. s**ustainable agriculture, water resource management, biodiversity conservation,** p**olicy support and development,** capacity building, and legal and regulatory frameworks tailored to the needs of individual countries by harnessing the expertise of a global network of technology companies and institutions. Overall, the CTCN promotes the accelerated transfer of environmentally sound technologies for low carbon and climate-resilient development, responding to the unique needs of developing countries through a global network of technology experts and institutions.

As countries update their NDCs and Technology Needs Assessments (TNAs), AI's role in supporting these commitments is becoming increasingly prominent. Meanwhile, the CTCN has been pivotal in supporting the deployment of AI solutions in various climate projects, demonstrating the potential for technology to drive significant progress in both mitigation and adaptation efforts. Furthermore, the UNFCCC's partnership with Microsoft aims to create an AI-powered platform to track global carbon emissions and assess progress under the Paris Agreement, enhancing transparency and accountability (Microsoft News Center 2023).

Against the preceding background, the report's key objectives are fourfold:

1. 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.
2. Address the challenges and risks posed by AI, particularly those relevant to Climate Action, including concerns about energy consumption and its climate and environmental impact, data security, gender bias, the digital divide, and harmful practices.
3. 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.
4. Showcase the opportunities and challenges of existing AI applications in developing countries, in particular for LDCs and SIDS in addressing climate change and improving environmental outcomes.

This report 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 report, covering the comprehensive literature review, semi-structured interviews with stakeholders, and the peer review process that were conducted to gather relevant data and insights. **Section 4** delves into AI for climate action in developing countries, presenting case studies and best practices that demonstrate the transformative potential of AI technologies in enhancing climate resilience and sustainability. This section highlights successful AI implementations, providing detailed insights into their impacts and the lessons learned, which can be adopted by other developing nations. **Section 5** explores the role of AI in implementing the Technology Mechanism Joint Work Program and Technology Needs Assessments (TNAs) outcomes, identifying opportunities for AI to enhance these frameworks. **Section 6** discusses the risks and challenges associated with AI deployment for climate action in developing countries, with a particular focus on energy consumption, data security, the digital divide, and gender bias. **Section 7** presents policy options for leveraging AI as a tool for advancing and scaling transformative climate solutions in developing countries, addressing the identified challenges and promoting sustainable development. **Section 8** provides a **conceptual framework for AI in climate action future outlook. Section 9** provides conclusions and recommendations, summarizing the key findings of the report and offering actionable steps for policymakers, researchers, and practitioners to effectively integrate AI into climate strategies in developing countries. **Section 10** is a call to action for these stakeholders to collaborate and leverage AI technologies in driving climate action and sustainable development. **Section 11** details the implementation framework, outlining the pathways and strategies necessary for the practical application of AI-driven climate solutions in developing countries.

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

AI encompasses a broad range of technologies designed to execute tasks that typically require human cognitive abilities. The focus here is on the conceptual definitions of AI and its common subfields or domains, namely ML, DL, Computer Vision (CV), Natural Language Processing (NLP), and Generative AI (GenAI), particularly focusing on their applications for climate action. Understanding these concepts is key to leveraging AI technologies effectively in mitigating and adapting to the impacts of climate change.

AI is the scientific and engineering discipline focused on creating computers capable of performing complex tasks that typically require human intelligence. It is a broad field that aims to simulate human cognitive processes and behaviors such as perception, learning, reasoning, problem-solving, language understanding, language generation, and planning. This enables computers to replicate human-like capabilities and actions. AI systems can process extensive datasets, identify patterns, predict outcomes, and make decisions either autonomously or with minimal human intervention using a set of algorithmic rules to govern their operations.

AI systems can also adapt to unfamiliar situations by continually learning from the new data they are exposed to over successive updates or iterations.

The capability of AI systems to autonomously enhance their performance through experience is termed ML. Contemporary AI heavily relies on ML, which involves a collection of algorithms and statistical models that identify patterns in large, sometimes unstructured, datasets without the need for explicit programming or human-defined pattern descriptions. ML is a foundational component in the development and functioning of various AI models. Its core techniques enable AI models to learn from data, improve over time, and augment their decision capabilities based the insights drawn from data (Sharifani and Amini 2023; Shinde and Shah 2018; Verma et al. 2024).

Furthermore, ML models can be effectively utilized across various paradigms, including supervised learning, unsupervised learning, and reinforcement learning (Donti and Kolter 2021; Naeem et al. 2023). **In supervised learning, models are trained on labeled 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 labeled 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.

AI encompasses several subfields, including ML, DL, CV, NLP, and GenAI (Figure 1). Each of these focuses on specific aspects of AI applications, and their synergistic integration and collaboration enhance the overall capabilities and versatility of AI systems. DL is a subset of ML that uses Artificial Neural Networks (ANNs) with many layers to analyze and interpret complex data patterns. These layers are particularly effective for handling large amounts of data and advanced data-driven tasks. CV is a subfield of AI that enables machines to interpret and make decisions based on visual data from the world. NLP is a branch of AI focused on the interaction between computers and humans through natural language.

Additionally, GenAI is a class of models that use massive datasets to produce new content, such as text, images, audio, or code as outputs in response to prompts, based on learned patterns. Unlike traditional AI systems that perform tasks based on predefined rules or make predictions based solely on past data, GenAI can generate original outputs by learning complex patterns, structures, and relationships in large datasets. Pretrained Foundation Models (PFMs) (e.g., Bommasani et al. 2022; Huang et al. 2024; Jakubik et al. 2023; Janowicz 2023; Liu et al. 2024; Zhou et al. 2023) are versatile models trained on vast datasets and designed to perform a wide range of tasks, extending beyond language. Among them, Large Language Models (LLMs) (e.g., Brown et al. 2020; Wolf et al. 2020) are specifically developed to deeply understand and generate human language. This includes specific domains such as generating scientific ontologies for optimizing intermodal freight transportation (Tupayachi et al. 2024) and providing in-depth, accurate, and accessible insights across various aspects of climate science (Thulke et al. 2024). LLMs are specialized for tasks like text generation, summarization, translation, and question-answering, excelling at producing coherent and contextually relevant text, making them integral to enhancing various text-based applications.

Each of those subfields has its specialized models tailored to different tasks. **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 essential 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 modeling and sequence prediction. These diverse AI models and techniques demonstrate the breadth and depth of AI's capabilities across different applications and tasks.

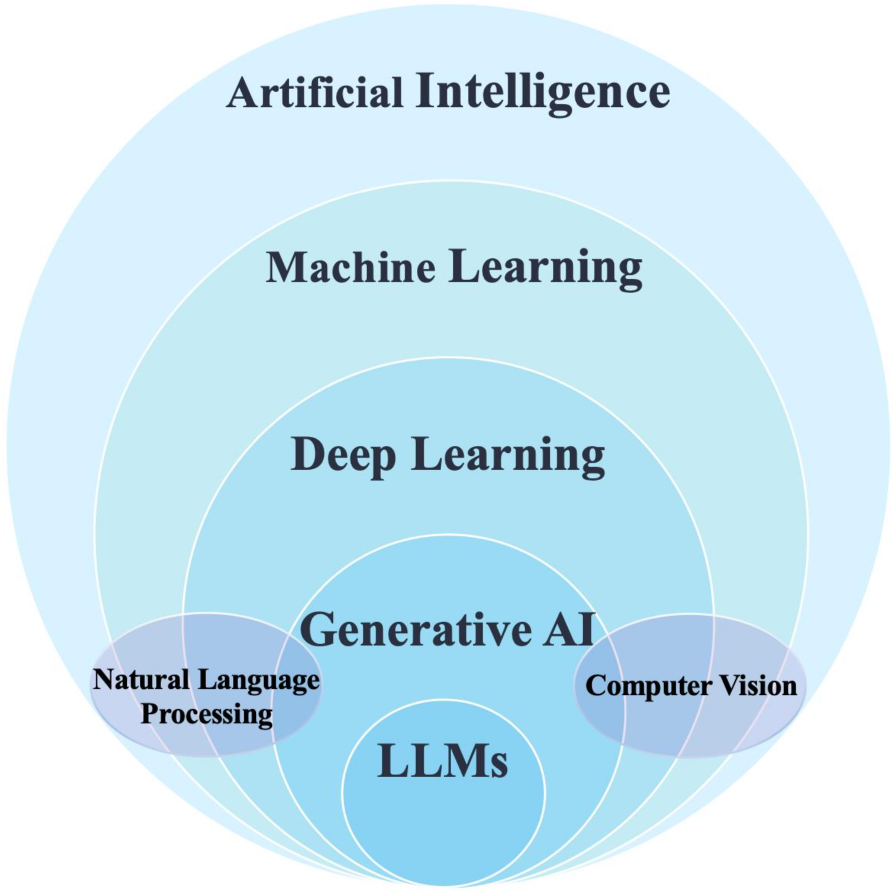

Figure 1. Artificial Intelligence and its subfields or domains

In particular, the successes of DL techniques in image recognition, speech recognition, language generation, and robotics have reignited interest in AI. ML algorithms form the foundation for various tasks in DL, CV, NLP, and GenAI tasks (Azevedo et al. 2024; Castelli and Manzoni 2022; Mahadevkar et al. 2022; Sharma et al. 2021). This adaptability is particularly beneficial in addressing climate change mitigation and adaptation challenges. For example, ML models are frequently used to solve optimization problems. The integration of ML with optimization methods, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), enhances the capability to explore and discover optimal solutions for environmental sustainability (Bibri et al. 2023). In essence, ML applied to optimization provides robust tools for addressing environmental challenges.

ML and DL techniques are key to the success of CV models, enabling them to accurately recognize and interpret visual data. CV utilizes ML/DL to process and analyze visual information from the world (e.g., Alam et al., 2021; Zhao et al. 2024), making it essential for applications involving image and video analysis (Ranjana et al. 2022; Sharma et al. 2021). The relationship between CV and ML, especially DL, is indeed synergistic. While advancements in ML/DL have significantly enhanced CV capabilities, enabling more precise object detection, image classification, and real-time video processing. the innovations, data generation, and application-driven requirements of CV tasks substantially aid in the development and refinement of ML/DL models. This reciprocal relationship drives continuous improvements and cross-disciplinary advancements, enhancing both fields.

Similarly, NLP harnesses ML and DL techniques to comprehend and generate human language.DL's robust learning capabilities empower NLP models to excel in various applications (Torfi et al. 2020), including language translation, sentiment analysis, and the development of sophisticated conversational agents. These advancements enhance the accuracy and efficiency of language processing tasks and enable more nuanced understanding and generation of human languages across different contexts and domains. These advancements enhance the accuracy and efficiency of language processing tasks and enable large-scale processing and generation of human language at a scale and speed unattainable by humans across different domains, enabling applications that require extensive data handling and analysis.

Likewise, GenAI uses ML and DL techniques to create new data instances that resemble a given dataset. This includes generating images, code, text, and audio, highlighting the creative potential of AI. The ability of generative models to synthesize new data has significant potential for augmenting training datasets in ML and DL, potentially improving model robustness and diversity (Lu et al. 2024). However, this field is still emerging, and AI-generated data can suffer from issues such as mode collapse, which may reduce data diversity. Further research and careful consideration are needed to address these challenges and harness the full benefits of AI-generated data.

GenAI models learn from large datasets to generate original content that mimics the patterns and structures found in the training data (e.g., Goodfellow et al. 2020; Kingma and Dhariwal, 2018). Examples of models used for GenAI, which include LLMs, are GPT-3 (Generative Pre-trained Transformer 3) (Brown et al. 2020), BERT (Wolf et al. 2020), CLIP (Contrastive Language–Image Pre-training) (e.g., Radford et al. 2021), and Generative Adversarial Networks (GANs) (Goodfellow 2020). These models rely heavily on ML and DL algorithms to function effectively. In particular, recent advancements in LLMs have significantly enhanced the capabilities of GenAI in NLP. While recent advancements in GenAI and LLMs offer potential for innovation, their utility in direct climate applications remains nascent but rapidly progressing. GenAI models have shown promise in generating synthetic data to augment training datasets, which could improve the robustness and diversity of models used in climate predictions. However, these advancements are still emerging, and there are concerns about data quality, diversity, and potential biases (Huang, Bibri, and Keel 2024). Continued research and integration of these emerging technologies could eventually augment existing AI solutions, driving further advancements in climate action. Therefore, while traditional AI and ML have a proven track record, exploring the potential of GenAI and LLMs remains instrumental to future innovation in climate solutions.

In the context of AI, methodologies such as ML and DL are particularly important for more effective climate action. Technologies like CV and NLP can also play significant roles in monitoring and analyzing environmental data. Additionally, GenAI has the potential to contribute through simulations and predictive modeling, although it is one of many useful AI paradigms for climate action (McCormack and Grierson 2024; Paramesha et al. 2024; Sha et al. (2024). Climate action entails concerted efforts and initiatives aimed at addressing climate change by mitigating its causes and adapting to its impacts. This involves reducing GHG emissions, enhancing resilience to climate-related hazards, and transitioning towards sustainable practices and technologies. AI technologies collectively offer advanced data analysis, predictive modeling, and decision-making capabilities that are essential for addressing complex climate challenges.

ML algorithms analyze vast datasets related to climate variables, emissions, and impacts to identify patterns, make predictions, and optimize processes. For instance, ML can predict weather patterns and climate trends, track environmental changes, optimize resource usage, and improve the efficiency of renewable energy systems. DL excels in processing complex data with multiple layers of abstraction. DL models can be used to analyze satellite imagery to monitor deforestation or urban heat islands—critical indicators of climate change. CV methods enable automated analysis of visual data from satellite imagery or drones, facilitating real-time monitoring of environmental changes like land use changes, glacier retreats, deforestation, and wildlife movements, providing significant data for environmental conservation efforts. This helps in assessing the impact of climate change and implementing appropriate interventions. 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, like other AI approaches, simulate climate models to predict future scenarios and develop adaptive strategies based on individual or regional climate data.

These AI technologies enhance the capacity for data-driven decision-making, optimize resource management, improve predictive capabilities for extreme weather events, and support the development of sustainable policies and technologies. Climate action efforts can be significantly bolstered by leveraging AI's capabilities across these domains, thus contributing to more effective mitigation and adaptation strategies in the face of climate change threats.

3. Methodology

This report, commissioned by the Technology Executive Committee (TEC), employs a comprehensive methodology to examine the role of AI in climate action, especially in the context of developing countries, including LDCs and SIDS. As the policy arm of the UNFCCC technology mechanism, the TEC's strategic guidance is pivotal. It shapes the report’s framework to ensure that the exploration of AI technologies aligns with global climate action goals and addresses specific needs of member states in technology-related decisions. This alignment helps to foster technological cooperation and facilitates the transfer of relevant AI technologies to enhance climate resilience. The TEC's role extends beyond oversight, as it actively engages in disseminating the findings to global stakeholders and supports the integration of AI solutions into national policies and strategies. The methodology of the report includes a thorough literature review to assess the landscape of AI's benefits, risks, and challenges, coupled with semi-structured interviews with stakeholders involved in AI initiatives for climate action in developing countries to gather diverse insights and experiences. These interviews help to identify practical and impactful AI applications, ensuring that the collected data is directly relevant to ongoing efforts. In addition, the TEC facilitates a rigorous peer review process that elevates the report's academic and practical quality and ensures that the recommendations are robust, actionable, and tailored to the nuanced challenges faced by developing nations, particularly SIDS and LDCs. The TEC enhances the report's utility and applicability in real-world settings by ensuring a multi-disciplinary approach and integrating diverse expert opinions.

3.1. 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. Regarding 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 in climate action in developing countries. The search criteria were aligned with the thematic focus of the report, which includes exploring current AI applications in climate mitigation and adaptation strategies, analyzing case studies from LDCs and SIDS, and evaluating the benefits and challenges of AI adoption, with the aim of providing recommendations for policy-makers 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 included 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, with a specific focus on studies conducted in developing countries, including LDCs and SIDS, aligning with the thematic scope of this report.

Inclusion and exclusion criteria*:* Publications from the timeframe 2017-2024 were included to ensure the most current information and credibility of the data through peer-reviewed articles, research papers, and reports directly addressing the pre-defined themes of the report. Non-peer-reviewed articles and studies and those beyond this period were excluded to maintain the integrity and relevance of the review, focusing solely on publications that directly pertain to the use of AI for climate action in the specified contexts.

Search and selection: Relevant publications were identified through a comprehensive search across selected databases using specific keywords and phrases, based on the inclusion and exclusion criteria. These publications were subsequently scrutinized based on their abstracts and alignment with the research objectives.

Detailed analysis: This phase entailed a thorough examination of selected scholarly articles, research papers, and reports to extract nuanced insights into the benefits, risks, and challenges associated with AI for climate action in developing countries, with a specific focus on LDCs and SIDS. The objective was to analyze the pre-defined themes related to the implications of AI adoption in climate action in these countries and regions. Detailed information relevant to these themes was extracted from the selected studies, including key findings, conclusions, and specific insights. Each study underwent critical evaluation to assess its relevance, methodological rigor, and credibility to ensure robust and reliable synthesis of findings. The extracted data were organized and categorized according to pre-determined themes or topics of interest, facilitating focused analysis on aspects such as AI technologies applied, observed positive outcomes, existing and anticipated challenges, geographical or regional variations, and policy implications.

Synthesis of findings: This phase consolidated and integrated insights gathered during the analysis to offer a cohesive overview of the current landscape of AI for climate action in developing countries. Synthesizing data from selected scholarly articles, research papers, and reports enabled the identification of patterns, contexts, and relationships across the examined body of literature. This synthesized understanding forms the foundation for the subsequent sections of the report, guiding discussions on the transformative potential of AI technologies in addressing climate change challenges in developing countries. The synthesis also included suggestions for optimizing AI climate strategies and leveraging opportunities to enhance climate resilience and sustainability in LDCs and SIDS.

3.2. Justification of 2017-2024 Timeframe

Worth noting is that the timeline from 2017 to 2024 for the literature review on AI and its applied models for climate action is well-justified due to several key factors. First, there have been rapid technological advancements in AI, ML, and related fields during this period. These advancements have significantly enhanced the capabilities and applications of AI in addressing complex global challenges, including climate change. The integration of AI with other emerging technologies, notably IoT, has further bolstered its potential in environmental sustainability.

The proliferation of AI research specifically targeting climate action has been particularly notable since 2017. The period 2017-2024 captures the most relevant and recent studies, ensuring that the literature review includes the latest developments and insights in the field. The focus on this timeline allowed for a comprehensive understanding of how AI technologies have evolved and been applied to climate action, reflecting cutting-edge trends and innovations.

Moreover, the global awareness and urgency regarding climate change have dramatically increased during 2017-2024. Major international agreements and frameworks like the Paris Agreement, UN SDG, and UNFCCC have underscored the need for effective measures and immediate solutions to combat climate change, prompting a surge in research and innovation in AI technologies for climate action. This heightened awareness has spurred governments, organizations, and the scientific community to explore and implement AI-driven solutions for climate mitigation and adaptation. Additionally, practical implementations and case studies during this period provide valuable insights into the effectiveness of AI in real-world implementations. These examples highlight the practical benefits and challenges of using AI for climate action, providing lessons and best practices that can inform future efforts.

Overall, focusing on the period from 2017 to 2024 ensures that the literature review encompasses a comprehensive and up-to-date overview of AI's role in climate action, capturing the significant advancements, increased awareness, and practical implementations that have characterized this critical period in the fight against climate change.

3.3. Semi-Structured Interviews

Interviews were conducted with a range of stakeholders actively involved in AI initiatives in developing countries, specifically targeting those engaged in research or the implementation of AI-related projects pertaining to SIDS and LDCs. The group of interviewees included academic researchers, practitioners, industry professionals, and policy makers who are directly involved in the deployment and management of AI technologies in various domains. These interviews were instrumental in gathering in-depth insights and firsthand 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 typically comprises international experts from academia, industry, NGOs, and governmental bodies who are recognized for their work in AI, climate science, policy implementation, and related issues. These individuals are selected based on their specific expertise to ensure that the paper benefits from a range of insights that enhance its scientific rigor and practical relevance. Key aspects of their involvement include:

- **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 report to improve its readability, impact, and ability to communicate key messages effectively to policymakers as well as practitioners and researchers.

This collaborative approach helps to ensure that the report adheres to high academic standards but also addresses the practical needs of the target audience, thereby enhancing the potential for real-world impact.

In summary, by adhering to this methodology, the report endeavors to deliver a comprehensive and thorough evaluation of the current state of knowledge on AI for climate action. It aims to establish a robust framework for understanding how AI can enhance climate solutions and strategies in developing countries, with a specific focus on LDCs and SIDS. This detailed approach ensures that the conclusions and suggestions are grounded in the most recent research and practical insights derived from the interdisciplinary field of AI and climate change mitigation and adaptation.

4. Artificial Intelligence for Climate Action in Developing Countries

AI is emerging as a powerful tool in advancing global climate action, with its applications spanning both developed and developing countries. AI can drive significant improvements across various sectors, especially where large amounts of data need to be collected, analyzed, and leveraged for climate solutions. This section offers a comprehensive analysis of existing literature and empirical evidence, focusing on the role of AI in addressing climate challenges across different global contexts. The analysis highlights the unique opportunities in developing countries, particularly in LDCs and SIDS, to learn from and adapt AI technologies. It explores both the benefits and risks associated with AI adoption in these regions while examining the regulatory landscapes that influence AI deployment. By exploring specific case studies from SIDS and LDCs, the section illustrates how AI can effectively and innovatively drive climate action in these regions, which are among the most vulnerable to climate change impacts.

4.1. Monitoring and Data Collection

Effective climate action relies heavily on robust monitoring and data collection strategies. Advanced technologies, such as satellite imagery, IoT sensor networks, and AI-driven systems, are essential for acquiring accurate and comprehensive environmental data. Leveraging these technologies, along with ML models, enhances the understanding of climate dynamics, improves the prediction of environmental changes, and enables the implementation of timely interventions to mitigate adverse effects.

4.1.1. Satellite Imagery and Monitoring Data Analysis

The utilization of satellite imagery, advanced data analysis, and AI and ML techniques plays a significant role in monitoring and addressing climate change. The following areas highlight the key applications in this regard:

4.1.1.1. Examination of Sea Level Rise and Coastal Transformations

Advanced satellite imagery and AI and ML models allows for precise monitoring of sea level changes and coastal transformations. This includes tracking the extent of coastal erosion, mapping shoreline changes, and identifying areas at risk of storm surges. The data gathered are essential for developing mitigation strategies and informing coastal management policies. For example, 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). However, Vignudelli et al. (2019) explore the advancements in satellite altimetry for coastal sea level monitoring. The authors highlight the improvements in data processing techniques over the last decade, emphasizing the role of synthetic aperture radar (SAR) and Ka-band (Altika) frequency in enhancing data accuracy and reliability. Naheem et al. (2021) discuss the advances in traditional sea level estimation methods, focusing on tide gauges and satellite altimetry. The authors emphasize the importance of integrating tide gauge data with satellite measurements and ancillary systems for a comprehensive understanding of sea level changes. Coastal altimetry has evolved to address the challenges of measuring sea level near coastlines, employing advanced radar systems for higher spatial resolution and lower noise (Cipollini et al, 2017; Vignudelli et al. 2019). The Copernicus Sentinel-6, a two-satellite mission, represents the latest effort in this domain, offering enhanced global sea level measurements and climate monitoring capabilities (Donlon et al. 2021).

Sea level prediction and monitoring are critical for mitigating the impacts of climate change on coastal communities and ecosystems. The accurate prediction and monitoring of sea level rise are important for the protection of coastal areas and the planning of mitigation strategies. Various AI-based methods have been developed to address this complex issue, significantly enhancing the accuracy and efficiency of sea level predictions. By utilizing advanced algorithms such as ML, DL, and ensemble modeling, these AI approaches are capable of processing vast datasets and extracting intricate patterns, leading to more reliable and precise forecasts and improvement of our understanding of sea level dynamics. Bahari et al. (2023) reviewed the application of AI for predicting sea level rise, highlighting the use of ML and DL techniques. These AI methods are capable of extracting meaningful patterns and relationships from extensive datasets, improving prediction accuracy. 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. However, it comes with the black-box issue.

Balogun and Adebisi (2021) integrate a broad range of ocean-atmospheric variables to predict sea level variations along the West Peninsular Malaysia coastline using ML (ARIMA and SVR) and DL (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.

Accarino et al. (2021) present a multi-model architecture based on LSTM neural networks for short-term sea level forecasting in the Mediterranean. Their approach outperforms traditional forecasting systems, showing that DL can provide accurate and timely predictions essential for coastal management. Žust et al. (2021) introduce HIDRA, an ensemble DL-based sea level forecasting method for the Adriatic Sea. HIDRA integrates atmospheric and sea level data, outperforming traditional ocean circulation models in both accuracy and computational efficiency.

Overall, integrating AI enhances the accuracy and reliability of predictions in assessing sea level rise and coastal transformations, which is essential for mitigating the impacts of climate change on coastal regions. While traditional methods like satellite altimetry and tide gauges remain key to long-term and large-scale sea level monitoring, AI-based approaches offer substantial improvements in prediction accuracy and efficiency. The integration of AI models with traditional observation systems promises a more reliable and robust and precise framework for addressing the challenges posed by sea level rise. Non-AI-based methods, such as satellite altimetry, continue to evolve, providing indispensable data for coastal monitoring and long-term sea level research. Combining these approaches can highly advance our understanding and management of sea level changes, particularly in coastal and vulnerable regions.

4.1.1.2. Detection of Deforestation and Forest Degradation, Pollution Sources, Biodiversity, and Nuanced Land Use Alterations Through Advanced Algorithms

Satellite imagery, combined with sophisticated AI algorithms and remote sensing technology, enables the detection and monitoring of deforestation and forest degradation, and can identify pollution sources, assess biodiversity levels, and analyze land use changes with high precision. Additionally, IoT sensor networks play an instrumental role in providing real-time data for these analyses. AI has proven effective in optimizing forest management by identifying high CO_2 storage (high carbon stock) forests and improving conservation efforts. These capabilities support efforts to combat illegal logging, manage natural resources, and preserve biodiversity, particularly in regions such as the Amazon and Southeast Asia, which are critical for global biodiversity.

4.1.1.2.1. 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 sophisticated AI algorithms, enables the detection and monitoring of deforestation and forest degradation. AI models analyze high-resolution optical and laser-based satellite images, often coupled with ground-truth biomass 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 analyzing the strengths and limitations of IoT, satellite imagery, drones, and AI algorithms, the study underscores their potential in forest conservation. The findings highlight the importance of these technologies in safeguarding forests and the species they harbor, providing valuable insights for future research and practical policy-making in forest conservation.

Nguyen-Trong and Tran-Xuan (2022) focused on improving forest cover change detection using AI-based remote sensing techniques in Vietnam. 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 Vietnam.

Debus et al. (2024) focused on understanding direct deforestation drivers in Cameroon by employing Earth Observation imagery. The researchers developed a labeled dataset designed for AI applications to classify deforestation drivers in areas experiencing forest loss. This dataset includes satellite imagery from Landsat and PlanetScope, coupled with auxiliary data on infrastructure and biophysical properties. The labels cover a comprehensive range of deforestation drivers, such as large-scale plantations (oil palm, timber, fruit, rubber), small-scale agriculture, mining, selective logging, infrastructure development, wildfires, and hunting activities. This dataset aims to provide a detailed, locally-adapted resource for better monitoring and management of deforestation in the Congo Basin.

The recent research on deforestation detection contributes to climate change by providing advanced techniques for monitoring forest ecosystems, which are essential for both mitigation and adaptation efforts. By improving the accuracy and efficiency of deforestation detection, AI supports efforts to combat forest loss and degradation, contributing to broader climate change mitigation and adaptation strategies. Worth noting is that over half of SIDS have forests covering more than 50% of their total land area, with Land Use, Land-Use Change, and Forestry (LULUCF) acting as a net sink for 19.87 million tonnes of CO_2 equivalent (Crumpler et al. 2020). The potential for adopting Reducing Emissions from Deforestation and Forest Degradation (REDD+), which includes conservation, sustainable forest management, and enhancement of forest carbon stocks, is significant for Caribbean SIDS (Mohan et al. 2022). Currently, only four countries in the region—Belize, Dominican Republic, Guyana, and Suriname—have operational systems and mechanisms for accessing REDD+ finance (Mohan 2023). However, the region faces limitations in LULUCF knowledge and is constrained by insufficient institutional and technical capacity, LULUCF data and inventory, human resources, and technology (Crumpler et al. 2020).

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 to monitor deforestation and protect the biodiversity of the ecosystem. Project Guacamaya is an innovative initiative aimed at combating deforestation in the Amazon rainforest through the use of advanced AI technology. This project combines satellite imagery, camera traps, and bioacoustic data to monitor and analyze deforestation patterns rapidly and accurately. By leveraging AI models developed in collaboration with Microsoft and other organizations, the project significantly reduces 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. This AI-driven approach offers a scalable solution to monitor and protect the Amazon, addressing a critical environmental challenge

AI technologies can significantly contribute to overcoming these challenges by enhancing data collection, analysis, and monitoring capabilities. AI can streamline the inventory process, optimize resource allocation, and provide real-time insights for better forest management. This technological integration can support the region in adopting effective REDD+ strategies and improving overall forest conservation efforts.

4.1.1.2.2. Detection of Pollution Sources

In addition to harming human health, pollution hinders sustainable ecological growth. AI and ML algorithms applied to satellite imagery, remote sensing, IoT, and big data analytics can identify and monitor pollution sources, such as industrial emissions, chemical substances, and wastewater discharge points. These technologies can detect contamination levels in air, soil, and water bodies by analyzing the spectral signatures of various pollutants and chemicals. The data-driven insights can aid in pinpointing pollution hotspots and assessing the effectiveness of pollution control measures.

Remote sensing and historical aerial photographs have been pivotal 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 modeling 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).

Aerial imagery's effectiveness in detecting and analyzing hazardous waste is key to environmental monitoring and management. The study by Wani et al. (2023) emphasizes how advanced imagery techniques can aid in monitoring hazardous waste sites, waste-disposal sites, and landfills, proving effective in detecting and analyzing the presence of hazardous waste (Wani et al., 2023), as well as ensuring better regulatory compliance and enhancing environmental protection efforts. This indirectly supports climate action by promoting sustainable waste management practices. Landfills and waste disposal sites are significant sources of methane, a potent GHG. Effective monitoring and management of these sites can help reduce methane emissions, contributing to climate change mitigation efforts. Moreover, improper disposal of hazardous waste can lead to soil and water contamination, affecting ecosystems. In addition, Efficient monitoring aids in better management of resources and waste. Promoting recycling and proper waste management reduces the need for new resource extraction, which is energy-intensive and contributes to GHG emissions.

Advancements in AI have significantly enhanced environmental monitoring capabilities, enabling more efficient detection and analysis of hazardous substances and enhancing the capability to manage environmental hazards and safeguard human health and ecosystems. The integration of AI in environmental monitoring has become increasingly popular due to its ability to detect threats that humans cannot perceive, such as odorless, colorless, and tasteless gases (Visvanathan et al. 2018; Daam et al. 2019; Emaminejad and Akhavian 2022). AI-powered sensors and devices, specifically equipped with ML algorithms, can analyze real-time data to identify specific hazardous materials and predict their potential impact on human health and the environment (Yang et al. 2021).

One notable application of AI in environmental monitoring is the use of electronic nose (E-nose) technologies. These technologies employ olfactory algorithms to analyze 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). The role of E-nose technologies in environmental monitoring indirectly supports efforts to mitigate climate change. They provide essential data for managing and reducing pollutants that contribute to global warming, highlighting their relevance in climate change discussions. Monitoring pollutants, such as volatile organic compounds (VOCs) and methane, helps manage and reduce their levels, which is crucial for mitigating climate change. E-noses are also used to monitor emissions from industrial activities. Providing real-time data on pollutants allows industries to take corrective actions to reduce emissions, thereby helping to mitigate climate change. Monitoring VOCs and other harmful emissions from factories to ensure they meet environmental regulations and reduce their carbon footprint.

Furthermore, Wang et al. (2019) identified the characteristics and trace the origins of water pollutants from industrial point sources using an integrated AI system. This system combined a long short-term memory network (LSTM) with cross-correlation and association rules (Apriori) to analyze water quality. The study demonstrates that changes in water quality are influenced by various industries and the distribution and production cycles of pollutant sources. Using water quality correlation maps, the researchers effectively identified regular and abnormal fluctuations in pollutant emissions by highlighting changes in water quality characteristics. The association rules derived frequent itemsets in water quality indices, helping trace pollutants back to specific industries. Additionally, the LSTM model accurately traced the origins of future water quality changes, proving the effectiveness of the AI system in monitoring and managing water pollution. By identifying and managing pollutant sources, this AI system indirectly supports climate change mitigation efforts by promoting cleaner industrial practices. Furthermore, improving water quality can enhance ecosystem resilience against climate change impacts.

In addition, Popescu et al. (2024) focused on the integration of AI, sensors, and IoT in monitoring environmental pollution, such as air pollutants, water contaminants, and soil toxins. AI-driven sensor systems offer promising solutions for detecting and responding to environmental risks, addressing the growing concerns about the impact of hazardous substances on ecosystems and human health. The study highlights the significant potential of ML methods in environmental science. It examines the complexities involved in predicting and tracking pollution changes due to the dynamic nature of the environment and the challenges posed by data sharing. It underscores the importance of developing advanced monitoring systems that can efficiently detect, analyze, and mitigate environmental hazards, contributing to improved human wellbeing and ecosystem protection. By utilizing AI and IoT technologies, the study indirectly supports climate change mitigation by promoting sustainable practices and reducing pollutant emissions. Moreover, enhanced monitoring capabilities contribute to better adaptation strategies, increasing resilience against climate change impacts.

Overall, climate change impacts various contaminants and pollutants in water systems and soil, linking these issues directly to environmental and human health. Increased temperatures and altered precipitation patterns can increase the mobilization and concentration of pollutants, such as heavy metals and pesticides, in water bodies and soil. These changes can lead to more frequent and severe contamination events, exacerbating water quality issues and affecting agricultural productivity. In addition, extreme weather events, such as floods and droughts, can disrupt waste management systems and cause the overflow or leakage of contaminants into the environment. Addressing these pollutants in the context of climate change is key to protecting ecosystems and ensuring the health and resilience of communities.

In sum, the integration of AI and IoT-driven technologies in environmental pollution monitoring and management represents a significant advancement, offering real-time detection, analysis, and response capabilities for various environmental pollutants. Additionally, the incorporation of remote sensing and aerial imagery enhances the opportunities of environmental monitoring efforts. The ability to monitor air, water, and soil quality with high precision and efficiency supports proactive measures to protect human health and ecosystems.

Moreover, the creation of AI-driven sensors for monitoring hazardous environmental substances has the potential to transform how we detect and address environmental threats. These sensors, capable of processing large datasets in real-time and identifying patterns and anomalies indicating hazardous substances, can significantly enhance our ability to safeguard public health and the environment. However, numerous challenges remain, such as ensuring the accuracy and reliability of these sensors and finding optimal methods to integrate them into current environmental monitoring systems. Nevertheless, the potential advantages of AI-driven sensors make them a promising area for future research and development in environmental monitoring.

Overall, the deployment of AI, IoT, remote sensing, and aerial imagery solutions will play an important role in mitigating the impacts of environmental pollution, as research and development in this field continue to evolve.

