GEF/STAP/C.70/Inf.03
November 21, 2025

70th GEF Council Meeting
December 15-19, 2026
Virtual

ARTIFICIAL INTELLIGENCE AND THE GEF: STAP'S EARLY THOUGHTS

Artificial Intelligence and the GEF: STAP's early thoughts

STAP Information Note

November 2025

STAP SCIENTIFIC AND TECHNICAL ADVISORY PANEL
An independent group of scientists that advises the Global Environment Facility

gef

UN environment programme

Artificial Intelligence and the GEF: STAP's early thoughts

A STAP Information Note

Executive summary

The Global Environment Facility (GEF) plays a crucial role in addressing some of the world's most pressing environmental challenges, including biodiversity loss, climate change, land degradation, and pollution. As these challenges grow more complex and interconnected, the GEF is increasingly turning to innovation to deliver Global Environmental Benefits (GEBs) and adaptation benefits, and to accelerate system transformation. Among the most powerful technological advances shaping this future is Artificial Intelligence (AI).

AI refers to a set of technologies that enable computers to perform tasks that typically require human intelligence, such as analyzing data, recognizing patterns, or generating text. In the context of environmental sustainability, AI offers game-changing tools for improving how we monitor ecosystems, design interventions, manage risks, and track progress. However, as AI applications expand, so do the risks, which range from increased energy, water, natural resource use, and electronic waste (e-waste) generation, to societal concerns such as the widening digital divide, data gaps and bias, possible job loss, and concerns regarding transparency, accountability, and governance.

This paper, developed by the Scientific and Technical Advisory Panel (STAP) of the GEF, presents a perspective on AI's relevance to the GEF's mission. It synthesizes recent scientific literature, case studies, and expert insights to highlight how AI can be responsibly integrated into GEF-financed projects and operations, while also identifying the environmental and social risks that must be managed.

AI can support achieving all GEF focal area objectives

AI is already enhancing environmental action across all GEF focal areas. In biodiversity, AI helps detect and prevent poaching and automates species identification through image and acoustic analysis. In climate mitigation, AI optimizes renewable energy grids and monitors emissions. For

adaptation, AI strengthens early warning systems and forecasts climate impacts. AI also plays a role in managing land degradation, transboundary waters, and chemicals and waste management by enabling precision agriculture, smart monitoring, and circular economy strategies.

GEF's own portfolio includes early applications of AI, and other development partners are also advancing its use. For example, the United Nations Development Program (UNDP), through GEF funds, has deployed AI to help over 50 countries align their biodiversity strategies with global goals. A World Bank project (Project ID: 4617) also introduced AI-based automation to enhance real-time monitoring and optimize combustion processes in waste-to-energy facilities. Meanwhile, the Bezos Earth Fund's project, being implemented by the World Conservation Society (WCS), utilizes machine learning to analyze coral reef imagery 700 times faster than traditional methods, empowering local scientists, managers, and communities with the data needed to protect biodiversity, fisheries, and coastal livelihoods and achieve the global "30×30" conservation targets.

But beyond specific project applications, AI can enhance how the GEF designs, delivers, and learns from its portfolio. It can support better project design through faster synthesis of data and documents, aid in implementation through predictive analytics and real-time monitoring, and improve knowledge management and learning by extracting lessons from large volumes of reports. With tools like large language models (LLMs), AI can summarize findings, compare results, and identify emerging trends. These capabilities can make the GEF more agile, responsive, and data-driven, provided they are deployed with strong oversight and ethical safeguards.

AI adoption needs to happen responsibly

Despite its benefits, AI poses notable risks. Training large models consumes a significant amount of energy and water, often in resource-stressed regions. AI hardware depends on rare minerals, contributing to land degradation and e-waste. Socially, AI can deepen inequality if countries lack access to infrastructure or capacity. Bias in datasets can marginalize local knowledge, while opaque algorithms may reduce transparency in decision-making. Without strong governance, AI could further entrench existing power imbalances.

To mitigate these risks, a "Green-in-AI" approach is essential—one that promotes energy-efficient models, circular hardware use, carbon-aware training, and environmental reporting. Equally, social safeguards are needed to ensure AI supports, rather than displaces, communities and local expertise.

Implications and action areas for the GEF

STAP proposes that the GEF consider the following to guide its strategic approach to AI:

1. **Strengthen internal operations** by responsibly adopting AI to enhance portfolio analysis, knowledge management, and monitoring.
2. **Develop Partnership-wide AI guidance and readiness assessments**, enabling all GEF agencies to deploy AI effectively and equitably.
3. **Convene learning partnerships** to foster innovation and learning, including through collaborations with philanthropic, private, and multilateral actors.
4. **Support equitable access to AI** by investing in foundational infrastructure, open models, and AI literacy for recipient countries.
5. **Promote human oversight** in all AI applications and avoid overreliance on automated outputs, especially in high-stakes contexts.
6. **Align with international governance frameworks** such as those by the United Nations Educational, Scientific and Cultural Organization (UNESCO), the United Nations International Telecommunications Union (ITU), and the Organization for Economic Cooperation and Development (OECD), ensuring human rights and sustainability are core to AI adoption.
7. **Integrate AI considerations into environmental and social safeguards**, using global standards to address transparency, bias, and environmental impacts.

AI presents the GEF with an opportunity to scale environmental action, enhance program design and effectiveness, and drive systems transformation. But this potential must be pursued with caution, guided by principles of sustainability, inclusion, and transparency. By taking a proactive and ethical approach, the GEF can ensure that AI serves as a catalyst for global environmental progress, helping to achieve its objective of addressing the planet's most pressing challenges in an integrated way.

Table of Contents

Acronyms

AI	Artificial Intelligence
CI	Conservation International
CIERA	Conservation International Ecosystem Restoration Assistant
CODES	Coalition for Digital Environmental Sustainability
Disruptive KIDS	Knowledge, Insights and Data Services
DL	Deep Learning
ESG	Environmental, Social and Governance
GBF	Kunming-Montreal Global Biodiversity Framework
GEBs	Global Environmental Benefits
GEF	Global Environmental Facility
GPT	Generative Pre-trained Transformer
IEO	Independent Evaluation Office
IFAD	International Fund for Agricultural Development
IoT	Internet of Things
IPs	Integrated Programs
ITU	International Telecommunications Union
IWMI	International Water Management Institute
LLM	Large Language Model
LPF	Livable Planet Fund
ManglarIA	Manglar Initiative
ML	Machine Learning

MTRs	Mid-term Reviews
MWh	Mega-watt hours
NBSAPs	National Biodiversity Strategies and Action Plans
NDCs	Nationally Determined Contributions
NLP	Natural Language Processing
OECD	Organization of Economic Cooperation and Development
PAWS	Protection Assistant for Wildlife Security
POPs	Persistent Organic Pollutants
REEs	Rare earth elements
RFCx	Rainforest Connection
SLM	Small Language Model
STAP	Science and Technical Advisory Panel to the Global Environment Facility
TEs	Terminal Evaluations
UNCTAD	United Nations Conference on Trade and Development
UNDP	United Nations Development Program
UNEP	United Nations Environment Program
UNESCO	United Nations Educational, Science and Culture Organization
uPOPs	Unintentional Persistent Organic Pollutants
WaPOR	Water Productivity through Open access of Remotely Sensed Data
WCS	Wildlife Conservation Society
WWF	World Wildlife Federation

1. Introduction

The Global Environment Facility (GEF) provides financial support to help developing countries address complex environmental challenges across various focal areas, including biodiversity conservation, climate change (adaptation and mitigation), land degradation, international waters, and chemicals and waste. The GEF recognizes that traditional approaches may not be sufficient to address the complex and interconnected issues that it seeks to address. Hence, the GEF has increasingly recognized that it must embrace innovative solutions to help deliver Global Environmental Benefits (GEBs) and accelerate systems transformation. GEF's emphasis on innovation spans various domains, including technology, institutional, business models, finance, and policy innovations.[1]

Artificial Intelligence (AI) is an example of technological innovation poised to reshape how we tackle environmental challenges of interest to the GEF. AI systems promise wide applications across GEF focal areas, from climate change[2] to biodiversity loss,[3] as well as in improving operational efficiencies in project design, management, implementation, evaluation, and knowledge management and learning. On the other hand, AI is often viewed as a double-edged sword. The new opportunities it presents come with uncertainties and risks, from AI's own environmental footprint to ethical and governance dilemmas.[4]

Already, some GEF-funded projects are applying AI. The GEF Independent Evaluation Office (IEO) report on Technological Innovations noted 12 GEF-funded projects that have already adopted AI in their interventions.[5] Given the rapid advances in the development, deployment, and adoption of AI systems, it is expected that an increasing number of GEF projects will incorporate AI systems.

Given this dual nature, this STAP information note presents AI's relevance to the GEF as a forward-looking effort. It reviews both the potential benefits and risks in relation to the GEF's objectives to inform responsible adoption in GEF investments. The document presents scientific evidence

[1] As noted in STAP papers (Donaldson et al. (2023) and Toth et al. (2018).
[2] UNFCCC. (2025); WEF (2024)
[3] WRI (2025)
[4] UNEP (2025a)
[5] GEF IEO (2025)

and case studies of AI environmental applications and risks, and considers the implications for ensuring an ethical, sustainable, and inclusive application in GEF investments.

2. AI and environmental sustainability

While there is no universally agreed-upon definition for AI, it can be simply described as "a set of technologies that empowers computers to learn, reason, and perform a variety of advanced tasks that used to require human intelligence, such as understanding language, analyzing data, and providing helpful suggestions."[6] Box 1 provides an overview of AI systems.

It is essential to view AI through a sustainability lens, as it can be both a source of environmental impact and a tool for deploying environmental solutions. "Green AI" has emerged as an umbrella framework for making AI sustainable.[7] It refers broadly to prioritizing energy efficiency and environmental sustainability as a primary metric when developing and deploying AI. By contrast, "Red AI" often prioritizes higher accuracy by utilizing more computing power to address a need, resulting in significant energy consumption and carbon costs.[8] Two complementary concepts can be distinguished within the Green AI framework, offering a lens for assessing AI's role in sustainability: Green-by-AI (harnessing AI to promote sustainability in other sectors) and Green-in-AI (reducing the environmental footprint of AI development and deployment).[9]

Box 1: An overview of AI systems

AI systems can be defined as "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal."[10] It encompasses a range of computational methods

[6] Google Cloud (2023)
[7] Bolón-Canedo et al. (2024); Schwartz et al. (2019); Chan et al. (2024); Deloitte (2024); Tabbakh et al. (2024).
8 Schwartz et al. (2019); Lifset et al. (2024); Lifset et al. (2025).
9 Bolón-Canedo et al. 2024.
[10] European Commission (n.d.)

and architectures designed to mimic or augment human cognitive functions such as perception, reasoning, learning, and decision-making by combining data, algorithms, and computing power to process large and complex datasets (structured or unstructured).[11] AI systems can be rule-based, using explicit logic and expert-defined rules, or adaptive, where performance improves autonomously as new data becomes available.[12]

Machine Learning (ML) is a subfield of AI in which models are trained to recognize patterns in data. Once trained, ML models can make predictions on data they have not seen, implying that they develop the capacity to act without being explicitly programmed.[13] ML algorithms, trained on historical datasets, can make predictions or classifications, for example, identifying land-use changes or optimizing renewable energy grids.[14]

Deep Learning (DL), also known as Deep Neural Networks, is a subset of ML, which employs multiple-layered artificial neural networks to enable AI systems to recognize patterns (e.g., imagery, audio, or sensor readings) in input data and perform decision-making processes similar to those of a human brain. DL techniques have achieved breakthroughs in environmental monitoring, including automatic detection of coral bleaching.[15]

Natural Language Processing (NLP) is another subfield of AI that enables the processing of human language data (e.g., speech or text), allowing AI systems to understand, interpret, and generate meaningful insights from human language.[16] This can be helpful for extracting early-warning signals from global news and social media streams or analyzing information streams to detect emerging risks.[17]

Large Language Models (LLMs), trained on vast amounts of data, can enhance NLP capabilities by performing reasoning, translation, and synthesis across multiple domains; hence they can help accelerate knowledge discovery and integration, automatically synthesizing scientific literature, environmental assessments, and policy documents to inform project design and learning.

[11] Russell & Norvig (2021)
[12] Goodfellow et al. (2016).
[13] Janiesch et al. (2021).
[14] Wang et al. (2022); Donti and Kolter (2021).
[15] González-Rivero (2020).
[16] Jurafsky and Martin (2023).
[17] Tounsi and Temimi (2023).

Small Language Models (SLMs) are emerging as an important aspect of AI. SLMs are trained to process, understand, and/or generate natural language, but with a significantly smaller parameter count and reduced resource requirements compared to LLMs, without a significant reduction in performance.[18]

Several other subfields and subsets enable AI systems to perform additional functions.[19] To generate accurate, unbiased, and contextually relevant outputs, AI systems must be trained on diverse, high-quality, and sufficiently large datasets that capture the variability and complexity of the real-world phenomena they aim to model. Hence, the lifecycle of an AI system typically begins with identifying the problem to be solved, followed by collecting and preparing relevant data. This includes data acquisition, cleaning, and pre-processing to ensure quality and representativeness. The next stages involve building and training the model using appropriate algorithms, evaluating its performance, and iteratively refining it, often by obtaining additional or higher-quality data, until the system meets the desired performance criteria.

2.1 Green-by-AI: Harnessing AI for environmental benefits

Green-by-AI refers to utilizing AI as a tool to drive sustainability outcomes in other domains–in the context of the GEF, to generate GEBs, adaptation benefits, and facilitate system transformation. This involves harnessing the power of AI (large-scale data analysis, pattern recognition, and optimization) to address environmental challenges. In other words, Green-by-AI asks: How can AI help solve environmental problems or green other sectors?

Green-by-AI is a rapidly growing area offering significant potential to generate GEBs and adaptation benefits across the GEF areas of work. Here, we present a review of examples of Green-by-AI applications across GEF focal areas. Box 2 summarizes some AI applications within and outside the GEF Partnership.

[18] Corradini et al. (2025); Caballar (2025)
[19] Allen (2020).