4.1.1.2.3. Biodiversity Monitoring and Assessment

Biodiversity is in decline across the globe at a catastrophic rate, as threats from human settlement expansion, illegal wildlife killing, and climate change place enormous pressure on wildlife populations. Conservation biologists are faced with the daunting – but urgent – task of surveying wildlife populations and making policy recommendations to governments and industry. What species need legal protection from hunting? A road needs to connect two cities; which route will have the least detrimental impact on wildlife habitat? Where will it be most effective to build underpasses as wildlife migration corridors? Where should we deploy anti-poaching resources? Informed policy decisions on questions like these start with data: just as your doctor can only prescribe treatment after running trusted diagnostic tests, policymakers and protected area managers can only act to protect biodiversity if robust, up-to-date data is available when they need it.

Data, in this case, are wildlife population estimates, for which remote sensing has become the most powerful tool in the conservation toolbox. But currently, collecting data about how animals use their habitats – or even how many animals live in a given area – is dependent on tremendous amounts of manual data annotation: it often takes years for a small NGO to annotate millions of images or audio recordings for a single project. This bottleneck precludes real-time applications, and often delays critical answers to conservation questions so long that by the time they're available, they're no longer relevant. AI is poised to break this annotation logjam, and to greatly accelerate conservation decision-making.

Satellite imagery, enhanced by AI algorithms, is used to assess biodiversity levels in different ecosystems. AI algorithms can identify various species and habitats from satellite images, providing data on species distribution and habitat health. Moreover, AI leverages new methods to address biodiversity problems by analyzing spatial and temporal data, offering insights into ecosystem dynamics and conservation strategies. This information is of significance to conservation planning and biodiversity protection efforts. Silvestro et al. (2022) highlighted the substantial potential of AI to improve the conservation and sustainable use of biological and ecosystem values in a rapidly changing and resource-limited world. Protecting biodiversity is directly linked to climate change mitigation and adaptation, as healthy ecosystems play a vital role in regulating the climate, sequestering carbon, and maintaining resilience against climate impacts

Numerous examples of AI demonstrate its growing use 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 modeling ecosystem services (see, e.g., 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 (2022), 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 analyze and classify high-resolution images for species identification and habitat mapping, providing critical data for conservation efforts (Christin et al. 2019). Random Forest (DF) 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).

Many studies in biodiversity research have developed ML and NLP solutions to predict ecosystem services, leveraged social media data to model public opinion, and modeled habitat suitability and availability for biodiversity conservation (Nishant et al. 2020; Bagstad et al. 2016; Toivonen et al., 2019). Additionally, SVM, ANN, FL, and Genetic Algorithms (GA) are employed to assist in predicting species presence and habitat quality based on environmental variables extracted from satellite data (Bibri 2024; Bibri et al. 2023; Nishant et al. 2020). SVMs handle classification tasks, ANNs model complex data relationships, FL handles vague and ambiguous information, and GA optimize the selection of relevant environmental variables for accurate predictions. These techniques are frequently used due to their effectiveness in handling complex data and predicting ecological outcomes. GA optimize solutions by mimicking natural selection, ANN simulate brain-like processing for pattern recognition, FL manages uncertainty and imprecision, and BN represent probabilistic relationships among variables, making them highly suitable for ecosystem modeling. This comprehensive approach ensures that diverse AI techniques are effectively utilized to address the complexities of biodiversity and ecosystem health.

Furthermore, Christin et al. (2019) illustrated that DL has been effectively employed to identify species, classify animal behaviors, and estimate biodiversity from extensive datasets, including camera-trap images, audio recordings, and videos. They indicate that DL techniques can significantly benefit various ecological disciplines, particularly in applied contexts such as wildlife management and conservation efforts. These techniques enable more precise and efficient monitoring of biodiversity and ecosystem management, which is essential for developing targeted conservation strategies. Silvestro et al. (2022) introduced a novel framework for spatial conservation prioritization using reinforcement learning to enhance biodiversity protection policies. The methodology, named Conservation Area Prioritization through Artificial Intelligence (CAPTAIN), balances the costs and benefits of area and biodiversity protection, safeguarding more species compared to random or naive methods. It also produces more reliable conservation targets and interpretable prioritization maps using empirical data. Moreover, by utilizing both visual and audio data, AI can conduct real-time monitoring of wildlife populations to inform conservation strategies (Norouzzadeh et al. 2018). This is achieved through CV and bioacoustic analysis enabled by various sensors (e.g., camera traps, cell phone microphones, drones, remote sensing), and by incorporating citizen science through crowdsourced data (Stowell 2022; Tuia et al. 2022; Willi 2019).

In summary, integrating AI technologies into biodiversity and ecosystem modeling enhances our ability to monitor, predict, and protect biodiversity. Techniques like ARIES, GA, ANN, Bayesian networks, and FL provide robust tools for managing complex ecological data, optimizing conservation efforts, and addressing uncertainties and imprecision inherent in ecological modeling. These advancements underscore the key role of AI in promoting sustainable environmental practices and effective conservation strategies.

4.1.1.2.4. Nuanced Land Use Alterations

The relationship between climate and land use is pivotal, as 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 detect subtle changes in land use, such as urban expansion, agricultural activities, and infrastructure development. AI-equipped satellites can collect vast amounts of land resource data over varying periods. 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 enhances land classification by making it more intelligent and automated, facilitating decision-making. Kerins et al. (2020) demonstrated the viability of automated urban land use/land cover mapping using ML models and medium-resolution 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 aids in understanding the impacts of human activities on the environment and in planning sustainable land use practices.

Dousari et al. (2022) utilized SVM and ANN 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 2022). CNNs, which excel in many image classification tasks, outperform SVMs, RF, and k-nearest neighbors (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-meter 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 favorably 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 policy-making 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 support vector machine (SVM) classification, they mapped LULC for 1990–2018 and analyzed 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 water bodies 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.

In conclusion, AI-powered technologies substantially improve the detection and monitoring of land use changes, contributing to more efficient urban and environmental planning. By utilizing satellite imagery and ML models, AI enables accurate and timely analysis of land resource data, improving decision-making processes. These advancements offer substantial benefits in terms of cost savings, precision, and the ability to monitor and predict environmental impacts. The role of AI in supporting sustainable land use practices and urban planning has become increasingly important, particularly in resource-limited regions.

4.1.1.3. Monitoring of Carbon Dioxide and Methane Emissions

Satellites and remote sensing, enhanced by AI, provide valuable data on carbon dioxide (CO_2) and methane emissions. This AI-driven monitoring is essential for verifying compliance with emission reduction commitments, understanding emission sources, and guiding policy decisions to address climate change effectively. AI algorithms can analyze vast amounts of satellite data quickly and accurately, offering real-time insights into GHG levels and their sources. Das et al. (2020) proposed a robot designed for deployment in unknown and uneven environments, capable of recognizing hazardous gases such as CO_2 and liquefied petroleum gas with an average accuracy of 98%. The robot is equipped 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 color-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 CFD-GA methods. This efficiency stems from the ANN's lower computational demands and its ability to handle large datasets and variable parameters effectively, showcasing 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 CO_2 management processes. Gupta (2022) examined various CO_2 capture, storage, transportation, and utilization (CCSTU) processes and explore their enhancement through ML methods. The review covers several carbon capture technologies, including absorption, adsorption, membranes, chemical looping, pyrogenic carbon capture and storage (PyCCS), hydrates, and mineral sequestration. It also classifies hybrid processes that combine multiple methods for CO_2 capture and utilization. The results highlight that ML methods have been successfully applied to optimize CCSTU processes and incorporate new materials design, thereby improving efficiency. They authors highlight the need to consider the carbon impact of AI-driven models and to foster collaboration among ML experts, experimentalists, and computational modelers to accelerate the commercialization of low-carbon technologies.

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, showcasing its adaptability to individual health conditions. Similarly, Sowmya and Ragiphani (2022) proposed an air quality monitoring system leveraging IoT and AI 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 analyzing the air quality index using sensor data. Alimissis et al. (2018) utilized ANN and multiple linear regression, discovering that ANN offer computational advantages, especially when the density of air quality monitoring networks is limited.

Furthermore, 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 can predict the behavior of CO_2 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 CO_2 management, represents another significant strength (Zhang et al. 2022).

In sum, AI-driven sensor data analysis is essential for accurate tracking of GHG emissions and air quality, enabling proactive measures to mitigate pollution and protect human health. Leveraging ML algorithms and integrating IoT systems enable real-time detection, analysis, and response to various environmental pollutants. The ability to predict and manage emissions and enhance air quality monitoring demonstrates the significant potential of AI in promoting sustainable practices and mitigating climate change impacts. Importantly, the collaboration among AI experts, environmental scientists, and policymakers will be indispensable in driving further advancements in AI and ensuring its effective application for environmental conservation.

4.1.2. Power of the Internet of Things Devices and Sensor Networks

The advent of IoT devices and sensor networks has revolutionized data collection and monitoring across various domains, particularly in environmental sustainability and climate change. These devices are equipped with advanced sensors that measure numerous environmental parameters, enabling continuous and real-time data acquisition. IoT represents a network of interconnected devices that communicate, transmit, and share data over the internet and other networks. IoT devices are strategically deployed to gather real-time climate data across various domains. The data collected from these sensors are vital for understanding climate patterns, monitoring environmental changes, and predicting potential climate-related events. When integrated with AI, these IoT devices form an intelligent network and technological framework known as AIoT, which enhances data analysis and intelligent decision-making and automation processes, particularly in the domains of environmental sustainability and climate change (Bibri 2024).

4.1.2.1. Strategic Deployment of Sensors for Real-Time Climate Data Acquisition

IoT devices can be strategically placed in various locations to continuously monitor environmental conditions and capture real-time climate data. This includes weather stations, water quality sensors, air quality monitors, and soil moisture sensors. The real-time data collected from these sensors provides a continuous stream of information, allowing for more accurate and timely responses to climate-related events. This strategic deployment across diverse geographical areas allows for the continuous collection of real-time climate data, providing a holistic view of climate patterns and changes. Such real-time data acquisition is critical for timely and accurate climate analysis, which forms the basis for developing effective climate action strategies. By deploying a network of interconnected sensors, comprehensive datasets can be gathered, offering detailed insights into local and global climate patterns.

Real-time data acquisition is essential for monitoring environmental changes, predicting weather events, and understanding long-term climate trends. IoT devices are capable of measuring various environmental parameters such as temperature, humidity, precipitation, air quality, atmospheric pressure, wind speed, solar radiation, soil moisture, salinity, sea levels, ocean currents, and GHG concentrations. This vast array of sensors provides comprehensive data necessary for monitoring climate patterns. In their study, Aditama et al. (2023) focused on modernizing climate monitoring in Indonesia by developing an IoT-based Digital Climate Station (DCS) at the Dramaga Climate Observational Station. The DCS aims to replace conventional manual methods with an automatic, internet-based system for real-time climate monitoring. The station measures key climate parameters such as air temperature, relative humidity, solar radiation, air pressure, wind, rainfall, and soil temperature. Managed by the Indonesia Meteorological Administration (BMKG), the system uses the Campbell CR1000X datalogger, various meteorological sensors, and a solar-powered system. The sensors, which have a maximum error of 2.38%, transmit data via the Amazon AWS IoT Core MQTT Broker using the MQTT protocol. This data is then stored in a MySQL database and displayed through Grafana, accessible on both desktop and mobile devices. The system demonstrated a high data transmission reliability, with over 97% data completion from 1440 daily records. This innovative approach not only enhances data accuracy and real-time monitoring capabilities but also serves as a model for future automation of climate observation stations across Indonesia.

In their study, Durodola et al. (2022) addressed the challenges faced by developing countries like Nigeria in importing weather monitoring systems due to erratic exchange rates. To overcome these challenges, they developed an Environment and Climate Data Acquisition System (EC-DAQS) tailored for radio propagation studies. The EC-DAQS utilizes an Arduino Mega2560 microcontroller and six environment and weather sensors to measure, record, and display atmospheric parameters, including temperature, ultraviolet rays, humidity, and sound levels.The system was validated by comparing its temperature readings to those of a standard infrared thermometer, showing a mean bias error (MBE) of 0.16°C and a root mean square error (RMSE) of 0.51°C, indicating high accuracy. Additionally, the modeling equation showed a near unity slope (0.994) and a correlation of 99.98%, demonstrating the system's reliability. The EC-DAQS offers a cost-effective and efficient alternative to imported weather stations, providing invaluable data for meteorological research and radio propagation studies. This home-grown solution is expected to significantly benefit weather-related research and applications in Nigeria.

In their study, Avalon-Cullen et al. (2023) explored the application of Earth Observations (EO) to improve flood and landslide risk assessment in Jamaica, acknowledging the Caribbean region's high vulnerability to multiple hazards. The authors highlighted that the region suffers from limited records and data related to hazards, risks, damage, and losses, which are essential for effective National Disaster Risk Reduction (DRR) planning and response. They emphasized the need for high-quality data to generate actionable insights and guide policy improvements. The study focused on floods and landslides, two common disasters in Jamaica, and assessed how EO could enhance the country's DRR strategies. This analysis aimed to serve as a model for other Small Island Developing States (SIDS) in the Pacific region, which face similar threats from increasing extreme weather events and climate change impacts. The study concluded that integrating EO data, models, and tools into the DRR framework could significantly strengthen national preparedness and response.

A comparative analysis of these studies on sensor deployment for real-time climate data acquisition is particularly relevant for understanding how different methodologies and technologies can be applied across various regions and contexts to enhance climate monitoring and disaster resilience. The three studies by Aditama et al. (2023), Durodola et al. (2022), and Avalon-Cullen et al. (2023) highlight the critical role of strategically deploying sensors for real-time climate data acquisition. Aditama et al. (2023) and Durodola et al. (2022) emphasize the development of IoT-based climate stations and data acquisition systems to provide accurate and continuous environmental monitoring. Aditama et al. focus on a digital climate station in Indonesia, while Durodola et al. address the development of a cost-effective system for Nigeria to overcome challenges related to importing weather instruments. Avalon-Cullen et al. (2023) emphasize the lack of sufficient data on hazards, risks, damage, and losses in the Caribbean region. This shortage of comprehensive data poses challenges for national disaster preparedness and response efforts against multiple and compounding hazards.

The relationship between these three studies demonstrates the relevance and importance of strategic deployment of sensors for real-time climate data acquisition. Aditama et al. (2023) and Durodola et al. (2022) provide examples of successful sensor deployment for climate and environmental monitoring, which can inform approaches to address data shortages highlighted by Avalon-Cullen et al. (2023). By integrating the methodologies and insights from these studies, comprehensive and actionable data can be gathered to enhance national preparedness, disaster resilience, and overall climate action strategies. This approach improves the accuracy of environmental monitoring and strengthens the ability to respond to climate-related challenges effectively.

Overall, the strategic deployment of IoT devices and sensor networks is essential for effective climate data acquisition, enabling continuous monitoring of environmental conditions across diverse geographical locations, including remote and hard-to-reach areas. These sensors measure various environmental parameters, thereby collecting vast amounts of real-time data essential for accurate climate change monitoring, analysis, prediction, and response. These real-time data are fundamental for understanding climate patterns, predicting weather events, and informing timely interventions to mitigate climate-related impacts. The integration of such comprehensive data collection efforts enhances our ability to develop effective climate action strategies and improve resilience against environmental challenges.

4.1.2.2. Integration of Artificial Intelligence-Driven Data Analysis to Fortify Early Warning Systems

The data collected by IoT sensors and from other sources is vast and complex, requiring advanced analytical tools to process and interpret. AI-driven data analysis plays an essential role in this context. The integration of AI with IoT enhances the functionality and robustness of early warning systems by enabling sophisticated data analysis and modeling capabilities. AI, when integrated with IoT, can utilize identified climate patterns to provide advanced warnings of forthcoming weather phenomena, including extreme events. This combination allows for enhanced real-time data analysis and predictive modeling, significantly improving the accuracy and timeliness of early warning systems. While the development of Earth System Models (ESMs) is important, there should be a concurrent focus on utilizing AI and ML to better understand and maximize the potential of existing data and simulations (Huntingford et al. 2019).

AI and ML algorithms can analyze historical and real-time data to detect patterns, behaviors, and trends indicative of impending climatic events. These insights significantly enhance early warning systems, enabling timely alerts for natural disasters such as floods, droughts, hurricanes, and wildfires. By improving the accuracy of event predictions, AI-powered early warning systems facilitate proactive measures to mitigate the impacts of extreme weather events, saving lives and reducing economic losses. Consequently, these insights provide communities and governments with advanced notice, allowing for preventive actions to minimize damage and the impact of climate-related disasters. Indeed, the synergistic interplay between IoT and AI enhances intelligent decision-making capabilities.

Numerous examples provided throughout this report have validated and demonstrated the applications of integrating AI- or AIoT-driven data analysis to fortify early warning systems. Notable examples include:

- Flood warning systems: AI algorithms analyze rainfall data, river levels, and weather patterns collected by IoT sensors to predict flood events. These systems have been effectively implemented in several regions, providing communities with timely alerts and enabling proactive measures to minimize damage. The following initiatives align well with the context of AI-driven flood warning systems, showcasing real-world applications where AI, Earth observation data, and predictive analytics are being used to address climate risks like flooding:

- **WMO-GEOGLOW**: The World Meteorological Organization collaborates with the Global Earth Observation - Global Flood Awareness System (GEOGLOWS) to offer global flood forecasts. This system uses Earth observation data and AI models to deliver crucial flood warnings, helping vulnerable regions prepare and respond effectively.
- **USAID-NASA SERVIR**: SERVIR, a joint project by USAID and NASA, applies satellite data and AI models to support flood forecasting in developing countries. This initiative enhances disaster resilience and climate adaptation by providing real-time flood information, particularly in regions like Africa and Southeast Asia.
- **Google's FloodHub**: Google's FloodHub leverages AI and ML to predict floods by analyzing river levels, historical data, and weather patterns. Implemented in countries like India and Bangladesh, FloodHub provides real-time flood predictions, helping communities take timely action to reduce risks.

These systems illustrate how AI-driven flood warning solutions empower communities to take timely and effective measures, ultimately reducing loss and damage. They demonstrate how AI, when combined with Earth observation data and predictive analytics, plays a crucial role in developing robust early warning systems. Through collaborations between international organizations, governments, and tech companies, these initiatives enhance global efforts to protect vulnerable communities from climate-induced flooding and other extreme weather events.

- Food security early warning system: AI algorithms utilize data from weather stations, satellite imagery, and soil sensors to provide harvest management insights and predictions. This technology helps 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 remove sensing data with AI-driven analysis helps in accurately predicting the path and intensity of hurricanes. This has been significant in disaster preparedness and evacuation planning, as seen in the enhanced early warning systems used during 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.

These applications underscore the significant potential of AI- or AIoT-driven data analysis in strengthening early warning systems. The integration of AI and IoT, or AIoT, creates intelligent, responsive systems capable of addressing complex challenges, enhancing our ability to respond to environmental changes and natural disasters efficiently. These advancements highlight the importance of continued innovation and investment in AI technologies to improve our resilience against climate-related threats. Emphasizing the synergistic use of AI and IoT will be vital in developing robust, real-time monitoring and predictive systems for effective climate action.

AI can significantly bolster ongoing global efforts by providing advanced predictive analytics, real-time data processing, and efficient resource allocation, thus enhancing the effectiveness and reach of early warning systems. In reference to harnessing AI to mitigate risks through advanced early warning systems, Mura (2024) highlighted that approximately one-third of the world's population still lacks access to early warning systems, particularly in LDCs and SIDS. UNESCO, a pioneer in developing early warning systems for various natural hazards, particularly tsunamis, plays a vital role in this initiative and collaborates with member states to achieve this goal. Over recent decades, UNESCO has expanded its early warning capabilities to include additional risks such as floods, droughts, wildfires, and glacier melts (Mura 2024). Through AI's capabilities, these systems can become more robust, providing timely and accurate warnings that can save lives and reduce economic losses.

The collaboration between the TEC and the Group on Earth Observation (GEO) (United Nations Climate Change 2023b) is focused on supporting vulnerable countries in leveraging Earth observation technologies for climate policy design and adaptation projects. Under the **Early Warnings for All** initiative, the partnership brings together the TEC's mandate of advancing climate technology with GEO's expertise in Earth observations. The goal is to enhance disaster risk knowledge and information, which is crucial for adaptation and resilience efforts in LDCs and SIDS.

This initiative aligns with the global push to ensure that everyone on Earth is protected from hazardous weather, water, and climate events by 2027. As part of this effort, the TEC and GEO, along with partners such as the Green Climate Fund and the Adaptation Fund, will create knowledge products that focus on improving disaster risk information sharing for policymakers and climate project teams.

The objective of the collaboration is to address the interconnected crises of climate change, biodiversity loss, and environmental degradation. The TEC and GEO aim to deliver equitable access to Earth observations technology and data, which are critical for enhancing climate action and transparency, particularly in vulnerable countries like Belize, where disaster risk data is essential for effective climate resilience strategies. This partnership is part of a broader strategy to leverage innovative technologies to bridge gaps in global early warning systems, with a focus on supporting the world's most vulnerable communities.

The UN Early Warnings for All Initiative (EW4All) (United Nations 2024) serves as a pivotal strategy to enhance global resilience against climate-induced disasters. This initiative targets a critical advancement in disaster readiness. By integrating cutting-edge technologies such as AI and satellite imagery, EW4All aims to establish comprehensive early warning systems across the globe by 2027, focusing particularly on the most vulnerable regions SIDS and LDCs.

UN Early Warnings for All Initiative (EW4All)

Country:
LDCs and SIDS - Ethiopia

Entities involved: Microsoft, Planet Labs, 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 Adaption 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.

Together with teams at the United Nations Disaster Risk Reduction (UNDRR) and other partners contributing to the Early Warnings for All initiative, we are working with Ethiopia's Ministry of Irrigation and Lowland and the Ethiopian AI Institute to assist in identifying communities at risk of disaster impacts, often linked to climate change. Building on this initiative, we aim to expand our efforts to the needs of additional Early Warnings for All priority countries.

We have already witnessed the transformative potential of AI and satellite imagery 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. Through firsthand experience, we have recognized the power of utilizing high-resolution satellite data provided by Planet Labs PBC combined with artificial intelligence to help those who are impacted. We are committed to assisting 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 provide valuable lessons:

The Importance of Comprehensive Global Mapping: One critical lesson learned from this project is the stark realization that, in the Global North, there exists an illusion that our 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 has now become more attainable using AI and thanks to the availability of Planet’s daily satellite data. This capability represents a transformative 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 pertains to 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. We believe that this innovation will be a critical step forward in enhancing the efficiency and inclusivity of disaster management efforts worldwide.

In summary, the integration of IoT devices and AI technologies, coupled with satellite imagery, has transformed climate data acquisition and early warning systems. The strategic deployment of sensors allows for comprehensive, real-time environmental monitoring, while AI-driven data analysis enhances the accuracy and effectiveness of predictions and alerts. This powerful combination improves our understanding of climate dynamics and supports proactive measures to protect communities and ecosystems from the adverse effects of climate change. The application of AIoT, as it continues to advance, in climate monitoring and disaster management will undoubtedly become even more sophisticated and impactful.

4.1.2.3. Artificial Intelligence of Things for Advancing Climate Change Mitigation and Adaptation Strategies

The AIoT framework for real-time monitoring and data collection and processing highlights the essential role of integrating AI and IoT technologies in advancing our understanding of climate change and in devising effective mitigation and adaptation strategies. This framework enhances the accuracy and timeliness of climate monitoring and analysis, enabling more informed decision-making and proactive responses to climate-related challenges thanks to the integration of real-time data acquisition from IoT devices with advanced AI-driven analytics models.

The recent groundbreaking convergence of AI and IoT, known as AIoT, augments IoT systems with new intelligence capabilities. This convergence demonstrates applications across numerous areas of environmental sustainability and climate change (Bibri 2024; Bibri et al. 2023, 2024b; El Himer et al., 2022; Dheeraj et al., 2020; Ohopra et al., 2022; Popescu et al. 2024; Rane et al. 2024; Tomazzoli et al., 2020; Samadi 2022). Equipped with advanced sensors, IoT devices enable the collection of vast amounts of data from the environment, which AI systems can then process and analyze to generate actionable insights. These insights can be used to improve resource management, enhance predictive capabilities, and develop more efficient environmental monitoring systems, ultimately aiding in more effective climate change mitigation and adaptation strategies. The synergistic and collaborative integration of AIoT leverages the strengths of both AI and IoT to create intelligent, responsive systems that can address complex environmental challenges (Bibri et al. 2024a).

Numerous illustrative examples have been provided throughout the report, demonstrating the power of the strategic deployment of IoT devices and sensor networks in enhancing environmental monitoring and data collection. These examples underscore the critical role of AI techniques in processing and analyzing the vast amounts of data collected, enabling more accurate predictions and informed decision-making, and hence in addressing various challenges of climate change. For instance, in flood monitoring (Ibarreche et al. 2020), strategically deployed IoT sensors can detect rising water levels and predict potential flood events, allowing for timely evacuations and resource deployment. During extreme weather events, AI systems can analyze IoT-generated data to provide early warnings and optimize emergency responses. In precision agriculture, sensors monitor soil moisture, weather conditions, and crop health, enabling farmers to make data-driven decisions that enhance productivity and sustainability. Energy optimization benefits from AIoT through smart grid management and efficient energy distribution based on real-time consumption patterns. AIoT in renewable energy further enhances the integration and optimization of renewable energy sources, promoting more reliable and resilient energy systems. Other areas where AIoT plays a significant role include monitoring and managing wildfires, tracking deforestation rates, assessing air and water quality, and even optimizing urban planning to mitigate heat island effects. Overall, the deployment of AIoT solutions augments the capability to respond proactively to environmental changes, ultimately contributing to a more sustainable and resilient future.

The functioning of AIoT leverages advanced data analytics and AI techniques to process and interpret the vast amounts of data generated by IoT devices, enhancing our understanding of various environmental parameters and changes. This integration allows for more accurate predictions and efficient responses to environmental challenges, thereby improving the effectiveness of climate change mitigation and adaptation strategies (Bibri 2024; Bibri et al. 2023; Dheeraj et al. 2020; Mishra 2023; Popescu et al. 2024; Samadi 2022; Rane et al. 2024; Shaamala et al. 2024). In other words, AIoT plays a significant role in addressing climate change by providing advanced tools and methodologies for monitoring, predicting, and mitigating environmental impacts. Thamik et al. (2024) discussed the applications of AIoT for SDGs, exploring how AIoT can be utilized to achieve specific SDGs related to environmental protection, renewable energy technology, sustainable farming, water management, and so on. They also covered ML, DL, CV, NLP, and IoT platforms, and examined the opportunities associated with leveraging these technologies to achieve the SDGs.

Based on the studies examined throughout this report, it is evident that AIoT holds significant potential in various environmental applications. AIoT systems can deploy IoT sensors across diverse environments to collect comprehensive data on air and water quality, soil conditions, and weather patterns. ML algorithms analyze these data to detect anomalies and predict environmental changes, enabling proactive measures to mitigate potential risks. In climate modeling and prediction, DL models integrated with IoT data enhance the accuracy of climate models and forecasts. These models simulate various climate scenarios, aiding policymakers and scientists in understanding potential impacts and developing strategies to mitigate risks. In disaster response, AIoT is significantly instrumental in response efforts through real-time data and predictive analytics. For instance, CV-equipped drones can assess damage following natural disasters, while ML models can predict the likelihood of future events, thereby improving preparedness and resource allocation. Through the integration of ML, DL, and CV, AIoT offers robust solutions for climate change mitigation and adaptation, addressing complex environmental challenges with intelligent, responsive systems.

4.2 Climate Modeling and Prediction

As climate change intensifies, the need for accurate climate modeling and prediction becomes increasingly critical. AI, including ML, offers transformative capabilities in understanding and forecasting climatic phenomena. These technologies enhance our ability to predict extreme weather events, evaluate climate impacts, and develop effective adaptation strategies by leveraging vast datasets and sophisticated algorithms.

4.2.1 Machine Learning's Transformative Role in Climate Modeling

ML significantly contributes to climate modeling by enhancing the accuracy and efficiency of predicting weather events and understanding climate change impacts. Additionally, it aids in the development of adaptive strategies by identifying patterns and trends in climate data, which are vital for informed decision-making and policy development.

4.2.1.1. Utilization of Algorithms to Predict Extreme Weather Events and Disaster Scenarios

The vast amount of data provided by observation satellites, coupled with the complexity of climate models, has made AI and ML technologies increasingly essential in weather forecasting and disaster scenarios. Advanced AI and ML algorithms are employed to predict extreme weather events such as hurricanes, tornadoes, thunderstorms, floods, and heatwaves by analyzing vast amounts of historical and real-time weather data. This underscores the need and significance of enhanced observational and calculation techniques, which AI and ML provide by enabling more precise forecasts and timely interventions.

NASA and IBM Research have collaborated to develop the Prithvi-weather-climate foundational model, an AI-powered tool designed to improve weather and climate forecasting at both regional and global scales (Barnett 2023). 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. Prithvi-weather-climate is one of several models in the Prithvi family, aligning 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 can aid in mitigating climate change by improving the prediction of extreme weather events. Crucially, weather forecasting is fundamentally a data issue, and as the volume of data analyzed by AI increases, its accuracy will improve, thereby reducing the impacts of extreme weather events (Chen et al. 2023). By analyzing vast amounts of historical weather data, AI 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 analyze 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 modeling and prediction. These techniques can reveal hidden insights from climate data, contributing to more precise and actionable forecasts.

Using these hidden patterns, AI models can forecast the likelihood and potential severity of extreme weather events with greater accuracy, thereby improving early warning systems. To do so, they process data from a variety of 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).

Recent studies highlight the significant potential of AI and ML/DL in enhancing disaster and extreme weather management, offering innovative solutions to predict, prepare for, and mitigate the impacts of natural disasters. Gupta et al. (2022) focused on enhancing disaster, extreme weather, and emergency management through AI and cloud-based collaborative platforms. They developed the 4-AIDE framework using qualitative methods, including semi-structured interviews with experts. The study highlighted AI's role in facilitating two-way communication, data collection, analysis, and strategic response formulation. The results showed that these technologies enable effective management strategies, enhance resilience, and aid policymakers in preparing for unexpected extreme weather events. 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 analyzed 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.

As regards the prediction of other climatic characteristics, Chen et al. (2020) calculated daily evapotranspiration in the Northeast China Plain by comparing three models—deep neural network, time CNNs, and short-term memory neural network—with SVM, random model, and empirical equation. Duan et al. (2021) utilized CNNs to develop a data-driven model for reconstructing radar reflectivity and rain rate (RR) using DL and Himawari-8 radiation data. Pullman et al. (2019) employed DL to identify infrared brightness temperature and other hail-related parameters for hail detection. Adikari et al. (2021) compared the predictive capabilities of wavelet decomposition function, CNNs, short-term memory network, and adaptive neuro-fuzzy inference system (ANFIS) in predicting flood and drought events.

AI's capability to process and analyze large datasets aids in identifying long-term climate trends, informing policy decisions aimed at reducing GHG emissions and promoting sustainable practices. AI enables policymakers to create more effective climate action plans that address both mitigation and adaptation needs. For instance, during hurricane season, these models can provide updated forecasts that help governments and communities make informed decisions about evacuations, resource allocation, and emergency response strategies. Similarly, for flood prediction, ML models can analyze rainfall patterns, river levels, and soil moisture content to predict flooding events, thereby enabling proactive measures (Samadi 2022). Jiang et al. (2023) employed AI to enhance early detection and warning capabilities for solar activity, which significantly impacts climate change, particularly in relation to droughts and floods. The authors utilized three-dimensional recognition techniques to identify meteorological and ecological drought events and subsequently extracted propagating drought events using spatiotemporal overlap rules. Overall, the integration of ML algorithms in weather prediction enhances the accuracy of forecasts and plays a key role in mitigating the impact of extreme weather events by facilitating timely and effective response strategies.

4.2.1.1. Assessment of the Ramifications of Climate Change on Local Ecosystems Through Sophisticated AI Models

Sophisticated AI models, particularly those leveraging ML techniques, play an essential role in assessing the impacts of climate change on local ecosystems. These models can simulate various climate scenarios, enabling researchers to predict changes in biodiversity, vegetation patterns, and water resources. This predictive capability is essential for developing targeted conservation strategies and informing policy decisions to mitigate the adverse effects of climate change on ecosystems. Additionally, AI models can integrate data from different sources, such as satellite imagery and ground-based sensors, to provide a comprehensive understanding of ecosystem dynamics and their responses to changing climatic conditions. These insights are of crucial importance for enhancing our ability to adapt to and manage the impacts of climate change at local and regional levels.

Recent advancements in ML have expanded data-driven modeling (DDM) capabilities, enabling AI to infer system behaviors by computing and exploiting correlations between observed variables (Willcock et al. 2018). Willcock et al. (2018) utilized ARIES and Weka software to model firewood use in South Africa. Their findings show that DDM, with an accuracy of 64-91%, can identify areas with high firewood use as effectively as conventional modeling techniques, which have an accuracy of 54-77%. This demonstrates that DDM can reliably pinpoint regions with significant firewood usage, providing valuable insights for resource management and policy-making. The study concludes that DDM has a key role in modeling ecosystem services.

Similarly, Zhu et al. (2022) examined the use of ML in evaluating water quality, demonstrating its effectiveness in analyzing complex datasets and predicting water conditions. Ahmed et al. (2019) further explored ML techniques for water quality prediction, emphasizing their potential to improve predictive accuracy and support better water resource management. Yin et al. (2021) developed an innovative method combining a dynamic ANN architecture, a Bayesian framework, and a genetic algorithm to predict short-term irrigation water use with minimal data. This technique categorizes ecological sources, establishes environmental channels and strategic points, and provides planning for urban growth and terrestrial ecosystem restoration. Neural networks and advanced algorithms can greatly enhance efforts to preserve ecosystem health and biodiversity, combat desertification, prevent soil degradation, and reduce marine pollution (e.g., Mohamadi et al.; Nunes et al. 2020; Vinuesa et al. 2020). These technologies enable the development of coordinated actions by providing accurate predictions, identifying critical intervention points, and optimizing resource management strategies.

AI can effectively analyze data from drones and satellites to evaluate soil health and aid in the restoration of degraded agricultural land. It can predict various soil properties and conditions, including sand and clay fractions, moisture content, pH levels, organic carbon content, and nutrient levels, by utilizing data from remote sensing, ground sensors, and historical soil databases (Li et al. 2022). Additionally, by integrating data from various sources such as microbial DNA sequencing, AI can assess soil biodiversity and overall health (Wilhelm et al. 2022). By enhancing the monitoring of soil moisture, AI offers valuable insights into drought patterns and dryness trends (Skulovich and Gentine 2023). This advanced monitoring capability supports sustainable agricultural practices and contributes to climate change mitigation by optimizing water usage and improving soil carbon sequestration, thereby enhancing the land's resilience to climate impacts.

ML techniques are used to analyze environmental data, providing insights into how climate variables affect local flora and fauna. ML algorithms facilitate the utilization of ever-increasing deluge of big data, thereby aiding in the application of ecosystem service models across various scales (Willcock et al. 2018). This approach allows for the detailed analysis and prediction of the flows of ecosystem services to distinct beneficiary groups. Liu et al. (2024) investigated the long-term dynamics of land use and ecosystem services in the Loess Hilly-Gully region from 1980 to 2020, utilizing AI and multi-model simulations. The study identified critical ecological nodes that enhance landscape connectivity and ecosystem services. It highlighted how environmental stressors like climate change and poor land management significantly affect land use and ecosystem services, with climate change being the most influential factor. The findings underscore the importance of improved environmental management to mitigate the impacts on ecosystems, especially in the context of escalating climate change threats.