For biodiversity, AI, combined with the Internet of Things (IoT) and remote sensing technologies, can aid in environmental monitoring, including for the detection, prediction, and prevention of deforestation[20] and to support species conservation efforts.[21] For example, in anti-poaching efforts, the Protection Assistant for Wildlife Security (PAWS) AI system analyzes patrol and terrain data to predict poaching risk levels in wildlife preserves, thereby enabling rangers to target patrols more efficiently.[22] Other applications include automated acoustic sensors with machine learning to recognize species' calls or illicit sounds (e.g., gunshots) from continuous audio recordings.[23] See Box 2 for examples, including those for coral reef monitoring, deforestation prevention, and anti-poaching efforts.

For climate change mitigation, AI can be utilized across various sectors, including power, food, manufacturing, transport, aviation, and building.[24] For example, it has been used to inform and optimize the deployment of renewable energy systems, as well as to enhance energy efficiency by optimizing energy production and consumption.[25] AI-powered emission monitoring systems can identify hotspots of greenhouse gas emissions and track changes over time to inform mitigation efforts.[26] Due to its ability to process vast datasets and run complex simulations, AI has been utilized to enhance the modeling of climate systems, informing behavioral change and policy interventions across various sectors and under diverse scenarios.[27]

AI can enhance climate change adaptation (and resilience) through climate-impact forecasting, early warning systems, and improved financial and human risk management, enabling more strategic and anticipatory adaptation planning.[28] For example, AI systems have been utilized to enhance water management during droughts by optimizing water resource allocation, thereby improving resilience, e.g., through early detection of water leakages, or mitigation of the impacts of water stress.[29]

---

[20] Haq et al. (2024).
[21] Ullah et al. (2025); Wang et al. (2025); Lynam et al. (2025).
[22] Zewe (2019).
[23] Browning et al (2017).
[24] Sandalow (2024).
[25] Biswas (2024); Ukoba et al. (2024).
[26] Adegbite et al. (2024); Whig et al. (2025); Olawade et al. (2024); Climate Trace (2025).
[27] Stern et al. (2025).
[28] Stern et al. (2025); Cowls et al.(2023); Olawade et al. (2024); Camps-Valls et al. (2025).
[29] Lakhiar et al. (2024).

For land degradation, AI-powered systems are increasingly instrumental in combating land degradation and advancing ecosystem restoration by enabling high-resolution monitoring, predictive modelling, and targeted intervention strategies.[30] AI has been deployed to detect early indicators of land degradation, such as soil erosion[31] and nutrient depletion[32] and to predict the onset of desertification.[33] It has also been applied in agriculture to enable precision farming and facilitate agroecological practices, yielding benefits such as increased crop productivity, reduced resource use, and lower environmental impacts, including the pollution of ground and surface water reservoirs.[34]

In the context of international waters, AI is being leveraged to strengthen transboundary water resources management by enhancing data sharing, forecasting, and collaborative governance of shared water resources.[35] For example, in the Limpopo River Basin, a complex system spanning four countries, the International Water Management Institute (IWMI) and Microsoft developed an AI-driven “Water Copilot” that integrates real-time river and dam data with a digital twin (virtual replica of real real-world object or, system, or process) to generate science-based insights for basin managers.[36] Furthermore, AI systems have been deployed to support the detection and policing of illegal fishing[37] and for monitoring coral reef health,[38] plastic pollution,[39] marine biodiversity,[40] and fish stock dynamics.[41]

Lastly, for chemicals and waste, AI systems help to enhance industrial process efficiency, enabling advanced monitoring of chemical use and emissions, and underpinning circular economy strategies such as materials reuse and resource recovery.[42] For instance, AI can optimize process conditions to minimize hazardous by-products, reduce raw-material input, and extend asset lifespans, supporting waste reduction and circular flows of materials.[43] Additionally, AI systems,

---

[30] Moorthy, S. (2025).
[31] Selmy et al. (2025); Parajuli et al. (2025); Ikram et al. (2025).
[32] Borah et al. (2025).
[33] Alsubai et al. (2025).
[34] Schöning et al. (2021); Warrik & Borthakur (2024); Sustainability Directory (2025a).
[35] For example, Bocchino and AtKisson (2020); AtKisson. (2024).Sustainability Directory (2025a); Kim and Ahmad (2025).
[36] IWMI (2025).
[37] Zuzanna et al.(2022); Klawikowska et al (2022).
[38] Latha et al. (2024); Nunes et al. (2020).
[39] Perera et al. (2025a).
[40] Lal et al. (2024).
[41] Mandal et al. (2024).
[42] O’Connell-Hussey et al. (2025).
[43] Ellen MacArthur Foundation (2019); Kumar and Shahin (2025); O’Connell-Hussey et al. (2025).

including machine learning and computer vision, are utilized to detect and sort waste streams with high precision, thereby enhancing recycling rates and minimizing contamination. [44] Furthermore, AI is being leveraged to enable industries to gain deeper insights into their waste-generation patterns, identify opportunities for reduction, and implement more effective waste-management strategies,[45] and it can also be deployed to support the rapid prediction of chemical toxicity and the design of mitigation measures. [46] AI systems can potentially accelerate the transition to circular business models by designing circular products, operating circular infrastructure (e.g., reverse logistics, remanufacturing), and optimizing resource flows across scales.[47]

Box 2: Case studies of Greening-by-AI within and outside the GEF Partnership

This box provides a summary of examples of Green-by-AI applications across GEF focal areas. Details of each example can be found in the accompanying citations.

The World Bank has invested $200 million as seed funding in the Livable Planet Fund (LPF) and its **Livable Planet Observatory**. The LPF aims to incentivize middle-income countries to address critical global challenges with a fundraising goal of $400 million by the end of 2025. The Livable Planet Observatory is a digital initiative that leverages knowledge, insights, and data to drive evidence-based decisions for sustainable, climate-resilient development. The Geospatial Platform provides the core geospatial data infrastructure, while the **Disruptive KIDS (Knowledge, Information and Data Services) platform**[48] acts as the content and product layer interface that develops and curates interactive tools from a myriad of sources. The World Bank is also developing its **Geoinsight platform**, which will enable users to interact with geospatial data, facilitating the easier generation of insights and predictions. It will also develop digital environmental profiles and digital twins for all financed projects, enabling more holistic planning. While these tools are still in early stages, they hold significant potential to transform how data is

[44] Antony et al. (2024); Raut et al. (2025); Snoun et al. (2025); Fang et al. (2023); Yu et al. (2021).
[45] EnicompMedia (2025).
[46] Pérez et al. (2021).
[47] Ellen MacArthur Foundation (2019); Huang et al. (2025).
[48] https://spatialagent.org/KIDS/

used to drive more adaptive, inclusive, and impactful solutions across different sectors[49]. The World Bank also worked with China to deploy AI in a GEF-5 municipal solid waste management project approved in 2014.[50] The project introduced AI-based automation to enhance real-time monitoring and optimize combustion processes in waste-to-energy facilities, thereby supporting improved operational efficiency and reduction in dioxin (uPOPs) and other pollutant emissions.

The World Wildlife Foundation (WWF)'s Manglar Initiative (ManglarIA)[51] uses machine learning models developed with support from Google.org to analyze satellite imagery and environmental data, creating a model that informs climate-smart ecosystem conservation. By informing policies that reduce transboundary pressures and strengthen natural defenses against climate impacts, ManglarIA enhances the management of shared large marine ecosystems in the Gulf of Mexico and Caribbean. Positioned at the intersection of climate mitigation, adaptation, and international waters, it integrates AI-driven monitoring with ecosystem-based planning to advance sustainable blue carbon solutions and climate-resilient livelihoods. WWF also developed the **SpeciesNet** open-source AI model for automatically classifying camera-trap images of wildlife.[52] Camera traps produce millions of images that SpeciesNet can sift through in minutes.[53] Trained by WWF/Google on a globally diverse set of ~65 million images, it recognizes over 2,000 species and higher taxa. The model detects animals in 99.4% of images and correctly identifies species in approximately 94–98% of cases. SpeciesNet has dramatically accelerated biodiversity surveys (e.g., identifying 37 jaguars in Peru) and can aid anti-poaching monitoring. By speeding image review, it delivers near-real-time data to inform conservation decisions.

The United Nations Environment Program (UNEP) is deploying AI to enhance global pollution monitoring. Through its **International Methane Emissions Observatory**,[54] satellite imagery and machine learning enable the detection of major methane releases, facilitating rapid mitigation. In the oil and gas sector, government and company responses to satellite-based alerts increased

[49] Kim & Damania (2025).
[50] China - Global Environment Facility (GEF) Municipal Solid Waste Management Project: environmental assessment (Vol. 9 of 9): Executive summary of environmental assessment (English). China: s.n. http://documents.worldbank.org/curated/en/717791468218393308
[51] WWF (2023).
[52] Google (2025).
[53] Hehmeyer (2025).
[54] UNEP (2025b); UNEP (2025c); UNEP (2025d)

by more than tenfold last year[55]. To combat plastic pollution, UNEP partnered with Google to apply AI to geospatial and citizen-science data to map and understand the magnitude of the plastic pollution in the Mekong River system and strengthen regional capacity for targeted interventions through its CounterMEASURE **project** with the Government of Sri Lanka.[56]

Conservation International's CIERA (Conservation International Ecosystem Restoration Assistant) is an AI-powered restoration tool developed with support from Microsoft's AI for Good initiative.[57] It utilizes satellite imagery, ecological data, and machine learning, combined with information pulled from public policies, government guidelines, and scientific articles, to identify degraded landscapes and recommend tailored, nature-based restoration strategies. CIERA rapidly identifies priority areas where restoration can deliver the greatest benefits for people, nature, and climate. It allows anyone—rural landowners, local community members, policymakers—to get detailed and personalized information to inform ecosystem restoration decision-making, making restoration efforts smarter and more scalable.[58]

The Food and Agriculture Organization of the United Nations launched an AI-enabled monitoring and early warning system, **FAMEWS,** to help farmers sustainably manage the invasive fall armyworm.[59] Users submit smartphone photos through an app, which AI confirms and geotags to populate a live global map and improve targeted interventions. As of 2024, over 10,000 users in more than 60 countries contributed FAW sightings. Additionally, the FAO developed **WaPOR** (Water Productivity through Open-access of Remotely Sensed Data)–a public, database built on satellite imagery to monitor agricultural water use efficiency.[60] WaPOR helps identify irrigation gaps and optimize water allocation under conditions of drought and land degradation.[61] For example, the WaterPIP project utilized WaPOR datasets, combined with machine learning, in its "DroughtObserve" system to map and forecast drought intensity across

[55] UNEP (2025d)
[56] MRC (2021); UNEP (2021); Zweig List (2021).
[57] McCoy (2025).
[58] McCoy (2025)
[59] FAO (2024)
[60] FAO (2021); IHE Delft Institute for Water Education. (2016); IWMI (2021)
[61] IWMI (2024).

Africa and the Middle East and North African region.[62] These capabilities support policymakers and farmers in closing water productivity gaps and building more water-resilient agriculture.

Climate TRACE offers one of the most advanced real-world applications of AI for global emissions monitoring. Using satellite imagery, remote-sensing data, and machine-learning models, the coalition produces independent, facility-level greenhouse gas estimates across major sectors, including power, oil and gas, industry, and land use, often revealing emissions that are far higher than self-reported figures. For example, Climate TRACE identified significant under-reported methane emissions from oil and gas facilities in multiple countries, enabling governments and investors to target high-impact mitigation actions.[63] This AI-enabled transparency enhances global accountability and supports more effective climate policy interventions.

Rainforest Connection (RFCx) uses AI-enabled acoustic monitoring to detect illegal logging and protect biodiversity in remote tropical forests. By deploying solar-powered "Guardian" devices that capture real-time forest sounds, RFCx trains machine-learning models to recognize the sounds of different species as well as those of chainsaws, trucks, and gunshots amid complex natural soundscapes. RFCx operates in 37 countries to date, monitoring over 730,000 hectares of forest and providing protection for more than 400 threatened species.[64] Examples of cases include the Tembé Tribal Reserve in Brazil, Alto Mayo in Peru, and Cerro Blanco in Ecuador.[65]

LandCoverNet is an open-access global training dataset for AI-driven land-cover mapping, built by the Radiant Earth Foundation. It combines high-resolution satellite imagery with seven key land-cover classes labeled by experts.[66] The latest global version contains 8,941 image chips, enabling AI models to train and produce high-resolution annual land-cover maps.[67] Such maps can reveal land-use changes (e.g., deforestation, cropland expansion, urban growth) and are vital for biodiversity and ecosystem monitoring, and can support tracking of achievement of GEBs and Sustainable Development Goals.

---

[62] FAO (2025); FAO (2020).
[63] Climate Trace (2023).
[64] Rainforest Connection (n.d). Tropical Commons (2018).
[65] Tropical Commons (2018).
[66] See https://gee-community-catalog.org/projects/lcnet/
[67] MundoGeo (2022)

The Bezos Earth Fund's AI for Climate and Nature Grand Challenge, a $100 million initiative launched in 2024, has provided funding for a range of initiatives using AI to address climate and nature challenges, including optimizing electric vehicle charging for renewable grid stability, detecting poaching and monitoring biodiversity via sound, designing an open-source AI model for sustainable protein products, using AI to assemble and interpret genomes for endangered species conservation, deploying edge AI to curb illegal fishing in the Pacific, and building an AI platform to convert food waste into microbial protein, among others. Award recipients also include the Wildlife Conservation Society (WCS)'s "Coral Watch: AI Reef Protection Network." WCS, with support from Amazon Web Services, Google.org, NVIDIA, and Microsoft, is scaling its open-source coral MERMAID platform[68] to apply AI-driven image analysis to reef monitoring.[69] The system ingests diver- and citizen-scientist-submitted reef photos and uses machine learning to classify coral species, processing imagery roughly 700 times faster than manual methods. An AI model is being trained to recognize over 100 coral species and generate real-time maps of climate-resilient reefs. These tools aim to vastly expand reef survey coverage (working toward monitoring 100% of the world's reefs by 2030[70]) and to pinpoint the reefs best able to survive warming seas. By empowering local scientists, managers, and communities with this data, the project aims to protect biodiversity, fisheries, and coastal livelihoods and help achieve the global "30×30" conservation targets.

2.2 Environmental impacts of AI

While AI offers promising benefits for sustainability, it also contributes to significant direct and indirect environmental pressures. These risks arise throughout the AI lifecycle, from semiconductor manufacturing to model training, deployment, and end-of-life disposal. Understanding these adverse impacts is crucial for informed adoption and governance. This section discusses the environmental impacts of AI systems, which serve as a basis for the discussion of Green-in-AI (Section 2.3).

[68] WCS (n.d.)
[69] Bezos Earth Fund (2025)
[70] Amazon Web Services (2025)

Energy demand and climate change impacts: AI systems, especially large deep-learning models, are highly energy-intensive. Training state-of-the-art models can require hundreds of megawatt-hours of electricity, resulting in substantial greenhouse gas emissions when grids remain dependent on fossil fuels.[71] Analysis showed that training a single NLP model emitted 284 metric tons of CO_2e–five times the lifetime emissions of an average car.[72] Similarly, training large transformer models can require several hundred megawatt-hours (MWh), depending on hardware efficiency.[73]

Water consumption and hydrological impacts: AI systems can indirectly and directly drive increased water consumption, primarily for server cooling and electricity generation.[74] During the training of Generative Pre-trained Transformer 3 (GPT-3), Microsoft used a total of 700,000 liters of freshwater for onsite cooling. The global AI water demand is projected to reach up to 6.6 billion cubic meters of water withdrawal by 2027–exceeding the total annual water withdrawal of Denmark or half of the United Kingdom.[75] The location of major data centers in water-stressed regions has also exacerbated local water scarcity, for example, in India and China[76]. This creates social and environmental trade-offs, as communities increasingly compete with digital infrastructure for limited hydrological resources.

Land use, materials demand, and supply-chain pressures: AI depends on high-performance computing infrastructure and advanced semiconductor manufacturing, both of which are resource-intensive.[77] Semiconductor fabrication requires substantial quantities of silicon, cobalt, rare earth elements, copper, and water, generating upstream environmental pressures. Producing a single 2-kg computer requires ~800 kg of raw materials, reflecting the magnitude of resources needed to be extracted.[78] Mining of cobalt, nickel, and rare earth elements (REEs), critical for AI hardware, is associated with land degradation, deforestation, heavy-metal contamination, and

[71] Royal Academy of Engineering (2025).
[72] Strubell et al. (2019); ITU (2024)
[73] Patterson et al. (2021).
[74] Royal Academy of Engineering (2025).
[75] Li et al. (2023).
[76] Mytton et al. (2021); Krishnamurthy (2025); Jiang et al. (2025).
[77] Royal Academy of Engineering (2025).
[78] UN (2024).

community health impacts.[79] As AI adoption drives increased demand for such materials, cumulative environmental pressures could intensify in already vulnerable mining regions. Additionally, data center land consumption is also accelerating, with large-scale facilities requiring 10–50 hectares each, and the needed land area expected to triple by 2030.[80]

Electronic waste and end-of-life impacts: AI hardware has a short operational lifespan (1-3 years) due to rapid performance improvement cycles.[81] This accelerates electric waste (e-waste) generation, already one of the world's fastest-growing waste streams. In 2022, global e-waste reached approximately 62 million metric tons, with AI-relevant categories (such as servers, chips, and data-center cooling components) projected to rise significantly.[82] Improper disposal results in the leakage of hazardous substances, including lead, mercury, and flame retardants (persistent organic pollutants, or POPs), posing risks to soil, groundwater, and human health. The Basel Convention Secretariat reports that only approximately 17% of global e-waste is formally recycled, meaning the vast majority enter uncontrolled waste streams, often in low-income countries.[83]

Indirect and system-level environmental effects: Beyond discrete lifecycle impacts, AI contributes to system-level environmental risks. Increased demand for AI workloads can delay the retirement of fossil-fuel power infrastructure.[84] Infrastructure buildouts (power lines, substations, cooling towers) for AI systems carry their own land and ecological footprints. Additionally, AI can produce rebound effects, as efficiency gains in computing lower the cost of running models, potentially leading to increased total usage.[85] Without governance, efficiency improvements may paradoxically have unintended adverse environmental consequences.

2.3 Green-in-AI: Reducing the environmental footprint of AI

Green-in-AI focuses on reducing the environmental footprint of AI system development, training, deployment, and hardware lifecycles, as discussed above. It considers the lifecycle of AI through development, deployment, monitoring, and management (Box 1 and Figure 1). Green-in-AI

[79] UNEP (2020); Ali et al. (2017).
[80] Roundy (2025).
[81] Kshirsagar (2025).
[82] Balde et al. (2024).
[83] Balde et al. (2024).
[84] Kearney & Gardner (2025).
[85] Ertel et al (2025); Sorrell et al. (2020).

provides a sustainability framework to ensure AI deployment aligns with climate and environmental goals.[86]

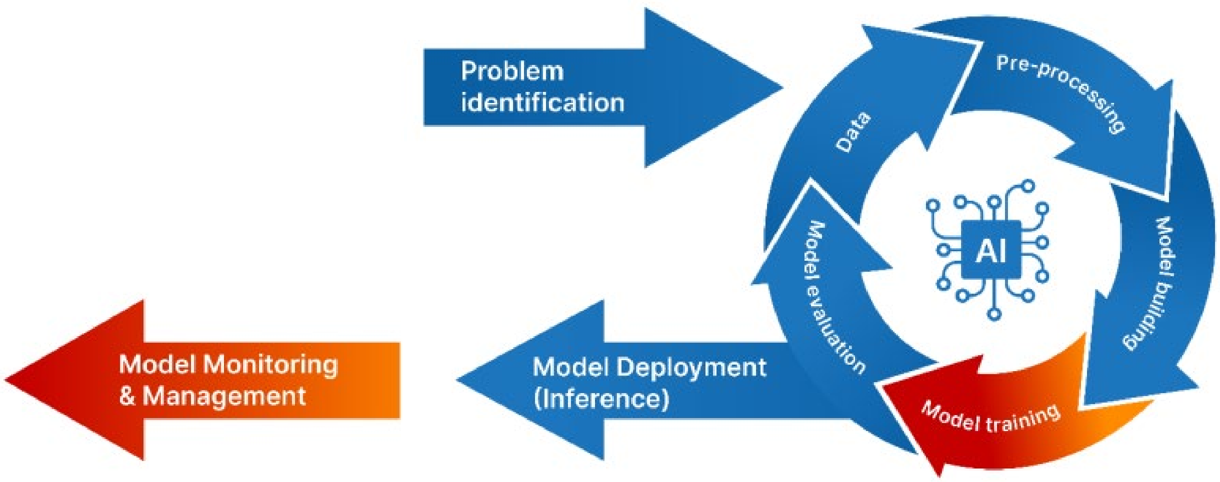

Figure 1: The lifecycle of AI. The AI lifecycle is a continuous, iterative process that moves through several key stages. It begins with problem identification (defining the specific challenge to be addressed by AI). Next, data is collected, followed by pre-processing, during which the data is cleaned, transformed, and prepared for modelling. Model building involves designing the appropriate AI architecture, while model training teaches the model to learn patterns from the processed data. The system then undergoes model evaluation to ensure accuracy and effectiveness against defined metrics. If not satisfactory, the process is repeated, for example, after incorporating additional data. After validation, the model is made operational in real-world settings (model deployment). Finally, model monitoring and management continuously track performance, ensuring the model remains reliable and prompting updates that may loop back to earlier lifecycle stages. Source: Adapted from The United Nations International Telecommunications Union (ITU).[87]

[86] Bolón-Canedo et al. (2024); Schwartz et al. (2019); Deloitte. (2024); Tabbakh et al. (2024).
[87] ITU (2024).

A core pillar of Green-in-AI is **enhancing model efficiency** by reducing computational requirements while maintaining model performance.[88] For example, smaller or domain-specific models, such as SLMs, can achieve competitive performance on targeted tasks with a fraction of the energy and material cost of large general-purpose models.[89]

Green-in-AI also involves **adopting efficient training and deployment practices**. Transfer learning[90] and few-shot learning[91] reduce the need for full retraining on large datasets, while carbon-aware scheduling aligns energy-intensive training with periods of low grid carbon intensity or high renewable generation.[92] These approaches directly help mitigate AI's contribution to climate-related emissions. Ensuring that AI workloads operate on renewable or carbon-free electricity is an increasingly important part of Green-in-AI strategies, along with locating facilities in cooler climates and integrating data center cooling with water generation to reduce both energy and water demands.[93]

Material efficiency and circularity are increasingly central to Green-in-AI. Embodied emissions from hardware manufacturing can account for a significant share of AI systems' overall environmental footprint. Green-in-AI promotes longer-lived, modular hardware, refurbishment pathways, design for repairability, and compliance with circular-economy and extended-producer-responsibility frameworks.[94]

Green-in-AI requires **transparency and environmental reporting**. Tracking the computational demand, energy use, carbon intensity, and water footprint associated with model training enables accountability and supports informed evaluation of environmental trade-offs.[95] Using **open-source models** or **pre-trained systems** can reduce redundant training cycles, enabling smaller institutions to benefit from cutting-edge tools without incurring additional environmental costs.[96]

[88] Różycki et al. (2025).
[89] Kumar et al. (2025).
[90] Transferring knowledge gained through one model training to another instead of new training altogether (Murel 2025).
[91] Few-shot learning allows models to generalize from a very small number of labeled examples, rather than requiring massive datasets (IBM n.d.)
[92] Patterson et al. (2021).
[93] Karimi et al. (2025); Magrini at al. (2017).
[94] Ellen MacArthur Foundation (2019).
[95] Strubell et al. (2019).
[96] Alzoubi and Mishra (2024).

3. Harnessing AI for GEF operations and portfolio management

Beyond its specific application across focal areas, the GEF can leverage AI to enhance the design, execution, and oversight of its project portfolio, as well as to streamline operations. Development sector agencies already utilize AI to streamline operations and simplify data analysis, while enabling more advanced capabilities, such as predictive analytics and decision support.[97]

3.1 AI in project design and planning

Integrating AI at the project design stage can inform project interventions. Generative AI tools can collate past project data and technical literature to inform the crafting of well-aligned projects. A study commissioned by the evaluation units of the Adaptation Fund, Climate Investment Funds, Green Climate Fund, and the GEF noted that LLMs can significantly enhance the quality and time-effectiveness of proposal development, helping to generate overlooked ideas and information.[98] (It is, however, essential to prioritize SLMs that can achieve similar performance with lesser environmental impacts).

AI-driven analysis can also support strategic planning by sifting through vast environmental datasets to pinpoint priority areas and effective solutions. For example, the UNEP and the United Nations Conference on Trade and Development (UNCTAD) employ AI to model the impacts of public financing on biodiversity and climate outcomes, while FAO applies AI-driven remote sensing for near-real-time data on water and agricultural productivity.[99] The International Fund for Agricultural Development (IFAD)'s example in Box 3 illustrates how AI can be utilized to analyze vast datasets and inform decision-making. By leveraging similar capabilities, the GEF agencies can base project designs on richer evidence, modeling various scenarios to ensure interventions consider all aspects, and the GEF can utilize the generated knowledge to inform its strategy and policies.

[97] The Borgen Project (2023).
[98] AF-TERG, CIF, GEF IEO, GCF IEU (2025).
[99] UNDP (2024).

AI's predictive analytics can forecast environmental trends or project outcomes, allowing planners to anticipate challenges and optimize project objectives and resource allocations.[100] This can help align projects more closely with global environmental goals and the targets of the Multilateral Environment Agreements for which the GEF serves as a financing mechanism from the outset.

However, it is essential to note that generative AI systems can produce plausible-sounding but false information (a phenomenon known as "hallucination"),[101] which poses significant risks in high-stakes contexts such as proposal development, strategic planning, or evaluation. Guarding against this risk requires robust human oversight (human-in-the-loop[102]), thorough factual validation, and responsible deployment to ensure output remains accurate and trustworthy.

3.2 AI for implementation, monitoring, evaluation, and adaptive management

During project implementation, AI can serve as a real-time decision-support and monitoring aid. AI-powered systems can analyze incoming project data across multiple indicators and geographies, providing continuous performance tracking and early warning on issues. Advanced algorithms can automatically flag anomalies or deviations from expected patterns, enabling proactive management and rapid course corrections.[103] For instance, machine learning models can detect if a conservation project's deforestation rates diverge from targets or if a climate adaptation project faces emerging risks, prompting timely adjustments.

With high-quality and relevant data, the right model, strong evaluation, and ongoing governance, AI-driven predictive analytics can help project teams anticipate risks such as conflict outbreaks, climate-related disruptions, or operational bottlenecks[104] so that mitigation measures can be taken in advance. In the GEF context, where projects often operate in complex environments, these predictive insights can safeguard project outcomes and improve resilience. For example, the World Food Programme's HungerMap LIVE[105] uses machine-learning predictive analytics to

[100] Wai (2025); Matthews (2024); Das (2025).
[101] GAO (2025).
[102] "Human-in-the-loop (HITL) refers to a system or process in which a human actively participates in the operation, supervision or decision-making of an automated system. In the context of AI, HITL means that humans are involved at some point in the AI workflow to ensure accuracy, safety, accountability or ethical decision-making." (Stryker n.d.)
[103] EvalCommunity Academy (2025).
[104] Sablich (2025).
[105] See: https://innovation.wfp.org/project/hungermap-live

forecast food insecurity 30–60 days ahead in highly complex, conflict- and climate-affected environments such as Yemen, Mali, Syria, and Nigeria. By integrating data on conflict events, weather, prices, macroeconomic shocks, and mobile phone surveys, the system reliably anticipates emerging hunger hotspots and informs operational decisions, such as scaling assistance or prepositioning supplies.[106] Furthermore, AI-driven environmental monitoring can enable near-real-time environmental monitoring and evaluation of project impacts, reducing reliance on infrequent field surveys.

AI can facilitate coordination across the GEF Partnership by integrating data from multiple agencies. Shared AI platforms might analyze cross-agency project data to spot synergies or overlaps, or to ensure coherence in multifaceted initiatives. Additionally, AI can be utilized to analyze or evaluate policies within or across countries or regions to assess their coherence and inform project design and implementation strategy.[107] Indeed, pilots suggest that AI can uncover the drivers of effective policy coherence by parsing through diverse policy documents (see Box 3 for an example from UNDP), offering insight into how different policies and projects can reinforce each other.[108] Harnessing such capabilities will enable the GEF to function more as an integrated network, aligning efforts across its implementing agencies, focal areas, and Integrated Programs (IPs).

Overall, infusing AI into implementation, monitoring, and evaluation may enable the GEF to transition from periodic, hindsight-focused reviews to continuous, forward-looking oversight that learns and adapts over time, making projects and programs more responsive and outcome-driven, and enhancing adaptive management.