Yin et al. (2021) proposed an AI-assisted intelligent planning framework to manage environmental restoration in the Changsha–Zhuzhou–Xiangtan urban area by creating a biological retreat configuration. This framework uses ML to identify environmental components in existing biodefense zones, improving green resource prediction and understanding the impact of urban growth on environmentally relevant processes. The ecological berm vegetation screening and backpropagation are based on soil moisture sensitive to climatic changes and vegetation growth conditions.

The project **"Using ML to Identify Priority Sites for Integrating Mangrove Restoration with Sustainable Aquaculture Intensification"** leverages AI to address environmental challenges in developing countries, focusing on the integration of mangrove restoration with sustainable aquaculture intensification in Indonesia and the Philippines (Klinger and Yoshioka 2024). This initiative highlights the collaborative efforts between academia, conservation organizations, and technology experts to enhance food security, support local livelihoods, and boost coastal resilience against climate change.

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, Konservasi Indonesia, and Thinking Machines. Funding was provided by the Climate Change AI Innovation Grants program, with support from the Quadrature Climate Foundation, Schmidt Futures, and the Canada Hub of Future Earth.

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 to improve shrimp production and restore mangroves in a program called Climate Smart Shrimp (CSS).

Shrimp aquaculture has grown 100-fold over the last 40 years, from an estimated 74,000 metric tons in 1980 to 7.5 million metric tons 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 to 2020), at least 35% of global mangroves were deforested in the late twentieth century, and the ecosystem services and climate benefits they provided remain lost.

Conservation International's CSS program 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 more efficiently and effectively apply CSS in shrimp aquaculture geographies to support livelihoods and food security 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 did not have sufficient resources to develop robust datasets.
- AI tool developers need to consider unintended uses prior to product development. Had we been successful in developing land cost and land tenure datasets/layers, they could have been used for purposes with negative climate outcomes (e.g., coastal development and resource extraction).

In conclusion, the strategic deployment of sophisticated AI models and ML techniques plays an important role in understanding and mitigating the impacts of climate change on local ecosystems. By simulating various climate scenarios and predicting changes in biodiversity, vegetation, and water resources, these technologies provide critical insights necessary for effective environmental management and policy-making. The integration of diverse data sources enables a comprehensive understanding of ecosystem dynamics, while advancements in ML enhance the accuracy and applicability of data-driven models. Overall, AI-driven approaches offer significant potential in improving climate resilience and informing targeted conservation efforts and strategies by providing advanced tools for understanding and managing the impacts of climate change.

4.2.2 Artificial Intelligence Contributions to Climate Scenario Simulations

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 enhances 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.

4.2.2.1. Evaluation of Potential Adaptation Strategies with the Aid of Artificial Intelligence

AI models simulate various adaptation strategies to assess their effectiveness in mitigating climate impacts. These models encompass a range of areas including water management, agriculture, disaster response, infrastructure resilience, coastal management, and public health. For instance, reinforcement learning can be used to optimize land use and water management practices, helping communities adapt to changing climate conditions. Leal Filho et al. (2022) examined the role of AI in climate change research, particularly focusing on its utility in climate change adaptation. The study highlighted that water management issues have received the most attention, representing 38% of the reviewed studies, compared to earth-related issues and agriculture. This evidence suggests that AI can significantly aid global efforts to understand and manage the complex challenges of climate change, thereby effectively supporting adaptation strategies. This study responds to, among others, the gap identified by Doorn (2021), who emphasized the relatively underdeveloped application of AI techniques in the water sector and identified four primary application areas: modeling, prediction and forecasting, decision support and operational management, and optimization. Together, these studies highlight the potential of AI to enhance water management and address broader climate adaptation needs.

The initiative led by Brescia University and Thuyloi University and supported by Climate Change AI explores the implementation of AI technologies to enhance water management in Vietnam's Red River Delta (Serina and Ranzi 2023), focusing on optimizing resource allocation amidst the challenges of climate change.

Artificial Intelligence for Water Management in the Red River Delta

Country: Vietnam

Entities Involved: Brescia University (Italy) and Thuyloi University (Vietnam), supported by Climate Change AI (https://www.climatechange.ai/)

Brief Description

This project focuses on the use of AI techniques for the water management of the Red River Delta area in Vietnam (Figure 2). 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 SeaWater Intrusion (SWI) in the estuaries of the rivers. Constraints are the need to ensure the dam's safety by not exceeding a maximum or minimum water level.

Figure 2. The Red River Delta area in Vietnam

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 criteria and 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

The process of data analysis is challenging due to the non-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, we need to execute a data screening and correction procedure 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 our research. In this context, we decided to use the demand indicated in Decision 50 issued by the Vietnamese government in 2023. 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, making us more reliant on good-quality data.

Leal Filho et al. (2021) conducted a comprehensive study using case studies from five SIDS in the Caribbean and Pacific regions—Barbados, Trinidad and Tobago, Cook Islands, Fiji, Solomon Islands, and Tonga—to identify key adaptation limits faced by these nations. They revealed that adaptable SIDS are characterized by awareness of various values, an understanding of diverse impacts and vulnerabilities, and the acceptance of certain losses through change. They justified why these nations continue to face significant impacts from climate change and suggests policies that could support SIDS in coping with these threats. They concluded that while technological and ecological limits (hard limits) constrain natural systems, complex societal factors (soft limits) also hinder adaptation. However, these soft limits can be addressed through more adequate adaptation strategies.

By understanding these hard and soft limits, AI can contribute to overcoming some of these challenges by providing innovative solutions and strategies. AI can enhance data collection and analysis, providing more accurate predictions and actionable insights that can inform policy and adaptation strategies. For instance, AI-driven models can help monitor environmental changes in real-time, optimize resource allocation, and simulate various adaptation scenarios, thereby supporting more responsive strategies to address the unique vulnerabilities of SIDS.

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.

Building on this framework of utilizing advanced technologies for environmental planning, the report published by Tokunaga et al. (2021) analyzed the vulnerability of SIDS and LDCs to ocean-derived risks. These coastal communities are highly vulnerable due to their heavy dependence on the sea for critical sectors like fisheries and tourism, which support their livelihoods and food security. The exposure and sensitivity of SIDS and LDCs to various biophysical and anthropogenic stressors are evolving, impacting their ability to adapt and respond effectively. The study highlighted the fragility of livelihoods and food security in these regions, exacerbated by their reliance on imports. Through a synthesis of peer-reviewed and grey literature, empirical data, and case studies, the report describes significant stressors, identifies key social-ecological features that shape vulnerabilities, and suggests strategies to mitigate ocean risks and build resilience in SIDS and LDCs.

The integration of AI can play an instrumental role in addressing the challenges identified in the report by Tokunaga et al. (2021). AI can enhance predictive modeling to forecast the impacts of ocean-derived risks, enabling early warning systems for natural disasters like cyclones and tsunamis. ML algorithms can analyze vast amounts of data to identify patterns and trends in oceanic conditions, helping to optimize fisheries management and protect marine ecosystems. AI can also support decision-making by providing policymakers with data-driven insights into the socio-economic and environmental vulnerabilities of SIDS and LDCs, thereby facilitating the development of targeted strategies to build resilience. Overall, the application of AI has the potential to enhance the capacity of these regions to adapt to and mitigate ocean-related risks, thereby safeguarding their livelihoods and food security.

Furthermore, with the widespread availability of high-resolution satellite and aerial imagery, it is now feasible to monitor crop conditions and agricultural yield on a large scale and develop early warning systems to prevent crises (Kaack et al. 2020). AI automates this process, significantly increasing the number of images that can be analyzed and detecting subtle cues that may be overlooked by humans. Anshuman and Mallick (2023) investigated how AI is revolutionizing agriculture, particularly in developing countries facing challenges in sustainable food production for rapidly growing populations. AI solutions support traditional agricultural extension systems by providing data-driven insights and technologies such as drones, sensors, and AI-driven crop surveillance. These technologies optimize resource use, enhance crop yields, and enable timely pest and disease management. Despite the benefits, challenges include high costs, digital literacy needs, and the importance of maintaining human interaction in extension services.

More to the role of AI in climate change adaptation, 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. In food processing, AI is central for improving modeling, prediction, control tools, sensory evaluation, quality control, and tackling complex challenges. The study concluded that AI significantly boosts the efficiency, sustainability, and productivity of agri-food systems and underscored the need for expand its application across the agri-food supply chain, thereby contributing to global food security and addressing key agricultural challenges. In line with this research, Kakani et al. (2020) investigated diverse scenarios and applications of ML, DL, and CV from a global sustainability perspective. They highlighted the growing demand in the AgTech industry for CV and AI, suggesting these technologies could pave the way for sustainable food production to meet future needs.

Advancements in AI for processing colossal climate data enable the identification of more comprehensive future climate change scenarios and the development of advanced predictive notification systems. AI-driven tools can process vast amounts of environmental data, identifying patterns and trends that would be challenging for humans to discern. This enhanced analytical capacity can lead to more accurate climate models, better predictions of extreme weather events, and more effective resource management strategies. Numerous studies have demonstrated the potential of AI in evaluating and refining adaptation strategies, thereby significantly improving our ability to respond to a changing climate.

In this context, Ullah et al. (2018) evaluated the effectiveness of diurnal temperature range (DTR) compared to daily mean temperature (Tmean) as metrics for predicting millet yield under climate change scenarios. Using a historical dataset (1980–2010) and projections from Model for Interdisciplinary Research on Climate version 5 (MIROC5) and Geophysical Fluid Dynamics Laboratory (GFDL) climate models, the study focused on two environments in Punjab, Pakistan: arid (Layyah) and semi-arid (Faisalabad). The findings showed that the projected DTR increased relative to the baseline in both environments, with Tmax and Tmin highly correlated

(0.90–0.99). MIROC5 accurately predicted Tmax and Tmin, while GFDL effectively forecasted precipitation. Using a Genetic Algorithm (GA), the study predicted negative impacts on pearl millet yield (11–12%) due to future warming. The study suggests expanding the use of this method to other regions with similar climate regimes to validate the findings.

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. Adhikari et al. (2021) evaluated and compared the effectiveness of three prominent AI-based approaches—CNNs, LSTM, and Wavelet decomposition functions combined with the Adaptive Neuro-Fuzzy Inference System (WANFIS)—in forecasting floods and droughts in arid and tropical regions. The study measures fluvial floods by the runoff 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.

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.

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 a. (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)

Table 1: Studies on adaptation strategies using Artificial Intelligence models

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.

AI has emerged as a powerful tool in evaluating potential adaptation strategies to mitigate the impacts of climate change. By simulating various scenarios, AI models offer comprehensive insights into the effectiveness of adaptation measures across diverse areas. These models help predict outcomes, optimize resource allocation, and identify the most effective strategies to cope with climate variability and extreme weather events. Through ML and DL techniques, communities can better adapt to changing environmental conditions, ensuring more robust and sustainable responses. The integration of AI in climate adaptation strategies both enhances predictive accuracy as well as supports the development of proactive and informed decision-making processes, essential for building climate resilience.

4.2.2.2. Provision to Decision-Makers with Actionable Insights Through Simulations and Analysis of Sensor Data

AI processes data from sensors to provide real-time analysis and simulations, helping decision-makers understand potential future scenarios and plan accordingly. Consequently, AI augments the capabilities of decision-makers to formulate informed climate change strategies through the integration and analysis of data from sensors. AI processes vast amounts of real-time data from weather stations, satellites, and environmental (IoT) sensors, offering precise climate models and risk assessments.

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. Moreover, this further research is important for enhancing decision-making through actionable insights derived from simulations and sensor data analysis.

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. The AI models provided accurate, real-time forecasts, essential for managing coastal flooding risks. Similarly, Jeon et al. (2018) utilized deterministic and decision support models to evaluate the performance of Best Management Practices (BMPs) under various climate scenarios, refining BMPs for future conditions. In urban settings, Skiba et al. (2017) used artificial neural networks to model the economic dependence between urban policy and energy efficiency, offering insights for energy-efficient urban development.

These studies collectively underscore the importance of advancing decision-making through actionable insights derived from simulations and sensor data analysis. By improving models and leveraging advanced data analytics, we can better predict and mitigate the impacts of climate change, optimize resource management, and develop adaptive strategies across various sectors. This approach ensures more informed and effective decision-making processes.

Numerous examples have been provided throughout this technical report that emphasize the role of simulations and analysis of sensor data in providing decision-makers with actionable insights in the context of climate change mitigation and adaptation. The integration of these advanced methodologies equips decision-makers with the tools needed to develop proactive and informed responses to environmental and societal challenges, ensuring sustainable development and resilience in the face of future uncertainties.

Furthermore, the convergence of AI and IoT further amplifies these capabilities by enabling intelligent decision-making based on comprehensive, real-time data analysis in the fields of environmental sustainability and climate change (Bibri 2024; Dheeraj et al. 2020). For example, AIoT systems integrate crowd intelligence, ML, and NLP to improve flood situational awareness and risk assessment. These systems can dynamically update and prioritize at-risk locations based on real-time data, providing actionable insights to decision-makers. Decision-makers can—thanks to AIoT—benefit from enhanced situational awareness, predictive analytics, and more effective resource management (Samadi 2022). The integration of AI with diverse data sources allows for the creation of adaptive AI systems that evolve with changing climatic conditions, reducing uncertainty and bias in climate predictions (Kadow et al. 2020).

The integration of AI and IoT plays a central role in enhancing intelligent decision-making for climate change adaptation and mitigation. AIoT systems can collect and analyze vast amounts of data in real-time from various sensors and devices, providing accurate and timely insights for decision-makers (see Subsection 3.1.2). This integration enables more effective monitoring, prediction, and management of climate-related impacts, ensuring that adaptive and mitigative strategies are both efficient and responsive to changing conditions. AIoT contributes to building robust infrastructure, optimizing resource use, and developing sustainable practices, thereby advancing efforts to combat climate change and to strengthen the resilience and sustainability of communities.

4.2.2.2. The Role of Artificial Intelligence in Decreasing Energy Consumption in Climate Modeling

AI techniques optimize the computational efficiency of climate models, reducing energy consumption. Advanced algorithms that streamline data processing and model training can significantly lower the carbon footprint of extensive climate simulations. Techniques like sparse modeling, ensemble modeling, and efficient neural network architectures are critical in achieving these energy savings.

For example, sparse modeling 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 essential 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 modeling 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 broadly applicable across different studies on population responses to climate. Overall, sparse modeling makes climate simulations more efficient, leading to significant energy savings.

Ensemble modeling involves running multiple climate models or variations of a model to generate a range of possible outcomes. It combines predictions from multiple base models to enhance overall performance. This approach helps capture uncertainties and provides a more robust prediction by averaging the results. In the context of energy consumption, ensemble modeling can decrease energy usage by optimizing computational resources and improving model prediction accuracy. 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 programs. 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 center operations to lower energy consumption and minimize the carbon footprint of AI systems (Wheeldon et al. 2020).

Yokoyama et al. (2023) conducted pioneering research on innovative techniques for optimizing energy consumption in AI hardware, highlighting the potential for sustainable computing solutions to reduce environmental impact. The recent comprehensive study by Raman et al. (2024) focused on Green AI, utilizing thematic analysis and BERTopic modeling 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 policy-making aimed at integrating sustainability into AI research and development, including climate modeling.

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. (2020) 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.

Concluding, these studies aim to curb emerging consumption in climate modeling. By developing and implementing more efficient AI algorithms and hardware, the overall energy consumption and carbon footprint of climate models can be greatly reduced. This not only promotes environmental sustainability but also ensures that advanced climate modeling remains feasible and accessible, driving progress in climate science and policy.

4.3. Resource Management

Effective resource management is important for sustainable development and directly impacts climate change mitigation and adaptation efforts. AI interventions have shown significant promise in optimizing the management and preservation of natural resources, which is vital for addressing climate change. For instance, AI-driven analytics can enhance agricultural practices by optimizing water usage and reducing GHG from soil. In fisheries, AI systems help in monitoring and managing fish populations, ensuring sustainable harvesting practices that maintain ecological balance and reduce carbon footprints. AI systems improve resource management practices across various domains and contribute to broader climate resilience strategies by integrating advanced data analytics, ML, and real-time monitoring. This holistic approach ensures that resource management practices are both sustainable and effective in combating climate change.

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

AI technologies are playing a vital role in enhancing fisheries management and marine life preservation. AI aids in promoting sustainable fishing practices by tracking fish stocks, protecting marine areas, and combating illegal fishing activities-

4.3.1.1. Tracking Fish Stocks and Marine Protected Area 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 is greatly improving marine conservation efforts, particularly in safeguarding marine ecosystems and defining MPAs (Şeyma 2023). ML algorithms analyze 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.

AI research has drastically 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; Ridge 2020; Seyma 2023) For example, ML techniques can be employed to analyze 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 AI techniques such as ML, FL, NLP, or Expert Systems (ES), 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 (Seyma 2023). Automation and AI have the potential to transform marine research by introducing new perspectives and enhancing data collection and processing (Ditria et al. 2022; Addison et al. 2018).

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 1,197 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. Each identification by the CNN took an average of 0.06 seconds using standard hardware. These findings suggest that DL methods, particularly CNNs, can efficiently and accurately identify fish species in underwater images, offering a promising solution for cost-effective, video-based monitoring of marine biodiversity. Worth pointing out is 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.

A growing number of large and complex datasets from ocean observation systems and satellite remote sensing are now being analyzed with AI and automation (Patel et al. 2022). Utilizing ML algorithms to analyze these datasets can uncover patterns and trends that are challenging to detect manually, thereby enhancing our understanding of ocean processes and climate impacts and improving the management of marine resources. While AI and automation hold great promise for monitoring and managing marine resources, forecasting ocean conditions, and data collection and analysis, further research is needed to fully harness their potential, as these technologies are still in their early stages (Song et al. 2023). One of the significant research gaps and challenges in MPAs is the need for further investigation into developing automated monitoring tools and utilizing AI to detect illegal activities, enhance real-time monitoring capabilities, and address the lack of data on illegal fishing activities (Şeyma 2023). Nevertheless, AI enhance marine conservation efforts by drastically improving data collection, processing, monitoring, and analysis, leading to more informed and efficient conservation strategies and marine ecosystem management.

4.3.1.2. Combating Illegal Fishing Activities

Illegal, unreported, and unregulated (IUU) fishing poses a significant threat to marine ecosystems. AI-driven solutions, such as predictive analytics and real-time monitoring systems, are being employed to combat IUU fishing. These systems use data from various sources, including satellite tracking and automatic identification systems (AIS), to identify suspicious activities and notify authorities. The use of AI in these applications enhances the ability to detect and respond to illegal fishing more efficiently, thereby protecting marine resources and promoting sustainable fishing practices.

Appana et al. (2020) 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 analyzing fishing vessel behavior 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 behavior. To effectively handle this large volume of data, AI algorithms are increasingly applied. Various sources for studying fishing vessel behavior are covered, along with AI methods used to monitor and extract behavioral patterns, and research on the physical, ecological, and social factors affecting these behaviors is synthesized. This AI aims to considerably aid in the detection and prevention of illegal fishing activities.

Backker (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 analyzed 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. AI can also help in monitoring MPAs to ensure compliance with regulations and detect illegal activities such as overfishing and poaching.

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 fishermen 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 fishermen 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.

In summary, AI-driven solutions play a strategic role in combating IUU fishing by providing advanced tools for real-time monitoring and analysis. They help identify suspicious activities, enhance surveillance of marine protected areas, and improve the overall management of marine resources, significantly contributing to the protection of marine ecosystems. By providing real-time data and insights, AI enables more efficient and effective enforcement of conservation regulations, supporting sustainable fishing practices and ensuring the long-term health of marine biodiversity.

4.3.1.3. Implementation of Sustainable Fishing Practices

Human activities, such as overfishing, IUU fishing, and pollution, present substantial risks to marine ecosystems and species. The oceans are a vital source of biodiversity and support a global seafood market valued at over $120 billion, making them essential to nearly half of the world's population (United Nations SDG 14 2022). The overfishing resulting from IUU fishing severely depletes fisheries, costing society $23.5 billion annually (NOAA 2022). Successful conservation management depends on scientific research, community involvement, and robust governance, and strategies include establishing MPAs, enforcing fishing quotas, and implementing pollution control measures (Seyma 2023).

A pivotal strategy for climate adaptation and mitigation in LDCs and SIDS is the concept of blue carbon, which leverages coastal ecosystems for carbon sequestration. These regions, home to some of the world’s most biodiverse hotspots, including vast mangrove and seagrass beds, hold significant potential for carbon storage, offering benefits such as emission reduction, enhanced food security, and poverty alleviation. Integrating AI into these efforts can enhance blue carbon sequestration by improving data efficiency, transparency, and accuracy, developed in close collaboration with affected communities

Incorporating community-based approaches, AI can play a innovative role in enhancing sustainable fishing practices. AI systems can analyse data on fish populations, environmental conditions, and fishing activities to recommend fishing quotas, seasonal closures, and other management measures. By tailoring these AI solutions to local challenges through community needs assessments and participatory design, they can more effectively address the specific needs of local fishing communities. Additionally, AI can support the development of aquaculture by optimizing feeding practices, monitoring water quality, and preventing diseases, thus promoting sustainable seafood production.

Samaei and Hassanabad (2024) focused on the intersection of marine industries, seas, and AI within the framework of sustainable development. The primary focus is on enhancing sustainable fishing practices and other marine activities with the aid of AI technologies. AI's transformative impact or supportive potential is highlighted through various applications, including optimizing navigation, promoting sustainable fishing, and enhancing renewable energy initiatives in the maritime domain. 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.

Amuthakkannan et al. (2023) explored the application of AI in fishing boat automation to enhance safety, security, navigation, and information sharing for Omani fishermen. The study emphasizes the need for modern technology to address challenges such as weather changes, border tracking, navigation issues, illegal fishing, pirate attacks, oil spills, and technical faults. By implementing AI in boat automation, the fishing experience can be made more sustainable and secure. High-quality fishing boats equipped with advanced communication devices are essential for providing necessary information to both fishermen and control rooms. This study highlights the importance of AI in ensuring a sustainable and efficient fishing experience in Oman.

The integration of AI in marine resource management plays a key role in various aspects. It has led to increased efficiency, cost savings, personalized customer experiences, and predictive analytics, positioning AI as a driving force behind innovative solutions for a sustainable and environmentally responsible future in the marine sector (Samaei and Hassanabad 2024).

AI technologies are instrumental in monitoring fish populations and the health of marine ecosystems, facilitating the preservation of MPAs and ensuring sustainable resource management. AI-driven surveillance systems are essential in detecting and preventing IUU fishing. These systems analyze data from satellite imagery and maritime traffic to identify and respond to suspicious activities, protecting marine life and sustaining fish populations. AI supports sustainable fishing by optimizing resource use and minimizing environmental impact. Predictive analytics and real-time data collection enable informed decisions on fishing quotas, seasons, and locations, promoting the long-term health and productivity of marine ecosystems. Together, these advancements highlight the significant role of AI in enhancing marine resource management.

4.3.2. 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.

4.3.2.1. Improving Agriculture with Data-Driven Insights

AI and applied ML techniques are being leveraged to enhance agricultural practices. By integrating advanced algorithms and real-time data analysis, AI empowers 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.

Precision farming technologies use AI to analyze 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.

In particular, precision agriculture leverages advanced sensors and predictive analytics to collect real-time data on critical environmental parameters and labor costs and availability to enhance agricultural yields and improve decision-making (Raj et al. 2021). In their investigation of critical variables in ANN case studies for sustainable land management, López Santos et al. (2019) found that orchard yields depend on physical planting conditions, climate utilization ability, and farmers' crop knowledge through random sampling of orchards. These insights enable farmers to make informed decisions about irrigation, fertilization, and pest control, leading to increased yields and reduced resource use. Precision agriculture enhances agricultural productivity and sustainability by utilizing AI to boost output and mitigate environmental effects (Das et al. 2018; Ampatzidis et al. 2020; Reddy et al. 2022; Wei et al. 2020). 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. The authors demonstrate how these technologies manage the impacts of climate change by optimizing resource utilization and reducing human interference. By integrating IoT and AI, data collected from field sensors are analyzed 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 and demonstrating the potential of AI and IoT to address climate change effectively.

In summary, AI and applied ML techniques are revolutionizing agricultural practices by providing farmers with critical, real-time data and actionable insights. Precision farming technologies, leveraging advanced sensors and predictive analytics, enable precise monitoring of crop health, soil conditions, pest infestations, and environmental factors. The integration of AI with IoT technologies optimizes resource utilization and mitigates climate change impacts. By utilizing hyperlocal, geo-referenced data and combining it with satellite imagery and ground-truth data, AI enhances the accuracy of predictions and recommendations tailored to climate vulnerable regions like Sub-Saharan Africa. AI-driven systems offer predictive insights for crop yields and early warnings of potential crop failures, supporting proactive decision-making and climate-change adaptation. For smallholder farmers, who are often highly dependent on traditional methods and face significant challenges due to limited resources, these advancements provide invaluable support and opportunities for increased productivity and resilience. Additionally, the availability of open, high-quality datasets fosters collaboration and supports broader agricultural practices, boosting output and promoting environmental sustainability. Overall, AI-driven precision agriculture provides advanced solutions to the challenges posed by climate change, enhancing both productivity and resilience.

4.3.2.2. Adaptive Strategies for Navigating Changing Climate Conditions

Climate change poses a significant challenge to agriculture, necessitating the development of adaptive strategies to ensure food security. AI plays an indispensable role in this area by helping farmers anticipate and respond to changing weather patterns and environmental conditions. Through predictive analytics and real-time monitoring, AI can guide the implementation of adaptive farming practices, such as drought-resistant crops and optimized irrigation systems, to mitigate the adverse effects of climate change.

Among the climate change challenges related to agriculture are altered growing seasons, increased pest and disease pressures, and extreme weather events. AI can help farmers develop adaptive strategies to navigate these challenges. Precision agriculture utilizes AI 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 et al. 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.

The project operating in Kenya (Spratt 2023) showcases the innovative use of AI to bolster agricultural resilience and food security. The AI-driven early warning system developed in this project empowers smallholder farmers with critical insights for enhancing crop yield predictions and optimizing harvest management.

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 (GZ) - FAIR Forward

Brief Description

The cooperation between LDRI and GIZ's FAIR Forward project aims at allowing 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 significantly 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 incorporation of local languages, including KiEmbu, Luhya, Kikuyu, and Kiswahili, ensures that the advice is accessible to a diverse range of farmers, improving the system's effectiveness across different linguistic groups.

Climate Change Mitigation and/or Adaption 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.

Plans are underway 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 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 application was critical for efficient data collection.

Elahi et al. (2019) estimated the target values of agrochemicals for rice farms while maintaining current yield levels in the Hafizabad and Sheikhupura districts. The authors found that pesticide inputs could be reduced by 52.6% and pure nitrogen fertilizer inputs by 43.6%, leading to a favorable and significant impact. Putra et al. (2020) modeled 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.

AI is valuable for assessing the impacts of climate change on agriculture. For instance, Crane-Droesch (2018) developed a ML model that predicts corn production under various climate change scenarios. Similarly, Jakariya et al. (2020) created a mobile application using ML methods to assess the vulnerability of farmers in coastal Bangladesh based on their responses to a questionnaire. Many farmers in Africa continue to rely on rainfed agriculture, rendering them highly vulnerable to the impacts of climate change (Serdeczny et al. 2017). Consistent with this observation, there is a scarcity of digital data on local climate projections and weather forecasts necessary for optimizing farming practices in the region (Balogun et al. 2020). These findings align with the broader observation of unequal access to resources such as AI, a gap that remains underexplored in existing literature (Walsh et al. 2020). Additionally, as mentioned earlier, AI can assist in disaster preparedness by providing early warnings and risk assessments for extreme weather events, helping farmers protect their crops and livelihoods.

Etminan et al. (2019) explored the application of ANN to identify the best drought tolerance indices for agronomy and plant breeding, highlighting the role of intelligent agriculture in enhancing crop resilience. In another study, Tran et al. (2020) examined the factors influencing the adoption of climate-smart agriculture technologies in rice production in Vietnam, underscoring the importance of supportive policies and farmer education. Meanwhile, Jung et al. (2021) emphasized the potential of remote sensing and AI to bolster the resilience of agricultural production systems by providing timely and accurate data for decision-making. Together, these studies illustrate the significant role of AI and related technologies in advancing sustainable agricultural practices and improving climate adaptability.

The integration of advanced AI technologies in agriculture demonstrates the practical potential of these innovations. Precision spraying technologies reduce chemical usage, lower costs, and minimize environmental impact by targeting herbicide application only where needed. This approach enhances the ability to adapt to changing climate conditions by ensuring more sustainable agricultural practices. Simultaneously, data-driven insights from intelligent pest management systems optimize pesticide use and improve pest control efficiency, leading to more effective and sustainable agricultural operations. Collectively, these advancements highlight the key contribution of AI to creating resilient, sustainable, and adaptive agricultural systems.

4.3.3. Artificial Intelligence for Other Resource Management

AI is increasingly critical to optimizing resource management across various sectors, including water resource management and forestry and land management. In water resource management, AI aids in optimizing usage, predicting shortages, and managing distribution systems. For forestry and land management, AI supports efforts to monitor deforestation, assess land use changes, and enhance reforestation initiatives. These sectors can achieve smarter, more adaptive management strategies essential for sustainability and resilience in the face of climate change by leveraging emerging AI and ML technologies.

4.3.3.1. 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 plays a central role in optimizing water resource management. AI and ML algorithms analyze 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 analyze 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 modeling the stage–discharge relationship, which is essential 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. Pluchinotta et al. (2021) utilized a system dynamics model to investigate various sustainable urban water resource management policies in Ebbsfleet Garden City. The authors developed an innovative technique combining a dynamic ANN architecture, a Bayesian framework, and a GA to predict short-term irrigation water use with minimal data. Xiang et al. (2021) introduced an adaptive intelligent dynamic water resource planning system to sustain the water environment in metropolitan areas and enhance water resource usage. Their approach effectively manages urban water resources by streamlining the information transformation process with AI modeling.

In summary, AI applications in water resource optimization have significantly enhanced the conservation and efficient use of water resources. These technologies analyze data from various sources to predict water demand, optimize irrigation schedules, and detect leaks, thereby improving water use efficiency and ensuring sustainable management. Advanced models like ANNs, ANFIS, and hybrid techniques combining AI with optimization algorithms have shown superior performance in predicting water distribution parameters and modeling relationships, essential for effective water management. Dynamic approaches in urban water planning and quality evaluation further highlight AI's role in fostering sustainable water resource management practices. Overall, AI's integration into water resource management represents a major advancement towards achieving sustainable and efficient use of water resources.

4.3.3.2. Forestry and Land Management

AI technologies are also applied in forestry and land management to monitor forest health, track deforestation, and manage land use. Remote sensing data combined with AI algorithms can detect changes in forest cover, identify areas at risk of deforestation, and assess the impacts of land use changes on biodiversity and ecosystem services. These insights support the development of sustainable land management practices and conservation strategies.

Dominguez et al. (2022) utilized a dense neural network for spatial data modeling 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. Tien Bui et al. (2017) utilized particle swarm optimization neuro-fuzzy techniques to model forest fires, optimizing parameter values and accurately predicting the causes of forest fires in Vietnam. This approach, along with RF and SVM models, enhances predictive accuracy of the causes and occurrences of forest fires.

The ecological value of tropical forests in water conservation districts is significant due to their rich vegetation and high biomass density. However, monitoring these forests poses challenges such as high forest density, complex structures, and difficult access. Liu et al. (2021) tackled these challenges by employing advanced Unmanned Aerial Vehicle-Structure from Motion (UAV-SfM) technology combined with CNNs methods to accurately assess forest biomass distribution and biodiversity. The findings indicate an overall classification accuracy of 0.61 and a Kappa coefficient of 0.59. The Root Mean Square Error (RMSE) for plane and elevation measurements were 0.432 m and 0.989 m, respectively, showcasing the superior effectiveness of these techniques. This innovative approach enables precise monitoring and evaluation, providing essential data for sustainable forest management plans and supporting forest ecological environment sustainability research.

Saputra and Leef (2019) simulated and predicted land use and land cover (LULC) changes in North Sumatra, Indonesia, using an ANN-based cellular automaton (ANN-CA) model. The model utilizes five criteria—altitude, slope, aspect, distance from the road, and soil type—as exploratory data to determine their impacts on LULC changes between 1990 and 2000. Results indicate that altitude and distance from the road have strong impacts on LULC changes. The model predicts that by 2050 and 2070, plantation areas will increase by over 4%, while forest and crop areas will decrease by approximately 1.2% and 1.6% by 2050, and by 1.2% and 1.7% by 2070, respectively. This indicates a shift from forests and croplands to plantations. The study demonstrates that the ANN-CA model can reliably predict future LULC changes.

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 modeling. 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 modeling.

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. 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 vital 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 such data has proven essential for accurate mapping and understanding of the impact of agricultural expansion (Kalischeket 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, providing high-resolution maps of canopy top height with an accuracy of 86%, is essential for classifying High Carbon Stock forests and degraded areas and has produced the first high carbon stock map for Indonesia, Malaysia, and the Philippines (Lang et al, 2021). This approach is critical for advancing AI methodologies and global maps in forest monitoring and protection.

The project "AI for Forest Conservation: AI-Generated Indicative High Carbon Stock (HCS) Maps in Indonesia and India" (FAIR Forward 2023) involves an innovative approach to environmental management through the application of AI. It utilizes AI to create detailed maps of HCS forests, essential for climate change mitigation efforts in the region. It combines remote sensing technology with advanced ML algorithms to classify diverse forest areas, ensuring effective conservation strategies and enhanced carbon accounting practices.

AI for forest conservation: AI-generated Indicative High Carbon Stock Maps in Indonesia and India

Country:
Indonesia

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

Brief Description

In Indonesia, the FAIR Forward initiative has collaborated with JKPP (Network for Participatory Mapping), 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 3) 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.

Figure 3. The field plot data collection

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.

Additionally, the open-access nature of these datasets 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, demonstrating 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.

AI technologies have proven to be invaluable in forestry and land management by enabling precise monitoring and assessment of forest health, deforestation, and land use changes. Through the integration of remote sensing data and advanced AI algorithms, it is possible to detect changes in forest cover, identify areas at risk of deforestation, and evaluate the impacts of land use changes on biodiversity and ecosystem services. These insights facilitate the development of sustainable land management practices and conservation strategies. AI-driven approaches for forecasting deforestation rates, modeling forest fires, assessing forest biomass, and predicting land use changes enhance predictive accuracy and provide essential data for proactive measures, supporting sustainable forest management and the conservation of ecological environments.

4.4. 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. AI plays an instrumental role in this sector by enhancing efficiency, enabling the deployment of renewable energy technologies, and fostering sustainable practices. 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.

4.4.1. Artificial Intelligence Interventions in Energy Management

AI has transformed energy management by providing advanced tools to optimize energy efficiency across various levels. The role of AI in energy efficiency optimization has shown significant potential to contribute to reducing the impacts of climate change impacts (Chen et al. 2023) and mitigating the challenges of environmental sustainability (Bibri 2024).

AI algorithms, such as neural networks and ML, are used to analyze 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 seamlessly integrate 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. 2024). Indeed, AI has increasingly become a powerful tool in the energy sector, presenting new opportunities for improving energy efficiency and achieving sustainable development objectives (Baysan et al. 2019; Farghali et al. 2023).

AI enhances 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 significantly 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 (Ahmed 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 can provide early identification of maintenance needs for grid elements and generating facilities, and propose optimized preventive maintenance roadmaps, resulting in reduced equipment downtime and favoring 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 could reduce energy consumption and carbon emissions by 8% to 19% by 2050. Moreover, AI 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, AI 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 and AIoT 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, AI or AIoT techniques applied, application areas, and key findings. Table 3 provides a comprehensive overview and comparative analysis, offering insights into the diverse ways AI and AIoT are being leveraged to tackle energy challenges and transform energy management practices.