3.3 AI for knowledge management and learning

With a portfolio spanning thousands of projects and decades of lessons, the GEF stands to gain immensely from AI-driven knowledge management. The GEF's IEO already hosts data from over 2,000 evaluated projects[109]—a trove that AI can mine for insights. The various mid-term reviews

---

[106] Foini et al. (2023)
[107] OECD (2025).
[108] UNDP (2024).
[109] See: https://www.gefieo.org/en/data-rating

(MTRs) and terminal evaluations (TEs) are also a rich source of knowledge that can inform future GEF investments. Indeed, the IEO indicated that it used AI in a supportive role in preparing the Eighth Comprehensive Evaluation of the GEF (OPS8)[110] and plans to utilize AI in the future to extract lessons learned from MTRs and TEs.[111]

Similarly, GEF-related data and information are available across the 18 agencies, and NLP algorithms can review vast libraries of these documents, technical reports, and evaluations, extracting valuable patterns and lessons across focal areas. Language models can summarize lengthy reports, compare documents, extract key information, and analyze themes or sentiments across textual data far more quickly and efficiently than manual analysis.[112] By deploying AI-based knowledge platforms, the GEF partnership could query past experiences and instantly retrieve synthesized answers drawn from its collective experience to inform decision-making. See IFAD's example in Box 3.

Additionally, AI can be deployed to synthesize cross-country lessons from the GEF IPs, identifying systemic leverage points and best practices across targeted systems and sectors, and can catalyze peer-to-peer learning and collaboration. It can help connect the various IP knowledge platforms, thereby facilitating interoperability.[113] The GEF can also use AI to rapidly analyze diverse project IP data to identify high-impact interventions and monitor environmental progress at scale, supporting innovation, coordinated action, and adaptive management across countries and agencies.

It is, however, essential to note that AI tools do not replace human judgment; instead, they serve as intelligent assistants that highlight connections in data and surface evidence that might otherwise remain hidden. Hence, their use should be subject to rigorous human oversight, transparent validation processes, and clear accountability frameworks that define when and how human experts must review, approve, or override AI-generated outputs.

[110] GEF-IEO (2025b)
[111] Personal communication between STAP Chair and the IEO Director.
[112] AF-TERG, CIF, GEF IEO, GCF IEU (2025).
[113] Jarrahi et al. (2023); Market Logic (2025).

Box 3: Case studies of AI applications in operations, portfolio management, and governance

The case studies in this box demonstrate how AI has been used in organizational operations, portfolio management, and approaches to addressing safeguards and governance issues. Details of each example can be found in the accompanying citations.

Conservation International (CI)[114] is actively integrating AI to enhance both **internal operations and environmental programming**. It has established an internal AI working group, launched AI literacy initiatives across its teams, and created a centralized inventory of AI projects to streamline learning and collaboration. Operationally, CI has deployed AI-powered tools, including Microsoft Copilot and Power BI, to automate and accelerate project monitoring and evaluation processes. For example, CI's GEF Monitoring and Evaluation team is utilizing a natural language-enabled dashboard to extract data from project documents, enabling them to respond to evaluation queries more efficiently and significantly reducing data processing times from days to hours. These tools support knowledge management, workflow optimization, translation, and communications, thereby improving staff efficiency and enabling more timely decision-making. CI's approach demonstrates how tailored AI integration, supported by internal capacity-building, can lead to measurable improvements in organizational effectiveness.

UNDP's AI for Kunming–Montreal Global Biodiversity Framework (GBF) Early Action Support,[115] **funded by the GEF**, deploys AI to support 54 countries in **aligning their national biodiversity strategies with the GBF**. Using OpenAI's GPT-3.5, UNDP conducted 62 national assessments covering over 3,000 biodiversity targets, producing actionable insights and alignment scores (high, medium, low, or no similarity) for each country in a matter of hours–work that would otherwise have taken weeks or months. The output helps countries identify policy gaps and coherence, raise political will, and demonstrate resource needs to potential donors. These AI-generated outputs were validated by national experts, ensuring contextual relevance and reducing risks of misinterpretation or bias. The process also adhered to principles of

---

[114] Based on a presentation by CI's Carly Batist at the STAP virtual workshop on "Maximising the Benefits and Managing the Risks of AI in the GEF", 4th November 2025.

[115] Based on UNDP's Juan Calles López presentation at the STAP virtual workshop on "Maximising the Benefits and Managing the Risks of AI in the GEF", 4th November 2025, and UNDP 2024 report on leveraging AI.

transparency and responsible AI, with all data sourced from publicly available National Biodiversity Strategies and Action Plans (NBSAPs), codes made openly available on GitHub, and data cleaned down to the smallest unit to minimize unnecessary energy and water consumption. This initiative enabled countries to redirect resources toward stakeholder engagement and policy dialogue, thereby enhancing national ownership. Building on this success, UNDP aims to apply similar AI approaches to analyze coherence between NBSAPs and Nationally Determined Contributions (NDCs). The project illustrates how human-centered AI can bridge capacity gaps and accelerate policy coherence in global biodiversity planning.

UNEP's digital and AI capacity readiness.[116] As part of a system-wide digital transformation, UNEP has undertaken a comprehensive institutional effort to integrate digital technologies into the agencies core operations and programmatic work. Backed by a $1.5 million internal investment, UNEP established a Digital Transformation Task Force and conducted a baseline readiness assessment across 40 indicators, achieving an 84% readiness score within two years. UNEP developed a five-part typology of AI use cases, including coordination, resource optimization, dematerialization, behavioral influence, and sense-making, with the latter emerging as the most prevalent. Foundational systems such as the World Environment Situation Room and Environment GPT (still under development) support real-time data synthesis and provide information based on vetted, authoritative sources. Meanwhile, digital literacy programs and revised governance frameworks enhance organizational capacity. UNEP's experience underscores that cultural and institutional factors, such as leadership support, staff incentives, and procurement reform, are often more decisive than the underlying technology itself in determining the success of AI adoption.

UNESCO's global data governance.[117] In 2024, UNESCO established a global multi-stakeholder working group on data and AI governance to address the growing fragmentation of data frameworks and the rising risks associated with datafication and AI-driven decision-making. Building on extensive regional consultations across Southeast Asian, Latin America, Central

[116] Based on UNEP's David Jensen's presentation at the STAP virtual workshop on "Maximising the Benefits and Managing the Risks of AI in the GEF", 4th November 2025.
[117] Based on UNESCO's Leona Verdadero's presentation at the STAP virtual workshop on "Maximising the Benefits and Managing the Risks of AI in the GEF", 4th November 2025.

Europe, the Arab States, and Africa, the Broadband Commission Working Group on Data Governance (co-chaired by UNESCO, UNDP, ITU, and the African Union) launched the Data Governance Toolkit[118] in 2025. It is a practical resource that guides countries in improving data quality, lifecycle management, interoperability, and public trust. The toolkit operationalizes a holistic framework based on principles, people, processes, and practices, providing actionable guidance on privacy, consent, and data protection while emphasizing governance across the entire data lifecycle, from collection to sharing and use. UNESCO stresses that effective AI governance requires not only national policies but also internal institutional safeguards, urging organizations to adopt policies that regulate staff use of generative AI and ensure alignment with UN values, human rights standards, and international norms.

UNDP's AI governance and safeguards[119] are being embedded across its projects and portfolios to ensure the ethical, inclusive, and sustainable deployment of AI. Recognizing AI as both an opportunity and a development challenge, UNDP integrates its AI risks into its Social and Environmental Screening Procedure to assess risks related to bias, inequity, energy use, and freshwater consumption. To reduce environmental footprints, UNDP promotes lifecycle-aware model design, frugal and energy-efficient AI, transparent procurement requirements, and the use of sustainable cloud providers. UNDP pairs these technical measures with governance principles that ensure inclusivity by engaging women, Indigenous Peoples, and youth, as well as capacity-building through Digital Public Infrastructure approaches and Digital Readiness Assessments, particularly for countries facing digital deficits. The combined focus on safeguards, governance, and system-wide capacity demonstrates how responsible AI can accelerate nature and climate goals while minimizing social and environmental harm.

IFAD launched the ATHENA AI project to address a core institutional challenge: decades of project reports and portfolio data were dispersed and underutilized, limiting IFAD’s ability to learn systematically and design evidence-based rural development investments. The project aims to unlock the potential of AI to **accelerate knowledge generation and strengthen data-driven**

[118] BCSD (2025).
[119] Based on UNDP’s Reina Otsuka’s presentation at the STAP virtual workshop on “Maximising the Benefits and Managing the Risks of AI in the GEF”, 4th November 2025.

decision-making. Machine learning and text mining were applied to over 30 years of portfolio data and more than 2,300 project documents in four languages, generating systematic reviews and prediction models for project performance and impact.[120] Building on this work, ATHENA created an AI "toolbox" that includes an AI-based intervention dashboard, a lessons-learned web application, trend analyses on strategic themes, and models to predict project performance, impact, and optimal targeting.[121] Early results show that ATHENA has helped systematize IFAD's portfolio, automate synthesis of lessons, and support ex-ante, data-driven project design and reporting on mainstreaming themes and Sustainable Development Goals, thereby strengthening IFAD's knowledge management and decision-making framework.[122]

----

4. Social and economic considerations

Apart from the environmental risks discussed in Section 2.2, the deployment of AI also raises significant societal and socioeconomic concerns. These risks stem from structural inequities in access to data, infrastructure, and technical capacity, as well as from governance gaps that affect transparency, accountability, and the distribution of benefits. The issues discussed below highlight the need for a precautionary, ethical, and equity-centered approach when integrating AI into environmental sustainability efforts.

Data gaps, bias in data and algorithms, and misalignment with local priorities. Environmental and socioeconomic datasets used to train AI systems often underrepresent low-income regions, Indigenous territories, or ecologically unique areas.[123] This could introduce structural biases that can distort model outputs, influencing decision-making.[124] When AI systems are designed or trained in high-income contexts, they may prioritize donor or corporate interests over local environmental needs, leading to poor adoption or unintended negative consequences.[125] The

---

[120] See: https://www.ifad.org/innovation-challenge/05AIBigData.html
[121] See: https://aiforgood.itu.int/about-us/un-ai-actions/ifad/
[122] See: https://www.ifad.org/innovation-challenge/05AIBigData.html and https://aiforgood.itu.int/about-us/un-ai-actions/ifad/
[123] Perera et al. (2025b); Trehan (2025); Khan, et al. (2024).
[124] Trehan (2025); Sustainability Directory (2025c); Khani (2025)
[125] Juma (2016).

misalignment between model objectives and local values or governance structures can undermine community trust and exacerbate social tensions. These issues may be addressed by expanding dataset diversity, especially from rural, inland, and underrepresented communities, to reduce bias and enhance the accuracy and fairness of AI models. Indeed, there are ongoing efforts to integrate Indigenous and local knowledge into AI models, including in Canada,[126] New Zealand,[127] and India.[128] Increasing data representativeness and relevance by promoting community-driven data collection, e.g., through citizen science, can also help, as well as strengthening governance and institutions, and investing in local skill development.[129]

Widening digital divide and economic barriers. Countries with limited digital infrastructure, low bandwidth, and insufficient access to cloud computing are at risk of being excluded from AI-driven climate services, environmental monitoring, and early warning systems.[130] Research shows a strong correlation between national income levels and access to advanced digital technologies, with low-income and climate-vulnerable countries disproportionately constrained.[131] High costs of data acquisition, storage, remote sensing imagery, cloud computing, and specialized technical staff pose further barriers, reinforcing existing inequalities in environmental governance. Strengthening foundational digital and data infrastructure is crucial to preventing AI from exacerbating global inequalities. Complementary investments in local technical capacity are crucial for enabling low-income and climate-vulnerable countries to reap meaningful benefits from the use of AI in environmental sustainability.[132]

Loss of local and traditional knowledge. AI tools risk overshadowing traditional ecological knowledge, which is often central to sustainable resource management, particularly in Indigenous and rural communities.[133] Over-reliance on algorithmic systems may shift authority and solutions away from local experts to distant institutions.[134] This can erode community ownership of environmental decisions, diminish cultural ties to land, and weaken established adaptive

[126] Canavera (n.d.)
[127] Time (2024).
[128] The Times of India (2025).
[129] Khan et al (2024); Lin et al. (2025).
[130] UNESCO (2022); UNDP. (2022).
[131] Roberts et al (2022); Anwar & Graham (2022).
[132] Khan et al (2024); Gulamali et al. (2025).
[133] Yun-Pu Tu (2025).
[134] Berkes (2018).

knowledge systems that have supported resilience for generations.[135] Safeguarding traditional knowledge requires embedding participatory governance into AI-driven environmental initiatives, ensuring communities shape indicators and decisions.[136] Blending AI with Indigenous and local knowledge improves resilience outcomes and strengthens long-term community ownership of environmental decisions.[137]

Job displacement and unequal workforce transitions. AI-driven automation in agriculture, energy systems, waste management, and conservation may lead to job loss.[138] While AI can enhance efficiency and even create new types of jobs, its benefits may have a negative impact on workers unless deliberate investments are made in reskilling and social protection. Studies show that automation disproportionately affects low-skilled or informal workers in the Global South, where alternative livelihoods are limited and reskilling options are scarce.[139] Without inclusive transition policies, the adoption of AI may exacerbate unemployment and deepen socioeconomic inequality. A just transition is therefore essential to ensure AI-driven environmental solutions do not displace workers.[140]

Transparency, accountability, and governance gaps. Many AI systems used for climate modelling, conservation planning, and resource monitoring are “black boxes,” making their methods and assumptions inaccessible to regulators, practitioners, and affected communities.[141] Lack of explainability can obscure errors or biases, undermine accountability, and limit the ability of communities to contest harmful decisions. This is particularly concerning when AI outputs inform enforcement actions, protected-area boundaries, or disaster response allocations. Requiring explainable AI systems—especially for high-stakes functions such as enforcement—and clear documentation of assumptions, risks, and model performance can enhance transparency and accountability.[142] Additionally, independent audits and oversight bodies can further ensure fairness and accountability.

---

[135] Yun-Pu Tu 2025.
[136] Berkes (2018); Perera et al. (2025)
[137] Sustainability Directory. (2025d); Canavera (n.d.).
[138] ILO. (2021).
[139] For example, Giwa and Ngepah (2024); Katz et al. (2021)
[140] Georgieva (2024)
[141] Burrell (2016); Selbst et al (2019)
[142] Explainable AI incorporate methods and processes to help users understand and trust AI's results by making its decision-making transparent, addressing the "black box" problem of complex AI algorithms (Doshi-Velez and Kim 2017).