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 analyze the adoption and impact of AI and digital technologies in the energy sector.	AI, Big Data, IoT, Robotics, Blockchain	Energy sector	AI enhances 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 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 reduces energy consumption, improves control, reliability, and automation in smart buildings, enhancing efficiency.	Farzaneh et al. (2021)
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 optimizes 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 improves 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 optimize energy consumption, production, and grid management, addressing issues in developing countries.	Mhlanga (2023)

Table 2: Artificial Intelligence and Artificial Intelligence of Things applications in energy management

While the adoption of AI in energy efficiency is anticipated to rise due to the growing necessity to reduce energy consumption, lessen environmental impact, and achieve sustainable development (Bibri et al. 2024b; Chen et al. 2023), the high cost of AI technology remains a major obstacle, as developing and deploying AI-based systems requires substantial investment, which might exceed the financial capabilities of certain organizations (Enholm et al., 2022; Yang, 2022; Zhao et al., 2022; Ahmed et al., 2022).

Nonetheless, AI is starting to prove to be a relevant tool in energy management, making a vital contribution to the efficiency of energy generation, distribution, transmission, and consumption. The integration of AI and IoT, or the use of AIoT, in energy management has further shown significant potential in optimizing energy systems and contributing to SDGs. The reviewed studies illustrate the diverse applications of AI across various energy domains. The findings underscore the importance of AI and AIoT in addressing contemporary energy challenges, reducing costs, and improving the reliability and sustainability of energy systems. As these advanced technologies continue to evolve, their role in energy management is expected to expand, driving further advancements in the pursuit of a sustainable energy future.

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

AI and ML are transforming renewable energy strategies by significantly improving efficiency, reliability, and sustainability. Moreover, the rapid increase in renewable energy utilization globally has significantly impacted the energy sector and its alignment with Sustainable Development Goals (SDGs). AI and ML are called to play an important role in optimizing the operation and efficiency of renewable energy systems and enhancing their safety and reliability, thus contributing to SDGs. Hannan et al. (2021) evaluated the increasing utilization of renewable energy in the global energy mix and its impact on achieving SDGs and assessed the emerging role of AI in enhancing renewable energy's contribution to achieving SDGs. The findings revealed that renewable energy positively influences the achievement of 75 targets across the 17 SDGs, categorized into environmental, societal, and economic pillars. They also highlighted potential negative impacts on 27 targets. Nevertheless, AI is recognized as a critical enabler and supportive tool in facilitating the attainment of 42 out of 169 SDG targets, highlighting the need for regulatory and technological advancements to support this growth. AI plays a key role in the substantial increase in renewable energy utilization and its integration into the energy mix, holding the potential to transform the renewable energy sector (Rane et al. 2024; Vinuesa et al. 2020).

The integration of AI and AIoT in renewable energy technologies is key to their efficient use and widespread adoption. AI models are 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 on back-up generation just on time, ensuring a stable supply and reducing reliance on fossil fuels. AIoT optimizes 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.

Furthermore, AI enhances the efficiency of energy storage systems by predicting energy demand and optimizing charge-discharge cycles(Banu et al. 2022; Jin et al. 2022; Olabi et al. 2023; Rane et al. 2024). This ensures that renewable energy is stored at renewable surplus moments and made available when needed, thus mitigating the intermittency issue associated with renewable sources. This extends market opportunities to storage and renewable energy providers while resulting in reduced energy prices for the end consumer. Moreover, AI facilitates the seamless integration of renewable energy into existing power grids. It continuously oversees the variability of renewable sources and proposes preventive measures in real-time, thus promoting grid stability (Farh et al. 2022). Moreover, Rane et al. (2024) concluded that AI and ML are pivotal in reducing costs through advanced analytics and predictive maintenance, support real-time decision-making and adaptive control to ensure optimal energy distribution and minimizing waste, and help reduce the environmental impact of renewable energy by optimizing processes and lowering emissions.

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 (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. Important to note is that, like Table 2, the results include only the key finding per study to maintain clarity and conciseness. Summarizing the primary key findings helps to distill the most significant contributions of each study, making it easier to quickly grasp the essential insights of each research work. For a detailed account of results beyond this tabular format, the interested reader might be directed to the synthesized studies.

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, k-NN, SVM, ANN	Solar photovoltaic, wind energy, fuel cells	AI-based modeling 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 reduces integration costs of VREs, enhancing system value and efficiency.	Boza and Evgeniou (2021)
Large-scale renewable integrations for carbon neutrality	To analyze AI techniques for large-scale renewable energy integrations and carbon neutrality transition.	AI techniques	Multi-energy systems, renewable energy	AI optimizes 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 significantly 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 Network based Fuzzy Inference System (ANFIS)	Household, industrial energy systems	AI models enhance renewable energy generation efficiency, with ANN outperforming ANFIS.	Puri et al. (2019)

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 modeling 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.	Attention-based Bidirectional Long Short-Term Memory (BiLSTM), Coyote Optimization Algorithm (COA)	Hybrid renewable energy sources	The proposed AI technique optimizes ESS for hybrid renewable energy, outperforming recent methods.	Banu et al. (2022)
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)
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 enhance efficiency, reliability, and sustainability in renewable energy systems through precise forecasting, optimized energy production and distribution, and predictive maintenance.	Rane et al. (2024)

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

The reviewed studies highlight diverse applications of AI and AIoT, from predictive maintenance in wind farms to optimizing thermal energy storage and integrating large-scale renewable energy systems. The findings underscore the critical role of AI in addressing contemporary energy challenges and advancing towards a sustainable energy future. As AI and AIoT technologies continue to evolve, their application in renewable energy is expected to expand, driving further advancements in the renewable energy sector.

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 (Chopra et al., 2022; 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 (Chai et al., 2022).

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. As the global energy landscape continues to evolve, the integration of AI and AIoT in renewable energy systems will be paramount in achieving energy sustainability and mitigating climate change impacts. The continuous innovation and implementation of AI- and AIoT-driven solutions can pave the way for a more resilient and sustainable energy future.

4.5. 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.

4.5.1. Artificial Intelligence Interventions in Transport Management

AI-driven technologies contribute to the development of smarter and more sustainable transportation networks. Moreover, implementing AI in transport management offers promising solutions to mitigate greenhouse gas emissions by increasing the efficiency of transportation systems. Especially, the transport sector is a significant contributor to greenhouse gas emissions, accounting for nearly one-third of global emissions (Solaymani 2019). As the world grapples with the challenges of climate change, reducing transportation emissions has emerged as a critical priority. Through optimizing routes based on traffic patterns, road conditions, and weather patterns (Chavhan et al. 2020) and hence improving fuel efficiency, reducing travel times, and decreasing emissions, AI play a significant role in reducing the environmental footprint of the transport sector. Leveraging

AI to enhance transportation systems and reduce the carbon footprint offers promising solutions (Fatemidokht et al. 2021) for mitigating climate change impacts.

AI offers a range of solutions to optimize transportation systems and diminish their carbon footprints. AI-powered traffic management systems use real-time data from sensors, cameras, and GPS devices to monitor traffic flow and adjust traffic signals dynamically. For instance, AI can enhance traffic flow, predict congestion, and optimize routes, thereby reducing emissions from idling and unnecessary detours. AI algorithms, leveraging extensive data on traffic patterns, passenger demand, and weather conditions, can significantly reduce emissions and enhance efficiency in transportation systems, resulting in substantial cost savings, decreased greenhouse gas emissions, and a more sustainable transportation sector (Chen et al. 2023). Speaking of sustainable transportation, its integration with AI is revolutionizing how we approach environmental and mobility challenges. AI technologies enable smarter, more efficient transportation systems, significantly reducing carbon footprints and enhancing overall sustainability. In this context, Puri et al. (2020) endeavored to enhance urban transportation systems through the integration of bicycle-sharing schemes by harnessing the capabilities of IoT and AI—AIoT. The proposed system includes sensors for harmful exhaust gases, a GPS receiver, a camera, and fall detection capabilities. The data collected was analyzed using ANN and SVM. The findings indicate that ANN outperforms SVM in terms of root mean square error (RMSE) and coefficient of correlation (R^2), demonstrating superior performance in monitoring and analyzing bicycle-sharing data.

Furthermore, AI can be utilized to enhance public transit systems by optimizing scheduling and route planning (Nikitas et al. 2020) and encouraging users to switch to lower-emission transportation modes, such as public transit or electric vehicles (Olayode et al. 2020). AI achieves this by analyzing extensive datasets to predict passenger demand, identify the most efficient routes, and adjust schedules in real-time. Also, AI-driven incentives, such as dynamic pricing and personalized recommendations, can motivate individuals to choose more sustainable transport options. By analyzing data on passenger demand, traffic patterns, and user behavior, transit systems can optimize routes, reduce the number of empty buses or trains, and promote the adoption of more sustainable transportation modes (Chen et al. 2023).

In addition, AI in autonomous vehicles has ushered in an epoch of transformation in transportation, characterized by unprecedented advancements in vehicle autonomy. AI is central to the development of Autonomous Vehicles (AVs), which promise to revolutionize transportation by reducing accidents, enhancing mobility for those unable to drive, and optimizing traffic patterns. Moreover, AVs have the potential to significantly reduce emissions by improving fuel efficiency and alleviating traffic congestion (Tyagi and Aswathy 2021). AI algorithms can be employed to control these vehicles, enhancing their performance and reducing energy consumption. Othman (2022) provided a broad overview of the implications of AVs, focusing on their potential benefits, including, in addition to improved mobility, reduced energy consumption and lower emissions.

The concept of AVs frequently intersects with the idea of vehicle sharing (Othman 2022). This alignment is largely attributed to the benefits of Shared Autonomous Electric Vehicles (SAEVs), which can alleviate traffic congestion, make more efficient use of urban space, and reduce GHG emissions (Ahmed et al., 2023). Jones and Leibowicz (2019) explored the climate impacts and potential benefits of adopting SAVs compared to Privately Owned Vehicles (POVs) by integrating the electricity and transport sectors using an energy system optimization model. The authors found that widespread SAVs adoption can lower emissions and costs and offer substantial environmental and economic benefits, especially when electric SAV charging aligns with renewable electricity generation. SAV adoption is identified as a more impactful lever for decarbonizing vehicle travel than a carbon tax in the short to medium term. In line with this study, Liao et al. (2021) examined the economic and environmental benefits of integrating Vehicle-to-Grid (V2G) services within SAEV fleets. Their study show that V2G services could reduce operating costs and GHG emissions for SAEV fleets. Over a 30-year period, V2G services could cut costs by 19.6% for long-range SAEVs and reduce GHG emissions by an average of 66.5 tons per vehicle annually. The study highlights the potential of V2G services to enhance the environmental performance of SAEV fleets while generating additional revenue.

However, Saleh et al. (2022) delved into the risks related to SAEVs, particularly the increased mileage and fleet turnover associated with vehicle sharing. These factors could lead to higher overall emissions, potentially offsetting the benefits of optimized charging schedules. The study suggests that while SAEVs can reduce emissions in specific scenarios, the overall impact may be less favorable due to these risks.

Also, Ahmed et al. (2023) investigated the environmental impacts of SAEVs compared to Privately Owned Electric Vehicles (POEVs), focusing on Global Warming Potential (GWP), water footprint, and energy demand. Their analysis revealed that SAEVs typically have a higher environmental footprint due to factors like increased power consumption and deadheading. However, the application of circular economy practices can mitigate these impacts significantly. Specifically, these practices reduced GWP by 21.4%, water footprint by 18.2%, and energy demand by 17.3%. When SAEVs utilize a 100% clean energy mix from the projected 2050 U.S. energy grid, the reductions are even more substantial, with GWP, water footprint, and energy demand decreasing by 73.2%, 51.2%, and 29.1%, respectively.

Kopelias et al. (2020) reviewed the environmental impacts of Connected and Autonomous Vehicles (CAVs) and electric vehicles. They identified eleven factors influencing these impacts, categorized into vehicle, road network, and user-related factors. The study highlights that while CAVs have the potential to reduce fuel consumption and emissions, they also raise concerns about increased environmental noise and its effects on public health. It underscores the need for further research to balance the technological benefits with the associated environmental risks.

Silva et al. (2022) conducted a comprehensive review of the environmental impacts of AVs (AVs), extending beyond air pollution to include land use, noise, and light pollution. Their findings suggest that AVs could offer significant environmental benefits, such as improved traffic flow and reduced emissions. However, these benefits depend on factors like adoption rates and integration with other transport modes. The study also notes that AVs may also lead to negative outcomes such as changes in land use that impact soil and water quality. They highlight that the potential improvements in noise and light pollution are not well understood, indicating a need for further research.

Furthermore, Othman (2022) discussed the challenges posed by current legal frameworks, which are not fully prepared for the rapid advancements in AVs technology. The study emphasizes the need for more detailed studies to explore the full range of environmental benefits offered by AVs.

The studies provide a comprehensive view of the environmental impacts of AVs and SAEVs. On the positive side, SAEVs and AVs can offer significant environmental benefits, particularly when supported by advanced practices and technologies. Ahmed et al. (2023) and Saleh et al. (2022) show that practices like circular economy and optimized charging schedules can substantially reduce environmental impacts. Liao et al. (2021) further demonstrates the potential of Vehicle-to-Grid (V2G) services to enhance both economic and environmental outcomes for SAEVs. However, the studies also highlight notable risks. Ahmed et al. (2023)

and Saleh et al. (2022) discuss the higher environmental footprint of SAEVs compared to private EVs, attributed to factors like increased power consumption and deadheading. Silva et al. (2022) and Kopelias et al. (2020) point out additional risks such as changes in land use, noise pollution, and other environmental concerns that need more detailed study.

Overall, while SAEVs and AVs have the potential to contribute positively to environmental sustainability, their benefits must be carefully weighed against their risks. The balance between these factors will be critical in determining how these technologies can be deployed sustainably. Continued research and implementation of supportive practices are essential to maximize the environmental advantages while minimizing the risks associated with these emerging technologies.

From a technical perspective, the recent study by Garikapati and Shetiya (2024) reveals the evolving usage and types of AI algorithms in the automotive industry, highlighting statistical trends over the years. Key insights include the important role of parameter optimization in refining AI algorithms for trucks and cars, which enhances vehicle adaptability, learning, and performance improvement over time. Moreover, the study outlines different levels of vehicle autonomy, detailing the specific AI algorithms used at each level and discussing the automation of key tasks along with the software package sizes. This comprehensive analysis underscores the dynamic research landscape and the critical factors influencing the successful integration of AI in autonomous vehicle development. From another perspective, Norazman et al. (2024) explored the application of ANNs in analyzing road crash data and their potential to enhance the performance of autonomous vehicles. Their findings indicate that ANNs are highly effective in modeling and predicting crash incidents, offering significant benefits for improving road safety. In addition, ANNs are instrumental in the operations of autonomous vehicles, enabling them to perceive their environment, make informed decisions, and operate safely and efficiently. However, the implementation of ANNs faces challenges such as lack of transparency, the need for large amounts of well-curated data, and high computational demands.

However, the integration of AI in transportation raises several ethical challenges, primarily concerning user data privacy and security, and trust issues. AI systems rely heavily on extensive data collection, including real-time location, travel patterns, and personal preferences, which can lead to significant privacy concerns if not handled with stringent security measures. Ensuring that user data is protected from breaches and misuse is key to maintaining public trust. It is essential to building trust in AI-driven transportation systems and preventing any potential exploitation of sensitive information (Chen et al. 2023). Additionally, the transparency and fairness of AI decision-making processes in general are important, as users need to trust that AI is not biased and that their personal information is used responsibly (Bibri et al. 2023, 2024b). Addressing these ethical challenges is essential for the sustainable and ethical deployment of AI in transportation. Indeed, developing AI-powered transportation technologies should prioritize user needs and involve continuous engagement with users to ensure their effectiveness and acceptance (Hahn et al. 2021).

4.5.2. Artificial Intelligence for Industry Production

AI technologies are transforming industry production and freight transportation. AI can enhance the efficiency of logistics and supply chain operations, reducing costs and emissions. AI 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 can monitor and identify issues with specific food products, aiding supply chain management during large-scale food supply disruptions (Pournader 2021).

Additionally, AI 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 also enhances 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 lifecycle 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).

AI is revolutionizing manufacturing by enhancing flexibility, resilience, and efficiency in production processes. AI supports a range of functions from data analysis to real-time decision-making, ultimately optimizing production lines and resource management. AI can upload information from intelligent devices used in flexible and resilient manufacturing to the cloud, enabling remote manipulation of production processes even when managers are not on-site, thus enhancing the agility and resilience of the production process (Chen et al. 2023). According to Oruganti et al. (2023), this model aids assembly lines in industrial processes by effectively handling accidents and reducing the pressure on managers. Moreover, Cohen et al. (2019) noted that precomponent production necessitates significant data analysis. They emphasized that if component data problems arise during modeling, 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 enhances 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 CO_2 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 substantially 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.

These synthesized studies highlight the significant potential of AI in the manufacturing industry, underscoring innovative opportunities to enhance efficiency, drive technological advancements, and optimize processes. AI's ability to enhance production efficiency, optimize logistics, and improve operational management is evident across various industry sectors. They emphasize the need for robust policies and continued research to fully leverage AI's capabilities. The manufacturing industry can achieve significant advancements in efficiency, innovation, and sustainability by addressing these challenges and promoting AI adoption.

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 substantially 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. Meanwhile, Wamba-Taguimdje et al. (2020) conducted an in-depth exploration of case studies across various industries to analyze the business value of AI-driven transformation projects. Their findings reveal how AI technologies, such as machine translation, chatbots, and self-learning algorithms, enhance firms' understanding and response to their environments. AI adoption helps organizations optimize processes, improve automation, and enhance information and transformation effects, thereby boosting performance at both organizational and process levels. Together, these two studies underscore the critical importance of integrating AI into strategic frameworks to enhance global competitiveness and firm efficiency.

4.5.3. Artificial Intelligence for Freight Transportation Management

AI is revolutionizing various aspects of freight transportation and logistics, offering innovative solutions for improving efficiency, safety, and sustainability. The integration of AI techniques such as ML, NLP, and LLMs is addressing complex challenges in these sectors. Liachovičius et al. (2023) focused on enhancing the performance of road freight transportation companies by forecasting demand and freight rates using econometric and AI methods. Their study revealed that econometric models like Auto-Regressive Integrated Moving Average (ARIMA) performed well for demand prognosis. However, for freight rate forecasting, AI-based methods such as MultiLayer Perceptron (MLP) outperformed traditional models. A key finding was the strong correlation (0.86) between spot and contract rates, suggesting that current spot rates can effectively predict contract rates.

Brezulianu et al. (2023) developed the FERODATA AI engine to optimize the scheduling of locomotive drivers in rail freight transportation. This AI/ML software module uses a supervised random forest model to assign conductors based on various parameters, including tiredness score, distance to departure point, availability, and circulation history. The model demonstrated high performance with an accuracy of 95% on the training set and 84% on the test set. The study concluded that AI can significantly improve operational efficiency, cost savings, regulatory compliance, and safety in rail freight transport.

Katreddi et al. (2022) explored the applications of AI in the heavy-duty trucking industry, addressing challenges such as emissions, driver safety, and travel demand. The study highlighted AI's potential in enhancing productivity, sustainability, and reliability through applications like fuel consumption prediction, emissions estimation, self-driving technology, and predictive maintenance. The use of AI and ML methods allows for efficient data analysis and insights, important for meeting fuel consumption and emission standards and ensuring driver safety. In a similar vein, AI can be utilized to manage vehicle fleets more efficiently by optimizing maintenance schedules and fueling (Alexandru et al. 2022), developing autonomous vehicles, and regulating demand (Abduljabbar et al. 2019). AI systems optimize routing and scheduling for freight transportation, taking into account factors such as traffic conditions, fuel efficiency, and delivery deadlines. This ensures timely deliveries and minimizes operational costs.

Tupayachi et al. (2024) investigated the use of AI-powered large language models (LLMs) to generate scientific ontologies for optimizing intermodal freight transportation. By utilizing the ChatGPT API and NLP techniques, the study developed an integrated workflow for creating scenario-based ontologies. The outcomes included knowledge graphs that enhance data and metadata modeling, integration of complex datasets, and coupling of multi-domain simulation models. The methodology was validated through a case study, demonstrating its effectiveness in supporting informed decision-making in complex urban freight systems.

These studies underscore the innovative potential of AI in freight transportation. From optimizing freight rate and demand forecasting to enhancing locomotive driver scheduling, improving heavy-duty truck operations, and developing sophisticated decision support systems, AI is proving to be a game-changer. The integration of AI technologies not only improves efficiency and reduces costs but also addresses critical issues related to safety, sustainability, and regulatory compliance. As AI continues to evolve, its applications in freight transportation are expected to expand, offering even more innovative solutions to industry challenges.

4.6. Disaster Risk Reduction

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

4.6.1. Artificial Intelligence Support for Disaster Preparedness

Early warning of extreme climate events saves lives and reduces economic losses. Given the increasing frequency and intensity of extreme storms, wildfires, and heatwaves, there is an urgent need to protect every person on Earth with early warning technology. The United Nations Early Warnings for All Initiative is an example of how AI is used as an invaluable tool in enhancing disaster preparedness, providing governments and organizations with advanced capabilities to anticipate, plan, and respond to natural and human-made disasters. Leveraging AI technologies significantly improves disaster management strategies, resulting in more effective and efficient mitigation of risks, reduction of damages, and saving lives, especially in the most vulnerable countries, including LDCs and SIDS.

4.6.1.1. Predictive Analytics Shaping Mitigation, Early Warning and Early Action Planning

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. Mitigation, early warning, 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 percent 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.

4.6.1.2. Predictive Analytics Shaping Evacuation Planning

AI models greatly 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 analyzing 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 2022). Climate change predictions enable authorities to identify high-risk areas and develop effective evacuation routes and strategies. For instance, AI 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 significantly 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 2022; Rolnick et al. 2012).

AI-powered solutions are increasingly being utilized to tackle the challenges of flood prediction and management, showcasing their potential in enhancing disaster response strategies. 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.

4.6.1.3. Coordination of Response Efforts During Disasters

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 (Omdena and WFP 2020). 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 optimizes resource allocation by analyzing 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.

In the realm of AIoT, 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 handle 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.

In the context of AI, 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 throughput 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 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 communitiesIt 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 improved improving the efficiency and effectiveness of disaster management strategies.

While Saleem and Mehrotra (2022) provide an overview of AI techniques used to process disaster-related social media content across different disaster management phases, Abid et al. (2021) offer a broader overview of AI applications spanning all disaster management phases, illustrating how AI, combined with GIS and RS, enhances disaster planning, situational awareness, and recovery efforts. AI's capabilities in data analysis and visualization enable rapid decision-making and efficient resource allocation, which is of crucial importance for effective disaster management. The study emphasizes the importance of AI in all phases of disaster management: mitigation, preparedness, response, and recovery. AI applications such as tracking, mapping, geospatial analysis, remote sensing, robotics, and ML substantially enhance the ability to manage disasters efficiently. The study underscores the potential of AI to lead to faster, more equipped disaster responses and better overall disaster management strategies.

4.6.1.4. Disasters Risk Assessment: A Multi-Perspective Approach

AI supports disaster preparedness through risk assessment, early warning systems, and community education. AI-driven risk assessment tools help identify vulnerable areas and populations, enabling targeted interventions before disasters strike (e.g., Kuglitsch et al. 2022). 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 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 socioeconomic 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 aids 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 analyze these challenges to ensure that AI is 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 2024).

In sum, AI's contribution to disaster preparedness is multifaceted, encompassing predictive analytics, response coordination, risk assessment, and early warning. By harnessing the power of AI, authorities can enhance their preparedness strategies, ensuring more effective and timely interventions during disasters. As AI technologies continue to advance, their role in disaster preparedness is likely to become even more critical, offering new and innovative solutions to mitigate the impacts of future disasters.

4.6.2. AI Support for Post-Disaster Recovery and Reconstruction

AI has emerged as a valuable tool in the post-disaster recovery and reconstruction phase. By utilizing advanced data analytics, ML models, and AI-driven technologies, the efficiency and effectiveness of recovery efforts can be significantly improved.

4.6.2.1. Assessment of Damage and Prioritizing Recovery Efforts

In the aftermath of a disaster, one of the immediate challenges is assessing the extent of the damage over large and often inaccessible areas. AI-powered drones and satellite imagery play an instrumental role in this context by providing rapid and comprehensive damage assessments. Amprius (2024) highlights the significant potential of drones in disaster response scenarios. In this context, drones make it easier to access areas that are challenging for people to reach, providing them with aerial views of disaster zones. These data serve as a valuable tool for first responders to a disaster site, enabling them to assess the situation and plan their actions accordingly. Drones can also be used to transport essential supplies quickly and efficiently, such as medical aid, food, and communication equipment, thus expediting relief efforts. In addition, drones are essential in search and rescue missions, providing information needed to identify survivors and guide rescue teams. These drone-based disaster relief efforts require fewer resources compared to conventional methods.

AI models further enhance these efforts by analyzing drone-collected data to rapidly assess damage levels and prioritize recovery efforts. Kim et al. (2022) evaluated the applicability of UAV photogrammetry and AI for managing natural disasters. The authors demonstrate how AI can detect and identify disaster events from aerial imagery captured by drones. The research presents an AI technique for disaster detection and proposes an UAV-based investigation procedure for assessing disaster-damaged areas during the recovery phase. It compares the mapping accuracy and work efficiency of drone mapping with traditional labor-intensive field surveys. The study finds that drone mapping, with ortho-images having a resolution of less than 5cm GSD, can effectively identify damage information such as destroyed facilities and soil erosion. This photogrammetry-based approach offers timely and efficient disaster site assessments.

Concerning AI models, 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 analyze 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 socioeconomic 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 analyzing 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.

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.

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. 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 swiftly and cost-effectively identify damaged buildings following a disaster 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 small island developing states 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 4), 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 4. An AI-generated map of building footprints in Salisbury, Dominica. Drone image is taken from OpenAerialMap

Figure 5 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.

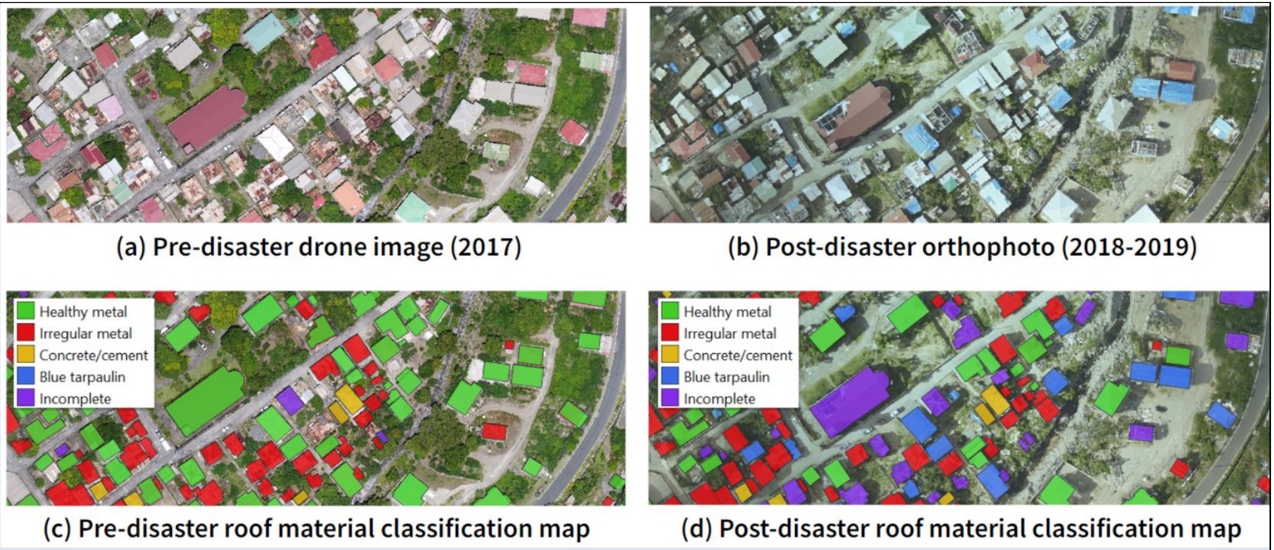

Figure 5. Pre- and post-disaster roof material classification maps in Colihaut, Dominica

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.

4.6.2.2. Efficient Post-Disaster Rebuilding Processes

Once the damage has been assessed and recovery priorities established, the focus shifts to reconstruction. AI systems promote significant advancements in the efficiency of rebuilding processes by optimizing resource allocation, scheduling tasks, and ensuring compliance with safety standards and regulations. These systems also monitor ongoing construction work to ensure adherence to safety protocols and regulatory requirements, reducing the risk of future vulnerabilities. By streamlining these complex processes, AI helps accelerate the reconstruction timeline while maintaining high standards of safety and quality. Şimşek et al. (2023).assessed the role and methods of AI in post-disaster management. They found that AI systems can effectively minimize logistical challenges during disaster interventions. The findings underscore AI's potential in enhancing post-disaster recovery efforts through improved efficiency and real-time assessments. Archie 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.

Further to post-disaster management, 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-labeled 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.

AI supports post-disaster recovery in other significant ways. For example, AI-driven communication platforms can facilitate coordination among various stakeholders, including government agencies, non-profit organizations, and local communities. AI can also be used to analyze social media and other communication channels to gauge public sentiment and identify urgent needs, allowing for more responsive and adaptive recovery efforts. In addition, AI can aid in financial planning and insurance claims processing, expediting the distribution of funds and resources to affected individuals and businesses.

AI's contribution to disaster preparedness, response, and recovery is multifaceted, encompassing predictive analytics, response coordination, risk assessment, early warning, damage assessment, and efficient rebuilding processes. AI enhances early warning systems and risk assessment by analyzing vast datasets to predict the likelihood and severity of disasters, allowing for timely and targeted interventions. During the response phase, AI optimizes resource allocation and coordinates efforts through real-time situational awareness, integrating data from various sources to streamline emergency operations. In the recovery phase, AI facilitates rapid damage assessment and the efficient allocation of resources for rebuilding efforts, utilizing technologies such as drones and AI-driven analytics to prioritize and expedite recovery processes. These innovations enhance the immediate response to disasters and contribute to long-term resilience and sustainability in disaster management practices. As AI technologies continue to evolve, their role in mitigating the impacts of future disasters will become increasingly critical, offering new and innovative solutions to enhance community resilience and adaptive capacity.

The project spearheaded by MedEWSa (2024) focuses on the use of AI-powered solutions to enhance preparedness, response, and recovery efforts, thereby addressing the challenges posed by natural hazards exacerbated by climate change. It underscores the innovative potential of AI in enhancing climate resilience and adaptation.

Fortifying Ethiopia's National Parks: Building Resilience Against Wildfires and Extreme Weather

Country:
LDC, 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, ESA. All these stakeholders will benefit from MedEWSa's objective 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.

A specific pilot in Ethiopia focuses on three national parks of high biodiversity and tourism relevance: Simien, Bale Mountains and Gambella National Park. A holistic wildfire management approach based on monitoring and forecasting tools benefits the preparedness, response and recovery in very different contexts: high/low capacity, densely/sparsely populated areas, and focus on protecting human life/ecosystem services. MedEWSa will deliver a sophisticated, comprehensive, and innovative pan-European Mediterranean–African solution comprising various complementary services. Building on existing tools, MedEWSa will develop a fully integrated impact-based multi-hazard EWS.

Climate Change Mitigation and/or Adaption Impacts and Results

Through eight selected pilot sites (areas in Europe, the southern Mediterranean, and Africa with a history of being impacted by 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 bi-directional 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 time scales.
- 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 nactions, (patrolling areas at risk) and rapid deployment of FRs, mitigation measures (prescribed burnings), and preparedness activities.

4.7. Generative Artificial Intelligence Applications in Climate Action

GenAI is an emerging field that has garnered significant attention for its potential to contribute to climate change mitigation and adaptation efforts, transforming various domains by providing advanced solutions to complex challenges. This is evidenced by recent studies that highlight the diverse applications and impacts of GenAI in strengthening resilience, improving extreme weather forecasts, simulating climate events, supporting nature-based solutions, and enhancing decision-making and efficiency. However, despite the initial excitement and these promising exploratory studies, the impact of GenAI in this domain has yet to fully materialize in practical, transformative ways.

4.7.1. Emerging Research on Generative Artificial Intelligence and Large Language Models

Butler and Lupton (2024) conducted a scoping review that explores how novel generative AI tools are being applied within environmental and ecosystem-related contexts. They identify several areas where GenAI and LLMs are now being utilized in emerging research projects and industry practices. Key applications highlighted include agriculture and plant cultivation, environmental sustainability efforts, biodiversity conservation, climate change initiatives, and nature preservation programs. The study also examined the environmental costs and ethical concerns associated with the production, training, and infrastructure needed to support generative AI and LLMs.

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 analyzing artificially generated data, the researchers could identify pioneer species capable of promoting greater biodiversity in distinct patches. The findings highlight the potential of generative AI in advancing ecological research by overcoming the limitations of traditional methods and offering new insights into species coexistence and community assembly. This approach opens up opportunities for deeper exploration of biodiversity maintenance in complex ecosystems.

Paramesha et al. (2024) explored how integrating GenAI models, particularly ChatGPT, can significantly bolster resilience across multiple domains. The study demonstrates that ChatGPT enhances communication, aids in policy development, and provides real-time data analysis, which are critical for effective decision-making and preparedness in climate resilience. In urban contexts, ChatGPT helps optimize resource management, predict hazards, and engage communities, thereby strengthening city resilience. For business continuity and crisis management, the GenAI model offers tools for risk assessment and crisis response, ensuring organizations remain robust during disruptions. Additionally, ChatGPT supports community and social resilience by facilitating communication and mental health support. In cybersecurity, ChatGPT enhances threat detection and incident management, bolstering organizational defenses. This study highlights the instrumental role of GenAI technologies like ChatGPT in building a more adaptive, knowledgeable, and interconnected global community, ultimately contributing to sustainable development and improved quality of life.

Building on these advancements, 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.

Sha et al. (2024) proposed an innovative method combining a 3-D Vision Transformer (ViT) with a Latent Diffusion Model (LDM) to enhance the probabilistic forecasts of extreme precipitation events across the conterminous United States. This approach improves the accuracy of 6-hourly precipitation ensemble forecasts by producing spatiotemporally consistent precipitation trajectories. These enhanced forecasts, verified against Climate-Calibrated Precipitation Analysis (CCPA) data, show improved skill in predicting extreme precipitation events, as indicated by better Continuous Ranked Probabilistic Skill Scores (CRPSSs) and Brier Skill Scores (BSSs). This work demonstrates how GenAI can address the limitations of small numerical ensembles, providing larger and more accurate ensembles necessary for identifying extreme precipitation events effectively.

McCormack and Grierson (2024) explored the use of GenAI technologies to create realistic simulations for climate disaster preparedness. Their focus is on immersive and narrative-driven simulations, which allow users to experience the impacts of extreme climate events safely, facilitating better planning and preparedness. The study examines the current capabilities of GenAI models and discusses future advancements needed to enhance simulation realism. This approach emphasizes the value of experiential learning in preparing for climate-related disasters, using GenAI to create scenarios that help stakeholders plan and respond effectively before actual events occur.