Privacy, surveillance, and the risk of misuse. Environmental AI systems applications, such as satellite monitoring, drones, acoustic sensors, and smart meters, can inadvertently capture sensitive information about households, land users, or community activities.[143] Without clear rules, such systems can facilitate environmental or political surveillance, especially in fragile or authoritarian contexts.[144] These risks underscore the need for rights-based governance frameworks that safeguard privacy, consent, and community oversight. Rights-based data governance can help prevent the inappropriate use of environmental monitoring tools, requiring safeguards such as consent, data minimization, and secure storage.[145] Embedding principles of data justice and privacy-by-design into sensors, drones, and Earth observation systems will help protect communities and ensure ethical use of environmental data.[146]

Structural inequalities and reinforcement of existing power dynamics. AI-mediated environmental interventions may reinforce existing inequalities when technology design, data governance, and deployment are controlled by external actors. The concentration of AI capabilities among a few corporations and research institutions can reduce the agency of local scientists and environmental authorities, narrowing the space for participatory governance. Moreover, when control of training data, computational power, and frontier foundation models is concentrated in a handful of corporations and high-income countries, other nations risk being marginalized in the design of AI systems for environmental management. The imbalance in the concentration of AI resources can be mitigated through open science, open-source models, and shared public datasets. Having data openness requirements, interoperability standards, and antitrust oversight, combined with South–South cooperation and support for local innovation ecosystems, can facilitate equitable participation in AI-enabled sustainability efforts.[147]

---

[143] Sustainability Directory (2025e); Miller et al. (2025).
[144] Peron et al. (2025); Tokson (2025).
[145] BSR (2025); Jones (2023).
[146] Benjamin (2019).
[147] UNCTAD (2025)

5. Implications for the GEF

Integrating AI into GEF operations and funded initiatives offers opportunities to enhance environmental outcomes. Yet realizing these benefits requires a deliberate and proactive approach to ensure AI is deployed ethically, sustainably, and inclusively across the GEF Partnership. Here, STAP suggests cross-cutting implications to inform how the GEF responds to the rapid advancement in the development of AI, based on our review of the scientific and practitioner literature, as well as input from experts within and outside the GEF Partnership during a workshop organized in collaboration with the GEF Secretariat and the IEO.[148]

1. **Strengthen internal GEF operations and knowledge integration.** Internally, AI can significantly improve the efficiency and responsiveness of GEF operations. AI tools can streamline project pipeline analysis, risk screening, portfolio reviews, and pre- and post-project knowledge synthesis. As noted during the workshop,[149] these tools can automate literature reviews, generate reports from document repositories, and support lessons-learned integration across focal areas. However, deployment must be accompanied by strong governance, including clear guidelines on responsible use, data privacy, version control, and traceability of AI-generated content. It is essential that AI is only used where the stakes justify the need for, and the complexity of, AI systems.
2. **Develop integrated guidance and readiness within the GEF Partnership.** To ensure Partnership-wide coherence, the GEF could consider supporting the development of AI guidance tailored to its implementing agencies and executing partners. This could take the form of an AI Ethics and Sustainability Toolkit for GEF projects. The first step is to review existing guidance and standards and assess institutional readiness within the Partnership (see Box 3 for UNEP's example). This will support the creation of a

[148] STAP, in collaboration with the GEF Secretariat and the GEF IEO, organized a virtual consultative workshop on 4 November 2025 titled "Maximizing the benefits and managing the risks of Artificial Intelligence in the GEF." The event brought together participants and speakers from over 30 institutions across 15 countries, representing GEF Agencies, International Organizations, academia, civil society, and the private sector. Panelists and moderators represented, among others, the World Resources Institute, ITU, UNEP, the World Bank, CI, UNDP, UNESCO, Code for Africa, and the UK Royal Academy of Engineering. See Annex 1 for the workshop agenda.

[149] The GEF Secretariat Senior Knowledge Management Specialist, Jenner Guzman, spoke during the workshop about leveraging AI to improve environmental outcomes globally.

Partnership-wide standard and promote consistent and equitable technology governance.

3. **Convene learning opportunities and strengthen strategic partnerships.** To responsibly harness the potential of AI, the GEF should deepen its role as both a convener and collaborator across the global AI–environment ecosystem. As a knowledge institution, the GEF is uniquely positioned to foster learning platforms and structure experimentation on responsible AI applications for environmental sustainability. This includes supporting cross-agency pilots, transparent performance reporting, and independent evaluations of environmental and social outcomes. Such efforts can help identify scalable best practices and ensure AI adoption aligns with GEF's core values. Simultaneously, the GEF can strengthen strategic partnerships with actors working at the frontier of AI and environmental action. Multi-stakeholder coalitions such as the Coalition for Digital Environmental Sustainability (CODES)[150] and the UNEP/ITU-led Coalition for Sustainable AI [151] align AI development with environmental sustainability. Research networks like Climate Change AI[152] connect machine-learning experts with climate scientists to accelerate innovation. Corporate programs, such as Microsoft's AI for Earth and its Planetary Computer, offer cloud credits, models, and curated datasets for projects in agriculture, water, biodiversity, and climate.[153] Philanthropic initiatives, such as the Bezos Earth Fund's AI for Climate and Nature Grand Challenge, provide funding for transformative AI applications in climate and nature.[154] Through such alliances, the GEF can help broker equitable AI research partnerships, especially for developing countries, ensuring inclusive co-development of tools that deliver global environmental benefits.
4. **Support equitable access and avoid technological marginalization.** As AI development remains concentrated in a few countries, there is a risk that developing countries, many of whom are GEF recipients, could be left behind. To address this, the

[150] See CODES website: https://www.codes.global/
[151] See the Coalition website: https://www.sustainableaicoalition.org/
[152] See Climate Change AI website: https://www.climatechange.ai/
[153] Derrick (2025)
[154] Bezos Earth Fund (2025)

GEF could provide support for foundational elements of digital infrastructure, including cloud access, data systems, standards, and acquisition, as well as open AI models, especially at the national level, and AI literacy among environmental institutions in the countries it supports. Such support should focus on environmental sustainability-specific applications and could aim to leverage the investment of agencies and partners that are already supporting countries along this line, for example, Multilateral Development Banks, or those that are already investing in AI applications (Boxes 2 and 3 show that several GEF agencies are already applying AI). The introduction of small, task-specific models and resource-efficient algorithms (Section 2.3: Green-in-AI strategies) should be prioritized to ensure relevance and feasibility in resource-constrained settings. While such investments may not be directly linked to GEB delivery and adaptation benefits (the core mandate of the GEF), they provide the foundation for achieving these benefits and can help facilitate long-term system transformation.

5. **Promote human oversight and transparency.** As large language models and generative AI tools are introduced in project preparation, monitoring, and knowledge synthesis, as demonstrated in CI's GEF Monitoring and Evaluation dashboard using Copilot and Power BI (see Box 3 for CI's example), it is critical to ensure that AI supports, rather than replaces, human judgment. Layered review processes, including audit trails and human-in-the-loop mechanisms, can prevent over-reliance on potentially hallucinated or biased outputs. These protocols are already being trialed in an AI-supported GEF project focused on aligning NBSAPs under the Kunming-Montreal Global Biodiversity Framework, as exemplified by the UNDP in Box 3.[155]
6. **Align with international AI governance norms.** It is essential that GEF's strategic approach aligns with emerging global AI governance frameworks. Key references include UNESCO's Recommendation on the Ethics of AI,[156] OECD's AI principles,[157]

[155] UNDP (2024).
[156] UNESCO (2022).
[157] OECD (n.d.a) https://www.oecd.org/en/topics/sub-issues/ai-principles.html

recommendations,[158] and Global Partnership on AI,[159] as well as the recommendations in the report of the UN Secretary-General's Advisory Body on AI,[160] which all advocate for human rights–centered, environmentally sustainable, and inclusive AI systems. These frameworks provide normative guidance that the GEF can adapt for environmental financing and sustainability contexts, particularly within multi-stakeholder partnerships and the mandate of the Multilateral Environmental Agreements (MEAs) for which it serves as a financing mechanism.

7. **Integrate AI dimensions into GEF's environmental and social safeguards.** AI applications embedded within GEF-financed interventions carry new types of environmental and social risks, including algorithmic bias, lack of transparency, exclusion of local knowledge systems, and increased resource consumption. The GEF needs to ensure that its policy and guidelines on Environmental and Social Safeguards address AI-specific concerns. This could be based on the Environmental, Social and Governance (ESG)-AI framework[161] and methodologies for measuring AI's environmental impacts developed by the OECD and the ITU.[162] Integrating environmental lifecycle assessments for AI systems, especially high-compute applications (tasks that require a massive amount of processing power, data, and speed that exceeds the capabilities of standard computers), and embedding principles of data justice and transparency are essential.[163] Refer to Box 3 for an example illustrating the incorporation of AI risk into social and environmental safeguards by the UNDP.

---

[158] OECD (2019).
[159] OECD (n.d.b)
[160] United Nations (2024).
[161] Lee et al. (2025) proposed an ESG-AI framework that emphasizes three pillars: assessing the material ESG impacts of specific AI use-cases, evaluating corporate AI governance and accountability, and strengthening risk management across environmental, social, and governance dimensions. The framework seeks to ensure that AI deployment aligns with ESG principles, supports responsible innovation, and enables clearer disclosure and investment decisions.
[162] See the OECD's measuring the environmental impacts of AI compute and applications report (OECD, 2022) and the ITU report on measuring what matters (ITU, 2025).
[163] Luccioni et al. 2025.

6. Conclusions

Artificial intelligence presents a transformative opportunity for the GEF to accelerate the delivery of GEBs and systems transformation. As this paper has outlined, AI applications are rapidly emerging across GEF focal areas, enabling real-time environmental monitoring, improving predictive analytics for climate and biodiversity action, streamlining operational processes, and enhancing knowledge synthesis. Yet, these opportunities come with important environmental, social, and governance considerations. From the high resource demands of AI systems to concerns about bias, exclusion, and transparency, integrating AI into environmental interventions requires a principled and precautionary approach. The GEF must ensure that AI adoption is responsible, inclusive, and strategically aligned with its mission. This entails strengthening environmental and social safeguards to address AI-specific risks, fostering digital readiness across the Partnership, and supporting the development of foundational digital infrastructure and AI literacy in recipient countries. Equally, the GEF can play a leadership role by anchoring AI governance in human rights and sustainability norms, aligning with global frameworks, and brokering inclusive partnerships that democratize access to AI innovations. As AI continues to evolve, the GEF has the opportunity to shape its use in the service of planetary health, ensuring that digital transformation contributes meaningfully to the goals of equity, resilience, and environmental stewardship.

7. Annex: Agenda of the STAP workshop

Agenda for STAP Artificial Intelligence (AI) Workshop
Title of the workshop: Maximizing the Benefits and Managing the Risks of Artificial Intelligence (AI) in the GEF
Date: Tuesday, 4th November 2025
Time: 10:00 – 13:00 EST

Agenda

Time	Sessions	Key Question/Theme	Speaker
10:00 -10:10	Opening Remarks	Welcome remarks and framing: What is the GEF, and its interest in AI?	**Rosina Bierbaum**, Chair of STAP
10:10 - 10:15	Scene setting – STAP moderated by **Ngonidzashe Chirinda**, Climate Change Mitigation Panel Member, STAP (5-minute introduction by Ngoni)		
10:15 - 10:22 (7 minutes)	AI for Nature, Pollution, and Climate Action	How can AI help address the challenges of the triple planetary crisis?	**Evan Tachovsky**, Global Director of World Resources Institute Data Lab
10:22 - 10:29 (7 minutes)	Environmental Impact of AI Systems	What are the environmental impacts of AI systems?	**Thomas Basikolo,** ITU AI for Good and ITU Green Computing Pillar of the Green Digital Action
10:29 - 10:39	Moderated Q&A by Ngonidzashe Chirinda		
10:40 -10:45	Thematic Segments 1 and 2 Moderated by **Geeta Batra**, Director, GEF Independent Evaluation Office (IEO) (5-minute introduction by Geeta)		
10:45 - 10:52 (7 minutes) 10:52 - 10:59 (7 minutes)	Segment 1: Institutional Readiness	Digital and AI capacity and readiness in GEF agencies and the current best practice	**David Jensen**, Digital Transformation, UNEP **Nagaraja Rao Harshadeep** (Harsh) Global Lead (Disruptive Technology) & Lead Environmental Specialist, World Bank
11:00 - 11:07 (7 minutes) 11:07 - 11:14 (7 minutes)	Segment 2: GEF Agencies' Experience with AI use	How has AI been used in GEF and non-GEF projects/programs by GEF agencies, and what lessons can be learned from these projects/programs	**Carly Batist,** Nature Tech & AI Innovation Manager, Conservation International **Marc Lepage**, Principal Information Technology Specialist, Asian Development Bank
11:15 - 11:25	Moderated Q&A by Geeta Batra		

11:25 - 11:30	Thematic Segments 3 Moderated by **Mohamed Bakarr**, Manager, Integration and Knowledge Division, GEF (5-minute introduction by Mohamed)		
11:30 - 11:37 (7 minutes) 11:37 - 11:44 (7 minutes)	Segment 3: Use of AI in organizations' operations, including Knowledge Management, and Learning	How can AI be used in streamlining organizational operations as well as in project design, implementation, monitoring, evaluation, and knowledge management and learning?	**Jenner Guzman,** Senior Knowledge Management Specialist, Integration and Knowledge Division at GEF **Alicia Olago,** Senior Product Manager, Code For Africa/sensors Africa
11:44 - 11:54	Moderated Q&A by Mohamed Bakarr		
11:55 - 12:00	Thematic Segments 4: Moderated by **Susanne Schmeier,** International Waters Panel Member, STAP (5-minute introduction by Susanne)		
12:00 – 12:07 (7 minutes) 12:07 - 12:14 (7 minutes) 12:14 - 12:21 (7 minutes)	Segment 4: Data Governance and Safeguards, Responsible AI	Data sharing, automation, open data, training datasets. How can we harness the benefits of AI while minimizing its unintended negative consequences?	**Leona Verdadero**, Programme Specialist, Digital Policies and Digital Transformation Section, UNESCO **Reina Otsuka**, UNDP, and representing *The Coalition for Digital Environmental Sustainability* (CODES) **Eliot Gillings,** AI expert and Policy Advisor, Royal Academy of Engineering
12: 21 - 12:31	Moderated Q&A by **Susanne Schmeier,** followed by open discussion		
12:31 - 12:55	Guiding questions: • What institutional capacities, digital infrastructure, and governance frameworks can help across GEF agencies to responsibly scale AI solutions for environmental sustainability? • What lessons from current AI-enabled projects can inform future programming, particularly in maximizing environmental benefits while minimizing sustainability risks? • How can AI be practically integrated into project design, implementation, and monitoring to enhance efficiency and reduce burdens on practitioners? • What principles and safeguards should guide the use of data and automation in AI systems to ensure transparency, equity, and environmental integrity across the GEF portfolio?		
12: 55 - 13:00	Closing: **Rosina Bierbaum**, Chair of STAP		

8. References

Adegbite, A. O., Barrie, I., Osholake, S. F., Alesinloye, T., & Bello, A. B. (2024). *Artificial intelligence in climate change mitigation: A review of predictive modeling and data-driven solutions for reducing greenhouse gas emissions*. Scribd. https://www.scribd.com/document/880173478/Adegbite-Et-Al-2024

AF-TERG, CIF, GEF IEO, & GCF IEU. (2025). *Scoping study on the use of AI in evaluations* [Report]. Adaptation Fund. https://www.adaptation-fund.org/wp-content/uploads/2025/03/Scoping-Study-on-Use-of-AI-in-Evaluations-03.24.25v2.pdf

Ali, S., Giurco, D., Arndt, N. et al. (2017). Mineral supply for sustainable development requires resource governance. Nature 543, 367–372 (2017). https://doi.org/10.1038/nature21359

Allen, G. (2020). Understanding AI technology. Joint Artificial Intelligence Center (JAIC) Department of Defense. https://apps.dtic.mil/sti/html/tr/AD1099286/.

Alsubai, S., Mosleh, M. A. A., Al-Hadhrami, S. A., & Bhatia, M. (2025). *Artificial intelligence-inspired comprehensive framework for desertification prediction*. *International Journal of Cognitive Computing in Engineering, 6*, 462–476. https://doi.org/10.1016/j.ijcce.2025.02.007

Alzoubi, H., & Mishra, J. L. (2024). *Artificial intelligence and sustainability: Towards a circular economy*. *Journal of Cleaner Production, 438*, 143090. https://doi.org/10.1016/j.jclepro.2024.143090

Amazon Web Services (AWS). (2025, October). *How the Wildlife Conservation Society uses AWS to accelerate coral reef monitoring worldwide*. https://aws.amazon.com/blogs/publicsector/how-the-wildlife-conservation-society-uses-aws-to-accelerate-coral-reef-monitoring-worldwide/

Antony Jose, S., Cook, C. A. D., Palacios, J., Seo, H., Torres Ramirez, C. E., Wu, J., & Menezes, P. L. (2024). *Recent advancements in artificial intelligence in battery recycling*. *Batteries, 10*(12), 440. https://doi.org/10.3390/batteries10120440

Anwar, M. A., and Graham, M. (2022). The Digital Continent: Placing Africa in Planetary Networks of Work. Oxford: Oxford University Press.

AtKisson, A. (2024). The AI imperative: accelerating water management processes in the era of climate change. Global Water Partnership. https://www.gwp.org/en/About/more/news/2024/the-ai-imperative-accelerating-water-management-processes-in-the-era-of-climate-change

Baldé, C.P., Kuehr, R., Yamamoto, T. et al. (2024). The global e-waste monitor 2024. International Telecommunication Union (ITU) and United Nations Institute for Training and Research (UNITAR). https://ewastemonitor.info/the-global-e-waste-monitor-2024/

BCSD (Broadband Commission for Sustainable Development). (2025). Data Governance Toolkit. Broadband Commission for Sustainable Development. https://www.broadbandcommission.org/publication/the-data-governance-toolkit/

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim Code*. Polity Press. https://www.politybooks.com/bookdetail?book_slug=race-after-technology-abolitionist-tools-for-the-new-jim-code--9781509526390

Berkes, F. (2018). Sacred Ecology (4th ed.). Routledge. https://doi.org/10.4324/9781315114644

Bezos Earth Fund. (2025, May). *Coral Watch AI Reef Protection Network* [Grant description]. https://www.bezosearthfund.org/grants/coral-watch-ai-reef-protection-network

Biswas, P., Rashid, A., Biswas, A., Nasim, M. A. A., Chakraborty, S., Gupta, K. D., & George, R. (2024). *AI-driven approaches for optimizing power consumption: A comprehensive survey*. *Discover Artificial Intelligence, 4*, Article 116. https://doi.org/10.1007/s44163-024-00211-7

Bocchino, C., & Adkisson, K. (2020, July 28). *Using big data analytics for transboundary water management*. *New Security Beat*. https://www.newsecuritybeat.org/2020/07/big-data-analytics-transboundary-water-management/

Bolón-Canedo, V. (2024). *A review of green artificial intelligence: Towards a more sustainable future*. *Neurocomputing, 622*, Article 104121. https://doi.org/10.1016/j.neucom.2024.104121

Borah, S. K., Pal, D., Sarkar, S., & Sethi, L. N. (2025). *AI-powered drones for sustainable agriculture and precision farming*. In S. M. Sadiq et al. (Eds.), *Advancing global food security with Agriculture 4.0 and 5.0* (pp. 69–98). IGI Global. https://doi.org/10.4018/979-8-3693-9964-4.ch004

Browning, E., Gibb, R., Glover-Kapfer, P., & Jones, K. E. (2017). *Acoustic monitoring: Guidelines for wildlife-related sound recording* (WWF Conservation Technology Series No. 2). WWF-UK. https://www.wwf.org.uk/sites/default/files/2019-04/Acousticmonitoring-WWF-guidelines.pdf

Burrell (2016); Selbst, A., Boyd, D., Friedler, S., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and Abstraction in Sociotechnical Systems. https://doi.org/10.1145/3287560.3287598

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society. https://doi.org/10.1177/2053951715622512

Caballar, R.D. (2025). What are small language models? In IBM 2025 Guide to Machine Learning. IBM. https://www.ibm.com/think/topics/small-language-models?

Camps-Valls, G., Fernández-Torres, M.-Á., Cohrs, K.-H., Höhl, A., Castelletti, A., Pascal, A., … Williams, T. (2025). *Artificial intelligence for modeling and understanding extreme weather and climate events*. *Nature Communications, 16*, Article 1919. https://doi.org/10.1038/s41467-025-56573-8

Canavera (n.d.). Blending Indigenous Knowledge and Artificial Intelligence to enable adaptation. World Wildlife Fund. https://www.arcticwwf.org/the-circle/stories/blending-indigenous-knowledge-and-artificial-intelligence-to-enable-adaptation/

Chan, K., West, D., Teo, M., Brown, H., Westgarth, T., & Smith, T. (2024). *Greening AI: A policy agenda for the artificial intelligence and energy revolutions*. Tony Blair Institute for Global Change. https://www.institute.global/insights/climate-and-energy/greening-ai-a-policy-agenda-for-the-artificial-intelligence-and-energy-revolutions

Chan, K., West, D., Teo, M., Brown, H., Westgarth, T., & Smith, T. (2024). *Greening AI: A policy agenda for the artificial intelligence and energy revolutions*. Tony Blair Institute for Global

Change. https://www.institute.global/insights/climate-and-energy/greening-ai-a-policy-agenda-for-the-artificial-intelligence-and-energy-revolutions

Climate TRACE. (2023, December 3). *Climate TRACE Unveils Open Emissions Database of More Than 352 Million Assets.* Climate Trace. https://climatetrace.org/news/climate-trace-unveils-open-emissions-database-of-more-than

Climate Trace. (2025). When, where, and how. Source-level solutions for turning climate ambition into on-the-ground action. Climate Trace. https://media.climatetrace.org/Climate_TRACE_whitepaper_When_Where_And_How_Source_Level_Emissions_Reduction_Solutions_202511_v_Final2_7e633a9448.pdf

Corradini, F., Leonesi, M., & Piangerelli, M. (2025). State of the Art and Future Directions of Small Language Models: A Systematic Review. Big Data and Cognitive Computing, 9(7), 189. https://doi.org/10.3390/bdcc9070189

Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2023). *The AI gambit: Leveraging artificial intelligence to combat climate change—opportunities, challenges, and recommendations*. *AI & Society, 38*(1), 283–307. https://doi.org/10.1007/s00146-021-01294-x

Das, M. (2025). AI in Project Management: Resource Planning & Delivery. Celoxis. https://www.celoxis.com/article/ai-in-project-management-resource-planning-execution

Deloitte Global. (2024). *Powering artificial intelligence: A study of AI's environmental footprint—today & tomorrow*. Deloitte. https://www.deloitte.com/content/dam/assets-shared/docs/about/2024/powering-artificial-intelligence.pdf

Derrick, M. (2025). How Microsoft is Saving Wetlands with AI Mapping and ML. https://technologymagazine.com/news/microsofts-role-in-the-ai-map-tool-for-climate-protection

Donaldson, A., et al. (2023). *Leveraging innovation for transformation change*. Scientific and Technical Advisory Panel to the Global Environment Facility.

https://cdn.unenvironment.org/stapgef/public/2024-05/J0426_UNEP_Advisory_Leveraging-Innovation-Paper_AW_Web.pdf

Donti, P. L., & Kolter, J. Z. (2021). *Machine learning for sustainable energy systems*. *Annual Review of Environment and Resources, 46*(1), 719–747. https://doi.org/10.1146/annurev-environ-020220-061831

Doshi-Velez, F. & Kim, B. (2017). Towards A Rigorous Science of Interpretable Machine Learning. arXiv:1702.08608v2. https://doi.org/10.48550/arXiv.1702.08608

Ellen MacArthur Foundation. (2019). *Artificial intelligence and the circular economy: AI as a tool to accelerate the transition*. https://www.ellenmacarthurfoundation.org/artificial-intelligence-and-the-circular-economy

EnicompMedia. (2025, July 1). *How AI is reducing industrial waste through predictive insights*. Enicomp. https://enicomp.com/how-ai-is-reducing-industrial-waste-through-predictive-insights/

Ertel, W., & Bonenberger, C. (2025). *Rebound effects caused by artificial intelligence and automation in private life and industry*. *Sustainability, 17*(5), 1988. https://doi.org/10.3390/su17051988

European Commission (n.d.) Artificial Intelligence & Big Data. https://monitor-industrial-ecosystems.ec.europa.eu/technologies/artificial-intelligence-big-data

EvalCommunity Academy. (2025). How AI is Transforming Monitoring and Evaluation (M&E). EvalCommunity Academy. https://academy.evalcommunity.com/how-ai-is-transforming-monitoring-and-evaluation-me/

Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., Hamza, E. H., Rooney, D. W., & Yap, P.-S. (2023). *Artificial intelligence for waste management in smart cities: A review*. *Environmental Chemistry Letters, 21*(4), 1959–1989. https://doi.org/10.1007/s10311-023-01604-3

FAO (Food and Agriculture Organization of the United Nations). (2021). *WaPOR: FAO portal to monitor Water Productivity through Open access of Remotely sensed derived data* [Aquastat geospatial information]. https://www.fao.org/aquastat/en/geospatial-information/wapor/

FAO (Food and Agriculture Organization of the United Nations). (2024). *FAMEWS mobile app | Global Action for Fall Armyworm Control*. https://www.fao.org/fall-armyworm/monitoring-tools/famews-mobile-app/en/

FAO (Food and Agriculture Organization of the United Nations). (2025). *Drought-Observe: Near-real-time drought monitoring for Africa and MENA using FAO WaPOR data*. https://www.fao.org/in-action/remote-sensing-for-water-productivity/applications-and-uses/applications-catalogue/product-detail/Drought-Observe-near-real-time-drought-monitoring-for-Africa-and-MENA-using-FAO-WaPOR-data_1638819/

FAO (Food and Agriculture Organization of the United Nations). (2020). *Remote sensing for water productivity: Applications and uses* [Report]. https://openknowledge.fao.org/server/api/core/bitstreams/7c5b5e90-12c0-47c9-a183-40187f530e92/content

Foini, P., Tizzoni, M., Martini, G. et al. (2023). On the forecastability of food insecurity. Sci Rep 13, 2793. https://doi.org/10.1038/s41598-023-29700-y

GAO (2025). Artificial Intelligence. Generative AI use and management at Federal Agencies. https://www.gao.gov/assets/gao-25-107653.pdf

GEF-IEO (Independent Evaluation Office of the GEF). (2025). *Ninth GEF replenishment: Highlights of evaluation findings 2022–2025*. https://www.thegef.org/sites/default/files/documents/2025-04/GEF.R9.02-Preliminary%20Findings-of-the-Eight-Overall-Performance-Study-of-the-GEF.pdf

GEF-IEO (Independent Evaluation Office of the Global Environment Facility). (2025). Evaluation of GEF support for technological innovation. Independent Evaluation Office of the Global Environment Facility. https://www.gefieo.org/en/types/evaluations/advanced-technologies

Georgieva, K. (2024). AI Will Transform the Global Economy. Let's Make Sure It Benefits Humanity. IMFBlog, International Monetary Fund. https://www.imf.org/en/blogs/articles/2024/01/14/ai-will-transform-the-global-economy-lets-make-sure-it-benefits-humanity

Giwa, F., Ngepah, N. (2024). The relationship between artificial intelligence and low-skilled employment in South Africa. Heliyon, 10, 23, e40640. https://doi.org/10.1016/j.heliyon.2024.e40640

González-Rivero, M., Beijbom, O., Rodriguez-Ramirez, A., Bryant, D. E. P., Ganase, A., Gonzalez-Marrero, Y., Herrera-Reveles, A., Kennedy, E. V., Kim, C. J. S., Lopez-Marcano, S., Markey, K., Neal, B. P., Osborne, K., Reyes-Nivia, C., Sampayo, E. M., Stolberg, K., Taylor, A., Vercelloni, J., Wyatt, M., & Hoegh-Guldberg, O. (2020). Monitoring of Coral Reefs Using Artificial Intelligence: A Feasible and Cost-Effective Approach. Remote Sensing, 12(3), 489. https://doi.org/10.3390/rs12030489

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press. https://mitpress.mit.edu/9780262035613/deep-learning/

Google Cloud. (2023). Artificial intelligence (AI): a simple-to-understand guide. https://cloud.google.com/learn/what-is-artificial-intelligence

Google. (2025). *cameratrapai: AI models trained by Google to classify species in images from motion-triggered wildlife cameras* [Code repository]. GitHub. https://github.com/google/cameratrapai

Gulamali, F., Kim, J.Y., Pejavara, K., et al. (2025). Eliminating the AI digital divide by building local capacity. PLOS Digit Health. 2025 Oct 23;4(10):e0001026. https://doi.org/10.1371/journal.pdig.0001026

Haq, B., Jamshed, M. A., Ali, K., Kasi, B., Arshad, S., Kasi, M. K., ... & Ur-Rehman, M. (2024). Tech-driven forest conservation: combating deforestation with internet of things, artificial intelligence, and remote sensing. IEEE Internet of Things Journal, 11(14), 24551-24568.