Richards et al. (2024) investigated the potential of GenAI to automate and scale up the communication and implementation of nature-based solutions. The study showcases three examples: reporting on ecosystem services and land use options for farms, providing interactive guidance for biodiversity-friendly garden design, and visualizing future landscape scenarios that integrate nature-based and technological solutions. These demonstrate how GenAI can facilitate the dissemination of nature-based design strategies, reaching a broader audience and promoting sustainability. However, the study also highlights the risks associated with GenAI, such as bias, misinformation, data privacy issues, mistrust, and high energy consumption. To maximize the benefits and mitigate these risks, the authors call for integrated social research into ethics, public acceptability, and user experience.

Generative AI technologies are becoming increasingly useful for enhancing resilience, improving extreme weather forecasts, simulating climate events, and supporting nature-based solutions. The studies reviewed demonstrate the diverse applications and progressive potential of GenAI across various sectors. However, it is crucial to address the associated risks and ethical considerations to ensure these technologies are used responsibly and effectively. By harnessing the power of GenAI alongside human expertise, we can tackle complex challenges and build a more resilient and sustainable future.

Current research on the role of GenAI in climate action primarily consists of experimental work and the development of initial prototypes. These studies demonstrate how GenAI can be applied to various aspects of climate change, such as generating predictive models for environmental changes, optimizing resource management strategies, or even producing synthetic data to improve the training of other AI systems. For instance, GenAI could simulate the impact of different climate policies on global ecosystems. However, many of these applications remain in the conceptual or early testing stages, and few have been implemented at scale in real-world settings. The gap between theoretical potential and practical impact highlights several challenges that need to be addressed before GenAI can truly contribute to climate change mitigation and adaptation.

One significant challenge is the complexity of the climate system itself. Climate change is influenced by a vast array of interdependent factors, making it difficult to model and predict outcomes with precision. GenAI, while powerful, is still limited by the quality and availability of data, as well as the ability to accurately simulate complex, dynamic systems over long periods. This can lead to models that work well in controlled environments but struggle to deliver accurate or actionable insights when applied to the real world.

In addition, the integration of GenAI into existing climate action frameworks requires more than just technical innovation. It necessitates interdisciplinary collaboration, involving not just AI researchers but also climate scientists, policymakers, and industry stakeholders. This collaboration is crucial to ensure that AI-generated solutions are practical, ethical, and aligned with broader climate goals. However, fostering such collaboration can be challenging due to differences in expertise, priorities, and approaches across disciplines.

Another hurdle is the ethical and societal implications of deploying GenAI in climate action. There are concerns about the transparency and accountability of AI systems, particularly when they are used to make decisions that impact large populations or critical environmental resources. Ensuring that GenAI is used responsibly, with safeguards against unintended consequences, is essential for building trust and ensuring that these technologies contribute positively to climate goals. Moreover, the deployment of GenAI at scale requires significant resources and infrastructure, including computational power, access to high-quality data, and robust regulatory frameworks. These requirements can be prohibitive, particularly in regions where resources are limited or where climate impacts are most severe, like in SIDS and LDCs.

Overall, while GenAI holds great promise for contributing to climate change mitigation and adaptation, the field is still in the early stages of development. The current body of research, though promising, has yet to translate into widespread, transformative applications. Overcoming the challenges of data quality, interdisciplinary collaboration, ethical considerations, and resource availability will be crucial for realizing the full potential of generative AI in addressing climate change. Until these challenges are addressed, the impact of GenAI on climate action will remain largely theoretical, with much work needed to turn initial explorations into practical, scalable solutions.

4.7.2. LLMs Applications for SIDS and LDCs

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.

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 modeling, 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.

The project Climind explores the integration of AI into climate action strategies in Hong Kong through the Climind platform (CLIMIND 2024). This AI initiative leverages advanced LLMs and Retrieval-Augmented Generation (RAG) to improve decision-making and operational efficiency in tackling climate change challenges.

AI Enabler for Climate Solutions

Country:
Hong Kong

Entities Involve: 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 (Figure 6), Climind enables precise report generation, carbon pricing insights, climate risk assessments, and carbon trading information.

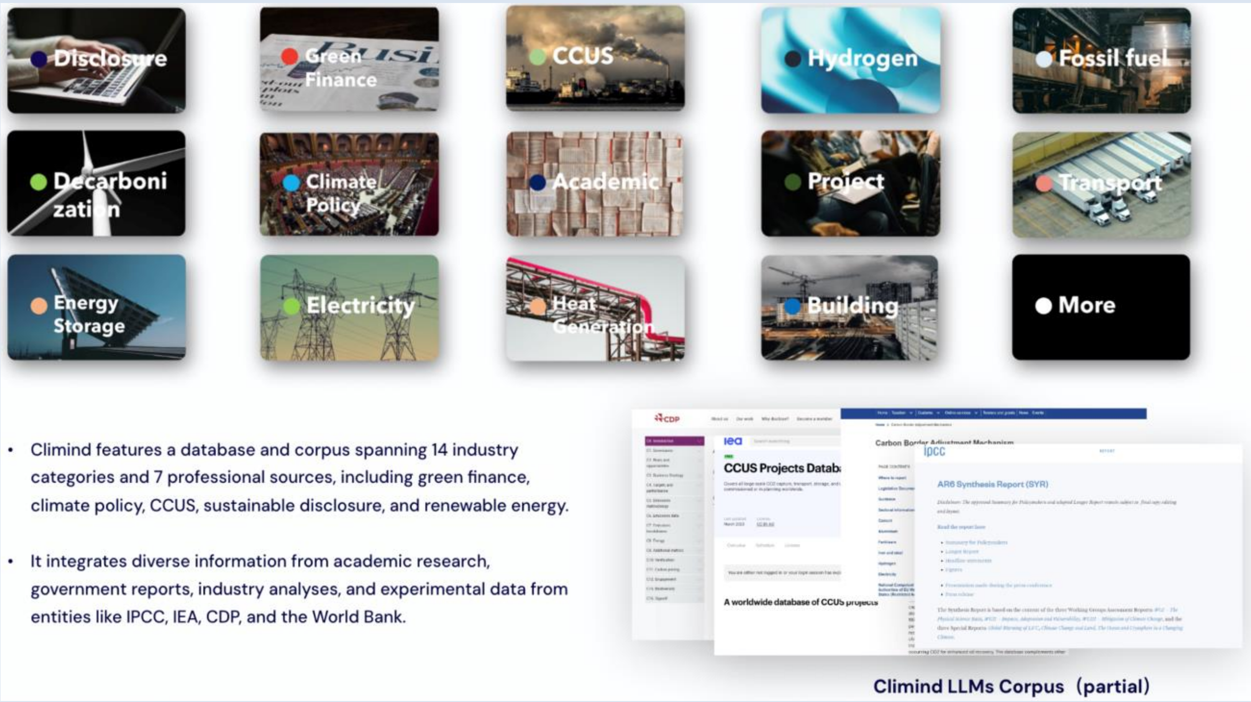

Figure 6. Databases and corpus

Climate Change Mitigation and/or Adaption 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 beyond. 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 startups 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 particular 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.

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
Climate Migration	• Climate and Natural hazard early warning systems • Migration early warning 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 analyzing 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
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 combating 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

Table 4. Emerging applications of Large Language Models in Enhancing Climate Resilience and Sustainability for LDCs and SIDS

While LLMs are becoming increasingly accessible, the assertion that they are not necessarily more accessible to developing countries, especially SIDS and LDCs, remains valid. The computational demands, high costs of fine-tuning, and deployment challenges pose significant barriers, particularly in resource-constrained regions.

The extensive data, computing power, large-scale data centers, and expertise required to effectively train and deploy these models are typically available only to large tech companies or institutions in developed countries, making LLMs out of reach for many institutions in developing regions. In contrast, smaller AI/ML models with lower computational requirements are often more practical and accessible for use in resource-constrained environments like SIDS and LDCs, highlighting critical disparities in AI accessibility.

Furthermore, most major LLMs are trained predominantly on English-language data, which limits their relevance and effectiveness in non-English-speaking regions. In developing countries where local languages and dialects are predominant, the utility of these models is diminished. This language bias can lead to poorer performance in generating culturally relevant content or understanding regional nuances, further widening the digital divide (see Subsection 6.3. for further detail).

The development and training of LLMs are controlled by a few large entities like OpenAI, Google, and Meta. This centralization means that smaller players, especially those in developing countries, have little to no influence over the direction and focus of these models. The high cost of training such models also puts them out of reach for many organizations, reinforcing existing inequalities in AI access and development.

The disparities in access to LLMs have broader implications for knowledge representation and inclusion in AI systems. As LLMs are disproportionately trained on data from developed regions, they often fail to capture diverse global perspectives, which is crucial for creating AI systems that are equitable and relevant worldwide.

Overall, while LLMs are technically accessible via platforms like OpenAI, their development, training, and practical utility remain largely restricted to well-resourced entities, making them less accessible to developing countries compared to smaller, more specialized AI/ML models. Addressing these challenges requires targeted efforts to democratize AI resources, including multilingual training data, open-source initiatives, and scalable AI models that can be more easily adapted to different local contexts.

4.8. Education and Community Engagement

Education and community engagement are critical components in the global effort to combat climate change. AI offers innovative tools and approaches that can enhance these efforts by making climate information more accessible, engaging, and actionable. AI capabilities enable communities to enhance their understanding of climate issues, promote sustainable practices, and foster a culture of resilience and proactive adaptation. There are various ways AI can support education and community engagement and contribute to empowering communities to take informed actions towards a sustainable future.

4.8.1. Raising Awareness of Artificial Intelligence for Climate Action

AI can play a critical role in raising awareness about climate action by providing powerful tools for data visualization, predictive modeling, 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.

TEC and CTCN, as the policy and implementation arms of the Technology Mechanism, are collaborating on the #AI4ClimateAction Initiative (UNFCCC 2024a). This initiative aims to leverage AI to advance and scale up transformative climate solutions for mitigation and adaptation action, particularly focusing on developing countries, LDCs, and SIDS. It provides a platform for policy discussions, raises awareness **about AI's**

potential, facilitates knowledge exchange among stakeholders, and supports capacity-building efforts to harness AI and develop locally-led climate solutions. Public awareness campaigns can leverage AI to personalize messages and reach a broader audience through social media and other digital platforms. Additionally, AI can help identify and target key demographics, ensuring that climate action messages resonate with diverse audiences. **However, it is important to note that TEC and CTCN are not currently leveraging AI for social media purposes; instead, they are raising awareness about AI's role in climate action.** Furthermore, at COP 28, parties, who adopted a decision on enhancing climate technology development and transfer through the Technology Mechanism, requested TEC and CTCN to implement the #AI4ClimateAction Initiative (UNFCCC 2024b). They emphasized the need to raise awareness about AI's potential roles and impacts in advancing the outcomes of technology needs assessments and the joint work program of the Technology Mechanism for 2023–2027.

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.

4.8.2. Artificial Intelligence-Powered Tools for Climate Change Education

AI-powered educational tools can significantly enhance 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 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 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 can analyze vast amounts of climate data, creating more accurate and dynamic VR simulations that reflect real-time changes in the environment. AIoT integrates AI 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 enable VR experiences to become more engaging and informative, ultimately fostering greater awareness and proactive behavior 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 significantly 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.

In relation to AI for climate change education, the findings underscore the significance of designing AI tools that are user-friendly and perceived as useful by educators and students alike. By addressing these key factors, educational institutions can enhance the acceptance and effectiveness of AI-powered educational tools, thereby improving climate change education and fostering a culture of sustainability. This aligns with the goal of creating AI-driven educational tools that are easy to use, an approach that can lead to more effective and engaging learning experiences, ultimately contributing to a better understanding and response to climate change challenges. In their study, Shaikh et al. (2021) explored the impact of AI and ML on creating digital classrooms and their sustainable effects on education during pandemics. They found that these technologies greatly enhanced the learning experience by providing personalized learning paths and real-time feedback to students. The study emphasizes the supportive role of AI and ML in fostering an adaptive and resilient educational ecosystem during global disruptions. Other educational services provided by AI include developing and conducting lectures, seminars, and practical classes; offering teacher consultations; creating educational programs and electronic courses; developing assignments and simulating their solutions; organizing various educational events; and evaluating student work (Bakhmat 2024).

Mannuru et al. (2023) focused on the impact of GenAI on developing countries, evaluating both its potential benefits and drawbacks across various domains including information, culture, and industry. The findings indicate that while GenAI offers significant advantages, these benefits are not uniformly accessible, particularly in developing nations where technological access and infrastructure are often limited. The study highlights the necessity of providing adequate support and infrastructure to ensure GenAI fosters inclusive development and does not exacerbate existing inequalities.

In sum, AI-powered educational tools offer advanced tools for climate change education by creating interactive, personalized, and up-to-date learning experiences. These tools can engage students deeply, provide real-time feedback, and adapt to individual learning needs. AIoT enable educational environments to become even more dynamic and responsive, enhancing the overall effectiveness of climate change education. Ensuring these technologies are user-friendly and accessible will be essential for their widespread adoption and impact, ultimately fostering greater climate awareness and proactive behavior in students.

4.8.3. Artificial Intelligence Powered Tools for Raising Awareness and Promoting Sustainable Practices

AI can support the promotion of sustainable practices by providing insights into individual and collective behaviors 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. Moreover, AI can help design and implement public policies that encourage sustainable practices, using data-driven approaches to optimize resource allocation and track the effectiveness of interventions (Bibri et al. 2024a).

Kandlhofer et al. (2023) presented an international AI education and awareness project, 'ENARIS,' designed to build awareness, foster acceptance, and provide a foundational understanding of AI as a disruptive technology. It focused on sparking young people's interest in AI and delivering a basic technical understanding through a train-the-trainer model for teachers and the creation of open educational resources. It also sought to increase public awareness of the social, economic, environmental, and technical aspects of AI. The results demonstrated that the teaching materials and workshops were well-received and significantly improved AI awareness and knowledge among participants.

The findings of this study can be extended to raise awareness of AI for climate change by highlighting how AI technologies can contribute to climate mitigation and adaptation strategies. Educating the public on the potential of AI to address environmental challenges fosters a broader understanding and support for AI-driven climate solutions. Future studies can focus on extending these findings to develop more comprehensive educational frameworks and tools, ensuring that the potential of AI in climate action is fully realized and effectively communicated. Additionally, research can explore the integration of AI with other emerging technologies, such as IoT, AR, VR, and digital twin, to enhance the effectiveness and reach of climate education initiatives.

Maria Kasinidou (2023) focused on the growing necessity for public AI literacy due to the growing 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 programs. Enhancing public understanding of AI's applications in environmental contexts can drive more informed support for AI-driven climate initiatives.

Youth engagement in policy-making, capacity building, and innovation is critical to addressing climate change effectively. Kandlhofer et al. (2023) demonstrated through the ENARIS project that educating young people about AI and its potential impacts can significantly enhance awareness and knowledge. Similarly, Maria Kasinidou (2023) highlighted the importance of AI literacy across all demographics, including children and adults. Building on these studies, emphasizing youth engagement in policy decisions can empower young stakeholders to influence climate strategies actively. Providing targeted training and capacity building can prepare them as practitioners equipped with the necessary skills to implement AI-driven climate solutions. Furthermore, fostering youth involvement in innovation and the development of future technologies ensures that the voices of those most affected by climate change are heard and that they contribute directly to creating resilient and sustainable solutions. By investing in youth education and participation, we support future generations in their critical role as key stakeholders, ensuring they are well-prepared to tackle the environmental challenges they will inevitably face.

Goralski and Tan (2020) focused on the rapid advancements in AI and their profound impacts on business, corporate practices, and governmental policy. They examined how AI and robotics with DL capabilities disrupt and enable various sectors, influencing global sustainability trends. The study analyzes three case studies to assess AI's impact on sustainable development, focusing on the advancement of the SDGs and deriving lessons for managerial learning and business leadership in the context of global sustainability. The findings suggest that AI has the potential to drive substantial progress on the SDGs, but it also presents challenges that must be managed carefully. The study emphasizes the need for future business leaders to understand and navigate the complexities of AI to promote global sustainability effectively. This entails integrating AI literacy into management education to prepare business leaders for the challenges and opportunities presented by AI in fostering sustainable development.

Speaking of opportunities, AI and related technologies are indeed transforming various industries and businesses by promoting sustainable practices. Table 5 provides a comparative analysis of various studies, offering insights into how AI contributes to sustainability and showcasing the diverse applications of AI across different sectors.

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 enhances efficiency in recruitment, reduces bias, and promotes eco-engagement among employees.	John and Pramila (2024)
AI in adopting green HRM practices	AI	Organizational sustainability, green environment	Human resource management	AI aids 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 helps recognize environmental issues, supports sustainable finance, and enhances 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)

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 Chmielewska (2024)
AI in sustainable education	AI	Environmental responsibility, resource efficiency	Education	AI enhances sustainability education through personalized learning, curriculum development	Harish et al. (2023)

Table 5: Artificial Intelligence powered tools for promoting sustainable practices

The analysis highlights the significant potential of AI in fostering sustainable practices across diverse sectors. From enhancing HRM processes and promoting green HRM to driving sustainable finance, improving business operations, advancing green shipping, mitigating waste in the fashion industry, assessing energy efficiency in real estate, and promoting sustainable education, AI and related technologies offer significant benefits. These studies underscore the importance of integrating AI with other emerging technologies to achieve sustainability objectives and address environmental challenges effectively.

4.8.4. Artificial Intelligence-Powered Tools for the Engagement of Local Communities in Climate Action

Engaging local communities in climate action is of value for driving grassroots change. AI 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 can also facilitate participatory decision-making by analyzing community feedback and integrating it into policy development. Furthermore, AI can support local climate initiatives by providing tools for monitoring and reporting progress, ensuring transparency and accountability.

In the age of AI, where our daily lives are increasingly shaped by AI technologies, we are simultaneously confronting the climate crisis. This dual challenge necessitates exploring how AI can be leveraged to address this crisis, emphasizing the need for educational tasks that foster community awareness and action in the AI era. Reflecting this necessity, Cheong, E. (2022) highlighted the need to integrate educational tasks addressing global warming within the context of AI. The author explored community awareness education under the theme “Community Awareness Education in the Era of AI: The Third Neighbor.” The study argues that to address the climate crisis effectively, we must transcend traditional dichotomous worldviews and embrace AI as a co-existing intelligence. It proposes the development of "AI humanities" to guide AI’s evolution in a way that promotes coexistence and addresses global challenges like climate change.

Investigating the societal impact of AI from a human-centered 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 labeling 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 generalizable 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).

The Community Innovation Labs for Climate Resilience (Co_LABS) project in Indonesia an initiative intended to enhance climate resilience through community-driven innovation (Common Room Network Foundation 2021). It emphasizes the synergy between local knowledge and advanced technologies, including AI and IoT, creating sustainable, localized solutions for the challenges posed by climate change.

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 kicked-off by planted 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 adapting technology to fit 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.

In summary, AI-powered tools hold significant promise for enhancing community engagement in climate action. By focusing on participatory design, these tools can address specific regional concerns and empower local communities to drive meaningful change. The integration of AI in citizen science frameworks promotes collaboration and co-creation, ensuring that community voices are amplified and their needs are met. As we continue to face the dual challenges of climate change and rapid AI advancements, it is imperative to explore how these technologies can be harnessed to foster sustainability and social impact at the grassroots level. This approach underscores the importance of developing AI systems that are not only technologically advanced but also socially inclusive.

4.8.5. Incorporation of Indigenous Knowledge in Local Artificial Intelligence Models

Incorporating indigenous knowledge (IK) into local AI models can enrich climate action strategies with traditional ecological wisdom and practices. AI can help document and analyze IK, ensuring that it is preserved and integrated into broader climate solutions. For instance, AI can be used to map and monitor traditional land-use practices, identify patterns in ecological data, and predict the outcomes of applying indigenous techniques. Collaboration with indigenous communities is essential to ensure that their knowledge is respected and accurately represented. This approach can lead to more holistic and culturally sensitive climate action strategies, benefiting both local communities and the broader ecosystem.

From a general perspective, Williams and Shipley (2021) focused on how integrating indigenous wisdom into AI can enhance its utility and ethical grounding. They highlighted the potential of indigenous concepts that emphasize harmony, balance, and interconnectedness. By incorporating such values, AI systems can transcend their reductionist origins and reflect a more inclusive worldview. Doing so can profoundly shift AI applications towards more holistic and beneficial outcomes. Maitra (2020) emphasized the need for a relational shift in how we approach AI, advocating for the inclusion of indigenous epistemologies that value interconnectedness and non-human entities. This study proposed that integrating these perspectives into AI could foster a symbiotic relationship between technology and traditional knowledge systems.

In the specific context of climate change, Chakravarty (2023) 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 emphasize 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. They found that traditional methods, when combined with modern AI systems, offer dynamic and accurate weather predictions. This synergy highlights the practical benefits of incorporating IK into AI models, which can improve climate adaptation strategies for pastoral communities.

Molino (2023) examined interreligious perspectives on integrating AI and IK for environmental preservation. They reveal that different religious traditions, such as Christianity, Islam, and Buddhism, recognize the potential of AI to enhance environmental stewardship. This aligns with the concept of incorporating IK into AI models by emphasizing the ethical and cultural dimensions necessary for sustainable environmental practices. Integrating diverse worldviews enable AI models to become more inclusive and ethically sound.

Chakravarty (2023) also formulated a strategy for climate resilience that integrates climate communication channels, AI, and IK. This study emphasized the need for precise and timely climate information, which can be significantly enhanced by combining AI with indigenous knowledge. This approach improves climate modeling, risk assessment, and adaptive strategies, highlighting the benefits of integrating IK into AI models.

These studies collectively highlight the progressive potential of integrating IK with AI systems. Leveraging traditional wisdom in harmony with advanced technological solutions paves the way for developing more robust, culturally sensitive, and sustainable climate action strategies. This synergy enhances predictive capabilities, resource management, and resilience, fostering a balanced and inclusive approach to addressing climate change. Continued collaboration between indigenous communities and technological experts is essential to ensure the respectful and accurate representation of IK, ultimately benefiting both local communities and the global ecosystem.

All in all, AI-powered solutions offer tremendous potential to enhance education and community engagement in climate action. From raising awareness and providing interactive educational tools to promoting sustainable practices and engaging local communities, AI can drive meaningful change. By incorporating IK and leveraging AI's capabilities, we can develop more inclusive and effective strategies for combating climate change. As we advance these technologies, it is important to ensure that they are accessible, equitable, and aligned with the needs and values of all stakeholders.

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

The integration of AI technologies into climate action strategies holds significant potential for enhancing resilience and sustainability in developing countries, particularly in LDCs and SIDS. 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 essential 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.

Category	Sub-Category	Details
Climate Resilience and Adaptation	**Agricultural Resilience and Food Security**	- **AI-powered mobile apps for localized crop recommendations and weather forecasts to smallholder farmers** - **Drought-resistant crop variety development using ML** - Precision agriculture for small-scale farming - **Early warning systems for pests and diseases** - Smart irrigation systems for water optimization
	Water Resource Management	- **AI-enhanced flood prediction and early warning systems** - Automated water quality monitoring with AI analysis - **Groundwater mapping and sustainable extraction using ML** - Rainfall harvesting optimization - **AI-assisted transboundary water planning and conflict resolution**
	Public Health Systems	- **Vector-borne disease prediction and control using AI and local data** - AI-driven heat wave 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 - Migration early warning 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**
	Energy Efficiency	- Building energy management systems for tropical climates - Industrial process optimization for key industries

Category	Sub-Category	Details
		- Smart city energy solutions for urbanizing areas - AI-powered improved cookstove technologies - Energy-efficient transportation for urban centers
	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 modeling 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
	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 modeling 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

Category	Sub-Category	Details
		- 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 programs** - 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**

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

To offer a more comprehensive exploration of AI's potential in developing countries, particularly LDCs and SIDS, this report integrates additional examples and case studies of AI applications throughout its chapters. These case studies provide concrete illustrations of how AI is actively transforming key sectors. Highlighted in blue boxes, these AI applications draw attention to noteworthy initiatives and best practices, serving as both informative and practical resources. The diverse case studies showcase real-world applications of AI in climate action within SIDS and LDCs, demonstrating how AI-driven solutions are being implemented in various contexts. The practical insights drawn from these case studies underscore AI's critical role in addressing both climate change mitigation and adaptation challenges, thereby paving the way for more resilient communities globally.

The application of AI technologies across various domains presents a tremendous opportunity for developing countries, particularly LDCs and SIDS, to tackle climate change effectively. These countries can enhance their adaptive capacities, optimize resource management, and promote sustainable development by focusing on these key areas and leveraging AI's capabilities. The comprehensive table provided highlights specific AI applications that can drive significant improvements, ensuring that AI-driven climate solutions are inclusive, equitable, and tailored to the unique needs of the most vulnerable regions.

5. Artificial Intelligence for the Implementation of the Technology Mechanism Joint Work Program and Technology Needs Assessment Outcomes

AI emerges as a potent technological tool for advancing and scaling transformative climate solutions in developing countries, particularly in LDCs and SIDS. AI's potential to bolster climate action strategies outlined in the Technology Mechanism Joint Work Program (2023-2027) and TNAs outcomes for these regions is substantial, aiming to harness AI's capabilities to effectively address climate challenges.

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 TEC's rolling workplan (2023-2027) and the CTCN Program 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's 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 Agreemen

This section reviews the thematic areas covered by the aforementioned frameworks and identifies opportunities where AI-powered solutions can enhance their implementation. It draws on insights from Section 4, which explores AI applications across various domains of climate action.

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

The Technology Mechanism Joint Work Program outlines strategic priorities and key thematic areas where AI can play a transformative 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 can advance National Innovation Systems (NIS) by facilitating more efficient and effective research, development, and deployment of new technologies tailored to local climate challenges. NIS play a critical role in fostering technological advancements. AI can enhance data-driven decision-making processes, optimize resource allocation, and foster innovation ecosystems conducive to sustainable development. AI-powered data analytics and ML models can analyze large datasets to identify emerging trends, predict technological breakthroughs, and optimize research funding allocations. In addition, AI can support monitoring and evaluating the performance of innovation policies and programs, ensuring optimal resource use and positively impacting AI integration to drive environmentally sustainable development

From a different perspective, 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 Global North 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 developed in the Global North 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 address 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 centers play a role in this process, offering training and development programs to nurture local talent.

Developing homegrown 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 startups 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 nations. 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 play a vital role 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, and food systems by optimizing resource use and improving efficiency. In precision agriculture, AI analyzes data from IoT sensors to optimize irrigation, fertilization, and pest control, thus increasing crop yields and reducing water and energy consumption. In the energy sector, AI can predict demand and supply patterns, optimize grid operations, and integrate renewable energy sources more effectively. Additionally, AI supports water management by predicting usage patterns, detecting leaks, and optimizing water distribution networks. These integrated AI applications enhance the sustainability and resilience of water-energy-food systems by optimizing resource allocation, predicting supply-demand dynamics, and mitigating risks associated with climate variability.

The interconnected nature of water, energy, and 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 revolutionize energy systems by enhancing the efficiency and reliability of energy production, distribution, and consumption, while accelerating the deployment of renewable energy technologies. Efficient energy systems are important for sustainable development. AI enables predictive maintenance of infrastructure, optimization of energy distribution networks, and seamless integration of renewable energy sources.

AI algorithms significantly contribute to optimizing the operation of renewable energy sources such as wind, solar, and thermal energy. By predicting weather patterns, AI can adjust generation schedules accordingly, maximizing energy output and grid stability. Moreover, AI enhances the management of energy grids by detecting anomalies, preventing outages, and balancing supply and demand in real-time. Smart grids powered by AI facilitate the integration of distributed energy resources, supporting the transition to a more decentralized and resilient energy system.

AI-driven demand response programs empower consumers to reduce their energy usage during peak periods, thereby enhancing overall energy efficiency and grid reliability. Case studies underscore AI's practical implications for increasing energy efficiency and reducing GHG emission in developing countries.

5.1.4. Buildings and Resilient Infrastructure

AI plays a critical role in enhancing the resilience and sustainability of buildings and 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 optimizes various aspects of building management, including heating, ventilation, air conditioning (HVAC), lighting, and other operational systems. By analyzing real-time data, AI can adjust these systems to reduce energy consumption and enhance occupant comfort. For instance, AI 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 preemptive 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 supports the design and construction of resilient infrastructure by analyzing 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 can model different scenarios and their potential impacts, providing valuable insights that inform better disaster preparedness strategies and building practices.

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

Overall, AI-driven innovations in building management and resilient infrastructure are pivotal for climate adaptation. By enhancing energy efficiency, enabling predictive maintenance, and supporting resilient design and construction, AI contributes to the development of sustainable and resilient infrastructure essential for mitigating the impacts of climate change.

5.1.5. Business and Industry

AI innovations in the business and industry sectors promote sustainable practices and operational efficiencies. AI-powered analytics enable industries to minimize environmental footprints, optimize supply chains, adopt sustainable practices, and meet regulatory standards. These solutions drive substantial improvements by enhancing operational efficiency, lowering costs, and fostering innovation.

In business operations, AI automates routine tasks, analyzes vast datasets for actionable insights, and optimizes supply chain logistics. This improves efficiency and reduces errors and enhances decision-making processes.

By harnessing AI capabilities, businesses can better forecast demand, manage inventory, and streamline logistics operations, thus reducing waste and improving service delivery.

In the manufacturing sector, AI enhances production processes through several key applications. Predictive maintenance is one these applications, where AI algorithms analyze data from machinery to predict potential failures before they occur, thereby minimizing downtime and extending the lifespan of equipment. Quality control is another critical area, with AI systems capable of detecting defects in real-time, ensuring consistent product quality and reducing the costs associated with rework and scrap.

Additionally, AI supports process optimization by using data analytics and ML to refine production schedules, resource allocation, and workflow processes. This results in enhanced operational efficiency, reduced energy consumption, and minimized waste. Furthermore, AI can improve supply chain management by forecasting demand, optimizing inventory levels, and streamlining logistics, thereby reducing lead times and improving customer satisfaction.

AI also plays a significant role in driving sustainable practices within industries. It enables the monitoring and reduction of energy usage, the optimization of resource consumption, and the minimization of waste generation. Businesses can develop more sustainable production methods and contribute to environmental conservation by integrating AI technologies.

Overall, AI-driven innovations in the business and industry sectors not only enhance productivity and operational efficiency but also support sustainable development and environmental stewardship. These advancements highlight the significant potential of AI in driving both economic growth and sustainability in the industrial landscape.

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 plays a critical role in improving early warning systems by analyzing 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 optimizes site selection and monitors 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 contributes to building climate-resilient communities and enhancing overall societal resilience by fostering the adoption of resilient technologies.

Furthermore, AI empowers 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 supports evidence-based policymaking by analyzing 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 and transformational 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 Program across various thematic areas. From enhancing NSI and optimizing water-energy-food systems to revolutionizing energy systems, buildings, and infrastructure, AI can drive efficiency, sustainability, and resilience. AI can play a central role in achieving the objectives of the joint work program 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).

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 system 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.

Table 7. Examples of CTCN Technical Assistance Initiatives on Emerging Digital Technologies for Climate Action

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 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 programs aim to support the adoption of AI in climate technology by providing training and resources to local stakeholders. These programs 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 Program. 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 roadmap 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 report, which explores AI applications in climate action across diverse domains. Among the key opportunities identified where AI-powered solutions can support the implementation of TNA outcomes include:

***Energy sector**:* AI can optimize energy production, distribution, and consumption by predicting demand patterns, managing grid operations, and integrating renewable energy sources effectively. AI-driven analytics can enhance energy efficiency measures and support the deployment of smart grid technologies.

Agriculture and food security: AI-powered tools can optimize irrigation, fertilizer use, and pest management through data-driven insights from IoT sensors. This improves crop yields while conserving water and reducing environmental impact. AI can also support food security initiatives by predicting crop yields and optimizing food distribution networks.

Water management: AI facilitates real-time monitoring of water resources, predicts usage patterns, detects leaks, and optimizes water distribution networks. These capabilities contribute to sustainable water management practices and resilience against climate-induced water stresses.

***Infrastructure and resilient construction**:* AI-driven predictive maintenance enhances the lifespan of infrastructure by monitoring structural health, predicting maintenance needs, and scheduling repairs proactively. AI can simulate the impacts of climate hazards on infrastructure to inform resilient construction practices, ensuring infrastructure durability in the face of climate change impacts.

Industry and manufacturing**:** AI optimizes industrial processes through predictive maintenance, quality control, and supply chain management. This improves operational efficiency, reduces resource consumption, and supports the adoption of sustainable manufacturing practices. AI also assists in developing new technologies resilient to climate impacts, fostering innovation in industrial sectors.

Disaster risk reduction: AI enhances disaster preparedness and response by analyzing large datasets to predict and mitigate the risks associated with extreme weather events. AI-powered early warning systems for extreme weather events provide timely alerts to vulnerable communities, facilitating proactive disaster management strategies and reducing human and economic losses. By simulating different hazard scenarios, AI helps in planning and implementing effective response strategies. This includes designing evacuation routes, optimizing resource allocation during emergencies, and improving communication systems to ensure timely dissemination of information.

These opportunities leverage AI's capabilities to address specific challenges outlined in TNAs, contributing to more sustainable climate action strategies in developing countries.

In addition, the integration of AI into technology action plans derived from TNAs enhances their effectiveness by harnessing AI's capabilities in data analytics, predictive modeling, and decision support systems. These advancements can enable LDCs and SIDS to overcome existing challenges and accelerate progress towards climate resilience and sustainability. AI-driven insights also allow governments and stakeholders to prioritize technology investments, allocate resources efficiently, and monitor the progress of climate adaptation initiatives. Case studies from developing countries demonstrate AI's role in scaling up climate technologies and achieving SDGs.

In conclusion, AI presents significant opportunities to enhance the implementation of TNA outcomes across critical thematic areas for climate action in developing countries, thereby accelerating their transition towards sustainable and climate-resilient development pathways. The integration of AI into TNA outcomes stimulates technological innovation, bolsters adaptive capacity, and enhances resilience against climate change impacts. Policymakers and practitioners can optimize climate strategies, mitigate risks, and promote inclusive and sustainable development pathways by unlocking AI's potential across key sectors.

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 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.

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 freshwater	• 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.
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.

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

By aligning AI-powered solutions with these specific SDG goals and targets, developing countries can effectively implement TNA outcomes, enhancing their climate resilience and contributing to sustainable development.

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

As developing countries embrace AI technologies for climate action, they encounter unique risks and challenges that can impede the effectiveness and equity of these technologies, unlike those faced by developed nations. These challenges stem from a variety of factors and understanding these challenges is essential for developing strategies that maximize the benefits of AI while minimizing its adverse impacts or harmful practices, ensuring that the use of AI technologies is responsible, ethical, and equitable for all.

6.1. Energy and Water Consumption

The lifecycle of AI technologies—including their development, deployment, maintenance, and disposal—systematically stresses energy supplies and significantly contributes to GHG emissions. These impacts are categorized as *direct*, *indirect*, and *systemic* effects on the environment (Bibri et al., 2023). *Direct* effects refer to the energy-intensive processes involved in training and running AI models, which directly increase GHG emissions, especially when data centers rely on non-renewable energy sources. For example, the electricity demand for training large language models like GPT-4 and operating AI systems can lead to substantial carbon emissions, depending on the energy mix of the data centers involved.

Indirect effects involve the secondary consequences 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.

The *systemic* effects go beyond these direct and indirect 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 behaviors, 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. By recognizing these challenges and proactively addressing them, society can leverage AI to pave the way for a sustainable future. In this context, proactive measures include accelerating the decarbonization of electric grids, fostering markets for low-carbon materials such as green cement and steel, and promoting the development of energy-efficient hardware. Optimizing AI algorithms and encouraging sustainable practices in AI development are also critical steps toward reducing the environmental footprint of AI.

The International Telecommunication Union (ITU 2024b, c) underscores the impact of the ICT sector on environmental sustainability, with a special emphasis on the role of AI, as part of its **Green Digital Action Initiative**. 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. However, 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. AI technologies, notably ML/DL and GenAI, are becoming increasingly sophisticated, leading to greater computational demands. This escalation significantly contributes to the ICT sector's energy usage and environmental footprint. As AI systems increasingly rely on energy-intensive data centers and communication network infrastructures, their environmental impact grows. The construction and operation of these data centers often require significant energy, typically derived from non-renewable sources, which substantially contribute to GHG emissions. Furthermore, the cooling systems in these data centers consume vast amounts of water, exacerbating environmental concerns.

Currently, the deployment of AI technologies in developing countries for climate action presents significant challenges, particularly related to water and energy consumption. The extensive water use required for cooling data centers and producing AI hardware can exacerbate water scarcity issues in these countries, including LDCs and SIDS, while intensive energy consumption for AI operations can strain already limited energy resources. The use of water for cooling data centers can strain local water resources, creating competition with essential needs such as agriculture and human consumption. In regions already facing water scarcity, this additional demand can exacerbate existing challenges, leading to potential conflicts over water use. For instance, in agricultural communities where water is essential for crop irrigation, diverting significant amounts of water to cool data centers can negatively impact food production and livelihoods. Furthermore, the production of AI technologies, similar to other advanced ICT, involves significant water consumption as one of its direct effects on the environment. Manufacturing hardware for AI, such as semiconductors and other electronic components, requires large amounts of water. This water usage adds to the environmental footprint of AI and related machines, technologies, and infrastructures, encompassing both their production and operational phases. Thus, water consumption in the creation and maintenance of AI systems is a direct environmental impact.

As regards increased energy consumption, it can exacerbate GHG emissions, undermining the very SDG 13 AI technologies aim to achieve, specifically targets such as 13.1 (Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters) and 13.2 (Integrate climate change measures into national policies, strategies, and planning). For example, the carbon footprint of data centers can offset the benefits gained from AI applications in climate modeling and renewable energy management, thereby negating their positive impact. The computing power needed to train state-of-the-art AI models, such as those in DL, largely depends on energy-intensive data centers and extensive communication networks.

AI, particularly DL methods, necessitates large quantities of data, which must be acquired, transferred, stored, and processed, all of which require significant equipment and energy, thereby having environmental impacts (Ligozat et al. 2021). AI depends on data centers that require significant energy to compute, analyze, and categorize data (Brevini et al 2021). Training DL models requires substantial computation time and resources, as the model learns a comprehensive representation for better data analysis, with costs increasing further if the model engages 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 programs and found that a typical AI training model in NLP can emit over 284 tonnes of CO_2 equivalent (Strubell et al., 2019). The study highlighted the energy consumption and carbon footprint impacts of training NLP models. Henderson et al. (2020) stress the importance of accurately reporting energy and carbon usage to understand the climate impacts of ML/DL research.

With the growing adoption of AI, the energy consumption of data centers 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 centers, 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 2024b), electricity consumption from data centers and AI systems is projected to double by 2026. Data centers are key drivers of increased electricity demand across various regions. In 2022, these centers consumed an estimated 460 terawatt-hours (TWh) of electricity worldwide. By 2026, their total electricity consumption could surpass 1,000 TWh, which is approximately equivalent to Japan’s entire electricity usage. To mitigate this substantial rise in energy consumption, updated regulations and technological advancements, especially focused on efficiency improvements, will be essential. To accurately track historical developments and better predict future trends, enhanced monitoring and detailed electricity usage data for the data center industry will be critical (EAI 2024a).

Recent GenAI models (e.g., pre-trained foundation models) could exacerbate local resource challenges due to their substantial computational resource requirements for training large models (Jakubik et al. 2023; Janowicz 2023; Bommasani et al. 2022), resulting in higher energy consumption and hence increased carbon emissions. Additionally, as these applications proliferate and become more advanced (Huang, Bibri and Keel 2024; Castelli and Manzoni 2022), the ongoing demand for data and model refinement could create a cycle of energy-intensive usage, potentially negating the progress made by sustainable AI initiatives.

Numerous studies have assessed the substantial energy consumption required for producing and training generative AI models. For instance, researchers estimated that the development of GPT-3 consumed approximately 1,287 megawatt hours of electricity and generated 552 tons of CO_2 equivalent—comparable to the emissions produced by 123 gasoline-powered passenger vehicles driven for one year (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 centers (Luccioni 2023). Data centers, 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 liters of water (Dolby 2023). Moreover, there are location-specific variables that influence the energy and water usage of large language models (LLMs). For example, Microsoft reported that its data centers 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 AI models, extending beyond energy consumption to include broader resource use and location-dependent inefficiencies.

Furthermore, researchers estimate that training a model like GPT-4 generates approximately 300 tonnes of carbon, which is equivalent to the emissions produced by 125 round-trip flights between New York and Beijing (Kumar and Davenport 2023; Deeb and Garel-Frantzen 2023). As AI technology advances, this carbon footprint is expected to grow, as 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 generative AI 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 generative AI (Kumar and Davenport 2023). In addition to energy demands, generative AI 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-milliliter bottle of water, depending on where the electricity powering the interaction is generated (Dolby 2023).

While other studies emphasize AI’s growing resource demands, globally, AI currently contributes a small fraction of global GHG emissions—around 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 (Luers et al., 2024). 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; Chen et al. 2024). 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). Like any technology, AI relies on water, energy, and other resources, which need to be minimized and sourced sustainably. In response, data centers should be constructed using low-carbon materials and powered by zero-carbon energy sources to mitigate these impacts and align with sustainability goals.

Nonetheless, research in green AI, or generally green computing, 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. 2020; 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 center operations. Especially, 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 (e.g., Schwartz et al. 2020; Raman et al. 2024), ensuring that advancements in AI do not come at the expense of ecological health.

In addition to the above, ITU (2024b, c) emphasizes the need to address the environmental implications of AI to ensure sustainable AI development. This includes enhancing the energy efficiency of AI systems and promoting the use of renewable energy sources for powering data centers. In fact, many data centers use solar/wind power in conjunction with other renewable resources to ensure consistent power availability.

Geothermal energy is being used as a renewable energy source to power data centers (Cooding 2024; The Verge 2023). Although solar and wind energy are among the most prominent renewable energy sources available to power data centers, both have distinct challenges that affect their viability as primary energy sources, including:

- Intermittency issues: Solar energy is only generated during daylight hours and is affected by weather conditions. This intermittency means that solar alone may not provide a reliable power source without supplementary systems like battery storage or backup generators. Like solar, wind is also intermittent; it relies on weather patterns and may not always align with peak demand periods for data centers. Therefore, integrating wind power often requires additional infrastructure for energy storage or hybrid systems that combine multiple energy sources.
- Location dependency: Wind farms typically need to be located in areas with strong and consistent winds, which often means they are situated far from urban centers where many data centers are located. This can lead to increased transmission costs.
- Efficiency and Cost: Solar panels have become increasingly efficient and cost-effective over the years, with installation costs dropping significantly. However, they still require substantial space; a large number of panels may be needed to meet the energy demands of a sizable data center.

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. This makes them particularly advantageous for use in resource-constrained environments, such as in LDCs and SIDs, and for specific climate-related applications where efficiency is crucial.

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. SLMs offer significant advantages for LDCs and SIDs with limited energy or server/GPU resources, as well as for climate-related use cases with carefully defined parameters. For example, GPT-4 contains 1.76 trillion parameters, while open-source SLMs like Llama2 7B contain only 7 billion parameters, indicating that SLMs generally require significantly less computation and energy. These open-source SLMs are already being adopted by leading firms and made available to the public.

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 once thought impossible, enables dynamic scaling of memory resources in a virtual (cloud-based) AI infrastructure architecture. For example, memory can be expanded beyond a single physical server, allowing resources to be linked across an entire data center in a unified image for AI training purposes. 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 center power consumption in AI applications and offers similar benefits for Edge AI use cases.

SLMs represent a promising shift toward more sustainable AI practices, offering significant energy and computational savings, especially during the intensive pre-training phase. By reducing resource consumption and potentially minimizing bias through the use of smaller, more focused datasets, SLMs stand to play a crucial role in democratizing AI access and supporting climate-friendly initiatives. The integration of technologies like software-defined storage further enhances the efficiency of AI infrastructure, offering scalable and adaptable solutions that can dramatically cut power usage, making SLMs and related innovations essential tools in the future of AI development.

Promoting responsible and sustainable AI design standards is important, considering end-of-life impacts and avoiding unnecessary data collection. To ensure the responsible development and use of AI technologies, governments and regulatory agencies should establish clear standards and regulations. Collaboration between businesses, academia, and policymakers is also essential for fostering sustainable AI practices.

The competing development priorities necessitate careful planning and sustainable practices to ensure that AI implementation does not detract from other critical developmental goals. Integrating renewable energy sources for powering data centers can mitigate some of the negative impacts on GHG emissions. For instance, solar or wind energy can be used to power data centers, reducing their reliance on fossil fuels. Additionally, employing advanced cooling technologies that require less water, such as liquid cooling or free-air cooling, can help alleviate the pressure on local water resources.

Policymakers and developers must work together to create frameworks that balance the benefits of AI with the need to protect and sustain local resources. This includes implementing stringent regulations on energy efficiency and water usage for data centers, as well as incentivizing the adoption of green technologies. Capacity-building initiatives that educate stakeholders about the sustainable deployment of AI technologies can also play an important role in achieving these objectives.

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 centers remains limited, often due to infrastructure constraints and high operational costs. Consequently, a significant portion of AI-related data processing is outsourced to data centers in more developed regions, where electricity consumption and water usage are substantial concerns. However, with global efforts to expand digital infrastructure, there is increasing interest in establishing local data centers, which could further strain energy and water resources in these regions.**

The scale of AI-related electricity and water demand in these developing countries is increasingly relevant, given their vulnerability to climate change and resource scarcity. **In LDCs and SIDS, where energy access is already limited, the introduction of large-scale data centers could potentially divert resources from critical sectors, thereby compromising developmental goals. Moreover, inadequate regulatory frameworks and the lack of sustainable energy solutions exacerbate the risks of increased greenhouse gas emissions and water stress.**

Through sustainable practices, collaborative planning, and proactive regulation, it is possible to harness the power of AI for climate action without compromising essential developmental goals. **The need for efficient, localized data centers powered by renewable energy sources is becoming more urgent to ensure that the deployment of AI aligns with both national and global climate objectives.** By addressing these challenges responsibly, AI can be integrated into climate strategies without exacerbating resource-related issues, paving the way for a sustainable future.

6.2. Data Security

Data security is a paramount concern when using AI for climate action in both developing and developed countries. The collection and analysis of large datasets can pose significant privacy risks, especially if sensitive information is not adequately protected. Personal data could be exposed to unauthorized access, leading to potential misuse or exploitation. For instance, information about land use and agricultural practices collected for climate modeling could be misappropriated by third parties for commercial gain, or sensitive community data could be exposed to cyber threats.

AI systems are vulnerable to attacks by hackers, leading to significant cybersecurity risks. For instance, AI systems often ingest large amounts of data from various sources, making them susceptible to data poisoning attacks where malicious data can alter the AI system’s behavior in unpredictable ways. Additionally, the storage and processing of data by AI systems can expose sensitive information to unauthorized parties, both within and outside of organizations and institutions. The outputs generated by AI systems, which are also data, are equally subject to these cybersecurity risks. This broad exposure underscores the need for robust security measures to protect AI systems and the data they handle from potential cyber threats.

The lack of robust data protection frameworks in many developing countries exacerbates these risks, potentially leading to misuse of data and erosion of public trust. In countries where legal and regulatory structures for data protection are weak or non-existent, there is a heightened risk of data breaches and unauthorized data sharing. This can deter communities from participating in data collection initiatives, reducing the quality and comprehensiveness of data available for AI-driven climate action.

In terms of ML models, the studies by Paracha et al. (2024), Rosenberg et al. (2021), and Goldblum et al. (2022) collectively address the security and privacy challenges in ML, emphasizing various threats and corresponding defense mechanisms. Paracha et al. (2024) focused on threats and countermeasures specific to ML security and privacy. They highlight the diverse attack vectors and the necessity for robust defenses to protect ML models and data. Rosenberg et al. (2021) focused on adversarial ML attacks within the cybersecurity domain. They categorize different types of attacks and explore various defense strategies to mitigate these threats, stressing the evolving nature of adversarial tactics. Goldblum et al. (2022) examine dataset security, particularly concerning data poisoning and backdoor attacks. They discuss the implications of compromised datasets on ML model integrity and propose strategies to detect and defend against such malicious activities. Together, these studies highlight the critical need for comprehensive security measures in ML, addressing both model and data vulnerabilities to enhance overall system resilience. Although quantum computing promises to enhance ML models and increase processing speed, it will also escalate the speed of hacking attempts (Denning 2019).

Addressing security challenges requires the development of comprehensive data security policies and practices that safeguard privacy. 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. Indeed, AI applications for environmental sustainability have not adequately addressed these challenges, which typically fall under broader data governance concerns.

With the growing integration of AI technology across various fields, including environmental sustainability and climate change, it becomes critically important to safeguard the security of AI systems and the sensitive information they handle. AI applications aimed at addressing environmental sustainability face the challenge of heightened cybersecurity risks, particularly as they are applied to critical areas like climate change mitigation and adaption. Employing AI techniques for environmental sustainability necessitates the integration of diverse datasets from various owners, sources, formats, structures, and platforms. This process brings heightened cybersecurity and data management risks, necessitating the ability to navigate data standards and integration protocols effectively.

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 2020), and security awareness and training (Solomon, 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 programs are vital 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 vital concern in the development and deployment of AI technologies.

AI and ML are transforming the security risk landscape for individuals, organizations, and institutions. 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 greatly 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 with minimal human intervention. Ansari (2022) demonstrated that ML algorithms outperform humans in delivering security. Jada and Mayayise (2024) found that while AI can influence cybersecurity across its entire lifecycle, 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. Further, AI security applications employ advanced ML techniques and methodologies to quickly detect and mitigate vulnerabilities, unauthorized access, and malicious activities. These systems can monitor network patterns, evaluate user behavior, and identify anomalies that may indicate security breaches (Habbal et al. 2024; Gopalan et al. 2020). All these findings confirm AI's positive impact on cybersecurity landscape, improving efficiency, effectiveness, and resilience.

However, the utilization of AI technology requires massive amounts of data, making data protection a paramount concern of protection. The sheer volume of data processed by AI systems increases the attack surface, making them attractive targets for cybercriminals. 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 promising solution for ensuring the reliability and trustworthiness of AI systems and has proven effective in fostering innovation, building trust, and creating value across different AI applications (Habbal et al. 2024). Various methods have been proposed to prevent or mitigate the damage from cyber-attacks, with some being operational and others in research phases. Li and Liu (2021) comprehensively explored standard advances in cyber security, detailing the types of cyber-attacks, security frameworks, and the evolution of cyber security methods, as well as emerging trends and recent developments in the field. In particular, advanced AI security applications allow organizations to leverage the TRiSM framework to set up security protocols and measures that prevent unauthorized access. Ensuring the robustness and resilience of ML models against adversarial attacks is essential to maintain the integrity and reliability of AI systems.

The rapid progress of AI technology often outpaces existing regulatory frameworks, highlighting the need for flexible and adaptable policies to ensure AI systems comply with ethical and legal standards and guidelines (Di Vaio 2020). Implementing robust data governance practices ensures that data security and hence data privacy are maintained and that AI systems are used responsibly. Also, promoting security awareness among administrators, developers, and users of AI systems through training programs and educational initiatives is equally important. This helps cultivate a security-conscious culture and minimize potential risks. Regular training and updates on the latest security practices are vital to keep all stakeholders informed and prepared for potential threats.

In conclusion, while AI and ML significantly enhance cybersecurity capabilities, they also introduce new challenges. Addressing these challenges requires a comprehensive approach that includes robust data protection, adaptive regulatory frameworks, and continuous education and training to foster a security-conscious culture. Collaboration between policymakers, industry leaders, and researchers is key to developing and implementing effective strategies that address the evolving landscape of AI security risks.

The findings and insights from recent research can significantly contribute to AI security in climate action. The comprehensive understanding of cyber-attacks and security methods can be leveraged to protect the vast amounts of data and AI systems involved in climate action initiatives. AI technologies can be securely deployed to monitor environmental changes, predict climate patterns, and develop sustainable solutions—by addressing the cybersecurity challenges and implementing robust security frameworks. Future research endeavors could focus on developing specialized AI security protocols tailored to the unique needs of climate action, ensuring that AI technologies contribute effectively and securely to global environmental sustainability efforts.

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

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. It has been extensively studied and addressed in various policy frameworks, yet it continues to pose challenges, especially as we transition into the era of AI. 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 centers, 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. Essentially, it involves all the necessary components to facilitate AI development and deployment, ensuring that these systems can operate efficiently and effectively.

The prevailing economic landscape of ML as a technological domain suggests a trend toward 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, ML exhibits 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 programs for AI and climate change, governments should prioritize addressing the global digital divide, which currently leaves billions worldwide without internet access (Sandaw 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).

The digital divide poses significant challenges to the equitable access of AI technologies for climate action. Developing countries, especially LDCs, which are already disproportionately affected by climate change, often lack the necessary infrastructure, resources, and expertise to fully leverage AI-driven solutions or develop their solutions for local contexts. This exacerbates existing inequalities and hampers global efforts to combat climate change in these countries. The implementation of AI for climate action requires access to large datasets and pretrained models, substantial computational power, cloud infrastructure, and the expertise to develop and maintain sophisticated models. Without addressing these disparities, the benefits of AI-driven climate solutions will remain out of reach for many vulnerable populations, further entrenching the digital divide and limiting the effectiveness of global climate initiatives. Enhancing equitable access to AI technologies and resources, such as open AI training and testing data and open-source models, is crucial for fostering sustainable and inclusive outcomes in environmental actions. This approach ensures that AI-driven solutions for climate action are widely accessible, supporting diverse global efforts towards sustainable development.

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 unique challenges that exacerbate the digital divide, affecting their ability to implement advanced AI solutions for climate action. Data scarcity in climate action reflects a broader issue of unequal access to AI resources, an aspect that remains inadequately explored in current literature (Walsh et al. 2020). This disparity deepens the digital divide in SIDS and LDCs where the infrastructure for data collection and the availability of high-quality data are frequently insufficient or sparse. For instance, crucial digital data that could enhance agricultural practices in developing countries, such as local climate forecasts and weather predictions, is often scant (Balogun et al. 2020). These conditions hinder the development of AI solutions tailored for local climate challenges. Addressing this gap involves improving data collection infrastructures and advocating for open data initiatives, as well as fostering international collaborations to ensure equitable access to AI technologies and climate data. This approach is essential for developing effective AI solutions that enhance climate resilience in vulnerable regions.

SIDS and LDCs frequently lack the robust infrastructure necessary for large-scale data collection. 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. The data available in SIDS and LDCs are often of lower quality or resolution, which can hinder the performance of AI systems that rely on high-quality inputs for accurate predictions and analyses. Additionally, there might be restricted access to global data sets due to high costs or licensing restrictions, further limiting local researchers' and policymakers' ability to leverage AI effectively. AI models developed in data-rich environments may not perform well when applied to settings where data are scarce or not representative of local conditions. This can lead to AI solutions that are ineffective or inappropriate for local climate challenges, intensifying existing vulnerabilities to climate impacts.

Overcoming data scarcity requires strategic approaches to build robust and inclusive AI systems for climate action, particularly in SIDS and LDCs. Initiatives, such as building local data collection capacities through investments in infrastructure like weather stations and IoT sensors, are crucial. These efforts are complemented by training programs for local personnel 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 pivotal 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.

The initiative "Closing the Climate Data Divide in the Global South" (Microsoft 2022) plays an important role in democratizing access to essential climate data. Led by Microsoft's AI for Good Lab and supported by collaborations with organizations like Planet Labs PBC and various African institutions, this project is designed to equip decision-makers in the Global South with essential tools and information. In doing so, it seeks to enhance climate resilience and foster sustainable development across some of the world's most vulnerable regions.

Closing the Climate Data Divide in the Global South

Country:
LDC or SIDS

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

Brief Description

In order to avoid the worst effects of climate change, governments and decision-makers in the Global South equally need access to reliable climate data. This push to democratize access to data aligns with Microsoft's broader effort to accelerate and support progress toward the 17 SDGs, adopted by UN member states in 2015 as part of the 2030 Agenda for Sustainable Development. Data have the power to unlock adaptation and resilience projects so that the resources available are directed to places that can make the greatest impact both before and immediately following climate-related disasters. We recognize that not only is there insufficient reliable climate data in the Global South, but also a significant lack of data scientists to work with the data available. Our research shows that there are approximately five data scientists in the Global North for every one data scientist in the Global South – meaning there is a significant gap in the Global South's ability to turn climate data into insights for decision-making and action. In Africa, the gap is wider still – one data scientist for 14 in the Global North. In short, we face a climate data divide – and at Microsoft we want to do our part to help close that divide.

Microsoft is working to help close that climate data divide through the AI for Good Lab and new partnerships underway across the Global South to accelerate action. The AI for Good Lab applies AI, ML, and statistical modeling 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 works to improve climate resilience across Africa.

Climate change Mitigation and/or Adaption Impacts and Results

It is a challenging time for our planet 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 amongst the world's countries, with a greater burden falling on the Global South. The Global South has contributed far less than the Global North 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 Global South that were under high climate risk.

In September of 2022, we announced a collaboration with Planet Labs PBC and The Nature Conservancy to build the Global Renewables Watch – a first-of-its-kind living atlas 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

We know that addressing and mitigating the effects of climate change requires a collective effort across industry, government, academia and civil society. In early conversations about this expansion with Kenyan stakeholders, we made it clear that our ideal outcome was to have African researchers working on projects that benefit Africa in Africa. To support this principle and to help inform our work, we have collaborated with leading African organizations, such as the African Development Bank, African Risk Capacity and African Climate Foundation to identify opportunities to improve climate resilience with data and AI, and facilitate ways to generate additional climate data and drive continued research. In addition to these organizations, we are pleased to be working in collaboration with the Kenya Red Cross Society, PATH, Institute for Health Metrics and Evaluation (IHME), and Integrated Food Security Phase Classification (IPC) to turn data into climate action.

While the digital divide remains a significant challenge, it is essential to acknowledge that AI-enabled data can still provide substantial benefits to people in developing countries, even when the technology and data are developed primarily by large multinational tech firms headquartered in developed countries. The divide is not absolute. Multinational tech companies often make valuable AI tools and datasets freely available or partner with local governments and businesses to drive development in underserved regions. For example, initiatives like Google's Project Loon, which provides internet access in remote areas using high-altitude balloons, demonstrate how tech giants are extending access to underserved populations. Additionally, partnerships and subsidies can help lower the cost of AI technologies, making these tools more accessible to low-income communities. Specific programs like Microsoft's AI for Humanitarian Action and IBM's Africa Skills Initiative highlight how tech companies collaborate with local stakeholders to apply AI for social good, further narrowing the gap between developed and developing nations. By recognizing both the barriers and the ways in which these divides are being addressed through global partnerships and accessible AI solutions, this section can better highlight the complex interplay between technology, inequality, and opportunity.

From a different perspective, the EMPIRIC_AI project showcases the role of AI in enhancing cyclone resilience for health infrastructures in Pacific Island Countries (PICs) (Climate Change AI 2023). This innovative initiative utilizes ensemble projections of synthetic cyclone tracks to anticipate and mitigate the impacts of climate-induced disasters on vital healthcare facilities. The project addresses the critical challenge of data scarcity in the region, enabling more effective planning and response strategies by generating and analyzing thousands of synthetic data points. This approach bolsters the resilience of health infrastructure and exemplifies the potential of AI to bridge data gaps and enhance climate adaptation efforts in vulnerable areas.

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. Michelle McCrystall, Dr. Chris Horvat, Dr Liz McLeod, Dr Berlin Kafoa, Dr Craig McClain, 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 but yet lack robust climate-specific data. The region comprises 10,000 islands and atolls but yet 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 health care facilities in PICs. The project EMPIRIC_AI (EMulation of Pacific Island Risk to Infrastructure from Climate) addresses these issues using new statistical modeling and AI techniques. We generate thousands of observationally-constrained synthetic tropical cyclones tracks using a statistical model, and we emulate the pan-Pacific impacts of these storms using a modified U-net. 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. With these data, health governing bodies can then make informed decisions about future planning for health infrastructure.

Climate Change Mitigation and Adaptation Impacts

The primary aim of this project is to give site-specific impacts of climate change to different health facilities across the Pacific Island Countries. This level of information will detail which hospitals sites are likely most at 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

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.

Addressing data scarcity through these strategies can help bridge the digital divide, enabling SIDS and LDCs to leverage AI more effectively for climate change mitigation and adaptation. This approach enhances local capacities and ensures that the benefits of AI for climate action are more equitably distributed.

Furthermore, 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 advices due to lack of internet access, limiting their ability to benefit from advanced farming techniques. In developing countries, satellite internet emerges as a promising solution to bridging the digital divide, nevertheless, especially in rural and remote areas where traditional broadband infrastructure is either lacking or entirely non-existent. By leveraging satellites orbiting the Earth, this technology provides a reliable wireless connection that does not rely on physical cables, making it accessible even in the most isolated locations. Satellite internet's ability to reach areas untouched by conventional fiber-optic networks positions it as a key enabler of digital inclusion. This connectivity can substantially enhance access to educational resources and economic opportunities. Furthermore, by improving internet accessibility, satellite internet can facilitate the deployment of AI technologies in developing countries, allowing these regions to harness the power of AI for local development and innovation. As more satellites are launched, and the technology continues to advance, the potential for satellite internet to foster global connectivity and economic growth becomes increasingly attainable.

Moreover, limited access to advanced ICT can result in a digital divide, affecting individuals' ability to engage with AI-based technologies like social robots and virtual digital assistants (Lutz 2019; van der Zeeuw et al. 2019). This gap restricts opportunities to utilize and understand AI benefits. Additionally, the digital divide encompasses disparities in skills and expertise required to use AI technologies (van Dijk 2020). Therefore, the digital divide can be a significant factor influencing AI literacy among people. Also, geographical disparities highlight the unequal distribution of technological resources, with many rural and underdeveloped areas lacking the infrastructure needed to support AI technologies. Algorithmic literacy and digital skills are essential to enable individuals and communities to effectively use AI tools and understand their implications. 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. It suggests a stronger integration of digital inequalities research with critical algorithm studies and contemporary discussions on datafication, digital footprints, and information privacy.

The digital divide issue emphasizes the need for global majority countries to develop their own AI ecosystems as a means to enhance digital sovereignty and reduce dependencies on external technologies. This approach is notably significant given the global power imbalances and economic inequalities that can exacerbate exploitation in less developed regions. Indeed, Birhane (2020) and Muldoon et al. (2023) critically reflect on the dominance of Western technology companies in providing digital infrastructure and AI applications to the African continent, noting that they exploit historically marginalized, equity-seeking communities through neo-colonialist data extraction practices which exacerbate existing disparities.

By fostering local AI development, majority countries aim to tailor solutions that are more attuned to their specific socio-economic contexts and challenges, rather than relying on one-size-fits-all solutions from more developed nations. The focus on building indigenous AI capabilities 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. 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.

To bridge the AI divide and ensure that development capacities for climate-relevant AI solutions are accessible to everyone, supporting digital public goods and socio-technical approaches are crucial. These approaches must address various factors such as access to essential development resources, geographical disparities, algorithmic literacy, and digital skills. Celik (2023) developed a model incorporating factors such as the digital divide, cognitive absorption, and computational thinking. The findings revealed that computational thinking significantly influences AI literacy, enhancing the ability to use, recognize, and evaluate AI technologies. Moreover, they indicated that individuals with better access to ICT are more likely to engage with AI. The study also highlighted that motivation and skills in using ICTs enable individuals to critically evaluate AI outcomes. Convenient ICT access fosters deeper involvement with AI, and higher motivation and skills lead to more enjoyable experiences with AI technologies. However, 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).

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 crucial 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. This fragmentation underscores the need for greater coordination and standardization within the open-source AI community.

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.

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 pivotal role in democratizing access to AI tools and enabling innovation, particularly in resource-constrained environments

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 neighborhoods and overlook critical hotspots, while a higher resolution can reveal these peaks but potentially introduce noise (McGovern et al. 2022).

McGovern et al. (2022) 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 properly designed and managed, leading to unfair outcomes that disproportionately affect marginalized groups, including racial bias. 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 digital and algorithmic literacy is essential to empower users to engage with AI critically and effectively. Unbiased AI outcomes are necessary to ensure fairness and equity in AI applications, which requires rigorous testing and validation processes to detect and mitigate biases. Moreover, AI system providers must ensure that development is carried out with a human-rights-based approach, emphasizing the protection of human rights.** Effective regulation is needed to establish standards and guidelines that promote equitable access and use of AI technologies and address market concentration. **There are significant initiatives by the UN and the EU that aim to regulate the development and use of AI with a human rights approach, ensuring that AI technologies are used responsibly and ethically.** Addressing these factors allow for working towards a more equitable AI landscape where the transformative power of AI benefits all sectors, including climate action, and contributes to sustainable and inclusive development.

In addition, data gaps and biases in data collection and analysis 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 underrepresented populations. For example, if data collection efforts primarily focus on urban areas, rural communities may be underrepresented in climate action plans, leading to ineffective or even detrimental outcomes for those regions. 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. Moreover, transparency in data collection processes and the involvement of local communities in these processes and equitable data sharing practices such as commons-based data governance schemes can help build trust and ensure that the data collected are representative and useful for climate action and available to benefit local communities

Moreover, the affordability of AI technologies and the capacity to develop and maintain AI solutions are critical challenges. High costs associated with AI hardware, software, access to relevant high-quality data, and skilled personnel can make these technologies inaccessible to many communities. Small-scale farmers, for instance, may find it prohibitively expensive to adopt AI tools for crop management, while local governments may lack the financial resources to invest in AI-driven disaster risk reduction systems.

Without addressing these disparities, there is a risk that AI-driven climate action will benefit only a select few, exacerbating existing inequalities. Those with access to AI technologies and the resources to use them effectively will gain more from climate action initiatives, while marginalized communities may be left behind. This can widen the gap between different socioeconomic groups and regions, undermining the overall goal of equitable climate resilience.

To effectively address the digital divide, it is crucial to focus on more than just building infrastructure. Development resources should be made openly available as digital public goods to foster local innovation. This includes providing open access to data and open-source AI models, making high-quality technological solutions affordable or free, thus supporting AI research that benefits a broader global audience. Enhancing digital skills and ensuring that individuals have opportunities to use technology effectively are essential steps.

Capacity-building programs are key to ensuring that local populations have the knowledge to develop and maintain AI solutions. Training programs for local engineers, data scientists, and policymakers can help build a sustainable ecosystem for AI development in developing countries. Addressing the digital divide can ensure that AI-driven climate action is inclusive and benefits all segments of society, promoting greater resilience and adaptation to climate change.

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. In addition to physical infrastructure like electricity and internet access, governments and international organizations should focus on building data centers and other essential AI infrastructure in underserved areas. These efforts ensure that the foundational elements necessary for AI development and deployment are robust.

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 financial mechanisms can reduce the cost of AI technologies, making them more accessible and promoting equitable technological advancements. These multifaceted approaches are vital for closing the digital divide and enhancing the capacity of communities worldwide to leverage AI for sustainable development.

6.4. Gender Bias

Gender bias in AI poses a significant challenge to its effective use for climate action in both developed and developing countries. AI systems can perpetuate and even exacerbate existing gender inequalities if not carefully designed and implemented. This bias can manifest in various ways, such as underrepresentation 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 to include diverse 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.

6.4.1. Gender Bias in Artificial Intelligence

Gender bias in AI can affect the effectiveness and equity of climate action initiatives, particularly in developing countries. The inclusion of gendered aspects in AI-driven climate change initiatives can significantly benefit LDCs and SIDS. Currently, the Caribbean has one of the highest female participation rates in employment and firm ownership worldwide (Mohan et al. 2023). For instance, in St. Vincent and the Grenadines, 76% of firms have female ownership, which is the third highest rate in the world (Mohan et al. 2023). The Paris Agreement and UNFCCC mandate the participation of women in shaping climate policies and actions, emphasizing the integration of a gender perspective. Indeed, 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. The Global Environment Facility (GEF) has been assisting LDCs and SIDS in developing TNAs to better utilize international climate finance and promote gender equality. Addressing gender bias in AI can thus enhance relevant efforts, ensuring that AI technologies for climate action are more inclusive by leveraging the valuable insights and contributions of women.

The UNFCCC report titled "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.

Of particular relevance, the UNFCCC report (2023) includes various case studies that showcase how LDCs and SIDS are incorporating gender considerations into their climate adaptation strategies. These case studies demonstrate the significance of recognizing the unique vulnerabilities and contributions of women in climate action and detail the measures taken to ensure gender-responsive adaptation efforts. Table 9 summarizes the approaches and outcomes of gender-responsive climate adaptation strategies from several LDCs and SIDS from the UNFCCC report.

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.

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

These case studies illustrate the diverse ways in which LDCs and SIDS are addressing gender-specific impacts of climate change, aiming to advance gender equality and women's empowerment through tailored adaptation actions. The report emphasize the need for ongoing support to ensure that gender-responsive measures are fully integrated into national adaptation strategies.

AI can specifically address the gender biases and enhance the benefits of the climate adaptation initiatives highlighted in the case studies provided. The LDCs and SIDS can benefit in several ways by utilizing AI technologies. AI can improve data integration and analysis by incorporating diverse datasets from various regions and sources, thereby enhancing the accuracy and comprehensiveness of climate models. This integration allows for more precise predictions and tailored adaptation strategies. Additionally, AI-driven tools can provide real-time monitoring and evaluation of gender-responsive adaptation projects, helping to optimize resource allocation and project implementation for timely and effective interventions. By analyzing gender-disaggregated data, AI ensures that climate predictions and adaptation strategies are equitable and effective across different demographics, promoting fairness in climate action efforts. Furthermore, AI can support decision-making processes by identifying patterns and trends in climate data, aiding policymakers in developing more successful adaptation strategies. Finally, AI can optimize resource utilization in climate adaptation projects, ensuring that funding and efforts are directed where they are most needed and will have the greatest impact. Incorporating AI into these initiatives allows LCDs and SIDS to overcome challenges such as data gaps and ensure that the benefits of climate action are equitably distributed, ultimately enhancing resilience and sustainability on a global scale.

Speaking of these challenges, in reference to the responsible AI for Africa's agriculture and food systems report (Ozor et al. 2023), among the primary challenges identified include gender disparities, insufficient skilled researchers, a lack of implementation data, absence of targeted policies and institutional support, environmental concerns related to carbon footprint information, and technological deficiencies. These challenges are compounded by the digital divide, which exacerbates disparities in access to AI technologies and hinders the equitable development and deployment of AI solutions across different regions in Africa.

To achieve equitable AI development, incorporating gender diversity is important. Numerous awareness-raising initiatives from international organizations, notably UNFCCC, UN SDGs, UN-Habitat, UNESCO, and UNDP have provided recommendations to integrate gender perspectives into public policies, educational programs, industry, and many other sectors. These efforts also aim to address and overcome gender biases in emerging AI-driven solutions. The increasing integration of AI has prompted a growing awareness of the inherent gender biases in emerging AI systems. Recent studies have focused on understanding the root causes, implications, and strategies to mitigate these biases to promote fairness and inclusivity.