Hehmeyer, A. (2025, March 3). *Using the power of AI to identify and track species*. World Wildlife Fund. https://www.worldwildlife.org/news/stories/using-the-power-of-ai-to-identify-and-track-species/

Huang, D., Zhan, Y., & Lonsdale, C. (2025). *Utilising artificial intelligence to enhance firm circular economy maturity: A thematic review via machine learning*. *Business Strategy and the Environment, 34*(5), 6135–6158. https://doi.org/10.1002/bse.4291

IBM (n.d.). What is few-shot learning? IBM. https://www.ibm.com/think/topics/few-shot-learning

IHE Delft Institute for Water Education. (2016). *Using remote sensing to support solutions to reduce agricultural water productivity gaps* [Water Accounting report]. https://wateraccounting.un-ihe.org/en/using-remote-sensing-support-solutions-reduce-agricultural-water-productivity-gaps

Ikram, R. M. A., Wang, M., Moayedi, H., Ahmadi Dehrashid, A., Gharibi, S., & Han, J.-C. (2025). *Application of smart technologies for predicting soil erosion patterns*. *Scientific Reports, 15*, Article 26479. https://doi.org/10.1038/s41598-025-12125-0

ILO (International Labour Organization). (2021). World Employment and Social Outlook 2021: The Role of Digital Labour Platforms. ILO Publications.

International Water Management Institute. (2021). *WaPOR: Monitoring water productivity* [Project page]. https://www.iwmi.org/projects/wapor/

ITU (International Telecommunication Union) (2024). AI and the Environment - International Standards for AI and the Environment 2024 Report. International Telecommunication Union. https://www.itu.int/dms_pub/itu-t/opb/env/T-ENV-ENV-2024-1-PDF-E.pdf

ITU (International Telecommunication Union) (2025). Measuring what matters: How to assess AI’s environmental impact. International Telecommunication Union. https://www.itu.int/hub/publication/s-gen-gda-001-2025/

IWMI (International Water Management Institute). (2021). *WaPOR: Monitoring water productivity* [Project page]. https://www.iwmi.org/projects/wapor/

IWMI (International Water Management Institute). (2024, September 24). *AI agent by IWMI and Microsoft to drive new thinking in water management*. https://www.iwmi.org/news/ai-agent-by-iwmi-and-microsoft-to-drive-new-thinking-in-water-management/

IWMI (International Water Management Institute). 2025. AI agent by IWMI and Microsoft to drive new thinking in water management. International Water Management Institute. https://www.iwmi.org/news/ai-agent-by-iwmi-and-microsoft-to-drive-new-thinking-in-water-management/

Janiesch, C., et al. (2021). *Machine learning and business process management*. arXiv. https://arxiv.org/pdf/2104.05314

Jarrahi, M.H., Askay, D., Eshraghi, A., Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. Business Horizon, 66. https://doi.org/10.1016/j.bushor.2022.03.002

Jiang, F., Duan, C., & Chen, B. (2025). *Facility-level energy-driven water footprint and scarcity implications of Chinese data centers: A bottom-up analysis and scenario-based projection*. *Applied Energy, 399*, 126522. https://doi.org/10.1016/j.apenergy.2025.126522

Juma, C. (2016). *Innovation and Its Enemies: Why People Resist New Technologies.* Oxford University Press.

Jurafsky, D., & Martin, J. H. (2025). *Speech and Language Processing* (3rd ed.) [Manuscript]. Stanford University. https://web.stanford.edu/~jurafsky/slp3/

Karimi, L., Shinh, R., Laisure-Pool, C., Green, M., Yacuel, L., Ashby, J., Hickenbottom, K.L. (2025). Energy and water dynamics in data center cooling: Insights from a modeling study in hot-arid climates. Applied Thermal Engineering, 276. https://doi.org/10.1016/j.applthermaleng.2025.126802

Katz, R., Callorda, F., & Jung, J. (2021). The impact of automation on employment and its social implications: evidence from Chile. Economics of Innovation and New Technology, 32(5), 646–662. https://doi.org/10.1080/10438599.2021.1991798

Kearney, J., & Gardner, T. (2025, September 25). *U.S. urges utilities to keep coal-fired plants running as AI demand booms*. Reuters. https://www.reuters.com/sustainability/climate-energy/us-urges-utilities-keep-coal-fired-plants-running-ai-demand-booms-energy-2025-09-25/

Khan, M.S., Umer, H. & Faruqe, F. (2024). Artificial intelligence for low income countries. Humanit Soc Sci Commun 11, 1422. https://doi.org/10.1057/s41599-024-03947-w

Khani, M.M. (2025). Data repurposing, algorithmic bias and Indigenous privacy in the age of AI. https://iapp.org/news/a/data-repurposing-algorithmic-bias-and-indigenous-privacy-in-the-age-of-ai

Kim, K., Ahmad, A.S. (2025). Making water knowledge with Artificial Intelligence: A qualitative study of expert interviews on water diplomacy. Ambio (2025). https://doi.org/10.1007/s13280-025-02272-z

Kim, S & Damania, R. (2025). Digital pathways to a thriving and livable planet. World Bank Blogs. https://blogs.worldbank.org/en/voices/digital-pathways-to-a-thriving-and-livable-planet

Klawikowska, Z., Ujazdowski, T., Grochowski, M., & Piotrowski, R. (2022). *How high-tech solutions support the fight against IUU and ghost fishing: A review of innovative approaches, methods, and trends*. *IEEE Access, 10*, 129130–129153. https://doi.org/10.1109/access.2022.3212384

Krishnamurthy, R. (2025, November 5). *India's data centers drain water-stressed regions*. Earth Journalism Network. https://earthjournalism.net/stories/indias-data-centers-drain-water-stressed-regions

Kshirsagar, M. (2025). Lifespan of AI Chips: The $300 Billion Question. CITP Blog. https://blog.citp.princeton.edu/2025/10/15/lifespan-of-ai-chips-the-300-billion-question/

Kumar, V. V., & Shahin, K. (2025). *Artificial intelligence and machine learning for sustainable manufacturing: Current trends and future prospects*. *Intelligent and Sustainable Manufacturing, 2*(1), Article 10002. https://doi.org/10.70322/ism.2025.10002

Kumar, V. V., & Shahin, K. (2025). *Artificial intelligence and machine learning for sustainable manufacturing: Current trends and future prospects*. *Intelligent and Sustainable Manufacturing, 2*(1), Article 10002. https://doi.org/10.70322/ism.2025.10002

Lakhiar, I. A., Yan, H., Zhang, C., Wang, G., He, B., Hao, B., ... & Rakibuzzaman, M. (2024). A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints. Agriculture, 14(7), 1141.

Lal, S., Arora, M. K., Riswandi, B. A., Singh, N., & Singh, B. (2024). *Melding artificial intelligence and remote sensing data for real-time monitoring of marine biodiversity*. In *AI applications for clean energy and sustainability* (pp. 299–319). IGI Global. https://www.igi-global.com/chapter/melding-artificial-intelligence-and-remote-sensing-data-for-real-time-monitoring-of-marine-biodiversity/354469

Latha, K., Kumar, M. M., Balaji, S., & Lakshman, Y. A. (2024, April). Smart coral reef monitoring system using ai. In 2024 International Conference on Communication, Computing and Internet of Things (IC3IoT) (pp. 1-6). IEEE.

Lee, S.U., Perera, H., Liu, Y., Xia, B. (2025). Integrating ESG and AI: a comprehensive responsible AI assessment framework. AI and Ethics 5(5):5121-5148. https://doi.org/10.1007/s43681-025-00741-5

Li, P., Yang, J., Islam, M. A., & Ren, S. (2025). Making AI less' thirsty'. Communications of the ACM, 68(7), 54-61. https://doi.org/10.1145/3724499

Lifset, R., & Porter, A. (2024). *What is in Red AI? Scoping the energy and environmental impacts of artificial intelligence*. *IAEE Energy Forum, Second Quarter*. https://www.iaee.org/publications/newsletterdl.aspx?id=1091

Lifset, R., Porter, A., Newman, N., & Lee, T. (2025). *Artificial Intelligence's environmental impacts: Exploring research on "Red AI"* (SSRN Scholarly Paper No. 5311903). Social Science Research Network. https://doi.org/10.2139/ssrn.5311903

Lin, Z., Dou, H., Lin, S. (2025). Community-powered AI: Enhancing regional development through dataset diversity and ethical governance. Technovation, 147. https://doi.org/10.1016/j.technovation.2025.103315

Luccioni, A.S., Sefala, R., Moorosi, N. (2025). arXiv:2504.00797v1 [cs.CY]. https://arxiv.org/html/2504.00797v1

Lynam, A. J., Cronin, D. T., Wich, S. A., Steward, J., Howe, A., Kolla, N., Markovina, M., Torrico, O., Reyes, V., Sophalrachana, K., Stevens, X., Schmidt, E., & Cox, H. (2025). *The rising tide of conservation technology: Empowering the fight against poaching and unsustainable wildlife harvest*. *Frontiers in Ecology and Evolution, 13*, Article 1527976. https://doi.org/10.3389/fevo.2025.1527976

Magrini, A., Cattani, L., Cartesegna, M., Magnani, L. (2017). Water Production from Air Conditioning Systems: Some Evaluations about Sustainable Use of Resources. Sustainability, 9, 1309. https://doi.org/10.3390/su9081309

Mandal, A., & Ghosh, A. R. (2024). Role of artificial intelligence (AI) in fish growth and health status monitoring: A review on sustainable aquaculture. Aquaculture International, 32(3), 2791-2820.

Market Logic. (2025). Creating a knowledge-sharing culture with the help of AI. Market Logic. https://marketlogicsoftware.com/blog/creating-a-knowledge-sharing-culture-with-the-help-of-ai/

Matthews, B. (2024). How AI Is Changing Project Management: Uses, Impacts, & Trends. Project – Management.com. https://project-management.com/ai-project-management/

McCoy, M. K. (2025, March 28). *AI-based tool for nature wins big*. Conservation International. https://www.conservation.org/news/future-of-nature-restoration-conservation-international-wins-microsoft-challenge

Miller, T., Durlik, I., Kostecka, E., Kozlovska, P., Łobodzińska, A., Sokołowska, S., & Nowy, A. (2025). Integrating Artificial Intelligence Agents with the Internet of Things for Enhanced Environmental Monitoring: Applications in Water Quality and Climate Data. Electronics, 14(4), 696. https://doi.org/10.3390/electronics14040696

Moorthy, S. (2025, May 15). Risks and benefits of artificial intelligence in locally led nature restoration (IIED Research Report No. 22638G). International Institute for Environment and Development. https://www.iied.org/sites/default/files/pdfs/2025-05/22638g.pdf

MRC (Mekong River Commission) Secretariat. (2021, March 15). *Partnership for plastic-free Mekong River*. https://www.mrcmekong.org/news_and_events/partnership-for-plastic-free-mekong-river

MundoGEO. (2022, July 11). *LandCoverNet: The first global multi-satellite training dataset for land cover classification*. https://mundogeo.com/en/2022/07/11/landcovernet-the-first-global-multi-satellite-training-dataset-for-land-cover-classification/

Murel, J. (2025). What is transfer learning? IBM. https://www.ibm.com/think/topics/transfer-learning

Mytton, D. (2021). *Data centre water consumption*. *npj Clean Water, 4*(11), 1–8. https://doi.org/10.1038/s41545-021-00084-2

Nunes, J. A. C. C., Cruz, I. C. S., Nunes, A., Pinheiro, H. T., & et al. (2020). *Speeding up coral reef conservation with AI-aided automated image analysis*. *Nature Machine Intelligence, 2*, 292. https://doi.org/10.1038/s42256-020-0192-3

O'Connell-Hussey, E., Thomas, V. G., Rangel Leon, V., Garcia, C., McCormack, D., & Brennan, G. T. (2025). *Artificial intelligence as an enabler of the circular economy* (Research Report No. 492).

Environmental Protection Agency, Ireland. https://www.epa.ie/publications/research/circular-economy/Research_Report-492.pdf

OECD (Organisation for Economic Co-operation and Development). (2025). Governing with Artificial Intelligence. The State of Play and Way Forward in Core Government Functions. https://www.oecd.org/en/publications/2025/06/governing-with-artificial-intelligence_398fa287/full-report/ai-in-policy-evaluation_c88cc2fd.html

OECD (Organisation for Economic Co-operation and Development). (2022). Measuring the environmental impacts of artificial intelligence compute and applications. https://www.oecd.org/en/publications/measuring-the-environmental-impacts-of-artificial-intelligence-compute-and-applications_7babf571-en.html

OECD (Organisation for Economic Co-operation and Development). (2019). Recommendation of the Council on Artificial Intelligence. Organisation for Economic Co-operation and Development. https://legalinstruments.oecd.org/en/instruments/oecd-legal-0449

OECD (Organisation for Economic Co-operation and Development). (n.d.a). AI principles. Organisation for Economic Co-operation and Development. https://www.oecd.org/en/topics/sub-issues/ai-principles.html

OECD (Organisation for Economic Co-operation and Development). (n.d.b). *Global Partnership on Artificial Intelligence*. OECD. https://www.oecd.org/en/about/programmes/global-partnership-on-artificial-intelligence.html

Olawade, D. B., Wada, O. Z., David-Olawade, A. C., Fapohunda, O., Ige, A. O., & Ling, J. (2024). *Artificial intelligence potential for net zero sustainability: Current evidence and prospects*. *Next Sustainability, 4*, Article 100041. https://doi.org/10.1016/j.nxsust.2024.100041

Parajuli, M., Cristan, R., Daniel, M. J., Rijal, A., Mitchell, D., McDonald, T., & Gallagher, T. (2025). *Integrating high-resolution imagery, deep learning, and GIS to estimate soil erosion following timber harvesting*. *Remote Sensing Applications: Society and Environment, 37*, 101498. https://doi.org/10.1016/j.rsase.2025.101498

Patterson, D., Gonzalez, J., Le, Q., Liang, C., Munguia, L.-M., Rothchild, D., So, D., Texier, M., & Dean, J. (2021). *Carbon emissions and large neural network training*. arXiv. https://arxiv.org/abs/2104.10350

Perera, I. J. J. U. N., Sandaruwan, R. D. C., & Bellanthudawa, B. K. A. (2025a). Coastal and Marine Plastic Pollution Monitoring and Control Using Remote Sensing (RS) and Artificial Intelligence (AI) Technologies. Coastal and Marine Pollution: Source to Sink, Mitigation and Management, 329-345.

Perera, M., Vidanaarachchi, R., Chandrashekeran, S., Kennedy, M., Kennedy, B., & Halgamuge, S. (2025b). Indigenous peoples and artificial intelligence: A systematic review and future directions. *Big Data & Society*, *12*(2). https://doi.org/10.1177/20539517251349170

Pérez Santín, E., Rodríguez Solana, R., González García, M., García Suárez, M. D. M., Blanco Díaz, G. D., Cima Cabal, M. D., Moreno Rojas, J. M., & López Sánchez, J. I. (2021). *Toxicity prediction based on artificial intelligence: A multidisciplinary overview*. *Wiley Interdisciplinary Reviews: Computational Molecular Science, 11*(5), e1516. https://doi.org/10.1002/wcms.1516

Peron, A. E. dos R., Almstadter Mattar de Magalhães, D., & Caetano, G. F. (2025). Beyond digital repression: techno-authoritarianism in radical right governments. Cogent Social Sciences, 11(1). https://doi.org/10.1080/23311886.2025.2528457

Raut, S. (2025). *Application of artificial intelligence in circular economy*. *Sustainable Futures Review, 2*, Article 100784. https://doi.org/10.1016/j.sftr.2025.100784

Roberts, T., Cowls, J., Morley, J., & Taddeo, M. (2022). The Impact of AI on Global Inequality. World Development, 157, 105939. https://doi.org/10.1016/j.worlddev.2022.105939

Roundy, L. (2025). *The increasing concern of data center land acquisition* [Article]. TechTarget. https://www.techtarget.com/searchdatacenter/feature/The-increasing-concern-of-data-center-land-acquisition

Royal Academy of Engineering. (2025). *Foundations for sustainable AI* [NEPC report]. https://nepc.raeng.org.uk/media/2aggau2j/foundations-for-sustainable-ai-nepc-report.pdf

Różycki, R., Solarska, D. A., & Waligóra, G. (2025). Energy-Aware Machine Learning Models—A Review of Recent Techniques and Perspectives. Energies, 18(11), 2810. https://doi.org/10.3390/en18112810

Russell, S. J., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson. https://aima.cs.berkeley.edu/global-index.html

Sablich, J. (2025). 7 global development roles that are being transformed by AI. Devex. https://www.devex.com/news/7-global-development-roles-that-are-being-transformed-by-ai-110550

Sandalow, D., McCormick, C., Kucukelbir, A., Friedmann, J., Nachmany, M., Lee, H., Hill, A., Loehr, D., Wald, M., Halff, A., Glatt, R., Benoit, P., Karl, K., et al. (2024). *Artificial intelligence for climate change mitigation roadmap* (Second Edition). Innovation for Cool Earth Forum. https://www.icef.go.jp/wp-content/themes/icef_new/pdf/roadmap/icef2024_roadmap_AI-Climate-Second-Edition.pdf

Schöning, J., & Richter, M. L. (2021, October). *AI-based crop rotation for sustainable agriculture worldwide*. In *2021 IEEE Global Humanitarian Technology Conference (GHTC)* (pp. 1–6). IEEE. https://doi.org/10.1109/GHTC53159.2021.9612460

Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2019). *Green AI*. arXiv. https://doi.org/10.48550/arXiv.1907.10597

Selmy, S. A. H., & Moursy, A. R. (2025). *Integrating remote sensing, GIS, and AI technologies in soil erosion studies*. In A. R. Moursy (Ed.), *Soil Erosion Studies*. IntechOpen. https://doi.org/10.5772/intechopen.1008677

Snoun, A., Mufida, M. K., El-Cadi, A. A., & Delot, T. (2025). *AI-driven innovations in waste management: Catalyzing the circular economy*. *Engineering Proceedings, 97*(1), Article 12. https://doi.org/10.3390/engproc2025097012

Sorrell, S., Gatersleben, B., & Druckman, A. (2020). *The limits of energy sufficiency: A review of the evidence for rebound effects in energy services*. *Energy Research & Social Science, 64*, 101439. https://doi.org/10.1016/j.erss.2020.101439

Stern, N., Romani, M., Pierfederici, R., Braun, M., Barraclough, D., Lingeswaran, S., Weirich-Benet, E., & Niemann, N. (2025). *Green and intelligent: The role of AI in the climate transition*. *npj Climate Action, 4*, Article 56. https://doi.org/10.1038/s44168-025-00252-3

Strubell, E., Ganesh, A., & McCallum, A. (2019). *Energy and policy considerations for deep learning in NLP*. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 3645–3650). https://aclanthology.org/P19-1355

Stryker, C. (n.d.). What is human-in-the-loop? IBM. https://www.ibm.com/think/topics/human-in-the-loop

Sustainability Directory (2025c). What Role Does Data Bias Play in Green AI? Prism Sustainability Directory. https://lifestyle.sustainability-directory.com/question/what-role-does-data-bias-play-in-green-ai/

Sustainability Directory (2025e). Ethical Implications of AI Environmental Monitoring. Prism Sustainability Directory. https://prism.sustainability-directory.com/scenario/ethical-implications-of-ai-environmental-monitoring/

Sustainability Directory. (2025a, October 8). *The role of AI in transboundary water cooperation*. https://prism.sustainability-directory.com/scenario/the-role-of-ai-in-transboundary-water-cooperation/

Sustainability Directory. (2025d). AI and Indigenous Knowledge Climate Adaptation Strategies. Prism Sustainability Directory. https://prism.sustainability-directory.com/scenario/ai-and-indigenous-knowledge-climate-adaptation-strategies/

Tabbakh, A., Al Amin, L., Islam, M., Mahmud, G. M. I., Chowdhury, I. K., & Mukta, M. S. H. (2024). *Towards sustainable AI: A comprehensive framework for Green AI*. *Discover Sustainability, 5*(1), Article 408. https://doi.org/10.1007/s43621-024-00641-4

The Borgen Project. (2023). AI In International Development: The Benefits and Drawbacks. The Borgen Project. https://borgenproject.org/ai-in-international-development-the-benefits-and-drawbacks/

The Times of India (2025). IIIT-H gives voice to tribal languages with AI powered tools. The Times of India. https://timesofindia.indiatimes.com/city/hyderabad/iiit-h-gives-voice-to-tribal-languages-with-ai-powered-tools/articleshow/123724962.cms

Time (2024). Peter-Lucas Jones. TIME100 AI 2024. https://time.com/7012841/peter-lucas-jones/

Tokson, M. (2025). The Authoritarian Risks of AI Surveillance. LAWFARE. https://www.lawfaremedia.org/article/the-authoritarian-risks-of-ai-surveillance

Toth, F., 2018. *Innovation and the GEF*. Scientific and Technical Advisory Panel to the Global Environment Facility, Washington, DC. https://www.stapgef.org/resources/advisory-documents/innovation-and-gef

Tounsi, A., & Temimi, M. (2023). *A systematic review of natural language processing applications for hydrometeorological hazards assessment*. *Natural Hazards, 116*(3), 2819–2870. https://doi.org/10.1007/s11069-023-05842-0

Trehan, A. (2025). Bias in Green AI Addressing Disparities in Data and Algorithms. In P. William & S. Kulkarni (Eds.), Advancing Social Equity Through Accessible Green Innovation (pp. 63-76). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-9471-7.ch005

Tropical Commons. (2018, September 5). *Rainforest Connection: Recycled smartphones alert rangers to deforestation in the Amazon*. https://tropicalcommons.co/en/2018/09/05/rainforest-connection-recycled-smart-phones-alert-rangers-to-deforestation-in-the-amazon/

Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T. C., & Madyira, D. M. (2024). *Optimizing renewable energy systems through artificial intelligence: Review and future prospects*. *Energy & Environment, 35*(7), 3833–3879. https://doi.org/10.1177/0958305X241256293

Ullah, F., Saqib, S., & Xiong, Y. C. (2025). Integrating artificial intelligence in biodiversity conservation: bridging classical and modern approaches. Biodiversity and Conservation, 34(1), 45-65.

UNCTAD (United Nations Conference on Trade and Development). (2025). 2025 Technology and innovation report. United Nations Conference on Trade and Development. https://unctad.org/publication/technology-and-innovation-report-2025

UNDP (United Nations Development Programme). (2022). UNDP Digital Strategy 2022–2025. United Nations Development Programme. https://digitalstrategy.undp.org/

UNDP (United Nations Development Programme). (2024). Leveraging artificial intelligence to enhance early action towards the Kunming-Montreal Global Biodiversity Framework. United Nations Development Programme. https://www.undp.org/publications/leveraging-artificial-intelligence-enhance-early-action-towards-kunming-montreal-global-biodiversity-framework

UNEP (United Nations Environment Programme). (2021, August 20). *UNEP and Government of Sri Lanka announce new collaboration to fight plastic pollution in rivers*. https://www.unep.org/news-and-stories/press-release/unep-and-government-sri-lanka-announce-new-collaboration-fight

UNEP (United Nations Environment Programme). (2025b). *Eye on Methane data platform*. https://methanedata.unep.org/

UNEP (United Nations Environment Programme). (2025c). *International Methane Emissions Observatory (IMEO)*. https://www.unep.org/topics/energy/methane/international-methane-emissions-observatory

UNEP (United Nations Environment Programme). (2025d, October 22). *Better data driving action on methane emissions, but more work needed*. https://www.unep.org/news-and-stories/press-release/better-data-driving-action-methane-emissions-more-work-needed

UNESCO (United Nations Educational, Scientific and Cultural Organization). (2022). Recommendation on the Ethics of Artificial Intelligence. United Nations Educational, Scientific and Cultural Organization. https://www.unesco.org/en/articles/recommendation-ethics-artificial-intelligence

UNFCCC (United Nations Framework Convention on Climate Change). (2025). *AI and climate action: Opportunities, risks and challenges for developing countries*. https://unfccc.int/news/ai-and-climate-action-opportunities-risks-and-challenges-for-developing-countries

United Nations Environment Programme. (2020). *Mineral resource governance in the 21st century* [Report]. https://www.unep.org/resources/report/mineral-resource-governance-21st-century

United Nations Environment Programme. (2025a). *AI has an environmental problem. Here's what the world can do about it*. https://www.unep.org/news-and-stories/story/ai-has-environmental-problem-heres-what-world-can-do-about

United Nations. (2024). *Governing AI for humanity: Final report of the Secretary-General's High-level Advisory Body on Artificial Intelligence*. United Nations. https://www.un.org/sites/un2.un.org/files/governing_ai_for_humanity_final_report_en.pdf

Wai, F. (2025). AI in Project Forecasting: Trends, Transformations & the Road Ahead. Digital Project Manager. https://thedigitalprojectmanager.com/project-management/ai-in-project-forecasting/;

Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). *Machine learning in modelling land-use and land-cover change (LULCC): Current status, challenges and prospects*. *Science of the Total Environment, 822*, 153559. https://doi.org/10.1016/j.scitotenv.2022.153559

Wang, J., Song, X., Yousefi, R., & Jiang, Z. (2025). *Optimal learning and management of threatened species*. *Management Science, 71*(6), 4757–4776. https://doi.org/10.1287/mnsc.2023.01753

Warrik, J., & Borthakur, S. (2024, September 10). *Farms of the future: How can AI accelerate regenerative agriculture?* World Economic Forum. https://www.weforum.org/stories/2024/09/farms-ai-accelerate-regenerative-agriculture/

WEF (World Economic Forum). (2024). *9 ways AI is helping tackle climate change*. https://www.weforum.org/stories/2024/02/ai-combat-climate-change/

Whig, P. (2025). *Green AI: Balancing computational power with environmental responsibility*. *Transaction on Recent Developments in Industrial IoT, 17*(17). https://journals.threws.com/index.php/TRDAIoT/article/view/396

Wildlife Conservation Society (WCS). (n.d.). *MERMAID: Monitoring coral reefs in a changing climate*. https://www.wcs.org/our-work/species/coral/mermaid

World Wildlife Fund. (2023, July). *ManglarIA: Using artificial intelligence to save mangroves in a changing climate*. https://www.worldwildlife.org/our-work/oceans/mangroves/manglaria-using-artificial-intelligence-to-save-mangroves-in-a-changing-climate/

WRI (World Resources Institute). (2025). *AI for Nature: How AI can democratize and scale action for Nature* [Working paper]. https://www.gstatic.com/gumdrop/sustainability/google-2025-AI-for-Nature.pdf

Yu, K. H., Zhang, Y., Li, D., Montenegro-Marin, C. E., & Kumar, P. M. (2021). *Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence*. *Environmental Impact Assessment Review, 86*, 106492. https://doi.org/10.1016/j.eiar.2020.106492

Yun-Pu Tu, M. (2025). AI threatens Indigenous data sovereignty and digital self-determination. Policy Options. https://policyoptions.irpp.org/2025/05/ai-indigenous-data/

Zewe, A. (2019, October 10). *Outsmarting poachers: Artificial intelligence helps rangers protect endangered wildlife*. Harvard John A. Paulson School of Engineering and Applied Sciences. https://seas.harvard.edu/news/2019/10/outsmarting-poachers

Zuzanna, K., Tomasz, U., Michał, G., & Robert, P. (2022). How high-tech solutions support the fight against IUU and ghost fishing: a review of innovative approaches, methods, and trends. IEEE Access, 10, 112539-112554.

Zweig List (2021). UNEP and Google partner to hunt for plastic pollution with machine learning. Zweig List. https://zweiglist.com/unep-and-google-partner-to-hunt-for-plastic-pollution-with-machine-learning/