Lima et al. (2023) categorized gender bias into societal, technical, and individual types, with societal and socio-technical aspects being primary causes. They emphasized debiasing, dataset design, and gender sensitivity as key strategies for overcoming bias, proposing capacity building and policy implications to address these challenges comprehensively. The study lays a foundational understanding of the multifaceted nature of gender bias in AI and offers a broad spectrum of strategies to mitigate it. Building on Lima et al. (2023), Nadeem et al. (2022) revealed that gender bias is a socio-technical problem and proposed a theoretical framework combining technological, organizational, and societal approaches to mitigate it. They emphasized the need for addressing gender bias through an integrated approach, aligning closely with the strategies suggested by Lima et al. (2023).

Patón-Romero et al. (2022) highlighted the intersection of gender equality and AI within the framework of social sustainability, particularly under the UN SDGs. They noted the limited joint development of AI and gender equality fields. Nonetheless, they observed an increasing number of proposals aimed at addressing these issues. Their findings support the need for integrating gender equality considerations into AI development.

Nadeem et al. (2020) addressed the contributing factors and mitigating strategies for gender bias in AI, identifying a lack of diversity in data and developers, programmer bias, and societal gender biases as primary contributors. They stressed that biases in AI stem from human biases, echoing the findings of Lima et al. (2023) regarding the societal roots of gender bias. Their study also aligns with the broader framework proposed by Nadeem et al. (2022), highlighting the need for comprehensive strategies to address these biases.

Any examination of bias in AI needs to recognize the deficiency of the models and systems we create and train as a reflection of ourselves. Indeed, there have been numerous high-profile cases of gender bias, including NLP, CV, DL, and GenAI systems for gender recognition that reported higher error rates for recognizing women. For example, Sun et al. (2019) focused on gender bias in NLP, highlighting how societal biases are often embedded in training data. They discussed various debiasing methods and their effectiveness, contributing to the understanding of technical approaches to mitigate gender bias. The study provides practical insights into the specific application of debiasing strategies.

These studies collectively uncover the multifaceted nature of gender bias in AI, identifying societal, technical, and individual factors as key contributors. They stress the significance and relevance of comprehensive strategies involving debiasing techniques, diverse data representation, and inclusive practices in AI development. The convergence of these findings points to the necessity for ongoing research and collaboration across disciplines to create more equitable AI systems.

AI risks extend beyond gender bias to include broader 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. While AI has the potential to highlight and mitigate these disparities by identifying inequities in environmental impacts, resource distribution, and social opportunities, it also poses risks. 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 attend to its perils.”

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 datasets that reflect the unique socio-economic, cultural, and environmental conditions of developing countries, ultimately leading to more equitable and impactful outcomes.

The insights gained from the above studies and discussions on gender bias can aid in advancing AI applications in climate action. The use of AI in climate change mitigation and adaptation raises important ethical considerations and potential biases, necessitating not only equality but also fairness, transparency, accountability, and other algorithmic biases in their development and deployment (Bibri et al. 2023; Jain et al. 2023). By adopting comprehensive strategies to mitigate gender bias, AI systems used in climate action can become more effective and equitable. Ensuring diversity in training datasets, implementing debiasing techniques, and fostering an inclusive development environment are key steps. These practices improve the fairness of AI systems and enhance their reliability and robustness, which is essential for accurate climate modeling and decision-making. They ensure that AI technologies contribute effectively to global environmental sustainability efforts, benefiting all communities from advancements in AI-driven climate solutions.

6.4.2. Gender Bias in AI Use for Climate Action in Developing Countries

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, drawing upon insights from the reviewed studies and their insights and discussions. The integration of AI into climate action presents both significant opportunities and challenges. One of the critical aspects that need careful consideration is the potential for AI systems to replicate or even amplify existing gender biases. Addressing these biases is essential across various sectors to ensure that AI contributes to comprehensive and equitable climate solutions. The importance of gender inclusivity in AI applications within these sectors lies in its potential to promote social equity, climate justice, and broader sustainability goals.

Climate modeling and prediction*:* In climate modeling and prediction, gender bias can arise from the underrepresentation of women in the data used to train AI models. Generally, Varona et al. (2021) focused on existing gaps in achieving fairness within AI predictive systems, emphasizing that ML inherently contains limitations that can perpetuate and automate biases in the design of predictive systems. Historical data often reflects male-dominated activities and perspectives, leading to models that fail to account for the different ways climate change impacts men and women. Ignoring their knowledge can weaken disaster risk reduction strategies and increase vulnerabilities. If AI models do not consider these gender-specific impacts, they can produce inaccurate predictions and ineffective policy recommendations. Ensuring that data used for climate modeling includes diverse gender perspectives can improve the accuracy and relevance of these models.

For instance, women often play essential roles in community-based disaster preparedness and response. In flood-prone areas, the impacts of flooding can differ significantly between men and women due to varying social roles, responsibilities, and access to resources. Women, especially in rural and developing regions, are often responsible for securing household resources, such as water and food, which can be severely disrupted during floods. If AI systems used for flood prediction and management fail to incorporate gender-disaggregated data, they might consequently fail to address the specific needs and vulnerabilities of women. As an example, evacuation plans and resource distribution during floods might not consider the mobility constraints faced by pregnant women, the elderly, or those caring for young children, leading to inadequate support and increased risk. Ensuring that AI models for flood prediction and management integrate diverse gender perspectives can enable policymakers to develop more inclusive and effective flood response strategies. This could include tailored communication strategies, gender-sensitive evacuation plans, and targeted distribution of relief resources to ensure that all affected groups receive appropriate and timely assistance.

Resource management*:* AI applications in resource management, such as water, agriculture, and fisheries can perpetuate gender biases if they fail to consider the roles and needs of women. In many developing countries, women are primarily responsible for managing household water supplies, agricultural, and fishery activities. AI solutions that overlook women's knowledge and practices can lead to resource management strategies that are less effective or even detrimental to women. For example, water management systems that do not consider the specific needs of women may allocate resources inefficiently, exacerbating gender inequalities. Integrating gender-sensitive data and involving women in the development of AI resource management tools can help address these issues. As another example, women often engage in different agricultural practices compared to men. AI models that lack data on these practices may fail to optimize crop management and climate resilience strategies for female farmers.

In addition, Wabnitz et al. (2021) synthesized findings from various studies and case examples from SIDS and LDCs to highlight gender disparities in fisheries, outlining efforts to promote gender equity and resilience to ocean-related challenges. They stressed the critical roles of fisheries in achieving the SDGs, noting women's significant contributions across these sectors. Despite their importance, women's roles, priorities, and interests are often overlooked and undervalued in policy and management, exacerbated by restrictive social-cultural norms that limit their participation in decision-making.

Forest management: Addressing gender biases in AI development is equally important for achieving comprehensive and equitable climate solutions. Women play key roles in forest ecosystems, managing resources and gathering non-timber forest products. Inclusive AI systems that recognize these roles can optimize resource use, enhance conservation efforts, and improve overall efficiency. Biases in data collection that overlook these roles can result in AI solutions that do not account for women's contributions, thereby reinforcing gender disparities. Moreover, ensuring equal access to financing and training for women can prevent job displacement and promote economic resilience. Integrating gender inclusivity into AI-driven forest management can create effective, equitable, and sustainable strategies that benefit all stakeholders.

***Energy management**:* Gender bias in AI-driven energy management systems can affect access to and control over energy resources. Similarly, in many developing countries, women are more likely to use traditional biomass for cooking and heating, while men may have greater access to modern energy sources. AI systems that do not account for these differences can fail to address the specific energy needs of women, reinforcing existing disparities. For example, AI solutions focused on improving energy efficiency in urban areas may neglect rural women who rely on biomass, leaving them without sustainable alternatives. Women's energy needs and usage patterns can differ significantly from those of men. To mitigate this bias, AI energy management systems should consider the diverse energy needs and usage patterns of both men and women. AI-driven energy solutions that do not consider these differences may fail to provide effective and equitable energy access.

Addressing gender biases in AI development is necessary for AI-driven energy systems to achieve comprehensive and equitable climate solutions. AI can optimize energy use by tailoring energy efficiency programs and renewable energy initiatives to meet the needs of both men and women. However, biases in data collection can reflect existing gender disparities, which AI might then reinforce. Moreover, the underrepresentation of women in the tech and energy sectors means AI systems may lack gender-sensitive perspectives. This inclusive approach promotes gender equality and supports the transition to sustainable and low-carbon energy systems.

***Transport management**:* Transport management systems driven by AI can also exhibit gender bias, impacting the mobility and safety of women. Women in developing countries often have different transportation needs and patterns compared to men, such as traveling at different times or using different modes of transport. The failure of AI systems in incorporating these gender-specific patterns can result in transportation solutions that are less accessible or safe for women. For example, route optimization algorithms that prioritize efficiency over safety might not account for areas that are less safe for women to travel through. Incorporating gender-specific data and consulting with women can lead to more better transport management systems.

Moreover, addressing gender biases in AI development is instrumental to AI-driven transport systems to achieve comprehensive and equitable climate solutions. Inclusive transport planning ensures that AI systems do not perpetuate existing inequalities, thereby contributing to social equity and climate justice. For example, addressing issues such as the lack of public transport options during off-peak hours or creating routes that cater to non-traditional itineraries like home-school or home-market can significantly improve accessibility and equity. This approach aligns with broader sustainability goals, making gender inclusivity in AI for transport essential for creating effective, equitable, and resilient climate strategies.

***Disaster risk reduction**:* AI applications in DRR can inadvertently reinforce gender biases if they fail to account for the distinct vulnerabilities and capacities of women. Women often face greater risks during disasters due to social and economic inequalities, such as patriarchal norms that limit their movements out of the house and limited access to information and resources. AI systems that do not account for these gendered structural barriers can lead to disaster response strategies that are less effective for or discriminatory to women. For instance, early warning systems that disseminate information through channels less accessible to women can leave them more vulnerable. Ensuring that AI-driven DRR solutions incorporate gender-specific data and involve women in planning and implementation can enhance their effectiveness and inclusivity. Inclusive AI can help design early warning systems, evacuation plans, and recovery programs that consider the different impacts on men and women, thereby enhancing community resilience and reducing overall disaster risk.

***Education and community engagement**:* Gender bias in AI for education and community engagement can limit the participation and benefits for women and girls. AI-driven educational tools that do not address gender disparities in access to technology can widen the digital divide. For example, e-learning platforms that assume equal access to digital devices and the internet may overlook the fact that women and girls in many developing countries have less access to these resources. Community engagement efforts using AI that fail to take into consideration women's roles and voices can also fail to address their specific needs and concerns. Developing gender-sensitive AI tools and ensuring equal access to educational resources can promote greater inclusion and empowerment of women and girls.

Addressing gender bias in AI for climate action in developing countries is essential for achieving optimal outcomes. Across various thematic areas, AI systems must consider the distinct needs and perspectives of women. Integrating gender-sensitive and -disaggregated data, involving women in the development and implementation of AI solutions, and ensuring equal access to technology and resources, can mitigate gender bias and promote more inclusive strategies for climate action. This approach will help ensure that AI technologies contribute to sustainable and equitable development for all members of society.

All in all, while AI holds significant promise for advancing climate action in developing countries, it is important to recognize and address the associated risks and challenges. Energy and water consumption, data security, the digital divide, and gender bias are key areas that require careful consideration and strategic intervention. Developing countries can harness the potential of AI to drive sustainable climate action by proactively managing and mitigating these risks. Effective policies, capacity-building, and inclusive practices are essential to ensure that AI technologies contribute positively to SDG 13 without exacerbating existing environmental, ethical, and social challenges.

6.5. Youth Engagement

Youth engagement is critical in leveraging AI for climate action, especially in developing countries where young populations form a significant part of the demographic. Engaging youth in AI-driven climate initiatives can harness their innovation, energy, and unique perspectives. However, several challenges need to be addressed to ensure effective and equitable participation of young people in these efforts.

Education and capacity building; Limited access to quality education and training in AI and climate science for young people in developing countries can hinder their ability to contribute effectively to AI-driven climate action. Invest in educational programs and partnerships that provide training in AI, data science, and climate change. Create accessible online courses, workshops, and mentorship opportunities.

Digital Divide: Many young people in developing countries lack access to necessary technology and internet connectivity, exacerbating the digital divide and limiting their participation in AI initiatives. Implement policies and programs to improve internet infrastructure and provide affordable access to digital tools. Promote initiatives that offer devices and connectivity to underserved youth communities.

Inclusion and equity: Socio-economic barriers and gender disparities can prevent equitable participation of all youth in AI and climate action projects. Develop inclusive programs that target marginalized and underrepresented groups. Ensure gender-responsive approaches in training and capacity-building initiatives. Foster an inclusive environment that encourages diverse voices and perspectives.

Empowerment and leadership*:* Young people often lack platforms and opportunities to take on leadership roles in AI and climate action initiatives. Create platforms for youth to lead and participate in decision-making processes. Establish youth councils or advisory boards focused on AI and climate action. Support youth-led projects and provide funding and mentorship to young innovators.

Awareness and advocacy: There is often a lack of awareness among youth about the potential of AI in climate action and the ways they can get involved. Conduct awareness campaigns and informational sessions about the role of AI in climate action. Encourage youth participation in climate advocacy and policy dialogue. Leverage social media and other digital platforms to engage young people and spread awareness.

Engaging youth in AI-driven climate action presents both opportunities and challenges. Developing countries can harness the potential of their youth populations to drive innovative and impactful climate solutions by addressing the educational, technological, socio-economic, and leadership barriers faced by young people. Proactive measures to involve youth in AI and climate initiatives will not only empower the next generation but also ensure sustainable and inclusive climate resilience.

AI governance is key to ensuring that AI technologies are used ethically and responsibly. As AI systems become increasingly integrated into various aspects of society, it is essential to establish a robust ecosystem of governance to oversee their development and deployment. Regulatory frameworks for AI are beginning to emerge, aiming to address issues such as fairness, transparency, accountability, and security. For example. in 2024, the European Commission endorsed the AI Act, which aims to ensure that AI is safe, transparent, non-discriminatory, and environmentally friendly, with different rules applying to varying levels of risk (European Commission 2024). These frameworks seek to prevent biases, protect individual rights, and ensure that AI systems are aligned with societal values. Effective AI governance requires collaboration between governments, industry stakeholders, academia, and civil society to create comprehensive policies and standards that guide the ethical use of AI. Establishing these regulatory measures can harness the benefits of AI while mitigating its risks and ensuring it serves the public good.

6.6. AI’s Role in Promoting Consumerism, Accelerating Fossil Fuel Extraction and Exploitation, and Spreading Climate Misinformation: Implications for Environmental Sustainability

AI is increasingly recognized as a powerful and versatile tool with a broad spectrum of applications, ranging from supporting and advancing climate action to facilitating activities that actively undermine these efforts. 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 is being leveraged to enhance fossil fuel exploration and extraction, directly contradicting global efforts to transition to renewable energy. Moreover, AI plays a central role in targeted advertising that perpetuates consumerism and encourages unsustainable behaviors, driving demand for products and services that contribute to environmental degradation. Additionally, AI systems are increasingly used to amplify the spread of climate misinformation, further complicating efforts to address environmental challenges. These risks underscore the need for responsible development and governance that prioritize sustainable applications over those that exacerbate ecological harm. Ensuring AI is aligned with global environmental sustainability goals will be critical to shaping a future where technology supports, rather than hinders, environmental stewardship.

AI-driven algorithms assist oil and gas companies in identifying new reserves and enhancing extraction efficiency. Li et al. (2024) explored the application of Artificial General Intelligence (AGI) in the oil and gas industry, specifically in upstream operations. They highlight how LLMs and advanced CV systems enhance production efficiency, safety, and drilling techniques. The integration of AGI offers the potential to automate tasks, optimize operations, and improve decision-making. However, challenges such as the need for specialized expertise and limited datasets remain obstacles for large-scale deployment. The study also emphasizes the innovative role of GenAI models, like ChatGPT and SAM, which are making AI more accessible and specialized for industry-specific applications.

Similarly, 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 significantly contributes to improving efficiency and boosting hydrocarbon recovery in the oil and gas industry. In some cases, AI has 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).

Additionally, AI systems can be exploited to spread climate misinformation at scale, influencing public opinion and shaping policy discussions in ways that hinder meaningful climate action. The digital news landscape is undergoing a significant transformation. The proliferation of online social platforms and the emergence of GenAI tools are drastically altering how quickly misinformation regarding climate change circulates globally. Sophisticated AI models are capable of generating misleading content that appears credible and authoritative, allowing misinformation to proliferate rapidly across social media and other platforms. This can lead to public confusion, distrust in scientific consensus, and the promotion of narratives that downplay the urgency of the climate crisis. Such misinformation campaigns can delay critical policy measures, erode support for environmental initiatives, and shift attention away from necessary climate action.

Galaz et al. (2023) reported on the rapid transformation of the digital news ecosystem driven by the expansion of social networks, recommender systems, automation, and GenAI tools. This transformation has significantly increased the speed and reach of climate change and sustainability misinformation. The authors stress the urgent need for collaboration among policymakers, researchers, and the public to counter the dangerous combination of opaque social media algorithms, polarizing social bots, and AI-generated content. Their brief report was developed as a collaborative contribution to the 2023 Nobel Prize Summit on "Truth, Trust, and Hope."

Chu-Ke and Dong (2024) discussed the global challenge of misinformation in the context of GenAI, reviewing both theoretical developments and empirical evidence. The authors focus on how AI-driven misinformation complicates the landscape and argue for ethical AI development through stricter regulations and increased AI literacy. They outline a framework for AI literacy that includes understanding the cultural and ethical implications of AI, critically evaluating AI-generated content, and using feedback mechanisms to manage AI’s influence at an institutional level.

Treen et al. (2020) examine the dynamics of online climate change misinformation, linking it to skepticism, denial, and contrarianism. The authors identify a network of actors responsible for producing and amplifying misinformation, and how social media platforms—through echo chambers, polarization, and confirmation bias—facilitate its spread. The authors argue that addressing climate misinformation requires a multidisciplinary approach, including educational, technological, and regulatory interventions. They also highlight gaps in current research, such as understanding the diffusion of misinformation on social media and whether it extends to exaggerated climate alarmism.

Galaz et al. (2023), Chu-Ke and Dong (2024), and Treen et al. (2020) collectively highlight the critical issue of climate-related misinformation, with a particular focus on the role of AI and digital platforms in its spread. Galaz et al. (2023) focus on the acceleration of misinformation due to digital and AI tools, emphasizing the need for coordinated action across multiple sectors. Chu-Ke and Dong (2024) extend the discussion by examining the rise of AI-generated content and advocating for ethical AI development, regulation, and AI literacy. **Treen et al.** (2020)provide a comprehensive overview of how misinformation is perpetuated in the climate debate, discussing the interplay between social networks and cognitive biases.

All three studies converge on the idea that combating climate misinformation requires a multi-faceted approach, integrating policy interventions, educational strategies, and technological oversight. 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.

Furthermore, one of the most pervasive impacts of AI in modern society is its ability to shape consumer behavior through sophisticated targeting strategies. AI-driven algorithms are specifically designed to maximize user engagement by delivering highly tailored advertisements that are strategically aligned with individual preferences and behaviors. These personalized ads often encourage excessive consumption by promoting products and services based on past interests, purchasing habits, and browsing history. This dynamic deepens the overuse of natural resources and reinforces consumption patterns that are fundamentally misaligned with global environmental sustainability goals. The precision of AI in micro-targeting specific audiences leads to more frequent and impulsive purchases, promoting a culture of continuous consumption that accelerates the depletion of the planet’s finite resources and drives waste generation and worsen its environmental impact. These AI systems contribute to a cycle of unsustainable consumerism that poses a significant challenge to achieving long-term environmental resilience by prioritizing engagement and profit over sustainability.

The paradox of AI's dual influence lies in how it simultaneously drives both innovation and unsustainable practices. On one hand, AI enhances operational efficiency and resource management; on the other hand, it facilitates harmful practices. Addressing these negative applications of AI should be balanced with an acknowledgment of AI's constructive potential. Indeed, while AI can spread misinformation, it can also be harnessed to disseminate accurate climate information, raise awareness, and empower communities with knowledge to drive sustainable practices, as discussed earlier. For instance, AI-driven models can tailor climate communication strategies to resonate more effectively with different audiences, ensuring that key environmental messages are both impactful and engaging. Moreover, AI-driven innovations are central to various positive climate initiatives, such as optimizing renewable energy grids, advancing climate research, and developing precision agriculture solutions that reduce resource use, as discussed throughout the report. To reiterate, AI's ability to process large datasets and generate precise predictions supports better management of renewable resources, improves disaster response strategies, and enhances practices in sustainable land and water management.

This duality presents a critical challenge: as AI continues to evolve and permeate more industries, the need to balance its positive applications against its potential to perpetuate harmful practices becomes increasingly important. Achieving this balance is essential to harnessing AI's full potential while mitigating its adverse impacts on sustainability and climate goals. Ensuring that AI applications align with environmental sustainability objectives requires thoughtful governance, responsible development, and a concerted effort to encourage applications that drive climate resilience and environmental sustainability while discouraging those that do harm. Fostering ethical AI practices and enacting appropriate regulations can enable society to leverage AI's capabilities to promote both environmental innovation and sustainability, ensuring that technological advancements contribute positively to the future.

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

The integration of AI as a technological tool for advancing and scaling up transformative climate solutions is vital for effective mitigation and adaptation in developing countries, especially LDCs and SIDS. The key emphasis is placed on outlining policy options to enhance the deployment of AI in these countries while addressing associated challenges and risks.

7.1. Promote AI Applications in Climate Change Mitigation and Adaptation Strategies

Climate mitigation: Encourage the use of AI in reducing GHG emissions by optimizing energy systems. Support the use of AI to forecast renewable energy production based on weather patterns to help balance supply and demand. Promote AI solutions to monitor and optimize industrial processes, identifying inefficiencies and suggesting real-time improvements to decrease the carbon footprint of manufacturing and other industrial activities.

Climate adaptation: Utilize AI to enhance the resilience of communities to climate impacts. Support the deployment of AI for advanced climate modeling and predictive analytics. Promote the implementation of AI-driven early warning systems that use real-time data from sensors and satellite imagery to detect and predict natural disasters such as floods, hurricanes, heatwaves, and droughts. Encourage the integration of AI into adaptive management strategies to enhance the resilience of ecosystems and communities.

This policy option outlines how AI can be effectively used for both climate change mitigation and adaptation, highlighting the need for support, promotion, and integration of AI technologies to achieve climate goals.

7.2. Develop Inclusive and Sustainable AI 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 centers and communication networks, and setting standards for energy efficiency in AI applications. Implement policies that require a lifecycle 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: 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 essential to build trust in AI systems.

Digital divide: Invest in digital infrastructure to improve access to AI technologies in 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 LDCs and SIDS, public infrastructure for AI development, digital literacy programs, particularly in remote and underserved areas, and providing training on AI technologies. 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 and Gender-Responsive Approaches

Incorporate indigenous knowledge: Recognize and integrate indigenous knowledge systems into AI models and climate strategies. Leveraging indigenous knowledge can enhance the relevance and effectiveness of AI applications by aligning them with local contexts and practices. This approach respects and utilizes centuries-old wisdom and environmental understanding, enriching AI-driven climate action with culturally pertinent insights.

Gender-responsive AI policies: Ensure that AI policies and programs are inclusive and address gender disparities. Promote the active participation of women in AI-related fields through targeted education, training programs, and career opportunities. Ensure that AI applications consider the specific needs and contributions of women in climate action, fostering equitable solutions that benefit all community members.

7.4. Meaningful Youth Inclusion in Climate Action

Youth play a role in the fight against climate change, bringing fresh perspectives, innovative solutions, and a strong drive for sustainable development. Involving young people in policy decision-making, capacity building, and providing sustained support and financing for their initiatives is essential for the successful implementation of AI-driven climate solutions. Policy options for ensuring meaningful youth inclusion in climate action efforts are outlined.

7.4.1. Youth in Policy Decision-Making

Youth representation: Ensure that young people are represented in climate policy decision-making processes at local, national, and international levels. Establish youth advisory boards and include youth representatives in governmental and intergovernmental climate bodies.

Youth consultation: Regularly consult with youth organizations and networks when developing and implementing climate policies. This can be facilitated through public consultations, youth forums, and interactive platforms that allow for the direct input of young people.

Capacity building for advocacy: Provide training and resources to empower young people to effectively advocate for climate action. This includes workshops on policy development, negotiation skills, and public speaking.

7.4.2. Capacity Building and Skills Development

Education and training programs: Invest in educational initiatives that equip young people with the skills needed for AI and climate science. Partner with educational institutions, NGOs, and international organizations to offer courses, workshops, and mentorship programs focused on AI, data science, and climate change.

Digital literacy: Enhance digital literacy among youth to bridge the digital divide. Implement programs that teach young people how to use AI tools and technologies, ensuring they can actively participate in and contribute to AI-driven climate solutions.

Entrepreneurial support: Foster an entrepreneurial spirit by providing training in business development, project management, and innovation. Encourage the creation of youth-led startups focused on AI and climate action.

7.4.3. Sustained Support and Financing

Funding opportunities: Establish dedicated funding streams for youth-led initiatives in AI and climate action. This can include grants, scholarships, and seed funding for startups. Ensure that funding opportunities are accessible and well-publicized to young innovators and include a trajectory to access further funding stages beyond seed funding, e.g. through partners.

Innovation hubs and incubators: Support the development of innovation hubs and incubators that provide young entrepreneurs with the resources, mentorship, and networking opportunities needed to develop and scale their AI-driven climate solutions.

Public-private partnerships: Encourage partnerships between governments, private sector companies, and international organizations to co-fund and support youth-led projects. These partnerships can provide additional resources and expertise, enhancing the impact and sustainability of youth initiatives.

Meaningful youth inclusion in AI-driven climate action is not only a matter of equity but also a strategic imperative for achieving sustainable and innovative climate solutions. By integrating young people into policy decision-making, building their capacities, and providing sustained support and financing, policymakers can harness the full potential of youth to drive transformative climate action. These efforts will ensure that the next generation is well-equipped to lead the charge against climate change, fostering a resilient and sustainable future for all.

7.5. Promote Socially Inclusive AI Development

Inclusive AI development: Ensure that AI development and deployment processes are inclusive, considering the needs and perspectives of marginalized communities, including women and indigenous groups. Develop policies that ensure equitable access to AI technologies, focusing on affordability and infrastructure development in underserved areas. This approach aims to democratize AI, ensuring that AI's use, development, benefits and governance are inclusive and reach all societal segments, particularly those who are often left behind in technological advancements.

Community engagement: Engage local communities in the design and implementation of AI-driven climate solutions, ensuring that they are culturally appropriate and socially acceptable. Implement targeted programs to support the participation of marginalized groups in AI training and deployment. This ensures that AI solutions are not only effective but also resonate with the community's values and needs, fostering greater acceptance and success of AI initiatives in climate action.

7.6. Foster International Cooperation, Capacity-Building, and Knowledge Sharing

Establish collaborative frameworks: Develop international partnerships and cooperative frameworks to share knowledge, technologies, and best practices. This includes collaborations with developed nations, international organizations, and private sector stakeholders. Establishing these frameworks will ensure the transfer of AI technologies and expertise, fostering a global effort to tackle climate change.

Capacity-building programs: Implement training programs 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 AI 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 catalog 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.

7.7. 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.

7.8 Invest in and Foster AI 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 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 startups and innovation Hubs: Create supportive environments for startups and innovation hubs focusing on AI for climate action. Provide grants, tax incentives, and incubation support to foster innovation in the private sector.

AI holds immense potential to transform climate action in LDCs and SIDS. By implementing these policy options, policymakers can harness AI's capabilities to advance climate mitigation and adaptation strategies, ensuring sustainable and inclusive development. These efforts will address immediate climate challenges and build a resilient future for vulnerable communities in developing countries.

To fully leverage AI for climate action, it is imperative that policymakers, researchers, and practitioners work collaboratively. Policymakers can establish frameworks and incentives for AI adoption, while researchers provide the scientific and technical expertise necessary to develop effective AI models. Practitioners play a key role in testing and implementing AI-driven solutions in real-world scenarios. Including researchers and practitioners in policy development ensures strategies are grounded in scientific evidence and practical feasibility, enhancing the sustainability and robustness of climate solutions. This collaborative approach integrates scientific research, technological development, and practical application, creating a holistic strategy to effectively address climate change challenges. Ultimately, these combined efforts will maximize the benefits of AI technologies while mitigating associated risks, paving the way for a sustainable and resilient future for all.

8. A Conceptual Framework for AI in Climate Action Future Outlook

The integration of AI into climate action strategies presents a transformative opportunity for developing countries. By leveraging AI technologies, these nations can significantly enhance their capacity to mitigate and adapt to climate change impacts. In this context, it is important to outline a detailed and strategic conceptual framework for the future outlook of AI in climate action, focusing on temporal horizons, key dimensions of AI evolution, spheres of impact, cross-cutting themes, potential paradigm shifts, methodological approaches, stakeholder perspectives, and uncertainty factors. This framework is intended to guide policymakers, researchers, industry leaders, and civil society in effectively harnessing AI for sustainable development and climate resilience.

8.1. Temporal Horizons

Short-term (1-3 years): *Current AI Applications and Immediate Developments**:***

- Deployment of AI-powered decision support systems for real-time disaster response and risk assessment.
- Utilization of ML algorithms to optimize renewable energy grid management and enhance energy efficiency.
- Implementation of AI-driven predictive analytics for early warning systems, improving community preparedness for extreme weather events.
- Integration of advanced neural networks and DL models to improve climate forecasting accuracy and environmental monitoring.

Medium-term (3-7 years): *Emerging AI Technologies and Their Potential Climate Impacts***:**

- Development of AI-driven smart grids and microgrid systems to enhance energy distribution and resilience in remote and underserved areas.
- Adoption of AI-enabled precision agriculture techniques to increase crop yields, optimize water usage, and reduce environmental impacts.
- **Implementation of AI in circular economy practices** to facilitate efficient resource recovery and recycling processes, thereby minimizing waste and promoting sustainability.
- **Advancement in AI-driven carbon capture and storage technologies** to optimize carbon capture processes, leading to more efficient storage solutions and reduced atmospheric CO2 levels.

Long-term (7-15 years): *Disruptive AI Scenarios and Their Implications for Climate Strategies:*

- Exploration of fully autonomous AI systems for managing large-scale environmental restoration projects and carbon sequestration initiatives.
- Implementation of global real-time climate governance frameworks powered by AI to coordinate international climate action efforts. AI-driven data transparency for climate governance, with human oversight ensuring policy decisions reflect value-driven considerations.
- Development of AI-human hybrid decision-making systems to enhance the adaptability and effectiveness of long-term climate strategies.
- **Integration of AI with advanced sensor networks for planetary-scale climate monitoring to** provide comprehensive data for understanding climate dynamics and developing global climate strategies.

8.2. Key Dimensions of AI Evolution

Computational Power: *Advancements in Processing Capabilities:*

Continuous improvements in computational power and creation of more compute-efficient development and deployment practices will enable more complex climate models and simulations. These advancements will provide better predictive capabilities, enhance decision support systems, and allow for real-time processing of vast climate data, thus improving the precision and effectiveness of climate action strategies.

Data Availability and Quality: *Improvements in Climate-Related Data Collection and Access:*

Enhanced satellite technologies, sensor networks, and big data analytics will provide high-resolution, real-time climate data. This influx of quality data will facilitate more accurate climate modeling, timely interventions, and informed decision-making, enabling proactive measures in climate action and resource management.

Algorithm Sophistication: *Development of More Advanced AI Models and Techniques:*

Progress in AI research will lead to the creation of more sophisticated models and techniques capable of analyzing vast amounts of data, identifying patterns, and making precise predictions related to climate dynamics. These advanced algorithms will enhance the capability to understand and forecast climate phenomena, driving innovative solutions in climate resilience and adaptation. While certainly bigger models made a lot of progress, smaller, task-specific models are especially in LDCs and SIDS extremely relevant, as their deployment is more realistic given the limited availability infrastructure.

Integration and Interoperability: *AI Systems Working Seamlessly Across Different Domains:*

Development of interoperable AI systems will enable seamless integration across various sectors such as energy, agriculture, water management, and urban planning. This integration will enhance overall climate resilience by ensuring that AI systems can communicate and operate cohesively, leading to more coordinated and efficient climate action efforts.

Autonomous Decision-Making: *Increasing AI Autonomy in Climate-Related Processes:*

Growth in AI's autonomous decision-making capabilities will reduce human intervention, streamline processes, and improve the efficiency of climate action initiatives. Autonomous systems will be able to rapidly analyze data, make decisions, and execute actions, leading to quicker and more effective responses to climate challenges.

8.3. Spheres of Impact

Scientific Understanding: *AI's Role in Advancing Climate Science:*

AI will enhance climate research by providing powerful tools for data analysis, enabling scientists to uncover new insights and improve our understanding of climate change mechanisms. This enhanced understanding will facilitate the development of more accurate climate models, better prediction of climate events, and informed strategies for mitigation and adaptation.

Technological Solutions: *AI-Driven Innovations in Clean and Adaptive Technologies:*

AI will drive innovation in clean technologies such as renewable energy systems, sustainable agriculture practices, and climate-resilient infrastructure. These innovations will promote environmental sustainability by optimizing resource use, reducing emissions, and enhancing the resilience of critical systems and communities to climate impacts.

Policy and Governance: *AI's Influence on Climate Policy Formulation and Implementation:*

AI tools will support the development of data-driven, evidence-based climate policies, enhancing their effectiveness and facilitating their implementation at local, national, and international levels. AI can provide policymakers with valuable insights, predictive models, and decision support systems, enabling more strategic and impactful climate governance.

Economic Systems: *AI's Impact on Sustainable Economic Models and Practices:*

AI will optimize resource use, improve industrial efficiency, and support the transition to circular and low-carbon economies. By enhancing productivity and reducing waste, AI can foster sustainable economic growth and help align economic activities with environmental sustainability goals.

Social Dynamics: *AI's Effect on Individual and Community Climate Action:*

AI will empower individuals and communities by providing accessible information, fostering engagement in climate initiatives, and promoting sustainable behaviors through personalized recommendations and education. This empowerment will drive grassroots climate action and enhance community resilience to climate impacts.

8.4. Cross-Cutting Themes

Ethics and Equity: *Ensuring Fair and Responsible AI Development and Use in Climate Action:*

Addressing ethical considerations, promoting transparency, and ensuring equitable access to AI development resources and technologies will be critical to avoid exacerbating social inequalities and to maximize the benefits of AI for all communities. Developing ethical guidelines and frameworks will ensure responsible AI development and deployment in climate action.

Capacity and Access: Addressing the AI Divide in Climate Capabilities:

Bridging the gap in access to AI resources and capabilities and addressing market imbalances between developed and developing regions through policy-making, capacity-building initiatives, knowledge transfer, and equitable access to AI resources will be essential for inclusive climate action. Investments in education, infrastructure, datasets and models, and international cooperation will be essential to enhance AI capabilities globally.

Energy-AI Nexus: *Balancing AI's Energy Consumption with Its Climate Benefits**:***

Developing energy-efficient AI technologies and practices will be necessary to minimize the environmental footprint of AI and maximize its positive impacts on climate action. Innovations in green computing and sustainable AI practices will help balance the energy demands of AI with its contributions to climate resilience.

Human-AI Collaboration: Evolving Relationships Between Human Experts and AI Systems:

Fostering effective collaboration between human experts and AI systems will enhance decision-making, creativity, and problem-solving in climate action. This synergy will combine the strengths of human intuition and AI precision, leading to more robust and adaptive climate strategies.

Resilience and Adaptability: *AI's Role in Enhancing Climate Resilience:*

AI will play an instrumental role in developing adaptive strategies, improving disaster response, and enhancing the resilience of communities and ecosystems to climate impacts. AI can significantly strengthen climate resilience by providing real-time data, predictive insights, and autonomous response capabilities.

8.5. Potential Paradigm Shifts

AI-Driven Earth Systems Management: *Advanced Approaches to Managing Earth Systems:*

Envisioning AI-driven systems capable of managing and optimizing Earth's natural processes and resources on a global scale, enhancing environmental sustainability and resilience. These systems could autonomously monitor and regulate key environmental parameters, ensuring the long-term health and stability of global ecosystems.

Global Real-Time Climate Governance: *Real-Time, AI-Powered Global Climate Governance:*

Implementation of real-time climate monitoring and governance systems powered by AI to enable swift and coordinated global responses to climate events. Such systems could facilitate international cooperation, ensure compliance with climate agreements, and rapidly mobilize resources during climate emergencies.

AI-Human Hybrid Climate Decision Making: *Synergistic Decision-Making Frameworks:*

Development of hybrid decision-making frameworks that combine human judgment with AI insights to enhance the effectiveness and adaptability of climate strategies. This approach leverages the strengths of both human expertise and AI's analytical power to address complex climate challenges.

Autonomous Climate-Positive Systems: *Self-Regulating, Climate-Beneficial Technologies**:***

Innovation of autonomous systems designed to operate independently and contribute positively to climate goals, such as carbon-neutral industrial processes and self-sustaining ecosystems. These technologies would continuously optimize their operations to minimize environmental impact and support climate resilience.

8.6. Methodological Approaches

Scenario Planning: *Developing Plausible Future Narratives:*

Creating detailed scenarios to explore potential future developments in AI and climate action, helping stakeholders anticipate and prepare for various outcomes. Scenario planning allows for the examination of different pathways and their implications for climate resilience.

Trend Analysis: *Identifying and Extrapolating Current AI and Climate Trends:*

Analyzing current trends in AI and climate data to project future developments and inform strategic planning. This approach helps in understanding the trajectory of technological advancements and their potential impact on climate action.

Expert Elicitation: *Gathering Insights from AI and Climate Experts:*

Engaging with experts in AI and climate science to gather diverse perspectives and inform the development of robust and comprehensive climate strategies. Expert elicitation ensures that strategies are grounded in the latest scientific and technological knowledge.

Backcasting: *Working Backwards from Desired Future States:*

Defining long-term climate goals and working backwards to identify the steps needed to achieve those goals, integrating AI as a key component. Backcasting helps in creating actionable roadmaps for achieving climate resilience and sustainability.

Systems Dynamics Modeling: *Mapping Complex Interactions Between AI and Climate Systems:*

Utilizing systems dynamics modeling to understand the complex interactions between AI technologies and climate systems, providing insights into potential feedback loops and system behaviors. This approach helps in identifying leverage points and potential risks in AI-driven climate strategies.

8.7. Stakeholder Perspectives

Policymakers: *Implications for Governance and International Cooperation:*

Exploring how AI can support climate policy development, international cooperation, and governance frameworks to enhance global climate action. Policymakers need to understand the potential of AI to inform and improve climate policies. Inclusion of LDCs and SIDS in policy making is critical to fostering inclusive policy development that represents the perspective of the jurisdictions in which they apply.

Researchers: *Future Research Priorities and Interdisciplinary Needs:*

Identifying key research priorities and fostering interdisciplinary collaboration to advance AI applications in climate science and action. Researchers play a role in developing innovative AI solutions and understanding their implications for climate resilience.

Industry: *Business Opportunities and Challenges in AI-Climate Solutions*

Assessing the opportunities and challenges for businesses in developing and deploying AI-driven climate solutions, and identifying potential areas for innovation and investment. Industries can leverage AI to optimize processes, reduce costs, and develop new market opportunities in the realm of sustainably built technologies that can be applied for climate solutions.

Civil Society: *Societal Impacts and Ethical Considerations:*

Evaluating the social implications of AI in climate action, including ethical considerations, community engagement, and the promotion of inclusive and equitable climate solutions. Civil society organizations can contribute to advocating for responsible AI use and ensuring that benefits are shared equitably.

International Organizations: Global Coordination and Capacity Building Needs:

Highlighting the role of international organizations in facilitating global coordination, capacity building, and the dissemination of AI technologies for climate action. These organizations can provide critical support for cross-border initiatives, knowledge sharing, and funding for AI projects in developing countries.

8.8. Uncertainty Factors

Technological Breakthroughs: *Unpredictable Advancements in AI Capabilities:*

Recognizing the potential for unforeseen technological breakthroughs that could significantly alter the landscape of AI applications in climate action. Such breakthroughs could either accelerate progress or introduce new challenges, necessitating adaptive and flexible strategies.

Geopolitical Dynamics: *Shifts in International Relations Affecting AI and Climate Cooperation:*

Considering the impact of geopolitical dynamics on international cooperation and the deployment of AI technologies for climate action. Political changes and international tensions can influence the flow of resources, collaboration opportunities, and the implementation of global climate initiatives.

Socioeconomic Changes: *Evolving Societal Attitudes Towards AI and Climate Change:*

Monitoring changes in public perception and societal attitudes towards AI and climate change, which can influence policy and adoption rates. Public acceptance and support for AI-driven climate initiatives are key to their successful implementation.

Environmental Tipping Points: Unforeseen Climate System Behaviors:

Accounting for the possibility of reaching environmental tipping points that could drastically change the urgency and nature of climate action required. Sudden shifts in climate systems can have profound impacts on ecosystems and human societies, necessitating rapid and effective AI interventions.

Regulatory Landscapes: *Evolution of AI and Climate-Related Laws and Policies:*

Keeping abreast of changes in regulatory frameworks that govern AI and climate action, ensuring compliance and adaptability to new policies. As AI and climate technologies evolve, so too must the laws and regulations that govern their use to ensure they are safe, ethical, and effective.

The conceptual framework presented provides a strategic roadmap for integrating AI into climate action efforts in developing countries. By addressing various temporal horizons, key dimensions of AI evolution, spheres of impact, cross-cutting themes, potential paradigm shifts, methodological approaches, stakeholder perspectives, and uncertainty factors, this framework offers a comprehensive guide for stakeholders to navigate the complex interplay between AI and climate action. Embracing these strategies will be pivotal for leveraging AI's full potential in enhancing climate resilience, promoting sustainable development, and achieving global climate goals.

9. Conclusions and Recommendations

AI has emerged as a powerful technological tool for advancing and scaling up transformative climate solutions for mitigation and adaptation action in developing countries, with a particular emphasis on LDCs and SIDS. The report identifies both the pivotal role of AI in enhancing the effectiveness and efficiency of climate action and the associated challenges and risks that need to be addressed and overcome to ensure effective and inclusive implementation. It underscores the innovative potential of AI to advance both climate mitigation and adaptation strategies through data-driven insights, predictive analytics, intelligent decision-making, and innovative solutions. Despite its tremendous opportunities, AI for climate action faces critical challenges, including intensive energy and water consumption, data security concerns, the digital divide, and gender bias.

9.1. Summary of Key Findings

Key findings and insights highlight AI's role in enhancing various areas critical to climate action. Key areas where AI can contribute include improving climate monitoring and data collection, enhancing climate modeling and predictions, advancing environmental monitoring, optimizing resource management, boosting energy efficiency, streamline renewable energy sources, supporting disaster risk reduction, and promoting education and community engagement. These findings illustrate how AI-driven solutions can significantly improve the accuracy and efficiency of climate data analysis, optimize resource allocation, predict extreme weather events, and foster sustainable practices across sectors. AI's potential to transform climate action strategies highlights the importance of tailoring advanced technologies to the specific capacities and needs of developing countries, particularly LDCs and SIDS. By focusing on scalable, cost-effective solutions, fostering local capacity-building, and ensuring that AI applications are aligned with regional contexts, AI can better serve as a critical tool for building resilience and promoting sustainable development in these vulnerable regions.

Advanced AI and ML algorithms significantly enhance the detection and monitoring of sea level rise, coastal transformations, deforestation, forest degradation, pollution sources, biodiversity, and nuanced land use alterations. AI also aids in monitoring CO_2 and methane emissions, providing critical data for climate action. Additionally, the strategic deployment of IoT sensors for real-time climate data acquisition, coupled with AI-driven data analysis, fortifies early warning systems, enabling continuous monitoring and timely alerts to mitigate climate-related risks.

AI and ML algorithms bring precision and accuracy to the prediction of extreme weather events and disaster scenarios while assessing climate change impacts on local ecosystems. This predictive capability supports the development of adaptive strategies to mitigate risks and enhance resilience. Moreover, AI evaluates potential adaptation strategies through climate scenario simulations, providing decision-makers with actionable insights and contributing to climate action.

In resource management, AI and ML play an instrumental role in fisheries management and marine life preservation by tracking fish stocks, preserving marine protected areas, combating illegal fishing, and implementing sustainable fishing practices. These efforts contribute to the sustainability and conservation of marine resources. In farming management, AI provides data-driven insights and adaptive strategies for navigating changing climate conditions, optimizing irrigation, fertilization, and pest control to enhance crop yields and sustainability. AI also optimizes the management of various natural resources like agriculture, food, and water, ensuring efficient and sustainable utilization.

AI and ML enhance and optimize the efficiency of energy generation, distribution, transmission, and consumption, leading to more sustainable and reliable energy systems. It promotes the efficient use and deployment of renewable energy sources, facilitating the transition to low-carbon economies and reducing greenhouse gas emissions.

In the transport sector, AI and ML enhances the efficiency of transportation systems by optimizing route planning, reducing fuel consumption, and minimizing delays in logistics. This leads to more sustainable transport solutions with reduced emissions. Specifically, AI and ML manage freight transportation by improving logistics and supply chain management, resulting in enhanced operational efficiency, cost savings, and a reduced environmental impact.

In industry production and manufacturing, AI and ML enhances flexibility and resilience in production processes by enabling remote manipulation and real-time responsiveness. AI-driven predictive maintenance minimizes downtime and extends the lifespan of machinery. Process optimization through AI and ML enhances operational efficiency, reduces waste, and improves resource management. AI and ML support integrated and collaborative production systems that adapt to real-time changes in factory and supply networks. Additionally, AI-driven logistics and supply chain management optimize inventory levels and streamline operations, improving efficiency.

AI and ML support disaster risk reduction by enabling predictive analytics for evacuation planning and coordinating response efforts during disasters, thus enhancing community resilience and minimizing the socio-economic impacts of climate-related events. Moreover, AI and ML aid in damage assessment and prioritizes recovery efforts, ensuring efficient rebuilding processes and resource allocation.

AI-powered tools contribute significantly to educating communities on climate action and promoting sustainable practices, providing accessible information and fostering a culture of sustainability. Moreover, AI incorporates indigenous knowledge into local models and engages local communities in climate action, ensuring that climate strategies are culturally appropriate and socially acceptable.

These findings demonstrate AI's essential role in monitoring, predicting, managing, and mitigating climate change impacts, offering valuable insights and technological innovations that support sustainable development in LDCs and SIDS. Developing countries can enhance their resilience to climate change and promote sustainable development practices by harnessing AI capabilities.

For SIDS and LDCs, AI presents a unique opportunity to leapfrog traditional development hurdles by adopting cutting-edge technologies. The inclusion of many case studies from these regions in this report—in the form of practical applications and as part of research studies—highlights the critical role these regions play in the global climate action narrative. These case studies demonstrate how AI-driven technologies are being utilized to address unique environmental challenges faced by these vulnerable areas. By focusing on LDCs and SIDS, the report emphasizes the potential of AI to foster resilience and sustainable development in regions most at risk from climate change. The report also includes case studies from developed countries to draw lessons and best practices that developing countries can adopt. However, the successful integration of AI requires targeted support in terms of capacity-building, infrastructure development, and inclusive policy frameworks.

Additionally, initiatives led by the CTCN have been instrumental in facilitating technology transfer and capacity building in these regions, helping them adapt to and mitigate the effects of climate change. Additionally, the Adaptation Fund, Green Climate Fund (GCF), Global Environment Facility (GEF), and Multilateral Development Banks (MDBs) have provided substantial financial and technical assistance to LDCs and SIDS to bolster their climate resilience. These initiatives demonstrate the collaborative effort needed at both national and international levels to ensure that AI-driven climate solutions are accessible and aligned with the capacities and needs of vulnerable regions. By leveraging these mechanisms, policymakers can better tailor climate action strategies to the specific challenges faced by LDCs and SIDS, ensuring more inclusive and equitable climate resilience.

According to United Nations Climate Change (2023a), climate finance was a major focus at COP28, with Executive Secretary Simon Stiell emphasizing it as the "great enabler of climate action." The Green Climate Fund (GCF) received a significant boost with six countries pledging additional resources, bringing the total for its second replenishment to a record USD 12.8 billion from 31 countries, with more contributions anticipated. Additionally, eight donor governments committed over USD 174 million to the LDCF and Special Climate Change Fund (SCCF), while the Adaptation Fund secured nearly USD 188 million in new pledges during the conference. Despite these positive steps, the global stocktake highlighted that these commitments fall far short of the trillions needed to support clean energy transitions, climate adaptation, and the implementation of national climate plans in developing countries. To address this gap, the global stocktake stresses the need for reforms in the multilateral financial architecture and the acceleration of innovative funding mechanisms.

However, the deployment of AI in these regions also presents notable challenges and risks. These include high energy and water consumption, concerns about data security and privacy, the digital divide, and gender bias in AI applications. Addressing these challenges is important for ensuring that the benefits of AI are equitably distributed and that the implementation of AI technologies does not exacerbate existing inequalities or create new ones. These challenges must be tackled through robust governance frameworks, ethical guidelines, and inclusive policy measures to ensure that AI negatives are minimized and AI positives are maximized.

9.2. Actionable Recommendations

The recommendations provided here are designed to guide policymakers, researchers, and practitioners in harnessing AI's transformative or supportive role in climate action in developing countries. These actionable recommendations focus on fostering international cooperation, promoting inclusive and ethical AI development, and addressing the specific challenges and opportunities identified throughout this report to advance sustainable and resilient climate solutions.

9.2.1 Integrating Artificial Intelligence in Climate Change Mitigation and Adaptation Strategies in Developing Countries

Promote AI Applications in Climate Change Mitigation and Adaptation Strategies

Recommendation:

- Encourage the use of AI and equip stakeholders with knowledge and resources about AI to leverage it effectively in reducing GHG emissions and enhancing resilience to climate impacts through supportive policies, local training programs, and the integration of AI technologies in national and regional climate strategies.

Implementation Steps:

1. Data Collection and Preparation:
    - Gather data on current energy systems, renewable energy potentials, and industrial processes.
    - Collect climate impact data relevant to community resilience.
2. Model/Tool Development:
    - Develop AI models for optimizing energy systems and integrating renewable energy.
    - Create predictive analytics tools for early warning systems and adaptive management.
3. User Interface Design:
    - Design interfaces that provide easy access to AI tools and predictive analytics for local users.
    - Implement interactive dashboards for real-time monitoring and decision-making.
4. Feature Integration:
    - Integrate multi-criteria decision analysis (MCDA) for prioritizing AI applications.
    - Include features for generating comprehensive reports and visualizations.
5. Stakeholder Engagement:
    - Involve local communities and stakeholders in the development process.
    - Provide training programs and workshops to build local expertise in AI for climate action.
6. Testing and Refinement:
    - Conduct pilot projects to test AI applications in real-world scenarios.
    - Gather feedback from users and refine the tools based on their inputs.
7. Continuous Monitoring and Evaluation:
    - Measure the intended and unintended outcomes of the AI application on a continuous basis, and make adjustments as necessary.

Example Use Case: A coastal community in an LDC uses AI to develop early warning systems for flood prediction and adaptive management practices. The AI system analyzes real-time data from weather sensors and satellite imagery to forecast flood events, providing timely alerts to residents and local authorities. This enables the community to take proactive measures, such as evacuations and reinforcing flood defenses, thereby reducing the impact of floods and enhancing resilience to climate change.

Promote International Cooperation, Infrastructure Investments, Capacity-Building, and Knowledge Sharing

Recommendation:

- Foster global partnerships and develop capacity-building programs to enhance the skills and capabilities of local stakeholders in using AI for climate strategies.

Implementation Steps:

1. Global Partnerships:
    - Establish partnerships with international organizations, developed countries, and private sector stakeholders.
2. Capacity-Building Programs:
    - Develop specialized training programs for local stakeholders in LDCs and SIDS.
    - Organize workshops and seminars on AI applications for climate action.
3. Funding Mechanisms:
    - Create international funding mechanisms to support AI research and development.
    - Allocate funds for projects focused on climate resilience.
4. Open Data Platforms:
    - Develop open data platforms and use the DPG registry for sharing climate-related data and AI models.
    - Ensure data is standardized and accessible to all stakeholders.
5. Public-Private Collaboration:
    - Encourage collaborations between public and private sectors to enhance data accessibility and transparency.

Example Use Case: A regional alliance of SIDS collaborates with international organizations to develop a shared AI platform for climate data and predictive analytics. The platform aggregates data from various sources, including weather stations, satellites, and local sensors, and uses AI to provide real-time climate insights. Stakeholders across the region, from government agencies to local communities, use the platform to make informed decisions on climate adaptation and mitigation. This collaborative approach enhances the region's collective resilience to climate impacts and fosters a culture of knowledge sharing and innovation.

Develop Inclusive and Sustainable Policies

Recommendation:

- Formulate policies that promote energy-efficient AI technologies, ensure data security, and bridge the digital divide.

Implementation Steps:

1. Energy Efficiency Policies:
    - Develop standards for energy-efficient AI technologies and green computing practices.
    - Incentivize research into energy-saving algorithms and hardware.
2. Data Security Frameworks:
    - Implement robust data protection laws and data governance frameworks.
    - Establish guidelines for data collection, storage, and sharing.
3. Bridging the Digital Divide:
    - Invest in digital infrastructure to expand internet connectivity, access to computing power, cloud infrastructure, and datasets and models.
    - Enhance digital literacy programs in underserved areas.

Example Use Case: A developing country implements policies to promote green computing, improve data security, and expand internet connectivity. The government collaborates with tech companies to introduce energy-efficient data centers powered by renewable energy. Additionally, nationwide digital literacy programs are launched to educate citizens on using AI tools effectively. These initiatives ensure that AI technologies are accessible to all, promoting inclusive growth and sustainability.

Integrate Indigenous Knowledge and Gender-Responsive Approaches
Recommendation:

- Promote inclusive AI development and deployment processes by considering the needs and perspectives of women, indigenous groups, black people, and local communities.

Implementation Steps:

1. Inclusive AI Development:
    - Engage local communities in designing AI-driven climate solutions.
    - Ensure cultural appropriateness and social acceptance of AI applications.
2. Targeted Programs:
    - Implement programs to support the inclusive participation of all social groups in AI training and deployment.
    - Develop gender-responsive AI policies to prevent perpetuating inequalities.
    - Invest in gender-disaggregated data collection that can feed AI systems more appropriately.
3. Community Engagement:
    - Involve indigenous communities in the integration of their knowledge systems with AI models.
    - Promote active participation of women in AI-related fields through education and career opportunities.

Example Use Case: An AI project in a developing country integrates indigenous knowledge and involves women in the design and implementation of climate-resilient agricultural practices. The project utilizes AI to analyze traditional farming techniques and optimize them for current climate conditions. Indigenous women lead community workshops to share their expertise and train others on using AI tools. This approach not only enhances agricultural productivity but also ensures that the benefits of AI are equitably distributed.

Establish Robust Monitoring and Evaluation Frameworks
Recommendation:

- Develop frameworks to monitor and evaluate the impact of AI applications in achieving climate goals.

Implementation Steps:

1. Impact Assessment:
    - Define performance metrics for AI applications in climate action.
    - Regularly review and assess the effectiveness of AI solutions.
2. Continuous Improvement:
    - Use evaluation results to refine and improve AI strategies.
    - Ensure alignment with sustainable development goals.

Example Use Case: A developing country uses a robust monitoring framework to assess the impact of AI-driven climate solutions. The framework includes metrics for measuring reductions in GHG emissions, improvements in community resilience, and cost-effectiveness of AI applications. Regular assessments identify successful strategies and areas for improvement, ensuring continuous progress towards climate goals.

Transparency and Accountability
Recommendation:
• Ensure transparency and accountability in AI initiatives by making data and findings publicly accessible.

Implementation Steps:
1. Data Transparency:
- Make AI data, methodologies, and findings accessible to stakeholders.
- Promote transparency through public reporting and open data platforms.

2. Accountability Mechanisms:
- Establish mechanisms to track progress and address issues in AI projects.
- Implement regular reporting and feedback loops.

Example Use Case: A national AI climate project publishes its data and findings on an open platform, ensuring transparency and fostering public trust. Stakeholders, including government agencies, NGOs, and the public, can access detailed reports and provide feedback. This open approach promotes accountability and encourages continuous improvement.

Invest in AI Research, Development, and Innovation
Recommendation:
• Allocate funding and support for AI projects addressing climate challenges in LDCs and SIDS.
• Promote and strengthen national and local innovation systems.

Implementation Steps:
1. Funding Allocation:
- Provide grants and tax incentives for AI-driven climate solutions.
- Support startups and innovation hubs focusing on AI for climate action.

2. Interdisciplinary Research:
- Promote research at the intersection of computer science and climate science.
- Facilitate collaboration between academic institutions and industry.

3. Innovation Support:
- Create supportive environments for innovation through funding and resources.
- Encourage public-private partnerships to drive AI innovation.

Example Use Case: A SIDS invests in an AI innovation hub that develops climate-resilient technologies. The hub receives government grants and private sector investment to support research and development. Startups and researchers at the hub create AI tools for disaster prediction, water management, and renewable energy optimization. This fosters local entrepreneurship, generates job opportunities, and enhances the island's overall resilience to climate change.

9.2.2. Climate Technology Processes and Funding

1. AI-Enhanced Technology Needs Assessment (TNA) Tool
Recommendation:
Develop an AI-powered TNA tool to streamline and enhance the technology needs assessment process for developing countries.

Implementation Steps:
1. Create a comprehensive database of climate technologies, including their applications, costs, and development stages.
2. Implement an LLM-based interface to guide users through the TNA process, providing context-specific suggestions and explanations.
3. Develop a ML model to analyze country-specific data (e.g., emissions profiles, economic indicators, geographical features) and suggest relevant technologies.
4. Include a multi-criteria decision analysis (MCDA) module enhanced by AI to help prioritize technology options.
5. Integrate a feature for stakeholder input collection and analysis using NLP.

Example Use Case: An LDC uses the AI-enhanced TNA tool to assess its technology needs for the agriculture sector. The tool suggests a range of appropriate technologies based on the country's climate, soil conditions, and socio-economic factors. It then guides stakeholders through a prioritization process, generating a comprehensive TNA report with justified technology selections.

2. LLM-Powered Technology Action Plan (TAP) Generator
Recommendation:
Create an LLM-based system to assist in developing detailed and actionable Technology Action Plans based on TNA outcomes.

Implementation Steps:
1. Train an LLM on a dataset of successful TAPs and best practices in technology transfer.
2. Develop a user interface that guides users through the TAP development process, prompting for necessary information.
3. Implement a module to suggest actionable steps, timelines, and resource requirements for each prioritized technology.
4. Include a feature for automatically generating draft TAP documents in multiple languages.
5. Integrate a collaboration tool allowing multiple stakeholders to contribute to and review the TAP in real-time.

Example Use Case: Following its TNA, a SIDS uses the TAP Generator to develop a detailed plan for implementing solar desalination technology. The system suggests concrete actions, estimates costs, identifies potential barriers, and proposes solutions. It generates a draft TAP document, which stakeholders collaboratively refine through the integrated review system.

3. AI-Driven GCF Readiness Proposal Developer
Recommendation:
Create an AI-powered tool to assist developing countries in preparing high-quality GCF Readiness and Preparatory Support Program proposals.

Implementation Steps:
1. Develop an LLM trained on successful GCF Readiness proposals and GCF guidelines.
2. Create an interactive interface that guides users through each section of the Readiness proposal template.

3. Implement a ML model to suggest appropriate activities and budgets based on country context and proposed outcomes.
4. Include a module for automatically checking proposal completeness and alignment with GCF criteria.
5. Develop a feature for generating visualizations and logical frameworks to strengthen the proposals.

Example Use Case: A developing country uses the tool to prepare a Readiness proposal focused on strengthening its National Designated Authority. The AI suggests relevant activities, helps formulate clear outcomes and outputs, and ensures the proposal meets all GCF requirements. The system also helps generate a clear theory of change and a detailed budget, increasing the proposal's chances of approval.

4. Integrated TNA-TAP-GCF Proposal Alignment System
Recommendation:
Develop an AI system that ensures alignment and coherence between TNAs, TAPs, and GCF funding proposals.

Implementation Steps:
1. Create a ML model to analyze the content of TNAs, TAPs, and GCF proposal templates.
2. Implement an LLM-based interface to suggest ways of aligning these documents and highlighting any inconsistencies.
3. Develop a feature for automatically transferring relevant information between TNA, TAP, and GCF proposal documents.
4. Include a module for tracking the evolution of technology needs and plans over time, suggesting updates as necessary.
5. Integrate a collaboration tool allowing various national stakeholders to work together on maintaining alignment across these processes.

Example Use Case: A country that has completed its TNA and TAP uses the system to develop a GCF funding proposal. The AI ensures that the proposed project aligns with the prioritized technologies from the TNA and the action steps outlined in the TAP. It suggests ways to strengthen the proposal by explicitly linking it to these prior analyses, increasing the likelihood of successful funding.

5. AI-Powered Climate Technology Monitoring and Evaluation Platform
Recommendation:
Create an AI-enhanced platform for monitoring and evaluating the implementation of technologies identified in TNAs and TAPs, and the progress of GCF-funded projects.

Implementation Steps:
1. Develop ML models to process various data sources (satellite imagery, IoT sensors, project reports) for tracking technology implementation.
2. Implement an LLM-based interface for generating regular progress reports and responding to stakeholder queries.
3. Create a predictive analytics module to forecast project outcomes and flag potential implementation challenges.
4. Include a feature for automated data visualization and report generation for various stakeholders (e.g., national governments, GCF, UNFCCC).

5. Integrate a learning mechanism to continuously improve technology performance benchmarks based on implementation data.

Example Use Case: A country uses the platform to monitor the implementation of a GCF-funded solar energy project identified in its TNA and detailed in its TAP. The system processes satellite imagery to track solar panel installations, analyzes energy production data, and generates monthly progress reports. It also predicts potential maintenance issues based on performance data, allowing for proactive interventions.

By implementing these recommendations, developing countries can effectively take advantage of AI to advance climate action, ensuring sustainable and inclusive development. It is imperative for policymakers, researchers, and practitioners to work collaboratively, integrating scientific research, technological development, and practical application to create a resilient future for vulnerable communities. By collectively addressing the challenges and maximizing the opportunities identified, AI can catalyze innovative solutions that benefit vulnerable communities and ecosystems worldwide.

10. Call to Action for Policymakers, Researchers, and Practitioners

In light of the findings and recommendations presented, key stakeholders must urgently collaborate to harness AI's potential in driving climate action and sustainable development.

10.1. Policymakers

Policymakers play a primary role in fostering AI innovation and ensuring its ethical and equitable use. They should implement policies that support the integration of AI in climate action, emphasizing transparency, accountability, and inclusivity. By creating an enabling environment for AI deployment, policymakers can accelerate the adoption of AI-driven climate solutions and ensure they benefit all segments of society. This includes establishing regulatory frameworks that encourage innovation while protecting data security and users' rights, providing incentives for sustainable AI applications, and promoting international cooperation to share knowledge and resources.

10.2. Researchers

Researchers are essential in advancing AI technologies and developing innovative solutions tailored to the specific needs of developing countries. Involving researchers from LDCs and SIDS in interdisciplinary research collaboration is important for shaping inclusive outcomes. All researchers are encouraged to pursue collaborative projects that bridge theoretical AI research and practical climate solutions. They should focus on interdisciplinary research that combines AI with climate science, ensuring that AI applications are grounded in robust scientific understanding. Encouraging interdisciplinary research is key to addressing the multifaceted challenges of climate change. Combining computer science and data science with environmental science and social sciences can yield comprehensive insights and innovative solutions. For instance, integrating environmental data with socio-economic models can help predict the impacts of climate policies on different communities and ecosystems. Collaboration across disciplines can foster a holistic approach to climate action, ensuring that technological advancements are aligned with social and economic realities. Indeed, it enhances the relevance and applicability of research findings.

Researchers should also focus on developing robust, transparent, and interpretable AI models that can be easily adopted by practitioners and policymakers. Engaging with local communities and incorporating indigenous knowledge can enrich AI models and make them more effective in addressing specific climate challenges. By conducting case studies, researchers can demonstrate the practical benefits of AI in climate action, providing evidence-based recommendations to guide policy decisions.

10.3. Practitioners

Practitioners, including industry leaders and community organizations, play an important role in implementing AI solutions on the ground. They should collaborate with policymakers and researchers to ensure that AI technologies are effectively integrated into existing systems and processes. By engaging local communities and incorporating indigenous knowledge, practitioners can develop AI-driven solutions that are culturally appropriate and socially accepted.

Practitioners are at the forefront of implementing AI-driven tools in climate initiatives. They should deploy these tools in climate monitoring, disaster response, and resource management, continuously monitoring their effectiveness and making necessary adjustments. Practitioners should also engage with local communities to raise awareness about the benefits of AI in combating climate change. Providing training and capacity-building opportunities can empower communities to actively participate in and benefit from AI-driven climate action.

The integration of AI into climate action strategies offers unprecedented opportunities to enhance resilience and sustainability, particularly in vulnerable regions. By leveraging the strengths and overcoming the challenges of AI, stakeholders can work together to create a future where technology and nature coexist harmoniously, ensuring a stable and healthy planet for future generations. The concerted efforts of policymakers, researchers, and practitioners are essential to harnessing the full potential of AI in the fight against climate change.

11. Implementation and Monitoring Framework

To effectively integrate AI into climate action strategies in developing countries, particularly LDCs and SIDS, a robust implementation and monitoring framework is essential. This framework will ensure that AI applications are deployed strategically, their impacts are monitored, and necessary adjustments are made to optimize outcomes.

11.1. Strategic Planning and Goal Setting

Establish clear, measurable goals for the integration of AI in climate action, aligned with national and regional climate objectives. This includes setting specific targets for emissions reduction, resilience building, and sustainability. Policymakers should collaborate with AI experts, climate scientists, and local stakeholders to define these goals and ensure they are realistic and achievable. They should also meaningfully engage women, youth, and indigenous peoples and local communities to design resilient, sustainable solutions that reflect the needs of most affected populations. And lastly, they should advocate for policies that advance the sustainable use of AI:

11.2. Stakeholder Engagement and Participation

Engage a wide range of stakeholders, including women, youth, indigenous people and local communities, private sector partners, and international organizations, in the planning and implementation process. This inclusive approach ensures that diverse perspectives are considered and that AI applications are culturally appropriate and socially accepted.

11.3. Data Management and Security

Implement robust data management practices to ensure the quality, security, and privacy of data used in AI applications. Establish guidelines for data collection, storage, and sharing, and ensure compliance with international data protection standards. This helps build trust among stakeholders and protects sensitive information.

11.4. Continuous Improvement and Adaptation

Foster a culture of continuous improvement and adaptation by regularly updating AI models and climate strategies based on new data and insights. Encourage innovation and experimentation to refine AI applications and enhance their effectiveness in addressing climate challenges.

11.5. Funding and Resource Allocation

Secure sustainable funding sources to support the long-term implementation of AI-driven climate solutions. This includes leveraging international climate finance, public-private partnerships, and grants from development organizations. Ensure that resources are allocated efficiently to maximize impact.

11.6. Policy Integration and Coordination

Integrate AI-driven climate action strategies into broader national and regional policies. Ensure coordination among different government agencies and sectors to create a cohesive and comprehensive approach to climate resilience and sustainability.

Implementing a strategic and well-coordinated framework ensures that AI applications are effectively integrated, monitored, and adapted to meet evolving climate challenges.

List of Abbreviations

AI: Artificial Intelligence
AIoT: Artificial Intelligence of Things
ANNs: Artificial Neural Networks
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
APSO: Advanced Particle Swarm Optimization
AR: Augmented Reality
ARIES: Artificial Intelligence for Ecosystem Services
ARIMA: Auto-Regressive Integrated Moving Average
ARMA: Autoregressive Moving Average
BBBC: Big-Bang–Big-Crunch
BiLSTM: Attention-based Bidirectional Long Short-Term Memory
BN: Bayesian Network
BO: Bonobo Optimizer
BOA: Butterfly Optimization Algorithm
BR: Bayesian Regularization
CAVs: Connected and Autonomous Vehicles (CAVs)
CDNN: Convolutional Deep Neural Networks
CNNs: Convolutional Neural Networks
COA: Coyote Optimization Algorithm
CS: Crow Search
CV: Computer Vision
DL: Deep Learning
DNNs: Deep Neural Networks
DPG: Digital Public Goods
DRM: Disaster Risk Management
ESM: Earth System Model
FAIS: Flood Analytics Information System
FTMA: Fine-Tuning Metaheuristic Algorithm
GA: Genetic Algorithm
GBM: Gradient Boosting Machine
GenAI: Generative Artificial Intelligence
GMDH: Group Method of Data Handling
GRU: Gated Recurrent Unit
GVC: Global Value Chain
GWP: Global Warming Potential
HCSA: High Carbon Stock Approach
HCS: High Carbon Stock
IoT: Internet of Things
IKS: Indigenous Knowledge Systems
IPM: Integrated Pest Management
IRSA: Improved Reptile Search Algorithm
IUU: Illegal, Unreported, and Unregulated (fishing)

IVR: Immersive Virtual Reality
KNN: K-Nearest Neighbors
LDCs: Least Developed Countries (LDCs)
LLMs: Large Language Models
LSTM: Long Short-Term Memory
LULC: Land Use and Land Cover
MAANN: Mode Adaptive Artificial Neural Network
ML: Machine Learning
MLFFNN: Multilayer Feed-Forward Neural Network
MLP: Multilayer Perceptron
NDCs: Nationally Determined Contributions
NLP: Natural Language Processing
ORESTE: Organization, Rangement et Synthèse de Donnes Relationnelle
POVs: Privately Owned Vehicles
PSO: Particle Swarm Optimization
RF: Random Forest
RNNs: Recurrent Neural Networks
SAVs: Shared Autonomous Vehicles
SDGs: Sustainable Development Goals
SIDS: Small Island Developing States
SRC: Stage-Discharge Rating Curve
SVM: Support Vector Machine
SVR: Support Vector Regression
Swarm ANFIS: Swarm Adaptive Neuro-Fuzzy Inference System
I2PDM: Intelligent and Integrated Pest and Disease Management
RMSE: Root Mean Square Error
MAE: Mean Absolute Error
NSE: Nash-Sutcliffe Efficiency
POVs: Privately Owned Vehicles
POEVs: Privately Owned Electric Vehicles
SAEVs: Shared Autonomous Electric Vehicles
UAV-SfM: Unmanned Aerial Vehicle-Structure from Motion
V2G: Vehicle-to-Grid
VR: Virtual Reality
VOCs: Volatile Organic Compounds
WANFIS: Wavelet decomposition functions combined with the Adaptive Neuro-Fuzzy Inference System

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